2. Recommender Systems

Recommenders Everywhere

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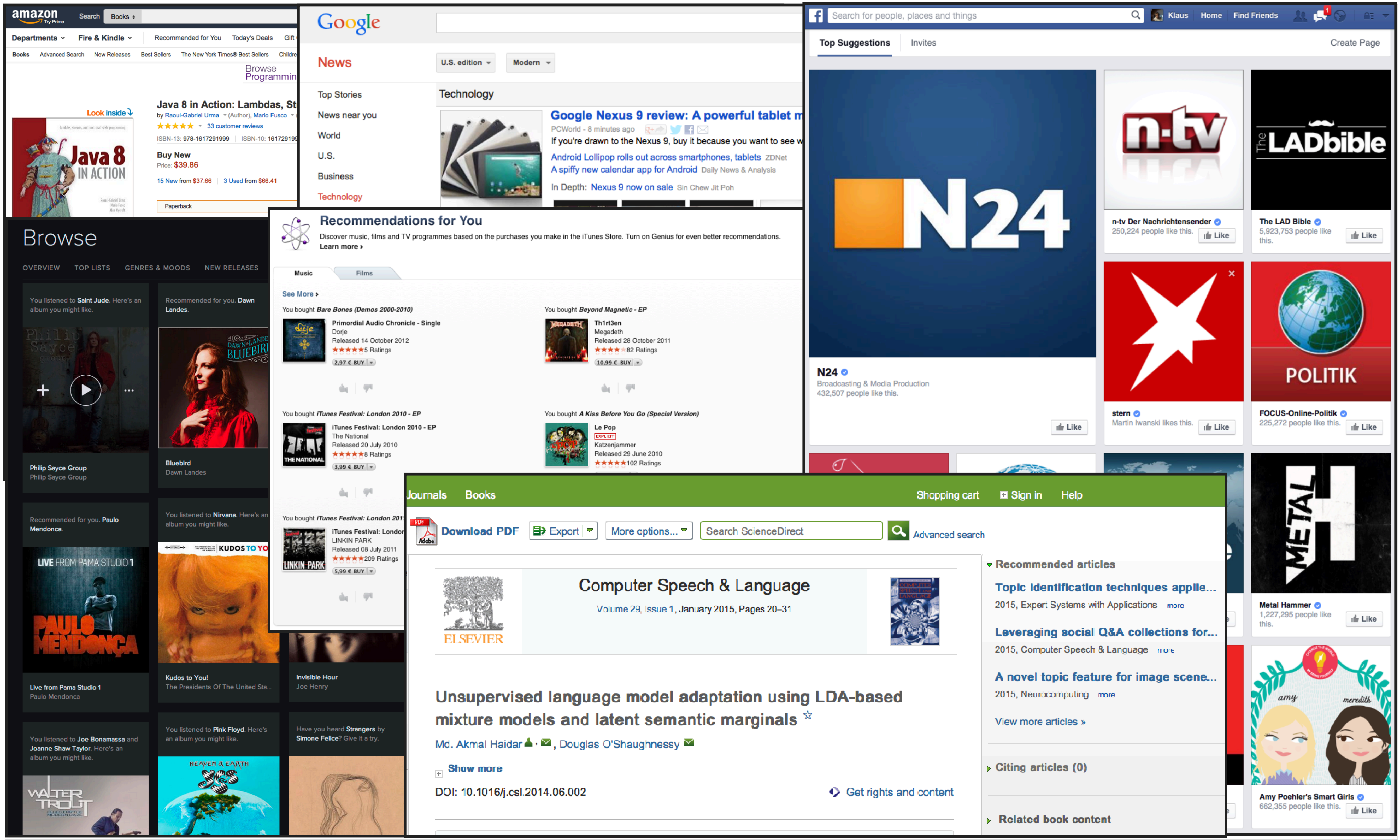

Outline

1. What are Recommender Systems?

- Recommender systems are about **matching users and items**
- Recommender systems are **about discovery not search**
  - no explicit information need; no explicit query
  - rather: *“entertain me”*, *“show me something interesting”*
- Recommender systems have **big business impact** [5]
  - 66% of movies watched on Netflix have been recommended
  - 35% of sales of Amazon.com are based on recommendations

Goals

- User: A good recommender brings up items that are
  - **relevant** (i.e., the user likes them once he uses them)
  - **novel** (i.e., the user does not yet know about the items)
  - **surprising** (i.e., the items are different from what the user already knows)

- Company: A good recommender brings up items that
  - users are likely to purchase (i.e., buy, rent, watch)
  - have high margins (e.g., to drive earnings)

Netflix Prize

- **Competition** by Netflix video rental company
  - **driver** for research in recommender systems
  - ran over **three years** (2007 – 2009)
  - goal was to **beat CineMatch** (Netflix's recommendation algorithm) **by more than 10%** in terms of **root mean squared error** (RMSE)
  - award: **$1,000,000**
  - included a **data release** (100M ratings from 480K users for 17K movies); now **retracted** due to legal issues
  - winning approach **BellKor's Pragmatic Chaos** [2] was a combination of several independently proposed approaches

Approaches

- **Different research communities** (e.g., DM, IR, ML) have worked on recommender systems and come up with **very different ideas**
- **Collaborative filtering** only assumes (partial) knowledge about how useful specific items are to specific users (e.g., ratings)
- **Content-based recommendation**, in addition, knows about properties of the items (e.g., cast of movie, content of book)
- **Hybridization strategies** aim to provide better recommendations by systematically combining multiple baseline recommenders

2. Collaborative Filtering

- **Collaborative filtering** only assumes (partial) knowledge about **how useful specific items are to specific users** (e.g., ratings)
- **No background knowledge** about items (e.g., cast or content) or users (e.g., age, gender, location)
- Challenges:
    - recommend **few** items from a **large** pool
    - **data sparsity** (large number of users and items)
    - **scalability**

Explicit vs. Implicit Utility

- **Explicit utility values** are directly provided by users (e.g., ratings)
  - **none available for new users** (cold start problem)
  - users are **typically reluctant** to provide ratings
  - **not necessarily comparable** (pessimists vs. optimists)

- **Implicit utility values** can be obtained by observing users
  - based on **transactions** (e.g., purchases or clicks)
  - by **measuring engagement** (e.g., time spend watching video)

Utility Matrix

	5	4			
	1		3	2	
			4		
	3		3		
	2	1			1

Utility Matrix

					
	5	4			
$r_{2,3} = 3$	1		3	2	
			4		
	3		3		
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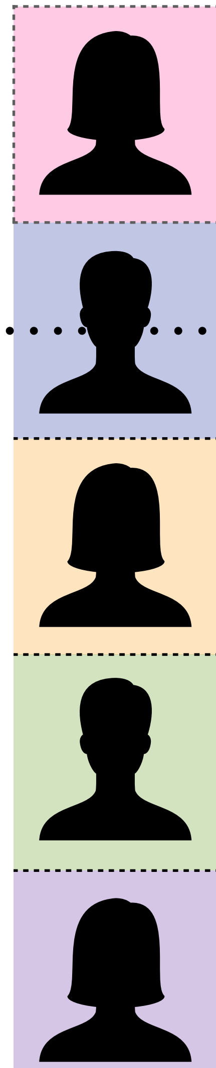
Utility Matrix



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$I_2 = \{1, 3, 4\}$

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$$\overline{r}_2 = \frac{6}{3} = 2$$

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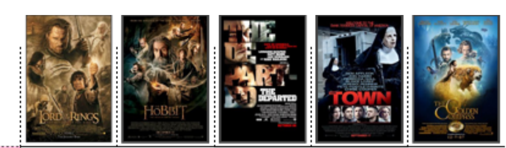
$U_2 = \{1, 5\}$

Characteristics

- **Most values** of the utility matrix **are missing**, i.e., the **data is very sparse** (e.g., in Netflix dataset only 1% of values is known)

- **Missing values** are **different from zeros** and do not indicate that the user dislikes the item

- **Magnitude of utility values** (e.g., ratings) differs from user to user (optimists vs. pessimists)

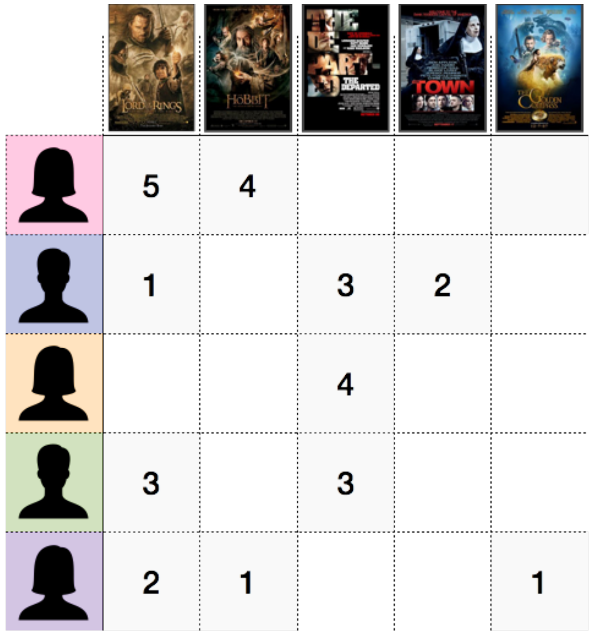


	5	4	?	?	?
	1	?	3	2	?
	?	?	4	?	?
	3	?	3	?	?
	2	1	?	?	1

2.1. User-User Collaborative Filtering

- User-user collaborative filtering aka. **k-NN collaborative filtering** as first generation of recommenders (proposed in early 1990's)

- <u>Idea</u>: Recommend items that are of high utility to **similar users**



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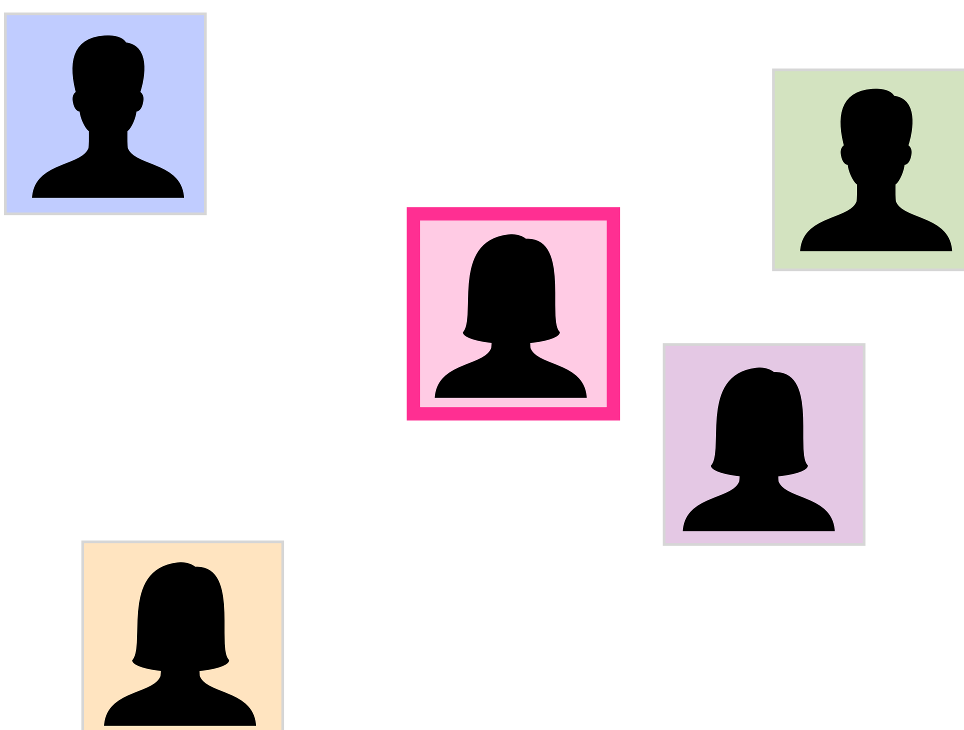

