Recommending Products

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Where we see recommender systems

Personalization is transforming our experience of the world

YouTube

100 Hours a Minute
What do I care about?

Information overload

↓

Browsing is "history"

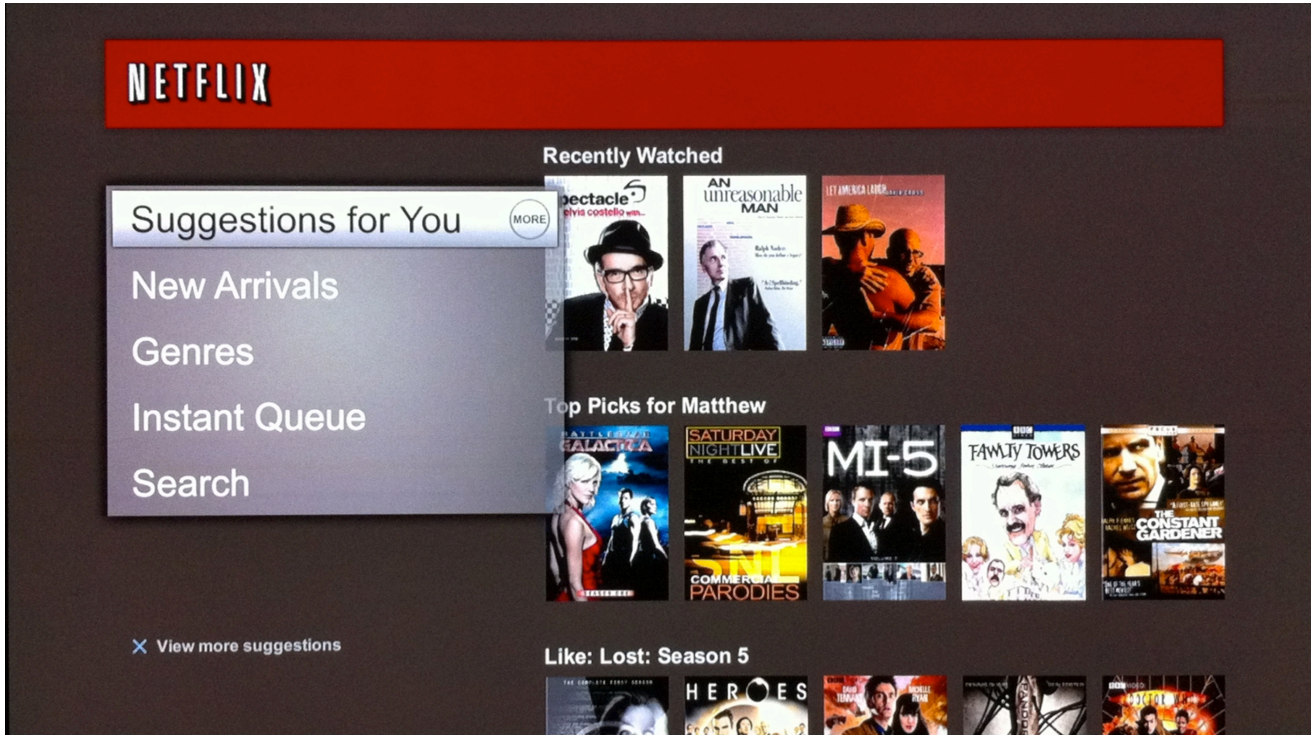
– Need new ways to discover content

Personalization: Connects *users & items*

viewers → users

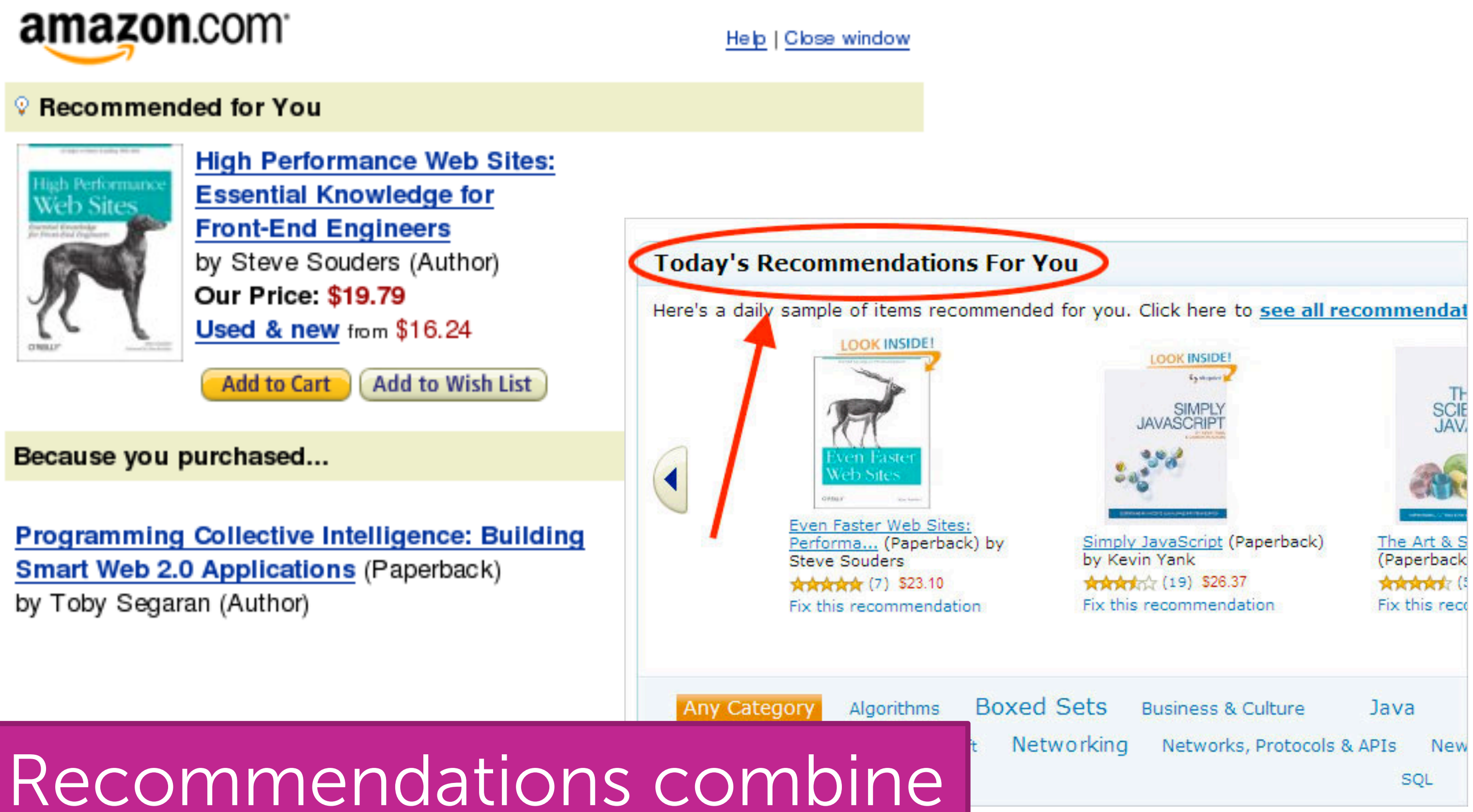
videos → items

Movie recommendations



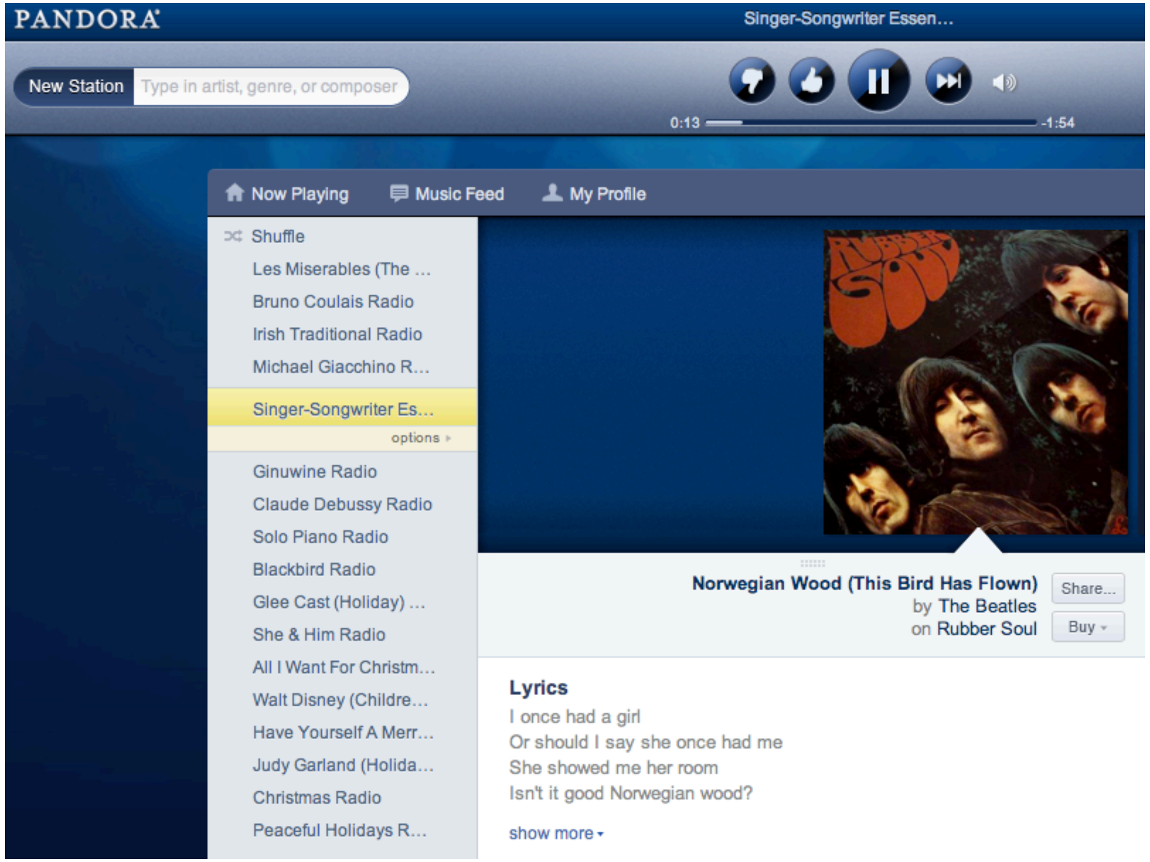
Connect users with movies they may want to watch

