Week6 - Section 3 - Tree-based Models

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1 Group 5 - Final Report

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[104]:
```
#Libraries Imported
import pandas as pd
import numpy as np
from numpy import mean, where
from datetime import date
import geopy.distance
from math import sin, cos, sqrt, atan2, radians, log
import time
from collections import Counter
import xgboost as xgb

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

[2]:
```
from imblearn.pipeline import Pipeline
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
```

[3]:
```
from sklearn.model_selection import train_test_split
from sklearn import tree, metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification
from sklearn.metrics import confusion_matrix,classification_report,make_scorer,␣
 ↪mean_squared_error
from sklearn.metrics import roc_curve, roc_auc_score, accuracy_score,␣
 ↪precision_score, recall_score
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

1.0.2 EDA - Data Loading

[4]:
```
df_test=pd.read_csv('fraudTest.csv')
df_train=pd.read_csv('fraudTrain.csv')

fraud_df= df_test.append(df_train)
fraud_df.head()
```

[4]:
```
   Unnamed: 0 trans_date_trans_time            cc_num  \
0           0   2020-06-21 12:14:25  2291163933867244
1           1   2020-06-21 12:14:33  3573030041201292
2           2   2020-06-21 12:14:53  3598215285024754
3           3   2020-06-21 12:15:15  3591919803438423
4           4   2020-06-21 12:15:17  3526826139003047

                              merchant        category    amt   first  \
0                 fraud_Kirlin and Sons   personal_care   2.86    Jeff
1                  fraud_Sporer-Keebler   personal_care  29.84  Joanne
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness  41.28  Ashley
3                     fraud_Haley Group        misc_pos  60.05   Brian
4                 fraud_Johnston-Casper          travel   3.19  Nathan

       last gender                       street  …      lat      long  \
0   Elliott      M            351 Darlene Green  …  33.9659  -80.9355
1  Williams      F             3638 Marsh Union  …  40.3207 -110.4360
2     Lopez      F         9333 Valentine Point  …  40.6729  -73.5365
3  Williams      M  32941 Krystal Mill Apt. 552  …  28.5697  -80.8191
4    Massey      M     5783 Evan Roads Apt. 465  …  44.2529  -85.0170

   city_pop                        job         dob  \
0    333497        Mechanical engineer  1968-03-19
1       302  Sales professional, IT  1990-01-17
2     34496        Librarian, public  1970-10-21
3     54767             Set designer  1987-07-25
4      1126       Furniture designer  1955-07-06

                          trans_num   unix_time  merch_lat  merch_long  \
0  2da90c7d74bd46a0caf3777415b3ebd3  1371816865  33.986391  -81.200714
1  324cc204407e99f51b0d6ca0055005e7  1371816873  39.450498 -109.960431
2  c81755dbbbea9d5c77f094348a7579be  1371816893  40.495810  -74.196111
3  2159175b9efe66dc301f149d3d5abf8c  1371816915  28.812398  -80.883061
4  57ff021bd3f328f8738bb535c302a31b  1371816917  44.959148  -85.884734

   is_fraud
0         0
1         0
2         0
```

```
3          0
4          0

[5 rows x 23 columns]
```

1.0.3 EDA - Data Preprocessing

[5]:
```
# Checking for missing values
fraud_df.isnull().any().sum()
```

[5]:
```
0
```

[6]:
```
fraud_df.nunique()
```

[6]:
```
Unnamed: 0               1296675
trans_date_trans_time    1819551
cc_num                       999
merchant                     693
category                      14
amt                        60616
first                        355
last                         486
gender                         2
street                       999
city                         906
state                         51
zip                          985
lat                          983
long                         983
city_pop                     891
job                          497
dob                          984
trans_num                1852394
unix_time                1819583
merch_lat                1754157
merch_long               1809753
is_fraud                       2
dtype: int64
```

[7]:
```
fraud_df.dtypes
```

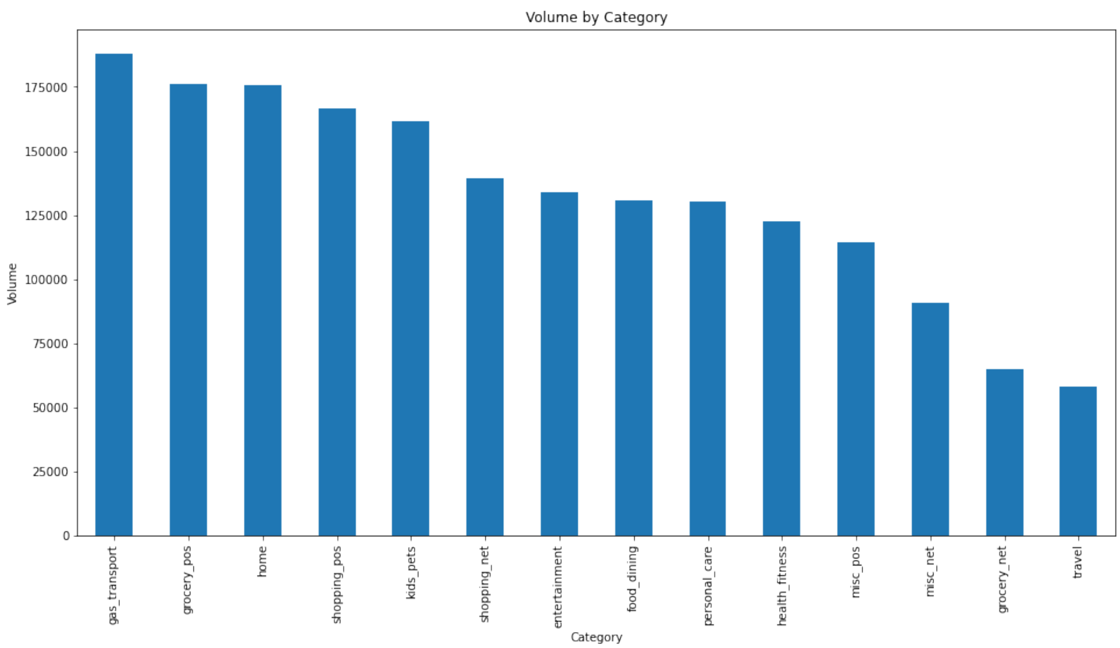
[7]:
```
Unnamed: 0                 int64
trans_date_trans_time     object
cc_num                     int64
merchant                  object
category                  object
amt                      float64
```

```
first                           object
last                            object
gender                          object
street                          object
city                            object
state                           object
zip                              int64
lat                            float64
long                           float64
city_pop                         int64
job                             object
dob                             object
trans_num                       object
unix_time                        int64
merch_lat                      float64
merch_long                     float64
is_fraud                         int64
dtype: object
```

1.0.4 EDA - Column Exploration

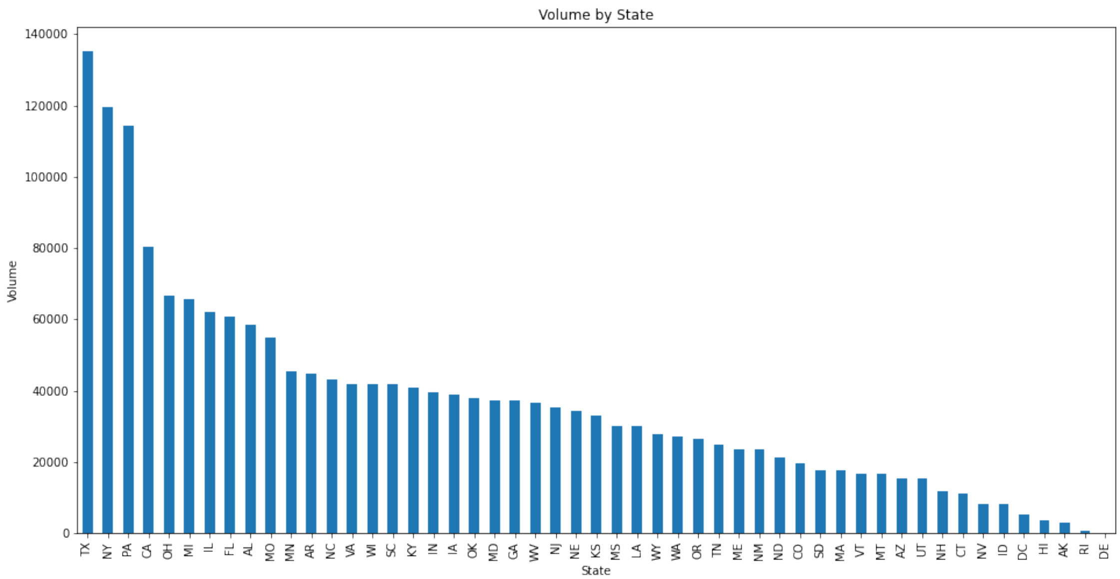
[8]:
```
plt = pd.value_counts(fraud_df['category']).plot.bar(figsize=(16, 8),␣
 ↪title="Volume by Category")
plt.set_xlabel('Category')
plt.set_ylabel('Volume')
```

[8]:
```
Text(0, 0.5, 'Volume')
```



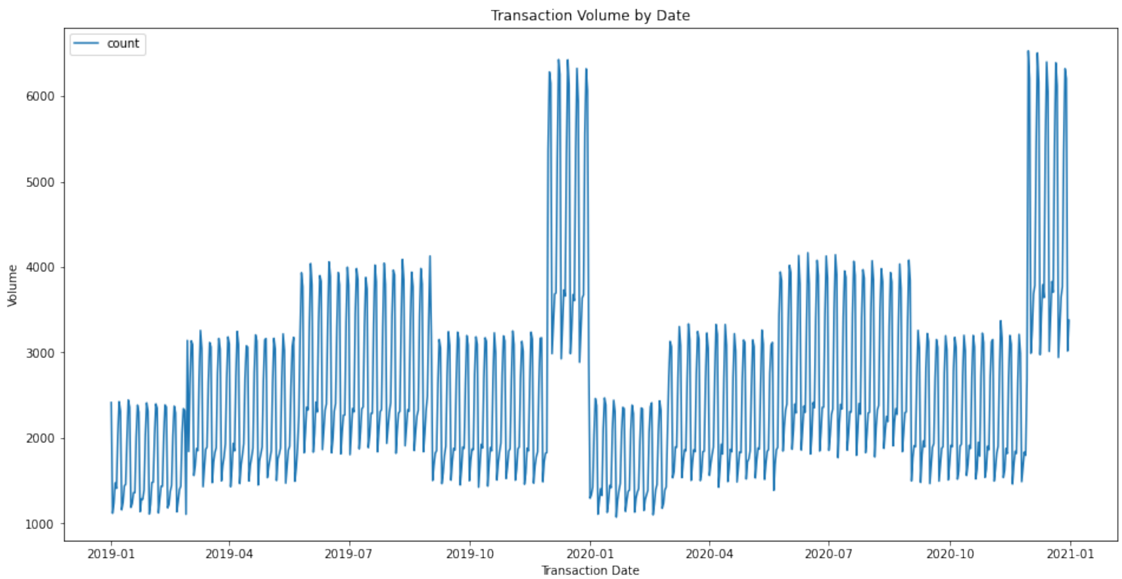
```
[9]: plt = pd.value_counts(fraud_df['state']).plot.bar(figsize=(16, 8),␣
      ↪title="Volume by State")
     plt.set_xlabel('State')
     plt.set_ylabel('Volume')
```

```
[9]: Text(0, 0.5, 'Volume')
```



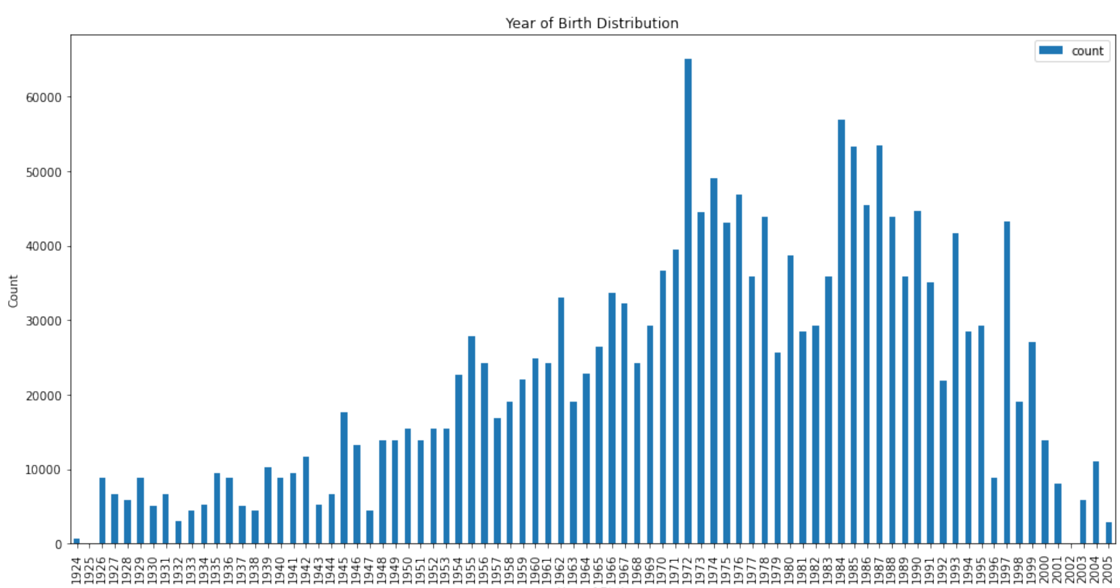

```
[10]: fraud_df['txn_datetime'] =  pd.to_datetime(fraud_df['trans_date_trans_time'],␣
       ↪format='%Y-%m-%d %H:%M:%S')

      fraud_df['date_of_birth'] =  pd.to_datetime(fraud_df['dob'], format='%Y-%m-%d')
      fraud_df['year_of_birth'] = fraud_df['date_of_birth'].dt.year
      fraud_df['date_of_birth'] = fraud_df['date_of_birth'].dt.date

      fraud_df['txn_date'] = fraud_df['txn_datetime'].dt.date
      txn_count_by_date = fraud_df['txn_date'].value_counts().sort_index().
       ↪reset_index()
      txn_count_by_date.columns = ['txn_date','count']
      plt = txn_count_by_date.plot.line(x='txn_date', y='count', figsize=(16, 8),␣
       ↪title="Transaction Volume by Date")
      plt.set_xlabel('Transaction Date')
      plt.set_ylabel('Volume')
```

```
[10]: Text(0, 0.5, 'Volume')
```



[11]:
```
dob_counts = fraud_df['year_of_birth'].value_counts().sort_index().reset_index()
dob_counts.columns = ['year_of_birth','count']

plt = dob_counts.plot.bar(x='year_of_birth', y='count', figsize=(16, 8),␣
 ↪title="Year of Birth Distribution")
plt.set_xlabel('Year of Birth')
plt.set_ylabel('Count')
```

[11]: Text(0, 0.5, 'Count')

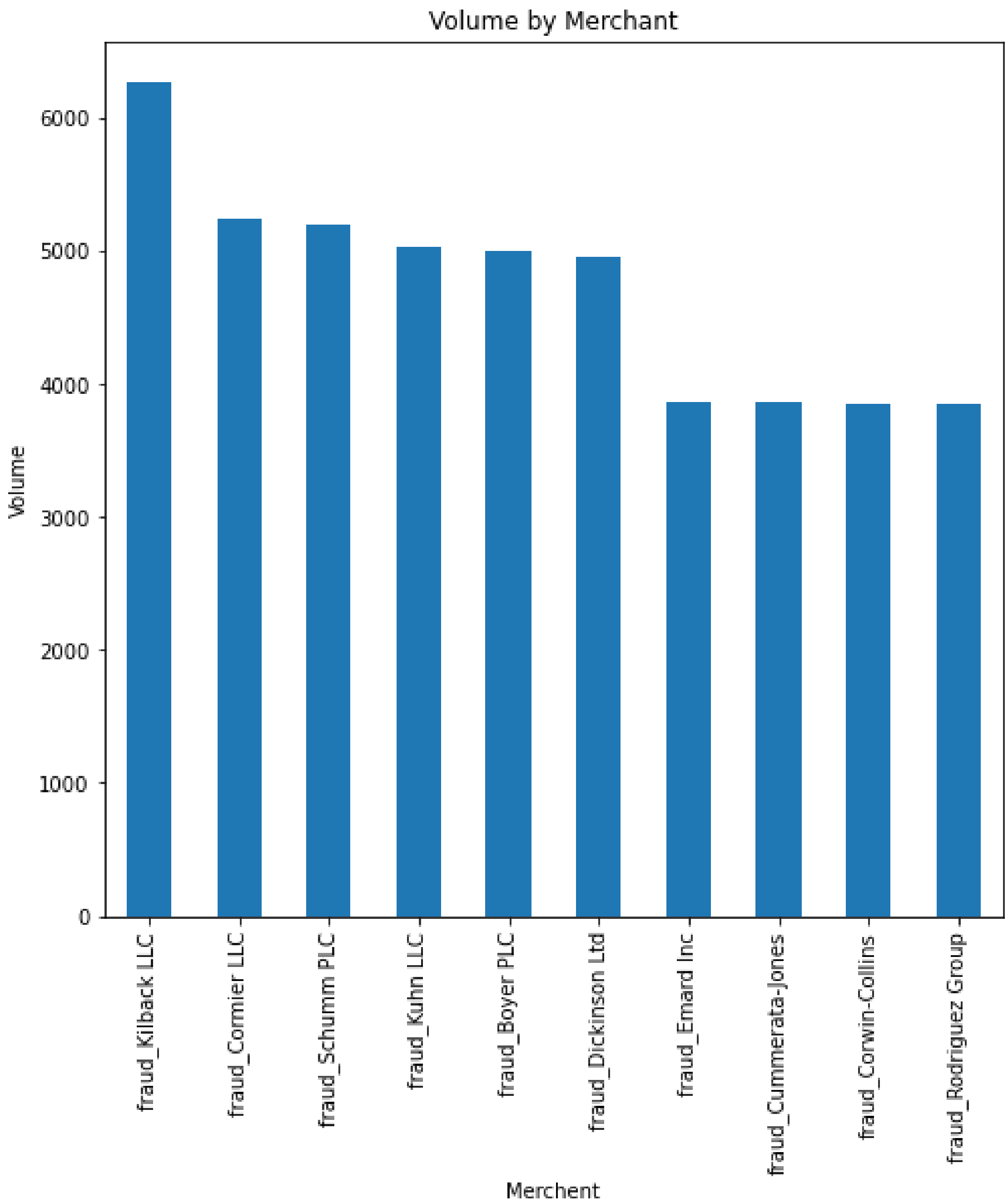


[12]:
```python
# Number of merchants in the dataset

print(f"Number of merchants: {fraud_df['merchant'].nunique()}")

# Number of cards in the dataset

print(f"Number of cards: {fraud_df['cc_num'].nunique()}")

# Number of cards in the dataset

print(f"Number of unique users: {fraud_df.groupby(['first', 'last', 'gender',␣
↪'street', 'city']).ngroups}")
```

```
Number of merchants: 693
Number of cards: 999
Number of unique users: 999
```

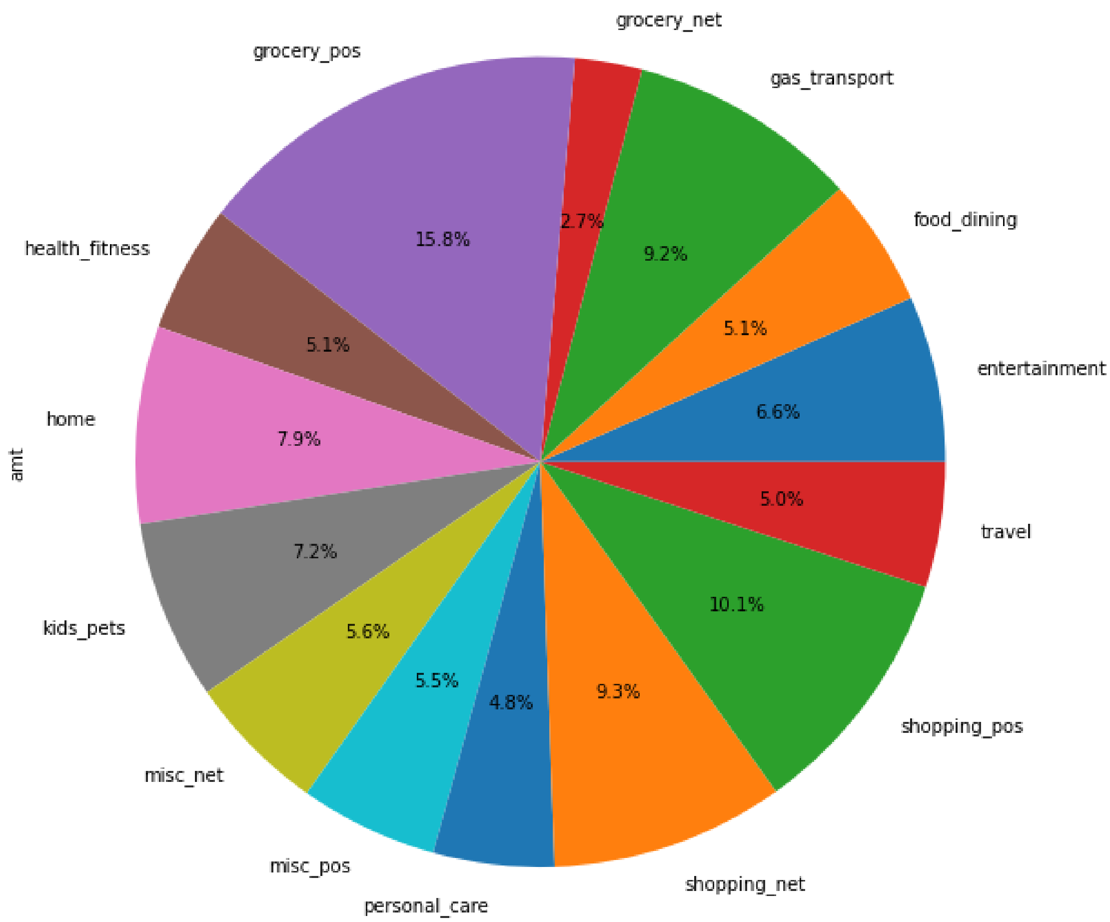
[13]:
```python
plt = pd.value_counts(fraud_df['merchant']).nlargest(10).plot.bar(figsize=(8,␣
↪8), title="Volume by Merchant")
plt.set_xlabel('Merchent')
plt.set_ylabel('Volume')
```

