Credit Card Fraud - Prevention through Data Science

Team 3 - Brianne Bell, Michael Nguyen, and Dave Friesen
ADS-505-02-FA22

GitHub link: https://github.com/davefriesen/cc-fraud-prevention

In [1]:
```
__authors__ = ['Brianne Bell', 'Michael Nguyen', 'Dave Friesen']
__contact__ = ['bbell@sandiego.edu', 'michaelnguyen@sandiego.edu', 'dfriesen@sandiego.edu']
__date__ = '2022-10-17'
__license__ = 'MIT'
__version__ = '1.0.0'
```

Setup

In [50]:
```
# Set working directory for 'custom' (profiler, model_process) .py find and data access
#   UNIQUE TO COLLABORATOR
import os, sys

#src_dir = 'C:/Users/breel.B-E-BELL/OneDrive/Documents/USD_MastersAppliedDataScience/ADS-505 ADSforBusiness/Fi
#data_dir = 'C:/Users/breel.B-E-BELL/OneDrive/Documents/USD_MastersAppliedDataScience/ADS-505 ADSforBusiness/F

src_dir = '/Users/davidfriesen/Desktop/OneDrive/projects/cc-fraud-protection/src'
data_dir = '/Users/davidfriesen/Desktop/OneDrive/projects/cc-fraud-protection/data/'

sys.path.append(src_dir)
os.chdir(data_dir)
```

In [55]:
```
# Import basic libraries
import numpy as np
import pandas as pd

# Import visualization libraries
import matplotlib.pyplot as plt
%matplotlib inline
from dmba import gainsChart

# Import custom EDA library
from profiler import profile, profile_cat

# Import model and performance evaluation libraries
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LogisticRegression, Perceptron
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.svm import LinearSVC

from sklearn.neighbors import KNeighborsClassifier

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier

from sklearn.neural_network import MLPClassifier

# Import custom model library
from model_process import ModelProcess

# Import utility libraries
import copy
from utils import ctrl_count
```

In [56]:
```
# Set basic np, pd, and plt output defaults (keeping this code 'clean')
%run -i '{src_dir}/defaults.py'
```

Set simple notebook style and auto-avoid scrollable output windows

In [5]:
```
%%html
<style>
    h1, h2 {font-size: 0.9em; color: #0070c0;}
    h1, h2, h3 {line-height: 1.2em !important; margin-top: 2em !important;}
    h4, p {font-size: 1.2em !important; line-height: 1.2em !important;}
</style>
```

In [6]:
```
%%javascript
    IPython.OutputArea.prototype._should_scroll = function(lines) {
        return false;
    }
```

Data Load and Validation

Fraud e-commerce: 'Fraud_Data' and 'IpAddress_to_Country'

In [7]:
```
# Ref: https://www.kaggle.com/datasets/vbinh002/fraud-ecommerce?resource=download

# Create and confirm fraud dataframe
fraud_fname = data_dir + 'c-Fraud_Data.csv'
fraud_ctrl = ctrl_count(fraud_fname)
fraud_df = pd.read_csv(fraud_fname, on_bad_lines = 'skip', low_memory = False)

print('\nFraud: file=%0d, import=%0d, delta=%0d' %
      (fraud_ctrl, len(fraud_df), fraud_ctrl - len(fraud_df)))
print('\nFraud rows, columns: ', fraud_df.shape)
print('\nFraud dataframe:'); __ = fraud_df.info()
print('\nFraud data:\n', fraud_df.head(5))

# Dataframe comparision e.g., if have sep training/test sets - n/a here
#print('\nSame? ', np.array_equal(fundr_df.columns, ffundr_df.columns))
```

```
Fraud: file=151113, import=151112, delta=1

Fraud rows, columns:  (151112, 11)

Fraud dataframe:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 151112 entries, 0 to 151111
Data columns (total 11 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   user_id         151112 non-null  int64
 1   signup_time     151112 non-null  object
 2   purchase_time   151112 non-null  object
 3   purchase_value  151112 non-null  int64
 4   device_id       151112 non-null  object
 5   source          151112 non-null  object
 6   browser         151112 non-null  object
 7   sex             151112 non-null  object
 8   age             151112 non-null  int64
 9   ip_address      151112 non-null  float64
 10  class           151112 non-null  int64
dtypes: float64(1), int64(4), object(6)
memory usage: 12.7+ MB

Fraud data:
    user_id      signup_time         purchase_time      purchase_value   device_id    source browser sex  age
ip_address   class
0   22058   2015-02-24 22:55:49  2015-04-18 02:47:11        34        QVPSPJUOCKZAR   SEO   Chrome   M  39   73
2758368.80     0
1   333320   2015-06-07 20:39:50  2015-06-08 01:38:54        16        EOGFQPIZPYXFZ   Ads   Chrome   F  53   35
0311387.87     0
2    1359   2015-01-01 18:52:44  2015-01-01 18:52:45        15        YSSKYOSJHPPLJ   SEO    Opera   M  53  262
1473820.11     1
3   150084   2015-04-28 21:13:25  2015-05-04 13:54:50        44        ATGTXKYKUDUQN   SEO   Safari   M  41  384
0542443.91     0
4   221365   2015-07-21 07:09:52  2015-09-09 18:40:53        39        NAUITBZFJKHWW   Ads   Safari   M  45   41
5583117.45     0
```

In [8]:
```
# Ref: https://www.kaggle.com/datasets/vbinh002/fraud-ecommerce?resource=download

# Create and confirm IP dataframe
ip_fname = data_dir + 'c-IpAddress_to_Country.csv'
ip_ctrl = ctrl_count(ip_fname)
ip_df = pd.read_csv(ip_fname, on_bad_lines = 'skip', low_memory = False)

print('\n\nIP: file=%0d, import=%0d, delta=%0d' %
      (ip_ctrl, len(ip_df), ip_ctrl - len(ip_df)))
print('\nIP rows, columns: ', ip_df.shape)
print('\nIP dataframe:'); __ = ip_df.info()
print('\nIP data:\n', ip_df.head(5))
```

```
IP: file=138847, import=138846, delta=1

IP rows, columns:  (138846, 3)

IP dataframe:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 138846 entries, 0 to 138845
Data columns (total 3 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   lower_bound_ip_address  138846 non-null  float64
 1   upper_bound_ip_address  138846 non-null  int64
 2   country                 138846 non-null  object
dtypes: float64(1), int64(1), object(1)
memory usage: 3.2+ MB

IP data:
    lower_bound_ip_address  upper_bound_ip_address  country
0       16777216.00              16777471         Australia
1       16777472.00              16777727             China
2       16777728.00              16778239             China
3       16778240.00              16779263         Australia
4       16779264.00              16781311             China
```

Data Profiling

In [9]:
```
# Profile base dataframe(s)
profile(fraud_df)
profile(ip_df)
```

	Dtype	count	unique	na	na%	mean	std	min	max	skew(>=3)	<v0.01	VIF(>=10)
user_id	int64	151112	151112			200171.0	115369.3	2.0	400000.0			
signup_time	object	151112	151112									
purchase_time	object	151112	150679									
purchase_value	int64	151112	122			36.9	18.3	9.0	154.0			
device_id	object	151112	137956									
source	object	151112	3									
browser	object	151112	5									
sex	object	151112	2									
age	int64	151112	58			33.1	8.6	18.0	76.0			
ip_address	float64	151112	143512			2152145331.0	1248497030.1	52093.5	4294850499.7			
class	int64	151112	2			0.1	0.3		1.0			

	Dtype	count	unique	na	na%	mean	std	min	max	skew(>=3)	<v0.0
lower_bound_ip_address	float64	138846	138846			2724531562.5	897521519.7	16777216.0	3758096128.0		
upper_bound_ip_address	int64	138846	138846			2724557062.2	897497915.5	16777471.0	3758096383.0		
country	object	138846	235								

Univariate Analysis and Data Preparation

Attribute Names (confirm/update)

In [10]:
```
# Rename columsn to simplify and/or avoid usage issues later - n/a here

# examples:
#cols = {'homeowner dummy': 'homeowner', 'gender dummy': 'gender'}
#fundr_df.rename(columns=cols, inplace=True)
```

Target and Preliminary Feature Identification *(preliminary)*

In [11]:
```
# Preliminarily identify attributes and types for best further processing
id_nominal_cols = ['user_id', 'device_id', 'ip_address']

cat_nominal_cols = ['source', 'browser', 'sex']
cat_ordinal_cols = []
cat_binary_cols = []

date_interval_cols = ['signup_time', 'purchase_time']

num_interval_cols = ['age']
num_ratio_cols = ['purchase_value']

# Set classification target
target_cls_col = ['class']

# Set regression target (n/a for this excercise)
target_reg_col = []

# Set preliminary feature reduction (removed below)
reduce_X_cols = id_nominal_cols + date_interval_cols + target_cls_col + target_reg_col
```

Data Types (confirm/update)

In [12]:
```
# making columns in question float type
ip_df['lower_bound_ip_address'] = ip_df['lower_bound_ip_address'].astype('float') # technically already is floa
ip_df['upper_bound_ip_address'] = ip_df['upper_bound_ip_address'].astype('float') # integer, needs to be float
fraud_df['ip_address'] = fraud_df['ip_address'].astype('float') # tecnically already is float
# checking
print(ip_df.info())

# other examples:
#df[cat_nominal_cols] = df[cat_nominal_cols].astype('Int64')
#df[date_interval_cols] = df[date_interval_cols].astype('datetime64')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 138846 entries, 0 to 138845
Data columns (total 3 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   lower_bound_ip_address  138846 non-null  float64
 1   upper_bound_ip_address  138846 non-null  float64
 2   country                 138846 non-null  object
dtypes: float64(2), object(1)
memory usage: 3.2+ MB
None
```

Data Enrichment

Combining dataframes where IP in fraud_df is within bounds of the IP bounds of ip_df to get Country name

Filling in Country values

If the IP address doesn't fit into the bounds of the ip dataframe then it is assumed they are from VPN users.

In [13]:
```
# function takes in ip_address (fraud_df) and compares it to upper/lower bounds in ip_df to return country name
def ip_to_country(ip):
    try:
        return ip_df.country[
            (ip_df.lower_bound_ip_address < ip) &
            (ip_df.upper_bound_ip_address > ip)].iloc[0]
    except IndexError:
        return 'VPNuser'

# calling the function
fraud_df['ipCountry'] = fraud_df['ip_address'].apply(ip_to_country)

# saving to csv file to speed up when opening notebook next time
# fraud_df.to_csv('C:/Users/breel.B-E-BELL/OneDrive/Documents/USD_MastersAppliedDataScience/ADS-505 ADSforBusi

# checking
fraud_df.head(5)
```

Out[13]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	age	ip_address	class	ipCour
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	QVPSPJUOCKZAR	SEO	Chrome	M	39	732758368.80	0	Ja
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	EOGFQPIZPYXFZ	Ads	Chrome	F	53	350311387.87	0	Un Sta
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	YSSKYOSJHPPLJ	SEO	Opera	M	53	2621473820.11	1	Un Sta
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	ATGTXKYKUDUQN	SEO	Safari	M	41	3840542443.91	0	VPNu
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	NAUITBZFJKHWW	Ads	Safari	M	45	415583117.45	0	Un Sta

In [14]:
```
# seeing how many were unknown
print('There were %i unknown Country values (likely using a VPN service)' %fraud_df['ipCountry'].value_counts()
print('This is %.1f percent of the data' %(fraud_df['ipCountry'].value_counts()['VPNuser']/len(fraud_df)*100))
```

```
There were 21966 unknown Country values (likely using a VPN service)
This is 14.5 percent of the data
```

Datetime Manipulations

In [15]:
```
# calculating time difference between signing up and purchasing
fraud_df['time_diff_day'] = (pd.to_datetime(fraud_df['purchase_time'])
                             - pd.to_datetime(fraud_df['signup_time'])).astype('timedelta64[D]')

fraud_df.head(5)
```

Out[15]:

	user_id	signup_time	purchase_time	purchase_value	device_id	source	browser	sex	age	ip_address	class	ipCour
0	22058	2015-02-24 22:55:49	2015-04-18 02:47:11	34	QVPSPJUOCKZAR	SEO	Chrome	M	39	732758368.80	0	Ja
1	333320	2015-06-07 20:39:50	2015-06-08 01:38:54	16	EOGFQPIZPYXFZ	Ads	Chrome	F	53	350311387.87	0	Un Sta
2	1359	2015-01-01 18:52:44	2015-01-01 18:52:45	15	YSSKYOSJHPPLJ	SEO	Opera	M	53	2621473820.11	1	Un Sta
3	150084	2015-04-28 21:13:25	2015-05-04 13:54:50	44	ATGTXKYKUDUQN	SEO	Safari	M	41	3840542443.91	0	VPNu
4	221365	2015-07-21 07:09:52	2015-09-09 18:40:53	39	NAUITBZFJKHWW	Ads	Safari	M	45	415583117.45	0	Un Sta

In [16]:
```
#fraud_df = fraud_df.drop(['Unnamed: 0'], axis=1)
# renaming
df = fraud_df.copy()
df = df.rename(columns= {'signup_time':'signup', 'purchase_time':'purchase', 'ipCountry':'ip_country'})
df = df.drop(['user_id'], axis=1)
```

In [17]:
```
# converting from_date to datetime (date and time separate columns) instead of string
df['signup_date'] = pd.to_datetime(df['signup']).dt.strftime('%m/%d/%y')
df['signup_time'] = pd.to_datetime(df['signup']).dt.strftime('%H:%M:%S')

# converting booking_created to datetime (date and time separate columns) instead of string
df['purchase_date'] = pd.to_datetime(df['purchase']).dt.strftime('%m/%d/%y')
df['purchase_time'] = pd.to_datetime(df['purchase']).dt.strftime('%H:%M:%S')

#checking
#df.head(3)
```

In [18]:
```
# making date a month instead of full date
df['signup_month'] = pd.to_datetime(df['signup']).dt.month_name()
df['purchase_month'] = pd.to_datetime(df['purchase']).dt.month_name()

# checking, can comment out
# df.head(2)
```

In [19]:
```
# looking days of week
df['signup_day'] = pd.to_datetime(df['signup_date']).dt.day_name()
df['purchase_day'] = pd.to_datetime(df['purchase_date']).dt.day_name()

# zooming in on just weekend (saturday, sunday) or weekday (monday-friday)
    # np.where(condition, when true it's this, when not it's this)
df['signup_weektype'] = np.where((df['signup_day']=='Saturday') | #first condition followed by | (or)
                                 (df['signup_day']=='Sunday'), # second condition
                                'Weekend', 'Weekday') # if true response, if false response

df['purchase_weektype'] = np.where((df['purchase_day']=='Saturday') | #first condition followed by | (or)
                                 (df['purchase_day']=='Sunday'), # second condition
                                'Weekend', 'Weekday') # if true response, if false response
# checking
#df.head(5)
```

In [20]:
```
# splitting time into categories instead of times for leaving data
# AM: 0-11, PM: 12-23
sign_timewise = [(pd.to_datetime(df['signup_time']).dt.hour.between(0, 11)), # am
           (pd.to_datetime(df['signup_time']).dt.hour.between(12, 23)), # pm
           ]
time_values = ['AM', 'PM']

# bringing the splitting into the df3 via np.select(timewise, time_values):
df['signup_timegroup'] = np.select(sign_timewise, time_values)

# purchase
purch_timewise = [(pd.to_datetime(df['purchase_time']).dt.hour.between(0, 11)), # am
           (pd.to_datetime(df['purchase_time']).dt.hour.between(12, 23)), # pm
           ]


# bringing the splitting into the df3 via np.select(timewise, time_values):
df['purchase_timegroup'] = np.select(purch_timewise, time_values)

#checking
#df.head(3)
```

In [21]:
```
#np.unique(df['time_diff_day'])
# splitting time_diff_day into day_of (0), days (1-6), weeks (7-28), month(28-31), longer
def time_thinking(row):
    if row['time_diff_day']== 0:
        return 'day_of'
    elif row['time_diff_day']>1 and row['time_diff_day']<=6:
        return 'days'
    elif row['time_diff_day']>7 and row['time_diff_day']<=28:
        return 'weeks'
    elif row['time_diff_day']>28 and row['time_diff_day']<=31:
        return 'month'
    elif row['time_diff_day']>31:
        return 'longer'

df['time_diff'] = df.apply(lambda row: time_thinking(row), axis=1)
df.head(3)
```

Out[21]:

	signup	purchase	purchase_value	device_id	source	browser	sex	age	ip_address	class	ip_country	time_diff_day
0	2015-02-24 22:55:49	2015-04-18 02:47:11	34	QVPSPJUOCKZAR	SEO	Chrome	M	39	732758368.80	0	Japan	52.00
1	2015-06-07 20:39:50	2015-06-08 01:38:54	16	EOGFQPIZPYXFZ	Ads	Chrome	F	53	350311387.87	0	United States	0.00
2	2015-01-01 18:52:44	2015-01-01 18:52:45	15	YSSKYOSJHPPLJ	SEO	Opera	M	53	2621473820.11	1	United States	0.00

In [22]:
```
# dropping signup, purchase, signup_date, signup_time, purchase_date, purchase_time, ip_address columns, device
df = df.drop(['signup', 'purchase', 'signup_date', 'signup_time', 'purchase_date',
              'purchase_time', 'time_diff_day', 'ip_address', 'device_id'],
             axis=1)

# we can drop the day of the week one if we'd like so then we just have weekday vs weekend

# checking
df.head(3)
```

Out[22]:

	purchase_value	source	browser	sex	age	class	ip_country	signup_month	purchase_month	signup_day	purchase_day	signup
0	34	SEO	Chrome	M	39	0	Japan	February	April	Tuesday	Saturday	
1	16	Ads	Chrome	F	53	0	United States	June	June	Sunday	Monday	
2	15	SEO	Opera	M	53	1	United States	January	January	Thursday	Thursday	

Categorical Data Updates

In [23]:
```
# "Invalid Country Name: 'Bonaire; Sint Eustatius; Saba'" from running country conversion code so dropping that
df.drop(df[df['ip_country']=='Bonaire; Sint Eustatius; Saba'].index, inplace=True)
df.drop(df[df['ip_country']=='Reunion'].index, inplace=True)
df.shape
```

Out[23]:
```
(151108, 16)
```

In [24]:
```
# making a copy of dataframe in case it goes weird
df2 = df.copy()
```

In [25]:
```
# changing formatting for troublesome names
df2.loc[df2['ip_country']=='Korea Republic of', 'ip_country'] = 'Korea, Republic of'

df2.loc[df2['ip_country']=='Taiwan; Republic of China (ROC)', 'ip_country'] = 'Taiwan'

df2.loc[df2['ip_country']=='Iran (ISLAMIC Republic Of)', 'ip_country'] = 'Iran'

df2.loc[df2['ip_country']=='Moldova Republic of', 'ip_country'] = 'Moldova, Republic of'

df2.loc[df2['ip_country']=='Croatia (LOCAL Name: Hrvatska)', 'ip_country'] = 'Croatia'

df2.loc[df2['ip_country']=='Slovakia (SLOVAK Republic)', 'ip_country'] = 'Slovakia'

df2.loc[df2['ip_country']=="Cote D'ivoire", 'ip_country'] = 'Ivory Coast'

df2.loc[df2['ip_country']=='Virgin Islands (U.S.)', 'ip_country'] = 'United States'

df2.loc[df2['ip_country']=='Tanzania United Republic of', 'ip_country'] = 'Tanzania, United Republic of'

df2.loc[df2['ip_country']=='Congo The Democratic Republic of The', 'ip_country'] = 'Congo'
```

In [26]:
```
import pycountry_convert as pc

def country_to_continent(country_name):
    if country_name == 'VPNuser':
        return 'VPNuser'
    if country_name == 'European Union':
        return 'Europe'
    if country_name == 'Libyan Arab Jamahiriya':
        return 'Africa'
    if country_name == 'Bosnia and Herzegowina':
        return 'Europe'
    if country_name == 'Palestinian Territory Occupied':
        return 'Africa'
    if country_name == 'Curacao':
        return 'South America'
    if country_name == 'Bonaire; Sint Eustatius; Saba':
        return 'North America'
    if country_name == 'Reunion':
        return 'Africa'
    country_alpha2 = pc.country_name_to_country_alpha2(country_name)
    country_continent_code = pc.country_alpha2_to_continent_code(country_alpha2)
    country_continent_name = pc.convert_continent_code_to_continent_name(country_continent_code)

    return country_continent_name

# calling the function
df2['continent'] = df2['ip_country'].apply(lambda x: country_to_continent(x))
```

In [27]:
```
# checking for unique continents (should be no surprises)
df2['continent'].unique()
```

Out[27]:
```
array(['Asia', 'North America', 'VPNuser', 'South America', 'Europe',
       'Africa', 'Oceania'], dtype=object)
```

In [28]:
```
plt.hist(df2['continent'])
plt.show()
```

```
/var/folders/zk/0yy_5gzj2kn3ln4fjthkpxxh0000gn/T/ipykernel_27930/2996879449.py:2: UserWarning: Matplotlib is cu
rrently using agg, which is a non-GUI backend, so cannot show the figure.
  plt.show()
```

In [29]:
```
# marking categorical columns (browser, source, sex, signup_month, purchase_month,
# signup_day, purchase_day, signup_weektype, purchase_weektype, signup_timegroup, purchase_timegroup)
df2.source = df2.source.astype('category')
df2.browser = df2.browser.astype('category')
df2.sex = df2.sex.astype('category')
df2.ip_country = df2.ip_country.astype('category')
df2.signup_month = df2.signup_month.astype('category')
df2.purchase_month = df2.purchase_month.astype('category')
df2.signup_day = df2.signup_day.astype('category')
df2.purchase_day = df2.purchase_day.astype('category')
df2.signup_weektype = df2.signup_weektype.astype('category')
df2.purchase_weektype = df2.purchase_weektype.astype('category')
df2.signup_timegroup = df2.signup_timegroup.astype('category')
df2.purchase_timegroup = df2.purchase_timegroup.astype('category')
df2.time_diff = df2.time_diff.astype('category')
df2.continent = df2.continent.astype('category')

# checking
#df2.info()
```

In [30]:
```
# listing categorical columns to keep object ones (device_id) from being included

#df3 = df2.copy()
# getting dummy variables for categorical values
#cats = df3[['browser', 'source', 'sex', 'continent', 'signup_month', 'purchase_month',
#            'signup_day', 'purchase_day', 'signup_weektype', 'purchase_weektype',
#            'signup_timegroup', 'purchase_timegroup', 'time_diff']]

#cat_dummies = pd.get_dummies(cats)
#cat_dummies.head(3)
```

In [31]:
```
#nums = df3[['purchase_value', 'age', 'class']]

#df_combo = pd.concat([cat_dummies, nums], axis=1)
#df_combo.head(3)
```

In [32]:
```
df2
```

Out[32]:

	purchase_value	source	browser	sex	age	class	ip_country	signup_month	purchase_month	signup_day	purchase_day	s
0	34	SEO	Chrome	M	39	0	Japan	February	April	Tuesday	Saturday	
1	16	Ads	Chrome	F	53	0	United States	June	June	Sunday	Monday	
2	15	SEO	Opera	M	53	1	United States	January	January	Thursday	Thursday	
3	44	SEO	Safari	M	41	0	VPNuser	April	May	Tuesday	Monday	
4	39	Ads	Safari	M	45	0	United States	July	September	Tuesday	Wednesday	
...	...	...	...	...	...	...	...	...	...	...	...	
151107	43	SEO	Chrome	M	28	1	United States	January	March	Tuesday	Sunday	
151108	35	SEO	Safari	M	32	0	Netherlands	May	May	Friday	Tuesday	
151109	40	SEO	IE	F	26	0	Japan	March	May	Tuesday	Wednesday	
151110	46	SEO	Chrome	M	37	0	United States	July	September	Thursday	Monday	
151111	20	Direct	IE	M	38	0	VPNuser	June	July	Wednesday	Tuesday	

151108 rows × 17 columns

Feature Updates (identification)

In [33]:
```
cat_nominal_cols = cat_nominal_cols +\
    ['ip_country', 'signup_month', 'purchase_month', 'signup_day',
     'purchase_day', 'signup_weektype', 'purchase_weektype',
     'signup_timegroup', 'purchase_timegroup', 'time_diff', 'continent']
```

Categorical Data Profiling

In [34]:
```
#fraudclass_zero = round(((fraudorig_df['class'].value_counts()[0])/len(fraudorig_df))*100,2)
#fraudclass_one = round(((fraudorig_df['class'].value_counts()[1])/len(fraudorig_df))*100,2)
#print('% fraud class 0: ', fraudclass_zero, 'no fraud')
#print('% fraud class 1: ', fraudclass_one, 'fraud detected')

# Better understand 'categorical' data, including balance
profile_cat(df2, cat_nominal_cols + cat_ordinal_cols + cat_binary_cols + target_cls_col)
```

```
source -
   SEO 40.11
   Ads 39.63
Direct 20.26

browser -
 Chrome 40.65
     IE 24.31
 Safari 16.32
FireFox 16.29
  Opera  2.43

sex -
M 58.43
F 41.57

ip_country -
 United States 38.42
       VPNuser 14.54
         China  7.97
         Japan  4.83
United Kingdom  2.97
..... and 173 more

signup_month -
January 17.85
  March 12.94
   July 12.87
    May 12.80
  April 12.50
..... and 3 more

purchase_month -
  July 12.91
   May 12.81
  June 12.51
August 12.35
 April 10.95
..... and 7 more

signup_day -
  Sunday 14.63
  Friday 14.62
Thursday 14.48
  Monday 14.47
Saturday 14.40
..... and 2 more

purchase_day -
  Sunday 14.57
  Monday 14.37
Saturday 14.33
Thursday 14.28
  Friday 14.24
..... and 2 more

signup_weektype -
Weekday 70.97
Weekend 29.03

purchase_weektype -
Weekday 71.10
Weekend 28.90

signup_timegroup -
PM 50.06
AM 49.94

purchase_timegroup -
PM 50.21
AM 49.79

time_diff -
longer 69.70
 weeks 16.74
day_of  5.80
  days  3.91
 month  2.31
..... and 1 more

continent -
North America 41.38
         Asia 20.55
       Europe 17.22
      VPNuser 14.54
South America  3.50
..... and 2 more

class -
0 90.64
1  9.36
```

Data Partitioning

In [35]:
```
# Create predictor and target dataframes
fraud_X = df2.loc[:, ~df2.columns.isin(reduce_X_cols)].copy()
fraud_y = df2[target_cls_col]
```

In [36]:
```
# Split data and confirm proportions
train_ratio = 0.7; val_ratio = 0.20; test_ratio = 0.10

X_train, X_test, y_train, y_test = train_test_split(
    fraud_X, fraud_y, test_size=1-train_ratio,
    random_state=42, stratify=fraud_y)
X_val, X_test, y_val, y_test = train_test_split(
    X_test, y_test, test_size=test_ratio/(test_ratio+val_ratio),
    random_state=42, stratify=y_test)

trows = fraud_X.shape[0]
print('\nTrain/validation/test: ', X_train.shape[0], '/', X_val.shape[0], '/', X_test.shape[0])

profile_cat(y_train, target_cls_col)
```

```
Train/validation/test:  105775 / 30222 / 15111

class -
0 90.63
1  9.37
```

In [37]:
```
# Potentially create test set from independent source data - n/a here
#X_test = ffundr_df.loc[:, ~ffundr_df.columns.isin(reduce_X_cols)].copy()
#y_test = ffundr_df[target_cls_col]
```

Additional Uni/Multivariate EDA and Feature Engineering/Selection

> **Missing/null values (find/impute/drop) - not needed but handled in classification pipeline below**
> **Categorical features (encoding) - handled in classification pipeline**
> **Outliers (convert/drop) - code available below but not needed**
> **Centering/scaling (standardizing/normalizing) - handled in classification pipeline**
> **"Bad"/duplicate data (find/convert/drop) - not needed**
> **Other multivariate (e.g., correlation, etc.) - ref. below**

Outliers (convert/drop)

In [38]:
```
# Simple function to remove column-level outliers (note this needs expanding
#   to row-level and/or conversion, for best results)
def remove_outliers(df_col):
    q1 = df_col.quantile(0.1)
    q3 = df_col.quantile(0.9)
    iqr = q3 - q1
    lbound = q1 - (1.5 * iqr)
    ubound = q3 + (1.5 * iqr)
    df_out = df_col[(df_col >= lbound) & (df_col <= ubound)]
    removed = len(df_col) - len(df_out)
    if removed > 0:
        print(df_col.name, 'outliers removed: ', removed)
    return df_out

# Per note above, holding this out here but example:
#for c in num_ratio_cols:
#    fraud_df[c] = remove_outliers(fraud_df[c])
```

Correlation Analysis

In [39]:

```python
# Show ~relatively strong correlations to consider, using approach similar to
#   what is used in profile() function to highlight >= threshhold
CORR_TH = 0.5
corr_df = pd.DataFrame(
    X_train[num_interval_cols + num_ratio_cols].corr())\
        .apply(lambda x: abs(x*(x>=CORR_TH)))
corr_df = round(corr_df, 1).astype(str)
corr_df.replace(['0', '0.0', 'nan', 'False'], '', inplace=True)
corr_df
```

Out[39]:

	age	purchase_value
age	1.0	
purchase_value		1.0

In [40]:

```python
# To consider for categorical value correlation?

def cramers_corrected_stat(confusion_matrix):
    """ calculate Cramers V statistic for categorical-categorical association.
        uses correction from Bergsma and Wicher,
        Journal of the Korean Statistical Society 42 (2013): 323-328
    """
    chi2 = ss.chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2/n
    r,k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return np.sqrt(phi2corr / min( (kcorr-1), (rcorr-1)))

#cols = bin_cols
#corrM = np.zeros((len(cols),len(cols)))
# there's probably a nice pandas way to do this
#for col1, col2 in itertools.combinations(cols, 2):
#    idx1, idx2 = cols.index(col1), cols.index(col2)
#    corrM[idx1, idx2] = cramers_corrected_stat(pd.crosstab(building_df[col1], building_df[col2]))
#    corrM[idx2, idx1] = corrM[idx1, idx2]

#corr = pd.DataFrame(corrM, index=cols, columns=cols)
#fig, ax = plt.subplots(figsize=(7, 6))
#ax = sns.heatmap(corr, annot=True, ax=ax); ax.set_title("Cramer V Correlation between Variables");
```

Data Mining (Unsupervised)

> **This is a placeholder for future opportunity, e.g., pre-supervised model clustering to support feature selection.**

Modeling

Model Setup (selection)

In [41]:

```python
# Set feature cols for appropriate pipeline preprocessing
cat_cols = cat_nominal_cols + cat_ordinal_cols + cat_binary_cols  # one-hot encoding, imputing (if necc)
num_cols = num_interval_cols + num_ratio_cols  # scaling, imputing (if necc)

# Set model list
mp_queue = (
    (LogisticRegression(), {'random_state': 42}),
    (Perceptron(), {'class_weight': 'balanced'}),
    (LinearDiscriminantAnalysis(), None),
    (LinearSVC(), {'max_iter': 500}),

    (KNeighborsClassifier(), {'n_neighbors': 3}),
    (KNeighborsClassifier(), {'n_neighbors': 5}),
    (KNeighborsClassifier(), {'n_neighbors': 7}),

    (DecisionTreeClassifier(), {'max_depth': 4, 'random_state': 42}),
    (DecisionTreeClassifier(), {'max_depth': 5, 'random_state': 42}),

    (RandomForestClassifier(), {'max_depth': 4, 'random_state': 42}),
    (RandomForestClassifier(), {'max_depth': 5, 'random_state': 42}),

    (AdaBoostClassifier(), {'n_estimators': 10, 'random_state': 42}),

    (MLPClassifier(), {'random_state': 42}),
)
```

Model Run and Evaluation (Iteration n)

