Measuring and Mitigating Biases in Location-based Recommender Systems

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

[1] Instituto de Investigación Tecnológica (IIT), Universidad Pontificia Comillas

[2]Universidad Autónoma de Madrid

[3]University of Cagliari

June 20, 2024

*Summary of a work Published in **Data Mining and Knowledge Discovery** journal on February 2023 [Sánchez et al., 2023].

Overview

1. Point-Of-Interest recommendation

2. Analyze biases in Point-Of-Interest recommendation

3. Conclusions and future work

Overview

1. Point-Of-Interest recommendation
2. Analyze biases in Point-Of-Interest recommendation
3. Conclusions and future work

Point-Of-Interest (POI) Recommendation

- Recommending **new venues** to the users when they are in a specific city or region.

Point-Of-Interest (POI) Recommendation

- Recommending **new venues** to the users when they are in a specific city or region.
- The recommenders exploit the information of **Location-Based Social Networks** (e.g. Foursquare or Gowalla), where the users register the **check-ins** they perform to different venues.
- Differences with classical recommendation:

Point-Of-Interest (POI) Recommendation

- Recommending **new venues** to the users when they are in a specific city or region.
- The recommenders exploit the information of **Location-Based Social Networks** (e.g. Foursquare or Gowalla), where the users register the **check-ins** they perform to different venues.
- Differences with classical recommendation:
  - **Greater sparsity**: Movielens20M (0.539%) and Netflix (1.177%) density vs Foursquare (0.0034%) and Gowalla (0.0047%) density.

Point-Of-Interest (POI) Recommendation

- Recommending **new venues** to the users when they are in a specific city or region.
- The recommenders exploit the information of **Location-Based Social Networks** (e.g. Foursquare or Gowalla), where the users register the **check-ins** they perform to different venues.
- Differences with classical recommendation:
  - **Greater sparsity**: Movielens20M (0.539%) and Netflix (1.177%) density vs Foursquare (0.0034%) and Gowalla (0.0047%) density.
  - **Implicit** and **repeated interactions**: users visit the same places more than once.

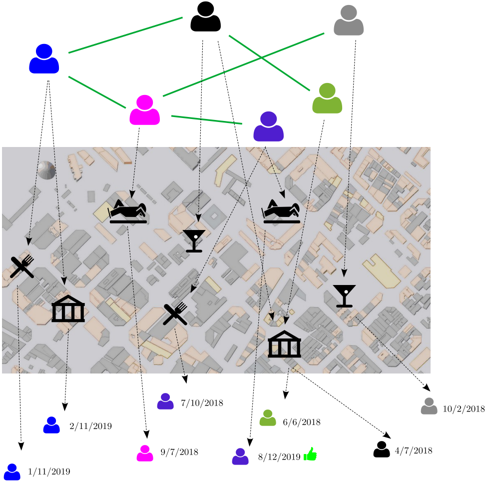
Point-Of-Interest (POI) Recommendation

- Recommending **new venues** to the users when they are in a specific city or region.
- The recommenders exploit the information of **Location-Based Social Networks** (e.g. Foursquare or Gowalla), where the users register the **check-ins** they perform to different venues.
- Differences with classical recommendation:
  - **Greater sparsity**: Movielens20M (0.539%) and Netflix (1.177%) density vs Foursquare (0.0034%) and Gowalla (0.0047%) density.
  - **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]

POI recommendation

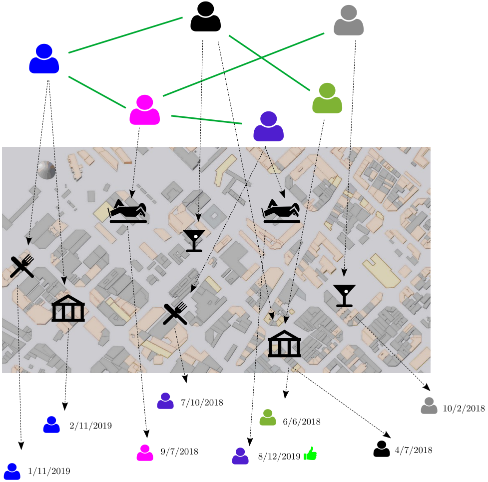
$$p^*(u) = \arg\max_{p \in \mathcal{P}} g(u, p, C) \quad (1)$$



