

# D212\_Task\_3

April 11, 2024

**A1: Research Question** The question that I will be asking is “Which combinations of telecom products and services are most frequently purchased together by customers at risk of churn?”

**A2: Goal of the Data Analysis** The goal is to identify patterns in the combinations of products and services purchased by customers. By understanding these patterns, we can develop targeted marketing strategies and personalized offers to enhance customer retention.

**B1: Market Basket Analysis Explained** Market Basket Analysis (MBA) is a data mining technique used to enhance marketing strategies by identifying relationships between items that customers buy together frequently. In this project, we apply the Apriori algorithm, a classic MBA method, to uncover these relationships within the telecommunications dataset.

The Apriori algorithm identifies frequent individual items in the dataset and extends them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The key metrics used to express the strength of associations are: \* Support - which indicates how frequently the itemset appears in the data set. \* Confidence - which indicates the likelihood of item Y being purchased when item X is purchased. \* Lift - which indicates the likelihood of item Y being purchased when item X is purchased, while controlling for the popularity of Y.

This analysis will help us understand which combinations of products and services are most appealing to customers at risk of churn, thus informing targeted marketing strategies to enhance customer retention.

(365 Data Science)

**B2: Example of Transactions in the Dataset** An example of a transaction from the dataset includes several items that suggest a technologically savvy customer with needs ranging from computing essentials to accessories for convenience and maintenance. Specifically, the customer purchased a “Logitech M510 Wireless Mouse,” indicating the need for computer peripherals, “HP 63 Ink” and “HP 65 Ink,” showing they own and use a printer frequently, and a “nonda USB C to USB Adapter,” which is typically used for devices that require a USB-C connection. They also bought a “10ft iPhone Charger Cable,” likely for ease of device charging over longer distances, and “Creative Pebble 2.0 Speakers,” which are compact speakers that could be used for personal entertainment or as part of a home office setup. This transaction reflects a customer whose purchases are geared towards enhancing their digital and computing experience.

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```

import seaborn as sns
from mlxtend.frequent_patterns import association_rules, apriori
from mlxtend.preprocessing import TransactionEncoder

# Loading the dataset
df = pd.read_csv(r'C:\Users\Hien\
↳Ta\OneDrive\WGU\MSDA\D212\Task_3\teleco_market_basket.csv')

# Check data types, number of values and size of dataframe
df.info()
df.head()

```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 15002 entries, 0 to 15001
```

```
Data columns (total 20 columns):
```

#	Column	Non-Null Count	Dtype
0	Item01	7501 non-null	object
1	Item02	5747 non-null	object
2	Item03	4389 non-null	object
3	Item04	3345 non-null	object
4	Item05	2529 non-null	object
5	Item06	1864 non-null	object
6	Item07	1369 non-null	object
7	Item08	981 non-null	object
8	Item09	654 non-null	object
9	Item10	395 non-null	object
10	Item11	256 non-null	object
11	Item12	154 non-null	object
12	Item13	87 non-null	object
13	Item14	47 non-null	object
14	Item15	25 non-null	object
15	Item16	8 non-null	object
16	Item17	4 non-null	object
17	Item18	4 non-null	object
18	Item19	3 non-null	object
19	Item20	1 non-null	object

```
dtypes: object(20)
```

```
memory usage: 2.3+ MB
```

```
[1]:
```

	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

The dataset consists of transactions, each representing a customer's purchase history, with up to 20 items per transaction. Many transactions contain NaN values, indicating customers who purchased fewer than 20 items. For market basket analysis, we need to transform this dataset into a suitable format that lists each item per transaction as a separate entry. The dataset consists of transactions, each representing a customer's purchase history, with up to 20 items per transaction. Many transactions contain NaN values, indicating customers who purchased fewer than 20 items. For market basket analysis, we need to transform this dataset into a suitable format that lists each item per transaction as a separate entry.

**B3: Summarize one assumption of market basket analysis** Market basket analysis operates under the assumption that the purchase of certain items together within a transaction is not random, but has an underlying pattern that can be discovered and leveraged. It assumes that if a group of items is frequently purchased together, it is because customers have a particular preference or need that leads them to buy these items in combination. This preference is expected to persist over time, allowing the company to predict future buying behaviors and tailor their marketing and sales strategies accordingly. The assumption is that uncovering these patterns can lead to better customer insights and more effective cross selling opportunities.

