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New Objective Functions for Social Collaborative Filtering

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Received: date / Accepted: date

Abstract Insert your abstract here. Include keywords, PACS and mathematical subject classification numbers as needed.

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1 Introduction

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2 Experiments

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2.1 Experiment 1

For the first experiment, we evaluated each algorithm using 10-fold cross validation by training and testing on only ACTIVE data. Objectives for each

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	Accuracy	Precision	Recall	F1
Constant True	0.4333	0.4333	1.0000	0.6047
Constant False	0.5666	0.0000	0.0000	0.0000
FIW	0.7065	0.9163	0.3553	0.5120
FUW	0.5668	0.2000	3.2733E-4	6.5359E-4
Global	0.4972	0.2273	0.0668	0.1032
Hybrid	0.9510	0.9443	0.9429	0.9435
Logistic Regression	0.8943	0.8801	0.8761	0.8778
Matchbox	0.9275	0.9479	0.8812	0.9133
NN	0.4333	0.4333	1.0000	0.6047
Soc. Hybrid	**0.9526**	**0.9507**	**0.9396**	**0.9450**
Soc. Matchbox	0.9335	0.9605	0.8830	0.9200
Spec. Copreference	0.9315	0.9526	0.8861	0.9181
SVM	0.9033	0.8792	0.9010	0.8898
Spec. Matchbox	0.9303	0.9499	0.8859	0.9168

algorithm were optimized via gradient descent. λ's for the matrix factorization based algorithms were tuned prior to the start of the trial by a systematic line (grid) search over 10^n for $n \in \{-10, -9, ..., 10\}$ to maximize accretion on 10% held-out data, training on the other 90%. This was repeated for $K \in \{3, 5, 7, 10, 15, 20, 30\}$ to find the best K. N and C were tuned similarly via line search over $N \in \{1, 2, ..., 250\}$ and $C \in [2^{-15}, 2^{15}]$.

As can be seen in table, the best performing algorithm was Soc. Hybrid with an accuracy of 0.9526.

2.2 Experiment 2

For the 2nd experiment, we wanted to see whether including PASSIVE data improves on the results over using solely ACTIVE data. To test this, we evaluated the algorithms by training them on UNION data and testing on ACTIVE data. The train/test split over the ACTIVE data is exactly the same as in Experiment 1, but this time we supplement each training with additional PASSIVE data. The PASSIVE data used are all the links that were "liked" by the users on Facebook. The hyper parameters were tuned as in Experiment 1.

Again, Soc. Hybrid was the best performing accuracy. However, most algorithms performed worse with the addition of PASSIVE data during training than with just using ACTIVE data. This suggests that the "likes" on the PASSIVE data aren't as informative of the user's preferences than the explicit "likes" and "dislikes" in the ACTIVE data.

2.3 Experiment 3

For Experiment 3, we wanted to check weather the addition of user ad item features actually helps with the performance of the algorithms, over just using the latent features in matrix factorization. We repeated the same experiments as in Experiment 1 for Matchbox and Soc. Matchbox, but removed the user and

	Accuracy	Precision	Recall	F1
Constant True	0.4333	0.4333	1.0000	0.6047
Constant False	0.5667	0.0000	0.0000	0.0000
FUW	0.4333	0.4333	1.0000	0.6047
FIW	0.7960	0.7958	0.7119	0.7515
Global	0.4333	0.4333	1.0000	0.6047
Hybrid	0.9435	0.9220	0.9502	0.9359
LogisticRegression	0.8926	0.8694	0.8856	0.8773
Matchbox	0.9291	0.9465	0.8866	0.9155
NN	0.4333	0.4333	1.0000	0.6047
Soc. Hybrid	**0.9480**	**0.9252**	**0.9574**	**0.9411**
Soc. Matchbox	0.9333	0.9567	0.8863	0.9201
Spec. Copreference	0.9299	0.9450	0.8902	0.9167
Spec. Matchbox	0.9298	0.9465	0.8884	0.9164
SVM	0.8833	0.8387	0.9051	0.8705

	Accuracy	Precision	Recall	F1
Matchbox	0.9275	0.9479	0.8812	0.9133
Matchbox (No Features)	0.9382	0.9674	0.8873	0.9256
Soc. Matchbox	0.9335	0.9605	0.8830	0.9200
Social Matchbox (No Features)	**0.9388**	**0.9710**	**0.8853**	**0.9261**

	Accuracy	Precision	Recall	F1
Global	0.4578	0.4578	1.0000	0.6011
FUW	0.4578	0.45783	1.0000	0.6011
FIW	0.8155	0.6271	0.6868	0.6496
Hybrid	**0.9368**	**0.9263**	**0.9160**	**0.9130**
LogisticRegression	0.8913	0.8684	0.8424	0.8421
Matchbox	0.9119	0.9160	0.8433	0.8672
NN	0.4578	0.4578	1.0000	0.6011
SocialHybrid	0.9357	0.9207	0.9088	0.9058
SocialMatchbox	0.9155	0.9213	0.8432	0.8706
SpectralCopreference	0.9136	0.9133	0.8496	0.8695
SpectralMatchbox	0.9139	0.9178	0.8484	0.8708
SVM	0.8929	0.8612	0.8650	0.8499

item features. Matchbox hence basically becomes the PMF algorithm described in Salakhutdinov and Mnih.

The results show that for both Matchbox and Soc. Matchbox, the addition of user and item features actually lowered their accuracies.

2.4 Experiment 4

For the next experiment, we wanted to reevaluate the algorithms again in the same manner as in Experiment 1, but using Macro Averaging when calculating the metric.

Using this metric calculation, the Hybrid algorithm had the best accuracy.

	Accuracy	Precision	Recall	F1
SocialMatchbox	0.9334	0.9583	0.8849	0.9201
SpectralMatchbox	0.9328	**0.9522**	**0.8895**	**0.9198**

	Accuracy	Precision	Recall	F1
SocialMatchbox	**0.9345**	**0.9629**	**0.8828**	**0.9211**
SpectralMatchbox	0.9292	0.9494	0.8838	0.9154

	Accuracy	Precision	Recall	F1
SocialMatchbox	0.9335	0.9537	0.8897	0.9206
SpectralMatchbox	0.9310	0.9497	0.8879	0.9177

Algorithm	Accuracy	Precision	Recall	F1
SocialMatchbox	0.9336	0.9540	0.8899	0.9207
SpectralMatchbox	0.9311	0.9516	0.8863	0.9177

2.5 Experiment 5

For Experiment 5, we tested the Social Matchbox and Spectral Matchbox algorithms using different ways of normalizing the Social Interaction measure between the two users. For Social Matchbox, doing max normalization and taking the logarithm provided the best accuracy whereas for Spectral Matchbox, just doing max normalization provided the best accuracy.

MaxNormalizationNoLog

MaxNormalizationWithLog

MaxNormalizationWithLogPlus1

MeanNormalizationNoLog

MeanNormalizationWithLog

MeanNormalizationWithLogPlus1

Algorithm	Accuracy	Precision	Recall	F1
SocialMatchbox	0.9335	0.9605	0.8830	0.9200
SpectralMatchbox	0.9311	0.9500	0.8877	0.9178

Algorithm	Accuracy	Precision	Recall	F1
SocialMatchbox	0.9334	0.9579	0.8854	0.9202
SpectralMatchbox	0.9303	0.9499	0.8859	0.9168