POI recommendation

$$p^*(u) = \arg\max_{p \in \mathcal{P}} g(u, p, C) \quad (1)$$

Social



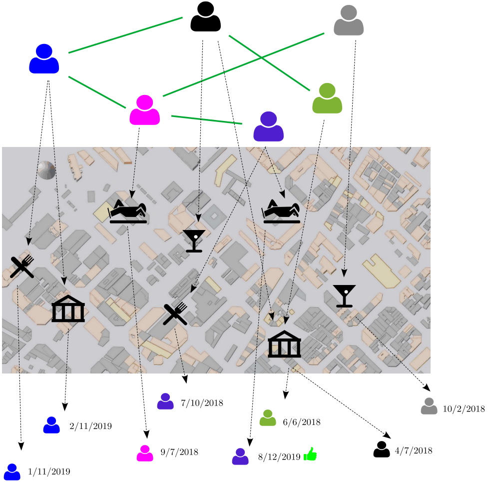
POI recommendation

$$p^*(u) = \arg\max_{p \in \mathcal{P}} g(u, p, C) \tag{1}$$

Social

Geographical

Categorical



Location-Based Social Networks

POI recommendation

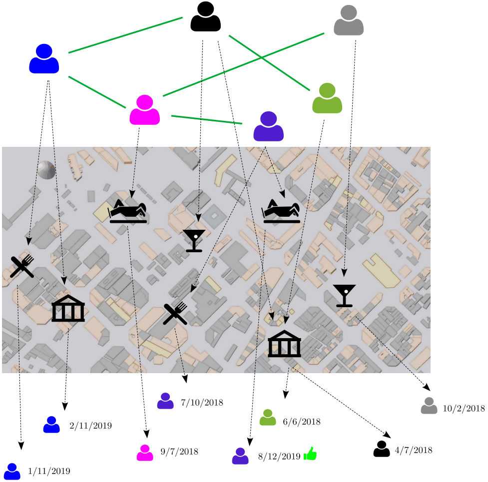
$$p^*(u) = \arg\max_{p \in \mathcal{P}} g(u, p, C) \quad (1)$$

Social

Geographical

Categorical

Temporal



Overview

Motivation

Bias

Bias normally refers to the **phenomenon** of **unfairly favoring** a group of people or an **opinion**. —[Färber et al., 2023]

Bias

Bias normally refers to the **phenomenon** of **unfairly favoring** a group of people or an **opinion**. —[Färber et al., 2023]

- Recommender Systems are **multi-stakeholder environments**, as they **affect** the users **receiving** the **recommendations**, and those behind the **recommended items** (providers).
- In Point-Of-Interest recommendation, the **business** of **venue owners strongly depends** on the **venue recommendations**.

Motivation

Bias

Bias normally refers to the **phenomenon** of **unfairly favoring** a group of people or an **opinion**. —[Färber et al., 2023]

- Recommender Systems are **multi-stakeholder environments**, as they **affect** the users **receiving** the **recommendations**, and those behind the **recommended items** (providers).
- In Point-Of-Interest recommendation, the **business** of **venue owners strongly depends** on the **venue recommendations**.
- Hence, it is important to consider **possible biases** that can be produced using **Artificial Inteligence** (AI) **tools**.

- **Popularity bias**: bias produced when a **more popular** venue is **ranked higher** than a **less popular one**, when **considering** the **top-n items** recommended to a user.

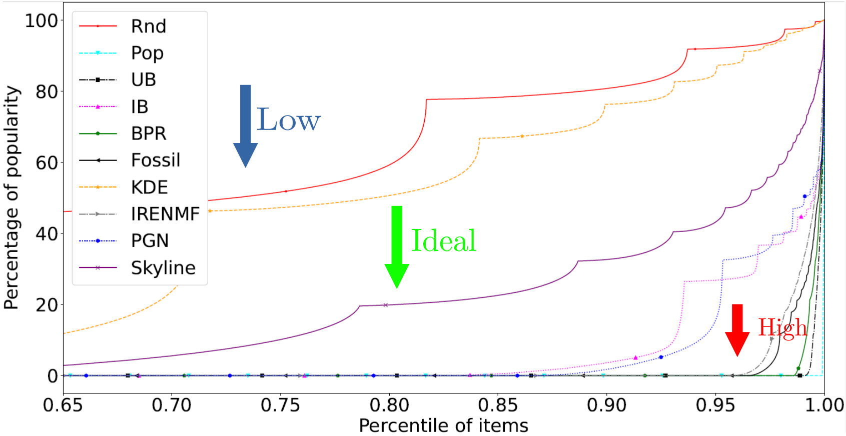
Proposed Bias Measurements: Popularity bias

