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CUSTOMER SPENDING PATTERN ANALYSIS WITH MARKET BASKET ANALYSIS TO PRODUCE PRODUCT STRATEGY AND PRICE BUNDLING AT KOPI SOE MEKARWANGI BANDUNG

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ABSTRACT: Coffee industry in Indonesia will always grow significantly. With the return of consumptions in coffee shops and take away coffee shops after the pandemic, Kopi Soe Mekarwangi Bandung as one of the players in Bandung's coffee industries hope to experience increases in sales and profit. But what happened was the contrary, for in January 2022-January 2023, Kopi Soe Mekarwangi experienced a decline in their sales and profit. Based on the data gained from the International Coffee Organization and Toffin, coffee shops should be increasing their sales in that period. To get a deeper knowledge about the research object, an interview with the owner of Kopi Soe Mekarwangi Bandung was done and it was found that they have one fundamental marketing problem in the term of their bundle. For their bundling strategy, the basis of their decision is either (1) introducing new products, or (2) boosting slow moving products. Based on the literature and journals, it was found that the best basis for marketing strategies should be the customer spending pattern. The customer's spending pattern can be seen in their transactions and can be analyzed using data mining techniques such as market basket analysis. It's hoped that the result of this mining can be used to determine the best bundling strategies for Kopi Soe Mekarwangi Bandung in the future.

Keywords: customer's spending pattern, product bundling, price bundling, market basket analysis

INTRODUCTION

The development of technology has had an impact on all aspects of human life, including in the fields of business and marketing. Interactions and transactions through digital platforms such as cashier applications or websites generate data sets called big data. Big data is large and complex data, cannot be processed with ordinary database management devices (Maryanto, 2017). The use of big data can provide many benefits for businesses, such as helping to make the right decisions based on data, understanding market trends and consumer desires, and planning strategies based on consumer behavior. Business owners who are able to analyze and utilize big data well can design bundled products that are more targeted and effective. *Knowledge discovery in database* is the process of discovering new information from various data sources, including steps such as data preparation, data cleansing and pre-processing, data mining, and data visualization (Maksood &; Achuthan, 2016). A number of previous studies have proposed algorithms or *methods of big data analytics* to produce promos and product variations in the form of effective bundles. Some of the studies in the *Scopus database* include research by Birtolo et al (2013) who proposed the *Intelligent Bundle Suggestion and Generation System* (IBSAG). This method considers the limitations of merchants in selling difficult products and adapts them to consumer transaction patterns. Another study by Do, Lauw, and Wang (2015) proposed *a Matching Based Algorithm* and *Greedy Algorithm* to create bundles with *maximum revenue* by considering the willingness to pay consumers. However, the study did not consider the relationship between products or consumer spending patterns. Research by Young & Law (2022) proposes a *Competition-Aware Bundling Algorithm* to find bundles with maximum *expected revenue*, assuming competitors also have the same product and inventory. Although creating bundles under competitive conditions, this method also does not consider the relationship between products. Based on these studies, the most effective method to create *the best product* and *price bundle* from consumer spending patterns is *Market Basket Analysis*.

Market Basket Analysis or *Association Rule Mining* is a branch of data mining science in knowledge discovery in database used to understand the purchasing patterns of goods by consumers (Ramadana, Satyahadewi, and Perdana, 2022). This *Market Basket Analysis* method is done by analyzing consumer spending habits and looking for relationships between several items that are often purchased together in the shopping basket (Gunadi and Sensuse, 2012). The results of *Market Basket Analysis* are valuable as a basis for analyzing shopping patterns and consumer preferences, which become important in the creation of product bundles that will be offered by companies. Previously, research to create product recommendations using *Market Basket Analysis* (MBA) has been carried out in various industrial sectors.

For example, Suhandi & Gustriansyah (2021) use the MBA method to provide product recommendations in printing companies, while Widyadhini, Wibawa, and Ardiantono (2021) use MBA to provide product recommendations in fertilizer companies, and Rizky, Sembiring, and Maulana (2022) use the MBA method to provide product recommendations in coffee shops with a menu number of under 30 products. However, no research has been found that combines product recommendations from *Market Basket Analysis* with determining the right *reservation price* to create product bundles and prices in coffee shops. Based on the description above, it is known that Kopi Soe Mekarwangi Bandung has the potential to gain a competitive advantage over its competitors because it has adopted *cashier digital database* technology since 2018 and has big data that can be utilized. This study aims to utilize big data by using *Market Basket Analysis* to recognize consumer spending patterns and create product recommendations. Furthermore, these product recommendations will be developed by considering the determination of *the right reservation price* to create product bundles and prices that are attractive to consumers. Therefore, this study is entitled "*Customer Spending Pattern* Analysis with *Market Basket Analysis* to Produce *Product* Strategy and *Price Bundling* at Kopi Soe Mekarwangi Bandung."

METHOD

This study aims to determine *the variables of product* bundle and *price bundle* based on consumer spending patterns without looking for relationships between variables, so the type of research is descriptive. The approach used is a deductive approach, which originates from general things and is applied to specific things, is formal, and emphasizes the structuring of reason. The strategy applied in this study is *archival research*, which involves searching and extracting information or evidence from the original archive. Transaction data of Kopi Soe Mekarwangi Bandung until January 2023 became the study population, with a total of 13,951 transactions. However, this study will use a sample of transaction data that occurred from January 2022 to January 2023 as many as 12,832 transactions, because previous data did not accurately reflect consumer spending patterns. The sampling technique used is *purposive sampling*, which is a sampling technique based on certain objectives. The data source consists of primary data in the form of interviews with the owner of Kopi Soe Mekarwangi Bandung and secondary data in the form of transaction data from Kopi Soe Mekarwangi Bandung. This research uses big data analytics-based data analysis techniques*, which include* *steps such as* data selection, data transformation, data *cleaning and preprocessing, modeling,* to making *product and price bundling*. The results of the analysis from this study will help determine the *product strategy and price bundling* that is suitable to be applied at Kopi Soe Mekarwangi Bandung in the future.

RESULT AND DISCUSSION

Data Selection and Transformation

Data selection is a stage where researchers download the *dataset* of Kopi Soe Mekarwangi Bandung transactions in the period January 2022-January 2023 in csv form. *Data transformation* is a process where the *dataset* is uploaded on the *Google Collaborator platform using the* Python *programming language* after previously researchers *imported pandas* and *numpy* packages for number processing. The *data selection* and *transformation process* can be seen in the following figure.

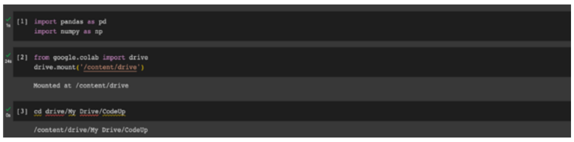


Figure 1 *Data selection*

The next process is a check of the upload process in *Google Collaborator*. This check can be done with a simple algorithm, which is to create a variable named data and *attribute a csv reading* of the dataset *to that variable and give the* data command. The process can be seen in the following figure.

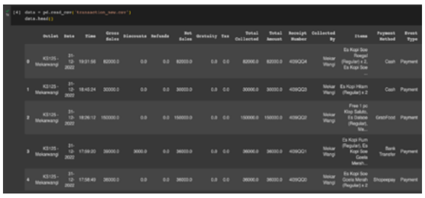


Figure 2 *Data transformation checking*

Data Cleaning and Preprocessing

The process *of data cleaning and preprocessing* is the process of 'cleaning' data from rows or characters that can reduce the accuracy of the results. This process is divided into several stages, namely:

Null checking

The *null checking* process is a process to discard incomplete or empty data. To do this, researchers must see if there are empty data/rows in the *dataset*. The algorithm for doing this can be seen in the following figure.

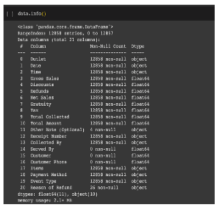


Figure 3 *Null checking*

From the results of the algorithm above, we can know that columns such as *Other Note (Optional), Served by, Customer, Customer Phone*, and *Reason of Refund* have a lot of empty rows. In the *Reason of Refund* column, for example, out of 12,858 rows, there are only 26 rows that have content. Because the comparison between fill rows and blank rows is too one-sided, the columns will be removed with the following algorithm.