(365 Data Science)

**C1 Data Transformation** To prepare the dataset for Market Basket Analysis (MBA), we first transform the raw transaction data into a format suitable for the Apriori algorithm. The transformation process includes:

Data Cleaning: \* Removal of NaN values which represent missing items in transactions. \* Exclusion of transactions that do not contain any items post-cleanup.

Data Encoding: \* Application of a `TransactionEncoder` to convert the list of transaction items into a one-hot encoded matrix. Each column corresponds to a product available in the dataset, and each row corresponds to a transaction where '1' indicates the presence of the item in that transaction, and '0' indicates its absence.

The cleaned and encoded data is essential for the effective application of the Apriori algorithm, ensuring that my analysis only includes valid and complete transactions.

```
[2]: # Check data types, number of values and size of dataframe
df.info()
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15002 entries, 0 to 15001
Data columns (total 20 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Item01      7501 non-null    object
1   Item02      5747 non-null    object
2   Item03      4389 non-null    object
3   Item04      3345 non-null    object
4   Item05      2529 non-null    object
5   Item06      1864 non-null    object
6   Item07      1369 non-null    object
7   Item08      981 non-null     object
8   Item09      654 non-null     object
9   Item10      395 non-null     object
10  Item11      256 non-null     object
11  Item12      154 non-null     object
12  Item13      87 non-null      object
13  Item14      47 non-null      object
14  Item15      25 non-null      object
15  Item16      8 non-null       object
16  Item17      4 non-null       object
17  Item18      4 non-null       object
18  Item19      3 non-null       object
19  Item20      1 non-null       object
dtypes: object(20)
memory usage: 2.3+ MB
```

```
[2]:
```

	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

```
[3]: # Transforming the dataset to a list of lists and removing NaN values
transactions = df.apply(lambda x: x.dropna().tolist(), axis=1).tolist()

# Remove empty transactions
transactions = [transaction for transaction in transactions if transaction]

# Convert the non-empty transactions list of lists into a DataFrame
transactions_df = pd.DataFrame({'Transaction': [' ', '.join(transaction) for
↳ transaction in transactions]})

transactions_df
```

```
[3]: Transaction
0 Logitech M510 Wireless mouse, HP 63 Ink, HP 65...
1 Apple Lightning to Digital AV Adapter, TP-Link...
2 UNEN Mfi Certified 5-pack Lightning Cable
3 Cat8 Ethernet Cable, HP 65 ink
4 Dust-Off Compressed Gas 2 pack, Screen Mom Scr...
...
7496 SanDisk 32GB Ultra SDHC card, Vsco 70 pack sti...
7497 Apple Lightning to Digital AV Adapter, Nylon B...
7498 Falcon Dust Off Compressed Gas
7499 HP 63XL Ink, Apple USB-C Charger cable
7500 Apple Pencil, SanDisk Ultra 128GB card, RUNMUS...

[7501 rows x 1 columns]
```

```
[4]: # Saving the cleaned dataset without empty transactions
cleaned_file_path = r'C:\Users\Hien\
↳ Ta\OneDrive\WGU\MSDA\D212\Task_3\teleco_market_basket_CLEAN.csv'
transactions_df.to_csv(cleaned_file_path, index=False)
```

## C2: Confidence of the Association Rule

```
[5]: # transactions_df is the DataFrame loaded from the CSV with a single
↳ 'Transaction' column
transactions_list = transactions_df['Transaction'].apply(lambda x: x.split(',
↳ ')).tolist()
```

```

encoder = TransactionEncoder()
transactions_encoded = encoder.fit_transform(transactions_list)
transactions_onehot = pd.DataFrame(transactions_encoded, columns=encoder.
    ↪columns_)

transactions_onehot

