MARKET-BASKET INSIGHT

Phase 5 Documentation

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Introduction:

In the highly competitive landscape of retail and e-commerce, understanding customer behavior and preferences is paramount to success. Retailers and businesses strive to enhance their offerings, optimize inventory management, and tailor marketing strategies to meet the evolving needs of their customers. A Market Basket Insight Project is a data-driven approach that can provide valuable insights into customer purchasing patterns and behaviors.This project revolves around the analysis of transaction data, specifically, the items that customers purchase in a single shopping session. By identifying correlations and associations between different products and customer behaviors, businesses can gain a deeper understanding of their customers' preferences and make data-driven decisions.

Overview:

This notebook is part of a project focused on market basket analysis. We will begin by loading andpreprocessing the dataset.

Dataset Information:

The dataset is stored in the file Assignment-1_Data.xlsx located at /kaggle/input/market-basket-analysis/. It contains information related to market transactions.

Loading the Dataset:

Let’s start by loading the dataset into a DataFrame using pandas.

```
import pandas as pd

# Load the dataset
dataset_path = '/kaggle/input/market-basket-analysis/Assignment-1_Data.xlsx'
    df = pd.read_excel(dataset_path)
```

Initial Exploration

We’ll perform an initial exploration of the dataset to understand its structure and characteristics.

Code

```
# Display basic information about the dataset print("Number of rows and
    columns:", df.shape) print("\nData Types and Missing Values:")
    print(df.info())
print("\nFirst few rows of the dataset:") print(df.head())
```

Output

```
Number of rows and columns: (522064, 7)

Data Types and Missing Values:
<class
'pandas.core.frame.DataFra
me'> RangeIndex: 522064
entries, 0 to 522063 Data
columns (total 7 columns):
 #   Column      Non-Null Count  Dtype
---  -------     --------------  ------
 0   BillNo      522064 non-null object
 1   Itemname    520609 non-null object
 2   Quantity    522064 non-null int64
 3   Date        522064 non-null datetime64[ns]
 4   Price       522064 non-null float64
 5   CustomerID  388023 non-null float64
 6   Country     522064 non-null object
dtypes: datetime64[ns](1), float64(2), int64(1),
object(3)memory usage: 27.9+ MB
None

First few rows of the dataset:
```

	BillNo	Itemname	Quantity	Date	\
0	536365	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	
1	536365	WHITE METAL LANTERN	6	2010-12-01 08:26:00	
2	536365	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	
3	536365	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	
4	536365	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	

```
   Price  CustomerID         Country
0  2.55     17850.0  United Kingdom
1  3.39     17850.0  United Kingdom
2  2.75     17850.0  United Kingdom
3  3.39     17850.0  United Kingdom
4  3.39     17850.0  United Kingdom
```

Preprocessing:

We’ll preprocess the data to ensure it’s ready for analysis.

Code

```
#Check Missing Values
print("Missing Values:")
print(df.isnull().sum())
#Drop Rows with Missing Values
df.dropna(inplace=True)
```

Output

```
Missing
Values: BillNo      0
Itemname       1455
Quantity          0
Date              0
Price             0
CustomerID   134041
Country           0
dtype: int64
```

Code

```
# Convert dataframe into transaction data
transaction_data = df.groupby(['BillNo', 'Date'])['Itemname'].apply(lambda x: ␣
↪', '.join(x)).reset_index()

#Drop Unnecessary Columns
```

```
columns_to_drop = ['BillNo', 'Date']
transaction_data.drop(columns=columns_to_drop, inplace=True)


# Save the transaction data to a CSV file
transaction_data_path = '/kaggle/working/transaction_data.csv'
transaction_data.to_csv(transaction_data_path, index=False)
```

Code

```
# Display the first few rows of the transaction data print("\nTransaction Data for Association Rule Mining:")

print(transaction_data.head())
```

Output

Transaction Data for Association Rule Mining:

```
                                          Itemname
0  WHITE HANGING HEART T-LIGHT HOLDER, WHITE META...
1  HAND WARMER UNION JACK, HAND WARMER RED POLKA DOT
2  ASSORTED COLOUR BIRD ORNAMENT, POPPY'S PLAYHOU...
3  JAM MAKING SET WITH JARS, RED COAT RACK PARIS ...
4                           BATH BUILDING BLOCK WORD
```

Formatting the transaction data in a suitable format for insight:

Developing the preprocessed data into analysis. Split the ‘Itemname’ column in transaction_data into individual items using str.split(', ', expand=True).Concatenate the original DataFrame (transaction_data) with the items DataFrame (items_df) using pd.concat.Drop the original ‘Itemname’ column since individual items are now in separate columns.Display the resulting Data Frame.

Code

```
# Split the 'Itemname' column into individual items

items_df = transaction_data['Itemname'].str.split(', ', expand=True)

# Concatenate the original DataFrame with the new items DataFrame

transaction_data = pd.concat([transaction_data, items_df], axis=1)

# Drop the original 'Itemname' column

transaction_data = transaction_data.drop('Itemname', axis=1)
```

# Display the resulting DataFrame
print(transaction_data.head())

Output

```
0  WHITE HANGING HEART T-LIGHT HOLDER WHITE METAL LANTERN
1            HAND WARMER UNION JACK HAND WARMER RED POLKA
             DOT
2      ASSORTED COLOUR BIRD ORNAMENT      POPPY'S PLAYHOUSE
       BEDROOM
3          JAM MAKING SET WITH JARS       RED COAT RACK
           PARIS FASHION
4          BATH BUILDING BLOCK WORD                 None

                   2                              3   \
0  CREAM CUPID HEARTS COAT HANGER   KNITTED UNION FLAG HOT
   WATER BOTTLE
1                       None                          None
2      POPPY'S PLAYHOUSE KITCHEN    FELTCRAFT     PRINCESS
       CHARLOTTE DOLL
3  YELLOW COAT RACK PARIS FASHION BLUE COAT RACK PARIS
   FASHION
4                       None                          None

                            4                         5   \
0  RED WOOLLY HOTTIE WHITE HEART.   SET 7 BABUSHKA NESTING
   BOXES
1                       None                         None
2        IVORY KNITTED MUG COSY     BOX OF 6 ASSORTED
         COLOUR TEASPOONS
3                       None                         None
4                       None                         None

                              6                      7   \
0  GLASS STAR FROSTED T-LIGHT HOLDER                None
1                         None                      None
2      BOX OF VINTAGE JIGSAW BLOCKS     BOX OF VINTAGE
       ALPHABET BLOCKS
3                         None                      None


                     8                        9    …534  535   536  \
0      None                None                    … None  None  None
1      None                None                    … None  None  None
2      BUILDING    BLOCKLOVE BUILDING BLOCK        … None  None  None
   HOM WORD                WORD
E
```

```
3        None                None                ... None  None   None
4        None                None                ... None  None   None

      537  538    539    540      541    542    543
0   None None   None   None     None   None   None
1   None None   None   None     None   None   None
2   None None   None   None     None   None   None
3   None None   None   None     None   None   None
4   None None   None   None     None   None   None
```

Association Rules - Data Mining

Converting Items to Boolean Columns

Prepare the data for association rule mining, we convert the items in the transaction_data DataFrame into boolean columns using one-hot encoding. This is achieved through the pd.get_dummies function, which creates a new DataFrame (df_encoded) with boolean columns representing the presence or absence of each item.

Code

```
# Convert items to boolean columns
df_encoded = pd.get_dummies(transaction_data, prefix='', prefix_sep='').
↪groupby(level=0, axis=1).max()


# Save the transaction data to a CSV file
df_encoded.to_csv('transaction_data_encoded.csv', index=False)
```

Association Rule Mining

We apply the Apriori algorithm to perform association rule mining on the encoded transaction data. The min_support parameter is set to 0.007 to filter out infrequent itemsets. The resulting frequent itemsets are then used to generate association rules based on a minimum confidence threshold of 0.5.Finally, we print the generated association rules.

