Store Inventory

Maxmium Selling Product

Product that maximum time sell together:

basket	recommendations
frozenset({'0 Calorie Strawberry Dragonfruit Water Beverage'})	frozenset({'0 Calorie Fuji Apple Pear Water Beverage'})
frozenset({'Cheez-It Cheddar Cracker', 'Zero Calorie Cola'})	frozenset({'Soda'})

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/instacart-market-basket-analysis/departments.csv.zip
/kaggle/input/instacart-market-basket-analysis/sample_submission.csv.zip
/kaggle/input/instacart-market-basket-analysis/order_products__train.csv.zip
/kaggle/input/instacart-market-basket-analysis/order_products__prior.csv.zip
/kaggle/input/instacart-market-basket-analysis/orders.csv.zip
/kaggle/input/instacart-market-basket-analysis/products.csv.zip
/kaggle/input/instacart-market-basket-analysis/aisles.csv.zip
```

```
# For ignore the warnings
import warnings
warnings.filterwarnings("ignore")
# To see complete view of the product
pd.set_option('display.max_colwidth', -1)

```

Import Packages

```
from zipfile import ZipFile  # working with zipped input
from mlxtend.frequent_patterns import fpgrowth, association_rules  # MBA
from scipy import sparse  # sparse matrices
import numpy as np
import pandas as pd
import os
import matplotlib.pyplot as plt
```

Extracting files from zip

```
# Loading & processing data
def preDot(text):
    return text.rsplit('.',1)[0]

np.random.seed(73)
dataDict = {}

for dirname,i,filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname,filename))
        with ZipFile(os.path.join(dirname,filename), 'r') as zipf:
            unzipped_fn = preDot(filename)
            with zipf.open(unzipped_fn) as f:
                dataDict[preDot(unzipped_fn)] = pd.read_csv(f)


```

```
/kaggle/input/instacart-market-basket-analysis/departments.csv.zip
/kaggle/input/instacart-market-basket-analysis/sample_submission.csv.zip
/kaggle/input/instacart-market-basket-analysis/order_products__train.csv.zip
/kaggle/input/instacart-market-basket-analysis/order_products__prior.csv.zip
/kaggle/input/instacart-market-basket-analysis/orders.csv.zip
/kaggle/input/instacart-market-basket-analysis/products.csv.zip
/kaggle/input/instacart-market-basket-analysis/aisles.csv.zip
```

Get train data

```
#Dividing train_orders
train_orders = dataDict['orders'][dataDict['orders']['eval_set'] == 'train'].drop('eval_set', axis=1)
prior_orders = dataDict['orders'][dataDict['orders']['eval_set'] == 'prior'].drop('eval_set', axis=1)
test_orders = dataDict['orders'][dataDict['orders']['eval_set'] == 'test'].drop('eval_set', axis=1)
```

```
order_products__train = dataDict['order_products__train']
```

Data Prepartion

```
# we need our data is above format so use two column
small_train = order_products__train[['order_id','product_id']]
small_train
```

	order_id	product_id
0	1	49302
1	1	11109
2	1	10246
3	1	49683
4	1	43633
...	...	...
1384612	3421063	14233
1384613	3421063	35548
1384614	3421070	35951
1384615	3421070	16953
1384616	3421070	4724

1384617 rows × 2 columns

```
# In Product csv files, product name are present
prod = dataDict['products']
```

```
# create product counts using Counter() from collections package
from collections import Counter
from wordcloud import WordCloud
from PIL import Image
from io import BytesIO
import requests
product_counts = Counter(prod["product_name"])

wordcloud = WordCloud(width = 1000,
                      height = 500,
                      background_color = 'white',
                      max_font_size = 90,
                      random_state = 9).generate_from_frequencies(product_counts)
plt.figure(figsize=(20,10))
plt.axis("off")
plt.imshow(wordcloud);
plt.savefig('stock_inventory.jpg')
```


