CHAPTER 6

# Association Analysis

The beer and diaper association story in Analytics circle is (urban) legendary (Power, 2002). There are many variations of this story, but the basic idea is that a supermarket company discovered that customers who buy diapers also tend to buy beer. The beer and diaper relationship heralded what unusual, unknown, and quirky nuggets can be learned from the purchase transaction data of a supermarket. How did the supermarket determine such a relationship between products existed? Answer: data mining. Specifically, association analysis.

Association analysis measures the strength of co-occurrence between one item and another. The objective of this class of data mining algorithms is not to predict an occurrence of an item, like classification or regression do, but to find usable patterns in the co-occurrences of the items. Association rules learning is a branch of an unsupervised learning process that discovers hidden patterns in data, in the form of easily recognizable *rules*.

Association algorithms are widely used in retail analysis of transactions, recommendation engines, and online clickstream analysis across web pages. One of the popular applications of this technique is called *market basket analysis*, which finds co-occurrences of one retail item with another item within the same retail purchase transaction (Agrawal et al., 1993). If patterns within data tell us that baby formula and diapers are usually purchased together in the same transaction, a retailer can take advantage of this association for bundle pricing, product placement, and even shelf space optimization within the store layout. Similarly, in an online business setting, this information can be leveraged for real-time cross selling, recommendations, cart offers and post purchase marketing strategies. In the case of retail business, many of the association rules results are commonly known, for example a burger with fries or baby formula with diapers; however, uncommon relationships are the prized discoveries, the ones businesses can take advantage of. The downside is association analysis may also yield spurious relationships between items. When dealing with data containing billions of transactions, we would find transactions with all kinds of possibilities with strange combinations of item sets (e.g., nicotine patch and cigarettes). It takes analytical skill and business knowledge to successfully apply the outcome of association



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analysis. The model outcome of an association analysis can be represented as a set of rules, like the one below:

{Item A} -> {Item B}

This rule indicates that based on the history of all the transactions, if Item A is found in a transaction or a basket, there is a strong propensity of occurrence of Item B within the *same* transaction. Here, Item A is the *antecedent* or *premise* of the rule and Item B is *consequent* or *conclusion* of the rule. The antecedent and consequent of the rule can contain more than one item, like {Item A and Item C}. To mine these kinds of rules from the data, we would need to analyze all previous customer purchase transactions. In a retail business, there would be millions of transactions made in a day with thousands of Stock Keeping Units (SKU), which are unique identifiers for a product or an item sold and stocked. Hence, two of the key considerations of association analysis are computational time and resources. However, over the last two decades newer and more efficient algorithms have been developed to mitigate this problem.

## CROSS SELLING: CUSTOMERS WHO BOUGHT THIS ALSO BOUGHT…

Consider an e-commerce website that sells a large selection of products online. One of the objectives in managing e-commerce business is to increase the average order value of the visit. Optimizing order size is even more critical when the businesses pay for acquisition traffic through search engine marketing, online advertisements, and affiliate marketing. Businesses attempt to increase average order value by cross-selling and up-selling relevant products to the customer, many times based on what they have purchased or are currently purchasing in the current transaction (a common fast-food equivalent: "Do you want fries with the burger?"). Businesses need to be careful by weighing the benefit of suggesting an extremely relevant product against the risk of irritating a customer who is already making a transaction. In a business where there are limited products (e.g., fast-food industry), cross-selling a product with another product is straightforward and is quite inherent in the business. But, when the number of unique products runs in thousands and millions, determining a set of *affinity products* when customers are looking at a product is quite a tricky problem.

To better learn about product affinity, we turn to purchase history data. The information on how one product creates affinity to another product relies on the fact that both the products appear in the same transaction. If two products are bought together, then we can speculate that the necessity of those products arise in the same time frame for the customer. If the two products are bought together many times, by a large number of customers, then there is definitely an affinity pattern within these products. In a new later transaction, if a customer picks one of those affinity products, then there is an increased likelihood that the other product will be picked by the customer, in the same transaction.

The key input for affinity analysis is a list of past transactions with product information. Based on the analysis of these transactions, we can determine what the most frequent product pairs are. We need to define a threshold for "frequent" because a few appearances of a product pair doesn't qualify as a pattern. The result of the affinity analysis is a rule set that says, "If product A is purchased, there is an increased likelihood that product B will be purchased in the same transaction." This rule set can be leveraged to provide cross sell recommendations on the product page of product A. Affinity analysis is the concept behind the web widgets which state, "Customers who bought this also bought…"

## 6.1 CONCEPTS OF MINING ASSOCIATION RULES

Basic association analysis just deals with the *occurrence* of one item with another. More complicated analysis can take into consideration the quantity of occurrence, price, and sequence of occurrence, etc. The method for finding association rules through data mining involves the following sequential steps:

**Step 1**: Prepare the data in transaction format. An association algorithm needs input data to be formatted in a particular format.
**Step 2**: Short-list frequently occurring *item sets*. Item sets are combination of items. An association algorithm limits the analysis to the most frequently occurring items, so the final rule set extracted in next step is more meaningful.
**Step 3**: Generate *relevant* association rules from item sets. Finally, the algorithm generates and filters the rules based on the interest measure.

To start with, let's consider a media website, like BBC or Yahoo News, with categories such as news, politics, finance, entertainment, sports, and arts. A session or transaction in this example is one visit for the website, where the same user accesses content from different categories, within a certain session period. A new session usually starts after 30 minutes of inactivity. Sessions are very much similar to transactions in a traditional brick and mortar model and the pages accessed can be related to items purchased. In online news sites, items are *visits* to the categories such as News, Finance, Entertainment, Sports, and Arts. We can collect the data as shown in Table 6.1, with a list of sessions and media categories accessed during a given session. Our objective in this data mining task is to find associations between media categories.

For association analysis of these media categories, we would need a data set in a particular transaction format. To get started with association analysis, it would be helpful to pivot the data in the format shown in Table 6.2.

This binary format indicates the presence or absence of article categories and ignores qualities such as minutes spent viewing or the sequence of access, which can be important in certain sequence analyses. For now, we are focusing on basic association analysis and we shall review the terminologies used in association rules.

**Table 6.1**

| Session ID | List of media categories accessed |
|---|---|
| 1 | {News, Finance} |
| 2 | {News, Finance} |
| 3 | {Sports, Finance, News} |
| 4 | {Arts} |
| 5 | {Sports, News, Finance} |
| 6 | {News, Arts, Entertainment} |

**Table 6.2** Clickstream Data Set

| Session ID | News | Finance | Entertainment | Sports | Arts |
|---|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 | 0 |
| 4 | 0 | 0 | 0 | 0 | 1 |
| 5 | 1 | 1 | 0 | 1 | 0 |
| 6 | 1 | 0 | 1 | 0 | 1 |

### 6.1.1 Item Sets

In the examples of association rules we discussed so far, the antecedent and consequent of the rules had only one item. But, as mentioned before, they can involve multiple items. For example a rule can be of the following sort:

{News, Finance} -> {Sports}

This rule implies, if users have accessed news and finance in the same session, there is a high likelihood that they would also access sports articles, based on historical transactions. The combination of news and finance item is called an *item set*. An item set can occur either in the antecedent or in the consequent portion of the rule; however, both sets should be disjointed, which means there should not be any common item on both sides of the rules. Obviously, there is no practical relevance for the rules like "News and Finance users are most likely to visit News and Sports page." Instead, rules like "If users visited Finance page they are more likely to visit News and Sports page" make more sense. Introduction of the item set with more than one item greatly increases the permutations of rules to be considered and tested for the strength of relationships.

