Recommender Systems

Schwartz

August 16, 2017

Recommender Systems: the ultimate win win?

Stephen Covey's *The 7 Habits of Highly Effective People* are:

Self-Mastery

1. *Be Proactive* in your Circle of Influence/Circle of Concern
2. *Begin with the End in Mind*
3. *Put First Things First*:

	Important	Not Important
Urgent	Do This	AVOID*
Not Urgent	Then this	Never do this

*Tyranny of the Urgent

Interdependence

4. *Think Win-Win*: why are recommender systems win-wins?
5. *Seek First to Understand, Then to be Understood*
6. *Synergize*

Sharpening the Saw

7. *"Always be Getting Better"*

Objectives

- Recommender Systems
  - Popularity
  - Content-Based
  - **Collaborative Filtering**
- Cold Start
- Matrix Factorization
  - SVD vs UVD vs NMF
  - UVD via SGD
  - Bias modeling
  - Regularization
  - Performance
- Evalutation

The Ultimate Win-Win Opportunity

- Know what the user will *enjoy*: e.g., Facebook
- Know what the user will *click*: e.g., GoogleAds
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Test: RMSE for 2,817,131 ratings; average user rated over 200 movies; average movie rated by over 5000 users

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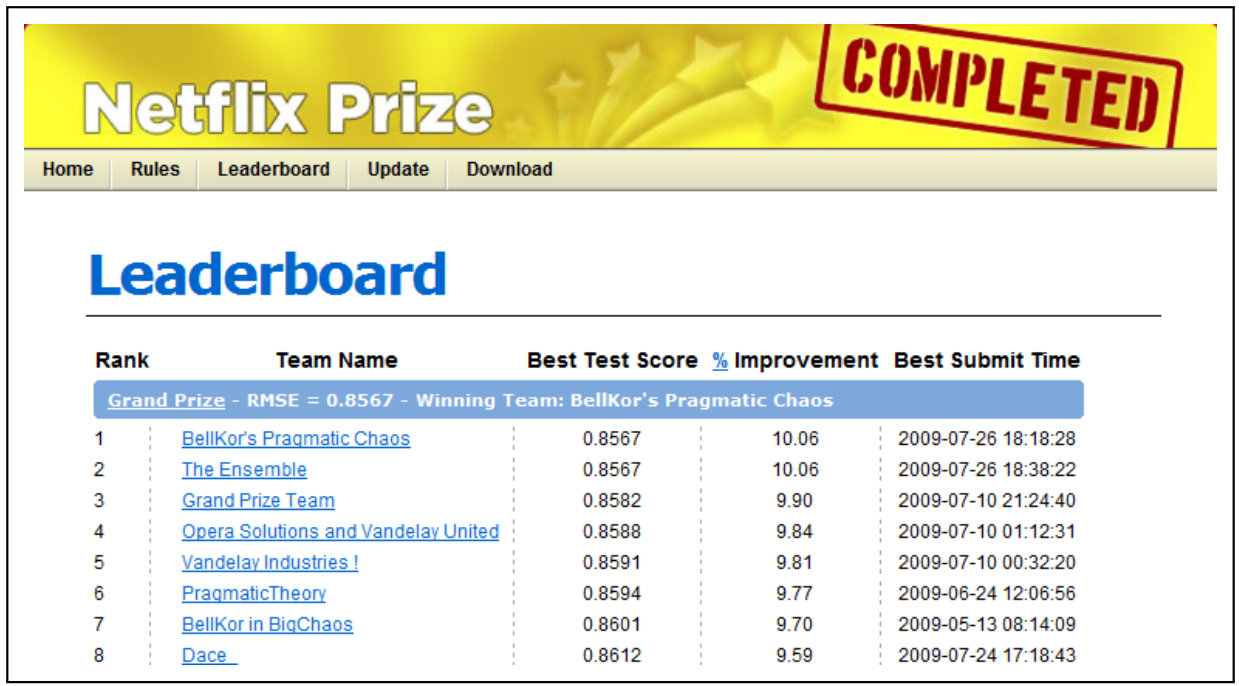

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- Netflix would award the $1M prize for beating Netflix's own model by 10% (RMSE of 0.9514 to 0.8563)
- It took almost 3 years; "progress prizes" were awarded every year; 8.43% improvement after one year
- Final top two teams were merger of several top teams and Netflix never implemented the winning solution

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Matrix Factorization Methods

- Find and Leverage Latent Features (factors)
- Expands NMF methodology

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Many Recommender Systems are Hybrids of These!

Collaborative Filtering

Utility Matrix (the data)

n users and p items

	Item				
	A	B	C	D	$\cdots$
Al	1	?	2	?	
Bob	?	2	3	4	
Cat	3	?	1	5	
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Ed	2	?	?	1	
$\vdots$					

Table: Netflix Rating Data

User-Item Utility Matrix

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Table: Youtube Next Data

User-Item Utility Matrix

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n users and p items

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User-Item Utility Matrix

$$O(n \times n \times p)$$

Item Similarity

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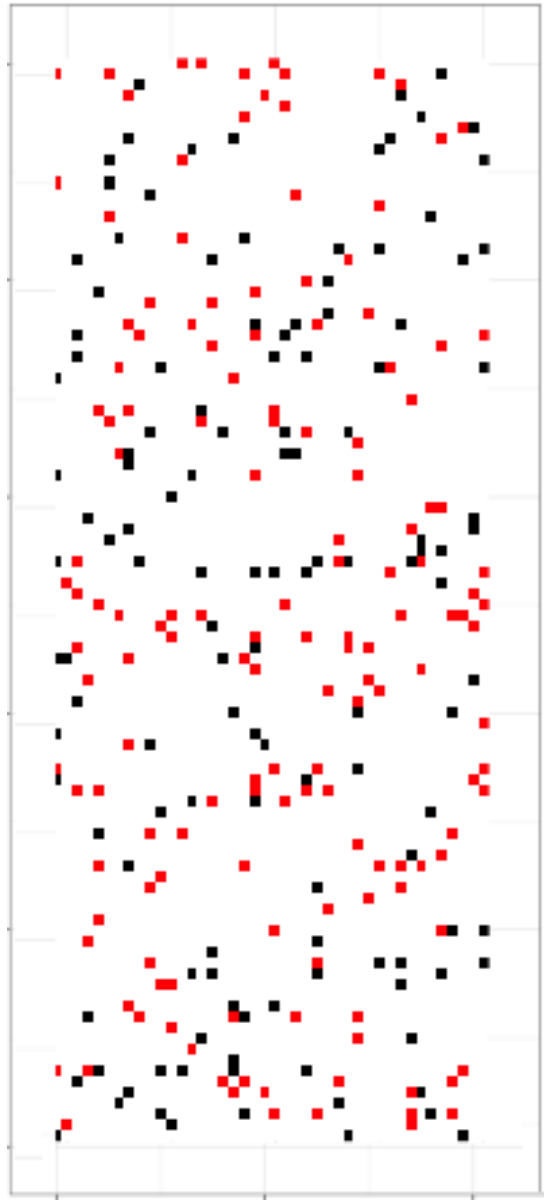
Many businesses have $n > p$



