# 2-1: Introduction to Non-Personalized Recommenders

Learning Objectives

- To understand the value of non-personalized recommenders, and domains where they are most useful

- To understand the drawbacks of non-personalized recommender systems

- To understand the basics of:
  - Aggregated opinion recommenders
  - Basic product association recommenders

- Review examples of the above …

The Story of Zagat
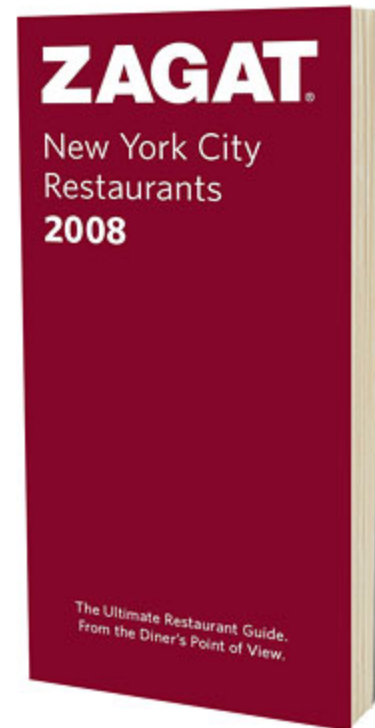
The Zagat Guide ...

hail the new chef – Michael Anthony, formerly of Blue Hill at Sto
Barns – and salute his "spellbinding" market-centric cuisine ......

Gary Danko
San Francisco | American

Food	Decor	Service	Cost
29	26	28	$104

"Gary Swanko" "fully merits its superb reputation" gush "flush" "
ies" who vote the "celebrity" chef-owner's "sleek" New American
"temple of gastronomy" in Fisherman's Wharf No. 1 ......

Charlie Trotter's
Chicago | American

Food	Decor	Service	Cost
27	25	27	VE

"A religious experience" "worth a mortgage payment" awaits at
Lincoln Parker, the "epitome of [New] American gastronomy" an
Chicagoland's Most Popular restaurant, where customers ......

Babbo
New York | Italian

Food	Decor	Service	Cost
27	25	27	$76

"When it's this good" "it's not hype" is still the consensus as Ma
Batali and Joe Bastianich celebrate the 10th anniversary of thei
"fabulously popular" Village flagship that's voted NYC's No. 1 ...

Spago
Los Angeles | Californian

Food	Decor	Service	Cost
27	25	25	$73

"Forget Gibraltar, this place is the rock of Los Angeles" sum up

Secrets Revealed!

- The "secret" formula

  Rating = {0, 1, 2, 3}

  Score = round (MEAN(ratings) * 10)

  – OK, maybe not so secret – but effective!

Crystal Cruises

CRUISE LINE WEBSITE

READERS' CHOICE AWARDS

94.2

COMPLETE RCA

OVERALL SCORE

1 of 2

Score	Category
94.5	ITINERARIES
88.4	EXCURSIONS
97.7	SERVICE
91.6	CABINS
96.5	FOOD
94.2	ACTIVITIES
96.4	DESIGN

See Methodology »

READERS' CHOICE AWARDS

📍 Top 10 Midsize-Ship Lines

GOLD LIST

🏆 2013

THIS FLEET SAILS TO:

South America

Its two ships' itineraries recently extended to Antarctica, Alaska, and West Africa. Excursions include local volunteer programs, helicopter rides in New Zealand, and splurges like a drive through Monte Carlo in a Lamborghini. On board, expect "the best lecturers and personalities of any cruise line." Rooms have "more than enough hanging and drawer space, and spectacular marble bathrooms"; Crystal Penthouses come with ocean view hot tubs, and some have Swarovski chandeliers. "The true standouts are the restaurants," which are all complimentary and include Silk Road and the Sushi Bar, a specialty dining room where the sushi is made by Nobu-trained chefs and "is beyond compare." Year to year, "staff remember your favorite cocktails." The spas use Elemis skin products, and there are Nordic Walking fitness classes.

Subscribe to The Daily Traveler Newsletter

enter your e-mail address   SUBMIT

SEE AN EXAMPLE | PRIVACY POLICY

Same idea, different formula

- Conde Nast Traveller tallies the percentage of people who rate a particular hotel, cruise, etc. as "very good" or "excellent"

- Relative merits of the two techniques …

  – How do we treat a score of "good" vs. "awful"

Many other examples

- Tripadvisor travel reviews and ratings
- Billboard top 200/100/20 …
- Movie charts by box office revenue

