Pump it Up: Data Mining the Water Table-Project#3

- Student name: ***Deepali Sharma***
- Student pace: ***Flex***
- Scheduled project review date/time: ***January, 2023***
- Instructor name: ***Abhineet Kulkarni***

Data Exploration and Business Problem

- The data was obtained from the **Pump it Up: Data Mining the Water Table** provided at [DrivenData (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/23/)](https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/23/). The data is collected from Taarifa and the Tanzanian Ministry of Water, and is used to predict which pumps are functional, which need some repairs, and which don't work at all! The Taarifa Platform is an open source API designed to use citizen feedback on local problems.The major goal of this project is to provide clean water access to the people of Tanzania. Currently, the people of Tanzania have poor access to clean drinking water throughout the entire country. Approximately 47% of all Tanzanian citizens do not have access to clean drinking water. Over 1.4 billion dollars in foreign aid has been giving to Tanzania in an attempt to help fix the freshwater crisis. However, the Tanzanian government has been struggling to fix this issue.

- The main focus of this study is to predict the functionality of water pumps using machine learning models. If models are accurate, this could help save the Tanzanian government a lot of time and money. Predicting correctly the faulty water pumps would help to cut the cost needed to send workers to each and every water pump for inspection. The government can use this study to find the water pumps that are working, need repair and the ones aren’t working at all.
- A complete list of variables in the dataset is given below

Target Feature:

- `status_group` - If the water pump is functional, non-functional or need repairs

Predictive Features:

- `amount_tsh` - Total static head (amount water available to waterpoint)
- `date_recorded` - The date the row was entered
- `funder` - Who funded the well
- `gps_height` - Altitude of the well
- `installer` - Organization that installed the well

- `longitude` - GPS coordinate
- `latitude` - GPS coordinate
- `wpt_name` - Name of the waterpoint if there is one
- `num_private` -
- `basin` - Geographic water basin
- `subvillage` - Geographic location
- `region` - Geographic location
- `region_code` - Geographic location (coded)
- `district_code` - Geographic location (coded)
- `lga` - Geographic location
- `ward` - Geographic location
- `population` - Population around the well
- `public_meeting` - True/False
- `recorded_by` - Group entering this row of data
- `scheme_management` - Who operates the waterpoint
- `scheme_name` - Who operates the waterpoint
- `permit` - If the waterpoint is permitted
- `construction_year` - Year the waterpoint was constructed
- `extraction_type` - The kind of extraction the waterpoint uses
- `extraction_type_group` - The kind of extraction the waterpoint uses
- `extraction_type_class` - The kind of extraction the waterpoint uses
- `management` - How the waterpoint is managed
- `management_group` - How the waterpoint is managed
- `payment` - What the water costs
- `payment_type` - What the water costs
- `water_quality` - The quality of the water
- `quality_group` - The quality of the water
- `quantity` - The quantity of water
- `quantity_group` - The quantity of water
- `source` - The source of the water
- `source_type` - The source of the water
- `source_class` - The source of the water
- `waterpoint_type` - The kind of waterpoint
- `waterpoint_type_group` - The kind of waterpoint

Modeling

1. The data was split into training and test sets.
2. The data was pre-processed. This is a classification problem with three classes! A detailed data exploration was done to understand different variables provided in the dataset. See Notebook eda.ipynb in the same github repository
3. Several types of classifiers were built, tuned (using GridSearchCV to test combinations of hyperparameters) and validated:

   - Logistic Regression
   - Random Forest
   - XGradient Boosted
   - Stacking Classifier (using above models)

Evaluation

4. I used Roc_Auc mostly and also looked at f-scores as the scoring metric for tuning hyperparameters and evaluating model performance.

   - The Roc_Auc metric utilizes **"probabilities"** of class prediction. Based on that, we're able to more precisely evaluate and compare the models. We also
   - We also care equally about positive and negative classes, and the roc curve gives a desirable balance between **sensitivity/recall (maximizing True positive Rate)** and and .
   - To bulid a good model one needs to carefully evaluate the predictions and understand the role of different features that drive the model predictions. A careful comparison between test and train data helps to understand to a great extent the model characteristics

Major Issues

- It was a challenging dataset given its length ~(60K entries) and number of categorical variables (which cause issue in one-hot encoding that generates too many columns). This was a major issue when I had to run GridSearchCV for hyperparameter tunings. I wasnt able to run even one model even after reducing the number of columns from 41 to 23. I killed the process after waiting for 1.5 days. This is when I found out about [HalvingGridSearchCV (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.HalvingGridSearchCV.html)](https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.HalvingGridSearchCV.html). This reduces the running time by factors anywhere ranging from 2-5. Sklearn says its still in experimentation and examples show that the parameters found by two methods are pretty much same. Using this I was able to run GridSearch in a few hours for each model scenario. However this feature is only available in recent version of sklearn and so I had to update it
- The second issue was that this is a ternary classification problem (not the usual Yes/No binary), so I had to use **ovr (One vs Rest)** option and to plot ROC curves for this multi-label problem required update sklearn as well.

Results

- XGB Classifier is the best model found in this study with an **roc_auc_score** of about 91% for the training set and 89% for the test data.

Next steps to be implemented

- One of the things that I really want to do is to see if there is any effect of installer and/or funder in the model predictions. My naive thinking tells me that there should be. However my preliminary test with installer column includes showed almost same results for scores as without it (~0.1% difference). But since the model was taking considerable large time to run even after I compressed the values where I grouped similar values to one broader category, I had to drop it from my final dataset. But I do want to explore it more and see if this really doesnt make any difference. If I submit this project for the competition, I will certainly explore this!
- The other column that I didnt study at all was **"scheme_name"**. This column has 47% missing data. Time permitting I would have studied this, but I ran short of time. So in future, I would like to study if this variable will have any effect on modeling.
- One more thing that I need to do is to see if there is a difference in the resulting best model from GridSearchCV if I use "roc_scoring" instead of "f1_weighted" option. There is difference in the two approaches as one considers harmonic mean between sensitivity /recall while roc_score maximizes the probablities for different classes.

In [1]:
```
import os, sys, time
print(sys.executable)
```

```
/usr/local/anaconda3/bin/python
```

In [80]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
#pd.set_option('display.max_rows', 10)
import seaborn as sns
#sns.set_style("whitegrid")
import numpy as np
import matplotlib as mpl
import matplotlib.ticker as mticker
import missingno as mssno

from sklearn.preprocessing import OneHotEncoder, StandardScaler, Funct
from sklearn.impute import MissingIndicator, SimpleImputer
from sklearn.dummy import DummyClassifier


from sklearn.model_selection import train_test_split, cross_val_score,
```

```
from sklearn.feature_selection import SelectFromModel

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingC
from xgboost import XGBClassifier


from sklearn.metrics import roc_curve, auc
#from sklearn.metrics import plot_confusion_matrix # plot_confusion_ma
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import confusion_matrix # if you are running an o
from sklearn.metrics import classification_report
from sklearn.metrics import RocCurveDisplay, roc_curve, roc_auc_score
from sklearn.metrics import precision_score, recall_score, accuracy_sc
from sklearn.model_selection import StratifiedKFold

from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.ensemble import StackingRegressor

from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline # You need imblearn Pipeline fo
from itertools import cycle
from sklearn.inspection import permutation_importance

import warnings
warnings.filterwarnings("ignore")
%load_ext autotime
```

```
The autotime extension is already loaded. To reload it, use:
  %reload_ext autotime
time: 9.78 ms (started: 2023-01-04 19:41:00 -05:00)
```

In [3]:
```
from xgboost import XGBClassifier
```

```
time: 432 µs (started: 2023-01-03 15:10:17 -05:00)
```

In [116]:
```
# This function plots confusion matrix (train) as well as roc_auc, rec

def model_evaluation_roc_auc(model):
    with plt.style.context('seaborn-talk'):
        fig, (ax1,ax2) = plt.subplots(ncols=2,figsize=(12, 5))

        # Plot confusion matrix for the test set
        ConfusionMatrixDisplay.from_estimator(baseline_logreg, X_test,
        ConfusionMatrixDisplay.from_estimator(baseline_logreg, X_trair
        ax1.grid(False)
        ax2.set_title("Confusion Matrix - Train")
```

```
ax2.set_title('Confusion Matrix - Train')

# plot Roc curve for the test and train
#plot_roc_curve(model,X_test,y_test,ax=axs[1,0])
#plot_roc_curve(model,X_train,y_train,ax=axs[1,1])
plt.show()

# Print classification Scores for the test set
y_true = y_test
y_pred = model.predict(X_test)
divider = ('----' * 14)
table_title = 'Classification Report - Test:'
table = classification_report(y_true, y_pred, digits=3)
print('\n', divider, table_title, divider, table, divider, div

# Print roc_auc for test and train
#roc_score_train_cv = cross_val_score(estimator=model, X=X_tra
                                # cv=StratifiedKFold(shuffle=T
roc_score_train = roc_auc_score(y_train, model.predict_proba(X
roc_score_test = roc_auc_score(y_test, model.predict_proba(X_t

y_train_pred   = model.predict(X_train)
y_test_pred    = model.predict(X_test)
# Find F- Scores:
recall_score_train = recall_score(y_train, y_train_pred, avera
recall_score_test = recall_score(y_test, y_test_pred, average=

# Print accuracy for test and train
acc_score_train = accuracy_score(y_train, y_train_pred)
acc_score_test = accuracy_score(y_test,   y_test_pred)

#print(f" Mean Cross Validated Roc_Auc Score: {roc_score_train
print(f" Train Roc_Auc Score: {roc_score_train :.2%}")
print(f" Test Roc_Auc Score: {roc_score_test :.2%}")
print('\n', divider, '\n' , sep='\n')

print(f" Train Accuracy Score: {acc_score_train :.2%}")
print(f" Test Accuracy Score: {acc_score_test :.2%}")
print('\n', divider, '\n' , sep='\n')

print(f" Train Sensitivity/Recall score: {recall_score_train :
print(f" Test Sensitivity/Recall score: {recall_score_test :.2
print('\n', divider, '\n' , sep='\n')


print('Train Weighted Precision: {:.2f}'.format(precision_scor
print('Test Weighted Precision: {:.2f}'.format(precision_score
print("Train Score:{:.2f} ".format(model.score(X_train, y_trai
print("Test Score:{:.2f} ".format(model.score(X_test, y_test))
```

```
time: 1.77 ms (started: 2023-01-04 19:59:21 -05:00)
```

In [290]:
```
## This function is to plot ROC curve. Foe multi-label problem one nee
def plot_roc_curve(model,X_test=X_test,y_test=y_test):
    y_onehot_test = label_binarizer.transform(y_test)
    y_score = model.predict_proba(X_test)
    # store the fpr, tpr, and roc_auc for all averaging strategies
    fpr, tpr, roc_auc = dict(), dict(), dict()
    # Compute micro-average ROC curve and ROC area
    fpr["micro"], tpr["micro"], _ = roc_curve(y_onehot_test.ravel(), y
    roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

    print(f"Micro-averaged One-vs-Rest ROC AUC score:\n{roc_auc['micro
    fig, ax = plt.subplots(figsize=(6, 6))

    plt.plot(
        fpr["micro"],
        tpr["micro"],
        label=f"micro-average ROC curve (AUC = {roc_auc['micro']:.2f})
        color="deeppink",
        linestyle=":",
        linewidth=4,
        )

    for class_id, color in zip(range(n_classes), colors):
        RocCurveDisplay.from_predictions(
            y_onehot_test[:, class_id],
            y_score[:, class_id],
            name=f"ROC curve for {[class_id]}",
            color=color,
            ax=ax,
        )

    plt.plot([0, 1], [0, 1], "k--", label="ROC curve for chance level
    plt.axis("square")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("Extension of Receiver Operating Characteristic\nto One-
    plt.legend()
```

```
time: 3.12 ms (started: 2023-01-09 14:10:14 -05:00)
```

In [ ]:

In [291]:
```
## This function is used for Feature engineering dataset. installer co
#many of those into similar broad categories.e.g. we can replace ('fir
#'finwate') with just finw as they all seem to fall under this one cat
# to a broader group. This helps us to reduce the number of one-hot en
def clean_installer(df):
```

```
def clean_installer(df):

    df['installer'] = df['installer'].astype(str).str.lower()
    df['installer'].replace(
        to_replace=(
            'fini water', 'fin water', 'finn water', 'finwater', 'finw
        value='finw', inplace=True)
    df['installer'].replace(to_replace=('jaica co'), value='jaica', in
    df['installer'].replace(
        to_replace=(
            'district water department', 'district water depar', 'dist
            'district counci', 'village council orpha','kibaha town co
            'village council', 'coun', 'village counil', 'council',
            'mbulu district council', 'counc', 'village council .oda',
            'sangea district coun', 'songea district coun', 'villege c
            'district  council', 'quick win project /council', 'mbozi
            'village  council', 'municipal council', 'tabora municipal
            'wb / district council'),
        value='council', inplace=True)
    df['installer'].replace(
        to_replace=(
            'rc church', 'rc churc', 'rcchurch/cefa', 'irc', 'rc', 'rc
            'rc church/central gover', 'kkkt church', 'pentecost churc
            'rc/mission', 'rc church/cefa', 'lutheran church', 'tag ch
            'free pentecoste church of tanz', 'rc c', 'church', 'rc ca
            'morovian church', 'cefa/rc church', 'rc mission', 'anglic
            'church of disciples', 'anglikana church', 'cetral governm
            'pentecostal church', 'cg/rc', 'rc missionary', 'sda churc
            'rc msufi', 'haidomu lutheran church', 'baptist church', '
            'st magreth church', 'anglica church', 'global resource co
            'baptist church of tanzania', 'fpct church', 'rc njoro', '
            'rc mis', 'batist church', 'churc', 'dwe/anglican church',
            'ndanda missions', 'rc/mission', 'cvs miss', 'missionaries
            'luthe', 'haydom lutheran hospital', 'lutheran', 'missio',
            'grail mission kiseki bar', 'missionary', 'heri mission',
            'wamissionari wa kikatoriki', 'neemia mission', 'wamisiona
        value='church', inplace=True)
    df['installer'].replace(
        to_replace=(
            'central government', 'gove', 'central govt', 'gover', 'ci
            'governme', 'adra /government', 'isf/government', 'adra/go
            'government /tcrs', 'village govt', 'government', 'governm
            'concern /government', 'goverm', 'village government', 'ce
            'govern', 'cebtral government', 'government /sda', 'tcrs /
            'tanzania government', 'centra govt', 'colonial government
            'government and community', 'cetral government /rc', 'conc
            'government of misri', 'lwi &central government', 'governm
            'centra government'),
        value='tanzanian government', inplace=True)
    df['installer'].replace(
        to_replace=(
```

```
            'world vission', 'world division', 'word divisio','world v
        value='world vision', inplace=True)
    df['installer'].replace(to_replace=('unicrf'), value='unicef', inp
    df['installer'].replace(
        to_replace=(
            'commu', 'olgilai village community', 'adra /community', '
            'rwe/ community', 'killflora /community', 'communit', 'tab
            'arab community', 'adra/ community', 'sekei village commun
            'arabs community', 'village community', 'government /commu
            'dads/village community', 'killflora/ community', 'mtuwasa
            'rwe /community', 'ilwilo community', 'summit for water/co
            'igolola community', 'ngiresi village community', 'rwe com
            'african realief committe of ku', 'twesa /community', 'she
            'twesa/ community', 'marumbo community', 'government and c
            'community bank', 'kitiangare village community', 'oldadai
            'twesa/community', 'tlc/community', 'maseka community', 'i
            'district community j', 'village water commission', 'villa
            'tcrs/village community', 'village water committee', 'comu
        value='community', inplace=True)
    df['installer'].replace(
        to_replace=(
            'danid', 'danda','danida co', 'danny', 'daniad', 'dannida'
        value='danida', inplace=True)
    df['installer'].replace(
        to_replace=(
            'hesaws', 'huches', 'hesaw', 'hesawz', 'hesawq', 'hesewa')
        value='hesawa', inplace=True)
    df['installer'].replace(
        to_replace=(
            'dwsp', 'kkkt _ konde and dwe', 'rwe/dwe', 'rwedwe', 'dwe/
            'dwe}', 'dwt', 'dwe /tassaf', 'dwe/ubalozi wa marekani', '
            'dwe & lwi', 'ubalozi wa marekani /dwe', 'dwe&', 'dwe/tass
            'dw e', 'tcrs/dwe', 'dw#', 'dweb', 'tcrs /dwe', 'water aid
        value='dwe', inplace=True)
    df['installer'].replace(
        to_replace=(
            'africa muslim', 'muslimu society(shia)', 'africa muslim a
            'african muslims age', 'muslimehefen international','islam
            'the isla', 'islamic agency tanzania',  'islam', 'nyabibuy
        value='muslims', inplace=True)
    df['installer'].replace(
        to_replace=(
            'british colonial government', 'british government', 'brit
        value='british', inplace=True)
    df['installer'].replace(
        to_replace=(
            'tcrs/tlc', 'tcrs /care', 'cipro/care/tcrs', 'tcrs kibondo
            'tcrs /twesa', 'tassaf /tcrs', 'tcrs/care', 'tcrs twesa', 
            'tcrs/twesa', 'tassaf/ tcrs', 'tcrs/ tassaf', 'tcrs/ twesa
            'tassaf/tcrs'),
```

```
        value='tcrs', inplace=True)
    df['installer'].replace(
        to_replace=(
            'kkkt-dioces ya pare', 'kkkt leguruki', 'kkkt ndrumangeni'
            'kkkt kilinga', 'kkkt canal', 'kkkt katiti juu', 'kkkt mar
        value='kkkt', inplace=True)
    df['installer'].replace(to_replace=('norad/'), value='norad', inpl
    df['installer'].replace( to_replace=('tasaf/dmdd', 'dmdd/solider')
        value='dmdd', inplace=True)
    df['installer'].replace(
        to_replace=('cjejow construction', 'cjej0'), value='cjejow', i
    df['installer'].replace(
        to_replace=(
            'china henan constuction', 'china henan contractor', 'chin
        value='china', inplace=True)
    df['installer'].replace(
        to_replace=(
            'local contract', 'local technician', 'local', 'local  tec
            'locall technician', 'local te', 'local technitian', 'loca
            'local fundi', 'local technical', 'localtechnician', 'vill
            'local l technician'),
        value='local', inplace=True)
    df['installer'].replace(
        to_replace=(
            'oikos e .africa', 'oikos e.africa', 'africa amini alama',
            'africa islamic agency tanzania', 'africare', 'african dev
            'oikos e. africa', 'oikos e.afrika', 'afroz ismail', 'afri
            'oikos e africa', 'farm africa', 'africaone', 'tina/africa
            'african reflections foundation', 'africa m'),
        value='africa', inplace=True)
    df['installer'].replace(to_replace=('0', 'nan', '-'), value='other
    df_installer_cnt = df.groupby('installer')['installer'].count()
    other_list = df_installer_cnt[df_installer_cnt<71].index.tolist()
    df['installer'].replace(to_replace=other_list, value='other', inpl
```

time: 1.68 ms (started: 2023-01-09 14:13:16 -05:00)

In [292]:

```
 Similar to above installer function, thes imilar group of values are 
f clean_funder(df):

  df['funder'] = df['funder'].astype(str).str.lower()
  df['funder'].replace(
      to_replace=(
          'kkkt_makwale', 'kkkt-dioces ya pare', 'world vision/ kkkt',
          'kkkt leguruki', 'kkkt ndrumangeni', 'kkkt dme', 'kkkt canal
          'kkkt mareu'),
      value='kkkt', inplace=True)
  df['funder'].replace(
      to_replace=(
          'government of tanzania', 'norad /government', 'government/ 
          'cipro/government', 'isf/government', 'finidagermantanzania
```

```
            'cipro/government', 'isf/government', 'finidagermantanzania 
            'government /tassaf', 'finida german tanzania govt', 'villag
            'tcrs /government', 'village govt', 'government/ world bank'
            'danida /government', 'dhv/gove', 'concern /govern', 'vgover
            'lwi & central government', 'government /sda', 'koica and ta
            'world bank/government', 'colonial government', 'misri gover
            'government and community', 'concern/governm', 'government o
            'government/tassaf', 'government/school', 'government/tcrs',
            'government /world vision', 'norad/government'),
        value='government', inplace=True)
    df['funder'].replace(
        to_replace=(
            'british colonial government', 'japan government', 'china go
            'finland government', 'belgian government', 'italy governmen
            'irish government', 'egypt government', 'iran gover', 'swedi
        value='foreign government', inplace=True)
    df['funder'].replace(
        to_replace=(
            'rc church', 'anglican church', 'rc churc', 'rc ch', 'rcchur
            'irc', 'rc', 'churc', 'hw/rc', 'rc church/centr', 'pentecost
            'roman church', 'rc/mission', "ju-sarang church' and bugango
            'lutheran church', 'roman cathoric church', 'tag church ub',
            'free pentecoste church of tanz', 'tag church', 'fpct church
            'baptist church', 'morovian church', 'cefa/rcchurch', 'rc mi
            'bukwang church saints', 'agt church', 'church of disciples'
            "gil cafe'church'", 'pentecostal church', 'bukwang church sa
            'eung am methodist church', 'rc/dwe', 'cg/rc', 'eung-am meth
            'rc missionary', 'sda church', 'methodist church', 'rc msufi
            'haidomu lutheran church', 'nazareth church', 'st magreth ch
            'agape churc', 'rc missi', 'rc mi', 'rc njoro', 'world visio
            'pag church', 'batist church', 'full gospel church', 'nazale
            'dwe/anglican church', 'missi', 'mission', 'missionaries', '
            'cvs miss', 'grail mission kiseki bar', 'shelisheli commissi
            'heri mission', 'german missionary', 'wamissionari wa kikato
            'rc missionary', 'germany missionary', 'missio', 'neemia mis
            'hydom luthelani', 'luthe', 'lutheran church',  'haydom luth
            'village council/ haydom luther', 'lutheran', 'haidomu luthe
            'resolute golden pride project', 'resolute mininggolden prid
            'germany cristians'),
        value='church', inplace=True)
    df['funder'].replace(
        to_replace=(
            'olgilai village community', 'commu', 'community', 'arab com
            'sekei village community', 'arabs community', 'village commu
            'mtuwasa and community', 'ilwilo community', 'igolola commun
            'ngiresi village community', 'marumbo community', 'village c
            'comune di roma', 'comunity construction fund', 'community b
            "oak'zion' and bugango b' commu", 'kitiangare village commun
            'oldadai village community', 'tlc/community', 'maseka commun
            'islamic community',  'tcrs/village community', 'buluga subv
            'okutu village community'),
```

```
    value='community', inplace=True)
df['funder'].replace(
    to_replace=(
        'council', 'wb / district council', 'cdtfdistrict council',
        'sangea district council', 'mheza distric counc', 'kyela cou
        'kibaha town council', 'swidish', 'mbozi district council',
        'village council/ rose kawala',  'songea municipal counci',
        'quick win project /council', 'village council', 'villege co
        'tabora municipal council', 'kilindi district co', 'kigoma m
        'district council', 'municipal council', 'district medical',
        'sengerema district council', 'town council', 'mkinga  distr
        'songea district council', 'district rural project', 'mkinga
        'dadis'),
    value='district', inplace=True)
df['funder'].replace(
    to_replace=(
        'tcrs.tlc', 'tcrs /care', 'tcrst', 'cipro/care/tcrs', 'tcrs/
    value='tcrs', inplace=True)
df['funder'].replace(
    to_replace=(
        'fini water', 'finw', 'fin water', 'finn water', 'finwater')
    value='fini', inplace=True)
df['funder'].replace(
    to_replace=(
        'islamic', 'the isla', 'islamic found', 'islamic agency tanz
        'islam', 'muislam', 'the islamic', 'nyabibuye islamic center
        'muslims', 'answeer muslim grou', 'muslimu society(shia)',
        'unicef/african muslim agency', 'muslim world', 'muslimehefe
        'shear muslim', 'muslim society'),
    value='islam', inplace=True)
df['funder'].replace(
    to_replace=('danida', 'ms-danish', 'unhcr/danida', 'tassaf/ dani
    value='danida', inplace=True)
df['funder'].replace(
    to_replace=(
        'hesawa', 'hesawz', 'hesaw', 'hhesawa', 'hesawwa', 'hesawza'
        'hesawa and concern world wide'),
    value='hesawa', inplace=True)
df['funder'].replace(
    to_replace=('world vision/adra', 'game division', 'worldvision')
    value='world vision', inplace=True)
df['funder'].replace(
    to_replace=(
        'germany republi', 'a/co germany', 'aco/germany', 'bingo fou
        'africa project ev germany', 'tree ways german'),
    value='germany', inplace=True)
df['funder'].replace(to_replace=('0', 'nan', '-'), value='other', in
df_funder_cnt = df.groupby('funder')['funder'].count()
other_list = df_funder_cnt[df_funder_cnt<98].index.tolist()
df['funder'].replace(to_replace=other_list, value='other', inplace=T
```

```
time: 2.13 ms (started: 2023-01-09 14:13:49 -05:00)
```

In [4]:
```
df_data = pd.read_csv("Data_train.csv")
df_labels = pd.read_csv("Data_train_labels.csv")
df = pd.merge(df_data,df_labels,how='inner',left_on='id', right_on='ic
df.head()
```

Out[4]:

rivate	...	water_quality	quality_group	quantity	quantity_group	source	source_type	sourc
0	...	soft	good	enough	enough	spring	spring	grou
0	...	soft	good	insufficient	insufficient	rainwater harvesting	rainwater harvesting	
0	...	soft	good	enough	enough	dam	dam	
0	...	soft	good	dry	dry	machine dbh	borehole	grou
0	...	soft	good	seasonal	seasonal	rainwater harvesting	rainwater harvesting	

```
time: 1.1 s (started: 2023-01-03 15:10:17 -05:00)
```

Data Exploration, Cleaning and Feature Engineering

In [26]:
```
df_clean= df
```

```
time: 11.9 ms (started: 2023-01-03 17:56:47 -05:00)
```

- This is a temporary dataframe to show some of the main results from EDA notebook (project_v3.ipynb). That notebook contains a lot of plots and other stuff that I did to find and study relevant columns

In [295]:
```
df_ana = df
```

```
time: 206 µs (started: 2023-01-09 14:23:38 -05:00)
```

Feature Engineering

- I want to create an **age** variable based on the **construction_year** information. However, a large subset of data has **0** for construction_year. So I will assign it as 60 under the assumption that those wells construction date is unknown and most likely predates 1960 which is the earliest recorded year in this dataset. The most recent year in the data is 2013. So I define age from 2014.
- Also I will bin the age in 5 years intervals

In [27]:
```
from datetime import date
from datetime import datetime
df_clean['date_recorded']=pd.to_datetime(df_clean['date_recorded'])
df_clean['yr_record']=df_clean['date_recorded'].dt.year.astype('int')
df_clean['month_record']=df_clean['date_recorded'].dt.month.astype('ir
df_clean[['date_recorded','yr_record','month_record']]
df_clean['age'] = (2014 - df_clean['construction_year'])
df_clean['age'] = df_clean['age'].replace(2014, 60)
```

time: 359 ms (started: 2023-01-03 17:56:49 -05:00)

In [28]:
```
conditions = [
    (df_clean['age'] <=5),
    (df_clean['age'] > 5) & (df_clean['age'] <= 10),
    (df_clean['age'] > 10) & (df_clean['age'] <= 15),
    (df_clean['age'] > 15) & (df_clean['age'] <= 20),
    (df_clean['age'] > 20) & (df_clean['age'] <= 25),
    (df_clean['age'] > 25) & (df_clean['age'] <= 30),
    (df_clean['age'] > 30) & (df_clean['age'] <= 35),
    (df_clean['age'] > 35) & (df_clean['age'] <= 40),
    (df_clean['age'] > 40) & (df_clean['age'] <= 45),
    (df_clean['age'] > 45) & (df_clean['age'] <= 50),
    (df_clean['age'] > 50) & (df_clean['age'] <= 55),
    (df_clean['age'] > 5) & (df_clean['age'] <= 60),
     ]
choices =[5,10,15,20,25,30,35,40,45,50,55,60]
df_clean['age'] = np.select(conditions,choices, default=0)
```

time: 71.3 ms (started: 2023-01-03 17:56:51 -05:00)

- Engineering the installer and Funder columns so as to merge the similar groups using the functions defined above

In [296]:
```
clean_installer(df_ana)
clean_funder(df_ana)
```

```
time: 1.37 s (started: 2023-01-09 14:23:53 -05:00)
```

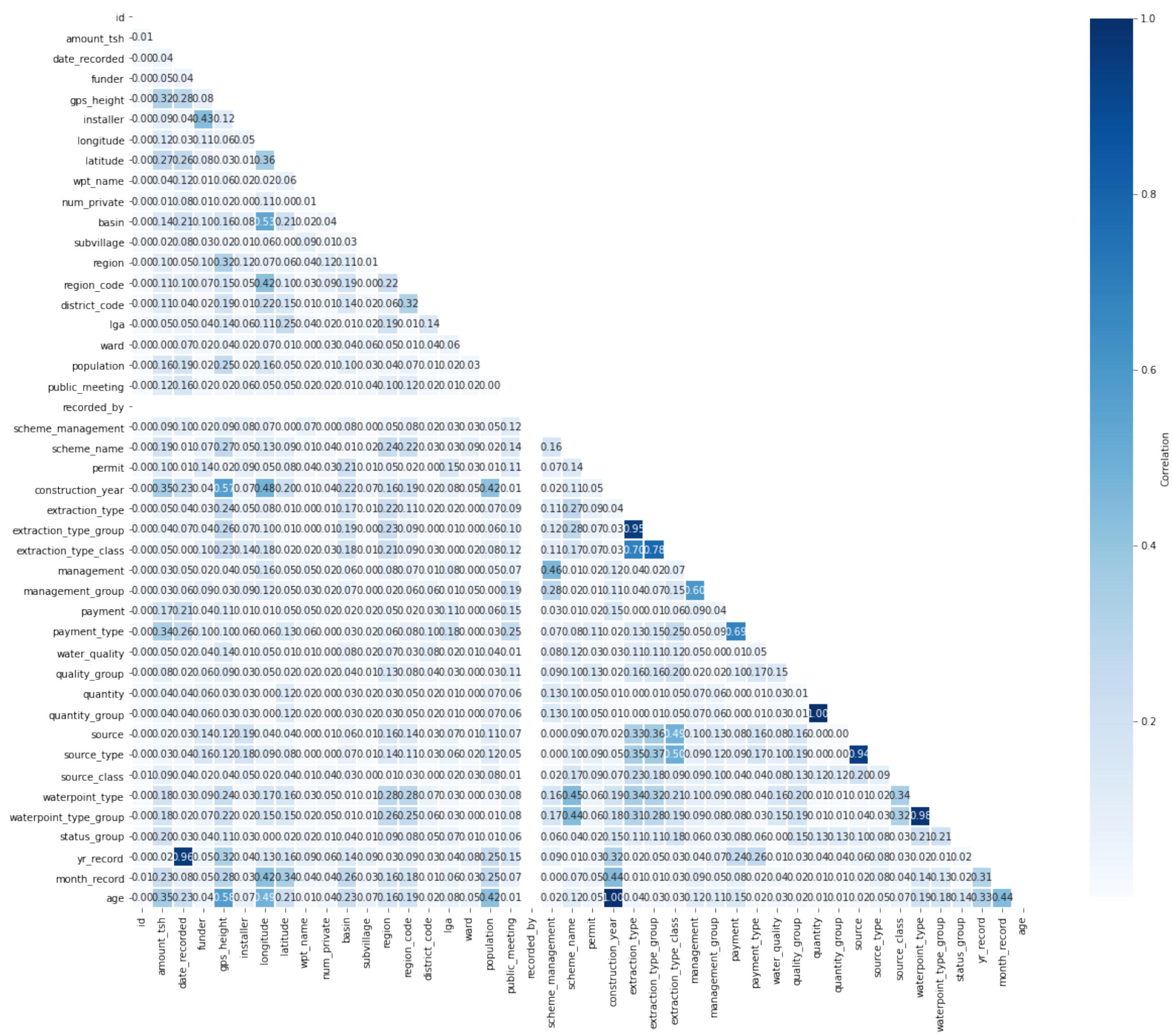
- lets check if we have correlated columns and also find the columns with missing values

In [300]:
```
df_ana.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 44 columns):
id                          59400 non-null int64
amount_tsh                  59400 non-null float64
date_recorded               59400 non-null datetime64[ns]
funder                      59400 non-null object
gps_height                  59400 non-null int64
installer                   59400 non-null object
longitude                   59400 non-null float64
latitude                    59400 non-null float64
wpt_name                    59400 non-null object
num_private                 59400 non-null int64
basin                       59400 non-null object
subvillage                  59029 non-null object
region                      59400 non-null object
region_code                 59400 non-null int64
district_code               59400 non-null int64
lga                         59400 non-null object
ward                        59400 non-null object
population                  59400 non-null int64
public_meeting              56066 non-null object
recorded_by                 59400 non-null object
scheme_management           55523 non-null object
scheme_name                 31234 non-null object
permit                      56344 non-null object
construction_year           59400 non-null int64
extraction_type             59400 non-null object
extraction_type_group       59400 non-null object
extraction_type_class       59400 non-null object
management                  59400 non-null object
management_group            59400 non-null object
payment                     59400 non-null object
payment_type                59400 non-null object
water_quality               59400 non-null object
quality_group               59400 non-null object
quantity                    59400 non-null object
quantity_group              59400 non-null object
source                      59400 non-null object
```

```
source_type             59400 non-null object
source_class            59400 non-null object
waterpoint_type         59400 non-null object
waterpoint_type_group   59400 non-null object
status_group            59400 non-null object
yr_record               59400 non-null int64
month_record            59400 non-null int64
age                     59400 non-null int64
dtypes: datetime64[ns](1), float64(3), int64(10), object(30)
memory usage: 20.4+ MB
time: 47.2 ms (started: 2023-01-09 14:28:36 -05:00)
```

In [301]:
```
data_cat = df_ana
data_cat = data_cat.apply(lambda x: x.astype('category').cat.codes)
corr = data_cat.corr().abs()
fig, ax=plt.subplots(figsize=(20,20))
matrix = np.triu(corr) # Getting the Upper Triangle of the correlation
cbar_kws={"label": "Correlation", "shrink":0.8}
heatmap = sns.heatmap(data = corr, cmap='Blues', linewidths = 1, squar
fig.suptitle('Heatmap of Correlation Between All Variables (Including
heatmap;
```

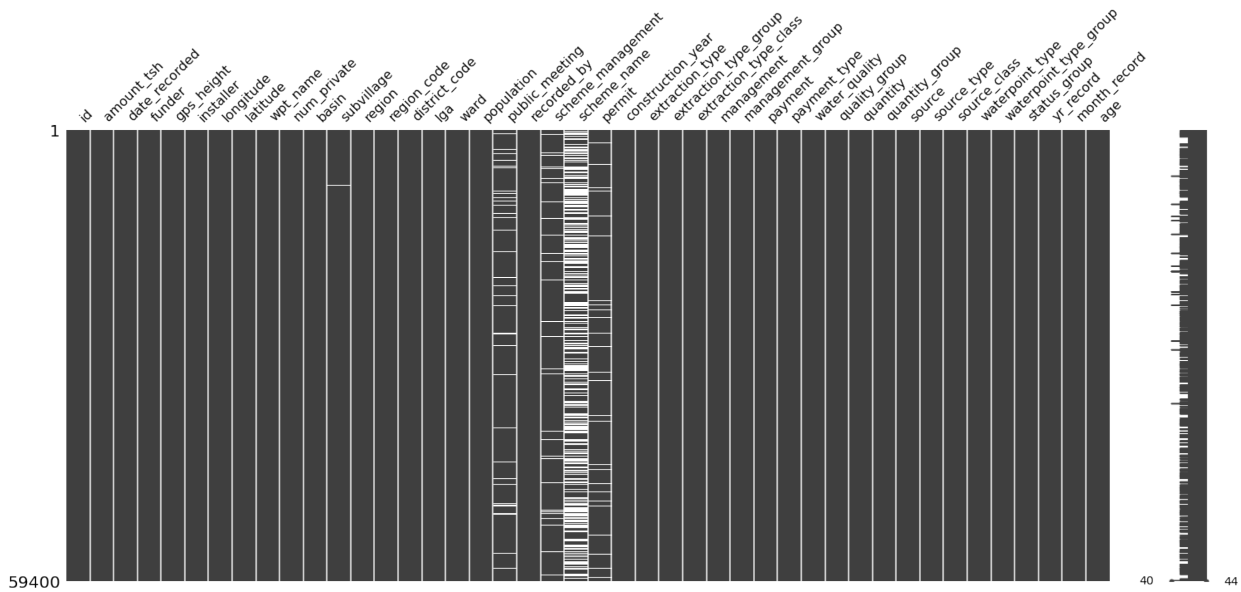


time: 5.69 s (started: 2023-01-09 14:29:20 -05:00)

- Based on this heatmap, one can see that there are a few columns that have high correlations such as extraction_class, extraction_type_group, and extraction_type. These columns contains same information and one of them usually superseeds the rest. Other examples include columns with quantity, source, waterpoints,payment, management etc. As such I will delete these columns. Also by construction age and recorded_yr are correlated and so will delete recorded_yr.

In [305]:
```
mssno.matrix(df)
```

Out[305]:
```
<AxesSubplot:>
```




```
time: 777 ms (started: 2023-01-09 14:38:45 -05:00)
```

In [306]:
```
mssno.dendrogram(df)
```

Out[306]:
```
<AxesSubplot:>
```

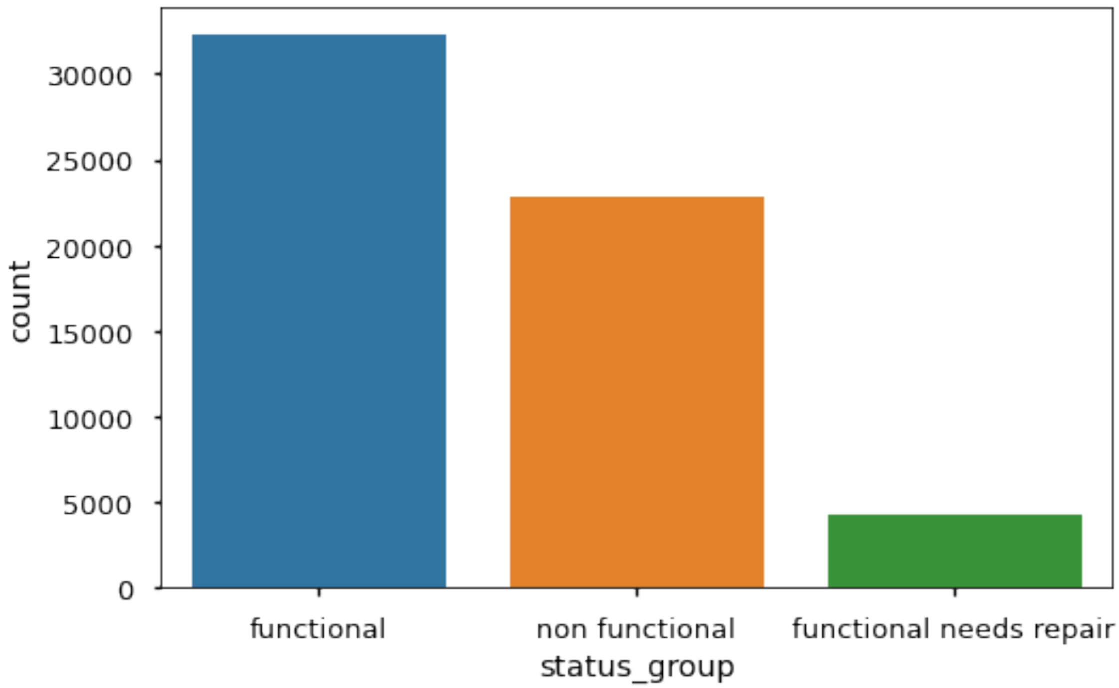

```
time: 611 ms (started: 2023-01-09 14:38:51 -05:00)
```

In [307]:
```
nulls = ((df_ana.isnull().sum()*100) / len(df_ana)).sort_values(ascenc
nulls[nulls > 0]
```

Out[307]:
```
scheme_name          47.417508
scheme_management     6.526936
public_meeting        5.612795
permit                5.144781
subvillage            0.624579
dtype: float64
```

```
time: 43.7 ms (started: 2023-01-09 14:39:09 -05:00)
```

In [308]:
```
with plt.style.context('seaborn-talk'):
    fig, ax1 = plt.subplots(figsize=(8, 5))
    sns.countplot(df_ana['status_group'], ax= ax1);
```



time: 103 ms (started: 2023-01-09 14:39:41 -05:00)

In [309]:
```
## This is the function that can plot a given column grouped by a give
## distribution as a function of water pumps functionality"
def get_and_plot_groups(df, col_to_study,col_to_group,ax=None, Flen=10
    df_new = pd.DataFrame(df[[col_to_study,col_to_group]]\
                      .groupby([col_to_study,col_to_group])\
                      .agg(({col_to_group: ['count']})))
    df_new.columns = ['_'.join(col) for col in df_new.columns.values]
    df_new   = df_new.reset_index()
    sorteddf = df_new.sort_values(df_new.columns[2], ascending=False)
    sorteddf.head()
    fig, ax = plt.subplots(figsize=(Flen,Fhgt))
    if (orient==None):
        ax      = sns.barplot(x=df_new.columns[0], y=df_new.columns[2]
                        hue=df_new.columns[1],orient=orient)
    elif orient=='h':
        ax      = sns.barplot(x=df_new.columns[2], y=df_new.columns[0]
                        hue=df_new.columns[1],orient='h')
    ax.legend(loc='upper right')
    #return fig, ax
```

time: 575 µs (started: 2023-01-09 14:42:46 -05:00)

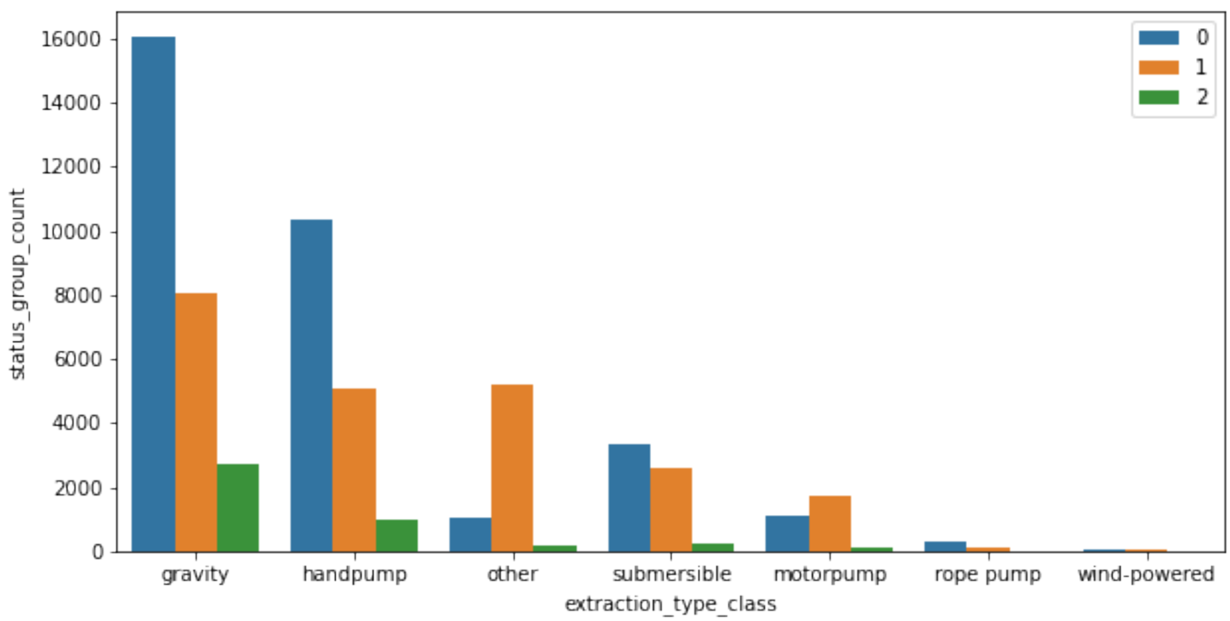
- I am converting target feature **"status_group"** to a numeric feature that gives me flexibilty to plot bar charts by grouping a given column as a feature of this function using the function defined above. A few cells below show the distribution of different variables when grouped as a function of **status_group**

In [310]:
```
## I am converting target feature "status_group" to a numeric feature
#to plot bar charts by grouping a given column as a feature of this fu
dic = {'functional':0, 'non functional':1,'functional needs repair':2
df_ana.replace({"status_group": dic}, inplace=True)
df_ana["status_group"].value_counts()
```

Out[310]:
```
0    32259
1    22824
2     4317
Name: status_group, dtype: int64
```

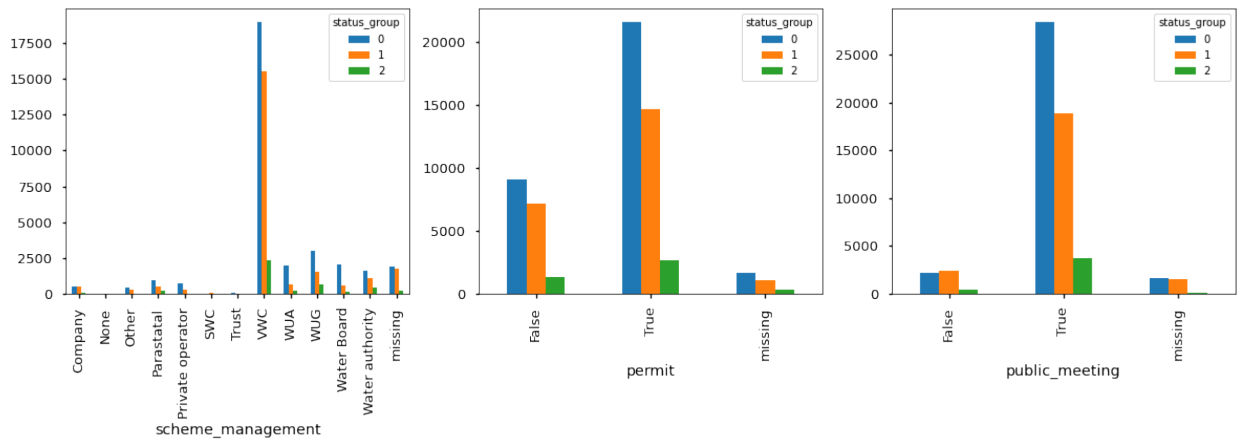
time: 29.6 ms (started: 2023-01-09 14:44:48 -05:00)

In [311]:
```
get_and_plot_groups(df_ana,'extraction_type_class','status_group',ax='
```



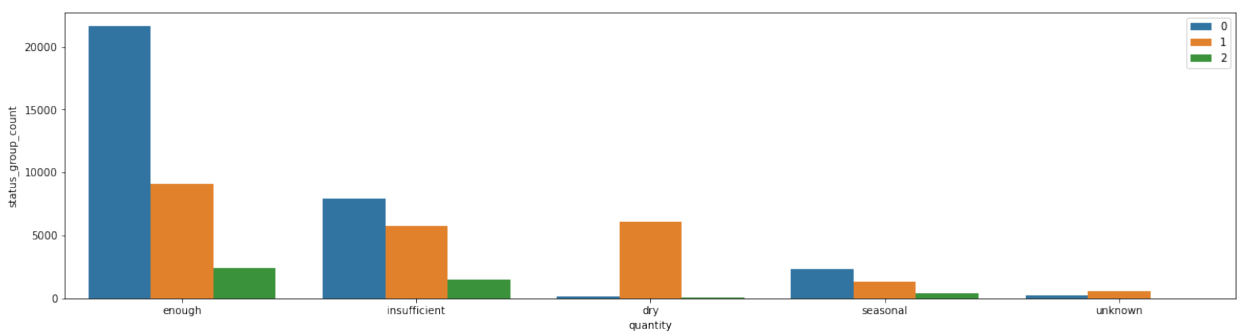
time: 191 ms (started: 2023-01-09 14:45:52 -05:00)

In [322]:
```
vars = ['scheme_management', 'permit', 'public_meeting']

with plt.style.context('seaborn-talk'):
    fig, ax_list = plt.subplots(ncols = 3, figsize=(20,5))

for i in [0,1,2]:
    df_ana[vars[i]] = df_ana[vars[i]].fillna('missing')
    counts = df_ana[['status_group',vars[i]]].groupby(['status_group',
    counts.plot.bar(ax=ax_list[i])

#get_and_plot_groups(df_ana,'public_meeting','status_group',ax='ax2',F
```



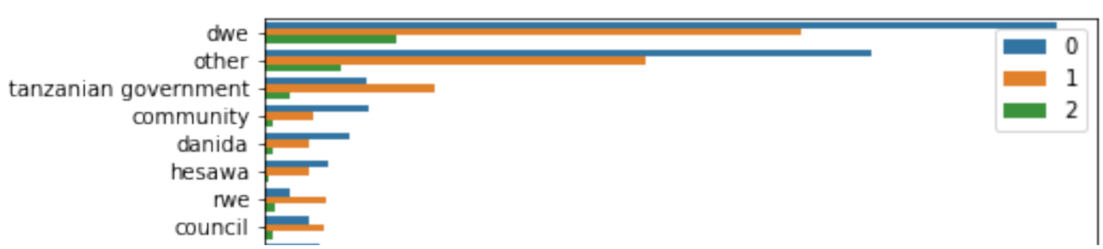

```
time: 494 ms (started: 2023-01-09 15:39:29 -05:00)
```

In [312]:
```
get_and_plot_groups(df_ana,'quantity','status_group',ax='ax2',Flen=20,
```

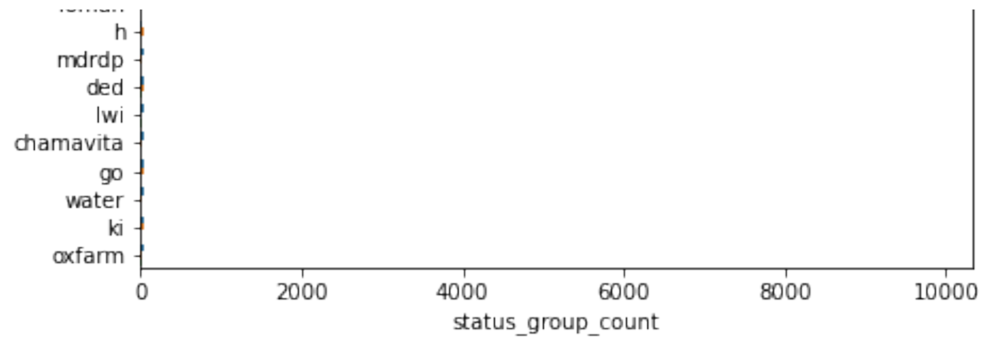



```
time: 144 ms (started: 2023-01-09 14:46:09 -05:00)
```

In [315]:
```
get_and_plot_groups(df_ana,'installer','status_group',ax='ax3',Flen=7,
```

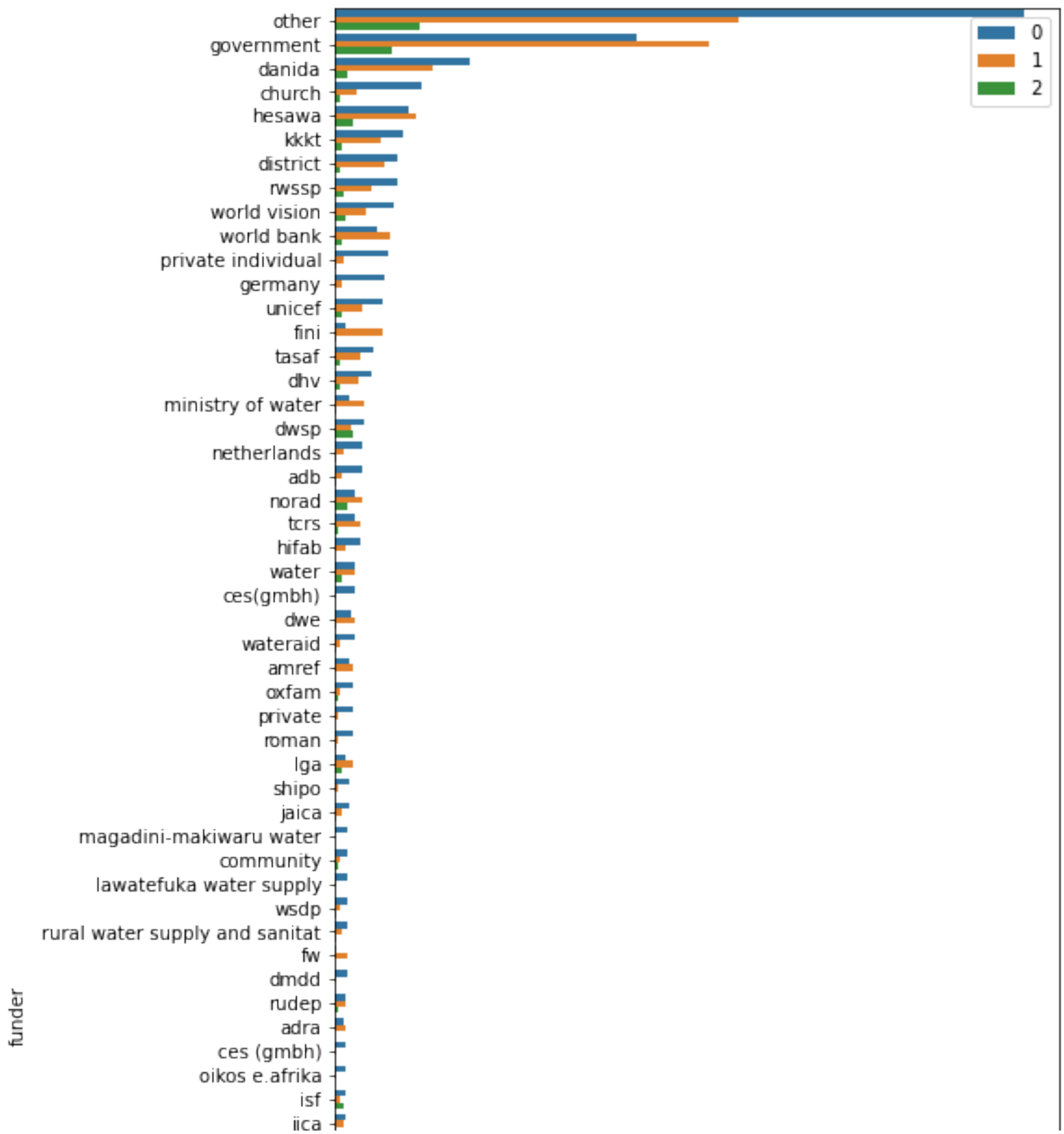


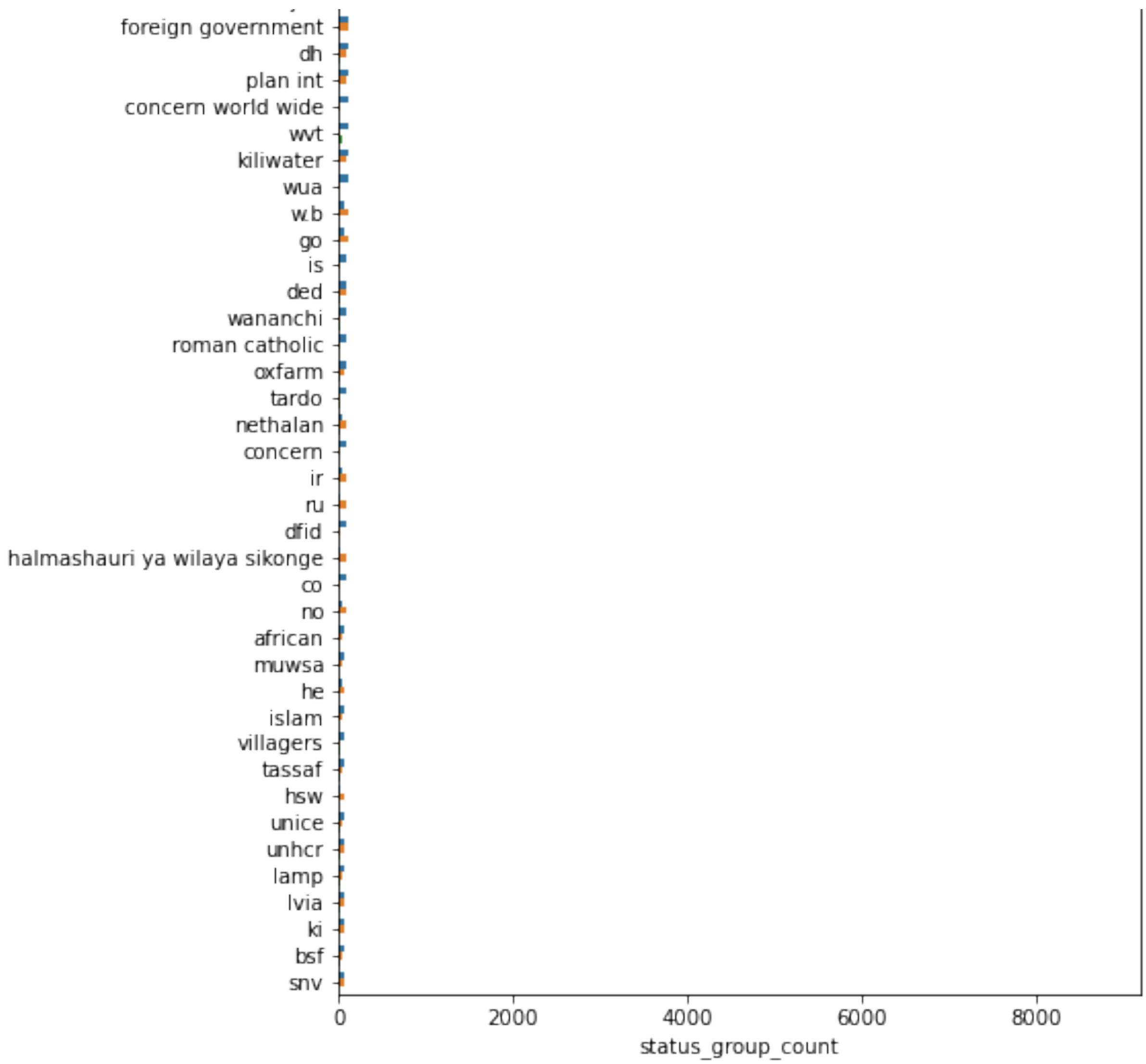

church
finw
ces
world vision
kkkt
tcrs
dmdd
acra
wedeco
wu
amref
tasaf
lga
da
twesa
sema
shipo
jaica
magadini-makiwaru wa
lawatefuka water sup
villagers
norad
fw
local
idara ya maji
oxfam
centr
is
unicef
private
wananchi
dh
sengerema water department
kiliwater
wvt
kuwait
africa
twe
distri
rwssp
water aid
handeni trunk main(
jica
world bank
tardo
adra
ir
unisef
mwe
halmashauri ya wilaya sikonge
cefa
muwsa
region water department
vwc
he
artisan
isf
wizara ya maji
angli
hsw
consulting engineer
ddca
aict
water board
world
installer



time: 1.54 s (started: 2023-01-09 14:47:10 -05:00)

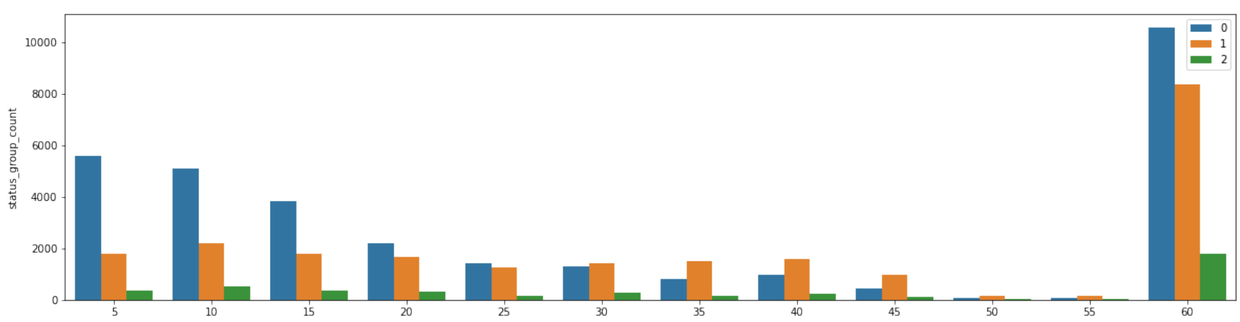
In [316]:
```
get_and_plot_groups(df_ana,'funder','status_group',ax='ax3',Flen=7,Fhg
```





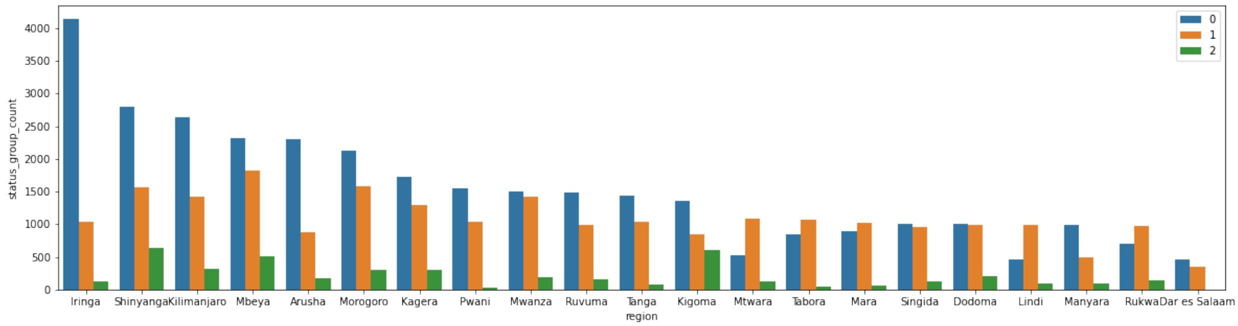
time: 1.55 s (started: 2023-01-09 14:47:28 -05:00)

In [330]:
```
get_and_plot_groups(df_ana,'age','status_group',ax='ax2',Flen=20,Fhgt=
```



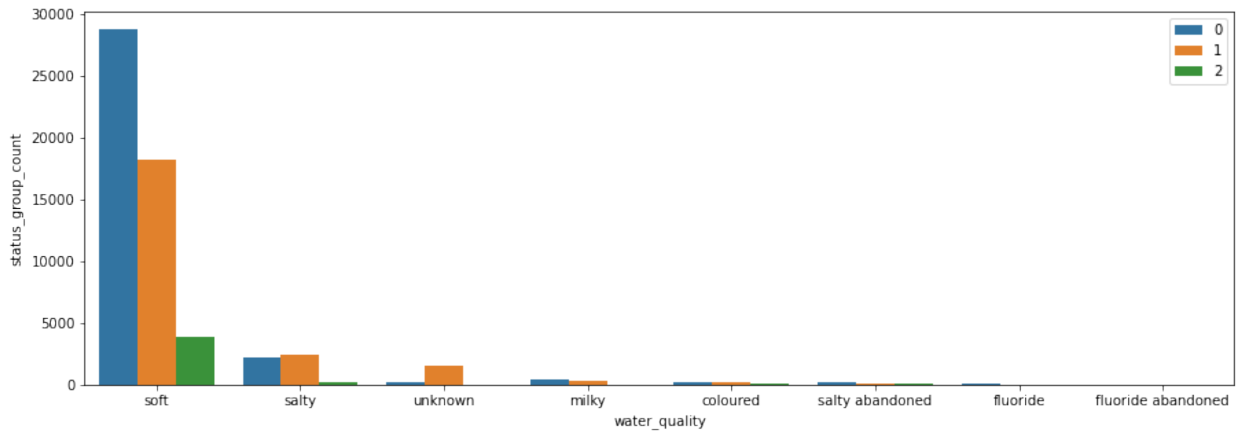
time: 231 ms (started: 2023-01-09 17:41:48 -05:00)

In [317]:
```
get_and_plot_groups(df_ana,'region','status_group',ax='ax2',Flen=20,Fh
```



time: 328 ms (started: 2023-01-09 14:47:47 -05:00)

In [324]:
```
get_and_plot_groups(df_ana,'water_quality','status_group',ax='ax3',Fle
```



time: 229 ms (started: 2023-01-09 15:49:22 -05:00)

In [327]:
```
#get_and_plot_groups(df_ana,'scheme_name','status_group',ax='ax3',Flen
```

time: 159 µs (started: 2023-01-09 15:50:52 -05:00)

Summary of Data Exploration

- For most of the variables, one sees that the functional wells dominate, as compared to non-functional and needs repairs categories, when looked among the most of the subgroups that the given varaiable has. One can see the trend reversal in some subgroups such as
  - `dry_quantity" in "quantity" variable`,
  - `unknown and salty for water_quality`,
  - `tanzanian govt category in installer`
  - `age >35 yrs`
- **Missing Values** Except for the **"scheme_name"**, I dont see a lot of missing values as can be seen above from the missingno plot as well as null value counts. Since schema_name has 47% missing data, I would drop this column for now. However, I do want to include this column by defining "missing" category for those missing values. Since rest of the variables.
- The columns listed below will be deleted to build models. Most of these are deleted as they contain duplicated information as explained above in correlation plot. Installer and Funder are deleted for now because the logistic regression model based on the dataset that included these two columns showed very similar ROC/ accuracy scores as the models below without including them.
  - `Train (Test) ROC scores` - **89.11(82.56)** with installer included.
  - `Train (Test) ROC scores` -**89.69% (81.81%)** model below with installer and funder removed.
- Ideally I would want to include as many as columns as I can but since categorical columns create a hige overhead, the models run slower and one needs time on the order of days to get one successful run.

- We will clean the data table by removing the columns and as above changing the status group to a numeric column

In [ ]:
```
cols_to_delete = ['id', 'recorded_by','funder', 'installer','yr_recorc
                 'lga', 'ward', 'region','scheme_management',
                  'wpt_name','scheme_name', 'extraction_type_class',
                  'extraction_type_group','management', 'payment_type',
                  'quality_group', 'source_type', 'source',
                  'waterpoint_type_group', 'quantity_group', 'basin',
                  'num_private','construction_year','date_recorded','mc
```

In [32]:
```
df_clean = df_clean.drop(cols_to_delete,axis=1)
```

```
time: 504 ms (started: 2023-01-03 17:57:10 -05:00)
```

In [18]:
```
df_clean=df_clean.drop('yr_record',axis=1)
```

```
time: 193 ms (started: 2023-01-03 17:27:16 -05:00)
```

In [33]:
```
df_clean
```

Out[33]:

	amount_tsh	gps_height	longitude	latitude	basin	subvillage	region_code	d
0	6000.0	1390	34.938093	-9.856322	Lake Nyasa	Mnyusi B	11	
1	0.0	1399	34.698766	-2.147466	Lake Victoria	Nyamara	20	
2	25.0	686	37.460664	-3.821329	Pangani	Majengo	21	
3	0.0	263	38.486161	-11.155298	Ruvuma / Southern Coast	Mahakamani	90	
4	0.0	0	31.130847	-1.825359	Lake Victoria	Kyanyamisa	18	
...	...	...	...	...	...	...	...	
59395	10.0	1210	37.169807	-3.253847	Pangani	Kiduruni	3	
59396	4700.0	1212	35.249991	-9.070629	Rufiji	Igumbilo	11	
59397	0.0	0	34.017087	-8.750434	Rufiji	Madungulu	12	
59398	0.0	0	35.861315	-6.378573	Rufiji	Mwinyi	1	
59399	0.0	191	38.104048	-6.747464	Wami / Ruvu	Kikatanyemba	5	

59400 rows × 20 columns

```
time: 165 ms (started: 2023-01-03 17:57:16 -05:00)
```

In [35]:
```
dic = {'functional':0, 'non functional':1,'functional needs repair':2
df_clean.replace({"status_group": dic}, inplace=True)
df_clean["status_group"].value_counts()
```

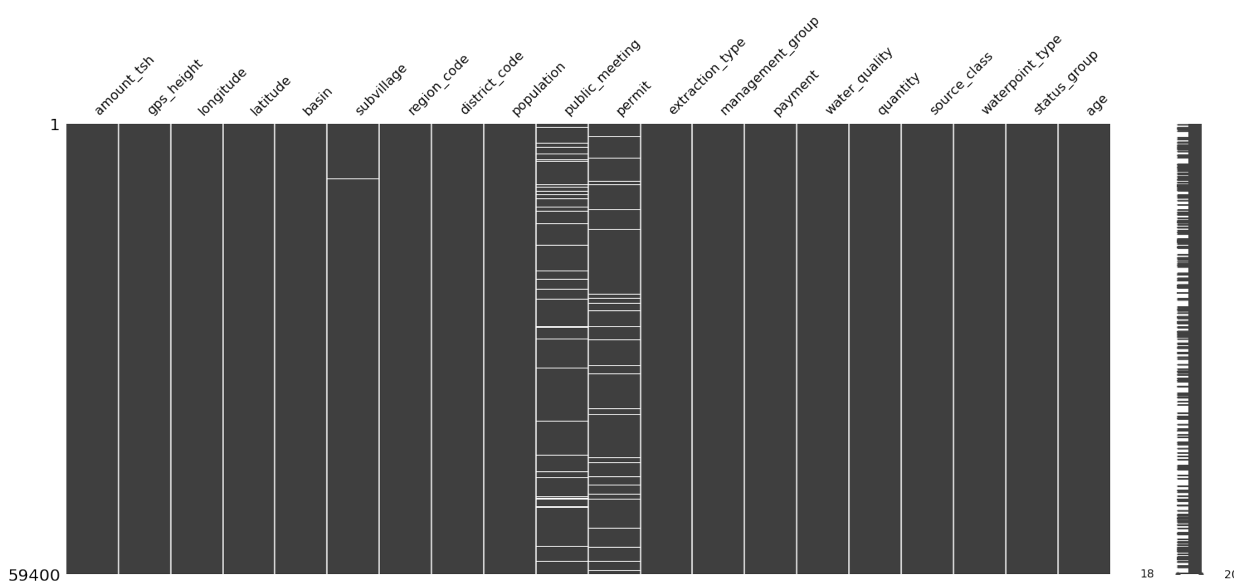
Out[35]:
```
0    32259
1    22824
2     4317
Name: status_group, dtype: int64

time: 459 ms (started: 2023-01-03 18:03:21 -05:00)
```

In [36]:
```
df_clean.columns.to_series().groupby(df.dtypes).groups
```

Out[36]:
```
{dtype('int64'): Index(['gps_height', 'region_code', 'district_code',
'population', 'age'], dtype='object'),
 dtype('float64'): Index(['amount_tsh', 'longitude', 'latitude'], dty
pe='object'),
 dtype('O'): Index(['basin', 'subvillage', 'public_meeting', 'permit'
, 'extraction_type',
        'management_group', 'payment', 'water_quality', 'quantity',
        'source_class', 'waterpoint_type', 'status_group'],
       dtype='object')}

time: 32.8 ms (started: 2023-01-03 18:03:22 -05:00)
```

In [328]:
```
mssno.matrix(df_clean)
```

Out[328]:
```
<AxesSubplot:>
```




```
time: 405 ms (started: 2023-01-09 16:01:19 -05:00)
```

Variables with the Null Values

- There are only three variables in the clean dataset that have missing values. Based on the type of these variables we will use following strategies

Binary Columns:

`public_meeting`:`permit`:

```
* These two variables are binary with values **(True/False)**
* Given that the proportion of null values are not too high fo
r these variables, the null values will be replaced with the *
*most frequent**.
```

Categorical Columns:

`subvillage`:

```
   * There is no intrinsinc ordering to this variables, so the
null values will be replaced with a **constant('missing')** cr
eating its own level before one-hot encoding these variables.D
uring missing rows for
```

- Splitting the variables according to their types to preprocess them before feeding them into the model

In [41]:
```
numeric_columns=['gps_height', 'region_code', 'district_code', 'popula
                 'longitude', 'latitude','age']
cols_cat_binary = ['public_meeting','permit']
cols_categorical = ['basin', 'subvillage', 'extraction_type',
                    'management_group', 'payment', 'water_quality', 'q
                    'source_class', 'waterpoint_type']
```

```
time: 23.4 ms (started: 2023-01-03 18:05:19 -05:00)
```

Specify X and y:

In [40]:
```
X = df_clean.drop('status_group',axis=1)
y = df_clean.status_group
```

```
time: 500 ms (started: 2023-01-03 18:05:03 -05:00)
```

Test-Train split the data:

- In order to avoid any data leakage of training data into test data, we should split the data before applying any scaling/preprocessing techniques.

In [42]:
```
#Default Train and Test data split of 75 and 25%
X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=42,shu
```

```
time: 639 ms (started: 2023-01-03 18:05:24 -05:00)
```

In [329]:
```
## Just a function to grab numeric values
def grab_numeric(df):
    return df.select_dtypes(exclude=[object])
GrabNumeric = FunctionTransformer(grab_numeric)
```

```
time: 336 µs (started: 2023-01-09 16:08:49 -05:00)
```

- Split the train data into different sub-groups based on the different data types as explained above

In [43]:
```
X_train_binary  = X_train[cols_cat_binary]
X_train_cat     = X_train[cols_categorical]
X_train_numeric = X_train[numeric_columns]

print("X_train shape", X_train.shape)
print("binary shape", X_train_binary.shape)
print("cateogorical shape", X_train_cat.shape)
print("numeric shape", X_train_numeric.shape)
```

```
X_train shape (44550, 19)
binary shape (44550, 2)
cateogorical shape (44550, 9)
numeric shape (44550, 8)
time: 180 ms (started: 2023-01-03 18:05:42 -05:00)
```

Preprocessing Steps:

- **NA imputation** for ***binary and categorical*** variables
  - For the binary/numerical variables, impute with the ***most frequent***.
  - For the categorical variables, impute with a constant: the string **'*missing*'**.
- **One-Hot-Encoding** for the ***categorical variables*** only.
- **Scaling** for the ***numerical variables*** only (since binary and categorical variables are already encoded as 0 and 1).

In [44]:
```
preprocess_numeric = Pipeline(steps=[
    ('num', GrabNumeric),
    ('ss', StandardScaler())
])
```

time: 45.1 ms (started: 2023-01-03 18:06:03 -05:00)

In [45]:
```
preprocess_binary = Pipeline(steps=[
    ('binary_impute', SimpleImputer(strategy='most_frequent')),
    ('ohe', OneHotEncoder(sparse=False, handle_unknown='ignore'))
])
```

time: 31.1 ms (started: 2023-01-03 18:06:17 -05:00)

In [46]:
```
preprocess_categorical= Pipeline(steps=[
    ('cat_impute', SimpleImputer(strategy='constant', fill_value='miss
    ('ohe', OneHotEncoder(sparse=False,handle_unknown='ignore'))
])
```

time: 19.7 ms (started: 2023-01-03 18:06:28 -05:00)

In [47]:
```
# This applies transformers to columns of an array or pandas DataFrame
# This estimator allows different column subsets to be transformed sep
# and the features generated by each transformer will be concatenated
preprocessor = ColumnTransformer(transformers=
                                 [('preprocess_binary', preprocess_bin
                                  ('preprocess_categorical', preproces
                                  ('preprocess_numeric',preprocess_num
                                   remainder='passthrough')#,
                             #remainder='passthrough')
```

time: 42 ms (started: 2023-01-03 18:23:26 -05:00)

PREDICTING WATER PUMP FUNCTIONALITY:

using `roc_auc` and `f1_weighted` as the scoring metric :

- The target variable isimbalanced so the harmonic mean of precision and recall is more meaningful. So I will use f1_scoring as the optimizig paparameter for tuning hyperparameters for the several models.
- We care equally about positive and negative classes, being able to classify as many 0s and 1s as possible. The Roc_Auc metric utilizes **"probabilities"** of class prediction. This is therefore a good metric to evaluate and compare the models.
- Computing Roc_Auc on train set, will tell if model is confident in it's learning or not.
- Computing Roc_Auc on test set will tell, how good it performed on unknown dataset - generalizability.
- For the models comparisons, I will be using train, validation and test sets, where I will use hyper parameter tuning on the train with cross validation on validation sets, Roc_Auc based model selection and final evaluation based on test set.

BASELINE MODEL #1 Logistic Regression:

This is the baseline out of box model without any hyperparamter tuning

In [50]:
```
baseline_logreg = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator", LogisticRegression(random_state=42))])#,multi_class=

