Classifer Modeling

Evaluation Metric: Accuracy

The DrivenData Challenge Evaluation Metric is "Classification Rate" (AKA, Accuracy).

"The metric used for this competition is the classification rate, which calculates the percentage of rows where the predicted class y^ in the su
the actual class, y in the test set. The maximum is 1 and the minimum is 0. The goal is to maximize the classification rate.

Classes: Functional, Non Functional, and Functional Needs Repair

Class Frequency of the classes represented in the Training dataset:

- Functional: 54.5%
- Non Functional: 38.7%
- Functional Needs Repair: 6.8%

There is a class imbalance issue, with **Functional Needs Repair** as the rare class.

In [2]:

```
# Load in libraries
import warnings
from importlib import reload
warnings.filterwarnings('ignore')

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

%matplotlib inline
plt.style.use('seaborn')
import seaborn as sns

import scipy.stats as scs
import statsmodels.api as sm
import statsmodels.formula.api as sms

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, plot_confusio
from sklearn.metrics import roc_curve, auc, roc_auc_score # needed?

from sklearn.preprocessing import OneHotEncoder

from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier

from xgboost import XGBClassifier
```

Define local functions

In [8]:

```
def plot_hist(the_df, the_col):
    plt.figure(figsize=(8,5))
    plt.grid(linestyle='dashed', alpha=0.3, zorder=0)
    plt.hist(the_df[the_col], alpha=0.8, zorder=2)
    plt.title(the_col.capitalize())
    plt.show()


def plot_confusion(ytrue, ypred):
    cm_norm = confusion_matrix(ytrue, ypred, normalize='true')
    sns.heatmap(cm_norm, cmap=sns.color_palette('Blues'), fmt='0.5g', annot=True, annot_kws={"va":
    cm = confusion_matrix(ytrue, ypred)
    sns.heatmap(cm, cmap=sns.color_palette('Blues'), fmt='0.5g', annot=True, annot_kws={"va":"top"
    plt.show()


def print_accuracy(model, X_train, y_train, X_test, y_test, cm=False, cr=False, get_y_hat=False):
    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)
    acc_test = round(accuracy_score(y_test, y_pred_test),3) * 100
    acc_train = round(accuracy_score(y_train, y_pred_train),3) * 100
    print(f'Test accuracy: {acc_test} %')
    print(f'Train accuracy: {acc_train} %')
    if cm == True:
        print(confusion_matrix(y_test, y_pred_test))
    if cr == True:
        print(classification_report(y_test, y_pred_test))
    if get_y_hat == True:
        return y_pred_test


def plot_confusion(model, X_test, y_test, normalize=None, form='.2f'):
    plot_confusion_matrix(model, X_test, y_test,
                          cmap=plt.cm.Blues, xticks_rotation='vertical',
                          normalize=normalize, values_format=form)
    plt.show()


def plot_feature_importance(model, ohencoder, X_encoder_input, num_features=25):
    top_features_list = []
    for item in zip(ohencoder.get_feature_names(X_encoder_input.columns), model.feature_importance
        if item[1] > 0:
            top_features_list.append(item)
    top_feats = sorted(top_features_list, key=lambda x: x[1], reverse=True)
    x_feats_importance = list(map(lambda x: x[1], top_feats[:num_features]))
    y_feats_labels = list(map(lambda x: x[0], top_feats[:num_features]))
    fig, ax = plt.subplots(figsize=(10,10))
    plt.barh(y_feats_labels, x_feats_importance, align='center', color='purple', alpha=0.8)
    ax.set_yticks(y_feats_labels)
    ax.set_yticklabels(y_feats_labels)
    ax.invert_yaxis()  # labels read top-to-bottom
    ax.set_xlabel('Importance')
    ax.set_ylabel('Features')
    ax.set_title(f'Top {num_features} Features Ranked by Importance')
    plt.show()
```

Load in Training Data

In [9]:

```
# read in the cleand training data
train_df = pd.read_csv('../data/train_processed_labeled.csv', index_col='id')
```

We created the following new columns for our EDA, but we do not want to use them in modeling for our Classifier.

