Business Data Analytics

MTAT.03.319

Lecture 6

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Till now and today !

Lecture 1:
Intro BDA

Lecture 2:
Data Exploration
prerequisite task

Lecture 3: Customer segmentation

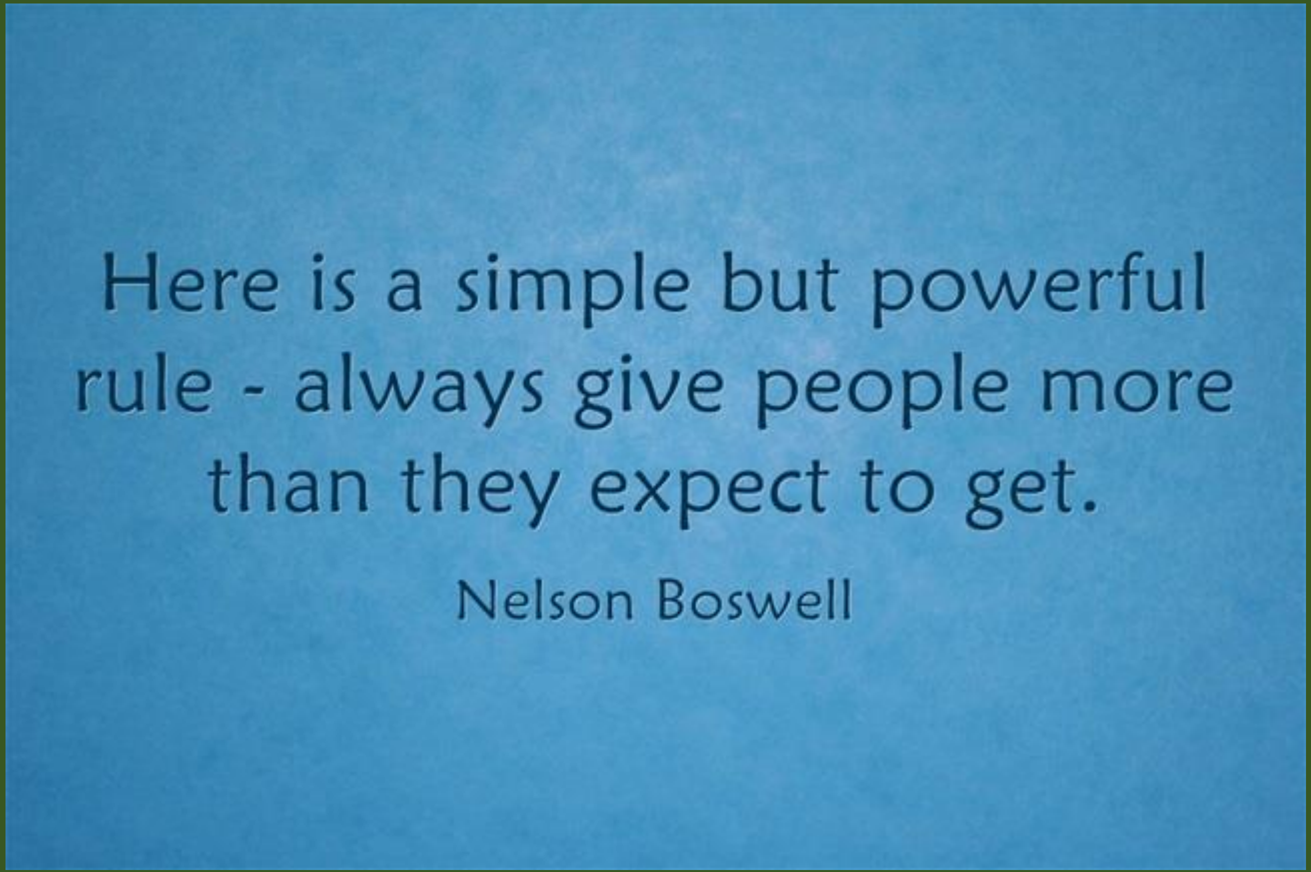
Lecture 4: Customer Lifecycle Management (CLM)
Regression problems

Lecture 5: Customer Lifecycle Management (CLM)
Classification problems

Lecture 6: Cross-sell/Up-selling

Cross Selling & Upselling

How to sell more ?



Tips

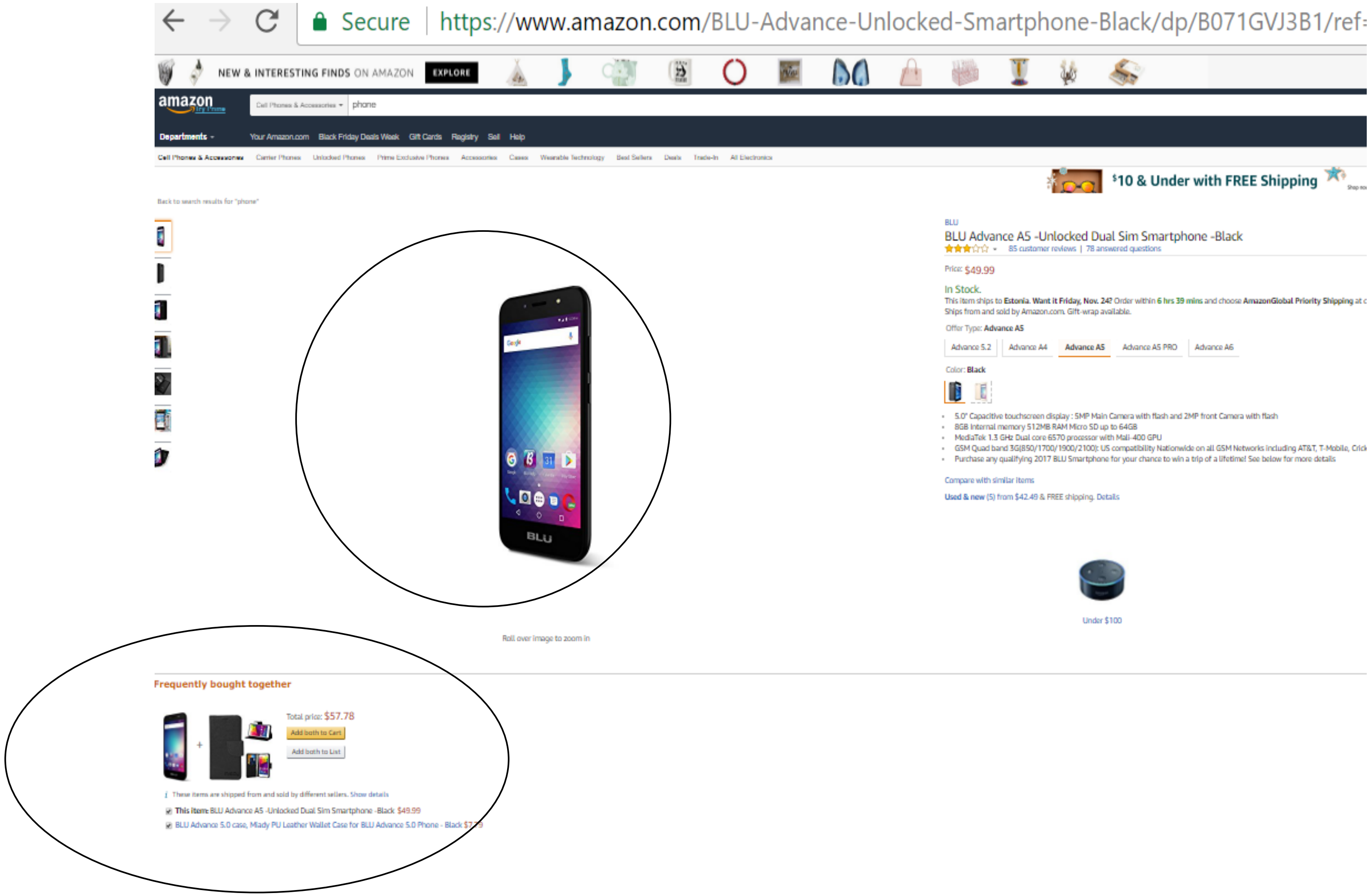
- You already know about following tips
  - *"The cost of acquiring a new customer is often around 4 times more expensive than it is to sell to an existing customer. "*
- So better to sell it to existing customers.
- But how ?
  - *The most successful business practices to achieve this are by up-selling and cross-selling.*

