Untitled

August 26, 2019

1 IEEE-CIS Fraud Detection

Can you detect fraud from customer transactions?

- In this problem, we have the to train a model to spot fraudulent activity using feature-rich data based on real-world e-commerce transactions.

2 Data Description

In this problem we are predicting the probability that an online transaction is fraudulent, as denoted by the binary target isFraud.

The data is broken into two files identity and transaction, which are joined by TransactionID. Not all transactions have corresponding identity information. Categorical Features - Transaction

```
ProductCD
card1 - card6
addr1, addr2
P_emaildomain
R_emaildomain
M1 - M9
```

Categorical Features - Identity

```
DeviceType
DeviceInfo
id_12 - id_38
```

The TransactionDT feature is a timedelta from a given reference datetime (not an actual timestamp). Files

```
train_{transaction, identity}.csv - the training set
test_{transaction, identity}.csv - the test set (you must predict the isFraud value for these o
sample_submission.csv - a sample submission file in the correct format
```

3 Various columns present in each Table

3.0.1 Transaction Table

Transaction Table

- TransactionDT: timedelta from a given reference datetime (not an actual timestamp)
- TransactionAMT: transaction payment amount in USD
- ProductCD: product code, the product for each transaction
- card1 - card6: payment card information, such as card type, card category, issue bank, country, etc.
- addr: address
- dist: distance
- P_ and (R__) emaildomain: purchaser and recipient email domain
- C1-C14: counting, such as how many addresses are found to be associated with the payment card, etc. The actual meaning is masked.
- D1-D15: timedelta, such as days between previous transaction, etc.
- M1-M9: match, such as names on card and address, etc.
- Vxxx: Vesta engineered rich features, including ranking, counting, and other entity relations.

Categorical Features:

- ProductCD
- card1 - card6
- addr1, addr2
- Pemaildomain Remaildomain
- M1 - M9

3.0.2 Identity Table

Identity Table

Variables in this table are identity information – network connection information (IP, ISP, Proxy, etc) and digital signature (UA/browser/os/version, etc) associated with transactions. They're collected by Vesta's fraud protection system and digital security partners. (The field names are masked and pairwise dictionary will not be provided for privacy protection and contract agreement)

Categorical Features:

- DeviceType
- DeviceInfo
- id12 - id38

In [1]:
```
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")

import numpy as np
```

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
from sklearn import metrics, preprocessing
from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler, RobustScaler
from tqdm import tqdm


from plotly import plotly
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
```

4 1.1 Reading Data

This function as it's name suggests is used for reducing the memory used for storing a dataframe while it's is use. So while the dataframe is loaded in the memory it's is stored in a such a way that it uses less memory.

```
In [3]: # reduce memory ussage kaggle      ------------------>     https://www.kaggle.com/gemar
        def reduce_mem_usage(df):
            """ iterate through all the columns of a dataframe and modify the data type
                to reduce memory usage.
            """
            start_mem = df.memory_usage().sum() / 1024**2

            for col in df.columns:
                col_type = df[col].dtype

                if col_type != object:
                    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).
                        #    df[col] = df[col].astype(np.float16)
```

```
                #el
                if c_min > np.finfo(np.float32).min and c_max < np.finfo(np.float32).ma
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)
        #else:
            #df[col] = df[col].astype('category')

    end_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage of dataframe is {:.2f} MB --> {:.2f} MB (Decreased by {:.1f}%)
        start_mem, end_mem, 100 * (start_mem - end_mem) / start_mem))
    return df

def import_data(file):
    """create a dataframe and optimize its memory usage"""
    df = pd.read_csv(file, parse_dates=True, keep_date_col=True)
    df = reduce_mem_usage(df)
    return df
```

In [4]:
```
%%time
# reading data from the csv files those are provided to us
# we have different files for train and test data and also we have two different fiels
# one is trasanction table and the other one is identity table


####################################### transaction ##################################
train_transact = import_data('train_transaction.csv')
test_transact  = import_data('test_transaction.csv')

####################################### identity #####################################
train_ident = import_data('train_identity.csv')
test_ident  = import_data('test_identity.csv')
```

```
Memory usage of dataframe is 1775.15 MB --> 916.30 MB (Decreased by 48.4%)
Memory usage of dataframe is 1519.24 MB --> 785.71 MB (Decreased by 48.3%)
Memory usage of dataframe is 45.12 MB --> 31.91 MB (Decreased by 29.3%)
Memory usage of dataframe is 44.39 MB --> 31.40 MB (Decreased by 29.3%)
Wall time: 7min 1s
```

Above we can see that for storing transaction data almost 50% less memory is used using our reduce_mem_usage function, which is really helpful to conserve your RAM for later use.

In [5]:
```
print('Number of datapoints in train transaction :',train_transact.shape)
print('Number of datapoints in test transaction  :',test_transact.shape)
print('Number of datapoints in train identity    :',train_ident.shape)
print('Number of datapoints in test identity     :',test_ident.shape)
```

```
Number of datapoints in train transaction : (590540, 394)
Number of datapoints in test transaction  : (506691, 393)
```

```
Number of datapoints in train identity    : (144233, 41)
Number of datapoints in test identity     : (141907, 41)
```

In [6]:
```
train_transact.head()
```

Out[6]:
```
   TransactionID  isFraud  TransactionDT  TransactionAmt ProductCD  card1  \
0        2987000        0          86400            68.5         W  13926
1        2987001        0          86401            29.0         W   2755
2        2987002        0          86469            59.0         W   4663
3        2987003        0          86499            50.0         W  18132
4        2987004        0          86506            50.0         H   4497

   card2  card3       card4  card5  ...  V330  V331  V332  V333  V334 V335  \
0    NaN  150.0    discover  142.0  ...   NaN   NaN   NaN   NaN   NaN  NaN
1  404.0  150.0  mastercard  102.0  ...   NaN   NaN   NaN   NaN   NaN  NaN
2  490.0  150.0        visa  166.0  ...   NaN   NaN   NaN   NaN   NaN  NaN
3  567.0  150.0  mastercard  117.0  ...   NaN   NaN   NaN   NaN   NaN  NaN
4  514.0  150.0  mastercard  102.0  ...   0.0   0.0   0.0   0.0   0.0  0.0

  V336  V337  V338  V339
0  NaN   NaN   NaN   NaN
1  NaN   NaN   NaN   NaN
2  NaN   NaN   NaN   NaN
3  NaN   NaN   NaN   NaN
4  0.0   0.0   0.0   0.0

[5 rows x 394 columns]
```

In [7]:
```
test_transact.head()
```

Out[7]:
```
   TransactionID  TransactionDT  TransactionAmt ProductCD  card1  card2  \
0        3663549       18403224       31.950001         W  10409  111.0
1        3663550       18403263       49.000000         W   4272  111.0
2        3663551       18403310      171.000000         W   4476  574.0
3        3663552       18403310      284.950012         W  10989  360.0
4        3663553       18403317       67.949997         W  18018  452.0

   card3       card4  card5  card6  ...   V330  V331  V332  V333 V334 V335  \
0  150.0        visa  226.0  debit  ...    NaN   NaN   NaN   NaN  NaN  NaN
1  150.0        visa  226.0  debit  ...    NaN   NaN   NaN   NaN  NaN  NaN
2  150.0        visa  226.0  debit  ...    NaN   NaN   NaN   NaN  NaN  NaN
3  150.0        visa  166.0  debit  ...    NaN   NaN   NaN   NaN  NaN  NaN
4  150.0  mastercard  117.0  debit  ...    NaN   NaN   NaN   NaN  NaN  NaN

   V336  V337  V338  V339
0   NaN   NaN   NaN   NaN
1   NaN   NaN   NaN   NaN
2   NaN   NaN   NaN   NaN
```

```
3   NaN   NaN   NaN   NaN
4   NaN   NaN   NaN   NaN

[5 rows x 393 columns]
```

As above we can observe that in train_transact data set we have 394 features where as in test_transact we have 393 features, so we need to find out which column is not present in test and only present in train data set.

