Libraries and Imports

```
import pandas as pd
from pandas import DataFrame
from pandas import Series
import numpy as np
import colorsys
import cv2
import matplotlib.pyplot as plt
from numpy import ndarray
import itertools
import heapq
import time
import seaborn as sns
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, f1_score, precision_score,
recall_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn import metrics
from sklearn.metrics import ConfusionMatrixDisplay
```

Reading the data

```
aisles = pd.read_csv('aisles.csv')
departments = pd.read_csv('departments.csv')
products = pd.read_csv('products.csv')
orders = pd.read_csv('orders.csv')
target = pd.read_csv('target.csv')
order_products__prior = pd.read_csv('order_products__prior.csv')
order_products__train_test =
pd.read_csv('order_products__train_test.csv')
```

Section A: Exploring the data

```
orders

         order_id  user_id eval_set  order_number  order_dow
0         2539329        1    prior             1          2  \
1         2398795        1    prior             2          3
2          473747        1    prior             3          3
3         2254736        1    prior             4          4
4          431534        1    prior             5          4
...           ...      ...      ...           ...        ...
3346078   2134068   124107     test             7          6
```

```
3346079   2113602    70278     test           100          4
3346080   2342325   175026     test             4          4
3346081   3367040   179234     test            19          5
3346082   1828606    98632     test             4          4

         order_hour_of_day  days_since_prior_order
0                        8                     NaN
1                        7                    15.0
2                       12                    21.0
3                        7                    29.0
4                       15                    28.0
...                    ...                     ...
3346078                  9                     7.0
3346079                 13                     5.0
3346080                 17                    11.0
3346081                 23                    30.0
3346082                 14                    27.0

[3346083 rows x 7 columns]
```

departments.head()

```
   department_id department
0              1     frozen
1              2      other
2              3     bakery
3              4    produce
4              5    alcohol
```

order_products__prior

```
          order_id  product_id  add_to_cart_order  reordered
0                2       33120                  1          1
1                2       28985                  2          1
2                2        9327                  3          0
3                2       45918                  4          1
4                2       30035                  5          0
...            ...         ...                ...        ...
32434484   3421083       39678                  6          1
32434485   3421083       11352                  7          0
32434486   3421083        4600                  8          0
32434487   3421083       24852                  9          1
32434488   3421083        5020                 10          1

[32434489 rows x 4 columns]
```

order_products__train_test

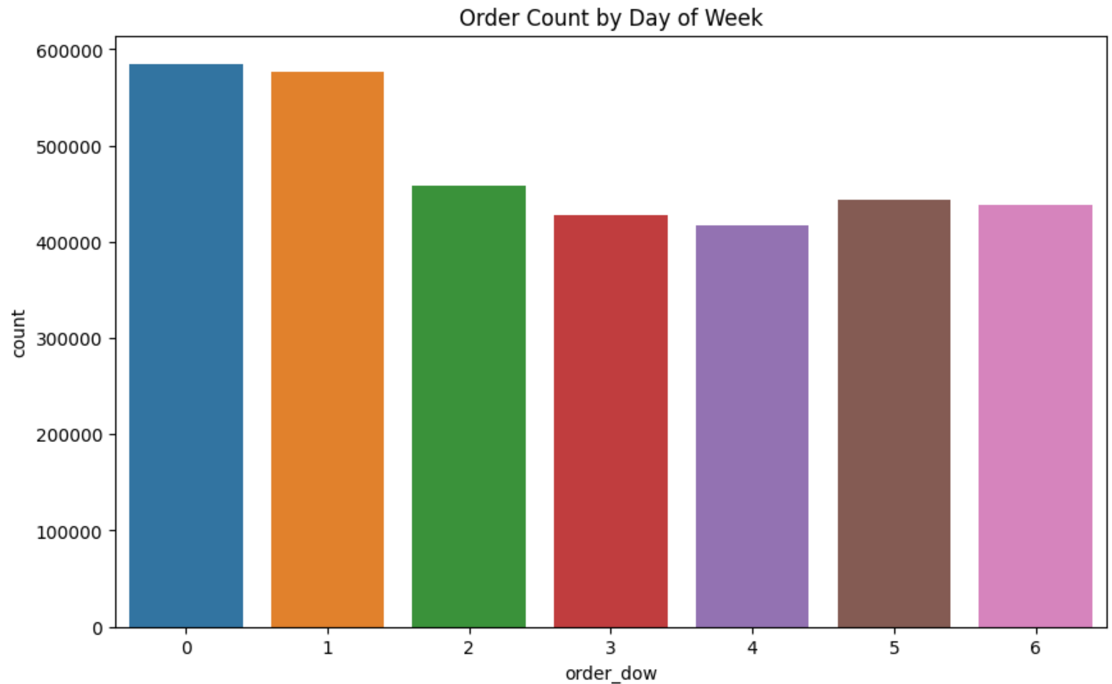
```
         order_id  product_id  add_to_cart_order  reordered
0               1       49302                  1          1
1               1       11109                  2          1
```

```
2                1      10246                  3          0
3                1      49683                  4          0
4                1      43633                  5          1
...            ...        ...                ...        ...
1384612    3421063      14233                  3          1
1384613    3421063      35548                  4          1
1384614    3421070      35951                  1          1
1384615    3421070      16953                  2          1
1384616    3421070       4724                  3          1

[1384617 rows x 4 columns]
```

```
target
```

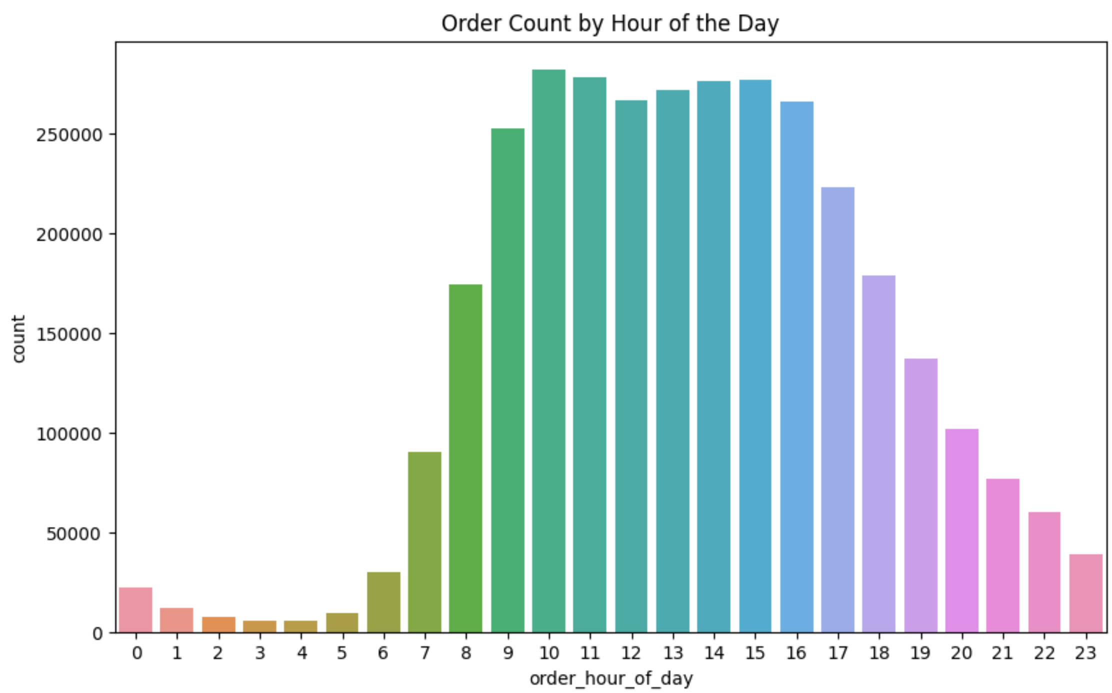
```
         order_id  product_id  was_in_order
0         1187899       196.0             1
1         2757217       196.0             1
2          632715       196.0             1
3         1167274       196.0             1
4         3347074       196.0             1
...           ...         ...           ...
2959120   3421070      4987.0             0
2959121   3421070      8230.0             0
2959122   3421070     39468.0             0
2959123   3421070     39139.0             0
2959124   3421070     48208.0             0

[2959125 rows x 3 columns]
```

```
plt.figure(figsize=(10,6))
sns.countplot(x='order_dow', data=orders)
plt.title('Order Count by Day of Week')
plt.show()
```



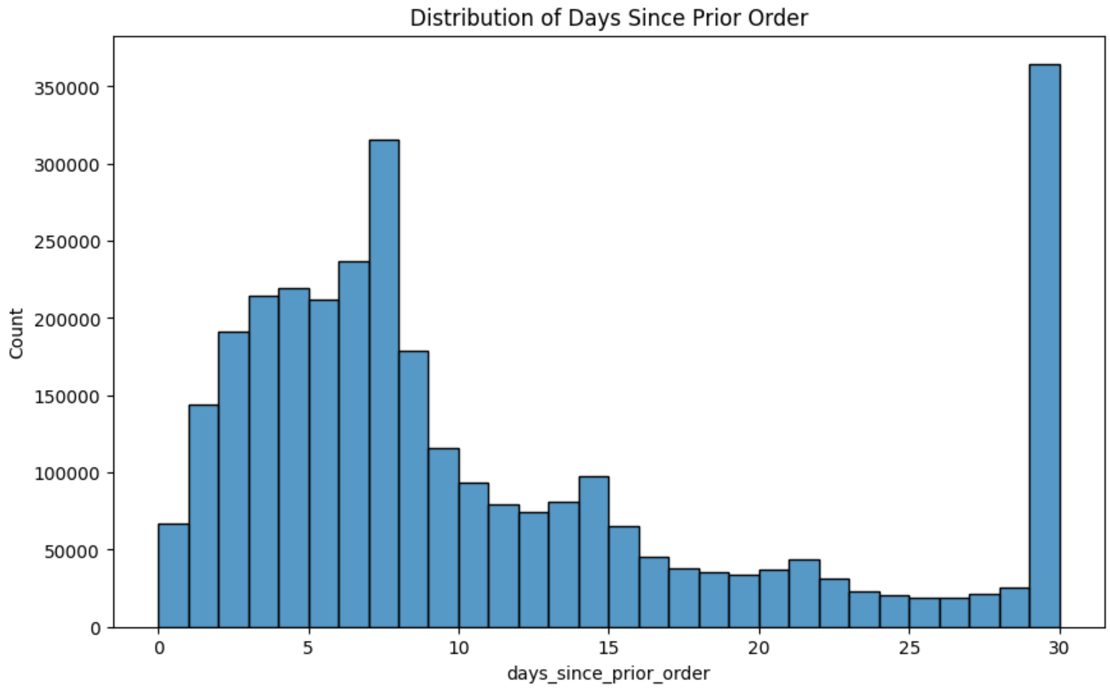
we can see that most people tend to make orders at the beginning of the week

```
plt.figure(figsize=(10,6))
sns.countplot(x='order_hour_of_day', data=orders)
plt.title('Order Count by Hour of the Day')
plt.show()
```



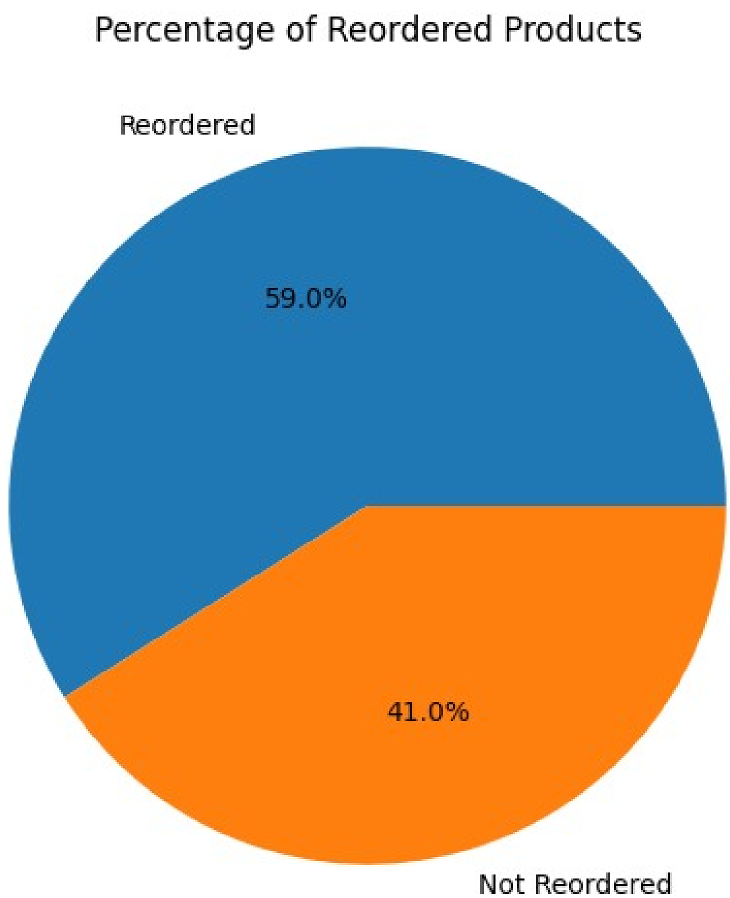

```
plt.figure(figsize=(10,6))
sns.histplot(orders['days_since_prior_order'].dropna(), bins=30,
```

```
kde=False)
plt.title('Distribution of Days Since Prior Order')
plt.show()
```

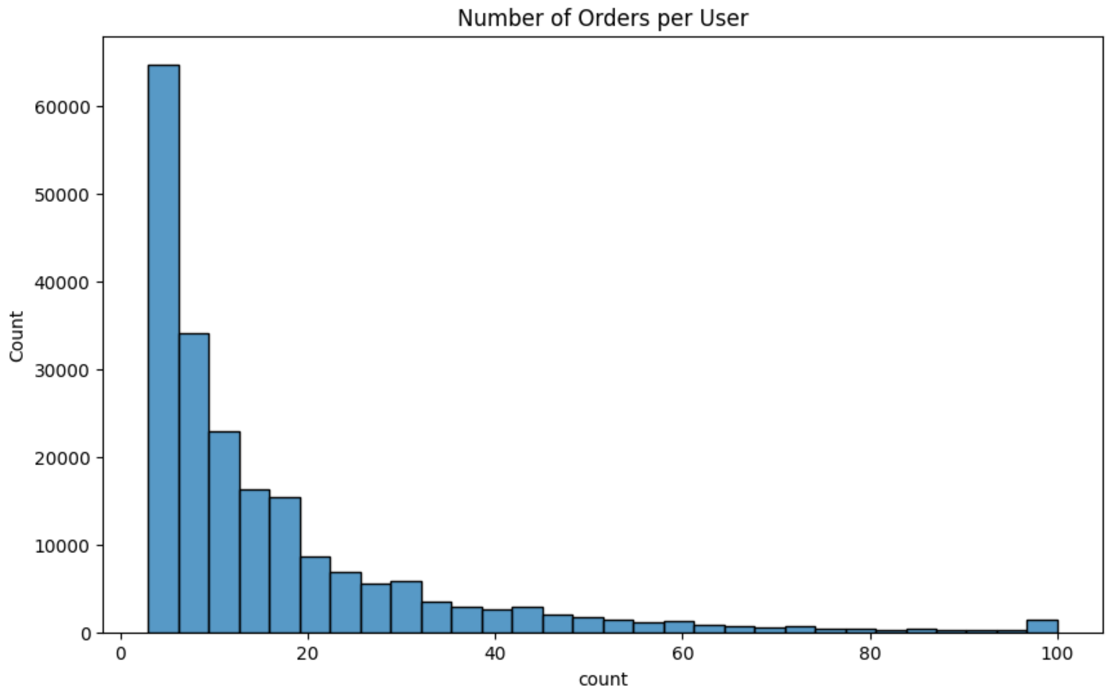


We can say that users tend to place and order every 7 days, 30 days.

```
reorders = order_products__prior['reordered'].value_counts()

plt.figure(figsize=(6,6))
plt.pie(reorders, labels=['Reordered', 'Not Reordered'],
autopct='%1.1f%%')
plt.title('Percentage of Reordered Products')
plt.show()
```

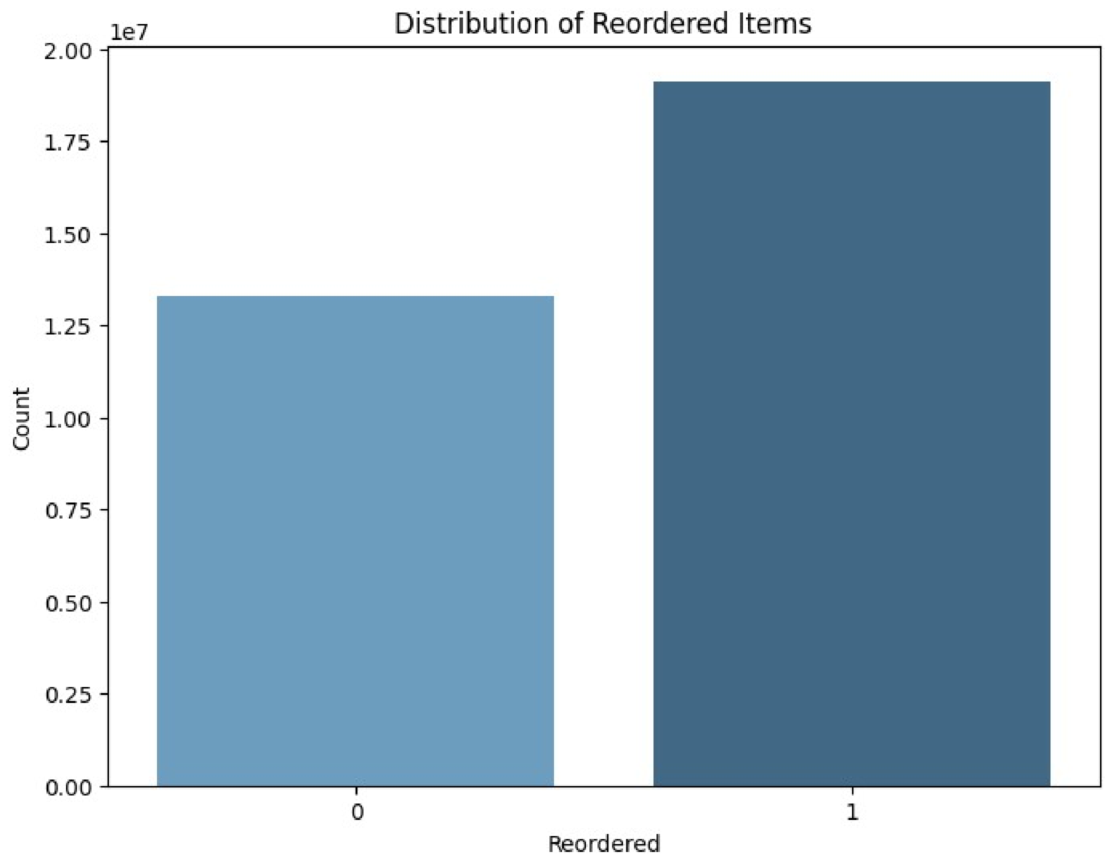



```
orders_per_user = orders['user_id'].value_counts()

plt.figure(figsize=(10,6))
sns.histplot(orders_per_user, bins=30, kde=False)
plt.title('Number of Orders per User')
plt.show()
```



The tail on the right represents the regular customers, who orders frequently, while the peak on left represents the customers who orders less frequently.

```
# Calculate the distribution of reordered values
reorder_counts = order_products__prior['reordered'].value_counts()

# Plot
plt.figure(figsize=(8, 6))
sns.barplot(x=reorder_counts.index, y=reorder_counts.values,
palette="Blues_d")
plt.title('Distribution of Reordered Items')
plt.xlabel('Reordered')
plt.ylabel('Count')
plt.show()
```



Section B: Data Pre-Processing

Merging the data

```
prior_orders = pd.merge(order_products__prior, orders, on='order_id', how='left')

prior_orders.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32434489 entries, 0 to 32434488
Data columns (total 10 columns):
 #   Column                  Dtype
---  ------                  -----
 0   order_id                int64
 1   product_id              int64
 2   add_to_cart_order       int64
 3   reordered               int64
 4   user_id                 int64
 5   eval_set                object
 6   order_number            int64
 7   order_dow               int64
 8   order_hour_of_day       int64
 9   days_since_prior_order  float64
```

```
dtypes: float64(1), int64(8), object(1)
memory usage: 2.4+ GB
```

Downcasting the types of data to save memory

```
prior_orders['order_id'] = pd.to_numeric(prior_orders['order_id'],
downcast='integer')
prior_orders['product_id'] = pd.to_numeric(prior_orders['product_id'],
downcast='integer')
prior_orders['add_to_cart_order'] =
pd.to_numeric(prior_orders['add_to_cart_order'], downcast='integer')
prior_orders['reordered'] = pd.to_numeric(prior_orders['reordered'],
downcast='integer')
prior_orders['user_id'] = pd.to_numeric(prior_orders['user_id'],
downcast='integer')
prior_orders['order_number'] =
pd.to_numeric(prior_orders['order_number'], downcast='integer')
prior_orders['order_dow'] = pd.to_numeric(prior_orders['order_dow'],
downcast='integer')
prior_orders['order_hour_of_day'] =
pd.to_numeric(prior_orders['order_hour_of_day'], downcast='integer')
prior_orders['days_since_prior_order'] =
pd.to_numeric(prior_orders['days_since_prior_order'],
downcast='float')
```

After downcasting:

```
prior_orders.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 32434489 entries, 0 to 32434488
Data columns (total 10 columns):
 #   Column                  Dtype
---  ------                  -----
 0   order_id                int32
 1   product_id              int32
 2   add_to_cart_order       int16
 3   reordered               int8
 4   user_id                 int32
 5   eval_set                object
 6   order_number            int8
 7   order_dow               int8
 8   order_hour_of_day       int8
 9   days_since_prior_order  float32
dtypes: float32(1), int16(1), int32(3), int8(4), object(1)
memory usage: 928.0+ MB
```

Checking and dealing with missing values

```
prior_orders.isnull().sum()

order_id                          0
product_id                        0
add_to_cart_order                 0
```

```
reordered                       0
user_id                         0
eval_set                        0
order_number                    0
order_dow                       0
order_hour_of_day               0
days_since_prior_order    2078068
dtype: int64
```

Imputation: only days_since_prior_order has missing values, we will fill them with -1, which means that the order was made for the first time, 0 means that the order was made in the same after the previous one.

```
# Filling missing values in days_since_prior_order with -1
prior_orders['days_since_prior_order'].fillna(-1, inplace=True)
```

```
print(prior_orders.isnull().sum()/len(prior_orders))
```

```
order_id                  0.0
product_id                0.0
add_to_cart_order         0.0
reordered                 0.0
user_id                   0.0
eval_set                  0.0
order_number              0.0
order_dow                 0.0
order_hour_of_day         0.0
days_since_prior_order    0.0
dtype: float64
```

Featrue Engineering

We want to create features that describes:

1. each user's behaviour.
2. each product.
3. each user's behaviour towards the products.

```
# creating dataframe for the user's features.
userData = prior_orders[['user_id']].drop_duplicates()

# creating dataframe for the product's features.
prodData = prior_orders[['product_id']].drop_duplicates()

# creating dataframe for the user's behaviour towards the products.
prodUserData = prior_orders[['user_id',
'product_id']].drop_duplicates()
```

Creating requested features:

Weekday Purchase Probability

```
# Creating a new feature: probability of a product being ordered on a specific day of the week
total_orders = prior_orders.groupby('product_id')['order_id'].count()
day_of_week_orders = prior_orders.groupby(['product_id', 'order_dow'])
['order_id'].count()
weekday_purchase_prob = day_of_week_orders / total_orders
prodData['probability'] =
weekday_purchase_prob.reset_index(name='weekday_purchase_prob')
['weekday_purchase_prob']
merged_prior = prior_orders.copy()
```

Product Purchase Frequency

```
# Creating a new feature: previous purchases of a product by a user
prodUserData['previous_purchases'] = merged_prior.groupby(['user_id',
'product_id'])['order_id'].transform('count')
```

Days Since Last Order

```
# Creating a new feature: days since last order
merged_prior = merged_prior.sort_values(by=['user_id', 'product_id',
'order_number'])
merged_prior['order_gap'] = merged_prior.groupby(['user_id',
'product_id'])['order_number'].diff()
merged_prior['days_since_last_order'] =
merged_prior.groupby(['user_id', 'product_id'])
['days_since_prior_order'].cumsum()
prodUserData['days_since_last_order'] =
merged_prior['days_since_last_order'] -
merged_prior['days_since_prior_order']
merged_prior = merged_prior.drop(['order_gap'], axis=1)
```

Creating another 7 features:

```
# 1. User's total orders
userData['total_orders'] = merged_prior.groupby('user_id')
['order_number'].transform('max')

# 2. Average basket size
userData['avg_basket_size'] = merged_prior.groupby('user_id')
['product_id'].transform('count') / userData['total_orders']

# 3. Average reorder ratio
userData['avg_reorder_ratio'] = merged_prior.groupby('user_id')
['reordered'].transform('mean')

# 4. Product purchase frequency
prodUserData['product_purchase_frequency'] =
merged_prior.groupby('product_id')['user_id'].transform('count') /
userData['user_id'].nunique()
```

```
# 5. Order_hour_of_day_period (Assuming 0-6 is night, 7-12 is morning,
13-18 is afternoon and 19-23 is evening)
bins = [0, 6, 12, 18, 23]
#Night=1, Morning=2, Afternoon=3, Evening=4
labels = ['0', '1', '2', '3']
userData['order_hour_of_day_period'] =
pd.cut(merged_prior['order_hour_of_day'], bins=bins, labels=labels,
include_lowest=True)

#prod ratio
prodData['prod_ratio'] = merged_prior.groupby('product_id')
['order_id'].transform('count') / merged_prior['order_id']

#average days between orders
userData['average_days_between_orders'] =
merged_prior.groupby('user_id')
['days_since_prior_order'].transform('mean')

userData

          user_id  total_orders  avg_basket_size  avg_reorder_ratio  \
0          202279             8        11.250000           0.477778
9          205970            25        12.920000           0.588235
17         178520            56        16.482143           0.884074
30         156122            52        18.596154           0.840745
56          22352             8        11.375000           0.087912
...           ...           ...              ...                ...
30480369   106087             3         8.333333           0.120000
30557497     9295             3         3.333333           0.400000
30756656   106586             3         5.000000           0.066667
30944334   181902             3        20.333333           0.262295
31084004   179441             3         7.000000           0.285714

         order_hour_of_day_period  average_days_between_orders
0                               1                    19.322222
9                               2                     9.337461
17                              1                     6.631636
30                              2                     6.834540
56                              1                    22.857143
...                           ...                          ...
30480369                        2                     1.800000
30557497                        3                    20.400000
30756656                        1                    15.533334
30944334                        3                     3.901639
31084004                        1                    14.190476

[206209 rows x 6 columns]

prodData
```

```
          product_id  probability    prod_ratio
0              33120     0.108531  9.700000e+03
1              28985     0.215983  3.372450e+04
2               9327     0.146328  3.149500e+03
3              45918     0.141469  3.720000e+02
4              30035     0.159287  2.845000e+02
...              ...          ...           ...
30670613        7726          NaN  6.182264e-07
30954037       43492          NaN  6.125389e-07
30974732       33097          NaN  3.060724e-07
32168896       38977          NaN  2.947113e-07
32242079       23624          NaN  2.940482e-07

[49677 rows x 3 columns]
```

prodUserData

```
          user_id  product_id  previous_purchases
days_since_last_order
0          202279       33120                   5                    -
1.0  \
1          202279       28985                   5
19.0
2          202279        9327                   1
0.0
3          202279       45918                   5
20.0
4          202279       30035                   3
0.0
...           ...         ...                 ...                    .
..
32434480    25247       45309                   1
0.0
32434481    25247       21162                   1
0.0
32434483    25247       35211                   1
0.0
32434485    25247       11352                   1
0.0
32434486    25247        4600                   1
0.0

          product_purchase_frequency
0                           0.094079
1                           0.327090
2                           0.030547
3                           0.003608
4                           0.002759
...                              ...
32434480                    0.005941
```

```
32434481                    0.026977
32434483                    0.000548
32434485                    0.034281
32434486                    0.012730

[13307953 rows x 5 columns]
```

Transformation - Normalizing, and Splitting the new Features to numerical and catagorical.

```
def normalize(df,k):
    for col in df.columns[k:]:
        if len(df[col].unique()) <= 25 or col.endswith('dow') or
col.endswith('hour') or col.endswith('period') or
col.endswith('preference'):
            df[col] = df[col].astype('category')
        else:
            df[col] = df[col].astype('float32')

#call normalize with userData, prodData, prodUserData
normalize(userData, 1)
normalize(prodData, 1)
normalize(prodUserData, 2)

Normalized
```

Section C: Future Order Prediction

Creating Train and Test Dataframes

```
#merge orders with target
final = pd.merge(target, orders, on='order_id', how='left')

final

         order_id  product_id  was_in_order  user_id eval_set
order_number
0         1187899       196.0             1        1     test
11  \
1         2757217       196.0             1       67     test
25
2          632715       196.0             1      676    train
12
3         1167274       196.0             1      760     test
5
4         3347074       196.0             1      804    train
16
...           ...         ...           ...      ...      ...
...
2959120   3421070      4987.0             0   139822     test
15
2959121   3421070      8230.0             0   139822     test
15
```

```
2959122   3421070     39468.0             0   139822     test
15
2959123   3421070     39139.0             0   139822     test
15
2959124   3421070     48208.0             0   139822     test
15

         order_dow  order_hour_of_day  days_since_prior_order
0                4                  8                    14.0
1                0                 11                     5.0
2                0                 13                    26.0
3                4                 10                     8.0
4                3                 21                     5.0
...            ...                ...                     ...
2959120          6                 10                     8.0
2959121          6                 10                     8.0
2959122          6                 10                     8.0
2959123          6                 10                     8.0
2959124          6                 10                     8.0

[2959125 rows x 9 columns]
```

```
final = final[['user_id', 'eval_set',
'order_id','product_id','was_in_order']]

#merging prodData with order_train_test
order_train_test = pd.merge(final,userData, on='user_id', how='left')

#merging prodData with order_train_test
order_train_test = pd.merge(order_train_test,prodData,
on='product_id', how='left')

#merging prodUserData with order_train_test
order_train_test = pd.merge(order_train_test,prodUserData,
on=['user_id', 'product_id'], how='left')

order_train_test
```

```
         user_id eval_set  order_id  product_id  was_in_order
total_orders
0              1     test   1187899       196.0             1
10.0  \
1             67     test   2757217       196.0             1
24.0
2            676    train    632715       196.0             1
11.0
3            760     test   1167274       196.0             1
4.0
4            804    train   3347074       196.0             1
15.0
...          ...      ...       ...         ...           ...
```

```
...
2959120   139822     test   3421070      4987.0             0
14.0
2959121   139822     test   3421070      8230.0             0
14.0
2959122   139822     test   3421070     39468.0             0
14.0
2959123   139822     test   3421070     39139.0             0
14.0
2959124   139822     test   3421070     48208.0             0
14.0

         avg_basket_size  avg_reorder_ratio order_hour_of_day_period

0               5.900000           0.694915
2  \
1               3.375000           0.716049                        2

2               1.727273           0.631579                        1

3               2.000000           0.375000                        1

4               7.466667           0.732143                        1

...                  ...                ...                      ...

2959120         2.142857           0.633333                        2

2959121         2.142857           0.633333                        2

2959122         2.142857           0.633333                        2

2959123         2.142857           0.633333                        2

2959124         2.142857           0.633333                        2


         average_days_between_orders  probability   prod_ratio
0                          18.457626     0.500000  2753.153809  \
1                           7.283951     0.500000  2753.153809
2                          19.315790     0.500000  2753.153809
3                           7.375000     0.500000  2753.153809
4                          16.178572     0.500000  2753.153809
...                              ...          ...          ...
2959120                    11.066667     0.033333     0.084243
2959121                    11.066667     0.153846    42.982250
2959122                    11.066667     0.250000     5.676349
2959123                    11.066667     0.154472     0.015088
2959124                    11.066667          NaN     0.000065
```

```
         previous_purchases  days_since_last_order
product_purchase_frequency
0                      10.0                   64.0
0.173567
1                      19.0                   95.0
0.173567
2                       7.0                   14.0
0.173567
3                       1.0                    0.0
0.173567
4                       NaN                    NaN
NaN
...                     ...                    ...
...
2959120                 NaN                    NaN
NaN
2959121                 NaN                    NaN
NaN
2959122                 NaN                    NaN
NaN
2959123                 NaN                    NaN
NaN
2959124                 NaN                    NaN
NaN

[2959125 rows x 15 columns]
```

```
#display null ratio
print(order_train_test.isnull().sum()/len(order_train_test))
```

```
user_id                           0.000000
eval_set                          0.000000
order_id                          0.000000
product_id                        0.000000
was_in_order                      0.000000
total_orders                      0.000000
avg_basket_size                   0.000000
avg_reorder_ratio                 0.000000
order_hour_of_day_period          0.000000
average_days_between_orders       0.000000
probability                       0.069912
prod_ratio                        0.000019
previous_purchases                0.703579
days_since_last_order             0.703579
product_purchase_frequency        0.703579
dtype: float64
```

note : it's better to drop the columns that has >50% nulls, but because 2 were given in the homework, we will not delete any.

Distribution of numerical values - before filling NaNs

```
# order_train_test.iloc[:, -10:].hist(bins=50, figsize=(15, 15))

#interpolate using group by user_id lambda x method ffill
order_train_test = order_train_test.groupby('user_id').apply(lambda x:
x.interpolate(method='ffill'))

#filling last nulls with 0
for col in order_train_test.columns[-5:]:
    order_train_test[col].fillna(0, inplace=True)

print(order_train_test.isnull().sum()/len(order_train_test))
```

```
user_id                        0.0
eval_set                       0.0
order_id                       0.0
product_id                     0.0
was_in_order                   0.0
total_orders                   0.0
avg_basket_size                0.0
avg_reorder_ratio              0.0
order_hour_of_day_period       0.0
average_days_between_orders    0.0
probability                    0.0
prod_ratio                     0.0
previous_purchases             0.0
days_since_last_order          0.0
product_purchase_frequency     0.0
dtype: float64
```

Distribution of numerical values - after filling NaNs

```
# order_train_test.iloc[:, -10:].hist(bins=50, figsize=(15, 15))
```

Probability: The statistics remain roughly the same except that the mean becomes negative (approaches zero). The negative skewness suggests a longer tail on the left side of the distribution.

Previous Purchases: Similarly, the mean is near zero and standard deviation is near 1, which means data are standardized. The positive skewness indicates a longer tail on the right side, suggesting more customers with lower previous purchases.

User Total Orders: The data distribution is similar to that of Previous Purchases, but it is negatively skewed now, indicating a longer tail on the left side.

Avg Days Between Orders: The skewness is negative, suggesting that there are more instances of shorter average days between orders. The low kurtosis suggests the distribution is platykurtic (less outliers or extreme values).

Avg Basket Size: The skewness is slightly negative suggesting a longer tail on the left side of the distribution. The positive kurtosis indicates a leptokurtic distribution, suggesting there may be more extreme values or outliers.

Avg Reorder Ratio: The distribution now shows a negative skewness, indicating a longer tail on the left side. The positive kurtosis suggests more outliers in the data.

Product Purchase Frequency: The skewness is positive and quite large, indicating a longer tail on the right side. The kurtosis is also quite large, suggesting that the distribution has heavy tails and more outliers.

Product Reorder Ratio: The distribution is negatively skewed, suggesting a longer tail on the left side. The kurtosis is greater than zero, indicating a leptokurtic distribution with more outliers or extreme values.

