Selecting Products

Venky Harinarayan
(venky@cambrianventures.com)

Problem Statement

Select a multi-set (set with number) of products, subject to certain constraints, that maximizes profit

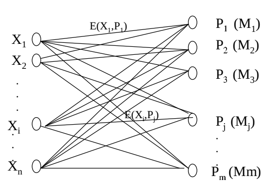
Essence of Selling

- What products do I stock in my stores?
  - Constraint: capital tied up in keeping products in stores (inventory)
- What products do I keep in my end-caps (checkout counters)?
  - Constraint: shelf-space
- What paid-listings do I show first in a search?
  - Constraint: online real-estate
- For a given customer, what's the best product to advertise?
  - Constraint: online real-estate

Two Scenarios

- Focus on aggregate customer behavior
  - Problem definition
    - E.g. what products do I stock in my stores?
  - No information available about individual customers
- Focus on individual customer
  - personalization

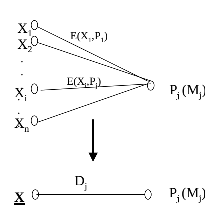
General Framework



X_i: Person$_i$, P_i: Product$_i$.
$E(X_i, P_j)$: Expected number of P_j that X_i buys (clicks through, etc…)
M_j: Profit-Margin on P_j

Aggregate User Case

Collapse all the X_i's to one node



Demand, $D_j = \Sigma_i E(X_i,P_j)$

Problem Statement

Profit, $\$_j = k_j * M_j$

Maximize: $\Sigma_j k_j * M_j$ *Turns*, $k_j = 0,1,2,\ldots$ *(number of* P_j *selected)*

Subject to : $\Sigma_j k_j * c_j <= C$, c_j *– cost associated with* P_j *&*

$k_j <= D_j$ *not to exceed demand*

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Example

	Margin	Demand	Cost	Margin/Cost
P1	3	12	25	12%
P2	9	3	40	22.5%
P3	10	1	55	18.2%

Constraint: total cost <= 100 (***C***)

Greedy (pick maximal margin/cost at each step): $\{P_2^2\}$

LP: $\{ P_3, P_2\}$

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Retailers and LP

- In general product selection can be set up as a linear/integer program (LP)
- Retailers are giant multi-stage LP execution engines!

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In real life…

- Space of products may be too large
  - Eg. Wal-mart has millions of products to consider
- All information may not be available
- Implementation complexity and Performance impact
  - Problems too large to run in real-time
- Intractability
- *Buyers* do the job of product selection
  - More in line with greedy algorithm

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Product Selection in Retailers

- If all retailers solve the same equations, why don't they all have the same products?
- Product Selection defines Retailer (brand)
  - Brand constraint: maximize profits in the future
    - E.g. Wal-mart brand constraint: select only products that will be bought by 80% of population
    - E.g. Gucci brand constraint: select only high-value (margin) products

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Example

	Margin	Demand	Cost	Margin/Cost
P1	3	12	25	12%
P2	9	3	40	22.5%
P3	10	1	55	18.2%

Constraint: total cost <= 100 (***C***)

Wal-mart brand constraint: maximize turns: $\{P_1^4\}$

Gucci brand constraint: no low-margin products: $\{ P_3, P_2\}$

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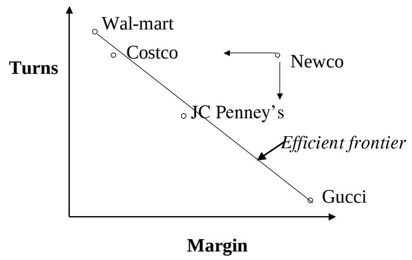
Classifying Retailers



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Online Search

- ◆Overture
- ◆Amazon
- ◆Google

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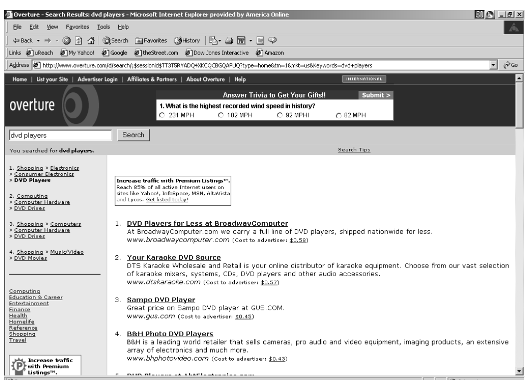
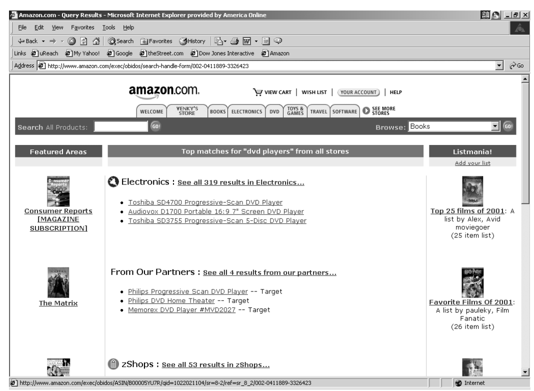
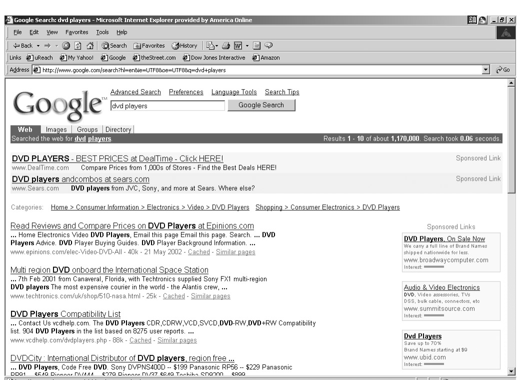
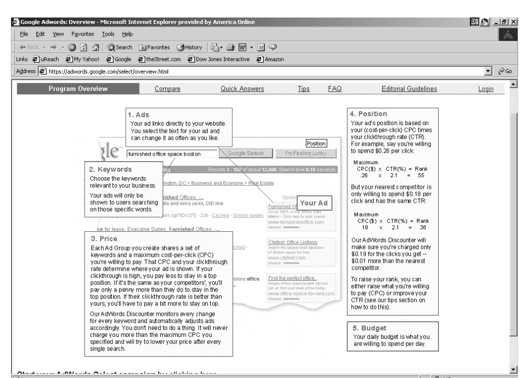








Personalization

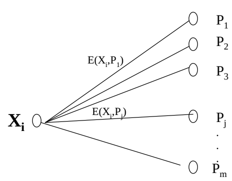
- ◆Given customer □i, what products do I recommend to her?
  - □i is a loyal customer □purchase history available
    - Collaborative-Filtering based Recommender Systems
  - □i is a new customer □has done certain operations on the site like search, view products, etc…
    - Assortment of techniques
  - □i is a new customer □know nothing about her
    - Mass merchandizing as in offline retailers, bestsellers,…
- ◆In practice, combination of all of the above

Personalization

- ◆ Offline retail: merchandizers (analog of buyers) pick products to advertise
  - One size fits all □no personalization
- ◆Millions of customers, cannot have human merchandizing to each customer
- ◆Algorithms that look at only customer's data do not work well
- ◆**Heuristic: customers help each other**
  - Algorithms enable this to happen!

Recommender Systems

Purchase History of X_i available
What new products to advertise to X_i?

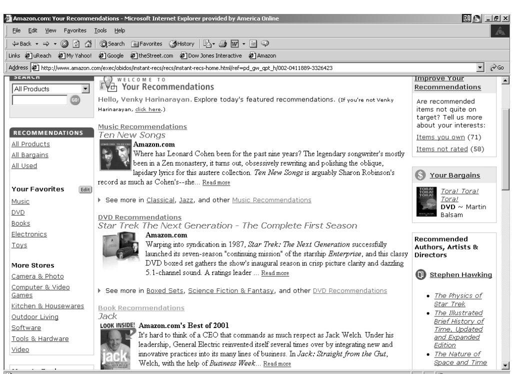


Given set of products that X_i has bought $B = \{ P_{i1}, P_{i2},\ldots P_{in}\}$

Find P_j, such that $E(X_i,P_j)$ is maximum

Recommender Systems

- ◆Intuition:
  - Ask your friends, what products they like
- ◆ Friends = people who have similar behavior to you



Collaborative Filtering

- ◆ Representation of Customer and Product data
- ◆Neighborhood formation (find my friends)
- ◆Recommendation Generation from neighborhood

Representation

- M*N customer product matrix, R
  - $r_{ij} = 1$ if X_i has bought P_j , 0 otherwise
- Issues:
  - Sparsity
    - Mostly 0's. E.g. Amazon.com 2 million books, less than 0.1% is 1
  - Scalability
    - Very large data sets
  - Authority
    - Take into account similarity between products
      - E.g. paperback "Cold Mountain" is same as hardcover "Cold Mountain"

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Finding Neighbors

- Similar to clustering
  - cluster around a given customer
- First compute similarity between customers: X_a, X_b
  - X_a^ -- *corresponding product vector*
  - Cosine measure
    - Cosine of angle between vectors gives similarity
    - $Sim(X_a, X_b) = X_a\hat{}\cdot X_b\hat{} / | X_a\hat{} | \, | X_b\hat{} |$
    - See class on Clustering for examples, more info

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Neighbors

- Pearson Correlation
  - How "proportional" are the vectors
    - Is there a linear relationship between them?
- Good indicator of both strength and direction of similarity (correlation)
  - +1: strongly, positively correlated
  - 0 : no correlation
  - -1 : strongly, negatively correlated

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Example

$X_a\hat{} = (1\ 2\ 3)$
$X_b\hat{} = (2\ 5\ 6)$

Pearson correlation measures how close to a line (1,2) (2,5) (3,6) are

$$Sim(X_a, X_b) = \frac{X_a\hat{}.\ X_b\hat{} - (\Sigma X_a\hat{}\ \Sigma X_b\hat{} /N)}{sqrt((\Sigma X_a\hat{}^{\,2} - (\Sigma X_a\hat{})^2/N)\ )(\Sigma X_b\hat{}^{\,2} - (\Sigma X_b\hat{})^2/N)))}$$

= 0.9608 (strongly positively correlated)

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Neighborhood

- Now compute neighborhood of X_a
  - Center-based
    - Select *k* closest neighbors to X_a
  - Centroid-based
    - Assume *j* closest neighbors selected
    - Select j+1st neighbor by picking customer closest to centroid of first j neighbors
    - Repeat 1..k

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Generating Recommendations

- From the neighborhood among products X_a has not bought yet, pick:
  - most frequently occuring
  - Weighted Average based on similarity
  - Based on Association Rules
- See Sarwar et al (sections 1-3) (http://www-users.cs.umn.edu/~karypis/publications/Papers/PDF/ec00.pdf)

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Example

	Shrek	*Star Wars*	*MIB*	*Harry Potter*	*X-files*
John		1	1		1
Jane	1	1	1		1
Pete			1	1	
Jeff	1	1			
Ellen	1	?	1	?	?

What new movie should we recommend to Ellen?

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Similarity Function

	Shrek	*Star Wars*	*MIB*	*Harry Potter*	*X-files*	Similarity to Ellen
John		1	1		1	1/sqrt(6) = 0.41
Jane	1	1	1		1	1/sqrt(2) = 0.71
Pete			1	1		1/2
Jeff	1	1				1/2
Ellen	1	?	1	?	?	

Use Cosine measure for similarity

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Neighbors

	Shrek	*Star Wars*	*MIB*	*Harry Potter*	*X-files*	Similarity to Ellen
John		1	1		1	0.41
Jane	**1**	**1**	**1**		**1**	**0.71**
Pete			**1**	**1**		**0.5**
Jeff	**1**	**1**				**0.5**
Ellen	1	?	1	?	?	

Use Center-based approach and pick 3 closest neighbors

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Recommendation

	Shrek	*Star Wars*	*MIB*	*Harry Potter*	*X-files*	
Jane	1	1	1		1	
Pete			1	1		
Jeff	1	1				
Ellen	1	*2*	1	*1*	*1*	

Recommend Star Wars

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Implementation Issues

- Serious application
  - Large data sizes: millions of users * millions of products
  - CPU cycles
- Scalability key
  - Partition the data set and the processing
- Real-time vs Batch
  - Real-time can lead to poor response times
  - Real-time preferable – recommend immediately after a customer purchase!
  - Incremental solution key for real time

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Implementation Issues

- Sparsity
  - Use navigation history along with purchase history
  - Poorer data quality but reduces sparsity somewhat

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Personalization with Limited Information

- Based only on navigation history and current location of customer
- Crucial to relate products to one another
  - Richer user experience
  - Each link drives potential revenue
  - Links built by human labor, explicit customer information, derived customer information, manufacturer info, etc…
  - Much effort in online retailers spent here

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Relating Products

- Product Authority
  - Same as one another. E.g. paperback/h.c.
- By Attributes
  - Same author, star, band, manufacturer,…
- By Usage
  - Accessories
- By Explicit User Grouping
  - Lists on Amazon.com
- By Similar Customers Purchasing
  - Customers who bought A also bought B

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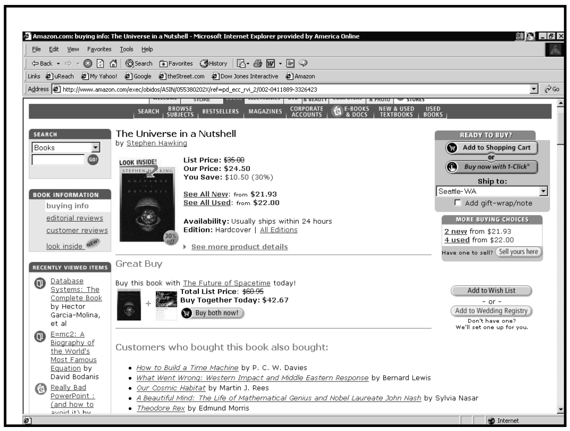

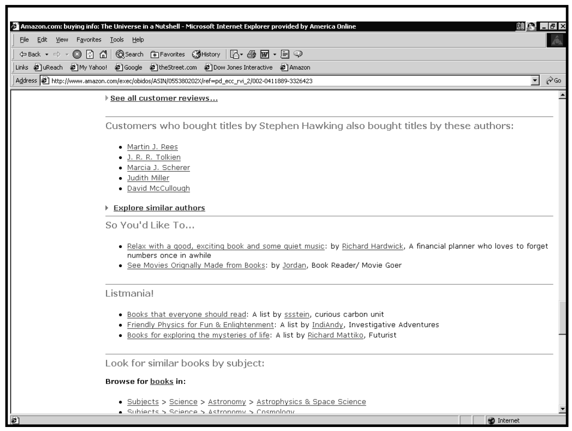

□uality

- □uality between products and customers
  - Can use interchangeably in problem formulation
  - Real-life feasibility/value□
- E.g. Recommender Systems
  - Use purchase history of customers to recommend new product most similar to other products bought by active customer
    - □If you□re □enky, check out this new Star Wars □□□
  - Use buying history of products to recommend new customer, most similar to other customers that have purchased the active product
    - □If you□re on the Star Wars □□□page, check out the home page of this customer from Seattle, WA

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Summary

- Product Selection is the essence of retailing
- Personalization is unique to online retailing
  - Every customer can have their own store
- Most successful personalization techniques, get customers to help one another
  - Algorithms, like C□, enable this interaction
- In real life, algorithms are complex monsters due to scaling issues, repeated tweaking, etc…

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