GENERAL ASSEMBLY

INTRO TO DATA SCIENCE

RECOMMENDATION ENGINES

I. DATA TYPES
II. GENERAL DESIGN
III. CONTENT-BASED FILTERING
IV. COLLABORATIVE FILTERING
V. THE NETFLIX PRIZE

A recommendation system aims to match users to products/items/brands/etc that they likely haven't experienced yet and/or predict a user's preference based on past observations.

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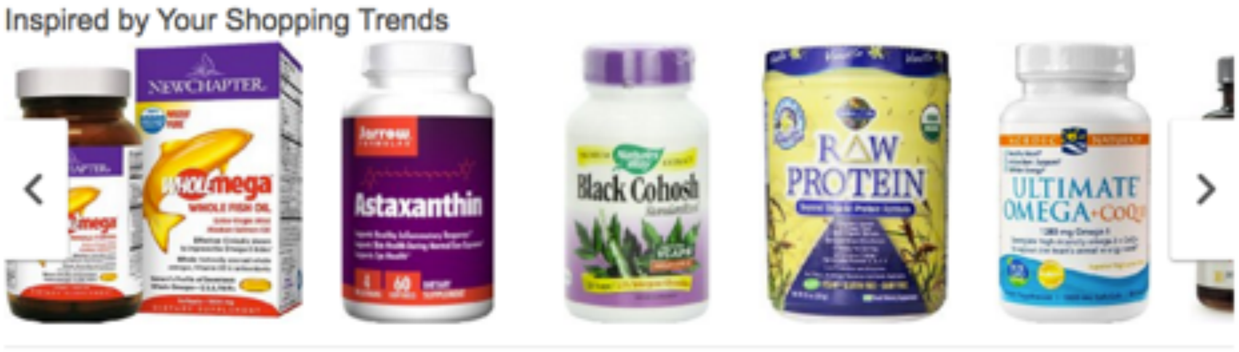
A **ranking** or **prediction** is produced by analysing other user/item ratings (and sometimes item characteristics) to provide personalised recommendations to users.

I. TYPES OF DATA

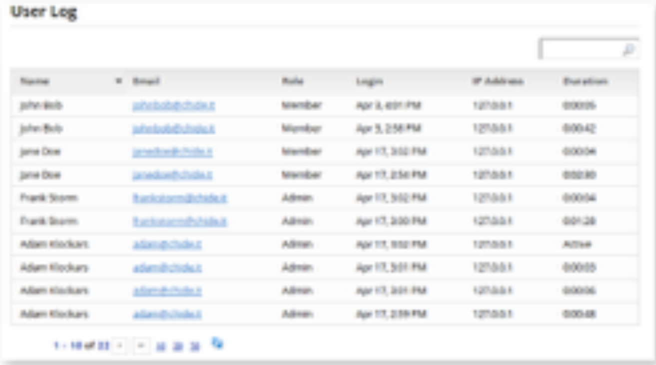
THE KIND OF RECOMMENDATIONS YOU CAN GIVE, ARE DEPENDENT ON THE DATA YOU HAVE.



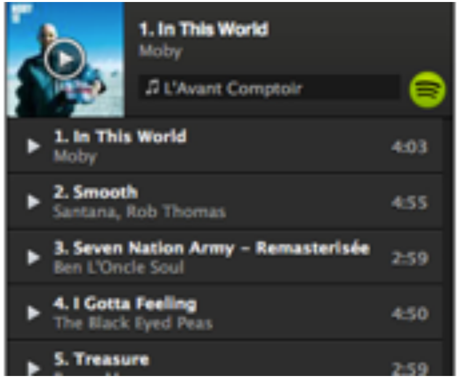
WE NEED DATA TO RECOMMEND

- **Preferences**
- **Ratings**
- **Item meta-data**
- **User Behavior**

Ratings
Upvotes / Downvotes
Weighted Scale
Grades
Relevance Feedback



Access Logs
Session Lengths
Time spent on a page
Clicks / Non-Clicks
Purchase History
Product Descriptions



Listening History
Playlist Creates
Follows / Unfriend
Impressions
Email Reads / Impressions

Recommenders need feedback to be useful.

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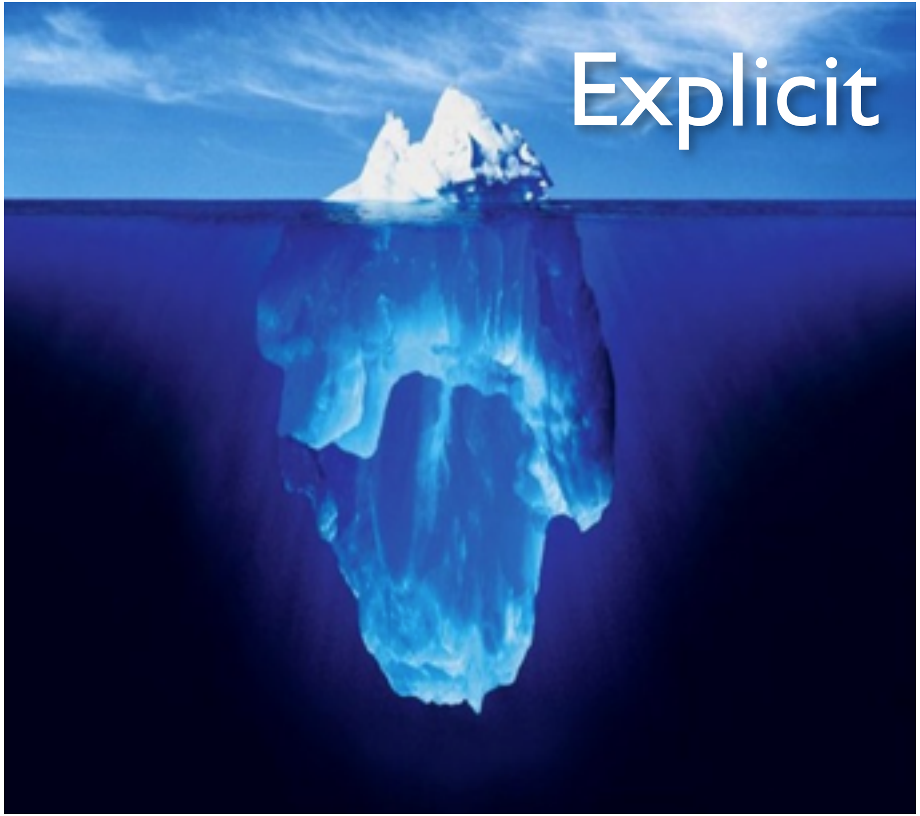
Explicit

- Explicitly given
- Pro-actively acquired
- Expensive to collect



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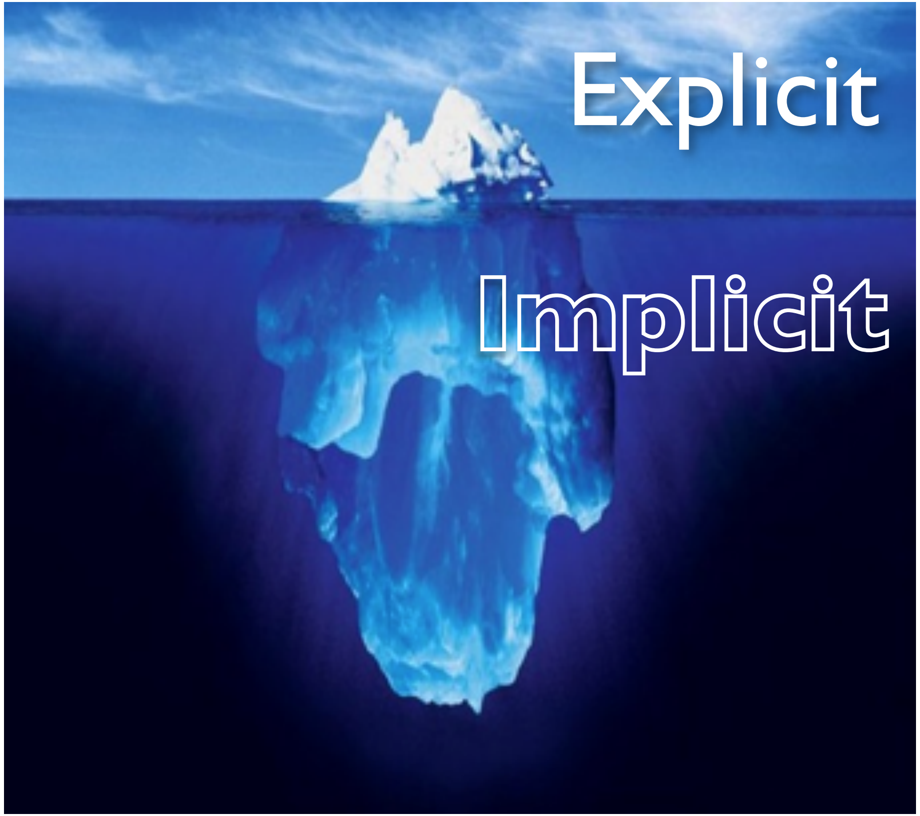
Explicit

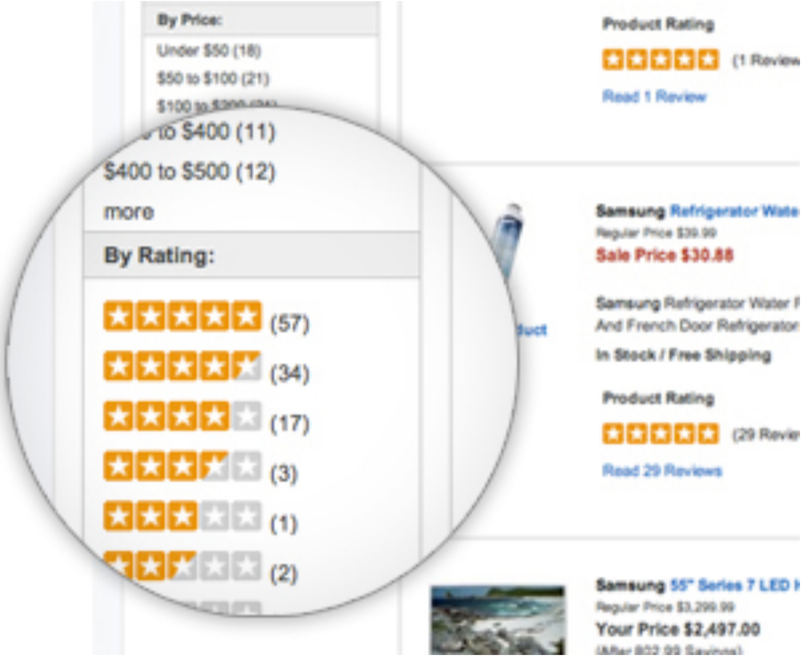
- Explicitly given
- Pro-actively acquired
- Expensive to collect

Implicit

- Indirectly given
- Larger quantity
- Latent qualities



Explicit or Implicit?



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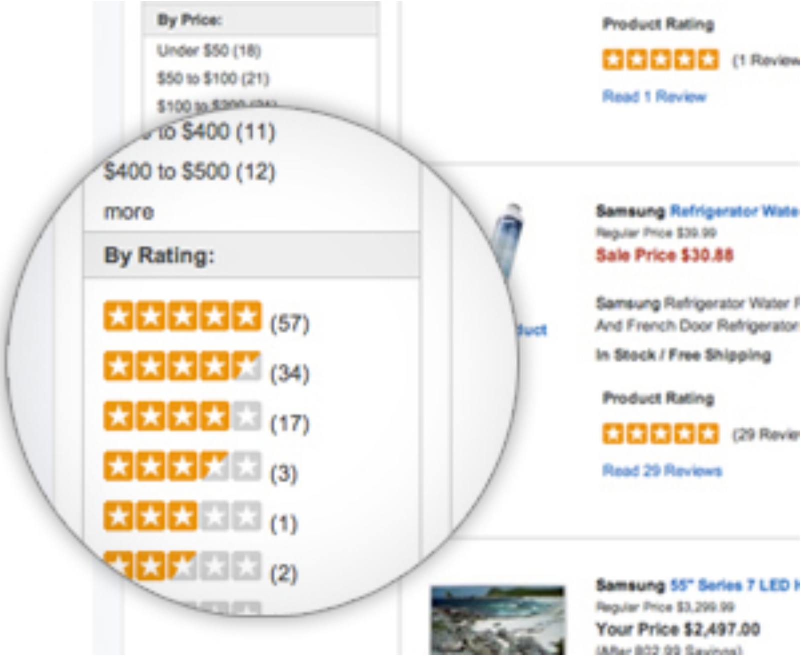
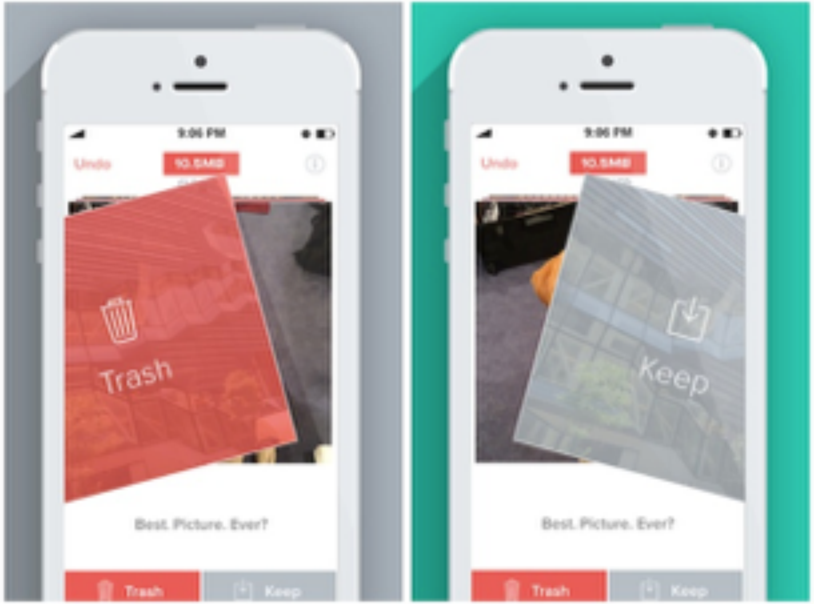
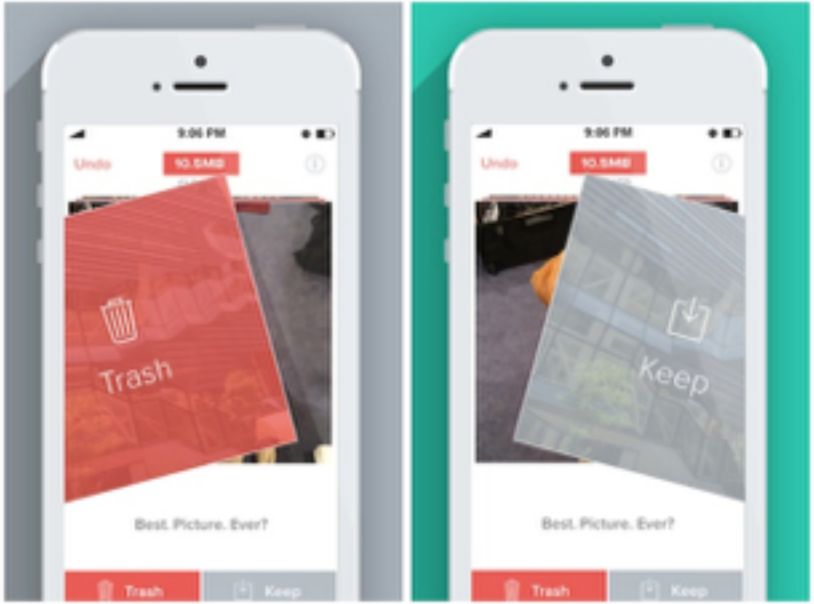


Explicit or Implicit?

Ratings: *Explicit*

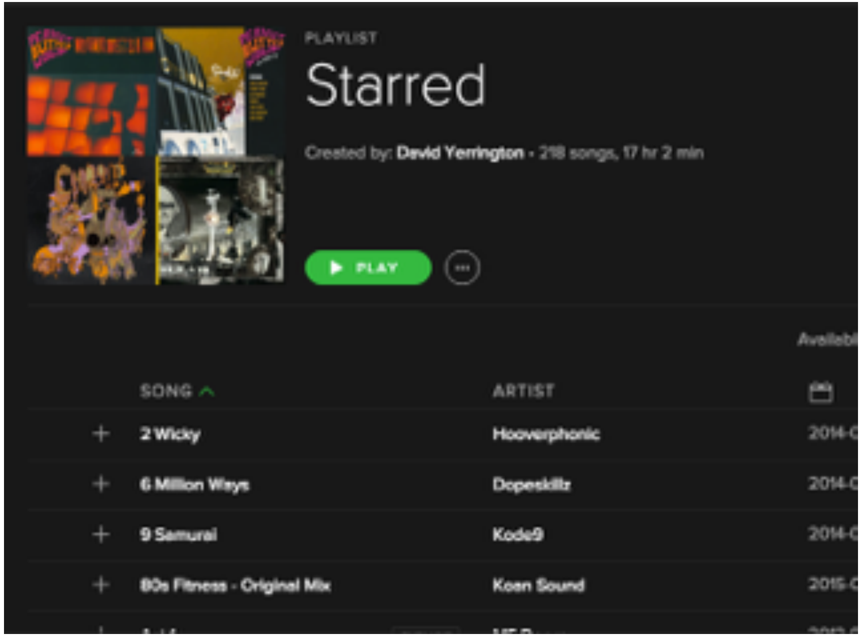


Explicit or Implicit?

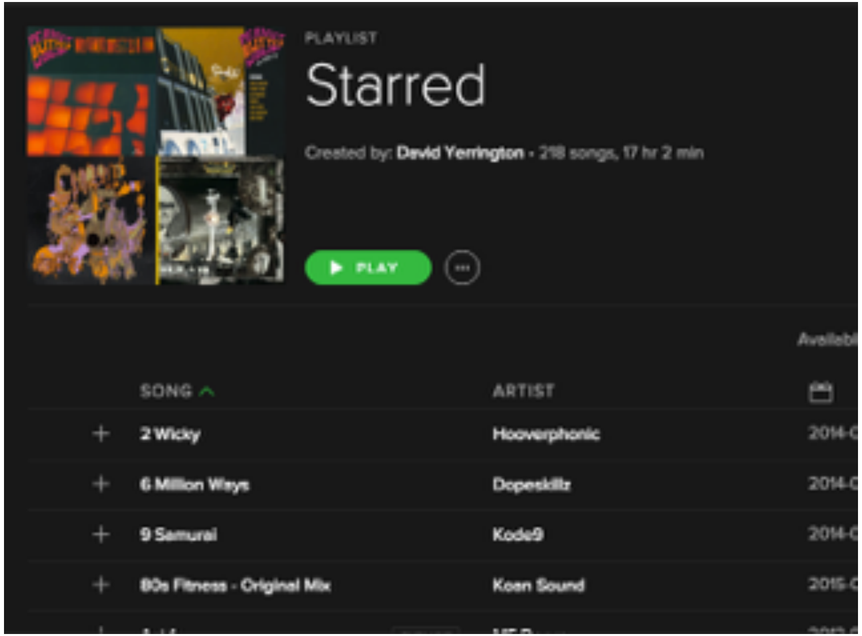


Explicit or Implicit?

Swipes: *Explicit*



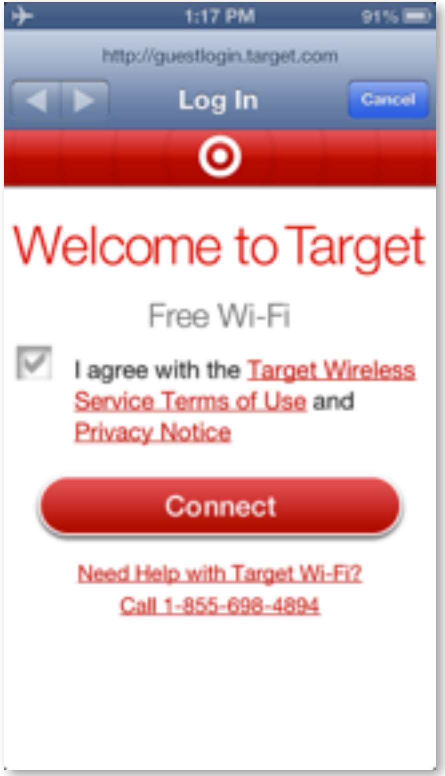
Explicit or Implicit?



Explicit or Implicit?

Both!

Explicit or Implicit?



Explicit or Implicit?

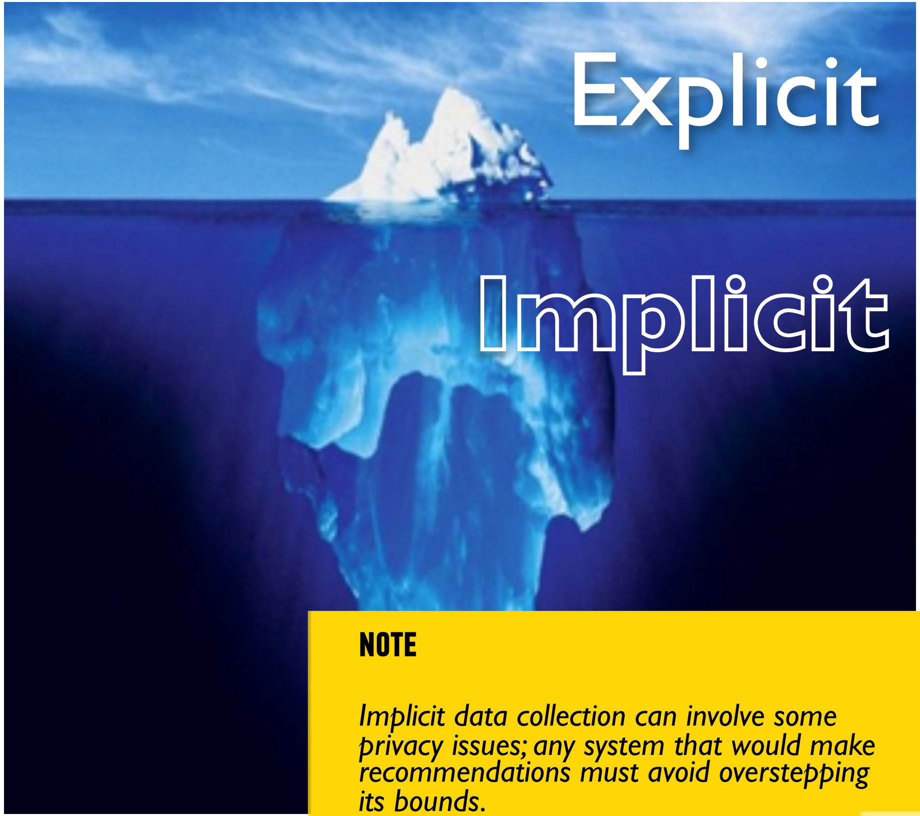
Wifi logs: *Implicit!*

Explicit

- Ie: Ratings, surveys, reviews
- Easy to interpret
- Expensive

Implicit

- Ie: Activity logs, clicks, impressions
- Hard to interpret
- Cheap



NOTE

Implicit data collection can involve some privacy issues; any system that would make recommendations must avoid overstepping its bounds.

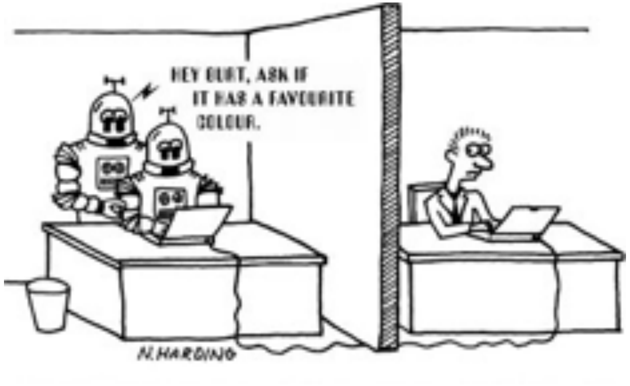
Implicit + Explicit Feedback: Final Caveat

Take care when creating explicit data from implicit data.

- **Does the set of actions reflect a preference?**
- **Does the scale make sense?**
- **Is the outcome prediction (ratings) or recommendation?**

Explicit

- Higher value with respect to preferences
- Usually collected as a “rating”
- Collection is responsibility of user
- More direct evaluation of items



Implicit

- Easy to collect in large quantities
- More difficult to work with
- Assumes nothing about the user (could be anyone!)
- Goal is to convert into preferences

II. GENERAL DESIGN

There are two general approaches to the design:

There are many approaches to the design, but these are common modelling techniques:

In **content-based filtering**, *items are mapped into a feature space, and recommendations depend on item characteristics.*

In contrast, an important assumption underlying all of ***collaborative filtering***, *is: users who have similar preferences in the past are likely to have similar preferences in the future.*

EXAMPLES – AMAZON CONTENT-BASED

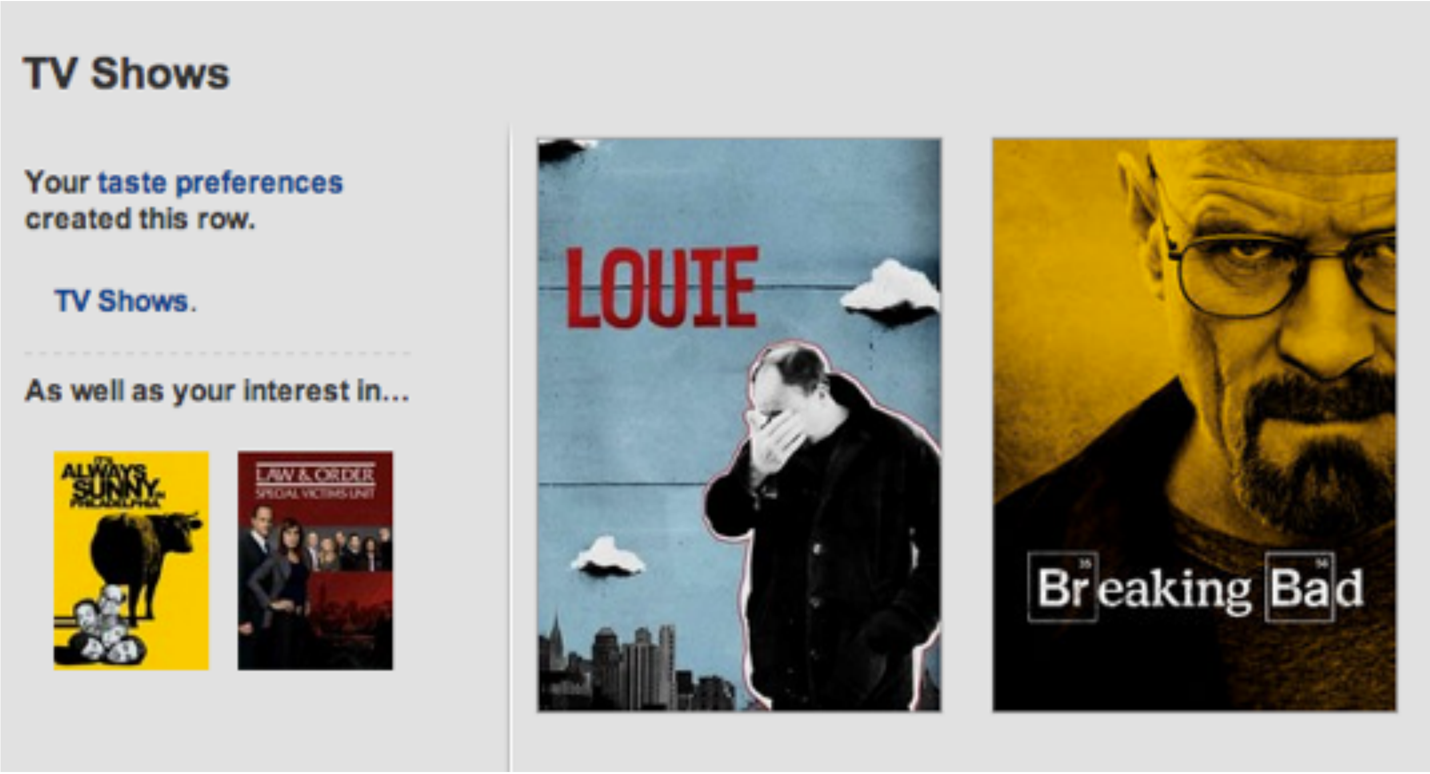
Customers Who Bought This Item Also Bought