```
In [8]: # we are trying to find out if there is any feature which is missing in test dataset w

        [col for col in train_transact.columns if col not in test_transact.columns]

Out[8]: ['isFraud']

In [9]: train_ident.head()

Out[9]:    TransactionID  id_01     id_02  id_03  id_04  id_05  id_06  id_07  id_08  \
        0        2987004    0.0   70787.0    NaN    NaN    NaN    NaN    NaN    NaN
        1        2987008   -5.0   98945.0    NaN    NaN    0.0   -5.0    NaN    NaN
        2        2987010   -5.0  191631.0    0.0    0.0    0.0    0.0    NaN    NaN
        3        2987011   -5.0  221832.0    NaN    NaN    0.0   -6.0    NaN    NaN
        4        2987016    0.0    7460.0    0.0    0.0    1.0    0.0    NaN    NaN

           id_09            ...                            id_31  id_32  \
        0    NaN            ...                samsung browser 6.2   32.0
        1    NaN            ...                 mobile safari 11.0   32.0
        2    0.0            ...                        chrome 62.0    NaN
        3    NaN            ...                        chrome 62.0    NaN
        4    0.0            ...                        chrome 62.0   24.0

               id_33           id_34  id_35 id_36 id_37  id_38  DeviceType  \
        0  2220x1080  match_status:2      T     F     T      T      mobile
        1   1334x750  match_status:1      T     F     F      T      mobile
        2        NaN             NaN      F     F     T      T     desktop
        3        NaN             NaN      F     F     T      T     desktop
        4   1280x800  match_status:2      T     F     T      T     desktop

                             DeviceInfo
        0  SAMSUNG SM-G892A Build/NRD90M
        1                    iOS Device
        2                       Windows
        3                           NaN
        4                         MacOS

        [5 rows x 41 columns]
```

4.1 Merging both transaction and identity features

```
In [10]: train_transact_ident = pd.merge(train_transact, train_ident,how='left',on='Transactio
         test_transact_ident  = pd.merge(test_transact,  test_ident, how='left',on='Transactio
```

In [11]: train_transact_ident.shape

Out[11]: (590540, 434)

In [12]: test_transact_ident.shape

Out[12]: (506691, 433)

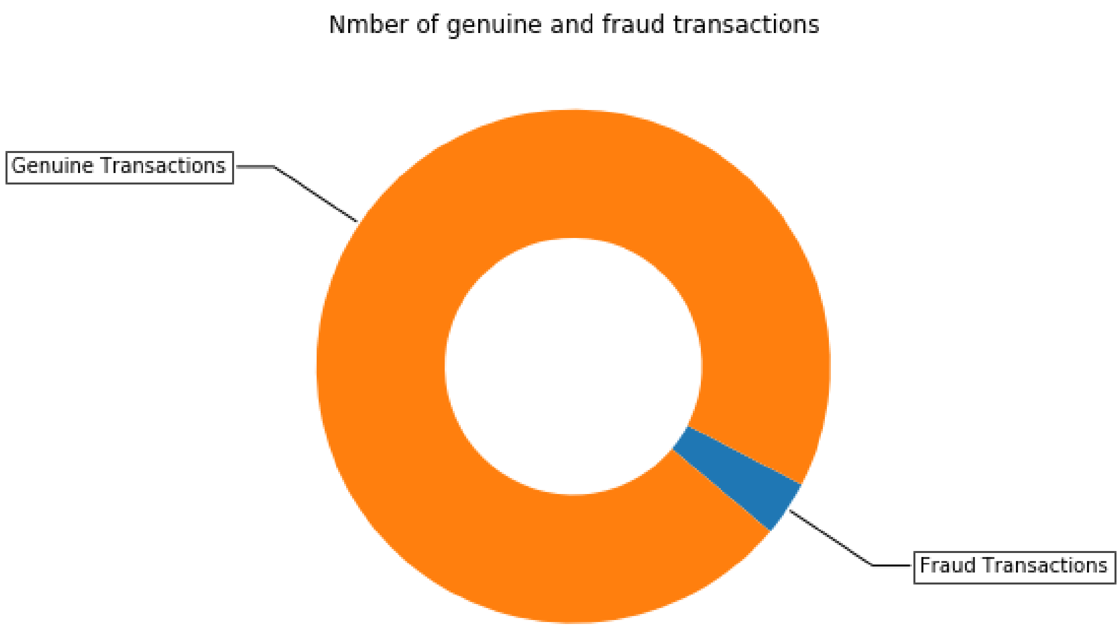
4.1.1 Freeing the space beacuse we no longer needed these as we already merged this data

In [13]:
```
del train_transact, train_ident, test_transact, test_ident
```

4.2 Data Analysis

In [14]:
```
# this code is taken from
# https://matplotlib.org/gallery/pie_and_polar_charts/pie_and_donut_labels.html#sphx-


y_value_counts = train_transact_ident['isFraud'].value_counts()
print("Number of genuine transactions: ", y_value_counts[0], ", (", (y_value_counts[0
print("Number of Fraud transactions  : ", y_value_counts[1], ", (", (y_value_counts[1

fig, ax = plt.subplots(figsize=(6, 6), subplot_kw=dict(aspect="equal"))
recipe = ["Fraud Transactions", "Genuine Transactions"]

data = [y_value_counts[1], y_value_counts[0]]

wedges, texts = ax.pie(data, wedgeprops=dict(width=0.5), startangle=-40)

bbox_props = dict(boxstyle="square,pad=0.3", fc="w", ec="k", lw=0.72)
kw = dict(xycoords='data', textcoords='data', arrowprops=dict(arrowstyle="-"),
          bbox=bbox_props, zorder=0, va="center")

for i, p in enumerate(wedges):
    ang = (p.theta2 - p.theta1)/2. + p.theta1
    y = np.sin(np.deg2rad(ang))
    x = np.cos(np.deg2rad(ang))
    horizontalalignment = {-1: "right", 1: "left"}[int(np.sign(x))]
    connectionstyle = "angle,angleA=0,angleB={}".format(ang)
    kw["arrowprops"].update({"connectionstyle": connectionstyle})
    ax.annotate(recipe[i], xy=(x, y), xytext=(1.35*np.sign(x), 1.4*y),
                horizontalalignment=horizontalalignment, **kw)

ax.set_title("Nmber of genuine and fraud transactions")

plt.show()
```

```
Number of genuine transactions:  569877 , ( 96.50099908558268 %)
Number of Fraud transactions  :  20663 , ( 3.4990009144173126 %)
```



4.2.1 One thing we can observe from this visual is our data is highly imbalanced, fraud transactions are extremely low as compared to genuine transactions(which is a good thing in general) which makes the whole data set really imbalanced.

