```
import pandas as pd
# Load the sales data
sales_data = pd.read_csv('sales_data.csv')
# Display the first few rows of the dataframe
sales_data.head()
⇒ Show hidden output
# Count the occurrences of each product
product_counts = sales_data['Product Name'].value_counts()
# Display the most prevalent products
print(product_counts.head())
Show hidden output
# Define a large basket as having more than a certain number of items
large_basket_threshold = 5
# Group by CustomerID and count the number of items in each basket
basket_sizes = sales_data.groupby('CustomerID').size()
# Count the number of large baskets
large basket counts = basket sizes[basket sizes > large basket threshold].count()
# Display the frequency of large buyers
print(large_basket_counts)
→ 10
# Group by StoreID and count the number of large baskets in each store
large_basket_stores = sales_data[sales_data['CustomerID'].isin(basket_sizes[basket_sizes > large_basket_threshold].index)]
store_large_basket_counts = large_basket_stores['StoreID'].value_counts()
# Display the stores with large-basket buyers
print(store_large_basket_counts)
    Show hidden output
import matplotlib.pyplot as plt
# Plot the top stores with large-basket buyers
store_large_basket_counts.head(10).plot(kind='bar')
plt.title('Top Stores with Large-Basket Buyers')
plt.xlabel('StoreID')
plt.ylabel('Number of Large Baskets')
plt.show()
₹
     Show hidden output
# Get the products in large baskets
large_basket_products = large_basket_stores['Product Name'].value_counts()
# Display the top-N products
top n = 10
print(large_basket_products.head(top_n))
     Show hidden output
# Group by CustomerID and get the average basket makeup
basket_makeup = sales_data.groupby('CustomerID')['Product Name'].apply(lambda x: x.value_counts(normalize=True))
# Display the average categorical makeup of baskets
print(basket_makeup.head())
     Show hidden output
# Plot the categorical makeup of baskets
basket_makeup_df = basket_makeup.unstack().mean().sort_values(ascending=False)
```

```
basket_makeup_df.plot(kind='bar')
plt.title('Average Categorical Makeup of Baskets')
plt.xlabel('Product Name')
plt.ylabel('Average Proportion in Basket')
plt.show()
```

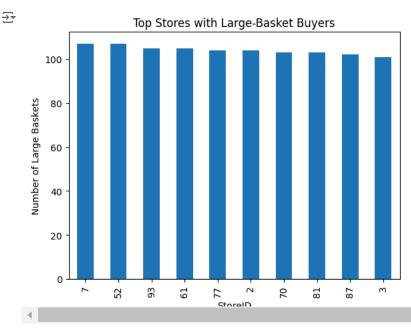
PROJECT #3 Below here

```
1. Analysis of Product Occurrences
# Count the occurrences of each product (PROJECT 3)
product_counts = sales_data['Product Name'].value_counts()
# Display the most prevalent products
print("Most Prevalent Products:")
print(product_counts.head())
→ Most Prevalent Products:
     Product Name
     Veggie
                    1176
     Pepperoni
                    1143
     Margherita
                    1136
     Meat Lovers
                   1124
                   1117
     Hawaiian
     Name: count, dtype: int64
   2. Analysis of Large Baskets
# Define a large basket as having more than a certain number of items (PROJECT 3)
large_basket_threshold = 5
# Group by CustomerID and count the number of items in each basket
basket_sizes = sales_data.groupby('CustomerID').size()
# Count the number of large baskets
large_basket_counts = basket_sizes[basket_sizes > large_basket_threshold].count()
# Display the frequency of large buyers
print("Number of Large Baskets:")
print(large_basket_counts)
Number of Large Baskets:
   3. Store Analysis: Identify stores with the highest number of large-basket buyers.
# Group by StoreID and count the number of large baskets in each store (PROJECT 3)
large_basket_stores = sales_data[sales_data['CustomerID'].isin(basket_sizes[basket_sizes > large_basket_threshold].index)]
store_large_basket_counts = large_basket_stores['StoreID'].value_counts()
# Display the stores with large-basket buyers
print("Stores with Large-Basket Buyers:")
print(store_large_basket_counts)
    Stores with Large-Basket Buyers:
     StoreID
           107
     52
           107
     93
           105
     61
           105
     77
           104
     44
            75
     65
            75
     8
            75
     76
            74
     20
     Name: count, Length: 100, dtype: int64
```

4. Plot Top Stores with Large-Basket Buyers: Visualize the top stores with large-basket buyers.

```
import matplotlib.pyplot as plt

# Plot the top stores with large-basket buyers (PROJECT 3)
store_large_basket_counts.head(10).plot(kind='bar')
plt.title('Top Stores with Large-Basket Buyers')
plt.xlabel('StoreID')
plt.ylabel('Number of Large Baskets')
plt.show()
```