- **Popularity bias**: bias produced when a **more popular** venue is **ranked higher** than a **less popular one**, when **considering** the **top-n items** recommended to a user.

Popularity bias

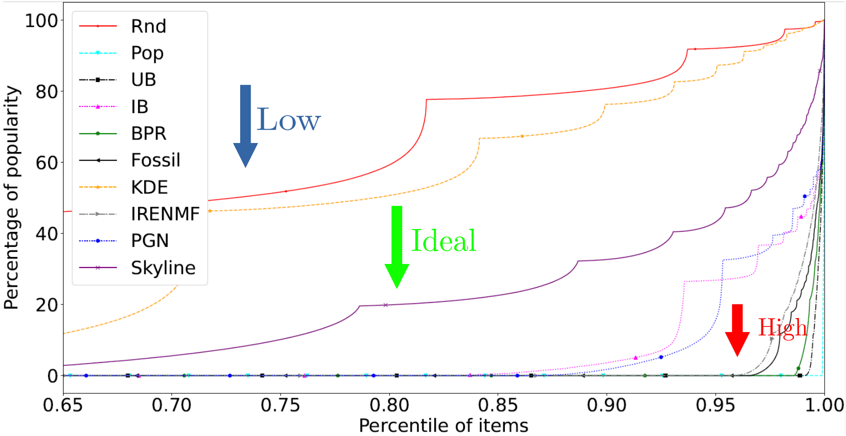
- We measure the **area under the curve** generated by the **cumulative distribution** of the recommended items by each recommender.
- **Higher values** means that **more items with different popularity** values **are being recommended**.

Popularity bias analysis (in the city of Tokyo).



- Personalized recommenders (except PGN and IB) tend to suffer from popularity bias.

Popularity bias analysis (in the city of Tokyo).



- Personalized recommenders (except PGN and IB) tend to suffer from popularity bias.
- It is difficult to approach the reduced popularity bias of the test set (Skyline).

Proposed Bias Measurements: Exposure bias

- **Item exposure**: ability of the model to **recommend items proportionally** to the **number of times** the users will consider that **item in the future**.

Proposed Bias Measurements: Exposure bias

- **Item exposure**: ability of the model to **recommend items proportionally** to the **number of times** the users will consider that **item in the future**.

Item exposure bias

- We compare the number of times an item has been recommended (Recommender Exposure, RE) against its actual exposure (Actual Exposure, AE).
- The **lower** the value, the **better** (the less diference between the recommended exposure and the actual exposure).

Proposed Bias Measurements: Geographical bias

- **Geographical bias**: bias produced by a **recommender** when **suggesting venues far** from the **current position** of the user (or with respect to the rest of the recommended venues).

- **Geographical bias**: bias produced by a **recommender** when **suggesting venues far** from the **current position** of the user (or with respect to the rest of the recommended venues).

Geographic distance bias

- First metric: **sums the distance of the recommended POIs** as if the user accepted those recommendations and visited those venues in order.
- Second metric: computes the **total distance** between each **recommended POI** and the **user historical midpoint**.
- We need to **compare** these results with the ones **exhibited** by the users in test.