```
In [24]: # Not all transactions have corresponding identity information.
         #len([c for c in train_trn['TransactionID'] if c not in train_id['TransactionID'].val

         # Not all fraud transactions have corresponding identity information.
         fraud_id = train_transact[train_transact['isFraud'] == 1]['TransactionID']
         fraud_id_in_trn = [i for i in fraud_id if i in train_ident['TransactionID'].values]
         print(len(fraud_id), len(fraud_id_in_trn))
```

```
20663 11318
```

4.3 Univariat Analysis

4.3.1 Transaction features

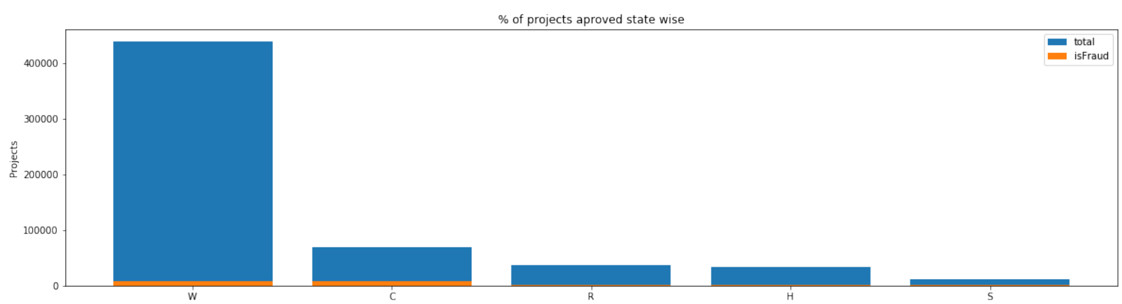
```
In [12]: #stacked bar plots matplotlib: https://matplotlib.org/gallery/lines_bars_and_markers/
         def stack_plot(data, xtick, col2='isFraud', col3='total'):
             ind = np.arange(data.shape[0])

             plt.figure(figsize=(20,5))
             p1 = plt.bar(ind, data[col3].values)
```

```
    p2 = plt.bar(ind, data[col2].values)

    plt.ylabel('Projects')
    plt.title('% of projects aproved state wise')
    plt.xticks(ind, list(data[xtick].values))
    plt.legend((p1[0], p2[0]), ('total', 'isFraud'))
    plt.show()
```

```
In [13]: def univariate_barplots(data, col1, col2='isFraud', top=False):
    # Count number of zeros in dataframe python: https://stackoverflow.com/a/51540521/
    temp = pd.DataFrame(train_transact_ident.groupby(col1)[col2].agg(lambda x: x.eq(1)

    # Pandas dataframe grouby count: https://stackoverflow.com/a/19385591/4084039
    temp['total'] = pd.DataFrame(train_transact_ident.groupby(col1)[col2].agg({'total
    temp['Avg']   = pd.DataFrame(train_transact_ident.groupby(col1)[col2].agg({'Avg':

    temp.sort_values(by=['total'],inplace=True, ascending=False)

    if top:
        temp = temp[0:top]

    stack_plot(temp, xtick=col1, col2=col2, col3='total')
    print(temp.head(5))
    print("="*50)
    print(temp.tail(5))
```

4.4 Uninvariate Analysis ProductCD

```
In [14]: univariate_barplots(train_transact_ident, 'ProductCD', 'isFraud', False)
```

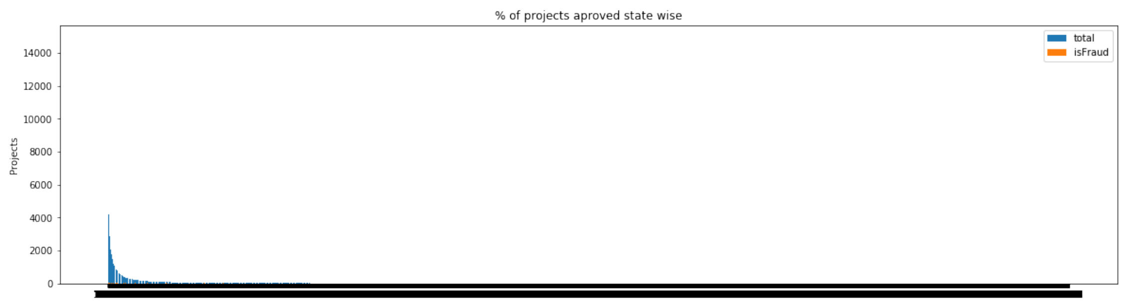



```
  ProductCD  isFraud   total       Avg
4         W     8969  439670  0.020399
0         C     8008   68519  0.116873
2         R     1426   37699  0.037826
1         H     1574   33024  0.047662
3         S      686   11628  0.058996
```

```
=====================================================
  ProductCD  isFraud   total       Avg
4         W     8969  439670  0.020399
0         C     8008   68519  0.116873
2         R     1426   37699  0.037826
1         H     1574   33024  0.047662
3         S      686   11628  0.058996
```

4.5 Uninvariate Analysis Card1

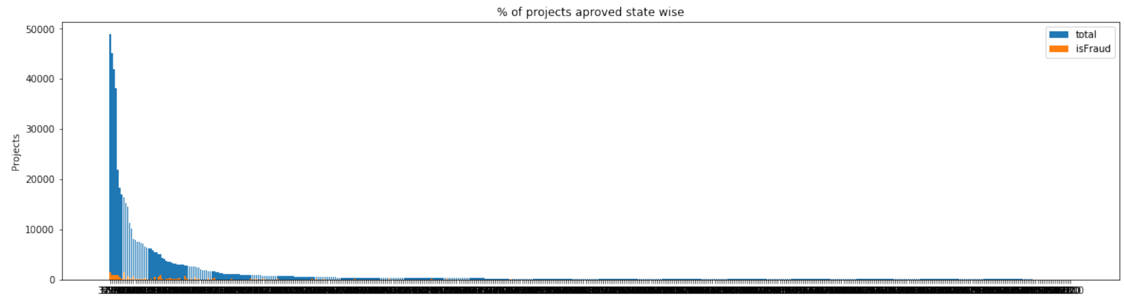
```
In [37]: univariate_barplots(train_transact_ident, 'card1', 'isFraud', False)
```




