Assignment Project Exam Help Recommendation Engines

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Agenda

Start	End	Item
		Business Context
		Association Rules
		Code Example
	As	signment/Project Exam Help
		Code Example https://powcoder.com Personalized Reco Engine
		Add WeChat powcoder



What are Association Rules?

- Study of "what goes with what"
 - "Customers who bought X also bought Y"
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- Transaction-based or event-based
 - Customer A bought peanur butter and bread.
 - When someone has body aches, and fever they also have chills Add WeChat powcoder
- Also called "market basket analysis" and "affinity analysis"
- Originated with study of customer transactions databases to determine associations among items purchased



What are some other recommendation systems you have encountered?

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Many business profit by having exceptional recommendation analysis.



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Before Data Mining

Heuristic Based - A heuristic is a mental shortcut that allows people to solve problems and make judgments quickly and efficiently.

"Hey Lumberg, you should put the salsa next to the tortilla chips in the grocery aisle."

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Based on experience and/or intuition based on existing mental maps.

- Reduces Effort
- Fast and Cognitively Frugal

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With Data Mining - Association Rules

Hypothesis driven

Supported by robustissignment Project Exam He level data

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Example Association Rule

Association Rule Based – Using transactional data, identify antecedent & consequent itemsets.

If a customer buys tortilla chips then they will seek out hapd: pprohases also makes als

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Enabled by computers, affinity analysis can explore relationships more complex than previously possible with heuristics alone.

- Increased number of relationships yielding additional consumer insight, and \$\$
- DRAWBACKS
 - Technical Acumen
 - Without shortcuts, computationally intensive

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Example Association Rule

If a customer buys <u>tortilla chips</u> then they will seek out and purchase <u>salsa</u>.

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- "IF" part = antecedent
- "THEN" part = datts g://ptowcoder.com

Association rules must be "disjoint" meaning items in the antecedent & consequent are not shared. WeChat powcoder

<u>ITEMSET = {tortilla chips, salsa}</u>

Using R, we will identify many rules with antecedents and consequents.

Affected Items



Association

Example Association Rule

If a customer buys <u>salsa</u> then they will seek out and purchase <u>tortilla chips</u>.

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- "IF" part = antecedent
- "THEN" part = datts subject to the subject to the

Association rules must be "disjoint" meaning items in the antecedent & consequent are not shared. WeChat powcoder

ITEMSET = {tortilla chips, salsa}

Because this is transaction based, there is really no 1st item to determine the antecedent/consequent order. As a result, the items are a set which can be reordered into two rules.



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Assignment Project Exam Help If a patient has poor circulation then check oxygen levels.

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Antecedent Add WeChat powcoder

Consequent

{ poor circulation, oxygen levels}



If a customer listens to Imagine Dragons then they may listen to Imagine Dragons the I

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Assignment Project Exam Help
If a customer listens to Imagine Dragons then they may listen

https://powcoder.comL-Nation & 21 Pilots

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Antecedent

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Consequent

{ Imagine Dragons, AWOL-Nation, 21 Pilots}

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Assignment Project Exam Help
If a customer buys bread then they will buy cheese, meat and
https://poweoder.com

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If a customer buys bread the project Exam Help will buy cheese, meat and https://powedder.com

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{ BREAD, meat, cheese, BREAD}



Not Disjoint



Tiny Example: Phone Faceplates

Transaction	Faceplate Colors Purchased
1	Assignment Project Exam Help
2	white orange
3	white blue
4	red https://poweoder.com
5	red blue
6	white blue 1
7	white Addan We Chat powcoder white Addan We Chat powcoder
8	red white blue green
9	red white blue
10	yellow



Many Rules are Possible

Transaction 1 supports several rules, such as

- "If red, then white" ("If a red faceplate is purchased, then so is a white one") Assignment Project Exam Help
- "If white, then red"
- "If red and white the serepwooder.com
- + several more

Transaction	Fa Fa	apale Co	Mreturh	atapowcod	ler
1	red	white	green		



Rules on Rules on Rules...10 transactions yet many possibilities

TD 4:	E 1 . C .	D 1 1
Transaction	Faceplate Color	rs Purchased
1	red white	green
2	white orange	
3	white blue	
4	red white	orange
5	red blue	amont Project
6	white Analysis	nment Projec
7	white orange	
8	red white	ths://powco
9	red white	blue Power
10	yellow	11777 01
	<u> </u>	dd WeChat



Single Antecedent

{red, white}
{red, white, green}
{white, red}
{white, green}
{red, green}
{red, green}
{green, ...}

Double Antecedent

{red, white, green} {white, green, red} {red, green, white}

<u>Triple Antecedent</u>

{red, white, blue, green}

Haven't even gotten to orange, blue, and yellow.

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Frequent Item Sets

- Ideally, we want to create all possible combinations of items
- **Problem:** computation time grows exponentially as # items increases

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- Solution: consider only the government of the contract of th
- Criterion for frequent: Support Powcoder

Focusing on frequent item sets keeps your rules from finding pockets of associations that have little evidence or business value.

E.g. If a person buys bread at Wal-Mart, then they will also buy a bike lock...sure that happens but likely not as often as other consequent items.



Support

Transaction	Face	olate Colc	rs Purchased	<u>Support for an itemset</u> = # of
1	red	white	green	transactions that include an
2	white	orange		itemset
3	white	blue		
4	red	white	orange	Example: support for the item
5	red	Ablue	nment Pr	oject Fet fred [Walte] is 4 out of 10
6	white 2	blue		oject Fet ared, [We]te) is 4 out of 10 transactions, or 40%
7	white	orange		
8	red	white	ttps://pov	vcoder.com
9	red	white	blue	Support for a rule = # of
10	yellow		dd WeC	hat ptransastlens that include both
		\Box	au WEC	the antecedent and the
				consequent

Number of transactions with Item Set

Total Number of Transactions



SUPPORT =

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Generating Frequent Item Sets

For *k* products...

- 1. User sets a minimum support criterion
- 2. Next, generate list of one-item sets
- 3. Reduce the set of 1 items to only those meeting the support criterion
- 4. Use the reduced list of one-Item sets to generate list of two-item sets, omitting any items that were previously removed.
- 5. Reduce the set of 2 items to only those meeting the support criterion
- 6. Use the reduced list of two-item sets to generate list of three-item sets, omitting any items that were previously removed.
- 7. Reduce the set of 3 items to only those meeting the support criterion
- 8. Continue up through *k*-item sets

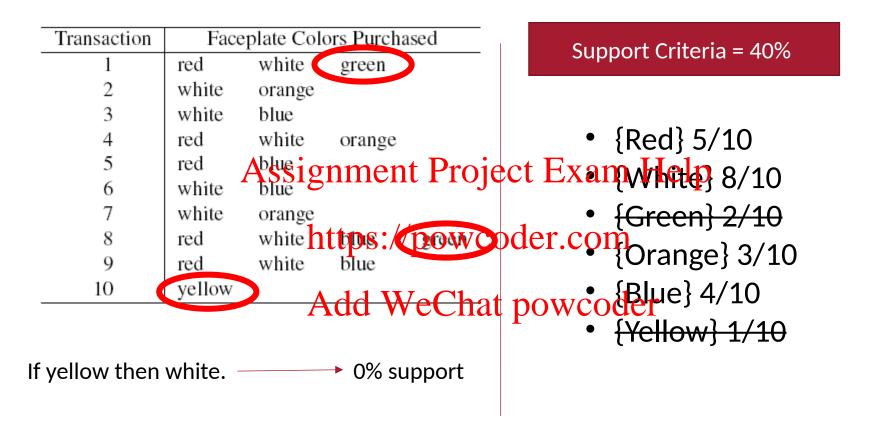
By calculating the first run of 1 item sets (if white, then red) you learn about frequencies as you find more complex item sets. If item sets don't have support in the first run, they won't have support in later runs.



Transaction	Fac	eplate Colo	ors Purchased	I
1	red	white	green	
2	white	orange		
3	white	blue		
4	red	white	orange	
5	red	Ablue 10	nment Proje	ct Exam Help
6	white	blue		
7	white	orange		
8	red	white	ttps://powco	der.com
9	red	white	blue	
10	yellow		dd WeChat	powcoder
If yellow then	white.		→ 0% support	

Since {yellow, and any other color} has no support, there is no need to check it for subsequent item sets such as {yellow, white, blue} or {yellow, white, blue, green}

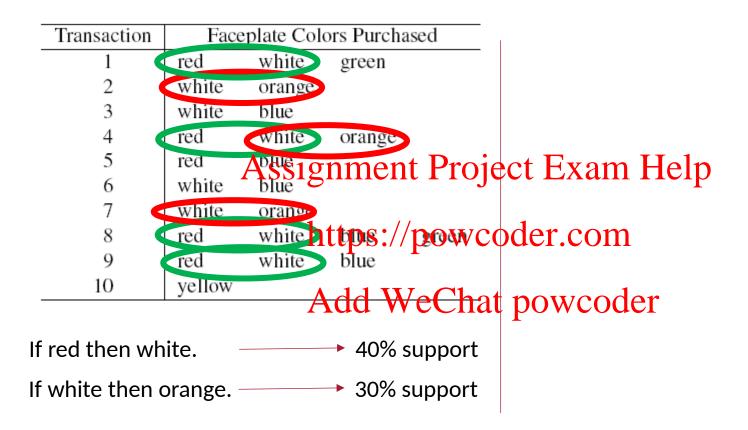
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Since {yellow, and any other color} has no support, there is no need to check it for subsequent item sets such as {yellow, white, blue} or {yellow, white, blue, green}

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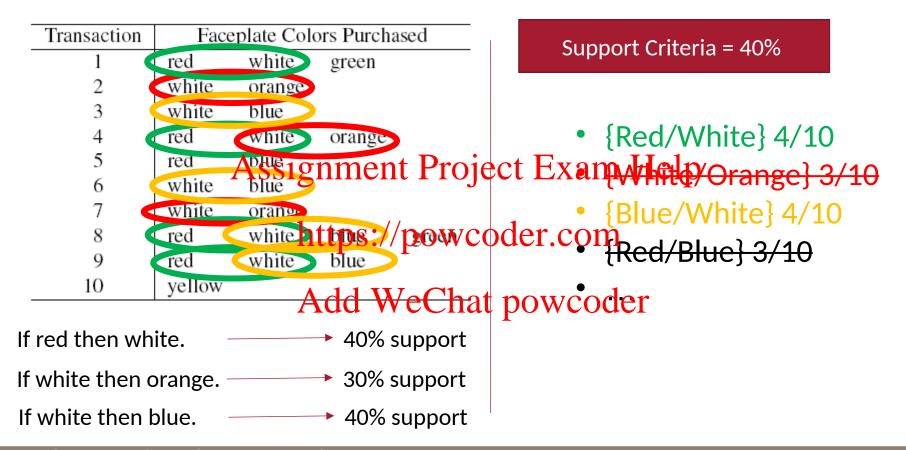
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Since {red, white} and {white, orange} are above our 30% criterion, we should check for three item sets. However if our support criterion is 40% we wouldn't explore {white, orange ...} because its support is 30%

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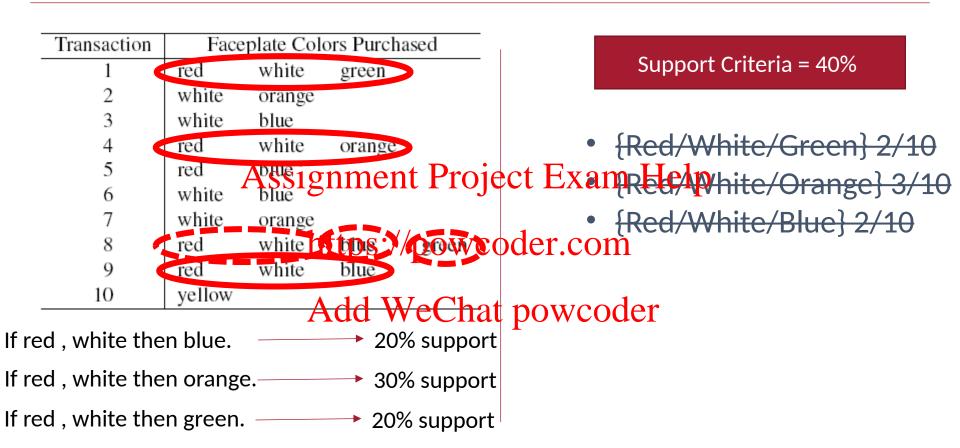


Since {red, white} and {white, orange} are above our fake 30% criterion, we should check for three item sets.