Fast Food Seller

Would you like potatoes with that ? ☺

Cross Selling

Cross Selling: Amazon Shopping



Cross Selling: Definition

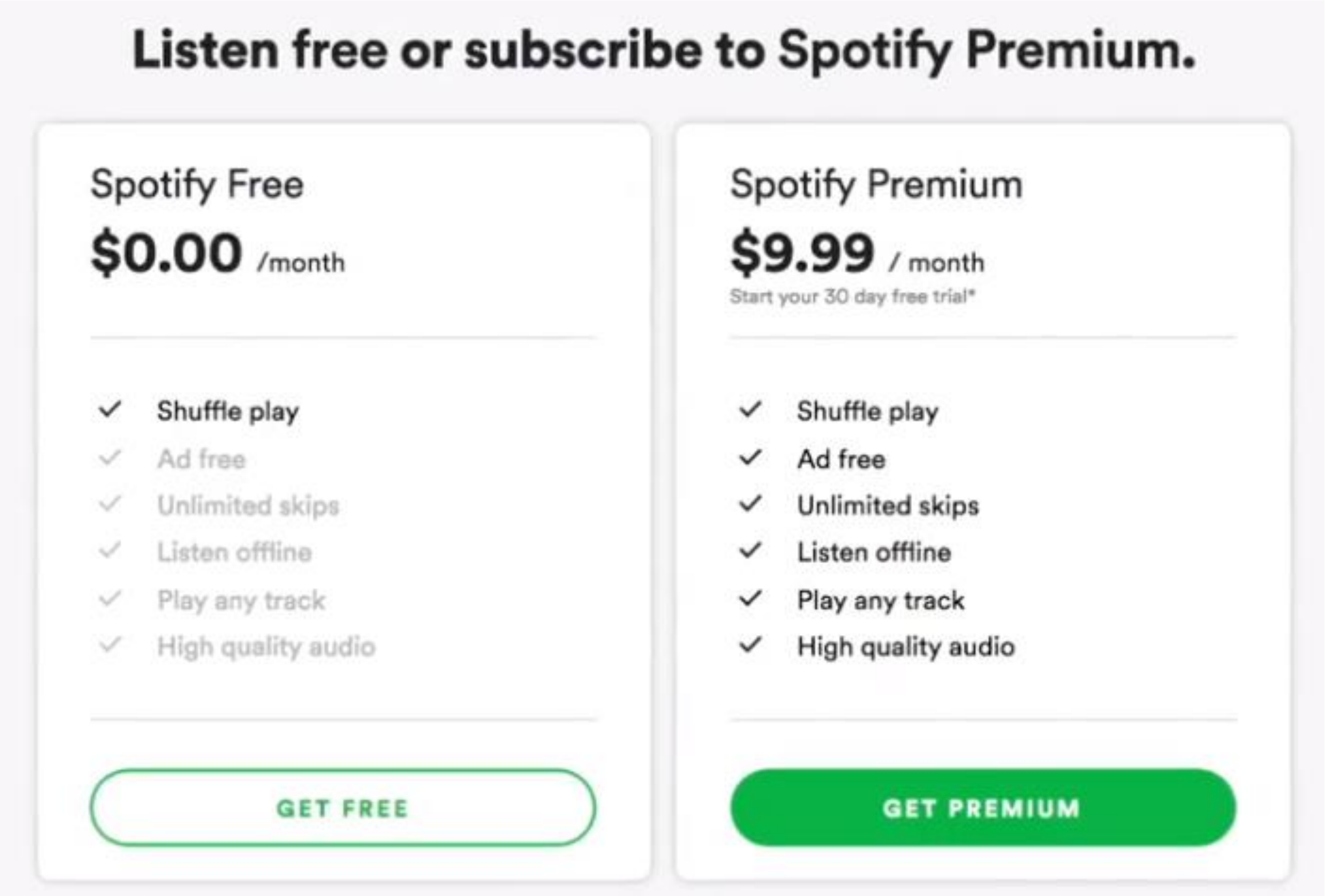
- To sell related or complementary products to a new or existing customer.

https://www.investopedia.com/terms/c/cross-sell.asp

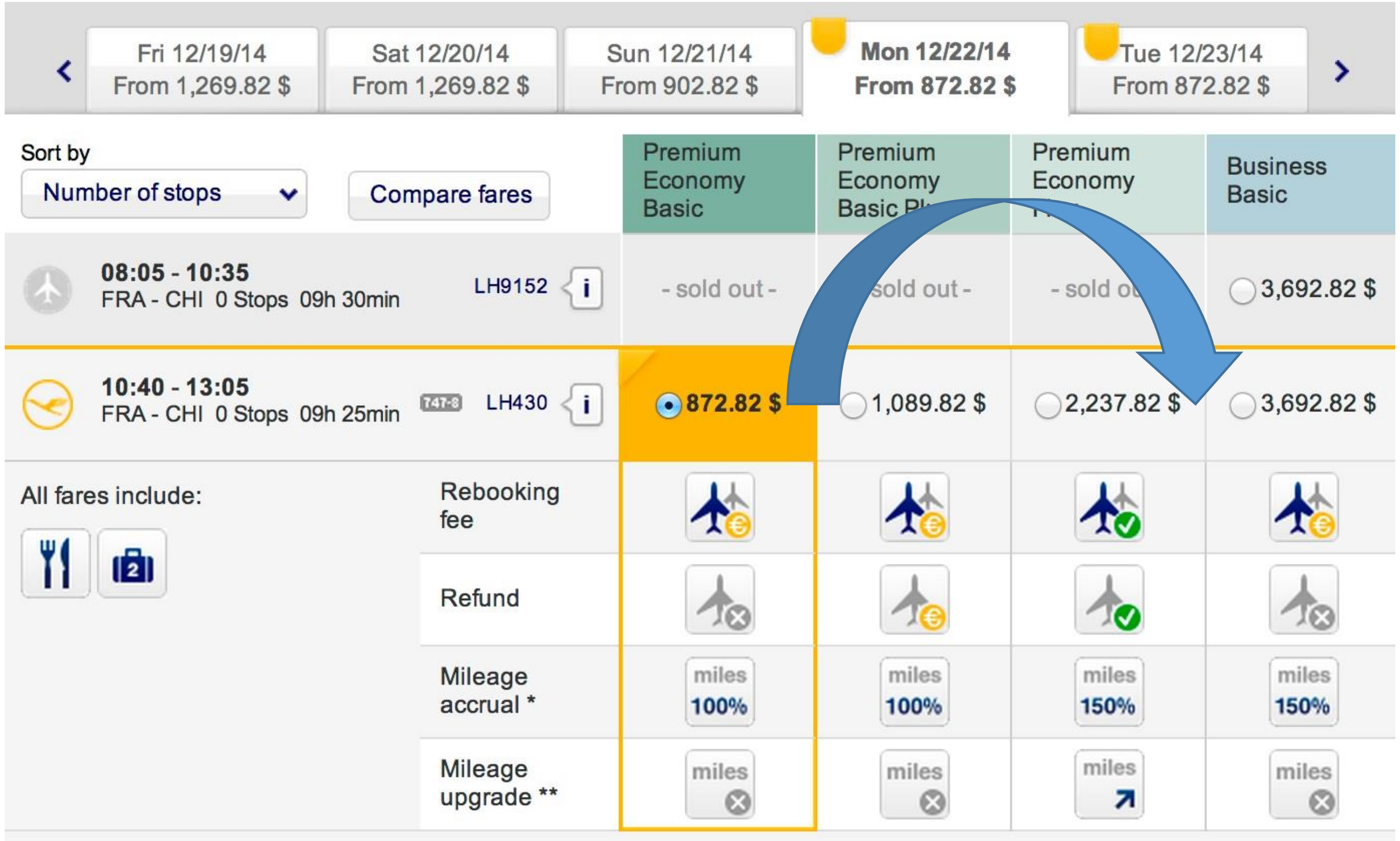
- Cross-selling is a sales technique used to get a customer to spend more by purchasing a product that's related to what's being bought already.

