Introduction and Problem Statement

Tanzania, as a developing country, struggles with providing clean water to its population of over 57,000,000. There are many water points already established in the country, but some are in need of repair while others have failed altogether.

The aim of this project is to build a classifier that predicts the condition of a water well (functional, non-function, or functional but needs repair), using information such as the extraction type, how it is managed, payment type, waterpoint type, the water source, whether it has a permit, and whether a public meeting was held.

With this model, the aim is to help the Government of Tanzania find patterns in non-functional wells to influence how new wells are built.

Objectives

1. Analyze the relationship between the following variables and the `status_group` (functional, non-functional, functional but needs repair) to identify patterns in non-functional wells:

- `Payment` : What the water costs
- `source` : The source of the water
- `management_group` : How the waterpoint is managed
- `extraction_type` : The kind of extraction the waterpoint uses
- `permit` : If the waterpoint is permitted
- `public _meeting` : Whether a public meeting was held for the well

1. Develop a classification model to predict the condition of a well (functional, non-functional, or non-functional but needs repair)

Data Understanding

The original data can be obtained on the DrivenData 'Pump it Up: Data Mining the Water Table' competition. Basically, there are 4 different data sets; submission format, training set, test set and train labels set which contains status of wells. With given training set and labels set, competitors are expected to build predictive model and apply it to test set to determine status of the wells and submit.

In this project, we will use train set and train label set. Train set has 59400 water points data with 40 features. Train labels data has the same 59400 water points as train set, but just has information about id of these points and status of them.

Limitations of the data

1. The target labels are ternary and highly imbalanced:

- functional: 32259
- non functional: 22824

- functional needs repair: 4317

  This might impact the performance of the model

1. The data contains 40 features, which are very many, which means that a lot of work will go into EDA and feature elimination

Methods/Data Analysis

After opening the raw training datasets with pandas, we cleaned and prepared the data by imputing missing values, eliminating some redundant columns that contained similar information, identifying the columns with the most variable information for modeling, removing outliers from some numerical columns, encoding categorial variables for modeling.
The 15 final selected features for the model were:

- `basin`
- `month_recorded`
- `region`
- `extraction_type_class`
- `management_group`
- `payment`
- `quality_group`
- `quantity`
- `source`
- `waterpoint_type`
- `gps_height`
- `population`
- `construction_age`
- `permit`
- `public_meeting`

Imports and Data Loading

Imports

In [831…

```
import warnings

# Figures
import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import statistics

# Data
import pandas as pd
import numpy as np
from operator import itemgetter
import itertools
from collections import defaultdict
from datetime import datetime
```

```python
# Models, metrics, scalers and functionalities
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn import svm

from sklearn.model_selection import cross_val_score, cross_val_predict, cross_validate
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV

from sklearn.metrics import confusion_matrix, accuracy_score

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.preprocessing import LabelEncoder

from sklearn.feature_selection import SelectKBest, chi2, mutual_info_classif
from sklearn.feature_selection import RFE, RFECV
from sklearn.feature_selection import SelectFromModel

from sklearn.neighbors import KNeighborsClassifier

from sklearn.decomposition import PCA

from sklearn.tree import DecisionTreeClassifier

from IPython.display import Image
from sklearn.tree import export_graphviz

from sklearn.ensemble import RandomForestClassifier
from scipy.stats import randint

import xgboost
import pandas as pd
import numpy as np
```

Data Loading

In [832…

```python
training_set_values = pd.read_csv("data/training-set-values.csv")
training_set_labels = pd.read_csv("data/training-set-labels.csv")
print(training_set_values.shape)
print(training_set_labels.shape)
```

```
(59400, 40)
(59400, 2)
```

Both the training labels and values csvs have 59,400 rows. We will now combine them to deal with one training dataset

In [833…

```python
training_data = training_set_values.merge(training_set_labels, on='id')
training_data.head()
```

Out[833]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	

4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni

5 rows × 41 columns

EDA and Feature Exploration

In [834…
```
training_data.shape
```

Out[834]:
```
(59400, 41)
```

We now have one dataframe with 59,400 rows and 41 columns, with the 41st column being the status_group column

In [835…
```
training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 41 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   id                     59400 non-null  int64  
 1   amount_tsh             59400 non-null  float64
 2   date_recorded          59400 non-null  object 
 3   funder                 55765 non-null  object 
 4   gps_height             59400 non-null  int64  
 5   installer              55745 non-null  object 
 6   longitude              59400 non-null  float64
 7   latitude               59400 non-null  float64
 8   wpt_name               59400 non-null  object 
 9   num_private            59400 non-null  int64  
 10  basin                  59400 non-null  object 
 11  subvillage             59029 non-null  object 
 12  region                 59400 non-null  object 
 13  region_code            59400 non-null  int64  
 14  district_code          59400 non-null  int64  
 15  lga                    59400 non-null  object 
 16  ward                   59400 non-null  object 
 17  population             59400 non-null  int64  
 18  public_meeting         56066 non-null  object 
 19  recorded_by            59400 non-null  object 
 20  scheme_management      55523 non-null  object 
 21  scheme_name            31234 non-null  object 
 22  permit                 56344 non-null  object 
 23  construction_year      59400 non-null  int64  
 24  extraction_type        59400 non-null  object 
 25  extraction_type_group  59400 non-null  object 
 26  extraction_type_class  59400 non-null  object 
 27  management             59400 non-null  object 
 28  management_group       59400 non-null  object 
 29  payment                59400 non-null  object 
 30  payment_type           59400 non-null  object 
 31  water_quality          59400 non-null  object 
 32  quality_group          59400 non-null  object 
 33  quantity               59400 non-null  object 
 34  quantity_group         59400 non-null  object 
 35  source                 59400 non-null  object 
 36  source_type            59400 non-null  object 
 37  source_class           59400 non-null  object 
 38  waterpoint_type        59400 non-null  object 
 39  waterpoint_type_group  59400 non-null  object 
```

```
 40  status_group           59400 non-null  object
dtypes: float64(3), int64(7), object(31)
memory usage: 19.0+ MB
```

In [836…
```
training_data.columns
```

Out[836]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', 'recorded_by',
       'scheme_management', 'scheme_name', 'permit', 'construction_year',
       'extraction_type', 'extraction_type_group', 'extraction_type_class',
       'management', 'management_group', 'payment', 'payment_type',
       'water_quality', 'quality_group', 'quantity', 'quantity_group',
       'source', 'source_type', 'source_class', 'waterpoint_type',
       'waterpoint_type_group', 'status_group'],
      dtype='object')
```

These are all the columns and their descriptions:

- **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
- **status_group** - The labels in this dataset with three possible values: functional, non-functional, and functional needs repair

In [837…

```python
training_data.isna().sum() # to see the null values
```

Out[837]:

```
id                           0
amount_tsh                   0
date_recorded                0
funder                    3635
gps_height                   0
installer                 3655
longitude                    0
latitude                     0
wpt_name                     0
num_private                  0
basin                        0
subvillage                 371
region                       0
region_code                  0
district_code                0
lga                          0
ward                         0
population                   0
public_meeting            3334
recorded_by                  0
scheme_management         3877
scheme_name              28166
permit                    3056
construction_year            0
extraction_type              0
extraction_type_group        0
extraction_type_class        0
management                   0
management_group             0
payment                      0
payment_type                 0
water_quality                0
quality_group                0
quantity                     0
quantity_group               0
source                       0
source_type                  0
source_class                 0
waterpoint_type              0
waterpoint_type_group        0
status_group                 0
dtype: int64
```

The columns with missing values are:

Funder : 3635

Installer: 3635

Subvillage: 371

Public meeting: 3334

scheme_management:3877

scheme_name: 28166

permit: 3056

There are some columns which contain null and the same information in the data set.

Now, we will drop one for each because the same values or dublicated values do not affect our target, and when we simplify our data we can run our models easier. These are `management and scheme_management`, `payment and payment type`, `quantity and quantity group`, `waterpoint_type and waterpoint_type_group`, `extraction_type, extration_type_class, and extraction_type_group`, `source, source_type, and source_class`, `water_quality and quality_group` Let's assess them to confirm.

Dealing with columns that have the same information

Management and Scheme_management

In [838…
```
print(training_data.management.value_counts())
print("---------------------------------")
print(training_data.scheme_management.value_counts())
```

```
vwc                 40507
wug                  6515
water board          2933
wua                  2535
private operator     1971
parastatal           1768
water authority       904
other                 844
company               685
unknown               561
other - school         99
trust                  78
Name: management, dtype: int64
---------------------------------
VWC                 36793
WUG                  5206
Water authority      3153
WUA                  2883
Water Board          2748
Parastatal           1680
Private operator     1063
Company              1061
Other                 766
SWC                    97
Trust                  72
None                    1
Name: scheme_management, dtype: int64
```

These two columns has nearly same information. Scheme_management represents who operates the water point, 'management' represents how the water point is managed. There are 3877 null values in 'scheme_management' column so we prefer to keep the 'management' column.

In [839…
```
training_data.drop('scheme_management', axis=1, inplace=True)
```

Payment and Payment type

In [840…
```
# Looking at payment and payment_type
print(training_data.payment.value_counts())
```

```
print("--------------------------------")
print(training_data.payment_type.value_counts())
```

```
never pay                25348
pay per bucket            8985
pay monthly               8300
unknown                   8157
pay when scheme fails     3914
pay annually              3642
other                     1054
Name: payment, dtype: int64
--------------------------------
never pay     25348
per bucket     8985
monthly        8300
unknown        8157
on failure     3914
annually       3642
other          1054
Name: payment_type, dtype: int64
```

These two columns have the same exact information, but `payment` has more details on the column naming, so we will keep it and drop `payment_type`

In [841…

```
training_data.drop('payment_type', axis=1, inplace=True)
```

Quantity and Quantity_Group

In [842…

```
# Looking at `quantity and quantity group`
print(training_data.quantity.value_counts())
print("--------------------------------")
print(training_data.quantity_group.value_counts())
```

```
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity, dtype: int64
--------------------------------
enough          33186
insufficient    15129
dry              6246
seasonal         4050
unknown           789
Name: quantity_group, dtype: int64
```

These have the same exact information, so we can drop either

In [843…

```
training_data.drop('quantity_group', axis=1, inplace=True)
```

Waterpoint Type and Waterpoint_type_group

In [844…

```
# Looking at the waterpoint_type and waterpoint_type_group columns
print(training_data.waterpoint_type.value_counts())
print("--------------------------------")
print(training_data.waterpoint_type_group.value_counts())
```

```
communal standpipe             28522
hand pump                      17488
other                           6380
communal standpipe multiple     6103
improved spring                  784
cattle trough                    116
```

```
dam                                   7
Name: waterpoint_type, dtype: int64
---------------------------------
communal standpipe    34625
hand pump             17488
other                  6380
improved spring         784
cattle trough           116
dam                       7
Name: waterpoint_type_group, dtype: int64
```

`Waterpoint_type` has more information and distribution, so we will keep it and drop `waterpoint_type_group`

In [845…
```
training_data.drop(columns = 'waterpoint_type_group', axis=1, inplace=True)
```

Extraction_type, Extraction_type_class and Extraction_type_group columns

In [846…
```
# Let's look at the extraction_type, extraction_type_class and extraction_type_group col
print(training_data.extraction_type.value_counts())
```

```
gravity                        26780
nira/tanira                     8154
other                           6430
submersible                     4764
swn 80                          3670
mono                            2865
india mark ii                   2400
afridev                         1770
ksb                             1415
other - rope pump                451
other - swn 81                   229
windmill                         117
india mark iii                    98
cemo                              90
other - play pump                 85
walimi                            48
climax                            32
other - mkulima/shinyanga          2
Name: extraction_type, dtype: int64
```

In [847…
```
print(training_data.extraction_type_group.value_counts())
```

```
gravity            26780
nira/tanira         8154
other               6430
submersible         6179
swn 80              3670
mono                2865
india mark ii       2400
afridev             1770
rope pump            451
other handpump       364
other motorpump      122
wind-powered         117
india mark iii        98
Name: extraction_type_group, dtype: int64
```

In [848…
```
print(training_data.extraction_type_class.value_counts())
```

```
gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
```

```
rope pump           451
wind-powered        117
Name: extraction_type_class, dtype: int64
```

`extraction_type_class` is an even further simplification of `extraction_type`. Since it is the simplest feature of the three, this is the one selected for use, and the handling of category level other will take place after dummification.

In [849…
```
training_data.drop('extraction_type_group', axis=1, inplace=True)
```

In [850…
```
training_data.drop('extraction_type', axis=1, inplace=True)
```

Source, Source_type_and Source_class

In [851…
```
# Let's assess the source, source_type_and source_class columns
# SOURCE
print(training_data.source.value_counts())
```

```
spring                  17021
shallow well            16824
machine dbh             11075
river                    9612
rainwater harvesting     2295
hand dtw                  874
lake                      765
dam                       656
other                     212
unknown                    66
Name: source, dtype: int64
```

In [852…
```
# SOURCE TYPE
print(training_data.source_type.value_counts())
```

```
spring                  17021
shallow well            16824
borehole                11949
river/lake              10377
rainwater harvesting     2295
dam                       656
other                     278
Name: source_type, dtype: int64
```

In [853…
```
# SOURCE CLASS
print(training_data.source_class.value_counts())
```

```
groundwater    45794
surface        13328
unknown          278
Name: source_class, dtype: int64
```

It is obvious that these columns have the same information. We will keep the `source` column and drop the rest since it has more information

In [854…
```
training_data.drop('source_type', axis=1, inplace=True)
```

In [855…
```
training_data.drop('source_class', axis=1, inplace=True)
```

Water_quality and Quality_group

In [856…
```
# Looking at the water_quality and quality_group columns
print(training_data.water_quality.value_counts())
```

```
print("--------------------------------")
print(training_data.quality_group.value_counts())
```

```
soft                  50818
salty                  4856
unknown                1876
milky                   804
coloured                490
salty abandoned         339
fluoride                200
fluoride abandoned       17
Name: water_quality, dtype: int64
---------------------------------
good        50818
salty        5195
unknown      1876
milky         804
colored       490
fluoride      217
Name: quality_group, dtype: int64
```

Since `quality_group` has less categories, we will keep it and drop `water_quality`

In [857…
```
training_data.drop('water_quality', axis=1, inplace=True)
```

In [858…
```
# Let's look at our new data
training_data.columns
```

Out[858]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lga',
       'ward', 'population', 'public_meeting', 'recorded_by', 'scheme_name',
       'permit', 'construction_year', 'extraction_type_class', 'management',
       'management_group', 'payment', 'quality_group', 'quantity', 'source',
       'waterpoint_type', 'status_group'],
      dtype='object')
```

In [859…
```
training_data.head()
```

Out[859]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude	wpt_name	num_
0	69572	6000.0	2011-03-14	Roman	1390	Roman	34.938093	-9.856322	none	
1	8776	0.0	2013-03-06	Grumeti	1399	GRUMETI	34.698766	-2.147466	Zahanati	
2	34310	25.0	2013-02-25	Lottery Club	686	World vision	37.460664	-3.821329	Kwa Mahundi	
3	67743	0.0	2013-01-28	Unicef	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	
4	19728	0.0	2011-07-13	Action In A	0	Artisan	31.130847	-1.825359	Shuleni	

5 rows × 32 columns

Conclusion from dealing with columns that have similar data

We dropped the following columns in favor of those with more robust data:

- `scheme_management`, `payment_type`, `quantity_group`, `waterpoint_type_group`, `extraction_type`, `extration_type_group`, `source_type`, `source_class`, `water_quality`

The kept columns are:

- `management` , `payment` , `quantity` , `waterpoint` , `extraction_type_class` , `source` , `quality_group`

Dealing with Null Values

In [860…
```
training_data.isna().sum()
```

Out[860]:
```
id                          0
amount_tsh                  0
date_recorded               0
funder                   3635
gps_height                  0
installer                3655
longitude                   0
latitude                    0
wpt_name                    0
num_private                 0
basin                       0
subvillage                371
region                      0
region_code                 0
district_code               0
lga                         0
ward                        0
population                  0
public_meeting           3334
recorded_by                 0
scheme_name             28166
permit                   3056
construction_year           0
extraction_type_class       0
management                  0
management_group            0
payment                     0
quality_group               0
quantity                    0
source                      0
waterpoint_type             0
status_group                0
dtype: int64
```

Let's deal with the columns containing missing values, starting with Funder

Funder

In [861…
```
training_data.funder.value_counts()
```

Out[861]:
```
Government Of Tanzania    9084
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
                          ... 
Kenyans Company              1
Rodri                        1
Uniceg                       1
Tasad                        1
```

```
Mbuzi Mawe                     1
Name: funder, Length: 1897, dtype: int64
```

In [862…
```
training_data.funder.value_counts()
```

Out[862]:
```
Government Of Tanzania    9084
Danida                    3114
Hesawa                    2202
Rwssp                     1374
World Bank                1349
                          ...
Kenyans Company              1
Rodri                        1
Uniceg                       1
Tasad                        1
Mbuzi Mawe                   1
Name: funder, Length: 1897, dtype: int64
```

The `funder` column has 1897 unique values, hence it will be difficult to fill the null ones. We will drop it

In [863…
```
training_data.drop('funder', axis=1, inplace=True)
```

Subvillage

In [864…
```
training_data["subvillage"].value_counts()
```

Out[864]:
```
Madukani          508
Shuleni           506
Majengo           502
Kati              373
Mtakuja           262
                 ...
Mutoju              1
Migombani B         1
Majaribio           1
Makongoroni         1
Nyuma Ya Mlims      1
Name: subvillage, Length: 19287, dtype: int64
```

In [865…
```
len(training_data[training_data["subvillage"].isnull()]["subvillage"])/len(training_data
```

Out[865]:
```
0.6245791245791246
```

Given the great scatter (not one subvillage accounts for 1% or more of the examples) this feature is not informative, and therefore dropped.

In [866…
```
training_data.drop('subvillage', axis=1, inplace=True)
```

Public Meeting

In [867…
```
training_data["public_meeting"].value_counts(dropna = False)/len(training_data)*100
```

Out[867]:
```
True     85.877104
False     8.510101
NaN       5.612795
Name: public_meeting, dtype: float64
```

As it is hard to assume whether or not public meetings were actually held, we consider binning this variable into:

True

False

Unknown

In [868…
```
training_data["public_meeting"] = training_data["public_meeting"].astype("category")
training_data["public_meeting"] = training_data["public_meeting"].cat.add_categories('Un
```

In [869…
```
training_data.public_meeting.value_counts()
```

Out[869]:
```
True       51011
False       5055
Unknown     3334
Name: public_meeting, dtype: int64
```

Scheme Name

In [870…
```
training_data["scheme_name"].value_counts(dropna = False)/len(training_data)*100
```

Out[870]:
```
NaN                              47.417508
K                                 1.148148
None                              1.084175
Borehole                          0.919192
Chalinze wate                     0.681818
                                    ...
NYEHUNGE WATER SUPPLY             0.001684
Kiranjeranje  Water supply        0.001684
Kasota                            0.001684
BL Motomati                       0.001684
Arashi water scheme               0.001684
Name: scheme_name, Length: 2697, dtype: float64
```

`scheme_name` has about half the entries as NaN, and the rest are greatly scattered. Feature `scheme_name` is consequently dropped as well.

In [871…
```
training_data.drop('scheme_name', axis=1, inplace=True)
```

Permit

In [872…
```
training_data["permit"].value_counts(dropna = False)/len(training_data)*100
```

Out[872]:
```
True     65.407407
False    29.447811
NaN       5.144781
Name: permit, dtype: float64
```

`permit` is an intuitive binary feature. About 5% of the values are missing (NaN). It is reasonable to assume that absence of a permit record implies the absence of the permit itself, and hence the NaN values could be imputed as False

In [873…
```
training_data = training_data.replace({"permit": {np.nan: False}})
```

In [874…
```
training_data.permit.value_counts()
```

Out[874]:
```
True     38852
False    20548
Name: permit, dtype: int64
```

Conclusion from dealing with null values

We dropped the following columns:

- `funder`, `subvillage`, and `scheme_name`

The following columns were kept

- `public_meeting` - NaN values were imputed with 'Unknown', introducing a new category
- `permit` - NaN values were imputed with False

Checking for duplicates

In [875…
```
training_data.duplicated().sum()
```

Out[875]:
```
0
```

There are no duplicates

Exploring the columns inferred as numeric

In [876…
```
# Find numeric variables
numerical_columns = [var for var in training_data.columns if training_data[var].dtype!='

print('There are {} numerical variables\n'.format(len(numerical_columns)))

print('The numerical variables are :', numerical_columns)
```

```
There are 12 numerical variables

The numerical variables are : ['id', 'amount_tsh', 'gps_height', 'longitude', 'latitud
e', 'num_private', 'region_code', 'district_code', 'population', 'public_meeting', 'perm
it', 'construction_year']
```

In [877…
```
training_data[numerical_columns].head(3)
```

Out[877]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code	district_code	population
0	69572	6000.0	1390	34.938093	-9.856322	0	11	5	109
1	8776	0.0	1399	34.698766	-2.147466	0	20	2	280
2	34310	25.0	686	37.460664	-3.821329	0	21	4	250

Check for null values in numerical columns

In [878…
```
training_data[numerical_columns].isnull().sum()
```

Out[878]:
```
id                   0
amount_tsh           0
gps_height           0
longitude            0
latitude             0
num_private          0
region_code          0
district_code        0
population           0
public_meeting       0
permit               0
construction_year    0
dtype: int64
```

None of the numeric columns have missing data

In [879…
```
training_data[numerical_columns].describe()
```

Out[879]:

	id	amount_tsh	gps_height	longitude	latitude	num_private	region_code
count	59400.000000	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000
mean	37115.131768	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	15.297003
std	21453.128371	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	17.587406
min	0.000000	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	1.000000
25%	18519.750000	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	5.000000
50%	37061.500000	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	12.000000
75%	55656.500000	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	17.000000
max	74247.000000	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	99.000000

Amount tsh

Total static head shows us the height of the flow from the surface. Mostly there are zero values in our dataset. But for zero values no need for pump , because it means we are already in surface.

In [880…

```
training_data["amount_tsh"].value_counts()
```

Out[880]:

```
0.0         41639
500.0        3102
50.0         2472
1000.0       1488
20.0         1463
            ...
8500.0          1
6300.0          1
220.0           1
138000.0        1
12.0            1
Name: amount_tsh, Length: 98, dtype: int64
```

In [881…

```
training_data["amount_tsh"].value_counts()/len(training_data)*100
```

Out[881]:

```
0.0         70.099327
500.0        5.222222
50.0         4.161616
1000.0       2.505051
20.0         2.462963
              ...
8500.0       0.001684
6300.0       0.001684
220.0        0.001684
138000.0     0.001684
12.0         0.001684
Name: amount_tsh, Length: 98, dtype: float64
```

We decided to drop this column because 70% of the column has no informative values. So, this column will not be informative to our model and we will drop it.

In [882…

```
training_data.drop('amount_tsh',axis=1, inplace=True)
```

GPS Height

In [883…

```
training_data["gps_height"].value_counts()/len(training_data)*100    # 34% of waterpoint
```

Out[883]:

```
 0      34.407407
-15      0.101010
-16      0.092593
```

```
-13        0.092593
-20        0.087542
             ...
 2285      0.001684
 2424      0.001684
 2552      0.001684
 2413      0.001684
 2385      0.001684
Name: gps_height, Length: 2428, dtype: float64
```

In [884…

```
training_data[training_data["gps_height"] > 0]["gps_height"].count()/len(training_data)*
training_data[training_data["gps_height"] < 0]["gps_height"].count()/len(training_data)*
```

Out[884]:

```
2.5185185185185186
```

Gps height shows the level of the water point from sea level. There are 34% zero values but maybe 34% of the water points are at the sea level so we do not change this column now.

Let's use the median

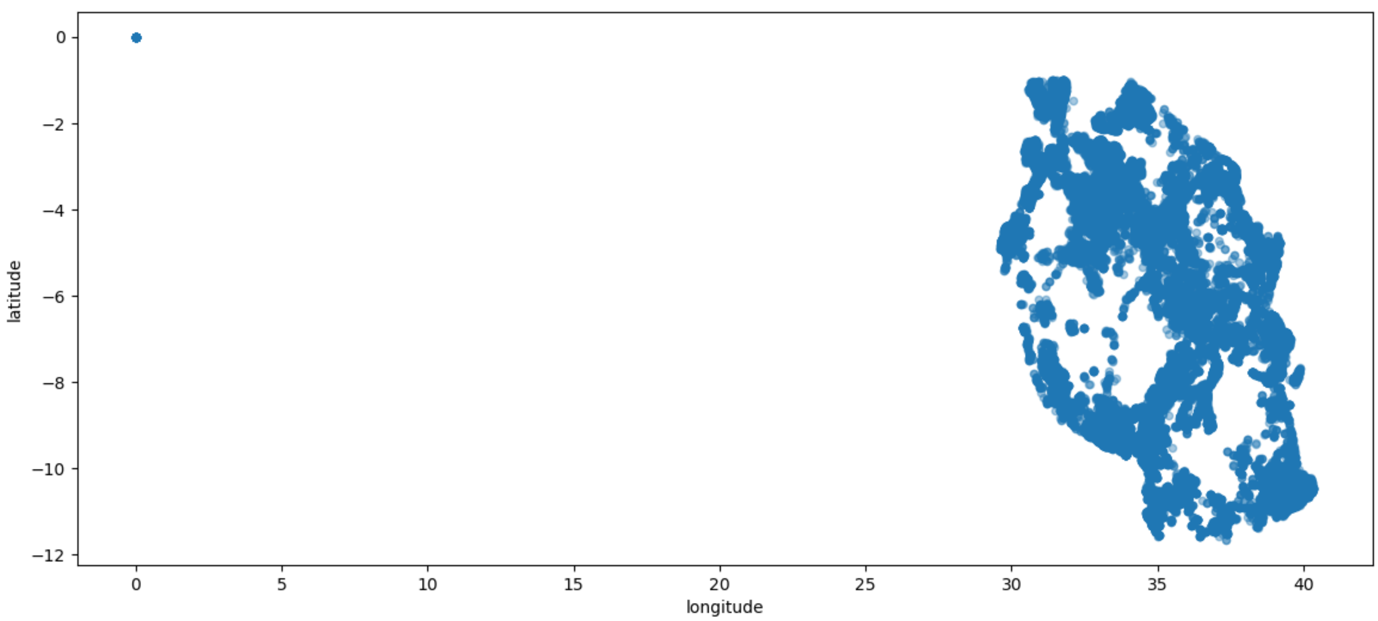
Longitude and Latitude

latitude values make sense (between just below the equator down to 12°S)

longitude values have inconsistencies (0°E is not possible for Tanzania)

In [885…

```
training_data.plot(kind='scatter', x="longitude", y="latitude", alpha=0.4, figsize=(14,6
# To see the outliers
```



In [886…

```
training_data.loc[training_data['longitude']==0].head() # to check outside of Tanzania
```

Out[886]:

	id	date_recorded	gps_height	installer	longitude	latitude	wpt_name	num_private	basin
21	6091	2013-02-10	0	DWE	0.0	-2.000000e-08	Muungano	0	Lake Victoria
53	32376	2011-08-01	0	Government	0.0	-2.000000e-08	Polisi	0	Lake Victoria
168	72678	2013-01-30	0	WVT	0.0	-2.000000e-08	Wvt Tanzania	0	Lake Victoria
177	56725	2013-01-17	0	DWE	0.0	-2.000000e-	Kikundi	0	Lake

						08	Cha Wakina Mama		Victoria
253	13042	2012-10-29	0	DWE	0.0	-2.000000e-08	Kwakisusi	0	Lake Victoria

5 rows × 28 columns

In [887…
```
training_data.loc[training_data['longitude']!=0].describe() # to find the non-zero value
```

Out[887]:

	id	gps_height	longitude	latitude	num_private	region_code	district_code	p
count	57588.00000	57588.000000	57588.000000	57588.000000	57588.000000	57588.000000	57588.000000	575
mean	37106.48807	689.325137	35.149669	-5.885572	0.489060	15.217615	5.728311	1
std	21454.51421	693.564188	2.607428	2.809876	12.426954	17.855254	9.760254	4
min	0.00000	-90.000000	29.607122	-11.649440	0.000000	1.000000	0.000000	
25%	18522.75000	0.000000	33.285100	-8.643841	0.000000	5.000000	2.000000	
50%	37054.50000	426.000000	35.005943	-5.172704	0.000000	12.000000	3.000000	
75%	55667.25000	1332.000000	37.233712	-3.372824	0.000000	17.000000	5.000000	2
max	74247.00000	2770.000000	40.345193	-0.998464	1776.000000	99.000000	80.000000	305

It is obviously seen that it is written as 0 when the longtitude is unknown.
Because, the zero points can seen easily in the graph above outliers and outside of Tanzania.
So, we replaced this with the mean longitude value

In [888…
```
training_data['longitude'].replace(to_replace = 0 , value =35.15, inplace=True) # changi
```

Num Private

num_private column has no description and most of the colum contains zeros and is not intuitive to infer.
We will drop it

In [889…
```
training_data["num_private"].value_counts()/len(training_data)*100
```

Out[889]:
```
0      98.725589
6       0.136364
1       0.122896
5       0.077441
8       0.077441
          ...
180     0.001684
213     0.001684
23      0.001684
55      0.001684
94      0.001684
Name: num_private, Length: 65, dtype: float64
```

In [890…
```
training_data.drop('num_private',axis=1, inplace=True )
```

Region_code

In [891…
```
training_data["region_code"].nunique()
```

Out[891]:
```
27
```

In [892…
```
training_data['region_code'].value_counts()
```
Out[892]:
```
11    5300
17    5011
12    4639
3     4379
5     4040
18    3324
19    3047
2     3024
16    2816
10    2640
4     2513
1     2201
13    2093
14    1979
20    1969
15    1808
6     1609
21    1583
80    1238
60    1025
90     917
7      805
99     423
9      390
24     326
8      300
40       1
Name: region_code, dtype: int64
```
This is a categorical value

District_code

In [893…
```
training_data['district_code'].nunique()
```
Out[893]:
```
20
```
In [894…
```
training_data['district_code'].value_counts()
```
Out[894]:
```
1     12203
2     11173
3      9998
4      8999
5      4356
6      4074
7      3343
8      1043
30      995
33      874
53      745
43      505
13      391
23      293
63      195
62      109
60       63
0        23
80       12
67        6
Name: district_code, dtype: int64
```
This is a categorical value

Population

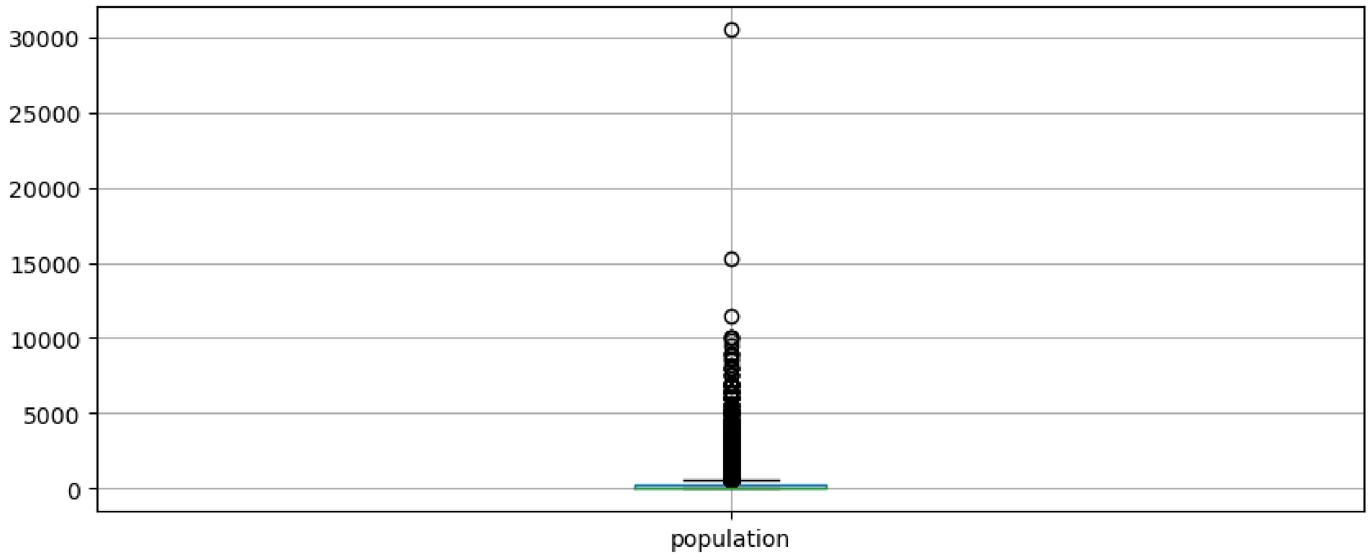
In the `population` column, 36% of rows have value 0. These could be mistakes or numeric encoding for NA (maybe waterpoints where population ultimately migrated?).

Do we impute these entries? The distribution is considerably skewed.

In [895…
```
print(training_data['population'].skew())
```

```
12.660713588843592
```

In [896…
```
plt.figure(figsize=(10,4))
training_data.boxplot(['population'], grid=True, fontsize=10)
plt.show()
```



In [897…
```
training_data["population"].describe()
```

Out[897]:
```
count    59400.000000
mean       179.909983
std        471.482176
min          0.000000
25%          0.000000
50%         25.000000
75%        215.000000
max      30500.000000
Name: population, dtype: float64
```

imputation is prefered to be with the median considering the significant skewness.

In [898…
```
population_median = training_data[(training_data["population"] != 0)]["population"].desc
```

In [899…
```
training_data["population"] = training_data["population"].replace({0:population_median})
```

In [900…
```
training_data.population.value_counts()
```

Out[900]:
```
150     23273
1        7025
200      1940
250      1681
300      1476
        ...
406         1
1960        1
1685        1
2248        1
```

```
1439        1
Name: population, Length: 1048, dtype: int64
```

Permit

In [901…

```
training_data['permit']
```

Out[901]:

```
0        False
1         True
2         True
3         True
4         True
         ...
59395     True
59396     True
59397    False
59398     True
59399     True
Name: permit, Length: 59400, dtype: bool
```

In [902…

```
training_data["permit"].value_counts(dropna = False)/len(training_data)*100
```

Out[902]:

```
True     65.407407
False    34.592593
Name: permit, dtype: float64
```

`Permit` is an intuitive binary feature with Boolean values (True or False)

Construction_year

In [903…

```
print(training_data['construction_year'].skew())
```

```
-0.6349277865999228
```

In [904…

```
training_data["construction_year"].value_counts()/len(training_data)*100
```

Out[904]:

```
0       34.863636
2010     4.452862
2008     4.398990
2009     4.264310
2000     3.520202
2007     2.671717
2006     2.476431
2003     2.164983
2011     2.114478
2004     1.890572
2012     1.824916
2002     1.809764
1978     1.745791
1995     1.707071
2005     1.702020
1999     1.648148
1998     1.626263
1990     1.606061
1985     1.590909
1980     1.365320
1996     1.365320
1984     1.311448
1982     1.252525
1994     1.242424
1972     1.191919
1974     1.138047
1997     1.084175
1992     1.077441
1993     1.023569
```

```
2001    0.909091
1988    0.877104
1983    0.821549
1975    0.735690
1986    0.730640
1976    0.696970
1970    0.691919
1991    0.545455
1989    0.531987
1987    0.508418
1981    0.400673
1977    0.340067
1979    0.323232
1973    0.309764
2013    0.296296
1971    0.244108
1960    0.171717
1967    0.148148
1963    0.143098
1968    0.129630
1969    0.099327
1964    0.067340
1962    0.050505
1961    0.035354
1965    0.031987
1966    0.028620
Name: construction_year, dtype: float64
```

In [905…
```
training_data[(training_data["construction_year"] != 0)]['construction_year'].describe()
```

Out[905]:
```
count    38691.000000
mean      1996.814686
std         12.472045
min       1960.000000
25%       1987.000000
50%       2000.000000
75%       2008.000000
max       2013.000000
Name: construction_year, dtype: float64
```

Imputation is preferred to be with the mean of non-zero years, as it is considered that a majority a missing values stem from older decades.

In [906…
```
construction_year_mean = training_data[(training_data["construction_year"] != 0)]["const
```

In [907…
```
training_data["construction_year"] = training_data["construction_year"].replace({0:const
```

In [908…
```
training_data["construction_year"].value_counts()/len(training_data)*100
```

Out[908]:
```
1996    36.228956
2010     4.452862
2008     4.398990
2009     4.264310
2000     3.520202
2007     2.671717
2006     2.476431
2003     2.164983
2011     2.114478
2004     1.890572
2012     1.824916
2002     1.809764
1978     1.745791
1995     1.707071
2005     1.702020
```

```
1999    1.648148
1998    1.626263
1990    1.606061
1985    1.590909
1980    1.365320
1984    1.311448
1982    1.252525
1994    1.242424
1972    1.191919
1974    1.138047
1997    1.084175
1992    1.077441
1993    1.023569
2001    0.909091
1988    0.877104
1983    0.821549
1975    0.735690
1986    0.730640
1976    0.696970
1970    0.691919
1991    0.545455
1989    0.531987
1987    0.508418
1981    0.400673
1977    0.340067
1979    0.323232
1973    0.309764
2013    0.296296
1971    0.244108
1960    0.171717
1967    0.148148
1963    0.143098
1968    0.129630
1969    0.099327
1964    0.067340
1962    0.050505
1961    0.035354
1965    0.031987
1966    0.028620
Name: construction_year, dtype: float64
```

Conclusion from exploring numeric values

- `Amount_tsh` was dropped
- `GPS Height` remains as it is
- `Longitude` remains as is
- For `latitude`, we imputed the 0 values with the mean since it does not make sense to have a latitude of 0 in Tanzania
- `Num private` was dropped
- `Region code and district code` are categorical values and remain as they are
- `Population` needs to be imputed with the median for the years listed as zero
- `Permit` is an intuitive binary feature with Boolean values (True or False)
- `Construction year` will be imputed with the mean of non-zero years for the years listed as zero

Let's look at our new data

In [909…
```
training_data.columns
```

Out[909]:
```
Index(['id', 'date_recorded', 'gps_height', 'installer', 'longitude',
       'latitude', 'wpt_name', 'basin', 'region', 'region_code',
       'district_code', 'lga', 'ward', 'population', 'public_meeting',
```

```
       'recorded_by', 'permit', 'construction_year', 'extraction_type_class',
       'management', 'management_group', 'payment', 'quality_group',
       'quantity', 'source', 'waterpoint_type', 'status_group'],
      dtype='object')
```

Explore the columns inferred as non-numeric

Initially all these columns are inferred as type object

In [910…

```
categorical_columns = [col for col in training_data.columns if training_data[col].dtypes

categorical_columns
```

Out[910]:

```
['date_recorded',
 'installer',
 'wpt_name',
 'basin',
 'region',
 'lga',
 'ward',
 'recorded_by',
 'extraction_type_class',
 'management',
 'management_group',
 'payment',
 'quality_group',
 'quantity',
 'source',
 'waterpoint_type',
 'status_group']
```

In [911…

```
training_data[categorical_columns].isnull().sum()
```

Out[911]:

```
date_recorded               0
installer                3655
wpt_name                    0
basin                       0
region                      0
lga                         0
ward                        0
recorded_by                 0
extraction_type_class       0
management                  0
management_group            0
payment                     0
quality_group               0
quantity                    0
source                      0
waterpoint_type             0
status_group                0
dtype: int64
```

Date_recorded

We can see that the data type of `Date` variable is object. I will parse the date currently coded as object into datetime format.

In [912…

```
training_data["date_recorded"] = pd.to_datetime(training_data["date_recorded"])
```

In [913…

```
# extract year from date
```

```
training_data['year_recorded'] = training_data['date_recorded'].dt.year
training_data['year_recorded'].head()
```

Out[913]:
```
0    2011
1    2013
2    2013
3    2013
4    2011
Name: year_recorded, dtype: int64
```

In [914…
```
training_data['month_recorded'] = training_data['date_recorded'].dt.month

training_data['month_recorded'].head()
```

Out[914]:
```
0    3
1    3
2    2
3    1
4    7
Name: month_recorded, dtype: int64
```

In [915…
```
# extract day from date

training_data['day_recorded'] = training_data['date_recorded'].dt.day

training_data['day_recorded'].head()
```

Out[915]:
```
0    14
1     6
2    25
3    28
4    13
Name: day_recorded, dtype: int64
```

In [916…
```
# again view the summary of dataset

training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 0 to 59399
Data columns (total 30 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   id                     59400 non-null  int64
 1   date_recorded          59400 non-null  datetime64[ns]
 2   gps_height             59400 non-null  int64
 3   installer              55745 non-null  object
 4   longitude              59400 non-null  float64
 5   latitude               59400 non-null  float64
 6   wpt_name               59400 non-null  object
 7   basin                  59400 non-null  object
 8   region                 59400 non-null  object
 9   region_code            59400 non-null  int64
 10  district_code          59400 non-null  int64
 11  lga                    59400 non-null  object
 12  ward                   59400 non-null  object
 13  population             59400 non-null  int64
 14  public_meeting         59400 non-null  category
 15  recorded_by            59400 non-null  object
 16  permit                 59400 non-null  bool
 17  construction_year      59400 non-null  int64
 18  extraction_type_class  59400 non-null  object
 19  management             59400 non-null  object
 20  management_group       59400 non-null  object
 21  payment                59400 non-null  object
 22  quality_group          59400 non-null  object
 23  quantity               59400 non-null  object
```

```
 24   source                 59400 non-null  object
 25   waterpoint_type        59400 non-null  object
 26   status_group           59400 non-null  object
 27   year_recorded          59400 non-null  int64
 28   month_recorded         59400 non-null  int64
 29   day_recorded           59400 non-null  int64
dtypes: bool(1), category(1), datetime64[ns](1), float64(2), int64(9), object(16)
memory usage: 13.3+ MB
```

We can see that there are three additional columns created from `date_recorded` variable. Now, I will drop the original `date_recorded` variable from the dataset.

In [917…
```
training_data.drop('date_recorded', axis=1, inplace = True)
```

In [918…
```
training_data.head()
```

Out[918]:

	id	gps_height	installer	longitude	latitude	wpt_name	basin	region	region_code	district_c
0	69572	1390	Roman	34.938093	-9.856322	none	Lake Nyasa	Iringa	11	
1	8776	1399	GRUMETI	34.698766	-2.147466	Zahanati	Lake Victoria	Mara	20	
2	34310	686	World vision	37.460664	-3.821329	Kwa Mahundi	Pangani	Manyara	21	
3	67743	263	UNICEF	38.486161	-11.155298	Zahanati Ya Nanyumbu	Ruvuma / Southern Coast	Mtwara	90	
4	19728	0	Artisan	31.130847	-1.825359	Shuleni	Lake Victoria	Kagera	18	

5 rows × 29 columns

Installer

In [919…
```
training_data["installer"].value_counts(dropna = False)/len(training_data)*100
```

Out[919]:
```
DWE                        29.296296
NaN                         6.153199
Government                  3.072391
RWE                         2.030303
Commu                       1.784512
                              ...
Water  Aid/Maji tech        0.001684
Taboma/Community            0.001684
COMPASION INTERNATIO        0.001684
KDPA                        0.001684
NZILA                       0.001684
Name: installer, Length: 2146, dtype: float64
```

Given the scatter of installers with only one entry, and that with 2146 different funders it seems complicated to find a common cluster parameter for the specific feature, it is decided to drop installer.

wpt_name

In [920…
```
training_data["wpt_name"].value_counts()/len(training_data)*100
```

Out[920]:
```
none                   5.998316
Shuleni                2.942761
Zahanati               1.397306
```

```
Msikitini            0.900673
Kanisani             0.543771
                       ...
Kwa Chesi            0.001684
Kwa Padi             0.001684
Kwa Amai             0.001684
Dip Kilulini         0.001684
Kwa Mzee Kunenda     0.001684
Name: wpt_name, Length: 37400, dtype: float64
```

`wpt_name` should play the role of a label but it has null values ("none") and it is not unique (also, the numeric column id is already a valid index). Hence, `wpt_name` is dropped.

In [921…
```
training_data.drop('wpt_name', axis=1, inplace = True)
```

Basin

In [922…
```
training_data["basin"].value_counts()/len(training_data)*100
```

Out[922]:
```
Lake Victoria              17.252525
Pangani                    15.050505
Rufiji                     13.427609
Internal                   13.106061
Lake Tanganyika            10.828283
Wami / Ruvu                10.079125
Lake Nyasa                  8.560606
Ruvuma / Southern Coast     7.563973
Lake Rukwa                  4.131313
Name: basin, dtype: float64
```

basin is a nice clustering feature (hydrographic clustering) and has no null values.

Region

In [923…
```
training_data["region"].value_counts()/len(training_data)*100
```

Out[923]:
```
Iringa           8.912458
Shinyanga        8.387205
Mbeya            7.809764
Kilimanjaro      7.372054
Morogoro         6.744108
Arusha           5.639731
Kagera           5.582492
Mwanza           5.222222
Kigoma           4.740741
Ruvuma           4.444444
Pwani            4.436027
Tanga            4.287879
Dodoma           3.705387
Singida          3.523569
Mara             3.314815
Tabora           3.297980
Rukwa            3.043771
Mtwara           2.912458
Manyara          2.664983
Lindi            2.602694
Dar es Salaam    1.355219
Name: region, dtype: float64
```

There are 21 distinct values, whereas region_code had 27. Either of them could work as geographic clustering feature.

Lga

In [924…
```
training_data["lga"].value_counts()/len(training_data)*100
```

Out[924]:
```
Njombe          4.213805
Arusha Rural    2.107744
Moshi Rural     2.106061
Bariadi         1.981481
Rungwe          1.861953
                  ...
Moshi Urban     0.132997
Kigoma Urban    0.119529
Arusha Urban    0.106061
Lindi Urban     0.035354
Nyamagana       0.001684
Name: lga, Length: 125, dtype: float64
```

`lga` could be an administrative/political clustering feature, but it has too many levels and classification is not intuitive. Therefore, this feature is dropped.

In [925…
```
training_data.drop('lga', axis=1, inplace=True)
```

Ward

In [926…
```
training_data["ward"].value_counts()/len(training_data)*100
```

Out[926]:
```
Igosi        0.516835
Imalinyi     0.424242
Siha Kati    0.390572
Mdandu       0.388889
Nduruma      0.365320
               ...
Mitole       0.001684
Nyamtinga    0.001684
Mawenzi      0.001684
Uchindile    0.001684
Kinungu      0.001684
Name: ward, Length: 2092, dtype: float64
```

`ward` seems too scattered to be informative (not one value accounts for even 0.6%) and is therefore dropped.

In [927…
```
training_data.drop('ward', axis=1, inplace=True)
```

In [928…
```
training_data['public_meeting'].value_counts()
```

Out[928]:
```
True       51011
False       5055
Unknown     3334
Name: public_meeting, dtype: int64
```

Recorded by

In [929…
```
training_data["recorded_by"].value_counts()/len(training_data)*100
```

Out[929]:
```
GeoData Consultants Ltd    100.0
Name: recorded_by, dtype: float64
```

`recorded_by` comprises only one value, constant across the whole dataset. This feature is uninformative and must be dropped.

In [930…
```
training_data.drop('recorded_by', axis=1, inplace=True)
```

Scheme name

Scheme name was dropped when dealing with null values

Extraction type class

This was handled when eliminating redundant categories

Management

This was handled when dealing with redundant categories

In [931…
```
training_data['management'].value_counts()
```

Out[931]:
```
vwc                 40507
wug                  6515
water board          2933
wua                  2535
private operator     1971
parastatal           1768
water authority       904
other                 844
company               685
unknown               561
other - school         99
trust                  78
Name: management, dtype: int64
```

Management Group

In [932…
```
training_data['management_group'].value_counts()
```

Out[932]:
```
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
```

management_group is chosen over management. It has nulls (0.91%) as unknown that are handled after dummification.
We will drop the management column

In [933…
```
training_data.drop('management', axis=1, inplace=True)
```

Payment

This was dealt with when dealing with redundant columns

Quality Group

This was dealt with when dealing with redundant columns

Quantity

In [934…
```
training_data["quantity"].value_counts()/len(training_data)*100
```

Out[934]:
```
enough          55.868687
insufficient    25.469697
dry             10.515152
seasonal         6.818182
```

```
unknown           1.328283
Name: quantity, dtype: float64
```

Source

This was dealt with when dealing with redundant columns

Waterpoint Type

This was dealt with when dealing with redundant columns

Conclusion from dealing with non-numeric columns

The following columns were dropped:

- `wpt_name` , `installer` , `recorded_by` , `scheme_name`

The following columns were kept:

- `date_recorded` was converted into datetime format
- `basin` was kept
- `region`
- `lga`
- `ward`
- `extraction_type_class`
- `management_group`
- `payment`
- `quality_group`
- `source`
- `waterpoint_type`

Let's look at our new dataset

In [935…
```
training_data.head()
```

Out[935]:

	id	gps_height	installer	longitude	latitude	basin	region	region_code	district_code	popula
0	69572	1390	Roman	34.938093	-9.856322	Lake Nyasa	Iringa	11	5	
1	8776	1399	GRUMETI	34.698766	-2.147466	Lake Victoria	Mara	20	2	
2	34310	686	World vision	37.460664	-3.821329	Pangani	Manyara	21	4	
3	67743	263	UNICEF	38.486161	-11.155298	Ruvuma / Southern Coast	Mtwara	90	63	
4	19728	0	Artisan	31.130847	-1.825359	Lake Victoria	Kagera	18	1	

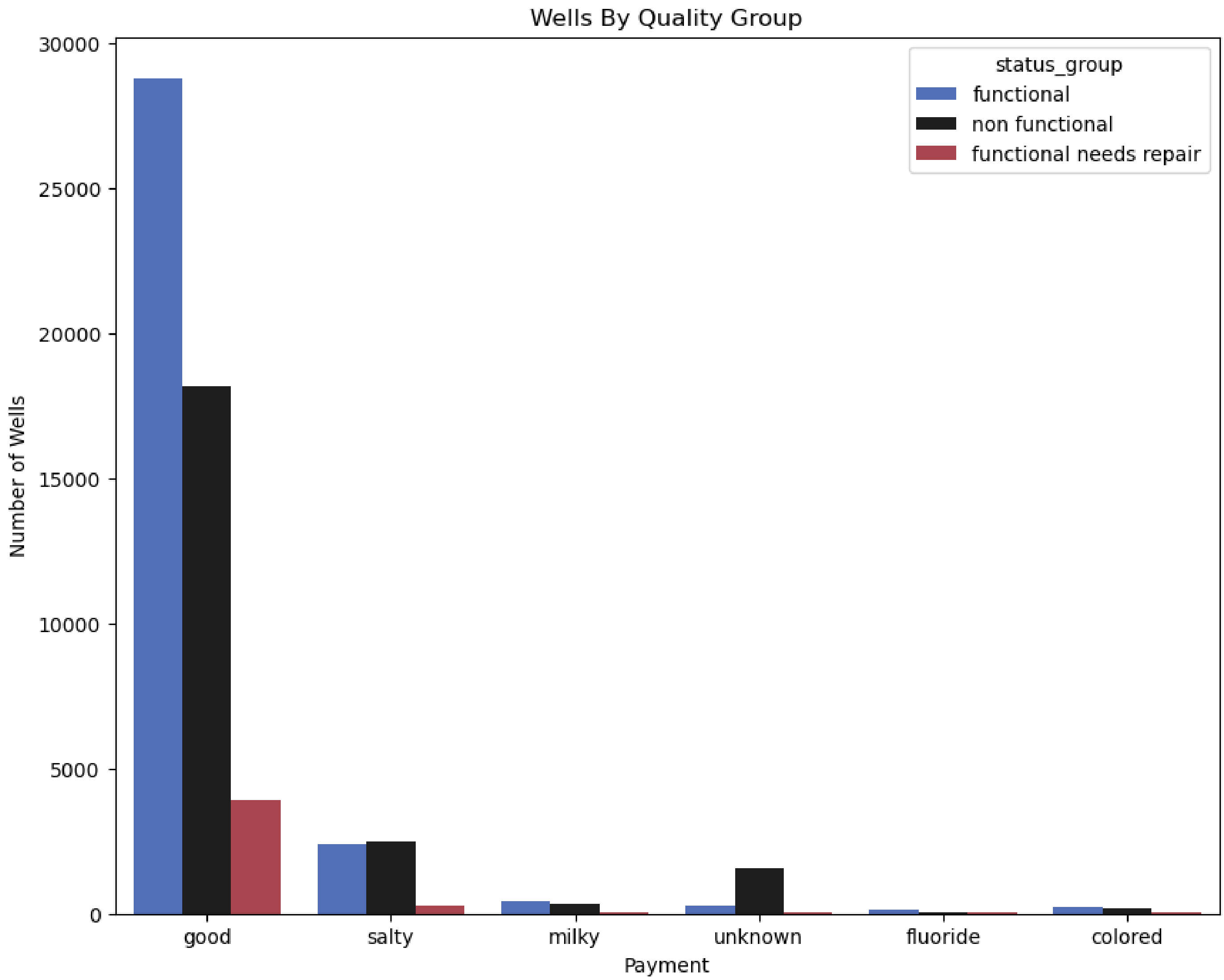
5 rows × 24 columns

Visualizations

Water Quality by Number of Wells

In [936…

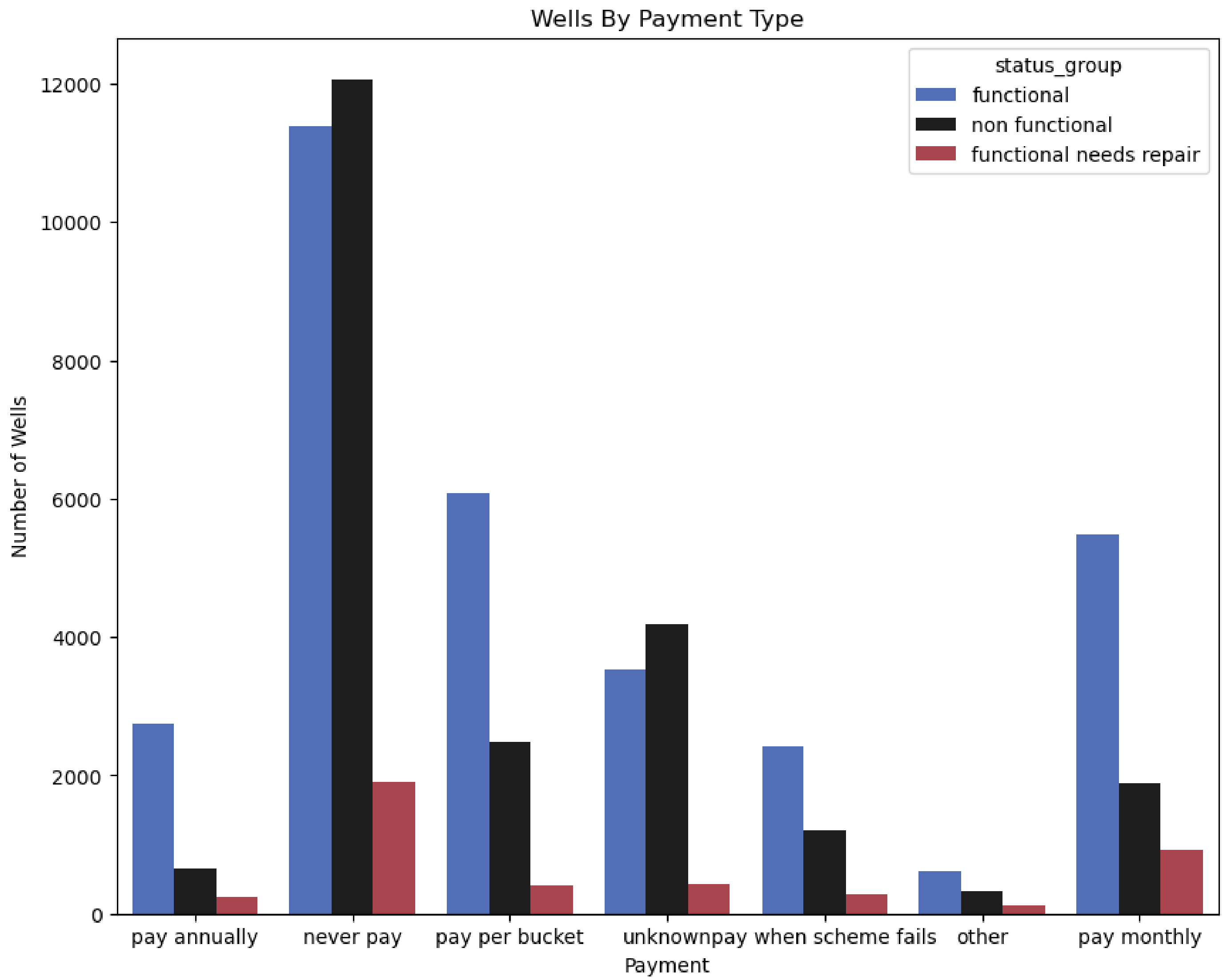
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='quality_group', hue="status_group", data=training_data, palette =
ax.set_xlabel('Payment')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Quality Group');
```



Wells by Payment Type

In [937…

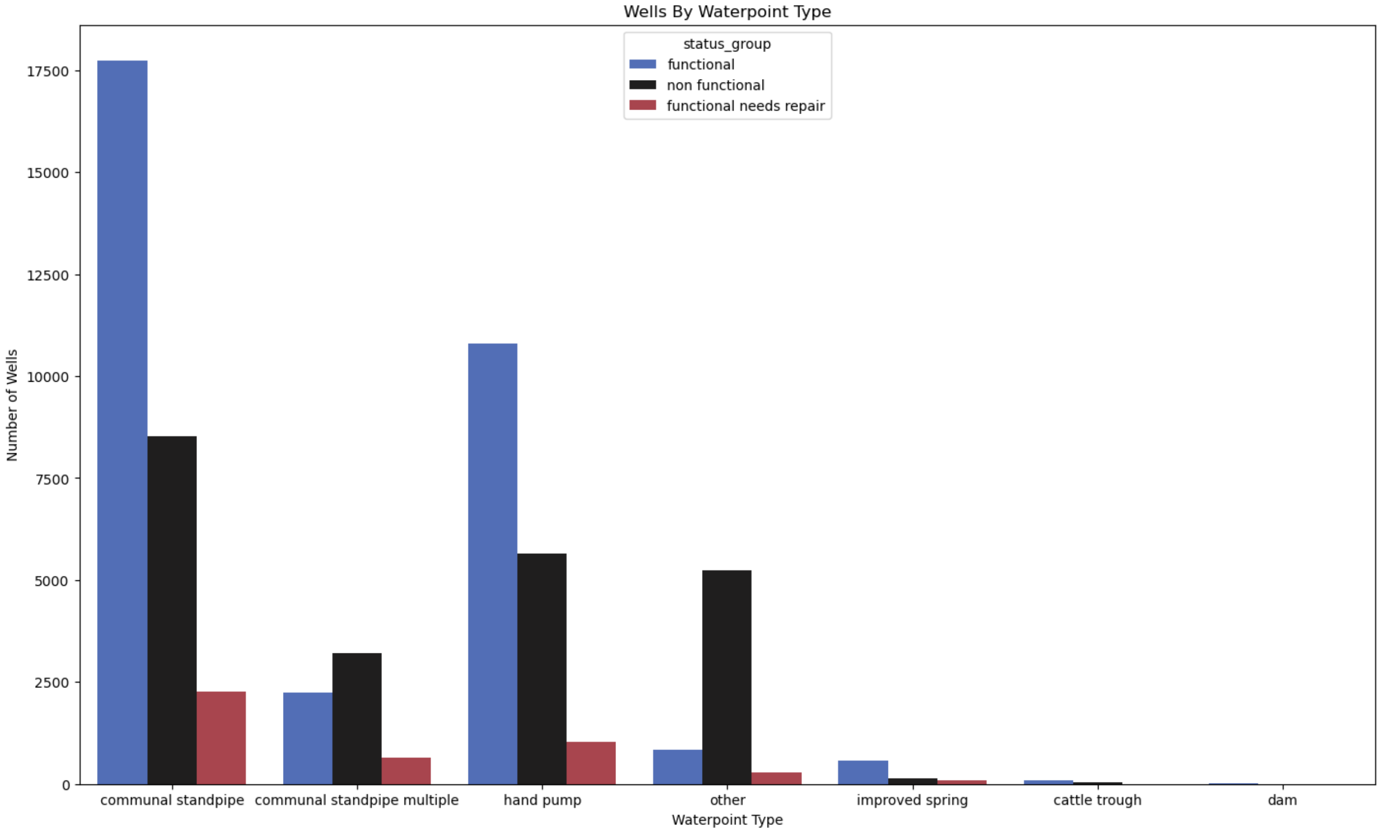
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='payment', hue="status_group", data=training_data, palette = 'icefi
ax.set_xlabel('Payment')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Payment Type');
```



Wells by Waterpoint Type

In [938…

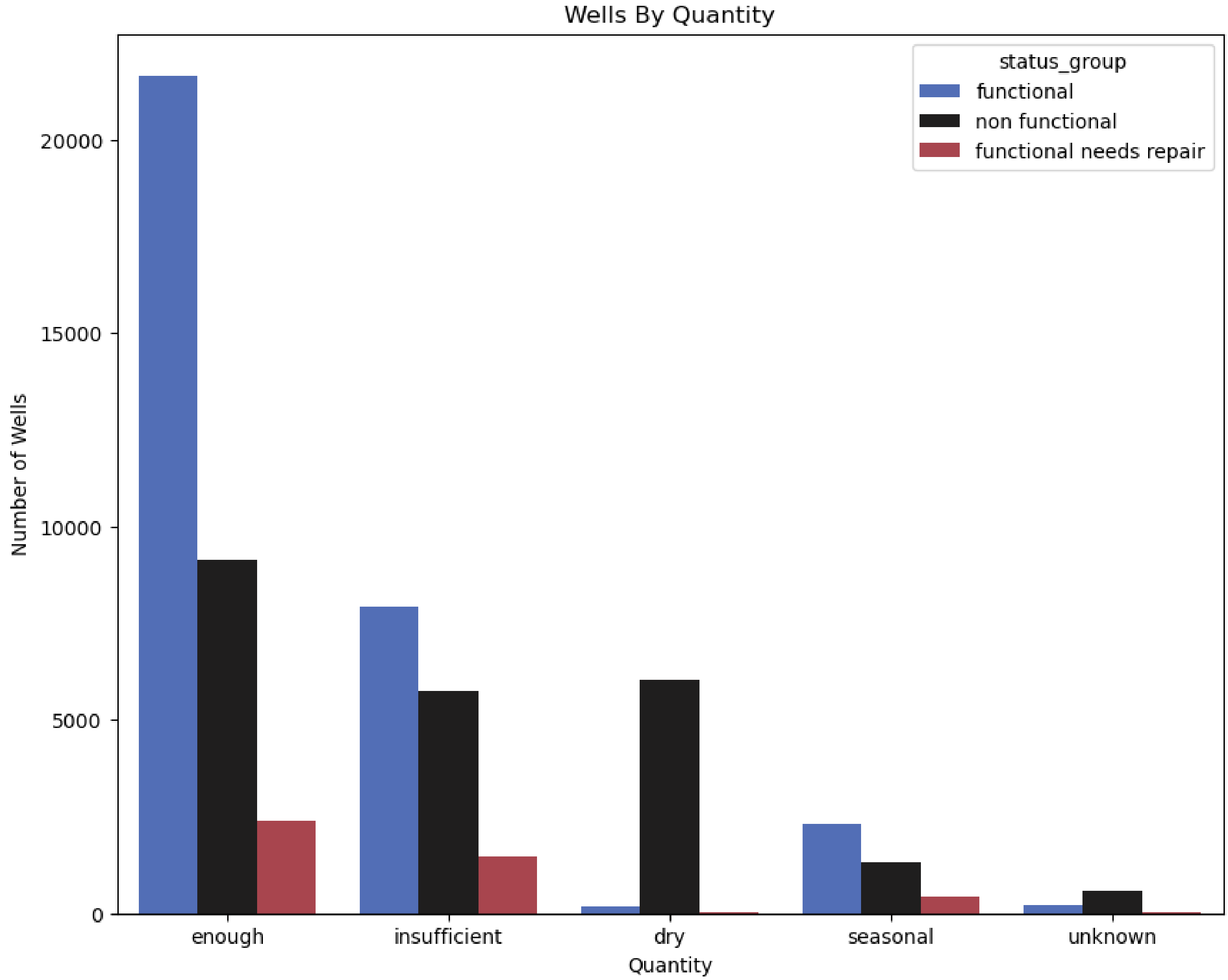
```
plt.figure(figsize=(17,10))
ax = sns.countplot(x='waterpoint_type', hue="status_group", data=training_data, palette
ax.set_xlabel('Waterpoint Type')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Waterpoint Type');
```



Wells by Quantity

In [939…

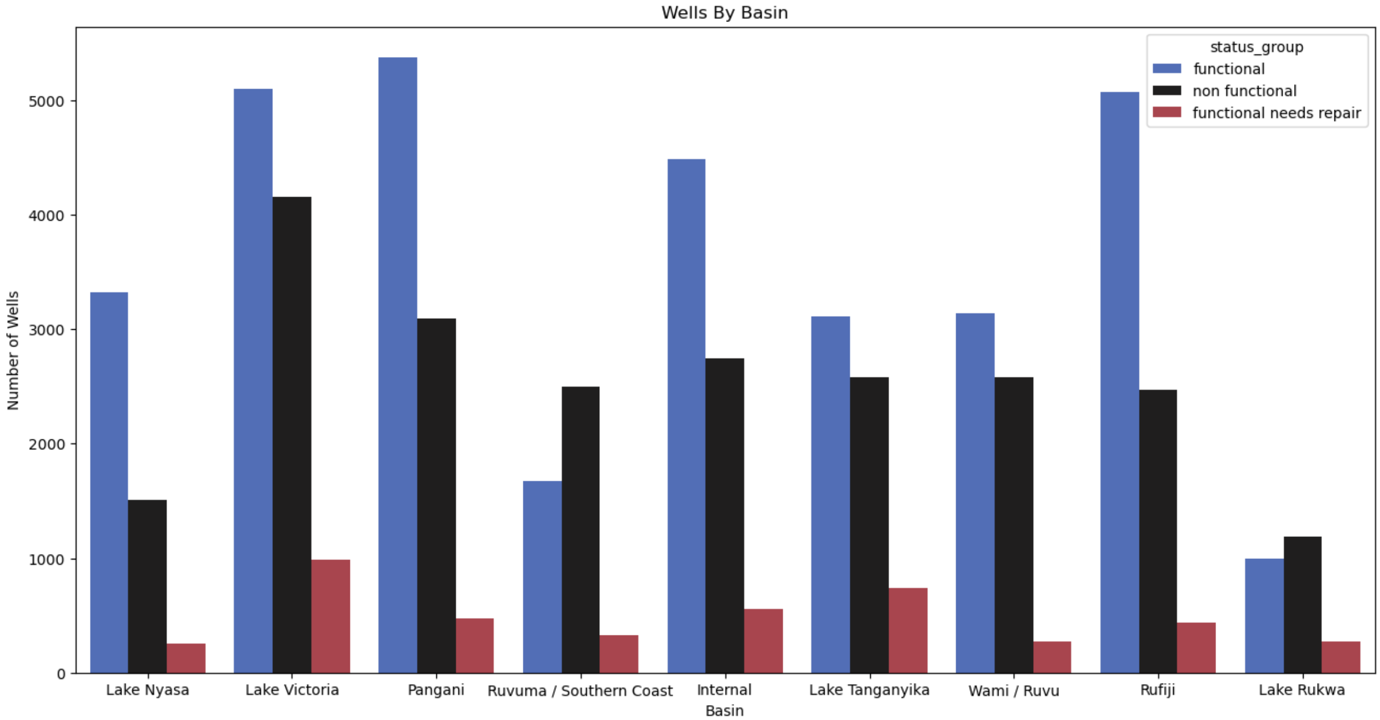
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='quantity', hue="status_group", data=training_data, palette = 'icef
ax.set_xlabel('Quantity')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Quantity');
```



Wells By Basin

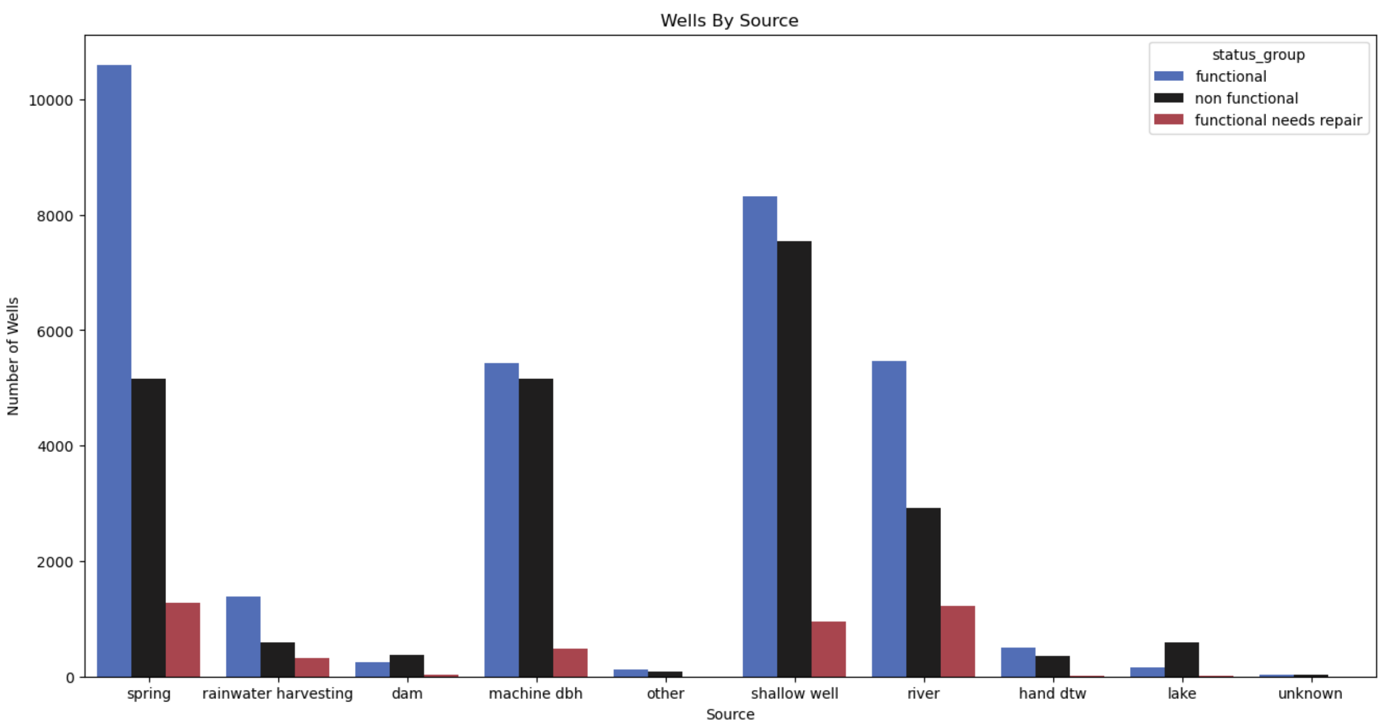
In [940…

```
plt.figure(figsize=(16,8))
ax = sns.countplot(x='basin', hue="status_group", data=training_data, palette = 'icefire
ax.set_xlabel('Basin')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Basin');
```



Wells by Source

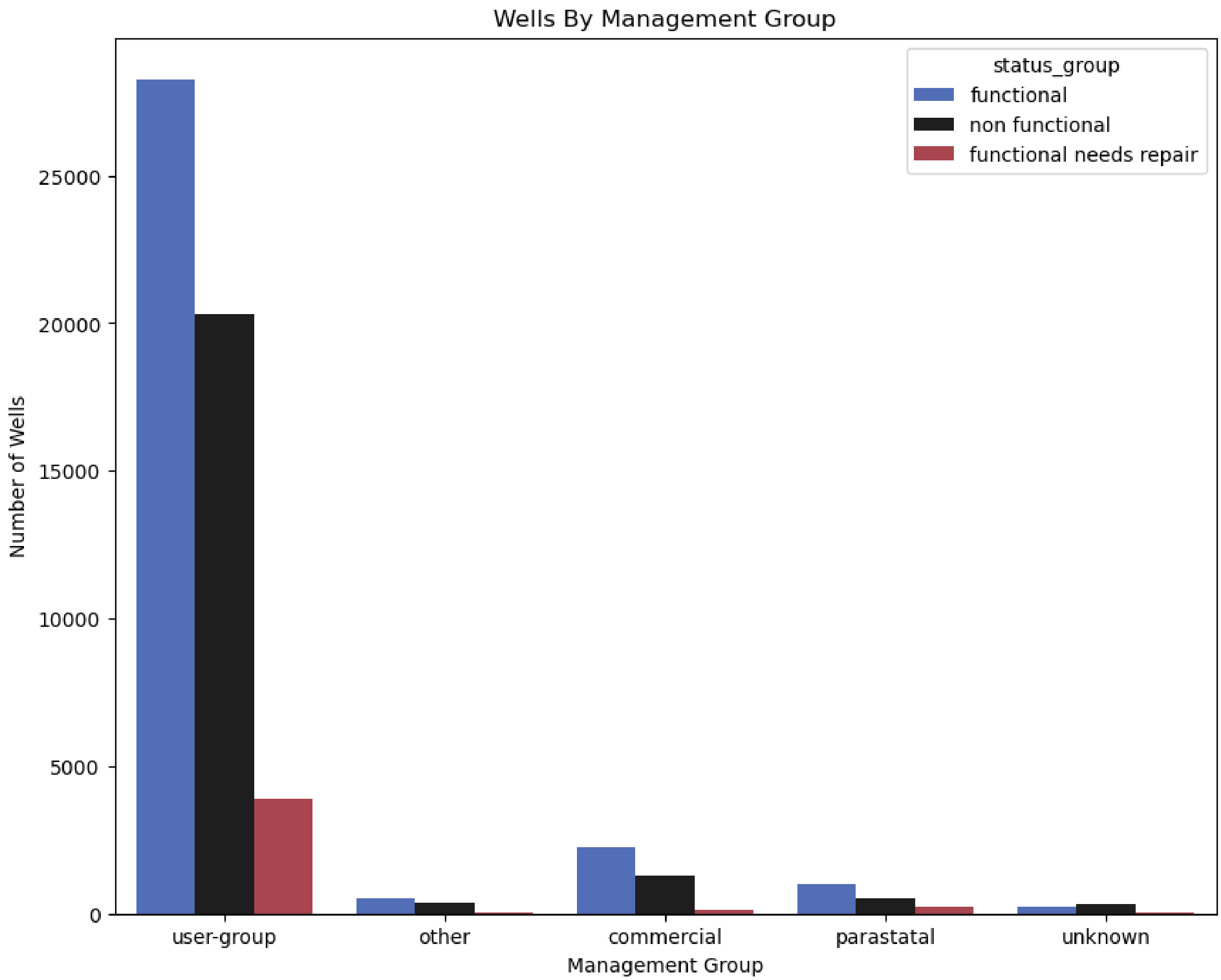
In [941…
```
plt.figure(figsize=(16,8))
ax = sns.countplot(x='source', hue="status_group", data=training_data, palette = 'icefir
ax.set_xlabel('Source')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Source');
```



Wells By Management Group

In [942…
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='management_group', hue="status_group", data=training_data, palette
ax.set_xlabel('Management Group')
```

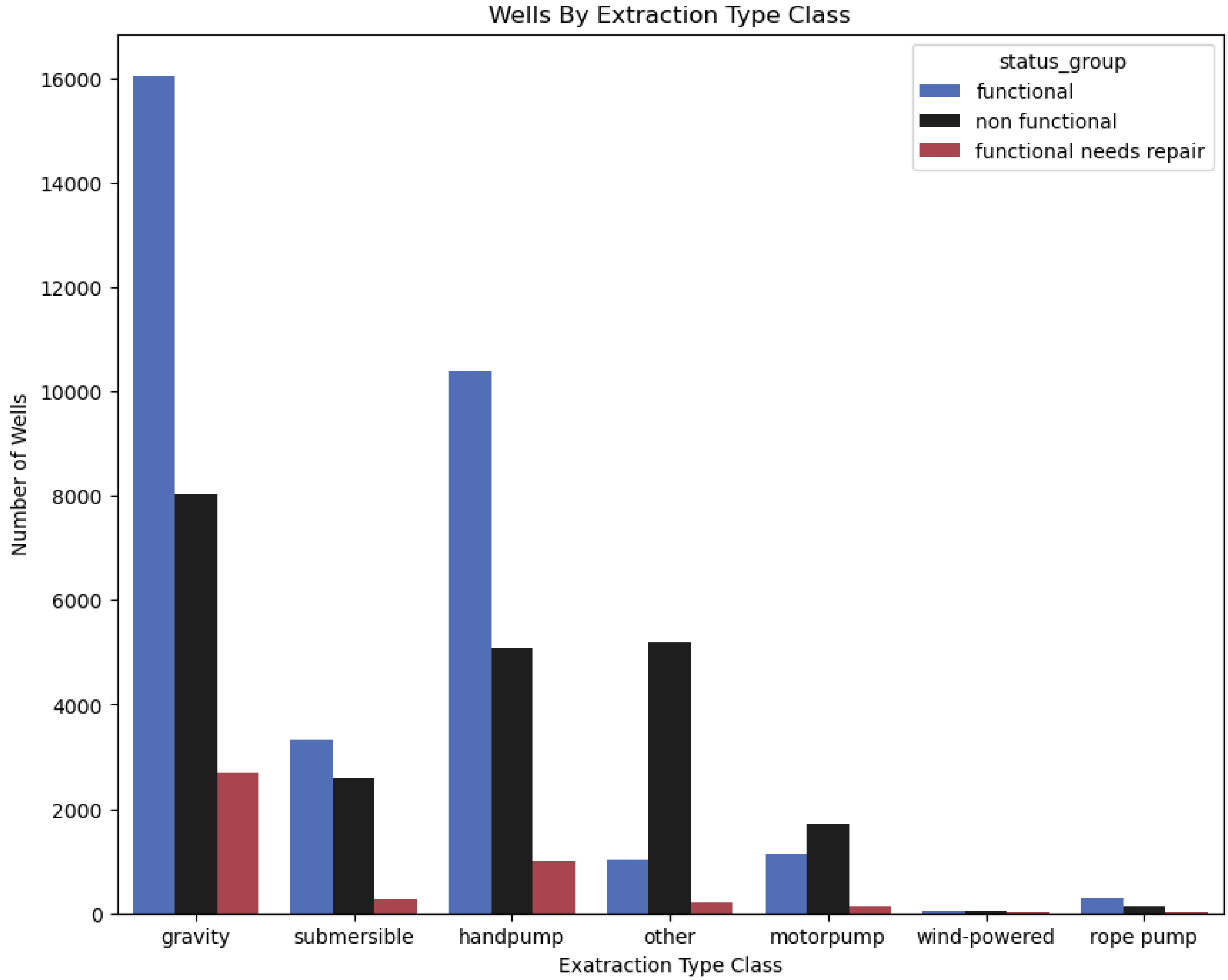
```
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Management Group');
```



Wells By Extraction Type Class

In [943…

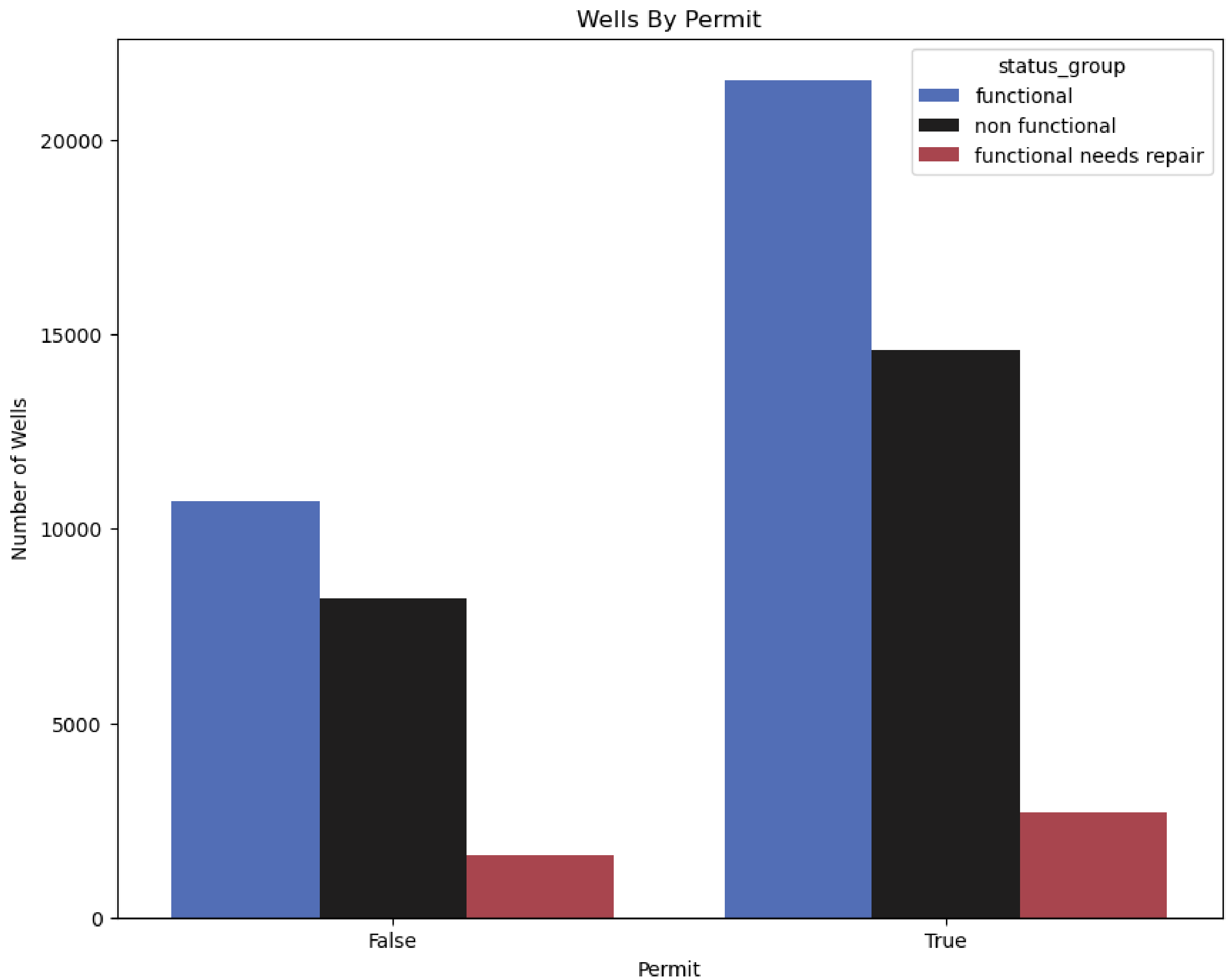
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='extraction_type_class', hue="status_group", data=training_data, pa
ax.set_xlabel('Exatraction Type Class')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Extraction Type Class');
```



Wells By Permit

In [944…

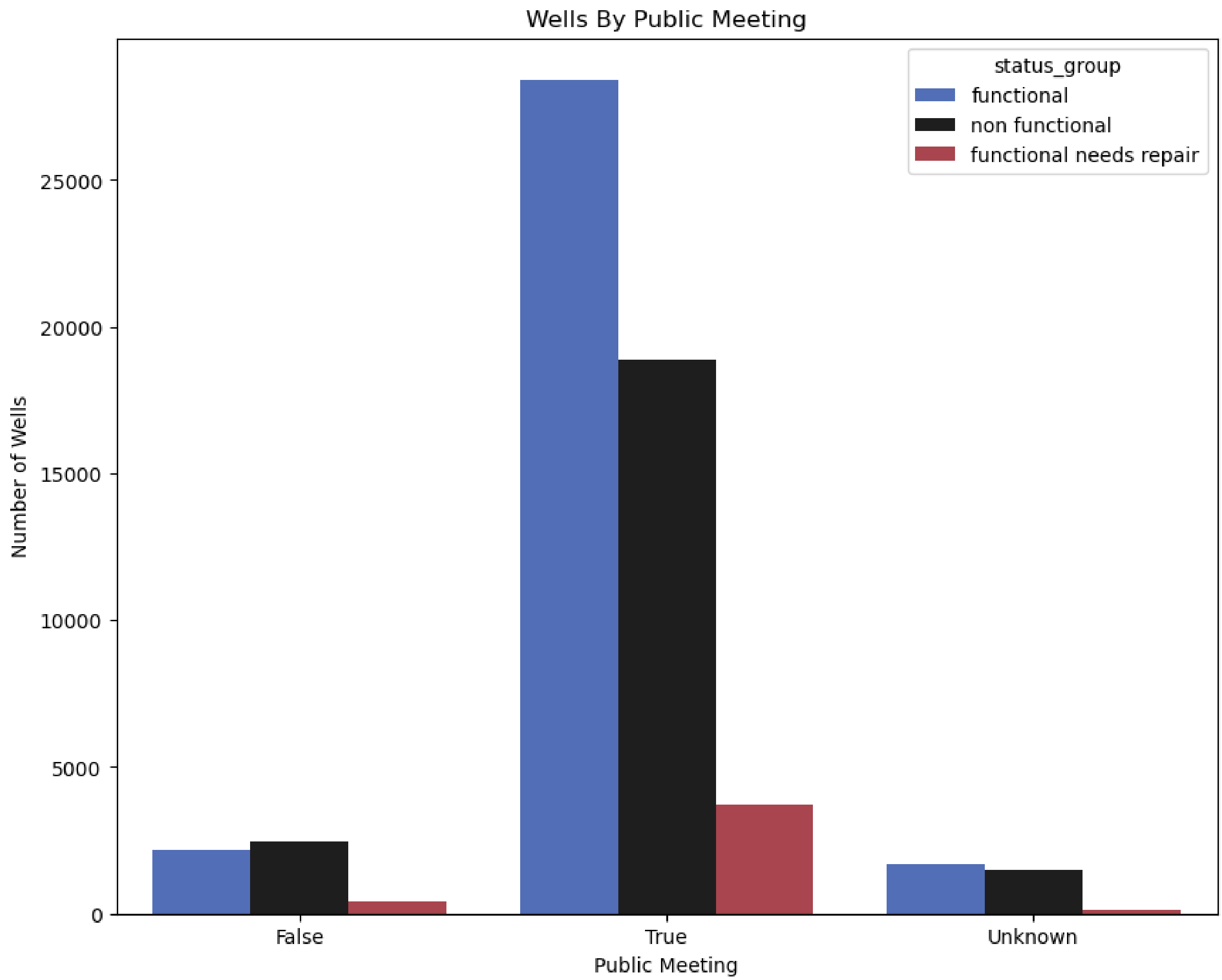
```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='permit', hue="status_group", data=training_data, palette = 'icefir
ax.set_xlabel('Permit')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Permit');
```



Wells By Public Meeting

In [945…

```
plt.figure(figsize=(10,8))
ax = sns.countplot(x='public_meeting', hue="status_group", data=training_data, palette =
ax.set_xlabel('Public Meeting')
ax.set_ylabel('Number of Wells')
ax.set_title('Wells By Public Meeting');
```



Modeling

Create an initial dataframe dropping all the uninformative features, as well as the categorical features with a large number of levels:

In [946…
```
initial_numeric_cols = ["id", "gps_height",
                        "population",
                        "construction_year"]
```

In [947…
```
initial_object_cols = ["basin",
                       "month_recorded",
                       "region",
                       "public_meeting",
                       "permit",
                       "extraction_type_class",
                       "management_group",
                       "payment",
                       "quality_group",
                       "quantity",
                       "source",
                       "waterpoint_type"]
```

In [948…
```
Xy_init = training_data[initial_numeric_cols + initial_object_cols + ["status_group"]].c
```

In [949…
```
Xy_init = Xy_init.set_index("id")
```

Check missing values

In [950…
```
Xy_init.isnull().sum()
```

Out[950]:
```
gps_height               0
population               0
construction_year        0
basin                    0
month_recorded           0
region                   0
public_meeting           0
permit                   0
extraction_type_class    0
management_group         0
payment                  0
quality_group            0
quantity                 0
source                   0
waterpoint_type          0
status_group             0
dtype: int64
```

No missing values

In [951…
```
Xy_init.head()
```

Out[951]:

id	gps_height	population	construction_year	basin	month_recorded	region	public_meeting	permit
69572	1390	109	1999	Lake Nyasa	3	Iringa	True	False
8776	1399	280	2010	Lake Victoria	3	Mara	Unknown	True
34310	686	250	2009	Pangani	2	Manyara	True	True
67743	263	58	1986	Ruvuma / Southern Coast	1	Mtwara	True	True
19728	0	150	1996	Lake Victoria	7	Kagera	True	True

Feature Engineering

Outliers in numeric variables

In [952…
```
training_data[initial_numeric_cols].isnull().sum()
```

Out[952]:
```
id                   0
gps_height           0
population           0
construction_year    0
dtype: int64
```

For `construction_year`, it was decided to impute the zero years with the mean. Also, it may be more suitable to derive a numeric feature construction_age expressing the time delta since construction instead of the original feature.

In [953…
```
Xy_init.construction_year.isnull().sum()
```
Out[953]:
```
0
```
In [954…
```
current = datetime.now()
```
In [955…
```
Xy_init["construction_age"] = (current.year - Xy_init["construction_year"]).astype("int"
```
In [956…
```
Xy_init.construction_age.value_counts()
```
Out[956]:
```
28    21520
14     2645
16     2613
15     2533
24     2091
17     1587
18     1471
21     1286
13     1256
20     1123
12     1084
22     1075
46     1037
29     1014
19     1011
25      979
26      966
34      954
39      945
44      811
40      779
42      744
30      738
52      708
50      676
27      644
32      640
31      608
23      540
36      521
41      488
49      437
38      434
48      414
54      411
33      324
35      316
37      302
43      238
47      202
45      192
51      184
11      176
53      145
64      102
57       88
61       85
56       77
55       59
60       40
62       30
63       21
59       19
```

```
58        17
Name: construction_age, dtype: int64
```

Drop `construction_year`

In [957…
```
Xy_init.drop('construction_year', axis=1, inplace=True)
```

In [958…
```
clean_numeric_cols = [
                        "gps_height",
                        "population",
                        "construction_age"]
clean_numeric_cols
```

Out[958]:
```
['gps_height', 'population', 'construction_age']
```

In [959…
```
print(round(Xy_init[clean_numeric_cols].describe()),2)
```

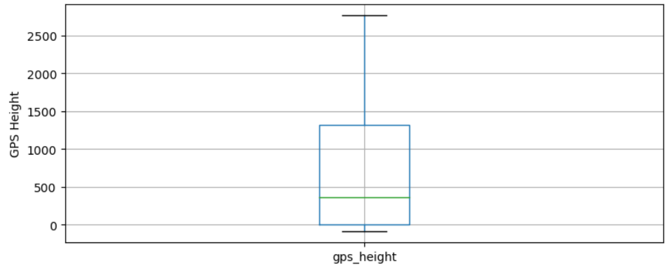
```
       gps_height  population  construction_age
count     59400.0     59400.0           59400.0
mean        668.0       234.0              27.0
std         693.0       456.0              10.0
min         -90.0         1.0              11.0
25%           0.0       100.0              20.0
50%         369.0       150.0              28.0
75%        1319.0       215.0              28.0
max        2770.0     30500.0              64.0 2
```

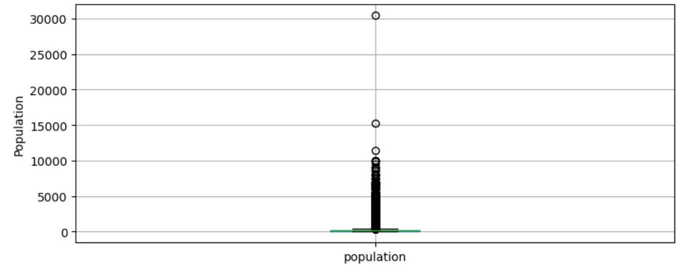
In [960…
```
Xy_init.construction_age.isnull().sum()
```

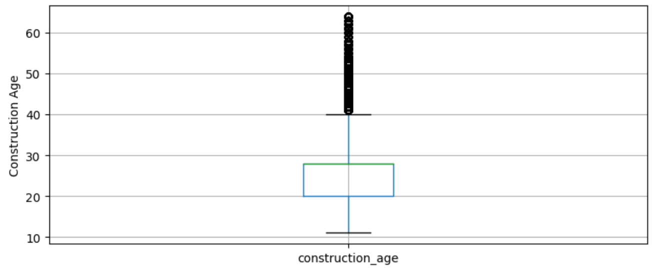
Out[960]:
```
0
```

I will draw boxplots to visualise outliers in the above variables.

In [961…
```
plt.figure(figsize=(20,8))


plt.subplot(2, 2, 1)
fig = Xy_init.boxplot(column='gps_height')
fig.set_title('')
fig.set_ylabel('GPS Height')

plt.subplot(2, 2, 2)
fig = Xy_init.boxplot(column='population')
fig.set_title('')
fig.set_ylabel('Population')

plt.subplot(2, 2, 3)
fig = Xy_init.boxplot(column='construction_age')
fig.set_title('')
fig.set_ylabel('Construction Age');
```





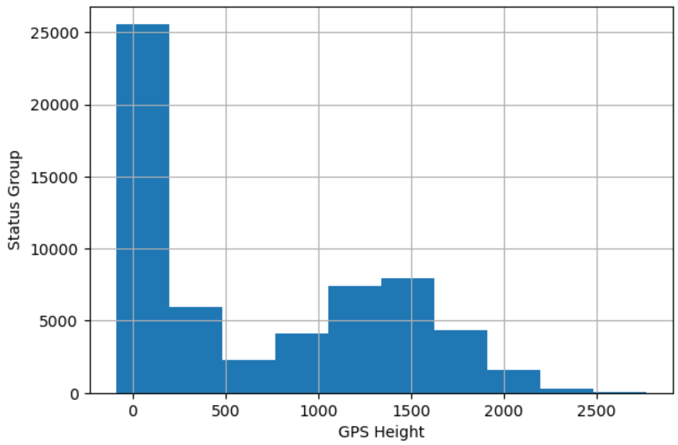


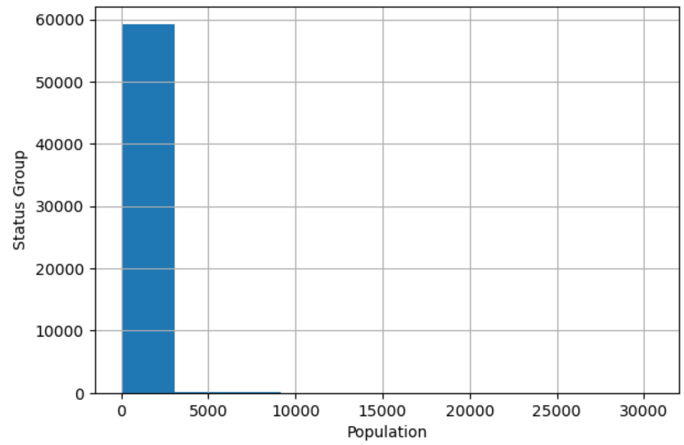
Check the distribution of variables

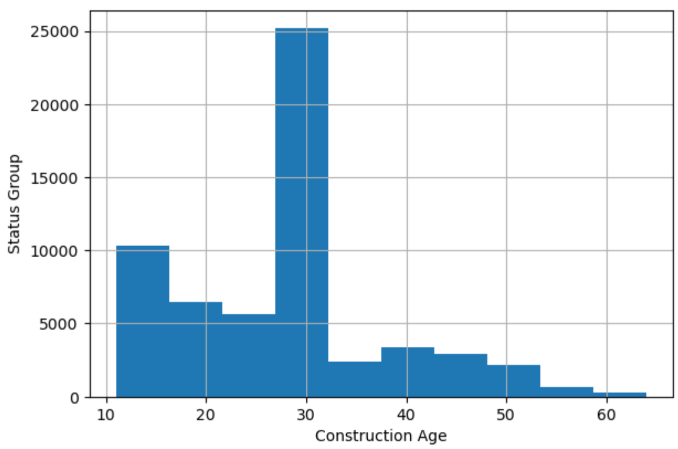
Now, I will plot the histograms to check distributions to find out if they are normal or skewed. If the variable follows normal distribution, then I will do `Extreme Value Analysis` otherwise if they are skewed, I will find IQR (Interquantile range).

In [962…

```
# plot histogram to check distribution

plt.figure(figsize=(15,10))


plt.subplot(2, 2, 1)
fig = Xy_init["gps_height"].hist(bins=10)
fig.set_xlabel('GPS Height')
fig.set_ylabel('Status Group')

plt.subplot(2, 2, 2)
fig = Xy_init["population"].hist(bins=10)
fig.set_xlabel('Population')
fig.set_ylabel('Status Group')

plt.subplot(2, 2, 3)
fig = Xy_init["construction_age"].hist(bins=10)
fig.set_xlabel('Construction Age')
fig.set_ylabel('Status Group');
```







We can see that all the four variables are skewed. So, I will use interquantile range to find outliers.

GPS Height

In [963…

```
# find outliers for GPS Height variable

IQR = Xy_init["gps_height"].quantile(0.75) - Xy_init.gps_height.quantile(0.25)
Lower_fence = Xy_init["gps_height"].quantile(0.25) - (IQR * 3)
Upper_fence = Xy_init["gps_height"].quantile(0.75) + (IQR * 3)
print('GPS Height outliers are values < {lowerboundary} or > {upperboundary}'.format(low
```

```
GPS Height outliers are values < -3957.75 or > 5277.0
```

For `gps_height`, the minimum and maximum values are -90.0 and 2770.0. So, the outliers are values > 5277. There are no outliers

Population

In [964…

```
# find outliers for Population variable

IQR = Xy_init["population"].quantile(0.75) - Xy_init.population.quantile(0.25)
Lower_fence = Xy_init["population"].quantile(0.25) - (IQR * 3)
Upper_fence = Xy_init["population"].quantile(0.75) + (IQR * 3)
print('population outliers are values < {lowerboundary} or > {upperboundary}'.format(low
```

```
population outliers are values < -245.0 or > 560.0
```

For `population`, the minimum and maximum values are 1.0 and 30500.0. So, the outliers are values > 560.

Construction Age

In [965…

```
# find outliers for Construction Age Variable
```

```
IQR = Xy_init["construction_age"].quantile(0.75) - Xy_init.construction_age.quantile(0.2
Lower_fence = Xy_init["construction_age"].quantile(0.25) - (IQR * 3)
Upper_fence = Xy_init["construction_age"].quantile(0.75) + (IQR * 3)
print('Construction Age outliers are values < {lowerboundary} or > {upperboundary}'.form
```

```
Construction Age outliers are values < -4.0 or > 52.0
```

For `construction_age`, the minimum and maximum values are 11.0 and 64.0. So, the outliers are values > 52.0.

In [966…
```
Xy_init['permit'] = Xy_init['permit'].astype(bool).astype(int) #converting from T/F to 0
```

In [967…
```
Xy_init['public_meeting'] = Xy_init['public_meeting'].astype(bool).astype(int) #converti
```

Re-declaring numeric anc categorical columns. Moving `permit` and `public_meeting` to numeric now that they are 0-1

In [968…
```
initial_numeric_cols = ["id",
                        "gps_height",
                        "population",
                        "construction_year",
                        'permit',
                        'public_meeting']
```

In [969…
```
initial_object_cols = ['basin',
 'month_recorded',
 'region',
 'extraction_type_class',
 'management_group',
 'payment',
 'quality_group',
 'quantity',
 'source',
 'waterpoint_type']
```

In [970…
```
Xy_init[initial_object_cols] = Xy_init[initial_object_cols].astype("category")
```

In [971…
```
Xy_init.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 59400 entries, 69572 to 26348
Data columns (total 16 columns):
 #   Column                 Non-Null Count  Dtype   
---  ------                 --------------  -----   
 0   gps_height             59400 non-null  int64   
 1   population             59400 non-null  int64   
 2   basin                  59400 non-null  category
 3   month_recorded         59400 non-null  category
 4   region                 59400 non-null  category
 5   public_meeting         59400 non-null  int32   
 6   permit                 59400 non-null  int32   
 7   extraction_type_class  59400 non-null  category
 8   management_group       59400 non-null  category
 9   payment                59400 non-null  category
 10  quality_group          59400 non-null  category
 11  quantity               59400 non-null  category
 12  source                 59400 non-null  category
 13  waterpoint_type        59400 non-null  category
 14  status_group           59400 non-null  object  
 15  construction_age       59400 non-null  int32   
```

```
dtypes: category(10), int32(3), int64(2), object(1)
memory usage: 3.1+ MB
```

Declare feature vector and target variable

In [972…
```
target_status_group = {'functional':0,
                       'non functional': 2,
                       'functional needs repair': 1}
Xy_init['status_group'] = Xy_init['status_group'].replace(target_status_group)
```

To make our model, we changed the target variable to 0,1 and 2 values.

In [973…
```
training_data['status_group'].value_counts()
```

Out[973]:
```
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
```

In [974…
```
X = Xy_init.drop(['status_group'], axis=1)

y = Xy_init['status_group']
```

9. Split data into separate training and test set

In [975…
```
# split X and y into training and testing sets

from sklearn.model_selection import train_test_split

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

In [976…
```
# check the shape of X_train and X_test

X_train.shape, X_test.shape
```

Out[976]:
```
((47520, 15), (11880, 15))
```

In [977…
```
# Check data types in x train

X_train.dtypes
```

Out[977]:
```
gps_height                  int64
population                  int64
basin                    category
month_recorded           category
region                   category
public_meeting              int32
permit                      int32
extraction_type_class    category
management_group         category
payment                  category
quality_group            category
quantity                 category
source                   category
waterpoint_type          category
construction_age            int32
dtype: object
```

We already know that there are no missing values, but we can check to confirm

In [978…

```
X_train.isnull().sum()
```

Out[978]:

```
gps_height               0
population               0
basin                    0
month_recorded           0
region                   0
public_meeting           0
permit                   0
extraction_type_class    0
management_group         0
payment                  0
quality_group            0
quantity                 0
source                   0
waterpoint_type          0
construction_age         0
dtype: int64
```

In [979…

```
X_test.isnull().sum()
```

Out[979]:

```
gps_height               0
population               0
basin                    0
month_recorded           0
region                   0
public_meeting           0
permit                   0
extraction_type_class    0
management_group         0
payment                  0
quality_group            0
quantity                 0
source                   0
waterpoint_type          0
construction_age         0
dtype: int64
```

Engineering outliers in numerical variables

We have seen that the `population` and `construction_age` , columns contain outliers

In [980…

```
upper_thresholds = {
    'population': 560.0,
    'construction_age': 52.0,
}

for df3 in [X_train, X_test]:
    for column, top in upper_thresholds.items():
        df3[column] = df3[column].clip(upper=top)
```

In [981…

```
print(round(X_train[clean_numeric_cols].describe()),2)
```

```
       gps_height  population  construction_age
count     47520.0     47520.0           47520.0
mean        669.0       184.0              27.0
std         693.0       153.0              10.0
min         -63.0         1.0              11.0
25%           0.0       100.0              20.0
50%         370.0       150.0              28.0
75%        1320.0       213.0              28.0
max        2770.0       560.0              52.0 2
```

In [982…

```
print(round(X_test[clean_numeric_cols].describe()),2)
```

```
      gps_height  population  construction_age
count    11880.0     11880.0           11880.0
mean       667.0       185.0              27.0
std        694.0       152.0              10.0
min        -90.0         1.0              11.0
25%          0.0       100.0              20.0
50%        365.0       150.0              28.0
75%       1316.0       220.0              28.0
max       2623.0       560.0              52.0 2
```

We can see that the outliers in `population` and `construction_age` have been removed

Encode categorical variables

In [983…
```
initial_object_cols
```

Out[983]:
```
['basin',
 'month_recorded',
 'region',
 'extraction_type_class',
 'management_group',
 'payment',
 'quality_group',
 'quantity',
 'source',
 'waterpoint_type']
```

In [984…
```
X_train[initial_object_cols].head()
```

Out[984]:

id	basin	month_recorded	region	extraction_type_class	management_group	payment	quality_group
454	Internal	2	Manyara	gravity	user-group	pay per bucket	good
510	Internal	3	Dodoma	handpump	user-group	never pay	good
14146	Lake Rukwa	7	Mbeya	other	user-group	never pay	good
47410	Rufiji	4	Mbeya	gravity	user-group	pay monthly	good
1288	Wami / Ruvu	4	Morogoro	other	user-group	pay when scheme fails	salty

In [985…
```
X_train.head()
```

Out[985]:

id	gps_height	population	basin	month_recorded	region	public_meeting	permit	extraction_type_cla
454	2092	160.0	Internal	2	Manyara	1	1	gra
510	0	150.0	Internal	3	Dodoma	1	1	handpu
14146	0	150.0	Lake Rukwa	7	Mbeya	1	0	ot
47410	0	150.0	Rufiji	4	Mbeya	1	1	gra
1288	1023	120.0	Wami / Ruvu	4	Morogoro	1	1	ot

In [986…

```
# using ohe Recommended

import category_encoders as ce

ohe = ce.one_hot.OneHotEncoder(cols=['basin','month_recorded','region', 'extraction_type
                             'quantity', 'source', 'waterpoint_type'], handle_missing="v

ohe.fit(X_train)

X_train = ohe.transform(X_train)
X_test = ohe.transform(X_test)
```

Encode Status_group variable- Target

In [987…

```
# import category_encoders as ce

# binary_encoder = ce.BinaryEncoder(cols=['RainToday'])

# X_train = binary_encoder.fit_transform(X_train)

# X_test = binary_encoder.transform(X_test)
```

In [988…

```
X_train.head()
```

Out[988]:

	gps_height	population	basin_1	basin_2	basin_3	basin_4	basin_5	basin_6	basin_7	basin_8	...	s
id												
454	2092	160.0	1	0	0	0	0	0	0	0	...	
510	0	150.0	1	0	0	0	0	0	0	0	...	
14146	0	150.0	0	1	0	0	0	0	0	0	...	
47410	0	150.0	0	0	1	0	0	0	0	0	...	
1288	1023	120.0	0	0	0	1	0	0	0	0	...	

5 rows × 94 columns

In [989…

```
X_test.head()
```

Out[989]:

	gps_height	population	basin_1	basin_2	basin_3	basin_4	basin_5	basin_6	basin_7	basin_8	...	s
id												
37098	0	150.0	0	0	0	0	0	1	0	0	...	
14530	0	150.0	0	0	0	0	0	1	0	0	...	
62607	1675	148.0	1	0	0	0	0	0	0	0	...	
46053	0	150.0	0	1	0	0	0	0	0	0	...	
47083	1109	235.0	1	0	0	0	0	0	0	0	...	

5 rows × 94 columns

We now have training and testing set ready for model building. Before that, we should map all the feature variables onto the same scale. It is called `feature scaling`. I will do it as follows.

In [990…
```python
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()

scaler.fit(X_train)
```

Out[990]:
```
MinMaxScaler
MinMaxScaler()
```

In [991…
```python
X_train = pd.DataFrame(
    scaler.transform(X_train),
    columns=X_train.columns
    )
```

In [992…
```python
X_test = pd.DataFrame(
    scaler.transform(X_test),
    columns=X_test.columns
    )
```

In [993…
```python
X_train.head()
```

Out[993]:

	gps_height	population	basin_1	basin_2	basin_3	basin_4	basin_5	basin_6	basin_7	basin_8	...	sourc
0	0.760678	0.284436	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
1	0.022238	0.266547	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
2	0.022238	0.266547	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	
3	0.022238	0.266547	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	
4	0.383339	0.212880	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	...	

5 rows × 94 columns

In [994…
```python
X_train.isnull().sum()
```

Out[994]:
```
gps_height           0
population           0
basin_1              0
basin_2              0
basin_3              0
                    ..
waterpoint_type_4    0
waterpoint_type_5    0
waterpoint_type_6    0
waterpoint_type_7    0
construction_age     0
Length: 94, dtype: int64
```

In [995…
```python
X_test.isnull().sum()
```

Out[995]:
```
gps_height           0
population           0
basin_1              0
basin_2              0
basin_3              0
                    ..
waterpoint_type_4    0
waterpoint_type_5    0
waterpoint_type_6    0
waterpoint_type_7    0
construction_age     0
Length: 94, dtype: int64
```

We now have `X_train` dataset ready to be fed into the Logistic Regression classifier. I will do it as follows.

Model Training

Model 1: Logistic Regression Iteration 1

In [996…

```
# instantiate the model
logreg = LogisticRegression(solver='sag', max_iter=400, multi_class='auto', random_state


# fit the model
logreg.fit(X_train, y_train)
```

Out[996]:

```
LogisticRegression
LogisticRegression(max_iter=400, random_state=42, solver='sag')
```

In [997…

```
y_pred_test = logreg.predict(X_test)

y_pred_test
```

Out[997]:

```
array([2, 0, 0, ..., 2, 0, 0], dtype=int64)
```

In [998…

```
# Check accuracy score

from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred_test)))
```

```
Model accuracy score: 0.7297
```

Here, **y_test** are the true class labels and **y_pred_test** are the predicted class labels in the test-set.

Compare the train-set and test-set accuracy

Now, I will compare the train-set and test-set accuracy to check for overfitting.

In [999…

```
y_pred_train = logreg.predict(X_train)

y_pred_train
```

Out[999]:

```
array([0, 0, 2, ..., 2, 0, 2], dtype=int64)
```

In [100…

```
print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred_tra
```

```
Training-set accuracy score: 0.7322
```

Check for overfitting or underfitting

In [100…

```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(logreg.score(X_test, y_test)))
```

```
Training set score: 0.7322
Test set score: 0.7297
```

The training-set accuracy score is 0.7311 while the test-set accuracy is 0.7297. These two values are quite comparable. So, there is no question of overfitting.

In Logistic Regression, we use default value of C = 1. It provides good performance with approximately 73% accuracy on both the training and the test set. But the model performance on both the training and test set are very comparable. It is likely the case of underfitting.

I will increase C and fit a more flexible model.

In [100…

```
# fit the Logsitic Regression model with C=100

# instantiate the model
logreg100 = LogisticRegression(C=100, solver='sag', random_state=42)


# fit the model
logreg100.fit(X_train, y_train)
```

```
c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear_model\_sag.py:3
50: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
```

Out[1002]:

```
LogisticRegression
LogisticRegression(C=100, random_state=42, solver='sag')
```

In [100…

```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg100.score(X_train, y_train)))

print('Test set score: {:.4f}'.format(logreg100.score(X_test, y_test)))
```

```
Training set score: 0.7304
Test set score: 0.7294
```

We can see that, C=100 results in slightly test set accuracy and also a slightly reduced training set accuracy. So, we can conclude that a more complex model does not perform better.

Now, I will investigate, what happens if we use more regularized model than the default value of C=1, by setting C=0.01.

In [100…

```
# fit the Logsitic Regression model with C=001

# instantiate the model
logreg001 = LogisticRegression(C=0.01, solver='sag', random_state=42)


# fit the model
logreg001.fit(X_train, y_train)
```

Out[1004]:

```
LogisticRegression
LogisticRegression(C=0.01, random_state=42, solver='sag')
```

In [100…

```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg001.score(X_train, y_train)))
```

```
print('Test set score: {:.4f}'.format(logreg001.score(X_test, y_test)))
```

```
Training set score: 0.7303
Test set score: 0.7307
```

The training and test set accuracy scores are also lower than the original, so we will continue from the one that used default c= 1

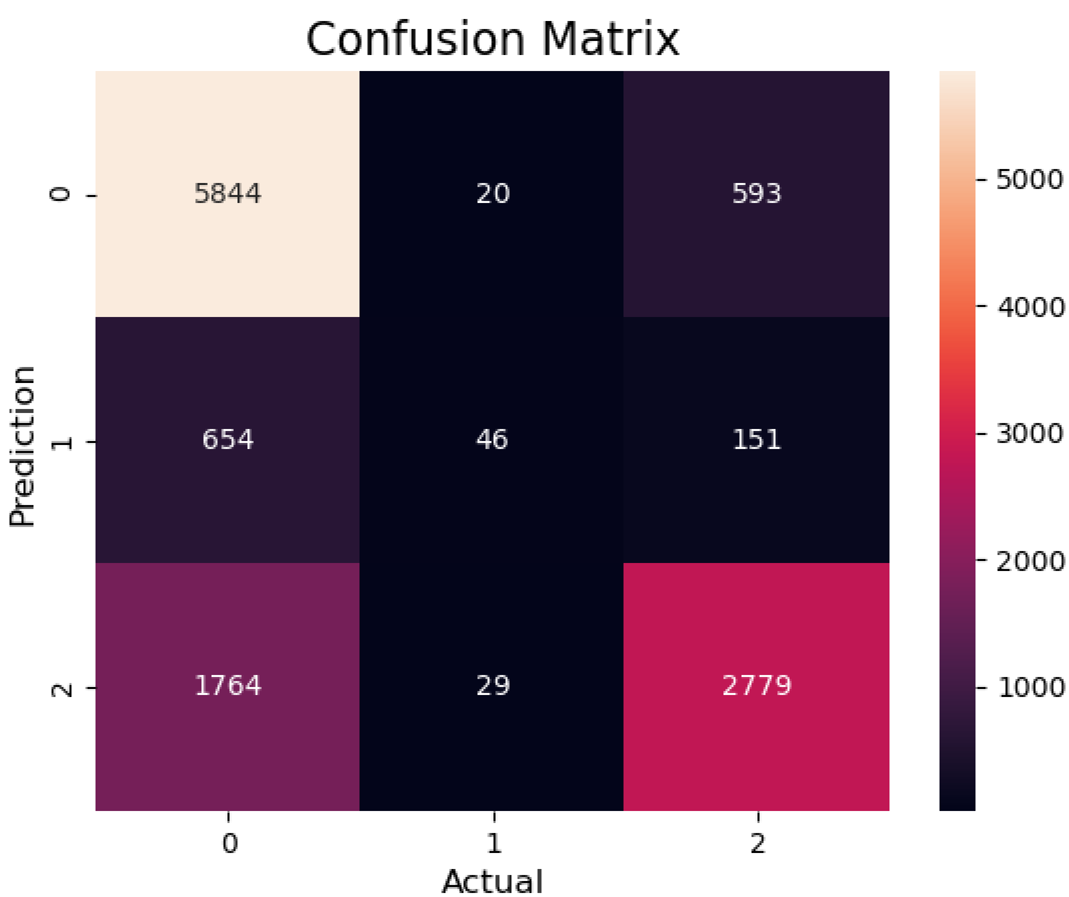
This will be our baseline model. Now let's try to change up some things and see what that does to our model

In [100…

```
from sklearn.metrics import confusion_matrix


cm_logreg1 = confusion_matrix(y_test, y_pred_test)
print('Confusion matrix\n\n', cm_logreg1)

sns.heatmap(cm_logreg1, annot=True,fmt='d')
plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=16)
# plt.show();
```

```
Confusion matrix

 [[5844   20  593]
 [ 654   46  151]
 [1764   29 2779]]
```

Out[1006]:
```
Text(0.5, 1.0, 'Confusion Matrix')
```



Remember that:

0: Functional:

1: functional needs repair

2: non-functional

In [100…

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test))
```

```
              precision    recall  f1-score   support

           0       0.71      0.91      0.79      6457
           1       0.48      0.05      0.10       851
           2       0.79      0.61      0.69      4572

    accuracy                           0.73     11880
   macro avg       0.66      0.52      0.53     11880
weighted avg       0.72      0.73      0.70     11880
```

`weighted`: Calculate precision and recalls metrics for each label, and find their average weighted by support (the number of true instances for each label).
This alters 'macro' to account for label imbalance; it can result in an F-score that is not between precision and recall.

In [100…

```
from sklearn.metrics import precision_score, recall_score, balanced_accuracy_score, f1_s

precision = precision_score(y_test, y_pred_test, average='weighted')
recall = recall_score(y_test, y_pred_test, average = "weighted")
f1_score = f1_score(y_test, y_pred_test, average="weighted")

accuracy_score = accuracy_score(y_test, y_pred_test)

print("The weighted precision is: ",precision)
print("The weighted recall is: ",recall)
print("The accuracy score is: ", accuracy_score)
print("The weighted f1score is: ", f1_score)
print(" ")

print("Weighted precision, f1 score, and recall are ideal measures because the target la
```

```
The weighted precision is:  0.7227097828639878
The weighted recall is:  0.7297138047138048
The accuracy score is:  0.7297138047138048
The weighted f1score is:  0.7027969482071396

Weighted precision, f1 score, and recall are ideal measures because the target labels ar
e imbalanced
```

Precision: 72%

Recall: 73%

The weighted average precision and recall are preferred as evaluation metrics.
It is appropriate to use weighted averaging. This approach takes into account the balance of classes. You weigh each class based on its representation in the dataset. Then, you compute precision and recall as a weighted average of the precision and recall in individual classes.

Simply put, it would work like macro-averaging, but instead of dividing precision and recall by the number of classes, you give each class a fair representation based on the proportion it takes in the dataset.

This approach is useful if you have an imbalanced dataset, like we have here but want to assign larger importance to classes with more examples.

Model 2- Logistic Regression Iteration Two

Our target variable is hughly imbalanced. We will create a copy and use SMOTE to balance it then create a second iteration

In [100…
```
Xy_init.status_group.value_counts()
```

Out[1009]:
```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
```

In [101…
```
Xy_init_smote = Xy_init.copy() # assign to protect original one

X_smote = Xy_init_smote.drop(['status_group'], axis=1) # assign X variables

y_smote = Xy_init_smote['status_group'] # Assign y variable

from sklearn.model_selection import train_test_split

X_train2, X_test2, y_train2, y_test2 = train_test_split(X_smote, y_smote, test_size = 0.

# Remove outliers for numerical data

upper_thresholds = {
    'population': 560.0,
    'construction_age': 52.0,
}

for df3 in [X_train2, X_test2]:
    for column, top in upper_thresholds.items():
        df3[column] = df3[column].clip(upper=top)

# Obe Hot encode categorical data

import category_encoders as ce

ohe = ce.one_hot.OneHotEncoder(cols=['basin','month_recorded','region', 'extraction_type
                             'quantity', 'source', 'waterpoint_type'], handle_missing="v

ohe.fit(X_train2)

X_train2 = ohe.transform(X_train2)
X_test2 = ohe.transform(X_test2)

# Scale the data

from sklearn.preprocessing import MinMaxScaler

scaler2 = MinMaxScaler()

scaler2.fit(X_train2)


X_train2 = pd.DataFrame(
    scaler.transform(X_train2),
    columns=X_train2.columns
    )


X_test2 = pd.DataFrame(
    scaler.transform(X_test2),
```

```
    columns=X_test2.columns
    )

# SMOTE
from imblearn.over_sampling import SMOTE


smt = SMOTE(sampling_strategy = 'auto', n_jobs = -1)

X_smote_sampled, y_smote_sampled = smt.fit_resample(X_train2, y_train2)

print(y_smote.value_counts())

y_smote_sampled = pd.Series(y_smote_sampled) # converting from array to np.series to see

print(y_smote_sampled.value_counts())




# # Instantiate and Fit Logistic Regression Model
# # instantiate the model
logreg2 = LogisticRegression(solver='sag', multi_class='auto', random_state=42)


# # fit the model
logreg2.fit(X_smote_sampled, y_smote_sampled)
```

```
0    32259
2    22824
1     4317
Name: status_group, dtype: int64
2    25802
1    25802
0    25802
Name: status_group, dtype: int64
```

```
c:\Users\rosew\anaconda3\envs\learn-env\lib\site-packages\sklearn\linear_model\_sag.py:3
50: ConvergenceWarning: The max_iter was reached which means the coef_ did not converge
  warnings.warn(
```

Out[1010]:

```
LogisticRegression
LogisticRegression(random_state=42, solver='sag')
```

In [101…

```
y_pred_test2 = logreg2.predict(X_test2)

y_pred_test2
```

Out[1011]:

```
array([2, 0, 0, ..., 2, 1, 0], dtype=int64)
```

In [101…

```
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test2, y_pred_test2)))
```

```
Model accuracy score: 0.6215
```

Compare the train-set and test-set accuracy

Now, I will compare the train-set and test-set accuracy to check for overfitting.

In [101…

```
y_pred_train2 = logreg2.predict(X_train2)

y_pred_train2
```

Out[1013]: array([0, 0, 2, ..., 2, 1, 2], dtype=int64)

In [101…
```
print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train2, y_pred_tr
```

```
Training-set accuracy score: 0.6273
```

Check for overfitting or underfitting

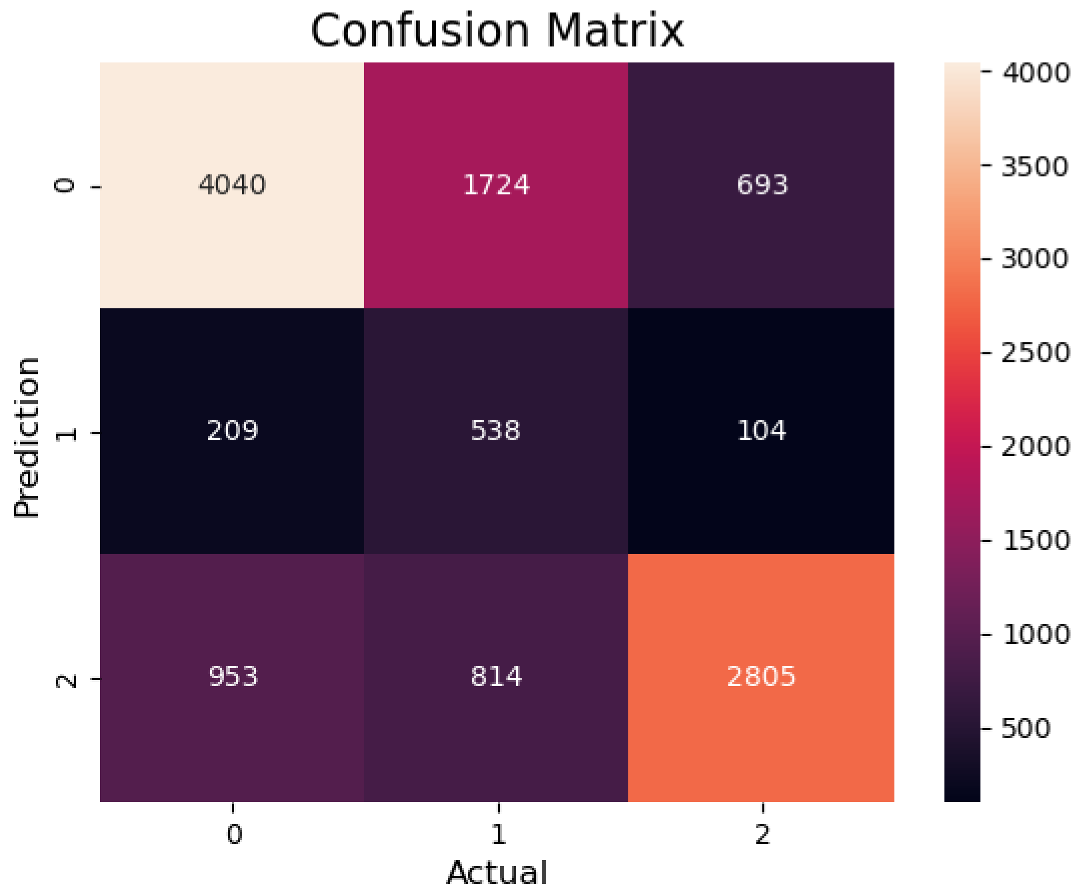
In [101…
```
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg2.score(X_train2, y_train2)))

print('Test set score: {:.4f}'.format(logreg2.score(X_test2, y_test2)))
```

```
Training set score: 0.6273
Test set score: 0.6215
```

The training and test accuracy score are much lower than the first model (62%), meaning that it is less accurate. Using SMOTE does not improve our model

In [101…
```
from sklearn.metrics import confusion_matrix


cm_logreg3 = confusion_matrix(y_test2, y_pred_test2)
print('Confusion matrix\n\n', cm_logreg3)

sns.heatmap(cm_logreg3, annot=True,fmt='d')
plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=16)
plt.show();
```

```
Confusion matrix

 [[4040 1724  693]
 [ 209  538  104]
 [ 953  814 2805]]
```



In [101…
```
from sklearn.metrics import classification_report

print(classification_report(y_test2, y_pred_test2))
```

```
              precision    recall  f1-score   support

           0       0.78      0.63      0.69      6457
           1       0.17      0.63      0.27       851
           2       0.78      0.61      0.69      4572

    accuracy                           0.62     11880
   macro avg       0.58      0.62      0.55     11880
weighted avg       0.73      0.62      0.66     11880
```

`weighted` : Calculate precision and recalls metrics for each label, and find their average weighted by support (the number of true instances for each label).
This alters 'macro' to account for label imbalance; it can result in an F-score that is not between precision and recall.

In [101…
```
from sklearn.metrics import precision_score, recall_score, balanced_accuracy_score, f1_s

precision2 = precision_score(y_test, y_pred_test2, average='weighted')
recall2 = recall_score(y_test, y_pred_test2, average = "weighted")
f1_score2 = f1_score(y_test, y_pred_test2, average="weighted")

accuracy_score2 = accuracy_score(y_test, y_pred_test2)

print("The weighted precision is: ",precision2)
print("The weighted recall is: ",recall2)
print("The accuracy score is: ", accuracy_score2)
print("The weighted f1score is: ", f1_score2)
print(" ")
```

```
print("Weighted precision, f1 score, and recall are ideal measures because the target la
```

```
The weighted precision is:  0.7343331320769583
The weighted recall is:  0.6214646464646465
The accuracy score is:  0.6214646464646465
The weighted f1score is:  0.6604305711351062

Weighted precision, f1 score, and recall are ideal measures because the target labels ar
e imbalanced
```

Precision: 74%

Recall: 62%

Let's now try using the standard scaler instead on the MinMax Scaler on the original data to see if this creates a better model

Model 3: Linear Regression Iteration 3

In [101…

```
Xy_init_std_scaler = Xy_init.copy() # assign to protect original one

X_std_scaler = Xy_init_std_scaler.drop(['status_group'], axis=1) # assign X variables

y_std_scaler = Xy_init_std_scaler['status_group'] # Assign y variable

from sklearn.model_selection import train_test_split

X_train3, X_test3, y_train3, y_test3 = train_test_split(X_std_scaler, y_std_scaler, test

# Remove outliers for numerical data

upper_thresholds = {
    'population': 560.0,
    'construction_age': 52.0,
}

for df3 in [X_train3, X_test3]:
    for column, top in upper_thresholds.items():
        df3[column] = df3[column].clip(upper=top)

# Obe Hot encode categorical data

import category_encoders as ce

ohe = ce.one_hot.OneHotEncoder(cols=['basin','month_recorded','region', 'extraction_type
                             'quantity', 'source', 'waterpoint_type'], handle_missing="v

ohe.fit(X_train3)

X_train3 = ohe.transform(X_train3)
X_test3 = ohe.transform(X_test3)

# Scale the data

from sklearn.preprocessing import StandardScaler

scaler3 = StandardScaler()

scaler3.fit(X_train3)


X_train3 = pd.DataFrame(
    scaler3.transform(X_train3),
```

```
    columns=X_train3.columns
    )


X_test3 = pd.DataFrame(
    scaler3.transform(X_test3),
    columns=X_test3.columns
    )


# # Instantiate and Fit Logistic Regression Model
# # instantiate the model
logreg3 = LogisticRegression(solver='sag', multi_class='auto', random_state=42)


# # fit the model
logreg3.fit(X_train3, y_train3)
```

Out[1019]:

```
LogisticRegression
LogisticRegression(random_state=42, solver='sag')
```

In [102…

```
y_pred_test3 = logreg3.predict(X_test3)

y_pred_test3
```

Out[1020]:

```
array([2, 0, 0, ..., 2, 0, 0], dtype=int64)
```

In [102…

```
from sklearn.metrics import accuracy_score

print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test3, y_pred_test3)))
```

```
Model accuracy score: 0.7295
```

Compare the train-set and test-set accuracy

Now, I will compare the train-set and test-set accuracy to check for overfitting.

In [102…

```
### Compare the train-set and test-set accuracy


# Now, I will compare the train-set and test-set accuracy to check for overfitting.
y_pred_train3 = logreg3.predict(X_train3)

y_pred_train3

print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train3, y_pred_tr
# Check for overfitting or underfitting
# print the scores on training and test set

print('Training set score: {:.4f}'.format(logreg3.score(X_train3, y_train3)))

print('Test set score: {:.4f}'.format(logreg3.score(X_test3, y_test3)))
```

```
Training-set accuracy score: 0.7323
Training set score: 0.7323
Test set score: 0.7295
```

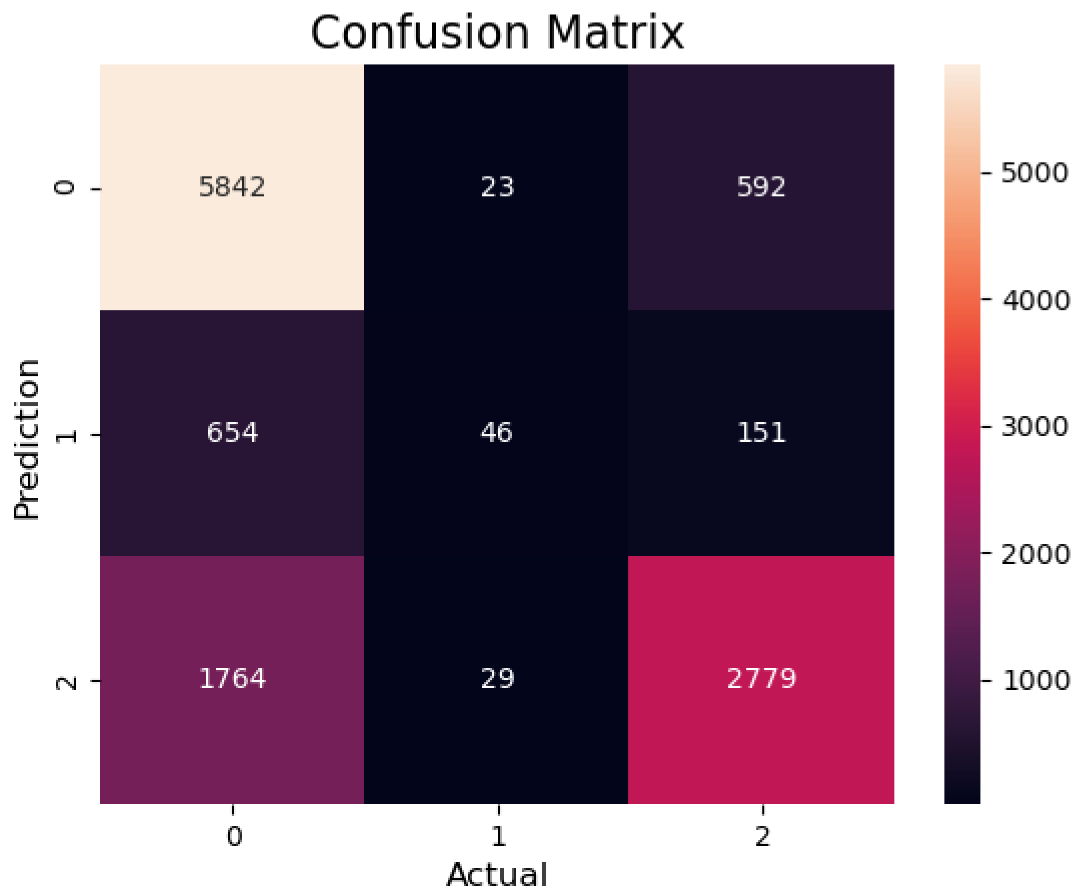
The training and test accuracy score are similar to the first model at 0.73 and 0.729

In [102…

```
from sklearn.metrics import confusion_matrix
```

```
cm_logreg4 = confusion_matrix(y_test3, y_pred_test3)
print('Confusion matrix\n\n', cm_logreg4)

sns.heatmap(cm_logreg4, annot=True,fmt='d')
plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=16)
plt.show();
```

```
Confusion matrix

 [[5842   23  592]
 [ 654   46  151]
 [1764   29 2779]]
```



In [102…

```
from sklearn.metrics import classification_report

print(classification_report(y_test3, y_pred_test3))
```

```
              precision    recall  f1-score   support

           0       0.71      0.90      0.79      6457
           1       0.47      0.05      0.10       851
           2       0.79      0.61      0.69      4572

    accuracy                           0.73     11880
   macro avg       0.66      0.52      0.53     11880
weighted avg       0.72      0.73      0.70     11880
```

`weighted`: Calculate precision and recalls metrics for each label, and find their average weighted by support (the number of true instances for each label).
This alters ‘macro’ to account for label imbalance; it can result in an F-score that is not between precision and recall.

```
from sklearn.metrics import precision_score, recall_score, balanced_accuracy_score, f1_s
```

In [102…
```
precision3 = precision_score(y_test, y_pred_test3, average='weighted')
recall3 = recall_score(y_test, y_pred_test3, average = "weighted")
f1_score3 = f1_score(y_test, y_pred_test3, average="weighted")

accuracy_score3 = accuracy_score(y_test, y_pred_test3)

print("The weighted precision is: ",precision3)
print("The weighted recall is: ",recall3)
print("The accuracy score is: ", accuracy_score3)
print("The weighted f1score is: ", f1_score3)
print(" ")

print("Weighted precision, f1 score, and recall are ideal measures because the target la
```

```
The weighted precision is:  0.7216956617165646
The weighted recall is:  0.7295454545454545
The accuracy score is:  0.7295454545454545
The weighted f1score is:  0.702718498868645

Weighted precision, f1 score, and recall are ideal measures because the target labels ar
e imbalanced
```

Precision: 72%

Recall: 73%

Decision Tree

Model 4: Decision Tree- Model Iteration 1

In [102…
```
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
```

In [102…
```
dt= DecisionTreeClassifier(criterion='gini', splitter='best', random_state=42)
```

In [102…
```
dt.fit(X_train, y_train)
```

Out[1028]:
```
DecisionTreeClassifier
DecisionTreeClassifier(random_state=42)
```

Compare the train-set and test-set accuracy

Now, I will compare the train-set and test-set accuracy to check for overfitting.

In [102…
```
print('Accuracy score of train data :{}'.format(dt.score(X_train,y_train)))
print('Accuracy score of test data:{}'.format(dt.score(X_test,y_test)))
```

```
Accuracy score of train data :0.937962962962963
Accuracy score of test data:0.7570707070707071
```

This high variance in accuracy scores indicates that we are overfitting. Let's change the depth and use entropy and see the difference it brings

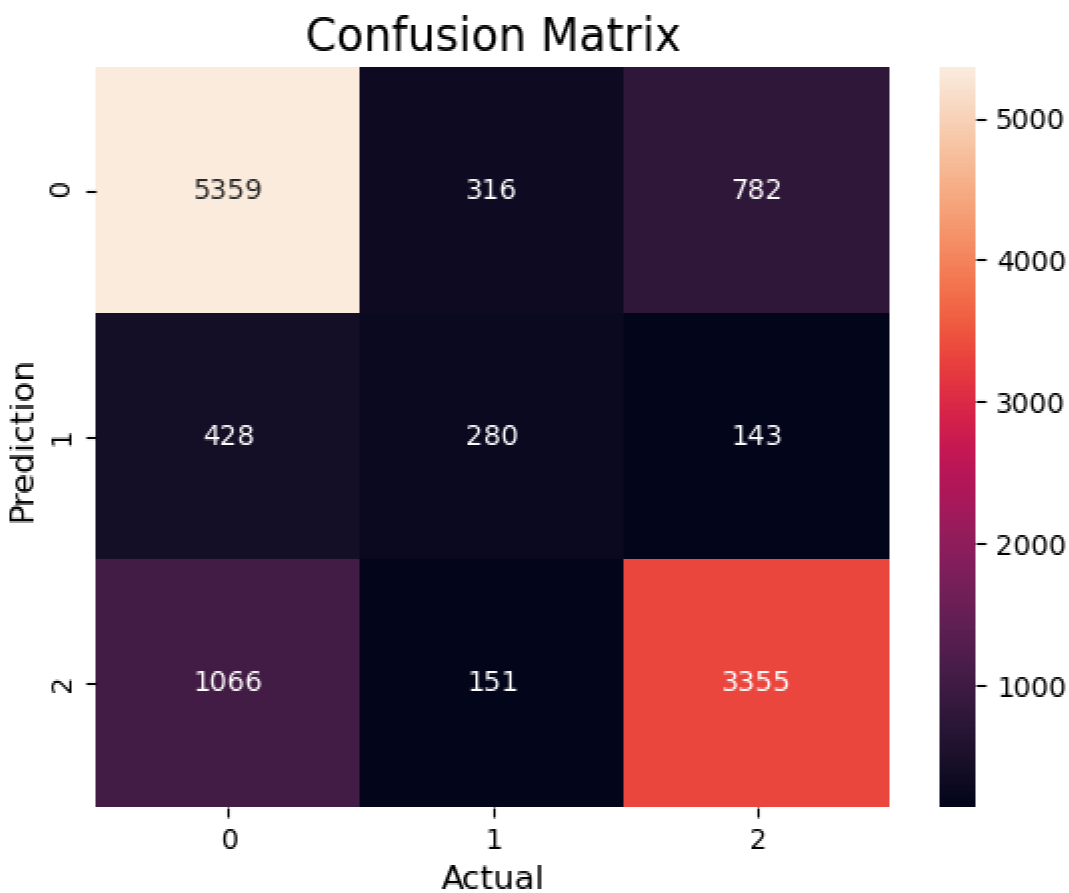
In [103…
```
y_pred_test4 = dt.predict(X_test)

y_pred_test4
```

Out[1030]: array([2, 0, 0, ..., 2, 2, 1], dtype=int64)

In [103…

```
from sklearn.metrics import confusion_matrix


cm_logreg2 = confusion_matrix(y_test, y_pred_test4)
print('Confusion matrix\n\n', cm_logreg2)

sns.heatmap(cm_logreg2, annot=True,fmt='d')

plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=16)
plt.show();
```

```
Confusion matrix

 [[5359  316  782]
 [ 428  280  143]
 [1066  151 3355]]
```



In [103…

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test4))
```

```
              precision    recall  f1-score   support

           0       0.78      0.83      0.81      6457
           1       0.37      0.33      0.35       851
           2       0.78      0.73      0.76      4572

    accuracy                           0.76     11880
   macro avg       0.65      0.63      0.64     11880
weighted avg       0.75      0.76      0.75     11880
```

`weighted`: Calculate precision and recalls metrics for each label, and find their average weighted by support (the number of true instances for each label).
This alters 'macro' to account for label imbalance; it can result in an F-score that is not between precision and recall.

In [103…
```
from sklearn.metrics import precision_score, recall_score, balanced_accuracy_score, f1_s

precision4 = precision_score(y_test, y_pred_test4, average='weighted')
recall4 = recall_score(y_test, y_pred_test4, average = "weighted")
f1_score4 = f1_score(y_test, y_pred_test4, average="weighted")

accuracy_score4 = accuracy_score(y_test, y_pred_test4)

print("The weighted precision is: ",precision4)
print("The weighted recall is: ",recall4)
print("The accuracy score is: ", accuracy_score4)
print("The weighted f1score is: ", f1_score4)
print(" ")

print("Weighted precision, f1 score, and recall are ideal measures because the target la
```

```
The weighted precision is:  0.7535526749600432
The weighted recall is:  0.7570707070707071
The accuracy score is:  0.7570707070707071
The weighted f1score is:  0.7544993679253735

Weighted precision, f1 score, and recall are ideal measures because the target labels ar
e imbalanced
```

Model 5: Decision Tree- Model Iteration Two: Hyperparameter Tuning for the Decision Tree

In [103…
```
dt2= DecisionTreeClassifier(criterion='entropy', splitter='best', max_depth= 14, random_
dt2.fit(X_train, y_train)

### Compare the train-set and test-set accuracy
# Now, I will compare the train-set and test-set accuracy to check for overfitting.

print('Accuracy score of train data :{}'.format(dt2.score(X_train,y_train)))
print('Accuracy score of test data:{}'.format(dt2.score(X_test,y_test)))
```

```
Accuracy score of train data :0.7965698653198653
Accuracy score of test data:0.7576599326599327
```

In [103…
```
y_pred_test5 = dt2.predict(X_test)

y_pred_test5
```

Out[1035]:
```
array([2, 0, 0, ..., 2, 0, 0], dtype=int64)
```

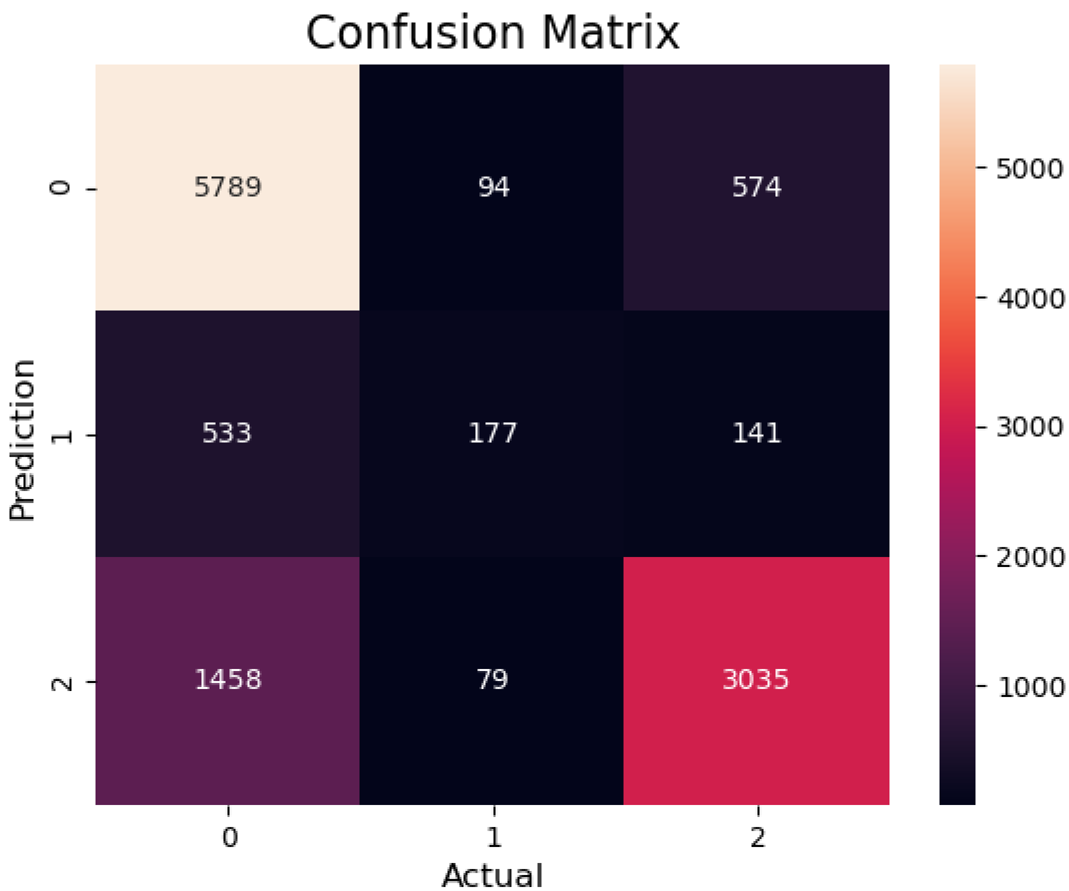
Accuracy = 75.8% .
This has improved both accuracy scores and we are not overfitting either. This could be perfect for the final model

Let's create a confusion matrix for this and obtain the other classification metrics

In [103…
```
from sklearn.metrics import confusion_matrix


cm_logreg5 = confusion_matrix(y_test, y_pred_test5)
```

```
print('Confusion matrix\n\n', cm_logreg5)

sns.heatmap(cm_logreg5, annot=True,fmt='d')

plt.ylabel('Prediction',fontsize=12)
plt.xlabel('Actual',fontsize=12)
plt.title('Confusion Matrix',fontsize=16)
plt.show();
```

```
Confusion matrix

 [[5789   94  574]
 [ 533  177  141]
 [1458   79 3035]]
```



Remember that:

0: Functional:

1: functional needs repair

2: non-functional

In [103…

```
from sklearn.metrics import classification_report

print(classification_report(y_test, y_pred_test5))
```

```
              precision    recall  f1-score   support

           0       0.74      0.90      0.81      6457
           1       0.51      0.21      0.29       851
           2       0.81      0.66      0.73      4572

    accuracy                           0.76     11880
   macro avg       0.69      0.59      0.61     11880
weighted avg       0.75      0.76      0.74     11880
```

`weighted`: Calculate precision and recalls metrics for each label, and find their average weighted by

support (the number of true instances for each label).
This alters 'macro' to account for label imbalance; it can result in an F-score that is not between precision and recall.

In [103…

```
from sklearn.metrics import precision_score, recall_score, balanced_accuracy_score, f1_s

precision5 = precision_score(y_test, y_pred_test5, average='weighted')
recall5 = recall_score(y_test, y_pred_test5, average = "weighted")
f1_score5 = f1_score(y_test, y_pred_test5, average="weighted")

accuracy_score5 = accuracy_score(y_test, y_pred_test5)

print("The weighted precision is: ",precision5)
print("The weighted recall is: ",recall5)
print("The accuracy score is: ", accuracy_score5)
print("The weighted f1score is: ", f1_score5)
print(" ")

print("Weighted precision, f1 score, and recall are ideal measures because the target la
```

```
The weighted precision is:  0.7521218200489409
The weighted recall is:  0.7576599326599327
The accuracy score is:  0.7576599326599327
The weighted f1score is:  0.7438267978791073

Weighted precision, f1 score, and recall are ideal measures because the target labels ar
e imbalanced
```

Precision = 75%

Recall = 76%

Conclusion

1. The relationship between the following variables and the `status_group` (functional, non-functional, functional but needs repair):
Wells likely to be non-functional or needing repair:

- `payment` : Wells where no payments are made
- `source` : Wells with a shallow well as the water source
- `management_group` : Wells managed by the user group
- `extraction_type` : Wells with gravity as the extraction type
- `permit` : Wells that are permitted
- `public_meeting` : Wells where a public meeting was held

2. Modeling
The best model is the final one- Decision Tree Classifier with a maximum depth of 14 and entropy criterion
Its metrics are:

- Accuracy: 75.8%
- Precision = 75%
- Recall- 76%

Recommendations

- Consider engineering the ternary classification problem into a binary classification problem and see if this improves the model parameters
- More feature engineering to identify other features that could be useful for the model.
- Try other models like the Random Forest Classifier, KNN, and AdaBoost to see if they have better metrics

```
In [ ]:
```