CS188FinalProject

March 17, 2021

1 CS188 Final Project - NEXT Trucking

[1]:

```
# Importing many libraries from past projects
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt # this is used for the plot the graph
import os
import seaborn as sns # used for plot interactive graph.
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
import statsmodels.api as sm
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix
import sklearn.metrics.cluster as smc
from sklearn.model_selection import KFold
from sklearn import preprocessing
from sklearn.impute import SimpleImputer
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import make_pipeline
from sklearn.naive_bayes import GaussianNB
from sklearn.preprocessing import LabelEncoder
from sklearn.impute import KNNImputer
from sklearn.decomposition import PCA
from sklearn.ensemble import AdaBoostClassifier
from scipy import stats
import datetime
```

```
from matplotlib import pyplot
import itertools

%matplotlib inline

import random

random.seed(42)
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

[2]:
```
#if using google colab
from google.colab import drive
drive.mount('/content/gdrive', force_remount=False)
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call
drive.mount("/content/gdrive", force_remount=True).
```

[3]:
```
#if using local env
#import tarfile
#import urllib
#DATASET_PATH = ""

#def load_data(dpath):
#    csv_path = os.path.join(dpath, "training_dataset_V3.csv")
#    return pd.read_csv(csv_path)

#dirty_data = load_data(DATASET_PATH)

#def load_data2(dpath):
#    csv_path = os.path.join(dpath, "score_V3.csv")
#    return pd.read_csv(csv_path)

#kaggle_dirty = load_data2(DATASET_PATH)

#dirty_data.head()
```

[4]:
```
#if using google colab
DATASET_PATH = os.path.join("/content/gdrive/My Drive")

csv_path = os.path.join(DATASET_PATH, "training_dataset_V3.csv")
dirty_data = pd.read_csv(csv_path)

csv_path = os.path.join(DATASET_PATH, "score_V3.csv")
kaggle_dirty = pd.read_csv(csv_path)
```

```
#See fiirst few rows of data
dirty_data.head()
```

[4]:

```
   Unnamed: 0          dt  … brokerage_loads  total_loads
0           0  2019-12-16  …              45          483
1           1  2021-01-15  …               1           75
2           2  2019-12-26  …               2          182
3           3  2021-02-10  …               0           62
4           4  2017-07-24  …             314          371

[5 rows x 31 columns]
```

[5]:

```
# See some null values
sample_incomplete_dirty = dirty_data[dirty_data.isnull().any(axis=1)]
sample_incomplete_dirty.head(20)
```

[5]:

```
    Unnamed: 0          dt  … brokerage_loads  total_loads
0            0  2019-12-16  …              45          483
1            1  2021-01-15  …               1           75
2            2  2019-12-26  …               2          182
3            3  2021-02-10  …               0           62
4            4  2017-07-24  …             314          371
6            6  2019-08-26  …             137          137
7            7  2021-01-04  …               0           56
8            8  2021-02-03  …               1          115
9            9  2021-02-01  …               0           85
10          10  2016-09-18  …              35           35
11          11  2017-04-14  …             608          608
12          12  2016-04-04  …             114          114
13          13  2018-10-21  …             112          165
14          14  2020-07-30  …             167          607
15          15  2017-02-01  …              11           11
16          16  2020-03-11  …               2           13
17          17  2020-06-29  …               0           11
18          18  2017-06-12  …               3            5
19          19  2020-06-05  …               2          182
20          20  2021-02-10  …              13          200

[20 rows x 31 columns]
```

2 1) Generate Labels

We will drop the duplicate index column and sort by the most recent date

[6]:

```
unlabeled_data = dirty_data.drop(columns=['Unnamed: 0'])
kaggle_u_compressed = kaggle_dirty.drop(columns=['Unnamed: 0'])
```

```
unlabeled_data.head()
```

[6]:
```
           dt    weekday  …  brokerage_loads  total_loads
0  2019-12-16     Monday  …               45          483
1  2021-01-15     Friday  …                1           75
2  2019-12-26   Thursday  …                2          182
3  2021-02-10  Wednesday  …                0           62
4  2017-07-24     Monday  …              314          371

[5 rows x 30 columns]
```

[7]:
```
# Sort by load_day
u_sorted_data = unlabeled_data.sort_values(by=['load_day'], axis=0,␣
 ↪ascending=False)
u_sorted_data = u_sorted_data.reset_index().drop(columns=['index'])

u_sorted_data.head()
```

[7]:
```
           dt    weekday  …  brokerage_loads  total_loads
0  2021-02-17  Wednesday  …                0          131
1  2021-02-17  Wednesday  …                0          120
2  2021-02-17  Wednesday  …                0          121
3  2021-02-17  Wednesday  …              307          512
4  2021-02-17  Wednesday  …               37         1374

[5 rows x 30 columns]
```

[8]:
```
#Failed attempt to improve model F-score
#Improved cv accuracy but decreased F-score on test set

def get_accumulated_loads(df):
  num_entries = len(df)
  loads_per_id = {}
  for i in range(0, num_entries):
    driver = df["id_driver"][i]
    if (driver in loads_per_id):
      loads_per_id[driver].append(df["loads"][i])
    else:
      loads_per_id[driver] = [df["loads"][i]]

  for key in loads_per_id:
    loads_per_id[key] = np.sum(loads_per_id[key])

  return loads_per_id

accu_loads = get_accumulated_loads(u_sorted_data)
```

Next we will drop the duplicate drivers. After a long discussion abnout the cumulative loads on piazza, the best way to go about this is to collapse all rows by trimming duplicate drivers. This leaves the most recent entries with the cumulative features. We will have to keep an eye out for the distribution of these cumulative features as we proceed.

[9]:
```
# collapse by driver
u_sorted_data.drop_duplicates('id_driver', inplace = True)

u_compressed = u_sorted_data.sort_values(by=['load_day'], ascending=False)
u_compressed = u_compressed.reset_index().drop(columns=['index'])

u_compressed
```

[9]:
```
              dt    weekday  …  brokerage_loads  total_loads
0     2021-02-17  Wednesday  …                0          131
1     2021-02-17  Wednesday  …              150          268
2     2021-02-17  Wednesday  …               57          275
3     2021-02-17  Wednesday  …                1           68
4     2021-02-17  Wednesday  …              145          532
…            …        …  …              …          …
5286  2015-12-09  Wednesday  …               11           11
5287  2015-11-24    Tuesday  …               23           23
5288  2015-11-19   Thursday  …                1            1
5289  2015-10-29   Thursday  …                1            1
5290  2015-10-26     Monday  …                2            2

[5291 rows x 30 columns]
```

[10]:
```
#part of the failed loads accumulation strategy

#for i in range(0, len(u_compressed)):
#   driver = u_compressed["id_driver"][i]
#   u_compressed["loads"][i] = accu_loads[driver]

#u_compressed
```

[11]:
```
# Ensure collapsing is done correctly
print(np.max(u_compressed["total_loads"]))
print(np.min(u_compressed["total_loads"]))
print(np.max(dirty_data["total_loads"]))
print(np.min(dirty_data["total_loads"]))
```

```
4266
1
4266
1
```

We can now take the 75th percentile of the loads.

[12]:
```
u_compressed.quantile(.75)
```

[12]:
```
year                         2020.0
id_driver                   29290.5
num_trucks                     11.0
days_signup_to_approval       488.0
loads                           1.0
marketplace_loads_otr           2.0
marketplace_loads_atlas         0.0
marketplace_loads               4.0
brokerage_loads_otr             4.0
brokerage_loads_atlas           0.0
brokerage_loads                 5.0
total_loads                    17.0
Name: 0.75, dtype: float64
```

[13]:
```
percentile75 = u_compressed.quantile(.75)['total_loads']
percentile75
```

[13]:
```
17.0
```

The 75th percentile can be seen in the above output. This is the 75th percentile of 'total_loads'. We will now combine this with the 75th percentile of 'most_recent_load_date' below to generate our labels.

[14]:
```
top25_percent = int(len(u_compressed.index)*.25) # 1323
u_compressed["label"] = 0

for row in range(0, top25_percent):
  if u_compressed["total_loads"][row] >= percentile75:
    u_compressed["label"][row] = 1


labeled_data = u_compressed

grps = labeled_data.groupby('label')
grps.count()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[14]:
```
          dt  weekday  year  …  brokerage_loads_atlas  brokerage_loads
total_loads
label                        …
0       4585     4585  4585  …                   4585             4585
```

```
4585
1       706      706   706  …                    706              706
706

[2 rows x 30 columns]
```

We have 706 high performing drivers. Labels are considered unbalanced…with 706 being high-performing, and 4585 being not high performing. To deal with this, we will do some imputation of rows and downsample to make it a 4:1 ratio (2824:706). We need to remove 4585-2824 = 1761 rows to achieve this ratio.

[15]:
```python
zeros = grps.get_group(0)
zeros = zeros.reset_index().drop(columns=['index'])

ones = grps.get_group(1)
ones = ones.reset_index().drop(columns=['index'])

zeros
```

[15]:
```
              dt    weekday  year  …  brokerage_loads total_loads label
0     2021-02-17  Wednesday  2021  …               16          16     0
1     2021-02-17  Wednesday  2021  …                0           7     0
2     2021-02-17  Wednesday  2021  …                0          10     0
3     2021-02-16    Tuesday  2021  …                1           9     0
4     2021-02-16    Tuesday  2021  …               14          14     0
…            …          …     …  …                …           …     …
4580  2015-12-09  Wednesday  2015  …               11          11     0
4581  2015-11-24    Tuesday  2015  …               23          23     0
4582  2015-11-19   Thursday  2015  …                1           1     0
4583  2015-10-29   Thursday  2015  …                1           1     0
4584  2015-10-26     Monday  2015  …                2           2     0

[4585 rows x 31 columns]
```

[16]:
```python
drop_indices = np.random.choice(zeros.index, grps.count()["dt"][0]-4*grps.
↪count()["dt"][1], replace=False)
for i in drop_indices:
  driver_id = zeros['id_driver'][i]
  labeled_data = labeled_data[labeled_data.id_driver != driver_id]
labeled_data = labeled_data.reset_index().drop(columns=['index'])
labeled_data
```

[16]:
```
              dt    weekday  year  …  brokerage_loads total_loads label
0     2021-02-17  Wednesday  2021  …                0         131     1
1     2021-02-17  Wednesday  2021  …              150         268     1
2     2021-02-17  Wednesday  2021  …               57         275     1
3     2021-02-17  Wednesday  2021  …                1          68     1
4     2021-02-17  Wednesday  2021  …              145         532     1
```

```
…          …          …    …   …              …          …    …
3525  2015-12-31   Thursday  2015  …                     4           4      0
3526  2015-12-29    Tuesday  2015  …                     6           6      0
3527  2015-12-09  Wednesday  2015  …                    11          11      0
3528  2015-11-24    Tuesday  2015  …                    23          23      0
3529  2015-10-29   Thursday  2015  …                     1           1      0

[3530 rows x 31 columns]
```

[17]:
```python
labeled_data.groupby('label').count()
```

[17]:
```
         dt  weekday  year  …  brokerage_loads_atlas  brokerage_loads
total_loads
label                         …
0      2824     2824  2824  …                   2824             2824
2824
1       706      706   706  …                    706              706
706

[2 rows x 30 columns]
```

As can be seen above, we now have achieved our desired ratio of 4:1. While this is by no means well balanced data, it is far better than before and should provide better generalized training.

