Importing libraries and loading data

In [1]:
```
import numpy as np
import pandas as pd
import os
import statsmodels.formula.api as smf
import warnings
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import RandomForestRegressor
warnings.filterwarnings('ignore')
```

In [2]:
```
click = pd.read_csv("JD_click_data.csv")
order = pd.read_csv("JD_order_data.csv")
sku = pd.read_csv("JD_sku_data.csv")
user = pd.read_csv("JD_user_data.csv")
```

Data preprocessing ¶

creating a feature base on how many times a sku is clicked

In [3]:
```
click_count = click.groupby('sku_ID').size().reset_index(name='clic
click_and_count = pd.merge(click,click_count,on='sku_ID')
print(click_and_count.shape)
click_and_count.head()
```

```
(20214515, 5)
```

Out[3]:

	sku_ID	user_ID	request_time	channel	click_count_on_sku
0	a234e08c57	4c3d6d10c2	2018-03-01 23:57:53	wechat	624
1	a234e08c57	405246945e	2018-03-01 10:10:03	pc	624
2	a234e08c57	405246945e	2018-03-01 09:47:16	pc	624
3	a234e08c57	cb47a16a92	2018-03-01 09:39:32	pc	624
4	a234e08c57	34e76b1af1	2018-03-01 12:18:01	app	624

creating a feature base on how many skus are in each brand id

In [4]:
```
sku=sku.drop(columns=["attribute1","attribute2","activate_date","de
brand_count = sku.groupby('brand_ID').size().reset_index(name='sku_
sku_and_brand_count = pd.merge(sku,brand_count,on='brand_ID')
print(sku_and_brand_count.shape)
sku_and_brand_count.head()
```

(31868, 4)

Out[4]:

	sku_ID	type	brand_ID	sku_count_on_brand
0	a234e08c57	1	c3ab4bf4d9	4
1	9f785be866	1	c3ab4bf4d9	4
2	b6866bf66f	1	c3ab4bf4d9	4
3	0be89cc509	1	c3ab4bf4d9	4
4	6449e1fd87	1	1d8b4b4c63	26

merging click count and sku count in each brand

In [5]:
```
click_and_sku = pd.merge(click_and_count,sku_and_brand_count,on='sk
print(click_and_sku.shape)
click_and_sku.head()
```

(20214548, 8)

Out[5]:

	sku_ID	user_ID	request_time	channel	click_count_on_sku	type	brand_ID
0	a234e08c57	4c3d6d10c2	2018-03-01 23:57:53	wechat	624	1	c3ab4bf4d9
1	a234e08c57	405246945e	2018-03-01 10:10:03	pc	624	1	c3ab4bf4d9
2	a234e08c57	405246945e	2018-03-01 09:47:16	pc	624	1	c3ab4bf4d9
3	a234e08c57	cb47a16a92	2018-03-01 09:39:32	pc	624	1	c3ab4bf4d9
4	a234e08c57	34e76b1af1	2018-03-01 12:18:01	app	624	1	c3ab4bf4d9

clearing up order data and user data, then merging them together

In [6]:
```
print(order.shape)
print(user.shape)
order = order.drop(columns=["order_ID","order_date","order_time","q
                            "promise","direct_discount_per_unit","q
                            "bundle_discount_per_unit","coupon_disc
                            "dc_ori","dc_des"])
order = order.assign(discount=order['original_unit_price'] - order[
order = order.drop(columns=["original_unit_price"])
print(order.shape)
order.head()
```

```
(549989, 17)
(457298, 10)
(549989, 4)
```

Out[6]:

	user_ID	sku_ID	final_unit_price	discount
0	0abe9ef2ce	581d5b54c1	79.0	10.0
1	33a9e56257	067b673f2b	53.9	46.0
2	4ea3cf408f	623d0a582a	58.5	19.5
3	b87cb736cb	fc5289b139	35.0	26.0
4	4829223b6f	623d0a582a	53.0	25.0

In [7]:
```
user = user.drop(columns=["plus"])
order_and_user = pd.merge(order,user,on="user_ID",how='left')
print(order_and_user.info())
order_and_user.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 549989 entries, 0 to 549988
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   user_ID            549989 non-null  object 
 1   sku_ID             549989 non-null  object 
 2   final_unit_price   549989 non-null  float64
 3   discount           549989 non-null  float64
 4   user_level         549989 non-null  int64  
 5   first_order_month  549989 non-null  object 
 6   gender             549989 non-null  object 
 7   age                549989 non-null  object 
 8   marital_status     549989 non-null  object 
 9   education          549989 non-null  int64  
 10  city_level         549989 non-null  int64  
 11  purchase_power     549989 non-null  int64  
dtypes: float64(2), int64(4), object(6)
memory usage: 54.5+ MB
None
```

Out[7]:

	user_ID	sku_ID	final_unit_price	discount	user_level	first_order_month	gender
0	0abe9ef2ce	581d5b54c1	79.0	10.0	1	2013-06	F
1	33a9e56257	067b673f2b	53.9	46.0	1	2016-05	F
2	4ea3cf408f	623d0a582a	58.5	19.5	2	2013-02	F
3	b87cb736cb	fc5289b139	35.0	26.0	3	2014-08	F
4	4829223b6f	623d0a582a	53.0	25.0	1	2014-10	F

In [8]:
```
print(order_and_user.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 549989 entries, 0 to 549988
Data columns (total 12 columns):
 #   Column             Non-Null Count   Dtype  
---  ------             --------------   -----  
 0   user_ID            549989 non-null  object 
 1   sku_ID             549989 non-null  object 
 2   final_unit_price   549989 non-null  float64
 3   discount           549989 non-null  float64
 4   user_level         549989 non-null  int64  
 5   first_order_month  549989 non-null  object 
 6   gender             549989 non-null  object 
 7   age                549989 non-null  object 
 8   marital_status     549989 non-null  object 
 9   education          549989 non-null  int64  
 10  city_level         549989 non-null  int64  
 11  purchase_power     549989 non-null  int64  
dtypes: float64(2), int64(4), object(6)
memory usage: 54.5+ MB
None
```

filering out the top 5 brand based on click count

In [9]:
```
click_and_sku_sum = click_and_sku.groupby('brand_ID')['click_count_
sorted_click_and_sku = click_and_sku_sum.sort_values(by='click_coun
sorted_click_and_sku = sorted_click_and_sku.drop_duplicates('brand_
sorted_click_and_sku.head()
```

Out[9]:

	brand_ID	click_count_on_sku
1148	99d41501ff	914750382067
1158	9b0d3a5fc6	325725178406
482	43999af013	188366065478
647	5ab8ea8556	167247986280
436	3daeabd2ce	108479659167

In [10]:
```
top_five_brand = sorted_click_and_sku.iloc[:5]['brand_ID']
print(top_five_brand.shape)
top_five_brand.head()
```

```
(5,)
```

Out[10]:
```
1148    99d41501ff
1158    9b0d3a5fc6
482     43999af013
647     5ab8ea8556
436     3daeabd2ce
Name: brand_ID, dtype: object
```

filtering out customers who has clicked the top 5 brands

In [11]:
```
brand_users = click_and_sku[click_and_sku['brand_ID'].isin(top_five
brand_users = brand_users.drop(brand_users[brand_users['user_ID'] =
brand_users = brand_users.drop_duplicates('user_ID')
print(brand_users.shape)
brand_users.head()
```

```
(1092105, 8)
```

Out[11]:

	sku_ID	user_ID	request_time	channel	click_count_on_sku	type	brand_IC
6291	acad9fed04	8f10d63196	2018-03-01 13:40:19	wechat	5298	2	9b0d3a5fc6
6292	acad9fed04	9d4b9e82d1	2018-03-01 18:51:20	wechat	5298	2	9b0d3a5fc6
6296	acad9fed04	c87110cc99	2018-03-01 21:27:46	mobile	5298	2	9b0d3a5fc6
6297	acad9fed04	06a3e9a8ca	2018-03-01 22:12:32	mobile	5298	2	9b0d3a5fc6
6300	acad9fed04	2068e97a97	2018-03-01 20:00:56	app	5298	2	9b0d3a5fc6

In [12]:
```
user_ids = brand_users['user_ID']
user_ids.head()
```

Out[12]:
```
6291    8f10d63196
6292    9d4b9e82d1
6296    c87110cc99
6297    06a3e9a8ca
6300    2068e97a97
Name: user_ID, dtype: object
```

In [13]:
```
top_five_brand_user = order_and_user[order_and_user['user_ID'].isin
print(top_five_brand_user.shape)
top_five_brand_user.head()
```

(267022, 12)

Out[13]:

	user_ID	sku_ID	final_unit_price	discount	user_level	first_order_month	gender
1	33a9e56257	067b673f2b	53.9	46.0	1	2016-05	F
4	4829223b6f	623d0a582a	53.0	25.0	1	2014-10	F
5	0b07cae293	589c2b865b	38.9	41.0	2	2015-11	F
7	d5e8910932	d829f03a28	40.9	39.0	2	2017-07	F
8	d5e8910932	5f58bfd286	37.9	42.0	2	2017-07	F

