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Sales Strategy by Determining Tenant Position at Sriwijaya State Polytechnic Through Association Rules Analysis

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ABSTRACT

Purpose: The purpose of this research is to optimize the usefulness of sales transaction reports in Sriwijaya State Polytechnic (Polsri) foodcourt and extract sales transaction report data to become the knowledge that can be used in sales strategies that is recommendations for tenant positions in accordance with customer behavior by using association rules analysis.

Design/methodology/approach: The approach using Knowledge Discovery in Database through stages (1) Data Selection; (2) Data Classification; (3) Raw Itemset Table; (4) Data Mining Process using Association Rules Analysis; (5) Analysis Result Interpretation; (6) Marketing Strategy Recommendation.

Findings: The results of the study are recommendations for tenant positions in accordance with customer behavior tendencies

Research limitations/implications: Polsri foodcourt sales transaction report used in the period 01 May 2019 – 31 July 2019, with a total of 153,401 data records, data analysis using Association Rules Analysis with A Priori Algorithm, tools used are Microsoft Excel and WeKa 3.6.10

Practical implications: The recommended tenant position can be used as a sales strategy that makes it easier for customers to choose the product to be purchased and increase sales rate

Originality/value: The paper is original

Paper type: Research paper

Keyword: *Data Mining, Sales Strategy, Association Rules Analysis, Foodcourt Polsri*

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I. INTRODUCTION

Technological developments have a tremendous impact on the diversity and capacity of the data generated from the technology itself (Alrubaiee et al., 2012). The data generated from the impact of technology have the effect on the level of usefulness of a data. One of techniques used to increase the usefulness of the data is using data mining (Rezkiani et al., 2017). Data mining itself is part of the stages in the Knowledge Discovery in Database (KDD) or extracting information from a set of databases. This mining process uses statistical, mathematical, artificial intelligence and machine learning techniques to identify useful information and related knowledge from various large databases (Aggarwal, 2015).

KDD is an organized process of analyzing valid, up-to-date, useful and understandable patterns from complex data sets (Isa, 2021). The stages in KDD (Suad A. & Wesam S., 2017) begin with Data Selection from raw data where selecting and dividing data to be used and not used (Chen et al., 2015); Preprocessing data with data cleaning techniques and data integration (L. W. Santoso & Yulia, 2019); Data Transformation, where raw data is converted into datasets that can be analyzed, such as smoothing (clustering, regression and binning), aggregation (by calculating the summarize value), generalization and normalization (Firmansyah & Yulianto, 2021); Data Mining, where the transformed data is analyzed and extracted using analytical techniques contained in data mining, so as to produce new information/knowledge; and Interpretation/ Evaluation. The KDD process can be seen in Figure 1 below:

ISSN : 2597-4785 (ONLINE)
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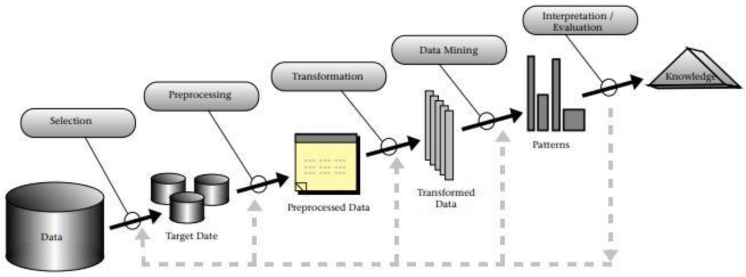

Figure 1. Stages of Knowledge Discovery in Database (KDD)

The use of data mining in the analysis of data generated from business processes has a significant impact in determining the direction of company policies (Plotnikova et al., 2020). For example, the use of data mining with predictive analysis, which are assessing the risk of fraudulent reports (fraud detector); Churn Prevention: Assumptions in the financial insurance industry have policy contracts for new consumers; sentiment analysis from certain product reviews collected from millions of online resources and analyzed to produce information / new knowledge; trading analysis and assessment of risk management, including detecting consumers with many chances of failure; calculating payments and credit scoring (Ruswati et al., 2018). These things can certainly be solved by the analytical techniques contained in data mining.

Several techniques are used in data mining, one of them is Association Rules Analysis or known as market basket analysis (Aprianti et al., 2017). Association analysis is one of the data mining techniques that can identify the behavior of special events or processes where association relationships appear in each event (Ruswati et al., 2018). Implementation of the Association Rules is generally used to determine business processes such as financial transaction analysis, marketing or sales strategies (M. H. Santoso, 2021) and customer behavior. Association Rules always use the A Priori algorithm (Marisa, 2013), which is a data retrieval algorithm with associative rules to determine the associative relationship of a combination of items (Fauzan et al., 2020).

Polsri has a foodcourt which is a food and beverage food court with 13 tenants. Polsri Foodcourt has been operating since 2000 with an average transaction of over 200 transactions per day. Sales reports are carried out on a daily and sales recapitulation is carried out within a month. During the sales transaction recapitulation process, the report is only done administratively and has not been optimized as an informative parameter that provides recommendations for policy directions for the foodcourt. Sales transaction reports that have been validated are then only stored in archives, even though when analyzed more deeply using data mining techniques, Polsri foodcourt can determine sales strategies as one way to increase profits. So in this study, we will implement data mining on sales transactions at Polsri foodcourt using Association Rules analysis. The result of the analysis of association rules in the sales transaction report is a marketing strategy that provides recommendations for tenant positions in Polsri foodcourt.

So the purpose of the research is to optimize the level of usefulness of the sales transaction reports in Polsri foodcourt and extract sales transaction report data to become new information or knowledge that can be used in sales strategies in the form of recommendations for tenant positions in accordance with customer behavior. The scope of this research is limited to Polsri foodcourt sales transaction report for the period 01 May 2019 to 31 July 2019, with a total of 153,401 data records. Data analysis using Association Rules with A Priori Algorithm, the tools used in this study are Microsoft Excel. and WeKa 3.6.10

II. METHODOLOGY

The stages in this research refer to the Knowledge Discovery in Database, as shown in the figure 2 below:

:: IJEBD ::
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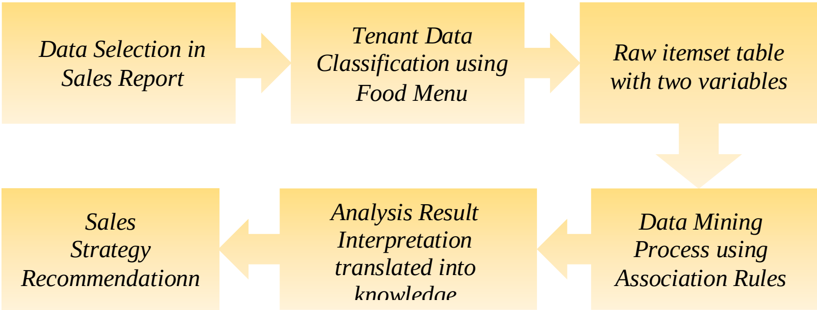

Figure 2. Research Methodology Stage

The following is the explanation of the stages of the research method:

1. Data Selection in Sales Report
   At this stage the data was taken from Polsri food court sales report for the period 01 May 2019 to 31 July 2019, while the data taken are product sales data items from 13 tenants in the foodcourt, with a total data of 153.401 transactions.
2. The next stage is to make a tenant classification with food menu. From this classification, 13 tenants were produced with a variety of food and beverage menus. Then, Tenant was named by TN, for example for Tenant 1 it is called TN 1 as shown in table 1 below:

Table 1. Food and Beverages Menu for Each Tenant

Tenant	*No*	*F and B Menu*	*Tenant*	*No*	*F and B Menu*
TN 1	*1*	*Martabak Kari Telor Ayam*	*TN 8*	*1*	*Jus Mangga*
	2	*Martabak Kari Sayur*		*2*	*Jus Jambu*
	3	*Martabak Kari Telor Bebek*		*3*	*Jus Jeruk*
	4	*Nasi Lemak*		*4*	*Jus Belimbing*
	5	*Nasi Minyak*		*5*	*Jus Stoberi*
	6	*Nasi Bakar*		*6*	*Jus Apel*
TN 2	*1*	*Pindang Patin*	*TN 9*	*1*	*Kopi Hitam*
	2	*Pindang Tulang*		*2*	*Moccachinno*
	3	*Pindang Kambing*		*3*	*Teh Manis Hangat*
	4	*Nasi Putih*		*4*	*Es Teh Manis*
	5	*Pindang Kakap*		*5*	*Susu*
	6	*Pindang Gabus*		*6*	*Thai Tea*
TN 3	*1*	*Bakso Bakar*	*TN 10*	*1*	*Nasi Goreng Ayam*

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

	2	Mie Ayam Bakso		2	Nasi Goreng Biasa
	3	Bakso Biasa		3	Nasi Goreng Telor
	4	Mie Ayam Pangsit		4	Nasi Goreng Petai
	5	Bakso Spesial		5	Mie Goreng Spesial
	6	Bakso Rudal		6	Kwetiau Goreng Spesial
TN 4	1	Lenjer	TN 11	1	Soto Ayam + Nasi
	2	Adaan		2	Soto Daging + Nasi
	3	Kapal Selam Kecil		3	Soto Bogor
	4	Kapal Selam Besar		4	Soto Babat + Nasi
	5	Kulit		5	Gulai Kambing + Nasi
	6	Model / Tekwan		6	Soto Bening
TN 5	1	Nasi + Rendang	TN 12	1	Nasi Timbel Komplit
	2	Nasi + Telor Dadar/ Bulat		2	Nasi Empal
	3	Nasi + Kikil		3	Karedok
	4	Nasi + Gulai Kakap		4	Nasi + Ayam Goreng Bogor
	5	Nasi + Tamusu/ Babat/ Paru		5	Nasi + Sop Buntut
	6	Nasi + Ayam Sayur / Goreng		6	Nasi + Sop Iga
TN 6	1	Gado-gado Biasa	TN 13	1	Bakmi Jawa
	2	Gado-gado + Lontong		2	Bakmi Polos
	3	Nasi+Cah Kangkung+Tahu/Tempe		3	Bakmi Pangsit
	4	Nasi+Ayam Goreng Lamongan		4	Yamin Manis Spesial
	5	Ketoprak		5	Yamin Asin Spesial
	6	Siomay / Batagor		6	Bakmi Bakso

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

TN 7	*1*	*Sate Ayam + Nasi*
	2	*Sate Kambing + Nasi*
	3	*Sate Ayam + Lontong*
	4	*Sate Kambing + Lontong*
	5	*Sop Ayam*
	6	*Sop Kambing*

3. Creating raw itemset table with 2 variables
   Transaction data that has been processed is then made into a table of 2 variables, defined by transactions and order menu which then generated to be tenant data. The data using dummy variables which is value of 0 and 1, which is done to simplify the analysis process.

4. Data Mining Process using Association Rules Analysis
   After obtaining the data through the sales itemset, the next step is extracting the data using the Association Rules analysis, to produce A Priori Algorithm, that is "IF.....THEN....." rule for two or more itemset variables involved (Karyawati & Winarko, 2011). The tools used to extract the data are Microsoft Excel and Weka Version 3.8. To simplify the analysis process, firstly the itemset table is converted to N for the value of 0 and Y for the value of 1.

5. Analysis Result Interpretation translated into knowledge
   The output results from the Association Rules analysis using the WeKa tools in the form of A Priori Algorithm, that is rules "IF....THEN..." with support and confident values according to the number of times the tenant appears in the itemset. From the results of these rules, they are converted into the distribution of tenant positions

6. Sales Strategy Recommendation
   Hasil analisis yang dilakukan pada tahapan sebelumnya, dimana menghasilkan aturan-aturan, maka dipilih aturan dengan nilai rata-rata support tinggi dengan nilai confident > 0.8 atau 80%. Sehingga analisis tersebut dapat direkomendasikan sebagai strategi pemasaran dalam posisi tenant di Foodcourt Politeknik Negeri Sriwijaya.
   The results of the analysis carried out in the previous stage, which resulted in the rules, then the rules with a high average support value and confident value of > 0.8 or 80% were chosen. So that the analysis can be recommended as a sales strategy in the tenant position at the Sriwijaya State Polytechnic Foodcourt.

III. RESULTS AND DISCUSSION

As previously explained, the data analyzed is the Sriwijaya State Polytechnic food court sales report for the period 01 May 2019 – 31 July 2019, with a total of 153.401 data records. The positions of food and beverage tenants at the Sriwijaya State Polytechnic foodcourt are shown in Figure 3:

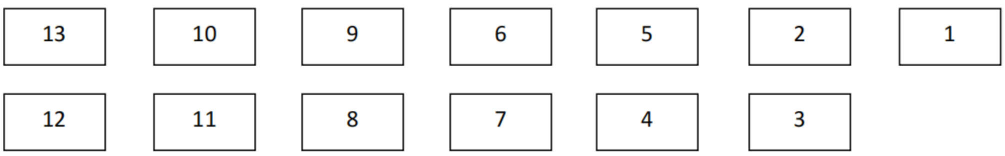

Figure 3. The position of the Sriwijaya State Polytechnic Foodcourt Tenant

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ISSN : 2597-4750 (PRINTED)

As the purpose of this research is a sales strategy by determining the position of tenants based on customer behavior, the data analyzed is in the form of Sales Data for a certain period of time, so that rules are generated and implemented in the recommendations for tenant positions. The selected sales report data is the transaction number and the products sold in the transaction. Figure 4 shows daily Polsri Foodcourt Sales Report:

Sales Report					
					Foodcourt Politekni Negeri Sriwijaya
					Print Date: 02 August 2019
No. Faktur: 2019PJ00001022					
No.	Order Menu	Price	Qty	Discount	Sub Totals
1	Nasi Lemak	12.000	1	0	12.000
2	Pindang Patin	15.000	1	0	15.000
3	Nasi Telor Balado	8.000	1	0	8.000
4	Sate Ayam + Nasi	13.000	1	0	13.000
5	Jus Mangga	6.000	1	0	6.000
6	Bakmi Polos	10.000	1	0	10.000
				Grand Totals	64.000

Figure 4. Daily Polsri Foodcourt Sales Report

As detailed in figure 4, the report consists of several fields, those are Invoice Number, Date, Order Menu, Price, Qty, Discount, Subtotal, Grand Total. However, in this study, not all data fields will be used, but only the Transaction Number (sorted by the N-th Transaction) and the Order Menu, so that the data is converted into the menu order transaction, as shown in table 2 below:

Table 2. Menu Order Transaction

No. Transaction/ Record	*Order Menu*
1	*Nasi Lemak, Pindang Patin, Nasi Telor Balado, Sate Ayam + Nasi, Jus Mangga, Bakmi Polos*
2	*Pindang Gabus, Bakso Biasa, Pempek Kapal Selam Besar, Nasi Rendang, Soto Bening*
3	*Martabak Kari Telor Ayam, Mie Ayam Bakso, Model, Nasi Kikil, Sop Ayam, Jus Jeruk*
4	*Bakso Rudal, Nasi + Ayam Sayur, Siomay, Jus Apel, Thai Tea, Bakmi Polos*
5	*Nasi Minyak, Pindang Tulang Ikan, Bakso Biasa, Nasi Gulai Kakap, Sop Ayam*
6	*Martabak Kari Telor Bebek, Bakso Spesial, Adaan, Gado gado, Es Teh Manis, Nasi Timbel Komplit*
7	*Nasi Lemak, Mie Ayam Pangsit, Nasi Rendang, Ketoprak, Sop Ayam, Nasi Timbel Komplit*
8	*Nasi Lemak, Gado gado+lontong, Sop Kambing, Jus Jambu, Gulai Kambing + Nasi, Bakmi Spesial*
9	*Nasi Bakar, Mie Ayam Pangsit, Nasi + Kikil, Jus Belimbing, Thai Tea, Bakmi Bakso*

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

10	*Nasi Bakar, Bakso Spesial, Batagor, Sop Ayam, Susu, Soto Bening, Yamin Bakso*
...	...
153.401	*Nasi Bakar, Pindang Patin, Mie Ayam Pangsit, Bakmi Jawa*

After collecting data on the food and beverage menus ordered, the next step is classifying food and beverage menu data into the category of tenant, where there are 13 Tenants with variable names TN 1, TN 2, TN 3, TN 4, TN 5, TN 6, TN 7, TN 8, TN 9, TN 10, TN 11, TN 12 and TN 13 based on the N-th Transaction, as shown in Table 3 below:

Table 3. Converted Menu Order Transaction

No. Transaction/ Record	*Order Menu*
1	*TN1, TN2, TN5, TN7, TN8,TN13*
2	*TN2, TN3, TN4, TN5, TN6, TN11, TN13*
3	*TN1, TN3, TN4, TN5, TN7, TN8*
4	*TN3, TN5, TN6, TN8, TN9, TN13*
5	*TN1, TN2, TN3, TN4, TN5, TN6, TN7, TN8, TN13*
6	*TN1, TN3, TN4, TN6, TN9, TN11, TN12*
7	*TN1, TN3, TN5, TN6, TN7, TN12*
8	*TN1, TN6, TN7, TN8, TN11, TN12, TN13*
9	*TN1, TN3, TN5, TN8, TN9, TN13*
10	*TN1, TN3, TN6, TN7, TN9, TN11, TN13*
...	...
153.401	*TN1, TN2, TN3, TN13*

To make it easy in the data analysis process, the next step is to convert the tenant table into a dummy variable table by including the tenant into a field, for tenants that is on the transaction, they are given a value of 1, and for tenants that is not on the transaction then given the number 0. As shown in table 4 below:

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

Table 4. Dummy Variable

Transaction	*TN1*	*TN2*	*TN3*	*TN4*	*TN5*	*TN6*	*TN7*	*TN8*	*TN9*	*TN10*	*TN11*	*TN12*	*TN13*
1	*1*	*1*	*0*	*0*	*1*	*0*	*1*	*1*	*0*	*0*	*0*	*0*	*1*
2	*0*	*1*	*1*	*1*	*1*	*1*	*0*	*0*	*0*	*0*	*1*	*0*	*1*
3	*1*	*0*	*1*	*1*	*1*	*0*	*1*	*1*	*0*	*0*	*0*	*0*	*0*
4	*0*	*0*	*1*	*0*	*1*	*1*	*0*	*1*	*1*	*0*	*0*	*0*	*1*
5	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*0*	*0*	*0*	*0*	*1*
6	*1*	*0*	*1*	*1*	*0*	*1*	*0*	*0*	*1*	*0*	*1*	*1*	*0*
7	*1*	*0*	*1*	*0*	*1*	*1*	*1*	*0*	*0*	*0*	*0*	*1*	*0*
8	*1*	*0*	*0*	*0*	*0*	*1*	*1*	*1*	*0*	*0*	*1*	*1*	*1*
9	*1*	*0*	*1*	*0*	*1*	*0*	*0*	*1*	*1*	*0*	*0*	*0*	*1*
10	*1*	*0*	*1*	*0*	*0*	*1*	*1*	*0*	*1*	*0*	*1*	*0*	*1*
...	...	...	...	...	...	...	...	...	...	...	...	...	...
153.401	*1*	*1*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*1*

The data mining process in this study was carried out to extract sales data that had been transformed into dummy variables, to determine consumer tendencies in purchasing decisions for foods and beverages items on tenants at Polsri foodcourt. The analysis involved association rules analysis. Manually, the steps in the analysis of association rules are:

1. Determine the minimum itemset
2. Determine the frequency itemset for 2 and 3 tenants
3. Build a rule based on the frequency itemset.
4. Calculate the Support and Confident values from the total rules
5. Recommend rules that have the highest confident value, which in this study will take on rules that have score > 0.8 or 80%

The tools used in this stage use Microsoft Excel 2010 and WEKA 3.8.2 applications. In order to facilitate data processing, the dummy variable is converted to Y for data with a value of 1 and N for data with a value of 0. The data is saved in .csv format, as shown in table 5 below:

Table 5. Dummy Variable Conversion Data

Transac-tion	*TN1*	*TN2*	*TN3*	*TN4*	*TN5*	*TN6*	*TN7*	*TN8*	*TN9*	*TN10*	*TN11*	*TN12*	*TN13*
1	*Y*	*Y*	*N*	*N*	*Y*	*N*	*Y*	*Y*	*N*	*N*	*N*	*N*	*Y*

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

2	*N*	*Y*	*Y*	*Y*	*Y*	*Y*	*N*	*N*	*N*	*N*	*Y*	*N*	*Y*
3	*Y*	*N*	*Y*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*N*	*N*	*N*	*N*
4	*N*	*N*	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*Y*	*N*	*N*	*N*	*Y*
5	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*Y*	*N*	*N*	*N*	*N*	*Y*
6	*Y*	*N*	*Y*	*Y*	*N*	*Y*	*N*	*N*	*Y*	*N*	*Y*	*Y*	*N*
7	*Y*	*N*	*Y*	*N*	*Y*	*Y*	*Y*	*N*	*N*	*N*	*N*	*Y*	*N*
8	*Y*	*N*	*N*	*N*	*N*	*Y*	*Y*	*Y*	*N*	*N*	*Y*	*Y*	*Y*
9	*Y*	*N*	*Y*	*N*	*Y*	*N*	*N*	*Y*	*Y*	*N*	*N*	*N*	*Y*
10	*Y*	*N*	*Y*	*N*	*N*	*Y*	*Y*	*N*	*Y*	*N*	*Y*	*N*	*Y*
...													
153.401	*Y*	*Y*	*Y*	*N*	*N*	*N*	*N*	*N*	*N*	*N*	*N*	*N*	*Y*

The dummy variable conversion data is then processed to produce 10 rules with a confidence value of > 80%. The basic methodology of association rules is divided into two stages (ISA & Jhoansyah, 2019):

1. Analysis of High Frequency Pattern

This stage is looking for a combination of items that meet the minimum requirements of the support value in the database. The support value of an item is obtained by the following formula:

$$Support\ A = \frac{Total\ of\ Transaction\ contain\ A}{Total\ of\ Transaction} \tag{1}$$

While the support value of the 2 items is obtained from the following formula:

$$Support\ (\ A\ \cap\ B\ ) = \frac{Total\ of\ Transaction\ contain\ A\ and\ B}{Total\ of\ Transaction} \tag{2}$$

2. Formation of Association Rules

After all high-frequency patterns are found, then look for the associative rule that appropriate to the the minimum requirements for confidence by calculating the confidence of the associative rule A → B. The confidence value of the A → B rule is obtained from the following formula:

$$P\ (\ A\ \cap\ B\ ) = \frac{Total\ of\ Transaction\ contain\ A\ and\ B}{Total\ of\ Transaction\ contain\ A} \tag{3}$$

So from this calculation, the WEKA tool version 3.8.2 produces the top 10 rules with a confidence level > 0.70 or 70%. The resulting rules are as follows:

a. TN 11=N 101595 ==> TN 8=N 51806 <conf:(0.90)>
b. TN 8=N 102041 ==> TN 11=N 51806 <conf:(0.90)>
c. TN 3=N 101169 ==> TN 8=N 51271 <conf:(0.86)>
d. TN 11=Y 101048 ==> TN 13=Y 51221 <conf:(0.83)>
e. TN 13=N 101017 ==> TN 10=N 51190 <conf:(0.79)>

ISSN : 2597-4785 (ONLINE)
ISSN : 2597-4750 (PRINTED)

f.	TN 2=Y 101292	==>	TN 13=Y 51302	<conf:(0.79)>
g.	TN 11=N 101595	==>	TN 10=Y 51398	<conf:(0.70)>
h.	TN 4=Y 101175	==>	TN 8=N 51184	<conf:(0.70)>
i.	TN 13=Y 101626	==>	TN 8=N 51407	<conf:(0.70)>
j.	TN 2=Y 101292	==>	TN 1=N 51231	<conf:(0.70)>

From the data rules, it can be interpreted that:

a. If the buyer does not buy on Tenant 11, then does not buy on Tenant 8. With a confidence level of 90% **(Recommendation Rule)**
b. If the buyer does not buy on Tenant 8, then does not buy on Tenant 11. With a confidence level of 90% **(Recommendation Rule)**
c. If the buyer does not buy on Tenant 3, then does not buy on Tenant 8. With a confidence level of 86% **(Recommendation Rule)**
d. If the buyer buys on Tenant 11, then buys on Tenant 13. With a confidence level of 83% **(Recommendation Rule)**
e. If the buyer does not buy on Tenant 13, then does not buy on Tenant 10. With a confidence level of 79%
f. If the buyer buys on Tenant 2, then buys on Tenant 13. With a confidence level of 79%
g. If the buyer does not buy on Tenant 11, then buys on Tenant 10. With a confidence level of 70%
h. If the buyer buys on Tenant 4, then does not buy on Tenant 8. With a confidence level of 70%
i. If the buyer buys on Tenant 13, then he does not buy on Tenant 8. With a confidence level of 70%
j. If the buyer buys on Tenant 2, then does not buy on Tenant 8. With a confidence level of 90%

The rules that are recommended in this study with a confidence value > 80%, where there are 4 rules namely rule a, rule b, rule c and rule d. If it is observed, the tendency of buyers when they do not buy in tenant 11 then do not buy also in tenant 8 which appears in “rule a”, otherwise in “rule b” where the tendency of buyers when they do not buy in tenant 11 then do not buy also in tenant 8. This can be a strategy marketing, where the positions of tenants 8 and 11 can be spread not close together so that the focus of buyers is not in one point.

The same thing is also found in “rule c” where when a buyers do not buy in tenant 3, then do not buy at tenant 8. While in “rule d” that the tendency of buyers buy at tenant 11, the buyers buy at tenant 13. So that tenants 11 and 13 are positioned close together to make it easier for buyers to make purchases which automatically increases sales. The recommended tenant positions can be seen in Figure 5 below:

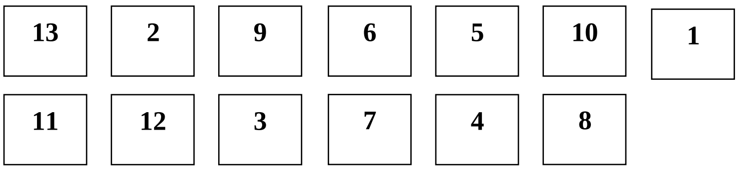

Figure 5. Polsri Foodcourt Tenant Position Recommendation

Figure 5 above shows the recommended tenant positions, where tenants 8 and 11 are placed far apart, which were originally in side-by-side positions. Tenants 3 and 8 just swap positions, because they are originally all far apart. Meanwhile, tenants 11 and 13 are positioned close together which makes it easier for buyers to find the desired product, especially for tenants 11 and 13.

IV. CONCLUSION

The results of the Association Rules analysis in this study with the research object that is Sriwijaya State Polytechnic (Polsri) Foodcourt Sales Report for the period 01 May 2019 - 31 July 2019, with a total of 153,401 data records producing 10 rules with 4 rules with a confident value of 0.80 or 80%, those are :

1. If the buyer does not buy on Tenant 11, then does not buy on Tenant 8.
2. If the buyer does not buy on Tenant 8, then does not buy on Tenant 11.
3. If the buyer does not buy on Tenant 3, then does not buy on Tenant 8.
4. If the buyer buys on Tenant 11, then buys on Tenant 13.

So from these rules it can be concluded that tenant positions 8, 11 and 3 are recommended to be spread in far apart places to see how high the sales level is after the tenants are distributed. Meanwhile, tenant 11 is

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brought closer to tenant 13 to make it easier for buyers to make purchases which otomatically increases sales. The suggestion from this research is that the data should be analyzed over a long period of time, to produce a specific analysis, for example data in along of 1 year.

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