Product recommendations



Recommendations combine global & session interests

Music recommendations



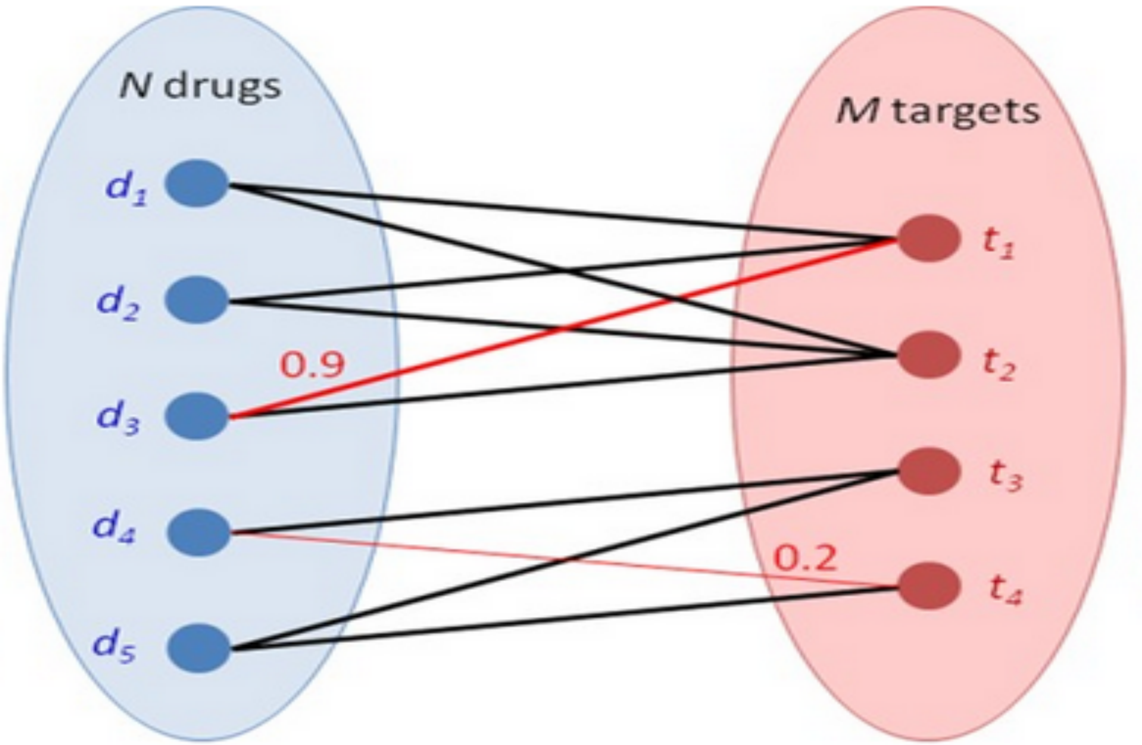
Recommendations form coherent & diverse sequence

Friend recommendations

Users and "items"
are of the same "type"

Drug-target interactions

Cobanoglu et al. '13



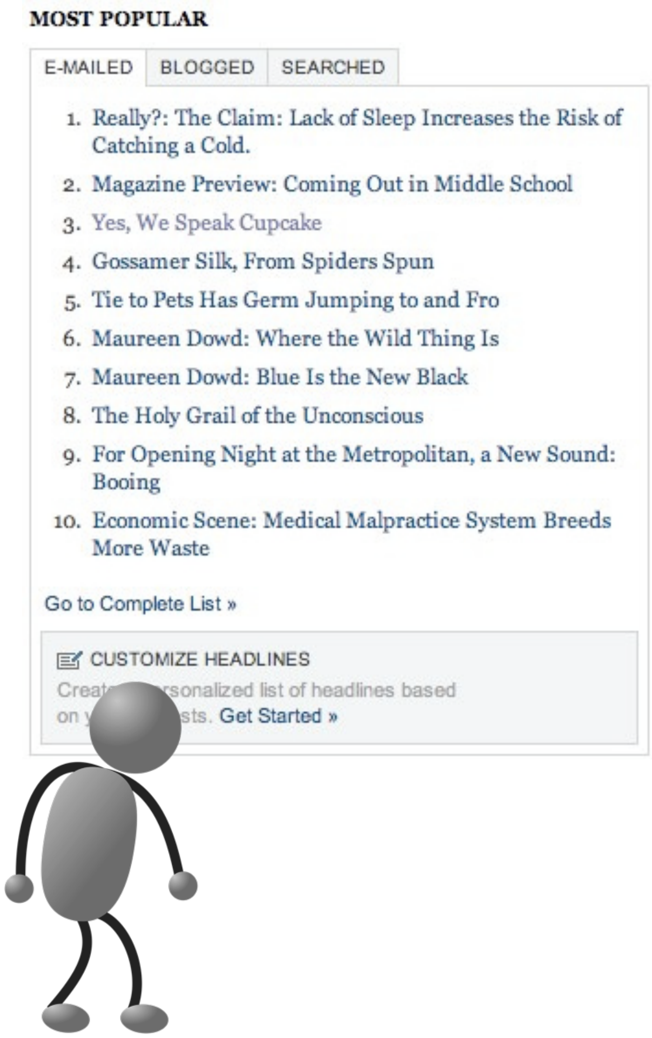
What drug should we "repurpose" for some disease?

Building a recommender system

Solution 0: Popularity

Simplest approach: Popularity

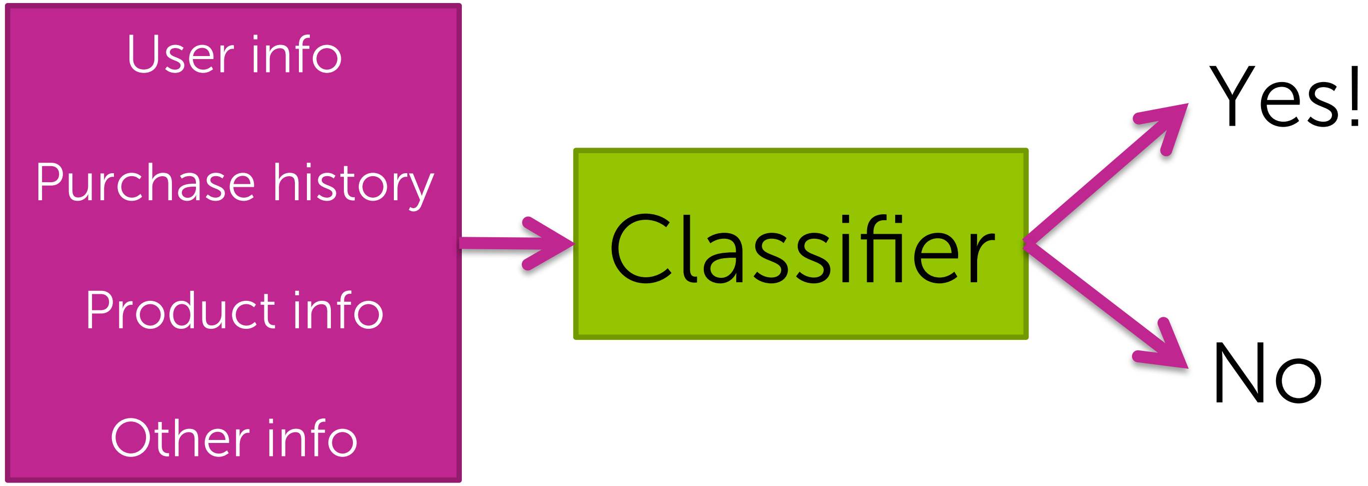
- What are people viewing now?
  - Rank by global popularity



