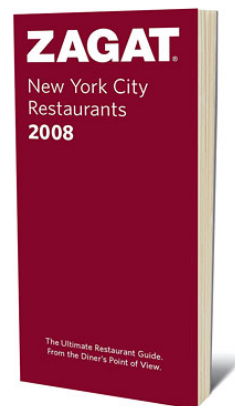


2-1: Introduction to Non-Personalized Recommenders

Introduction to Recommender Systems

The Story of Zagat















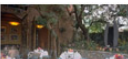



Introduction to Recommender Systems

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 ...

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The Zagat Guide ...

		hail the new chef – Michael Anthony, formerly of Blue Hill at St. Barns – and salute his “spellbinding” market-centric cuisine					
		Gary Danko   		Food	Decor	Service	Cost
San Francisco American				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   		Food	Decor	Service	Cost
Chicago American				27	25	27	VE
		“A religious experience” “worth a mortgage payment” awaits at Lincoln Parker, the “epitome of [New] American gastronomy” at Chicagoland’s Most Popular restaurant, where customers					
		Babbo  		Food	Decor	Service	Cost
New York Italian				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 their “fabulously popular” Village flagship that’s voted NYC’s No. 1 ..					
		Spago   		Food	Decor	Service	Cost
Los Angeles Californian				27	25	25	\$73
		“Forget Gibraltar, this place is the rock of Los Angeles” sum up					

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Secrets Revealed!

- The “secret” formula
 - Rating = {0, 1, 2, 3}
 - Score = round (MEAN(ratings) * 10)
- OK, maybe not so secret – but effective!

Introduction to Recommender Systems

The screenshot shows the Crystal Cruises website. At the top, it says "Crystal Cruises: Condé Nast Traveler". Below that, it says "Crystal Cruises" and "CRUISE LINE WEBSITE". A large circular badge displays the "READERS' CHOICE AWARDS 94.2 COMPLETE PCA OVERALL SCORE". To the right of the badge is a table of scores for various categories:

Category	Score
ITINERARIES	94.5
EXCURSIONS	88.4
SERVICE	97.7
CABINS	91.6
FOOD	96.3
ACTIVITIES	94.2
DESIGN	96.4

Below the table, there is a section titled "READERS' CHOICE AWARDS" with a link to "Top 10 Midsize-Ship Lines". To the right of the table, there is a section titled "GOLD LIST" with a link to "2013". Below that, there is a section titled "THIS FLEET SAILS TO:".

On the right side of the page, there is a section titled "MOST POPULAR" with a list of 5 items:

- The Best New Bars Around the World
- Airport Restaurants That Really Are Worth the Trip
- We Dare You to Walk Across These Bridges
- Patriotic Places that Will Make You Proud to Be an American
- Artisanal Gelato: How to Spot the Fakes

Below the list, there is a section titled "SEABOURN 2014 WORLD CRUISE VOYAGES" with a "LEARN MORE" link. At the bottom right, there is a "Subscribe to The Daily Traveler Newsletter" form with a "SUBMIT" button and a link to "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”

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Many other examples

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

- All non-personalized

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The screenshot shows the Billboard website. At the top, it says "Charts | Billboard". Below that, it says "billboard" and "SEARCH BILLBOARD". There is a navigation bar with links to "VIDEOS", "PHOTOS", "ARTICLES", and "ARTISTS". Below the navigation bar, there is a section titled "Charts" with a link to "SUBSCRIBE". Below the "Charts" section, there is a table of charts:

Chart	Score
Hot 100	100
Billboard 200	100
Genres	100
International	100
All Charts	100
Summer 2013	100

Below the table, there is a section titled "Overall Popularity" with a link to "TOP". Below the "Overall Popularity" section, there is a table of songs:

Song	Score
The Hot 100	100
Billboard 200	100
On-Demand Songs	100

On the right side of the page, there is a section titled "HAYDEN PANETTIERE'S CLOSET" with a link to "WATCH NOW". Below the section, there is a video player showing a scene from the show "Grey's Anatomy".

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)

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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!

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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, ...)?

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Computing the ranking

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

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

- 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

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Take two – does X make Y more likely??

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

$$\frac{\begin{array}{c} \text{X and Y} \\ \hline \text{X} \end{array}}{\begin{array}{c} \text{!X and Y} \\ \hline \text{!X} \end{array}}$$

- This formula focuses on increase in Y associated with X

Other solutions ...

- Association rule mining brings us the lift metric:

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

- This looks at non-directional association
- More generally association rules look at baskets of products, not just individuals

Take two – does X make Y more likely??

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

$$\frac{\begin{array}{c} \text{X and Y} \\ \hline \text{X} \end{array}}{\begin{array}{c} \text{!X and Y} \\ \hline \text{!X} \end{array}}$$

Handwritten example:
 100X: $\frac{50}{100} = \frac{1}{2}$
 !X: $\frac{450}{99,900} = \frac{1}{2000}$
 Ratio: $\frac{1/2}{1/2000} = 1000$
 Anchovy: $\frac{95}{100} = 0.95$
 banana: $\frac{99,905}{99,900} \approx 1.00005$
 = 1

- This formula focuses on increase in Y associated with X

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)

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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!

Introduction to Recommender Systems

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