[13]:
```
Text(0, 0.5, 'Volume')
```



[14]:
```
category_amt = fraud_df.groupby("category")["amt"].sum()
category_amt.plot.pie(autopct="%.1f%%", figsize=(10, 12))
```

[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb0f3d2b20>



1.0.5 EDA - Special Features Engineering

Calculating Age from Date of Birth Column

[15]:
```
#Calculate Age
def calculate_age(born):
    today = date.today()
    return today.year - born.year - ((today.month, today.day) < (born.month,␣
↪born.day))

if 'dob' in fraud_df.columns:
    fraud_df['age'] = [calculate_age(d) for d in pd.
↪to_datetime(fraud_df['dob'], format='%Y-%m-%d')]
```

Calculating Distance between card holder and merchant

```
[16]: def calculate_distance(row):
          coords_1 = (row['lat'], row['long'])
          coords_2 = (row['merch_lat'], row['merch_long'])
          return geopy.distance.geodesic(coords_1, coords_2).km

      # Answer from https://stackoverflow.com/questions/19412462/
       ↪getting-distance-between-two-points-based-on-latitude-longitude
      # The answers above are based on the Haversine formula, which assumes the earth␣
       ↪is a sphere,
      # which results in errors of up to about 0.5% (according to help(geopy.
       ↪distance)).
      # Vincenty distance uses more accurate ellipsoidal models such as WGS-84, and␣
       ↪is implemented in geopy. For example,
      def calculate_distance2(row):
          # approximate radius of earth in km
          R = 6373.0

          lat1 = radians(row['lat'])
          lon1 = radians(row['long'])
          lat2 = radians(row['merch_lat'])
          lon2 = radians(row['merch_long'])

          dlon = lon2 - lon1
          dlat = lat2 - lat1

          a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
          c = 2 * atan2(sqrt(a), sqrt(1 - a))

          distance = R * c
          print(distance)

      if set(['lat', 'long', 'merch_lat', 'merch_long']).issubset(set(fraud_df.
       ↪columns)):
           fraud_df['distance'] = [calculate_distance(row) for _, row in fraud_df.
       ↪iterrows()]
```

Separating Time Buckets from Datetime Column

```
[17]: fraud_df['hour'] = fraud_df['txn_datetime'].dt.hour
      fraud_df['day'] = fraud_df['txn_datetime'].dt.day
      fraud_df['month'] = fraud_df['txn_datetime'].dt.month
      fraud_df['year'] = fraud_df['txn_datetime'].dt.year
```

Removing Columns used to derive new features

```
[18]: fraud_df.drop([
          'Unnamed: 0',
```

```
    'trans_num',
    'unix_time',
    'first',
    'last',
    'street',
    'city',
    'state',
    'zip',
    'dob',
    'trans_date_trans_time',
    'lat',
    'long',
    'merch_lat',
    'merch_long'
], axis=1, errors='ignore', inplace=True)

cols = list(fraud_df.columns)
cols.insert(0, cols.pop(cols.index("txn_datetime")))
cols.append(cols.pop(cols.index('is_fraud')))
fraud_df = fraud_df[cols]

fraud_df.head()
```

[18]:

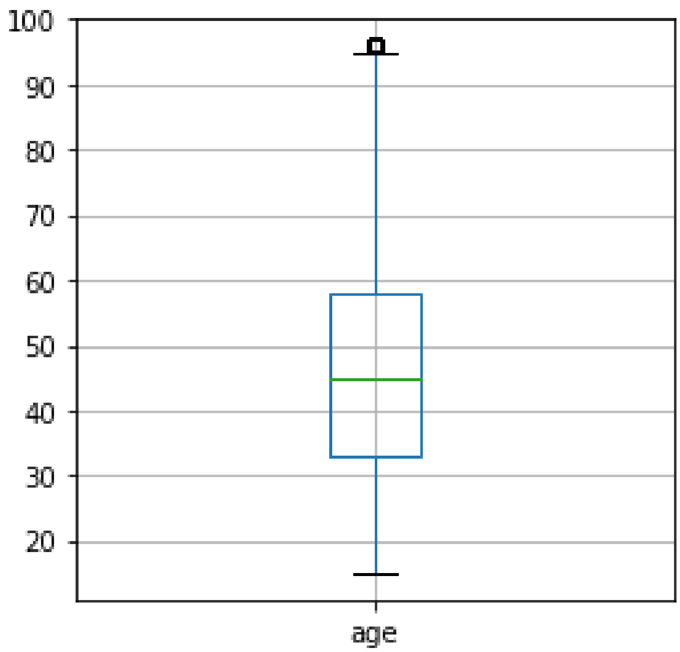
```
         txn_datetime            cc_num                                merchant  \
0 2020-06-21 12:14:25  2291163933867244                 fraud_Kirlin and Sons
1 2020-06-21 12:14:33  3573030041201292                  fraud_Sporer-Keebler
2 2020-06-21 12:14:53  3598215285024754  fraud_Swaniawski, Nitzsche and Welch
3 2020-06-21 12:15:15  3591919803438423                     fraud_Haley Group
4 2020-06-21 12:15:17  3526826139003047                 fraud_Johnston-Casper

         category    amt gender  city_pop                      job  \
0   personal_care   2.86      M    333497      Mechanical engineer
1   personal_care  29.84      F       302  Sales professional, IT
2  health_fitness  41.28      F     34496        Librarian, public
3        misc_pos  60.05      M     54767             Set designer
4          travel   3.19      M      1126       Furniture designer

  date_of_birth  year_of_birth    txn_date  age    distance  hour  day  month  \
0    1968-03-19           1968  2020-06-21   52   24.613746    12   21      6
1    1990-01-17           1990  2020-06-21   30  104.834043    12   21      6
2    1970-10-21           1970  2020-06-21   50   59.204796    12   21      6
3    1987-07-25           1987  2020-06-21   33   27.615117    12   21      6
4    1955-07-06           1955  2020-06-21   65  104.423175    12   21      6

   year  is_fraud
0  2020         0
1  2020         0
```

```
2  2020        0
3  2020        0
4  2020        0
```

1.0.6 EDA - Outlier Detection

[19]:
```
fraud_df.boxplot(column='age', figsize=(4, 4))
```

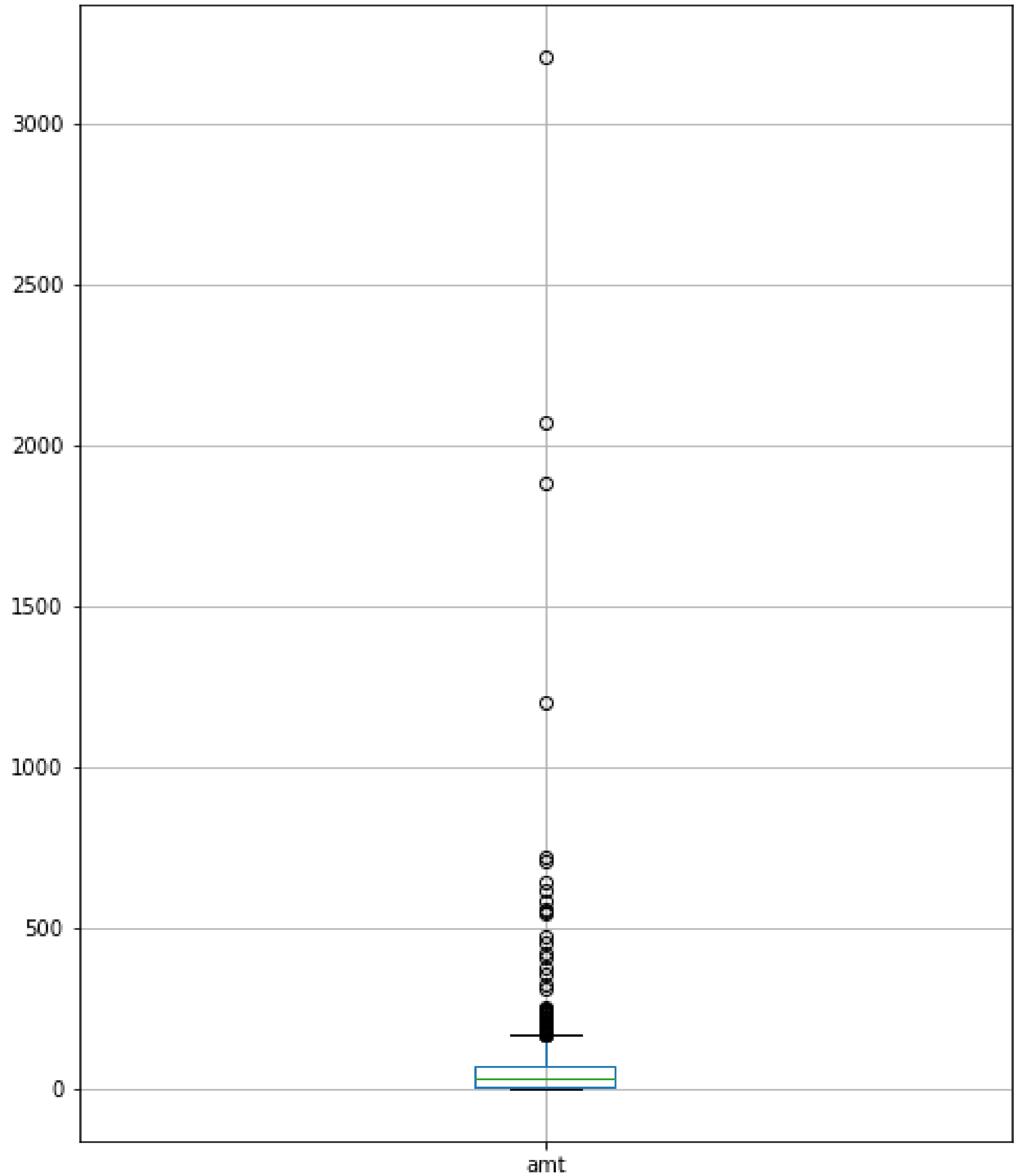
[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb1fa41bb0>



