full_notebook

March 21, 2018

1 Kaggle Midterm Notebook / Report

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1.1 Overview

The notebook is split into five sections, following the chronological order in which I approache

Preliminary Graphing and Looking at the Data
Bootstrapping the Dataset
Feature Engineering
Using My Feature Engineering Pipeline
Boosted Trees
Conclusion

Comments and thoughts accompany the code where necessary. While much of the project was explorat

2 Part 1 Preliminary Inspection

2.1 Feature Engineering

2.1.1 Load the data and split it

Initial loading of data

```
In [32]: import numpy as np
         import math as m
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         from mpl_toolkits.mplot3d import Axes3D
         from IPython.core.interactiveshell import InteractiveShell
         from pandas.plotting import scatter_matrix
         from sklearn.metrics import confusion_matrix
         from sklearn.model_selection import LeaveOneOut
         from sklearn.model_selection import train_test_split
         from sklearn.model_selection import cross_val_score
         from sklearn.linear_model import Ridge
```

```
from sklearn.linear_model import Lasso
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelBinarizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score
from IPython import get_ipython

import graphviz
import lime
import xgboost as xgb
InteractiveShell.ast_node_interactivity = "all"
```

In [33]:
```
def getTestFeatures():
    test_data = pd.read_csv("test.csv")
    test_data.F6 = np.log(test_data.F6)
    test_features = test_data.drop(['id'], axis=1)
    return np.array(test_features)

def makeSubmission(preds):
    new_index = np.arange(16384,32769,1)
    id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
    y_hat = pd.DataFrame(preds, columns=['Y'])
    frames = [id_col, y_hat]
    pred = pd.concat(frames, axis=1)
    return pred
```

In [34]:
```
filename = 'train.csv'
filepath = ''

data = pd.read_csv(filepath + filename)
#labels = data['Y']
#features = data.drop(['id', 'Y'], axis=1)
```

2.1.2 Take a quick look

In [35]:
```
data.describe()
data.head()
#features.isnull().sum()
#print(features['F25'])
#features.dtypes
```

Out[35]:

	id	Y	F1	F2	F3 \
count	16383.000000	16383.000000	16383.000000	16383.000000	16383.000000
mean	8192.000000	0.941464	44312.117256	26032.070927	0.048953
std	4729.509065	0.234762	34815.325971	35742.773305	0.281347
min	1.000000	0.000000	999.000000	43.000000	0.000000
25%	4096.500000	1.000000	21896.000000	4603.000000	0.000000

```
50%     8192.000000      1.000000   36806.000000   13819.000000      0.000000
75%    12287.500000      1.000000   75414.000000   41799.500000      0.000000
max    16383.000000      1.000000  314150.000000  311733.000000      7.000000

                 F4             F5            F6             F7            F8  \
count  16383.000000   16383.000000  1.638300e+04   16383.000000  16383.000000
mean      40.002991  121039.419459  6.272233e+03  201731.398767      1.043216
std        4.998992    5802.987367  1.124685e+05  100732.735724      0.249209
min       21.000000  118751.000000  1.000000e+03   15429.000000      1.000000
25%       37.000000  119325.000000  1.000000e+03  130752.000000      1.000000
50%       40.000000  119868.000000  1.000000e+03  143236.000000      1.000000
75%       43.000000  120739.000000  2.000000e+03  303218.000000      1.000000
max       59.000000  269481.000000  1.108900e+07  333172.000000      9.000000

      ...           F18            F19           F20           F21  \
count ...  16383.000000   16383.000000  16383.000000  16383.000000
mean  ...      1.047183  118208.827077      1.043460      1.043277
std   ...      0.285203   11021.402921      0.250144      0.268421
min   ...      1.000000    5163.000000      1.000000      1.000000
25%   ...      1.000000  118832.000000      1.000000      1.000000
50%   ...      1.000000  119453.000000      1.000000      1.000000
75%   ...      1.000000  119703.000000      1.000000      1.000000
max   ...     13.000000  312049.000000     12.000000      8.000000

                 F22           F23            F24  F25  F26  F27
count   16383.000000  16383.000000   16383.000000  0.0  0.0  0.0
mean   127587.576634      1.042361   52450.117256  NaN  NaN  NaN
std     19031.948437      0.247142   34815.325971  NaN  NaN  NaN
min     13223.000000      1.000000    9137.000000  NaN  NaN  NaN
25%    126972.000000      1.000000   30034.000000  NaN  NaN  NaN
50%    127528.000000      1.000000   44944.000000  NaN  NaN  NaN
75%    129100.000000      1.000000   83552.000000  NaN  NaN  NaN
max    295412.000000      8.000000  322288.000000  NaN  NaN  NaN

[8 rows x 29 columns]
```

Out[35]:

```
   id  Y     F1     F2  F3  F4      F5    F6      F7  F8 ...   F18     F19  \
0   1  1  38733  61385   0  38  118751  1000   32020   1 ...     1  118830
1   2  1  34248  51329   0  41  120800  1000  130630   1 ...     1  118832
2   3  1  15830   5522   0  50  118779  1000  303218   2 ...     1  118832
3   4  1  19417   6754   0  45  123163  2000   19024   1 ...     1  118832
4   5  1  42122  16991   0  41  119193  1000  303218   1 ...     1  118832

   F20  F21     F22  F23    F24  F25  F26  F27
0    1    1  126461    1  46871  NaN  NaN  NaN
1    1    1  130296    1  42386  NaN  NaN  NaN
2    1    2  127063    1  23968  NaN  NaN  NaN
3    1    1   15274    1  27555  NaN  NaN  NaN
```

```
4     1     1  133491     1  50260  NaN  NaN  NaN

[5 rows x 29 columns]
```

Immediately we see that the last three columns are all floats, but listed as NaN. These can all be safely deleted.

```
In [36]: garbage = ['F25', 'F26', 'F27']
         data.drop(garbage, axis=1, inplace=True)
```

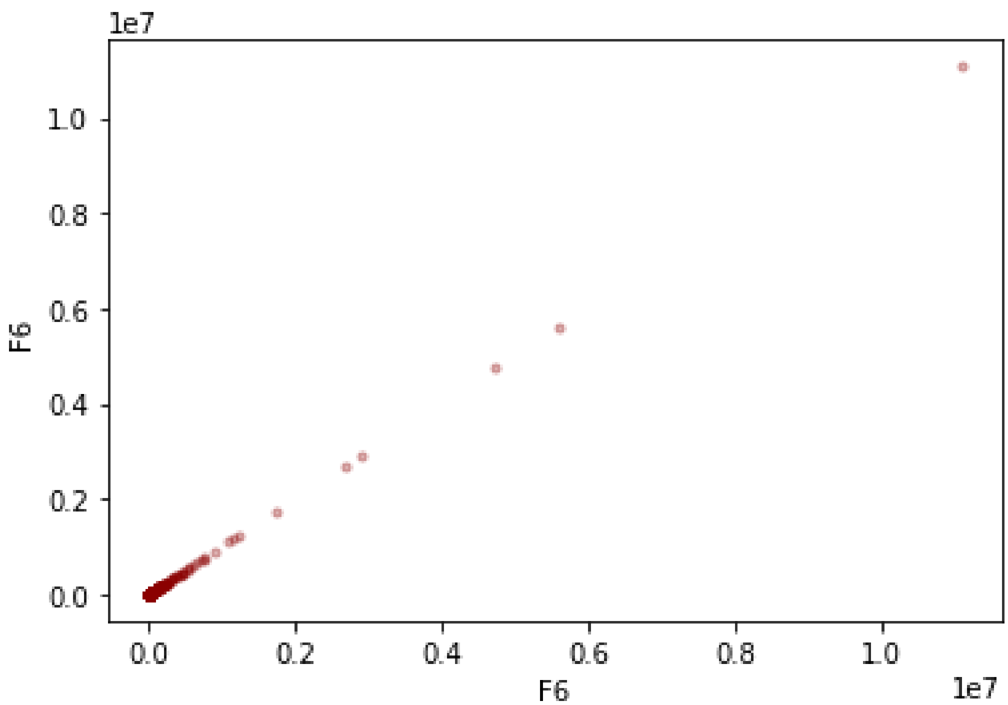
2.1.3 Look for Outliers

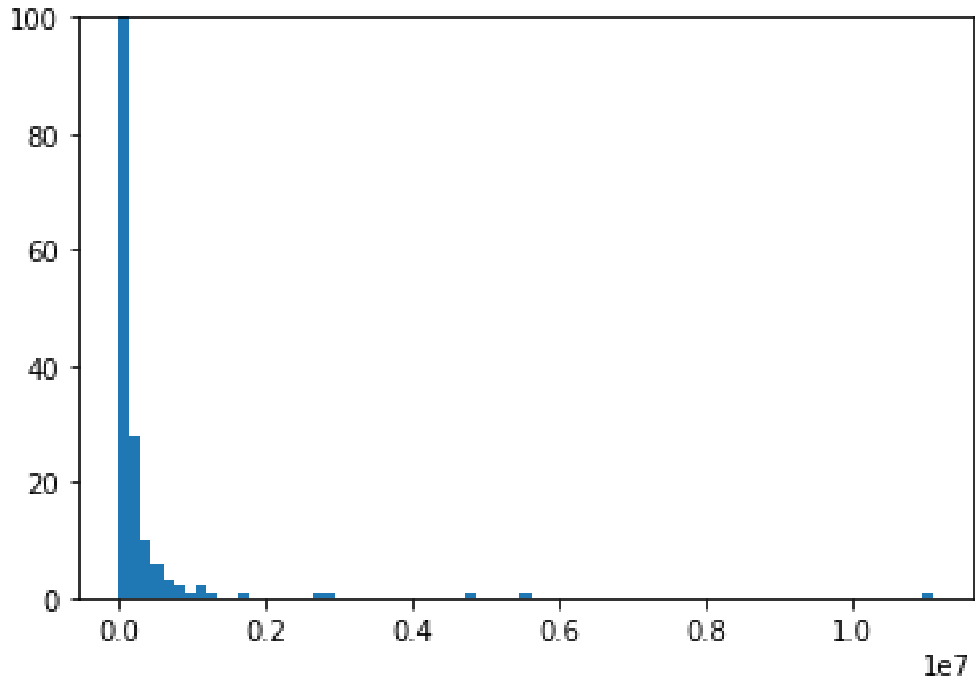
Lets make a quick scatter plot of each feature column. (Output supressed for brevity)

```
In [37]: #sns.set_style("whitegrid")
         #for column in features.columns:
         #     _ = sns.regplot(features[column], features[column], scatter_kws={"color":"darkred'
         #     plt.show()
```

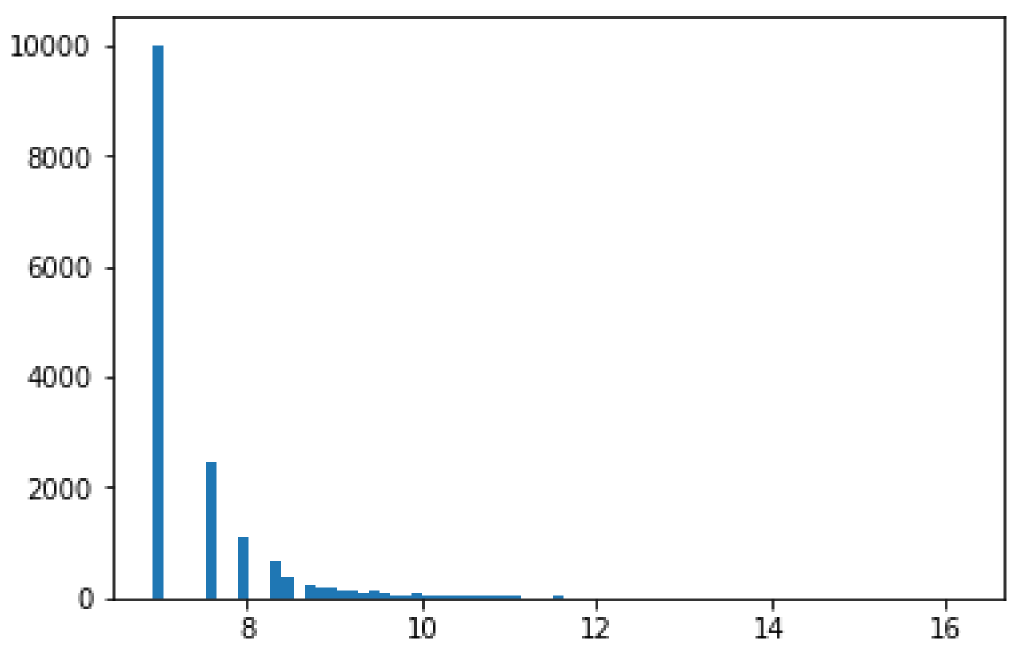
We notice severe outliers in:`F6F16F20` We notice moderate outliers in:`F3F5F8F18F24` We notice odd groupings in `F7F10F12F19F22` Going in order, `F6`

```
In [38]: _ = sns.regplot(data.F6, data.F6, scatter_kws={"color":"darkred","alpha":0.3,"s":10}, f
         plt.show()
         _ = plt.hist(data['F6'], bins=75)
         _ = plt.ylim([0, 100])
         plt.show()
```



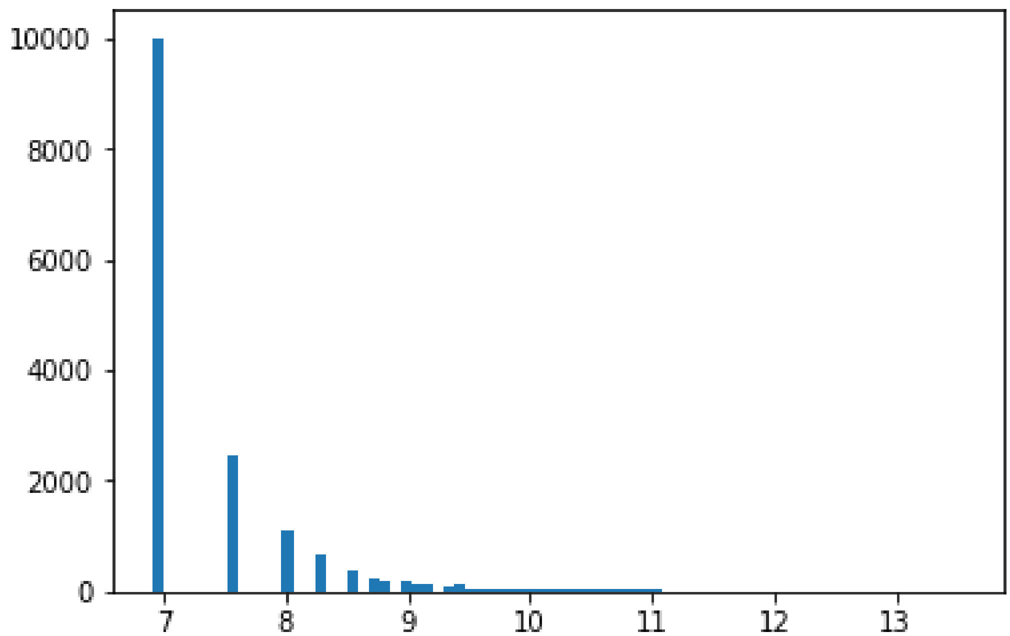



```
In [39]: _ = plt.hist(np.log(data.F6), bins=75)
```



We can afford to lose 10 data points out of 14,000. Drop the ten huge outliers...

```
In [40]: for i in range(10):
             data_point = data['F6'].idxmax()
             data.drop([data_point], inplace=True)
         _ = plt.hist(np.log(data.F6), bins=75)
```



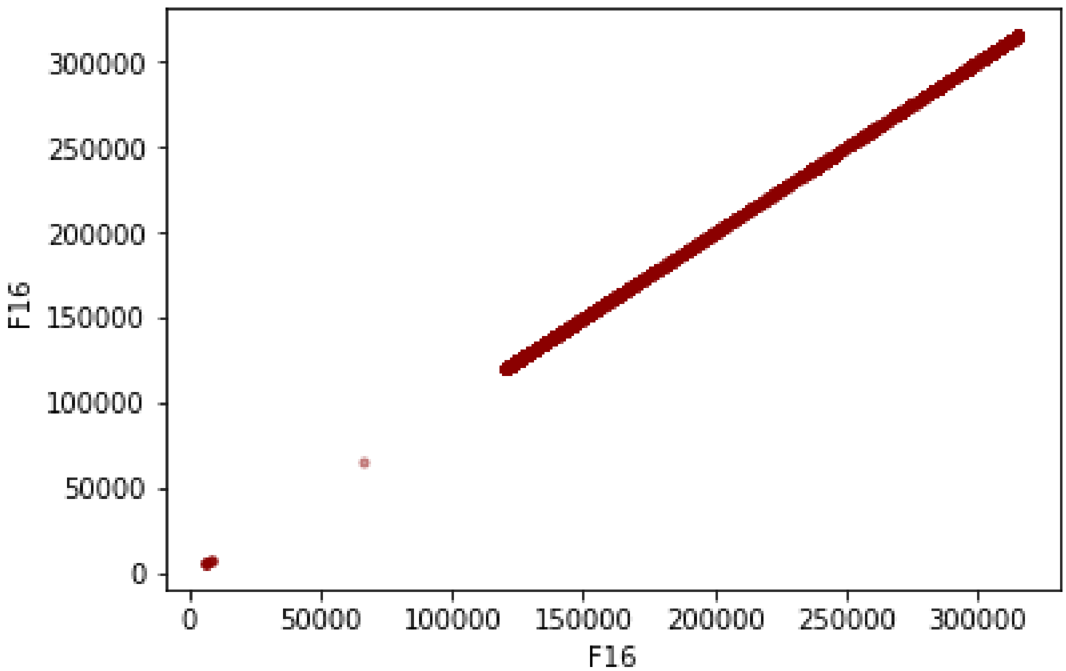
This feature looks more usable in this form. Lets keep it for now, but keep an eye on it.

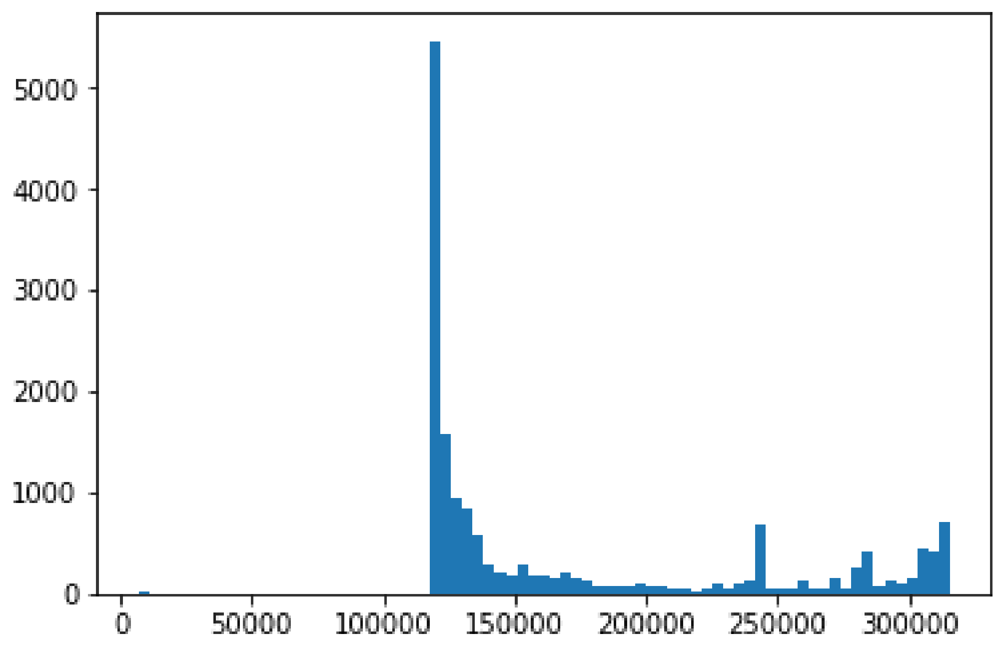
```
In [41]: data.F6 = np.log(data.F6)
```

```
In [42]: #data_point = features['F6'].idxmax()
         #while features.iloc[data_point]['F6'] > 0.6*10**7:
         #    data_point = features['F6'].idxmax()
         #    features.drop([data_point], inplace=True)
         #    labels.drop([data_point], inplace=True)

         #print(features.shape)
         #print(labels.shape)
```

Now lets clean up F16

```
In [43]: _ = sns.regplot(data.F16, data.F16, scatter_kws={"color":"darkred","alpha":0.4,"s":10},
         plt.show()
         _ = plt.hist(data['F16'], bins=75)
         plt.show()
```





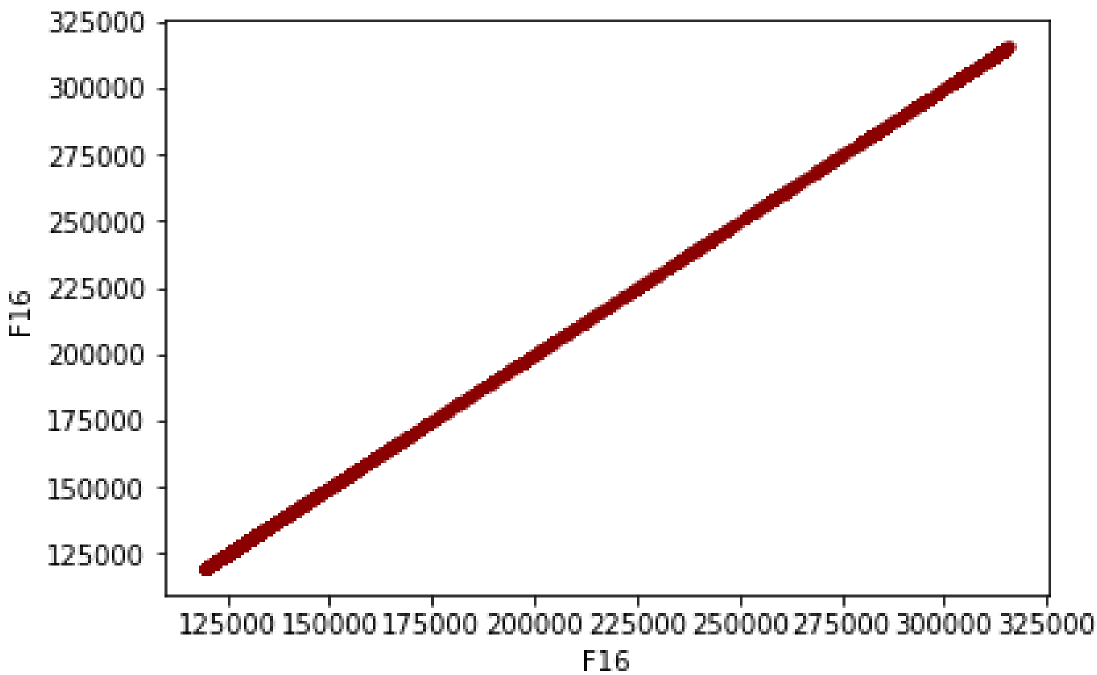
Whatever this is, its clearly bounded by about 120,000 on the bottom and about 325,000 above. We can safely drop all values outside of that range.

```
In [44]: print("Mode of F16 is: {}".format(data.F16.mode()))
         bound = 119774
         print("Counts of occurences of {} is: {}".format(bound,
                                                          data.F16[data.F16 == 119774].count()))
```

```
Mode of F16 is: 0    119777
dtype: int64
Counts of occurences of 119774 is: 0
```

```
In [45]: data = data[data.F16 >= 119000]
```

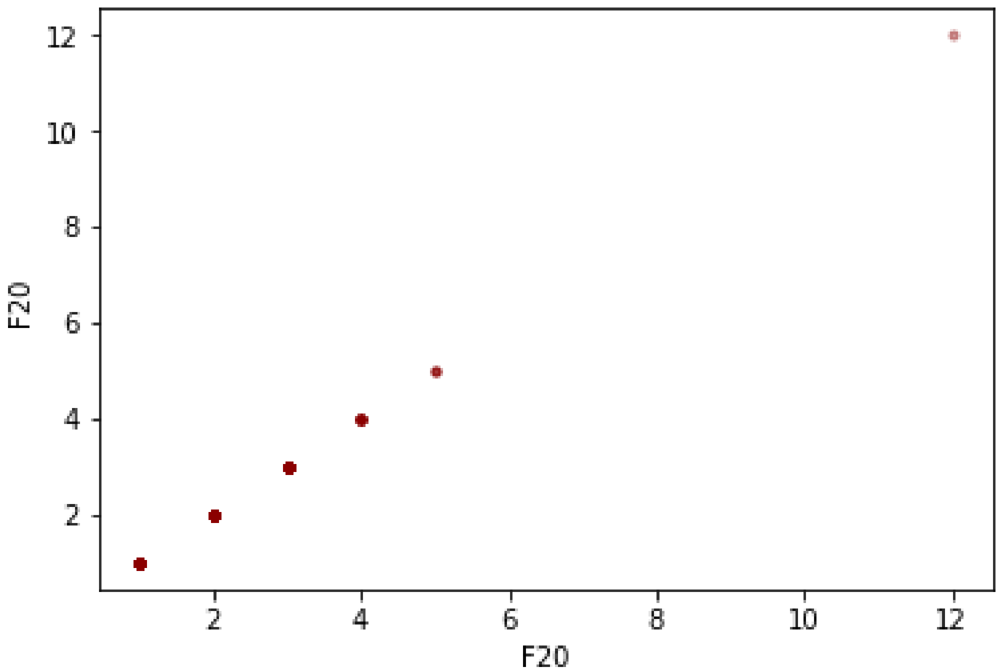
```
In [46]: _ = sns.regplot(data.F16, data.F16, scatter_kws={"color":"darkred","alpha":0.4,"s":10},
         plt.show()
         data.shape
```

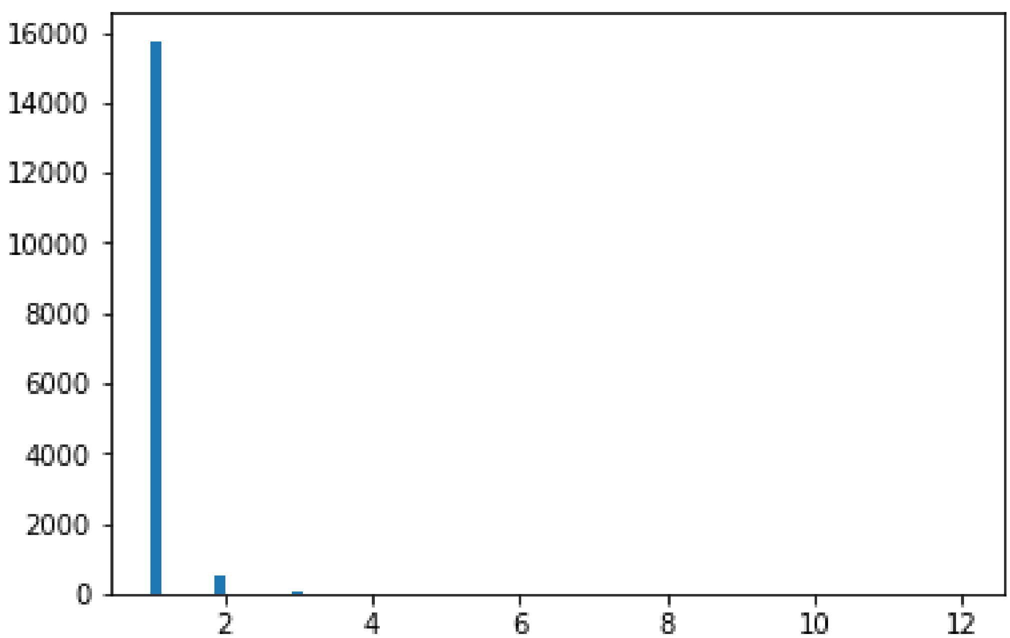



```
Out[46]: (16360, 26)
```

Now we look at F20

```
In [47]: _ = sns.regplot(data.F20, data.F20, scatter_kws={"color":"darkred","alpha":0.4,"s":10},
         plt.show()
         _ = plt.hist(data['F20'], bins=75)
         plt.show()
```





Upon closer inspection, this data looks categorical, with almost all counts being in category 1. For simplicity, lets take those random 12s and scoot them closer in.

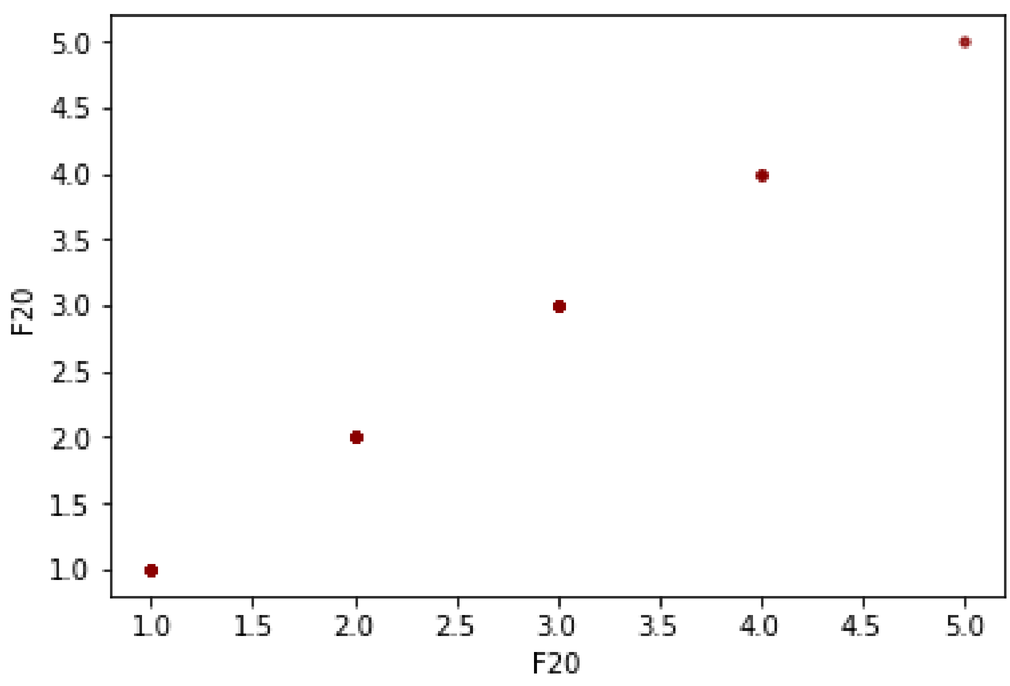
```
In [48]: for i in range(6,13):
             print("There are {} {}'s.".format(data.F20[data.F20 == i].count(), i))
```

```
There are 0 6's.
There are 0 7's.
There are 0 8's.
There are 0 9's.
There are 0 10's.
There are 0 11's.
There are 1 12's.
```

Since there is only one 12, and almost all the other data points are 1, let's just find that 12 and drop it.

```
In [49]: data = data[data.F20 != 12]
```

```
In [50]: _ = sns.regplot(data.F20, data.F20, scatter_kws={"color":"darkred","alpha":0.4,"s":10},
         plt.show()
         data.shape
```




```
Out[50]: (16359, 26)
```

At this point all the severe outliers are removed, and we can run a few preliminary models before moving on to some finer data inspection and feature engineering.

2.2 Preliminary Modeling

```
In [51]: labels = data['Y']
         features = data.drop(['id', 'Y'], axis=1)
```

2.2.1 Simple Logistic Regression

10 fold CV, and average the accuracies. We will try with L1 penalty and L2 penalty.

```
In [52]: accuracies = []
         weights_L1 = []
         for i in range(10):
             rand = np.random.randint(1, 100)
             X_train, X_test, y_train, y_test = train_test_split(features, labels)
             clf = LogisticRegression(penalty='l1', max_iter=1000, random_state=rand)
             _ = clf.fit(X_train, y_train)
             accuracies.append(clf.score(X_test, y_test))
             weights_L1.append(clf.coef_)

         accuracies = np.array(accuracies)
         print("Mean for L1 norm is: {}".format(np.mean(accuracies, axis=0)))
         print("St Dev for L1 norm is: {}".format(np.std(accuracies, axis=0)))
         print('')

         accuracies = []
         weights_L2 = []
         for i in range(10):
             rand = np.random.randint(1, 100)
             X_train, X_test, y_train, y_test = train_test_split(features, labels)
             clf = LogisticRegression(penalty='l2', max_iter=1000, random_state=rand)
             _ = clf.fit(X_train, y_train)
             accuracies.append(clf.score(X_test, y_test))
             weights_L2.append(clf.coef_)

         accuracies = np.array(accuracies)
         print("Mean for L2 norm is: {}".format(np.mean(accuracies, axis=0)))
         print("St Dev for L2 norm is: {}".format(np.std(accuracies, axis=0)))
```

```
Mean for L1 norm is: 0.9406601466992666
St Dev for L1 norm is: 0.0028198034575810083

Mean for L2 norm is: 0.9419559902200488
St Dev for L2 norm is: 0.0027274493432536714
```

Lets just average all these weights and use them.

```
In [53]: #avgs = np.array([weights_L1, weights_L2])
         #avgs = np.mean(np.mean(avgs, axis = 0), axis=2).reshape(10,)
```

```
        clf = LogisticRegression(penalty='l2', max_iter=1000, random_state=rand)
        _ = clf.fit(features, labels)
```

```
In [54]: test_data = pd.read_csv("test.csv")
```

```
In [55]: test_data.F6 = np.log(test_data.F6)
         test_features = test_data.drop(['id'], axis=1)
         _ = clf.predict(test_features)
         new_index = np.arange(16384,32769,1)
```

```
In [56]: id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
         y_hat = pd.DataFrame(_, columns=['Y'])
         frames = [id_col, y_hat]
         pred = pd.concat(frames, axis=1)
```

```
In [57]: filename = 'prediction_logistic.csv'
         pred.to_csv(filename, encoding='utf-8', index=False)
```

Once I finally got the submission in correctly, this only gave a score of 0.50, not great.

2.2.2 K-Nearest Neighbors

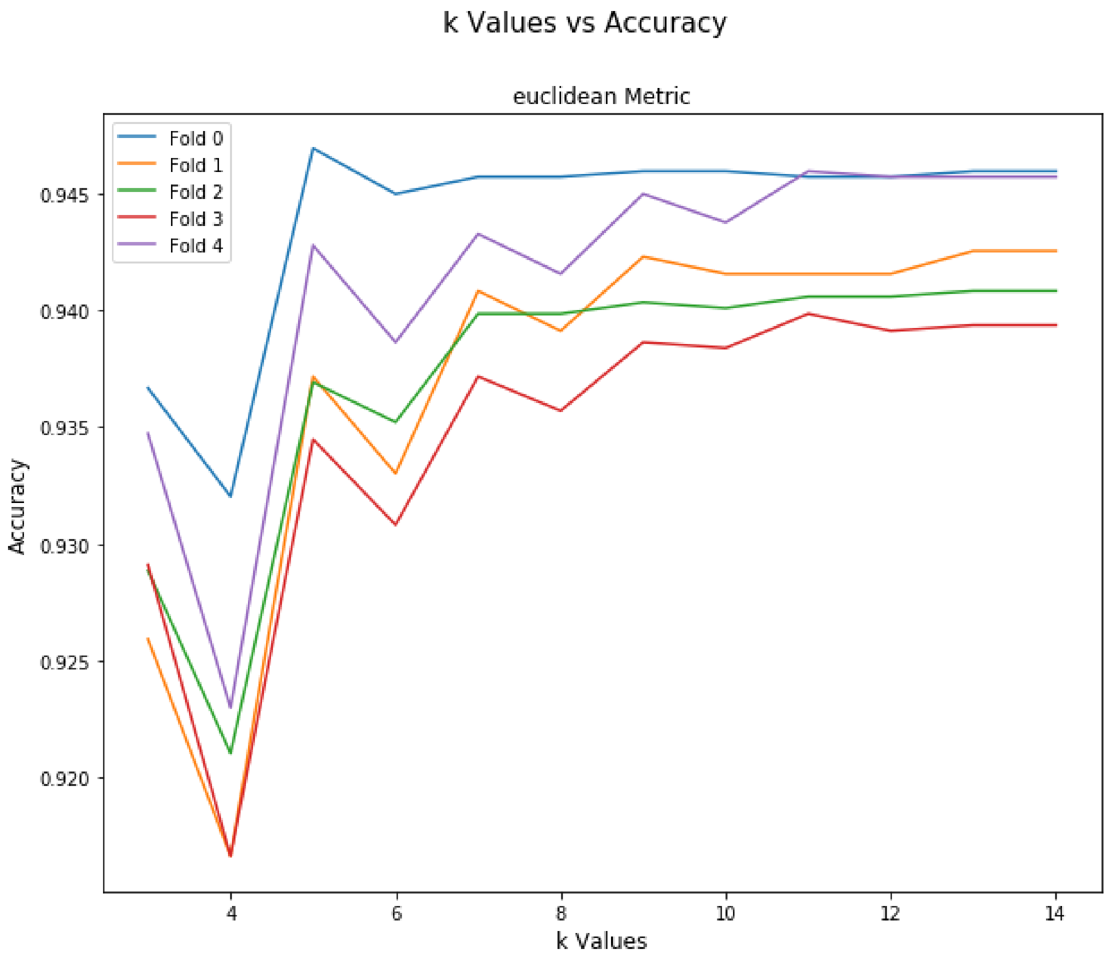
10 fold CV, and n from 1 to 10 and average the accuracies.

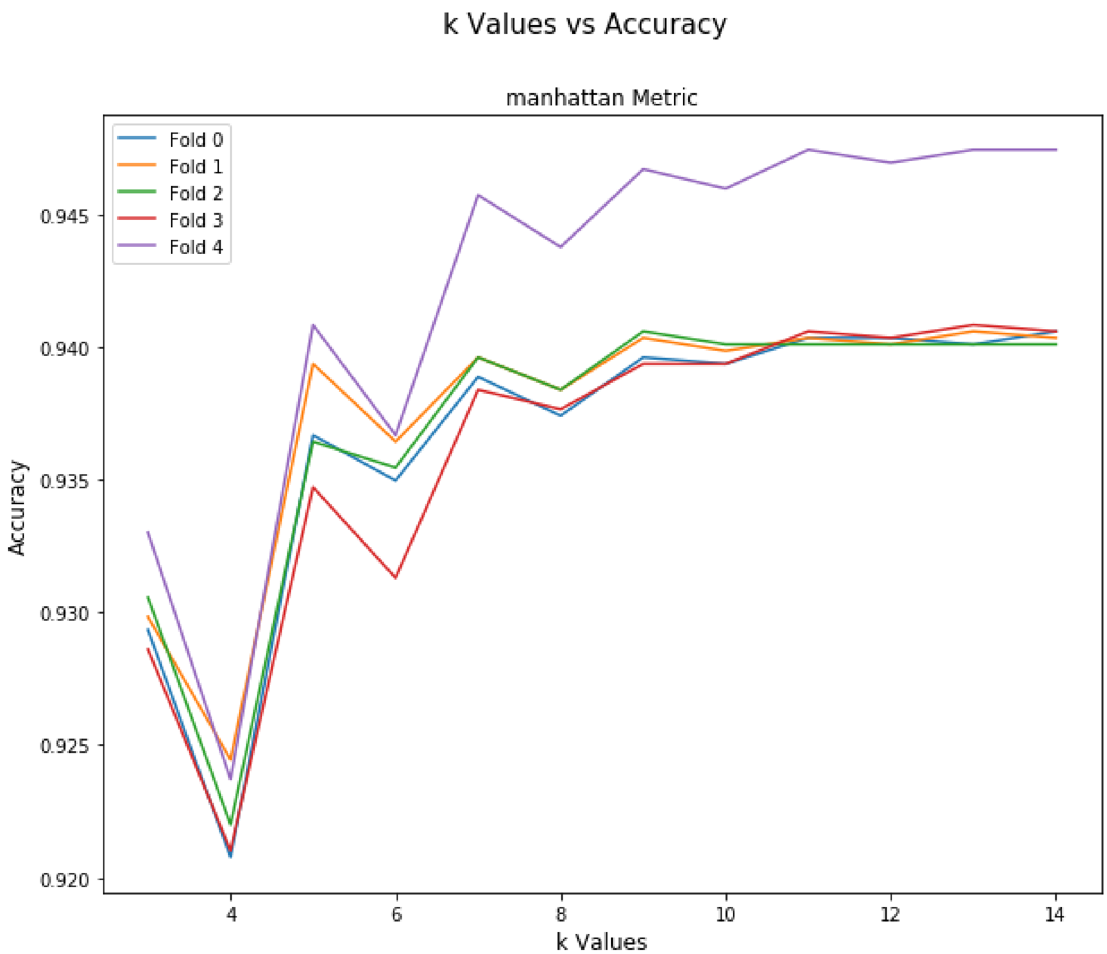
```
In [58]: labels = data['Y']
         features = data.drop(['id', 'Y'], axis=1)
```

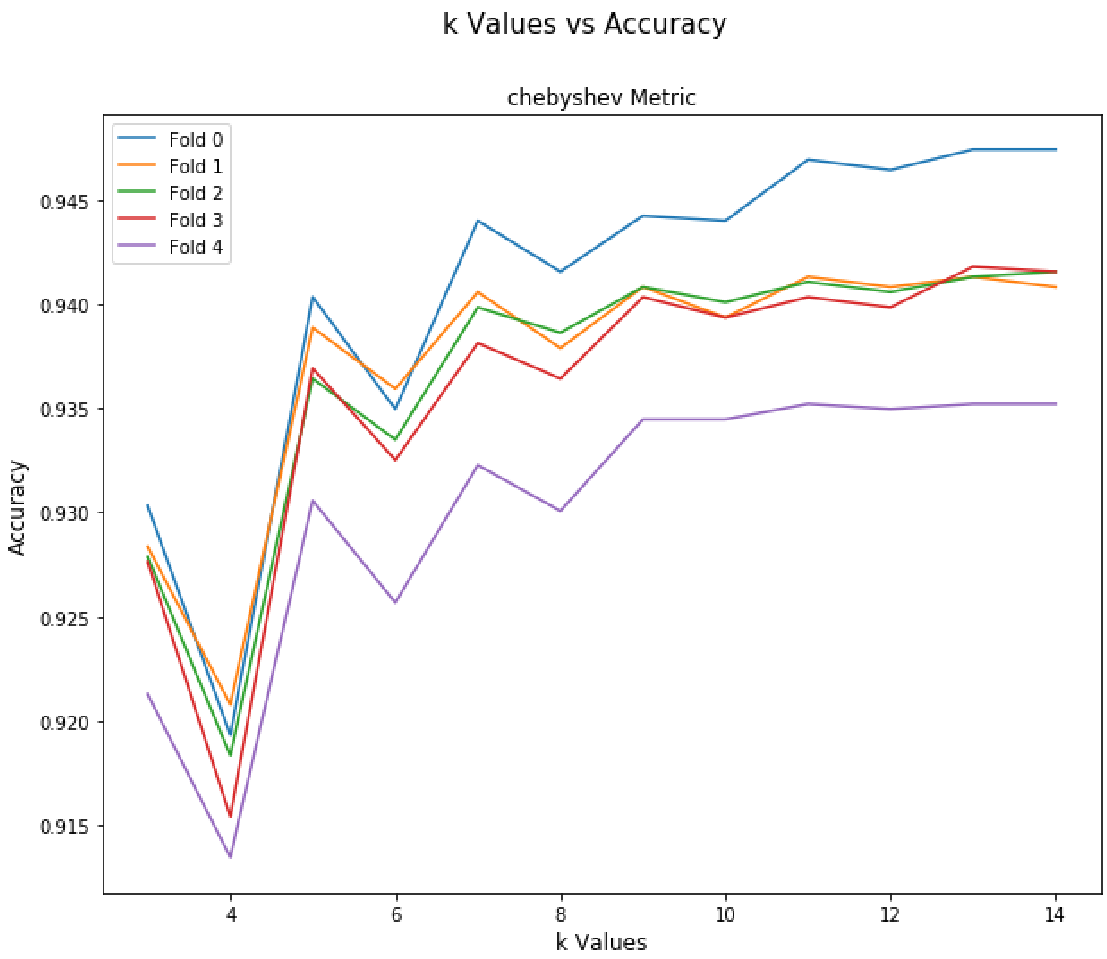
Note this cell takes a long time to run

```
In [59]: metrics = ['euclidean', 'manhattan', 'chebyshev']
         folds = 5
         k_vals = np.arange(3, 15, 1)
         scores = np.empty((folds,len(k_vals)))

         for metric in metrics:
             for i in range(folds):
                 score = []
                 X_train, X_test, y_train, y_test = train_test_split(features, labels)
                 for k in k_vals:
                     clf = KNeighborsClassifier(n_neighbors=k, metric=metric)
                     _ = clf.fit(X_train, y_train)
                     score.append(clf.score(X_test, y_test))
                 scores[i, :] = score
             _ = plt.figure(figsize = (10,8))
             for i in range(folds):
                 _ = plt.plot(k_vals, scores[i,:], label="Fold {}".format(i))

             _ = plt.xlabel("k Values", fontsize=12)
             _ = plt.ylabel("Accuracy", fontsize=12)
```

```python
_ = plt.suptitle("k Values vs Accuracy", fontsize=15)
_ = plt.title("{} Metric".format(metric))
_ = plt.legend()
```




k Values vs Accuracy
manhattan Metric
Fold 0
Fold 1
Fold 2
Fold 3
Fold 4
0.945
0.940
0.935
0.930
0.925
0.920
Accuracy
4
6
8
10
12
14
k Values



2.2.3 XGBoost

```
In [60]: labels = data['Y']
         features = data.drop(['id', 'Y'], axis=1)
```

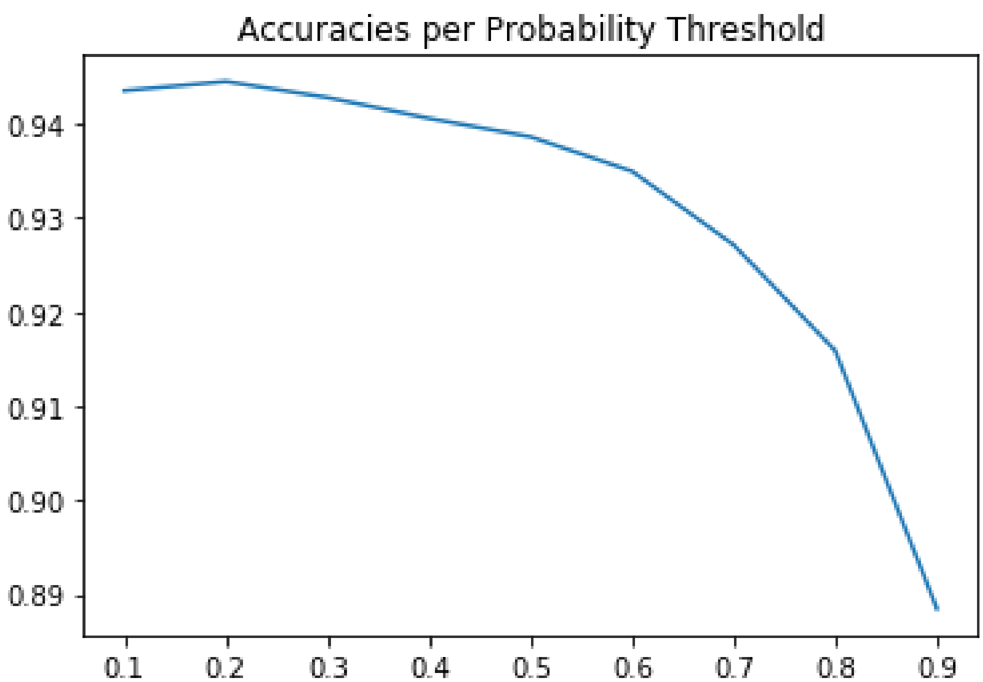
```
In [61]: X_train, X_test, y_train, y_test = train_test_split(features, labels)
         y_train = y_train.reshape(12269,1)
         dtrain = xgb.DMatrix(X_train, label=y_train)
         dtest = xgb.DMatrix(X_test)
```

```
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/ipykernel_launcher.py:2: FutureWar
```

```
In [62]: # specify parameters via map
         param = {'max_depth':7, 'eta':0.7, 'gamma':0.8, 'silent':1, 'objective':'binary:logisti
                  'early_stopping_rounds':5}
         num_round = 200
```

```
bst = xgb.train(param, dtrain, num_round)
#pred = bst.predict(dtest)
```

In [63]:
```
thresholds = np.arange(0.1, 1, 0.1)
scores = []
for alpha in thresholds:
    pred = bst.predict(dtest)
    for i in range(len(pred)):
        if pred[i] > alpha:
            pred[i] = 1
        else:
            pred[i] = 0
    scores.append(accuracy_score(y_test, pred))

_ = plt.plot(thresholds, scores)
_ = plt.title('Accuracies per Probability Threshold')
```



In [64]:
```
scores
```

Out[64]:
```
[0.943520782396088,
 0.9444987775061124,
 0.9427872860635697,
 0.9405867970660147,
 0.9386308068459658,
```

```
 0.9349633251833741,
 0.9271393643031784,
 0.9158924205378973,
 0.8885085574572127]
```

```
In [65]: #test_data = pd.read_csv("test.csv")
         #test_data.F6 = np.log(test_data.F6)
         test_features = test_data.drop(['id'], axis=1)
         dtest = xgb.DMatrix(test_features)
         _ = bst.predict(dtest)
         new_index = np.arange(16384,32769,1)
         id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
         y_hat = pd.DataFrame(_, columns=['Y'])
         frames = [id_col, y_hat]
         pred = pd.concat(frames, axis=1)
         filename = 'prediction_xgb.csv'
         pred.to_csv(filename, encoding='utf-8', index=False)
```

```
In [66]: # Plotting the tree
         #_ = xgb.plot_tree(bst)
         #fig = plt.gcf()
         #fig.set_size_inches(150, 100)
         #plt.show()
```

It looks like the base models are maxing out accuracy around 0.94. ~~Time to do some more feature engineering and see if we can improve.~~ For curiosity, I want to submit just a column of ones.

```
In [67]: ones = np.ones((32769-16384, 1))
         new_index = np.arange(16384,32769,1)
         id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
         y_hat = pd.DataFrame(ones, columns=['Y'])
         frames = [id_col, y_hat]
         pred = pd.concat(frames, axis=1)
         filename = 'prediction_lazyones.csv'
         pred.to_csv(filename, encoding='utf-8', index=False)
```

For the record this did just as good as my logistic regression and KNN models.

3 Part 2 Bootstrapping

I wanted to try to bootstrap an enormous data set and see if it was able to fit the data better, since I wasn't having much luck so far.

```
In [68]: get_ipython().magic('reset -sf') #reset workspace variables
         import numpy as np
         import math as m
         import pandas as pd
```

```
import seaborn as sns
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
from IPython.core.interactiveshell import InteractiveShell

from pandas.plotting import scatter_matrix

from sklearn.metrics import confusion_matrix

from sklearn.model_selection import LeaveOneOut
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelBinarizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier

from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score

import graphviz
import lime
import xgboost as xgb
InteractiveShell.ast_node_interactivity = "all"
```

In [69]:
```
############################################################
# Pipeline for train.csv
############################################################
def pipeline(data):
    # Drop empty columns
    garbage = ['F25', 'F26', 'F27']
    data.drop(garbage, axis=1, inplace=True)

    # Drop columns with very low correlation to label
    low_corr = ['F20', 'F23', 'F21', 'F18', 'F1', 'F24',
            'F11', 'F13', 'F2', 'F15', 'F8', 'F14', 'F22']
    data.drop(low_corr, axis=1, inplace=True)
    data.drop(['id'], axis=1, inplace=True)

    # Drop duplicate columns
    dups = ['F9', 'F12']
    data.drop(dups, axis=1, inplace=True)

    # F6
    for i in range(10):
```

```python
    data_point = data['F6'].idxmax()
    data.drop([data_point], inplace=True)
data.F6 = np.log(data.F6)

# F16
data = data[data['F16'] > 115000]
data.F16 -= data.F16.min()
data.F16 /= m.sqrt(data.F16.std())

# F20
#data = data[data.F20 != 12]

# F3
data.F3 += 1
data.F3 = np.log(data.F3)

# F4
data = zeroMean(data, 'F4')

# F5
data = data[data.F5 < 180000]
data.F5 -= data.F5.min()
data.F5 /= m.sqrt(data.F5.std())

# F7
column = 'F7'
data.loc[data[column] < 75000, column] = 1
data.loc[(data[column] < 215000) & (data[column] > 2), column] = 2
data.loc[data[column] > 215000, column] = 3

# F10
column = 'F10'
data = data[data[column] < 200000]
data = data[data[column] > 120000]
data.F10 -= data.F10.min()
data.F10 /= m.sqrt(data.F10.std())

# F17
column = 'F17'
data.F17 -= data.F17.min()
data.F17 /= m.sqrt(data[column].std())

# F19
data = data[data.F19 < 300000]
data.F19 /= m.sqrt(data.F19.std())

return data
```

```python
###############################################################
# Pipeline for test.csv
###############################################################
def testPipeline(data):
     # Drop columns with very low correlation to label
    low_corr = ['F20', 'F23', 'F21', 'F18', 'F1', 'F24',
            'F11', 'F13', 'F2', 'F15', 'F8', 'F14', 'F22']
    data.drop(low_corr, axis=1, inplace=True)
    data.drop(['id'], axis=1, inplace=True)

    # Drop duplicate columns
    dups = ['F9', 'F12']
    data.drop(dups, axis=1, inplace=True)

    # F6
    data.F6 = np.log(data.F6)

    # F16
    data.F16 -= data.F16.min()
    data.F16 /= m.sqrt(data.F16.std())

    # F20
    #data = data[data.F20 != 12]

    # F3
    data.F3 += 1
    data.F3 = np.log(data.F3)

    # F4
    data = zeroMean(data, 'F4')

    # F5
    data.F5 -= data.F5.min()
    data.F5 /= m.sqrt(data.F5.std())

    # F7
    column = 'F7'
    data.loc[data[column] < 75000, column] = 1
    data.loc[(data[column] < 215000) & (data[column] > 2), column] = 2
    data.loc[data[column] > 215000, column] = 3

    # F10
    data.F10 -= data.F10.min()
    data.F10 /= m.sqrt(data.F10.std())

    # F17
    column = 'F17'
    data.F17 -= data.F17.min()
```

```
        data.F17 /= m.sqrt(data[column].std())

        # F19
        data.F19 /= m.sqrt(data.F19.std())

        return data

    ############################################################
    # Writes a file for Kaggle Submission
    ############################################################
    def makeFile(pred, filename):
        new_index = np.arange(16384,32769,1)
        id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
        y_hat = pd.DataFrame(pred, columns=['Y'])
        frames = [id_col, y_hat]
        pred = pd.concat(frames, axis=1)
        pred.to_csv(filename, encoding='utf-8', index=False)

    def zeroMean(data, column):
        data[column] -= data[column].mean()
        data[column] /= m.sqrt(data[column].std())
        return data
```

```
In [70]: filename = 'train.csv'
         filepath = ''
         data = pd.read_csv(filepath + filename)
```

```
In [71]: new_data = pipeline(data)
```

```
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/pandas/core/generic.py:3643: Setti
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#
  self[name] = value
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/ipykernel_launcher.py:136: Setting
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#
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/ipykernel_launcher.py:137: Setting
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#
```

```
In [72]: X_boot = np.zeros((10**6, new_data.shape[1]))
```

Note this cell runs for a long time

```
In [73]: for i in range(X_boot.shape[0]):
             #seed = np.random.randint(0,100)
             rand = np.random.randint(0, new_data.shape[0])
             X_boot[i][:] = new_data.iloc[rand,:]
```

```
In [74]: labels = X_boot[:,0]
         features = X_boot[:,1:]
```

3.0.1 Logistic Regression

Note this cell runs for a long time

```
In [75]: accuracies = []
         weights_L1 = []
         for i in range(10):
             rand = np.random.randint(1, 100)
             X_train, X_test, y_train, y_test = train_test_split(features, labels)
             clf = LogisticRegression(penalty='l1', max_iter=1000, random_state=rand)
             _ = clf.fit(X_train, y_train)
             accuracies.append(clf.score(X_test, y_test))
             weights_L1.append(clf.coef_)

         accuracies = np.array(accuracies)
         print("Mean for L1 norm is: {}".format(np.mean(accuracies, axis=0)))
         print("St Dev for L1 norm is: {}".format(np.std(accuracies, axis=0)))
         print('')
```

```
Mean for L1 norm is: 0.9421592000000001
St Dev for L1 norm is: 0.00039964704427780396
```

```
In [76]: _ = clf.fit(features, labels)
```

```
In [79]: test_data = pd.read_csv('test.csv')
         test_data = testPipeline(test_data)
         preds = clf.predict(test_data)
         pred = makeFile(preds, 'prediction_bootstrap_log.csv')
```

Logistic Regression doesnt seem to work very well ever on this data set. I'm going to retire it.

3.0.2 Gradient Boosting

```
In [80]: new_data.columns
```

```
Out[80]: Index(['Y', 'F3', 'F4', 'F5', 'F6', 'F7', 'F10', 'F16', 'F17', 'F19'], dtype='object')
```

Note this cell runs for a long time

```
In [81]: clf = GradientBoostingClassifier(loss='exponential', learning_rate=0.1,
                                          n_estimators=500, max_depth=6, subsample=0.5)
         _ = clf.fit(features, labels)
         test_data = pd.read_csv('test.csv')
         test_data = testPipeline(test_data)
         pred = clf.predict(test_data)
         makeFile(pred, 'prediction-pipelined-bootstrapped-gradboost.csv')
```

None of the bootstrapping seemed to work very well. Looking back, this could have been because of my feature engineering. I did not have enough days (submissions) at the end to try it again combined with later methods to see if it worked better. At this point I decided I had to do some more feature engineering to get more out of this data set.

4 Part 3 Feature Engineering

Coming back to Part 1 We notice severe outliers in:`F6F16F20` We notice moderate outliers in:`F3F5F8F18F24` We notice odd groupings in `F7F10F12F19F22` Lets quickly fix F6, F16, and F20 again.

```
In [82]: get_ipython().magic('reset -sf')
         import numpy as np
         import math as m
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         from mpl_toolkits.mplot3d import Axes3D
         from IPython.core.interactiveshell import InteractiveShell

         from pandas.plotting import scatter_matrix

         from sklearn.metrics import confusion_matrix

         from sklearn.model_selection import LeaveOneOut
         from sklearn.model_selection import train_test_split
         from sklearn.model_selection import cross_val_score
         from sklearn.linear_model import Ridge
         from sklearn.linear_model import Lasso
         from sklearn.linear_model import LogisticRegression
         from sklearn.preprocessing import StandardScaler
         from sklearn.preprocessing import LabelBinarizer
         from sklearn.neighbors import KNeighborsClassifier

         from sklearn.metrics import mean_squared_error
         from sklearn.metrics import accuracy_score

         import graphviz
```

```
import lime
import xgboost as xgb
InteractiveShell.ast_node_interactivity = "all"
```

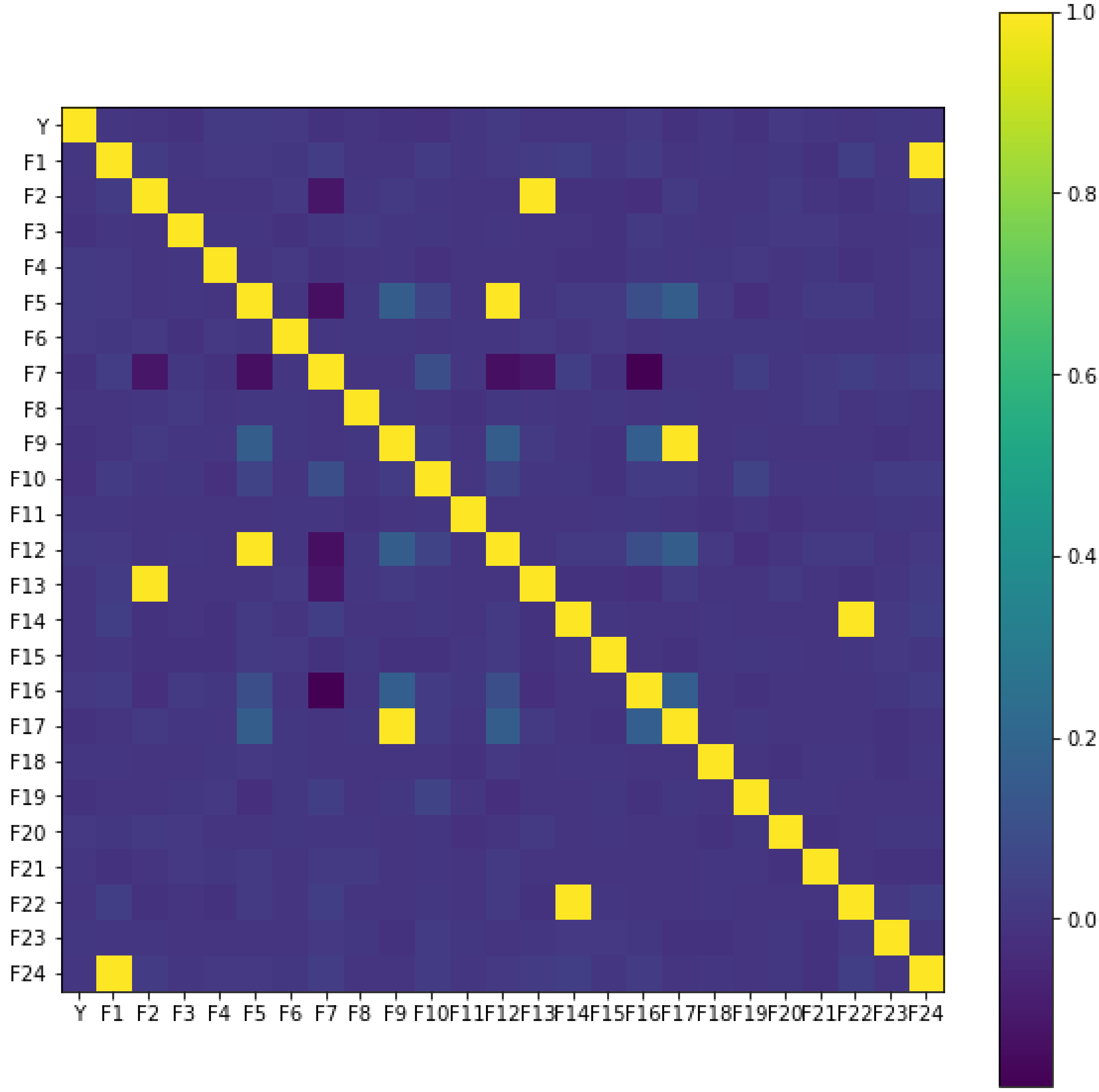
In [83]:
```
def corrHeatMap(data):
    cols = data.columns
    xticks = np.arange(0,len(cols), 1)
    fig, ax = plt.subplots(figsize=(10,10))
    _ = plt.imshow(data.corr())
    _ = plt.colorbar()
    _ = ax.set_xticks(xticks)
    _ = ax.set_yticks(xticks)
    _ = ax.set_xticklabels(data.columns)
    _ = ax.set_yticklabels(data.columns)

def pltHist(data, column, num_bins=50):
    _ = plt.hist(data[column], num_bins, normed=1, facecolor='green', alpha = 0.5)
    _ = plt.xlabel(column)
    _ = plt.title('Histogram of {}'.format(column))

def zeroMean(data, column):
    data[column] -= data[column].mean()
    data[column] /= m.sqrt(data[column].std())
    return data

def dropKLargest(data, column, k):
    for i in range(k):
        data_point = data[column].idxmax()
        data.drop([data_point], inplace=True)

        # check this functionality
def dropLargestBound(data, column, bound):
    data_point = data[column].idxmax()
    print(data.iloc[data_point][column])
    while(data.iloc[data_point][column] > bound):
        data.drop([data_point], axis=0, inplace=True)
        data_point = data[column].idxmax()
        print(data_point)

# Assumes id column has already been stripped
def splitData(data):
    labels = data['Y']
    features = data.drop(['Y'], axis=1)
    return features, labels
```

In [84]:
```
filename = 'train.csv'
filepath = ''
data = pd.read_csv(filepath + filename)
```

```
data.drop(['id'], axis=1, inplace=True)

# Drop empty columns
garbage = ['F25', 'F26', 'F27']
data.drop(garbage, axis=1, inplace=True)

# F6
for i in range(10):
    data_point = data['F6'].idxmax()
    data.drop([data_point], inplace=True)
data.F6 = np.log(data.F6)

# F16
data = data[data.F16 >= 119000]

# F20
data = data[data.F20 != 12]
```

```
In [85]: mod_outliers = ['F3', 'F5', 'F8', 'F18', 'F24']
         _ = sns.pairplot(data[mod_outliers])
```


```
In [86]: _ = corrHeatMap(data)
```



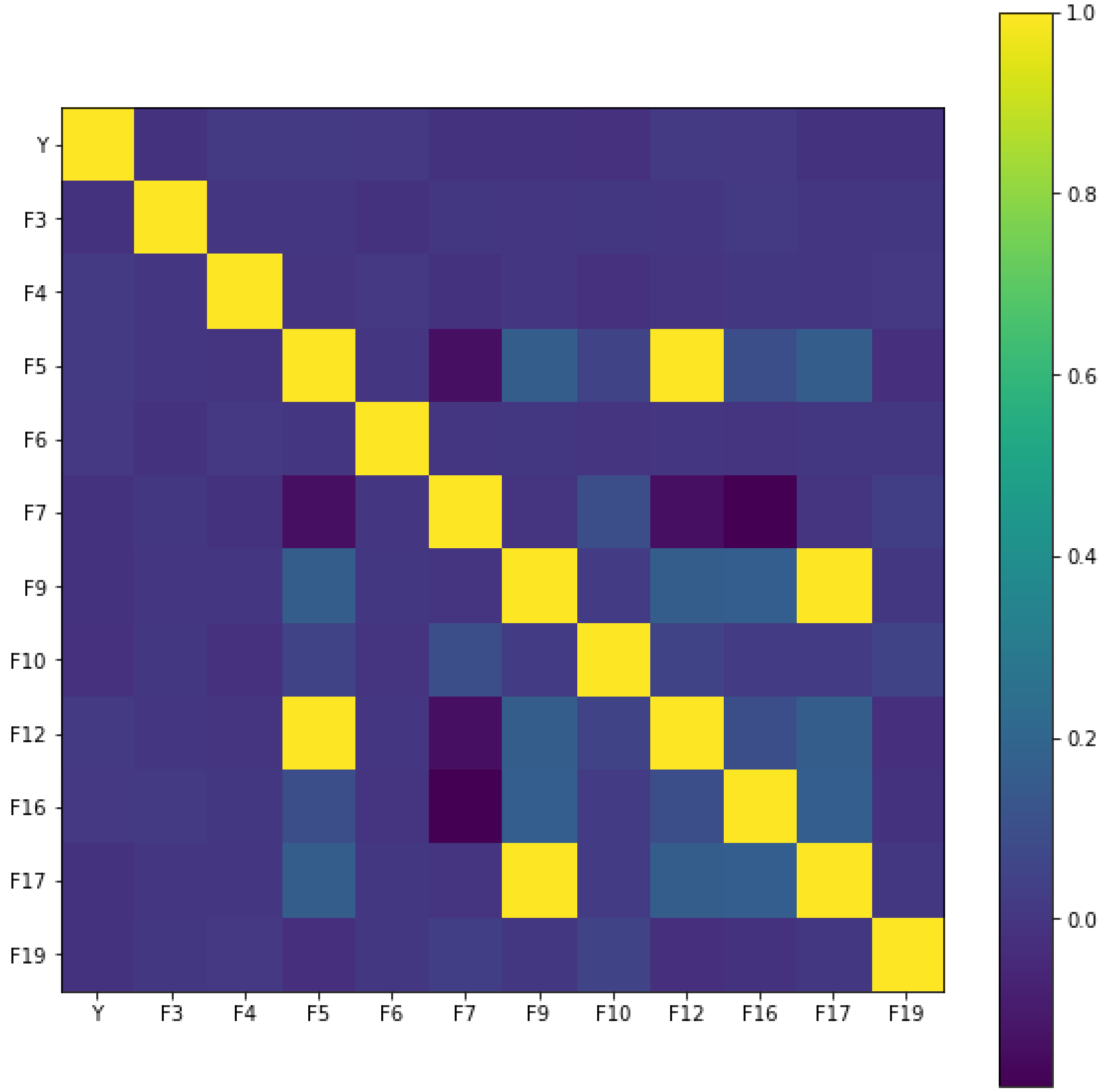

```
In [87]: corr_matrix = data.corr()
         print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F5     0.017506
F12    0.017506
F4     0.014835
F16    0.011408
F6     0.010885
F20    0.009697
F23    0.006785
F21    0.004126
F18    0.003530
```

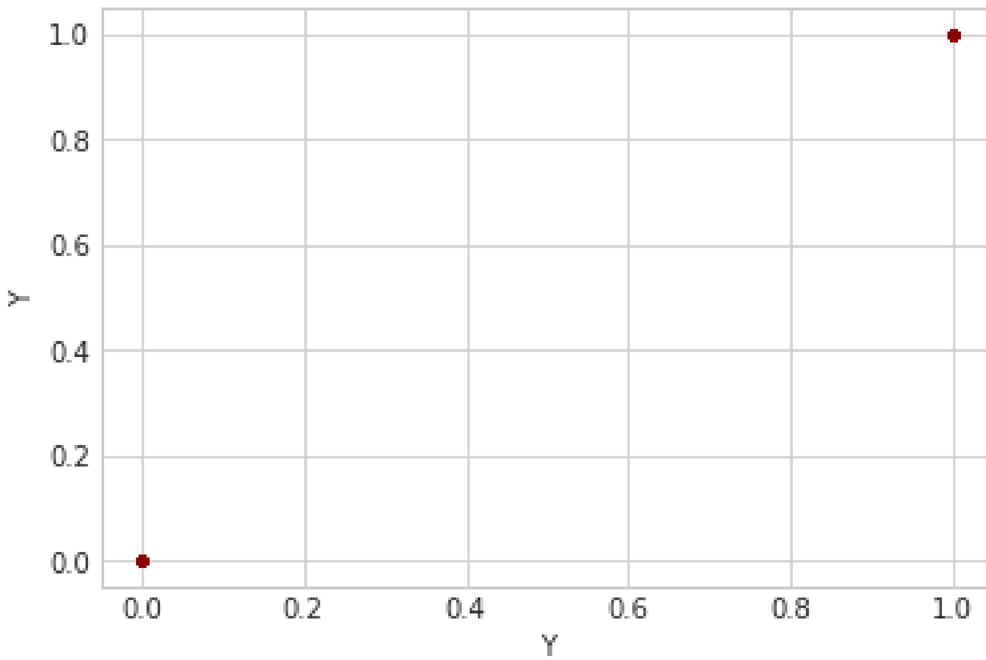
```
F1      0.002134
F24     0.002134
F11     0.001027
F13    -0.000850
F2     -0.000850
F15    -0.004088
F8     -0.005040
F14    -0.005283
F22    -0.005283
F9     -0.009537
F17    -0.009537
F3     -0.009586
F7     -0.010218
F19    -0.011999
F10    -0.014681
Name: Y, dtype: float64
```

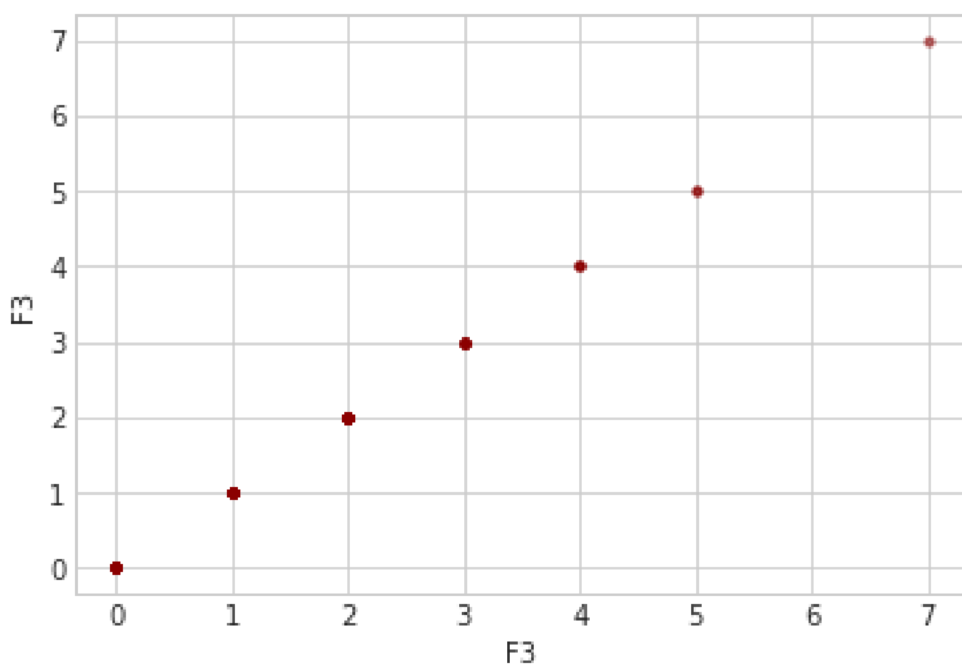
To be honest this looks like the columns are mostly garbage. I am going to save myself some trouble and drop columns with less than 1 percent correlation to the label.

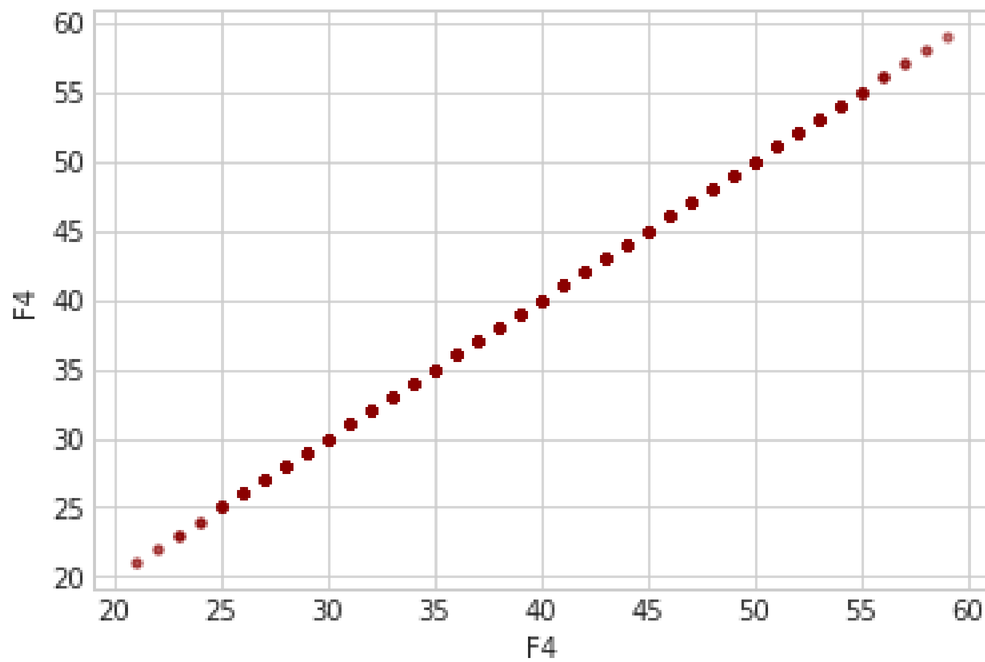
```
In [88]: low_corr = ['F20', 'F23', 'F21', 'F18', 'F1', 'F24',
                     'F11', 'F13', 'F2', 'F15', 'F8', 'F14', 'F22']
         data.drop(low_corr, axis=1, inplace=True)

In [89]: _ = corrHeatMap(data)
```

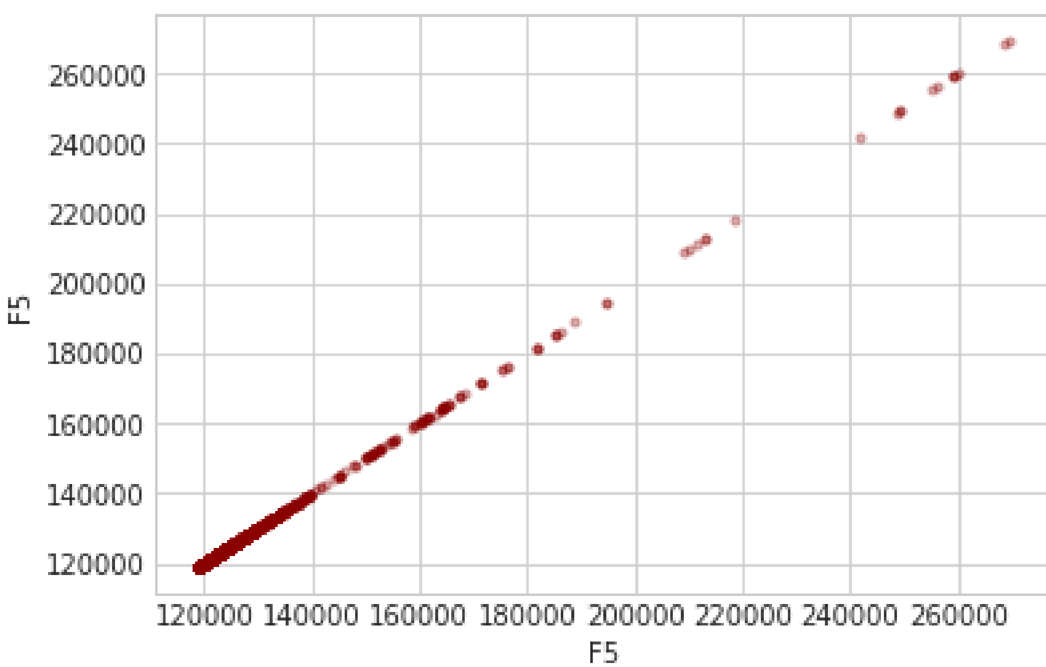


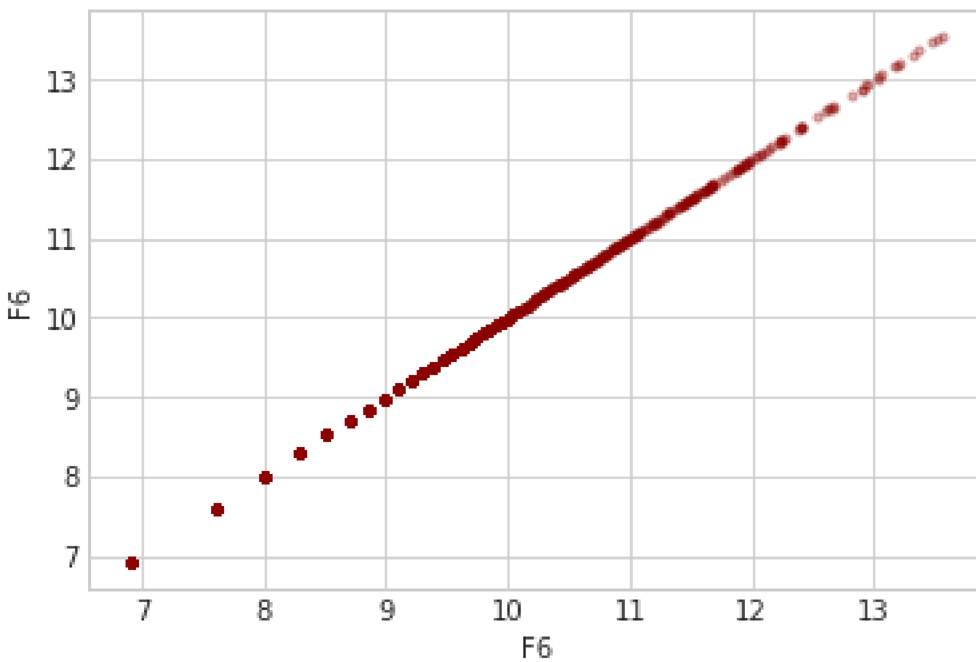

```
In [90]: sns.set_style("whitegrid")
         for column in data.columns:
             _ = sns.regplot(data[column], data[column], scatter_kws={"color":"darkred","alpha":
             plt.show()
```

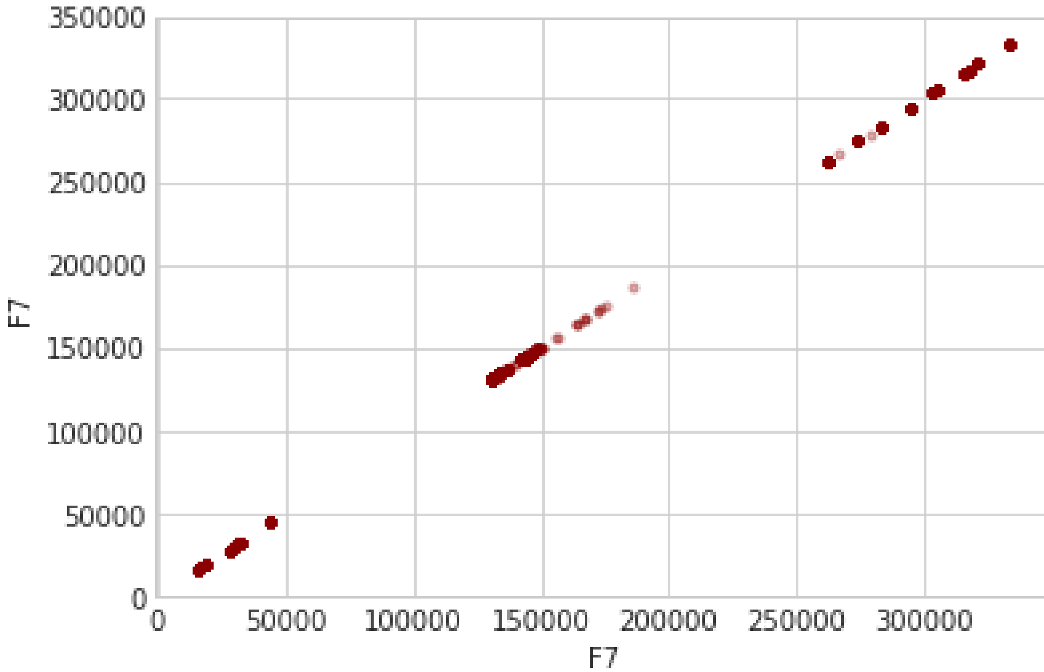

1.0
0.8
0.6
0.4
0.2
0.0
Y
0.0
0.2
0.4
0.6
0.8
1.0
Y

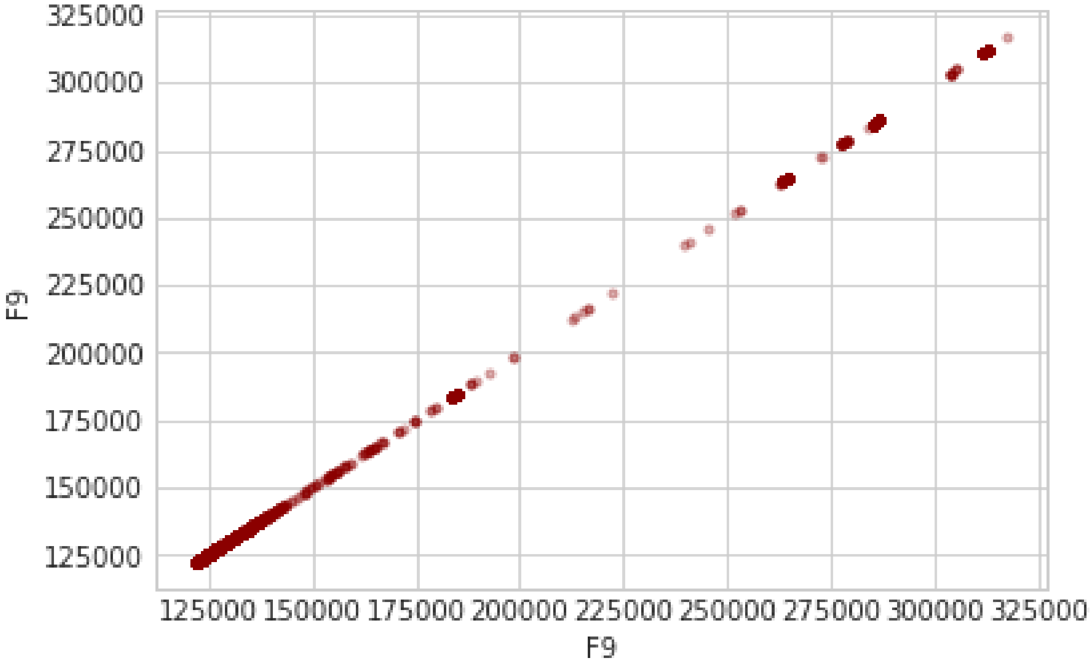

7
6
5
4
3
2
1
0
F3
0
1
2
3
4
5
6
7
F3

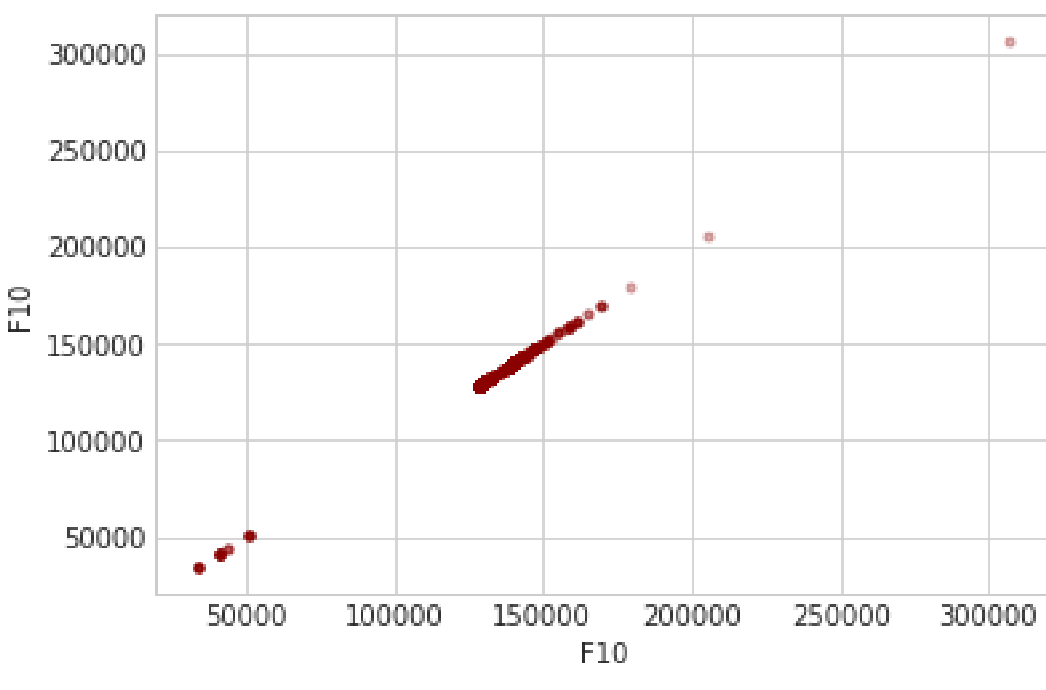

F4
F4
20
25
30
35
40
45
50
55
60

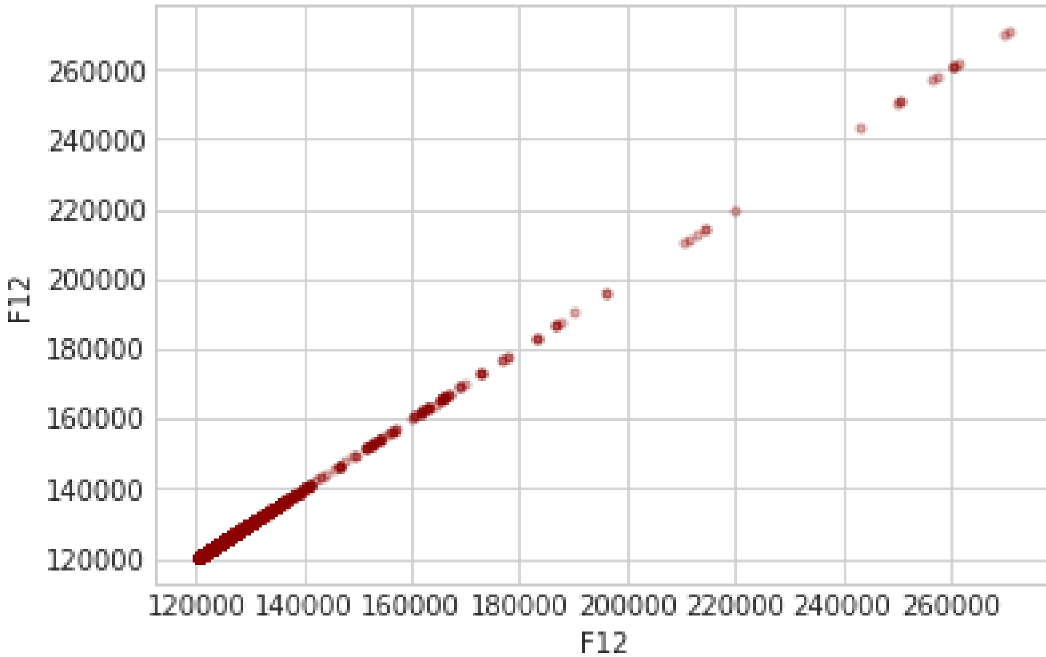

F5
F5
120000
140000
160000
180000
200000
220000
240000
260000

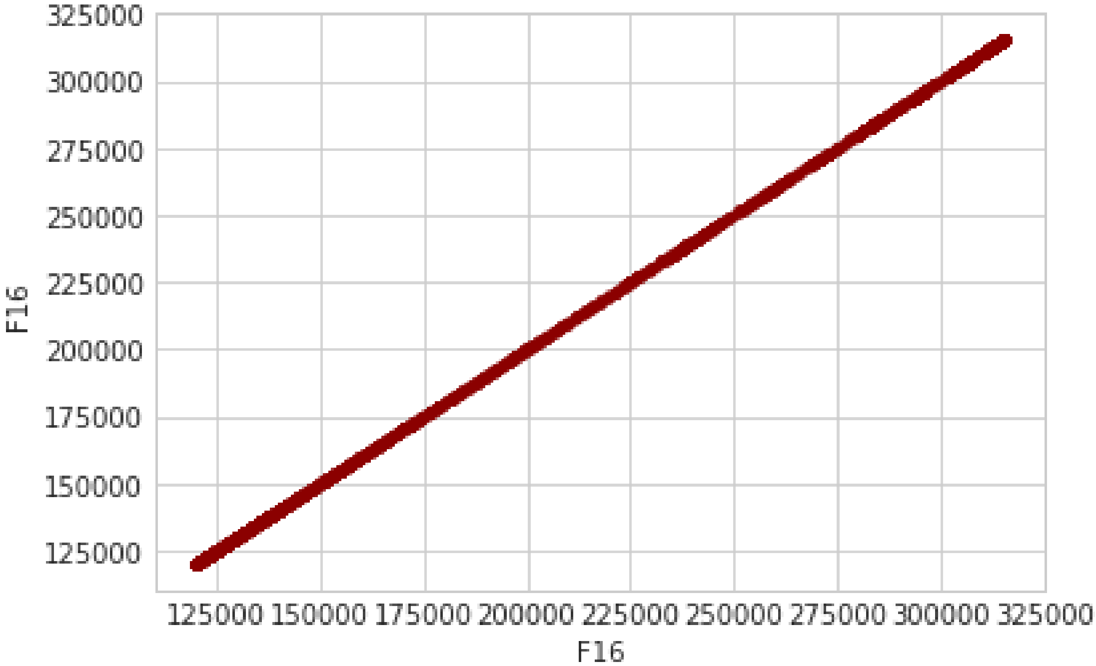

13
12
11
10
9
8
7
F6
7
8
9
10
11
12
13
F6

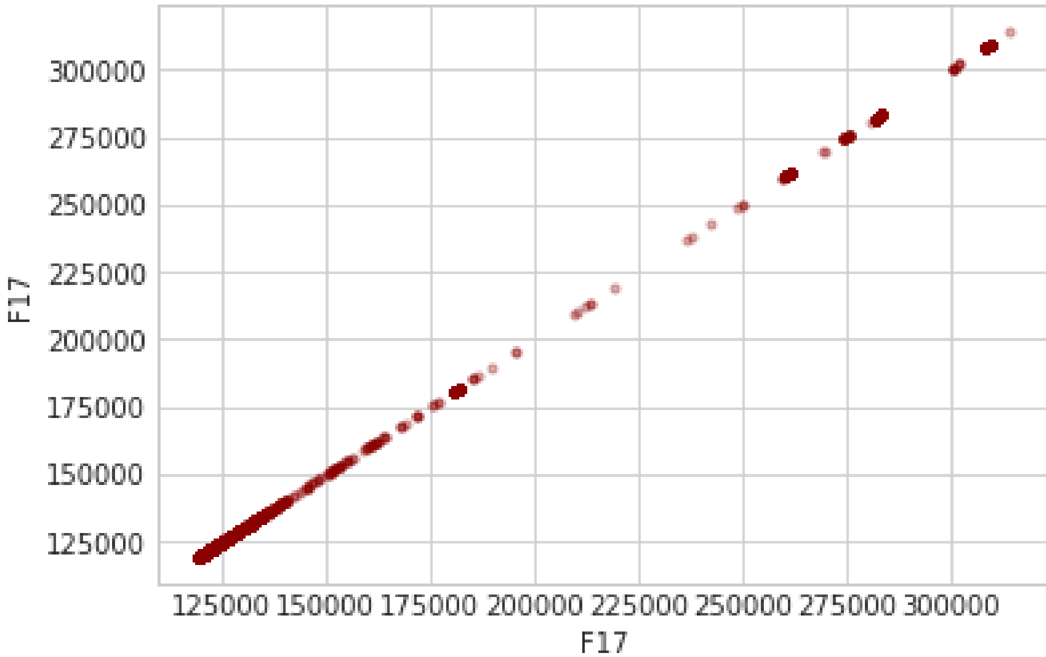

350000
300000
250000
200000
150000
100000
50000
0
F7
0
50000
100000
150000
200000
250000
300000
F7

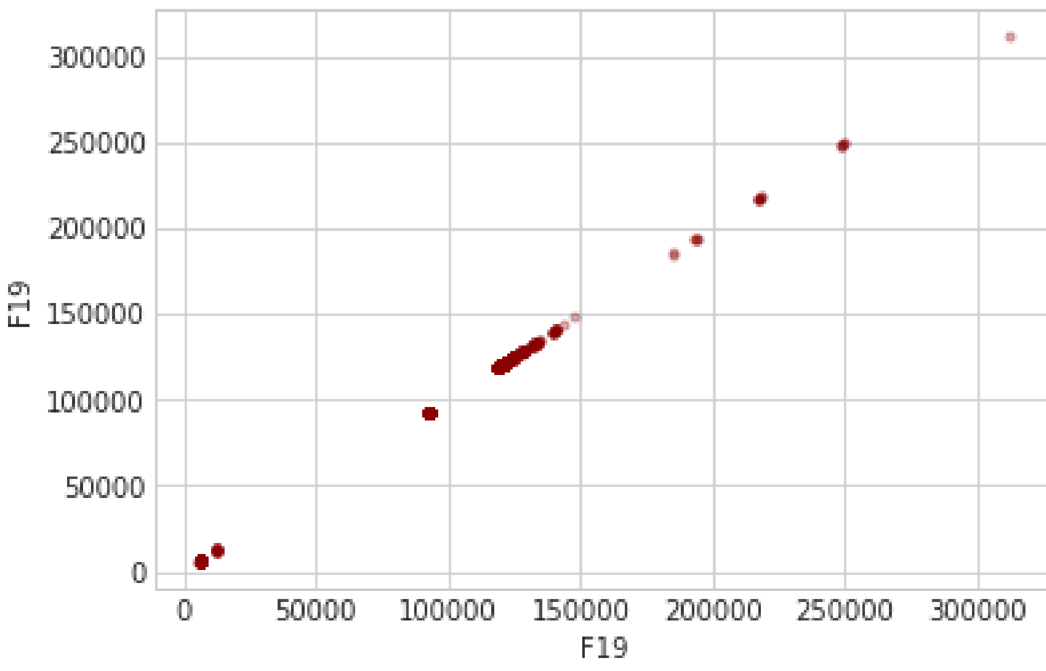

325000
300000
275000
250000
225000
200000
175000
150000
125000
F9
125000 150000 175000 200000 225000 250000 275000 300000 325000
F9


300000
250000
200000
150000
100000
50000
F10
50000 100000 150000 200000 250000 300000
F10


260000
240000
220000
200000
180000
160000
140000
120000
F12
120000 140000 160000 180000 200000 220000 240000 260000
F12

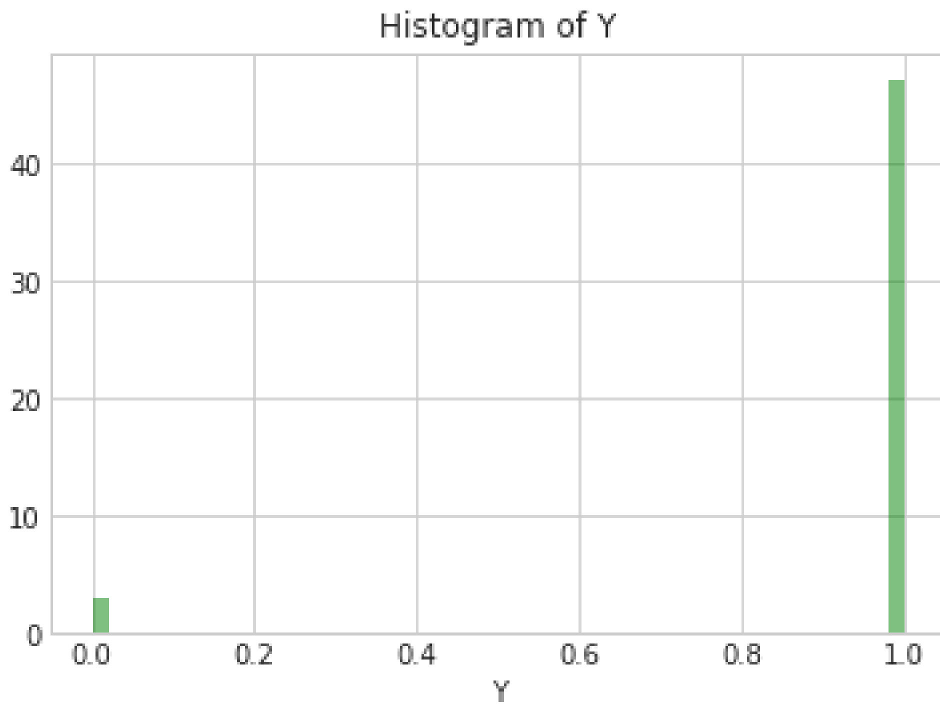

325000
300000
275000
250000
225000
200000
175000
150000
125000
F16
125000 150000 175000 200000 225000 250000 275000 300000 325000
F16

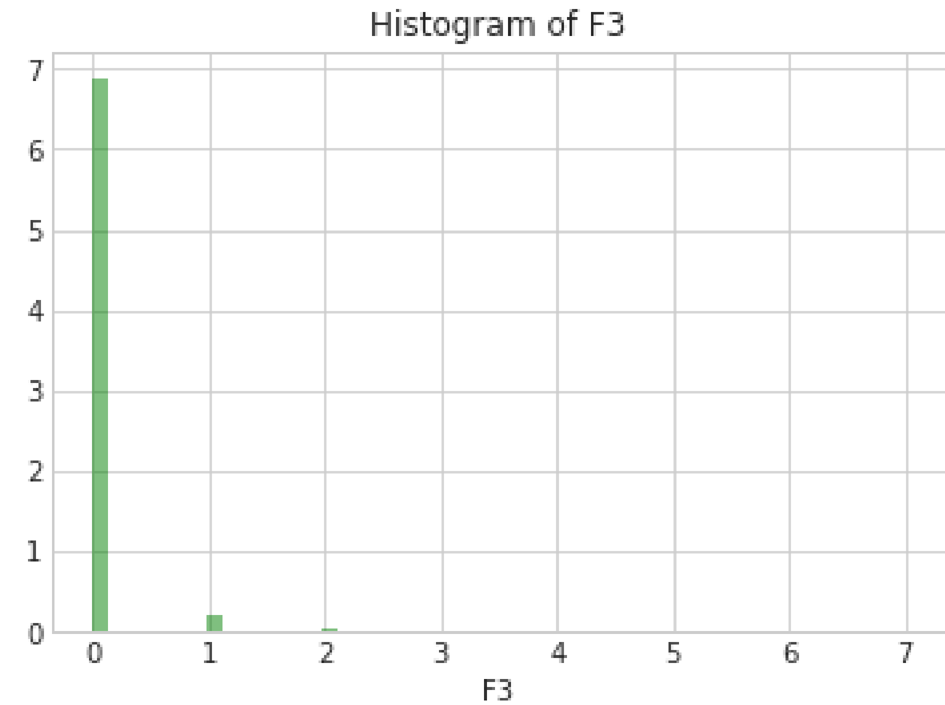


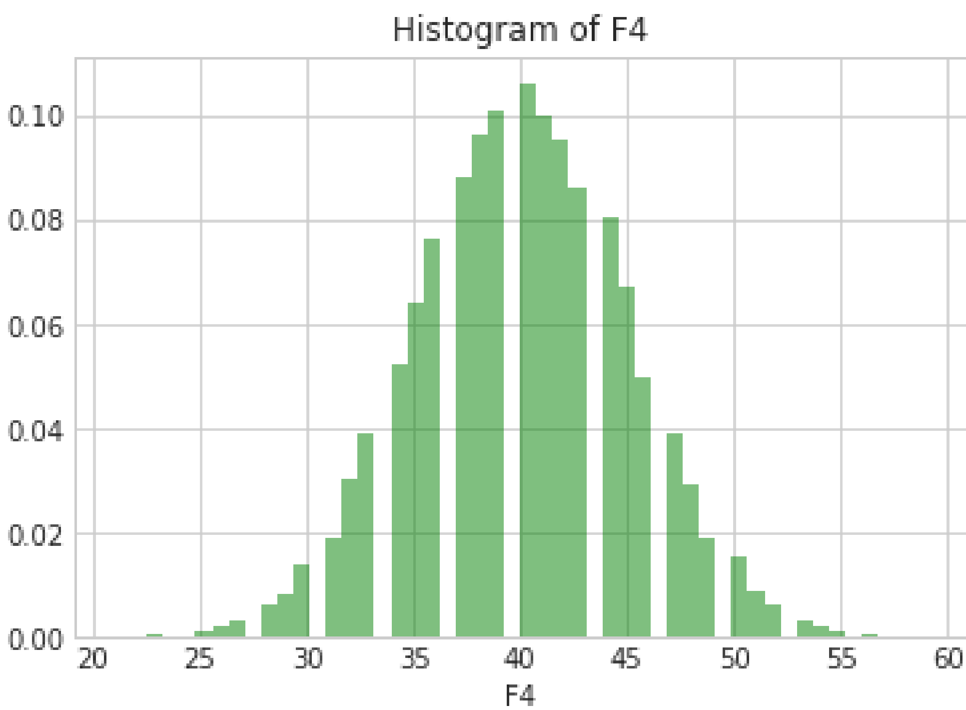


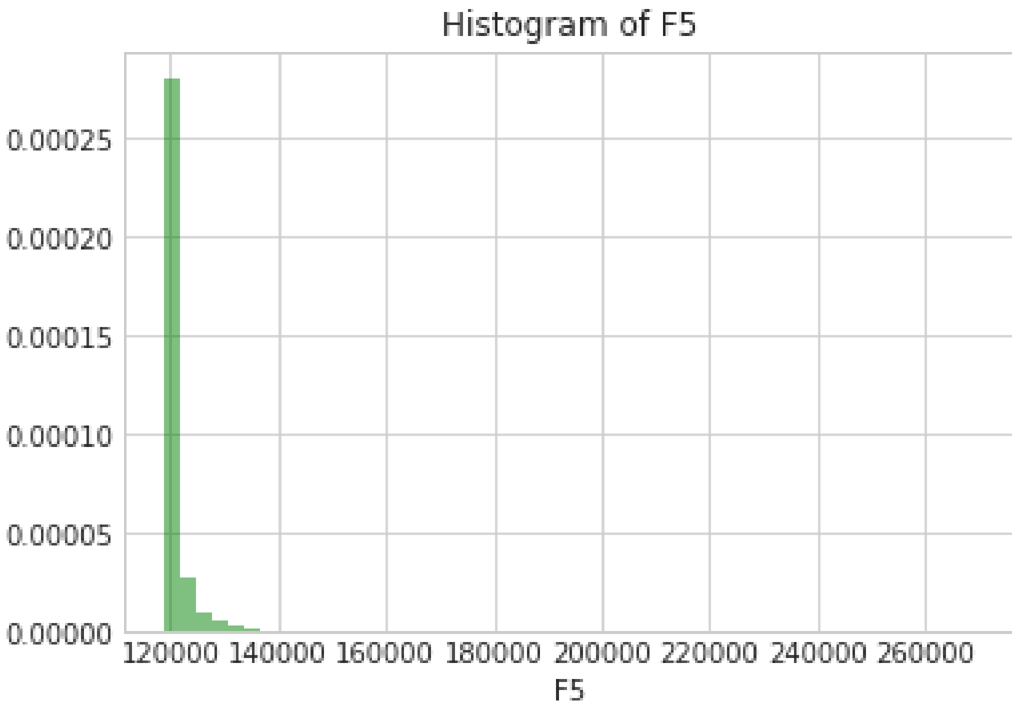

```
In [91]: num_bins = 50
         for column in data.columns:
```

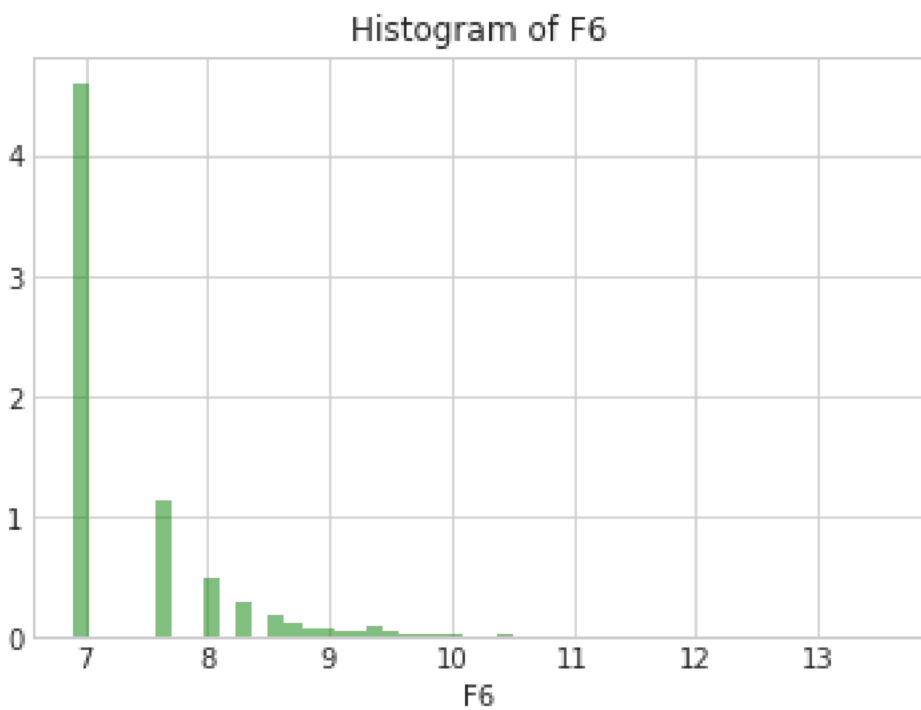
```
_ = plt.hist(data[column], num_bins, normed=1, facecolor='green', alpha = 0.5)
_ = plt.xlabel(column)
_ = plt.title('Histogram of {}'.format(column))
plt.show()
```

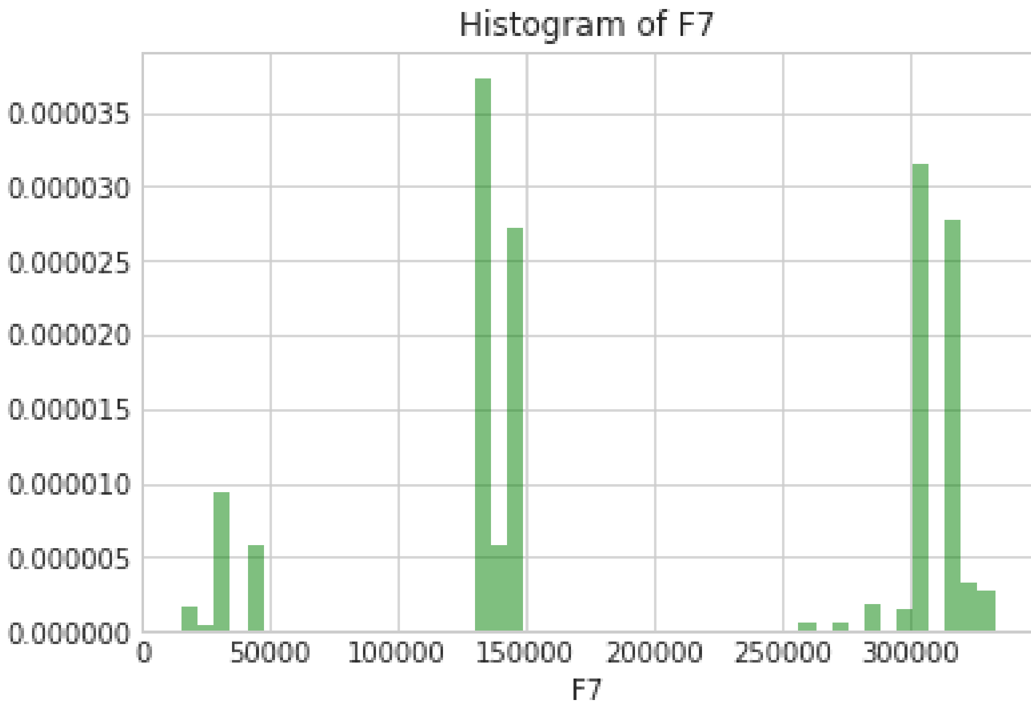


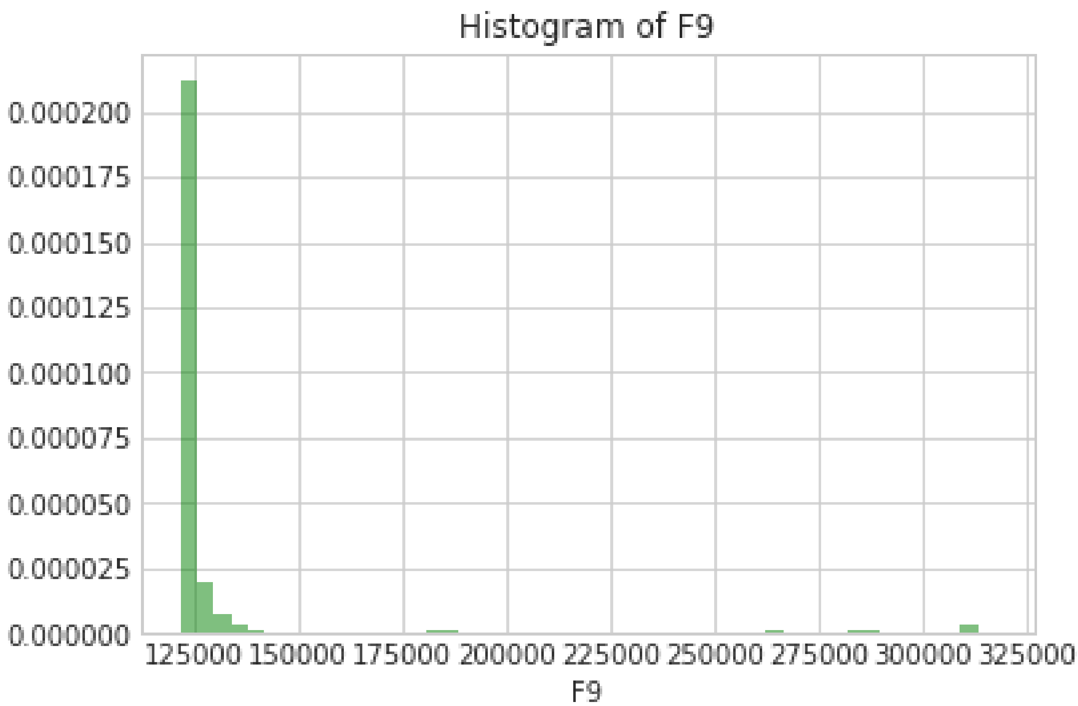

Histogram of F3
7
6
5
4
3
2
1
0
0
1
2
3
4
5
6
7
F3

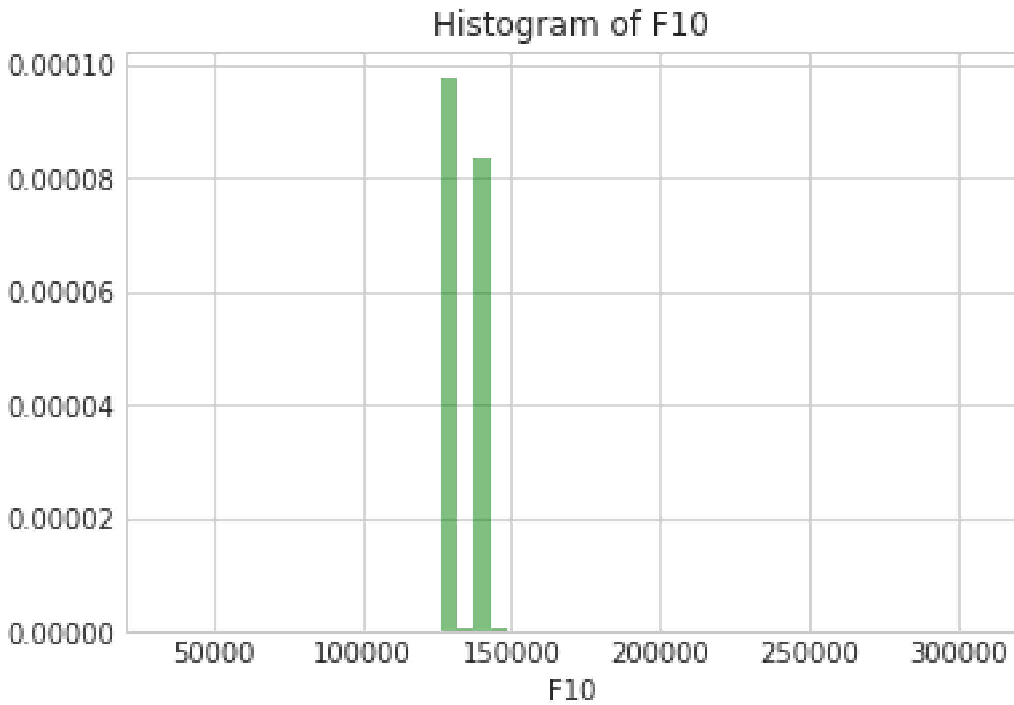

Histogram of F4
0.10
0.08
0.06
0.04
0.02
0.00
20
25
30
35
40
45
50
55
60
F4

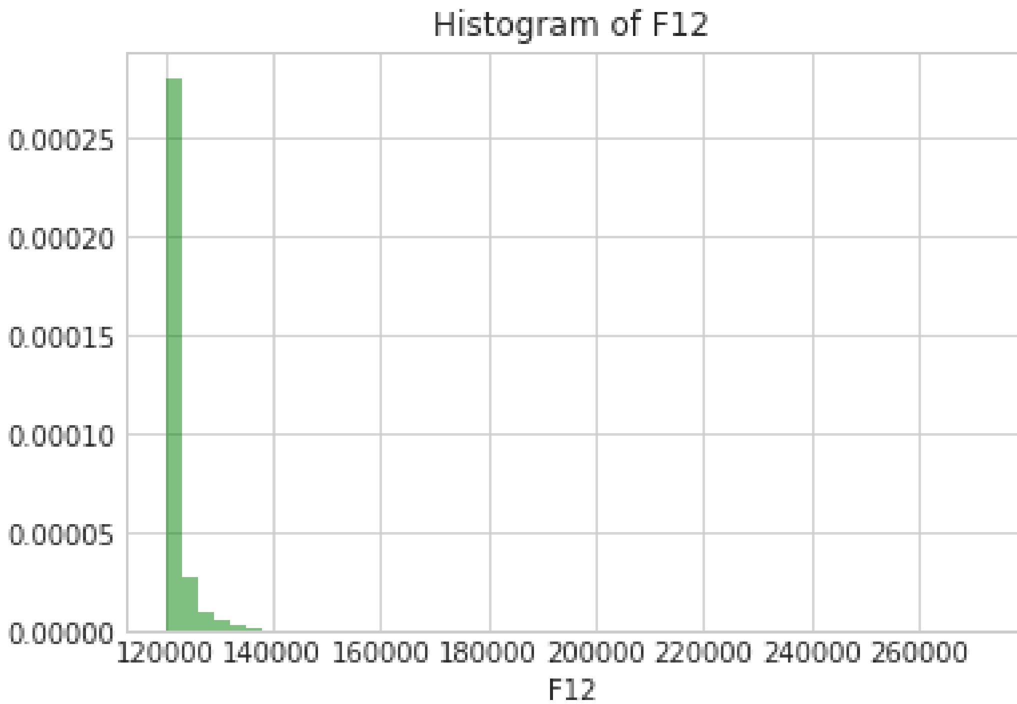

Histogram of F5
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
120000 140000 160000 180000 200000 220000 240000 260000
F5

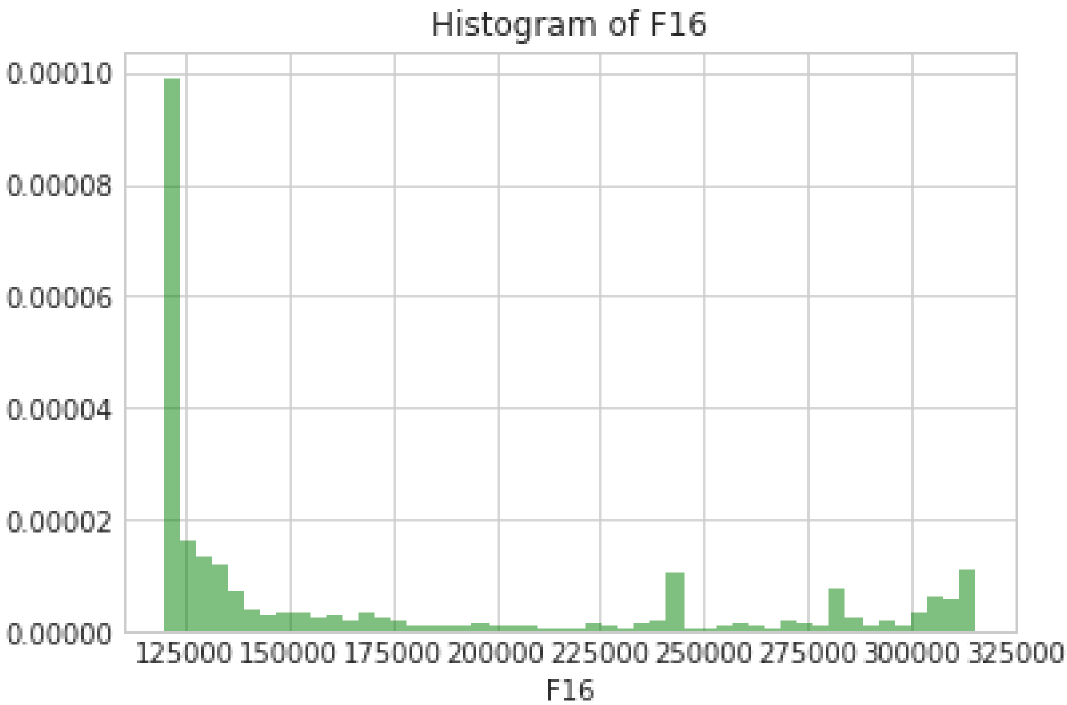

Histogram of F6
4
3
2
1
0
7 8 9 10 11 12 13
F6

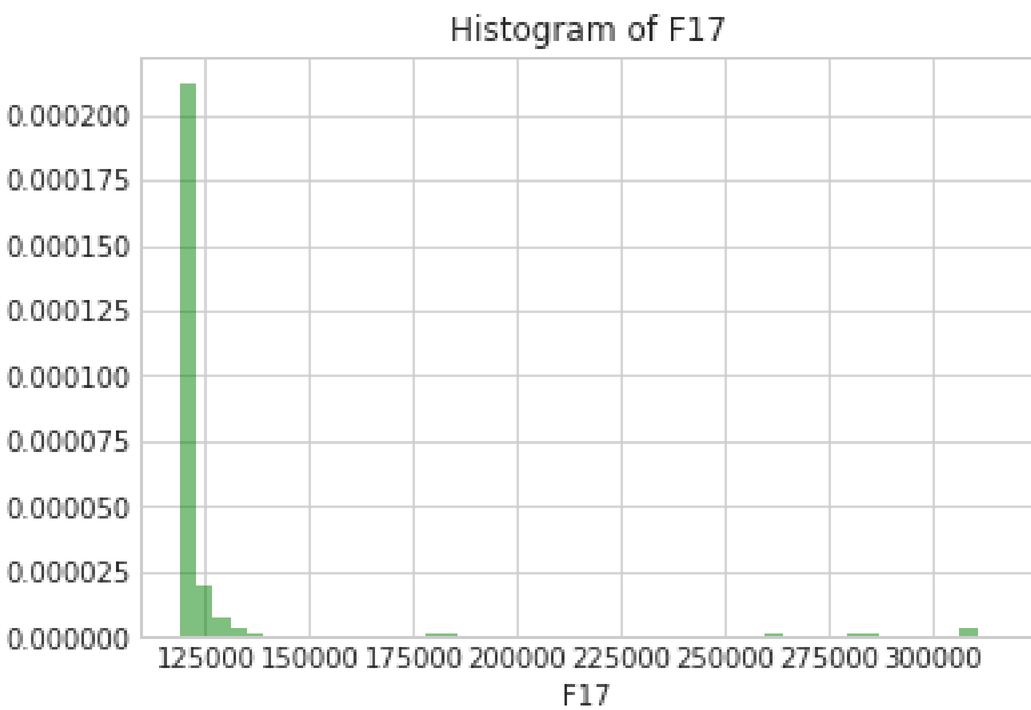

Histogram of F7
0.000035
0.000030
0.000025
0.000020
0.000015
0.000010
0.000005
0.000000
0
50000
100000
150000
200000
250000
300000
F7

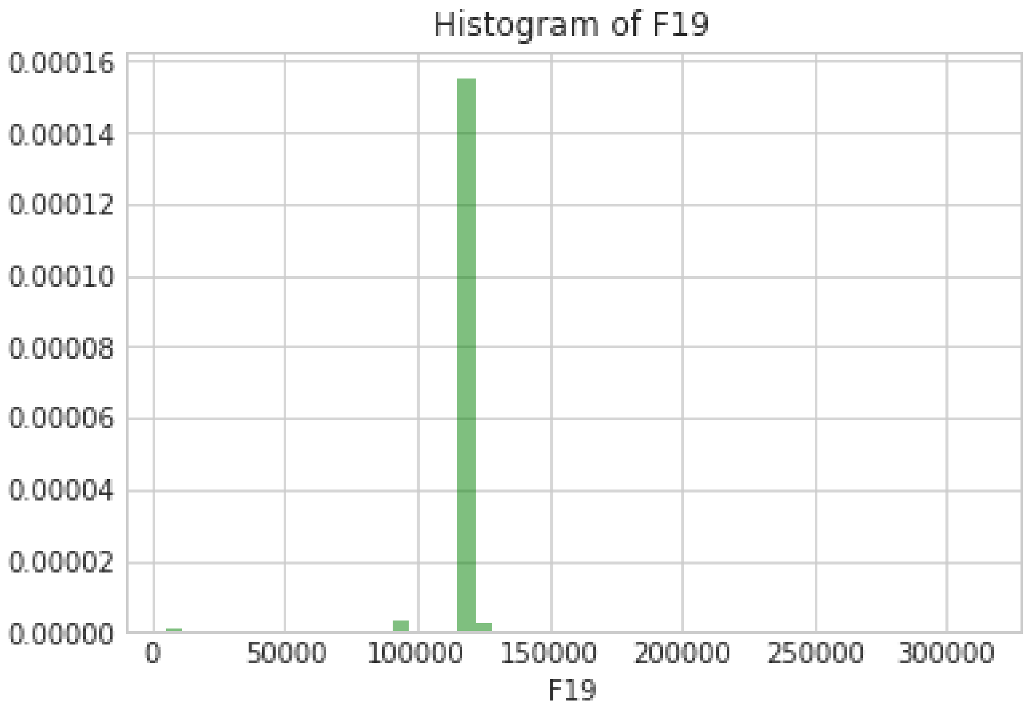

Histogram of F9
0.000200
0.000175
0.000150
0.000125
0.000100
0.000075
0.000050
0.000025
0.000000
125000
150000
175000
200000
225000
250000
275000
300000
325000
F9


Histogram of F10
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
50000
100000
150000
200000
250000
300000
F10


Histogram of F12
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
120000
140000
160000
180000
200000
220000
240000
260000
F12


Histogram of F16
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
125000 150000 175000 200000 225000 250000 275000 300000 325000
F16


Histogram of F17
0.000200
0.000175
0.000150
0.000125
0.000100
0.000075
0.000050
0.000025
0.000000
125000 150000 175000 200000 225000 250000 275000 300000
F17



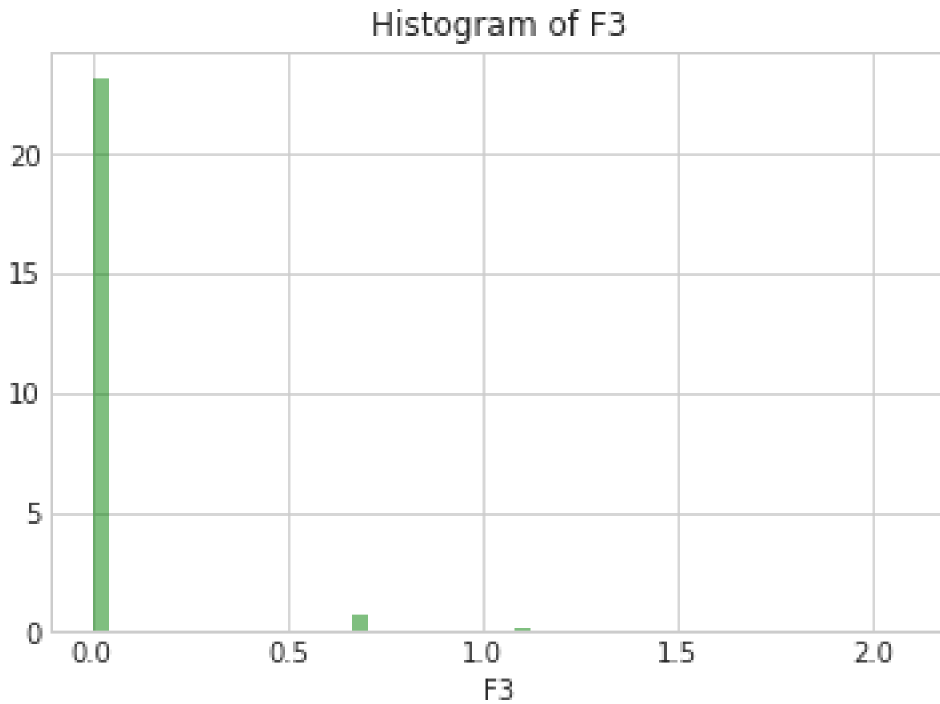
4.1 Start changing stuff

Let's take them in order.

F3 Lets convert it to log data.

```
In [92]: data.F3 += 1
         data.F3 = np.log(data.F3)
```

```
In [93]: column = 'F3'
         pltHist(data, column)
```



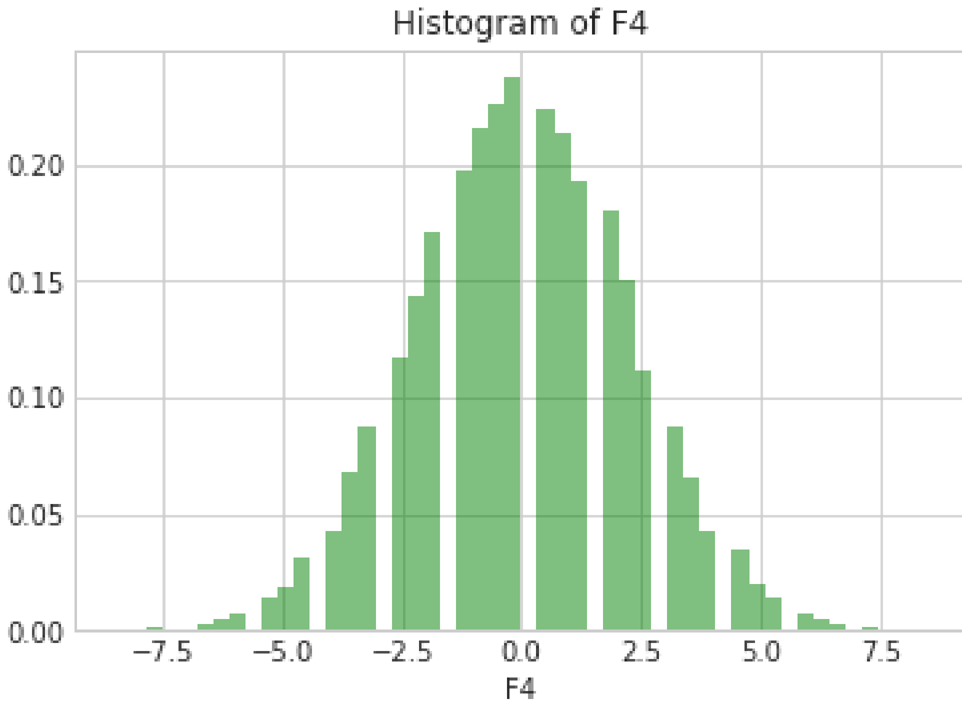

```
In [94]: corr_matrix = data.corr()
         print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y       1.000000
F12     0.017506
F5      0.017506
F4      0.014835
F16     0.011408
F6      0.010885
F17    -0.009537
F9     -0.009537
F7     -0.010218
F3     -0.011799
F19    -0.011999
F10    -0.014681
Name: Y, dtype: float64
```

F4 This is obviously normal. Let's leave it in for now, it may make the model more robust to noise. I will convert it to standard normal.

```
In [95]: column = 'F4'
         data = zeroMean(data, column)
```

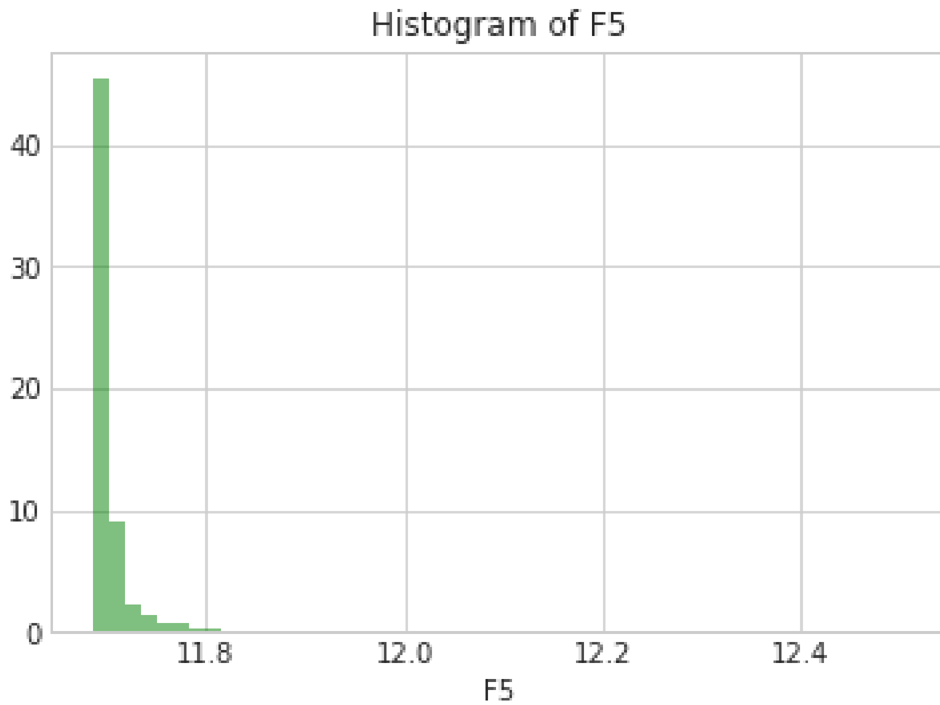
In [96]: pltHist(data, column)



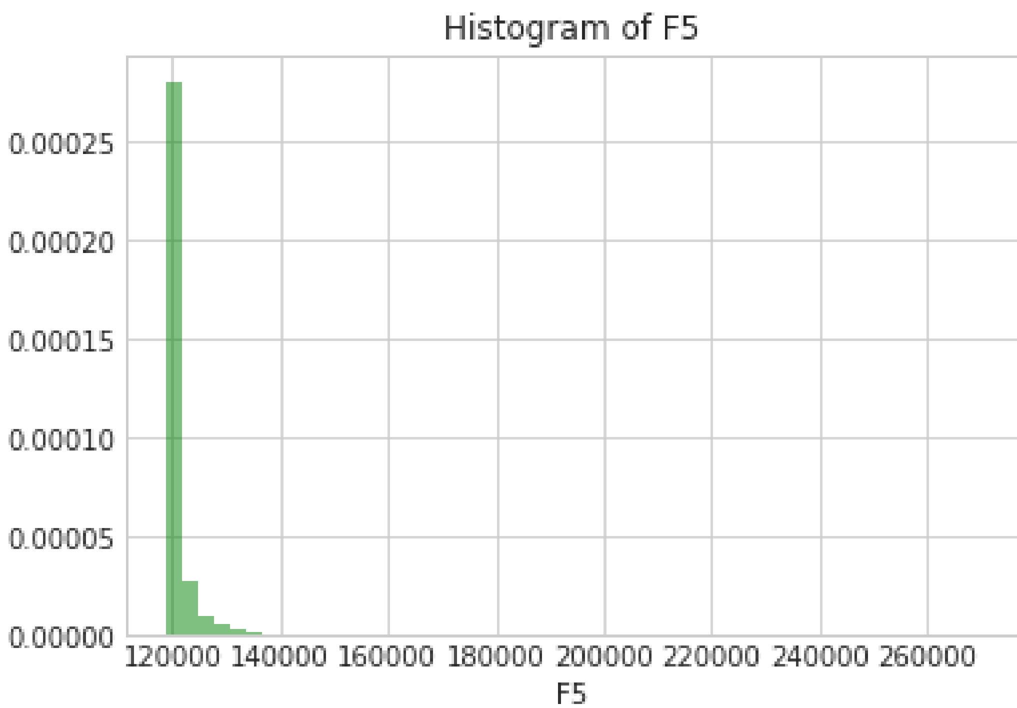
At least that is scaled. We can remove it later if necessary.

F5 Lets look at a log histogram.

```
In [97]: column = 'F5'
         _ = plt.hist(np.log(data[column]), num_bins, normed=1, facecolor='green', alpha = 0.5)
         _ = plt.xlabel(column)
         _ = plt.title('Histogram of {}'.format(column))
```

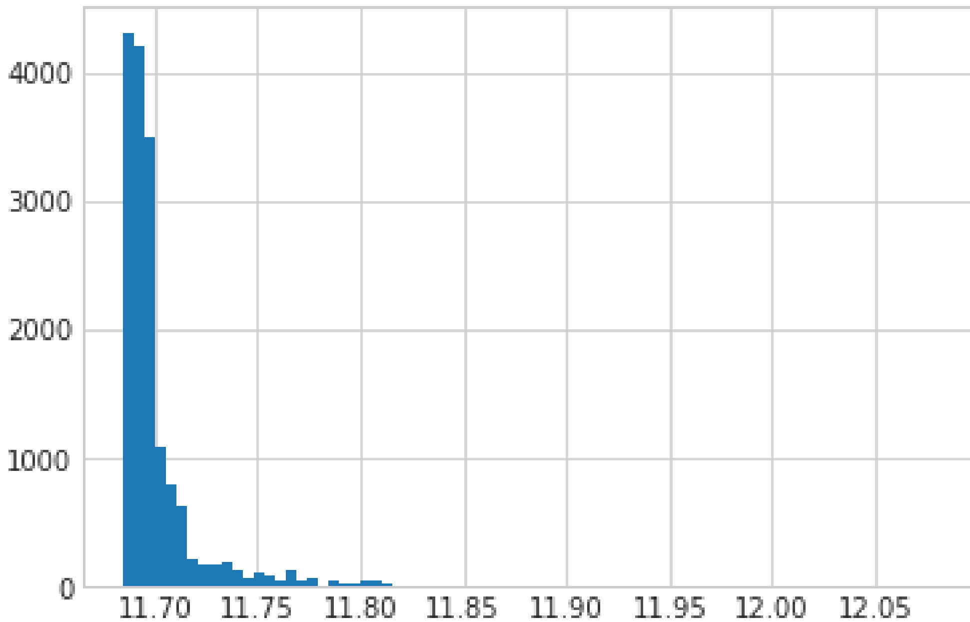



```
In [98]: pltHist(data, column)
```



```
In [99]: k = data[data[column] > 180000].count().F5
```

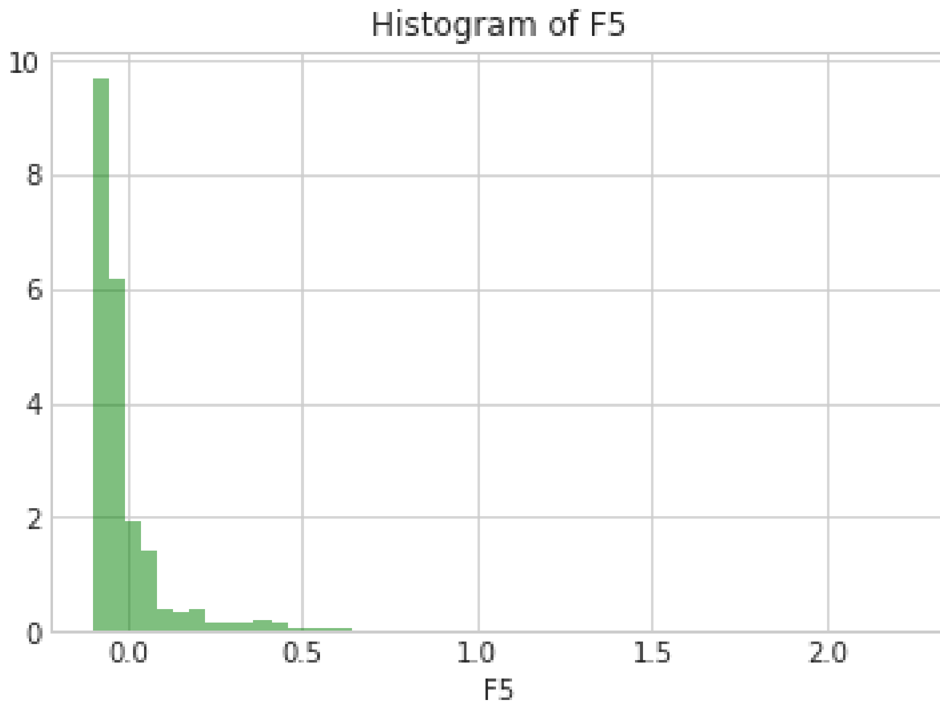
```
In [100]: dropKLargest(data, column, k)
          _ = plt.hist(np.log(data[column]), bins=75)
```




```
In [101]: data.F5 = np.log(data.F5)
```

```
In [102]: data = zeroMean(data, column)
```

```
In [103]: pltHist(data, column)
```




```
In [104]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

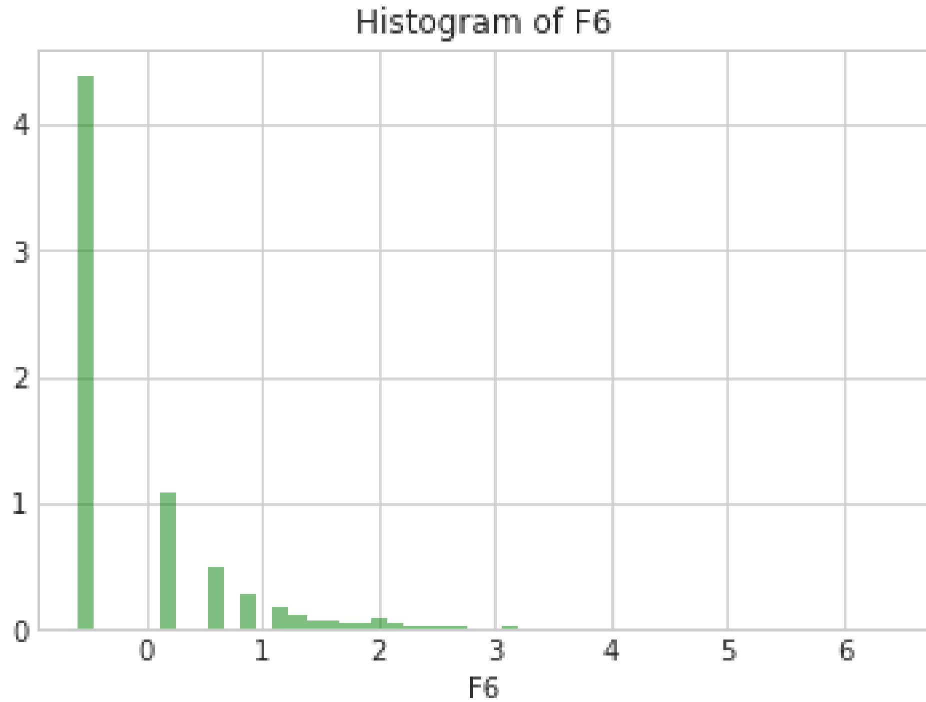
```
Y      1.000000
F5     0.020867
F12    0.020457
F4     0.015103
F16    0.011235
F6     0.010746
F7    -0.010140
F17   -0.010343
F9    -0.010343
F3    -0.011934
F19   -0.012046
F10   -0.014530
Name: Y, dtype: float64
```

We improved F5's correlation.

F6 This one has some interesting structure, lets zero mean it for now.

```
In [105]: column = 'F6'
          data = zeroMean(data, column)
```

```
In [106]: pltHist(data, column)
```

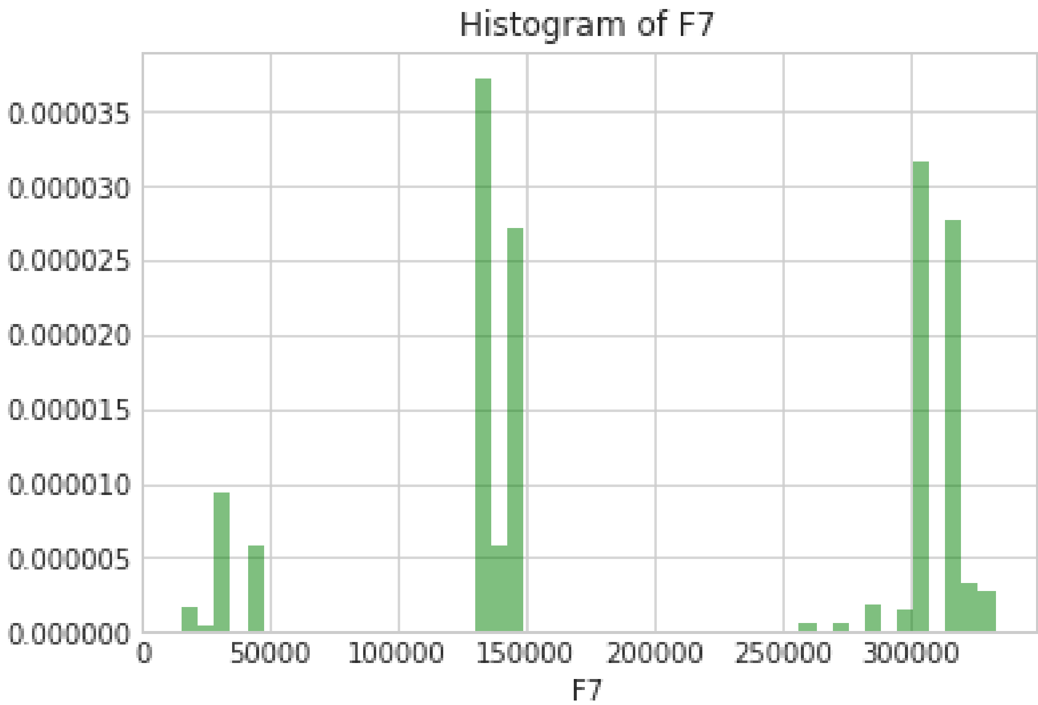



```
In [107]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

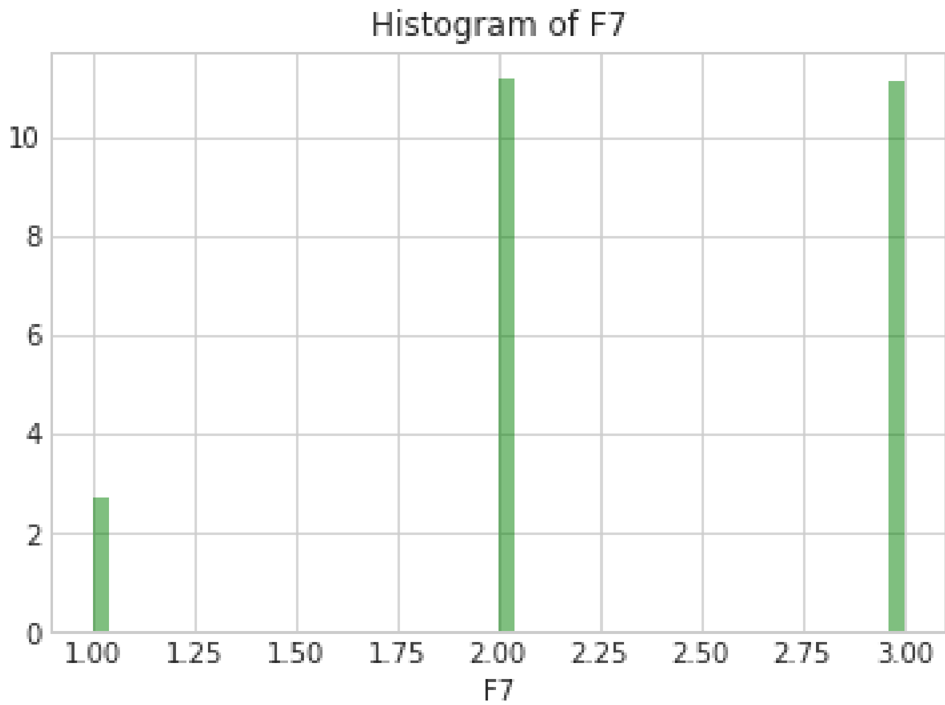
```
Y      1.000000
F5     0.020867
F12    0.020457
F4     0.015103
F16    0.011235
F6     0.010746
F7    -0.010140
F17   -0.010343
F9    -0.010343
F3    -0.011934
F19   -0.012046
F10   -0.014530
Name: Y, dtype: float64
```

F7 This column is definitely 3 categories. Lets lump them all together.

```
In [108]: column = 'F7'
          pltHist(data, column)
```




```
In [109]: data.loc[data[column] < 75000, column] = 1
          data.loc[(data[column] < 215000) & (data[column] > 2), column] = 2
          data.loc[data[column] > 215000, column] = 3

In [110]: pltHist(data, column)
```




```
In [111]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F5     0.020867
F12    0.020457
F4     0.015103
F16    0.011235
F6     0.010746
F7     0.003744
F17   -0.010343
F9    -0.010343
F3    -0.011934
F19   -0.012046
F10   -0.014530
Name: Y, dtype: float64
```

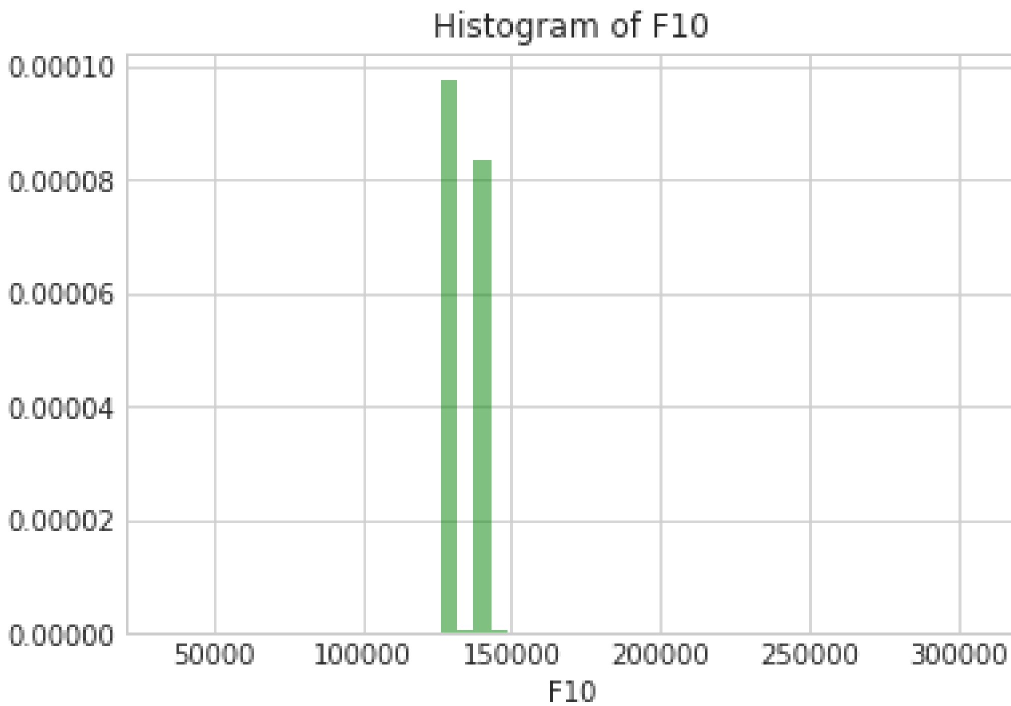
This didnt seem to help. We might as well leave F7 as is, or drop it.

F9 F9 is a duplicate of F17. Lets drop it and deal with it at the end.

```
In [112]: data.drop('F9', axis=1, inplace=True)
```

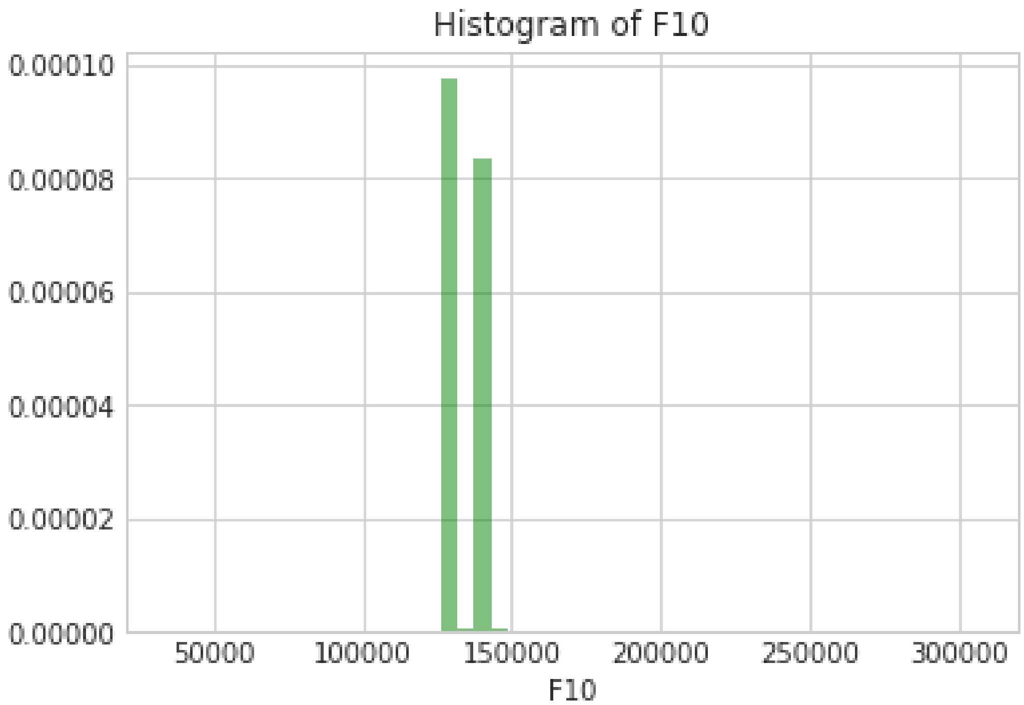
F10 F10 is heavily concentrated, but has significant outliers on the 'left' side. Lets drop the ones on the right side.

```
In [113]: column = 'F10'
          pltHist(data, column)
          k = data[data[column] > 200000].count().F10
```




```
In [114]: #dropKLargest(data, column, k)
```

```
In [115]: pltHist(data, column)
```



In [116]:
```
data[data[column] < 120000].Y
```

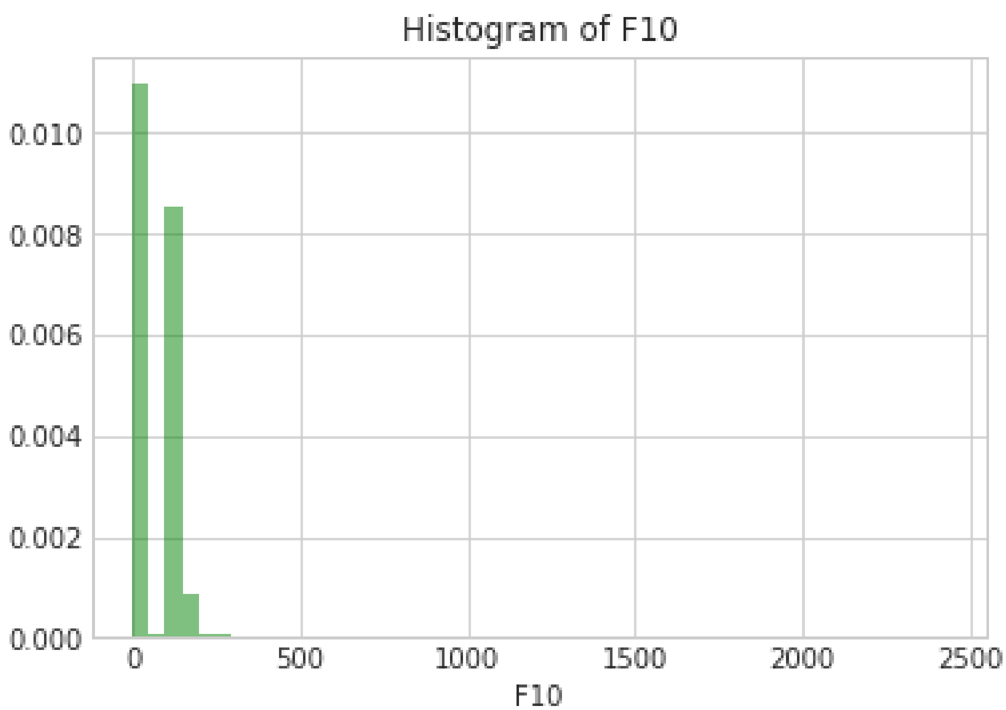
Out[116]:
```
62       1
173      1
208      1
1714     1
1932     1
2022     1
3111     1
3197     1
3723     1
3846     1
4082     1
4204     1
4553     1
4727     1
4836     1
7294     1
8129     0
8164     1
8184     1
10033    1
10138    1
10523    1
```

```
10928    1
11481    0
13326    1
13493    1
14498    1
15412    1
15518    1
15738    1
Name: Y, dtype: int64
```

~~On nothing but my intuition, I am dropping all these far left outliers.~~ I ended up dropping just the far left, and keeping the far right.

```
In [117]: data = data[data[column] > 120000]
```

```
In [118]: #data = zeroMean(data, column)
          data.F10 -= data.F10.min()
          data.F10 /= m.sqrt(data.F10.std())
          pltHist(data, column)
```




```
In [119]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F5     0.020871
```

```
F12     0.020461
F4      0.015123
F16     0.011061
F6      0.010908
F7      0.003719
F17    -0.010492
F19    -0.012023
F3     -0.012033
F10    -0.018158
Name: Y, dtype: float64
```

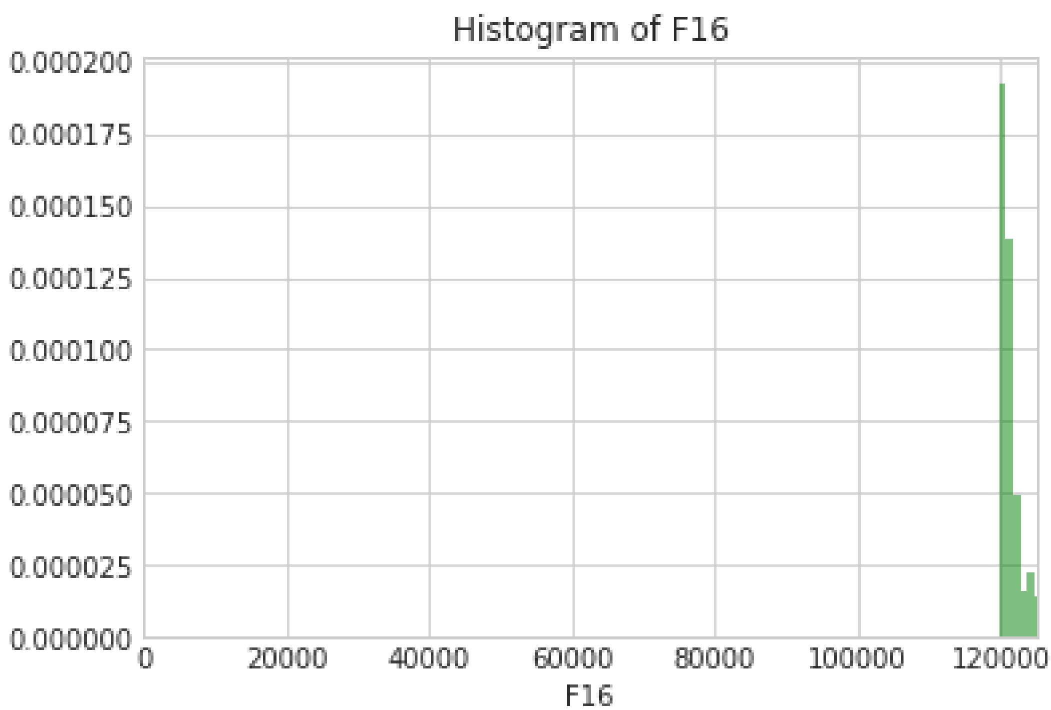
Our correlation went up. ~~Lets take the log also and see if that helps.~~ It did not help, so I removed those two cells.

F12 F12 is the same as F5, lets drop it.

```
In [120]: data.drop('F12', axis=1, inplace=True)
```

F16

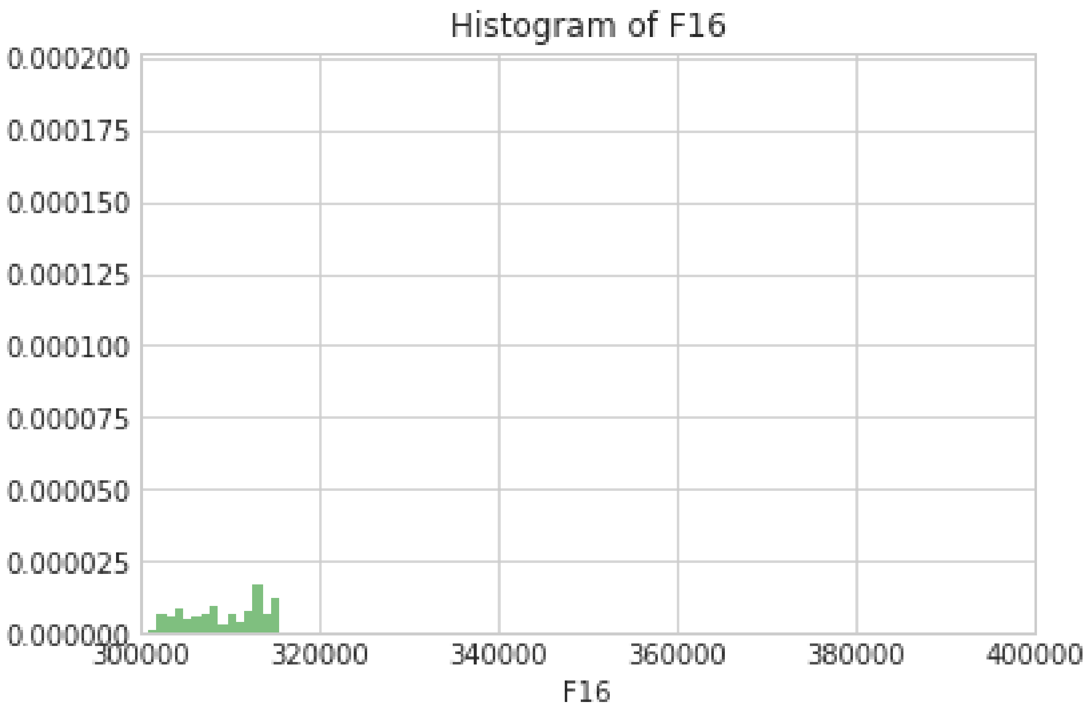
```
In [121]: column = 'F16'
          pltHist(data, column, num_bins=200)
          _ = plt.xlim([0, 125000])
```



```
In [122]: data[data[column] < 118000].count().F16
```

```
Out[122]: 0
```

```
In [123]: pltHist(data, column, num_bins=200)
          _ = plt.xlim([300000, 400000])
```

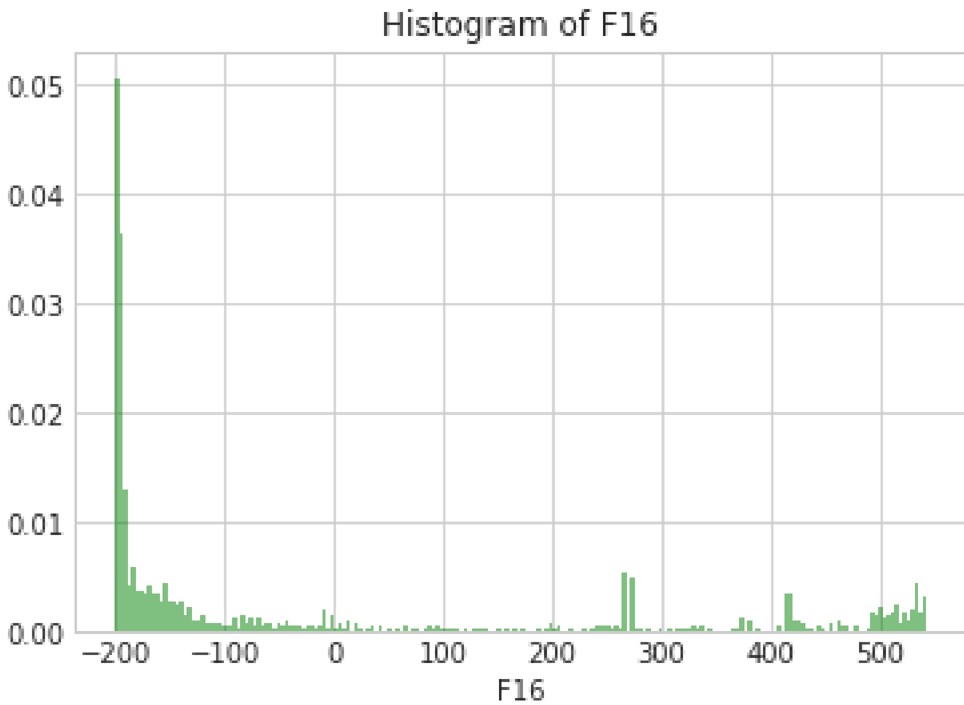



```
In [124]: data[data[column] > 320000].count().F16
```

```
Out[124]: 0
```

```
In [125]: data = zeroMean(data, column)
```

```
In [126]: pltHist(data, column, num_bins=200)
```



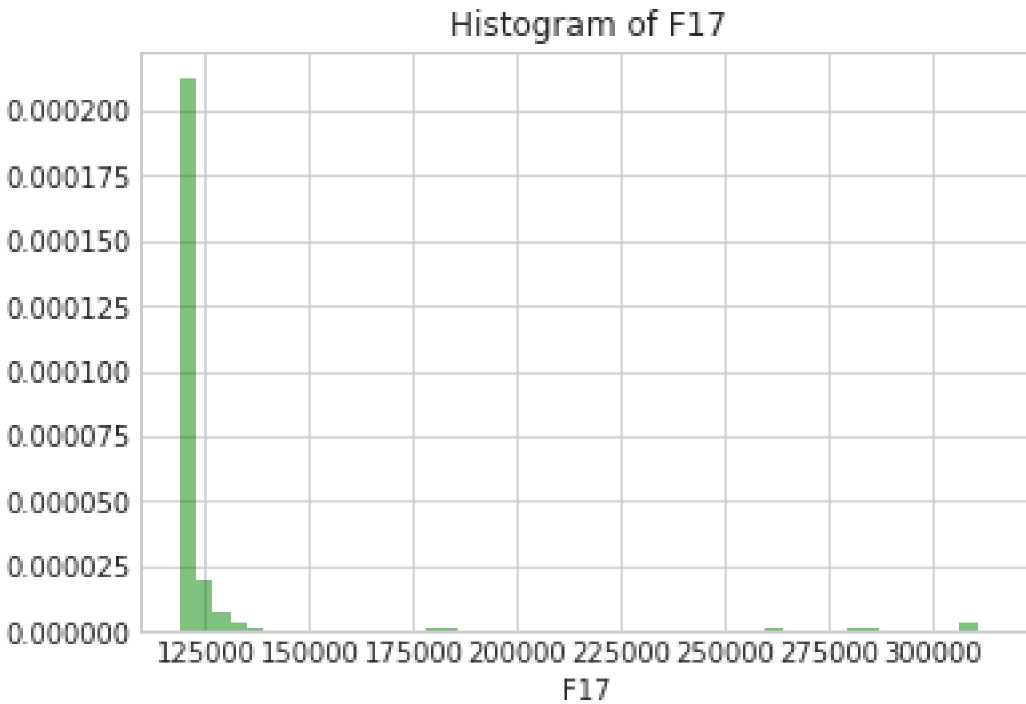

```
In [127]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F5     0.020871
F4     0.015123
F16    0.011061
F6     0.010908
F7     0.003719
F17   -0.010492
F19   -0.012023
F3    -0.012033
F10   -0.018158
Name: Y, dtype: float64
```

F16's correlation with the labels actually decreased slightly. Not sure what to do to this column. I'm going to leave it for now.

F17

```
In [128]: column = 'F17'
          pltHist(data, column)
```




```
In [129]: outliers = data[data[column] > 200000]
          corr_matrix = outliers.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F4     0.040493
F17    0.021215
F10    0.003480
F5    -0.014851
F7    -0.017980
F19   -0.027720
F6    -0.056986
F3    -0.090701
F16   -0.103681
Name: Y, dtype: float64
```

Now that is interesting. The highest correlations I have seen so far are in the data points that are the outliers on this column. ~~Lets drop all those F17 outliers, log transform it, and zero mean it, and see what happens.~~

```
In [130]: #data_copy = data[data[column] < 200000]
          #data_copy = zeroMean(data_copy, column)
          #data_copy['F17'] = np.log(data_copy['F17'])
```

```
#corr_matrix = data_copy.corr()
#print(corr_matrix['Y'].sort_values(ascending=False))
```

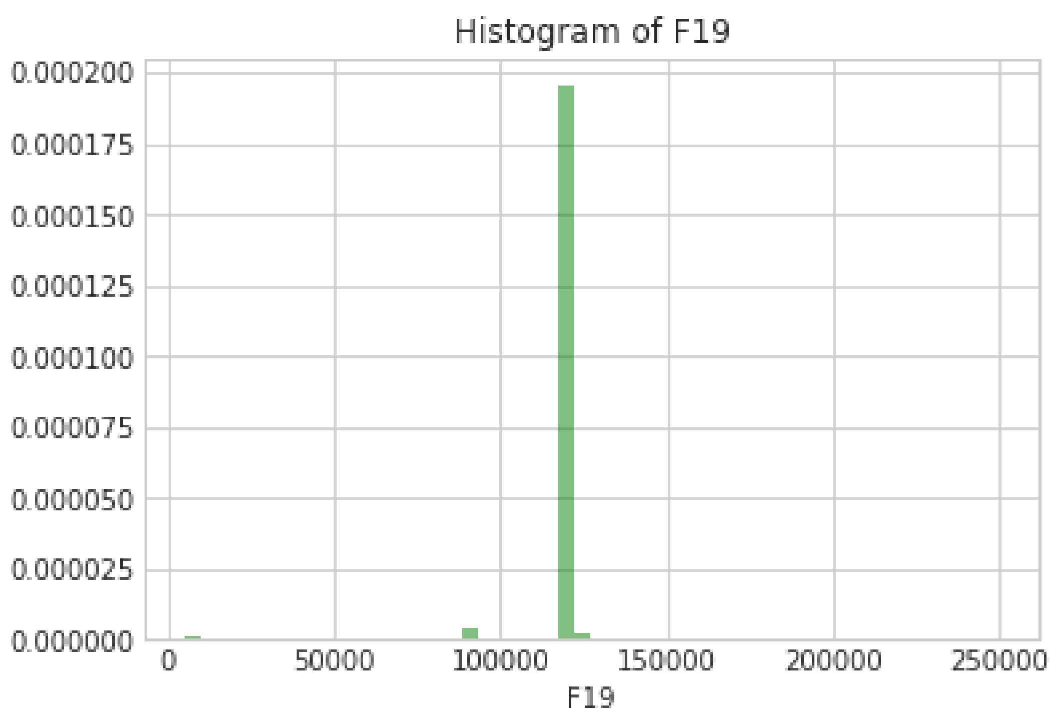
In [131]:
```
data.F17 -= data.F17.min()
data.F17 /= m.sqrt(data[column].std())
#data.F17 = np.exp(data.F17 + 1)
```

In [132]:
```
corr_matrix = data.corr()
print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
F5     0.020871
F4     0.015123
F16    0.011061
F6     0.010908
F7     0.003719
F17   -0.010492
F19   -0.012023
F3    -0.012033
F10   -0.018158
Name: Y, dtype: float64
```

F19 Lets drop the outlier and shift it.

In [133]:
```
column = 'F19'
data = data[data.F19 < 300000]
pltHist(data, column)
```



```
In [134]: data.F19 -= data.F19.mean()
          data.F19 /= m.sqrt(data.F19.std())

In [135]: corr_matrix = data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))

Y      1.000000
F5     0.020817
F4     0.015114
F16    0.011068
F6     0.010905
F7     0.003727
F17   -0.010576
F3    -0.012030
F19   -0.012408
F10   -0.018148
Name: Y, dtype: float64
```

At this point I feel satisfied with my data engineering. The correlations started poor and did not improve much so I think its time to move on to some other things. First lets see if anything I did worked.

5 Part 4 Trying to Use My Pipeline

```
In [136]: get_ipython().magic('reset -sf')
          import numpy as np
          import math as m
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          from mpl_toolkits.mplot3d import Axes3D
          from IPython.core.interactiveshell import InteractiveShell

          from pandas.plotting import scatter_matrix

          from sklearn.metrics import confusion_matrix

          from sklearn.model_selection import LeaveOneOut
          from sklearn.model_selection import train_test_split
          from sklearn.model_selection import cross_val_score
          from sklearn.linear_model import Ridge
          from sklearn.linear_model import Lasso
          from sklearn.linear_model import LogisticRegression
          from sklearn.preprocessing import StandardScaler
```

```python
from sklearn.preprocessing import LabelBinarizer
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import PolynomialFeatures

import graphviz
import lime
import xgboost as xgb
InteractiveShell.ast_node_interactivity = "all"
```

In [137]:
```python
##############################################################
# Pipeline for train.csv
##############################################################
def pipeline(data):
    # Drop empty columns
    garbage = ['F25', 'F26', 'F27']
    #if garbage in data.columns:
    data.drop(garbage, axis=1, inplace=True)

    # Drop columns with very low correlation to label
    #low_corr = ['F20', 'F23', 'F21', 'F18', 'F1', 'F24', 'F4',
    #         'F11', 'F13', 'F2', 'F15', 'F8', 'F14', 'F22']
    #data.drop(low_corr, axis=1, inplace=True)
    data.drop(['id'], axis=1, inplace=True)

    # Drop duplicate columns
    dups = ['F9', 'F12']
    data.drop(dups, axis=1, inplace=True)

    # F6
    #for i in range(10):
    #    data_point = data['F6'].idxmax()
    #    data.drop([data_point], inplace=True)
    data.F6 = np.log(data.F6)

    # F16
    data = data[data['F16'] > 115000]
    data.F16 -= data.F16.min()
    data.F16 /= m.sqrt(data.F16.std())

    # F20
    #data = data[data.F20 != 12]

    # F3
    data.F3 += 1
    data.F3 = np.log(data.F3)
```

```python
    # F4
    #data.F4 -= data.F4.mean()
    #data.F4 /= m.sqrt(data.F4.std())

    # F5
    data = data[data.F5 < 180000]
    data.F5 -= data.F5.min()
    data.F5 /= m.sqrt(data.F5.std())

    # F7
    column = 'F7'
    #data.loc[data[column] < 75000, column] = 1
    #data.loc[(data[column] < 215000) & (data[column] > 2), column] = 2
    #data.loc[data[column] > 215000, column] = 3


    # F10
    column = 'F10'
    data = data[data[column] < 200000]
    data = data[data[column] > 120000]
    data.F10 -= data.F10.min()
    data.F10 /= m.sqrt(data.F10.std())

    # F17
    column = 'F17'
    data.F17 -= data.F17.min()
    data.F17 /= m.sqrt(data[column].std())

    # F19
    data = data[data.F19 < 300000]
    data.F19 /= m.sqrt(data.F19.std())

    return data

################################################################
# Pipeline for test.csv
################################################################
def testPipeline(data):
     # Drop columns with very low correlation to label
    #low_corr = ['F20', 'F23', 'F21', 'F18', 'F1', 'F24', 'F4',
    #         'F11', 'F13', 'F2', 'F15', 'F8', 'F14', 'F22']
    #data.drop(low_corr, axis=1, inplace=True)
    data.drop(['id'], axis=1, inplace=True)

       # Drop duplicate columns
    dups = ['F9', 'F12']
    data.drop(dups, axis=1, inplace=True)
```

```
# F6
#for i in range(10):
#    data_point = data['F6'].idxmax()
#    data.drop([data_point], inplace=True)
data.F6 = np.log(data.F6 + 1)

# F16
#data = data[data['F16'] > 115000]
data.F16 -= data.F16.min()
data.F16 /= m.sqrt(data.F16.std())

# F20
#data = data[data.F20 != 12]

# F3
data.F3 += 1
data.F3 = np.log(data.F3)

# F4
#data.F4 -= data.F4.mean()
#data.F4 /= m.sqrt(data.F4.std())

# F5
#data = data[data.F5 < 180000]
data.F5 -= data.F5.min()
data.F5 /= m.sqrt(data.F5.std())

# F7
column = 'F7'
#data.loc[data[column] < 75000, column] = 1
#data.loc[(data[column] < 215000) & (data[column] > 2), column] = 2
#data.loc[data[column] > 215000, column] = 3


# F10
column = 'F10'
#data = data[data[column] < 200000]
#data = data[data[column] > 120000]
data.F10 -= data.F10.min()
data.F10 /= m.sqrt(data.F10.std())

# F17
column = 'F17'
data.F17 -= data.F17.min()
data.F17 /= m.sqrt(data[column].std())

# F19
```

```
    #data = data[data.F19 < 300000]
    data.F19 /= m.sqrt(data.F19.std())

    return data

#############################################################
# Writes a file for Kaggle Submission
#############################################################
def makeFile(pred, filename):
    new_index = np.arange(16384,32769,1)
    id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
    y_hat = pd.DataFrame(pred, columns=['Y'])
    frames = [id_col, y_hat]
    pred = pd.concat(frames, axis=1)
    pred.to_csv(filename, encoding='utf-8', index=False)
```

In [138]:
```
#############################################################
# Pipeline 2 for train.csv
#############################################################
def pipeline2(data):
    data = pipeline(data)
    features, labels = splitData(data)
    poly = PolynomialFeatures(2)
    return poly.fit_transform(features), labels

#############################################################
# Test Pipeline 2 for train.csv
#############################################################
def testPipeline2(data):
    data = testPipeline(data)
    poly = PolynomialFeatures(2)
    return poly.fit_transform(data)
```

In [139]:
```
def zeroMean(data, column):
    data[column] -= data[column].mean()
    data[column] /= m.sqrt(data[column].std())
    return data

def dropKLargest(data, column, k):
    for i in range(k):
        data_point = data[column].idxmax()
        data.drop([data_point], inplace=True)

# TODO        # check this functionality
def dropLargestBound(data, column, bound):
    data_point = data[column].idxmax()
    print(data.iloc[data_point][column])
    while(data.iloc[data_point][column] > bound):
```

```
                data.drop([data_point], axis=0, inplace=True)
                data_point = data[column].idxmax()
                print(data_point)

        # Assumes id column has already been stripped
        def splitData(data):
            labels = data['Y']
            features = data.drop(['Y'], axis=1)
            return features, labels

        def pltHist(data, column, num_bins=50):
            _ = plt.hist(data[column], num_bins, normed=1, facecolor='green', alpha = 0.5)
            _ = plt.xlabel(column)
            _ = plt.title('Histogram of {}'.format(column))
```

```
In [144]: filename = 'train.csv'
          filepath = ''
          data = pd.read_csv(filepath + filename)
```

5.1 Gradient Boosting

```
In [147]: features, labels = splitData(pipeline(data))
```

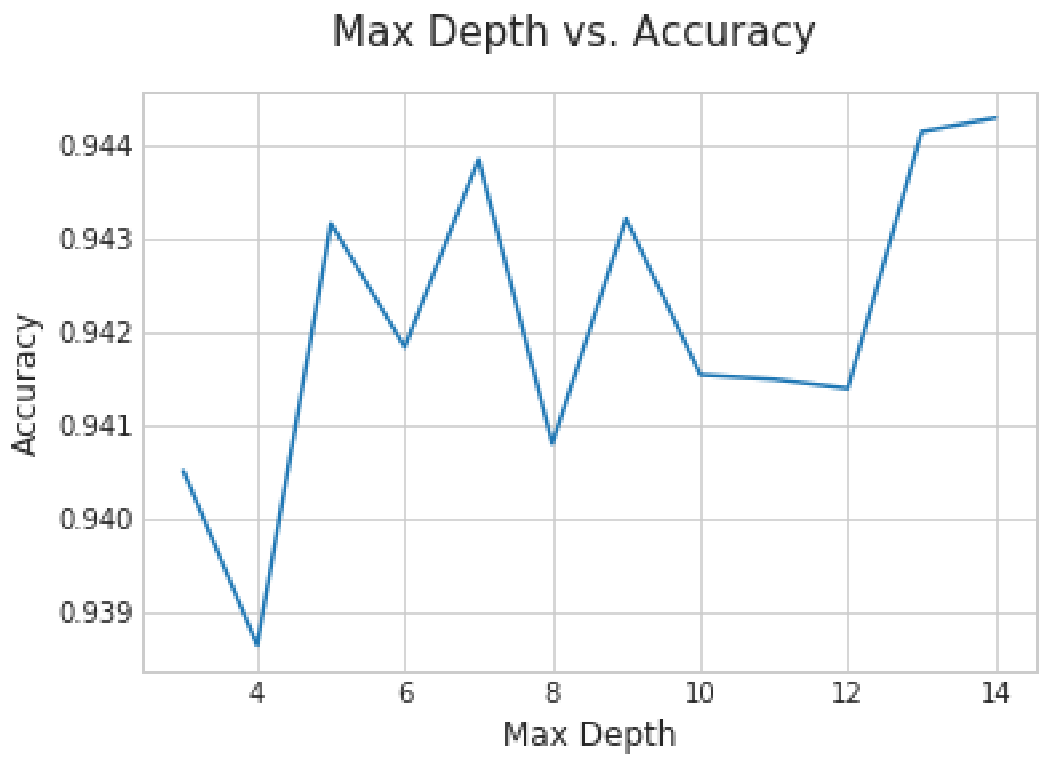
```
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/pandas/core/generic.py:3643: Setti
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self[name] = value
```

Note this cell runs for a long time

```
In [149]: # Some 5 Fold CV
          depths = np.arange(3,15,1)
          scores = np.empty((len(depths), 2))
          count = 0
          for depth in depths:
              accuracy = []
              for i in range(5):
                  X_train, X_test, y_train, y_test = train_test_split(features, labels)
                  clf = GradientBoostingClassifier(loss='exponential', learning_rate=0.1,
                                                   n_estimators=500, max_depth=depth)
                  _ = clf.fit(X_train, y_train)
                  accuracy.append(clf.score(X_test, y_test))
                  #print(accuracy)
              accuracies = np.array(accuracy)
              scores[count, 0] = np.mean(accuracies, axis=0)
```

```
            scores[count, 1] = np.std(accuracies, axis=0)
            count += 1
```

```
In [150]: _ = plt.plot(depths, scores[:,0], label="Fold {}".format(i))
          _ = plt.xlabel("Max Depth", fontsize=12)
          _ = plt.ylabel("Accuracy", fontsize=12)
          _ = plt.suptitle("Max Depth vs. Accuracy", fontsize=15)
```




```
In [151]: clf = GradientBoostingClassifier(loss='exponential', learning_rate=0.1,
                                          n_estimators=500, max_depth=14, subsample=0.5)
          _ = clf.fit(features, labels)
          test_data = pd.read_csv('test.csv')
          test_data = testPipeline(test_data)
          pred = clf.predict(test_data)
          makeFile(pred, 'prediction-pipelined-gradboost.csv')
```

Still not very impressive scores.

Lets try some polynomial data

```
In [155]: filename = 'train.csv'
          filepath = ''
          data = pd.read_csv(filepath + filename)
```

```
In [156]: poly_data, labels = pipeline2(data)
```

```
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/pandas/core/generic.py:3643: Setti
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#
  self[name] = value
```

```
In [157]: clf = GradientBoostingClassifier(loss='exponential', learning_rate=0.1,
                                           n_estimators=500, max_depth=6, subsample=0.5)
          _ = clf.fit(poly_data, labels)
```

```
In [158]: test_data = pd.read_csv('test.csv')
          test_data = testPipeline2(test_data)
          pred = clf.predict(test_data)
          makeFile(pred, 'prediction-pipelined-polynomial-gradboost.csv')
```

That one didnt do very well either.

5.2 A different direction

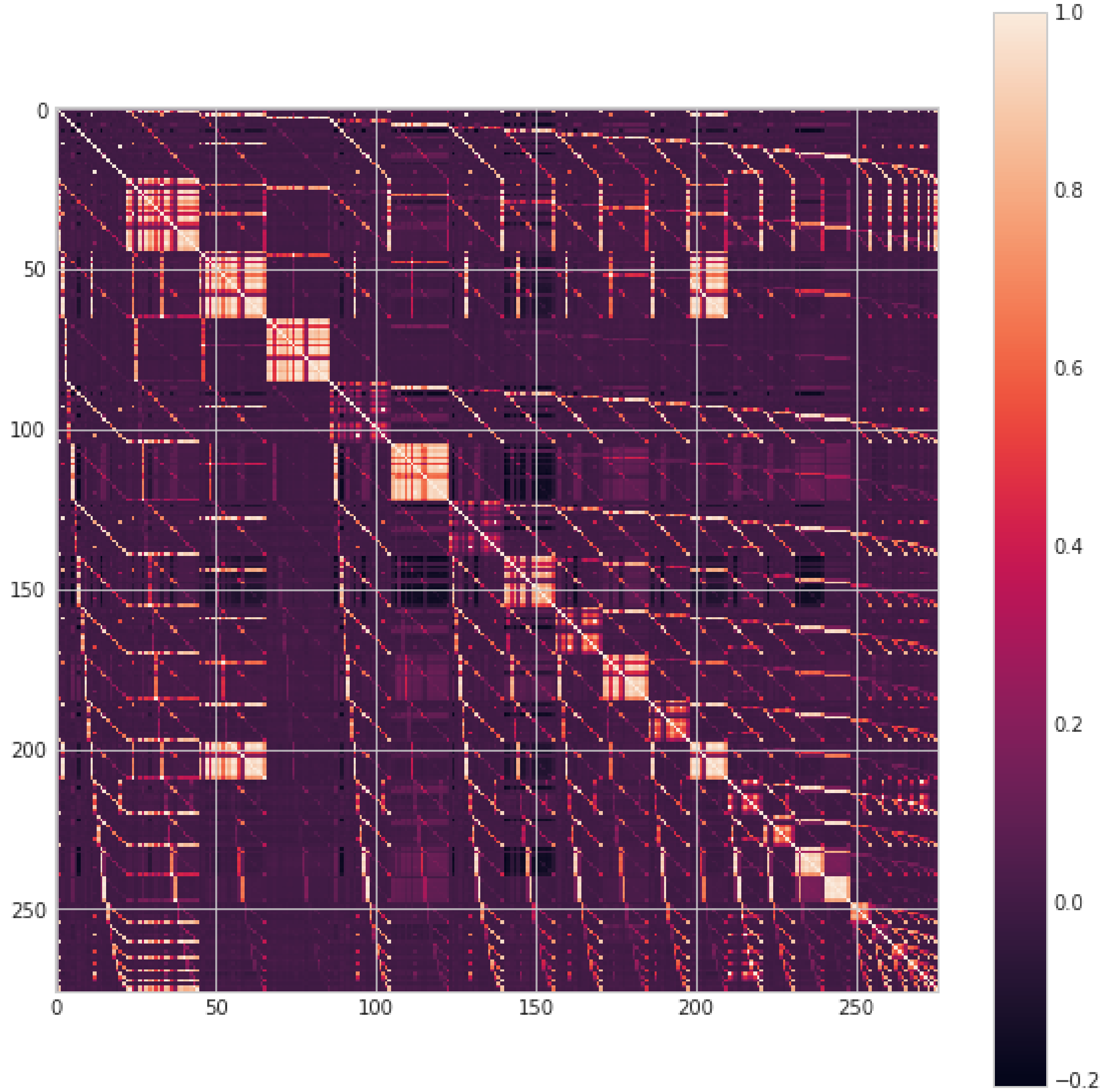
Lets polynomial fit all the features and drop the ones that have less than one percent correlation with the labels.

```
In [159]: data = pd.read_csv('train.csv')
```

```
In [160]: data = pipeline(data)
          features, labels = splitData(data)
          poly = PolynomialFeatures(2)
          poly_data = poly.fit_transform(features)
          poly_data = pd.DataFrame(poly_data[1:,1:])
          frames = [labels, poly_data]
          full_poly_data = pd.concat(frames, axis=1)
```

```
/mnt/c/programming/Kaggle-Midterm/lib/python3.5/site-packages/pandas/core/generic.py:3643: Setti
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#
  self[name] = value
```

```
In [161]: fig, ax = plt.subplots(figsize=(10,10))
          _ = plt.imshow(full_poly_data.corr())
          _ = plt.colorbar()
```




```
In [162]: corr_matrix = full_poly_data.corr()
          print(corr_matrix['Y'].sort_values(ascending=False))
```

```
Y      1.000000
88     0.017580
139    0.015357
150    0.015222
85     0.014909
6      0.014373
148    0.014148
149    0.013323
3      0.013296
152    0.012618
```

144	0.012460
151	0.012176
91	0.012104
99	0.011861
201	0.011777
57	0.011769
142	0.011768
101	0.011632
93	0.011366
153	0.010828
123	0.010788
189	0.010319
140	0.010069
222	0.009850
240	0.009566
212	0.009444
244	0.009406
96	0.009386
246	0.009352
71	0.009193
	...
160	-0.009199
273	-0.009237
34	-0.009337
229	-0.009565
228	-0.009577
170	-0.009642
178	-0.009793
180	-0.009890
125	-0.009904
179	-0.010485
76	-0.010755
27	-0.011006
138	-0.011302
129	-0.011794
174	-0.012271
182	-0.012350
5	-0.012373
133	-0.012384
122	-0.012634
137	-0.012823
108	-0.013574
121	-0.014719
26	-0.015968
64	-0.016275
208	-0.016288
23	-0.017268
32	-0.017276

```
274    -0.017730
43     -0.017960
22     -0.018199
Name: Y, Length: 276, dtype: float64
```

These correlations were so bad I didn't actually try it here. I wanted to come back to it at the end using the non engineered data set with boosted trees. It may have done better there.

6 Part 5 Boosted Trees

```
In [163]: get_ipython().magic('reset -sf')
          import numpy as np
          import math as m
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          import xgboost as xgb
```

```
In [164]: def makeSubmission(preds):
              new_index = np.arange(16384,32769,1)
              id_col = pd.DataFrame(new_index, columns=['id'], dtype='int32')
              y_hat = pd.DataFrame(preds, columns=['Y'])
              frames = [id_col, y_hat]
              pred = pd.concat(frames, axis=1)
              return pred
```

```
In [165]: data = pd.read_csv('train.csv')
          data.drop(['id'], axis=1, inplace=True)
          garbage = ['F25', 'F26', 'F27']
          data.drop(garbage, axis=1, inplace=True)
          dups = ['F12', 'F13', 'F17', 'F22', 'F24']
          data.drop(dups, axis=1, inplace=True)
```

```
In [166]: dtrain = xgb.DMatrix(data.drop('Y', axis=1), label=data.Y)
```

```
In [167]: depths = [6, 7, 8, 9, 10]
          bsts = []

          for i in range(len(depths)):
              param = {'max_depth':depths[i], 'eta':0.7, 'gamma':0.8, 'silent':1,
                       'objective':'binary:logistic', 'early_stopping_rounds':5}
              num_round = 500
              bsts.append(xgb.train(param, dtrain, num_round))
```

```
In [168]: for i in range(len(bsts)):
              test = pd.read_csv('test.csv')
              test.drop(['id'], axis=1, inplace=True)
```

```
        dups = ['F12', 'F13', 'F17', 'F22', 'F24']
        test.drop(dups, axis=1, inplace=True)
        dtest = xgb.DMatrix(test)
        pred = makeSubmission(bsts[i].predict(dtest))
        filename = 'xgboost_pred_depth_' + str(depths[i])
        pred.to_csv(filename, encoding='utf-8', index=False)
```

Those all improved my scores. Lets do the same thing with the log of the data. We are also going to lower learning rate, increase the number of rounds, and remove early stopping.

```
In [169]: data = pd.read_csv('train.csv')
          data.drop(['id'], axis=1, inplace=True)
          garbage = ['F25', 'F26', 'F27']
          data.drop(garbage, axis=1, inplace=True)
          dups = ['F12', 'F13', 'F17', 'F22', 'F24']
          data.drop(dups, axis=1, inplace=True)
          features = np.log(data.iloc[:,1:] + 1)
          labels = data.Y
```

```
In [170]: dtrain = xgb.DMatrix(features, label=labels)
          depths = [6, 7, 8, 9, 10]
          bsts = []

          for i in range(len(depths)):
              param = {'max_depth':depths[i], 'eta':0.2, 'gamma':0.8, 'silent':1,
                       'objective':'binary:logistic'}
              num_round = 700
              bsts.append(xgb.train(param, dtrain, num_round))

          for i in range(len(bsts)):
              test = pd.read_csv('test.csv')
              test.drop(['id'], axis=1, inplace=True)
              dups = ['F12', 'F13', 'F17', 'F22', 'F24']
              test.drop(dups, axis=1, inplace=True)
              test = np.log(test + 1)
              dtest = xgb.DMatrix(test)
              pred = makeSubmission(bsts[i].predict(dtest))
              filename = 'xgboost_pred_depth_' + str(depths[i]) + 'logdata'
              pred.to_csv(filename, encoding='utf-8', index=False)
```

Those did better, lets do it again, more depth and higher gamma.

```
In [171]: data = pd.read_csv('train.csv')
          data.drop(['id'], axis=1, inplace=True)
          garbage = ['F25', 'F26', 'F27']
          data.drop(garbage, axis=1, inplace=True)
          dups = ['F12', 'F13', 'F17', 'F22', 'F24']
          data.drop(dups, axis=1, inplace=True)
          features = np.log(data.iloc[:,1:] + 1)
          labels = data.Y
```

In [172]:
```
dtrain = xgb.DMatrix(features, label=labels)
depths = [9, 10, 11, 12, 13]
bsts = []

for i in range(len(depths)):
    param = {'max_depth':depths[i], 'eta':0.2, 'gamma':2, 'silent':1,
             'objective':'binary:logistic'}
    num_round = 700
    bsts.append(xgb.train(param, dtrain, num_round))

for i in range(len(bsts)):
    test = pd.read_csv('test.csv')
    test.drop(['id'], axis=1, inplace=True)
    dups = ['F12', 'F13', 'F17', 'F22', 'F24']
    test.drop(dups, axis=1, inplace=True)
    test = np.log(test + 1)
    dtest = xgb.DMatrix(test)
    pred = makeSubmission(bsts[i].predict(dtest))
    filename = 'xgboost_pred_depth_' + str(depths[i]) + '_logdata_highergamma'
    pred.to_csv(filename, encoding='utf-8', index=False)
```

Those scored a little bit higher. The highest had depth 12. Lets raise gamma again, and go one level deeper.

In [173]:
```
data = pd.read_csv('train.csv')
data.drop(['id'], axis=1, inplace=True)
garbage = ['F25', 'F26', 'F27']
data.drop(garbage, axis=1, inplace=True)
dups = ['F12', 'F13', 'F17', 'F22', 'F24']
data.drop(dups, axis=1, inplace=True)
features = np.log(data.iloc[:,1:] + 1)
labels = data.Y
dtrain = xgb.DMatrix(features, label=labels)
depths = [10, 11, 12, 13, 14]
bsts = []

for i in range(len(depths)):
    param = {'max_depth':depths[i], 'eta':0.2, 'gamma':3, 'silent':1,
             'objective':'binary:logistic'}
    num_round = 800
    bsts.append(xgb.train(param, dtrain, num_round))

for i in range(len(bsts)):
    test = pd.read_csv('test.csv')
    test.drop(['id'], axis=1, inplace=True)
    dups = ['F12', 'F13', 'F17', 'F22', 'F24']
    test.drop(dups, axis=1, inplace=True)
    test = np.log(test + 1)
```

```
        dtest = xgb.DMatrix(test)
        pred = makeSubmission(bsts[i].predict(dtest))
        filename = 'xgboost_pred_depth_' + str(depths[i]) + '_logdata_highergamma_again'
        pred.to_csv(filename, encoding='utf-8', index=False)
```

The scores went back down a little bit. Lets lower gamma, eta, and rounds.

```
In [174]: data = pd.read_csv('train.csv')
          data.drop(['id'], axis=1, inplace=True)
          garbage = ['F25', 'F26', 'F27']
          data.drop(garbage, axis=1, inplace=True)
          dups = ['F12', 'F13', 'F17', 'F22', 'F24']
          data.drop(dups, axis=1, inplace=True)
          features = np.log(data.iloc[:,1:] + 1)
          labels = data.Y
          dtrain = xgb.DMatrix(features, label=labels)
          depths = [10, 11, 12, 13, 14]
          bsts = []

          for i in range(len(depths)):
              param = {'max_depth':depths[i], 'eta':0.1, 'gamma':1.8, 'silent':1,
                       'objective':'binary:logistic'}
              num_round = 600
              bsts.append(xgb.train(param, dtrain, num_round))

          for i in range(len(bsts)):
              test = pd.read_csv('test.csv')
              test.drop(['id'], axis=1, inplace=True)
              dups = ['F12', 'F13', 'F17', 'F22', 'F24']
              test.drop(dups, axis=1, inplace=True)
              test = np.log(test + 1)
              dtest = xgb.DMatrix(test)
              pred = makeSubmission(bsts[i].predict(dtest))
              filename = 'xgboost_pred_depth_' + str(depths[i]) + '_logdata_lowergamma'
              pred.to_csv(filename, encoding='utf-8', index=False)
```

I think lowering the learning rate hurt me here. Lets bump the learning rate up and keep the gamma that did the best, which was 2.

```
In [176]: data = pd.read_csv('train.csv')
          data.drop(['id'], axis=1, inplace=True)
          garbage = ['F25', 'F26', 'F27']
          data.drop(garbage, axis=1, inplace=True)
          dups = ['F12', 'F13', 'F17', 'F22', 'F24']
          data.drop(dups, axis=1, inplace=True)
          features = np.log(data.iloc[:,1:] + 1)
          labels = data.Y
          dtrain = xgb.DMatrix(features, label=labels)
          depths = [11, 12, 13, 14]
```

```
bsts = []

for i in range(len(depths)):
    param = {'max_depth':depths[i], 'eta':0.4, 'gamma':2, 'silent':1,
             'objective':'binary:logistic'}
    num_round = 800
    bsts.append(xgb.train(param, dtrain, num_round))

for i in range(len(bsts)):
    test = pd.read_csv('test.csv')
    test.drop(['id'], axis=1, inplace=True)
    dups = ['F12', 'F13', 'F17', 'F22', 'F24']
    test.drop(dups, axis=1, inplace=True)
    test = np.log(test + 1)
    dtest = xgb.DMatrix(test)
    pred = makeSubmission(bsts[i].predict(dtest))
    filename = 'xgboost_pred_depth_' + str(depths[i]) + '_logdata_gamma_highereta'
    pred.to_csv(filename, encoding='utf-8', index=False)
```

The above cell was first run with $\eta = 0.8$ which produced a much lower score when submitted, so η was revised down to 0.4 for my final round of submissions.

7 Part 6 Conclusion

Overall, boosted trees were the obvious winner. I believe the feature engineering didn't work be

7.1 Moving Forward

Some ideas moving forward would be to:

Normalize or zero mean the features and check correlation and scores.
Try to identify the sets of data points with the highest correlation with Y and bootstra
Try using sklearn's PolyFeatures on the data set as is in combination with XGBoost, inst
Stacking prediction columns into the data set in combination with XGBoost.
Tried different boosted tree models, such as [this one](https://github.com/Microsoft/Lig

7.2 Final Submissions

I chose my final submissions based on the best scoring classifier from my several rounds of XGBo

Among the models I chose, the number of rounds was kept high, as gradient boosted trees are robu

Gamma The gamma was increased from the default of 0 to help prevent overfitting. In XGBoost, gamma is the minimum loss reduction required to make a further partition on a leaf node of the tree. Increasing this value then makes the algorithm more conservative so it generalizes better.

Tree Depth

The depth of the tree directly affects the model complexity. Higher depths decrease training err

Eta

I did not have enough time to experiment with the learning rate as much as I would have liked. I