D212 – OFM3 TASK 3 – ASSOCIATION RULES AND LIFT ANALYSIS

Part I: Research Question

A. Describe the purpose of this data mining report by doing the following:

1. Propose **one** question relevant to a real-world organizational situation that you will answer using market basket analysis.

What are the products that are usually bought together? When stakeholders have this knowledge, they will be able to come up with a marketing strategy to offer these products for example, at a discounted price, possibly reducing the customer churn.

2. Define **one** goal of the data analysis. Ensure that your goal is reasonable within the scope of the scenario and is represented in the available data.

Since acquiring a new customer is 10 times more costly than keeping one, the number one goal is to retain customers. In order to achieve this, stakeholders have to understand not only customer behavior in order to predict churn, but also what kind of products are interesting to a customer. To lower churn probability, stakeholders would be able to offer products that interest customers found in the same rule.

Part II: Market Basket Justification

B. Explain the reasons for using market basket analysis by doing the following:

1. Explain how market basket analyzes the selected dataset. Include expected outcomes.

Market Basket Analysis is a data mining technique that identifies products that exhibit strong relationships[1]. Using this analysis we will find out which combination of products are usually bought together (by association rule) and what is the relationship they present.

An expected outcome is to find the optimal combination of items to offer in a possible discounted price.

2. Provide **one** example of transactions in the dataset.

Every row represents a customer. Columns indicate what each customer bought (a customer can buy from 1 item to 20 items). For example, our second customer (row 5), bought 3 items:

- Apple Lightning to Digital AV Adapter;
- TP-Link AC1750 Smart WiFi Router and
- Apple Pencil.

3. Summarize **one** assumption of market basket analysis.

One assumption in market basket analysis is when two or more products are bought together, they are complementary, and therefore purchase of one will lead to purchase of the other(s).

Part III: Data Preparation and Analysis

C. Prepare and perform market basket analysis by doing the following:

1. Transform the dataset to make it suitable for market basket analysis. Include a copy of the cleaned dataset.

In order to make the provided dataset suitable for market basket analysis, first we need to clean the dataset then we have to create lists of the itemsets. The cleaned dataset will be uploaded along with this document.

Cleaning the dataset:

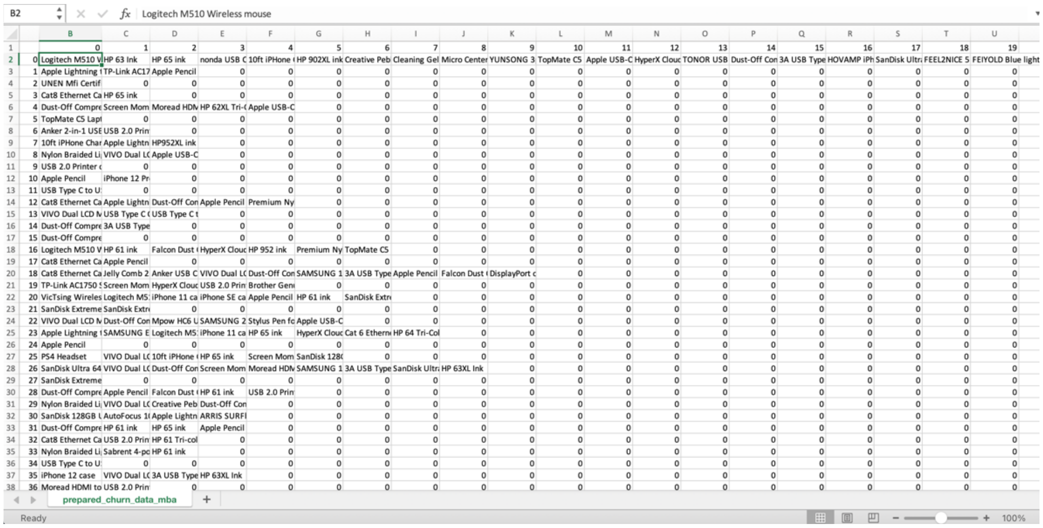
```
#Finding missing values in my dataset
churn_df.isnull().any(axis=1)
null_values = churn_df.isna().any()
print(null_values)

#Lets drop missing values
churn_df.dropna(how='all', inplace = True)

churn_df.fillna(0, inplace = True)

#New Dataset
print('Clean Dataset Shape: ', churn_df.shape)

#Checking if we have "0" in the dataset
print(churn_df.head())

churn_df.info()
```