[20]:
```
stats = fraud_df['amt'].describe()
print("Transaction Amount:")
print(stats)
fraud_df.head(1000).boxplot(column='amt', figsize=(8, 10))
```

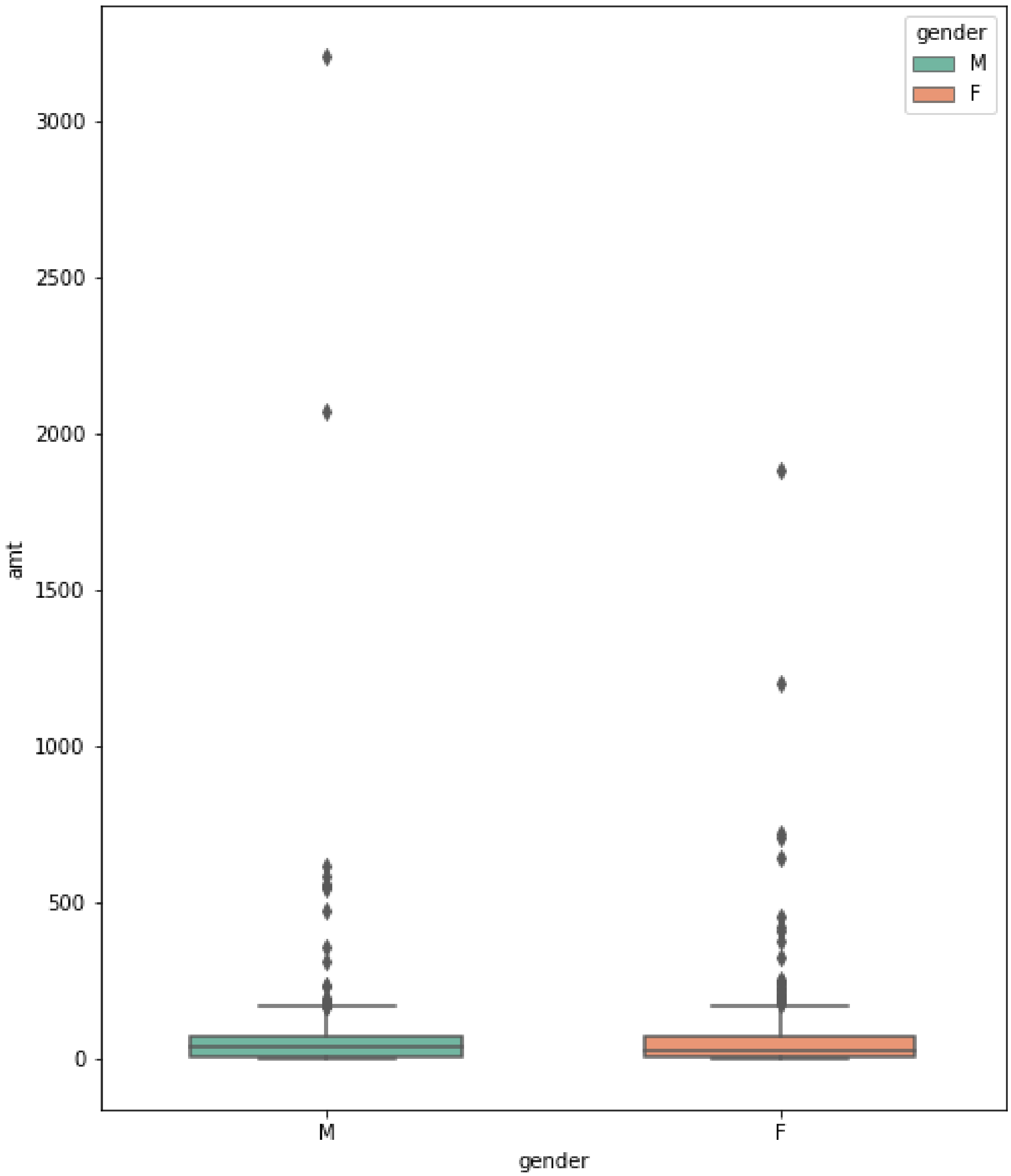
```
Transaction Amount:
count    1.852394e+06
mean     7.006357e+01
std      1.592540e+02
min      1.000000e+00
25%      9.640000e+00
50%      4.745000e+01
75%      8.310000e+01
max      2.894890e+04
Name: amt, dtype: float64
```

[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb1f7a4ee0>



[24]:
```
gender_amt = pd.DataFrame(fraud_df.head(1000), columns = ['amt', 'gender'])
plt.figure(figsize=(8,10))
sns.boxplot(y='amt', x='gender', data=gender_amt, hue='gender', dodge=False,␣
 ↪width = 0.6, palette= 'Set2')
```

[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7fbb1fa3ae50>



1.0.7 EDA - Imbalance Identification

[31]:
```
fraud_counts = fraud_df['is_fraud'].value_counts().sort_index().reset_index()
fraud_counts.columns = ['is_fraud','count']

# print(fraud_counts)
```

```
no_fraud_count = fraud_counts.loc[fraud_counts['is_fraud'] == 0].
↪iloc[0]['count']
fraud_count = fraud_counts.loc[fraud_counts['is_fraud'] == 1].iloc[0]['count']

percent_with_fraud = "{:.2f}".format(((fraud_count / no_fraud_count) * 100))

print(f"No Fraud Count: {no_fraud_count}")
print(f"Fraud Count: {fraud_count}")
print(f"Fraud Percentage: {percent_with_fraud}%")
```

```
No Fraud Count: 1842743
Fraud Count: 9651
Fraud Percentage: 0.52%
```

1.0.8 Data Encoding - One Hot Encoder

[32]:
```
cat_col = ['category','gender']
fraud_df['Target'] = fraud_df['amt']
#This one hot encodes the categorical columns and create a new variable to hold␣
↪the nex column headers
if len(cat_col)>0:
    cat_onehotencode = pd.get_dummies(fraud_df[cat_col],drop_first = True)
    cat_col_onehotencode = list(cat_onehotencode.columns)
    fraud_df = pd.concat([fraud_df,cat_onehotencode], axis = 1)

else:
    cat_col_onehotencode = []
fraud_df[cat_col_onehotencode].head()
```

[32]:
```
   category_food_dining  category_gas_transport  category_grocery_net  \
0                     0                       0                     0
1                     0                       0                     0
2                     0                       0                     0
3                     0                       0                     0
4                     0                       0                     0

   category_grocery_pos  category_health_fitness  category_home  \
0                     0                        0              0
1                     0                        0              0
2                     0                        1              0
3                     0                        0              0
4                     0                        0              0

   category_kids_pets  category_misc_net  category_misc_pos  \
0                   0                  0                  0
1                   0                  0                  0
2                   0                  0                  0
```

```
3                   0                   0                   1
4                   0                   0                   0

   category_personal_care  category_shopping_net  category_shopping_pos  \
0                       1                      0                      0
1                       1                      0                      0
2                       0                      0                      0
3                       0                      0                      0
4                       0                      0                      0

   category_travel  gender_M
0                0         1
1                0         0
2                0         0
3                0         1
4                1         1
```

[33]:
```
fraud_df.to_csv('df_cat.csv', index=False)
```

[34]:
```
df=pd.read_csv('df_cat.csv')
df.head(10)
```

[34]:
```
          txn_datetime           cc_num  \
0  2020-06-21 12:14:25  2291163933867244
1  2020-06-21 12:14:33  3573030041201292
2  2020-06-21 12:14:53  3598215285024754
3  2020-06-21 12:15:15  3591919803438423
4  2020-06-21 12:15:17  3526826139003047
5  2020-06-21 12:15:37    30407675418785
6  2020-06-21 12:15:44   213180742685905
7  2020-06-21 12:15:50  3589289942931264
8  2020-06-21 12:16:10  3596357274378601
9  2020-06-21 12:16:11  3546897637165774

                               merchant        category     amt gender  \
0                 fraud_Kirlin and Sons   personal_care    2.86      M
1                  fraud_Sporer-Keebler   personal_care   29.84      F
2  fraud_Swaniawski, Nitzsche and Welch  health_fitness   41.28      F
3                     fraud_Haley Group        misc_pos   60.05      M
4                 fraud_Johnston-Casper          travel    3.19      M
5                   fraud_Daugherty LLC       kids_pets   19.55      F
6                  fraud_Romaguera Ltd  health_fitness  133.93      F
7                     fraud_Reichel LLC   personal_care   10.37      F
8      fraud_Goyette, Howell and Collier    shopping_pos    4.37      M
9                    fraud_Kilback Group     food_dining   66.54      F

   city_pop                                     job date_of_birth  \
```

```
0   333497                   Mechanical engineer    1968-03-19
1      302                Sales professional, IT    1990-01-17
2    34496                     Librarian, public    1970-10-21
3    54767                          Set designer    1987-07-25
4     1126                    Furniture designer    1955-07-06
5      520                       Psychotherapist    1991-10-13
6     1139              Therapist, occupational    1951-01-15
7      343  Development worker, international aid    1972-03-05
8     3688                         Advice worker    1973-05-27
9      263                             Barrister    1956-05-30

   year_of_birth  … category_health_fitness  category_home  \
0           1968  …                       0              0
1           1990  …                       0              0
2           1970  …                       1              0
3           1987  …                       0              0
4           1955  …                       0              0
5           1991  …                       0              0
6           1951  …                       1              0
7           1972  …                       0              0
8           1973  …                       0              0
9           1956  …                       0              0

   category_kids_pets  category_misc_net  category_misc_pos  \
0                   0                  0                  0
1                   0                  0                  0
2                   0                  0                  0
3                   0                  0                  1
4                   0                  0                  0
5                   1                  0                  0
6                   0                  0                  0
7                   0                  0                  0
8                   0                  0                  0
9                   0                  0                  0

   category_personal_care  category_shopping_net  category_shopping_pos  \
0                       1                      0                      0
1                       1                      0                      0
2                       0                      0                      0
3                       0                      0                      0
4                       0                      0                      0
5                       0                      0                      0
6                       0                      0                      0
7                       1                      0                      0
8                       0                      0                      1
9                       0                      0                      0
```

```
   category_travel  gender_M
0                0         1
1                0         0
2                0         0
3                0         1
4                1         1
5                0         0
6                0         0
7                0         0
8                0         1
9                0         0

[10 rows x 33 columns]
```

[35]:
```python
df.drop([
    'cc_num',
    'merchant',
    'category',
    'last',
    'job',
    'date_of_birth',
    'year_of_birth',
    'gender',
    'txn_datetime',
    'txn_date',
    'Target'
], axis=1, errors='ignore', inplace=True)
df.head()
```

[35]:
```
     amt  city_pop  age    distance  hour  day  month  year  is_fraud  \
0   2.86    333497   52   24.613746    12   21      6  2020         0
1  29.84       302   30  104.834043    12   21      6  2020         0
2  41.28     34496   50   59.204796    12   21      6  2020         0
3  60.05     54767   33   27.615117    12   21      6  2020         0
4   3.19      1126   65  104.423175    12   21      6  2020         0

   category_food_dining  …  category_health_fitness  category_home  \
0                     0  …                        0              0
1                     0  …                        0              0
2                     0  …                        1              0
3                     0  …                        0              0
4                     0  …                        0              0

   category_kids_pets  category_misc_net  category_misc_pos  \
0                   0                  0                  0
1                   0                  0                  0
2                   0                  0                  0
```

```
3                   0                   0                   1
4                   0                   0                   0

   category_personal_care  category_shopping_net  category_shopping_pos  \
0                       1                      0                      0
1                       1                      0                      0
2                       0                      0                      0
3                       0                      0                      0
4                       0                      0                      0

   category_travel  gender_M
0                0         1
1                0         0
2                0         0
3                0         1
4                1         1

[5 rows x 23 columns]
```

[36]:
```
df.nunique()
```

[36]:
```
amt                          60616
city_pop                       891
age                             82
distance                   1852394
hour                            24
day                             31
month                           12
year                             2
is_fraud                         2
category_food_dining             2
category_gas_transport           2
category_grocery_net             2
category_grocery_pos             2
category_health_fitness          2
category_home                    2
category_kids_pets               2
category_misc_net                2
category_misc_pos                2
category_personal_care           2
category_shopping_net            2
category_shopping_pos            2
category_travel                  2
gender_M                         2
dtype: int64
```

[37]:
```
#df.sum
```

[38]:
```
#Breaking it into two parts, separate the target variable from the other columns
X=df.drop('is_fraud',axis=1).copy()
X.head()
```

[38]:
```
     amt  city_pop  age    distance  hour  day  month  year  \
0   2.86    333497   52   24.613746    12   21      6  2020
1  29.84       302   30  104.834043    12   21      6  2020
2  41.28     34496   50   59.204796    12   21      6  2020
3  60.05     54767   33   27.615117    12   21      6  2020
4   3.19      1126   65  104.423175    12   21      6  2020

   category_food_dining  category_gas_transport  …  category_health_fitness  \
0                     0                       0  …                        0
1                     0                       0  …                        0
2                     0                       0  …                        1
3                     0                       0  …                        0
4                     0                       0  …                        0

   category_home  category_kids_pets  category_misc_net  category_misc_pos  \
0              0                   0                  0                  0
1              0                   0                  0                  0
2              0                   0                  0                  0
3              0                   0                  0                  1
4              0                   0                  0                  0

   category_personal_care  category_shopping_net  category_shopping_pos  \
0                       1                      0                      0
1                       1                      0                      0
2                       0                      0                      0
3                       0                      0                      0
4                       0                      0                      0

   category_travel  gender_M
0                0         1
1                0         0
2                0         0
3                0         1
4                1         1

[5 rows x 22 columns]
```

[39]:
```
y=df['is_fraud'].copy()
y.head()
```

[39]:
```
0    0
1    0
2    0
```

```
3    0
4    0
Name: is_fraud, dtype: int64
```

[40]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.3 ,␣
↪stratify=y)
```

[41]:
```
print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

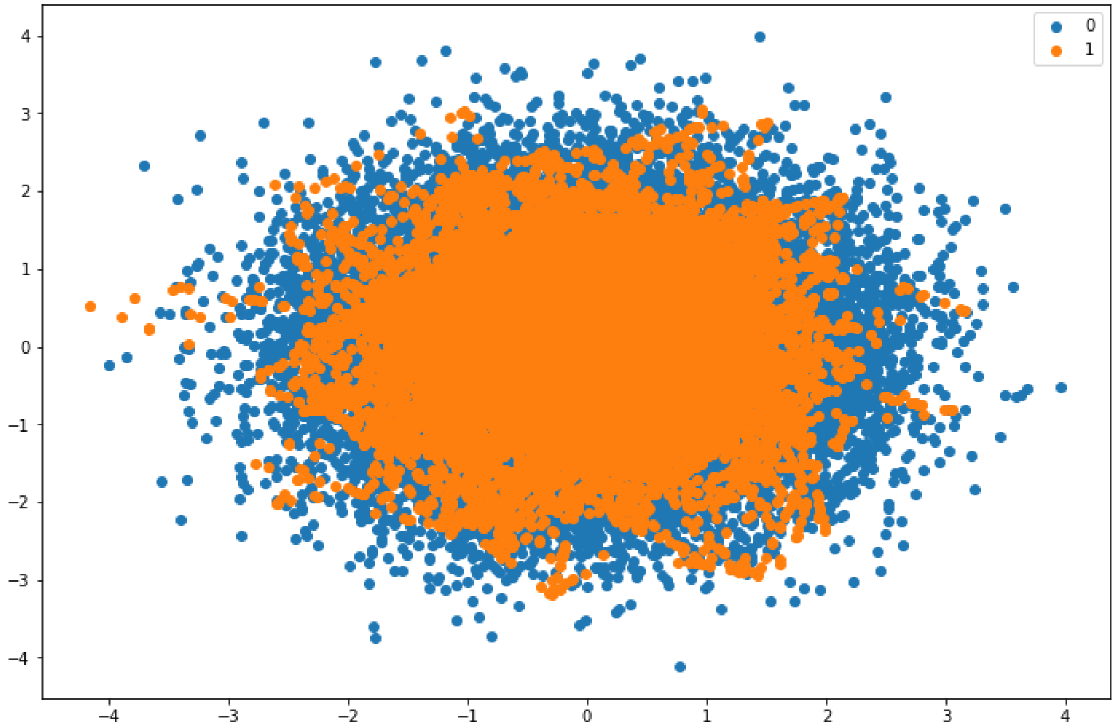
```
(1296675, 22)
(1296675,)
(555719, 22)
(555719,)
```

1.0.9 Resampling

[158]:
```
# Oversample with SMOTE and random undersample for imbalanced dataset
# Define dataset
X_train, y_train = make_classification(n_samples=100000, n_features=22,␣
↪n_redundant=2, n_clusters_per_class=2,
                           weights=[0.99], flip_y=0, random_state=1)

# Summarize class distribution
counter = Counter(y_train)
print(counter)

# Define pipeline
over = SMOTE(sampling_strategy=0.2)
under = RandomUnderSampler(sampling_strategy=0.6)
steps = [('o', over), ('u', under)]
pipeline = Pipeline(steps=steps)

# Transform the dataset
X_train, y_train = pipeline.fit_resample(X_train, y_train)

# Summarize the new class distribution
counter = Counter(y_train)
print(counter)


# Scatter plot of examples by class label
plt.figure(figsize=(12, 8))
for label, _ in counter.items():
    row_ix = where(y_train == label)[0]
```

```
    plt.scatter(X_train[row_ix, 0], X_train[row_ix, 1], label=str(label))

plt.legend()
plt.show()
```

```
Counter({0: 99000, 1: 1000})
Counter({0: 33000, 1: 19800})
```



[43]:
```
print('After resampling, the shape of X_train: {}'.format(X_train.shape))
print('After resampling, the shape of y_train: {} \n'.format(y_train.shape))

print("After resampling, counts of label '1': {}".format(sum(y_train == 1)))
print("After resampling, counts of label '0': {}".format(sum(y_train == 0)))
```

```
After resampling, the shape of X_train: (52800, 22)
After resampling, the shape of y_train: (52800,)

After resampling, counts of label '1': 19800
After resampling, counts of label '0': 33000
```

1.1 Tree-based Models

1.1.1 Decision Tree

[77]:
```
#Create a Baseline Model
dt=DecisionTreeClassifier(random_state = 12)

dt.fit(X_train, y_train)
dt.score(X_train, y_train)

# Predict Output
y_preds = dt.predict(X_test)

print('Baseline Decision Tree')

# Accuracy Score on test dataset
dt_acc_test = metrics.accuracy_score(y_test, y_preds)
print('\nAccuracy: %.2f%%' % (dt_acc_test * 100.0))

# Calculate roc auc
dt_probs_test = dt.predict_proba(X_test)[:, 1]
dt_roc_value_test = roc_auc_score(y_test, dt_probs_test)
print('\nROC AUC: ', round(dt_roc_value_test,2))
```

```
Baseline Decision Tree

Accuracy: 63.66%

ROC AUC:  0.46
```

[45]:
```
#Create Optimized Model

ccp_alpha=[0.0,0.2]
class_weight=[None]
criterion=['gini','entropy']
max_depth=[3,4,5]
max_features=["auto", "sqrt", "log2","none"]
max_leaf_nodes=[3,4,5]
min_impurity_decrease=[0.0]
min_impurity_split=[None]
min_samples_leaf=[1,2,5,10]
min_samples_split=[1,2,5,10]
min_weight_fraction_leaf=[0.0,0.1,0.25]
random_state=[24]
splitter=['best','random']

#param_grid
```

```
param_grid_dt = {'ccp_alpha': ccp_alpha,
 'class_weight': class_weight,
 'criterion': criterion,
 'max_depth': max_depth,
 'max_features': max_features,
 'max_leaf_nodes': max_leaf_nodes,
 'min_impurity_decrease': min_impurity_decrease,
 'min_impurity_split': min_impurity_split,
 'min_samples_leaf': min_samples_leaf,
 'min_samples_split': min_samples_split,
 'min_weight_fraction_leaf': min_weight_fraction_leaf,
 'random_state': random_state,
 'splitter': splitter}

print(param_grid_dt)
```

```
{'ccp_alpha': [0.0, 0.1, 0.2, 0.5], 'class_weight': [None], 'criterion':
['gini', 'entropy'], 'max_depth': [3, 4, 5, 10], 'max_features': ['auto',
'sqrt', 'log2', 'none'], 'max_leaf_nodes': [3, 4, 5, 10],
'min_impurity_decrease': [0.0], 'min_impurity_split': [None],
'min_samples_leaf': [1, 2, 5, 10], 'min_samples_split': [1, 2, 5, 10],
'min_weight_fraction_leaf': [0.0, 0.1, 0.25], 'random_state': [24], 'splitter':
['best', 'random']}
```

[46]:
```
# create the cross-validation by grid method
auc_scoring = make_scorer(roc_auc_score)

dt_grid = GridSearchCV(estimator = dt, param_grid = param_grid_dt,
                            cv = 5, scoring=auc_scoring,verbose = 1, n_jobs =␣
 ↪-1,
                            error_score=0)

# fit the random search model
t1 = time.time()
dt_grid.fit(X_train, y_train)
t2 = time.time()
print('Elapsed Time:',(t2-t1))

print('Best Parameters:',dt_grid.best_params_)
```

```
Fitting 5 folds for each of 49152 candidates, totalling 245760 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    2.2s
[Parallel(n_jobs=-1)]: Done 560 tasks      | elapsed:    6.0s
[Parallel(n_jobs=-1)]: Done 1560 tasks      | elapsed:   13.3s
[Parallel(n_jobs=-1)]: Done 2960 tasks      | elapsed:   22.9s
[Parallel(n_jobs=-1)]: Done 4760 tasks      | elapsed:   35.4s
```

```
[Parallel(n_jobs=-1)]: Done 6992 tasks      | elapsed:   47.1s
[Parallel(n_jobs=-1)]: Done 12192 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 18192 tasks      | elapsed:  2.0min
[Parallel(n_jobs=-1)]: Done 24992 tasks      | elapsed:  2.7min
[Parallel(n_jobs=-1)]: Done 32592 tasks      | elapsed:  3.6min
[Parallel(n_jobs=-1)]: Done 40992 tasks      | elapsed:  4.6min
[Parallel(n_jobs=-1)]: Done 50192 tasks      | elapsed:  5.8min
[Parallel(n_jobs=-1)]: Done 60192 tasks      | elapsed:  7.1min
[Parallel(n_jobs=-1)]: Done 70992 tasks      | elapsed:  8.2min
[Parallel(n_jobs=-1)]: Done 82592 tasks      | elapsed:  9.7min
[Parallel(n_jobs=-1)]: Done 94992 tasks      | elapsed: 11.2min
[Parallel(n_jobs=-1)]: Done 108192 tasks      | elapsed: 12.8min
[Parallel(n_jobs=-1)]: Done 122192 tasks      | elapsed: 14.8min
[Parallel(n_jobs=-1)]: Done 136992 tasks      | elapsed: 16.6min
[Parallel(n_jobs=-1)]: Done 152592 tasks      | elapsed: 18.5min
[Parallel(n_jobs=-1)]: Done 168992 tasks      | elapsed: 20.6min
[Parallel(n_jobs=-1)]: Done 182056 tasks      | elapsed: 22.7min
[Parallel(n_jobs=-1)]: Done 191056 tasks      | elapsed: 23.7min
[Parallel(n_jobs=-1)]: Done 200456 tasks      | elapsed: 25.0min
[Parallel(n_jobs=-1)]: Done 210256 tasks      | elapsed: 26.2min
[Parallel(n_jobs=-1)]: Done 225800 tasks      | elapsed: 28.2min
[Parallel(n_jobs=-1)]: Done 244208 tasks      | elapsed: 30.8min
[Parallel(n_jobs=-1)]: Done 245760 out of 245760 | elapsed: 30.9min finished
```

```
Elapsed Time: 1853.7536578178406
Best Parameters: {'ccp_alpha': 0.0, 'class_weight': None, 'criterion':
'entropy', 'max_depth': 3, 'max_features': 'auto', 'max_leaf_nodes': 3,
'min_impurity_decrease': 0.0, 'min_impurity_split': None, 'min_samples_leaf': 1,
'min_samples_split': 2, 'min_weight_fraction_leaf': 0.1, 'random_state': 24,
'splitter': 'best'}
```

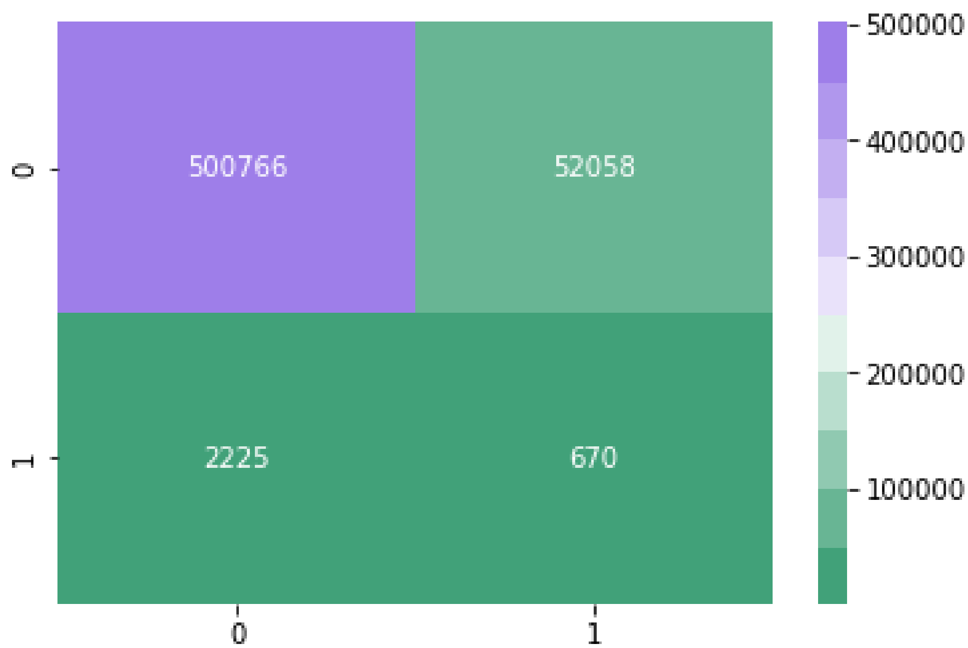
[78]:
```
print('Optimized Decision Tree')

y_preds_grid = dt_grid.best_estimator_.predict_proba(X_test)[:,1]

dt_opt_acc = accuracy_score(y_test, y_preds_grid.round())
print('\nAccuracy: %.2f%%' % (dt_opt_acc * 100.0))

dt_opt_auc = roc_auc_score(y_test, y_preds_grid)
print('\nROC AUC: ', round(dt_opt_auc,2))
```

```
Optimized Decision Tree

Accuracy: 90.23%

ROC AUC:  0.57
```

1.1.2 Confusion Matrix

[102]:
```
# confusion matrix
DTmatrix = confusion_matrix(y_test, y_preds_grid.round())
print('Confusion matrix : \n',DTmatrix)

# classification report for precision, recall f1-score and accuracy
DTmatrix1 = classification_report(y_test,y_preds_grid.round())
print('Classification report : \n',DTmatrix1)

cmap =  sns.diverging_palette(150, 275, s=80, l=60, n=10)
sns.heatmap(DTmatrix, annot=True,fmt='.0f',cmap=cmap)
plt.show()
```

```
Confusion matrix :
 [[500766  52058]
 [  2225    670]]
Classification report :
               precision    recall  f1-score   support

           0       1.00      0.91      0.95    552824
           1       0.01      0.23      0.02      2895

    accuracy                           0.90    555719
   macro avg       0.50      0.57      0.49    555719
weighted avg       0.99      0.90      0.94    555719
```



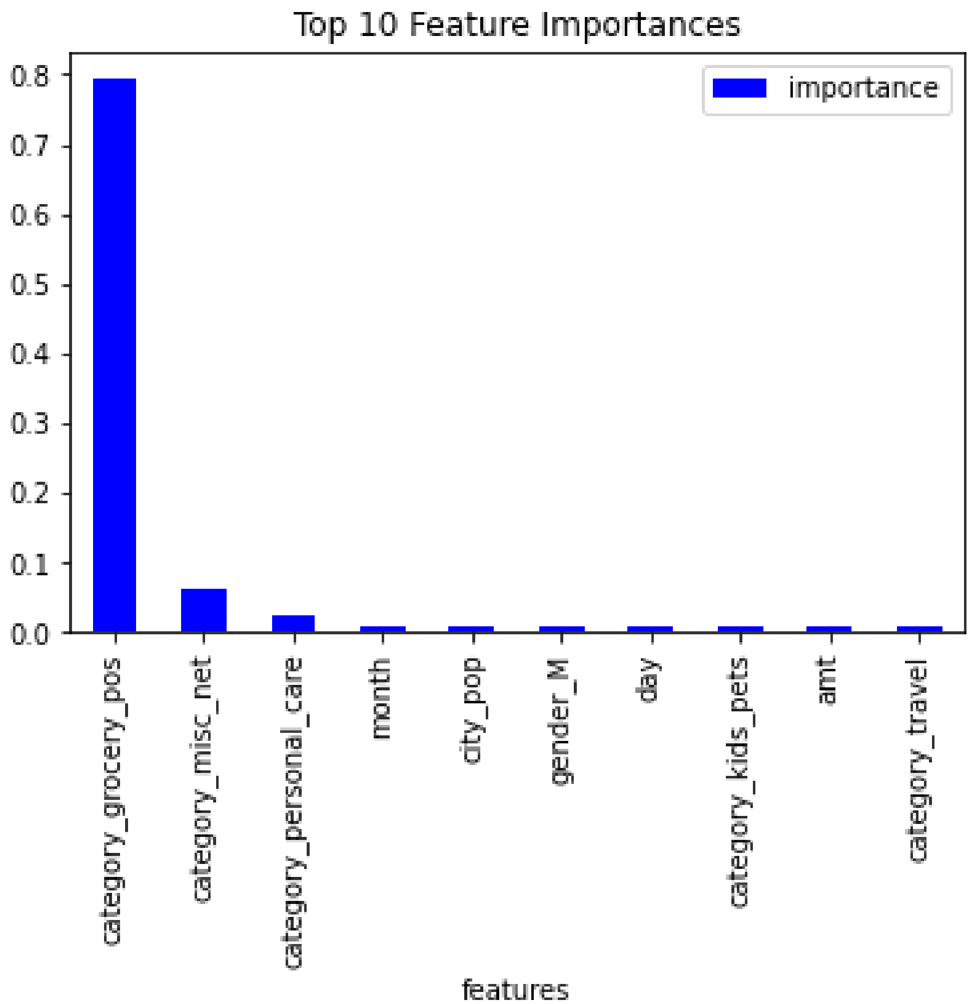
1.1.3 Feature Importances

[91]:
```
# Extract feature importances
DT_Feature_Imp = pd.DataFrame({'features': list(X),
                    'importance': dt.feature_importances_}).\
                     sort_values('importance', ascending = False)
DT_Feature_Imp = DT_Feature_Imp.head(10)
DT_Feature_Imp
```

[91]:

	features	importance
11	category_grocery_pos	0.794296
15	category_misc_net	0.060506
17	category_personal_care	0.024574
6	month	0.008582
1	city_pop	0.007731
21	gender_M	0.007692
5	day	0.007543
14	category_kids_pets	0.007280
0	amt	0.007257
20	category_travel	0.007095

[92]:
```
DT_Feature_Imp.plot(x ='features', y='importance', kind = 'bar', color ='blue',␣
 ↪title='Top 10 Feature Importances')
plt.show()
```



1.1.4 Random Forest

[81]:
```
#Create a Baseline Model
rf=RandomForestClassifier(random_state = 12)

rf.fit(X_train, y_train)

rf_preds = rf.predict(X_test)

print('Baseline Random Forest')

print('\nNumber of Trees used : ', rf.n_estimators)

rf_acc = accuracy_score(y_test,rf_preds)
print('\nAccuracy: %.2f%%' % (rf_acc * 100.0))
```

```
rf_base_auc = roc_auc_score(y_test, rf_preds)
print('\nROC AUC: ', round(rf_base_auc,2))
```

```
Baseline Random Forest

Number of Trees used :  100

Accuracy: 99.48%

ROC AUC:  0.5
```

[82]:

```
#Create Optimized Model

bootstrap=[True,False]
ccp_alpha=[0.0,0.2]
class_weight=[None]
criterion=['gini','entropy']
max_depth=[3,4,5]
max_features=["auto", "sqrt", "log2","none"]
max_leaf_nodes=[None]
max_samples=[0,.5,1]
min_impurity_decrease=[0.0]
min_impurity_split=[None]
min_samples_leaf=[1,2,10]
min_samples_split=[1,2,10]
n_estimators=[10,100,250]
n_jobs=[-1]
oob_score=[True,False]
random_state=[12]
verbose=[1]
warm_start=[True,False]

#param_grid

param_grid_rf = {'bootstrap': bootstrap,
 'ccp_alpha': ccp_alpha,
 'class_weight': class_weight,
 'criterion': criterion,
 'max_depth': max_depth,
 'max_features': max_features,
 'max_leaf_nodes': max_leaf_nodes,
 'max_samples': max_samples,
 'min_impurity_decrease': min_impurity_decrease,
 'min_impurity_split': min_impurity_split,
 'min_samples_leaf': min_samples_leaf,
 'min_samples_split': min_samples_split,
```

```
 'min_weight_fraction_leaf': min_weight_fraction_leaf,
 'n_estimators': n_estimators,
 'n_jobs': n_jobs,
 'oob_score': oob_score,
 'random_state': random_state,
 'verbose': verbose,
 'warm_start': warm_start}

print(param_grid_rf)
```

```
{'bootstrap': [True, False], 'ccp_alpha': [0.0, 0.2], 'class_weight': [None],
'criterion': ['gini', 'entropy'], 'max_depth': [3, 4, 5], 'max_features':
['auto', 'sqrt', 'log2', 'none'], 'max_leaf_nodes': [None], 'max_samples': [0,
0.5, 1], 'min_impurity_decrease': [0.0], 'min_impurity_split': [None],
'min_samples_leaf': [1, 2, 10], 'min_samples_split': [1, 2, 10],
'min_weight_fraction_leaf': [0.0, 0.1, 0.25], 'n_estimators': [10, 100, 250],
'n_jobs': [-1], 'oob_score': [True, False], 'random_state': [12], 'verbose':
[1], 'warm_start': [True, False]}
```

[83]:
```
#Random grid search used for time constraints:
rf_rand = RandomizedSearchCV(estimator = rf, param_distributions =␣
 ↪param_grid_rf,
                             n_iter = 1000, cv = 5, scoring=auc_scoring,verbose␣
 ↪= 1, n_jobs = -1,
                             error_score=0, random_state=12)


# fit the random search model (this will take a few minutes)
t1 = time.time()
rf_rand.fit(X_train, y_train)
t2 = time.time()
print('Elapsed Time:',(t2-t1))

print('Best Parameters:',rf_rand.best_params_)
```

```
Fitting 5 folds for each of 1000 candidates, totalling 5000 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    4.3s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:   24.3s
[Parallel(n_jobs=-1)]: Done 464 tasks      | elapsed:  2.3min
[Parallel(n_jobs=-1)]: Done 816 tasks      | elapsed:  3.6min
[Parallel(n_jobs=-1)]: Done 1266 tasks      | elapsed:  6.8min
[Parallel(n_jobs=-1)]: Done 1854 tasks      | elapsed:  9.4min
[Parallel(n_jobs=-1)]: Done 2506 tasks      | elapsed: 13.1min
[Parallel(n_jobs=-1)]: Done 3488 tasks      | elapsed: 15.9min
[Parallel(n_jobs=-1)]: Done 4354 tasks      | elapsed: 21.1min
[Parallel(n_jobs=-1)]: Done 5000 out of 5000 | elapsed: 23.8min finished
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:    0.6s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:    2.3s
[Parallel(n_jobs=-1)]: Done 250 out of 250 | elapsed:    3.0s finished
```

```
Elapsed Time: 1435.5347800254822
Best Parameters: {'warm_start': False, 'verbose': 1, 'random_state': 12,
'oob_score': True, 'n_jobs': -1, 'n_estimators': 250,
'min_weight_fraction_leaf': 0.0, 'min_samples_split': 10, 'min_samples_leaf': 2,
'min_impurity_split': None, 'min_impurity_decrease': 0.0, 'max_samples': 0.5,
'max_leaf_nodes': None, 'max_features': 'sqrt', 'max_depth': 5, 'criterion':
'gini', 'class_weight': None, 'ccp_alpha': 0.0, 'bootstrap': True}
```

[93]:
```
print('Optimized Random Forest')
y_preds_rand = rf_rand.best_estimator_.predict_proba(X_test)[:,1]

rf_opt_acc = accuracy_score(y_test,y_preds_rand.round())
print('\nAccuracy: %.2f%%' % (rf_opt_acc * 100.0))

rf_opt_auc = roc_auc_score(y_test, y_preds_rand.round())
print('\nROC AUC: ', round(rf_opt_auc,2))
```

```
Optimized Random Forest
```

```
[Parallel(n_jobs=8)]: Using backend ThreadingBackend with 8 concurrent workers.
[Parallel(n_jobs=8)]: Done  34 tasks      | elapsed:    0.2s
[Parallel(n_jobs=8)]: Done 184 tasks      | elapsed:    0.9s


Accuracy: 90.23%

ROC AUC:  0.57
```

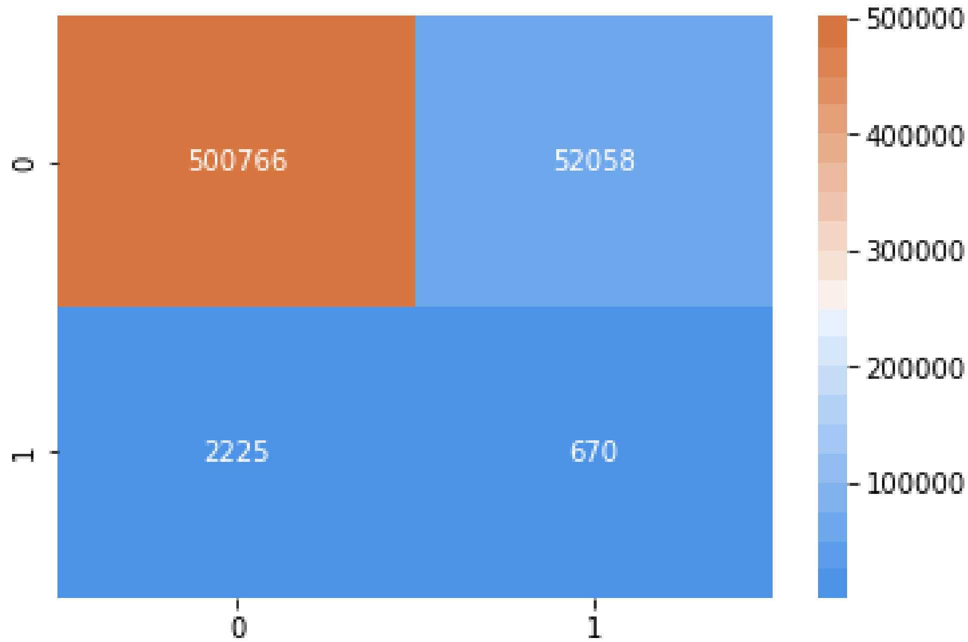
```
[Parallel(n_jobs=8)]: Done 250 out of 250 | elapsed:    1.2s finished
```

1.1.5 Confusion Matrix

[159]:
```
# confusion matrix
RFmatrix = confusion_matrix(y_test, y_preds_rand.round())
print('Confusion matrix : \n',RFmatrix)

# classification report for precision, recall f1-score and accuracy
RFmatrix1 = classification_report(y_test,y_preds_rand.round())
print('Classification report : \n',RFmatrix1)

cmap =  sns.diverging_palette(250, 30, s=80, l=60, n=20)
sns.heatmap(RFmatrix, annot=True,fmt='.0f', cmap=cmap)
plt.show()
```

```
Confusion matrix :
```

```
 [[500766  52058]
 [  2225    670]]
Classification report :
               precision    recall  f1-score   support

           0       1.00      0.91      0.95    552824
           1       0.01      0.23      0.02      2895

    accuracy                           0.90    555719
   macro avg       0.50      0.57      0.49    555719
weighted avg       0.99      0.90      0.94    555719
```



1.1.6 Feature Importances

[89]:
```python
# Extract feature importances
RF_Feature_Imp = pd.DataFrame({'features': list(X),
                   'importance': rf.feature_importances_}).\
                    sort_values('importance', ascending = False)
RF_Feature_Imp = RF_Feature_Imp.head(10)
RF_Feature_Imp
```

