GA_Data_Science_Chellenge_Yu-Ting_Shen

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1 GA Data Science Chellenge (V4)

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2 Yu-Ting Shen

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3 Question 1: Data Query

3.1 a.) List the top 5 user_id which had the highest number of CTR filed during in any 7 days window period. (5 points)

Answer:

```
SELECT User_id, MAX(sum_CTR)
FROM (
      SELECT t1.User_id, SUM(t2.CTR) AS sum_CTR
      FROM transactions t1
      JOIN transactions t2
      ON t1.User_id = t2.User_id
      WHERE t2.Timestamp >= t1.Timestamp AND
            t2.Timestamp < DATE(t1.Timestamp, '+7 days')
      GROUP BY t1.User_id, DATE(t1.Timestamp)
      ORDER BY t1.User_id, DATE(t1.Timestamp)
     )
GROUP BY User_id
ORDER BY 2 DESC
LIMIT 5;
```

3.2 b.) List top 5 user_id which had the largest amount of incoming amount over any 30 day period exceeding $1,000,000? (5 points)

Answer:

```sql
SELECT User_id, MAX(income)
FROM (
      SELECT t1.User_id, SUM(t2.Amount) as income
      FROM transactions t1
      JOIN transactions t2
      ON t1.User_id = t2.User_id
      WHERE t2.Timestamp >= t1.Timestamp AND
            t2.Timestamp < DATE(t1.Timestamp, '+30 days') AND
            t2.CashDirection = 'In'
      GROUP BY 1, DATE(t1.Timestamp)
      ORDER BY 1, DATE(t1.Timestamp)
     )
WHERE income > 1000000
GROUP BY User_id
ORDER BY MAX(income) DESC
LIMIT 5;
```

---

4 Question 2: Modeling

4.1 a.) For a not 'Male' customer, what is the most important features in predicting likelihood of customer doing cryptocurrency transaction? (5 points)

Answer:

Because all the features are **not in the same scale**, it is very hard to know what is the most important features from the coefficient only. Firstly, we can calculate the **z-score** of each features by taking the ratio of coefficient and standard error.

Variable	Coefficient	Standar Error	z-score
Male	2.45	0.12	20.42
Account Balance	-0.109	0.041	-2.66
Age	-0.0135	0.00096	-14.062
Age_Sq	0.0001	0.000029	3.45
Investor	3.21	0.67	4.223
Works_at_Y	-5.12	0.399	-12.803
Constant	2.8	0.584	4.79

All the absolute values of z-score are greater than 2, which means the coefficients are significant different from zero. Therefore, we have to keep all the coefficients.

Since the variables `Investor` and `Works_at_Y` are binary, they have the same scale. Therefore, they can be compared directly. We can see the coefficient of `Works_at_Y` is larger than `Investor`. This means the variable `Works_at_Y` is more important than the `Investor`. However, we cannot compare the coefficients of `Account Balance`, `Age`, `Age_Sq`, and `Works_at_Y` directly because their scale are different.

We can evaluate the effect of logits by using two different values of a variable while fix the other variables. Here are the two different values we use for variables `Account Balance`, `Age`,

`Age_Sq`, and `Works_at_Y`.

Variable	Value1	Value2
Account Balance	1	10^9
Age	1	100
Works_at_Y	1	0

The formula of logits is

$$\ln \frac{p}{1-p} = \sum_{i=0}^{n} \theta_i x_i$$

And the difference in logits while using two values for one variable is:

$$\Delta(\ln \frac{p}{1-p}) = \theta_i (x_{i,val1} - x_{i,val2})$$

1.) We use `Account Balance` = 1 and 10^9 and fix the other variables.

$$\Delta(\ln \frac{p}{1-p})\Big|_{balance} = -0.109 \times (\ln 10^9 - \ln 1) = -2.2588$$

2.) We use `Age` = 1 and 100 and fix the other variables.

$$\Delta(\ln \frac{p}{1-p})\Big|_{age} = -0.0135 \times (100 - 1) = -1.3365$$

3.) We use `Works_at_Y` = 1 and 0 and fix the other variables.

$$\Delta(\ln \frac{p}{1-p})\Big|_{Y} = -5.12 \times (1 - 0) = -5.12$$

From above calculations, we see changing the values of `Works_at_Y` causes large effect in the logits. So `Works_at_Y` is the most important feature.

4.2 b.) How do we interpret the difference in probability using cryptocurrency exchange between users of different ages? (5 points)

Answer:
Because the coefficient of the variable `Age` is negative value, which means the older customers the lower probability using cryptocurrency exchange.

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5 Question 3: Data Analysis

5.1 a.) How you would determine if an amount is unusual for a bank's user? (3 points)

Answer:
We can calculate the IQR of the user's incoming amount. If the incoming amount is greater than **1.5** $\times$ **IQR**, then the transaction is suspicious and considerd as unusual.

5.2 b.) A relative of user is defined as someone who shares same phone number. Find the set of relatives for all user_id's. (3 points)

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
```

In [2]:
```
# Load data
df = pd.read_csv('transaction_data.csv', index_col=0)

# Check data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 459995 entries, 0 to 459994
Data columns (total 9 columns):
user_id                      459995 non-null int64
date                         459995 non-null object
trx_type                     459995 non-null object
activity_type                459995 non-null object
counter_party                459995 non-null int64
amount                       459995 non-null float64
user_phone_number            459995 non-null object
counter_party_phone_number   10433 non-null object
Y                            459995 non-null int64
dtypes: float64(1), int64(3), object(5)
memory usage: 35.1+ MB
```

From the above summary, we can see the counter_party_phone_number has missing values.

In [3]:
```
# Show data
df.head()
```

Out[3]:
```
   user_id        date     trx_type activity_type  counter_party  \
0  1001517  1971-06-17          ACH      Incoming        6504238
1  1001517  1971-12-13          ACH      Incoming        6504238
2  1001517  1971-09-13          ACH      Outgoing        2501016
3  1001517  1971-12-13          ACH      Outgoing        7328482
4  1001517  1971-02-05  Credit_Card      Incoming        6366609

         amount user_phone_number counter_party_phone_number  Y
0  28815.726712      409-242-7201                        NaN  0
1   7578.565233      279-587-7765                        NaN  0
2  75919.208014      696-429-7698                        NaN  0
3   3050.378441      261-891-2975                        NaN  0
4    116.239215      329-791-3754                        NaN  0
```

In [4]:
```
def find_relatives(df):
    relatives = {}
```

