Pump it Up: Data Mining the Water Table - Classification Rate: .8243

Load libraries:

In [24]:
```
import numpy as np
import pandas as pd
import random
import scipy
from scipy.stats import skew
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Load the data:

In [25]:
```
watertrain = pd.read_csv("/Users/cris/Desktop/Courses/Second Semester/M
achine Learning II/Assignment 2/watertrain.csv")
watertest = pd.read_csv("/Users/cris/Desktop/Courses/Second Semester/Ma
chine Learning II/Assignment 2/watertest.csv")
target = pd.read_csv("/Users/cris/Desktop/Courses/Second Semester/Machi
ne Learning II/Assignment 2/watertrainlab.csv")
```

Next, lets take a look at the shape and the distribution of the target variable.

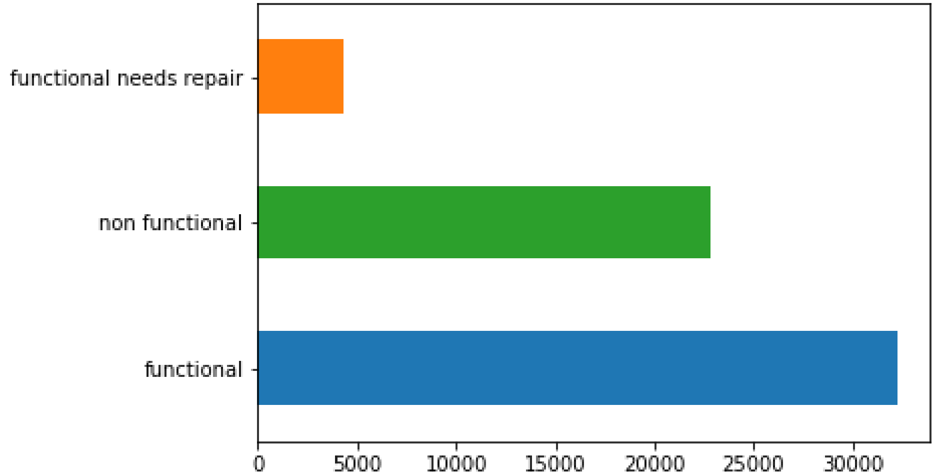
In [26]:
```
print("training data shape: ",watertrain.shape,"\ntesting data shape: "
, watertest.shape)
palette=[sns.color_palette()[0],sns.color_palette()[2],sns.color_palett
e()[1]]

# get counts for each
target.status_group.value_counts().plot(kind='barh', color=palette)
target.groupby('status_group').nunique()
```

```
training data shape:  (59400, 40)
testing data shape:  (14850, 40)
```

Out[26]:

	id	status_group
status_group		
functional	32259	1
functional needs repair	4317	1
non functional	22824	1



In [27]:

```
# take a quick look at the data
watertrain.head()
```

Out[27]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitu
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.85632

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitu
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.14746
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.82132
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.1552
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.82535

5 rows × 40 columns

Checking for duplicates

In [28]:
```
print(len(np.unique(watertrain['id'])) == len(watertrain))
len(np.unique(watertest['id'])) == len(watertest)

# Check the length of the training set for reference
len(watertrain)
```

```
True
```

Out[28]:
```
59400
```

In [29]:
```
# We can remove the id column and remember that the training set has 5
9,400 rows
watertrain_id = watertrain['id']
watertest_id = watertest['id']
target_id = target['id']

# drop id column
```

```
watertrain = watertrain.drop(['id'], axis=1)
watertest = watertest.drop(['id'], axis=1)
target = target.drop(['id'], axis=1)

# combine
waterfull = pd.concat([watertrain, watertest]).reset_index(drop=True)
waterfull.shape
```

Out[29]: (74250, 39)

In [30]:
```
# get an idea of what we are working with
waterfull.describe(include = ['O'])
```

Out[30]:

	date_recorded	funder	installer	wpt_name	basin	subvillage	region	
count	74250	69746	69718	74250	74250	73780	74250	7425
unique	369	2140	2410	45684	9	21425	21	125
top	2011-03-17	Government Of Tanzania	DWE	none	Lake Victoria	Shuleni	Iringa	Njom
freq	695	11299	21751	4440	12871	646	6599	3128

4 rows × 30 columns

Now, we will take a look at the null in the data frame.

In [31]:
```
# create a function to check nulls
def check_nulls(df):
    nulls = np.sum(df.isnull())
    nullcols = nulls.loc[(nulls != 0)]
    dtypes = df.dtypes
    dtypes2 = dtypes.loc[(nulls != 0)]
    info = pd.concat([nullcols, dtypes2], axis=1).sort_values(by=0, asc
ending=False)
    print(info)
```

```
    print("There are", len(nullcols), "columns with missing values")

# use the function
check_nulls(waterfull)
```

```
                        0       1
scheme_name         35258  object
scheme_management    4846  object
installer            4532  object
funder               4504  object
public_meeting       4155  object
permit               3793  object
subvillage            470  object
There are 7 columns with missing values
```

Next, lets drop the unnecesary features. After playing around with different combinations, we finally decided to drop the following features which gave us the higher score.

In [32]:
```
# drop num_private since there is no documentation on it for now
waterfull = waterfull.drop(['num_private'], axis=1)

# drop scheme_name since there are more than half NaN and thousands of
 distinct variables
waterfull = waterfull.drop(['scheme_name'], axis=1)

# recorded_by has only one variable so we can get rid of
waterfull.recorded_by.nunique()
waterfull = waterfull.drop(['recorded_by'], axis=1)

# there are many columns where the group or type of it are just more br
oader categories of the same thing, so we remove
waterfull = waterfull.drop(['extraction_type_group'], axis=1)
waterfull = waterfull.drop(['extraction_type_class'], axis=1)
waterfull = waterfull.drop(['management_group'], axis=1)
waterfull = waterfull.drop(['payment_type'], axis=1)
waterfull = waterfull.drop(['quality_group'], axis=1)
waterfull = waterfull.drop(['quantity_group'], axis=1)
waterfull = waterfull.drop(['source_type'], axis=1)
```

```
waterfull = waterfull.drop(['source_class'], axis=1)
waterfull = waterfull.drop(['waterpoint_type_group'], axis=1)
```

In [33]:
```
# check nulls
check_nulls(waterfull)
```

```
                        0       1
scheme_management    4846  object
installer            4532  object
funder               4504  object
public_meeting       4155  object
permit               3793  object
subvillage            470  object
There are 6 columns with missing values
```

Next, we imputed NaNs

In [34]:
```
# impute NA for now
waterfull['scheme_management'] = waterfull['scheme_management'].fillna(
waterfull['scheme_management'].mode()[0])
waterfull['installer'] = waterfull['installer'].fillna('unknown')

# assume NaN is False
waterfull['public_meeting'] = waterfull['public_meeting'].fillna('Fals
e')

# turn 0 for construction_year to null then impute median
waterfull['construction_year'] = waterfull['construction_year'].replace
(0,np.NaN)
waterfull['construction_year'] = waterfull.construction_year.fillna(wat
erfull['construction_year'].mean()) # better than the mode
waterfull['construction_year'] = waterfull['construction_year'].round()
waterfull['construction_year'] = waterfull['construction_year'].astype(
int)

# for population since many have 0 and why would there be a water pump
 where no one lives
waterfull['population'] = waterfull['population'].replace(0,np.NaN)
```

```
waterfull['population'] = waterfull['population'].fillna(waterfull['pop
ulation'].mode()[0]) # mode gets higher score
waterfull['population'] = waterfull['population'].round()

# permit fill with most used
waterfull['permit'] = waterfull['permit'].fillna(waterfull['permit'].mo
de()[0])


# for the second try
waterfull['subvillage'] = waterfull['subvillage'].fillna('unknown')
waterfull['funder'] = waterfull['funder'].fillna('unknown')

# check nulls again
check_nulls(waterfull)
```

```
              0       1
installer  4532  object
There are 1 columns with missing values
```

Decided to parse the date_recorded feature to create some additional features.

In [35]:

```
import datetime

# Copied from MrBeer from GitHub
def date_parser(df):
    date_recorder = list(map(lambda x: datetime.datetime.strptime(str(x
), '%Y-%m-%d'),
                             df['date_recorded'].values))
    df['year_recorder'] = list(map(lambda x: int(x.strftime('%Y')), dat
e_recorder))
    df['weekday_recorder'] = list(map(lambda x: int(x.strftime('%w')),
date_recorder))
    df['yearly_week_recorder'] = list(map(lambda x: int(x.strftime('%W'
)), date_recorder))
    df['month_recorder'] = list(map(lambda x: int(x.strftime('%m')), da
te_recorder))
    df['wpt_age'] = df['year_recorder'].values - df['construction_year'
].values
```

```
    #del df['date_recorded']
    return df

date_parser(waterfull)

# drop since we don't need anymore
waterfull = waterfull.drop(['date_recorded'], axis=1) # keep constructi
on_year
```

Out[35]:

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
0	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.8
1	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.1
2	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.8
3	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-1.1
4	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.8
5	20.0	2011-03-13	Mkinga Distric Coun	0	DWE	39.172796	-4.7
6	0.0	2012-10-01	Dwsp	0	DWSP	33.362410	-3.7
7	0.0	2012-10-09	Rwssp	0	DWE	32.620617	-4.2

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
8	0.0	2012-11-03	Wateraid	0	Water Aid	32.711100	-5.1
9	0.0	2011-08-03	Isingiro Ho	0	Artisan	30.626991	-1.2
10	0.0	2011-02-20	Private	62	Private	39.209518	-7.0
11	200.0	2013-02-18	Danida	1062	DANIDA	35.770258	-1.0
12	0.0	2012-10-14	World Vision	0	World vision	33.798106	-3.2
13	0.0	2013-03-15	Lawatefuka Water Supply	1368	Lawatefuka water sup	37.092574	-3.1
14	0.0	2012-10-20	Biore	0	WEDECO	34.364073	-3.6
15	0.0	2011-08-04	Rudep	1645	DWE	31.444121	-8.2
16	500.0	2011-07-04	Unicef	1703	DWE	34.642439	-9.1
17	0.0	2011-09-04	Unicef	1656	DWE	34.569266	-9.0
18	0.0	2011-07-22	Hesawa	1162	DWE	32.920154	-1.9

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
19	500.0	2011-02-22	Danida	1763	Danid	34.508967	-9.8
20	200.0	2011-02-27	Twe	2216	TWE	34.473430	-9.5
21	0.0	2013-02-10	Dwsp	0	DWE	0.000000	-2.0
22	0.0	2011-10-04	Unicef	1510	DWE	34.586901	-8.9
23	500.0	2013-11-03	Isf	672	ISF	37.940029	-4.1
24	0.0	2013-01-21	African Development Bank	1645	DWE	29.747066	-4.4
25	0.0	2013-02-25	Government Of Tanzania	1273	DWE	37.422751	-3.3
26	500.0	2013-01-16	Sobodo	200	Kilolo Star	39.370777	-9.9
27	0.0	2011-07-11	Hesawa	0	DWE	31.104257	-1.7
28	0.0	2013-03-05	Government Of Tanzania	1443	District council	37.611126	-3.2
29	0.0	2013-03-16	Lawatefuka Water Supply	1256	Lawatefuka water sup	37.061688	-3.1
...	...	...	...	...	...	...	...

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
74220	0.0	2013-01-27	Dbfpe	265	DBFPE	38.504640	-1.0
74221	5.0	2013-03-29	Ces (gmbh)	1322	DWE	37.261731	-3.2
74222	50.0	2013-01-22	Lga	640	LGA	39.297410	-1.0
74223	0.0	2011-04-03	unknown	0	NaN	33.918953	-9.2
74224	0.0	2011-04-20	Po	574	Po	37.070462	-6.5
74225	0.0	2013-02-02	Fin Water	331	FIN WATER	38.761961	-1.0
74226	0.0	2012-10-24	World Vision	0	World vision	32.243937	-3.3
74227	0.0	2011-07-23	Hesawa	0	HESAWA	32.985694	-2.7
74228	50.0	2011-02-20	Private	78	Private	39.254272	-7.0
74229	0.0	2013-01-03	Government Of Tanzania	836	Government	35.227320	-1.1
74230	0.0	2013-03-19	Tcrs	1651	TCRS	37.962243	-4.4

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
74231	0.0	2012-10-26	Hesawa	0	DWE	0.000000	-2.0
74232	0.0	2013-03-25	Kkkt	1393	KKKT	36.930169	-3.2
74233	1000.0	2011-03-05	Kkkt	1729	Commu	34.302104	-9.4
74234	0.0	2011-03-27	Kirde	0	DWE	35.840727	-4.6
74235	0.0	2013-01-25	Rwssp	0	DWE	32.442886	-3.6
74236	0.0	2011-03-18	Amref	-7	AMREF	39.140091	-7.4
74237	500.0	2013-02-10	Tasaf	1241	TASAF	30.114667	-4.1
74238	3000.0	2011-03-11	Kkkt	2046	Commu	34.345525	-9.5
74239	0.0	2011-03-11	Devon Aid Korogwe	347	Local technician	38.613415	-4.8
74240	0.0	2013-02-24	Villagers	1291	Villagers	35.345384	-9.8
74241	0.0	2012-10-26	Dwsp	0	DWE	0.000000	-2.0
74242	600.0	2013-01-27	Isf	808	DWE	29.740224	-4.8

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	
74243	0.0	2013-02-04	Oxfarm	1641	OXFARM	29.768139	-4.4
74244	0.0	2012-11-07	Netherlands	0	DWE	34.096878	-3.0
74245	0.0	2011-02-24	Danida	34	Da	38.852669	-6.5
74246	1000.0	2011-03-21	Hiap	0	HIAP	37.451633	-5.3
74247	0.0	2013-03-04	unknown	1476	NaN	34.739804	-4.5
74248	0.0	2013-02-18	Germany	998	DWE	35.432732	-1.0
74249	0.0	2013-02-13	Government Of Tanzania	481	Government	34.765054	-1.1

74250 rows × 31 columns

We had some outliers for longitude and latitude, so we will impute with the means of their respected regions.

In [ ]:

```
# view Long and Lat
watertrain['status_group'] = target
sns.lmplot(x='longitude', y='latitude', data=watertrain, fit_reg=False,

           hue = 'status_group', scatter_kws={'alpha':0.2})

# we can see that we have some outliers
```

In [39]:

```
a = waterfull[waterfull["longitude"] < 1]
```

```
a.iloc[:,waterfull.columns == "latitude"]= np.nan
a.iloc[:,waterfull.columns == "longitude"]= np.nan
waterfull[waterfull["longitude"] < 1] = a
waterfull["longitude"] = waterfull.groupby("region_code").transform(lam
bda x: x.fillna(x.mean())).longitude
waterfull["latitude"] = waterfull.groupby("region_code").transform(lamb
da x: x.fillna(x.mean())).latitude


a= waterfull[waterfull["gps_height"] < 1]
a.iloc[:,waterfull.columns == "gps_height"]= np.nan
waterfull[waterfull["gps_height"] < 1] = a
waterfull["gps_height"] = waterfull.groupby("region_code").transform(la
mbda x: x.fillna(x.mean())).gps_height

waterfull=waterfull.fillna(waterfull.mean())
```

```
/Users/cris/anaconda3/lib/python3.6/site-packages/pandas/core/indexing.
py:537: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-d
ocs/stable/indexing.html#indexing-view-versus-copy
  self.obj[item] = s
```

In [41]:

```
# This was our original code, but the one above worked better so we wil
l just leave it here for reference

# for longitude, we will replace value that is less than 29 with the me
an
def replace_long(group):
    mean = group.mean()
    outliers = (group < 29)
    group[outliers] = mean
    return group
waterfull['longitude'] = waterfull['longitude'].transform(replace_long)

# for latitude, we will replace all values that are greater than -0.9 w
```

```
ith the mean
def replace_lat(group):
    mean = group.mean()
    outliers = (group > -0.9)
    group[outliers] = mean
    return group
waterfull['latitude'] = waterfull['latitude'].transform(replace_lat)
```

```
/Users/cris/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.p
y:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

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

Both installer and funder features had over 2,000 distinct values, with many of them having mutliple features that were misspelled. We imputed a few that we errors but after doing a more in depth imputation, it made our score worse for some reason. So we will just leave the changes only to these below.

In [44]:

```
waterfull.installer.value_counts()

waterfull['installer'].replace('Gover', 'Government',inplace=True)
waterfull['installer'].replace('Commu', 'Community',inplace=True)
waterfull['installer'].replace('District council', 'District Council',i
nplace=True)
waterfull['installer'].replace('DW', 'DWE',inplace=True)
waterfull['installer'].replace('World vision', 'World Vision',inplace=T
rue)
waterfull['installer'].replace('hesawa', 'HESAWA',inplace=True)
waterfull['installer'].replace('Central government', 'Government',inpla
ce=True)
waterfull['installer'].replace('Gove', 'Government',inplace=True)
waterfull['installer'].replace('0','unknown',inplace=True)
waterfull['installer'].replace('Da', 'DANIDA',inplace=True)
waterfull['installer'].replace('DANID', 'DANIDA',inplace=True)
waterfull['installer'].replace('Hesawa', 'HESAWA',inplace=True)
```

In [46]:

```
waterfull.funder.value_counts()

waterfull['funder'].replace('Water', 'Ministry of Water',inplace=True)
waterfull['funder'].replace('Fini Water', 'Ministry of Water',inplace=True)
waterfull['funder'].replace('Water', 'Ministry of Water',inplace=True)
waterfull['funder'].replace('Government Of Tanzania', 'Government',inplace=True)
waterfull['funder'].replace('Germany Republi', 'Government',inplace=True)
waterfull['funder'].replace('Netherlands', 'Government',inplace=True)
waterfull['funder'].replace('0', 'unknown',inplace=True)
waterfull['funder'].replace('Netherlands', 'Government',inplace=True)
waterfull['funder'].replace('Ministry Of Water', 'Ministry of Water',inplace=True)
waterfull['funder'].replace('Private Individual', 'Private',inplace=True)
```

We also computed the frequence that each value for installer had, to give some extra features.

In [49]:

```
#Compute the frequency for each category instead of the name of the category
def col_freq(df, col_names):
    for col in col_names:
        print('Changing to frequency %s' % col)
        val_counts = df[col].value_counts()
        df[col + '_freq'] = np.zeros((df.shape[0],))
        for i, val in enumerate(df[col].values):
            df[col + '_freq'].iat[i] = int(val_counts.at[val])
    return df

waterfull = col_freq(waterfull, ['installer'])
```

```
Changing to frequency installer
```

Population is skewed, so we will transform it.

```
In [51]: #Skew population as it has two dsitribution
waterfull.population = waterfull.population.apply(lambda x: np.log10(x+
1))
```

Instead of creating dummy variables for each value, which would have led to over 70,000 features, we decided to use label encoding to transform all the object variables into numericals.

```
In [52]: from sklearn import preprocessing

# separate all the non numerical values
objects = []
for i in waterfull.columns:
    if waterfull[i].dtype == object or waterfull[i].dtype == bool:
        objects.append(i)

# apply LabelEncoder
for factor in objects:
    waterfull[factor] = preprocessing.LabelEncoder().fit_transform(wate
rfull[factor].astype(str))

# view
waterfull.head()
```

Out[52]:

	amount_tsh	funder	gps_height	installer	longitude	latitude	basin	subvillage	reg
0	6000.0	1542	1390.0	1696	34.938093	-9.856322	1	13116	3
1	0.0	518	1399.0	603	34.698766	-2.147466	4	17596	9
2	25.0	920	686.0	2282	37.460664	-3.821329	5	10096	8
3	0.0	1955	263.0	2068	38.486161	-11.155298	7	9998	12
4	0.0	19	26.0	132	31.130847	-1.825359	4	8583	4

5 rows × 31 columns

Split the data to apply MinMax Scaler to help normalize the data since we are dealing with large amounts of different values for numerous features.

In [53]:
```
# split data frame
watertrain = waterfull.iloc[:59400,:]
watertest = waterfull.iloc[59400:,:]


print("train shape: ",watertrain.shape,"test shape: ",watertest.shape,
"target shape: ",target.shape)
```

```
train shape:  (59400, 31) test shape:  (14850, 31) target shape:  (5940
0, 1)
```

In [54]:
```
from sklearn.preprocessing import MinMaxScaler

# convert to MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(watertrain)
train_scaled = scaler.transform(watertrain)
test_scaled= scaler.transform(watertest)
train_scaled=pd.DataFrame(train_scaled)
test_scaled=pd.DataFrame(test_scaled)
train_scaled.columns = watertrain.columns
test_scaled.columns = watertest.columns
train = train_scaled
test = test_scaled
```

THE MODEL

After trying several models, we decided to stick with random forest classifier since it gave us the highest score for the competition and works well with our data set.

Also, we did not split the training data into training and testing, but instead used cross validation on the grid search to find the optimal parameters.

In [55]:
```
from sklearn import datasets
from sklearn import metrics
from sklearn.svm import SVC
from sklearn import model_selection
from sklearn.ensemble import BaggingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.datasets import make_blobs
import math
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as
 LDA
from sklearn import decomposition
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint as sp_randint
from time import time
from sklearn.ensemble import RandomForestClassifier
from scipy import stats
from sklearn.metrics import make_scorer, roc_auc_score
```

PCA

We tried using PCA to reduce the dimensionality of a data set, but it was not effective. Here is the code for our attempt at it.

In [ ]:
```
#PCA to reduce the number of predictors in case there are correlated
pca = decomposition.PCA(n_components=32)
pca.fit(train)
train = pca.transform(train)
```

In [ ]:
```
# grid search for optimal parameters
from sklearn.model_selection import cross_val_score, GridSearchCV
grid = {
    "n_estimators": [500,1000],
    "min_samples_split": [10],
    #"criterion": ['gini'],
    #"max_features": ["auto", len(factors)],
    "bootstrap": [False],
```

```
    "random_state": [69]
}

grid_search = GridSearchCV(RandomForestClassifier(), param_grid = grid,
 cv = 3, verbose=2)
grid_search.fit(train, np.ravel(target))
optimal_model = grid_search.best_estimator_

print("Fine Tuned Model: {0}".format(optimal_model))
```

In [ ]:
```
# random forest model
model = RandomForestClassifier(bootstrap=False, class_weight=None, crit
erion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=10,
            min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=1,
            oob_score=False, random_state=69, verbose=0, warm_start=Fal
se)

model.fit(train, np.ravel(target))
```

XGBOOST

We also tried xgboost but it did not give us a higher score than using random forest.

In [ ]:
```
from xgboost import XGBClassifier

model = XGBClassifier(max_depth=500, learning_rate=0.001, n_jobs=20)
model.fit(train, target)
```

RANDOM FOREST - OUR MODEL

Random Forest Classifier was our optimal model for this competition. After trying both grid and random search, grid search gave us our best parameters. We applied a cross validation to ensure we were getting the best parameters. To reduce waiting time, we just stuck with the three most effective parameters for the model.

In [ ]:
```
# GRID SEARCH

rfc = RandomForestClassifier(n_jobs=10, max_features='sqrt', oob_score
= True)

# Use a grid over parameters of interest
param_grid = {
           "n_estimators" : [9, 18, 27, 32, 45, 54, 63],
           "max_depth" : [10, 50, 60, 70, 100, 150, 200, 350, 500],
           "min_samples_leaf" : [1, 2, 4, 6, 8, 10]}

CV_rfc = GridSearchCV(estimator=rfc, param_grid=param_grid, cv= 10)
CV_rfc.fit(train, target)
print(CV_rfc.best_params_)
```

In [59]:
```
# random forest with grid search parameters
rfc = RandomForestClassifier(bootstrap=False, class_weight=None, criter
ion='gini',
            max_depth=50, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=2, min_samples_split=10,
            min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=1,
            oob_score=False, random_state=69, verbose=0, warm_start=Fal
se)
rfc.fit(train, np.ravel(target))
```

Out[59]:
```
RandomForestClassifier(bootstrap=False, class_weight=None, criterion='g
ini',
            max_depth=50, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=2, min_samples_split=10,
            min_weight_fraction_leaf=0.0, n_estimators=500, n_jobs=1,
            oob_score=False, random_state=69, verbose=0, warm_start=Fal
se)
```

In [60]:
```
predictions = rfc.predict(test)
```

```python
# submission
submission = pd.DataFrame(predictions, columns=['status_group'])
submission.insert(0, 'id', watertest_id)
submission.reset_index()
submission.to_csv('submission.csv', index = False)
```

Our score for the Pump It Water: Data Mining the Water Table was a .8243, which (as of 30/03/2018) put us at rank 77 out of 4649 competitors, top 1.6%!

One key takeaway is that a lot of the things that we thought should have made our score better, such as fixing the errors in installer and funder features, did not work. Even keeping the waterpoint name feature, which should be irrelevant to the condition of the water pump, made our score better.