However if our support criterion is 40% we wouldn't explore {white, orange ...} because its support is 30%

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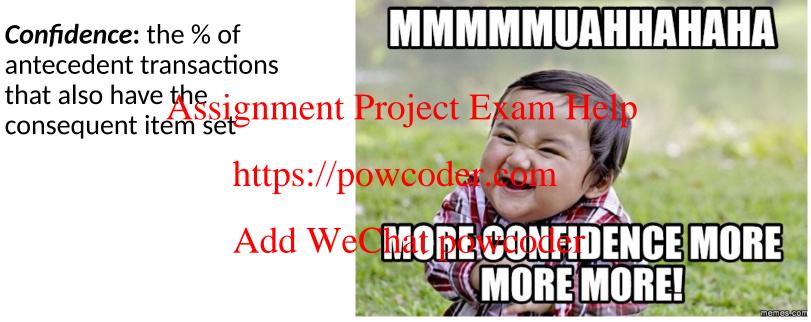
You only check rules that are still in the pool, so no sets with {yellow} or with {white, orange}. We show {white, red, orange} but its not really in the pool any longer.

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Measures of Rule Performance

Confidence: the % of antecedent transactions

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How confident are you that the <u>antecedent</u> isn't just naturally occurring.



Confidence

Suppose you have 100,000 transactions.

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KPI Example - Baseline Transactions

Suppose you have 100,000 transactions.

If candles, cake mix, then any other items to Exam Help Transactions

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If candles, cake mix, then bill be that powcoder 100 Transactions

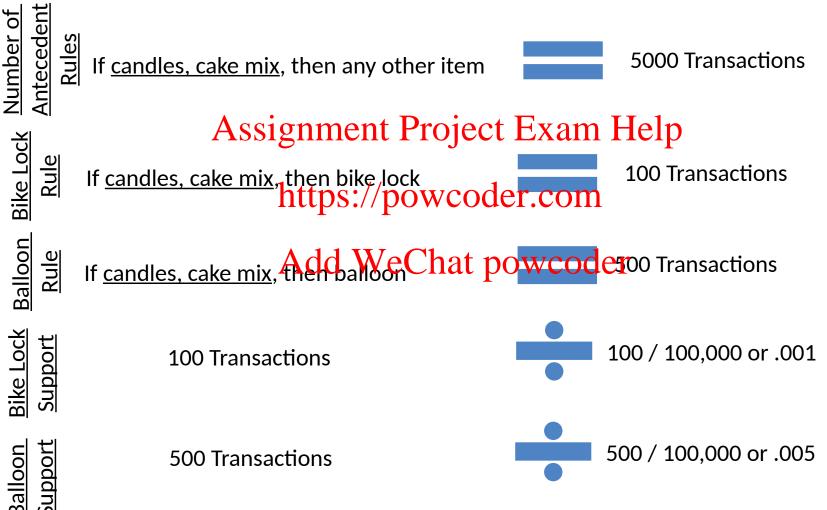
If candles, cake mix, then balloon

500 Transactions



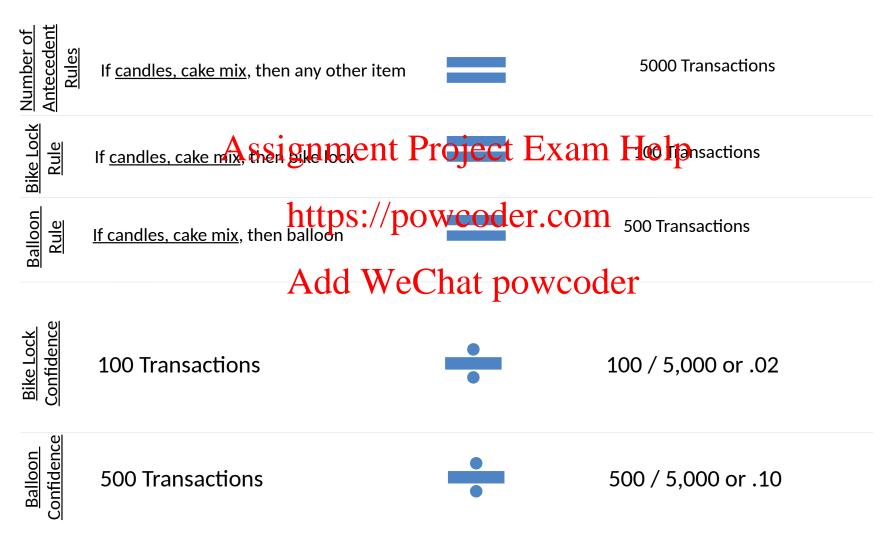
SUPPORT – frequency among all transactions

Suppose you have 100,000 transactions.



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CONFIDENCE - better than natural occurrence



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Confidence

Item Set	Support	Confidence
{candles, cake mix, bike lock}	.001	.02
{candles, cake mix, balloon}	.005	.10
•	(D •	TT 1

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Both have low support, meaning its an infrequent purchase. BUT when it does happen the confidence is higher that balloons will be purchased.

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Measures of Rule Performance

Lift = confidence/(benchmark confidence)

Assignment Project Example Benchmark confidence =

transactions with onsequent as coder.com of all transactions

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Lift > 1 indicates a rule that is useful in finding consequent items sets (i.e., more useful than just selecting transactions randomly)



People naturally buy or select the <u>consequent</u> at some rate, how much better is this specific antecedent item(s)?



Lift

Ballooon confidence is 0.1

<u>Benchmark</u> CONFIDENCE

"then balloon" occurs 600 times out of 100k transactions or .006

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Lift

Now you know confidence is .1.

Benchmark CONFIDENCE

"then balloon," occurs 600 times out of 100k transactions or .006

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For balloon purchase how when better than the oder average occurrence is the rule?



.1 / .006 or 16.6

This rule is providing lift over the natural propensity to purchase balloons.

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Alternate Data Format: Binary Matrix

Transaction	Red	White	Blue	Orange	Green	Yellow
1	1	1	0	0	1	0
2 Λ_{CC}	ionn	ent Pi	coiect	Exam	H_{elp}^{0}	0
3 138	nghin		Office	Lam	110th	0
4	1, 1,		0	1	0	0
5	nttp	s://pov	wcpa	er.com	0	0
6	0	_1	1	0	0	0
7	Add	l WeC	hat p	owood	er o	0
8	1	1	1	0	1	0
9	1	1	1	0	0	0
10	0	0	0	0	0	1



Process of Rule Selection

Generate all rules that meet specified support & confidence

- 1. Find frequent item sets (those with sufficient support see previous)
- Avoids investigating possible all rules (a priori algorithm)

 2. From the frequent item sets, generate rules with sufficient confidence & lift
 - Only use rulet tip syou per typice of the entire and the control of the control o natural (confidence)
 - Only use rules where the antecedent / consequent relationship is stronger than (lift) how often the diservent och at powcoder



Generating Rules in R

```
P(green) if you use the rule

Assignment Project Exam Healipou select randomly

1hs

15 {Red, White} => {Green} 0.2 (0.5) (2.5)00000

5 {Green} => Red (0.7) (1.666667)

14 {White, Green} => {Red (0.7) (1.666667)

4 {Orange} => {White} 0.2 (1.0) (1.428571)

6 {Green} => {White} (0.7) (1.428571)

13 {Red, Green} => {White} (0.7) (1.428571)

14 {Red, Green} => {White} (0.7) (1.428571)

15 {Red, Green} => {White} (0.7) (1.428571)

16 {Green} => {White} (0.7) (1.428571)

17 {Red, Green} => {White} (0.7) (1.428571)

18 {Red, Green} => {White} (0.7) (1.428571)

19 {Red, Green} => {White} (0.7) (1.428571)

10 {Red, Green} => {White} (0.7) (1.428571)

11 {Red, Green} => {White} (0.7) (1.428571)

12 {Red, Green} => {White} (0.7) (1.428571)

13 {Red, Green} => {White} (0.7) (1.428571)

14 {Red, Green} => {White} (0.7) (1.428571)

15 {Red, Green} => {White} (0.7) (1.428571)

16 {Red, Green} => {White} (0.7) (1.428571)

17 {Red, Green} => {White} (0.7) (1.428571)

18 {Red, Green} => {White} (0.7) (1.428571)

19 {Red, Green} => {White} (0.7) (1.428571)

10 {Red, Green} => {White} (0.7) (1.428571)

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14 {Red, Green} => {White} (0.7) (1.428571)

15 {Red, Green} => {White} (0.7) (1.428571)

16 {Red, Green} => {White} (0.7) (1.428571)

17 {Red, Green} => {White} (0.7) (1.428571)
```

- **Support**: red, white, green occurs 2 out of 10 times (0.20)
- **Confidence**: 50% of the time, red/white will result with green.
- <u>Lift</u>: Red/white will result in green 2.5 times more often than green usually.



