
Application of Recommendation System in Banking Industry

Jason Huo
Jan 2019

Agenda

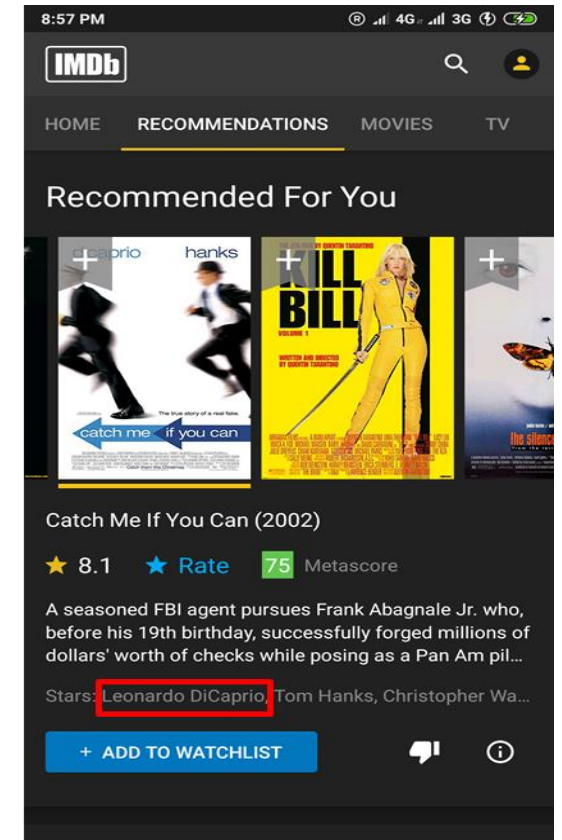
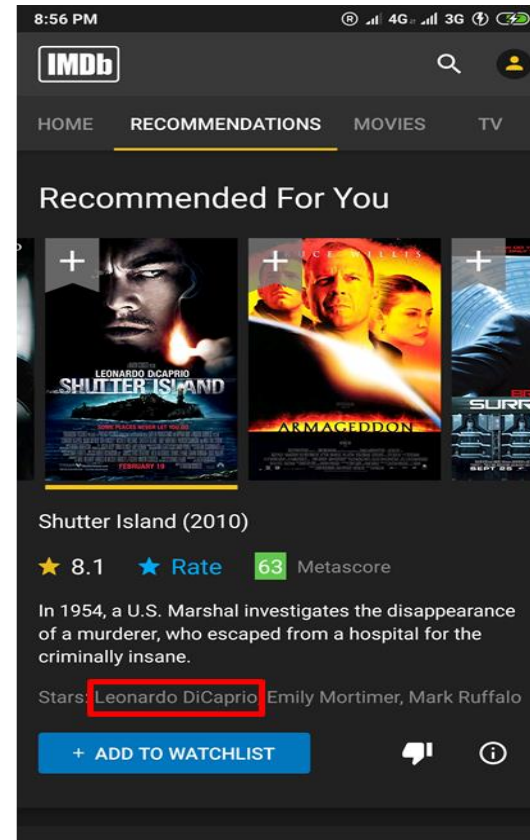
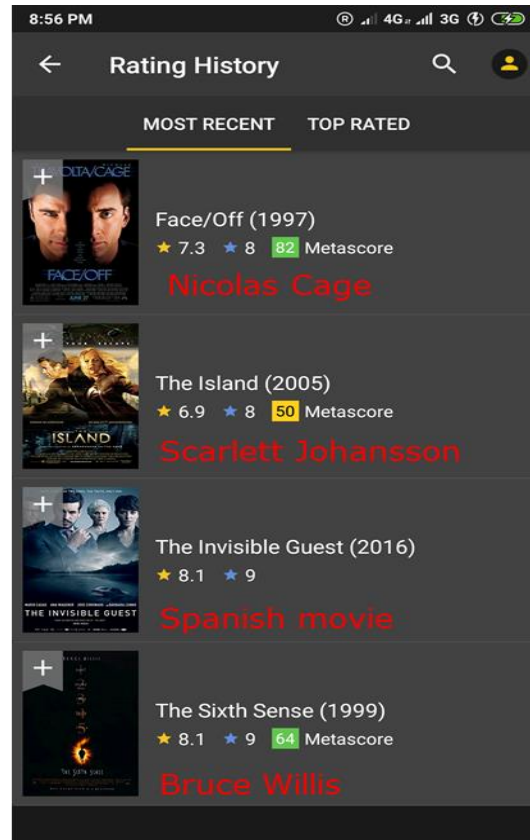
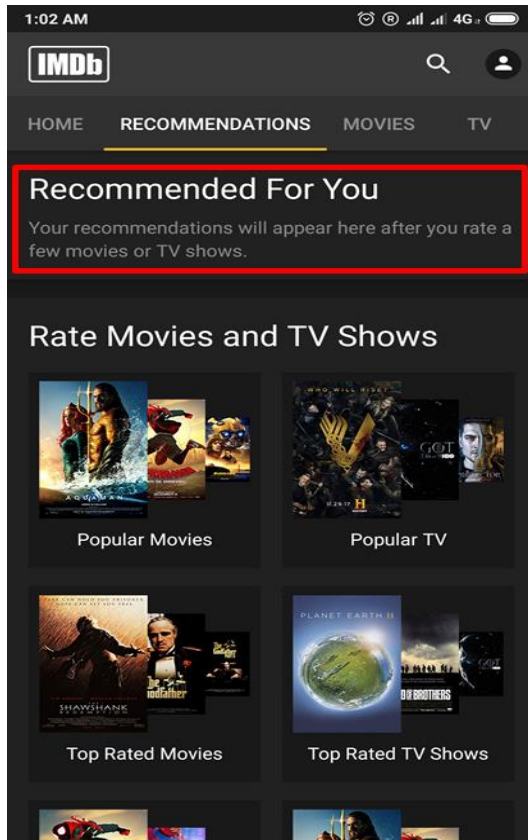
- ❑ How IMDb recommend movies ?
- ❑ Content-Based Filtering
- ❑ Collaborative Filtering
- ❑ Collaborative vs Content-based: Pros and Cons
- ❑ Use Case: Credit Card Offer Recommendation

How IMDb recommend movies ?

“Your recommendations will appear here after you rate a few movie or TV shows”

I rate 4 movies of Thriller/Adventure/Si-Fi/Mystery, stars by Nicolas Cage/Scarlett Johansson/Bruce Willis

- A list of 50 movies are recommended **REAL TIME!** Most are of similar genre as the movies I rate, and I watched more than half of the list.
- IMDb knows **Leonardo DiCaprio** is my favorite star !



Content-Based Filtering

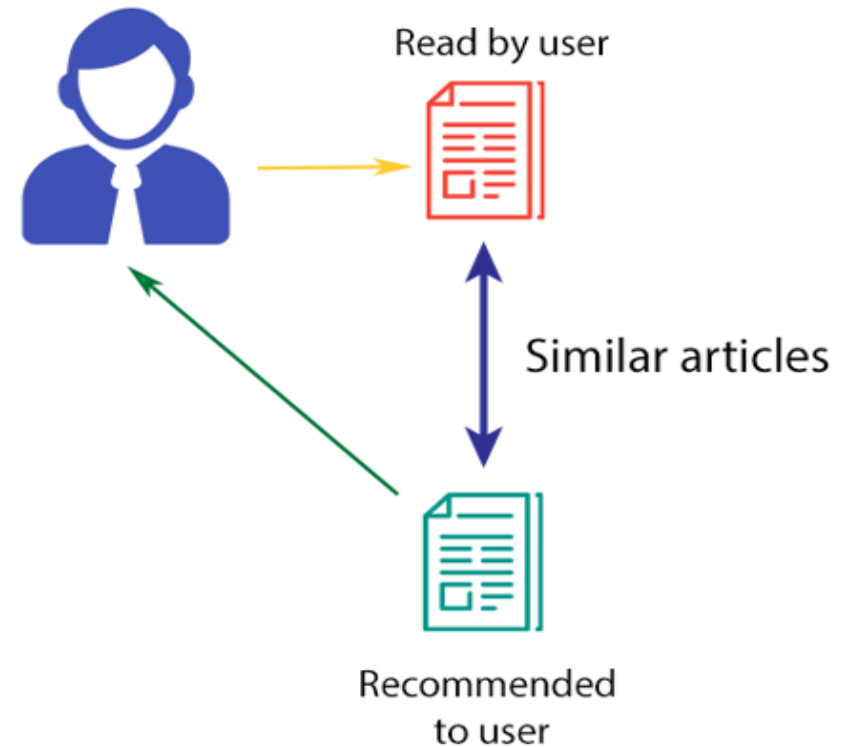
Customers who buy a specific item in the past, will buy similar items in the future !



items you may like ...



How content-base filtering works?

