# Water-Well-Classification-PT2

## Part 2: Exploring a Few Different Approaches

#### Loading libraries and data

In [1]:
```
# Import the relevant libraries
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, explained_variance_score, confusion_matrix,
accuracy_score, classification_report, log_loss
from math import sqrt

%matplotlib inline

# Increase column width to display df
pd.set_option('display.max_columns', None)

# Increases the size of sns plots
sns.set(rc={'figure.figsize':(12,10)})
```

In [10]:
```
# Load the data
raw_df1 = pd.read_csv('dfA.csv')

# print the shape
print("Raw_df1:", raw_df1.shape)
```

```
Raw_df1: (35303, 18)
```

In [11]:
```
raw_df1.head()
```

Out[11]:

| | Unnamed: 0 | amount_tsh | gps_height | longitude | latitude | basin | region | population | permit | construc |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0.0 | 1399 | 34.698766 | -2.147466 | Lake Victoria | Mara | 280 | 1.0 | |
| **1** | 2 | 25.0 | 686 | 37.460664 | -3.821329 | Pangani | Manyara | 250 | 1.0 | |
| **2** | 3 | 0.0 | 263 | 38.486161 | -11.155298 | Ruvuma / Southern Coast | Mtwara | 58 | 1.0 | |
| **3** | 5 | 20.0 | 0 | 39.172796 | -4.765587 | Pangani | Tanga | 1 | 1.0 | |
| **4** | 10 | 0.0 | 62 | 39.209518 | -7.034139 | Wami / Ruvu | Pwani | 345 | 0.0 | |

In [107]:
```
# raw_df1 = raw_df1.drop(columns=['Unnamed: 0'], axis=1)
raw_df1.head(2)
```

Out[107]:

| | amount_tsh | gps_height | longitude | latitude | basin | region | population | permit | construction_year | ext |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | Lake Victoria | Mara | 280 | 1.0 | 2010 | |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | Pangani | Manyara | 250 | 1.0 | 2009 | |

#### Data preperation

In [14]:
```
# The BIG SWITCHEROO - making the 3 class target into a 2 class target
# raw_df1['status_group'] = raw_df1['status_group'].map({0:0, 1:1, 2:1})
raw_df1.head(2)
```

Out[14]:

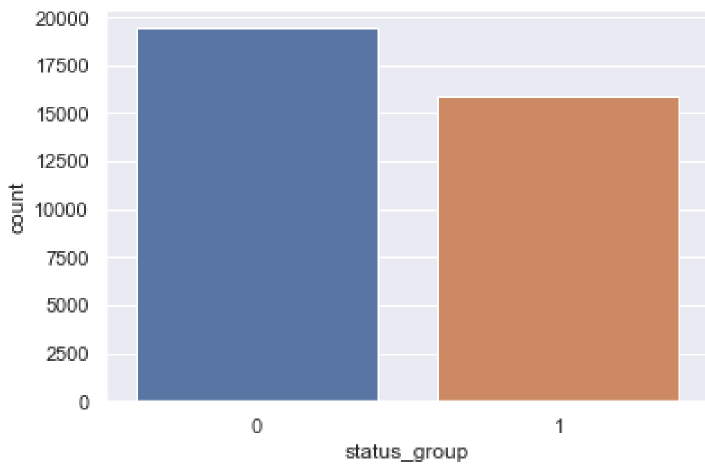
| | amount_tsh | gps_height | longitude | latitude | basin | region | population | permit | construction_year | ext |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | Lake Victoria | Mara | 280 | 1.0 | 2010 | |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | Pangani | Manyara | 250 | 1.0 | 2009 | |

In [17]:
```
# Checking the new distribuiton of Target varialbe
print (raw_df1['status_group'].value_counts())
print (raw_df1['status_group'].value_counts(normalize=True))
sns.countplot(x = 'status_group', data = raw_df1)
```

```
0    19439
1    15864
Name: status_group, dtype: int64
0    0.550633
1    0.449367
Name: status_group, dtype: float64
```

Out[17]: 

```
<AxesSubplot:xlabel='status_group', ylabel='count'>
```




In [18]:
```
# Time to split take categorical variables and do some one-hot encoding. Not "drop first" this time.
categorical_variables = raw_df1[['basin', 'region', 'management', 'payment', 'quantity','quality_group', 'source_type', 'extraction_type_class', 'waterpoint_type_group']]
categorical_dummies = pd.get_dummies(categorical_variables)
categorical_dummies.head()
```

Out[18]:

| | basin_Internal | basin_Lake Nyasa | basin_Lake Rukwa | basin_Lake Tanganyika | basin_Lake Victoria | basin_Pangani | basin_Rufiji | basin_Ruvuma / Southern Coast |
|---|---|---|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **1** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **2** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| **3** | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **4** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

In [19]:
```
categorical_dummies.shape
```

Out[19]:

```
(35303, 76)
```

In [20]:
```
categorical_dummies.columns = categorical_dummies.columns.str.replace('/','_')
```

In [21]:
```
categorical_dummies.columns = categorical_dummies.columns.str.replace('-','_')
```

In [22]:
```
categorical_dummies.columns = categorical_dummies.columns.str.replace(' ','')
```

In [23]:
```
categorical_dummies.head()
```

Out[23]:

| | basin_Internal | basin_LakeNyasa | basin_LakeRukwa | basin_LakeTanganyika | basin_LakeVictoria | basin_Pangan |
|---|---|---|---|---|---|---|
| **0** | 0 | 0 | 0 | 0 | 1 | ( |
| **1** | 0 | 0 | 0 | 0 | 0 | - |
| **2** | 0 | 0 | 0 | 0 | 0 | ( |
| **3** | 0 | 0 | 0 | 0 | 0 | - |
| **4** | 0 | 0 | 0 | 0 | 0 | ( |

In [24]:
```
raw_df2 = raw_df1.drop(['basin', 'region', 'management', 'payment', 'quantity','qu
ality_group', 'source_type', 'extraction_type_class', 'waterpoint_type_group'], ax
is=1)
print(raw_df2.shape)
raw_df2.head()
```

```
(35303, 8)
```

Out[24]:

| | amount_tsh | gps_height | longitude | latitude | population | permit | construction_year | status_group |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | 280 | 1.0 | 2010 | 0 |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | 250 | 1.0 | 2009 | 0 |
| **2** | 0.0 | 263 | 38.486161 | -11.155298 | 58 | 1.0 | 1986 | 1 |
| **3** | 20.0 | 0 | 39.172796 | -4.765587 | 1 | 1.0 | 2009 | 0 |
| **4** | 0.0 | 62 | 39.209518 | -7.034139 | 345 | 0.0 | 2011 | 0 |

In [25]:
```
data_redux = pd.concat([raw_df2, categorical_dummies], axis=1)
print(data_redux.shape)
data_redux.head()
```

```
(35303, 84)
```

Out[25]:

| | amount_tsh | gps_height | longitude | latitude | population | permit | construction_year | status_group | basin_I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | 280 | 1.0 | 2010 | 0 | |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | 250 | 1.0 | 2009 | 0 | |
| **2** | 0.0 | 263 | 38.486161 | -11.155298 | 58 | 1.0 | 1986 | 1 | |
| **3** | 20.0 | 0 | 39.172796 | -4.765587 | 1 | 1.0 | 2009 | 0 | |
| **4** | 0.0 | 62 | 39.209518 | -7.034139 | 345 | 0.0 | 2011 | 0 | |

In [26]:
```
# Need to split data into X and y dataframes.
y = data_redux['status_group']
X = data_redux.drop(columns=['status_group'], axis=1)
print(y.shape)
print(X.shape)
```

```
(35303,)
(35303, 83)
```

In [27]:
```
# Create train and test sets.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_s
tate=42)
print(X_train.shape)
print(X_test.shape)

print(y_train.shape)
print(y_test.shape)
```

```
(26477, 83)
(8826, 83)
(26477,)
(8826,)
```

In [ ]:

**Modelling**

## Decision Tree Model: B1

This is using the same columns but with 2 classes only and with No SMOTE.