Converting to list:

```
#Converting to list so we can use Apriori Algorithm
churn_df_list = []
for i in range(0, 7501):
    churn_df_list.append([str(churn_df.values[i,j])for j in range(0,20)])
churn_df_clean = pd.DataFrame(churn_df_list)

print(churn_df_clean.head())
```

Extracting the clean dataset:

```
#Extract the "Prepared"" dataset
churn_df_clean.to_csv('prepared_churn_data_mba.csv')
churn_df = pd.read_csv('prepared_churn_data_mba.csv')
df = churn_df.columns
print('The dataset columns are ', df)
```



B2 | Logitech M510 Wireless mouse

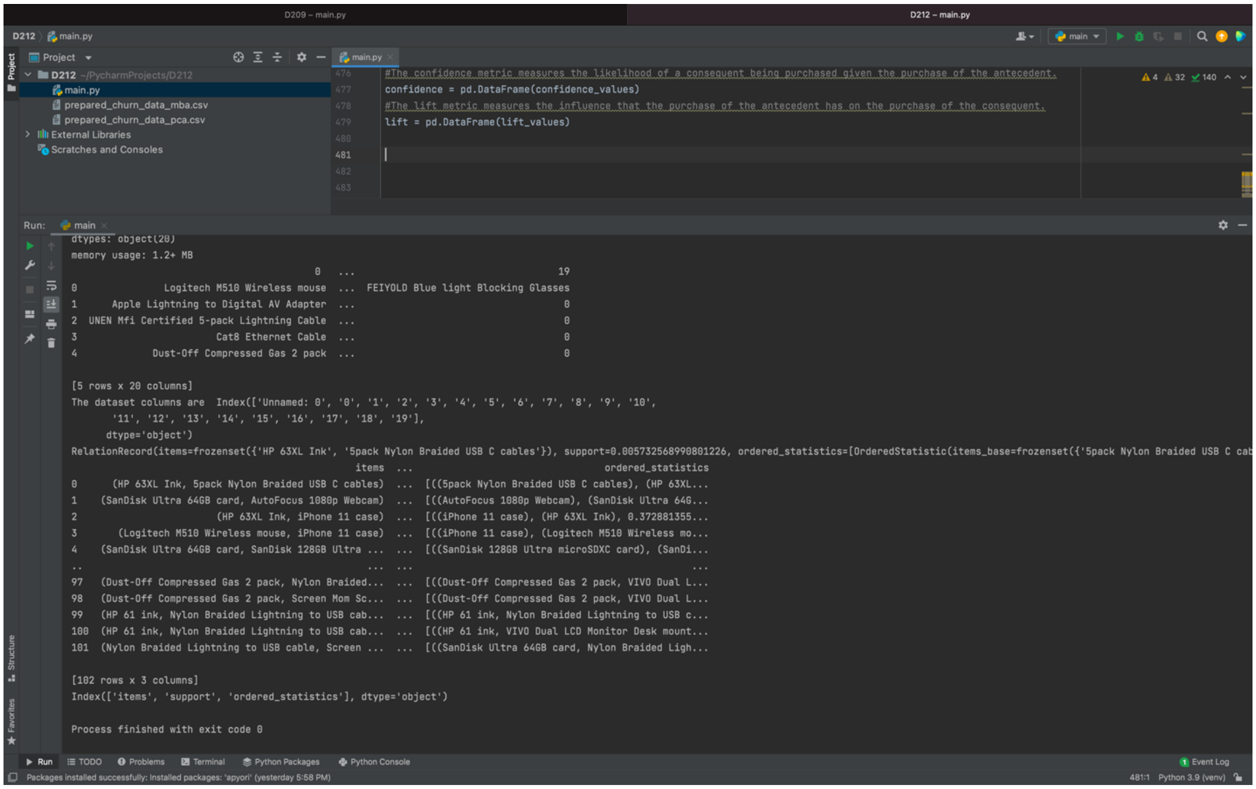
		B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1		0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
2	0	Logitech M510 V	HP 63 Ink	HP 65 ink	nonda USB C	10ft iPHone (	HP 902XL ink	Creative Peb	Cleaning Gel	Micro Center	YUNSONG 3	TopMate C5	Apple USB-C	HyperX Clouc	TONOR USB	Dust-Off Con	3A USB Type	HOVAMP iPh	SanDisk Ultra	FEEL2NICE 5	FEIYOLD Blue light
3	1	Apple Lightning 1	TP-Link AC17	Apple Pencil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	2	UNEN Mfi Certif	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	3	Cat8 Ethernet Ca	HP 65 ink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	4	Dust-Off Compre	Screen Mom	Moread HDM	HP 62XL Tri-(	Apple USB-C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
7	5	TopMate C5 Lapt	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	6	Anker 2-in-1 USE	USB 2.0 Prin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	7	10ft iPHone Char	Apple Lightn	HP952XL ink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	8	Nylon Braided Li	VIVO Dual LC	Apple USB-C	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	9	USB 2.0 Printer c	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	10	Apple Pencil	iPhone 12 Pr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	11	USB Type C to U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	12	Cat8 Ethernet Ca	Apple Lightn	Dust-Off Con	Apple Pencil	Premium Ny	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	13	VIVO Dual LCD M	USB Type C (	USB Type C t	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	14	Dust-Off Compre	3A USB Type	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	15	Dust-Off Compre	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
18	16	Logitech M510 V	HP 61 ink	Falcon Dust (	HyperX Clouc	HP 952 ink	Premium Ny	TopMate C5	0	0	0	0	0	0	0	0	0	0	0	0	0
19	17	Cat8 Ethernet Ca	Apple Pencil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
20	18	Cat8 Ethernet Ca	Jelly Comb 2	Anker USB C	VIVO Dual LC	Dust-Off Con	SAMSUNG 1	3A USB Type	Apple Pencil	Falcon Dust (	DisplayPort c	0	0	0	0	0	0	0	0	0	0
21	19	TP-Link AC1750 S	Screen Mom	HyperX Clouc	USB 2.0 Prin	Brother Geni	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
22	20	VicTsing Wireles	Logitech M5	iPhone 11 ca	iPhone SE ca	Apple Pencil	HP 61 ink	SanDisk Extre	0	0	0	0	0	0	0	0	0	0	0	0	0
23	21	SanDisk Extreme	SanDisk Extre	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	22	VIVO Dual LCD M	Dust-Off Con	Mpow HC6 U	SAMSUNG 2	Stylus Pen fc	Apple USB-C	0	0	0	0	0	0	0	0	0	0	0	0	0	0
25	23	Apple Lightning 1	SAMSUNG E	Logitech M5	iPhone 11 ca	HP 65 ink	HyperX Clouc	Cat 6 Etherne	HP 64 Tri-Col	0	0	0	0	0	0	0	0	0	0	0	0
26	24	Apple Pencil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	25	PS4 Headset	VIVO Dual LC	10ft iPHone (	HP 65 ink	Screen Mom	SanDisk 128(	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	26	SanDisk Ultra 64	VIVO Dual LC	Dust-Off Con	Screen Mom	Moread HDM	SAMSUNG 1	3A USB Type	SanDisk Ultra	HP 63XL Ink	0	0	0	0	0	0	0	0	0	0	0
29	27	SanDisk Extreme	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	28	Dust-Off Compre	Apple Pencil	Falcon Dust (	HP 61 ink	USB 2.0 Prin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
31	29	Nylon Braided Li	VIVO Dual LC	Creative Peb	Dust-Off Con	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	30	SanDisk 128GB U	AutoFocus 10	Apple Lightn	ARRIS SURFI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	31	Dust-Off Compre	HP 61 ink	HP 65 ink	Apple Pencil	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	32	Cat8 Ethernet Ca	USB 2.0 Prin	HP 61 Tri-col	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
35	33	Nylon Braided Li	Sabrent 4-pc	HP 61 ink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	34	USB Type C to U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	35	iPhone 12 case	VIVO Dual LC	3A USB Type	HP 63XL Ink	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	36	Moread HDMI to	USB 2.0 Prin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 1: Screen Shot of Dataset for MBA

2. Execute the code used to generate association rules with the Apriori algorithm. Provide screenshots that demonstrate the error-free functionality of the code.

The **apriori algorithm** is an efficient alternative that helps identify frequent itemsets while filtering out the infrequent ones. It can remove itemsets from consideration without having to evaluate them[1].

```
#Training the Algorithm
apriori_list = apriori(churn_df_list, min_support=0.003, min_confidence=0.3,
min_lift=3, min_lenght=2)

apriori_list = list(apriori_list)
print(apriori_list[0])

dataset = pd.DataFrame(apriori_list)

print(dataset)

#Since I couldnt visualize all columns in dataset (items, support,
ordered_stats)
print(dataset.columns)

#Lets separate columns in their own
support = dataset.support

#Antecedent, Consequence, confidence, lift
antecedent_values = []
consequent_values = []
confidence_values = []
lift_values = []

for i in range(dataset.shape[0]):
    single_list = dataset['ordered_statistics'][i][0]
    antecedent_values.append(list(single_list[0]))
    consequent_values.append(list(single_list[1]))
    confidence_values.append(single_list[2])
    lift_values.append(single_list[3])

#From List to Dataframe
antecedent = pd.DataFrame(antecedent_values)
consequent = pd.DataFrame(consequent_values)
#The confidence metric measures the likelihood of a consequent being
purchased given the purchase of the antecedent.
confidence = pd.DataFrame(confidence_values, columns=['CONFIDENCE'])
#The lift metric measures the influence that the purchase of the antecedent
has on the purchase of the consequent.
lift = pd.DataFrame(lift_values, columns=['LIFT'])

#Concatenate lists into a dataframe
dataframe = pd.concat([antecedent, consequent, support, confidence, lift],
axis = 1)
dataframe.fillna(value = '', inplace= True)

print(dataframe)

print(dataframe.columns)
print(dataframe.head())
```



```
#The confidence metric measures the likelihood of a consequent being purchased given the purchase of the antecedent.
confidence = pd.DataFrame(confidence_values)
#The lift metric measures the influence that the purchase of the antecedent has on the purchase of the consequent.
lift = pd.DataFrame(lift_values)
```

```
dtypes: object(20)
memory usage: 1.2+ MB
                                      0  ...                             19
0            Logitech M510 Wireless mouse  ...  FEIYOLD Blue light Blocking Glasses
1      Apple Lightning to Digital AV Adapter  ...                              0
2  UNEN Mfi Certified 5-pack Lightning Cable  ...                              0
3                      Cat8 Ethernet Cable  ...                              0
4              Dust-Off Compressed Gas 2 pack  ...                              0

[5 rows x 20 columns]
The dataset columns are  Index(['Unnamed: 0', '0', '1', '2', '3', '4', '5', '6', '7', '8', '9', '10',
       '11', '12', '13', '14', '15', '16', '17', '18', '19'],
      dtype='object')
RelationRecord(items=frozenset({'HP 63XL Ink', '5pack Nylon Braided USB C cables'}), support=0.005732568990801226, ordered_statistics=[OrderedStatistic(items_base=frozenset({'5pack Nylon Braided USB C cab
                                         items  ...                                   ordered_statistics
0      (HP 63XL Ink, 5pack Nylon Braided USB C cables)  ...  [((5pack Nylon Braided USB C cables), (HP 63XL...
1    (SanDisk Ultra 64GB card, AutoFocus 1080p Webcam)  ...  [((AutoFocus 1080p Webcam), (SanDisk Ultra 64G...
2                      (HP 63XL Ink, iPhone 11 case)  ...  [((iPhone 11 case), (HP 63XL Ink), 0.372881355...
3       (Logitech M510 Wireless mouse, iPhone 11 case)  ...  [((iPhone 11 case), (Logitech M510 Wireless mo...
4    (SanDisk Ultra 64GB card, SanDisk 128GB Ultra ...  ...  [((SanDisk 128GB Ultra microSDXC card), (SanDi...
..                                               ...  ...                                                ...
97   (Dust-Off Compressed Gas 2 pack, Nylon Braided...  ...  [((Dust-Off Compressed Gas 2 pack, VIVO Dual L...
98   (Dust-Off Compressed Gas 2 pack, Screen Mom Sc...  ...  [((Dust-Off Compressed Gas 2 pack, VIVO Dual L...
99   (HP 61 ink, Nylon Braided Lightning to USB cab...  ...  [((HP 61 ink, Nylon Braided Lightning to USB c...
100  (HP 61 ink, Nylon Braided Lightning to USB cab...  ...  [((HP 61 ink, VIVO Dual LCD Monitor Desk mount...
101  (Nylon Braided Lightning to USB cable, Screen ...  ...  [((SanDisk Ultra 64GB card, Nylon Braided Ligh...

[102 rows x 3 columns]
Index(['items', 'support', 'ordered_statistics'], dtype='object')

Process finished with exit code 0
```

