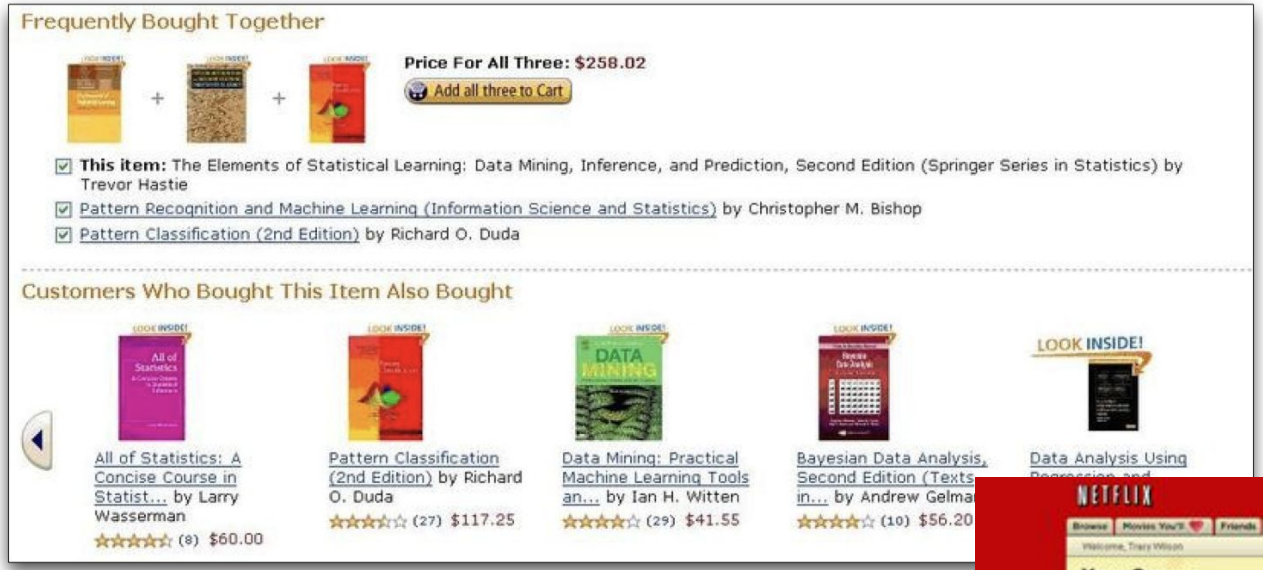
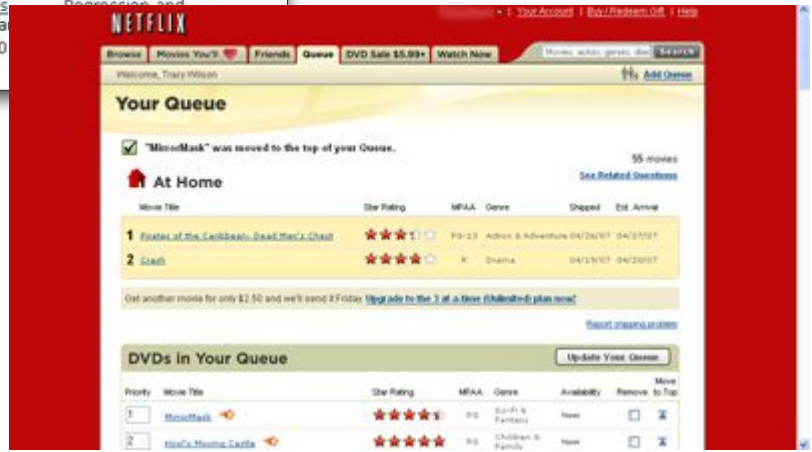
Week 13

Agenda

- What is a recomendar system?
- Early recommender systems: Content vs Behavior
- Collaborative Filtering
- Netflix Prize: Ensembles and MF
- How most companies do recommendation today
- What the few top companies (e.g. Netflix, Amazon, Spotify) are doing today

AMAZON CIRCA 2005



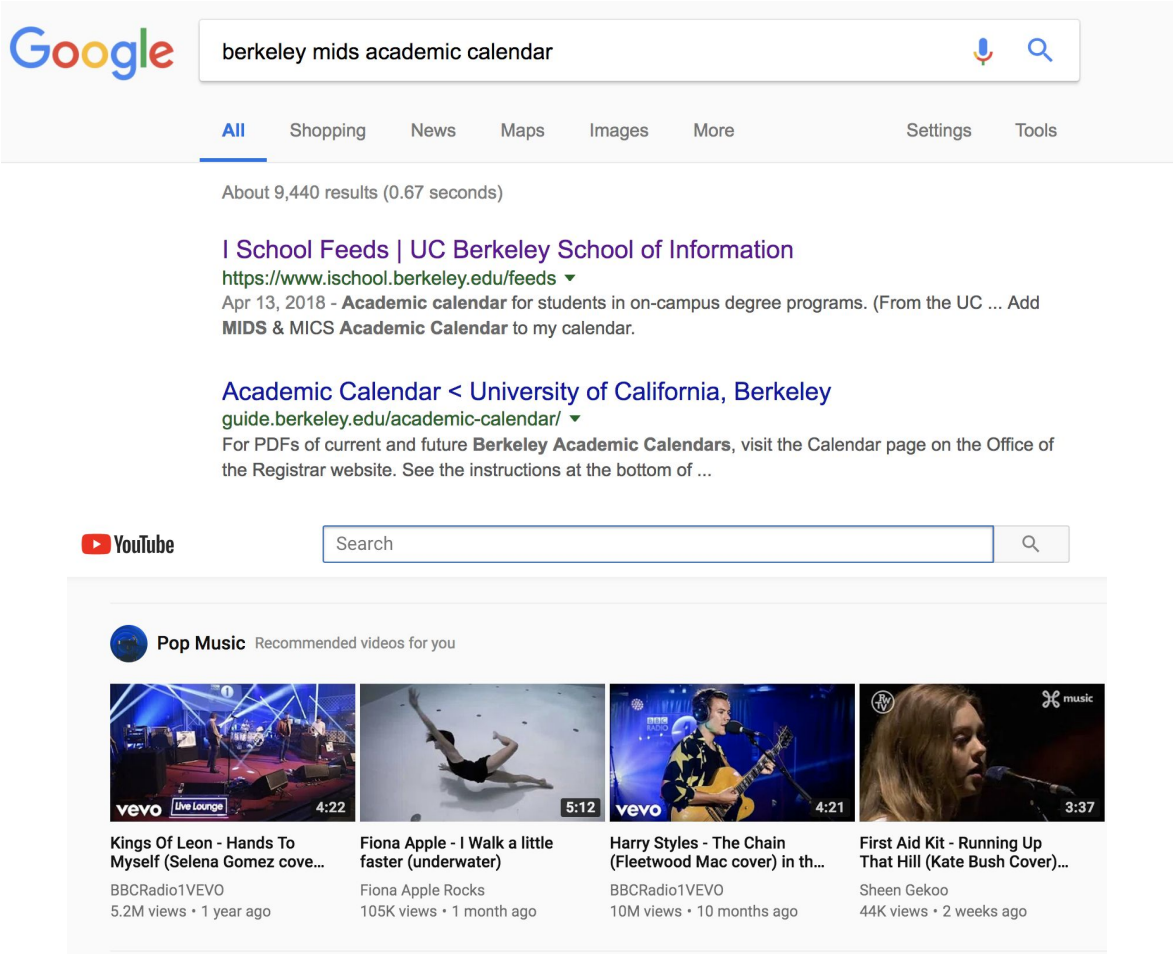


BRIAN BARRETT BUSINESS 03.25.19 06:17 PM

MCDONALD'S BITES ON BIG DATA WITH $300 MILLION ACQUISITION

McDonald's Corp., in its largest acquisition in 20 years, is buying a decision-logic technology company to better personalize menus in its digital push.

The world's biggest restaurant chain is spending more than $300 million on Dynamic Yield Ltd., according to a person familiar with the matter. With the new technology, McDonald's restaurants can vary their electronic menu boards' display of items, depending on factors such as the weather—more coffee on cold days and McFlurries on hot days, for example—and the time of day or regional preferences. The menus will also suggest add-on items to customers.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https://www.ischool.berkeley.edu/feeds
Apr 13, 2018 - Academic calendar for students in on-campus degree programs. (From the UC ... Add MIDS & MICS Academic Calendar to my calendar.
Academic Calendar < University of California, Berkeley
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For PDFs of current and future Berkeley Academic Calendars, visit the Calendar page on the Office of the Registrar website. See the instructions at the bottom of ...
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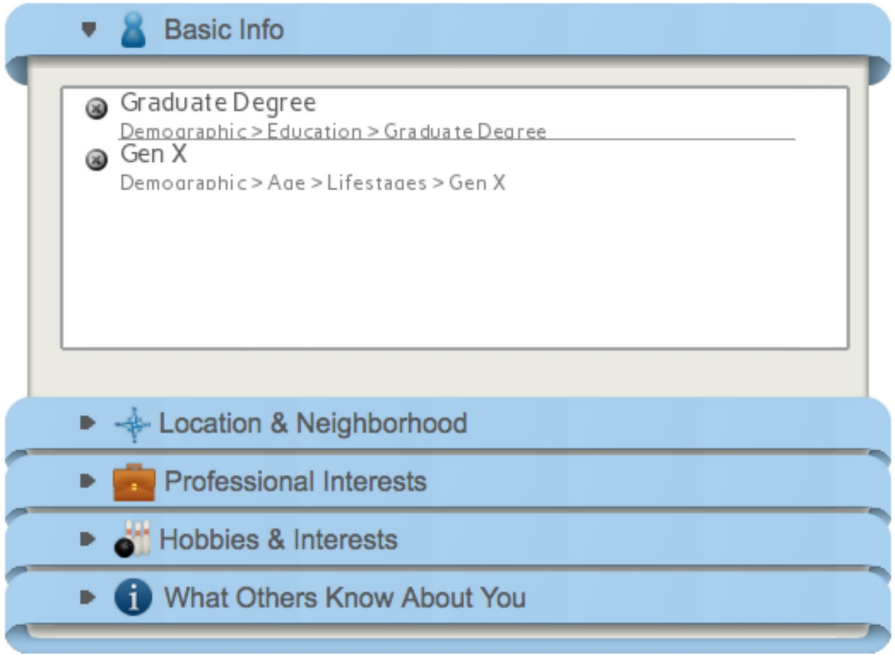
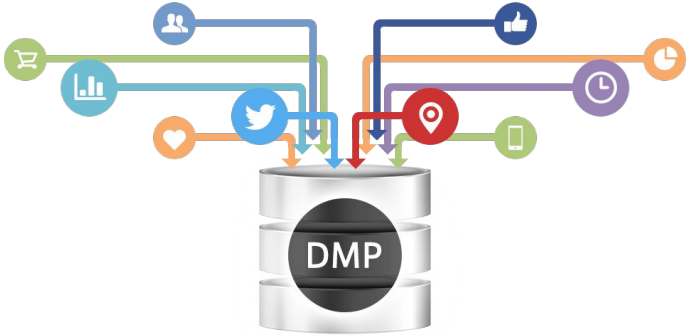
Kings Of Leon - Hands To Myself (Selena Gomez cove...
BBCRadio1VEVO
5.2M views • 1 year ago
Fiona Apple - I Walk a little faster (underwater)
Fiona Apple Rocks
105K views • 1 month ago
Harry Styles - The Chain (Fleetwood Mac cover) in th...
BBCRadio1VEVO
10M views • 10 months ago
First Aid Kit - Running Up That Hill (Kate Bush Cover)...
Sheen Gekoo
44K views • 2 weeks ago

Personal Data Marketplaces

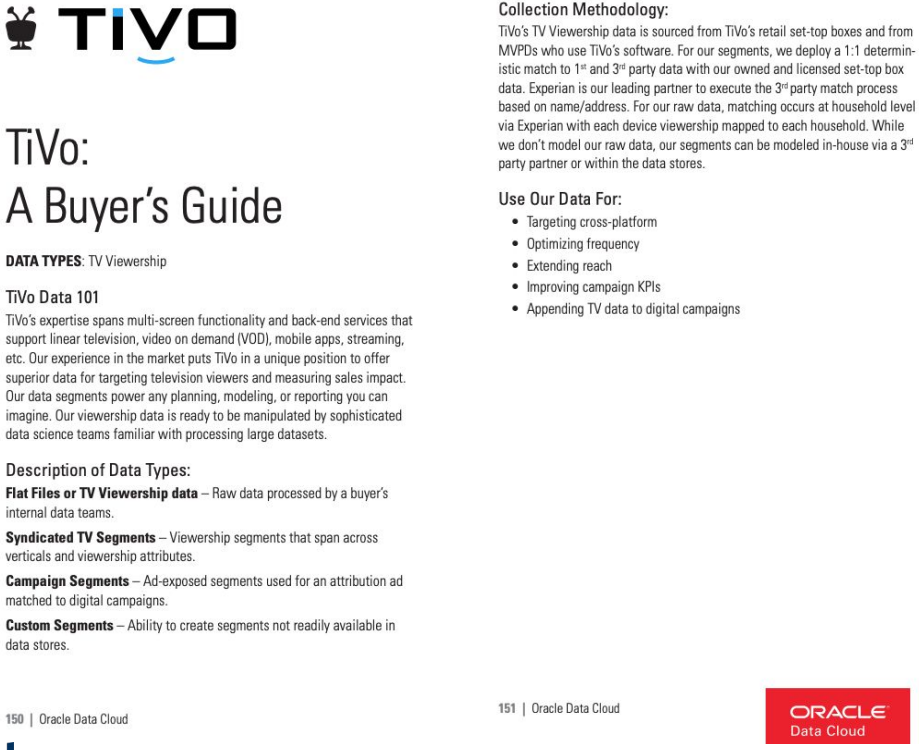




DMPs: Personal data marketplaces

- Bluekai.com/registry
- Discuss.
- How do you feel about them?
- Which datasets about yourself do you assume are public?