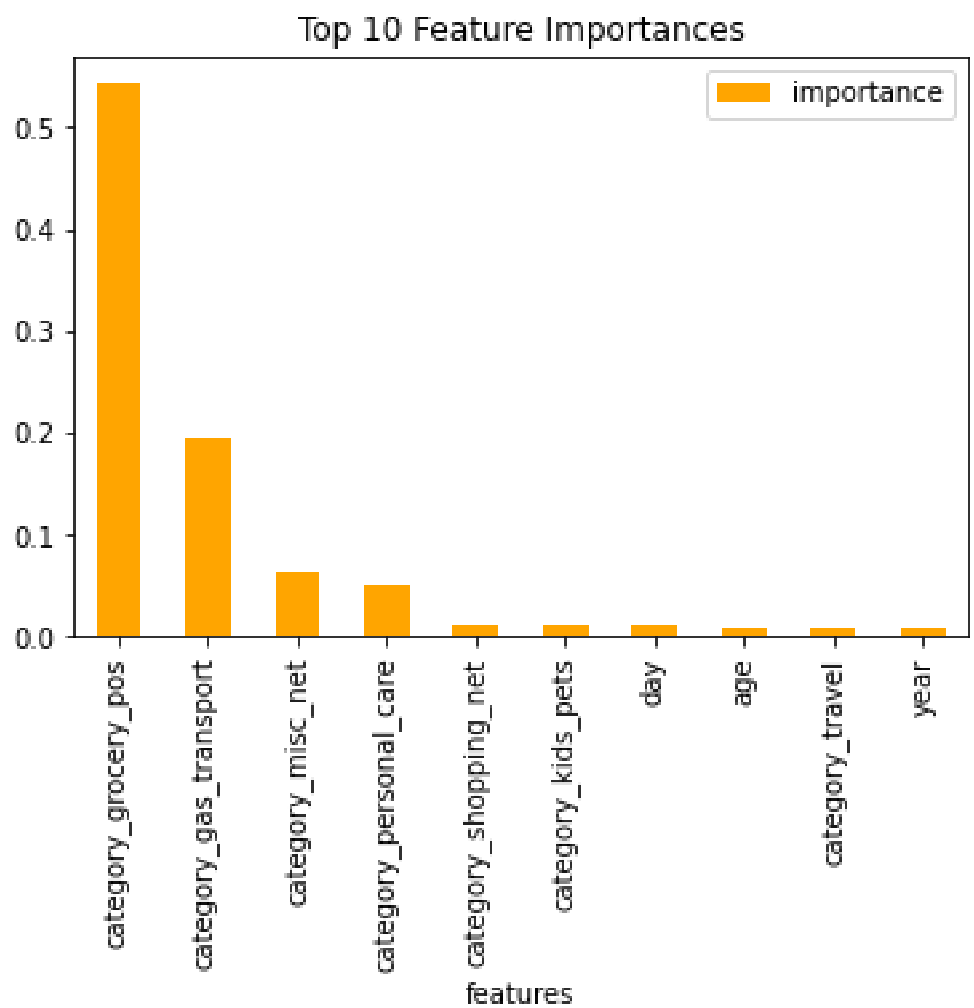
[89]:

	features	importance
11	category_grocery_pos	0.543077
9	category_gas_transport	0.195319

```
15        category_misc_net    0.062333
17  category_personal_care    0.048829
18    category_shopping_net    0.010499
14       category_kids_pets    0.010089
5                       day    0.009976
2                       age    0.009289
20          category_travel    0.008875
7                      year    0.008441
```

[90]:

```
RF_Feature_Imp.plot(x ='features', y='importance', kind = 'bar', color␣
 ↪='orange', title='Top 10 Feature Importances')
plt.show()
```



1.2 XgBoost Model

[115]:
```
count = len(df)
train2 = df[:count]
test2 = df[count:]
X2 = train2.drop(['is_fraud'], axis=1)
y2 = train2['is_fraud'].astype('int')
test2 = test2.drop(['is_fraud'], axis=1)
X_train2,X_test2, y_train2,y_test2 = train_test_split(X2, y2, test_size=0.
↪3,random_state=123)

print(X_train2.shape)
print(y_train2.shape)
print(X_test2.shape)
print(y_test2.shape)
```

```
(1296675, 22)
(1296675,)
(555719, 22)
(555719,)
```

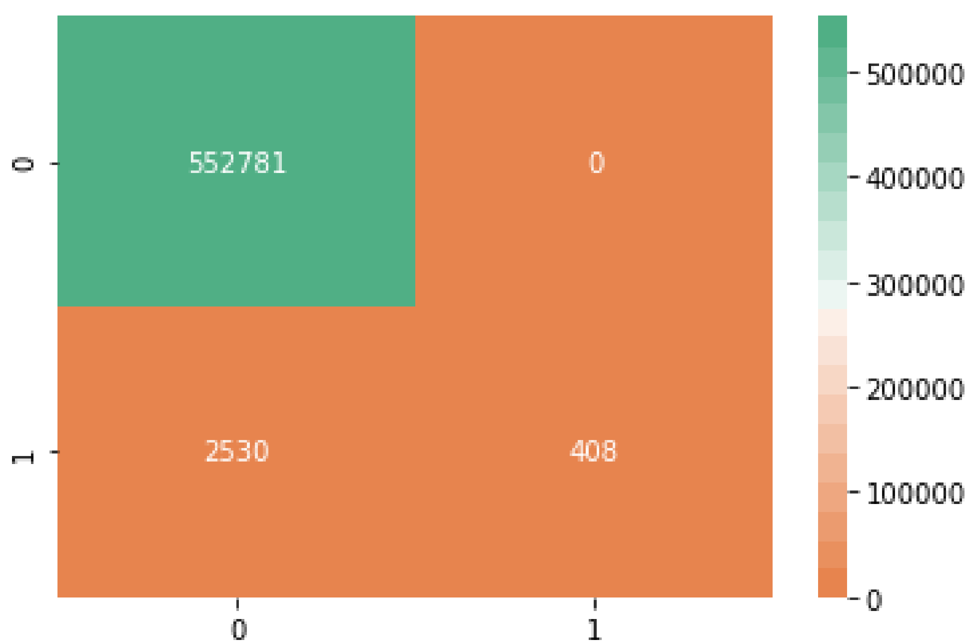
[116]:
```
XGB = xgb.XGBClassifier(n_estimators = 50, objective='binary:logistic',␣
↪booster='gbtree',
                        colsample_bytree = 0.3, learning_rate = 0.1,max_depth =␣
↪5, alpha = 10)

XGB.fit(X_train2,y_train2)

# Predict Output
XGB_pred = XGB.predict(X_test2)

# Accuracy Score on test dataset
XGB_accuracy = accuracy_score(y_test2,XGB_pred)
print("Accuracy: %.2f%%" % (XGB_accuracy * 100.0))

XGB_probs = XGB.predict_proba(X_test2)[:, 1]

# Calculate roc auc
XGB_roc_value = roc_auc_score(y_test2, XGB_probs)
print('\nROC AUC : ', round(XGB_roc_value,2))
```

```
Accuracy: 99.54%

ROC AUC :  0.98
```

1.2.1 Confusion Matrix

[161]:
```
# confusion matrix
XGBmatrix = confusion_matrix(y_test2, XGB_pred)
print('Confusion matrix : \n',XGBmatrix)

# classification report for precision, recall f1-score and accuracy
XGBmatrix1 = classification_report(y_test2,XGB_pred)
print('Classification report : \n',XGBmatrix1)

cmap =  sns.diverging_palette(30, 150, s=75, l=65, n=20)
sns.heatmap(XGBmatrix, annot=True,fmt='.0f', cmap=cmap)
plt.show()
```

```
Confusion matrix :
 [[552781      0]
 [  2530    408]]
Classification report :
               precision    recall  f1-score   support

           0       1.00      1.00      1.00    552781
           1       1.00      0.14      0.24      2938

    accuracy                           1.00    555719
   macro avg       1.00      0.57      0.62    555719
weighted avg       1.00      1.00      0.99    555719
```



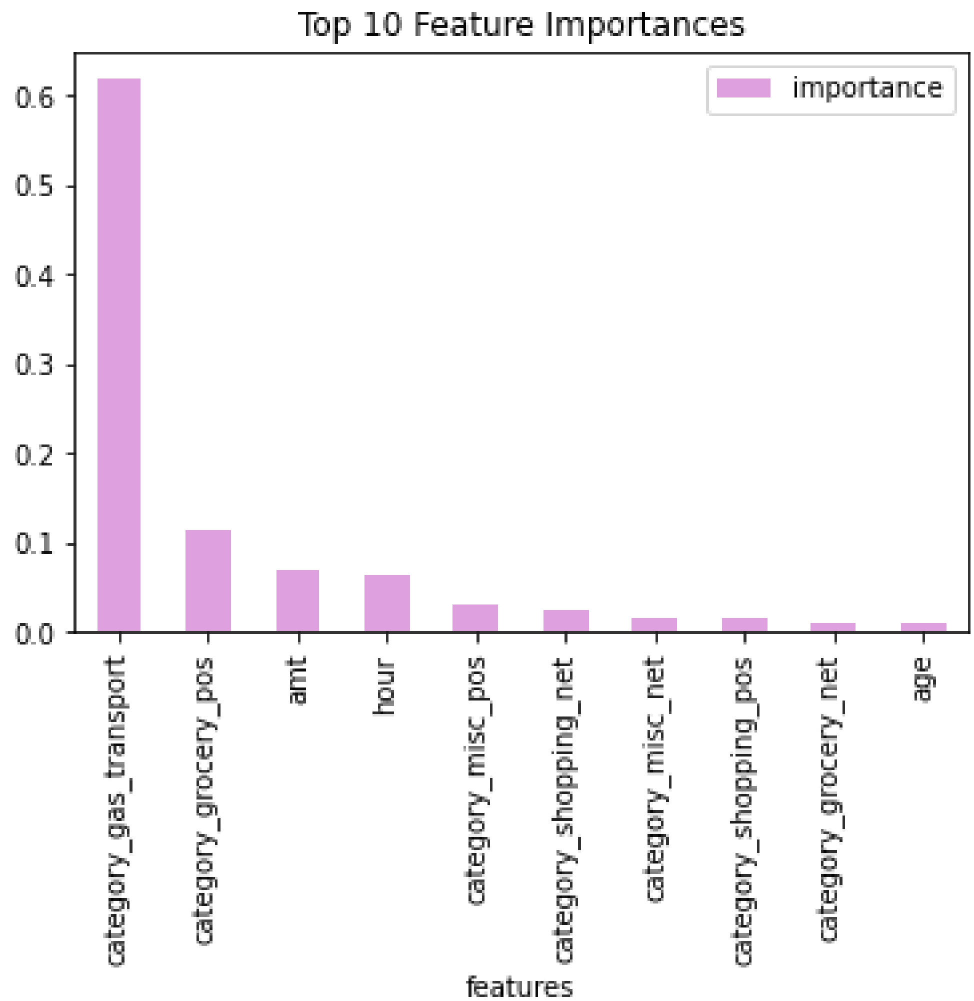
1.2.2 Feature Importances

[153]:
```
# Extract feature importances
XGB_Feature_Imp = pd.DataFrame({'features': list(X),
                   'importance': XGB.feature_importances_}).\
                    sort_values('importance', ascending = False)
XGB_Feature_Imp = XGB_Feature_Imp.head(10)
XGB_Feature_Imp
```

[153]:

	features	importance
9	category_gas_transport	0.618332
11	category_grocery_pos	0.114567
0	amt	0.067872
4	hour	0.061888
16	category_misc_pos	0.029923
18	category_shopping_net	0.023106
15	category_misc_net	0.016268
19	category_shopping_pos	0.015123
10	category_grocery_net	0.008890
2	age	0.008029

[155]:
```
XGB_Feature_Imp.plot(x ='features', y='importance', kind = 'bar', color␣
↪='plum', title='Top 10 Feature Importances')
plt.show()
```


Top 10 Feature Importances
importance
0.6
0.5
0.4
0.3
0.2
0.1
0.0
category_gas_transport
category_grocery_pos
amt
hour
category_misc_pos
category_shopping_net
category_misc_net
category_shopping_pos
category_grocery_net
age
features