```
        card1  isFraud  total       Avg
5365     7919      112  14932  0.007501
6615     9500      528  14162  0.037283
11593   15885      444  10361  0.042853
12616   17188      278  10344  0.026875
10950   15066      313   7945  0.039396
=====================================================
        card1  isFraud  total  Avg
7157    10200        0      1  0.0
7151    10191        0      1  0.0
7148    10187        0      1  0.0
7145    10184        0      1  0.0
13552   18396        0      1  0.0
```

4.6 Uninvariate Analysis Card2

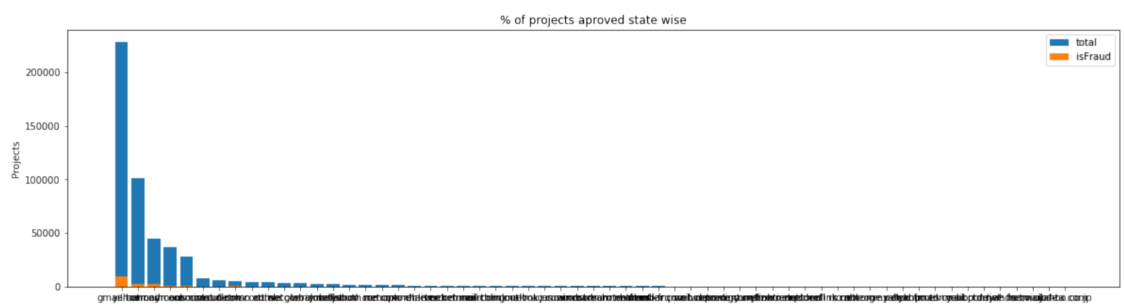
```
In [38]: univariate_barplots(train_transact_ident, 'card2', 'isFraud', False)
```




```
     card2  isFraud  total       Avg
220  321.0     1396  48935  0.028528
10   111.0      978  45191  0.021641
454  555.0      959  41995  0.022836
389  490.0      916  38145  0.024014
482  583.0      899  21803  0.041233
==================================================
     card2  isFraud  total       Avg
346  447.0        1     39  0.025641
52   153.0        0     38  0.000000
456  557.0        0     37  0.000000
372  473.0        0     18  0.000000
481  582.0        0     14  0.000000
```

4.7 Uninvariate Analysis P_emaildomain

In [39]:
```
univariate_barplots(train_transact_ident, 'P_emaildomain', 'isFraud', False)
```



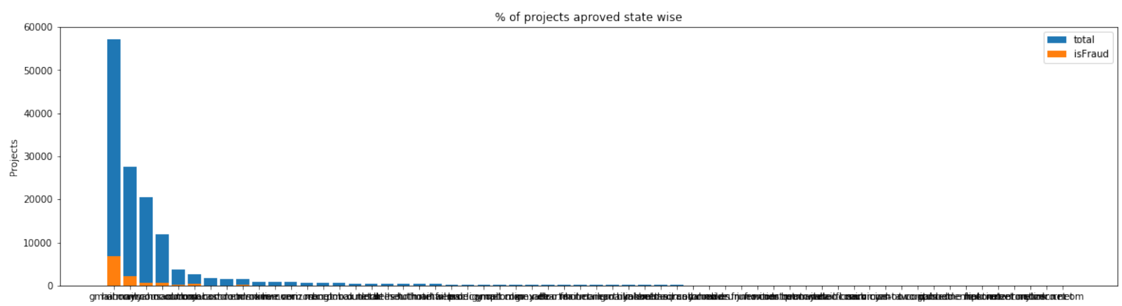

```
    P_emaildomain  isFraud   total       Avg
16      gmail.com     9943  228355  0.043542
53      yahoo.com     2297  100934  0.022757
19    hotmail.com     2396   45250  0.052950
1   anonymous.com      859   36998  0.023217
```

```
2         aol.com      617   28289  0.021811
==================================================
       P_emaildomain  isFraud  total  Avg
27           live.fr        0     56  0.0
52        yahoo.co.uk       0     49  0.0
20         hotmail.de       0     43  0.0
45   servicios-ta.com       0     35  0.0
51        yahoo.co.jp       0     32  0.0
```

- mostly used email domain from here we can see that is gmail.com, out of which 4% transactions are fraud.
- most number of fraud transactions are seem to use hotmail.com as their email domain.

4.8 Uninvariate Analysis R_emaildomain

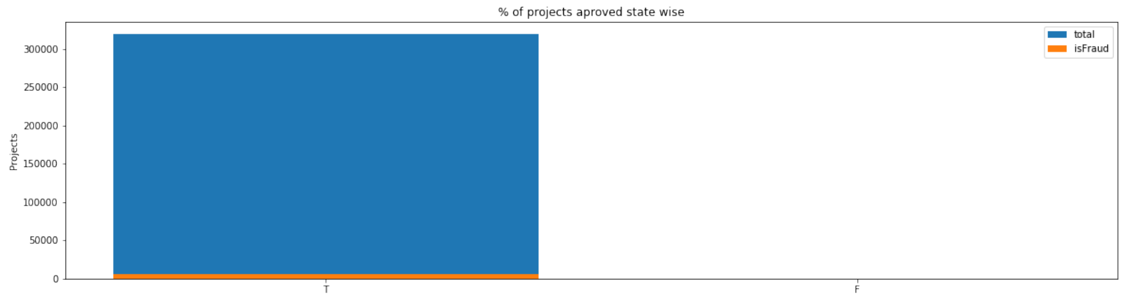
```
In [40]: univariate_barplots(train_transact_ident, 'R_emaildomain', 'isFraud', False)
```




```
    R_emaildomain  isFraud  total       Avg
16      gmail.com     6811  57147  0.119184
19    hotmail.com     2140  27509  0.077793
1   anonymous.com      598  20529  0.029130
54      yahoo.com      610  11842  0.051512
2         aol.com      129   3701  0.034855
==================================================
      R_emaildomain  isFraud  total       Avg
14  frontiernet.net        0     14  0.000000
32      netzero.com        0     14  0.000000
6   centurylink.net        0     12  0.000000
33      netzero.net        2      9  0.222222
44        sc.rr.com        0      8  0.000000
```

4.9 Univariate Analysis M1

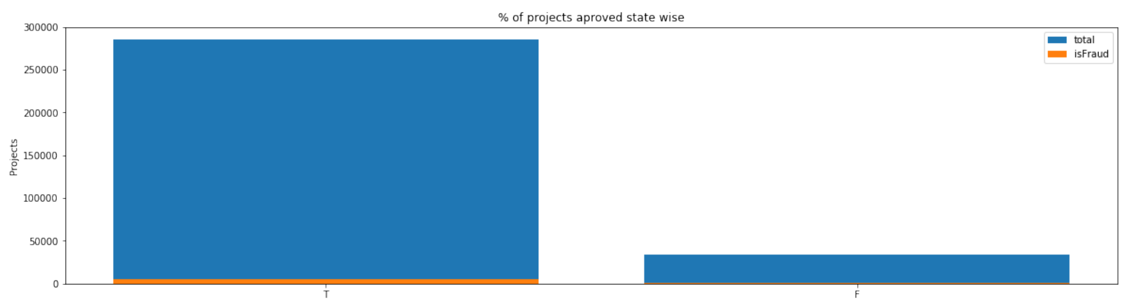
```
In [42]: univariate_barplots(train_transact_ident, 'M1', 'isFraud', False)
```




```
  M1  isFraud   total       Avg
1  T     6342  319415  0.019855
0  F        0      25  0.000000
==================================================
  M1  isFraud   total       Avg
1  T     6342  319415  0.019855
0  F        0      25  0.000000
```

4.10 Univariate Analysis M2

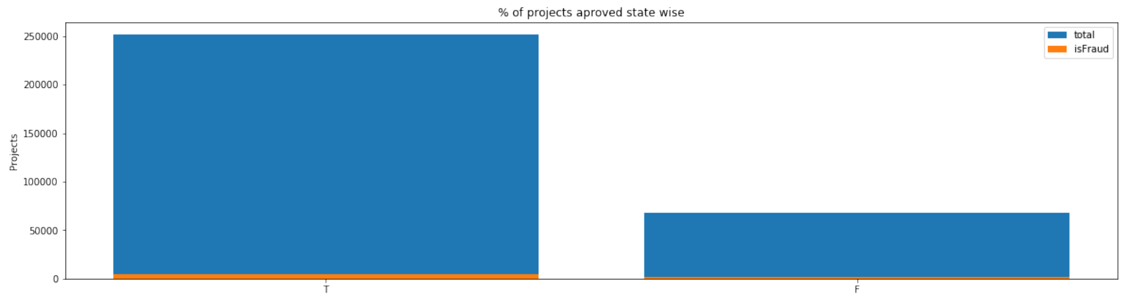
```
In [43]: univariate_barplots(train_transact_ident, 'M2', 'isFraud', False)
```




```
  M2  isFraud   total       Avg
1  T     5158  285468  0.018069
0  F     1184   33972  0.034852
==================================================
  M2  isFraud   total       Avg
1  T     5158  285468  0.018069
0  F     1184   33972  0.034852
```

4.11 Univariate Analysis M3

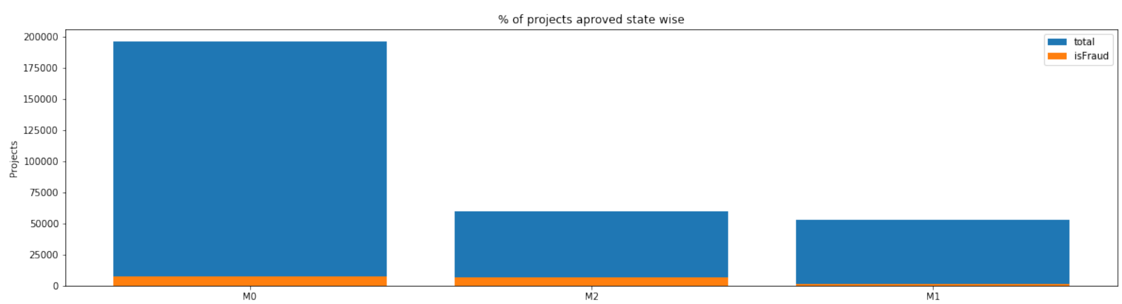
```
In [44]: univariate_barplots(train_transact_ident, 'M3', 'isFraud', False)
```




```
  M3  isFraud   total       Avg
1  T     4293  251731  0.017054
0  F     2049   67709  0.030262
==================================================
  M3  isFraud   total       Avg
1  T     4293  251731  0.017054
0  F     2049   67709  0.030262
```

4.12 Univariate Analysis M4

```
In [45]: univariate_barplots(train_transact_ident, 'M4', 'isFraud', False)
```

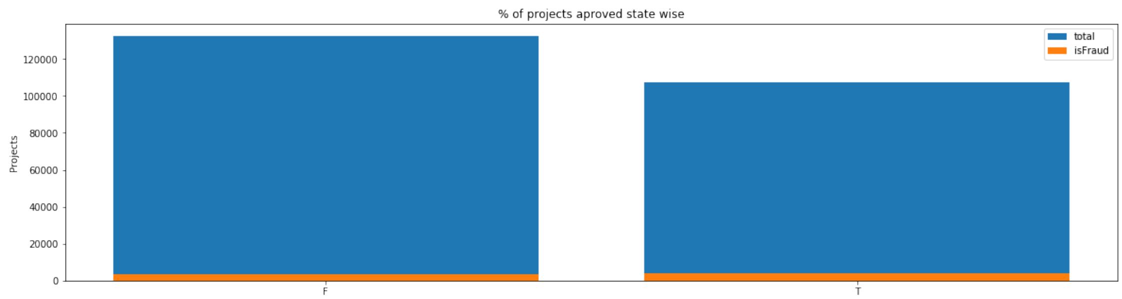



```
   M4  isFraud   total       Avg
0  M0     7198  196405  0.036649
2  M2     6809   59865  0.113739
1  M1     1429   52826  0.027051
==================================================
   M4  isFraud   total       Avg
0  M0     7198  196405  0.036649
```

```
2  M2      6809    59865   0.113739
1  M1      1429    52826   0.027051
```

4.13 Univariate Analysis M5

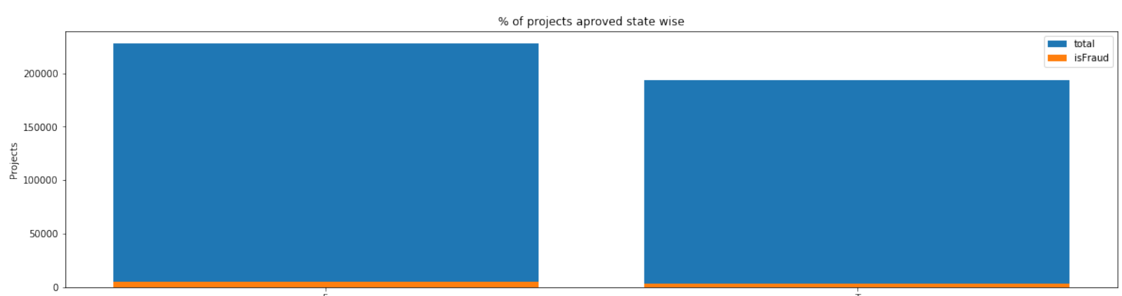
```
In [46]: univariate_barplots(train_transact_ident, 'M5', 'isFraud', False)
```




```
  M5  isFraud   total       Avg
0  F     3514  132491  0.026523
1  T     4055  107567  0.037697
==================================================
  M5  isFraud   total       Avg
0  F     3514  132491  0.026523
1  T     4055  107567  0.037697
```

4.14 Univariate Analysis M6

```
In [47]: univariate_barplots(train_transact_ident, 'M6', 'isFraud', False)
```

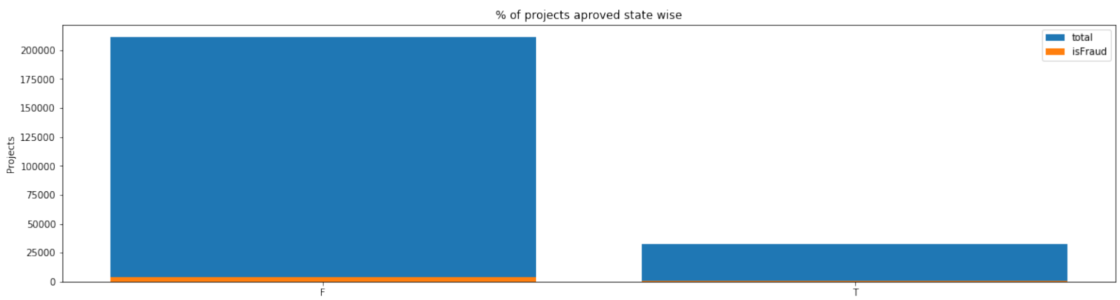



```
  M6  isFraud   total       Avg
0  F     5397  227856  0.023686
1  T     3295  193324  0.017044
```

```
==================================================
  M6  isFraud   total       Avg
0  F     5397  227856  0.023686
1  T     3295  193324  0.017044
```

4.15 Univariate Analysis M7

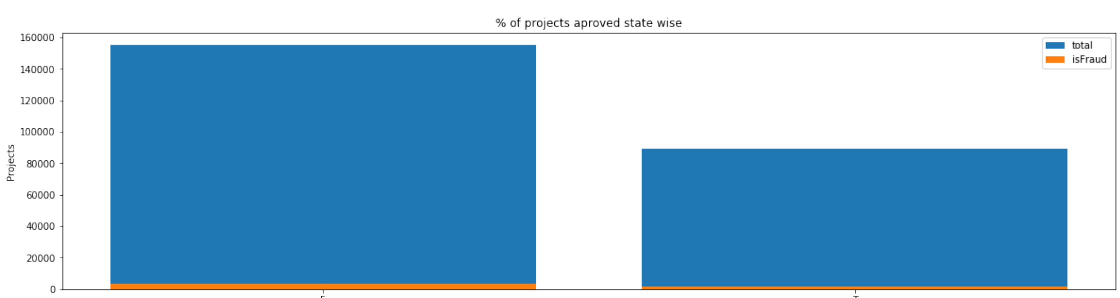
```
In [48]: univariate_barplots(train_transact_ident, 'M7', 'isFraud', False)
```




```
  M7  isFraud   total       Avg
0  F     4089  211374  0.019345
1  T      728   32901  0.022127
==================================================
  M7  isFraud   total       Avg
0  F     4089  211374  0.019345
1  T      728   32901  0.022127
```

4.16 Univariate Analysis M8

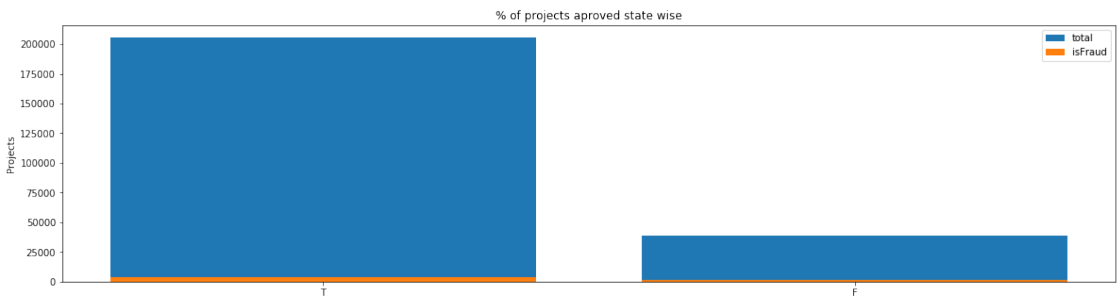
```
In [49]: univariate_barplots(train_transact_ident, 'M8', 'isFraud', False)
```



```
  M8  isFraud   total       Avg
0  F     3373  155251  0.021726
1  T     1444   89037  0.016218
==================================================
  M8  isFraud   total       Avg
0  F     3373  155251  0.021726
1  T     1444   89037  0.016218
```

4.17 Univariate Analysis M9

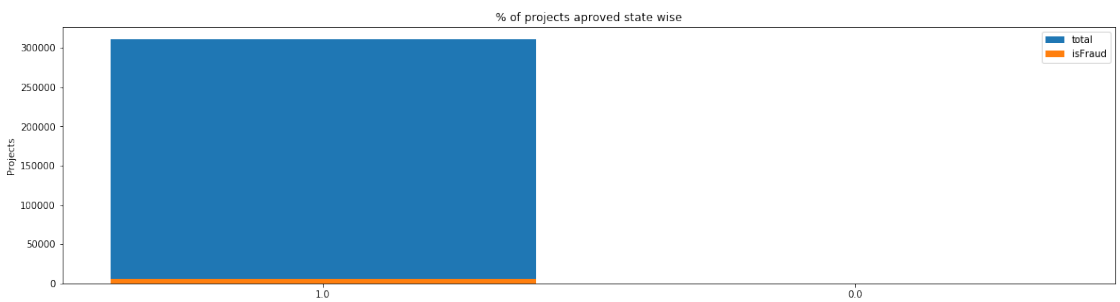
```
In [50]: univariate_barplots(train_transact_ident, 'M9', 'isFraud', False)
```




```
  M9  isFraud   total       Avg
1  T     3658  205656  0.017787
0  F     1159   38632  0.030001
==================================================
  M9  isFraud   total       Avg
1  T     3658  205656  0.017787
0  F     1159   38632  0.030001
```

4.18 Univariate Analysis V1

```
In [51]: univariate_barplots(train_transact_ident, 'V1', 'isFraud', False)
```



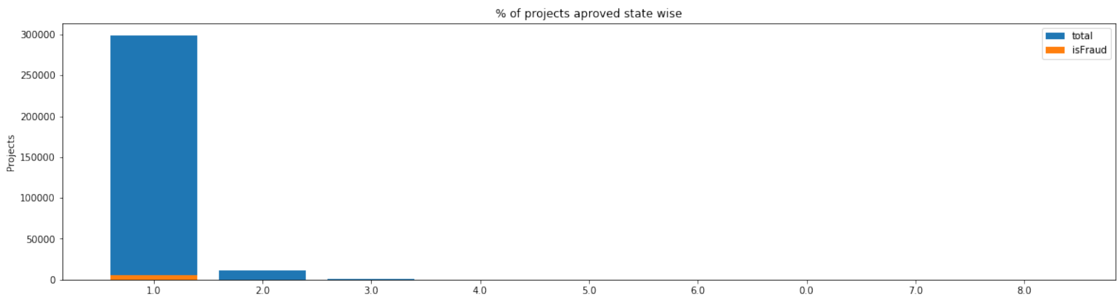
	V1	isFraud	total	Avg
1	1.0	6106	311236	0.019619
0	0.0	0	17	0.000000

==

	V1	isFraud	total	Avg
1	1.0	6106	311236	0.019619
0	0.0	0	17	0.000000

4.19 Univariate Analysis V2