Source: https://www.shopify.com/encyclopedia/cross-selling

UpSelling


Listen free or subscribe to Spotify Premium.
Spotify Free
$0.00 /month
Shuffle play
Ad free
Unlimited skips
Listen offline
Play any track
High quality audio
GET FREE
Spotify Premium
$9.99 / month
Start your 30 day free trial*
Shuffle play
Ad free
Unlimited skips
Listen offline
Play any track
High quality audio
GET PREMIUM

Up-Selling



Fri 12/19/14 From 1,269.82 $
Sat 12/20/14 From 1,269.82 $
Sun 12/21/14 From 902.82 $
Mon 12/22/14 From 872.82 $
Tue 12/23/14 From 872.82 $
Sort by
Number of stops
Compare fares
Premium Economy Basic
Premium Economy Basic Pl
Premium Economy
Business Basic
08:05 - 10:35
FRA - CHI 0 Stops 09h 30min
LH9152
- sold out -
sold out -
- sold o
3,692.82 $
10:40 - 13:05
FRA - CHI 0 Stops 09h 25min
747-8
LH430
872.82 $
1,089.82 $
2,237.82 $
3,692.82 $
All fares include:
2
Rebooking fee
Refund
Mileage accrual *
miles 100%
miles 100%
miles 150%
miles 150%
Mileage upgrade **
miles
miles
miles
miles

Cross and Up Selling: Definition

- Up-selling: is a sales technique where a seller induces the customer to purchase more expensive items, upgrades or other add-ons in an attempt to make a more profitable sale.

Source: https://en.wikipedia.org/wiki/Upselling

- Cross-selling: To sell related or complementary products to a new or existing customer.

Tips For Cross/Up selling?

Cross Selling

- Peers Also Bought
- Incentives
- Discounted Second Buy
- Build A Relationship And Then Ask

Up Selling

- Sell the benefits of the up-sell
- Keep The Up-Sell Below 25% Of The Original Order

Return of Cross/Up Selling Strategy?

- Amazon reportedly attributes as much as 35 percent of its sales to cross-selling through its options on every product page
  - “customers who bought this item also bought” and
  - “frequently bought together”.

Cross Selling | Up Selling

Who?

- Identify the customer or a cluster for a better approach.
- Present relevant offers based on his buying history and/or social-demographics characteristics.

What?

- Identify the products or services which best fit the buying situation.
- Constantly analyze buying behavior in order to identify new trends (predictive models)

When, Where?

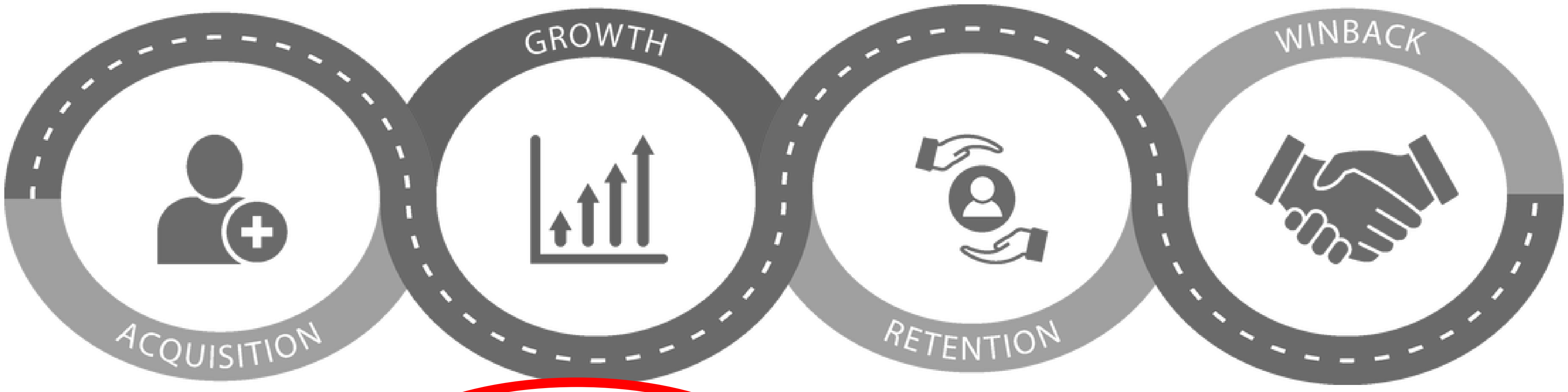
- Identify the best moment during the buying flow to offer another product or service.
- Respect the users main objective

How?

- Identify the best position on the screen
- Identify the best model (text based, txt+img, advertising, radiobuttons, checkboxes, etc)

Source: https://www.slideshare.net/dmedeiros/crossselecommerce07

Customer Lifecycle Management



Lead propensity

Cross-sell/up-sell propensity

Response modeling / buying propensity

Fault/Complaint prediction

Churn propensity

Win-back propensity

How to solve this problem ?

- Question: What products to recommend to whom?
- Solution: Recommendation Systems

- What products ?
  - Popularity
  - Market Basket Analysis
  - Collaborative filtering

- What products to whom ?
  - Collaborative filtering

What products to recommend to whom ? : Recommender Systems

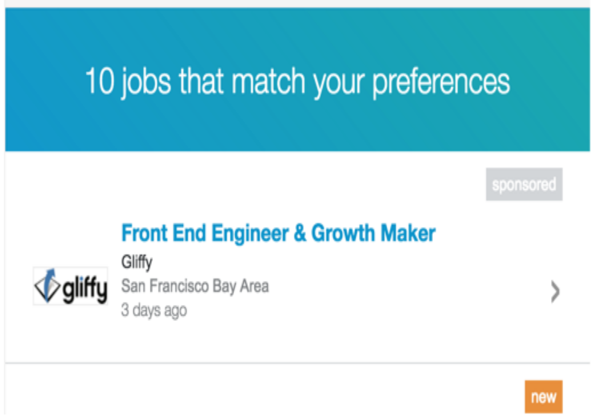
Goal of a Recommender System:
Identify products most relevant to the user (Eg. Top n offers).

Recommendation Examples in Online Markets

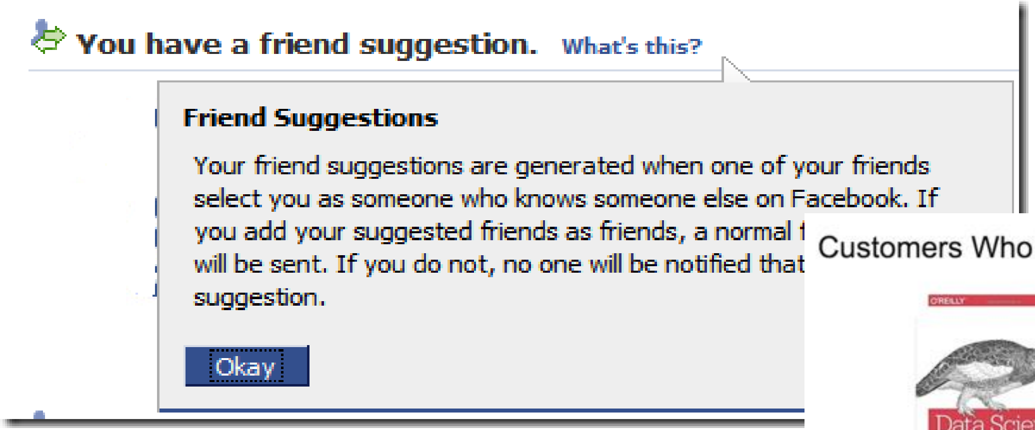
Platforms

Recommendations

Jobs



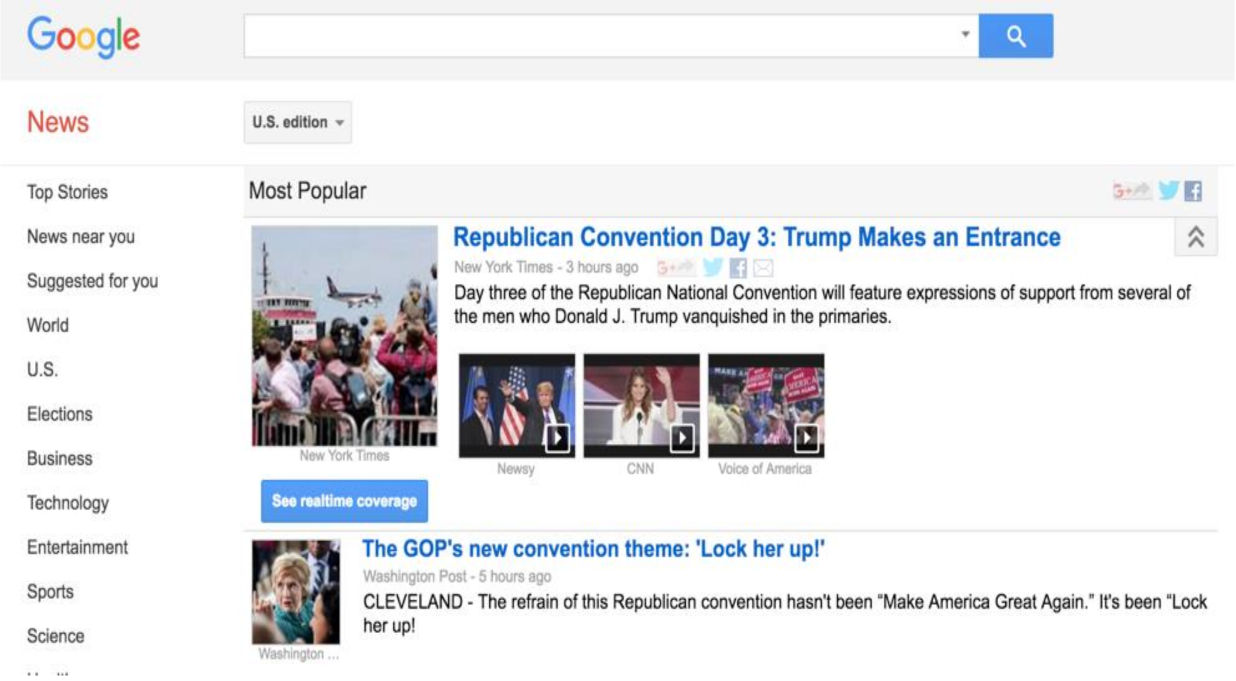
Friends

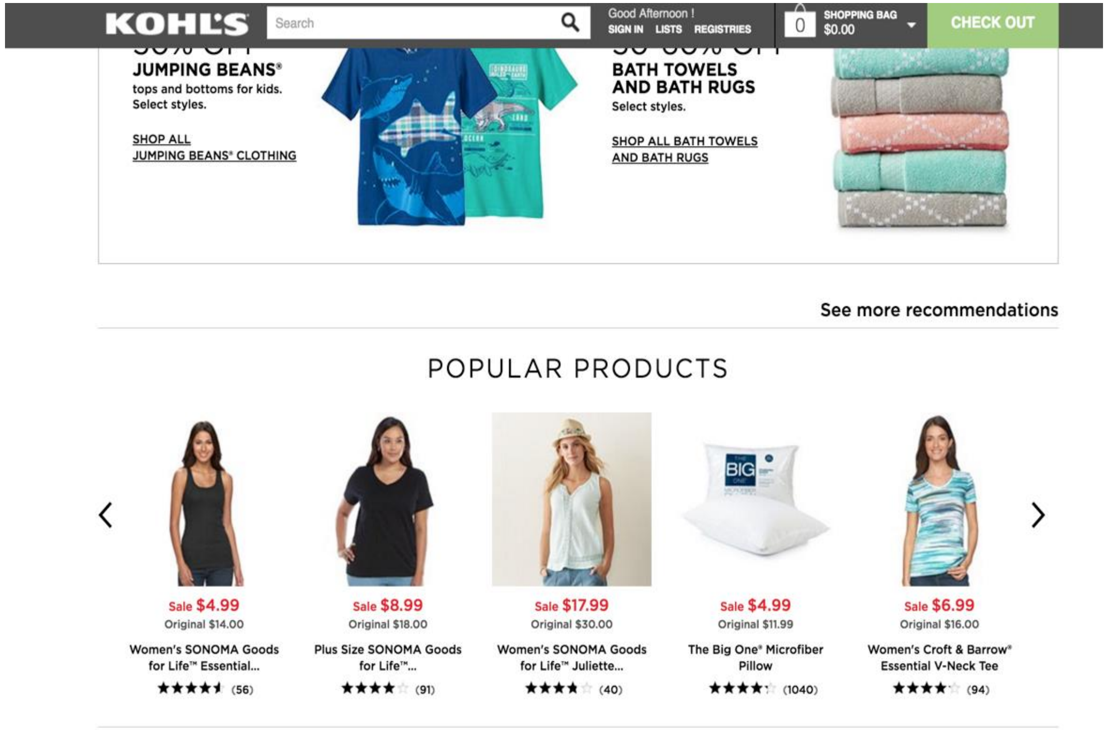


Books

Solution 1: Popularity based Recommender System

Recommend items viewed/purchased by most people
Recommendations: Ranked list of items by their purchase count

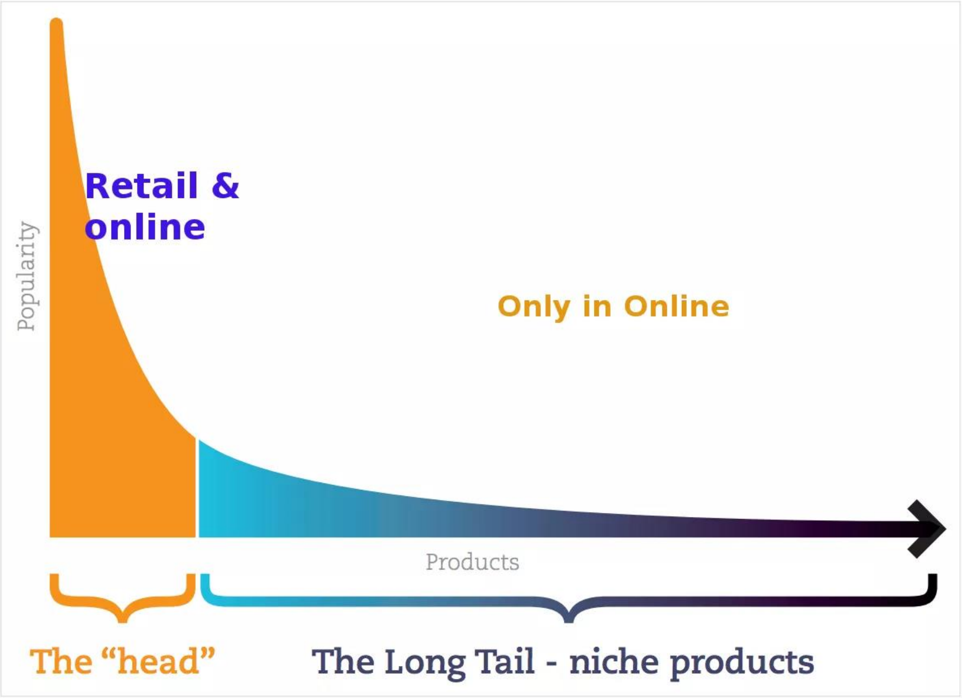




Popularity follows almost Pareto Law

- 20% (highly valued customers) of customers bring 80% of profit
- 20% of products bring 80% of the profit
  - But what about rest of the 80% products ?