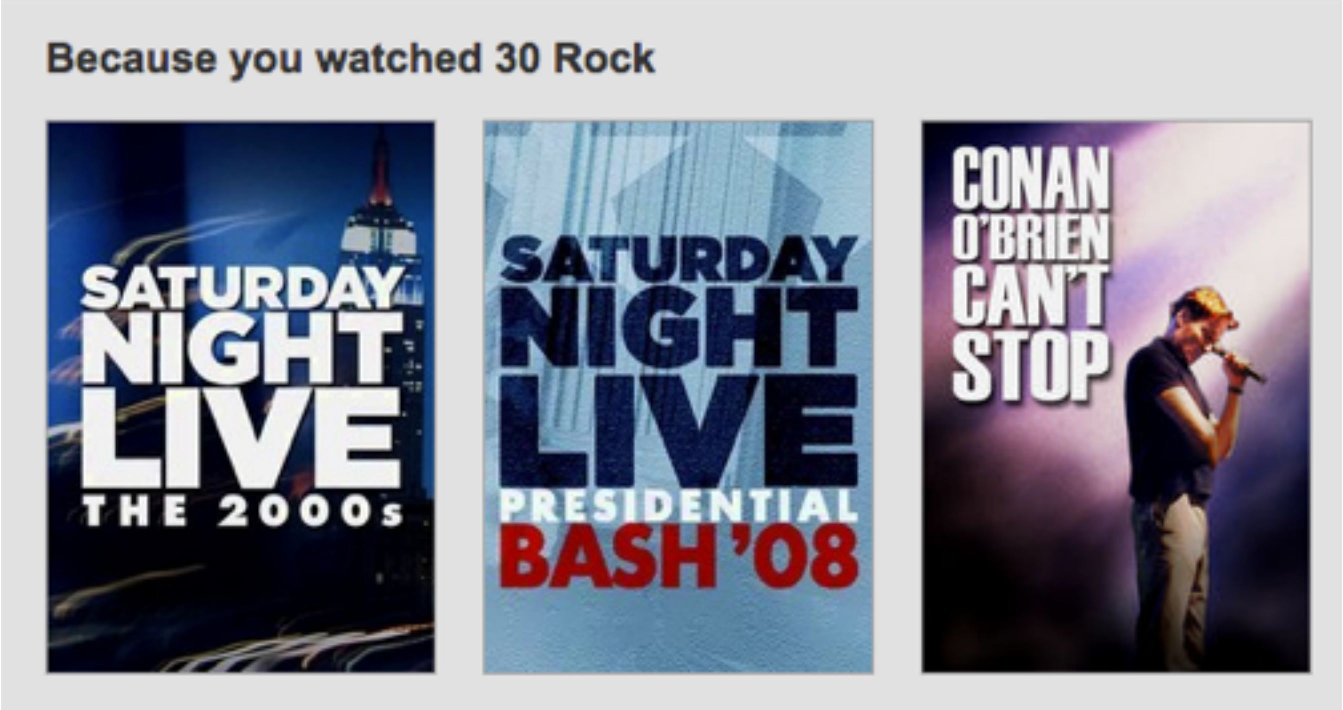
Pitch Dark (NYRB Classics)
› Renata Adler
Paperback
$11.54