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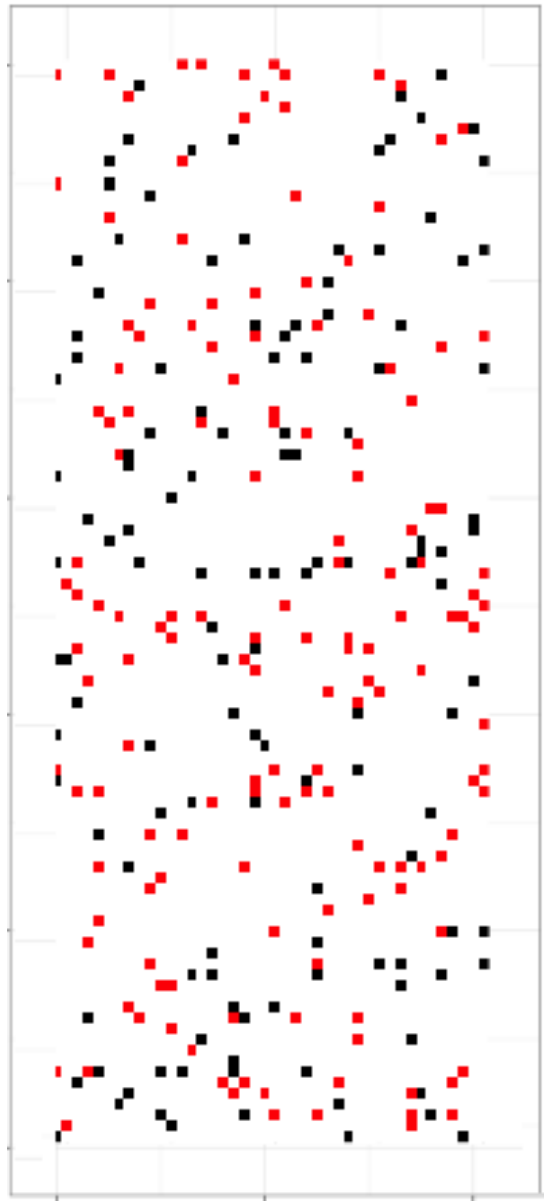

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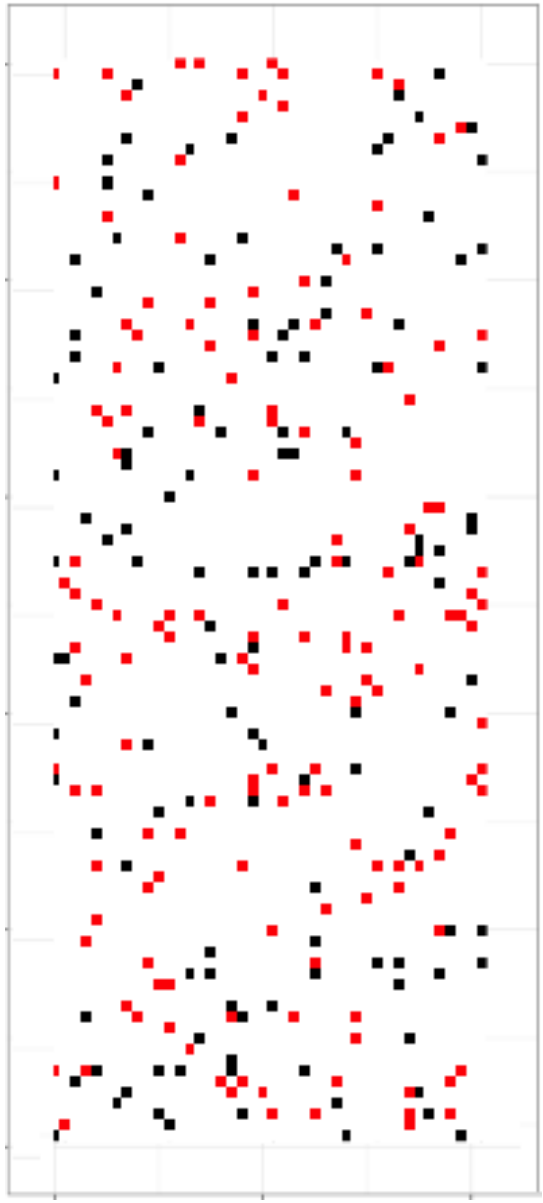
Many businesses have $n > p$

1. Computation:
   $O(p \times p \times n) < O(n \times n \times p)$
2. Stability:
   $Item_a$-$Item_b$ > $User_1$-$User_2$ overlap

Less "cold start":
quicker to onboard new items



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- *How do these work?*

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- *How do these work? What do they do for similarly rated items?*

Similarity Metrics II (similar $\rightarrow$ 1; dissimilar $\rightarrow$ 0)

- **Euclidean**

$$EuclideanSimilarity(a, b) = \frac{1}{1 + Dist(a, b)}$$

- **Pearson Correlation**

$$PearsonSimilarity(a, b) = \frac{1}{2} + \frac{1}{2} Pearson(a, b)$$

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- **Jaccard Index**

$$JaccardSimilarity(a, b) = \frac{|U_a \cap U_b|}{|U_a \cup U_b|}$$

where U_{item} is the set of users who rated *item*

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For user u and item i we can predict user rating based on a weighted average of the other items the user has rated I_u

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N_i is the set of the n items most similar to item i

The Cold-Start Problem

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- Content-Based?
- Popularity Recommender?

Matrix Factorization Methods

UV Decomposition (UVD)

$$\underset{n\times p}{X} \approx \underset{n\times k}{U} \quad \underset{k\times p}{V}$$

$$X_{ij} \approx U_{i.}V_{.j} = \hat{X}_{ij}$$

$$\underset{U,V}{argmin} \sum_{i,j}(X_{ij} - U_{i.}V_{.j})^2$$

UVD

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- $X = U\Sigma V^T$

NMF

- $X \approx WH; W, H \geq 0$

UVD

- $X \approx UV$

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NMF

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- U, V^T orthogonal
- single solution

NMF

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- non-unique solutions

UVD

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- analytical solution

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- iterative optimization

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- analytical solution
- no missing values

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How do we learn U and V?

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- **Gradient Descent**

$$\frac{\partial}{\partial U_{i'k}} \sum_{i,j} (X_{ij} - U_{i\cdot} \ V_{\cdot j})^2 = \sum_{j} -2(X_{i'j} - U_{i'k} \ V_{kj}) V_{kj}$$

$$\frac{\partial}{\partial V_{kj'}} \sum_{i,j} (X_{ij} - U_{i\cdot} \ V_{\cdot j})^2 = \sum_{i} -2(U_{ij'} - U_{ik} \ V_{kj'}) U_{ik}$$

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- **Alternating Lease Squares (ALS)**
  1. Update $V_{\cdot j}$ using OLS: $X_{\cdot j} = \mathbf{U} V_{\cdot j} + \epsilon_{\cdot j}$

$$\begin{bmatrix} & | & \\ & | & \\ & | & \end{bmatrix} = \begin{bmatrix} \rightarrow\rightarrow \\ \rightarrow\rightarrow \\ \rightarrow\rightarrow \end{bmatrix} \begin{bmatrix} & \downarrow & \\ & \downarrow & \\ & \downarrow & \end{bmatrix}$$

  2. Update $W_{i\cdot}$ using OLS: $X_{i\cdot}^T = \mathbf{V^T} U_{i\cdot}^T + \epsilon_{i\cdot}^T$

$$\begin{bmatrix} - & - \\ & \end{bmatrix}^T = \left(\begin{bmatrix} \rightarrow\rightarrow \\ \end{bmatrix} \begin{bmatrix} \downarrow & \downarrow & \downarrow & \downarrow \\ \downarrow & \downarrow & \downarrow & \downarrow \\ \downarrow & \downarrow & \downarrow & \downarrow \end{bmatrix} \right)^T$$

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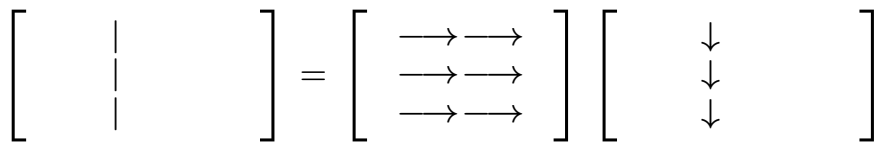

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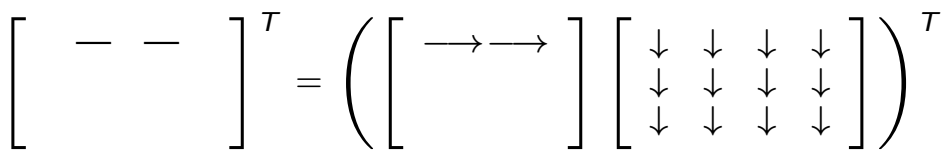

- **Lee and Seung's "multiplicative update rules"**
  Initialize non-negative H and W; update with non-negativity constraint:

$$W'_{ik} = W_{ik} \frac{(XH^T)_{ik}}{(WHH^T)_{ik}} \qquad H'_{kj} = H_{kj} \frac{(W^T X)_{kj}}{(W^T WH)_{kj}}$$

Numerical Estimation Comparisons

Alternating Least Squares

Multiplicative Updates

Stochastic Gradient Decent

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- Simple idea/implementation
- Parallelizes very well
- Available in Spark/MLlib

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- Faster than ALS (per CPU)

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- Easy implementation
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- Can handle NA's with care

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- Need to turn learning rate
- Thought to outperform ALS
- Works with NA's

Multiplicative Updates

- Easy implementation
- Faster than SGD
- No turning parameter
- Only works for NMF
- Can't handle NA's

UVD + SGD is best in class

Used by the winning Netflix Challenge entry

- No need to impute missing values
- Can model time dynamics (evolving user preference)
- Plus it can do all of these:

$$\underset{U,V}{argmin} \sum_{i,j} (X_{ij} - (U_{i\cdot} V_{\cdot j}))^2$$

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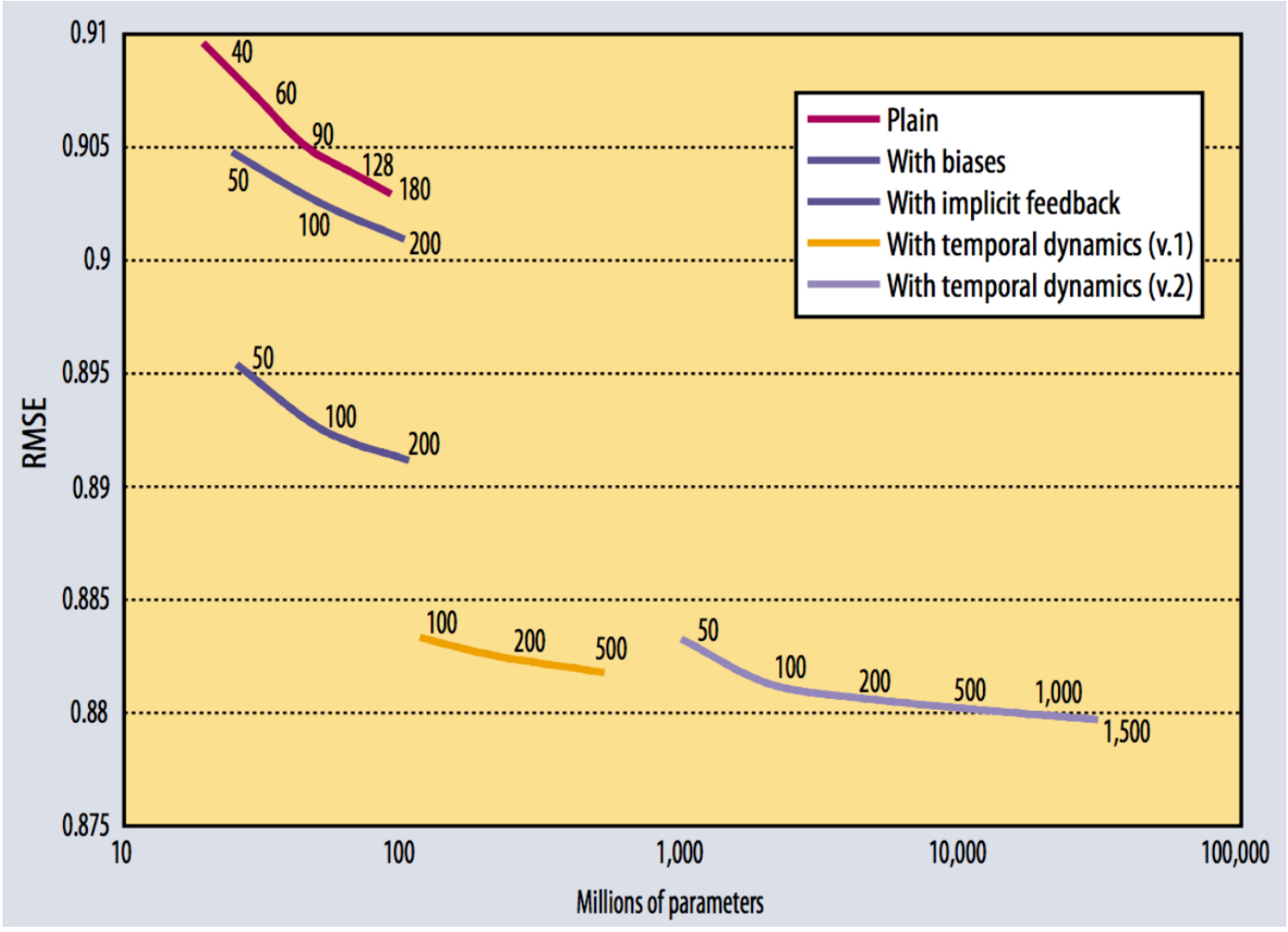
And Don't Forget *k*!!!

Matrix Factorization Methods on the Netflix Challenge

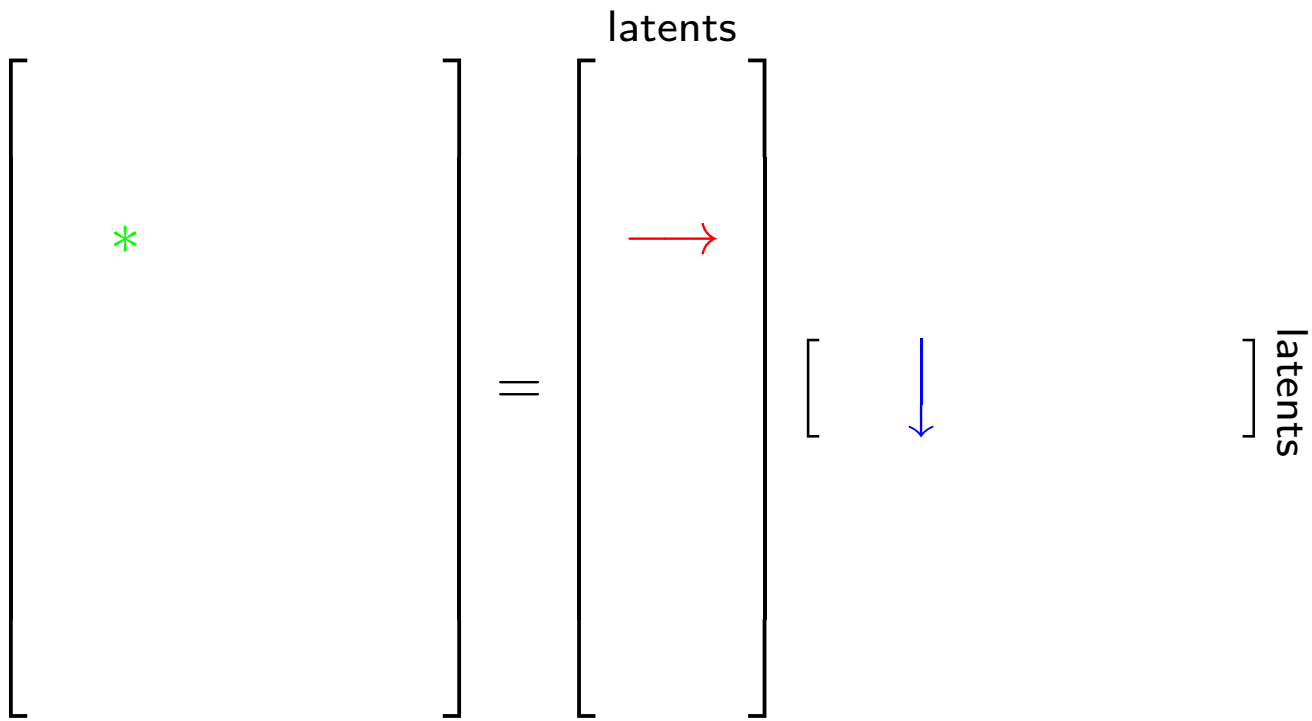
Netflix's in-house model achieves RMSE=0.9514



"Matrix Factorization Techniques for Recommender Systems"

What are the *"latent factors"*?

$$X = U \quad V$$



"item composition"

"user parts"

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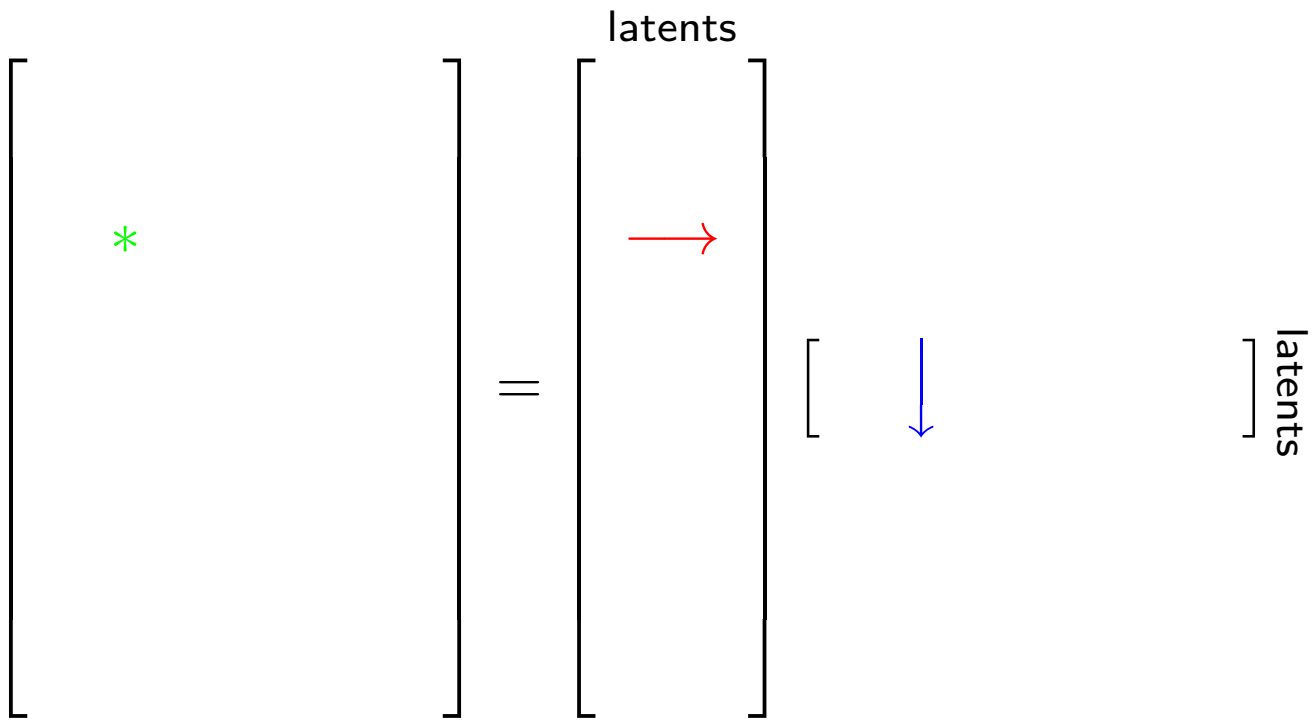

so rows are "item topics" $\longrightarrow$ *"item composition"*

"user parts" $\longleftarrow$ *and columns are "user archetypes"*

Wrap Up

$$\underset{U,V,\beta_{Ui},\beta_{Ij},\mu}{argmin} \sum_{i,j} (X_{ij} - \left(\mu + \beta_{Ui} + \beta_{Ij} + U_{i\cdot} V_{\cdot j}\right))^2 + \lambda_1 \left(||U_{i\cdot}||^2 + ||V_{\cdot j}||^2\right) + \lambda_2 \left(\beta_{Ui}^2 + \beta_{Ij}^2\right)$$

PROS

CONS

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At Request Time: Serve up best prediction score

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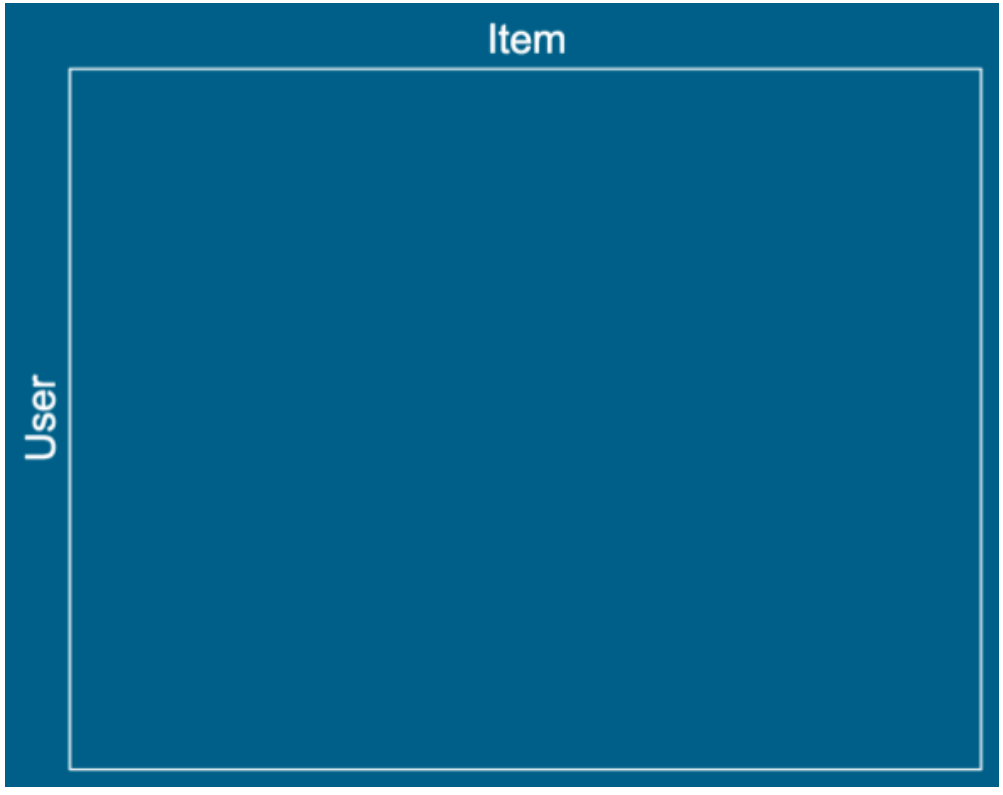
During Down Time: Compute pairwise similarity, N_i, and predictions

or re-factorize matrix based on newly acquired data

BIG FINISH: *Evaluating the Recommender*

The difficulty is how do you get a system in the first place?



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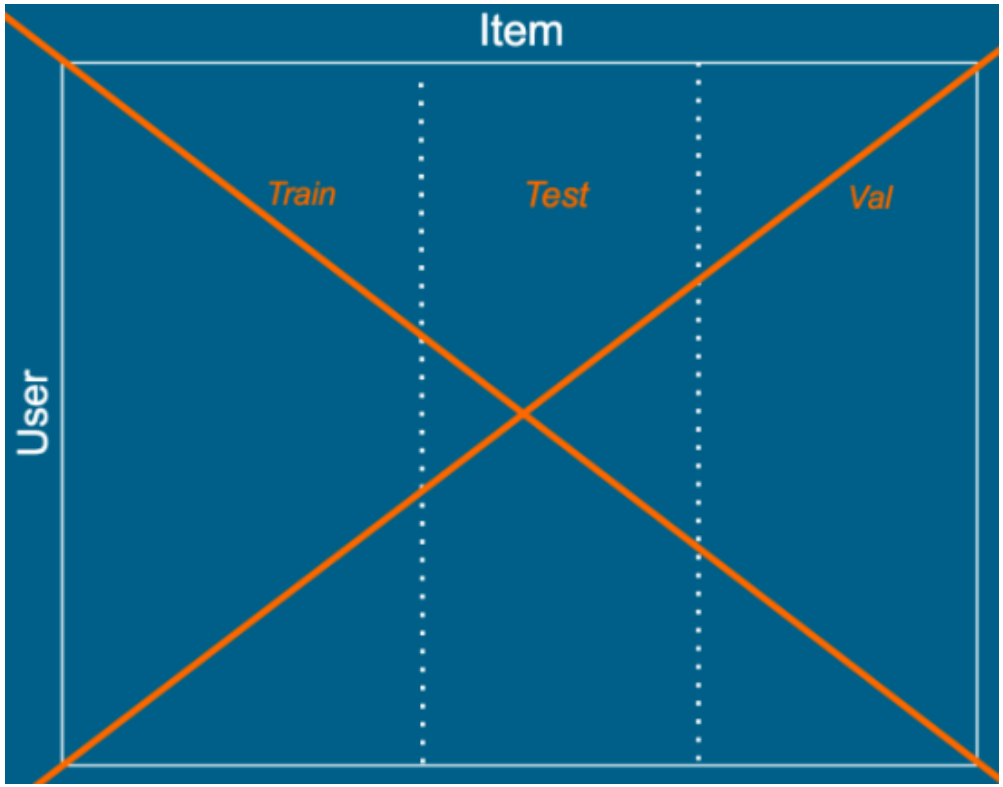

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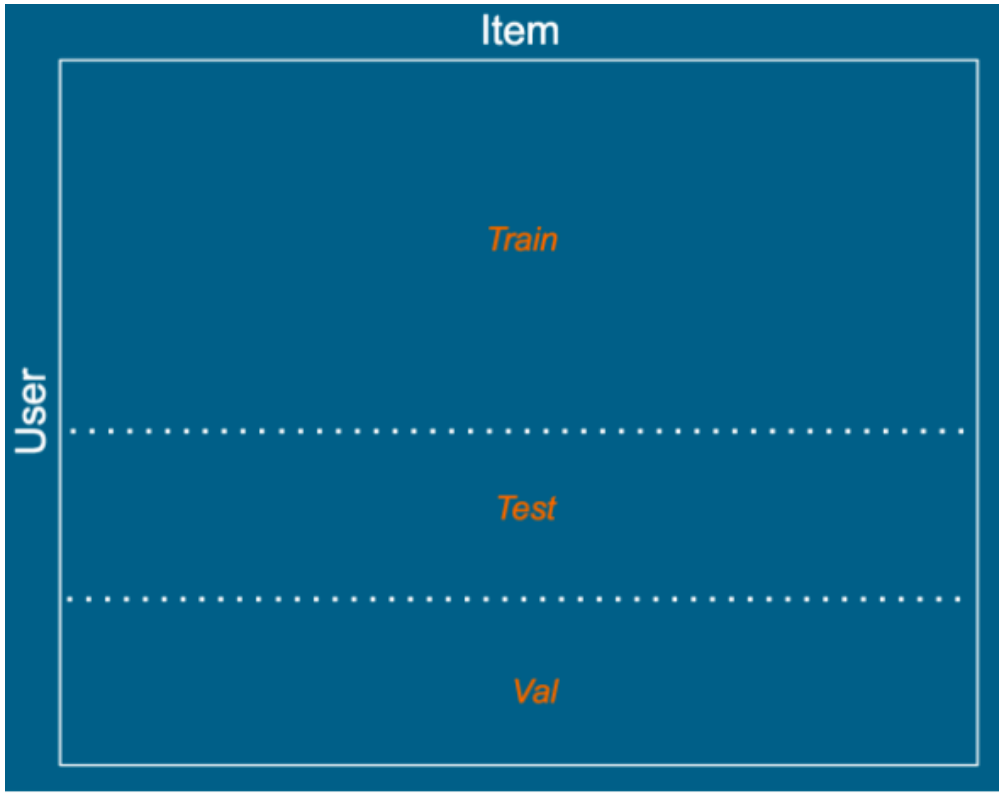

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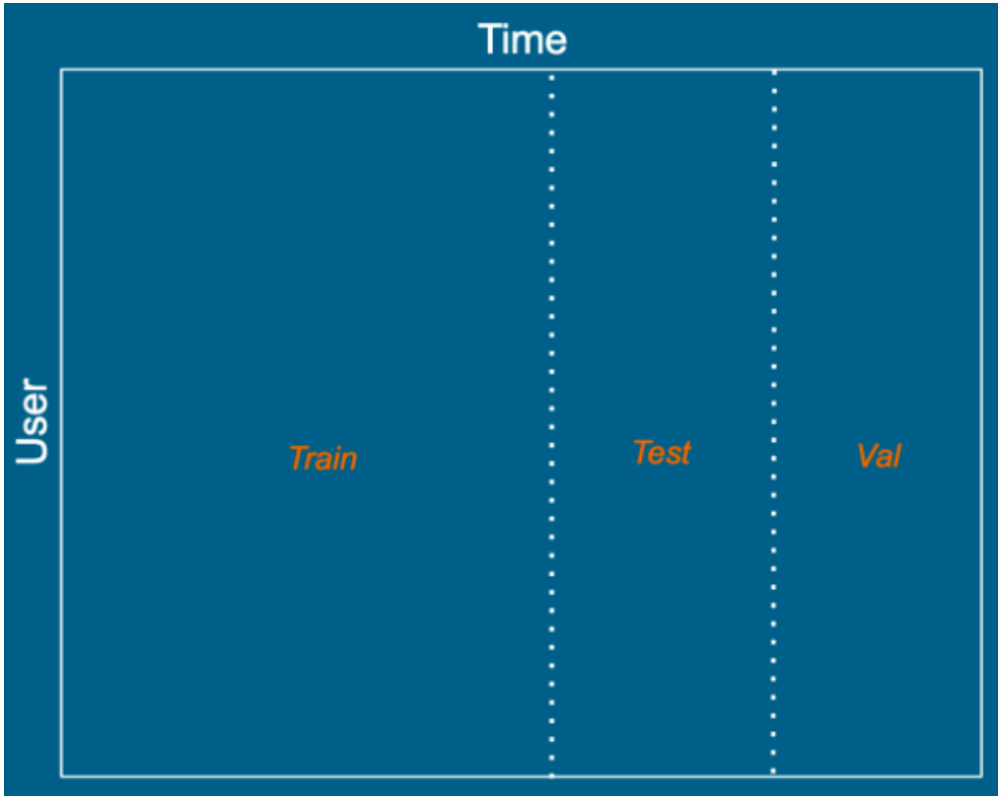

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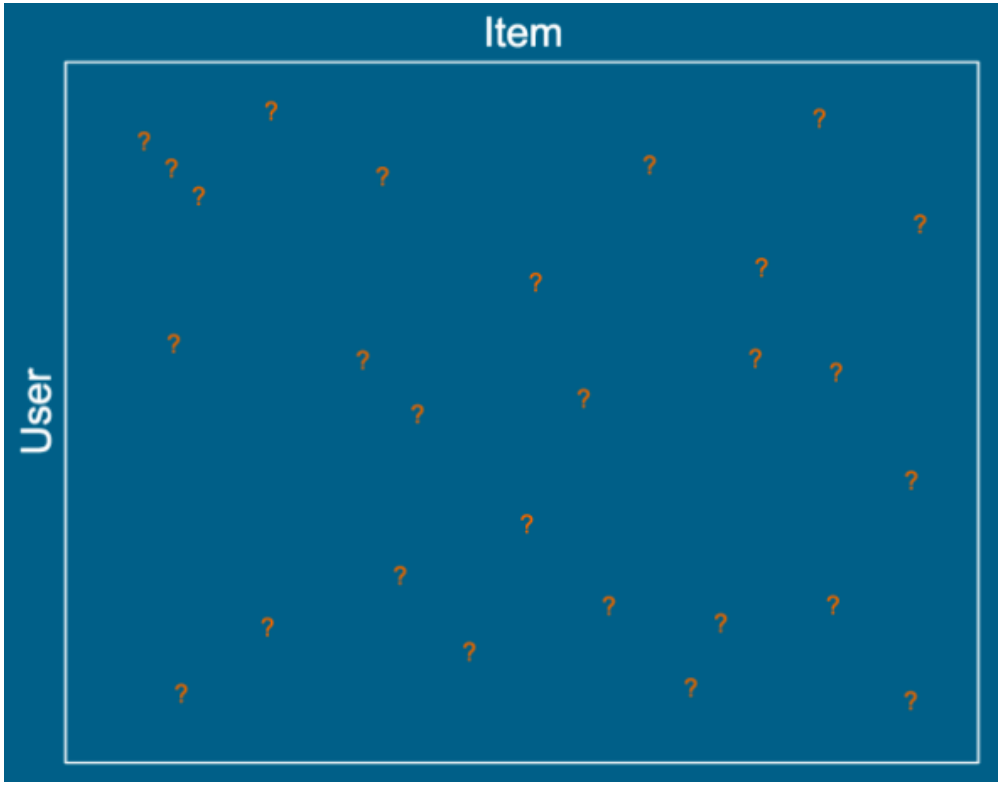

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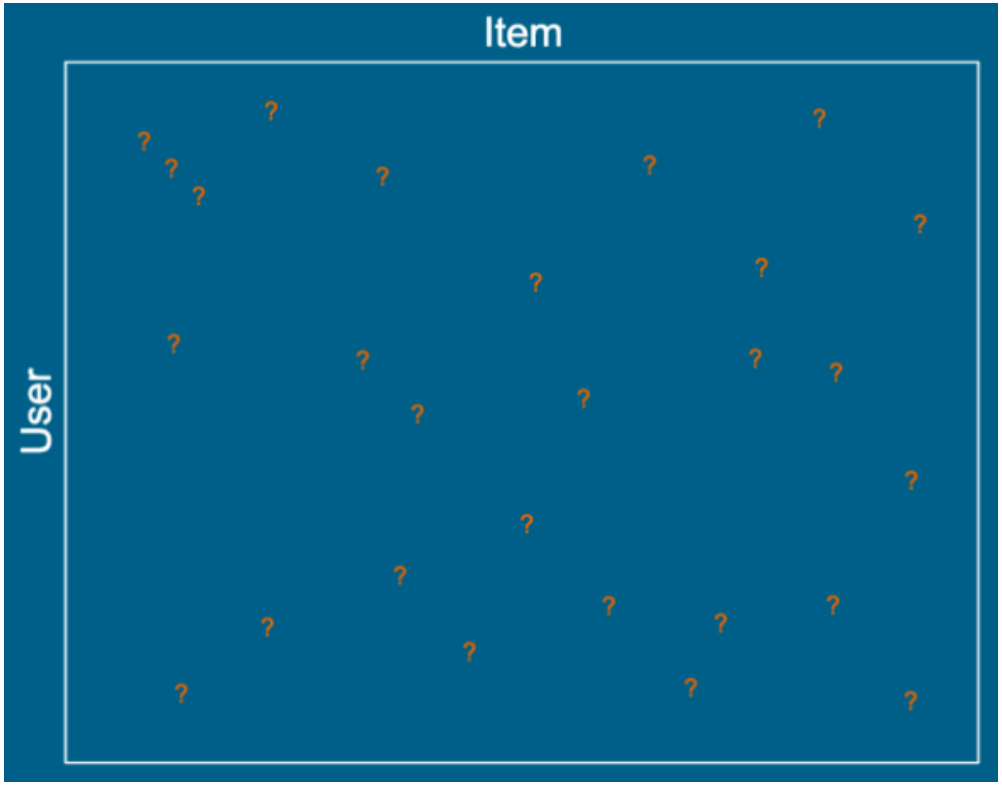

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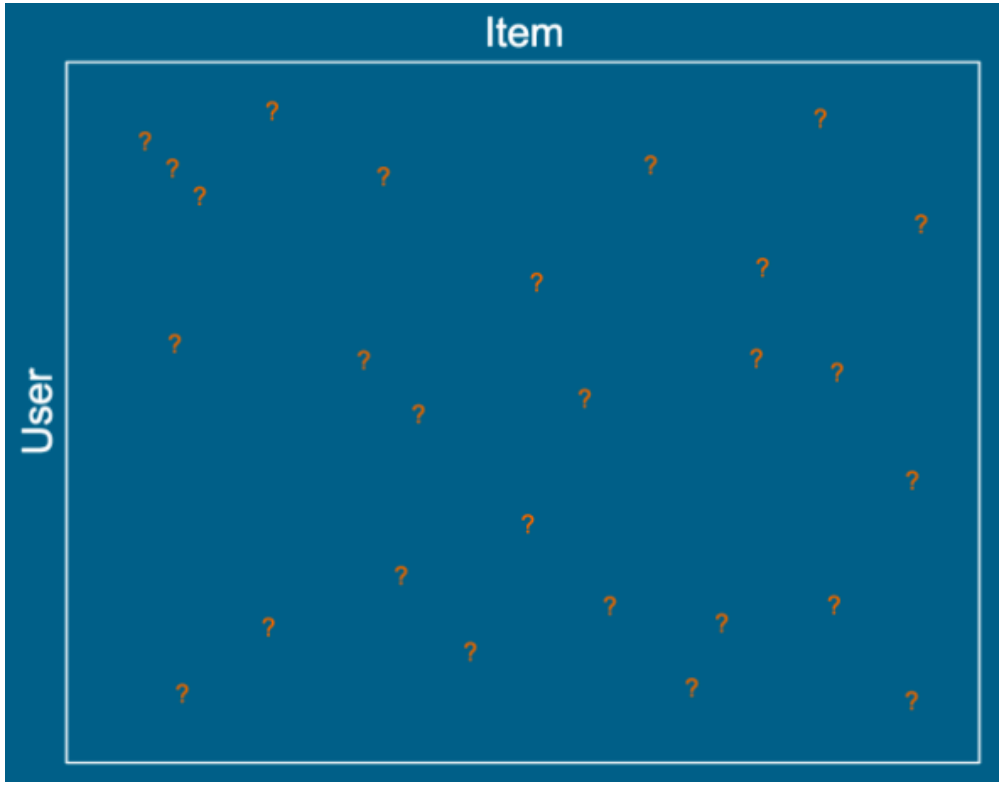

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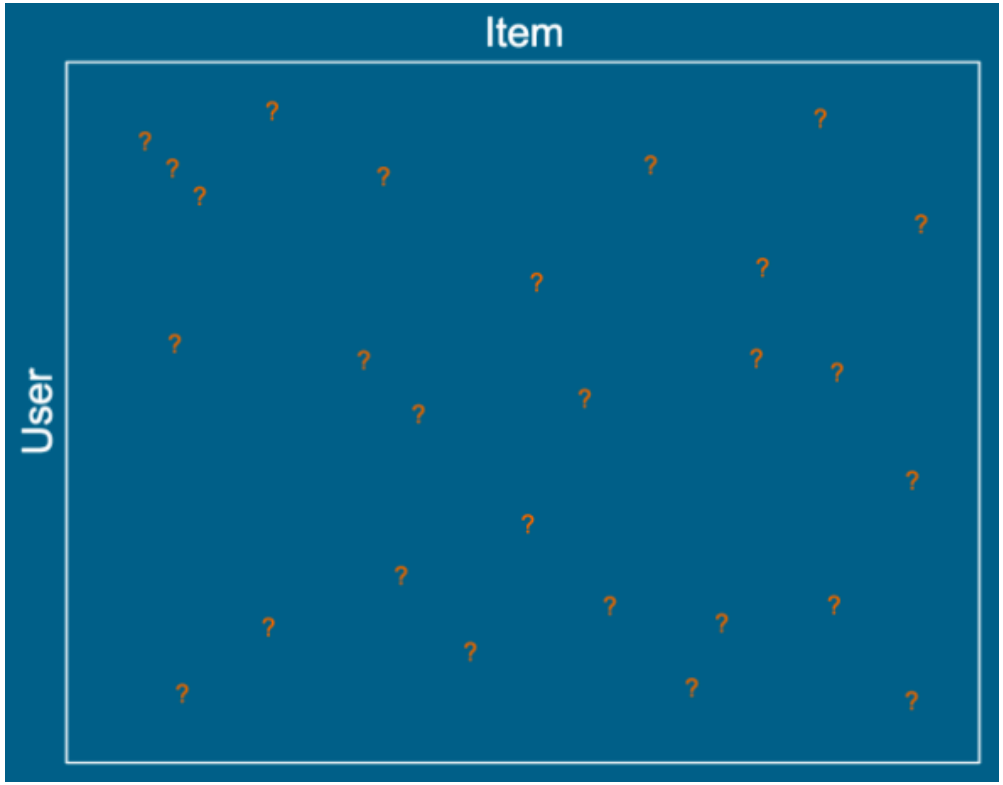

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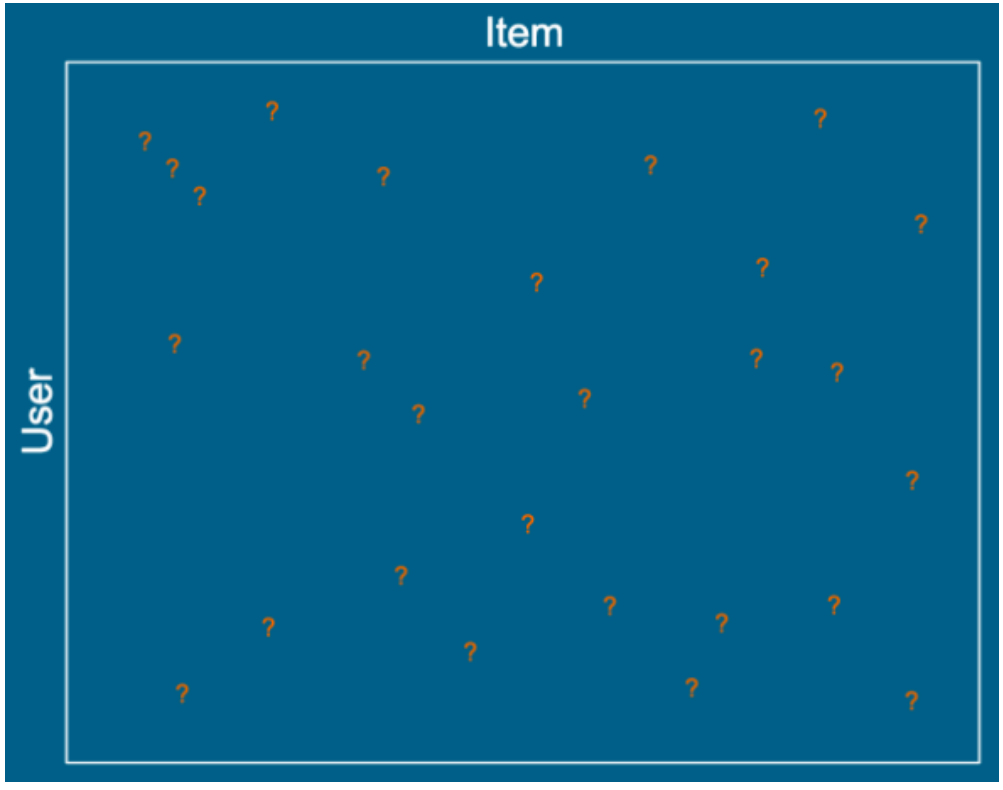

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So many challenges...
A/B testing, anyone?

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bleh