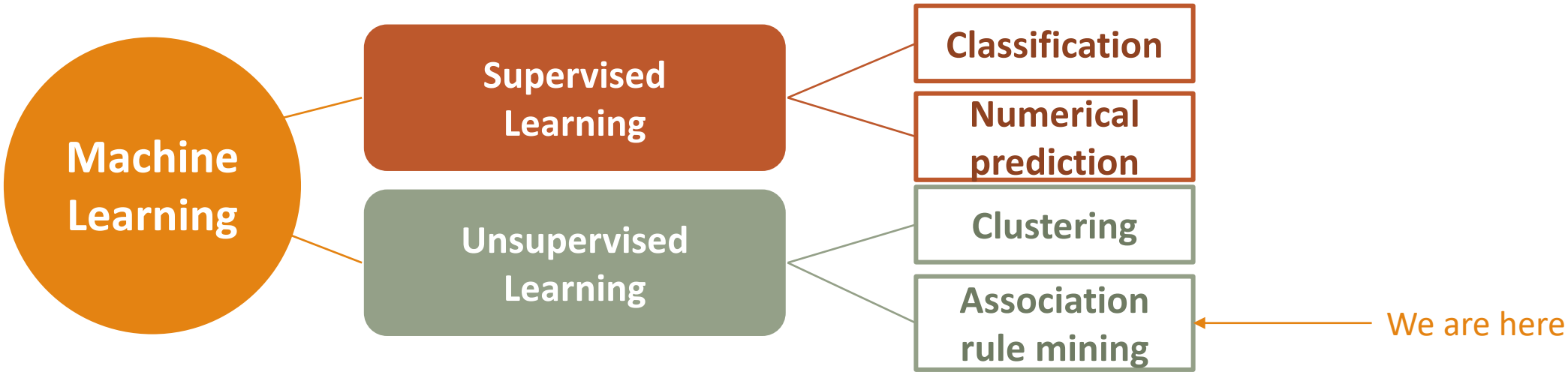
Lecture 10:Unsupervised Learning: Association Rule Mining

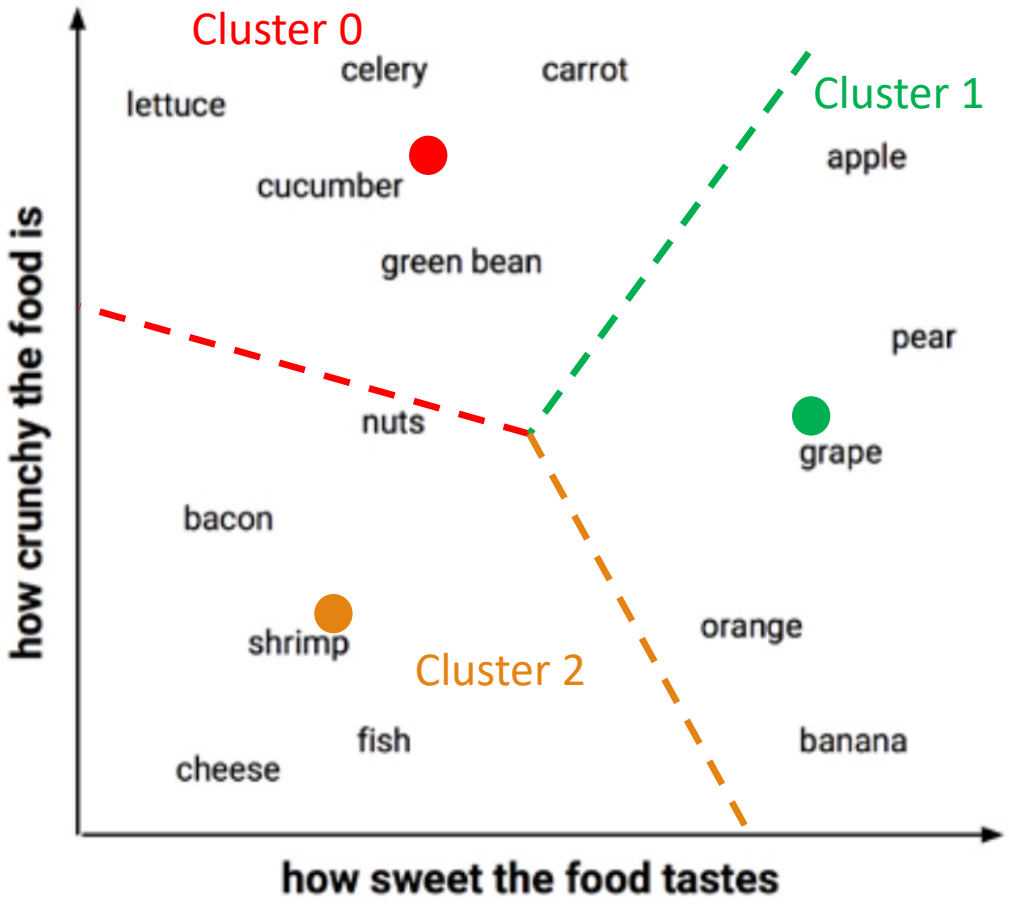
Data Mining Tasks: Recap



The k-means Clustering Algorithm: Recap

- Step 1: Randomly select *k* points in the feature space to serve as the cluster centers.
- Step 2: Assigning the remaining examples to the cluster that is nearest according to the distance.
- Step 3: Recalculate the centroid of each cluster
- Step 4: Repeat step 2 and step 3 until the centroids stop shifting.