Algorithm	Accuracy	Precision	Recall	F1
Global	0.4218	0.4218	1.0000	0.5897
FUW	0.4218	0.4218	1.0000	0.5897
FIW	0.8038	0.8744	0.6296	0.7248
Hybrid	0.9477	0.9461	0.9253	0.9352
LogisticRegression	0.8980	0.8788	0.8741	0.8760
Matchbox	0.9292	0.9508	0.8756	0.9110
NN	0.4218	0.4218	1.0000	0.5897
SocialHybrid	**0.9483**	**0.9439**	**0.9281**	**0.9353**
SocialMatchbox	0.9313	0.9534	0.8766	0.9130
SpectralCopreference	0.9294	0.9520	0.8735	0.9105
Spectral Matxhbox	0.9304	0.9504	0.8778	0.9122
SVM	0.8999	0.8524	0.9161	0.8827

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2.6 Experiment 6

For the last experiment, we simulated the cold-start problem by giving each algorithm more 25% more training data for each user. We wanted to see if the additional training data helps improve the training. Aside from the additional training data, the experimental setup is the same as in Experiment 1.

The best performing algorithm was Social Hybrid once again, with an accuracy of 0.9483. This is slightly better than the result it got in Experiment 1, which was 0.9480. This was the same for most of the algorithms, they generally outperformed their results in Experiment 1. This suggests that the increase in training data does indeed help improve accuracy.

Paragraph headings Use paragraph headings as needed.

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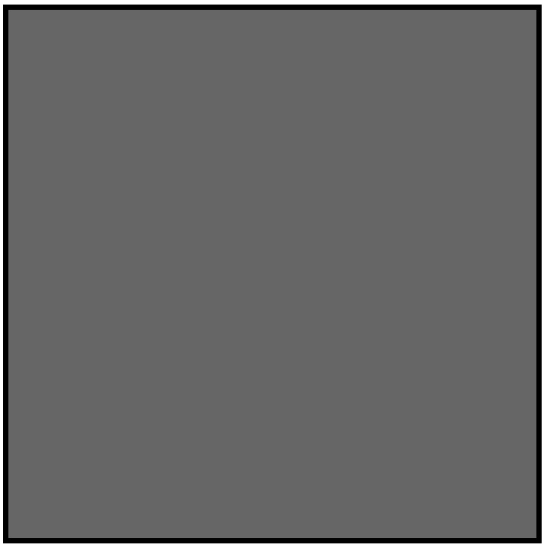
References

1. Author, Article title, Journal, Volume, page numbers (year)
2. Author, Book title, page numbers. Publisher, place (year)



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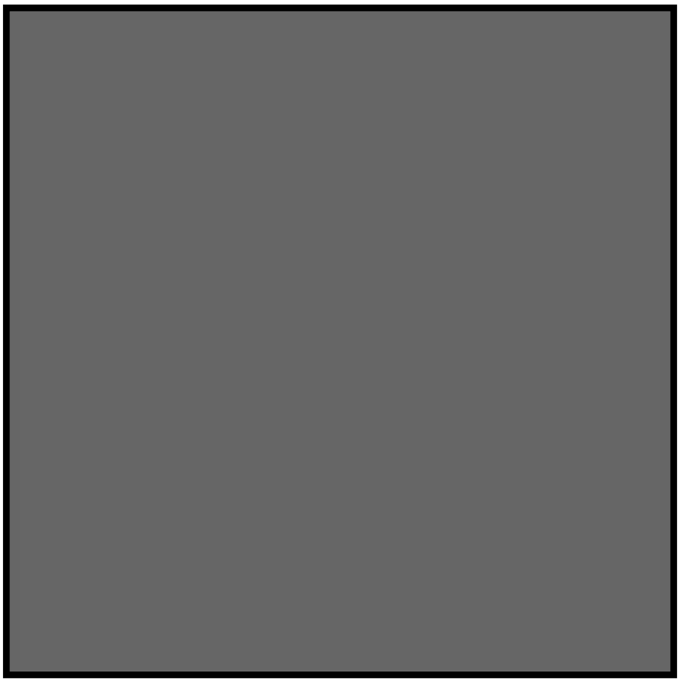

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