Flatiron School Phase 3 Project

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Blog post URL: [https://medium.com/@angelo.turri/multi-class-classification-poorly-defined-categories-f525b13f6688 (https://medium.com/@angelo.turri/multi-class-classification-poorly-defined-categories-f525b13f6688)](https://medium.com/@angelo.turri/multi-class-classification-poorly-defined-categories-f525b13f6688)

INTRODUCTION

Stakeholder

A charity organization has a list of Tanzanian water pumps. These pumps can either be:

- entirely functional,
- functional with some defects in need of repair,
- or totally non-functional.

This organization wants to **fix as many of these pumps as it can**. However, they have **limited funds**. To make the most of these funds, they need to be as efficient as possible – this means dispatching **only what is necessary** to each waterpoint to get the job done. In this hypothetical scenario, non functional water pumps require significantly more resources to repair than functional-needs-repair water pumps.

It is our job to use our available data to make predictions about the waterpoints that this charity organization gave us. The organization wants us to maximize our predictive accuracy for all three categories.

Data: Origin & Usage

The data was taken from [https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/ (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/)](https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/data/)

Descriptions of any of the original variables can be found **below in the dictionary**. These descriptions are also provided here [https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/25/ (https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/25/)](https://www.drivendata.org/competitions/7/pump-it-up-data-mining-the-water-table/page/25/).

We will be using both numeric and categorical variables in our models. The categorical models will be one-hot-encoded, and the numeric variables will be standardized using a scaler from scikit-learn.

Methods Justification & Value to Stakeholder

Our current project centers around a ternary classifier, **status_group**, which categorizes a waterpoint into one of three levels of functionality. We will therefore be using a variety of classification models on our data.

Furthermore, we will be taking an **iterative modeling approach**, meaning we will be starting with a basic model and making decisions from there according to our chosen model metrics.

This project yields predictions for all of the water wells that the charity asked us to classify, as well as some further recommendations for overall allocation of resources.

Limitations

The size of the dataset (roughly 60,000 records) is not optimal, limiting what our models will be able to gather.

Model Evaluation

Going forward, we need to decide our metrics for evaluating model success. My metric of choice will be the f1-score for each category in the target variable. The f1-score is a balanced average of recall and precision (recall being the number of instances in a category you successfully identify, and precision being how accurate you are in identifying an instance when you predict it). Both recall and precision offer incomplete pictures of model success, but the f1-score gets the best of both metrics. The better the f1-score, the better our model is able to predict wells from that category, and the better off our stakeholder will be.

There is also one kind of error that I would like to use as a secondary metric – when a model incorrectly classifies a non-functional well as functional. This error is particularly serious, since you would be leaving certain communities without water. This is the sort of thing our stakeholders do not want to do, and so avoiding it will contribute to their objective.

I will be choosing the model that has the best balance between the f1-scores and this particularly bad kind of error.

In [1]:
```
import numpy as np
import pandas as pd
import geopandas as gpd
from matplotlib import pyplot as plt
import seaborn as sns
from tqdm import tqdm
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder, Ordinal
Encoder
from sklearn.metrics import confusion_matrix, classification_report, D
etCurveDisplay, RocCurveDisplay, roc_curve, auc
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
, AdaBoostClassifier, GradientBoostingClassifier, HistGradientBoosting
Classifier, ExtraTreesClassifier
from sklearn.feature_selection import SelectKBest, chi2, mutual_info_c
lassif
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE
from IPython.display import clear_output, display_html
import time, sys
from collections import Counter
from itertools import product
import scipy.stats as ss
import researchpy as rp
import joblib

# Suppresses needless warnings
import warnings
warnings.filterwarnings("ignore")

# Makes visualizations nicer
sns.set_theme()
sns.set_style("darkgrid")
sns.despine();

# Random state for any function in the notebook that uses one.
# This is for reproducibility.
state = 42
```

<Figure size 640x480 with 0 Axes>

In [2]:

```
def cramers_df(df):

    """
    Takes a dataframe of categorical data, computes
    the correlation dataframe based on the cramer's v effect
    size for the chi-squared statistic between each of the variables.

    Returns the correlation dataframe.
    """

    # Enables us to see all the correlations in this dataframe, as the
re are quite a few
    pd.set_option('display.max_columns', None)
    pd.set_option('display.max_rows', None)

    # Gets all possible pairs of categorical features
    combs = list(product(list(df.columns), repeat=2))

    # Cramer's V: effect size for chi-square test
    # Tells us how strongly two categorical variables are correlated
    cramer_vs = {x: None for x in combs}

    for comb in combs:
        col1 = comb[0]
        col2 = comb[1]

        crosstab, test_results, expected = rp.crosstab(df[col1], df[co
l2],
                                                       test= "chi-square",
                                                       expected_freqs= Tru
e,
                                                       prop= "cell")

        cramer_vs[comb] = test_results['results'][2] # assigns cramer'
s v to dictionary

    comb_df = {col: [None for i in df.columns] for col in df.columns}
    comb_df = pd.DataFrame(comb_df, index=df.columns)

    # Populates empty dataframe with values from dictionary
    for v in list(cramer_vs.keys()):
        comb_df[v[0]][v[1]] = cramer_vs[v]

    # Resets the custom visual settings we had in place for Pandas
    # If we didn't reset them, pandas would attempt to show every row
for large datasets
    # This would crash our notebook
    pd.reset_option('max_columns')
    pd.reset_option('max_rows')

    return comb_df
```

In [3]:

```
def find_bad_vars(dataframe, groups):

    """
    Out of any group of variables, it computes the cramer's V
    effect size of those variables to a target variable, and returns
    a dataframe of their effect sizes.

    This function also determines which variable out of each group
    correlates the strongest with the target variable, and compiles
    a list of all the other variables to be dropped.
    """


    to_drop=[]
    for group in groups:
        dictionary = {'feature': group, 'cramers_v': []}
        for x in group:
                crosstab, test_results, expected = rp.crosstab(datafra
me[x], y,
                                                       test= "chi-square",
                                                       expected_freqs= Tru
e,
                                                       prop= "cell")
                dictionary['cramers_v'].append(test_results['results']
[2]) # assigns cramer's v to dictionary

        df = pd.DataFrame(dictionary).sort_values(by=['cramers_v'], as
cending=False)
        to_drop += list(df['feature'].iloc[1:])
        display(df)

    return to_drop
```

In [4]:
```
def scale_ohe(df):

    """
    Makes a dataset suitable for modeling.
    Scales numeric data and one-hot encodes categorical
    data.
    """

    df_cat = df.select_dtypes(exclude=['float64', 'int64'])
    df_numeric = df.select_dtypes(include=['float64', 'int64'])

    df_cat = pd.get_dummies(df_cat, drop_first=True)

    mms = MinMaxScaler()
    mms.fit(df_numeric)
    df_numeric = pd.DataFrame(mms.transform(df_numeric),
                              columns = df_numeric.columns,
                              index = df_numeric.index)

    df = pd.concat([df_numeric, df_cat], axis=1)
    return df
```

In [5]:

```
def get_results(est, resample):

    """
    Takes two arguments: a classifier and a triple tuple.
    This tuple has a resampling strategy, an X-dataset, and
    a y-dataset.

    This function will fit the estimator to the datasets
    and generate predictions for a specific dataset (X_test).

    It returns the original sampling strategy, the predictions,
    a classification report with various model metrics,
    a confusion matrix, the percentage of non functional wells
    incorrectly classified as functional, and the fitted estimator.
    """

    ratio = resample[0]
    X = resample[1]
    y = resample[2]

    #Copies estimator so it doesn't fit the original
    estimator = sklearn.base.clone(est)
    estimator.fit(X, y)
    predictions = estimator.predict(X_test)

    matrix = pd.DataFrame(confusion_matrix(y_test, predictions))

    # Percentage of Non functional wells classified as functional
    error = matrix[2][0]/len(y_test[y_test==0])

    cols = ['non functional', 'functional needs repair', 'functional',
'accuracy', 'macro avg', 'weighted avg']
    report = pd.DataFrame(classification_report(y_test, predictions, o
utput_dict=True))
    report.columns = cols
    report['bad_error'] = [error, None, None, None]

    return ratio, predictions, report, matrix, error, estimator
```

In [6]:
```
def cts(val):

    """
    Takes any value in a dataframe.
    Will format it as red if it is >0.7
    or less than -0.7.
    """

    if (val > 0.7):
        color = 'red'
    elif (val<-0.7):
        color = 'red'
    else:
        color = 'black'
    return 'color: %s' % color
```

In [7]:
```
# For aesthetics

class color:
   PURPLE = '\033[95m'
   CYAN = '\033[96m'
   DARKCYAN = '\033[36m'
   BLUE = '\033[94m'
   GREEN = '\033[92m'
   YELLOW = '\033[93m'
   RED = '\033[91m'
   BOLD = '\033[1m'
   UNDERLINE = '\033[4m'
   END = '\033[0m'
```

Importing Data

In [8]:
```
# testing is the set of labels the charity wants us to generate predic
tions for

testing = pd.read_csv("data/X_test.csv")
X = pd.read_csv("data/X_train.csv")
y = pd.read_csv("data/y_train.csv")['status_group'].map({'functional':
2, 'functional needs repair': 1, 'non functional': 0})
```

Feature Selection

There are quite a few features in this dataset (40). The descriptions of each of these features was taken from Kaggle and listed below. We will not be using all the features, for several reasons:

- Some do not correlate with the target variable (status_group), e.g., the row ID;
- Others have too many categories;
- Some variables differ massively in their values from one dataset to another;
- Others are near copies of different variables in the same dataset, making it pointless to use them.

