

Recommenders

By ~~Ralph Lauren~~
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(heavily based on the slides/notes of Ryan
Henning, Dan Becker, and Giovanna)



- What kind of data do we use for recommenders?
- High-level approaches to building recommenders:
 - Content-based
 - Collaborative filtering
 - Matrix factorization
- How do we evaluate our recommender models?
- How to deal with “cold start”?
- What are the computational performance concerns?
- Where have you seen or used recommenders?

Where are recommenders used?

Recommended for you, Mark



coursera

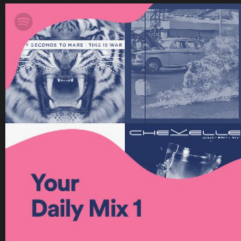
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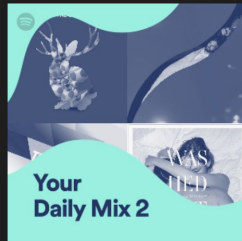
We combed our catalog and found courses and Specializations that we think match your interests. Browse our recommendations below, and start learning something new today.

Your Daily Mixes

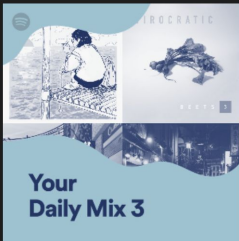
Play the music you love, without the effort. Packed with your favorites and new discoveries.



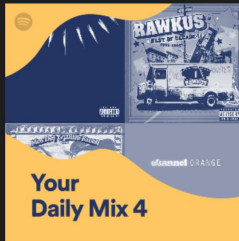
Daily Mix 1
Thirty Seconds To Mars, Rage Against The Machine, Linkin Park and more
MADE FOR MARK



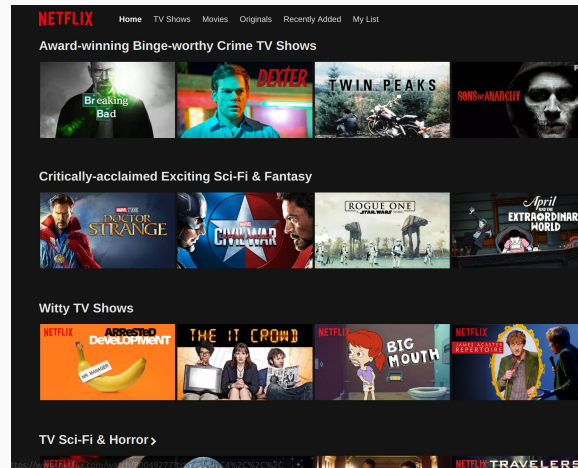
Daily Mix 2
Mikie Snow, Breakbot, The Knife and more
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Daily Mix 3
Tompapabats, Birocratic, Brock Berrigan and more
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Daily Mix 4
Jay Rock, Mos Def, Black Star and more
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Where are recommenders used?

They don't always get things right...

Top Picks for Mark



Business Goals:

What will the user **like**?

What will the user **buy**?

What will the user **click**?

Name a business that
cares are each of these,
and tell us why they care.

Data Science Canon:

Netflix's \$1,000,000 Prize (Oct. 2006 - July 2009)

NETFLIX

Netflix Prize

COMPLETED

Home Rules Leaderboard Update

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	0.8582	9.90	2009-07-10 21:24:40
4	Opera Solutions and Vandelay United	0.8588	9.84	2009-07-10 01:12:31

Goal: Beat Netflix's own recommender by 10%.

Took almost 3 years.

The winning team used gradient boosted decision trees over the predictions of **500** other models.

Netflix never deployed the winning algorithm. (Why?)

Let's learn recommenders.

Today we'll learn:

1. How to **build** a recommender,
2. How to **evaluate** your recommender, and
3. How to **deploy** your recommender.

... and when you get back from break we'll do a case study with recommender systems.

What are some guiding concepts around creating good recommenders?

- **Serendipity** - Did we find something unexpected and novel?
- **Personalization** - Did we make recommendations based on individual taste/want/need?
- **Diversity** - Did we not just recommend overly similar things? Next movie in a series?
- **Persistence** - How much do we recommend what we already know people like? Did how much they like or want it change over time?
- **Modality** - Context? Are there other people involved? Weather? Special Occasion?
- **Privacy** - Did we recommend something *very personal* based on a past purchase?
- **Motivation** - Best match? Best product value? Most profitable?
- **Trust** - Do customers trust the data and the predictions as being authentic?
- **Confidence** - Are the predictions valid?

Popularity:

- Make the **same** recommendation to **every** user, based only on the popularity of an item.
- E.g. Twitter “Moments”

[What is this most like in other problems we’ve tackled?]

Content-based (aka, Content filtering):

- Predictions are made based on the properties/characteristics of an item.
- User behavior is **not** considered.
- E.g. Pandora Radio

Collaborative filtering:

- Only consider past user behavior. (**not** content properties...)
- User-User similarity: ...
- Item-Item similarity: ...
- E.g.
 - Netflix & Amazon Recommendations,
 - Google Ads,
 - Facebook Ads, Search, Friends Rec., News feed, Trending news, Rank Notifications, Rank Comments

Matrix Factorization Methods:

- Find latent features (aka, factors)
- NMF’s fraternal twin

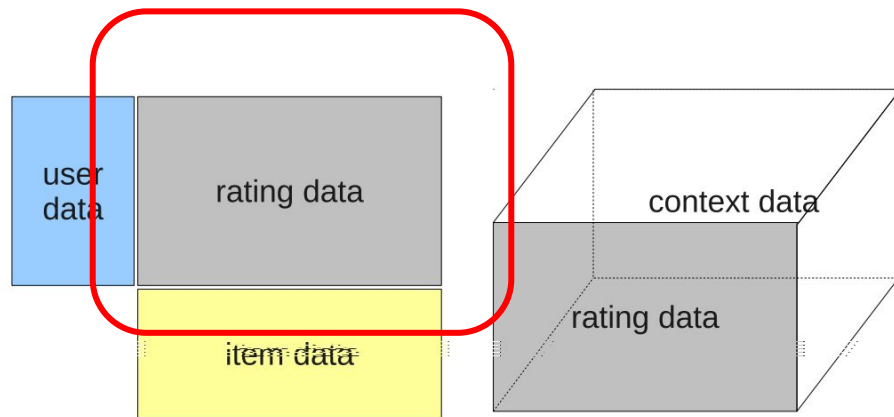


Figure 1: Attribute-aware methods can take additional information about the user or the item separately into account (left), whereas context-aware methods are more general and can analyze data that is simultaneously attached to all ‘modes’, i.e. the whole rating event (right).

What does our dataset look like?

User	Item				
	A	B	C	D	...
	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5
	Dan	?	2	?	?
	Ed	2	?	?	1
	...				

We have explicit ratings, plus a bunch of missing values.

What company might have data like this?



Btw, we call this the *utility matrix*.

What does our dataset look like?

User	Item				
	A	B	C	D	...
	Al	0	1	0	1
	Bob	0	0	1	0
	Cat	0	1	1	1
	Dan	1	0	0	1
	Ed	0	1	0	0
	...				

We have implicit feedback, and no missing values.

What company might have data like this?



Btw, we call this the *utility matrix*.



	Item				
	A	B	C	D	...
User	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5

We look at all pairs of users and calculate their similarity.

How can we calculate the similarity of these row vectors?
(We'll get there.)

User	Item			
	A	B	C	D
	1	?	2	?
	?	2	3	4
	3	?	1	5
	?	2	?	?
	2	?	?	1
	...			

We look at all pairs of items and calculate their similarity.

How can we calculate the similarity of these column vectors?
(We'll get there.)

User-User:

		Item				
User		A	B	C	D	...
	Al	1	?	2	?	
	Bob	?	2	3	4	
	Cat	3	?	1	5	

Let: $m = \text{\#users,}$ $n = \text{\#items}$

We want to compute the similarity of all pairs.

What is the algorithmic efficiency of each approach?


Item-Item:

		Item			
User		A	B	C	D
	Al	1	?	2	?
	Bob	?	2	3	4
	Cat	3	?	1	5
	Dan	?	2	?	?
	Ed	2	?	?	1
	...				

User-User: $O(m^2n)$ **Item-Item:** $O(mn^2)$

Which one is better?

Similarity Metric using Euclidean Distance

What's the range? 

$$\text{dist}(a, b) = ||a - b|| = \sqrt{\sum_i (a_i - b_i)^2}$$


But we're interested in a **similarity**, so let's do this instead:

When use
this?

What's the range? 

$$\text{similarity}(a, b) = \frac{1}{1 + \text{dist}(a, b)}$$


Similarity Metric using Pearson Correlation

What's the range? 

$$\text{pearson}(a, b) = \frac{\text{cov}(a, b)}{\text{std}(a) * \text{std}(b)} = \frac{\sum_i (a_i - \bar{a})(b_i - \bar{b})}{\sqrt{\sum_i (a_i - \bar{a})^2} \sqrt{\sum_i (b_i - \bar{b})^2}}$$


But we're interested in a **similarity**, so let's do this instead:

When use
this?

What's the range? 

$$\text{similarity}(a, b) = 0.5 + 0.5 * \text{pearson}(a, b)$$


Similarity Metric using Cosine Similarity

What's the range? 

$$\cos(\theta_{a,b}) = \frac{a \cdot b}{||a|| ||b||} = \frac{\sum_i a_i b_i}{\sqrt{\sum_i a_i^2} \sqrt{\sum_i b_i^2}}$$


But we're interested in a **standardized similarity**, so let's do this instead:

When use
this?

What's the range? 

$$\text{similarity}(a, b) = 0.5 + 0.5 * \cos(\theta_{a,b})$$

Similarity Metric using Jaccard Index

What's the range?  $\text{similarity}(a, b) = \frac{|U_a \cap U_b|}{|U_a \cup U_b|}$

U_k denotes the set of users who rated item k

When use this?

The Similarity Matrix

Pick a similarity metric, create the similarity matrix:

	item 1	item 2	item 3	...
item 1	1	0.3	0.2	...
item 2	0.3	1	0.7	...
item 3	0.2	0.7	1	...
...

Say user u hasn't rated item i . We want to predict the rating that this user *would* give this item.

$$\text{rating}(u, i) = \frac{\sum_{j \in I_u} \text{similarity}(i, j) * r_{u,j}}{\sum_{j \in I_u} \text{similarity}(i, j)}$$

I_u = set of items rated by user u

$r_{u,j}$ = user u 's rating of item j

We order by descending predicted rating for a single user, and recommend the top k items to the user.

This calculation of predicted ratings can be very costly. To mitigate this issue, we will only consider the n most similar items to an item when calculating the prediction.

$$\text{rating}(u, i) = \frac{\sum_{j \in I_u \cap N_i} \text{similarity}(i, j) * r_{u,j}}{\sum_{j \in I_u \cap N_i} \text{similarity}(i, j)}$$

I_u = set of items rated by user u

$r_{u,j}$ = user u 's rating of item j

N_i is the n items which are most similar to item i

Deploying the recommender

In the middle of the night:

- Compute similarities between all pairs of items.
- Compute the neighborhood of each item.

At request time:

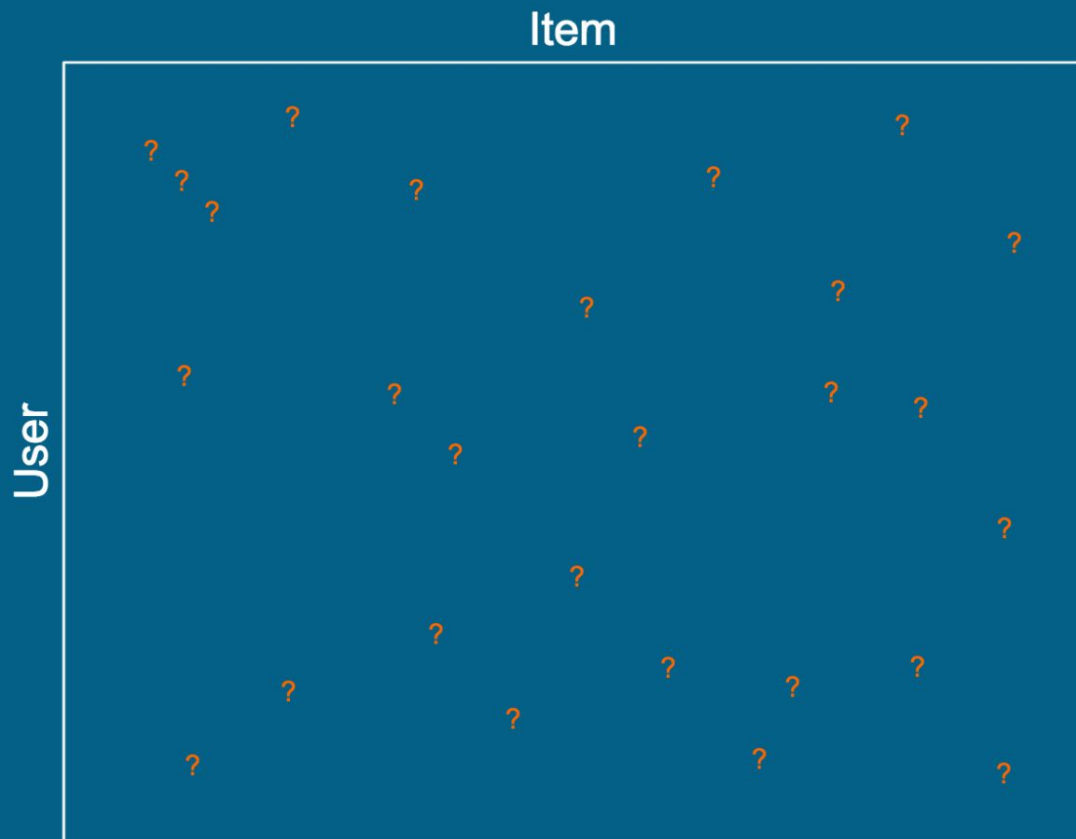
- Predict scores for candidate items, and make a recommendation.

How do we evaluate our recommender system?

Is it possible to do cross-validation like normal?

Before we continue, let's review: Why do we perform cross-validation?

Quick warning: Recommenders are inherently hard to validate. There is a lot of discussion in academia (research papers) and industry (here, Kaggle, Netflix, etc) about this. There is no ONE answer for all dataset.



For this slide, the question marks denote the holdout set (**not** missing values).

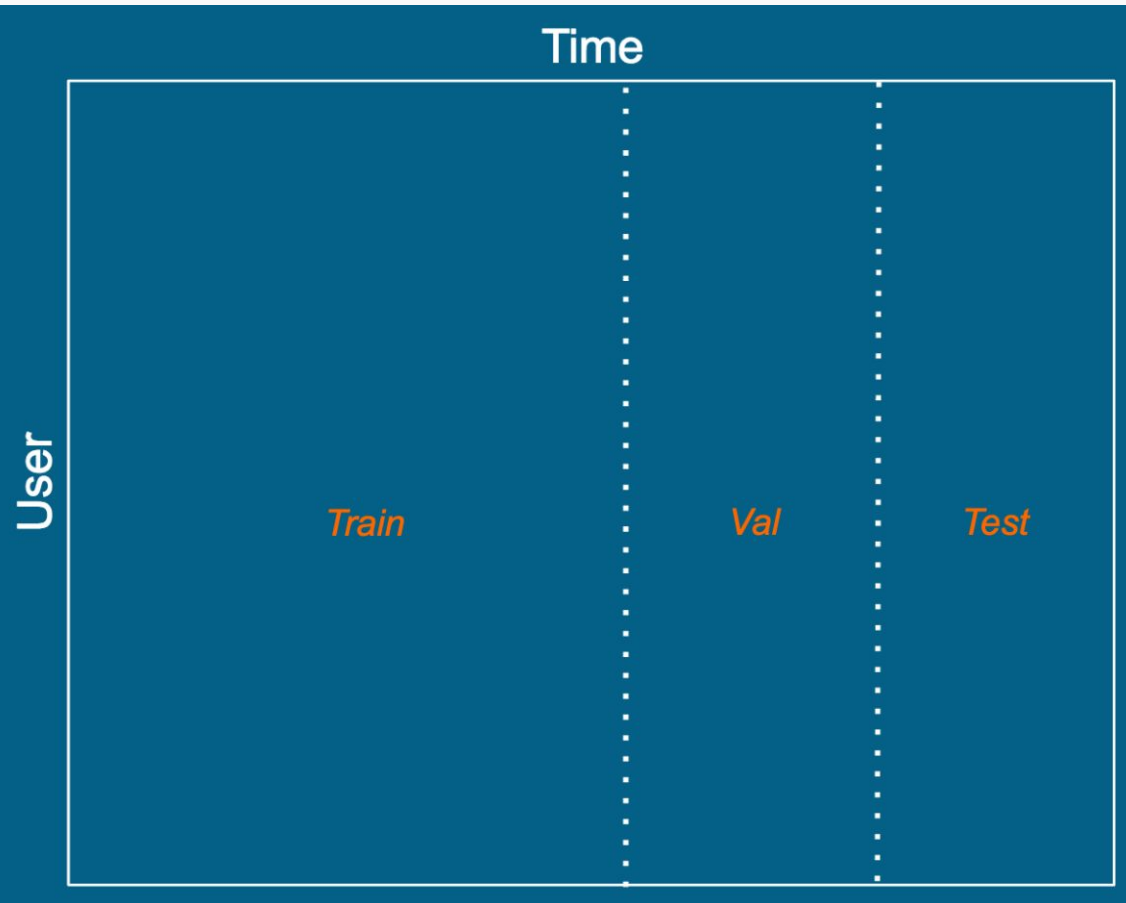
We can calculate MSE between the targets and our predictions over the holdout set.

(K-fold cross-validation is optional.)

Recall: Why do we perform cross-validation?

Why isn't the method above a true estimate of a recommender's performance in the field?

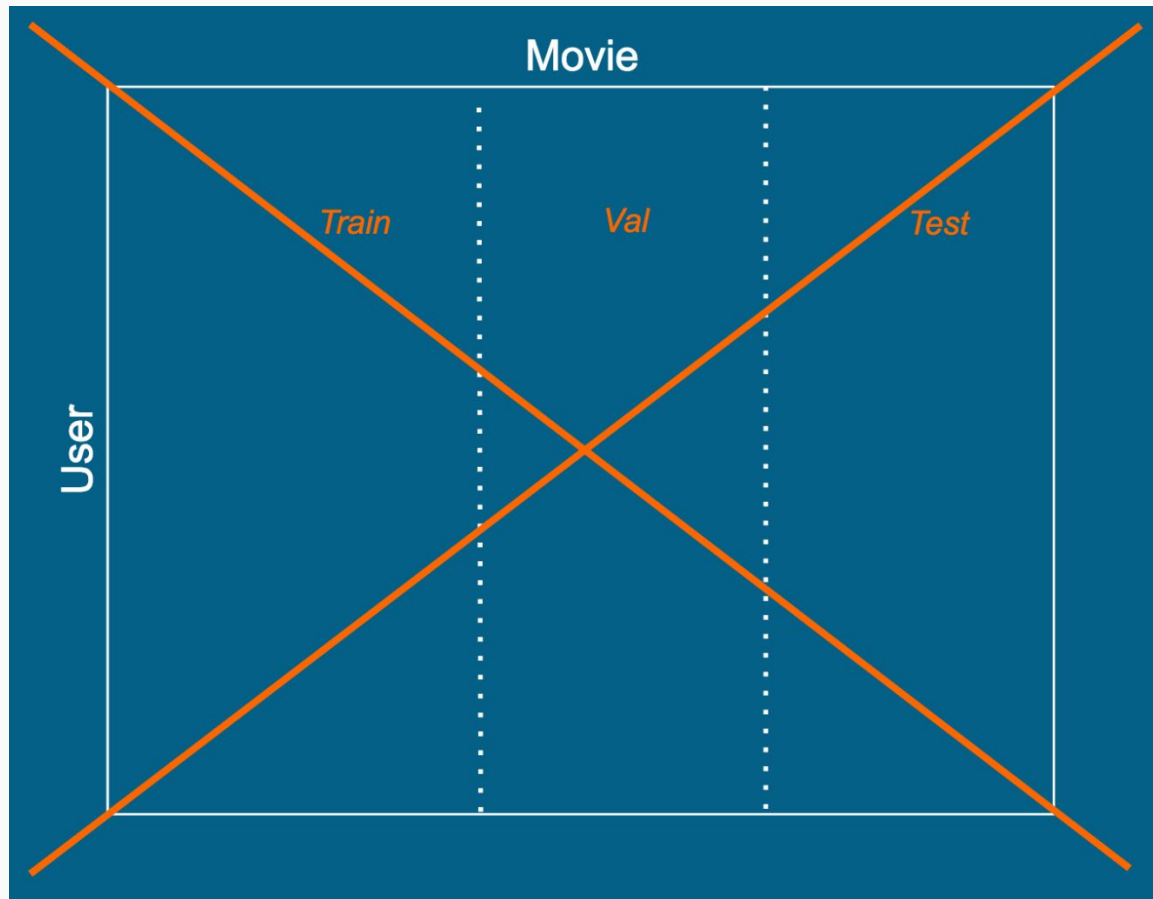
Why would A/B testing be better?



What's the deal with this?

I.e. Why might we prefer doing this instead of the more “normal” cross-validation from the previous slide?

DON'T DO THIS! Why?



How to deal with “cold start”?

Scenario: A new user signs up.

What will our recommender do (assume we're using item-item similarities)?

One strategy: Force users to rate 5 items as part of the signup process. AND/OR Recommend popular items at first.

Scenario: A new item is introduced.

What will our recommender do (assume we're using item-item similarities)?

One strategy: Put it in the “new releases” section until enough users rate it AND/OR use item metadata if any exists.

How to deal with “cold start”?

Scenario: A new user signs up.

What will our recommender do (assume we're Youtube and we're using item popularity to make recommendations)?

This really isn't a problem...

Scenario: A new item is introduced.

What will our recommender do (assume we're Youtube and we're using item popularity to make recommendations)?

One strategy: Don't use total number of views as the popularity metric (we'd have a *rich-get-richer* situation). Use something else...

Matrix Factorization for Recommendation

Warning: There are a lot of acronyms
in this lecture!

Mark Llorente
Based off Ryan Henning's Slides



- UV Decomposition (UVD)
- SVD vs UVD
- UVD vs NMF
- UVD via Stochastic Gradient Descent (SGD)
- Matrix Factorization for Recommendation:
 - Basic system:
 - UVD + SGD... FTW
 - Intermediate topics:
 - regularization
 - accounting for biases


$$R_{m \times n} \approx U_{m \times k} V_{k \times n}$$

$$r_{ij} \approx u_{i:} \cdot v_{:j}$$

- You choose k .
- UV approximates R by necessity if k is less than the rank of R .
- Usually choose: $k \ll \min(n, m)$
- Compute U and V such that:

$$\arg \min_{U, V} \sum_{i, j} (r_{ij} - u_{i:} \cdot v_{:j})^2$$

Least
Squares!



SVD vs UVD

SVD:

- $R = USV^T$
- U is an orthogonal matrix
- S is a diagonal matrix of decreasing positive “singular” values
- V is an orthogonal matrix
- Has a unique, exact solution

UVD:

- $R \approx UV$
- U and V will not (likely) be orthogonal
- Has many approximate, non-unique solutions:
 - non-convex optimization; has many local minima
- Has a tunable parameter k

UVD vs NMF

UVD:

- By convention: $R \approx UV$
- ... (see previous slides)

NMF is a specialization of **UVD**!

Both are approximate factorizations, and both optimize to reduce the RSS.

NMF:

- By convention: $V \approx WH$
- Same as UVD, but with one extra constraint:
all values of V , W , and H must be non-negative!

UVD vs NMF (*continued*)

UVD and NMF are both solved using either:

- Alternating Least Squares (ALS)
- Stochastic Gradient Descent (SGD)

You did **ALS** last week,
so let's do **SGD** today!

(and we'll see why SGD has some
advantages for recommender systems)

UVD via Stochastic Gradient Descent (SGD)

Boardwork...

ALS vs SGD

ALS:

- Parallelizes very well
- Available in Spark/MLlib
- Only appropriate for matrices that don't have missing values
(we'll call this a **dense** matrix in this lecture)

SGD:

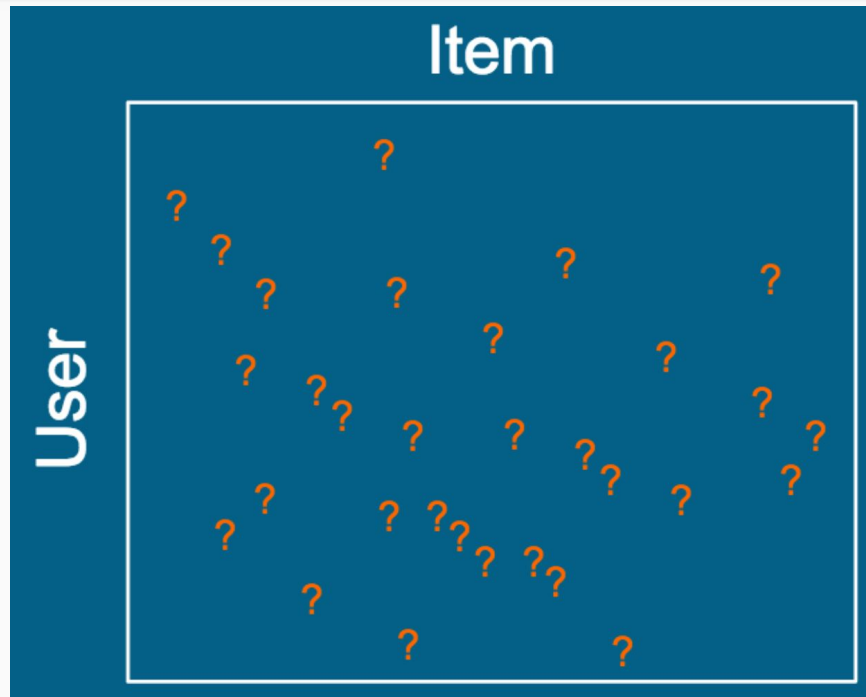
- Faster (if on single machine)
- Requires tuning learning rate
- Anecdotal evidence of better results...
- Works with missing values
(we'll call this a **sparse** matrix in this lecture)
(we'll see how missing values are handled soon!)

Matrix Factorization for Recommendation

Recall: An explicit-rating utility matrix is usually VERY sparse...

We've previously used SVD to find latent features (aka, factors)... Would SVD be good for this sparse utility matrix?
(Hint: No!)

What's the problem with using SVD on this sparse utility matrix?



Would UVD (or NMF) work better than SVD to find latent factors when the utility matrix is sparse?

(Hint: Consider ways to change the SGD algorithm to handle missing values in the sparse utility matrix.)



SVD vs UVD (*revisited*)


SVD:

- $R = USV^T$
- ...
- **Bad if R has missing values!**
 - You are forced to fill in missing values.
 - Solution fits these fill-values (which is silly).
 - Makes for a much larger memory footprint.
 - Slow to compute for large matrices.

UVD:

- $R \approx UV$
- ...
- **Handles missing values when computed via SGD.**

$$\arg \min_{U,V} \sum_{i,j \in \mathcal{K}} (r_{ij} - u_{i:} \cdot v_{:j})^2$$

 Set of indices of known rating

UVD (or NMF) + SGD... FTW!

UVD + SGD makes a lot of sense for recommender systems.


In fact, **UVD + SGD** is '**best in class**' option for *many* recommender domains:

- No need to impute missing values.
- Use regularization to avoid overfitting.
- Optionally include biases terms to communicate prior knowledge.
- Can handle time-dynamics (e.g. change in user preference over time).
- Used by the winning entry in the Netflix challenge.

Warning: Don't forget to regularize!

Since now we're fitting a large parameter set to sparse data, you'll most certainly need to regularize!

$$\arg \min_{U, V} \sum_{i, j \in \mathcal{K}} (r_{ij} - u_{i:} \cdot v_{:j})^2 + \lambda(||u_{i:}||^2 + ||v_{:j}||^2)$$

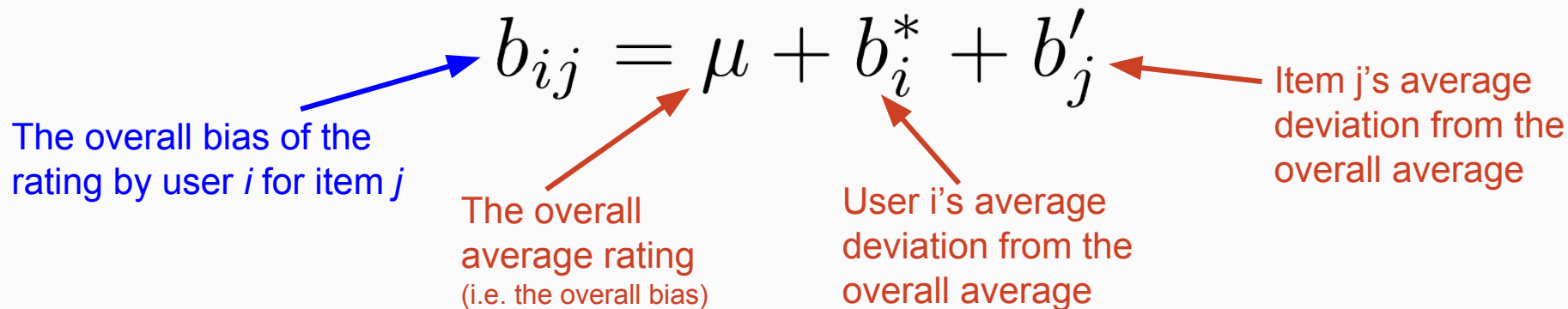


Tune lambda:
the amount of
regularization

In practice, much of the observed variation in rating values is due to item bias and user bias:

- Some items (e.g. movies) have a tendency to be rated high, some low.
- Some users have a tendency to rate high, some low.

We can capture this prior domain knowledge using a few bias terms:



The diagram illustrates the equation $b_{ij} = \mu + b_i^* + b'_j$ with four explanatory arrows:

- A blue arrow points from the text "The overall bias of the rating by user i for item j " to the variable b_{ij} .
- A red arrow points from the text "The overall average rating (i.e. the overall bias)" to the variable μ .
- A red arrow points from the text "User i 's average deviation from the overall average" to the variable b_i^* .
- A red arrow points from the text "Item j 's average deviation from the overall average" to the variable b'_j .

$$b_{ij} = \mu + b_i^* + b'_j$$

We added bias terms... now: The 4 parts of a prediction

$$r_{ij} \approx \mu + b_i^* + b'_j + u_{i:} \cdot v_{:j}$$

The prediction
of user i rating
item j

The average
rating

User i's
tendency to
deviate from
the average

Item j's
tendency to
deviate from
the average

The prediction of
how user i will
interact with
item j

Ratings are now estimated as:

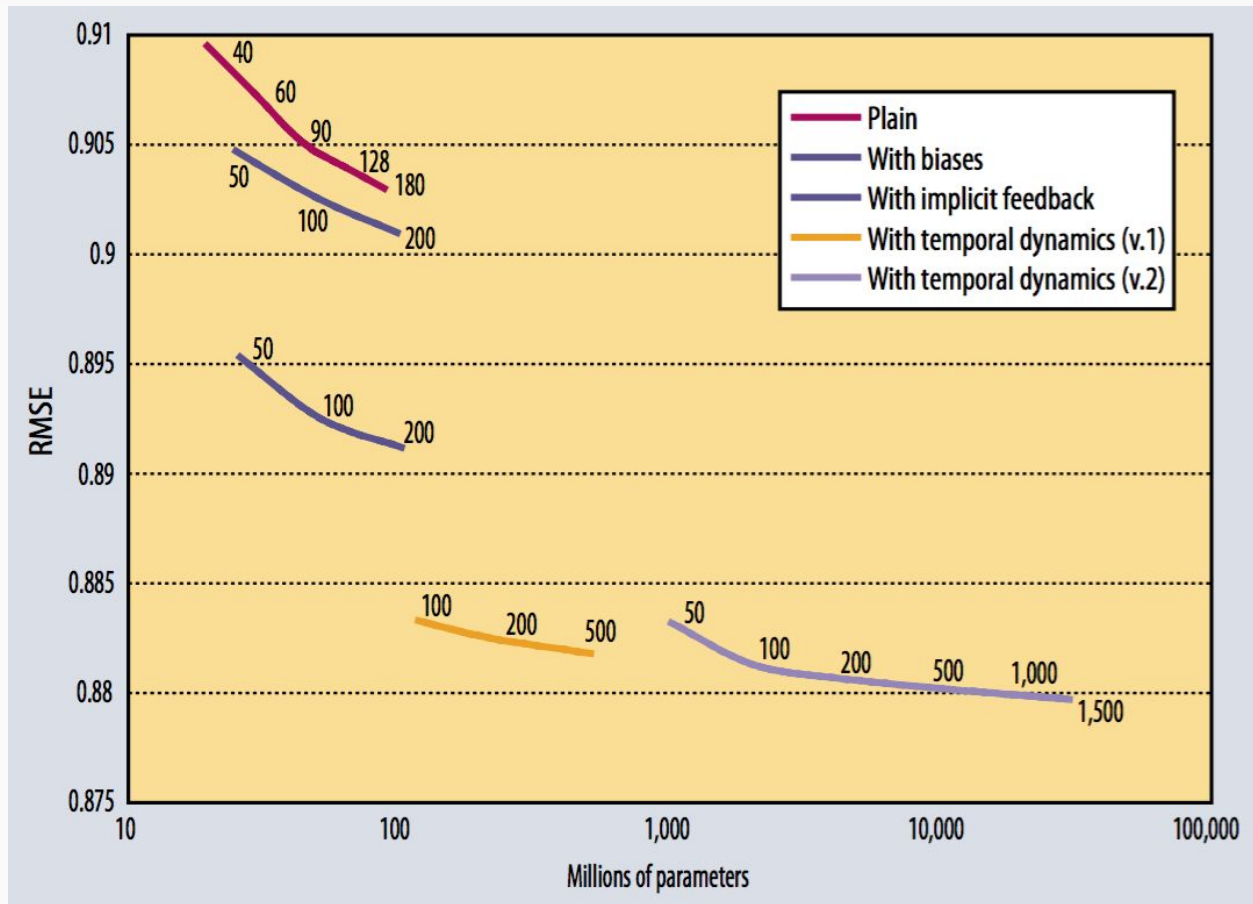
$$r_{ij} \approx \mu + b_i^* + b'_j + u_{i:} \cdot v_{:j}$$

The new cost function, with the biases included:

$$\arg \min_{U, V, b^*, b'} \sum_{i, j \in \mathcal{K}} (r_{ij} - \mu - b_i^* - b'_j - u_{i:} \cdot v_{:j})^2 + \lambda_1 (\|u_{i:}\|^2 + \|v_{:j}\|^2) + \lambda_2 ((b_i^*)^2 + (b'_j)^2)$$

New part!

New part!



Root mean square error over the Netflix dataset using various matrix factorization models.

Numbers on the chart denote each model's dimensionality (k).

The more refined models perform better (have lower error).

Netflix's inhouse model performs at RMSE=0.9514 on this dataset, so even the simple matrix factorization models are beating it!

Read the paper for details; it's a good read!