3 2) Drop 'total_loads' and 'most_recent_load_date' from your data frame

[18]:
```python
labeled_data = labeled_data.drop(columns=['total_loads',␣
↪'most_recent_load_date'])
labeled_data.head()
```

[18]:
```
           dt    weekday  year  …  brokerage_loads_atlas brokerage_loads label
0  2021-02-17  Wednesday  2021  …                      0               0     1
1  2021-02-17  Wednesday  2021  …                    148             150     1
2  2021-02-17  Wednesday  2021  …                     56              57     1
3  2021-02-17  Wednesday  2021  …                      1               1     1
4  2021-02-17  Wednesday  2021  …                    145             145     1

[5 rows x 29 columns]
```

As can be seen above the 'total_loads' and 'most_recent_load_date' columns are both no longer present.

4 3) Run some basic statistics on your variables including correlations with labels and report findings

3a) We need to change all categorical variables so that we can get proper correlations and more informative statistics from all columns.

[19]:
```
labeled_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3530 entries, 0 to 3529
Data columns (total 29 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   dt                       3530 non-null   object 
 1   weekday                  3530 non-null   object 
 2   year                     3530 non-null   int64  
 3   id_driver                3530 non-null   int64  
 4   id_carrier_number        3530 non-null   object 
 5   dim_carrier_type         3530 non-null   object 
 6   dim_carrier_company_name 3528 non-null   object 
 7   home_base_city           3519 non-null   object 
 8   home_base_state          3519 non-null   object 
 9   carrier_trucks           3530 non-null   object 
 10  num_trucks               3501 non-null   float64
 11  interested_in_drayage    3530 non-null   object 
 12  port_qualified           3530 non-null   object 
 13  signup_source            3530 non-null   object 
 14  ts_signup                3530 non-null   object 
 15  ts_first_approved        2671 non-null   object 
 16  days_signup_to_approval  2671 non-null   float64
 17  driver_with_twic         3530 non-null   object 
 18  dim_preferred_lanes      129 non-null    object 
 19  first_load_date          3530 non-null   object 
 20  load_day                 3530 non-null   object 
 21  loads                    3530 non-null   int64  
 22  marketplace_loads_otr    3530 non-null   int64  
 23  marketplace_loads_atlas  3530 non-null   int64  
 24  marketplace_loads        3530 non-null   int64  
 25  brokerage_loads_otr      3530 non-null   int64  
 26  brokerage_loads_atlas    3530 non-null   int64  
 27  brokerage_loads          3530 non-null   int64  
 28  label                    3530 non-null   int64  
dtypes: float64(2), int64(10), object(17)
memory usage: 799.9+ KB
```

To do this, we had to remove or alter the Object data types. We ended up purging some of these columns from the dataset, and encoding others.

Cols with Null Values: 1. dim_carrier_company_name (5) - dropped because this would have required too many dimensions to one-hot encode and the variance provided by this would likely be captured in other features

2. home_base_city (6) - dropped because there were far too many to encode and home_base_state seemed precise enough to capture the desired amount of variance
3. home_base_state (6) - encoded with 1 being CA and 0 being any other state due to the extremely high number of CA and a desire to keep dimensionality low
4. num_trucks (25) - KNN inputed, replaced null values by selecting K=2 closest values (based on other features) and averaging their num_trucks
5. ts_first_approved (806) - dropped as there were an extremely high number of null values
6. days_signup_to_approval (806) - dropped as there were an extremely high number of null values
7. dim_preferred_lanes (3416) - dropped as a majority were null values and this feature didn't seem to provide much useful information when it was included

[20]:
```
labeled_data.shape
```

[20]:
```
(3530, 29)
```

[21]:
```
labeled_data.describe()
```

[21]:
```
              year     id_driver  …  brokerage_loads        label
count  3530.000000   3530.000000  …      3530.000000  3530.000000
mean   2018.830028  18346.243909  …        21.217847     0.200000
std       1.492402  11755.986044  …       118.055721     0.400057
min    2015.000000     20.000000  …         0.000000     0.000000
25%    2018.000000   8397.250000  …         0.000000     0.000000
50%    2019.000000  15977.000000  …         1.000000     0.000000
75%    2020.000000  29972.250000  …         7.000000     0.000000
max    2021.000000  38096.000000  …      4266.000000     1.000000

[8 rows x 12 columns]
```

Dropping columns that were either deemed to complex to accurately encode or that clearly had their variance captured in other features.

[22]:
```
# Remove the duplicate dates cols as sorting caused some of the cols␣
↪representing dates to be identical.
labeled_data = labeled_data.drop(columns=['load_day'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['load_day'])

# Almost all data is NaN
labeled_data = labeled_data.drop(columns=['dim_preferred_lanes'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['dim_preferred_lanes'])

# Too challenging to encode/less relevant
```

```
labeled_data = labeled_data.drop(columns=['ts_signup', 'ts_first_approved'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['ts_signup',␣
↪'ts_first_approved'])

# Less relevant/no connection between data
labeled_data = labeled_data.drop(columns=['id_carrier_number'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['id_carrier_number'])

# Too many companies
labeled_data = labeled_data.drop(columns=['dim_carrier_company_name'])
kaggle_u_compressed = kaggle_u_compressed.
↪drop(columns=['dim_carrier_company_name'])

# Too many cities, states to encode efficiently
labeled_data = labeled_data.drop(columns=['home_base_city'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['home_base_city'])

# Weird with the different types, seems like even poweronly can be labeled a 1,␣
↪so we cut it
labeled_data = labeled_data.drop(columns=['carrier_trucks'])
kaggle_u_compressed = kaggle_u_compressed.drop(columns=['carrier_trucks'])

# Seemed weird since most are zero but even a 936 is a 1
labeled_data = labeled_data.drop(columns=['days_signup_to_approval'])
kaggle_u_compressed = kaggle_u_compressed.
↪drop(columns=['days_signup_to_approval'])
```

Label Encoding of non int/float values:

[23]:
```
label_encoder = LabelEncoder()

# Label Encode port_qualified
integer_encoded = label_encoder.fit_transform(labeled_data["port_qualified"])
labeled_data["port_qualified"] = integer_encoded

integer_encoded = label_encoder.
↪fit_transform(kaggle_u_compressed["port_qualified"])
kaggle_u_compressed["port_qualified"] = integer_encoded

# Label Encode driver_with_twic
integer_encoded = label_encoder.fit_transform(labeled_data["driver_with_twic"])
labeled_data["driver_with_twic"] = integer_encoded

integer_encoded = label_encoder.
↪fit_transform(kaggle_u_compressed["driver_with_twic"])
kaggle_u_compressed["driver_with_twic"] = integer_encoded
```

```
# Label Encode signup_source
integer_encoded = label_encoder.fit_transform(labeled_data["signup_source"])
labeled_data["signup_source"] = integer_encoded

integer_encoded = label_encoder.
↪fit_transform(kaggle_u_compressed["signup_source"])
kaggle_u_compressed["signup_source"] = integer_encoded

# Label Encode interested_in_drayage
integer_encoded = label_encoder.
↪fit_transform(labeled_data["interested_in_drayage"])
labeled_data["interested_in_drayage"] = integer_encoded

integer_encoded = label_encoder.
↪fit_transform(kaggle_u_compressed["interested_in_drayage"])
kaggle_u_compressed["interested_in_drayage"] = integer_encoded

# Label Encode dim_carrier_type
integer_encoded = label_encoder.fit_transform(labeled_data["dim_carrier_type"])
labeled_data["dim_carrier_type"] = integer_encoded

integer_encoded = label_encoder.
↪fit_transform(kaggle_u_compressed["dim_carrier_type"])
kaggle_u_compressed["dim_carrier_type"] = integer_encoded

# Label Encode weekday_type
integer_encoded = label_encoder.fit_transform(labeled_data["weekday"])
labeled_data["weekday"] = integer_encoded

integer_encoded = label_encoder.fit_transform(kaggle_u_compressed["weekday"])
kaggle_u_compressed["weekday"] = integer_encoded
```

Custom encoding of 'home_base_state' as described above:

[24]:
```
#Label encode state for CA to be 1 and others to be 0
for i in labeled_data.index:
  if labeled_data["home_base_state"][i] == "CA":
    labeled_data["home_base_state"][i] = 1
  else:
    labeled_data["home_base_state"][i] = 0
newStates = pd.to_numeric(labeled_data["home_base_state"])
labeled_data["home_base_state"] = newStates

for i in kaggle_u_compressed.index:
  if kaggle_u_compressed["home_base_state"][i] == "CA":
    kaggle_u_compressed["home_base_state"][i] = 1
  else:
```

```
    kaggle_u_compressed["home_base_state"][i] = 0
newStates = pd.to_numeric(kaggle_u_compressed["home_base_state"])
kaggle_u_compressed["home_base_state"] = newStates
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:12:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  if sys.path[0] == '':
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:14:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Encoding of dates as integers where the value is the number of seconds since the POSIX Epoch.

[25]:
```
for i in labeled_data.index:
  listDate = labeled_data['dt'][i].split('-')
  labeled_data['dt'][i] = int(datetime.datetime(int(listDate[0]),␣
 ↪int(listDate[1]), int(listDate[2]),0,0).timestamp())
newTimes = pd.to_numeric(labeled_data["dt"])
labeled_data["dt"] = newTimes

for i in kaggle_u_compressed.index:
  listDate = kaggle_u_compressed['dt'][i].split('-')
  kaggle_u_compressed['dt'][i] = int(datetime.datetime(int(listDate[0]),␣
 ↪int(listDate[1]), int(listDate[2]),0,0).timestamp())
newTimes = pd.to_numeric(kaggle_u_compressed["dt"])
kaggle_u_compressed["dt"] = newTimes
```