```
        for idx, row in df.iterrows():
            uid = row['user_id']
            number = row['user_phone_number']

            if number in relatives:
                relatives[number].append(uid)
            else:
                relatives[number] = [uid]
        return relatives

    results = find_relatives(df[['user_id', 'user_phone_number']])
```

Now the dictionary `results` contains the key-value pairs. * key: the phone number * value: a list of user_id which share the same phone number

For example, let's show 5 phone numbers and the `user_id` share the same number

```
In [5]: i = 0
        for key, val in results.items():
            if i > 4:
                break
            print('number: ' + key + '\n' + 'user_id:', val, '\n')
            i += 1
```

```
number: 409-242-7201
user_id: [1001517, 1190469, 1447636, 2095830, 2233072, 2692753, 3709844, 4404279, 4492440, 452

number: 279-587-7765
user_id: [1001517, 1096821, 1494876, 1655593, 2213934, 2233072, 2297947, 2302817, 2415654, 246

number: 696-429-7698
user_id: [1001517, 1117432, 2355376, 3252372, 4074368, 5165201, 5429950, 5602669, 6443101, 804

number: 261-891-2975
user_id: [1001517, 1039572, 1782394, 2045388, 3022056, 3800553, 4245246, 4445856, 5041999, 691

number: 329-791-3754
user_id: [1001517, 1392582, 2361490, 3063959, 3104808, 4594668, 6062401, 6460866, 6602899, 680
```

5.3 c.) When a transaction happens among relatives, call it circulatory (among relatives) transaction. Create a binary feature if a transaction is circulatory transaction. (4 point)

The `row['user_phone_number']` returns a number and `results[number]` returns a list of `user_id` and they share the same phone number. If `counter_party` is in the list, then this transcation is called circulatory.

In [6]:
```
df['circulatory'] = df.apply(lambda row: 1 if row['counter_party'] in results[row['use

df.head()
```

Out[6]:
```
   user_id       date     trx_type activity_type  counter_party  \
0  1001517 1971-06-17          ACH      Incoming        6504238
1  1001517 1971-12-13          ACH      Incoming        6504238
2  1001517 1971-09-13          ACH      Outgoing        2501016
3  1001517 1971-12-13          ACH      Outgoing        7328482
4  1001517 1971-02-05  Credit_Card      Incoming        6366609

         amount user_phone_number counter_party_phone_number  Y  circulatory
0  28815.726712      409-242-7201                        NaN  0            0
1   7578.565233      279-587-7765                        NaN  0            0
2  75919.208014      696-429-7698                        NaN  0            0
3   3050.378441      261-891-2975                        NaN  0            0
4    116.239215      329-791-3754                        NaN  0            0
```

5.4 d.) Suppose that you would like to track weekly incoming (from counterparty to user's account) and outgoing (from user's account to counterparty's account) amount (i.e. sum of weekly amount). If this amount is more than $100,000, then an alert should be generated. Create features using these logics. (5 points)

In [7]:
```
# Convert date to datetime64
df['date'] = pd.to_datetime(df['date'])

# Resample by weekly and sum the amount
df_weekly = df.set_index('date').groupby(['user_id'])['amount'].resample('W').sum().res

# Select the events which amount > 100,000
df_alert = df_weekly[df_weekly['amount'] > 100000].reset_index()
```

In [8]:
```
df_alert.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8646 entries, 0 to 8645
Data columns (total 4 columns):
index      8646 non-null int64
user_id    8646 non-null int64
date       8646 non-null datetime64[ns]
amount     8646 non-null float64
dtypes: datetime64[ns](1), float64(1), int64(2)
memory usage: 270.3 KB
```

In [9]:
```
# Find the date belong which week of the year
df_alert['week_number'] = df_alert['date'].dt.week

df_alert.head()
```

```
Out[9]:    index  user_id       date         amount  week_number
        0    101  1003411 1971-01-10  170778.213699            1
        1    108  1003411 1971-02-28  122195.913984            8
        2    112  1003411 1971-03-28  154276.335030           12
        3    119  1003411 1971-05-16  106100.056347           19
        4    306  1010626 1971-01-31  139526.472116            4
```

Create a dictionary `week_number` which contains the `user_id` as key and the list of week number as value. The value lists the key has incoming + outgoint amount > $100,000

```
In [10]: week_number = {}
         for idx, row in df_alert.iterrows():
             uid = row['user_id']
             if uid in week_number:
                 week_number[uid].append(row['week_number'])
             else:
                 week_number[uid] = [row['week_number']]
```

```
In [11]: # Create a week number features in df
         df['week_number'] = df['date'].dt.week

         # Create a alert features in df
         # If the user's incoming + outgoing amount > $100,000 in a week, then alert is set to
         df['alert'] = df.apply(lambda row: 1 if row['user_id'] in week_number and row['week_nu
```

```
In [12]: # Show the results
         df.head()
```

```
Out[12]:   user_id       date     trx_type activity_type  counter_party        amount  \
         0  1001517 1971-06-17          ACH      Incoming        6504238  28815.726712
         1  1001517 1971-12-13          ACH      Incoming        6504238   7578.565233
         2  1001517 1971-09-13          ACH      Outgoing        2501016  75919.208014
         3  1001517 1971-12-13          ACH      Outgoing        7328482   3050.378441
         4  1001517 1971-02-05  Credit_Card      Incoming        6366609    116.239215

          user_phone_number counter_party_phone_number  Y  circulatory  week_number  \
         0      409-242-7201                        NaN  0            0           24
         1      279-587-7765                        NaN  0            0           50
         2      696-429-7698                        NaN  0            0           37
         3      261-891-2975                        NaN  0            0           50
         4      329-791-3754                        NaN  0            0            5

            alert
         0      0
         1      0
         2      0
         3      0
         4      0
```

