1. Overview

In this Python Script, we will apply all the data transformations that were done in the 01_data_preprocessing python script on the test dataset. Moreover, we will also generate predictions of the test dataset with the best logistic regression model that was trained in the 02_model_creation. With all this, we will be able to obtain the predicted values and determine whether a pump will be functional or non-functional

2. Data Understanding

2.1 Data Description

This notebook will use the test dataset given to us from DrivenData called: Test_set_values

2.2 Import Necessary Libraries

In [1]:

```
import pickle
import pandas as pd
import re  # Import regular expressions library
import warnings
warnings.simplefilter('ignore')
```

2.3 Define global variables

In [2]:

```
INPUT_PATH_Test_set_values = "../Data/Test_set_values.csv"
```

2.4 Functions

In [3]:

```
def categorize_funder(funder):
    """
    Categorizes a funder name into specific groups based on keywords.

    Args:
    funder (str): A string representing the name of the funder to categori

    Returns:
    str: A category name representing the type of organization the funder

    This function takes a funder name, converts it to lowercase, removes l
    and categorizes it into predefined groups like 'Government', 'Religiou
    'International Aid', 'Private Companies', or 'Individual/Other' based
    """
    funder = funder.lower().strip()  # convert to lowercase and strip whit
    if any(x in funder for x in ['government','ministry','gov','minis']):
        return 'Government'
    elif any(x in funder for x in ['church', 'muslim','mus', 'islamic','is
        return 'Religious Organizations'
    elif any(x in funder for x in ['ngo', 'foundation', 'fund', 'trust', '
        return 'NGO'
    elif any(x in funder for x in ['international','internatio', 'un', 'wo
        return 'International Aid'
    elif any(x in funder for x in ['ltd', 'company','compa', 'group', 'ent
        return 'Private Companies'
    else:
        return 'Individual/Other'

```

In [4]:

```
def categorize_installer(installer):
    """
    Categorizes an installer name into specific groups based on keywords.

    Args:
    installer (str): A string representing the name of the installer to ca

    Returns:
    str: A category name representing the type of entity the installer bel

    This function processes an installer name by converting it to lowercas
    any leading/trailing whitespace. It categorizes the name into predefir
    'DWE', 'Government', 'Community', 'NGO', 'Private Company', 'Instituti
    based on specific keywords present in the installer's name. This helps
    installer data for better analysis and insight extraction.
    """
    installer = installer.lower().strip()  # convert to lowercase and stri
    if 'dw' in installer:
        return 'DWE'
    elif any(x in installer for x in ['government', 'govt', 'gove']):
        return 'Government'
    elif any(x in installer for x in ['resource']):
        return 'Other'
    elif any(x in installer for x in ['community', 'villagers', 'village',
        return 'Community'
    elif any(x in installer for x in ['ngo', 'unicef', 'foundat']):
        return 'NGO'
    elif 'company' in installer or 'contractor' in installer:
        return 'Private Company'
    elif any(x in installer for x in ['school','schoo','church', 'rc']):
        return 'Institutional'
    else:
        return 'Other'
```

In [5]:

```
def group_scheme_management(value):
    """
    Categorizes scheme management types into broader, more generalized gro
    
    Args:
    value (str): A string representing the scheme management type to categ
    
    Returns:
    str: A generalized category name representing the type of scheme manag
    
    This function takes a specific scheme management type and categorizes
    more generalized groups such as 'Government', 'Community', 'Private Se
    'Water Board', or 'Other'. This categorization aids in simplifying the
    and understanding of the data by reducing the number of distinct categ
    making trends and patterns more discernible.
    """
    if value in ['VWC', 'Water authority', 'Parastatal']:
        return 'Government'
    elif value in ['WUG', 'WUA']:
        return 'Community'
    elif value in ['Company', 'Private operator']:
        return 'Private Sector'
    elif value == 'Water Board':
        return 'Water Board'  # Retain this as a separate category if dist
    else:
        return 'Other'
```

In [6]:

```
def clean_text(text):
    """
    Cleans a text string by converting to lowercase, removing non-alphanum
    and replacing multiple spaces with a single space. If the input is sol
    
    Args:
    text (str or NaN): The text to be cleaned; can be a string, numeric, c
    
    Returns:
    str or NaN: The cleaned text, with all characters in lowercase, non-al
                and multiple spaces collapsed to a single space, or the or
    
    This function standardizes a text string by making it lowercase, strip
    and then replacing sequences of spaces with a single space, facilitati
    is numeric, it is assumed to be standardized already and is returned w
    """
    if pd.isna(text):
        return text
    if isinstance(text, (int, float)):  # Check if the input is numeric
        return text
    text = text.lower()  # Convert to lowercase
    text = ''.join(char for char in text if char.isalpha() or char.isspace
    text = re.sub(r'\s+', ' ', text)  # Replace multiple spaces with a sir
    return text
```

3. Code

3.1 Import the dataset

In [7]:
```
df_predict = pd.read_csv(INPUT_PATH_Test_set_values)
df_predict.head()
```

Out[7]:

	id	amount_tsh	date_recorded	funder	gps_height	installer	longitude	latitude
0	50785	0.0	2013-02-04	Dmdd	1996	DMDD	35.290799	-4.059696
1	51630	0.0	2013-02-04	Government Of Tanzania	1569	DWE	36.656709	-3.309214
2	17168	0.0	2013-02-01	NaN	1567	NaN	34.767863	-5.004344
3	45559	0.0	2013-01-22	Finn Water	267	FINN WATER	38.058046	-9.418672
4	49871	500.0	2013-03-27	Bruder	1260	BRUDER	35.006123	-10.950412

5 rows × 40 columns

In [8]:
```
# Modifying columns to keep the structure of the data that the models wher

df_predict['permit'] = df_predict['permit'].replace({True:1})

df_predict['public_meeting'] = df_predict['public_meeting'].replace({True:
```

3.2 Apply the same data transformations on df_predict as the ones done in 00_data_understanding

3.2.1 Applying transformation functions

Column 'funder'

In [9]:
```
# Handling NaN values with a filler string like 'Unknown'
df_predict['funder'] = df_predict['funder'].fillna('Unknown').astype(str)

# Apply the mapping function to the 'funder' column
df_predict['funder_type'] = df_predict['funder'].apply(categorize_funder)

# Check the categorized data
print(df_predict['funder_type'].value_counts())
```

```
Individual/Other          9955
Government                2438
International Aid         2093
Religious Organizations    329
NGO                         29
Private Companies            6
Name: funder_type, dtype: int64
```

Column 'installer'

In [10]:
```
# Handling NaN values with a filler string like 'Unknown'
df_predict['installer'] = df_predict['installer'].fillna('Unknown').astype
 
# Apply the mapping function to the 'installer' column
df_predict['installer_type'] = df_predict['installer'].apply(categorize_in

# Now you can check your categorized data
print(df_predict['installer_type'].value_counts())
```

```
Other              8480
DWE                4537
Government          926
Community           599
Institutional       185
NGO                  93
Private Company      30
Name: installer_type, dtype: int64
```

Column 'scheme_management_grouped'

In [11]:
```
# Apply the grouping function to the 'scheme_management' column
df_predict['scheme_management_grouped'] = df_predict['scheme_management'].

# Check the new value counts to see the grouped data
print(df_predict['scheme_management_grouped'].value_counts(normalize=True)
```

```
Government        0.699663
Community         0.131852
Other             0.083838
Water Board       0.048081
Private Sector    0.036566
Name: scheme_management_grouped, dtype: float64
```

3.2.2 Converting data types

In [12]:
```
# Converting 'construction_year' to object
df_predict['construction_year'] = df_predict['construction_year'].astype('
```

In [13]:
```
df_predict.columns
```

Out[13]:
```
Index(['id', 'amount_tsh', 'date_recorded', 'funder', 'gps_height',
       'installer', 'longitude', 'latitude', 'wpt_name', 'num_private',
       'basin', 'subvillage', 'region', 'region_code', 'district_code', 'lg
a',
       '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', 'funder_type', 'installer_type',
       'scheme_management_grouped'],
      dtype='object')
```

3.2.3 Drop unnecesary columns

In [14]:
```
drop_column_list = ['scheme_name', 'num_private', 'wpt_name', 'subvillage'
                    'extraction_type', 'management', 'payment', 'water_qua
                    'waterpoint_type_group', 'date_recorded','funder','ins
                    'longitude','latitude','region_code','district_code','
```

In [15]:
```
df_predict = df_predict.drop(drop_column_list, axis=1)
```

3.2.3 Cleaning the data set

In [16]:
```
# Apply the cleaning function to each object-type column in the DataFrame
for col in df_predict.select_dtypes(include='object').columns:
    df_predict[col] = df_predict[col].apply(clean_text)
```

3.2 Fillna with the modes calculated in 01_data_preprocessing

In [17]:
```
(df_predict.isna().sum()/len(df_predict))*100
```

Out[17]:
```
id                          0.000000
amount_tsh                  0.000000
gps_height                  0.000000
basin                       0.000000
region                      0.000000
population                  0.000000
public_meeting              5.528620
permit                      4.962963
extraction_type_class       0.000000
management_group            0.000000
payment_type                0.000000
quality_group               0.000000
quantity_group              0.000000
source_type                 0.000000
waterpoint_type             0.000000
funder_type                 0.000000
installer_type              0.000000
scheme_management_grouped   0.000000
dtype: float64
```

From the python script 01_data_preprocessing we know that public_meeting_mode is 1.0 and the permit_mode is 1.0. So we are going to directly fill the NaNs of public_meeting and of permit with the value 1.0

Fillna in column 'public_meeting'

In [18]:
```
df_predict['public_meeting'].fillna(1.0, inplace=True)
```

Fillna in column 'permit'

In [19]:
```
df_predict['permit'].fillna(1.0, inplace=True)
```

Let's check that there are no more null-values left

In [20]:
```
(df_predict.isna().sum()/len(df_predict))*100
```

Out[20]:
```
id                          0.0
amount_tsh                  0.0
gps_height                  0.0
basin                       0.0
region                      0.0
population                  0.0
public_meeting              0.0
permit                      0.0
extraction_type_class       0.0
management_group            0.0
payment_type                0.0
quality_group               0.0
quantity_group              0.0
source_type                 0.0
waterpoint_type             0.0
funder_type                 0.0
installer_type              0.0
scheme_management_grouped   0.0
dtype: float64
```

3.3 Doing target enconder on the categorical columns

Let's apply a one hot encoder for the categorical columns that have 6 or less categories

In [21]:
```
# Capture categorical columns from X_train for encoding
categorical_columns = df_predict.select_dtypes(include=['object', 'categor


# Encoding the categorical columns in df_predict
for col in categorical_columns:
    if df_predict[col].nunique() <= 6:
        # Apply OneHotEncoder for columns with 6 or fewer unique values
        df_predict = pd.get_dummies(df_predict, columns=[col], drop_first=
```

Let's call in the saved fits (for the categorical columns that have more than 6 categories) applied to the categorical columns in the 01_data_preprocessing script

In [22]:
```
df_predict.columns
```

Out[22]:
```
Index(['id', 'amount_tsh', 'gps_height', 'basin', 'region', 'population',
       'extraction_type_class', 'payment_type', 'source_type',
       'waterpoint_type', 'installer_type', 'public_meeting_1', 'permit_1',
       'management_group_other', 'management_group_parastatal',
       'management_group_unknown', 'management_group_usergroup',
       'quality_group_fluoride', 'quality_group_good', 'quality_group_milky',
       'quality_group_salty', 'quality_group_unknown', 'quantity_group_enoug
h',
       'quantity_group_insufficient', 'quantity_group_seasonal',
       'quantity_group_unknown', 'funder_type_individualother',
       'funder_type_international aid', 'funder_type_ngo',
       'funder_type_private companies', 'funder_type_religious organization
s',
       'scheme_management_grouped_government',
       'scheme_management_grouped_other',
       'scheme_management_grouped_private sector',
       'scheme_management_grouped_water board'],
      dtype='object')
```

In [23]:
```
# Column 'basin'
basin_pickle = pickle.load(open('model_objects/basin_target_encoder.pkl',
df_predict['basin'] = basin_pickle.transform(df_predict['basin'])

# Column 'extraction_type_class'
extraction_type_class_pickle = pickle.load(open('model_objects/extraction_
df_predict['extraction_type_class'] = extraction_type_class_pickle.transfo

# Column 'installer_type'
installer_type_pickle = pickle.load(open('model_objects/installer_type_tar
df_predict['installer_type'] = installer_type_pickle.transform(df_predict[

# Column 'payment_type'
payment_type_pickle = pickle.load(open('model_objects/payment_type_target_
df_predict['payment_type'] = payment_type_pickle.transform(df_predict['pay

# Column 'region_target'
region_target_pickle = pickle.load(open('model_objects/region_target_encod
df_predict['region'] = region_target_pickle.transform(df_predict['region']

# Column 'source_type'
source_type_pickle = pickle.load(open('model_objects/source_type_target_en
df_predict['source_type'] = source_type_pickle.transform(df_predict['sourc

# Column 'waterpoint_type'
waterpoint_type_pickle = pickle.load(open('model_objects/waterpoint_type_t
df_predict['waterpoint_type'] = waterpoint_type_pickle.transform(df_predic
```

3.4 Dealing with numerical columns

Let's call in the saved fits applied to the numerical columns in the 01_data_preprocessing script

In [24]:
```
df_predict.columns
```

Out[24]:
```
Index(['id', 'amount_tsh', 'gps_height', 'basin', 'region', 'population',
       'extraction_type_class', 'payment_type', 'source_type',
       'waterpoint_type', 'installer_type', 'public_meeting_1', 'permit_1',
       'management_group_other', 'management_group_parastatal',
       'management_group_unknown', 'management_group_usergroup',
       'quality_group_fluoride', 'quality_group_good', 'quality_group_milky',
       'quality_group_salty', 'quality_group_unknown', 'quantity_group_enoug
h',
       'quantity_group_insufficient', 'quantity_group_seasonal',
       'quantity_group_unknown', 'funder_type_individualother',
       'funder_type_international aid', 'funder_type_ngo',
       'funder_type_private companies', 'funder_type_religious organization
s',
       'scheme_management_grouped_government',
       'scheme_management_grouped_other',
       'scheme_management_grouped_private sector',
       'scheme_management_grouped_water board'],
      dtype='object')
```

In [25]:
```
# Capture numerical columns
numerical_columns = df_predict.select_dtypes(include=['int64', 'float64'])

# Let's also drop column 'id' from the numerical_columns as they don't ser
numerical_columns = numerical_columns.drop('id')

# The desired order of columns according to when it was fitted in notebook
desired_order = [
    'amount_tsh', 'gps_height', 'population', 'basin', 'region',
    'extraction_type_class', 'payment_type', 'source_type',
    'waterpoint_type', 'installer_type'
]

# Numerical Columns
numerical_columns_pickle = pickle.load(open('model_objects/numerical_colum
df_predict[desired_order] = numerical_columns_pickle.transform(df_predict[
```

In [26]:
```
1 df_predict.columns
```

Out[26]:
```
Index(['id', 'amount_tsh', 'gps_height', 'basin', 'region', 'population',
       'extraction_type_class', 'payment_type', 'source_type',
       'waterpoint_type', 'installer_type', 'public_meeting_1', 'permit_1',
       'management_group_other', 'management_group_parastatal',
       'management_group_unknown', 'management_group_usergroup',
       'quality_group_fluoride', 'quality_group_good', 'quality_group_milky',
       'quality_group_salty', 'quality_group_unknown', 'quantity_group_enoug
h',
       'quantity_group_insufficient', 'quantity_group_seasonal',
       'quantity_group_unknown', 'funder_type_individualother',
       'funder_type_international aid', 'funder_type_ngo',
       'funder_type_private companies', 'funder_type_religious organization
s',
       'scheme_management_grouped_government',
       'scheme_management_grouped_other',
       'scheme_management_grouped_private sector',
       'scheme_management_grouped_water board'],
      dtype='object')
```

3.5 Apply the Decision Tree Classifier created in 02_model_creation

In [27]:
```
1 df_predict
```

Out[27]:

	id	amount_tsh	gps_height	basin	region	population	extraction_type_class	p
0	50785	-0.100621	1.915327	-0.540016	-0.633090	0.299241	2.617222	
1	51630	-0.100621	1.299135	-0.569630	-1.180350	0.254822	-0.521411	
2	17168	-0.100621	1.296248	-0.540016	0.663779	0.677863	2.617222	
3	45559	-0.100621	-0.579749	2.497921	2.407560	0.149062	2.617222	
4	49871	0.055600	0.853225	2.497921	-0.015500	-0.252826	-0.521411	
...	...	...	...	...	...	...	...	
14845	39307	-0.100621	-0.915985	0.697368	0.103890	-0.337435	1.165688	
14846	18990	0.211821	-0.965049	-0.569630	0.234762	5.881260	-0.463637	
14847	28749	-0.100621	1.164929	-0.540016	0.663779	0.043302	-0.521411	
14848	33492	-0.100621	0.475139	-1.230325	-0.015500	-0.062458	-0.521411	
14849	68707	-0.100621	-0.270931	-1.230325	-0.015500	-0.295131	-0.521411	

14850 rows × 35 columns

In [28]:
```
# Loading the pickle for the best Decision Tree Classifier
best_tree_pickle = pickle.load(open('model_objects/best_tree.pkl', 'rb'))

# Let's drop the 'id' column
df_predict_copy = df_predict.drop('id', axis=1)
```

In [29]:
```
df_predict_copy.rename(columns={'public_meeting_1':'public_meeting_1.0', '

# Let's reorder the columns
df_predict_copy = df_predict_copy[list(best_tree_pickle.feature_names_in_)
```

In [30]:
```
# Decision Tree Classifier
df_predict['status_group'] = best_tree_pickle.predict_proba(df_predict_cop
```

In [31]:
```
# Apply a threshold to the probabilities of status_group to determine to w
df_predict['status_group_class'] = df_predict['status_group'].map(lambda x
```

In [32]:
```
df_predict[['id','status_group', 'status_group_class']]
```

Out[32]:

	id	status_group	status_group_class
0	50785	0.000000	Functional
1	51630	0.000000	Functional
2	17168	0.000000	Functional
3	45559	0.989969	Non-functional
4	49871	0.179576	Functional
...	...	...	...
14845	39307	0.866786	Non-functional
14846	18990	0.255741	Functional
14847	28749	0.038544	Functional
14848	33492	0.698860	Non-functional
14849	68707	0.994873	Non-functional

14850 rows × 3 columns

4. Export the data

In [33]:
```
df_predict[['id', 'status_group_class']].to_excel('Final_results.xlsx', ir
```