Phase3_project

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1 Water Pump Status

Flatiron Data Science Course - Project 3

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1.1 Project Overview

For this project we will solving a classification problem. We will use models appropriate for classification to make prediction for given unseen data. The dateset is split into two, one for training the models and the other for testing/verifying the performance of our models. Also, we take the approach of trying a couple of different models starting out with simple model with low performance and working toward better models with better performance.

1.2 Technical Summary

This project is a binary classification problem where prediction models are trained to predict the status of water pumps, especially those water pumps needing repair or operationally non-functional. Because of our business objective, we have decided to use recall for our model primary metric and accuracy for overall performance. Recall in this situation means what percentage of water pumps that are broken or need repair can our model predict correctly. RandomForest is our best model with a recall of 0.77 and accuracy of 0.83.

1.3 Business Problem

We have been tasked by our stakeholder, Tanzanian Ministry of Water, to setup a model that can predict water pumps needing repair or operationally non-functional. Because of our business objective, we have decided to use recall for our model metric. Recall in this situation means what percentage of water pumps that are broken or need repair can our model predict correctly.

1.4 Master Dataset

The dataset was obtained from from DrivenData and the records were collected by Taarifa and Tanzanian Ministry of Water. After the data was read into pandas dataframe it was split into two where 70% of data (41,580 records) was used for training the models and 30% (17,820 records) was used to verify prediction performance of the various models.

1.5 Data Cleaning,Feature Engineering and Processing

The original target consisted of three categories: 'functional', 'non-functional' and 'functional needs repair'. This was feature engineered into two categories by creating a new column. If the the pump was 'functional' a value of 0 was assigned to this new column and if the pump was 'non-fuctional' or 'functional needs repair' a value of 1 was assigned to this new column. Missing or NAN values for categorical features was filled with most frequent value and for numerical features the average for the column was used to fill in or replace. Most this was accomplished with sklearn Imputer. The the categorical features were then processed with sklearn's OneHotEncoder and the numerical features were processed with StandardScaler. The data was then split into train and test.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import time

from sklearn.model_selection import train_test_split,␣
↪cross_validate,GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.impute import SimpleImputer
from sklearn.dummy import DummyClassifier
from sklearn import metrics
from sklearn.metrics import recall_score,accuracy_score,plot_confusion_matrix
from sklearn.metrics import RocCurveDisplay,confusion_matrix
from sklearn.preprocessing import OneHotEncoder,StandardScaler,OrdinalEncoder
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
import xgboost as xgb
import time


%matplotlib inline
```

[2]:
```
# Load data features

features = pd.read_csv('data/4910797b-ee55-40a7-8668-10efd5c1b960.csv')
features.head()
```

[2]:
```
      id  amount_tsh date_recorded        funder  gps_height     installer  \
0  69572      6000.0    2011-03-14         Roman        1390         Roman
1   8776         0.0    2013-03-06       Grumeti        1399       GRUMETI
2  34310        25.0    2013-02-25  Lottery Club         686  World vision
3  67743         0.0    2013-01-28        Unicef         263        UNICEF
4  19728         0.0    2011-07-13   Action In A           0       Artisan
```

```
   longitude   latitude              wpt_name  num_private  … payment_type  \
0  34.938093  -9.856322                  none            0  …     annually
1  34.698766  -2.147466              Zahanati            0  …    never pay
2  37.460664  -3.821329           Kwa Mahundi            0  …   per bucket
3  38.486161 -11.155298  Zahanati Ya Nanyumbu            0  …    never pay
4  31.130847  -1.825359               Shuleni            0  …    never pay

  water_quality quality_group      quantity  quantity_group  \
0          soft          good        enough          enough
1          soft          good  insufficient    insufficient
2          soft          good        enough          enough
3          soft          good           dry             dry
4          soft          good      seasonal        seasonal

                 source           source_type  source_class  \
0                spring                spring   groundwater
1  rainwater harvesting  rainwater harvesting       surface
2                   dam                   dam       surface
3           machine dbh              borehole   groundwater
4  rainwater harvesting  rainwater harvesting       surface

               waterpoint_type waterpoint_type_group
0           communal standpipe    communal standpipe
1           communal standpipe    communal standpipe
2  communal standpipe multiple    communal standpipe
3  communal standpipe multiple    communal standpipe
4           communal standpipe    communal standpipe

[5 rows x 40 columns]
```

[3]:
```
# Load data target

target = pd.read_csv('data/0bf8bc6e-30d0-4c50-956a-603fc693d966.csv')
target.head()
```

[3]:
```
      id    status_group
0  69572      functional
1   8776      functional
2  34310      functional
3  67743  non functional
4  19728      functional
```

[4]:
```
# Combine data features and target into single dataframe

combined_df = pd.concat([features,target['status_group']],axis=1)
combined_df.head()
```

[4]:
```
      id  amount_tsh date_recorded        funder  gps_height     installer  \
0  69572      6000.0    2011-03-14         Roman        1390         Roman
1   8776         0.0    2013-03-06       Grumeti        1399       GRUMETI
2  34310        25.0    2013-02-25  Lottery Club         686  World vision
3  67743         0.0    2013-01-28        Unicef         263        UNICEF
4  19728         0.0    2011-07-13   Action In A           0       Artisan

   longitude   latitude              wpt_name  num_private  … water_quality  \
0  34.938093  -9.856322                  none            0  …          soft
1  34.698766  -2.147466              Zahanati            0  …          soft
2  37.460664  -3.821329           Kwa Mahundi            0  …          soft
3  38.486161 -11.155298  Zahanati Ya Nanyumbu            0  …          soft
4  31.130847  -1.825359               Shuleni            0  …          soft

  quality_group      quantity  quantity_group                source  \
0          good        enough          enough                spring
1          good  insufficient    insufficient  rainwater harvesting
2          good        enough          enough                   dam
3          good           dry             dry           machine dbh
4          good      seasonal        seasonal  rainwater harvesting

            source_type source_class              waterpoint_type  \
0                spring  groundwater           communal standpipe
1  rainwater harvesting      surface           communal standpipe
2                   dam      surface  communal standpipe multiple
3              borehole  groundwater  communal standpipe multiple
4  rainwater harvesting      surface           communal standpipe

  waterpoint_type_group    status_group
0    communal standpipe      functional
1    communal standpipe      functional
2    communal standpipe      functional
3    communal standpipe  non functional
4    communal standpipe      functional

[5 rows x 41 columns]
```

[5]:
```
combined_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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: 18.6+ MB
```

[6]:
```
# check for NAN
combined_df.isna().sum()
```

[6]:
```
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
```

[7]:
```
# check for blank entries

combined_df[(combined_df == '') | (combined_df == ' ')].sum()
```

[7]:
```
id                       0.0
amount_tsh               0.0
date_recorded            0.0
```

```
funder                   0.0
gps_height               0.0
installer                0.0
longitude                0.0
latitude                 0.0
wpt_name                 0.0
num_private              0.0
basin                    0.0
subvillage               0.0
region                   0.0
region_code              0.0
district_code            0.0
lga                      0.0
ward                     0.0
population               0.0
public_meeting           0.0
recorded_by              0.0
scheme_management        0.0
scheme_name              0.0
permit                   0.0
construction_year        0.0
extraction_type          0.0
extraction_type_group    0.0
extraction_type_class    0.0
management               0.0
management_group         0.0
payment                  0.0
payment_type             0.0
water_quality            0.0
quality_group            0.0
quantity                 0.0
quantity_group           0.0
source                   0.0
source_type              0.0
source_class             0.0
waterpoint_type          0.0
waterpoint_type_group    0.0
status_group             0.0
dtype: float64
```

[8]:
```
# Check for duplicated records

combined_df[combined_df.duplicated()]
```

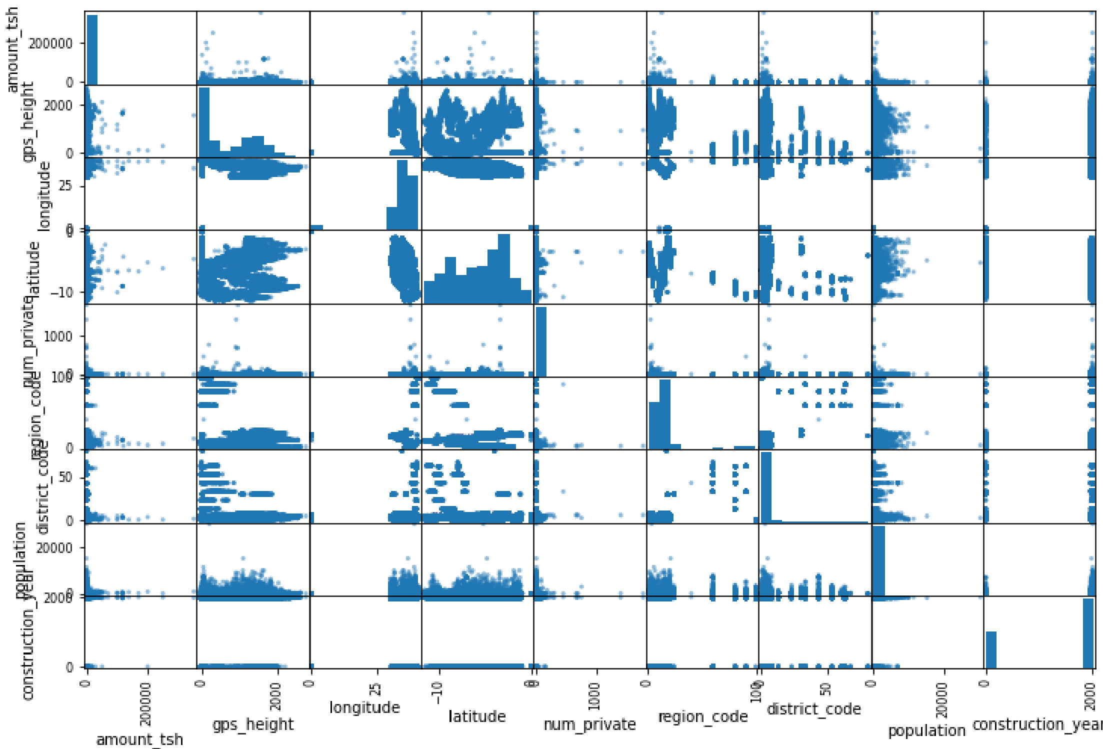
[8]:
```
Empty DataFrame
Columns: [id, amount_tsh, date_recorded, funder, gps_height, installer,
longitude, latitude, wpt_name, num_private, basin, subvillage, region,
```

```
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]
Index: []

[0 rows x 41 columns]
```

[9]:
```python
combined_df.describe()
```

[9]:
```
                 id      amount_tsh     gps_height     longitude      latitude  \
count  59400.000000   59400.000000  59400.000000  59400.000000  5.940000e+04
mean   37115.131768     317.650385    668.297239     34.077427 -5.706033e+00
std    21453.128371    2997.574558    693.116350      6.567432  2.946019e+00
min        0.000000       0.000000    -90.000000      0.000000 -1.164944e+01
25%    18519.750000       0.000000      0.000000     33.090347 -8.540621e+00
50%    37061.500000       0.000000    369.000000     34.908743 -5.021597e+00
75%    55656.500000      20.000000   1319.250000     37.178387 -3.326156e+00
max    74247.000000  350000.000000   2770.000000     40.345193 -2.000000e-08

        num_private   region_code  district_code    population  \
count  59400.000000  59400.000000   59400.000000  59400.000000
mean       0.474141     15.297003       5.629747    179.909983
std       12.236230     17.587406       9.633649    471.482176
min        0.000000      1.000000       0.000000      0.000000
25%        0.000000      5.000000       2.000000      0.000000
50%        0.000000     12.000000       3.000000     25.000000
75%        0.000000     17.000000       5.000000    215.000000
max     1776.000000     99.000000      80.000000  30500.000000

       construction_year
count       59400.000000
mean         1300.652475
std           951.620547
min             0.000000
25%             0.000000
50%          1986.000000
75%          2004.000000
max          2013.000000
```

[10]:
```python
# Check plot matrix for numeric columns
numeric_features = combined_df.select_dtypes(include=['int64','float64'])
numeric_cols_names = list(numeric_features.columns)
numeric_cols_names.pop(0)
pd.plotting.scatter_matrix(combined_df[numeric_cols_names],figsize=(12,8));
```




```
[11]: # split categorical features for from numerical
categorical_features = combined_df.select_dtypes(include=['object'])
numerical_features = combined_df.select_dtypes(include=['int64','float64'])
```

```
[12]: print('===== Categorical EDA ===='*3)
```

```
===== Categorical EDA ========= Categorical EDA ========= Categorical EDA ====
```

```
[13]: # Select which categorical features to include
categorical_columns = list(categorical_features.columns)
print(categorical_columns)
print(len(categorical_columns))
```

```
['date_recorded', 'funder', 'installer', 'wpt_name', 'basin', 'subvillage',
'region', 'lga', 'ward', 'public_meeting', 'recorded_by', 'scheme_management',
'scheme_name', 'permit', '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']
31
```

[14]:
```
# Go through each categorical column and decide which ones to include for
# analysis

num = 30
print(categorical_columns[num])
print(categorical_features[categorical_columns[num]].value_counts())

possible_cat_features_include =␣
↪['date_recorded','basin','region','public_meeting',
                         'scheme_management',
                   'permit','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']


cat_features_exclude =␣
↪['funder','installer','wpt_name','subvillage','lga','ward',
                   'recorded_by','scheme_name']


num_nans = categorical_features[categorical_columns[num]].isna().sum()
print('='*40)
print(f'Number of NaN for {categorical_columns[num]}: {num_nans}')
```

```
status_group
functional                 32259
non functional             22824
functional needs repair     4317
Name: status_group, dtype: int64
========================================
Number of NaN for status_group: 0
```

[15]:
```
# compare the following categorical features to if they have the same␣
↪information
# 'extraction_type','extraction_type_group','extraction_type_class'
# ==> use extraction_type and drop 'extraction_type_group'and␣
↪'extraction_type_class'

a = combined_df['extraction_type'].value_counts()
b = combined_df['extraction_type_group'].value_counts()
c = combined_df['extraction_type_class'].value_counts()
print(a,b,c)
print('='*80)
```

```
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 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 gravity         26780
handpump        16456
other            6430
submersible      6179
motorpump        2987
rope pump         451
wind-powered      117
Name: extraction_type_class, dtype: int64
================================================================================
```

[16]:
```python
# Compare 'management'and 'management_group' columns

print(combined_df['management'].value_counts())
print(combined_df['management_group'].value_counts())
print('='*80)
```

```
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
user-group    52490
commercial     3638
parastatal     1768
other           943
unknown         561
Name: management_group, dtype: int64
================================================================================
```

[17]:
```
# Compare 'payment' and 'payment_type' columns
# ==> use 'payment_type' and drop 'payment'

print(combined_df['payment'].value_counts())
print(combined_df['payment_type'].value_counts())
print('='*80)
```

```
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
================================================================================
```

[18]:
```
# Compare 'water_quality' and 'quality_group'
# ==> use water quality and drop quality_group
```

```
print(combined_df['water_quality'].value_counts())
print(combined_df['quality_group'].value_counts())
print('='*80)
```

```
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
================================================================================
```

[19]:

```
# Compare 'quantity' and 'quantity_group'
# ==> use quantity and drop quantity_group

print(combined_df['quantity'].value_counts())
print(combined_df['quantity_group'].value_counts())
print('='*80)
```

```
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
================================================================================
```

[20]:

```
# Determined number of wells constructed before 2002

a = combined_df[combined_df['construction_year'] < 2002]
```

```
b = len(a)/len(combined_df)*100
b
```

[20]: 69.93265993265993

[21]:
```
# Compare 'waterpoint_type'and 'waterpoint_type_group'
# Keep water_type and drop the other

print(combined_df['waterpoint_type'].value_counts())
print(combined_df['waterpoint_type_group'].value_counts())
print('='*40)
```

```
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
========================================
```

[ ]:

[22]:
```
print('=========== Numerical EDA ============' * 2)
```

```
=========== Numerical EDA ======================= Numerical EDA ============
```

[23]:
```
# Check numerical colums
numerical_features.info()
```

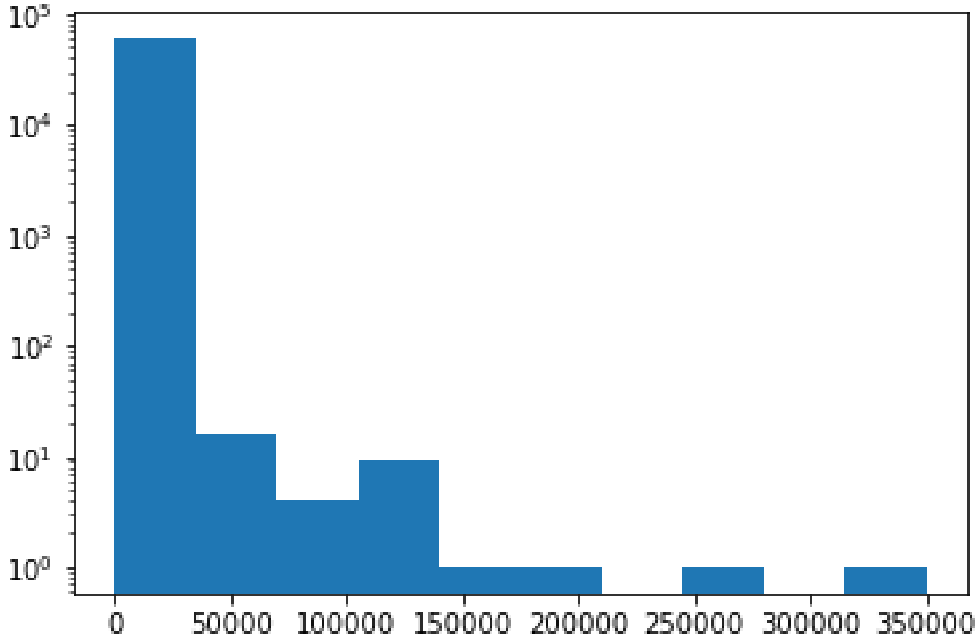
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 59400 non-null  int64
 1   amount_tsh         59400 non-null  float64
 2   gps_height         59400 non-null  int64
 3   longitude          59400 non-null  float64
 4   latitude           59400 non-null  float64
```

```
 5   num_private        59400 non-null  int64
 6   region_code        59400 non-null  int64
 7   district_code      59400 non-null  int64
 8   population         59400 non-null  int64
 9   construction_year  59400 non-null  int64
dtypes: float64(3), int64(7)
memory usage: 4.5 MB
```

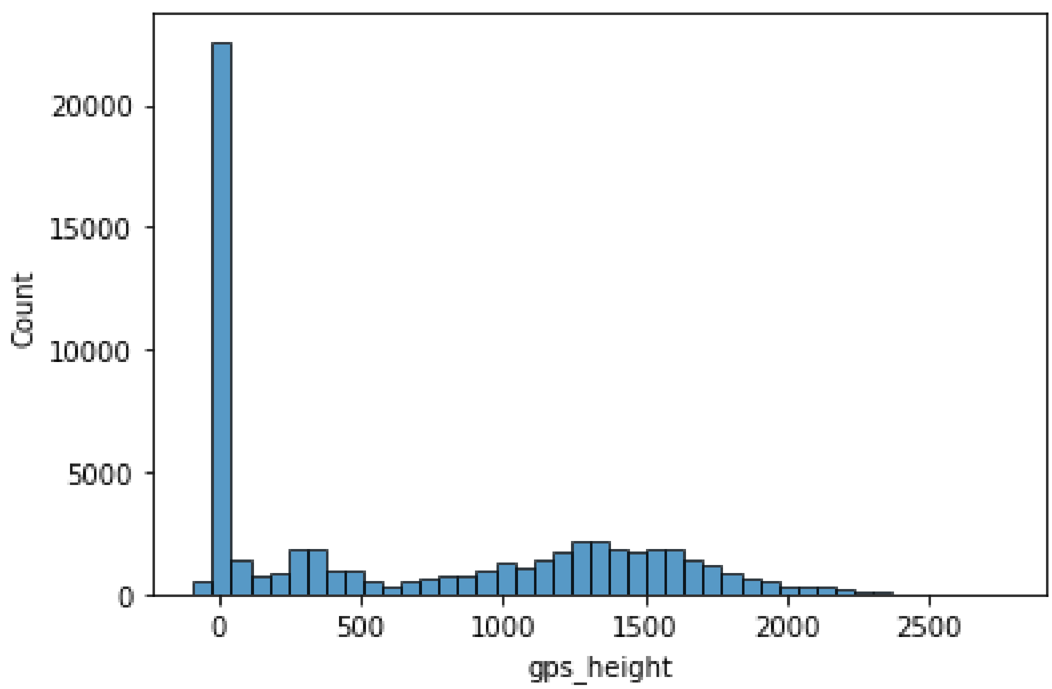
[24]:
```
numerical_features.describe()
```

[24]:
```
                 id     amount_tsh    gps_height     longitude      latitude  \
count  59400.000000   59400.000000  59400.000000  59400.000000  5.940000e+04
mean   37115.131768     317.650385    668.297239     34.077427 -5.706033e+00
std    21453.128371    2997.574558    693.116350      6.567432  2.946019e+00
min        0.000000       0.000000    -90.000000      0.000000 -1.164944e+01
25%    18519.750000       0.000000      0.000000     33.090347 -8.540621e+00
50%    37061.500000       0.000000    369.000000     34.908743 -5.021597e+00
75%    55656.500000      20.000000   1319.250000     37.178387 -3.326156e+00
max    74247.000000  350000.000000   2770.000000     40.345193 -2.000000e-08

        num_private   region_code  district_code    population  \
count  59400.000000  59400.000000   59400.000000  59400.000000
mean       0.474141     15.297003       5.629747    179.909983
std       12.236230     17.587406       9.633649    471.482176
min        0.000000      1.000000       0.000000      0.000000
25%        0.000000      5.000000       2.000000      0.000000
50%        0.000000     12.000000       3.000000     25.000000
75%        0.000000     17.000000       5.000000    215.000000
max     1776.000000     99.000000      80.000000  30500.000000

       construction_year
count       59400.000000
mean         1300.652475
std           951.620547
min             0.000000
25%             0.000000
50%          1986.000000
75%          2004.000000
max          2013.000000
```

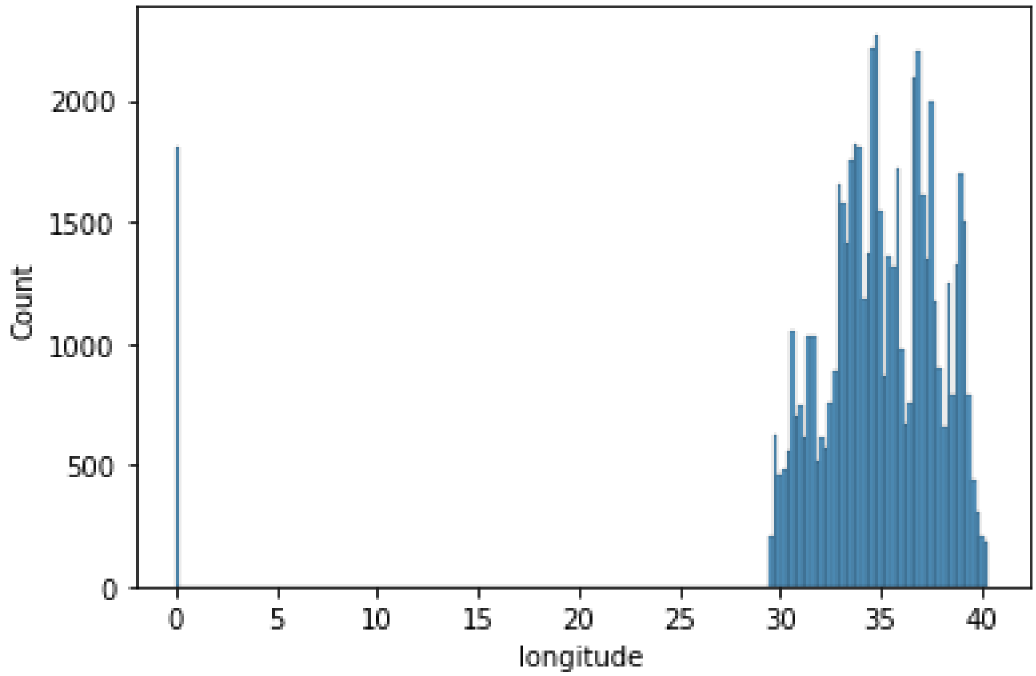
[25]:
```
# amount_tsh
plt.hist(data=numerical_features, x='amount_tsh',bins=10,log=True);
```



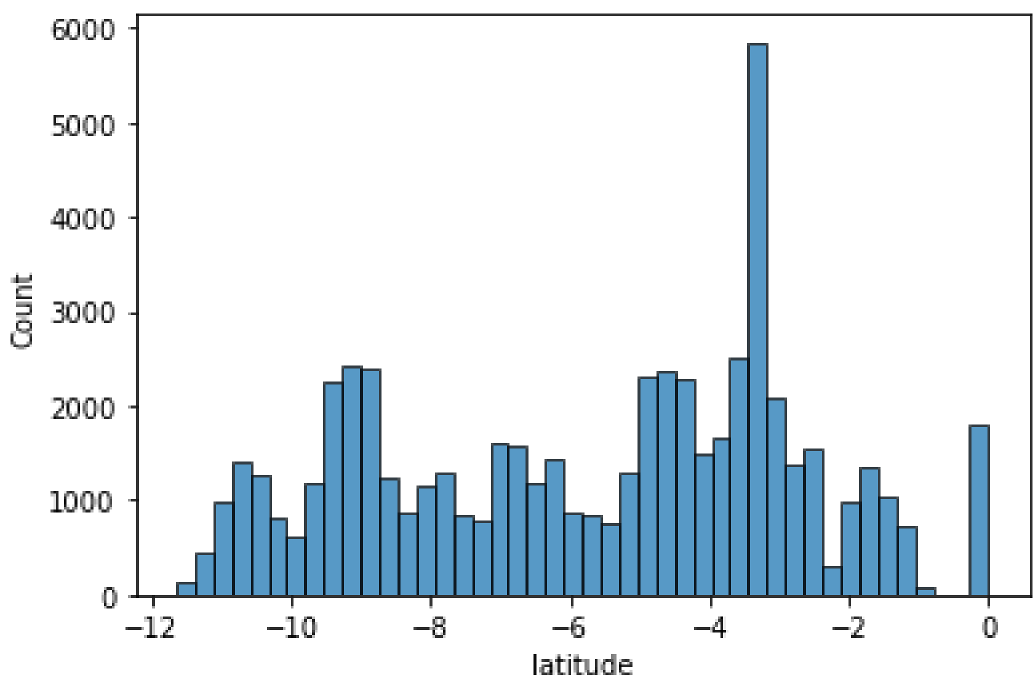
[26]:
```
# gps_height
sns.histplot(data=numerical_features, x='gps_height');
```



[27]:
```
# longitude
sns.histplot(data=numerical_features, x='longitude');
```

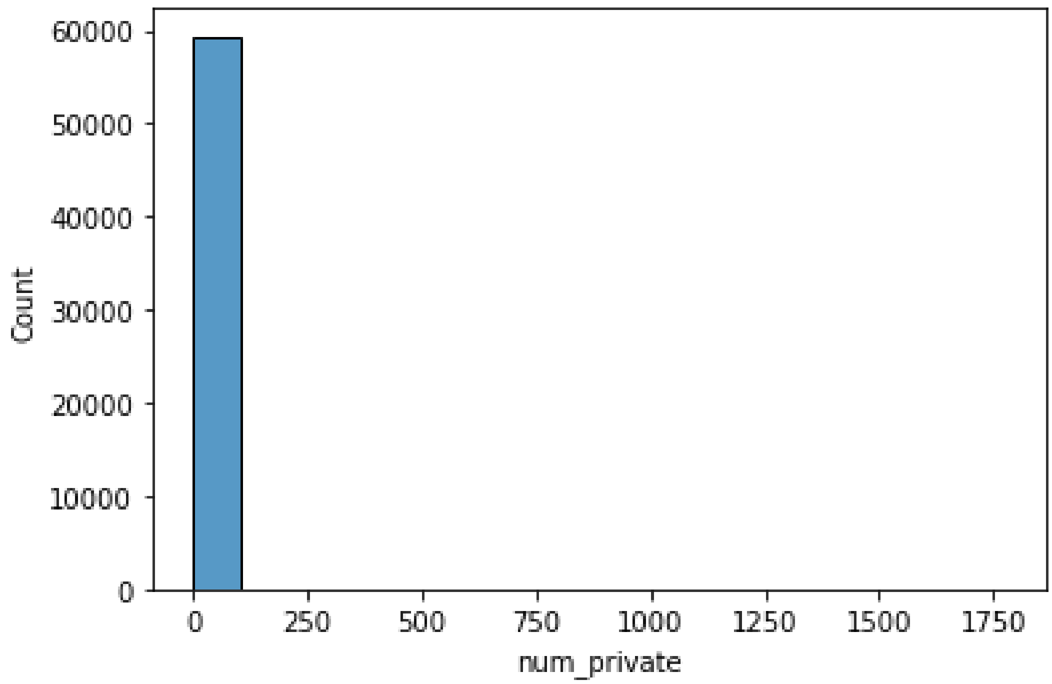


[28]:
```
# latitude
sns.histplot(data=numerical_features, x='latitude');
```



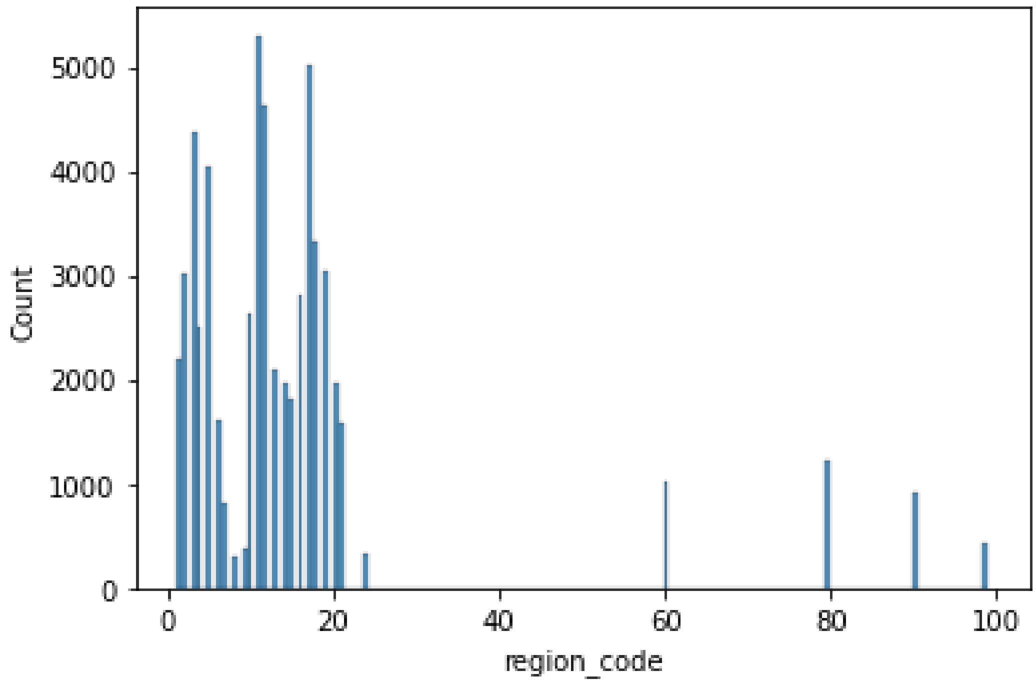
[29]:

```
# 'num_private'
# ==> drop 'num_private'

sns.histplot(data=numerical_features, x='num_private');
```

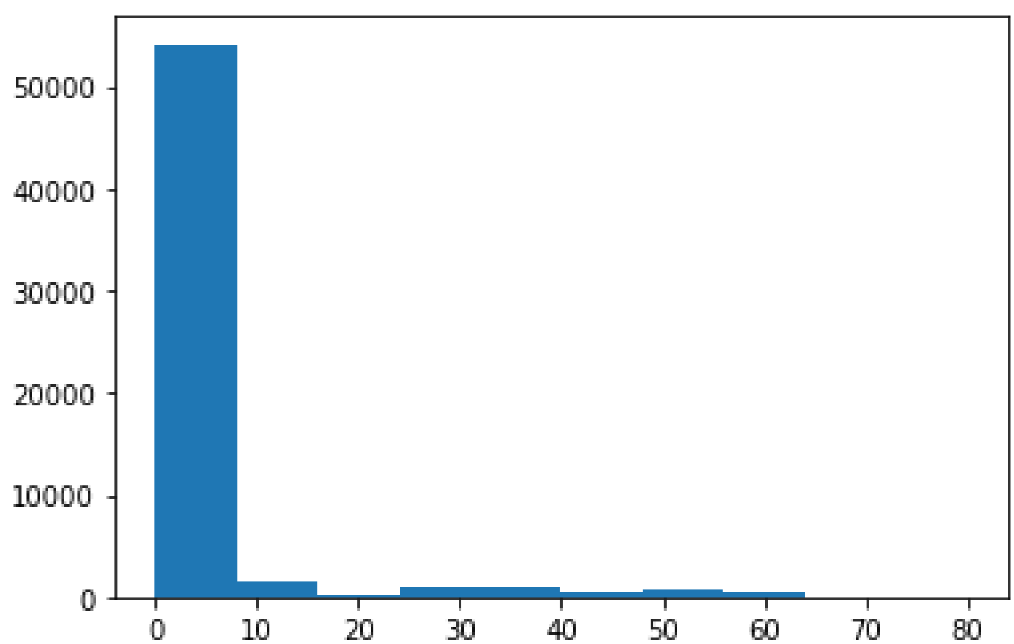


[30]:

```
# region_code
sns.histplot(data=numerical_features, x='region_code');
```

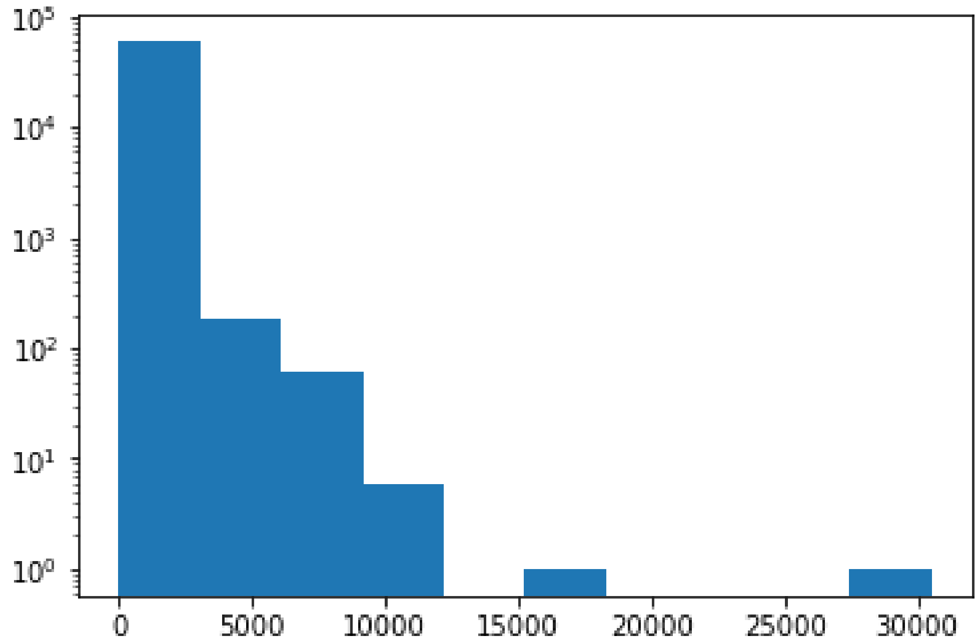


[31]:
```
#district_code
#sns.histplot(data=numerical_features, x='district_code')
plt.hist(data=numerical_features, x='district_code');
```



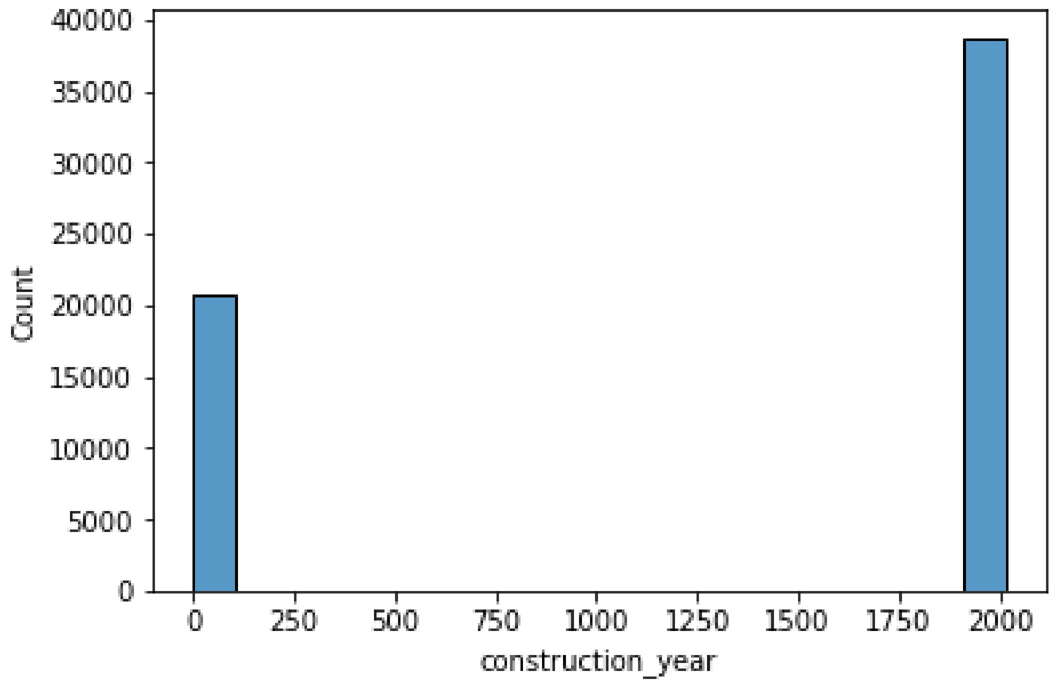
[32]:

```
# population
#sns.histplot(data=numerical_features, x='population')
plt.hist(data=numerical_features, x='population',log=True);
```



[33]:

```
# construction_year
# ==> construction year has a lot of zeros, need to fix construction_year

sns.histplot(data=numerical_features, x='construction_year',bins=20);
```



[ ]:

[34]:
```
# Include the following categorical and numerical features based on EDA

cols_to_drop = ['extraction_type_group', 'extraction_type_class', 'payment',
                'quality_group', 'quantity_group',
                'waterpoint_type_group','funder','installer','wpt_name',
                'subvillage','lga','ward','recorded_by','scheme_name','id',
                'num_private']

keep_columns = [col for col in combined_df.columns if(col not in cols_to_drop)]

combined_final_df = combined_df[keep_columns].copy()


combined_final_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 25 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   amount_tsh         59400 non-null  float64
 1   date_recorded      59400 non-null  object
 2   gps_height         59400 non-null  int64
```

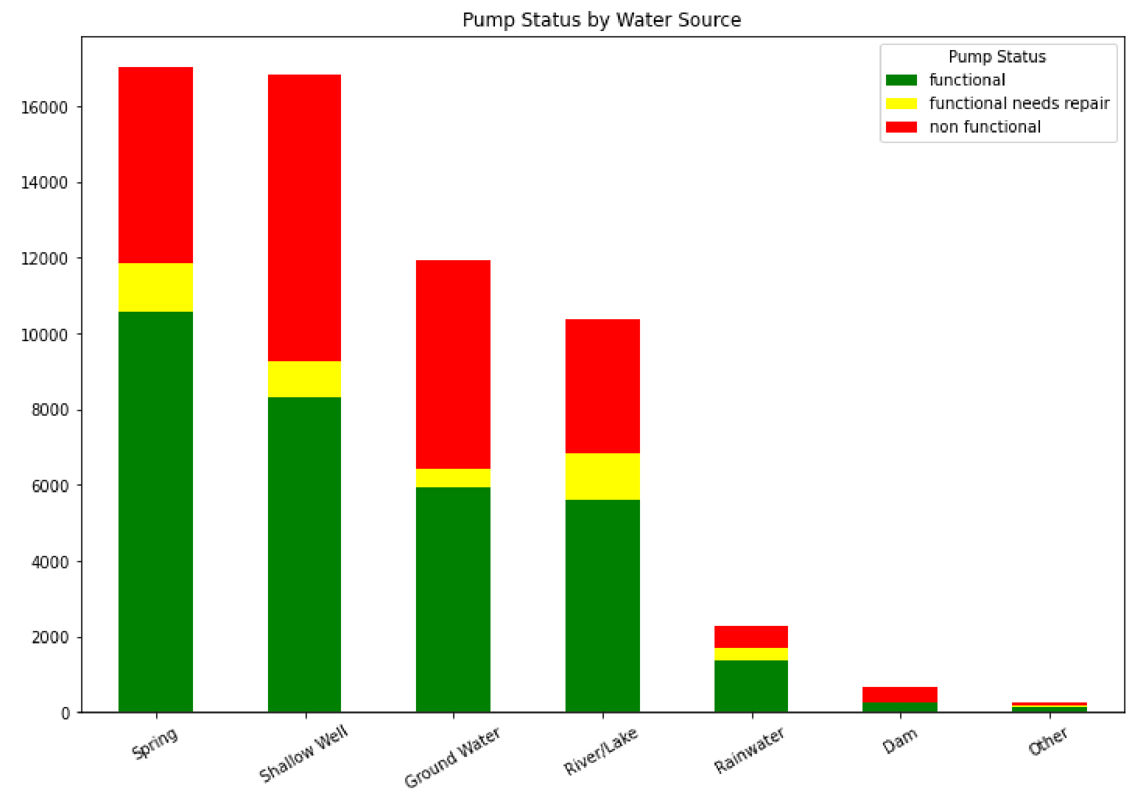
```
 3   longitude          59400 non-null  float64
 4   latitude           59400 non-null  float64
 5   basin              59400 non-null  object
 6   region             59400 non-null  object
 7   region_code        59400 non-null  int64
 8   district_code      59400 non-null  int64
 9   population         59400 non-null  int64
 10  public_meeting     56066 non-null  object
 11  scheme_management  55523 non-null  object
 12  permit             56344 non-null  object
 13  construction_year  59400 non-null  int64
 14  extraction_type    59400 non-null  object
 15  management         59400 non-null  object
 16  management_group   59400 non-null  object
 17  payment_type       59400 non-null  object
 18  water_quality      59400 non-null  object
 19  quantity           59400 non-null  object
 20  source             59400 non-null  object
 21  source_type        59400 non-null  object
 22  source_class       59400 non-null  object
 23  waterpoint_type    59400 non-null  object
 24  status_group       59400 non-null  object
dtypes: float64(3), int64(5), object(17)
memory usage: 11.3+ MB
```

[35]:
```
# Create a 'rev_status' colum, assign 0 if 'status_group' equals functional
# and assign 1 if 'status_group' eqauls not functional or functional needs␣
↪repair

combined_final_df['rev_status'] = combined_final_df['status_group'].map(lambda␣
↪x: 0 if(x == 'functional') else 1)
combined_final_df['rev_status'].value_counts(normalize=True)
```

[35]:
```
0    0.543081
1    0.456919
Name: rev_status, dtype: float64
```

[36]:
```
# Display pump status by water source

status_by_source = combined_final_df.
↪groupby(['source_type','status_group'])['status_group'].agg('count')



table = pd.pivot_table(combined_final_df,values='gps_height',
                       index='source_type',columns='status_group',
                       aggfunc='count')
```

```
#print(table)
#print('='*80)


table = table.reindex(table['functional'].sort_values(ascending=False).index)
table_plot = table.plot.bar(figsize=(12,8),stacked=True,
              title='Pump Status by Water Source',
              color=['green','yellow','red'])

#table_plot.set_yscale('log')
table_plot.set_xticklabels(rotation=30,labels=['Spring','Shallow Well','Ground␣
↪Water',
                                               'River/Lake', 'Rainwater', 'Dam',␣
↪'Other'])
table_plot.set_xlabel('')
table_plot.legend(title='Pump Status');

#plt.savefig('pump_status2.jpeg')
```



[37]:
```
# Split dataframe into features and target copies
```

```
final_features = combined_final_df.drop(['status_group','rev_status'],axis=1).
 ↪copy()
final_target = combined_final_df['rev_status'].copy()
final_features.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 59400 entries, 0 to 59399
Data columns (total 24 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   amount_tsh         59400 non-null  float64
 1   date_recorded      59400 non-null  object
 2   gps_height         59400 non-null  int64
 3   longitude          59400 non-null  float64
 4   latitude           59400 non-null  float64
 5   basin              59400 non-null  object
 6   region             59400 non-null  object
 7   region_code        59400 non-null  int64
 8   district_code      59400 non-null  int64
 9   population         59400 non-null  int64
 10  public_meeting     56066 non-null  object
 11  scheme_management  55523 non-null  object
 12  permit             56344 non-null  object
 13  construction_year  59400 non-null  int64
 14  extraction_type    59400 non-null  object
 15  management         59400 non-null  object
 16  management_group   59400 non-null  object
 17  payment_type       59400 non-null  object
 18  water_quality      59400 non-null  object
 19  quantity           59400 non-null  object
 20  source             59400 non-null  object
 21  source_type        59400 non-null  object
 22  source_class       59400 non-null  object
 23  waterpoint_type    59400 non-null  object
dtypes: float64(3), int64(5), object(16)
memory usage: 10.9+ MB
```

[ ]:

```

```

[38]:

```
# Split final_features and final_target for train_test_split

X_train, X_test, y_train, y_test = train_test_split(final_features,
                                                    final_target,
                                                     test_size = 0.3,
                                                    random_state=1234,
                                                    stratify=final_target)
```

[39]:
```
print(y_train.value_counts(normalize=True))
print(y_test.value_counts(normalize=True))
```

```
0    0.543074
1    0.456926
Name: rev_status, dtype: float64
0    0.543098
1    0.456902
Name: rev_status, dtype: float64
```

[40]:
```
X_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41580 entries, 42910 to 11242
Data columns (total 24 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   amount_tsh         41580 non-null  float64
 1   date_recorded      41580 non-null  object
 2   gps_height         41580 non-null  int64
 3   longitude          41580 non-null  float64
 4   latitude           41580 non-null  float64
 5   basin              41580 non-null  object
 6   region             41580 non-null  object
 7   region_code        41580 non-null  int64
 8   district_code      41580 non-null  int64
 9   population         41580 non-null  int64
 10  public_meeting     39283 non-null  object
 11  scheme_management  38872 non-null  object
 12  permit             39445 non-null  object
 13  construction_year  41580 non-null  int64
 14  extraction_type    41580 non-null  object
 15  management         41580 non-null  object
 16  management_group   41580 non-null  object
 17  payment_type       41580 non-null  object
 18  water_quality      41580 non-null  object
 19  quantity           41580 non-null  object
 20  source             41580 non-null  object
 21  source_type        41580 non-null  object
 22  source_class       41580 non-null  object
 23  waterpoint_type    41580 non-null  object
dtypes: float64(3), int64(5), object(16)
memory usage: 7.9+ MB
```

[41]:
```
# Create X_trian for numerical features

X_train_nums = X_train.select_dtypes(['float64','int64'])
```

```
X_train_nums.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41580 entries, 42910 to 11242
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   amount_tsh         41580 non-null  float64
 1   gps_height         41580 non-null  int64
 2   longitude          41580 non-null  float64
 3   latitude           41580 non-null  float64
 4   region_code        41580 non-null  int64
 5   district_code      41580 non-null  int64
 6   population         41580 non-null  int64
 7   construction_year  41580 non-null  int64
dtypes: float64(3), int64(5)
memory usage: 2.9 MB
```

[42]:
```
# Create X_train for categorical features

X_train_cats = X_train.select_dtypes('object')
X_train_cats.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41580 entries, 42910 to 11242
Data columns (total 16 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   date_recorded      41580 non-null  object
 1   basin              41580 non-null  object
 2   region             41580 non-null  object
 3   public_meeting     39283 non-null  object
 4   scheme_management  38872 non-null  object
 5   permit             39445 non-null  object
 6   extraction_type    41580 non-null  object
 7   management         41580 non-null  object
 8   management_group   41580 non-null  object
 9   payment_type       41580 non-null  object
 10  water_quality      41580 non-null  object
 11  quantity           41580 non-null  object
 12  source             41580 non-null  object
 13  source_type        41580 non-null  object
 14  source_class       41580 non-null  object
 15  waterpoint_type    41580 non-null  object
dtypes: object(16)
memory usage: 5.4+ MB
```

[43]:
```
# Setup numerical and categorical pipeline and incorporate both into
# ColumnTransformer

num_pipeline = Pipeline(steps=[
    ('num_impute',SimpleImputer(strategy='mean')),
    ('num_ss',StandardScaler())])

cat_pipeline = Pipeline(steps=[
    ('cat_impute',SimpleImputer(strategy='most_frequent')),
    ('cat_ohe', OneHotEncoder(sparse=False,handle_unknown='ignore'))])

cat_pipeline2 = Pipeline(steps=[
    ('cat_impute',SimpleImputer(strategy='most_frequent')),
    ('cat_ord',OrdinalEncoder())])

trans = ColumnTransformer(transformers=[
    ('numerical',num_pipeline,X_train_nums.columns),
    ('categorical',cat_pipeline,X_train_cats.columns)])

trans2 = ColumnTransformer(transformers=[
    ('numerical',num_pipeline,X_train_nums.columns),
    ('categorical',cat_pipeline,X_train_cats.columns)])
```

2 Model Development

For model development we ultilized sklearn Pipeline and GridSearchCV to efficiently test out our models. We evaluated the data with the following models: * DummyClassifier as base model * Logistic Regression * DecisionTreeClassifier * KNeighborsClassifier * VotingClassifier with DecisionTreeClassifier and KNeighborsClassifier * RandomForestClassifier

[44]:
```
# Use this function to plot ROC curve

def plot_roc_curve(y_actuals,y_predict,model_name):
    '''
    Compute false positive rates(fpr) and true positive rates(tpr) and display␣
 ↪ROC curve.
    '''

    #fig,ax = plt.subplots(figsize=(10,10))
    fpr, tpr, thresholds = metrics.roc_curve(y_actuals, y_predict)
    roc_auc = metrics.auc(fpr, tpr)
    display = metrics.RocCurveDisplay(fpr=fpr, tpr=tpr, roc_auc=roc_auc,
                                      estimator_name=model_name)
    display.plot();
```

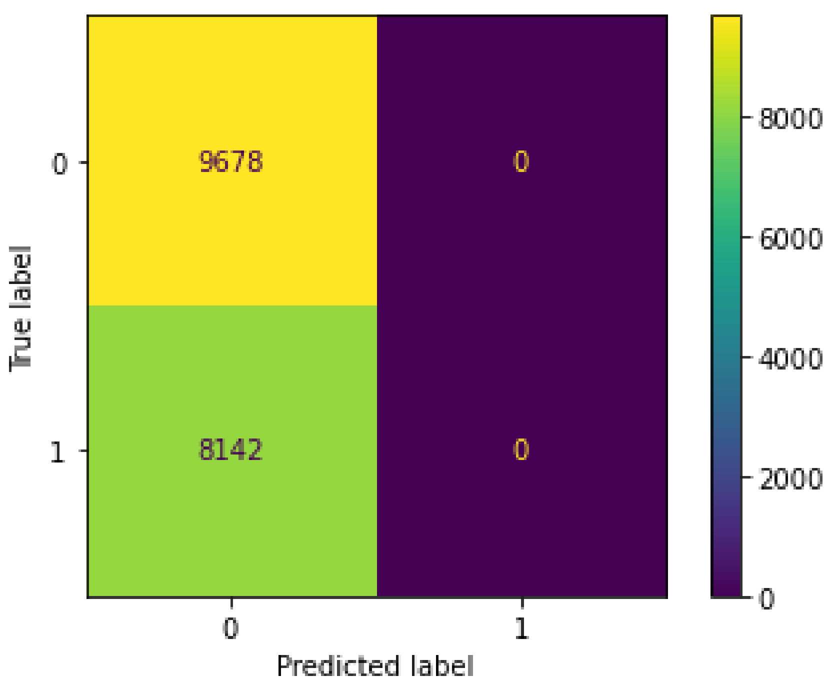
[45]:
```
def show_results(model,actuals,predictions,model_name):
    '''
    Print out metrics for validation and test samples.
    '''

    # Incorporate cv_results into pandas dataframe
    base_cv_results = pd.DataFrame([model.cv_results_])
    accuracy = base_cv_results['mean_test_accuracy'].mean()[0]

    print('='*40)
    print(f'Validation recall score: {model.best_score_}')
    print(f'Validation accuracy score: {accuracy}')
    print(f'Best paramets: {model.best_params_}')
    print('='*40)

    # Predict for X_test samples
    print(f'Test sample prediction result for: {model_name}.')

    recall = recall_score(actuals,predictions)
    accuracy = accuracy_score(actuals,predictions)
    print(f'Test recall score: {recall}\nTest accuracy score: {accuracy}')
    print('='*40)
```

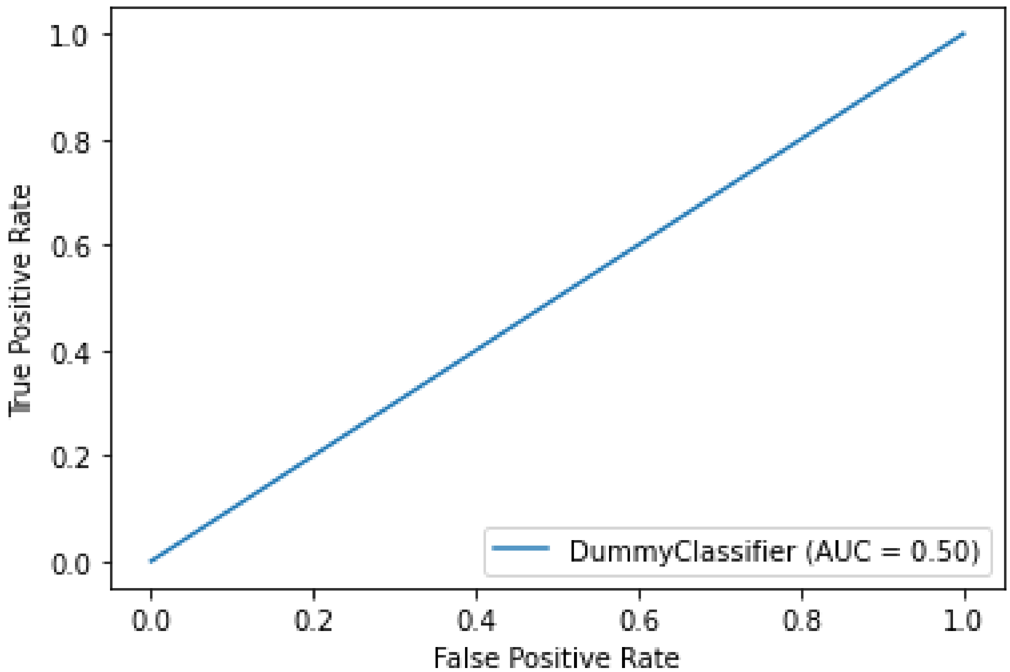
[46]:
```
# Create base model Pipe for DummyClassifier

start = time.time()
base_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('dummy_model',DummyClassifier(strategy='prior'))])

# Specify parameters for DummyClassifier GridSearch and incorpoare base model
# Pipe into GridSearchCV
base_parameters = {
    'dummy_model__random_state': [1234],
    'dummy_model__strategy' : ['prior']
}

base_grid_model = GridSearchCV(estimator = base_model_pipe,
                          param_grid=base_parameters,refit='recall',
                         scoring=['recall','accuracy'])

# Fit train data for base model
base_grid_model.fit(X_train,y_train)

stop = time.time()
print(f'Time run this DummyClassifier: {stop-start}')
```

```
Time run this DummyClassifier: 32.915385007858276
```

[47]:
```python
# Predict for test samples

base_y_test_pred = base_grid_model.predict(X_test)

show_results(base_grid_model,y_test,base_y_test_pred,'DummyClassifier')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(base_grid_model,X_test,y_test);
plot_roc_curve(y_test,base_y_test_pred,'DummyClassifier')
```

```
========================================
Validation recall score: 0.0
Validation accuracy score: 0.543073593073593
Best paramets: {'dummy_model__random_state': 1234, 'dummy_model__strategy':
'prior'}
========================================
Test sample prediction result for: DummyClassifier.
Test recall score: 0.0
Test accuracy score: 0.5430976430976431
========================================
```





[48]:

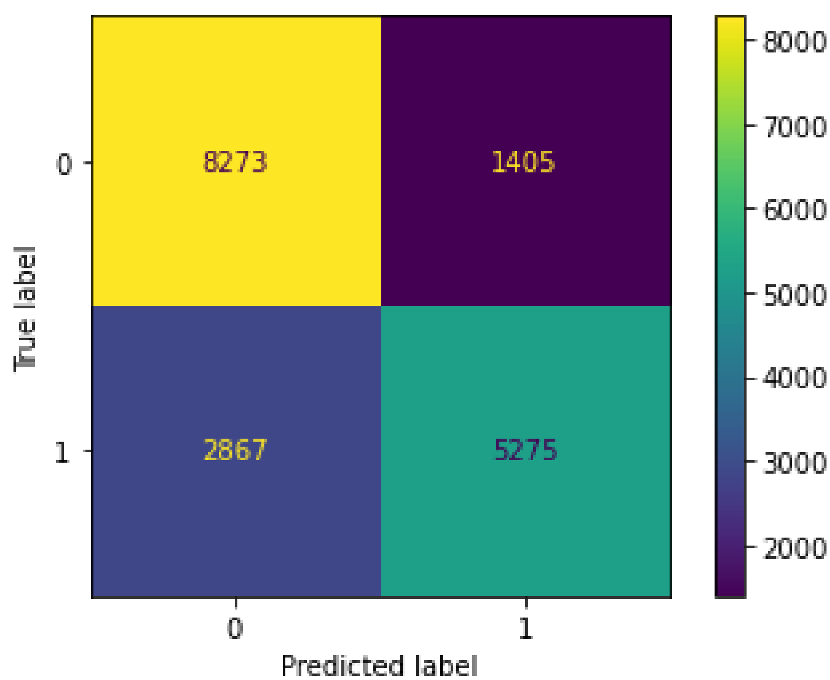
```
# Create model Pipe for Logistic Regression
start = time.time()
lr_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('lr_model',LogisticRegression())])

# Specify grid parameters for lr_model and incorporate into GridSearch
lr_parameters = {
    'trans__numerical__num_ss__with_mean' : [True],  #tried False
    #'lr_model__penalty' : ['l2','l1','elasticnet'], #too many warnings gets␣
 ↪generated
    'lr_model__random_state' : [1234],
    'lr_model__C' : [1e3],  #tried 1e-3,1,10e3 and 10e9
    'lr_model__max_iter' : [5e3],  #tried 1e4
    'lr_model__solver' : ['lbfgs'] #tried also 'liblinear'
}

lr_grid_model = GridSearchCV(estimator = lr_model_pipe,
                          param_grid=lr_parameters,refit='recall',
                          scoring=['recall','accuracy'])

# Train model with train sample
lr_grid_model.fit(X_train,y_train)
stop = time.time()
```

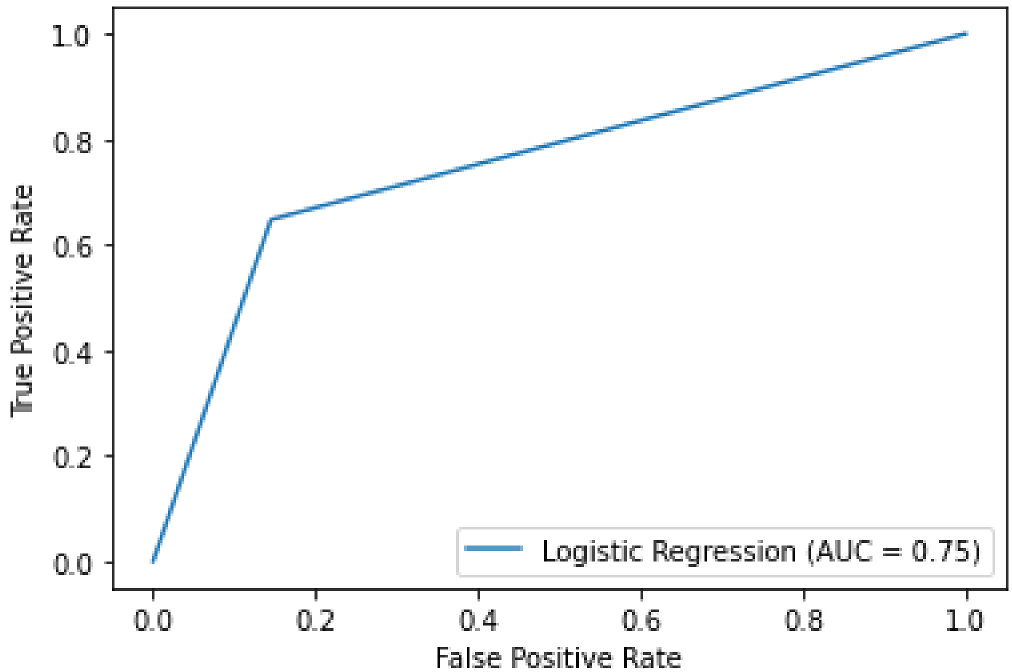
```
print(f'Time to run this Logistic Classifier grid: {stop-start}')
```

```
Time to run this Logistic Classifier grid: 230.6871440410614
```

[49]:
```
# Predict for test samples

lr_y_test_pred = lr_grid_model.predict(X_test)

show_results(lr_grid_model,y_test,lr_y_test_pred,'Logistic Regression')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(lr_grid_model,X_test,y_test);
plot_roc_curve(y_test,lr_y_test_pred,'Logistic Regression')
```

```
========================================
Validation recall score: 0.6378758537565288
Validation accuracy score: 0.7519480519480052
Best paramets: {'lr_model__C': 1000.0, 'lr_model__max_iter': 5000.0,
'lr_model__random_state': 1234, 'lr_model__solver': 'lbfgs',
'trans__numerical__num_ss__with_mean': True}
========================================
Test sample prediction result for: Logistic Regression.
Test recall score: 0.6478752149349054
Test accuracy score: 0.7602693602693603
========================================
```





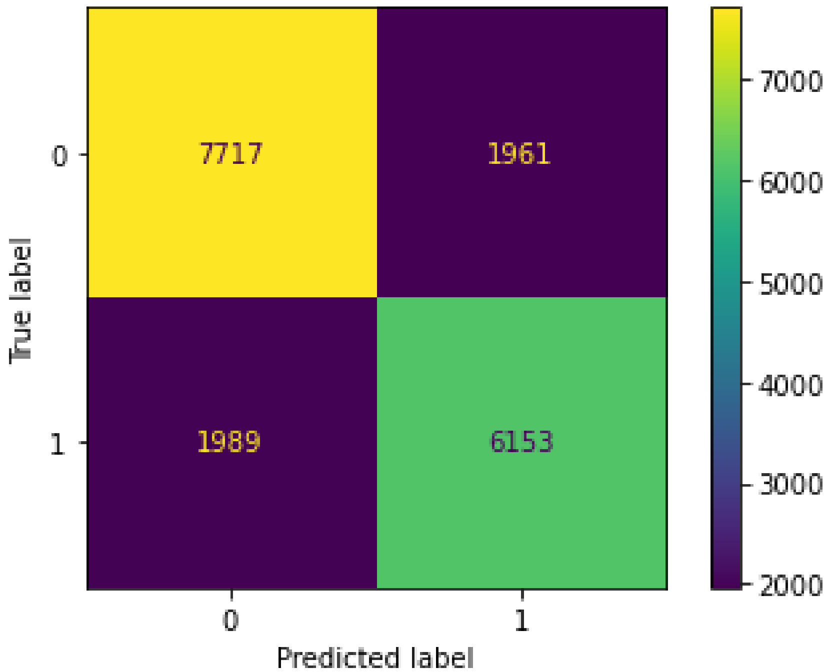
[50]:
```
# Create base model Pipe for DecisionTreeClassifier
start = time.time()
dt_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('dtree_model',DecisionTreeClassifier())])

# Specify parameters for DecisionTreeClassifier GridSearch and incorpoare
# dtree_model Pipe into GridSearchCV
dt_parameters = {
    'dtree_model__random_state' : [1234],
    'dtree_model__max_depth': [45],   #tried 3,5,10,30,60(best),90
    'dtree_model__min_impurity_decrease' : [0], # tried 0,0.3
    'dtree_model__max_features' : ['auto'] #tried 'sqrt'
}

dtree_grid_model = GridSearchCV(estimator = dt_model_pipe,
                                 param_grid=dt_parameters,refit='recall',
                                scoring=['recall','accuracy'])

# Fit train data into dtree_grid_model
dtree_grid_model.fit(X_train,y_train)
```

```
stop = time.time()
print(f'Time to run this Decision Tree Classifier grid: {stop-start}.')
```

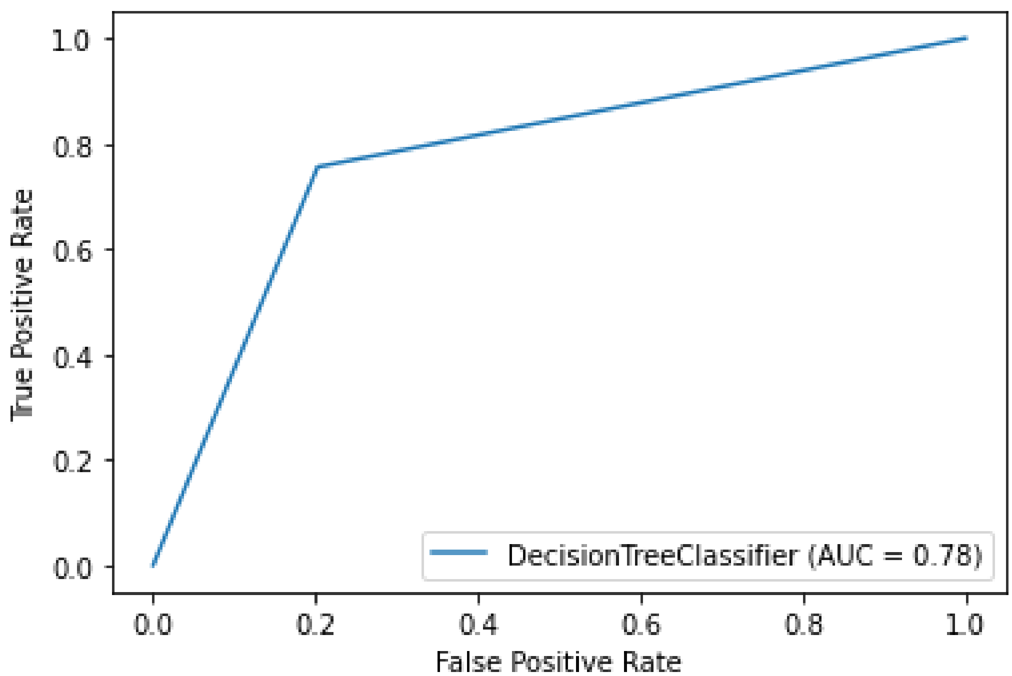
```
Time to run this Decision Tree Classifier grid: 32.69727897644043.
```

[51]:
```
# Predict for test samples

dtree_y_test_pred = dtree_grid_model.predict(X_test)

show_results(dtree_grid_model,y_test,dtree_y_test_pred,'DecisionTreeClassifier')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(dtree_grid_model,X_test,y_test);
plot_roc_curve(y_test,dtree_y_test_pred,'DecisionTreeClassifier')
```

```
========================================
Validation recall score: 0.745354982613153
Validation accuracy score: 0.770947570947571
Best paramets: {'dtree_model__max_depth': 45, 'dtree_model__max_features':
'auto', 'dtree_model__min_impurity_decrease': 0, 'dtree_model__random_state':
1234}
========================================
Test sample prediction result for: DecisionTreeClassifier.
Test recall score: 0.7557111274871039
Test accuracy score: 0.7783389450056116
========================================
```



7717
1961
1989
6153
0
1
True label
Predicted label
7000
6000
5000
4000
3000
2000



DecisionTreeClassifier (AUC = 0.78)
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0


```
[ ]:
```

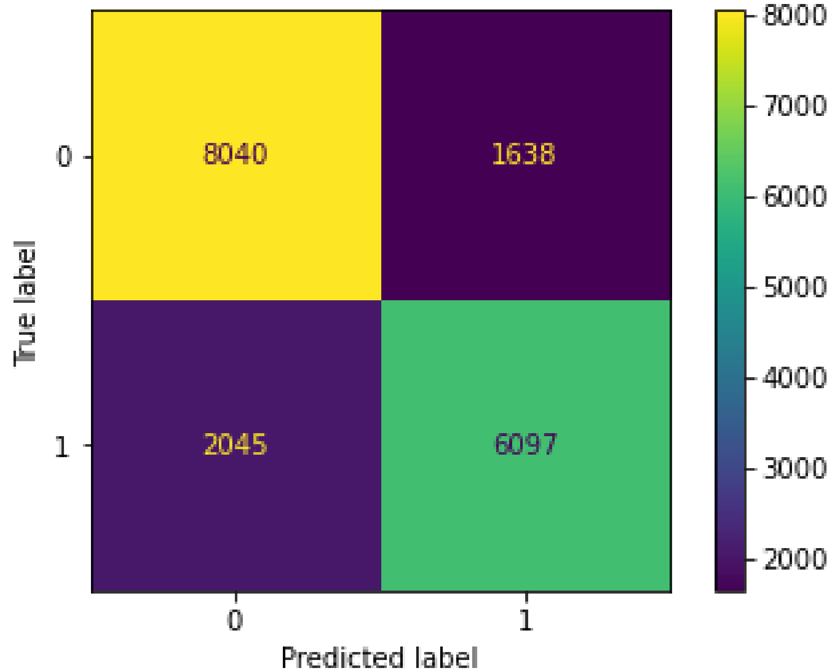
[52]:
```
# Create model Pipe for KNeighborsClassifier
start = time.time()
knn_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('knn_model',KNeighborsClassifier())])

# Specify parameters for KNeighborsClassifier GridSearch and incorpoare
# knn_model Pipe into GridSearchCV
knn_parameters = {
    'knn_model__n_neighbors' : [3], #tried 3(best),5,10 and 1 may take too long
    'knn_model__weights' : ['uniform'],   #tried ['uniform','distance']␣
↪distance(best)
    'knn_model__leaf_size' : [5] # 5,15
}

knn_grid_model = GridSearchCV(estimator = knn_model_pipe,
                          param_grid=knn_parameters,refit='recall',
                          scoring=['recall','accuracy'])

# Fit train data into knn_grid_model
knn_grid_model.fit(X_train,y_train)


stop = time.time()
print(f'Time to run KNeighbor Classifier grid: {stop-start}.')
```

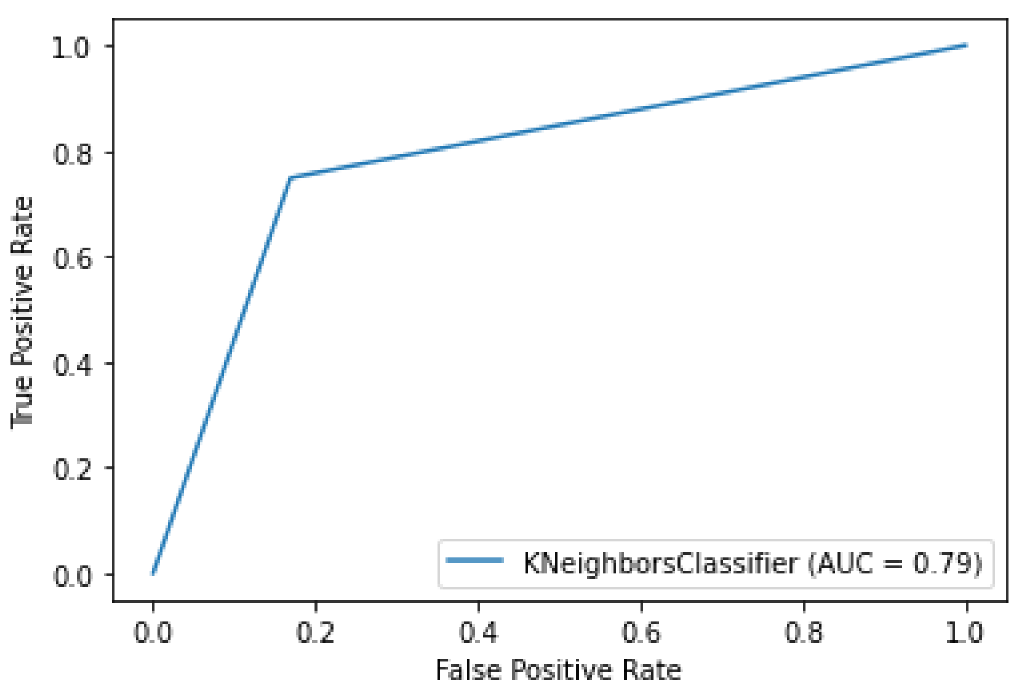
```
Time to run KNeighbor Classifier grid: 169.7671082019806.
```

[53]:
```
# Predict for test samples

knn_y_test_pred = knn_grid_model.predict(X_test)

show_results(knn_grid_model,y_test,dtree_y_test_pred,'KNeighborsClassifier')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(knn_grid_model,X_test,y_test);
plot_roc_curve(y_test,knn_y_test_pred,'KNeighborsClassifier')
```

```
========================================
Validation recall score: 0.7341959934054669
Validation accuracy score: 0.782058682058682
Best paramets: {'knn_model__leaf_size': 5, 'knn_model__n_neighbors': 3,
'knn_model__weights': 'uniform'}
========================================
Test sample prediction result for: KNeighborsClassifier.
```

```
Test recall score: 0.7557111274871039
Test accuracy score: 0.7783389450056116
========================================
```





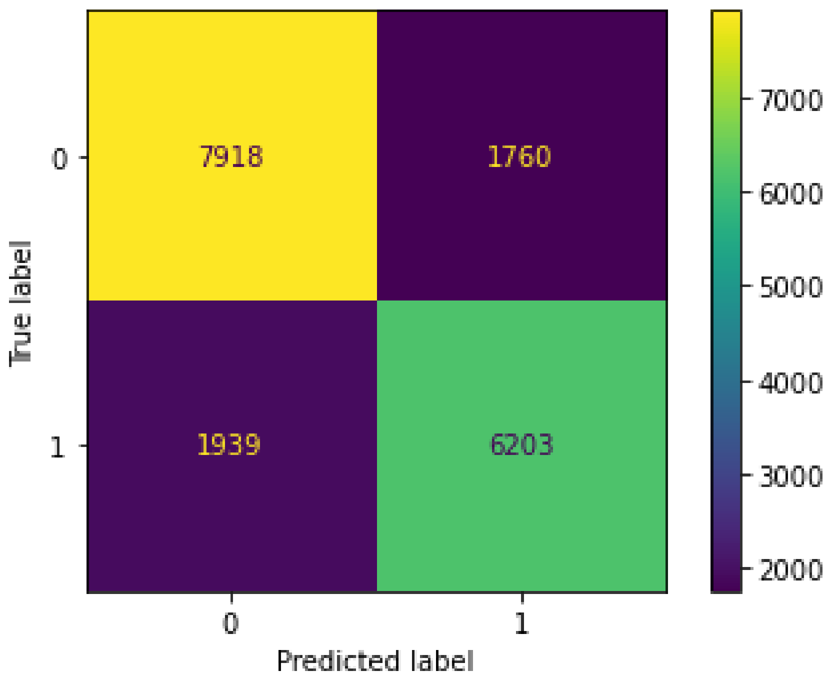
[54]:
```
# Instantiate DecisionTreeClassifier and KNeighbors estimater with specified
# parameters and then instantiate VotingClassifier and incoporate decision tree
# knn estimators into it
start = time.time()
dctree = DecisionTreeClassifier(random_state=1234,max_depth=60,
                                max_features='auto')

knneighbor = KNeighborsClassifier(n_neighbors=3,␣
 ↪leaf_size=15,weights='distance')

vc_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('vc_model',VotingClassifier(estimators=[
        ('dctree',dctree),('knneighbor',knneighbor)]))])

# Specify parameters for vc_model and incorporate into GridSearch
vc_parameters = {
    'vc_model__voting' : ['soft'],
    'vc_model__weights': [[0.4,0.6]] #tried [0.4,0.6],[0.2,0.8]
}


vc_grid_model = GridSearchCV(estimator = vc_model_pipe,
                          param_grid=vc_parameters,refit='recall',
                          scoring=['recall','accuracy'])

# Fit train data into vc_grid_model
vc_grid_model.fit(X_train,y_train)


stop = time.time()
print(f'Time to run this vc_model grid: {stop-start}')
```

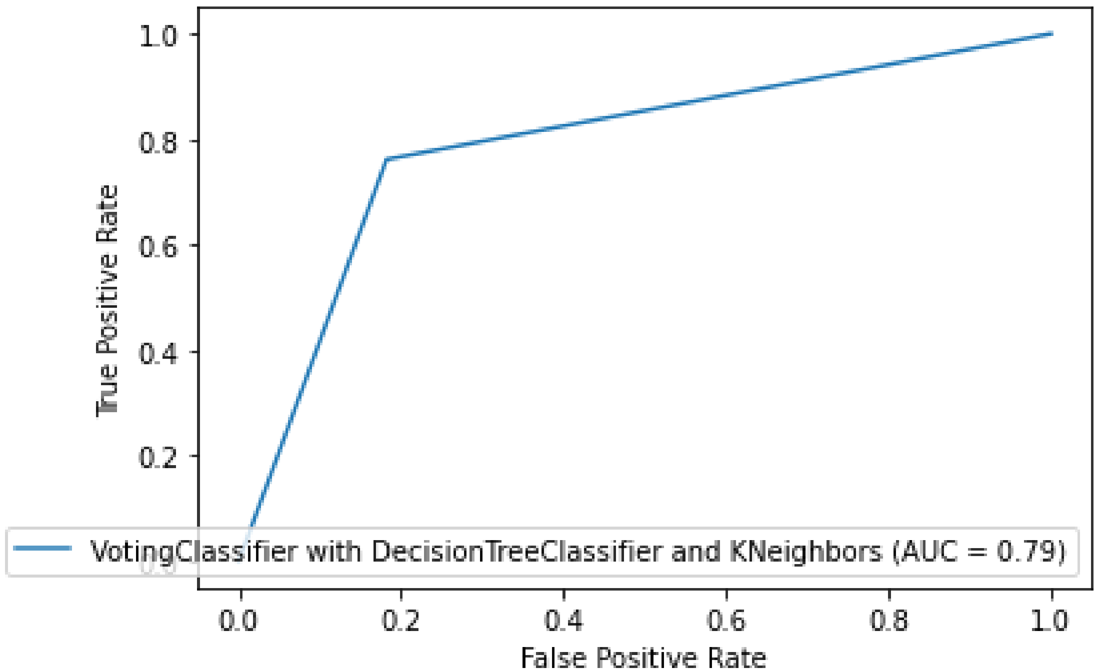
```
Time to run this vc_model grid: 159.66827702522278
```

[55]:
```
# Predict for test samples

vc_y_test_pred = vc_grid_model.predict(X_test)

show_results(vc_grid_model,y_test,vc_y_test_pred,
             'VotingClassifier with DecisionTreeClassifier and KNeighbors')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(vc_grid_model,X_test,y_test);
```

```
plot_roc_curve(y_test,vc_y_test_pred,
               'VotingClassifier with DecisionTreeClassifier and KNeighbors')
```

```
========================================
Validation recall score: 0.7531447195245287
Validation accuracy score: 0.785954785954786
Best paramets: {'vc_model__voting': 'soft', 'vc_model__weights': [0.4, 0.6]}
========================================
Test sample prediction result for: VotingClassifier with DecisionTreeClassifier
and KNeighbors.
Test recall score: 0.7618521247850651
Test accuracy score: 0.7924242424242425
========================================
```





[ ]:

[56]:

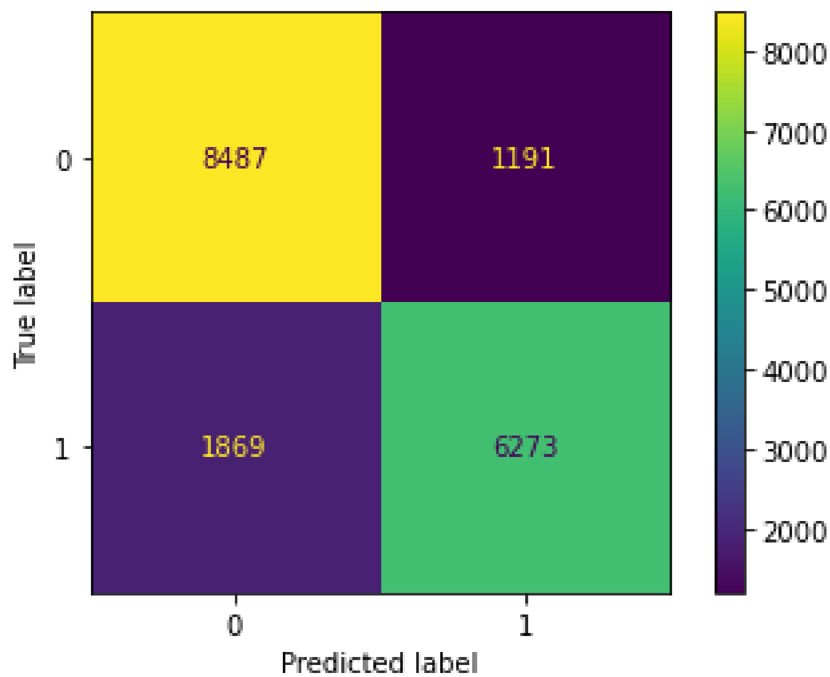
```
# Create model Pipe for RandomForestClassifier
start = time.time()
rfc_model_pipe = Pipeline(steps=[
    ('trans',trans),
    ('rfc_model',RandomForestClassifier())])

# Specify parameters rfc_model_pipe GridSearch and incorpoare
# rfc_model pipe into GridSearchCV
rfc_parameters = {
    'rfc_model__n_estimators': [100], #tried 100,200
    'rfc_model__criterion' : ['gini', 'entropy'],  #log_loss gives warnings
    'rfc_model__max_samples' : [0.5],  # tried 0.3,0.5
    'rfc_model__max_features' : ['sqrt'], # tried 'sqrt','log2'
    'rfc_model__random_state' : [123],
    'rfc_model__max_depth' : [60] # tried 30,60,75
}

rfc_grid_model = GridSearchCV(estimator = rfc_model_pipe,
                          param_grid=rfc_parameters,refit='recall',
                          scoring=['recall','accuracy'])

# Fit train data into rfc_grid_model
rfc_grid_model.fit(X_train,y_train)
```

```
stop = time.time()
print(f'Time to run this rfc_grid_model and grid: {stop-start}.')
```

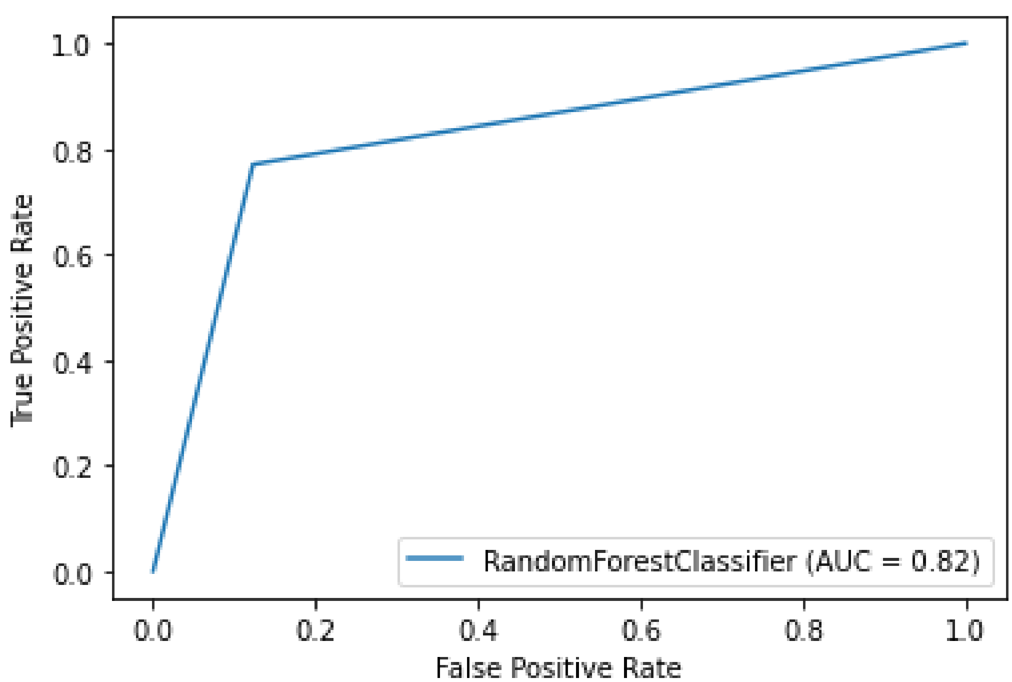
```
Time to run this rfc_grid_model and grid: 142.37469696998596.
```

[57]:
```
# Predict for test samples

rfc_y_test_pred = rfc_grid_model.predict(X_test)

show_results(rfc_grid_model,y_test,rfc_y_test_pred,'RandomForestClassifier')


# Plot confusion and ROC curve
#print(confusion_matrix(y_test,base_y_test_pred))
plot_confusion_matrix(rfc_grid_model,X_test,y_test);
plot_roc_curve(y_test,rfc_y_test_pred,'RandomForestClassifier')
```

```
========================================
Validation recall score: 0.7571974480819053
Validation accuracy score: 0.8162097162097162
Best paramets: {'rfc_model__criterion': 'entropy', 'rfc_model__max_depth': 60,
'rfc_model__max_features': 'sqrt', 'rfc_model__max_samples': 0.5,
'rfc_model__n_estimators': 100, 'rfc_model__random_state': 123}
========================================
Test sample prediction result for: RandomForestClassifier.
Test recall score: 0.7704495210022108
Test accuracy score: 0.8282828282828283
========================================
```



8487
1191
1869
6273
0
1
True label
0
1
Predicted label
8000
7000
6000
5000
4000
3000
2000



1.0
0.8
0.6
0.4
0.2
0.0
True Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate
RandomForestClassifier (AUC = 0.82)

3 Conclusion

This project is a binary classification problem where prediction models are trained to predict the status of water pumps, especially those water pumps needing repair or operationally non-functional. Because of our business objective, we have decided to use recall for our model primary metric and accuracy for overall performance. Recall in this situation means what percentage of water pumps that are broken or need repair can our model predict correctly. Our base model is DummyClassifier which gave a recall 0 and accuracy of 0.54. Logistic Regression provides better predictions with a recall of 0.65 and accuracy of 0.76. The next four models which are DecisionTree, KNeighbors, VotingClassifier (with DecisonTree and KNeighbors and Random Forest give similar result with a recall between 0.76 - 0.77 and accuracy between 0.78 - 0.83. RandomForest gives a slightly better performance with a recall of 0.77 and accuracy of 0.83 and therefore it is our best model.

[ ]:

```
```