```
In [13]: # Check the results, make sure there are events with alert = 1
         df[df['alert'] == 1].head()
```

```
Out[13]:     user_id        date trx_type activity_type  counter_party        amount  \
         61  1003411  1971-01-04      ACH      Incoming        8526218  90209.868455
         62  1003411  1971-01-06      ACH      Incoming        9316225  80568.345244
         68  1003411  1971-02-23      ACH      Incoming        7758628  29700.332415
         69  1003411  1971-02-24      ACH      Incoming        8211985   3806.013001
         70  1003411  1971-02-24      ACH      Incoming        9943935  18278.205311

            user_phone_number counter_party_phone_number  Y  circulatory  week_number  \
         61      967-174-5576                        NaN  0            0            1
         62      312-541-8087                        NaN  0            0            1
         68      710-163-4420                        NaN  0            0            8
         69      662-699-9600                        NaN  0            0            8
         70      847-838-8340                        NaN  0            0            8

             alert
         61      1
         62      1
         68      1
         69      1
         70      1
```

5.5 e.) Addition to features in d), you would like to use features which tracks weekly number of transaction by "trx_type" and "activity_type". Create features which uses this logic. (5 points)

```
In [14]: df['trx_type'].value_counts()
```

```
Out[14]: Debit_Card     205343
         ACH            120669
         Credit_Card     99678
         Check           31944
         Cash             2096
         Wire              265
         Name: trx_type, dtype: int64
```

```
In [15]: df['activity_type'].value_counts()
```

```
Out[15]: Outgoing    302532
         Incoming    157463
         Name: activity_type, dtype: int64
```

There are 6 categories for `trx_type` and 2 categories for `activity_type`. So 6 x 2 = 12 combinations. Firstly, let's create a new feature `type` which contains 12 combinations and a new features `count` with value 1.

```
In [16]: df['type'] = df.apply(lambda row: row['trx_type'] + "_" + row['activity_type'], axis=
         df['count'] = 1
         df.head()
```

```
Out[16]:    user_id        date     trx_type activity_type  counter_party        amount  \
         0  1001517  1971-06-17          ACH      Incoming        6504238  28815.726712
         1  1001517  1971-12-13          ACH      Incoming        6504238   7578.565233
         2  1001517  1971-09-13          ACH      Outgoing        2501016  75919.208014
         3  1001517  1971-12-13          ACH      Outgoing        7328482   3050.378441
         4  1001517  1971-02-05  Credit_Card      Incoming        6366609    116.239215

           user_phone_number  counter_party_phone_number  Y  circulatory  week_number  \
         0      409-242-7201                         NaN  0            0           24
         1      279-587-7765                         NaN  0            0           50
         2      696-429-7698                         NaN  0            0           37
         3      261-891-2975                         NaN  0            0           50
         4      329-791-3754                         NaN  0            0            5

            alert                  type  count
         0      0          ACH_Incoming      1
         1      0          ACH_Incoming      1
         2      0          ACH_Outgoing      1
         3      0          ACH_Outgoing      1
         4      0  Credit_Card_Incoming      1
```

New we group by user_id, type, week_number and sum over count.

```
In [17]: df_temp = df.groupby(['user_id', 'type', 'week_number']).sum()
         df_temp.head()
```

```
Out[17]:                                         counter_party        amount  Y  \
         user_id type                 week_number
         1001517 ACH_Incoming         24                6504238  28815.726712  0
                                      50                6504238   7578.565233  0
                 ACH_Outgoing         37                2501016  75919.208014  0
                                      50                7328482   3050.378441  0
                 Credit_Card_Incoming 5                 6366609    116.239215  0

                                                  circulatory  alert  count
         user_id type                 week_number
         1001517 ACH_Incoming         24                    0      0      1
                                      50                    0      0      1
                 ACH_Outgoing         37                    0      0      1
                                      50                    0      0      1
                 Credit_Card_Incoming 5                     0      0      1
```

Convert df_temp to pivot table

```
In [18]: df_temp_pivot = pd.pivot_table(df_temp, index=['user_id', 'week_number'], columns=['ty

         # Fill NaN using 0
         df_temp_pivot = df_temp_pivot.fillna(0)
         df_temp_pivot.head()
```

```
Out[18]: type                  ACH_Incoming  ACH_Outgoing  Cash_Incoming  Cash_Outgoing  \
         user_id week_number
         1001517 5                     0.0           0.0            0.0            0.0
                 10                    0.0           0.0            0.0            0.0
                 14                    0.0           0.0            0.0            0.0
                 18                    0.0           0.0            0.0            0.0
                 19                    0.0           0.0            0.0            0.0

         type                  Check_Incoming  Check_Outgoing  Credit_Card_Incoming  \
         user_id week_number
         1001517 5                        0.0             0.0                   1.0
                 10                       0.0             0.0                   1.0
                 14                       0.0             0.0                   1.0
                 18                       0.0             0.0                   1.0
                 19                       0.0             0.0                   1.0

         type                  Credit_Card_Outgoing  Debit_Card_Incoming  \
         user_id week_number
         1001517 5                              0.0                  0.0
                 10                             0.0                  0.0
                 14                             0.0                  0.0
                 18                             0.0                  0.0
                 19                             0.0                  0.0

         type                  Debit_Card_Outgoing  Wire_Incoming  Wire_Outgoing
         user_id week_number
         1001517 5                             0.0            0.0            0.0
                 10                            0.0            0.0            0.0
                 14                            0.0            0.0            0.0
                 18                            0.0            0.0            0.0
                 19                            0.0            0.0            0.0
```

Now we can combine the df and df_temp_pivot tables to produce the final table which will be used for building predictive model.