The strength of an association rule is commonly quantified by the *support* and *confidence* measures of a rule. There are few more quantifications like *lift* and *conviction* measures that can be used in special cases. All these measures are based on the relative frequency of occurrences of a particular item set in the transactions data set used for training. Hence, it is important that the training set used for rule generation is unbiased and truly represents the universe of transactions. We will go through each of these frequency metrics in the following sections.

#### *Support*

The *support of an item* is simply the relative frequency of occurrence of an item set in the transaction set. In the data set shown in Table 6.2, support of {News} is five out of six transactions, 5/6 = 0.83. Similarly, support of an item set

{News, Finance} is the co-occurrence of both news and finance in a transaction with respect to all the transactions:

Support({News}) = 5/6 = 0.83
Support({News, Finance}) = 4/6 =0.67
Support({Sports}) = 2/6 = 0.33

The *support of a rule* is a measure of how all the items in a rule are represented in overall transactions. For example, in the rule {News}->{Sports}, News and Sports occur in two of six transactions and hence support for the rule {News} -> {Sports} is 0.33. The support measure for a rule indicates whether a rule is worth considering. Since the support measure favors the items where there is high occurrence, it uncovers the patterns that are worth taking advantage of and investigating. This is particularly interesting for businesses because leveraging patterns in high volume items leads to more incremental revenue. Rules with low support have either infrequently occurring items or an item relationship occurs just by chance, which may yield spurious rules. In association analysis, a threshold of support is specified to filter out infrequent rules. Any rule that exceeds the support threshold is then considered for further analysis.

### Confidence

The *confidence of a rule* measures the likelihood of occurrence of the consequent of the rule out of all the transactions that contain the antecedent of the rule. Confidence provides the reliability measure of the rule. Confidence of the rule (X -> Y) is calculated by

$$\text{Confidence}\,(X \text{ -> } Y) = \frac{\text{Support}(X \cup Y)}{\text{Support}\,(X)} \tag{6.1}$$

In the case of the rule {News, Finance} -> {Sports}, the question that the confidence measure answers is, if an transaction has both News and Finance, what is the likelihood of seeing Sports in it?

$$\begin{aligned}\text{Confidence}\,(\{\text{News, Finance}\} \text{ -> } \{\text{Sports}\}) &= \frac{Support\,(\{News, Finance, Sports\})}{Support\,(\{News, Finance\})}\\ &= \frac{2/6}{4/6}\\ &= 0.5\end{aligned}$$

Half of the transactions that contain News and Finance also contain Sports. This means 50% of users who visit the news and finance pages also visit sports pages.

### Lift

Though confidence of the rule is widely used, the frequency of occurrence of a rule consequent (conclusion) is largely ignored. In some transaction item sets, this can provide spurious scrupulous rule sets because of the presence of infrequent items in the rule consequent. To solve this, we can have the support of a consequent in the denominator of a confidence calculation. This measure is called the *lift of the rule*. The lift of the rule can be calculated by

$$\text{Lift (X ->Y)} = \frac{Support\ (X \cup Y)}{Support\ (X) * Support\ (Y)} \tag{6.2}$$

In the case of our example:

$$\text{Lift (\{News, Finance\}->\{Sports\})} = \frac{Support\ (X \cup Y)}{Support\ (X) * Support\ (Y)}$$

$$= \frac{0.333}{0.667 * 0.33} = 1.5$$

Lift is the ratio of the observed support of {News + Finance} and {Sports} with what is expected if {News + Finance} and {Sports} usage were completely independent. Lift values closer to 1 mean the antecedent and consequent of the rules are independent and the rule is not interesting. The higher the value of lift, the more interesting the rules are.

### *Conviction*

The *conviction of the rule* X -> Y is the ratio of the expected frequency of X occurring in spite of Y and the observed frequency of incorrect predictions. Conviction takes into account the direction of the rule. The conviction of (X -> Y) is not the same as conviction of (Y -> X). Conviction of a rule (X -> Y) can be calculated by

$$\text{Conviction (X -> Y)} = \frac{1 - Support\ (Y)}{1 - Confidence\ (X \rightarrow Y)} \tag{6.3}$$

For our example,

$$\text{Conviction (\{news, finance\} -> \{sports\})} = \frac{1 - 0.33}{1 - 0.5} = 1.32$$

A conviction of 1.32 means that the rule ({News, Finance} -> {Sports}) would be incorrect 32% more often if the relationship between {News, Finance} and {Sports} is purely random.

## 6.1.2 The Process of Rule Generation

The process of generating meaningful association rules from the data set can be broken down into two basic tasks.

1. *Finding all frequent item sets.* For an association analysis of *n* items it is possible to find $2^n - 1$ item sets excluding the null item set. As the number of items increase, there is an exponential increase in the number of item sets. Hence it is critical to set a minimal support threshold to discard less frequently occurring item sets in the transaction

universe. All possible item sets can be expressed in a visual lattice form like the diagram shown in Figure 6.1. In this figure one item {Arts} is excluded from the item set generation. It is not uncommon to exclude items so that the association analysis can be focused on subset of important relevant items. In Supermarket example, some filler items like grocery bag can be excluded from the analysis. An item set tree (or lattice) helps demonstrate the methods to easily find frequent item sets.

2. *Extracting rules from frequent item sets.* For the data set with n items it is possible to find $3^n - 2^{n+1} + 1$ rules (Tan et al., 2005). This step extracts all the rules with a confidence higher than a minimum confidence threshold.