Interpretation

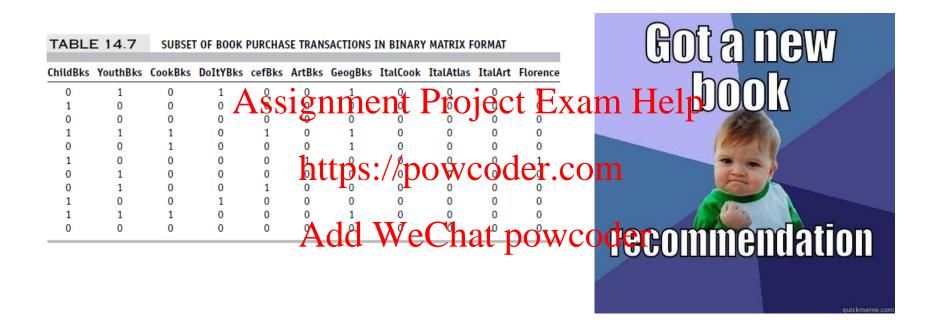
- Support measures overall occurrence
- Confidence shows the rate at which consequents will be found given an antecedent (useful in learning costs of promotion)

https://powcoder.com

• Lift ratio shows how effective the rule is in finding consequents above or below the pattwal selection of the consequence



Example: Charles Book Club



Row 1, e.g., is a transaction in which books were bought in the following categories: Youth, Do it Yourself, Geography



Let's Practice! Open A_AssociationRules.R

VARIABLE NAMES	DESCRIPTIONS				
Seq#	Sequence number in the partition				
ID#	Identification number in the full (unpartitioned) market test data set				
Gender	O=Male, 1=Female				
M	Monetary- Total money spent on books				
R	Recency- Months since last purchase				
F	Freque Ays soignumber en utch Project Exam Help				
FirstPurch	Months since first purchase				
ChildBks	Number of purchases from the category: Child books				
YouthBks	Number of purchaset post of powers. COM				
CookBks	Number of purchases from the category: Cookbooks				
DoItYBks	Number of purchases from the category Do It Yourself books Add Wechat DOWCOder				
RefBks	Number of purchases from the category: Reference books (Atlases, Encyclopedias, Dictionaries)				
ArtBks	Number of purchases from the category: Art books				
GeoBks	Number of purchases from the category: Geography books				
ItalCook	Number of purchases of book title: "Secrets of Italian Cooking."				
ItalAtlas	Number of purchases of book title: "Historical Atlas of Italy."				
ItalArt	Number of purchases of book title: "Italian Art."				
Florence	=1 "The Art History of Florence." was bought, =0 if not				
Related purchase	Number of related books purchased				

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Summary – Association Rules

- Association rules (or affinity analysis, or market basket analysis)
 produce rules on associations between items from a database of
 transactions
- Widely used in recommender systems
- Most popular Anethodin Anti Piral zerith Enxam Help
- To reduce computation, we consider only "frequent" item sets (=support) https://powcoder.com
- Performance of rules is measured by confidence and lift
- Can produce a profusion of rules; review is required to identify useful rules and to reduce redundancy



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Collaborative Filtering

- User based methods
- Item based methods

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Customers Who Bought This Item Also Bought





Practical Management

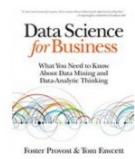
Science (with Essential

Textbook Resources...

> Wayne L. Winston







Data Science for Business: What You Need to Know about Data Mining and... > Foster Provost



Item-user matrix

- Cells are user preferences, r_{ii}, for items
- Preferences can be ratings, or binary (buy, click, like)

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User ID
$$I_1$$
 I_2 \cdots I_p
 U_1 Add We Chat poweder
 U_2 \vdots
 U_n $v_{n,1}$ $v_{n,2}$ \cdots $v_{n,p}$



More efficient to store as rows of triplets

Each row has the user ID, the item ID, and the user's rating of that item

```
> head(songListens) https://powcoder.com
userID song_id listens

1 b80344d063b5ccb3212f76538f3d9e43d87dca9e SOAKIMP12A8C130995 1
2 b80344d063b5ccb3212f76538f3d9e43d87dca9e SOBBMDR12A8C13253B 2
3 b80344d063b5ccb3212f76538f3d9e43d87dca9e SOBYHAJ12A6701BFID 1
5 b80344d063b5ccb3212f76538f3d9e43d87dca9e SOBYHAJ12A6701BFID 1
6 b80344d063b5ccb3212f76538f3d9e43d87dca9e SODACBL12A8C13C273 1
6 b80344d063b5ccb3212f76538f3d9e43d87dca9e SODDNQT12A6D4F5F7E 5
```



Triplets restructure as a longer format but are more memory efficient.



User-based Collaborative Filtering

- Start with a single user who will be the target of the recommendations
- Find other designment mosping la Frage de Imparing preference vectors

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Association rules is a frequentist look at items or transactions. Collaborative filtering is seeking to identify similarities by user preference or item features.



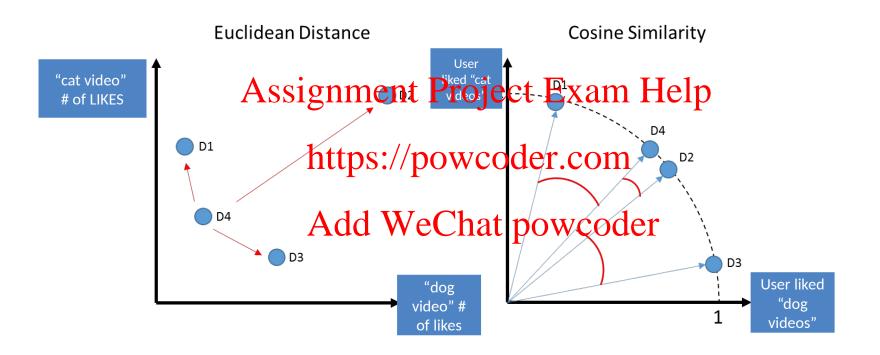
Measuring Proximity Pearson Correlation

- Like nearest-neighbor algorithm
- But Euclidean distance does not do well
- Correlation Aproximity dons petter the Franch Help
- For each user pair, find the co-rated items, calculate correlation between the vedtotpof their vatings for those items

$$Corr(U_1, U_2) = \frac{\sum_{i=1}^{r} (r_{2,i} - \overline{r}_2)}{\sqrt{\sum_{i=1}^{r} (r_{2,i} - \overline{r}_2)^2}}$$



Proximity Measure - Cosine Similarity



K-Means Clustering

Outliers affect algo.

Spherical K-Means

Outliers have no affect.



Major Challenge to Collaborative Filtering

COLD START

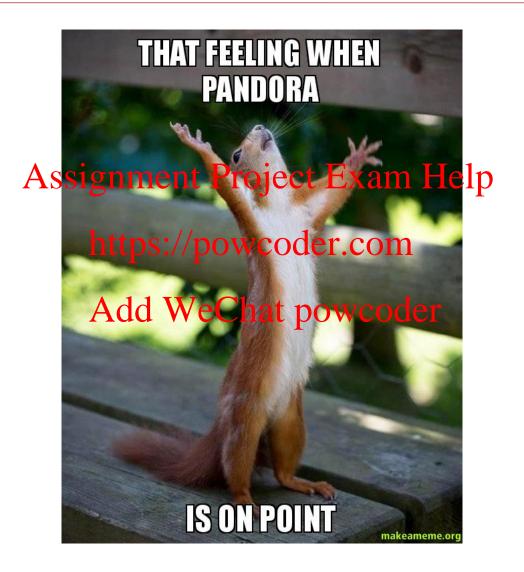
For users with Austsing Intercept it Proviets tust are meighbor preither cosine similarity nor correlation produces useful metric. What do you do with new

users?





Open B_CollaborativeFiltering.R





Summary - Collaborative Filtering

 User-based – for a new user, find other users who share his/her preferences, recommend the highest-rated item that new user does not have.

• Item-based - Act of permusent of user preferences represented as previous transactions://powcoder.com

• Ability to calculate item-item correlations in advance greatly speeds up the

algorithm





Association Rules vs. Collaborative Filtering

- AR: focus entirely on frequent (popular) item combinations. Data rows are single transactions. Ignores user dimension. Often used in displays (what goes with what).
- CF: focus is on user preferences. Data rows are user purchases or ratings over time for a user or a particular item. Can capture "long tail" of user preferences useful for recommendations involving unusual or a large number of items https://powcoder.com

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