Predicting a Binary Classifier

The purpose of this project is to create a machine learning model to predict whether entries in the dataset belong to a specific class ('y'). This dataset was provided by a client as skills assessment, and the objectives and guidelines for the project were outlined by the client in advance. The steps required to complete the project will be:

- · Data Cleansing
- · Feature Engineering and Selection
- · Building two different models on training dataset
- · Model tuning
- Generating predictions for test dataset
- · Comparing modeling approaches in a writeup
- · Preparing all files for submission

Initial Analysis and Data Cleansing

To begin, I will import the 'training' dataset into a pandas dataframe and perform initial analysis to determine what cleansing steps need to be taken.

```
In [2]: # Importing necessary data manipulation/visualization libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

# Expanding number of rows and columns allowed in view
pd.set_option('max_columns', 180)
pd.set_option('max_rows', 200000)
pd.set_option('max_colwidth', 5000)
```

```
In [3]: # Reading training and test data into dataframes
train = pd.read_csv('traindata.csv')
test = pd.read_csv('testdata.csv')
```

In [4]: # Exploring shape and head of test data
 print(test.shape)
 test.head()

(10000, 100)

Out[4]:

	х0	x1	x2	х3	x4	x5	х6	х7	
0	0.519093	-4.606038	13.707586	-17.990903	12.873394	14.910935	2.915341	-10.110081	_
1	-12.357004	13.874141	14.052924	34.129247	34.511107	34.583336	-0.482540	-6.583407	
2	1.834922	2.665252	-44.873210	21.941920	10.102981	5.962249	-5.733909	-4.061670	
3	20.972483	11.548506	-40.924625	-35.296796	-35.253101	-14.601890	5.045075	10.841771	
4	-9.916044	5.509811	31.749288	-0.803916	-4.005098	20.912490	0.419346	-2.949516	

In [5]: # Exploring shape and head of train data
print(train.shape)
train.head()

(40000, 101)

Out[5]:

	x0	x1	x2	х3	x4	х5	х6	х7	
0	0.963686	6.627185	-45.224008	9.477531	-3.216532	13.216874	9.754747	5.245851	-1
1	-1.770062	-23.610459	-0.964003	-31.981497	-10.294599	-10.240251	-1.518888	-1.675208	0
2	9.962401	-8.349849	23.248891	-24.196879	8.937480	10.965000	-7.490596	-3.025094	0
3	-5.780709	-25.261584	1.383115	-11.786929	7.993078	-11.245752	-2.607351	-3.513896	-0
4	1.211541	1.119963	7.512938	21.987312	-5.155392	10.339416	3.045180	-0.619230	-0

Out[6]:

	х0	x1	x2	х3	x4	x 5	
count	39988.000000	39990.000000	39993.000000	39987.000000	39993.000000	39992.000000	3999
mean	2.020255	-3.924559	1.006619	-1.378330	0.070199	-0.715213	
std	9.590599	18.768656	21.062970	29.397779	20.243287	18.268807	
min	-36.842503	-79.156374	-89.728356	-126.652341	-76.412886	-73.743342	-1
25%	-4.461433	-16.591552	-13.230956	-21.297149	-13.580632	-13.092873	
50%	2.022412	-4.061703	1.184946	-1.224625	0.091600	-0.657601	
75%	8.389979	8.529110	15.221205	18.530623	13.722427	11.610239	
max	44.478690	77.682652	84.625640	117.004453	85.934044	74.465465	;

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40000 entries, 0 to 39999
Data columns (total 101 columns):
x0
       float64
x1
       float64
x2
       float64
x3
       float64
x4
       float64
x5
       float64
       float64
х6
x7
       float64
x8
       float64
x9
       float64
x10
       float64
x11
       float64
x12
       float64
x13
       float64
x14
       float64
x15
       float64
x16
       float64
x17
       float64
x18
       float64
x19
       float64
x20
       float64
x21
       float64
x22
       float64
x23
       float64
x24
       float64
x25
       float64
x26
       float64
x27
       float64
x28
       float64
x29
       float64
x30
       float64
x31
       float64
x32
       float64
x33
       float64
x34
       object
x35
       object
x36
       float64
x37
       float64
x38
       float64
x39
       float64
x40
       float64
x41
       object
x42
       float64
x43
       float64
x44
       float64
x45
       object
       float64
x46
x47
       float64
x48
       float64
x49
       float64
x50
       float64
x51
       float64
x52
       float64
```

float64

```
x54
       float64
x55
       float64
x56
       float64
x57
       float64
x58
       float64
x59
       float64
x60
       float64
x61
       float64
x62
       float64
x63
       float64
x64
       float64
x65
       float64
x66
       float64
x67
       float64
x68
       object
x69
       float64
x70
       float64
       float64
x71
x72
       float64
x73
       float64
x74
       float64
x75
       float64
x76
       float64
x77
       float64
x78
       float64
x79
       float64
x80
       float64
x81
       float64
x82
       float64
x83
       float64
x84
       float64
x85
       float64
x86
       float64
x87
       float64
x88
       float64
x89
       float64
x90
       float64
x91
       float64
x92
       float64
x93
       object
x94
       float64
x95
       float64
x96
       float64
x97
       float64
x98
       float64
x99
       float64
       int64
dtypes: float64(94), int64(1), object(6)
memory usage: 30.8+ MB
```

```
In [8]: # Checking null counts of each feature
    nullcounts = train.isnull().sum()
    nullcounts.sort_values(ascending=False, inplace=True)
    nullcounts
```

20		
Out[8]:	x55	16
	x13	15
	x18	14
	x96	14
	x3	13
	x99	13
	x51	13
	x62	13
	x73	13
	x21	12
	x85	12
	x 0	12
	x60	12
	x56	11
	x24	11
	x17	11
	x33	11
	x69	11
	x42	11
	x12	11
	x77	11
	x65	10
	x7	10
	x59	10
	x39 x35	10
	x26	10 10
	x20 x1	
	x1	10
	x89	10 10
	x75	10
	x28	9
	x11	9
	x23	9
	x46	9
	x94	9
	x6	9
	x87	9
	x58	9
	x97	9
	x31	9
	x68	9
	x72	9
	x74	9
	x19	8
	x15	8
	x78	8
	x5	8
	x48	8
	x82	8
	x16	8
	x34	8
	x63	8
	x40	8
	x76	8
	x57	8
	×25	7

```
7
x90
         7
x80
x4
         7
         7
x45
x79
         7
x10
         7
         7
x27
         7
x95
         7
x52
         7
x93
x61
         7
         7
x86
         7
x2
         7
x67
         7
x9
x22
         6
x70
         6
x36
         6
         6
x38
         6
x71
         6
x8
x92
         6
x54
         6
         5
x14
         5
x50
x53
         5
         5
x88
x37
         5
x64
         5
x20
         4
x98
         4
x83
         4
x49
         4
x41
         4
x47
         3
x29
         3
x44
         3
         3
x81
         3
x84
x32
         3
x91
         2
         2
x30
x43
         1
         0
У
dtype: int64
```

```
In [9]: # Printing total of all null values
    print(nullcounts.sum())
    nullpct = nullcounts.sum()/len(train)
    print(nullpct)
```

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Initial Observations

After a guick exploration of the training dataset, a few key observations stand out:

- The data is comprised of 40,000 entries, with 100 features.
- A small portion of the features are string objects, with the rest stored as numeric (float) features
- The features apppear to be of different ranges and sizes, but based on the min and max values and standard deviations there do not appear to be any huge outliers.
- Each feature has some null values, with only 16 in any one column and 806 null values overall. This is a small percentage of the overall dataset (2.01% of total data).
- The 'y', or target, column is binary. Each entry is listed as a 0 or 1 in this column, and there are no null values.
- The target column is unbalanced. Approximately 20% of the data is categorized as a '1' and 80% as a '0'. I will need to account for this imbalance in the machine learning models.

Cleansing Steps Needed

To prepare the data for model training and testing, I need to cleanse the data. This will include:

- Examining and standardizing the text-based features
- · Converting text-based features to dummy variables
- · Handling null values for each feature
- Standardizing all columns with a min-max scaler for efficient machine learning input

Note: Because these same processes will need to be performed on the testing dataset, the data cleansing will need to be incorporated into a function that can be applied to the test dataset at a later point.

Data Cleansing

Text-Based Features

```
In [10]: # Identifying text columns
    text_vals = train.select_dtypes(include=['object'])
    text_vals.head()
```

Out[10]:

	x34	x35	x41	x45	x68	x93
0	chrystler	thur	\$-865.28	0.02%	sept.	asia
1	volkswagon	thur	\$325.27	-0.01%	July	asia
2	bmw	thurday	\$743.91	0.0%	July	asia
3	nissan	thurday	\$538.48	0.01%	July	asia
4	volkswagon	wed	\$-433.65	0.0%	Jun	asia

```
In [11]: # Cleaning the values of x41 and x45, storing as float
    text_vals['x41'] = text_vals['x41'].str.replace('$','').astype('float')
    text_vals['x45'] = text_vals['x45'].str.replace('%','').astype('float')
```

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_la uncher.py:2: SettingWithCopyWarning:

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

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

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_la uncher.py:3: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

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

This is separate from the ipykernel package so we can avoid doing imports until

```
In [12]: # Checking value counts of x34
         text_vals['x34'].value_counts(sort=True)
Out[12]: volkswagon
                        12622
         Toyota
                        10968
         bmw
                         7262
         Honda
                         5174
         tesla
                         2247
         chrystler
                         1191
         nissan
                          326
         ford
                          160
         mercades
                           31
         chevrolet
                          11
         Name: x34, dtype: int64
```

These values seem to be fairly standardized, and are not significantly skewed. Several contain spelling errors which can be quickly cleaned with a mapping dictionary.

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_la uncher.py:8: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

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

```
In [14]: # Checking value counts of x35
         text vals['x35'].value counts(sort=True)
Out[14]: wed
                       14820
         thurday
                       13324
         wednesday
                        5938
         thur
                        4428
         tuesday
                         884
         friday
                         517
         monday
                          53
         fri
                          26
         Name: x35, dtype: int64
```

Again, these are not significantly skewed, but several are misspelled and miscategorized. This can be quickly cleaned.

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:7: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d ocs/stable/indexing.html#indexing-view-versus-copy import sys

```
In [16]: # Checking value counts of x68
          text vals['x68'].value counts(sort=True)
Out[16]: July
                     11114
         Jun
                      9317
                      8170
         Aug
         May
                      4744
         sept.
                      3504
                      1629
         Apr
         Oct
                       885
         Mar
                       407
         Nov
                       145
         Feb
                        48
         Dev
                        16
         January
                        12
         Name: x68, dtype: int64
```

These can again be cleaned with simple mapping. The one exception is the "Dev" value, which I am assuming is a misspelling of December.

```
In [17]: # Creating mapping dictionary
         dict = {'July':'jul','Jun':'jun',
                 'Aug': 'aug', 'May': 'may',
                 'sept.':'sep','Apr':'apr',
                 'Oct':'oct','Mar':'mar',
                 'Nov': 'nov', 'Feb': 'feb',
                 'Dev': 'dec', 'January': 'jan'}
         # Replacing values using dictionary
         text vals['x68'] = text vals['x68'].replace(dict)
         /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel la
         uncher.py:9: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
         See the caveats in the documentation: http://pandas.pydata.org/pandas-d
         ocs/stable/indexing.html#indexing-view-versus-copy
           if __name__ == '__main__':
In [18]: # Checking value counts of x93
         text vals['x93'].value counts(sort=True)
Out[18]: asia
                    35384
         america
                     3167
         euorpe
                     1442
```

This feature seems to be heavily weighted in one category 'asia', representing 88% of the total entries. This kind of heavily skewed feature can be problematic for the machine learning model, so this feature should be dropped.

Name: x93, dtype: int64

```
In [19]: # Drop x93 from text vals dataframe
           text vals = text vals.drop(columns='x93')
In [20]: text_vals.head()
Out[20]:
                          x35
                                 x41
                                       x45 x68
                     x34
            0
                 chrysler
                              -865.28
                                       0.02
                          thu
                                            sep
              volkswagen
                          thu
                               325.27
                                      -0.01
                                             jul
            2
                    bmw
                          thu
                               743.91
                                       0.00
                                             jul
                               538.48
                                       0.01
            3
                   nissan
                          thu
                                             jul
            4 volkswagen wed
                              -433.65
                                       0.00
                                           jun
```

Now that I have cleaned and standardized the text columns, I want to transform them into dummy categories to ensure the machine learning model is operating on stricly numeric data.

```
In [21]: # Selecting only text columns
    textcols = ['x34','x35','x68']
    # Get dummy prefix names
    prefixes = list(text_vals[textcols].columns)
    # Getting dummy features for each text column
    text_dummies = pd.get_dummies(text_vals, prefix=prefixes)
In [22]: # Dropping dirty text columns from original dataset
    dropcols = ['x34','x35','x41','x45','x68','x93']
    train = train.drop(columns=dropcols)

In [23]: # Reintroducing our cleaned data into the original dataset
    train = pd.concat([train,text_dummies], axis=1)
```

In [24]: train.info(verbose=True)

<class 'pandas.core.frame.DataFrame'> RangeIndex: 40000 entries, 0 to 39999 Data columns (total 124 columns): x0float64 x1float64 x2 float64 x3float64 x4float64 x5 float64 float64 х6 float64 x7 x8 float64 x9 float64 x10 float64 x11 float64 float64 x12 x13 float64 x14 float64 x15 float64 x16 float64 x17 float64 float64 x18 x19 float64 x20 float64 x21 float64 x22 float64 x23 float64 x24 float64 x25 float64 x26 float64 x27 float64 x28 float64 x29 float64 x30 float64 x31 float64 x32 float64 x33float64 x36 float64 x37 float64 x38 float64 x39 float64 x40 float64 x42 float64 x43 float64 x44float64 x46 float64 x47 float64 x48 float64 x49 float64 x50 float64 x51 float64 x52 float64 x53 float64 x54 float64 x55 float64 x56 float64

float64

x57

x58	float64
x59	float64
x60	float64
x61	float64
x62	float64
x63	float64
x64	float64
x65	float64
x66	float64
x67	float64
x69	float64
x70	float64
x71	float64
x72	float64
x73	float64
x74	float64
x75	float64
x76	float64
x77	float64
x78	float64
x79	float64
x80	float64
x81	float64
x82	float64
x83	float64
x84	float64
x85	float64
x86	float64
x87	float64
x88	float64
x89	
	float64
x90	float64
x91	float64
x92	float64
x94	float64
x95	float64
x96	float64
x97	float64
x98	float64
x99	float64
У	int64
x41	float64
x45	float64
x34_bmw	uint8
x34_chevrolet	uint8
x34_chrysler	uint8
x34_ford	uint8
x34_honda	uint8
x34_mercedes	uint8
x34_nissan	uint8
x34_tesla	uint8
x34_toyota	uint8
x34_volkswagen	uint8
x35_fri	uint8
x35_mon	uint8
x35 thu	uint8
x35_tue	uint8

