In [0]:

```
a = []
while(1):
    a.append(1)
```

Elo world

In this kernel, I build a LGBM model that aggregates the new_merchant_transactions.csv and historical_transactions.csv tables to the main train table. New features are built by successive grouping oncard_id and month_lag, in order to recover some information from the time series.

1) Problem Statement :

> Develop algorithms to identify and serve the most relevant opportunities to individuals, by uncovering signal in customer loyalty.

2) Real world/Business Objectives and constraints

> Predict a loyalty score for credit cards based on historical data and merchant information.
>
> Some form of interpretability.

3) Mapping to an ML problem:Data overview:

totally we have 5 csv files

> The data is formatted as follows:
>
> "train.csv" and "test.csv" contain card_ids and information about the card itself."train.csv" also contains the target.
>
> "historical_transactions.csv" and "new_merchant_transactions.csv" are designed to be joined with "train.csv", "test.csv", and "merchants.csv". They contain information about transactions for each card, as described above.
>
> "merchants" can be joined with the transaction sets to provide additional merchant-level information.

Performance metric :

> Root Mean Square Error

We'll be using the root mean squared error as our evaluation metric:

$$RMSE(y, \hat{y}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

In [0]:

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

```
import lightgbm as lgb
from sklearn.model_selection import KFold
import warnings
import gc
import time
import sys
import datetime
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error
warnings.simplefilter(action='ignore', category=FutureWarning)
pd.set_option('display.max_columns', 500)
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19: FutureWarning: p
andas.util.testing is deprecated. Use the functions in the public API at pandas.testing i
nstead.
  import pandas.util.testing as tm
```

Memory usage

In [0]:

```
def reduce_mem_usage(df, verbose=True):
    numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
    start_mem = df.memory_usage().sum() / 1024**2
    for col in df.columns:
        col_type = df[col].dtypes
        if col_type in numerics:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(np.int8).max:
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinfo(np.int16).max:
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinfo(np.int32).max:
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinfo(np.int64).max:
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finfo(np.float16).max
:
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.finfo(np.float32).m
ax:
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
    end_mem = df.memory_usage().sum() / 1024**2
    if verbose: print('Mem. usage decreased to {:5.2f} Mb ({:.1f}% reduction)'.format(en
d_mem, 100 * (start_mem - end_mem) / start_mem))
    return df
```

4) Reading Data

In [0]:

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

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=94731898
9803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%
3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.co
m%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fww
w.googleapis.com%2fauth%2fdrive.photos.readonly%20https%3a%2f%2fwww.googleapis.com%2fauth
%2fpeopleapi.readonly

Enter your authorization code:
..........
```

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

4.1) Reading `train_data`

In [0]:

```
e = pd.read_excel('/content/drive/My Drive/Elo Merchant/Data Dictionary.xlsx', sheet_name
='train')
e
```

Out[0]:

	train.csv	Unnamed: 1
0	NaN	NaN
1	Columns	Description
2	card_id	Unique card identifier
3	first_active_month	'YYYY-MM', month of first purchase
4	feature_1	Anonymized card categorical feature
5	feature_2	Anonymized card categorical feature
6	feature_3	Anonymized card categorical feature
7	target	Loyalty numerical score calculated 2 months af...

-Looks like, we have 3 categorical features `feature_1`, `feature_2` & `feature_3`.

- `first_active_month` will be helpful in extracting date features

- `target` is a label

In [0]:

```
%%time
train_data = reduce_mem_usage(pd.read_csv("/content/drive/My Drive/Elo Merchant/train.csv
", parse_dates=['first_active_month']))
print('Number of data points : ', train_data.shape[0])
print('Number of features : ', train_data.shape[1])
print('Features : ', train_data.columns.values)
train_data.head()
```

```
Mem. usage decreased to  4.04 Mb (56.2% reduction)
Number of data points :  201917
Number of features :  6
Features :  ['first_active_month' 'card_id' 'feature_1' 'feature_2' 'feature_3'
 'target']
CPU times: user 219 ms, sys: 106 ms, total: 325 ms
Wall time: 1.21 s
```

In [0]:

```
train_data = train_data.drop_duplicates()
print('Number of points after removing duplicates  :', train_data.shape[0])
```

```
Number of points after removing duplicates  : 201917
```

In [0]:

```
train_data.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  datetime64[ns]
```

```
 1   card_id              201917 non-null  object
 2   feature_1            201917 non-null  int8
 3   feature_2            201917 non-null  int8
 4   feature_3            201917 non-null  int8
 5   target               201917 non-null  float16
dtypes: datetime64[ns](1), float16(1), int8(3), object(1)
memory usage: 4.0+ MB
```

In [0]:

```
#Visualizing Null data in Dataframe
#https://www.kaggle.com/residentmario/simple-techniques-for-missing-data-imputation
%%time
train_data.isnull().sum()
```

```
CPU times: user 14 ms, sys: 0 ns, total: 14 ms
Wall time: 13.4 ms
```

Out[0]:

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

There are no Null values in `train_data`.

In [0]:

```
train_data['feature_1'].unique()
```

Out[0]:

```
array([5, 4, 2, 1, 3])
```

In [0]:

```
train_data['feature_2'].unique()
```

Out[0]:

```
array([2, 1, 3])
```

In [0]:

```
train_data['feature_3'].unique()
```

Out[0]:

```
array([1, 0])
```

Feature Engineering

In [0]:

```
#https://medium.com/@swethalakshmanan14/simple-ways-to-extract-features-from-date-variabl
e-using-python-60c33e3b0501
train_data["month"] = train_data["first_active_month"].dt.month
train_data["year"] = train_data["first_active_month"].dt.year
train_data["diff_time"] = (train_data['first_active_month'].dt.date.max() - train_data['
first_active_month'].dt.date).dt.days
```

4.2) Reading `test_data`

In [0]:

```
%%time
```

```
test_data =pd.read_csv("/content/drive/My Drive/Elo Merchant/test.csv" , parse_dates=["fi
rst_active_month"])
print('Number of data points : ', test_data.shape[0])
print('Number of features : ', test_data.shape[1])
print('Features : ', test_data.columns.values)
test_data.head()
```

```
Number of data points :  123623
Number of features :  5
Features :  ['first_active_month' 'card_id' 'feature_1' 'feature_2' 'feature_3']
CPU times: user 141 ms, sys: 5.02 ms, total: 146 ms
Wall time: 179 ms
```

In [0]:

```
test_data = test_data.drop_duplicates()
print('Number of points after removing duplicates  :', test_data.shape[0])
```

```
Number of points after removing duplicates  : 123623
```

Exploratory Data Analysis

Exploratory Data Analysis - Train & Test dataset

`Target`

In [0]:

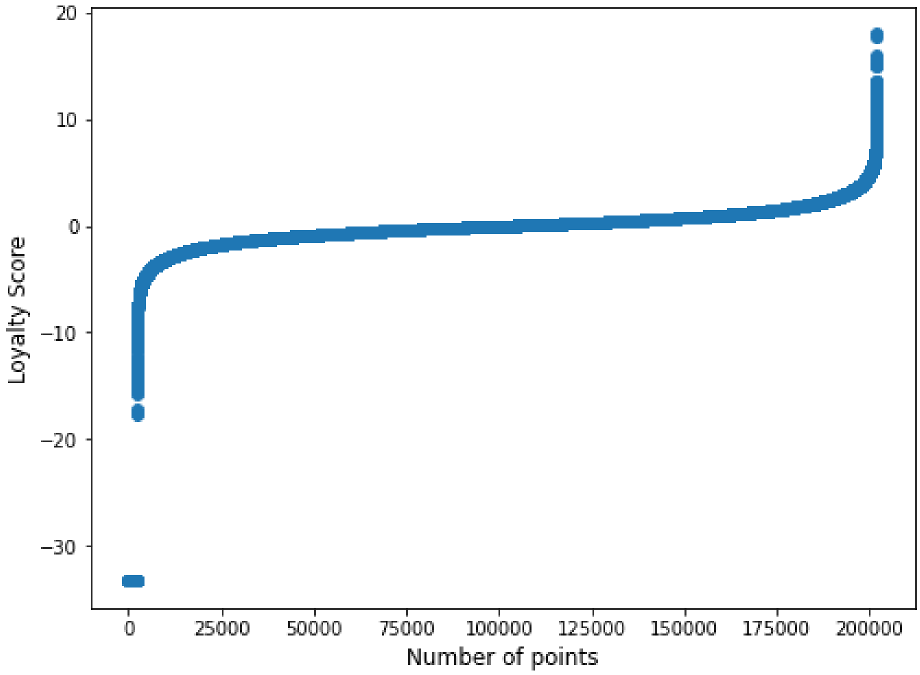
```
sns.countplot(train_data['target'], palette='Set3')
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f15f7f4aa58>
```

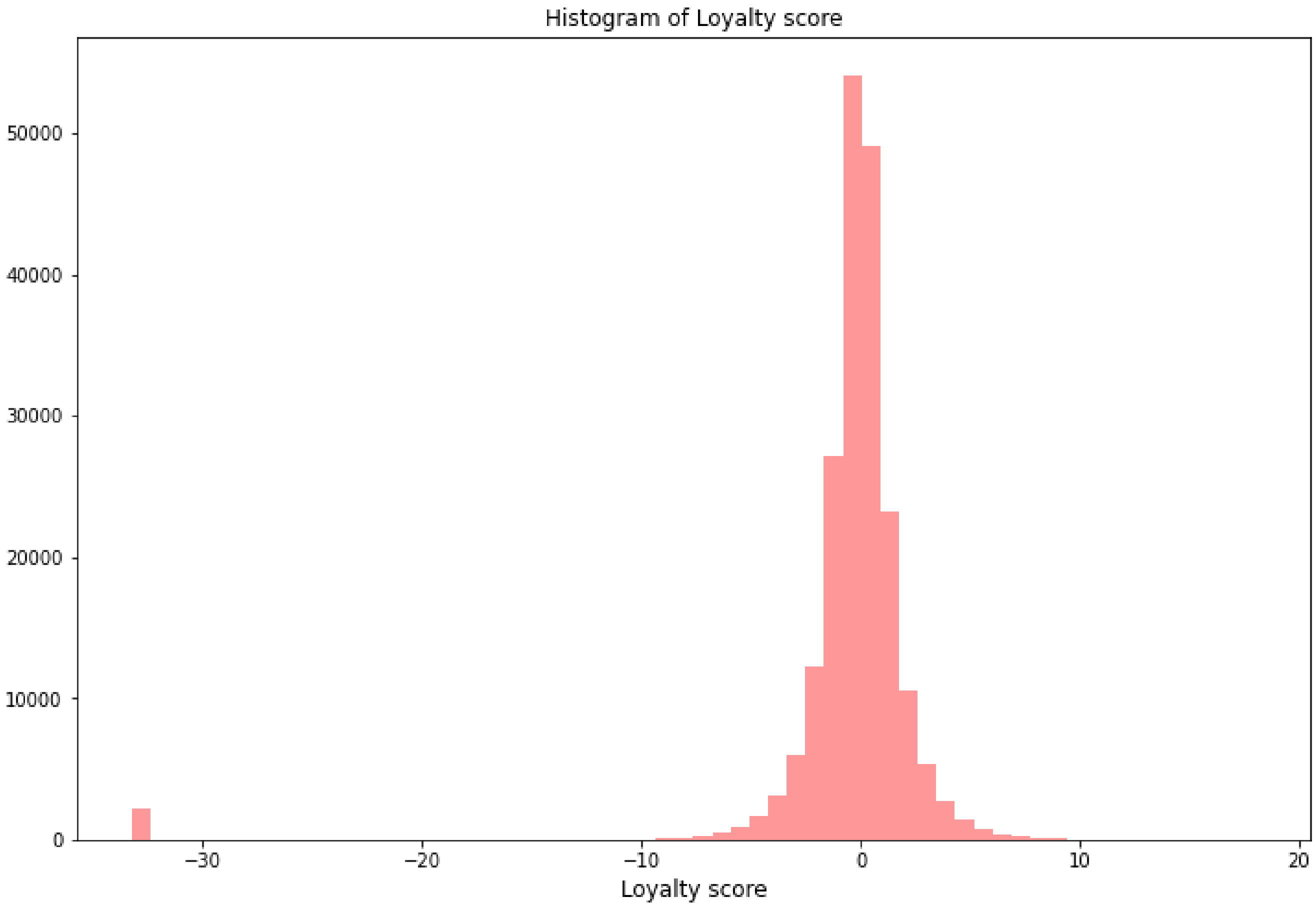
In [0]:

```
#https://www.kaggle.com/sudalairajkumar/simple-exploration-notebook-elo
target_col = "target"
plt.figure(figsize=(8,6))
plt.scatter(range(train_data.shape[0]), np.sort(train_data[target_col].values))
plt.xlabel('Number of points', fontsize=12)
plt.ylabel('Loyalty Score', fontsize=12)
plt.show()
```



In [0]:

```
#https://www.kaggle.com/sudalairajkumar/simple-exploration-notebook-elo
plt.figure(figsize=(12,8))
sns.distplot(train_data[target_col].values, bins=60, kde=False, color="red")
plt.title("Histogram of Loyalty score")
plt.xlabel('Loyalty score', fontsize=12)
plt.show()
```



it is evident from the above graph, most of the loyalty scores in the range of -10 to 10.

looks like there are some potential numbers of loyalty scores in -30, may be they were outliers.

In [0]:

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

Out[0]:

```
2207
```

Percentiles

Since, we have few outliers when the data is posed on Histogram.

Let us use percentiles to trace its exact origin.

In [0]:

```
#Calculating 0-100th percentile to find a the correct percentile value for removal of out
liers
for i in range(0,100,10):
    var =train_data[target_col].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
print ("100 percentile value is ",var[-1])
```

```
0 percentile value is -33.21928095
10 percentile value is -2.04231327
20 percentile value is -1.14604394
```

```
30 percentile value is -0.66396308
40 percentile value is -0.31220831
50 percentile value is -0.02343689
60 percentile value is 0.23620054
70 percentile value is 0.56450565
80 percentile value is 1.01425572
90 percentile value is 1.83029589
100 percentile value is  17.9650684
```

Value at zeroth percentile looks strange. Let us check its origin deeply

Looks, like 100th percentile value looks slight deviation from the rest of the points.

In [0]:

```
#Looking further from the 1st percecntile
for i in range(1,11):
    var =train_data[target_col].values
    var = np.sort(var,axis = None)
    print("{} percentile value is {}".format(i,var[int(len(var)*(float(i)/100))]))
#print ("10 percentile value is ",var[-1])
```

```
1 percentile value is -33.21928095
2 percentile value is -5.01608376
3 percentile value is -4.06331826
4 percentile value is -3.49376358
5 percentile value is -3.10796501
6 percentile value is -2.80808288
7 percentile value is -2.56256564
8 percentile value is -2.36228882
9 percentile value is -2.19336416
10 percentile value is -2.04231327
```

clearly looks like an outlier from the above percentiles.

Therefore, total number of data points present was 201917, out of which 2207 were found out to be outliers.

In [0]:

```
#removing further outliers based on the 1st percentile value
train_df=train_data[(train_data[target_col]>-5) & (train_data[target_col]<18)]
train_df.shape[0]
```

Out[0]:

```
197848
```

`first_active_month`

Train data :

In [0]:

```
#start date of a training dataset
train_df["first_active_month"].min()
```

Out[0]:

```
Timestamp('2011-11-01 00:00:00')
```

In [0]:

```
#End date of a training dataset
train_df["first_active_month"].max()
```

Out[0]:

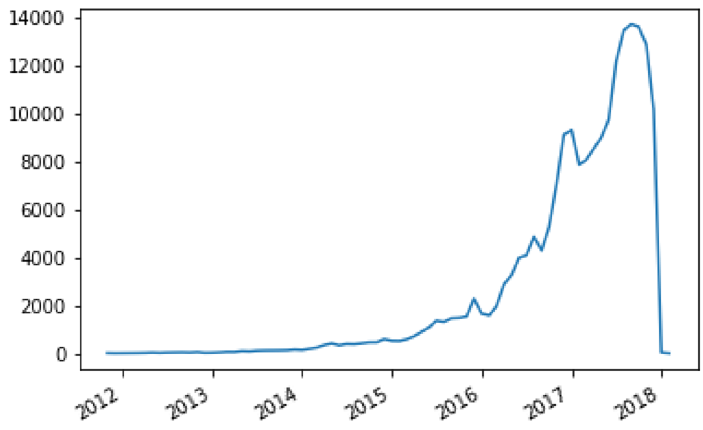
```
Timestamp('2018-02-01 00:00:00')
```

In [0]:

```
train_df["first_active_month"].value_counts().plot()
```

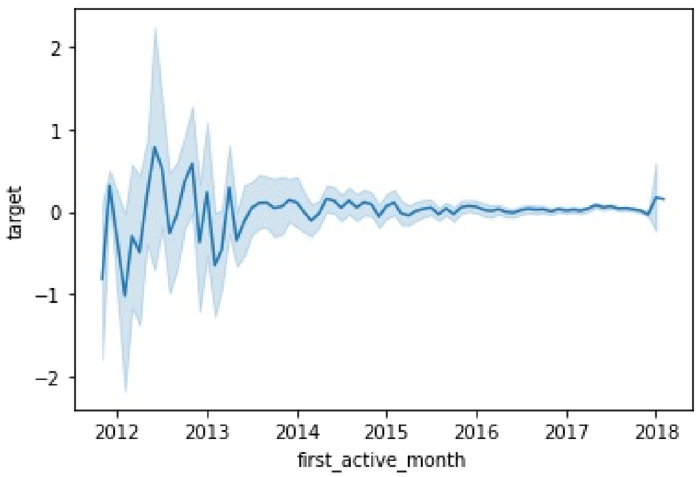
Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f09c7e2a4e0>
```



In [0]:

```
# first_active_month vs loyalty score
sns.lineplot(x='first_active_month', y='target', data=train_df)
plt.show()
```



From the above graph, it is evident that Loyalty scores improve gradually over a period of time.

And takes a steady steep, post 2014.

Test data:

In [0]:

```
#start date of a test dataset
test_data["first_active_month"].min()
```

Out[0]:

```
Timestamp('2011-11-01 00:00:00')
```

In [0]:

```
#End date of a test dataset
test_data["first_active_month"].max()
```

Out[0]:

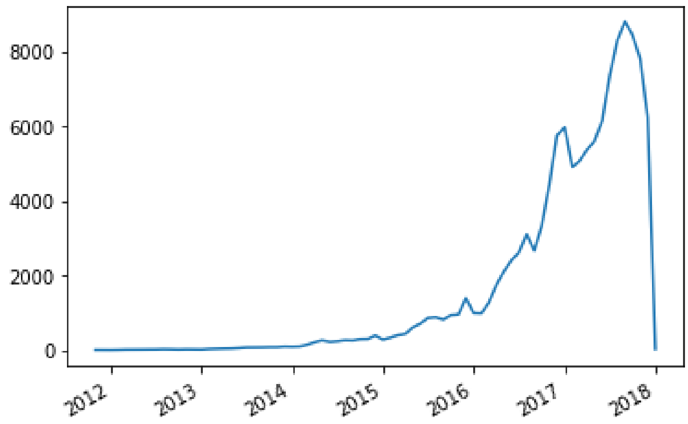
```
Timestamp('2018-01-01 00:00:00')
```

In [0]:

```
test_data["first_active_month"].value_counts().plot()
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f09c3e94160>
```

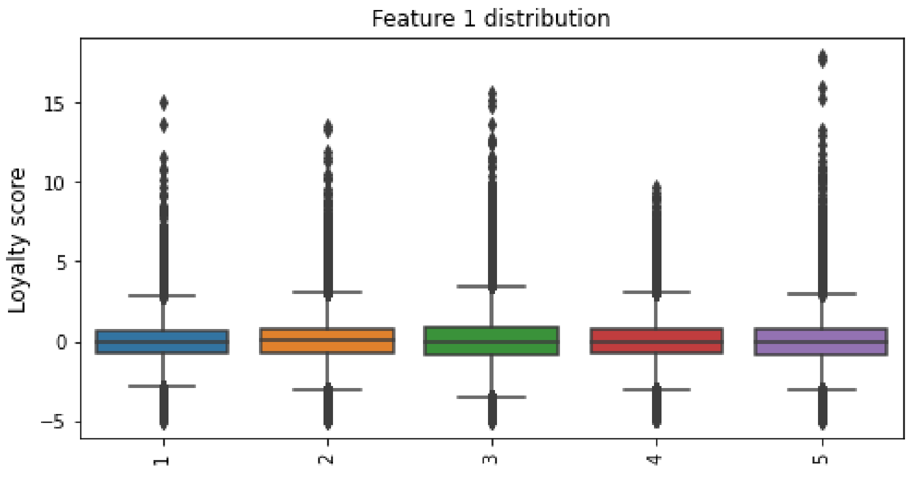


Both the distributions of "first_active_month" for train and test data looks similar.

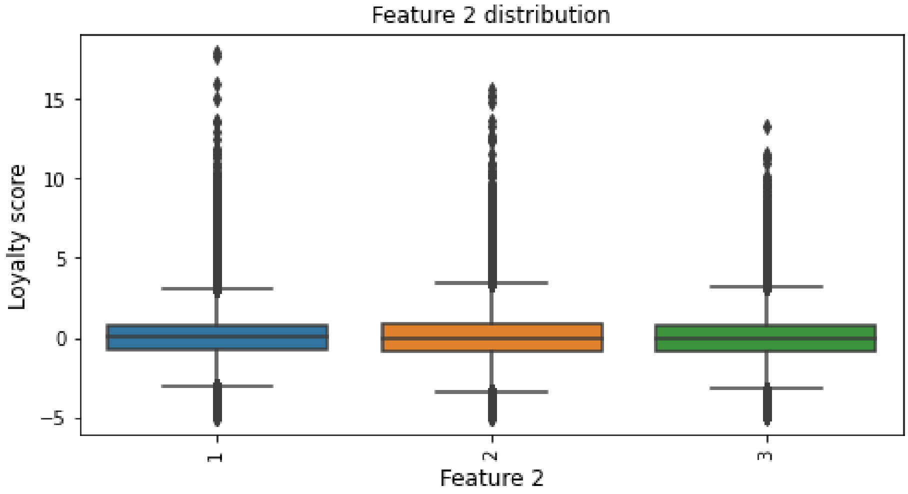
\`feature_1\`, \`feature_2\` & \`feature_3\`

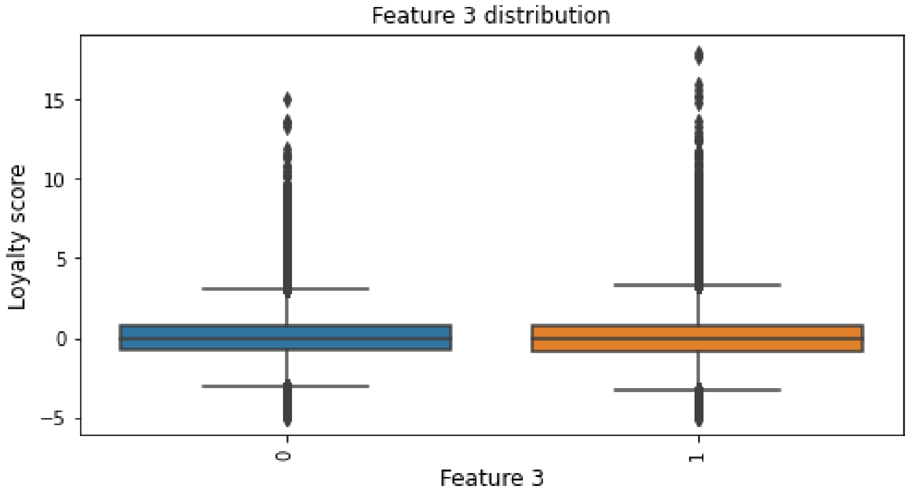
In [0]:

```
#https://www.kaggle.com/sudalairajkumar/simple-exploration-notebook-elo
# feature 1
plt.figure(figsize=(8,4))
sns.boxplot(x="feature_1", y=target_col, data=train_df)
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.boxplot(x="feature_2", y=target_col, data=train_df)
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.boxplot(x="feature_3", y=target_col, data=train_df)
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





Even the distributions of 3 features were looks similar.

Therefore, it is evident that from the above plots the dataset has some outliers. If we remove the outliers the dataset looks imbalance and to overcome this we have to use oversampling and then pose the problem as classification teachnique to solve this.

Now, without considering the outliers the dataset looks like a regression model and if we apply any one of the baseline models and selects the best model.

Our approach on this problem is:

1) Apply linear regression baseline models to achieve less RMSE value

2) Remove outliers and apply oversampling on top of it and slove it by a classification technique.

Till now we have visualise Train and Test csv files,

Now, let us visualise the rest of the features from the other csv files.

4.3) Reading `historical transactions`

In [0]:

```
e = pd.read_excel('/content/drive/My Drive/Elo Merchant/Data Dictionary.xlsx', sheet_name
='history')
e
```

Out[0]:

historical_transactions.csv	Unnamed: 1

	historical_transactions.csv	Unnamed: 1
0	NaN	NaN
1	Columns	Description
2	card_id	Card identifier
3	month_lag	month lag to reference date
4	purchase_date	Purchase date
5	authorized_flag	Y' if approved, 'N' if denied
6	category_3	anonymized category
7	installments	number of installments of purchase
8	category_1	anonymized category
9	merchant_category_id	Merchant category identifier (anonymized)
10	subsector_id	Merchant category group identifier (anonymized)
11	merchant_id	Merchant identifier (anonymized)
12	purchase_amount	Normalized purchase amount
13	city_id	City identifier (anonymized)
14	state_id	State identifier (anonymized)
15	category_2	anonymized category

`category_1`, `category_2`, `category_3` **are categotical features.**

Since, few of the line itmes in category features have nan values..Now, let us convert this in to numerical features and look for any similarities between the features. If the features looks similar then we are dropping this off from the dataset and if the features are different we continue to add this in the dataset.

In [0]:

```
%%time
hist = reduce_mem_usage(pd.read_csv('/content/drive/My Drive/Elo Merchant/historical_tran
sactions.csv'))
print('Number of data points : ', hist.shape[0])
print('Number of features : ', hist.shape[1])
print('Features : ', hist.columns.values)
hist.head()
```

```
Mem. usage decreased to 1749.11 Mb (43.7% reduction)
Number of data points :  29112361
Number of features :  14
Features :  ['authorized_flag' 'card_id' 'city_id' 'category_1' 'installments'
 'category_3' 'merchant_category_id' 'merchant_id' 'month_lag'
 'purchase_amount' 'purchase_date' 'category_2' 'state_id' 'subsector_id']
CPU times: user 49.4 s, sys: 17.9 s, total: 1min 7s
Wall time: 1min 21s
```

In [0]:

```
hist_1 = pd.merge(left=train_data, right=hist, on="card_id", how="left")
hist_1.head()
```

Out[0]:

	first_active_month	card_id	feature_1	feature_2	feature_3	target	authorized_flag	city_id	category_1	installm
0	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N	
1	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N	
2	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N	
3	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N	

4	first_active_month 2017-06-01	C_ID_92a2005557 card_id	feature_1 5	feature_2 2	feature_3 1	target -0.820312	authorized_flag Y	city_69	category_1 N	installm

In [0]:

```
hist_1=hist_1.drop_duplicates(subset=['card_id'], keep="first")
```

In [0]:

```
%%time
hist_1.isnull().sum()
```

```
CPU times: user 150 ms, sys: 0 ns, total: 150 ms
Wall time: 149 ms
```

Out[0]:

```
first_active_month      0
card_id                 0
feature_1               0
feature_2               0
feature_3               0
target                  0
authorized_flag         0
city_id                 0
category_1              0
installments            0
category_3              0
merchant_category_id    0
merchant_id             0
month_lag               0
purchase_amount         0
purchase_date           0
category_2              0
state_id                0
subsector_id            0
dtype: int64
```

In [0]:

```
hist_1['category_2'] = hist_1['category_2'].replace(np.nan, 1.0)
hist_1['category_3'] = hist_1['category_3'].replace(np.nan, 'A')
hist_1['merchant_id'] = hist_1['merchant_id'].replace(np.nan, 'M_ID_00a6ca8a8a')
```

In [0]:

```
#Installments
hist['installments'].value_counts()
```

Out[0]:

```
 0      15336465
 1      11621828
 2        666348
 3        538099
 4        179497
-1        170952
 6        132609
 10       118818
 5        116046
 12        55056
 8         20471
 7         10902
 9          5771
 11          830
 999         188
Name: installments, dtype: int64
```

Here we have a hiccup, installments starts from the range of 0-11 months.

But here we have -1 and 999 looks strange.

This might be a false transactions.

In [0]:

```
# let's convert the authorized_flag to a binary value.
hist['authorized_flag'] = hist['authorized_flag'].apply(lambda x: 1 if x == 'Y' else 0)
```

In [0]:

```
hist.groupby(['installments'])['authorized_flag'].mean()
```

Out[0]:

```
installments
-1      0.888612
 0      0.928268
 1      0.907247
 2      0.884101
 3      0.862425
 4      0.820030
 5      0.809472
 6      0.779857
 7      0.693451
 8      0.692541
 9      0.663836
 10     0.702065
 11     0.660241
 12     0.653753
 999    0.031915
Name: authorized_flag, dtype: float64
```

In [0]:

```
#removing further outliers based on the 1st percentile value
hist_f=hist[(hist['installments']>0) & (hist['installments']<12)]
hist_f.shape[0]
```

Out[0]:

```
13411219
```

EDA on "Historical_transactions".csv

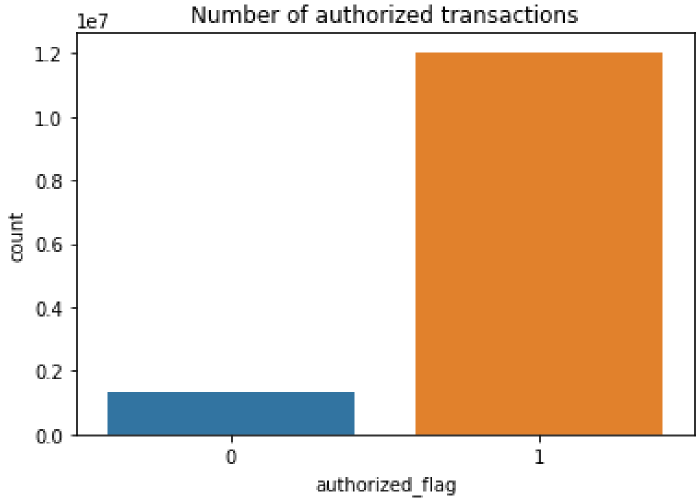
In [0]:

```
hist_f.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 13383837 entries, 400 to 29112357
Data columns (total 14 columns):
 #   Column                Dtype
---  ------                -----
 0   authorized_flag       int64
 1   card_id               object
 2   city_id               int64
 3   category_1            int64
 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(8), object(4)
memory usage: 1.5+ GB
```

In [0]:

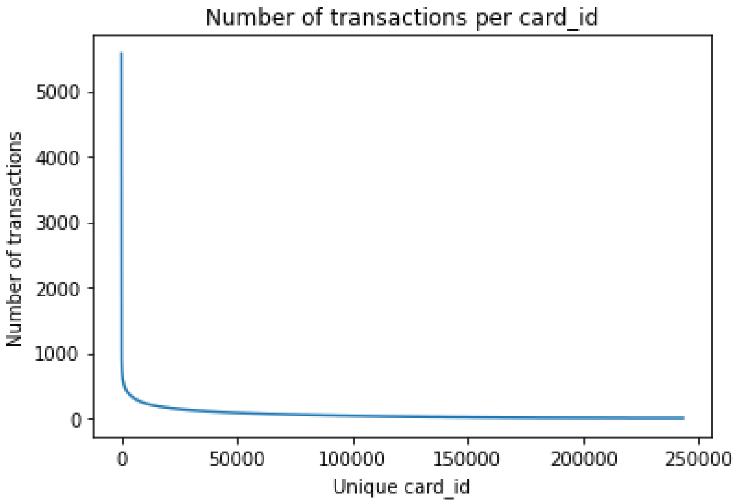
```
#Authorised flag
sns.countplot(x='authorized_flag', data=hist_f)
plt.title('Number of authorized transactions')
plt.show()
```



seems like, most of the transactions were Authorized.

In [0]:

```
# card_id
plt.plot(hist_f['card_id'].value_counts().values)
plt.xlabel('Unique card_id')
plt.ylabel('Number of transactions')
plt.title('Number of transactions per card_id')
plt.show()
```



seems like very few card_id has the most number of transactions

In [0]:

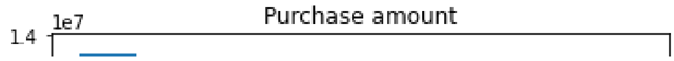
```
#hist['installments'] = hist['installments'].astype('category')
```

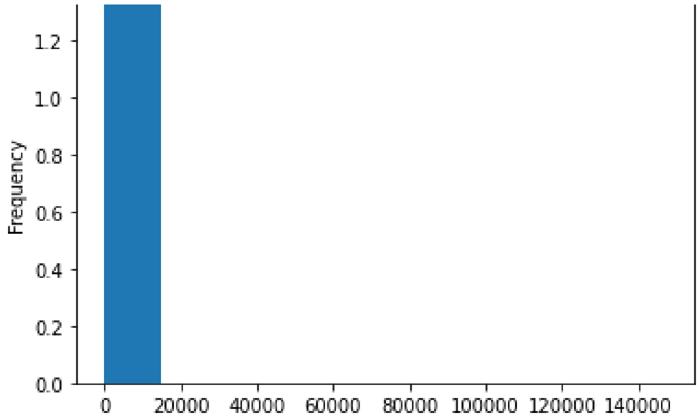
In [0]:

```
hist_f['purchase_date'] = pd.to_datetime(hist_f['purchase_date'])
```

In [0]:

```
#Purchase_amount
plt.title('Purchase amount');
hist_f['purchase_amount'].plot(kind='hist');
```

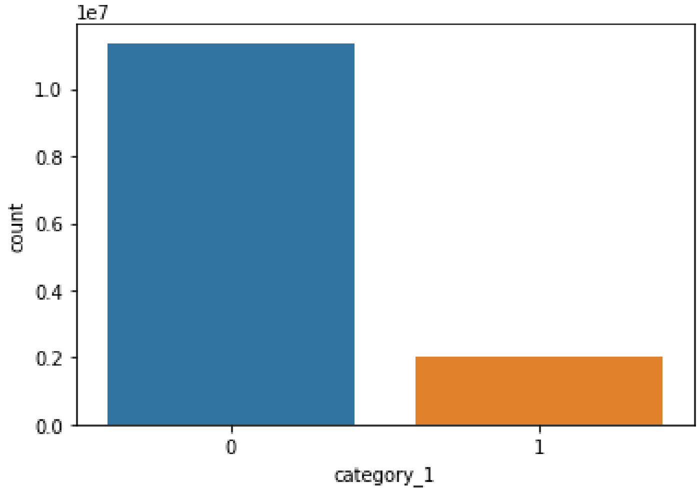




Looks like Purchase amount is Normalised.

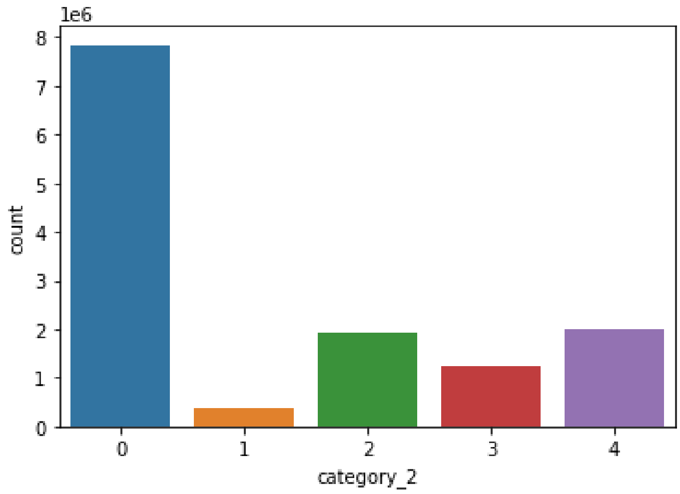
In [0]:

```
#from matplotlib.ticker import FormatStrFormatter
# category_1
sns.countplot(x='category_1', data=hist_f)
plt.show()
```



In [0]:

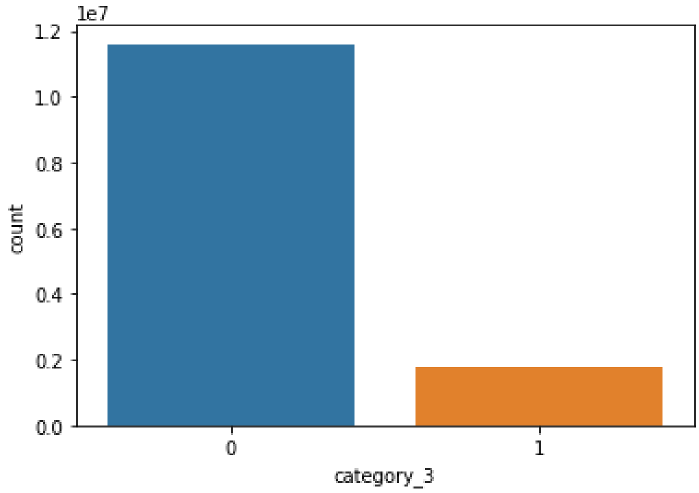
```
# category_2
from matplotlib.ticker import FormatStrFormatter
sns.countplot(x='category_2', data=hist_f)
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



In [0]:

```
# category_3
sns.countplot(x='category_3', data=hist_f)
```

```
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



Initially, we have 3 categories before removing the outliers from 'installments'.

we are left with 2 categories post removing the outliers from 'installments'.

All the Categories are quite different.

Other categorical data are:

In [0]:

```
for col in ['city_id', 'merchant_category_id', 'merchant_id', 'state_id', 'subsector_id']
:
    print(f"There are {hist_f[col].nunique()} unique values in {col}.")
```

```
There are 308 unique values in city_id.
There are 323 unique values in merchant_category_id.
There are 281886 unique values in merchant_id.
There are 25 unique values in state_id.
There are 41 unique values in subsector_id.
```

4.4)Reading `new_merchant_transactions`

In [0]:

```
e = pd.read_excel('/content/drive/My Drive/Elo Merchant/Data Dictionary.xlsx', sheet_name
='new_merchant_period')
e
```

Out[0]:

	new_merchant_period.csv	Unnamed: 1
0	NaN	NaN
1	Columns	Description
2	card_id	Card identifier
3	month_lag	month lag to reference date
4	purchase_date	Purchase date
5	authorized_flag	Y' if approved, 'N' if denied
6	category_3	anonymized category
7	installments	number of installments of purchase
8	category_1	anonymized category
9	merchant_category_id	Merchant category identifier (anonymized)
10	merchant_id	Merchant identifier (anonymized)

	new_merchant_period.csv	Unnamed: 1
10	subsector_id	Merchant category group identifier (anonymized)
11	merchant_id	Merchant identifier (anonymized)
12	purchase_amount	Normalized purchase amount
13	city_id	City identifier (anonymized)
14	state_id	State identifier (anonymized)
15	category_2	anonymized category

`category_1`, `category_2`, `category_3` **are categotical features.**

Even feature `installments` looks like a categorical one, all the installments range between 0-11 months.

In [0]:

```
%%time
new_merch =reduce_mem_usage(pd.read_csv("/content/drive/My Drive/Elo Merchant/new_merchan
t_transactions.csv"))
print('Number of data points : ', new_merch.shape[0])
print('Number of features : ', new_merch.shape[1])
print('Features : ', new_merch.columns.values)

new_merch.head(3)
```

```
Mem. usage decreased to 114.20 Mb (45.5% reduction)
Number of data points :  1963031
Number of features :  14
Features :  ['authorized_flag' 'card_id' 'city_id' 'category_1' 'installments'
 'category_3' 'merchant_category_id' 'merchant_id' 'month_lag'
 'purchase_amount' 'purchase_date' 'category_2' 'state_id' 'subsector_id']
CPU times: user 3.69 s, sys: 364 ms, total: 4.05 s
Wall time: 5.59 s
```

In [0]:

```
hist_2 = pd.merge(left=hist_1, right=new_merch, on="card_id", how="left")
hist_2.head()
```

Out[0]:

	first_active_month	card_id	feature_1	feature_2	feature_3	target	authorized_flag_x	city_id_x	category_1_x
0	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N
1	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N
2	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N
3	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N
4	2017-06-01	C_ID_92a2005557	5	2	1	-0.820312	Y	69	N

In [0]:

```
hist_2=hist_2.drop_duplicates(subset=['card_id'], keep="first")
```

Merchant_id can never be an empty or Nan.. This should have an ID, without an ID the transactions might look meaningless. So, I have removed the transactions beloging to Nan in Merchant_id.

Merchant_id and card_id are the unique fields that shouldn't be empty.

In [0]:

```
hist_2['category_2_y'] = hist_2['category_2_y'].replace(np.nan, 1.0)
```

```
hist_2['category_3_y'] = hist_2['category_3_y'].replace(np.nan, 'A')
hist_2['merchant_id_y'] = hist_2['merchant_id_y'].replace(np.nan, 'M_ID_00a6ca8a8a')
hist_2['authorized_flag_y'] = hist_2['authorized_flag_y'].replace(np.nan, 'Y')
```

In [0]:

```
#https://stackoverflow.com/questions/57577188/replace-nan-values-by-user-defined-values-i
n-categorical-variables
#replacing category_2 which has Null values using user defined values

def nan_impute(df, col):
  p = df[col].value_counts(normalize=True)   # Series of probabilities
  m = df[col].isnull()

  np.random.seed(42)
  rand_fill = np.random.choice(p.index, size=m.sum(), p=p)

  df.loc[m, col] = rand_fill
```

In [0]:

```
nan_impute(hist_2, 'merch_price')
```

In [0]:

```
#Installments
new_merch['installments'].value_counts()
```

Out[0]:

```
 0      909084
 1      825304
 2       54729
-1       53740
 3       44750
 4       14815
 6       10389
 5        9296
 10       8899
 12       2850
 8        1555
 7         863
 9         478
 11         61
 999         2
Name: installments, dtype: int64
```

Here we have a hiccup, installments starts from the range of 0-11 months.

But here we have -1 and 999 looks strange.

This might be a false transactions.

In [0]:

```
# let's convert the authorized_flag to a binary value.
new_merch['authorized_flag'] = new_merch['authorized_flag'].apply(lambda x: 1 if x == 'Y
' else 0)
```

In [0]:

```
#removing further outliers based on the 1st percentile value
new_merch_f=new_merch[(new_merch['installments']>0) & (new_merch['installments']<12)]
new_merch_f.shape[0]
```

Out[0]:

```
971139
```

EDA for New_merchants.csv

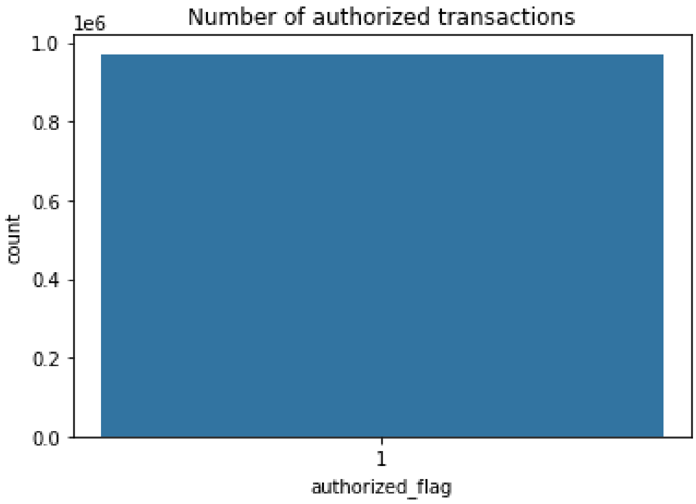
In [0]:

```
new_merch_f.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 971128 entries, 0 to 1963028
Data columns (total 14 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   authorized_flag       971128 non-null  int64  
 1   card_id               971128 non-null  object 
 2   city_id               971128 non-null  int64  
 3   category_1            971128 non-null  int64  
 4   installments          971128 non-null  int64  
 5   category_3            971128 non-null  object 
 6   merchant_category_id  971128 non-null  int64  
 7   merchant_id           971128 non-null  object 
 8   month_lag             971128 non-null  int64  
 9   purchase_amount       971128 non-null  float64
 10  purchase_date         971128 non-null  object 
 11  category_2            971128 non-null  float64
 12  state_id              971128 non-null  int64  
 13  subsector_id          971128 non-null  int64  
dtypes: float64(2), int64(8), object(4)
memory usage: 111.1+ MB
```

In [0]:

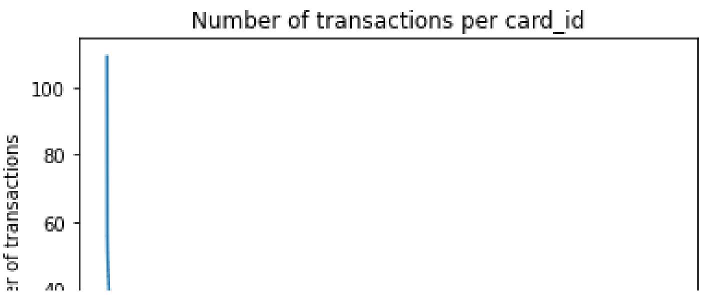
```
#Authorised flag
sns.countplot(x='authorized_flag', data=new_merch_f)
plt.title('Number of authorized transactions')
plt.show()
```

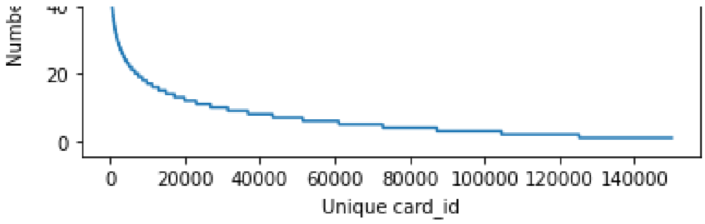


in this, all the transactions were authorised.

In [0]:

```
# card_id
plt.plot(new_merch_f['card_id'].value_counts().values)
plt.xlabel('Unique card_id')
plt.ylabel('Number of transactions')
plt.title('Number of transactions per card_id')
plt.show()
```





very few customers made multiple transactions, where as majority of the transactions were below less than 20 by the customers.

In [0]:

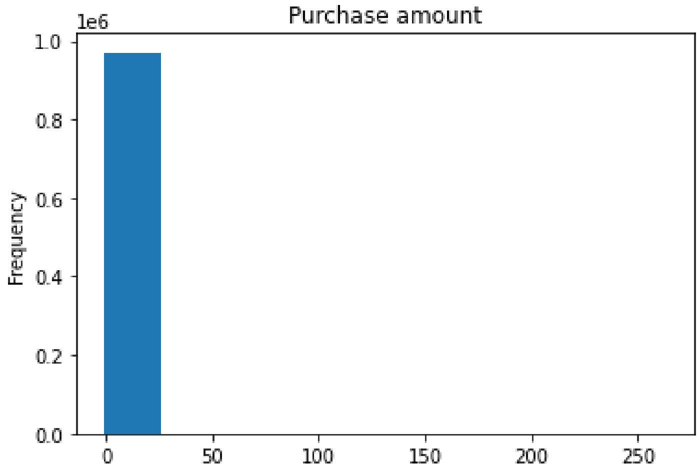
```
#new_merch['installments'] = new_merch['installments'].astype('category')
```

In [0]:

```
new_merch_f['purchase_date'] = pd.to_datetime(new_merch_f['purchase_date'])
```

In [0]:

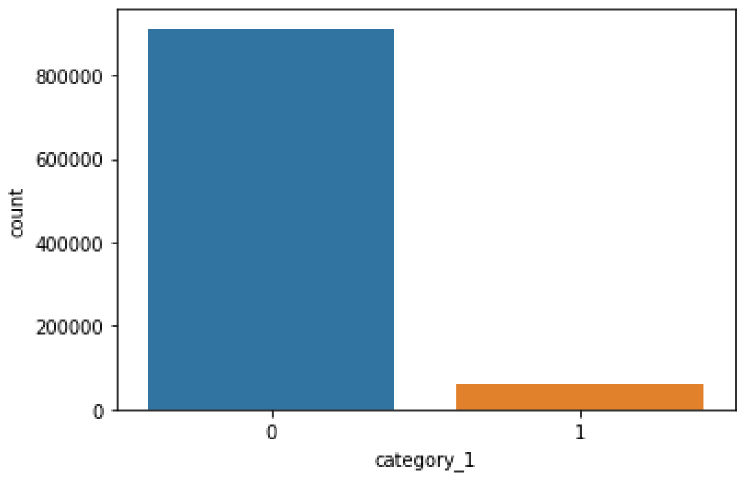
```
#Purchase_amount
plt.title('Purchase amount');
new_merch_f['purchase_amount'].plot(kind='hist');
```



Looks like Purchase amount is Normalised

In [0]:

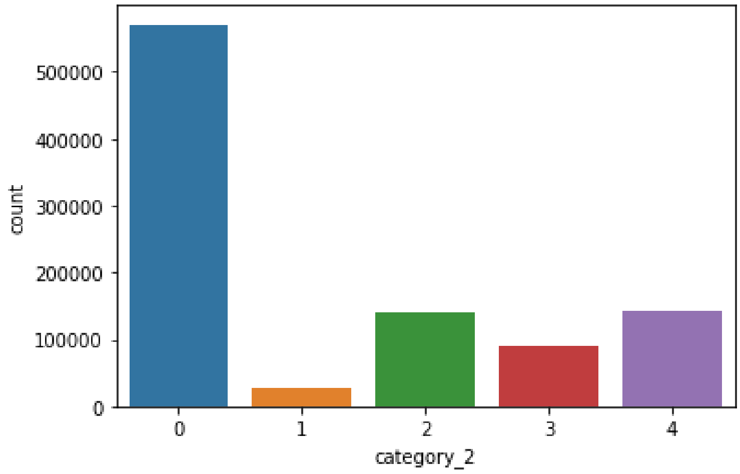
```
#from matplotlib.ticker import FormatStrFormatter
# category_1
sns.countplot(x='category_1', data=new_merch_f)
plt.show()
```



In [0]:

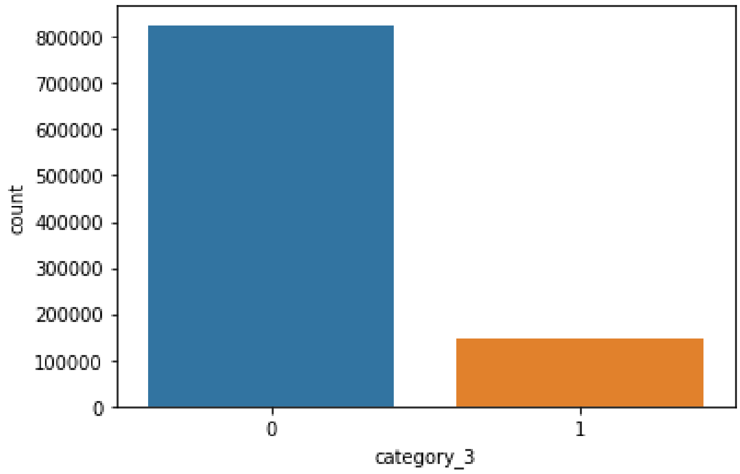
```
# category_2
```

```
# category_2
from matplotlib.ticker import FormatStrFormatter
sns.countplot(x='category_2', data=new_merch_f)
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



In [0]:

```
# category_3
sns.countplot(x='category_3', data=new_merch_f)
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



All the 3 categories are quite different

Other categorical data are:

In [0]:

```
for col in ['city_id', 'merchant_category_id', 'merchant_id', 'state_id', 'subsector_id']
:
    print(f"There are {new_merch_f[col].nunique()} unique values in {col}.")
```

```
There are 308 unique values in city_id.
There are 302 unique values in merchant_category_id.
There are 165778 unique values in merchant_id.
There are 25 unique values in state_id.
There are 41 unique values in subsector_id.
```

In [0]:

```
hist_2.to_csv('hist_2.csv')
```

4.5) Reading `merchants`

In [0]:

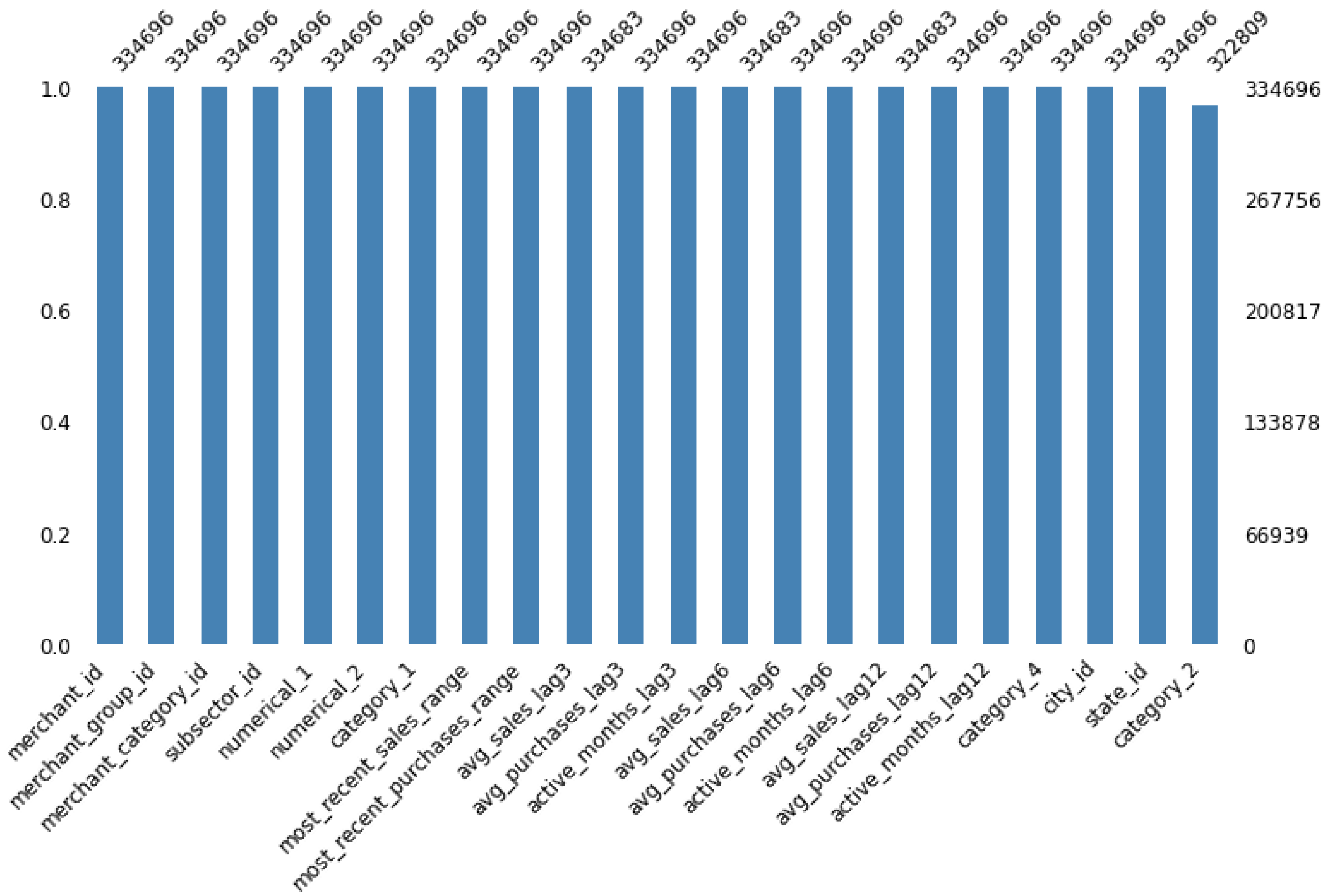
```
%%time
merch =pd.read_csv("/content/drive/My Drive/Elo Merchant/merchants.csv")
print('Number of data points : ', merch.shape[0])
print('Number of features : ', merch.shape[1])
print('Features : ', merch.columns.values)
merch.head()
```

```
Number of data points :  334696
Number of features :  22
Features :  ['merchant_id' 'merchant_group_id' 'merchant_category_id' 'subsector_id'
 'numerical_1' 'numerical_2' 'category_1' 'most_recent_sales_range'
 'most_recent_purchases_range' 'avg_sales_lag3' 'avg_purchases_lag3'
 'active_months_lag3' 'avg_sales_lag6' 'avg_purchases_lag6'
 'active_months_lag6' 'avg_sales_lag12' 'avg_purchases_lag12'
 'active_months_lag12' 'category_4' 'city_id' 'state_id' 'category_2']
CPU times: user 898 ms, sys: 73.4 ms, total: 971 ms
Wall time: 3.49 s
```

In [0]:

```
%%time
#Visualizing Null data in Dataframe
#https://www.kaggle.com/residentmario/simple-techniques-for-missing-data-imputation
import missingno as msno
import matplotlib.pyplot as plt
msno.bar(merch, figsize=(12, 6), fontsize=12, color='steelblue')
```

```
CPU times: user 188 ms, sys: 4.84 ms, total: 193 ms
Wall time: 192 ms
```



`avg_sales_lag12` , `avg_sales_lag6` , `avg_sales_lag3` **&** `category_2` **has Null values.**

Once we have uploaded all the csv files,

Let us look at the features of each file and check its distributions, variance or any outliers present using EDA.

EDA on Merchants.csv

EDA on Merchants.csv

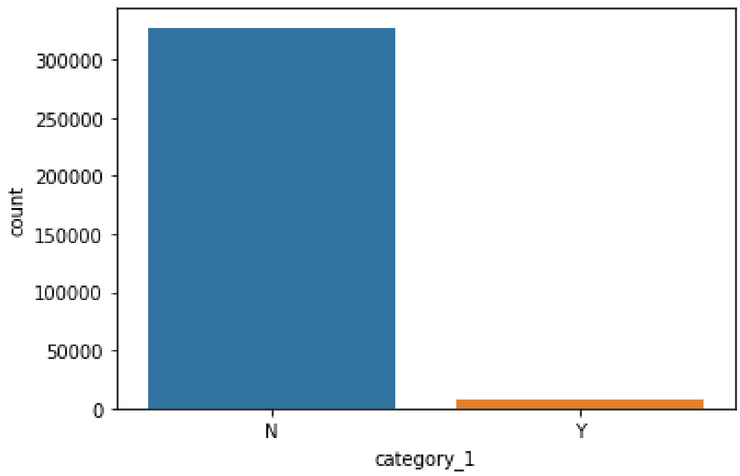
In [0]:

```
merch.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 334696 entries, 0 to 334695
Data columns (total 22 columns):
merchant_id                    334696 non-null object
merchant_group_id              334696 non-null int64
merchant_category_id           334696 non-null int64
subsector_id                   334696 non-null int64
numerical_1                    334696 non-null float64
numerical_2                    334696 non-null float64
category_1                     334696 non-null object
most_recent_sales_range        334696 non-null object
most_recent_purchases_range    334696 non-null object
avg_sales_lag3                 334683 non-null float64
avg_purchases_lag3             334696 non-null float64
active_months_lag3             334696 non-null int64
avg_sales_lag6                 334683 non-null float64
avg_purchases_lag6             334696 non-null float64
active_months_lag6             334696 non-null int64
avg_sales_lag12                334683 non-null float64
avg_purchases_lag12            334696 non-null float64
active_months_lag12            334696 non-null int64
category_4                     334696 non-null object
city_id                        334696 non-null int64
state_id                       334696 non-null int64
category_2                     322809 non-null float64
dtypes: float64(9), int64(8), object(5)
memory usage: 56.2+ MB
```

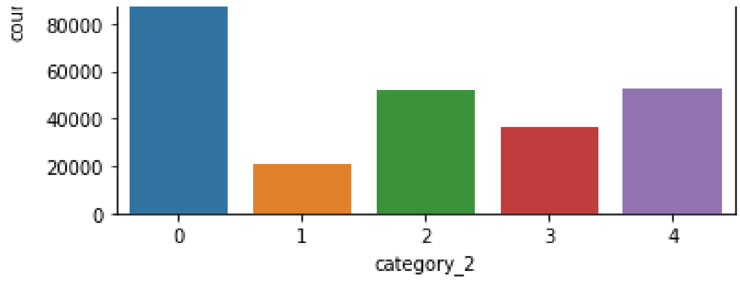
In [0]:

```
#from matplotlib.ticker import FormatStrFormatter
# category_1
sns.countplot(x='category_1', data=merch)
plt.show()
```



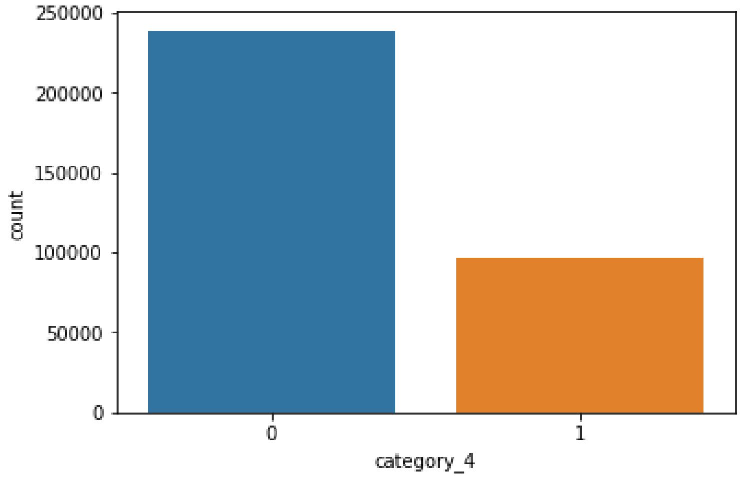
In [0]:

```
# category_2
from matplotlib.ticker import FormatStrFormatter
sns.countplot(x='category_2', data=merch)
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



In [0]:

```
# category_3
sns.countplot(x='category_4', data=merch)
plt.gca().xaxis.set_major_formatter(FormatStrFormatter('%.0f'))
plt.show()
```



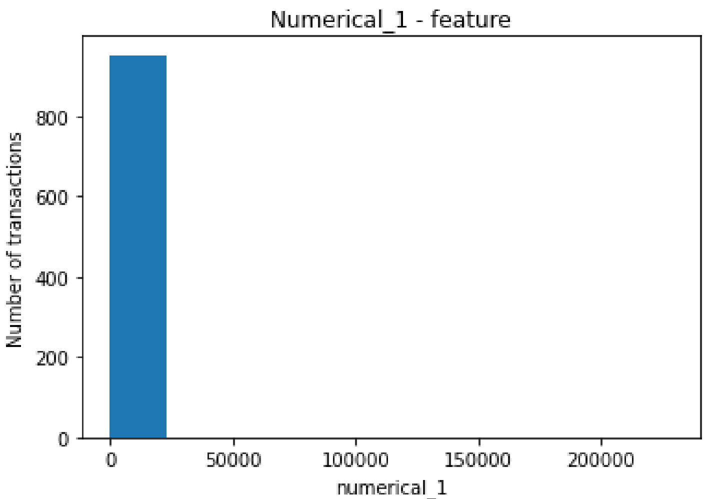
All the 3 categories looks quite different

Numerical data

Numerical_1

In [0]:

```
# numerical_1
plt.hist(merch['numerical_1'].value_counts().values)
plt.xlabel('numerical_1')
plt.ylabel('Number of transactions')
plt.title('Numerical_1 - feature')
plt.show()
```



In [0]:

```
np.percentile(merch['numerical_1'], 95)
```

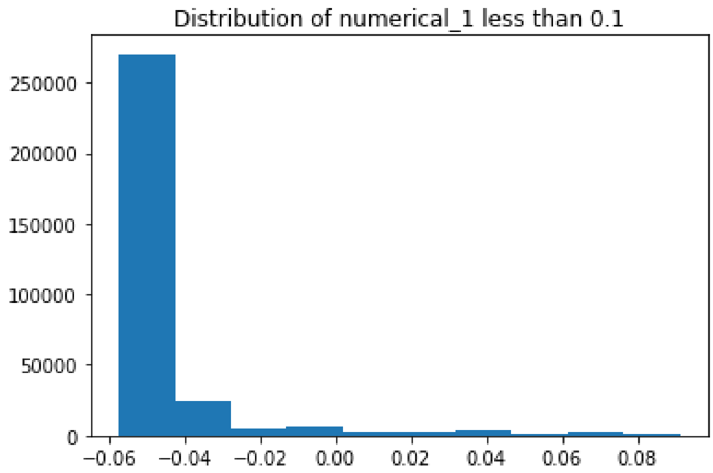
Out[0]:

```
0.09125291
```

95% of values are less than 0.1

In [0]:

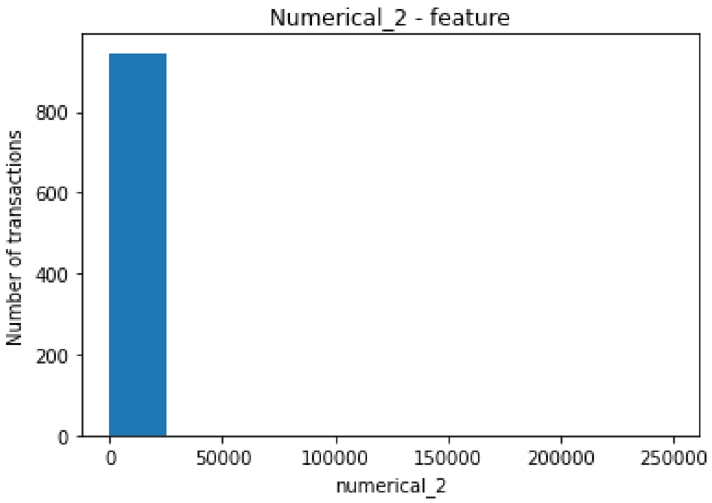
```
#https://www.kaggle.com/artgor/elo-eda-and-models
plt.hist(merch.loc[merch['numerical_1'] < 0.1, 'numerical_1']);
plt.title('Distribution of numerical_1 less than 0.1');
```



Numerical_2

In [0]:

```
# numerical_2
plt.hist(merch['numerical_2'].value_counts().values)
plt.xlabel('numerical_2')
plt.ylabel('Number of transactions')
plt.title('Numerical_2 - feature')
plt.show()
```



above plot doesn't help in providing any insight on the data.

In [0]:

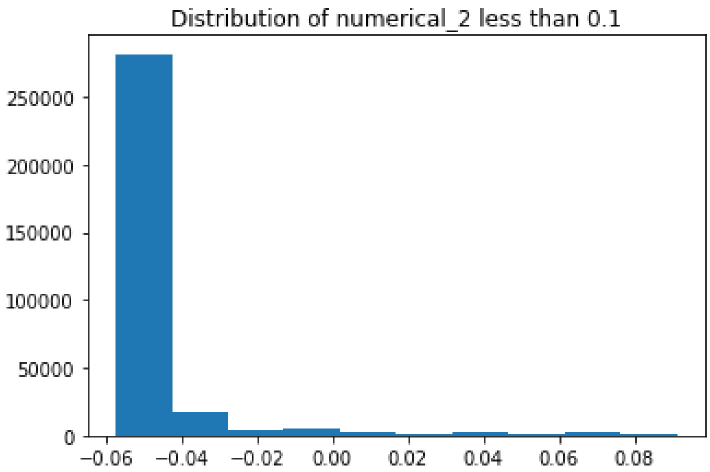
```
np.percentile(merch['numerical_2'], 95)
```

Out[0]:

```
0.08133801
```

In [0]:

```
#https://www.kaggle.com/artgor/elo-eda-and-models
plt.hist(merch.loc[merch['numerical_2'] < 0.1, 'numerical_2']);
plt.title('Distribution of numerical_2 less than 0.1');
```

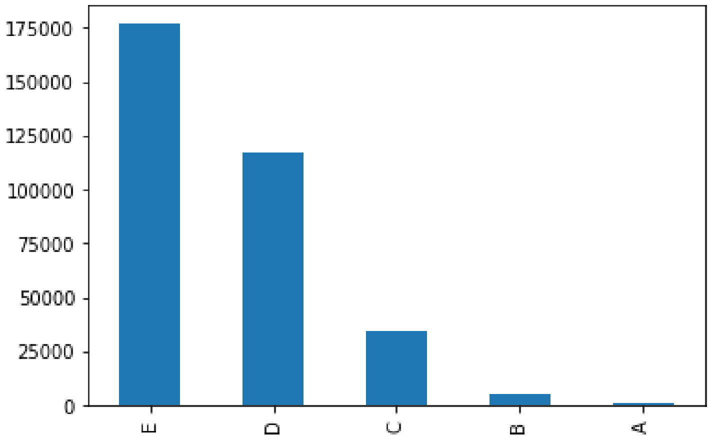


Both the distributions of `numerical_1` & `numerical_2` looks similar

most_recent_sales_range

In [0]:

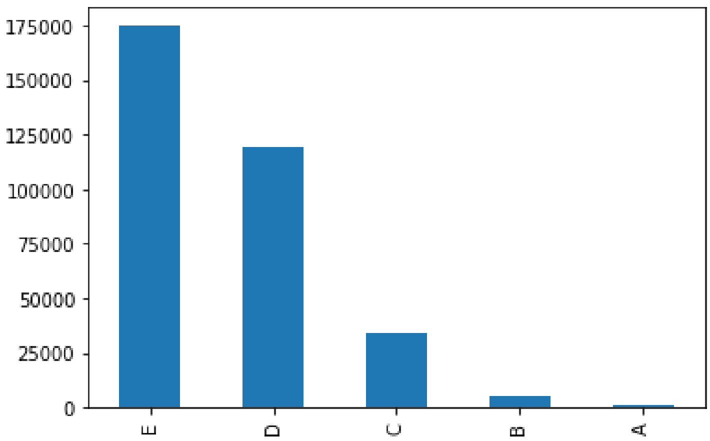
```
#most_recent_sales_range
merch['most_recent_sales_range'].value_counts().plot('bar');
```



most_recent_purchases_range

In [0]:

```
#most_recent_purchases_range
merch['most_recent_purchases_range'].value_counts().plot('bar');
```



Both the distributions of `most_recent_purchases_range` & `most_recent_purchases_sales` are similar

avg_sales_lag

avg_sales_lag3

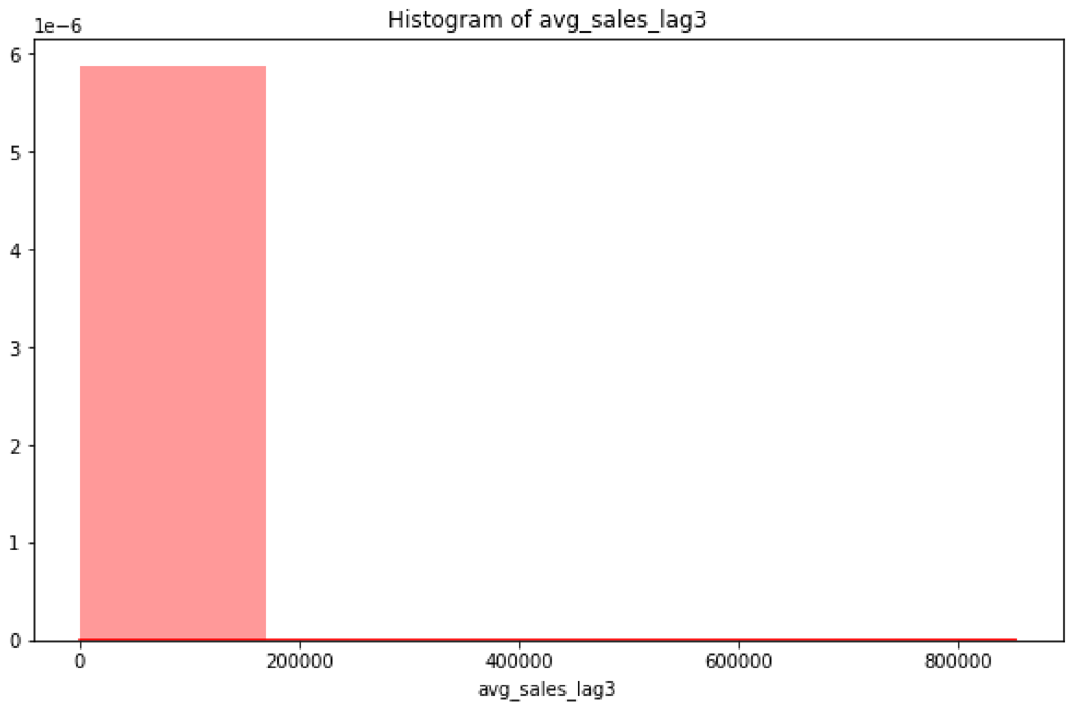
In [0]:

```
for col in ['avg_sales_lag3', 'avg_sales_lag6', 'avg_sales_lag12']:
    print(f'Max value of {col} is {merch[col].max()}')
    print(f'Min value of {col} is {merch[col].min()}')
```

```
Max value of avg_sales_lag3 is 851844.64
Min value of avg_sales_lag3 is -82.13
Max value of avg_sales_lag6 is 1513959.0
Min value of avg_sales_lag6 is -82.13
Max value of avg_sales_lag12 is 2567408.0
Min value of avg_sales_lag12 is -82.13
```

In [0]:

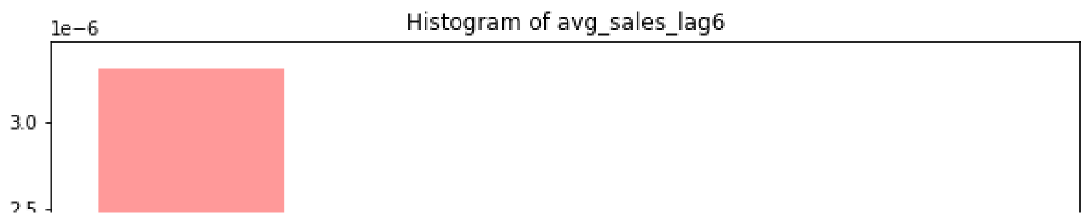
```
plt.figure(figsize=(10,6))
sns.distplot(merch['avg_sales_lag3'].values, bins=5, color="red")
plt.title("Histogram of avg_sales_lag3")
plt.xlabel('avg_sales_lag3', fontsize=10)
plt.show()
```

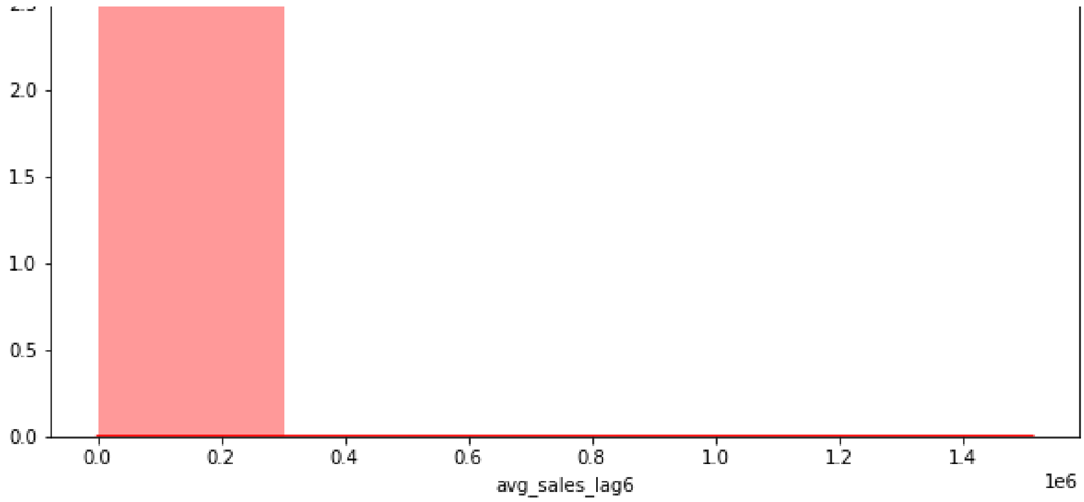


avg_sales_lag6

In [0]:

```
plt.figure(figsize=(10,6))
sns.distplot(merch['avg_sales_lag6'].values, bins=5, color="red")
plt.title("Histogram of avg_sales_lag6")
plt.xlabel('avg_sales_lag6', fontsize=10)
plt.show()
```

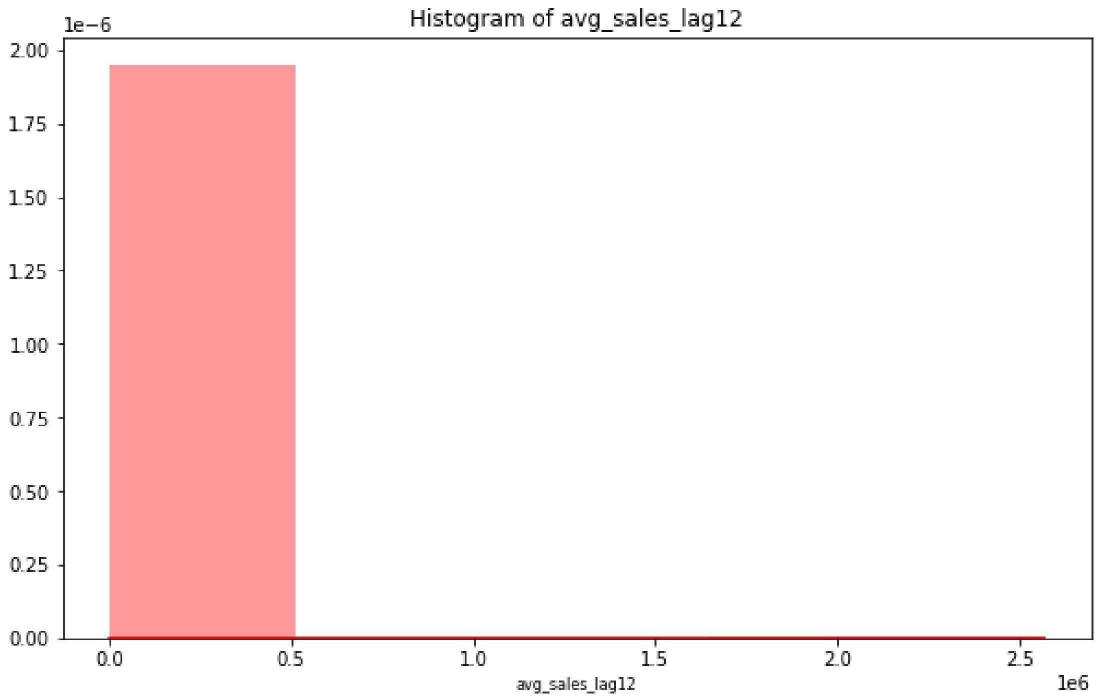




avg_sales_lag12

In [0]:

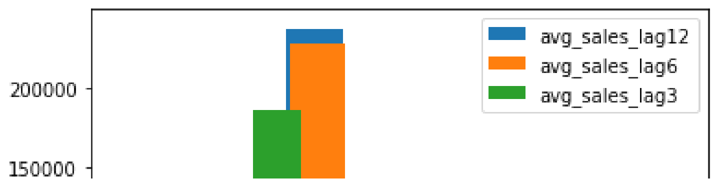
```
plt.figure(figsize=(10,6))
sns.distplot(merch['avg_sales_lag12'].values, bins=5, color="red")
plt.title("Histogram of avg_sales_lag12")
plt.xlabel('avg_sales_lag12', fontsize=8)
plt.show()
```

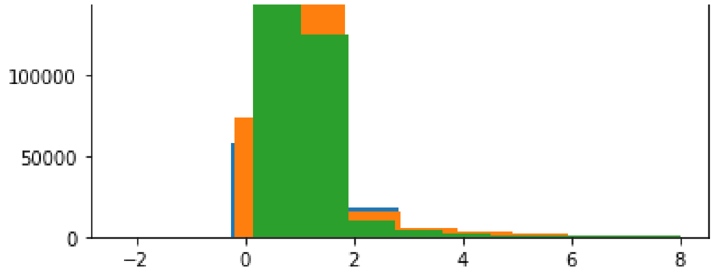


data in the columns of `avg_sales_lag12`, `avg_sales_lag3` & `avg_sales_lag6` are Normalised.

In [0]:

```
#https://www.kaggle.com/artgor/elo-eda-and-models
plt.hist(merch.loc[(merch['avg_sales_lag12'] < 8) & (merch['avg_sales_lag12'] > -10), 'a
vg_sales_lag12'], label='avg_sales_lag12');
plt.hist(merch.loc[(merch['avg_sales_lag6'] < 8) & (merch['avg_sales_lag6'] > -10), 'avg
_sales_lag6'], label='avg_sales_lag6');
plt.hist(merch.loc[(merch['avg_sales_lag3'] < 8) & (merch['avg_sales_lag3'] > -10), 'avg
_sales_lag3'], label='avg_sales_lag3');
plt.legend();
```





More or less, all the distributions looks similar(each feature is overlapping with each other).

avg_purchases_lag

`avg_purchases_lag3`, `avg_purchases_lag6` & `avg_purchases_lag12`

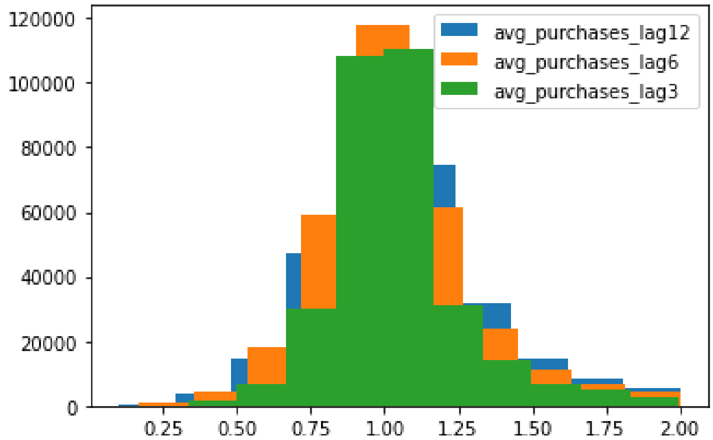
In [0]:

```
for col in ['avg_purchases_lag3', 'avg_purchases_lag6', 'avg_purchases_lag12']:
    print(f'Max value of {col} is {merch[col].max()}')
    print(f'Min value of {col} is {merch[col].min()}')
```

```
Max value of avg_purchases_lag3 is inf
Min value of avg_purchases_lag3 is 0.33349533
Max value of avg_purchases_lag6 is inf
Min value of avg_purchases_lag6 is 0.16704466
Max value of avg_purchases_lag12 is inf
Min value of avg_purchases_lag12 is 0.09832954
```

In [0]:

```
plt.hist(merch.loc[(merch['avg_purchases_lag12'] < 2), 'avg_purchases_lag12'], label='av
g_purchases_lag12');
plt.hist(merch.loc[(merch['avg_purchases_lag6'] < 2), 'avg_purchases_lag6'], label='avg_
purchases_lag6');
plt.hist(merch.loc[(merch['avg_purchases_lag3'] < 2), 'avg_purchases_lag3'], label='avg_
purchases_lag3');
plt.legend();
```



Even all the distributions looks similar.

Therefore, all the distributions of features looks similar and we can ignore the merchant file for not further adding to the existing train and test files. By adding Merchant file in to the train and test dataset will be not be effective in deciding the predicted value.

Why we are not considering the features ?

Each independent feature should be different to each other to predict an output and also it is very important in playing a significant role in `feature selection`**.**