```
In [19]: df_merged = df.merge(df_temp_pivot, on=['user_id', 'week_number'])

         df_merged.head()
```

```
Out[19]:    user_id        date     trx_type activity_type  counter_party         amount  \
         0  1001517  1971-06-17          ACH      Incoming        6504238   28815.726712
         1  1001517  1971-06-16  Credit_Card      Incoming        7167533     414.361427
         2  1001517  1971-12-13          ACH      Incoming        6504238    7578.565233
         3  1001517  1971-12-13          ACH      Outgoing        7328482    3050.378441
         4  1001517  1971-09-13          ACH      Outgoing        2501016   75919.208014

           user_phone_number counter_party_phone_number  Y  circulatory       ...         \
         0      409-242-7201                        NaN  0            0       ...
```

```
1      278-173-1195                         NaN  0             0       ...
2      279-587-7765                         NaN  0             0       ...
3      261-891-2975                         NaN  0             0       ...
4      696-429-7698                         NaN  0             0       ...

   Cash_Incoming  Cash_Outgoing Check_Incoming  Check_Outgoing  \
0            0.0            0.0            0.0             0.0
1            0.0            0.0            0.0             0.0
2            0.0            0.0            0.0             0.0
3            0.0            0.0            0.0             0.0
4            0.0            0.0            0.0             0.0

   Credit_Card_Incoming  Credit_Card_Outgoing  Debit_Card_Incoming  \
0                   1.0                   0.0                  0.0
1                   1.0                   0.0                  0.0
2                   0.0                   0.0                  0.0
3                   0.0                   0.0                  0.0
4                   0.0                   0.0                  0.0

   Debit_Card_Outgoing  Wire_Incoming  Wire_Outgoing
0                  0.0            0.0            0.0
1                  0.0            0.0            0.0
2                  0.0            0.0            0.0
3                  0.0            0.0            0.0
4                  0.0            0.0            0.0

[5 rows x 26 columns]
```

5.6 f.) Using the features as created in part (c), (d) and (e), build a statistical machine learning model to detect the suspicious money laundering cases. (To build a model, data (features, and Y) can be aggregated at ["user_id", "date"] level.) Report model performance using a relevant metric (and why you would choose this metric?) (8+2 points)

```
In [20]: # List of features
         df_merged.columns
```

```
Out[20]: Index(['user_id', 'date', 'trx_type', 'activity_type', 'counter_party',
                'amount', 'user_phone_number', 'counter_party_phone_number', 'Y',
                'circulatory', 'week_number', 'alert', 'type', 'count', 'ACH_Incoming',
                'ACH_Outgoing', 'Cash_Incoming', 'Cash_Outgoing', 'Check_Incoming',
                'Check_Outgoing', 'Credit_Card_Incoming', 'Credit_Card_Outgoing',
                'Debit_Card_Incoming', 'Debit_Card_Outgoing', 'Wire_Incoming',
                'Wire_Outgoing'],
               dtype='object')
```

There are many features but we only need part of them to build predictive model.

```
In [21]: columns = df_merged.columns.difference(['trx_type', 'activity_type', 'type', 'counter
         print(columns)
```

```
Index(['ACH_Incoming', 'ACH_Outgoing', 'Cash_Incoming', 'Cash_Outgoing',
       'Check_Incoming', 'Check_Outgoing', 'Credit_Card_Incoming',
       'Credit_Card_Outgoing', 'Debit_Card_Incoming', 'Debit_Card_Outgoing',
       'Wire_Incoming', 'Wire_Outgoing', 'Y', 'alert', 'amount', 'circulatory',
       'date', 'user_id'],
      dtype='object')
```

```
In [22]: # The dataframe for building model
         df_model = df_merged[columns]

         # Aggreate by user_id and date
         df_model = df_model.groupby(['user_id', 'date']).sum()

         df_model.head()
```

```
Out[22]:                     ACH_Incoming  ACH_Outgoing  Cash_Incoming  Cash_Outgoing  \
         user_id date
         1001517 1971-02-05           0.0           0.0            0.0            0.0
                 1971-03-11           0.0           0.0            0.0            0.0
                 1971-04-06           0.0           0.0            0.0            0.0
                 1971-05-05           0.0           0.0            0.0            0.0
                 1971-05-10           0.0           0.0            0.0            0.0

                             Check_Incoming  Check_Outgoing  Credit_Card_Incoming  \
         user_id date
         1001517 1971-02-05             0.0             0.0                   1.0
                 1971-03-11             0.0             0.0                   1.0
                 1971-04-06             0.0             0.0                   1.0
                 1971-05-05             0.0             0.0                   1.0
                 1971-05-10             0.0             0.0                   1.0

                             Credit_Card_Outgoing  Debit_Card_Incoming  \
         user_id date
         1001517 1971-02-05                   0.0                  0.0
                 1971-03-11                   0.0                  0.0
                 1971-04-06                   0.0                  0.0
                 1971-05-05                   0.0                  0.0
                 1971-05-10                   0.0                  0.0

                             Debit_Card_Outgoing  Wire_Incoming  Wire_Outgoing  Y  \
         user_id date
         1001517 1971-02-05                  0.0            0.0            0.0  0
                 1971-03-11                  0.0            0.0            0.0  0
                 1971-04-06                  0.0            0.0            0.0  0
```

```
            1971-05-05                 0.0            0.0            0.0   0
            1971-05-10                 0.0            0.0            0.0   0

                        alert      amount  circulatory
user_id date
1001517 1971-02-05          0  116.239215            0
        1971-03-11          0  608.308096            0
        1971-04-06          0  391.071690            0
        1971-05-05          0  302.650516            0
        1971-05-10          0   34.903677            0
```

In [24]:
```python
selected_features = df_model.columns.difference(['user_id', 'date', 'Y'])
print(selected_features)