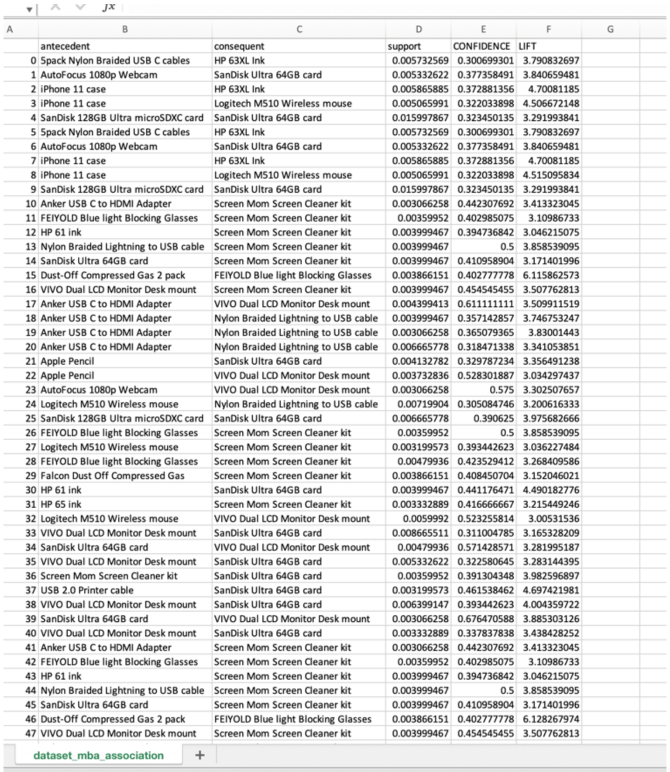
Packages installed successfully: Installed packages: 'apyori' (yesterday 5:58 PM)

Figure 2: Error free code using Apriori Algorithm

3. Provide values for the support, lift, and confidence of the association rules table.

```
#Association Rules
dataframe.columns = ['antecedent', 1, 2, 'consequent', 1, 2, 'support',
'CONFIDENCE', 'LIFT']
print(dataframe.columns)
dataframe_1 = dataframe[['antecedent', 'consequent', 'support', 'CONFIDENCE',
'LIFT']]

#Export the dataframe_1 into csv
dataframe_1.to_csv('dataset_mba_association.csv')
```

Attached to this document it will be also uploaded another spreadsheet called dataset_mba_association.csv. This spreadsheet contains all support, lift and confidence values for the association rules table. Here is a screen shot of it:



	antecedent	consequent	support	CONFIDENCE	LIFT
0	5pack Nylon Braided USB C cables	HP 63XL Ink	0.005732569	0.300699301	3.790832697
1	AutoFocus 1080p Webcam	SanDisk Ultra 64GB card	0.005332622	0.377358491	3.840659481
2	iPhone 11 case	HP 63XL Ink	0.005865885	0.372881356	4.70081185
3	iPhone 11 case	Logitech M510 Wireless mouse	0.005065991	0.322033898	4.506672148
4	SanDisk 128GB Ultra microSDXC card	SanDisk Ultra 64GB card	0.015997867	0.323450135	3.291993841
5	5pack Nylon Braided USB C cables	HP 63XL Ink	0.005732569	0.300699301	3.790832697
6	AutoFocus 1080p Webcam	SanDisk Ultra 64GB card	0.005332622	0.377358491	3.840659481
7	iPhone 11 case	HP 63XL Ink	0.005865885	0.372881356	4.70081185
8	iPhone 11 case	Logitech M510 Wireless mouse	0.005065991	0.322033898	4.515095834
9	SanDisk 128GB Ultra microSDXC card	SanDisk Ultra 64GB card	0.015997867	0.323450135	3.291993841
10	Anker USB C to HDMI Adapter	Screen Mom Screen Cleaner kit	0.003066258	0.442307692	3.413323045
11	FEIYOLD Blue light Blocking Glasses	Screen Mom Screen Cleaner kit	0.00359952	0.402985075	3.10986733
12	HP 61 ink	Screen Mom Screen Cleaner kit	0.003999467	0.394736842	3.046215075
13	Nylon Braided Lightning to USB cable	Screen Mom Screen Cleaner kit	0.003999467	0.5	3.858539095
14	SanDisk Ultra 64GB card	Screen Mom Screen Cleaner kit	0.003999467	0.410958904	3.171401996
15	Dust-Off Compressed Gas 2 pack	FEIYOLD Blue light Blocking Glasses	0.003866151	0.402777778	6.115862573
16	VIVO Dual LCD Monitor Desk mount	Screen Mom Screen Cleaner kit	0.003999467	0.454545455	3.507762813
17	Anker USB C to HDMI Adapter	VIVO Dual LCD Monitor Desk mount	0.004399413	0.611111111	3.509911519
18	Anker USB C to HDMI Adapter	Nylon Braided Lightning to USB cable	0.003999467	0.357142857	3.746753247
19	Anker USB C to HDMI Adapter	Nylon Braided Lightning to USB cable	0.003066258	0.365079365	3.83001443
20	Anker USB C to HDMI Adapter	Nylon Braided Lightning to USB cable	0.006665778	0.318471338	3.341053851
21	Apple Pencil	SanDisk Ultra 64GB card	0.004132782	0.329787234	3.356491238
22	Apple Pencil	VIVO Dual LCD Monitor Desk mount	0.003732836	0.528301887	3.034297437
23	AutoFocus 1080p Webcam	VIVO Dual LCD Monitor Desk mount	0.003066258	0.575	3.302507657
24	Logitech M510 Wireless mouse	Nylon Braided Lightning to USB cable	0.00719904	0.305084746	3.200616333
25	SanDisk 128GB Ultra microSDXC card	SanDisk Ultra 64GB card	0.006665778	0.390625	3.975682666
26	FEIYOLD Blue light Blocking Glasses	Screen Mom Screen Cleaner kit	0.00359952	0.5	3.858539095
27	Logitech M510 Wireless mouse	Screen Mom Screen Cleaner kit	0.003199573	0.393442623	3.036227484
28	FEIYOLD Blue light Blocking Glasses	Screen Mom Screen Cleaner kit	0.00479936	0.423529412	3.268409586
29	Falcon Dust Off Compressed Gas	Screen Mom Screen Cleaner kit	0.003866151	0.408450704	3.152046021
30	HP 61 ink	SanDisk Ultra 64GB card	0.003999467	0.441176471	4.490182776
31	HP 65 ink	Screen Mom Screen Cleaner kit	0.003332889	0.416666667	3.215449246
32	Logitech M510 Wireless mouse	VIVO Dual LCD Monitor Desk mount	0.0059992	0.523255814	3.00531536
33	VIVO Dual LCD Monitor Desk mount	SanDisk Ultra 64GB card	0.008665511	0.311004785	3.165328209
34	SanDisk Ultra 64GB card	VIVO Dual LCD Monitor Desk mount	0.00479936	0.571428571	3.281995187
35	VIVO Dual LCD Monitor Desk mount	SanDisk Ultra 64GB card	0.005332622	0.322580645	3.283144395
36	Screen Mom Screen Cleaner kit	SanDisk Ultra 64GB card	0.00359952	0.391304348	3.982596897
37	USB 2.0 Printer cable	SanDisk Ultra 64GB card	0.003199573	0.461538462	4.697421981
38	VIVO Dual LCD Monitor Desk mount	SanDisk Ultra 64GB card	0.006399147	0.393442623	4.004359722
39	SanDisk Ultra 64GB card	VIVO Dual LCD Monitor Desk mount	0.003066258	0.676470588	3.885303126
40	VIVO Dual LCD Monitor Desk mount	SanDisk Ultra 64GB card	0.003332889	0.337837838	3.438428252
41	Anker USB C to HDMI Adapter	Screen Mom Screen Cleaner kit	0.003066258	0.442307692	3.413323045
42	FEIYOLD Blue light Blocking Glasses	Screen Mom Screen Cleaner kit	0.00359952	0.402985075	3.10986733
43	HP 61 ink	Screen Mom Screen Cleaner kit	0.003999467	0.394736842	3.046215075
44	Nylon Braided Lightning to USB cable	Screen Mom Screen Cleaner kit	0.003999467	0.5	3.858539095
45	SanDisk Ultra 64GB card	Screen Mom Screen Cleaner kit	0.003999467	0.410958904	3.171401996
46	Dust-Off Compressed Gas 2 pack	FEIYOLD Blue light Blocking Glasses	0.003866151	0.402777778	6.128267974
47	VIVO Dual LCD Monitor Desk mount	Screen Mom Screen Cleaner kit	0.003999467	0.454545455	3.507762813

Figure 3: Association Rules Results

4. Identify the top **three** rules generated by the Apriori algorithm. Include a screenshot of the top rules along with their summaries.

