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

Manuscript submitted to ACM

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. Generated by Spread-LaTeX

Algorithm	Hyperparameter	Range	Type	Distribution
UserKNN, ItemKNN	topK	5 - 1000	Integer	uniform
	similarity	cosine, jaccard, dice, pearson, euclidean	Categorical	
$RP^3\beta$	topK	5 - 1000	Integer	uniform
	alpha	0 - 2	Real	uniform
	beta	0 - 2	Real	uniform
	normalization	True, False	Categorical	
SLIM	topK	5 -1000	Integer	uniform
	l1 ratio	0.00001 - 1	Real	log-uniform
	alpha	0.01 - 1	Real	uniform
$EASE^R$	l2 norm	1 - 10000000	Real	log-uniform
MF2020	num factors	8, 16, 32, 64, 128, 256	Integer	
	epochs	30 - 100	Integer	uniform
	learning rate	0.00001 - 1	Real	log-uniform
	reg	0.00001 - 0.1	Real	log-uniform
	negative sample	4,6,8	Integer	
iALS	num factors	1 - 200	Integer	uniform
	scaling	linear, log	Categorical	
	alpha	0.001 - 50	Real	uniform
	epsilon	0.001 - 10	Real	uniform
	reg	0.001 - 0.01	Real	uniform
BPRMF	num factors	8, 16, 32, 64, 128, 256	Integer	
	learning rate	0.00001 - 1	Real	log-uniform
	batch size	128, 256, 512	Integer	
	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
NeuMF	num factors	8, 16, 32, 64, 128, 256	Integer	
	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. Generated by Spread-LaTeX

Algorithm	Hyperparameter	Movilens	Amazon	Epinions
UserKNN	topK	117	226	139
	similarity	correlation	cosine	cosine
ItemNN	topK	95	798	137
	similarity	cosine	cosine	cosine
$RP^3\beta$	topK	158	803	144
	alpha	1.4350197	0.4973207	0.8719344
	beta	0.3265517	0.2836938	0.2483698
	normalization	true	false	true
SLIM	topK	518	663	663
	l1 ratio	0.0000420	0.0000108	0.0000108
	alpha	0.2978543	0.0486771	0.0486771
$EASE^R$	l2 norm	238.5621338	238.5621338	238.5621338
MF2020	num factors	128	64	16
	epochs	72	92	97
	learning rate	0.1295965	0.1295965	0.0154435
	reg	0.0087583	0.0125009	0.0223642
	negative sample	4	8	4
iALS	num factors	51	200	178
	epochs	27	70	145
	scaling	log	log	log
	alpha	6.3818930	9.1219718	2.8537184
	epsilon	5.6496278	0.4921936	2.3098481
	reg	0.0494734	0.4921936	0.0411491
BPRMF	num factors	256	64	256
	epochs	73	86	63
	learning rate	0.0378936	0.1265624	0.1004075
	batch size	256	256	256
	reg user	0.0157839	0.0058673	0.0002613
	reg positive item	0.0005651	0.0052985	0.0034511
	reg negative item	0.0012779	0.0009577	0.0328127
NeuMF	num factors	16	128	32
	epochs	93	100	39
	learning rate	0.0000366	0.0001365	0.0000465
	batch size	256	64	256
	negative sample	6	6	8
MultiVAE	epochs	100	205	200
	learning rate	0.0001545	0.0000723	0.0001003
	batch_size	128	128	128
	intermediate dim	674	721	674
	latent dim	175	279	175
	reg	0.0000105	0.1153400	0.0020018

REFERENCES

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