Combining Predictions for Accurate Recommender Systems

[KDD 2010, July 25–28, 2010, Washington D.C., USA]

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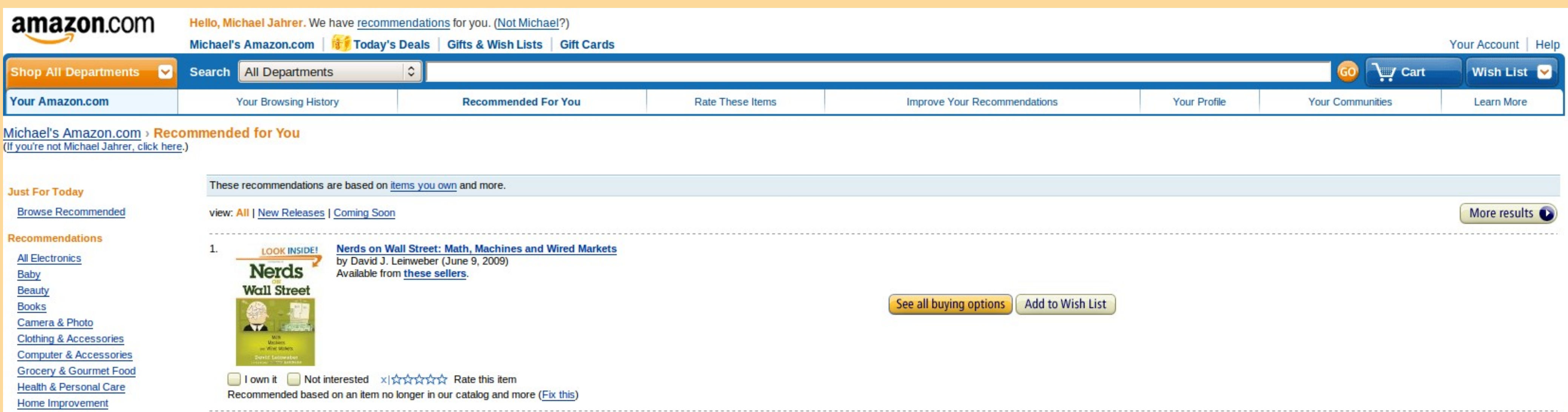
Outline

- Motivation
- Collaborative Filtering Algorithms
- Blending Algorithms
- Experimental Results on Netflix Data
- Application example: KDD Cup 2010

Motivation

- <u>Accurate recommendations</u> may increase the sales
- Guides users to the products, they want to purchase
- Better cross-selling
- Increasing user activity



Collaborative filtering

- All algorithms have been successfully applied on the Netflix Prize dataset
  - SVD – Singular Value Decomposition
  - KNN – K-Nearest Neighbors (item - item)
  - AFM – Asymmetric Factor Model
  - RBM – Restricted Boltzmann Machines
  - GE – Global Effects

SVD

u...user i...item
$\hat{r}_{ui}$...prediction
$\boldsymbol{p}$ ...item feature
$\boldsymbol{q}$ ...user feature

- Very popular since the Netflix Prize
- Accurate and good scaling properties

$$\hat{r}_{ui} = \boldsymbol{p}^T \boldsymbol{q} \quad = \quad \underbrace{\begin{bmatrix} p_0 & p_1 & p_3 \end{bmatrix}}_{\text{item feature}} * \underbrace{\begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix}}_{\text{user feature}}$$

KNN

u...user i...item
$\hat{r}_{ui}$...prediction
$R(u,i)$...item set
c_{ij}...corr between item i and j
r_{ui}...user rating

- Natural approach
- Predict a rating $\hat{r}_{ui}$
  - Find k-best correlating items $R(u,i)$
  - Make a weighted sum

$$\hat{r}_{ui} = \frac{\sum_{j \in R(u,i)} c_{ij} r_{uj}}{\sum_{j \in R(u,i)} |c_{ij}|}$$

- Quadratic runtime for 1x prediction O(N²) N = #items

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AFM

u...user i...item
$\hat{r}_{ui}$...prediction
$N(u)$...ratings of u
$\boldsymbol{p}$ ...item feature
$\boldsymbol{q}$ ...asym. item feature

- Like SVD
- A user is represented via his rated items $N(u)$
- ☺ New users can be integrated without re-training

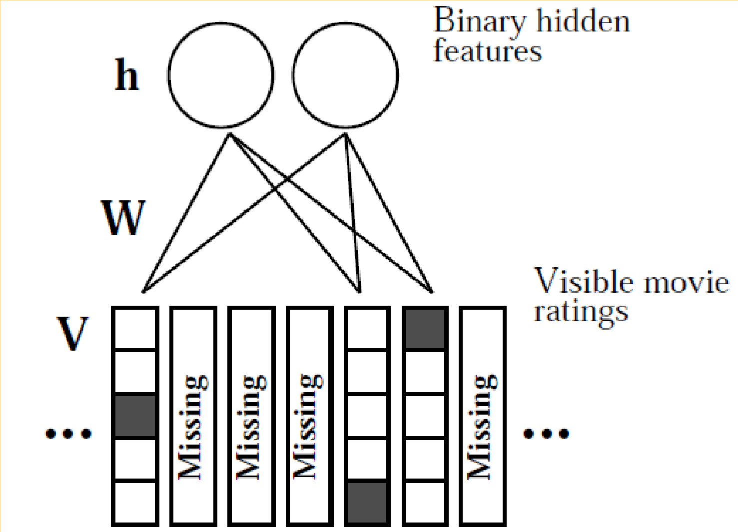
$$\hat{r}_{ui} = \boldsymbol{p}^T \underbrace{\left(\frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} \boldsymbol{q}_j \right)}_{\text{user feature (virtual)}} = \begin{bmatrix} p_0 & p_1 & p_3 \end{bmatrix} * \frac{1}{\sqrt{3}} \left(\begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix} + \begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix} + \begin{bmatrix} q_0 \\ q_1 \\ q_2 \end{bmatrix} \right)$$

