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Exploring attributes, sequences, and time in Recommender Systems: From classical to Point-of-Interest recommendation

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Overview

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Introduction

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amazon

NETFLIX

Spotify

STEAM

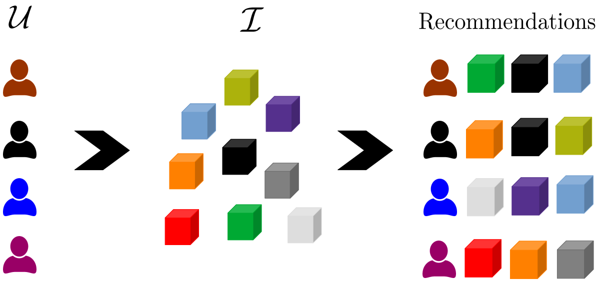
twitter

yelp

YouTube

LinkedIn

foursquare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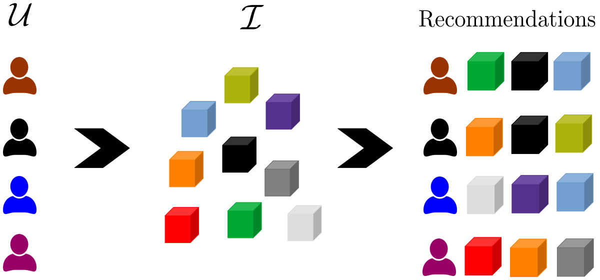
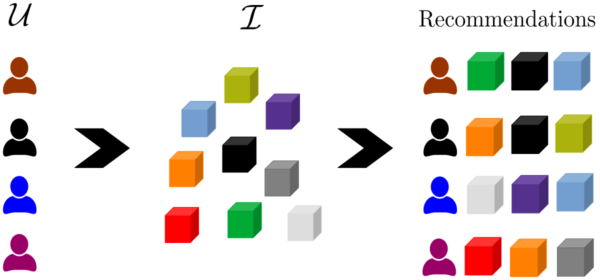
$\mathcal{I}$
Recommendations



	i_1	i_2	i_3	i_4	$\cdots$
u_1	-	-	-	3	$\cdots$
u_2	4	-	4	-	$\cdots$
u_3	5	5	-	-	$\cdots$
u_4	-	2	1	-	$\cdots$
u_5	-	-	-	-	$\cdots$
u_6	-	-	-	1	$\cdots$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$

Sparsity $\sim$ 99%



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Objective: maximize the **usefulness** of the items for the target user ($\max \boldsymbol{g(u,i)}$)

Recommender Systems

$$i^*(u) = \arg\max_{i \in \mathcal{I}} g(u, i) \tag{1}$$

—[Adomavicius and Tuzhilin, 2005]

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- More information: **Chapter 2**

Recommender Systems: offline evaluation

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- Metrics:
  - Error metrics (rating prediction): MAE, RMSE, ...

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  - Novelty and diversity: Item Coverage (IC), Gini, EPC, ...

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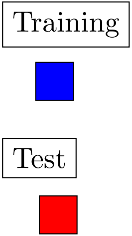
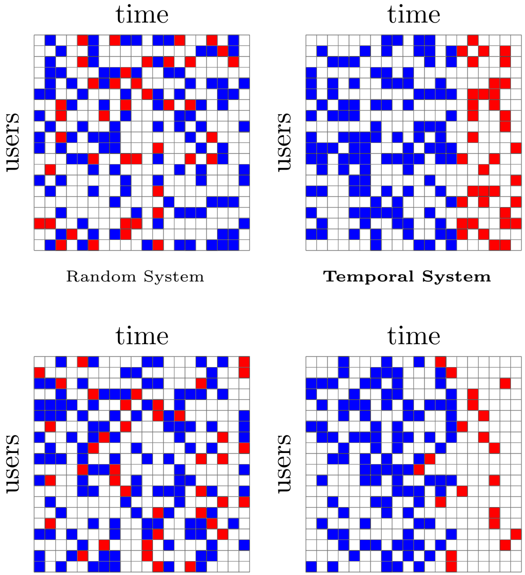
$$\mathrm{IC} = \left| \bigcup_{u \in \mathcal{U}} R_u \right| \tag{4}$$

Recommender Systems: types of data splitting





Random System

Temporal System

Random Per User

Temporal Per User

- Data splitting
  - Random vs Temporal
  - Per user vs system

Recommender Systems: types of data splitting

Training

Test

- Data splitting
  - Random vs Temporal
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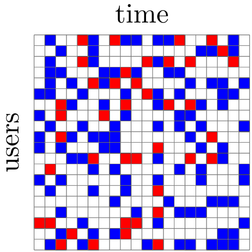

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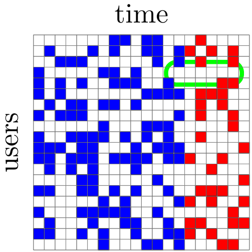
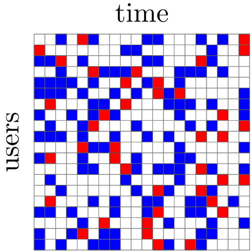
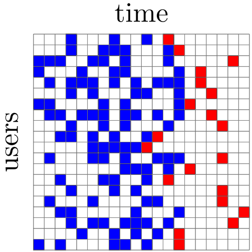


Temporal System



Random Per User



Temporal Per User

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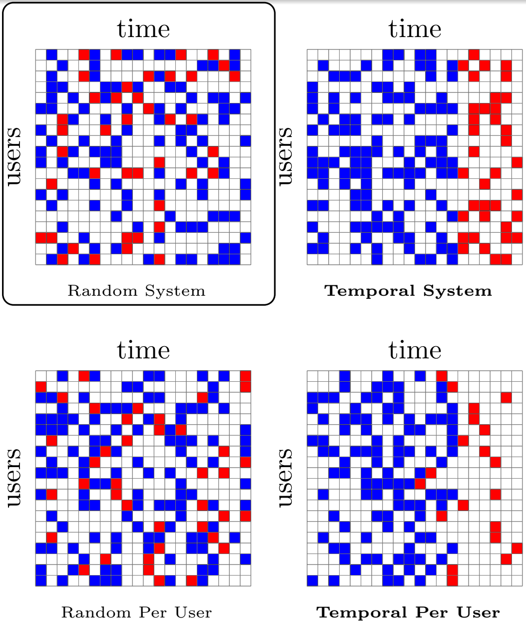

- Data splitting
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Research Objectives

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- RO1: Integrating **additional dimensions beyond relevance** in evaluation metrics
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  - We use temporal information, attributes, and low ratings for evaluating the recommenders
  - We obtain more complete results of the performance of the recommenders and we detect additional biases
- RO2: Incorporate **sequentiality** in **neighborhood-based recommenders**
  - We develop a sequential similarity metric and we redefine the formulation of k-NN recommenders
  - Our approaches are highly competitive in relevance, novelty and diversity

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  - We characterize POI recommendation works between 2011 and 2019 analyzing the algorithms, the information, and the evaluation methodology used

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  - We propose multi-city aggregation strategies to augment the information of the recommenders
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- RO5: **Generate full sequences** from **Location-Based Social Networks** data
  - We will use reranking techniques to generate routes from independent POIs
  - We demonstrate how we can improve the recommendations across different dimensions (category and/or distance) using our reranking approaches

Overview

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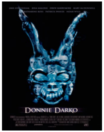
  2. Anti-relevance models
  3. User and item attributes
- **Contributions published** in ECIR [Sánchez and Bellogín, 2018b] and RecSys [Sánchez and Bellogín, 2019a, Sánchez and Bellogín, 2018a]

Time-aware novelty metrics

Time-aware novelty metrics

R_1



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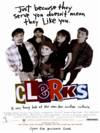

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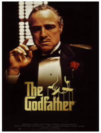
R_2



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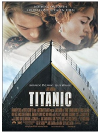

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R_3

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Time-aware novelty metrics

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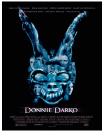

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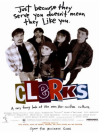

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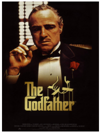

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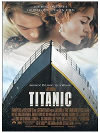

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- Best in Relevance?

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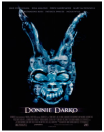

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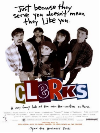

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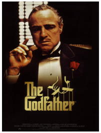

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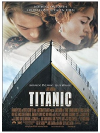

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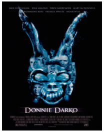

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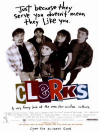

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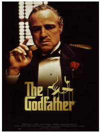

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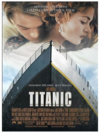

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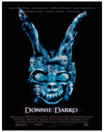

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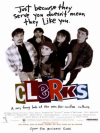

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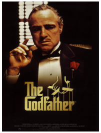

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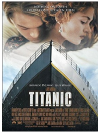

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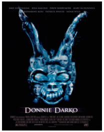

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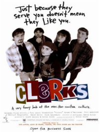

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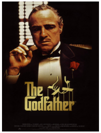

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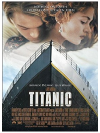

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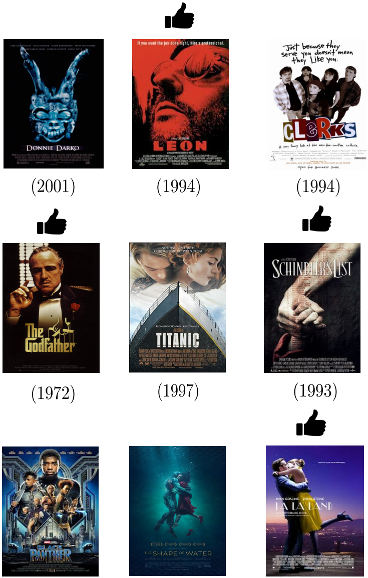

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Time-aware novelty metrics

- Probabilistic framework from [Vargas and Castells, 2011]

$$m(R_u \mid \theta) = C \sum_{i_n \in R_u} \mathrm{disc}(n) p(rel \mid i_n, u) \mathrm{nov}(i_n \mid \theta) \tag{5}$$

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- Where:
  - R_u items recommended to user u
  - θ contextual variable (e.g., the user profile)
  - $\mathrm{disc}(n)$ is a discount model (e.g. nDCG)
  - $p(rel \mid i_n, u)$ relevance component
  - $\mathrm{nov}(i_n \mid \theta)$ **novelty model**

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- For example, when using $\mathrm{nov}(i_n \mid \theta) = (1 - p(\mathrm{seen}|i))$ we obtain the Expected Popularity Complement (EPC) metric
- However, all the metrics derived from this framework are *time-agnostic*
- We propose to replace the novelty component defining new **time-aware novelty models**

- Every item in the system can be modeled with a temporal representation:

$$\theta_t = \{\theta_t(i)\} = \{(i, \langle t_1(i), \cdots, t_n(i)\rangle)\} \tag{7}$$

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- We will use the rating history of the items for generating the temporal representation
- We explore 4 aggregation functions: the first interaction (FIN), the last interaction (LIN), the **average of the ratings times (AIN)** and the **median of the ratings times (MIN)**

Time-aware novelty metrics

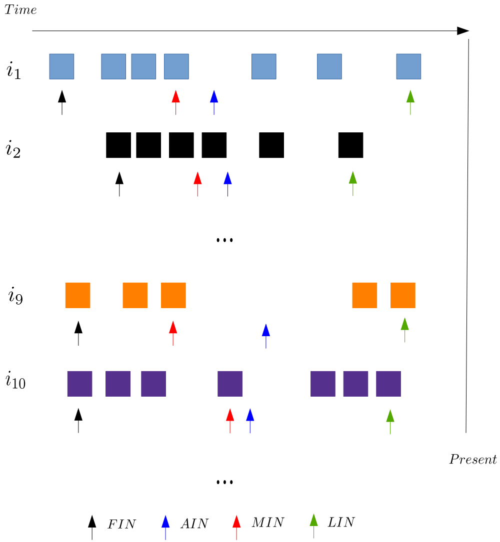
- Every item in the system can be modeled with a temporal representation:

$$\theta_t = \{\theta_t(i)\} = \{(i, \langle t_1(i), \cdots, t_n(i)\rangle)\} \tag{7}$$

- We will use the rating history of the items for generating the temporal representation
- We explore 4 aggregation functions: the first interaction (FIN), the last interaction (LIN), the **average of the ratings times (AIN)** and the **median of the ratings times (MIN)**
- We normalize the values to be suitable for the probabilistic framework (min-max normalization)

Time-aware novelty metrics

- Differences between the proposed aggregation functions



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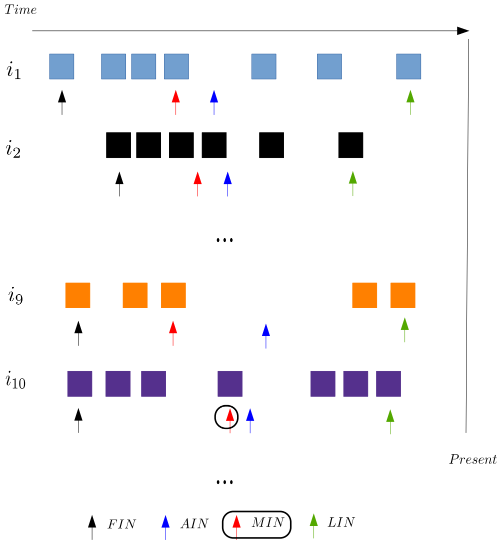

- MIN

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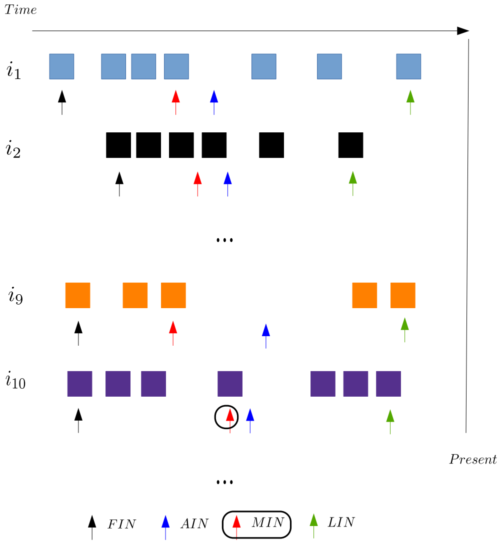

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  - $i_{10} > i_2 > i_9 > i_1$

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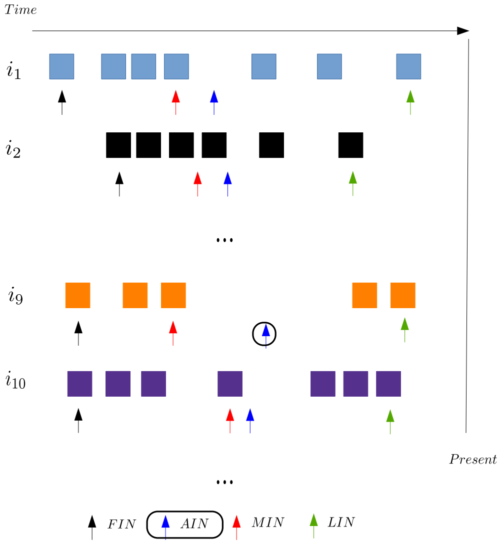

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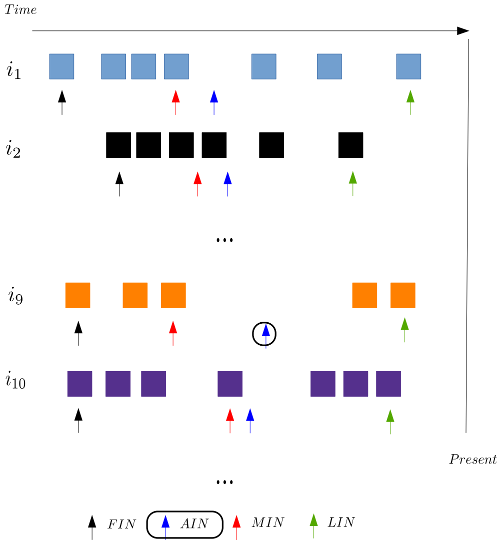

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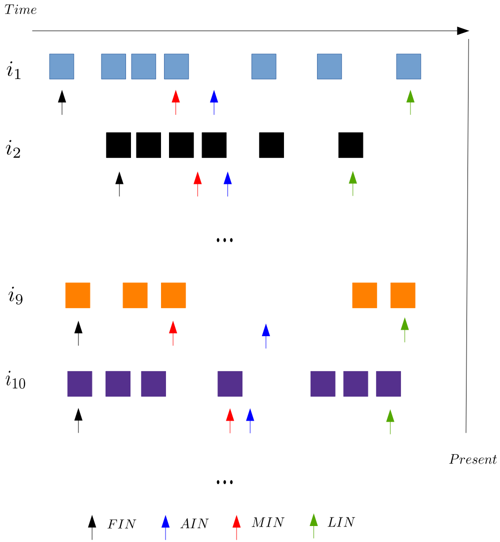

- MIN
  - $i_{10} > i_2 > i_9 > i_1$
- AIN
  - $i_9 > i_{10} > i_2 > i_1$
- FIN
  - $i_2 > i_{10} > i_9 > i_1$
- LIN
  - $i_9 > i_1 > i_{10} > i_2$

Time-aware novelty metrics: a summary

- We propose metrics that **exploit** the **temporal information** of the **interactions of the items**

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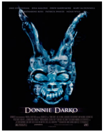
- Our metrics allow us to measure the **temporal novelty** of the items in the system
- Our metrics are **integrated** in a previous defined **novelty framework**
- We believe that **AIN** and **MIN** are the strategies that capture better the **temporal evolution** of the items

Anti-relevance metrics

Anti-relevance metrics

R_1



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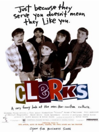
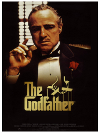
(1994)



(1994)

R_2



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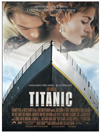

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(1993)

R_3

(2018)

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Anti-relevance metrics

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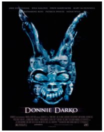

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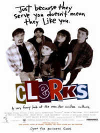

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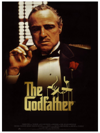

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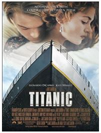

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Anti-relevance metrics

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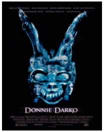

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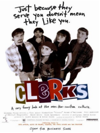

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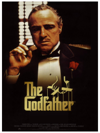

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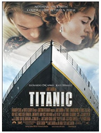

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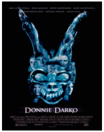

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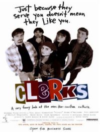

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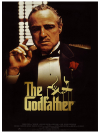

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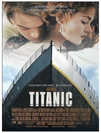

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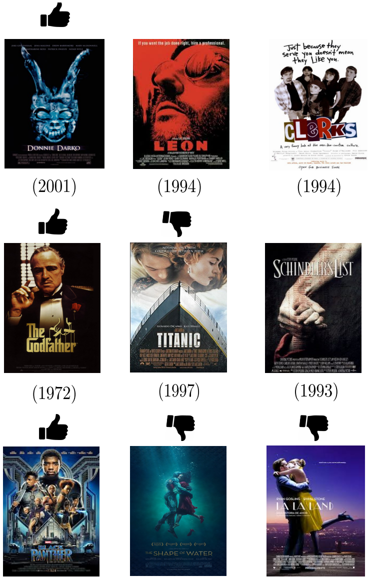

R_1: (2001) (1994) (1994)

R_2: (1972) (1997) (1993)

R_3: (2018) (2017) (2016)

- Best recommmendation list?
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- But R_3 return 2 bad items
- We should also **measure** the **anti-relevant** items

Anti-relevance metrics

- The Probabilistic Ranking Principle (PRP):

> *If a system's response to a query is a ranking of documents in order of decreasing probability of relevance, the overall effectiveness of the system to its users will be maximized*
>
> —[Robertson, 1997]

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> —[Robertson, 1997]

- Most ranking-based accuracy metrics are formulated to estimate the classical PRP:

$$m(R_u|\theta_{rel}) = C \sum_{i \in R_u} m(\theta_{rel}(r_{ui})|u, i) \tag{8}$$

Anti-relevance metrics

- We study the dual PRP problem:

$$\overline{m}(R_u|\theta_{arel}) = C \sum_{i \in R_u} (1 - \overline{m}(\theta_{arel}(r_{ui})|u,i)) \propto$$
$$\propto 1 - C' \sum_{i \in R_u} m(\theta_{arel}(r_{ui})|u,i) = \boxed{1 - m(R_u|\theta_{arel})} \quad (9)$$

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- Our anti-relevance metrics formulation is equivalent to computing any relevance-based metric using an anti-relevance model (where an item is relevant if $r_{ui} \leq \tau_{AR}$) and returning its complement. **Higher value implies less anti-relevant items recommended**

Anti-relevance metrics: a summary

- Relevance metrics **only measure** the amount of **highly relevant** items recommended by the user

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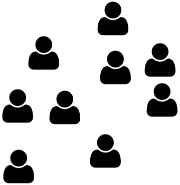
- However, we should also **measure** the number of items **with low ratings** that we are recommending to the users. Users tend to **penalize** the recommenders **mistakes**
- We can analyze the **anti-relevance** of the items by computing classical relevance metrics with an **anti-relevance models**

Incorporating user and item attributes in our metrics

- We **usually** assume that all users in the system are **equal**



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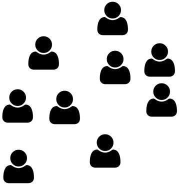

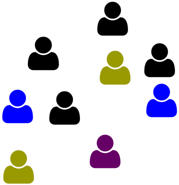

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- Should not we be analyzing the **performance** of **specific groups** of users?

$$m(\theta) = C^{-1} \sum_{u \in \mathcal{U}} c(u) \cdot m(R_u, \theta) \qquad (10)$$

Item attributes

- In every recommendation we can distinguish the **items that appear in the test set $\boldsymbol{w^+}$**, non-relevant items that share similarity with the items in test w^* and the rest w^-

$$m(R_u, \theta) \propto \sum_{\boldsymbol{i \in I^+(u)}} \boldsymbol{w^+(u,i)} + \sum_{i \in I^*(u)} w^*(u,i) + \sum_{i \in I^-(u)} w^-(u,i) \tag{11}$$

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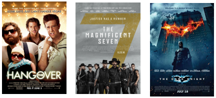
Test

R_1



Test $\sim R_1$

$|I^+| = 0$

$|I^*| = 0$

$|I^-| = 3$

R_2

Test $\approx R_2$

$|I^+| = 0$

$|I^*| = 3$

$|I^-| = 0$

Attributes in evaluation: a summary

- We can use **user attributes** to **detect** possible **biases** in the algorithms. The recommendations might be biased toward the majority groups

Attributes in evaluation: a summary

- We can use **user attributes** to **detect** possible **biases** in the algorithms. The recommendations might be biased toward the majority groups
- **Item attributes** can be integrated into classical relevance metrics to consider more items in the recommendations as **partially relevant**

- Objective: **test our metrics in well-known datasets**

Experiments on new metrics

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- Datasets:
  - **Movielens1M: 6k users, 3.7k items, 1M ratings (1-5)**
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- Splits:
  - **Temporal system split (TS, 80% training)**
  - Random system split (RS, 80% training)

Experiments: time-aware novelty metrics

- Skyline obtain high results in our time-aware novelty metrics. Temporal novel items are relevant

Recommender	FIN	AIN	MIN	LIN
Rnd	**0.118**	**0.630**	**0.616**	0.971
Rnd_{CF}	0.112	0.626	0.611	0.972
Pop	0.000	0.614	0.592	†**1.000**
Pop_{CF}	0.000	0.613	0.591	1.000
UBCB	0.001	0.608	0.579	0.999
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Experiments: time-aware novelty metrics. Metrics @5

- Some sequential recommenders do not obtain high results in time-aware novelty metrics

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Experiments: anti-relevance metrics

- Rnd recommender achieves highest values in anti-relevance metrics

Recommender	**P**	$\overline{\textbf{P}}$	**nDCG**	$\overline{\textbf{nDCG}}$
Rnd	0.019	0.993	0.012	0.996
Rnd_{CF}	0.015	**0.994**	0.008	**0.997**
Pop	**0.281**	0.977	**0.221**	0.981
Pop_{CF}	0.210	0.979	0.161	0.983
UBCB	0.254	0.979	0.195	0.985
IB	0.234	0.979	0.177	0.987
UB	0.248	0.985	0.195	0.990
HKV	0.257	0.985	0.202	0.990
BPRMF	0.231	0.975	0.172	0.983
TD	0.248	0.987	0.194	0.990
MC	0.177	0.972	0.134	0.978
FPMC	0.212	0.979	0.159	0.985
Fossil	0.227	0.974	0.170	0.984
Caser	0.192	0.969	0.136	0.977
Skyline	†**0.943**	†**1.000**	†**1.000**	†**1.000**
$\text{Skyline}_{\text{CF}}$	0.911	1.000	0.999	1.000
$\overline{\text{Skyline}}$	0.000	0.189	0.000	0.001
$\overline{\text{Skyline}_{\text{CF}}}$	0.000	0.221	0.000	0.001

Experiments: anti-relevance metrics. Metrics @5

- Personalized recommenders sometimes fail in the recommendations

Recommender	**P**	$\overline{\mathbf{P}}$	**nDCG**	$\overline{\mathbf{nDCG}}$
Rnd	0.019	0.993	0.012	0.996
Rnd_{CF}	0.015	**0.994**	0.008	**0.997**
Pop	**0.281**	0.977	**0.221**	0.981
Pop_{CF}	0.210	0.979	0.161	0.983
UBCB	0.254	0.979	0.195	0.985
IB	0.234	0.979	0.177	0.987
UB	0.248	0.985	0.195	0.990
HKV	0.257	0.985	0.202	0.990
BPRMF	0.231	0.975	0.172	0.983
TD	0.248	0.987	0.194	0.990
MC	0.177	0.972	0.134	0.978
FPMC	0.212	0.979	0.159	0.985
Fossil	0.227	0.974	0.170	0.984
Caser	0.192	0.969	0.136	0.977
Skyline	†**0.943**	†**1.000**	†**1.000**	†**1.000**
$\text{Skyline}_{\text{CF}}$	0.911	1.000	0.999	1.000
$\overline{\text{Skyline}}$	0.000	0.189	0.000	0.001
$\overline{\text{Skyline}_{\text{CF}}}$	0.000	0.221	0.000	0.001

Experiments: user and item attributes

Experiments: user and item attributes (nDCG@5)

- In Movielens1M, users with more than 56 years (∼5%) tend to obtain lower results in terms of relevance

Family	Std	Gender		Age				Test Quartile			
		F	M	1	18	35	56	Q1	Q2	Q3	Q4
Rnd	0.012	0.011	0.012	0.011	0.014	0.009	0.005	0.003	0.004	0.016	0.023
Rnd_{CF}	0.008	0.010	0.008	0.003	0.009	0.009	0.000	0.002	0.003	0.006	0.027
Pop	0.221	0.177	**0.238**	0.192	**0.250**	**0.190**	0.132	0.055	0.160	0.260	**0.406**
Pop_{CF}	0.161	0.131	0.171	0.185	0.178	0.135	0.101	0.043	0.114	0.219	0.344
UBCB	0.195	0.177	0.202	0.195	0.206	0.180	0.164	0.057	**0.178**	0.264	0.368
IB	0.177	0.153	0.185	0.168	0.187	0.161	0.166	0.052	0.144	0.239	0.351
UB	0.195	0.173	0.202	0.194	0.208	0.176	0.160	0.067	0.165	0.274	0.352
HKV	**0.202**	**0.184**	0.209	**0.207**	0.213	0.185	**0.191**	**0.074**	0.166	**0.284**	0.366
BPRMF	0.172	0.166	0.175	0.180	0.179	0.164	0.144	0.056	0.144	0.232	0.330
TD	0.194	0.176	0.200	0.188	0.205	0.178	0.171	0.066	0.162	0.270	0.358
MC	0.134	0.127	0.137	0.127	0.142	0.123	0.122	0.052	0.109	0.170	0.257
FPMC	0.159	0.139	0.166	0.196	0.176	0.134	0.085	0.044	0.124	0.215	0.327
Fossil	0.170	0.178	0.168	0.160	0.177	0.160	0.172	0.062	0.134	0.221	0.333
Caser	0.136	0.141	0.135	0.114	0.143	0.128	0.129	0.044	0.109	0.202	0.248
Skyline	†**1.000**	†**1.000**	†**1.000**	†**1.000**	†**1.000**	†**0.999**	†**1.000**	†**1.000**	†**1.000**	†**0.999**	†**1.000**
$\text{Skyline}_{\text{CF}}$	0.999	1.000	0.999	1.000	1.000	0.999	1.000	1.000	1.000	0.998	1.000

- In Movielens1M and FS (Tokyo), females (∼27% and ∼11%) also tend to obtain lower in terms of relevance

Family	Std	Gender		Age				Test Quartile			
		F	M	1	18	35	56	Q1	Q2	Q3	Q4
Rnd	0.012	0.011	0.012	0.011	0.014	0.009	0.005	0.003	0.004	0.016	0.023
Rnd_{CF}	0.008	0.010	0.008	0.003	0.009	0.009	0.000	0.002	0.003	0.006	0.027
Pop	0.221	0.177	**0.238**	0.192	**0.250**	**0.190**	0.132	0.055	0.160	0.260	**0.406**
Pop_{CF}	0.161	0.131	0.171	0.185	0.178	0.135	0.101	0.043	0.114	0.219	0.344
UBCB	0.195	0.177	0.202	0.195	0.206	0.180	0.164	0.057	**0.178**	0.264	0.368
IB	0.177	0.153	0.185	0.168	0.187	0.161	0.166	0.052	0.144	0.239	0.351
UB	0.195	0.173	0.202	0.194	0.208	0.176	0.160	0.067	0.165	0.274	0.352
HKV	**0.202**	**0.184**	0.209	**0.207**	0.213	0.185	**0.191**	**0.074**	0.166	**0.284**	0.366
BPRMF	0.172	0.166	0.175	0.180	0.179	0.164	0.144	0.056	0.144	0.232	0.330
TD	0.194	0.176	0.200	0.188	0.205	0.178	0.171	0.066	0.162	0.270	0.358
MC	0.134	0.127	0.137	0.127	0.142	0.123	0.122	0.052	0.109	0.170	0.257
FPMC	0.159	0.139	0.166	0.196	0.176	0.134	0.085	0.044	0.124	0.215	0.327
Fossil	0.170	0.178	0.168	0.160	0.177	0.160	0.172	0.062	0.134	0.221	0.333
Caser	0.136	0.141	0.135	0.114	0.143	0.128	0.129	0.044	0.109	0.202	0.248
Skyline	**†1.000**	**†1.000**	**†1.000**	**†1.000**	**†1.000**	**†0.999**	**†1.000**	**†1.000**	**†1.000**	**†0.999**	**†1.000**
$\text{Skyline}_{\text{CF}}$	0.999	1.000	0.999	1.000	1.000	0.999	1.000	1.000	1.000	0.998	1.000

Experiments: user and item attributes (nDCG@5)

- The higher the test quartile, the higher the results obtained (more items in the test set)

		Gender		Age				Test Quartile			
Family	**Std**	**F**	**M**	**1**	**18**	**35**	**56**	**Q1**	**Q2**	**Q3**	**Q4**
Rnd	0.012	0.011	0.012	0.011	0.014	0.009	0.005	0.003	0.004	0.016	0.023
Rnd_{CF}	0.008	0.010	0.008	0.003	0.009	0.009	0.000	0.002	0.003	0.006	0.027
Pop	0.221	0.177	**0.238**	0.192	**0.250**	**0.190**	0.132	0.055	0.160	0.260	**0.406**
Pop_{CF}	0.161	0.131	0.171	0.185	0.178	0.135	0.101	0.043	0.114	0.219	0.344
UBCB	0.195	0.177	0.202	0.195	0.206	0.180	0.164	0.057	**0.178**	0.264	0.368
IB	0.177	0.153	0.185	0.168	0.187	0.161	0.166	0.052	0.144	0.239	0.351
UB	0.195	0.173	0.202	0.194	0.208	0.176	0.160	0.067	0.165	0.274	0.352
HKV	**0.202**	**0.184**	0.209	**0.207**	0.213	0.185	**0.191**	**0.074**	0.166	**0.284**	0.366
BPRMF	0.172	0.166	0.175	0.180	0.179	0.164	0.144	0.056	0.144	0.232	0.330
TD	0.194	0.176	0.200	0.188	0.205	0.178	0.171	0.066	0.162	0.270	0.358
MC	0.134	0.127	0.137	0.127	0.142	0.123	0.122	0.052	0.109	0.170	0.257
FPMC	0.159	0.139	0.166	0.196	0.176	0.134	0.085	0.044	0.124	0.215	0.327
Fossil	0.170	0.178	0.168	0.160	0.177	0.160	0.172	0.062	0.134	0.221	0.333
Caser	0.136	0.141	0.135	0.114	0.143	0.128	0.129	0.044	0.109	0.202	0.248
Skyline	**†1.000**	**†1.000**	**†1.000**	**†1.000**	**†1.000**	**†0.999**	**†1.000**	**†1.000**	**†1.000**	**†0.999**	**†1.000**
$\text{Skyline}_{\text{CF}}$	0.999	1.000	0.999	1.000	1.000	0.999	1.000	1.000	1.000	0.998	1.000

Experiments: user and item attributes (nDCG@5)

- Using the both main and secondary features we obtain higher results than the pure metric

Family	nDCG $\tau = 0$	τ_m	τ_s	τ_{ms}
Rnd	0.012	0.034	0.269	0.276
Rnd_{CF}	0.008	0.023	0.251	0.255
Pop	**0.221**	**0.244**	0.361	0.372
Pop_{CF}	0.161	0.189	0.308	0.322
UBCB	0.195	0.221	0.356	0.366
IB	0.177	0.206	0.322	0.337
UB	0.195	0.224	0.347	0.360
HKV	0.202	0.230	**0.364**	**0.375**
BPRMF	0.172	0.201	0.334	0.347
TD	0.194	0.223	0.347	0.361
MC	0.134	0.170	0.312	0.327
FPMC	0.159	0.181	0.314	0.325
Fossil	0.170	0.195	0.331	0.342
Caser	0.136	0.166	0.309	0.321
Skyline	†**1.000**	†**1.000**	†**1.000**	†**1.000**
$\text{Skyline}_{\text{CF}}$	0.999	0.999	0.999	0.999

$\tau = 0$: pure metric
τ_m: main feature (directors)
τ_s: secondary feature (genres)

Experiments: user and item attributes (nDCG@5)

- Misleading results might be obtained using higher values of the similarities (Rnd recommender becomes competitive)

$\tau = 0$: pure metric
τ_m: main feature (directors)
τ_s: secondary feature (genres)

	nDCG			
Family	$\tau = 0$	τ_m	τ_s	τ_{ms}
Rnd	0.012	0.034	0.269	0.276
Rnd_{CF}	0.008	0.023	0.251	0.255
Pop	**0.221**	**0.244**	0.361	0.372
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HKV	0.202	0.230	**0.364**	**0.375**
BPRMF	0.172	0.201	0.334	0.347
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Fossil	0.170	0.195	0.331	0.342
Caser	0.136	0.166	0.309	0.321
Skyline	†**1.000**	†**1.000**	†**1.000**	†**1.000**
$\text{Skyline}_{\text{CF}}$	0.999	0.999	0.999	0.999

Summary

- Analyzing **only** the **relevance** of recommendations is **incomplete**

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Summary

- Analyzing **only** the **relevance** of recommendations is **incomplete**
- There is a **relationship** between **time-aware novelty metrics** and **relevance**
- The RS community should further **analyze** the **bad recommendations** of the algorithms

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- There is a **relationship** between **time-aware novelty metrics** and **relevance**
- The RS community should further **analyze** the **bad recommendations** of the algorithms
- The RS community should **exploit** the **attributes** of both users and items to better analyze the performance of the recommenders

- Second objective: develop mechanisms to **incorporate sequentiality** in **k-NN recommender systems**

k-NN recommender systems

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- We will define a **sequential similarity metric** based on LCS

k-NN recommender systems

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k-NN recommender systems

- Second objective: develop mechanisms to **incorporate sequentiality** in ***k*-NN recommender systems**
- We will define a **sequential similarity metric** based on LCS
- We will also **redefine** the classical formulation of ***k*-NN recommender systems**
- **Contributions published** in Information Processing and Management [Sánchez and Bellogín, 2020b] journal. Based on the future work of [Sánchez and Bellogín, 2019b] and [Bellogín and Sánchez, 2017]. Research conducted during the master's degree.

Defining a new similarity metric

k-NN recommender systems

- Classic formulation of k-NN recommender systems:

$$\hat{r}_{ui} = \sum_{v \in \mathcal{N}_i(u)} r_{vi} \boxed{w_{uv}} \tag{12}$$

k-NN recommender systems

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$$\hat{r}_{ui} = \sum_{v \in \mathcal{N}_i(u)} r_{vi} \boxed{w_{uv}} \tag{12}$$

$$\text{Cosine similarity}(u,v) = \frac{\sum_{i \in \mathcal{I}_{uv}} r_{ui} r_{vi}}{\sqrt{\sum_{i \in \mathcal{I}_u} r_{ui}^2 \sum_{j \in \mathcal{I}_v} r_{vj}^2}} \tag{13}$$

$$\text{Pearson correlation}(u,v) = \frac{\sum_{i \in \mathcal{I}_{uv}} (r_{ui} - \overline{r}_u)(r_{vi} - \overline{r}_v)}{\sqrt{\sum_{i \in \mathcal{I}_{uv}} (r_{ui} - \overline{r}_u)^2 \sum_{i \in \mathcal{I}_{uv}} (r_{vi} - \overline{r}_v)^2}} \tag{14}$$

- Classic formulation of k-NN recommender systems:

$$\hat{r}_{ui} = \sum_{v \in \mathcal{N}_i(u)} r_{vi} \boxed{w_{uv}} \tag{12}$$

$$\cancel{\text{Cosine similarity}(u,v) = \frac{\sum_{i \in \mathcal{I}_{uv}} r_{ui} r_{vi}}{\sqrt{\sum_{i \in \mathcal{I}_u} r_{ui}^2 \sum_{j \in \mathcal{I}_v} r_{vj}^2}}} \tag{13}$$

$$\cancel{\text{Pearson correlation}(u,v) = \frac{\sum_{i \in \mathcal{I}_{uv}} (r_{ui} - \overline{r}_u)(r_{vi} - \overline{r}_v)}{\sqrt{\sum_{i \in \mathcal{I}_{uv}} (r_{ui} - \overline{r}_u)^2 \sum_{i \in \mathcal{I}_{uv}} (r_{vi} - \overline{r}_v)^2}}} \tag{14}$$

- We propose a sequential similarity metric between users u and v:

$$\boldsymbol{w_{uv} \sim LCS(u,v)}$$

Longest Common Subsequence

- Applications on text comparison and DNA sequences

```
procedure LCS(x, y)                                  ▷ LCS between x and y
    L[0···m, 0···n] ← 0
    for i ← 1, m do
        for j ← 1, n do                              ▷ There is a match
            if x_i = y_j then
                L[i, j] ← L[i − 1, j − 1] + 1
            else
                L[i, j] ← max(L[i, j − 1], L[i − 1, j])
            end if
        end for
    end for
    return L[m, n]   ▷ L[m, n] contains the length of the LCS between x_1 ... x_i and y_1 ... y_j
end procedure
```

Longest Common Subsequence

- Applications on text comparison and DNA sequences

procedure LCS(x, y) ▷ LCS between x and y
    $L[0 \cdots m, 0 \cdots n] \leftarrow 0$
    for $i \leftarrow 1, m$ **do**
        for $j \leftarrow 1, n$ **do** ▷ There is a match
            if $x_i = y_j$ **then**
                $L[i, j] \leftarrow L[i-1, j-1] + 1$
            else
                $L[i, j] \leftarrow \max(L[i, j-1], L[i-1, j])$
            end if
        end for
    end for
    return $L[m, n]$ ▷ $L[m, n]$ contains the length of the LCS between $x_1 \ldots x_i$ and $y_1 \ldots y_j$
end procedure

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \quad (15)$$

	∅	A	G	G	T	A	C
∅							
G							
C							
G							
T							
G							
C							

Longest Common Subsequence: example

Longest Common Subsequence

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	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G							
C							
G							
T							
G							
C							

Longest Common Subsequence: example

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	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C							
G							
T							
G							
C							

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G							
T							
G							
C							

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	$\emptyset$	A	G	G	T	A	C
$\emptyset$	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T							
G							
C							

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T	0	0	1	2	3	3	3
G							
C							

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T	0	0	1	2	3	3	3
G	0	0	1	2	3	3	3
C							

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T	0	0	1	2	3	3	3
G	0	0	1	2	3	3	3
C	0	0	1	2	3	3	4

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \quad (15)$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T	0	0	1	2	3	3	3
G	0	0	1	2	3	3	3
C	0	0	1	2	3	3	4

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
T	0	0	1	2	3	3	3
G	0	0	1	2	3	3	3
C	0	0	1	2	3	3	4

Longest Common Subsequence: example

Longest Common Subsequence

$$L[i,j] = \begin{cases} 0 & \text{if i=0 or j=0} \\ L[i-1,j-1]+1 & \text{if } i,j>0 \text{ and } X_i = Y_j \\ \max(L[i,j-1], L[i-1,j]) & \text{if } i,j>0 \text{ and } X_i \neq Y_j \end{cases} \tag{15}$$

	∅	A	G	G	T	A	C
∅	0	0	0	0	0	0	0
G	0	0	1	1	1	1	1
C	0	0	1	1	1	1	2
G	0	0	1	2	2	2	2
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The LCS may not be unique

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Longest Common Subsequence for RS

procedure LCS_RecSys(u, v, f, δ) ▷ The LCS of users u and v applying transformation f
    $(x, y) \leftarrow (f(u), f(v))$ ▷ String x contains m symbols
    $L[0 \cdots m, 0 \cdots n] \leftarrow 0$
    for $i \leftarrow 1, m$ **do**
        for $j \leftarrow 1, n$ **do** ▷ There is a δ-matching
            if `match`(x_i, y_j, δ) **then**
                $L[i, j] \leftarrow L[i-1, j-1] + 1$
            else
                $L[i, j] \leftarrow \max(L[i, j-1], L[i-1, j])$
            end if
        end for
    end for
    return $L[m, n]$
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    for i ← 1, m do
        for j ← 1, n do             ▷ There is a δ-matching
            if match(x_i, y_j, δ) then
                L[i, j] ← L[i − 1, j − 1] + 1
            else
                L[i, j] ← max(L[i, j − 1], L[i − 1, j])
            end if
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                $L[i, j] \leftarrow L[i-1, j-1] + 1$

            else

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            end if

        end for

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    return $L[m, n]$

end procedure

LCS normalizations

- LCS algorithm obtain values in the $[0, min(|f(u)|, |f(v)|)]$ interval

$$\mathrm{sim}_1^{f,\delta}(u,v) \quad = \quad \text{LCS\_Recsys}(u,v,f,\delta) \tag{16}$$

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$$\mathrm{sim}_1^{f,\delta}(u,v) = \mathrm{LCS\_Recsys}(u,v,f,\delta) \tag{16}$$

$$\mathrm{sim}_2^{f,\delta}(u,v) = \frac{\mathrm{sim}_1^{f,\delta}(u,v)^2}{|f(u)| \cdot |f(v)|} \tag{17}$$

$$\mathrm{sim}_3^{f,\delta}(u,v) = \frac{2 \cdot \mathrm{sim}_1^{f,\delta}(u,v)}{|f(u)| + |f(v)|} \tag{18}$$

$$\mathrm{sim}_4^{f,\delta}(u,v) = \frac{\mathrm{sim}_1^{f,\delta}(u,v)}{\max\left(|f(u)|, |f(v)|\right)} \tag{19}$$

$$\mathrm{sim}_5^{f,\delta}(u,v) = \frac{\mathrm{sim}_1^{f,\delta}(u,v)}{\min\left(|f(u)|, |f(v)|\right)} \tag{20}$$

Redefining k-NN recommender systems

Redefining k-NN RS: Backward-Forward algorithm

- Obtain the neighbors using any similarity metric (classical or sequential)

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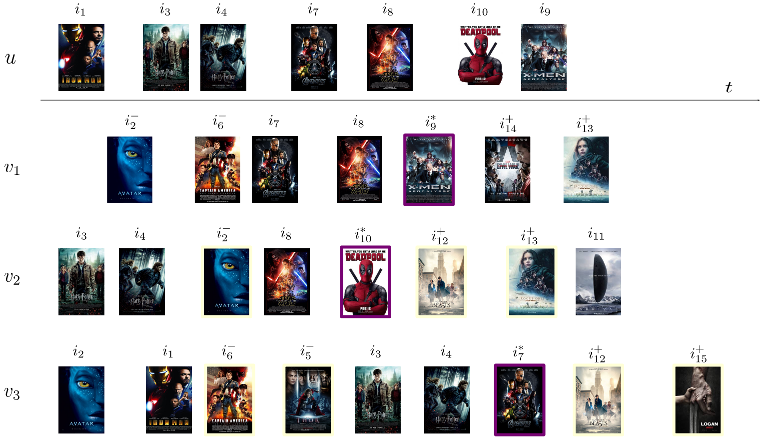
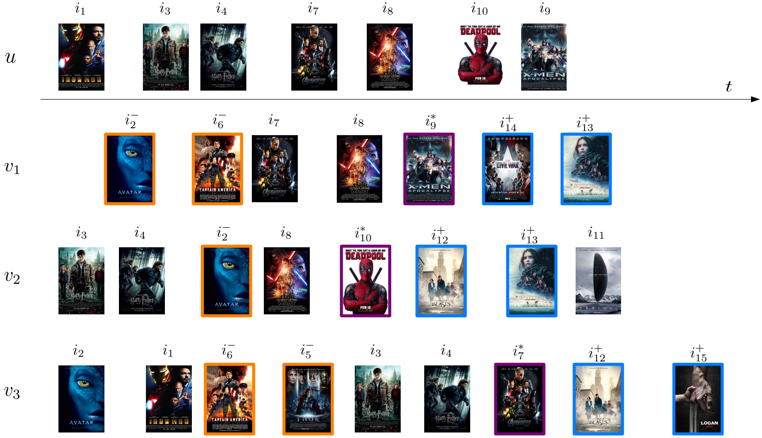


Backward-Forward algorithm (2)



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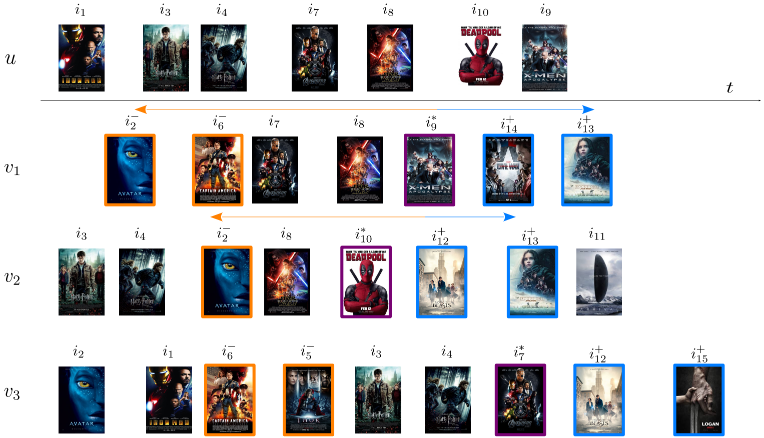

$$L_2^+(v_1; u) = (i_{14}, i_{13}), L_2^-(v_1; u) = (i_6, i_2)$$
$$L_2^+(v_2; u) = (i_{12}, i_{13}), L_2^-(v_2; u) = (i_2)$$
$$L_2^+(v_3; u) = (i_{12}, i_{15}), L_2^-(v_3; u) = (i_5, i_6)$$

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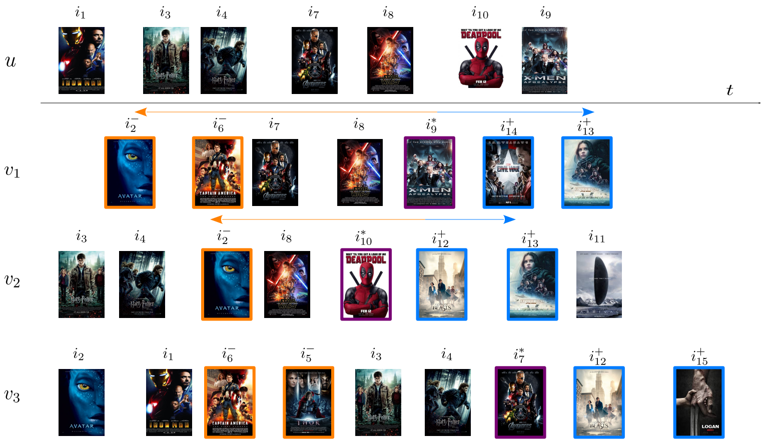

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$$L_2^+(v_3;u) = (i_{12}, i_{15}), L_2^-(v_3;u) = (i_5, i_6)$$

- Normalize the rankings obtained for each neighbor
  - Standard normalization: $x' = \frac{x - x_{min}}{x_{min} - x_{max}}$
  - Rank normalization: $x' = 1 - \frac{rank(x) - 1}{|X|}$
  - Default normalization: $x' = x$
  - Other

Backward-Forward algorithm (3)

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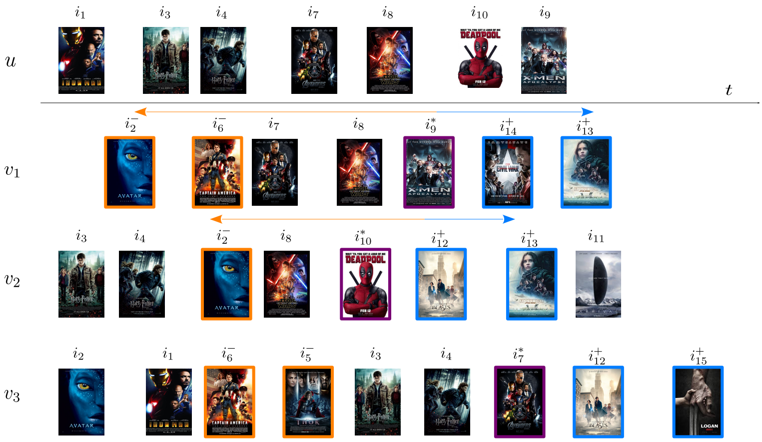
  - Standard normalization: $x' = \frac{x - x_{min}}{x_{min} - x_{max}}$
  - Rank normalization: $x' = 1 - \frac{rank(x) - 1}{|X|}$
  - Default normalization: $x' = x$
  - Other
- Generate a single list for each user using her neighbors rankings
  - **Sum combiner**
  - Min combiner
  - Max combiner
  - Other

Backward-Forward algorithm (4)



$$\boldsymbol{BF_2^+ = \{i_{12}, i_{13}\}}$$

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Experiments: sequences in k-NN RS

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- Foursquare from [He and McAuley, 2016] and MovieTweetings from [Dooms et al., 2016].
- **Temporal** split: per user vs system

Dataset	**Users**	**Items**	**Ratings**	**Density**	**Scale**	**Unique times**	**Time interval**
Foursquare	16k	3k	105k	0.205%	1	102k	Dec 2011 - Apr 2012
MovieTweetings	15k	8k	519k	0.399%	0-10	517k	Feb 2013 - Apr 2017

- Relevance (nDCG), novelty (EPC), temporal-novelty (MIN), diversity (IC)

MovieTweetings

Recommender	nDCG	EPC	MIN	IC
Rnd	0.001	†**0.996**	0.410	†**0.949**
Rnd_{CF}	0.000	0.996	0.411	0.900
Pop	0.003	0.853	0.207	0.006
Pop_{CF}	0.003	0.854	0.210	0.006
IB	0.010	0.914	0.585	0.126
UB	0.016	0.907	0.585	0.030
HKV	0.024	0.934	0.573	0.081
BPRMF	0.016	0.923	0.579	0.125
TD	0.023	0.916	0.697	0.053
BFUB	0.031	0.927	0.728	0.077
BFsUB	**0.034**	0.936	†**0.828**	0.076
MC	0.031	0.919	0.707	0.043
FPMC	0.020	0.913	0.634	0.040
Fossil	0.025	0.915	0.647	0.028
Caser	0.026	0.939	0.771	0.129
Skyline	0.806	0.977	0.588	0.295
$\text{Skyline}_{\text{CF}}$	†**0.812**	0.977	0.616	0.251

Foursquare

Recommender	nDCG	EPC	MIN	IC
Rnd	0.001	0.998	0.615	†**1.000**
Rnd_{CF}	0.001	†**0.998**	0.612	1.000
Pop	0.130	0.879	0.515	0.004
Pop_{CF}	0.130	0.879	0.515	0.004
IB	0.155	0.952	0.613	0.828
UB	0.173	0.929	0.573	0.293
HKV	0.154	0.949	0.585	0.029
BPRMF	0.146	0.886	0.511	0.071
TD	0.170	0.929	0.582	0.307
BFUB	0.173	0.929	0.573	0.293
BFsUB	**0.174**	0.921	0.569	0.281
MC	0.133	0.945	0.624	0.269
FPMC	0.133	0.935	0.608	0.196
Fossil	0.163	0.938	**0.624**	0.131
Caser	0.170	0.929	0.610	0.301
Skyline	†**0.998**	0.960	†**0.671**	0.577
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Experiments: BF. Temporal System. All metrics @5

- Sequential recommenders highly competitive in MovieTweetings but not in Foursquare

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- Our Backward-Forward approaches are the best in terms of relevance and competitive in other dimensions

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- Sequential recommenders are less competitive in this split for both datasets

MovieTweetings

Recommender	**nDCG**	**EPC**	**MIN**	**IC**
Rnd	0.000	†**0.996**	0.383	0.980
Rnd_{CF}	0.000	0.996	0.383	†**0.980**
Pop	0.024	0.870	0.159	0.005
Pop_{CF}	0.024	0.870	0.159	0.005
IB	0.050	0.919	0.402	0.185
UB	0.049	0.910	0.360	0.038
HKV	0.050	0.934	0.367	0.075
BPRMF	0.037	0.933	0.363	0.218
TD	0.081	0.916	0.451	0.077
BFUB	0.070	0.918	0.424	0.054
BFsUB	**0.111**	0.928	**0.518**	0.086
MC	0.062	0.905	0.436	0.073
FPMC	0.038	0.913	0.365	0.065
Fossil	0.050	0.909	0.386	0.045
Caser	0.083	0.928	0.483	0.158
Skyline	†**1.000**	0.962	†**0.525**	0.260
$\text{Skyline}_{\text{CF}}$	1.000	0.962	†**0.525**	0.260

Foursquare

Recommender	**nDCG**	**EPC**	**MIN**	**IC**
Rnd	0.001	0.998	0.540	†**1.000**
Rnd_{CF}	0.002	†**0.998**	0.538	1.000
Pop	0.133	0.878	0.501	0.004
Pop_{CF}	0.133	0.878	0.501	0.004
IB	0.186	0.950	0.535	0.829
UB	0.191	0.926	0.516	0.169
HKV	0.174	0.948	0.503	0.032
BPRMF	0.157	0.947	0.515	0.489
TD	0.185	0.929	0.536	0.232
BFUB	**0.192**	0.927	0.515	0.176
BFsUB	0.190	0.925	0.515	0.259
MC	0.159	0.940	0.558	0.185
FPMC	0.145	0.933	0.554	0.149
Fossil	0.177	0.939	**0.563**	0.080
Caser	0.182	0.932	0.559	0.307
Skyline	†**1.000**	0.960	†**0.568**	0.687
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- Our Backward-Forward approaches are still competitive against state-of-the-art algorithms

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- We have **redefined** the k-NN recommenders by exploiting the **last common interactions** between the neighbors named Backward-Forward (BF)
- Our Backward-Forward algorithm can be used with **any kind** of **similarity** (sequential or not sequential)
- Our approach is **highly competitive** in two datasets using a time-aware evaluation

Overview

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- We develop mechanisms to **increase the performance** of the recommenders in POI recommendation by using cross-domain techniques
- **Contributions under review** in ACM Computing Surveys journal **(2º round of review)** and **published** in the Information Processing and Management journal [Sánchez and Bellogín, 2021] **(new)**

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Point-Of-Interest (POI) Recommendation

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  - **Implicit** and **repeated interactions**: users visit the same places more than once
  - **External influences**: **geographical**, temporal, social, and sequential influences

Everything is related to everything else, but near things are more related than distant things —[Miller, 2004]

Point-Of-Interest recommendation: a survey

- Types of algorithms: based on similarities, factorization machines, neural networks, ...
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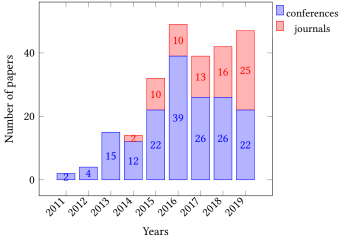
Source	Papers retrieved	Valid papers
Scopus	321	238
ScienceDirect	36	22
ACM	46	24
Unique papers	347	**244**



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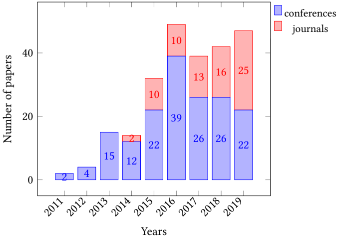

- More information in **Chapter 3**

Point-Of-Interest recommendation: a survey

Details			Evaluation configuration							Baselines			Split type			Split level	
Year	Reference	Acronym	Filter data	Validation	Error	Ranking	Region Split	Check-in(✓) POI(✗)	Cold Start Analysis	C. Non Personalized	C. Personalized	Geographical	Random	Temporal	Other	System	Per User
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2012	[Levandoski et al., 2012]	LARS					✓	✗			✓	✓	✓			✓	
2012	[Bao et al., 2012]	(N.A.)	✓			✓	✓	✗			✓				✓		
2013	[Yang et al., 2013]	LBSMF	✓		✓		✓	✓			✓		✓			✓	
2013	[Liu et al., 2013]	GT-BNMF				✓	✓	✓			✓		✓			✓	
2013	[Yuan et al., 2013]	UTE+SE	✓	✓		✓	✓	✗			✓	✓	✓				✓
2014	[Ying et al., 2014]	UPOI-Walk			✓	✓	✓	?			✓	✓					
2014	[Yuan et al., 2014]	GTAG	✓	✓		✓	✓	✗			✓	✓	✓				✓
2014	[Lian et al., 2014]	GeoMF	✓			✓		✗			✓		✓				✓
2015	[Yin et al., 2015]	LA-LDA		✓		✓		✗	✓			✓	✓				✓
2015	[Li et al., 2015]	RankGeoFM		✓		✓	✓	✓			✓	✓		✓			✓
2015	[Zhang and Chow, 2015]	GeoSoCa				✓	✓	✓				✓		✓		✓	
2015	[Feng et al., 2015]	PRME-G	✓	✓		✓	✓	✓		✓	✓			✓		✓	
2016	[Li et al., 2016]	ASMF	✓			✓	✓	✗	✓		✓	✓		✓			✓
2016	[Zhao et al., 2016]	STELLAR	✓			✓		✓			✓			✓		✓	
2017	[Zhao et al., 2017]	Geo-Teaser	✓			✓		✓			✓	✓		✓			✓
2017	[Yang et al., 2017]	PACE	✓			✓		✓				✓		✓			✓
2017	[Ren et al., 2017]	TGSC-PMF	✓		✓	✓		✓				✓	✓			✓	
2018	[Ma et al., 2018]	SAE-NAD	✓			✓	✓	✗			✓	✓	✓				✓
2018	[Gao et al., 2018]	GeoEISo	✓			✓	✓	✓			✓	✓	✓			✓	
2018	[Wang et al., 2018]	GeoIE	✓	✓		✓		✓				✓		✓			✓
2019	[Ying et al., 2019]	MEAP-T	✓	✓		✓	✓	✓		✓	✓			✓			✓
2019	[Si et al., 2019]	APRA-SA			✓	✓		✓			✓	✓	✓				✓
2019	[Qian et al., 2019]	STA		✓		✓		✓	✓			✓		✓			✓
Most Representatives			24	10	5	38	23	C:21 P:16	7	3	30	26	18	17	1	13	22
Total			135	37	22	229	135	C:150 P:66	27	29	147	142	123	82	14	101	104

- Most POI models use **ranking based accuracy metrics**

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2014	[Ying et al., 2014]	UPOI-Walk			✓	✓	✓	?			✓	✓					
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- Some researchers **apply some data filtering**

Point-Of-Interest recommendation: a survey

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2013	[Yuan et al., 2013]	UTE+SE	✓	✓		✓	✓	✗			✓	✓	✓				✓
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2014	[Yuan et al., 2014]	GTAG	✓	✓		✓	✓	✗			✓	✓	✓				✓
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- It is **not common** to use a **validation split**

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2013	[Yuan et al., 2013]	UTE+SE	✓	✓		✓	✓	✗			✓	✓	✓				✓
2014	[Ying et al., 2014]	UPOI-Walk			✓	✓	✓	?			✓	✓					
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2014	[Lian et al., 2014]	GeoMF	✓			✓		✗			✓		✓				✓
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- **No standard procedure** for evaluating the models

Point-Of-Interest recommendation: a survey

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2014	[Ying et al., 2014]	UPOI-Walk			✓	✓	✓	?			✓	✓					
2014	[Yuan et al., 2014]	GTAG	✓	✓		✓	✓	✗			✓	✓	✓				✓
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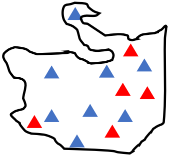
- Some researchers use some kind of **region/city split**

Improving POI recommendation performance

- Some researchers tend to consider each city/region as an independent dataset (same city/region for training and test)

Training with one city
and test with the same city



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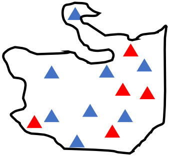
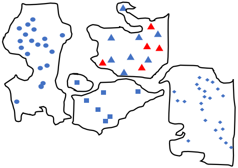


Training with many cities
and test with one city



- We propose different strategies to select the training cities: based on distance (N-MCA and C-MCA) and based on the number of check-ins (most popular, P-MCA)

- Objective: **test our MCA strategies** in a LBSN dataset

Experiments: POI recommendation

- Objective: **test our MCA strategies** in a LBSN dataset
- **8 different cities** from the Global-scale check-in dataset [Yang et al., 2016]: Istanbul, Jakarta, Kuala Lumpur, Mexico City, Moscow, Santiago, São Paulo and Tokyo

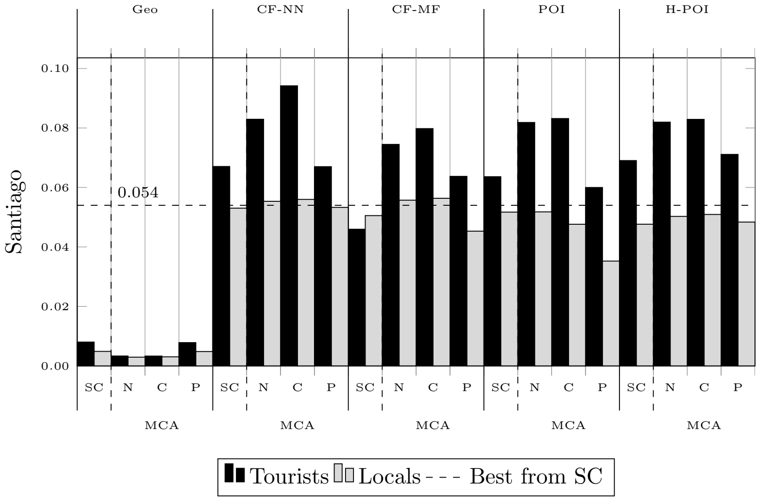
- Objective: **test our MCA strategies** in a LBSN dataset
- **8 different cities** from the Global-scale check-in dataset [Yang et al., 2016]: Istanbul, Jakarta, Kuala Lumpur, Mexico City, Moscow, Santiago, São Paulo and Tokyo
- **Temporal system split**

- Objective: **test our MCA strategies** in a LBSN dataset
- **8 different cities** from the Global-scale check-in dataset [Yang et al., 2016]: Istanbul, Jakarta, Kuala Lumpur, Mexico City, Moscow, Santiago, São Paulo and Tokyo
- **Temporal system split**
- **3 different MCA** strategies: the test set is always formed by the target city

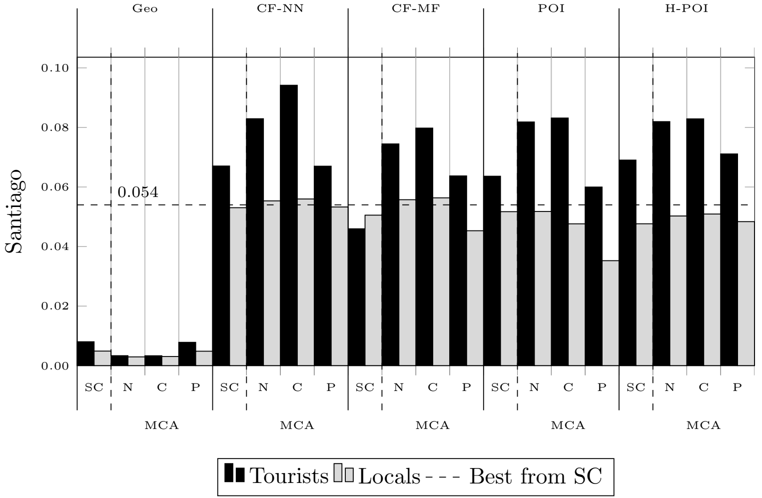
Experiments: POI recommendation

- Objective: **test our MCA strategies** in a LBSN dataset
- **8 different cities** from the Global-scale check-in dataset [Yang et al., 2016]: Istanbul, Jakarta, Kuala Lumpur, Mexico City, Moscow, Santiago, São Paulo and Tokyo
- **Temporal system split**
- **3 different MCA** strategies: the test set is always formed by the target city
- **2 different** groups of users: **tourists and locals**

Experiments: POI recommendation. nDCG@5

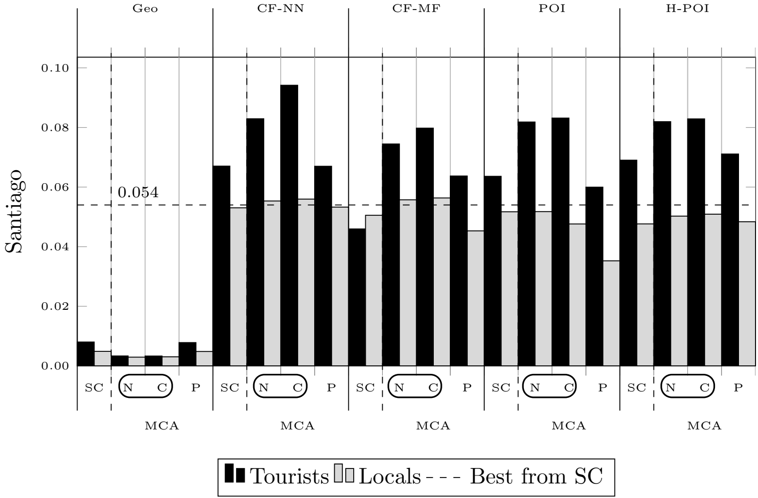


- Families: Geo, CF-NN, CF-MF, POI, H-POI



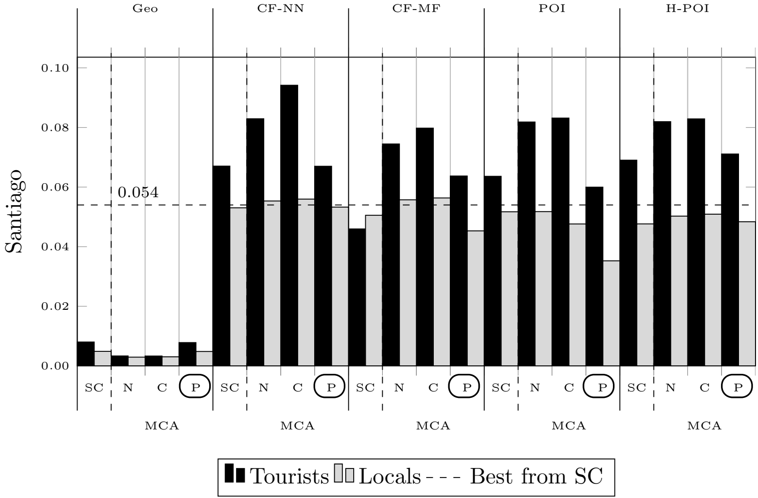
- N-MCA (closest), C-MCA (country), P-MCA (popular)

Experiments: POI recommendation. nDCG@5



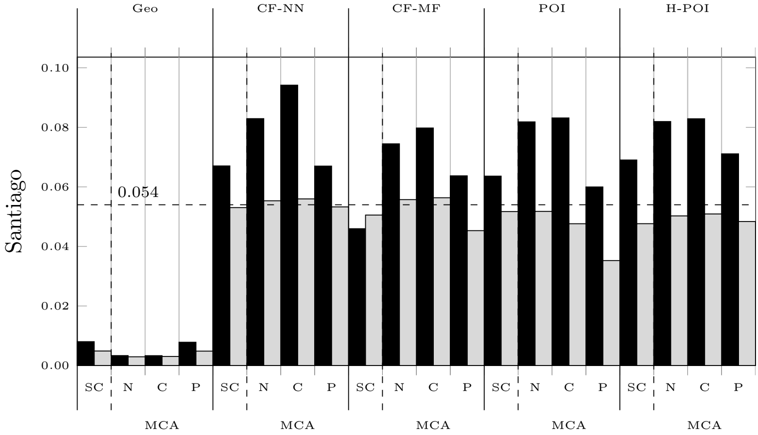
- N-MCA and C-MCA increase relevance

Experiments: POI recommendation. nDCG@5



- P-MCA sometimes decreases relevance

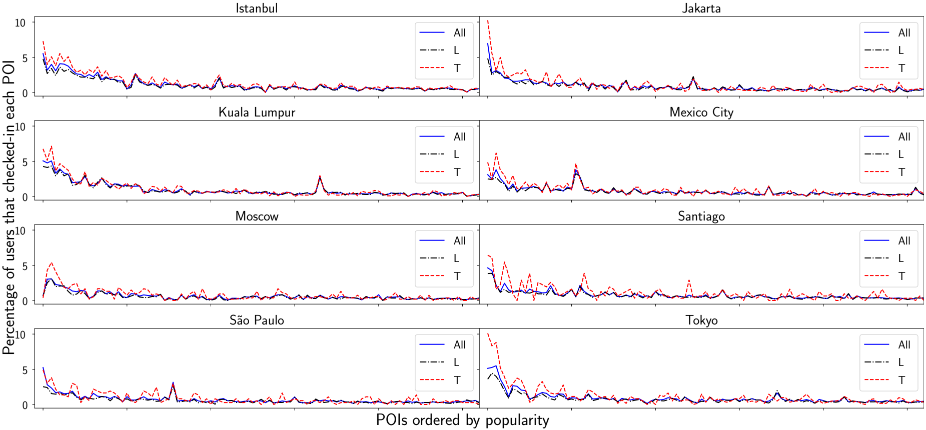
Experiments: POI recommendation. nDCG@5



Tourists Locals - - - Best from SC

- Great differences between tourists and locals

Experiments: popularity bias in tourists



- Tourist tend to visit the most popular venues

- **Most POI** recommendation algorithms **are not comparable** between them

Summary

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Summary

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- **Quality** over quantity (of the data)

Overview

Sequences in POI recommendation

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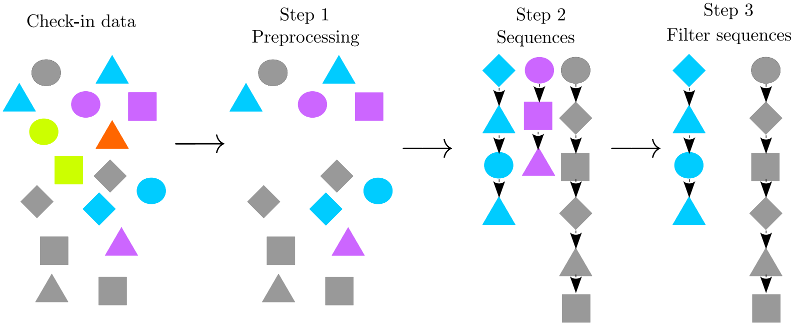
- **Contributions published** in User Modeling and User-Adapted Interaction [Sánchez and Bellogín, 2020a] journal

Generate sequences from check-in data

- From LBSN like Foursquare or Gowalla



Each color represents a user

Each figure represents a POI category

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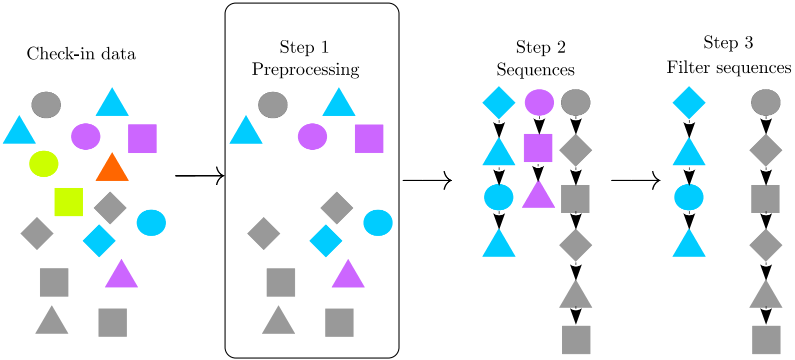

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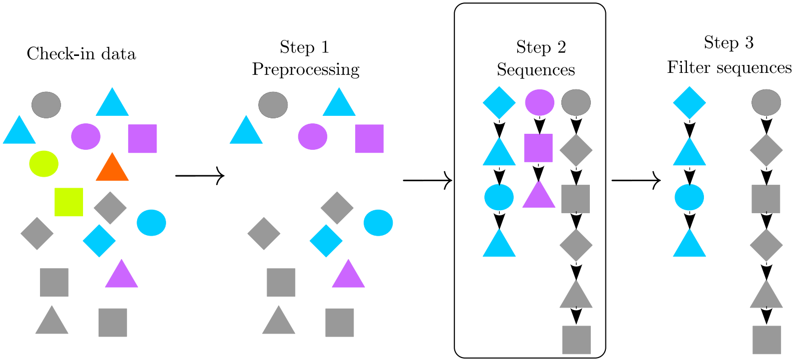

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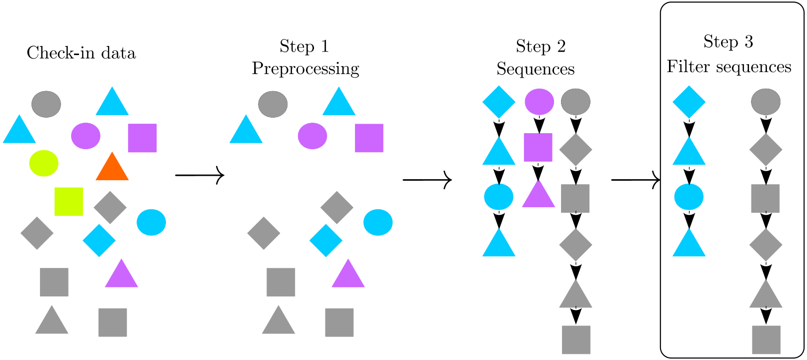

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Using reranking techniques to generate routes

$$f_{obj}(u, i, R_u) = \lambda \cdot f_{rec}(u, i) + (1 - \lambda) \cdot f_{seq}(u, i, R_u)$$

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  3. Dependent on the whole sequence
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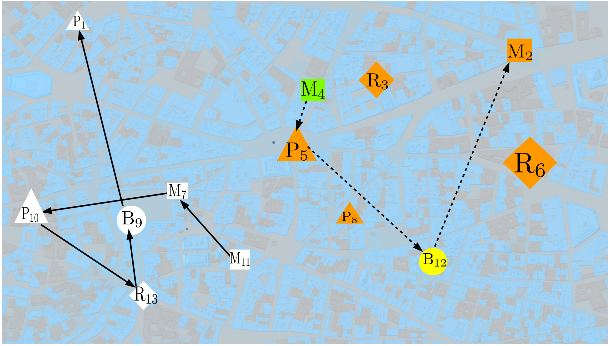
     - Suffix tree: $f_{seq}^{stree}(u,i,R_u) = \delta_{ST(u^a)}(\{(R_u+i)^a\}_m)$
     - Oracle: $f_{seq}^{oracle}(u,i,R_u) = order_{test}(u,i)$

Using reranking techniques to generate routes



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Training   Recommended venues   First venue in the sequence

Venue in test not recommended   Test route of the user

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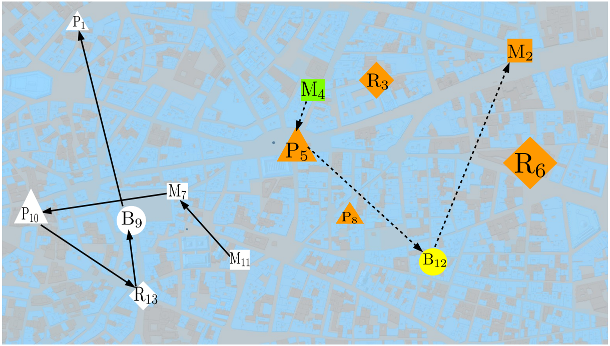

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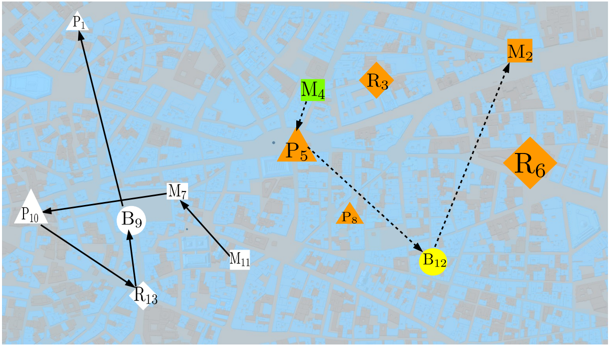

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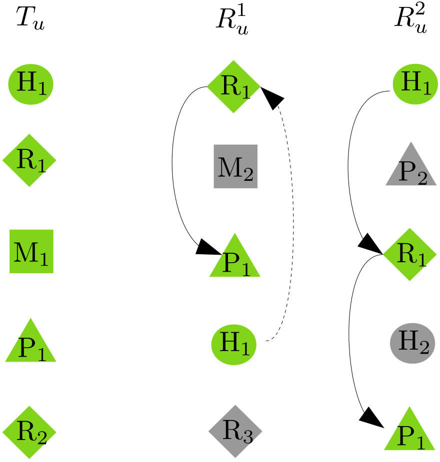
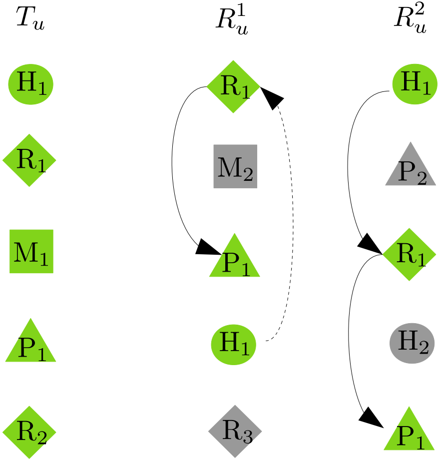


$$\mathrm{P}(R_u^1) = \mathrm{P}(R_u^2) = 3/5$$

Sequential evaluation



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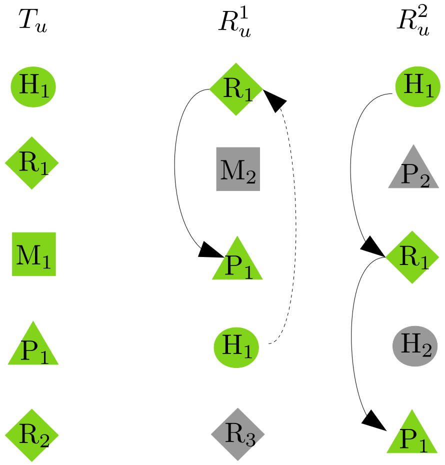

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$$\mathrm{P_s}\ (R_u^2) = \mathrm{P}(R_u^2) = 3/5$$
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Experiments: sequences in POI recommendation

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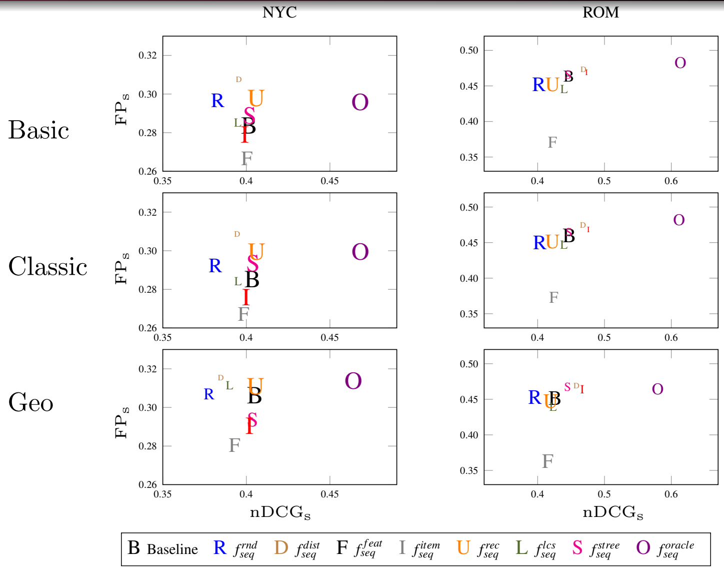
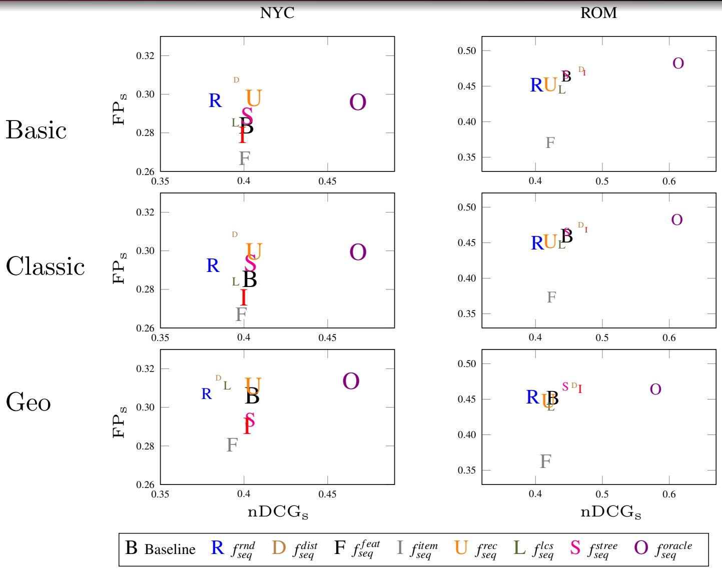
- Analysis on relevance, **sequential relevance**, novelty, diversity, **attribute evaluation** and **distance**

Experiments: effect of rerankers



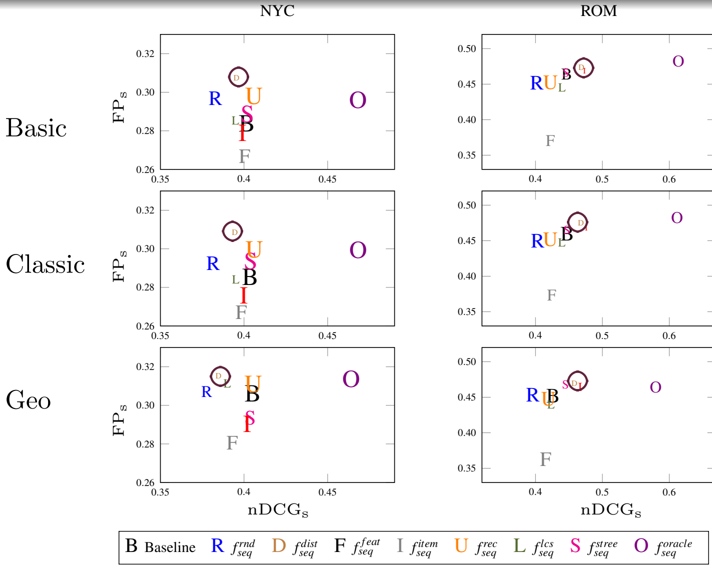
- Accuracy (x-axis), feature accuracy (y-axis), distance (size)

Experiments: effect of rerankers



- There is always at least one reranker that improves the baseline

Experiments: effect of rerankers



- Distance reranker often improves the relevance

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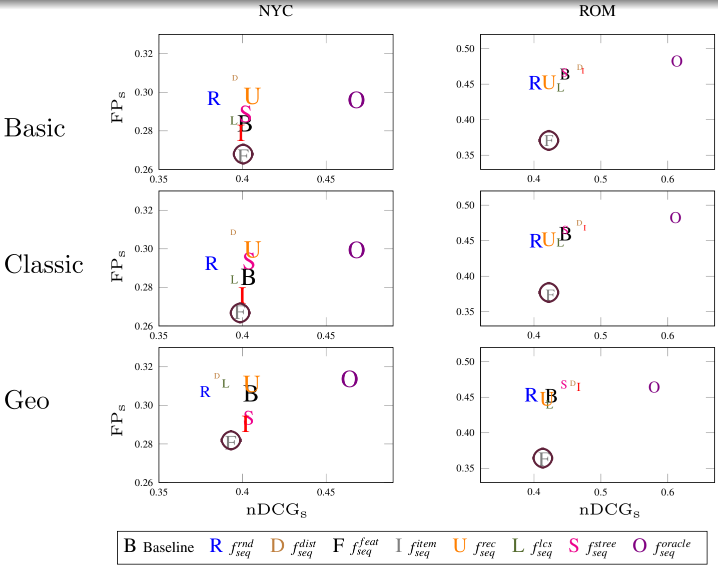

- Categorical rerankers do not always obtain better results

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- We have shown how we can use **reranking techniques** for **generating routes** optimizing different criteria

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  - With the **user attributes** we may detect **biases** in specific **groups of users**. With **item attributes** we can **increase** the performance of the recommenders in very sparse datasets

Conclusions (II)

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  - Our proposal was **highly competitive** against other **state-of-the-art** algorithms in **different dimensions**

Conclusions (III)

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  - **Useful information** is better than more information

Conclusions (V)

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    - We can use **reranking techniques** for generating routes improving dimensions like **feature precision** and/or **distance**

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- On Recommender Systems evaluation
  - Test our **novelty metrics** in **online environments**
  - Test our **anti-relevance models** in domains with **implicit information**
  - Detect **biases in different groups** of users and in other recommendation domains
  - Apply our **attribute metrics** in **other domains** like music

Future Work (II)

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  - Propose different **aggregation strategies** and use other algorithms based on **items similarities** like Factored Item Similarity Models (FISM) or Sparse Linear Methods (SLIM)

Exploring attributes, sequences, and time in Recommender Systems: From classical to Point-of-Interest recommendation

Pablo Sánchez Pérez

Under the supervision of
Alejandro Bellogín Kouki

Information Retrieval Group
Department of Computer Science
Universidad Autónoma de Madrid, Spain

July 8, 2021

Thank you

`https://bitbucket.org/PabloSanchezP`

Publications: journals

1. **Pablo Sánchez** and Alejandro Bellogín. (2020). Point-of-Interest Recommender Systems: A Survey from an Experimental Perspective. Submitted to *ACM Computing Surveys*. Under Review (2nd round of review)
2. **Pablo Sánchez** and Alejandro Bellogín. On the effects of aggregation strategies for different groups of users in venue recommendation. *Information Processing and Management*, 58(5):102609, 2021.
3. **Pablo Sánchez** and Alejandro Bellogín. Applying reranking strategies to route recommendation using sequence-aware evaluation. *User Modeling and User-Adapted Interaction*, 30(4):659-725, 2020
4. **Pablo Sánchez** and Alejandro Bellogín. Time and sequence awareness in similarity metrics for recommendation. *Information Processing and Management*, 57(3):102228, 2020
5. **Pablo Sánchez** and Alejandro Bellogín. Building user profiles based on sequences for content and collaborative filtering. *Information Processing and Management*, 56(1):192-211, 2019.
6. Alejandro Bellogín and **Pablo Sánchez**. Collaborative filtering based on subsequence matching: A new approach. *Information Sciences*, 418:432-446, 2017

Publications: conferences

1. **Pablo Sánchez** and Alejandro Bellogín. Time-aware novelty metrics for recommender systems. In Gabriella Pasi, Benjamin Piwowarski, Leif Azzopardi, and Allan Hanbury, editors, *Advances in Information Retrieval - 40th European Conference on IR Research*, ECIR 2018, Grenoble, France, March 26-29, 2018, Proceedings, volume 10772 of Lecture Notes in Computer Science, pages 357-370. Springer, 2018
2. **Pablo Sánchez** and Alejandro Bellogín. Measuring anti-relevance: a study on when recommendation algorithms produce bad suggestions. In Sole Pera, Michael D. Ekstrand, Xavier Amatriain, and John O'Donovan, editors, *Proceedings of the 12th ACM Conference on Recommender Systems*, RecSys 2018, Vancouver, BC, Canada, October. 2-7, 2018, pages 367-371. ACM, 2018
3. **Pablo Sánchez** and Alejandro Bellogín. Attribute-based evaluation for recommender systems: incorporating user and item attributes in evaluation metrics. In Toine Bogers, Alan Said, Peter Brusilovsky, and Domonkos Tikk, editors, *Proceedings of the 13th ACM Conference on Recommender Systems*, RecSys 2019, Copenhagen, Denmark, September 16-20, 2019., pages 378-382. ACM, 2019

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Feng, S., Li, X., Zeng, Y., Cong, G., Chee, Y. M., and Yuan, Q. (2015).
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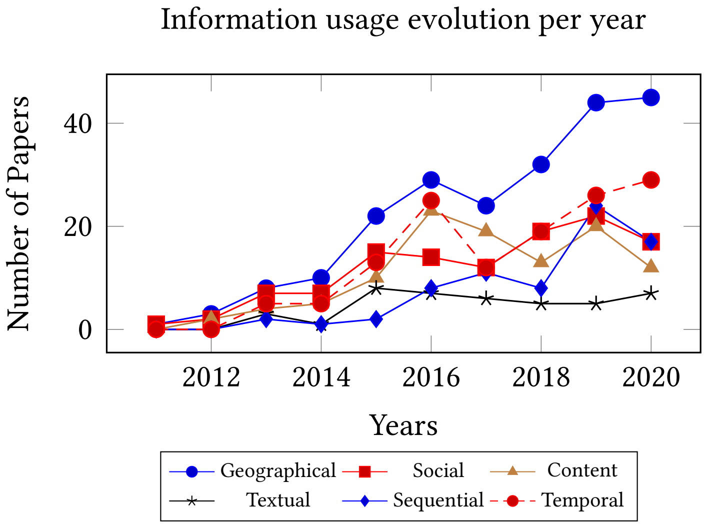
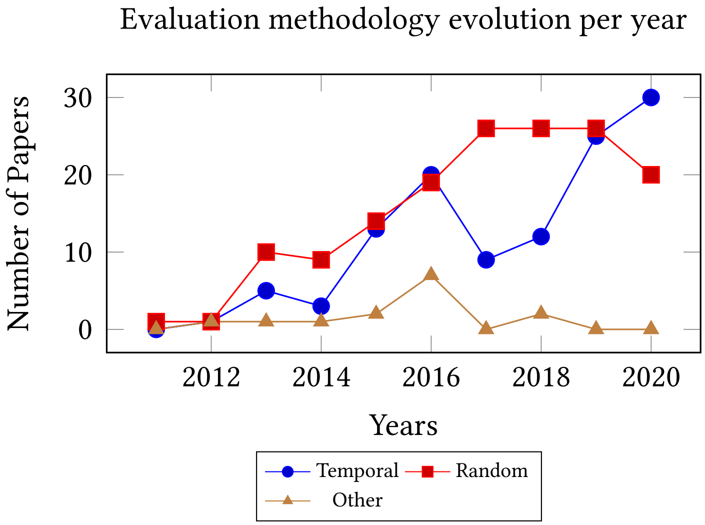
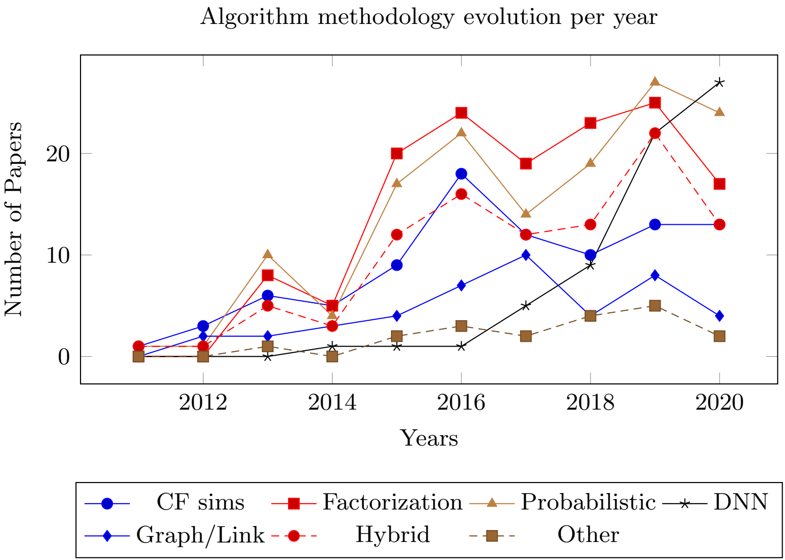
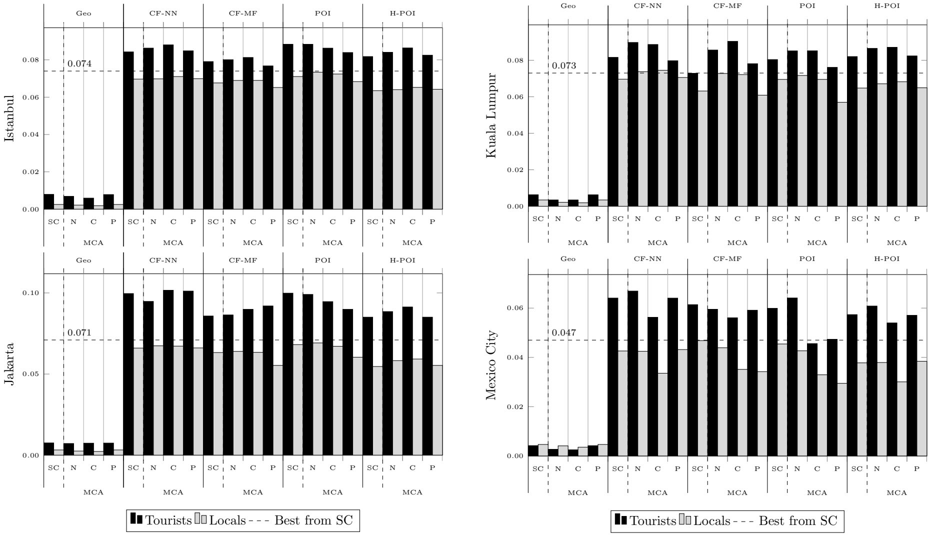

Information usage evolution per year
Number of Papers
0
20
40
2012
2014
2016
2018
2020
Years
Geographical
Social
Content
Textual
Sequential
Temporal


Evaluation methodology evolution per year
Number of Papers
30
20
10
0
2012
2014
2016
2018
2020
Years
Temporal
Random
Other

Point-Of-Interest recommendation: a survey



Experiments: POI recommendation. nDCG@5



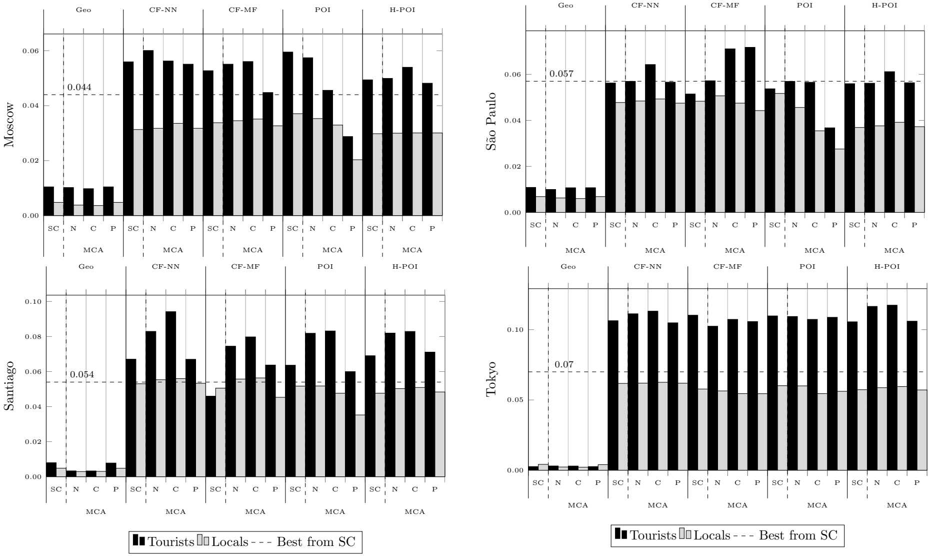

Moscow
Geo
CF-NN
CF-MF
POI
H-POI
0.044
SC N C P
MCA
São Paulo
0.057
Santiago
0.054
Tokyo
0.07
Tourists
Locals
Best from SC

Table: Performance in terms of nDCG@5 of the Popularity recommender in all cities in both Tourists and Locals.

City	All Users	Tourists	Locals	Δ Tourists (%)	Δ Locals (%)
Istanbul	0.054	0.064	0.048	19.04	−9.77
Jakarta	0.066	0.091	0.053	38.33	−19.92
Kuala Lumpur	0.066	0.077	0.060	17.34	−8.46
Mexico City	0.041	0.059	0.034	45.69	−15.70
Moscow	0.027	0.037	0.026	34.02	−4.48
Santiago	0.051	0.067	0.044	30.47	−13.21
São Paulo	0.053	0.061	0.031	14.85	−40.33
Tokyo	0.069	0.106	0.056	53.48	−18.73

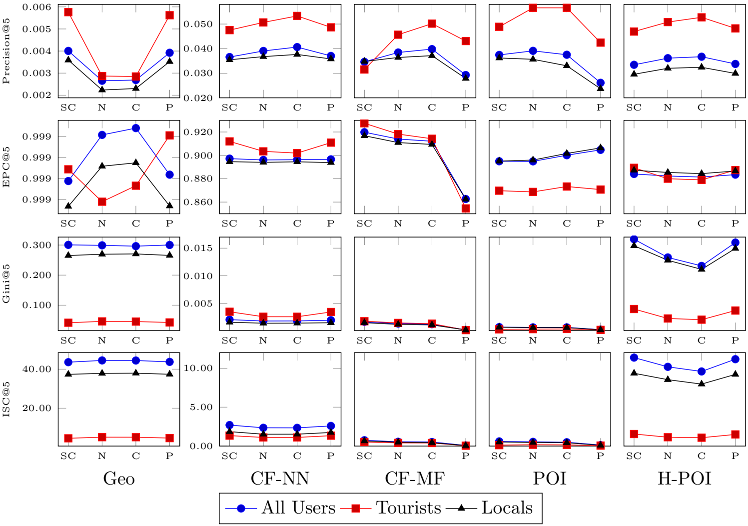


Figure: Results of tourists (7.62% of the users) and local (72.43% of the users) users in Santiago.

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Basic	Baseline	0.402	0.284	43.9	0.447	0.464	5.0	0.404	0.245	35.0
	f_{seq}^{rnd}	0.383	0.297	28.0	0.402	0.452	5.9	0.387	0.274	29.5
	f_{seq}^{dist}	0.396	**▲0.308**	**▲4.1**	0.469	**†0.474**	**▲1.4**	**†0.409**	**▲0.296**	**▲7.2**
	f_{seq}^{feat}	0.400	0.267	33.3	0.422	0.371	5.0	0.402	0.267	33.2
	f_{seq}^{item}	0.399	0.279	37.8	**†0.473**	0.469	1.8	0.408	0.262	19.5
	f_{seq}^{rec}	**†0.406**	0.298	42.4	0.422	0.452	6.0	0.407	0.271	26.3
	f_{seq}^{lcs}	0.395	0.285	17.8	0.440	0.446	2.3	0.403	0.274	14.8
	f_{seq}^{stree}	0.402	0.289	38.4	0.446	0.466	3.2	0.403	0.263	25.9
	f_{seq}^{oracle}	**▲0.468**	0.296	43.2	**▲0.614**	**▲0.482**	4.2	**▲0.456**	0.247	34.2
Classic	Baseline	0.404	0.285	45.3	0.447	0.460	6.3	0.408	0.270	30.0
	f_{seq}^{rnd}	0.382	0.292	30.3	0.403	0.450	5.9	0.394	0.278	30.7
	f_{seq}^{dist}	0.395	**0.309**	**▲4.2**	0.468	**†0.475**	**▲1.4**	**†0.410**	**▲0.294**	**▲7.4**
	f_{seq}^{feat}	0.398	0.267	33.5	0.424	0.373	5.0	0.402	0.269	34.0
	f_{seq}^{item}	0.400	0.276	38.0	**†0.476**	0.468	1.8	0.409	0.268	18.5
	f_{seq}^{rec}	**†0.406**	0.300	42.4	0.422	0.452	6.0	0.407	0.273	26.5
	f_{seq}^{lcs}	0.395	0.284	17.9	0.440	0.447	2.3	0.405	0.279	13.2
	f_{seq}^{stree}	0.404	0.294	38.6	0.447	0.465	3.7	0.405	0.275	22.1
	f_{seq}^{oracle}	**▲0.468**	0.300	44.3	**▲0.612**	**▲0.482**	4.9	**▲0.455**	0.269	29.0
Temporal	Baseline	**†0.404**	0.302	42.4	0.447	**†0.469**	4.9	**†0.416**	0.285	26.6
	f_{seq}^{rnd}	0.379	0.317	25.3	0.409	0.449	6.0	0.383	0.308	28.1
	f_{seq}^{dist}	0.389	**▲0.319**	**▲3.5**	0.464	0.468	**▲1.4**	0.412	**▲0.326**	**▲5.6**
	f_{seq}^{feat}	0.388	0.272	30.6	0.421	0.375	5.0	0.397	0.291	30.2
	f_{seq}^{item}	0.400	0.293	37.2	**†0.474**	0.465	1.9	0.412	0.283	17.5
	f_{seq}^{rec}	0.403	0.309	41.5	0.422	0.452	6.1	0.407	0.292	26.1
	f_{seq}^{lcs}	0.388	0.314	10.8	0.441	0.447	2.3	0.407	0.311	10.9
	f_{seq}^{stree}	0.398	0.311	29.6	0.445	0.468	3.1	0.411	0.301	17.3
	f_{seq}^{oracle}	**▲0.462**	0.308	39.9	**▲0.608**	**▲0.482**	4.1	**▲0.457**	0.287	25.8

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Basic	Baseline	0.402	0.284	43.9	0.447	0.464	5.0	0.404	0.245	35.0
	f_{seq}^{rnd}	0.383	0.297	28.0	0.402	0.452	5.9	0.387	0.274	29.5
	f_{seq}^{dist}	0.396	▲**0.308**	▲**4.1**	0.469	†**0.474**	▲**1.4**	†**0.409**	▲**0.296**	▲**7.2**
	f_{seq}^{feat}	0.400	0.267	33.3	0.422	0.371	5.0	0.402	0.267	33.2
	f_{seq}^{item}	0.399	0.279	37.8	†**0.473**	0.469	1.8	0.408	0.262	19.5
	f_{seq}^{rec}	†**0.406**	0.298	42.4	0.422	0.452	6.0	0.407	0.271	26.3
	f_{seq}^{lcs}	0.395	0.285	17.8	0.440	0.446	2.3	0.403	0.274	14.8
	f_{seq}^{stree}	0.402	0.289	38.4	0.446	0.466	3.2	0.403	0.263	25.9
	f_{seq}^{oracle}	▲**0.468**	0.296	43.2	▲**0.614**	▲**0.482**	4.2	▲**0.456**	0.247	34.2
Classic	Baseline	0.404	0.285	45.3	0.447	0.460	6.3	0.408	0.270	30.0
	f_{seq}^{rnd}	0.382	0.292	30.3	0.403	0.450	5.9	0.394	0.278	30.7
	f_{seq}^{dist}	0.395	**0.309**	▲**4.2**	0.468	†**0.475**	▲**1.4**	†**0.410**	▲**0.294**	▲**7.4**
	f_{seq}^{feat}	0.398	0.267	33.5	0.424	0.373	5.0	0.402	0.269	34.0
	f_{seq}^{item}	0.400	0.276	38.0	†**0.476**	0.468	1.8	0.409	0.268	18.5
	f_{seq}^{rec}	†**0.406**	0.300	42.4	0.422	0.452	6.0	0.407	0.273	26.5
	f_{seq}^{lcs}	0.395	0.284	17.9	0.440	0.447	2.3	0.405	0.279	13.2
	f_{seq}^{stree}	0.404	0.294	38.6	0.447	0.465	3.7	0.405	0.275	22.1
	f_{seq}^{oracle}	▲**0.468**	0.300	44.3	▲**0.612**	▲**0.482**	4.9	▲**0.455**	0.269	29.0
Temporal	Baseline	†**0.404**	0.302	42.4	0.447	†**0.469**	4.9	†**0.416**	0.285	26.6
	f_{seq}^{rnd}	0.379	0.317	25.3	0.409	0.449	6.0	0.383	0.308	28.1
	f_{seq}^{dist}	0.389	▲**0.319**	▲**3.5**	0.464	0.468	▲**1.4**	0.412	▲**0.326**	▲**5.6**
	f_{seq}^{feat}	0.388	0.272	30.6	0.421	0.375	5.0	0.397	0.291	30.2
	f_{seq}^{item}	0.400	0.293	37.2	†**0.474**	0.465	1.9	0.412	0.283	17.5
	f_{seq}^{rec}	0.403	0.309	41.5	0.422	0.452	6.1	0.407	0.292	26.1
	f_{seq}^{lcs}	0.388	0.314	10.8	0.441	0.447	2.3	0.407	0.311	10.9
	f_{seq}^{stree}	0.398	0.311	29.6	0.445	0.468	3.1	0.411	0.301	17.3
	f_{seq}^{oracle}	▲**0.462**	0.308	39.9	▲**0.608**	▲**0.482**	4.1	▲**0.457**	0.287	25.8

Experiments: Sequences in POI recommendation

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Basic	Baseline	0.402	0.284	43.9	0.447	0.464	5.0	0.404	0.245	35.0
	f^{rnd}_{seq}	0.383	0.297	28.0	0.402	0.452	5.9	0.387	0.274	29.5
	f^{dist}_{seq}	0.396	**▲0.308**	**▲4.1**	0.469	**†0.474**	**▲1.4**	**†0.409**	**▲0.296**	**▲7.2**
	f^{feat}_{seq}	0.400	0.267	33.3	0.422	0.371	5.0	0.402	0.267	33.2
	f^{item}_{seq}	0.399	0.279	37.8	**†0.473**	0.469	1.8	0.408	0.262	19.5
	f^{rec}_{seq}	**†0.406**	0.298	42.4	0.422	0.452	6.0	0.407	0.271	26.3
	f^{lcs}_{seq}	0.395	0.285	17.8	0.440	0.446	2.3	0.403	0.274	14.8
	f^{stree}_{seq}	0.402	0.289	38.4	0.446	0.466	3.2	0.403	0.263	25.9
	f^{oracle}_{seq}	**▲0.468**	0.296	43.2	**▲0.614**	**▲0.482**	4.2	**▲0.456**	0.247	34.2
Classic	Baseline	0.404	0.285	45.3	0.447	0.460	6.3	0.408	0.270	30.0
	f^{rnd}_{seq}	0.382	0.292	30.3	0.403	0.450	5.9	0.394	0.278	30.7
	f^{dist}_{seq}	0.395	**0.309**	**▲4.2**	0.468	**†0.475**	**▲1.4**	**†0.410**	**▲0.294**	**▲7.4**
	f^{feat}_{seq}	0.398	0.267	33.5	0.424	0.373	5.0	0.402	0.269	34.0
	f^{item}_{seq}	0.400	0.276	38.0	**†0.476**	0.468	1.8	0.409	0.268	18.5
	f^{rec}_{seq}	**†0.406**	0.300	42.4	0.422	0.452	6.0	0.407	0.273	26.5
	f^{lcs}_{seq}	0.395	0.284	17.9	0.440	0.447	2.3	0.405	0.279	13.2
	f^{stree}_{seq}	0.404	0.294	38.6	0.447	0.465	3.7	0.405	0.275	22.1
	f^{oracle}_{seq}	**▲0.468**	0.300	44.3	**▲0.612**	**▲0.482**	4.9	**▲0.455**	0.269	29.0
Temporal	Baseline	**†0.404**	0.302	42.4	0.447	**†0.469**	4.9	**†0.416**	0.285	26.6
	f^{rnd}_{seq}	0.379	0.317	25.3	0.409	0.449	6.0	0.383	0.308	28.1
	f^{dist}_{seq}	0.389	**▲0.319**	**▲3.5**	0.464	0.468	**▲1.4**	0.412	**▲0.326**	**▲5.6**
	f^{feat}_{seq}	0.388	0.272	30.6	0.421	0.375	5.0	0.397	0.291	30.2
	f^{item}_{seq}	0.400	0.293	37.2	**†0.474**	0.465	1.9	0.412	0.283	17.5
	f^{rec}_{seq}	0.403	0.309	41.5	0.422	0.452	6.1	0.407	0.292	26.1
	f^{lcs}_{seq}	0.388	0.314	10.8	0.441	0.447	2.3	0.407	0.311	10.9
	f^{stree}_{seq}	0.398	0.311	29.6	0.445	0.468	3.1	0.411	0.301	17.3
	f^{oracle}_{seq}	**▲0.462**	0.308	39.9	**▲0.608**	**▲0.482**	4.1	**▲0.457**	0.287	25.8

Experiments: Sequences in POI recommendation

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Geo	Baseline	0.405	0.306	43.9	0.427	0.457	5.6	0.406	0.286	30.0
	f_{seq}^{rnd}	0.378	0.307	22.5	0.397	0.447	5.9	0.390	0.307	25.1
	f_{seq}^{dist}	0.385	0.315	▲**3.6**	0.456	†**0.468**	▲**1.4**	0.405	▲**0.315**	▲**5.8**
	f_{seq}^{feat}	0.393	0.281	32.8	0.414	0.364	5.3	0.397	0.282	26.8
	f_{seq}^{item}	0.402	0.291	37.1	†**0.467**	0.466	2.1	†**0.412**	0.270	18.8
	f_{seq}^{rec}	†**0.405**	0.311	42.0	0.417	0.453	6.0	0.407	0.290	25.8
	f_{seq}^{lcs}	0.390	0.311	11.9	0.426	0.440	2.2	0.401	0.308	10.5
	f_{seq}^{stree}	0.402	**0.321**	31.3	0.431	0.458	3.5	0.404	0.302	19.4
	f_{seq}^{oracle}	▲**0.464**	0.314	41.7	▲**0.586**	▲**0.472**	4.6	▲**0.449**	0.287	28.8
Tour	Baseline	0.391	0.279	44.9	†**0.477**	0.473	2.0	0.403	0.240	28.4
	f_{seq}^{rnd}	0.364	0.305	23.9	0.400	0.448	5.7	0.390	0.291	30.8
	f_{seq}^{dist}	0.381	0.311	▲**4.2**	0.467	†**0.474**	▲**1.4**	†**0.412**	▲**0.309**	▲**7.1**
	f_{seq}^{feat}	0.374	0.277	20.9	0.420	0.359	5.0	0.401	0.278	31.6
	f_{seq}^{item}	0.397	0.283	38.1	0.477	0.470	1.8	0.406	0.271	16.9
	f_{seq}^{rec}	†**0.403**	0.289	41.4	0.427	0.451	5.8	0.408	0.273	26.6
	f_{seq}^{lcs}	0.382	▲**0.312**	12.0	0.438	0.446	2.1	0.406	0.290	13.9
	f_{seq}^{stree}	0.386	0.295	32.4	0.457	0.466	2.4	0.403	0.272	21.5
	f_{seq}^{oracle}	▲**0.442**	0.285	44.4	▲**0.600**	▲**0.482**	3.0	▲**0.455**	0.244	28.0

Experiments: Sequences in POI recommendation

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Geo	Baseline	0.405	0.306	43.9	0.427	0.457	5.6	0.406	0.286	30.0
	f_{seq}^{rnd}	0.378	0.307	22.5	0.397	0.447	5.9	0.390	0.307	25.1
	f_{seq}^{dist}	0.385	0.315	**▲3.6**	0.456	**†0.468**	**▲1.4**	0.405	**▲0.315**	**▲5.8**
	f_{seq}^{feat}	0.393	0.281	32.8	0.414	0.364	5.3	0.397	0.282	26.8
	f_{seq}^{item}	0.402	0.291	37.1	**†0.467**	0.466	2.1	**†0.412**	0.270	18.8
	f_{seq}^{rec}	**†0.405**	0.311	42.0	0.417	0.453	6.0	0.407	0.290	25.8
	f_{seq}^{lcs}	0.390	0.311	11.9	0.426	0.440	2.2	0.401	0.308	10.5
	f_{seq}^{stree}	0.402	**0.321**	31.3	0.431	0.458	3.5	0.404	0.302	19.4
	f_{seq}^{oracle}	**▲0.464**	0.314	41.7	**▲0.586**	**▲0.472**	4.6	**▲0.449**	0.287	28.8
Tour	Baseline	0.391	0.279	44.9	**†0.477**	0.473	2.0	0.403	0.240	28.4
	f_{seq}^{rnd}	0.364	0.305	23.9	0.400	0.448	5.7	0.390	0.291	30.8
	f_{seq}^{dist}	0.381	0.311	**▲4.2**	0.467	**†0.474**	**▲1.4**	**†0.412**	**▲0.309**	**▲7.1**
	f_{seq}^{feat}	0.374	0.277	20.9	0.420	0.359	5.0	0.401	0.278	31.6
	f_{seq}^{item}	0.397	0.283	38.1	0.477	0.470	1.8	0.406	0.271	16.9
	f_{seq}^{rec}	**†0.403**	0.289	41.4	0.427	0.451	5.8	0.408	0.273	26.6
	f_{seq}^{lcs}	0.382	**▲0.312**	12.0	0.438	0.446	2.1	0.406	0.290	13.9
	f_{seq}^{stree}	0.386	0.295	32.4	0.457	0.466	2.4	0.403	0.272	21.5
	f_{seq}^{oracle}	**▲0.442**	0.285	44.4	**▲0.600**	**▲0.482**	3.0	**▲0.455**	0.244	28.0

Family	Reranker	New York nDCG$_s$	New York FP$_s$	New York Dist	Rome nDCG$_s$	Rome FP$_s$	Rome Dist	Petaling Jaya nDCG$_s$	Petaling Jaya FP$_s$	Petaling Jaya Dist
Geo	Baseline	0.405	0.306	43.9	0.427	0.457	5.6	0.406	0.286	30.0
	f_{seq}^{rnd}	0.378	0.307	22.5	0.397	0.447	5.9	0.390	0.307	25.1
	f_{seq}^{dist}	0.385	0.315	▲**3.6**	0.456	†**0.468**	▲**1.4**	0.405	▲**0.315**	▲**5.8**
	f_{seq}^{feat}	0.393	0.281	32.8	0.414	0.364	5.3	0.397	0.282	26.8
	f_{seq}^{item}	0.402	0.291	37.1	†**0.467**	0.466	2.1	†**0.412**	0.270	18.8
	f_{seq}^{rec}	†**0.405**	0.311	42.0	0.417	0.453	6.0	0.407	0.290	25.8
	f_{seq}^{lcs}	0.390	0.311	11.9	0.426	0.440	2.2	0.401	0.308	10.5
	f_{seq}^{stree}	0.402	**0.321**	31.3	0.431	0.458	3.5	0.404	0.302	19.4
	f_{seq}^{oracle}	▲**0.464**	0.314	41.7	▲**0.586**	▲**0.472**	4.6	▲**0.449**	0.287	28.8
Tour	Baseline	0.391	0.279	44.9	†**0.477**	0.473	2.0	0.403	0.240	28.4
	f_{seq}^{rnd}	0.364	0.305	23.9	0.400	0.448	5.7	0.390	0.291	30.8
	f_{seq}^{dist}	0.381	0.311	▲**4.2**	0.467	†**0.474**	▲**1.4**	†**0.412**	▲**0.309**	▲**7.1**
	f_{seq}^{feat}	0.374	0.277	20.9	0.420	0.359	5.0	0.401	0.278	31.6
	f_{seq}^{item}	0.397	0.283	38.1	0.477	0.470	1.8	0.406	0.271	16.9
	f_{seq}^{rec}	†**0.403**	0.289	41.4	0.427	0.451	5.8	0.408	0.273	26.6
	f_{seq}^{lcs}	0.382	▲**0.312**	12.0	0.438	0.446	2.1	0.406	0.290	13.9
	f_{seq}^{stree}	0.386	0.295	32.4	0.457	0.466	2.4	0.403	0.272	21.5
	f_{seq}^{oracle}	▲**0.442**	0.285	44.4	▲**0.600**	▲**0.482**	3.0	▲**0.455**	0.244	28.0