X = df_model[selected_features].values
y = df_model['Y'].values
```

```
Index(['ACH_Incoming', 'ACH_Outgoing', 'Cash_Incoming', 'Cash_Outgoing',
       'Check_Incoming', 'Check_Outgoing', 'Credit_Card_Incoming',
       'Credit_Card_Outgoing', 'Debit_Card_Incoming', 'Debit_Card_Outgoing',
       'Wire_Incoming', 'Wire_Outgoing', 'alert', 'amount', 'circulatory'],
      dtype='object')
```

In [25]:
```python
# Check the labels
df_model['Y'].value_counts()
```

Out[25]:
```
0    350150
1       719
Name: Y, dtype: int64
```

Build model Because this is imbalance data, we need to use SMOTE to handel the inputs.

In [26]:
```python
from collections import Counter
from sklearn.datasets import make_classification
from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X, y) # Use SMOTE to resample inputs
```

train test split

In [27]:
```python
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_res, y_res, test_size=0.3, rand
```

Define metric

```
In [28]: from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, r

         def get_performance_metrics(y_train, p_train_pred, y_test, p_test_pred, threshold=0.5)
             metric_names = ['AUC', 'Accuracy', 'Precision', 'Recall', 'f1-score']

             metric_values_train = [roc_auc_score(y_train, p_train_pred),
                                    accuracy_score(y_train, p_train_pred > threshold),
                                    precision_score(y_train, p_train_pred > threshold),
                                    recall_score(y_train, p_train_pred > threshold),
                                    f1_score(y_train, p_train_pred > threshold)]

             metric_values_test = [roc_auc_score(y_test, p_test_pred),
                                   accuracy_score(y_test, p_test_pred > threshold),
                                   precision_score(y_test, p_test_pred > threshold),
                                   recall_score(y_test, p_test_pred > threshold),
                                   f1_score(y_test, p_test_pred > threshold)]

             all_metrics = pd.DataFrame({'metrics': metric_names,
                                         'train': metric_values_train,
                                         'test': metric_values_test},
                                         columns=['metrics', 'train', 'test'])

             all_metrics.set_index('metrics')
             print(all_metrics)
```

Define ploting functions

```
In [29]: from sklearn.metrics import roc_curve, auc

         def plot_roc_curve(y_train, p_train_pred, y_test, p_test_pred):
             roc_auc_train = roc_auc_score(y_train, p_train_pred)
             fpr_train, tpr_train, _ = roc_curve(y_train, p_train_pred)

             roc_auc_test = roc_auc_score(y_test, p_test_pred)
             fpr_test, tpr_test, _ = roc_curve(y_test, p_test_pred)

             lw=2
             plt.figure()
             plt.plot(fpr_train, tpr_train, color='green', linewidth=lw, label='ROC Train (AUC
             plt.plot(fpr_test, tpr_test, color='darkorange', linewidth=lw, label='ROC Test (AU
             plt.plot([0, 1], [0, 1], color='navy', linewidth=lw, linestyle='--')
             plt.xlim([0.0, 1.0])
             plt.ylim([0.0, 1.05])
             plt.xlabel('False Positive Rate')
             plt.ylabel('True Positive Rate')
             plt.title('Receiver operating characteristic example')
```

```
            plt.legend(loc='lower right')
            plt.show()
```

```
In [30]: def plot_feature_importance(model):
             df_feature_importance = pd.DataFrame()
             df_feature_importance['feature'] = selected_features
             df_feature_importance['importance'] = model.feature_importances_
             df_feature_importance.sort_values('importance', inplace=True)

             ax = df_feature_importance.plot(kind='barh', figsize=(20, 10))
             t = np.arange(len(df_feature_importance['feature']))
             ax.set_yticks(t)
             ax.set_yticklabels(df_feature_importance['feature'])
             plt.show()
```

Define model and performance function

```
In [31]: def train_test_model(clf, X_train, y_train, X_test, y_test):
             clf.fit(X_train, y_train)

             y_train_pred = clf.predict(X_train)
             y_train_prob = clf.predict_proba(X_train)[:, 1]

             y_test_pred = clf.predict(X_test)
             y_test_prob = clf.predict_proba(X_test)[:, 1]

             get_performance_metrics(y_train, y_train_prob, y_test, y_test_prob)
             plot_roc_curve(y_train, y_train_prob, y_test, y_test_prob)
```

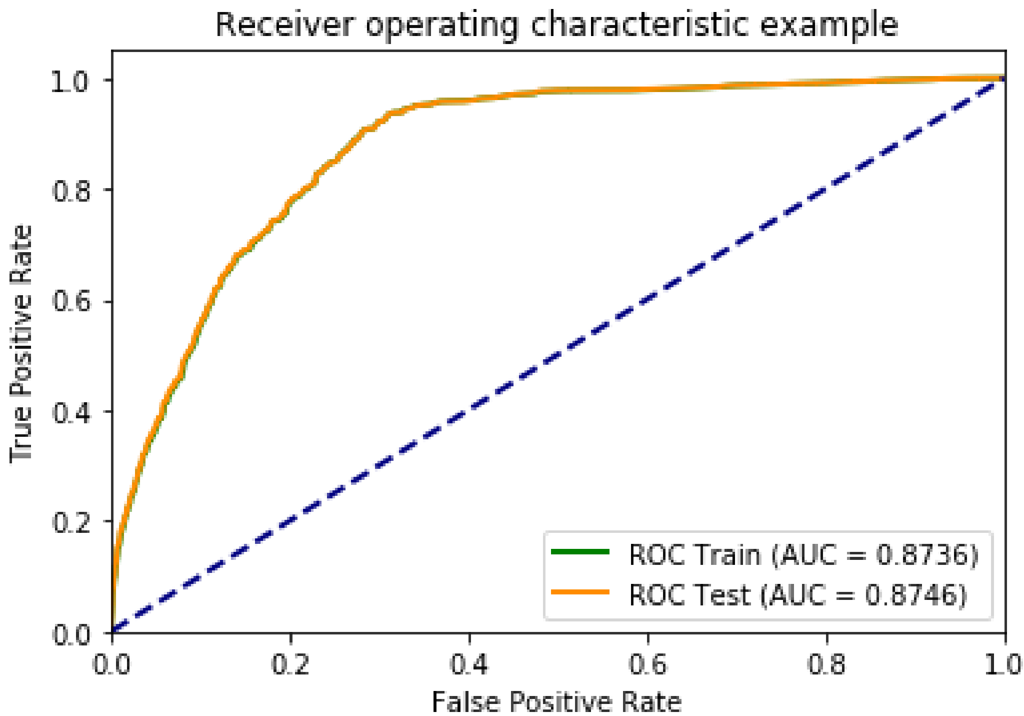
Run model

Logistic Regression

```
In [32]: from sklearn.linear_model import LogisticRegression
         lr = LogisticRegression(C=1.0, penalty='l2')
         train_test_model(lr, X_train, y_train, X_test, y_test)
```

```
/usr/local/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/logistic.py:433: FutureWa
  FutureWarning)
```

```
     metrics     train      test
0        AUC  0.873596  0.874638
1   Accuracy  0.499555  0.501161
2  Precision  0.499540  0.501135
3     Recall  1.000000  1.000000
4   f1-score  0.666258  0.667675
```



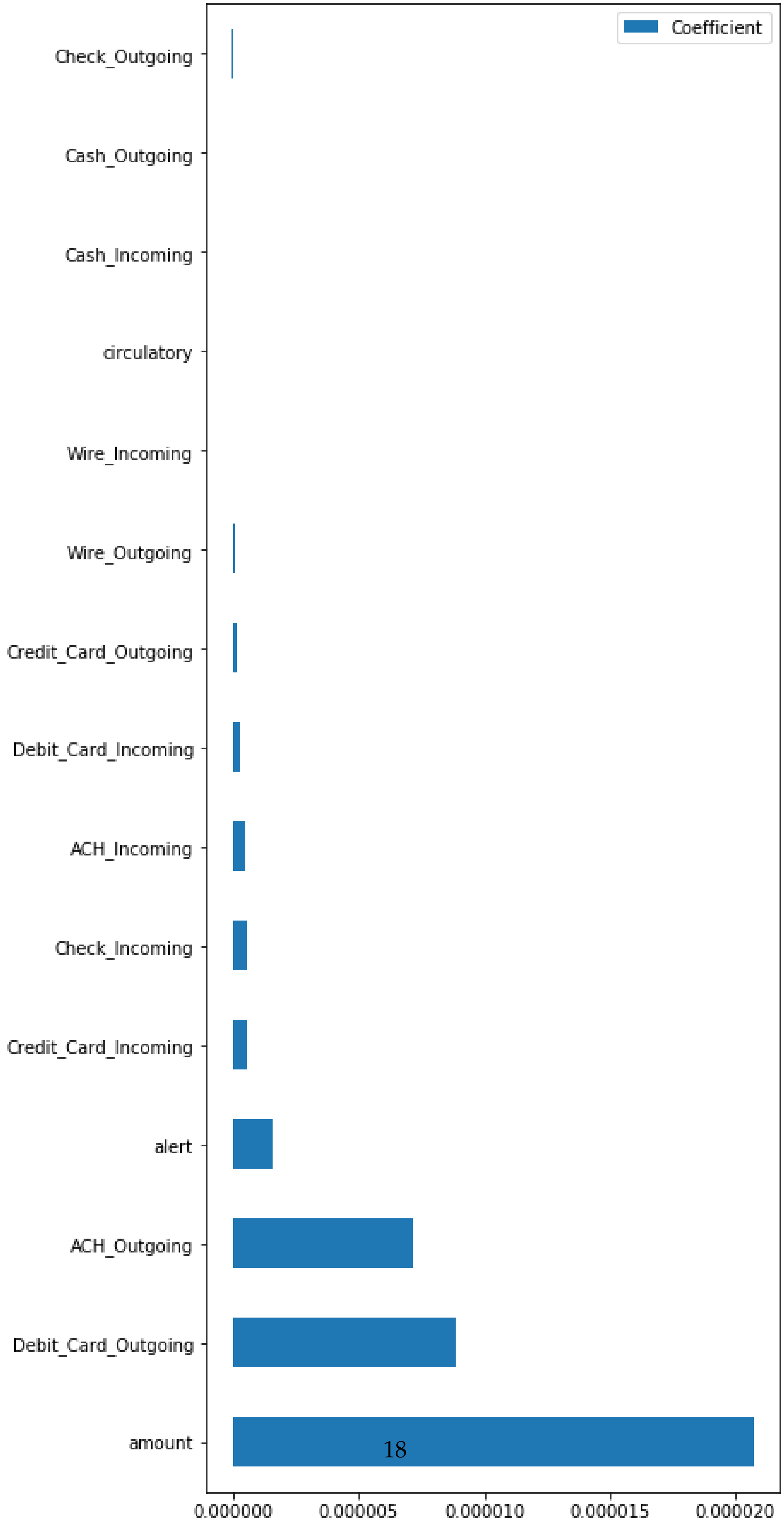
In [34]:
```
coef_values = zip(selected_features, lr.coef_.flatten()) # connect feature names and
df_coeffs = pd.DataFrame(list(coef_values))
df_coeffs.columns = ['Feature', 'Coefficient']
df_coeffs.sort_values(by='Coefficient', ascending=False, inplace=True)
df_coeffs
```

Out[34]:

	Feature	Coefficient
13	amount	2.071239e-05
9	Debit_Card_Outgoing	8.868644e-06
1	ACH_Outgoing	7.173269e-06
12	alert	1.560496e-06
6	Credit_Card_Incoming	5.746693e-07
4	Check_Incoming	5.298029e-07
0	ACH_Incoming	4.789250e-07
8	Debit_Card_Incoming	2.443133e-07
7	Credit_Card_Outgoing	1.471014e-07
11	Wire_Outgoing	5.436046e-08
10	Wire_Incoming	7.984206e-09
14	circulatory	0.000000e+00
2	Cash_Incoming	-1.298619e-08
3	Cash_Outgoing	-3.769388e-08
5	Check_Outgoing	-6.198035e-08

In [35]:
```
ax = df_coeffs.plot(kind='barh')
ax.set_yticks( np.arange(X.shape[1]) )
```

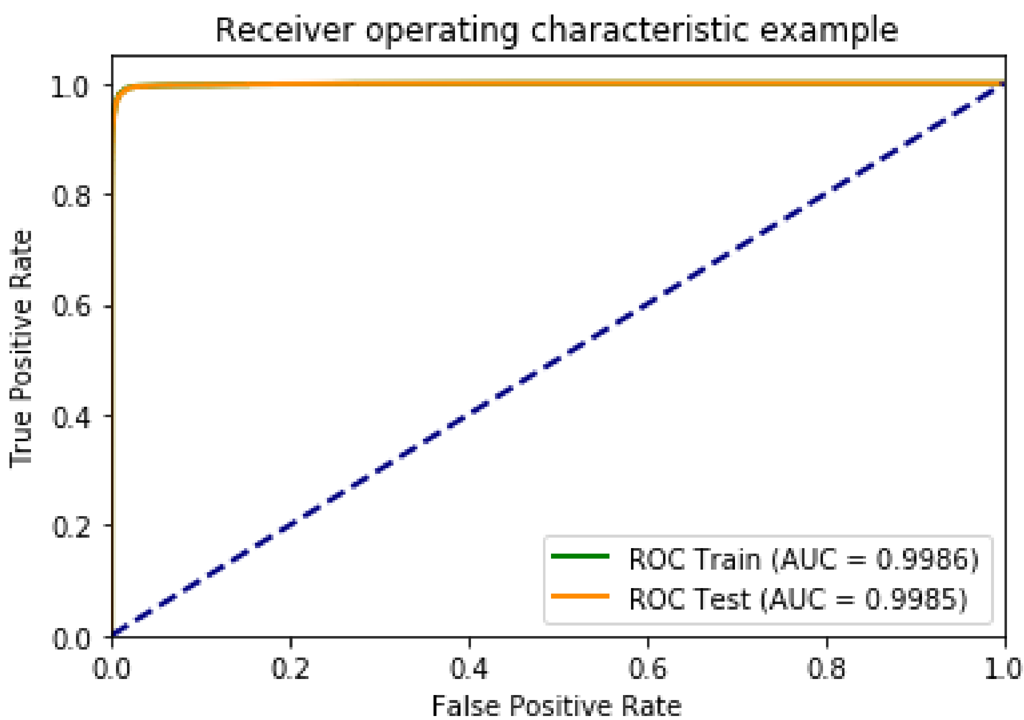
```
ax.set_yticklabels(df_coeffs['Feature'])
plt.gcf().set_size_inches(6, 16)
plt.show()
```


Coefficient
Check_Outgoing
Cash_Outgoing
Cash_Incoming
circulatory
Wire_Incoming
Wire_Outgoing
Credit_Card_Outgoing
Debit_Card_Incoming
ACH_Incoming
Check_Incoming
Credit_Card_Incoming
alert
ACH_Outgoing
Debit_Card_Outgoing
amount
0.000000
0.000005
0.000010
0.000015
0.000020

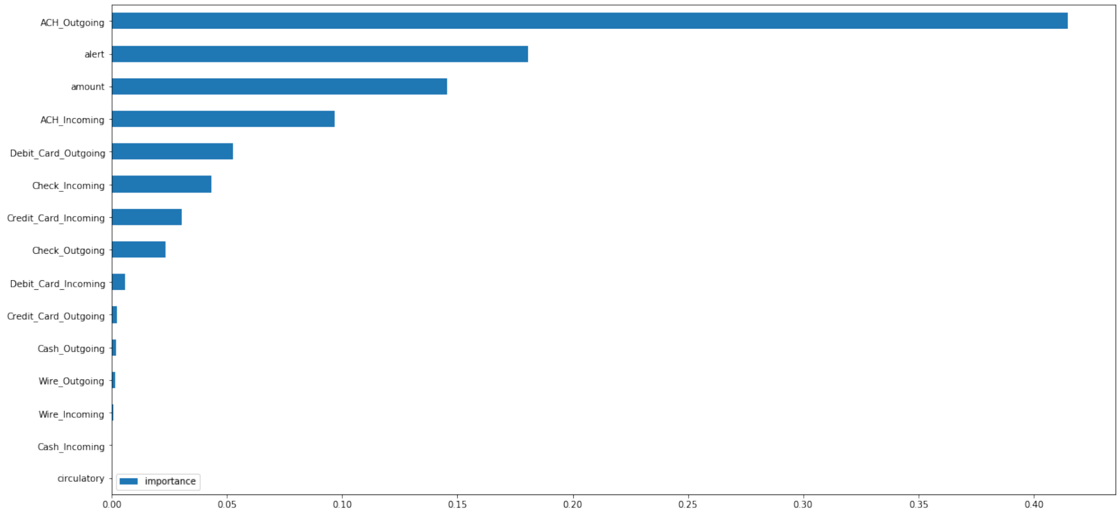
Random Forest

```
In [36]: from sklearn.ensemble import RandomForestClassifier
         paras_rf = {'n_estimators': 50,
                     'max_features': 'auto',
                     'criterion': 'gini',
                     'max_depth': 20,
                     'min_samples_split': 2,
                     'min_samples_leaf': 20,
                     'random_state': 0,
                     'n_jobs': -1}
         rf = RandomForestClassifier(**paras_rf)

         train_test_model(rf, X_train, y_train, X_test, y_test)
```

	metrics	train	test
0	AUC	0.998604	0.998498
1	Accuracy	0.986228	0.985720
2	Precision	0.981253	0.980774
3	Recall	0.991371	0.990929
4	f1-score	0.986286	0.985825



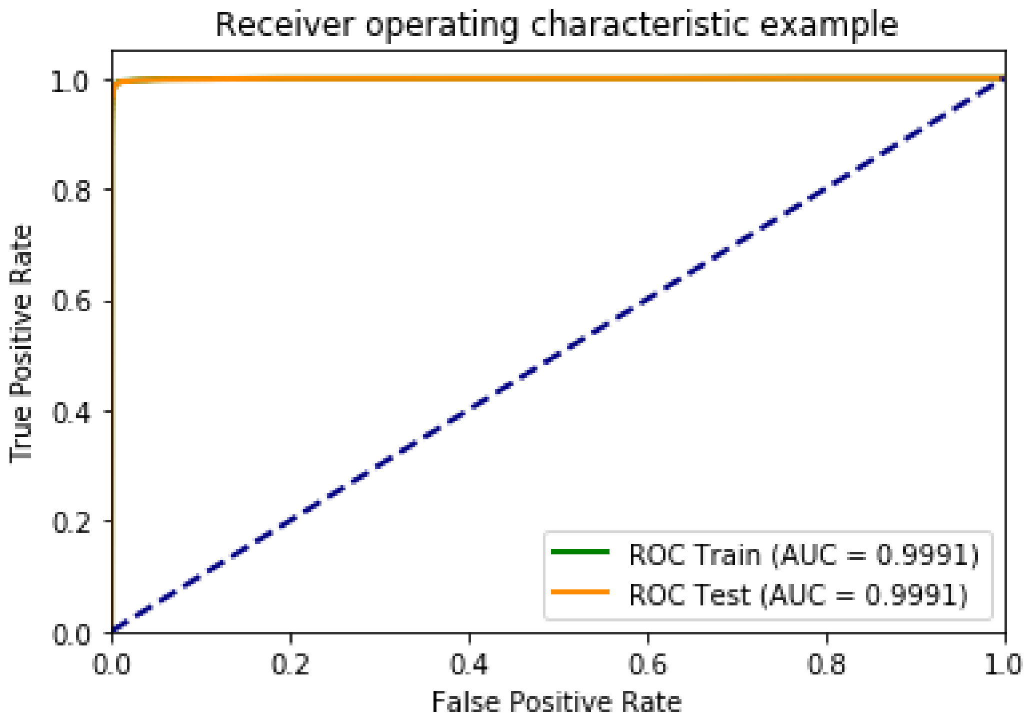
In [37]: plot_feature_importance(rf)



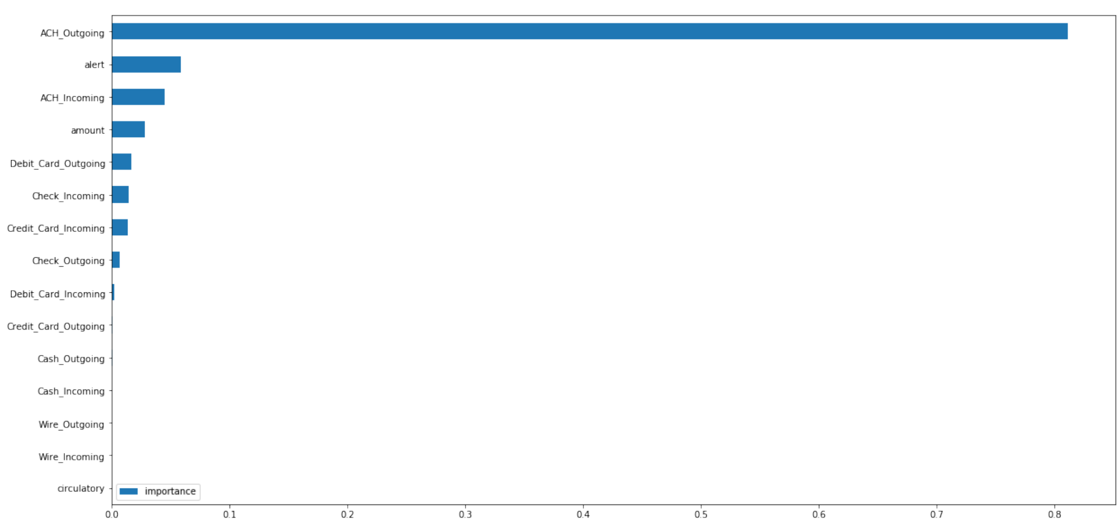
Gradient Boosting Trees

```
In [38]: from sklearn.ensemble import GradientBoostingClassifier
         params_gbt = {'n_estimators': 50,
                       'max_depth': 5,
                       'learning_rate': 0.2,
                       'random_state': 42}

         gbt = GradientBoostingClassifier(**params_gbt)

         train_test_model(gbt, X_train, y_train, X_test, y_test)
```

	metrics	train	test
0	AUC	0.999109	0.999073
1	Accuracy	0.992046	0.991447
2	Precision	0.992113	0.991601
3	Recall	0.991963	0.991328
4	f1-score	0.992038	0.991464




```
In [39]: plot_feature_importance(gbt)
```



Model performance

- In the ROC curve we look at:

- TPR = TP / (TP+FN)
- FPR = FP / (FP+TN)
- Precision and recall are:
- Precision = TP/(TP+FP)
- Recall = TP / (TP+FN)

Because TPR is exactly Recall, we can compare FPR and Precision. Since this data is highly imbalance, the TN is ver large causing FPR is very small. Therefore, the Precision is more important in this study. Following are the metrics using 3 different model, we can see the random forest and gradient boosting trees have better performance than logistic regression. For this case, the precision of logistic regression is only about half of tree-based models.

Using logistic regression:

metrics	train	test
AUC	0.873596	0.874638
Accuracy	0.499555	0.501161
Precision	0.499540	0.501135
Recall	1.000000	1.000000
f1-score	0.666258	0.667675

Using random forest

metrics	train	test
AUC	0.998604	0.998498
Accuracy	0.986228	0.985720
Precision	0.981253	0.980774
Recall	0.991371	0.990929
f1-score	0.986286	0.985825

Using gradient boosting trees

metrics	train	test
AUC	0.999109	0.999073
Accuracy	0.992046	0.991447
Precision	0.992113	0.991601
Recall	0.991963	0.991328
f1-score	0.992038	0.991464

```
In [ ]:
```