Personal Data Marketplaces



TiVo:
A Buyer's Guide

DATA TYPES: TV Viewership

TiVo Data 101

TiVo's expertise spans multi-screen functionality and back-end services that support linear television, video on demand (VOD), mobile apps, streaming, etc. Our experience in the market puts TiVo in a unique position to offer superior data for targeting television viewers and measuring sales impact. Our data segments power any planning, modeling, or reporting you can imagine. Our viewership data is ready to be manipulated by sophisticated data science teams familiar with processing large datasets.

Description of Data Types:

Flat Files or TV Viewership data – Raw data processed by a buyer's internal data teams.

Syndicated TV Segments – Viewership segments that span across verticals and viewership attributes.

Campaign Segments – Ad-exposed segments used for an attribution ad matched to digital campaigns.

Custom Segments – Ability to create segments not readily available in data stores.

150 | Oracle Data Cloud

Collection Methodology:

TiVo's TV Viewership data is sourced from TiVo's retail set-top boxes and from MVPDs who use TiVo's software. For our segments, we deploy a 1:1 deterministic match to 1st and 3rd party data with our owned and licensed set-top box data. Experian is our leading partner to execute the 3rd party match process based on name/address. For our raw data, matching occurs at household level via Experian with each device viewership mapped to each household. While we don't model our raw data, our segments can be modeled in-house via a 3rd party partner or within the data stores.

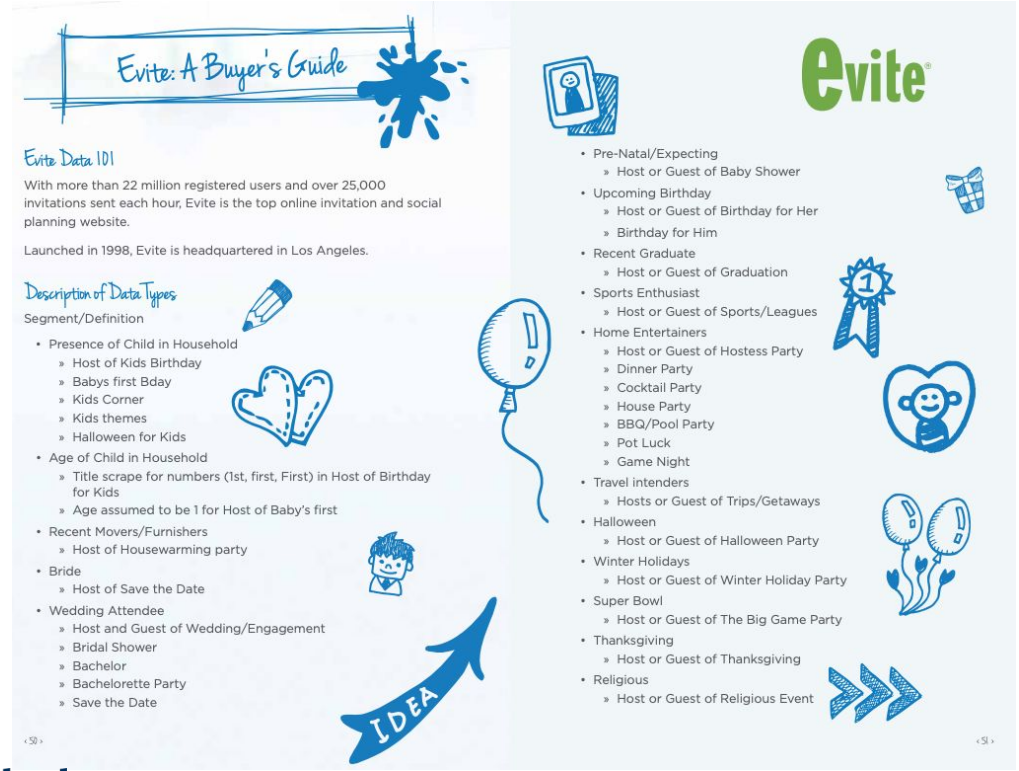
Use Our Data For:

- Targeting cross-platform
- Optimizing frequency
- Extending reach
- Improving campaign KPIs
- Appending TV data to digital campaigns

151 | Oracle Data Cloud

ORACLE Data Cloud

Personal Data Marketplaces



Evite: A Buyer's Guide

Evite Data 101

With more than 22 million registered users and over 25,000 invitations sent each hour, Evite is the top online invitation and social planning website.

Launched in 1998, Evite is headquartered in Los Angeles.

Description of Data Types

Segment/Definition

- Presence of Child in Household
  - » Host of Kids Birthday
  - » Babys first Bday
  - » Kids Corner
  - » Kids themes
  - » Halloween for Kids
- Age of Child in Household
  - » Title scrape for numbers (1st, first, First) in Host of Birthday for Kids
  - » Age assumed to be 1 for Host of Baby's first
- Recent Movers/Furnishers
  - » Host of Housewarming party
- Bride
  - » Host of Save the Date
- Wedding Attendee
  - » Host and Guest of Wedding/Engagement
  - » Bridal Shower
  - » Bachelor
  - » Bachelorette Party
  - » Save the Date

IDEA

‹ 50 ›

evite

- Pre-Natal/Expecting
  - » Host or Guest of Baby Shower
- Upcoming Birthday
  - » Host or Guest of Birthday for Her
  - » Birthday for Him
- Recent Graduate
  - » Host or Guest of Graduation
- Sports Enthusiast
  - » Host or Guest of Sports/Leagues
- Home Entertainers
  - » Host or Guest of Hostess Party
  - » Dinner Party
  - » Cocktail Party
  - » House Party
  - » BBQ/Pool Party
  - » Pot Luck
  - » Game Night
- Travel intenders
  - » Hosts or Guest of Trips/Getaways
- Halloween
  - » Host or Guest of Halloween Party
- Winter Holidays
  - » Host or Guest of Winter Holiday Party
- Super Bowl
  - » Host or Guest of The Big Game Party
- Thanksgiving
  - » Host or Guest of Thanksgiving
- Religious
  - » Host or Guest of Religious Event

‹ 51 ›

Personal Data Marketplaces

TECH

Vizio nears $17 million settlement for TV data-tracking lawsuit

The deal is still subject to final approval

By Chaim Gartenberg | @cgartenberg | Oct 4, 2018, 1:30pm EDT

SHARE

Photo by James Bareham / The Verge

Personal Data Marketplaces

"One of the biggest challenges in protecting privacy is that many of the violations are invisible," Cook writes. "For example, you might have bought a product from an online retailer–something most of us have done. But what the retailer doesn't tell you is that it then turned around and sold or transferred information about your purchase to a 'data broker'–a company that exists purely to collect your information, package it, and sell it to yet another buyer.

"The trail disappears before you even know there is a trail. Right now, all of these secondary markets for your information exist in a shadow economy that's largely unchecked–out of sight of consumers, regulators, and lawmakers. Let's be clear: You never signed up for that. We think every user should have the chance to say, 'Wait a minute. That's my information that you're selling, and I didn't consent.'"

Taste Domains

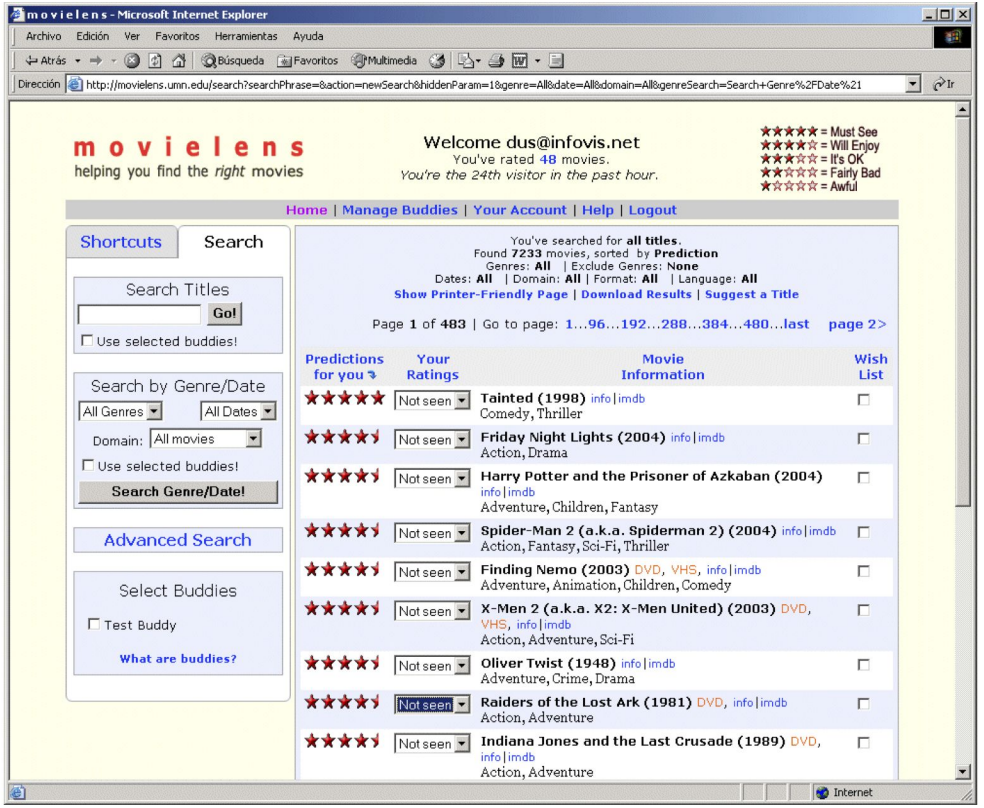
Taste Domains

- Early research focused on ‘taste’ domains, particularly movies, music, and books.
- In these domains, 'finding' often involved suggestions from friends or tastemakers
- Researchers created collaborative filtering and other approaches as means of emulating this process
- Usually cast as ratings prediction problem in part because its relatively easy to collect ratings data

1996 MovieLens (Minnesota)

- http://en.wikipedia.org/wiki/MovieLens
- Research project collected ratings on movies, etc
- Very early Amazon and Netflix strongly influenced by this
- User based CF: Find k-nearest users and use their ratings
- 2001 Item based CF: Find k nearest items to those items a user prefers. http://files.grouplens.org/papers/www10_sarwar.pdf
- Still popular recommendation algorithm

Movielens (Late 90's)

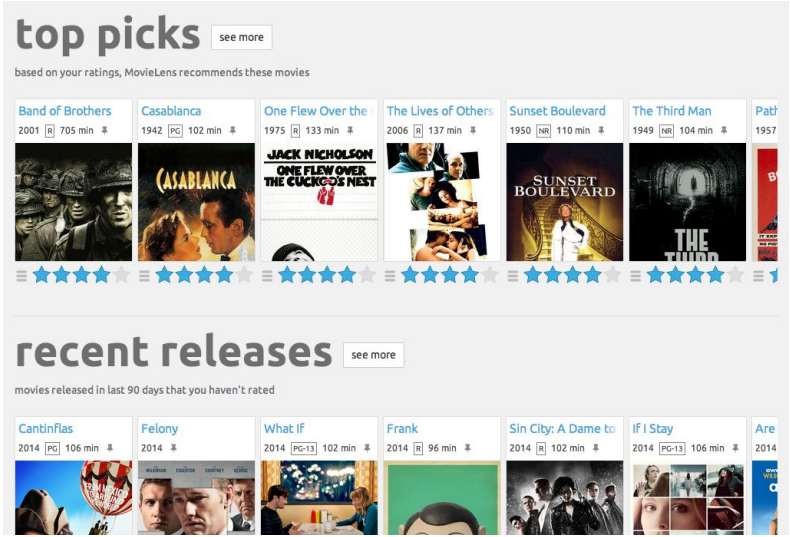


Movielens (Today)