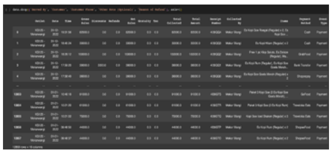
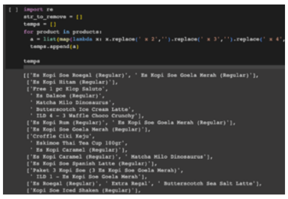


Figure 4 *Dataset* after *null columns* are deleted

Once it is confirmed that there are no more columns with empty rows, the researcher can proceed to the next stage.

Character checking

In the *Items* column, there are still transactions that have unnecessary characters such as 'x3' which refers to the frequency of purchases or *'Full Refund', 'Partial Refund', 'Custom Amount', 'Change to', 'Take Away Charges*' and '*Extra*' which does not refer to a particular product. These characters must be removed using the following algorithm.



```
import re
str_to_remove = []
temps = []
for product in products:
  a = list(map(lambda x: x.replace(' x 2','').replace(' x 3','').replace(' x 4',
  temps.append(a)

temps
```

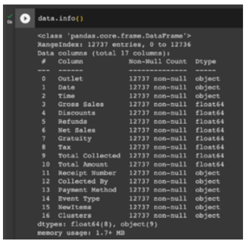
```
[['Es Kopi Soe Roegal (Regular)', ' Es Kopi Soe Goela Merah (Regular)'],
 ['Es Kopi Hitam (Regular)'],
 ['Free 1 pc Klop Saluto',
  ' Es Dalsoe (Regular)',
  ' Matcha Milo Dinosaurus',
  ' Butterscotch Ice Cream Latte',
  ' ILD 4 - 3 Waffle Choco Crunchy'],
 ['Es Kopi Rum (Regular)', ' Es Kopi Soe Goela Merah (Regular)'],
 ['Es Kopi Soe Goela Merah (Regular)'],
 ['Croffle Ciki Keju',
  ' Eskimoe Thai Tea Cup 100gr',
  ' Es Kopi Caramel (Regular)'],
 ['Es Kopi Caramel (Regular)', ' Matcha Milo Dinosaurus'],
 ['Es Kopi Soe Spanish Latte (Regular)'],
 ['Paket 3 Kopi Soe (3 Es Kopi Soe Goela Merah)',
  ' ILD 1 - Es Kopi Soe Goela Merah'],
 ['Es Roegal (Regular)', ' Extra Regal', ' Butterscotch Sea Salt Latte'],
 ['Kopi Soe Iced Shaken (Regular)'],
```

Figure 5 Character checking *process*

The *Items column that has been cleaned up by* the character checking process *produces a new column named* NewItems *as follows.*

Figure 6 *Dataset* after *Character Checking*

This *character checking process* also reduces the number of transactions, because transactions that do not involve products (only transactions to add sugar/*espresso* for example) have been deleted. Thus, the number of the most recent rows of the *dataset* is as follows.



```
data.info()
```

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 12737 entries, 0 to 12736
Data columns (total 17 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Outlet            12737 non-null  object
 1   Date              12737 non-null  object
 2   Time              12737 non-null  object
 3   Gross Sales       12737 non-null  float64
 4   Discounts         12737 non-null  float64
 5   Refunds           12737 non-null  float64
 6   Net Sales         12737 non-null  float64
 7   Gratuity          12737 non-null  float64
 8   Tax               12737 non-null  float64
 9   Total Collected   12737 non-null  float64
 10  Total Amount      12737 non-null  float64
 11  Receipt Number    12737 non-null  object
 12  Collected By      12737 non-null  object
 13  Payment Method    12737 non-null  object
 14  Event Type        12737 non-null  object
 15  NewItems          12737 non-null  object
 16  Clusters          12737 non-null  object
dtypes: float64(8), object(9)
memory usage: 1.7+ MB
```

Figure 7 Number of rows in dataset after *character checking*

Once it is confirmed that there are no characters that do not refer to the product, the researcher can proceed to the next stage.

Data transpose

The format of the *NewItems table* must be changed to a table of the existence of *items* in each transaction with the following algorithm.

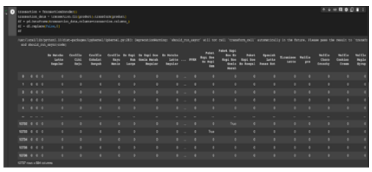


Figure 8 NewItems table in each transaction

From this *transpose table,* it can be known the relationship between *items* in each transaction, so the next stage that will be carried out is *modeling* with *Market Basket Analysis* and *bundling pricing*.

MODELLING

FP Growth Algorithm

In this study, *frequent item sets* will be created using *the FP Growth* algorithm. While to make a compilation of *rules* that are important and those that are not, the parameters used are *support value (support* value) and *confidence value (*confidence value). Previous research from Rizky, Sembiring, and Maulana (2022) used a minimum *support* of 50% and a *minimum confidence value* of 95%. But in processing, it was found that the magnitude did not produce the expected results.

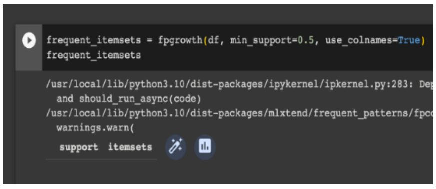


Figure 9 Results of *Frequent Item sets* with *50%* Minimum Support

According to Witten et al (2011), the next step that must be taken is to reduce the minimum support value by 5% to get 10 *rules* with 90% confidence to reach *the minimum support* value *of 10%*. However, the results of data processing with *a minimum support* value of 10% are as follows.

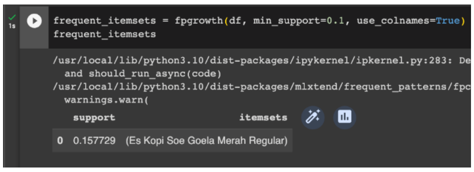
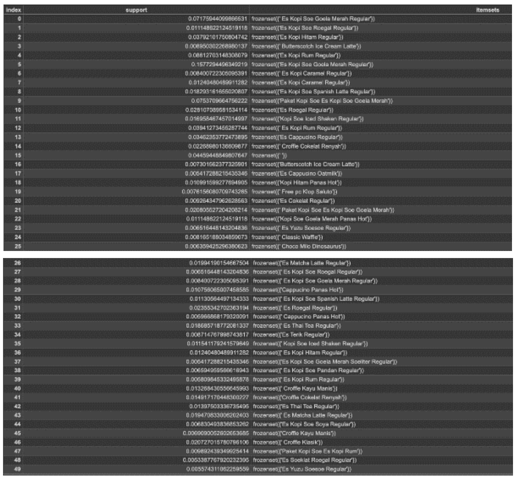


Figure 10 Results of *Frequent Itemsets* with *10%* Minimum Support

The transaction data of the object of study is very compound and varied. So the next step that researchers do is to reduce the minimum value of *support* until *a rule* is obtained that has a minimum confidence value of 10%. Here are the results of the *association rules* algorithm using *a minimum support* of 0.5%.



index	support	itemsets
0	0.07175944099866531	frozenset({' Es Kopi Soe Goela Merah Regular'})
1	0.011148622124519118	frozenset({'Es Kopi Soe Roegal Regular'})
2	0.03792101750804742	frozenset({'Es Kopi Hitam Regular'})
3	0.006950302268980137	frozenset({' Butterscotch Ice Cream Latte'})
4	0.06812703148308079	frozenset({'Es Kopi Rum Regular'})
5	0.1577294496349219	frozenset({'Es Kopi Soe Goela Merah Regular'})
6	0.008400722305095391	frozenset({' Es Kopi Caramel Regular'})
7	0.012404804899112 82	frozenset({'Es Kopi Caramel Regular'})
8	0.018293161655020807	frozenset({'Es Kopi Soe Spanish Latte Regular'})
9	0.0753709664756222	frozenset({'Paket Kopi Soe Es Kopi Soe Goela Merah'})
10	0.028107089681534114	frozenset({'Es Roegal Regular'})
11	0.016958467457014997	frozenset({'Kopi Soe Iced Shaken Regular'})
12	0.03941273465287744	frozenset({' Es Kopi Rum Regular'})
13	0.03462353772473895	frozenset({'Es Cappucino Regular'})
14	0.022688801366099877	frozenset({' Croffle Cokelat Renyah'})
15	0.04459448849807647	frozenset({' '})
16	0.007301562377325901	frozenset({'Butterscotch Ice Cream Latte'})
17	0.006417288215435346	frozenset({'Es Cappucino Oatmilk'})
18	0.010991589277694905	frozenset({'Kopi Hitam Panas Hot'})
19	0.0076156080709743285	frozenset({' Free pc Kop Saluto'})
20	0.009264347962628563	frozenset({'Es Cokelat Regular'})
21	0.020805627204208214	frozenset({' Paket Kopi Soe Es Kopi Soe Goela Merah'})
22	0.011148622124519118	frozenset({'Kopi Soe Goela Merah Panas Hot'})
23	0.006516448143204836	frozenset({' Es Yuzu Soesoe Regular'})
24	0.008165188034859073	frozenset({' Classic Waffle'})
25	0.006359425296380623	frozenset({' Choco Milo Dinosaurus'})
26	0.01994190154687504	frozenset({'Es Matcha Latte Regular'})
27	0.006516448143204836	frozenset({' Es Kopi Soe Roegal Regular'})
28	0.008400722305085391	frozenset({' Es Kopi Soe Goela Merah Regular'})
29	0.010758065007458585	frozenset({'Cappucino Panas Hot'})
30	0.01130564497134333	frozenset({' Es Kopi Soe Spanish Latte Regular'})
31	0.02355342702363194	frozenset({' Es Roegal Regular'})
32	0.005966868179320091	frozenset({' Cappucino Panas Hot'})
33	0.018685718772081337	frozenset({' Es Thai Tea Regular'})
34	0.008714767898743817	frozenset({'Es Tenk Regular'})
35	0.011541179241579849	frozenset({' Kopi Soe Iced Shaken Regular'})
36	0.01240480489911282	frozenset({' Es Kopi Hitam Regular'})
37	0.006417288215435346	frozenset({'Es Kopi Soe Goela Merah Soelter Regular'})
38	0.006594959586618943	frozenset({' Es Kopi Soe Pandan Regular'})
39	0.006809845332495878	frozenset({' Es Kopi Rum Regular'})
40	0.013268430556645993	frozenset({' Croffle Kayu Manis'})
41	0.014817170448300227	frozenset({'Croffle Cokelat Renyah'})
42	0.01397503336735495	frozenset({'Es Thai Tea Regular'})
43	0.019470833006202403	frozenset({' Es Matcha Latte Regular'})
44	0.006830493836853262	frozenset({'Es Kopi Soe Soya Regular'})
45	0.0069090052602653685	frozenset({'Croffle Kayu Manis'})
46	0.020727015780786106	frozenset({' Croffle Klasik'})
47	0.009892439349925414	frozenset({'Paket Kopi Soe Es Kopi Rum'})
48	0.005338776792023236	frozenset({'Es Soeklat Roegal Regular'})
49	0.005574311062258559	frozenset({'Es Yuzu Soesoe Regular'})

Figure 11 *Frequent Item sets* with *Minimum Support* value of 0.5%

Bundling Strategy

It is known that the selling price of Es Kopi Soe Goela Merah is Rp 18.000,- and the selling price of Es Kopi Rum is Rp 21.000,-. While a detailed explanation of the capital price for the two products is:

Table 1 Capital Price *Product Association Rules*

Brown Sugar Soe Iced Coffee	• Brown sugar : Rp 775,- (20 gr) • *Cup* : Rp 541,- (1 cup) • Regular milk : Rp 1.305,- (75 gr) • Liquid coffee : Rp 5.834,- (35 gr) • Ice: Rp 340,- (1 cup) • Sunbay *milk* : Rp 2.566,- (75 gr) Total harga modal untuk 1 *cup* : Rp 11.361,-
Iced Coffee Rum	• Rum : Rp 2.600,- (20 gr) • *Cup* : Rp 541,- (1 cup) • Regular milk : Rp 1.305,- (75 gr) • Liquid coffee : Rp 5.834,- (35 gr) • Ice : Rp 340,- (1 cup) • Sunbay *milk* : Rp 2.566,- (75 gr) Total capital price for 1 *cup*: Rp 13.186,-

From the two data above, the *profit margin* of both products can be determined by the following calculation:

Table 3 Calculation of *product profit margin* separately