```
for i in labeled_data.index:
  listDate = labeled_data['first_load_date'][i].split('-')
  labeled_data['first_load_date'][i] = int(datetime.datetime(int(listDate[0]),␣
 ↪int(listDate[1]), int(listDate[2]),0,0).timestamp())
newTimes = pd.to_numeric(labeled_data["first_load_date"])
labeled_data["first_load_date"] = newTimes

for i in kaggle_u_compressed.index:
  listDate = kaggle_u_compressed['first_load_date'][i].split('-')
  kaggle_u_compressed['first_load_date'][i] = int(datetime.
 ↪datetime(int(listDate[0]), int(listDate[1]), int(listDate[2]),0,0).
 ↪timestamp())
newTimes = pd.to_numeric(kaggle_u_compressed["first_load_date"])
kaggle_u_compressed["first_load_date"] = newTimes
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing imports
until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:9:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  if __name__ == '__main__':
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:15:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  from ipykernel import kernelapp as app
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:21:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

Replacing null values for ‘num_trucks’ with KNN method as described above:

[26]:
```python
imputer = KNNImputer(n_neighbors=2)
let_me_see = imputer.fit_transform(labeled_data)
let_me_see = pd.DataFrame(data=let_me_see)
labeled_data["num_trucks"] = let_me_see[6]

imputer = KNNImputer(n_neighbors=2)
let_me_see = imputer.fit_transform(kaggle_u_compressed)
let_me_see = pd.DataFrame(data=let_me_see)
kaggle_u_compressed["num_trucks"] = let_me_see[6]
```

[27]:
```python
test = labeled_data[labeled_data.isnull().any(axis=1)]
test.head(30)
```

[27]:
```
Empty DataFrame
Columns: [dt, weekday, year, id_driver, dim_carrier_type, home_base_state,
num_trucks, interested_in_drayage, port_qualified, signup_source,
driver_with_twic, first_load_date, loads, marketplace_loads_otr,
marketplace_loads_atlas, marketplace_loads, brokerage_loads_otr,
brokerage_loads_atlas, brokerage_loads, label]
Index: []
```

[28]:
```python
labeled_data.shape
```

[28]:
```
(3530, 20)
```

As can be seen above we now have 20 features and no null values in any of them.

4.1 3b) This is the actual requirements of #3

Basic statistics of each feature:

[29]:
```python
labeled_data.describe()
```

[29]:
```
                 dt      weekday  …  brokerage_loads        label
count  3.530000e+03  3530.000000  …      3530.000000  3530.000000
mean   1.555809e+09     3.203399  …        21.217847     0.200000
std    4.531879e+07     2.257443  …       118.055721     0.400057
min    1.446077e+09     0.000000  …         0.000000     0.000000
25%    1.523923e+09     1.000000  …         0.000000     0.000000
50%    1.562112e+09     4.000000  …         1.000000     0.000000
75%    1.597018e+09     5.000000  …         7.000000     0.000000
max    1.613520e+09     6.000000  …      4266.000000     1.000000

[8 rows x 20 columns]
```

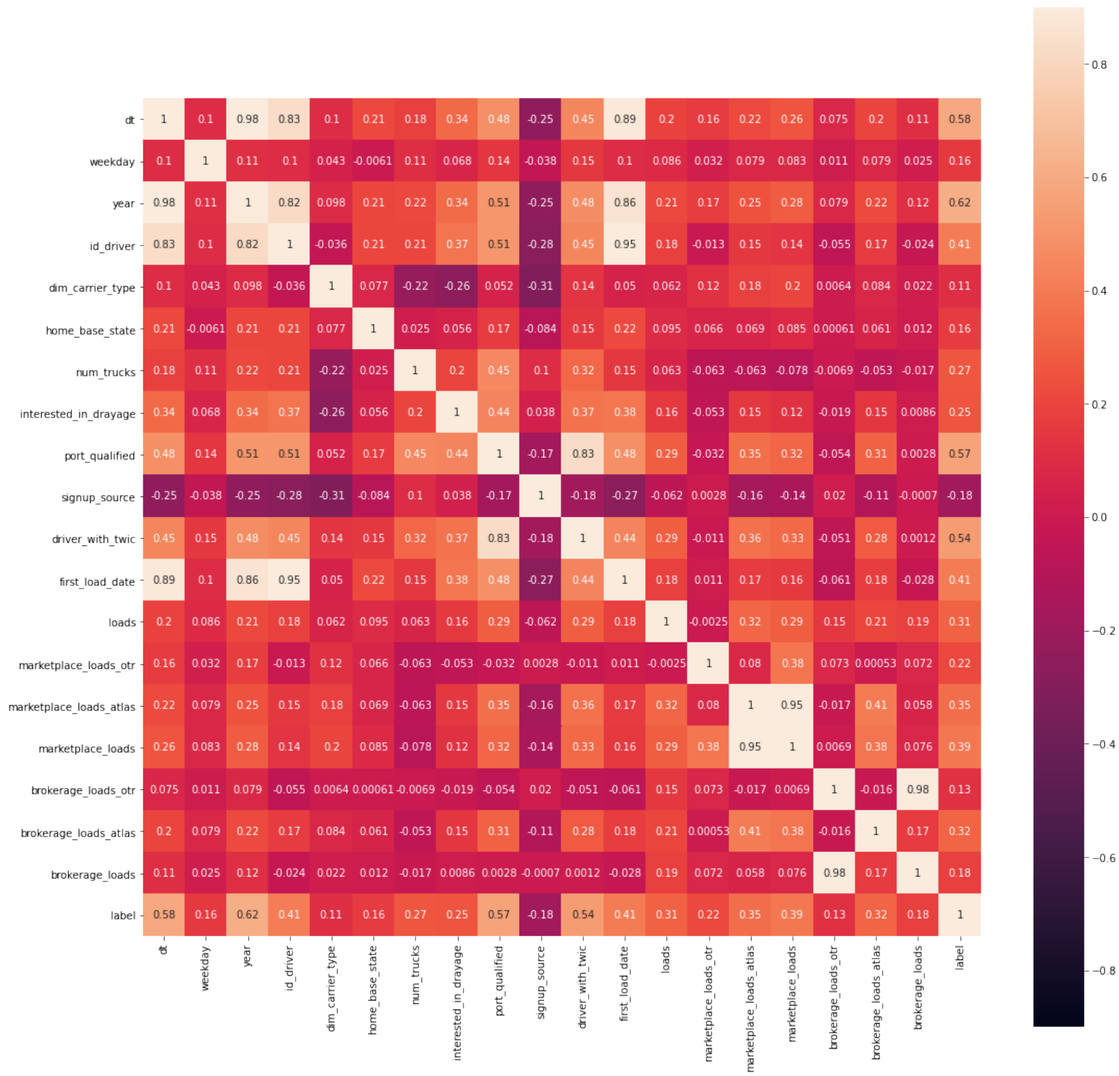
The types and number of non-null values for each feature. All have been made to have no null-values and be of either float or int types.

[30]:
```python
labeled_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3530 entries, 0 to 3529
Data columns (total 20 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   dt                        3530 non-null   int64
 1   weekday                   3530 non-null   int64
 2   year                      3530 non-null   int64
 3   id_driver                 3530 non-null   int64
 4   dim_carrier_type          3530 non-null   int64
 5   home_base_state           3530 non-null   int64
 6   num_trucks                3530 non-null   float64
 7   interested_in_drayage     3530 non-null   int64
 8   port_qualified            3530 non-null   int64
 9   signup_source             3530 non-null   int64
 10  driver_with_twic          3530 non-null   int64
 11  first_load_date           3530 non-null   int64
 12  loads                     3530 non-null   int64
 13  marketplace_loads_otr     3530 non-null   int64
 14  marketplace_loads_atlas   3530 non-null   int64
 15  marketplace_loads         3530 non-null   int64
 16  brokerage_loads_otr       3530 non-null   int64
 17  brokerage_loads_atlas     3530 non-null   int64
 18  brokerage_loads           3530 non-null   int64
 19  label                     3530 non-null   int64
dtypes: float64(1), int64(19)
memory usage: 551.7 KB
```

A correlation matrix showing how each variable is correlated to all others including the label:

[31]:
```python
import seaborn as sns;
corr_data = labeled_data.corr(method ='pearson')
f, ax = plt.subplots(figsize=(18, 18))
ax = sns.heatmap(corr_data, square=True, vmin=-.9, vmax=.9, annot=True)
```

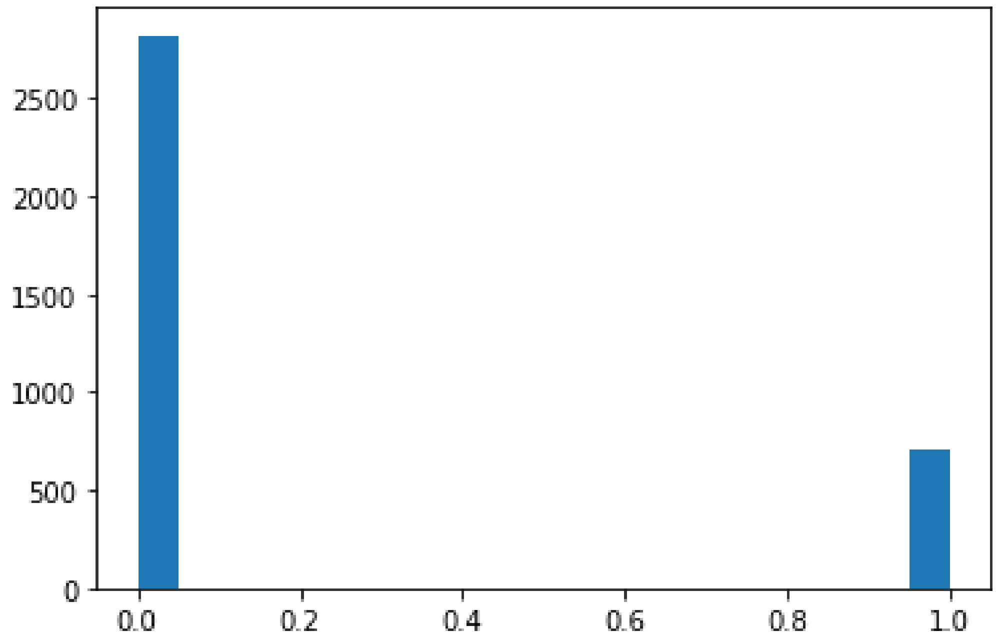


4.1.1 Here we need to be aware of colinearities in our data. We see that dt, year, id_driver, and first_load_date are all highly correlated. In addition, it looks like brokerage_loads and brokerage_loads_otr are also very correlated.

Below is the balance of our dataset as displayed by a histogram of the labels. We have the expected 4:1 ratio of not high performing drivers to high performing drivers.

[32]:
```
plt.hist(labeled_data['label'], bins=20)
plt.show
labeled_data['label'].value_counts()
```

[32]:
```
0    2824
1     706
Name: label, dtype: int64
```



5 4) Create a data feature extraction plan and implement a pipeline to execute it

5.1 4a) Determine which fields to retain and which to drop

We drop columns that are shown by the correlation matrix to have had an extremely low correlation with the label.

[33]:
```
# Signup source has very little effect
labeled_data = labeled_data.drop(columns=['weekday','signup_source'])
kaggle_u_compressed = kaggle_u_compressed.
 ↪drop(columns=['weekday','signup_source'])
```

Additionally we dropped columns that were deemed to be too complex to encode or to have too many null values to be useful before generating statistics. See above in step 3a.

5.2 4b) Determine a categorization strategy

We encoded all data for retained columns in step 3a above. This was so that we could generate the correlation matrix above as well as other useful statistics.

5.3 4c) Determine an imputation strategy

We largely handled this above in step 3a. Below is a brief synopsis:

1. For num_trucks we used a KNN imputation where the value that replaces null is based on k similar rows

2. ts_first_approved, days_signup_to_approval, and dim_preferred_lanes were all dropped entirely due to having too high of a percentage of null values with little percieved value
3. home_base_state handled this in its encoding by changing null values to "0" which represents any state that is not CA
4. dim_carrier_company_name and home_base_city were dropped in their entirety due to being too difficult to encode without gaining a large amount of dimensionality

5.4 4d, 4e, and 4f

Pipeline:

Save labels for later:

[34]:
```
labels = labeled_data["label"]
labels.shape
```

[34]:
```
(3530,)
```

Remove labels to use in training:

[35]:
```
unlabeled_data = labeled_data.drop("label", axis=1)
unlabeled_data.shape
```

[35]:
```
(3530, 17)
```

5.4.1 Create an augmented feature for 4d)

Our augmented feature is a feature cross between date and first load date to roughly represent the longevity of the driver.

[36]:
```
unlabeled_data["longevity"] = unlabeled_data["dt"]/
 ↪unlabeled_data["first_load_date"]
kaggle_u_compressed["longevity"] = kaggle_u_compressed["dt"]/
 ↪kaggle_u_compressed["first_load_date"]
unlabeled_data.head()
```

[36]:
```
           dt  year  …  brokerage_loads  longevity
0  1613520000  2021  …                0   1.013624
1  1613520000  2021  …              150   1.019545
2  1613520000  2021  …               57   1.046394
3  1613520000  2021  …                1   1.001824
4  1613520000  2021  …              145   1.007336

[5 rows x 18 columns]
```

Below is our implementation for 4e and 4f utilizing the standard scaler and a simple imputation strategy of median value imputation for any null values not handled already. The pipline also adds the augmented feature when passed a True agrument as the second parameter.

[37]:

```python
imputer = SimpleImputer(strategy="median")

# column index
dt_ix, first_ix = 0, 9

#
class AugmentFeatures(BaseEstimator, TransformerMixin):
    '''
    implements the previous features we had defined
    labeled_data["longevity"] = labeled_data["dt"]/
 ↪labeled_data["first_load_date"]
    '''
    def __init__(self, add_longevity):
        self.add_longevity = add_longevity
    def fit(self, X, y=None):
        return self  # nothing else to do
    def transform(self, X):
        if self.add_longevity:
          longevity = X[:, dt_ix] / X[:, first_ix]
          return np.c_[X, longevity]
        else:
          return np.c_[X]

def our_pipeline(dataset, augment):
  attr_adder = AugmentFeatures(add_longevity=augment)
  trucking_extra_attribs = attr_adder.transform(dataset.values)

  num_pipeline = Pipeline([
          ('imputer', SimpleImputer(strategy="median")),
          ('attribs_adder', AugmentFeatures(add_longevity=augment)),
          ('std_scaler', StandardScaler()),
      ])

  trucking_tr = num_pipeline.fit_transform(dataset)
  numerical_features = list(dataset)

  full_pipeline = ColumnTransformer([
          ("num", num_pipeline, numerical_features)
      ])

  return full_pipeline.fit_transform(dataset)

trucking_prepared = our_pipeline(unlabeled_data, True)
kaggle_prepared = our_pipeline(kaggle_u_compressed, True)
```

5.5 4g) Document your data strategy in your report

See report Methodology section for details on data strategy as well as experiments ran to select data.

6 5) Implement a basic Linear Regression

[38]:
```
trucking_reg = labeled_data.drop(columns=['id_driver', 'year', 'label',␣
 ↪'first_load_date', 'brokerage_loads_otr'])
reg_prepped = our_pipeline(trucking_reg, False)
trucking_reg.head()
```

[38]:
```
           dt  dim_carrier_type  …  brokerage_loads_atlas  brokerage_loads
0  1613520000                 0  …                      0                0
1  1613520000                 1  …                    148              150
2  1613520000                 1  …                     56               57
3  1613520000                 0  …                      1                1
4  1613520000                 1  …                    145              145

[5 rows x 13 columns]
```

Above we dropped values with high colinearity for the linear regression model, including 'first_load_date'. Thus, when we run the pipeline on this subset of our data we do not include the augmented longevity feature since it is based off some of the dropped values. These determinations were made bassed off our correlation matrix in step 3b.

[39]:
```
X2 = sm.add_constant(reg_prepped)
est = sm.OLS(labels, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  label   R-squared:                       0.530
Model:                            OLS   Adj. R-squared:                  0.528
Method:                 Least Squares   F-statistic:                     330.1
Date:                Thu, 18 Mar 2021   Prob (F-statistic):               0.00
Time:                        03:25:28   Log-Likelihood:                -442.80
No. Observations:                3530   AIC:                             911.6
Df Residuals:                    3517   BIC:                             991.8
Df Model:                          12
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.2000      0.005     43.239      0.000       0.191       0.209
x1             0.1344      0.006     23.869      0.000       0.123       0.145
x2             0.0046      0.005      0.887      0.375      -0.006       0.015
```

```
x3              0.0042      0.005      0.881      0.378      -0.005       0.014
x4              0.0419      0.006      7.422      0.000       0.031       0.053
x5             -0.0161      0.006     -2.894      0.004      -0.027      -0.005
x6              0.0773      0.010      8.088      0.000       0.059       0.096
x7              0.0488      0.009      5.745      0.000       0.032       0.066
x8              0.0319      0.005      6.264      0.000       0.022       0.042
x9              0.0543      0.005     11.562      0.000       0.045       0.063
x10             0.0108      0.003      3.319      0.001       0.004       0.017
x11             0.0267      0.003      9.984      0.000       0.021       0.032
x12             0.0384      0.005      7.250      0.000       0.028       0.049
x13             0.0394      0.005      8.184      0.000       0.030       0.049
==============================================================================
Omnibus:                      264.167   Durbin-Watson:                   1.517
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              490.478
Skew:                           0.529   Prob(JB):                    3.12e-107
Kurtosis:                       4.488   Cond. No.                     1.24e+15
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 8.31e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

We see that we should take these results with a grain of salt as there is still some colinearity present as per warining 2. That being said the p-values for x2 and x3 are well above 0.05 and thus are not likely to have any significant impact on the label prediction. Below we drop these values and repipeline our data to adjust for this fact.

[40]:
```python
unlabeled_data = unlabeled_data.
 ↪drop(columns=['dim_carrier_type','home_base_state'])
kaggle_u_compressed = kaggle_u_compressed.
 ↪drop(columns=['dim_carrier_type','home_base_state'])

first_ix = 7

trucking_prepared = our_pipeline(unlabeled_data, True)
kaggle_prepared = our_pipeline(kaggle_u_compressed, True)
```

[41]:
```python
all_drivers = pd.concat([kaggle_u_compressed, unlabeled_data], axis=0)
all_drivers = all_drivers.sort_values(by=['dt'], axis=0, ascending=False)
all_drivers = all_drivers.reset_index().drop(columns=['index'])

all_drivers.drop_duplicates('id_driver', inplace = True)

all_drivers
```

[41]:
```
                dt  year  …  brokerage_loads  longevity
0     1613520000  2021  …              159   1.024860
1     1613520000  2021  …                0   1.003978
2     1613520000  2021  …              144   1.042306
3     1613520000  2021  …                0   1.014009
4     1613520000  2021  …               47   1.013514
…            …     …   …              …          …
4522  1451347200  2015  …                6   1.002387
4524  1450310400  2015  …                5   1.000358
4525  1449619200  2015  …               11   1.003109
4527  1448323200  2015  …               23   1.001075
4529  1446076800  2015  …                1   1.000000

[3692 rows x 16 columns]
```

7 6) Implement Principle Component Analysis (PCA)

[42]:
```python
pca = PCA(n_components=7)
pca_vecs = pca.fit_transform(trucking_prepared)

print(pca.explained_variance_ratio_)

print(pca.singular_values_)

pca_vecs.shape
```

```
[0.30942371 0.17081783 0.11961424 0.0965457  0.08108702 0.05042855
 0.04559789]
[136.26634411 101.24612643  84.72337515  76.11640898  69.75695105
  55.01106761  52.30993745]
```

[42]:
```
(3530, 7)
```

[43]:
```python
pca = PCA(n_components=7)
kaggle_pca_vecs = pca.fit_transform(kaggle_prepared)
```

[44]:
```python
pca = PCA(n_components=7)
all_drivers_pca = pca.fit_transform(all_drivers)
```

7.1 Should we try having more PCA vecs???

8 7) Ensamble Method

We chose to use AdaBoost as our primary ensamble method given this method seems to be a relatively new and high performing model that avoids overfitting through the use of many weak learners.

8.0.1 AdaBoost

[45]:
```
X_train, X_test, y_train, y_test = train_test_split(pca_vecs, labels,␣
↪test_size=0.2, random_state=0, shuffle=True)
X_train.shape
```

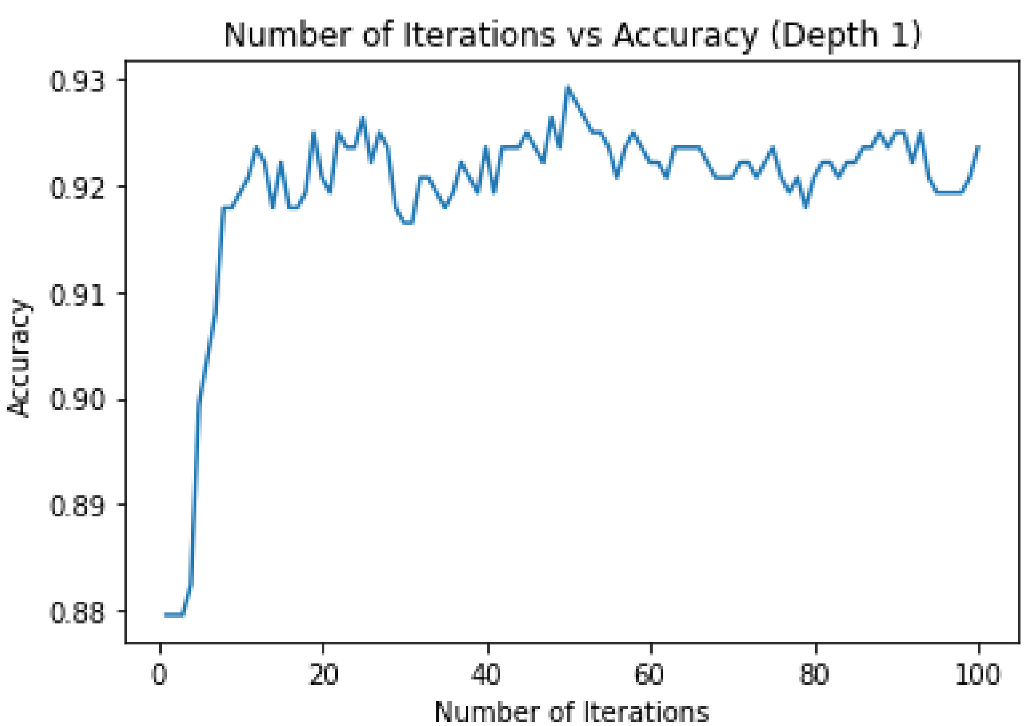
[45]: (2824, 7)

[46]:
```
from sklearn.metrics import accuracy_score
tests = np.linspace(start=1, stop=100, num=100)
accus = []

for num_est in tests:
    ada = AdaBoostClassifier(base_estimator=None, random_state=10,␣
↪learning_rate=1, n_estimators=int(num_est))
    ada.fit(X_train, y_train)
    y_pred_ada = ada.predict(X_test)
    accus.append(accuracy_score(y_test, y_pred_ada))

accu_arr = np.array(accus)
```

[47]:
```
plt.plot(tests, accu_arr)
plt.xlabel("Number of Iterations")
plt.ylabel("Accuracy")
plt.title("Number of Iterations vs Accuracy (Depth 1)")
plt.show()
```

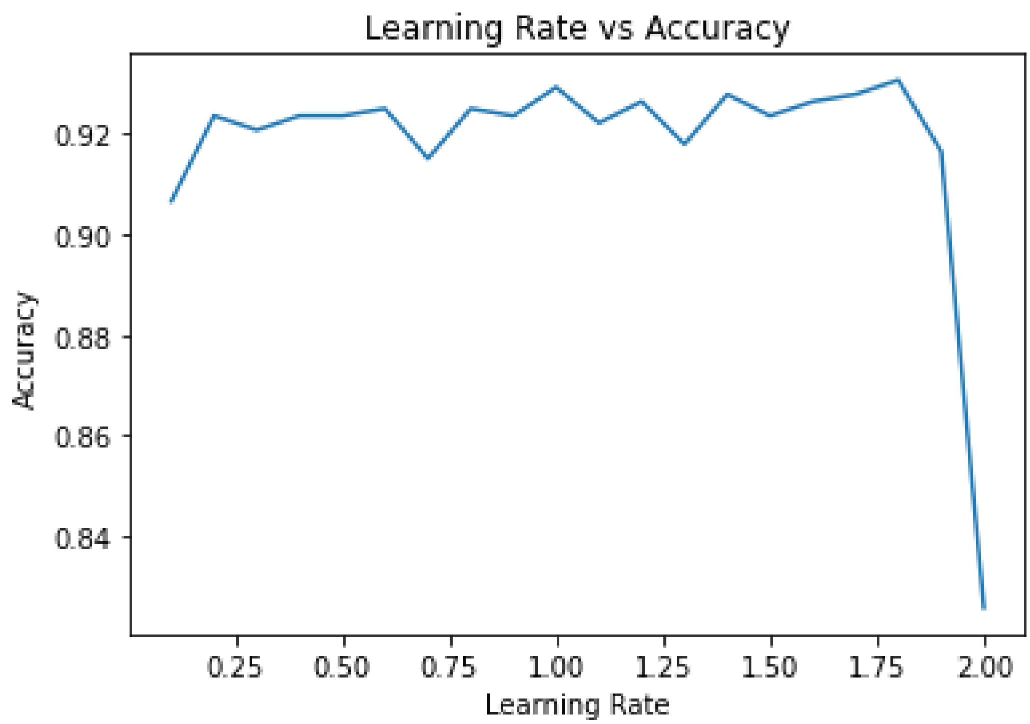


[48]:
```
accus2 = []
rates = np.linspace(start=0.1, stop=2.0, num=20)

for lr in rates:
    ada = AdaBoostClassifier(base_estimator=None, random_state=10,␣
 ↪n_estimators=50, learning_rate=lr)
    ada.fit(X_train, y_train)
    y_pred_ada = ada.predict(X_test)
    accus2.append(accuracy_score(y_test, y_pred_ada))

accu_arr = np.array(accus2)
```

[49]:
```
plt.plot(rates, accu_arr)
plt.xlabel("Learning Rate")
plt.ylabel("Accuracy")
plt.title("Learning Rate vs Accuracy")
plt.show()
```



[50]:
```
from sklearn.model_selection import RandomizedSearchCV
import pprint
```

```python
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 1, stop = 500, num = 20)]

# Learning Rate
learning_rate = [float(x) for x in np.linspace(start = 0.1, stop = 2.0, num =␣
↪20)]

# Maximum number of levels in tree
#max_depth = [int(x) for x in np.linspace(1, 5, num = 5)]
#max_depth.append(None)

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'learning_rate': learning_rate}
               #'max_depth': max_depth}

random_grid
```

```
[50]: {'learning_rate': [0.1,
  0.2,
  0.3,
  0.4,
  0.5,
  0.6,
  0.7,
  0.7999999999999999,
  0.8999999999999999,
  0.9999999999999999,
  1.0999999999999999,
  1.2,
  1.3,
  1.4,
  1.5,
  1.5999999999999999,
  1.7,
  1.8,
  1.9,
  2.0],
 'n_estimators': [1,
  27,
  53,
  79,
  106,
  132,
  158,
  184,
```

```
  211,
  237,
  263,
  289,
  316,
  342,
  368,
  394,
  421,
  447,
  473,
  500]}
```

The above grid of parameters are used to test for the best possible combination of parameters. Below is the code to determine these parameters via 5 fold kfold cross validation.

[51]:
```python
sonic = AdaBoostClassifier()

rf_random = RandomizedSearchCV(estimator = sonic, param_distributions =␣
 ↪random_grid,
                               n_iter = 100, cv = 5, verbose=2, random_state=10,␣
 ↪n_jobs = -1)

rf_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   37.6s
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:  2.3min
[Parallel(n_jobs=-1)]: Done 361 tasks      | elapsed:  5.5min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  7.1min finished
```

[51]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=AdaBoostClassifier(algorithm='SAMME.R',
                                                base_estimator=None,
                                                learning_rate=1.0,
                                                n_estimators=50,
                                                random_state=None),
                   iid='deprecated', n_iter=100, n_jobs=-1,
                   param_distributions={'learning_rate': [0.1, 0.2, 0.3, 0.4,
                                                          0.5, 0.6, 0.7,
                                                          0.7999999999999999,
                                                          0.8999999999999999,
                                                          0.9999999999999999,
                                                          1.0999999999999999,
                                                          1.2, 1.3, 1.4, 1.5,
                                                          1.5999999999999999,
```

```
                                           1.7, 1.8, 1.9, 2.0],
                          'n_estimators': [1, 27, 53, 79, 106,
                                           132, 158, 184, 211,
                                           237, 263, 289, 316,
                                           342, 368, 394, 421,
                                           447, 473, 500]},
          pre_dispatch='2*n_jobs', random_state=10, refit=True,
          return_train_score=False, scoring=None, verbose=2)
```

[52]:
```
rf_random.best_params_
```

[52]:
```
{'learning_rate': 0.3, 'n_estimators': 184}
```

[53]:
```
ada = AdaBoostClassifier(base_estimator=None, random_state=10, learning_rate=1,␣
 ↪n_estimators=368)
ada.fit(X_train, y_train)
y_pred_ada = ada.predict(X_test)
print(f"Accuracy of best parameters: {accuracy_score(y_test, y_pred_ada)}")
```

```
Accuracy of best parameters: 0.9263456090651558
```

9 8) Neural net

We implemented two different forms of Neural Networks. We started by taking the starter code and retrofitting it for our needs using pytorch.

[54]:
```
import numpy as np
import torch
import torchvision
from torchvision.datasets import MNIST
from torchvision import transforms
SEED = 1
# CUDA?
cuda = False

# For reproducibility
torch.manual_seed(SEED)
if cuda:
    torch.cuda.manual_seed(SEED)
```

[55]:
```
from torch.utils.data import TensorDataset, DataLoader
X_train_float = X_train.astype(np.float32)
y_train_long = y_train.astype(np.long)

X_test_float = X_test.astype(np.float32)
y_test_long = y_test.astype(np.long)
```

```
X_train_torch = torch.from_numpy(X_train_float)
y_train_torch = torch.from_numpy(y_train_long.to_numpy())
X_test_torch = torch.from_numpy(X_test_float)
y_test_torch = torch.from_numpy(y_test_long.to_numpy())

train_dataset = TensorDataset(X_train_torch, y_train_torch)
test_dataset = TensorDataset(X_test_torch, y_test_torch)

train_loader = DataLoader(train_dataset, batch_size=1)
test_loader = DataLoader(test_dataset, batch_size=1)
```

[56]:

```
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
```

[57]:

```
# One hidden Layer NN
class Model(nn.Module):
    def __init__(self):
        super(Model, self).__init__()
        self.fc = nn.Linear(7, 100)
        self.fc2 = nn.Linear(100, 10)

    def forward(self, x):
        x = x.view((-1, 7))
        h = F.relu(self.fc(x))
        h = self.fc2(h)
        return F.log_softmax(h)

#initialize the model
network = Model()
if cuda:
    model.cuda() # CUDA!
#initialize the optimizer
learning_rate = 0.025
momentum = 0.25
optimizer = optim.SGD(network.parameters(), lr=learning_rate,
                      momentum=momentum)
```

[58]:

```
n_epochs = 3
train_losses = []
train_counter = []
test_losses = []
test_counter = [i*len(train_loader.dataset) for i in range(n_epochs + 1)]
log_interval = 100
```

[59]:
```
def train(epoch):
  network.train()
  for batch_idx, (data, target) in enumerate(train_loader):
    optimizer.zero_grad()
    output = network(data)
    loss = F.nll_loss(output, target)
    loss.backward()
    optimizer.step()
    if batch_idx % log_interval == 0:
      print('Train Epoch: {} [{}/{} ({:.0f}%)]\tLoss: {:.6f}'.format(
        epoch, batch_idx * len(data), len(train_loader.dataset),
        100. * batch_idx / len(train_loader), loss.item()))
      train_losses.append(loss.item())
      train_counter.append(
        (batch_idx*64) + ((epoch-1)*len(train_loader.dataset)))
```

[60]:
```
def test():
  network.eval()
  test_loss = 0
  correct = 0
  with torch.no_grad():
    for data, target in test_loader:
      output = network(data)
      test_loss += F.nll_loss(output, target, size_average=False).item()
      pred = output.data.max(1, keepdim=True)[1]
      correct += pred.eq(target.data.view_as(pred)).sum()
  test_loss /= len(test_loader.dataset)
  test_losses.append(test_loss)
  print('\nTest set: Avg. loss: {:.4f}, Accuracy: {}/{} ({:.2f}%)\n'.format(
    test_loss, correct, len(test_loader.dataset),
    100. * correct / float(len(test_loader.dataset))))
```

[61]:
```
test()
for epoch in range(1, n_epochs + 1):
  train(epoch)
  test()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:12: UserWarning:
Implicit dimension choice for log_softmax has been deprecated. Change the call
to include dim=X as an argument.
  if sys.path[0] == '':
/usr/local/lib/python3.7/dist-packages/torch/nn/_reduction.py:42: UserWarning:
size_average and reduce args will be deprecated, please use reduction='sum'
instead.
  warnings.warn(warning.format(ret))


Test set: Avg. loss: 2.3442, Accuracy: 37/706 (5.24%)
```

```
Train Epoch: 1 [0/2824 (0%)]	Loss: 2.453657
Train Epoch: 1 [100/2824 (4%)]	Loss: 0.013942
Train Epoch: 1 [200/2824 (7%)]	Loss: 0.021404
Train Epoch: 1 [300/2824 (11%)]	Loss: 0.130228
Train Epoch: 1 [400/2824 (14%)]	Loss: 0.000137
Train Epoch: 1 [500/2824 (18%)]	Loss: 0.114912
Train Epoch: 1 [600/2824 (21%)]	Loss: 0.002487
Train Epoch: 1 [700/2824 (25%)]	Loss: 0.000055
Train Epoch: 1 [800/2824 (28%)]	Loss: 0.000434
Train Epoch: 1 [900/2824 (32%)]	Loss: 0.103703
Train Epoch: 1 [1000/2824 (35%)]	Loss: 0.000002
Train Epoch: 1 [1100/2824 (39%)]	Loss: 0.000000
Train Epoch: 1 [1200/2824 (42%)]	Loss: 0.047142
Train Epoch: 1 [1300/2824 (46%)]	Loss: 0.006304
Train Epoch: 1 [1400/2824 (50%)]	Loss: 0.000055
Train Epoch: 1 [1500/2824 (53%)]	Loss: 0.958577
Train Epoch: 1 [1600/2824 (57%)]	Loss: 0.207303
Train Epoch: 1 [1700/2824 (60%)]	Loss: 0.000024
Train Epoch: 1 [1800/2824 (64%)]	Loss: 0.005747
Train Epoch: 1 [1900/2824 (67%)]	Loss: 0.000054
Train Epoch: 1 [2000/2824 (71%)]	Loss: 0.217375
Train Epoch: 1 [2100/2824 (74%)]	Loss: 0.000000
Train Epoch: 1 [2200/2824 (78%)]	Loss: 0.000741
Train Epoch: 1 [2300/2824 (81%)]	Loss: 0.000000
Train Epoch: 1 [2400/2824 (85%)]	Loss: 0.122898
Train Epoch: 1 [2500/2824 (89%)]	Loss: 0.000001
Train Epoch: 1 [2600/2824 (92%)]	Loss: 0.000022
Train Epoch: 1 [2700/2824 (96%)]	Loss: 0.000002
Train Epoch: 1 [2800/2824 (99%)]	Loss: 0.019189

Test set: Avg. loss: 0.2408, Accuracy: 632/706 (89.52%)

Train Epoch: 2 [0/2824 (0%)]	Loss: 0.000319
Train Epoch: 2 [100/2824 (4%)]	Loss: 0.000002
Train Epoch: 2 [200/2824 (7%)]	Loss: 0.000161
Train Epoch: 2 [300/2824 (11%)]	Loss: 0.063307
Train Epoch: 2 [400/2824 (14%)]	Loss: 0.000000
Train Epoch: 2 [500/2824 (18%)]	Loss: 0.022361
Train Epoch: 2 [600/2824 (21%)]	Loss: 0.000124
Train Epoch: 2 [700/2824 (25%)]	Loss: 0.000000
Train Epoch: 2 [800/2824 (28%)]	Loss: 0.000007
Train Epoch: 2 [900/2824 (32%)]	Loss: 0.089871
Train Epoch: 2 [1000/2824 (35%)]	Loss: 0.000000
Train Epoch: 2 [1100/2824 (39%)]	Loss: 0.000000
Train Epoch: 2 [1200/2824 (42%)]	Loss: 0.021540
Train Epoch: 2 [1300/2824 (46%)]	Loss: 0.044817
Train Epoch: 2 [1400/2824 (50%)]	Loss: 0.000000
```

```
Train Epoch: 2 [1500/2824 (53%)]        Loss: 0.968500
Train Epoch: 2 [1600/2824 (57%)]        Loss: 0.092611
Train Epoch: 2 [1700/2824 (60%)]        Loss: 0.000001
Train Epoch: 2 [1800/2824 (64%)]        Loss: 0.002212
Train Epoch: 2 [1900/2824 (67%)]        Loss: 0.000002
Train Epoch: 2 [2000/2824 (71%)]        Loss: 0.420986
Train Epoch: 2 [2100/2824 (74%)]        Loss: 0.000000
Train Epoch: 2 [2200/2824 (78%)]        Loss: 0.000074
Train Epoch: 2 [2300/2824 (81%)]        Loss: 0.000000
Train Epoch: 2 [2400/2824 (85%)]        Loss: 0.127486
Train Epoch: 2 [2500/2824 (89%)]        Loss: 0.000000
Train Epoch: 2 [2600/2824 (92%)]        Loss: 0.000005
Train Epoch: 2 [2700/2824 (96%)]        Loss: 0.000000
Train Epoch: 2 [2800/2824 (99%)]        Loss: 0.070246

Test set: Avg. loss: 0.1897, Accuracy: 651/706 (92.21%)

Train Epoch: 3 [0/2824 (0%)]    Loss: 0.000720
Train Epoch: 3 [100/2824 (4%)]  Loss: 0.000000
Train Epoch: 3 [200/2824 (7%)]  Loss: 0.000034
Train Epoch: 3 [300/2824 (11%)] Loss: 0.047071
Train Epoch: 3 [400/2824 (14%)] Loss: 0.000000
Train Epoch: 3 [500/2824 (18%)] Loss: 0.011883
Train Epoch: 3 [600/2824 (21%)] Loss: 0.000035
Train Epoch: 3 [700/2824 (25%)] Loss: 0.000000
Train Epoch: 3 [800/2824 (28%)] Loss: 0.000001
Train Epoch: 3 [900/2824 (32%)] Loss: 0.043905
Train Epoch: 3 [1000/2824 (35%)]        Loss: 0.000000
Train Epoch: 3 [1100/2824 (39%)]        Loss: 0.000000
Train Epoch: 3 [1200/2824 (42%)]        Loss: 0.015363
Train Epoch: 3 [1300/2824 (46%)]        Loss: 0.023165
Train Epoch: 3 [1400/2824 (50%)]        Loss: 0.000000
Train Epoch: 3 [1500/2824 (53%)]        Loss: 0.754682
Train Epoch: 3 [1600/2824 (57%)]        Loss: 0.066766
Train Epoch: 3 [1700/2824 (60%)]        Loss: 0.000000
Train Epoch: 3 [1800/2824 (64%)]        Loss: 0.001532
Train Epoch: 3 [1900/2824 (67%)]        Loss: 0.000000
Train Epoch: 3 [2000/2824 (71%)]        Loss: 0.570051
Train Epoch: 3 [2100/2824 (74%)]        Loss: 0.000000
Train Epoch: 3 [2200/2824 (78%)]        Loss: 0.000021
Train Epoch: 3 [2300/2824 (81%)]        Loss: 0.000000
Train Epoch: 3 [2400/2824 (85%)]        Loss: 0.112582
Train Epoch: 3 [2500/2824 (89%)]        Loss: 0.000000
Train Epoch: 3 [2600/2824 (92%)]        Loss: 0.000002
Train Epoch: 3 [2700/2824 (96%)]        Loss: 0.000000
Train Epoch: 3 [2800/2824 (99%)]        Loss: 0.061281

Test set: Avg. loss: 0.1774, Accuracy: 653/706 (92.49%)
```