Code

```
# Load transaction data into a DataFrame
df_encoded = pd.read_csv('transaction_data_encoded.csv')
from mlxtend.frequent_patterns import apriori, association_rules
# Association Rule Mining
```

```
frequent_itemsets = apriori(df_encoded, min_support=0.007,
use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence", ␣
↪min_threshold=0.5)
```

```
# Display information of the rules
print("Association Rules:")
print(rules.head())
```

Output

```
Association Rules:
 antecedentsconsequents \

0 (CHOCOLATE BOX RIBBONS)
  (6 RIBBONS RUSTIC CHARM)
1 (60 CAKE CASES DOLLY GIRL
DESIGN) (PACK OF 72 RETROSPOT
CAKE CASES)
2 (60 TEATIME FAIRY CAKE
CASES) (PACK OF 72 RETROSPOT
CAKE CASES)
3 (ALARM CLOCK BAKELIKE
CHOCOLATE) (ALARM CLOCK
BAKELIKE GREEN)
4 (ALARM CLOCK BAKELIKE
CHOCOLATE) (ALARM CLOCK
BAKELIKE PINK)


antecedent support consequent support
  support confidence
  lift \ 0 0.012368
  0.039193 0.007036
  0.568889 14.515044
1 0.018525 0.054529 0.010059
  0.543027 9.958409
2 0.034631 0.054529 0.017315
  0.500000 9.169355
3 0.017150 0.042931 0.011379
  0.663462 15.454151
```

4	0.017150	0.032652	0.009125	
	0.532051	16.294742		

	Leverage	conviction	zhangs_metric
0	0.006551	2.228676	0.942766
1	0.009049	2.068984	0.916561
2	0.015427	1.890941	0.922902
3	0.010642	2.843862	0.951613
4	0.008565	2.067210	0.955009

Visualization

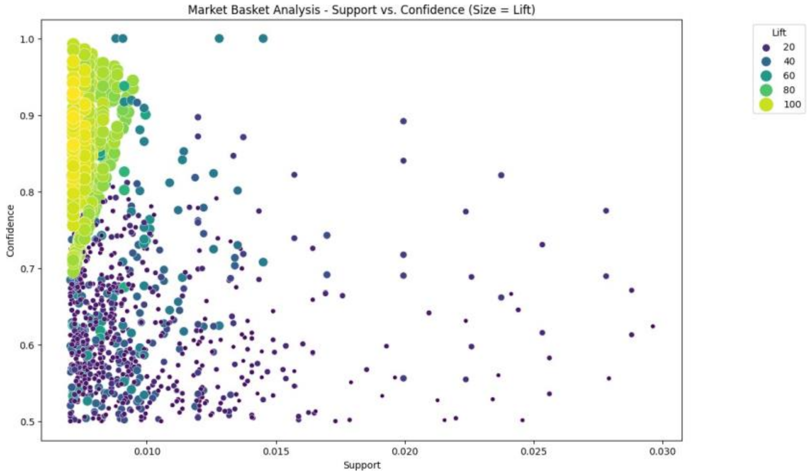
Visualizing Market Basket Insight Results:

We use matplotlib and seaborn libraries to create a scatterplot visualizing the results of the market basket analysis. The plot depicts the relationship between support, confidence, and lift for the generated association rules.

Code

```
import matplotlib.pyplot as plt import seaborn as sns

# Plot scatterplot for Support vs. Confidence

plt.figure(figsize=(12, 8))

sns.scatterplot(x="support", y="confidence", size="lift", data=rules,␣

↪hue="lift", palette="viridis", sizes=(20, 200))

plt.title('Market Basket Analysis - Support vs. Confidence (Size = Lift)')
plt.xlabel('Support')
plt.ylabel('Confidence')
plt.legend(title='Lift', loc='upper right', bbox_to_anchor=(1.2, 1))
plt.show()
```

Output



Interactive Market Basket Insight Visualization

We leverage the Plotly Express library to create an interactive scatter plot visualizing the results of the market basket analysis. This plot provides an interactive exploration of the relationship between support, confidence, and lift for the generated association rules.

Code

import plotly.express as px

Convert frozensets to lists for serialization rules['antecedents'] = rules['antecedents'].apply(list) rules['consequents'] = rules['consequents'].apply(list)

Create an interactive scatter plot using plotly express

fig = px.scatter(rules, x="support", y="confidence", size="lift", color="lift", hover_name="consequents",

title='Market Basket Analysis - Support vs. Confidence', labels={'support': 'Support', 'confidence': 'Confidence'})

Customize the layout

fig.update_layout(xaxis_title='Support', yaxis_title='Confidence', coloraxis_colorbar_title='Lift',showlegend=**True)**

 # Show the interactive plot

fig.show()

Output

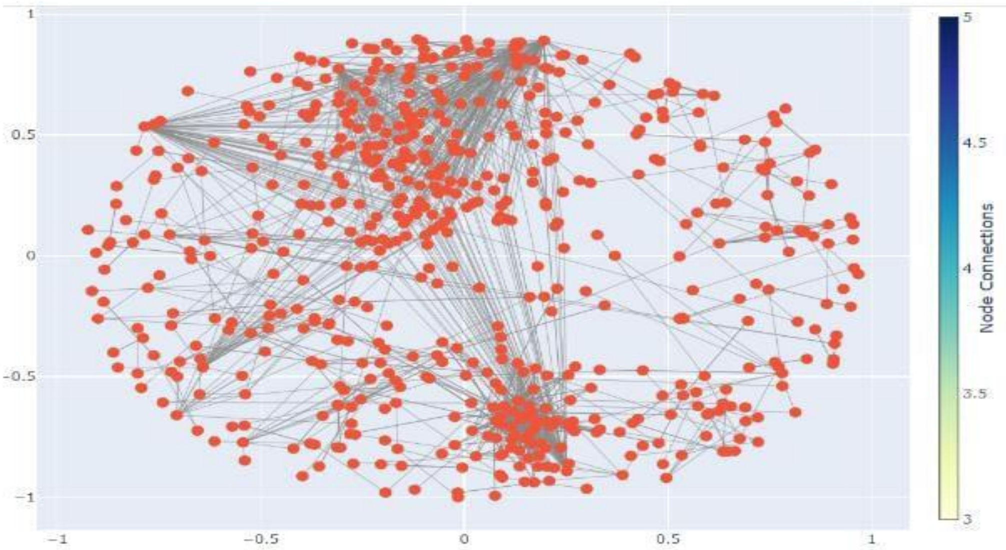
Interactive Network Visualization for Association Rules

We utilize the NetworkX and Plotly libraries to create an interactive network graph visualizing the association rules. This graph represents relationships between antecedent and consequent items, showcasing support as edge weights.

Code

```
import networkx as nx

import matplotlib.pyplot as
plt import
plotly.graph_objects as go
# Create a directed graph

G = nx.DiGraph()

# Add nodes and edges from association rules
for idx, row in rules.iterrows():
    G.add_node(tuple(row['antecedents']), color='skyblue')
    G.add_node(tuple(row['consequents']), color='orange')
    G.add_edge(tuple(row['antecedents']),
    tuple(row['consequents']), ␣
  ↪weight=row['support'])

# Set node positions using a spring layout

pos = nx.spring_layout(G)
```

```
# Create an interactive plot using plotlyedge_x = []edge_y = []
for edge in
    G.edges(data=True): x0,
    y0 = pos[edge[0]]

x1, y1 = pos[edge[1]]edge_x.append(x0)
node_x
= []
node_y
= []
for node in
    G.nodes(): x, y =
    pos[node]
    node_x.append(
    x)
    node_y.append(
    y)

node_trace =
    go.Scatter(
    x=node_x,
    y=node_y,
    mode='markers',
    hoverinfo='text',
    marker=dict(
        showscale=True,
        colorscale='YlGn
        Bu', size=10,
        colorbar=dict(
            thickness=15,
            title='Node Connections',
            xanchor='left',
            titleside='right'
        )
    )
)

# Customize the layout

layout = go.Layout(
    showlegend=False,
    hovermode='closest',
    margin=dict(b=0, l=0, r=0,
    t=0),
)

# Create the figure

fig = go.Figure(data=[edge_trace, node_trace], layout=layout)

# Show the interactive graph

fig.show()
```



Output

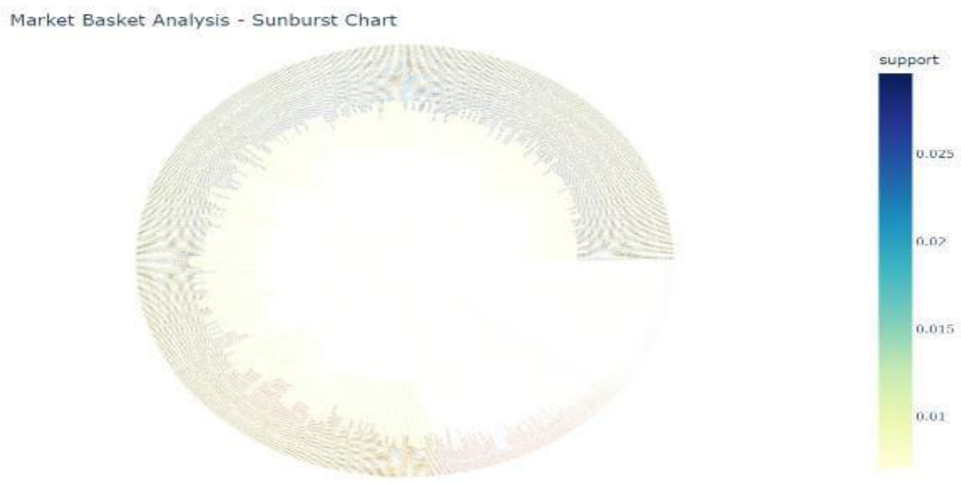
Interactive Sunburst Chart for Association Rules

We use Plotly Express to create an interactive sunburst chart visualizing association rules. This chart represents the relationships between antecedent and consequent items, showcasing lift as well as support through color intensity.

Code

```
import plotly.express as px


# Combine antecedents and consequents into a single column for each rule

rules['rule'] = rules['antecedents'].astype(str) + ' -> ' + ␣
 ↪rules['consequents'].astype(str)

# Create a sunburst chart

fig = px.sunburst(rules, path=['rule'], values='lift',
                  title='Market Basket Analysis - Sunburst Chart',
                  color='support', color_continuous_scale='YlGnBu')

# Customize the layout
```

```
fig.update_layout(
    margin=dict(l=0, r=0, b=0, t=40),
)
# Show the  interactive  plot
fig.show()
```



Output

CONCLUSION

The Market Basket Insight Project represents a pivotal step in harnessing the power of data analytics to understand customer behavior, optimize business operations, and enhance the overall shopping experience. By uncovering the intricate web of connections between products and customers, this project empowers retailers and businesses with invaluable insights.

Through the diligent application of association rule mining and customer segmentation, businesses can identify hidden patterns and trends within transaction data. These findings have far-reaching implications, from the strategic placement of products on shelves to more personalized marketing campaigns. The benefits of this project extend beyond immediate sales, encompassing inventory management, customer satisfaction, and long-term profitability.

As we conclude this project, it is evident that the Market Basket Insight Project is not merely a data analysis endeavor; it is a strategic imperative for modern retailers and businesses. The ability to anticipate customer needs, make informed decisions, and offer a more tailored shopping experience is a competitive advantage that cannot be understated.

In a world where customer preferences are continually evolving, the insights generated from this project serve as a guiding light for businesses, enabling them to navigate the ever-changing landscape of retail and e-commerce. With data as their compass, businesses are poised to make informed decisions that resonate with their customers, ultimately leading to greater success and sustainability in an increasingly competitive market.