- **Limitation:**
  - No personalization

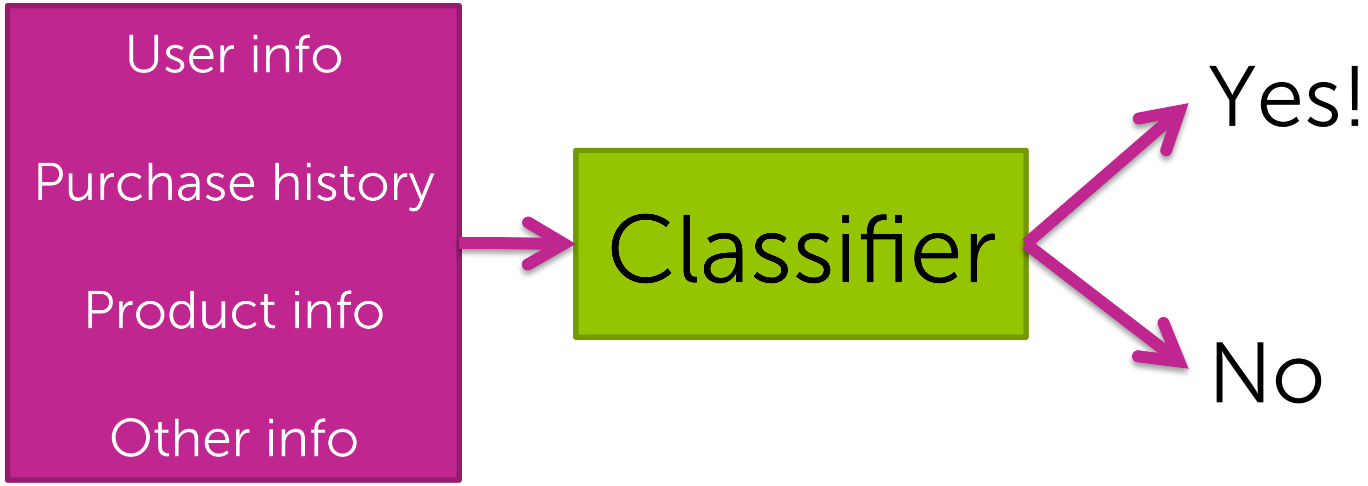
Solution 1: Classification model

What's the probability I'll buy this product?



- **Pros:**
  - Personalized:
    Considers user info & purchase history
  - Features can capture context:
    Time of the day, what I just saw,…
  - Even handles limited user history: Age of user, …

Limitations of classification approach



- Features may not be available
- Often doesn't perform as well as collaborative filtering methods (next)

Solution 2: People who bought this also bought…

Co-occurrence matrix

- People who bought *diapers* also bought *baby wipes*

- **Matrix C:**
  store # users who bought both items ***i & j***
  – (# items **x** # items) matrix

  – Symmetric: # purchasing ***i & j*** same as # for ***j & i*** ($C_{ij} = C_{ji}$)

Making recommendations using co-occurences

- User  purchased *diapers*

1. Look at *diapers* row of matrix

2. Recommend other items with largest counts
   - *baby wipes*, *milk*, *baby food*,…

Co-occurrence matrix must be normalized

- What if there are very popular items?
  - Popular baby item: *Pampers Swaddlers diapers*

  - For any baby item (e.g., ***i***=*Sophie giraffe* ) large count C_{ij} for ***j***=*Pampers Swaddlers*

- Result:
  - Drowns out other effects
  - Recommend based on popularity

Normalize co-occurrences: Similarity matrix

- Jaccard similarity: normalizes by popularity
  - Who purchased *i* and *j* *divided by* who purchased *i* or *j*

- Many other similarity metrics possible, e.g., cosine similarity

Limitations

- Only current page matters, no history
  - Recommend similar items to the one you bought
- What if you purchased many items?
  - Want recommendations based on purchase history

(Weighted) Average of purchased items

- User  bought items {*diapers*, *milk*}
  - Compute user-specific score for each item j in inventory by combining similarities:

    Score( *, baby wipes)* =

    $$\frac{1}{2}\left(S_{\text{baby wipes, diapers}} + S_{\text{baby wipes, milk}}\right)$$