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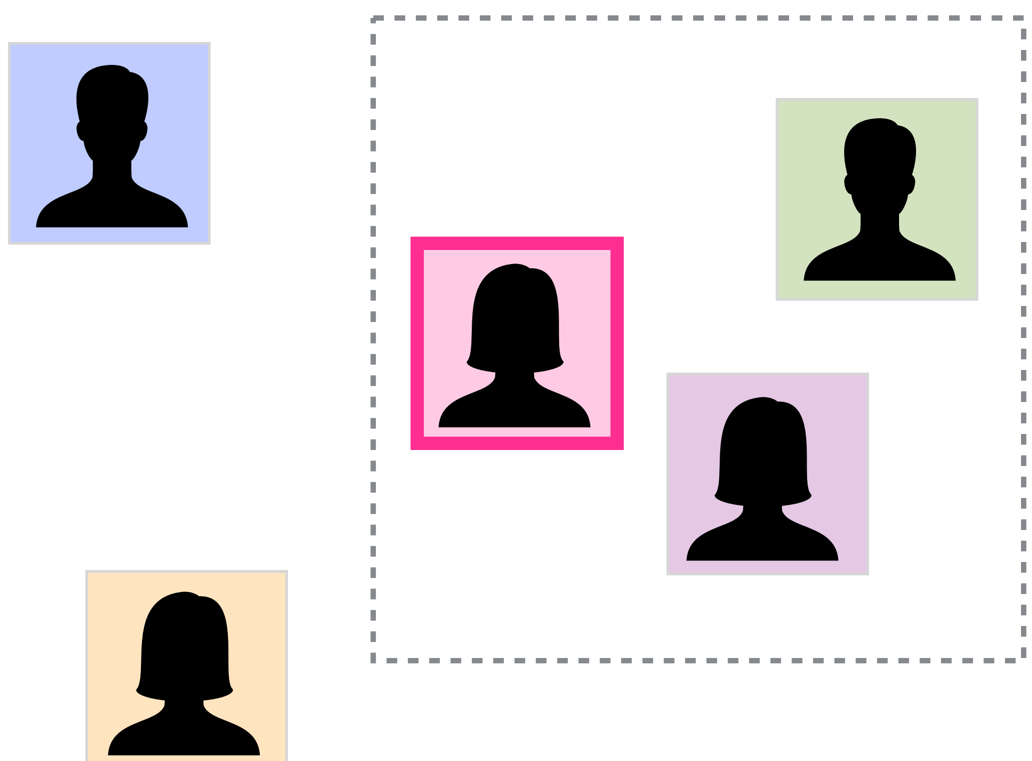

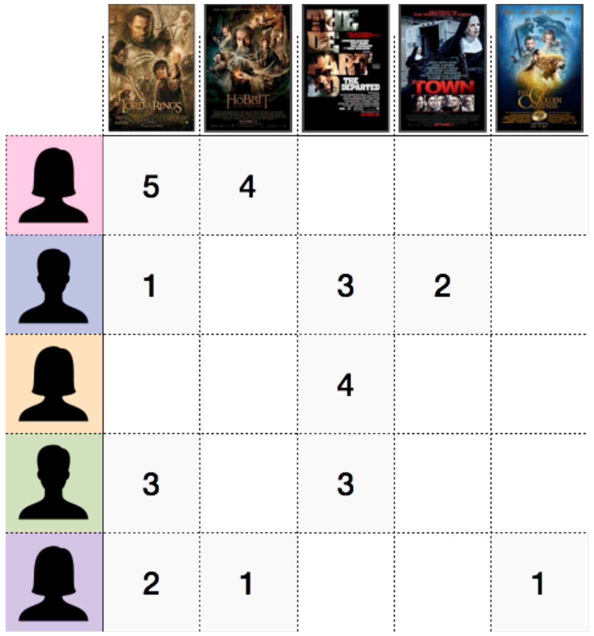

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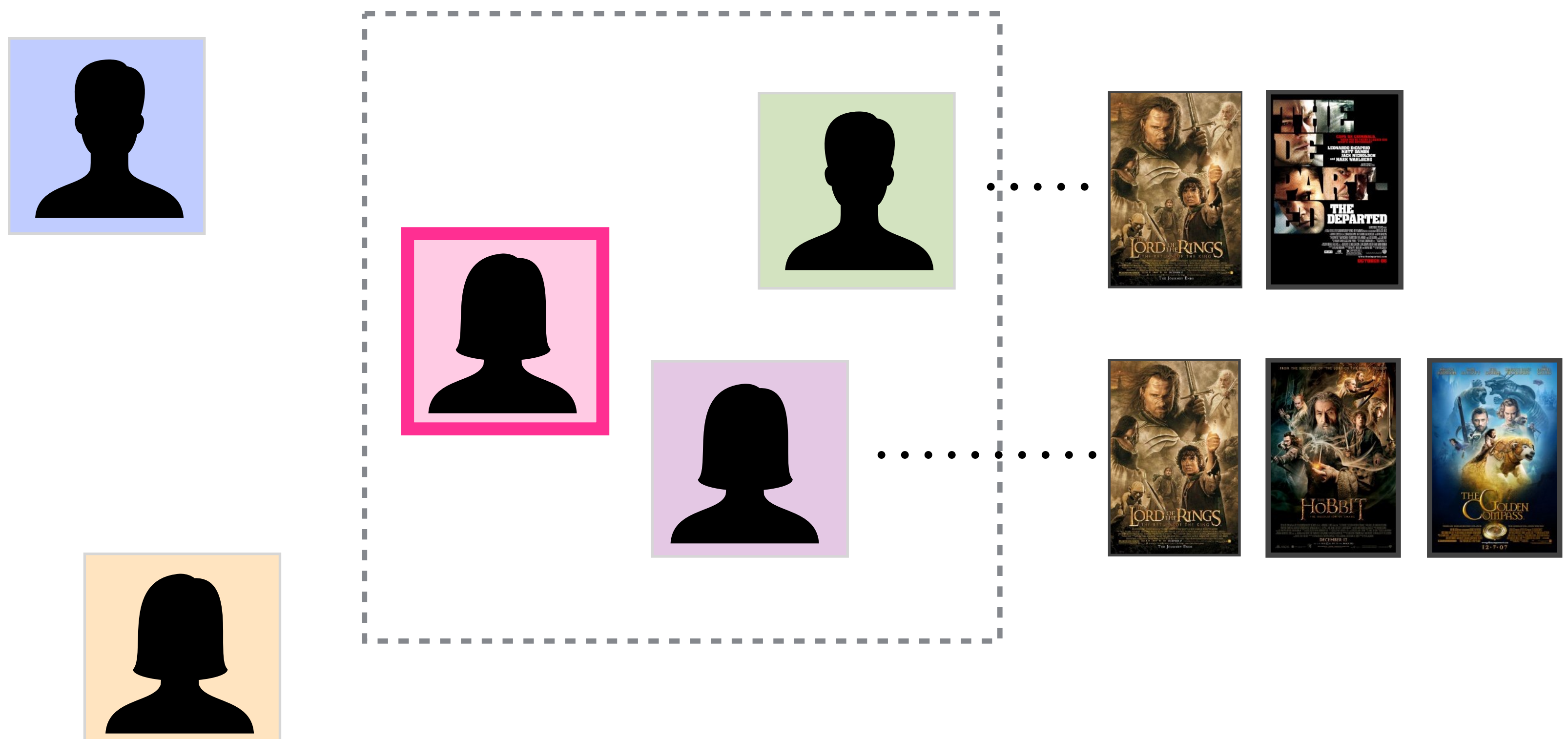

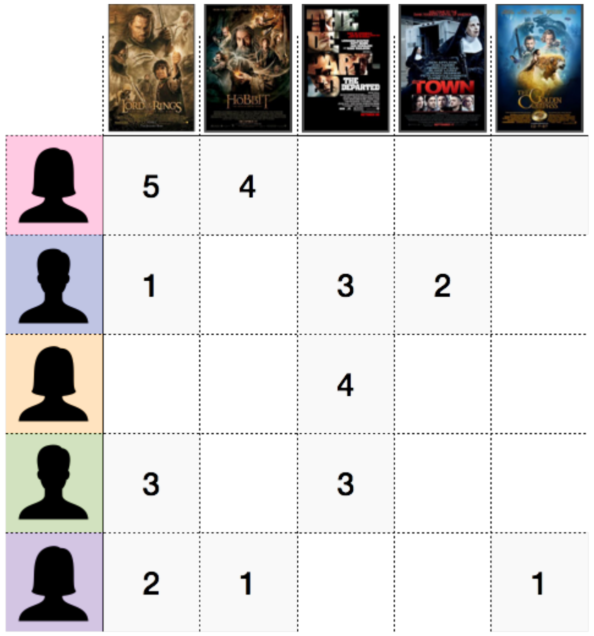

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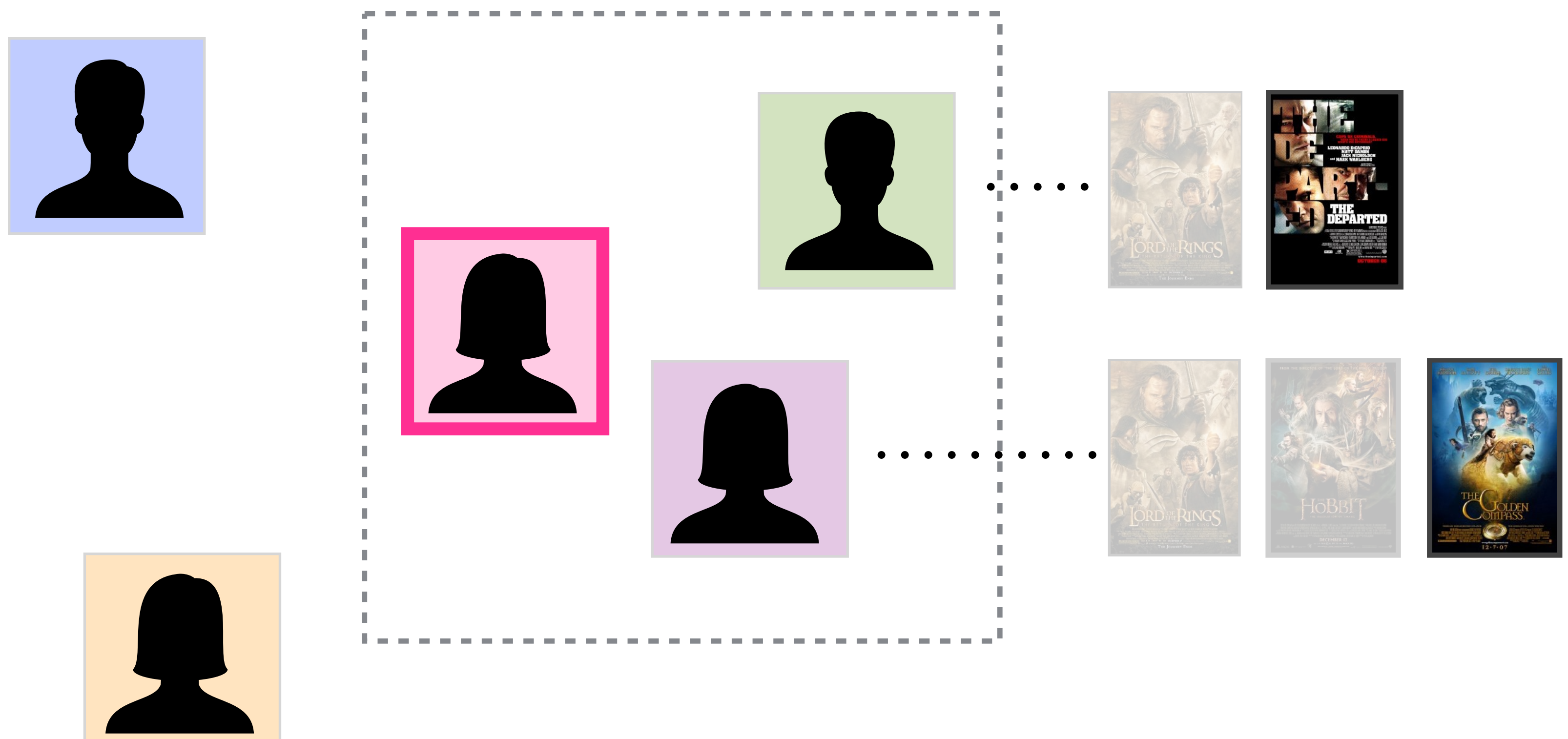

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Measures of User Similarity

- How can we measure the similarity between two users **u** and **v**?

- **Pearson correlation** (on items with known utility for both users)

$$s(u,v) = \frac{\sum_{i \in I_u \cap I_v} (r_{u,i} - \overline{r}_u) \cdot (r_{v,i} - \overline{r}_v)}{\sqrt{\sum_{i \in I_u \cap I_v} (r_{u,i} - \overline{r}_u)^2} \cdot \sqrt{\sum_{i \in I_u \cap I_v} (r_{v,i} - \overline{r}_v)^2}}$$

- **Cosine similarity** (missing utility values as zeros)

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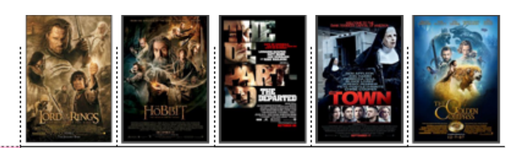

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Generating Recommendations

- Identify **neighborhood** N(u,k) of k **users most similar** to u
- **Predict utility** of item i as

$$\hat{r}_{u,i} = \underbrace{\overline{r}_u}_{\text{Baseline prediction}} + \frac{\sum_{v \in N(u,k)} s(u,v) \cdot \overbrace{(r_{v,i} - \overline{r}_v)}^{\text{Deviation of similar user v}}}{\sum_{v \in N(u,k)} s(u,v)}$$

- Recommend **n** items having **highest predicted utility**

Discussion

- **Pearson correlation** and **cosine similarity** only work if users **u** and **v** have **known utility values for common item** (e.g., have rated at least one common movie)

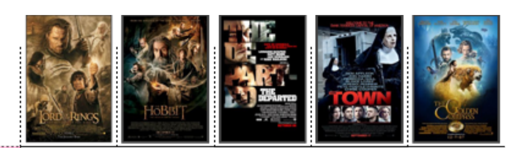
- User similarity is **sensitive to updates** (e.g., additional ratings) so that precomputing user similarities is not attractive

- **Neighborhood computation** is computationally expensive

2.2. Item-Item Collaborative Filtering

- **Item-item collaborative filtering** addresses the shortcomings of user-user collaborative filtering (proposed in early 2000's)

- <u>Idea</u>: Recommend **items that are similar** to items of high utility



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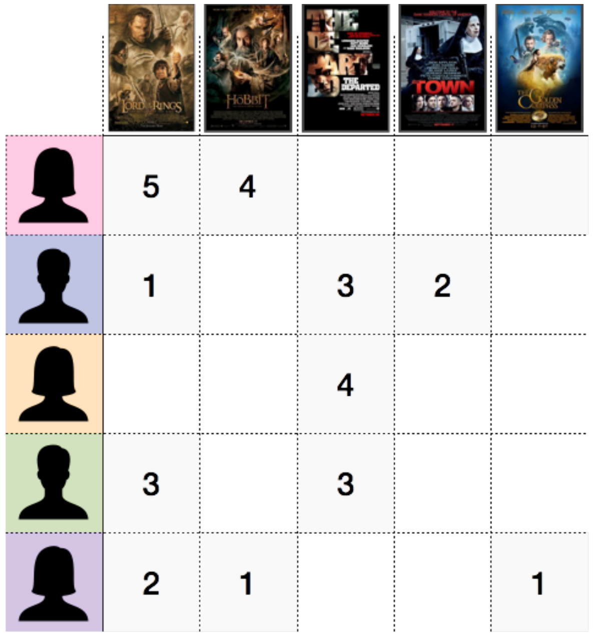

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Generating Recommendations

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  with S(u,i,k) as the set of k items with **known utility** for user u that are **most similar** to item i

- Recommend n items having **highest predicted utility**

Discussion

- **Pearson correlation** and **cosine similarity** only work if items i and j have **known utility values for common user** (e.g., have been rated by the same user)
- Item similarity is **less sensitive to updates** (e.g., additional ratings), assuming that there are **many more users than items**
- In practice, **item similarities are typically precomputed**, and **truncated** (keeping top-k most similar items per item)

2.3. Association Rules

- **Association rule mining** developed for **market basket analysis** to learn rules (patterns) from **customer transactions** (e.g., buys **soda** and **beer** => buys **snacks**)

- Association rules can be used to **generate recommendations** by considering **items with known utility** per user a transaction

- Let A and B be set of items, we are interested in identifying association rules A => B with sufficient **support** and **confidence**

Support and Confidence

- For a set of items (itemset) A its **support s(A)** is the **fraction of transactions that contains** A

$$s(A) = \frac{\#\ \text{transactions containing } A}{\#\ \text{transactions}}$$

- For an association rule A => B its **confidence** c(A=>B) is the **fraction of transactions containing** A **that also contain** B

$$c(A \Rightarrow B) = \frac{\#\ \text{transactions containing } A \cup B}{\#\ \text{transactions containing } A}$$

Identifying Frequent Itemsets

- **Apriori algorithm** [1] can be used to **identify frequent itemsets** having a support above a minimum support threshold

- **Iterative algorithm** exploiting **anti-monotonicity of supports**

$$A \subset B \Rightarrow s(A) \geq s(B)$$

- Sketch:
  - **identify** frequent **1**-itemsets (i.e., containing a single item)
  - **repeat** (until no frequent **k**-itemsets are found)
    - **generate candidates** by joining frequent **(k-1)**-itemsets
    - **prune** infrequent candidates and emit frequent **k**-itemsets

Generating Association Rules

- Generate **association rules** from frequent itemset X
  - consider every **non-empty subset** $A \subset X$ and let $B = X \setminus A$
  - output **association rule** A => B if c(A => B) above threshold

Generating Recommendations

- Consider all items I_u with **known utility** for user **u**
  - identify all association rules A => B so that $A \subseteq I_u$
  - items from $B \setminus I_u$ are **candidates** for recommendation; for each candidate keep track of **highest confidence** of any association rule suggesting it
  - recommend **n** items having highest confidence

2.4. Dimensionality Reduction

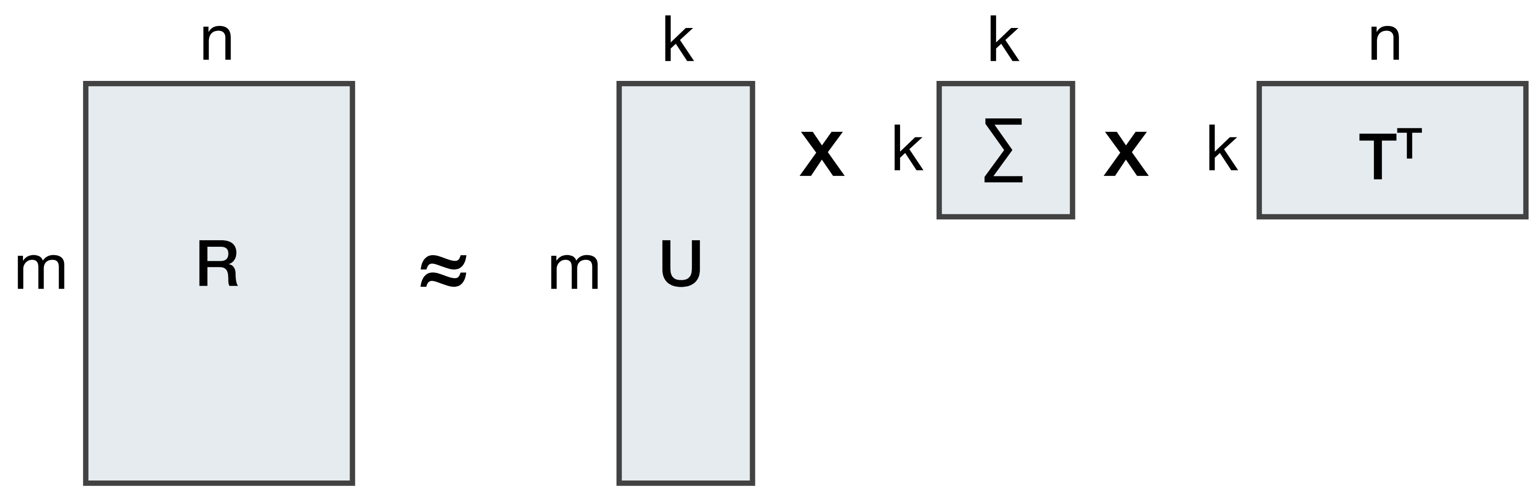
- Idea: Identify a **small number** (in comparison to **m** and **n**) **of common interests** (topics) to represent users and items; recommend items to users that belong to the same topics

- Utility matrix **R** can be seen as user vectors (in a **m**-dimensional vector space) or item vectors (in a **n**-dimensional vector space)

- **Dimensionality reduction** methods reveal the **latent structure** of a matrix by representing it as a **product of multiple smaller matrices** (e.g., UV decomposition, singular value decomposition, principal component analysis)

Singular Value Decomposition

- Determine **k-SVD of utility matrix** R (m x n)



as best possible rank-**k** approximation under Frobenius norm

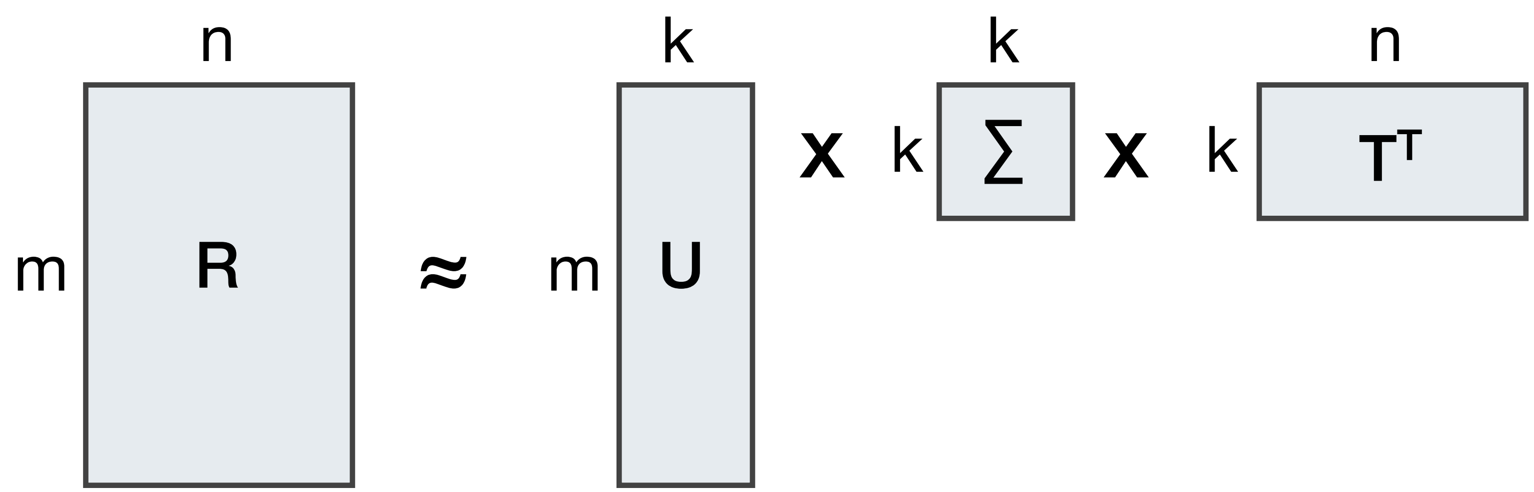
- **U** captures **user-topic associations**
- ∑ captures **topic importance**
- **T** captures **item-topic associations**

Imputation

- **SVD** requires a **complete matrix** but R **misses a lot of values**

- **Imputation** is the process of filling missing values with defaults
  - average utility assigned to item by different users
  - average utility assigned to other items by same user
  - other baseline predictors

Generating Recommendations



- **Predict utility** of item **i** for user **u** as

$$\hat{r}_{u,i} = \sum_k U_{u,k} \cdot \Sigma_{k,k} \cdot T^T_{k,i}$$

- **Predict utilities** of all items for user **u** as

$$U_u \times \Sigma \times T^T$$

3. Content-Based Recommendation

- **Content-based recommendation** assumes (partial) knowledge about **how useful specific items are to specific users** and background knowledge about **properties of the items**

- Idea: Recommend **items that are similar** to items of high utility

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- Idea: Recommend **items that are similar** to items of high utility

Actors:
VM, LT, IMK

Year:
2003

Content:
Third part of fantasy trilogy. Involves dwarfs and hobbits.

Actors:
DC, NK, IMK

Year:
2002

Content:
First part of fantasy trilogy. Involves polar bears and dust.

Items and Users as Vectors

- Represent **items as vectors** in a high-dimensional vector space (works well, for instance, for text documents with tf.idf weighting)

$$\vec{v}_{RoK} = \begin{bmatrix} 0.13 \\ \vdots \\ 0.65 \end{bmatrix} \qquad \vec{v}_{GC} = \begin{bmatrix} 0.04 \\ \vdots \\ 0.55 \end{bmatrix}$$

- Represent **user as vector** obtained as **weighted combination of item vectors** of items with known utility values

$$\vec{u} = \sum_{i \in I_u} \frac{r_{u,i}}{\sum_{j \in I_u} r_{u,j}} \cdot \vec{v}_i$$

- Recommend items with **high cosine similarity** to user vector

Domain-Specific Item Similarity

- **Not all item properties** are suitable for representation in vector and we may loose their semantics when doing so
  - **Category** (e.g., /Travel/U.S.A., /Travel/Canada, /Cooking/Italian)
  - **Year** (e.g., 1980 should be less similar to 2002 than 1981)

- Define **domain-specific item similarity** based on their properties, for instance, as weighted sum of property-specific similarities

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$$
\begin{aligned}
s(RoK, GC) = \; & \alpha \cdot s_a(RoK, GC) \\
& + \beta \cdot s_y(RoK, GC) \\
& + \gamma \cdot s_c(RoK, GC)
\end{aligned}
$$

Domain-Specific Item Similarity

- Recommend **items that are similar** to items of high utility

$$score(u,j) = \sum_{i \in I_u} r_{u,i} \cdot s(i,j)$$

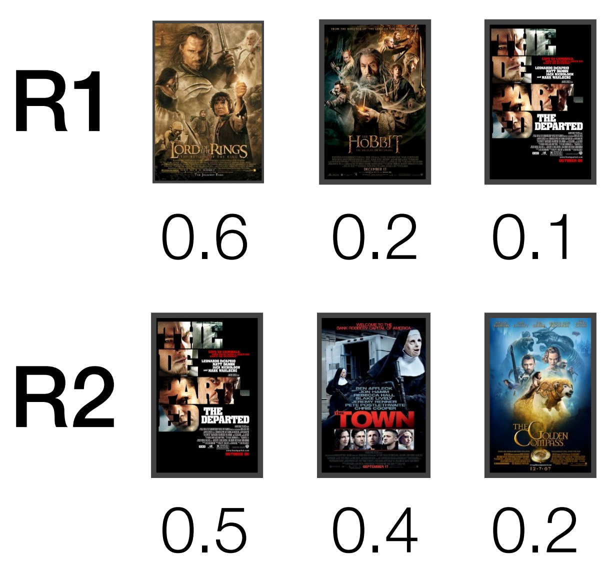
4. Hybridization & Evaluation

- **Combining different recommenders** can be attractive
  - improved recommendations (cf. winner of Netflix competition)
  - overcoming cold start problems
  - improved performance

- **Hybridization strategies** systematically combine recommenders
  - **Ensemble** (combine outputs of different recommenders)
  - **Switch** (choose recommender to use)

Ensemble

- Obtain (top-k) recommendations from **multiple recommenders**
- **Combine recommendations** by aggregating per item
  - **predicted utility** by different recommenders
  - **reciprocal rank** in output of different recommenders
  - **votes** (item in output) from different recommenders



utility	0.6	0.6	0.4	0.2	0.2
1/rank	1/1	4/3	1/2	1/3	1/2
vote	1	2	1	1	1

Switch

- **Decide** (or learn to decide) when to use **which recommender**

- Example: Collaborative filtering suffers from **cold start problem**
  - use content-based recommender, if user has too few known utility values (e.g.,, has rated too few items)
  - otherwise, use item-item collaborative filtering

Evaluation

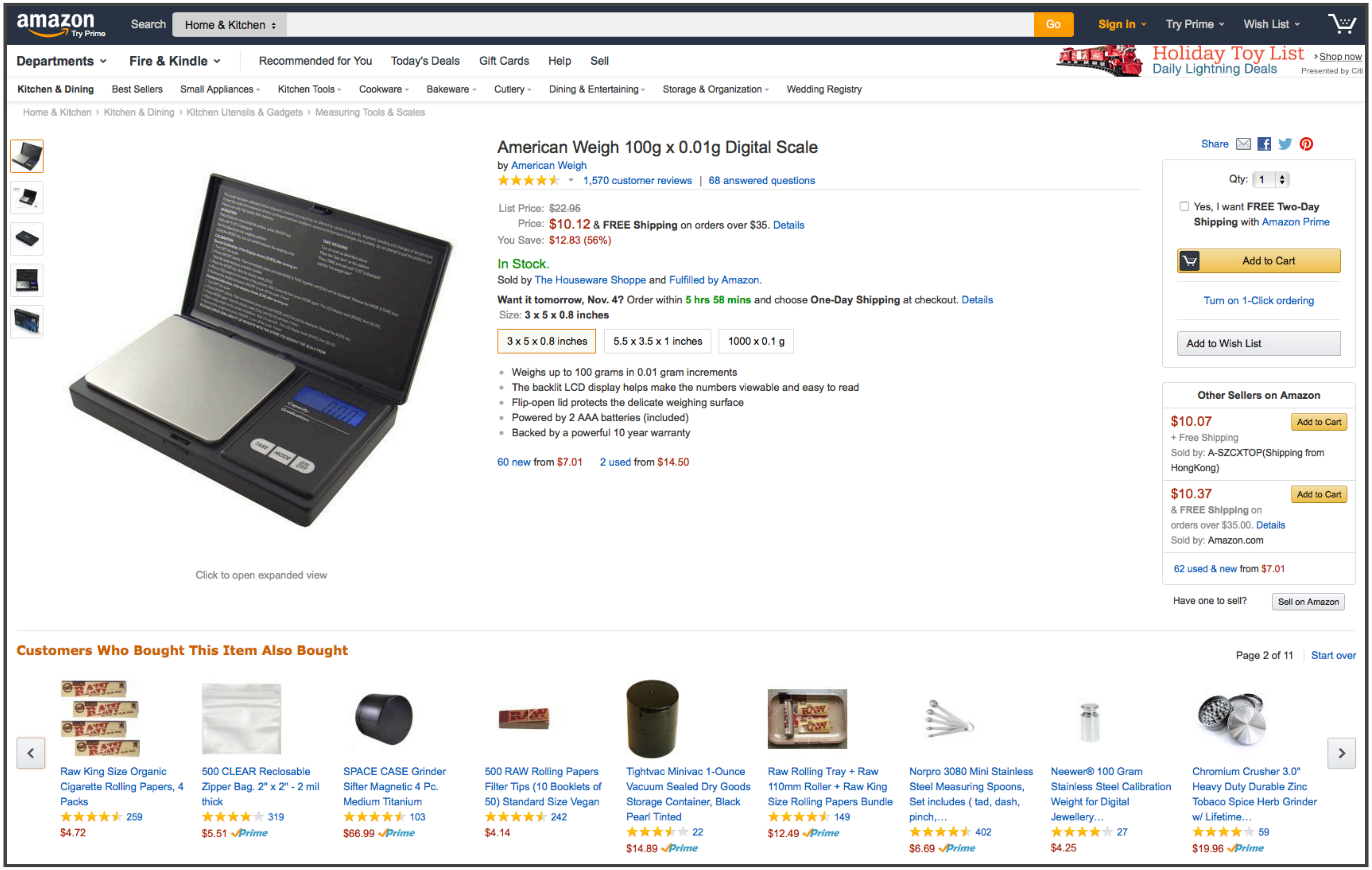
- Recommender systems can be evaluated like other IR systems
  - user judges **whether recommended items are relevant**
  - determine **precision, recall, F1**
  - captures only whether relevant items are returned
- More commonly, the **focus is on prediction accuracy**
  - **split utility values** from dataset (e.g., movie ratings) into **training and test data** (repeat multiple times)
  - measure **mean absolute absolute error** on test data

$$\frac{1}{n} \sum_{(u,i)} \left| \hat{r}_{u,i} - r_{u,i} \right|$$

Summary

- **Recommender systems** help users to discover relevant and surprising items and drive many of today's businesses
- **Collaborative filtering** uses only knowledge about how useful items are to users; variety of approaches have been proposed
- **Content-based recommendation** also uses knowledge about properties of the items (e.g., content); IR-style approaches
- **Hybridization strategies** combine multiple recommenders, for instance, to obtain better recommendations or performance
- **Evaluation of recommender systems** usually focuses on prediction accuracy and uses training/test splitting of data

When Recommender Systems Fail



Source: Alexis C. Madrigal: *The (Unintentional) Amazon Guide to Dealing Drugs*, The Atlantic, April 15 2014
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