

# THE IMPLEMENTATION OF ASSOCIATION RULES IN ANALYZING THE SALES OF AMIGO GROUP

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## *Abstract*

*A retail company usually produce large sales transactions data. These data can be utilized with the application of data mining, which is also known as knowledge data discovery. Association rules is one of the most famous data mining study that can be used to generate items that frequently purchased together in sales transactions.*

*This project is a web-based data mining project for a company called Amigo Group. The algorithm used for association rules implementation is called FP-Growth algorithm. This algorithm will form a data structure called FP-Tree and extract the rules based on its FP-Tree. The result of this application will be used to help Amigo Group's managers understand about customers buying behavior and analyze pattern of items which are usually purchased together. Then, the manager can create marketing strategies in order to increase sales of the items.*

**Key Words:** Data Mining, FP-Growth, FP-Tree.

## **1. Introduction**

### **1.1. Problem background**

There are some problems underlying the existence of this project. The first problem is that there is no data mining techniques implemented in Amigo Group's system yet. Amigo Group's managers and assistants still decide the price and make assumption based on the previous transaction manually (manual system). The second problem is the capabilities of the shop managers to do manual analysis are not good because most of them are only graduates from senior high school level and do not continue to higher education level. Based on those problems, the managerial level of Amigo Group decide that they need a data mining system with affinity analysis capabilities to help their managers in doing analysis on sales transactions data.

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## 1.2. Constrains

Application constraints regarding with this application are as follow:

- The system uses **three years data** (2006 - 2008) from 'Bimbo' shop (one of Amigo Group's branches).
- The system will provide **six special event** options for the system.
- The system will generate **only pair of items** in every rule generated.
- User (**Manager**) cannot recover his / her own password.
- The dashboard visualization's method is using **Bar Charts**.

## 2. Basic of Theories

### 2.1. Support and confidence

Understanding *Support* and *Confidence* is one of the most important thing in building an association rule application. *Support* is the occurrence frequency of an item while confidence number reflects the answer of *how sure the generated rules can be trusted*. *Support* and *confidence* values are usually displayed in percentage format. These two factors measures the interestingness of the items based on the minimum threshold. If the rules satisfy both of the threshold (*minimum support* and *minimum confidence*), then the rules are considered as an interesting rule.

### 2.2. FP-Growth Algorithm

FP-Growth Algorithm is one of the currently fastest and most popular algorithm for frequent itemset mining. There are two big steps to implement FP-Growth Algorithm:

- Step 1: Build a compact data structure called FP-Tree
- Step 2: Extracts frequent itemset directly from the FP-tree

#### 2.2.1. Step 1: Build FP-Tree

First of all, prepare the transaction data that will be used for this application. Figure 1 display an example of sales transactions data in a table.

TID	Items Bought
100	f, a, c, d, g, l, m, p
200	a, b, c, f, l, m, o
300	b, f, h, j, o, w
400	b, c, k, s, p
500	a, f, c, e, l, p, m, n

**Figure 1.** 'sales transactions' table

The next step is to decide minimum support of the system. Minimum support is one example of threshold that must be set in order to eliminate items that are not satisfied the number of support in the sales transactions data. For this example, set the minimum support = 3.

The next step is to create two tables called 'header item' table and 'ordered sales transactions' table. The 'header item' table can be generated by counting support of each item and then remove the items that are not satisfy the minimum support. The rest of the items that satisfy the number of threshold then ordered in descending sort and inserted into 'ordered sales transaction' table.

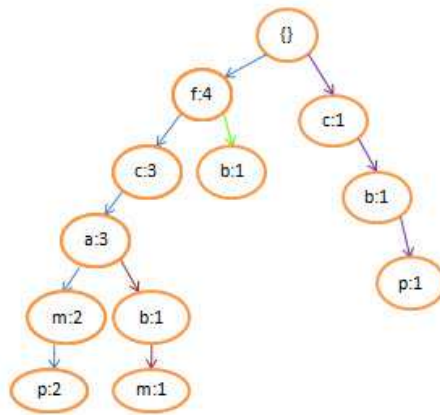
Item	Frequency
f	4
c	4
a	3
b	3
m	3
p	3

**Figure 2.** 'header item' table

TID	(ordered) frequent items
100	f, c, a, m, p
200	f, c, a, b, m
300	f, b
400	c, b, p
500	f, c, a, m, p

**Figure 3.** 'ordered sales transaction' table

The final step of this step 1 is to create the FP-Tree based on the data on Figure 3. The top node of the tree is always called a "ROOT" and direct child of "ROOT" is called a 'level 1 node'. The first item in each of the TID is the 'level 1 node' of the tree, but if the 'level 1 node' is already existing, just add 1 (+1) to its support. There is no need to create a new node for the same path. The final creation of the tree is displayed on Figure 4.

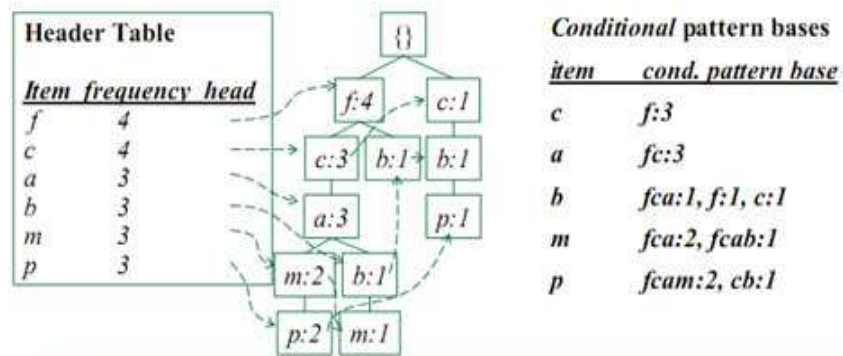


**Figure 4.** The FP-Tree

### 2.2.2 Step 2: Extract and Mining Rules from FP-Tree

In the beginning of ‘Step 2’, The FP-Tree data that has been generated from the previous process will be processed into ‘conditional pattern bases’ table. To create ‘conditional pattern bases’ table, do these following steps for non-level 1 node:

- Starting at the frequent header table in the FP-Tree.
- Traverse the FP-Tree by following the link of each frequent item.
- Accumulate all of transformed prefix paths of that item to form conditional pattern base.



**Figure 5.** The process of making ‘conditional pattern bases’ table

After the ‘conditional pattern bases’ table has been generated, the next step is create ‘conditional pattern tree’ from each of frequent item in ‘conditional pattern bases’ table. At this time, remember that the minimum support is three. For each of the item on ‘conditional pattern bases’ table, extract the frequent item and its support. Find nodes with same value and merge it into one value with summed support value. An example on Figure 6 tells the creation of conditional FP-Tree data for node ‘m’.

Because 'm' has {fca:2},{fcab:1} as its conditional pattern-base data, then the extraction of the pattern become:

- f:2, c:2, a:2
- and
- f:1, c:1, a:1, b:1

The same nodes are f, c, and a, The merged nodes value for each of them are f:3, c:3, a:3 and b:1. At this stage, the minimum support elimination occur again, b:1 will be eliminated because its support is not satisfy the minimum support value. So, f:3, c:3, and a:3 becomes the conditional FP-Tree data for node 'm'.

- **Create conditional FP-Tree for each item based on conditional pattern bases. Example:**

Item	Conditional pattern-base
p	{(fcam:2), (cb:1)}
m	{(fca:2), (fcab:1)}
b	{(fca:1), (f:1), (c:1)}
a	{(fc:3)}
c	{(f:3)}
f	Empty

Conditional FP-Tree for item m

- f:2 - c:2 - a:2
- f:1 - c:1 - a:1 - b:1

Based on that 2 patterns, sum each value → f:3, c:3, a:3, b:1

Minimum support = 3

**Result:**  
f:3, c:3, a:3 → the conditional FP-Tree data for node 'm'

**Figure 6.** Process of creating conditional FP-Tree data for node 'm'.

The final steps of every association rules algorithm is to mine the frequent-pattern (the rules) generated from the processes. The rules can be generated by doing combination on pivot items with its 'conditional FP-Tree' items. Figure 7 display the final result (frequent-pattern generated) table based on the example case.

Item	Conditional FP-Tree	Frequent pattern generated
p	c:3	p->c
m	f:3, c:3, a:3	m->f, m->c, m->a, mf->c, mc->f, mf->a, ma->f, mc->a, ma->c, <u>mfc-&gt;a</u> , mfa->c, mac->f, ...
b	empty	Empty
a	f:3, c:3	a->f, a->c, a->fc, <u>af-&gt;c</u> , ac->f
c	f:3	c->f
f	empty	Empty

Figure 7. 'Frequent-pattern generated' table

### 3. Implementation

The implementation of FP-Growth algorithm comes in a form of wizard setup. To run the wizard, a user must log into the system by using 'manager' level of user account. The setup wizard will have six steps (six pages) and must be done sequentially in order to generate the result. The result of this wizard will be displayed in the 'dashboard' page and 'rules' page.

#### 3.1. Capture of some steps in the wizard page

Figure 8. Steps of the wizard – input shop and minimum support

**PILIH RENTANG WAKTU DATA YANG AKAN DIGUNAKAN**

- Semua data
- Lebaran 2006 (17 Oktober 2006 - 31 Oktober 2006)
- Lebaran 2007 (05 Oktober 2007 - 19 Oktober 2007)
- Lebaran 2008 (24 September 2008 - 08 Oktober 2008)
- Natal 06 dan Tahun baru 07 (22 Desember 2006 - 5 Januari 2007)
- Natal 07 dan Tahun baru 08 (22 Desember 2007 - 5 Januari 2008)
- Natal 08 dan Tahun baru 09 (22 Desember 2008 - 5 Januari 2009)

atau isi form di bawah ini jika Anda ingin menggunakan tanggal yang di custom.

Ccontoh Format pengisian (YYYY-MM-DD) : from 2006-01-01 to 2007-12-01

from  to

Cek kembali informasi yang telah Anda masukkan. Selanjutnya, tekan tombol Next.

Next

Figure 9. Steps of the wizard – chose data range based on period of time

Home | Dashboard | Setup Wizard | Rules Table | Edit Profile | Logout

**FREQUENT-ITEMSET GENERATION**

Pada tahapan ini FP-Tree telah berhasil dibentuk.  
Langkah selanjutnya adalah melakukan Frequent-Itemset Generation dari FP-Tree yang telah dibentuk tersebut.  
Proses ini mungkin membutuhkan waktu yang beragam dan cukup lama. Harap bersabar.  
Klik tombol next untuk meneruskan.

Next

Figure 10. Steps of the wizard – frequent itemset generation

3.2. Capture of the result interface in the ‘rules’ page

ASSOCIATION RULES GENERATED RESULT

Show 10 entries

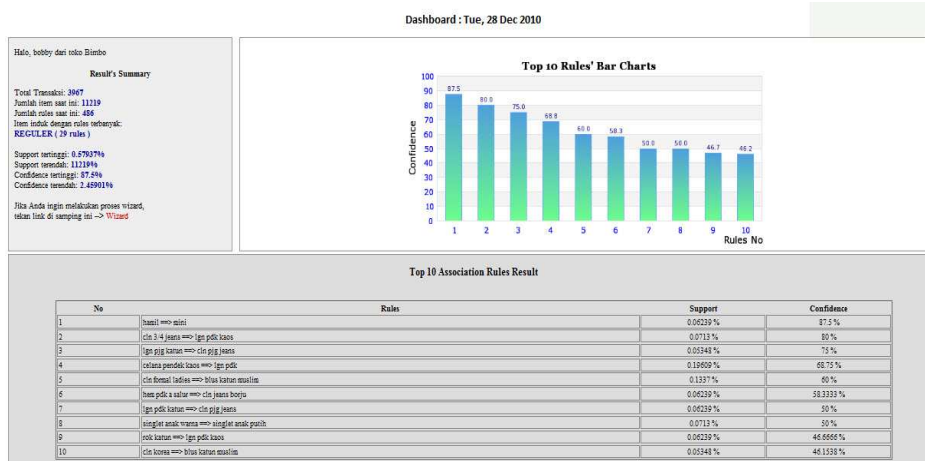
No	Item	Related Items	Support (%)	Confidence (%)
1	HAMIL	MINI	0.06239	87.5
2	CLN 3/4 JEANS	LGN PDK KAOS	0.0713	80
3	LGN PIG KATUN	CLN PIG JEANS	0.05348	75
4	CELANA PENDEK KAOS	LGN PDK	0.19609	68.75
5	CLN FORMAL LADIES	BLUS KATUN MUSLIM	0.1337	60
6	HEM PDK A SALUR	CLN JEANS BORJU	0.06239	58.3333
7	LGN PDK KATUN	CLN PIG JEANS	0.06239	50
8	SINGLET ANAK WARNA	SINGLET ANAK PUTIH	0.0713	50
9	ROK KATUN	LGN PDK KAOS	0.06239	46.6666
10	CLN KOREA	BLUS KATUN MUSLIM	0.05348	46.1538

Showing 1 to 10 of 488 entries

Jumlah seluruh item dalam data transaksi yang dipilih sebanyak 11219 items

Figure 11. Rules generated in ‘datatables’ interface

3.3. Capture of the result interface in the ‘dashboard’ page



**Figure12.** Rules generated in dashboard interface

#### 4. Result Analysis and Explanation

To analyze the generated rules, several tables have been made to compare the result of this application.

**Table 1.** Result of top 3 rules from January 2006 – December 2008  
 (minimum support > 100)

No	Rules	Support	Confidence
1	CELANA PENDEK KAOS ==> LGN PDK	0.0590 %	74.161 %
2	CLN COKLAT FAMATEX ==> HEM KOJAR PUTRA	0.0190 %	56.6137 %
3	CELANA PENDEK JEANS ==> LGN PDK	0.0910 %	54.3374

Table 1 display the top 3 rules based on the confidence level of the rules. By looking at those top 3 rules, an analysis can be made, the sales transactions data shows that most of 'Bimbo' shop customers are usually buy shorts and shirts together. The second rule reflects that a male trouser with brand 'FAMATEX' is usually purchased together with t-shirts with brand 'KOJAR'. These rules are generated based on three years data. The support level of rules 1 (0.0590 %) means that the numbers of transactions that include shorts and shirts together is 0.0590 % compared with the total numbers of items available in the database during three years period. The confidence percentage of rules 1 (74.161 %) reflects the confidentiality level / how sure we can trust the integrity of rule: 'CELANA PENDEK KAOS ==> LGN PDK'.

**Table 2.** Comparison of top 1 rule from three years 'Idul Fitri' data  
 (minimum support > 10)

Event	Rules	Support	Confidence
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Idul Fitri 2006	Daleman kerudung => Sarung dewasa	0.13408 %	61.9047 %
Idul Fitri 2007	Celana pendek kaos => Lgn Pdk	0.20287 %	68.75 %
Idul Fitri 2008	Hem PJ kotak => Cln jeans borju	0.16258 %	46.6666 %

In retail business, there are some events or periods of time when sales are highly increased. The sales on events like Idul Fitri, Christmas, new semester and students orientation are usually increased because lots of customers need new stuff to support their daily activities.

Table 2 display the comparison of the most popular items that frequently purchased together during the 'Idul Fitri' Feast Day based on the confidence level of the rules. By looking at those rules, the manager can realize that there is a trend changing of customer's wear during the 'Idul Fitri' Feast Day. The 2006 result shows that most of the customer are still buy Moslem wear to overcome the 'Idul Fitri' Feast Day. They purchased 'Daleman kerudung' for woman together with 'Sarung dewasa' for men in one transaction. But in 2007 and 2008 'Idul Fitri' Feast Day, the pattern of items that bought together do not related with Moslem wear anymore. Customers pretend to choose more casual wear like shorts, shirts, t-shirts, and long jeans. The managers can take advantages here by creating a promotional product mix for the most 'famous' items that usually purchased together or even for some items that are still in the average support and confidence number in order to increase their point of sales.

**Table 3.** Comparison of top 1 rule from three years 'Christmas and New year' data  
(*minimum support > 5*)

Event	Rules	Support	Confidence
Christmas 2006 – New Year 2007	Cln dlm putra => Cln dlm putri	0.66666 %	80 %
Christmas 2007 – New Year 2008	Celana pendek kaos => Lgn pdk	0.70654 %	62.5 %
Christmas 2008 – New Year 2009	Mini => Full	1.53301 %	68.421 %

Table 3 display the comparison of the most popular items that frequently purchased together during the 'Christmas and New Year' period based on the confidence level of the rules. By looking at those rules, the manager can realize that items that occurs in the top rules are not highly affected by Christmas / New Year, but more related with geographical weather and the rainy season during the end of the year. The shop employees of Amigo Group can do cross-selling to their customers to offer items that usually purchased together in the end of the year. Based on the result, underwear for women are the most frequent items that usually bought during the 'Christmas and New Year' period. This is considering as an interesting rule because the application can generate result that is unpredictable (there is no relation between underwear and Christmas).

In addition, the manager can also make per-year rules analysis to create a catalog design. The catalog design can contain promotional product mix, best-offer products and special price for most frequent-pattern. Hopefully, this catalog design will help the company to increase sales and gain more business profits.

#### **4. Conclusion**

Based on research and rules that have been generated, the conclusions are as follow:

- 1) This application can be used as a tool to help sales transaction analysis and the result reflects affinity analysis between items.
- 2) The rules which are generated by the system can be used for marketing strategies and decision making to support business strategies. The example of marketing strategies are promotional product mix, cross-selling and catalog design.
- 3) This project has met its objectives and the application successfully generate pair of association rules.
- 4) In the future, this application can be developed to generate more items combination in the rule.

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