In [28]:
```
# Loading relevant libraries and packages
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, roc_curve, auc
from sklearn.preprocessing import OneHotEncoder
from sklearn import tree

import sklearn.datasets as datasets
# from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz

from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
```

In [29]:
```
# Train a DT classifier
treeb1 = DecisionTreeClassifier(max_depth=3, random_state=10)
treeb1.fit(X_train, y_train)
```

Out[29]:
```
DecisionTreeClassifier(max_depth=3, random_state=10)
```

In [30]:
```
# Predict on training and test sets
training_preds = treeb1.predict(X_train)
test_preds = treeb1.predict(X_test)
```

In [31]:
```
# Get results
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Test Accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 70.7%
Test Accuracy: 71.14%
```

In [32]:

```python
# Get detailed results (Train and Test)

# Classification Report
print('--------------------------------------------------------------------------'
)
print('MODEL - Decision Trees B1')
print('Classification Report - TRAIN')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_train, training_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TRAIN')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicte
d'], margins=True))
print('\n-------------------------------------------------------------------------
-')
# Classification Report
print('--------------------------------------------------------------------------'
)
print('Classification Report - TEST')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_test, test_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TEST')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], m
argins=True))
print('--------------------------------------------------------------------------'
)
```

```
--------------------------------------------------------------------------
MODEL - Decision Trees B1
Classification Report - TRAIN
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.70      0.82      0.75     14600
           1       0.72      0.57      0.64     11877

    accuracy                           0.71     26477
   macro avg       0.71      0.69      0.70     26477
weighted avg       0.71      0.71      0.70     26477

--------------------------------------------------------------------------
Confusion Matrix - TRAIN
--------------------------------------------------------------------------
Predicted      0     1    All
True
0          11940  2660  14600
1           5097  6780  11877
All        17037  9440  26477

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Classification Report - TEST
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.70      0.82      0.76      4839
           1       0.73      0.58      0.64      3987

    accuracy                           0.71      8826
   macro avg       0.71      0.70      0.70      8826
weighted avg       0.71      0.71      0.71      8826

--------------------------------------------------------------------------
Confusion Matrix - TEST
--------------------------------------------------------------------------
Predicted     0     1   All
True
0          3972   867  4839
1          1680  2307  3987
All        5652  3174  8826
--------------------------------------------------------------------------
```

In [33]:
```
# Take a look at some feature importance and see if any differnt.
importance = pd.DataFrame(data={'features': X_train.columns, 'importance': treeb1.
feature_importances_})
importance = importance.sort_values('importance', ascending=False)
importance = importance.reset_index()
importance.drop('index', axis=1, inplace=True)
importance.head(20)
```

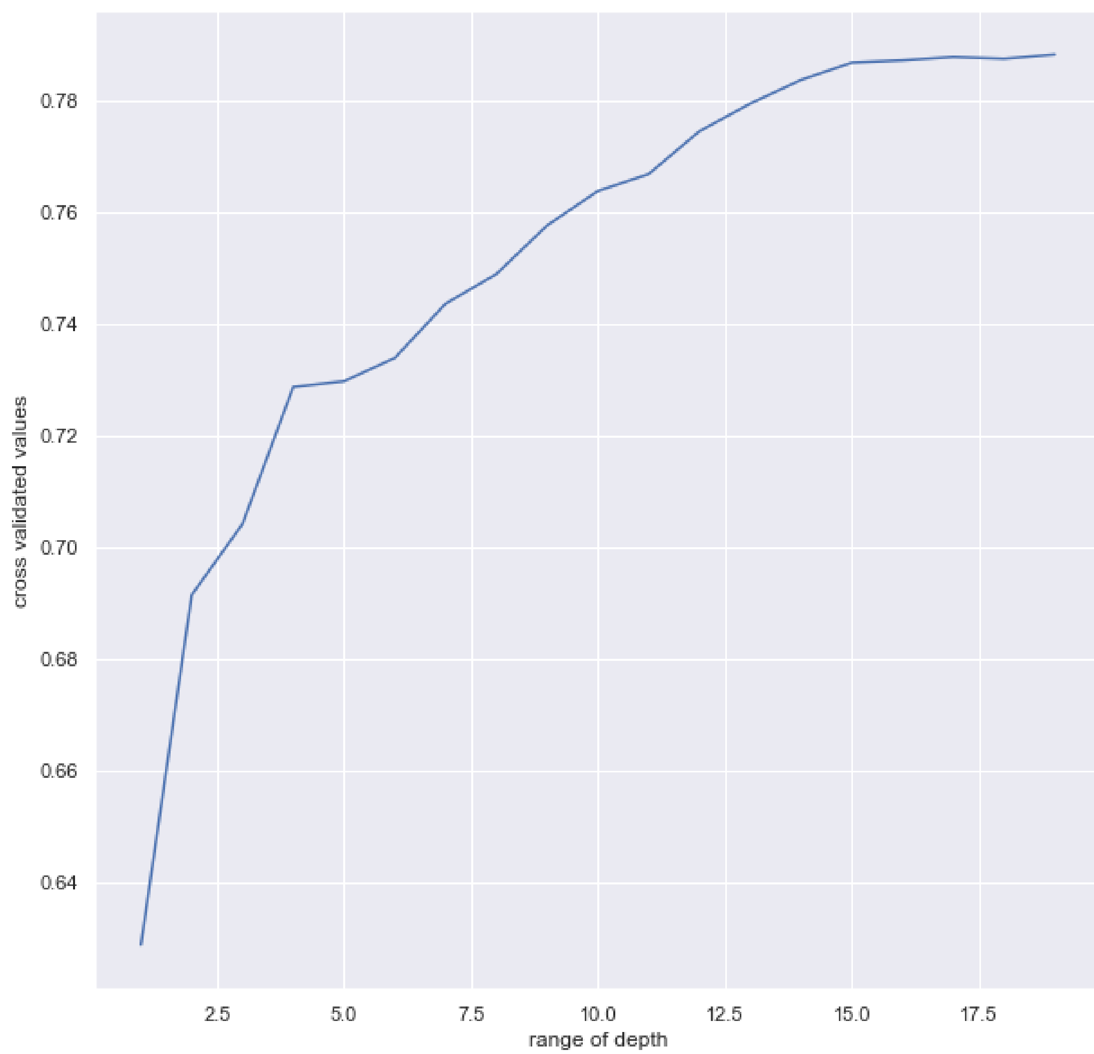
Out[33]:

| | features | importance |
|---|---|---|
| 0 | quantity_dry | 0.449725 |
| 1 | waterpoint_type_group_other | 0.379526 |
| 2 | construction_year | 0.168176 |
| 3 | latitude | 0.002335 |
| 4 | region_Morogoro | 0.000238 |
| 5 | quantity_insufficient | 0.000000 |
| 6 | quality_group_salty | 0.000000 |
| 7 | quality_group_milky | 0.000000 |
| 8 | quality_group_good | 0.000000 |
| 9 | quality_group_fluoride | 0.000000 |
| 10 | quality_group_colored | 0.000000 |
| 11 | quantity_unknown | 0.000000 |
| 12 | quantity_seasonal | 0.000000 |
| 13 | payment_neverpay | 0.000000 |
| 14 | quality_group_unknown | 0.000000 |
| 15 | payment_unknown | 0.000000 |
| 16 | payment_paywhenschemefails | 0.000000 |
| 17 | payment_payperbucket | 0.000000 |
| 18 | payment_paymonthly | 0.000000 |
| 19 | payment_payannually | 0.000000 |

In [34]:

```python
# cross validation to test tree depth values.
score = cross_val_score(treeb1, X, y, cv = 10)
score.mean()
depth_range = range(1,20)
val = []
for depth in depth_range:
    treeb1 = DecisionTreeClassifier(max_depth = depth)
    depth_score = cross_val_score(treeb1, X, y, cv = 10)
    val.append(depth_score.mean())
print(val)
plt.figure(figsize = (10,10))
plt.plot(depth_range, val)
plt.xlabel('range of depth')
plt.ylabel('cross validated values')
plt.show()
```

```
[0.6287285820530902, 0.691386425211582, 0.7041042871595411, 0.7286631077393831,
0.7296827532426271, 0.7338467944382534, 0.743590930351408, 0.7488877549956156, 0.
7575839248164578, 0.7637588802696954, 0.7667900658112725, 0.774466509900573, 0.77
94235596814295, 0.7836722657995592, 0.7867595549896786, 0.7871845724192763, 0.787
7794812919644, 0.7874678104012779, 0.7882325786257375]
```



### Observations on Model B1: Decision Tree with 2 class

Suprised to see that the accuracy score was not any better really, at 0.71. No overfiting as train was also at 0.71. The recall for class 1 was at 0.58. The feature importance only show 3 features contributing much, the top one being new to the mix, but one that makes sense: qty_dry. And similar to the other model, the optimal tree depth is reported to be pretty high - around 15, to get a score up to about 0.78.

In [35]:
```
# Train a DT classifier
treeb2 = DecisionTreeClassifier(max_depth=15, random_state=10)
treeb2.fit(X_train, y_train)
```

Out[35]:
```
DecisionTreeClassifier(max_depth=15, random_state=10)
```

In [36]:
```
# Predict on training and test sets
training_preds = treeb2.predict(X_train)
test_preds = treeb2.predict(X_test)
```

In [37]:
```
# Get results
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Test Accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 87.36%
Test Accuracy: 77.96%
```

In [38]:

```
# Get detailed results (Train and Test)

# Classification Report
print('--------------------------------------------------------------------------'
)
print('MODEL - Decision Trees B1')
print('Classification Report - TRAIN')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_train, training_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TRAIN')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicte
d'], margins=True))
print('\n-------------------------------------------------------------------------
-')
# Classification Report
print('--------------------------------------------------------------------------'
)
print('Classification Report - TEST')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_test, test_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TEST')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], m
argins=True))
print('--------------------------------------------------------------------------'
)
```

```
--------------------------------------------------------------------------
MODEL - Decision Trees B1
Classification Report - TRAIN
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.86      0.93      0.89     14600
           1       0.90      0.81      0.85     11877

    accuracy                           0.87     26477
   macro avg       0.88      0.87      0.87     26477
weighted avg       0.88      0.87      0.87     26477

--------------------------------------------------------------------------
Confusion Matrix - TRAIN
--------------------------------------------------------------------------
Predicted      0      1    All
True
0          13514   1086  14600
1           2262   9615  11877
All        15776  10701  26477

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Classification Report - TEST
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.78      0.83      0.81      4839
           1       0.78      0.71      0.75      3987

    accuracy                           0.78      8826
   macro avg       0.78      0.77      0.78      8826
weighted avg       0.78      0.78      0.78      8826

--------------------------------------------------------------------------
Confusion Matrix - TEST
--------------------------------------------------------------------------
Predicted     0     1   All
True
0          4035   804  4839
1          1141  2846  3987
All        5176  3650  8826
--------------------------------------------------------------------------
```

In [39]:
```
# Take a look at some feature importance and see if any differnt.
importance = pd.DataFrame(data={'features': X_train.columns, 'importance': treeb2.
feature_importances_})
importance = importance.sort_values('importance', ascending=False)
importance = importance.reset_index()
importance.drop('index', axis=1, inplace=True)
importance.head(20)
```

Out[39]:

| | features | importance |
|---|---|---|
| **0** | quantity_dry | 0.154350 |
| **1** | longitude | 0.137392 |
| **2** | waterpoint_type_group_other | 0.130257 |
| **3** | latitude | 0.107340 |
| **4** | construction_year | 0.102898 |
| **5** | gps_height | 0.072590 |
| **6** | population | 0.039401 |
| **7** | amount_tsh | 0.039079 |
| **8** | quantity_enough | 0.025860 |
| **9** | payment_payperbucket | 0.012536 |
| **10** | source_type_borehole | 0.011701 |
| **11** | extraction_type_class_gravity | 0.009556 |
| **12** | basin_Internal | 0.008711 |
| **13** | extraction_type_class_handpump | 0.008529 |
| **14** | region_Iringa | 0.008004 |
| **15** | extraction_type_class_submersible | 0.007753 |
| **16** | permit | 0.006853 |
| **17** | management_privateoperator | 0.006076 |
| **18** | source_type_river_lake | 0.005820 |
| **19** | region_Tanga | 0.005353 |

## Observations on Model B2: Decision Tree with 2 class AND depth of 15

As expected, the deeper tree yielded a better accuracy (0.78), but also overfitting (train accuracy of 0.87). Recall also increased to 0.71. By having a deeper tree, we also see more features being used and helps us see another view of feature importance. The top ones are similar to the shallower tree, but also figuring in the top are gps_height, amount_tsh, and some source and extraction type features show up here as well.

#### APPROACH TO CONSIDER:

Wonder if cut out the 3rd class entirely, if it would have an impact on our models? On the one hand it could be muddying up the current class one (by being added to it), but on the other hand it is only 4K observations and may not have much impact? However, if it is cut, it also will increase class imbalance between clas 0 and 1.

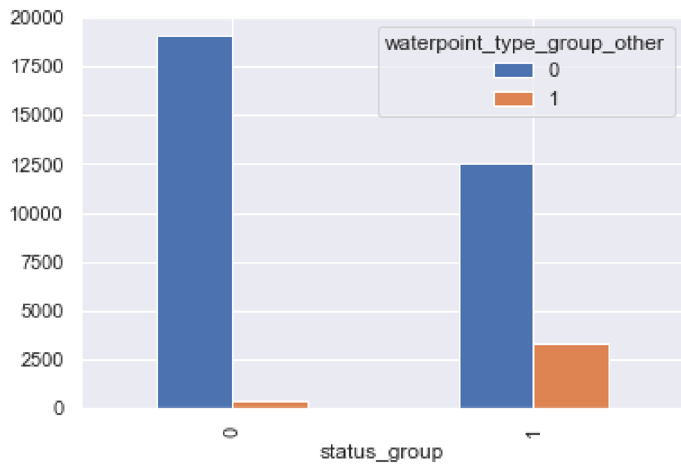
In [ ]:
```

```

### Some EDA on the 2 class approach

Taking a look at differences between the 2 target classes and some of the top variables for feature importance.

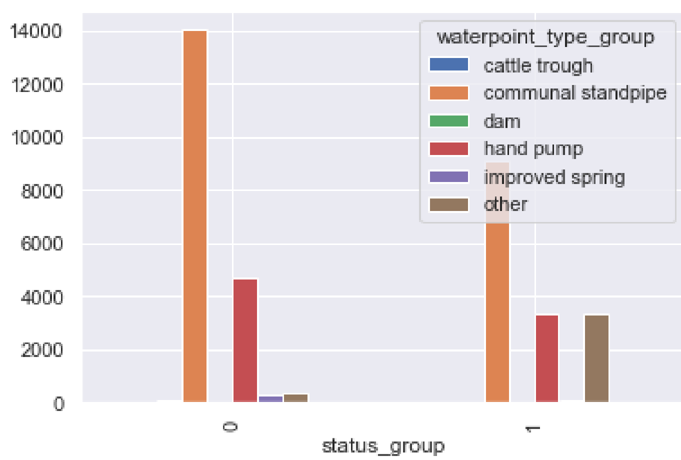
In [40]:
```
pd.crosstab(data_redux['status_group'],data_redux['waterpoint_type_group_other']).
plot.bar()
```

Out[40]: <AxesSubplot:xlabel='status_group'>



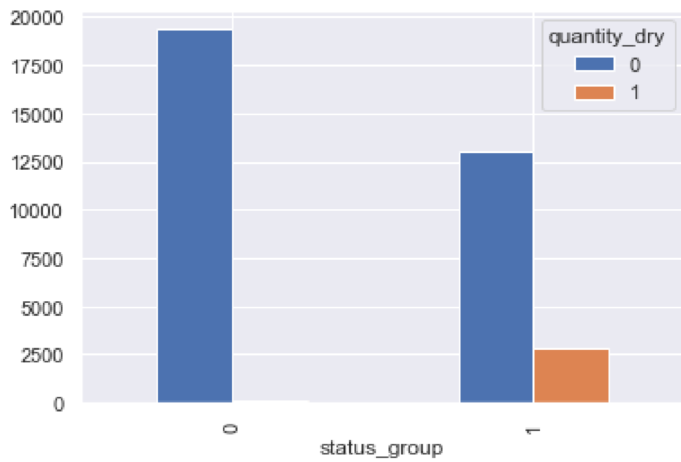

In [47]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['waterpoint_type_group']).plot.bar()
```

Out[47]: <AxesSubplot:xlabel='status_group'>



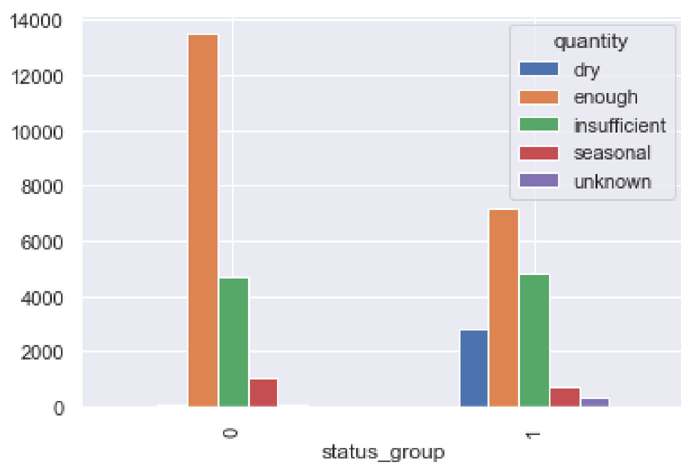
```
In [41]: pd.crosstab(data_redux['status_group'],data_redux['quantity_dry']).plot.bar()
```

Out[41]: <AxesSubplot:xlabel='status_group'>




```
In [48]: pd.crosstab(raw_df1['status_group'],raw_df1['quantity']).plot.bar()
```

Out[48]: <AxesSubplot:xlabel='status_group'>




```
In [42]: pd.crosstab(data_redux['status_group'],data_redux['quantity_enough']).plot.bar()
```

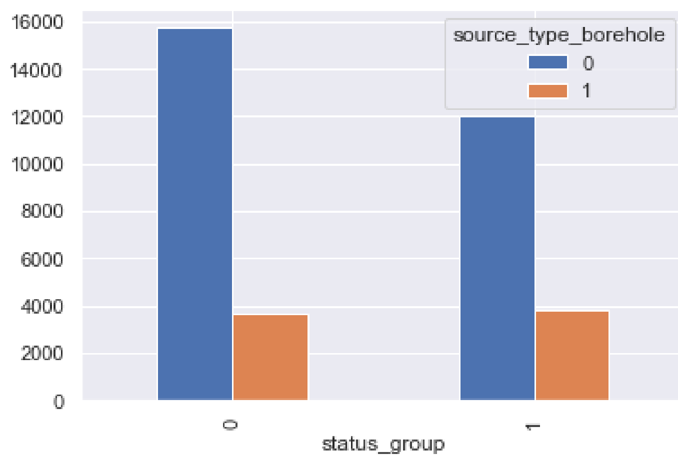
Out[42]: <AxesSubplot:xlabel='status_group'>

In [43]:
```
pd.crosstab(data_redux['status_group'],data_redux['payment_payperbucket']).plot.ba
r()
```

Out[43]: <AxesSubplot:xlabel='status_group'>

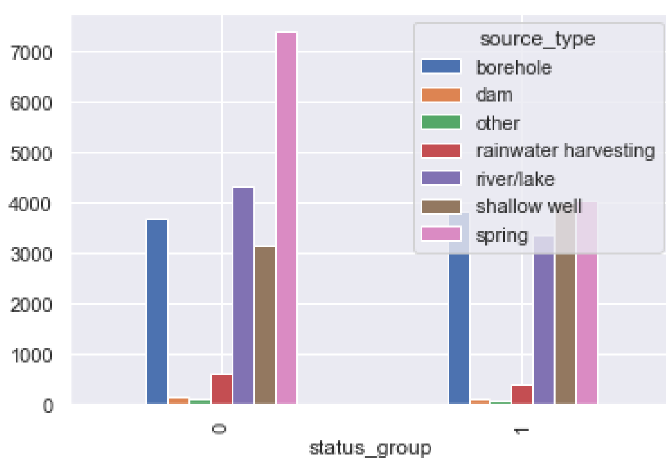

In [44]:
```
pd.crosstab(data_redux['status_group'],data_redux['source_type_borehole']).plot.ba
r()
```

Out[44]: <AxesSubplot:xlabel='status_group'>



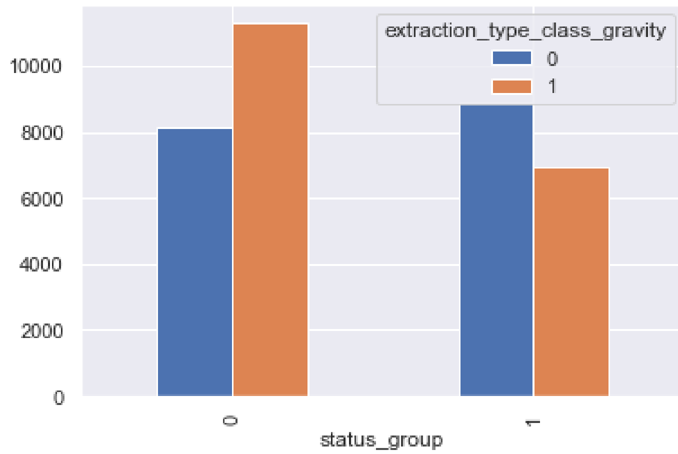

In [50]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['source_type']).plot.bar()
```

Out[50]: <AxesSubplot:xlabel='status_group'>



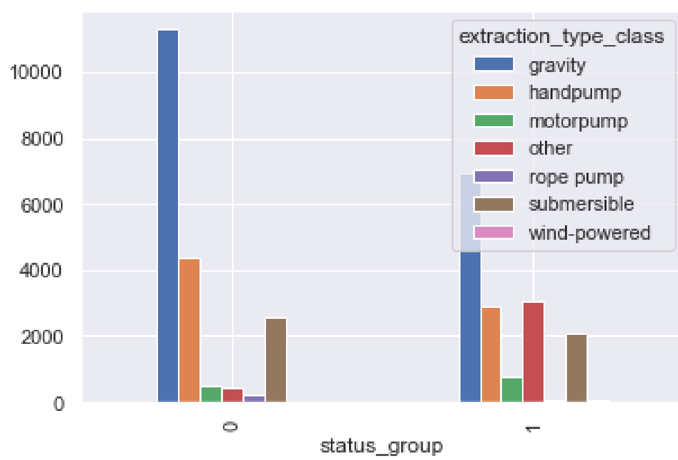
In [45]:
```
pd.crosstab(data_redux['status_group'],data_redux['extraction_type_class_gravity'
]).plot.bar()
```

Out[45]: <AxesSubplot:xlabel='status_group'>




In [49]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['extraction_type_class']).plot.bar()
```

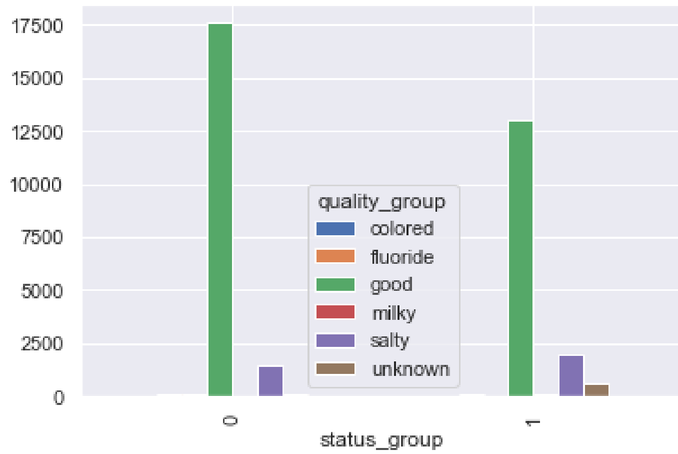
Out[49]: <AxesSubplot:xlabel='status_group'>



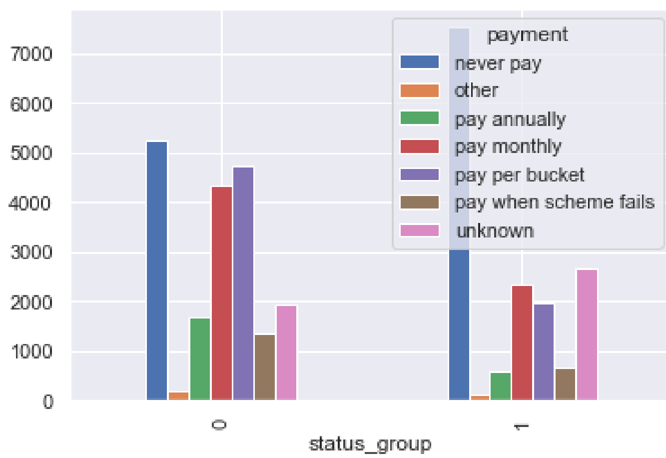

In [46]:
```
pd.crosstab(data_redux['status_group'],data_redux['extraction_type_class_handpump'
]).plot.bar()
```

Out[46]: <AxesSubplot:xlabel='status_group'>

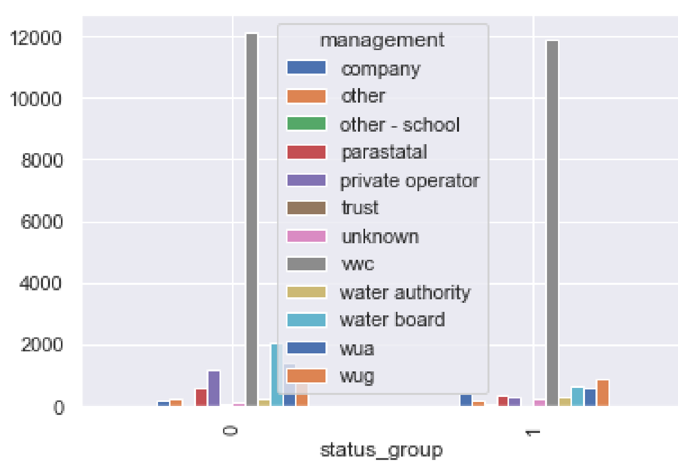
In [51]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['quality_group']).plot.bar()
```
Out[51]: <AxesSubplot:xlabel='status_group'>




In [52]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['payment']).plot.bar()
```
Out[52]: <AxesSubplot:xlabel='status_group'>

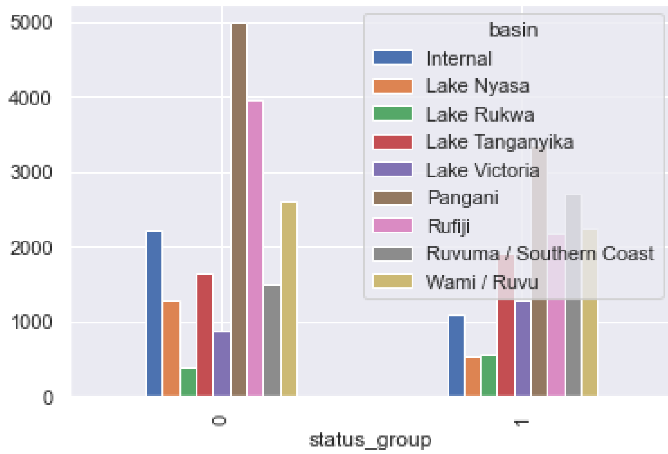



In [53]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['management']).plot.bar()
```
Out[53]: <AxesSubplot:xlabel='status_group'>



In [54]:
```
pd.crosstab(raw_df1['status_group'],raw_df1['basin']).plot.bar()
```

Out[54]: <AxesSubplot:xlabel='status_group'>




In [ ]:

## Simplify data based on feauture importance

This will be an intermediate approach to simplify the dataset. First we will try and make the data more interpretible by eliminating the "other" and "unknown" classes from the remainign categoricial features. Then I will cut out the columns that proved less important according to "feature importance" calculations. I will also cut 2 redundant location features (region abd basin).

In [56]:
```
print(data_redux.shape)
data_redux.head()
```

```
(35303, 84)
```

Out[56]:

| | amount_tsh | gps_height | longitude | latitude | population | permit | construction_year | status_group | basin_I |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | 280 | 1.0 | 2010 | 0 | |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | 250 | 1.0 | 2009 | 0 | |
| **2** | 0.0 | 263 | 38.486161 | -11.155298 | 58 | 1.0 | 1986 | 1 | |
| **3** | 20.0 | 0 | 39.172796 | -4.765587 | 1 | 1.0 | 2009 | 0 | |
| **4** | 0.0 | 62 | 39.209518 | -7.034139 | 345 | 0.0 | 2011 | 0 | |

In [58]:
```
data_redux.columns
```

Out[58]:
```
Index(['amount_tsh', 'gps_height', 'longitude', 'latitude', 'population',
       'permit', 'construction_year', 'status_group', 'basin_Internal',
       'basin_LakeNyasa', 'basin_LakeRukwa', 'basin_LakeTanganyika',
       'basin_LakeVictoria', 'basin_Pangani', 'basin_Rufiji',
       'basin_Ruvuma_SouthernCoast', 'basin_Wami_Ruvu', 'region_Arusha',
       'region_DaresSalaam', 'region_Iringa', 'region_Kigoma',
       'region_Kilimanjaro', 'region_Lindi', 'region_Manyara', 'region_Mara',
       'region_Morogoro', 'region_Mtwara', 'region_Mwanza', 'region_Pwani',
       'region_Rukwa', 'region_Ruvuma', 'region_Shinyanga', 'region_Singida',
       'region_Tanga', 'management_company', 'management_other',
       'management_other_school', 'management_parastatal',
       'management_privateoperator', 'management_trust', 'management_unknown',
       'management_vwc', 'management_waterauthority', 'management_waterboard',
       'management_wua', 'management_wug', 'payment_neverpay', 'payment_other',
       'payment_payannually', 'payment_paymonthly', 'payment_payperbucket',
       'payment_paywhenschemefails', 'payment_unknown', 'quantity_dry',
       'quantity_enough', 'quantity_insufficient', 'quantity_seasonal',
       'quantity_unknown', 'quality_group_colored', 'quality_group_fluoride',
       'quality_group_good', 'quality_group_milky', 'quality_group_salty',
       'quality_group_unknown', 'source_type_borehole', 'source_type_dam',
       'source_type_other', 'source_type_rainwaterharvesting',
       'source_type_river_lake', 'source_type_shallowwell',
       'source_type_spring', 'extraction_type_class_gravity',
       'extraction_type_class_handpump', 'extraction_type_class_motorpump',
       'extraction_type_class_other', 'extraction_type_class_ropepump',
       'extraction_type_class_submersible',
       'extraction_type_class_wind_powered',
       'waterpoint_type_group_cattletrough',
       'waterpoint_type_group_communalstandpipe', 'waterpoint_type_group_dam',
       'waterpoint_type_group_handpump',
       'waterpoint_type_group_improvedspring', 'waterpoint_type_group_other'],
      dtype='object')
```

In [59]:
```
df11 = data_redux.drop(['extraction_type_class_other', 'waterpoint_type_group_othe
r','source_type_other', 'quantity_unknown', 'quality_group_unknown','payment_unkno
wn', 'payment_other','management_unknown','management_other'], axis=1)
print(df11.shape)
```

```
(35303, 75)
```

In [60]:
```
df12 = df11.drop(['permit', 'basin_Internal',
       'basin_LakeNyasa', 'basin_LakeRukwa', 'basin_LakeTanganyika',
       'basin_LakeVictoria', 'basin_Pangani', 'basin_Rufiji',
       'basin_Ruvuma_SouthernCoast', 'basin_Wami_Ruvu', 'region_Arusha',
       'region_DaresSalaam', 'region_Iringa', 'region_Kigoma',
       'region_Kilimanjaro', 'region_Lindi', 'region_Manyara', 'region_Mara',
       'region_Morogoro', 'region_Mtwara', 'region_Mwanza', 'region_Pwani',
       'region_Rukwa', 'region_Ruvuma', 'region_Shinyanga', 'region_Singida',
       'region_Tanga', 'management_company',
       'management_other_school', 'management_parastatal',
       'management_privateoperator', 'management_trust',
       'management_vwc', 'management_waterauthority', 'management_waterboard',
       'management_wua', 'management_wug'], axis=1)
print(df12.shape)
```

```
(35303, 38)
```

In [61]:
```
df12.head(2)
```

Out[61]:

| | amount_tsh | gps_height | longitude | latitude | population | construction_year | status_group | payment_neverpa |
|---|---|---|---|---|---|---|---|---|
| **0** | 0.0 | 1399 | 34.698766 | -2.147466 | 280 | 2010 | 0 | |
| **1** | 25.0 | 686 | 37.460664 | -3.821329 | 250 | 2009 | 0 | |

In [62]:
```
# Need to split data into X and y dataframes.
y = df12['status_group']
X = df12.drop(columns=['status_group'], axis=1)
print(y.shape)
print(X.shape)
```

```
(35303,)
(35303, 37)
```

In [63]:
```
# Create train and test sets.
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_s
tate=42)
print(X_train.shape)
print(X_test.shape)

print(y_train.shape)
print(y_test.shape)
```

```
(26477, 37)
(8826, 37)
(26477,)
(8826,)
```

### Decision Tree Model: C1

This is using the 2 class target, with simplified data-set of 37 features.

In [87]:
```
# Train a DT classifier
treec1 = DecisionTreeClassifier(max_depth=3, random_state=10)
treec1.fit(X_train, y_train)
```

Out[87]:
```
DecisionTreeClassifier(max_depth=3, random_state=10)
```

In [88]:
```
# Predict on training and test sets
training_preds = treec1.predict(X_train)
test_preds = treec1.predict(X_test)
```

In [89]:
```
# Get results
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Test Accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 70.3%
Test Accuracy: 70.64%
```

In [90]:

```python
# Get detailed results (Train and Test)

# Classification Report
print('--------------------------------------------------------------------------')
print('MODEL - Decision Trees C1')
print('Classification Report - TRAIN')
print('--------------------------------------------------------------------------')
print(classification_report(y_train, training_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------')
print('Confusion Matrix - TRAIN')
print('--------------------------------------------------------------------------')
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicted'], margins=True))
print('\n--------------------------------------------------------------------------')
# Classification Report
print('--------------------------------------------------------------------------')
print('Classification Report - TEST')
print('--------------------------------------------------------------------------')
print(classification_report(y_test, test_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------')
print('Confusion Matrix - TEST')
print('--------------------------------------------------------------------------')
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], margins=True))
print('--------------------------------------------------------------------------')
```

```
--------------------------------------------------------------------------
MODEL - Decision Trees C1
Classification Report - TRAIN
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.68      0.87      0.76     14600
           1       0.75      0.50      0.60     11877

    accuracy                           0.70     26477
   macro avg       0.72      0.68      0.68     26477
weighted avg       0.71      0.70      0.69     26477

--------------------------------------------------------------------------
Confusion Matrix - TRAIN
--------------------------------------------------------------------------
Predicted      0     1    All
True
0          12631  1969  14600
1           5894  5983  11877
All        18525  7952  26477

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Classification Report - TEST
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.68      0.86      0.76      4839
           1       0.76      0.52      0.61      3987

    accuracy                           0.71      8826
   macro avg       0.72      0.69      0.69      8826
weighted avg       0.72      0.71      0.70      8826

--------------------------------------------------------------------------
Confusion Matrix - TEST
--------------------------------------------------------------------------
Predicted     0     1   All
True
0          4172   667  4839
1          1924  2063  3987
All        6096  2730  8826
--------------------------------------------------------------------------
```

In [109]:
```
# Take a look at some feature importance and see if any differnt.
importance = pd.DataFrame(data={'features': X_train.columns, 'importance': treec1.
feature_importances_})
importance = importance.sort_values('importance', ascending=False)
importance = importance.reset_index()
importance.drop('index', axis=1, inplace=True)
importance.head(7)
```

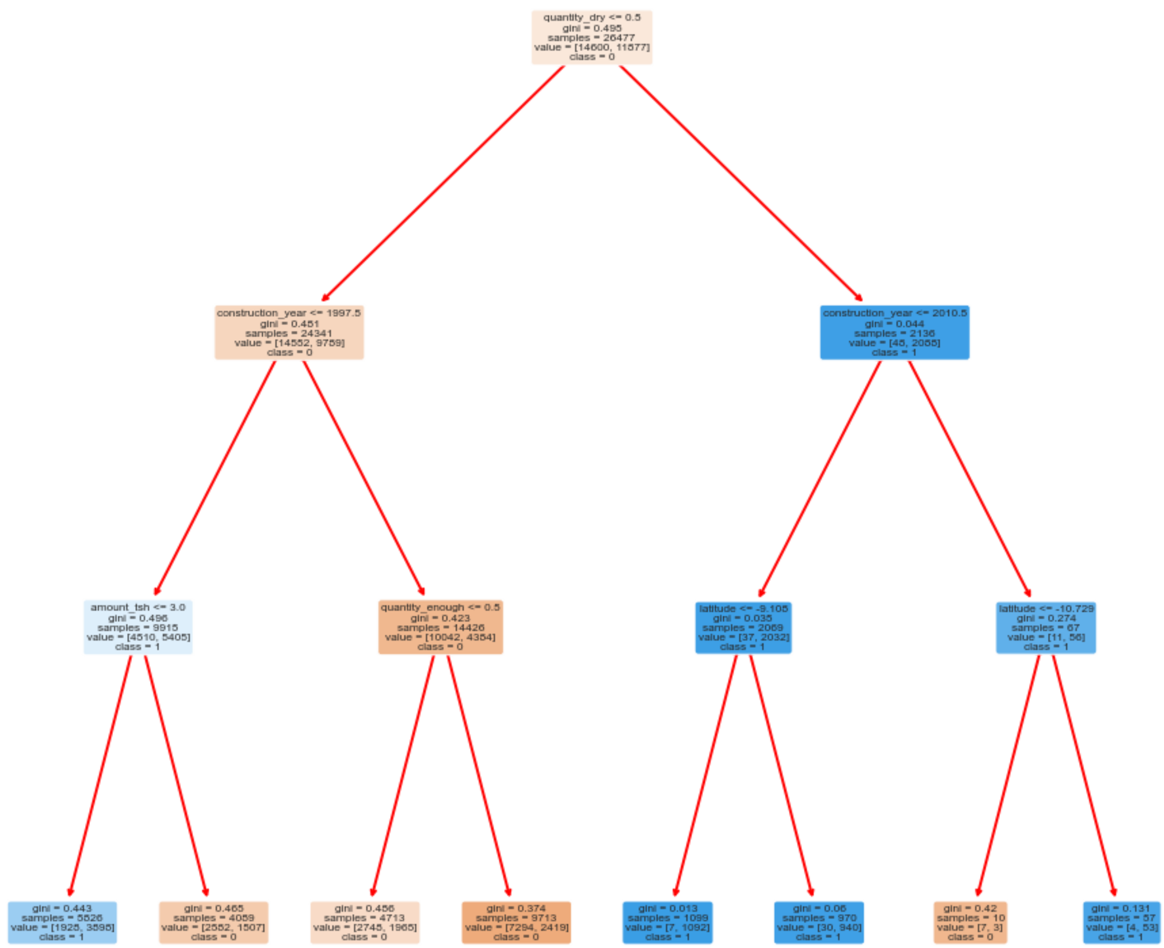
Out[109]:

| | features | importance |
|---|---|---|
| **0** | quantity_dry | 0.498694 |
| **1** | construction_year | 0.263405 |
| **2** | amount_tsh | 0.166462 |
| **3** | quantity_enough | 0.068612 |
| **4** | latitude | 0.002827 |
| **5** | source_type_river_lake | 0.000000 |
| **6** | source_type_shallowwell | 0.000000 |

## Observations on Model C1

The simplification of the data did not seem to have an effect on Accuracy or Recall of the model. At max_depth 3 the accuracy was 0.71 and recall for class 1 is 0.52. I tried various values for max_depth and got some improvement, as sfollows: @ 6 Ac=0.72; @12 Ac=0.78; @18 Ac=0.78 and Recaal for class 1 was 0.75. But lots of overtaining when max-depth at 18. Feature Importance was examined at max depth of 12 and not too many suproses. One thought is that the continuous variables seem to be playing a larger role - perhaps just in terms of the variety of data within?

In [92]:
```
# Plot of decision tree model at max_depth 3
fig, ax = plt.subplots(figsize=(16,16))
out = tree.plot_tree(treec1,
               feature_names=X.columns,
               class_names=np.unique(y).astype('str'),
               filled=True, rounded=True)
for o in out:
    arrow = o.arrow_patch
    if arrow is not None:
        arrow.set_edgecolor('red')
        arrow.set_linewidth(2)
```




## XGBoost Model: C1

Just curios to see if another type of model will react differently to the refined dataset... This is using the 2 class target, with simplified data-set of 37 features.

In [93]:
```
# Import libraries needed
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV
```

In [94]:
```
# Instantiate XGBClassifier
xgc1 = XGBClassifier()

# Fit XGBClassifier
xgc1.fit(X_train, y_train)

# Predict on training and test sets
training_preds = xgc1.predict(X_train)
test_preds = xgc1.predict(X_test)
```

In [95]:
```
# Get results
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Test Accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Training Accuracy: 77.23%
Test Accuracy: 76.59%
```

In [96]:

```
# Get detailed results for train and test
# Classification Report
print('--------------------------------------------------------------------------'
)
print('MODEL = XGBoost-C1')
print('\nClassification Report - TRAIN')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_train, training_preds))
print('--------------------------------------------------------------------------'
)
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TRAIN')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicte
d'], margins=True))
print('--------------------------------------------------------------------------'
)
print('--------------------------------------------------------------------------'
)
# Classification Report
print('--------------------------------------------------------------------------'
)
print('Classification Report - TEST')
print('--------------------------------------------------------------------------'
)
print(classification_report(y_test, test_preds))
print('--------------------------------------------------------------------------'
)
# Confusion Matrix
print('--------------------------------------------------------------------------'
)
print('Confusion Matrix - TEST')
print('--------------------------------------------------------------------------'
)
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], m
argins=True))
print('--------------------------------------------------------------------------'
)
```

```
--------------------------------------------------------------------------
MODEL = XGBoost-C1

Classification Report - TRAIN
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.76      0.86      0.81     14600
           1       0.79      0.67      0.72     11877

    accuracy                           0.77     26477
   macro avg       0.78      0.76      0.77     26477
weighted avg       0.77      0.77      0.77     26477

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Confusion Matrix - TRAIN
--------------------------------------------------------------------------
Predicted      0     1    All
True
0          12543  2057  14600
1           3971  7906  11877
All        16514  9963  26477
--------------------------------------------------------------------------
--------------------------------------------------------------------------
--------------------------------------------------------------------------
Classification Report - TEST
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.75      0.85      0.80      4839
           1       0.79      0.66      0.72      3987

    accuracy                           0.77      8826
   macro avg       0.77      0.76      0.76      8826
weighted avg       0.77      0.77      0.76      8826

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Confusion Matrix - TEST
--------------------------------------------------------------------------
Predicted     0     1   All
True
0          4116   723  4839
1          1343  2644  3987
All        5459  3367  8826
--------------------------------------------------------------------------
```

In [97]:

```
# Try some optimization w/ GridSearchCV
param_grid = {
    'learning_rate': [0.2, 0.4],
    'max_depth': [5, 7, 9],
    'min_child_weight': [2, 4],
    'subsample': [0.5, 0.7],
    'n_estimators': [100],
}
```

In [98]:

```python
# Code to run it

grid_xgc1 = GridSearchCV(xgc1, param_grid, scoring='accuracy', cv=None, n_jobs=1)
grid_xgc1.fit(X_train, y_train)

best_parameters = grid_xgc1.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_xgc1.predict(X_train)
test_preds = grid_xgc1.predict(X_test)
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.2
max_depth: 9
min_child_weight: 4
n_estimators: 100
subsample: 0.7

Training Accuracy: 89.78%
Validation accuracy: 81.69%
```

In [99]:

```
# Get detailed results (Train and Test)

# Classification Report
print('---------------------------------------------------------------------------'
)
print('MODEL = XGBoost-C1-Optimized1')
print('\nClassification Report - TRAIN')
print('---------------------------------------------------------------------------'
)
print(classification_report(y_train, training_preds))
# Confusion Matrix
print('---------------------------------------------------------------------------'
)
print('Confusion Matrix - TRAIN')
print('---------------------------------------------------------------------------'
)
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicte
d'], margins=True))
print('\n---------------------------------------------------------------------------
-')
# Classification Report
print('---------------------------------------------------------------------------'
)
print('Classification Report - TEST')
print('---------------------------------------------------------------------------'
)
print(classification_report(y_test, test_preds))

# Confusion Matrix
print('---------------------------------------------------------------------------'
)
print('Confusion Matrix - TEST')
print('---------------------------------------------------------------------------'
)
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], m
argins=True))
print('---------------------------------------------------------------------------'
)
```

```
---------------------------------------------------------------------------
MODEL = XGBoost-C1-Optimized1

Classification Report - TRAIN
---------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.88      0.94      0.91     14600
           1       0.92      0.85      0.88     11877

    accuracy                           0.90     26477
   macro avg       0.90      0.89      0.90     26477
weighted avg       0.90      0.90      0.90     26477

---------------------------------------------------------------------------
Confusion Matrix - TRAIN
---------------------------------------------------------------------------
Predicted      0      1    All
True
0          13674    926  14600
1           1781  10096  11877
All        15455  11022  26477

---------------------------------------------------------------------------
---------------------------------------------------------------------------
Classification Report - TEST
---------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.81      0.87      0.84      4839
           1       0.82      0.76      0.79      3987

    accuracy                           0.82      8826
   macro avg       0.82      0.81      0.81      8826
weighted avg       0.82      0.82      0.82      8826

---------------------------------------------------------------------------
Confusion Matrix - TEST
---------------------------------------------------------------------------
Predicted     0     1   All
True
0          4193   646  4839
1           970  3017  3987
All        5163  3663  8826
---------------------------------------------------------------------------
```

In [100]:

```
#try second round of GSCV
# Try some optimization w/ GridSearchCV
param_grid = {
    'learning_rate': [0.2, 0.3],
    'max_depth': [8, 9, 11],
    'min_child_weight': [4, 5],
    'subsample': [0.7, 0.8],
    'n_estimators': [100],
}
```

In [101]:

```
# Code to run it

grid2_xgc1 = GridSearchCV(xgc1, param_grid, scoring='accuracy', cv=3, n_jobs=1)
grid2_xgc1.fit(X_train, y_train)

best_parameters = grid2_xgc1.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid2_xgc1.predict(X_train)
test_preds = grid2_xgc1.predict(X_test)
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.2
max_depth: 11
min_child_weight: 4
n_estimators: 100
subsample: 0.7

Training Accuracy: 92.58%
Validation accuracy: 82.11%
```

In [108]:

```python
# Get detailed results (Train and Test)

# Classification Report
print('--------------------------------------------------------------------------')
print('MODEL = XGBoost-C1-Optimized1')
print('\nClassification Report - TRAIN')
print('--------------------------------------------------------------------------')
print(classification_report(y_train, training_preds))
# Confusion Matrix
print('--------------------------------------------------------------------------')
print('Confusion Matrix - TRAIN')
print('--------------------------------------------------------------------------')
print(pd.crosstab(y_train, training_preds, rownames=['True'], colnames=['Predicted'], margins=True))
print('\n--------------------------------------------------------------------------')
# Classification Report
print('--------------------------------------------------------------------------')
print('Classification Report - TEST  - XGBoost-C-Optimized2')
print('--------------------------------------------------------------------------')
print(classification_report(y_test, test_preds))

# Confusion Matrix
print('--------------------------------------------------------------------------')
print('Confusion Matrix - TEST - XGBoost-C-Optimized2')
print('--------------------------------------------------------------------------')
print(pd.crosstab(y_test, test_preds, rownames=['True'], colnames=['Predicted'], margins=True))
print('--------------------------------------------------------------------------')
```

```
--------------------------------------------------------------------------
MODEL = XGBoost-C1-Optimized1

Classification Report - TRAIN
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.91      0.95      0.93     14600
           1       0.94      0.89      0.92     11877

    accuracy                           0.93     26477
   macro avg       0.93      0.92      0.92     26477
weighted avg       0.93      0.93      0.93     26477

--------------------------------------------------------------------------
Confusion Matrix - TRAIN
--------------------------------------------------------------------------
Predicted      0      1    All
True
0          13942    658  14600
1           1306  10571  11877
All        15248  11229  26477

--------------------------------------------------------------------------
--------------------------------------------------------------------------
Classification Report - TEST  - XGBoost-C-Optimized2
--------------------------------------------------------------------------
              precision    recall  f1-score   support

           0       0.82      0.87      0.84      4839
           1       0.82      0.77      0.79      3987

    accuracy                           0.82      8826
   macro avg       0.82      0.82      0.82      8826
weighted avg       0.82      0.82      0.82      8826

--------------------------------------------------------------------------
Confusion Matrix - TEST - XGBoost-C-Optimized2
--------------------------------------------------------------------------
Predicted     0     1   All
True
0          4186   653  4839
1           926  3061  3987
All        5112  3714  8826
--------------------------------------------------------------------------
```

In [105]:
```
# Take a look at some feature importance for the original XGBoost model above...
importance = pd.DataFrame(data={'features': X_train.columns, 'importance': xgc1.fe
ature_importances_})
importance = importance.sort_values('importance', ascending=False)
importance = importance.reset_index()
importance.drop('index', axis=1, inplace=True)
importance.head(20)
```

Out[105]:

| | features | importance |
|---|---|---|
| **0** | quantity_dry | 0.201595 |
| **1** | extraction_type_class_gravity | 0.129216 |
| **2** | amount_tsh | 0.101596 |
| **3** | waterpoint_type_group_communalstandpipe | 0.063385 |
| **4** | quantity_enough | 0.059830 |
| **5** | extraction_type_class_handpump | 0.054976 |
| **6** | construction_year | 0.045690 |
| **7** | waterpoint_type_group_handpump | 0.042052 |
| **8** | source_type_shallowwell | 0.036609 |
| **9** | source_type_spring | 0.032746 |
| **10** | waterpoint_type_group_improvedspring | 0.028645 |
| **11** | longitude | 0.025695 |
| **12** | source_type_river_lake | 0.022085 |
| **13** | quality_group_good | 0.021056 |
| **14** | payment_paywhenschemefails | 0.020574 |
| **15** | gps_height | 0.019244 |
| **16** | quantity_seasonal | 0.019124 |
| **17** | source_type_borehole | 0.016783 |
| **18** | population | 0.015459 |
| **19** | extraction_type_class_motorpump | 0.011583 |

### Observations on XGBoost Model C1: with 2 classes and simplified dataset.

As expected, XGBoost did perform better than decision trees. The plain default model had an accuracy of 0.77 and recall of 0.66. I tried 2 rounds of tuning with GridSearchCV. Yes, some noticable overtraining but ended up with a model having max_depth = 11 and min_child = 4 and obtained an accuracy of 0.82 and recall of 0.77. In this model, the feature importances showed up differently with quantity, extraction_type, and waterpoint_type havign the most importance and location (longittude) falling down the list to number 11 (0.026).

In [ ]:

# APPENDIX

In [ ]:

```
# Different format of confusion matrix
pd.DataFrame(confusion_matrix(y_test, yhat), columns=['Pred +', 'Pred Fix', 'Pred
 -'], index=['Act +', 'Pred Fix', 'Act -'])
```

In [ ]:

```
# Confusion matrix plot
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, yhatGS)
np.set_printoptions(precision=2)

print (classification_report(y_test, yhatGS))

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=['Functional',
                                           'Functional needs repair',
                                           'Non functional'],
                                            normalize= False,
                                            title='Confusion matrix')
```

In [ ]: