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*

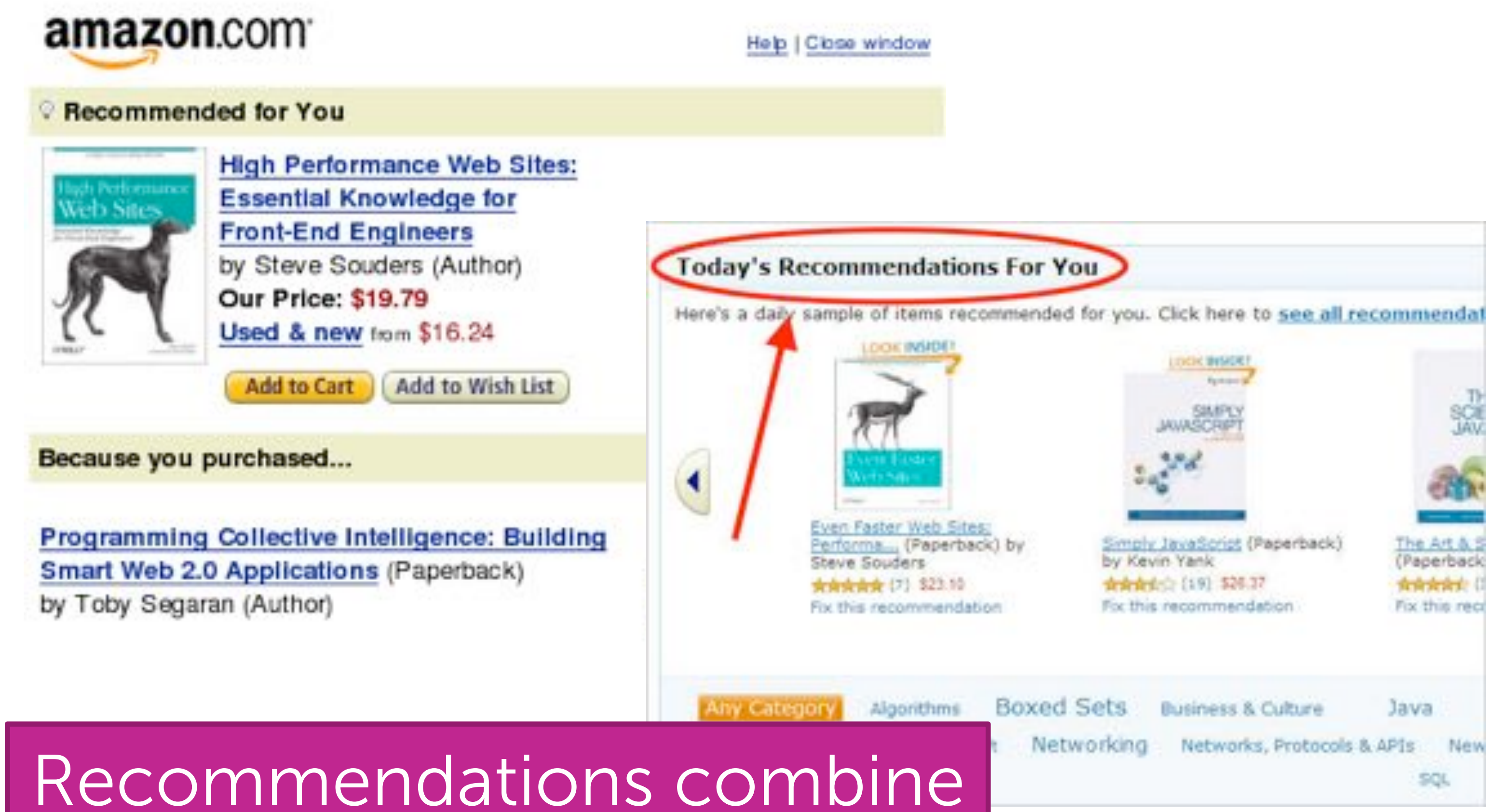
viewers

videos

Movie recommendations

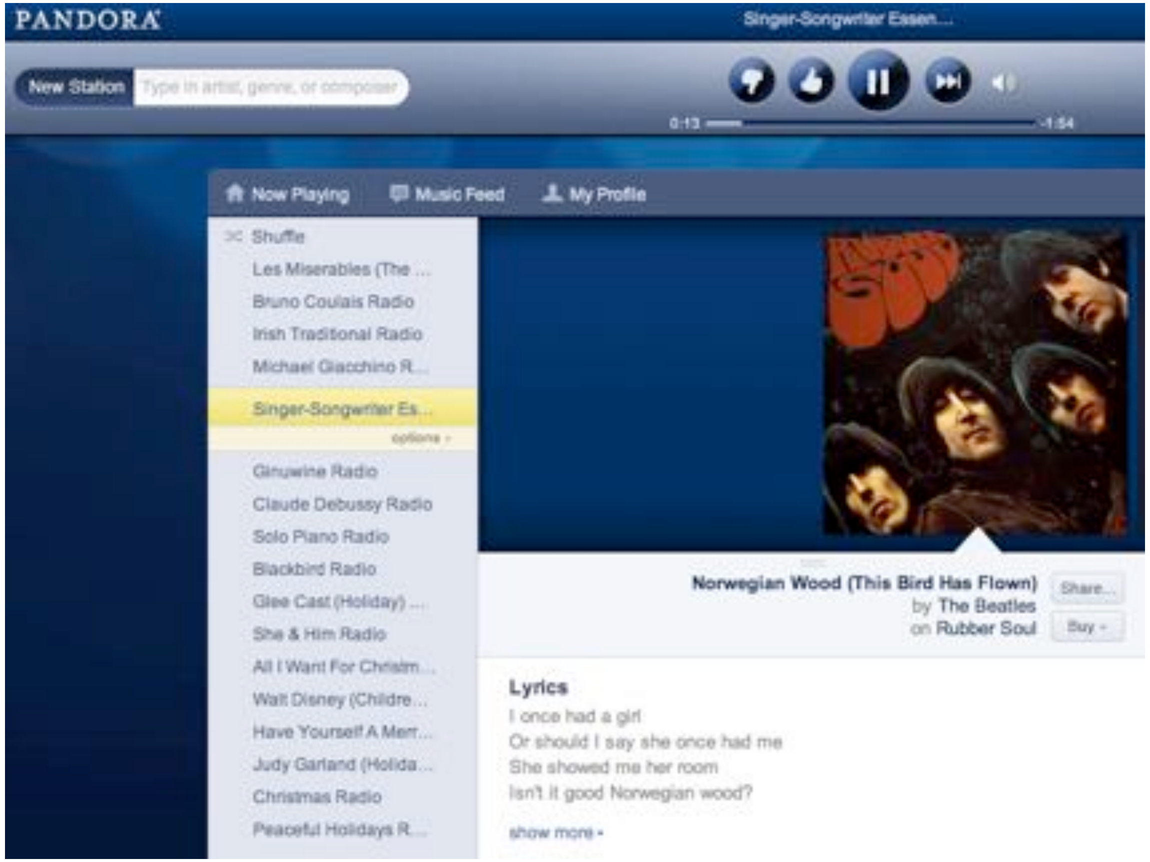
Connect users with movies they may want to watch

Product recommendations



Recommendations combine global & session interests

Music recommendations



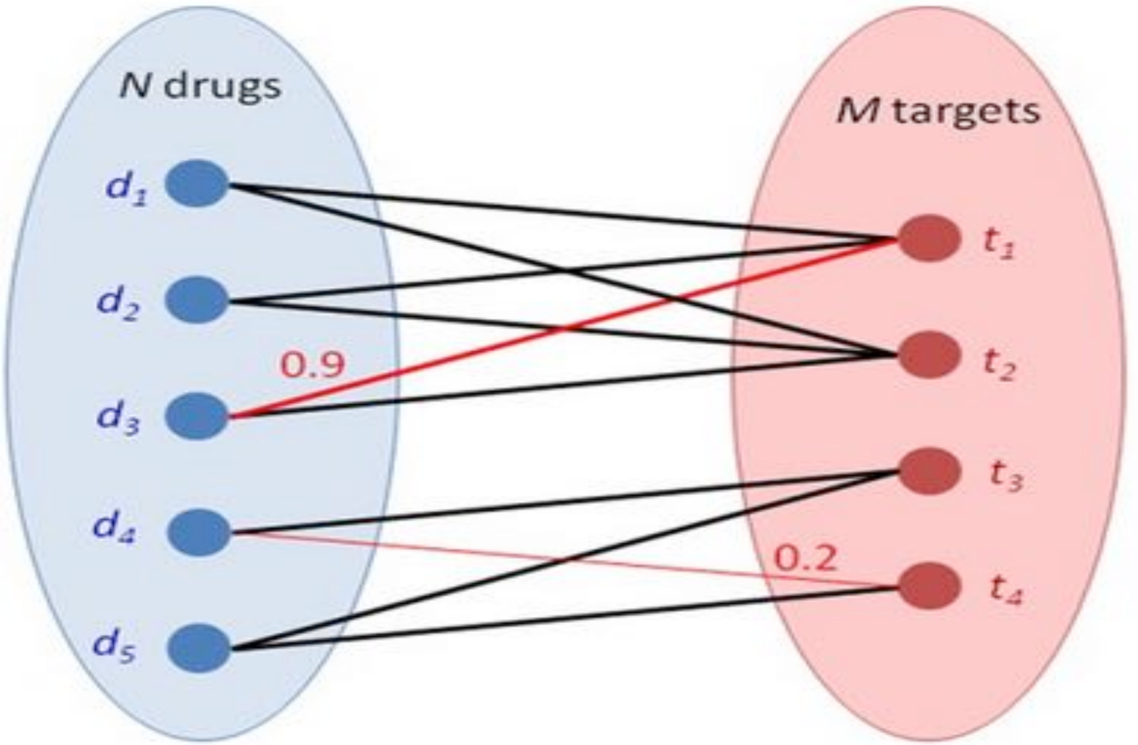
Recommendations form coherent & diverse sequence

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

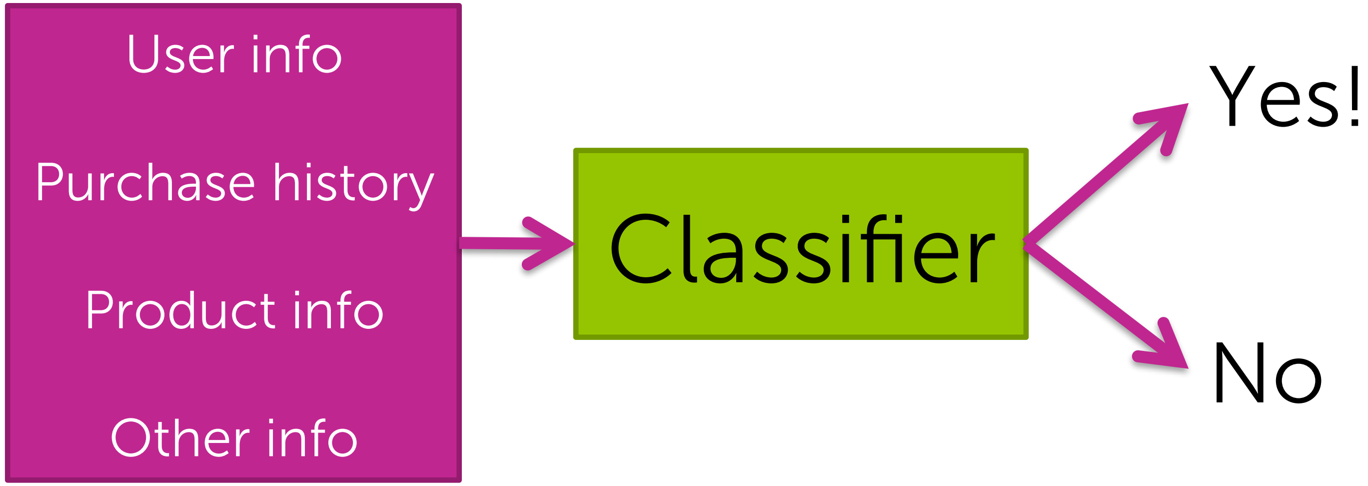
Simplest approach: Popularity

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

- **Limitation:**
  - No personalization

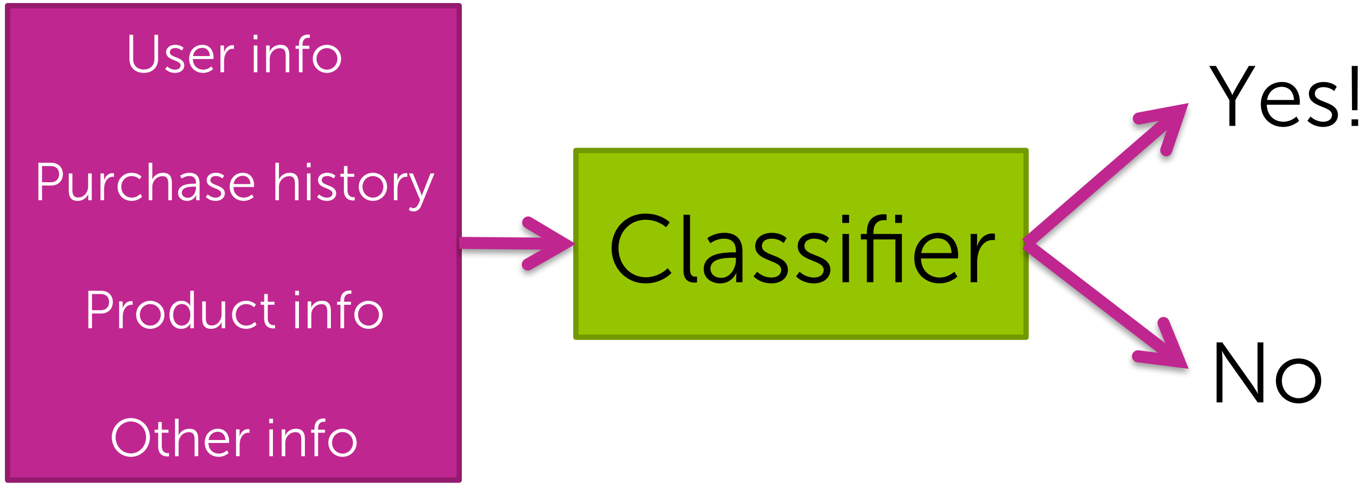
Solution 1: Classification model

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*) =

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

  - Could also weight recent purchases more

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

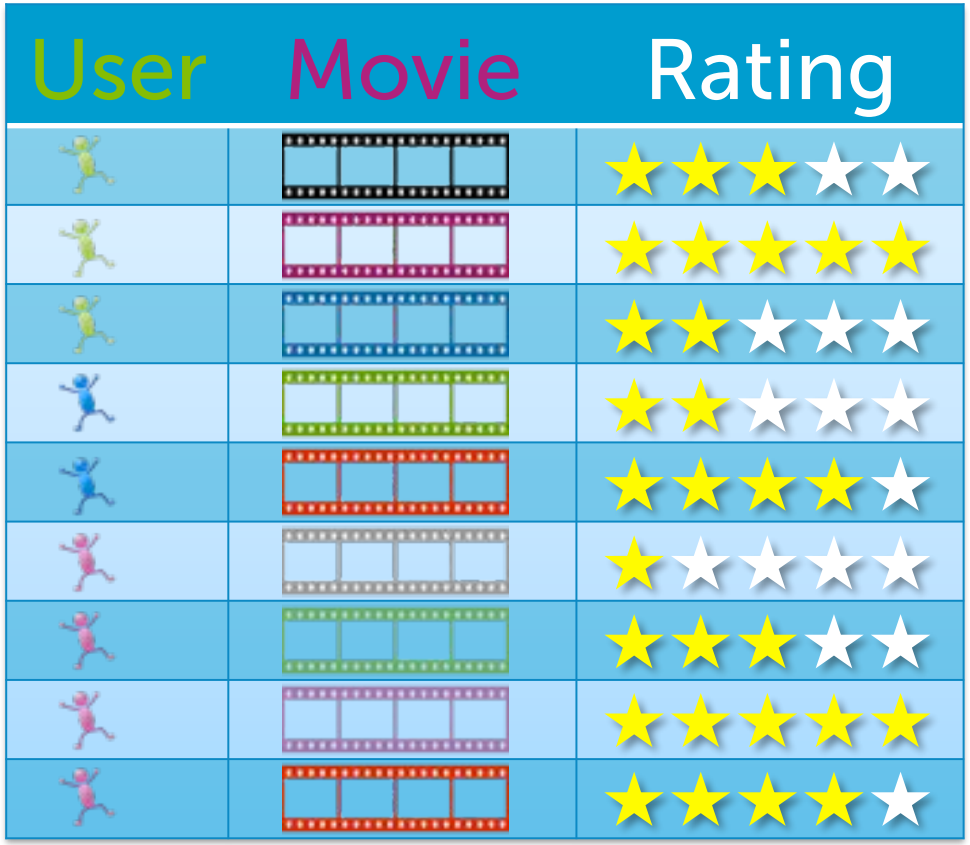
Limitations

- 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

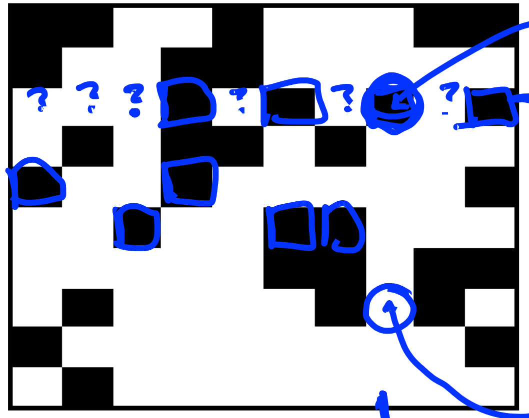
Movie recommendation

- Users watch movies and rate them



Each user only watches a few of the available movies

Matrix completion problem

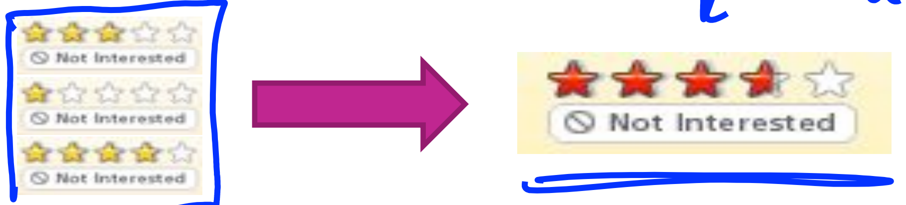
Rating = 

Rating of movie v by user u

- **Data:** Users score some movies

  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,…

$R_v = [\ 0.3 \quad 0.01 \quad 1.5 \quad \cdots\ ]$

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

estimate

$L_u = [\ 2.5 \quad 0 \quad 0.8 \quad \cdots\ ]$

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

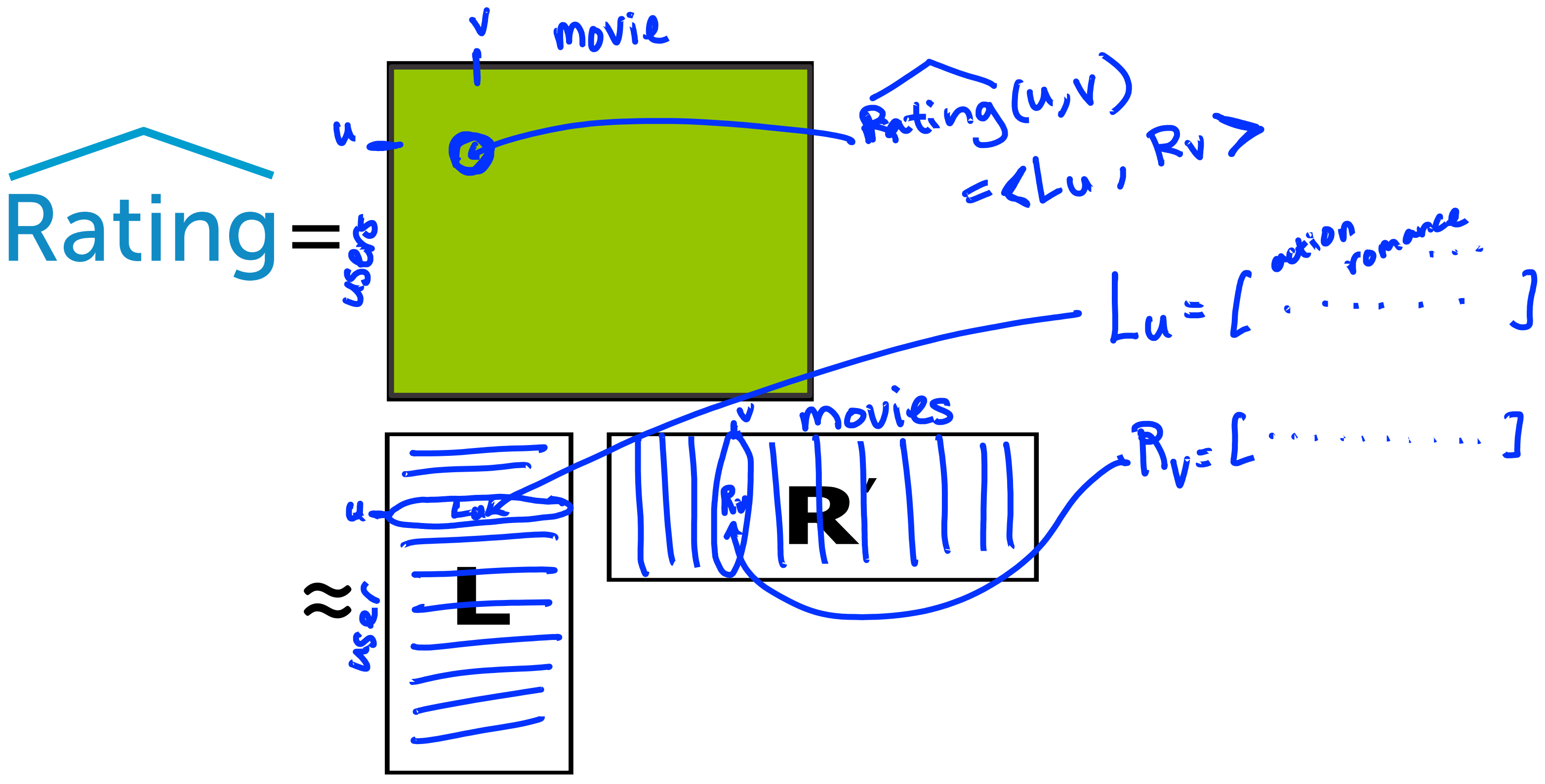
$R_v = [\ 0.3 \quad 0.01 \quad 1.5 \quad \cdots\ ]$

$L_u = [\ 2.5 \quad 0 \quad 0.8 \quad \cdots\ ]$ $\rightarrow 0.3 * 2.5 + 0 + 1.5 * 0.8 + \cdots = 7.2 > 5$

$L_{u'} = [\ 0 \quad 3.5 \quad 0.01 \quad \cdots\ ]$ $\rightarrow 0 + 0.01 * 3.5 + 1.5 * 0.01 + \cdots = 0.8$

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

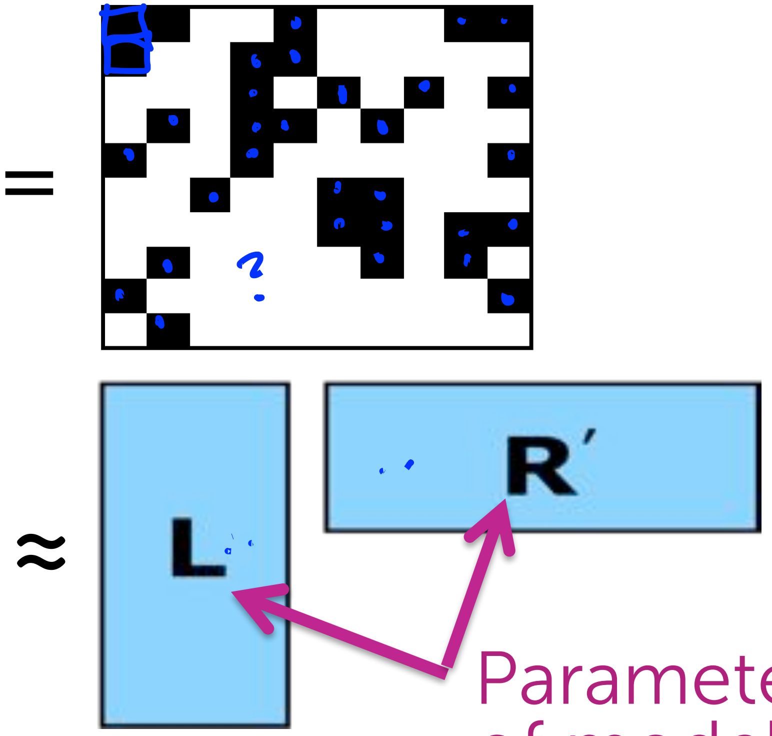
Predictions in matrix form



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

Matrix factorization model: Discovering topics from data

Rating =



Parameters of model

$RSS(L,R) =$

$\left(\text{Rating}(u,v) - \langle L_u, R_v \rangle\right)^2$ ← predicted rating

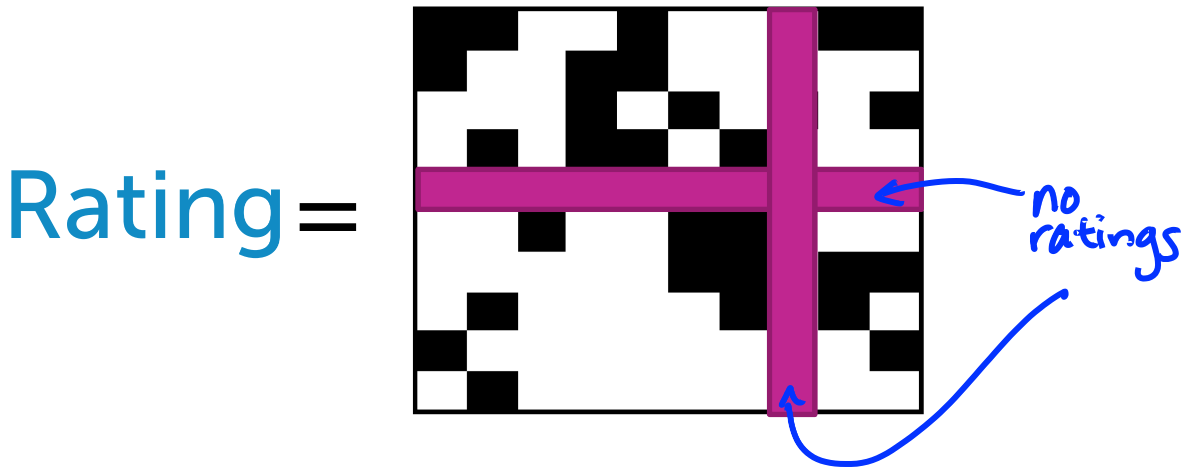
$+$ [include all (u',v') pairs where $\text{Rating}(u',v')$ are available]

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



Bringing it all together: Featurized matrix factorization

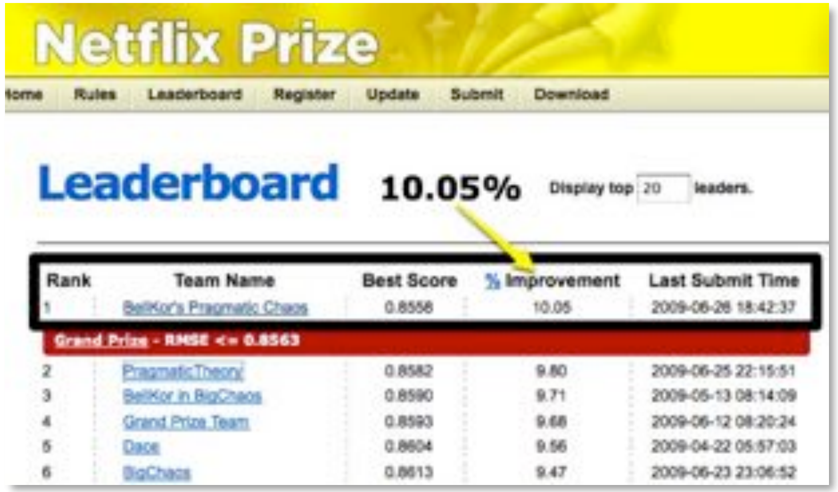
Combining features and discovered topics

- 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



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

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

$= 1$ $\frac{5}{5}$ ✓

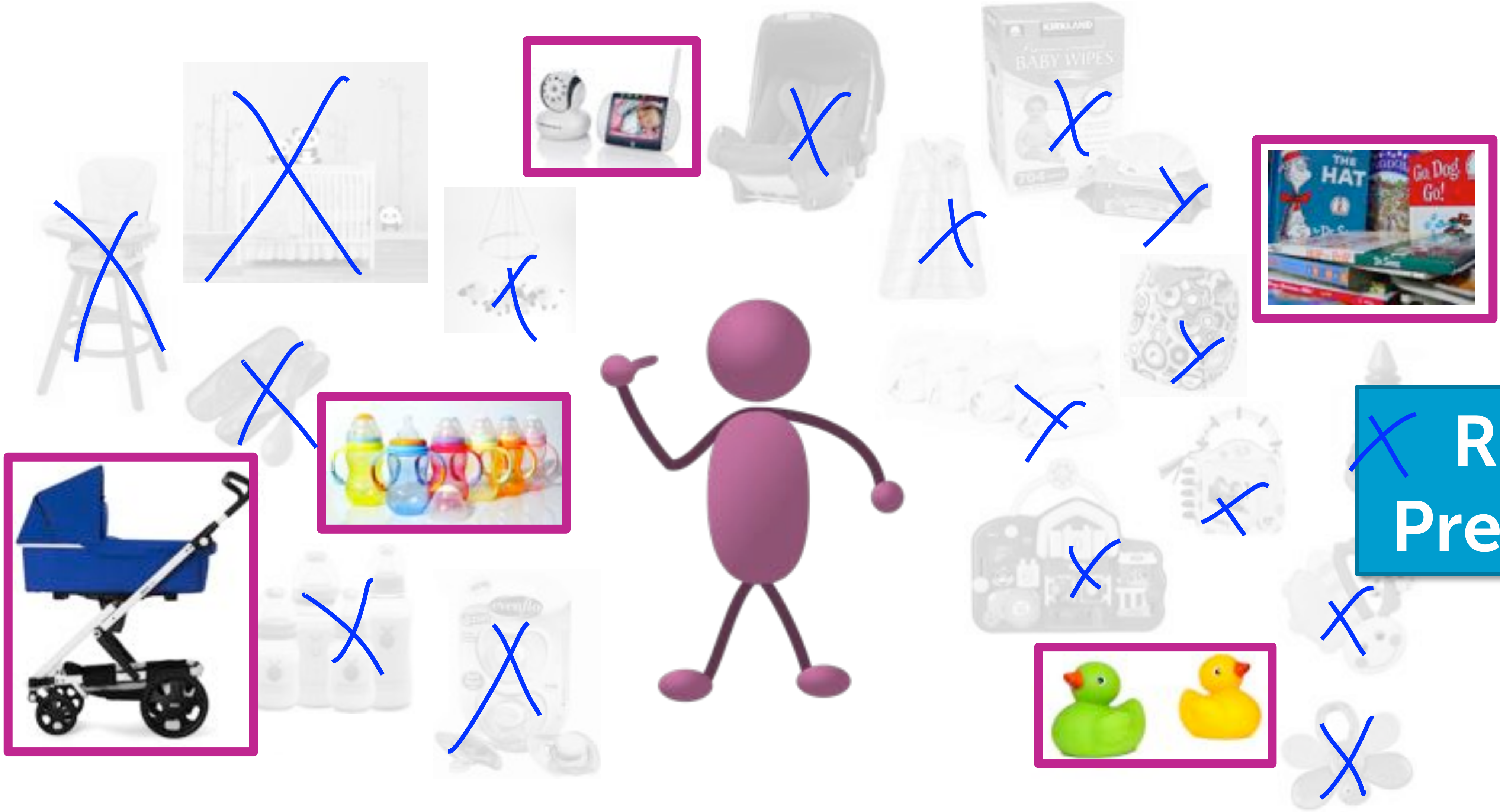
Resulting precision?

Precision

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

small,
maybe very
small

Optimal recommender

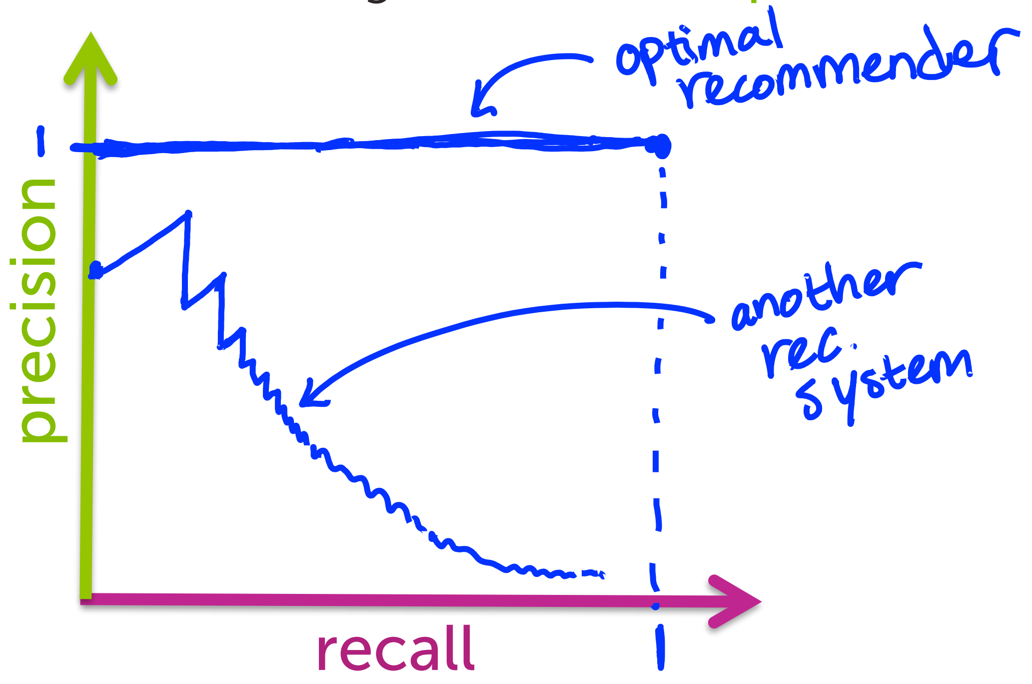


Recall =1
Precision = 1

Precision-recall curve

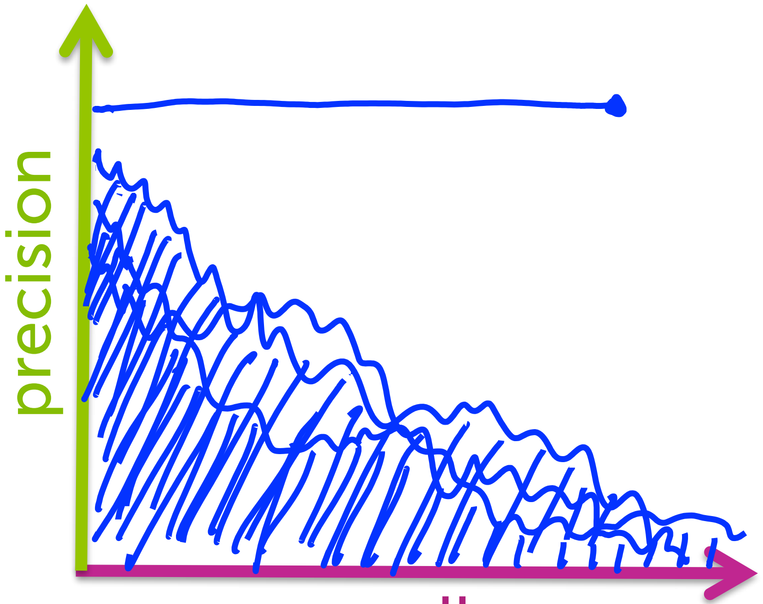
- **Input:** A specific recommender system
- **Output:** Algorithm-specific precision-recall curve

- 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 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