Project: Reduce Maintenance Cost Through Predictive Techniques

Kristen Groom - Data Scientist (Entry-Level), Product Analytics (Temporary) Position Analysis

September 11, 2019

Table of Contents

*Project structure follows basic template outline provided through the Udacity Data Analytics nanodegree found at: https://www.udacity.com/course/data-analyst-nanodegree--nd002 (https://www.udacity.com/course/data-analyst-nanodegree--nd002)

Introduction

- ## Background:

  Company (Cloud BOT) has a fleet of devices transmitting daily aggregated telemetry attributes. Predictive maintenance techniques are designed to help determine the condition of in-service equipment in order to predict when maintenance should be performed. This approach promises cost savings over routine or time- based preventive maintenance, because tasks are performed only when warranted.

- ## Goal:

  Build a predictive model using machine learning to predict the probability of a device failure. When building this model, be sure to minimize false positives and false negatives. The column you are trying to predict is called failure with binary value 0 for non-failure and 1 for failure.

- ## Code:

  We are looking for you to show off your coding skills using Python. Please keep in mind we are not looking for a correct answer. We are looking for you to show how you think and problem solve. The data is purposefully dirty and confusing.

- ## Data:

Columns	Description
Date	Date in YYYY-MM-DD format
Device	Device id
Failure	Non-failure is 0, failure is 1
Attribute 1-9	Daily aggregated telemetry

- ## Report:

  Please return a converted PDF document from Markdown displaying your code and thought process.

* Requirements:"Data_Scientist_Data_Challenge.pdf"

Data Wrangling

> In this section of the analysis, I will load in the data, check for cleanliness, and then trim and clean the dataset as needed for analysis.

In [341]:
```
# import libraries
import numpy as np
import pandas as pd
from scipy import stats
import matplotlib.pyplot as plt
%matplotlib inline
```

In [342]:
```
# read in the .csv file
df = pd.read_csv('device_failure_data_scientist.csv')
```

In [343]:
```
# view a section of the data
df.head()
```

Out[343]:

	date	device	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7
0	15001	S1F01085	215630672	56	0	52	6	407438	(
1	15001	S1F0166B	61370680	0	3	0	6	403174	(
2	15001	S1F01E6Y	173295968	0	0	0	12	237394	(
3	15001	S1F01JE0	79694024	0	0	0	6	410186	(
4	15001	S1F01R2B	135970480	0	0	0	15	313173	(

In [344]:
```
# size of dataset
df.shape
```

Out[344]:
```
(124494, 12)
```

In [345]:
```
# dataset variables and datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 124494 entries, 0 to 124493
Data columns (total 12 columns):
date          124494 non-null int64
device        124494 non-null object
attribute1    124494 non-null int64
attribute2    124494 non-null int64
attribute3    124494 non-null int64
attribute4    124494 non-null int64
attribute5    124494 non-null int64
attribute6    124494 non-null int64
attribute7    124494 non-null int64
attribute8    124494 non-null int64
attribute9    124494 non-null int64
failure       124494 non-null int64
dtypes: int64(11), object(1)
memory usage: 11.4+ MB
```

In [346]:
```
# look at date and device a bit more closely to see if these are all uni
que id's
df['device'].value_counts()

# I see that there are 1168 different devices so I will consider this an
idenfification attribute
# that will not be used in the final predictive models, however I will k
eep this attribute in the dataset to explore
# further within the Exploratory Data Analysis section.
```

```
Out[346]: W1F05X69    304
          S1F0FP0C    304
          Z1F0QL3N    304
          W1F0JXDL    304
          S1F0GPXY    304
          Z1F0KKN4    304
          W1F0JH87    304
          Z1F0QK05    304
          S1F0GGPP    304
          S1F0H6JG    304
          S1F0EGMT    304
          W1F0FY92    304
          S1F0E9EP    304
          S1F0GCED    304
          Z1F0GB8A    304
          W1F0FEH7    304
          W1F0SJJ2    304
          W1F0G9T7    304
          S1F0FGBQ    304
          W1F0FZPA    304
          Z1F0Q8RT    304
          Z1F0MA1S    304
          Z1F0KJDS    304
          Z1F0QLC1    304
          Z1F0GE1M    304
          S1F0KYCR    304
          W1F0JY02    304
          W1F0T0B1    299
          S1F13432    295
          Z1F0VNSW    295
                     ...
          S1F03RV3      5
          W1F0KDDQ      5
          Z1F0L4J2      5
          W1F0KJMC      5
          Z1F0LSNM      5
          S1F0B5QJ      5
          S1F0LDLW      5
          W1F0KCZ0      5
          S1F05NAJ      5
          S1F0CT09      5
          Z1F0L78Z      5
          S1F0LEBM      5
          Z1F1AGW1      5
          W1F0H9RN      5
          Z1F0LSQ2      5
          S1F08S38      5
          S1F0CVRM      5
          Z1F14F5V      5
          W1F1CAKS      5
          Z1F0LR8G      5
          W1F1CJKT      5
          W1F0ED5X      5
          Z1F118C9      5
          S1F0CT4F      5
          W1F0BJ6E      5
          Z1F17Z3N      5
```

```
Z1F0LT4K      5
S1F09MSM      5
S1F04KSC      4
W1F0WJFT      3
Name: device, Length: 1168, dtype: int64
```

In [347]:
```
df['date'].value_counts()

# There are 304 different date values, although these values are confusi
ng given my expected YYYY-MM-DD format.
# In practice, I would ask an expert for more information regarding the
 coding of the date b/c when I use
# pandas.to_datetime() method, the results are not what I would be expec
ting.
# At this point, I would like to continue to explore the dataset in orde
r
# to decide if I will keep this column to be used for the predictive mod
els.
```

```
Out[347]: 15002    1163
          15003    1163
          15001    1163
          15004    1162
          15005    1161
          15006    1054
          15007     798
          15008     756
          15009     756
          15011     755
          15012     755
          15010     755
          15013     755
          15014     716
          15017     715
          15015     715
          15016     715
          15029     715
          15018     714
          15019     713
          15020     713
          15024     712
          15039     712
          15031     712
          15030     712
          15025     712
          15038     712
          15028     712
          15021     712
          15027     712
                   ...
          15251     146
          15252     146
          15275     146
          15279     141
          15281     141
          15282     141
          15280     141
          15285     140
          15283     140
          15284     140
          15246     115
          15286     111
          15287     111
          15289     109
          15290     109
          15292     109
          15291     109
          15288     109
          15294      69
          15293      69
          15295      69
          15299      32
          15296      32
          15297      32
          15298      32
          15302      31
```

```
15300      31
15303      31
15306      31
15304      31
Name: date, Length: 304, dtype: int64
```

Dataset consists of 124,494 instances/rows of telemetry data, with 12 attributes/columns including the following:

- device - id attribute (String datatype): I will remove this attribute before performing my predictive analysis.
- date - numeric attribute, which according to the schema, we would be expecting to be in format YYYY-MM-DD, however given the ambiguity of the format, I will continue exploring before I decide to keep or to drop this column for analysis.
- Attributes - numeric attributes representing aggregated telemetry data.