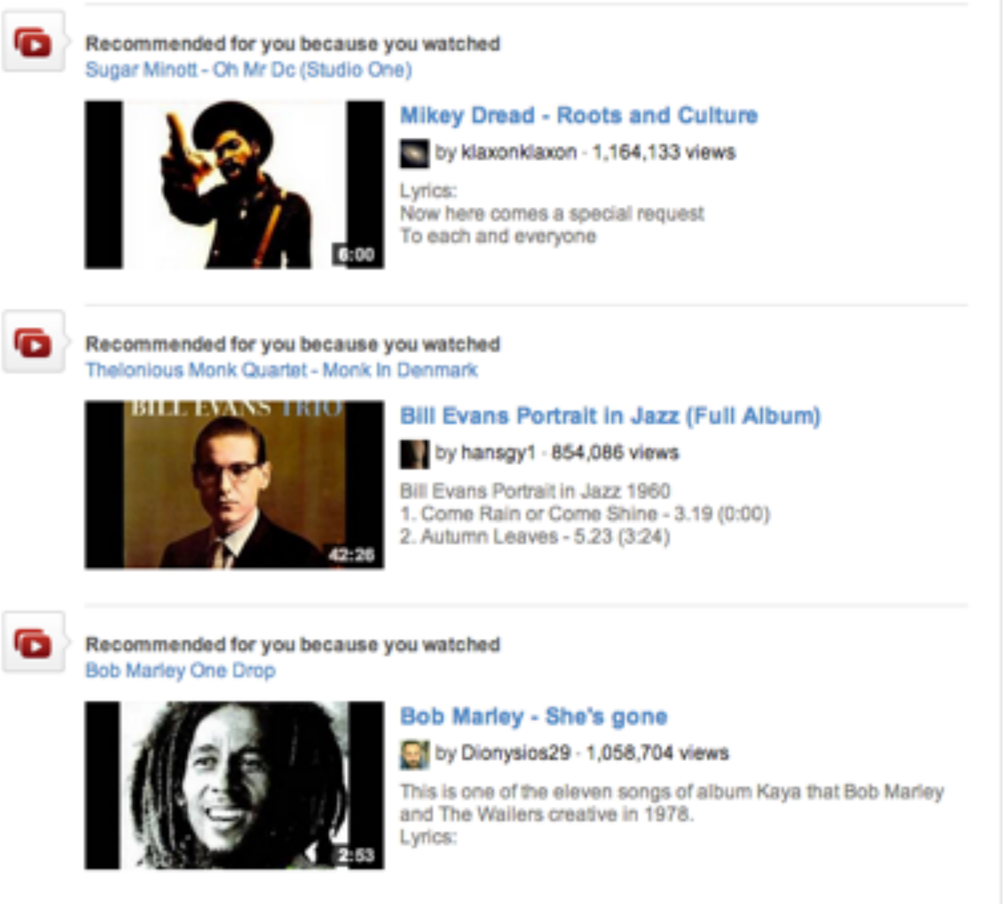
How Literature Saved My Life
› David Shields
★★★★☆ (60)
Hardcover
$18.08

Bleeding Edge
Thomas Pynchon
Hardcover
$18.05

The Flamethrowers: A Novel
› Rachel Kushner
★★★½☆ (17)
Hardcover
$15.79


TV Shows
Your taste preferences created this row.
TV Shows.
As well as your interest in...
LAW & ORDER
LOUIE
Breaking Bad


Because you watched 30 Rock
SATURDAY NIGHT LIVE
THE 2000s
SATURDAY NIGHT LIVE
PRESIDENTIAL
BASH '08
CONAN O'BRIEN CAN'T STOP


Recommended for you because you watched
Sugar Minott - Oh Mr Dc (Studio One)
Mikey Dread - Roots and Culture
by klaxonklaxon · 1,164,133 views
Lyrics:
Now here comes a special request
To each and everyone
6:00
Recommended for you because you watched
Thelonious Monk Quartet - Monk In Denmark
BILL EVANS TRIO
Bill Evans Portrait in Jazz (Full Album)
by hansgy1 · 854,086 views
Bill Evans Portrait in Jazz 1960
1. Come Rain or Come Shine - 3.19 (0:00)
2. Autumn Leaves - 5.23 (3:24)
42:26
Recommended for you because you watched
Bob Marley One Drop
Bob Marley - She's gone
by Dionysios29 · 1,058,704 views
This is one of the eleven songs of album Kaya that Bob Marley and The Wailers creative in 1978.
Lyrics:
2:53

How can we find good recommendations?

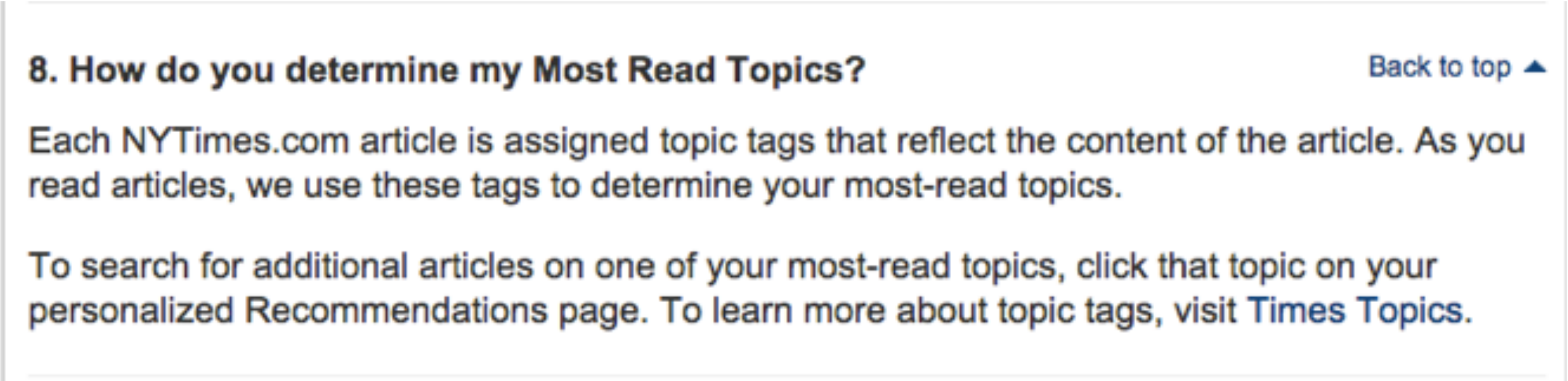
- Manual Curation
- Manually Tag Attributes
- Audio Content, Metadata, Text Analysis
- Collaborative Filtering

content-based filtering

EXAMPLES – NYTIMES.COM

MOST E-MAILED | RECOMMENDED FOR YOU

1. How Big Data Is Playing Recruiter for Specialized Workers
2. SLIPSTREAM
   When Your Data Wanders to Places You've Never Been
3. MOTHERLODE
   The Play Date Gun Debate
4. For Indonesian Atheists, a Community of Support Amid Constant Fear
5. Justice Breyer Has Shoulder Surgery
6. BILL KELLER
   Erasing History


8. How do you determine my Most Read Topics?

Back to top

Each NYTimes.com article is assigned topic tags that reflect the content of the article. As you read articles, we use these tags to determine your most-read topics.