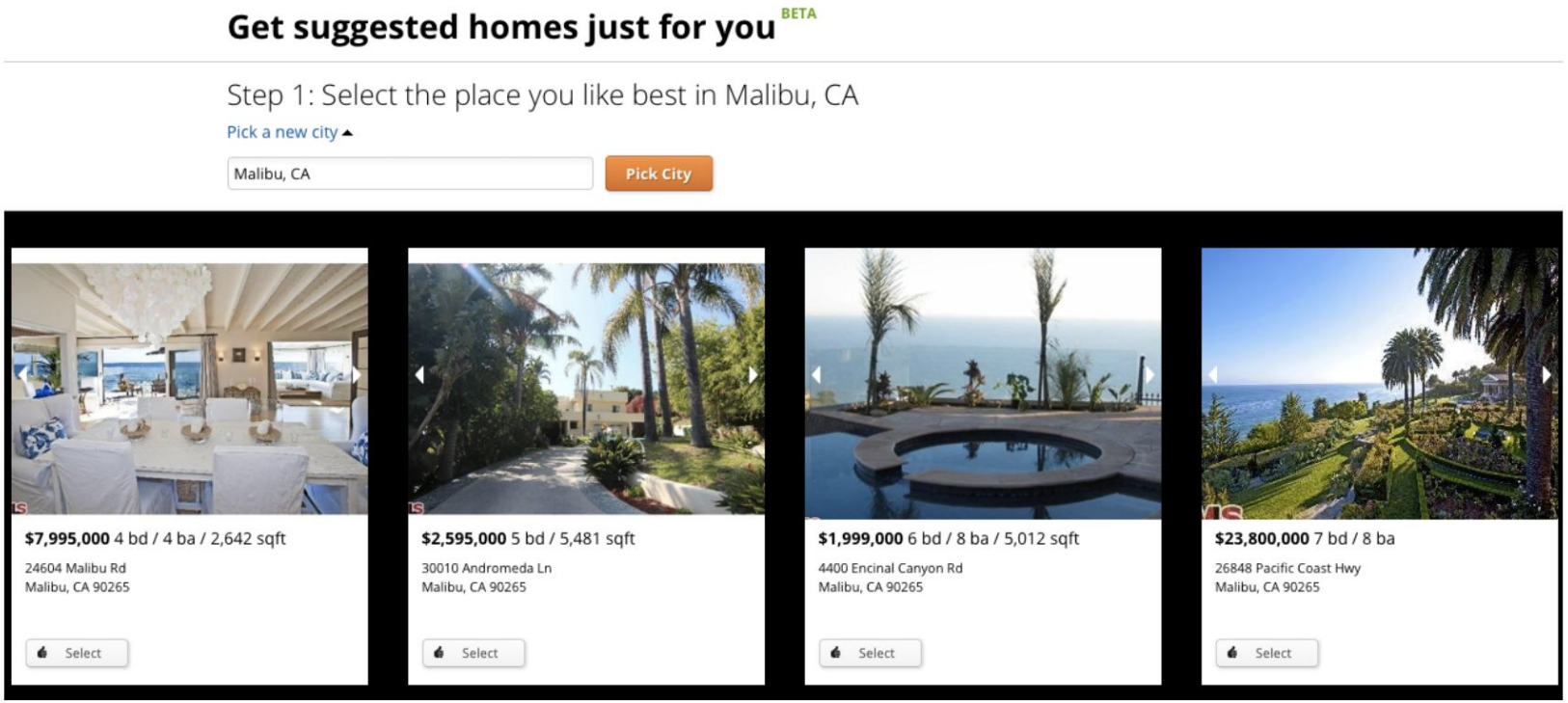
Stable benchmark dataset. 10 million ratings and 100,000 tag applications applied to 10,000 movies by 72,000 users. Released 1/2009.

- README.html
- ml-10m.zip (size: 63 MB, checksum)

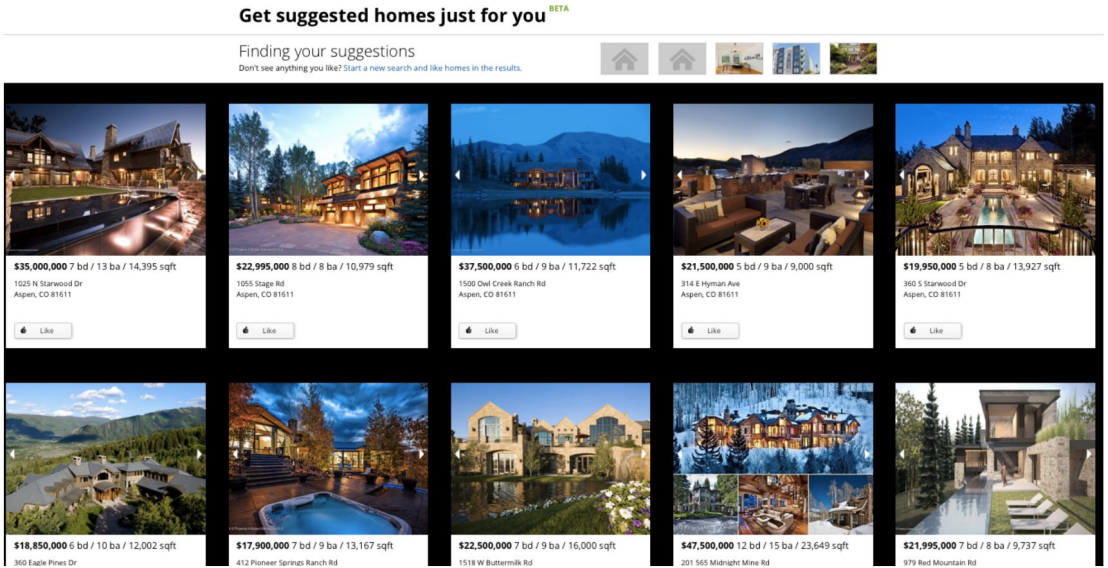
Permalink: http://grouplens.org/datasets/movielens/10m/



Recommending Houses



Recommending Houses



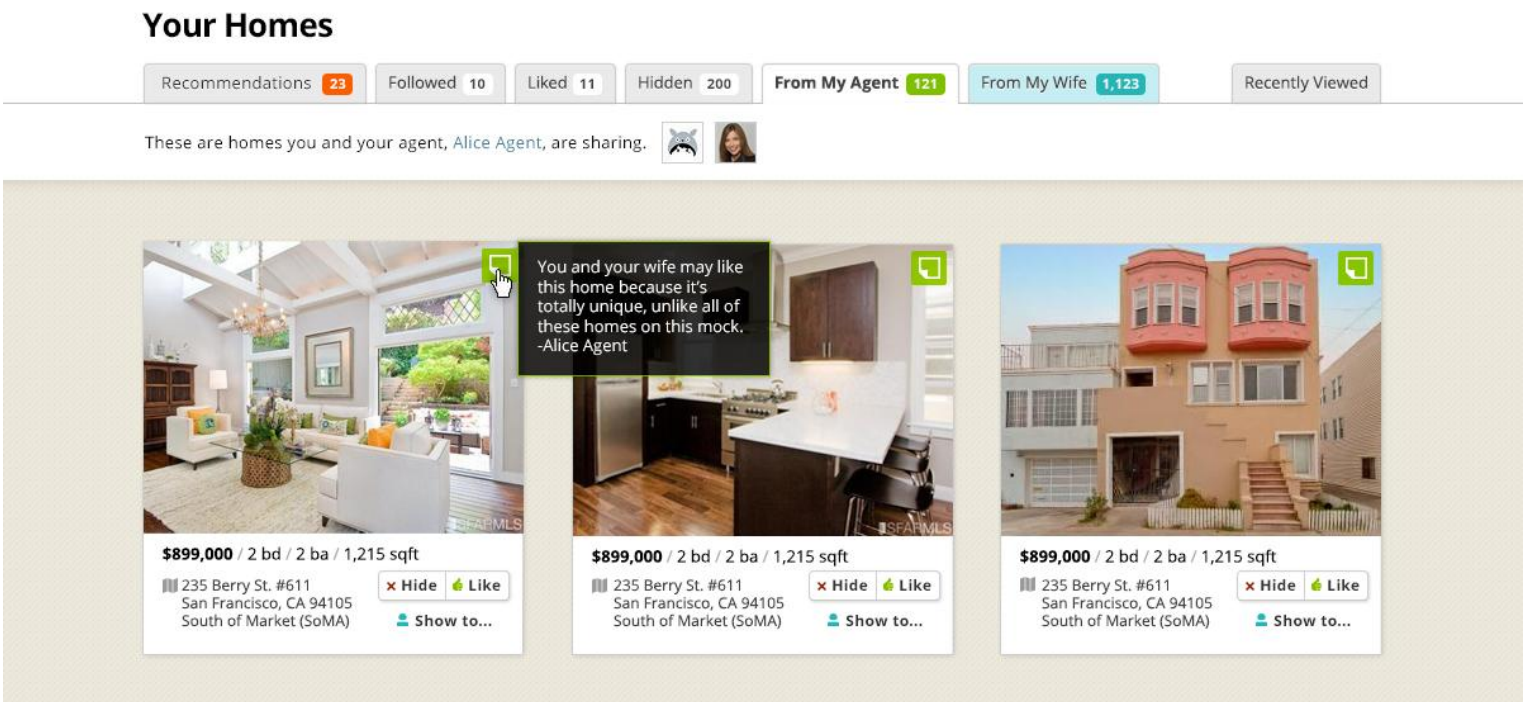
Search vs. Discovery

- Real estate search used to involve looking at classifieds in newspaper, Sites like Trulia are the online equivalent.
- Real estate recommendation used to (and still does) involve agents passing along listings. These recommendations get better as the agent learns more about the homebuyers.
- There are no real estate sites that emulate agent recommendations particularly well

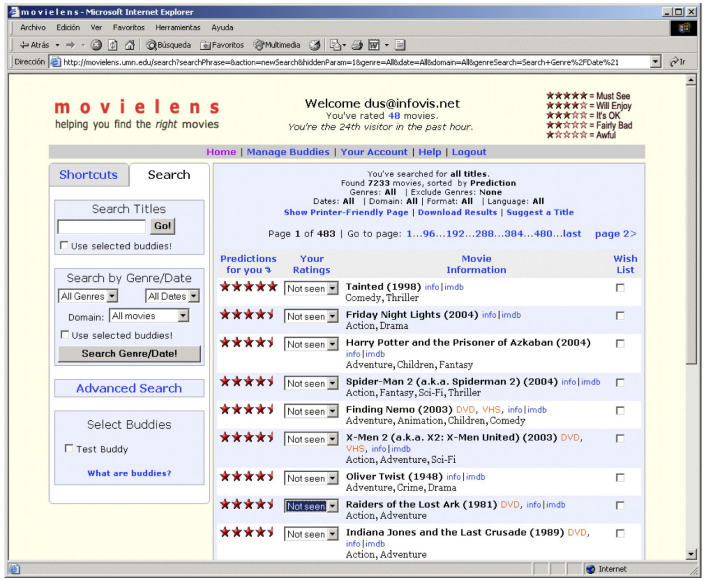
Listing Discovery

- Important decision in one's life
- Only partly a taste domain--utility also plays a role (e.g. space, commute distance)
- Decision making happens over a period of time
- Tastes sometimes evolve during search process
- Social component to both (family, agent, sometimes friends)

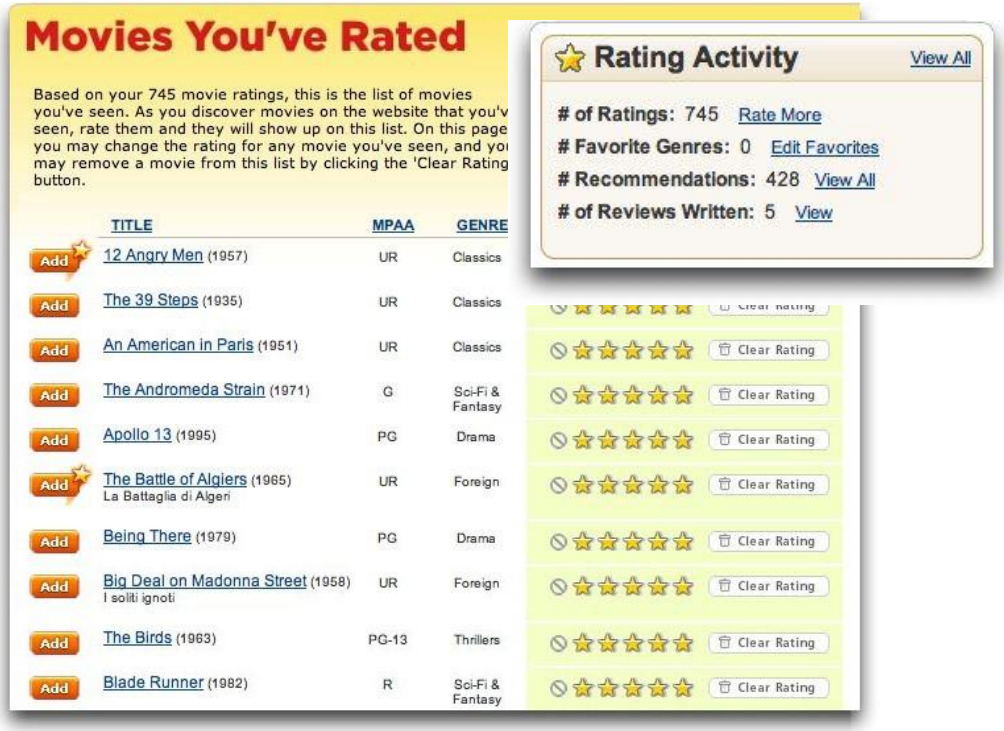
Recommending Houses



Netflix DVD Recommendations



Netflix DVD Recommendations



2002 Netflix DVDs

- Mailed 1-3 DVDs to users
- Brand based in part on ratings and recommendations
- Users could rate any movie, not just those recently watched
- Users were told recommendations get better with more ratings

Search and Discovery

- Amazon historically incorporated recommendations into search results, including to extend results
- Recommendations used at different stages of transaction (E.g. Product page, cart)

Amazon Recommendations (2003)

Figure 1. The "Your Recommendations" feature on the Amazon.com homepage. Using this feature, customers can sort recommendations and add their own product ratings.

Figure 2. Amazon.com shopping cart recommendations. The recommendations are based on the items in the customer's cart: The Pragmatic Programmer *and* Physics for Game Developers.

2003 Amazon

- Many people at time identified recommendations with Amazon
- Item-Item CF (http://www.cs.umd.edu/~samir/498/Amazon-Recommendations.pdf)
- Compares to User-Item based CF (as in GroupLens)
- Pointed to scalability: compute similarities between items offline, usually nightly. This is preferred as item similarities change less frequently than user similarities
- Use item similarities to recommend similar items to those a user has shown preference towards
- Item preference a weighted combination of views, ratings, cart adds, and purchases
- Added blended exponential decay to account for time
- Item similarities can also be used in non-personalized fashion ("users who considered this, also considered that…")
- Not fully real-time and suffers from cold-start problem
- Flawed problem setup: not directly optimizing sales

Amazon Recommendations

Item-based Collaborative Filtering Recommendation Algorithms

Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl

GroupLens Research Group/Army HPC Research Center
Department of Computer Science and Engineering
University of Minnesota, Minneapolis, MN 55455

{sarwar, karypis, konstan, riedl}@cs.umn.edu

Appears in WWW10, May 1-5, 2001, Hong Kong.

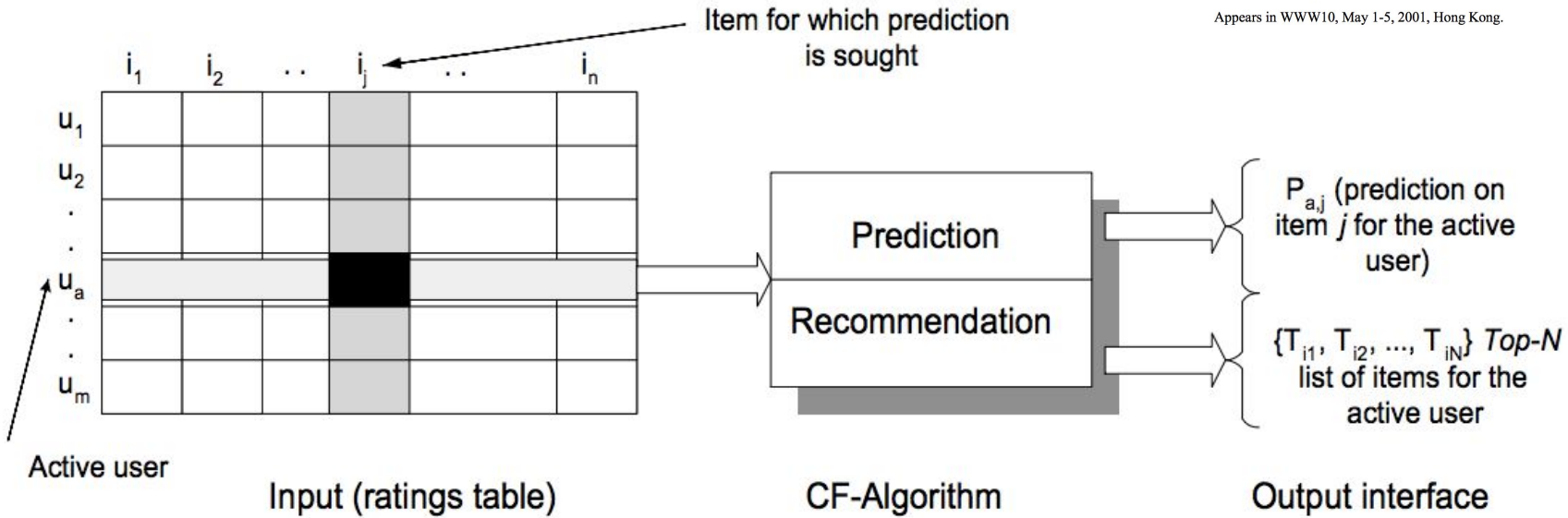


Figure 1: The Collaborative Filtering Process.

Amazon Recommendations

Item-based Collaborative Filtering Recommendation Algorithms

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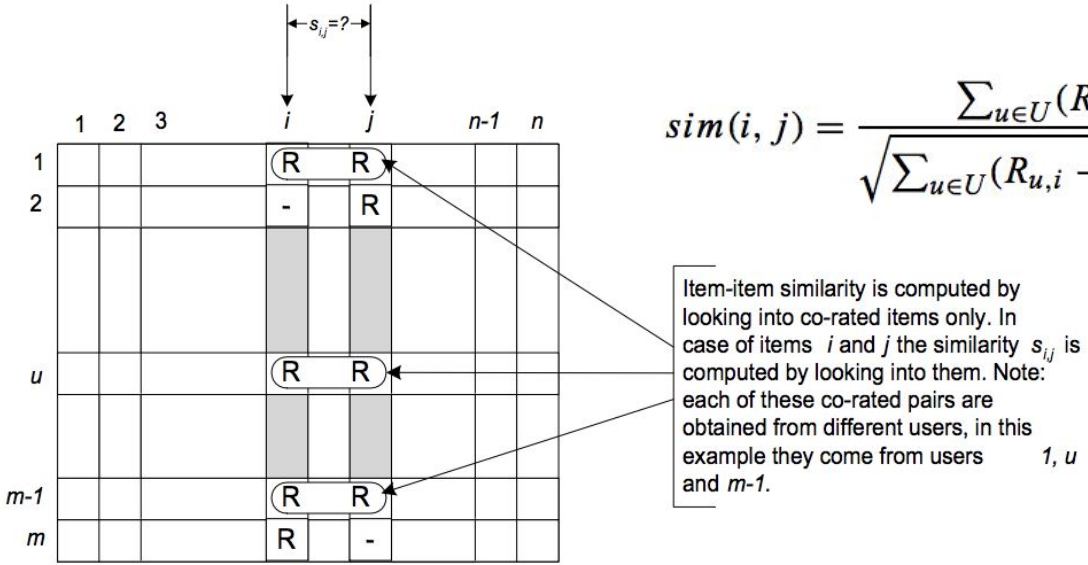

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \bar{R}_i)(R_{u,j} - \bar{R}_j)}{\sqrt{\sum_{u \in U}(R_{u,i} - \bar{R}_i)^2}\sqrt{\sum_{u \in U}(R_{u,j} - \bar{R}_j)^2}}.$$

Figure 2: Isolation of the co-rated items and similarity computation

Amazon Recommendations

Item-based Collaborative Filtering Recommendation Algorithms

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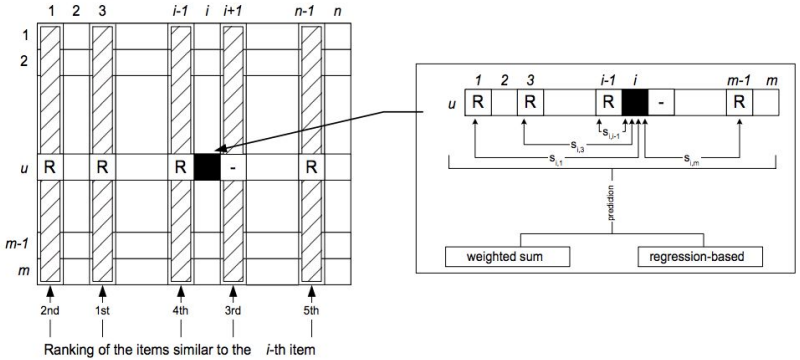


Figure 3: Item-based collaborative filtering algorithm. The prediction generation process is illustrated for 5 neighbors

the corresponding user average from each co-rated pair. Formally, the similarity between items i and j using this scheme is given by

$$sim(i,j) = \frac{\sum_{u \in U}(R_{u,i} - \bar{R}_u)(R_{u,j} - \bar{R}_u)}{\sqrt{\sum_{u \in U}(R_{u,i} - \bar{R}_u)^2}\sqrt{\sum_{u \in U}(R_{u,j} - \bar{R}_u)^2}}.$$

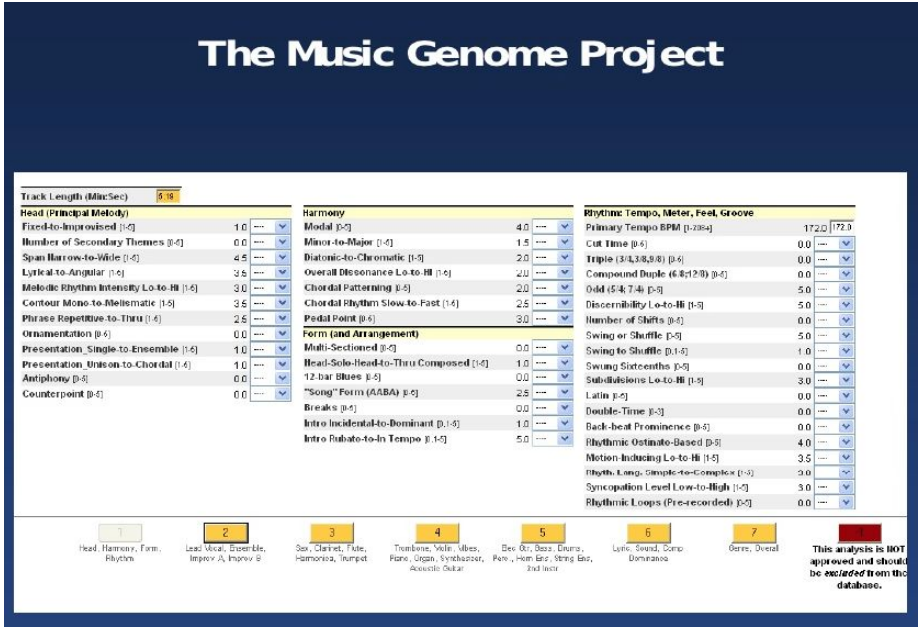
Here $\bar{R}_u$ is the average of the u-th user's ratings.

Cold Start Problem

How do we handle new items?

How do we handle new users?