```
In [52]: univariate_barplots(train_transact_ident, 'V2', 'isFraud', False)
```



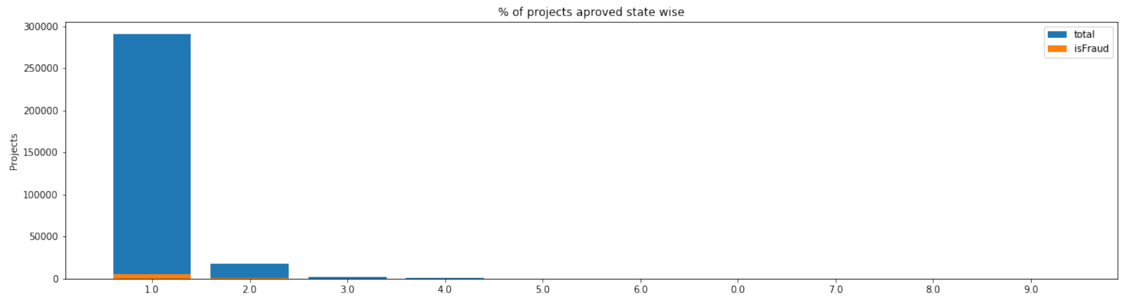
	V2	isFraud	total	Avg
1	1.0	5717	298894	0.019127
2	2.0	330	10926	0.030203
3	3.0	44	1181	0.037257
4	4.0	5	163	0.030675
5	5.0	1	36	0.027778

==

	V2	isFraud	total	Avg
5	5.0	1	36	0.027778
6	6.0	9	30	0.300000
0	0.0	0	20	0.000000
7	7.0	0	2	0.000000
8	8.0	0	1	0.000000

4.20 Univariate Analysis V3

```
In [53]: univariate_barplots(train_transact_ident, 'V3', 'isFraud', False)
```



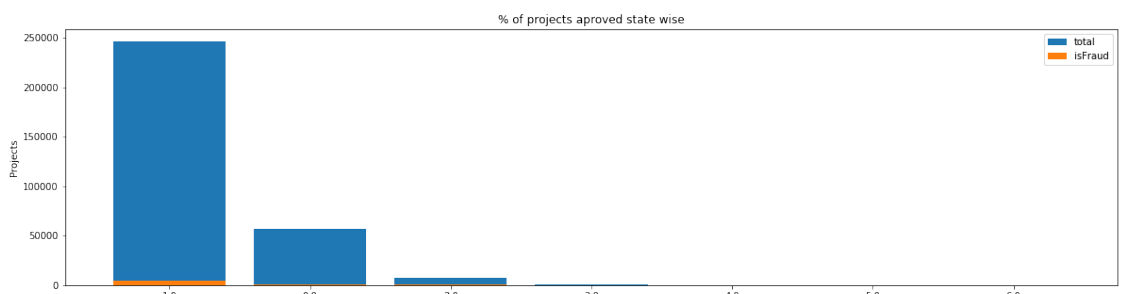
	V3	isFraud	total	Avg
1	1.0	5249	290583	0.018064
2	2.0	631	17763	0.035523
3	3.0	182	2335	0.077944
4	4.0	25	403	0.062035
5	5.0	10	93	0.107527

==

	V3	isFraud	total	Avg
6	6.0	5	34	0.147059
0	0.0	0	20	0.000000
7	7.0	4	18	0.222222
8	8.0	0	3	0.000000
9	9.0	0	1	0.000000

4.21 Univariate Analysis V4

```
In [54]: univariate_barplots(train_transact_ident, 'V4', 'isFraud', False)
```

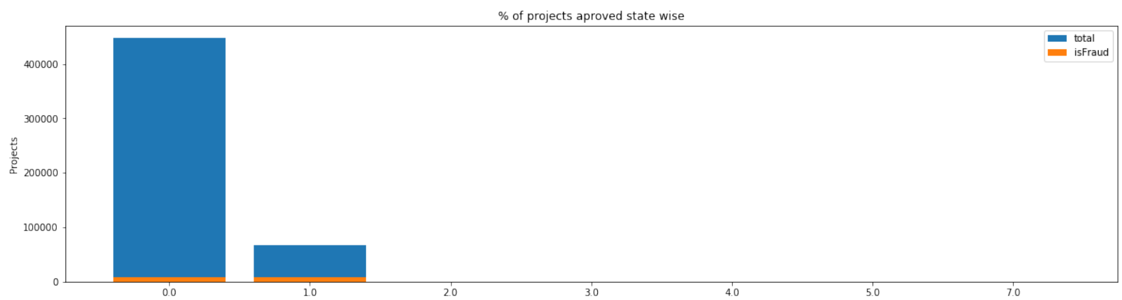


	V4	isFraud	total	Avg
1	1.0	4620	246500	0.018742
0	0.0	1113	56687	0.019634
2	2.0	343	7385	0.046445
3	3.0	18	564	0.031915

```
4   4.0       12      88   0.136364
==================================================
    V4  isFraud  total       Avg
2  2.0      343   7385  0.046445
3  3.0       18    564  0.031915
4  4.0       12     88  0.136364
5  5.0        0     26  0.000000
6  6.0        0      3  0.000000
```

4.22 Univariate Analysis V33

```
In [32]: univariate_barplots(train_transact_ident, 'V33', 'isFraud', False)
```

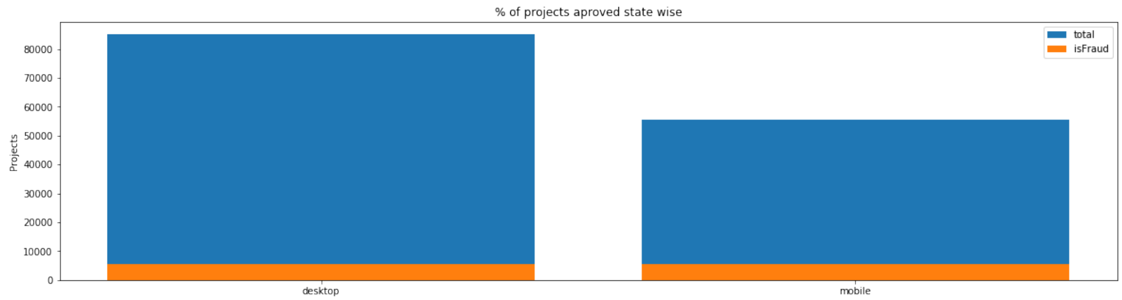



```
   V33  isFraud   total       Avg
0  0.0     9000  447769  0.020100
1  1.0     7672   66267  0.115774
2  2.0       79     338  0.233728
3  3.0       23      82  0.280488
4  4.0        1       9  0.111111
==================================================
   V33  isFraud  total       Avg
2  2.0       79    338  0.233728
3  3.0       23     82  0.280488
4  4.0        1      9  0.111111
5  5.0        1      1  1.000000
6  7.0        0      1  0.000000
```

4.22.1 Identity features

4.23 Univariate Analysis DeviceType

```
In [39]: univariate_barplots(train_transact_ident, 'DeviceType', 'isFraud', False)
```

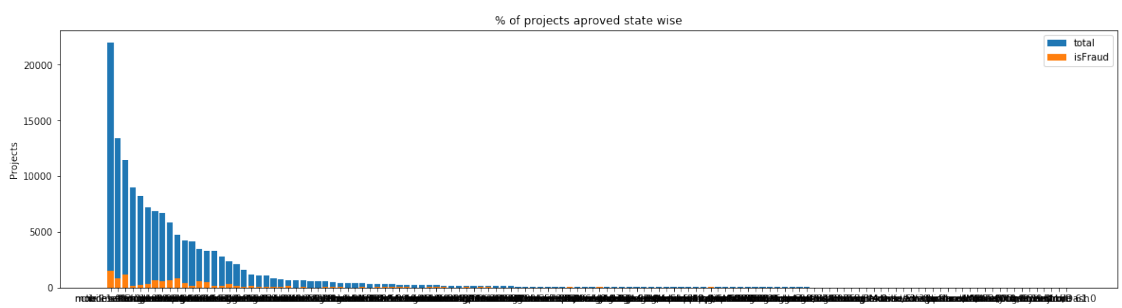



```
  DeviceType  isFraud  total       Avg
0    desktop     5554  85165  0.065215
1     mobile     5657  55645  0.101662
==================================================
  DeviceType  isFraud  total       Avg
0    desktop     5554  85165  0.065215
1     mobile     5657  55645  0.101662
```

4.23.1 Here we can observe that more number of fraud transactions are recorded if you are using mobile devices as compared as on desktop.

4.24 Univariate Analysis id_31

```
In [16]: univariate_barplots(train_transact_ident, 'id_31', 'isFraud', False)
```




```
                        id_31  isFraud  total       Avg
47                chrome 63.0     1503  22000  0.068318
98         mobile safari 11.0      842  13423  0.062728
101     mobile safari generic     1146  11474  0.099878
91        ie 11.0 for desktop      175   9030  0.019380
116            safari generic      205   8195  0.025015
==================================================
                  id_31  isFraud  total  Avg
```

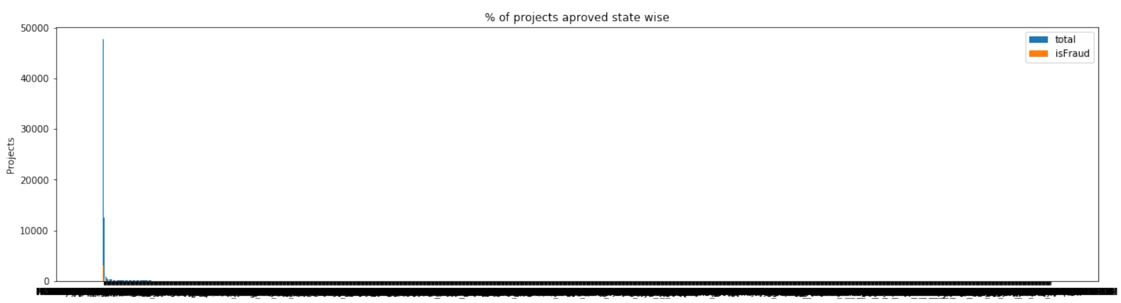
1	Cherry	0	1	0.0
66	cyberfox	0	1	0.0
85	firefox mobile 61.0	0	1	0.0
93	iron	0	1	0.0
0	BLU/Dash	0	1	0.0

4.24.1 So this shows chrome and safari browsers are not so secure browsers as most number of frauds are there while using chrome and safari browsers

4.24.2 firefox is more secure browser

4.25 Univariate Analysis DeviceInfo

```
In [40]: univariate_barplots(train_transact_ident, 'DeviceInfo', 'isFraud', False)
```



	DeviceInfo	isFraud	total	Avg
1598	Windows	3121	47722	0.065400
1727	iOS Device	1240	19782	0.062683
723	MacOS	278	12573	0.022111
1552	Trident/7.0	96	7440	0.012903
1743	rv:11.0	76	1901	0.039979

==

	DeviceInfo	isFraud	total	Avg
889	QwestIE8	0	1	0.0
892	R8106	0	1	0.0
1	0PJA2	0	1	0.0
899	RCT6K03W13	0	1	0.0
1785	xs-Z47b7VqTMxs	0	1	0.0

4.25.1 Windows and iOS devices are more prone to fraud transactions as compared to linux and unix devices

5 Model

```
In [15]: train_transact_ident.shape
```

```
Out[15]: (590540, 434)

In [13]: test_transact_ident.shape

Out[13]: (506691, 433)

In [17]: x_train.shape

Out[17]: (590540, 433)

In [16]: x_train = train_transact_ident[train_transact_ident['isFraud'].notnull()]
         x_test = test_transact_ident
         y_train = x_train.pop('isFraud')
         del train_transact_ident

In [20]: drop_lst = ['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain', 'M1', 'M

In [21]: x_train = x_train.drop(['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomai

In [22]: x_test = x_test.drop(['ProductCD', 'card4', 'card6', 'P_emaildomain', 'R_emaildomain'

In [23]: print(x_train.shape)
         print(x_test.shape)

(590540, 402)
(506691, 402)


In [21]: import lightgbm as lgb

In [ ]: params={'learning_rate': 0.04,
                'feature_fraction': 0.6
                'num_leaves': 64,
                'metric':'auc',
                'objective':'binary',
                'random_state':42,
                'num_threads': -1,
                'bagging_fraction': 1,
                'verbose': 1,
               }

        oof_preds = np.zeros(x_train.shape[0])
        sub_preds = np.zeros(x_test.shape[0])


        skf = StratifiedKFold(n_splits=6, random_state=42)
        for train_index, test_index in skf.split(x_train, y_train):
            clf = lgb.LGBMClassifier(**params, n_estimators=3000)
            clf.fit(x_train.iloc[train_index], y_train.iloc[train_index],
                    eval_set=[(x_train.iloc[test_index], y_train.iloc[test_index])], verbose=5
```

```
            oof_preds[test_index] = clf.predict_proba(x_train.iloc[test_index])[:,1]
            sub_preds += clf.predict_proba(x_test)[:,1] / skf.n_splits

        _='''
        clf = lgb.LGBMClassifier(**params, n_estimators=5000)
        clf.fit(X_train, Y_train, verbose=100)
        oof_preds = clf.predict_proba(X_train, num_iteration=clf.best_iteration_)[:,1]
        sub_preds = clf.predict_proba(X_test, num_iteration=clf.best_iteration_)[:,1]
        '''
```

```
[500]	valid_0's auc: 0.86869
[1000]	valid_0's auc: 0.860024
[1500]	valid_0's auc: 0.855093
[2000]	valid_0's auc: 0.854035
[2500]	valid_0's auc: 0.849607
[3000]	valid_0's auc: 0.847196
```