- All non-personalized
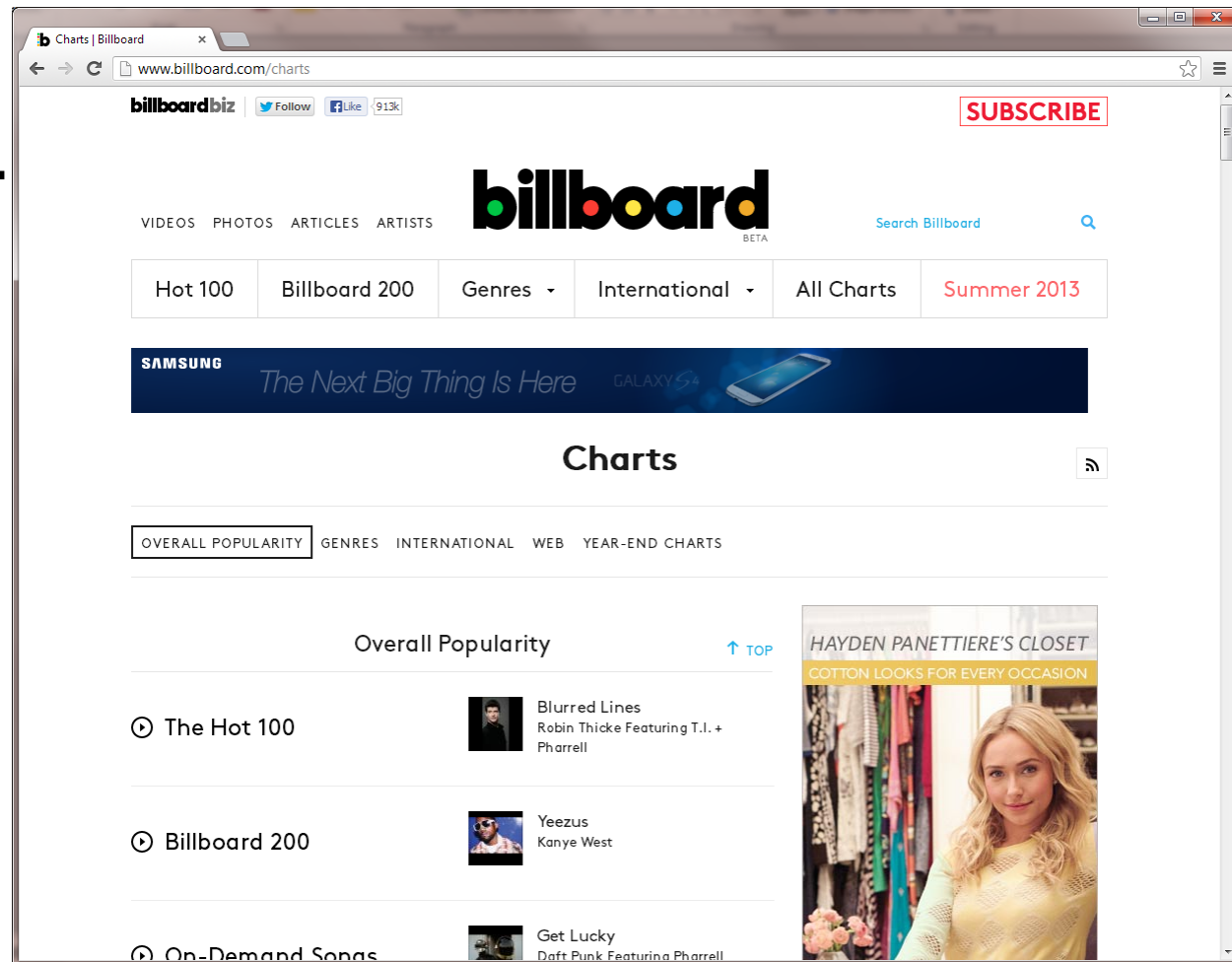
Averages can be Misleading

- Later this module … we'll discuss ways to mislead using averages.

- See if you can come up with examples or ideas (post to the class forum, and vote up the ones you find most compelling)

Averages Lack Context …

- Ordering an ice-cream sundae
  - You want a recommendation for a sauce
  - Do you want to hear that ketchup is the most popular sauce?
- One interesting context is a current product (or set of products) – what sauce is most commonly associated with a sundae??
- This leads to the concept of product association recommenders!

People who X also Y …

- Great idea, but how to formalize
- First, what's our dataset
  - User profiles (people who ever bought one and the other)? – not good for ketchup
  - Transaction data (people who bought them at the same time)? – not good for follow-up sales
  - User profiles but time-constrained (within a month, afterwards, …)?

Computing the ranking

- Start simple: percentage of X-buyers who also bought Y

$$\frac{X \text{ and } Y}{X}$$

  – Intuitively right, but is it useful? What if X is anchovy paste and Y is bananas??
  – Challenge – doesn't compensate for overall popularity of Y

Take two – does X make Y more likely??

- Let's adjust by looking at whether X makes Y more likely than not X(!X)

$$\frac{\dfrac{X \text{ and } Y}{X}}{\dfrac{!X \text{ and } Y}{!X}}$$

  - This formula focuses on increase in Y associated with X

Take two – does X make Y more likely??

- Let's adjust by looking at whether X makes Y more likely than not X(!X)

$$100X \quad \frac{50}{100} \quad \frac{1}{2} \quad \frac{X \text{ and } Y}{X}$$

$$\frac{450}{99,900} \quad \frac{9}{2000} \quad \frac{!X \text{ and } Y}{!X}$$

anchovy $\left.\begin{array}{c} \end{array}\right\} \dfrac{95}{100}$ banana

$$= 1$$

$$\frac{94,905}{99,900}$$

- This formula focuses on increase in Y associated with X

UNIVERSITY OF MINNESOTA

Other solutions …

- Association rule mining brings us the lift metric:

$$\frac{P(X\ AND\ Y)}{P(X) * P(Y)}$$

  – This looks at non-directional assocation

  – More generally association rules look at baskets of products, not just individuals

Back to Zagat

- Some early Zagat fans argue the guide has been getting worse. Why?
  - Too many mediocre restaurants with good scores
  - Too many excellent restaurants with mediocre scores
- What's happening here?
  - Self-selection bias
  - Increased diversity of raters

Some take-away lessons

- Non-personalized averages can be effective in the right application
    - Need to understand relationship between average and user need; correct average
- Product associations can provide useful non-personalized recommendations in a context
    - Need to identify context; data source/scope
- Still face challenges in a clustered diverse population (e.g., maybe we don't all want bananas)

Moving Forward

- Assignments this Module
  - Review an existing recommender
  - Hand-exercise: non-personalized recommender
  - Programming: non-personalized recommender
- Next lectures: about ratings, predictions and recommendations, rating scales
- Then, you should be able to:
  - Work out non-personalized recommendations
  - For programmers: program them too!

2-1: Introduction to Non-Personalized Recommenders