main_notebook

October 19, 2016

1 In-Class Kaggle Competition

1.1 Rohan Nagar (ran679)

```
In [64]: import pandas as pd
         import numpy as np
         import seaborn as sns
         import matplotlib as mpl
         import matplotlib.pyplot as plt

         from sklearn.model_selection import GridSearchCV

         %matplotlib inline
```

```
In [65]: def to_file(filename, ids, preds):
             with open(filename, 'w') as f:
                 f.write('id,Y\n')
                 for num, pred in zip(ids, preds):
                     f.write('{},{}\n'.format(num, pred))
```

First, let's read in the data and check it out.

```
In [66]: train = pd.read_csv('train.csv')
         test = pd.read_csv('test.csv')
```

```
In [67]: train.describe()
```

```
Out[67]:                 id             Y            F1            F2            F3  \
         count  49998.000000  49998.000000  49998.000000  49998.000000  49998.000000
         mean   24999.500000      0.067223      1.043682      0.240510      5.272668
         std    14433.323716      0.250410      0.266339      4.161531    224.530270
         min        1.000000      0.000000      1.000000      0.000000     -0.372758
         25%    12500.250000      0.000000      1.000000      0.000000      0.038775
         50%    24999.500000      0.000000      1.000000      0.000000      0.186073
         75%    37498.750000      0.000000      1.000000      0.000000      0.563830
         max    49998.000000      1.000000     18.000000     98.000000  29110.040580

                           F4            F5            F6            F7            F8  \
         count  49998.000000  48730.000000  4.999800e+04  49998.000000  49998.000000
         mean       0.043542      0.753478  2.454196e+05      1.045302      1.041502
         std        0.256063      1.112498  3.915193e+07      0.281518      0.247753
         min        0.000000      0.000000  1.000000e+00      1.000000      1.000000
         25%        0.000000      0.000000  1.000000e+00      1.000000      1.000000
         50%        0.000000      0.000000  2.000000e+00      1.000000      1.000000
```

```
75%         0.000000       1.000000  9.000000e+00       1.000000       1.000000
max         8.000000      10.000000  8.194102e+09      23.000000       9.000000

            ...           F18            F19           F20  \
count       ...  49998.000000   40170.000000  49998.000000
mean        ...    129.306232    6665.120065      1.045362
std         ...     14.797809   17780.169263      0.266208
min         ...     98.000000       0.000000      1.000000
25%         ...    118.000000    3400.000000      1.000000
50%         ...    129.000000    5362.000000      1.000000
75%         ...    140.000000    8200.000000      1.000000
max         ...    184.000000 3008750.000000     10.000000

                 F21           F22           F23           F24           F25  \
count   49998.000000  49998.000000  49998.000000  49998.000000  49998.000000
mean       32.148846      8.446638      5.273124      1.043482      0.423617
std      3644.384303      5.121070    224.529521      0.259602      4.199845
min         0.000000      0.000000      0.000000      1.000000      0.000000
25%         0.000000      5.000000      0.030389      1.000000      0.000000
50%         0.000000      8.000000      0.154672      1.000000      0.000000
75%         1.000000     11.000000      0.555344      1.000000      0.000000
max    630367.000000     58.000000  29110.000000     10.000000     98.000000

                F26           F27
count  49998.000000  49998.000000
mean      52.306232    362.038515
std       14.797809   2212.369706
min       21.000000      0.000000
25%       41.000000      0.176205
50%       52.000000      0.366524
75%       63.000000      0.875057
max      107.000000 329664.000000

[8 rows x 29 columns]
```

We have lots of features. Let's try to explore these a little more.

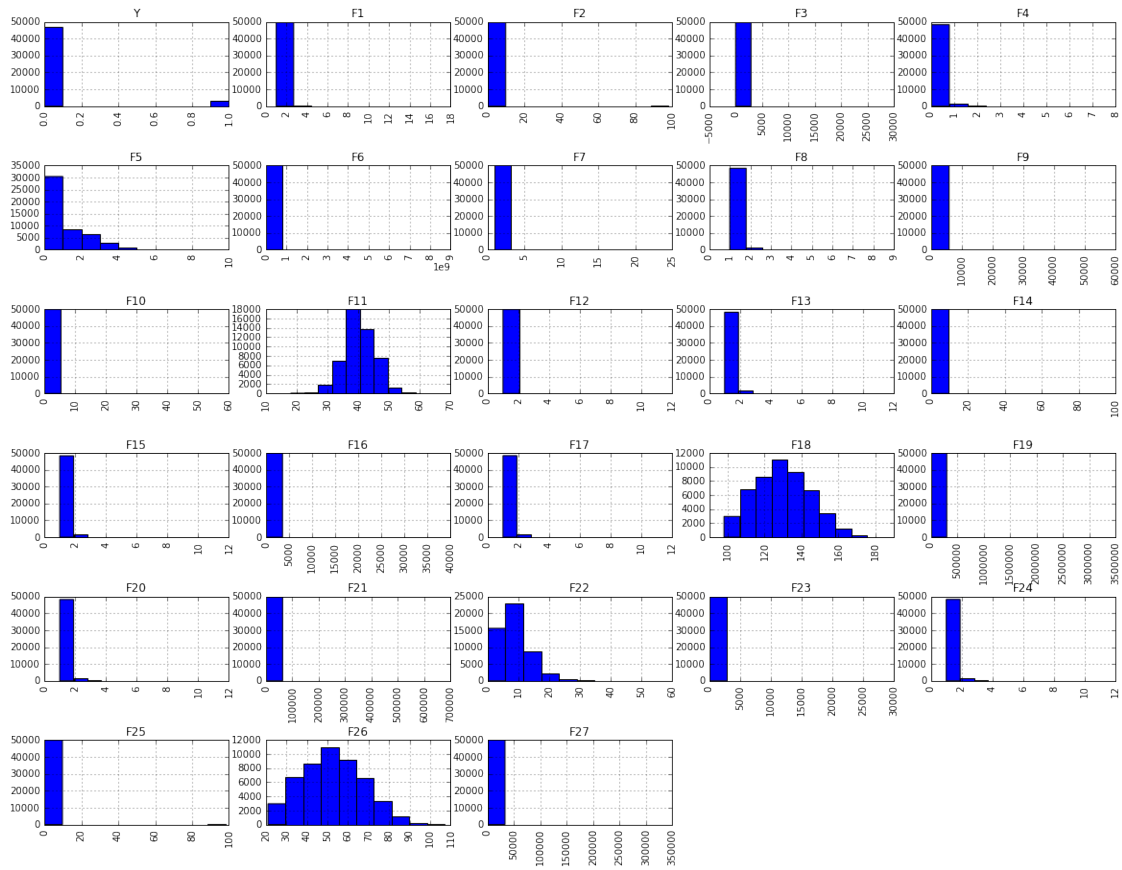
In [68]:
```
X_train = train.drop(['id', 'Y'], axis=1)
y_train = train['Y']

X_test = test.drop(['id'], axis=1)
ids = test['id']
```

In [26]:
```
def show_feature_dist(df):
    """ Plot the distribution for each feature. """
    fig = plt.figure(figsize=(20, 15))
    cols = 5
    rows = np.ceil(float(df.shape[1]) / cols)
    for i, col in enumerate(df.columns):
        ax = fig.add_subplot(rows, cols, i + 1)
        ax.set_title(col)
        if df.dtypes[col] == np.object:
            df[column].value_counts().plot(
                kind="bar", axes=ax)
        else:
```

```
                df[col].hist(axes=ax)
                plt.xticks(rotation="vertical")
        plt.subplots_adjust(hspace=0.7, wspace=0.2)
        plt.show()

    show_feature_dist(train.drop('id', axis=1))
```