In [9]:
```
desc = {'amount_tsh': 'Amount of water available to each 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',
        'id': 'unique identifier of waterpoint',
        'longitude': 'GPS coordinate',
        'latitude': 'GPS coordinate',
        'wpt_name': 'Name of the waterpoint if there is one',
        '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': 'The year each waterpoint was constructed
',
        'extraction_type': 'The kind of extraction the waterpoint uses
',
        'extraction_type_group': 'The kind of extraction the waterpoin
t uses',
        'extraction_type_class': 'The kind of extraction the waterpoin
t uses',
        'management': 'How the waterpoint is managed',
        'management_group': 'How the waterpoint is managed',
        'payment': 'How people pay for water at the waterpoint',
        'payment_type': 'How people pay for water at the waterpoint',
        'water_quality': 'The quality of the water',
        'quality_group': 'The quality of the water',
        'quantity': 'The quantity of water each waterpoint provides',
        'quantity_group': 'The quantity of water each waterpoint provi
des',
        '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',
        'num_private': 'number of private waterpoints available to the
owner',
        'vicinity_amount_tsh': 'average amount_tsh for wells in the vi
cinity',
        'vicinity_population': 'average population for wells in the vi
cinity'
    }
```

Filling null values / dtypes

In [10]:
```
# Filling null values / fixing some dtypes

for df in [X, testing]:
    df.scheme_management.fillna("None", inplace=True)
    df.permit.fillna('Unknown', inplace=True)
    df.public_meeting.fillna('Unknown', inplace=True)
    df['permit'] = df['permit'].map({True: 'Yes', False: 'No', 'Unknow
n': 'Unknown'})
    df['gps_height'] = df['gps_height'].astype('float64')
    df['population'] = df['population'].astype('float64')
    df['construction_year'] = df['construction_year'].astype('int64')
    df['region_code'] = df['region_code'].astype('str')
    df['district_code'] = df['district_code'].astype('str')
```

Feature Engineering

In [11]:

```
# Averages the numeric properties of other waterpoints in a well's vic
inity.

latitude_square, longitude_square = 0.02, 0.02 # Boundaries for region


for df in [X, testing]:

    for col in ['amount_tsh', 'population']:

        vicinity_means = []

        for i in list(range(len(df))):
            latitude, longitude = df.iloc[i].latitude, df.iloc[i].long
itude
            identifier = df.iloc[i].id

            # Gathers all wells in a surrounding region
            # Eliminates the reference well
            area = df[(df.latitude < latitude+latitude_square) &
                      (df.latitude > latitude-latitude_square) &
                      (df.longitude < longitude+longitude_square)
&
                      (df.longitude > longitude-longitude_square)
&
                      (df.id != identifier)]

            if len(area)==0:
                vicinity_means.append(0)

            else:
                vicinity_means.append(area[col].mean())

            # These outputs let us know how much is left to complete.
            # They are only shown on every 5th loop iteration to avoid
crashing
            # the console.
            if i%5==0:
                clear_output(wait=True)
                print(f"Feature: {'vicinity_' + col}")
                print(f"cell number {i+1} out of {len(df)} done.")
                percentage = (i+1)/len(df) * 100
                print(f"{round(percentage, 2)}% complete.")


        print("Features successfully engineered.")

        # Creates new column.
        df['vicinity_' + col] = vicinity_means
```

```
Feature: vicinity_population
cell number 14846 out of 14850 done.
99.97% complete.
Features successfully engineered.
```

Variable inconsistency across train and test sets

We were given two datasets for analysis – one training dataset, complete with feature and target variables, and a testing dataset, which only had the feature variables (the target values were hidden).

Our goal is to accurately predict the target values in the test dataset. To do this successfully, we must use features in our model that correlate well with the target.

Unfortunately, some of our categorical variables differ in their categories from one dataset to another. Therefore, any model that uses these variables will have less success in the test dataset than in the training dataset - because it will come across numerous unknown categories.

It seems like the following variables should be removed from our features:

- wpt_name
- subvillage
- installer
- funder
- scheme_name
- ward
- date_recorded

In [12]:
```
differences = []

# Only includes categorical variables
columns = list(X.select_dtypes(exclude=['float64', 'int64']).columns)

for col in columns:

    # This finds all the differences between two sets
    difference = set(list(X[col])) ^ set(list(testing[col]))
    differences.append(len(difference))

differences_df = pd.DataFrame({'column': list(columns), 'differences':
differences})
differences_df = differences_df.sort_values(by=['differences'], ascend
ing=False)
differences_df.head(10)
```

Out[12]:

	column	differences
3	wpt_name	43128
5	subvillage	15120
2	installer	1584
1	funder	1403
14	scheme_name	1251
10	ward	145
0	date_recorded	51
16	extraction_type	1
7	region_code	1
8	district_code	0

In [13]:
```
# Dropping all problem features from both test and train datasets

X = X.drop(list(differences_df['column'])[:7], axis=1)
testing = testing.drop(list(differences_df['column'])[:7], axis=1)
```

Dropping variables that do not correlate with the target column

Two variables, namely "id" and "recorded_by", do not correlate with the target column (status_group).

- **id** is a unique numerical identifier for waterpoints; each waterpoint has a different identifier. An identifier such as this one cannot meaningfully correlate with the target column.
- **recorded_by** has only one value in the entire dataset, and therefore cannot correlate with the target column.

In [14]:
```
X.recorded_by.value_counts()
```

Out[14]:
```
recorded_by
GeoData Consultants Ltd    59400
Name: count, dtype: int64
```

In [15]:
```
X = X.drop(['id', 'recorded_by'], axis=1)
testing = testing.drop(['id', 'recorded_by'], axis=1)
```

Checking for collinearity among the variables

We want to eliminate collinearity, because it's bad for model interpretability. These variables might be strongly correlated with each other, based on the names they were given:

- **region** and **region_code**
- **scheme_management** and **scheme_name**
- **extraction_type**, **extraction_type_group** and **extraction_type_class**
- **management** and **management_group**
- **payment** and **payment_type**
- **water_quality** and **quality_group**
- **quantity** and **quantity_group**
- **source**, **source_type** and **source_class**
- **waterpoint_type** and **waterpoint_type_group**

I will search amongst the correlations between all of our categorical features for evidence of collinearity.

In [16]:
```
# Ordinal encodes data to enable the chi-square test

X_cat = X.select_dtypes(exclude=['float64', 'int64'])
X_cat = X_cat.astype('str')

oe = OrdinalEncoder()
oe.fit(X_cat)
df_cat = pd.DataFrame(oe.transform(X_cat),
                      index = X_cat.index,
                      columns = X_cat.columns)
```

In [17]:
```
comb_df = cramers_df(X_cat)
display(comb_df.style.applymap(cts))
```

	basin	region	region_code	district_code	lga	public_meetin
basin	1.000000	0.767200	0.774000	0.314000	0.907800	0.16270
region	0.767200	1.000000	0.998100	0.325600	1.000000	0.35840
region_code	0.774000	0.998100	1.000000	0.419600	0.972700	0.36480
district_code	0.314000	0.325600	0.419600	1.000000	0.857600	0.18790
lga	0.907800	1.000000	0.972700	0.857600	1.000000	0.58040
public_meeting	0.162700	0.358400	0.364800	0.187900	0.580400	1.00000
scheme_management	0.246200	0.365500	0.381400	0.194200	0.626600	0.25290
permit	0.270500	0.446900	0.457100	0.242800	0.865800	0.10260
extraction_type	0.246100	0.261100	0.275700	0.119800	0.389200	0.13060
extraction_type_group	0.239800	0.291200	0.299400	0.129400	0.418700	0.11330
extraction_type_class	0.250500	0.358400	0.369800	0.148800	0.485100	0.10630
management	0.222200	0.343000	0.348100	0.145500	0.561100	0.27070
management_group	0.142100	0.222300	0.228100	0.107900	0.427400	0.21730
payment	0.245000	0.357500	0.368800	0.167400	0.563700	0.25180
payment_type	0.245000	0.357500	0.368800	0.167400	0.563700	0.25180
water_quality	0.119900	0.199000	0.208500	0.114600	0.356300	0.11550
quality_group	0.139200	0.215400	0.227500	0.130400	0.395300	0.10460
quantity	0.139000	0.213100	0.232500	0.152600	0.421500	0.14600
quantity_group	0.139000	0.213100	0.232500	0.152600	0.421500	0.14600
source	0.245000	0.322000	0.335200	0.147900	0.469200	0.12270
source_type	0.255000	0.356600	0.372700	0.165400	0.508000	0.10030
source_class	0.123700	0.221200	0.257500	0.198300	0.479700	0.05610
waterpoint_type	0.208600	0.294500	0.301400	0.120700	0.423100	0.07640
waterpoint_type_group	0.196600	0.271400	0.275400	0.118300	0.404600	0.07610

In [18]:
```
# Shows all correlations between numeric features
X_numeric = X.select_dtypes(include=['float64', 'int64'])
X_numeric.corr().style.applymap(cts)
```

Out[18]:

	amount_tsh	gps_height	longitude	latitude	num_private	population	cc
amount_tsh	1.000000	0.076650	0.022134	-0.052670	0.002944	0.016288	
gps_height	0.076650	1.000000	0.149155	-0.035751	0.007237	0.135003	
longitude	0.022134	0.149155	1.000000	-0.425802	0.023873	0.086590	
latitude	-0.052670	-0.035751	-0.425802	1.000000	0.006837	-0.022152	
num_private	0.002944	0.007237	0.023873	0.006837	1.000000	0.003818	
population	0.016288	0.135003	0.086590	-0.022152	0.003818	1.000000	
construction_year	0.067915	0.658727	0.396732	-0.245278	0.026056	0.260910	
vicinity_amount_tsh	0.282853	0.170784	0.049617	-0.116430	0.008578	0.012545	
vicinity_population	0.009378	0.186325	0.114432	-0.030184	0.006347	0.549685	

Strong correlations

My threshold for a strong correlation or effect size is 0.7 here.

These are the strong correlations we observed among our features:

- lga, basin, region, region_code, district_code, permit
- extraction_type, extraction_type_group, extraction_type_class
- management, scheme_management, management_group
- payment, payment_type
- water_quality, quality_group
- quantity, quantity_group
- source, source_type, source_class
- waterpoint_type, waterpoint_type_group

Of each of these groups, we must pick only one variable to keep.

In [19]:
```
# Groups of categorical variables that were strongly correlated
groups = [['lga', 'basin', 'region', 'region_code', 'district_code', '
permit'],
          ['extraction_type', 'extraction_type_group', 'extraction_typ
e_class'],
          ['management', 'scheme_management', 'management_group'],
          ['payment', 'payment_type'],
          ['water_quality', 'quality_group'],
          ['quantity', 'quantity_group'],
          ['source', 'source_type', 'source_class'],
          ['waterpoint_type', 'waterpoint_type_group']]

to_drop = find_bad_vars(X_cat, groups)
```

	feature	cramers_v
0	lga	0.3115
3	region_code	0.2084
2	region	0.2009
1	basin	0.1272
4	district_code	0.1187
5	permit	0.0296

	feature	cramers_v
0	extraction_type	0.2490
1	extraction_type_group	0.2473
2	extraction_type_class	0.2415

	feature	cramers_v
0	management	0.1324
1	scheme_management	0.1294
2	management_group	0.0492

	feature	cramers_v
0	payment	0.1827
1	payment_type	0.1827

	feature	cramers_v
0	water_quality	0.1385
1	quality_group	0.1330

	feature	cramers_v
0	quantity	0.3092
1	quantity_group	0.3092

	feature	cramers_v
0	source	0.1486
1	source_type	0.1267
2	source_class	0.0705

	feature	cramers_v
0	waterpoint_type	0.2504
1	waterpoint_type_group	0.2269

Which features to drop

This determines which variables we will keep, and which we will eliminate. The ones we will eliminate are shown below:

In [20]:
```
for i in to_drop:
    print("- " + i)
```

```
- region_code
- region
- basin
- district_code
- permit
- extraction_type_group
- extraction_type_class
- scheme_management
- management_group
- payment_type
- quality_group
- quantity_group
- source_type
- source_class
- waterpoint_type_group
```

In [21]:
```
# Eliminating problematic categorical features

X = X.drop(to_drop, axis=1)
testing = testing.drop(to_drop, axis=1)
```

Descriptive Statistics of Features

In [22]:
```
X_cat = X.select_dtypes(exclude=['float64', 'int64'])
X_numeric = X.select_dtypes(include=['float64', 'int64'])

print(f"\nWE USE {len(X_numeric.columns)} NUMERIC FEATURES:")
for i in list(X_numeric.columns):
    print(f"- {i}: {desc[i]}")

cat = X_cat
print(f"\n\n\n WE USE {len(X_cat.columns)} CATEGORICAL FEATURES:")
for i in list(cat.columns):
    print(f"- {i} ({desc[i]}): {X_cat[i].nunique()} categories. \n
'{X_cat[i].value_counts().index[0]}' is the most frequent category. \n
" )
```

WE USE 9 NUMERIC FEATURES:
- amount_tsh: Amount of water available to each waterpoint
- gps_height: Altitude of the well
- longitude: GPS coordinate
- latitude: GPS coordinate
- num_private: number of private waterpoints available to the owner
- population: Population around the well
- construction_year: The year each waterpoint was constructed
- vicinity_amount_tsh: average amount_tsh for wells in the vicinity
- vicinity_population: average population for wells in the vicinity

WE USE 9 CATEGORICAL FEATURES:
- lga (Geographic location): 125 categories.
  'Njombe' is the most frequent category.

- public_meeting (True/False): 3 categories.
  'True' is the most frequent category.

- extraction_type (The kind of extraction the waterpoint uses): 18 categories.
  'gravity' is the most frequent category.

- management (How the waterpoint is managed): 12 categories.
  'vwc' is the most frequent category.

- payment (How people pay for water at the waterpoint): 7 categories.
  'never pay' is the most frequent category.

- water_quality (The quality of the water): 8 categories.
  'soft' is the most frequent category.

- quantity (The quantity of water each waterpoint provides): 5 categories.
  'enough' is the most frequent category.

- source (The source of the water): 10 categories.
  'spring' is the most frequent category.

- waterpoint_type (The kind of waterpoint): 7 categories.
  'communal standpipe' is the most frequent category.

In [23]:
```
X_numeric.select_dtypes(['int64', 'float64']).describe()
```

Out[23]:

	amount_tsh	gps_height	longitude	latitude	num_private	population
count	59400.000000	59400.000000	59400.000000	5.940000e+04	59400.000000	59400.000000
mean	317.650385	668.297239	34.077427	-5.706033e+00	0.474141	179.909983
std	2997.574558	693.116350	6.567432	2.946019e+00	12.236230	471.482176
min	0.000000	-90.000000	0.000000	-1.164944e+01	0.000000	0.000000
25%	0.000000	0.000000	33.090347	-8.540621e+00	0.000000	0.000000
50%	0.000000	369.000000	34.908743	-5.021597e+00	0.000000	25.000000
75%	20.000000	1319.250000	37.178387	-3.326156e+00	0.000000	215.000000
max	350000.000000	2770.000000	40.345193	-2.000000e-08	1776.000000	30500.000000

Creating Test and Train Sets

The stakeholder asks us for predictions on the test set, but we do not know what the target values for this test set are (naturally – if we had those, there would be no need for the stakeholder to ask us to do this).

In order to evaluate the performance of our models, we need to create test and train sets from our complete data.

All scaling and encoding is done after the split to avoid data leakage.

In [24]:
```
# All the variables used for visualizations later
geography = pd.concat([X.select_dtypes(['int64', 'float64']).copy(),
                       y.map({0: 'non functional', 1: 'functional need
s repair', 2: 'functional'})], axis=1)

geography = geography[geography.longitude!=0]
```

In [25]:
```
#Creating a train-test-split for X and y
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state
=state, test_size=0.2)
```

In [26]:
```
# Preparing data for modeling
X_train = scale_ohe(X_train)
X_test = scale_ohe(X_test)
testing = scale_ohe(testing)
```

In [27]:
```
# One-hot encoding creates a lot of columns
# Any columns not shared between all three datasets will cause problem
s
# Only keeping columns shared by all three (195/196 columns)

common_cols = list(set(list(X_train.columns)).intersection(list(X_test
.columns), list(testing.columns)))
X_train = X_train[common_cols]
X_test = X_test[common_cols]
testing = testing[common_cols]
```

Resampled Datasets

In [28]:
```
# {1: 3466} – just the original dataset
# {1: 10000} – increasing instances of functional needs repair to 10,0
00
# {1: 15000} – increasing instances of functional needs repair to 15,0
00
# {1: 20000} – increasing instances of functional needs repair to 20,0
00
# auto – increasing instances of functional needs repair to whatever t
he most frequent class has

resampled_datasets = {str(n): SMOTE(sampling_strategy=n, random_state=
state).fit_resample(X_train, y_train) for n in [{1: 3466}, {1: 10000},
{1: 15000}, {1: 20000}, 'auto']}
resampled_datasets = [(name, key[0], key[1]) for name, key in resample
d_datasets.items()]
```

Base Model – Logistic Regression, No Regularization, No Resampling

In an iterative modeling approach, we start with a very basic model and work our way up from there. Therefore, we start with a simple Logistic Regression estimator with all default settings.

In [29]:
```
ratio, predictions, report, matrix, error, estimator = get_results(Log
isticRegression(random_state=state), resampled_datasets[0])
display(report.style.set_caption(f"resampling strategy: {ratio}"))
```

resampling strategy: {1: 3466}

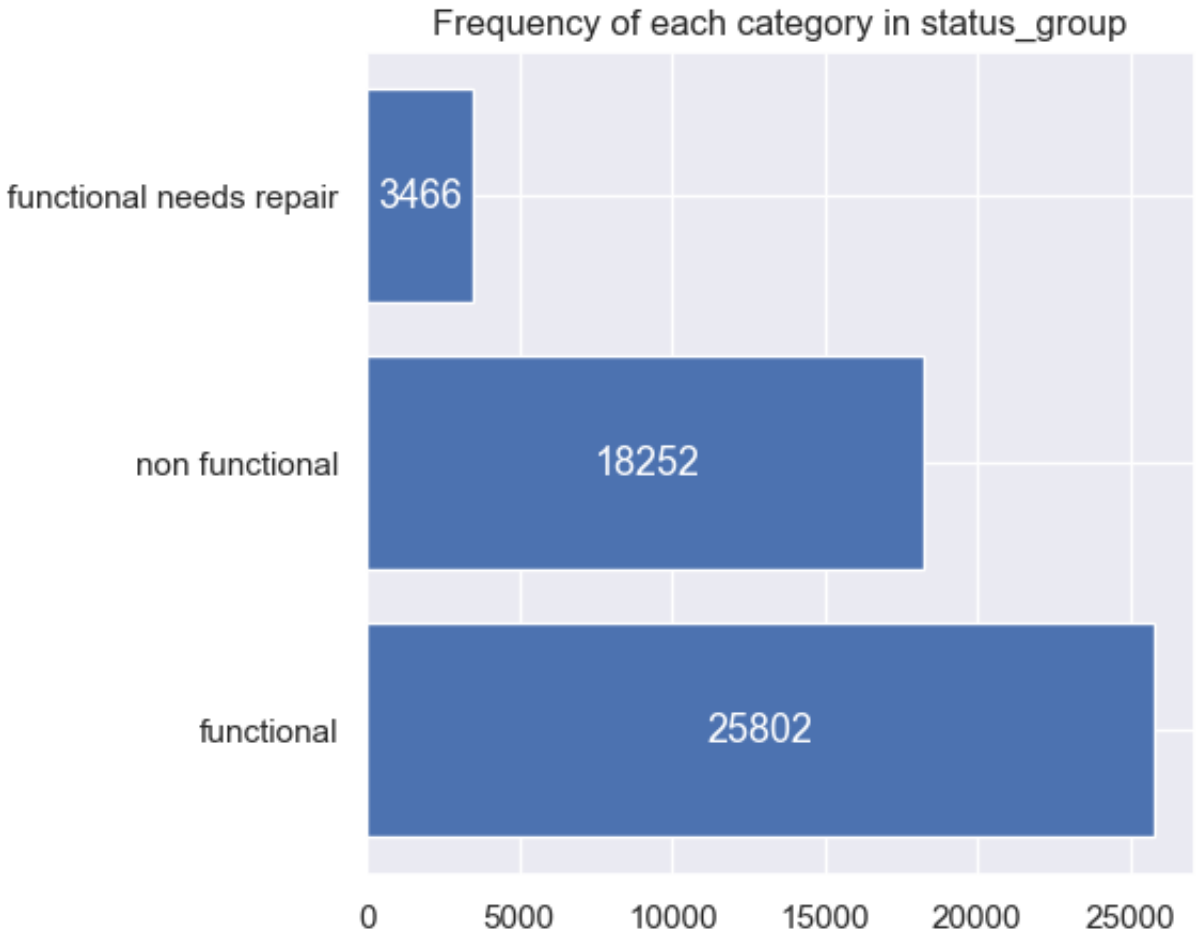
	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.794543	0.517949	0.727318	0.745034	0.679937	0.738192	0.342
recall	0.649606	0.118684	0.895153	0.745034	0.554481	0.745034	
f1-score	0.714801	0.193117	0.802555	0.745034	0.570158	0.725127	
support	4572.000000	851.000000	6457.000000	0.745034	11880.000000	11880.000000	

Major Issue – Imbalanced Target Categories

As you can see in the value counts of our target variable, the categories are extremely imbalanced. The category of "1", which means the waterpoint has a status of "functional needs repair," has way less values than 0 and 2, which mean "non functional" and "functional," respectively.

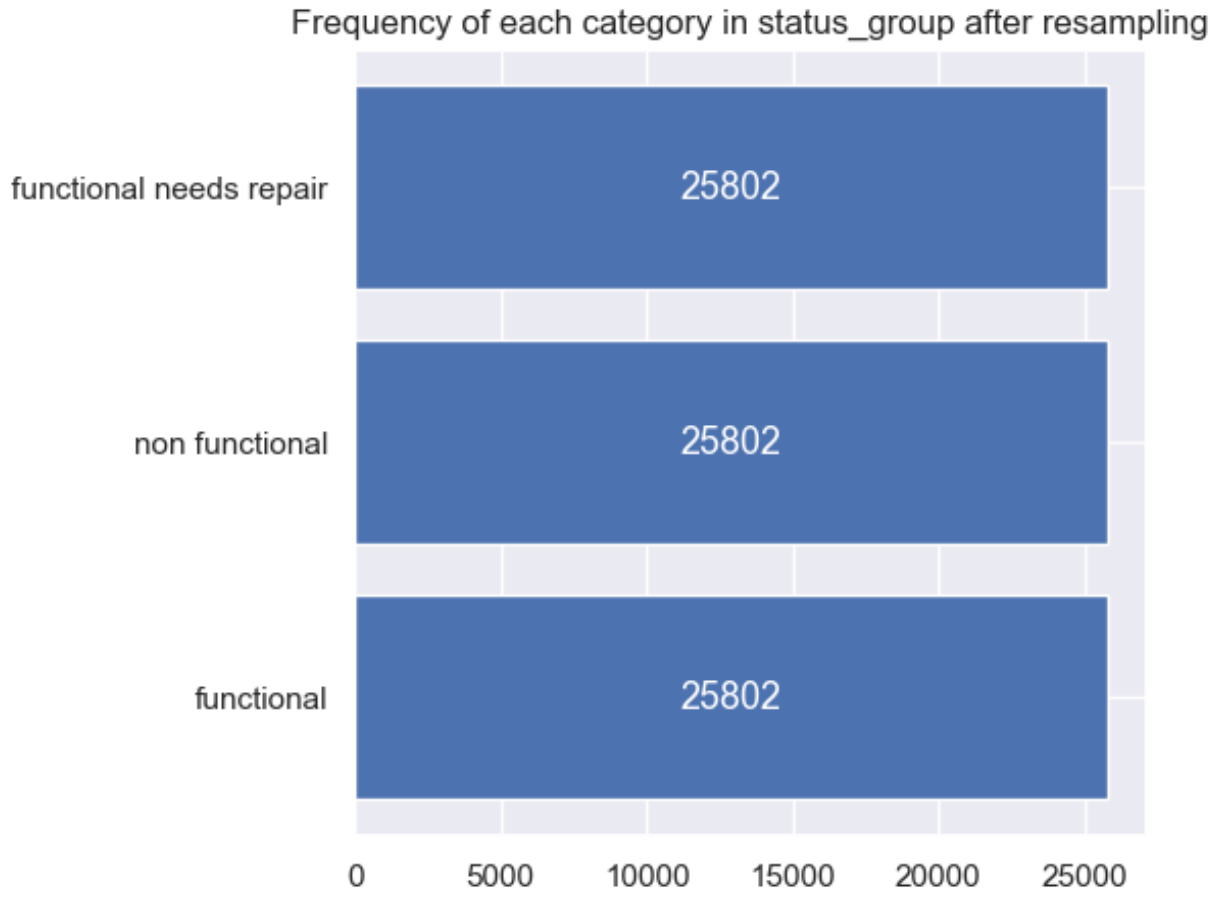
We can deal with this situation by introducing new artificial data points of the underrepresented category into our dataset, using SMOTE (Synthetic Minority Oversampling Technique). By default, this function gives each category the same number of occurrences as the most-frequent category, which in this case is "1" - "functional."

In [30]:
```
fig, ax = plt.subplots(figsize=(5,5))
counts = y_train.value_counts().sort_values(ascending=False)
barplot = ax.barh(['functional', 'non functional', 'functional needs r
epair'], list(counts))
ax.bar_label(barplot, labels=list(counts), label_type='center', color=
'white', fontsize='13');
ax.set_title(f"Frequency of each category in status_group");
```



In [31]:
```
#Resampling dataframes for model creation
smote = SMOTE(random_state=state)
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_t
rain)
```

In [32]:
```
fig, ax = plt.subplots(figsize=(5,5))
counts = y_train_resampled.value_counts().sort_values(ascending=False)
barplot = ax.barh(['functional', 'non functional', 'functional needs r
epair'], list(counts))
ax.bar_label(barplot, labels=list(counts), label_type='center', color=
'white', fontsize='13');
ax.set_title(f"Frequency of each category in status_group after resamp
ling");
```



In [33]:
```
ratio, predictions, report, matrix, error, estimator = get_results(Log
isticRegression(random_state=state), resampled_datasets[4])
display(report.style.set_caption(f"resampling strategy: {ratio}"))
```

resampling strategy: auto

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.770459	0.218400	0.789803	0.663131	0.592887	0.741427	0.205
recall	0.665136	0.641598	0.664550	0.663131	0.657095	0.663131	
f1-score	0.713934	0.325873	0.721783	0.663131	0.587196	0.690402	
support	4572.000000	851.000000	6457.000000	0.663131	11880.000000	11880.000000	

Analysis – Oversampling Effect

If our model is to be successful, we have to predict the "functional needs repair" instances with respectable accuracy. As we can see with our over-sampling technique, we can significantly improve our f1-score in this category, but it will slightly decrease our metrics in other categories.

Testing other over-sampling ratios reveals that resampling "functional needs repair" instances to about 10-15,000 instances is ideal.

However, our results still isn't good, so maybe it's time to use different estimators – e.g., random forests, gradient boosting techniques, etc.

In [34]:
```
for dataset in resampled_datasets[1:4]:
    ratio, predictions, report, matrix, error, estimator = get_results
(LogisticRegression(random_state=state), dataset)
    display(report.style.set_caption(f"resampling strategy: {ratio}"))
```

resampling strategy: {1: 10000}

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.803152	0.296226	0.743440	0.721717	0.614273	0.734385	0.31(
recall	0.635389	0.368978	0.829333	0.721717	0.611233	0.721717	
f1-score	0.709488	0.328624	0.784041	0.721717	0.607384	0.722727	
support	4572.000000	851.000000	6457.000000	0.721717	11880.000000	11880.000000	

resampling strategy: {1: 15000}

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.812215	0.255589	0.754650	0.702104	0.607484	0.741054	0.286
recall	0.622485	0.497062	0.785504	0.702104	0.635017	0.702104	
f1-score	0.704804	0.337590	0.769768	0.702104	0.604054	0.713809	
support	4572.000000	851.000000	6457.000000	0.702104	11880.000000	11880.000000	

resampling strategy: {1: 20000}

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.814675	0.228458	0.765278	0.677357	0.602804	0.745834	0.261
recall	0.614392	0.607521	0.731144	0.677357	0.651019	0.677357	
f1-score	0.700499	0.332049	0.747822	0.677357	0.593457	0.699827	
support	4572.000000	851.000000	6457.000000	0.677357	11880.000000	11880.000000	

Using different estimators

We will compile results from the following estimators and arrange them in an easily-understood format:

- Logistic Regression (re-do of what we did earlier)
- K Nearest Neighbors with n=3
- Bagging Classifier with a decision tree as its base estimator
- Random Forest
- XG-Boost
- Gradient Boosted Trees with a decision tree as its base estimator
- Extra Randomized Trees

In [35]:
```
# All the estimators to iterate through.

estimators = {'Logistic Regression': LogisticRegression(),
              'K-Nearest Neighbors n3': KNeighborsClassifier(n_neighbo
rs=3),
              'Bagging Classifier': BaggingClassifier(estimator=Decisi
onTreeClassifier()),
              'Random Forest': RandomForestClassifier(random_state=sta
te),
              'XG-Boost': XGBClassifier(n_estimators=100, objective='m
ulti:softmax', num_class=3, random_state=state),
              'Extra Randomized Trees': ExtraTreesClassifier(n_estimat
ors=100, random_state=state)}
```

In [36]:
```
# Dictionary for our results
results_dict = {name: None for name in estimators.keys()}

for estimator_name, estimator in estimators.items():

    # Helpful ticker #1
    print(f"Estimator: {estimator_name}")

    results = {}

    for dataset in resampled_datasets:

        # Helpful ticker #2
        print(f"Sampling ratio: {dataset[0]}")

        ratio, predictions, report, matrix, error, estimator = get_res
ults(estimator, dataset)

        # For this particular estimator and resampled dataset, we are
recording:
        # 1) Re-sampling strategy,
        #2) Our predictions,
        #3) Classification report,
        #4) Confusion matrix,
        #5 Bad error
        results[ratio] = (ratio, predictions, report, matrix, error, e
stimator)

    results_dict[estimator_name] = results
    clear_output(wait=True)
```

```
Estimator: Extra Randomized Trees
Sampling ratio: {1: 3466}
Sampling ratio: {1: 10000}
Sampling ratio: {1: 15000}
Sampling ratio: {1: 20000}
Sampling ratio: auto
```

In [37]:
```
# Prettifies our results

print("\n")
for estimator_name, results in results_dict.items():
    print(color.BOLD + estimator_name + color.END)
    for ratio, tup in results.items():
        display(tup[2].style.set_caption(f"resampled data (n = {ratio}
)"))
    print("\n\n")
```

Logistic Regression

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.794543	0.517949	0.727318	0.745034	0.679937	0.738192	0.342
recall	0.649606	0.118684	0.895153	0.745034	0.554481	0.745034	
f1-score	0.714801	0.193117	0.802555	0.745034	0.570158	0.725127	
support	4572.000000	851.000000	6457.000000	0.745034	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.803152	0.296226	0.743440	0.721717	0.614273	0.734385	0.310
recall	0.635389	0.368978	0.829333	0.721717	0.611233	0.721717	
f1-score	0.709488	0.328624	0.784041	0.721717	0.607384	0.722727	
support	4572.000000	851.000000	6457.000000	0.721717	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.812215	0.255589	0.754650	0.702104	0.607484	0.741054	0.286
recall	0.622485	0.497062	0.785504	0.702104	0.635017	0.702104	
f1-score	0.704804	0.337590	0.769768	0.702104	0.604054	0.713809	
support	4572.000000	851.000000	6457.000000	0.702104	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.814675	0.228458	0.765278	0.677357	0.602804	0.745834	0.261
recall	0.614392	0.607521	0.731144	0.677357	0.651019	0.677357	
f1-score	0.700499	0.332049	0.747822	0.677357	0.593457	0.699827	
support	4572.000000	851.000000	6457.000000	0.677357	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.770459	0.218400	0.789803	0.663131	0.592887	0.741427	0.205
recall	0.665136	0.641598	0.664550	0.663131	0.657095	0.663131	
f1-score	0.713934	0.325873	0.721783	0.663131	0.587196	0.690402	
support	4572.000000	851.000000	6457.000000	0.663131	11880.000000	11880.000000	

K-Nearest Neighbors n3

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.738361	0.401826	0.779182	0.742593	0.639790	0.736441	0.236
recall	0.738845	0.310223	0.802230	0.742593	0.617100	0.742593	
f1-score	0.738603	0.350133	0.790538	0.742593	0.626424	0.739003	
support	4572.000000	851.000000	6457.000000	0.742593	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.748309	0.319168	0.784385	0.727609	0.617287	0.737176	0.226
recall	0.725722	0.414806	0.770172	0.727609	0.636900	0.727609	
f1-score	0.736842	0.360756	0.777213	0.727609	0.624937	0.731845	
support	4572.000000	851.000000	6457.000000	0.727609	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.751023	0.297686	0.785680	0.721380	0.611463	0.737386	0.221
recall	0.722441	0.438308	0.757937	0.721380	0.639562	0.721380	
f1-score	0.736455	0.354563	0.771559	0.721380	0.620859	0.728179	
support	4572.000000	851.000000	6457.000000	0.721380	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.753666	0.293769	0.787938	0.719276	0.611791	0.739350	0.220
recall	0.719379	0.465335	0.752672	0.719276	0.645795	0.719276	
f1-score	0.736124	0.360164	0.769901	0.719276	0.622063	0.727551	
support	4572.000000	851.000000	6457.000000	0.719276	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.730179	0.285091	0.797481	0.711953	0.604250	0.734876	0.197
recall	0.739283	0.460635	0.725724	0.711953	0.641880	0.711953	
f1-score	0.734703	0.352201	0.759912	0.711953	0.615605	0.721005	
support	4572.000000	851.000000	6457.000000	0.711953	11880.000000	11880.000000	

Bagging Classifier

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.751152	0.390821	0.782253	0.746633	0.641409	0.742244	0.226
recall	0.748688	0.330200	0.800062	0.746633	0.626316	0.746633	
f1-score	0.749918	0.357962	0.791057	0.746633	0.632979	0.744201	
support	4572.000000	851.000000	6457.000000	0.746633	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.761474	0.296830	0.781796	0.731734	0.613367	0.739235	0.221
recall	0.736658	0.363102	0.776831	0.731734	0.625530	0.731734	
f1-score	0.748860	0.326638	0.779306	0.731734	0.618268	0.735163	
support	4572.000000	851.000000	6457.000000	0.731734	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.761699	0.283163	0.785148	0.726768	0.610003	0.740165	0.214
recall	0.733377	0.391304	0.766300	0.726768	0.630327	0.726768	
f1-score	0.747270	0.328564	0.775609	0.726768	0.617148	0.732680	
support	4572.000000	851.000000	6457.000000	0.726768	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.758400	0.273599	0.787445	0.718098	0.606481	0.739459	0.214
recall	0.725722	0.435958	0.749884	0.718098	0.637188	0.718098	
f1-score	0.741701	0.336203	0.768206	0.718098	0.615370	0.727060	
support	4572.000000	851.000000	6457.000000	0.718098	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.728211	0.269710	0.801900	0.707660	0.599940	0.735418	0.181
recall	0.756562	0.458284	0.705901	0.707660	0.640249	0.707660	
f1-score	0.742115	0.339573	0.750844	0.707660	0.610844	0.718024	
support	4572.000000	851.000000	6457.000000	0.707660	11880.000000	11880.000000	

Random Forest

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.809130	0.472340	0.782651	0.779798	0.688040	0.770613	0.236
recall	0.748250	0.260870	0.870528	0.779798	0.626549	0.779798	
f1-score	0.777500	0.336109	0.824254	0.779798	0.645954	0.771293	
support	4572.000000	851.000000	6457.000000	0.779798	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.819859	0.383693	0.789231	0.771380	0.664261	0.771968	0.230
recall	0.738626	0.376028	0.846678	0.771380	0.653778	0.771380	
f1-score	0.777126	0.379822	0.816946	0.771380	0.657964	0.770309	
support	4572.000000	851.000000	6457.000000	0.771380	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.816142	0.354508	0.791857	0.764310	0.654169	0.769874	0.226
recall	0.732065	0.406580	0.834288	0.764310	0.657645	0.764310	
f1-score	0.771821	0.378763	0.812519	0.764310	0.654367	0.765785	
support	4572.000000	851.000000	6457.000000	0.764310	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.823933	0.347076	0.796420	0.766414	0.655810	0.774820	0.220
recall	0.734908	0.425382	0.833669	0.766414	0.664653	0.766414	
f1-score	0.776879	0.382260	0.814619	0.766414	0.657919	0.769123	
support	4572.000000	851.000000	6457.000000	0.766414	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.795439	0.318853	0.805103	0.754461	0.639798	0.766552	0.196
recall	0.755249	0.431257	0.796500	0.754461	0.661002	0.754461	
f1-score	0.774823	0.366633	0.800779	0.754461	0.647412	0.759691	
support	4572.000000	851.000000	6457.000000	0.754461	11880.000000	11880.000000	

XG-Boost

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.826933	0.595918	0.754016	0.774411	0.725623	0.770753	0.295
recall	0.697069	0.171563	0.908626	0.774411	0.592419	0.774411	
f1-score	0.756468	0.266423	0.824133	0.774411	0.615675	0.758142	
support	4572.000000	851.000000	6457.000000	0.774411	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.840140	0.403394	0.767587	0.766835	0.670374	0.769420	0.280
recall	0.683946	0.363102	0.878736	0.766835	0.641928	0.766835	
f1-score	0.754039	0.382189	0.819409	0.766835	0.651879	0.762932	
support	4572.000000	851.000000	6457.000000	0.766835	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.857624	0.342222	0.767862	0.754461	0.655903	0.771917	0.281
recall	0.667979	0.452409	0.855506	0.754461	0.658631	0.754461	
f1-score	0.751014	0.389676	0.809318	0.754461	0.650003	0.756820	
support	4572.000000	851.000000	6457.000000	0.754461	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.861662	0.293584	0.775802	0.738300	0.643683	0.774302	0.266
recall	0.655293	0.532315	0.824222	0.738300	0.670610	0.738300	
f1-score	0.744440	0.378446	0.799279	0.738300	0.640722	0.748029	
support	4572.000000	851.000000	6457.000000	0.738300	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.812718	0.267857	0.804882	0.723990	0.628486	0.769429	0.201
recall	0.712817	0.581669	0.750658	0.723990	0.681715	0.723990	
f1-score	0.759497	0.366803	0.776825	0.723990	0.634375	0.740785	
support	4572.000000	851.000000	6457.000000	0.723990	11880.000000	11880.000000	

Extra Randomized Trees

resampled data (n = {1: 3466})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.802306	0.430195	0.785887	0.773316	0.672796	0.766727	0.230
recall	0.745626	0.311398	0.853802	0.773316	0.636942	0.773316	
f1-score	0.772928	0.361282	0.818438	0.773316	0.650883	0.768176	
support	4572.000000	851.000000	6457.000000	0.773316	11880.000000	11880.000000	

resampled data (n = {1: 10000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.810830	0.363450	0.792475	0.763721	0.655585	0.768807	0.224
recall	0.736877	0.415981	0.828558	0.763721	0.660472	0.763721	
f1-score	0.772087	0.387945	0.810115	0.763721	0.656716	0.765239	
support	4572.000000	851.000000	6457.000000	0.763721	11880.000000	11880.000000	

resampled data (n = {1: 15000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.810934	0.334227	0.798457	0.759091	0.647873	0.770005	0.215
recall	0.736439	0.439483	0.817253	0.759091	0.664392	0.759091	
f1-score	0.771894	0.379695	0.807745	0.759091	0.653111	0.763285	
support	4572.000000	851.000000	6457.000000	0.759091	11880.000000	11880.000000	

resampled data (n = {1: 20000})

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.813012	0.324764	0.799482	0.757576	0.645753	0.770684	0.211
recall	0.737970	0.445358	0.812606	0.757576	0.665312	0.757576	
f1-score	0.773676	0.375619	0.805991	0.757576	0.651762	0.762726	
support	4572.000000	851.000000	6457.000000	0.757576	11880.000000	11880.000000	

resampled data (n = auto)

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.792396	0.320755	0.805569	0.751010	0.639573	0.765771	0.196
recall	0.752187	0.459459	0.788602	0.751010	0.666749	0.751010	
f1-score	0.771768	0.377778	0.796995	0.751010	0.648847	0.757257	
support	4572.000000	851.000000	6457.000000	0.751010	11880.000000	11880.000000	

Comparing our base model and our best model

Our first model was a default Logistic Regression estimator with no resampling. Our best model was a Random Forest with a resampling ratio of 10,000. We will now look at the metrics of these models side-by-side.

Classification reports

Here we will find the F1 score of both models in each status category, accuracy, etc.

In [38]:
```
base_report = results_dict['Logistic Regression']['{1: 3466}'][2]
best_report = results_dict['Random Forest']['{1: 10000}'][2]
base_report_df = pd.DataFrame(base_report)
best_report_df = pd.DataFrame(best_report)

display (base_report_df.style.set_caption("base model: classification
report"))
display (best_report_df.style.set_caption("best model: classification
report"))
```

base model: classification report

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.794543	0.517949	0.727318	0.745034	0.679937	0.738192	0.342
recall	0.649606	0.118684	0.895153	0.745034	0.554481	0.745034	
f1-score	0.714801	0.193117	0.802555	0.745034	0.570158	0.725127	
support	4572.000000	851.000000	6457.000000	0.745034	11880.000000	11880.000000	

best model: classification report

	non functional	functional needs repair	functional	accuracy	macro avg	weighted avg	bad_e
precision	0.819859	0.383693	0.789231	0.771380	0.664261	0.771968	0.230
recall	0.738626	0.376028	0.846678	0.771380	0.653778	0.771380	
f1-score	0.777126	0.379822	0.816946	0.771380	0.657964	0.770309	
support	4572.000000	851.000000	6457.000000	0.771380	11880.000000	11880.000000	

Confusion Matrices

Here we will see the confusion matrices for both models. The rows are the actual labels, and the columns are the predicted labels. So, for example, in our base model: there were 618 functional wells classified as non-functional, 600 functional-needs-repair wells classified as functional, etc...

We want to see high numbers along the main diagonal of the confusion matrix, and low numbers everywhere else. We especially want to see low numbers on the top right corner cell of the matrix – these are non functional wells classified as functional, which leave communities without water.

You will see that more values are concentrated along the main diagonal of our best model than our base model, and far less values are seen in that top right cell.

In [39]:
```
base_matrix = results_dict['Logistic Regression']['{1: 3466}'][3].copy
()
best_matrix = results_dict['Random Forest']['{1: 10000}'][3].copy()
base_matrix.columns = ['non functional', 'functional needs repair', 'f
unctional']
base_matrix.index = ['non functional', 'functional needs repair', 'fun
ctional']
best_matrix.columns = ['non functional', 'functional needs repair', 'f
unctional']
best_matrix.index = ['non functional', 'functional needs repair', 'fun
ctional']

display (base_matrix.style.set_caption("base model: confusion matrix")
)
display (best_matrix.style.set_caption("best model: confusion matrix")
)
```

base model: confusion matrix

	non functional	functional needs repair	functional
non functional	2970	35	1567
functional needs repair	150	101	600
functional	618	59	5780

best model: confusion matrix

	non functional	functional needs repair	functional
non functional	3377	141	1054
functional needs repair	125	320	406
functional	617	373	5467

Visualizations

One-vs-rest ROC curves

ROC curves are for binary classifiers, not ternary ones. The only way to plot ROC curves is to collapse our ternary classifier into a binary classifier according to each of the three categories, and then plotting a ROC curve each time. So, an ROC curve with non-functional as a reference class would do the following:

- Collapse functional and functional-needs-repair into one category and encode it as 0
- Encode non-functional as 1
- Plot an ROC curve

ROC curves aim to hug the top left corner of the x-y axis. As you can see, our best model outperforms the initial model in every ROC curve, inching closer to the top left corner for every reference class.

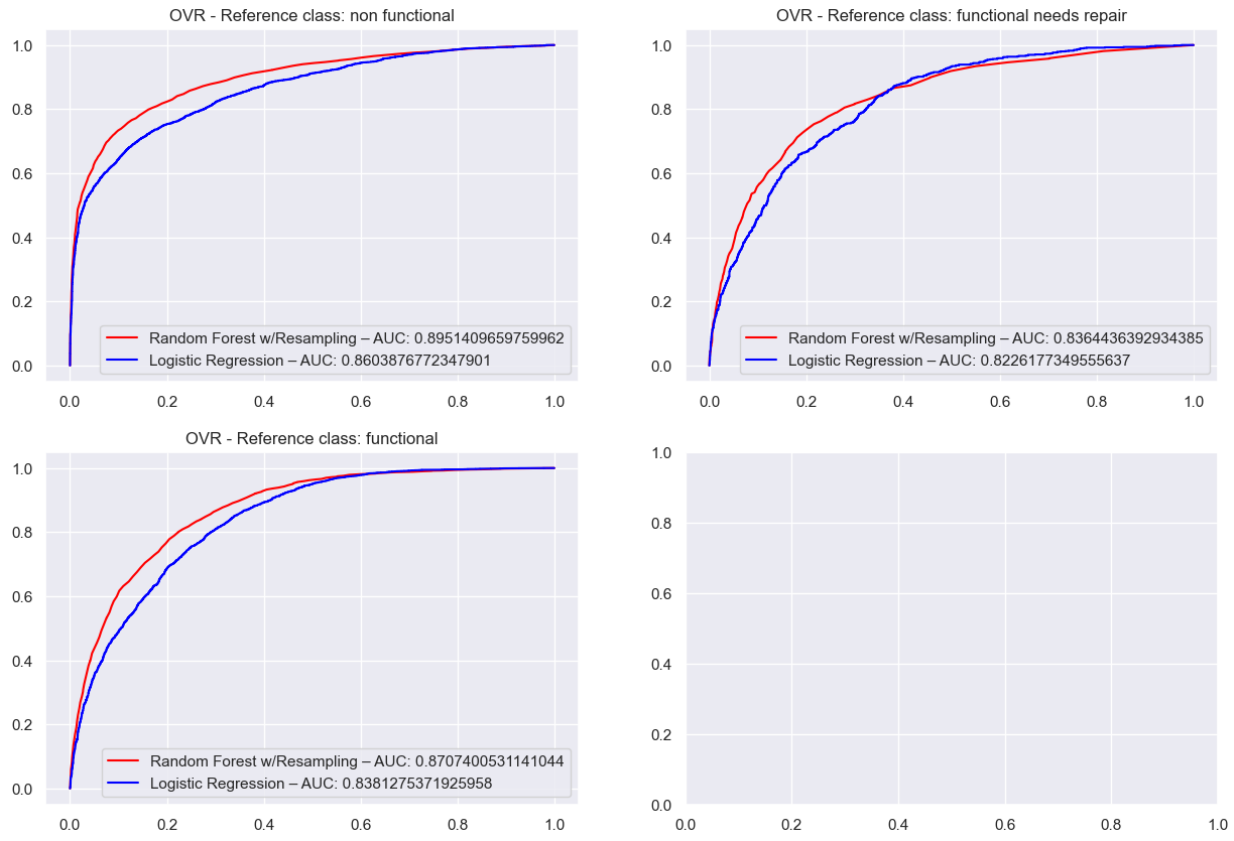
In [40]:
```
# Each map collapses the status variable into a binary classifier acco
rding to
# a different reference class
maps = [{0:1, 1:0, 2:0},
        {0:0, 1:1, 2:0},
        {0:0, 1:0, 2:1}]

# Names for our figures
namez = [f"OVR - Reference class: {Category}"
         for Category in ['non functional', 'functional needs repair',
'functional']]
```

In [41]:
```
# Extracting x-y coordinates from base estimator ROC curve

fig, ax = plt.subplots(2,2, figsize=(15,10))
xdatas, ydatas = [], []
for i in [0,1,2]:
    row = i//2
    col=i%2
    ovr_test = list(y_test.replace(maps[i]))
    ovr_train = list(y_train.replace(maps[i]))
    est = LogisticRegression(random_state=state)
    est.fit(X_train, ovr_train)
    plot = RocCurveDisplay.from_estimator(est, X_test, ovr_test, ax=ax
[row][col], name=namez[i]).line_
    xdata = plot.get_xdata()
    ydata = plot.get_ydata()
    xdatas.append(xdata)
    ydatas.append(ydata)
    plt.close(fig)
```

In [42]:

```
# Extracting x-y coordinates from best estimator ROC curve

fig, ax = plt.subplots(2,2, figsize=(15,10))
xdatas2, ydatas2 = [], []
for i in [0,1,2]:
    row = i//2
    col=i%2
    ovr_test = list(y_test.replace(maps[i]))
    ovr_train = list(resampled_datasets[1][2].replace(maps[i]))
    est = RandomForestClassifier(random_state=state)
    est.fit(resampled_datasets[1][1], ovr_train)
    plot = RocCurveDisplay.from_estimator(est, X_test, ovr_test, ax=ax
[row][col], name=namez[i]).line_
    xdata = plot.get_xdata()
    ydata = plot.get_ydata()
    xdatas2.append(xdata)
    ydatas2.append(ydata)
    plt.close(fig)
```

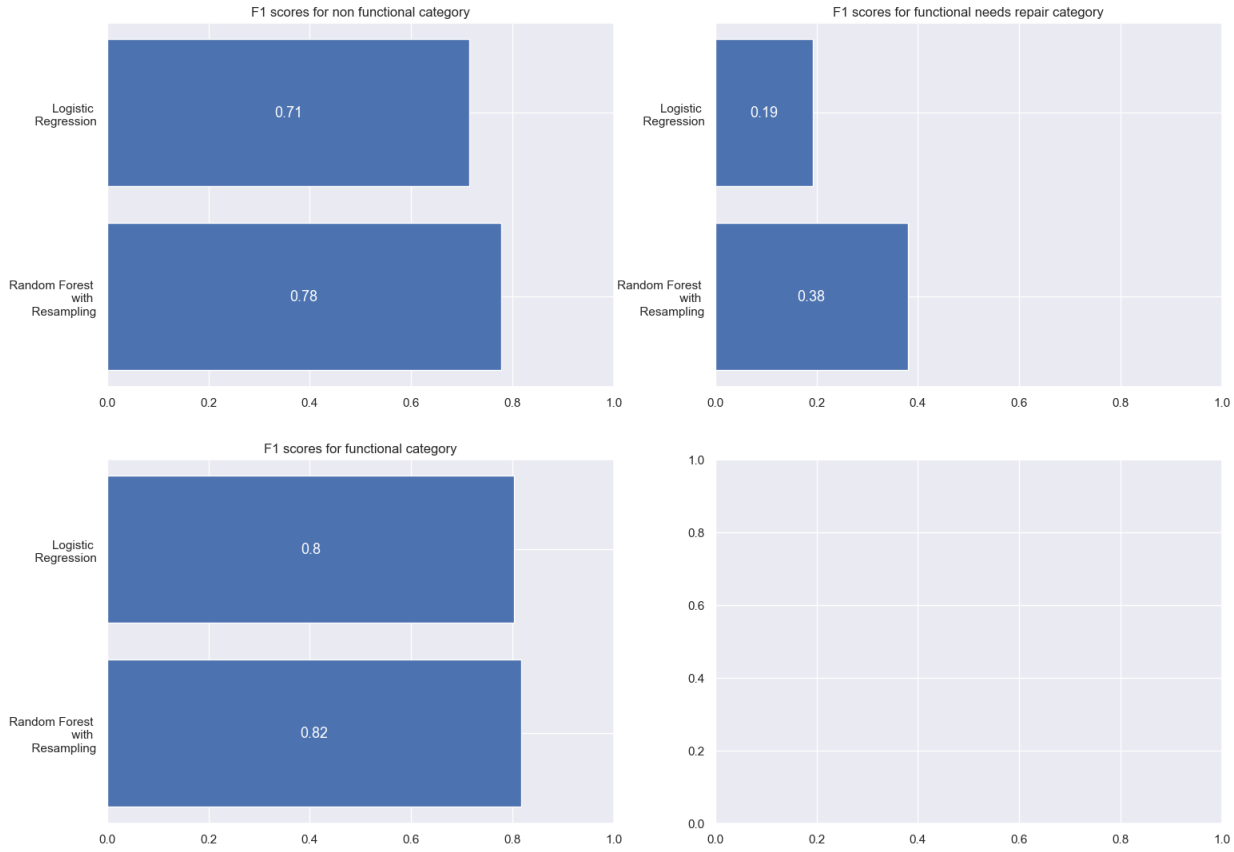
In [43]:
```
# Plots both sets of curves next to each other

fig, ax = plt.subplots(2,2, figsize=(15,10))
for i in [0,1,2]:
    row = i//2
    col=i%2
    ax[row][col].plot(xdatas2[i], ydatas2[i], color='red', label=f"Ran
dom Forest w/Resampling – AUC: {auc(xdatas2[i], ydatas2[i])}")
    ax[row][col].plot(xdatas[i], ydatas[i], color='blue', label=f"Logi
stic Regression – AUC: {auc(xdatas[i], ydatas[i])}")
    ax[row][col].set_title(namez[i])
    ax[row][col].legend(loc=4)
```



Comparing F1 Scores between models

Our best model has a better F1 score for each category.

In [44]:
```
status_map = {0: 'non functional', 1: 'functional needs repair', 2: 'f
unctional'}

fig, ax = plt.subplots(2,2, figsize=(18,13))
for x in [0,1,2]:
    row = x//2
    col=x%2
    f1_scores = [best_report[status_map[x]]['f1-score'], base_report[s
tatus_map[x]]['f1-score']]
    ax[row][col].set_title(f"F1 scores for {status_map[x]} category")
    barplot = ax[row][col].barh(['Random Forest \n with \n Resampling'
, 'Logistic \n Regression'], f1_scores)
    ax[row][col].bar_label(barplot, labels=[round(i,2) for i in f1_sco
res], label_type='center', color='white', fontsize='13');
    ax[row][col].set_xlim(0,1);
```

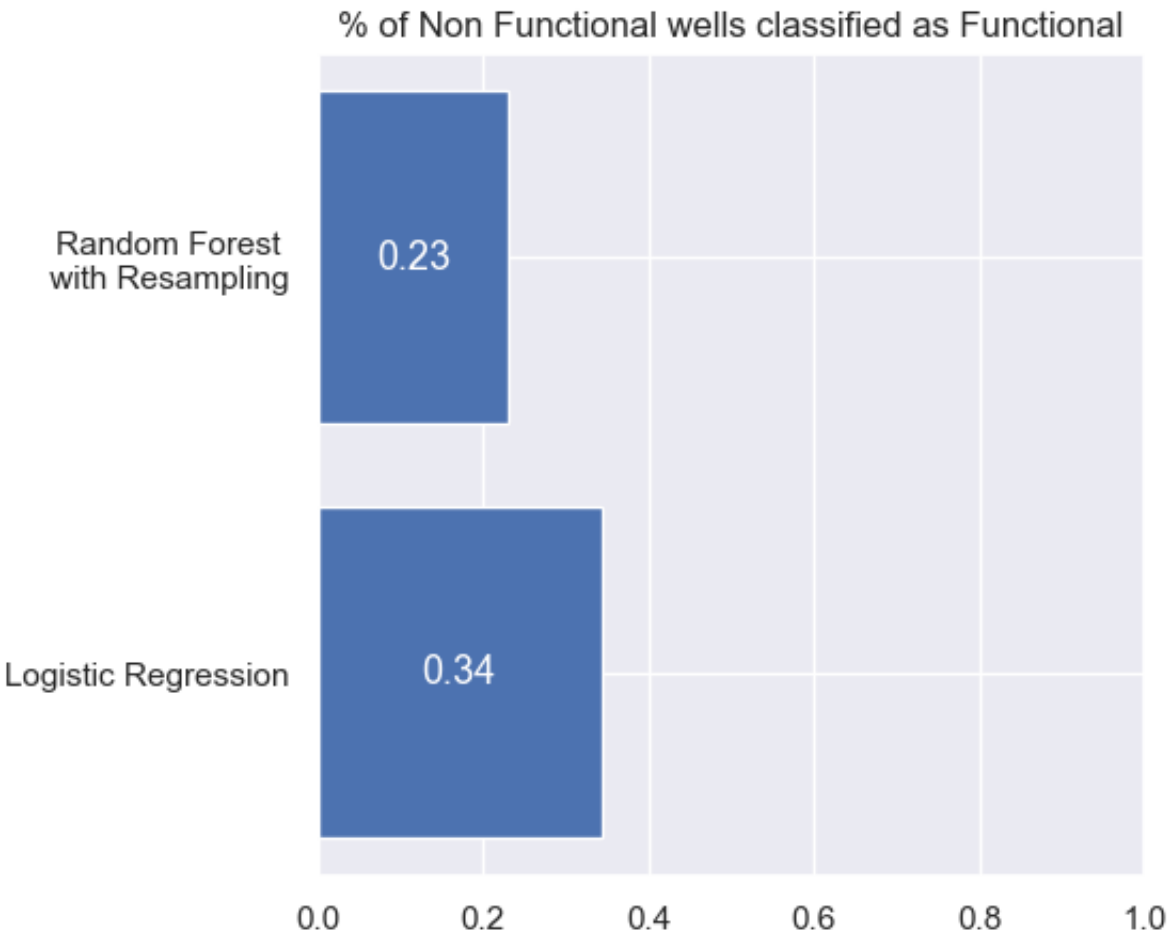


Comparing % of Incorrectly Classified Non-Functional Wells

Our first model incorrectly classified 34% of non functional wells as functional wells, meaning that 34% of communities without water were left stranded. Our best model managed to reduce that number to 23%.

In [45]:
```
f1_scores = [base_report['bad_error'][0], best_report['bad_error'][0]]

fig, ax = plt.subplots(figsize=(5,5))
ax.set_title("% of Non Functional wells classified as Functional")
barplot = ax.barh(['Logistic Regression', 'Random Forest \n with Resam
pling'], f1_scores)
ax.bar_label(barplot, labels=[round(i,2) for i in f1_scores], label_ty
pe='center', color='white', fontsize='13');
ax.set_xlim(0,1)
```

Out[45]:
```
(0.0, 1.0)
```

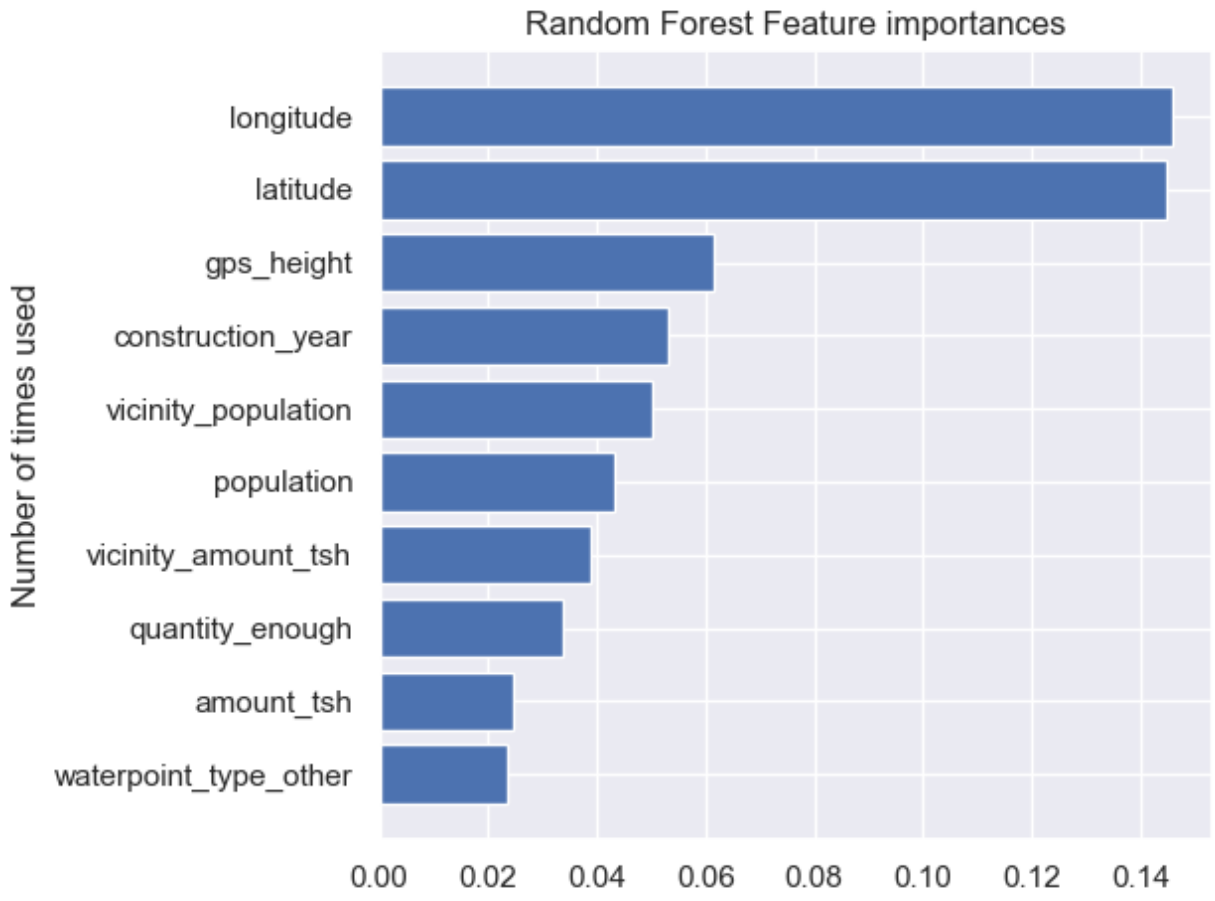


Feature Importances

These feature importances identify features that a random forest deemed highly important when categorizing well status. I pick some of these features and perform some visualizations on them to help inform recommendations for our stakeholders.

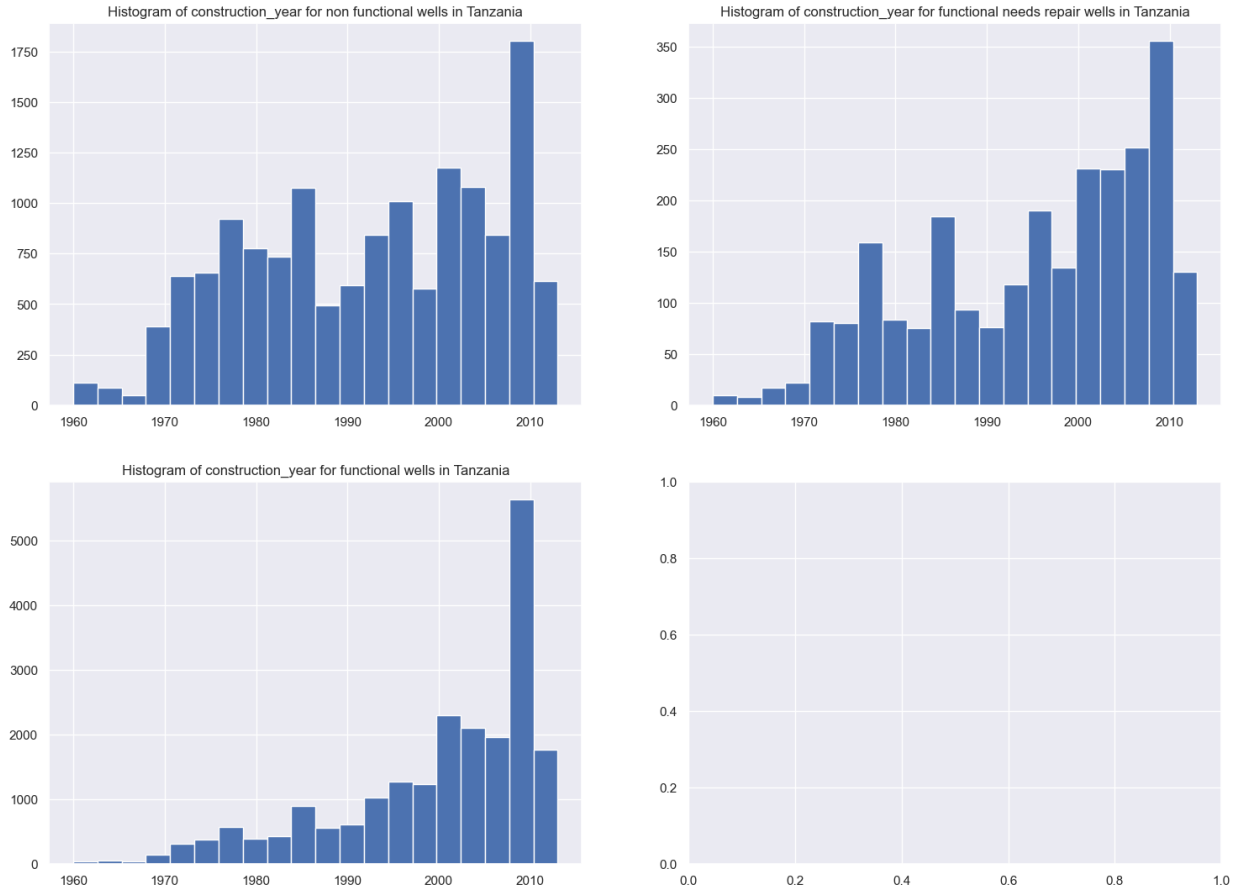
In [46]:
```
model = results_dict['Random Forest']['{1: 10000}'][5]
std = np.std([model.feature_importances_ for tree in model.estimators_
], axis=0)
importances_df = pd.DataFrame({'feature': model.feature_names_in_,
                               'importance': model.feature_importances
_})\
                            .sort_values(by='importance')[-10:]
```

In [47]:
```
fig, ax = plt.subplots()
ax.barh(importances_df['feature'], importances_df['importance'])
ax.set_title("Random Forest Feature importances")
ax.set_ylabel("Number of times used")
fig.tight_layout()
```



Distribution of construction year for each status

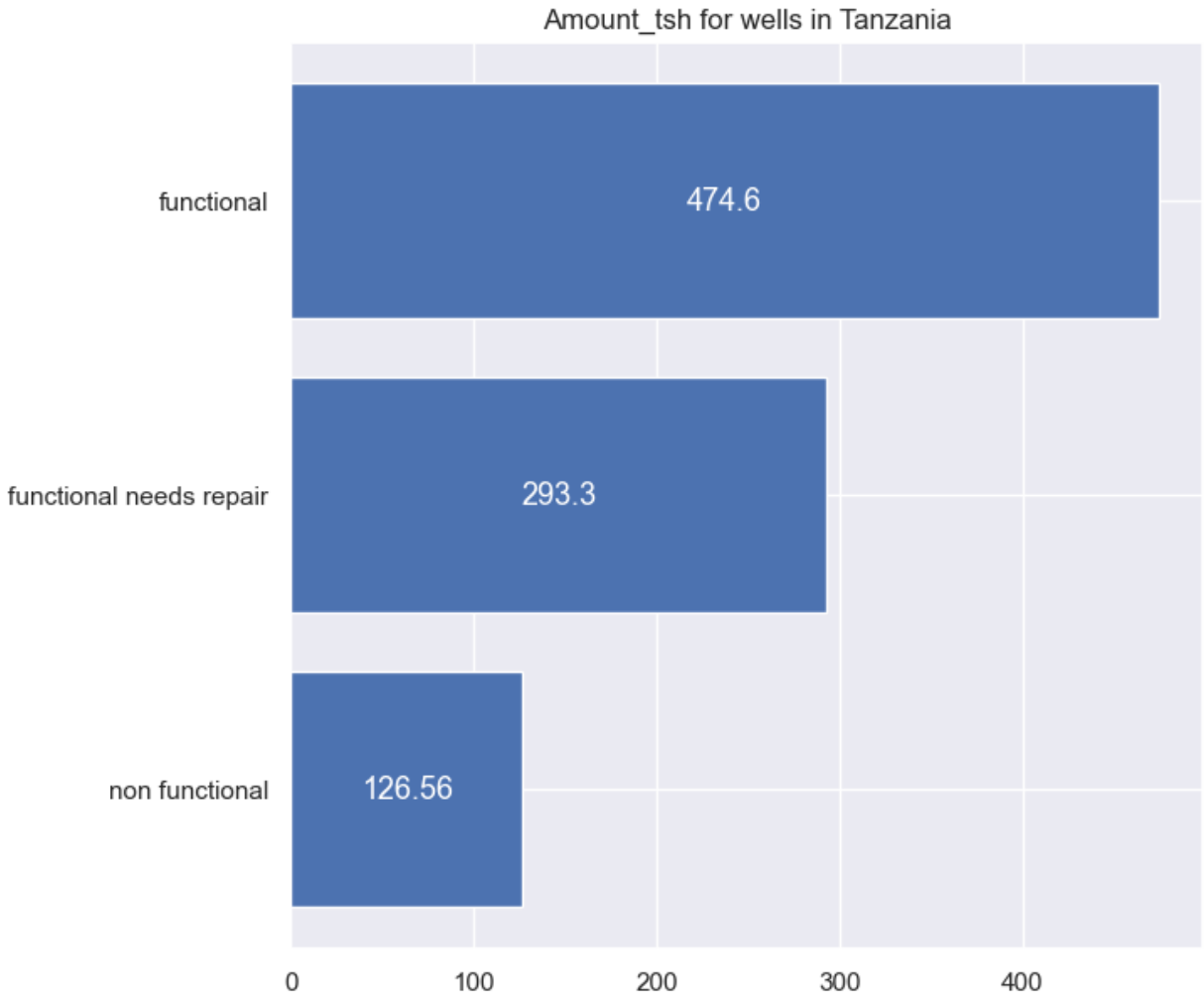
In [48]:
```
fig, ax = plt.subplots(2,2, figsize=(18,13))
for x in [0,1,2]:
    row = x//2
    col=x%2
    df = geography[(geography.status_group==status_map[x]) & (geography.construction_year!=0)]
    ax[row][col].hist(df.construction_year, bins=20)
    ax[row][col].set_title(f"Histogram of construction_year for {status_map[x]} wells in Tanzania")
```



Comparing average amount_tsh for each status

Remember, amount_tsh is the amount of water available to each water point.

In [49]:
```
fig, ax = plt.subplots(figsize=(7,7))
df = geography.groupby(by='status_group').mean()['amount_tsh'].sort_va
lues(ascending=True)
barplot = ax.barh(df.index, list(df))
ax.bar_label(barplot, labels=[round(i, 2) for i in list(df)], label_ty
pe='center', color='white', fontsize='13');
ax.set_title(f"Amount_tsh for wells in Tanzania");
```

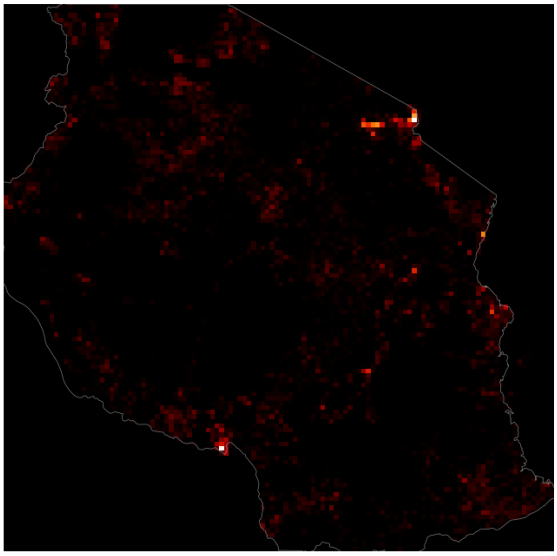


Heatmaps of wells across Tanzania, for each status

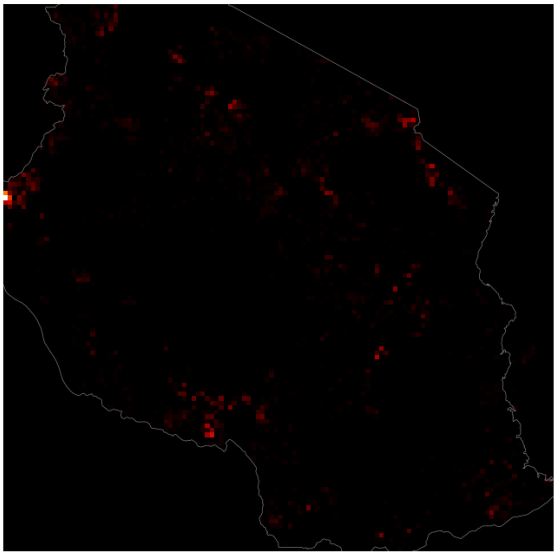
In [50]:

```
df = gpd.read_file('tanzania_polygon/ne_10m_admin_0_countries.shp')
tanzania = df.iloc[18].copy()
tanzania.geometry = list(list(df.iloc[18])[0].geoms)[0]
xx, yy = tanzania.geometry.exterior.coords.xy


fig, ax = plt.subplots(2,2, figsize=(18,18))

for x in [0,1,2]:
    row = x//2
    col=x%2
    df = geography[geography.status_group==status_map[x]]
    ax[row][col].plot(xx, yy, color='grey',  linewidth=0.5)
    ax[row][col].hist2d(df.longitude, df.latitude, bins=120, cmap='gis
t_heat')
    ax[row][col].set_axis_off()
    ax[row][col].set_title(f"Heatmap of {status_map[x]} wells in Tanza
nia")
```

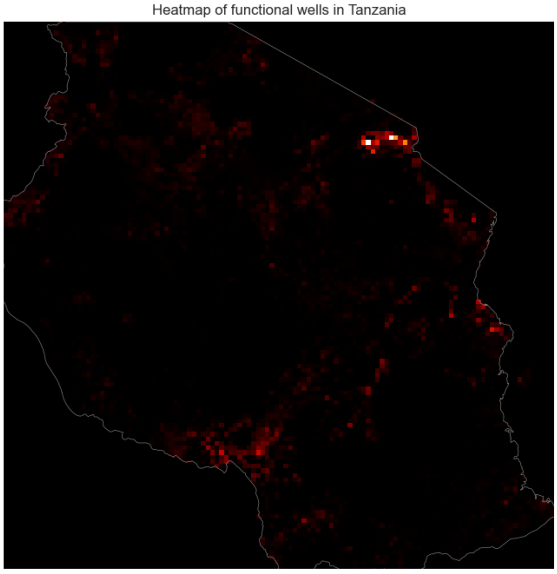
Heatmap of non functional wells in Tanzania

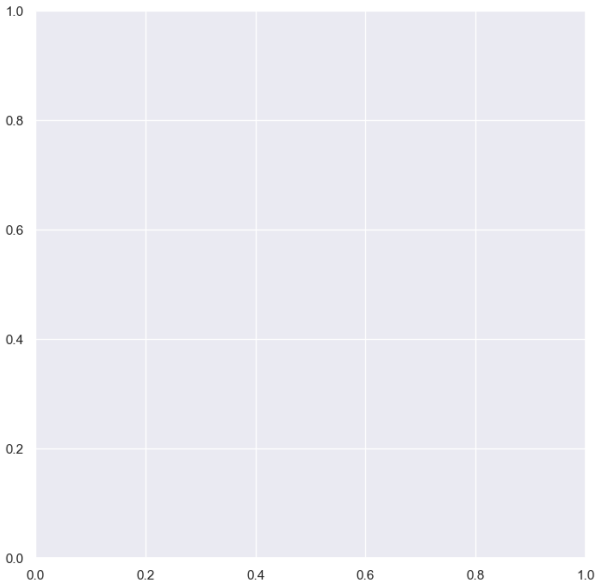


Heatmap of functional needs repair wells in Tanzania



Heatmap of functional wells in Tanzania





Recommendations

- Bear in mind that older wells are more likely to be dysfunctional.
- We suggest that the charity organization consult a heatmap of where non functional and functional-needs-repair wells are concentrated to better allocate their resources.
- We suggest that the charity organization prioritize wells that have less water available to them, since these wells are more likely to be non functional or in need of repair.
- Finally, we suggest that the charity organization prioritize non functional over functional-needs-repair wells. Despite making improvements in predicting functional-needs-repair wells, we were unable to achieve satisfactory accuracy in this category. Our best model only idenfitied 43% of all wells in this category, and when the model predicted such a well, it was only correct only 38% of the time.
    - This suggests that the category is ill-defined, and a well in "need of repair" could be almost totally fine, or almost completely broken and just barely functional.

Pickling model and exporting preprocessed data files

In [51]:
```
with open('models/random_forest_resampled_10k.pkl', 'wb') as f:
    joblib.dump(results_dict['Random Forest']['{1: 10000}'][5], f)
```

In [52]:
```
testing.to_csv('data/X_test_preprocessed.csv', index=False)
```