- recorded_year - Pulling out the year from date_recorded
- waterpoint_age - Calculate as recorded_year - construction_year
- recorded_good_quality - True if quality_group == 'good', False if anything other than 'good'
- recorded_good_quantity - True if quanity_group == 'sufficient', False if anythign other than 'sufficient'

In [10]:

```
train_df.drop(['recorded_year', 'waterpoint_age', 'recorded_good_quality', 'recorded_good_quantity
```

Feature Selection and Engineering

Inspecting all the features and making initial choices on which ones to use for modeling.

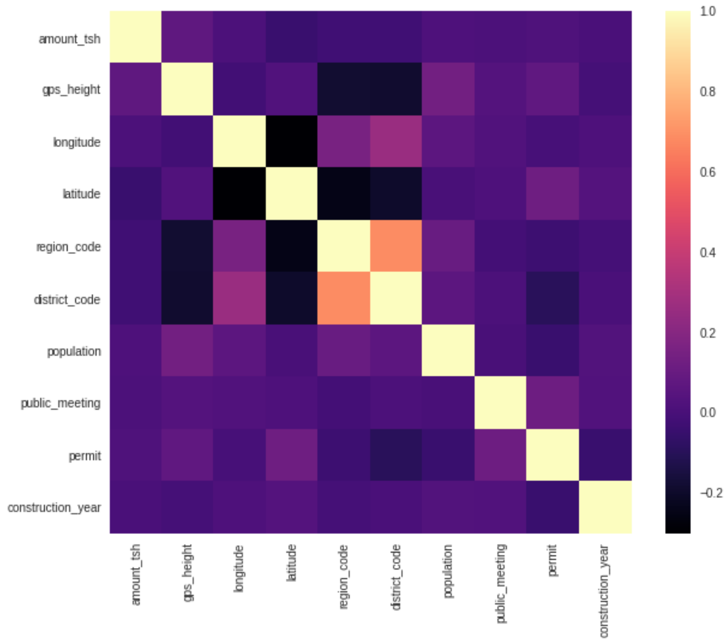
In [11]:

```
# Take the TRAIN dataset provided by the Challenge and make a train/test split for local model cre
X = train_df.drop(['status_group'], axis=1)
y = train_df['status_group']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

In [12]:
```
1 plt.figure(figsize=(10,8))
2 sns.heatmap(X_train.corr(), square=True, cmap='magma')
```

Out[12]: <AxesSubplot:>



Initial Feature Selection: NUMERIC

Opt to INCLUDE the following (starting out):

- **region_code** This is the code for the Region. This feature can take the place of doing One Hot Encoding on the region feature which ha the regions.
- **construction_year**

Opt to EXCLUDE the following (starting out):

- **district_code** feature is highly (positively) correlated to region_code as Regions are divided into Districts. Looking at the value counts c reveals that some districts are rarely represented. Favoring using region instead.
- **gps_height** feature is somewhat correlated to region_code
- **latitude** feature is somewhat correlated to region_code
- **longitude** feature is somewhat correlated to region_code
- **amount_tsh**
- **population**

Initial Feature Selection: CATEGORICAL

Opt to INCLUDE the following (starting out):

- **basin**
- **quantity_group**
- **payment_type**
- **public_meeting** - T/F values for some public meeting status
- **permit** - T/F values for has permit
- **funder** (w/ rare category encoding)
- **installer** (w/ rare category encoding)
- **scheme_management** (w/ rare category encoding)
- **extraction_type_class** (w/ rare category encoding)
- **management_group** (w/ rare category encoding)
- **quality_group** (w/ rare category encoding)
- **source_type** (w/ rare category encoding)
- **waterpoint_group_type** (w/ rare category encoding)

Opt to EXCLUDE the following:

- **wpt_name** - This identifier does not provide predictive information
- **scheme_name** - This identifier for the name of the management scheme does not provide predictive info
- **recorded_by** - All the same string/ does not provide predictive information
- **date_recorded** - This variable doesn't provide predictive information since it is the just the day the survey occured
- **region** - Information already captured by region_code, a numeric feature.
- Features that are sub-types of other features (ex: waterpoint_type is a sub-type of waterpoint_type_group)
- Features with too high a cardinality/ where even the category with the highest percentage was less than 5% (ex: subvillage w/ 16642 un

In [13]:

```
# Checking out the cardinality in categorical columns - # of different labels/ unique string value
for var in X_train.columns:
    # print the first 20 unique values in the Object columns
    if train_df[var].dtype == 'O':
        unique_vals = X_train[var].unique()
        print(var, ' cardinality:', unique_vals.size, ', first 20 unique:',  unique_vals[0:20], '\
```

```
date_recorded  cardinality: 348 , first 20 unique: ['2011-03-24' '2012-10-19' '2012-11-05' '2012-10-30
 '2011-02-27' '2013-01-15' '2011-03-03' '2013-02-19' '2011-02-25'
 '2013-01-24' '2011-04-08' '2011-07-06' '2013-03-22' '2011-03-20'
 '2011-03-17' '2013-03-03' '2011-04-04' '2011-07-24' '2011-07-07']

funder  cardinality: 1656 , first 20 unique: ['kkkt' 'world vision' 'government of tanzania' 'unicef/ 
nk'
 'dhv' 'kalitasi' 'mkuyu' 'kkkt church' 'kibaha independent school'
 'danida' 'wananchi' 'lga' 'hans' 'md' 'roman' 'moravian' 'is' 'mission'
 'water user as']

installer  cardinality: 1701 , first 20 unique: ['kkkt' 'world vision' 'government' 'rdc' 'gwasco l'
 'china henan contractor' 'dwe' 'kalitasi' 'mkuyu' 'district council'
 'kkkt church' 'handeni trunk main(' 'dawasco' 'danida' 'wananchi' 'hans'
 'dw' 'commu' 'is' 'consulting engineer']

wpt_name  cardinality: 30166 , first 20 unique: ['kwa mzee amili' 'kwa mgaiwa' 'kwa mtoba hila' 'mzamb
juma'
 'kwa boni' 'majengo mapya' 'idara ya maji' 'kwa mzee mpinda'
```

Rare categories inspection

Apply rare category encoding for:

- funder
- installer
- scheme_management
- extraction_type_class (has 2 out of 7 w >5%)
- management_group (has 3 of out 5 categories w/ > 5%)
- quality_group (has 3 out of 6 categories w/ > 5%)
- source_type (has 2 out of 7 categories w/ > 5%)
- waterpoint_type_group (has 3 out of 6 categories w/ >5%)

I am not include features that have too high a cardinality/where even the category with the highest percentage was less than 5%.

NOTE: some the features are sub-types (ex: waterpoint_type is a sub-type of waterpoint_type_group), so I'm using the highest type in these

- waterpoint_type_group
- source_type
- quality_group
- management_group
- extraction_type_class
- quantity_group - does not need rare category encoding applied
- payment_type (seems to be a duplicate of the payment feature) - does not need rare category encoding applied

In [14]:

```python
# Look for rarely occurring categories.

multi_cat_cols = []
multi_cat_series = []
for col in X_train.columns:

    if X_train[col].dtypes =='O': # if variable  is categorical

        if X_train[col].nunique() > 4: # choosing to inspect where there are more than 5 categorie

            multi_cat_cols.append(col)  # add to the list
            count_series = X_train.groupby(col)[col].count()
            multi_cat_series.append(count_series)
            print(count_series/ len(X_train)) #  print the percentage of observations within each
            print(count_series.values.max()/len(X_train), count_series.values.min()/len(X_train))
            print()
```

```
date_recorded
2002-10-14    0.000022
2004-01-07    0.000022
2004-03-01    0.000065
2004-03-06    0.000022
2004-04-01    0.000022
                ...
2013-11-02    0.000413
2013-11-03    0.003214
2013-12-01    0.000022
2013-12-02    0.000586
2013-12-03    0.004169
Name: date_recorded, Length: 348, dtype: float64
0.009793277164943976 2.1714583514288198e-05

funder
0                      0.013702
a/co germany           0.000261
aar                    0.000543
```

In [15]:
```
# Functions for rare category encoding
def find_non_rare_labels(df, col_name, tolerance):
    temp = df.groupby([col_name])[col_name].count() / len(df)
    non_rare = [x for x in temp.loc[temp>tolerance].index.values]
    return non_rare


def rare_encoding(X_train, X_test, col_name, tolerance):
    X_train = X_train.copy()
    X_test = X_test.copy()