item feature

RBM

u...user i...item
$\hat{r}_{ui}$...prediction

- Two-layer undirected graphical model
- Learning is performed with "contrastive divergence"
- RBM reconstructs the visible units
- Predictions $\hat{r}_{ui}$ are calculated over rating probabilites



[R.Salakhutdinov, A.Mnih, G.Hinton : **Restricted Boltzmann machines for collaborative filtering**, ICML '07]

Global Effects

- Calculate ”hand-crafted” features for users and items
- Equivalent to SVD with either fixed user or item features

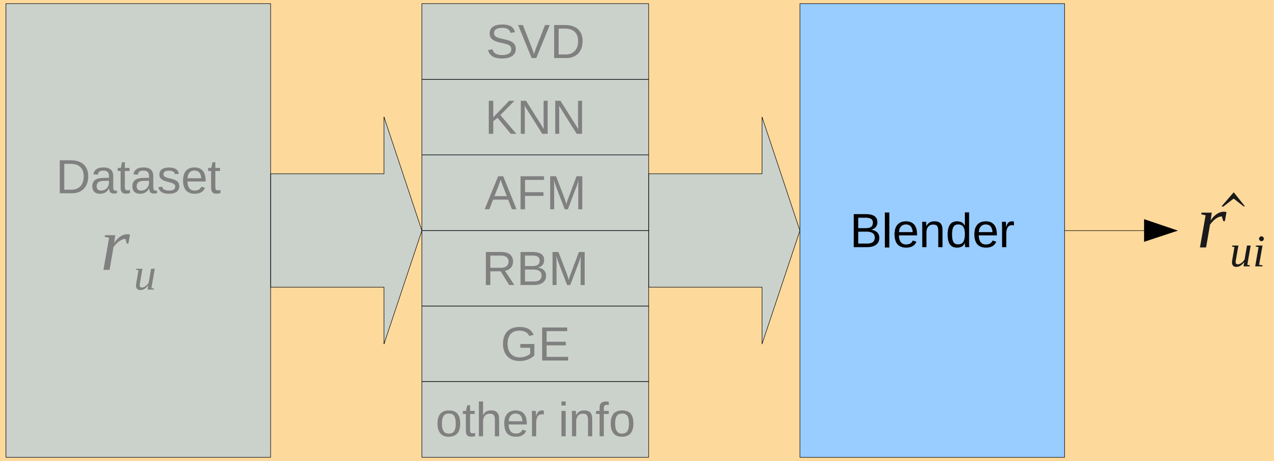
#	effect	shrinkage
1	Movie effect	α_1
2	User effect	α_2
3	User effect: user x sqrt(time(user))	α_3
4	User effect: user x sqrt(time(movie))	α_4
5	Movie effect: movie x sqrt(time(movie))	α_5
6	Movie effect: movie x sqrt(time(user))	α_6
7	User effect: user x average(movie)	α_7
8	User effect: user x votes(movie)	α_8
9	Movie effect: movie x average(user)	α_9
10	Movie effect: movie x votes(user)	α_{10}

[A.Töscher, M.Jahrer, R.Bell : **The BigChaos Solution to the Netix Grand Prize**, 2009]

Blending

u...user i...item
$\hat{r}_{ui}$...prediction
$N(u)$...ratings of u

- Apply a supervised learner for combining predictions
- Error: RMSE
- Additional information: $|N(u)|$ (the "support")



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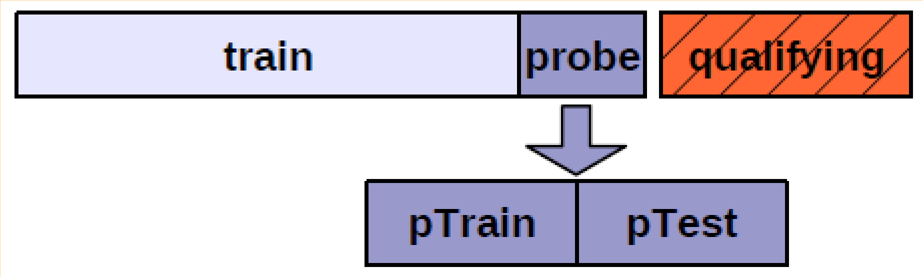
Evaluation schema

- Dataset for CF algorithms: **Netflix** (10^8 ratings, except probe)
- Dataset for Blending: **probe** (1.4M ratings)
- 50/50 random split of **probe**: **pTrain**, **pTest**



Blending

- **pTrain**: training set
- **pTest**: test set
- **qualifying**: another test set

Used CF algorithms

- 4x SVD
- 4x AFM
- 4x KNN
- 2x RBM
- 4x GE
- log(support) as additional input

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19 predictors

- Some are trained on residuals of others

nr	name	RMSE	description
1	AFM-1	0.9362	AFM, 200 features, $\eta = 1e{-}3$, $\lambda = 1e{-}3$, learnrate η is multiplied with 0.95 from epoch 30, trained for 120 epochs
2	AFM-2	0.9231	AFM, 2000 features, $\eta = 1e{-}3$, $\lambda = 2e{-}3$, trained for 23 epochs, based on residuals of KNN-4.
3	AFM-3	0.9340	AFM, 40 features, $\eta = 1e{-}4$, $\lambda = 1e{-}3$, trained for 96 epochs
4	AFM-4	0.9391	AFM, 900 features, $\eta = 1e{-}3$, $\lambda = 1e{-}2$, trained for 43 epochs
5	GE-1	0.9079	GE, 16 effects, based on residuals of KNN-1
6	GE-2	0.9710	GE, 16 effects, on raw ratings
7	GE-3	0.9443	GE, 16 effects, based on residuals of KNN-4
8	GE-4	0.9209	GE(with time), 24 effects, based on residuals of AFM-2
9	KNN-1	0.9110	KNN item, Pearson correlation, $k = 24$ neighbors, based on residuals of AFM-1
10	KNN-2	0.8904	KNN item, Set correlation [20], $k = 122$, based on residuals from a chain of algorithms RBM-KNN-GE(with time)
11	KNN-3	0.8970	KNN item, Pearson correlation, $k = 55$, based on residuals of a discrete RBM model with $nHid = 150$
12	KNN-4	0.9463	KNN item, Pearson correlation, $k = 21$, based on residuals of GE-2
13	RBM-1	0.9493	RBM, discrete, $nHid = 10$, $\eta = 0.002$, $\lambda = 0.0002$
14	RBM-2	0.9123	RBM, discrete, $nHid = 250$, $\eta = 0.002$, $\lambda = 0.0004$
15	SVD-1	0.9074	SVD, 300 features, $\eta = 8e{-}4$, $\lambda = 0.01$, trained for 158 epochs, based on residuals of 1GE (item mean)
16	SVD-2	0.9172	SVD, 20 features, $\eta = 0.002$, $\lambda = 0.02$, trained for 158 epochs, based on residuals of 1GE (item mean)
17	SVD-3	0.9033	SVD, 1000 features, with adaptive user factors (AUF [20]), $\eta = 0.001$, $\lambda = 0.015$, trained for 158 epochs
18	SVD-4	0.8871	SVD extended, 150 features, individual learnrates η and regularization constants λ are automatically tuned on the probe set [20].
19	support	-	The number of ratings per user; we take the natural logarithm of the support as additional input.

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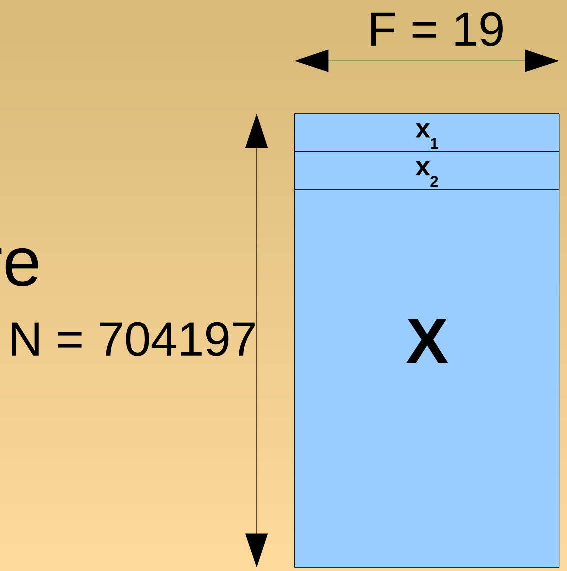
Blending (supervised setup)

- $\boldsymbol{X}$ … train set (N x F matrix)
- x_{ij} … feature value   i...sample, j...feature
- $\boldsymbol{y}$ … targets (1...5 ratings)

- $\boldsymbol{p}$ … predictions
- $\Omega(\boldsymbol{x})$ … model (the ”blender”)
- Error function

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\Omega(\boldsymbol{x}) - y_i\right)^2}$$



What is inside X ? (X=train set)

(first 20 rows)

Predictors																			Target
4,12	4,18	3,74	4,08	4,43	4,11	4,10	4,11	4,32	4,61	4,63	4,11	4,28	4,53	4,67	4,53	4,20	4,18	4,55	5
3,62	3,79	3,73	3,81	3,60	3,68	3,76	3,76	3,62	2,72	2,75	3,69	3,62	2,43	2,26	1,68	3,12	3,16	6,18	1
3,22	3,22	3,55	3,59	3,05	3,67	3,48	3,28	3,22	3,16	3,17	3,70	4,04	3,10	3,32	3,74	2,94	2,87	4,30	1
3,35	4,15	3,26	3,69	3,60	2,99	4,09	4,16	3,52	3,94	3,98	4,17	4,59	3,71	4,23	4,18	3,68	3,97	4,06	4
4,11	3,93	3,84	4,01	3,94	3,58	3,85	3,83	4,04	3,81	3,94	3,89	3,82	3,94	3,82	3,80	3,73	3,86	5,82	3
4,22	4,55	4,09	4,20	4,42	4,15	4,38	4,55	4,45	4,19	4,21	4,56	4,15	4,23	4,24	4,24	4,15	4,26	4,49	4
3,64	3,93	3,65	3,59	3,82	3,62	3,96	3,98	3,82	3,86	3,80	3,74	3,51	3,77	3,91	4,24	3,83	4,00	5,09	3
2,50	2,61	2,60	2,64	2,34	2,84	2,75	2,61	2,29	2,32	2,32	2,86	3,10	2,63	2,57	2,47	2,57	2,75	5,49	1
3,44	2,98	3,30	3,55	3,32	3,13	3,09	3,15	3,45	3,10	3,27	3,08	3,38	3,00	3,39	3,34	2,99	3,32	3,43	4
3,75	3,91	3,73	3,82	3,90	3,97	3,94	3,90	3,92	3,80	3,76	4,02	3,84	3,98	4,29	4,30	3,98	4,13	5,45	3
4,74	5,00	4,25	4,77	4,88	4,01	4,41	4,92	4,81	4,51	4,58	4,45	4,12	4,49	4,13	4,25	4,42	4,35	3,30	5
3,79	3,80	4,03	3,86	3,72	4,02	3,87	3,87	3,79	3,91	4,03	3,94	4,17	3,82	3,98	3,75	3,72	3,75	4,57	5
4,41	4,29	4,27	4,20	4,30	4,19	4,32	4,29	4,40	4,06	4,11	4,35	4,09	4,25	3,96	4,33	4,35	4,10	5,68	5
3,37	3,51	3,35	3,44	3,44	3,77	3,74	3,55	3,36	3,23	3,25	3,78	3,46	2,94	3,39	3,54	3,46	3,36	5,02	4
3,48	3,70	3,16	3,37	3,52	3,89	3,62	3,62	3,41	3,27	3,33	3,89	2,90	3,18	3,49	3,60	3,34	3,46	5,56	4
3,12	3,20	2,81	2,98	3,26	3,04	2,99	3,22	3,24	2,56	2,60	3,04	2,81	2,49	2,53	2,39	2,56	2,83	7,07	3
2,98	3,18	2,82	2,84	3,41	3,31	3,35	3,15	3,45	3,25	3,34	3,54	2,52	3,23	3,60	3,03	3,21	3,34	5,33	4
3,79	4,97	4,12	3,37	4,75	3,96	4,89	5,00	4,69	4,84	4,86	4,61	4,15	4,62	4,73	4,69	4,79	4,82	3,14	1
3,65	4,24	3,75	3,71	3,85	3,95	4,14	4,29	3,74	3,69	3,66	4,07	3,65	3,95	3,66	4,22	3,10	3,59	5,78	4
4,01	3,55	3,47	3,20	4,00	3,36	3,42	3,55	3,95	3,67	3,60	3,35	3,92	4,15	3,57	4,22	3,67	3,76	4,80	4
4,01	4,22	4,15	4,05	4,57	4,03	4,18	4,12	4,45	4,47	4,35	4,01	4,07	4,31	4,60	4,77	4,38	4,59	3,33	5

....

… 700k rows

Linear Regression

- Model: $\Omega(\boldsymbol{x}) = \boldsymbol{x}^T \boldsymbol{w}$
- Training: $\boldsymbol{w} = (\boldsymbol{X}^T \boldsymbol{X} + \lambda \boldsymbol{I})^{-1} \boldsymbol{X}^T \boldsymbol{y}$
- ☺ Fast

Determined by cross-validation
λ=0.000004

- RMSE$_{\text{pTest}}$: 0.87525
→ **Baseline**

regression coefficients
w_i

−0.083	AFM-1 (0.9362)
−0.084	AFM-2 (0.9231)
−0.077	AFM-3 (0.9340)
+0.088	AFM-4 (0.9391)
+0.098	GE-1 (0.9079)
−0.003	GE-2 (0.9710)
−0.081	GE-3 (0.9443)
+0.176	GE-4 (0.9209)
+0.029	KNN-1 (0.9110)
+0.272	KNN-2 (0.8904)
−0.094	KNN-3 (0.8970)
+0.010	KNN-4 (0.9463)
+0.025	RBM-1 (0.9493)
+0.066	RBM-2 (0.9123)
−0.008	SVD-1 (0.9074)
+0.094	SVD-2 (0.9172)
+0.080	SVD-3 (0.9033)
+0.227	SVD-4 (0.8871)
−0.008	log(support)
+3.673	const. 1

Binned Linear Regression

Lin.Reg Baseline: 0.8752

- Model: $\Omega(\boldsymbol{x}) = \boldsymbol{x}^T \boldsymbol{w}_b$ b … bin, each $\boldsymbol{w}_b$ per bin
- ☺ Fast, more accurate than LR
- 3 binning types
  - support: Number of ratings per user
  - date: Day of the rating
  - frequency: Number of votes from user u on day of the rating