User Product Reorder Ratio: The negative skewness suggests a longer tail on the left side of the distribution. The kurtosis being negative suggests a platykurtic distribution, with fewer outliers or extreme values than a normal distribution.

```
we can reject the null hypothesis of the data being normally
distributed.
This suggests that although the standardization has adjusted the scale
of the data, it hasn't made the data follow a normal distribution.
```

One-Hot Encoding

```
import pandas as pd

def analyze_and_encode(df):
    for col in df.columns:
        if df[col].dtype == 'category':
            print("column: ", col,"unique value counts: ",
df[col].value_counts())

    # Applying one-hot encoding to 'order_hour_of_day_period'
            df_encoded = pd.get_dummies(df, columns=[col])
    #drop the original column
    return df_encoded

#call analyze_and_encode function
order_train_test = analyze_and_encode(order_train_test)
```

```
column:  order_hour_of_day_period unique value counts:
order_hour_of_day_period
2    1366584
1    1137108
3     376152
0      79281
Name: count, dtype: int64
```

```
order_train_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 2959125 entries, (1, 0) to (206209, 1510784)
Data columns (total 18 columns):
 #   Column                       Dtype
```

```
---  ------                       -----
 0   user_id                      int64
 1   eval_set                     object
 2   order_id                     int64
 3   product_id                   float64
 4   was_in_order                 int64
 5   total_orders                 float32
 6   avg_basket_size              float32
 7   avg_reorder_ratio            float32
 8   average_days_between_orders  float32
 9   probability                  float32
 10  prod_ratio                   float32
 11  previous_purchases           float32
 12  days_since_last_order        float32
 13  product_purchase_frequency   float32
 14  order_hour_of_day_period_0   bool
 15  order_hour_of_day_period_1   bool
 16  order_hour_of_day_period_2   bool
 17  order_hour_of_day_period_3   bool
dtypes: bool(4), float32(9), float64(1), int64(3), object(1)
memory usage: 340.4+ MB
```

```
order_train_test
```

```
                 user_id eval_set  order_id  product_id  was_in_order

user_id

1       0              1     test   1187899       196.0             1
\
        2272           1     test   1187899     26088.0             1

        2408           1     test   1187899     26405.0             1

        2513           1     test   1187899     10258.0             1

        18097          1     test   1187899     13032.0             1

...                  ...      ...       ...         ...           ...

206209  1510780   206209    train    272231     24838.0             0

        1510781   206209    train    272231     14678.0             0

        1510782   206209    train    272231     31717.0             0

        1510783   206209    train    272231     49286.0             0

        1510784   206209    train    272231      1184.0             0
```

```
                 total_orders  avg_basket_size  avg_reorder_ratio  
user_id                                                            
1       0                10.0         5.900000           0.694915  \
        2272             10.0         5.900000           0.694915   
        2408             10.0         5.900000           0.694915   
        2513             10.0         5.900000           0.694915   
        18097            10.0         5.900000           0.694915   
...                       ...              ...                ...   
206209  1510780          13.0         9.923077           0.472868   
        1510781          13.0         9.923077           0.472868   
        1510782          13.0         9.923077           0.472868   
        1510783          13.0         9.923077           0.472868   
        1510784          13.0         9.923077           0.472868   

                 average_days_between_orders  probability  
prod_ratio  
user_id                                                    

1       0                          18.457626     0.500000  
2753.153809  \
        2272                       18.457626     0.146739  
6.403553   
        2408                       18.457626     0.111111  
0.267519   
        2513                       18.457626     0.196078  
4.334076   
        18097                      18.457626     0.500000  
9.692507   
...                                      ...          ...            ..
.   
206209  1510780                    18.131783     0.166667  
16523.000000   
        1510781                    18.131783     0.046512  
145.525177   
        1510782                    18.131783     0.154472  
6952.399902   
        1510783                    18.131783     0.154472  
0.000055   
        1510784                    18.131783     0.140401  
0.001093   

                 previous_purchases  days_since_last_order  
user_id                                                     
1       0                      10.0                   64.0  \
        2272                    2.0                   -1.0   
        2408                    2.0                   -1.0   
        2513                    9.0                   65.0   
        18097                   3.0                   15.0   
```

```
...                             ...                   ...
206209  1510780                10.0                  39.0
        1510781                10.0                  39.0
        1510782                10.0                  39.0
        1510783                10.0                  39.0
        1510784                10.0                  39.0

                 product_purchase_frequency
order_hour_of_day_period_0
user_id

1       0                          0.173567
False  \
        2272                       0.012235
False
        2408                       0.005887
False
        2513                       0.009437
False
        18097                      0.018190
False
...                                     ...                           ..
.
206209  1510780                    0.014917
False
        1510781                    0.014917
False
        1510782                    0.014917
False
        1510783                    0.014917
False
        1510784                    0.014917
False

                 order_hour_of_day_period_1
order_hour_of_day_period_2
user_id

1       0                             False
True  \
        2272                          False
True
        2408                          False
True
        2513                          False
True
        18097                         False
True
...                                     ...                           ..
.
```

```
206209  1510780                          False
True
        1510781                          False
True
        1510782                          False
True
        1510783                          False
True
        1510784                          False
True

                 order_hour_of_day_period_3
user_id
1       0                                False
        2272                             False
        2408                             False
        2513                             False
        18097                            False
...                                        ...
206209  1510780                          False
        1510781                          False
        1510782                          False
        1510783                          False
        1510784                          False

[2959125 rows x 18 columns]
```

Splitting that data to train and test sets and splitting the feature from the labels

```
# #split train into X and y
# X = order_train_test.drop(['was_in_order'], axis=1)
# y = order_train_test['was_in_order']

# #import smote
# from imblearn.over_sampling import SMOTE
# sm = SMOTE(random_state=42)
# X_res, y_res = sm.fit_resample(X, y)

# #do the same

train_data = order_train_test[order_train_test['eval_set'] == 'train']
train_data = train_data.set_index(['user_id', 'product_id'])
train_data.drop(['eval_set', 'order_id'], axis=1, inplace=True)
train_data =train_data.reset_index()

test_data = order_train_test[order_train_test['eval_set'] == 'test']
test_data = test_data.set_index(['user_id', 'product_id'])
test_data.drop(['eval_set', 'order_id'], axis=1, inplace=True)
test_data = test_data.reset_index()
```

```
#split train into X and y
X = train_data.drop(['was_in_order'], axis=1)
y = train_data['was_in_order']

#import smote
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X, y)

X_test = test_data.drop(['was_in_order'], axis=1)
```

```
y_res.value_counts()
```

```
was_in_order
1    1102152
0    1102152
Name: count, dtype: int64
```

Synthecizing the data so the label is split 50/50

```
y_train = train_data['was_in_order']
X_train = train_data.drop(['was_in_order'], axis=1)

y_test = test_data['was_in_order']
X_test = test_data.drop(['was_in_order'], axis=1)

#split train into X and y

#import smote
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_train, y_train = sm.fit_resample(X_train, y_train)
X_test, y_test = sm.fit_resample(X_test, y_test)


X_test.drop(['user_id', 'product_id'], axis=1, inplace=True)
X_train.drop(['user_id', 'product_id'], axis=1, inplace=True)
```

```
#value counts
y_train.value_counts()
```

```
was_in_order
1    1102152
0    1102152
Name: count, dtype: int64
```

```
#value counts
y_test.value_counts()
```

```
was_in_order
1    472356
```

```
0    472356
Name: count, dtype: int64
```

we will use 3 different metrics to evaluate the models: (ref: ML Example, Moodle)

1. Accuracy: refers to the ability to correctly predict both positive and negative obseravtions.
2. Sensitivity: refers to the ability to correctly predict positive obseravtions.
3. Specificity: refers to the ability to correctly predict negative obseravtions.

```
def get_metrics(y_test, y_pred):

    # actual_pos = y_test == 1
    # actual_neg = y_test == 0

    # # get confusion matrix
    # mat = metrics.confusion_matrix(y_test, y_pred)
    # true_neg, false_pos, false_neg, true_pos = mat.ravel()

    mat = metrics.confusion_matrix(y_test, y_pred)

    # handle case when confusion matrix is a single value
    if mat.shape == (1, 1):
        total_samples = mat.item()
        actual_pos = false_pos = false_neg = true_neg = total_samples
    else:
        actual_pos, false_pos, false_neg, true_neg = mat.ravel()


    # calculate sensitivity and specificity
    sensitivity = round(actual_pos / (actual_pos+false_neg), 3)
    specificity = round(true_neg / (true_neg + false_pos), 3)
    accuracy = accuracy_score(y_test, y_pred)
    F1_score = f1_score(y_test, y_pred)
    Precision = precision_score(y_test, y_pred)
    Recall = recall_score(y_test, y_pred)

    return sensitivity, specificity, accuracy, F1_score, Precision, 
Recall
```

We are using 3 different models to predict the future orders:

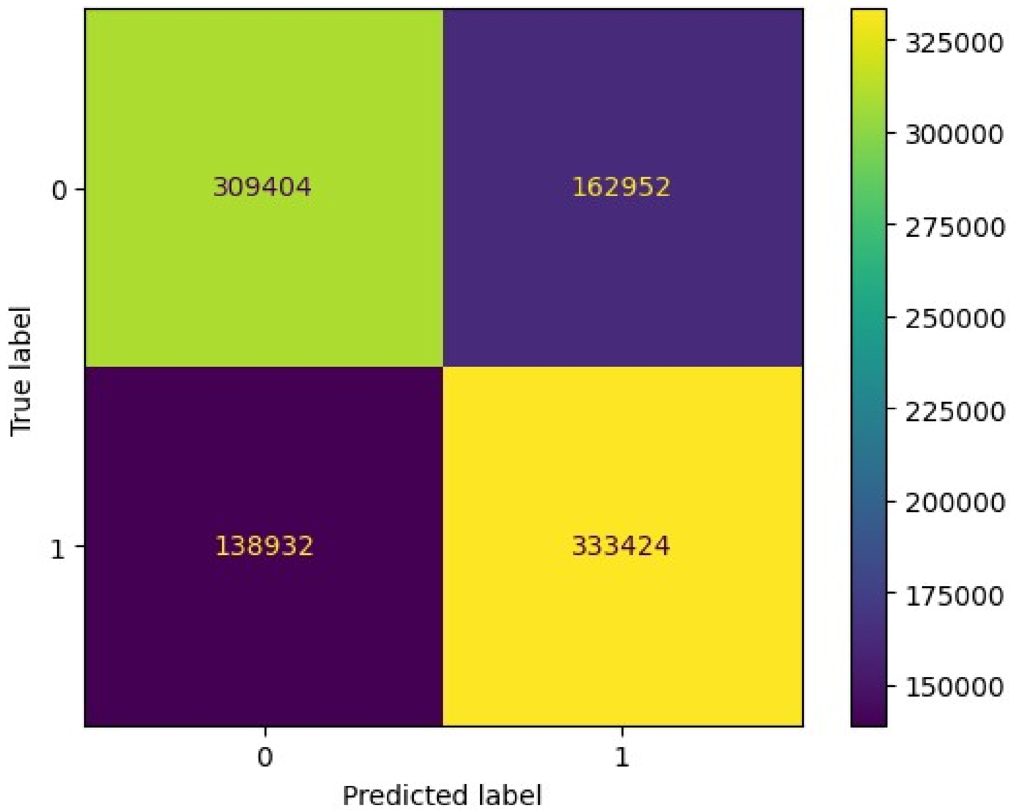
Ada Boost Classifier

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import AdaBoostClassifier

# Set the parameters by cross-validation
param_grid = {'n_estimators': [10, 25],  'learning_rate': [0.01, 0.3]}
```

```python
# Instantiate the grid search model
grid_search_ab = GridSearchCV(estimator = AdaBoostClassifier(),
param_grid = param_grid, cv = 3)

# Fit the grid search to the data
grid_search_ab.fit(X_train, y_train)

# Print the best parameters
print("Best parameters: ", grid_search_ab.best_params_)
y_pred = grid_search_ab.predict(X_test)

# Display metrics
sensitivity, specificity, accuracy, F1_score, Precision, Recall =
get_metrics(y_test, y_pred)
ab_df = pd.DataFrame([accuracy, sensitivity, specificity, F1_score,
Precision, Recall]).T
ab_df = ab_df.rename(index={0: 'Ada Boost Classifier'}, columns={0:
'Accuracy', 1: 'Sensitivity', 2: 'Specificity' , 3: 'F1_score', 4:
'Precision', 5: 'Recall'})
ab_df
```

```
Best parameters:  {'learning_rate': 0.3, 'n_estimators': 25}

                      Accuracy  Sensitivity  Specificity  F1_score
Precision
Ada Boost Classifier  0.680449         0.69        0.672  0.688372
0.671717  \

                        Recall
Ada Boost Classifier  0.705874
```

```python
comparison_df = pd.DataFrame(columns=['Model', 'Accuracy',
'Sensitivity', 'Specificity', 'F1_score', 'Precision', 'Recall'])
row = pd.Series({'Model': 'Ada Boost Classifier', 'Accuracy':
accuracy, 'Sensitivity': sensitivity, 'Specificity': specificity,
'F1_score': F1_score, 'Precision': Precision, 'Recall': Recall})
comparison_df.loc[0] = row
del accuracy, sensitivity, specificity, F1_score, Precision, Recall

cm = confusion_matrix(y_test, y_pred)
# Create the ConfusionMatrixDisplay object
cmd = ConfusionMatrixDisplay(cm)

# Plot the confusion matrix
cmd.plot()
plt.show()
```



Decision Tree

```
# defining the model
clf = DecisionTreeClassifier()

# define grid search
paramGrid = {
    #fill more on stronger PCs
    "max_depth": [3, 5],
    "min_samples_split": [2],
    "min_samples_leaf": [1],
    "criterion": ["gini", "entropy"],
}
grid_search_dt = GridSearchCV(estimator=clf, param_grid=paramGrid,
cv=3, scoring='accuracy')

# fit the model
grid_search_dt.fit(X_train, y_train)

# After the fitting process, print the best parameters and the best
score
print("Best Parameters: ", grid_search_dt.best_params_)

# Use the grid search (with best parameters) to make predictions on
```

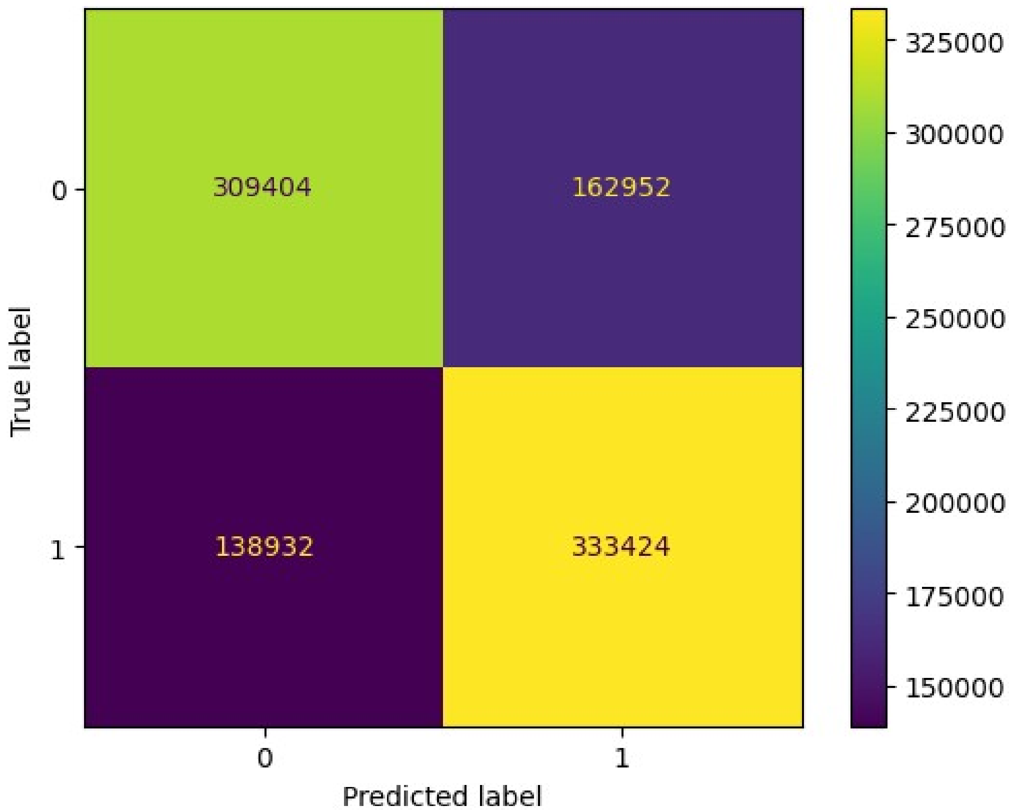
```
the test set

best = grid_search_dt.best_estimator_
y_pred = best.predict(X_test)
print(y_pred)
```

```
Best Parameters:  {'criterion': 'gini', 'max_depth': 5,
'min_samples_leaf': 1, 'min_samples_split': 2}
[1 0 0 ... 1 0 1]
```

```
# display metrics
sensitivity, specificity, accuracy, F1_score, Precision, Recall =
get_metrics(y_test, y_pred)
dt_df = pd.DataFrame([accuracy, sensitivity, specificity, F1_score,
Precision, Recall]).T
dt_df = dt_df.rename(index={0: 'Decision Tree Classifier'},
columns={0: 'Accuracy', 1: 'Sensitivity', 2: 'Specificity' , 3:
'F1_score', 4: 'Precision', 5: 'Recall'})
dt_df
```

```
                          Accuracy  Sensitivity  Specificity  F1_score

Decision Tree Classifier  0.715672        0.739        0.696   0.72894
\

                          Precision   Recall
Decision Tree Classifier   0.696441  0.76462
```

```
row = pd.Series({'Model': 'Decision Tree Classifier', 'Accuracy':
accuracy, 'Sensitivity': sensitivity, 'Specificity': specificity,
'F1_score': F1_score, 'Precision': Precision, 'Recall': Recall})
comparison_df.loc[1] = row
del accuracy, sensitivity, specificity, F1_score, Precision, Recall

cm = confusion_matrix(y_test, y_pred)
# Create the ConfusionMatrixDisplay object
cmd = ConfusionMatrixDisplay(cm)

# Plot the confusion matrix
cmd.plot()
plt.show()
```



XGB

```
paramGrid = {"max_depth":[5,8], "colsample_bytree":[0.3,0.5]}

# Define the XGBoost classifier
xgbc = XGBClassifier(objective='binary:logistic',
eval_metric='logloss', n_estimators=10)

# Apply GridSearchCV for parameter tuning
gridsearch = GridSearchCV(xgbc, paramGrid, cv=3, verbose=2, n_jobs=1)

model = gridsearch.fit(X_train, y_train)
print("The best parameters are: /n",  gridsearch.best_params_)
model = gridsearch.best_estimator_
```

```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
[CV] END ..................colsample_bytree=0.3, max_depth=5; total
time=   2.4s
[CV] END ..................colsample_bytree=0.3, max_depth=5; total
time=   2.4s
[CV] END ..................colsample_bytree=0.3, max_depth=5; total
time=   2.3s
[CV] END ..................colsample_bytree=0.3, max_depth=8; total
time=   3.0s
```

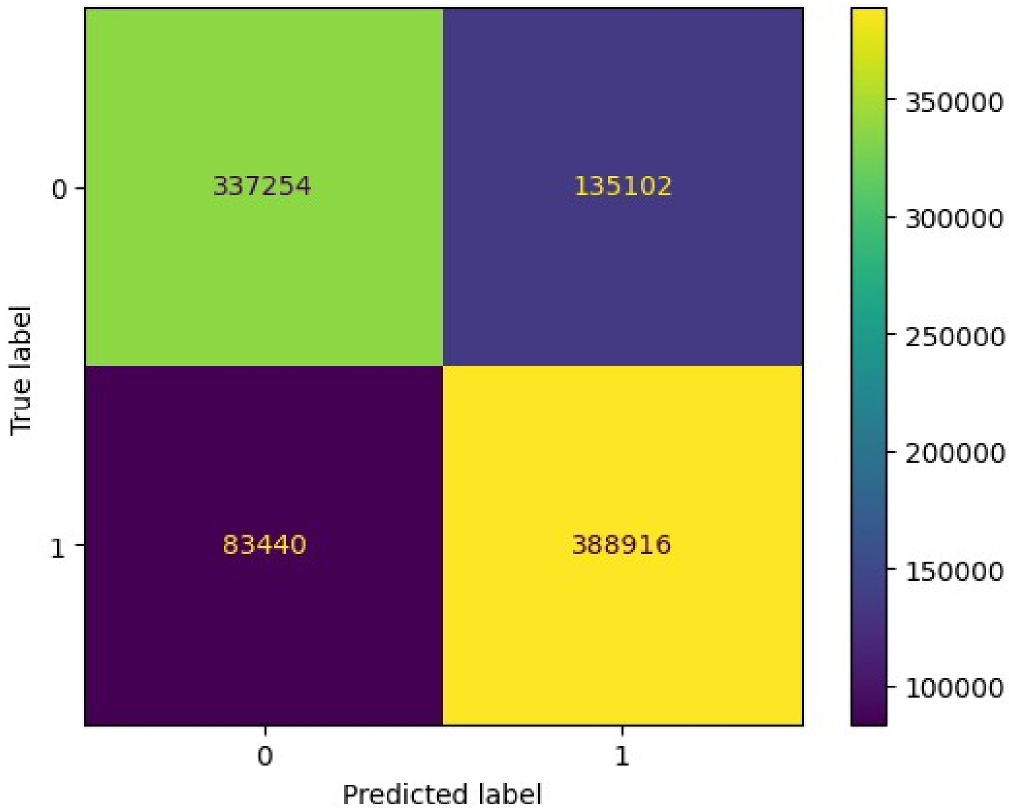
```
[CV] END ..................colsample_bytree=0.3, max_depth=8; total
time=   3.0s
[CV] END ..................colsample_bytree=0.3, max_depth=8; total
time=   2.9s
[CV] END ..................colsample_bytree=0.5, max_depth=5; total
time=   2.7s
[CV] END ..................colsample_bytree=0.5, max_depth=5; total
time=   2.7s
[CV] END ..................colsample_bytree=0.5, max_depth=5; total
time=   2.6s
[CV] END ..................colsample_bytree=0.5, max_depth=8; total
time=   3.7s
[CV] END ..................colsample_bytree=0.5, max_depth=8; total
time=   3.6s
[CV] END ..................colsample_bytree=0.5, max_depth=8; total
time=   3.5s
The best parameters are: /n {'colsample_bytree': 0.5, 'max_depth': 8}
```

```
y_pred = model.predict(X_test)
print(y_pred)

# display metrics
sensitivity, specificity, accuracy, F1_score, Precision, Recall =
get_metrics(y_test, y_pred)
gb_df = pd.DataFrame([accuracy, sensitivity, specificity, F1_score,
Precision, Recall]).T
gb_df = gb_df.rename(index={0: 'Gradient Boosting Classifier'},
columns={0: 'Accuracy', 1: 'Sensitivity', 2: 'Specificity' , 3:
'F1_score', 4: 'Precision', 5: 'Recall'})
gb_df
```

```
[1 1 1 ... 1 1 1]

                              Accuracy  Sensitivity  Specificity
F1_score
Gradient Boosting Classifier  0.768668        0.802        0.742
0.780663  \

                              Precision    Recall
Gradient Boosting Classifier   0.742181  0.823354
```

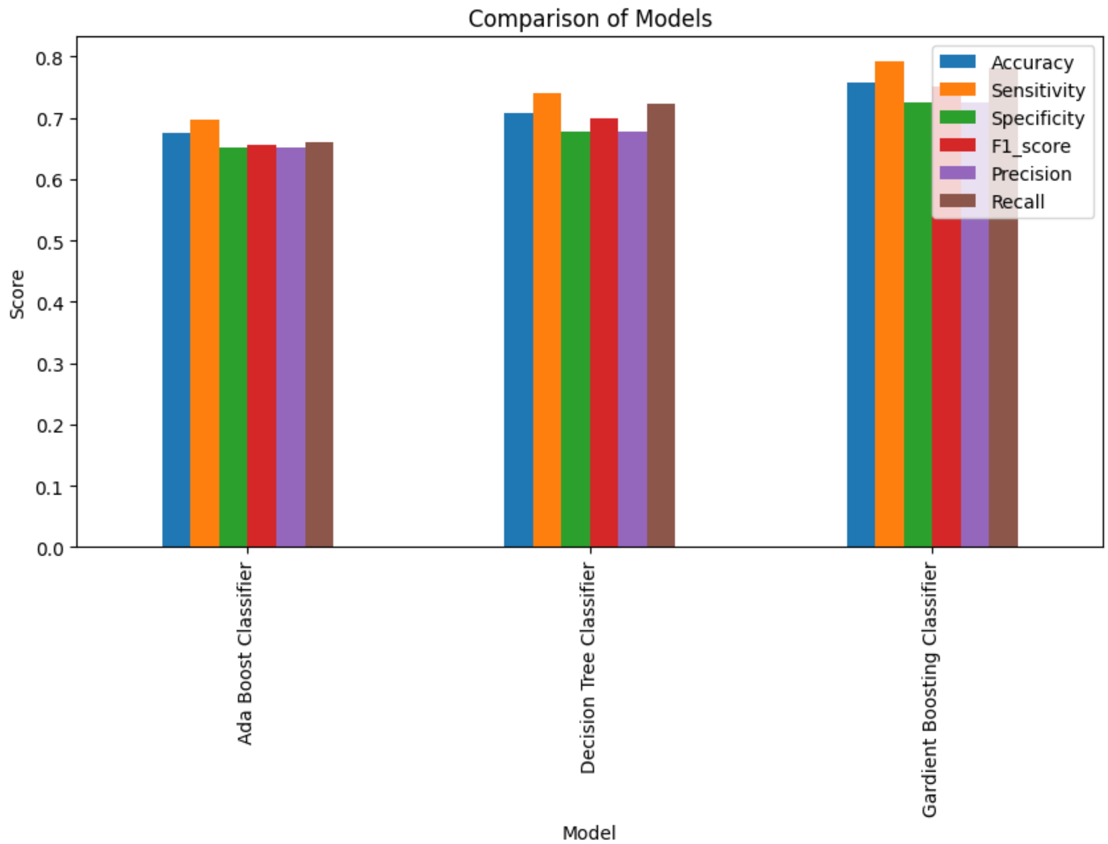
```
row = pd.Series({'Model': 'Gardient Boosting Classifier', 'Accuracy':
accuracy, 'Sensitivity': sensitivity, 'Specificity': specificity,
'F1_score': F1_score, 'Precision': Precision, 'Recall': Recall})
comparison_df.loc[2] = row

cm = confusion_matrix(y_test, y_pred)
# Create the ConfusionMatrixDisplay object
cmd = ConfusionMatrixDisplay(cm)

# Plot the confusion matrix
```

```
cmd.plot()
plt.show()
```



Comparing the results of the models

```
comparison_df.plot(kind='bar', x='Model', y=['Accuracy',
'Sensitivity', 'Specificity', 'F1_score', 'Precision', 'Recall'],
figsize=(10,5))
plt.title('Comparison of Models')
plt.ylabel('Score')
plt.show()
```



Section D: Clustering

Creating new features that describes customers buying behavior

```
clus_prior_orders = pd.merge(order_products__prior, orders,
on='order_id', how='left')
clus_prior_orders = pd.merge(clus_prior_orders, products,
on='product_id', how='left')
clus_prior_orders = clus_prior_orders[['user_id', 'product_id',
'aisle_id', 'department_id', 'order_id', 'order_dow',
'order_hour_of_day', 'days_since_prior_order']]


#calculate favorite day of week for each user
user_dow = clus_prior_orders.groupby(['user_id',
'order_dow']).size().reset_index(name='count')
user_dow = user_dow.sort_values(by=['user_id', 'count'],
ascending=False)
user_dow = user_dow.drop_duplicates(subset=['user_id'], keep='first')
user_dow = user_dow[['user_id', 'order_dow']]
user_dow = user_dow.rename(columns={'order_dow': 'favorite_dow'})
clus_prior_orders = pd.merge(clus_prior_orders, user_dow,
on='user_id', how='left')
```

```python
#favourite department for each user
user_department = clus_prior_orders.groupby(['user_id',
'department_id']).size().reset_index(name='count')
user_department = user_department.sort_values(by=['user_id', 'count'],
ascending=False)
user_department = user_department.drop_duplicates(subset=['user_id'],
keep='first')
user_department = user_department[['user_id', 'department_id']]
user_department = user_department.rename(columns={'department_id':
'favorite_department'})
clus_prior_orders = pd.merge(clus_prior_orders, user_department,
on='user_id', how='left')


clus_prior_orders = clus_prior_orders[['user_id',
'favorite_dow','favorite_department']]
clus_prior_orders =
clus_prior_orders.drop_duplicates(subset=['user_id'], keep='first')

clus_prior_orders = pd.merge(clus_prior_orders, userData,
on='user_id', how='left')

clus_prior_orders
```

```
        user_id  favorite_dow  favorite_department  total_orders  
0        202279             5                   13           8.0  \
1        205970             6                    4          25.0   
2        178520             1                   16          56.0   
3        156122             3                   16          52.0   
4         22352             1                    4           8.0   
...         ...           ...                  ...           ...   
206204   106087             6                    1           3.0   
206205     9295             6                   16           3.0   
206206   106586             5                   13           3.0   
206207   181902             0                    4           3.0   
206208   179441             0                    4           3.0   

        avg_basket_size  avg_reorder_ratio order_hour_of_day_period  
0             11.250000           0.477778                        1  \
1             12.920000           0.588235                        2   
2             16.482143           0.884074                        1   
3             18.596153           0.840745                        2   
4             11.375000           0.087912                        1   
...                 ...                ...                      ...   
206204         8.333333           0.120000                        2   
206205         3.333333           0.400000                        3   
206206         5.000000           0.066667                        1   
206207        20.333334           0.262295                        3   
206208         7.000000           0.285714                        1   
```

```
        average_days_between_orders
0                         19.322222
1                          9.337461
2                          6.631636
3                          6.834540
4                         22.857143
...                             ...
206204                     1.800000
206205                    20.400000
206206                    15.533334
206207                     3.901639
206208                    14.190476

[206209 rows x 8 columns]
```

```
clus_prior_orders = clus_prior_orders.drop(columns=['user_id'])
```

Might add more features

```
#import Kmeans and cdists
from sklearn.cluster import KMeans
from scipy.spatial.distance import cdist

def elbow_met(df):

    # k means determine k
    distortions = []
    K = range(1,10)
    for k in K:
        kmeanModel =
KMeans(n_clusters=k,n_init=10).fit(clus_prior_orders)
        kmeanModel.fit(clus_prior_orders)
        distortions.append(sum(np.min(cdist(clus_prior_orders,
kmeanModel.cluster_centers_, 'euclidean'), axis=1)) /
clus_prior_orders.shape[0])

    # Plot the elbow
    plt.plot(K, distortions, 'bx-')
    plt.xlabel('k')
    plt.ylabel('Within groups sum of squares')
    plt.title('The Elbow Method showing the optimal k')
    plt.show()

clus_prior_orders
```

```
        favorite_dow  favorite_department  total_orders
avg_basket_size
0                  5                   13           8.0
11.250000  \
1                  6                    4          25.0
12.920000
```

```
2                1                    16           56.0
16.482143
3                3                    16           52.0
18.596153
4                1                     4            8.0
11.375000
...            ...                   ...            ...                 .
..
206204           6                     1            3.0
8.333333
206205           6                    16            3.0
3.333333
206206           5                    13            3.0
5.000000
206207           0                     4            3.0
20.333334
206208           0                     4            3.0
7.000000

        avg_reorder_ratio order_hour_of_day_period
0                0.477778                        1  \
1                0.588235                        2
2                0.884074                        1
3                0.840745                        2
4                0.087912                        1
...                   ...                      ...
206204           0.120000                        2
206205           0.400000                        3
206206           0.066667                        1
206207           0.262295                        3
206208           0.285714                        1

        average_days_between_orders
0                         19.322222
1                          9.337461
2                          6.631636
3                          6.834540
4                         22.857143
...                             ...
206204                     1.800000
206205                    20.400000
206206                    15.533334
206207                     3.901639
206208                    14.190476

[206209 rows x 7 columns]
```

```
elbow_met(clus_prior_orders)
```

```
-----------------------------------------------------------------------
----
ValueError                                Traceback (most recent call
last)
Cell In[70], line 1
----> 1 elbow_met(clus_prior_orders)

Cell In[68], line 13, in elbow_met(df)
     11     kmeanModel =
KMeans(n_clusters=k,n_init=10).fit(clus_prior_orders)
     12     kmeanModel.fit(clus_prior_orders)
---> 13     distortions.append(sum(np.min(cdist(clus_prior_orders,
kmeanModel.cluster_centers_, 'euclidean'), axis=1)) /
clus_prior_orders.shape[0])
     15 # Plot the elbow
     16 plt.plot(K, distortions, 'bx-')

File
/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/
site-packages/scipy/spatial/distance.py:2939, in cdist(XA, XB, metric,
out, **kwargs)
   2937 if metric_info is not None:
   2938     cdist_fn = metric_info.cdist_func
-> 2939     return cdist_fn(XA, XB, out=out, **kwargs)
   2940 elif mstr.startswith("test_"):
   2941     metric_info = _TEST_METRICS.get(mstr, None)

ValueError: Unsupported dtype object
```

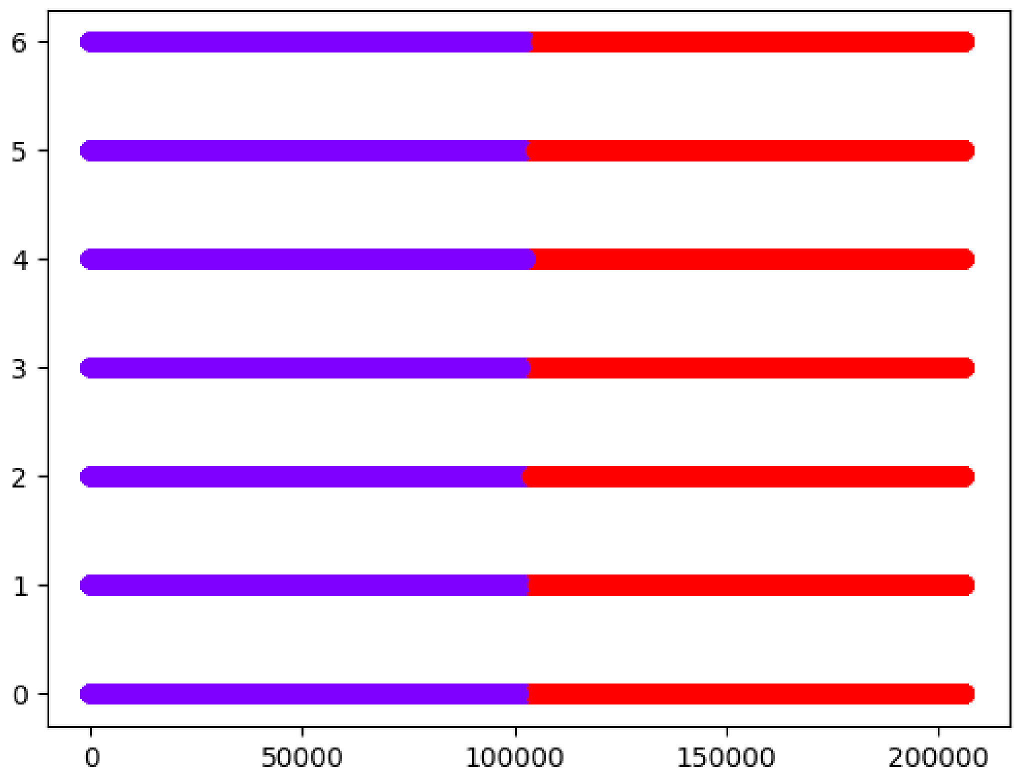
```
kmeans = KMeans(n_clusters=2,
random_state=0,n_init=10).fit(clus_prior_orders)
```

```
centroids = kmeans.cluster_centers_
print(centroids)
```

```
[[5.16770000e+04 2.52050739e+00 7.34059969e+00]
 [1.54781500e+05 2.52199191e+00 7.37228747e+00]]
```

```
#run kmeans with 2 and plot
kmeans = KMeans(n_clusters=2,
random_state=0,n_init=10).fit(clus_prior_orders)
plt.scatter(clus_prior_orders.iloc[:,0], clus_prior_orders.iloc[:,1],
c=kmeans.labels_, cmap='rainbow')
```

```
<matplotlib.collections.PathCollection at 0x13f05b79d50>
```



BONUS

PCA - 2 features

```
#apply pca for User data
from sklearn.decomposition import PCA
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(cluster_prior)
principalDf = pd.DataFrame(data = principalComponents

                , columns = ['principal component 1', 'principal
component 2'])

principalDf
```

```
----------------------------------------------------------------------
-----
NameError                                 Traceback (most recent call
last)
Cell In[88], line 4
      2 from sklearn.decomposition import PCA
      3 pca = PCA(n_components=2)
----> 4 principalComponents = pca.fit_transform(cluster_prior)
      5 principalDf = pd.DataFrame(data = principalComponents
      6
```

```
      7                  , columns = ['principal component 1',
'principal component 2'])
      9 principalDf

NameError: name 'cluster_prior' is not defined
```

```python
#plot PCA
plt.scatter(principalDf.iloc[:, 0], principalDf.iloc[:, 1], c=labels,
s=50, cmap='viridis')
```

```
<matplotlib.collections.PathCollection at 0x45600e3d0>
```