    # find the most frequent category
    frequent_cat = find_non_rare_labels(X_train, col_name, tolerance)

    # re-group rare labels
    X_train[col_name] = np.where(X_train[col_name].isin(
        frequent_cat), X_train[col_name], 'rare')

    X_test[col_name] = np.where(X_test[col_name].isin(
        frequent_cat), X_test[col_name], 'rare')

    return X_train, X_test


def plot_rare_catgories(df, cols):
    for col in cols:

        temp_df = pd.Series(df[col].value_counts() / len(df) )

        # make plot with the above percentages
        fig = temp_df.sort_values(ascending=False).plot.bar(rot=50, alpha = 0.80,  colormap='magma
        fig.set_xlabel(col)

        # add a line at 5 % to flag the threshold for rare categories
        fig.axhline(y=0.05, color='red')
        fig.set_ylabel('Percentage of categories')
        plt.show()
```

In [16]:
```
# Apply rare encoding to TRAIN and TEST
rare_cat_cols = ['funder', 'installer', 'scheme_management', 'extraction_type_class', 'management_
'waterpoint_type_group']
```

In [17]:
```
for col_name in rare_cat_cols:
    X_train, X_test = rare_encoding(X_train, X_test, col_name, 0.05)
```

In [18]:
```
## SELECTED FEATURES FOR MODELING
cont_features_to_use = ['region_code', 'construction_year']
cat_features_to_use = rare_cat_cols + ['basin', 'quantity_group', 'payment_type', 'permit', 'publi
features_to_use = cont_features_to_use + cat_features_to_use
```

One Hot Encode the chosen categorical features

In [19]:
```
# Did our test train spilt before exploring features in X_Train for rare label encoding.
# Now that I've selected some features based off of exploring X_Train ONLY, train the model on the
X_train = X_train[features_to_use]
X_test = X_test[features_to_use]

# OHE categorical features
ohe = OneHotEncoder(categories='auto', handle_unknown='ignore')
ohe.fit(X_train)
```

Out[19]:
```
OneHotEncoder(handle_unknown='ignore')
```

In [20]:
```
X_train_encoded = ohe.transform(X_train)
X_test_encoded = ohe.transform(X_test)
```

Modeling!

Try out the Baseline and Tuned verions of models from a few different Classification Algorithms

Random Forest

In [27]:
```
# Baseline RandomForest
base_rf_clf = RandomForestClassifier(verbose=1, n_jobs=-1, random_state=42)
base_rf_clf.fit(X_train_encoded, y_train)
```

```
[Parallel(n_jobs=-1)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:    8.4s
[Parallel(n_jobs=-1)]: Done 100 out of 100 | elapsed:   18.9s finished
```

Out[27]:
```
RandomForestClassifier(n_jobs=-1, random_state=42, verbose=1)
```

In [28]:
```python
print_accuracy(base_rf_clf, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.2s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.4s finished
[Parallel(n_jobs=4)]: Using backend ThreadingBackend with 4 concurrent workers.
[Parallel(n_jobs=4)]: Done  42 tasks      | elapsed:    0.0s
[Parallel(n_jobs=4)]: Done 100 out of 100 | elapsed:    0.1s finished
Test accuracy: 78.60000000000001 %
Train accuracy: 87.4 %
[[5531  150  592]
 [ 418  215  129]
 [1071  106 3301]]
                         precision    recall  f1-score   support

             functional       0.79      0.88      0.83      6273
functional needs repair       0.46      0.28      0.35       762
         non functional       0.82      0.74      0.78      4478

               accuracy                           0.79     11513
              macro avg       0.69      0.63      0.65     11513
           weighted avg       0.78      0.79      0.78     11513
```

In [29]:
```python
# Try tuning with GridSearchCV
tuned_rf_clf = RandomForestClassifier(verbose=1, random_state=42)
forest_param_grid = {"n_estimators" : [50, 75, 100, 125],
            'criterion' : ['gini', 'entropy'],
            'max_depth' : [6, 10],
            }

gs_forest = GridSearchCV(estimator=tuned_rf_clf, param_grid=forest_param_grid,
                          scoring='accuracy', cv=3, n_jobs=-1)
gs_forest.fit(X_train_encoded, y_train)
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:    2.7s finished
```

Out[29]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=42, verbose=1),
             n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'], 'max_depth': [6, 10],
                         'n_estimators': [50, 75, 100, 125]},
             scoring='accuracy')
```

In [30]:
```python
# Inspect the tuned random forest
print(gs_forest.best_params_)
print(gs_forest.score(X_train_encoded, y_train))
tuned_forest = gs_forest.best_estimator_
print(tuned_forest)
print_accuracy(gs_forest, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
{'criterion': 'entropy', 'max_depth': 10, 'n_estimators': 50}
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:    0.2s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
0.7459828020498567
RandomForestClassifier(criterion='entropy', max_depth=10, n_estimators=50,
                       random_state=42, verbose=1)
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:    0.2s finished
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  50 out of  50 | elapsed:    0.1s finished
Test accuracy: 74.2 %
Train accuracy: 74.6 %
[[6049    0  224]
 [ 679    1   82]
 [1988    0 2490]]
                         precision    recall  f1-score   support

             functional       0.69      0.96      0.81      6273
functional needs repair       1.00      0.00      0.00       762
         non functional       0.89      0.56      0.68      4478

               accuracy                           0.74     11513
              macro avg       0.86      0.51      0.50     11513
           weighted avg       0.79      0.74      0.71     11513
```

Random Forest conclusion:

- Baseline Random Forest model suffered from overfitting.
- Tuned Random Forest model did not overfit. Accuracy was respectable.

Gradient Boosting models

In [31]:
```python
# Baseline GradientBoostingClassifer
base_gb_clf = GradientBoostingClassifier(verbose=1, random_state=42)
base_gb_clf.fit(X_train_encoded, y_train)
```

```
      Iter       Train Loss   Remaining Time 
         1           0.8486           16.75s
         2           0.8232           15.54s
         3           0.8028           14.43s
         4           0.7862           14.27s
         5           0.7727           14.33s
         6           0.7614           14.39s
         7           0.7520           14.08s
         8           0.7434           14.17s
         9           0.7362           13.98s
        10           0.7298           13.83s
        20           0.6889           12.54s
        30           0.6668           10.69s
        40           0.6530            8.82s
        50           0.6423            7.16s
        60           0.6346            5.67s
        70           0.6286            4.19s
        80           0.6226            2.77s
        90           0.6177            1.38s
       100           0.6133            0.00s
```

Out[31]: `GradientBoostingClassifier(random_state=42, verbose=1)`

In [34]:
```python
print_accuracy(base_gb_clf, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
Test accuracy: 74.4 %
Train accuracy: 74.6 %
[[5893    7  373]
 [ 610   37  115]
 [1834   12 2632]]
                         precision    recall  f1-score   support

             functional       0.71      0.94      0.81      6273
functional needs repair       0.66      0.05      0.09       762
         non functional       0.84      0.59      0.69      4478

               accuracy                           0.74     11513
              macro avg       0.74      0.53      0.53     11513
           weighted avg       0.76      0.74      0.72     11513
```

In [35]:
```python
# Try tuning with GridSearchCV
tuned_gb_clf = GradientBoostingClassifier(verbose=2, random_state=42)
gb_param_grid = {'n_estimators':[32, 64, 100],
                'learning_rate' : [0.5, 0.1, 0.05],
                   'max_depth':[7,9,11]
                   }

gs_gb = GridSearchCV(estimator=tuned_gb_clf, param_grid=gb_param_grid,
                          scoring='accuracy', cv=3,
                          verbose=2, n_jobs=-1)

gs_gb.fit(X_train_encoded, y_train)
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:  5.9min
[Parallel(n_jobs=-1)]: Done  81 out of  81 | elapsed: 18.4min finished
      Iter       Train Loss   Remaining Time 
         1           0.8155            2.64m
         2           0.7672            2.61m
         3           0.7285            2.66m
         4           0.6970            2.66m
         5           0.6704            2.65m
         6           0.6482            2.62m
         7           0.6286            2.61m
         8           0.6119            2.56m
         9           0.5977            2.50m
        10           0.5853            2.46m
        11           0.5740            2.41m
        12           0.5640            2.37m
        13           0.5545            2.33m
        14           0.5452            2.29m
```

In [36]:
```
# Inspect the tuned Gradient Boosting model
print(gs_gb.best_params_)
print(gs_gb.score(X_train_encoded, y_train))
tuned_gb = gs_gb.best_estimator_
print(tuned_gb)
print_accuracy(gs_gb, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
{'learning_rate': 0.1, 'max_depth': 11, 'n_estimators': 100}
0.8510162425084686
GradientBoostingClassifier(max_depth=11, random_state=42, verbose=2)
Test accuracy: 78.60000000000001 %
Train accuracy: 85.1 %
[[5657  118  498]
 [ 457  198  107]
 [1193   86 3199]]
                         precision    recall  f1-score   support

             functional       0.77      0.90      0.83      6273
functional needs repair       0.49      0.26      0.34       762
         non functional       0.84      0.71      0.77      4478

               accuracy                           0.79     11513
              macro avg       0.70      0.63      0.65     11513
           weighted avg       0.78      0.79      0.78     11513
```

Gradient Boosting conclusion:

- Baseline model showed no signs of overfitting (test and train accuracy were consistent). Accuracy of 74% was acceptable.
- Tuned model had better accuracy at 78.6% but showed some overfitting. Is it acceptable?
- Choosing the Tuned model over the Baseline so that additional hyperparmeters could be set as part of Future Work

XG Boost Classifer

In [37]:
```
# XGBoost
base_xgbt_clf = XGBClassifier(random_state=42)
base_xgbt_clf.fit(X_train_encoded, y_train)
```

Out[37]:
```
XGBClassifier(objective='multi:softprob', random_state=42)
```

In [38]:
```
print_accuracy(base_xgbt_clf, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
Test accuracy: 73.4 %
Train accuracy: 73.6 %
[[5921    3  349]
 [ 656    1  105]
 [1951    0 2527]]
                         precision    recall  f1-score   support

             functional       0.69      0.94      0.80      6273
functional needs repair       0.25      0.00      0.00       762
         non functional       0.85      0.56      0.68      4478

               accuracy                           0.73     11513
              macro avg       0.60      0.50      0.49     11513
           weighted avg       0.72      0.73      0.70     11513
```

In [39]:
```
# try tuning the XGB
tuned_xgb_clf = XGBClassifier(random_state=42)

param_grid = {
    'max_depth': [4, 6, 8],
    'n_estimators': [100, 200],
}

gs_xgb = GridSearchCV(tuned_xgb_clf, param_grid, scoring='accuracy', cv=3, n_jobs=-1, verbose=2)
gs_xgb.fit(X_train_encoded, y_train)
```

```
Fitting 3 folds for each of 6 candidates, totalling 18 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:   58.2s finished
```

Out[39]:
```
GridSearchCV(cv=3, estimator=XGBClassifier(random_state=42), n_jobs=-1,
             param_grid={'max_depth': [4, 6, 8], 'n_estimators': [100, 200]},
             scoring='accuracy', verbose=2)
```

In [40]:
```
# Inspect the tuned XGBoost model
print(gs_xgb.best_params_)
print(gs_xgb.score(X_train_encoded, y_train))
tuned_xgb = gs_xgb.best_estimator_
print_accuracy(gs_xgb, X_train_encoded, y_train, X_test_encoded, y_test, cm=True, cr=True)
```

```
{'max_depth': 8, 'n_estimators': 200}
0.8120385651003214
Test accuracy: 78.5 %
Train accuracy: 81.2 %
[[5748   62  463]
 [ 508  137  117]
 [1286   45 3147]]
                         precision    recall  f1-score   support

             functional       0.76      0.92      0.83      6273
functional needs repair       0.56      0.18      0.27       762
         non functional       0.84      0.70      0.77      4478

               accuracy                           0.78     11513
              macro avg       0.72      0.60      0.62     11513
           weighted avg       0.78      0.78      0.77     11513
```

XGBoost conclusion:

- The Baseline model had similar accuracy for train and test so no overfiiting. Accuracy was respectable at 73%
- The Tuned model did showed very slight overfitting with a higher train accuracy but acceptable. Accuracy was better at 78.5%

Model Face Off!

Tuned Gradient Boosted and Tuned XGBoost both had Accuracy ~79%. Which is actually "better"?

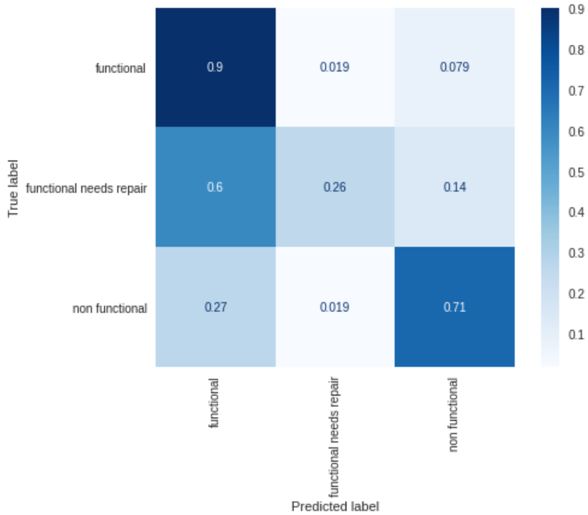
Inspect the Confusion Matrix of both to see how well they performed for each class.

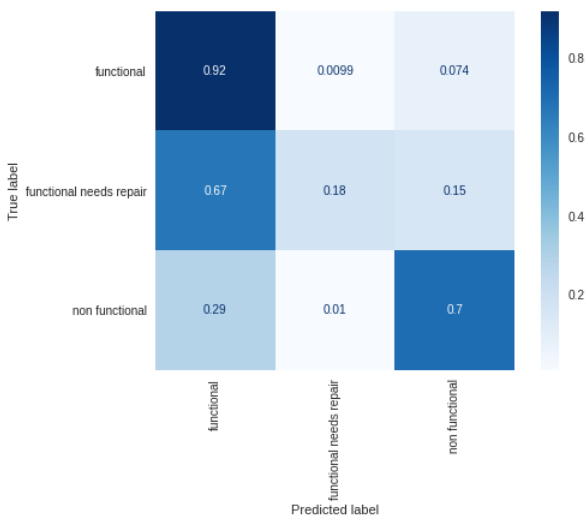
In [41]:
```
print('Tuned Gradient Boosted scores:')
print_accuracy(tuned_gb, X_train_encoded, y_train, X_test_encoded, y_test)
print('Tuned XGBoost scores:')
print_accuracy(tuned_xgb, X_train_encoded, y_train, X_test_encoded, y_test)
```

```
Tuned Gradient Boosted scores:
Test accuracy: 78.60000000000001 %
Train accuracy: 85.1 %
Tuned XGBoost scores:
Test accuracy: 78.5 %
Train accuracy: 81.2 %
```

In [42]:
```
# compare tuned Gradient Boosted to Tuned XGBoost
plot_confusion_matrix(tuned_gb, X_test_encoded, y_test, normalize='true', cmap=plt.cm.Blues, xtick
plt.grid(b=None)
plt.show()

plot_confusion_matrix(tuned_xgb, X_test_encoded, y_test, normalize='true', cmap=plt.cm.Blues, xtic
plt.grid(b=None)
plt.show()
```





Final Model Selection: Tuned Gradient Boosted Model

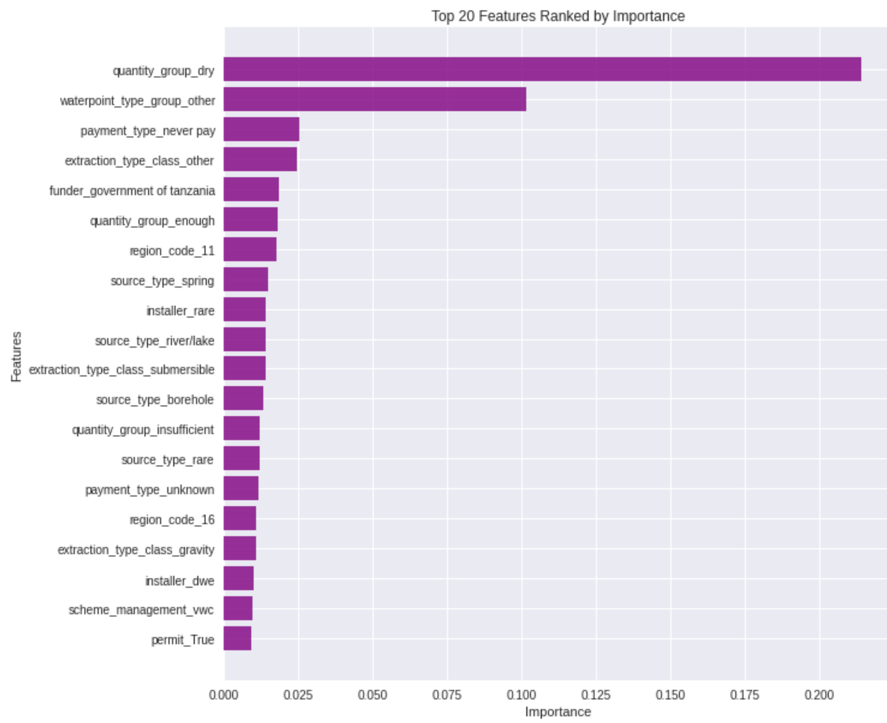
- Pros:
  - Best accuracy score of all attempted models
  - Best performance on classifying the rare class, functional needs repair (but still crummy at .26%)
- Cons:
  - Slight overfitting. Test accuracy: 78.6% Train accuracy: 85.1 %

In [44]:
```
final_model = tuned_gb
```

Important features

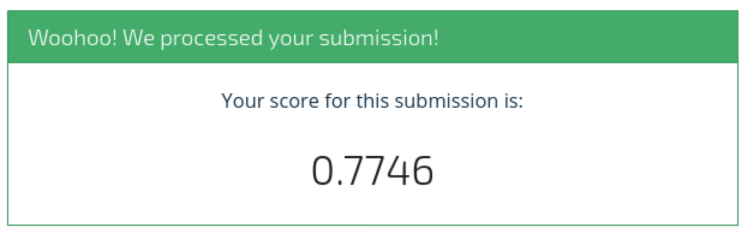
Intuition tells us that the feature quantity_group_dry would be a good indicator of operational status.

In [45]:
```
plot_feature_importance(final_model, ohe, X_train, num_features=20)
```



Predict on Pump it Up Challenge Test/Validation dataset

The challenge submission process involved making predictions on their supplied Test/Validation dataset. I used my final model (trained on 8 Challenge Training data) to make predictions for the Challenge.



Maybe later on I'll retain this tuned model on all of the Test data and resubmit.

In [133]:
```
# read in the cleaned test data
validation_df = pd.read_csv('../data/test_processed.csv', index_col='id')
validation_df.shape
```

Out[133]: (14850, 38)

In [134]:
```
X_validate = validation_df

# Did our test train spilt before exploring features in X_Train for rare label encoding.
# Now that I've selected some features based off of exploring X_Train ONLY, train the model on the
X_validate_selected_features = X_validate[features_to_use]

X_validate_encoded = ohe.transform(X_validate_selected_features)
```

In [23]:
```
y_validation = final_model.predict(X_validate_encoded)
predictions_df = pd.DataFrame(y_validation, index=X_validate_selected_features.index, columns=['sta
print(predictions_df.head())
print(predictions_df.shape)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-23-1af5fe253387> in <module>
----> 1 y_validation = final_model.predict(X_validate_encoded)
      2 predictions_df = pd.DataFrame(y_validation, index=X_validate_selected_features.index, columns=
'])
      3 print(predictions_df.head())
      4 print(predictions_df.shape)

NameError: name 'final_model' is not defined
```

In [137]:
```
# write the predictions out to file to submit to the Pump it Up challenge
predictions_df.to_csv('../data/challenge_submission.csv')
```

In [ ]:
```

```