The k-means Clustering Algorithm: Recap

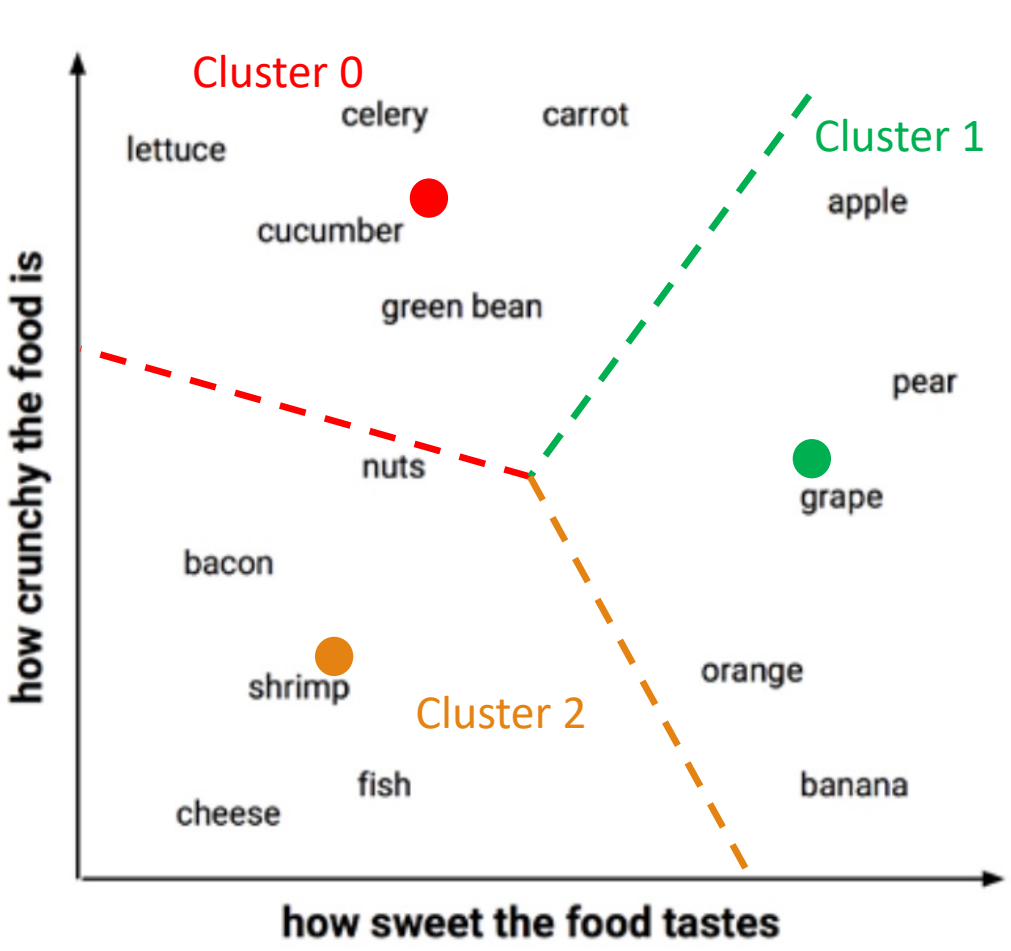


The k-means Clustering Algorithm: Recap

- Clustering results
  - The cluster assignments of each example (size of cluster)
  - Cluster centroids (cluster center)

- There is no training and testing process for unsupervised learning.

The k-means Clustering Algorithm: Recap



Cluster 0

Instances: lettuce, celery, carrot, cucumber, green bean
Centroid: crunchiness-high, sweetness-low

Cluster 1

Instances: apple, pear, grape, orange, banana
Centroid: crunchiness-medium, sweetness-high

Cluster 2

Instances: nuts, bacon, shrimp, fish, cheese
Centroid: crunchiness-low, sweetness-low

Clustering on BART Riders: Recap

Final cluster centroids:

Attribute	Full Data (5493.0)	Cluster# 0 (2368.0)	1 (1210.0)	2 (1915.0)
Age	3.4837	4.6917	3.2603	2.1311
DistToWork	11.4828	11.5051	11.5231	11.4298
DualInc	0.2439	0.4472	0.1694	0.0397
Education	3.8724	4.4054	4.1347	3.0475
Gender	0.5385	0.5904	0.4893	0.5055
Income	5.1606	6.9949	5.6868	2.5598
NbrInHouseHold	2.9053	2.7758	2.2653	3.47
NbrInHouseholdUnder18	0.7073	0.6326	0.3702	1.0125
YrsInArea	4.2922	4.5743	3.9256	4.1749
Rider	0.4285	0.1858	0.0149	0.9901
Language_English	0.9148	0.951	0.9612	0.8407
Language_Spanish	0.0553	0.0329	0.0256	0.1018
OwnRent_own	0.4353	0.9996	0	0.0125
OwnRent_Parent	0.2554	0	0.1157	0.6595

Students
Cluster 2

Young Professionals
Cluster 1

Managers
Cluster 0

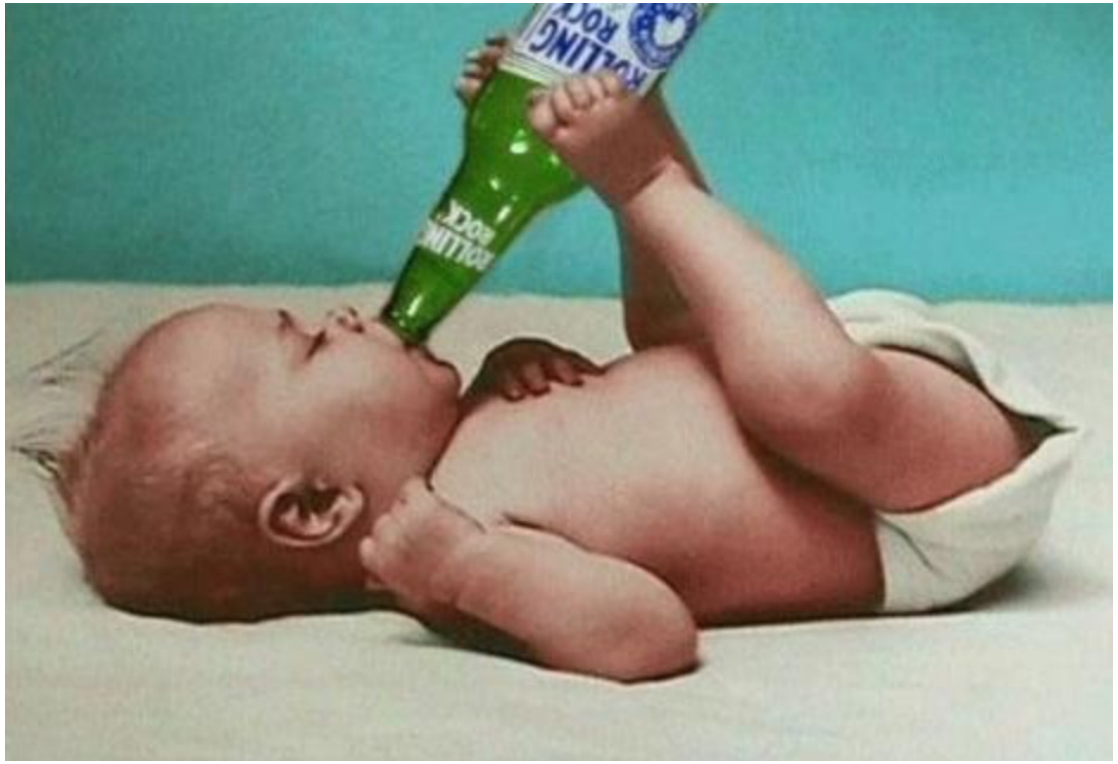
If we segment residents into 3 clusters, what marketing plans you can use to target each cluster?

Outline

- Finding Patterns – Market Basket Analysis
- Understanding Association Rules
- Apriori Algorithm for Association Rule Learning
- Measuring Rule Interest – Support, Confidence, and Lift

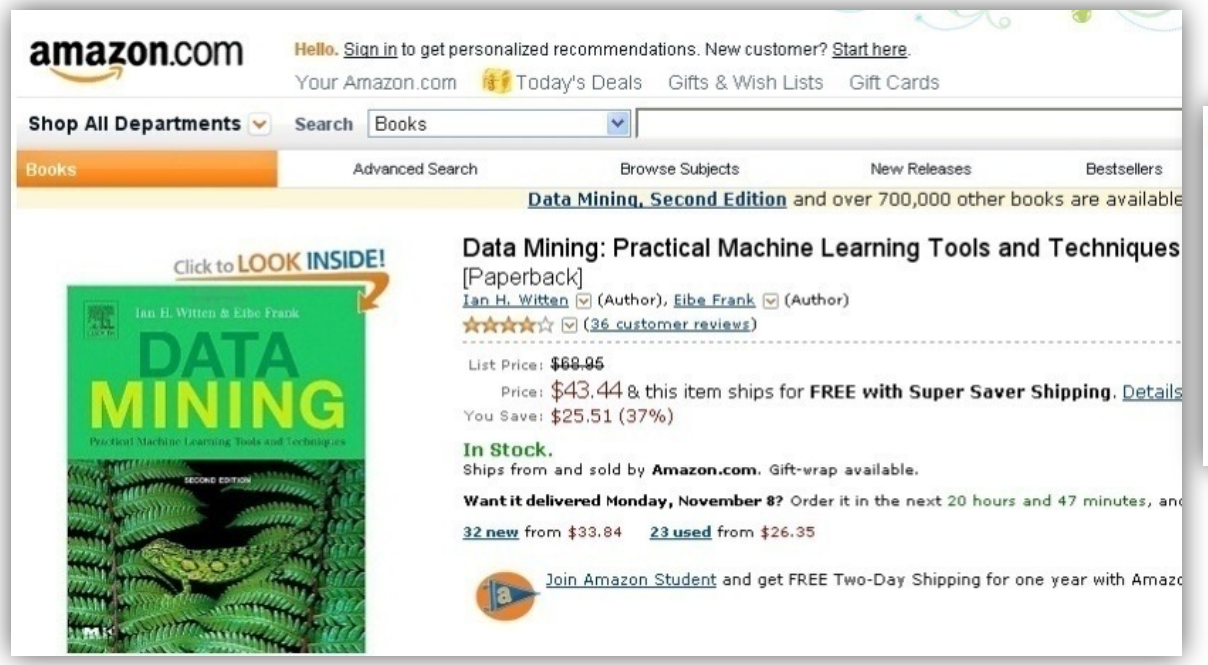
Market Basket Analysis

- **Unsupervised learning-Association rule mining**
  - A classic case: Diaper and Beer



Market Basket Analysis

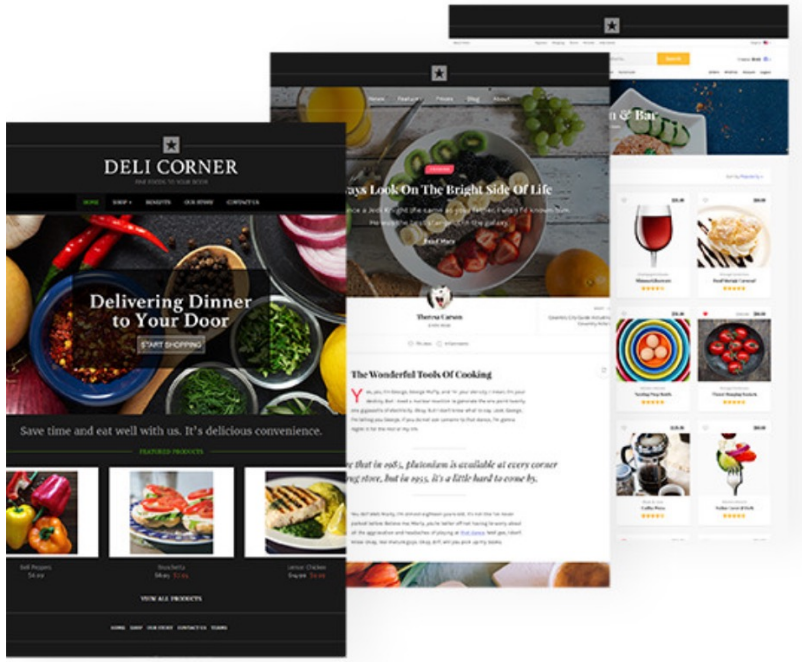
- **Unsupervised learning-Association rule mining**



Promotions to
retain customers
& increase sales

Market Basket Analysis

- **Web Log analysis:** Web sequential patterns are very useful to better structure a company's website for providing easier access to the most popular links.



- We can use association rules to discover the pages which are visited together even if they are not directly connected.
- The rules can be used for restructuring Web sites by adding links between those pages which are visited together.

Understanding Association Rules

- Association rule mining is **unsupervised learning**
  - No need for the algorithm to be trained
  - Data does not need to be labeled ahead of time
  - The program is simply unleashed on a dataset in the hope that interesting associations are found
  - No evaluation

Understanding Association Rules

- The following table shows five transactions in an hospital's gift shop:

Transaction number	Purchased items
1	*{flowers, get well card, soda}*
2	*{plush toy bear, flowers, balloons, candy bar}*
3	*{get well card, candy bar, flowers}*
4	*{plush toy bear, balloons, soda}*
5	*{flowers, get well card, soda}*

Understanding Association Rules

- The building blocks of a association rule mining are the **items** that may appear in any given transaction.
- **Transactions are specified in terms of itemset**.

Understanding Association Rules

- The result of a market basket analysis is a collection of **association rules** specify patterns found in the relationships among items in the itemsets.
  - Association rules are always composed from subsets of itemsets and are denoted by relating one itemset on the ***left-hand side (LHS)*** of the rule to another itemset on the ***right-hand side (RHS)*** of the rule.
  - The ***LHS is the condition*** that needs to be met in order to trigger the rule, and the ***RHS is the expected result*** of meeting that condition.

Understanding Association Rules

{flowers, get well card} ⟶ {soda}

- If *flowers* and *get well card* are purchased together, then *soda* is also likely to be purchased. In other words, " *flowers* and *get well card* imply *soda*."

Understanding Association Rules

- Association rule analysis: search for interesting connections among a very large number of elements.
  - Human beings are capable of such insight quite intuitively
  - It often takes expert-level knowledge or a great deal of experience to do what a rule learning algorithm can do in minutes or even seconds.
  - Additionally, some datasets are simply too large and complex

The Apriori Algorithm for Association Rule Learning

- The most-widely used approach for efficiently searching large databases for rules is known as **Apriori**.
- The following table shows five transactions in an hospital's gift shop:

Transaction number	Purchased items
1	*{flowers, get well card, soda}*
2	*{plush toy bear, flowers, balloons, candy bar}*
3	*{get well card, candy bar, flowers}*
4	*{plush toy bear, balloons, soda}*
5	*{flowers, get well card, soda}*

The Apriori Algorithm for Association Rule Learning

- The Apriori algorithm uses statistical measures of an itemset's "**interestingness**" to locate association rules in much larger transaction databases.
- Whether or not an association rule is deemed interesting is determined by two statistical measures: **support** and **confidence** measures.

The Apriori Algorithm for Association Rule Learning

- The **support** of an itemset or rule measures how frequently it occurs in the data.
  - Support for the itemset *X*: $\text{support}(X) = \frac{\text{count}(X)}{N}$
    - *N* is the number of transactions in the database and *count(X)* is the number of transactions containing itemset *X*
  - Support for a single item:
    - The support for *{candy bar}* is *2 / 5 = 0.4*
  - Support for itemset:
    - *{get well card, flowers}* has support of *3 / 5 = 0.6* in the hospital gift shop data
      - The support for *{get well card}* → *{flowers}* is also 0.6
      - The support for *{flowers}* →*{get well card}* is also 0.6

The Apriori Algorithm for Association Rule Learning

- A rule's **confidence** is defined as the support of the itemset containing both *X* and *Y* divided by the support of the itemset containing only *X*:

$$\text{confidence}(X \rightarrow Y) = \frac{\text{support}(X, Y)}{\text{support}(X)}$$

  - The confidence tells us the proportion of transactions where the presence of item or itemset *X* results in the presence of item or itemset *Y*

The Apriori Algorithm for Association Rule Learning

- **Confidence that *X* leads to *Y* is not the same as the confidence that *Y* leads to *X***
  - The confidence of *{flowers} → {get well card}* is *0.6 / 0.8 = 0.75*
  - The confidence of *{get well card} → {flowers}* is *0.6 / 0.6 = 1.0*
    - a purchase involving flowers is accompanied by a purchase of a get well card 75 percent of the time, while a purchase of a get well card is associated with flowers 100 percent of the time.

Transaction number	Purchased items
1	*{flowers, get well card, soda}*
2	*{plush toy bear, flowers, balloons, candy bar}*
3	*{get well card, candy bar, flowers}*
4	*{plush toy bear, balloons, soda}*
5	*{flowers, get well card, soda}*

High confidence value means if a customer bought the items on the left hand side, that customer also has a high chance to buy the items on the right hand side.

The Apriori Algorithm for Association Rule Learning

- Rules like *{get well card}* → *{flowers}* are known as **strong rules (interesting rules)**, because they have both high support and confidence.
  - Support value: 0.6
  - Confidence value: 1.0
- The way to find more strong rules would be to examine ***every possible combination of the items*** in the gift shop, measure the support and confidence value, and report back only those rules that meet certain levels of interest.

The Apriori Algorithm for Association Rule Learning

- Apriori algorithm creates rules in two phase:
  1. Identifying all the itemsets that meet a minimum support threshold.
  2. Creating rules from these frequent itemsets using those meeting a minimum confidence threshold.

Apriori Algorithm

- Consider a supermarket scenario
  - Sell five items: Onion, Burger, Potato, Milk, Beer.
  - The database consists of six transactions where 1 represents the presence of the item and 0 the absence.

Transaction ID	Onion	Potato	Burger	Milk	Beer
t_1	1	1	1	0	0
t_2	0	1	1	1	0
t_3	0	0	0	1	1
t_4	1	1	0	1	0
t_5	1	1	1	0	1
t_6	1	1	1	1	0

The Apriori Algorithm makes the following assumptions.

- All subsets of a frequent itemset should be frequent.
- The itemset containing infrequent items should be infrequent.
- Set a threshold support level. In our case, we shall fix it at 50%.

Apriori Algorithm

- **Step 1.** Create a frequency table of all the items that occur in all the transactions.
- **Step 2.** Here, support threshold is 50%, hence only those items are frequent which occur in equal or more than three transactions and such items are Onion(O), Potato(P), Burger(B), and Milk(M).
- **Step 3.** make all the possible pairs of the significant items (the order doesn't matter)

1-item itemsets

Item	Frequency (No. of transactions)
{Onion(O)}	4
{Potato(P)}	5
{Burger(B)}	4
{ Milk(M) }	4
{Beer(Be) }	2

Generate frequent items

1-item itemsets that meet the minimum support threshold

Item	Frequency (No. of transactions)
{Onion(O)}	4
{Potato(P)}	5
{Burger(B)}	4
{ Milk(M) }	4

2-item itemsets

Itemset	Frequency (No. of transactions)
{ OP }	4
{ OB }	3
{ OM }	2
{ PB }	4
{ PM }	3
{ BM }	2

- **Step 4.** Only those itemsets are significant which cross the support threshold (OP, OB, PB, and PM)
- **Step 5.** Now we would like to look for 3-item itemsets that are purchased together. We will use the item sets found in step 4 and create 3-item itemsets.
- **Step 6.** Applying the threshold rule again, we find that OPB is the only frequent 3-item itemset.

2-item itemsets

Itemset	Frequency (No. of transactions)
{ OP }	4
{ OB }	3
{ OM }	2
{ PB }	4
{ PM }	3
{ BM }	2

2-item itemsets that meet the minimum support threshold

Itemset	Frequency (No. of transactions)
{ OP }	4
{ OB }	3
{ OM }	2
{ PB }	4
{ PM }	3
{ BM }	2

3-item itemsets

Itemset	Frequency (No. of transactions)
{OPB}	4

The Apriori Algorithm for Association Rule Learning

- Frequent itemsets
  - {O}, {P}, {B}, {M}, {OP}, {OB}, {PB}, {PM}, and {OPB}
- From frequent itemsets to association rules
  - {O} -> {P}, {P} -> {O}
  - {O} -> {B}, {B} -> {O}
  - {P} -> {B}, {B} -> {P}
  - {P} -> {M}, {M} -> {P}
  - {O,P} -> {B}, {B,P} -> {O}, {O,B} -> {P}, {B} -> {O,P}, {O} -> {B,P}, {P} -> {O,B}
- Exam the confidence value to generate **strong rules**

The Apriori Algorithm for Association Rule Learning

- The first phase occurs in multiple iterations.
- Each successive iteration involves evaluating the support of a set of increasingly large itemsets.
  - Iteration 1 involves evaluating the set of 1-item itemsets
  - Iteration 2 evaluates 2-item itemsets, and so on.
- The result of each iteration *i* is a set of all the frequent i-item itemsets that meet the minimum support threshold.
- All the frequent itemsets from iteration *i* are combined in order to generate candidate itemsets for the evaluation in iteration *i + 1*.

The Apriori Algorithm for Association Rule Learning

- The second phase of the Apriori algorithm may begin.
  - Given the set of frequent itemsets, association rules are generated from all possible subsets.
    - For instance, {A, B} would result in candidate rules for {A} → {B} and {B} → {A}.
  - These are evaluated against a minimum confidence threshold, and any rule that does not meet the desired confidence level is eliminated.

Identifying Frequently Purchased Groceries with Association Rules

- Market basket analysis on grocery data
  - We will utilize the purchase data collected from one month of operation at a real-world grocery store. The data contains 9,835 transactions.
    - Transactional data is stored in a slightly different format than that we used previously. Transactional data is a more free form.
      - Each row in the data specifies a single transaction.
      - Rather than having a set number of features, each record comprises a comma-separated list of any number of items, from one to many.
      - The items may differ from example to example

Identifying Frequently Purchased Groceries with Association Rules

- The first five rows of the raw grocery.csv file are as follows:

	A	B	C	D	E
1	citrus fruit	semi-finished bread	margarine	ready soups	
2	tropical fruit	yogurt	coffee		
3	whole milk				
4	pip fruit	yogurt	cream cheese	meat spreads	
5	other vegetables	whole milk	condensed milk	long life bakery product	

- These lines indicate five separate grocery store transactions.

Identifying Frequently Purchased Groceries with Association Rules

```
> summary(groceries)
transactions as itemMatrix in sparse format with
 9835 rows (elements/itemsets/transactions) and
 169 columns (items) and a density of 0.02609146

most frequent items:
      whole milk other vegetables       rolls/buns             soda           yogurt          (Other)
            2513             1903             1809             1715             1372            34055

element (itemset/transaction) length distribution:
sizes
   1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16   17   18   19   20   21   22   23   24   26   27   28
2159 1643 1299 1005  855  645  545  438  350  246  182  117   78   77   55   46   29   14   14    9   11    4    6    1    1    1    1
  29   32
   3    1

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  1.000   2.000   3.000   4.409   6.000  32.000
```

The output 9835 rows refers to the number of transactions

The output 169 columns refers to the 169 different items that might appear in someone's grocery basket.

Items that were most commonly found in the transactional data

A total of 2,159 transactions contained only a single item, while one transaction had 32 items

Identifying Frequently Purchased Groceries with Association Rules

- groceries_rules <- apriori(groceries, parameter = list(support = 0.01, confidence = 0.3, maxlen=2))
  - Find the support and confidence parameters that produce a reasonable number of association rules
    - Set these levels too high: find no rules or rules that are too generic to be very useful
    - Set the threshold too low: an unwieldy number of rules; the operation might take a very long time or run out of memory during the learning phase.

Identifying Frequently Purchased Groceries with Association Rules

- One way to approach the problem of setting a minimum support threshold
  - Think about the smallest number of transactions you would need before you would consider a pattern interesting.
    - For instance, you could argue that if an item is purchased twice a day (about 60 times in a month of data), it may be an interesting pattern.
    - 60 out of 9,835 equals 0.006
- Setting the minimum confidence involves a delicate balance.
  - Confidence is too low: overwhelmed with a large number of unreliable rules
  - set confidence too high: limited to the rules that are obvious or inevitable

Identifying Frequently Purchased Groceries with Association Rules

- The first rule can be read in plain language as, "if a customer buys butter, he/she will also buy whole milk."

```
> # Display top 5 rules
> inspect(sort(groceries_rules, by = "confidence")[1:5])
    lhs                     rhs                support    confidence lift     count
[1] {butter}             => {whole milk}       0.02755465 0.4972477  1.946053 271
[2] {curd}               => {whole milk}       0.02613116 0.4904580  1.919481 257
[3] {domestic eggs}      => {whole milk}       0.02999492 0.4727564  1.850203 295
[4] {onions}             => {other vegetables} 0.01423488 0.4590164  2.372268 140
[5] {whipped/sour cream} => {whole milk}       0.03223183 0.4496454  1.759754 317
```

Identifying Frequently Purchased Groceries with Association Rules

- Support for association rule X->Y: $support(X,Y) = \frac{count(X,Y)}{N}$

- Confidence is defined as the support of the itemset containing both *X* and *Y* divided by the support of the itemset containing only *X*:

$$\text{confidence}(X \rightarrow Y) = \frac{\text{support}(X,Y)}{\text{support}(X)}$$

- The lift of a rule measures: how much more likely one item or itemset is purchased relative to its typical rate of purchase, given that you know another item or itemset has been purchased.
  - Unlike confidence where the item order matters, lift(X → Y) is the same as lift(Y → X).

$$\text{lift}(X \rightarrow Y) = \frac{\text{confidence}(X \rightarrow Y)}{\text{support}(Y)} = \frac{support(X,Y)}{support(X) * support(Y)}$$

Identifying Frequently Purchased Groceries with Association Rules

```
     lhs                rhs                support    confidence lift     count
[1] {butter}        => {whole milk}       0.02755465 0.4972477  1.946053 271
```

0.0554143366 (545/9835) 0.2555160142 (2513/9835)

- Support: 0.02755465 (271/9835)
  - The probability of buying butter and whole milk together is 0.02755465
  - 2.755% transactions include both butter and whole milk. This rule covers 2.755% transactions.
- Confidence: 0.4972477 (271/545)
  - When customers bought butter, they will also buy whole milk about 49.72477% of the time.
  - Among transactions including butter, 49.72477% of them also include whole milk.
- Lift: 1.946053 (0.02755465 /(0.0554143366*0.2555160142))
  - Butter and whole milk have positive effect (because lift value greater than 1) on each other.
  - Purchasing butter increases the probability of buying whole milk by 1.946 times.
  - Purchasing whole milk increases the probability of buying butter by 1.946 times.

Identifying Frequently Purchased Groceries with Association Rules

- {Onions} -> {other vegetables}

```
> # Display top 5 rules
> inspect(sort(groceries_rules, by = "confidence")[1:5])
    lhs                     rhs                support    confidence lift     count
[1] {butter}             => {whole milk}       0.02755465 0.4972477  1.946053 271
[2] {curd}               => {whole milk}       0.02613116 0.4904580  1.919481 257
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[4] {onions}             => {other vegetables} 0.01423488 0.4590164  2.372268 140
[5] {whipped/sour cream} => {whole milk}       0.03223183 0.4496454  1.759754 317
```

Identifying Frequently Purchased Groceries with Association Rules

In spite of the fact that the confidence and lift are high, does {butter} → {whole milk} seem like a very useful rule?

Identifying Frequently Purchased Groceries with Association Rules

- A common approach is to take the association rules and divide them into the following three categories:
  - Actionable
  - Trivial
  - Inexplicable
- Obviously, the goal of a market basket analysis is to find actionable rules that provide a clear and useful insight.
  - Some rules are clear, others are useful
  - it is less common to find a combination of both of these factors.

Identifying Frequently Purchased Groceries with Association Rules

- **Trivial rules** include any rules that are so obvious that they are not worth mentioning
  - They are clear, but not useful.
  - {diapers} → {formula}
- Rules are **inexplicable** if the connection between the items is so unclear that figuring out how to use the information is impossible or nearly impossible.
  - Simply be a random pattern in the data

Identifying Frequently Purchased Groceries with Association Rules

- The best rules are hidden gems—those undiscovered insights into patterns that seem obvious once discovered.
  - One could evaluate each and every rule.
    - Not the best judge of whether a rule is actionable, trivial, or inexplicable.

Identifying Frequently Purchased Groceries with Association Rules

```
> # Display top 5 rules
> inspect(sort(groceries_rules, by = "confidence")[1:5])
    lhs                     rhs                  support    confidence lift     count
[1] {butter}                => {whole milk}      0.02755465 0.4972477  1.946053 271
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[5] {whipped/sour cream}    => {whole milk}      0.03223183 0.4496454  1.759754 317
```

Identifying Frequently Purchased Groceries with Association Rules

```
> inspect(sort(groceries_rules, by = "lift"))
     lhs                      rhs                  support    confidence lift     count
[1]  {beef}                => {root vegetables}    0.01738688 0.3313953  3.040367 171
[2]  {onions}              => {other vegetables}   0.01423488 0.4590164  2.372268 140
[3]  {curd}                => {yogurt}             0.01728521 0.3244275  2.325615 170
[4]  {berries}             => {yogurt}             0.01057448 0.3180428  2.279848 104
[5]  {root vegetables}     => {other vegetables}   0.04738180 0.4347015  2.246605 466
[6]  {cream cheese}        => {yogurt}             0.01240468 0.3128205  2.242412 122
[7]  {chicken}             => {other vegetables}   0.01789527 0.4170616  2.155439 176
[8]  {hamburger meat}      => {other vegetables}   0.01382816 0.4159021  2.149447 136
[9]  {whipped/sour cream}  => {other vegetables}   0.02887646 0.4028369  2.081924 284
[10] {butter}              => {whole milk}         0.02755465 0.4972477  1.946053 271
[11] {beef}                => {other vegetables}   0.01972547 0.3759690  1.943066 194
[12] {pork}                => {other vegetables}   0.02165735 0.3756614  1.941476 213
```

Identifying Frequently Purchased Groceries with Association Rules

- Suppose the marketing team is excited about the possibilities of creating an advertisement to promote vegetables.
- Before finalizing the campaign, however, they ask you to investigate whether vegetables are often purchased with other items.
- To answer this question, we'll need to find all the rules that include vegetables in some form.
- The `subset()` function provides a method to search for subsets rules.

```
> vegetables_rules <- subset(groceries_rules2, items %in% "other vegetables")
> # Display rules containing "other vegetables"
> inspect(vegetables_rules)
    lhs                                  rhs                 support    confidence lift     count
[1] {whipped/sour cream}              => {other vegetables} 0.02887646 0.4028369  2.081924 284
[2] {root vegetables}                 => {other vegetables} 0.04738180 0.4347015  2.246605 466
[3] {other vegetables,root vegetables} => {whole milk}      0.02318251 0.4892704  1.914833 228
[4] {root vegetables,whole milk}      => {other vegetables} 0.02318251 0.4740125  2.449770 228
[5] {other vegetables,yogurt}         => {whole milk}       0.02226741 0.5128806  2.007235 219
```

Identifying Frequently Purchased Groceries with Association Rules

- The criteria for choosing the subset can be defined with several keywords and operators:
  - `items` matches an item appearing anywhere in the rule.
    - To limit the subset to where the match occurs only on the left- or right-hand side, use `lhs` and `rhs` instead.

```
> vegetables_rules_l <- subset(groceries_rules2, lhs %in% "other vegetables")
> inspect(vegetables_rules_l)
    lhs                                  rhs          support    confidence lift     count
[1] {other vegetables,root vegetables} => {whole milk} 0.02318251 0.4892704  1.914833 228
[2] {other vegetables,yogurt}          => {whole milk} 0.02226741 0.5128806  2.007235 219
> # Find and display rules containing "other vegetables" on the right-hand side
> vegetables_rules_r <- subset(groceries_rules2, rhs %in% "other vegetables")
> inspect(vegetables_rules_r)
    lhs                            rhs                support    confidence lift     count
[1] {whipped/sour cream}        => {other vegetables} 0.02887646 0.4028369  2.081924 284
[2] {root vegetables}           => {other vegetables} 0.04738180 0.4347015  2.246605 466
[3] {root vegetables,whole milk} => {other vegetables} 0.02318251 0.4740125  2.449770 228
```