In [348]:
```
# check for duplicated rows
sum(df.duplicated())
```

Out[348]: 0

In [349]:
```
# check for null values
df[df.isnull().any(axis = 1)]
```

Out[349]:

date	device	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7	attril

No duplicated rows or null values were found within the dataset, which is confirmed above when performing df.info().

In [350]:
```
# descriptive statistics
df.describe()
```

Out[350]:

	date	attribute1	attribute2	attribute3	attribute4	attribute5
count	124494.000000	1.244940e+05	124494.000000	124494.000000	124494.000000	124494.00000C
mean	15106.222798	1.223868e+08	159.484762	9.940455	1.741120	14.22269
std	78.412061	7.045960e+07	2179.657730	185.747321	22.908507	15.943021
min	15001.000000	0.000000e+00	0.000000	0.000000	0.000000	1.00000C
25%	15040.000000	6.127675e+07	0.000000	0.000000	0.000000	8.00000C
50%	15086.000000	1.227957e+08	0.000000	0.000000	0.000000	10.00000C
75%	15168.000000	1.833084e+08	0.000000	0.000000	0.000000	12.00000C
max	15306.000000	2.441405e+08	64968.000000	24929.000000	1666.000000	98.00000C

> In the above table, I can see that there appears to be highly skewed data distributions for some of the variables and I can see that there may be potential outliers. I am also noting large ranges of values between and within the variables which I will address in one way by scaling the data, although I would like to view some visualizations of the data to confirm my assumptions of skewness and potential outliers.

In [351]:
```
# check groupings of fail/no-fail for the devices
fail_count = df.groupby('failure')['device'].count()
```

In [352]:
```
# check values:
fail_count
```

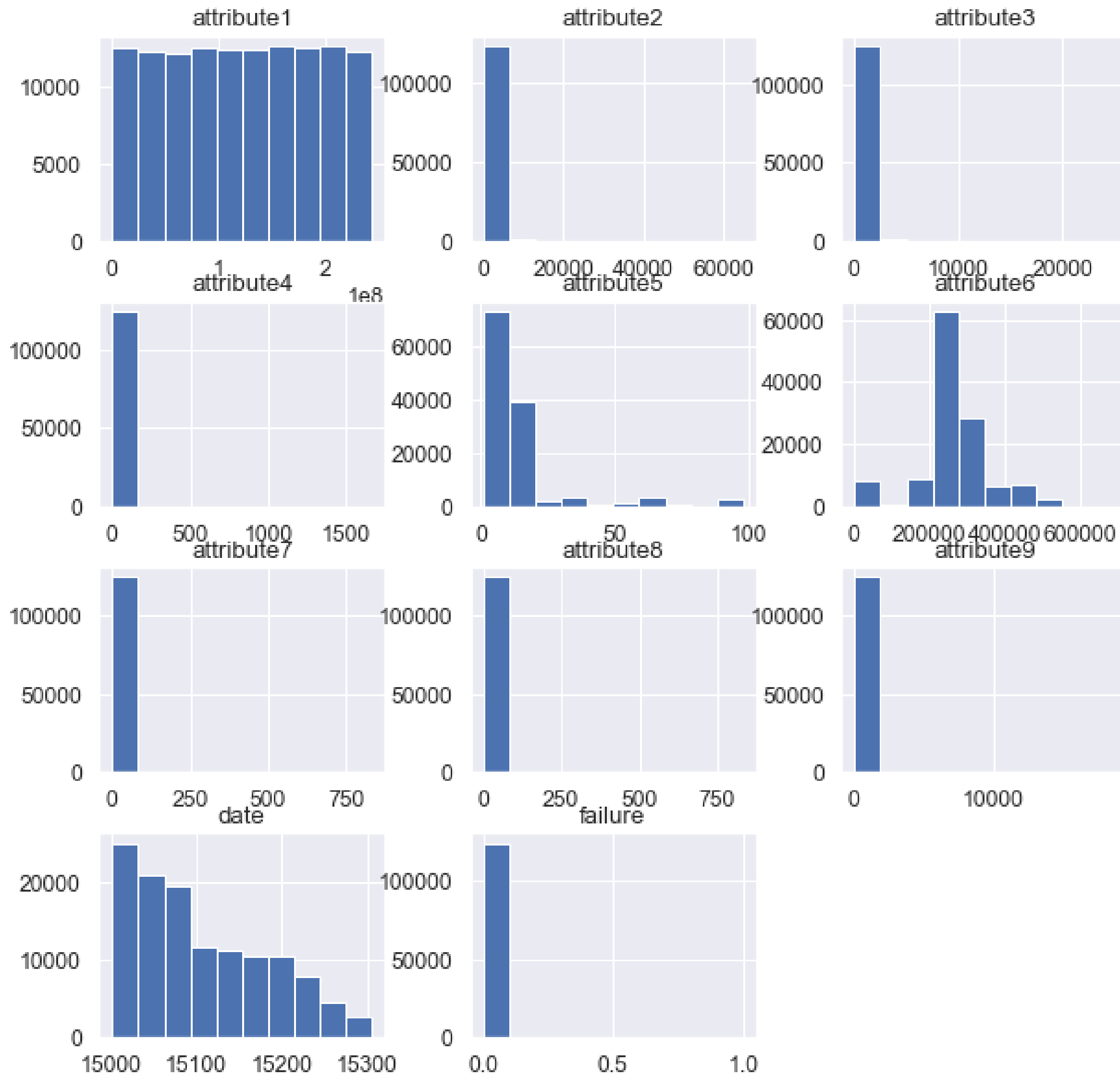
Out[352]:
```
failure
0    124388
1       106
Name: device, dtype: int64
```

In [353]:
```
# confirm percentage of failures (same value as mean for failure attribu
te)
fail_count[1]/fail_count[0]
```

Out[353]:
```
0.0008521722352638518
```

This dataset shows a high degree of class imbalance due to the very low percentage of failures for the dataset. This is also confirmed in the descriptive statistics for the dataset wherein the mean value for the failure attribute is 0.000851. I would initially assume this dataset to be a high recall issue dataset, meaning, False Negatives would be more detrimental - that is, having a system that is prone to failure but being misdiagnosed as healthy, which could lead to more significant repair costs for company Cloud Bot. I simultaneously acknowledge the company's goal of reducing False Positives and False Negatives so I will review various metrics including Recall, Precision, Accuracy, F1, and AUC in determining the best model for this dataset. I have been researching the best ways to deal with class imbalanced data and some options could be undersampling the no-failure class, or oversample the failure instances, or SMOTE (generating synthetic points). After reading this article: [https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28 (https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28)](https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28) I learned that reworking the data may not ideal or if I do choose to do so, I would, of course, need to be thoughtful about my choices and understand that bias will be introduced. Obtaining more features is not possible either so one way that I may attempt to resolve this issue is to perform stratified sampling of the data. I will continue to look for additional options.

In [354]:
```
df.hist(figsize=[10,10]);
```



I see right skewed distributions for the telemetry attributes with the majority of attribute values being 0. I will scale the data and check distributions once again prior to performing predictive analytics.

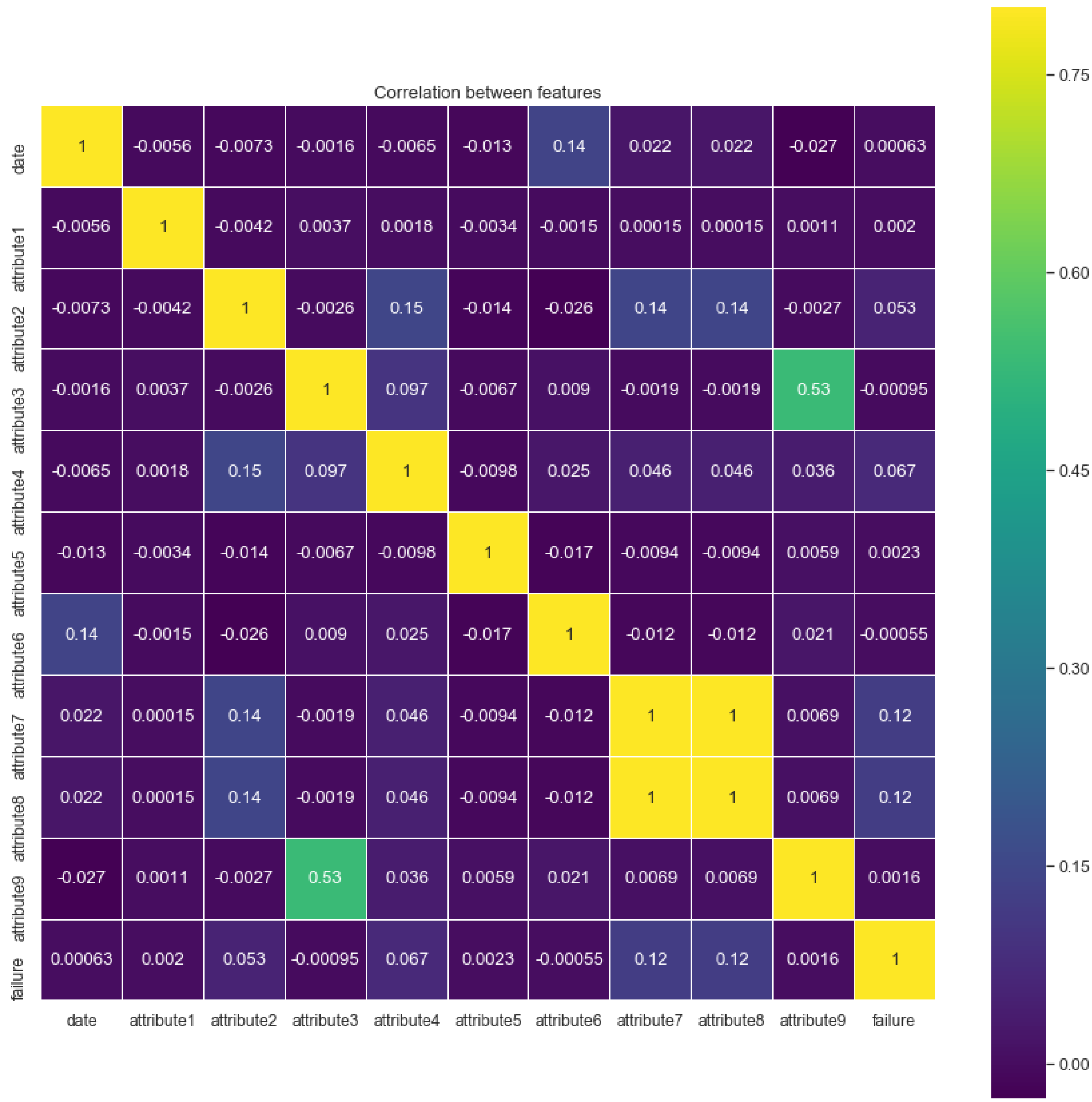
In [355]:
```
# view correlations among attributes
df.corr()
```

Out[355]:

	date	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7
date	1.000000	-0.005603	-0.007317	-0.001580	-0.006484	-0.013455	0.139643	0.021653
attribute1	-0.005603	1.000000	-0.004248	0.003702	0.001837	-0.003370	-0.001516	0.000151
attribute2	-0.007317	-0.004248	1.000000	-0.002617	0.146593	-0.013999	-0.026350	0.141367
attribute3	-0.001580	0.003702	-0.002617	1.000000	0.097452	-0.006696	0.009027	-0.001884
attribute4	-0.006484	0.001837	0.146593	0.097452	1.000000	-0.009773	0.024870	0.045631
attribute5	-0.013455	-0.003370	-0.013999	-0.006696	-0.009773	1.000000	-0.017051	-0.009384
attribute6	0.139643	-0.001516	-0.026350	0.009027	0.024870	-0.017051	1.000000	-0.012207
attribute7	0.021653	0.000151	0.141367	-0.001884	0.045631	-0.009384	-0.012207	1.000000
attribute8	0.021653	0.000151	0.141367	-0.001884	0.045631	-0.009384	-0.012207	1.000000
attribute9	-0.026538	0.001122	-0.002736	0.532366	0.036069	0.005949	0.021152	0.006861
failure	0.000627	0.001984	0.052902	-0.000948	0.067398	0.002270	-0.000550	0.119055

In [356]:

```
# visualize correlations:
# using template found at: https://www.kaggle.com/chapagain/house-prices
-eda-data-modelling-and-prediction

import seaborn as sns
sns.set(style="whitegrid", color_codes=True)

corr_matrix = df.corr()

sns.set(font_scale=1.10)
plt.figure(figsize=(15, 15))

sns.heatmap(corr_matrix, vmax=.8, linewidths=0.01,
            square=True, annot=True, cmap='viridis', linecolor="white")

plt.title('Correlation between features');
```



	date	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7	attribute8	attribute9	failure
date	1	-0.0056	-0.0073	-0.0016	-0.0065	-0.013	0.14	0.022	0.022	-0.027	0.00063
attribute1	-0.0056	1	-0.0042	0.0037	0.0018	-0.0034	-0.0015	0.00015	0.00015	0.0011	0.002
attribute2	-0.0073	-0.0042	1	-0.0026	0.15	-0.014	-0.026	0.14	0.14	-0.0027	0.053
attribute3	-0.0016	0.0037	-0.0026	1	0.097	-0.0067	0.009	-0.0019	-0.0019	0.53	-0.00095
attribute4	-0.0065	0.0018	0.15	0.097	1	-0.0098	0.025	0.046	0.046	0.036	0.067
attribute5	-0.013	-0.0034	-0.014	-0.0067	-0.0098	1	-0.017	-0.0094	-0.0094	0.0059	0.0023
attribute6	0.14	-0.0015	-0.026	0.009	0.025	-0.017	1	-0.012	-0.012	0.021	-0.00055
attribute7	0.022	0.00015	0.14	-0.0019	0.046	-0.0094	-0.012	1	1	0.0069	0.12
attribute8	0.022	0.00015	0.14	-0.0019	0.046	-0.0094	-0.012	1	1	0.0069	0.12
attribute9	-0.027	0.0011	-0.0027	0.53	0.036	0.0059	0.021	0.0069	0.0069	1	0.0016
failure	0.00063	0.002	0.053	-0.00095	0.067	0.0023	-0.00055	0.12	0.12	0.0016	1

The correlation matrix and the heatmap show that the majority of the variables do not indicate strong multicollinearity, which means that two variables show a strong linear relationship. I do, however, see a perfect correlation between attribute 7 and attribute 8 and a moderate correlation between attribute 9 and attribute 3. The perfect correlation could mean that these two attributes are basically the same attribute and one would need to be removed. I also may still perform logistic regression even though the scatterplot matrix shows non-linear relationships and I do not think that the slight multicollinearity of 9 and 3 should be problematic for the Machine Learning models that I will be building. I also notice that the attributes with the highest correlation with failure are attributes 7 and 8. Attributes 2 and 4, also show slightly more correlation to failure than some of the others. I see a very low correlation between date and failure so I will not choose to keep this attribute in the final predictive models.

In [ ]:

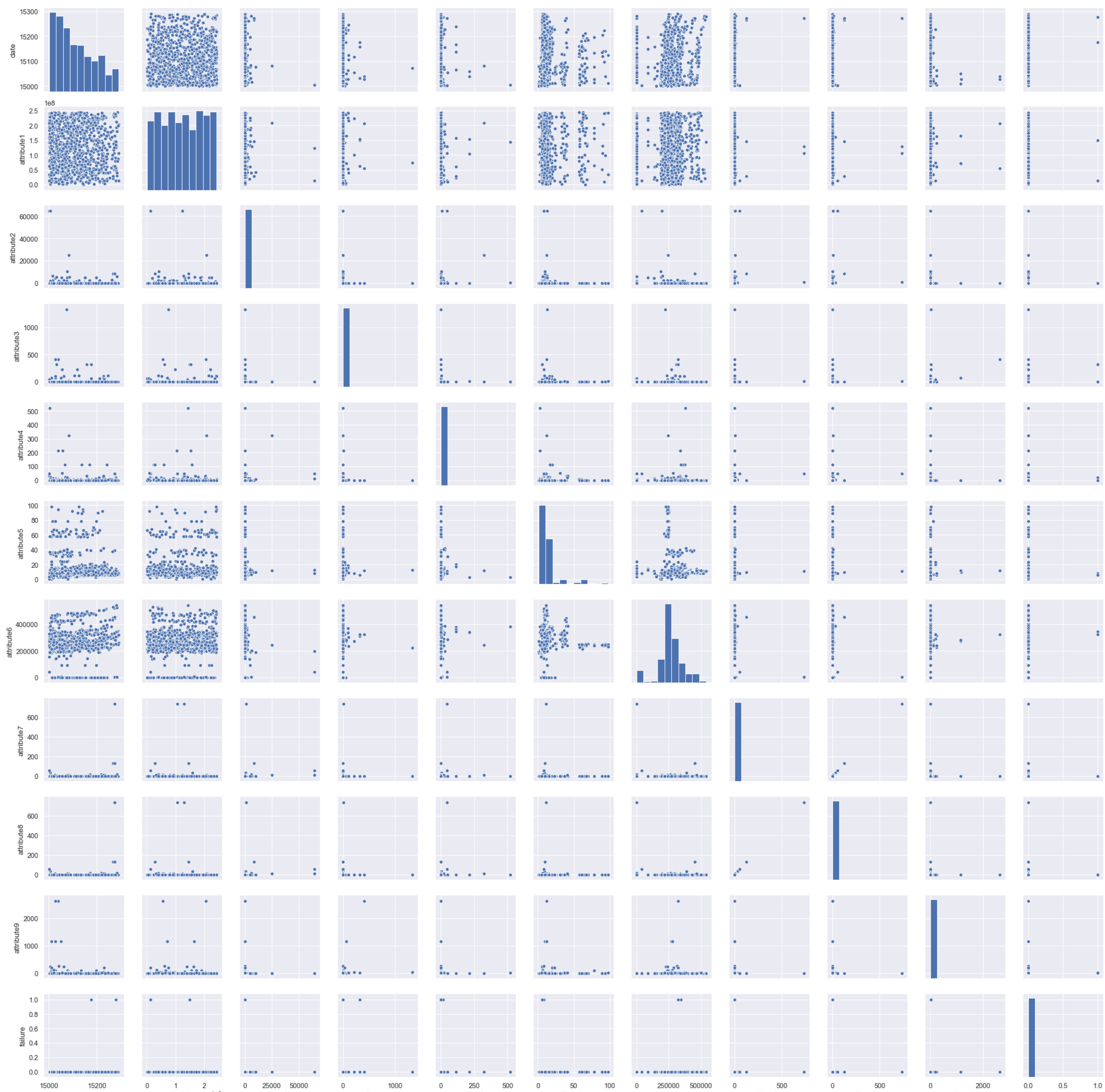
In [ ]:

Exploratory Data Analysis

The purpose of this section is to utilize EDA to further explore the data and note interesting findings

In [357]:
```
# check for outliers - although, given that I am unfamiliar with the tel
emetry data, if I find outliers, I will not
# remove them, because these values could be important information for o
ur analysis in predicting device failures.

# view scatter plots
# sns.pairplot(df, hue="failure");

# I tried to complete a full pairplot matrix, but it was taking a very l
ong time so I'll try with a sample of values:
sns.pairplot(df.sample(1000))
```

Out[357]: <seaborn.axisgrid.PairGrid at 0x1a4eebbc50>



The scatterplots are indicating non-linear relationships, which would make a linear model unreliable in predicting device failure. I would still like to perform Logistic Regression to predict probabilities in addition to other Machine Learning models that are less influenced by the linearity of the data. I see potential outliers and influential points in the scatter plots, and although I will perform further checks for outliers, I will not remove them, because these values could be keys to understanding which attributes contribute to the detection of failures.

In [358]:
```
# further outlier checking using z-scores

z = np.abs(stats.zscore(df.iloc[:, 2:]))
```

In [359]:
```
# seeing how many instances are > 3 standard deviations above the mean
threshold = 3

# tuple that holds two np.arrays - first with list of row nums, second w
ith respective col nums
z_greater_than_mean = np.where(z > 3)
```

In [360]:
```
print(len(z_greater_than_mean[0]))

# there are over 7000 instances of values that appear to be outliers.  I
am choosing to keep the values
# in the dataset for predictive analysis in order to avoid as much as po
ssible introducing bias in the data,
# although I would explore this large number of potential outliers furth
er in practice.
```

```
7575
```

In [361]:
```
# I'd like to explore which devices are the ones with the most failures
# first group the devices by the number of failures
device_fails = df.groupby('device')['failure'].sum()
device_fails.head()
```

Out[361]:
```
device
S1F01085    0
S1F013BB    0
S1F0166B    0
S1F01E6Y    0
S1F01JE0    0
Name: failure, dtype: int64
```

In [362]:
```
# find device/devices with largest number of failures
device_fails[device_fails == device_fails.max()]
```

Out[362]:
```
device
S1F023H2    1
S1F03YZM    1
S1F09DZQ    1
S1F0CTDN    1
S1F0DSTY    1
S1F0F4EB    1
S1F0GG8X    1
S1F0GJW3    1
S1F0GKFX    1
S1F0GKL6    1
S1F0GPFZ    1
S1F0GSD9    1
S1F0GSHB    1
S1F0J5JH    1
S1F0JD7P    1
S1F0JGJV    1
S1F0L0DW    1
S1F0LCTV    1
S1F0LCVC    1
S1F0LD15    1
S1F0LD2C    1
S1F0P3G2    1
S1F0PJJW    1
S1F0QF3R    1
S1F0QY11    1
S1F0RR35    1
S1F0RRB1    1
S1F0RSZP    1
S1F0S2WJ    1
S1F0S4CA    1
           ..
W1F1BS0H    1
W1F1BZTM    1
W1F1C9TE    1
W1F1C9WG    1
W1F1CB5E    1
W1F1CDDP    1
W1F1CJ1K    1
W1F1DQN8    1
Z1F04GCH    1
Z1F0B4XZ    1
Z1F0FSBY    1
Z1F0K451    1
Z1F0LSNZ    1
Z1F0LVGY    1
Z1F0LVPW    1
Z1F0MCCA    1
Z1F0MRPJ    1
Z1F0NVZA    1
Z1F0P16F    1
Z1F0P5D9    1
Z1F0QH0C    1
Z1F130LH    1
Z1F148T1    1
Z1F14BGY    1
Z1F1653X    1
```

```
Z1F1901P    1
Z1F1AG5N    1
Z1F1FCH5    1
Z1F1RJFA    1
Z1F1VQFY    1
Name: failure, Length: 106, dtype: int64
```

The maximum number of failures is 1, and there are approximately 100 devices that have failed once in this dataset.

In [363]:
```
# print mean values of attributes given fail/no-fail
for attribute in df.columns[2:-1]:
    print('{}: '.format(attribute))
    att_mean = df.groupby('failure')[attribute].mean()
    print(att_mean)
    print('*'*40)
```

```
attribute1:
failure
0    1.223827e+08
1    1.271755e+08
Name: attribute1, dtype: float64
****************************************
attribute2:
failure
0     156.118725
1    4109.433962
Name: attribute2, dtype: float64
****************************************
attribute3:
failure
0    9.945598
1    3.905660
Name: attribute3, dtype: float64
****************************************
attribute4:
failure
0     1.696048
1    54.632075
Name: attribute4, dtype: float64
****************************************
attribute5:
failure
0    14.221637
1    15.462264
Name: attribute5, dtype: float64
****************************************
attribute6:
failure
0    260174.451056
1    258303.481132
Name: attribute6, dtype: float64
****************************************
attribute7:
failure
0     0.266682
1    30.622642
Name: attribute7, dtype: float64
****************************************
attribute8:
failure
0     0.266682
1    30.622642
Name: attribute8, dtype: float64
****************************************
attribute9:
failure
0    12.442462
1    23.084906
Name: attribute9, dtype: float64
****************************************
```

> These results are interesting to me in that I can see that some of the mean values differ quite a bit for certain attributes, such as attribute2, attribute4, attribute7, attribute8, and attribute9. I still see that attributes 7 and 8 have the exact same values so I will remove one of these redundant attributes. The higher difference mean values could be informing us about the significance of these attributes in determining potential device failure, and these results confirm what I noticed in the heatmap, that attributes 2,4,7,8 showed the highest correlations to failure. I will perform feature selection in my predictive analysis to compare significant features with these results.

In [364]:
```
# before I move on to predictive models, I will get the dataset into the
proper format by removing the idenfication
# column: device, and the date column, and by normalizing the data so th
at it will be scaled appropriately.  I will
# also remove attribute8 as a redundant feature.

df = df.drop(columns=['device', 'date', 'attribute8'])
```

In [365]:
```
df.head()
```

Out[365]:

	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7	attribute9	failure
0	215630672	56	0	52	6	407438	0	7	(
1	61370680	0	3	0	6	403174	0	0	(
2	173295968	0	0	0	12	237394	0	0	(
3	79694024	0	0	0	6	410186	0	0	(
4	135970480	0	0	0	15	313173	0	3	(

In [366]:
```
# I do not want to scale failure so I will remove this column and hold i
t in its own variable:
target = df.failure
```

In [367]:
```
df = df.drop(columns=['failure'])
```

In [368]:
```
df.head()
```

Out[368]:

	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7	attribute9
0	215630672	56	0	52	6	407438	0	7
1	61370680	0	3	0	6	403174	0	0
2	173295968	0	0	0	12	237394	0	0
3	79694024	0	0	0	6	410186	0	0
4	135970480	0	0	0	15	313173	0	3

In [369]:
```
# normalization process using sklearn
from sklearn import preprocessing
```

In [370]:
```
# we first create an instance of MinMaxScaler() to use to fit data
min_max_scaler = preprocessing.MinMaxScaler()
min_max_scaler.fit(df)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:33
4: DataConversionWarning: Data with input dtype int64 were all converte
d to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

Out[370]:
```
MinMaxScaler(copy=True, feature_range=(0, 1))
```

In [371]:
```
# fit the data using the MinMaxScaler object
df_norm = min_max_scaler.fit_transform(df)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/data.py:33
4: DataConversionWarning: Data with input dtype int64 were all converte
d to float64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

In [372]:
```
# viewing results
np.set_printoptions(precision=4, linewidth=100)
df_norm[:1000]
```

Out[372]:
```
array([[8.8322e-01, 8.6196e-04, 0.0000e+00, ..., 5.9120e-01, 0.0000e+0
0, 3.7431e-04],
       [2.5137e-01, 0.0000e+00, 1.2034e-04, ..., 5.8502e-01, 0.0000e+0
0, 0.0000e+00],
       [7.0982e-01, 0.0000e+00, 0.0000e+00, ..., 3.4446e-01, 0.0000e+0
0, 0.0000e+00],
       ...,
       [2.1754e-01, 0.0000e+00, 0.0000e+00, ..., 2.1526e-01, 9.6154e-0
3, 0.0000e+00],
       [5.9188e-01, 0.0000e+00, 0.0000e+00, ..., 6.4633e-01, 0.0000e+0
0, 0.0000e+00],
       [9.4528e-02, 0.0000e+00, 0.0000e+00, ..., 6.4512e-01, 0.0000e+0
0, 0.0000e+00]])
```

In [373]:
```
# back to dataframe
df = pd.DataFrame(df_norm, columns=df.columns)
```

In [374]:
```
df.head()
```

Out[374]:

	attribute1	attribute2	attribute3	attribute4	attribute5	attribute6	attribute7	attribute9
0	0.883224	0.000862	0.00000	0.031212	0.051546	0.591204	0.0	0.000374
1	0.251374	0.000000	0.00012	0.000000	0.051546	0.585017	0.0	0.000000
2	0.709821	0.000000	0.00000	0.000000	0.113402	0.344461	0.0	0.000000
3	0.326427	0.000000	0.00000	0.000000	0.051546	0.595191	0.0	0.000000
4	0.556935	0.000000	0.00000	0.000000	0.144330	0.454420	0.0	0.000160

Machine Learning Predictive Models

> In this section, I will first need to decide how to deal with the class imbalance issue when deciding how to split my training and test data. After that, I will build three models that I feel would be good at determining potential device failure - Logistic Regression, Naive Bayes models, and I will be starting with RandomForestClassifier to practice getting the data more balanced. I will compare the performance of the models using various performance metrics, and I will not perform feature selection at this time to decide if we can achieve similar results with a reduction in the model complexity, however, in practice, I would definitely perform feature selection. I will perform 5-fold Cross-validation on the models as well. In practice, I would also perform GridSearchCV or RandomizedSearchCV for hyperparameter tuning.

In [375]:
```
# import libraries
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_scor
e, f1_score, roc_auc_score, confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
```

In [376]:
```
# I will be using some of my ML professor's template code found at: htt
p://www.caseybennett.com/teaching.html
# for the following analyses
```

In [377]:
```
# first get into correct format and split into test/train sets
data_np = np.asarray(df)
target_np = np.asarray(target)

X_train, X_test, y_train, y_test = train_test_split(data_np, target_np,
test_size=0.3, stratify=target_np)
```

In [378]:
```
clf = RandomForestClassifier(n_estimators=100, max_depth=None, min_sampl
es_split=3, criterion='entropy')
# fit the data using the clf object created in 198
clf.fit(X_train, y_train)
# performance calculated for for us below using test data
scores_ACC = clf.score(X_test, y_test)
print('Random Forest Acc:', scores_ACC)
scores_AUC = roc_auc_score(y_test, clf.predict_proba(X_test)[:,1])
print('Random Forest AUC:', scores_AUC)
```

```
Random Forest Acc: 0.999143216685855
Random Forest AUC: 0.7262495142964333
```

In [379]:
```
y_pred = clf.predict(X_test)
```

In [380]:
```
confusion_matrix(y_test, y_pred)
```

Out[380]:
```
array([[37317,     0],
       [   32,     0]])
```

In [381]:
```
# function found in Intro to Machine Learning Udacity Nanodegree practic
e: https://www.udacity.com/course/intro-to-machine-learning-nanodegree--
nd229
def print_scores(y_test, y_pred):
    print('Accuracy score: ', format(accuracy_score(y_test, y_pred)))
    print('Precision score: ', format(precision_score(y_test, y_pred)))
    print('Recall score: ', format(recall_score(y_test, y_pred)))
    print('F1 score: ', format(f1_score(y_test, y_pred)))
    print('AUC score: ', format(roc_auc_score(y_test, y_pred)))
```

In [382]:
```
print_scores(y_test, y_pred)
```

```
Accuracy score:  0.999143216685855
Precision score:  0.0
Recall score:  0.0
F1 score:  0.0
AUC score:  0.5

/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: Precision is ill-defined and being set
to 0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
```

I can see from the scores that using stratify=target_np, did not address the class imbalance issue. I was confused at first as to why I was getting 0 for precision, recall, and f1 but it makes sense to me because there were no True Negatives in the test set. I will try another strategy for dealing with imbalanced data.

In [383]:
```
# First try RandomForest Classifier with cross-validation

#Setup Crossval classifier scorers
scorers = {'Accuracy': 'accuracy', 'roc_auc': 'roc_auc', 'f1': 'f1'}

# checking time:
start_ts=time.time()

clf = RandomForestClassifier(n_estimators=100, max_depth=None, min_sampl
es_split=3, criterion='entropy')
# Run cross - validation with parameters
scores = cross_validate(estimator = clf, X=data_np, y=target_np, scoring
= scorers, cv=5, )

scores_Acc = scores['test_Accuracy']
print("Random Forest Acc: %0.2f (+/- %0.2f)" % (scores_Acc.mean(), score
s_Acc.std() * 2))
scores_AUC= scores['test_roc_auc']
print("Random Forest AUC: %0.2f (+/- %0.2f)" % (scores_AUC.mean(), score
s_AUC.std() * 2))
print("CV Runtime:", time.time()-start_ts)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)

Random Forest Acc: 1.00 (+/- 0.00)
Random Forest AUC: 0.78 (+/- 0.18)
CV Runtime: 38.75778913497925
```

It isn't surprising the Accuracy score would be 1 given that this score does not tell us very much about the goodness of the model due to the low failure rate. I will use AUC as my evaluation metric for the additional models.

In [384]:
```
# another attempt at balancing the data found at: https://stackoverflow.com/questions/35472712/how-to-split-data-on-balanced-training-set-and-test-set-on-sklearn
# and at: https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedShuffleSplit.html#sklearn.model_selection.StratifiedShuffleSplit
from sklearn.model_selection import StratifiedShuffleSplit
sss = StratifiedShuffleSplit(n_splits=3, test_size=0.5, random_state=0)
sss.get_n_splits(data_np, target_np)
print(sss)
```

```
StratifiedShuffleSplit(n_splits=3, random_state=0, test_size=0.5,
            train_size=None)
```

In [385]:
```
acc_vals = []
auc_vals = []
for train_index, test_index in sss.split(X, y):
    X_train, X_test = data_np[train_index], data_np[test_index]
    y_train, y_test = target_np[train_index], target_np[test_index]
    clf = RandomForestClassifier(n_estimators=100, max_depth=None, min_samples_split=3, criterion='entropy')
    # fit the data using the clf object created in 198
    clf.fit(X_train, y_train)
    # performance calculated for for us below using test data
    scores_ACC = clf.score(X_test, y_test)
    scores_AUC = roc_auc_score(y_test, clf.predict_proba(X_test)[:,1])
    acc_vals.append(scores_ACC)
    auc_vals.append(scores_AUC)
acc_vals = np.asarray(acc_vals)
auc_vals = np.asarray(auc_vals)
print('*'*40)
print("Random Forest ACC: %0.2f (+/- %0.2f)" % (acc_vals.mean(), acc_vals.std() * 2))
print("Random Forest AUC: %0.2f (+/- %0.2f)" % (auc_vals.mean(), auc_vals.std() * 2))
```

```
****************************************
Random Forest ACC: 1.00 (+/- 0.00)
Random Forest AUC: 0.70 (+/- 0.04)
```

In [386]:
```
# predictions from final split
rf_pred = clf.predict(X_test)
confusion_matrix(y_test, rf_pred)
```

Out[386]:
```
array([[62192,     2],
       [   53,     0]])
```

In [387]:
```
# same issue...
```

In [388]:
```
# Naive Bayes model - which I think will be a better model
naive_bayes = MultinomialNB()
naive_bayes.fit(X_train, y_train)
```

Out[388]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [389]:
```
# performance calculated for for us below using test data
scores_ACC = naive_bayes.score(X_test, y_test)
print('NB Acc:', scores_ACC)
scores_AUC = roc_auc_score(y_test, clf.predict_proba(X_test)[:,1])
print('NB AUC:', scores_AUC)
```

```
NB Acc: 0.9991485533439363
NB AUC: 0.7277490214732842
```

In [390]:
```
nb_pred = naive_bayes.predict(X_test)
confusion_matrix(y_test, nb_pred)
```

Out[390]:
```
array([[62194,     0],
       [   53,     0]])
```

In [391]:
```
# Naive Bayes Classifier with cross-validation and looking at F1 statist
ic since Accuracy is unhelpful

#Setup Crossval classifier scorers
scorers = {'Accuracy': 'accuracy', 'roc_auc': 'roc_auc', 'f1': 'f1'}

# checking time:
start_ts=time.time()

clf = MultinomialNB()
# Run cross - validation with parameters
scores = cross_validate(estimator = clf, X=data_np, y=target_np, scoring
= scorers, cv=5)

scores_Acc = scores['test_Accuracy']
print("Naive Bayes Acc: %0.2f (+/- %0.2f)" % (scores_Acc.mean(), scores_
Acc.std() * 2))
scores_AUC= scores['test_roc_auc']
print("Naive Bayes AUC: %0.2f (+/- %0.2f)" % (scores_AUC.mean(), scores_
AUC.std() * 2))
scores_F1 = scores['test_f1']
print("Naive Bayes F1: %0.2f (+/- %0.2f)" % (scores_F1.mean(), scores_F1
.std() * 2))
print("CV Runtime:", time.time()-start_ts)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)

Naive Bayes Acc: 1.00 (+/- 0.00)
Naive Bayes AUC: 0.76 (+/- 0.12)
Naive Bayes F1: 0.00 (+/- 0.00)
CV Runtime: 0.431962251663208

/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
/anaconda3/lib/python3.7/site-packages/sklearn/metrics/classification.p
y:1143: UndefinedMetricWarning: F-score is ill-defined and being set to
0.0 due to no predicted samples.
  'precision', 'predicted', average, warn_for)
```

In [392]:
```
# in order to predict probabilities:
naive_bayes.fit(X_train, y_train)
```

Out[392]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [393]:
```
naive_bayes.predict_proba(X_test)
# returns probabilities for classes [0, 1]
```

Out[393]:
```
array([[9.9933e-01, 6.6514e-04],
       [9.9939e-01, 6.1412e-04],
       [9.9920e-01, 7.9974e-04],
       ...,
       [9.9934e-01, 6.5795e-04],
       [9.9939e-01, 6.0634e-04],
       [9.9933e-01, 6.7157e-04]])
```

In [394]:
```
# Logistic Regression, I will try Logistic regression without the train_
test_split to see if I will get a better model
# first I will perform a basic Logistic Regression with weights balanced
and then I will implement GridSearchCV
clf = LogisticRegression(random_state=0, class_weight='balanced')
model = clf.fit(data_np, target_np)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
```

In [395]:
```
preds = model.predict(data_np)
confusion_matrix(target_np, preds)
```

Out[395]:
```
array([[119129,   5259],
       [    47,     59]])
```

In [396]:
```
# Ok, this is definitely looking better.  Check metrics
print_scores(target_np, preds)
```

```
Accuracy score:  0.9573794721030733
Precision score:  0.011094396389620158
Recall score:  0.5566037735849056
F1 score:  0.021755162241887904
AUC score:  0.7571623878054123
```

In [397]:
```
# this model is a decent Recall model, which may be most important for o
ur needs, but has a very bad F1 score though.
# now I will need to consider hyperparameter tuning to reduce False Nega
tives.  I will try adjusting C-parameter
# using GridSearchCV- found https://www.udacity.com/course/intro-to-mach
ine-learning-nanodegree--nd229

param_dist = {"C": [0.1, 0.5, 1, 3, 5]}

clf = LogisticRegression(random_state=0, class_weight='balanced')

# Run a randomized search over the hyperparameters
lr_search = RandomizedSearchCV(clf, param_distributions=param_dist)

# Fit the model on the training data
lr_search.fit(data_np, target_np)

# Make predictions on the test data
preds = svc_search.best_estimator_.predict(data_np)

print_scores(target_np, preds)
print(lr_search)
```

```
/anaconda3/lib/python3.7/site-packages/sklearn/model_selection/_split.p
y:2053: FutureWarning: You should specify a value for 'cv' instead of r
elying on the default value. The default value will change from 3 to 5
in version 0.22.
  warnings.warn(CV_WARNING, FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/model_selection/_search.
py:271: UserWarning: The total space of parameters 5 is smaller than n_
iter=10. Running 5 iterations. For exhaustive searches, use GridSearchC
V.
  % (grid_size, self.n_iter, grid_size), UserWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
```

```
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)
/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/logistic.p
y:433: FutureWarning: Default solver will be changed to 'lbfgs' in 0.2
2. Specify a solver to silence this warning.
  FutureWarning)

Accuracy score:  0.9643035005703086
Precision score:  0.013240574506283662
Recall score:  0.5566037735849056
F1 score:  0.025865848312143794
AUC score:  0.7606273522714381
RandomizedSearchCV(cv='warn', error_score='raise-deprecating',
          estimator=LogisticRegression(C=1.0, class_weight='balanced',
dual=False,
          fit_intercept=True, intercept_scaling=1, max_iter=100,
          multi_class='warn', n_jobs=None, penalty='l2', random_state=
0,
          solver='warn', tol=0.0001, verbose=0, warm_start=False),
          fit_params=None, iid='warn', n_iter=10, n_jobs=None,
          param_distributions={'C': [0.1, 0.5, 1, 3, 5]},
          pre_dispatch='2*n_jobs', random_state=None, refit=True,
          return_train_score='warn', scoring=None, verbose=0)
```

Conclusion

In this analysis, I discovered that my most significant issue with the dataset was not being able to resolve at this time the issue of imbalanced data. I will continue to research this issue in depth and reach out to experts in order to figure out best practices. As for which model I would consider best, given AUC as a metric, all models performed equally well with AUC scores approximately 76%. I would not consider Accuracy a useful metric with this dataset. I would also liked to have performed feature selection to minimize complexity, although with such a small number of features, I do not think this is critical for finding the best model. I will also continue to research and improve in my ability to tune hyperparameters so that I can find the best models more quickly.

Overall, I do not feel as though I found the best model for this data as of yet and will continue to learn more about these specific data issues in order to make better decisions in predictive analytics given imbalanced datasets.

References:

https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba (https://towardsdatascience.com/ways-to-detect-and-remove-the-outliers-404d16608dba) https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html (https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html) https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html (https://scikit-learn.org/stable/modules/generated/sklearn.naive_bayes.MultinomialNB.html) https://www.kaggle.com/chapagain/house-prices-eda-data-modelling-and-prediction (https://www.kaggle.com/chapagain/house-prices-eda-data-modelling-and-prediction) http://www.caseybennett.com/teaching.html (http://www.caseybennett.com/teaching.html) https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28 (https://towardsdatascience.com/handling-imbalanced-datasets-in-machine-learning-7a0e84220f28) https://stackoverflow.com/questions/35472712/how-to-split-data-on-balanced-training-set-and-test-set-on-sklearn (https://stackoverflow.com/questions/35472712/how-to-split-data-on-balanced-training-set-and-test-set-on-sklearn) https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedShuffleSplit.html#sklearn.model_selection.S (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.StratifiedShuffleSplit.html#sklearn.model_selection.S https://www.udacity.com/course/intro-to-machine-learning-nanodegree--nd229 (https://www.udacity.com/course/intro-to-machine-learning-nanodegree--nd229) https://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_l1_l2_sparsity.html (https://scikit-learn.org/stable/auto_examples/linear_model/plot_logistic_l1_l2_sparsity.html) https://chrisalbon.com/machine_learning/logistic_regression/handling_imbalanced_classes_in_logistic_regression (https://chrisalbon.com/machine_learning/logistic_regression/handling_imbalanced_classes_in_logistic_regressior

```
In [ ]:
```