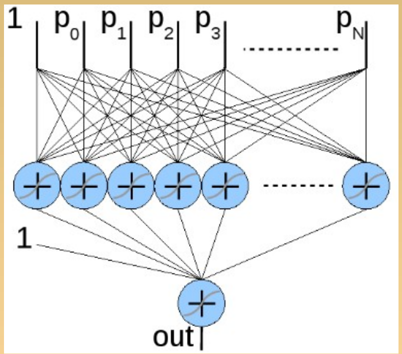
type	2 bins	5 bins	10 bins	20 bins
support	0.874877 (V:0.87517)	**0.874741** (V:0.8750)	0.874744 (V:0.87499)	0.87485 (V:0.87513)
date	0.875212 (V:0.87545)	**0.875195** (V:0.87541)	0.87527 (V:0.87544)	0.87537 (V:0.87558)
frequency	0.87518 (V:0.87537)	**0.87510** (V:0.87521)	0.87512 (V:0.8752)	0.87517 (V:0.87531)

→ support binning works best (5 bins)

Neural Network

Lin.Reg Baseline: 0.8752

- Stochastic gradient descent
- Decrease initial learning rate
- Bagging improves the accuracy
- ☺ Fast and accurate predictions
- ☹ Long training time

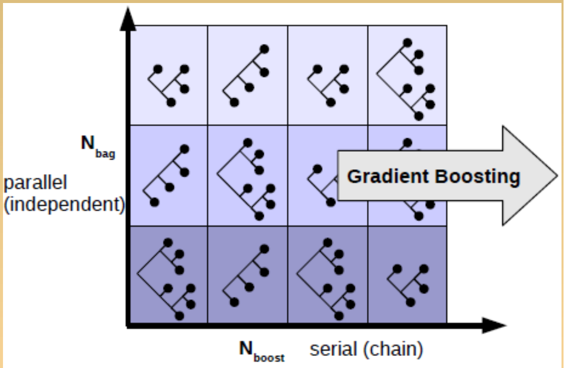


network setup	validation type	RMSE validation	train time	RMSE pTest
19-30-1	retraining 8-CV	0.873633	1.5[h]	0.873365
19-30-1	cross valid. mean 8-CV	0.873633	0.88[h]	0.873316
19-30-1	bagging size=32	0.87347	4.3[h]	0.873191
19-30-1	bagging size=128	0.873436	17.3[h]	0.873185
19-70-1	bagging size=128	0.87342	33.6[h]	0.873163
19-150-1	bagging size=128	0.873473	65.8[h]	0.873169
19-50-30-1	bagging size=128	0.873455	48.6[h]	0.87318

Bagged Gradient Boosted Decision Tree

Lin.Reg Baseline: 0.8752

- Prediction is generated by
  - Splits in a single tree are greedy (best RMSE)
  - Sum of trees (gradient boosting)
  - Averaging many chains (bagging)
- Lower RMSE when
  - Smaller learnrate
  - Larger bagging size
- Dataset dependent
  - Max. Number of leaves
  - Subspace size

