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Adaptive Aggregation of Recommender Systems

Olav Bjørkøy

Department of Computer and Information Science

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2006: The Netflix Challenge

- USD 1,000,000 prize for a 10% improvement in recommendation accuracy.
- Progress was slow until teams started combining their efforts.
- Team BellKor finally achieved a 10.06% improvement by combining 107 different recommender algorithms.



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Today: Web Search

Google

"Today we use more than 200 signals, including PageRank, to order websites, and we update these algorithms on a weekly basis." (google.com/corporate/tech.html)

Bing

"We use over 1,000 different signals and features in our ranking algorithm." (bing.com/community/site_blogs/b/search/archive/2011/02/01/thoughts-on-search-quality.aspx)



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Why multiple recommenders?

- One method can not capture the predictive nature of all available data.
- Number of different recommender systems only limited by patterns found in data.
- Accuracy of the combined blend is not determined by that of the individual recommenders.

Bell, R., Koren, Y., and Volinsky, C. (2007) (Netflix)

"Quite frequently we have found that the more accurate predictors are less useful within the full blend."



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The Problem: Latent Subjectivity

- Aggregation of predictions through generalized weights.
- Generalized weights treat all users and items the same.
- The system decides the individual algorithm importance.
- Varying accuracy for recommenders across users.
- Varying accuracy for recommenders across items.
- A case of misplaced subjectivity.

$$\hat{r}_{u,i} = \sum_{m \in M} w_m \times p(m, u, i) \quad (1)$$



Adaptive Recommenders

- Combine multiple disjoint recommender systems that look at various predictive patterns (content-based, collaborative filtering, auxiliary social data, etc).
- Automatically predict how relevant each recommender will be for each user, based on previous recommendations.
- Weigh each recommender prediction accordingly.

$$\hat{r}_{u,i} = \sum_{m \in M} p_w(m, u, i) \times p_r(m, u, i) \quad (2)$$



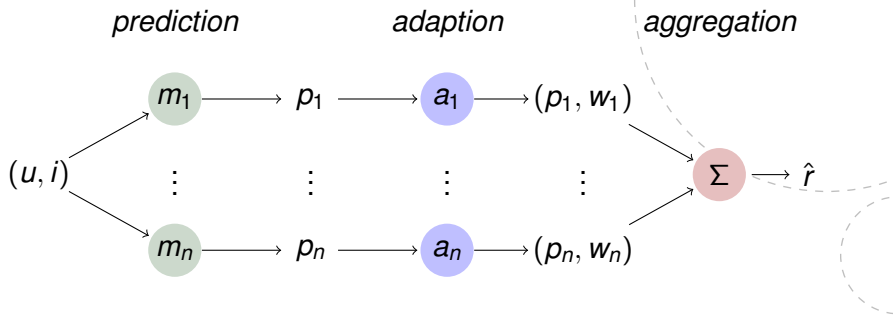


Figure: Layers of recommenders: The predictive layer consists of ordinary recommender systems. This produces a set of predicted ratings (p). The adaptive layer estimates how well each modeling method will perform for the current user and item. The aggregation weighs the predictions into a final score \hat{r} .



Training phase

- Split into two sets using bootstrap aggregation: (t_1, t_2) .
- Use t_1 to train the basic recommenders.
- Create an error matrix using the basic recommenders and t_2 .
- The error matrix values are predicted errors for (u, i, m) .
- Train adaptive recommenders on the error matrix.

$$\forall (u, i, r) \in (d_e - d_m) : E(m)_{u,i} = |r - p(m, u, i)| \quad (3)$$



Prediction phase

- Calculate each prediction $\hat{r}_{(u,i,m)}$.
- Calculate each predicted error $\hat{e}_{(u,i,m)}$.
- The adaptive weights are the inverses of the normalized error.
- Sum the weighted predictions to get the final \hat{r} .

$$\hat{r}_{u,i} = \sum_{(m_e, m_r) \in M} \left(1 - \frac{p(m_e, u, i)}{\text{error}(u, i)}\right) \times p(m_r, u, i) \quad \text{where} \quad \text{error}(u, i) = \sum_{m_e \in M} p(m_e, u, i) \quad (4)$$



Results

- Calculate RMSE values for basic recommenders, simple aggregations and adaptive aggregation.
- Used the Movielens movie rating dataset and the following recommenders (see paper for more details):
- Basic recommenders: 4x SVD, Slope One, Item Average, Baseline, Cosine Similarity, Pearson Correlation.
- Aggregate recommenders: Median, Average, Adaptive.



(a) RMSE values for the five disjoint subsets:

	method	d_1	d_2	d_3	d_4	d_5
S	svd1	1.2389	1.1260	1.1327	1.1045	1.1184
S	svd2	1.2630	1.1416	1.1260	1.1458	1.1260
S	svd3	1.0061	0.9825	0.9830	0.9815	0.9797
S	svd4	1.0040	0.9830	0.9849	0.9850	0.9798
S	slope_one	1.1919	1.0540	1.0476	1.0454	1.0393
S	item_avg	1.0713	0.9692	0.9662	0.9683	0.9725
S	baseline	1.0698	0.9557	0.9527	0.9415	0.9492
S	cosine	1.1101	0.9463	0.9412	0.9413	0.9382
S	knn	1.4850	1.1435	1.1872	1.2156	1.2022
A	median	0.9869	0.8886	0.8857	0.8857	0.8855
A	average	0.9900	0.8536	0.8525	0.8525	0.8519
A	adaptive	0.9324	0.8015	0.7993	0.8238	0.8192

(b) Statistics for the methods:

	method	min	max	mean	σ	Δ
S	knn	1.1435	1.4850	1.2467	0.3487	-
S	svd2	1.1260	1.2630	1.1605	0.2277	6.9%
S	svd1	1.1045	1.2389	1.1441	0.2197	1.4%
S	slope_one	1.0393	1.1919	1.0756	0.2415	5.9%
S	item_avg	0.9662	1.0713	0.9895	0.2023	8.0%
S	svd4	0.9798	1.0040	0.9873	0.0924	2.2%
S	svd3	0.9797	1.0061	0.9865	0.0991	0.1%
S	cosine	0.9382	1.1101	0.9754	0.2595	1.1%
S	baseline	0.9415	1.0698	0.9738	0.2196	1.6%
A	median	0.8855	0.9865	0.9065	0.2005	6.9%
A	average	0.8519	0.9900	0.8801	0.2344	2.9%
A	adaptive	0.7993	0.9324	0.8352	0.2225	5.1%



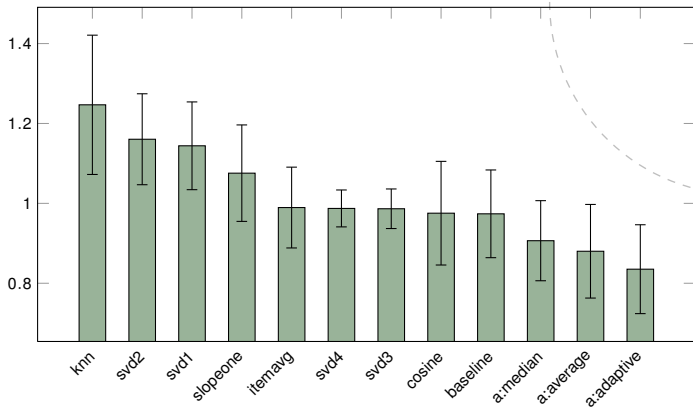


Figure: Average RMSE plot.



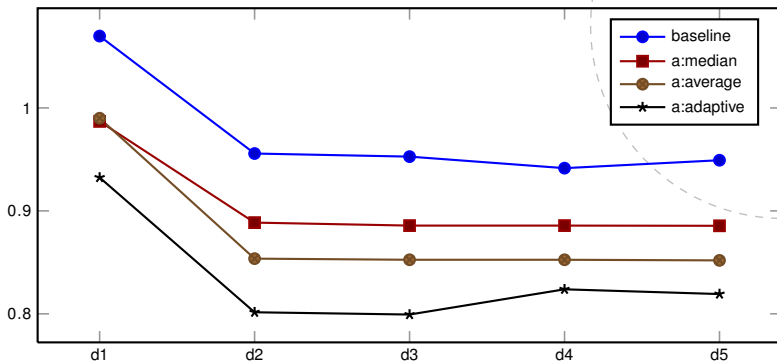


Figure: RMSE Variations: This plot shows that, while the standard deviation of each method may be high, this has more to do with the selected dataset than with their performance in comparison with each other.



Limitations

- Lots of added complexity for uncertain gains.
- Only tested on a few datasets, no real world situations.
- Only compared to simple aggregation methods.
- Neither the aggregators nor the basic recommenders were heavily optimized to the domain of the dataset.



Resulting Adaptive Aggregation

- Each recommender is weighted based on predicted accuracy.
- Accuracy predictions are contextually dependent on (u, i, m) .
- *Any* applicable recommender becomes a worthy addition.