Performance of the recommenders. Tokyo. @5

	Accuracy		Popularity Bias	Exposure		Distance		Coverage
Rec	**P**	**nDCG**	**PopI**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Rnd	0.000	0.000	**0.303**	**0.000**	**0.001**	37.2	34.7	**7,253**
Pop	**0.071**	*0.087*	0.000	0.131	0.121	*24.9*	*26.4*	**7,253**
UB	*0.070*	*0.087*	0.002	0.103	0.093	26.0	25.8	*6,931*
IB	0.063	0.080	*0.026*	0.064	0.057	23.2	25.0	*6,931*
HKV	0.064	0.078	0.003	*0.038*	*0.031*	*22.0*	*21.7*	*6,931*
BPR	0.066	0.081	0.003	0.123	0.112	25.6	27.7	*6,931*
FMFMGM	0.063	0.079	0.002	0.105	0.095	23.7	22.7	6,931
GEOBPR	0.065	0.081	0.001	0.120	0.110	23.7	24.2	6,931
IRENMF	*0.069*	0.083	0.008	*0.072*	*0.063*	23.9	23.8	6,931
PopGeoNN	0.068	*0.086*	*0.023*	0.110	0.100	*23.6*	*20.9*	**7,253**
Skyline	0.784	0.996	0.087	0.000	0.000	17.5	18.8	7,241

Performance of the recommenders. Tokyo. @5

	Accuracy		Popularity Bias	Exposure		Distance		Coverage
Rec	**P**	**nDCG**	**PopI**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Rnd	0.000	0.000	**0.303**	**0.000**	**0.001**	37.2	34.7	**7,253**
Pop	**0.071**	*0.087*	0.000	0.131	0.121	*24.9*	*26.4*	**7,253**
UB	*0.070*	*0.087*	0.002	0.103	0.093	26.0	25.8	*6,931*
IB	0.063	0.080	*0.026*	0.064	0.057	23.2	25.0	*6,931*
HKV	0.064	0.078	0.003	*0.038*	*0.031*	*22.0*	*21.7*	*6,931*
BPR	0.066	0.081	0.003	0.123	0.112	25.6	27.7	*6,931*
FMFMGM	0.063	0.079	0.002	0.105	0.095	23.7	22.7	6,931
GEOBPR	0.065	0.081	0.001	0.120	0.110	23.7	24.2	6,931
IRENMF	*0.069*	0.083	0.008	*0.072*	*0.063*	23.9	23.8	6,931
PopGeoNN	0.068	*0.086*	*0.023*	0.110	0.100	*23.6*	*20.9*	**7,253**
Skyline	0.784	0.996	0.087	0.000	0.000	17.5	18.8	7,241

- Skyline represents the results obtained by a **perfect recommender** (test set).

Performance of the recommenders. Tokyo. @5

	Accuracy		Popularity Bias	Exposure		Distance		Coverage
Rec	**P**	**nDCG**	**PopI**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Rnd	0.000	0.000	**0.303**	**0.000**	**0.001**	37.2	34.7	**7,253**
Pop	**0.071**	*0.087*	0.000	0.131	0.121	*24.9*	*26.4*	**7,253**
UB	*0.070*	*0.087*	0.002	0.103	0.093	26.0	25.8	*6,931*
IB	0.063	0.080	*0.026*	0.064	0.057	23.2	25.0	*6,931*
HKV	0.064	0.078	0.003	*0.038*	*0.031*	*22.0*	*21.7*	*6,931*
BPR	0.066	0.081	0.003	0.123	0.112	25.6	27.7	*6,931*
FMFMGM	0.063	0.079	0.002	0.105	0.095	23.7	22.7	6,931
GEOBPR	0.065	0.081	0.001	0.120	0.110	23.7	24.2	6,931
IRENMF	*0.069*	0.083	0.008	*0.072*	*0.063*	23.9	23.8	6,931
PopGeoNN	0.068	*0.086*	*0.023*	0.110	0.100	*23.6*	*20.9*	**7,253**
Skyline	0.784	0.996	0.087	0.000	0.000	17.5	18.8	7,241

- The performance of Pop and Rnd are **inverse**. **Pop** is among the **best** in terms of **accuracy** (but the worst in terms of bias, novelty and diversity), as **opposed to** Rnd.

Performance of the recommenders. Tokyo. @5

	Accuracy		Popularity Bias	Exposure		Distance		Coverage
Rec	**P**	**nDCG**	**PopI**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Rnd	0.000	0.000	**0.303**	**0.000**	**0.001**	37.2	34.7	**7,253**
Pop	**0.071**	*0.087*	0.000	0.131	0.121	*24.9*	*26.4*	**7,253**
UB	*0.070*	*0.087*	0.002	0.103	0.093	26.0	25.8	*6,931*
IB	0.063	0.080	*0.026*	0.064	0.057	23.2	25.0	*6,931*
HKV	0.064	0.078	0.003	*0.038*	*0.031*	*22.0*	*21.7*	*6,931*
BPR	0.066	0.081	0.003	0.123	0.112	25.6	27.7	*6,931*
FMFMGM	0.063	0.079	0.002	0.105	0.095	23.7	22.7	6,931
GEOBPR	0.065	0.081	0.001	0.120	0.110	23.7	24.2	6,931
IRENMF	*0.069*	0.083	0.008	*0.072*	*0.063*	23.9	23.8	6,931
PopGeoNN	0.068	*0.086*	*0.023*	0.110	0.100	*23.6*	*20.9*	**7,253**
Skyline	0.784	0.996	0.087	0.000	0.000	17.5	18.8	7,241

- **PopGeoNN** (an hybrid recommender) and **IB** obtain a **good balance** between **accuracy** and **novelty/diversity** and biases.

Overview

Conclusions

- **Different biases** are present in classical **POI recommenders** (specially, popularity bias).

Conclusions

- **Different biases** are present in classical **POI recommenders** (specially, popularity bias).
- There is a difficult **trade-off** between the dimensions of **accuracy, item exposure, and geographical distance**.

Conclusions

- **Different biases** are present in classical **POI recommenders** (specially, popularity bias).
- There is a difficult **trade-off** between the dimensions of **accuracy, item exposure, and geographical distance**.
- Simple techniques like creating **hybrid recommenders** and **reranking** might be useful to increase the **performance** across different **dimensions**.

Future work

- We plan to continue this **analysis** by **using different** groups of users (international **travelers, local travelers, or pure local** inhabitants in the city).

Future work

- We plan to continue this **analysis** by **using different** groups of users (international **travelers, local travelers, or pure local** inhabitants in the city).
- We are **studying** how to apply **imputation techniques** to **reduce** the **data sparsity** in POI recommendation and **improve** the **performance** of the **recommenders**.

Measuring and Mitigating Biases in Location-based Recommender Systems

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

[1] Instituto de Investigación Tecnológica (IIT), Universidad Pontificia Comillas

[2]Universidad Autónoma de Madrid

[3]University of Cagliari

June 20, 2024

Thank you

References I

- Färber, M., Coutinho, M., and Yuan, S. (2023).
  Biases in scholarly recommender systems: impact, prevalence, and mitigation.
  Scientometrics, 128(5):2703–2736.
- Miller, H. J. (2004).
  Tobler's first law and spatial analysis.
  Annals of the Association of American Geographers, 94(2):284–289.
- Sánchez, P., Bellogín, A., and Boratto, L. (2023).
  Bias characterization, assessment, and mitigation in location-based recommender systems.
  Data Min. Knowl. Discov., 37(5):1885–1929.

Proposed Bias Measurements: Popularity bias

- **Popularity bias**: bias produced when a **more popular** venue is **ranked higher** than a **less popular one**, when **considering** the **top-n items** recommended to a user.

- **Popularity bias**: bias produced when a **more popular** venue is **ranked higher** than a **less popular one**, when **considering** the **top-n items** recommended to a user.

Popularity bias

$$PopI@n(rec) = \frac{1}{2|m|} \sum_{k=2}^{|m|} \left(F_{\text{pop}}^{R(rec,n)}(x_{k-1}) + F_{\text{pop}}^{R(rec,n)}(x_k) \right) \quad (2)$$

- where m are the items in the training set (ordering them by the number of times they have been recommended by rec). $F_{\text{pop}}^{R(rec,n)}$ is the **cummulative popularity distribution** of item x (only if they belong to the recommendation list R).
- **Higher values** means that **more items with different popularity** values **are being recommended**.

Proposed Bias Measurements: Exposure bias

- **Item exposure**: ability of the model to **recommend items proportionally** to the **number of times** the users will consider that **item in the future**.

Proposed Bias Measurements: Exposure bias

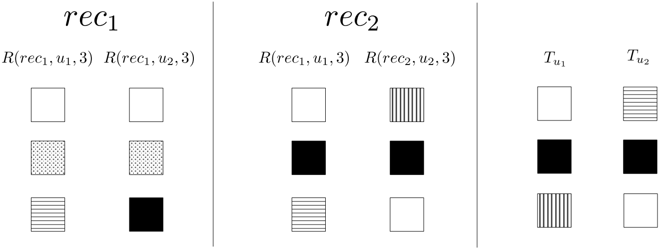
- **Item exposure**: ability of the model to **recommend items proportionally** to the **number of times** the users will consider that **item in the future**.

Item exposure bias

$$IE@n(rec;\pi) = \sum_{i \in I} (RE@n(i, rec) - AE(i;\pi))^2 \qquad (3)$$

- where $RE@n(i, rec)$ is the **recommender exposure** of item i, and $AE(i;\pi)$ is the **actual exposure** (number of times that item should be recommended).
- The **lower** the value, the **better** (the less diference between the recommended exposure and the actual exposure).

Proposed Bias Measurements: Exposure bias



- rec_2 would obtain a lower value because it is recommending the black item 2 times, as in the test set, and it is not recommending the dotted item, which does not appear in the test set. Hence, as the recommended items from rec_2 are more similar to the ground truth of the user than the ones recommended by rec_1 , the venue exposure polarization of rec_2 would be lower.

Proposed Bias Measurements: Geographical bias

- **Geographical bias**: bias produced by a **recommender** when **suggesting venues far** from the **current position** of the user (or with respect to the rest of the recommended venues).

Proposed Bias Measurements: Geographical bias

- **Geographical bias**: bias produced by a **recommender** when **suggesting venues far** from the **current position** of the user (or with respect to the rest of the recommended venues).

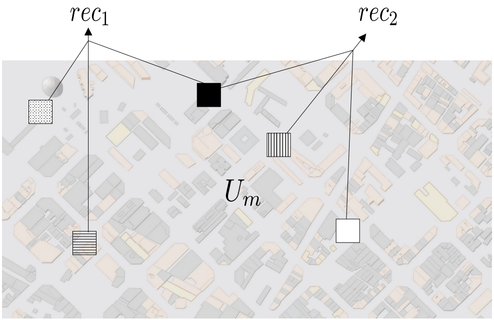
Geographic distance bias

$$\text{DistT@}n(R_u) = \sum_{i=2}^{\min(n,|R_u|)} \text{Hav}(R_{u,i-1}, R_{u,i}) \quad (4)$$

$$\text{DistU@}n(R_u) = \sum_{i=1}^{\min(n,|R_u|)} \text{Hav}(\vec{u}_m, R_{u,i}) \quad (5)$$

- where $\vec{u}_m$ is the user **midpoint** and Hav is the **haversine distance** between the coordinates.
- We need to **compare** these results with the ones **exhibited** by the users in test.

Proposed Bias Measurements: Geographical bias



- the second recommender will be preferred as the recommended venues are more geographically related between them and with respect to the user midpoint (represented by U_m).

Mitigating biases

Hybrid recommenders

$$s(i, u; \mathcal{R}, W) = \sum_{j=1}^{|\mathcal{R}|} w^j \frac{s(i, R_u^j) - \min(R_u^j)}{\max(R_u^j) - \min(R_u^j)} \tag{6}$$

- where $\mathcal{R}$ is a set of recommenders and W is a weight vector. We apply min-max normalization for every recommender.

Rerankers

$$f_{obj}(u, i; \lambda, R^j, R^k) = \lambda \cdot f_{R^j}(u, i) + (1 - \lambda) \cdot f_{R^k}(u, i) \tag{7}$$

- where R^j is the original recommender and R^k is the recommender to rerank.
- We use the parameter λ to balance the contribution of the original recommender and the reranked one.

Performance of hybrid and rerankers. Tokyo @5.

	Accuracy		**Novelty**	**Diversity**	**Pop. Bias**		**Exp.**		**Distance**		**Coverage**
Rec	**P**	**nDCG**	**EPC**	**Gini**	**PopI**	**PopC**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Popularity	0.071	0.087	0.746	0.000	0.000	0.960	0.131	0.121	24.9	26.4	**7,253**
H(0.2 Pop + 0.8 IB)	0.071	0.088	*0.801*	*0.019*	*0.022*	*0.921*	*0.078*	*0.069*	24.0	24.4	**7,253**
H(0.8 Pop + 0.2 IB)	0.072	0.089	0.746	0.000	0.000	0.962	0.131	0.120	24.9	26.3	**7,253**
H(0.5 Pop + 0.5 IB)	0.073	0.089	0.765	0.005	0.007	0.946	0.110	0.100	25.2	25.2	**7,253**
RR(Pop, IB)	*0.074*	*0.093*	0.758	0.000	0.000	0.968	0.111	0.101	*23.7*	*24.2*	**7,253**
UB	0.070	0.087	0.769	0.001	0.002	0.968	0.103	0.093	26.0	25.8	*6,931*
H(0.2 UB + 0.8 IB)	0.065	0.081	*0.811*	*0.020*	*0.022*	**0.918**	*0.069*	*0.061*	24.1	25.2	*6,931*
H(0.8 UB + 0.2 IB)	*0.070*	*0.087*	0.768	0.001	0.002	0.966	0.104	0.094	26.0	25.6	*6,931*
H(0.5 UB + 0.5 IB)	0.068	0.085	0.786	0.008	0.010	0.943	0.089	0.080	25.6	25.2	*6,931*
RR(UB, IB)	0.068	0.086	0.778	0.001	0.006	0.954	0.092	0.083	*23.5*	*24.6*	*6,931*
RR(IRENMF, IB)	0.070	0.087	0.784	0.003	0.007	0.951	0.087	0.078	**23.5**	24.2	*6,931*
PopGeoNN	0.068	0.086	0.777	0.014	**0.023**	0.932	0.110	0.100	*23.6*	**20.9**	**7,253**
H(0.2 PopGeoNN + 0.8 IB)	0.072	0.089	*0.803*	*0.019*	0.021	*0.922*	*0.076*	*0.067*	24.2	24.2	**7,253**
H(0.8 PopGeoNN + 0.2 IB)	0.073	0.091	0.760	0.003	0.006	0.956	0.117	0.107	25.3	23.9	**7,253**
H(0.5 PopGeoNN + 0.5 IB)	0.074	0.092	0.772	0.006	0.009	0.947	0.102	0.093	25.5	24.6	**7,253**
RR(PopGeoNN, IB)	**0.075**	**0.093**	0.766	0.001	0.003	0.961	0.103	0.093	23.7	23.5	**7,253**

Performance of hybrid and rerankers. Tokyo @5.

Rec	Accuracy		Novelty	Diversity	Pop. Bias		Exp.		Distance		Coverage
	P	nDCG	EPC	Gini	PopI	PopC	ExpP	ExpR	DistT	DistU	UC
Popularity	0.071	0.087	0.746	0.000	0.000	0.960	0.131	0.121	24.9	26.4	**7,253**
H(0.2 Pop + 0.8 IB)	0.071	0.088	*0.801*	*0.019*	*0.022*	*0.921*	*0.078*	*0.069*	24.0	24.4	**7,253**
H(0.8 Pop + 0.2 IB)	0.072	0.089	0.746	0.000	0.000	0.962	0.131	0.120	24.9	26.3	**7,253**
H(0.5 Pop + 0.5 IB)	0.073	0.089	0.765	0.005	0.007	0.946	0.110	0.100	25.2	25.2	**7,253**
RR(Pop, IB)	*0.074*	*0.093*	0.758	0.000	0.000	0.968	0.111	0.101	*23.7*	*24.2*	**7,253**
UB	0.070	0.087	0.769	0.001	0.002	0.968	0.103	0.093	26.0	25.8	*6,931*
H(0.2 UB + 0.8 IB)	0.065	0.081	*0.811*	*0.020*	*0.022*	**0.918**	*0.069*	*0.061*	24.1	25.2	*6,931*
H(0.8 UB + 0.2 IB)	*0.070*	*0.087*	0.768	0.001	0.002	0.966	0.104	0.094	26.0	25.6	*6,931*
H(0.5 UB + 0.5 IB)	0.068	0.085	0.786	0.008	0.010	0.943	0.089	0.080	25.6	25.2	*6,931*
RR(UB, IB)	0.068	0.086	0.778	0.001	0.006	0.954	0.092	0.083	*23.5*	*24.6*	*6,931*
RR(IRENMF, IB)	0.070	0.087	0.784	0.003	0.007	0.951	0.087	0.078	**23.5**	24.2	*6,931*
PopGeoNN	0.068	0.086	0.777	0.014	**0.023**	0.932	0.110	0.100	*23.6*	**20.9**	**7,253**
H(0.2 PopGeoNN + 0.8 IB)	0.072	0.089	*0.803*	*0.019*	0.021	*0.922*	*0.076*	*0.067*	24.2	24.2	**7,253**
H(0.8 PopGeoNN + 0.2 IB)	0.073	0.091	0.760	0.003	0.006	0.956	0.117	0.107	25.3	23.9	**7,253**
H(0.5 PopGeoNN + 0.5 IB)	0.074	0.092	0.772	0.006	0.009	0.947	0.102	0.093	25.5	24.6	**7,253**
RR(PopGeoNN, IB)	**0.075**	**0.093**	0.766	0.001	0.003	0.961	0.103	0.093	23.7	23.5	**7,253**

- The H(0.2 PopGeoNN + 0.8 IB) configuration **improves** the **performance** in terms of **accuracy** and **novelty and diversity** while **reducing** the **biases** of the recommendations.

Performance of hybrid and rerankers. Tokyo @5.

	Accuracy		Novelty	Diversity	Pop. Bias		Exp.		Distance		Coverage
Rec	**P**	**nDCG**	**EPC**	**Gini**	**PopI**	**PopC**	**ExpP**	**ExpR**	**DistT**	**DistU**	**UC**
Popularity	0.071	0.087	0.746	0.000	0.000	0.960	0.131	0.121	24.9	26.4	**7,253**
H(0.2 Pop + 0.8 IB)	0.071	0.088	*0.801*	*0.019*	*0.022*	*0.921*	*0.078*	*0.069*	24.0	24.4	**7,253**
H(0.8 Pop + 0.2 IB)	0.072	0.089	0.746	0.000	0.000	0.962	0.131	0.120	24.9	26.3	**7,253**
H(0.5 Pop + 0.5 IB)	0.073	0.089	0.765	0.005	0.007	0.946	0.110	0.100	25.2	25.2	**7,253**
RR(Pop, IB)	*0.074*	*0.093*	0.758	0.000	0.000	0.968	0.111	0.101	*23.7*	*24.2*	**7,253**
UB	0.070	0.087	0.769	0.001	0.002	0.968	0.103	0.093	26.0	25.8	*6,931*
H(0.2 UB + 0.8 IB)	0.065	0.081	*0.811*	*0.020*	*0.022*	**0.918**	*0.069*	*0.061*	24.1	25.2	*6,931*
H(0.8 UB + 0.2 IB)	*0.070*	*0.087*	0.768	0.001	0.002	0.966	0.104	0.094	26.0	25.6	*6,931*
H(0.5 UB + 0.5 IB)	0.068	0.085	0.786	0.008	0.010	0.943	0.089	0.080	25.6	25.2	*6,931*
RR(UB, IB)	0.068	0.086	0.778	0.001	0.006	0.954	0.092	0.083	*23.5*	*24.6*	*6,931*
RR(IRENMF, IB)	0.070	0.087	0.784	0.003	0.007	0.951	0.087	0.078	**23.5**	24.2	*6,931*
PopGeoNN	0.068	0.086	0.777	0.014	**0.023**	0.932	0.110	0.100	*23.6*	**20.9**	**7,253**
H(0.2 PopGeoNN + 0.8 IB)	0.072	0.089	*0.803*	*0.019*	0.021	*0.922*	*0.076*	*0.067*	24.2	24.2	**7,253**
H(0.8 PopGeoNN + 0.2 IB)	0.073	0.091	0.760	0.003	0.006	0.956	0.117	0.107	25.3	23.9	**7,253**
H(0.5 PopGeoNN + 0.5 IB)	0.074	0.092	0.772	0.006	0.009	0.947	0.102	0.093	25.5	24.6	**7,253**
RR(PopGeoNN, IB)	**0.075**	**0.093**	0.766	0.001	0.003	0.961	0.103	0.093	23.7	23.5	**7,253**

- Similar behavior is observed in H(0.2 Pop + 0.8 IB) .