```
x35_wed
                   uint8
x68_apr
                   uint8
x68 aug
                   uint8
x68 dec
                   uint8
x68_feb
                   uint8
x68_jan
                   uint8
x68_jul
                   uint8
x68 jun
                   uint8
x68 mar
                   uint8
x68 may
                   uint8
x68_nov
                   uint8
x68_oct
                   uint8
x68 sep
                   uint8
dtypes: float64(96), int64(1), uint8(27)
memory usage: 30.6 MB
```

We now have a dataframe including only numeric values.

Handling Missing Values

I will now correct any missing values. The amount of missing data is small in proportion to the overall dataset. I could easily replace null values with the mean of each feature. However, since I do not know the nature of each feature and what it represents, this could result in distorted, noisy information that skews the overall results of the model. Instead, I will simply drop any rows that contain null values.

```
In [25]: # Dropping rows with null values
train = train.dropna().copy()
```

```
In [26]:    nullcounts = train.isnull().sum()
    nullcounts
```

020		
Out[26]:	x0	0
	x1	0
	x2	0
	x3	0
	x4	0
	x5	0
	x 6	0
	x 7	0
	x8	0
	x9	0
	x10	0
	x11	0
	x12	0
	x13	0
	x14	0
	x15	0
	x16	0
	x17	0
	x18	0
	x19	0
	x20	0
	x21	0
	x22 x23	0
	x23 x24	0
	x25	0
	x26	0
	x27	0
	x28	0
	x29	0
	x30	0
	x31	0
	x32	0
	x33	0
	x36	0
	x37	0
	x38	0
	x39	0
	x40	0
	x42	0
	x43	0
	x44	0
	x46	0
	x47	0
	x48	0
	x49	0
	x50	0
	x51	0
	x52	0
	x53	0
	x54	0
	x55	0
	x56	0
	x57	0
	x58	0
	x59	0
	x60	0

x61 x62 x63 x64 x65 x66 x67 x69 x70 x70 x71 x72 x73 x74 x75 x75 x76 x77 x78 x79 x80 x81 x82 x83 x84 0 x81 0 x82 0 x83 0 x84 0 x85 x86 0 x87 x88 0 x87 x88 0 x89 x90 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x92 x94 0 x95 x96 x97 x98 x99 0 x91 x92 x94 x95 x96 x97 x98 x99 0 x91 x34_chevrolet 0 x34_chevrolet 0 x34_chrysler 0 x34_chrysler 0 x34_bonda 0 x34_mercedes 0 x34_honda 0 x34_honda 0 x34_honda 0 x34_honda 0 x34_toyota 0 x35_fri 0 x35_mon 0 x35_thu 0 x35_tue 0 x35_wed 0 x68_apr 0 x68_aug		
x62 0 x63 0 x64 0 x65 0 x67 0 x69 0 x70 x71 x72 0 x73 0 x74 0 x75 0 x76 0 x77 0 x78 0 x79 0 x80 0 x81 0 x82 0 x83 0 x84 0 x85 0 x86 0 x87 0 x88 0 x89 0 x90 0 x91 0 x92 0 x94 0 x95 0 x96 0 x97 0 x45 0 x34_bmw 0 x34_bmw 0 x34_honda 0 x34_honda	x61	0
x63 0 x65 0 x67 0 x69 0 x70 0 x71 0 x72 0 x73 0 x74 0 x75 0 x76 0 x77 0 x78 0 x79 0 x80 0 x81 0 x82 0 x83 0 x84 0 x85 0 x86 0 x87 0 x88 0 x89 0 x90 0 x91 0 x92 0 x94 0 x95 0 x96 0 x97 0 x45 0 x34_chrysler 0 x34_honda 0 x34_tesla 0 x34_toyota 0 x35_mon		0
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x68 dec
                             0
          x68 feb
          x68 jan
                             0
          x68 jul
                             0
          x68_jun
                             0
          x68_mar
                             0
          x68 may
                             0
          x68 nov
                             0
          x68 oct
                             0
          x68 sep
                             0
          dtype: int64
In [27]: print(len(train))
          print(len(train[train['y']==1]))
          39228
          7977
```

This process dropped only 772 overall values, and still left approximately 20% of the 1 values in the target category. This should be more than sufficient for our modeling purposes.

Scaling Features

Machine learning models, especially the classification models I will use on this data, are much more effective on standardized data. To transform this dataset into standardized data, I will use the "minmax" scaler from the scikit-learn library.

```
In [30]: train_clean.describe()
```

Out[30]:

	х0	x1	x2	х3	x4	x 5	
count	39228.000000	39228.000000	39228.000000	39228.000000	39228.000000	39228.000000	392;
mean	0.477927	0.479577	0.520466	0.514035	0.471174	0.492666	
std	0.117946	0.119690	0.120856	0.120769	0.124693	0.123240	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.398198	0.398858	0.438630	0.432242	0.387015	0.409138	
50%	0.478068	0.478641	0.521456	0.514728	0.471413	0.493099	
75%	0.556340	0.558898	0.601996	0.595674	0.555341	0.575851	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

Now all values have been scaled between the ranges of 0 and 1.

Feature Selection

Now I will narrow down the list of features to help improve the efficiency of the machine learning models. This will involve:

- · Checking for correlation with the target column.
- Eliminating features that seem to be unrelated to the target.
- Checking for colinearity to make sure no information is leaking (surving as a proxy for the target).
- · Creating a final dataframe for model testing.

```
In [31]: corr_values = abs(train_clean.corr()['y'])
```

In [32]: corr_values.sort_values(ascending=False, inplace=True)
 corr_values

Out[32]:	У	1.000000
	x75	0.204860
	x37	0.198846
	x97	0.187550
	x58	0.184349
	x41	0.176463
	x70	0.106727
	x1	0.104049
	x99	0.099482
	x22	0.098001
	x33	0.096947
	x66	0.096597
	x79	0.096069
	x69	0.095656
	x3	0.093992
	x21	0.092737
	x63	0.092689
	x40	0.092125
	x78	0.091484
	x96	0.091409
	x50	0.090401
	x83	0.090184
	x45	0.089987
	x73	0.089966
	x2	0.089283
	x56	0.088974
	x72	0.088764
	x5	0.087622
	x85	0.086100
	x51	0.086080
	x10	0.082422
	x20	0.080256
	x35_thu	0.073902
	x0	0.067035
	x35_wed	0.058920
	x44	0.054281
	x35_tue	0.049927
	x68_oct	0.026025
	x68_apr	0.025676
	x68_feb	0.022781
	x68_nov	0.022572
	x68_jul	0.021731
	x35_mon	0.018683
	x48	0.013672
	x53	0.013388
	x68_mar	0.013169
	x38	0.012941
	x29	0.011586
	x68_aug	0.011443
	x68_may	0.010876
	x9	0.009982
	x8	0.009883
	x74	0.009397
	x68_jun	0.009169
	x68_dec	0.008615
	x42	0.008502
	x68_sep	0.008000

x88	0.007870
x12	0.007306
x92	0.006818
x98	0.006504
x17	0.006355
x46	0.006313
x6	0.006223
x14	0.006138
x7	0.006066
x82	0.005897
x35_fri	0.005893
x30	0.005721
x16	0.005714
x34_chrysler	0.005634
x13	0.005620
x23	0.005538
x18 x65	0.005336 0.005181
x95	
x52	0.005096 0.004992
x34 mercedes	0.004992
x34_mercedes x34 chevrolet	0.004679
x54_cheviolet x54	0.004573
x67	0.004303
x62	0.004432
x80	0.004072
x36	0.004032
x31	0.004019
x25	0.003959
x43	0.003343
x60	0.003246
x94	0.002805
x34_toyota	0.002633
x86	0.002397
x57	0.002364
x34 honda	0.002300
x39	0.002262
x89	0.002231
x68_jan	0.002027
x64	0.002010
x47	0.001993
x76	0.001987
x34_volkswagen	0.001826
x27	0.001739
x34_tesla	0.001663
x19	0.001620
x49	0.001581
x55	0.001411
x81	0.001331
x91	0.001320
x90	0.001218
x4	0.001006
x34_ford	0.000929
x24	0.000896
x32	0.000895
x71	0.000841
x15	0.000820

```
x59
                   0.000712
x34 bmw
                   0.000710
x11
                   0.000648
x87
                   0.000585
x61
                   0.000513
                   0.000336
x34_nissan
x26
                   0.000223
                   0.000148
x28
x84
                   0.000028
x77
                   0.000020
Name: y, dtype: float64
```

It appears as though the values are not stronly correlated with the target variable. (Note: this correlation is being determined with a binary classifier, which is not ideal. Pearson correlation should be used mostly on continuous variables. However, the relative correlation between each feature is what we are interested in, so these results can still be useful for feature selection).

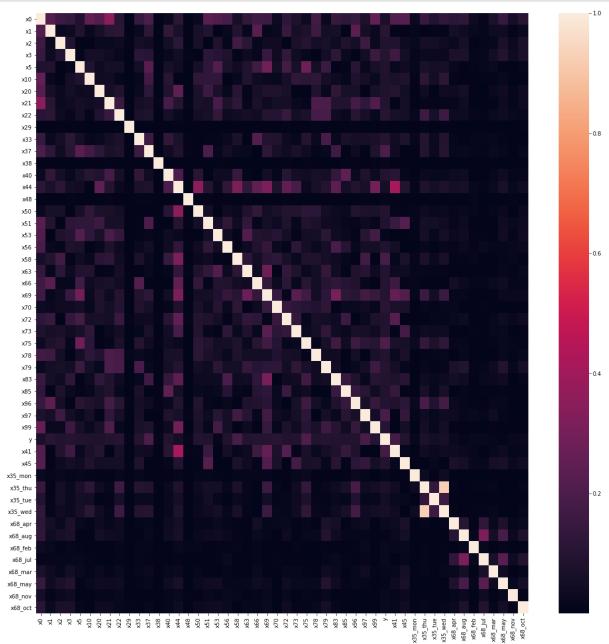
In order to make the model more efficient, I will eleminate any values whose [absolute] correlation is lower than .01

```
In [33]: # Create list of column names with correlations below .01
low_corr_names = list(corr_values[corr_values <= .01].index)

In [34]: # Dropping list of low correlation features from dataset
train_clean = train_clean.drop(columns=low_corr_names)</pre>
```

Now I will plot a correlation heatmap to check for colinearity among any of the remaining features

```
In [35]: # Creating correlation matrix
    train_corr = abs(train_clean.corr())
    # Mappting correlation matrix
    f, ax = plt.subplots(figsize=(20, 20))
    ax = sns.heatmap(train_corr)
```

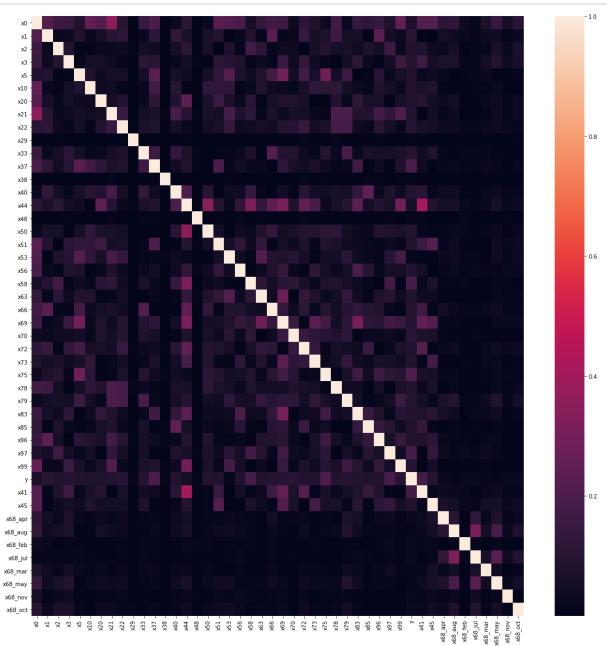


It seems as though the only highly correlated features are 'x35_wed' and 'x35_thu'. These are the dummy variables we created above, so they are not simply representing the same data. However, from the value counts we calculated earlier, the wednesday and thursday categories combined account for over 96% of the data. If these two variables are indeed collinear, then they are representing a larger category that is highly skewed in the wed/thu bucket.

Because of this, we should eliminate the 'x35' feature entirely so it does not throw off the results of the model.

```
In [36]: # Creating list of x35 categories to drop
dropcols = ['x35_mon','x35_tue','x35_wed','x35_thu']
train_clean = train_clean.drop(columns=dropcols)
```

```
In [37]: # Recreating correlation matrix
    train_corr = abs(train_clean.corr())
    # Mappting correlation matrix
    f, ax = plt.subplots(figsize=(20, 20))
    ax = sns.heatmap(train_corr)
```



It now appears that collinearity has been eliminated and we have a reduced set of features.

Recursive Feature Elimination

To help improve the model even further, I will use the scikit learn library's recursive feature elimination function to help narrow down the number of significant features for training. Since we are attempting to fit a binary classification model, I will implement this feature elimination using logistic regression with cross-fold validation.

```
In [379]: # Importing feature elimination
          from sklearn.feature selection import RFECV
          from sklearn.linear model import LogisticRegression
In [380]: # Creating feature and target sets
          all X = train clean.drop(columns='y')
          all_Y = train_clean['y']
In [383]: # Implementing a logistic regression model
          lr = LogisticRegression(max iter=1000)
          # Creating a selector for feature elimination
          selector = RFECV(lr, cv=10)
          # Fitting the selector and model to trianing data
          selector.fit(all X, all Y)
Out[383]: RFECV(cv=10,
                estimator=LogisticRegression(C=1.0, class weight=None, dual=Fals
          e,
                                              fit intercept=True, intercept scalin
          g=1,
                                              11 ratio=None, max iter=1000,
                                              multi class='auto', n jobs=None,
                                              penalty='12', random state=None,
                                              solver='lbfgs', tol=0.0001, verbose=
          0,
                                              warm start=False),
                min features to select=1, n jobs=None, scoring=None, step=1, verb
          ose=0)
         # Checking for optimized columns
In [384]:
          Optimized columns=all X.columns[selector.support]
```

```
In [387]: print(Optimized columns)
          print(len(Optimized columns))
          Index(['x0', 'x1', 'x2', 'x3', 'x5', 'x10', 'x20', 'x21', 'x22', 'x29',
          'x33',
                  'x37', 'x38', 'x40', 'x44', 'x48', 'x50', 'x51', 'x53', 'x56',
          'x58',
                  'x63', 'x66', 'x69', 'x70', 'x72', 'x73', 'x75', 'x78', 'x79',
          'x83',
                  'x85', 'x96', 'x97', 'x99', 'x41', 'x45', 'x68_aug', 'x68_feb',
                  'x68_mar', 'x68_nov', 'x68_oct'],
                dtype='object')
          42
In [391]: # finding columns not selected
          not selected=[]
          total_cols=list(all_X.columns)
          for col in total_cols:
              if col in Optimized columns:
                   pass
              else:
                  not selected.append(col)
In [392]: not_selected
Out[392]: ['x68_apr', 'x68_jul', 'x68_may']
```

After running this optimization, it seems as though the only features which were eliminated were the april, may and june features. We can eliminate these features from the overall dataset and continue with our machine learning process.

```
In [393]: train_clean = train_clean.drop(columns=not_selected)
```

Model Creation

Error Metric

The error metric I will use for testing the models is provided in the assessment description. Models will be evaluated based on AUC score, so I will use this metric to evaluate the success of each model.

```
In [404]: # Importing auc metric
from sklearn.metrics import roc_auc_score
# Import Kfold
from sklearn.model_selection import KFold
```

Logistic Regression

To begin the Machine Learning process, I will implement a basic logistic regression model, using the features that remain in the 'train_clean' dataset. Logistic regression is a great place to start for a binary classifier, and will give us a baseline against which to test any other models for improvement.

First, I will define a function for the logistic regresssion model with K-fold cross validation.

```
In [418]: # Def a function for training/testing
          def train_and_test(df, k=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              lr=LogisticRegression(max_iter=1000)
              # Building K-folds
              kf = KFold(n splits=k, shuffle=True)
              auc values = []
              for train index, test index, in kf.split(df):
                  # Creating train/test set for fold
                  train = df.iloc[train index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  lr.fit(train[features], train['y'])
                  predictions = lr.predict(test[features])
                  # Calculate AUC
                  auc = roc auc score(test['y'], predictions)
                  auc values.append(auc)
              # Averaging auc values
              avg auc = np.mean(auc values)
              var_auc = np.var(auc values)
              print(avg auc, var auc)
              return avg auc, var auc
```

Next, I will train the model with a variety of K-fold values to see which provides the best accuracy.

```
In [415]: # Creating a list of k-fold values
splits = [2, 4, 6, 8, 10]

# Creating a dictionary of values for auc and var
auc_dict = {}

# Training a model with training data
for i in splits:
    k_auc, k_var = train_and_test(train, i)
    auc_dict[i] = k_auc, k_var
```

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1):

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:

https://scikit-learn.org/stable/modules/preprocessing.html.

Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

extra_warning msg= LOGISTIC_SOLVER_CONVERGENCE_MSG)

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extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

0.7864077223358682 1.445338211400935e-07

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1):

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extra_warning msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

0.7863791958247519 2.2179188732573277e-05

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1):

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extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)

0.784796173973918 5.206692782180382e-05

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)

0.7863007769084782 0.00011849641462344976

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:

```
Binary Classifier Assignment

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge
(status=1):
```

Increase the number of iterations (max_iter) or scale the data as shown
in:

.n:
 https://scikit-learn.org/stable/modules/preprocessing.html.

Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)

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extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)

0.7853201730657504 0.00011457379001719168

```
/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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in:
    https://scikit-learn.org/stable/modules/preprocessing.html.
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
    extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

It appears as though the first iteration, with only 2 folds for cross validation, provided the highest AUC score and lowest variance in AUC scores.

Balanced Class Adjustment

To establish a true baseline, however, I need to run this test again using a 'balanced' class model. Since the 1 y-values are disproportionate to the 0 values, this will help balance out the classes and hopefully improve the accuracy of our model.

```
In [419]: # Redefining train/test function for balanced class
          def train and test(df, k=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              # Including balanced class
              lr=LogisticRegression(max_iter=1000, class_weight='balanced')
              # Building K-folds
              kf = KFold(n_splits=k, shuffle=True)
              auc_values = []
              for train_index, test_index, in kf.split(df):
                  # Creating train/test set for fold
                  train = df.iloc[train_index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  lr.fit(train[features], train['y'])
                  predictions = lr.predict(test[features])
                  # Calculate AUC
                  auc = roc_auc_score(test['y'], predictions)
                  auc values.append(auc)
              # Averaging auc values
              avg_auc = np.mean(auc_values)
              var_auc = np.var(auc_values)
              print(avg_auc, var_auc)
              return avg_auc, var_auc
```

```
In [420]: # Re-running model with balanced classes
# Creating a list of k-fold values
splits = [2, 4, 6, 8, 10]

# Creating a dictionary of values for auc and var
auc_dict = {}

# Training a model with training data
for i in splits:
    k_auc, k_var = train_and_test(train, i)
    auc_dict[i] = k_auc, k_var
```

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:

https://scikit-learn.org/stable/modules/preprocessing.html.

Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression

extra_warning msg= LOGISTIC_SOLVER_CONVERGENCE_MSG)

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1):

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extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

0.829410606406946 2.219268039043902e-11

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

0.8284743020457778 1.9726083728891866e-05

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG)

0.8295695189795288 1.3648832633338154e-05

STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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in:

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extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE MSG)

0.8293396643716002 3.137504571509923e-05

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Increase the number of iterations (max_iter) or scale the data as shown
in:

Binary Classifier Assignment https://scikit-learn.org/stable/modules/linear model.html#logisticregression extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG) /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/ logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT. Increase the number of iterations (max_iter) or scale the data as shown in: https://scikit-learn.org/stable/modules/preprocessing.html. Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear model.html#logisticregression extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG) /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar_model/ logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT. Increase the number of iterations (max iter) or scale the data as shown in: https://scikit-learn.org/stable/modules/preprocessing.html. Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear_model.html#logisticregression extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG) /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar model/ logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT. Increase the number of iterations (max iter) or scale the data as shown in: https://scikit-learn.org/stable/modules/preprocessing.html. Please also refer to the documentation for alternative solver options: https://scikit-learn.org/stable/modules/linear model.html#logisticregression extra warning msg= LOGISTIC SOLVER CONVERGENCE MSG) /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line ar model/ logistic.py:939: ConvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT. Increase the number of iterations (max_iter) or scale the data as shown in:

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extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

0.8288388692373765 5.0362273750487695e-05

```
/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/sklearn/line
ar_model/_logistic.py:939: ConvergenceWarning: lbfgs failed to converge
(status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:
    https://scikit-learn.org/stable/modules/preprocessing.html.
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
    extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

It now appears that our best model used 6 K-folds, returning the highest AUC score and still maintaining a low variance. This will be our threshold for improving model accuracy.

Next I will try a K Nearest Neighbors model.

K Nearest Neighbors & Hyperparameter Tuning

K Nearest Neighbors is an effective tool for binary classification models. Here I will implement a basic model and include some hyperparameter tuning through a grid search. This will create several models and evaluate the best hyperparameters to use.

```
In [423]: # Importing K Nearest Neighbors model
    from sklearn.neighbors import KNeighborsClassifier
    # Importing Grid Search
    from sklearn.model_selection import GridSearchCV

In [424]: # Creating features and target dataframes
    all_X = train_clean.drop(columns='y')
    all_Y = train_clean['y']
```

```
In [427]: # Dictionary of hyperparameters to test
          hyperparameters = {
              "n_neighbors": range(1,20,2),
              "weights": ["distance", "uniform"],
              "algorithm": ['brute'],
              "p": [1,2]
          # model selection
          knn = KNeighborsClassifier()
          # grid search cv (param=dictionary we created, cv=folds)
          grid = GridSearchCV(knn,param grid=hyperparameters,cv=10)
          grid.fit(all_X, all_Y)
          # returning best hyperparameters and score
          best_params = grid.best_params_
          best_score = grid.best_score_
          # training using the best model
          best knn = grid.best estimator
In [429]: best params
Out[429]: {'algorithm': 'brute', 'n neighbors': 5, 'p': 2, 'weights': 'distance'}
In [430]: # Redefining train/test function for optimized knn model
          def train and test knn(df, k=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              # Including balanced class
              knn = KNeighborsClassifier(n neighbors=5, weights='distance', algori
          thm=brute, p=2)
              # Building K-folds
              kf = KFold(n_splits=k, shuffle=True)
              auc values = []
              for train index, test index, in kf.split(df):
                   # Creating train/test set for fold
                  train = df.iloc[train index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  knn.fit(train[features], train['y'])
                  predictions = knn.predict(test[features])
                  # Calculate AUC
                  auc = roc_auc_score(test['y'], predictions)
                  auc values.append(auc)
              # Averaging auc values
              avg auc = np.mean(auc values)
              var auc = np.var(auc values)
              print(avg auc, var auc)
              return avg auc, var auc
```

KNN Results

After optimizing a K Nearest Neighbor model, the AOC score returned as .8145. This is close to the score of our best Logistic Regression model, but not quite as good.

Random Forest Classifier

The final basic model I will choose is a Random Forest Classifier. This algorithm is well suited to binary classification, and can eliminate the bias of a single decision tree.

I will use the same Grid Search optimization method to try and find the best hyperparameters for a Random Forest model.

```
In [61]: from sklearn.ensemble import RandomForestClassifier
```

```
In [437]: # Dictionary of hyperparameters to test
          hyperparameters = {
              "n_estimators": range(100,500,100),
              "max_depth": [10],
               'class_weight':['balanced'],
               'n_{jobs'}:[-1],
               'verbose':[1]
              }
          # model selection
          rf = RandomForestClassifier()
          # grid search cv (param=dictionary we created, cv=folds)
          grid = GridSearchCV(rf,param_grid=hyperparameters,cv=10)
          grid.fit(all_X, all_Y)
          # returning best hyperparameters and score
          best_params = grid.best_params_
          best_score = grid.best_score_
          # training using the best model
          best_rf = grid.best_estimator_
```

```
[Parallel(n jobs=-1)]: Using backend LokyBackend with 4 concurrent work
ers.
[Parallel(n jobs=-1)]: Done 42 tasks
                                           elapsed:
                                                         5.6s
[Parallel(n jobs=-1)]: Done 100 out of 100 | elapsed:
                                                         9.3s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
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                                                        0.1s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
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[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:
                                                         6.5s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
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                                                         6.4s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
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                                                        0.0s finished
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                                                         0.0s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
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[Parallel(n jobs=-1)]: Done 42 tasks
                                             elapsed:
                                                          2.9s
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                         12.6s
[Parallel(n jobs=-1)]: Done 200 out of 200 | elapsed:
                                                         13.1s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
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          workers.
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          [Parallel(n jobs=-1)]: Using backend LokyBackend with 4 concurrent work
          ers.
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          [Parallel(n_jobs=-1)]: Done 192 tasks
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          [Parallel(n jobs=-1)]: Done 400 out of 400 | elapsed:
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          [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
          workers.
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          [Parallel(n jobs=4)]: Done 192 tasks
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          [Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
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          [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
          workers.
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          [Parallel(n jobs=-1)]: Using backend LokyBackend with 4 concurrent work
          ers.
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          [Parallel(n jobs=-1)]: Done 192 tasks
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          [Parallel(n jobs=-1)]: Done 400 out of 400 | elapsed:
                                                                   31.9s finished
          [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
          workers.
          [Parallel(n jobs=4)]: Done 42 tasks
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                                                                   0.2s finished
          [Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
          workers.
          [Parallel(n jobs=-1)]: Done 42 tasks
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          [Parallel(n jobs=-1)]: Done 192 tasks
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                                                                   15.6s
          [Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                                   23.4s finished
In [438]:
          best params
Out[438]: {'class_weight': 'balanced',
           'max depth': 10,
            'n estimators': 300,
           'n jobs': -1,
           'verbose': 1}
```

```
In [441]: # Redefining train/test function for optimized random forest model
          def train and test rf(df, k=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              # Including balanced class
              rf = RandomForestClassifier(class_weight='balanced', max_depth=10, n
          _estimators=300, n_jobs=-1, verbose=1)
              # Building K-folds
              kf = KFold(n_splits=k, shuffle=True)
              auc values = []
              for train_index, test_index, in kf.split(df):
                  # Creating train/test set for fold
                  train = df.iloc[train index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  rf.fit(train[features], train['y'])
                  predictions = rf.predict(test[features])
                  # Calculate AUC
                  auc = roc_auc_score(test['y'], predictions)
                  auc_values.append(auc)
              # Averaging auc values
              avg_auc = np.mean(auc_values)
              var_auc = np.var(auc_values)
              print(avg_auc, var_auc)
              return avg_auc, var_auc
```

```
In [442]: # Running model for optimized rf
train_and_test_rf(train_clean, k=10)
```

```
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=-1)]: Done 42 tasks
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[Parallel(n jobs=-1)]: Done 192 tasks
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[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
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[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
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[Parallel(n jobs=4)]: Done 42 tasks
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[Parallel(n jobs=4)]: Done 192 tasks
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[Parallel(n_jobs=4)]: Done 300 out of 300 | elapsed:
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[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
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[Parallel(n_jobs=-1)]: Done 42 tasks
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[Parallel(n jobs=-1)]: Done 192 tasks
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                                                         11.3s
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         17.6s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
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[Parallel(n_jobs=4)]: Done 42 tasks
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[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
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                                                         17.6s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                            elapsed:
                                                         0.0s
[Parallel(n jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.1s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
[Parallel(n jobs=-1)]: Done 42 tasks
                                             elapsed:
                                                          2.5s
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                         11.2s
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         17.4s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                            elapsed:
                                                         0.0s
[Parallel(n jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.1s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=-1)]: Done 42 tasks
                                             elapsed:
                                                          2.6s
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                         11.3s
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         17.5s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                            elapsed:
                                                         0.0s
[Parallel(n jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.1s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=-1)]: Done 42 tasks
                                                          2.6s
                                             elapsed:
[Parallel(n_jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                         11.6s
                                                         17.8s finished
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
```

```
[Parallel(n jobs=4)]: Done 42 tasks
                                                         0.0s
                                           elapsed:
[Parallel(n jobs=4)]: Done 192 tasks
                                           elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.1s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n_jobs=-1)]: Done 42 tasks
                                            | elapsed:
                                                         2.6s
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                        13.2s
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         20.8s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                                        0.0s
                                           elapsed:
[Parallel(n_jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.2s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n_jobs=-1)]: Done 42 tasks
                                                         3.9s
                                            elapsed:
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                        17.5s
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         27.5s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                           elapsed:
                                                        0.0s
[Parallel(n_jobs=4)]: Done 192 tasks
                                            elapsed:
                                                        0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                        0.2s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n_jobs=-1)]: Done 42 tasks
                                            elapsed:
                                                          2.5s
[Parallel(n jobs=-1)]: Done 192 tasks
                                             elapsed:
                                                        12.9s
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         19.9s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                                        0.0s
                                            elapsed:
[Parallel(n jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                         0.2s finished
[Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=-1)]: Done 42 tasks
                                             elapsed:
                                                         2.7s
[Parallel(n jobs=-1)]: Done 192 tasks
                                                        12.0s
                                             elapsed:
[Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                         19.2s finished
[Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
workers.
[Parallel(n jobs=4)]: Done 42 tasks
                                            elapsed:
                                                         0.0s
[Parallel(n_jobs=4)]: Done 192 tasks
                                            elapsed:
                                                         0.1s
0.8653249605810925 0.00010615893586465878
[Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                        0.2s finished
```

Out[442]: (0.8653249605810925, 0.00010615893586465878)

Random Forest Results

This algorithm produced an AOC score of 0.865, significantly higher than previous models. The variance has increased, but not enough to rule out this model as the most effective so far.

Neural Network Application

Last, I will run two Neural Network models to see if the accuracy improves.

```
In [67]: # Importing Neural Network Classifier
          from sklearn.neural network import MLPClassifier
In [453]: # Redefining neural neetwork train and test function
          def train and test nn(df, k=0, n=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              # Including balanced class
              mlp = MLPClassifier(hidden layer sizes=(n,), max iter=500)
              # Building K-folds
              kf = KFold(n splits=k, shuffle=True)
              auc values = []
              for train index, test index, in kf.split(df):
                  # Creating train/test set for fold
                  train = df.iloc[train index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  mlp.fit(train[features], train['y'])
                  predictions = mlp.predict(test[features])
                  # Calculate AUC
                  auc = roc auc score(test['y'], predictions)
                  auc values.append(auc)
              # Averaging auc values
              avg auc = np.mean(auc values)
              var auc = np.var(auc values)
              print(avg auc, var auc)
              return avg auc, var auc
In [454]: # Running model for different neuron levels in one hidden layer
          neurons = [8, 16, 32]
          accuracies = {}
          for i in neurons:
              aoc score, aoc var = train and test nn(train clean, k=4, n=i)
              accuracies[i] = aoc score, aoc var
          0.8333999923376425 0.0006858904796699593
          0.8710044161766354 0.0003664845593469178
          0.908420581924953 0.0005757786280987429
```

This increased the accuracty level significantly, but also increased the variance of the accuracy levels in the K-fold testing. This could mean the model is over-fitting, but the variance level is still very small compared to the overall accuracy level.

Finally, I will run a Neural Network model with two hidden layers, with 16 nodes each.

```
In [455]: # Redefining neural network for 2 hidden layers
          def train and test nn2(df, k=0, n=0):
              # Splitting dataframe from target column
              features = df.columns.drop('y')
              # Including balanced class
              mlp = MLPClassifier(hidden layer sizes=(n,n), max iter=500)
              # Building K-folds
              kf = KFold(n_splits=k, shuffle=True)
              auc values = []
              for train index, test index, in kf.split(df):
                  # Creating train/test set for fold
                  train = df.iloc[train index]
                  test = df.iloc[test index]
                  # Fitting and predicting
                  mlp.fit(train[features], train['y'])
                  predictions = mlp.predict(test[features])
                  # Calculate AUC
                  auc = roc auc score(test['y'], predictions)
                  auc values.append(auc)
              # Averaging auc values
              avg auc = np.mean(auc values)
              var auc = np.var(auc values)
              print(avg auc, var auc)
              return avg auc, var auc
In [456]: # Running model for different neuron levels in one hidden layer
          neurons = [16]
          accuracies = {}
          for i in neurons:
              aoc score, aoc var = train and test nn2(train clean, k=4, n=i)
              accuracies[i] = aoc score, aoc var
          0.90822683719581 1.79273849200885e-05
In [457]: # Running model for different neuron levels in two hidden layers
          neurons = [32]
          accuracies = {}
          for i in neurons:
              aoc score, aoc var = train and test nn2(train clean, k=4, n=i)
              accuracies[i] = aoc score, aoc var
```

0.9302986826327426 1.603054636250812e-05

This model looks to be the best overall, with the highest AOC and one of the lowest variances of the models we have generated.

Generating Predictions

Based on this testing, it seems the two best fitting models are:

- Neural Network Classifier (AOC: 0.9303) Hyper-parameters: 2 hidden layers, 32 nodes each K-fold validation: 4 folds
- Random Forest Classifier (AOC: 0.8653) Hyper-parameters: class_weight: 'balanced', max_depth: 10,
 n_estimators: 300, n_jobs: -1 K-fold validation: 10 folds

Now I will use these models to generate predictions for the test data and save those predictions in the appropriate format as per the assessment instructions.

Test Data Cleaning

First, I need to clean the test data with the same process used above.

```
In [48]: # Reimporting test data to clean dataframe
         test = pd.read csv('testdata.csv')
In [49]: # Identifying text columns
         text vals = test.select dtypes(include=['object'])
         text vals.head()
         # Cleaning the values of x41 and x45, storing as float
         text vals['x41'] = text vals['x41'].str.replace('$','').astype('float')
         text vals['x45'] = text vals['x45'].str.replace('%','').astype('float')
         /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel la
         uncher.py:5: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
         See the caveats in the documentation: http://pandas.pydata.org/pandas-d
         ocs/stable/indexing.html#indexing-view-versus-copy
         /Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel la
         uncher.py:6: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
         See the caveats in the documentation: http://pandas.pydata.org/pandas-d
         ocs/stable/indexing.html#indexing-view-versus-copy
```

```
In [50]: # Creating a mapping dictionary for correct labeling
        'chrystler': 'chrysler', 'nissan': 'nissan',
                'ford': 'ford', 'mercades': 'mercedes',
               'chevrolet':'chevrolet'}
         # Replacing values using dictionary
        text vals['x34'] = text vals['x34'].replace(dict)
         # Creating mapping dictionary
        dict2 = {'July':'jul','Jun':'jun',
               'Aug': 'aug', 'May': 'may',
               'sept.':'sep','Apr':'apr',
               'Oct':'oct','Mar':'mar',
               'Nov': 'nov', 'Feb': 'feb',
               'Dev':'dec','January':'jan'}
         # Replacing values using dictionary
         text vals['x68'] = text vals['x68'].replace(dict2)
```

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_la uncher.py:8: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row_indexer,col_indexer] = value instead

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

/Users/eddiekirkland/anaconda3/lib/python3.7/site-packages/ipykernel_la uncher.py:18: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row indexer,col indexer] = value instead

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

```
In [51]: # Drop x93 from text vals dataframe
text_vals = text_vals.drop(columns='x93')
```

In [52]: text_vals.head()

Out[52]:

	x34	x35	x41	x45	x68
0	bmw	thurday	107.93	0.00	jun
1	tesla	thurday	-600.43	0.02	may
2	honda	thurday	103.08	-0.00	jun
3	volkswagen	thurday	1518.78	-0.01	sep
4	volkswagen	thurdav	-2324.39	-0.00	iun

```
In [53]: # Selecting only text columns
    textcols = ['x34','x35','x68']
    # Get dummy prefix names
    prefixes = list(text_vals[textcols].columns)
    # Getting dummy features for each text column
    text_dummies = pd.get_dummies(text_vals, prefix=prefixes)
```

```
In [54]: # Dropping dirty text columns from original dataset
dropcols = ['x34','x35','x41','x45','x68','x93']
test = test.drop(columns=dropcols)
```

```
In [55]: # Reintroducing our cleaned data into the original dataset
test = pd.concat([test,text_dummies], axis=1)
```

```
In [56]: # Filling null values with mean for feature
test.fillna(value=0, inplace=True)
```

In [57]: test.info(verbose=True)

<class 'pandas.core.frame.DataFrame'> RangeIndex: 10000 entries, 0 to 9999 Data columns (total 126 columns): x0float64 x1float64 x2 float64 x3float64 x4float64 x5 float64 float64 х6 x7float64 x8 float64 x9 float64 x10 float64 x11 float64 x12 float64 x13 float64 x14 float64 x15 float64 x16 float64 x17 float64 float64 x18 x19 float64 x20 float64 x21 float64 x22 float64 x23 float64 x24 float64 x25 float64 x26 float64 x27 float64 x28 float64 x29 float64 x30 float64 x31 float64 x32 float64 x33float64 x36 float64 x37 float64 x38 float64 x39 float64 x40 float64 x42 float64 x43 float64 x44float64 x46 float64 x47 float64 x48 float64 x49 float64 x50 float64 x51 float64 x52 float64 x53 float64 x54 float64 x55 float64 x56 float64

float64

x57

x58	float64
x59	float64
x60	float64
x61	float64
x62	float64
x63	float64
x64	float64
x65	float64
x66	float64
x67	float64
x69	float64
x70	float64
x71	float64
x72	float64
x73	float64
x74	float64
x75	float64
x76	float64
x77	float64
x78	float64
x79	float64
x80	float64
x81	float64
x82	float64
x83	float64
x84	float64
x85	float64
x86	float64
x87	float64
x88	float64
x89	float64
x90	float64
x91	float64
x92	float64
x94	float64
x95	float64
x96	float64
x97	float64
x98	float64
x99	float64
x41	float64
x45	float64
x34_bmw	uint8
x34_chevrolet	uint8
x34_chrysler	uint8
x34_ford	uint8
x34_honda	uint8
x34 mercedes	uint8
x34 nissan	uint8
x34 tesla	uint8
	uint8
x34_toyota	uint8
x34_volkswagen	
x35_fri	uint8
x35_friday	uint8
x35_monday	uint8
x35_thur	uint8
x35_thurday	uint8

```
x35 tuesday
                            uint8
         x35 wed
                            uint8
         x35 wednesday
                            uint8
         x68 apr
                            uint8
         x68 aug
                            uint8
         x68_dec
                            uint8
         x68 feb
                            uint8
         x68 jan
                            uint8
         x68_jul
                            uint8
         x68 jun
                            uint8
         x68 mar
                            uint8
         x68_may
                            uint8
         x68 nov
                            uint8
         x68 oct
                            uint8
         x68 sep
                            uint8
         dtypes: float64(96), uint8(30)
         memory usage: 7.6 MB
In [58]: # Saving column names for future dataframe
         colnames = test.columns
         # Creating minmax scaler instance
         mm scaler = preprocessing.MinMaxScaler()
         # Transforming data into scaled array
         df mm = mm scaler.fit transform(test)
         # Creating new dataframe with scaled data
         test clean = pd.DataFrame(df mm, columns=colnames)
In [59]: # Matching column names from training dataset
         train cols = train clean.drop(columns='y')
         keepcols = train cols.columns
         test clean = test clean[keepcols]
```

Predicting with Random Forest Classifier

```
In [62]: features = train clean.drop(columns='y')
         # Running Model on training data
         rf = RandomForestClassifier(class weight='balanced', max depth=10, n est
         imators=300, n jobs=-1, verbose=1)
         rf.fit(features, train clean['y'])
         predictions = rf.predict proba(test clean)
         [Parallel(n jobs=-1)]: Using backend ThreadingBackend with 4 concurrent
         workers.
         [Parallel(n jobs=-1)]: Done 42 tasks
                                                       elapsed:
                                                                   2.8s
         [Parallel(n jobs=-1)]: Done 192 tasks
                                                                  12.0s
                                                       elapsed:
         [Parallel(n jobs=-1)]: Done 300 out of 300 | elapsed:
                                                                  19.0s finished
         [Parallel(n jobs=4)]: Using backend ThreadingBackend with 4 concurrent
         workers.
         [Parallel(n jobs=4)]: Done 42 tasks
                                                      elapsed:
                                                                  0.0s
         [Parallel(n jobs=4)]: Done 192 tasks
                                                                  0.1s
                                                      elapsed:
         [Parallel(n jobs=4)]: Done 300 out of 300 | elapsed:
                                                                  0.2s finished
```

```
In [63]: # Saving 1 predictions to dataframe
    rf_predictions = pd.DataFrame(predictions[:,1])
In [65]: # Saving Random Forest predictions to file
    rf_predictions.to_csv('RFPredictions_EKirkland.csv')
```

Predicting with Neural Network Classifier

```
In [69]: features = train_clean.drop(columns='y')

# Running Model on training data
mlp = MLPClassifier(hidden_layer_sizes=(32,32), max_iter=500)
mlp.fit(features, train_clean['y'])
predictions = mlp.predict_proba(test_clean)
In [70]: # Saving 1 predictions to dataframe
nn_predictions = pd.DataFrame(predictions[:,1])
# Saving Neural Network predictions to file
nn_predictions.to_csv('NNPredictions_EKirkland.csv')
```