This two-step process generates hundreds of rules even for a small data set with dozens of items. Hence it is important to set a reasonable support and confidence threshold to filter out less frequent and less relevant rules in the search space. The generated rules can also be evaluated with support, confidence, lift,

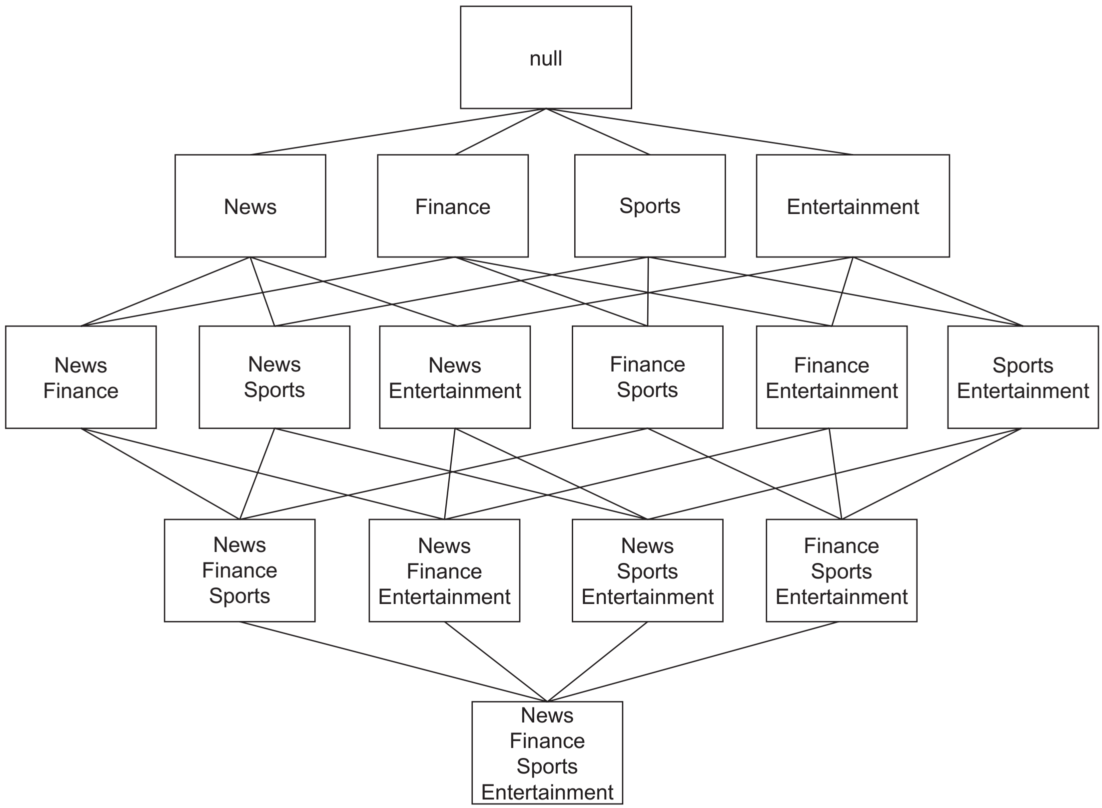



**FIGURE 6.1**
Item set tree.

and conviction measures. In terms of computational requirements, finding all the frequent item sets above a support threshold is more expensive than extracting the rules. Fortunately, there are some algorithmic approaches to efficiently find the frequent item sets. The Apriori and FP-Growth algorithms are two of the most popular association analysis algorithms.

## 6.2 APRIORI ALGORITHM

All association rule algorithms should efficiently find the frequent item sets from the universe of all the possible item sets. The Apriori algorithm leverages some simple logical principles on the lattice item sets to reduce the number of item sets to be tested for the support measure (Agrawal & Srikant, 1994). The Apriori principles states that "*If an item set is frequent, then all its subset items will be frequent.*" (Tan et al, 2005). The item set is "frequent" if the support for the item set is more that support threshold.

For example, if the item set {News, Finance, Sports} from the data set shown in Table 6.2 is a frequent item set, that is, its support measure (0.33) is higher

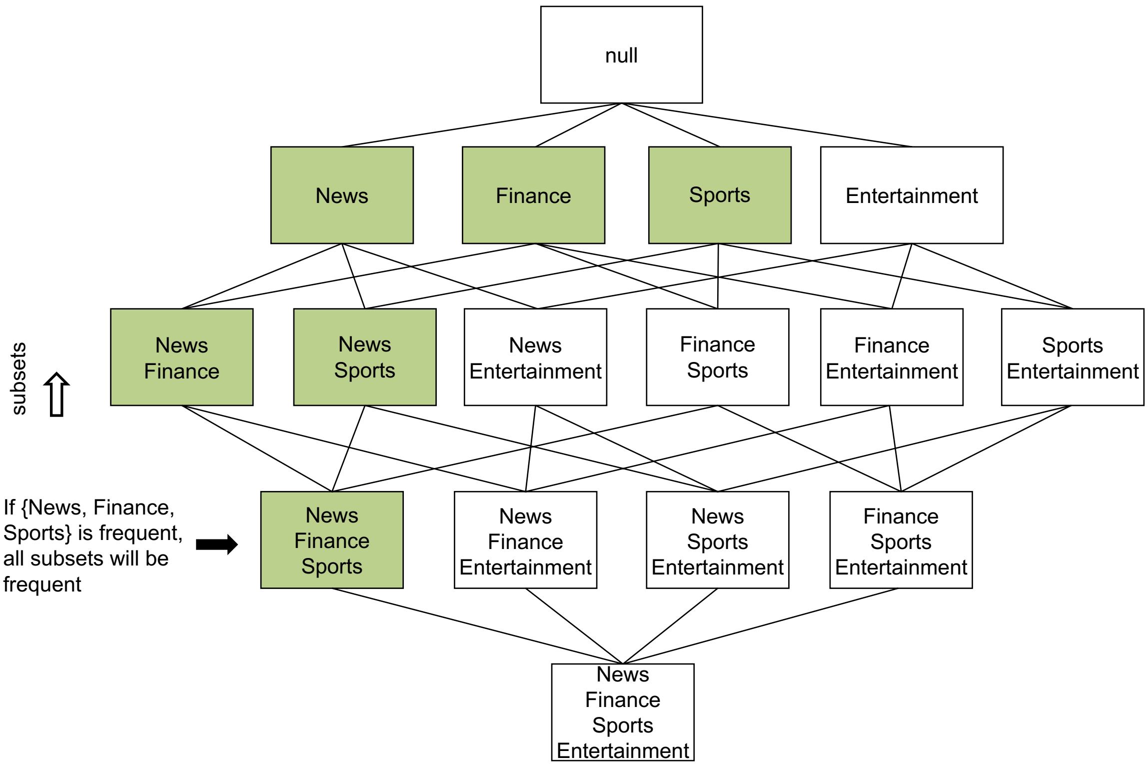



**FIGURE 6.2**
Frequent item sets using Apriori principle.

than the threshold support measure k (say, 0.25), then all of its subset items or item set will be frequent item sets. Subset item sets will have a support measure higher than or equal to the parent item set. Figure 6.2 shows the application of the Apriori principle in a lattice. The support measures of the subset item sets for {News, Finance, Sports} are

Support {News, Finance, Sports} = 0.33 (above threshold support)
Support {News, Finance} = 0.66
Support {News, Sports} = 0.33
Support {News} = 0.83
Support {Sports} = 0.33
Support {Finance} = 0.66

Conversely, if the item set is infrequent, then all its *super*sets will be infrequent. In this example, support of Entertainment is 0.16, and the support of all the supersets that contain Entertainment as an item will be less than or equal to 0.16, which is infrequent when considering the support threshold of 0.25. Superset exclusion of an infrequent item is shown in Figure 6.3.

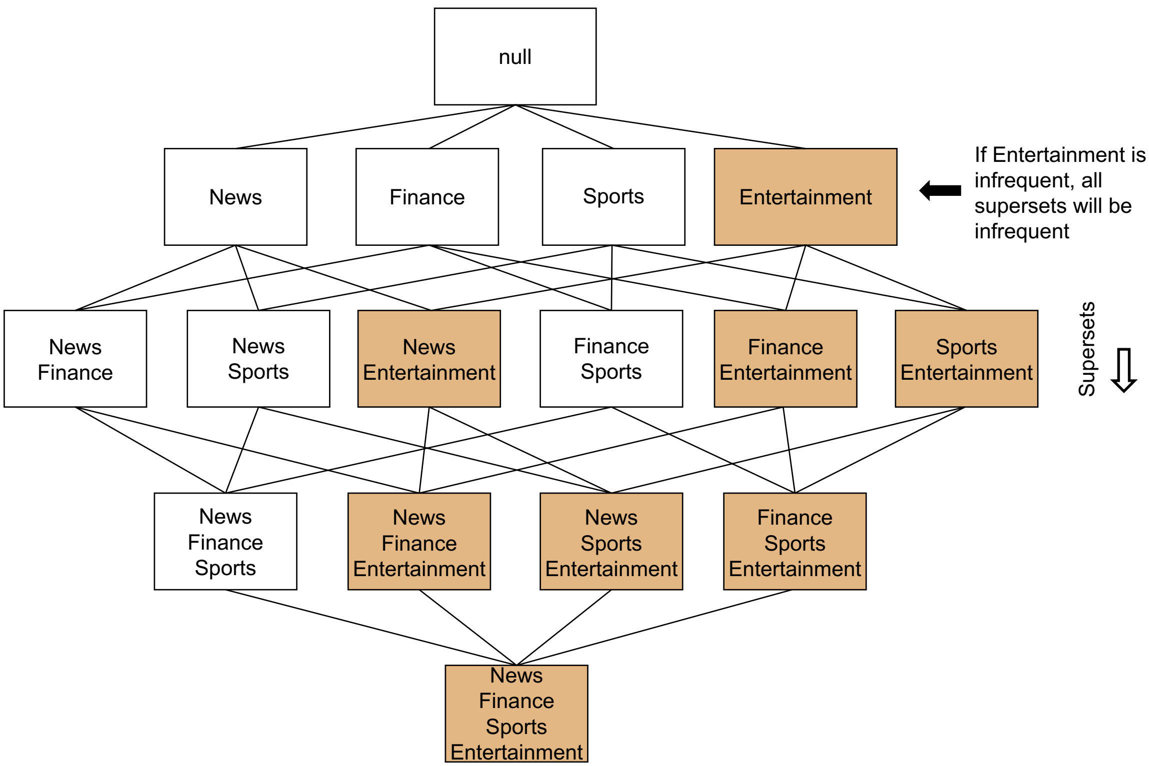



**FIGURE 6.3**
Frequent item sets using Apriori principle: Exclusion.

**Table 6.3** Clickstream Data Set: Condensed Version

| Session | News | Finance | Entertainment | Sports |
|---|---|---|---|---|
| 1 | 1 | 1 | 0 | 0 |
| 2 | 1 | 1 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 |
| 4 | 0 | 0 | 0 | 0 |
| 5 | 1 | 1 | 0 | 1 |
| 6 | 1 | 0 | 1 | 0 |

The Apriori principle is helpful because not all item sets have to be considered for a support calculation and tested for the support threshold; hence generation of the frequent item sets can be handled efficiently by eliminating a bunch of item sets that have an infrequent item or item sets (Bodon, 2005).

### 6.2.1 Frequent Item Set Generation Using the Apriori Principle

Let's consider the data set shown in Table 6.3, which is the condensed version of the example set discussed above. In this data set there are six transactions. If the support threshold is assumed to be 0.25, then we expect all items should appear in at least two out of six transactions.

We can now calculate support count and support for all item set(s). *Support count* is the absolute count of the transactions and support is the ratio of support count to total transaction count. Any one item set below the threshold support count (which is 2 in this example) can be eliminated from further processing. Table 6.4 shows the support count and support calculation for each item. Since {Entertainment} has a support count less than the threshold, it can been eliminated for the next iteration of item set generation. The next step is generating possible two-item set generations for {News}, {Finance}, and {Sports}, which yield three two-item sets. If the {Entertainment} item set is not eliminated, we would obtain six two-item sets. Figure 6.4 shows the visual representation of the item sets with elimination of {Entertainment} item.

This process is continued until all n-item sets are considered from previous sets. At the end, there are seven frequent item sets passing the support threshold. The total possible number of item sets is 15 (= $2^4 - 1$). By eliminating {Entertainment} in the first step, we don't have to generate seven additional item sets that would not pass the support threshold anyway (Witten & Frank, 2005).

**Table 6.4** Frequent Item Set Support Calculation

| Item | Support Count | Support |
|---|---|---|
| {News} | 5 | 0.83 |
| {Finance} | 4 | 0.67 |
| {Entertainment} | 1 | 0.17 |
| {Sports} | 2 | 0.33 |
| **Two-Item Sets** | **Support Count** | **Support** |
| {News, Finance} | 4 | 0.67 |
| {News, Sports} | 2 | 0.33 |
| {Finance, Sports} | 2 | 0.33 |
| **Three-Item Sets** | **Support Count** | **Support** |
| {News, Finance, Sports} | 2 | 0.33 |

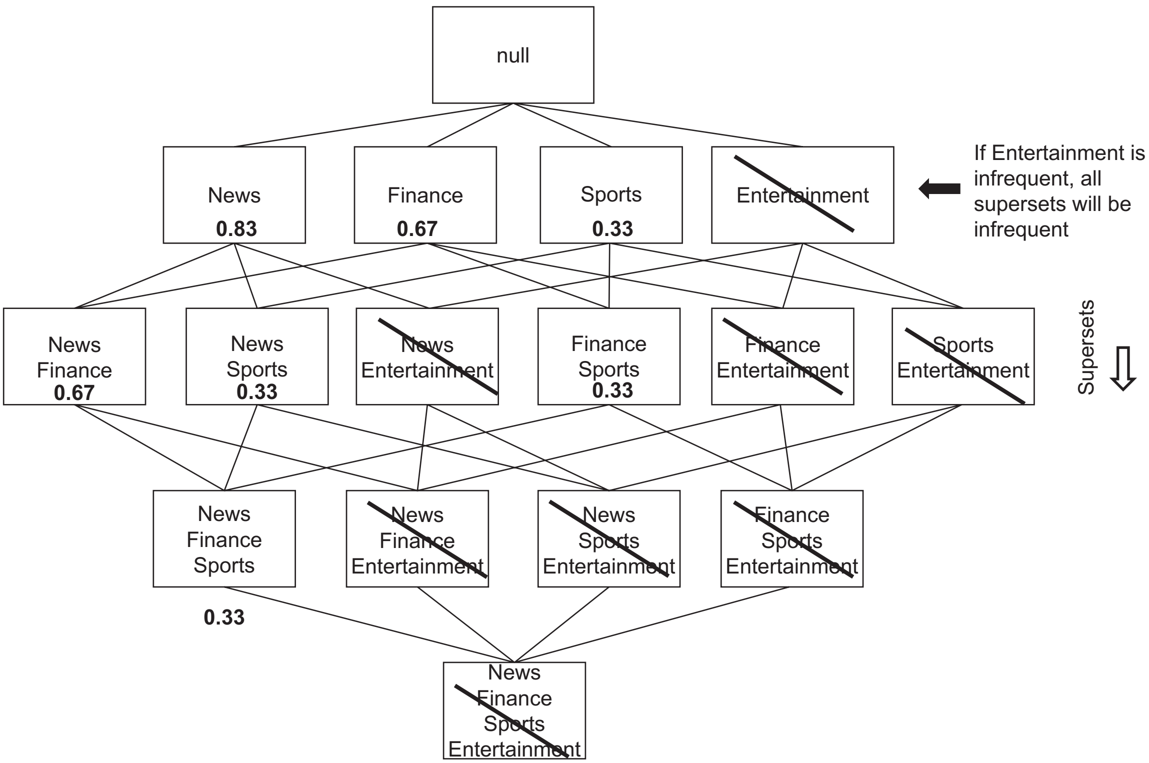



**FIGURE 6.4**
Frequent item set with support.

### 6.2.2 Rule Generation

Once the frequent item sets are generated, the next step in association analysis is generating useful rules which have a clear antecedent (premise) and consequent (conclusion), in the format of the following rule:

{Item A} -> {Item B}

The usefulness of the rule can be approximated by an objective measure of interest such as confidence, conviction, or lift. Confidence for the rule is calculated by the support scores of the individual items as given in Equation 6.1. Each frequent item set of n items can generate $2^n - 2$ rules. For example {News, Sports, Finance} can generate rules with the following confidence scores.

Rules and confidence scores

{News, Sports}->{Finance} – 0.33 / 0.33 = 1.0
{News, Finance}->{Sports} – 0.33 / 0.67 = 0.5
{Sports, Finance}->{News} – 0.33 / 0.33 = 1.0
{News}->{Sports, Finance} – 0.33 / 0.83 = 0.4
{Sports}->{News, Finance} – 0.33 / 0.33 = 1.0
{Finance}->{News, Sports} – 0.33 / 0.67 = 0.5

Since all the support scores have already been calculated in the item set generation step, there is no need for another set of computations for calculating confidence. However, it is possible to prune potentially low confidence rules using the same Apriori method. For a given frequent item set {News, Finance, Sports}, if the rule {News, Finance} -> {Sports} is a low confidence rule, then we can conclude any rules within the subset of the antecedent will be a low confidence rule. Hence we can discard all the rules like {News}->{Sports, Finance} and {Finance} -> {News, Sports}, which are in the subsets of the antecedent of the rule. The reason is that all three rules have the same numerator in the confidence score calculation (Equation 6.1), which is 0.33. The denominator calculation depends on the support of the antecedent. Since the support of a subset is always greater or equal to the set, we can conclude all further rules within a subset of an item set in the premises will be a low confidence rule, and hence can be ignored.

All the rules passing a particular confidence threshold are considered for output along with both support and confidence measures. These rules should be further evaluated for rational validity to determine if a useful relationship was uncovered, if there was an occurrence by chance, or if the rule confirms a known intuitive relationship.

## 6.3 FP-GROWTH ALGORITHM

The Frequent Pattern (FP)-Growth algorithm provides an alternative way of calculating a frequent item set by compressing the transaction records using a special graph data structure called *FP-Tree*. FP-Tree can be thought of as a transformation of the data set into graph format. Rather than the generate and test approach used in Apriori algorithm, FP-Growth first generates the FP-Tree and uses this compressed tree to generate the frequent item sets. The efficiency of the FP-Growth algorithm depends on how much compression can be achieved in generating the FP-Tree (Han, Pei, & Yin, 2000).

### 6.3.1 Generating the FP-Tree

Consider the data set shown in Table 6.5 containing six transactions of four items—news, finance, sports, and entrainment. To visually represent this data set in a tree diagram (Figure 6.6), we need to transform the list of transactions to a tree map, preserving all the information and representing the *frequent paths*. Let's build the FP-Tree for this data set step by step.

1. The first step is to sort all the items in each transaction in descending order of frequency (or support count). For example, News is the most frequent item and Sports is the least frequent item in the transaction, based on the data in Table 6.5. The third transaction of {Sports, News, Finance} has to be rearranged to {News, Finance, Sports}. This will help to simplify mapping frequent paths in later steps.
2. Once the items within a transaction are rearranged, we can now map the transaction to the FP-Tree. Starting with a null node, the first transaction {News, Finance} can be represented by Figure 6.5. The number within the parenthesis next to the item name is the number of transactions following the path.
3. Since the second transaction {News, Finance} is same as the first one, it follows the same path as first one. In this case, we can just increment the numbers.
4. The third transaction contains {News, Finance, Sports}. The tree is now extended to Sports and the item path count is incremented (Figure 6.6).
5. The fourth transaction only contains the {Sports} item. Since Sports is not preceded by News and Finance, a new path should be created from the null item and the item count should be noted. This node for Sports

**Table 6.5** Transactions List: Session and Items

| Session | Items |
|---|---|
| 1 | {News, Finance} |
| 2 | {News, Finance} |
| 3 | {News, Finance, Sports} |
| 4 | {Sports} |
| 5 | {News, Finance, Sports} |
| 6 | {News, Entertainment} |

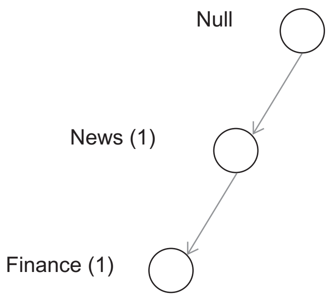



**FIGURE 6.5**
FP-Tree: Transaction 1.

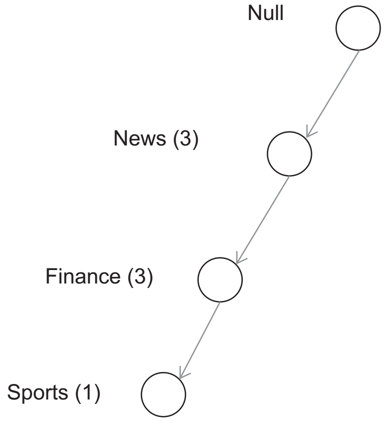



**FIGURE 6.6**
FP-Tree: Transactions 1, 2, and 3

is different from the Sports node next to Finance (the latter co-occurs with News and Finance). However, since both nodes indicate the same item, they should be linked by a dotted line.

6. This process is continued until all the transactions are scanned. All of the transaction records can be now represented by a compact FP-Tree (Figure 6.7).

The compression of the FP-Tree depends on how frequently a path occurs within a given transaction set. Since the key objective of association analysis is to identify these common paths, the data sets we use from this analysis contain many frequent paths. In the worst case, all transactions contain unique item set paths and there wouldn't be any compression. In that case the rule generation itself would be less meaningful for association analysis.

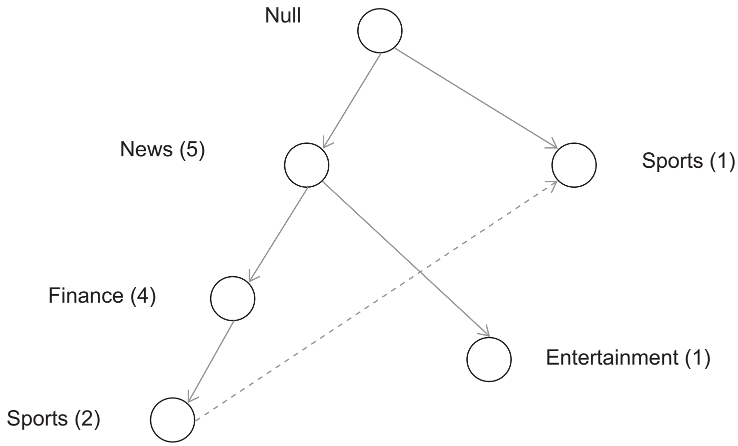



**FIGURE 6.7**
FP-Tree: Transactions 1 to 6.

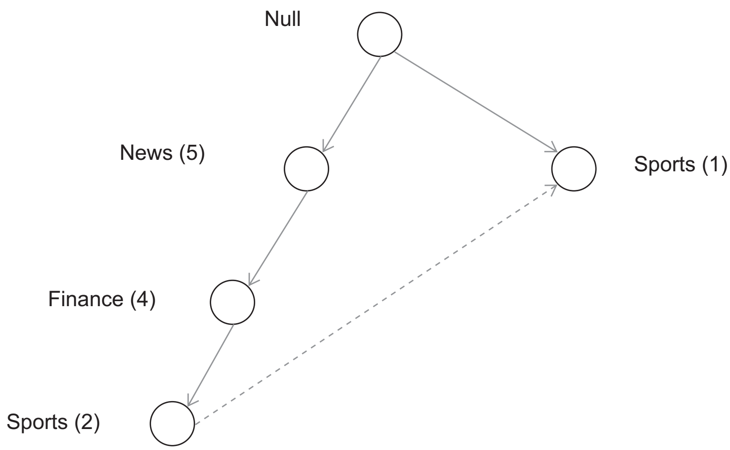



**FIGURE 6.8**
Trimmed FP-Tree.

### 6.3.2 Frequent Item Set Generation

Once the transaction set is expressed by a compact FP-Tree, the most frequent item set can be generated from the FP-Tree effectively. To generate the frequent item set, the FP-Growth algorithm adopts a bottoms-up approach of generating all the item sets starting with the least frequent items. Since the structure of the tree is ordered by the support count, the least frequent items can be found in leaves of tree. In Figure 6.8, the least frequent items are {Entertainment} and {Sports}, because the support count is just one transaction. If {Entertainment} is a frequent item

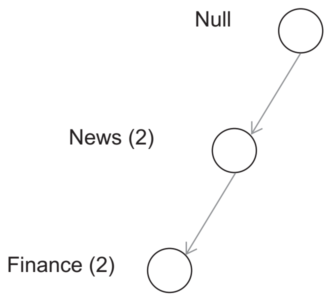



**FIGURE 6.9**
Conditional FP-Tree.

because the support exceeds the threshold, the algorithm finds all the item sets ending with entertainment, like {Entertainment} and {News, Entertainment}, by following the path from the bottom up. Since the support counts are mapped to the nodes, calculating the support for {News, Entertainment} will be instant. If {Entertainment} is not frequent, the algorithm skips the item and goes with the next item, {Sports}, and finds all possible item sets ending with sports: {Sports}, {Finance, Sports}, {News, Sports}, {News, Finance, Sports}.

Finding the entire item set ending with a particular item number is actually made possible by generating a prefix path and conditional FP-Tree for an item, as shown in Figure 6.9. The prefix path of an item is a subtree with only paths that contain the item of interest. A conditional FP-Tree for an item, say{Sports}, is the similar to the FP-Tree, but with the {Sports} item removed. Based on the conditional FP-Tree, the algorithm repeats the process of finding leaf nodes. Since leaf nodes of the sports conditional tree coexists with {Sports}, the algorithm finds the association with finance and generates {Finance, Sports}.

Rule generation in the FP-Growth algorithm is very similar to the Apriori algorithm. Since the intent is to find frequently occurring items, by definition, many of the transactions should have essentially the same path. Hence, in many practical applications the compaction ratio is very high. In those scenarios, the FP-Growth algorithm provides efficient results. Since the FP-Growth algorithm uses the graphs to map the relationship between frequent items, it has found applications beyond association analysis. It is now applied in research as a preprocessing phase for document clustering, text mining, and sentiment analysis (Akbar & Angryk, 2008). However, in spite of execution differences, both the FP-Growth and Apriori algorithms yield similar results. Rule generation from the frequent item sets is similar to the Apriori algorithm. Even though the concepts and explanation include analyzing graphs and subgraphs, FP-Growth algorithms can be easily ported to programming languages, particularly to SQL and PL/SQL programs on top of relational databases, where the transactions are usually stored (Shang et al., 2004).

### 6.3.3 How to Implement

The retrieval of association rules from a data set is implemented through the FP-Growth algorithm in RapidMiner. Since the modeling parameters and the result for most of the association algorithms are same, we will focus on the FP-Growth algorithm to observe the inputs, process, and the result of an association analysis implementation.

#### *Step 1: Data Preparation*

The Association analysis process expects transactions to be in a particular format. The input grid should have binominal (true or false) data with items in the columns and each transaction as a row. If the data set contains transaction IDs or session IDs, they can either be ignored or tagged as a special attribute in RapidMiner. Data sets in any other format have to be converted to this transactional format using data transformation operators. In this example, we have used the data shown in Table 6.3, with a session ID on each row and content accessed in the columns, indicated by 1 and 0. This integer format has to be converted to a binomial format by a *numerical to binominal* operator. The output of *Numerical to Binominal* is then connected to the *FP-Growth* operator to generate frequent item sets. The data set and RapidMiner process for association analysis can be accessed from the companion site of the book at www.LearnPredictiveAnalytics.com. Figure 6.10 shows the RapidMiner process of Association analysis with FP Growth algorithm.