  - Could also weight recent purchases more

- Sort *Score(*  *, j)* and find item j with highest similarity

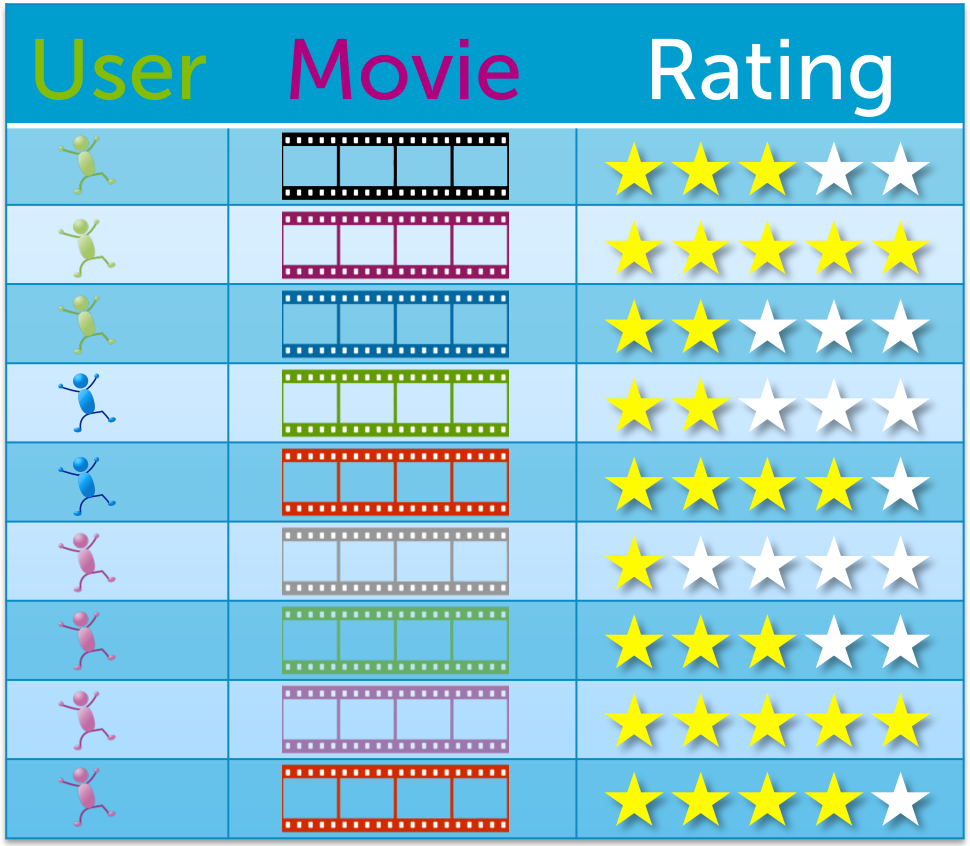
Limitations

- Does **not** utilize:
  - context (e.g., time of day)
  - user features (e.g., age)
  - product features (e.g., baby vs. electronics)
- Cold start problem
  - What if a new user or product arrives?

Solution 3: Discovering hidden structure by matrix factorization

Movie recommendation

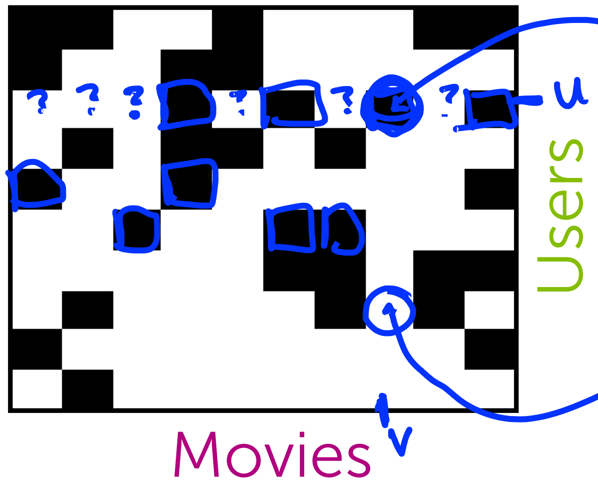
- Users watch movies and rate them



Each user only watches a few of the available movies

Matrix completion problem

Rating =



Rating of movie v by user u

?

- **Data:** Users score some movies

  $\boxed{\textit{Rating(u,v)}}$ known for black cells
  Rating(u,v) unknown for white cells

- **Goal:** Filling missing data?

filling in a ?

Suppose we had *d* topics for each user and movie

- Describe movie *v*  with topics R_v
  - How much is it action, romance, drama,…

$R_v = [\,0.3 \quad 0.01 \quad 1.5 \quad \ldots\,]$

- Describe user *u*  with topics L_u
  - How much she likes action, romance, drama,…

estimate

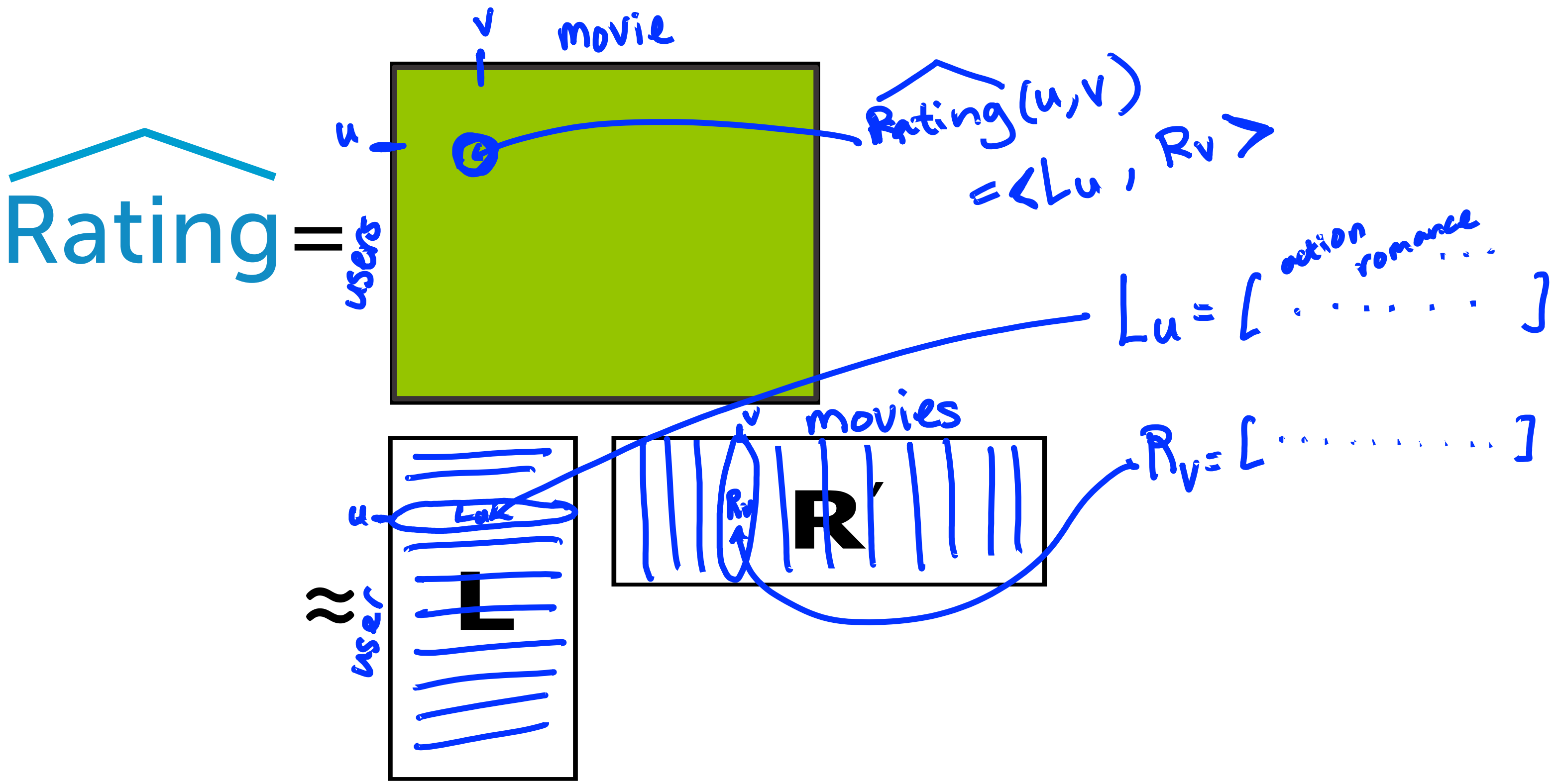
$L_u = [\,2.5 \quad 0 \quad 0.8 \quad \ldots\,]$

- $\widehat{\mathit{Rating}}(u,v)$ is the product of the two vectors

$R_v = [\,0.3 \quad 0.01 \quad 1.5 \quad \ldots\,]$
$L_u = [\,2.5 \quad 0 \quad 0.8 \quad \ldots\,] \rightarrow 0.3 * 2.5 + 0 + 1.5 * 0.8 + \ldots = 7.2 > 5$
$L_{u'} = [\,0 \quad 3.5 \quad 0.01 \quad \ldots\,] \rightarrow 0 + 0.01 * 3.5 + 1.5 * 0.01 + \ldots = 0.8$

- **Recommendations:** sort movies user hasn't watched by $\widehat{\mathit{Rating}}(u,v)$

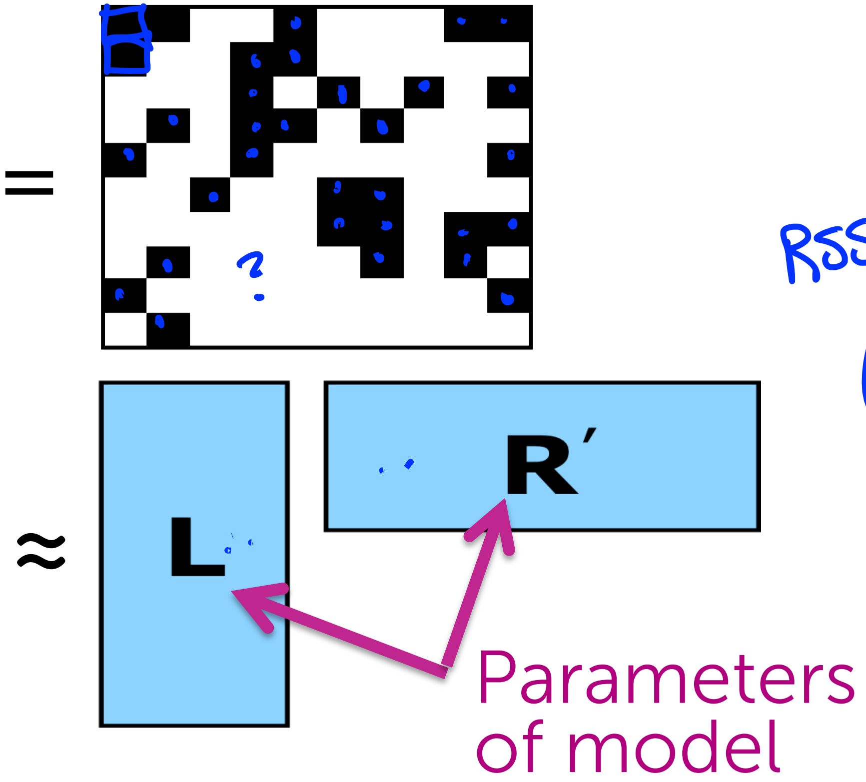
Predictions in matrix form



But we don't know topics of users and movies...

Matrix factorization model: Discovering topics from data

Rating =



$\mathrm{RSS}(L,R) =$

$(\mathrm{Rating}(u,v) - \langle L_u, R_v \rangle)^2$

predicted rating

+ [include all (u',v') pairs where $\mathrm{Rating}(u',v')$ are available]

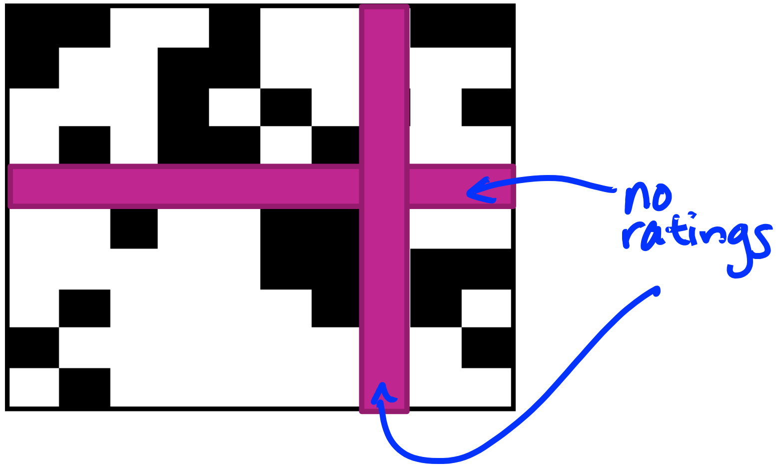
Many efficient algorithms for factorization

- Only use observed values to estimate "topic" vectors $\hat{L}_u$ and $\hat{R}_v$
- Use estimated $\hat{L}_u$ and $\hat{R}_v$ for recommendations