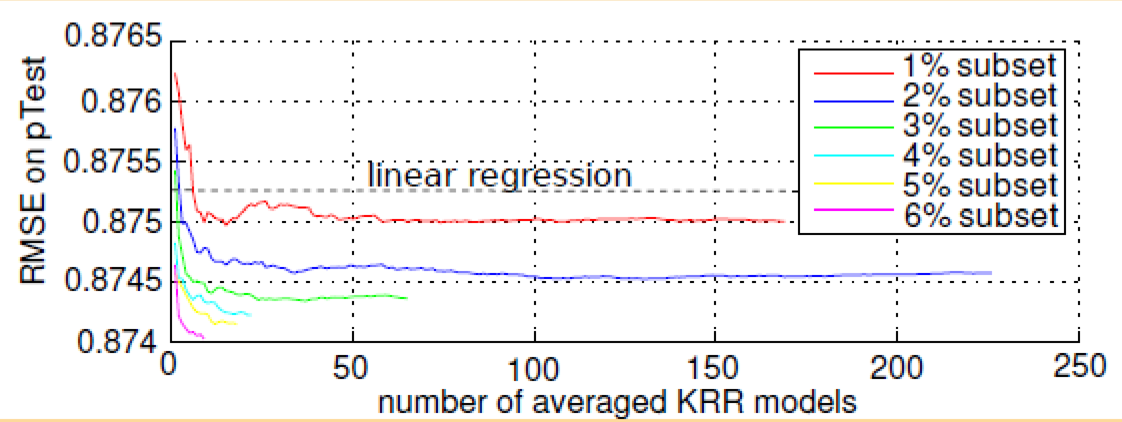


fixed:	$\eta = 0.1$	$\eta = 0.05$	$\eta = 0.03$	$\eta = 0.02$
$N_{bag} = 32$	0.874783	0.87467	0.874624	0.874593
$K = 300$	0.87437	0.874352	0.87433	**0.874309**
$S = 2$	0.62[h]	1.21[h]	1.94[h]	3.27[h]
fixed:	$K = 500$	$K = 300$	$K = 200$	$K = 100$
$N_{bag} = 32$	0.874838	0.874783	0.874767	0.874934
$\eta = 0.1$	0.874427	**0.87437**	0.874399	0.874546
$S = 2$	0.48[h]	0.62[h]	0.73[h]	1.39[h]
fixed:	$N_{bag} = 16$	$N_{bag} = 32$	$N_{bag} = 64$	$N_{bag} = 128$
$\eta = 0.02$	0.874936	0.874593	0.874554	0.874517
$K = 300$	0.874381	0.874309	0.874293	**0.874288**
$S = 2$	1.1[h]	3.27[h]	7.01[h]	14.66[h]
fixed:	$S = 1$	$S = 2$	$S = 4$	$S = 8$
$\eta = 0.1$	0.874838	0.874784	0.87477	0.874841
$K = 500$	0.874427	**0.874377**	0.874405	0.874504
$N_{bag} = 32$	0.48[h]	0.42[h]	0.68[h]	1.11[h]

Kernel Ridge Regression

Lin.Reg Baseline: 0.8752

- Cannot be applied to all 700k training samples
  - $O(N^3)$ runtime, $O(N^2)$ memory
- Average over smaller trainsets (random x % subset)