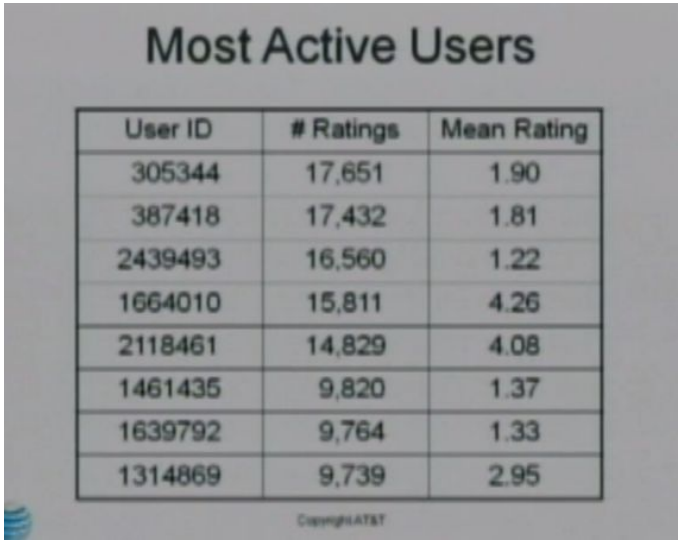
Pandora Recommendations

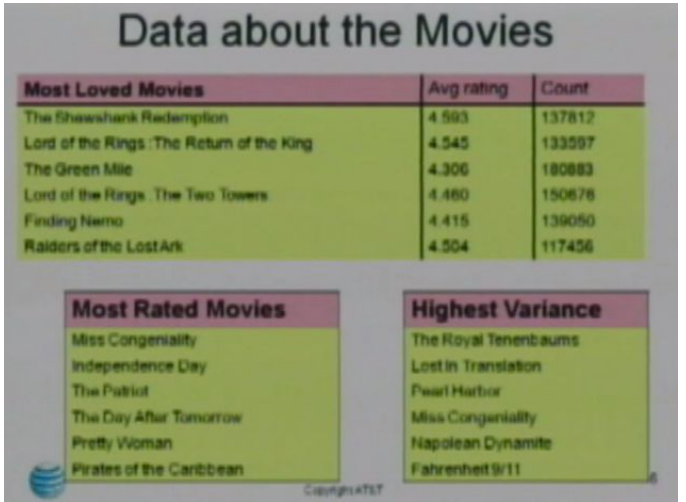


The Netflix Prize

- Training data
  - 100,480,507 ratings
  - 480,189 users
  - 17,770 movies
  - <user, movie, date of grade, grade>
  - <integer, integer, date, 1–5>
- Test data
  - 2,817,131 ratings
  - <integer, integer, date>
- Objective: minimize RMSE:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}$$





The Netflix Prize

The Netflix Prize

SVD for Rating Prediction

- User factor vectors $p_u \in \Re^f$ and item-factors vector $q_v \in \Re^f$
- Baseline $b_{uv} = \mu + b_u + b_v$ (user & item deviation from average)
- Predict rating as $r'_{uv} = b_{uv} + p_u^T q_v$
- SVD++ (Koren et. Al) asymmetric variation w. implicit feedback

$$r'_{uv} = b_{uv} + q_v^T \left(|R(u)|^{-\frac{1}{2}} \sum_{j \in R(u)} (r_{uj} - b_{uj}) x_j + |N(u)|^{-\frac{1}{2}} \sum_{j \in N(u)} y_j \right)$$

- Where
  - $q_v, x_v, y_v \in \Re^f$ are three item factor vectors
  - Users are not parametrized, but rather represented by:
    - R(u): items rated by user u
    - N(u): items for which the user has given implicit preference (e.g. rated vs. not rated)

The Netflix Prize

Simon Funk's SVD

- One of the most interesting findings during the Netflix Prize came out of a blog post
- Incremental, iterative, and approximate way to compute the SVD using gradient descent

Clustering

- Item-item CF didn't work well
- http://gigapan.com/gigapans/65469

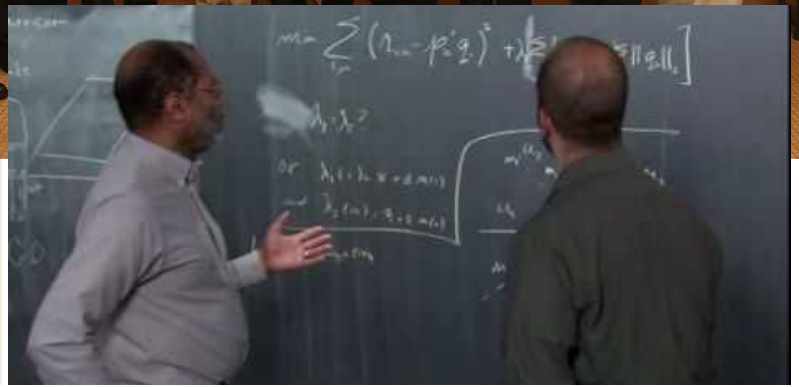
Matrix Factorization Approaches

- 'Simon Funk' released his matrix factorization solution, which supported data sparsity. Used in Netflix (for predicted rating) today
- Dim reduction on sparse data using SVD
- http://sifter.org/~simon/journal/20061211.html
- Later approaches added better formalization and incremental improvements

The Netflix Prize

What Happened

- October 2, 2006: contest launched—$1 million first prize
  - *Cinematch* RMSE = 0.9514
  - Naïve "average rating" RMSE = 1.0540
- October 8, 2006: "WXYZ" team beats *Cinematch*
- June 2007: 20,000 teams in competition (150 countries)
- September 2007: "BellKor" RMSE = 0.8728 ($50k)
- September 2008: "BellKor" RMSE = 0.8616 ($50k)
- July 2009: two teams hit 10% margin—no more entries
- September 2009: "BellKor's Pragmatic Chaos" wins $1 million with RMSE of 0.8567. Same RMSE matched by "The Ensemble," but submission made 20 minutes later. Tiebreaker went to BellKor's Pragmatic Chaos



The Netflix Prize

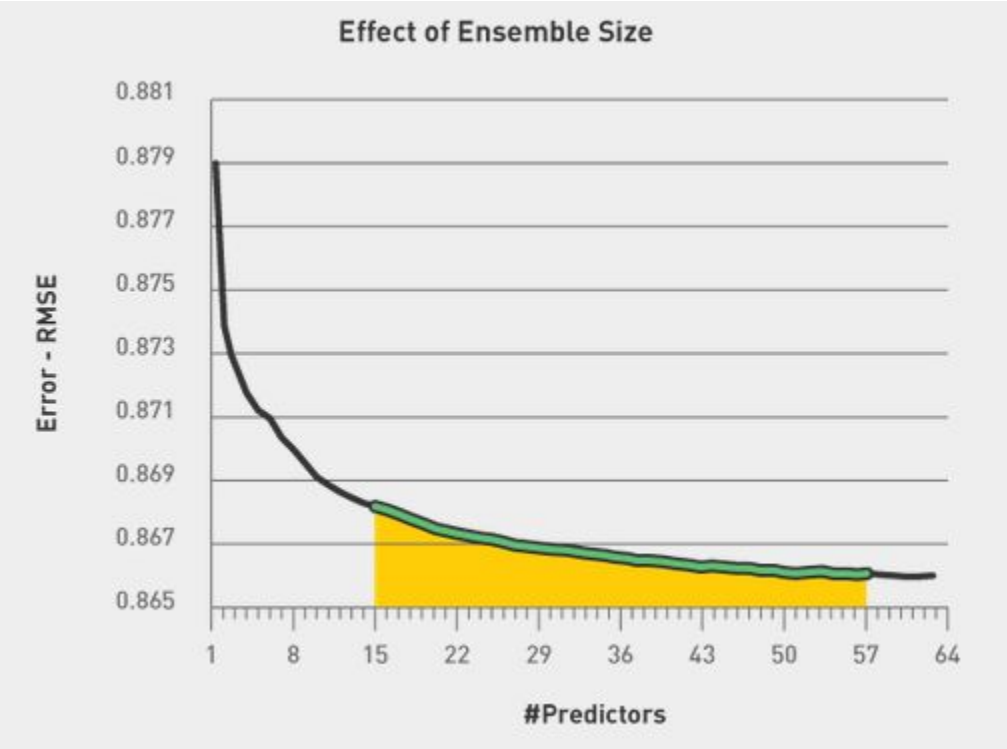
Netflix: The Winner (contd)

- Final product used ensemble methods, which combined results from several algorithms.
  - Neighborhood methods
  - Matrix decomposition methods
  - Regression
  - Boltzmann machines
  - *Et cetera*
- Combining results is topic of another lecture!
- Gradient-boosted decision trees combine 500+ models.

What Other Factors Matter?

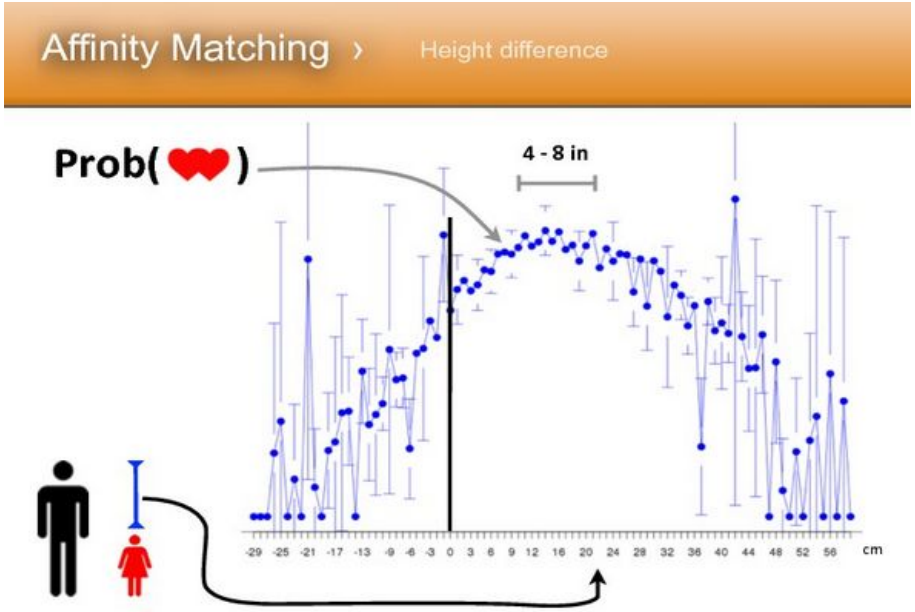
- The number of other people who have rated the movie
- The (square root of the) number of days since first rating
- The number of days since the movie's first rating
- Plus a bunch of others!

The Netflix Prize



Dating Recommendations - How would you do it?

EHarmony

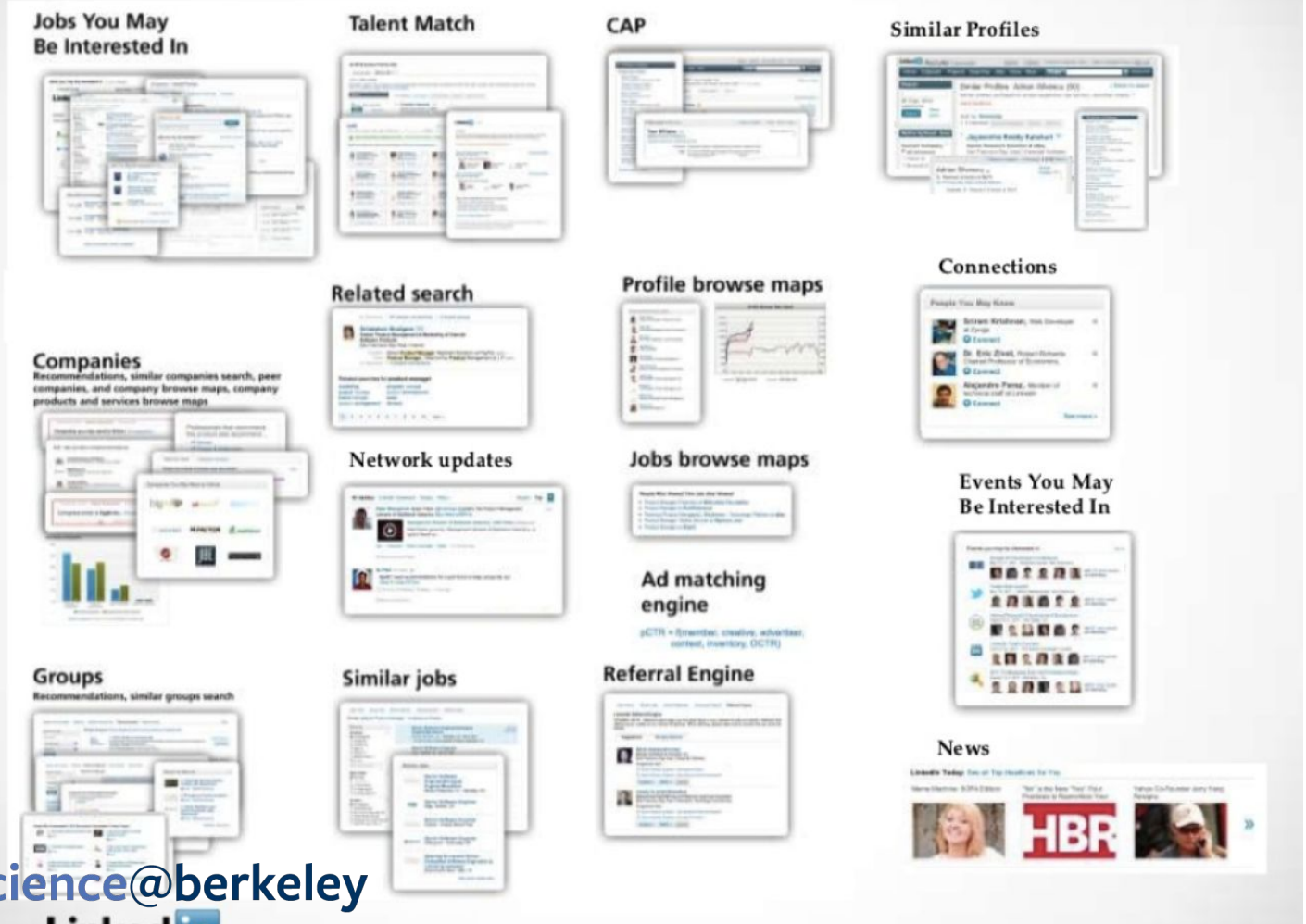


EHarmony

- Straightforward supervised learning approach to building a recommender system.
- Focus is on feature engineering
- 320 attributes (e.g. romantic, height, photo zoom, food preferences)
- Predict likelihood of 'successful match' using logistic regression (Vowpal Wabbit, GBM)
- For more info https://ieondemand.com/divisions/big-data/presentations/data-science-of-love-1

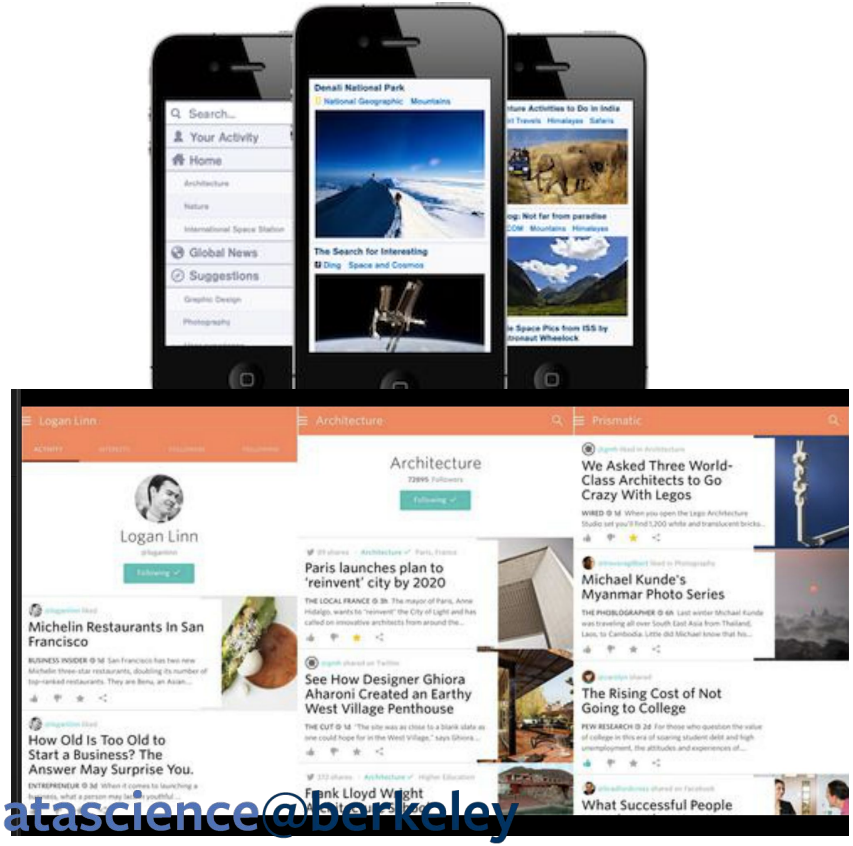
Job Recommendation - How would you do it?

The Recommender Ecosystem



News Recommendation - How would you do it?

News Recommendation



Prismatic (Acquired by MS in 2015)

- Apple news is almost identical
- Problem: Provide personal news feed
- Popular on mobile devices as way to kill time (e.g. on bus)
- Mobile usage impacts implicit data

ML Approach

- Doesn't use Netflix Prize style collaborative filtering
- Step 1: Featurization using Topic Modeling (25K+ topics)
- Step 2: Directly optimize likelihood to read using logistic regression

Netflix Today

Goodbye

& Cinematch

Hello

& % Match

Why?

+200% ratings volume

Clear link to personalization

Music Recommendation

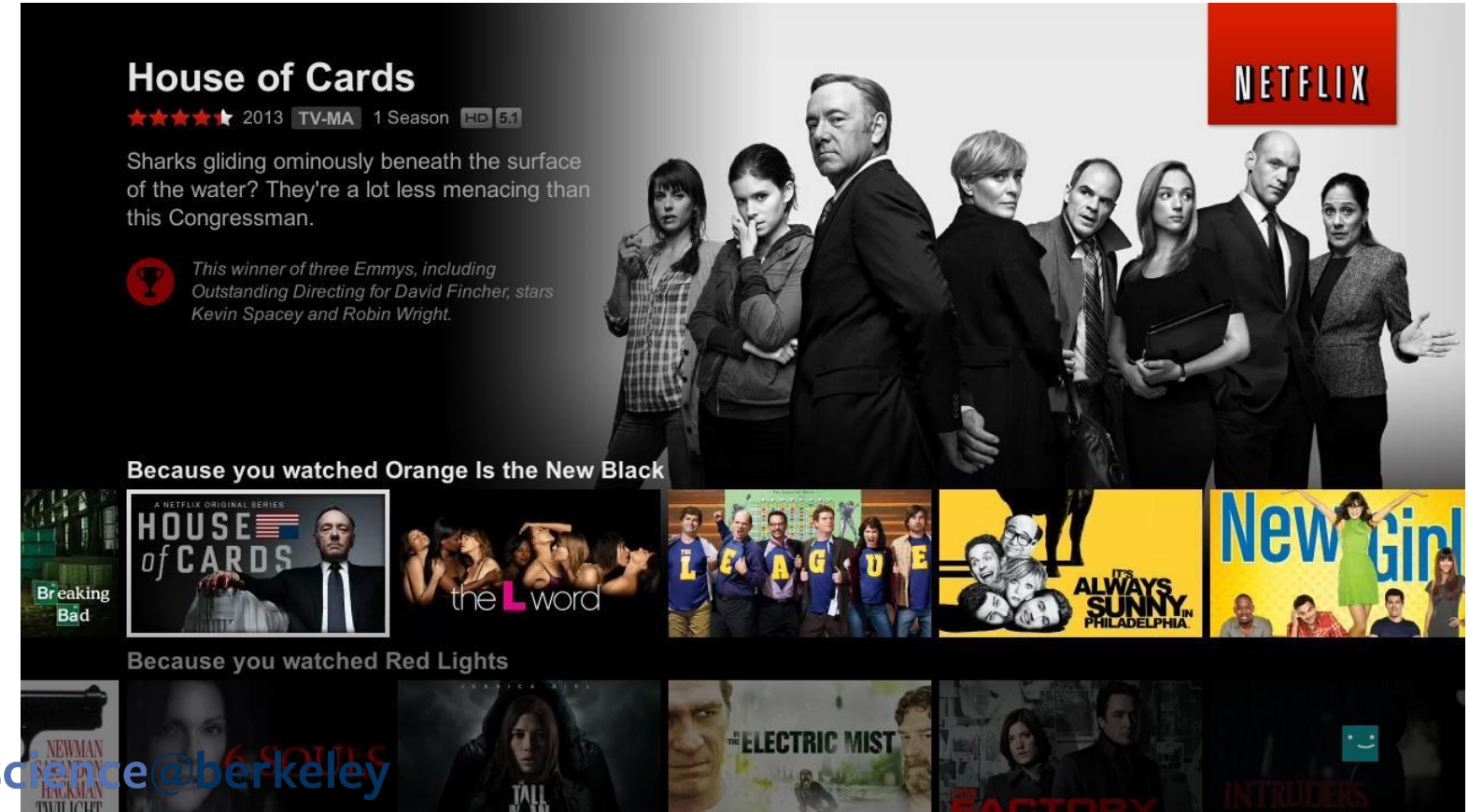
Duo Mix

Duo Mix is a playlist of songs that combines the music you and the other member of your Duo plan listens to.

It comes preloaded with songs based on genres, artists, and songs that you both have played on your own and updates the more you play.

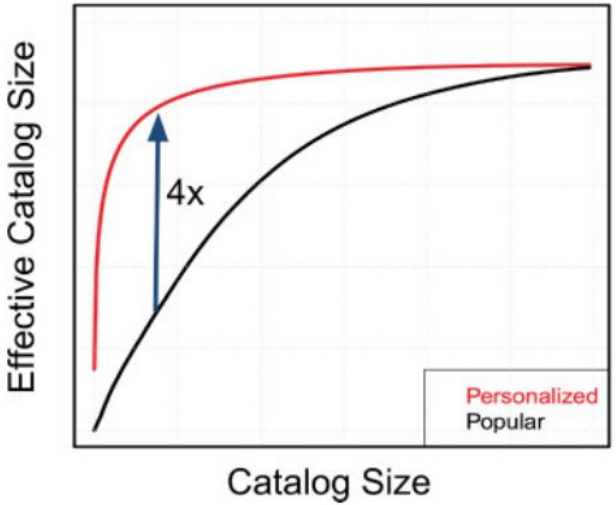
Tip: Don't have Premium Duo? Check out **Daily Mix** instead.

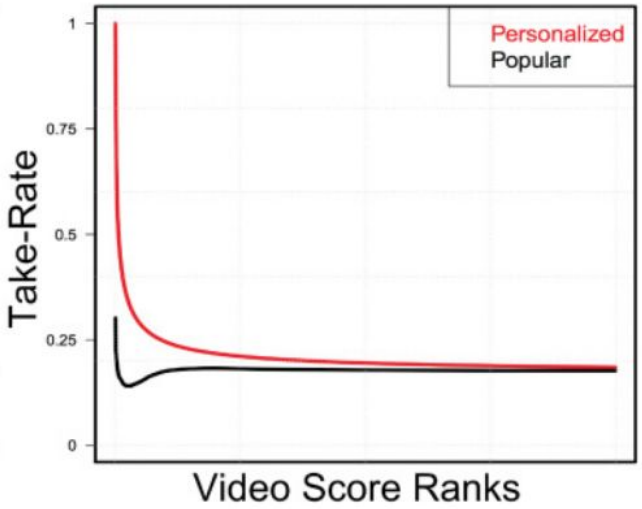
Netflix Today



Netflix Today

Netflix Today





The Netflix Recommender System: Algorithms, Business Value, and Innovation

CARLOS A. GOMEZ-URIBE and NEIL HUNT, Netflix, Inc.

Netflix Today

Netflix Today

Ranking

- Ranking = **Scoring** + **Sorting** + **Filtering** bags of movies for presentation to a user
- Goal: Find the best possible ordering of a set of *videos* for a *user* within a specific *context* in real-time
- Objective: maximize consumption
- Aspirations: Played & "enjoyed" titles have best score
- Akin to CTR forecast for ads/search results

- Factors
  - Accuracy
  - Novelty
  - Diversity
  - Freshness
  - Scalability
  - …

Netflix Today

Ranking

- Popularity is the obvious baseline
- Ratings prediction is a clear secondary data input that allows for personalization
- We have added many other features (and tried many more that have not proved useful)
- What about the weights?
  - Based on A/B testing
  - Machine-learned

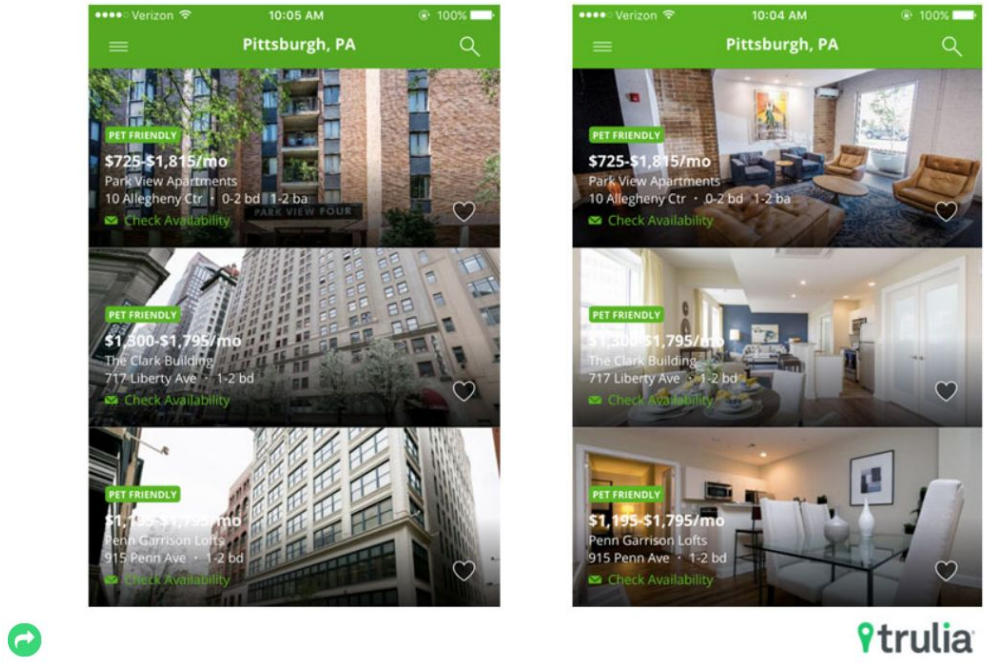
Netflix Today

Learning to Rank Approaches

1. Pointwise
   - Ranking function minimizes loss function defined on individual relevance judgment
   - Ranking score based on regression or classification
   - Ordinal regression, Logistic regression, SVM, GBDT, …
2. Pairwise
   - Loss function is defined on pair-wise preferences
   - Goal: minimize number of inversions in ranking
   - Ranking problem is then transformed into the binary classification problem
   - RankSVM, RankBoost, RankNet, FRank…

Learned Presentation

What Makes a Photo Click: Selecting Hero Images with Deep Learning



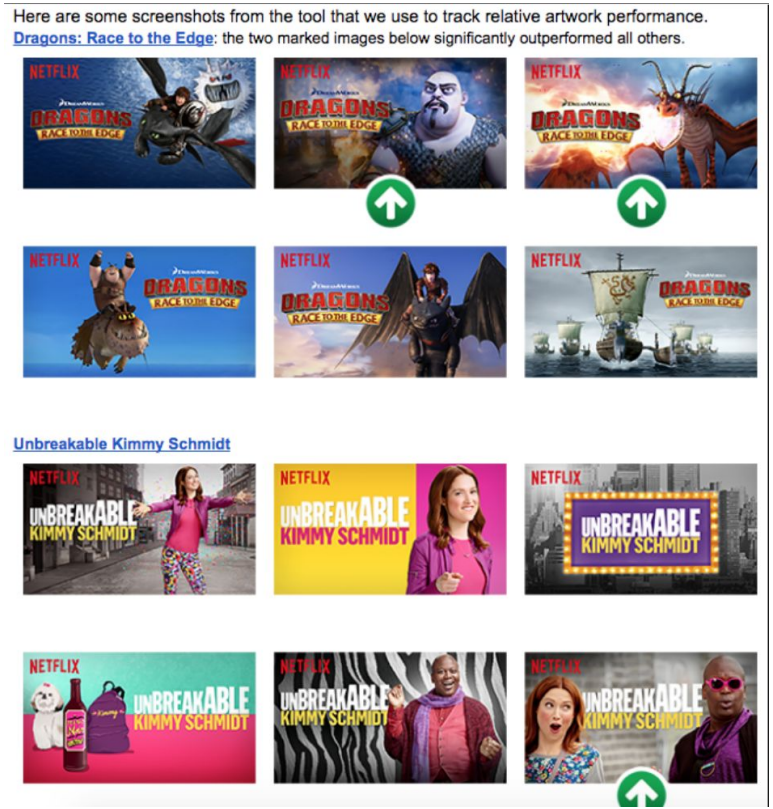
before (left) and after (right) implementing a hero image selection algorithm.

Learned Presentation

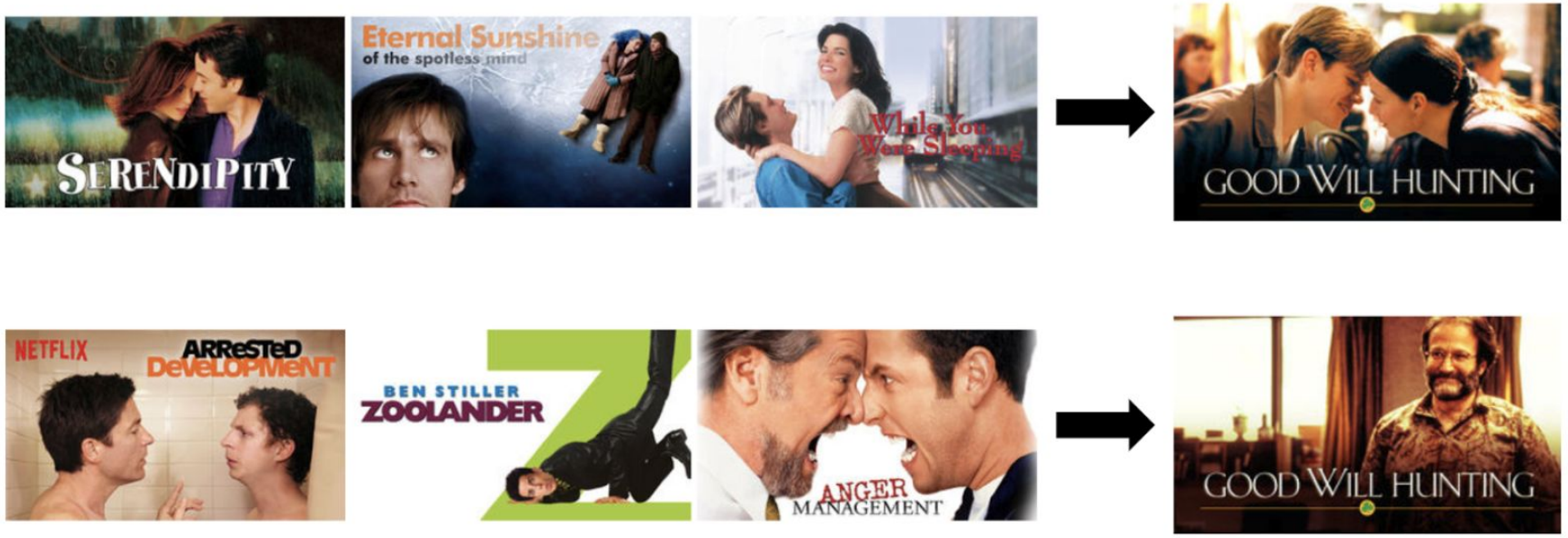
Using Deep Learning to automatically rank millions of hotel images

At idealo.de we trained two Deep Neural Networks to assess the aesthetic and technical quality of images 🙂😐😕

Personalized Presentation



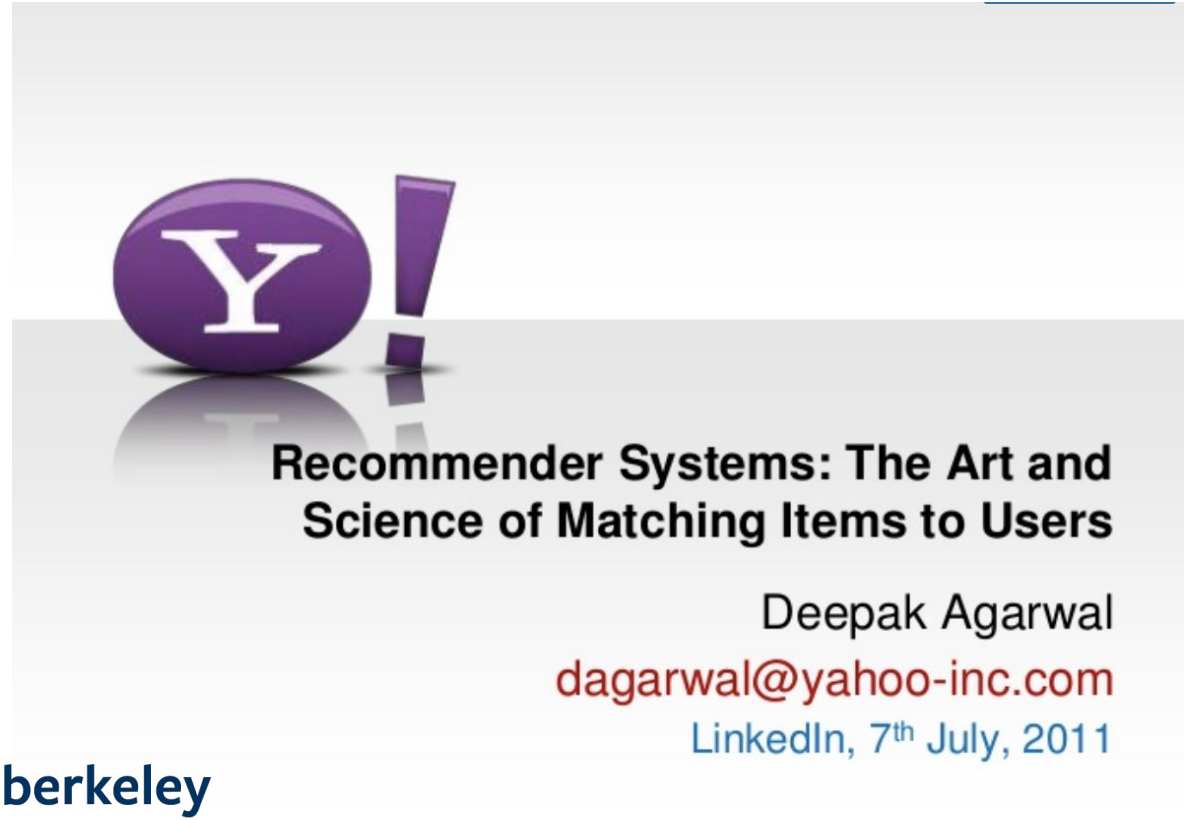
Personalized Presentation



Personalized Presentation

"We don't ask members for their race, gender or ethnicity so we cannot use this information to personalize their individual Netflix experience. The only information we use is a member's viewing history. In terms of thumbnails, these do differ and regularly change. This is to ensure that the images we show people are useful in deciding which shows to watch."

Bandits


Recommender Systems: The Art and Science of Matching Items to Users
Deepak Agarwal
dagarwal@yahoo-inc.com
LinkedIn, 7th July, 2011

Bandits


Content Optimization: Match articles to users
Clip slide
YAHOO!
Web Search
TODAY - July 14, 2010
World Cup octopus could make millions
TRENDING NOW
Anything you want, you got it with Ultimate Rewards.
Must-see music news & features
DAILY OFFERS

Bandits

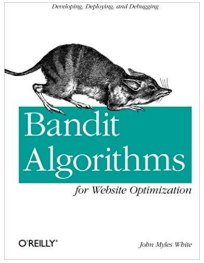
Back to Yahoo! front page

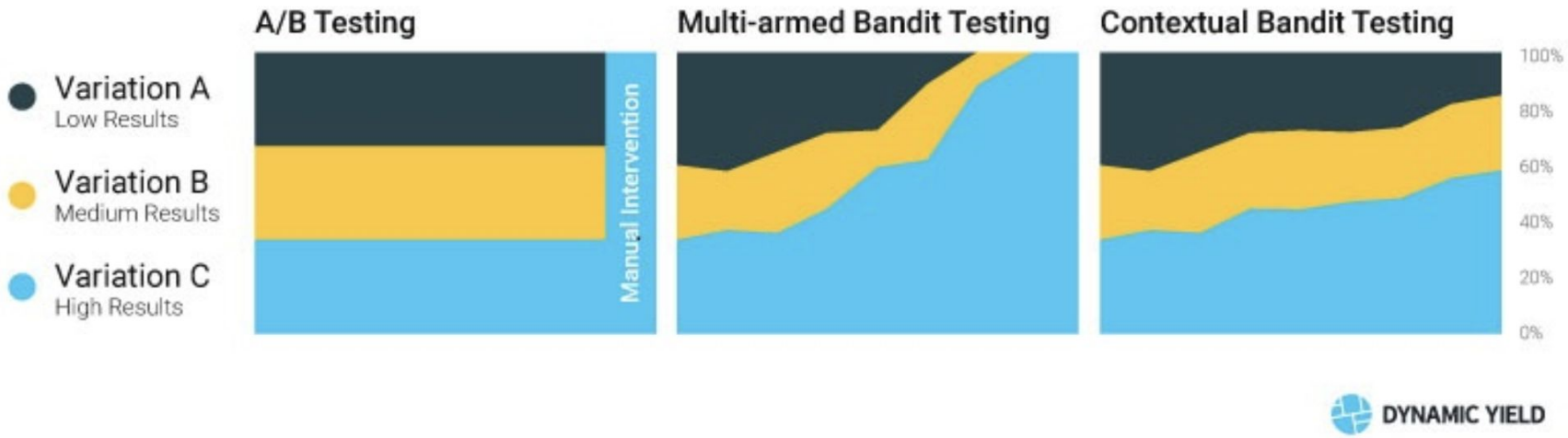
Recommend articles:
- Image
- Title, summary
- Links to other pages

For each user visit,
Pick 4 out of a pool of *K*

Routes traffic to other pages

Bandits


Developing, Deploying, and Debugging
Bandit Algorithms
for Website Optimization
O'REILLY
John Myles White


A/B Testing
Multi-armed Bandit Testing
Contextual Bandit Testing
Variation A
Low Results
Variation B
Medium Results
Variation C
High Results
Manual Intervention
100%
80%
60%
40%
20%
0%
DYNAMIC YIELD

Bandits

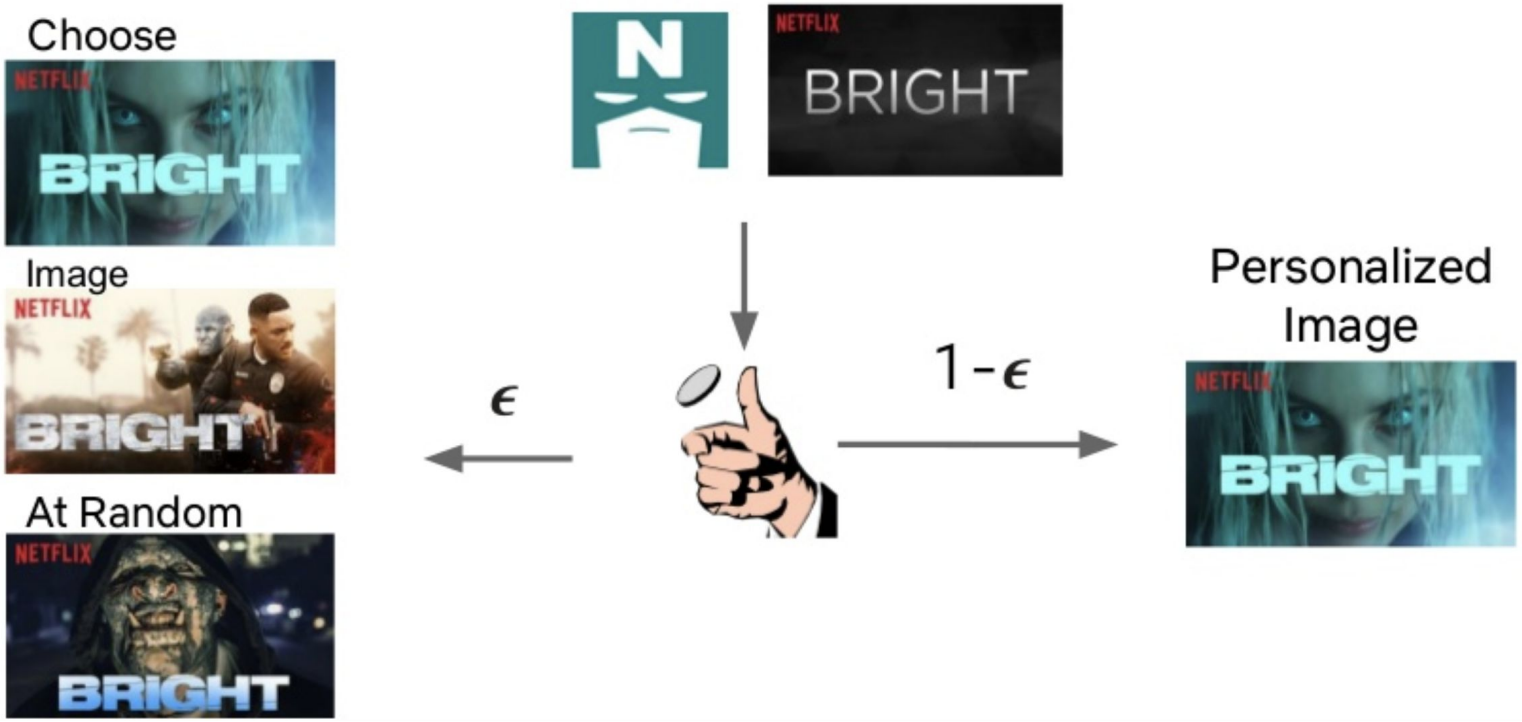
Epsilon-Greedy Example

									Observed Reward
1			0			1		0	2/4 (greedy)
	0				0			0	**0/3**
		0		1			0		1/3

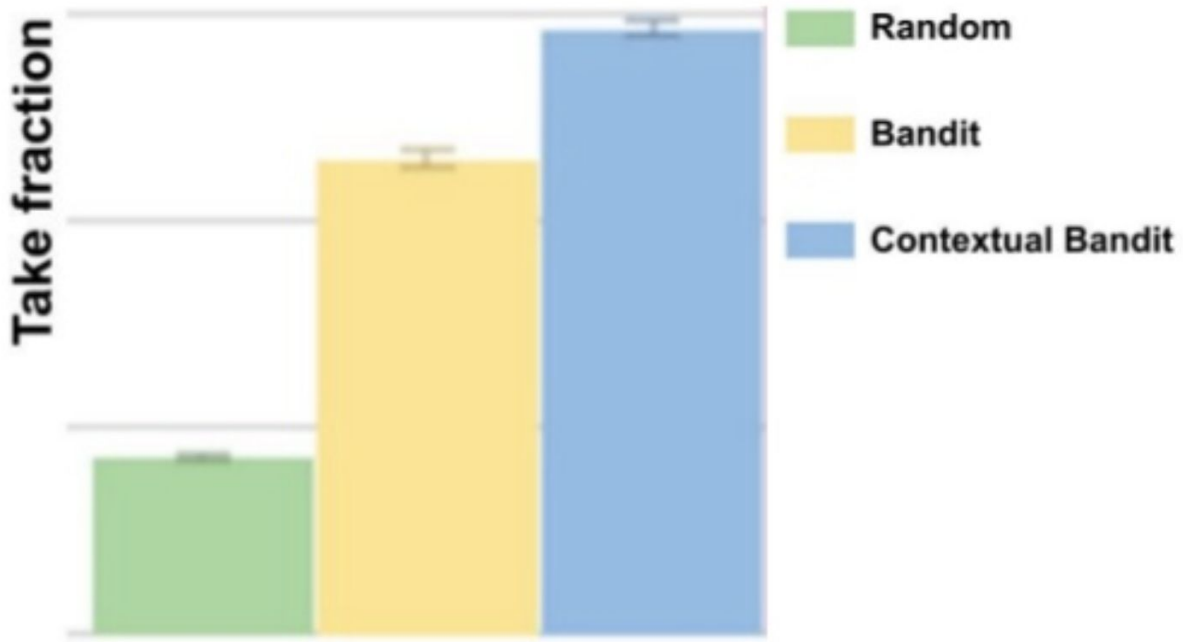
Bandits

- **Context**: Member, device, page, etc.

Bandits


Choose
Image
At Random
NETFLIX
BRIGHT
N
NETFLIX
BRIGHT
ϵ
1-ϵ
Personalized
Image
NETFLIX
BRIGHT

Bandits

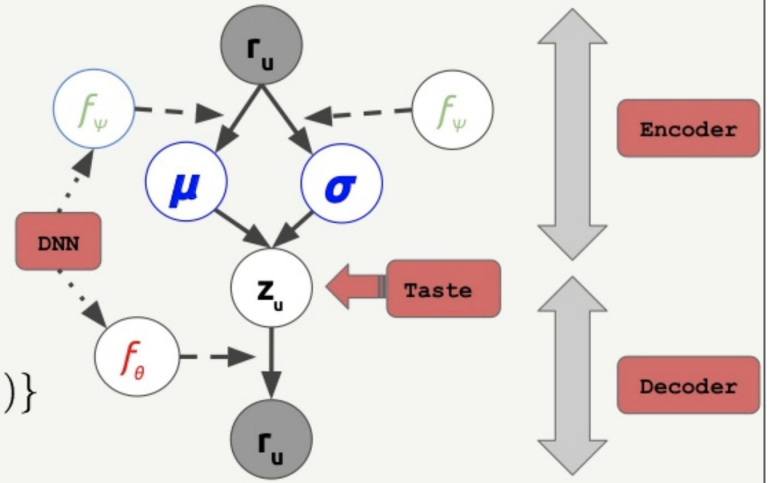


Frontier: Deep Latent Factors

Variational Autoencoders

Inference model:

$$q_\psi(\mathbf{z}_u \mid \mathbf{r}_u) = \mathcal{N}(\mu_\psi(\mathbf{r}_u), \text{diag}\{\sigma^2_\psi(\mathbf{r}_u)\})$$



Generative model:

$$\mathbf{z}_u \sim \mathcal{N}(0, \mathbf{I}_K), \;\; \pi(\mathbf{z}_u) \propto \exp\{f_\theta(\mathbf{z}_u)\}$$

$$\mathbf{r}_u \sim \text{Multi}(N_u, \pi(\mathbf{z}_u))$$

Liang et al. (2018), Variational Autoencoders for Collaborative Filtering, WWW.

Frontier: Whole Page Optimization

Beyond Ranking: Optimizing Whole-Page Presentation

Yue Wang[1*], Dawei Yin[2], Luo Jie[3†], Pengyuan Wang[2], Makoto Yamada[2,4], Yi Chang[2], Qiaozhu Mei[1,5]
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[2]Yahoo Labs, 701 First Avenue, Sunnyvale, CA, USA
[3]Snapchat, Inc., 64 Market St, Venice, CA, USA
[4]Bioinformatics Center, Institute for Chemical Research, Kyoto University, Uji, Kyoto, Japan
[5]School of Information, University of Michigan, Ann Arbor, MI, USA

Figure 1: Modern search engine result page.

The ACM Conference Series on
Recommender Systems

HOME RECSYS 2018 PAST CONFERENCES HONORS CONTACT search...

LATEST NEWS

July 26, 2018: Tentative lists of accepted short and long papers for RecSys 2018 are online!

July 12, 2018: This year's RecSys conference will feature a record number of six tutorials, taking place on Oct 2, prior to the main conference.

July 10, 2018: Acceptance notifications have been sent out: It was very competitive this year, with 18% acceptance rate for long and 25% for short papers.

July 4, 2018: Registration for RecSys 2018 is open!

June 12, 2018: The call for late-breaking results (posters) is out now, and the call for demos has been updated!

June 05, 2018: RecSys 2018 will feature three exciting keynotes by Elizabeth F. Churchill (Google), Lise Getoor (UCSC), and Christopher Berry (Canadian Broadcasting Corporation)!

May 30, 2018: The tutorial submission deadline has been extended to next Monday, June 4, 2018!

SHORTCUTS TO CONFERENCES

- RecSys 2018 (Vancouver)
- RecSys 2017 (Como)
- RecSys 2016 (Boston)
- RecSys 2015 (Vienna)
- RecSys 2014 (Silicon Valley)
- RecSys 2013 (Hong Kong)
- RecSys 2012 (Dublin)
- RecSys 2011 (Chicago)
- RecSys 2010 (Barcelona)
- RecSys 2009 (New York)
- RecSys 2008 (Lausanne)
- RecSys 2007 (Minnesota)

Final Thoughts?