```

```

[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
...                               ...                                ...
7496                             False                             False
7497                             False                             False
7498                             False                             False
7499                             False                             False
7500                             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
...                               ...                                ...
7496                             False                             False
7497                             False                             False
7498                             False                             False
7499                             False                             False
7500                             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
...                               ...                                ...
7496                             False                                False
7497                             False                                True
7498                             False                                False
7499                             False                                False
7500                             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
...	...	...
7496	False	False
7497	False	False
7498	False	False
7499	False	False
7500	False	False

	Anker USB C to HDMI Adapter	Apple Lightning to Digital AV Adapter ... \
0	False	False ...
1	False	True ...
2	False	False ...
3	False	False ...
4	False	False ...
...	...	... ...
7496	False	False ...
7497	False	True ...
7498	False	False ...
7499	False	False ...
7500	False	False ...

	hP 65 Tri-color ink	iFixit Pro Tech Toolkit	iPhone 11 case \
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
...	...	...	...
7496	False	False	False
7497	False	False	False
7498	False	False	False
7499	False	False	False
7500	False	False	False

	iPhone 12 Charger cable	iPhone 12 Pro case	iPhone 12 case \
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
...	...	...	...
7496	False	False	False

7497	False	False	False
7498	False	False	False
7499	False	False	False
7500	False	False	False

	iPhone Charger Cable Anker 6ft	iPhone SE case \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False
...	...	...
7496	False	False
7497	False	False
7498	False	False
7499	False	False
7500	False	False

	nonda USB C to USB Adapter	seenda Wireless mouse
0	True	False
1	False	False
2	False	False
3	False	False
4	False	False
...	...	...
7496	False	False
7497	False	False
7498	False	False
7499	False	False
7500	False	False

[7501 rows x 119 columns]

```
[6]: # Apply the Apriori algorithm
frequent_itemsets = apriori(transactions_onehot, min_support=0.01,
                             use_colnames=True)

frequent_itemsets

# (365 Data Science)
```

[6]:	support	itemsets
0	0.050527	(10ft iPhone Charger Cable 2 Pack)
1	0.042528	(3A USB Type C Cable 3 pack 6FT)
2	0.019064	(5pack Nylon Braided USB C cables)
3	0.010932	(ARRIS SURFboard SB8200 Cable Modem)
4	0.029463	(Anker 2-in-1 USB Card Reader)

```

..
252 0.017064 (VIVO Dual LCD Monitor Desk mount, SanDisk Ult...
253 0.015731 (VIVO Dual LCD Monitor Desk mount, Dust-Off Co...
254 0.011465 (VIVO Dual LCD Monitor Desk mount, Stylus Pen ...
255 0.010132 (USB 2.0 Printer cable, VIVO Dual LCD Monitor ...
256 0.010932 (HP 61 ink, VIVO Dual LCD Monitor Desk mount, ...

```

[257 rows x 2 columns]

```

[7]: # display association_rules
rules = association_rules(frequent_itemsets, metric="confidence",
    min_threshold=0.1)

# print out the DataFrame containing the association rules
print(rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])

```

```

                                antecedents \
0                (10ft iPhone Charger Cable 2 Pack)
1                (10ft iPhone Charger Cable 2 Pack)
2                (10ft iPhone Charger Cable 2 Pack)
3                (Screen Mom Screen Cleaner kit)
4                (10ft iPhone Charger Cable 2 Pack)
..
315 (USB 2.0 Printer cable, Dust-Off Compressed Ga...
316 (VIVO Dual LCD Monitor Desk mount, Dust-Off Co...
317      (HP 61 ink, VIVO Dual LCD Monitor Desk mount)
318      (HP 61 ink, Screen Mom Screen Cleaner kit)
319 (VIVO Dual LCD Monitor Desk mount, Screen Mom ...

                                consequents  support  confidence  lift
0      (Dust-Off Compressed Gas 2 pack)  0.023064    0.456464  1.914955
1                (HP 61 ink)  0.010132    0.200528  1.223888
2      (Screen Mom Screen Cleaner kit)  0.015198    0.300792  2.321232
3      (10ft iPhone Charger Cable 2 Pack)  0.015198    0.117284  2.321232
4      (VIVO Dual LCD Monitor Desk mount)  0.014265    0.282322  1.621513
..
315 (VIVO Dual LCD Monitor Desk mount)  0.010132    0.300395  1.725318
316      (USB 2.0 Printer cable)  0.010132    0.169643  0.992583
317      (Screen Mom Screen Cleaner kit)  0.010932    0.278912  2.152382
318 (VIVO Dual LCD Monitor Desk mount)  0.010932    0.340249  1.954217
319      (HP 61 ink)  0.010932    0.308271  1.881480

```

[320 rows x 5 columns]

**C3: values for the support, lift, and confidence of the association rules table**

```

[8]: # see attached codes

```

```
# print out the DataFrame containing the association rules
print(rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])
```

```

                                antecedents \
0          (10ft iPhone Charger Cable 2 Pack)
1          (10ft iPhone Charger Cable 2 Pack)
2          (10ft iPhone Charger Cable 2 Pack)
3          (Screen Mom Screen Cleaner kit)
4          (10ft iPhone Charger Cable 2 Pack)
..
315 (USB 2.0 Printer cable, Dust-Off Compressed Ga...
316 (VIVO Dual LCD Monitor Desk mount, Dust-Off Co...
317      (HP 61 ink, VIVO Dual LCD Monitor Desk mount)
318      (HP 61 ink, Screen Mom Screen Cleaner kit)
319 (VIVO Dual LCD Monitor Desk mount, Screen Mom ...

                                consequents  support  confidence  lift
0      (Dust-Off Compressed Gas 2 pack)  0.023064    0.456464  1.914955
1          (HP 61 ink)  0.010132    0.200528  1.223888
2      (Screen Mom Screen Cleaner kit)  0.015198    0.300792  2.321232
3      (10ft iPhone Charger Cable 2 Pack)  0.015198    0.117284  2.321232
4      (VIVO Dual LCD Monitor Desk mount)  0.014265    0.282322  1.621513
..
315 (VIVO Dual LCD Monitor Desk mount)  0.010132    0.300395  1.725318
316      (USB 2.0 Printer cable)  0.010132    0.169643  0.992583
317      (Screen Mom Screen Cleaner kit)  0.010932    0.278912  2.152382
318 (VIVO Dual LCD Monitor Desk mount)  0.010932    0.340249  1.954217
319          (HP 61 ink)  0.010932    0.308271  1.881480

```

[320 rows x 5 columns]

#### C4: Top 3 relavent rules

```
[9]: # see attached codes

top_three_rules = rules.sort_values(by='lift', ascending=False).head(3)
print(top_three_rules[['antecedents', 'consequents', 'support', 'confidence', 'lift']])
```

```

                                antecedents \
218          (SanDisk 128GB Ultra microSDXC card)
219          (SanDisk Ultra 64GB card)
303 (VIVO Dual LCD Monitor Desk mount, Dust-Off Co...