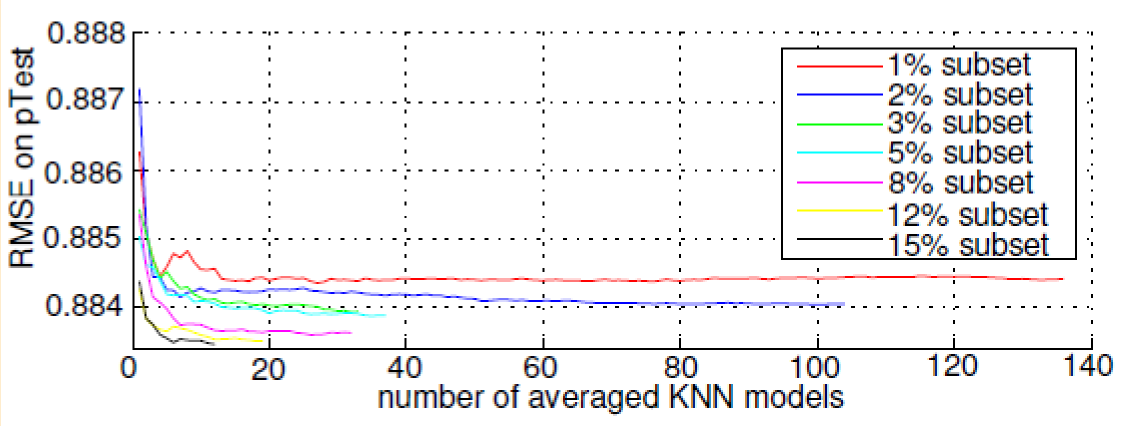
RMSE: 0.874

1% subset: 7k samples
6% subset: 42k samples

K-Nearest Neighbors Blending

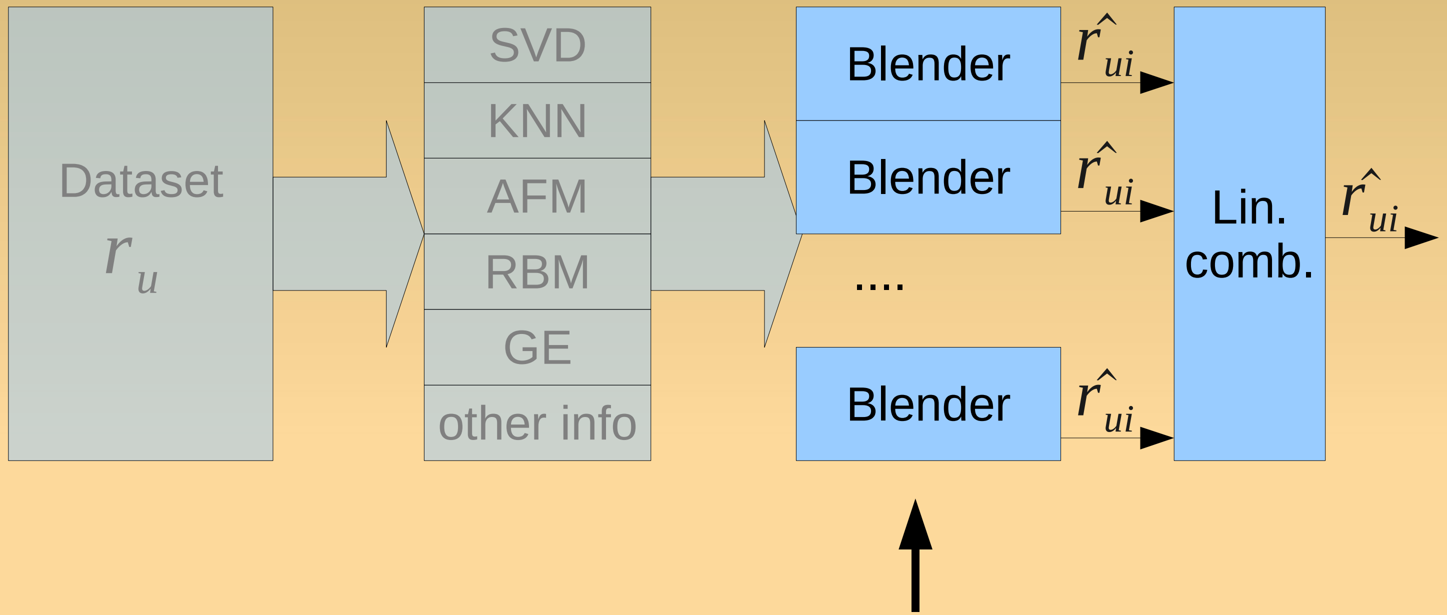
Lin.Reg Baseline: 0.8752

- Cannot be applied to all 700k training samples
  - $O(N^2)$ runtime, $O(N^2)$ memory
- Does not work (worse RMSE)



RMSE: 0.883

Bagging with Neural Networks, Polynomial Regression and GBDT



<u>Many Blenders are trained one after another</u>

→ Error feedback for stop training: RMSE of the linear combination

→ Linear Combination is calculated on the out-of-bag estimate

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Bagging with Neural Networks, Polynomial Regression and GBDT

Lin.Reg Baseline: 0.8752

- Stagewise optimization of a lin. combination of different learners

model	RMSE (blend)	weight	parameters
const. 1	-	-0.014	-
NN	0.87345 (0.873445)	0.170	19-100-1, $\alpha = 3.6$, $\beta = 3.0$, $\eta = 5e{-}4$, $\eta^{(-)} = 5e{-}7$, 870 epochs, 44.4[h]
GBDT	0.874111 (0.873387)	0.054	$S = 20$, $K = 50$, $\eta = 0.1$, 226 epochs, randomSplitPoint, 6.6[h]
GBDT	0.874603 (0.873384)	0.098	$S = 2$, $K = 300$, $\eta = 0.02$, 267 epochs, optSplitPoint, 8.1[h]
PR	0.874358 (0.87336)	0.141	order=2, $\lambda = 2.4e{-}6$, with cross interactions, 1.9[h]
PR	0.895951 (0.873351)	-0.033	order=3, $\lambda = 0.054$, no cross interactions, 0.3[h]
NN	0.87345 (0.873296)	0.202	19-100-1, $\alpha = 2$, $\beta = 3.0$, $\eta = 5e{-}4$, $\eta^{(-)} = 5e{-}7$, 998 epochs, 47.1[h]
NN	0.873449 (0.873227)	0.371	19-50-30-1, $\alpha = 2$, $\beta = 3.0$, $\eta = 5e{-}4$, $\eta^{(-)} = 5e{-}7$, 952 epochs, 49.8[h]
blend	0.873227 pTest:0.87297		total train time: 158.2[h] total prediction time 4.5[h]

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Results on qualifying set (the ”real” test set)

Lin.Reg Baseline: 0.8681

- 19-30-1 neural network: RMSE=0.8664
- Bagging with 7 models: RMSE=**0.8660**

0.0021
improvement

- Netflix Prize competitors use linear regression with meta features

Meta-Feature	Probe CV RMSE	Test RMSE
1	0.869889	0.863377
...	...	...
25	0.867501	0.861405

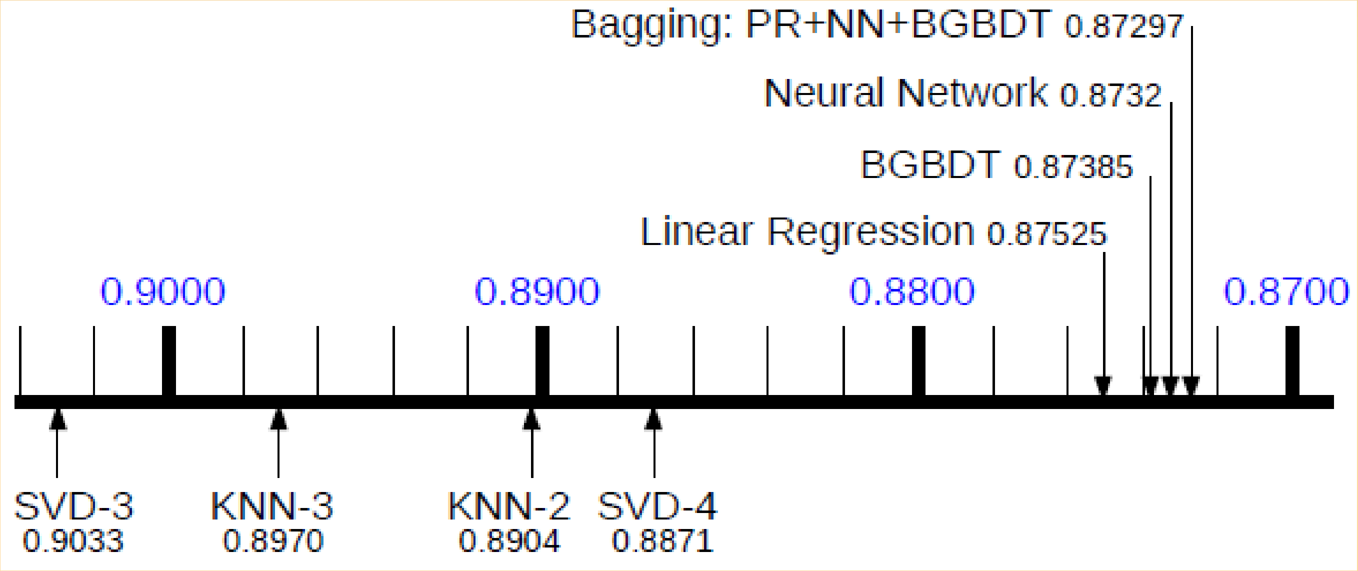
Table 2: RMSEs Using Cumulative Meta-Feature Sets

0.0020
improvement

[J. Sill, G. Takacs, L. Mackey, and D. Lin. : **Feature-weighted linear stacking**, 2009]

Summary

- The blend of many CF algorithms improves the accuracy!
- Neural network (as blender) is the best tradeoff between training time and accuracy



blended algorithms

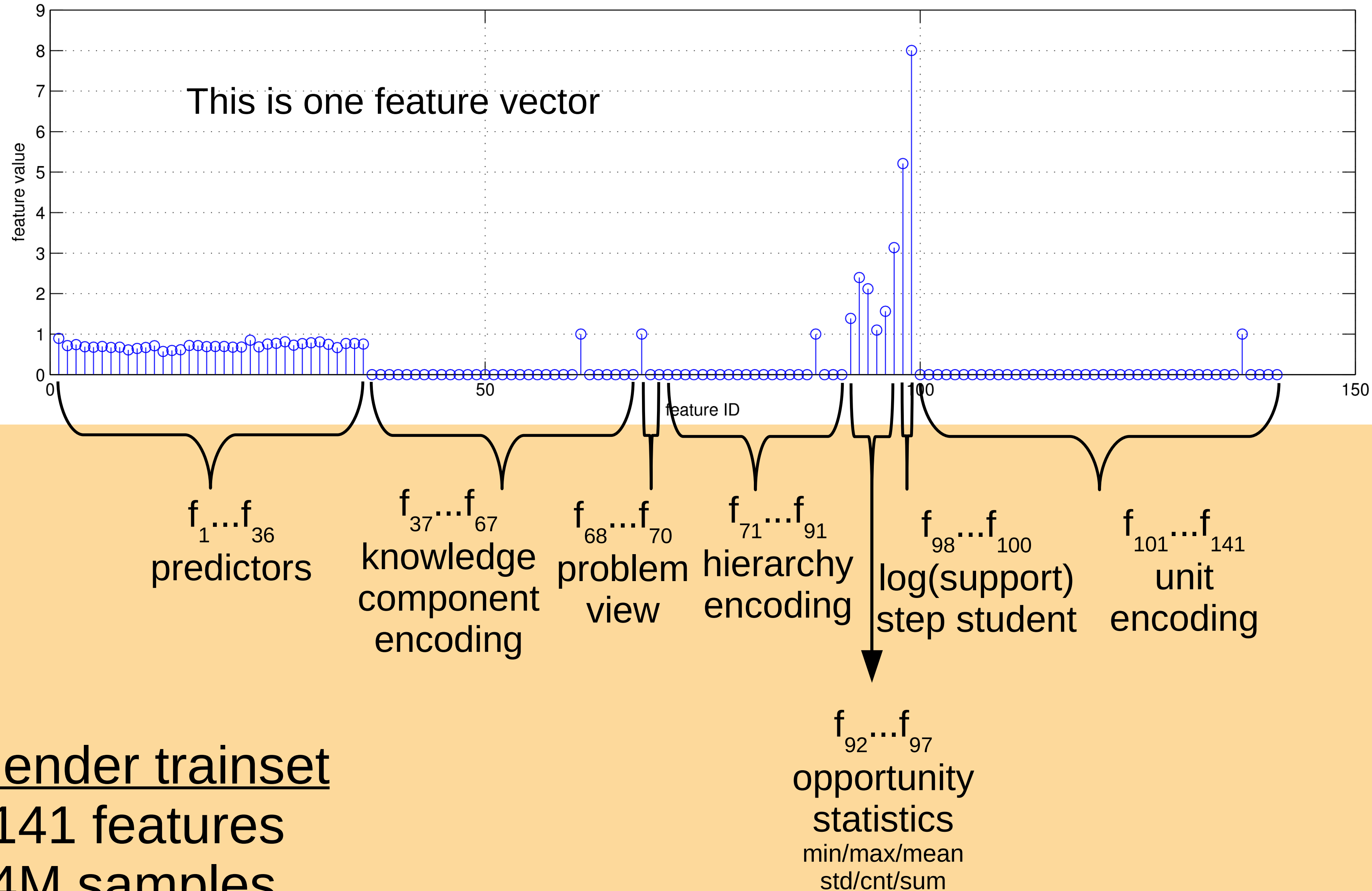
individual collaborative filtering algorithms

Software is Open Source!

- The data and the implementation can be found on: http://elf-project.sourceforge.net/
- Many examples are provided there

Happy hacking ☺

Application example: KDD Cup 2010



<u>Blender trainset</u>

- 141 features
- 4M samples

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Thank you for your attention!

Michael Jahrer
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