To search for additional articles on one of your most-read topics, click that topic on your personalized Recommendations page. To learn more about topic tags, visit Times Topics.

NOTE

Collaborative or Content based?

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CONTENT BASED ☺️

III. CONTENT-BASED FILTERING

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Ratings are generated by measuring similarity between user and/or item vectors.

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- *Must map items into a feature space (usually by hand!)*
- *Recommendations are limited in scope (items must be similar to each other)*
- *Hard to create cross-content recommendations (eg books/music films…this would require comparing elements from different feature spaces!)*

IV. COLLABORATIVE FILTERING

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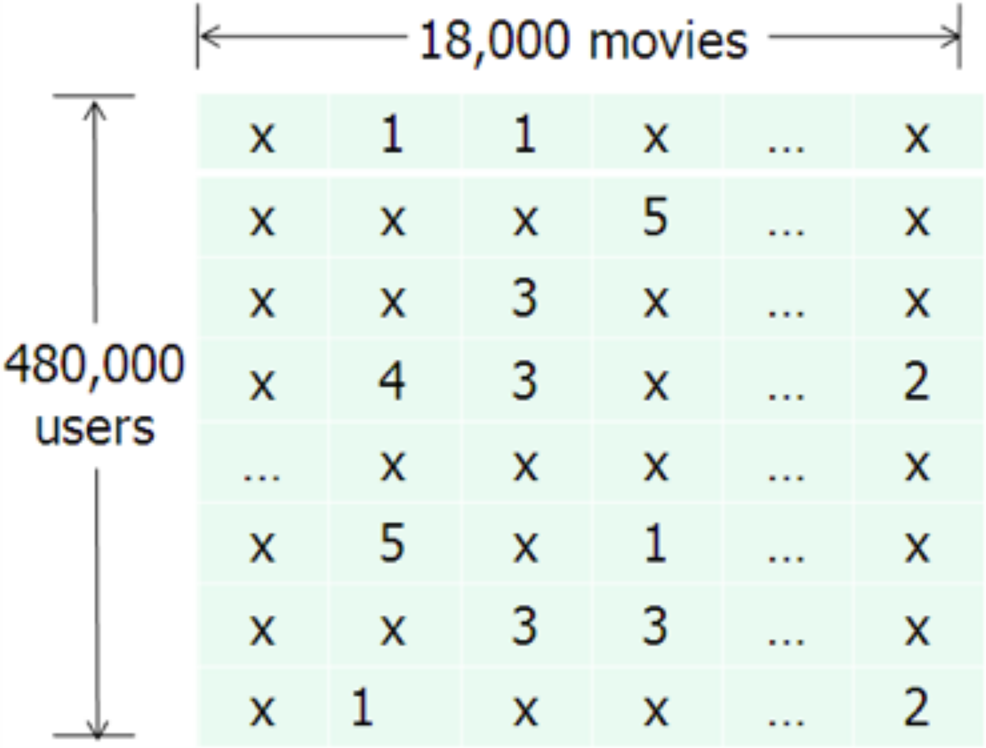
NOTE

The idea here is that users get value from recommendations based on other users with similar *tastes*.



NOTE

This matrix will always be *sparse*!

source: http://www.eecs.berkeley.edu/~zhanghao/main/publications/subfolder/netflix.png

Main difference between content and collaborative filtering:

Content Based:

maps items and users into a feature space

Collaborative:

relies on previous user-item ratings

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NOTE

Sounds familiar? It's similar to KNN!

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The system cannot draw inferences because it hasn’t gathered enough information yet.

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We can get around this by enhancing our recommendations using **implicit feedback***, which may include things like item browsing behaviour, search patterns, purchase history, etc.*

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While explicit feedback (ratings, likes, purchases) leads to high quality ratings, the data is sparse and cold starts are problematic.

Meanwhile implicit feedback (browsing behaviour, etc.) leads to less accurate ratings, the data is much more dense (and less invasive to collect).

V. THE NETFLIX PRIZE

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The ratings matrix contained >100mm numerical entries (1-5 stars) from ~500k users across ~17k movies. The data was split into train/quiz/test sets to prevent overfitting on the test data by answer submission (this was a clever idea!).

The competition began in 2006, and the grand prize was eventually awarded in 2009. The winning entry was a stacked ensemble of 100's of models (including neighbourhood and matrix factorisation models) that were blended using boosted decision trees.

Ultimately, the competition ended in a photo finish. The winning strategy came down to last-minute team mergers and creative blending schemes to shave 3rd & 4th decimals off RMSE (concerns that would not be important in practice).

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The competition did much to spur interest and research advances in recommender systems technology, and the prize money was donated to charity.

Though they adopted some of the modelling techniques that emerged from the competition, Netflix never actually implemented the prizewinning solution.

Why do you think that’s true?

VI. SUMMARY

- *Want to predict how users are going to rate items*
- *Obtain ratings implicitly or explicitly*
- *Try to predict these ratings through*
    - *Content based filtering*
    - *Collaborative filtering*
    - *Need to measure the similarity between user and item pairs*

- *Data Sparsity*
- *Cold Start*
- *Scalability*
- *Accurate but also recommendation of new content*
- *Evaluation*
- *Transparency to users*
- *Temporal changes*
- *Vulnerability to attacks*