```
1 df = order_products__train.merge(products,on='product_id')
```

```
1 from wordcloud import WordCloud
2 from PIL import Image
3 from io import BytesIO
4 import requests
5 product_counts = Counter(df["product_name"])
6
7 wordcloud = WordCloud(width = 1000,
8                       height = 500,
9                       background_color = 'white',
10                      max_font_size = 90,
11                      random_state = 9).generate_from_frequencies(product_counts)
12 plt.figure(figsize=(20,10))
13 plt.axis("off")
14 plt.imshow(wordcloud);
15 plt.savefig('selling_product.jpg')
```


```
1 # Split the train data so that it reduce the running time
2 small_train_split = (small_train[:461543], small_train[461543:461543*2-1], small_train[461543*2-1:])
```

```
1 #Getting list of unquie product id
2 pivots = []
3 for df in small_train_split:
4     pvt = ~(df.pivot(index='order_id', columns='product_id', values='product_id').isna())
5     pivots.append(pvt.astype(pd.SparseDtype(bool)))
6 del pvt
7
8 product_cols = sorted(small_train.product_id.unique())
```

```
1 len(product_cols)
```

```
39123
```

Converting the table into data mining algorithm format

```
1
2 for i in range(len(pivots)):
3     # reindexing to add extra columns and standardize the format for vstack
4     # we sparse them again here b/c otherwise we would end up having regular boolean columns
5     pivots[i] = pivots[i].reindex(columns=product_cols, fill_value=False).astype(pd.SparseDtype(bool))
6     pivots[i] = sparse.csr_matrix(pivots[i])
7 # concat vertically
8 pivots = sparse.vstack(pivots)
```

```
1 truth_table = pd.DataFrame(pivots.todense(), index=small_train.order_id.unique(), columns=product_cols)
```

```
1 truth_table.head()
```

	1	2	3	4	5	7	8	9	10	11	...	49677	49678	49679	49680	49681	49682	49683	496
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	True	Fal
36	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	Fal
38	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	Fal
96	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	Fal
98	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	Fal

5 rows × 39123 columns

Data mining algorithm

Use the minimum support to filter out non-frequent item

> Other algorithm: AIS, SETM and Apriori

```
1 # takes less than a minute to execute
2 frequent_itemsets = fpgrowth(truth_table, min_support=5/len(truth_table), use_colnames=True)
```

```
1 frequent_itemsets
```

	support	itemsets
0	0.117980	(13176)
1	0.055583	(47209)
2	0.018391	(49683)
3	0.015190	(22035)
4	0.008094	(10246)
...	...	...
861871	0.000053	(8833, 9497)
861872	0.000038	(9497, 1134)
861873	0.000038	(9497, 8833, 1134)
861874	0.000038	(15317, 12902)
861875	0.000038	(25421, 22965)

861876 rows × 2 columns

Compute and print the Association Rules

```
1 rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.8)
```

```
1 print("μ number of consequents:", rules['consequents'].apply(len).mean())
2 rules
```

```
μ number of consequents: 1.0391897394136809
```

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(47626, 49683, 4605, 21903)	(24852)	0.000076	0.142719	0.000069	0.900000	6.306104	0.000058	8.572811
1	(26209, 49683, 28204, 16797)	(24852)	0.000046	0.142719	0.000038	0.833333	5.838985	0.000032	5.143687
2	(49683, 39275, 48679)	(24852)	0.000046	0.142719	0.000038	0.833333	5.838985	0.000032	5.143687
3	(27104, 49683, 24964, 47766)	(24852)	0.000038	0.142719	0.000038	1.000000	7.006782	0.000033	inf
4	(42265, 40706, 49683, 24852)	(21903)	0.000046	0.074568	0.000038	0.833333	11.175474	0.000035	5.552592
...	...	...	...	...	...	...	...	...	...
29467	(26460)	(38936)	0.000046	0.000099	0.000038	0.833333	8410.833333	0.000038	5.999406

```
# selecting out rules that might potentially not be enhancing
rules = rules[rules.lift > 1]
```

```
# a simplification of the table
rules_ante_cons = rules[['antecedents', 'consequents']]
```

Recommendations

```
# creating customers' baskets
baskets = small_train.groupby('order_id')['product_id'].apply(frozenset)
baskets.name = "basket"  # antecedents
```

> Frozenset is similar to set in Python, except that frozensets are immutable, which implies that once generated, elements from the frozenset cannot be added or removed. This function accepts any iterable object as input and transforms it into an immutable object.

```
# Intialize one column with frozenset
recommendations = train_orders.join(baskets, on="order_id")
recommendations["recommendations"] = [frozenset() for _ in range(len(recommendations))]
```

```
recommendations['recommendations'].value_counts()
```

```
()    131209
Name: recommendations, dtype: int64
```

```
# computationally-intensive; might require an optimization
for idx, antecedent in enumerate(rules_ante_cons["antecedents"]):
    lookup = antecedent <= recommendations.basket, "recommendations"
    recommendations.loc[lookup] = recommendations.loc[lookup].apply(
        frozenset.union,
        args=(rules_ante_cons.loc[idx, "consequents"],)
    )
# recommendations = recommendations.rename(columns={"antecedents": "basket"})
# this may be changed earlier
recommendations.loc[:, "recommendations"] = recommendations.recommendations - recommendations.basket
```

```
# Removing all empty order, for that our reccommendation doesn't work
non_empty_recs = recommendations[recommendations.recommendations.apply(bool)]
```

Assigning each product id with its product name

```

# non-empty recommendations
non_empty_recs = recommendations[recommendations.recommendations.apply(bool)]
print("1 out of approx.", round(1/(len(non_empty_recs) / len(recommendations))), "transactions will result in a recommendation being s
# mappin g codes to product names
def map_products(codes):
    if isinstance(codes, pd.Series):
        return codes.apply(map_products)
```

```
    return frozenset(map(products.get, codes))

products = dataDict["products"]
products = products.set_index("product_id")["product_name"].to_dict()
non_empty_recs.loc[:, ["basket", "recommendations"]] = non_empty_recs[["basket", "recommendations"]].apply(map_products)

```

```
1 out of approx. 14 transactions will result in a recommendation being suggested to a customer.
```

Best product combination that small retail can also use

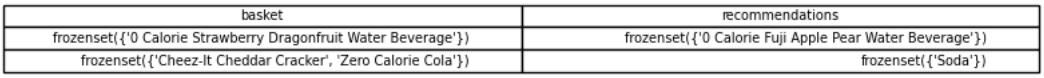
```
further = non_empty_recs[['basket','recommendations']]
```

```
# Filter rows based on number of items in "basket" column
filtered_rows = [row for row in range(len(further)) if len(further.iloc[row,0]) < 3]

# Create a new DataFrame with only the filtered rows
new_df = further.iloc[filtered_rows]
```

```
new_df
```

	basket	recommendations
482008	(0 Calorie Strawberry Dragonfruit Water Beverage)	(0 Calorie Fuji Apple Pear Water Beverage)
1827443	(Cheez-It Cheddar Cracker, Zero Calorie Cola)	(Soda)

```
# Plot the DataFrame
fig, ax = plt.subplots(figsize=(10, 5))
ax.axis('off')
ax.table(cellText=new_df.values,colLabels=new_df.columns,loc='center')

# Save the plot as an image file
plt.savefig('best_combo.jpg')
```



basket	recommendations
frozenset({'0 Calorie Strawberry Dragonfruit Water Beverage'})	frozenset({'0 Calorie Fuji Apple Pear Water Beverage'})
frozenset({'Cheez-It Cheddar Cracker', 'Zero Calorie Cola'})	frozenset({'Soda'})