In [42]:

```python
ModelProcess.show_progress = True

# Iterate models (note use of 'copy' is to preserve mutable elements
#   of model_queue tuple for possible later use)
mp_df = pd.DataFrame(mp_queue, columns=['algorithm', 'params'])
mp_df['mp'] = mp_df.apply(
    lambda mp: ModelProcess(copy.deepcopy(mp['algorithm']), None,
                            copy.copy(mp['params']),
                            X_train, y_train,
                            X_val, y_val,
                            X_test, y_test,
                            None,
                            cat_cols, num_cols).train_validate_test(), axis=1)

# Compile, sort, and display results
mp_df[['train_acc', 'train_f1', 'train_time',
       'val_acc', 'val_f1', 'val_time',
       'test_acc', 'test_f1', 'test_time']] =\
    mp_df['mp'].apply(
        lambda mp: sum(list(map(
            lambda dataset: mp.score[dataset] + [mp.time[dataset]], ['train', 'val', 'test'])), []).tolist()
mp_df.sort_values(by=['train_acc', 'val_acc', 'test_acc'],
                  ascending=[False, False, False], inplace=True)
mp_df.loc[:, mp_df.columns != 'mp']
#mp_df.loc[:, mp_df.columns != 'mp'].to_csv('results_table.csv')
```

```
LogisticRegression: train... done in 3.65s.
LogisticRegression: val... done in 0.18s.
LogisticRegression: test... done in 0.09s.
Perceptron: train... done in 0.96s.
Perceptron: val... done in 0.09s.
Perceptron: test... done in 0.05s.
LinearDiscriminantAnalysis: train... done in 3.54s.
LinearDiscriminantAnalysis: val... done in 0.15s.
LinearDiscriminantAnalysis: test... done in 0.08s.
LinearSVC: train... done in 7.13s.
LinearSVC: val... done in 0.08s.
LinearSVC: test... done in 0.04s.
KNeighborsClassifier: train... done in 78.73s.
KNeighborsClassifier: val... done in 22.39s.
KNeighborsClassifier: test... done in 11.16s.
KNeighborsClassifier: train... done in 78.46s.
KNeighborsClassifier: val... done in 22.28s.
KNeighborsClassifier: test... done in 11.04s.
KNeighborsClassifier: train... done in 77.02s.
KNeighborsClassifier: val... done in 21.82s.
KNeighborsClassifier: test... done in 10.99s.
DecisionTreeClassifier: train... done in 1.35s.
DecisionTreeClassifier: val... done in 0.15s.
DecisionTreeClassifier: test... done in 0.08s.
DecisionTreeClassifier: train... done in 1.47s.
DecisionTreeClassifier: val... done in 0.15s.
DecisionTreeClassifier: test... done in 0.08s.
RandomForestClassifier: train... done in 5.18s.
RandomForestClassifier: val... done in 0.45s.
RandomForestClassifier: test... done in 0.22s.
RandomForestClassifier: train... done in 5.75s.
RandomForestClassifier: val... done in 0.47s.
RandomForestClassifier: test... done in 0.23s.
AdaBoostClassifier: train... done in 3.13s.
AdaBoostClassifier: val... done in 0.26s.
AdaBoostClassifier: test... done in 0.14s.
MLPClassifier: train... done in 446.35s.
MLPClassifier: val... done in 0.19s.
MLPClassifier: test... done in 0.11s.
```

Out[42]:

	algorithm	params	train_acc	train_f1	train_time	val_acc	val_f1	val_time	test_acc	test_f1	test_time
12	MLPClassifier()	{'random_state': 42}	0.96	0.77	446.35	0.94	0.64	0.19	0.95	0.66	0.11
4	KNeighborsClassifier()	{'n_neighbors': 3}	0.96	0.71	78.73	0.95	0.65	22.39	0.95	0.67	11.16
8	DecisionTreeClassifier()	{'max_depth': 5, 'random_state': 42}	0.96	0.70	1.47	0.95	0.68	0.15	0.96	0.71	0.08
7	DecisionTreeClassifier()	{'max_depth': 4, 'random_state': 42}	0.96	0.70	1.35	0.95	0.68	0.15	0.96	0.71	0.08
10	RandomForestClassifier()	{'max_depth': 5, 'random_state': 42}	0.96	0.70	5.75	0.95	0.68	0.47	0.96	0.71	0.23
9	RandomForestClassifier()	{'max_depth': 4, 'random_state': 42}	0.95	0.69	5.18	0.95	0.67	0.45	0.96	0.70	0.22
0	LogisticRegression()	{'random_state': 42}	0.95	0.69	3.65	0.95	0.67	0.18	0.95	0.70	0.09
5	KNeighborsClassifier()	{'n_neighbors': 5}	0.95	0.69	78.46	0.95	0.66	22.28	0.95	0.69	11.04
6	KNeighborsClassifier()	{'n_neighbors': 7}	0.95	0.68	77.02	0.95	0.66	21.82	0.95	0.68	10.99
3	LinearSVC()	{'max_iter': 500}	0.95	0.67	7.13	0.95	0.66	0.08	0.95	0.68	0.04
11	AdaBoostClassifier()	{'n_estimators': 10, 'random_state': 42}	0.95	0.67	3.13	0.95	0.66	0.26	0.95	0.68	0.14
2	LinearDiscriminantAnalysis()	None	0.95	0.67	3.54	0.95	0.66	0.15	0.95	0.68	0.08
1	Perceptron()	{'class_weight': 'balanced'}	0.47	0.22	0.96	0.46	0.22	0.09	0.48	0.22	0.05

Feature Importance Review for Key (Candidate) Algorithms

In [43]:

```python
# Show top features for Logistic Regression (this could be 'baked' into the
#   ModelProcess() class or similar in future)
model = mp_df.loc[0]['mp'].model
features = mp_df.loc[0]['mp'].pipe['preprocessor'].transformers_[0][1]['onehotencoder'].get_feature_names_out(c
fi = pd.concat([pd.DataFrame(features, columns=['feature']),
                pd.DataFrame(num_cols, columns=['feature'])],
               ignore_index=True)

fi['importance'] = model.coef_[0]
fi['abs_importance'] = abs(fi['importance'])
fi.sort_values(by=['abs_importance', 'feature'],
               ascending=[False, True], inplace=True)
fi[fi['abs_importance'] >= 0.50][['feature', 'importance']]
```