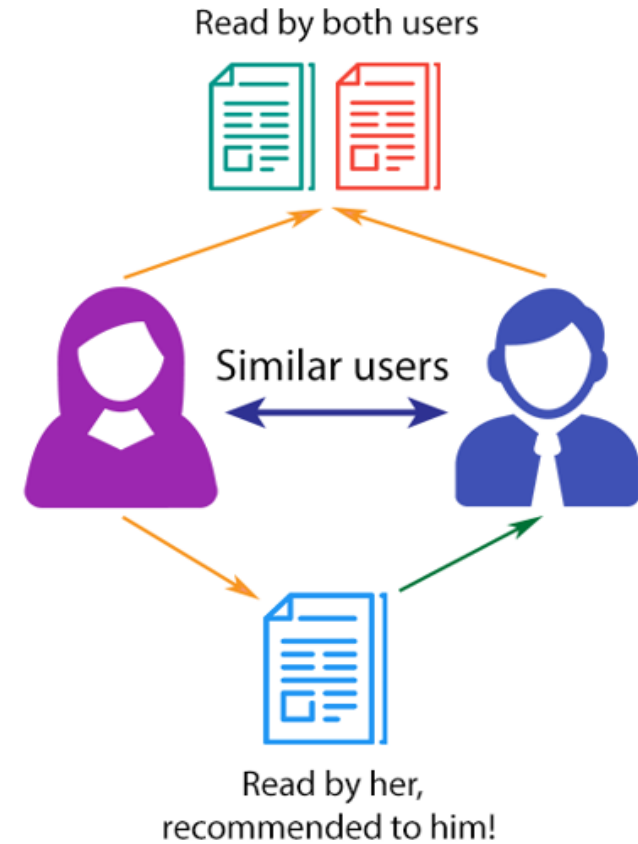


Collaborative Filtering

Customers who had similar tastes in the past, will have similar tastes in the future !



How collaborative filtering works?



Collaborative vs Content-based: Pros and Cons

Challenge	Collaborative Filtering	Content-based Filtering
First rater problem	Yes	No
Cold-start problem	Yes	No
Sparsity problem	Yes (may not be serious in banking)	No
Popularity bias problem	Yes	No
Complex feature selection	No	Yes

Some Handy Python Package for Recommendation System

The screenshot shows the website for surpriselib.com. The left sidebar contains the logo 'surprise' and a description: 'A Python scikit for recommender systems.' It also lists navigation links: 'Home', 'Documentation', and 'GitHub page', along with social media icons for 'Star' and 'Fork' and a prompt to 'Follow @Surpriselib'. It mentions 'Maintained by Nicolas Hug' and 'Page built with Jekyll and Hyde'.

The main content area displays two tables of performance metrics for different recommendation algorithms on the Movielens datasets.

Movielens 100k	RMSE	MAE	Time
SVD	0.934	0.737	0:00:11
SVD++	0.92	0.722	0:09:03
NMF	0.963	0.758	0:00:15
Slope One	0.946	0.743	0:00:08
k-NN	0.98	0.774	0:00:10
Centered k-NN	0.951	0.749	0:00:10
k-NN Baseline	0.931	0.733	0:00:12
Co-Clustering	0.963	0.753	0:00:03
Baseline	0.944	0.748	0:00:01
Random	1.514	1.215	0:00:01

Movielens 1M	RMSE	MAE	Time
SVD	0.873	0.686	0:02:13
SVD++	0.862	0.673	2:54:19
NMF	0.916	0.724	0:02:31
Slope One	0.907	0.715	0:02:31

Use Case: Credit Card Offer Recommendation



What's the best recommendation for individual customer?



Hybrid Recommendation System

G1: Non-existing customers

Recommend the Most Popular Items
(Cold-start)

- Know nothing about these customers, the most popular merchant offers will be recommended

G2: New customers without transaction

People like you also like...
(customer-to-customer similarity)

- Identify the ones who are similar to you based on demographics, e.g., income level, occupation, marital status, nationality, deposit balance, etc.
- Recommend based on these similar customers' preference

G3: Existing customer w/ $<X$ transactions

Those who like what you like also like...
(customer-to-item similarity)

- Not enough information to conclude customers' preference
- Identify customers who have similar preference as you, to recommend what they commonly prefer

G4: Existing customer w/ $\geq X$ transactions

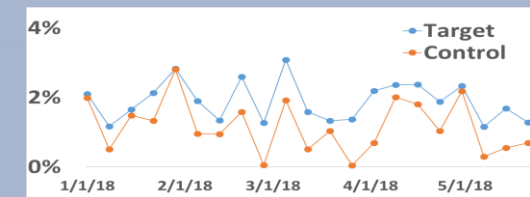
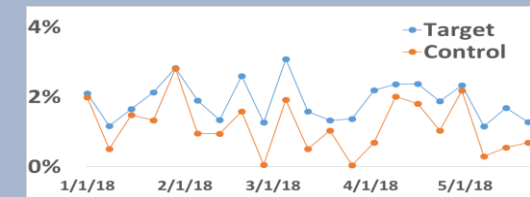
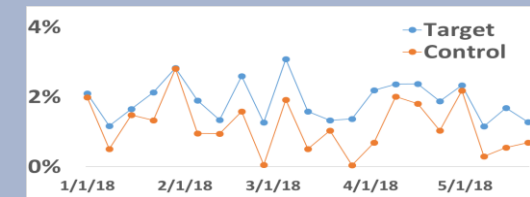
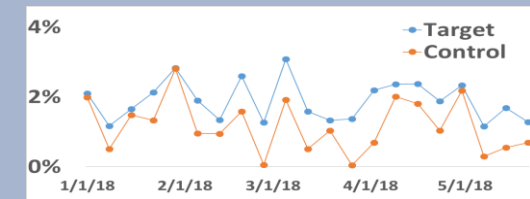
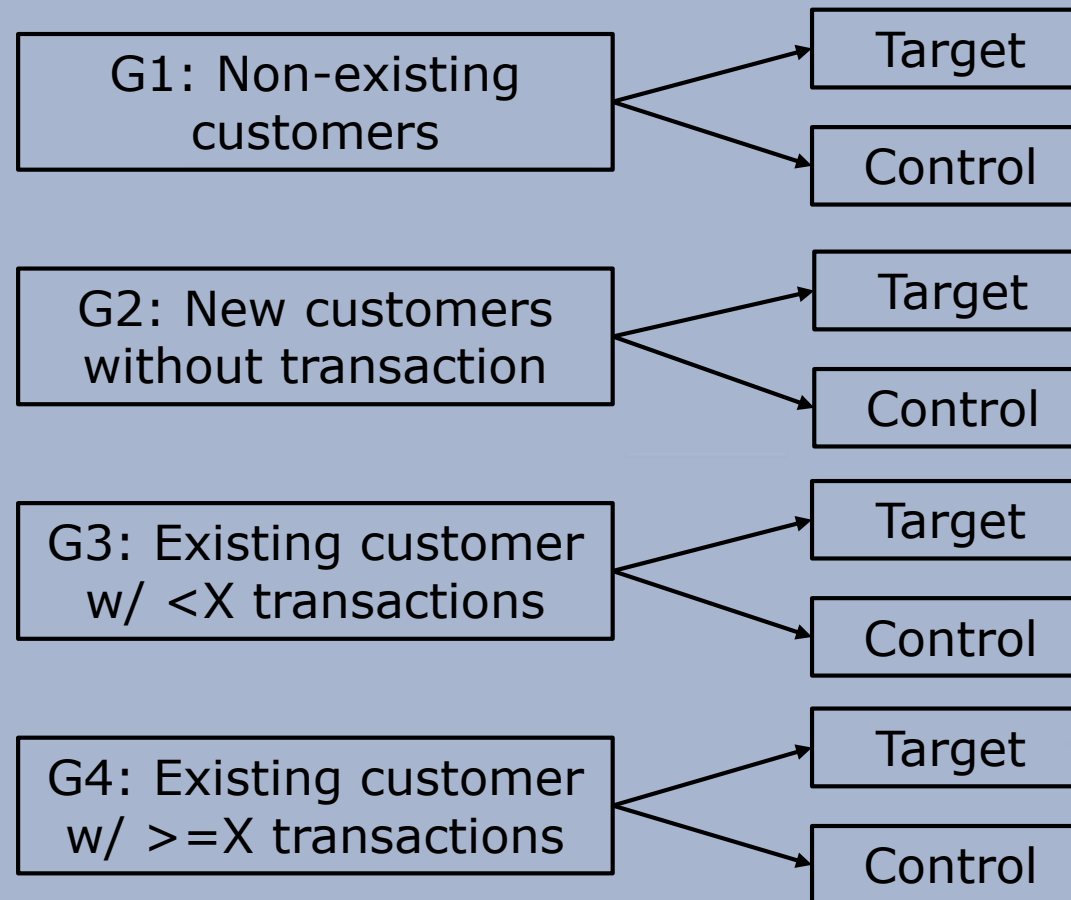
You may also like...
(item-to-item similarity + recency weighting)

- Identify customer preference based on transaction history, e.g., cuisine type / price range / dining location / merchant type / airline tier / hotel tier / travel seasonality, etc.
- More recent transactions would be assigned with higher weighting

Experimental Design for Measure of Success in terms of Click-through Rate, Incremental Sales & Revenue



Need test & learn on different groups of customers to improve the hybrid recommendation system design



Q & A