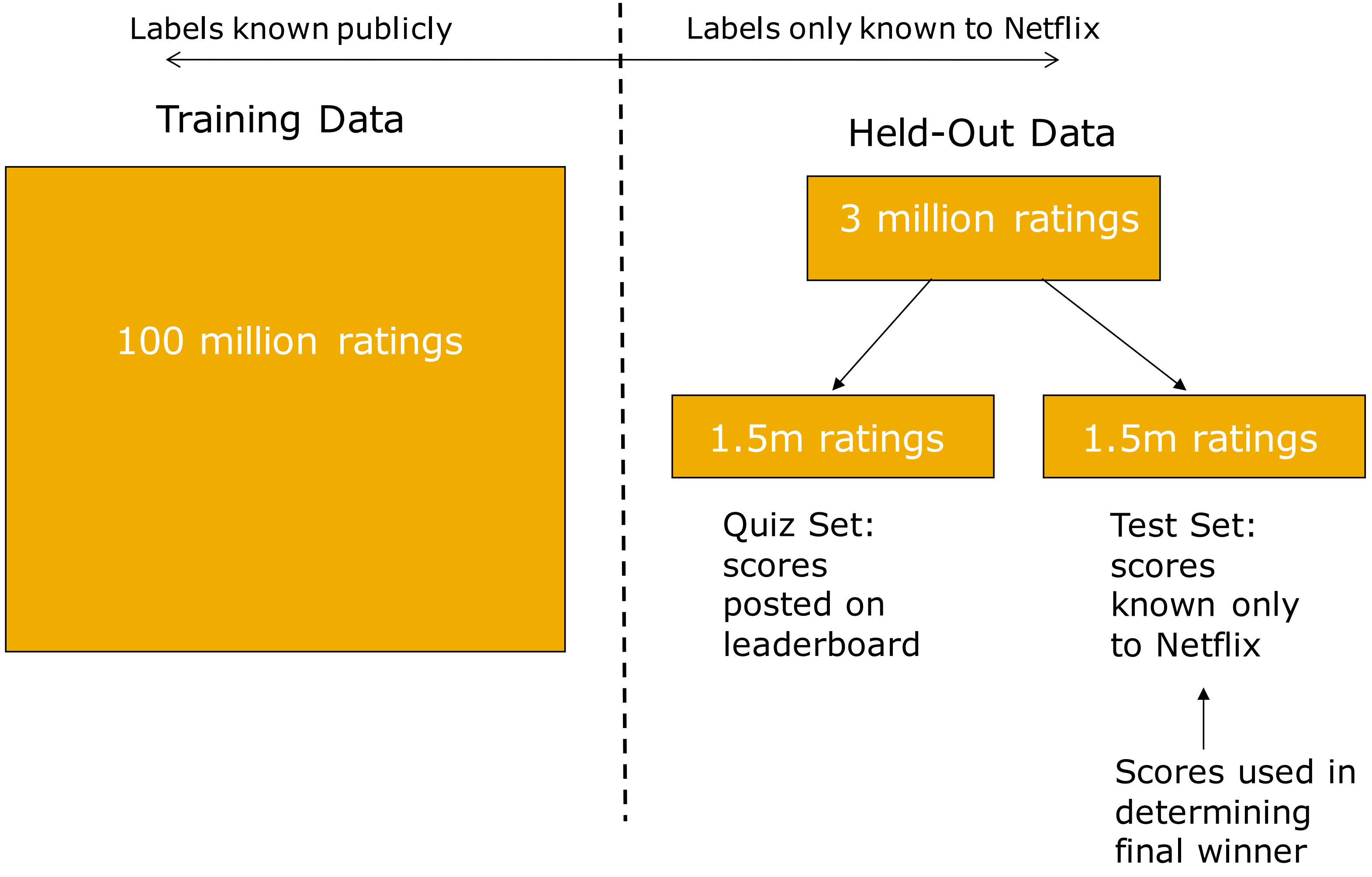
MIE524 Data Mining

Recommender Systems: The Netflix Prize

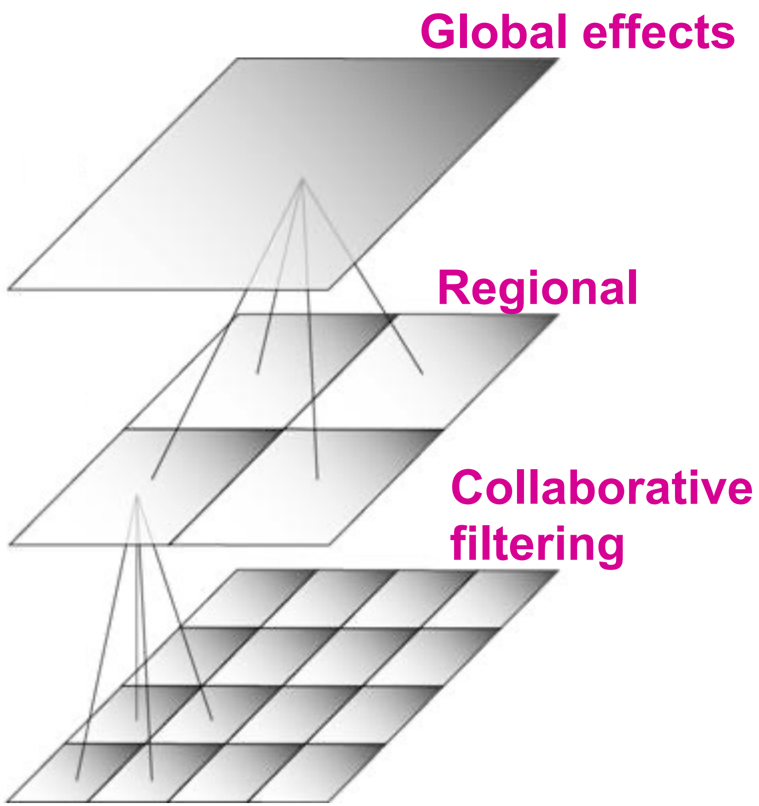
Slides adapted from:
Leskovec, Rajaraman, Ullman (http://www.mmds.org), Dimitris Sacharidis, Alex Smola

Netflix Prize: Competition Structure



BellKor Recommender System

- **The winner of the Netflix Challenge!**
- **Multi-scale modeling of the data:** Combine top level, “regional” modeling of the data, with a refined, local view:
  - **Global:**
    - Overall deviations of users/movies
  - **Regional:**
    - Addressing “regional” effects
  - **Collaborative filtering:**
    - Extract local patterns



Modeling Local & Global Effects

- **Global:**
  - Mean movie rating: **3.7 stars**
  - *The Sixth Sense* is **0.5** stars above avg.
  - Joe rates **0.2** stars below avg.
    ⇒ **Baseline estimation:**
    ***Joe* will rate *The Sixth Sense* 4 stars**

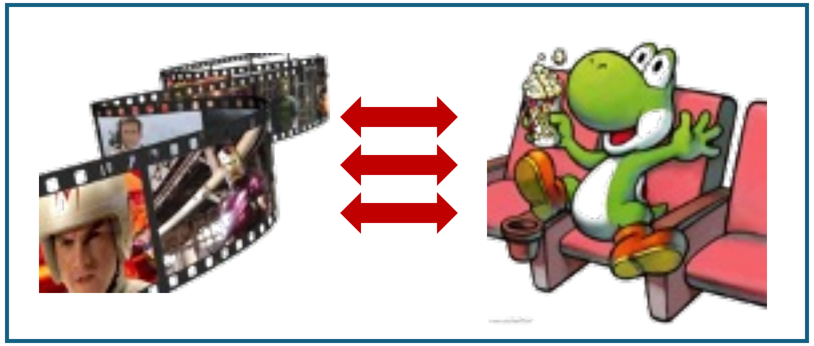
- **Local neighborhood (CF):**
  - *Joe* didn't like related movie *Signs*
  - ⇒ **Final estimate:**
    ***Joe* will rate *The Sixth Sense* 3.8 stars**

Modeling Biases and Interactions

user bias

movie bias

user-movie interaction



Baseline predictor

- Separates users and movies
- Benefits from insights into user's behavior
- Among the main practical contributions of the competition

User-Movie interaction

- Characterizes the matching between users and movies
- Attracts most research in the field
- Benefits from algorithmic and mathematical innovations

- μ = overall mean rating
- b_x = bias of user x
- b_i = bias of movie i

Baseline Predictor

- We have expectations on the rating by user ***x*** of movie ***i***, even without estimating ***x***'s attitude towards movies like ***i***

- Rating scale of user ***x***
- Values of other ratings user gave recently (day-specific mood, anchoring, multi-user accounts)

- (Recent) popularity of movie ***i***

Putting It All Together

$$r_{xi} = \underbrace{\mu}_{\text{Overall mean rating}} + \underbrace{b_x}_{\text{Bias for user } x} + \underbrace{b_i}_{\text{Bias for movie } i} + \underbrace{q_i \cdot p_x}_{\text{User-Movie interaction}}$$

- **Example:**
  - Mean rating: $\boldsymbol{\mu = 3.7}$
  - You are a critical reviewer: your ratings are 1 star lower than the mean: $\boldsymbol{b_x = -1}$
  - Star Wars gets a mean rating of *0.5* higher than average movie: $\boldsymbol{b_i = +\,0.5}$
  - Predicted rating for you on Star Wars:
    $\boldsymbol{= 3.7 - 1 + 0.5 = 3.2}$

Fitting the New Model

- **Solve:**

$$\min_{Q,P} \sum_{(x,i)\in R} \left(r_{xi} - (\mu + b_x + b_i + q_i\, p_x)\right)^2$$

goodness of fit

$$+\left(\lambda_1 \sum_i \|q_i\|^2 + \lambda_2 \sum_x \|p_x\|^2 + \lambda_3 \sum_x \|b_x\|^2 + \lambda_4 \sum_i \|b_i\|^2\right)$$

regularization

λ is selected via grid-search on a validation set

- **Stochastic gradient decent to find parameters**
  - **Note:** Both biases $\boldsymbol{b_x}$, $\boldsymbol{b_i}$ as well as interactions $\boldsymbol{q_i}$, $\boldsymbol{p_x}$ are treated as parameters (we estimate them)

Global average: 1.1296

User average: 1.0651

Movie average: 1.0533

Netflix: 0.9514

Basic Collaborative filtering: 0.94

Collaborative filtering++: 0.91

Latent factors: 0.90

Latent factors+Biases: 0.89

Grand Prize: 0.8563

Using implicit feedbacks

- Implicit Feedback:
  - Information about items the user has clicked, liked, purchased, etc.