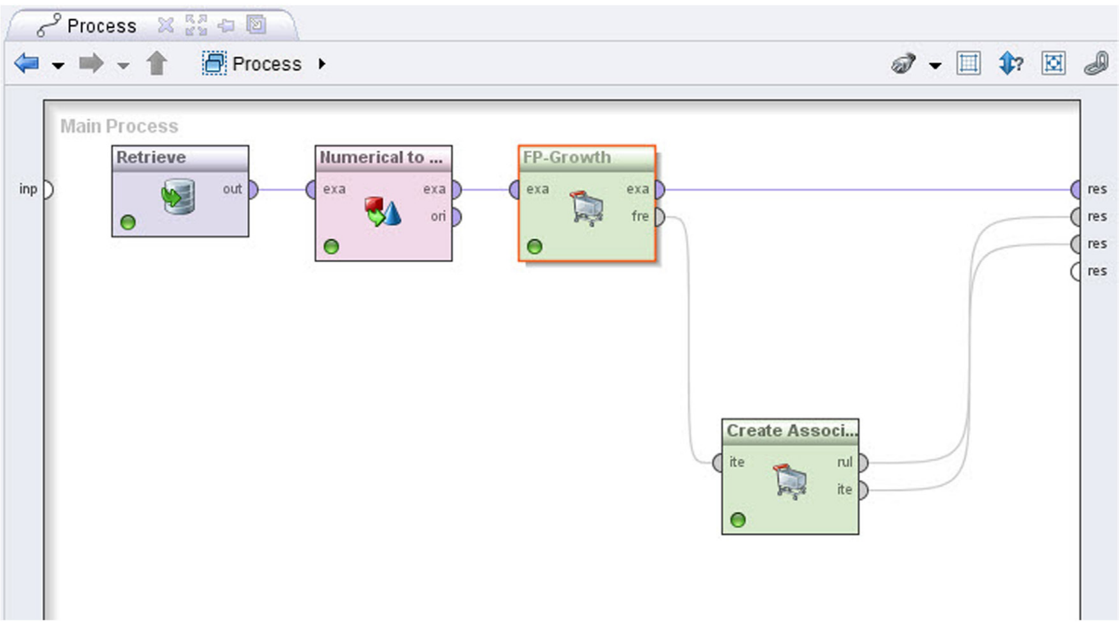


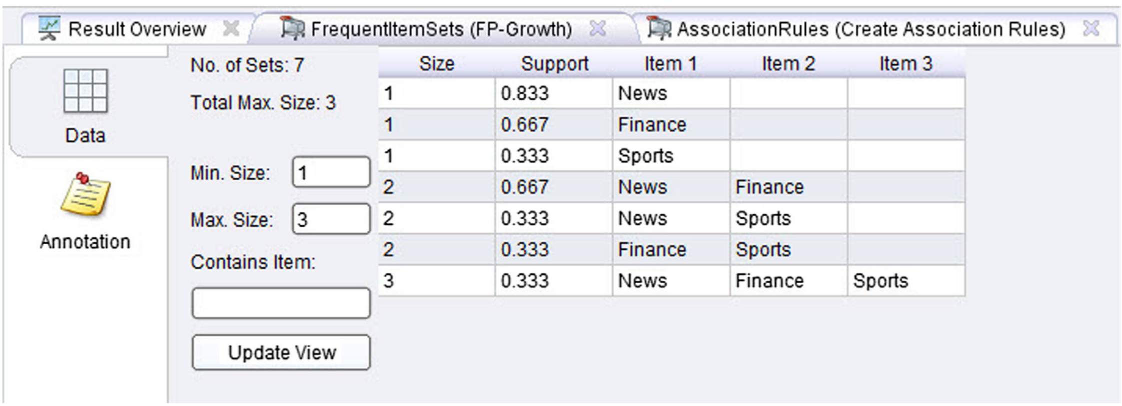

**FIGURE 6.10**
Data mining process for FP-Growth algorithm.

### *Step 2: Modeling Operator and Parameters*

The *FP-Growth* operator in RapidMiner generates all the frequent item sets from the input data set meeting a certain parameter criterion. The modeling operator is available at Modeling > Association and Item Set Mining folder. This operator can work in two modes, one with a specified number of high support item sets (default) and the other with minimum support criteria. The following parameters can be set in this operator there by affecting the behavior of the model.

- **Min Support:** Threshold for support measure. All the frequent item sets passing this threshold will be provided in the output
- **Max Items:** Maximum number of items in an item set. Specifying this parameter limits too many items in an item set.
- **Must Contain:** Regular expression to filter item sets to contain specified items. Use this option to filter out items.
- **Find Minimum Number of Item Sets:** This option allows the *FP-Growth* operator to lower the support threshold, if fewer item sets are generated with the given threshold. The support threshold is decreased by 20% in each retry.
  - **Min Number of Item Sets:** Value of minimum number of item sets to be generated.
  - **Max number of Retries:** Number of retries allowed in achieving minimum item sets

In this example, we are setting *Min Support* to 0.25. The result of the *FP-Growth* operator is the set of item sets generated, which can be viewed in the results page. The reporting options include filtering based on the number of items and sorting based on the support threshold. Figure 6.11 shows the output of




| Size | Support | Item 1 | Item 2 | Item 3 |
|---|---|---|---|---|
| 1 | 0.833 | News | | |
| 1 | 0.667 | Finance | | |
| 1 | 0.333 | Sports | | |
| 2 | 0.667 | News | Finance | |
| 2 | 0.333 | News | Sports | |
| 2 | 0.333 | Finance | Sports | |
| 3 | 0.333 | News | Finance | Sports |

**FIGURE 6.11**
Frequent item set output.

Frequent item sets operator where all possible item sets with support higher than the threshold can be seen.

### Step 3: Create Association Rules

The next step in association analysis is generation of the most interesting rules from the frequent item sets created from the *FP-Growth* operator. The *Create Association Rules* operator generate relevant rules from frequent item sets. The interest measure of the rule can be specified by providing the correct interest criterion based on the data set under investigation. The input of the Create *Association Rules* operator is frequent item sets of *FP-Growth* operator and the output generates all the association rules meeting the interest criterion. The following parameters govern the functionality of this operator:

- **Criterion:** Used to select the interest measure to filter the association rule. All other parameters change based on the criterion selection. Confidence, lift, and conviction are commonly used interest criterion.
- **Min Criterion Value:** Specifies the threshold. Rules not meeting the thresholds are discarded.
- The **Gain theta** and **Laplace** parameters are the values specified when using gain and Laplace for the interest measure.

In this example process, we are using confidence as the criterion and a confidence value of 0.5. Figure 6.10 shows the completed RapidMiner process for association analysis. The process can be saved and executed.

### Step 4: Interpreting the Results

The filtered association analysis rules extracted from the input transactions can be viewed in the results window (Figure 6.12). The listed association rules are in a table with columns including the premise and conclusion of the rule, as well as the

(FP-Growth) AssociationRules (Create Association Rules) ExampleSet (Numerical to Binominal)

| No. | Premises | Conclusion | Support | Confidence | LaPlace | Gain | p-s | Lift | Conviction |
|---|---|---|---|---|---|---|---|---|---|
| 1 | Finance | Sports | 0.333 | 0.500 | 0.800 | -1 | 0.111 | 1.500 | 1.333 |
| 2 | Finance | News, Sports | 0.333 | 0.500 | 0.800 | -1 | 0.111 | 1.500 | 1.333 |
| 3 | News, Finance | Sports | 0.333 | 0.500 | 0.800 | -1 | 0.111 | 1.500 | 1.333 |
| 4 | News | Finance | 0.667 | 0.800 | 0.909 | -1 | 0.111 | 1.200 | 1.667 |
| 5 | Finance | News | 0.667 | 1 | 1 | -0.667 | 0.111 | 1.200 | ∞ |
| 6 | Sports | News | 0.333 | 1 | 1 | -0.333 | 0.056 | 1.200 | ∞ |
| 7 | Sports | Finance | 0.333 | 1 | 1 | -0.333 | 0.111 | 1.500 | ∞ |
| 8 | Sports | News, Finance | 0.333 | 1 | 1 | -0.333 | 0.111 | 1.500 | ∞ |
| 9 | News, Sports | Finance | 0.333 | 1 | 1 | -0.333 | 0.111 | 1.500 | ∞ |
| 10 | Finance, Sports | News | 0.333 | 1 | 1 | -0.333 | 0.056 | 1.200 | ∞ |

**FIGURE 6.12**
Association rules output.

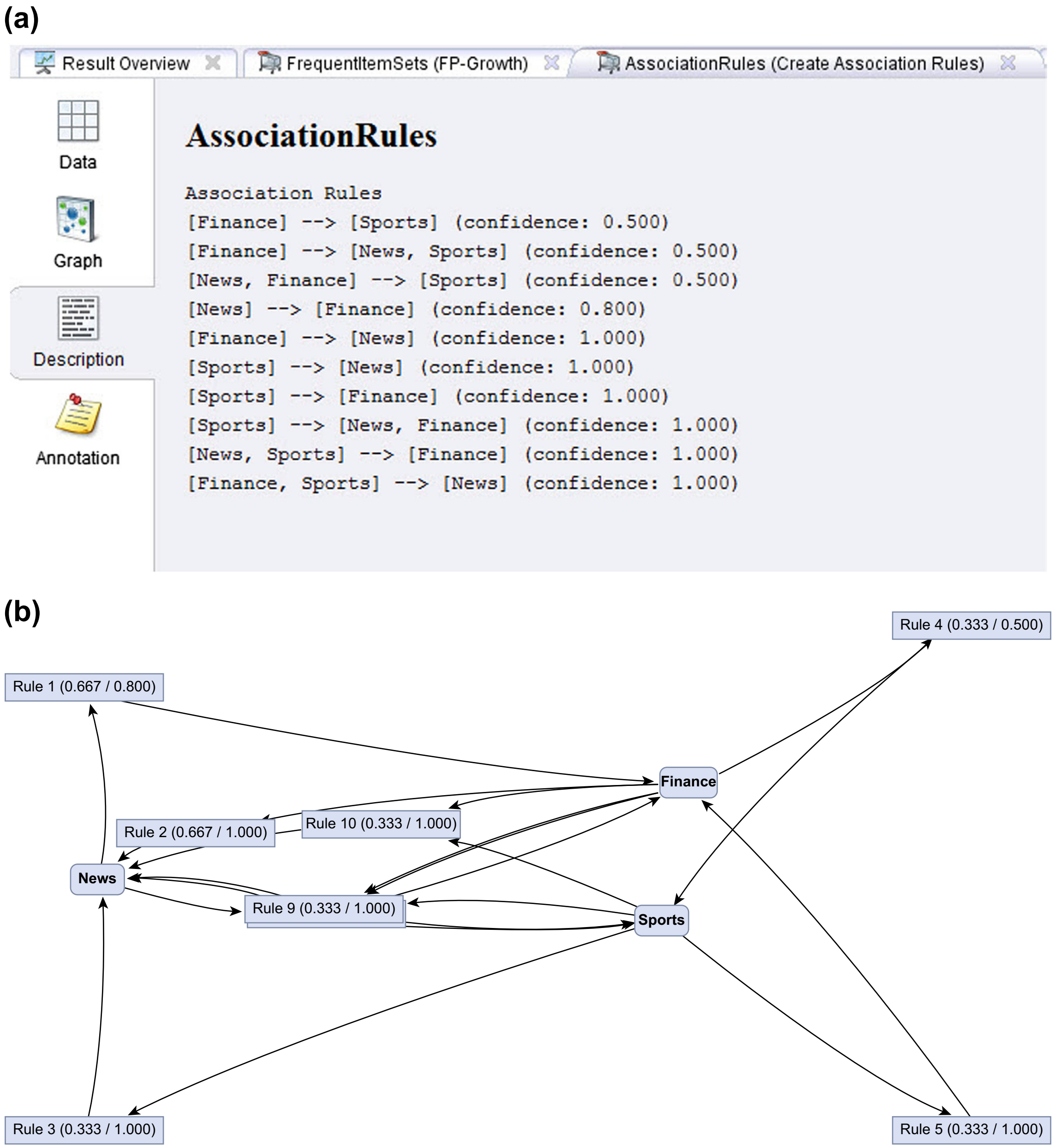



**FIGURE 6.13**
Association rules output (a) text view, (b) graph view.

support, confidence, gain, lift, and conviction of the rule. The interactive control window on the left-hand side of the screen allows the users to filter the processed rules to contain the selected item and ther is a slide bar to increase the confidence or criterion threshold, thereby showing fewer rules.

The main purpose of the association analysis is to understand the relationship between items. Since the items take the role of both premise and conclusion, a visual representation of relationships between all the items, through a rule, can help to comprehend the analysis. Figure 6.13 shows the rules in text format and by interconnected graph format through the results window, for selected items. Using the default option, the items selected are connected with the rules by arrows. The incoming item to a rule is the premise of the rule and the outgoing item is the conclusion of the association rule.

## CONCLUSION

Association rules analysis has gained popularity in the last two decades particularly in retail, online cross selling, recommendation engines, text analysis, document analysis, and web analysis. Typically, a commercial data mining software tool offers association analysis in its tool package. Though there may be a variation in how the algorithm is implemented in each commercial package, the framework of generating a frequent item set using a support threshold and generating rules from the item sets using an interest criterion is the same. Applications that involve very large amount of items and real-time decision making demand new approaches with efficient and scalable association analysis (Zaki, 2000). Association analysis is also one of the prevalent algorithms that is applied to information stored using big data technologies, data streams, and large databases (Tanbeer et al., 2008).

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