We struggled Cross validating this, so we used keras to make another model

[62]:
```
from keras import models
from keras import layers
from keras.wrappers.scikit_learn import KerasClassifier
from sklearn.datasets import make_classification
```

[63]:
```
# Number of features
number_of_features = 7

# Generate features matrix and target vector
features, target = make_classification(n_samples = int(pca_vecs.shape[0]/10),
                                       n_features = number_of_features,
                                       n_informative = 7,
                                       n_redundant = 0,
                                       n_classes = 7,
                                       random_state = 42)
```

[64]:
```
def create_network():
    network = models.Sequential()
    network.add(layers.Dense(units=100, activation='relu',␣
 ↪input_shape=(number_of_features,)))
    network.add(layers.Dense(units=100, activation='relu'))
    network.add(layers.Dense(units=1, activation='sigmoid'))

    network.compile(loss='binary_crossentropy', # Cross-entropy
                    optimizer='rmsprop', # Root Mean Square Propagation
                    metrics=['accuracy']) # Accuracy performance metric

    return network
```

Cross validation of this network shown below in section 9.

10 10) More Models

Moved part 10 above part 9 because part 9 cross validates all models including those implemented in 10

10.0.1 Random Forest/Bagging

[65]:
```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 1, stop = 500, num = 20)]

# Number of features to consider at every split
max_features = ['auto', 'sqrt', 1, 2, 3, 4, 5, 6]
```

```
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(1, 10, num = 10)]
max_depth.append(None)

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth}

random_grid
```

[65]:
```
{'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, None],
 'max_features': ['auto', 'sqrt', 1, 2, 3, 4, 5, 6],
 'n_estimators': [1,
  27,
  53,
  79,
  106,
  132,
  158,
  184,
  211,
  237,
  263,
  289,
  316,
  342,
  368,
  394,
  421,
  447,
  473,
  500]}
```

[66]:
```
from sklearn.ensemble import RandomForestClassifier

maokai = RandomForestClassifier()

rf_random = RandomizedSearchCV(estimator = maokai, param_distributions =␣
 ↪random_grid,
                               n_iter = 100, cv = 5, verbose=2, random_state=10,␣
 ↪n_jobs = -1)

# Fit the random search model

rf_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   37.7s
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 361 tasks      | elapsed:  4.8min
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  6.5min finished
```

[66]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    ccp_alpha=0.0,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    max_samples=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
min_weight_fraction_leaf=0.0,
                                                    n_estimators=100,
                                                    n_jobs…
                                                    warm_start=False),
                   iid='deprecated', n_iter=100, n_jobs=-1,
                   param_distributions={'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                      10, None],
                                        'max_features': ['auto', 'sqrt', 1, 2,
                                                         3, 4, 5, 6],
                                        'n_estimators': [1, 27, 53, 79, 106,
                                                         132, 158, 184, 211,
                                                         237, 263, 289, 316,
                                                         342, 368, 394, 421,
                                                         447, 473, 500]},
                   pre_dispatch='2*n_jobs', random_state=10, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

[67]:
```
rf_random.best_params_
```

[67]:
```
{'max_depth': None, 'max_features': 2, 'n_estimators': 106}
```

[68]:
```
groot = RandomForestClassifier(n_estimators=132, max_features=2,␣
 ↪max_depth=None, random_state=10, oob_score=True)
groot.fit(X_train, y_train)

groot_y_pred = groot.predict(X_test)
print(f"Accuracy of best parameters: {accuracy_score(y_test, groot_y_pred)}")
```

```
Accuracy of best parameters: 0.9575070821529745
```

10.0.2 GradientBoost

[69]:
```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 1, stop = 500, num = 20)]

# Number of features to consider at every split
max_features = ['auto', 'sqrt', 1, 2, 3, 4, 5, 6]

# learning rate
learning_rate = [float(x) for x in np.linspace(start = 0.1, stop = 2.0, num =␣
↪20)]

# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(1, 10, num = 10)]
max_depth.append(None)

# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'learning_rate': learning_rate,
               'max_depth': max_depth}

random_grid
```

[69]:
```
{'learning_rate': [0.1,
  0.2,
  0.3,
  0.4,
  0.5,
  0.6,
  0.7,
  0.7999999999999999,
  0.8999999999999999,
  0.9999999999999999,
  1.0999999999999999,
  1.2,
  1.3,
  1.4,
  1.5,
  1.5999999999999999,
  1.7,
  1.8,
  1.9,
  2.0],
 'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, None],
 'max_features': ['auto', 'sqrt', 1, 2, 3, 4, 5, 6],
 'n_estimators': [1,
```

```
  27,
  53,
  79,
  106,
  132,
  158,
  184,
  211,
  237,
  263,
  289,
  316,
  342,
  368,
  394,
  421,
  447,
  473,
  500]}
```

[70]:
```
from sklearn.ensemble import GradientBoostingClassifier

grade = GradientBoostingClassifier()

rf_random = RandomizedSearchCV(estimator = grade, param_distributions =␣
 ↪random_grid,
                               n_iter = 100, cv = 5, verbose=2, random_state=10,␣
 ↪n_jobs = -1)

# Fit the random search model

rf_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 100 candidates, totalling 500 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 2 concurrent workers.
[Parallel(n_jobs=-1)]: Done  37 tasks      | elapsed:   13.7s
[Parallel(n_jobs=-1)]: Done 158 tasks      | elapsed:   59.0s
[Parallel(n_jobs=-1)]: Done 361 tasks      | elapsed:  2.1min
[Parallel(n_jobs=-1)]: Done 497 out of 500 | elapsed:  2.8min remaining:    1.0s
[Parallel(n_jobs=-1)]: Done 500 out of 500 | elapsed:  2.9min finished
```

[70]:
```
RandomizedSearchCV(cv=5, error_score=nan,
                   estimator=GradientBoostingClassifier(ccp_alpha=0.0,
criterion='friedman_mse',
                                                        init=None,
                                                        learning_rate=0.1,
                                                        loss='deviance',
```

```
                                                    max_depth=3,
                                                    max_features=None,
                                                    max_leaf_nodes=None,
min_impurity_decrease=0.0,

                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,

min_weight_fraction_leaf=0.0,

                                                    n_estimators=100,
                                                    n_ite…
                                                      0.9999999999999999,
                                                      1.0999999999999999,
                                                      1.2, 1.3, 1.4, 1.5,
                                                      1.5999999999999999,
                                                      1.7, 1.8, 1.9, 2.0],
                                      'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9,
                                                    10, None],
                                      'max_features': ['auto', 'sqrt', 1, 2,
                                                       3, 4, 5, 6],
                                      'n_estimators': [1, 27, 53, 79, 106,
                                                       132, 158, 184, 211,
                                                       237, 263, 289, 316,
                                                       342, 368, 394, 421,
                                                       447, 473, 500]},
                   pre_dispatch='2*n_jobs', random_state=10, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

[71]:
```
rf_random.best_params_
```

[71]:
```
{'learning_rate': 0.1,
 'max_depth': 8,
 'max_features': 'sqrt',
 'n_estimators': 500}
```

[72]:
```
pikachu = GradientBoostingClassifier(n_estimators=500, learning_rate=0.1,␣
 ↪max_features='sqrt',
    max_depth=8, random_state=10)
pikachu.fit(X_train, y_train)
pikachu.score(X_test, y_test)
```

[72]:
```
0.953257790368272
```

10.0.3 K Nearest Neighbors

[73]:
```
from sklearn.neighbors import KNeighborsClassifier
best_score = 0
best_k = 0
```

```
for k in range(1, 41):
  neigh = KNeighborsClassifier(n_neighbors=k)
  neigh.fit(X_train, y_train)
  preds = neigh.predict(X_test)
  score = accuracy_score(preds, y_test)
  if score > best_score:
    best_score = score
    best_k = k
print(f"Accuracy of best KNearestNeighbors at k={best_k}: {best_score}")
```

```
Accuracy of best KNearestNeighbors at k=1: 0.9518413597733711
```

10.1 MLPClassifier: multi-layer perceptron classifier

[74]:
```
from sklearn.neural_network import MLPClassifier

mlp = MLPClassifier(random_state=10, max_iter=600, learning_rate='adaptive',␣
 ↪shuffle=True)
mlp.fit(X_train, y_train)
mlp.score(X_test, y_test)
```

[74]: 0.9660056657223796

10.1.1 Stacking

[76]:
```
from sklearn.ensemble import StackingClassifier


estimators = estimators = [
    ('rf', RandomForestClassifier(n_estimators=342, max_features='sqrt',␣
 ↪max_depth=None, random_state=10, oob_score=True)),
    ('ada', AdaBoostClassifier(base_estimator=None, random_state=10,␣
 ↪learning_rate=1, n_estimators=368)),
    ('grad', GradientBoostingClassifier(n_estimators=500, learning_rate=0.1,␣
 ↪max_features='sqrt',
    max_depth=8, random_state=10)),
    ('mlp', MLPClassifier(random_state=10, max_iter=600,␣
 ↪learning_rate='adaptive', shuffle=True))
    ]

stack = StackingClassifier(estimators=estimators, cv=5,␣
 ↪final_estimator=LogisticRegression())
stack.fit(X_train, y_train)
stack.score(X_test, y_test)
```

[76]: 0.9660056657223796

11 9) Cross Validation of All Models

KFold Cross-Validation

[77]:
```
from sklearn import model_selection
from sklearn.ensemble import RandomForestClassifier
kfold = model_selection.KFold(n_splits=10, random_state=42, shuffle=True)

gradBoost = GradientBoostingClassifier(n_estimators=500, learning_rate=0.1,␣
 ↪max_features='sqrt',
    max_depth=8, random_state=10)
bagging = RandomForestClassifier(n_estimators=342, max_features='sqrt',␣
 ↪max_depth=None, random_state=10, oob_score=True)
adaBoost = AdaBoostClassifier(base_estimator=None, random_state=10,␣
 ↪learning_rate=1, n_estimators=368)
neural_network = KerasClassifier(build_fn=create_network,
                                 epochs=5,
                                 batch_size=100,
                                 verbose=0)
k_nearest = KNeighborsClassifier(n_neighbors=6)
stack = StackingClassifier(estimators=estimators, cv=5,␣
 ↪final_estimator=LogisticRegression())
sk_mlp = MLPClassifier(random_state=10, max_iter=600, learning_rate='adaptive',␣
 ↪shuffle=True)

grad_results = model_selection.cross_val_score(gradBoost, pca_vecs, labels,␣
 ↪cv=kfold)
ada_results = model_selection.cross_val_score(adaBoost, pca_vecs, labels,␣
 ↪cv=kfold)
bag_results = model_selection.cross_val_score(bagging, pca_vecs, labels,␣
 ↪cv=kfold)
nn_results =  model_selection.cross_val_score(neural_network, pca_vecs, labels,␣
 ↪cv=kfold)
k_nearest_results =  model_selection.cross_val_score(k_nearest, pca_vecs,␣
 ↪labels, cv=kfold)
stack_results = model_selection.cross_val_score(stack, pca_vecs, labels,␣
 ↪cv=kfold)
mlp_results = model_selection.cross_val_score(sk_mlp, pca_vecs, labels,␣
 ↪cv=kfold)

print("Random Forest Accuracy: %.2f%%" % (ada_results.mean()*100.0))
print("AdaBoost Accuracy: %.2f%%" % (bag_results.mean()*100.0))
print("Neural Network Accuracy: %.2f%%" % (nn_results.mean()*100.0))
print("K Nearest Accuracy: %.2f%%" % (k_nearest_results.mean()*100.0))
print("GradientBoost Accuracy: %.2f%%" % (grad_results.mean()*100.0))
print("Stacking Accuracy: %.2f%%" % (stack_results.mean()*100.0))
print("mlp Accuracy: %.2f%%" % (mlp_results.mean()*100.0))
```

```
Random Forest Accuracy: 95.81%
AdaBoost Accuracy: 96.74%
Neural Network Accuracy: 95.33%
K Nearest Accuracy: 95.21%
GradientBoost Accuracy: 96.57%
Stacking Accuracy: 96.52%
mlp Accuracy: 97.28%
```

Stratified Shuffle Split

[78]:

```python
from sklearn.model_selection import StratifiedKFold
skf = StratifiedKFold(n_splits=10, random_state=42, shuffle=True)

gradBoost = GradientBoostingClassifier(n_estimators=500, learning_rate=0.1,␣
 ↪max_features='sqrt',
    max_depth=8, random_state=10)
bagging = RandomForestClassifier(n_estimators=342, max_features='sqrt',␣
 ↪max_depth=None, random_state=10, oob_score=True)
adaBoost = AdaBoostClassifier(base_estimator=None, random_state=10,␣
 ↪learning_rate=1, n_estimators=368)
neural_network = KerasClassifier(build_fn=create_network,
                                 epochs=5,
                                 batch_size=100,
                                 verbose=0)
k_nearest = KNeighborsClassifier(n_neighbors=6)
stack = StackingClassifier(estimators=estimators, cv=5,␣
 ↪final_estimator=LogisticRegression())
sk_mlp = MLPClassifier(random_state=10, max_iter=300, learning_rate='adaptive',␣
 ↪shuffle=True)

grad_results_skf = model_selection.cross_val_score(gradBoost, pca_vecs, labels,␣
 ↪cv=skf)
ada_results_skf = model_selection.cross_val_score(adaBoost, pca_vecs, labels,␣
 ↪cv=skf)
bag_results_skf = model_selection.cross_val_score(bagging, pca_vecs, labels,␣
 ↪cv=skf)
nn_results_skf =  model_selection.cross_val_score(neural_network, pca_vecs,␣
 ↪labels, cv=skf)
k_nearest_results_skf =  model_selection.cross_val_score(k_nearest, pca_vecs,␣
 ↪labels, cv=skf)
stack_results_skf = model_selection.cross_val_score(stack, pca_vecs, labels,␣
 ↪cv=skf)
mlp_results_skf = model_selection.cross_val_score(sk_mlp, pca_vecs, labels,␣
 ↪cv=skf)

print("Random Forest Accuracy: %.2f%%" % (ada_results_skf.mean()*100.0))
print("AdaBoost Accuracy: %.2f%%" % (bag_results_skf.mean()*100.0))
```

```python
print("Neural Network Accuracy: %.2f%%" % (nn_results_skf.mean()*100.0))
print("K Nearest Accuracy: %.2f%%" % (k_nearest_results_skf.mean()*100.0))
print("GradientBoost Accuracy: %.2f%%" % (grad_results_skf.mean()*100.0))
print("Stacking Accuracy: %.2f%%" % (stack_results_skf.mean()*100.0))
print("mlp Accuracy: %.2f%%" % (mlp_results_skf.mean()*100.0))
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (600) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
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/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
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/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
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/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
```

```
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

```
Random Forest Accuracy: 95.47%
AdaBoost Accuracy: 96.49%
Neural Network Accuracy: 95.30%
K Nearest Accuracy: 95.01%
GradientBoost Accuracy: 96.35%
Stacking Accuracy: 96.46%
mlp Accuracy: 97.25%
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/neural_network/_multilayer_perceptron.py:571:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (300) reached and
the optimization hasn't converged yet.
  % self.max_iter, ConvergenceWarning)
```

Our top performing model in both K-fold crossvalidation and stratified shuffle split validation was the MLP Neural Network. However, the best performing model on the Kaggle test set was AdaBoost.

12 11) Kaggle Attempts

[79]:
```
mlp_test = MLPClassifier(random_state=10, max_iter=600,␣
 ↪learning_rate='adaptive', shuffle=True)
mlp_test.fit(X_train, y_train)
predictions = mlp_test.predict(all_drivers_pca)
#d = {'ID': kaggle_dirty['Unnamed: 0'], 'Predicted': predictions}
#kaggle_sub = pd.DataFrame(data=d)
#kaggle_sub.head(20)
len(predictions)
d = {'id_driver': all_drivers['id_driver'], 'Predicted': predictions}
kaggle_temp = pd.DataFrame(data=d)
kaggle_temp
```

[79]:

	id_driver	Predicted
0	26358	0
1	37047	0
2	17092	0
3	34794	0
4	32587	0
…	…	…

```
4522         125          1
4524         106          1
4525          27          1
4527         143          1
4529          26          1

[3692 rows x 2 columns]
```

[80]:
```
driver_list = {}

for i in kaggle_temp.index:
  curr_driver = kaggle_temp['id_driver'][i]
  driver_list[curr_driver] = kaggle_temp['Predicted'][i]

new_predictions = []
for j in range(0, 1000):
  new_predictions.append(0)

kaggle_u_compressed['new_label'] = new_predictions

keys = []
for x in kaggle_u_compressed.index:
  key = kaggle_u_compressed['id_driver'][x]
  keys.append(key)
  if key in driver_list:
    kaggle_u_compressed['new_label'][x] = driver_list[key]

kaggle_u_compressed
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:18:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[80]:

	dt	year	id_driver	…	brokerage_loads	longevity	new_label
0	1569801600	2019	15857	…	168	1.018442	0
1	1571875200	2019	28620	…	34	1.001817	0
2	1567468800	2019	10694	…	21	1.028225	0
3	1565136000	2019	12198	…	18	1.020448	0
4	1540944000	2018	13222	…	64	1.004732	1
..	…	…	…	…	…	…	…
995	1537574400	2018	597	…	62	1.052644	1
996	1593648000	2020	32167	…	21	1.008144	0
997	1530057600	2018	7054	…	11	1.004082	0
998	1490054400	2017	638	…	119	1.020775	1
999	1604707200	2020	33543	…	73	1.013478	0

```
[1000 rows x 17 columns]
```

[81]:
```
d = {'ID': kaggle_dirty['Unnamed: 0'], 'Predicted':␣
↪kaggle_u_compressed['new_label']}
kaggle_sub = pd.DataFrame(data=d)
kaggle_sub.head(20)
```

[81]:
```
       ID  Predicted
0   83414          0
1   83415          0
2   83416          0
3   83417          0
4   83418          1
5   83419          0
6   83420          0
7   83421          0
8   83422          0
9   83423          0
10  83424          0
11  83425          0
12  83426          0
13  83427          0
14  83428          0
15  83429          0
16  83430          0
17  83431          0
18  83432          1
19  83433          1
```

[82]:
```
adaBoost = AdaBoostClassifier(base_estimator=None, random_state=10,␣
↪learning_rate=1, n_estimators=368)
adaBoost.fit(X_train, y_train)
predictions2 = adaBoost.predict(kaggle_pca_vecs)
predictions2 = predictions2.flatten()

d = {'ID': kaggle_dirty['Unnamed: 0'], 'Predicted': predictions2}
kaggle_sub2 = pd.DataFrame(data=d)
kaggle_sub2.head(20)
```

[82]:
```
       ID  Predicted
0   83414          0
1   83415          0
2   83416          0
3   83417          0
4   83418          0
5   83419          1
```

6	83420	1
7	83421	0
8	83422	1
9	83423	0
10	83424	0
11	83425	1
12	83426	0
13	83427	0
14	83428	0
15	83429	0
16	83430	0
17	83431	1
18	83432	0
19	83433	0

[85]:
```
#kaggle_sub.to_csv('/content/gdrive/My Drive/kaggle_mlp_full.csv', index=False)
```

[84]:
```
#kaggle_sub2.to_csv('/content/gdrive/My Drive/kaggle2-3.csv', index=False)
```