Red Goela Iced Coffee profit margin $= \frac{Profit}{Sales} * 100$ $= \frac{(18{,}000 - 11{,}361)}{18{,}000} * 100$ = 36,88%
Profit margin Es Kopi Rum $= \frac{Profit}{Sales} * 100$ $= \frac{(21{,}000 - 13{,}186)}{21{,}000} * 100$ = 37,21%

Assuming that the *reservation price for Red Goela Iced Coffee and Rum Iced Coffee products is the same as the product price in the past and the* bundle pricing requirements that (1) do not exceed the total product price separately and *(2) provide* a profit margin *that is not lower than* the product profit margin *separately, the bundle price of Red Goela Iced Coffee and Rum Iced Coffee can be* determined in *range* Rp 31.200,- to Rp 38.900,- with the following calculation:

Table 4 Price comparison and *profit margin* of products before and after *bundling*

	Products Before *Bundling*	Products After *Bundling*	Terms (1)	Profit Margin Before *Bundling*	Profit Margin After *Bundling*	Terms (2)
Minimum Price	Brown Sugar Iced Coffee Rp 18.000,-	Brown Sugar Iced Coffee Rp 18.000,-		36.88%	36.88%	
	Iced Coffee Rum Rp 21.000,-	Iced Coffee Rum Rp 13.300,-	✓	37.21%	0,85714286 %	✓
	Total Price Rp 39.000,-	***Bundling price*** **Rp 31.300,-**			**37.7371429%**	
Maximum Price	Brown Sugar Iced Coffee Rp 18.000,-	Brown Sugar Iced Coffee Rp 17.950,-		36.88%	36,7075209 %	
	Iced Coffee Rum Rp 21.000,-	Iced Coffee Rum Rp 21.000,-	✓	37.21%	37.21%	✓
	Total Price Rp 39.000,-	***Bundling price*** **Rp 38.950,-**			**73.9175209%**	

DISCUSSION

The results of processing transaction data of Kopi Soe Mekarwangi Bandung using Market Basket Analysis show that transaction data is very diverse, so the relationship between products is difficult to see with the minimum amount of support used previously. However, after setting the minimum support amount at 0.5%, it was found that the Red Goela Iced Coffee and Rum Iced Coffee products have a close relationship, with an average support of 0.88%. This means that out of 12,737 transactions, there were 112 transactions where both products were purchased simultaneously by consumers. This rule has an average confidence value of 14.73%, which means about 15 out of every 100 customers buy both products simultaneously. Based on these results, researchers apply the principle of bundle pricing from companies supported by theories from Kotler & Keller (2012: 402), namely (1) the bundle price does not exceed the total product price separately and (2) the bundle price provides a profit margin that is not lower than the product profit margin separately. Based on this principle, the price bundle price range for Goela Merah Iced Coffee and Rum Iced Coffee products is set between Rp 31,300 to Rp 38,950,-. With this price range, the research object can get a profit margin between 37.74% to 73.92%.

CONCLUSIONS

Based on transaction data and data processing, the following conclusions are obtained: 1). Using the MBA method, consumer spending patterns at Kopi Soe Mekarwangi Bandung for the period January 2022 to January 2023 are very plural. Of the 12,737 transactions, less than 10% had a strong product-to-product relationship. 2). Price bundling *that can be created based on consumer spending patterns at Kopi Soe Mekarwangi Bandung for the period January 2022 to January 2023 is* the bundling of Red Goela Iced Coffee and Rum Iced Coffee with a price range between IDR 31,300 to IDR 38,950,-. Both products were chosen to be used as *bundling* because they are two products that have the strongest relationship compared to other products. The selected price range also meets company policy and brings *profit margins* that are still profitable for the company.

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