3 Final Project Submission

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- pace: Part time
- Scheduled project review data/time: November 16th, 2021, 08:00 AM (Mountain Time)
- Course Instructor: Abhineet
- Blog post URL:https://callableleticia.blog/2021/11/14/3rd-project-machine-learning/ (https://callableleticia.blog/2021/11/14/3rd-project-machine-learning/)
- GitHub repository:https://github.com/lddrasler/Tanzania_Water_Pumps (https://github.com/lddrasler/Tanzania_Water_Pumps)

Importing packages and undarstanding Data

In [38]:

```
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import numpy as np
from datetime import datetime
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df_values = pd.read_csv('training_set_values.csv', index_col='id')
df_labels = pd.read_csv('training_set_labels.csv', index_col='id')

df_values.head()
```

Out[2]:

	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_
id									
69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	
8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	
67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	
19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	

5 rows × 39 columns

In [3]:

```
df_values.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 69572 to 26348
Data columns (total 39 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   amount_tsh             59400 non-null  float64
 1   date_recorded          59400 non-null  object 
 2   funder                 55765 non-null  object 
 3   gps_height             59400 non-null  int64  
 4   installer              55745 non-null  object 
 5   longitude              59400 non-null  float64
 6   latitude               59400 non-null  float64
 7   wpt_name               59400 non-null  object 
 8   num_private            59400 non-null  int64  
 9   basin                  59400 non-null  object 
 10  subvillage             59029 non-null  object 
 11  region                 59400 non-null  object 
 12  region_code            59400 non-null  int64  
 13  district_code          59400 non-null  int64  
 14  lga                    59400 non-null  object 
 15  ward                   59400 non-null  object 
 16  population             59400 non-null  int64  
 17  public_meeting         56066 non-null  object 
 18  recorded_by            59400 non-null  object 
 19  scheme_management      55523 non-null  object 
 20  scheme_name            31234 non-null  object 
 21  permit                 56344 non-null  object 
 22  construction_year      59400 non-null  int64  
 23  extraction_type        59400 non-null  object 
 24  extraction_type_group  59400 non-null  object 
 25  extraction_type_class  59400 non-null  object 
 26  management             59400 non-null  object 
 27  management_group       59400 non-null  object 
 28  payment                59400 non-null  object 
 29  payment_type           59400 non-null  object 
 30  water_quality          59400 non-null  object 
 31  quality_group          59400 non-null  object 
 32  quantity               59400 non-null  object 
 33  quantity_group         59400 non-null  object 
 34  source                 59400 non-null  object 
 35  source_type            59400 non-null  object 
 36  source_class           59400 non-null  object 
 37  waterpoint_type        59400 non-null  object 
 38  waterpoint_type_group  59400 non-null  object 
dtypes: float64(3), int64(6), object(30)
memory usage: 18.1+ MB
```

In [4]:
```
list(df_values.columns.values)
```

Out[4]:
```
['amount_tsh',
 'date_recorded',
 'funder',
 'gps_height',
 'installer',
 'longitude',
 'latitude',
 'wpt_name',
 'num_private',
 'basin',
 'subvillage',
 'region',
 'region_code',
 'district_code',
 'lga',
 'ward',
 'population',
 'public_meeting',
 'recorded_by',
 'scheme_management',
 'scheme_name',
 'permit',
 'construction_year',
 'extraction_type',
 'extraction_type_group',
 'extraction_type_class',
 'management',
 'management_group',
 'payment',
 'payment_type',
 'water_quality',
 'quality_group',
 'quantity',
 'quantity_group',
 'source',
 'source_type',
 'source_class',
 'waterpoint_type',
 'waterpoint_type_group']
```

In [5]:
```
df_labels.head(5)
```

Out[5]:

	status_group
id	
69572	functional
8776	functional
34310	functional
67743	non functional
19728	functional

In [6]:

```
df_labels.status_group.value_counts()
```

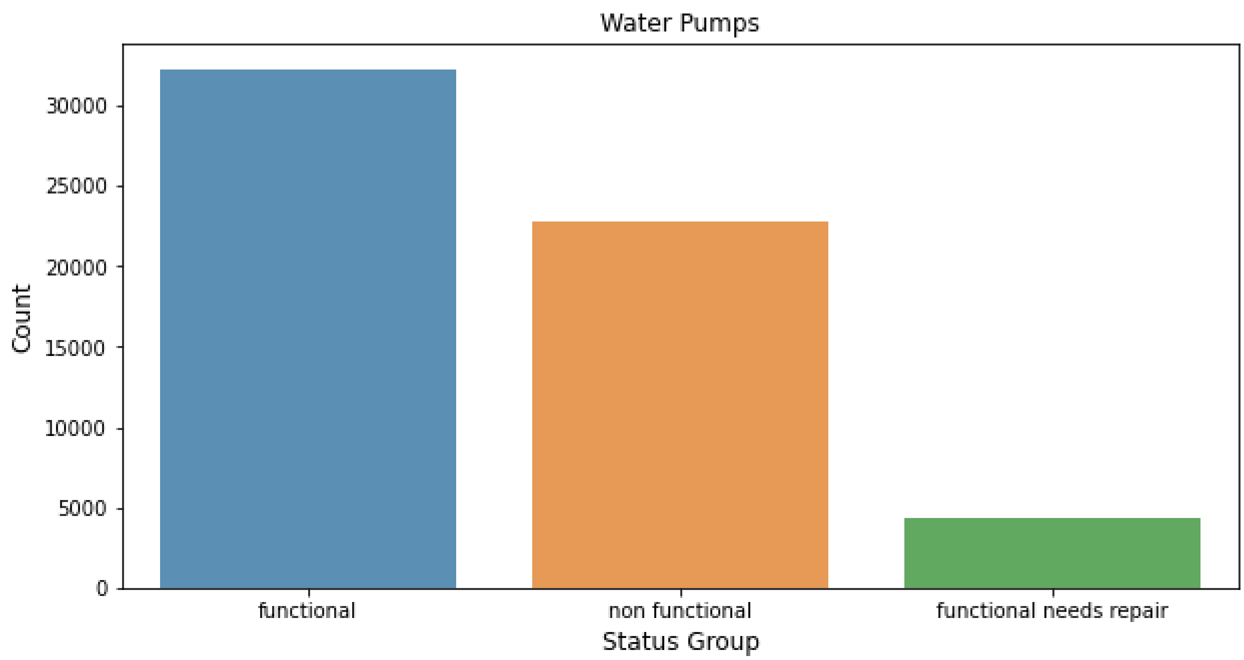
Out[6]:

```
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
```

Plotting variables to have a better understading and visualization

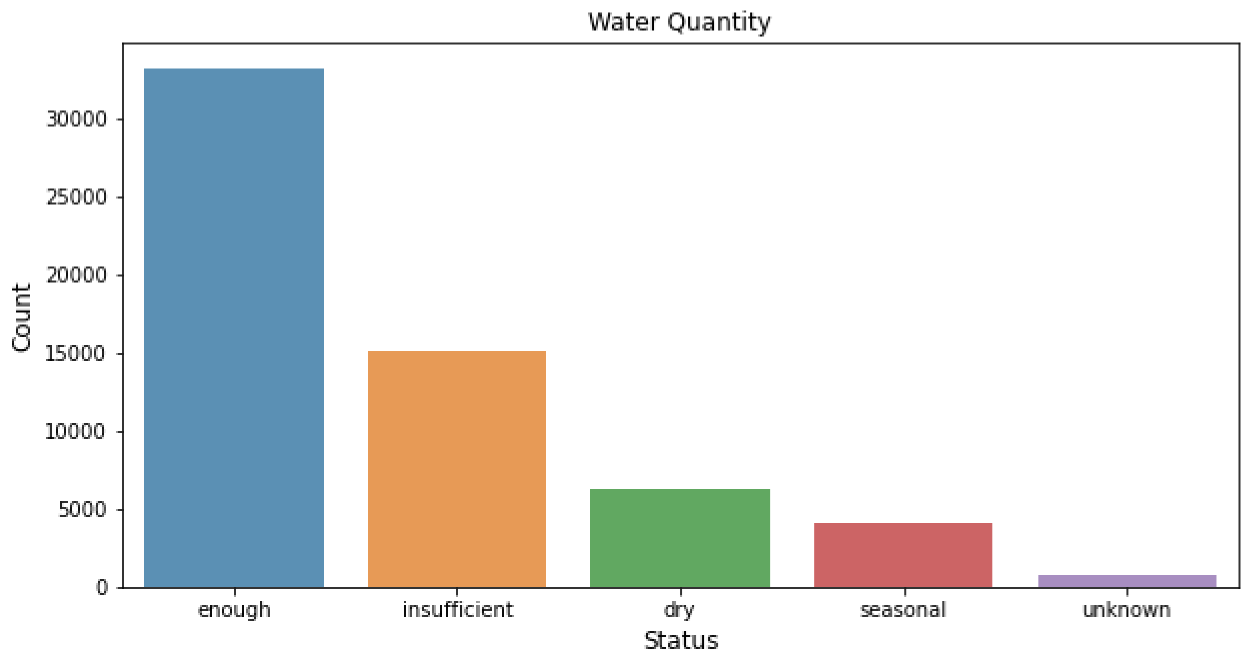
In [7]:

```
func_pump = df_labels['status_group'].value_counts()
func_pump = func_pump[:100,]
plt.figure(figsize=(10,5))
sns.barplot(func_pump.index, func_pump.values, alpha=0.8)
plt.title('Water Pumps')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Status Group', fontsize=12)
plt.show()
```



In [8]:

```
quantity = df_values['quantity'].value_counts()
quantity = quantity[:100,]
plt.figure(figsize=(10,5))
sns.barplot(quantity.index, quantity.values, alpha=0.8)
plt.title('Water Quantity')
plt.ylabel('Count', fontsize=12)
plt.xlabel('Status', fontsize=12)
plt.show()
```



Joing the two dataset, values and labels.

In [9]:
```python
df_training = pd.concat([df_labels, df_values], axis=1, join='inner')
df_training.head()
```

Out[9]:

	status_group	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	w
id									
69572	functional	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	
8776	functional	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	
34310	functional	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	
67743	non functional	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	N
19728	functional	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	

5 rows × 40 columns

Filling NaN and Dropping Columns

In [10]:
```python
to_drop =['num_private','date_recorded','longitude','latitude','subvillage',
          'region_code','district_code','lga','ward','recorded_by',
          'scheme_management','scheme_name', 'extraction_type_group',
          'extraction_type_class','management_group','payment',
          'quality_group','quantity_group','source_type',
          'source_class','waterpoint_type_group','wpt_name']
df_training.drop(to_drop,axis=1, inplace=True)
```

In [11]:
```python
df_training.public_meeting.fillna(False,inplace=True)
```

In [12]:
```python
df_training.permit.fillna(False,inplace=True)
```

Transforming and Binning values

- Funder
- Installer
- Construction Year
- Extraction

- Management
- Population

In [13]:
```
funder_bins=list(df_training.funder.value_counts().index[:8])
funder_bins
```

Out[13]:
```
['Government Of Tanzania',
 'Danida',
 'Hesawa',
 'Rwssp',
 'World Bank',
 'Kkkt',
 'World Vision',
 'Unicef']
```

In [14]:
```
funder_dict=dict(zip(funder_bins,range(1,len(funder_bins)+1)))
funder_dict
```

Out[14]:
```
{'Government Of Tanzania': 1,
 'Danida': 2,
 'Hesawa': 3,
 'Rwssp': 4,
 'World Bank': 5,
 'Kkkt': 6,
 'World Vision': 7,
 'Unicef': 8}
```

In [15]:
```
df_training['funder']=df_training['funder'].apply(
    lambda x: funder_dict[x] if x in funder_bins else 0)
```

In [16]:
```
installers=list(df_training.installer.value_counts()[:10].index)
installers.remove('0')
installers_dict = dict(zip(installers,range(1,len(installers)+1)))
df_training['installer']=df_training['installer'].apply(
    lambda x: installers_dict[x] if x in installers else 0)
```

In [17]:
```
management=list(df_training.management.value_counts()[:4].index)
management_dict = dict(zip(management,range(1,len(management)+1)))
df_training['management']=df_training['management'].apply(
    lambda x: management_dict[x] if x in management else 0)
```

In [18]:
```
max_year=df_training['construction_year'].describe()['max']
max_year = float(max_year)
min_year=df_training['construction_year'][df_training[
    'construction_year']!=0].sort_values(ascending=True).iloc[0]
min_year = float(min_year)
year_bins=np.linspace(min_year,max_year,7)
year_bins=[np.round(x) for x in year_bins ]
year_bins=[0,1]+year_bins[1:]
year_bins
```

Out[18]:
```
[0, 1, 1969.0, 1978.0, 1986.0, 1995.0, 2004.0, 2013.0]
```

In [19]:
```
df_training['construction_year']=pd.cut(df_training['construction_year'],[
    0,1,1960,1969,1978,1987,1995,2004,2013
],include_lowest=True,labels=[1,2,3,4,5,6,7,8])
```

In [20]:
```
extractions=list(df_training.extraction_type.value_counts()[0:4].index)
extractions.remove('other')
extractions_dict = dict(zip(extractions,range(1,len(extractions)+1)))
extractions_dict
```

Out[20]:
```
{'gravity': 1, 'nira/tanira': 2, 'submersible': 3}
```

In [21]:
```
df_training['extraction_type']=df_training['extraction_type'].apply(
    lambda x: extractions_dict[x] if x in extractions else 0
)
```

In [22]:
```
df_training.population=df_training.population.apply(
    lambda x: 1 if x>1 else 0
)
```

In [23]:
```
df_training.management.value_counts()
```

Out[23]:
```
1    40507
0     6910
2     6515
3     2933
4     2535
Name: management, dtype: int64
```

Creating Target Y and Predictor X

In [24]:
```
categoricals=['funder','installer','management','public_meeting',
              'construction_year','extraction_type','permit','basin',
              'region','population','water_quality','quantity','source',
              'waterpoint_type','payment_type'
             ]
```

In [25]:
```
status_map={'non functional':0,'functional':1,'functional needs repair':2}
y=df_training['status_group'].replace(status_map)
X=df_training.drop('status_group',axis=1)
```

In [26]:
```
X=pd.get_dummies(X,columns=categoricals,drop_first=True)
```

In [27]:
```
X_train, X_test, y_train, y_test = train_test_split (
    X, y, test_size = 0.25, random_state=42)
```