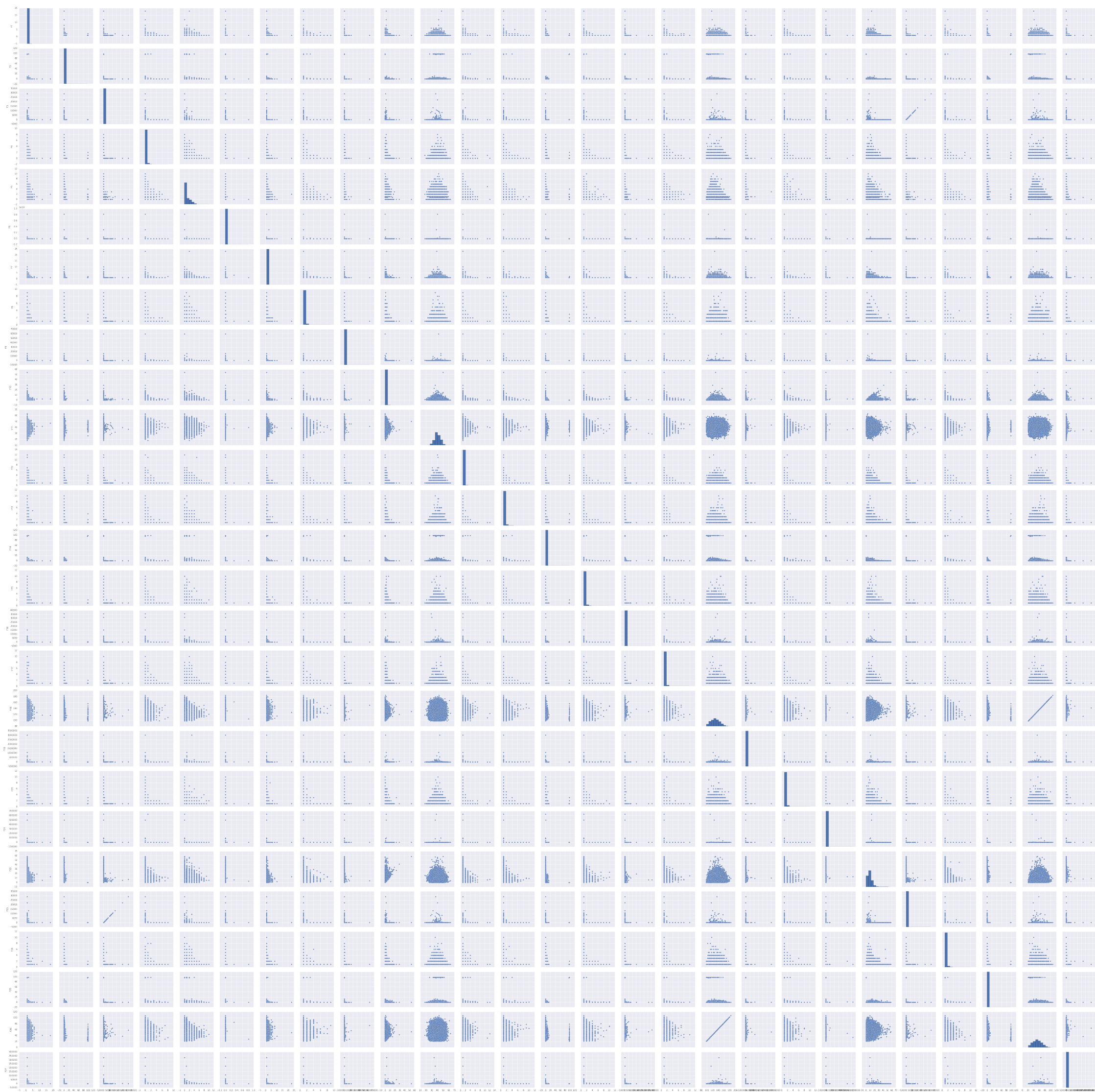


From this we can see that the classification problem for Y is lopsided. There are many more samples of class 0 than there are for class 1. We can also see that many of the features are not distributed very well. They tend to have many samples close together.

```
In [29]: sns.pairplot(X_train)
```

```
/Users/rohannagar/anaconda/lib/python3.5/site-packages/matplotlib/__init__.py:892: UserWarning: axes.colo
  warnings.warn(self.msg_depr % (key, alt_key))
```

```
Out[29]: <seaborn.axisgrid.PairGrid at 0x123b7f780>
```



From our pairplot, we can determine which features are highly correlated linearly. We can see that F18 and F26 are highly correlated, as well as F3 and F23. We can drop one from each pair to reduce our dimensionality.

In [69]:
```
# Fill NA values with the mean
train = train.fillna(train.mean())
test = test.fillna(train.mean())
train.describe()
```

Out[69]:

	id	Y	F1	F2	F3 \
count	49998.000000	49998.000000	49998.000000	49998.000000	49998.000000
mean	24999.500000	0.067223	1.043682	0.240510	5.272668
std	14433.323716	0.250410	0.266339	4.161531	224.530270
min	1.000000	0.000000	1.000000	0.000000	-0.372758
25%	12500.250000	0.000000	1.000000	0.000000	0.038775
50%	24999.500000	0.000000	1.000000	0.000000	0.186073
75%	37498.750000	0.000000	1.000000	0.000000	0.563830

```
max    49998.000000      1.000000     18.000000     98.000000  29110.040580

                 F4            F5            F6            F7            F8  \
count  49998.000000  49998.000000  4.999800e+04  49998.000000  49998.000000
mean       0.043542      0.753478  2.454196e+05      1.045302      1.041502
std        0.256063      1.098300  3.915193e+07      0.281518      0.247753
min        0.000000      0.000000  1.000000e+00      1.000000      1.000000
25%        0.000000      0.000000  1.000000e+00      1.000000      1.000000
50%        0.000000      0.000000  2.000000e+00      1.000000      1.000000
75%        0.000000      1.000000  9.000000e+00      1.000000      1.000000
max        8.000000     10.000000  8.194102e+09     23.000000      9.000000

           ...           F18             F19           F20  \
count      ...  49998.000000    49998.000000  49998.000000
mean       ...    129.306232     6665.120065      1.045362
std        ...     14.797809    15937.104788      0.266208
min        ...     98.000000        0.000000      1.000000
25%        ...    118.000000     3862.000000      1.000000
50%        ...    129.000000     6526.500000      1.000000
75%        ...    140.000000     7350.000000      1.000000
max        ...    184.000000  3008750.000000     10.000000

                 F21           F22           F23           F24           F25  \
count   49998.000000  49998.000000  49998.000000  49998.000000  49998.000000
mean       32.148846      8.446638      5.273124      1.043482      0.423617
std      3644.384303      5.121070    224.529521      0.259602      4.199845
min         0.000000      0.000000      0.000000      1.000000      0.000000
25%         0.000000      5.000000      0.030389      1.000000      0.000000
50%         0.000000      8.000000      0.154672      1.000000      0.000000
75%         1.000000     11.000000      0.555344      1.000000      0.000000
max    630367.000000     58.000000  29110.000000     10.000000     98.000000

                F26            F27
count  49998.000000   49998.000000
mean      52.306232     362.038515
std       14.797809    2212.369706
min       21.000000       0.000000
25%       41.000000       0.176205
50%       52.000000       0.366524
75%       63.000000       0.875057
max      107.000000  329664.000000

[8 rows x 29 columns]
```

In [70]:
```
X_train = train.drop(['id', 'Y'], axis=1)
y_train = train['Y']

X_test = test.drop(['id'], axis=1)
ids = test['id']
```

In [71]:
```
# Drop highly correlated features
X_train = X_train.drop(['F18', 'F3'], axis=1)
X_test = X_test.drop(['F18', 'F3'], axis=1)
```

1.2 Model Testing

```
In [43]: def print_cv_results(model):
             print("Best parameter set found:\n")
             print(model.best_params_)
             print()
             for params, mean_score, scores in model.grid_scores_:
                 print("{0:.3f} (+/-{1:.03f}) for {2}".format(mean_score, scores.std() * 2, params))
             print()
```

1.2.1 Logistic Regression

```
In [54]: from sklearn.linear_model import LogisticRegression

         params = {
             'penalty': ['l1', 'l2'],
             'C': [0.001, 0.01, 0.05, 0.1],
         }

         regr = GridSearchCV(LogisticRegression(), params, cv=10, n_jobs=-1, scoring='roc_auc')
         regr.fit(X_train, y_train)

         print("Best parameter set found on development set with cv=10:\n")
         print(regr.best_params_)
         print()
         for params, mean_score, scores in regr.grid_scores_:
             print("{0:.3f} (+/-{1:.03f}) for {2}".format(mean_score, scores.std() * 2, params))
         print()
```

```
Best parameter set found on development set with cv=10:

{'C': 0.1, 'penalty': 'l1'}

0.649 (+/-0.034) for {'C': 0.001, 'penalty': 'l1'}
0.636 (+/-0.033) for {'C': 0.001, 'penalty': 'l2'}
0.686 (+/-0.028) for {'C': 0.01, 'penalty': 'l1'}
0.636 (+/-0.033) for {'C': 0.01, 'penalty': 'l2'}
0.688 (+/-0.030) for {'C': 0.05, 'penalty': 'l1'}
0.636 (+/-0.034) for {'C': 0.05, 'penalty': 'l2'}
0.692 (+/-0.023) for {'C': 0.1, 'penalty': 'l1'}
0.636 (+/-0.034) for {'C': 0.1, 'penalty': 'l2'}

/Users/rohannagar/anaconda/lib/python3.5/site-packages/sklearn/model_selection/_search.py:662: Deprecati
  DeprecationWarning)
```

Our best score was 0.692, which is not very good. Let's train this model anyway so we can possibly use it in an ensemble later.

```
In [16]: from sklearn.linear_model import LogisticRegression

         regr = LogisticRegression(C=0.1, penalty='l1')
         regr.fit(X_train, y_train)
         preds = regr.predict_proba(X_test)[:, 1]
         to_file('logistic_regression.csv', ids, preds)
```

1.2.2 XGB

```
In [8]: import xgboost as xgb
        from sklearn.model_selection import RandomizedSearchCV

        parameters = {
            'max_depth': [6, 7, 8],
            'learning_rate': [0.1, 0.01],
            'n_estimators': [100, 200],
            'min_child_weight': [1/(0.05**(1/2)), 1/(0.95**(1/2))],
            'colsample_bytree': [0.4, 0.5]
        }

        xg_clf = RandomizedSearchCV(xgb.XGBClassifier(), parameters, n_iter=20, cv=10, n_jobs=-1, scorin
        xg_clf.fit(X_train, y_train)

        print("Best parameter set found on development set with cv=10:\n")
        print(xg_clf.best_params_)
        print()
        for params, mean_score, scores in xg_clf.grid_scores_:
            print("{0:.3f} (+/-{1:.03f}) for {2}".format(mean_score, scores.std() * 2, params))
        print()
```

```
Best parameter set found on development set with cv=10:

{'max_depth': 8, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight': 4.47213595499958, 'n

0.859 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.856 (+/-0.018) for {'max_depth': 6, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.858 (+/-0.018) for {'max_depth': 6, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.855 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':
0.860 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.01, 'colsample_bytree': 0.5, 'min_child_weight':
0.859 (+/-0.016) for {'max_depth': 7, 'learning_rate': 0.01, 'colsample_bytree': 0.5, 'min_child_weight':
0.858 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':
0.857 (+/-0.018) for {'max_depth': 7, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':
0.855 (+/-0.017) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.851 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.856 (+/-0.017) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.852 (+/-0.016) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.4, 'min_child_weight':
0.858 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight':
0.856 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':
0.858 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight':
0.860 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight':
0.853 (+/-0.019) for {'max_depth': 7, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':
0.859 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight':
0.860 (+/-0.018) for {'max_depth': 8, 'learning_rate': 0.01, 'colsample_bytree': 0.4, 'min_child_weight':
0.854 (+/-0.017) for {'max_depth': 6, 'learning_rate': 0.1, 'colsample_bytree': 0.5, 'min_child_weight':

/Users/rohannagar/anaconda/lib/python3.5/site-packages/sklearn/model_selection/_search.py:662: Deprecati
  DeprecationWarning)
```

Here we did much better. 0.860 was our best score! Let's train this one.

```
In [9]: xg = xgb.XGBClassifier(max_depth=8, learning_rate=0.3, n_estimators=155, min_child_weight=0.6, s
        xg.fit(X_train, y_train)
        preds = xg.predict_proba(X_test)[:, 1]
        to_file('xgb.csv', ids, preds)
```

1.2.3 Random Forest

This one actually does quite well with the parameters already set as shown.

```
In [7]: from sklearn.ensemble import RandomForestClassifier

        rf = RandomForestClassifier(n_estimators=2000, criterion='entropy', max_features='auto', bootst
        rf.fit(X_train, y_train)
        preds = rf.predict_proba(X_test)[:, 1]
        to_file('random_forest.csv', ids, preds)
```

1.2.4 AdaBoost

```
In [59]: from sklearn.ensemble import AdaBoostClassifier

         param_grid = [
             {'n_estimators': [1000],
              'learning_rate': [0.1, 1],
             },
         ]

         cv = 10
         ab_clf = GridSearchCV(AdaBoostClassifier(),
                               param_grid=param_grid, cv=cv, n_jobs=-1, scoring='roc_auc')
         ab_clf.fit(X_train, y_train)

         print_cv_results(ab_clf)
```

```
Best parameter set found:

{'n_estimators': 1000, 'learning_rate': 0.1}

0.855 (+/-0.021) for {'n_estimators': 1000, 'learning_rate': 0.1}
0.840 (+/-0.024) for {'n_estimators': 1000, 'learning_rate': 1}

/Users/rohannagar/anaconda/lib/python3.5/site-packages/sklearn/model_selection/_search.py:662: Deprecati
  DeprecationWarning)
```

AdaBoost does well too!

```
In [15]: from sklearn.ensemble import AdaBoostClassifier

         ab = AdaBoostClassifier(n_estimators=1000, learning_rate=0.1)
         ab.fit(X_train, y_train)
         preds = ab.predict_proba(X_test)[:, 1]
         to_file('adaboost.csv', ids, preds)
```

1.2.5 K-Nearest Neighbors

```
In [11]: from sklearn.neighbors import KNeighborsClassifier

         params = {
             'n_neighbors': [500, 750, 1000],
             'weights': ['distance']
         }
```

```
knn = GridSearchCV(KNeighborsClassifier(), param_grid=params, cv=10, n_jobs=-1, scoring='roc_a
knn.fit(X_train, y_train)

print_cv_results(knn)
```

```
Best parameter set found:

{'n_neighbors': 500, 'weights': 'distance'}

0.615 (+/-0.038) for {'n_neighbors': 500, 'weights': 'distance'}
0.612 (+/-0.042) for {'n_neighbors': 750, 'weights': 'distance'}
0.611 (+/-0.042) for {'n_neighbors': 1000, 'weights': 'distance'}

/Users/rohannagar/anaconda/lib/python3.5/site-packages/sklearn/model_selection/_search.py:662: Deprecati
  DeprecationWarning)
```

KNN didn't do so well, along the same lines as logistic regression.

1.2.6 Naive Bayes

```
In [17]: from sklearn.naive_bayes import GaussianNB
         from sklearn.model_selection import cross_val_score

         gnb = GaussianNB()
         score = cross_val_score(gnb, X=X_train, y=y_train, scoring='roc_auc', cv=15, n_jobs=-1)
         print(score)
         print(score.mean())
```

```
[ 0.50001143  0.5061122   0.51623455  0.54630709  0.56975141  0.52200409
  0.49054588  0.50741798  0.53882593  0.49631686  0.50011775  0.5377016
  0.50313965  0.49719277  0.53224797]
0.517595143588
```

Naive Bayes definitely didn't do well on our dataset. There are not really any parameters to adjust with this model, so this is the best we can get.

1.2.7 Tensor Flow Neural Net

```
In [11]: import skflow
         from sklearn.model_selection import cross_val_score

         classifier = skflow.TensorFlowDNNClassifier(hidden_units=[5], n_classes=2, steps=50000, learnin
         # classifier.fit(X_train, y_train)
         # score = accuracy_score(classifier.predict(indep_test), dep_test)
         # print("Accuracy: %f" % score)
         score = cross_val_score(classifier, X=X_train, y=y_train, scoring='roc_auc', cv=10, n_jobs=-1)
         print(score)
         print(score.mean())
```

```
[ 0.50192967  0.50130687  0.50033214  0.50150086  0.50160806  0.50171527
  0.50182247  0.50160841  0.49990298  0.49979608]
0.501152280851
Step #1, avg. loss: 1324.83167
Step #1, avg. loss: 1435.33801
Step #1, avg. loss: 1452.96289
Step #1, avg. loss: 1376.14307
```

```
Step #5001, epoch #3, avg. loss: 0.42124Step #5001, epoch #3, avg. loss: 82.00351Step #5001, epoch #3, a

Step #10001, epoch #7, avg. loss: 0.25577Step #10001, epoch #7, avg. loss: 0.24530Step #10001, epoch #7

Step #15001, epoch #10, avg. loss: 0.24665Step #15001, epoch #10, avg. loss: 0.24667Step #15001, epoch

Step #20001, epoch #14, avg. loss: 0.24614Step #20001, epoch #14, avg. loss: 0.24604Step #20001, epoch

Step #25001, epoch #17, avg. loss: 0.24644Step #25001, epoch #17, avg. loss: 0.24627Step #25001, epoch

Step #30001, epoch #21, avg. loss: 0.24634Step #30001, epoch #21, avg. loss: 0.24745Step #30001, epoch

Step #35001, epoch #24, avg. loss: 0.24666Step #35001, epoch #24, avg. loss: 0.24500Step #35001, epoch

Step #40001, epoch #28, avg. loss: 0.24657Step #40001, epoch #28, avg. loss: 0.24676Step #40001, epoch

Step #45001, epoch #31, avg. loss: 0.24596Step #45001, epoch #31, avg. loss: 0.24601Step #45001, epoch

Step #1, avg. loss: 1483.82751Step #1, avg. loss: 1458.41089Step #1, avg. loss: 1531.44812Step #1, avg.

Step #5001, epoch #3, avg. loss: 0.65653Step #5001, epoch #3, avg. loss: 0.30957Step #5001, epoch #3, a

Step #10001, epoch #7, avg. loss: 0.24748Step #10001, epoch #7, avg. loss: 0.24715Step #10001, epoch #7

Step #15001, epoch #10, avg. loss: 0.24554Step #15001, epoch #10, avg. loss: 0.24617Step #15001, epoch

Step #20001, epoch #14, avg. loss: 0.24725Step #20001, epoch #14, avg. loss: 0.24688Step #20001, epoch
```

```
Step #25001, epoch #17, avg. loss: 0.24636Step #25001, epoch #17, avg. loss: 0.24622Step #25001, epoch #

Step #30001, epoch #21, avg. loss: 0.24641Step #30001, epoch #21, avg. loss: 0.24613Step #30001, epoch #

Step #35001, epoch #24, avg. loss: 0.24581Step #35001, epoch #24, avg. loss: 0.24638Step #35001, epoch #

Step #40001, epoch #28, avg. loss: 0.24680Step #40001, epoch #28, avg. loss: 0.24672Step #40001, epoch #

Step #45001, epoch #31, avg. loss: 0.24641Step #45001, epoch #31, avg. loss: 0.24575Step #45001, epoch #

Step #1, avg. loss: 1494.09448Step #1, avg. loss: 1430.63806

Step #5001, epoch #3, avg. loss: 0.65514Step #5001, epoch #3, avg. loss: 0.65416

Step #10001, epoch #7, avg. loss: 0.24771Step #10001, epoch #7, avg. loss: 0.24762

Step #15001, epoch #10, avg. loss: 0.24547Step #15001, epoch #10, avg. loss: 0.24561

Step #20001, epoch #14, avg. loss: 0.24696Step #20001, epoch #14, avg. loss: 0.24672

Step #25001, epoch #17, avg. loss: 0.24636Step #25001, epoch #17, avg. loss: 0.24650

Step #30001, epoch #21, avg. loss: 0.24643Step #30001, epoch #21, avg. loss: 0.24658

Step #35001, epoch #24, avg. loss: 0.24580Step #35001, epoch #24, avg. loss: 0.24649

Step #40001, epoch #28, avg. loss: 0.24640Step #40001, epoch #28, avg. loss: 0.24620

Step #45001, epoch #31, avg. loss: 0.24654Step #45001, epoch #31, avg. loss: 0.24649

/Users/rohannagar/anaconda/lib/python3.5/site-packages/skflow/io/data_feeder.py:217: VisibleDeprecationW
  out.itemset((i, self.y[sample]), 1.0)
/Users/rohannagar/anaconda/lib/python3.5/site-packages/skflow/io/data_feeder.py:217: VisibleDeprecationW
  out.itemset((i, self.y[sample]), 1.0)
/Users/rohannagar/anaconda/lib/python3.5/site-packages/skflow/io/data_feeder.py:217: VisibleDeprecationW
  out.itemset((i, self.y[sample]), 1.0)
/Users/rohannagar/anaconda/lib/python3.5/site-packages/skflow/io/data_feeder.py:217: VisibleDeprecationW
  out.itemset((i, self.y[sample]), 1.0)
```

In [13]:
```
classifier = skflow.TensorFlowDNNClassifier(hidden_units=[5, 3, 4], n_classes=2, steps=50000, 
classifier.fit(X_train, y_train)
preds = classifier.predict_proba(X_test)[:, 1]
to_file('tnn2.csv', ids, preds)
```

```
Step #1, avg. loss: 21.75230
Step #5001, epoch #3, avg. loss: 0.33075
Step #10001, epoch #6, avg. loss: 0.24657
Step #15001, epoch #9, avg. loss: 0.24605
Step #20001, epoch #12, avg. loss: 0.24647
Step #25001, epoch #15, avg. loss: 0.25024
Step #30001, epoch #19, avg. loss: 0.24674
Step #35001, epoch #22, avg. loss: 0.24712
Step #40001, epoch #25, avg. loss: 0.24585
Step #45001, epoch #28, avg. loss: 0.24632

/Users/rohannagar/anaconda/lib/python3.5/site-packages/skflow/io/data_feeder.py:217: VisibleDeprecationW
  out.itemset((i, self.y[sample]), 1.0)
```

1.3 Ensembling

1.3.1 Ranked Average

Ranked average should be a good way to ensemble the results we've been getting from our previous models. Looking at the Kaggle forums here https://www.kaggle.com/c/predict-west-nile-virus/forums/t/14381/combine-models-result/81209, I was able to use code that people had described in the forums for rank-averaging.

See also: http://mlwave.com/kaggle-ensembling-guide/

Basically you rank the outputs, average the ranks, and then scale the ranks for the final result.

```
In [58]: from collections import defaultdict

         def rank_avg(files, outfile):
             with open(outfile, 'w') as out:
                 ranks = defaultdict(list)
                 for i, f in enumerate(files):
                     file_ranks = []

                     lines = open(f).readlines()
                     lines = [lines[0]] + sorted(lines[1:])
                     for e, line in enumerate(lines):
                         if e > 0:
                             r = line.strip().split(",")
                             file_ranks.append((float(r[1]), e, r[0]))

                     for rank, item in enumerate(sorted(file_ranks)):
                         ranks[(item[1],item[2])].append(rank)

                 average_ranks = []
                 for k in sorted(ranks):
                     average_ranks.append((sum(ranks[k])/len(ranks[k]), k))

                 ranked_ranks = []
                 for rank, k in enumerate(sorted(average_ranks)):
                     ranked_ranks.append((k[1][0], k[1][1], rank/(len(average_ranks) - 1)))

                 out.write('id,Y\n')
                 for k in sorted(ranked_ranks):
                     out.write('{},{}\n'.format(k[1], k[2]))
```

```
In [ ]: files = ['logistic_regression.csv', # Logistic Regression
                 'xgb.csv', # XGBoost
                 'random_forest.csv', # Random Forest
                 'adaboost.csv', # AdaBoost
                ]

        outfile = 'ranked_avg.csv'
        rank_avg(files, outfile)
```

1.3.2 Stacking

```
In [57]: # Use logistic regression as a feature
         preds = regr.predict_proba(X_train)[:, 1]
         X_train_lg = X_train
         X_train_lg['lg'] = preds

         preds = regr.predict_proba(X_test)[:, 1]
         X_test_lg = X_test
         X_test_lg['lg'] = preds
```

```
In [45]: # Train AdaBoost
         ab = AdaBoostClassifier(n_estimators=1000, learning_rate=0.1)
         ab.fit(X_train_lg, y_train)
```

```
In [58]: # Use AdaBoost as feature
         preds = ab.predict_proba(X_train_lg)[:, 1]
         X_train_lg_ab = X_train_lg
         X_train_lg_ab['ab'] = preds

         preds = ab.predict_proba(X_test_lg)[:, 1]
         X_test_lg_ab = X_test_lg
         X_test_lg_ab['ab'] = preds
```

```
In [60]: from sklearn.ensemble import RandomForestClassifier

         # Train Random Forest
         rf = RandomForestClassifier(n_estimators=2000, criterion='entropy', max_features='auto', boots
         rf.fit(X_train_lg_ab, y_train)
         preds = rf.predict_proba(X_test_lg_ab)[:, 1]
         to_file('logistic_adaboost_randomforest.csv', ids, preds)
```

```
In [61]: # Use RF as feature
         preds = rf.predict_proba(X_train_lg_ab)[:, 1]
         X_train_lg_ab_rf = X_train_lg_ab
         X_train_lg_ab_rf['rf'] = preds

         preds = rf.predict_proba(X_test_lg_ab)[:, 1]
         X_test_lg_ab_rf = X_test_lg_ab
         X_test_lg_ab_rf['rf'] = preds
```

```
In [63]: import xgboost as xgb

         # Train XGB
         xg = xgb.XGBClassifier(max_depth=8, learning_rate=0.3, n_estimators=155, min_child_weight=0.6,
         xg.fit(X_train_lg_ab_rf, y_train)
         preds = xg.predict_proba(X_test_lg_ab_rf)[:, 1]
         to_file('logistic_adaboost_randomforest_xgb.csv', ids, preds)
```

1.3.3 Try a different order

In [72]:
```
# Use logistic regression as a feature
preds = regr.predict_proba(X_train)[:, 1]
X_train_lg = X_train
X_train_lg['lg'] = preds

preds = regr.predict_proba(X_test)[:, 1]
X_test_lg = X_test
X_test_lg['lg'] = preds
```

In [73]:
```
# Train XGB
xg = xgb.XGBClassifier(max_depth=8, learning_rate=0.3, n_estimators=155, min_child_weight=0.6,
xg.fit(X_train_lg, y_train)
```

Out[73]:
```
XGBClassifier(base_score=0.5, colsample_bylevel=1, colsample_bytree=0.45,
       gamma=0, learning_rate=0.3, max_delta_step=0, max_depth=8,
       min_child_weight=0.6, missing=None, n_estimators=155, nthread=-1,
       objective='binary:logistic', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1.0)
```

In [74]:
```
# Use XGB as feature
preds = xg.predict_proba(X_train_lg)[:, 1]
X_train_lg_xg = X_train_lg
X_train_lg_xg['xg'] = preds

preds = xg.predict_proba(X_test_lg)[:, 1]
X_test_lg_xg = X_test_lg
X_test_lg_xg['xg'] = preds
```

In [75]:
```
# Train Random Forest
rf = RandomForestClassifier(n_estimators=2000, criterion='entropy', max_features='auto', boots
rf.fit(X_train_lg_xg, y_train)
```

Out[75]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_split=1e-07, min_samples_leaf=1,
            min_samples_split=2, min_weight_fraction_leaf=0.0,
            n_estimators=2000, n_jobs=1, oob_score=False,
            random_state=None, verbose=0, warm_start=False)
```

In [76]:
```
# Use RF as feature
preds = rf.predict_proba(X_train_lg_xg)[:, 1]
X_train_lg_xg_rf = X_train_lg_xg
X_train_lg_xg_rf['rf'] = preds

preds = rf.predict_proba(X_test_lg_xg)[:, 1]
X_test_lg_xg_rf = X_test_lg_xg
X_test_lg_xg_rf['rf'] = preds
```

In [78]:
```
# Train AdaBoost
ab = AdaBoostClassifier(n_estimators=1000, learning_rate=0.1)
ab.fit(X_train_lg_xg_rf, y_train)
preds = ab.predict_proba(X_test_lg_xg_rf)[:, 1]
to_file('logistic_xgb_randomforest_adaboost.csv', ids, preds)
```