    Popularity based techniques are not helpful



Popular products* !

2 most popular products

All Images News Videos Maps More Settings Tools

About 2,490,000,000 results (0.53 seconds)

There are many popular ecommerce products to sell them online like:

- Smartwatches.
- Video Doorbells.
- Facial Masks.
- Highlighters.
- Phone Cases.
- Avocado Oil.
- Bluetooth Speakers.
- Enamel Pins.

More items...

*Based on Dec 2018

Popularity is safe

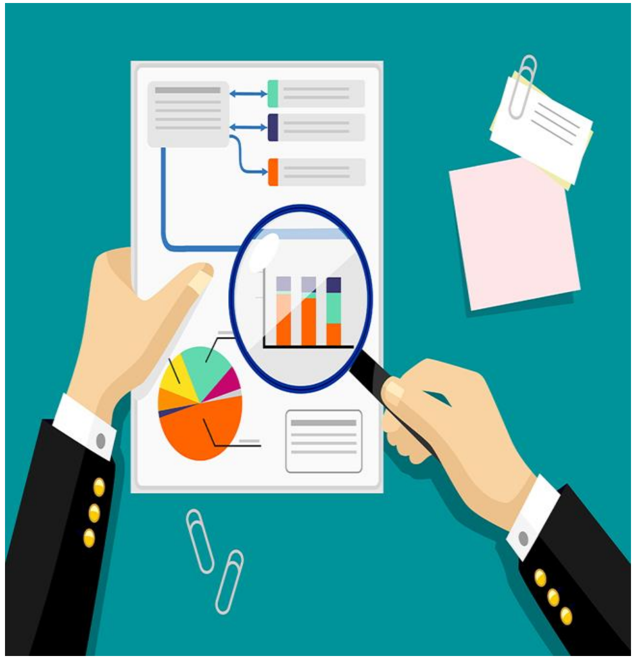
but

what about association among the products you recommend ?

Solution 2: Market Basket Analysis

Market

Basket



Analysis

MBA

MBA put sense while recommending products

Market Basket Analysis (MBA)

- Technique/Algorithm to identify the association rules from the data
- Input
  - List of purchases by customers over different visits
- Output
  - What items purchased together

MBA: Terminologies

- Items: Objects that we are identifying associations between.
- Examples:
  - In a supermarket, each item is a product.
  - For a publisher, each item might be an article, a blog post, a video etc.
- A group of items is an item set.
  - $\{i_{1,}\ i_{2,}\ i_{3\ \ldots,} i_k\}$

MBA: Terminologies Cont..

- Items: Objects that we are identifying associations between.
- Transactions: Transactions are instances of groups of items co-occurring together.
- Examples:
  - For an online retailer, a transaction is, generally, a group of items bought together
  - For a publisher, a transaction might be the group of articles read in a single visit to the website.
  - **NOTE:** It is up to the analyst to define over what period to measure a transaction.
- For each transaction, we have an item set.
  - $t_n = \{i_1, i_2, i_3 \ldots, i_k\}$

MBA: Terminologies Cont..

- Items: Objects that we are identifying associations between.
- Transactions: Transactions are instances of groups of items co-occurring together.
- Rules: are statements of the form
  - $\{i_{1,}\ i_{2,}\ i_{3\ \ldots.}\} \Rightarrow \{i_k\}$
  - if you have the items in item set (on the left hand side (LHS) of the rule i.e. $\{i_{1,}\ i_2, \ldots\}$, then it is likely that a visitor will be interested in the item on the right hand side (RHS) i.e. $\{i_k\}$.
  - In the example above, rule would be:
    - {flour, sugar} => {eggs}

MBA: Terminologies Cont..

- Items: Objects that we are identifying associations between.
- Transactions: Transactions are instances of groups of items co-occurring together.
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  - $\{i_{1,}\ i_{2,}\ i_{3\ ....}\} \Rightarrow \{i_k\}$
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  - In the example above, rule would be:
    - {flour, sugar} => {eggs}

This is what MBA finds

MBA: Terminologies Cont..

- Items: Objects that we are identifying associations between.
- Transactions: Transactions are instances of groups of items co-occurring together.
- Rules: Find associated items for sale
- **Output of MBA ?**

Market basket analysis is generally a set of rules, that we can then exploit to make business decisions (related to marketing or product placement, for example).

Association rules -> Generates rules
Example: (X -> Y)

Market Basket -> Assigns business outcome to those rules
Example: X,Y could be sold together

What MBA tries to find ?

- MBA investigates if association between A and B (that is A -> B) is
  - Random
  - Or there is some statistical basis of it
- Question: Can we come up with some quantitative metric for the above investigation ?
  - Answer: Lift
- Question: How to calculate Lift ?
- Answer: By using:
  - Support
  - Confidence
  - Expected Confidence

MBA: Terminologies Cont..

- It works basically on following concepts
  - Support: #(co-occurrence of A **and** B)/T
    - What is co-occurrence of two items name A and B
    - (Co-occurrence of A and B)/ Total Transactions.
  - Confidence: #(A **and** B)/#(A):
    - The proportion of transactions which contain A and also contain B.
    - How confident we are that B is present in presence of A.
    - Ratio of Support of (A and B), and Support of A.
  - Expected Confidence:
    - How confident we are that B is present in absence of A (or do not care about A).
    - # transactions where B is present /Total transactions

MBA: Terminologies Cont..

- Lift:
  - Ratio of Confidence and Expected Confidence
  - Ratio of (B in presence of A) and (B in absence of A)
  - Explains the change in probability of B over “presence of A” and “absence of A”
  - Lift <= 1
    - A has no impact on B
  - Lift > 1
    - Relationship between A and B is significant
    - Larger the lift ratio, the more significant the association.

Retail Case Study

Possible shopping Baskets (T)	
Transaction 1	Beer, Diaper, Chips, Aspirin
Transaction 2	Diaper, Beer, Chips, Lotion, Juice, Milk
Transaction 3	Soda, Chips, Milk
Transaction 4	Soup, Beer, Diaper, Milk, Icecream
Transaction 5	Soda, Coffee, Milk, Bread
Transaction 6	Beer , Chips

Retail Case Study

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Transaction 1	Beer, Diaper, Chips, Aspirin
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Transaction 3	Soda, Chips, Milk
Transaction 4	Soup, Beer, Diaper, Milk, Icecream
Transaction 5	Soda, Coffee, Milk, Bread
Transaction 6	Beer , Chips

Frequent Items (based on Ms = 30)
(Beer, Diaper) : with support 50 %
(Beer, Chips) : with support 50 %

Support = (Co-occurrence of A and B)/ Total Transactions.

Retail Case Study

Possible shopping Baskets (T)	
Transaction 1	Beer, Diaper, Chips, Aspirin
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Transaction 5	Soda, Coffee, Milk, Bread
Transaction 6	Beer , Chips

Frequent Items (based on Ms = 30)
(Beer, Diaper) : with support 50 %
(Beer, Chips) : with support 50 %

Support = (Co-occurrence of A and B)/ Total Transactions.

A is Beer and B is either Diaper or Chips

Confidence: #(A **and** B)/#(A)

Expected Confidence: # transactions where B is present /Total transactions

Lift= Confidence/ Expected Confidence

Rule 1 Beer -> Diaper
Confidence = 3/4 , Expected Confidence = 3/6
Lift = (3/4)/(3/6) = 1.5

Rule 2 Beer -> Chips
Confidence = 3/4, Expected Confidence = 4/6
Lift = (3/4)/(4/6) = 1.1

Let us summarize about the problem*

- Generate set of rules that link two or more products together.
- Each of these rules should have a lift greater than one.
- Also, we are interested in the support and confidence of those rules:
  - Higher confidence rules are ones where there is a higher probability of items on the RHS being part of the transaction given the presence of items on the LHS.
- Recommendations based on these rules to drive a higher response rate.
  - We're also better off actioning rules with higher support first, as these will be applicable to a wider range of instances.

*Problem: How to find rules which can help us in finding patterns ?

MBA is through association rules

- We have to generate rules
- 3 Types
  - Actionable Rules: On which you can take action.
  - Trivial Rules: Interesting and need to do more research on.
  - Inexplicable Rules: Complex or uncomprehensible (does not make sense)

Association rules -> Generates rules
Example: (X -> Y)

Market Basket -> Assigns business outcome to those rules
Example: X,Y could be sold together

How to make Personalized recommendation

Users who liked “Love Simon” also liked following movies

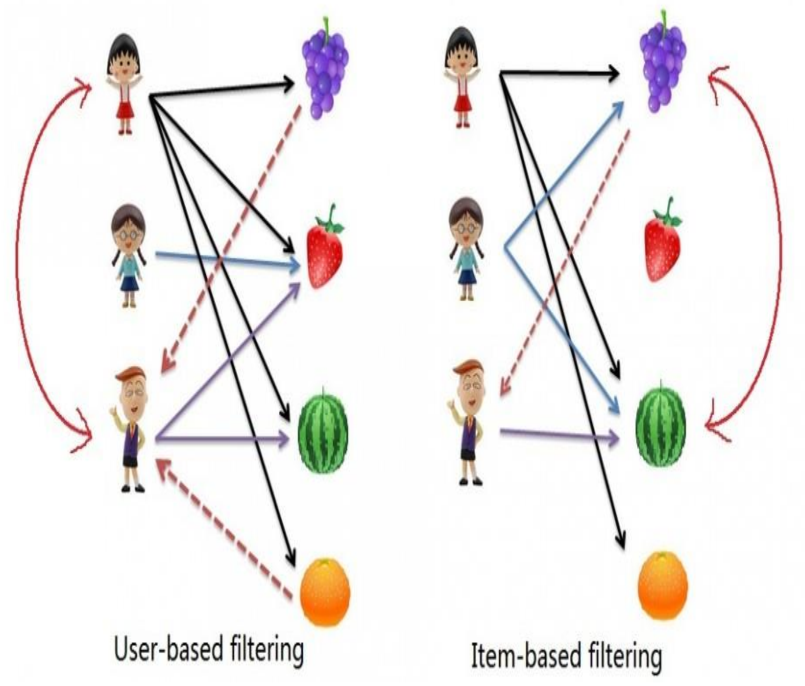
Solution 3: Collaborative Filtering (CF)

User-based

Find users who have a similar taste of products as the current user.

Similarity is based upon similarity in users' purchasing behaviour.

"User x is similar to user y because both purchased items A, B and C."



Item-based

Recommend items that are similar to the items the user bought.

Similarity is based upon co-occurence of purchases.

"Items A and B were purchased by user x, so they are similar."

Image Source: http://www.salemmarafi.com/code/collaborative-filtering-with-python/

Netflix Challenge !

DVD Rental
Utilizing the Inventory

→

Grand prize
of US$1,000,000
September 21, 2009

User – User Collaborative Filtering

Similar Users

Movies

Users

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- Consider users x and y with rating vectors r_x and r_y
- We need similarity metric Sim(x,y)
- Capture the intuition that Sim(A,B) > Sim(A,C)

Similar Users: Jaccard Similarity

Movies

Users

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

- Jaccard similarity(A,B) = $\frac{r_A \cap r_B}{r_A \cup r_B}$
- Jaccard distance = 1 - $\frac{r_A \cap r_B}{r_A \cup r_B}$
- Sim (A,B) = 1/5 ; Sim (A,C) = 2/4
  - Sim(A,B) < Sim(A,C) : Ignores the rating values

Similar Users: Cosine Similarity

Movies

Users	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4	0	0	5	1	0	0
B	5	5	4	0	0	0	0
C	0	0	0	2	4	5	0
D	0	3	0	0	0	0	3

NOTE: Fill empty values by 0

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

$$\text{Cosine similarity(A,B)} = \frac{4*5 + 0*5 + 0*4 + 5*0 + 1*0 + 0*0 + 0*0}{\text{Sqrt}\ (4^2 + 0^2 + 0^2 + 5^2 + 1^2 + 0^2 + 0^2) * \text{Sqrt}\ (5^2 + 5^2 + 4^2 + 0^2 + 0^2 + 0^2 + 0^2)}$$

$= 0.38$

Similar Users: Cosine Similarity

Movies

Users

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4	0	0	5	1	0	0
B	5	5	4	0	0	0	0
C	0	0	0	2	4	5	0
D	0	3	0	0	0	0	3

NOTE: Fill empty values by 0

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

- Cosine similarity(A,B) = Cos(r_A, r_B)
- -1 : dissimilar, 0: orthogonal; +1: similar
- Sim (A,B) = 0.38 ; Sim (A,C) = 0.32
  - Sim(A,B) > Sim(A,C) : but not much

Problem: Treat missing values as negative

Similar Users: Centered Cosine

Normalized ratings by subtracting the row mean

Movies

Users

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	4			5	1		
B	5	5	4				
C				2	4	5	
D		3					3

Avg. Rat
10/3
14/3
11/3
6/2 =3

In each row, original value – Avg. Rat

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	2/3	0	0	5/3	-7/3	0	0
B	1/3	1/3	-2/3	0	0	0	0
C	0	0	0	-5/3	1/3	4/3	0
D	0	0	0	0	0	0	0

Each row addition = 0

Ratings are centered around 0.

+ : users liked it

- : users did not like it

Similar Users: Centered Cosine (2)

Movies

Users

	HP1	HP2	HP3	TW	SW1	SW2	SW3
A	2/3	0	0	5/3	-7/3	0	0
B	1/3	1/3	-2/3	0	0	0	0
C	0	0	0	-5/3	1/3	4/3	0
D	0	0	0	0	0	0	0

Also known as pearson correlation.

- Sim (A,B) = 0.09 ; Sim (A,C) = -0.56
  - Sim(A,B) >> Sim(A,C) : but not much
- Captures intuition better
  - Missing ratings treated as "average"
  - Handles "tougher raters" and "easy raters"

Rating Predictions

- Goal: Prediction for user *X* and item *i*
- What we need:
  - Let r_X be the rating for the user *X*.
  - Let N be the set of k users most similar to *X*, who have rated item i.
- Option 1: $r_{xi} = \frac{1}{k}\sum_{y \in N} r_{yi}$ (Average)

For a neighbor y in (∈) the set N

s is the similarity of the user x and its neighbor y

- Option2*:* $r_{xi} = \frac{\sum_{y \in N} s_{xy} r_{yi}}{\sum_{y \in N} s_{xy}}$ (Weighted Average)

Item – Item Collaborative Filtering

Item – Item Collaborative Rating

- For item *i*, find other similar items.
- Estimate rating for item *i* based on ratings for similar items
- Can use some similarity metrics and prediction functions as in user-user model.

- $r_{xi} = \frac{\sum_{j \in N(i:x)} s_{ij} r_{xj}}{\sum_{j \in N(i:x)} s_{ij}}$

s_{ij} : similarity of items i and j
r_{xi}: ratings of item i by the user x
N(i:x) : set of items similar to i , rated by user x.

Item – Item Collaborative Filtering

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12
1	1		3		?	5			5		4	
2			5	4			4			2	1	3
3	2	4		1	2		3		4	3	5	
4		2	4		5			4			2	
5			4	3	4	2					2	5
6	1		3		3			2			4	

- estimate rating of movie 1 by user 5

Ratings are between 1 to 5
Empty boxes: unknown rating

? : Estimate the rating of movie 1 by the user 5

Neighborhood (N) = 2
Select 2 movies similar to “movie 1” and rated by user 5.

users

movies	1	2	3	4	**5**	6	7	8	9	10	11	12	sim(1,m)
1	1		3		?	5			5		4		1.00
2			5	4			4			2	1	3	-0.18
3	2	4		1	2		3		4	3	5		0.41
4		2	4		5			4			2		-0.10
5			4	3	4	2					2	5	-0.31
6	1		3		3			2			4		0.59

Remember N = 2
Select 2 movies similar to “movie 1” and rated by user 5.

$$r_{xi} = \frac{\sum_{j \in N(i;x)} s_{ij} r_{xj}}{\sum_{j \in N(i;x)} s_{ij}}$$

Sim = Pearson Coeff.
1) Subtract mean rating m_i from each movie i.
   1) m_1 = (1+3+5+5+4)/5 = 3.6
   2) Row 1 = (-2.6, 0, -0.6, 0, 0, 1.4, 0, 0, 1.4, 0, 0.4,0)
2) Compute Cosine similarities between rows

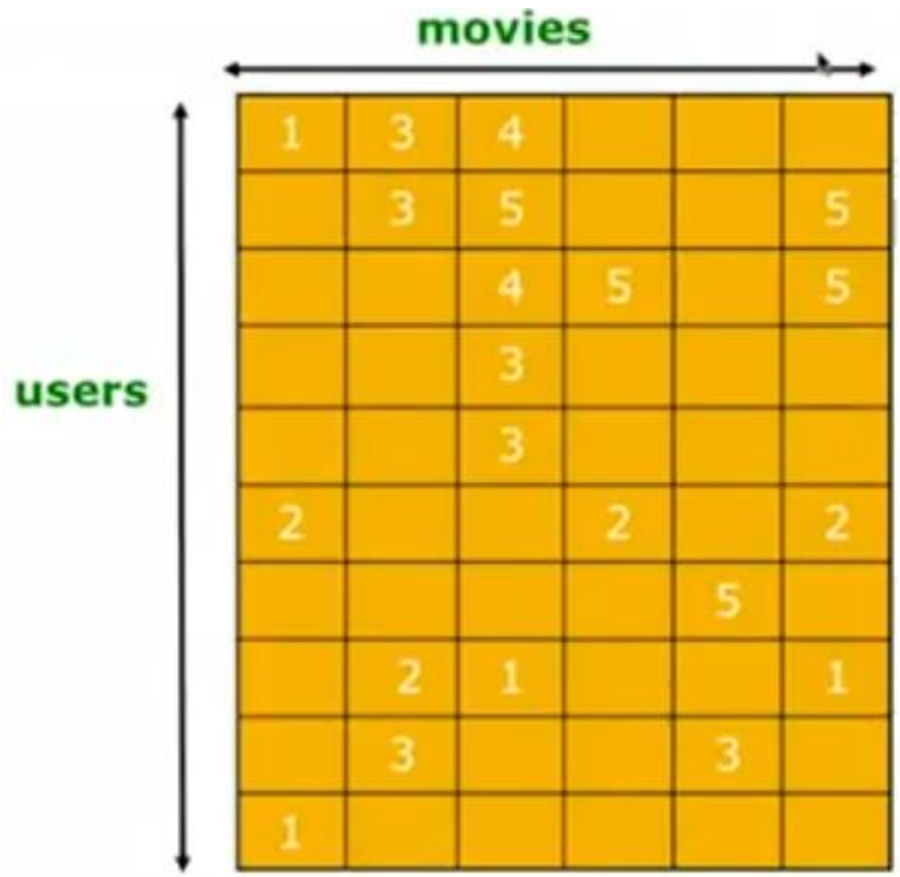
Weighted Average = (0.41*2 + 0.59*3)/(0.41+0.59)

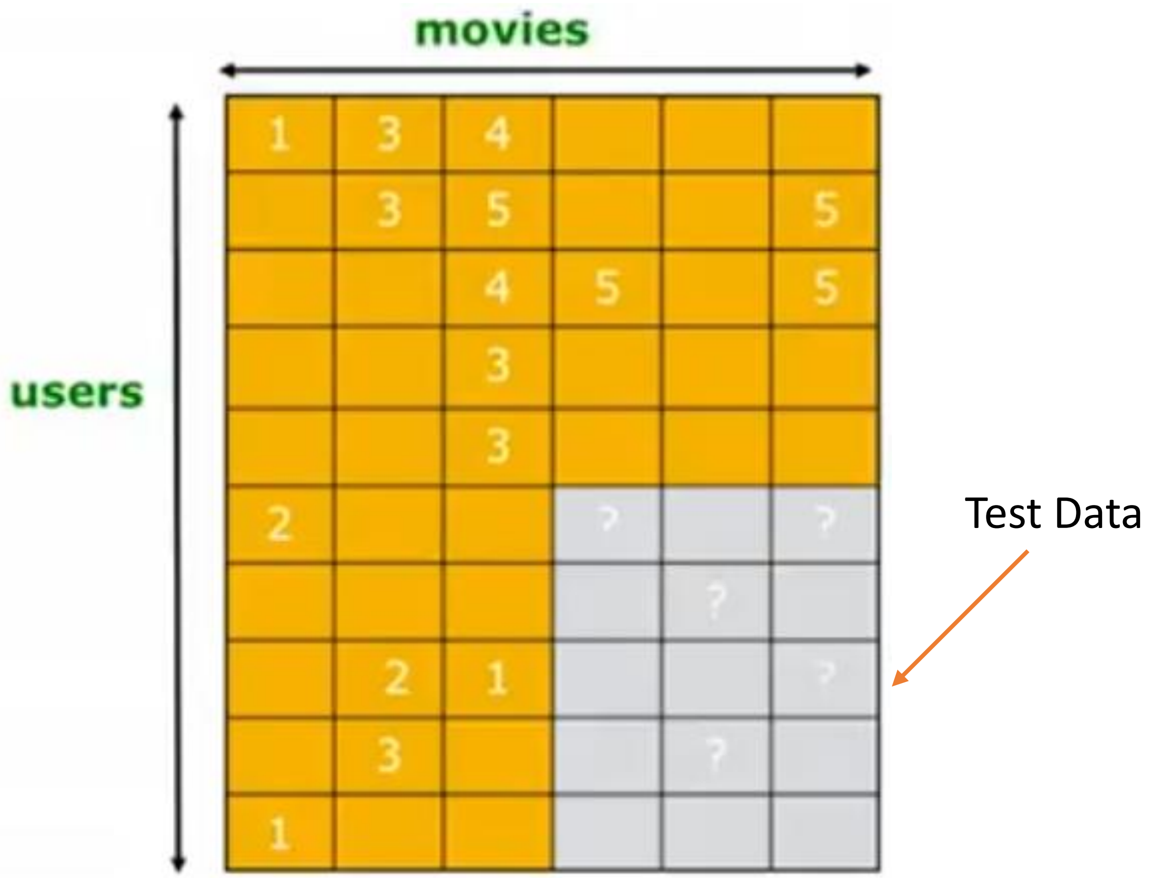
= 2.6

User to User Vs Item to Item

- Item-Item outperforms User-User
- Users are more complex than Items
  - Sparse: Users have limited interests (in buying)
  - Not all users can have likes/interests about all the items
- Items are simple: example: limited genres.
- Item similarity makes more sense than Users similarity

Evaluation





If you analyse it as regression problem

- MAE
- Mean Square Error
- Root Mean Square Error

If you analyse it as regression problem

- Problems of RMSE/MAE etc
  - Prediction diversity
  - Prediction context
  - Order of predictions

- Alternative: Precision at top-k
  - Percentage of predictions in the user's top-k withheld ratings

How can we find similar items ?

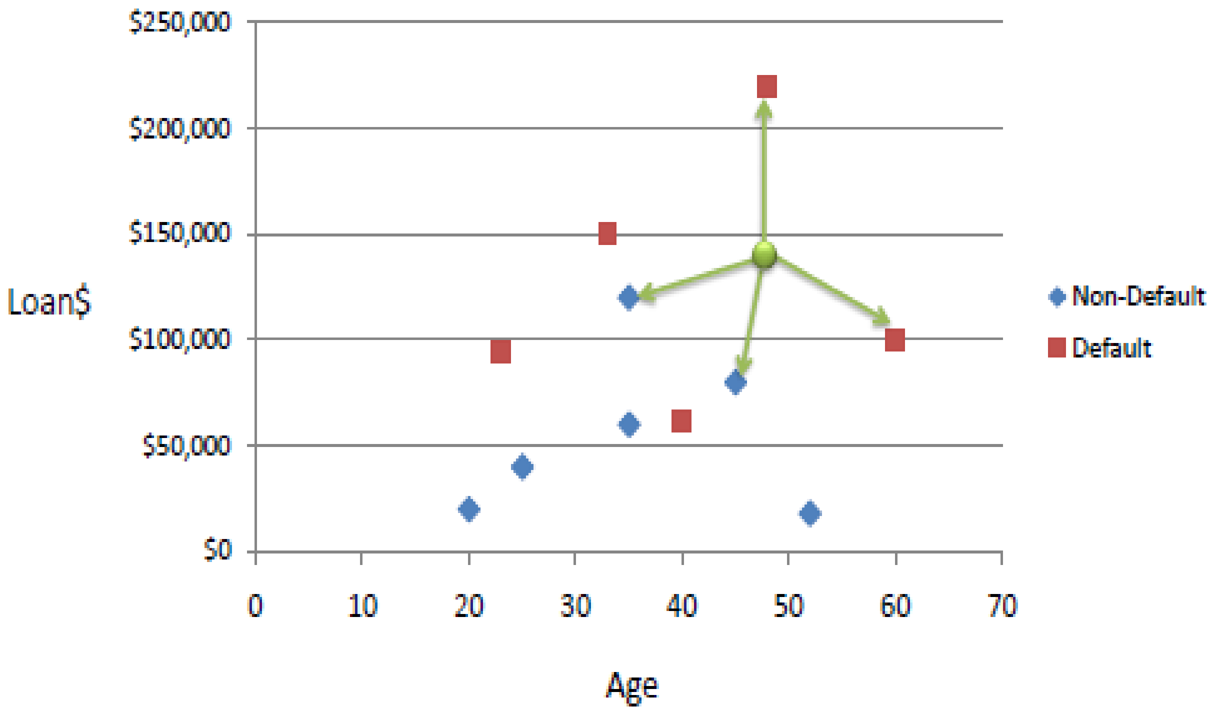
- You can use algorithm like KNN (K-Nearest Neighbor)
- It is a classification algorithm
- But basically you can use the idea of this algorithm for finding similar users ..

Loan Default Problem using KNN

Loan and Age are two input parameters/features

Red and Blue are the training data points

Green is the test data point



Q1 : How to classify (or predict) about the gender of the green data ?

Algorithm

1) Find K data points which are nearest to the green dot.
2) Assign (classify) the color (class) of the majority (among K neighbors) to the green (or the new data point)

Q2: How to find identify which K neighbors are nearest among all the neighbors ?

Answer: Use Distance metric

Distance Metrics revisited

Categorical

- Jaccard Distance: Ratio of Intersection/Union
- Hamming Distance

$$D_H = \sum_{i=1}^{k} |x_i - y_i|$$

$$x = y \Rightarrow D = 0$$

$$x \neq y \Rightarrow D = 1$$

X	Y	Distance
Male	Male	0
Male	Female	1

Continuous

Euclidean $\sqrt{\sum_{i=1}^{k} (x_i - y_i)^2}$

Manhattan $\sum_{i=1}^{k} |x_i - y_i|$

NOTE: Distance is (1- similarity)

How to Pick the value of K ?

- Inspect your data to choose the value of K: Visualize your data
- Historically, the optimal value of K=3 to 10
- Large K, reduces the noise but no guarantee
- If K is odd : Avoid ties
- If K is even: Flip a coin (randomly assign) or do not assign the category
- Set aside a data from your training data to determine a good value of K

K-NN

Age	Loan	Default	Distance	
25	$40,000	N	102000	
35	$60,000	N	82000	
45	$80,000	N	62000	
20	$20,000	N	122000	
35	$120,000	N	22000	
52	$18,000	N	124000	
23	$95,000	Y	47000	
40	$62,000	Y	80000	
60	$100,000	Y	42000	
48	$220,000	Y	78000	
33	$150,000	Y	8000	1
48	**$142,000**	?		

Euclidean Distance

$$D = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}$$

We can now use the training set to classify an unknown case (Age=48 and Loan=$142,000) using Euclidean distance.

D = Sqrt[(48-33)^2 + (142000-150000)^2]
D = 8000.01

If K=1 then the nearest neighbor is the last case in the training set with Default=Y.

K-NN

Age	Loan	Default	Distance	
25	$40,000	N	102000	
35	$60,000	N	82000	
45	$80,000	N	62000	
20	$20,000	N	122000	
35	$120,000	N	22000	2
52	$18,000	N	124000	
23	$95,000	Y	47000	
40	$62,000	Y	80000	
60	$100,000	Y	42000	3
48	$220,000	Y	78000	
33	$150,000	Y	8000	1
48	**$142,000**	?		

Euclidean Distance

$$D = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2}$$

We can now use the training set to classify an unknown case (Age=48 and Loan=$142,000) using Euclidean distance.

With K=3, there are two Default=Y and one Default=N out of three closest neighbors. The prediction for the unknown case is again Default=Y.

Standardized Distance

Age	Loan	Default	Distance	
0.125	0.11	N	0.7652	
0.375	0.21	N	0.5200	
0.625	0.31	N	0.3160	1
0	0.01	N	0.9245	
0.375	0.50	N	0.3428	
0.8	0.00	N	0.6220	
0.075	0.38	Y	0.6669	
0.5	0.22	Y	0.4437	
1	0.41	Y	0.3650	
0.7	1.00	Y	0.3861	
0.325	0.65	Y	0.3771	
0.7	**0.61**	**?**		

Standardized Variable

$$X_s = \frac{X - Min}{Max - Min}$$

If K = 1, then green dot = N

Remember: without non standardized, answer is Y

Comparison of MBA & CF

Market Basket Analysis

- Association Rule Mining
- Lacks the personalized approach
- Clustering problem
- Unsupervised approach
- No labeled data is provided
- Scalable
- No serendipity
- Mostly look for popular items

Collaborative Filtering

- User-user or Item-Item Filtering
- Can be used for personalized recomm.
- More of a regression problem
- UnSupervised approach
- Labels (ratings etc) are provided.
- Computationally expensive
- Serendipity possible
- Looks at products in the long tail
- Cons: Cold start, Sparisity, First Rater, popularity bias

Summary

- What is cross and up selling.
- Techniques
  - Popularity based
  - Market Basket Analysis
  - Collaborative Filtering
    - User-User CF
    - Item-Item CF
- K-NN algorithm