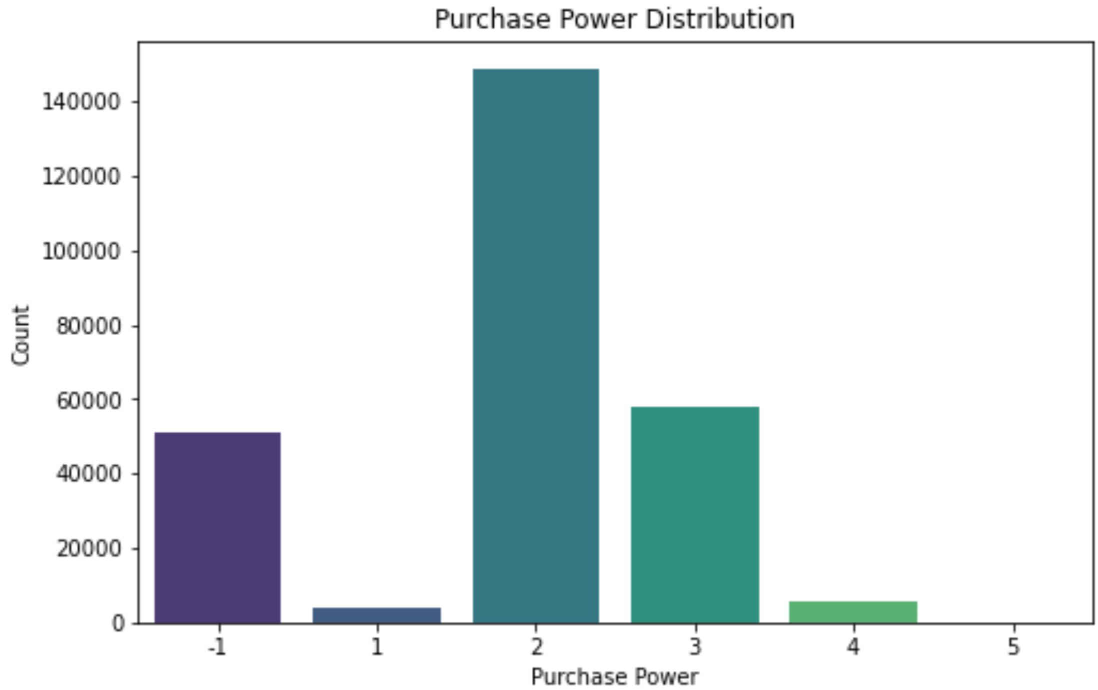
dropping cols

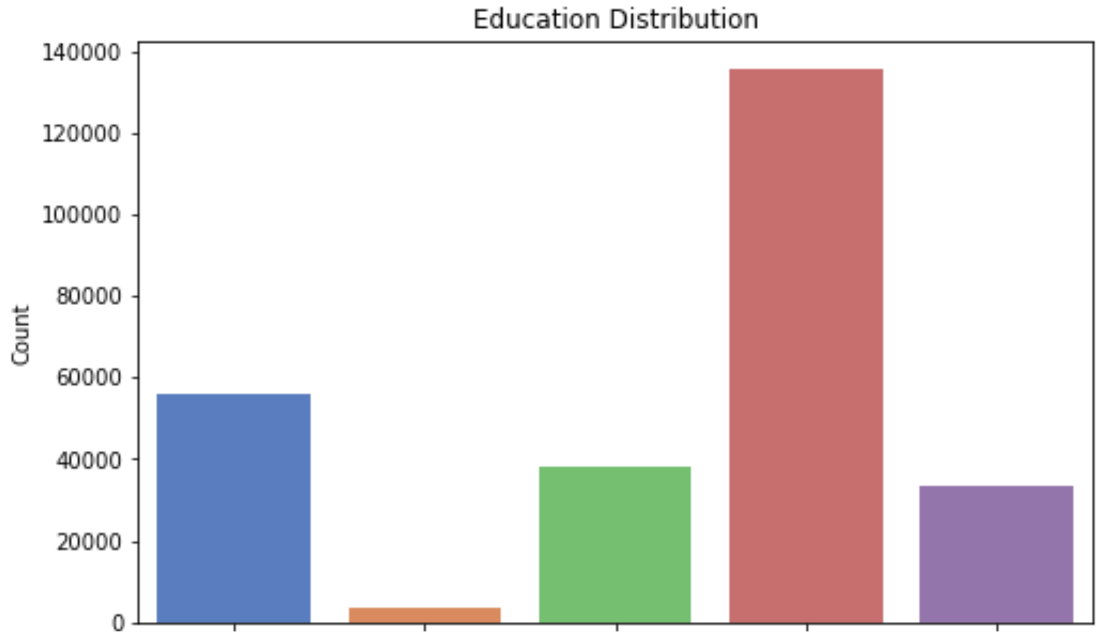
In [14]:
```
data = top_five_brand_user
data = data.drop(columns=["first_order_month","sku_ID"])
```

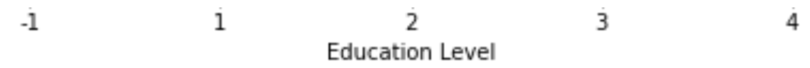
EDA

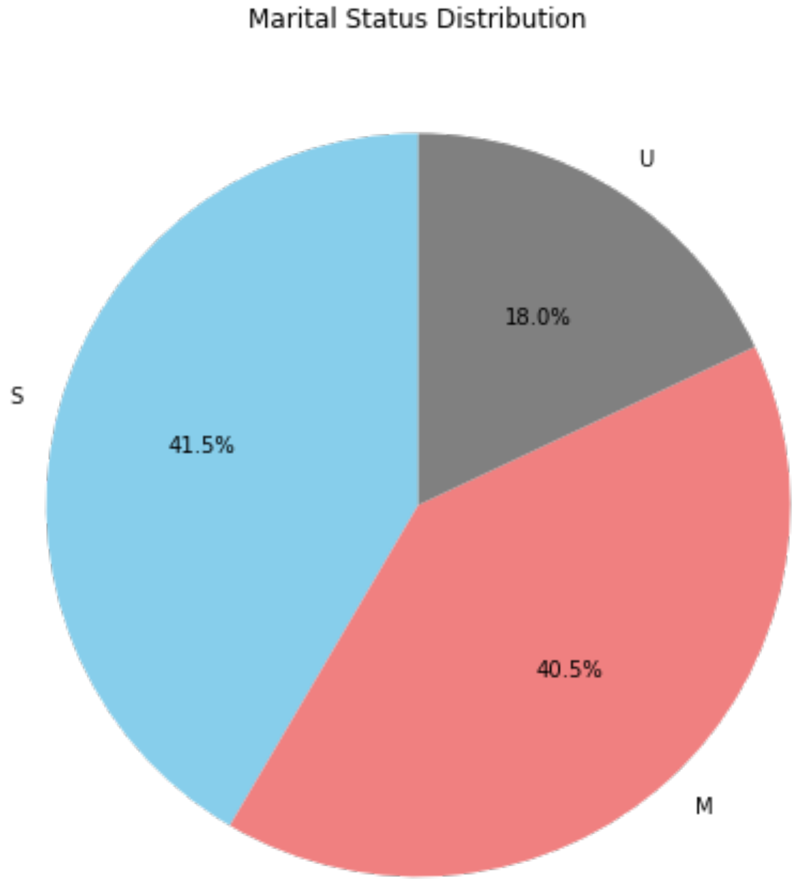
In [15]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Chart 1: Bar chart of purchase_power distribution
plt.figure(figsize=(8, 5))
sns.countplot(x='purchase_power', data=data, palette='viridis')
plt.title('Purchase Power Distribution')
plt.xlabel('Purchase Power')
plt.ylabel('Count')
plt.show()

# Chart 2: Bar chart of education distribution
plt.figure(figsize=(8, 5))
sns.countplot(x='education', data=data, palette='muted')
plt.title('Education Distribution')
plt.xlabel('Education Level')
plt.ylabel('Count')
plt.show()

# Chart 3: Pie chart of marital_status
# Count the occurrences of each marital status
marital_status_counts = data['marital_status'].value_counts()
```

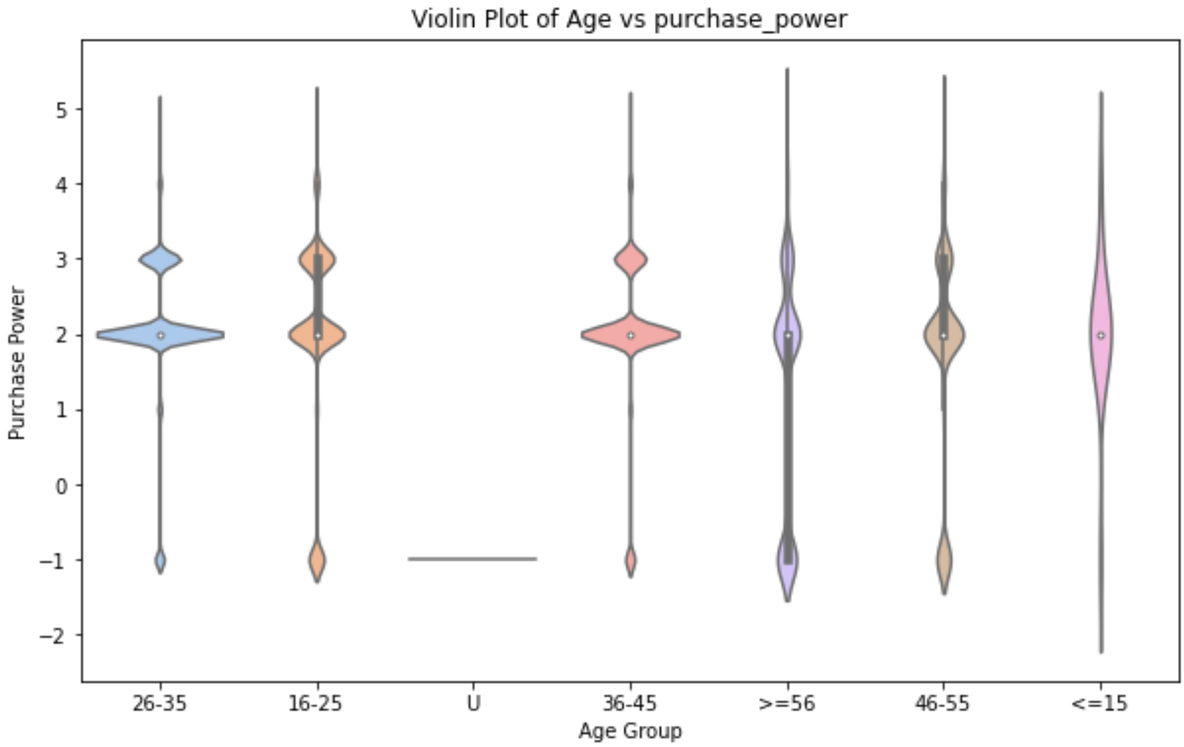
```python
marital_status_counts = data['marital_status'].value_counts()

# Plot a pie chart
plt.figure(figsize=(8, 8))
plt.pie(marital_status_counts, labels=marital_status_counts.index,
plt.title('Marital Status Distribution')
plt.show()

# Chart 4: Violin plot for the distribution of age
plt.figure(figsize=(10, 6))
sns.violinplot(x='age', y='purchase_power', data=data, palette='pas
plt.title('Violin Plot of Age vs purchase_power')
plt.xlabel('Age Group')
plt.ylabel('Purchase Power')
plt.show()
```






-1
1
2
3
4
Education Level


Marital Status Distribution
U
18.0%
S
41.5%
40.5%
M


Violin Plot of Age vs purchase_power
Purchase Power
5
4
3
2
1
0
−1
−2
26-35
16-25
U
36-45
>=56
46-55
<=15
Age Group

In [16]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 267022 entries, 1 to 549988
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   user_ID           267022 non-null  object 
 1   final_unit_price  267022 non-null  float64
 2   discount          267022 non-null  float64
 3   user_level        267022 non-null  int64  
 4   gender            267022 non-null  object 
 5   age               267022 non-null  object 
 6   marital_status    267022 non-null  object 
 7   education         267022 non-null  int64  
 8   city_level        267022 non-null  int64  
 9   purchase_power    267022 non-null  int64  
dtypes: float64(2), int64(4), object(4)
memory usage: 32.4+ MB
```

Data Preprocessing for model

one-hot encoding

In [17]:
```
print(sorted(pd.unique(data['gender'])))
print(sorted(pd.unique(data['age'])))
print(sorted(pd.unique(data['marital_status'])))
data['gender'].replace(['F', 'M', 'U'],[2,1,0],inplace=True)
data['age'].replace(['16-25', '26-35', '36-45', '46-55', '<=15', '>
data['marital_status'].replace(['M', 'S', 'U'],[2,1,0],inplace=True
```

```
['F', 'M', 'U']
['16-25', '26-35', '36-45', '46-55', '<=15', '>=56', 'U']
['M', 'S', 'U']
```

In [18]:
```
data = pd.get_dummies(data, columns = ['user_level', 'gender', 'age
```

In [19]:
```
data['purchase_power'] = data['purchase_power'].astype('category')
```

dropping missing values

In [20]:
```
any_missing = data.isnull().values.any()
print(f"{any_missing}")
```

```
False
```

In [21]:
```
len(data)
```

Out[21]: 267022

In [22]:
```
data.head()
```

Out[22]:

	user_ID	final_unit_price	discount	purchase_power	user_level_-1	user_level_0	user
1	33a9e56257	53.9	46.0	3	0	0	
4	4829223b6f	53.0	25.0	4	0	0	
5	0b07cae293	38.9	41.0	2	0	0	
7	d5e8910932	40.9	39.0	2	0	0	
8	d5e8910932	37.9	42.0	2	0	0	

5 rows × 35 columns

Data split

In [23]:
```
X = data.drop(['purchase_power','user_ID','discount','final_unit_pr
y = data['purchase_power']
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,
```

