

**Performance Assessment for
D212: Data Mining II
Task 3 Attempt 2**

Drew Mendez
MSDA Western Governors University
D212: Data Mining II
Dr. Kesselly Kamara
March 11th, 2025

March 11, 2025

1 Part I: Research Question

1.1 A. Purpose of Data Mining Report

1.1.1 A1. Research Question

Can Market Basket Analysis uncover which items are frequently purchased together by telecom customers?

1.1.2 A2. Goal of the Data Analysis

The goal of this analysis is to apply Market Basket Analysis which items are frequently purchased together in order to determine potential bundles of products or services. This could then be used to encourage purchases from the customer base and drive business growth.

2 Part II: Market Basket Justification

2.1 B. Reasons for using Market Basket Analysis

2.1.1 B1. How Market Basket Analyzes the Data Set

Market Basket Analysis is an unsupervised learning technique that can be used to identify purchasing patterns of customers by analyzing combinations of products purchased together (GeeksforGeeks, 2022). Market Basket Analysis uses the association rule, if the antecedent then the consequent, where the antecedent is an item in the data set and the consequent is an item found in combination with the antecedent (GeeksforGeeks, 2022).

The expected outcome is the discovery of combinations of items frequently purchased together. We will be able to measure each item's **support**, the rate at which an itemset appears in the data set, the **confidence**, or conditional probability representing the probability of finding the consequent in transactions with the antecedent, and the **lift**, or the ratio of observed support to that expected if the antecedent and consequent were independent.

For the antecedent, A, and the consequent, B, the formulas for determining support, confidence, and lift are as follows:

$$\text{support}(A \rightarrow B) = \frac{\text{number of transactions containing both } A \text{ and } B}{\text{total number of transactions}}$$

$$\text{confidence}(A \rightarrow B) = \frac{\text{support}(A \cup B)}{\text{support}(A)} = \frac{\text{number of transactions containing } A \text{ and } B}{\text{number of transactions containing } A}$$

$$\text{lift}(A \rightarrow B) = \frac{\text{support}(A \cup B)}{\text{support}(A) \times \text{support}(B)}$$

(Chaudhary, 2023)

2.1.2 B2. One Example of Transactions

One example of a transaction in the data set would be the 99th entry, as shown here. The code to obtain the 99th entry is given below. Items in the transaction include ‘Dust-Off Compressed Gas 2 pack’, ‘HP 61 ink’, and ‘HP ENVY 5055 printer’.

2.1.3 B3. Assumptions of Market Basket Analysis

- Transaction Independence: each entry in the dataset is assumed to represent an independent transaction, as they would otherwise impact the reliability of the association rules.
- Complete and Accurate Item Descriptions: the item descriptions are assumed to be accurate and complete, as inaccuracies or missing information may impact the analysis.
- Consistent Data Entry Practices: it is assumed that data entry practices are consistent, as inconsistencies or errors may lead to difficulties in accurately identifying associations.
- Representative Sample: it is assumed that the dataset is representative of overall customer transactions, as any biases may result in an analysis that inaccurately reflects the customer base.

(Deniran, 2023)

3 Part III: Data Preparation and Analysis

3.1 C. Data Preparation

3.1.1 C1. Data Transformation for Market Basket Analysis

The cells below contain the code necessary to transform the data set to make it suitable for market basket analysis.

```
[2]: import pandas as pd
from pandas import DataFrame
import numpy as np
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
import matplotlib
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

```
[3]: ## C1 The following cells include the annotated code used to prepare the data.
# See code attached, in D212_PA_MendezD_Task3.ipynb

# Load data into a data frame with Pandas' .read_csv() function
df_mba = pd.read_csv('/Users/drewmendez/Documents/WGU/D212/data/
↳teleco_market_basket.csv')

print(df_mba.shape)
df_mba.head(5)
```

(15002, 20)

```
[3]:
```

	Item01	Item02 \
0	NaN	NaN
1	Logitech M510 Wireless mouse	HP 63 Ink
2	NaN	NaN
3	Apple Lightning to Digital AV Adapter	TP-Link AC1750 Smart WiFi Router
4	NaN	NaN

	Item03	Item04	Item05 \
0	NaN	NaN	NaN
1	HP 65 ink nonda USB C to USB Adapter	10ft iPhone Charger Cable	
2	NaN	NaN	NaN
3	Apple Pencil	NaN	NaN
4	NaN	NaN	NaN

	Item06	Item07 \
0	NaN	NaN
1	HP 902XL ink Creative Pebble 2.0 Speakers	
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item08	Item09 \
0	NaN	NaN
1	Cleaning Gel Universal Dust Cleaner	Micro Center 32GB Memory card
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item10	Item11 \
0	NaN	NaN
1	YUNSONG 3pack 6ft Nylon Lightning Cable	TopMate C5 Laptop Cooler pad
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item12	Item13 \
0	NaN	NaN
1	Apple USB-C Charger cable	HyperX Cloud Stinger Headset
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item14	Item15 \
0	NaN	NaN
1	TONOR USB Gaming Microphone	Dust-Off Compressed Gas 2 pack
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item16	Item17 \
0	NaN	NaN
1	3A USB Type C Cable 3 pack 6FT	HOVAMP iPhone charger
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item18	Item19 \
0	NaN	NaN
1	SanDisk Ultra 128GB card	FEEL2NICE 5 pack 10ft Lighning cable
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item20
0	NaN
1	FEIYOLD Blue light Blocking Glasses
2	NaN
3	NaN
4	NaN

```
[4]: # Remove Nulls
```

```
df_mba = df_mba[df_mba['Item01'].notna()]
df_mba.reset_index(drop=True, inplace=True)

print(df_mba.shape)
df_mba.head(5)
```

```
(7501, 20)
```

```
[4]:
```

	Item01 \
0	Logitech M510 Wireless mouse
1	Apple Lightning to Digital AV Adapter

2 UNEN Mfi Certified 5-pack Lightning Cable
 3 Cat8 Ethernet Cable
 4 Dust-Off Compressed Gas 2 pack

	Item02	Item03 \
0	HP 63 Ink	HP 65 ink
1	TP-Link AC1750 Smart WiFi Router	Apple Pencil
2	NaN	NaN
3	HP 65 ink	NaN
4	Screen Mom Screen Cleaner kit	Moread HDMI to VGA Adapter

	Item04	Item05	Item06 \
0	nonda USB C to USB Adapter	10ft iPhone Charger Cable	HP 902XL ink
1	NaN	NaN	NaN
2	NaN	NaN	NaN
3	NaN	NaN	NaN
4	HP 62XL Tri-Color ink	Apple USB-C Charger cable	NaN

	Item07	Item08 \
0	Creative Pebble 2.0 Speakers	Cleaning Gel Universal Dust Cleaner
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item09	Item10 \
0	Micro Center 32GB Memory card	YUNSONG 3pack 6ft Nylon Lightning Cable
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item11	Item12 \
0	TopMate C5 Laptop Cooler pad	Apple USB-C Charger cable
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item13	Item14 \
0	HyperX Cloud Stinger Headset	TONOR USB Gaming Microphone
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

Item15	Item16 \
--------	----------

0	Dust-Off Compressed Gas 2 pack	3A USB Type C Cable 3 pack	6FT
1	NaN		NaN
2	NaN		NaN
3	NaN		NaN
4	NaN		NaN

	Item17	Item18 \
0	HOVAMP iPhone charger	SanDisk Ultra 128GB card
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

	Item19	Item20
0	FEEL2NICE 5 pack 10ft Lighning cable	FEIYOLD Blue light Blocking Glasses
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

```
[5]: # List of Lists

rows = df_mba.astype(str).values.tolist()

# Encoder

DE = TransactionEncoder()
array = DE.fit(rows).transform(rows)

transaction = pd.DataFrame(array, columns = DE.columns_)

print(transaction.shape)
transaction.head(10)
```

(7501, 120)

```
[5]: 10ft iPHone Charger Cable 10ft iPHone Charger Cable 2 Pack \
0 True False
1 False False
2 False False
3 False False
4 False False
5 False False
6 False False
7 False True
8 False False
9 False False
```

	3 pack Nylon Braided Lightning Cable	3A USB Type C Cable	3 pack 6FT	\
0	False		True	
1	False		False	
2	False		False	
3	False		False	
4	False		False	
5	False		False	
6	False		False	
7	False		False	
8	False		False	
9	False		False	

	5pack Nylon Braided USB C cables	ARRIS SURFboard SB8200 Cable Modem	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	
5	False	False	
6	False	False	
7	False	False	
8	False	False	
9	False	False	

	Anker 2-in-1 USB Card Reader	Anker 4-port USB hub	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	
5	False	False	
6	True	False	
7	False	False	
8	False	False	
9	False	False	

	Anker USB C to HDMI Adapter	Apple Lightning to Digital AV Adapter	...	\
0	False	False	False	...
1	False		True	...
2	False		False	...
3	False		False	...
4	False		False	...
5	False		False	...
6	False		False	...
7	False		False	...
8	False		False	...
9	False		False	...

	iFixit Pro Tech Toolkit	iPhone 11 case	iPhone 12 Charger cable	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
5	False	False	False	
6	False	False	False	
7	False	False	False	
8	False	False	False	
9	False	False	False	

	iPhone 12 Pro case	iPhone 12 case	iPhone Charger Cable Anker 6ft	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	
5	False	False	False	
6	False	False	False	
7	False	False	False	
8	False	False	False	
9	False	False	False	

	iPhone SE case	nan	nonda USB C to USB Adapter	seenda Wireless mouse
0	False	False	True	False
1	False	True	False	False
2	False	True	False	False
3	False	True	False	False
4	False	True	False	False
5	False	True	False	False
6	False	True	False	False
7	False	True	False	False
8	False	True	False	False
9	False	True	False	False

[10 rows x 120 columns]

```
[6]: # Remove NAN column from the dataset
cleaned_df = transaction.drop(['nan'], axis = 1)
cleaned_df.shape
```

[6]: (7501, 119)

```
[7]: # Cleaned Data Set
```

```
cleaned_df.to_csv('D212_PA_MendezD_Task3_variables.csv', sep = ',', encoding = 'utf-8', index = False)
```

[8]: *# Example Transaction*

```
example_transaction = cleaned_df.iloc[100]

# Filter for True values and get the item names
items_in_transaction = example_transaction[example_transaction == True].index.tolist()

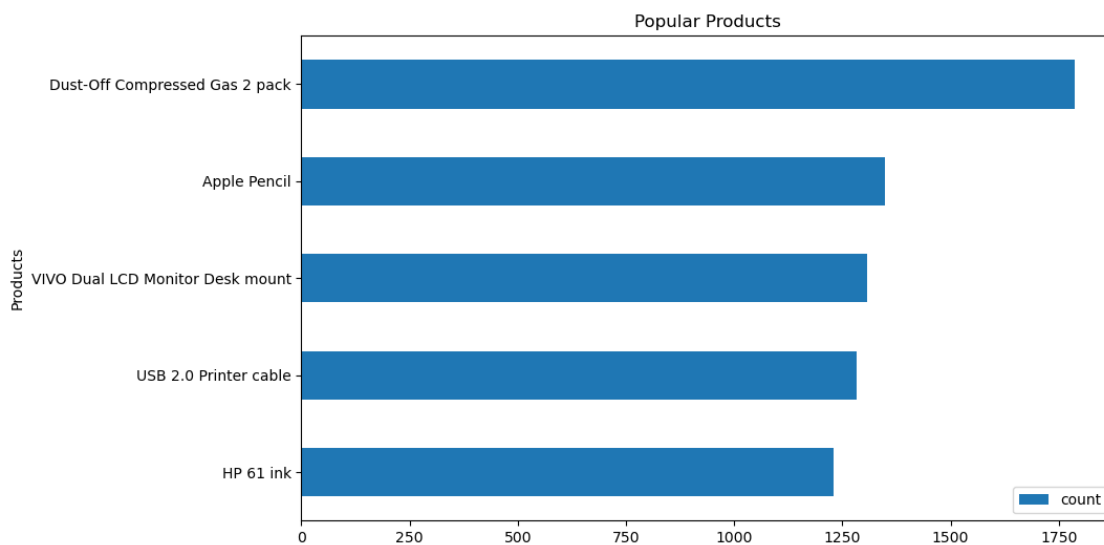
print("Items in the transaction:", items_in_transaction)
```

Items in the transaction: ['Dust-Off Compressed Gas 2 pack', 'HP 61 ink', 'HP ENVY 5055 printer']

[9]:

```
count = cleaned_df.loc[:, :].sum()
pop_item = count.sort_values(ascending = False).head(5)
pop_item = pop_item.to_frame()
pop_item = pop_item.reset_index()
pop_item = pop_item.rename(columns = {'index': 'Products', 0: 'count'})

%matplotlib inline
plt.rcParams['figure.figsize'] = (10, 6)
ax = pop_item.plot.barh(x = 'Products', y = 'count')
plt.title('Popular Products')
plt.gca().invert_yaxis()
```



3.1.2 C2. Association Rules with the Apriori Algorithm

Below is the code used to generate association rules with the Apriori algorithm.

```
[11]: ## C2 Creating Apriori Object

rules = apriori(cleaned_df, min_support = 0.02, use_colnames = True)
rules.head(5)
```

```
[11]:      support      itemsets
0  0.050527  (10ft iPhone Charger Cable 2 Pack)
1  0.042528  (3A USB Type C Cable 3 pack 6FT)
2  0.029463  (Anker 2-in-1 USB Card Reader)
3  0.068391  (Anker USB C to HDMI Adapter)
4  0.087188  (Apple Lightning to Digital AV Adapter)
```

3.1.3 C3. Support, Lift, and Confidence of the Association Rules Table

Values for the support, lift, and confidence of the association rules table. The complete rules table is provided in .csv format with the submission.

```
[40]: ## C3 Creating Rules Table

rules_table = association_rules(rules, metric = 'lift', min_threshold = 1)

rules_table.to_csv('D212_PA_MendezD_Task3_rules_table.csv', sep = ',', encoding_
↳ 'utf-8', index = False)

rules_table.head(15)
```

```
[40]:      antecedents \
0      (Dust-Off Compressed Gas 2 pack)
1      (10ft iPhone Charger Cable 2 Pack)
2      (Dust-Off Compressed Gas 2 pack)
3      (Anker USB C to HDMI Adapter)
4      (VIVO Dual LCD Monitor Desk mount)
5      (Anker USB C to HDMI Adapter)
6      (Apple Lightning to Digital AV Adapter)
7      (Apple Pencil)
8      (Apple Lightning to Digital AV Adapter)
9      (Dust-Off Compressed Gas 2 pack)
10     (USB 2.0 Printer cable)
11     (Apple Lightning to Digital AV Adapter)
12     (Apple Lightning to Digital AV Adapter)
13     (VIVO Dual LCD Monitor Desk mount)
14     (Apple USB-C Charger cable)

      consequents antecedent support \
```

0	(10ft iPhone Charger Cable 2 Pack)	0.238368
1	(Dust-Off Compressed Gas 2 pack)	0.050527
2	(Anker USB C to HDMI Adapter)	0.238368
3	(Dust-Off Compressed Gas 2 pack)	0.068391
4	(Anker USB C to HDMI Adapter)	0.174110
5	(VIVO Dual LCD Monitor Desk mount)	0.068391
6	(Apple Pencil)	0.087188
7	(Apple Lightning to Digital AV Adapter)	0.179709
8	(Dust-Off Compressed Gas 2 pack)	0.087188
9	(Apple Lightning to Digital AV Adapter)	0.238368
10	(Apple Lightning to Digital AV Adapter)	0.170911
11	(USB 2.0 Printer cable)	0.087188
12	(VIVO Dual LCD Monitor Desk mount)	0.087188
13	(Apple Lightning to Digital AV Adapter)	0.174110
14	(Apple Pencil)	0.132116

	consequent support	support	confidence	lift	representativity	\
0	0.050527	0.023064	0.096756	1.914955	1.0	
1	0.238368	0.023064	0.456464	1.914955	1.0	
2	0.068391	0.024397	0.102349	1.496530	1.0	
3	0.238368	0.024397	0.356725	1.496530	1.0	
4	0.068391	0.020931	0.120214	1.757755	1.0	
5	0.174110	0.020931	0.306043	1.757755	1.0	
6	0.179709	0.028796	0.330275	1.837830	1.0	
7	0.087188	0.028796	0.160237	1.837830	1.0	
8	0.238368	0.024397	0.279817	1.173883	1.0	
9	0.087188	0.024397	0.102349	1.173883	1.0	
10	0.087188	0.021997	0.128705	1.476173	1.0	
11	0.170911	0.021997	0.252294	1.476173	1.0	
12	0.174110	0.021464	0.246177	1.413918	1.0	
13	0.087188	0.021464	0.123277	1.413918	1.0	
14	0.179709	0.025463	0.192735	1.072479	1.0	

	leverage	conviction	zhangs_metric	jaccard	certainty	kulczynski
0	0.011020	1.051182	0.627330	0.086760	0.048690	0.276610
1	0.011020	1.401255	0.503221	0.086760	0.286354	0.276610
2	0.008095	1.037830	0.435627	0.086402	0.036451	0.229537
3	0.008095	1.183991	0.356144	0.086402	0.155399	0.229537
4	0.009023	1.058905	0.521973	0.094465	0.055628	0.213129
5	0.009023	1.190117	0.462740	0.094465	0.159746	0.213129
6	0.013128	1.224818	0.499424	0.120941	0.183552	0.245256
7	0.013128	1.086988	0.555754	0.120941	0.080026	0.245256
8	0.003614	1.057552	0.162275	0.081009	0.054420	0.191083
9	0.003614	1.016889	0.194486	0.081009	0.016609	0.191083
10	0.007096	1.047650	0.389069	0.093168	0.045482	0.190499
11	0.007096	1.108844	0.353384	0.093168	0.098160	0.190499
12	0.006283	1.095602	0.320707	0.089494	0.087260	0.184727

13	0.006283	1.041163	0.354460	0.089494	0.039536	0.184727
14	0.001721	1.016135	0.077869	0.088920	0.015879	0.167213

3.1.4 C4. Top Three Rules Generated by the Apriori algorithm

Explain the top three relevant rules generated by the Apriori algorithm. Include a screenshot of the top three relevant rules.

```
[15]: # Top Three by Support

top_three_supp = rules_table.sort_values('support', ascending = False).head(3)
top_three_supp
```

```
[15]:
```

	antecedents	consequents	\
62	(VIVO Dual LCD Monitor Desk mount)	(Dust-Off Compressed Gas 2 pack)	
63	(Dust-Off Compressed Gas 2 pack)	(VIVO Dual LCD Monitor Desk mount)	
41	(Dust-Off Compressed Gas 2 pack)	(HP 61 ink)	

	antecedent support	consequent support	support	confidence	lift	\
62	0.174110	0.238368	0.059725	0.343032	1.439085	
63	0.238368	0.174110	0.059725	0.250559	1.439085	
41	0.238368	0.163845	0.052660	0.220917	1.348332	

	representativity	leverage	conviction	zhangs_metric	jaccard	\
62	1.0	0.018223	1.159314	0.369437	0.169312	
63	1.0	0.018223	1.102008	0.400606	0.169312	
41	1.0	0.013604	1.073256	0.339197	0.150648	

	certainty	kulczynski
62	0.137421	0.296796
63	0.092566	0.296796
41	0.068256	0.271158

```
[16]: # Top Three by Confidence

top_three_conf = rules_table.sort_values('confidence', ascending = False).
    ↪head(3)
top_three_conf
```

```
[16]:
```

	antecedents	consequents	\
1	(10ft iPhone Charger Cable 2 Pack)	(Dust-Off Compressed Gas 2 pack)	
36	(FEIYOLD Blue light Blocking Glasses)	(Dust-Off Compressed Gas 2 pack)	
52	(SanDisk Ultra 64GB card)	(Dust-Off Compressed Gas 2 pack)	

	antecedent support	consequent support	support	confidence	lift	\
1	0.050527	0.238368	0.023064	0.456464	1.914955	
36	0.065858	0.238368	0.027596	0.419028	1.757904	
52	0.098254	0.238368	0.040928	0.416554	1.747522	

	representativity	leverage	conviction	zhangs_metric	jaccard	\
1	1.0	0.011020	1.401255	0.503221	0.086760	
36	1.0	0.011898	1.310962	0.461536	0.099759	
52	1.0	0.017507	1.305401	0.474369	0.138413	

	certainty	kulczynski
1	0.286354	0.276610
36	0.237201	0.267400
52	0.233952	0.294127

```
[17]: # Top Three by Lift
```

```
top_three_lift = rules_table.sort_values('lift', ascending = False).head(3)
top_three_lift
```

```
[17]:
```

	antecedents	consequents	\
85	(VIVO Dual LCD Monitor Desk mount)	(SanDisk Ultra 64GB card)	
84	(SanDisk Ultra 64GB card)	(VIVO Dual LCD Monitor Desk mount)	
65	(FEIYOLD Blue light Blocking Glasses)	(VIVO Dual LCD Monitor Desk mount)	

	antecedent support	consequent support	support	confidence	lift	\
85	0.174110	0.098254	0.039195	0.225115	2.291162	
84	0.098254	0.174110	0.039195	0.398915	2.291162	
65	0.065858	0.174110	0.022930	0.348178	1.999758	

	representativity	leverage	conviction	zhangs_metric	jaccard	\
85	1.0	0.022088	1.163716	0.682343	0.168096	
84	1.0	0.022088	1.373997	0.624943	0.168096	
65	1.0	0.011464	1.267048	0.535186	0.105651	

	certainty	kulczynski
85	0.140684	0.312015
84	0.272197	0.312015
65	0.210764	0.239939

4 Part IV: Data Summary and Implications

4.1 D. Summary of the Data Analysis

4.1.1 D1. Significance of Support, Lift, and Confidence

Support is an important metric used in identifying frequently purchased itemsets. In this data set, the most frequently co-occurring items were 10ft iPhone Charger Cable 2 Pack and Dust-Off Compressed Gas 2 pack, FEIYOLD Blue light Blocking Glasses and Dust-Off Compressed Gas 2 pack, and SanDisk Ultra 64GB card and Dust-Off Compressed Gas 2 pack. Since the support values range from 2.3% - 4.1%, they are relatively low, so they are not necessarily common but are still significant.

Confidence is a metric used for evaluating directional rules, such as if A is purchased then B is purchased. The pair of items with the highest confidence value of 0.456, **10ft iPhone Charger Cable 2 Pack** and **Dust-Off Compressed Gas 2 pack**, indicates that 45.6% of transactions of the charging cable also included the compressed gas. The pair **FEIYOLD Blue light Blocking Glasses** and **Dust-Off Compressed Gas 2 pack** has the second highest confidence of 0.419, indicating that 41.9% of transactions of the bluelight glasses also contained the compressed gas. The third highest pair with a confidence of 0.416, **SanDisk Ultra 64GB card** and **Dust-Off Compressed Gas 2 pack**, indicates that 41.7% of transactions of SD cards included the compressed gas yet again.

The Lift metric measures the strength of association between items. The two pairs of items, **VIVO Dual LCD Monitor Desk mount** and **SanDisk Ultra 64GB card** are 2.29 times more likely to be purchased together than expected by chance. The items **SanDisk Ultra 64GB card** and **VIVO Dual LCD Monitor Desk mount** are also 2.29 times more likely to be purchased together than expected by chance. The items **FEIYOLD Blue light Blocking Glasses** and **VIVO Dual LCD Monitor Desk mount** are 1.99 times more likely to be purchased together than expected by chance.

4.1.2 D2. Practical Significance of the Findings

The practical significance of support lies in its use in identifying popular itemsets and bundling opportunities, as it describes how frequently an itemset is purchased together. The practical significance of confidence consists of cross-selling strategies between items, as well as targeted marketing campaigns such as offering discounts for consequents to customers that have purchased antecedents. The lift metric also has practical significance, as measuring the association between items can also be used in bundling opportunities and targeted marketed campaigns as well.

4.1.3 D3. Recommended a Course of Action

By employing Market Basket Analysis, it was possible to uncover pairs of items that were frequently purchased together by telecom customers. It was shown that the most common consequent, based on support and confidence, was the **Dust-Off Compressed Gas 2 pack**. This may indicate that the compressed gas is sold with many items, so it could potentially be offered at a discount with a coupon with the purchase of any item. Additionally, the compressed gas could be strategically placed in the checkout aisles or in the “Frequently Bought Together” recommendations on the website to encourage purchases.

5 Part V: Attachments

5.1 E.Panopto Video

<https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=0ef53562-94f0-4543-99a4-b29b002c1dff>

5.2 F. Acknowledgement of Web Sources

Kamara, K. (n.d.). Data Mining II - D212 Task 3 [Review of Data Mining II - D212 Task 3]. Panopto; WGU. <https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=db85c4f1-0da5-4bde-a1a4-b07c0019d46d>

5.3 G. Acknowledgement of Sources

Chaudhary, S. (2023). Understanding Market Basket Analysis in Data Mining. Wwww.turing.com. <https://www.turing.com/kb/market-basket-analysis>

GeeksforGeeks. (2022, March 13). Market Basket Analysis in Data Mining. GeeksforGeeks. <https://www.geeksforgeeks.org/market-basket-analysis-in-data-mining/>

Deniran, Oluwakemi Helen. (2023, November 27). Boosting Sales with Data: The Power of Market Basket Analysis in Retail. Medium; Medium. <https://medium.com/@chemistry8526/boosting-sales-with-data-the-power-of-market-basket-analysis-in-retail-c79cc10a14df>

Wikipedia Contributors. (2019, May 18). Association rule learning. Wikipedia; Wikimedia Foundation. https://en.wikipedia.org/wiki/Association_rule_learning