5. Analysis of Products in Large Baskets

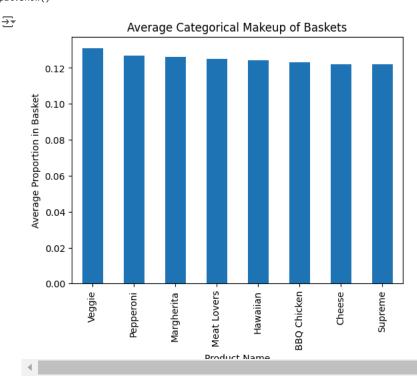
```
# Get the products in large baskets (PROJECT 3)
large_basket_products = large_basket_stores['Product Name'].value_counts()
# Display the top-N products
top_n = 10
print("Top Products in Large Baskets:")
print(large_basket_products.head(top_n))
    Top Products in Large Baskets:
     Product Name
                    1176
     Veggie
     Pepperoni
                    1143
     Margherita
                    1136
     Meat Lovers
                    1124
     Hawaiian
                    1117
     BBQ Chicken
                    1107
                    1097
     Supreme
     Cheese
                    1097
     Name: count, dtype: int64
```

6. Analysis of Basket Makeup

Hawaiian 0.130631 Meat Lovers 0.120495 Name: Product Name, dtype: float64

7. Plot Basket Makeup: Visualize the average categorical makeup of baskets.

```
# Plot the categorical makeup of baskets
basket_makeup_df = basket_makeup.unstack().mean().sort_values(ascending=False)
basket_makeup_df.plot(kind='bar')
plt.title('Average Categorical Makeup of Baskets')
plt.xlabel('Product Name')
plt.ylabel('Average Proportion in Basket')
plt.show()
```



8. Market Basket Analysis

3 0.983333

0.983333

(Margherita)

(Supreme)

```
from mlxtend.frequent_patterns import apriori, association_rules
# Create a basket for each store
basket = (sales_data.groupby(['StoreID', 'OrderID', 'Product Name'])['Product Name']
          .count().unstack().reset_index().fillna(0)
          .set_index(['StoreID', 'OrderID']))
# Convert the values to 1 and 0
def encode\_units(x):
    return 1 if x >= 1 else 0
basket_sets = basket.applymap(encode_units)
# Perform market basket analysis using the Apriori algorithm
frequent_itemsets = apriori(basket_sets, min_support=0.01, use_colnames=True)
# Generate the association rules, specifying num_itemsets
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1, support_only=False, num_itemsets=frequent_itemsets['itemsets'].
# Display the most frequently occurring itemsets
print(frequent_itemsets.sort_values(by='support', ascending=False).head())
# Display the association rules
print(rules.head())
₹
         support
                      itemsets
     7 0.990000
                      (Veggie)
     2 0.983333
                    (Hawaiian)
```

```
1 0.983333
                 (Cheese)
            antecedents
                                   consequents antecedent support \
0
                                  (BBQ Chicken)
                                                          0.980000
           (Meat Lovers)
           (BBQ Chicken)
                                  (Meat Lovers)
                                                          0.966667
                                 (BBQ Chicken)
2
   (Meat Lovers, Cheese)
                                                          0.963333
3
   (BBQ Chicken, Cheese)
                                  (Meat Lovers)
                                                          0.950000
           (Meat Lovers) (BBQ Chicken, Cheese)
                                                          0.980000
4
   consequent support
                        support
                                confidence
                                                lift representativity
0
            0.966667
                      0.950000
                                  0.969388 1.002815
                                                                   1.0
            0.980000
                      0.950000
                                  0.982759 1.002815
                                                                   1.0
1
                                  0.968858 1.002267
2
            0.966667
                      0.933333
                                                                   1.0
3
            0.980000
                      0.933333
                                  0.982456 1.002506
                                                                   1.0
4
            0.950000 0.933333
                                  0.952381 1.002506
                                                                   1.0
   leverage conviction zhangs_metric jaccard certainty kulczynski
0 0.002667
             1.088889
                             0.140351 0.953177
                                                 0.081633
                                                              0.976073
              1.160000
                                                  0.137931
                                                              0.976073
   0.002667
                              0.084211 0.953177
              1.070370
                                                              0.967188
  0.002111
                             0.061688 0.936455
                                                  0.065744
3 0.002333
              1.140000
                              0.050000 0.936455
                                                  0.122807
                                                              0.967419
4 0.002333
              1.050000
                             0.125000 0.936455
                                                  0.047619
                                                              0.967419
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell`
  and should_run_async(code)
<ipython-input-23-2ba1fc29c1ab>:12: FutureWarning: DataFrame.applymap has been deprecated. Use DataFrame.map instead.
 basket_sets = basket.applymap(encode_units)
```

/usr/local/lib/python3.10/dist-packages/mlxtend/frequent_patterns/fpcommon.py:161: DeprecationWarning: DataFrames with non-bool types re warnings.warn(

https://colab.research.google.com/drive/1YDMhhy4n39EMOJMiaGcPBPkf6b8e5deL?authuser=1#scrollTo=hd6MlzbVw7TS&printMode=true