In [24]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 186915 entries, 291962 to 212029
Data columns (total 31 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   user_level_-1     186915 non-null  uint8
 1   user_level_0      186915 non-null  uint8
 2   user_level_1      186915 non-null  uint8
 3   user_level_2      186915 non-null  uint8
 4   user_level_3      186915 non-null  uint8
 5   user_level_4      186915 non-null  uint8
 6   user_level_10     186915 non-null  uint8
 7   gender_0          186915 non-null  uint8
 8   gender_1          186915 non-null  uint8
 9   gender_2          186915 non-null  uint8
 10  age_0             186915 non-null  uint8
 11  age_1             186915 non-null  uint8
 12  age_2             186915 non-null  uint8
 13  age_3             186915 non-null  uint8
 14  age_4             186915 non-null  uint8
 15  age_5             186915 non-null  uint8
 16  age_6             186915 non-null  uint8
 17  marital_status_0  186915 non-null  uint8
 18  marital_status_1  186915 non-null  uint8
 19  marital_status_2  186915 non-null  uint8
 20  education_-1      186915 non-null  uint8
 21  education_1       186915 non-null  uint8
 22  education_2       186915 non-null  uint8
 23  education_3       186915 non-null  uint8
 24  education_4       186915 non-null  uint8
 25  city_level_-1     186915 non-null  uint8
 26  city_level_1      186915 non-null  uint8
 27  city_level_2      186915 non-null  uint8
 28  city_level_3      186915 non-null  uint8
 29  city_level_4      186915 non-null  uint8
 30  city_level_5      186915 non-null  uint8
dtypes: uint8(31)
memory usage: 7.0 MB
```

In [25]:
```
X_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 80107 entries, 257672 to 388291
Data columns (total 31 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   user_level_-1       80107 non-null  uint8
 1   user_level_0        80107 non-null  uint8
 2   user_level_1        80107 non-null  uint8
 3   user_level_2        80107 non-null  uint8
 4   user_level_3        80107 non-null  uint8
 5   user_level_4        80107 non-null  uint8
 6   user_level_10       80107 non-null  uint8
 7   gender_0            80107 non-null  uint8
 8   gender_1            80107 non-null  uint8
 9   gender_2            80107 non-null  uint8
 10  age_0               80107 non-null  uint8
 11  age_1               80107 non-null  uint8
 12  age_2               80107 non-null  uint8
 13  age_3               80107 non-null  uint8
 14  age_4               80107 non-null  uint8
 15  age_5               80107 non-null  uint8
 16  age_6               80107 non-null  uint8
 17  marital_status_0    80107 non-null  uint8
 18  marital_status_1    80107 non-null  uint8
 19  marital_status_2    80107 non-null  uint8
 20  education_-1        80107 non-null  uint8
 21  education_1         80107 non-null  uint8
 22  education_2         80107 non-null  uint8
 23  education_3         80107 non-null  uint8
 24  education_4         80107 non-null  uint8
 25  city_level_-1       80107 non-null  uint8
 26  city_level_1        80107 non-null  uint8
 27  city_level_2        80107 non-null  uint8
 28  city_level_3        80107 non-null  uint8
 29  city_level_4        80107 non-null  uint8
 30  city_level_5        80107 non-null  uint8
dtypes: uint8(31)
memory usage: 3.0 MB
```

Model

evaulation

In [26]:
```
from sklearn.metrics import precision_score, accuracy_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
```

Logistic Regression

In [27]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix


logreg = LogisticRegression(random_state=600,solver='newton-cg')
logreg.fit(X_train,y_train)

predictions = logreg.predict(X_test)

# Evaluate the model
print(classification_report(y_test, predictions))
print(confusion_matrix(y_test, predictions))
```

```
              precision    recall  f1-score   support

          -1       0.98      0.96      0.97     15332
           1       0.00      0.00      0.00      1215
           2       0.74      0.92      0.82     44382
           3       0.51      0.28      0.36     17465
           4       0.58      0.01      0.01      1694
           5       0.00      0.00      0.00        19

    accuracy                           0.76     80107
   macro avg       0.47      0.36      0.36     80107
weighted avg       0.72      0.76      0.72     80107

[[14697     0   388   247     0     0]
 [    1     0  1140    74     0     0]
 [   52     0 41011  3316     3     0]
 [  169     0 12360  4931     5     0]
 [  100     0   516  1067    11     0]
 [    1     0     4    14     0     0]]
```

In [28]:
```
y_hat_test = logreg.predict(X_test)
y_hat_test
```

Out[28]:
```
array([ 2,  2,  2, ...,  2, -1,  2])
```

In [29]:
```
y_train
```

Out[29]:
```
291962   -1
491443    1
548657   -1
51258    -1
539320    3
         ..
497715    2
405316    4
182181   -1
274818    4
212029    2
Name: purchase_power, Length: 186915, dtype: category
Categories (6, int64): [-1, 1, 2, 3, 4, 5]
```

Random Forest

In [30]:
```
def OSR2(model, X_test, y_test, y_train):

    y_pred = model.predict(X_test)
    SSE = np.sum((y_test - y_pred)**2)
    SST = np.sum((y_test - np.mean(y_train))**2)

    return (1 - SSE/SST)
```

In [31]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import KFold
from sklearn import feature_selection
import time
```

In [32]:
```
rf = RandomForestRegressor(max_features=5, min_samples_leaf=5,
                           n_estimators = 500, random_state=333, ve
rf.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concu
rrent workers.
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.1s remai
ning:    0.0s
```

```
building tree 1 of 500
building tree 2 of 500
building tree 3 of 500
building tree 4 of 500
building tree 5 of 500
building tree 6 of 500
building tree 7 of 500
building tree 8 of 500
building tree 9 of 500
building tree 10 of 500
building tree 11 of 500
building tree 12 of 500
building tree 13 of 500
building tree 14 of 500
building tree 15 of 500
```

In [33]:
```
grid_values = {'max_features': np.linspace(1,15,5, dtype='int32'),
               'max_depth': [2,3,4,5,6],
               'min_samples_leaf': [5],
               'n_estimators': [100],
               'random_state': [88]}

rf2 = RandomForestClassifier()

cv = KFold(n_splits=5,random_state=333,shuffle=True)
rf_cv = GridSearchCV(rf2, param_grid=grid_values, scoring='r2',cv=c
rf_cv.fit(X_train, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concu
rrent workers.

Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV] max_depth=2, max_features=1, min_samples_leaf=5, n_estimators
=100, random_state=88
[CV]  max_depth=2, max_features=1, min_samples_leaf=5, n_estimator
s=100, random_state=88, total=   2.7s
[CV] max_depth=2, max_features=1, min_samples_leaf=5, n_estimators
=100, random_state=88

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    2.7s remai
ning:    0.0s

[CV]  max_depth=2, max_features=1, min_samples_leaf=5, n_estimator
s=100, random_state=88, total=   2.8s
[CV] max_depth=2, max_features=1, min_samples_leaf=5, n_estimators
=100, random_state=88
[CV]  max_depth=2, max_features=1, min_samples_leaf=5, n_estimator
s=100, random_state=88, total=   2.7s
```

In [34]:
```
print('Best parameters', rf_cv.best_params_)
```

```
Best parameters {'max_depth': 2, 'max_features': 11, 'min_samples_
leaf': 5, 'n_estimators': 100, 'random_state': 88}
```

In [35]:
```
print('Cross-validated R2:', round(rf_cv.best_score_, 5))
```

```
Cross-validated R2: 0.79043
```

In [36]:
```
rf_best = rf_cv.best_estimator_
rf_best.feature_importances_
```

Out[36]:
```
array([0.00000000e+00, 0.00000000e+00, 4.12793092e-02, 3.08802177e
-04,
       5.96952960e-04, 1.77761276e-02, 0.00000000e+00, 1.25842305e
-01,
       4.95525712e-04, 0.00000000e+00, 5.06425820e-02, 0.00000000e
+00,
       4.66372707e-04, 1.16091626e-04, 0.00000000e+00, 0.00000000e
+00,
       0.00000000e+00, 4.39180542e-01, 1.74631315e-02, 9.27960501e
-03,
       2.76824857e-01, 0.00000000e+00, 7.75907917e-04, 1.10848013e
-02,
       4.05417133e-03, 3.81275791e-03, 0.00000000e+00, 1.39524355e
-07,
       0.00000000e+00, 1.71091567e-08, 0.00000000e+00])
```

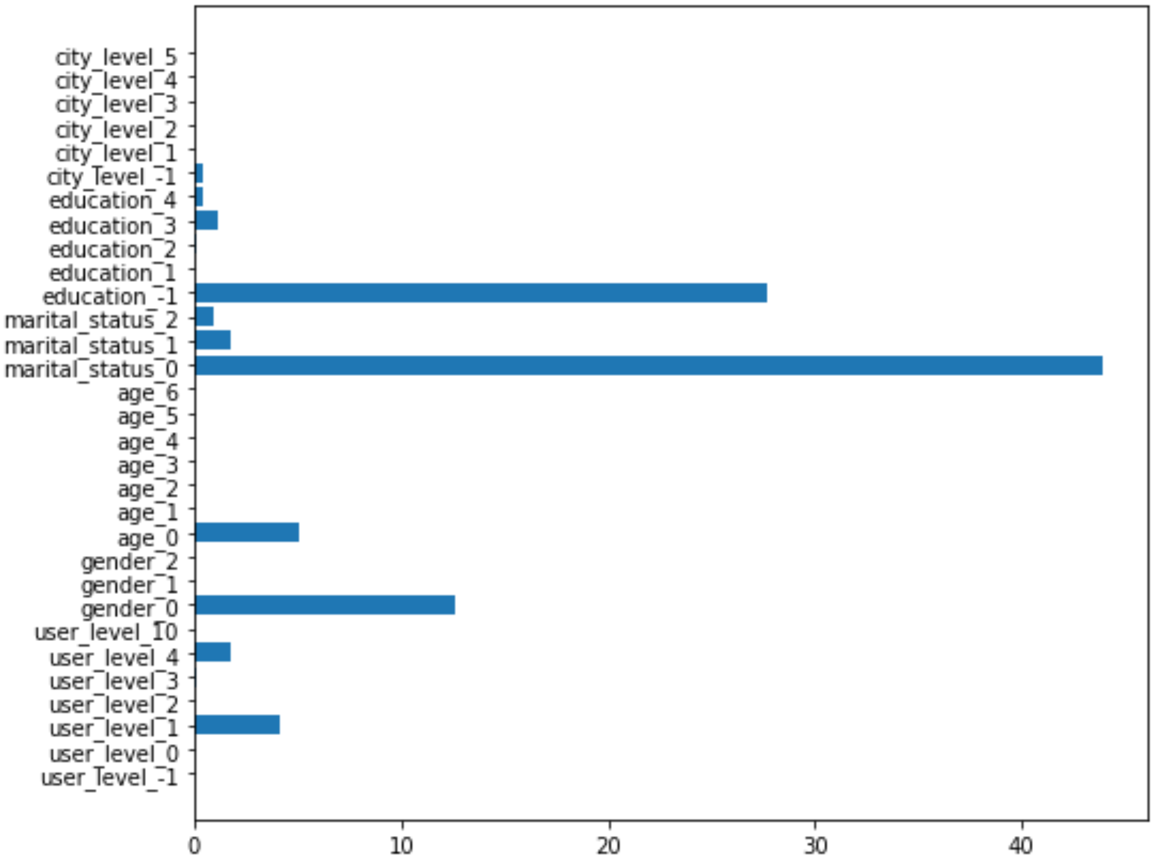
In [37]:
```
imp_df = pd.DataFrame({
    'Varname': X_train.columns,
    'imp': rf_best.feature_importances_
})

imp_df.sort_values(by='imp', ascending=False)
```

Out[37]:

	Varname	imp
17	marital_status_0	4.391805e-01
20	education_-1	2.768249e-01
7	gender_0	1.258423e-01
10	age_0	5.064258e-02
2	user_level_1	4.127931e-02
5	user_level_4	1.777613e-02
18	marital_status_1	1.746313e-02
23	education_3	1.108480e-02
19	marital_status_2	9.279605e-03
24	education_4	4.054171e-03
25	city_level_-1	3.812758e-03
22	education_2	7.759079e-04
4	user_level_3	5.969530e-04
8	gender_1	4.955257e-04
12	age_2	4.663727e-04

3	user_level_2	3.088022e-04
13	age_3	1.160916e-04
27	city_level_2	1.395244e-07
29	city_level_4	1.710916e-08
26	city_level_1	0.000000e+00
28	city_level_3	0.000000e+00
0	user_level_-1	0.000000e+00
15	age_5	0.000000e+00
21	education_1	0.000000e+00
16	age_6	0.000000e+00
1	user_level_0	0.000000e+00
14	age_4	0.000000e+00
11	age_1	0.000000e+00
9	gender_2	0.000000e+00
6	user_level_10	0.000000e+00
30	city_level_5	0.000000e+00

In [38]:
```
plt.figure(figsize=(8,7))
plt.barh(X_train.columns, 100*rf_cv.best_estimator_.feature_importa
plt.show()
```



CART

In [39]:
```
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(max_features='auto')
dt.fit(X_train,y_train)

y_pred = dt.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

print ("Confusion Matrix : \n", cm)
print('Precision:',precision_score(y_test, y_pred, average='weighte
print('Recall:',recall_score(y_test, y_pred, average='weighted'))
```

```
Confusion Matrix :
 [[14767     0   389   169     7     0]
 [    1     6  1130    78     0     0]
 [   82    20 41081  3182    17     0]
 [  223     5 12446  4716    75     0]
 [  135     1   518   983    57     0]
 [    1     0     2    15     1     0]]
Precision: 0.7184170894282075
Recall: 0.7568252462331632
```

With crosss validation

In [40]:
```
grid_values = {'ccp_alpha': np.linspace(0.001, 0.2, 201),# the choi
               'min_samples_leaf': [5],
               'min_samples_split': [20],
               'max_depth': [30],
               'random_state': [88]}


dtc = DecisionTreeClassifier()

cv = KFold(n_splits=5,random_state=1,shuffle=True)

dtc_cv_acc = GridSearchCV(dtc, param_grid = grid_values, scoring =
dtc_cv_acc.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 201 candidates, totalling 1005 fits

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concu
rrent workers.
[Parallel(n_jobs=1)]: Done 1005 out of 1005 | elapsed:  8.0min fin
ished
```

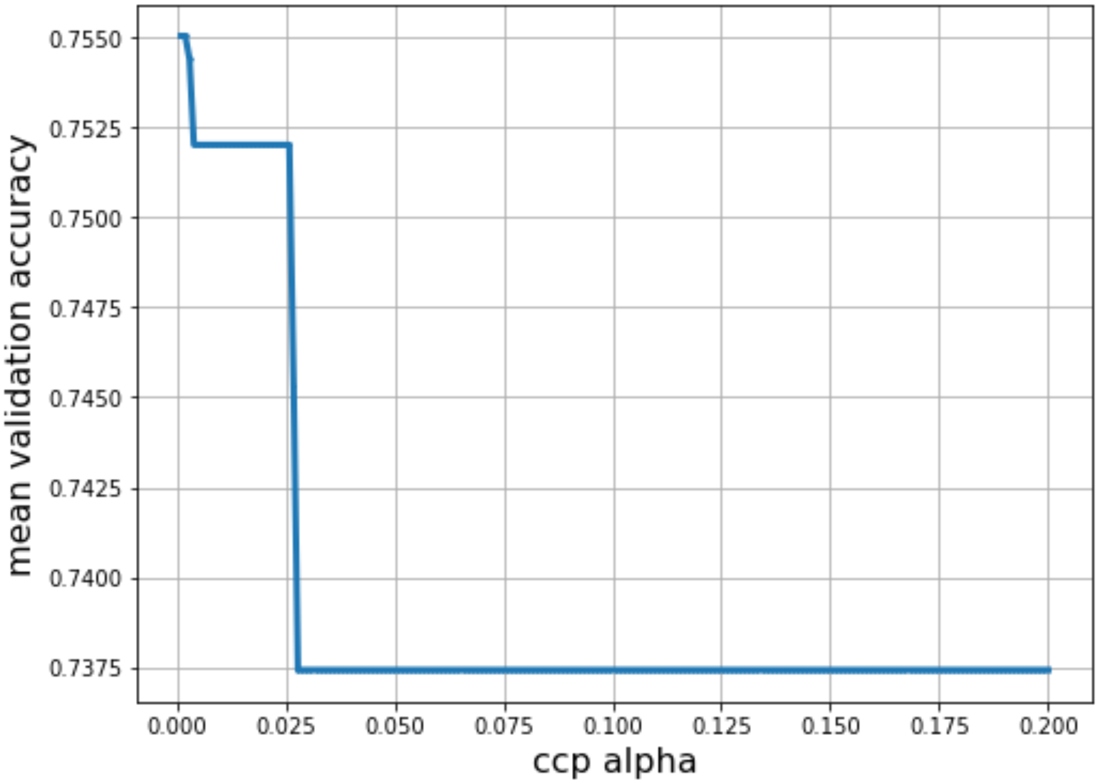
Out[40]:
```
GridSearchCV(cv=KFold(n_splits=5, random_state=1, shuffle=True),
             estimator=DecisionTreeClassifier(),
             param_grid={'ccp_alpha': array([0.001   , 0.001995, 0
.00299 , 0.003985, 0.00498 , 0.005975,
       0.00697 , 0.007965, 0.00896 , 0.009955, 0.01095 , 0.011945,
       0.01294 , 0.013935, 0.01493 , 0.015925, 0.01692 , 0.017915,
       0.01891 , 0.019905, 0.0209  , 0.021895, 0.02289 , 0.023885,
       0.02488 , 0.025875, 0.02...
       0.16816 , 0.169155, 0.17015 , 0.171145, 0.17214 , 0.173135,
       0.17413 , 0.175125, 0.17612 , 0.177115, 0.17811 , 0.179105,
       0.1801  , 0.181095, 0.18209 , 0.183085, 0.18408 , 0.185075,
       0.18607 , 0.187065, 0.18806 , 0.189055, 0.19005 , 0.191045,
       0.19204 , 0.193035, 0.19403 , 0.195025, 0.19602 , 0.197015,
       0.19801 , 0.199005, 0.2     ]),
                         'max_depth': [30], 'min_samples_leaf': [5
],
                         'min_samples_split': [20], 'random_state'
: [88]},
             scoring='accuracy', verbose=1)
```

In [41]:
```
acc = dtc_cv_acc.cv_results_['mean_test_score']
ccp = dtc_cv_acc.cv_results_['param_ccp_alpha'].data

pd.DataFrame({'ccp alpha' : ccp, 'Validation Accuracy': acc}).head(
```

Out[41]:

	ccp alpha	Validation Accuracy
0	0.001	0.755049
1	0.001995	0.755049
2	0.00299	0.754402
3	0.003985	0.752021
4	0.00498	0.752021
5	0.005975	0.752021
6	0.00697	0.752021
7	0.007965	0.752021
8	0.00896	0.752021
9	0.009955	0.752021
10	0.01095	0.752021
11	0.011945	0.752021
12	0.01294	0.752021
13	0.013935	0.752021
14	0.01493	0.752021
15	0.015925	0.752021
16	0.01692	0.752021
17	0.017915	0.752021
18	0.01891	0.752021
19	0.019905	0.752021

In [42]:
```
plt.figure(figsize=(8, 6))
plt.xlabel('ccp alpha', fontsize=16)
plt.ylabel('mean validation accuracy', fontsize=16)
plt.scatter(ccp, acc, s=2)
plt.plot(ccp, acc, linewidth=3)
plt.grid(True, which='both')
plt.show()
```



In [43]:
```
print('Grid best parameter ccp_alpha (max. accuracy): ', dtc_cv_acc
print('Grid best score (accuracy): ', dtc_cv_acc.best_score_)
```

```
Grid best parameter ccp_alpha (max. accuracy):  0.001
Grid best score (accuracy):  0.7550490864831609
```

Boosting

In [44]:
```
from sklearn.ensemble import AdaBoostClassifier

ada = AdaBoostClassifier(n_estimators=50, learning_rate=0.1)
bt_model = ada.fit(X_train, y_train)
```

In [45]:
```
y_pred1 = bt_model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred1))
```

```
Accuracy: 0.7466638371178549
```

With Cross Validation

In [46]:
```
grid_values = {'learning_rate': [0.1*i for i in range(1,10)],
               'n_estimators': [100],
               'random_state': [88]}

tic = time.time()

bt2 = AdaBoostClassifier()

cv = KFold(n_splits=5,random_state=88,shuffle=True)
bt2_cv = GridSearchCV(bt2, param_grid=grid_values, scoring='r2', cv
bt2_cv.fit(X_train, y_train)

toc = time.time()

print('time:', round(toc-tic, 2),'s')
```

```
Fitting 5 folds for each of 9 candidates, totalling 45 fits
[CV] learning_rate=0.1, n_estimators=100, random_state=88 ........
....

[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concu
rrent workers.

[CV]  learning_rate=0.1, n_estimators=100, random_state=88, total=
13.1s
[CV] learning_rate=0.1, n_estimators=100, random_state=88 ........
....

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   13.1s remai
ning:    0.0s

[CV]  learning_rate=0.1, n_estimators=100, random_state=88, total=
12.4s
[CV] learning_rate=0.1, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.1, n_estimators=100, random_state=88, total=
12.9s
[CV] learning_rate=0.1, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.1, n_estimators=100, random_state=88, total=
12.9s
[CV] learning_rate=0.1, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.1, n_estimators=100, random_state=88, total=
11.5s
[CV] learning_rate=0.2, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.2, n_estimators=100, random_state=88, total=
12.0s
[CV] learning_rate=0.2, n_estimators=100, random_state=88 ........
```

```
....
[CV]  learning_rate=0.2, n_estimators=100, random_state=88, total=
11.7s
[CV] learning_rate=0.2, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.2, n_estimators=100, random_state=88, total=
11.6s
[CV] learning_rate=0.2, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.2, n_estimators=100, random_state=88, total=
12.2s
[CV] learning_rate=0.2, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.2, n_estimators=100, random_state=88, total=
11.8s
[CV] learning_rate=0.30000000000000004, n_estimators=100, random_s
tate=88
[CV]  learning_rate=0.30000000000000004, n_estimators=100, random_
state=88, total=  11.9s
[CV] learning_rate=0.30000000000000004, n_estimators=100, random_s
tate=88
[CV]  learning_rate=0.30000000000000004, n_estimators=100, random_
state=88, total=  13.1s
[CV] learning_rate=0.30000000000000004, n_estimators=100, random_s
tate=88
[CV]  learning_rate=0.30000000000000004, n_estimators=100, random_
state=88, total=  13.0s
[CV] learning_rate=0.30000000000000004, n_estimators=100, random_s
tate=88
[CV]  learning_rate=0.30000000000000004, n_estimators=100, random_
state=88, total=  13.4s
[CV] learning_rate=0.30000000000000004, n_estimators=100, random_s
tate=88
[CV]  learning_rate=0.30000000000000004, n_estimators=100, random_
state=88, total=  11.9s
[CV] learning_rate=0.4, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.4, n_estimators=100, random_state=88, total=
11.6s
[CV] learning_rate=0.4, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.4, n_estimators=100, random_state=88, total=
11.5s
[CV] learning_rate=0.4, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.4, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.4, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.4, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.4, n_estimators=100, random_state=88 ........
....
```

```
[CV]  learning_rate=0.4, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.5, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.5, n_estimators=100, random_state=88, total=
11.6s
[CV] learning_rate=0.5, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.5, n_estimators=100, random_state=88, total=
11.7s
[CV] learning_rate=0.5, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.5, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.5, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.5, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.5, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.5, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.6000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.6000000000000001, n_estimators=100, random_s
tate=88, total=  11.4s
[CV] learning_rate=0.6000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.6000000000000001, n_estimators=100, random_s
tate=88, total=  11.7s
[CV] learning_rate=0.6000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.6000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.6000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.6000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.6000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.6000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.7000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.7000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.7000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.7000000000000001, n_estimators=100, random_s
tate=88, total=  11.5s
[CV] learning_rate=0.7000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.7000000000000001, n_estimators=100, random_s
```

```
tate=88, total=  11.4s
[CV] learning_rate=0.7000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.7000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.7000000000000001, n_estimators=100, random_st
ate=88
[CV]  learning_rate=0.7000000000000001, n_estimators=100, random_s
tate=88, total=  11.3s
[CV] learning_rate=0.8, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.8, n_estimators=100, random_state=88, total=
11.3s
[CV] learning_rate=0.8, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.8, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.8, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.8, n_estimators=100, random_state=88, total=
12.0s
[CV] learning_rate=0.8, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.8, n_estimators=100, random_state=88, total=
11.2s
[CV] learning_rate=0.8, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.8, n_estimators=100, random_state=88, total=
11.4s
[CV] learning_rate=0.9, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.9, n_estimators=100, random_state=88, total=
11.3s
[CV] learning_rate=0.9, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.9, n_estimators=100, random_state=88, total=
11.2s
[CV] learning_rate=0.9, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.9, n_estimators=100, random_state=88, total=
11.6s
[CV] learning_rate=0.9, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.9, n_estimators=100, random_state=88, total=
11.3s
[CV] learning_rate=0.9, n_estimators=100, random_state=88 ........
....
[CV]  learning_rate=0.9, n_estimators=100, random_state=88, total=
11.3s

[Parallel(n_jobs=1)]: Done  45 out of  45 | elapsed:  8.8min finis
hed

time: 542.17 s
```

In [47]:
```
print(bt2_cv.best_params_)
y_test_pred = bt2_cv.best_estimator_.predict(X_test)

print('Precision:',precision_score(y_test, y_test_pred, average='we
print('Recall:',recall_score(y_test, y_test_pred, average='weighted
```

```
{'learning_rate': 0.2, 'n_estimators': 100, 'random_state': 88}
Precision: 0.7074185670262768
Recall: 0.7547655011422223
```

In [48]:
```
print("Accuracy:", accuracy_score(y_test, y_test_pred))
```

```
Accuracy: 0.7547655011422223
```

In [ ]:
```

```