Based on the set parameters initially defined:

```
#Training the Algorithm
apriori_list = apriori(churn_df_list, min_support=0.003, min_confidence=0.3,
min_lift=3, min_lenght=2)
```

For these set of parameters, the algorithm returned 101 rules. Let’s analyze the top three rules generated by the algorithm.

Rule 1 is the most relevant rule that the algorithm identified from the given dataset:
Antecedent: 5pack Nylon Braided USB C cables
Consequent: HP 63XL Ink
Support: 0.00573256899080122
Confidence: 0.3006993006993
Lift: 3.79083269671504

From all customers who purchased the cables, only 30% also purchased the printer ink. Support means that from all transactions, only 0.57% contain both items. The lift value means that once customers have purchased the cables, they have 3.8 times more chances to also purchase the printer's ink.

Rule 2:
Antecedent: AutoFocus 1080p Webcam
Consequent: SanDisk Ultra 64GB card
Support: 0.00533262231702439
Confidence: 0.377358490566037
Lift: 3.84065948132408

In this case here, 37% of all customers who purchased the webcam also purchased the memory card. From all transactions, only 0.533% contain both items and customers who buy the webcam have 3.8 more chances in also buying the memory card.

Rule 3:
Antecedent: iPhone 11 case
Consequent: HP 63XL Ink
Support: 0.00586588454872683
Confidence: 0.372881355932203
Lift: 4.70081185016379

In the last case, 37% of all customers who purchased the iPhone case also bought the ink. From all transactions, only 0.586% contain both of these items and when customers buy the phone case, they have 4.7 more likely in also acquiring the ink.

Part IV: Data Summary and Implications

D. Summarize your data analysis by doing the following:

1. Summarize the significance of support, lift, and confidence from the results of the analysis.

Each pair of products A and B is evaluated on three measures[2]:

Support—the joint probability of finding the pair AB across all baskets. A low support means that the pair is not relevant because it is not purchased frequently enough.

Confidence—the conditional probability $p(B|A) = p(A \cap B)/p(A)$, which is often interpreted as the probability that purchase of product A will lead to purchase of product B.

Lift - measures the influence that the purchase of the antecedent has on the purchase of the consequent: $Lift(A, B) = \frac{Support(A,B)}{Support(A)*Support(B)}$. From this formula, we are looking for values greater than 1, meaning that the purchase of the antecedent increases the likelihood of the purchase of the consequent[1].

The results of my analysis did not show a good level of confidence. None of the 3 most relevant rules has a confidence level higher than 40%, far away from any good level.

We also obtained a very low support number, 0.5% which indicates that for the most relevant 3 rules, the purchase of the pair AB doesn't occur in more than half a percent.

Our highest lift is “4.7 more likely in buying” in the third rule, which means that when a customer buys the antecedent product “iPhone11 case” the same customer is 4.7 more likely to acquire the precedent product “XP 63XL ink”.

From these results we can say that our analysis did not achieve good measures of support, confidence and lift.

2. Discuss the practical significance of the findings from the analysis.

All measures are very low and I would say we do not have a practical significance of the findings from the analysis. Perhaps more data needs to be gathered and we need to reevaluate our data one more time.

3. Recommend a course of action for the real-world organizational situation from part A1 based on your results from part D1.

Our analysis did not bring any significant result. None of the 3 most relevant pairings would suggest any difference in the current marketing/customer service strategy for the telecom company.

Part V: Attachments

E. Provide a Panopto video recording that includes a demonstration of the functionality of the code used for the analysis and a summary of the programming environment.

Video Link: https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=fc245e35-ed14-4440-8a9b-ae0e01446d10

F. Record *all* web sources used to acquire data or segments of third-party code to support the application. Ensure the web sources are reliable.

G. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

[1] (2021, Nov 15th) NAIR, Aashish , Understanding Consumer Behavior With The Basket Market Analysis https://towardsdatascience.com/understanding-consumer-behavior-with-the-market-basket-analysis-3d0c017e5613

[2] (2012, May 22nd) KAMAKURA, Wagner, Sequencial Market Basket Analysis http://wak2.web.rice.edu/bio/My%20Reprints/Sequential%20Market%20Basket%20Analysist.pdf