# Train model
baseline_logreg.fit(X_train, y_train);
```

```
time: 1min 14s (started: 2023-01-04 18:17:10 -05:00)
```

- I want to see if by default the logistic regression took into account this as a multiclassification problem

In [235]:
```
baseline_logreg2 = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator", LogisticRegression(random_state=42,multi_class='multi

# Train model
baseline_logreg2.fit(X_train, y_train);
```

time: 1min 6s (started: 2023-01-06 13:54:59 -05:00)

In [51]:
```
baseline_logreg.score(X_train, y_train)
```

Out[51]: 0.7868686868686868

time: 11 s (started: 2023-01-04 18:20:27 -05:00)

In [236]:
```
baseline_logreg2.score(X_train, y_train)
```

Out[236]: 0.7868686868686868

time: 10.6 s (started: 2023-01-06 13:56:12 -05:00)

In [185]:
```
baseline_logreg['estimator'].get_params
```

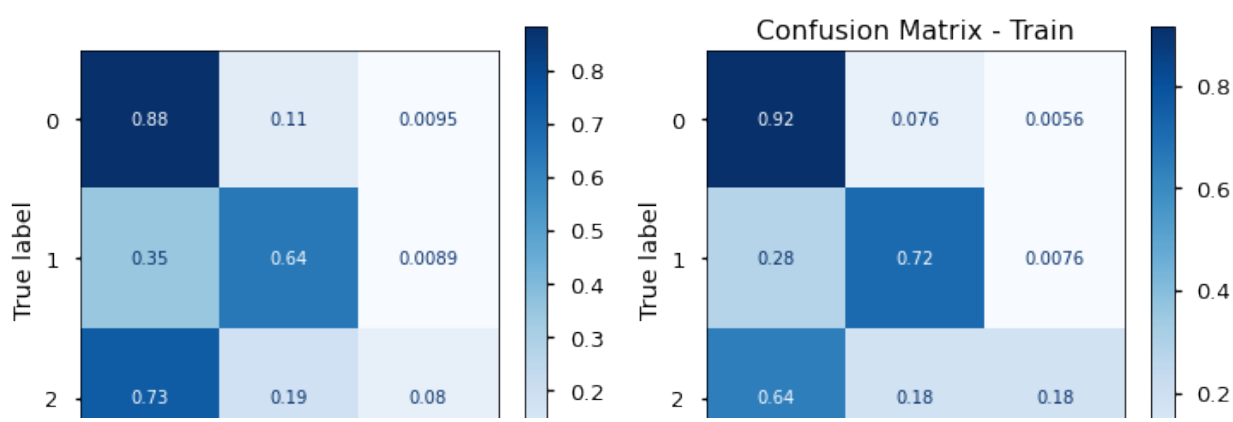
Out[185]: <bound method BaseEstimator.get_params of LogisticRegression(random_state=42)>

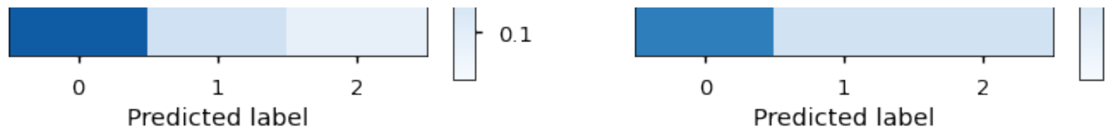
time: 1.74 ms (started: 2023-01-06 12:23:21 -05:00)

In [54]:
```
## We need this to plot ROC curves for multi classification problems
from sklearn.preprocessing import LabelBinarizer
n_classes = len(np.unique(y))
label_binarizer = LabelBinarizer().fit(y_train)
colors = cycle(["aqua", "darkorange", "cornflowerblue"])
```

time: 10.4 ms (started: 2023-01-04 18:22:27 -05:00)

In [55]:
```
model_evaluation_roc_auc(baseline_logreg)
```



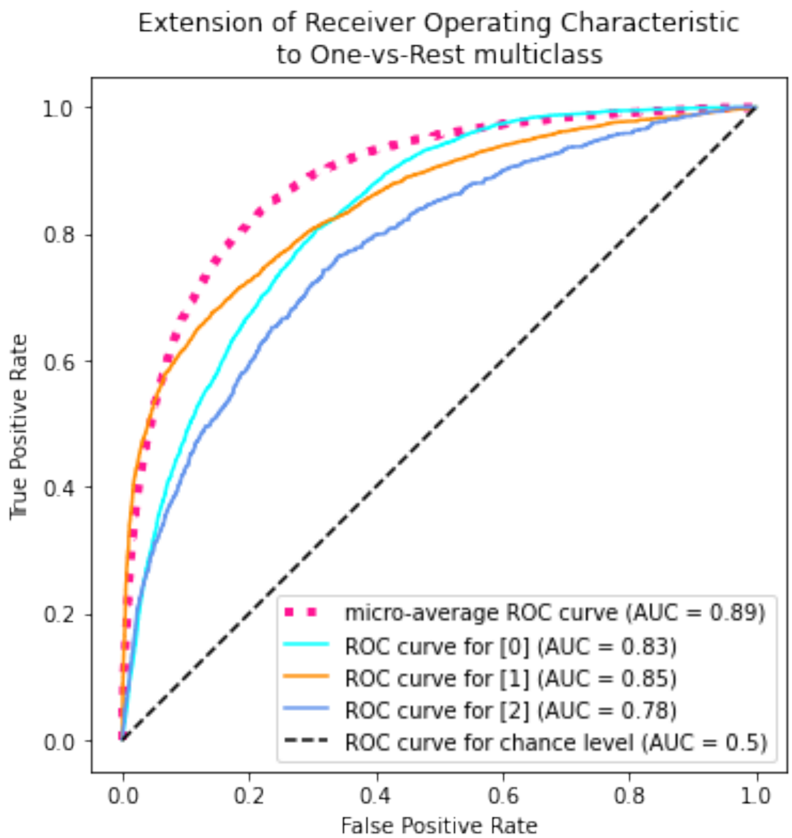


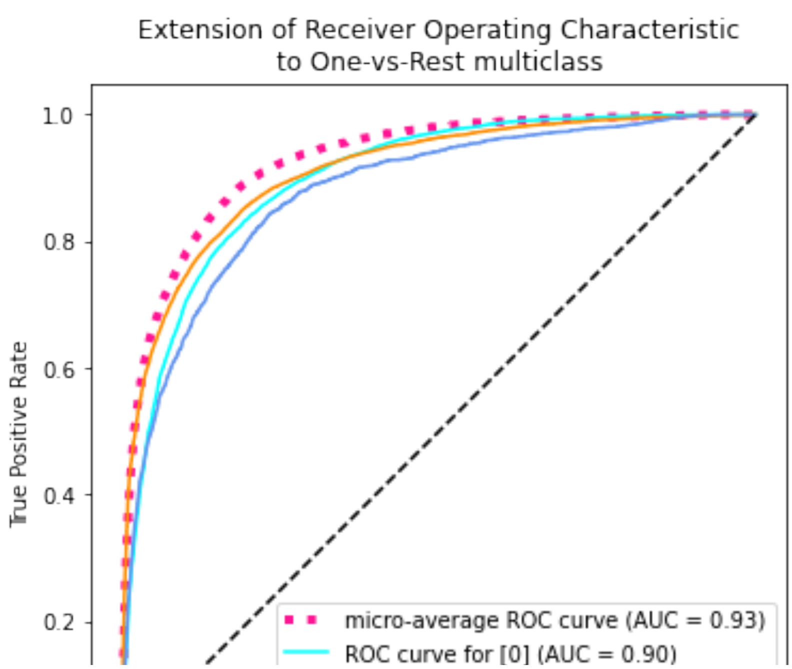

```
------------------------------------------------------------
Classification Report - Test:
------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.719     0.885     0.793      8065
           1      0.777     0.640     0.702      5706
           2      0.402     0.080     0.133      1079

    accuracy                          0.732     14850
   macro avg      0.632     0.535     0.543     14850
weighted avg      0.718     0.732     0.710     14850

------------------------------------------------------------
------------------------------------------------------------


 Train Roc_Auc Score: 89.69%
 Test Roc_Auc Score: 81.81%


------------------------------------------------------------


 Train Accuracy Score: 78.69%
 Test Accuracy Score: 73.24%


------------------------------------------------------------


 Train Sensitivity/Recall score: 78.69%
 Test Sensitivity/Recall score: 73.24%


------------------------------------------------------------


Train Weighted Precision: 0.79
Test Weighted Precision: 0.72
time: 33.2 s (started: 2023-01-04 18:22:47 -05:00)
```

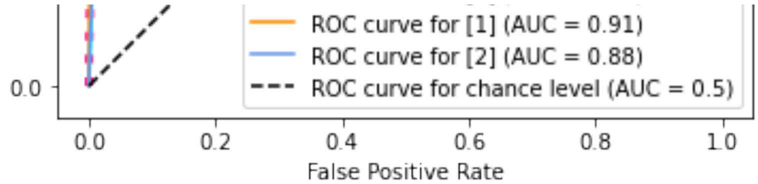
In [59]:

```
plot_roc_curve(baseline_logreg,X_test,y_test)
plot_roc_curve(baseline_logreg,X_train,y_train)
```

```
Micro-averaged One-vs-Rest ROC AUC score:
0.89
Micro-averaged One-vs-Rest ROC AUC score:
0.93
```








```
time: 11.3 s (started: 2023-01-04 18:24:13 -05:00)
```

- There is a some overfitting that the baseline model is doing.
- We will see what hyper-paramter tuning will do in the next section

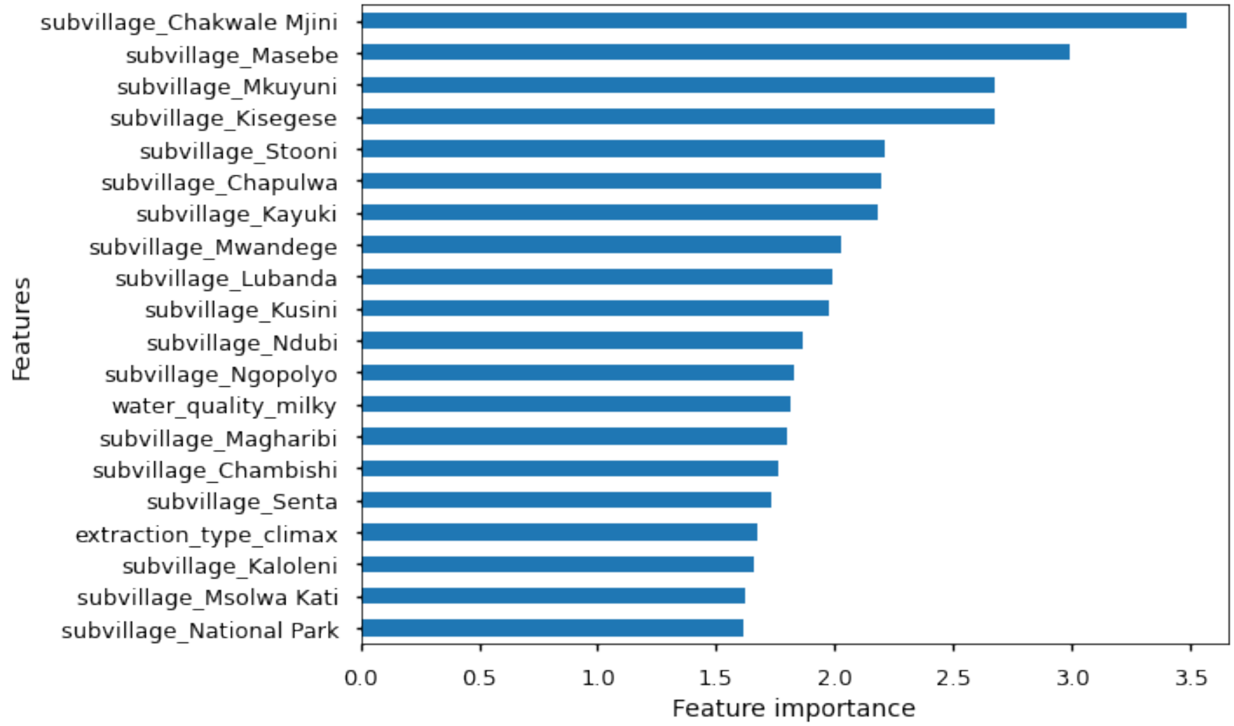
In [106]:
```
## This is to extract feature names from Preprocessor so that we can l
#for logistic regression
cat_features_binary=baseline_logreg['preprocessor'].transformers_[0][1
    ['ohe'].get_feature_names_out(X_train_binary.columns)
cat_feature_other = baseline_logreg['preprocessor'].transformers_[1][1
    ['ohe'].get_feature_names_out(X_train_cat.columns)
feature_names     = np.r_[cat_features_binary, cat_feature_other,X_tra
#feature_names = np.r_[X_not_cat.columns, cat_feature_names]
```

```
time: 6.52 ms (started: 2023-01-04 19:53:07 -05:00)
```

In [284]:
```
# visualize feature importance from a pipeline
def feature_importance_ML(model, modelname):
    coeffs = model.named_steps['estimator'].coef_
    importance = pd.Series(abs(coeffs[0]), index=feature_names) # logr
    with plt.style.context('seaborn-talk'):
        fig, ax = plt.subplots(figsize=(10,6))
        importance.sort_values().tail(20).plot.barh(ax=ax);

        ax.set_xlabel('Feature importance')
        ax.set_ylabel('Features')
        fig.tight_layout()
```

```
time: 583 µs (started: 2023-01-09 08:39:22 -05:00)
```

In [108]:
```
feature_importance_ML(baseline_logreg,"Log Reg")
```



time: 197 ms (started: 2023-01-04 19:53:09 -05:00)

BASELINE MODEL #2 Random Forest Classifier:

In [115]:
```
rfc = RandomForestClassifier(random_state=42,class_weight = 'balanced'

rfc_model_pipe = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator",rfc)
])
rfc_model_pipe.fit(X_train, y_train);
```

time: 4min 18s (started: 2023-01-04 19:55:02 -05:00)

In [187]:
```
 rfc_model_pipe['estimator'].get_params
```

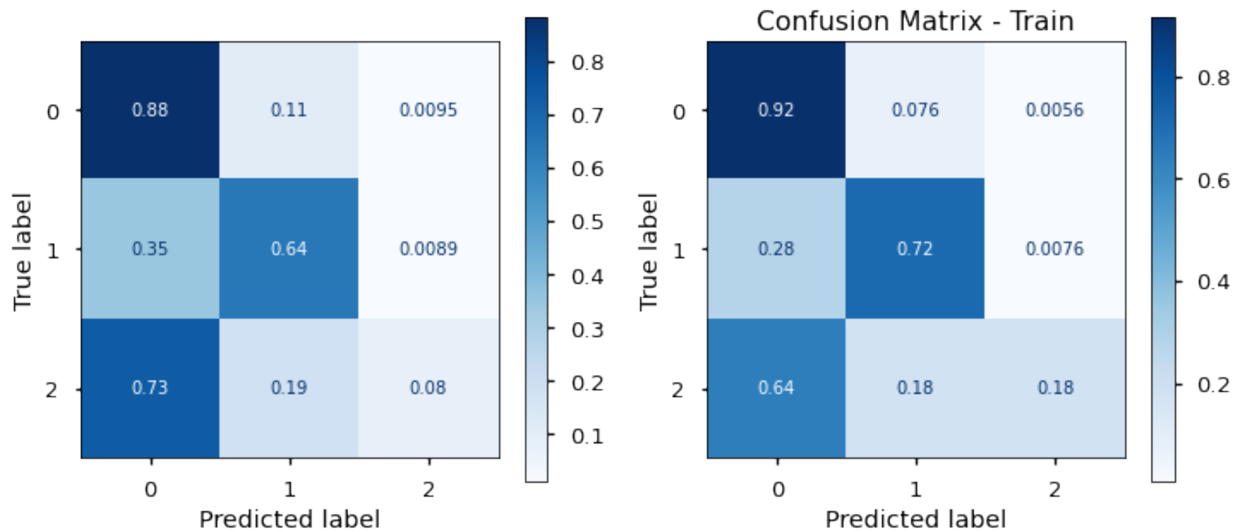
Out[187]:
```
<bound method BaseEstimator.get_params of RandomForestClassifier(clas
s_weight='balanced', random_state=42)>
```

time: 1.57 ms (started: 2023-01-06 12:24:05 -05:00)

In [203]:
```
rfc2 = RandomForestClassifier(random_state=42,class_weight = 'balanced
                              min_samples_leaf=2,max_features='log2')

rfc_model_pipe2 = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator",rfc2)
])
rfc_model_pipe2.fit(X_train, y_train);
```

```
time: 36.3 s (started: 2023-01-06 13:03:39 -05:00)
```

In [204]:
```
model_evaluation_roc_auc(rfc_model_pipe2)
```

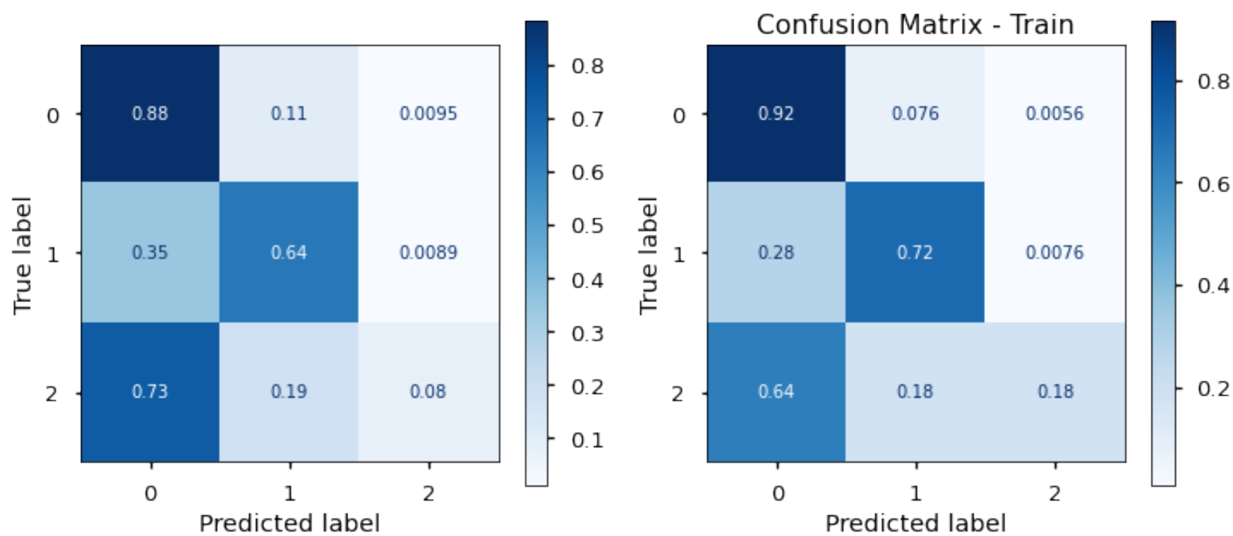



```
------------------------------------------------------------
Classification Report - Test:
------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.743     0.595     0.661      8065
           1      0.655     0.606     0.629      5706
           2      0.172     0.496     0.255      1079

    accuracy                          0.592     14850
   macro avg      0.523     0.566     0.515     14850
weighted avg      0.668     0.592     0.619     14850

------------------------------------------------------------
------------------------------------------------------------


 Train Roc_Auc Score: 78.91%
```

```
 Test Roc_Auc Score: 75.87%


-------------------------------------------------------


 Train Accuracy Score: 61.26%
 Test Accuracy Score: 59.21%


-------------------------------------------------------


 Train Sensitivity/Recall score: 61.26%
 Test Sensitivity/Recall score: 59.21%


-------------------------------------------------------


Train Weighted Precision: 0.69
Test Weighted Precision: 0.67
Train Score:0.61
Test Score:0.59
time: 52 s (started: 2023-01-06 13:04:20 -05:00)
```

In [117]:

```
model_evaluation_roc_auc(rfc_model_pipe)
```



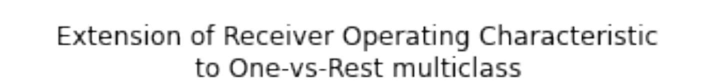

```
-------------------------------------------------------
Classification Report - Test:
-------------------------------------------------------
              precision    recall  f1-score   support
```

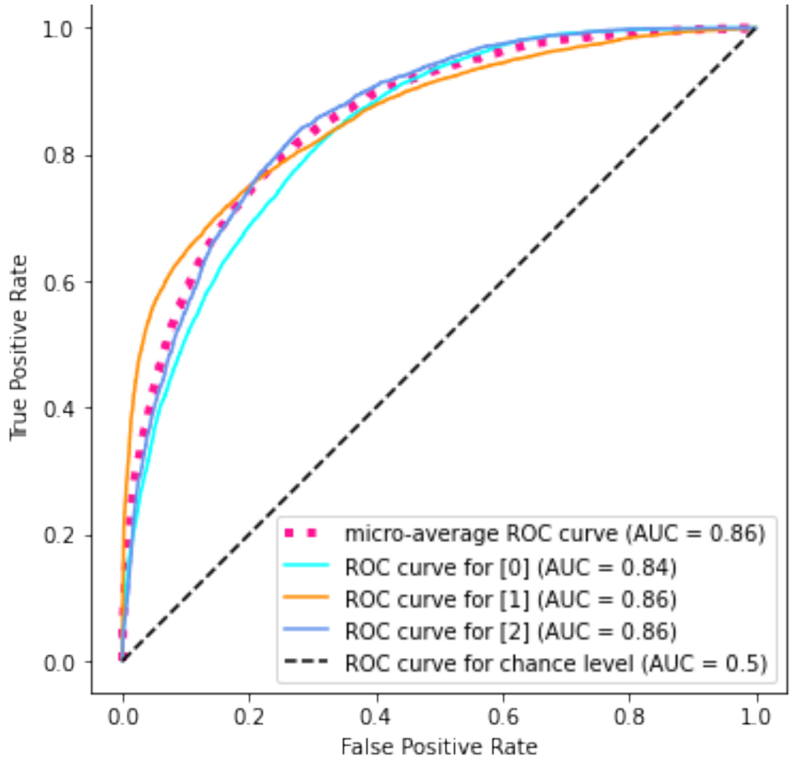
```
           0      0.799     0.891     0.842      8065
           1      0.841     0.771     0.804      5706
           2      0.536     0.307     0.390      1079

    accuracy                          0.803     14850
   macro avg      0.725     0.656     0.679     14850
weighted avg      0.796     0.803     0.795     14850

________________________________________________________
________________________________________________________


 Train Roc_Auc Score: 99.99%
 Test Roc_Auc Score: 88.81%


________________________________________________________


 Train Accuracy Score: 99.92%
 Test Accuracy Score: 80.26%


________________________________________________________


 Train Sensitivity/Recall score: 99.92%
 Test Sensitivity/Recall score: 80.26%


________________________________________________________


Train Weighted Precision: 1.00
Test Weighted Precision: 0.80
Train Score:1.00
Test Score:0.80
time: 1min 4s (started: 2023-01-04 20:01:08 -05:00)
```

In [191]:

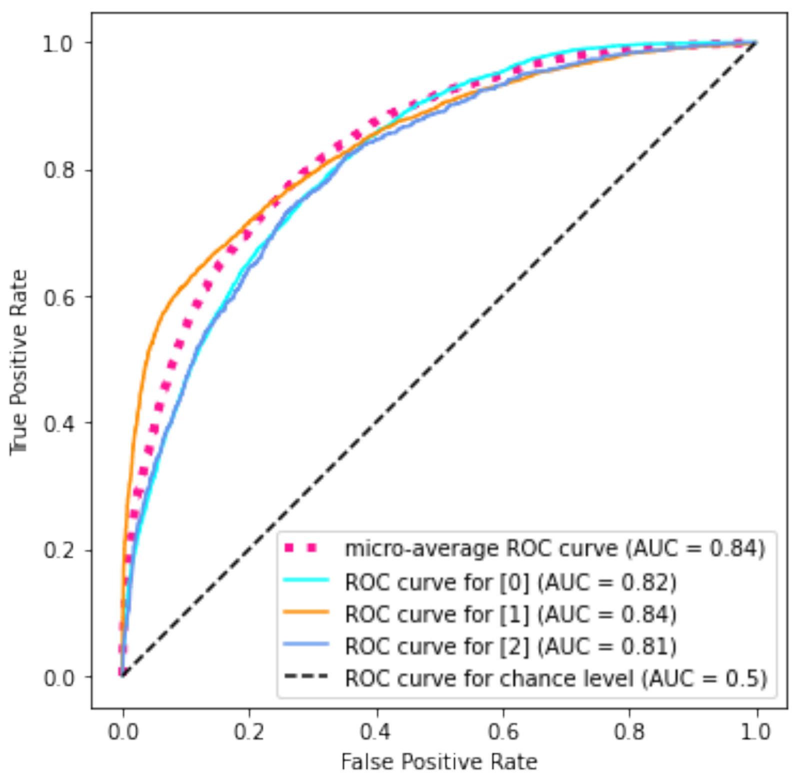
```python
plot_roc_curve(rfc_model_pipe2,X_train,y_train)
plot_roc_curve(rfc_model_pipe2,X_test,y_test)
```

```
Micro-averaged One-vs-Rest ROC AUC score:
0.86
Micro-averaged One-vs-Rest ROC AUC score:
0.84
```





Extension of Receiver Operating Characteristic
to One-vs-Rest multiclass

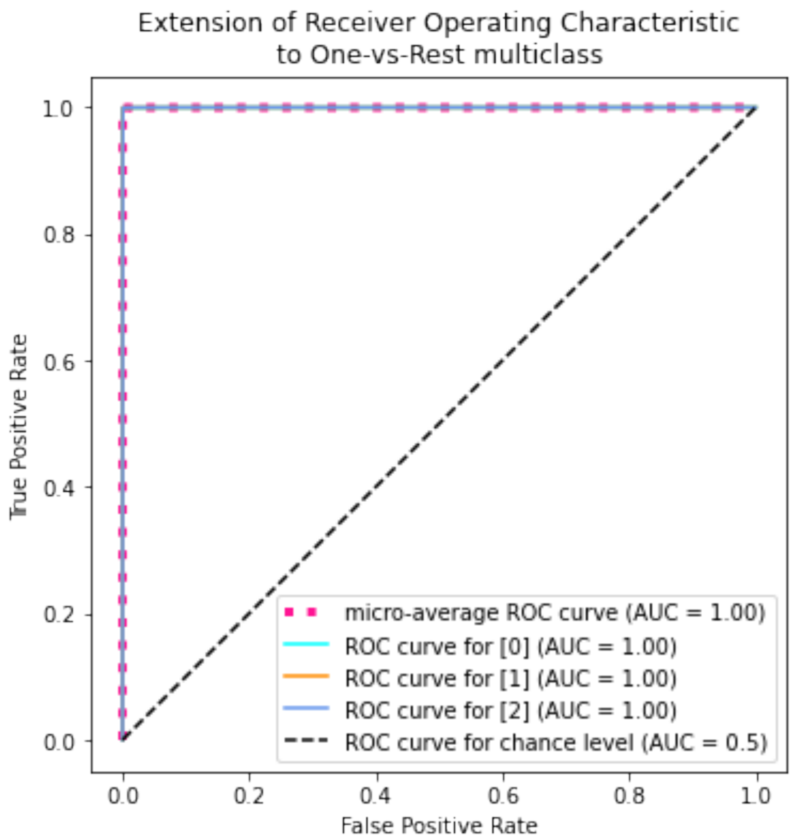


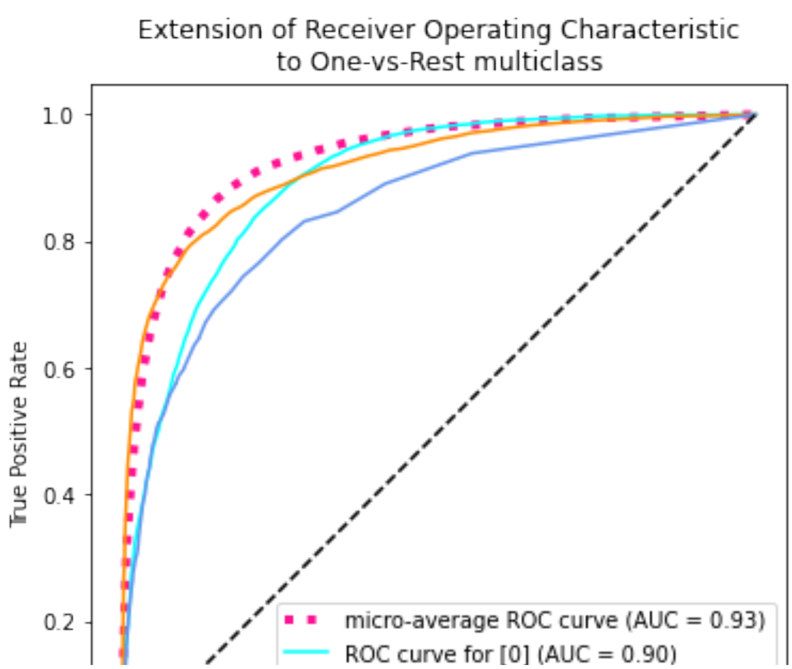

```
time: 15.6 s (started: 2023-01-06 12:32:01 -05:00)
```

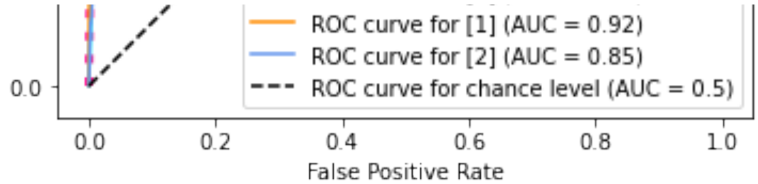
In [125]:

```
plot_roc_curve(rfc_model_pipe,X_train,y_train)
plot_roc_curve(rfc_model_pipe,X_test,y_test)
```

```
Micro-averaged One-vs-Rest ROC AUC score:
1.00
Micro-averaged One-vs-Rest ROC AUC score:
0.93
```



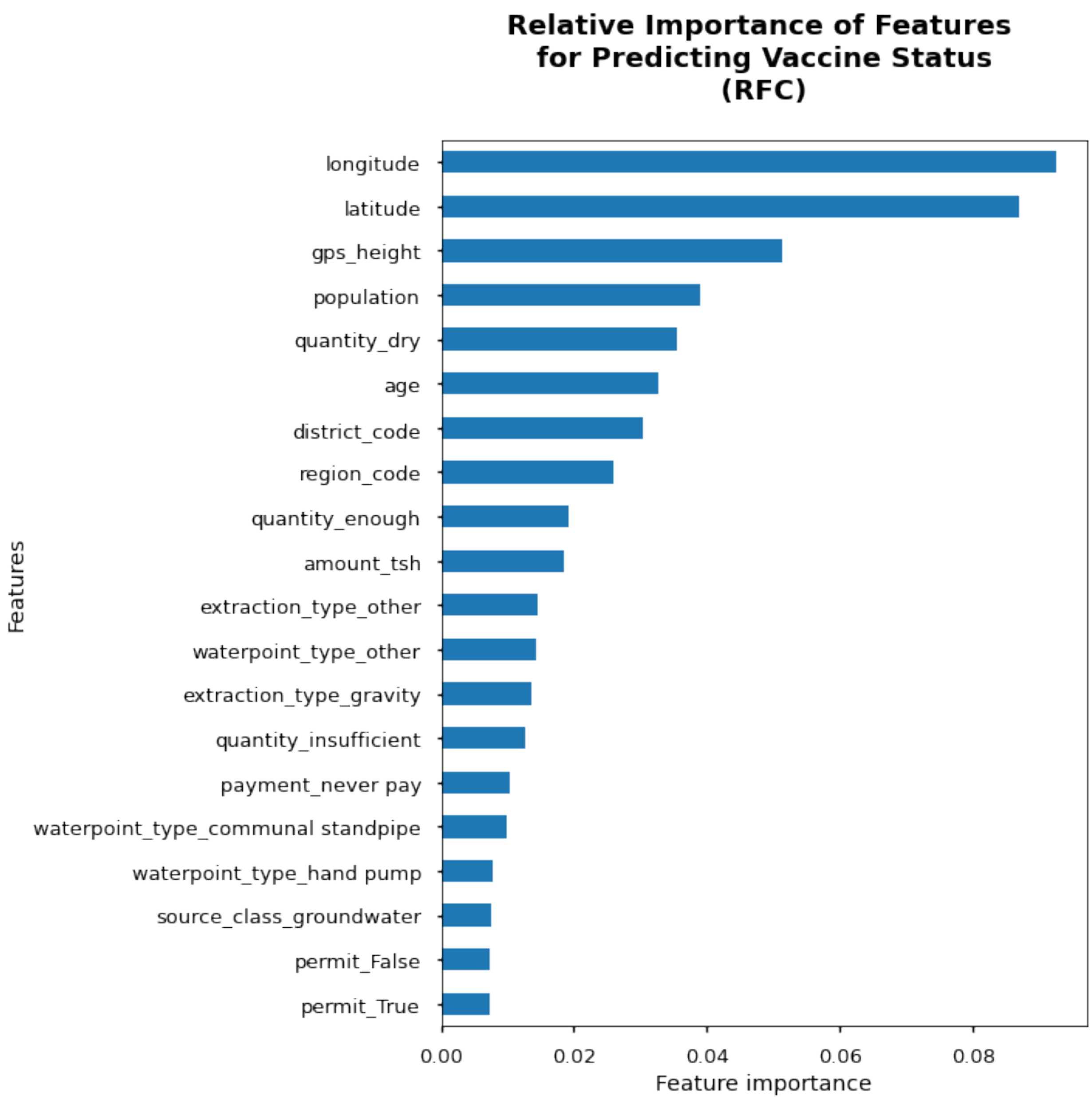





```
time: 17 s (started: 2023-01-04 20:48:07 -05:00)
```

In [ ]:

In [150]:
```
feature_importance_XGB(rfc_model_pipe,"RFC")
```




```
time: 239 ms (started: 2023-01-04 21:00:45 -05:00)
```

Baseline model is overfitting:

- The baseline model is clearly overfitting: the model picks up on patterns that are specific to the observations in the training data, but do not generalize to other observations.
- The model is able to make perfect predictions on the data it was trained on (roc_auc = 99.99), but is not able to make good predictictions on test data (roc_auc = 89.8).
- Playing with the hyperparameters fixed the overfitting issue but resulted in a roc_auc score of 78% and 75% on training and test data respectively.
- We will see how the hyperparamrter tuning will affect the model performance

BASELINE MODEL #3 XGBoost:

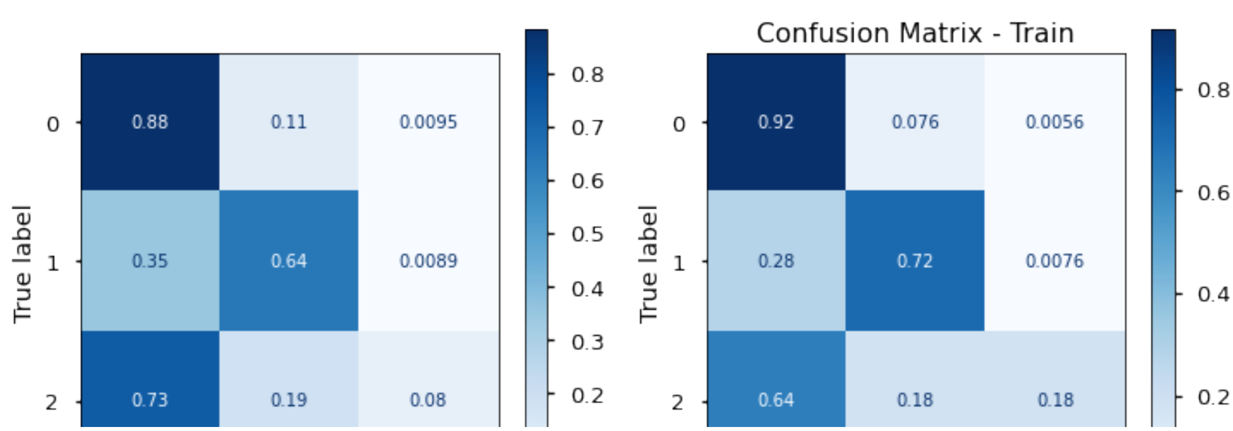
- XGBoost is a more regularized form of Gradient Boosting.
- XGBoost uses advanced regularization (L1 & L2), which improves model generalization capabilities.
- XGBoost delivers high performance as compared to Gradient Boosting.
- Its training is very fast and can be parallelized across clusters.

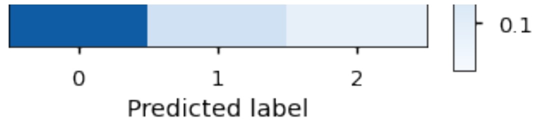
Baseline Model:

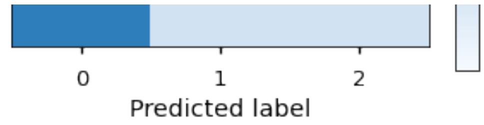
In [119]:
```
clf = XGBClassifier()
xgb_model_pipe = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator",clf)
])
xgb_model_pipe.fit(X_train, y_train);
```

```
time: 34min 25s (started: 2023-01-04 20:03:15 -05:00)
```

In [124]:
```
model_evaluation_roc_auc(xgb_model_pipe)
```



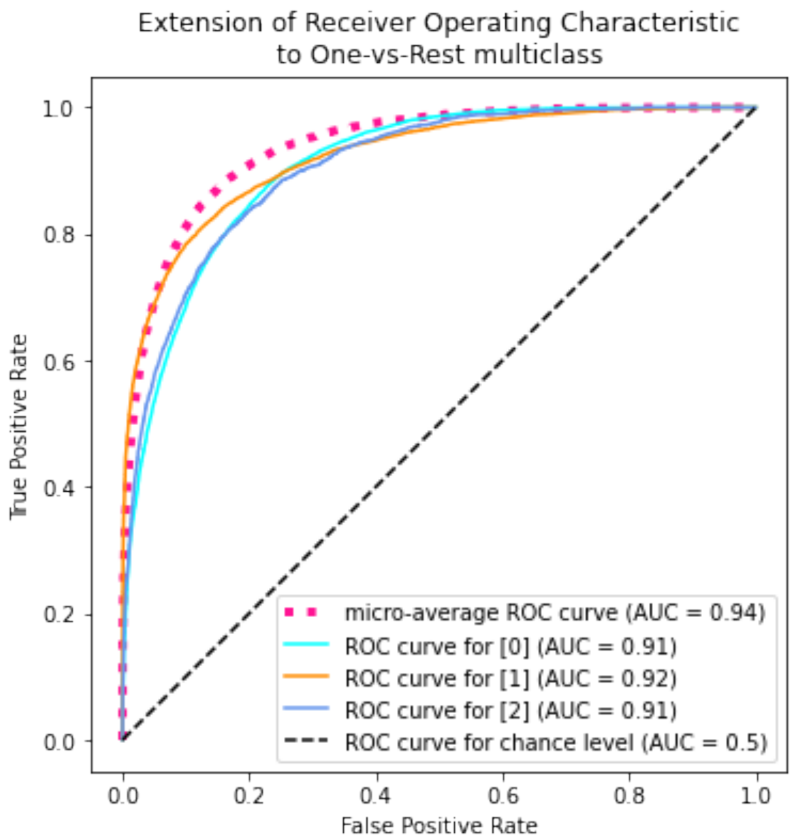


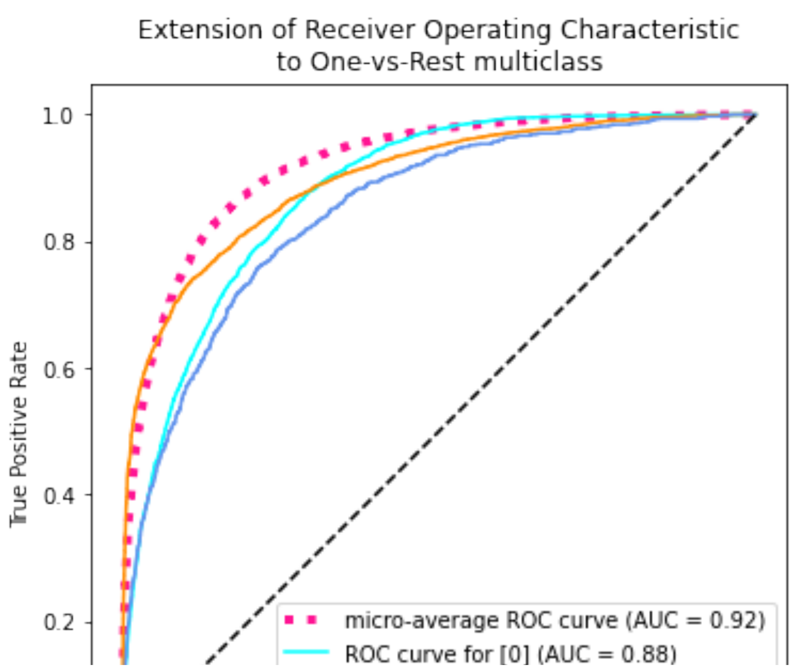


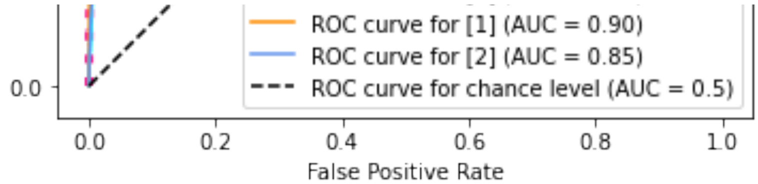

```
-------------------------------------------------------
Classification Report - Test:
-------------------------------------------------------
              precision    recall  f1-score   support

           0      0.751     0.922     0.828      8065
           1      0.846     0.687     0.758      5706
           2      0.647     0.194     0.298      1079

    accuracy                          0.779     14850
   macro avg      0.748     0.601     0.628     14850
weighted avg      0.780     0.779     0.763     14850

-------------------------------------------------------
-------------------------------------------------------


 Train Roc_Auc Score: 91.25%
 Test Roc_Auc Score: 87.58%


-------------------------------------------------------


 Train Accuracy Score: 80.40%
 Test Accuracy Score: 77.87%


-------------------------------------------------------


 Train Sensitivity/Recall score: 80.40%
 Test Sensitivity/Recall score: 77.87%


-------------------------------------------------------


Train Weighted Precision: 0.81
Test Weighted Precision: 0.78
Train Score:0.80
Test Score:0.78
time: 46 s (started: 2023-01-04 20:46:55 -05:00)
```

In [126]:
```
plot_roc_curve(xgb_model_pipe,X_train,y_train)
plot_roc_curve(xgb_model_pipe,X_test,y_test)
```

```
Micro-averaged One-vs-Rest ROC AUC score:
0.94
Micro-averaged One-vs-Rest ROC AUC score:
0.92
```





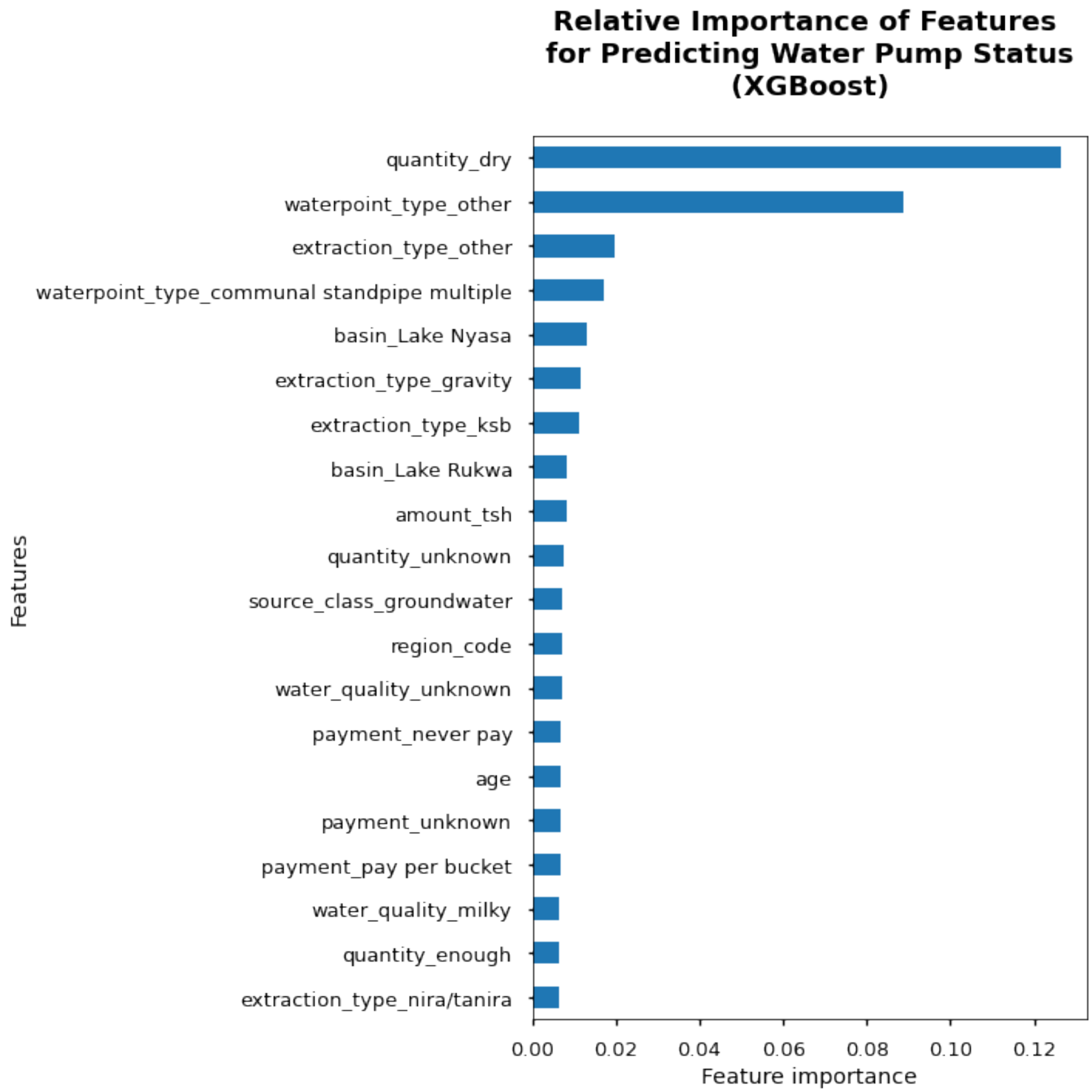


time: 11.3 s (started: 2023-01-04 20:48:51 -05:00)

In [285]:
```
# function to plot feature importance of XGB model
def feature_importance_XGB(model, modelname):
    feature_importances = model.named_steps['estimator'].feature_impor
    importance = pd.Series(feature_importances, index=feature_names) #
    with plt.style.context('seaborn-talk'):
        fig, ax = plt.subplots(figsize=(10,10))
        importance.sort_values().tail(20).plot.barh(ax=ax);
        ax.set_title("Relative Importance of Features \n for Predictin
        ax.set_xlabel('Feature importance')
        ax.set_ylabel('Features')
        plt.tight_layout()
```

time: 477 μs (started: 2023-01-09 08:39:38 -05:00)

In [286]:
```
feature_importance_XGB(xgb_model_pipe, "XGBoost")
```




```
time: 258 ms (started: 2023-01-09 08:39:42 -05:00)
```

Baseline model is overfitting again:

- The baseline model is doing **GOOD**
- The model is making good predictions on both the train(roc_auc = 96), but is not able to make the same predictions when 5-fold cross validated data was used (roc_auc = .85) or on test data (roc_auc = .86).

In [152]:
```
from sklearn.experimental import enable_halving_search_cv # noqa
from sklearn.model_selection import HalvingGridSearchCV
```

```
time: 5.56 ms (started: 2023-01-06 12:01:41 -05:00)
```

Hyperparameter Tuning for Three Models

Hyperparameters for Random Forests :

- **criterion** — Specify the norm of the penalty.
- **max_depth** - The maximum depth of the tree, most important feature to avoid overfitting. If it is not specified in the Decision Tree, the nodes will be expanded until all leaf nodes are pure. The deeper you allow, the more complex our model will become and more likely to overfit.
- **max_features** — Max_feature is the number of features to consider (randomly chosen) each time to make the split decision. It is used to control overfitting.
- **min_samples_split** — The minimum number of samples required to split an internal node.
- **min_samples_leaf** — The minimum number of samples required to be at a leaf node. Try setting these values greater than one. This has a similar effect as max_depth, it means the branch will stop splitting once the leaves have that number of samples each.
- **n_estimators**: The more trees, the less likely the RF algorithm is to overfit.

In [226]:
```
aseline model preprocessed and fit to a Random Forest Classifier
eline_model_RF = Pipeline([
 ("preprocessor", preprocessor),
 ("estimator", RandomForestClassifier(random_state=42, class_weight = '


yperparameters used for model tuning
ameters = {
 'estimator__n_estimators': [150],                 # default=100 Number
 'estimator__criterion': ['entropy', 'gini'],      # default = gini
 'estimator__max_depth': [5, 7,9],                   # default = None,
 'estimator__max_features': ['sqrt', 'log'],           # default = No
 'estimator__min_samples_split': [5, 10,20],      # default = 2, Higher
 'estimator__min_samples_leaf': [2, 4,6]          # default = 1, Higher


reate the grid, with "baseline_RF_insurance" as the estimator
st_model_RF = GridSearchCV(estimator = baseline_model_RF,   # model
                        param_grid = parameters,                # h
                        scoring ='f1_weighted',                 # m
                        cv = 3,                                 # r
                        n_jobs = -1                             # 1

t_model_RF = HalvingGridSearchCV(estimator = baseline_model_RF,   # moc
                       param_grid = parameters,                # hy
                       scoring ='f1_weighted',                 # me
                       cv = 3,                                 # nu
                       n_jobs = -1                             # 1


rain the pipeline (tranformations & predictor)
t_model_RF.fit(X_train, y_train);
```

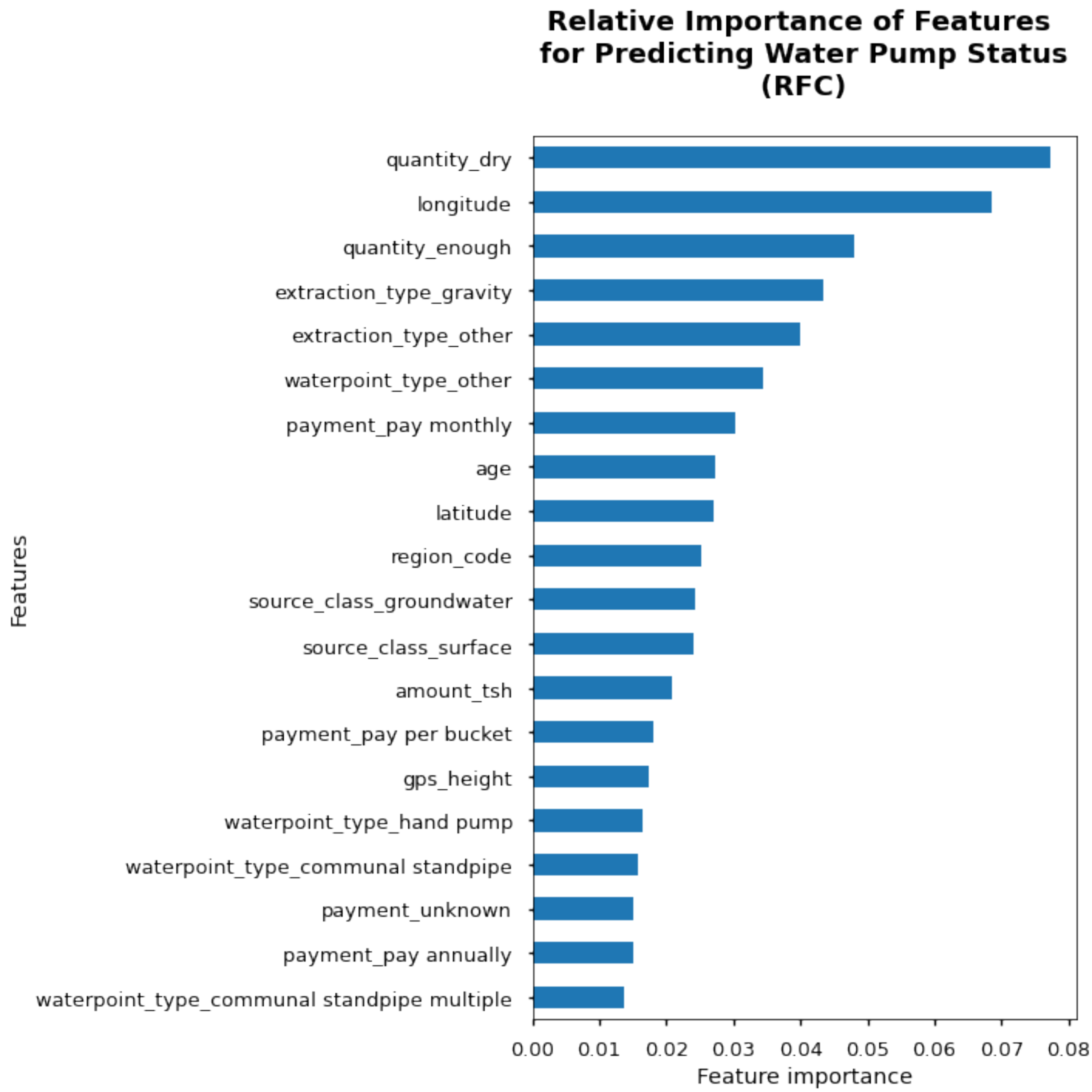
```
 time: 5min 15s (started: 2023-01-06 13:35:05 -05:00)
```

In [228]:
```
best_model_RF.best_estimator_[-1].get_params()
```

Out[228]:
```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': 'balanced',
 'criterion': 'entropy',
 'max_depth': 9,
 'max_features': 'sqrt',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_samples_leaf': 2,
 'min_samples_split': 5,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 150,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

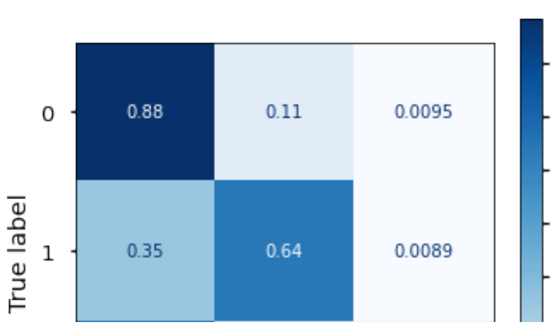
```
time: 2.06 ms (started: 2023-01-06 13:42:50 -05:00)
```

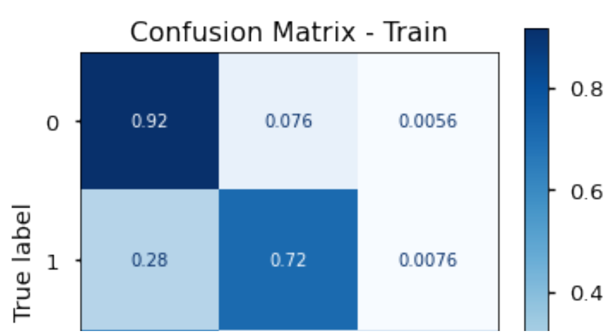
In [287]:
```
feature_importance_XGB(best_model_RF.best_estimator_,"RFC")
```

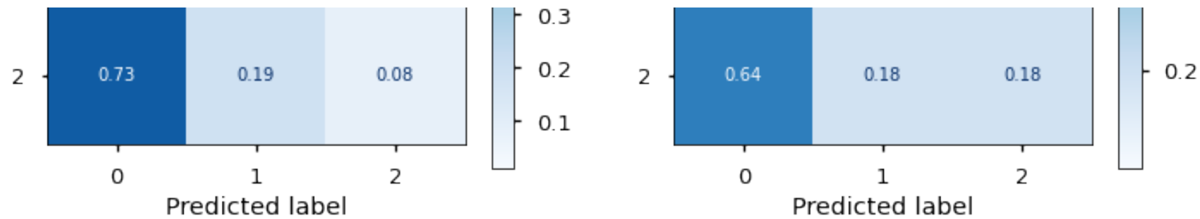


time: 258 ms (started: 2023-01-09 08:39:57 -05:00)

In [230]:
```
model_evaluation_roc_auc(best_model_RF.best_estimator_)
```








```
------------------------------------------------------------
Classification Report - Test:
------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.749     0.656     0.700      8065
           1      0.716     0.617     0.663      5706
           2      0.191     0.510     0.278      1079


    accuracy                          0.630     14850
   macro avg      0.552     0.594     0.547     14850
weighted avg      0.696     0.630     0.655     14850

------------------------------------------------------------
------------------------------------------------------------


 Train Roc_Auc Score: 79.58%
 Test Roc_Auc Score: 78.25%


------------------------------------------------------------


 Train Accuracy Score: 63.90%
 Test Accuracy Score: 63.02%


------------------------------------------------------------


 Train Sensitivity/Recall score: 63.90%
 Test Sensitivity/Recall score: 63.02%


------------------------------------------------------------


Train Weighted Precision: 0.71
Test Weighted Precision: 0.70
Train Score:0.64
```

```
Train Score:0.64
Test Score:0.63
time: 56.2 s (started: 2023-01-06 13:43:11 -05:00)
```

Hyperparameters for Logistic Regression:

- **penalty** — Specify the norm of the penalty.
- **fit_intercept** - Specify whether to use an interceot term or not.
- **C** — Inverse of regularization strength; smaller values specify stronger regularization.
- **solver** — Algorithm to use in the optimization problem.
- **max_iter** — Maximum number of iterations taken for the solvers to converge.

In [238]:
```
baseline_model_LR = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator", LogisticRegression(random_state=42,multi_class='mult

parameters = {
    'estimator__penalty' : ['l1','l2'], # default = l2 elasticnet is b
    'estimator__fit_intercept':[True, False],
    'estimator__C'       : [0.001,0.01,0.1,1,10,100], #np.logspace(-3,
    'estimator__solver'  : ['newton-cg', 'lbfgs', 'liblinear'], # defa
    'estimator__max_iter'  : [50,100]  # default = 100
}

best_model_LR = HalvingGridSearchCV(estimator = baseline_model_LR,   #
                          param_grid = parameters,
                          scoring ='f1_weighted',
                          cv = 3,
                          n_jobs = -1
)

# Train the pipeline (tranformations & predictor)
best_model_LR.fit(X_train, y_train);
```

```
time: 3h 52min 46s (started: 2023-01-06 13:57:34 -05:00)
```

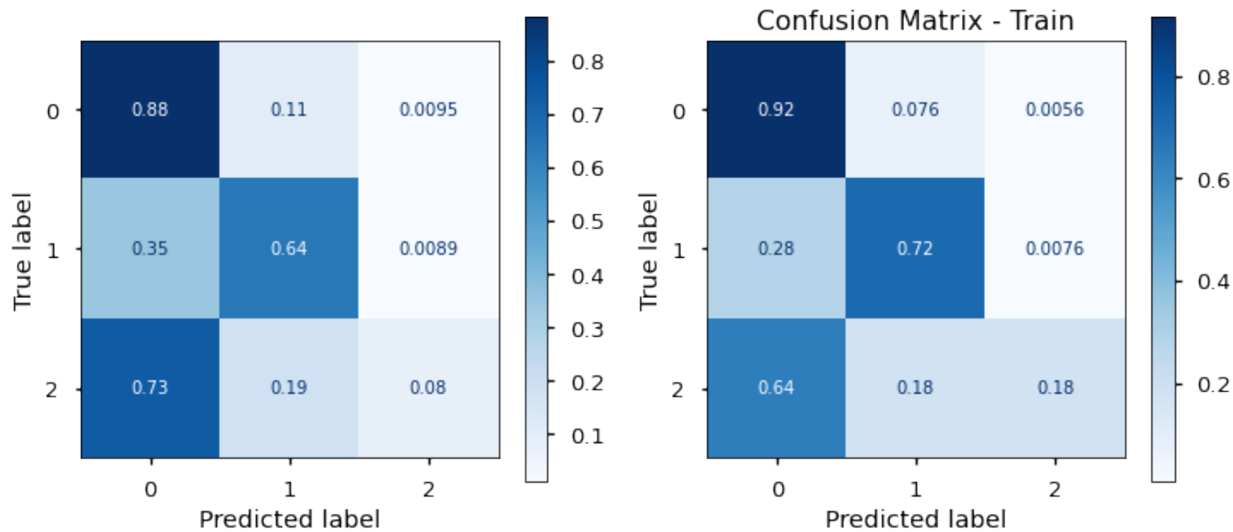
In [195]:
```
def get_params_pipe_model(model):
    for param, value in model[-1].get_params(deep=True).items():
        print(f"{param} -> {value}")
```

```
time: 338 µs (started: 2023-01-06 12:37:00 -05:00)
```

In [239]:
```
best_model_LR.best_params_
```

Out[239]:
```
{'estimator__C': 1,
 'estimator__fit_intercept': True,
 'estimator__max_iter': 50,
 'estimator__penalty': 'l2',
 'estimator__solver': 'newton-cg'}

time: 2.76 ms (started: 2023-01-06 18:03:34 -05:00)
```

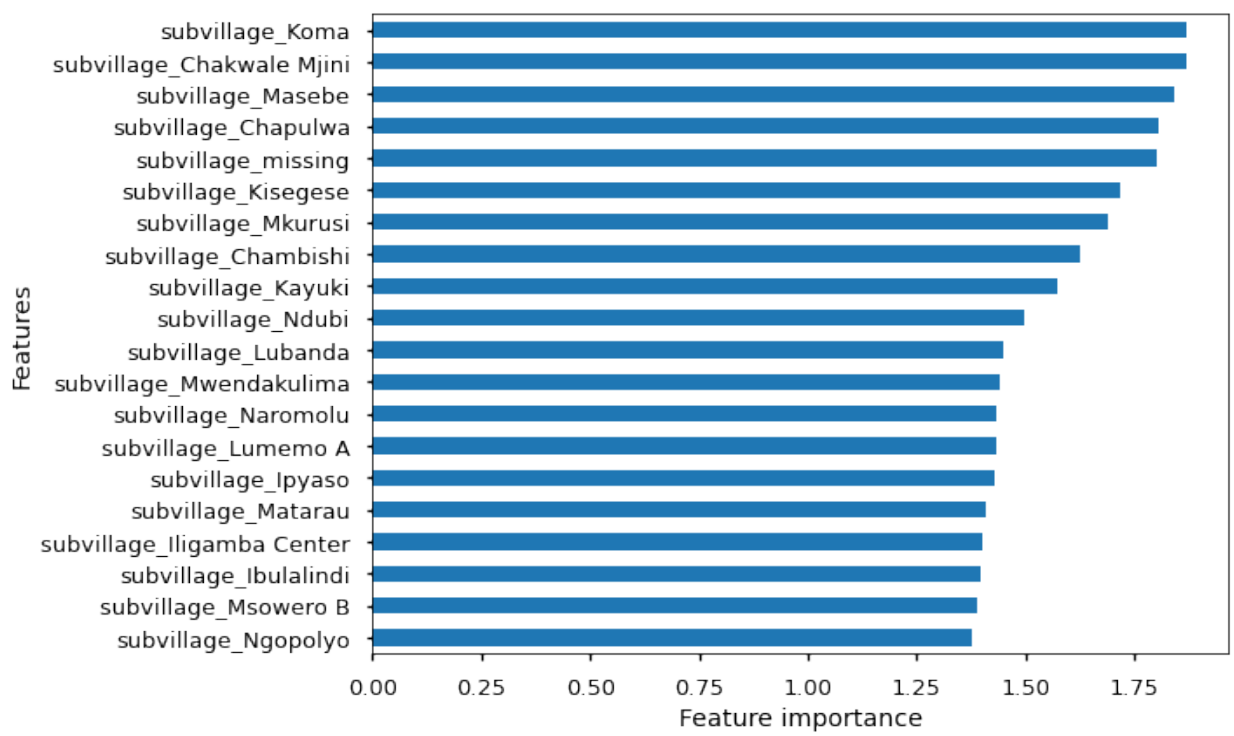
In [241]:
```
model_evaluation_roc_auc(best_model_LR)
```




```
------------------------------------------------------------
Classification Report - Test:
------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.727     0.889     0.800      8065
           1      0.786     0.654     0.714      5706
           2      0.479     0.104     0.171      1079

    accuracy                          0.742     14850
   macro avg      0.664     0.549     0.562     14850
weighted avg      0.732     0.742     0.721     14850

------------------------------------------------------------
------------------------------------------------------------


 Train Roc_Auc Score: 93.11%
 Test Roc_Auc Score: 82.77%
```

```
-------------------------------------------------------


 Train Accuracy Score: 81.70%
 Test Accuracy Score: 74.19%


-------------------------------------------------------


 Train Sensitivity/Recall score: 81.70%
 Test Sensitivity/Recall score: 74.19%


-------------------------------------------------------



Train Weighted Precision: 0.82
Test Weighted Precision: 0.73
Train Score:0.80
Test Score:0.72
time: 43 s (started: 2023-01-06 18:04:03 -05:00)
```

In [243]:
```
feature_importance_ML(best_model_LR.best_estimator_,"Log REg")
```




```
time: 206 ms (started: 2023-01-06 18:53:31 -05:00)
```

In [196]:
```
get_params_pipe_model(baseline_logreg)
```

```
C -> 1.0
class_weight -> None
dual -> False
fit_intercept -> True
intercept_scaling -> 1
l1_ratio -> None
max_iter -> 100
multi_class -> auto
n_jobs -> None
penalty -> l2
random_state -> 42
solver -> lbfgs
tol -> 0.0001
verbose -> 0
warm_start -> False
time: 605 µs (started: 2023-01-06 12:37:13 -05:00)
```

In [197]:
```
get_params_pipe_model(rfc_model_pipe)
```

```
bootstrap -> True
ccp_alpha -> 0.0
class_weight -> balanced
criterion -> gini
max_depth -> None
max_features -> sqrt
max_leaf_nodes -> None
max_samples -> None
min_impurity_decrease -> 0.0
min_samples_leaf -> 1
min_samples_split -> 2
min_weight_fraction_leaf -> 0.0
n_estimators -> 100
n_jobs -> None
oob_score -> False
random_state -> 42
verbose -> 0
warm_start -> False
time: 478 µs (started: 2023-01-06 12:37:28 -05:00)
```

In [205]:
```
get_params_pipe_model(xgb_model_pipe)
```

```
objective -> multi:softprob
use_label_encoder -> None
base_score -> 0.5
booster -> gbtree
callbacks -> None
colsample_bylevel -> 1
colsample_bynode -> 1
colsample_bytree -> 1
early_stopping_rounds -> None
enable_categorical -> False
eval_metric -> None
feature_types -> None
gamma -> 0
gpu_id -> -1
grow_policy -> depthwise
importance_type -> None
interaction_constraints -> 
learning_rate -> 0.300000012
max_bin -> 256
max_cat_threshold -> 64
max_cat_to_onehot -> 4
max_delta_step -> 0
max_depth -> 6
max_leaves -> 0
min_child_weight -> 1
missing -> nan
monotone_constraints -> ()
n_estimators -> 100
n_jobs -> 0
num_parallel_tree -> 1
predictor -> auto
random_state -> 0
reg_alpha -> 0
reg_lambda -> 1
sampling_method -> uniform
scale_pos_weight -> None
subsample -> 1
tree_method -> exact
validate_parameters -> 1
verbosity -> None
time: 34.9 ms (started: 2023-01-06 13:05:48 -05:00)
```

Hyperparameter Tuning:

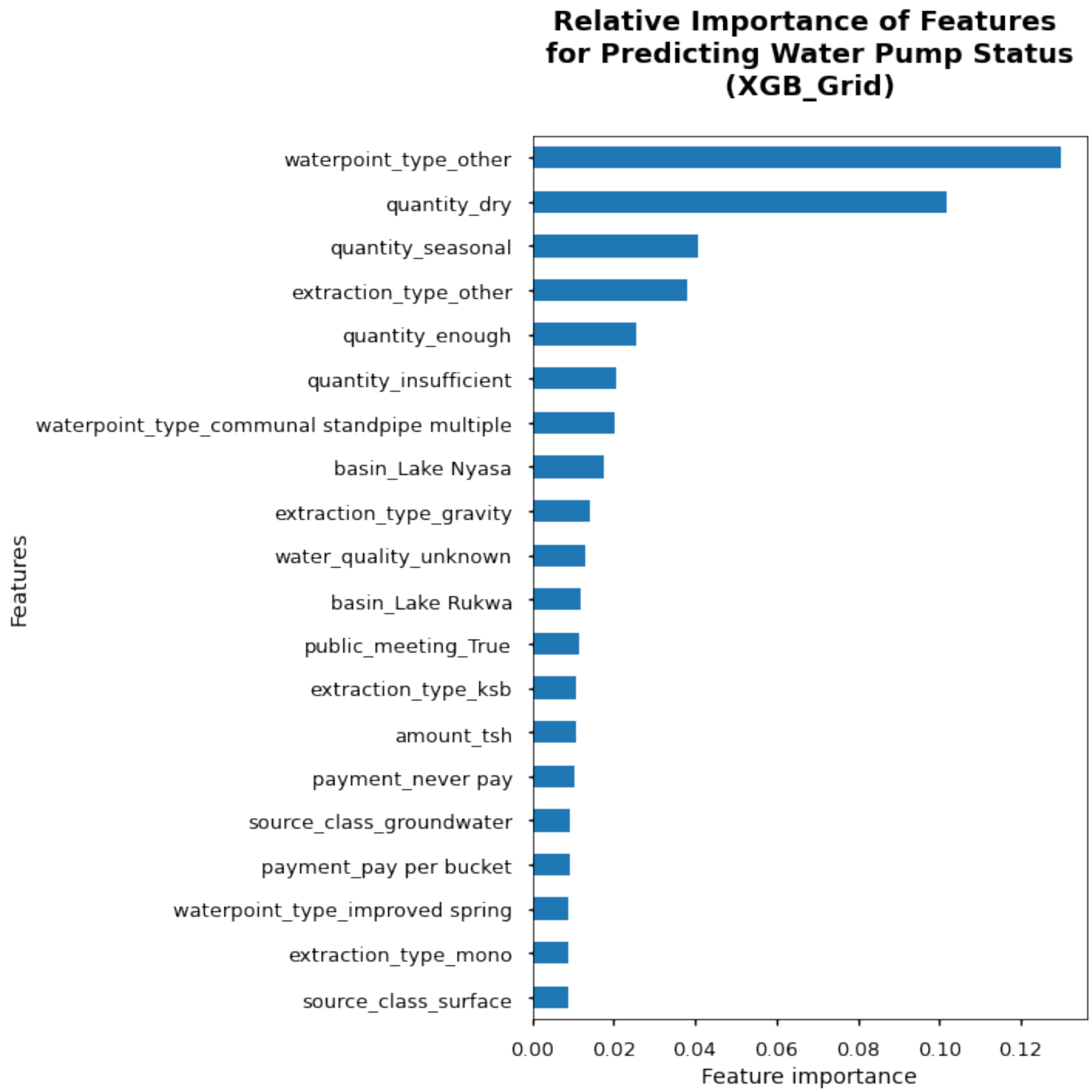
Hyperparameters for XG Boost :

- `n_estimators` : Training more trees in a Random Forest reduces the likelihood of overfitting, but training more trees with GBTs **increases** the likelihood of overfitting. To avoid overfitting use **fewer trees**.
- `learning_rate` : If you reduce the learning rate in your XGBoost model, your model will also be less likely to overfit. This will act as a regularization technique that prevents your model from paying too much attention to an unimportant feature. Models that are highly complex with many parameters tend to overfit more than models that are small and simple.
- `max_depth` : The deeper you allow, the more complex our model will become and more likely to overfit.
- `gamma` : The minimum loss reduction required to make a further split; Larger values avoid over-fitting
- `min_child_weight` : The minimum number of instances needed in a node. Larger values avoid over-fitting.
- `subsample` : The ratio of the training instances used (i.e. rows used). Lower ratios avoid over-fitting.
- `colsample_bytree` : The ratio of features used (i.e. columns used). Lower ratios avoid over-fitting.

In [245]:
```
baseline_model_xgb = Pipeline(steps=[
    ("preprocessor", preprocessor),
    ("estimator", XGBClassifier(random_state=42))])

parameters = {
    "estimator__n_estimators": [75],              # default = 100, To
    "estimator__learning_rate": [0.05, 0.2], # default = 0.3, Lower ra
    "estimator__max_depth": [4, 6],            # default = 6, It is us
    'estimator__gamma': [0.5, 1],                 # default = 0 , Larg
    'estimator__min_child_weight': [3, 4, 5],     # default = 1, Large
    'estimator__subsample': [0.5, 0.75],          # default = 1, Lower
    'estimator__colsample_bytree':[0.5, 0.75]     # default = 1, Lower
}

best_model_xgb = HalvingGridSearchCV(estimator = baseline_model_xgb,
                        param_grid = parameters,
                        scoring ='f1_weighted',
                        cv = 3,
                        n_jobs = -1
)

# Train the pipeline (tranformations & predictor)ui0
best_model_xgb.fit(X_train, y_train);
```

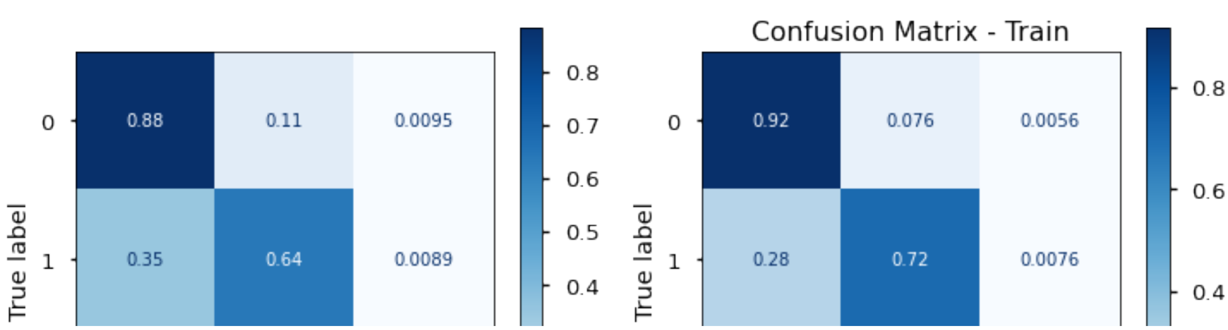
```
time: 3h 58s (started: 2023-01-06 18:57:27 -05:00)
```

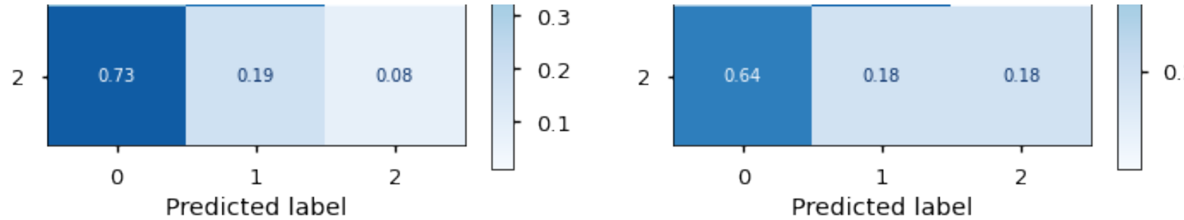
In [288]:
```
feature_importance_XGB(best_model_xgb.best_estimator_,"XGB_Grid")
```




```
time: 213 ms (started: 2023-01-09 08:40:10 -05:00)
```

In [248]:
```
model_evaluation_roc_auc(best_model_xgb)
```





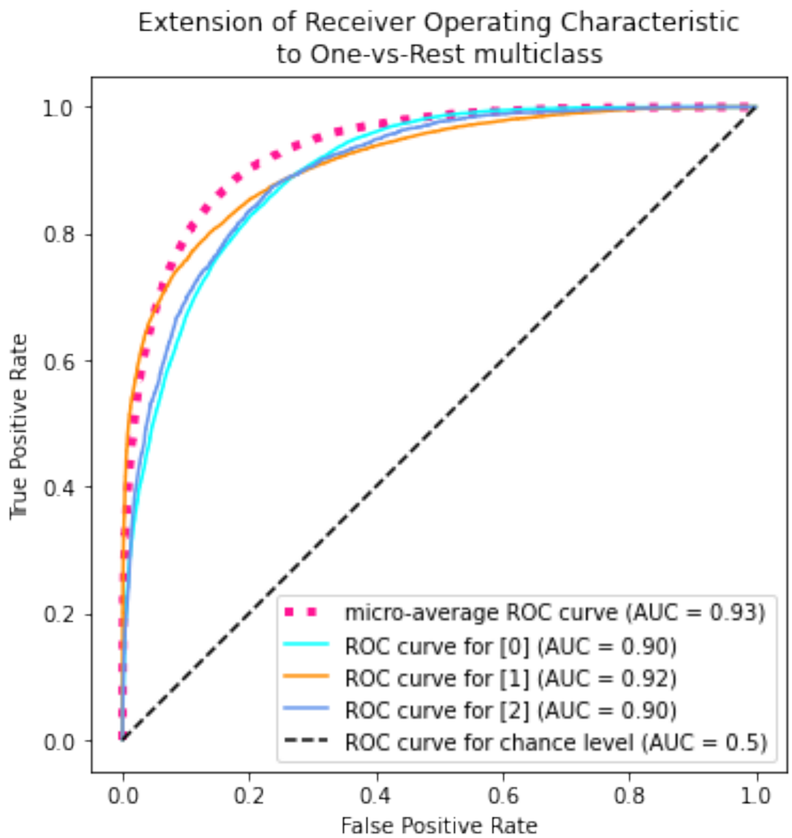

```
-------------------------------------------------------
Classification Report - Test:
-------------------------------------------------------
              precision    recall  f1-score   support

           0      0.751     0.922     0.828      8065
           1      0.840     0.684     0.754      5706
           2      0.649     0.185     0.288      1079


    accuracy                          0.777     14850
   macro avg      0.747     0.597     0.623     14850
weighted avg      0.778     0.777     0.760     14850

-------------------------------------------------------
-------------------------------------------------------


 Train Roc_Auc Score: 90.59%
 Test Roc_Auc Score: 87.75%


-------------------------------------------------------


 Train Accuracy Score: 79.58%
 Test Accuracy Score: 77.70%


-------------------------------------------------------


 Train Sensitivity/Recall score: 79.58%
 Test Sensitivity/Recall score: 77.70%


-------------------------------------------------------


Train Weighted Precision: 0.80
Test Weighted Precision: 0.78
Train Score:0.78
```

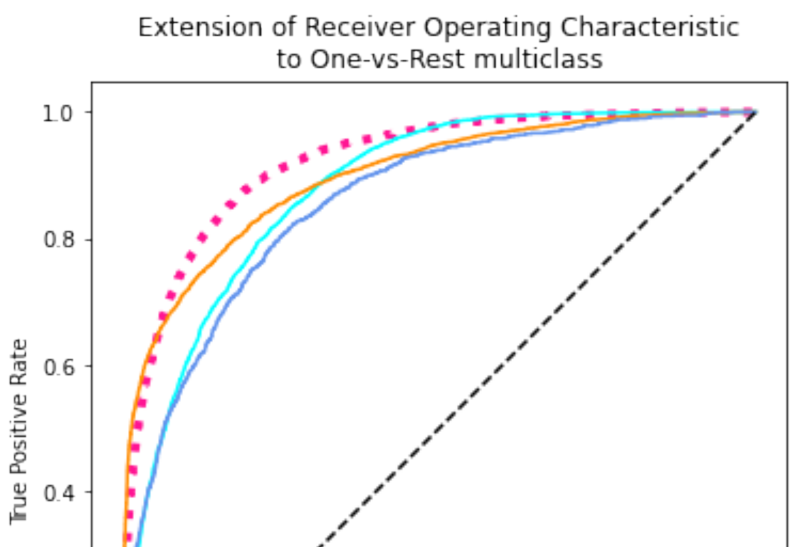
```
Train Score:0.78
Test Score:0.76
time: 46.8 s (started: 2023-01-06 22:27:47 -05:00)
```

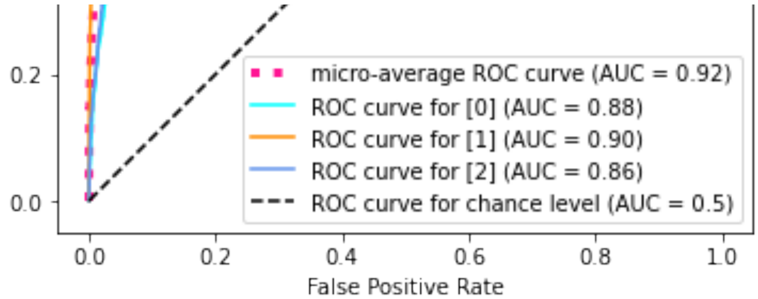
In [250]:

```
plot_roc_curve(best_model_xgb,X_train,y_train)
plot_roc_curve(best_model_xgb,X_test,y_test)
```

```
Micro-averaged One-vs-Rest ROC AUC score:
0.93
Micro-averaged One-vs-Rest ROC AUC score:
0.92
```







time: 10.4 s (started: 2023-01-06 22:29:41 -05:00)

In [252]:
```
best_model_xgb.best_estimator_.named_steps['estimator']
```

Out[252]:

▾ XGBClassifier

```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_byt
ree=0.75,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, feature_types=None, gamma=1, gpu_id=
-1,
              grow_policy='depthwise', importance_type=None,
              interaction_constraints='', learning_rate=0.2, max_bin
=256,
              max_cat_threshold=64, max_cat_to_onehot=4, max_delta_s
```

time: 5.78 ms (started: 2023-01-07 08:20:58 -05:00)

In [251]:
```
best_model_LR.best_estimator_.named_steps['estimator']
```

Out[251]:

▾ LogisticRegression

```
LogisticRegression(C=1, max_iter=50, multi_class='multinomial', rand
om_state=42,
                   solver='newton-cg')
```

time: 2.56 ms (started: 2023-01-07 08:10:48 -05:00)

In [253]:
```
best_model_RF.best_estimator_.named_steps['estimator']
```

Out[253]:
```
▾ RandomForestClassifier
RandomForestClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=9, min_samples_leaf=2, min_samples_
split=5,
                       n_estimators=150, random_state=42)
```

```
time: 3.14 ms (started: 2023-01-07 08:21:21 -05:00)
```

In [255]:
```
from sklearn.ensemble import StackingClassifier
```

```
time: 577 µs (started: 2023-01-07 08:22:01 -05:00)
```

Model #4: Stacked Model:

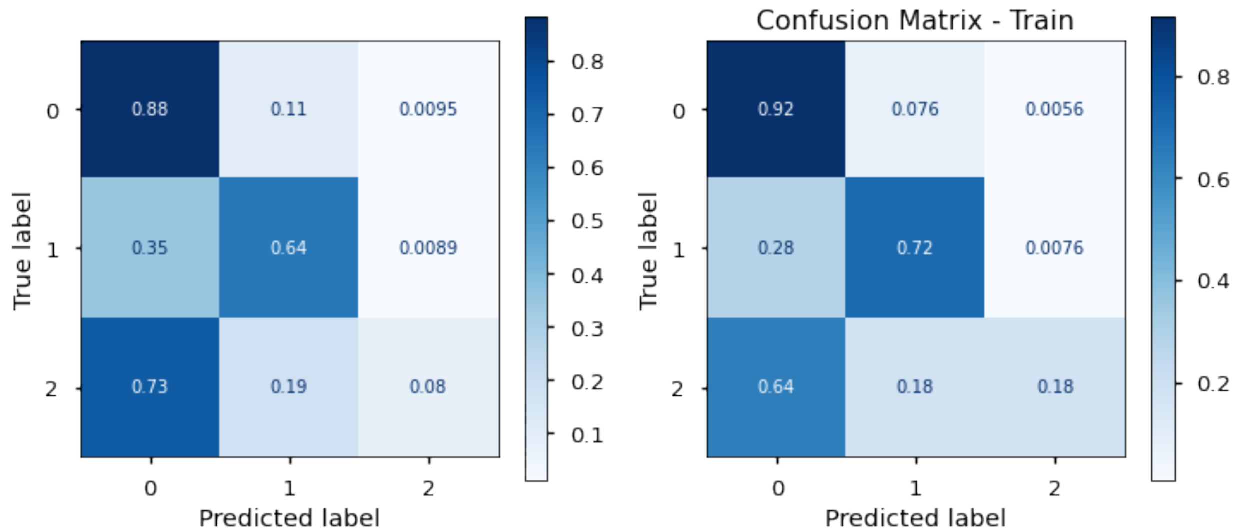
- Let's build a stacked model using the three best models obtained above

In [256]:
```
# Meta learner is XGBClassifier and the base learners are Random Fores
# Stacking often considers heterogeneous weak learners, learns them in

base_learners = [
                ('logreg', best_model_LR.best_estimator_.named_steps['
                ('RF', best_model_RF.best_estimator_.named_steps['esti
                ('XGB', best_model_xgb.best_estimator_.named_steps['es
                ]

ensemble = StackingClassifier(estimators=base_learners,
                              final_estimator = XGBClassifier(),
                              cv=3,
                              passthrough=False,
                              n_jobs=-1)

stacked_model = Pipeline([
        ("preprocessor", preprocessor),
        ('ensemble',ensemble)
])

stacked_model.fit(X_train, y_train);
```

```
time: 7h 4min 39s (started: 2023-01-07 08:22:02 -05:00)
```

In [257]:

```
model_evaluation_roc_auc(stacked_model)
```




```
------------------------------------------------------------
Classification Report - Test:
------------------------------------------------------------
              precision    recall  f1-score   support

           0      0.763     0.902     0.827      8065
           1      0.827     0.708     0.763      5706
           2      0.580     0.234     0.334      1079

    accuracy                          0.779     14850
   macro avg      0.723     0.615     0.641     14850
weighted avg      0.774     0.779     0.766     14850

------------------------------------------------------------
------------------------------------------------------------


 Train Roc_Auc Score: 92.13%
 Test Roc_Auc Score: 87.53%


------------------------------------------------------------


 Train Accuracy Score: 81.85%
 Test Accuracy Score: 77.88%


------------------------------------------------------------
```

```
 Train Sensitivity/Recall score: 81.85%
 Test Sensitivity/Recall score: 77.88%


________________________________________________________


Train Weighted Precision: 0.82
Test Weighted Precision: 0.77
Train Score:0.82
Test Score:0.78
time: 58.1 s (started: 2023-01-07 16:14:34 -05:00)
```

In [412]:
```
#stacked_model.named_steps
```

```
time: 181 µs (started: 2023-01-10 11:22:26 -05:00)
```

In [273]:
```
roc_auc_score(y_train, best_model_RF.predict_proba(X_train),multi_clas
```

Out[273]:
```
0.7958285574635743

time: 8.59 s (started: 2023-01-07 19:24:53 -05:00)
```

In [274]:
```
roc_auc_score(y_train, best_model_LR.predict_proba(X_train),multi_clas
```

Out[274]:
```
0.9311001881605073

time: 6.78 s (started: 2023-01-07 19:25:34 -05:00)
```

In [275]:
```
roc_auc_score(y_train, best_model_xgb.predict_proba(X_train),multi_cla
```

Out[275]:
```
0.9058720284867391

time: 7.87 s (started: 2023-01-07 19:25:43 -05:00)
```

In [276]:
```
roc_auc_score(y_train, stacked_model.predict_proba(X_train),multi_clas
```

Out[276]:
```
0.9213306260104325

time: 11.2 s (started: 2023-01-07 19:25:52 -05:00)
```

Summary of Models

In [277]:
```
def compare_roc_auc(names, models):

    cv_roc_auc_scores = []
    train_roc_auc_scores = []
    test_roc_auc_scores = []

    for i in range(len(names)):
        score_train_cv = cross_val_score(estimator=models[i], X=X_trai
                                         cv=StratifiedKFold(shuffle=Tr

        score_train = roc_auc_score(y_train, models[i].predict_proba(X
        score_test = roc_auc_score(y_test, models[i].predict_proba(X_t

        cv_roc_auc_scores.append(score_train_cv)
        train_roc_auc_scores.append(score_train)
        test_roc_auc_scores.append(score_test)

    scores_table = pd.DataFrame(list(zip(cv_roc_auc_scores, train_roc_
                                columns =['cv_train', 'train', 'test'], i
    return(scores_table)
```

time: 1.53 ms (started: 2023-01-07 19:26:08 -05:00)

In [264]:
```
cross_val_score(best_model_LR.best_estimator_,X=X_train,  y=y_train,cv
```

Out[264]: 0.8255891375564793

time: 37min 33s (started: 2023-01-07 16:31:06 -05:00)

In [279]:
```
names = ["Logistic Regression", "Random_Forest", "XG Boost"]#, "Stacke
models = [best_model_LR.best_estimator_,
          best_model_RF.best_estimator_, best_model_xgb.best_estimator

df_scores=compare_roc_auc(names, models)
```

time: 1h 26min 7s (started: 2023-01-08 10:52:27 -05:00)

In [280]:
```
df_scores
```

Out[280]:

	cv_train	train	test
Logistic Regression	0.827096	0.931100	0.827683
Random_Forest	0.780599	0.795829	0.782454
XG Boost	0.877268	0.905872	0.877508

```
time: 12.9 ms (started: 2023-01-08 14:11:11 -05:00)
```

In [ ]:
```
from sklearn.feature_selection import SelectFromModel
```

In [281]:
```
score_train_cv_stacked = cross_val_score(estimator=stacked_model, X=X_
                                         cv=StratifiedKFold(shuffle=Tr
score_train_stacked = roc_auc_score(y_train, stacked_model.predict_prc
score_test_stacked  = roc_auc_score(y_test, stacked_model.predict_prob
print(score_train_cv_stacked,score_train_stacked,score_test_stacked)
```

```
0.8725677860247358 0.9213306260104325 0.8752554146270765
time: 13h 8min 35s (started: 2023-01-08 14:40:21 -05:00)
```

In [282]:
```
new_row = {'cv_train':score_train_cv_stacked, 'train':score_train_stac
dfscores = df_scores.append(pd.DataFrame([new_row],index=['Stacked'],c
print(dfscores)
```

```
                     cv_train     train      test
Logistic Regression  0.827096  0.931100  0.827683
Random_Forest        0.780599  0.795829  0.782454
XG Boost             0.877268  0.905872  0.877508
Stacked              0.872568  0.921331  0.875255
time: 7.07 ms (started: 2023-01-09 08:38:21 -05:00)
```

In [283]:
```
dfscores
```

Out[283]:

	cv_train	train	test
Logistic Regression	0.827096	0.931100	0.827683
Random_Forest	0.780599	0.795829	0.782454
XG Boost	0.877268	0.905872	0.877508
Stacked	0.872568	0.921331	0.875255

```
time: 4.51 ms (started: 2023-01-09 08:38:29 -05:00)
```

Summary of Model Comparisons:

- With the exception of Logistic Regression, the train and test scores for the rest of the models are all close to one another, implying that there is no overfitting
- Both Roc_Auc and Accuracy Scores are considered **GOOD** for all the models.
- **XGBoost** is the best performing model followed by the Stacked model.

Overall comparison of different ML techniques:

In [358]:
```
def plot_roc_curve2(model,X_test=X_test,y_test=y_test,ax=ax,name='name
    y_onehot_test = label_binarizer.transform(y_test)
    y_score = model.predict_proba(X_test)
    # store the fpr, tpr, and roc_auc for all averaging strategies
    fpr, tpr, roc_auc = dict(), dict(), dict()
    # Compute micro-average ROC curve and ROC area
    fpr["micro"], tpr["micro"], _ = roc_curve(y_onehot_test.ravel(), y
    roc_auc["micro"] = round(auc(fpr["micro"], tpr["micro"]),2)

    print(f"Micro-averaged One-vs-Rest ROC AUC score:\n{roc_auc['micro
    #fig, ax = plt.subplots(figsize=(6, 6))

    ax.plot(
        fpr["micro"],
        tpr["micro"],
        #label=f"micro-average ROC curve (AUC = {roc_auc['micro']:.2f}
        color=color,
        linestyle=":",
        linewidth=4,label=name+" AUC="+str(roc_auc['micro'])
        )

    #for class_id, color in zip(range(n_classes), colors):
    #    RocCurveDisplay.from_predictions(
    #        y_onehot_test[:, class_id],
    #        y_score[:, class_id],
    #        #name=f"ROC curve for {[class_id]}",
    #        label=f"micro-average ROC curve (AUC = {roc_auc['micro']:
    #        color=color,
    #        ax=ax,
    #    )
    return ax
```

time: 1.07 ms (started: 2023-01-10 10:16:41 -05:00)

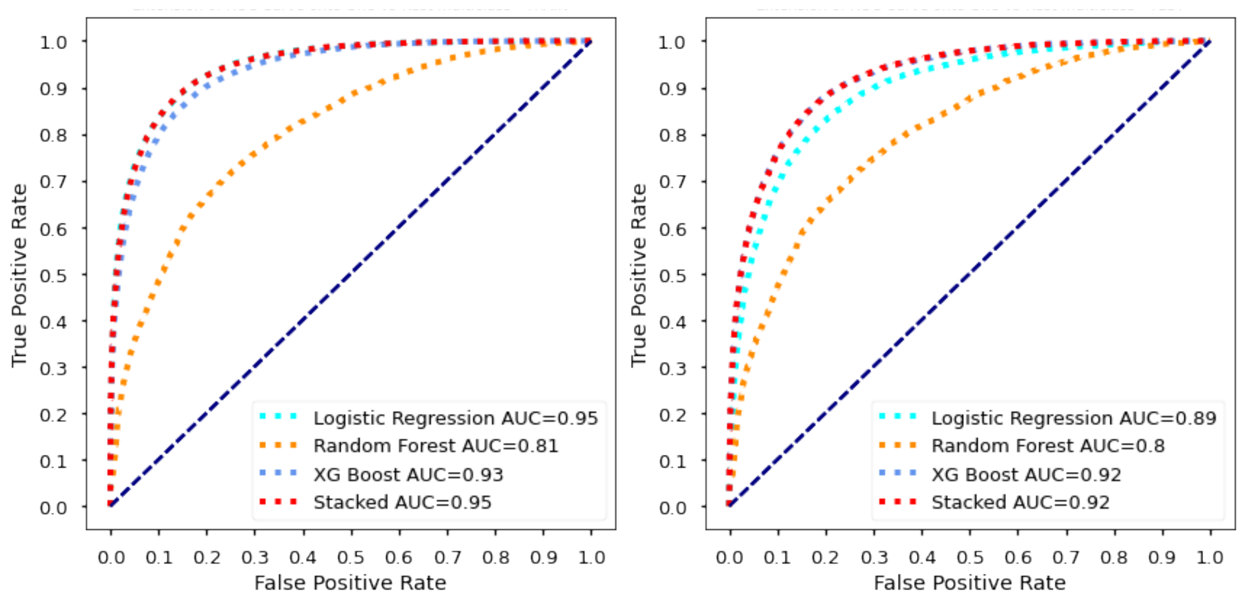
In [361]:

```
with plt.style.context('seaborn-talk'): #seaborn-whitegrid
    fig, (ax1, ax2) = plt.subplots(nrows=1, ncols =2, figsize=(12, 6))

    names = ["Logistic Regression", "Random Forest", "XG Boost", "Stac
    models = [best_model_LR.best_estimator_, best_model_RF.best_estima
              best_model_xgb.best_estimator_,stacked_model]
    colors2 = ["aqua", "darkorange", "cornflowerblue",'red']
    for i in range(len(names)):
        ax2 = plot_roc_curve2(models[i],X_test,y_test,ax2, names[i],co
        ax1=plot_roc_curve2(models[i],X_train,y_train,ax1,names[i],col
        ax1.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        ax1.set_xlim([-0.05, 1.05])
        ax1.set_ylim([-0.05, 1.05])
        ax1.set_yticks([i/10.0 for i in range(11)])
        ax1.set_xticks([i/10.0 for i in range(11)])
        ax1.set_xlabel('False Positive Rate')
        ax1.set_ylabel('True Positive Rate')
        ax1.set_title('Extension of ROC Curve onto One-vs-Rest multicl
        ax1.legend()
        ax1.grid()

        ax2.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
        ax2.set_xlim([-0.05, 1.05])
        ax2.set_ylim([-0.05, 1.05])
        ax2.set_yticks([i/10.0 for i in range(11)])
        ax2.set_xticks([i/10.0 for i in range(11)])
        ax2.set_xlabel('False Positive Rate')
        ax2.set_ylabel('True Positive Rate')
        ax2.set_title('Extension of ROC Curve onto One-vs-Rest multicl
        ax2.legend()
        ax2.grid()
        plt.tight_layout()
```

```
Micro-averaged One-vs-Rest ROC AUC score:
0.89
Micro-averaged One-vs-Rest ROC AUC score:
0.95
Micro-averaged One-vs-Rest ROC AUC score:
0.80
Micro-averaged One-vs-Rest ROC AUC score:
0.81
Micro-averaged One-vs-Rest ROC AUC score:
0.92
Micro-averaged One-vs-Rest ROC AUC score:
0.93
Micro-averaged One-vs-Rest ROC AUC score:
0.92
Micro-averaged One-vs-Rest ROC AUC score:
0.95
```

Extension of ROC Curve onto One-vs-Rest multiclass - TRAIN

Extension of ROC Curve onto One-vs-Rest multiclass - TEST




```
time: 58.2 s (started: 2023-01-10 10:20:16 -05:00)
```

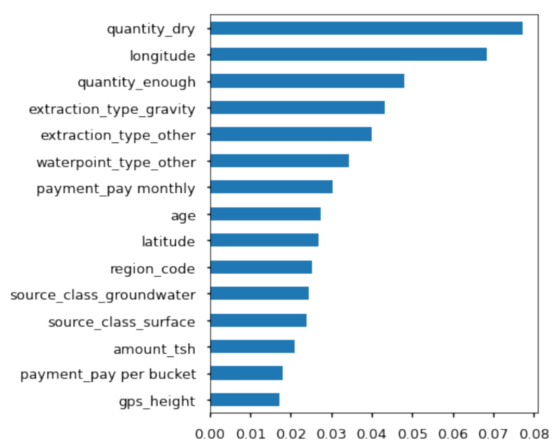
Compare Feature Importances from the best 2 models:

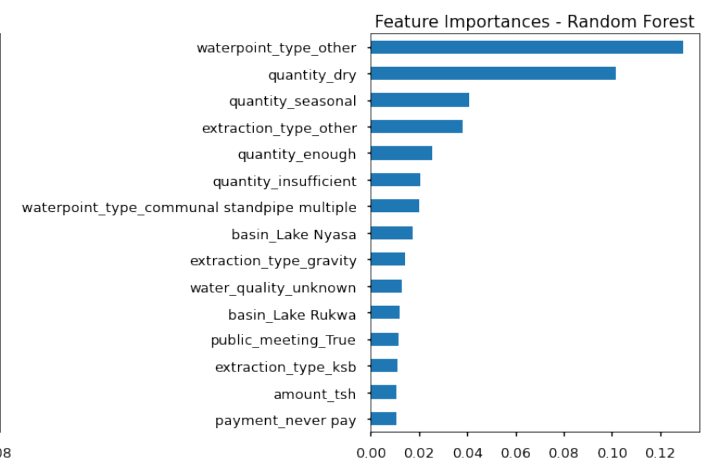
- I haven't figured how to plot feature_importance from stacked model yet!

In [413]:

```
```

```
with plt.style.context('seaborn-talk'):
    fig, (ax1,ax2) = plt.subplots(ncols = 2, figsize=(16,6))

    #coeffs = best_logreg.best_estimator_.named_steps['estimator'].coe
    #importance = pd.Series(abs(coeffs[0]), index=feature_names)
    #importance.sort_values().tail(15).plot.barh(ax=ax1);
    #ax1.set_title("Feature Importances - Logistic Regression")

    feature_importances = best_model_RF.best_estimator_.named_steps['e
    importance = pd.Series(feature_importances, index=feature_names)
    importance.sort_values().tail(15).plot.barh(ax=ax1);
    ax2.set_title("Feature Importances - Random Forest")

    feature_importances = best_model_xgb.best_estimator_.named_steps['
    importance = pd.Series(feature_importances, index=feature_names)
    importance.sort_values().tail(15).plot.barh(ax=ax2);
    ax3.set_title("Feature Importances - XGBoost")

    #feature_importances = stacked_model.named_steps['ensemble'].final
    #importance = pd.Series(feature_importances, index=feature_names)
    #importance.sort_values().tail(15).plot.barh(ax=ax3);
    #ax3.set_title("Feature Importances - Stacked Model")

    fig.tight_layout();
```






```
time: 357 ms (started: 2023-01-10 11:24:27 -05:00)
```

In [402]:
```
#steps=stacked_model.named_steps['ensemble']#.final_estimator.
```

```
time: 263 µs (started: 2023-01-10 10:52:33 -05:00)
```

In [507]:
```
stacked_model.named_steps['ensemble'].final_estimator
```

Out[507]:

XGBClassifier

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_ty
pes=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_
type=None,
              interaction_constraints=None, learning_rate=None, max_
bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
```

time: 3.43 ms (started: 2023-01-10 14:37:42 -05:00)

In [508]:
```
importance.sort_values().tail(10)
```

Out[508]:

```
water_quality_unknown                          0.013044
extraction_type_gravity                        0.014077
basin_Lake Nyasa                               0.017523
waterpoint_type_communal standpipe multiple    0.020127
quantity_insufficient                          0.020469
quantity_enough                                0.025437
extraction_type_other                          0.038027
quantity_seasonal                              0.040926
quantity_dry                                   0.101654
waterpoint_type_other                          0.129657
dtype: float32
```

time: 3.38 ms (started: 2023-01-10 14:37:45 -05:00)

In [514]:
```
final_model_train =best_model_xgb.best_estimator_
final_model_train.fit(X_train,y_train)
#feature_importances
#importance = pd.Series(feature_importances, index=feature_names)
```

Out[514]:
```
▸ Pipeline
▸ preprocessor: ColumnTransformer
▸ preprocess_binary    ▸ preprocess_categorical    ▸ preprocess_numeric    ▸ rem
▸ SimpleImputer        ▸ SimpleImputer             ▸ FunctionTransformer   ▸ pass
▸ OneHotEncoder        ▸ OneHotEncoder             ▸ StandardScaler
▸ XGBClassifier
```

time: 20min 17s (started: 2023-01-10 14:42:26 -05:00)

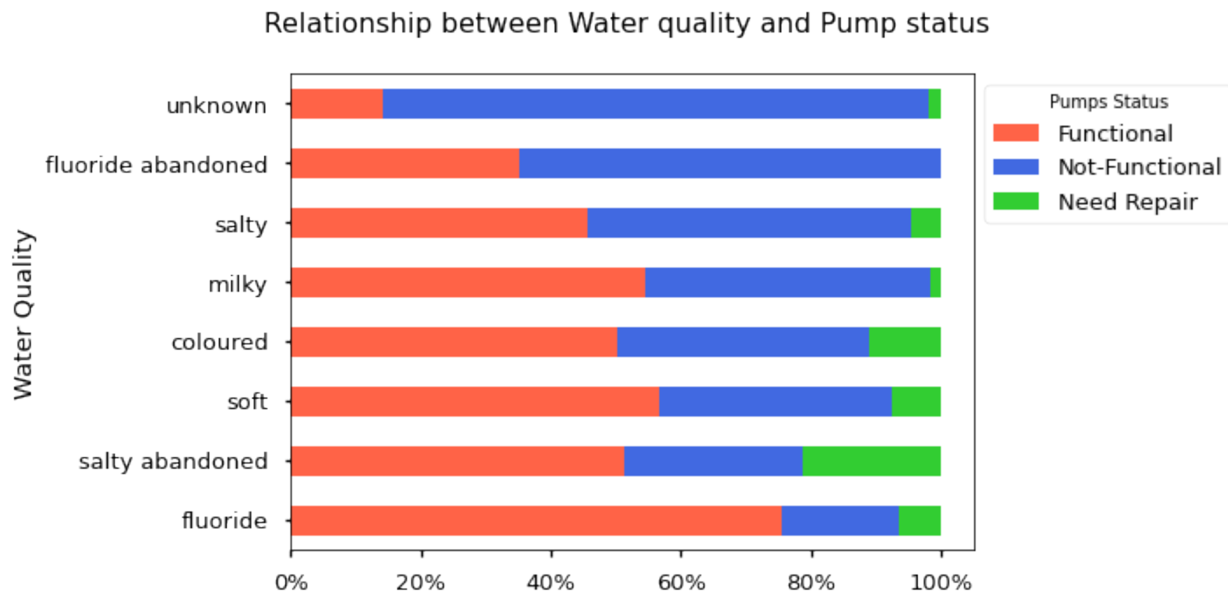
In [*]:
```
feature_importances = final_model_train.feature_importances_
importance = pd.Series(feature_importances, index=feature_names)
```

In [*]:
```
# Plot only the most important 10 features for the presentation:

feature_importances = best_model_xgb.best_estimator_.named_steps['esti
importance = pd.Series(feature_importances, index=feature_names)

with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(7,7))
    importance.sort_values().tail(10).plot.barh(ax=ax);
    ax.set_title("Relative Importance of Top 10 Features \n for Predic
    ax.set_xlabel('Feature importance')
    ax.set_ylabel('Features')
    ax.set_yticks([0,1,2,3,4,5,6,7,8,9])
    ax.set_yticklabels(['waterpoint_type_other','quantity_dry','quanti
                        'quantity_enough','quantity_insufficient','water
                        'extraction_type_gravity','water_quality_unknowr
    plt.tight_layout()
    plt.savefig("./images/FeatureImportances_top10.png", dpi=300, bbox
```

In [436]:
```
def props(dataframe, column, target):
    counts = dataframe[[column,target]].groupby([column, target]).size
    props = counts[[0,1,2]].multiply(100).div(counts.sum(axis=1), axis
    return props.sort_values(by = 1)
```

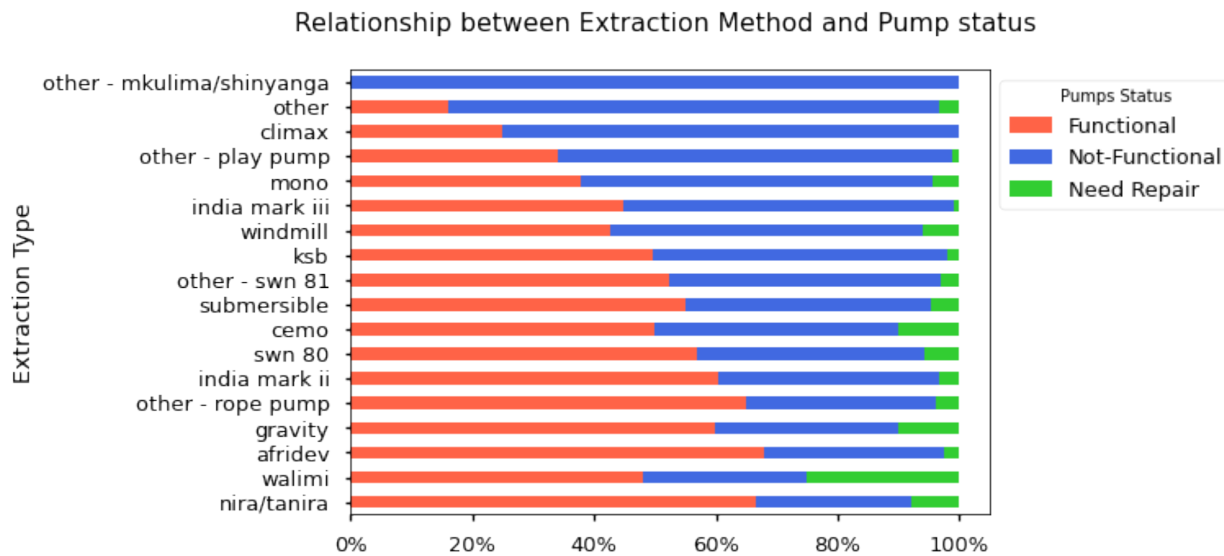
time: 370 µs (started: 2023-01-10 11:46:15 -05:00)

In [448]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(7, 5))
    props(df_ana,"water_quality","status_group").plot.barh(stacked=Tru
    ax.legend(bbox_to_anchor=(1, 1), labels = ['Functional', 'Not-Func
    ax.set_ylabel("Water Quality")
    #ax.set_yticks([0,1])
    #ax.set_yticklabels(["No", "YES"])
    ax.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('{x:,.0
    ax.set_title("Relationship between Water quality and Pump status \
```



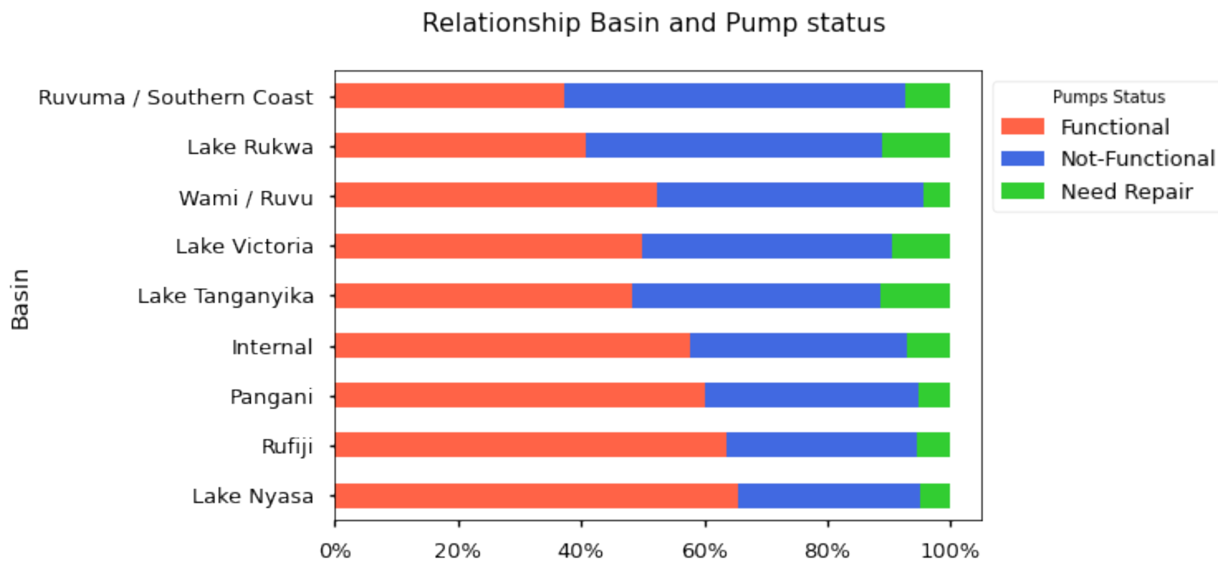
time: 185 ms (started: 2023-01-10 11:56:04 -05:00)

In [459]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(7, 5))
    props(df_ana,"extraction_type","status_group").plot.barh(stacked=T
    ax.legend(bbox_to_anchor=(1, 1), labels = ['Functional', 'Not-Func
    ax.set_ylabel("Extraction Type")
    #ax.set_yticks([0,1])
    #ax.set_yticklabels(["No", "YES"])
    ax.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('{x:,.0
    ax.set_title("Relationship between Extraction Method and Pump stat
```




```
time: 261 ms (started: 2023-01-10 13:34:43 -05:00)
```

In [458]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(7, 5))
    props(df_ana,"basin","status_group").plot.barh(stacked=True, color
    ax.legend(bbox_to_anchor=(1, 1), labels = ['Functional', 'Not-Func
    ax.set_ylabel("Basin")
    #ax.set_yticks([0,1])
    #ax.set_yticklabels(["No", "YES"])
    ax.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('{x:,.0
    ax.set_title("Relationship Basin and Pump status \n")
```



time: 192 ms (started: 2023-01-10 13:34:41 -05:00)

In [ ]:
```
with plt.style.context('seaborn-talk'):
    fig, ax = plt.subplots(figsize=(7, 5))
    props(df_ana,"quantity","status_group").plot.barh(stacked=True, co
    ax.legend(bbox_to_anchor=(1, 1), labels = ['Functional', 'Not-Func
    ax.set_ylabel("Water Quality")
    #ax.set_yticks([0,1])
    #ax.set_yticklabels(["No", "YES"])
    ax.xaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('{x:,.0
    ax.set_title("Relationship between Quantity and Pump status \n")
```

In [ ]:
```
# fit the best model to the whole dataset to be able to make predictic
X1 = X
y1 = y

best_xgb.best_estimator_.fit(X1,y1)

y_pred = best_xgb.best_estimator_.predict_proba(X1)[:, 1]
# Create a new column called seasonal_vaccine_pred with the predicted
X1['seasonal_vaccine_pred'] = y_pred
df_predicted= X1
# New data set with the predicted probabilities added:
df_predicted.head()
```

In [435]:
```
#counts = df_ana.groupby(['water_quality','status_group']).size().unst
#props = counts[[0,1,2]].multiply(100).div(counts.sum(axis=1), axis=0)
#props.sort_values(by = 1)
```

Out[435]:

status_group water_quality	0	1	2
fluoride	75.500000	18.000000	6.500000
salty abandoned	51.327434	27.433628	21.238938
soft	56.594120	35.723563	7.682317
coloured	50.204082	38.775510	11.020408
milky	54.477612	43.781095	1.741294
salty	45.716639	49.649918	4.633443
fluoride abandoned	35.294118	64.705882	NaN
unknown	14.072495	84.061834	1.865672

```
time: 10.4 ms (started: 2023-01-10 11:46:05 -05:00)
```

In [434]:
```
props
#df_ana.groupby(['water_quality','status_group']).size().unstack()
```

Out[434]:

status_group	0	1	2
water_quality			
coloured	50.204082	38.775510	11.020408
fluoride	75.500000	18.000000	6.500000
fluoride abandoned	35.294118	64.705882	NaN
milky	54.477612	43.781095	1.741294
salty	45.716639	49.649918	4.633443
salty abandoned	51.327434	27.433628	21.238938
soft	56.594120	35.723563	7.682317
unknown	14.072495	84.061834	1.865672

```
time: 3.96 ms (started: 2023-01-10 11:45:22 -05:00)
```

In [442]:
```
##ax = df_ana.groupby(['water_quality','status_group']).sum().unstack(
#.plot(kind='bar', stacked=True, figsize=(15,6))

#df_ana.groupby(['water_quality','status_group']).plot.barh(stacked=Tr
```

```
time: 172 µs (started: 2023-01-10 11:53:55 -05:00)
```

In [452]:
```
final_model =best_model_xgb.best_estimator_
```

```
time: 251 µs (started: 2023-01-10 12:24:48 -05:00)
```

In [453]:
```
final_model
```

Out[453]:

```
▸ Pipeline
▸ preprocessor: ColumnTransformer
▸ preprocess_binary    ▸ preprocess_categorical    ▸ preprocess_numeric    ▸ rem
▸ SimpleImputer        ▸ SimpleImputer             ▸ FunctionTransformer   ▸ pass
▸ OneHotEncoder        ▸ OneHotEncoder             ▸ StandardScaler
▸ XGBClassifier
```

time: 80.2 ms (started: 2023-01-10 12:24:53 -05:00)

In [454]:
```
X1 = X
y1 = y
final_model.fit(X1,y1)
```

Out[454]:

```
▸ Pipeline
▸ preprocessor: ColumnTransformer
▸ preprocess_binary    ▸ preprocess_categorical    ▸ preprocess_numeric    ▸ rem
▸ SimpleImputer        ▸ SimpleImputer             ▸ FunctionTransformer   ▸ pass
▸ OneHotEncoder        ▸ OneHotEncoder             ▸ StandardScaler
▸ XGBClassifier
```

time: 40min 39s (started: 2023-01-10 12:28:32 -05:00)

In [474]:
```
y_data_pred = final_model.predict_proba(X1)
```

time: 15 s (started: 2023-01-10 13:53:39 -05:00)

In [476]:

```
# Create a new column called seasonal_vaccine_pred with the predicted
X1['Pump_functioning_pred'] = y_data_pred[:,0]
X1['Pump_Notfunctioning_pred'] = y_data_pred[:,1]
X1['Pump_NeedRepairs_pred'] = y_data_pred[:,2]
df_predicted= X1
#New data set with the predicted probabilities added:
df_predicted.head()
```

Out[476]:

water_quality	quantity	source_class	waterpoint_type	age	Pump_status_pred	Pump_functio
soft	enough	groundwater	communal standpipe	15	0.019096	
soft	insufficient	surface	communal standpipe	5	0.161934	
soft	enough	surface	communal standpipe multiple	5	0.159973	
soft	dry	groundwater	communal standpipe multiple	30	0.988605	
soft	seasonal	surface	communal standpipe	60	0.171528	

time: 31.9 ms (started: 2023-01-10 13:57:18 -05:00)

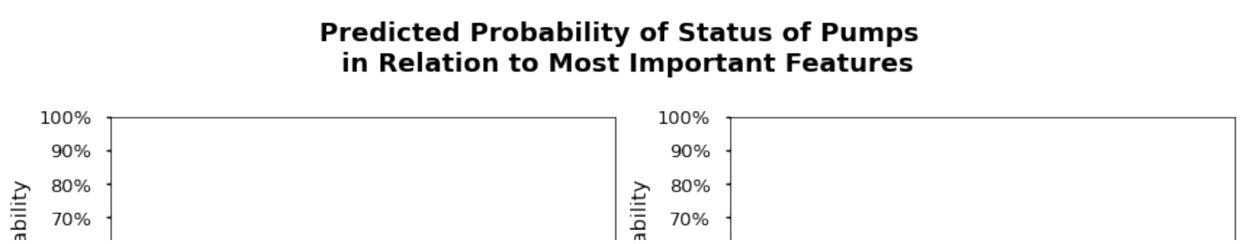
In [503]:

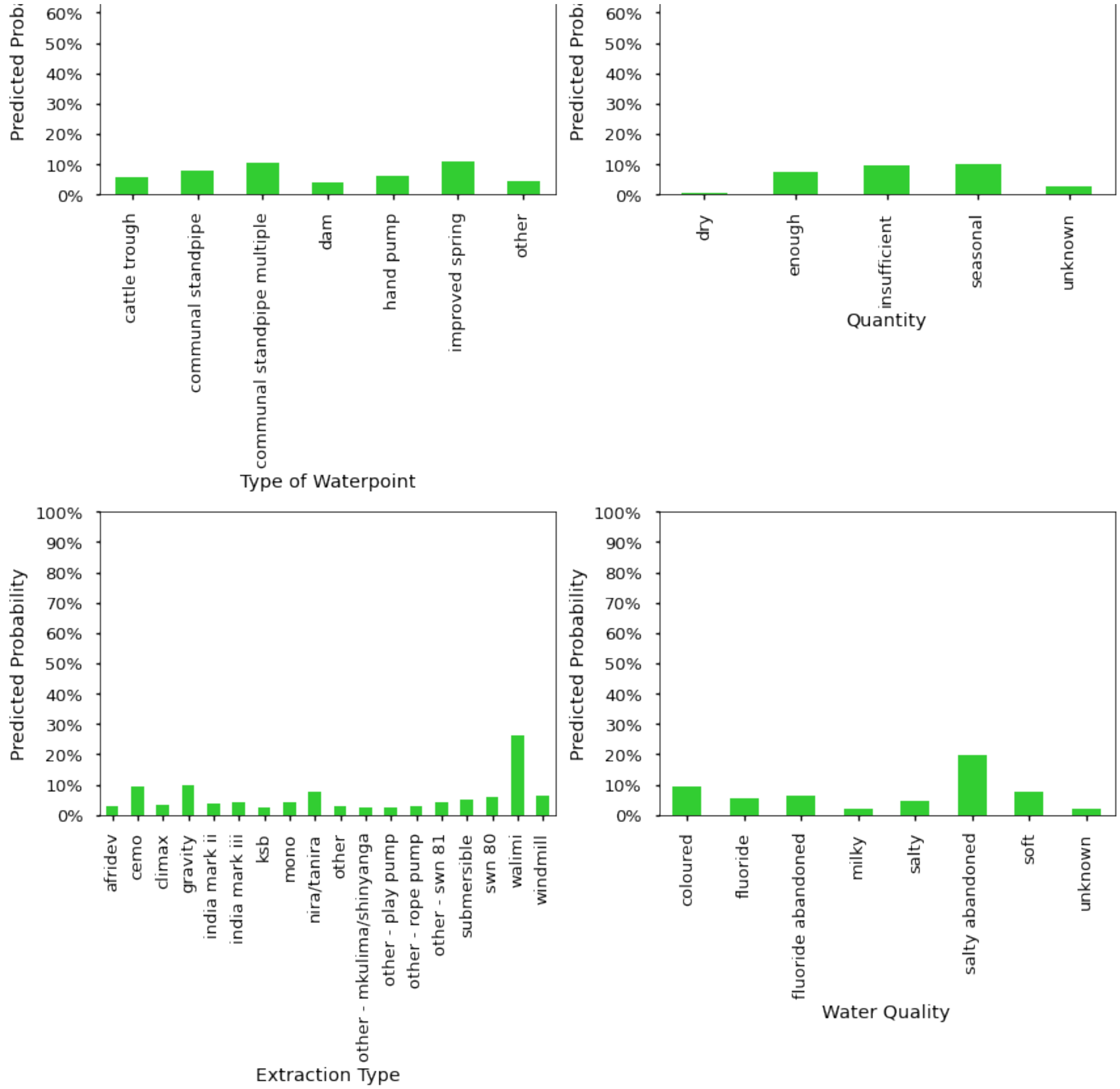
```
def probability_plot(data, column, target, ax, ind, color='color'):
    width = 0.35
    ind=ind+width
    (data.groupby(column)[target].mean()*100).plot.bar(np.hstack(targe
    ax.set_ylabel("Predicted Probability")
    ax.set_yticks(range(0,110,10))
    ax.yaxis.set_major_formatter(mpl.ticker.StrMethodFormatter('{x:,.0
```

time: 383 µs (started: 2023-01-10 14:14:31 -05:00)

In [505]:

```
columns = ['waterpoint_type','quantity','extraction_type','water_quali
labels = ["Type of Waterpoint", "Quantity", "Extraction Type", "Water 
target = ["Pump_functioning_pred",'Pump_Notfunctioning_pred','Pump_Nee
color  = ['tomato','royalblue','limegreen']
data = df_predicted

nrows =2
ncols =2

with plt.style.context('seaborn-talk'):
    fig, ax_list = plt.subplots(nrows = nrows, ncols = ncols, figsize=

    j=0
    for i in range(nrows):
        for u in range(ncols):
            #if (i!=2 & u!=1):
            #probability_plot(data, columns[j], target[0], ax = ax_lis
            #probability_plot(data, columns[j], target[1], ax = ax_lis
            probability_plot(data, columns[j], target[2], ax = ax_list
            ax_list[i,u].set_xlabel(labels[j])
            j = j+1

            #ax_list[0,0].set_xticks([0,1])
                #ax_list[0,0].set_xticklabels(["No", "YES"], rotation 

            #ax_list[0,1].set_xticks([0,1])
                #ax_list[0,1].set_xticklabels(["No", "YES"], rotation 

            #ax_list[1,0].set_xticks([0,1,2,3,4])
                #ax_list[1,0].set_xticklabels(["Not at all", "Not very

            #ax_list[1,1].set_xticks([0,1,2,3,4])
                #ax_list[1,1].set_xticklabels(["Very low", "Somewhat l

            #ax_list[2,0].set_xticks([0,1,2,3,4])
                #ax_list[2,0].set_xticklabels(["13-34", "35-44", "45-5

                #ax_list[2,1].set_xticks([0,1])
                #ax_list[2,1].set_xticklabels(["No", "YES"], rotation 

        fig.suptitle('Predicted Probability of Status of Pumps \n in R
        fig.tight_layout();
        #fig.savefig('./images/MostImportantFeatures_Probability_BarPl
```






```
time: 684 ms (started: 2023-01-10 14:15:09 -05:00)
```

In [*]:
```
df_predicted
```

In [ ]:
```
```