- Intuition: a user’s preferences are also conveyed by her/his clicks

- Learn additional k-dimensional latent vector for each item y_j

- Represent each user’s implicit preferences by $\sum_{j \in N(u)} y_j$
  - Where $N(u)$ is the set of items user u has interacted with (e.g., clicked)

Using implicit feedbacks

- User's preferences are representation by a combination of:
    - Latent user vector
    - Sum of the latent item feature vectors for the items they interacted with

- Putting this together:

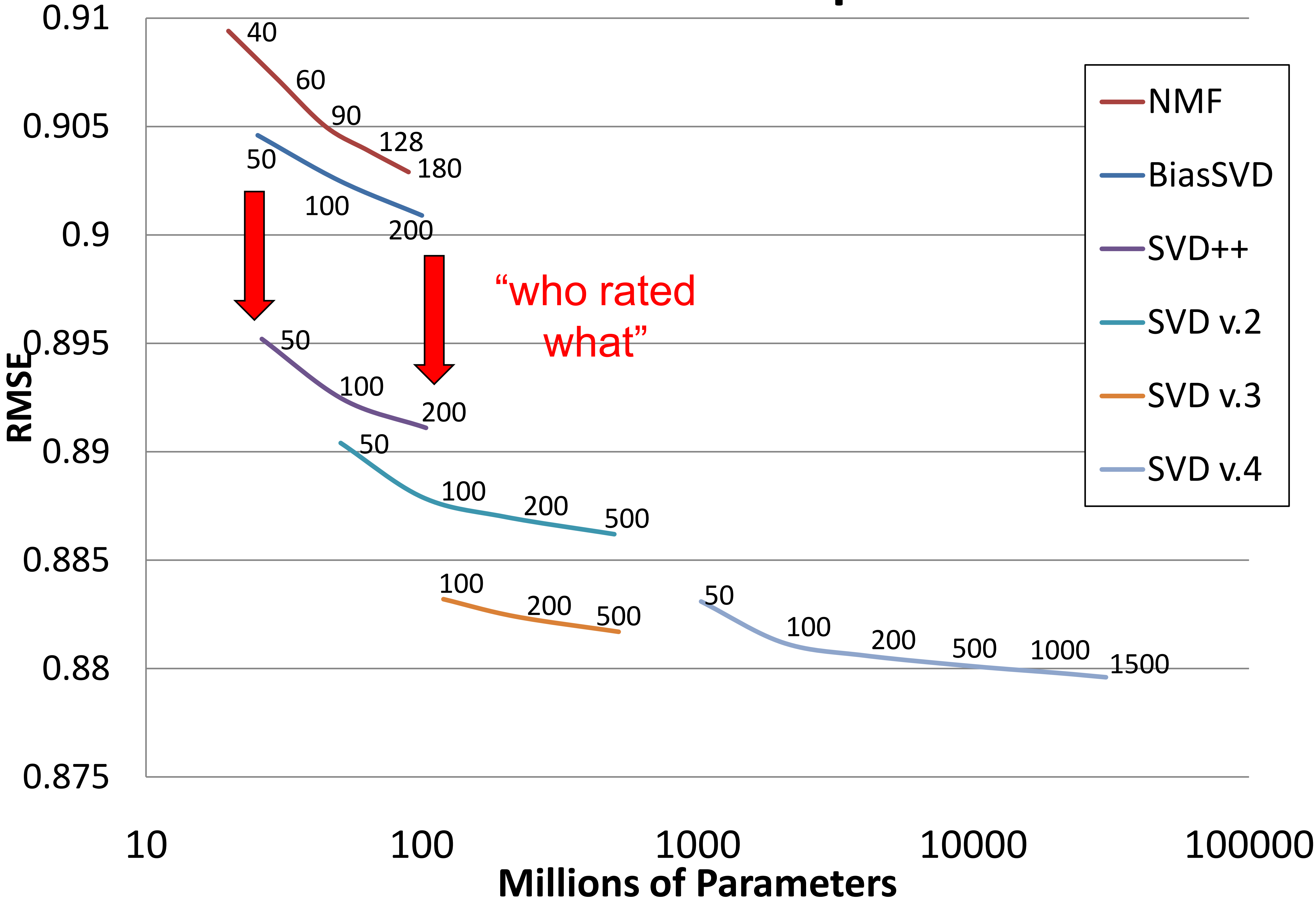
$$\hat{r}_{ui} = \underbrace{\mu + b_u + b_i}_{\text{baseline estimate}} + \underbrace{q_i^{\intercal}}_{\text{item model}} \left(\underbrace{p_u + |N(u)|^{-\frac{1}{2}} \sum_{j \in N(u)} y_j}_{\text{user model}} \right)$$

    - Where $|N(u)|^{\frac{1}{2}}$ is just normalizing the sum of latent item feature vectors

- This model is called SVD++

[2008 KDD Y. Koren] *Factorization meets the Neighborhood: a Multifaceted CF Model*

Factor models: Error vs. #parameters

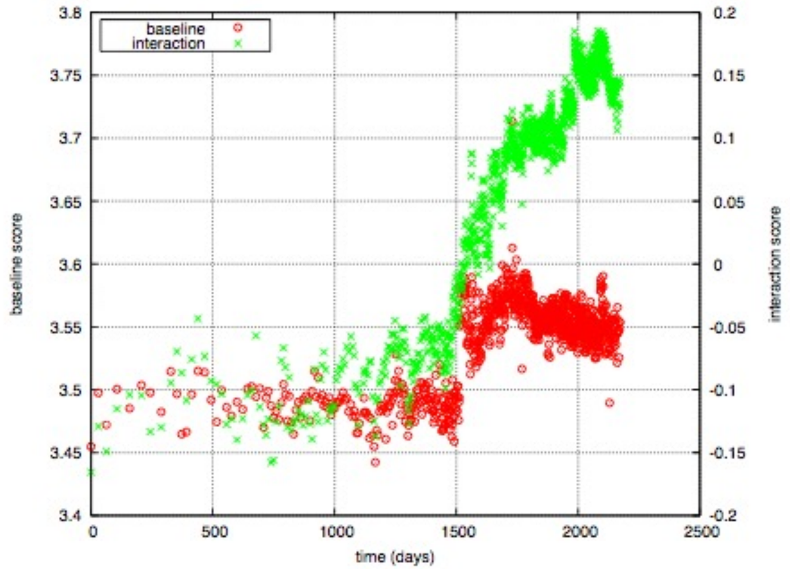


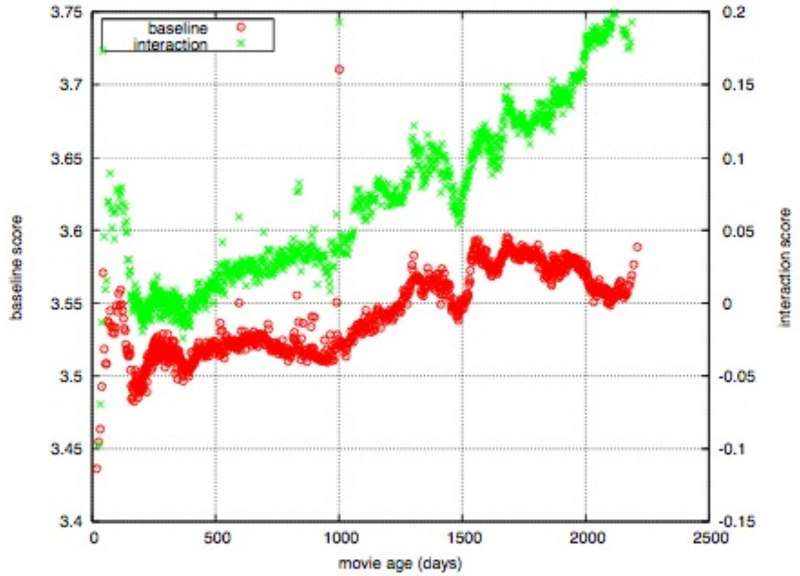
[Y. Koren, Collaborative filtering with temporal dynamics, KDD '09]

Temporal Biases Of Users

- **Sudden rise in the average movie rating** (early 2004)
  - Improvements in Netflix
  - GUI improvements
  - Meaning of rating changed

- **Ratings increase with the movie age at the time of the rating**





[Y. Koren, Collaborative filtering with temporal dynamics, KDD '09]

Temporal Biases & Factors

- **Original model (not including implicit feedback):**
  $r_{xi} = \mu + b_x + b_i + q_i \cdot p_x$
- **Add time dependence to biases:**
  $r_{xi} = \mu + b_x(t) + b_i(t) + q_i \cdot p_x$
  - Make parameters $\boldsymbol{b_x}$ and $\boldsymbol{b_i}$ to depend on time
  - **(1)** Parameterize time-dependence by linear trends
    (2) Each bin corresponds to 10 consecutive weeks

$$b_i(t) = b_i + b_{i,\mathrm{Bin}(t)}$$

- **Add temporal dependence to factors**
  - $\boldsymbol{p_x(t)}$… user preference vector on day $\boldsymbol{t}$

Global average: 1.1296

User average: 1.0651

Movie average: 1.0533

Netflix: 0.9514

Basic Collaborative filtering: 0.94

Collaborative filtering++: 0.91

Latent factors: 0.90

Latent factors+Biases: 0.89

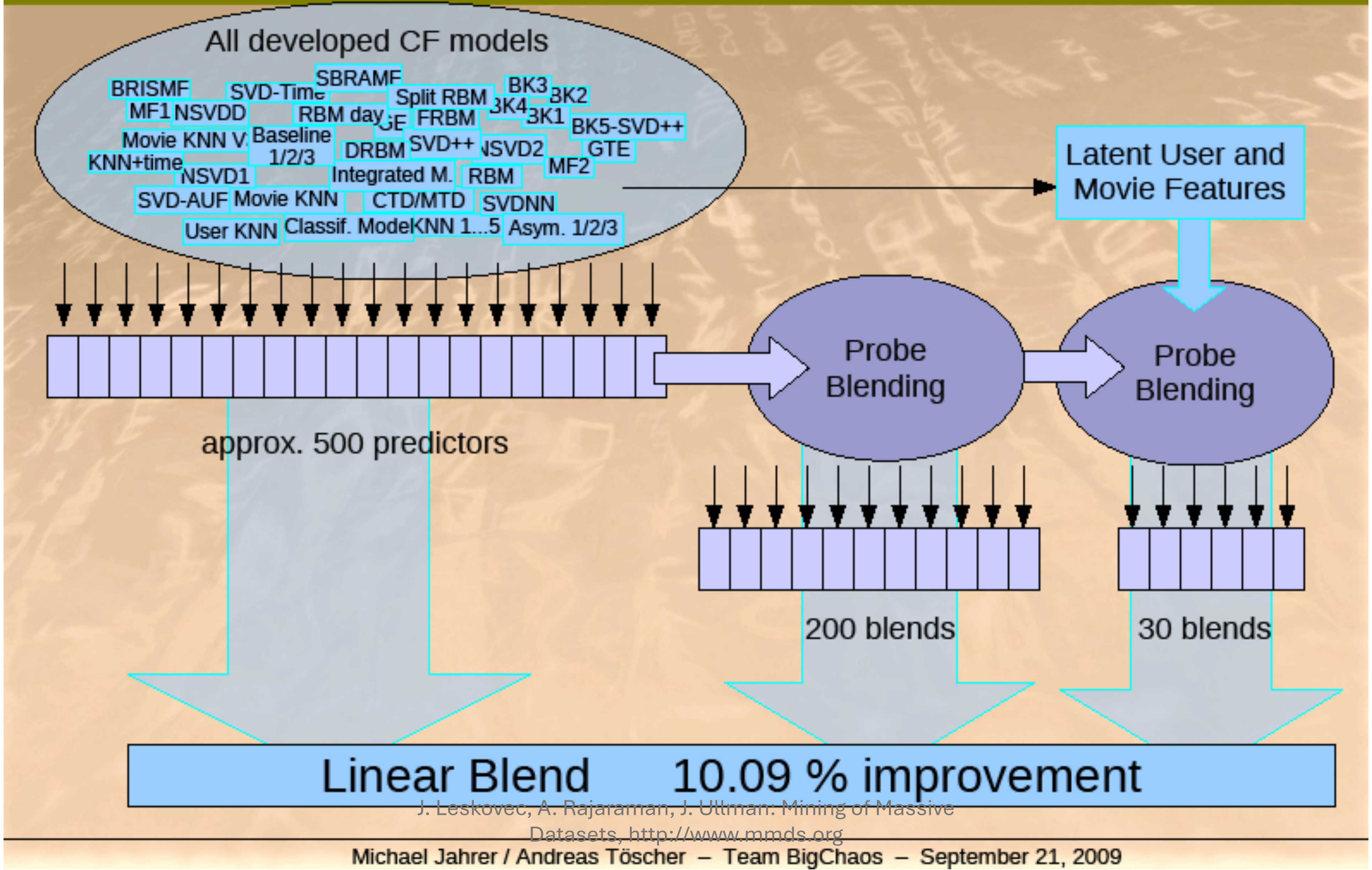
Latent factors+Biases+Time: 0.876

Grand Prize: 0.8563

Still no prize! ☹
Getting desperate.
Try a "kitchen sink" approach!

The big picture

Solution of BellKor's Pragmatic Chaos



Standing on June 26th 2009

NETFLIX

Netflix Prize

Home | Rules | Leaderboard | Register | Update | Submit | Download

Leaderboard

Display top 20 leaders.

Rank	Team Name	Best Score	% Improvement	Last Submit Time
1	BellKor's Pragmatic Chaos	0.8558	10.05	2009-06-26 18:42:37
Grand Prize - RMSE <= 0.8563				
2	PragmaticTheory	0.8582	9.80	2009-06-25 22:15:51
3	BellKor in BigChaos	0.8590	9.71	2009-05-13 08:14:09
4	Grand Prize Team	0.8593	9.68	2009-06-12 08:20:24
5	Dace	0.8604	9.56	2009-04-22 05:57:03
6	BigChaos	0.8613	9.47	2009-06-23 23:06:52
Progress Prize 2008 - RMSE = 0.8616 - Winning Team: BellKor in BigChaos				
7	BellKor	0.8620	9.40	2009-06-24 07:16:02
8	Gravity	0.8634	9.25	2009-04-22 18:31:32
9	Opera Solutions	0.8638	9.21	2009-06-26 23:18:13
10	BruceDengDaoCiYiYou	0.8638	9.21	2009-06-27 00:55:55
11	pengpengzhou	0.8638	9.21	2009-06-27 01:06:43
12	xlvector	0.8639	9.20	2009-06-26 13:49:04
13	xiangliang	0.8639	9.20	2009-06-26 07:47:34

June 26th submission triggers 30-day "last call"

The Last 30 Days

- **Ensemble team formed**
  - Group of other teams on leaderboard forms a new team
  - Relies on combining their models
  - Quickly also get a qualifying score over 10%

- **BellKor**
  - Continue to get small improvements in their scores
  - Realize that they are in direct competition with Ensemble

- **Strategy**
  - Both teams carefully monitoring the leaderboard
  - Only sure way to check for improvement is to submit a set of predictions
    - This alerts the other team of your latest score

24 Hours from the Deadline

- **Submissions limited to 1 a day**
  - Only 1 final submission could be made in the last 24h

- **24 hours before deadline…**
  - **BellKor** team member in Austria notices (by chance) that **Ensemble** posts a score that is slightly better than BellKor's

- **Frantic last 24 hours for both teams**
  - Much computer time on final optimization
  - Carefully calibrated to end about an hour before deadline
- **Final submissions**
  - **BellKor** submits a little early (on purpose), 40 mins before deadline
  - **Ensemble** submits their final entry 20 mins later
  - **….and everyone waits….**

NETFLIX

Netflix Prize

COMPLETED

Home | Rules | Leaderboard | Update | Download

Leaderboard

Showing Test Score. Click here to show quiz score

Display top 20 leaders.

