Recommendation Systems

June, 21 2017

WHAT

“ “A suggestion/proposal as to the best course of action”

Involves predicting user responses to options

WHERE

Possible applications: Product recommendations on sites like Amazon, Movie recommendations, News articles, HRS

For companies such as Netflix, and Spotify, recommender systems drive significant engagement and revenue.

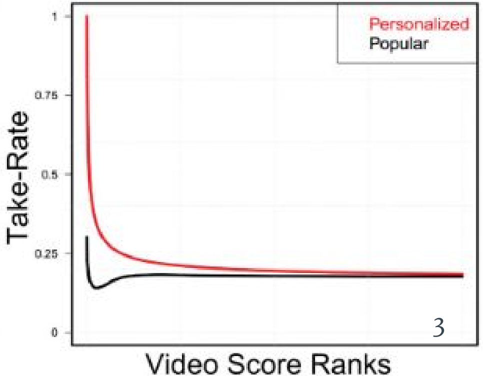
Netflix

Data

WHAT each Netflix member watches.
HOW each member watches (e.g., the device, time of day, day of week, intensity of watching).
The PLACE in the product in which each video was discovered.
Even the recommendations that were shown but NOT PLAYED in each session.

Statistics

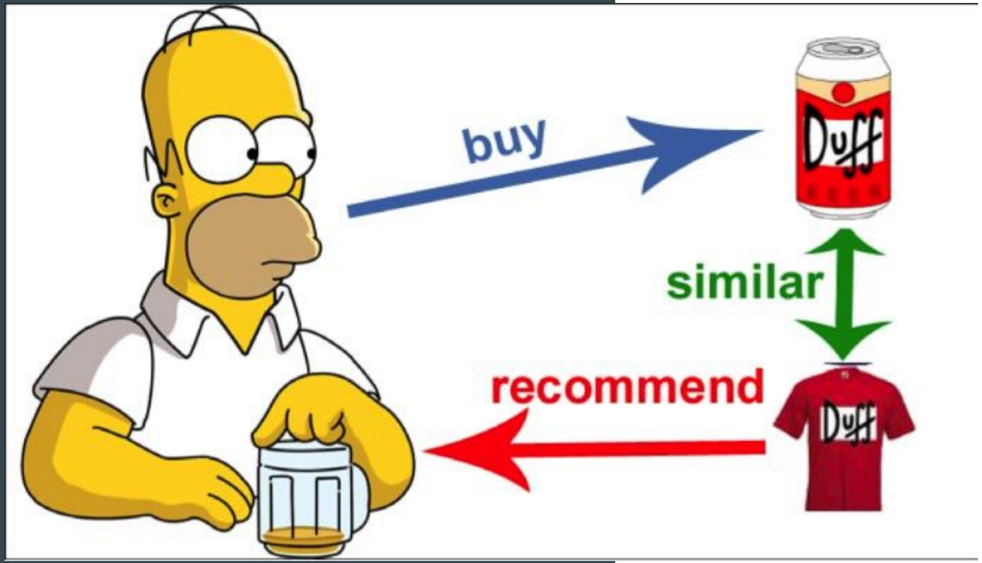
Influences choice for about **80% of hours** streamed at Netflix
Combined effect of personalization and recommendations save us more than $1B per year.



A PRACTICAL EXAMPLE

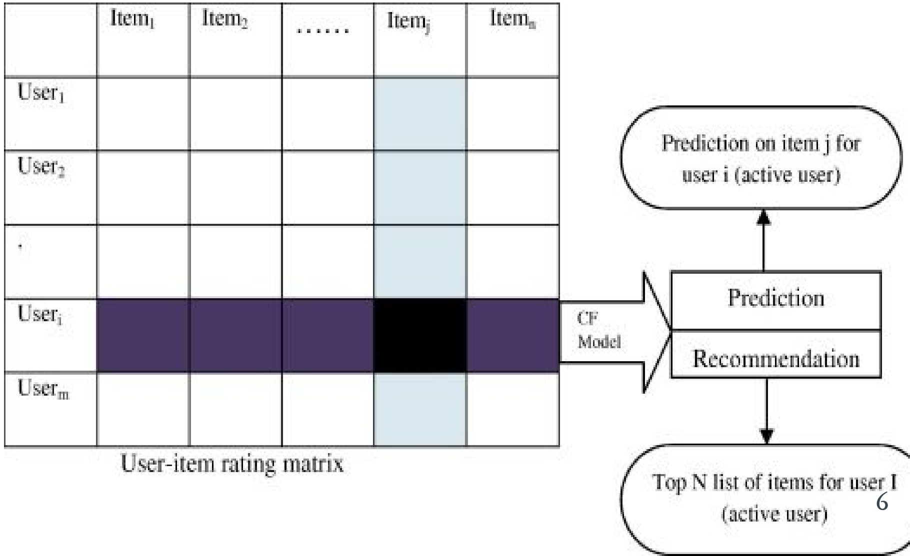
1. Show me items similar to what I have liked in the past.
2. Tell me what's popular among my peers.
3. A bit of both ..

Important Entities



Collaborative Filtering

- Matrix of preferences by users for items, predict missing preferences and recommend the items with high predictions.
- Used when we have a user-item ratings matrix



Memory Based

Entire dataset.

“Memory” - Dataset needs to be in computation memory

	Item1	Item2	Item3	Item4	Item5
Rohan	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Implications:

- Predictions are accurate
- Simple to implement
- Slow

Model Based

Where machine learning techniques come in.

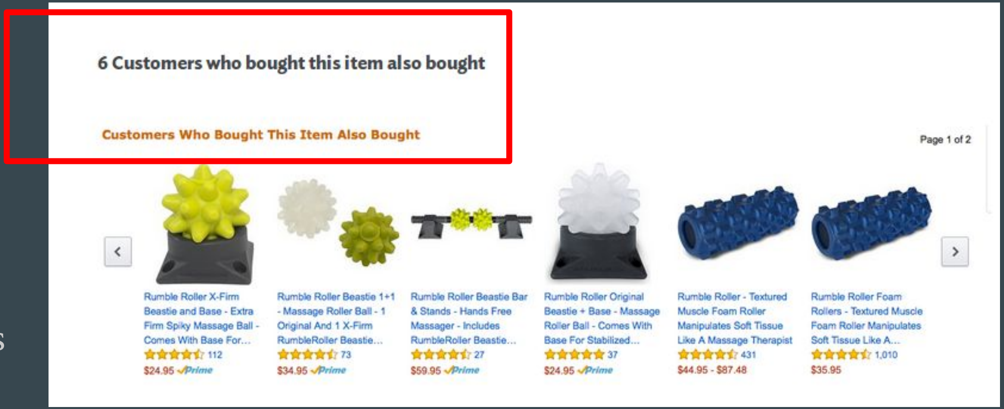
	Item1	Item2	Item3	Item4	Item5
Rohan	5	3	4	4	?
User1	3	1	2	3	3
User2	4	3	4	3	5
User3	3	3	1	5	4
User4	1	5	5	2	1

Implications:

- Analyze the user-item matrix to identify relations between items, similarity between items by comparing the ratings made by the same user.
- Quality of predictions

Use Case

- Amazon.com's "people who bought this item also bought these items".
- Item-Item CF
- Creates the expensive similar-items table offline
- The neighborhood to be used at run-time is small, only items are taken into account which the user has rated.
- Item similarities are supposed to be more stable than user similarities



Limitations

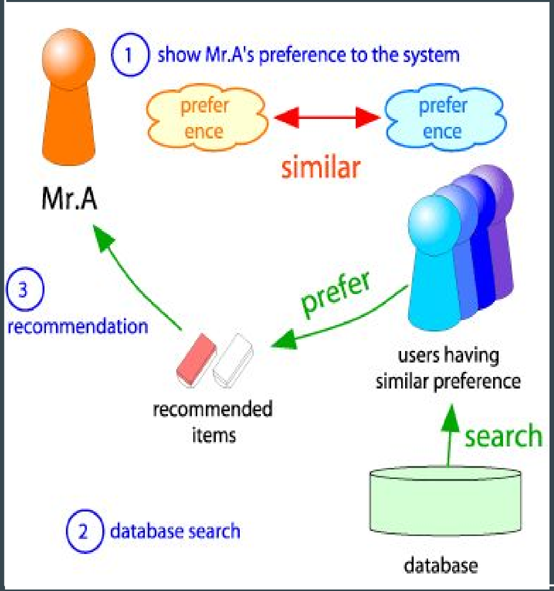
Low data

Where there are NO PREFERENCES at all, it can't generate any recommendations.

Or when there are millions of available preferences and not for all the items, leads to a sparse user-item matrix

Scalability

Similarity logic



Dissimilar naming

Very similar items to have different names or entries.

Sparsity

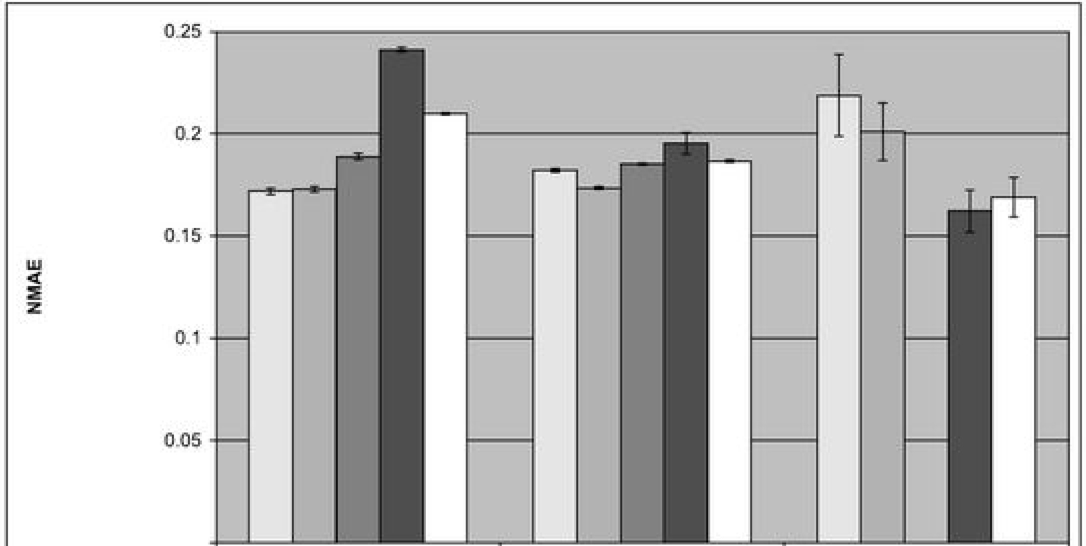
Consider only ratings of users on COMMON ITEMS or ratings made by the SAME USER on two different items .

Experiments in Joseph Stefan Institute, Slovenia on two standard, publicly available datasets and a real-life anonymous corporate dataset.

Quality of collaborative filtering recommendations, highly dependent on the sparsity of available data.

kNN - relatively low sparsity
SVM - based approaches may perform better on highly sparse data.

Sparsity (Contd.)



	Jester	EachMovie	Corporate (1/2/3/2)
kNN Pearson	0.1718246	0.1821964	0.2187814
kNN Cosine	0.1728898	0.1735166	0.2011448
SVM classifier	0.1888338	0.1851124	
SVM regression	0.2412224	0.1951874	0.1621678
Popularity	0.2098228	0.1865928	0.1688694

Content based

Focuses on the similarity of each item.

Doesn’t require as much user feedback to get going.

When documents such as web pages, publications and news are to be recommended, content-based filtering technique is the most successful.

- Create a feature vector items, feature sets comprise of words with high TF.IDF scores.

Represent items and users in the same way

Title	Genre	Author	Type	Price	Keywords
The Night of the Gun	Memoir	David Carr	Paperback	29.90	Press and journalism, drug addiction, personal memoirs, New York
The Lace Reader	Fiction, Mystery	Brunonia Barry	Hardcover	49.90	American contemporary fiction, detective, historical
Into the Fire	Romance, Suspense	Suzanne Brockmann	Hardcover	45.90	American fiction, murder, neo-Nazism

Title	Genre	Author	Type	Price	Keywords
…	Fiction	Brunonia, Barry, Ken Follett	Paperback	25.65	Detective, murder, New York

- Item recommendation: nearest neighbors

Use Case

- News Dude, personal news system that utilizes synthesized speech to read news stories to users.

- TF-IDF describes news stories in order to determine the short-term recommendations which is then compared with the Cosine Similarity Measure and finally supplied to a learning algorithm (NN).

Limitations

1. Item's feature vector is not so easily defined.
2. Such recommendations may also be too static over time, thereby failing to adjust to changes in individual user tastes and other shifts in the underlying data.

Hybrid: The best of both worlds

Hybrid

Simple weighted combination

The components have to be consistent relative accuracy across the product space and to perform uniformly.

Switching

Criteria

Sensitive to the weakness of the kinds of recommendation system

More complex

Cascaded

Successor's recommendation is restricted by the predecessor

Going from a coarse to a finer list of recommendation, it is more tolerant to noise.

Possible that the min no of recommendations is not found.

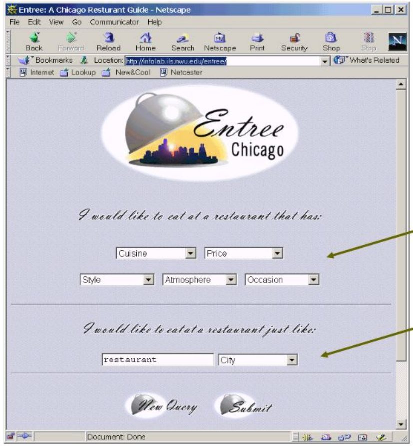
Use Cases

Switching - DailyLearner system

- News stories
- content-based recommendation method is applied first.
- If the content-based system cannot make a recommendation with sufficient confidence, then a collaborative recommendation is attempted.

Cascade - EntreeC

- it uses its knowledge of restaurants to make recommendations based on the user's stated interests. Buckets of equal preference, and the collaborative technique is employed to break ties, further ranking the suggestions in each bucket.



- Entree is a restaurant recommender system – it finds restaurants:
  1. matching some user goals (case features)
  2. or similar to restaurants the user knows and likes

Other recommender systems

Knowledge Based: “Recommend an item based on my list of specified needs”
Applications:

- Rarely purchased items (such as apartments, cars) => low number of available ratings.
- Complex item domains (e.g., "the maximum price of the car is X")

Not supported by approaches such as Collaborative filtering and Content-based filtering.
Also, Financial services, digital cameras, and tourist destinations.

Demographic: based on a demographic profile of the user. Combine ratings of users in demographic niches.
Applications:

- Very few, not used commercially since issues such as privacy occur.
- If the online retailer has information about the customers and only wants to sell products to a particular group, like young or old, men or women, educated or uneducated, etc. not all customers can be stereotyped

Utility-Based: makes suggestions based on computation of the utility of each object for the user, a user specific utility function
Applications:

- can factor non-product attributes (vendor reliability and product availability), check real time inventory of the object and display it to the user.

Good Recommendation

Precision & Recall

$$\text{Precision} = \frac{\text{Correctly recommended items}}{\text{Total recommended items}}$$

$$\text{Recall} = \frac{\text{Correctly recommended items}}{\text{Total useful recommended items}}$$

Problem of ground truth :

No rating available for most of the items

Considering unrated items as irrelevant?

How to count the ranked elements with unknown ground truth

Coverage: For how many users can we make recommendations? How many catalog items are ever recommended?

Diversity & Novelty: Avoiding monotone lists, discover new (families of) items

Serendipity: Unexpected and surprising items might be valuable

Familiarity: Give the user the impression of understanding his/her needs

Biases: Does the recommender only recommend popular items and blockbusters?

Thank You