Modeling

DecisionTree

In [28]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [29]:
```
clf = DecisionTreeClassifier(max_depth=4)
clf.fit(X_train, y_train)
```

Out[29]:
```
DecisionTreeClassifier(max_depth=4)
```

In [30]:
```
clf.decision_path(X_test)
```

Out[30]:
```
<14850x31 sparse matrix of type '<class 'numpy.int64'>'
	with 74250 stored elements in Compressed Sparse Row format>
```

In [31]:

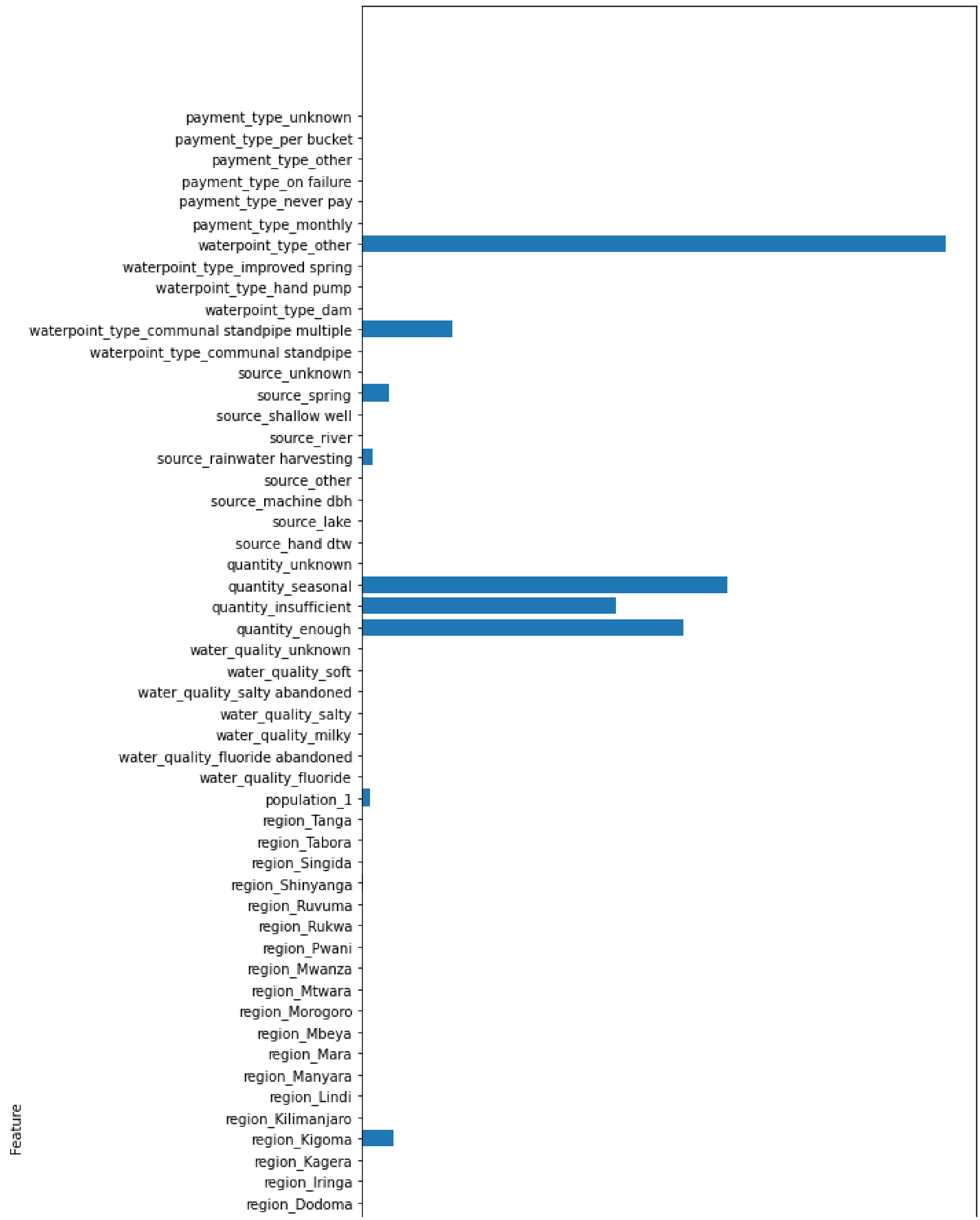
```
clf.feature_importances_
```

Out[31]:

```
array([0.03763677, 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.01667174, 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.00516299, 0.        ,
       0.        , 0.        , 0.        , 0.00946915, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.01740241, 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.0009062 ,
       0.        , 0.        , 0.        , 0.00440489, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.17638379, 0.13960131, 0.20064687, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.00623207,
       0.        , 0.        , 0.01526133, 0.        , 0.        ,
       0.04983702, 0.        , 0.        , 0.        , 0.32038347,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        ])
```

In [32]:

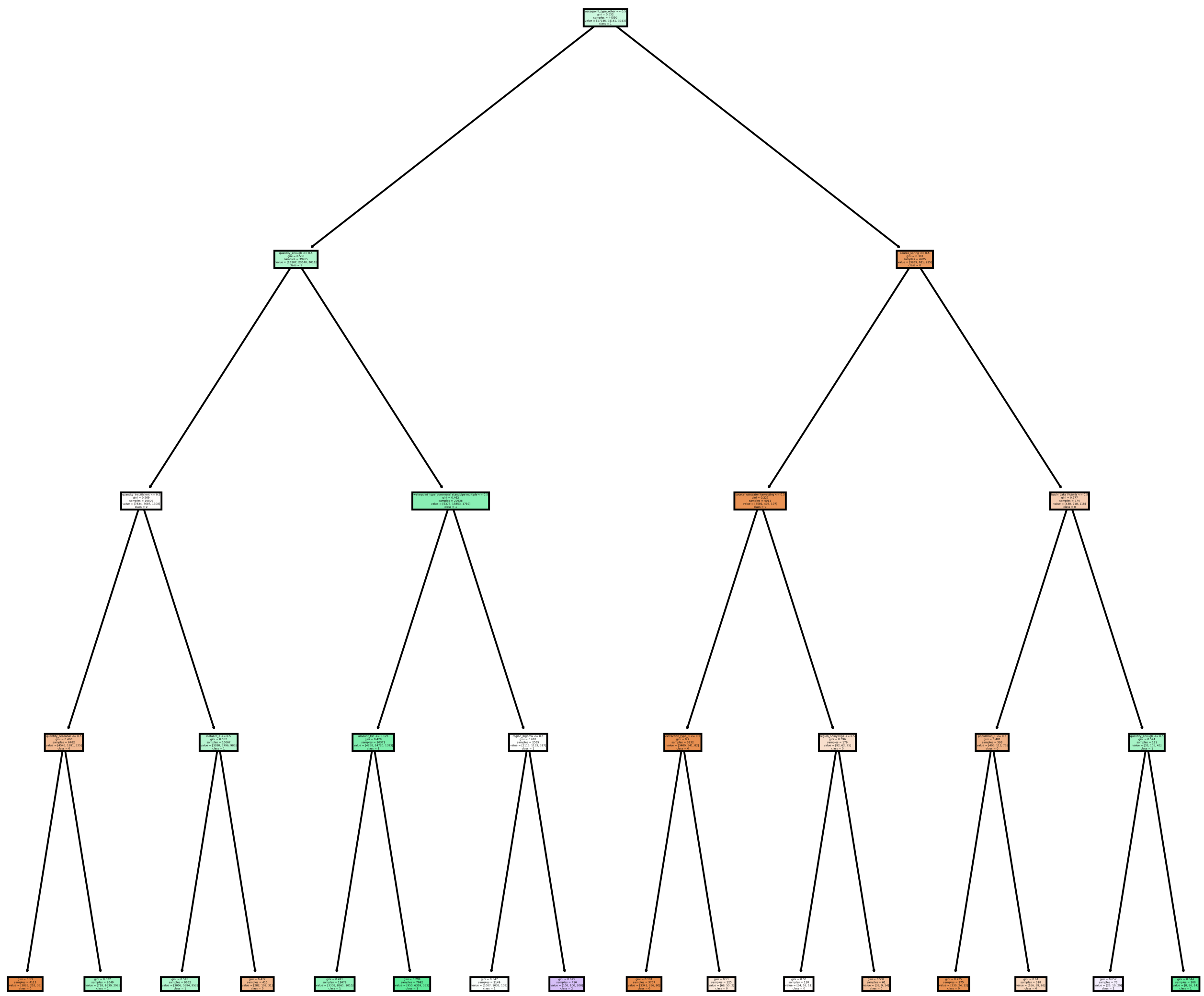
```python
def plot_feature_importances(model):
    n_features = X_train.shape[1]
    plt.figure(figsize=(8,30))
    plt.barh(range(n_features), model.feature_importances_, align='center')
    plt.yticks(np.arange(n_features), X_train.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(clf)
```




region_Dar es Salaam
basin_Wami / Ruvu
basin_Ruvuma / Southern Coast
basin_Rufiji
basin_Pangani
basin_Lake Victoria
basin_Lake Tanganyika
basin_Lake Rukwa
basin_Lake Nyasa
permit_True
extraction_type_3
extraction_type_2
extraction_type_1
construction_year_8
construction_year_7
construction_year_6
construction_year_5
construction_year_4
construction_year_3
construction_year_2
public_meeting_True
management_4
management_3
management_2
management_1
installer_9
installer_8
installer_7
installer_6
installer_5
installer_4
installer_3
installer_2
installer_1
funder_8
funder_7
funder_6
funder_5
funder_4
funder_3
funder_2
funder_1
gps_height
amount_tsh
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Feature importance

In [33]:

```python
from sklearn import tree
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (12,12), dpi=900)
tree.plot_tree(clf,
               feature_names = X_train.columns,
               class_names=np.unique(y).astype('str'),
               filled = True)
plt.show()
```



In [34]:
```python
y_preds=clf.predict(X_test)
```

In [39]:
```python
accuracy_score(y_test,y_preds)
```

Out[39]:
```
0.7034343434343434
```

In [40]:
```python
confusion_matrix(y_test,y_preds)
```

Out[40]:
```
array([[2618, 3001,   59],
       [ 306, 7746,   46],
       [  73,  919,   82]], dtype=int64)
```

In [41]:
```python
# DecisionTree does not has a good perfomance
# Confusion Matrix also does not look good
```

ROC CURVE

In [42]:
```python
from sklearn.metrics import roc_curve, auc

# Identify the optimal tree depth for given data

max_depth = range(1,32)
roc_train = []
roc_test = []
accuracy_scores_train=[]
accuracy_scores_test=[]
for test_parm in max_depth:
    dt = DecisionTreeClassifier(random_state=10,max_depth=test_parm)
    dt.fit(X_train, y_train)
    y_pred_train = dt.predict(X_train)
    y_pred_test = dt.predict(X_test)
    accuracy_scores_train.append((test_parm,accuracy_score(y_pred_train,y_train)))
    accuracy_scores_test.append((test_parm,accuracy_score(y_pred_test,y_test)))
```

In [43]:

```
accuracy_scores_train
```

Out[43]:

```
[(1, 0.6168125701459035),
 (2, 0.6201122334455668),
 (3, 0.6780246913580247),
 (4, 0.7053872053872053),
 (5, 0.7180920314253647),
 (6, 0.7256341189674523),
 (7, 0.7344781144781145),
 (8, 0.745342312008978 7),
 (9, 0.7536026936026936),
 (10, 0.7635914702581369),
 (11, 0.7753535353535354),
 (12, 0.7889786756453423),
 (13, 0.800695847362514),
 (14, 0.8149943883277216),
 (15, 0.8282379349046016),
 (16, 0.8404264870931537),
 (17, 0.8523456790123457),
 (18, 0.8637037037037038),
 (19, 0.874769921436588),
 (20, 0.8837037037037037),
 (21, 0.8925028058361392),
 (22, 0.899753086419753),
 (23, 0.9059708193041527),
 (24, 0.9111560044893379),
 (25, 0.915712682379349),
 (26, 0.9202693602693602),
 (27, 0.923658810325477),
 (28, 0.9269809203142536),
 (29, 0.9297643097643098),
 (30, 0.9320763187429854),
 (31, 0.9336026936026937)]
```

In [44]:

```
accuracy_scores_test
```

Out[44]:

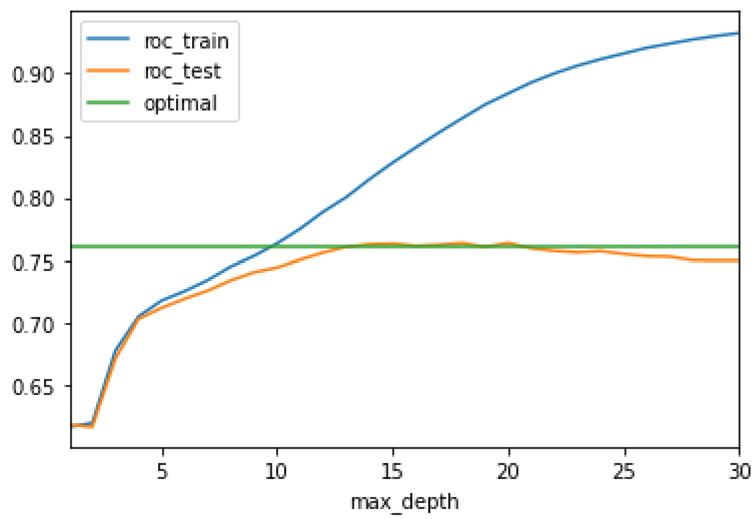
```
[(1, 0.6186531986531987),
 (2, 0.616902356902357),
 (3, 0.6715824915824916),
 (4, 0.7034343434343434),
 (5, 0.7122558922558923),
 (6, 0.7195286195286196),
 (7, 0.7260606060606061),
 (8, 0.7342760942760943),
 (9, 0.7406734006734007),
 (10, 0.7444444444444445),
 (11, 0.7506397306397307),
 (12, 0.7562962962962962),
 (13, 0.7608754208754209),
 (14, 0.7628956228956228),
 (15, 0.7633670033670034),
 (16, 0.7616161616161616),
 (17, 0.7624242424242424),
 (18, 0.7638383838383839),
 (19, 0.7607407407407407),
 (20, 0.7639057239057239),
 (21, 0.7596632996632997),
 (22, 0.7575757575757576),
 (23, 0.7564983164983164),
 (24, 0.7574410774410775),
 (25, 0.7551515151515151),
 (26, 0.7534680134680135),
 (27, 0.7530639730639731),
 (28, 0.7502356902356903),
 (29, 0.74996632996633),
 (30, 0.75010101010101),
 (31, 0.7489562289562289)]
```

In [45]:

```python
# Identify the optimal tree depth for given data

roc_train=[x[1] for x in accuracy_scores_train]
roc_test=[x[1] for x in accuracy_scores_test]
df_result=pd.DataFrame({'roc_train':roc_train,'roc_test':
                        roc_test,'max_depth':list(max_depth)})
df_result=df_result.set_index('max_depth')
df_result['optimal']=pd.Series(
    index=list(max_depth),data=np.ones(len(
        max_depth))*df_result.roc_test.iloc[15])

df_result.plot()
plt.xlim([1, 30])
```

Out[45]:

```
(1.0, 30.0)
```



In [46]:

```python
df_result.iloc[15]
```

Out[46]:

```
roc_train    0.840426
roc_test     0.761616
optimal      0.761616
Name: 16, dtype: float64
```

In [47]:

```python
# ROC CURVE we are able to show the best "max_depth" is around 15
# I decided not to use the DecisionTree results
```

BaggingClassifier, RandomForest

In [48]:
```
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier

bagged_tree = BaggingClassifier(DecisionTreeClassifier(
    criterion='gini', max_depth=15), n_estimators=20)

bagged_tree.fit(X_train,y_train)
```

Out[48]:
```
BaggingClassifier(base_estimator=DecisionTreeClassifier(max_depth=15),
                  n_estimators=20)
```

In [49]:
```
bagged_tree.score(X_train,y_train)
```

Out[49]:
```
0.843030303030303
```

In [50]:
```
bagged_tree.score(X_test,y_test)
```

Out[50]:
```
0.7794612794612794
```

In [51]:
```
rfc = RandomForestClassifier(criterion='gini', max_depth=5, n_estimators=10)

rfc.fit(X_train,y_train)
```

Out[51]:
```
RandomForestClassifier(max_depth=5, n_estimators=10)
```

In [52]:
```
rfc.score(X_train,y_train)
```

Out[52]:
```
0.697351290684624
```

In [53]:
```
rfc.score(X_test,y_test)
```

Out[53]:
```
0.6956228956228956
```

In [54]:
```
# BaggingClassifier has a better perfomance comparing to RandonForest
# I decided not to use RandonForest results
```

Accurancy Score BaggingClassifier

In [55]:

```
# Accurancy Score on BaggingClassifier

accuracy_scores_train={}
accuracy_scores_test={}
max_depth=range(1,20)
for test_parm in max_depth:
    dt = BaggingClassifier(DecisionTreeClassifier(
        criterion='gini',max_depth=test_parm), n_estimators=20)

    dt.fit(X_train, y_train)

    accuracy_scores_train[test_parm]=dt.score(X_train,y_train)
    accuracy_scores_test[test_parm]=dt.score(X_test,y_test)
```

In [56]:

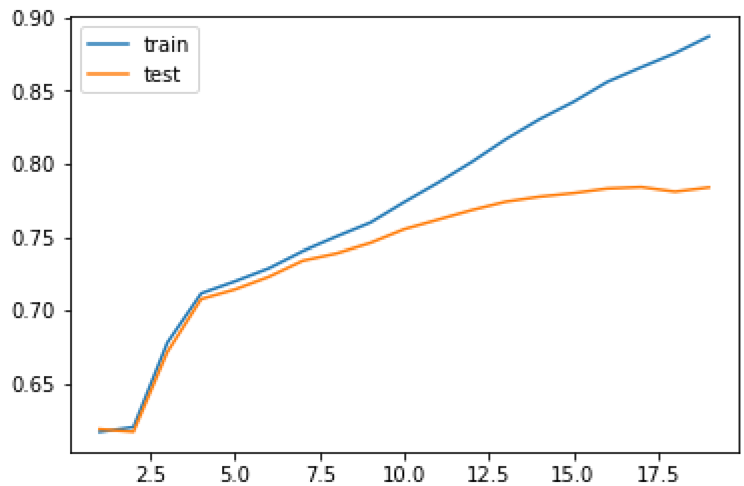
```
accuracy_scores_train
```

Out[56]:

```
{1: 0.6168125701459035,
 2: 0.6201122334455668,
 3: 0.6778900112233446,
 4: 0.7116498316498316,
 5: 0.7198877665544332,
 6: 0.7287766554433222,
 7: 0.7404489337822671,
 8: 0.7503254769921437,
 9: 0.7597979797979798,
 10: 0.7738047138047138,
 11: 0.7871156004489338,
 12: 0.801324354657688,
 13: 0.8168350168350168,
 14: 0.8305499438832772,
 15: 0.8424017957351291,
 16: 0.8560942760942761,
 17: 0.8660606060606061,
 18: 0.8757126823793491,
 19: 0.8872053872053872}
```

In [57]:
```python
df_test=pd.DataFrame(accuracy_scores_test.values(),
                     index=accuracy_scores_test.keys(),columns=['test'])

df_train=pd.DataFrame(accuracy_scores_train.values(),
                      index=accuracy_scores_train.keys(),columns=['train'])

df_train.join(df_test).plot()
```

Out[57]: <AxesSubplot:>



In [58]:
```python
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
y_pred_test = bagged_tree.predict(X_test)
print(classification_report(y_test, y_pred_test))
print(confusion_matrix(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.85      0.69      0.76      5678
           1       0.76      0.92      0.83      8098
           2       0.54      0.22      0.31      1074

    accuracy                           0.78     14850
   macro avg       0.72      0.61      0.63     14850
weighted avg       0.78      0.78      0.77     14850

[[3909 1695   74]
 [ 538 7433  127]
 [ 138  703  233]]
```

In [59]:
```python
# Overall the Confusion Matrix on BaggingClassifier
# it does not have a better perfomance than the DecisonTree
```

AdaBoostClassifier, GradientBoostingClassifier

In [60]:
```
from sklearn.ensemble import AdaBoostClassifier, GradientBoostingClassifier
adaboost_clf = AdaBoostClassifier(random_state=42)
gbt_clf = GradientBoostingClassifier(random_state=42)
adaboost_clf.fit(X_train,y_train)
gbt_clf.fit(X_train,y_train)
```

Out[60]:
```
GradientBoostingClassifier(random_state=42)
```

In [61]:
```
# AdaBoost model predictions
adaboost_train_preds = adaboost_clf.predict(X_train)
adaboost_test_preds = adaboost_clf.predict(X_test)

# GradientBoosting model predictions
gbt_clf_train_preds = gbt_clf.predict(X_train)
gbt_clf_test_preds = gbt_clf.predict(X_test)
```

In [62]:
```
accuracy_score(y_test,gbt_clf_test_preds)
```

Out[62]:
```
0.7490909090909091
```

In [63]:
```
accuracy_score(y_test,adaboost_test_preds)
```

Out[63]:
```
0.7155555555555555
```

In [64]:
```
# GradientBoostingClassifier does slightly better than AdaBoostClassifier
# Still they both do not have a great perfomace
```

XGBOOST

In [65]:

```
from xgboost import XGBClassifier

# Instantiate XGBClassifier
XGB = XGBClassifier()

# Fit XGBClassifier
XGB.fit(X_train, y_train)

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

# Accuracy of training and test sets
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

training_accuracy,test_accuracy
```

```
[21:00:08] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.0/src/
learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with t
he objective 'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly set
eval_metric if you'd like to restore the old behavior.
```

Out[65]:

```
(0.8182042648709316, 0.7851851851851852)
```

In [66]:

```
# XGBOOST has a good perfomance overall
# The gap between test and train is small
# The best results comparing to any other model
# I decided to keep it as my model
```

Parameter Grid

In [67]:

```
from sklearn.model_selection import GridSearchCV


param_grid = {
    'learning_rate': [0.02, 0.2],
    'max_depth': [6],
    'min_child_weight': [1, 2],
    'subsample': [0.5, 1],
    'n_estimators': [100],
}

param_grid_2 = {
    'learning_rate': [0.2, 0.3],
    'max_depth': [6],
    'min_child_weight': [1],
    'subsample': [0.5],
    'n_estimators': [100],
}

grid_clf = GridSearchCV(XGB, param_grid, scoring='accuracy', cv=None, n_jobs=1)
grid_clf.fit(X_train, y_train)
```

```
[21:00:28] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'multi:softprob' was changed from 'merror' to 'mloglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:00:51] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'multi:softprob' was changed from 'merror' to 'mloglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:01:14] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'multi:softprob' was changed from 'merror' to 'mloglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:01:37] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'multi:softprob' was changed from 'merror' to 'mloglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
[21:02:01] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.4.
0/src/learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric
used with the objective 'multi:softprob' was changed from 'merror' to 'mloglos
```

In [68]:

```
best_parameters = grid_clf.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_clf.predict(X_train)
test_preds = grid_clf.predict(X_test)
```

```
Grid Search found the following optimal parameters:
learning_rate: 0.2
max_depth: 6
min_child_weight: 1
n_estimators: 100
subsample: 0.5
```

In [69]:

```
training_accuracy = accuracy_score(y_train, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

training_accuracy,test_accuracy
```

Out[69]:

```
(0.8077441077441078, 0.7835016835016835)
```

In [70]:

```
print(confusion_matrix(y_test, test_preds))
```

```
[[4044 1587   47]
 [ 634 7355  109]
 [ 160  678  236]]
```

In [71]:

```
cf_matrix = confusion_matrix(y_test,test_preds)
sns.heatmap(cf_matrix/np.sum(cf_matrix),annot=True,fmt='2%',cmap='Blues')
```

Out[71]:

```
&lt;AxesSubplot:&gt;
```