Rank	Team Name	Best Test Score	% Improvement	Best Submit Time
Grand Prize - RMSE = 0.8567 - Winning Team: BellKor's Pragmatic Chaos				
1	BellKor's Pragmatic Chaos	0.8567	10.06	2009-07-26 18:18:28
2	The Ensemble	0.8567	10.06	2009-07-26 18:38:22
3	Grand Prize Team	[illegible]	[illegible]	[illegible]
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31
5	Vandelay Industries !	0.8591	9.81	2009-07-10 00:32:20
6	PragmaticTheory	0.8594	9.77	2009-06-24 12:06:56
7	BellKor in BigChaos	0.8601	9.70	2009-05-13 08:14:09
8	Dace_	0.8612	9.59	2009-07-24 17:18:43
9	Feeds2	0.8622	9.48	2009-07-12 13:11:51
10	BigChaos	0.8623	9.47	2009-04-07 12:33:59
11	Opera Solutions	0.8623	9.47	2009-07-24 00:34:07
12	BellKor	0.8624	9.46	2009-07-26 17:19:11
Progress Prize 2008 - RMSE = 0.8627 - Winning Team: BellKor in BigChaos				
13	xiangliang	0.8642	9.27	2009-07-15 14:53:22
14	Gravity	0.8643	9.26	2009-04-22 18:31:32
15	Ces	0.8651	9.18	2009-06-21 19:24:53
16	Invisible Ideas	0.8653	9.15	2009-07-15 15:53:04
17	Just a guy in a garage	0.8662	9.06	2009-05-24 10:02:54
18	J Dennis Su	0.8666	9.02	2009-03-07 17:16:17
19	Craig Carmichael	0.8666	9.02	2009-07-25 16:00:54
20	acmehill	0.8668	9.00	2009-03-21 16:20:50
Progress Prize 2007 - RMSE = 0.8723 - Winning Team: KorBell				

Million $ Awarded Sept 21st 2009

Regularization in MF

$$\min_{Q,P} \sum_{(x,i)\in R} \left(r_{xi} - (\mu + b_x + b_i + q_i\, p_x)\right)^2$$

goodness of fit

$$+\left(\lambda_1 \sum_i \|q_i\|^2 + \lambda_2 \sum_x \|p_x\|^2 + \lambda_3 \sum_x \|b_x\|^2 + \lambda_4 \sum_i \|b_i\|^2 \right)$$

regularization

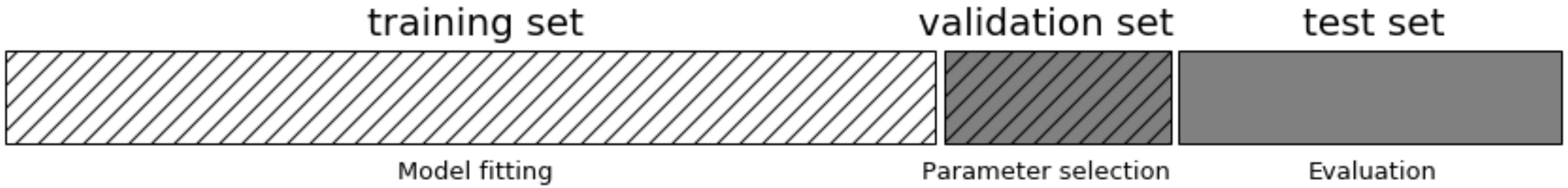
λ is selected via grid-search on a validation set

- Why are the regularization weights hyperparameters?
- How to decide their value?

Hyperparameters

- Hyperparameters are tunable aspects of the model that need to be specified before learning can happen, set outside the training procedure
  - Decision tree: max depth, purity criterion, etc.
  - NN: optimizer, learning rate, regularization, etc.

Threefold split



- Pros: fast, simple
- Cons: high variance, inefficient use of data

https://amueller.github.io/ml-training-intro/slides/03-cross-validation-grid-search.html

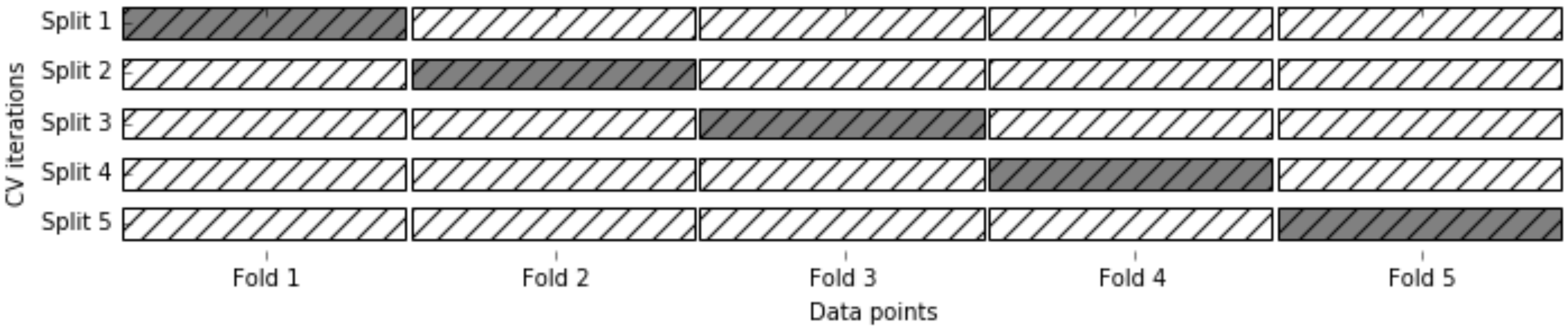
Scikit-learn threefold implementation

```
X_trainval, X_test, y_trainval, y_test = train_test_split(X, y)
X_train, X_val, y_train, y_val = train_test_split(X_trainval, y_trainval)

val_scores = []
neighbors = np.arange(1, 15, 2)
for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    val_scores.append(knn.score(X_val, y_val))
print("best validation score: {:.3f}".format(np.max(val_scores)))
best_n_neighbors = neighbors[np.argmax(val_scores)]
print("best n_neighbors:", best_n_neighbors)

knn = KNeighborsClassifier(n_neighbors=best_n_neighbors)
knn.fit(X_trainval, y_trainval)
print("test-set score: {:.3f}".format(knn.score(X_test, y_test)))
```

```
best validation score: 0.991
best n_neighbors: 11
test-set score: 0.951
```

https://amueller.github.io/ml-training-intro/slides/03-cross-validation-grid-search.html

Cross validation

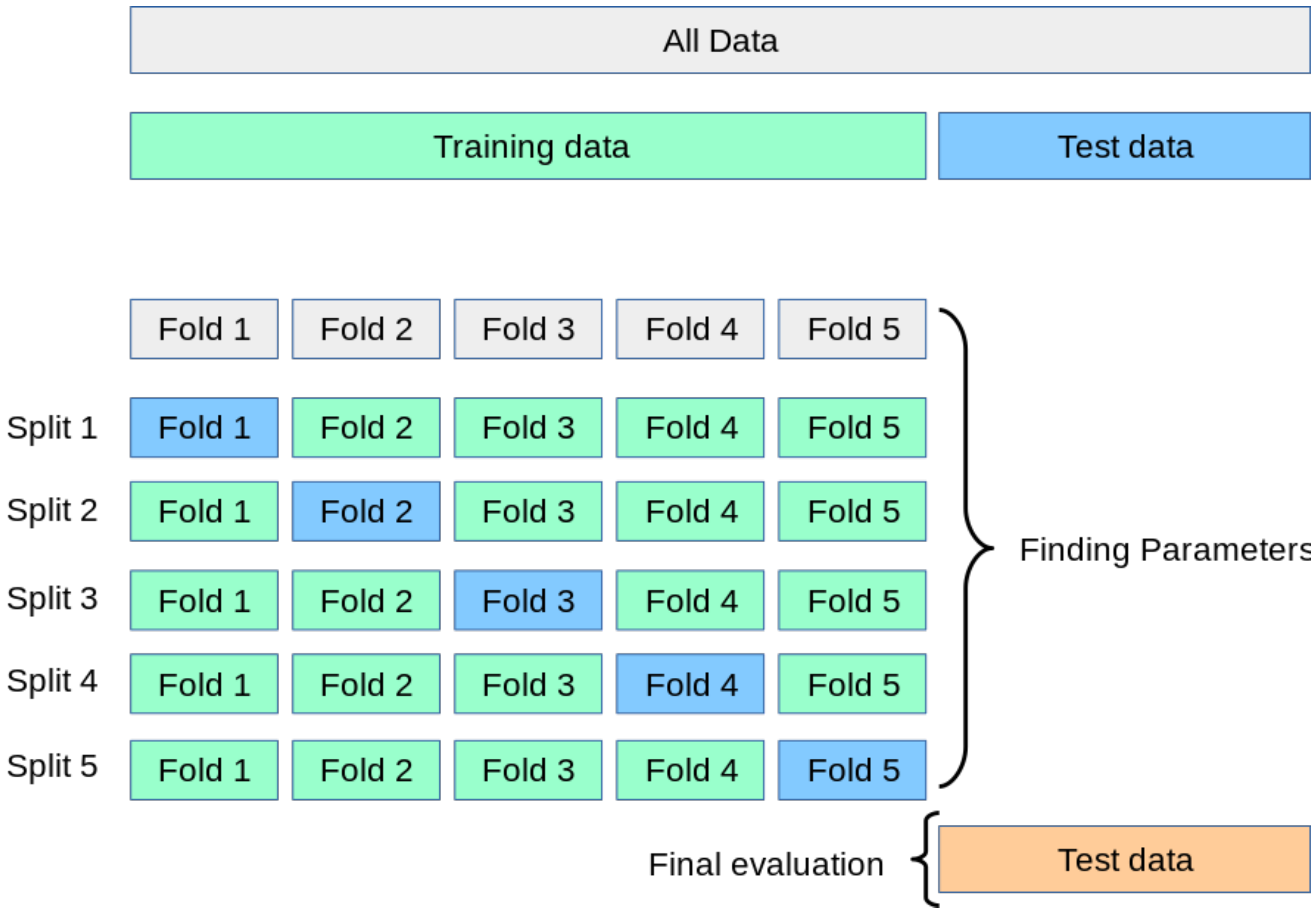


- Pros: more stable, use more data
- Cons: slower

- *Stratified* cross validation: ensures relative class frequencies in each fold reflect relative class frequencies on the whole dataset

https://amueller.github.io/ml-training-intro/slides/03-cross-validation-grid-search.html

Cross validation w/ Test set



https://amueller.github.io/ml-training-intro/slides/03-cross-validation-grid-search.html

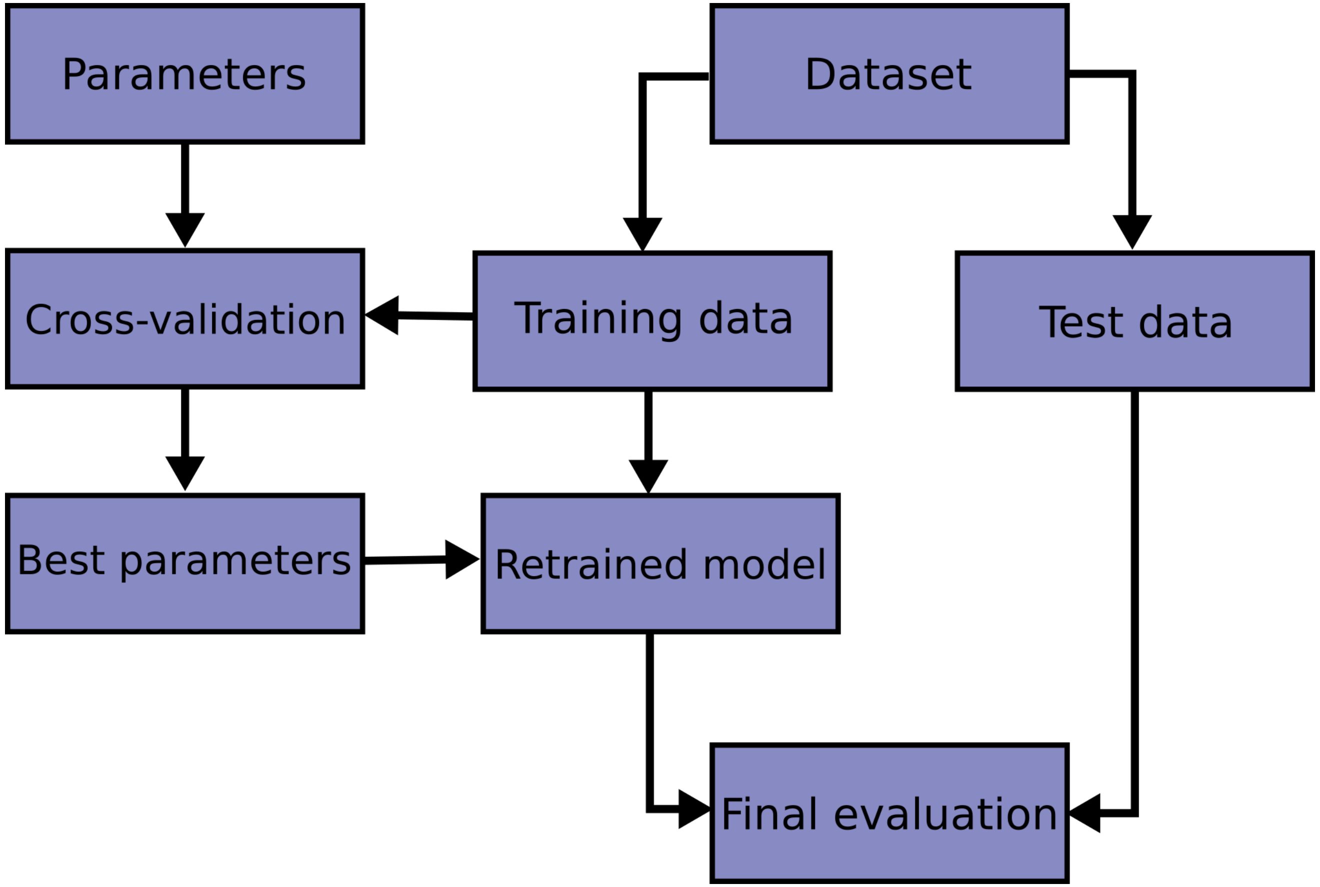
Scikit-learn cross validation implementation

```
from sklearn.model_selection import cross_val_score

X_train, X_test, y_train, y_test = train_test_split(X, y)
cross_val_scores = []

for i in neighbors:
    knn = KNeighborsClassifier(n_neighbors=i)
    scores = cross_val_score(knn, X_train, y_train, cv=10)
    cross_val_scores.append(np.mean(scores))

print("best cross-validation score: {:.3f}".format(np.max(cross_val_scores)))
best_n_neighbors = neighbors[np.argmax(cross_val_scores)]
print("best n_neighbors:", best_n_neighbors)

knn = KNeighborsClassifier(n_neighbors=best_n_neighbors)
knn.fit(X_train, y_train)
print("test-set score: {:.3f}".format(knn.score(X_test, y_test)))
```

```
best cross-validation score: 0.967
best n_neighbors: 9
test-set score: 0.965
```

https://amueller.github.io/ml-training-intro/slides/03-cross-validation-grid-search.html

Cross validation workflow



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