```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency,chisquare
from pandas.plotting import scatter_matrix
import plotly.graph_objs as go
import plotly.offline as py
from datetime import datetime, date
from IPython.display import Image
from matplotlib import colors
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
import xgboost as xgb
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Business problem/Real-world Problem

What is ELO?

It is one of the biggest and most reliable payment brands in Brazil. It planned a reward program to attract customers. So, the frequency of using their payment brand has increased.

What is a loyalty Score?

Loyalty is a numerical score calculated 2 months after the historical and evaluation period. It acts as a target feature in our training data.

This reward program is planned by the owners of a company to attract customers. So, the frequency of using their payment brand has increased. Basically, these programs make the customer's **choice more strongly towards the usage of Elo**. It is also necessary that policies made by the companies are known to his customers.

Why did ELO build ML model?

Elo built machine learning models to understand the most important aspects and preferences in their customer.

Metric function: Predictions are evaluated based on Root Mean Squared Error. RMSE(Root-mean-square-error) for reducing the difference between predicted and actual rating(Regression problem).

Objectives:

1.Predict loyalty score and help Elo reduce unwanted campaigns.

Data Overview: We have 5 dataset files for this problem.

All the files are in CSV format.

Historical_transactions: Contains up to 3 months of transactions for every card at any of the provided merchant_id's.

Merchant: contains the aggregate information for each merchant_id represented in the dataset.

New_merchant_transactions: contains the transactions at new merchants(merchant_ids that this particular card_id has not yet visited) over a period of two months.

Train: Contains 6 features, which is first_active_month, card_id, feature_1, feature_2, feature_3 and target.

Test: Contains the same feature as present in train data but the target feature is not present in this dataset.

There are 2 main datasets that contain a list of unique credit cards and the target variable to predict:

Train.csv

Test.csv

Then, there are 2 datasets that contain information about all **transactions of these cards** buying from different merchants:

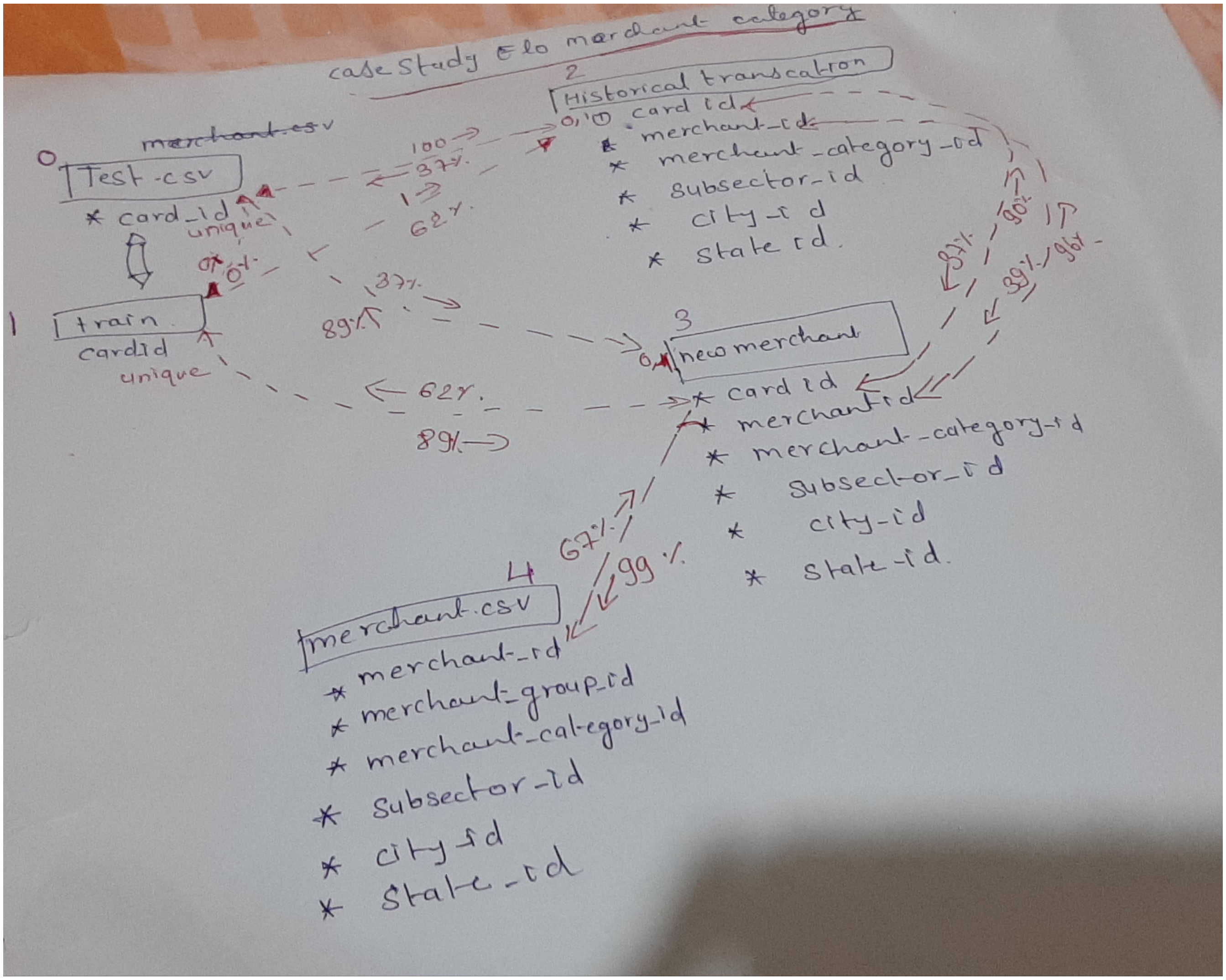
historical_transactions.csv new_merchant_transactions.csv

Lastly, there is 1 dataset that contains information about the merchants:

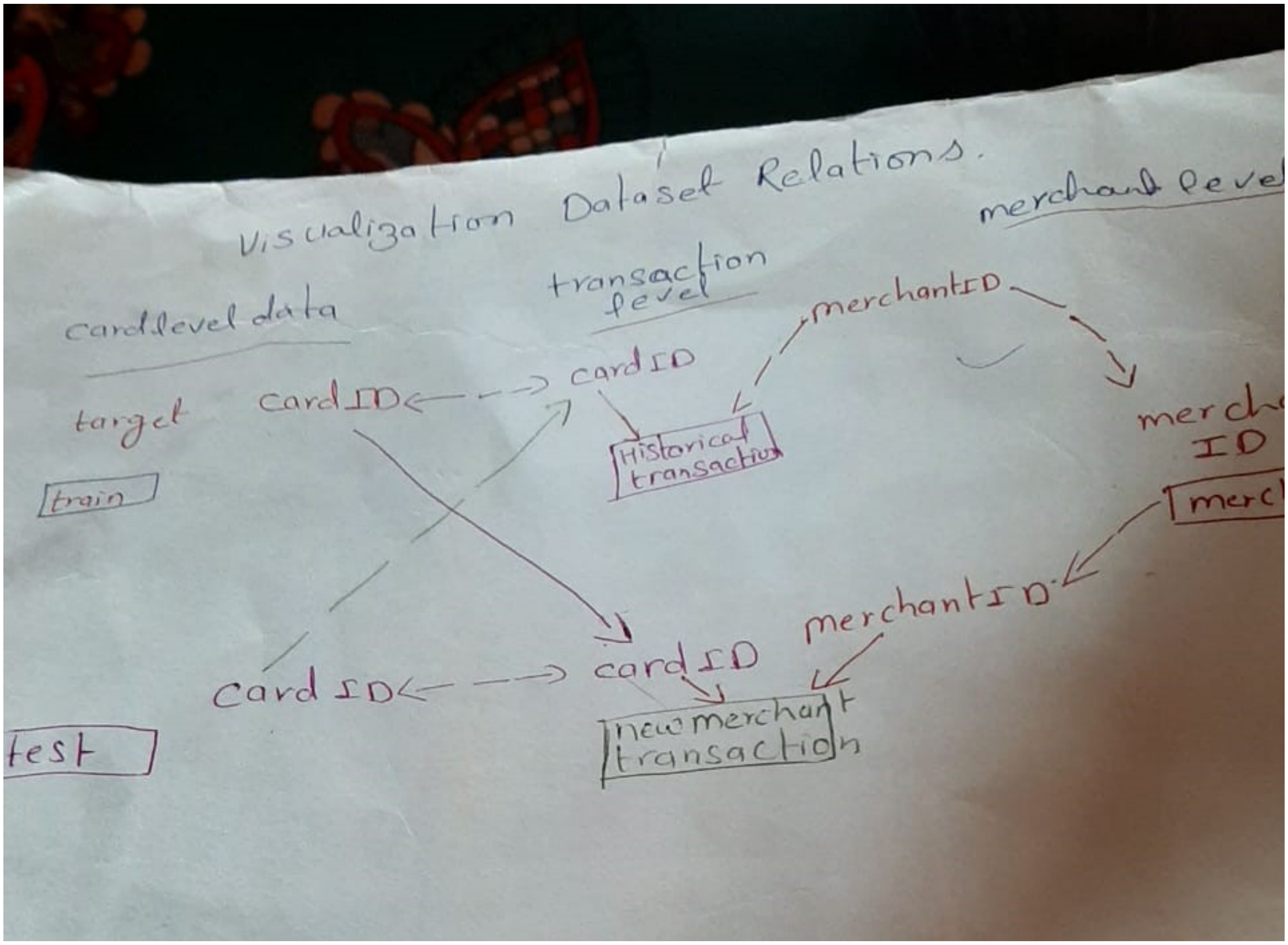
merchants.csv

Basically, this notebook explores all these datasets and their connections.

```
Image(filename='/content/drive/MyDrive/elo-merchant-category-recommendation/20210207_031609.j
```




```
Image(filename='/content/drive/MyDrive/elo-merchant-category-recommendation/image.jpeg')
```



ELo Merchant datasets has 3 levels of data

1.card_level data

2.transaction level data

3.merchant level dataset

merchants.csv

```
merchants = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/merchant
```

```
merchants.shape
```

```
(334696, 22)
```

```
merchants.head(5)
```

	merchant_id	merchant_group_id	merchant_category_id	subsector_id	numerical_1
0	M_ID_838061e48c	8353	792	9	-0.057471
1	M_ID_9339d880ad	3184	840	20	-0.057471
2	M_ID_e726bbae1e	447	690	1	-0.057471
3	M_ID_a70e9c5f81	5026	792	9	-0.057471
4	M_ID_64456c37ce	2228	222	21	-0.057471

```
merchants.dtypes
```

```
merchant_id                     object
merchant_group_id                int64
merchant_category_id             int64
subsector_id                     int64
numerical_1                    float64
numerical_2                    float64
category_1                      object
most_recent_sales_range         object
most_recent_purchases_range     object
avg_sales_lag3                 float64
avg_purchases_lag3             float64
active_months_lag3               int64
avg_sales_lag6                 float64
avg_purchases_lag6             float64
active_months_lag6               int64
avg_sales_lag12                float64
avg_purchases_lag12            float64
active_months_lag12              int64
category_4                      object
city_id                          int64
state_id                         int64
category_2                     float64
dtype: object
```

```
merchants.nunique(dropna=False,axis=0)
```

```
merchant_id                    334633
merchant_group_id              109391
merchant_category_id              324
subsector_id                       41
numerical_1                       954
numerical_2                       947
category_1                          2
most_recent_sales_range             5
most_recent_purchases_range         5
avg_sales_lag3                   3373
avg_purchases_lag3             100003
active_months_lag3                  3
avg_sales_lag6                   4508
avg_purchases_lag6             135202
active_months_lag6                  6
```

```
avg_sales_lag12              5010
avg_purchases_lag12        172917
active_months_lag12            12
category_4                      2
city_id                       271
state_id                       25
category_2                      6
dtype: int64
```

```
merchants.isnull().sum(axis=0)
```

```
merchant_id                     0
merchant_group_id               0
merchant_category_id            0
subsector_id                    0
numerical_1                     0
numerical_2                     0
category_1                      0
most_recent_sales_range         0
most_recent_purchases_range     0
avg_sales_lag3                 13
avg_purchases_lag3              0
active_months_lag3              0
avg_sales_lag6                 13
avg_purchases_lag6              0
active_months_lag6              0
avg_sales_lag12                13
avg_purchases_lag12             0
active_months_lag12             0
category_4                      0
city_id                         0
state_id                        0
category_2                  11887
dtype: int64
```

We can see that there are:

6 features type ID: merchant_id, merchant_group_id, merchant_category_id, subsector_id, city_id, state_id

3 features type integer/counter active_months_lag3, active_months_lag6, active_months_lag12

8 feature type numerical: numerical_1, numerical_2, avg_sales_lag3, avg_purchases_lag3, avg_sales_lag6, avg_purchases_lag6, avg_sales_lag12, avg_purchases_lag12

5 features type categorical: category_1, most_recent_sales_range, most_recent_purchases_range, category_4,category_4

```
merchants[["active_months_lag3","active_months_lag6","active_months_lag12","numerical_1","num
          "avg_sales_lag3","avg_purchases_lag3","avg_sales_lag6","avg_purchases_lag6","avg_sa
          "avg_purchases_lag12"]].describe()
```

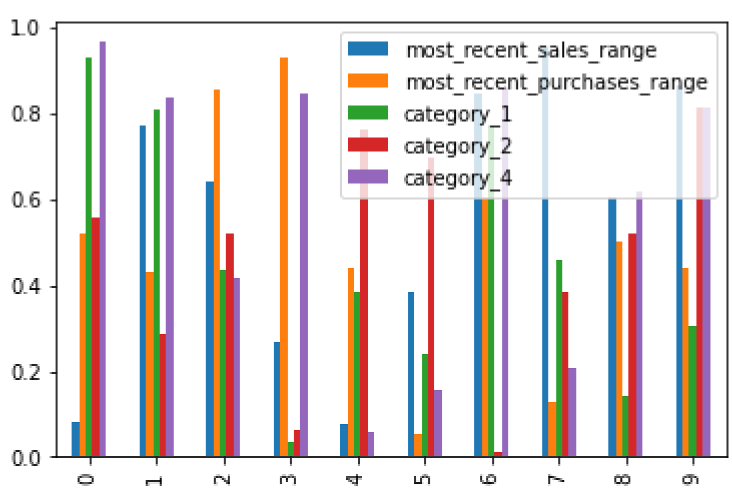
	active_months_lag3	active_months_lag6	active_months_lag12	numerical_1	nu
count	334696.000000	334696.000000	334696.000000	334696.000000	3346
mean	2.994108	5.947397	11.599335	0.011476	
std	0.095247	0.394936	1.520138	1.098154	
min	1.000000	1.000000	1.000000	-0.057471	
25%	3.000000	6.000000	12.000000	-0.057471	
50%	3.000000	6.000000	12.000000	-0.057471	
75%	3.000000	6.000000	12.000000	-0.047556	
max	3.000000	6.000000	12.000000	183.735111	1

```
merchants.groupby("most_recent_sales_range").size()
```

```
most_recent_sales_range
A      1005
B      5037
C     34075
D    117475
E    177104
dtype: int64
```

```
merchants.groupby("most_recent_purchases_range").size()
merchants.groupby("category_1").size()
merchants.groupby("category_2").size()
merchants.groupby("category_4").size()
```

```
dfcat = pd.DataFrame(np.random.rand(10, 5), columns=["most_recent_sales_range", "most_recent
dfcat.plot.bar();
```



Observation:

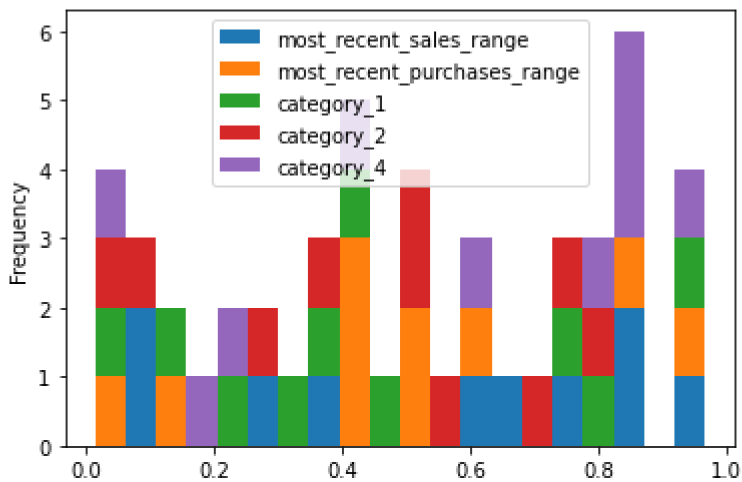
Can see most_recent_sales ,most_ recent_purchases_range are not constant .Can see some growth.

showing

```
plt.figure();
```

```
df2.plot.hist(stacked=True, bins=20);
```

```
<Figure size 432x288 with 0 Axes>
```

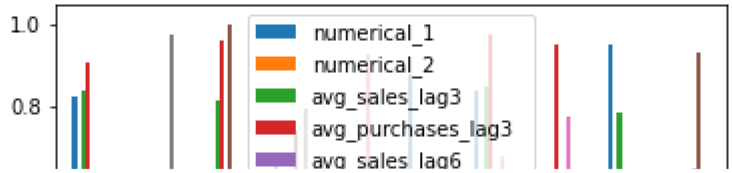


Observation :

can see growth on most_recent_sales_range

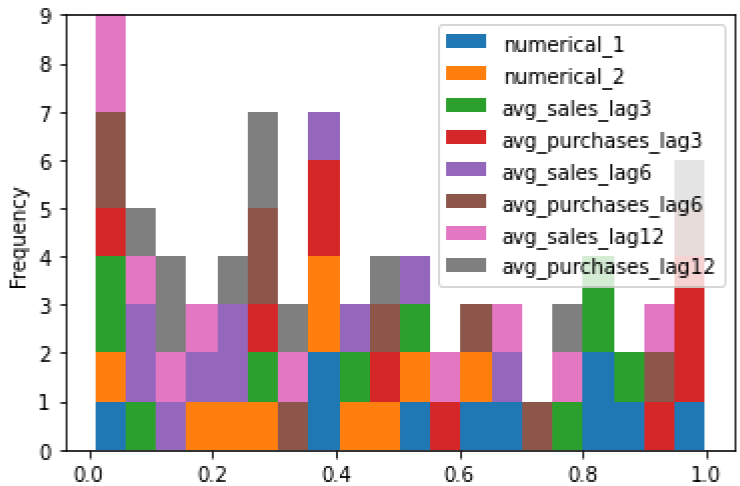
Numerical feature analysis of merchant csv

```
dfnum = pd.DataFrame(np.random.rand(10, 8), columns=["numerical_1", "numerical_2", "avg_sales
dfnum.plot.bar();
```




```
plt.figure();

dfnum.plot.hist(stacked=True, bins=20);
```

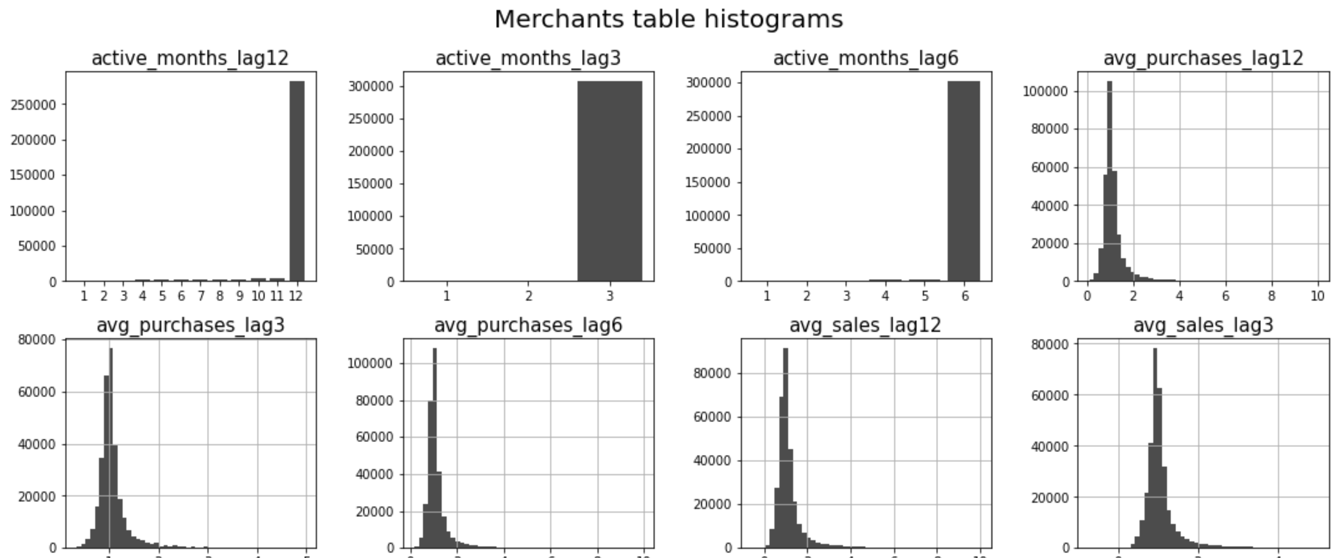
<Figure size 432x288 with 0 Axes>



merchants.csv have outliers that squeeze most of the data into one bin

```
merchants_outlier = merchants.loc[(merchants['numerical_1'] < 0.1) &
                                  (merchants['numerical_2'] < 0.1) &
                                  (merchants['avg_sales_lag3'] < 5) &
                                  (merchants['avg_purchases_lag3'] < 5) &
                                  (merchants['avg_sales_lag6'] < 10) &
                                  (merchants['avg_purchases_lag6'] < 10) &
                                  (merchants['avg_sales_lag12'] < 10) &
                                  (merchants['avg_purchases_lag12'] < 10)]


cat_cols = ['active_months_lag6','active_months_lag3','most_recent_sales_range', 'most_recent
num_cols = ['numerical_1', 'numerical_2','merchant_group_id','merchant_category_id','avg_sale

plt.figure(figsize=[15, 15])
plt.suptitle('Merchants table histograms', y=1.02, fontsize=20)
ncols = 4
nrows = int(np.ceil((len(cat_cols) + len(num_cols))/4))
last_ind = 0
for col in sorted(list(merchants_outlier.columns)):
    #print('processing column ' + col)
    if col in cat_cols:
        last_ind += 1
        plt.subplot(nrows, ncols, last_ind)
        vc = merchants_outlier[col].value_counts()
```

```
        vc = merchants_outlier[col].value_counts()
        x = np.array(vc.index)
        y = vc.values
        inds = np.argsort(x)
        x = x[inds].astype(str)
        y = y[inds]
        plt.bar(x, y, color=(0, 0, 0, 0.7))
        plt.title(col, fontsize=15)
    if col in num_cols:
        last_ind += 1
        plt.subplot(nrows, ncols, last_ind)
        merchants_outlier[col].hist(bins = 50, color=(0, 0, 0, 0.7))
        plt.title(col, fontsize=15)
    plt.tight_layout()
```



Observations:

Looks like merchant_group_ids, numerical_1 and numerical_2 are sorted in the descending order and Most recent purchase range and sales range are sorted in ascendig

```
heat_map(merchants)
```

Correlation Heatmap

Double-click (or enter) to edit

Double-click (or enter) to edit

** EDA on test.csv and train.csv.**

train.csv and test.csv column descriptions:

card_id: Unique card identifier

first_active_month: 'YYYY-MM', month of first purchase

feature_1: Anonymized card categorical feature

feature_2: Anonymized card categorical feature

feature_3: Anonymized card categorical feature

target: Loyalty numerical score calculated 2 months after historical and evaluation period!

```
train = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/train.csv")
```

```
train.shape
```

```
(201917, 6)
```

```
train.head(5)
```

	first_active_month	card_id	feature_1	feature_2	feature_3	target
0	2017-06	C_ID_92a2005557	5	2	1	-0.820283
1	2017-01	C_ID_3d0044924f	4	1	0	0.392913
2	2016-08	C_ID_d639edf6cd	2	2	0	0.688056
3	2017-09	C_ID_186d6a6901	4	3	0	0.142495
4	2017-11	C_ID_cdbd2c0db2	1	3	0	-0.159749

```
train.dtypes
```

```
first_active_month     object
card_id                object
feature_1               int64
feature_2               int64
feature_3               int64
target                float64
dtype: object
```

```
train.nunique(dropna=False,axis=0) #unique value
```

```
first_active_month        75
card_id               201917
feature_1                  5
feature_2                  3
feature_3                  2
target                197110
dtype: int64
```

```
train.isnull().sum(axis=0)
```

```
first_active_month    0
card_id               0
feature_1             0
feature_2             0
feature_3             0
target                0
dtype: int64
```

```
train[["target"]].describe()
```

	target
count	201917.000000
mean	-0.393636
std	3.850500
min	-33.219281
25%	-0.883110
50%	-0.023437
75%	0.765453
max	17.965068

```
train.groupby("feature_1").size()
```

```
feature_1
1    12037
2    55797
3    73573
4    19885
5    40625
dtype: int64
```

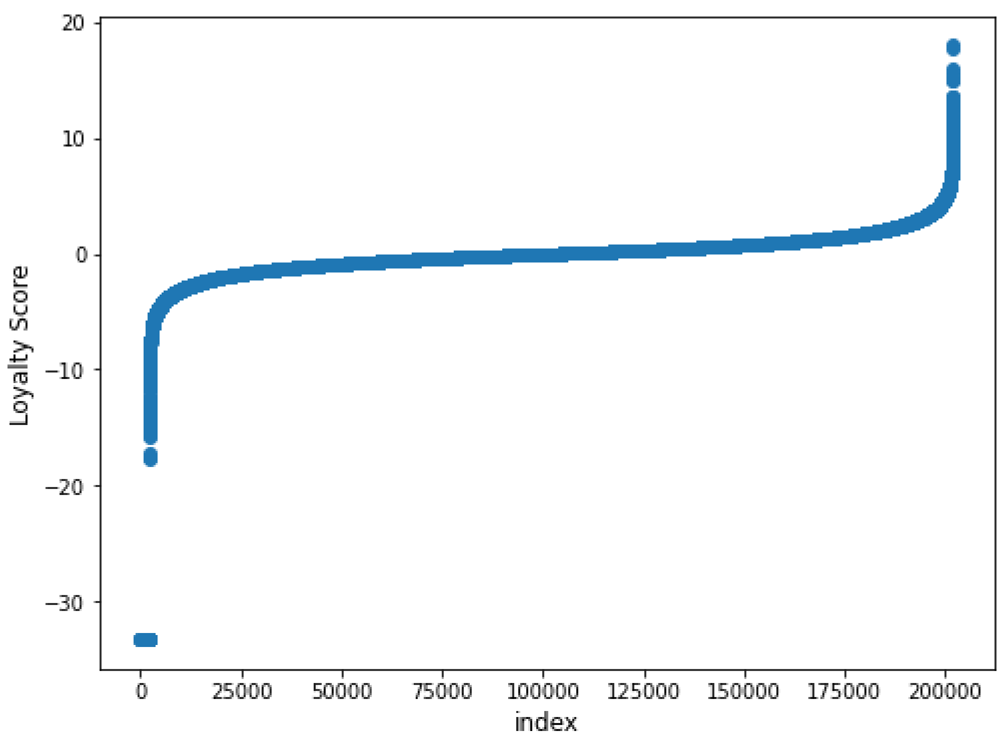
```
train.groupby("feature_2").size()
```

```
feature_2
1    89242
2    74839
3    37836
dtype: int64
```

```
train.groupby("feature_3").size()
```

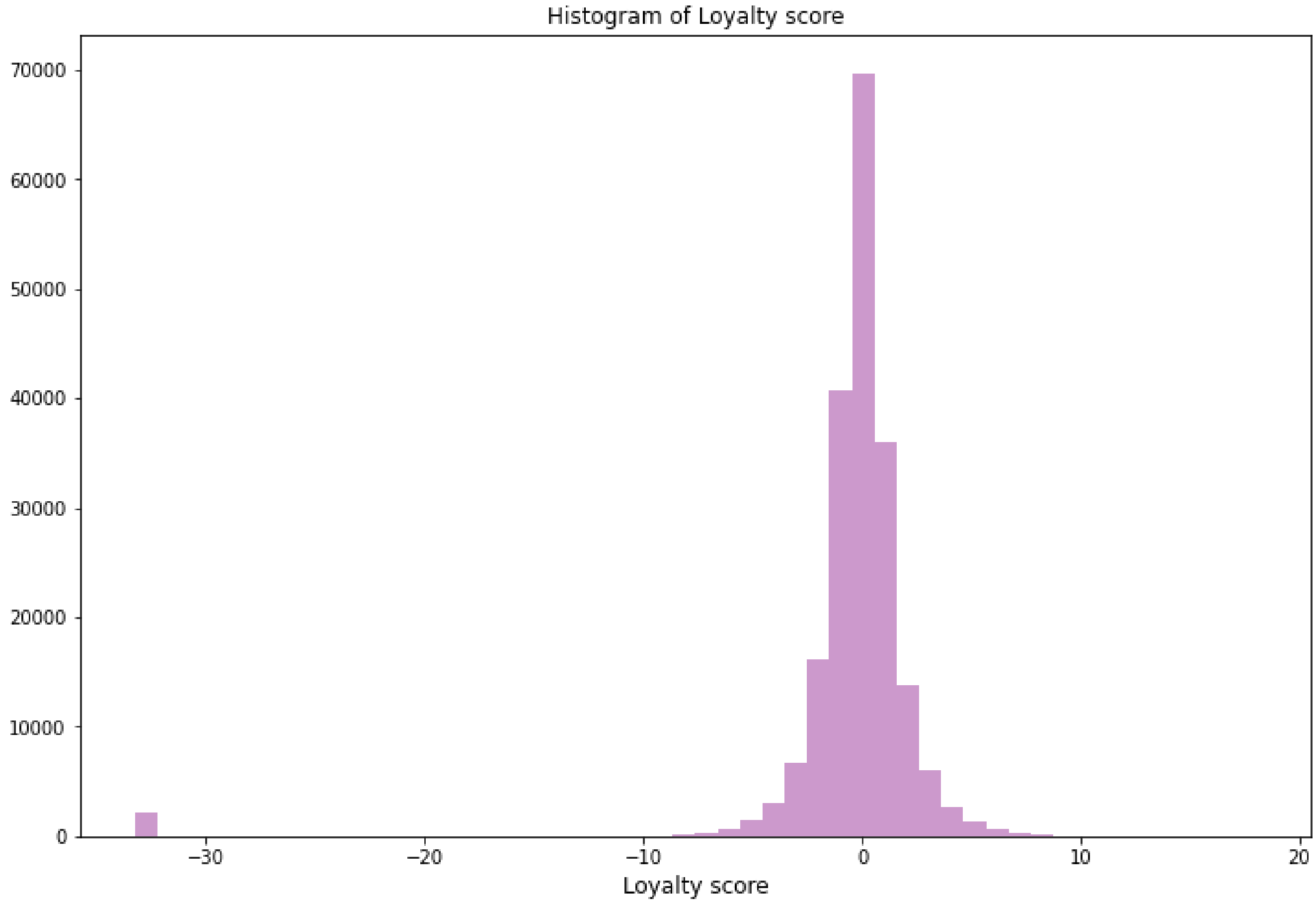
```
feature_3
0     87719
1    114198
dtype: int64
```

```
target_col = "target"

plt.figure(figsize=(8,6))
plt.scatter(range(train.shape[0]), np.sort(train[target_col].values))
plt.xlabel('index', fontsize=12)
plt.ylabel('Loyalty Score', fontsize=12)
plt.show()
```




```
plt.figure(figsize=(12,8))
sns.distplot(train[target_col].values, bins=50, kde=False, color="purple")
plt.title("Histogram of Loyalty score")
plt.xlabel('Loyalty score', fontsize=12)
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please ada
```



We can see that some of the loyalty values are far apart (less than -30) compared to others

```
(train[target_col]<-30).sum()
```

```
2207
```

We have about 2207 rows , which has values different from the rest

```
(train[target_col]>10).sum()
```

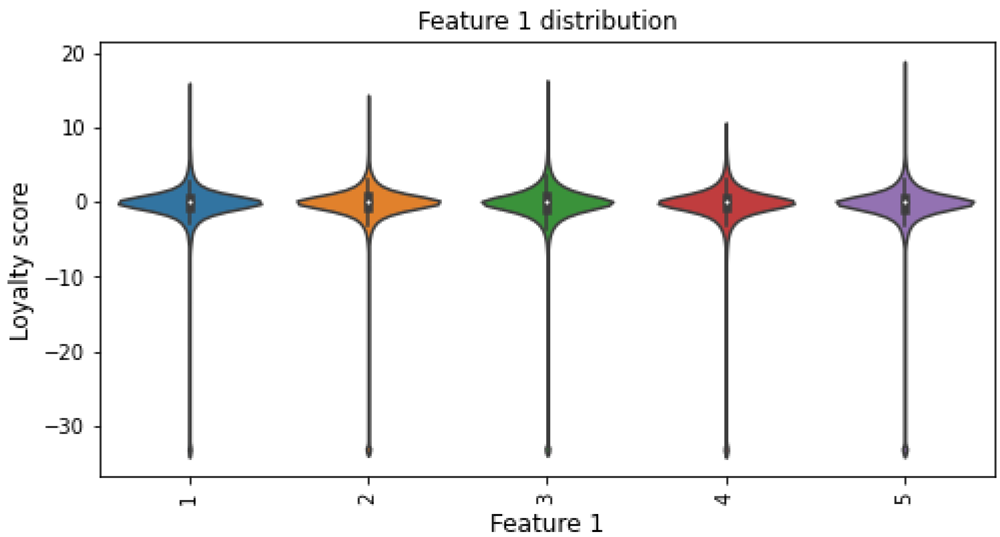
```
48
```

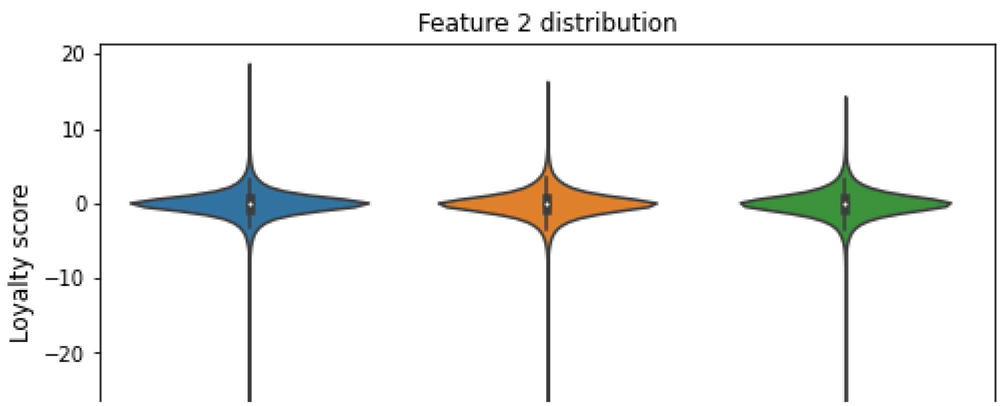
Extremely HIGH scores 48

Feature 1,2 & 3:

In this section, let us see if the other variables in the train dataset has good predictive power in finding the loyalty score.

```
# feature 1
plt.figure(figsize=(8,4))
sns.violinplot(x="feature_1", y=target_col, data=train)
plt.xticks(rotation='vertical')
plt.xlabel('Feature 1', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("Feature 1 distribution")
plt.show()

# feature 2
plt.figure(figsize=(8,4))
sns.violinplot(x="feature_2", y=target_col, data=train)
plt.xticks(rotation='vertical')
plt.xlabel('Feature 2', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("Feature 2 distribution")
plt.show()

# feature 3
plt.figure(figsize=(8,4))
sns.violinplot(x="feature_3", y=target_col, data=train)
plt.xticks(rotation='vertical')
plt.xlabel('Feature 3', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("Feature 3 distribution")
plt.show()
```





the distribution of the different categories in all three features look kind of similar

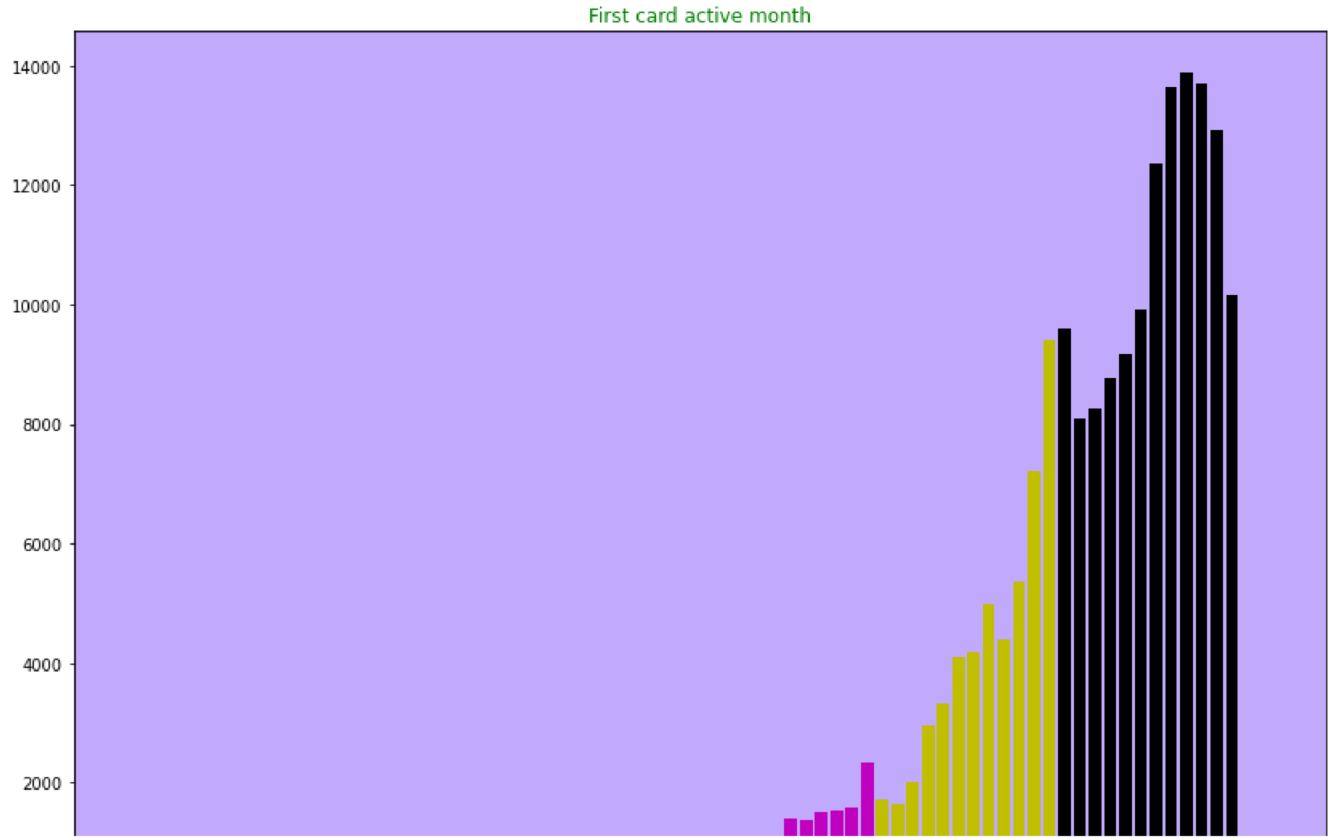

```
# feature 1
plt.figure(figsize=(8,4))
sns.histplot(x="feature_1", y=target_col, data=train)
plt.xticks(rotation='vertical')
plt.xlabel('Feature 1', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("Feature 1 distribution")
plt.show()

# feature 2
plt.figure(figsize=(8,4))
sns.histplot(x="feature_2", y=target_col, data=train)
plt.xticks(rotation='vertical')
plt.xlabel('Feature 2', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("Feature 2 distribution")
plt.show()


# feature 3
plt.figure(figsize=(8,4))
sns.histplot(x="feature_2", y=target_col, data=train)
plt.xticks(rotation='vertical')
```

```
    plt.xticks(rotation='vertical')
    plt.xlabel('Feature 3', fontsize=12)
    plt.ylabel('Loyalty score', fontsize=12)
    plt.title("Feature 3 distribution")
    plt.show()
```

Feature 1 distribution

Can see feature 2 & 3 have almost same distribution


```
#https://www.kaggle.com/maffei2443/elo-eda

first_mount = train.first_active_month.value_counts()
srt = first_mount.sort_index()
years = srt.index.str[:4].unique()

# WHITE color doesn't well... appear
MY_BASE_COLORS = colors.BASE_COLORS.copy()
del MY_BASE_COLORS['w']
MY_BASE_COLORS['purple'] = 'purple'

year_cmap = dict(zip(years, MY_BASE_COLORS))

cmap_seq = srt.index.map(lambda x: year_cmap[x[:4]])


fig = plt.figure(figsize=(14, 10))

plt.bar(
    srt.index,
    srt.values,
    color=cmap_seq,
)
plt.xticks(rotation='vertical');
plt.xlabel('First month');
plt.title('First card active month', color='g');

ax = plt.gca()
ax.set_facecolor((.6, .44, .98, .6))
# fig.patch.set_facecolor('xkcd:mint green')
for i, t in enumerate(plt.gca().get_xticklabels()):
    t.set_color( cmap_seq[i] )
plt.show()
```

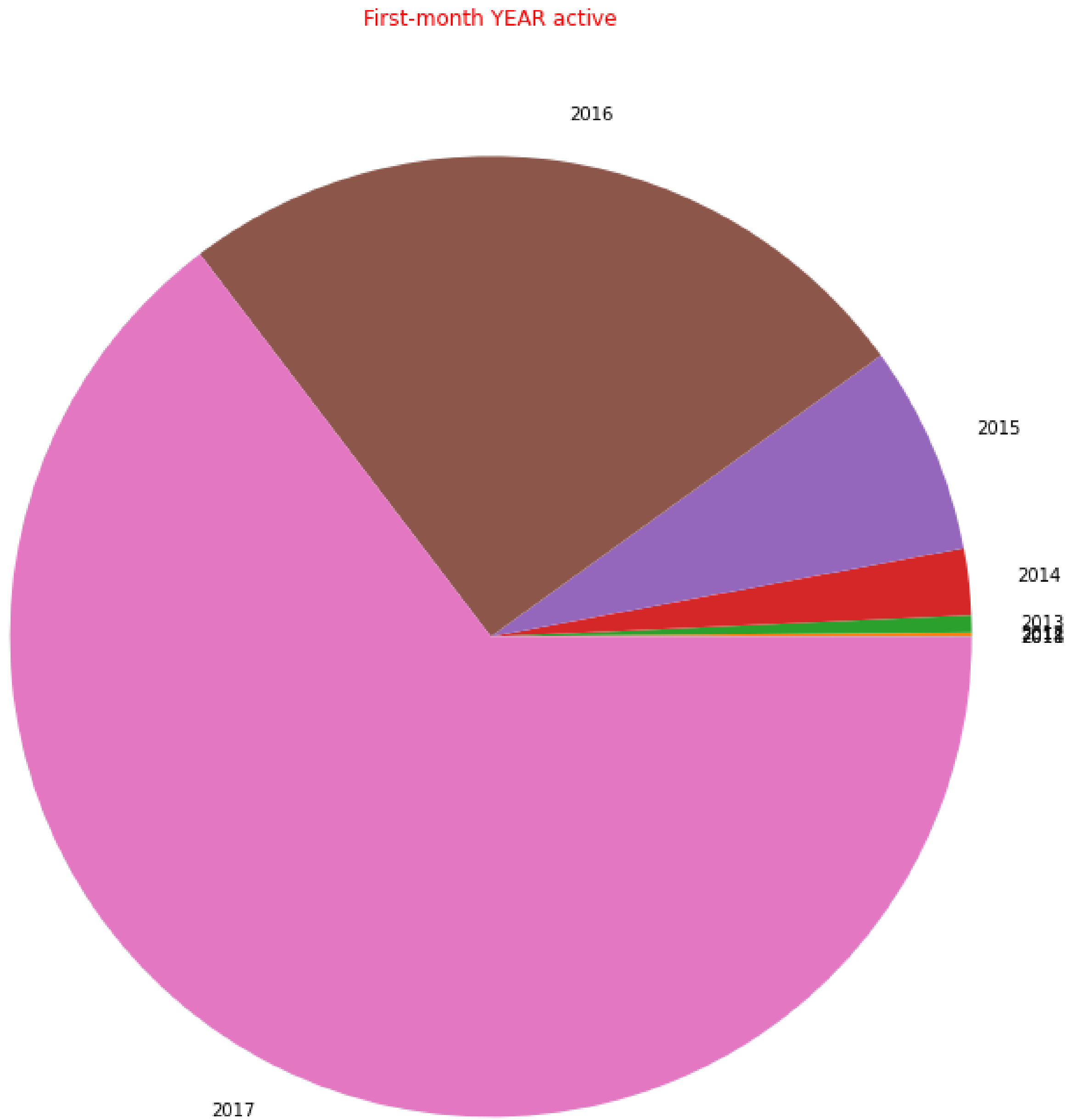


Double-click (or enter) to edit

Observation:

Can see 2017 has more transaction

```
#maffei2443/elo-eda

first_month = train.first_active_month.value_counts()
srt = first_month.sort_index()
years = srt.index.str[:4].unique()
year_cmap = dict(zip(years, MY_BASE_COLORS))

vc =train.first_active_month.str[:4].value_counts()
srt=vc.sort_index()

indices = np.arange(len(srt))
fig, ax = plt.subplots(figsize=(12.8, 12.6))
ax.pie(
    srt.values,
    labels=srt.index
)
ax.set_title('First-month YEAR active', fontdict={'color': 'red'});
plt.show()
```



Double-click (or enter) to edit

EDA on Test data

```
test = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv")
```

```
test.shape
```

```
(123623, 5)
```

```
test.dtypes
```

```
first_active_month    object
card_id               object
feature_1              int64
feature_2              int64
feature_3              int64
dtype: object
```

```
test.groupby("feature_1").size()
```

```
feature_1
1     7406
2    34115
3    44719
4    12332
5    25051
dtype: int64
```

```
test.groupby("feature_2").size()
```

```
feature_2
1    54775
2    45993
3    22855
dtype: int64
```

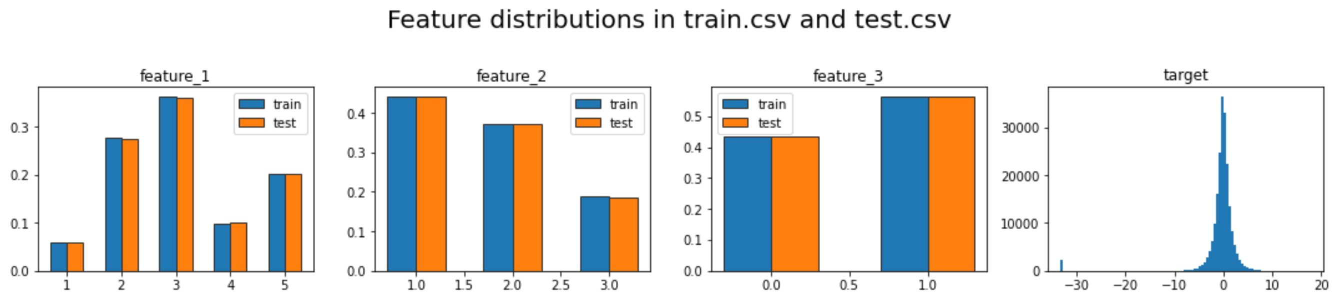
```
test.groupby("feature_3").size()
```

```
feature_3
0    53853
1    69770
dtype: int64
```

Feature distributions in train.csv and test.csv

```
%matplotlib inline
#Comparing Feature distributions in train & test Data

plt.figure(figsize=[15,5])
plt.suptitle('Feature distributions in train.csv and test.csv', fontsize=20, y=1.1)
for num, col in enumerate(['feature_1', 'feature_2', 'feature_3', 'target']):
    plt.subplot(2, 4, num+1)
    if col is not 'target':
        v_c = train[col].value_counts() / train.shape[0]
        plt.bar(v_c.index, v_c, label=('train'), align='edge', width=-0.3, edgecolor=[0.2]*3)
        v_c = test[col].value_counts() / test.shape[0]
        plt.bar(v_c.index, v_c, label=('test'), align='edge', width=0.3, edgecolor=[0.2]*3)
```

```
        plt.title(col)
        plt.legend()
    else:
        plt.hist(train[col], bins = 100) # Histogram of target variable
        plt.title(col)
    plt.tight_layout()
plt.tight_layout()
plt.show()
```



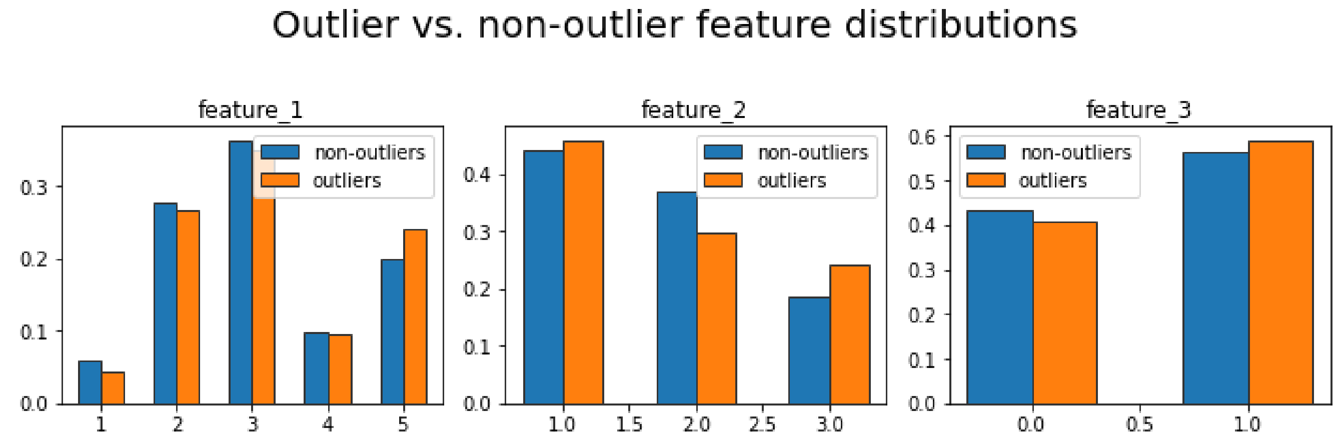
Observation:

We can see from above plots that test and train data are distributed similarly. there are some outliers in the target column.

** Outlier vs. non-outlier feature distributions**

```
# Separating outliers and non_outliers features in Target and plotting
outliers = train.loc[train['target'] < -30]
non_outliers = train.loc[train['target'] >= -30]
print('{:d} outliers found (target < -30)'.format(outliers.shape[0]))

#Outlier vs. non-outlier feature distributions
plt.figure(figsize=[10,5])
plt.suptitle('Outlier vs. non-outlier feature distributions', fontsize=20, y=1.1)

for num, col in enumerate(['feature_1', 'feature_2', 'feature_3', 'target']):
    if col is not 'target':
        plt.subplot(2, 3, num+1)
        v_c = non_outliers[col].value_counts() / non_outliers.shape[0]
        plt.bar(v_c.index, v_c, label=('non-outliers'), align='edge', width=-0.3, edgecolor=[
        v_c = outliers[col].value_counts() / outliers.shape[0]
        plt.bar(v_c.index, v_c, label=('outliers'), align='edge', width=0.3, edgecolor=[0.2]*
        plt.title(col)
        plt.legend()

plt.tight_layout()
plt.show()
```

```
2207 outliers found (target < -30)
```



Observation

We can see There are some very little differences between outliers and non-outliers

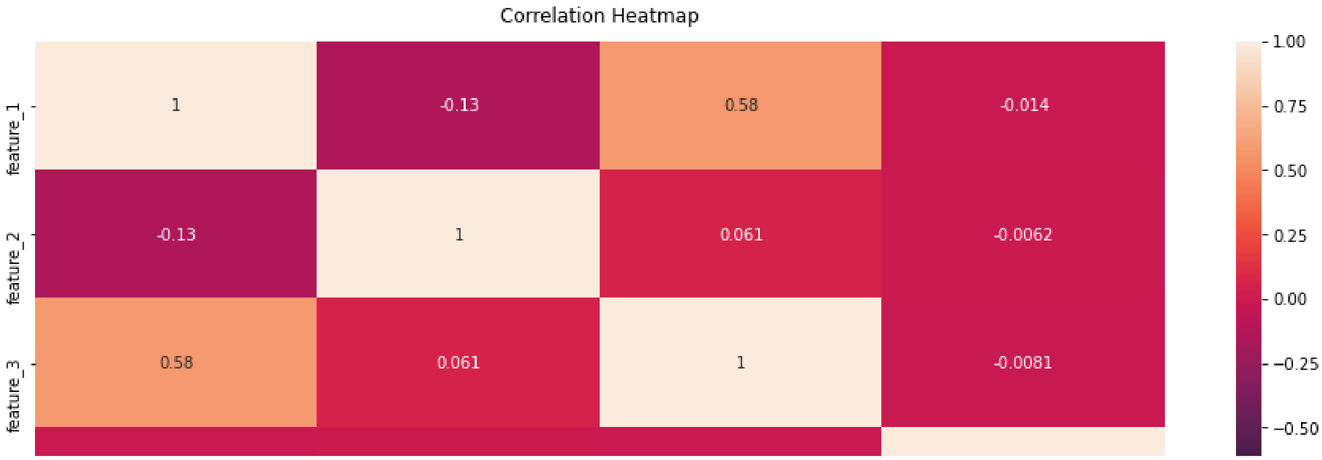
Correlation coefficients for all variables

```
train.corr()
```

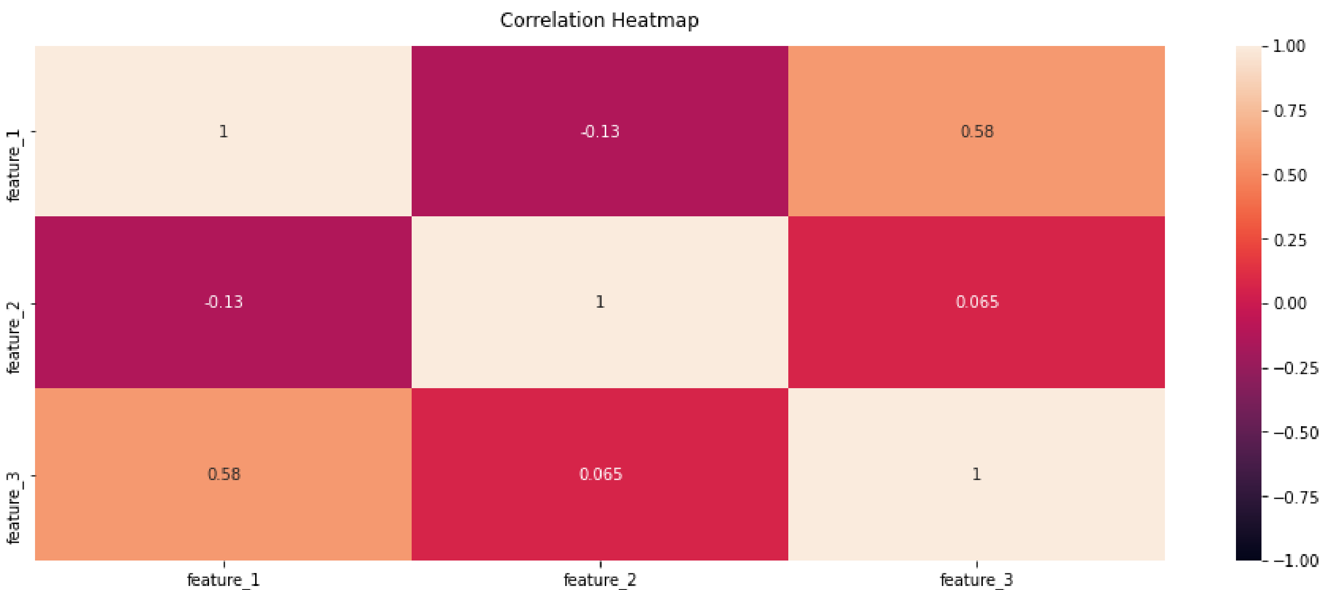
	feature_1	feature_2	feature_3	target
feature_1	1.000000	-0.130969	0.583092	-0.014251
feature_2	-0.130969	1.000000	0.060925	-0.006242
feature_3	0.583092	0.060925	1.000000	-0.008125
target	-0.014251	-0.006242	-0.008125	1.000000

```
def heat_map(df):
  plt.figure(figsize=(16, 6))
  heatmap = sns.heatmap(df.corr(), vmin=-1, vmax=1, annot=True)
  heatmap.set_title('Correlation Heatmap', fontdict={'fontsize':12}, pad=12);
```

```
heat_map(train)
```




```
heat_map(test)
```



Observation:-

In Train feature 1,2,3 are looking highly corelated

In Test features are looking less corelated.

historical_transactions.csv¶

```
historical_transactions = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommenc
```

```
historical_transactions.shape
```

```
(29112361, 14)
```

```
historical_transactions.head()
```

	authorized_flag	card_id	city_id	category_1	installments	category_3	mer
0	Y	C_ID_4e6213e9bc	88	N	0	A	
1	Y	C_ID_4e6213e9bc	88	N	0	A	
2	Y	C_ID_4e6213e9bc	88	N	0	A	
3	Y	C_ID_4e6213e9bc	88	N	0	A	
4	Y	C_ID_4e6213e9bc	88	N	0	A	

```
historical_transactions.dtypes
```

```
authorized_flag          object
card_id                  object
city_id                   int64
category_1               object
installments              int64
category_3               object
merchant_category_id      int64
merchant_id              object
month_lag                 int64
purchase_amount         float64
purchase_date            object
category_2              float64
state_id                  int64
subsector_id              int64
dtype: object
```

```
historical_transactions.nunique(dropna=False,axis=0)
```

```
authorized_flag                2
card_id                   325540
city_id                      308
category_1                     2
installments                  15
category_3                     4
merchant_category_id         327
merchant_id               326312
month_lag                     14
purchase_amount           215014
purchase_date           16395300
category_2                     6
```

```
state_id                  25
subsector_id              41
dtype: int64
```

```
historical_transactions.isnull().sum(axis=0)
```

```
authorized_flag               0
card_id                       0
city_id                       0
category_1                    0
installments                  0
category_3               178159
merchant_category_id          0
merchant_id              138481
month_lag                     0
purchase_amount               0
purchase_date                 0
category_2              2652864
state_id                      0
subsector_id                  0
dtype: int64
```

We can see that there are:

6 features type ID: card_id, merchant_category_id, subsector_id, merchant_id, city_id, state_id 2 features type integer/counter: month_lag, installments

1 feature type numerical: purchase_amount

1 feature type date: purchase_date

4 features type categorical: authorized_flag, category_3, category_1, category_2

```
historical_transactions[["month_lag","installments","month_lag","installments"]].describe()
```

	month_lag	installments	month_lag	installments
count	2.911236e+07	2.911236e+07	2.911236e+07	2.911236e+07
mean	-4.487294e+00	6.484954e-01	-4.487294e+00	6.484954e-01
std	3.588800e+00	2.795577e+00	3.588800e+00	2.795577e+00
min	-1.300000e+01	-1.000000e+00	-1.300000e+01	-1.000000e+00
25%	-7.000000e+00	0.000000e+00	-7.000000e+00	0.000000e+00
50%	-4.000000e+00	0.000000e+00	-4.000000e+00	0.000000e+00
75%	-2.000000e+00	1.000000e+00	-2.000000e+00	1.000000e+00
max	0.000000e+00	9.990000e+02	0.000000e+00	9.990000e+02

```
historical_transactions.groupby("authorized_flag").size()
```

```
historical_transactions.groupby("authorized_flag").size()
```

```
authorized_flag
N     2516909
Y    26595452
dtype: int64
```

```
historical_transactions.groupby("category_3").size()
```

```
category_3
A    15411747
B    11677522
C     1844933
dtype: int64
```

```
historical_transactions.groupby("category_1").size()
```

```
category_1
N    27028332
Y     2084029
dtype: int64
```

```
historical_transactions.groupby("category_2").size()
```

```
category_2
1.0    15177199
2.0     1026535
3.0     3911795
4.0     2618053
5.0     3725915
dtype: int64
```

```
historical_transactions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29112361 entries, 0 to 29112360
Data columns (total 14 columns):
 #   Column                Dtype  
---  ------                -----  
 0   authorized_flag       object 
 1   card_id               object 
 2   city_id               int64  
 3   category_1            object 
 4   installments          int64  
 5   category_3            object 
 6   merchant_category_id  int64  
 7   merchant_id           object 
 8   month_lag             int64  
 9   purchase_amount       float64
 10  purchase_date         object 
 11  category_2            float64
 12  state_id              int64  
```

```
 13  subsector_id          int64
dtypes: float64(2), int64(6), object(6)
memory usage: 3.0+ GB
```

```
historical_transactions=historical_transactions.drop(historical_transactions.columns[[2,3,5,6
```

```
historical_transactions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29112361 entries, 0 to 29112360
Data columns (total 3 columns):
 #   Column           Dtype  
---  ------           -----  
 0   card_id          object 
 1   installments     int64  
 2   purchase_amount  float64
dtypes: float64(1), int64(1), object(1)
memory usage: 666.3+ MB
```

new_merchant_transactions.csv

```
new_merchant_transactions = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recomme
```

```
new_merchant_transactions.shape
```

```
(1963031, 14)
```

```
new_merchant_transactions.head()
```

	authorized_flag	card_id	city_id	category_1	installments	category_3	mer
0	Y	C_ID_415bb3a509	107	N	1	B	
1	Y	C_ID_415bb3a509	140	N	1	B	
2	Y	C_ID_415bb3a509	330	N	1	B	
3	Y	C_ID_415bb3a509	-1	Y	1	B	
4	Y	C_ID_ef55cf8d4b	-1	Y	1	B	

```
new_merchant_transactions.dtypes
```

```
authorized_flag          object
```

```
card_id                  object
city_id                   int64
category_1               object
installments              int64
category_3               object
merchant_category_id      int64
merchant_id              object
month_lag                 int64
purchase_amount         float64
purchase_date            object
category_2              float64
state_id                  int64
subsector_id              int64
dtype: object
```

```
new_merchant_transactions.nunique(dropna=False,axis=0)
```

```
authorized_flag               1
card_id                  290001
city_id                     308
category_1                    2
installments                 15
category_3                    4
merchant_category_id        314
merchant_id              226130
month_lag                     2
purchase_amount           75190
purchase_date           1667025
category_2                    6
state_id                     25
subsector_id                 41
dtype: int64
```


```
new_merchant_transactions.nunique(dropna=False,axis=0)
```

```
authorized_flag               1
card_id                  290001
city_id                     308
category_1                    2
installments                 15
category_3                    4
merchant_category_id        314
merchant_id              226130
month_lag                     2
purchase_amount           75190
purchase_date           1667025
category_2                    6
state_id                     25
subsector_id                 41
dtype: int64
```


We can see that there are:

6 features type ID: card_id, merchant_category_id, subsector_id, merchant_id, city_id, state_id

2 features type integer/counter: month_lag, installments

1 feature type numerical: purchase_amount

1 feature type date: purchase_date

4 features type categorical: authorized_flag, category_3, category_1, category_2

Exploring the connections between datasets

```
def isin(a,b):
    From = pd.DataFrame(a)
    To = pd.DataFrame(b)
    return(np.mean(From[0].isin(To[0])))
```

% of unique credit cards from train.csv in test.csv

```
isin(train["card_id"].unique(),test["card_id"].unique())
```

```
0.0
```

unique credit cards from train.csv in historical_transactions.csv

```
isin(train["card_id"].unique(),historical_transactions["card_id"].unique())
```

```
1.0
```

% of unique credit cards from train.csv in new_merchant_transactions.csv

```
isin(train["card_id"].unique(),new_merchant_transactions["card_id"].unique())
```

```
0.8913860645710862
```

2.** test.csv with the rest**

% of unique credit cards from test.csv in train.csv

```
isin(test["card_id"].unique(),train["card_id"].unique())
```

```
0.0
```

% of unique credit cards from test.csv in historical_transactions.csv

```
isin(test["card_id"].unique(),historical_transactions["card_id"].unique())
```

```
1.0
```

% of unique credit cards from test.csv in new_merchant_transactions.csv

```
isin(test["card_id"].unique(),new_merchant_transactions["card_id"].unique())
```

```
0.8899233961317877
```

3. historical_transactions.csv with the rest

% of unique credit cards from historical_transactions.csv in train.csv

```
isin(historical_transactions["card_id"].unique(),train["card_id"].unique())
```

```
0.620252503532592
```

% of unique credit cards from historical_transactions.csv in test.csv

```
isin(historical_transactions["card_id"].unique(),test["card_id"].unique())
```

```
0.379747496467408
```

% of unique credit cards from historical_transactions.csv in new_merchant_transactions.csv

```
isin(historical_transactions["card_id"].unique(),new_merchant_transactions["card_id"].unique(
```

```
0.8908306198931006
```

% of unique merchants from historical_transactions.csv in merchants.csv

```
isin(historical_transactions["merchant_id"].unique(),merchants["merchant_id"].unique())
```

```
0.9999969354482826
```

4. new_merchant_transactions.csv with the rest

% of unique credit cards from new_merchant_transactions.csv in train.csv

```
isin(new_merchant_transactions["card_id"].unique(),train["card_id"].unique())
```

```
0.6206392391750374
```

% of unique credit cards from new_merchant_transactions.csv in test.csv

```
isin(new_merchant_transactions["card_id"].unique(),test["card_id"].unique())
```

```
0.3793607608249627
```

% of unique credit cards from new_merchant_transactions.csv in historical_transactions.csv

```
isin(new_merchant_transactions["card_id"].unique(),historical_transactions["card_id"].unique(
```

```
1.0
```

% of unique merchants from new_merchant_transactions.csv in merchants.csv

```
isin(new_merchant_transactions["merchant_id"].unique(),merchants["merchant_id"].unique())
```

```
0.9999955777650025
```

5. merchants.csv with the rest¶

% of unique merchants from merchants.csv in historical_transactions.csv

```
isin(merchants["merchant_id"].unique(),historical_transactions["merchant_id"].unique())
```

```
0.9751309643699216
```

% of unique merchants from merchants.csv in new_merchant_transactions.csv

```
isin(merchants["merchant_id"].unique(),new_merchant_transactions["merchant_id"].unique())
```

```
0.6757522420084092
```

Duplicated IDs in merchants.csv

Number of duplicates in merchants.csv using all features

```
tmp = merchants.drop_duplicates()
merchants.shape[0]-tmp.shape[0]
```

```
0
```

Number of duplicates in merchants.csv using the ID features merchant_id, merchant_category_id, subsector_id

```
tmp = merchants.drop_duplicates(subset=["merchant_id","merchant_category_id","subsector_id"])
merchants.shape[0]-tmp.shape[0]
```

```
62
```

Number of duplicates in merchants.csv using only ID feature merchant_id

```
tmp = merchants.drop_duplicates(subset="merchant_id")
merchants.shape[0]-tmp.shape[0]
```

```
63
```

Number of duplicates in merchants.csv using all ID features merchant_id, merchant_group_id, merchant_category_id, subsector_id, city_id",state_id*

```
tmp = merchants.drop_duplicates(subset=["merchant_id","merchant_group_id","merchant_category_
                                        "subsector_id","city_id","state_id"])
merchants.shape[0]-tmp.shape[0]
```

```
51
```

Number of duplicates in merchants.csv using the ID features merchant_id, merchant_group_id, merchant_category_id, subsector_id

```
tmp = merchants.drop_duplicates(subset=["merchant_id","merchant_group_id","merchant_category_
                                        "subsector_id"])
merchants.shape[0]-tmp.shape[0]
```

```
51
```

Number of duplicates in merchants.csv using the ID features merchant_id, merchant_category_id, subsector_id, city_id, state_id

```
tmp = merchants.drop_duplicates(subset=["merchant_id","merchant_category_id","subsector_id",'
                                        "state_id"])
merchants.shape[0]-tmp.shape[0]
```

```
62
```

```
pd.merge(historical_transactions, train, on='card_id')
```

	authorized_flag	card_id	city_id	category_1	installments	categor
0	N	C_ID_5037ff576e	322	N	1	
1	Y	C_ID_5037ff576e	138	N	1	
2	Y	C_ID_5037ff576e	138	N	1	
3	Y	C_ID_5037ff576e	226	N	1	
4	Y	C_ID_5037ff576e	330	N	1	
...	...	...	...	...	...	
18030004	Y	C_ID_2863d2fa95	-1	Y	1	
18030005	Y	C_ID_2863d2fa95	-1	Y	1	
18030006	Y	C_ID_5c240d6e3c	3	N	0	
18030007	Y	C_ID_5c240d6e3c	331	N	0	
18030008	Y	C_ID_5c240d6e3c	331	N	0	

18030009 rows × 19 columns

```
historical_transactions.info
```

Double-click (or enter) to edit

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 201917 entries, 0 to 201916
Data columns (total 6 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   first_active_month  201917 non-null  object 
 1   card_id             201917 non-null  object 
 2   feature_1           201917 non-null  int64  
 3   feature_2           201917 non-null  int64  
 4   feature_3           201917 non-null  int64  
 5   target              201917 non-null  float64
dtypes: float64(1), int64(3), object(2)
memory usage: 9.2+ MB
```

```
train=train.drop(train.columns[[0,2,3,4]], axis=1)
```

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 201917 entries, 0 to 201916
Data columns (total 6 columns):
 #   Column              Non-Null Count   Dtype  
---  ------              --------------   -----  
 0   first_active_month  201917 non-null  object 
 1   card_id             201917 non-null  object 
 2   feature_1           201917 non-null  int64  
 3   feature_2           201917 non-null  int64  
 4   feature_3           201917 non-null  int64  
 5   target              201917 non-null  float64
dtypes: float64(1), int64(3), object(2)
memory usage: 9.2+ MB
```

```
train1=pd.merge( train, historical_transactions, on='card_id')
```

```
train1.shape
```

```
(18030009, 6)
```

```
tr=train1.drop_duplicates(subset=['target']) #dropped all duplicate values
```

```
tr.shape
```

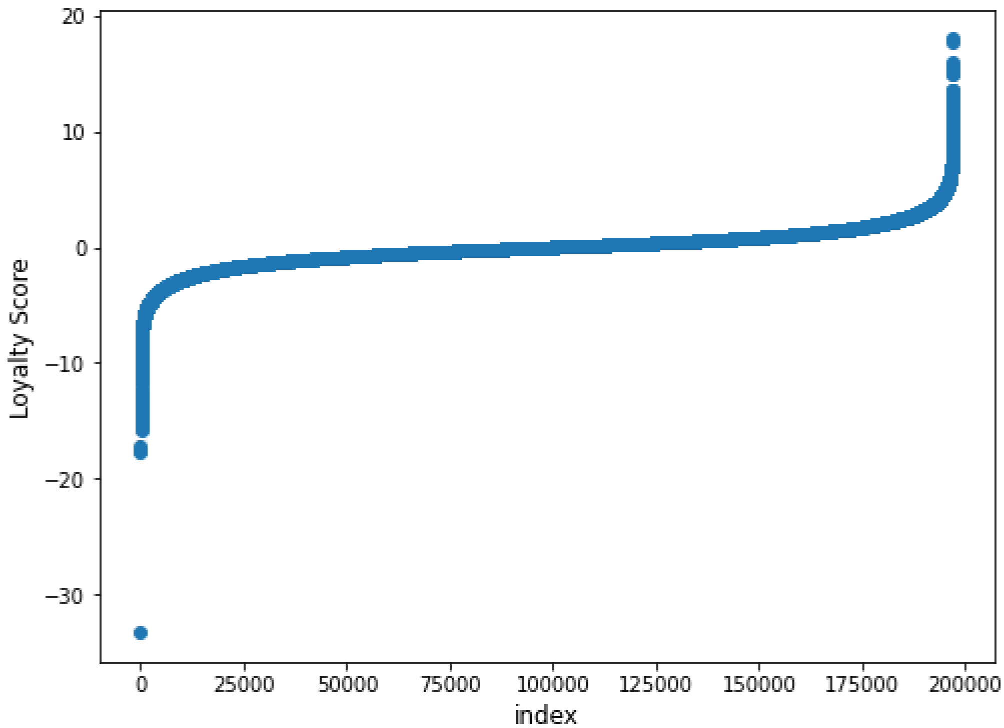
```
(197110, 6)
```

```
tr.shape
```

```
(100000, 4)
```

```
target_col = "target"
```

```
plt.figure(figsize=(8,6))
plt.scatter(range(tr.shape[0]), np.sort(tr[target_col].values))
plt.xlabel('index', fontsize=12)
plt.ylabel('Loyalty Score', fontsize=12)
plt.show()
```



OBSERVATION

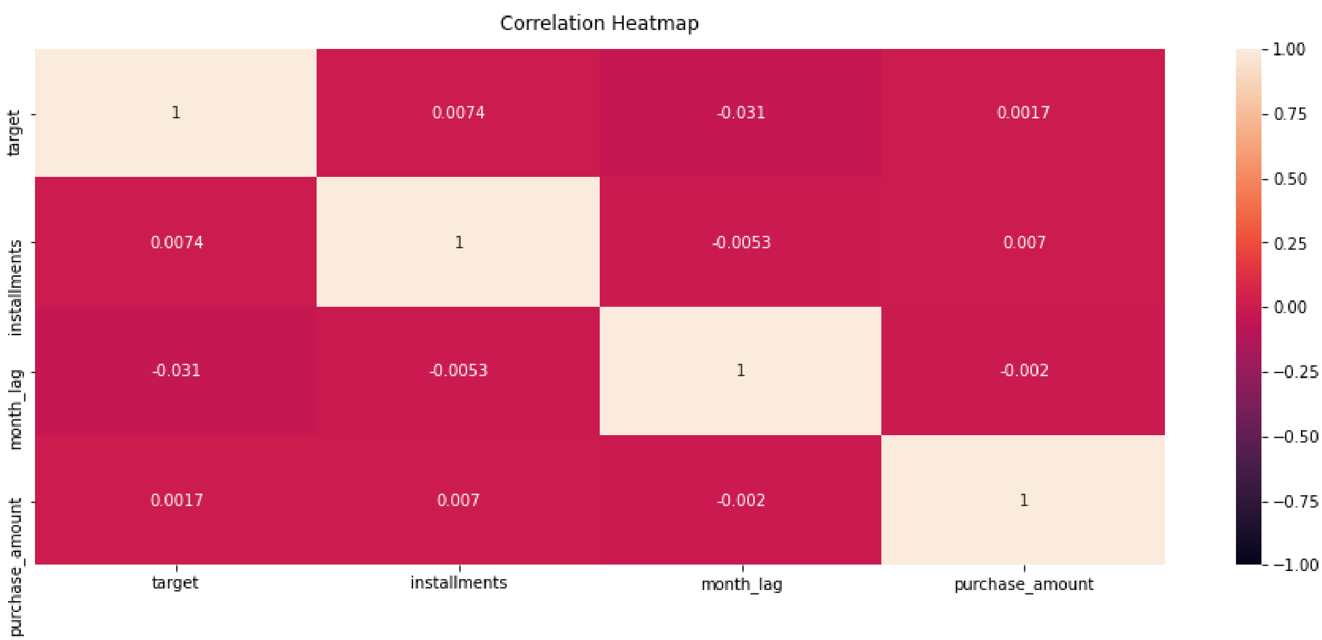
Can see some outlier.

Double-click (or enter) to edit

```
plt.figure(figsize=(12,8))
sns.distplot(tr[target_col].values, bins=50, kde=False, color="purple")
plt.title("Histogram of Loyalty score")
plt.xlabel('Loyalty score', fontsize=12)
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/seaborn/distributions.py:2557: FutureWarning:

`distplot` is a deprecated function and will be removed in a future version. Please ada
```


```
heat_map(tr)
```

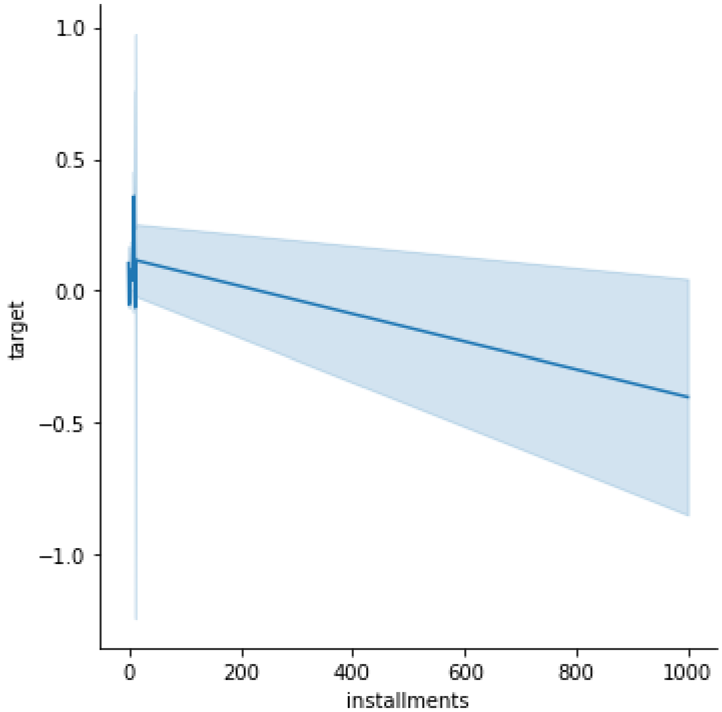


Observation

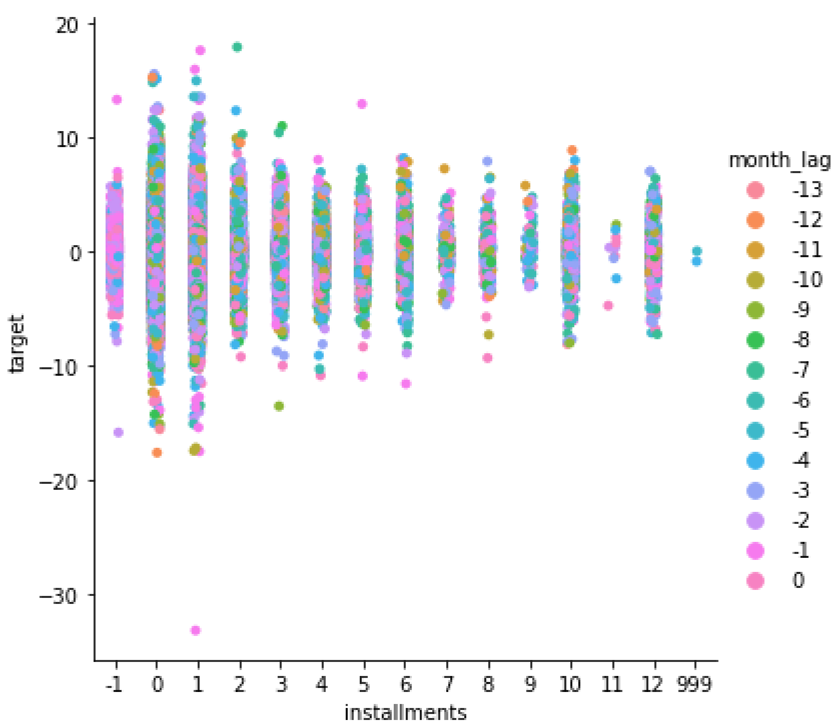
Purshase amount corelated well with installment and target.

```
sns.relplot(x="installments", y="target", kind="line", data=tr)
```

<seaborn.axisgrid.FacetGrid at 0x7f0dbb5d1d68>




```
sns.catplot(x="installments", y="target", hue="month_lag", data=tr);
```

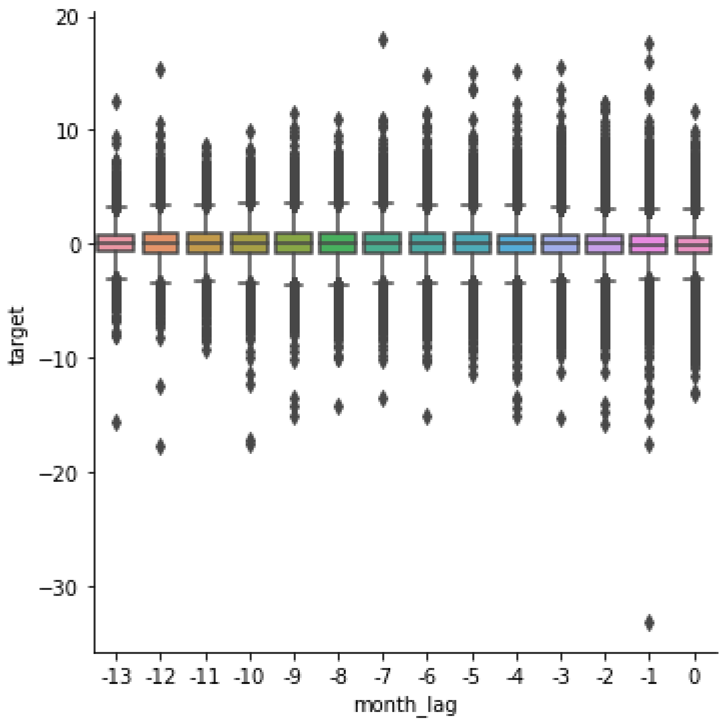


Observation

Very few month_lag found on negative side of target.

```
sns.catplot(x="month_lag", y="target", kind="box", data=tr);
```

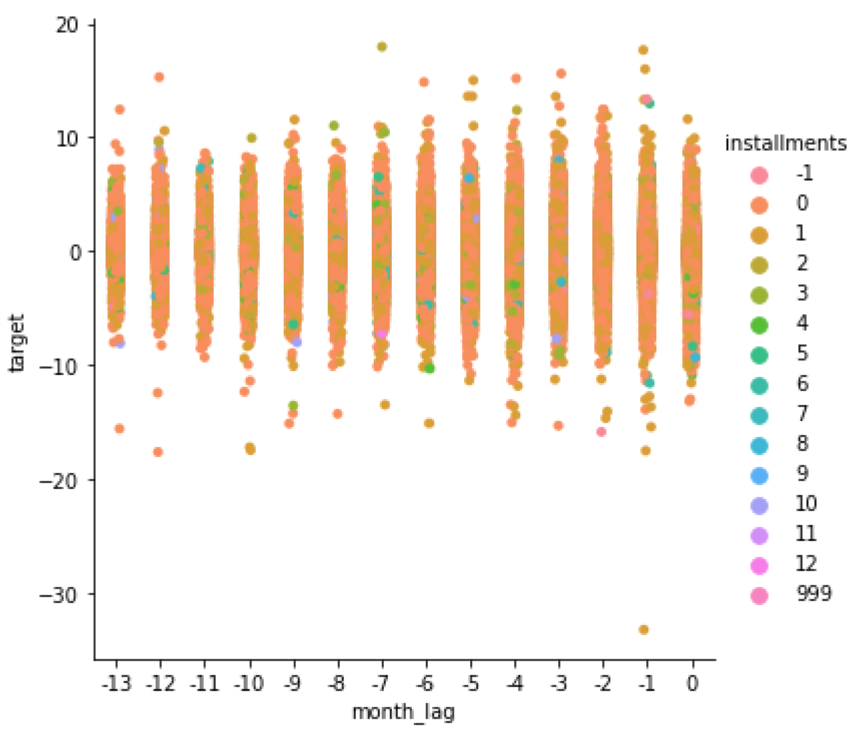
```
sns.catplot(x="month_lag", y="target", kind="box", data=tr);
```



Observation:-

can see outlier in month_lag -1

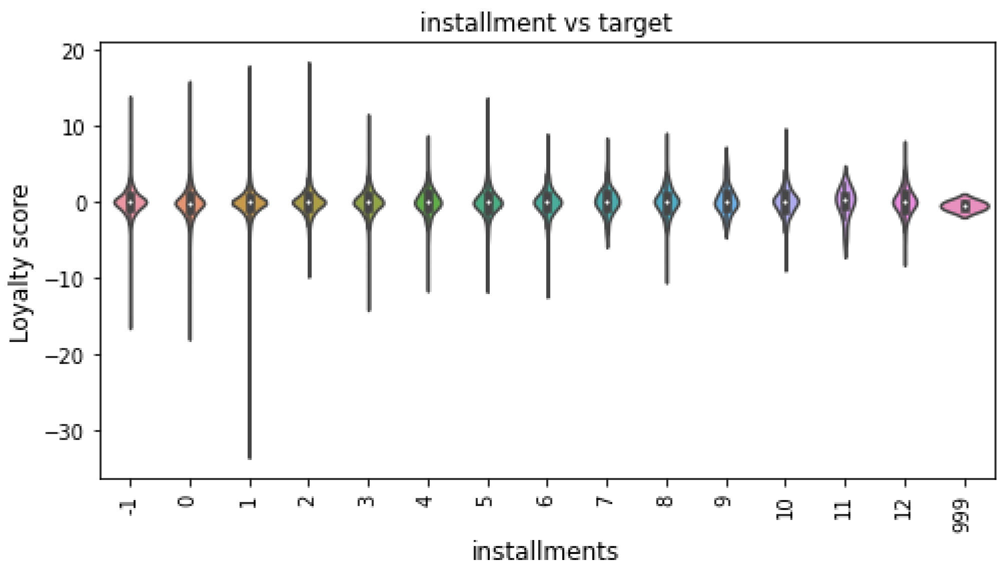
```
sns.catplot(x="month_lag", y="target", hue="installments",
            data=tr);
```



Observation:-

Can see most of the target score depends on first(1) insallments

```
# feature 1
plt.figure(figsize=(8,4))
sns.violinplot(x="installments", y="target", data=tr)
plt.xticks(rotation='vertical')
plt.xlabel('installments', fontsize=12)
plt.ylabel('Loyalty score', fontsize=12)
plt.title("installment vs target")
plt.show()
```



Observation

Can see some outlier in target

Final Observation:

Loyalty score distribution have some outliers it means some transactions which happened and exist in our train data is having some weird values.

```
# This is formatted as code
```

**Tried all model with limited Features but kaggle score did not improved much.

```
new_merchant_transactions = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recomme
```

```
historical_transactions = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommenc
```

```
train = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/train.csv")
```

```
test = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv")
```

```
def missingvalue(df):
    for i in df.columns:
        if df[i].dtype == "object":
            df[i] = df[i].fillna("other")
        elif (df[i].dtype == "int64" or df[i].dtype == "float64"):
            df[i] = df[i].fillna(df[i].mean())
        else:
            pass
    return df

# missing values for all datasets
for df in [train, test,new_merchant_transactions,  historical_transactions]:
    missingvalue(df)
```

```
train['outliers'] = 0
train.loc[train['target'] < -30, 'outliers'] = 1
train['outliers'].value_counts()
```

```
0    199710
1      2207
Name: outliers, dtype: int64
```

```
#https://towardsdatascience.com/machine-learning-with-datetime-feature-engineering-predicting

def train_testdatetime(df, col='first_active_month'):
    df['my_dates'] = pd.to_datetime(df[col], errors='coerce')


    #df['day'] = pd.to_datetime(dt_col).dt.weekday


    df['month'] = df['my_dates'].dt.month

    df['year'] = train['my_dates'].dt.year



    return df
```

```
#extraction of datetime values for train and test
train = train_testdatetime(train, col='first_active_month')
test = train_testdatetime(test, col='first_active_month')
```

```
train = pd.get_dummies(train, columns=['feature_1', 'feature_2'])
test = pd.get_dummies(test, columns=['feature_1', 'feature_2'])
```

```
historical_transactions['authorized_flag'] = historical_transactions['authorized_flag'].map({
```

```
def aggregate_transactions(trans, prefix):
  #trans.loc[:, 'purchase_date'] = pd.to_numeric(trans['purchase_date']).\
                                      # astype(np.int64) * 1e-9

  trans['purchase_date'] = pd.to_datetime(trans['purchase_date'], errors='coerce')
  #trans['purchase_date'] = df['purchase_date'].astype('datetime64').astype(int).astype(float
  trans['weekofyear'] = trans['purchase_date'].dt.weekofyear
  trans['month'] = trans['purchase_date'].dt.month# get the month
  trans['day'] = trans['purchase_date'].dt.day# get the day
  trans['weekday'] = trans.purchase_date.dt.weekday# get the week day
  trans['weekend'] = (trans.purchase_date.dt.weekday >=5).astype(int)# weekend
  trans['hour'] =trans['purchase_date'].dt.hour# hour from the purchase date
  # month diff is subtraction of purchase date from the today date
  trans['month_diff'] = ((datetime.today() - trans['purchase_date']).dt.days)//30
  trans['month_diff'] += trans['month_lag']
  # Here we get the duration when we multipluy the purchase amount and month_diff
  trans['duration'] = trans['purchase_amount']*trans['month_diff']
  #amount_month ratio is when we divide the purchase amount from month_diff
  trans['amount_month_ratio'] = trans['purchase_amount']/trans['month_diff']
  # price is when we divide the purchase amount from installments
  trans['price'] = trans['purchase_amount'] / trans['installments']
  agg_func = {
        'authorized_flag': ['sum', 'mean'],
        'purchase_amount': ['sum', 'mean', 'max', 'min', 'std'],
        'installments': ['sum', 'mean', 'max', 'min', 'std'],
       #'purchase_date': ['max','min'],
        'month_lag': ['min', 'max']
   }
  agg_trans = trans.groupby(['card_id']).agg(agg_func)
  agg_trans.columns = [prefix + '_'.join(col).strip()
                         for col in agg_trans.columns.values]
  agg_trans.reset_index(inplace=True)

  df = (trans.groupby('card_id')
```

```
            .size()
            .reset_index(name='{}transactions_count'.format(prefix)))

    agg_trans = pd.merge(df, agg_trans, on='card_id', how='left')

    return agg_trans
```

```
import gc
merch_hist = aggregate_transactions(historical_transactions, prefix='hist_')
del historical_transactions
gc.collect()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: FutureWarning:

Series.dt.weekofyear and Series.dt.week have been deprecated.  Please use Series.dt.iso

11
```

```
train = pd.merge(train, merch_hist, on='card_id',how='left')
test = pd.merge(test, merch_hist, on='card_id',how='left')
del merch_hist
gc.collect()
```

```
140
```

```
new_merchant_transactions['authorized_flag'] = new_merchant_transactions['authorized_flag'].m
```

```
merch_new = aggregate_transactions(new_merchant_transactions, prefix='new_')
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: FutureWarning:

Series.dt.weekofyear and Series.dt.week have been deprecated.  Please use Series.dt.iso
```

```
del new_merchant_transactions
gc.collect()
```

```
263
```

```
train = pd.merge(train, merch_new, on='card_id',how='left')
test = pd.merge(test, merch_new, on='card_id',how='left')
del merch_new
gc.collect()
```

```
88
```

```
final_feature = ['card_id', 'first_active_month', 'target','my_dates','outliers']
```

```
final_feature = ['card_id', 'first_active_month', 'target', 'my_dates', 'outliers']
use_cols = [c for c in train.columns if c not in final_feature]
use_test = [c for c in test.columns if c not in final_feature]


train=train.drop_duplicates(subset=['target'])


train_Y=train["target"]


Train_x=train[use_cols]


test=test[use_test]


Train_x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 197110 entries, 0 to 201916
Data columns (total 42 columns):
 #   Column                     Non-Null Count   Dtype
---  ------                     --------------   -----
 0   card_id                    197110 non-null  object
 1   feature_3                  197110 non-null  int64
 2   month                      197110 non-null  int64
 3   year                       197110 non-null  int64
 4   feature_1_1                197110 non-null  uint8
 5   feature_1_2                197110 non-null  uint8
 6   feature_1_3                197110 non-null  uint8
 7   feature_1_4                197110 non-null  uint8
 8   feature_1_5                197110 non-null  uint8
 9   feature_2_1                197110 non-null  uint8
 10  feature_2_2                197110 non-null  uint8
 11  feature_2_3                197110 non-null  uint8
 12  hist_transactions_count    197110 non-null  int64
 13  hist_authorized_flag_sum   197110 non-null  int64
 14  hist_authorized_flag_mean  197110 non-null  float64
 15  hist_purchase_amount_sum   197110 non-null  float64
 16  hist_purchase_amount_mean  197110 non-null  float64
 17  hist_purchase_amount_max   197110 non-null  float64
 18  hist_purchase_amount_min   197110 non-null  float64
 19  hist_purchase_amount_std   197110 non-null  float64
 20  hist_installments_sum      197110 non-null  int64
 21  hist_installments_mean     197110 non-null  float64
 22  hist_installments_max      197110 non-null  int64
 23  hist_installments_min      197110 non-null  int64
 24  hist_installments_std      197110 non-null  float64
 25  hist_month_lag_min         197110 non-null  int64
 26  hist_month_lag_max         197110 non-null  int64
 27  new_transactions_count     177861 non-null  float64
 28  new_authorized_flag_sum    177861 non-null  float64
 29  new_authorized_flag_mean   177861 non-null  float64
 30  new_purchase_amount_sum    177861 non-null  float64
 31  new_purchase_amount_mean   177861 non-null  float64
 32  new_purchase_amount_max    177861 non-null  float64
 33  new_purchase_amount_min    177861 non-null  float64
```

```
 34  new_purchase_amount_std    151870 non-null  float64
 35  new_installments_sum       177861 non-null  float64
 36  new_installments_mean      177861 non-null  float64
 37  new_installments_max       177861 non-null  float64
 38  new_installments_min       177861 non-null  float64
 39  new_installments_std       151870 non-null  float64
 40  new_month_lag_min          177861 non-null  float64
 41  new_month_lag_max          177861 non-null  float64
dtypes: float64(23), int64(10), object(1), uint8(8)
memory usage: 54.1+ MB
```

```
from sklearn.preprocessing import LabelEncoder
lbe = LabelEncoder()
lbe = lbe.fit(Train_x['card_id'])
card_id = lbe.transform(Train_x['card_id'])
Train_x['card_id'] = card_id
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user
```

```
lbetest = LabelEncoder()
lbetest = lbetest.fit(test['card_id'])
card_id = lbetest.transform(test['card_id'])
test['card_id'] = card_id
test['card_id'].head(5)
```

```
0      5148
1      9136
2     88476
3    101761
4     20931
Name: card_id, dtype: int64
```

```
for col in use_cols:
    for df in [train, test]:
        if df[col].dtype == "float64" :
            df[col] = df[col].fillna(df[col].mean())
```

```
train_Y.shape
```

```
(197110,)
```

```
y=train_Y[:123623]
```

```
Train_x.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 197110 entries, 0 to 201916
Data columns (total 42 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   card_id                    197110 non-null  int64  
 1   feature_3                  197110 non-null  int64  
 2   month                      197110 non-null  int64  
 3   year                       197110 non-null  int64  
 4   feature_1_1                197110 non-null  uint8  
 5   feature_1_2                197110 non-null  uint8  
 6   feature_1_3                197110 non-null  uint8  
 7   feature_1_4                197110 non-null  uint8  
 8   feature_1_5                197110 non-null  uint8  
 9   feature_2_1                197110 non-null  uint8  
 10  feature_2_2                197110 non-null  uint8  
 11  feature_2_3                197110 non-null  uint8  
 12  hist_transactions_count    197110 non-null  int64  
 13  hist_authorized_flag_sum   197110 non-null  int64  
 14  hist_authorized_flag_mean  197110 non-null  float64
 15  hist_purchase_amount_sum   197110 non-null  float64
 16  hist_purchase_amount_mean  197110 non-null  float64
 17  hist_purchase_amount_max   197110 non-null  float64
 18  hist_purchase_amount_min   197110 non-null  float64
 19  hist_purchase_amount_std   197110 non-null  float64
 20  hist_installments_sum      197110 non-null  int64  
 21  hist_installments_mean     197110 non-null  float64
 22  hist_installments_max      197110 non-null  int64  
 23  hist_installments_min      197110 non-null  int64  
 24  hist_installments_std      197110 non-null  float64
 25  hist_month_lag_min         197110 non-null  int64  
 26  hist_month_lag_max         197110 non-null  int64  
 27  new_transactions_count     197110 non-null  float64
 28  new_authorized_flag_sum    197110 non-null  float64
 29  new_authorized_flag_mean   197110 non-null  float64
 30  new_purchase_amount_sum    197110 non-null  float64
 31  new_purchase_amount_mean   197110 non-null  float64
 32  new_purchase_amount_max    197110 non-null  float64
 33  new_purchase_amount_min    197110 non-null  float64
 34  new_purchase_amount_std    197110 non-null  float64
 35  new_installments_sum       197110 non-null  float64
 36  new_installments_mean      197110 non-null  float64
 37  new_installments_max       197110 non-null  float64
 38  new_installments_min       197110 non-null  float64
 39  new_installments_std       197110 non-null  float64
 40  new_month_lag_min          197110 non-null  float64
 41  new_month_lag_max          197110 non-null  float64
dtypes: float64(23), int64(11), uint8(8)
memory usage: 54.1 MB
```

```
test.shape
```

```
(123623, 42)
```

```
Train_x.shape
```

```
(197110, 42)
```

MODEL RandomForestRegressor

Random Hyperparameter Grid

To use RandomizedSearchCV, we first need to create a parameter grid .

```
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint

param_dist = {"max_depth": [3, None],
              "max_features": sp_randint(1, train.shape[1]),
              "min_samples_split": sp_randint(2, 11),
              "bootstrap": [True, False],
              "n_estimators": sp_randint(100, 500)}
random_search = RandomizedSearchCV(estimator = rf, param_distributions = param_dist, n_iter =
# Fit the random search model
random_search.fit(Train_x, train_Y)
```

```
print(random_search.best_params_)
```

```
{'bootstrap': True, 'max_depth': 3, 'max_features': 8, 'min_samples_split': 6, 'n_estim
```

```
rf = RandomForestRegressor(n_estimators=1000, max_depth=10,min_samples_split=6,bootstrap=True
rf.fit(Train_x,train_Y)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=10, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=6, min_weight_fraction_leaf=0.0,
                      n_estimators=1000, n_jobs=None, oob_score=False,
                      random_state=42, verbose=0, warm_start=False)
```

```
pred=rf.predict(test)
print(np.sqrt(mean_squared_error(y, pred)))
```

```
1.822024493056381
```

```
sample = pd.read_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv'
```

```
lbe_sam = LabelEncoder()
```

```
lbe_sam = lbe_sam.fit(sample['card_id'])
card_id = lbe_sam.transform(sample['card_id'])
test['card_id'] = card_id
test['card_id'].head()
```

```
0      5148
1      9136
2     88476
3    101761
4     20931
Name: card_id, dtype: int64
```

```
final_pred = rf.predict(test)
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = final_pred
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde›
```

```
sample.head(10)
```

	card_id	target
0	C_ID_0ab67a22ab	-0.049002
1	C_ID_130fd0cbdd	-0.039538
2	C_ID_b709037bc5	0.207336
3	C_ID_d27d835a9f	0.083762
4	C_ID_2b5e3df5c2	-0.091648
5	C_ID_5814b4f13c	0.215658
6	C_ID_a1b3c75277	0.069796
7	C_ID_f7cada36d3	0.076552
8	C_ID_9d2bc8dfc4	-0.021982
9	C_ID_6d8dba8475	-0.016378

The above code block we have the following parameters:

max_depth: this specifies the depth of the tree that will be formed.

max_features: the total number of features to consider. This is going to be a random value between 1 and the maximum features that we have. In our case, the maximum number can be 7.

min_samples_split: this specifies the minimum number of samples to consider for each split. It will be a random value between 2 and 11.

bootstrap: whether or not to use bootstrap samples when building trees. If this is False, then the whole dataset will be used. n_estimators: the number of trees to use for building the random

XGBoost training

```
xg = xgb.XGBRegressor(
        max_depth = 3,
        learning_rate = 0.06,
        n_estimators = 2500,
        subsample = .9,
        colsample_bylevel = .9,
        colsample_bytree = .9,
        min_child_weight= .9,
        gamma = 0,
        random_state = 100,
        booster = 'gbtree',
        objective = 'reg:linear'
    )


xg.fit(Train_x,train_Y)
```

```
[13:17:09] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now d
XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=0.9,
             colsample_bynode=1, colsample_bytree=0.9, gamma=0,
             importance_type='gain', learning_rate=0.06, max_delta_step=0,
             max_depth=3, min_child_weight=0.9, missing=None, n_estimators=2500,
             n_jobs=1, nthread=None, objective='reg:linear', random_state=100,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
             silent=None, subsample=0.9, verbosity=1)
```

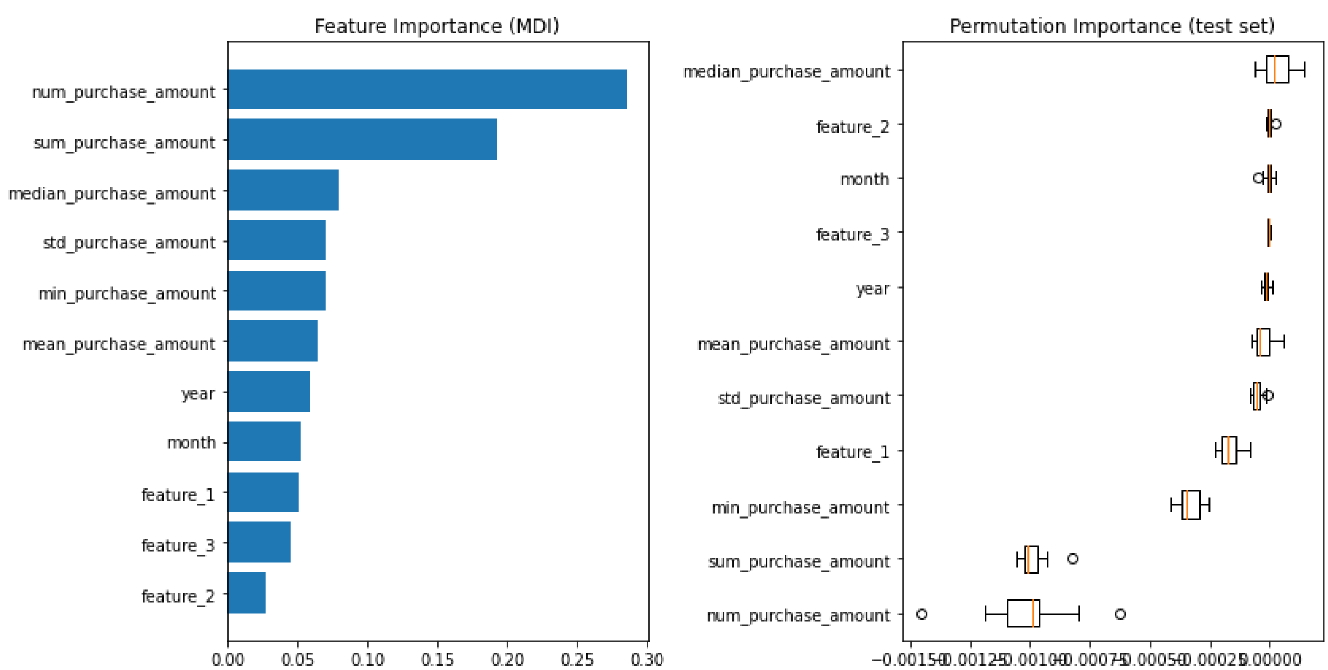
```
preds=xg.predict(test)
print(np.sqrt(mean_squared_error(y, preds)))
```

```
1.835841881737206
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = preds
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde
```

Plot feature importance¶

```
#https://scikit-learn.org/stable/auto_examples/ensemble/plot_gradient_boosting_regression.htm
# Feature importance
from sklearn.inspection import permutation_importance

imp_df = pd.DataFrame()
imp_df = train_features
feature_importance = xg.feature_importances_
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
fig = plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, np.array(imp_df)[sorted_idx])
plt.title('Feature Importance (MDI)')

result = permutation_importance(xg, test, y, n_repeats=10,
                                random_state=42, n_jobs=2)
sorted_idx = result.importances_mean.argsort()
plt.subplot(1, 2, 2)
plt.boxplot(result.importances[sorted_idx].T,
            vert=False, labels=np.array(imp_df)[sorted_idx])
plt.title("Permutation Importance (test set)")
fig.tight_layout()
plt.show()
```



CATBOOST

```
!pip3 install catboost
```

```
Collecting catboost
  Downloading https://files.pythonhosted.org/packages/96/3b/bb419654adcf7efff42ed8a3f84
    |████████████████████████████████| 65.7MB 54kB/s
Requirement already satisfied: numpy>=1.16.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (from catb
Requirement already satisfied: matplotlib in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: graphviz in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from ca
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages (from c
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-pa
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/l
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (
Installing collected packages: catboost
Successfully installed catboost-0.24.4
```

```
from catboost import CatBoostRegressor, FeaturesData, Pool
```

```
model = CatBoostRegressor(iterations=2000, learning_rate=0.05, depth=6)
# Fit model
model.fit(Train_x,train_Y)
# Get predictions
preds = model.predict(test)
```

```
0:	learn: 1.7187164	total: 56.5ms	remaining: 1m 52s
1:	learn: 1.7104972	total: 112ms	remaining: 1m 52s
2:	learn: 1.7028991	total: 167ms	remaining: 1m 51s
3:	learn: 1.6961729	total: 226ms	remaining: 1m 52s
4:	learn: 1.6897447	total: 295ms	remaining: 1m 57s
5:	learn: 1.6839082	total: 350ms	remaining: 1m 56s
6:	learn: 1.6787675	total: 405ms	remaining: 1m 55s
7:	learn: 1.6737446	total: 459ms	remaining: 1m 54s
8:	learn: 1.6693125	total: 524ms	remaining: 1m 55s
9:	learn: 1.6651749	total: 585ms	remaining: 1m 56s
10:	learn: 1.6612007	total: 641ms	remaining: 1m 55s
11:	learn: 1.6577140	total: 693ms	remaining: 1m 54s
12:	learn: 1.6544856	total: 752ms	remaining: 1m 54s
13:	learn: 1.6512523	total: 803ms	remaining: 1m 53s
14:	learn: 1.6483462	total: 858ms	remaining: 1m 53s
15:	learn: 1.6456682	total: 911ms	remaining: 1m 52s
16:	learn: 1.6432447	total: 976ms	remaining: 1m 53s
17:	learn: 1.6410582	total: 1.03s	remaining: 1m 53s
18:	learn: 1.6389565	total: 1.09s	remaining: 1m 53s
19:	learn: 1.6370752	total: 1.14s	remaining: 1m 52s
20:	learn: 1.6352505	total: 1.2s	remaining: 1m 53s
21:	learn: 1.6334595	total: 1.26s	remaining: 1m 53s
```

```
22:	learn: 1.6318729	total: 1.31s	remaining: 1m 53s
23:	learn: 1.6304393	total: 1.36s	remaining: 1m 52s
24:	learn: 1.6289971	total: 1.43s	remaining: 1m 52s
25:	learn: 1.6275265	total: 1.49s	remaining: 1m 52s
26:	learn: 1.6261634	total: 1.54s	remaining: 1m 52s
27:	learn: 1.6248883	total: 1.59s	remaining: 1m 52s
28:	learn: 1.6238647	total: 1.65s	remaining: 1m 52s
29:	learn: 1.6228962	total: 1.7s	remaining: 1m 51s
30:	learn: 1.6219228	total: 1.75s	remaining: 1m 51s
31:	learn: 1.6210081	total: 1.8s	remaining: 1m 50s
32:	learn: 1.6201364	total: 1.86s	remaining: 1m 50s
33:	learn: 1.6191416	total: 1.91s	remaining: 1m 50s
34:	learn: 1.6183311	total: 1.97s	remaining: 1m 50s
35:	learn: 1.6175549	total: 2.02s	remaining: 1m 50s
36:	learn: 1.6168352	total: 2.07s	remaining: 1m 49s
37:	learn: 1.6160744	total: 2.12s	remaining: 1m 49s
38:	learn: 1.6153141	total: 2.17s	remaining: 1m 49s
39:	learn: 1.6146467	total: 2.23s	remaining: 1m 49s
40:	learn: 1.6140872	total: 2.3s	remaining: 1m 49s
41:	learn: 1.6134344	total: 2.36s	remaining: 1m 49s
42:	learn: 1.6128700	total: 2.41s	remaining: 1m 49s
43:	learn: 1.6122512	total: 2.46s	remaining: 1m 49s
44:	learn: 1.6117551	total: 2.51s	remaining: 1m 49s
45:	learn: 1.6112896	total: 2.56s	remaining: 1m 48s
46:	learn: 1.6107940	total: 2.61s	remaining: 1m 48s
47:	learn: 1.6103373	total: 2.66s	remaining: 1m 48s
48:	learn: 1.6099274	total: 2.72s	remaining: 1m 48s
49:	learn: 1.6094751	total: 2.77s	remaining: 1m 47s
50:	learn: 1.6090576	total: 2.82s	remaining: 1m 47s
51:	learn: 1.6085203	total: 2.87s	remaining: 1m 47s
52:	learn: 1.6080949	total: 2.93s	remaining: 1m 47s
53:	learn: 1.6076879	total: 2.98s	remaining: 1m 47s
54:	learn: 1.6073003	total: 3.03s	remaining: 1m 47s
55:	learn: 1.6069413	total: 3.08s	remaining: 1m 47s
56:	learn: 1.6066141	total: 3.13s	remaining: 1m 46s
57:	learn: 1.6061926	total: 3.19s	remaining: 1m 46s
58:	learn: 1.6057608	total: 3.25s	remaining: 1m 46s
```

```
print(np.sqrt(mean_squared_error(y, preds)))
```

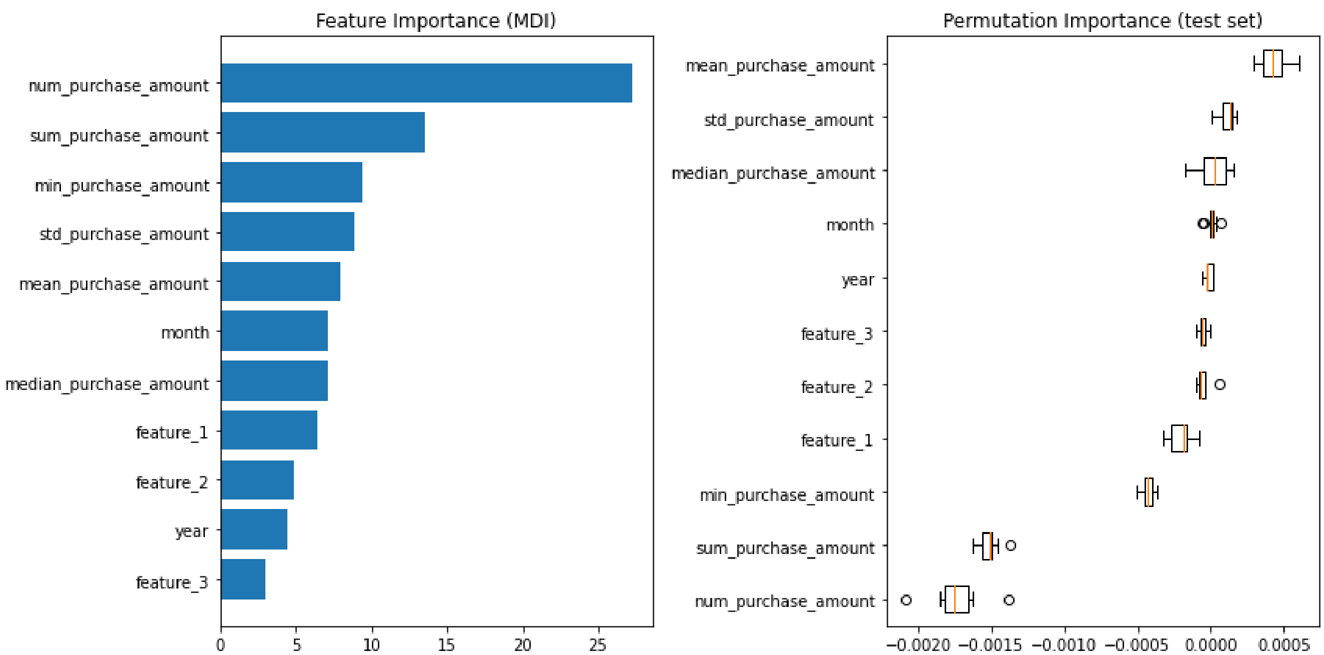
```
1.865456795516052
```

```
#final_pred = model.predict(test)
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] =  preds
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde›
```

Double-click (or enter) to edit

```
feature_importance = model.feature_importances_
sorted_idx = np.argsort(feature_importance)
pos = np.arange(sorted_idx.shape[0]) + .5
fig = plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.barh(pos, feature_importance[sorted_idx], align='center')
plt.yticks(pos, np.array(imp_df)[sorted_idx])
plt.title('Feature Importance (MDI)')

result = permutation_importance(model, test, y, n_repeats=10,
                                random_state=42, n_jobs=2)
sorted_idx = result.importances_mean.argsort()
plt.subplot(1, 2, 2)
plt.boxplot(result.importances[sorted_idx].T,
            vert=False, labels=np.array(imp_df)[sorted_idx])
plt.title("Permutation Importance (test set)")
fig.tight_layout()
plt.show()
```



AdaBoostRegressor

```
from sklearn.ensemble import AdaBoostRegressor
regr = AdaBoostRegressor(random_state=0, n_estimators=100)
regr.fit(Train_x,train_Y)
# Get predictions
preds = regr.predict(test)
print(np.sqrt(mean_squared_error(y, preds)))
```

```
2.038873643943124
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = preds
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde
```

StackingRegressor

```
from mlxtend.regressor import StackingRegressor
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.svm import SVR
```

```
lr = LinearRegression()
xg = xgb.XGBRegressor(
        max_depth = 3,
        learning_rate = 0.03,
        n_estimators = 100,
        subsample = .9,
        colsample_bylevel = .9,
        colsample_bytree = .9,
        min_child_weight= .9,
        gamma = 0,
        random_state = 100,
        booster = 'gbtree',
        objective = 'reg:linear'
    )


rf = RandomForestRegressor(n_estimators=199, max_depth=3,min_samples_split=6,bootstrap=True,r
cb = CatBoostRegressor(iterations=2000, learning_rate=0.05, depth=5)

stregr = StackingRegressor(regressors=[xg,rf,cb],
                           meta_regressor=cb)
stregr.fit(Train_x,train_Y)
# Get predictions
preds = stregr.predict(test)
print(np.sqrt(mean_squared_error(y, preds)))
```

```
[20:08:22] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now
0:      learn: 1.7194311        total: 114ms    remaining: 3m 48s
1:      learn: 1.7116215        total: 162ms    remaining: 2m 41s
2:      learn: 1.7044351        total: 212ms    remaining: 2m 21s
3:      learn: 1.6979635        total: 260ms    remaining: 2m 9s
4:      learn: 1.6920659        total: 320ms    remaining: 2m 7s
5:      learn: 1.6864283        total: 368ms    remaining: 2m 2s
```

```
6:	learn: 1.6813224	total: 416ms	remaining: 1m 58s
7:	learn: 1.6766034	total: 466ms	remaining: 1m 56s
8:	learn: 1.6723943	total: 512ms	remaining: 1m 53s
9:	learn: 1.6682771	total: 586ms	remaining: 1m 56s
10:	learn: 1.6644137	total: 636ms	remaining: 1m 55s
11:	learn: 1.6611492	total: 682ms	remaining: 1m 53s
12:	learn: 1.6582177	total: 730ms	remaining: 1m 51s
13:	learn: 1.6552441	total: 779ms	remaining: 1m 50s
14:	learn: 1.6526041	total: 833ms	remaining: 1m 50s
15:	learn: 1.6501372	total: 881ms	remaining: 1m 49s
16:	learn: 1.6478072	total: 927ms	remaining: 1m 48s
17:	learn: 1.6457855	total: 973ms	remaining: 1m 47s
18:	learn: 1.6437969	total: 1.02s	remaining: 1m 46s
19:	learn: 1.6419516	total: 1.07s	remaining: 1m 45s
20:	learn: 1.6402255	total: 1.12s	remaining: 1m 45s
21:	learn: 1.6385525	total: 1.16s	remaining: 1m 44s
22:	learn: 1.6370000	total: 1.21s	remaining: 1m 43s
23:	learn: 1.6354623	total: 1.26s	remaining: 1m 43s
24:	learn: 1.6339678	total: 1.31s	remaining: 1m 43s
25:	learn: 1.6327200	total: 1.36s	remaining: 1m 43s
26:	learn: 1.6315459	total: 1.41s	remaining: 1m 42s
27:	learn: 1.6304473	total: 1.45s	remaining: 1m 42s
28:	learn: 1.6293310	total: 1.5s	remaining: 1m 41s
29:	learn: 1.6282224	total: 1.55s	remaining: 1m 41s
30:	learn: 1.6271522	total: 1.59s	remaining: 1m 41s
31:	learn: 1.6261970	total: 1.64s	remaining: 1m 40s
32:	learn: 1.6253585	total: 1.68s	remaining: 1m 40s
33:	learn: 1.6244245	total: 1.73s	remaining: 1m 39s
34:	learn: 1.6235569	total: 1.78s	remaining: 1m 39s
35:	learn: 1.6228588	total: 1.82s	remaining: 1m 39s
36:	learn: 1.6220162	total: 1.87s	remaining: 1m 39s
37:	learn: 1.6213323	total: 1.91s	remaining: 1m 38s
38:	learn: 1.6205230	total: 1.96s	remaining: 1m 38s
39:	learn: 1.6198734	total: 2s	remaining: 1m 38s
40:	learn: 1.6191620	total: 2.06s	remaining: 1m 38s
41:	learn: 1.6186582	total: 2.1s	remaining: 1m 37s
42:	learn: 1.6181558	total: 2.14s	remaining: 1m 37s
43:	learn: 1.6176479	total: 2.19s	remaining: 1m 37s
44:	learn: 1.6171455	total: 2.23s	remaining: 1m 36s
45:	learn: 1.6164667	total: 2.28s	remaining: 1m 36s
46:	learn: 1.6159445	total: 2.33s	remaining: 1m 36s
47:	learn: 1.6154454	total: 2.38s	remaining: 1m 36s
48:	learn: 1.6150531	total: 2.42s	remaining: 1m 36s
49:	learn: 1.6144359	total: 2.47s	remaining: 1m 36s
50:	learn: 1.6139754	total: 2.52s	remaining: 1m 36s
51:	learn: 1.6135520	total: 2.56s	remaining: 1m 36s
52:	learn: 1.6131524	total: 2.6s	remaining: 1m 35s
53:	learn: 1.6127769	total: 2.65s	remaining: 1m 35s
54:	learn: 1.6123835	total: 2.7s	remaining: 1m 35s
55:	learn: 1.6120617	total: 2.74s	remaining: 1m 35s
56:	learn: 1.6117474	total: 2.78s	remaining: 1m 34s
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = preds
```

```
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde›
```

DEEP Learning Model

```
##imports
from tensorflow.keras.layers import Input, Dense, Activation, Dropout
from tensorflow.keras.models import Model
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras import Input, Model
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense, Dropout, Concatenat
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint, LearningRateScheduler,
tf.config.experimental_run_functions_eagerly(True)
```

```
WARNING:tensorflow:From <ipython-input-42-18ccac45a899>:9: experimental_run_functions_e
Instructions for updating:
Use `tf.config.run_functions_eagerly` instead of the experimental version.
```

```
#-------------------Build the Neural Network model-------------------
print('Building Neural Network model...')
from keras.models import Sequential
adam = optimizer=tf.keras.optimizers.Adam(lr = 0.0001, decay = 0.0000001)

model = Sequential()
model.add(Dense(48, input_dim=Train_x.shape[1],
                kernel_initializer='normal',
                #kernel_regularizer=regularizers.l2(0.02),
                activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(24,
                #kernel_regularizer=regularizers.l2(0.02),
                activation="tanh"))
model.add(Dropout(0.3))
model.add(Dense(1))
model.add(Activation("sigmoid"))
model.compile(loss="mean_squared_error", optimizer='adam')

history = model.fit(Train_x, train_Y, validation_split=0.2, epochs=3, batch_size=64)
```

```
Building Neural Network model...
/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504:

Even though the tf.config.experimental_run_functions_eagerly option is set, this option

/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504:

Even though the tf.config.experimental_run_functions_eagerly option is set, this option
```

```
Epoch 1/3
2461/2464 [============================>.] - ETA: 0s - loss: 2.9988/usr/local/lib/pytho

Even though the tf.config.experimental_run_functions_eagerly option is set, this option

2464/2464 [==============================] - 32s 13ms/step - loss: 2.9987 - val_loss: 2
Epoch 2/3
2464/2464 [==============================] - 32s 13ms/step - loss: 3.0136 - val_loss: 2
Epoch 3/3
2464/2464 [==============================] - 33s 14ms/step - loss: 3.0189 - val_loss: 2
```

```
#Predict on test set
pre= model.predict(test)
print(np.sqrt(mean_squared_error(y, pre)))
```

```
/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504:

Even though the tf.config.experimental_run_functions_eagerly option is set, this option

/usr/local/lib/python3.7/dist-packages/tensorflow/python/data/ops/dataset_ops.py:3504:

Even though the tf.config.experimental_run_functions_eagerly option is set, this option

1.7320966688280504
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')
```

```
sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = pre
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", index
```

LIGHTGBM

```
import lightgbm as lgb
from sklearn.model_selection import KFold, cross_val_score, train_test_split
```

```
params = {'num_leaves': 30,
         'min_data_in_leaf': 20,
         'objective': 'regression',
         'max_depth': 10,
         'learning_rate': 0.05,
         "boosting": "gbrt",
         "metric": 'rmse'}

lgb_model = lgb.LGBMRegressor(**params, n_estimators = 2000,  n_jobs = -1)
lgb_model.fit(Train_x, train_Y)
```

```
LGBMRegressor(boosting='gbrt', boosting_type='gbdt', class_weight=None,
              colsample_bytree=1.0, importance_type='split', learning_rate=0.05,
              max_depth=10, metric='rmse', min_child_samples=20,
              min_child_weight=0.001, min_data_in_leaf=20, min_split_gain=0.0,
              n_estimators=2000, n_jobs=-1, num_leaves=30,
              objective='regression', random_state=None, reg_alpha=0.0,
              reg_lambda=0.0, silent=True, subsample=1.0,
              subsample_for_bin=200000, subsample_freq=0)
```

```
#Predict on test set
pre= lgb_model.predict(test)
print(np.sqrt(mean_squared_error(y, pre)))
```

```
1.8421073701609205
```

```
n_folds = 5

def rmsle_cv(model):
    kf = KFold(n_folds, shuffle=True, random_state=42).get_n_splits(Train_x.values)
    rmse= np.sqrt(-cross_val_score(model, Train_x.values, train_Y, scoring="neg_mean_squared_
    return(rmse)
```

```
model = lgb.LGBMRegressor(objective='regression',num_leaves=5,max_depth= 10,
                          learning_rate=0.05, n_estimators=2000,
                          max_bin = 55, bagging_fraction = 0.8,
                          bagging_freq = 5, feature_fraction = 0.2319,
                          feature_fraction_seed=9, bagging_seed=9,
                          min_data_in_leaf =6, min_sum_hessian_in_leaf = 11)
score = rmsle_cv(model)
print("LGBM score: {:.4f} ({:.4f})\n" .format(score.mean(), score.std()))
```

```
LGBM score: 1.5848 (0.0140)
```

```
def rmsle(y, y_pred):
    return np.sqrt(mean_squared_error(y, y_pred))
```

```
model.fit(Train_x, train_Y)
train_prediction = model.predict(test)
prediction = np.expm1(model.predict(test.values))
print(rmsle(y, train_prediction))
```

```
1.8266959391402342
```

```
test2 = pd.read_csv('/content/drive/MyDrive/elo-merchant-category-recommendation/test.csv')

sub_df = pd.DataFrame({"card_id":test2["card_id"].values})
sub_df["target"] = pre
sub_df.to_csv("/content/drive/MyDrive/elo-merchant-category-recommendation/sample.csv", inde›
```

```
from prettytable import PrettyTable
x = PrettyTable()
```

Summary of the models

```
x.field_names = ["Model", "RMSE"]
x.add_row(["RandomForestRegressor",1.734710337960035])
x.add_row(["XGBoost", 1.7350464235009109])
x.add_row(["CATBoost", 1.7351781761487601])
x.add_row(["AdaBoostRegressor", 1.9096329269067964])
x.add_row(["StackingRegressor", 1.736662419422149])
x.add_row(["DEEP Learning Model", 1.7320945310575173])
x.add_row(["LightGBM", 1.7362417561827879])
print(x)
```

```
+-----------------------+--------------------+
|         Model         |        RMSE        |
+-----------------------+--------------------+
| RandomForestRegressor | 1.734710337960035  |
|        XGBoost        | 1.7350464235009109 |
|        CATBoost       | 1.7351781761487601 |
|   AdaBoostRegressor   | 1.9096329269067964 |
|   StackingRegressor   | 1.736662419422149  |
|  DEEP Learning Model  | 1.7320945310575173 |
|        LightGBM       | 1.7362417561827879 |
+-----------------------+--------------------+
```