Limitations of matrix factorization

- Cold-start problem
  - This model still cannot handle a new user or movie

Rating=



Bringing it all together: Featurized matrix factorization

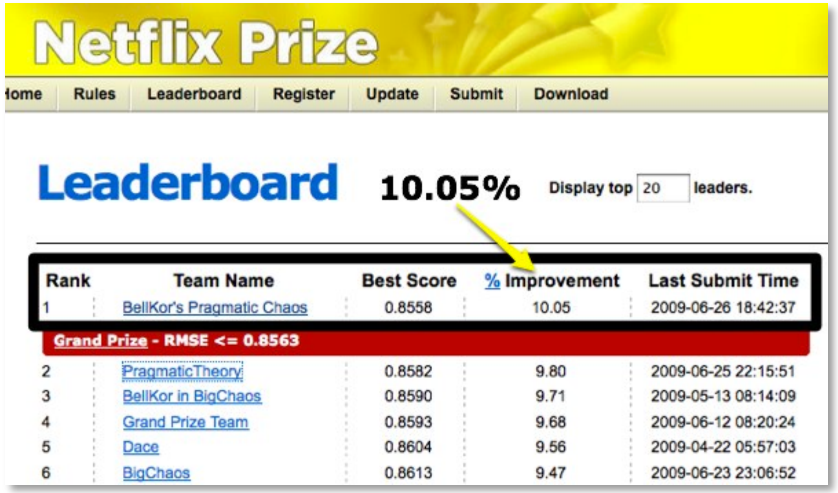
Combining features and discovered topics

- Features capture context
  - *Time of day, what I just saw, user info, past purchases,…*
- Discovered topics from matrix factorization capture groups of users who behave similarly
  - *Women from Seattle who teach and have a baby*

- **Combine** to mitigate cold-start problem
  - Ratings for a new user from features only
  - As more information about user is discovered, matrix factorization topics become more relevant

Blending models

- Squeezing last bit of accuracy by blending models
- Netflix Prize 2006-2009
  - 100M ratings
  - 17,770 movies
  - 480,189 users
  - Predict 3 million ratings to highest accuracy
  - Winning team blended over 100 models



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

A performance metric for recommender systems

The world of all baby products

User likes subset of items

Why not use classification accuracy?

- Classification accuracy =
  fraction of items correctly classified
  (*liked* vs. *not liked*)

- Here, **not** interested in what a person
  does not like

- Rather, how quickly can we discover the
  relatively few *liked* items?
  - (Partially) an imbalanced class problem

How many liked items were recommended?

Recall

$$\frac{\text{\# liked \& shown}}{\text{\# liked}} = \frac{3}{5}$$

How many recommended items were liked?

Precision

$$\frac{\#\ \text{liked \& shown}}{\#\ \text{shown}}$$

$$\boxed{= \frac{3}{11}}$$

Maximize recall:
Recommend everything

Recall

$$\frac{\#\ \text{liked}\ \&\ \text{shown}}{\#\ \text{liked}} = 1 \swarrow \frac{5}{5} \checkmark$$

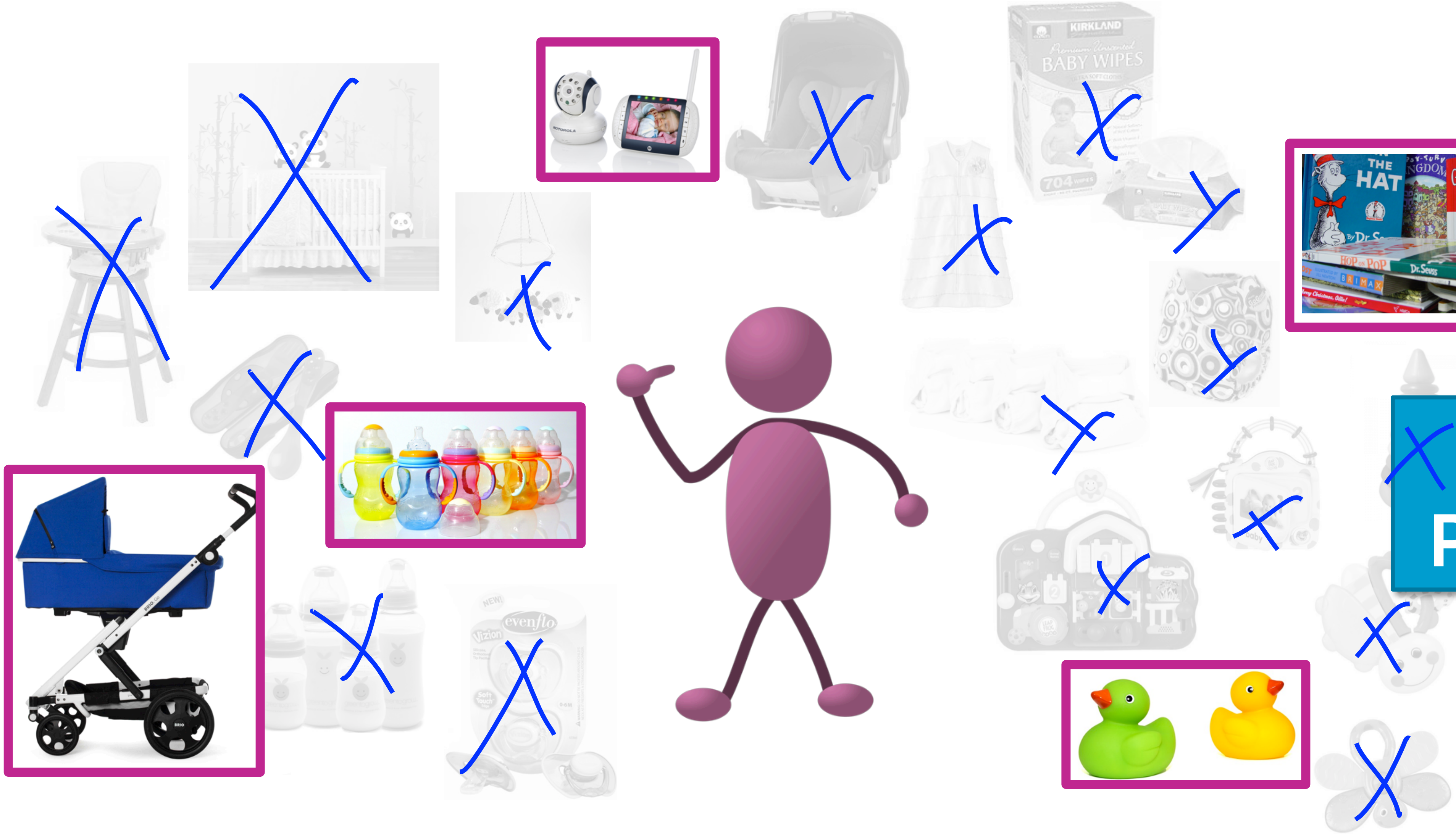
Resulting precision?

Precision

$$\frac{\text{\# liked \& shown}}{\text{\# shown}}$$

small,
maybe very
small

Optimal recommender



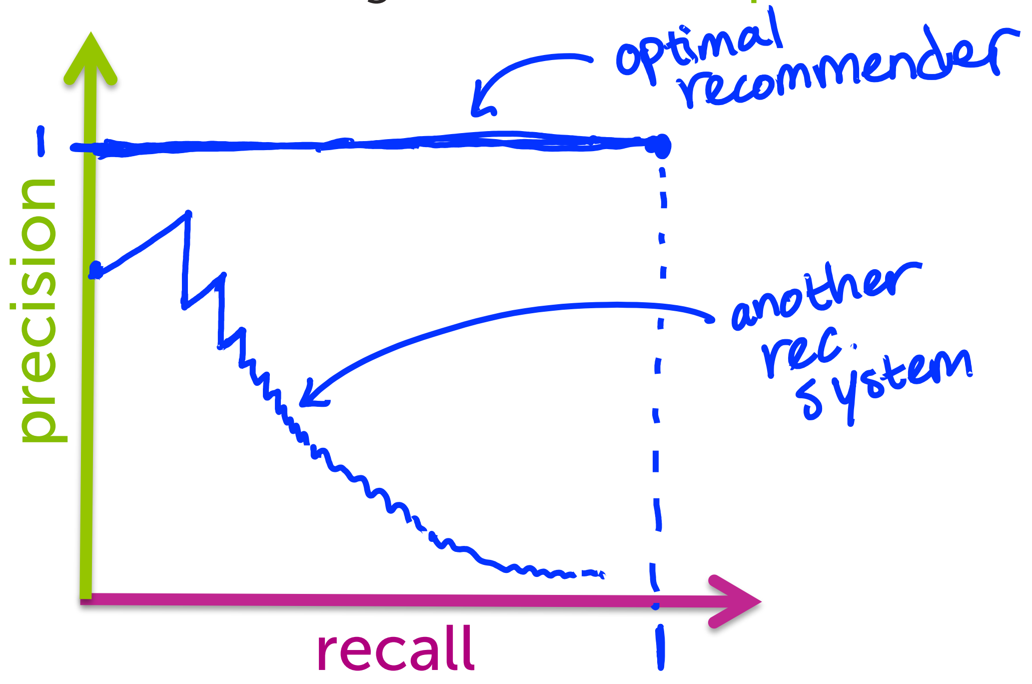
Recall =1

Precision = 1

Precision-recall curve

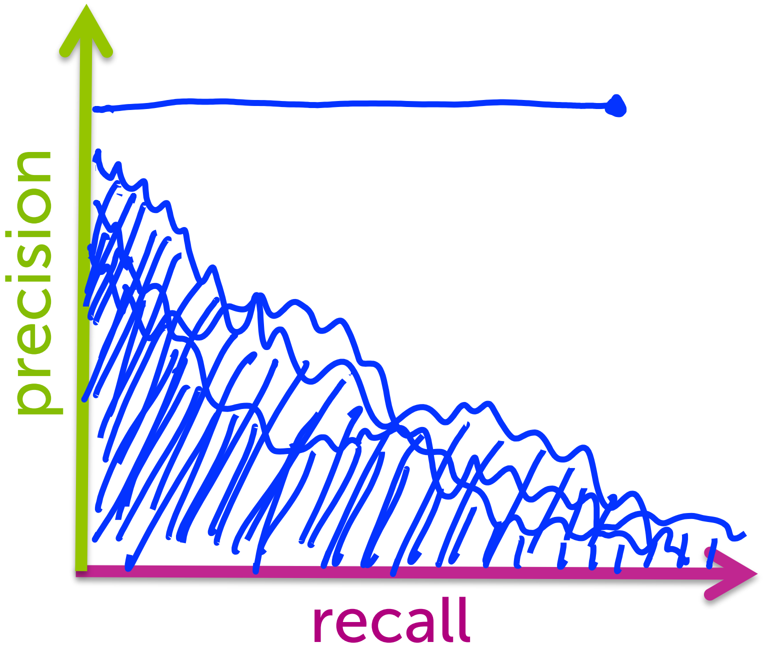
- **Input:** A specific recommender system
- **Output:** Algorithm-specific precision-recall curve

- To draw curve, vary threshold on # items recommended
  - For each setting, calculate the precision and recall



Which Algorithm is Best?

- For a given precision, want recall as large as possible (or vice versa)
- One metric: largest $\boxed{\text{area under the curve (AUC)}}$
- Another: set desired recall and maximize precision (precision at k)



Summary of recommender systems

What you can do now…

- Describe the goal of a recommender system
- Provide examples of applications where recommender systems are useful
- Implement a co-occurrence based recommender system
- Describe the input (observations, number of "topics") and output ("topic" vectors, predicted values) of a matrix factorization model
- Exploit estimated "topic" vectors (algorithms to come…) to make recommendations
- Describe the cold-start problem and ways to handle it (e.g., incorporating features)
- Analyze performance of various recommender systems in terms of precision and recall
- Use AUC or precision-at-k to select amongst candidate algorithms