                                consequents  support  confidence  lift
218          (SanDisk Ultra 64GB card)  0.015998    0.323450  3.291994
219 (SanDisk 128GB Ultra microSDXC card)  0.015998    0.162822  3.291994
303          (SanDisk Ultra 64GB card)  0.017064    0.285714  2.907928

```

- Rule 1: People who purchase a SanDisk 128GB Ultra microSDXC card also tend to purchase a SanDisk Ultra 64GB card. The support for this rule is about 1.6%, which means that this combination of items appears in 1.6% of all transactions. The confidence of 32.35% indicates that there's about a one-third chance that someone buying the 128GB card will also buy the 64GB card. The lift value of approximately 3.22 suggests that these two items are over three times more likely to be bought together than each item individually.
- Rule 2: The reverse is also true; those who buy a SanDisk Ultra 64GB card often purchase a SanDisk 128GB Ultra microSDXC card. This has the same support of 1.6%, indicating it's just as common as the reverse. However, the confidence is lower at 16.28%, suggesting that the 64GB card is less influential in leading to the purchase of the 128GB card. The lift remains the same, reinforcing the strength of the association.
- Rule 3: This rule indicates that when customers buy both Dust-Off Compressed Gas 2 pack and VIVO Dual LCD Monitor Desk Mount, they are also likely to buy a SanDisk Ultra 64GB card. The support of approximately 1.71% suggests that these three items appear together in roughly 1.71% of all transactions. The confidence of about 28.57% implies that there's about a 28.57% chance that the 64GB SanDisk card will be bought when the other two items are purchased together. The lift of roughly 2.91 indicates that the presence of the gas pack and monitor desk mount in a transaction is about three times more likely to lead to the purchase of the 64GB SanDisk card than if the purchases were independent.

These rules can be quite insightful for the retailer or the marketing team. The first two rules suggest that customers are perhaps upgrading their storage options or buying for multiple devices with different storage needs. The third rule may point towards a demographic that is interested in maintaining and setting up tech products, indicating a crossover in the market for electronics maintenance and office ergonomics.

### D1: Summarize the Significance of Support, Lift, and Confidence

- Support is the measure of the prevalence of an item or itemset within all transactions. A higher support value indicates that items are more common in the dataset. In market basket analysis, rules with higher support are seen as more significant as they affect a larger portion of the transactions.
- Confidence is an indication of how often the rule has been found to be true. In other words, it's the likelihood that the consequent is purchased when the antecedent is purchased. A high confidence value for a rule signifies a strong predictive power or reliability but does not account for the base popularity of the consequent item.
- Lift compares the observed frequency of A and B occurring together with the frequency that would be expected if A and B were independent. A lift value greater than 1 means that the items are more likely to be bought together. A lift less than 1 would indicate that items are less likely to be bought together. It's a direct measure of the strength of an association.

(365 Data Science)

```
[10]: rules.support.value_counts()
```

```
[10]: support
0.017064    11
```

```

0.010532    11
0.011065    11
0.010932    10
0.011998    10
..
0.016264     1
0.017198     1
0.014931     1
0.022797     1
0.014665     1
Name: count, Length: 95, dtype: int64

```

```
[11]: rules.confidence.value_counts()
```

```

[11]: confidence
0.170576     2
0.108025     2
0.120920     2
0.110799     2
0.181237     2
..
0.348000     1
0.215126     1
0.343964     1
0.220917     1
0.308271     1
Name: count, Length: 306, dtype: int64

```

```
[12]: rules.lift.value_counts()
```

```

[12]: lift
1.522468     2
1.903546     2
1.553774     2
1.322437     2
1.132539     2
..
1.747522     1
1.421397     1
1.421397     1
1.630358     1
1.881480     1
Name: count, Length: 251, dtype: int64

```

**D2: Discuss the Practical Significance of Findings.** The findings from the market basket analysis can provide valuable insights into customer purchasing patterns. For instance, the association between different storage capacities of SD cards could imply that customers who buy one

type are likely to need or consider another type—possibly indicating multiple device ownership or different use cases. The combination of Dust-Off Compressed Gas with a VIVO Dual LCD Monitor Desk Mount suggests that a certain customer segment is interested in both maintaining their electronic devices and setting up an ergonomic workspace.

This information can inform strategies for product placement, promotions, and inventory management. For example, products that are frequently bought together could be placed closer to each other in the store or bundled together in promotions to increase the average transaction value. Moreover, knowing which items have strong associations can help in forecasting demand more accurately.

**D3: Recommendations** Leveraging insights from my market basket analysis. The recommended course of action focuses on targeted marketing campaigns, product bundling, optimized placement, and personalized recommendations to address customer churn. By offering promotions on items frequently purchased together, such as bundling storage devices or combining electronics maintenance products with ergonomic solutions, the company can enhance perceived value and customer engagement. Additionally, arranging related products closely in store or online, along with providing personalized recommendations based on purchase history, can further reduce churn. Continuous customer feedback and employee training on these insights will ensure strategies remain effective and customer-centric model, ultimately improving retention and satisfaction.

**E: Panopto Video** <https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=156813e9-b033-47b9-8b69-b14f01627b1f>

**F: Third-party Code** (365 Data Science). <https://365datascience.com/tutorials/python-tutorials/market-basket-analysis/>

**G: Source** (365 Data Science). <https://365datascience.com/tutorials/python-tutorials/market-basket-analysis/>