Out[43]:

	feature	importance
227	time_diff_day_of	2.77
197	purchase_month_January	2.00
36	ip_country_Bulgaria	-1.39
111	ip_country_Malta	1.34
154	ip_country_Slovenia	-1.16
98	ip_country_Latvia	1.14
118	ip_country_Morocco	-1.08
228	time_diff_days	-1.04
12	ip_country_Algeria	0.97
232	time_diff_nan	-0.91
30	ip_country_Bolivia	0.82
16	ip_country_Armenia	0.76
231	time_diff_weeks	-0.69
80	ip_country_Iceland	0.67
92	ip_country_Kazakhstan	0.61
78	ip_country_Hong Kong	0.59
25	ip_country_Belgium	0.59
142	ip_country_Qatar	-0.57
131	ip_country_Oman	-0.57
19	ip_country_Azerbaijan	0.54
95	ip_country_Kuwait	0.53
96	ip_country_Kyrgyzstan	-0.51
143	ip_country_Romania	-0.51
170	ip_country_Turkmenistan	0.51
159	ip_country_Sudan	0.50

In [44]:

```python
# Show top features for Decision Tree with max depth of 5
model = mp_df.loc[8]['mp'].model
features = mp_df.loc[8]['mp'].pipe['preprocessor'].transformers_[0][1]['onehotencoder'].get_feature_names_out(c
fi = pd.concat([pd.DataFrame(features, columns=['feature']),
                pd.DataFrame(num_cols, columns=['feature'])],
               ignore_index=True)
fi['importance'] = model.feature_importances_
fi['abs_importance'] = abs(fi['importance'])
fi.sort_values(by=['abs_importance', 'feature'],
               ascending=[False, True], inplace=True)
fi[fi['abs_importance'] >= 0.05][['feature', 'importance']]
```

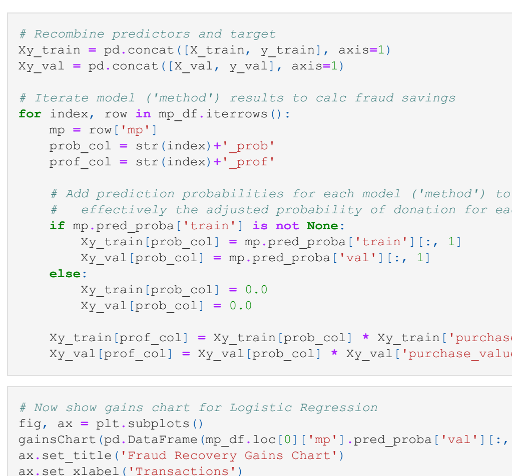
Out[44]:

	feature	importance
227	time_diff_day_of	0.88
197	purchase_month_January	0.12

Selected Model Performance Review

In [57]:

```python
# Show confusion matrix and summary for Logistic Regression
mp_df.loc[0]['mp'].confusion_matrix('val')
mp_df.loc[0]['mp'].summary('val')
```




```
LogisticRegression - val dataset

              precision    recall  f1-score   support

           0       0.95      1.00      0.97     27392
           1       0.94      0.52      0.67      2830

    accuracy                           0.95     30222
   macro avg       0.95      0.76      0.82     30222
weighted avg       0.95      0.95      0.95     30222
```

Selected Model Gains Review (in business terms)

In [58]:

```python
# Recombine predictors and target
Xy_train = pd.concat([X_train, y_train], axis=1)
Xy_val = pd.concat([X_val, y_val], axis=1)

# Iterate model ('method') results to calc fraud savings
for index, row in mp_df.iterrows():
    mp = row['mp']
    prob_col = str(index)+'_prob'
    prof_col = str(index)+'_prof'

    # Add prediction probabilities for each model ('method') to each row; these are
    #   effectively the adjusted probability of donation for each model type
    if mp.pred_proba['train'] is not None:
        Xy_train[prob_col] = mp.pred_proba['train'][:, 1]
        Xy_val[prob_col] = mp.pred_proba['val'][:, 1]
    else:
        Xy_train[prob_col] = 0.0
        Xy_val[prob_col] = 0.0

    Xy_train[prof_col] = Xy_train[prob_col] * Xy_train['purchase_value']
    Xy_val[prof_col] = Xy_val[prob_col] * Xy_val['purchase_value']
```

In [59]:

```python
# Now show gains chart for Logistic Regression
fig, ax = plt.subplots()
gainsChart(pd.DataFrame(mp_df.loc[0]['mp'].pred_proba['val'][:, 1])[0], ax=ax)
ax.set_title('Fraud Recovery Gains Chart')
ax.set_xlabel('Transactions')
ax.set_ylabel('Cumulative Fraud Recovery')
plt.show()
```


In [60]:

```python
# Show fraud recovery dollars for Logistic Regression
print('\nFraud recovery estimate: ${:0,.0f}'.format(sum(Xy_val['0_prof'])))
print('\nFraud recovery estimate as percentage of total: {:0,.1f}%'.\
      format(sum(Xy_val['0_prof']) / sum(Xy_val['purchase_value']) * 100.0))
```

```
Fraud recovery estimate: $103,435

Fraud recovery estimate as percentage of total: 9.3%
```

In [ ]: