Top-N Recommendation Algorithms: A Quest for the State-of-the-Art

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SUPPLEMENTAL MATERIAL

1 INTER-METRIC CORRELATIONS - BEYOND ACCURACY METRICS

In this section we report the correlations between each pair of beyond-accuracy metrics. For each dataset, the tables indicate the Pearson product-moment correlation coefficient, unveiling strong direct and inverse correlations. Please note we do not report same analysis for accuracy metrics here, since the topic of correlation among those metrics has been extensively studied in prior literature. Please refer to Valcarce et al. [2], and Anelli et al. [1] for further details.

Table 1. Detailed Metric Correlations. The tables show how much each beyond-accuracy metric (computed on recommendation lists of ten items for each user) correlates with each other. Specifically, the table shows the Pearson product-moment correlation coefficient for each dataset.

Movielens	EFD	Gini	IC	PopREO	PopRSP	ACLT	APLT	ARP
EPC	1.00	-0.73	-0.36	0.75	0.79	-0.79	-0.79	0.20
EFD		-0.74	-0.37	0.77	0.81	-0.80	-0.80	0.23
Gini			0.86	-0.99	-0.99	0.99	0.99	-0.81
IC				-0.86	-0.79	0.80	0.80	-0.95
PopREO					0.99	-0.99	-0.99	0.78
PopRSP						-1.00	-1.00	0.74
ACLT							1.00	-0.74
APLT								-0.74
Amazon	EFD	Gini	IC	PopREO	PopRSP	ACLT	APLT	ARP
EPC	1.00	-0.10	0.45	-0.26	0.09	-0.04	-0.04	-0.46
EFD		-0.05	0.49	-0.32	0.03	0.02	0.02	-0.50
Gini			0.78	-0.85	-0.96	0.88	0.88	-0.69
IC				-0.93	-0.74	0.70	0.70	-0.88
PopREO					0.87	-0.87	-0.87	0.84
PopRSP						-0.97	-0.97	0.60
ACLT							1.00	-0.58
APLT								-0.58
Epinions	EFD	Gini	IC	PopREO	PopRSP	ACLT	APLT	ARP
EPC	0.83	-0.05	-0.11	-0.94	-0.84	0.91	0.91	-0.81
EFD		-0.54	-0.59	-0.62	-1.00	0.97	0.97	-0.67
Gini			1.00	-0.25	0.55	-0.43	-0.43	-0.18
IC				-0.19	0.60	-0.49	-0.49	-0.12
PopREO					0.63	-0.74	-0.74	0.81
PopRSP						-0.99	-0.99	0.64
ACLT							1.00	-0.69
APLT								-0.69

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2 F1 SCORES - ADDITIONAL NUMERICAL EXAMPLES

The F1 score represents the harmonic mean of Precision and Recall. In the recommendation domain, when evaluating lists of k items (top-k evaluation), it is usually defined as follows:

$$F1 Score = \frac{1}{|U|} \sum_{u \in U} 2 * \frac{P_u @k * R_u @k}{P_u @k + R_u @k}$$

$$\tag{1}$$

where U is the set of the users in the population, and where Pu@k and Ru@k are the Precision and Recall values for a user u's top-k recommendations, respectively. In an alternative formulation, the F1 Score could be computed after obtaining the average Precision and Recall values across all users:

$$P@k = \frac{1}{|U|} \sum_{u \in U} P_u@k \tag{2}$$

$$R@k = \frac{1}{|U|} \sum_{u \in U} R_u@k \tag{3}$$

$$F1 \, Score = 2 * \frac{P@k * R@k}{P@k + R@k} \tag{4}$$

These alternative formulations may lead to different results, as we highlight in the following examples. Let us consider a population of five users for whom we have computed the Precision and Recall values for a recommendation system A (see Table 2a).

Table 2. Accuracy results for the toy recommendation systems. P@k, R@k, and F@k stands for individual Precision, Recall, and F1 Score with a list of k recommendations, respectively. *Average* reports the overall Precision and Recall values. Per-user F1 and average-based F1 indicates the F1 scores computed using Equation 1 and Equation 4, respectively.

Population	$P_u@k$	$R_u@k$	$F_u@k$
$user_0$	0.2	0.3	0.240
$user_1$	0.5	0.6	0.545
$user_2$	0.3	0.4	0.343
$user_3$	0.6	0.3	0.400
$user_4$	0.2	0.3	0.240
	P@k	R@k	F@k
Average	0.36	0.38	
Per-user F1			0.354
Average-based F1			0.370

⁽a) Toy recommendation system A.

Population	$P_u@k$	$R_u@k$	$F_u@k$
$user_0$	0.2	0.4	0.267
$user_1$	0.5	0.2	0.286
$user_2$	0.4	0.4	0.400
$user_3$	0.2	0.6	0.300
$user_4$	0.5	0.4	0.444
	P@k	R@k	F@k
Average	0.36	0.40	
Per-user F1			0.339
Average-based F1			0.379

(b) Toy recommendation system B.

It is worth noticing that the F1 formulation from Equation 1, denoted as *Per-User F1*, returns an F1 score that is lower than the overall averaged values of Precision and Recall. This can happen due to the product of individual Precision and Recall values. If one of the two is small, it affects the result and impacts the F1 score. Conversely, this behavior is not likely to occur when the F1 is computed on already averaged Precision and Recall values (Average-based F1).

Furthermore, suppose that we evaluate the performance of two recommender systems, A and B (Table 2b). The two systems lead to the same average Precision value, and B leads to a higher Recall value than A. It may now be surprising to see that A has a higher *per-user* F1 score than B. As a consequence of the previously discussed phenomenon, it is

indeed possible. That is, although the Precision value of system B is equal to system A, some individual Precision values lead to poor individual F1 results that affect the overall value of the metric. Some examples of such cases can be found in the accuracy results of the paper.

3 HYPERPARAMETERS RANGE

Table 3. Hyperparameter values for our baselines.

Algorithm	Hyperparameter	Range	Type	Distribution
UserKNN,	topK	5 - 1000	Integer	uniform
ItemKNN	similarity	cosine, jaccard, dice, pearson, euclidean	Categorical	
	topK	5 - 1000	Integer	uniform
$RP^3\beta$	alpha	0 - 2	Real	uniform
RΓ <i>p</i>	beta	0 - 2	Real	uniform
	normalization	True, False	Categorical	
	topK	5 -1000	Integer	uniform
SLIM	l1 ratio	0.00001 - 1	Real	log-uniform
	alpha	0.01 - 1	Real	uniform
EASE ^R	l2 norm	1 - 10000000	Real	log-uniform
	num factors	8, 16, 32, 64, 128, 256	Integer	
	epochs	30 - 100	Integer	uniform
MF2020	learning rate	0.00001 - 1	Real	log-uniform
	reg	0.00001 - 0.1	Real	log-uniform
	negative sample	4,6,8	Integer	
	num factors	1 - 200	Integer	uniform
	scaling	linear, log	Categorical	
iALS	alpha	0.001 - 50	Real	uniform
	epsilon	0.001 - 10	Real	uniform
	reg	0.001 - 0.01	Real	uniform
	num factors	8, 16, 32, 64, 128, 256	Integer	
	learning rate	0.00001 - 1	Real	log-uniform
BPRMF	batch size	128, 256, 512	Integer	
DIKMI	reg user	0.00001 - 0.1	Real	log-uniform
	reg positive item	0.00001 - 0.1	Real	log-uniform
	reg negative item	0.00001 - 0.1	Real	log-uniform
	num factors	8, 16, 32, 64, 128, 256	Integer	
NeuMF	epochs	30 - 100	Integer	uniform
	learning rate	0.00001 - 1	Real	log-uniform
	batch size	128, 256, 512	Integer	
	negative sample	4,6,8	Integer	
MultiVAE	epochs	100 - 300	Integer	uniform
	learning rate	0.00001 - 1	Real	log-uniform
	batch_size	64, 128, 256	Integer	
	intermediate dim	400 - 800	Integer	uniform
	latent dim	100-400	Integer	uniform
	reg	0.00001 - 1	Real	log-uniform

Table 4. Hyperparameter values for our baselines on all datasets.

UserKNN topK similarity 117 correlation cosine cosine cosine ItemNN topK similarity 95 798 137 topK similarity cosine cosine cosine topK alpha 1.4350197 0.4973207 0.8719344 beta 0.3265517 0.2836938 0.2483698 normalization true false true topK 518 663 663 SLIM 11 ratio 0.0000420 0.0000108 0.0000108 alpha 0.2978543 0.0486771 0.0486771 EASE ^K 12 norm 238.5621338 238.5621338 238.5621338 num factors 128 64 16 16 epochs 72 92 97 97 MF2020 learning rate 0.1295965 0.1295965 0.0154435 reg 0.0087583 0.0125009 0.0223642 negative sample 4 8 4 num factors 51 200 178 <th>Algorithm</th> <th>Hyperparameter</th> <th>Movilens</th> <th>Amazon</th> <th>Epinions</th>	Algorithm	Hyperparameter	Movilens	Amazon	Epinions
ItemNN topK 55 798 137		topK	117	226	139
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SLIM		normalization	true	false	true
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