Project_updated_code-maybe_final

December 6, 2021

[166]:
```
# Load the packages needed for this part
# create spark and sparkcontext objects
from pyspark.sql import SparkSession
import numpy as np

#spark = SparkSession.builder.config('','4g').getOrCreate()
spark = SparkSession.builder.config('spark.driver.memory','4g').getOrCreate()

sc = spark.sparkContext

import pyspark
from pyspark.ml import feature, regression, Pipeline
from pyspark.sql import functions as func, Row
from pyspark import sql

from pyspark.sql.functions import *
from pyspark.sql.types import IntegerType, DoubleType, FloatType

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

[167]:
```
train_df = spark.read.csv('fraudTrain.csv', header=True, inferSchema=True)
test_df = spark.read.csv('fraudTest.csv', header=True, inferSchema=True)
```

[168]:
```
train_df.printSchema()
```

```
root
 |-- _c0: integer (nullable = true)
 |-- trans_date_trans_time: string (nullable = true)
 |-- cc_num: long (nullable = true)
 |-- merchant: string (nullable = true)
 |-- category: string (nullable = true)
 |-- amt: double (nullable = true)
 |-- first: string (nullable = true)
 |-- last: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- street: string (nullable = true)
```

```
 |-- city: string (nullable = true)
 |-- state: string (nullable = true)
 |-- zip: integer (nullable = true)
 |-- lat: double (nullable = true)
 |-- long: double (nullable = true)
 |-- city_pop: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- dob: string (nullable = true)
 |-- trans_num: string (nullable = true)
 |-- unix_time: integer (nullable = true)
 |-- merch_lat: double (nullable = true)
 |-- merch_long: double (nullable = true)
 |-- is_fraud: integer (nullable = true)
```

[169]:

```
# Combine train and test data and use cross validation later
combined_df = train_df.union(test_df)
row = combined_df.count()
col = len(combined_df.columns)
print(f'Dimension of the Dataframe is: {(row,col)}')
```

```
Dimension of the Dataframe is: (1852394, 23)
```

[170]:

```
# generating column age, day_of_week, hour_of_transaction

from pyspark.sql.functions import *
from pyspark.sql.types import IntegerType, DoubleType


# Function to calculate the distance between two adress
def haversine(lon1, lat1, lon2, lat2):
    lon1, lat1, lon2, lat2 = map(np.radians, [lon1, lat1, lon2, lat2])
    newlon = lon2 - lon1
    newlat = lat2 - lat1
    haver_formula = (
        np.sin(newlat / 2.0) ** 2
        + np.cos(lat1) * np.cos(lat2) * np.sin(newlon / 2.0) ** 2
    )
    dist = 2 * np.arcsin(np.sqrt(haver_formula))
    miles = 3958 * dist
    return float(miles)

# create a udf for implementing python function in pyspark
udf_haversine = udf(haversine, DoubleType())

def create_column(data):
```

```
    # day of week and the transaction hour
    data = data.withColumn('day_of_week', date_format('trans_date_trans_time',␣
↪'EEEE')) #1st col added
    data = data.withColumn('hour_of_transaction',␣
↪hour('trans_date_trans_time')) #2nd col added

    #month_year
    data = data.withColumn('year', year('trans_date_trans_time'))
    data = data.withColumn('month', month('trans_date_trans_time'))
    data = data.withColumn('month_year', concat_ws('-', data.year ,data.month)).
↪drop(*['year', 'month']) #3rd col added

    # trans_date
    data = data.withColumn("trans_date", func.to_date(func.
↪col("trans_date_trans_time")))

    #age
    #data = data.
↪withColumn("age",round(months_between(current_date(),col("dob"))/lit(12),2))
    data = data.
↪withColumn("age",round(months_between(col('trans_date'),col("dob"))/
↪lit(12),2))
    data = data.withColumn("age", data["age"].cast(IntegerType()))

    # distance between merchant and client
    # data = data.withColumn("distance", udf_haversine("long", "lat",␣
↪"merch_long","merch_lat"))

    return data

combined_df = create_column(combined_df)
train_df = create_column(train_df)
test_df = create_column(test_df)
```

[171]:
```
# finding distance between merchant and customer

udf_haversine = udf(haversine, DoubleType())
combined_df = combined_df.withColumn("distance", udf_haversine("long", "lat",␣
↪"merch_long","merch_lat"))
```

[172]:
```
combined_df.printSchema()
```

```
root
 |-- _c0: integer (nullable = true)
 |-- trans_date_trans_time: string (nullable = true)
 |-- cc_num: long (nullable = true)
 |-- merchant: string (nullable = true)
```

```
 |-- category: string (nullable = true)
 |-- amt: double (nullable = true)
 |-- first: string (nullable = true)
 |-- last: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- street: string (nullable = true)
 |-- city: string (nullable = true)
 |-- state: string (nullable = true)
 |-- zip: integer (nullable = true)
 |-- lat: double (nullable = true)
 |-- long: double (nullable = true)
 |-- city_pop: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- dob: string (nullable = true)
 |-- trans_num: string (nullable = true)
 |-- unix_time: integer (nullable = true)
 |-- merch_lat: double (nullable = true)
 |-- merch_long: double (nullable = true)
 |-- is_fraud: integer (nullable = true)
 |-- day_of_week: string (nullable = true)
 |-- hour_of_transaction: integer (nullable = true)
 |-- month_year: string (nullable = false)
 |-- trans_date: date (nullable = true)
 |-- age: integer (nullable = true)
 |-- distance: double (nullable = true)
```

[173]:

```
# count unique credit cards
from pyspark.sql.functions import countDistinct
combined_df.select(countDistinct('cc_num').alias('CreditCard_Count')).show()
```

```
+----------------+
|CreditCard_Count|
+----------------+
|             999|
+----------------+
```

We have data of 999 credit cards. Credit card fraud detection is based on analysis of a card's spending behaviour. It is important to know the past transaction history of a credit card. Thus, we need to use feature engineering to create columns that can study a card's frequency of transaction in past 1 day, 1 week, 1 month and 3 months.

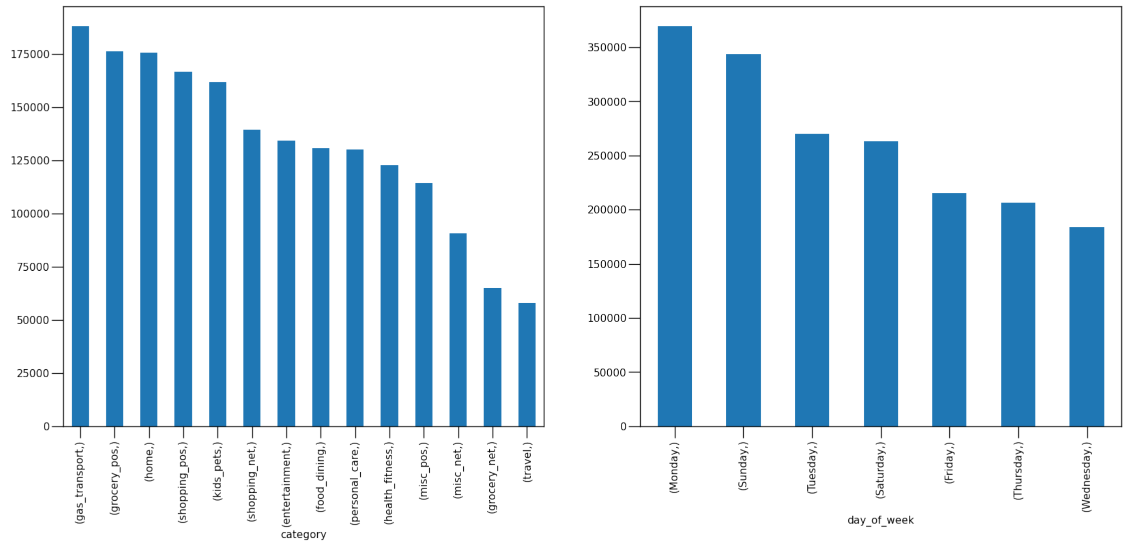
[174]:

```
# Adding dervided columns to understand the credit card usage behaviour Dayly,␣
↪Monthly and weekly.
combined_df.createOrReplaceTempView("combined_df")

new_df = \
```

```
    spark.sql(
    """SELECT *, mean(amt) OVER (
        PARTITION BY cc_num
        ORDER BY CAST(trans_date AS timestamp)
        RANGE BETWEEN INTERVAL 0 DAYS PRECEDING AND CURRENT ROW
     ) AS rolling_24h_avg_amt,

     mean(amt) OVER (
        PARTITION BY cc_num
        ORDER BY CAST(trans_date AS timestamp)
        RANGE BETWEEN INTERVAL 6 DAYS PRECEDING AND CURRENT ROW
     ) AS rolling_1_week_avg_amt,

     mean(amt) OVER (
        PARTITION BY cc_num
        ORDER BY CAST(trans_date AS timestamp)
        RANGE BETWEEN INTERVAL 29 DAYS PRECEDING AND CURRENT ROW
     ) AS rolling_1month_avg_amt,

     count(_c0) OVER (
    PARTITION BY cc_num, trans_date
    ) AS number_trans_24h,

    count(_c0) OVER (
    PARTITION BY cc_num, day_of_week
    ) AS number_trans_specific_day,

    count(_c0) OVER (
    PARTITION BY cc_num, month_year
    ) AS number_trans_month,

    sum(amt) OVER (
        PARTITION BY cc_num
        ORDER BY CAST(trans_date AS timestamp)
        RANGE BETWEEN INTERVAL 89 DAYS PRECEDING AND CURRENT ROW
     ) AS total_3month_amt

     FROM combined_df""")

new_df = new_df.
 ↪withColumn('weekly_avg_amt_over_3_months',(col('total_3month_amt')/ (1.
 ↪0*12)))
new_df = new_df.drop(*['total_3month_amt'])
```

0.0.1 Creating Visualizations

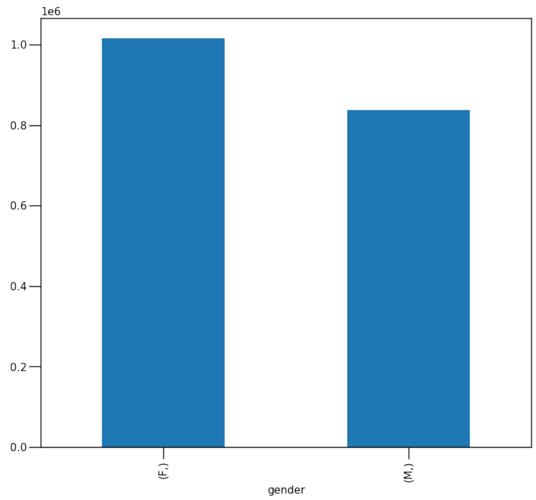
[175]:
```
plt.figure(figsize=(20,8))
plt.subplot(1,2,1)
new_df.select('category').toPandas().value_counts().plot.bar();
plt.subplot(1,2,2)
new_df.select('day_of_week').toPandas().value_counts().plot.bar();
```

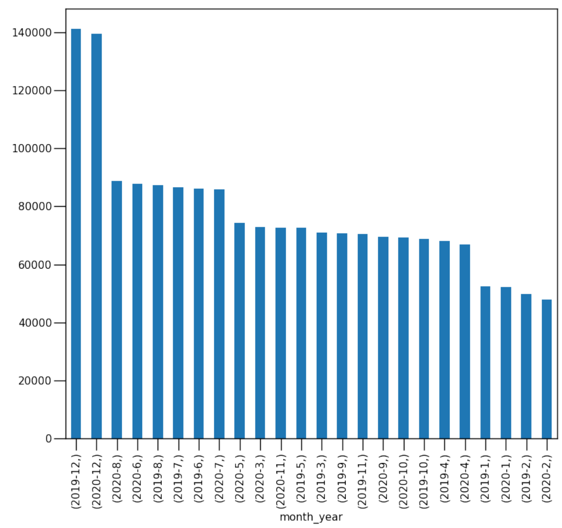


As we can see in the above visualizations the no. of transactions happening at gas_transport category are more and for travel category are less.

Also, from the second graph we can visualize that more number of transactions happen on Monday and less on Wednesday.

[176]:
```
plt.figure(figsize=(20,8))
plt.subplot(1,2,1)
new_df.select('gender').toPandas().value_counts().plot.bar();
plt.subplot(1,2,2)
new_df.select('month_year').toPandas().value_counts().plot.bar();
```





[177]:
```
# changing the transdate_trans_time and dob to timestamp

new_df = new_df.withColumn('trans_date_trans_time_new',␣
 ↪to_timestamp('trans_date_trans_time'))
new_df = new_df.drop('trans_date_trans_time')
new_df = new_df.
 ↪withColumnRenamed('trans_date_trans_time_new','trans_date_trans_time')
```

[178]:
```
new_df = new_df.withColumn('dob_new', to_date('dob'))
new_df = new_df.drop('dob')
new_df = new_df.withColumnRenamed('dob_new','dob')
```

[179]:
```
new_df.printSchema()
```

```
root
 |-- _c0: integer (nullable = true)
 |-- cc_num: long (nullable = true)
 |-- merchant: string (nullable = true)
 |-- category: string (nullable = true)
 |-- amt: double (nullable = true)
 |-- first: string (nullable = true)
 |-- last: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- street: string (nullable = true)
 |-- city: string (nullable = true)
 |-- state: string (nullable = true)
 |-- zip: integer (nullable = true)
 |-- lat: double (nullable = true)
 |-- long: double (nullable = true)
```

```
 |-- city_pop: integer (nullable = true)
 |-- job: string (nullable = true)
 |-- trans_num: string (nullable = true)
 |-- unix_time: integer (nullable = true)
 |-- merch_lat: double (nullable = true)
 |-- merch_long: double (nullable = true)
 |-- is_fraud: integer (nullable = true)
 |-- day_of_week: string (nullable = true)
 |-- hour_of_transaction: integer (nullable = true)
 |-- month_year: string (nullable = false)
 |-- trans_date: date (nullable = true)
 |-- age: integer (nullable = true)
 |-- distance: double (nullable = true)
 |-- rolling_24h_avg_amt: double (nullable = true)
 |-- rolling_1_week_avg_amt: double (nullable = true)
 |-- rolling_1month_avg_amt: double (nullable = true)
 |-- number_trans_24h: long (nullable = false)
 |-- number_trans_specific_day: long (nullable = false)
 |-- number_trans_month: long (nullable = false)
 |-- weekly_avg_amt_over_3_months: double (nullable = true)
 |-- trans_date_trans_time: timestamp (nullable = true)
 |-- dob: date (nullable = true)
```

[180]:
```
np.round(new_df.select('age').toPandas().describe())
```

[180]:

	age
count	1852394.0
mean	46.0
std	17.0
min	13.0
25%	32.0
50%	44.0
75%	57.0
max	96.0

[181]:
```
new_df.select('age').describe().show()
```

```
+-------+------------------+
|summary|               age|
+-------+------------------+
|  count|           1852394|
|   mean|45.767610994205334|
| stddev| 17.41244464440168|
|    min|                13|
|    max|                96|
+-------+------------------+
```

33-57 age people are 50% of our customers

Minimum age of customer is 14

Maximum age of customer is 96

Modifying the age variable with Categorical distinctions as follows:

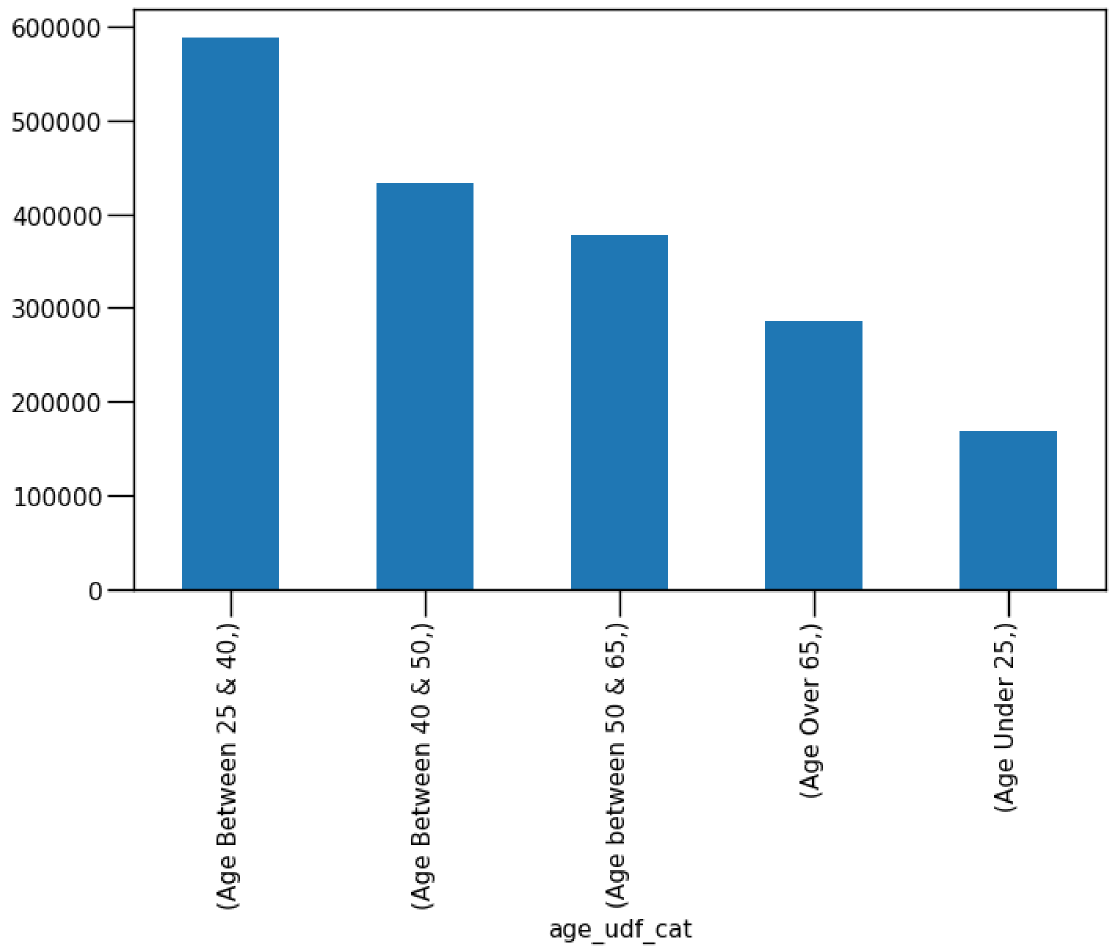
[182]:
```
def udf_age_category(age):
    if (age < 25):
        return 'Age Under 25'
    elif (age >= 25 and age < 40):
        return 'Age Between 25 & 40'
    elif (age >= 40 and age < 50):
        return 'Age Between 40 & 50'
    elif (age >=50 and age < 65):
        return 'Age between 50 & 65'
    elif (age >=65):
        return 'Age Over 65'
    else: return 'N/A'

age_udf = udf(udf_age_category)

new_df = new_df.withColumn('age_udf_cat',age_udf('age'))
```

[183]:
```
age_distribution = new_df.select('age_udf_cat').groupBy('age_udf_cat').
 ↪agg(count(col('age_udf_cat')).alias('Age_Count')).sort('Age_Count',␣
 ↪ascending = False).show(truncate = False)
age_distribution
```

```
+-------------------+---------+
|age_udf_cat        |Age_Count|
+-------------------+---------+
|Age Between 25 & 40|588955   |
|Age Between 40 & 50|433516   |
|Age between 50 & 65|377176   |
|Age Over 65        |284802   |
|Age Under 25       |167945   |
+-------------------+---------+
```

[184]:
```
new_df.select('age_udf_cat').toPandas().value_counts().plot.bar()
```

[184]: <AxesSubplot:xlabel='age_udf_cat'>



[185]:
```
np.round(((new_df.select('amt')).toPandas().describe(percentiles = [0.25,0.5,0.
↪75,0.95,0.999])),3)
```

[185]:
```
                amt
count  1852394.000
mean        70.064
std        159.254
min          1.000
25%          9.640
50%         47.450
75%         83.100
95%        195.340
99.9%     1517.241
max      28948.900
```

[186]:
```
np.round(((new_df.select('amt').filter(col('is_fraud') == 0)).toPandas().
↪describe(percentiles = [0.25,0.5,0.75,0.95,0.999])),3)
```

[186]:

	amt
count	1842743.000
mean	67.651
std	153.548
min	1.000
25%	9.610
50%	47.240
75%	82.560
95%	189.590
99.9%	1519.623
max	28948.900

[ ]:

```

```

[187]:

```
np.round(((new_df.select('amt').filter(col('is_fraud') == 1)).toPandas().
↪describe(percentiles = [0.25,0.5,0.75,0.95,0.999])),3)
```

[187]:

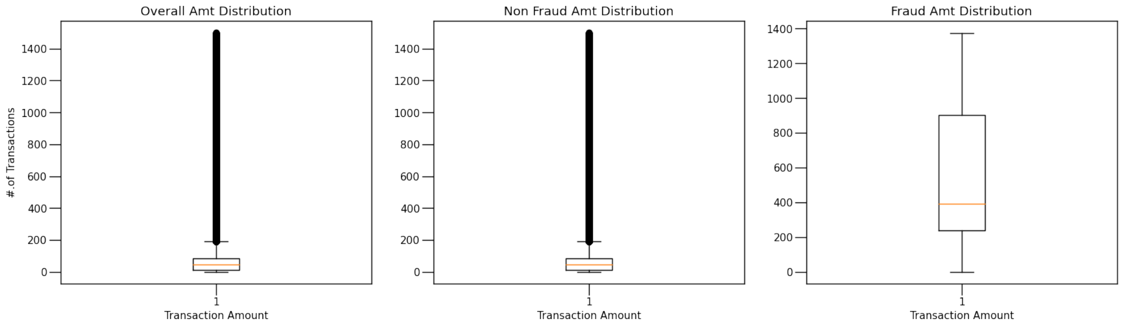
	amt
count	9651.000
mean	530.661
std	391.029
min	1.060
25%	240.075
50%	390.000
75%	902.365
95%	1084.090
99.9%	1293.127
max	1376.040

As we can see in the above distribution around 99% of total records are approximatly below 1500 amt.

[188]:

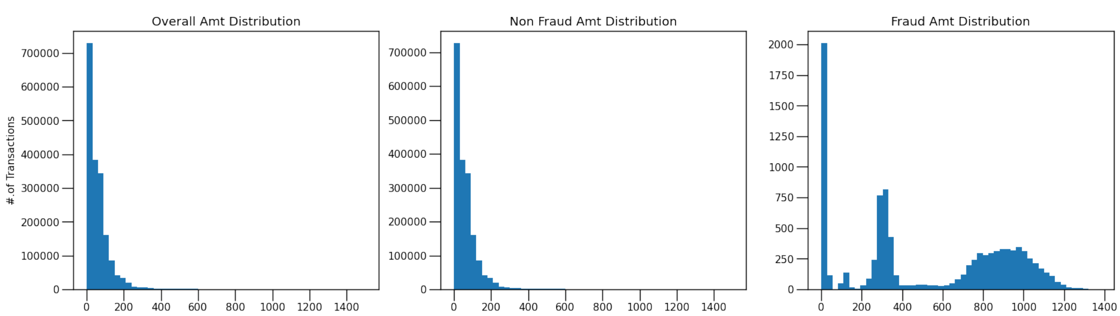
```
# boxplot distribution
fig, ax = plt.subplots(1,3,figsize=(20,5))
ax[0].boxplot((new_df.select('amt').filter(col('amt') <= 1500.0)).toPandas())
ax[1].boxplot((new_df.select('amt').filter((col('amt') <= 1500.0) &␣
↪(col('is_fraud') == 0))).toPandas())
ax[2].boxplot((new_df.select('amt').filter((col('amt') <= 1500.0) &␣
↪(col('is_fraud') == 1))).toPandas())

ax[0].set_title('Overall Amt Distribution')
ax[1].set_title('Non Fraud Amt Distribution')
ax[2].set_title('Fraud Amt Distribution')

ax[0].set_xlabel('Transaction Amount')
ax[0].set_ylabel('#.of Transactions')
```

```python
ax[1].set_xlabel('Transaction Amount')
ax[2].set_xlabel('Transaction Amount')
plt.show()
```



[189]:

```python
# histogram distribution
fig, ax = plt.subplots(1,3,figsize=(20,5))
ax[0].hist((new_df.select('amt').filter(col('amt') <= 1500.0)).toPandas(),bins = 50)
ax[1].hist((new_df.select('amt').filter((col('amt') <= 1500.0) & (col('is_fraud') == 0))).toPandas(),bins = 50)
ax[2].hist((new_df.select('amt').filter((col('amt') <= 1500.0) & (col('is_fraud') == 1))).toPandas(),bins = 50)

ax[0].set_title('Overall Amt Distribution')
ax[1].set_title('Non Fraud Amt Distribution')
ax[2].set_title('Fraud Amt Distribution')

ax[0].set_xlabel('Transaction Amount')
ax[0].set_ylabel('#.of Transactions')

ax[1].set_xlabel('Transaction Amount')
ax[2].set_xlabel('Transaction Amount')
plt.show()
```



0.0.2 Time Series plots to understand trends

[190]:
```
# used pandas to get visualizations and tables based on monthly transactions␣
↪and fraud transactions.
df = new_df.select(to_date('month_year').alias('month_year'),col('trans_num').
↪alias('number_of_transactions'),
                                col('cc_num').
↪alias('number_of_customers'),col('is_fraud'),col('gender'),
                                   col('category')).toPandas()
```

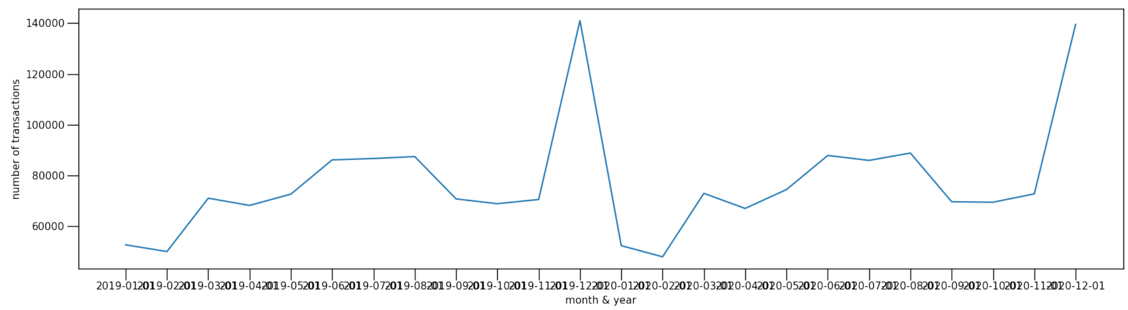
[191]:
```
df_ts_month_trans = df.
↪groupby(df['month_year'])[['number_of_transactions','number_of_customers']].
↪nunique().reset_index()
#df_ts_month_trans = df_ts_month_trans.sort_values(by = ['month_year'])
df_ts_month_trans
```

[191]:

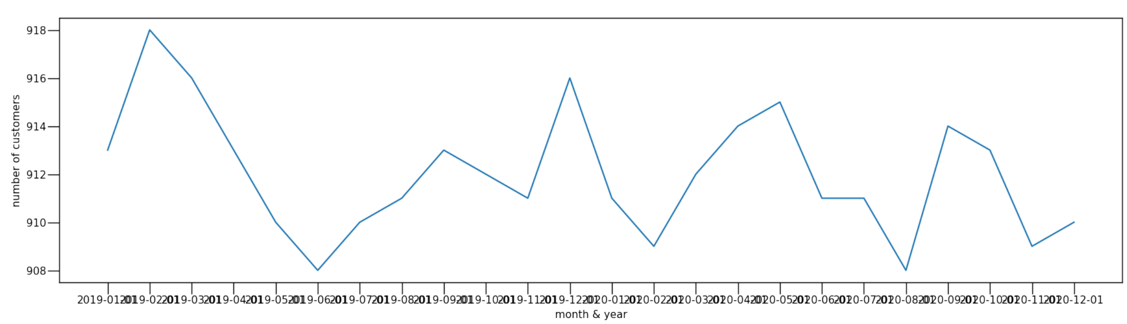
	month_year	number_of_transactions	number_of_customers
0	2019-01-01	52525	913
1	2019-02-01	49866	918
2	2019-03-01	70939	916
3	2019-04-01	68078	913
4	2019-05-01	72532	910
5	2019-06-01	86064	908
6	2019-07-01	86596	910
7	2019-08-01	87359	911
8	2019-09-01	70652	913
9	2019-10-01	68758	912
10	2019-11-01	70421	911
11	2019-12-01	141060	916
12	2020-01-01	52202	911
13	2020-02-01	47791	909
14	2020-03-01	72850	912
15	2020-04-01	66892	914
16	2020-05-01	74343	915
17	2020-06-01	87805	911
18	2020-07-01	85848	911
19	2020-08-01	88759	908
20	2020-09-01	69533	914
21	2020-10-01	69348	913
22	2020-11-01	72635	909
23	2020-12-01	139538	910

[192]:
```
x = np.arange(0,len(df_ts_month_trans),1)
```

```
fig, ax = plt.subplots(1,1,figsize=(20,5))
ax.plot(x,df_ts_month_trans['number_of_transactions'])
ax.set_xticks(x)
ax.set_xticklabels(df_ts_month_trans['month_year'])

ax.set_xlabel('month & year')
ax.set_ylabel('number of transactions')
plt.show()
```



[193]:
```
x = np.arange(0,len(df_ts_month_trans),1)

fig, ax = plt.subplots(1,1,figsize=(20,5))
ax.plot(x,df_ts_month_trans['number_of_customers'])
ax.set_xticks(x)
ax.set_xticklabels(df_ts_month_trans['month_year'])

ax.set_xlabel('month & year')
ax.set_ylabel('number of customers')
plt.show()
```



[194]:
```
df_fraud_transactions = df[df['is_fraud']==1]
```

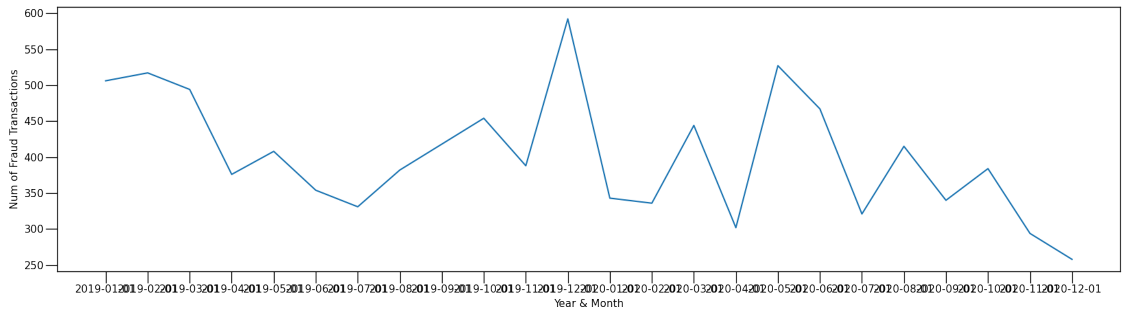
```
df_ts_fraud_month_trans = df_fraud_transactions.
↪groupby(df_fraud_transactions['month_year'])[['number_of_transactions','number_of_customers
↪nunique().reset_index()
df_ts_fraud_month_trans.columns =␣
↪['month_year','num_of_fraud_transactions','fraud_customers']
df_ts_fraud_month_trans
```

[194]:

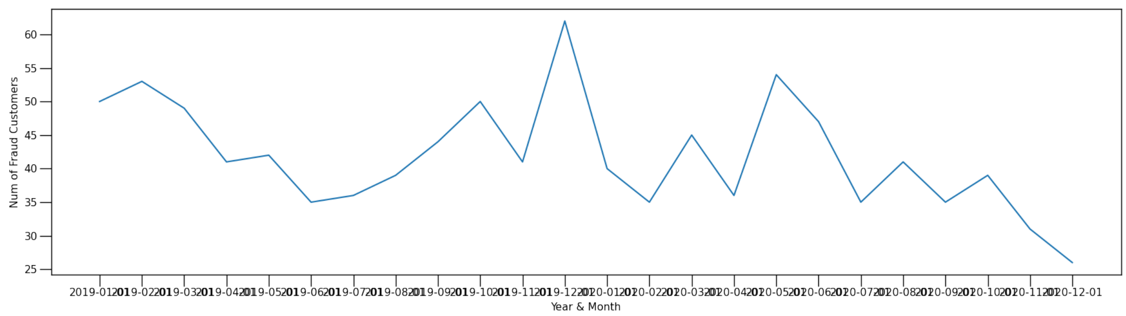
	month_year	num_of_fraud_transactions	fraud_customers
0	2019-01-01	506	50
1	2019-02-01	517	53
2	2019-03-01	494	49
3	2019-04-01	376	41
4	2019-05-01	408	42
5	2019-06-01	354	35
6	2019-07-01	331	36
7	2019-08-01	382	39
8	2019-09-01	418	44
9	2019-10-01	454	50
10	2019-11-01	388	41
11	2019-12-01	592	62
12	2020-01-01	343	40
13	2020-02-01	336	35
14	2020-03-01	444	45
15	2020-04-01	302	36
16	2020-05-01	527	54
17	2020-06-01	467	47
18	2020-07-01	321	35
19	2020-08-01	415	41
20	2020-09-01	340	35
21	2020-10-01	384	39
22	2020-11-01	294	31
23	2020-12-01	258	26

[195]:

```
x = np.arange(0,len(df_ts_fraud_month_trans),1)

fig, ax = plt.subplots(1,1,figsize=(20,5))
ax.plot(x,df_ts_fraud_month_trans['num_of_fraud_transactions'])
ax.set_xticks(x)
ax.set_xticklabels(df_ts_fraud_month_trans['month_year'])

ax.set_xlabel('Year & Month')
ax.set_ylabel('Num of Fraud Transactions')
plt.show()
```



[196]:
```
x = np.arange(0,len(df_ts_fraud_month_trans),1)

fig, ax = plt.subplots(1,1,figsize=(20,5))
ax.plot(x,df_ts_fraud_month_trans['fraud_customers'])
ax.set_xticks(x)
ax.set_xticklabels(df_ts_fraud_month_trans['month_year'])

ax.set_xlabel('Year & Month')
ax.set_ylabel('Num of Fraud Customers')
plt.show()
```



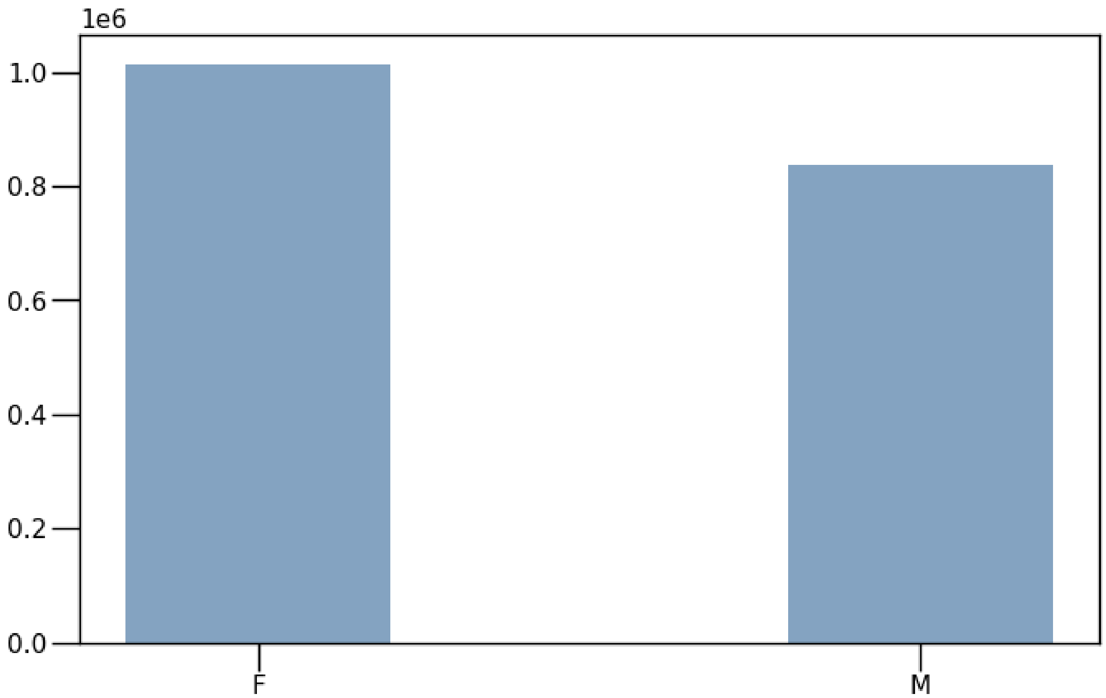
[197]:
```
df_gender = df[['gender','number_of_transactions']].groupby(['gender']).count().
↪reset_index()

df_gender.columns = ['Gender','gender_count']

df_gender['percent'] = (df_gender['gender_count']/df_gender['gender_count'].
↪sum())*100

df_gender
```

[197]:

	Gender	gender_count	percent
0	F	1014749	54.780408

```
1      M         837645   45.219592
```

[198]:
```
plt.bar(df_gender['Gender'], df_gender['gender_count'], color=(0.2, 0.4, 0.6, 0.
↪6),
        width = 0.4)

plt.show()
```



[199]:
```
df_fraud_gender = df[['gender','is_fraud','number_of_transactions']].
↪groupby(['gender','is_fraud']).count().reset_index()
df_fraud_gender.columns = ['Gender','is_fraud','count']

df_fraud_gender = df_fraud_gender.
↪merge(df_gender[['Gender','gender_count']],how='inner',\
                                  left_on='Gender',right_on='Gender')


df_fraud_gender['percent_grp'] = (df_fraud_gender['count']/
↪df_fraud_gender['gender_count'])*100


df_fraud_gender
```

[199]:

	Gender	is_fraud	count	gender_count	percent_grp
0	F	0	1009850	1014749	99.517221
1	F	1	4899	1014749	0.482779
2	M	0	832893	837645	99.432695
3	M	1	4752	837645	0.567305

[200]:

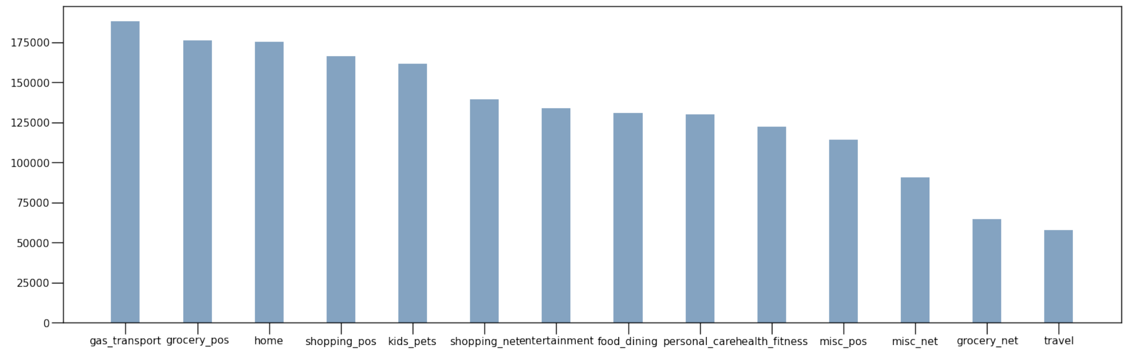
```
df_category = df[['category','number_of_transactions']].groupby(['category']).
↪count().reset_index()
df_category.columns = ['Category','category_count']

df_category['percent'] = (df_category['category_count']/
↪df_category['category_count'].sum())*100

df_category = (df_category.sort_values(by = ['percent'], ascending=False).
↪reset_index()).drop('index',axis = 1)
df_category
```

[200]:

	Category	category_count	percent
0	gas_transport	188029	10.150594
1	grocery_pos	176191	9.511529
2	home	175460	9.472067
3	shopping_pos	166463	8.986371
4	kids_pets	161727	8.730702
5	shopping_net	139322	7.521186
6	entertainment	134118	7.240252
7	food_dining	130729	7.057300
8	personal_care	130085	7.022534
9	health_fitness	122553	6.615925
10	misc_pos	114229	6.166561
11	misc_net	90654	4.893883
12	grocery_net	64878	3.502387
13	travel	57956	3.128708

[201]:

```
fig = plt.figure(figsize = (20, 6))


plt.bar(df_category['Category'], df_category['category_count'], color=(0.2, 0.
↪4, 0.6, 0.6),
        width = 0.4)

plt.show()
```



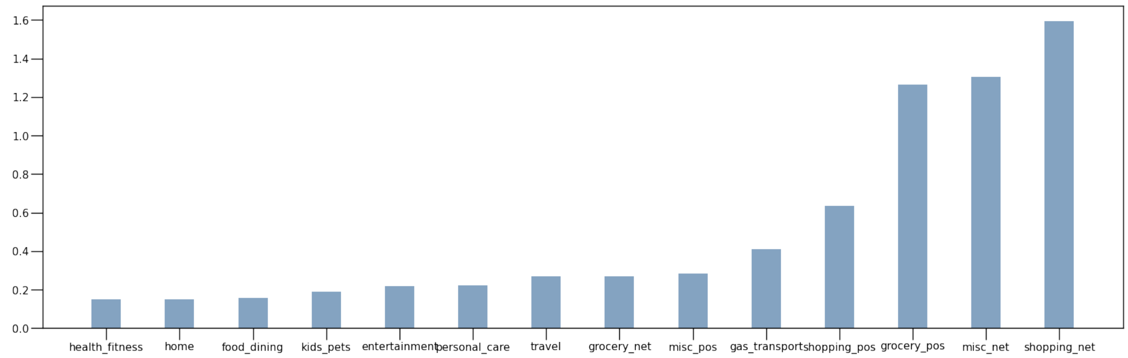
[202]:
```
df_fraud_category = df[['category','is_fraud','number_of_transactions']].
↪groupby(['category','is_fraud']).count().reset_index()
df_fraud_category.columns = ['Category','is_fraud','count']

df_fraud_category = df_fraud_category.
↪merge(df_category[['Category','category_count','percent']],how='inner',\
                                          left_on='Category',right_on='Category')


df_fraud_category['percent_grp'] = (df_fraud_category['count']/
↪df_fraud_category['category_count'])*100

df_fraud=df_fraud_category[df_fraud_category['is_fraud'] == 1].sort_values(by =␣
↪['percent_grp'])
df_fraud
```

[202]:

	Category	is_fraud	count	category_count	percent	percent_grp
11	health_fitness	1	185	122553	6.615925	0.150955
13	home	1	265	175460	9.472067	0.151032
3	food_dining	1	205	130729	7.057300	0.156813
15	kids_pets	1	304	161727	8.730702	0.187971
1	entertainment	1	292	134118	7.240252	0.217719
21	personal_care	1	290	130085	7.022534	0.222931
27	travel	1	156	57956	3.128708	0.269170
7	grocery_net	1	175	64878	3.502387	0.269737
19	misc_pos	1	322	114229	6.166561	0.281890
5	gas_transport	1	772	188029	10.150594	0.410575
25	shopping_pos	1	1056	166463	8.986371	0.634375
9	grocery_pos	1	2228	176191	9.511529	1.264537
17	misc_net	1	1182	90654	4.893883	1.303859
23	shopping_net	1	2219	139322	7.521186	1.592713

[203]:
```
fig = plt.figure(figsize = (20, 6))
```

```
plt.bar(df_fraud['Category'] , df_fraud['percent_grp'], color=(0.2, 0.4, 0.6, 0.
↪6),
        width = 0.4)

plt.show()
```

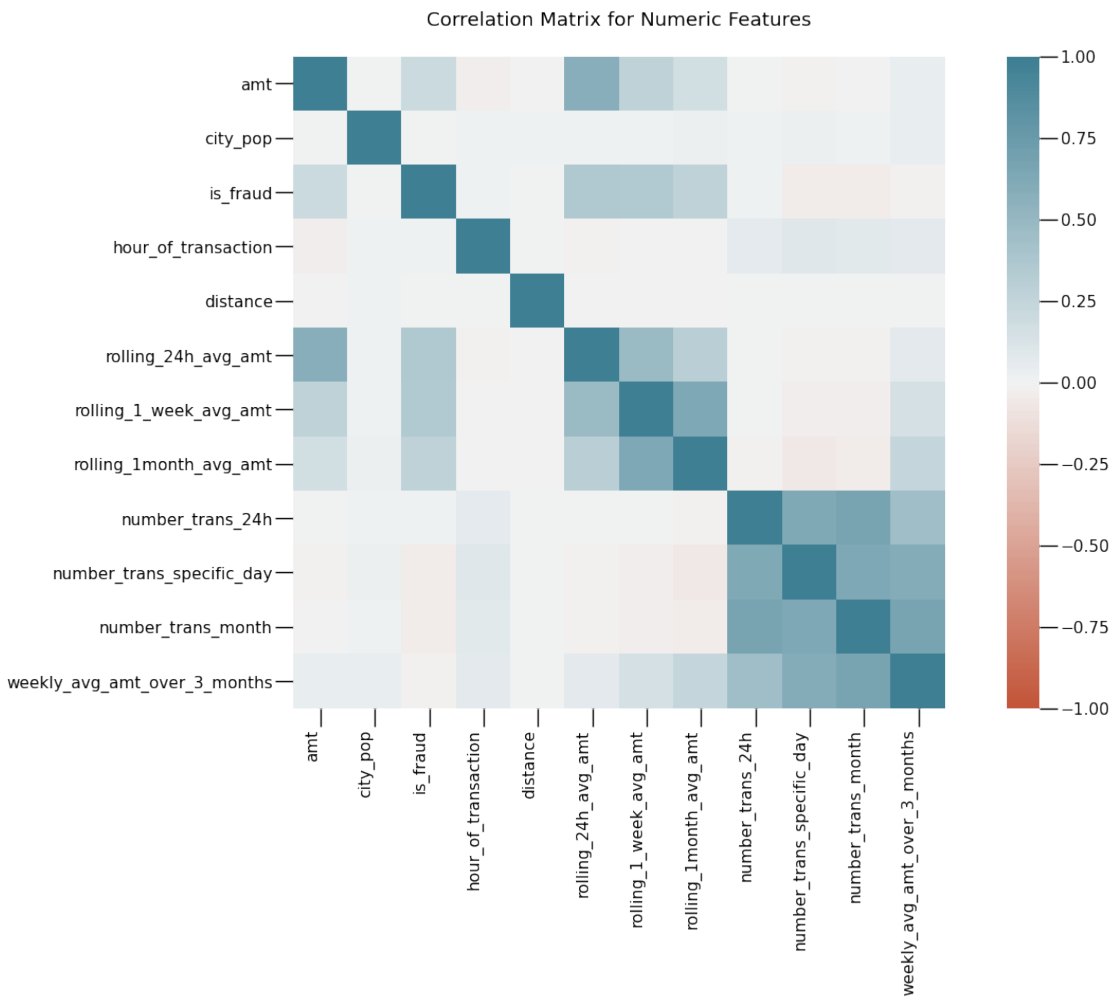


[ ]:

```
[204]: cols = ['_c0', 'age', 'trans_date_trans_time', 'cc_num', 'merchant', 'first',␣
↪'last', 'street', 'city', \
        'zip', 'job', 'dob', 'state','unix_time', 'trans_num','lat',␣
↪'long','month_year', 'trans_date', 'merch_lat', 'merch_long']
preprocessed_data = new_df.drop(*cols)
```

```
[205]: # checking correlation between numerical features

from pyspark.ml.stat import Correlation
from pyspark.ml.feature import VectorAssembler

numeric_features = [t[0] for t in preprocessed_data.dtypes if t[1] != 'string']
numeric_features_df = preprocessed_data.select(numeric_features)

# convert to vector column first
vector_col = "corr_features"
assembler = VectorAssembler(inputCols=numeric_features_df.columns,␣
↪outputCol=vector_col)
df_vector = assembler.transform(numeric_features_df).select(vector_col)

# Generating Correlation Matrix
matrix = Correlation.corr(df_vector, vector_col).collect()[0][0]
corrmatrix = matrix.toArray().tolist()
```

[206]:
```python
import seaborn as sns
plt.figure(figsize = (15,8))
ax = sns.heatmap(
    corrmatrix,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_title("Correlation Matrix for Numeric Features\n")
ax.set_xticklabels(
    numeric_features_df.columns,
    rotation=90,
    horizontalalignment='right'
);
ax.set_yticklabels(numeric_features_df.columns,
    rotation=0,
    horizontalalignment='right'
);
plt.show()
```



[207]:

```
#spark.createDataFrame(corrmatrix,numeric_features_df.columns).toPandas()
```

1 One-hot encoding and VectorAssembler

[208]:

```
# Count of fraud transactions and non-fraud transactions
preprocessed_data.groupBy('is_fraud').count().show()
```

```
+--------+-------+
|is_fraud|  count|
+--------+-------+
|       1|   9651|
|       0|1842743|
+--------+-------+
```

Tried different approach for using String Indexer, One Hot encoder and vector assembler as follows:

[209]:
```
from pyspark.ml.feature import OneHotEncoder, StringIndexer, VectorAssembler

def transformColumnsToNumeric(df, inputCol):

    #apply StringIndexer to inputCol
    inputCol_indexer = StringIndexer(inputCol = inputCol, outputCol = inputCol␣
↪+ "-index").fit(df)
    df = inputCol_indexer.transform(df)

    onehotencoder_vector = OneHotEncoder(inputCol = inputCol + "-index",␣
↪outputCol = inputCol + "-vector")
    df = onehotencoder_vector.fit(df).transform(df)

    return df

    pass
```

[210]:
```
df = transformColumnsToNumeric(preprocessed_data, "category")
df = transformColumnsToNumeric(df, "gender")
df = transformColumnsToNumeric(df, "age_udf_cat")
df = transformColumnsToNumeric(df, "day_of_week")
```

[211]:
```
from pyspark.ml.feature import VectorAssembler

cols = [
 'amt',
 'city_pop',
 'hour_of_transaction',
 'distance',
 'rolling_24h_avg_amt',
 'rolling_1_week_avg_amt',
 'rolling_1month_avg_amt',
 'number_trans_24h',
 'number_trans_specific_day',
 'number_trans_month',
 'weekly_avg_amt_over_3_months',
 'category-vector',
 'gender-vector',
 'age_udf_cat-vector',
 'day_of_week-vector']

vectorAssembler = VectorAssembler().setInputCols(cols).
↪setOutputCol('finalfeatures')
df = vectorAssembler.transform(df)
```

[212]:
```
# creating train test set
train, validate, test = df.randomSplit([0.6, 0.3, 0.1])
```

[213]:
```
train.groupBy('is_fraud').count().show()
```

```
+--------+-------+
|is_fraud|  count|
+--------+-------+
|       1|   5751|
|       0|1105910|
+--------+-------+
```

[214]:
```
validate.groupBy('is_fraud').count().show()
```

```
+--------+------+
|is_fraud| count|
+--------+------+
|       1|  2914|
|       0|552396|
+--------+------+
```

[215]:
```
test.groupBy('is_fraud').count().show()
```

```
+--------+------+
|is_fraud| count|
+--------+------+
|       1|   986|
|       0|184437|
+--------+------+
```

2 Logistic Regression

2.1 Model training with 3 different parameters

[53]:
```
from pyspark.ml.classification import LogisticRegression
from pyspark.ml import feature, classification

# default parameters, regParam = 0.0, elasticNetParam = 0.0
lr = LogisticRegression(featuresCol='finalfeatures', labelCol='is_fraud')
lr_model = lr.fit(train)
validations_lr = lr_model.transform(validate)

# Lasso (L1) Regularization, regParam = 0.5, elasticNetParam = 0.0
```

```
lr_lasso = LogisticRegression(featuresCol='finalfeatures', labelCol='is_fraud',␣
↪regParam=0.5)
lr_lasso_model = lr_lasso.fit(train)
validations_lr_lasso = lr_lasso_model.transform(validate)

# Ridge (L2) Regularization, regParam = 0.0, elasticNetParam = 0.5
lr_ridge = LogisticRegression(featuresCol='finalfeatures', labelCol='is_fraud',␣
↪elasticNetParam=1.0)
lr_ridge_model = lr_ridge.fit(train)
validations_lr_ridge = lr_ridge_model.transform(validate)


# Defining the evaluator to find out the best cross validated model

from pyspark.ml.evaluation import BinaryClassificationEvaluator

# Area under PR curve (main focus since this is imbalanced dataset)
bce_pr = BinaryClassificationEvaluator(labelCol = 'is_fraud',␣
↪metricName='areaUnderPR')

# Area under ROC
bce_roc = BinaryClassificationEvaluator(labelCol = 'is_fraud')

print('Area under PR curve for Logistic Regression with no regularization: {0}'.
↪format(bce_pr.evaluate(validations_lr)))
print('Area under ROC curve for Logistic Regression with no regularization:␣
↪{0}'.format(bce_roc.evaluate(validations_lr)))
print('')

print('Area under PR curve for Logistic Regression with L1 regularization: {0}'.
↪format(bce_pr.evaluate(validations_lr_lasso)))
print('Area under ROC curve for Logistic Regression with L1 regularization:␣
↪{0}'.format(bce_roc.evaluate(validations_lr_lasso)))
print('')

print('Area under PR curve for Logistic Regression with L2 regularization: {0}'.
↪format(bce_pr.evaluate(validations_lr_ridge)))
print('Area under ROC curve for Logistic Regression with L2 regularization:␣
↪{0}'.format(bce_roc.evaluate(validations_lr_ridge)))
```

```
Area under PR curve for Logistic Regression with no regularization:
0.5432947036051969
Area under ROC curve for Logistic Regression with no regularization:
0.9590660126103625

Area under PR curve for Logistic Regression with L1 regularization:
0.44765211651665493
```

```
Area under ROC curve for Logistic Regression with L1 regularization:
0.9874267035549548

Area under PR curve for Logistic Regression with L2 regularization:
0.5430387755959999
Area under ROC curve for Logistic Regression with L2 regularization:
0.9590663116122362
```

2.2 Estimating generalization performance for no regularization model

[54]:
```
predictions_lr = lr_model.transform(test)

from pyspark.sql.types import FloatType
from pyspark.mllib.evaluation import MulticlassMetrics

#select only prediction and label columns
preds_and_labels_lr = predictions_lr.select(['prediction','is_fraud']).\
                                withColumn('is_fraud', func.col('is_fraud').
 ↪cast(FloatType())).orderBy('prediction')
```

2.2.1 Confusion Matrix

[55]:
```
confusion_matrix_lr = MulticlassMetrics(preds_and_labels_lr.rdd.map(tuple)).
 ↪confusionMatrix().toArray()
confusion_matrix_lr
```

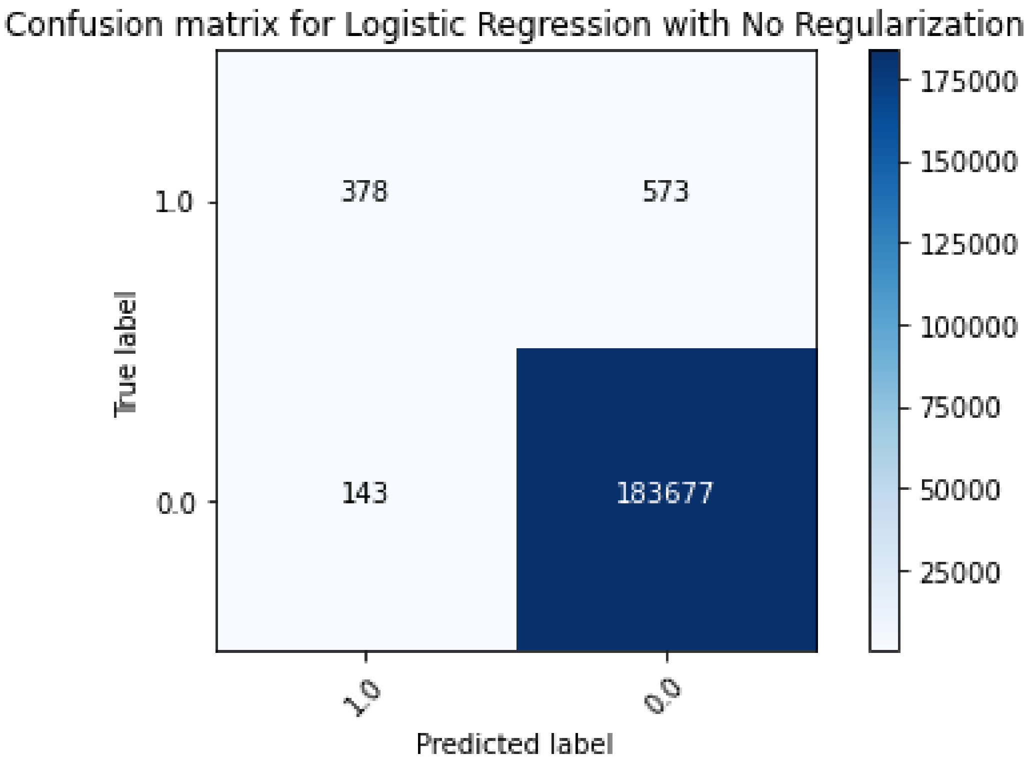
[55]:
```
array([[1.83677e+05, 1.43000e+02],
       [5.73000e+02, 3.78000e+02]])
```

[56]:
```
# function to plot confusion matrix. Necessary to execute next cell

class_names=[1.0,0.0]
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
```

```
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

[57]:
```
from sklearn.metrics import confusion_matrix

class_names=[1.0,0.0]

y_true_lr = predictions_lr.select("is_fraud")
y_true_lr = y_true_lr.toPandas()

y_pred_lr = predictions_lr.select("prediction")
y_pred_lr = y_pred_lr.toPandas()

cnf_matrix = confusion_matrix(y_true_lr, y_pred_lr,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix for Logistic Regression with No␣
 ↪Regularization')
plt.show()
```

```
Confusion matrix, without normalization
[[   378    573]
 [   143 183677]]
```



2.2.2 Precision, Recall and F1 Score

[45]:
```
precision_lr = confusion_matrix_lr[1,1]/np.add(confusion_matrix_lr[0,1],␣
 ↪confusion_matrix_lr[1,1])
print("Precision: ",precision_lr)
recall_lr = confusion_matrix_lr[1,1]/np.add(confusion_matrix_lr[1,0],␣
 ↪confusion_matrix_lr[1,1])
print("recall: ",recall_lr)
f1_score_lr = 2*(precision_lr*recall_lr)/(precision_lr+recall_lr)
print("f1_score: ",f1_score_lr)
```

```
Precision:  0.759765625
recall:  0.3736791546589817
f1_score:  0.5009658725048294
```

2.2.3 Area under ROC Curve and Precision-Recall Curve

[58]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator

# Let's use the run-of-the-mill evaluator
evaluator = BinaryClassificationEvaluator(labelCol='is_fraud')

# We have only two choices: area under ROC and PR curves :-(
auroc_lr = evaluator.evaluate(predictions_lr, {evaluator.metricName:␣
 ↪"areaUnderROC"})
auprc_lr = evaluator.evaluate(predictions_lr, {evaluator.metricName:␣
 ↪"areaUnderPR"})
print("Area under ROC Curve for test data: {:.4f}".format(auroc_lr))
print("Area under PR Curve for test data: {:.4f}".format(auprc_lr))
```

```
Area under ROC Curve for test data: 0.9602
Area under PR Curve for test data: 0.5379
```

2.2.4 Using handyspark package to draw curves

[59]:
```
!pip install handyspark
```

```
WARNING: Value for scheme.headers does not match. Please report this to
<https://github.com/pypa/pip/issues/9617>
distutils: /opt/conda/include/python3.8/UNKNOWN
sysconfig: /opt/conda/include/python3.8
WARNING: Additional context:
user = False
home = None
root = None
prefix = None
Collecting handyspark
  Downloading handyspark-0.2.2a1-py2.py3-none-any.whl (39 kB)
Collecting pyarrow
  Downloading
pyarrow-6.0.1-cp38-cp38-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (25.6 MB)
     |                  | 25.6 MB 9.7 MB/s eta 0:00:01
Requirement already satisfied: scipy in /opt/conda/lib/python3.8/site-
packages (from handyspark) (1.6.2)
Requirement already satisfied: findspark in /opt/conda/lib/python3.8/site-
packages (from handyspark) (1.4.2)
Requirement already satisfied: pandas in /opt/conda/lib/python3.8/site-packages
(from handyspark) (1.2.4)
```

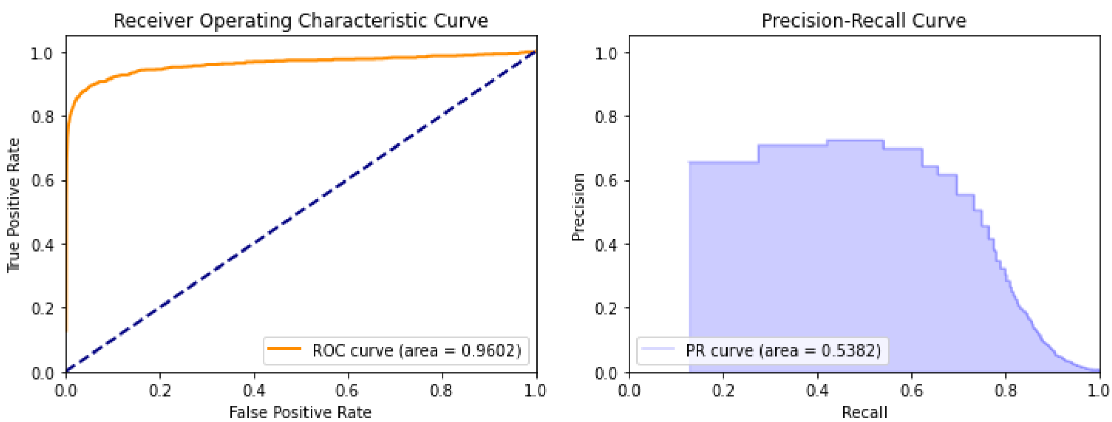
```
Requirement already satisfied: pyspark in /opt/conda/lib/python3.8/site-packages
(from handyspark) (3.1.2)
Requirement already satisfied: scikit-learn in /opt/conda/lib/python3.8/site-
packages (from handyspark) (0.24.1)
Requirement already satisfied: seaborn in /opt/conda/lib/python3.8/site-packages
(from handyspark) (0.11.1)
Requirement already satisfied: numpy in /opt/conda/lib/python3.8/site-packages
(from handyspark) (1.19.5)
Requirement already satisfied: matplotlib in /opt/conda/lib/python3.8/site-
packages (from handyspark) (3.3.4)
Requirement already satisfied: kiwisolver>=1.0.1 in
/opt/conda/lib/python3.8/site-packages (from matplotlib->handyspark) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /opt/conda/lib/python3.8/site-
packages (from matplotlib->handyspark) (0.10.0)
Requirement already satisfied: python-dateutil>=2.1 in
/opt/conda/lib/python3.8/site-packages (from matplotlib->handyspark) (2.8.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in
/opt/conda/lib/python3.8/site-packages (from matplotlib->handyspark) (2.4.7)
Requirement already satisfied: pillow>=6.2.0 in /opt/conda/lib/python3.8/site-
packages (from matplotlib->handyspark) (8.1.2)
Requirement already satisfied: six in /opt/conda/lib/python3.8/site-packages
(from cycler>=0.10->matplotlib->handyspark) (1.15.0)
Requirement already satisfied: pytz>=2017.3 in /opt/conda/lib/python3.8/site-
packages (from pandas->handyspark) (2021.1)
Requirement already satisfied: py4j==0.10.9 in /opt/conda/lib/python3.8/site-
packages (from pyspark->handyspark) (0.10.9)
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.8/site-
packages (from scikit-learn->handyspark) (1.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/opt/conda/lib/python3.8/site-packages (from scikit-learn->handyspark) (2.1.0)
Installing collected packages: pyarrow, handyspark
WARNING: Value for scheme.headers does not match. Please report this to

<https://github.com/pypa/pip/issues/9617>

distutils: /opt/conda/include/python3.8/UNKNOWN

sysconfig: /opt/conda/include/python3.8
WARNING: Additional context:

user = False

home = None

root = None

prefix = None
Successfully installed handyspark-0.2.2a1 pyarrow-6.0.1
```

[60]:

```
# !pip install handyspark
from handyspark import *
# Creates instance of extended version of BinaryClassificationMetrics
# using a DataFrame and its probability and label columns, as the output
# from the classifier
bcm = BinaryClassificationMetrics(predictions_lr, scoreCol='probability',␣
↪labelCol='is_fraud')

# But now we can PLOT both ROC and PR curves!
fig, axs = plt.subplots(1, 2, figsize=(12, 4))
bcm.plot_roc_curve(ax=axs[0])
bcm.plot_pr_curve(ax=axs[1])

# We can also get all metrics (FPR, Recall and Precision) by threshold
#bcm.getMetricsByThreshold().filter('fpr between 0.19 and 0.21').toPandas()

# And get the confusion matrix for any threshold we want
#bcm.print_confusion_matrix(.415856)
```

[60]:

```
<AxesSubplot:title={'center':'Precision-Recall Curve'}, xlabel='Recall',
ylabel='Precision'>
```



2.2.5 Hyperparameter tuning to find the best lr model. Parameters: regParam = [0.01, 0.1, 0.5], elasticNetParam = [0.01, 0.1, 0.5]

[61]:

```
# https://dhiraj-p-rai.medium.com/logistic-regression-in-spark-ml-8a95b5f5434c

from pyspark.ml.tuning import ParamGridBuilder, CrossValidator

train_cv, hold_out_test_cv = df.randomSplit([0.9, 0.1])
```

```
lr = LogisticRegression(labelCol="is_fraud", featuresCol="finalfeatures",␣
 ↪maxIter=100)

paramGrid = ParamGridBuilder()\
    .addGrid(lr.regParam,[0.0, 0.1, 1.0])\
    .addGrid(lr.elasticNetParam,[0.0, 0.1, 1.0])\
    .build()

# Create 5-fold CrossValidator
lr_cvEstimator = CrossValidator(estimator=lr, estimatorParamMaps=paramGrid, \
                              ␣
 ↪evaluator=BinaryClassificationEvaluator(metricName='areaUnderPR',␣
 ↪labelCol='is_fraud'),\
                              numFolds=3, seed = 101)

# Run cross validations
lr_cvModel = lr_cvEstimator.fit(train_cv)
```

[62]:
```
lr_cvModel.getEstimatorParamMaps()[np.argmax(lr_cvModel.avgMetrics)]
```

[62]:
```
{Param(parent='LogisticRegression_a830879fa459', name='regParam',
doc='regularization parameter (>= 0).'): 0.0,
 Param(parent='LogisticRegression_a830879fa459', name='elasticNetParam',
doc='the ElasticNet mixing parameter, in range [0, 1]. For alpha = 0, the
penalty is an L2 penalty. For alpha = 1, it is an L1 penalty.'): 0.0}
```

After 3-fold Cross Validation and Hyperparameter tuning, we see that the best L1 and L2 regularization parameters are 0. So, the best model is the model above with default parameters

[131]:
```
best_lrPredictions.select('probability').count()
```

[131]:
```
185563
```

[132]:
```
hold_out_test_cv.count()
```

[132]:
```
185563
```

[130]:
```
best_lrModel = lr.setElasticNetParam(0.0).setRegParam(0.0).fit(train_cv)



best_lrPredictions = best_lrModel.transform(hold_out_test_cv)
best_predsAndLabels_lr = best_lrPredictions.select(['prediction','is_fraud']).\
                                withColumn('is_fraud', func.col('is_fraud').
 ↪cast(FloatType())).orderBy('prediction')

# Precision, Recall and F1 Score
```

```
best_confusionMatrix_lr = MulticlassMetrics(best_predsAndLabels_lr.rdd.
 ↪map(tuple)).confusionMatrix().toArray()
precision_lrBest = best_confusionMatrix_lr[1,1]/np.
 ↪add(best_confusionMatrix_lr[0,1], best_confusionMatrix_lr[1,1])
print("Precision: ",precision_lrBest)
recall_lrBest = best_confusionMatrix_lr[1,1]/np.
 ↪add(best_confusionMatrix_lr[1,0], best_confusionMatrix_lr[1,1])
print("recall: ",recall_lrBest)
f1_score_lrBest = 2*(precision_lrBest*recall_lrBest)/
 ↪(precision_lrBest+recall_lrBest)
print("f1_score: ",f1_score_lrBest)

# area under ROC and PR Curve
auroc_lrReg = evaluator.evaluate(best_lrPredictions, {evaluator.metricName:␣
 ↪"areaUnderROC"})
auprc_lrReg = evaluator.evaluate(best_lrPredictions, {evaluator.metricName:␣
 ↪"areaUnderPR"})
print("Area under ROC Curve for test data: {:.4f}".format(auroc_lrReg))
print("Area under PR Curve for test data: {:.4f}".format(auprc_lrReg))
```

```
Precision:  0.7222222222222222
recall:  0.3561643835616438
f1_score:  0.4770642201834862
Area under ROC Curve for test data: 0.9531
Area under PR Curve for test data: 0.5219
```

We will try to improve our model by using two more classification algorithms, Random Forest and Gradient Boosting.

3 Random Forest

[65]:
```
from pyspark.ml import feature, classification

# Default parameters
rf_model = classification.RandomForestClassifier(featuresCol='finalfeatures',␣
 ↪labelCol='is_fraud').\
    fit(train)
```

[66]:
```
feature_importance = pd.DataFrame(list(zip(cols, rf_model.featureImportances.
 ↪toArray())),
            columns = ['feature', 'importance']).sort_values('importance',␣
 ↪ascending=False)
feature_importance
```

[66]:

	feature	importance
5	rolling_1_week_avg_amt	0.312005
4	rolling_24h_avg_amt	0.182851
7	number_trans_24h	0.135521
0	amt	0.124823
2	hour_of_transaction	0.086644
6	rolling_1month_avg_amt	0.064435
12	gender-vector	0.020339
8	number_trans_specific_day	0.014551
9	number_trans_month	0.014383
10	weekly_avg_amt_over_3_months	0.002151
13	age_udf_cat-vector	0.000199
1	city_pop	0.000151
3	distance	0.000028
11	category-vector	0.000021
14	day_of_week-vector	0.000000

[67]:

```
from pyspark.ml.evaluation import BinaryClassificationEvaluator
bce = BinaryClassificationEvaluator(labelCol = 'is_fraud', metricName =␣
↪'areaUnderPR')

# Finding out area under PR curve for validation dataset
bce.evaluate(rf_model.transform(validate))
```

[67]: 0.847062423364698

3.1 Estimating Generalization Performance

[68]:

```
from pyspark.sql.types import FloatType
from pyspark.mllib.evaluation import MulticlassMetrics

predictions_rf = rf_model.transform(test)

#select only prediction and label columns
preds_and_labels_rf = predictions_rf.select(['prediction','is_fraud']).
↪withColumn('is_fraud', func.col('is_fraud').cast(FloatType())).
↪orderBy('prediction')
```

3.1.1 Confusion Matrix

[69]:

```
confusion_matrix_rf = MulticlassMetrics(preds_and_labels_rf.rdd.map(tuple)).
↪confusionMatrix().toArray()
confusion_matrix_rf
```

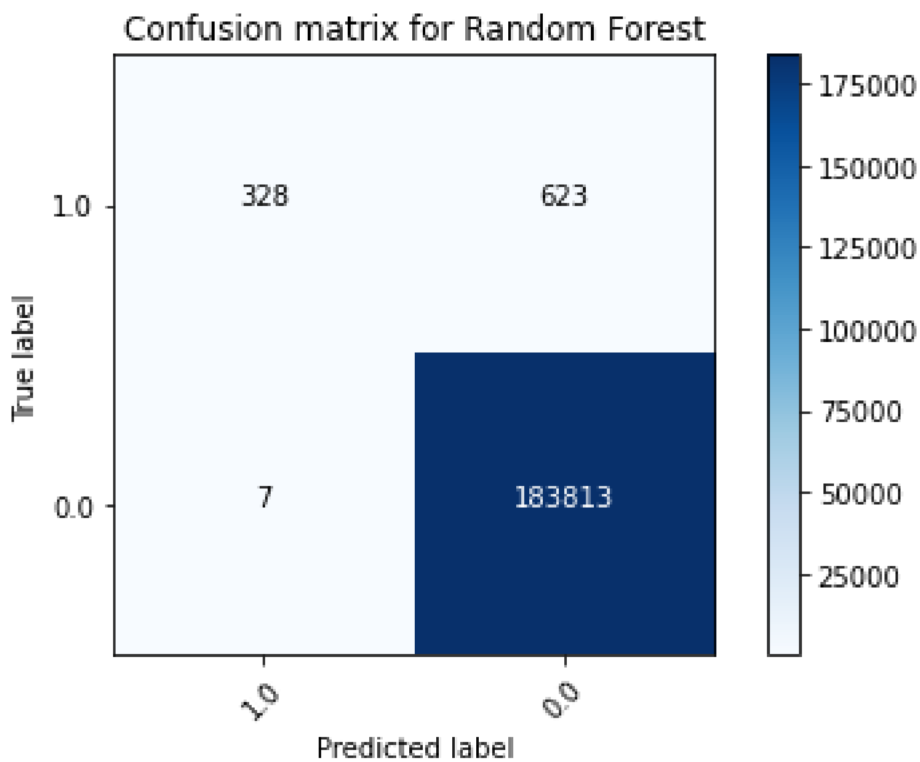
[69]: array([[1.83813e+05, 7.00000e+00],
       [6.23000e+02, 3.28000e+02]])

[70]:
```
class_names=[1.0,0.0]
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

[71]:
```
from sklearn.metrics import confusion_matrix

y_true_rf = predictions_rf.select("is_fraud")
y_true_rf = y_true_rf.toPandas()

y_pred_rf = predictions_rf.select("prediction")
y_pred_rf = y_pred_rf.toPandas()
```

```
cnf_matrix1 = confusion_matrix(y_true_rf, y_pred_rf,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix1, classes=class_names,
                      title='Confusion matrix for Random Forest')
plt.show()
```

```
Confusion matrix, without normalization
[[   328    623]
 [     7 183813]]
```



3.1.2 Precision, Recall and F1 Score

[72]:
```
precision_rf = confusion_matrix_rf[1,1]/np.add(confusion_matrix_rf[0,1],␣
 ↪confusion_matrix_rf[1,1])
print("Precision: ",precision_rf)
recall_rf = confusion_matrix_rf[1,1]/np.add(confusion_matrix_rf[1,0],␣
 ↪confusion_matrix_rf[1,1])
print("recall: ",recall_rf)
f1_score_rf = 2*(precision_rf*recall_rf)/(precision_rf+recall_rf)
print("f1_score: ",f1_score_rf)
```

```
Precision:  0.9791044776119403
recall:  0.3449001051524711
f1_score:  0.5101088646967341
```

3.1.3 ROC and Precision-Recall Curve

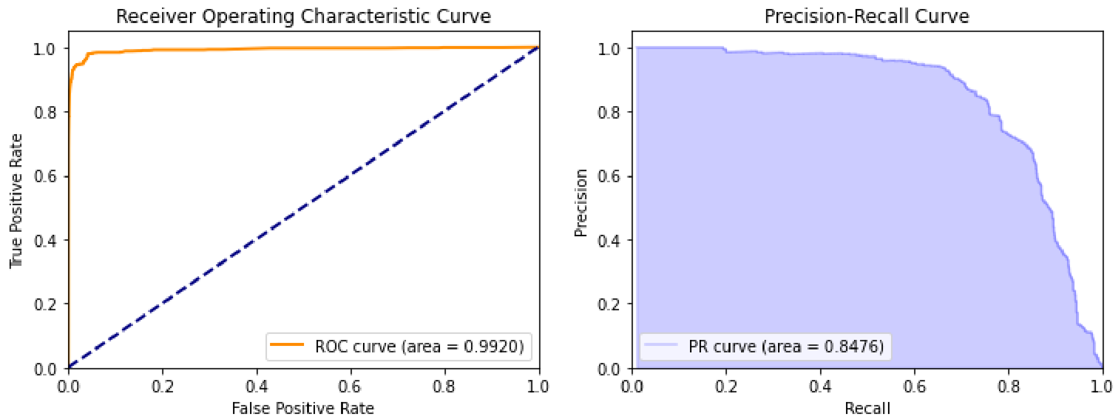
[73]:
```python
from pyspark.ml.evaluation import BinaryClassificationEvaluator

# Let's use the run-of-the-mill evaluator
evaluator = BinaryClassificationEvaluator(labelCol='is_fraud')

# We have only two choices: area under ROC and PR curves :-(
auroc_rf = evaluator.evaluate(predictions_rf, {evaluator.metricName:␣
↪"areaUnderROC"})
auprc_rf = evaluator.evaluate(predictions_rf, {evaluator.metricName:␣
↪"areaUnderPR"})
print("Area under ROC Curve: {:.4f}".format(auroc_rf))
print("Area under PR Curve: {:.4f}".format(auprc_rf))
```

```
Area under ROC Curve: 0.9920
Area under PR Curve: 0.8476
```

[74]:
```python
from handyspark import *
# Creates instance of extended version of BinaryClassificationMetrics
# using a DataFrame and its probability and label columns, as the output
# from the classifier
bcm = BinaryClassificationMetrics(predictions_rf, scoreCol='probability',␣
↪labelCol='is_fraud')

# We still can get the same metrics as the evaluator...
print("Area under ROC Curve: {:.4f}".format(bcm.areaUnderROC))
print("Area under PR Curve: {:.4f}".format(bcm.areaUnderPR))

# But now we can PLOT both ROC and PR curves!
fig, axs = plt.subplots(1, 2, figsize=(12, 4))
bcm.plot_roc_curve(ax=axs[0])
bcm.plot_pr_curve(ax=axs[1])

# We can also get all metrics (FPR, Recall and Precision) by threshold
#bcm.getMetricsByThreshold().filter('fpr between 0.19 and 0.21').toPandas()

# And get the confusion matrix for any threshold we want
#bcm.print_confusion_matrix(.415856)
```

```
Area under ROC Curve: 0.9920
Area under PR Curve: 0.8476
```

[74]: <AxesSubplot:title={'center':'Precision-Recall Curve'}, xlabel='Recall', ylabel='Precision'>



3.1.4 Hyperparameter Tuning on numTrees, impurity and maxDepth to try to improve the model

[75]:
```
from pyspark.ml.tuning import CrossValidator, ParamGridBuilder

train_cv, hold_out_test_cv = df.randomSplit([0.9, 0.1])

numFolds = 3

rf_model_cv = classification.RandomForestClassifier(labelCol="is_fraud",␣
↪featuresCol="finalfeatures", seed = 0)
evaluator_rfcv = BinaryClassificationEvaluator(metricName='areaUnderPR',␣
↪labelCol='is_fraud')

pipeline_rfcv = Pipeline(stages=[rf_model_cv])
paramGrid_rfcv = ParamGridBuilder()\
    .addGrid(rf_model_cv.numTrees, [10, 20, 30])\
    .addGrid(rf_model_cv.maxDepth, [3,5,10])\
    .addGrid(rf_model_cv.impurity, ['gini','entropy'])\
    .build()

crossval = CrossValidator(
    estimator=pipeline_rfcv,
    estimatorParamMaps=paramGrid_rfcv,
    evaluator=evaluator_rfcv,
    numFolds=numFolds)

rf_grid_model = crossval.fit(train_cv)
```

[76]:
```
print("The best parameters for the random forest models are:\n ",rf_grid_model.
↪getEstimatorParamMaps()[np.argmax(rf_grid_model.avgMetrics)])
```

```
The best parameters for the random forest models are:
  {Param(parent='RandomForestClassifier_00c0dbc23815', name='numTrees',
doc='Number of trees to train (>= 1).'): 20,
Param(parent='RandomForestClassifier_00c0dbc23815', name='maxDepth',
doc='Maximum depth of the tree. (>= 0) E.g., depth 0 means 1 leaf node; depth 1
means 1 internal node + 2 leaf nodes.'): 10,
Param(parent='RandomForestClassifier_00c0dbc23815', name='impurity',
doc='Criterion used for information gain calculation (case-insensitive).
Supported options: entropy, gini'): 'gini'}
```

3.1.5 Creating the best Random Forest Classifier

[77]:
```
best_model_rf = rf_model_cv.setImpurity('gini').setMaxDepth(10).setNumTrees(20).
↪fit(train_cv)
```

[ ]:
```
# Feature Importance
```

[78]:
```
best_rfPredictions = best_model_rf.transform(hold_out_test_cv)
best_predsAndLabels_rf = best_rfPredictions.select(['prediction','is_fraud']).\
                                withColumn('is_fraud', func.col('is_fraud').
↪cast(FloatType())).orderBy('prediction')
```

[79]:
```
# Precision, Recall and F1 Score

best_confusionMatrix_rf = MulticlassMetrics(best_predsAndLabels_rf.rdd.
↪map(tuple)).confusionMatrix().toArray()
precision_rfBest = best_confusionMatrix_rf[1,1]/np.
↪add(best_confusionMatrix_rf[0,1], best_confusionMatrix_rf[1,1])
print("Precision: ",precision_rfBest)
recall_rfBest = best_confusionMatrix_rf[1,1]/np.
↪add(best_confusionMatrix_rf[1,0], best_confusionMatrix_rf[1,1])
print("recall: ",recall_rfBest)
f1_score_rfBest = 2*(precision_rfBest*recall_rfBest)/
↪(precision_rfBest+recall_rfBest)
print("f1_score: ",f1_score_rfBest)
```

```
Precision:  0.9616858237547893
recall:  0.7367906066536204
f1_score:  0.8343490304709141
```

[80]:
```
auroc_rfBest = evaluator.evaluate(best_rfPredictions, {evaluator.metricName:␣
↪"areaUnderROC"})
```

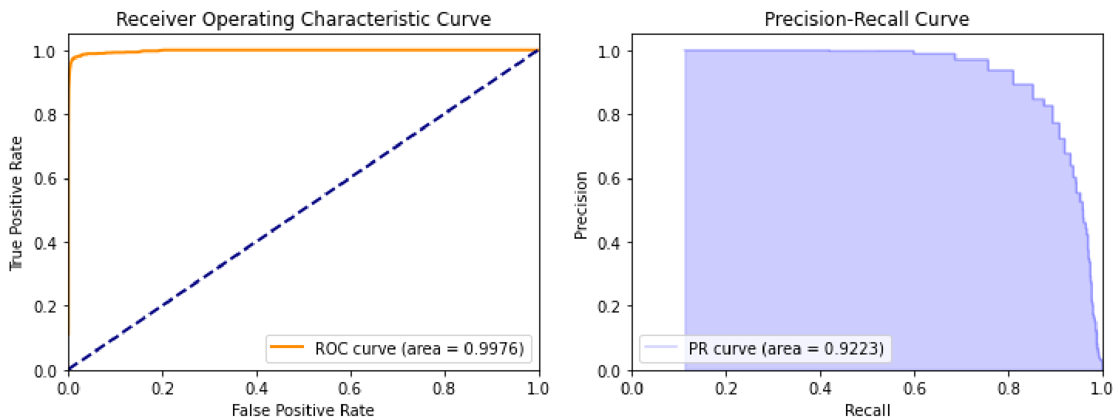
```
auprc_rfBest = evaluator.evaluate(best_rfPredictions, {evaluator.metricName:␣
↪"areaUnderPR"})
print("Area under ROC Curve for test data: {:.4f}".format(auroc_rfBest))
print("Area under PR Curve for test data: {:.4f}".format(auprc_rfBest))
```

```
Area under ROC Curve for test data: 0.9976
Area under PR Curve for test data: 0.9232
```

[81]:
```
from handyspark import *
# Creates instance of extended version of BinaryClassificationMetrics
# using a DataFrame and its probability and label columns, as the output
# from the classifier
bcm_best_rf = BinaryClassificationMetrics(best_rfPredictions,␣
↪scoreCol='probability', labelCol='is_fraud')

# We still can get the same metrics as the evaluator...
print("Area under ROC Curve: {:.4f}".format(bcm_best_rf.areaUnderROC))
print("Area under PR Curve: {:.4f}".format(bcm_best_rf.areaUnderPR))

# But now we can PLOT both ROC and PR curves!
fig, axs = plt.subplots(1, 2, figsize=(12, 4))
bcm_best_rf.plot_roc_curve(ax=axs[0])
bcm_best_rf.plot_pr_curve(ax=axs[1])

# We can also get all metrics (FPR, Recall and Precision) by threshold
#bcm.getMetricsByThreshold().filter('fpr between 0.19 and 0.21').toPandas()

# And get the confusion matrix for any threshold we want
#bcm.print_confusion_matrix(.415856)
```

```
Area under ROC Curve: 0.9976
Area under PR Curve: 0.9223
```

[81]:
```
<AxesSubplot:title={'center':'Precision-Recall Curve'}, xlabel='Recall',
ylabel='Precision'>
```



The best model gives us higher recall and precision.

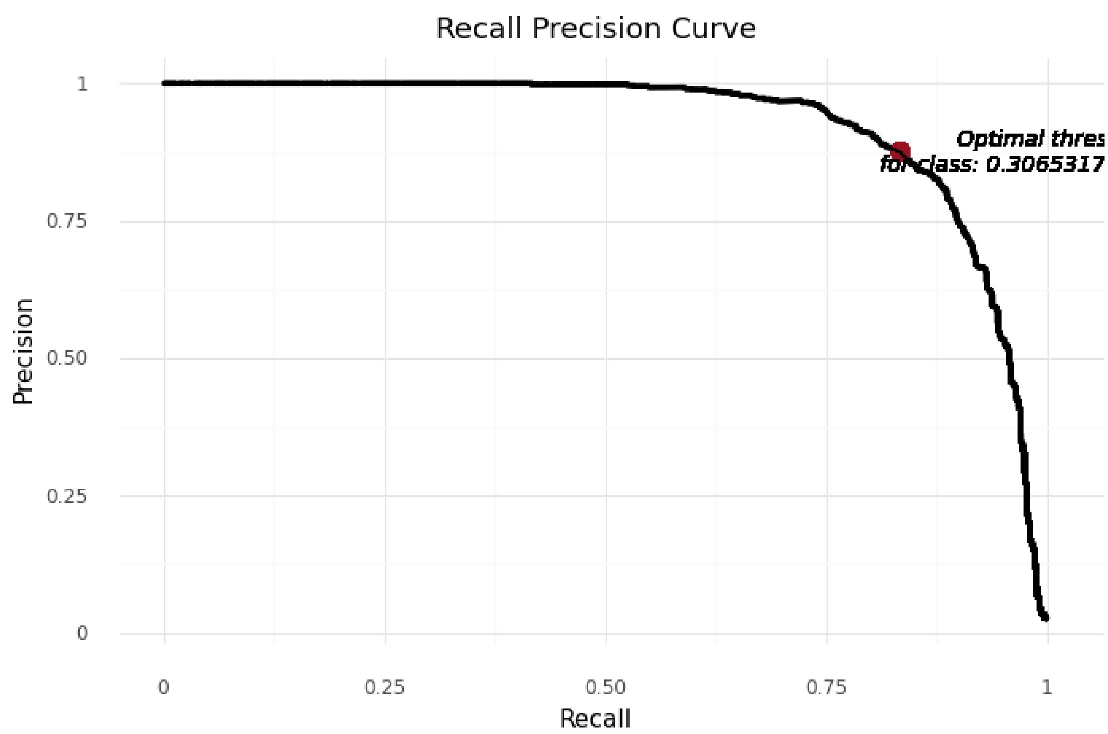
3.1.6 Visualization to understand the Best threshold value for classifying fraudulent and legitimate transactions.

[86]:

```
# The precision-Recall curve for finding the optimal threshold
# https://medium.com/@douglaspsteen/precision-recall-curves-d32e5b290248
#https://towardsdatascience.com/
↪optimal-threshold-for-imbalanced-classification-5884e870c293

from pyspark.sql.functions import udf
from pyspark.sql.types import FloatType
from sklearn.metrics import precision_recall_curve   # Calculate the␣
↪Precision-Recall curve
from sklearn.metrics import f1_score                 # Calculate the F-score
from plotnine import *
import plotnine

# creating a udf for extracting prob belonging to positive class
# https://stackoverflow.com/questions/44425159/
↪access-element-of-a-vector-in-a-spark-dataframe-logistic-regression-probability

secondelement=udf(lambda v:float(v[1]),FloatType())

# creating pandas dataframe y_test and y_pred for sklearn where y_pred contains␣
↪the probability of belonging to positive class
y_prob_rf = best_rfPredictions.select(secondelement('probability')).
↪withColumnRenamed('<lambda>(probability)', 'pos_class_prob').toPandas()
y_test_rf = hold_out_test_cv.select('is_fraud').toPandas()

y_pred_rf = best_rfPredictions.select('prediction')

from sklearn.metrics import precision_recall_curve   # Calculate the␣
↪Precision-Recall curve
from sklearn.metrics import f1_score                 # Calculate the F-score
# Import module for data visualization
from plotnine import *
import plotnine

# Create the Precision-Recall curve
precision, recall, thresholds = precision_recall_curve(y_test_rf, y_prob_rf)

# Plot the ROC curve
```

```python
df_recall_precision_rf = pd.DataFrame({'Precision':precision[:-1],
                                        'Recall':recall[:-1],
                                        'Threshold':thresholds})

# Calculate the f-score
fscore = (2 * precision * recall) / (precision + recall)

# Find the optimal threshold
index = np.argmax(fscore)
thresholdOpt = thresholds[index]
fscoreOpt = fscore[index]
recallOpt = recall[index]
precisionOpt = precision[index]
print('Best Threshold: {} with F-Score: {}'.format(thresholdOpt, fscoreOpt))
print('Recall: {}, Precision: {}'.format(recallOpt, precisionOpt))

# Create a data viz
plotnine.options.figure_size = (8, 4.8)
(
    ggplot(data = df_recall_precision_rf)+
    geom_point(aes(x = 'Recall',
                   y = 'Precision'),
               size = 0.4)+
    # Best threshold
    geom_point(aes(x = recallOpt,
                   y = precisionOpt),
               color = '#981220',
               size = 4)+
    geom_line(aes(x = 'Recall',
                  y = 'Precision'))+
    # Annotate the text
    geom_text(aes(x = recallOpt,
                  y = precisionOpt),
              label = 'Optimal threshold \n for class: {}'.format(thresholdOpt),
              nudge_x = 0.18,
              nudge_y = 0,
              size = 10,
              fontstyle = 'italic')+
    labs(title = 'Recall Precision Curve')+
    xlab('Recall')+
    ylab('Precision')+
    theme_minimal()
)
```

```
Best Threshold: 0.30653178691864014 with F-Score: 0.8547094188376754
Recall: 0.8346379647749511, Precision: 0.8757700205338809
```



[86]: <ggplot: (8788802681338)>

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

4 Gradient Boosting

4.1 Default Model

[88]:
```
from pyspark.ml import feature, classification

# default parameters
```

```
gbt_model = classification.GBTClassifier(featuresCol='finalfeatures',␣
↪labelCol='is_fraud').\
    fit(train)
```

[52]:
```
feature_importance_gbt = pd.DataFrame(list(zip(cols, gbt_model.
↪featureImportances.toArray())),
            columns = ['feature', 'importance']).sort_values('importance',␣
↪ascending=False)
feature_importance_gbt
```

[52]:

	feature	importance
4	rolling_24h_avg_amt	0.237055
0	amt	0.196343
2	hour_of_transaction	0.182893
5	rolling_1_week_avg_amt	0.114201
7	number_trans_24h	0.087963
12	gender-vector	0.042914
11	category-vector	0.032012
8	number_trans_specific_day	0.023775
9	number_trans_month	0.022377
6	rolling_1month_avg_amt	0.016834
1	city_pop	0.009179
10	weekly_avg_amt_over_3_months	0.004203
13	age_udf_cat-vector	0.001838
3	distance	0.000000
14	day_of_week-vector	0.000000

[89]:
```
print('Area under PR curve for Gradient Boosted Trees on validation set: {0}'.
↪format(bce.evaluate(gbt_model.transform(validate))))
# print('Area under PR curve for Gradient Boosted Trees on test set: {0}'.
↪format(bce.evaluate(gbt_model.transform(test))))
```

```
Area under PR curve for Gradient Boosted Trees on validation set:
0.901289237875301
```

[90]:
```
from pyspark.sql.types import FloatType
from pyspark.mllib.evaluation import MulticlassMetrics

predictions_gbt = gbt_model.transform(test)
preds_and_labels_gbt = predictions_gbt.select(['prediction','is_fraud']).
↪withColumn('is_fraud', func.col('is_fraud').cast(FloatType())).
↪orderBy('prediction')

# getting the predicted probabilities
prob_gbt = predictions_gbt.select('probability')
```

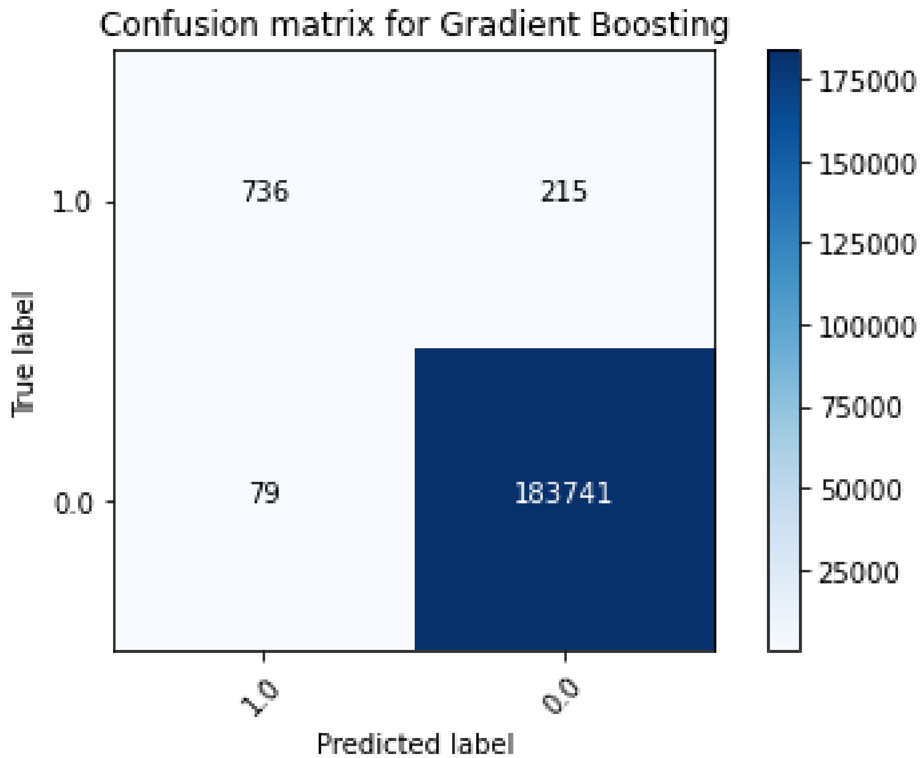
4.2 Confusion Matrix

[91]:
```
confusion_matrix_gbt = MulticlassMetrics(preds_and_labels_gbt.rdd.map(tuple)).
 ↪confusionMatrix().toArray()
confusion_matrix_gbt
```

[91]:
```
array([[1.83741e+05, 7.90000e+01],
       [2.15000e+02, 7.36000e+02]])
```

[92]:
```
from sklearn.metrics import confusion_matrix

y_true_gbt = predictions_gbt.select("is_fraud")
y_true_gbt = y_true_gbt.toPandas()

y_pred_gbt = predictions_gbt.select("prediction")
y_pred_gbt = y_pred_gbt.toPandas()

cnf_matrix2 = confusion_matrix(y_true_gbt, y_pred_gbt,labels=class_names)
#cnf_matrix
plt.figure()
plot_confusion_matrix(cnf_matrix2, classes=class_names,
                      title='Confusion matrix for Gradient Boosting')
plt.show()
```

```
Confusion matrix, without normalization
[[   736    215]
 [    79 183741]]
```



4.3 Precision, Recall and F1 Score

[93]:
```
precision_gbt = confusion_matrix_gbt[1,1]/np.add(confusion_matrix_gbt[0,1],
 ↪confusion_matrix_gbt[1,1])
print("Precision: ",precision_gbt)
recall_gbt = confusion_matrix_gbt[1,1]/np.add(confusion_matrix_gbt[1,0],
 ↪confusion_matrix_gbt[1,1])
print("recall: ",recall_gbt)
f1_score_gbt = 2*(precision_gbt*recall_gbt)/(precision_gbt+recall_gbt)
print("f1_score: ",f1_score_gbt)
```

```
Precision:  0.9030674846625767
recall:  0.7739221871713985
f1_score:  0.8335220838052095
```

4.4 Area under PR Curve and ROC

[94]:
```
from pyspark.ml.evaluation import BinaryClassificationEvaluator

# Let's use the run-of-the-mill evaluator
evaluator = BinaryClassificationEvaluator(labelCol='is_fraud')

# We have only two choices: area under ROC and PR curves :-(
auroc_gbt = evaluator.evaluate(predictions_gbt, {evaluator.metricName:␣
↪"areaUnderROC"})
auprc_gbt = evaluator.evaluate(predictions_gbt, {evaluator.metricName:␣
↪"areaUnderPR"})
print("Area under ROC Curve: {:.4f}".format(auroc_gbt))
print("Area under PR Curve: {:.4f}".format(auprc_gbt))
```

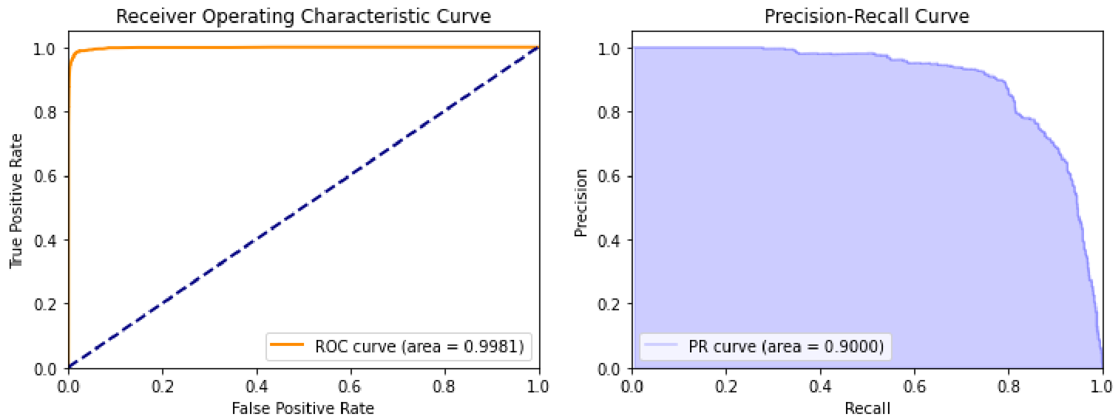
```
Area under ROC Curve: 0.9981
Area under PR Curve: 0.9000
```

4.5 Precision-Recall Curve and ROC

[95]:
```
from handyspark import *
# Creates instance of extended version of BinaryClassificationMetrics
# using a DataFrame and its probability and label columns, as the output
# from the classifier
bcm = BinaryClassificationMetrics(predictions_gbt, scoreCol='probability',␣
↪labelCol='is_fraud')

# We still can get the same metrics as the evaluator...
print("Area under ROC Curve: {:.4f}".format(bcm.areaUnderROC))
print("Area under PR Curve: {:.4f}".format(bcm.areaUnderPR))

# But now we can PLOT both ROC and PR curves!
fig, axs = plt.subplots(1, 2, figsize=(12, 4))
bcm.plot_roc_curve(ax=axs[0])
bcm.plot_pr_curve(ax=axs[1])

# We can also get all metrics (FPR, Recall and Precision) by threshold
#bcm.getMetricsByThreshold().filter('fpr between 0.19 and 0.21').toPandas()

# And get the confusion matrix for any threshold we want
#bcm.print_confusion_matrix(.415856)
```

```
Area under ROC Curve: 0.9981
Area under PR Curve: 0.9000
```

[95]:
```
<AxesSubplot:title={'center':'Precision-Recall Curve'}, xlabel='Recall',
ylabel='Precision'>
```

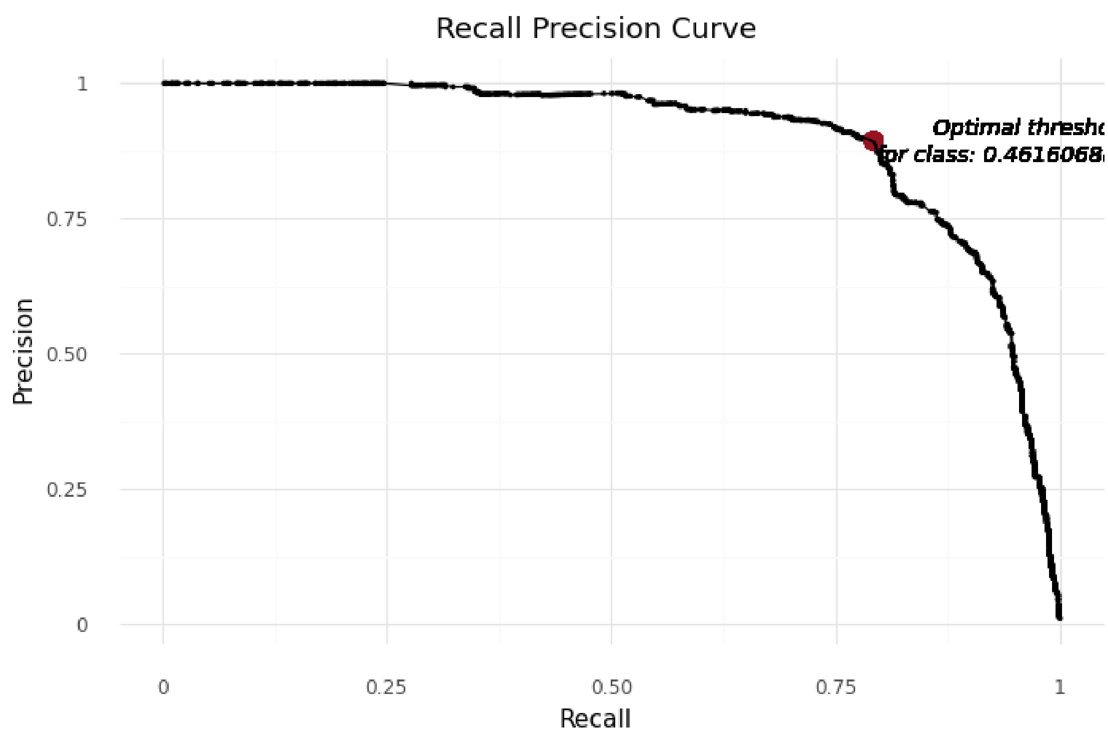


4.6 Finding the optimal threshold for classifying a transaction as fraud to achieve the highest F1 score

[97]:
```python
# The precision-Recall curve for finding the optimal threshold

# creating pandas dataframe y_test and y_pred for sklearn where y_pred contains the probability of belonging to positive class
y_prob_gbt = predictions_gbt.select(secondelement('probability')).withColumnRenamed('<lambda>(probability)', 'pos_class_prob').toPandas()
y_test_gbt = test.select('is_fraud').toPandas()

y_pred_gbt = predictions_gbt.select('prediction')

from sklearn.metrics import precision_recall_curve    # Calculate the Precision-Recall curve
from sklearn.metrics import f1_score                  # Calculate the F-score
# Import module for data visualization
from plotnine import *
import plotnine

# Create the Precision-Recall curve
precision, recall, thresholds = precision_recall_curve(y_test_gbt, y_prob_gbt)

# Plot the ROC curve
df_recall_precision_gbt = pd.DataFrame({'Precision':precision[:-1],
                                    'Recall':recall[:-1],
                                    'Threshold':thresholds})
```

```
# Calculate the f-score
fscore = (2 * precision * recall) / (precision + recall)

# Find the optimal threshold
index = np.argmax(fscore)
thresholdOpt = thresholds[index]
fscoreOpt = fscore[index]
recallOpt = recall[index]
precisionOpt = precision[index]
print('Best Threshold: {} with F-Score: {}'.format(thresholdOpt, fscoreOpt))
print('Recall: {}, Precision: {}'.format(recallOpt, precisionOpt))

# Create a data viz
plotnine.options.figure_size = (8, 4.8)
(
    ggplot(data = df_recall_precision_gbt)+
    geom_point(aes(x = 'Recall',
                   y = 'Precision'),
               size = 0.4)+
    # Best threshold
    geom_point(aes(x = recallOpt,
                   y = precisionOpt),
               color = '#981220',
               size = 4)+
    geom_line(aes(x = 'Recall',
                  y = 'Precision'))+
    # Annotate the text
    geom_text(aes(x = recallOpt,
                  y = precisionOpt),
              label = 'Optimal threshold \n for class: {}'.format(thresholdOpt),
              nudge_x = 0.18,
              nudge_y = 0,
              size = 10,
              fontstyle = 'italic')+
    labs(title = 'Recall Precision Curve')+
    xlab('Recall')+
    ylab('Precision')+
    theme_minimal()
)
```

```
Best Threshold: 0.46160688996315 with F-Score: 0.8401114206128134
Recall: 0.7928496319663512, Precision: 0.8933649289099526
```



[97]: <ggplot: (8788774289050)>

[ ]:

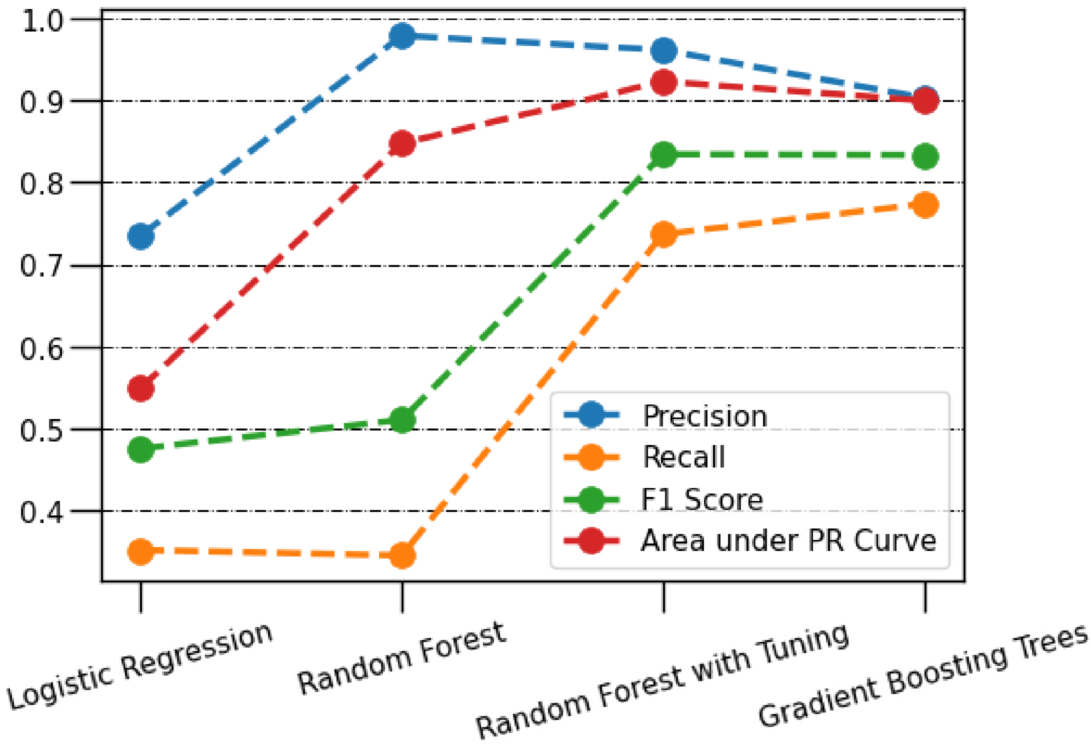
5 Combining results into DF

[125]:
```python
# initialize list of lists
data = [['Logistic Regression', precision_lrBest, recall_lrBest,␣
 ↪f1_score_lrBest, auroc_lrReg, auprc_lrReg], \
        ['Random Forest', precision_rf, recall_rf, f1_score_rf, auroc_rf,␣
 ↪auprc_rf], \
        ['Random Forest with Tuning', precision_rfBest, recall_rfBest,␣
 ↪f1_score_rfBest, auroc_rfBest, auprc_rfBest], \
        ['Gradient Boosting Trees', precision_gbt, recall_gbt, f1_score_gbt,␣
 ↪auroc_gbt, auprc_gbt]]

# Create the pandas DataFrame
results_df = pd.DataFrame(data, columns = ['Model', 'Precision',  'Recall',␣
 ↪'F1Score', 'AreaROC', 'AreaPRCurve'])

# print dataframe.
```

```
results_df
```

[125]:
```
                       Model  Precision    Recall   F1Score   AreaROC  \
0        Logistic Regression   0.734914  0.351184  0.475261  0.954301
1              Random Forest   0.979104  0.344900  0.510109  0.992028
2  Random Forest with Tuning   0.961686  0.736791  0.834349  0.997622
3     Gradient Boosting Trees  0.903067  0.773922  0.833522  0.998082

   AreaPRCurve
0     0.548695
1     0.847627
2     0.923232
3     0.900027
```

[164]:
```
# plot lines
plt.figure(figsize=(6,4))
plt.plot(results_df.Model, results_df.Precision, label = "Precision",␣
 ↪linestyle="--", linewidth=2.5, marker = 'o', markersize=10)
plt.plot(results_df.Model, results_df.Recall, label = "Recall", linestyle="--",␣
 ↪linewidth=2.5, marker = 'o', markersize=10)
plt.plot(results_df.Model, results_df['F1Score'], label = "F1 Score",␣
 ↪linestyle='--', linewidth=2.5, marker = 'o', markersize=10)
plt.plot(results_df.Model, results_df.AreaPRCurve, label = "Area under PR␣
 ↪Curve", linestyle='--', linewidth=2.5, marker = 'o', markersize=10)
plt.legend()
plt.xticks(rotation = 15) # Rotates X-Axis Ticks by 45-degrees
plt.grid(axis = 'y', linestyle='-.', linewidth=0.7)
plt.show()
```



[ ]:

```

```

[ ]:

```

```

[ ]:

```

```

[147]:

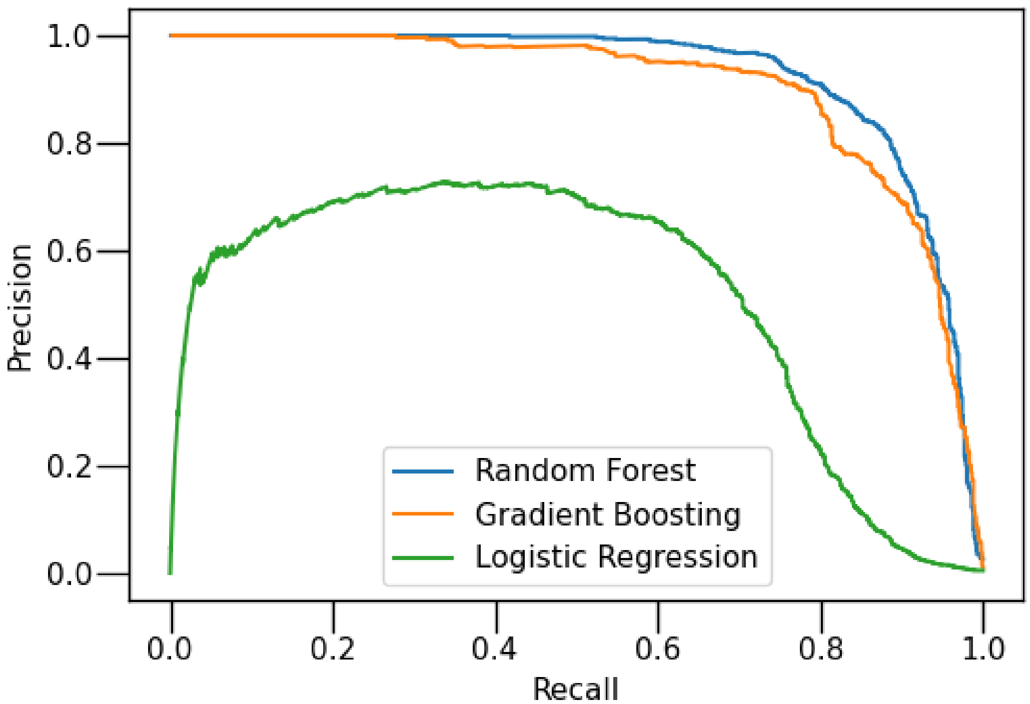
```
# creating pandas dataframe y_test and y_pred for sklearn where y_pred contains␣
↪the probability of belonging to positive class
y_prob_lr = best_lrPredictions.select(secondelement('probability')).
↪withColumnRenamed('<lambda>(probability)', 'pos_class_prob').toPandas()
y_test = hold_out_test_cv.select('is_fraud').toPandas()

y_pred_lr = best_lrPredictions.select('prediction')

# Create the Precision-Recall curve
precision, recall, thresholds = precision_recall_curve(y_test, y_prob_lr)

# Plot the ROC curve
df_recall_precision_lr = pd.DataFrame({'Precision':precision[:-1],
                                        'Recall':recall[:-1],
                                        'Threshold':thresholds})
```

[150]:
```
precision = precision[np.where(precision != 0)]
recall = recall[np.where(recall != 0)]
```

[ ]:
```
precision = precision[np.where(precision != 1)]

# Calculate the f-score
fscore = (2 * precision * recall) / (precision + recall)

# Find the optimal threshold
index = np.argmax(fscore)
thresholdOpt = thresholds[index]
fscoreOpt = fscore[index]
recallOpt = recall[index]
precisionOpt = precision[index]
print('Best Threshold: {} with F-Score: {}'.format(thresholdOpt, fscoreOpt))
print('Recall: {}, Precision: {}'.format(recallOpt, precisionOpt))

# Create a data viz
plotnine.options.figure_size = (8, 4.8)
(
    ggplot(data = df_recall_precision_lr)+
    geom_point(aes(x = 'Recall',
                   y = 'Precision'),
               size = 0.4)+
    # Best threshold
    geom_point(aes(x = recallOpt,
                   y = precisionOpt),
               color = '#981220',
               size = 4)+
    geom_line(aes(x = 'Recall',
                  y = 'Precision'))+
    # Annotate the text
    geom_text(aes(x = recallOpt,
                  y = precisionOpt),
              label = 'Optimal threshold \n for class: {}'.format(thresholdOpt),
              nudge_x = 0.18,
              nudge_y = 0,
              size = 10,
              fontstyle = 'italic')+
    labs(title = 'Recall Precision Curve')+
    xlab('Recall')+
    ylab('Precision')+
    theme_minimal()
)
```

[216]:
```
# Plot precision-recall curve
```

```
fig, ax = plt.subplots(figsize=(6,4))
ax.plot(df_recall_precision_rf.Recall, df_recall_precision_rf.Precision,␣
↪label='Random Forest')
ax.plot(df_recall_precision_gbt.Recall, df_recall_precision_gbt.Precision,␣
↪label='Gradient Boosting')
ax.plot(df_recall_precision_lr.Recall, df_recall_precision_lr.Precision,␣
↪label='Logistic Regression')

# baseline = len(y_test[y_test==1]) / len(y_test)
# ax.plot([0, 1], [baseline, baseline], linestyle='--', label='Baseline')
ax.set_xlabel('Recall')
ax.set_ylabel('Precision')
ax.legend();
```



[ ]:
```
# # Function to calculate Precision and Recall

# def calc_precision_recall(y_true, y_pred):

#     # Convert predictions to series with index matching y_true
#     y_pred = pd.Series(y_pred, index=y_true.index)

#     # Instantiate counters
#     TP = 0
```

```
#     FP = 0
#     FN = 0

#     # Determine whether each prediction is TP, FP, TN, or FN
#     for i in y_true.index:
#         if y_true[i]==y_pred[i]==1:
#            TP += 1
#         if y_pred[i]==1 and y_true[i]!=y_pred[i]:
#            FP += 1
#         if y_pred[i]==0 and y_test[i]!=y_pred[i]:
#            FN += 1

#     # Calculate true positive rate and false positive rate
#     # Use try-except statements to avoid problem of dividing by 0
#     try:
#         precision = TP / (TP + FP)
#     except:
#         precision = 1

#     try:
#         recall = TP / (TP + FN)
#     except:
#         recall = 1

#     return precision, recall


# # Containers for true positive / false positive rates
# precision_scores = []
# recall_scores = []

# # Define probability thresholds to use, between 0 and 1
# probability_thresholds = np.linspace(0, 1, num=100)

# # Find true positive / false positive rate for each threshold
# for p in probability_thresholds:

#     y_test_preds = []

#     for prob in y_test_probs:
#         if prob > p:
#             y_test_preds.append(1)
#         else:
#             y_test_preds.append(0)

#     precision, recall = calc_precision_recall(y_test, y_test_preds)
```

```
#     precision_scores.append(precision)
#     recall_scores.append(recall)
```

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```
from pyspark.ml.feature import Tokenizer
tokenizer = Tokenizer().setInputCol('job').setOutputCol('words')
tokenizer.transform(train_df_copy.select('job')).show()
```

[ ]:
```
from pyspark.ml.feature import CountVectorizer
count_vectorizer_estimator = CountVectorizer().setInputCol('words').
↪setOutputCol('features')
count_vectorizer_transformer = count_vectorizer_estimator.fit(tokenizer.
↪transform(train_df_copy.select('job')))
count_vectorizer_transformer.transform(tokenizer.transform(train_df_copy.
↪select('job'))).show()
```

[ ]:
```
count_vectorizer_transformer.vocabulary
```

[ ]:

[ ]:

[117]:
```
df[cols]
```

[117]:
```
DataFrame[amt: double, city_pop: int, hour_of_transaction: int, distance:
double, age: int, rolling_24h_avg_amt: double, rolling_1_week_avg_amt: double,
rolling_1month_avg_amt: double, number_trans_24h: bigint,
number_trans_specific_day: bigint, number_trans_month: bigint,
weekly_avg_amt_over_3_months: double, category-vector: vector, gender-vector:
vector, state-vector: vector, day_of_week-vector: vector]
```

[ ]:

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```

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```

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[ ]:

```

```

[161]:

```
train = df.sampleBy("is_fraud", fractions={0: 0.7, 1: 0.7}, seed=10)

  # Subtracting 'train' from original 'data' to get test set
test = df.subtract(train)
```

[162]:

```
train.groupBy('is_fraud').count().show()
```

```
+--------+-------+
|is_fraud|  count|
+--------+-------+
|       1|   6733|
|       0|1290089|
+--------+-------+
```

[163]:

```
test.groupBy('is_fraud').count().show()
```

```
+--------+------+
|is_fraud| count|
+--------+------+
|       1|  2871|
|       0|553168|
+--------+------+
```

[164]:

```
# Model training

from pyspark.ml.classification import LogisticRegression
from pyspark.ml import feature, classification

lr = LogisticRegression(featuresCol='finalfeatures', labelCol='is_fraud')
lr_model = lr.fit(train)
#predictions = lr_model.transform(validate)
```

[165]:

```
from pyspark.sql.types import FloatType
from pyspark.mllib.evaluation import MulticlassMetrics
predictions = lr_model.transform(test)
preds_and_labels = predictions.select(['prediction','is_fraud']).
 ↪withColumn('is_fraud', func.col('is_fraud').cast(FloatType())).
 ↪orderBy('prediction')
```

```
#select only prediction and label columns
preds_and_labels = preds_and_labels.select(['prediction','is_fraud'])



confusion_matrix = MulticlassMetrics(preds_and_labels.rdd.map(tuple)).
↪confusionMatrix().toArray()
confusion_matrix
precision = confusion_matrix[1,1]/np.add(confusion_matrix[0,1],␣
↪confusion_matrix[1,1])
print("Precision: ",precision)
recall = confusion_matrix[1,1]/np.add(confusion_matrix[1,0],␣
↪confusion_matrix[1,1])
print("recall: ",recall)
f1_score = 2*(precision*recall)/(precision+recall)
print("f1_score: ",f1_score)
```

```
Precision:  0.7247769389155799
recall:  0.367816091954023
f1_score:  0.4879852125693161
```

[ ]:
```
confusion_matrix
```

[ ]:
```
import statistics

predictionAndLabels = lr_model.transform(validate).select('is_','prediction')

tp = predictionAndLabels.where((predictionAndLabels.type == 1) &␣
↪(predictionAndLabels.prediction == 1)).count()
tn = predictionAndLabels.where((predictionAndLabels.type == 0) &␣
↪(predictionAndLabels.prediction == 0)).count()
fp = predictionAndLabels.where((predictionAndLabels.type == 0) &␣
↪(predictionAndLabels.prediction == 1)).count()
fn = predictionAndLabels.where((predictionAndLabels.type == 1) &␣
↪(predictionAndLabels.prediction == 0)).count()

precision = tp/(tp+fp)
recall = tp/(fn+tp)
data = [precision, recall]
f1_score = statistics.harmonic_mean(data)
```

[ ]:
```

```

[ ]:
```

```

[142]:
```
numericalColumns = [t[0] for t in preprocessed_data.dtypes if ((t[1] !=␣
↪'string') & (t[0] != 'is_fraud'))]
numericalColumns
```

[142]:
```
['amt',
 'city_pop',
 'hour_of_transaction',
 'distance',
 'rolling_24h_avg_amt',
 'rolling_1_week_avg_amt',
 'rolling_1month_avg_amt',
 'number_trans_24h',
 'number_trans_specific_day',
 'number_trans_month',
 'weekly_avg_amt_over_3_months']
```

[141]:
```
# creating the stages for Pipeline

from pyspark.ml.feature import OneHotEncoder, StringIndexer, VectorAssembler,␣
↪StandardScaler
from pyspark.ml.classification import LogisticRegression

categoricalColumns = [t[0] for t in preprocessed_data.dtypes if t[1] ==␣
↪'string']
categoricalColumns
```

[141]:
```
['category', 'gender', 'day_of_week', 'age_udf_cat']
```

[84]:
```
stages = []

for categoricalCol in categoricalColumns:
    stringIndexer = StringIndexer(inputCol=categoricalCol,␣
↪outputCol=categoricalCol + 'Index')
    encoder = OneHotEncoder(inputCols=[stringIndexer.getOutputCol()],␣
↪outputCols=[categoricalCol + 'classVec'])
    stages += [stringIndexer, encoder]

numericalColumns = [t[0] for t in combined_df_lr.dtypes if ((t[1] != 'string')␣
↪& (t[0] != 'is_fraud'))]

assemblerInputs = [c + "classVec" for c in categoricalColumns] +␣
↪numericalColumns
assembler = VectorAssembler(inputCols=assemblerInputs, outputCol="features")
stages += [assembler]

# scaler = StandardScaler(inputCol="vectorized_features", outputCol="features")
# stages += [scaler]
```

[85]:
```python
# creating the pipeline and transforming it to get the features.

from pyspark.ml import Pipeline
pipeline = Pipeline(stages = stages)
pipelineModel = pipeline.fit(combined_df_lr)
df = pipelineModel.transform(combined_df_lr)
```

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[109]:
```python
from pyspark.ml import feature, classification

rf_model = classification.RandomForestClassifier(featuresCol='features',␣
↪labelCol='is_fraud').\
    fit(df_train)
```

[110]:
```python
rf_model.transform(test)
```

[110]:
```
DataFrame[category: string, amt: double, gender: string, state: string,
city_pop: int, is_fraud: int, day_of_week: string, hour_of_transaction: int,
age: int, distance: double, rolling_24h_avg_amt: double, rolling_1_week_avg_amt:
double, rolling_1month_avg_amt: double, number_trans_24h: bigint,
number_trans_specific_day: bigint, number_trans_month: bigint,
weekly_avg_amt_over_3_months: double, categoryIndex: double, categoryclassVec:
vector, genderIndex: double, genderclassVec: vector, stateIndex: double,
stateclassVec: vector, day_of_weekIndex: double, day_of_weekclassVec: vector,
features: vector, rawPrediction: vector, probability: vector, prediction:
double]
```

[117]:
```python
df[cols]
```

[117]:
```
DataFrame[amt: double, city_pop: int, hour_of_transaction: int, distance:
double, age: int, rolling_24h_avg_amt: double, rolling_1_week_avg_amt: double,
rolling_1month_avg_amt: double, number_trans_24h: bigint,
number_trans_specific_day: bigint, number_trans_month: bigint,
weekly_avg_amt_over_3_months: double, category-vector: vector, gender-vector:
vector, state-vector: vector, day_of_week-vector: vector]
```

[119]:
```python
feature_importance = pd.DataFrame(list(zip(cols, rf_model.featureImportances.
↪toArray())),
            columns = ['feature', 'importance']).sort_values('importance',␣
↪ascending=False)
```

[120]:
```
feature_importance
```

[120]:
```
                       feature  importance
5          rolling_24h_avg_amt    0.428874
6       rolling_1_week_avg_amt    0.221340
0                          amt    0.108976
2          hour_of_transaction    0.084686
7       rolling_1month_avg_amt    0.067890
8             number_trans_24h    0.031970
10          number_trans_month    0.015911
11  weekly_avg_amt_over_3_months    0.010624
13               gender-vector    0.008395
9     number_trans_specific_day    0.004673
4                          age    0.002162
14                state-vector    0.000684
3                     distance    0.000298
12             category-vector    0.000140
1                     city_pop    0.000136
15          day_of_week-vector    0.000000
```

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```
# distribution of amount

plt.figure(figsize=(10,5), dpi=100)

sns.histplot(data = train_df_pandas, x = 'amt', hue = 'amt')
plt.show()
```

[ ]:

[ ]:
```
# Category

plt.figure(figsize=(10,5), dpi=100)

chart = sns.countplot(data = train_df_pandas, x = 'category'\
```

```
                     , order = train_df_pandas['category'].value_counts().
↪index)
chart.set_xticklabels(chart.get_xticklabels(), rotation = 45,␣
↪horizontalalignment = 'right')
plt.show()
```

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