Water Pump Operational Status Classification

# Module 3: Final Project

Water Pump Operational Status Classification

Competitive Data Science Project: Pump it Up: Data Mining the Water Table, hosted by DRIVENDATA

by Steven Contreras

### The problem

#### Context

"Taarifa is an open source platform for the crowd-sourced reporting and triaging of infrastructure related issues. Think of it as a bug tracker for the real world which helps to engage citizens with their local government. We are currently working on an Innovation Project in Tanzania, with various partners."

- Taarifa

The particular goal is to bring filtered-water, sourced and pumped from local water-sources, to disparate and impoverished geographic locations.

#### Problem statement

This is a multi-class classification machine learning problem.

The goal is to predict the operating condition of a waterpoint for each record in the dataset, which can be one of the three operational status classes: "functional", "functional needs repair", and "non functional".

# Solution

# Ensemble (VotingClassifier) of classification algorithms:

RandomForestClassifier and CatboostClassifier

### Competition Leaderboard:

Model Accuracy: 81.87%

• Competition Rank: **837/9751** 

Competition Percentile: > 91st

### Overview

#### Features

- 38 starting features (predictors), not including id
- Feature groups and data "overlap" see feature descriptions at
   <a href="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</a>
- o Dropped 21 features not contributing to classification, 17 features contributed to classification

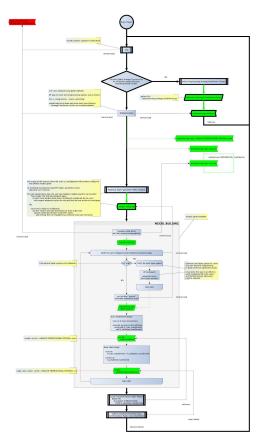
#### Approach

- Very thorough EDA time-investment
- o Greedy Algorithms: feature selection and transformation-option selection, hyper-parameter tuning
- Development/use of ensembling techniques provided best accuracy

#### • Links:

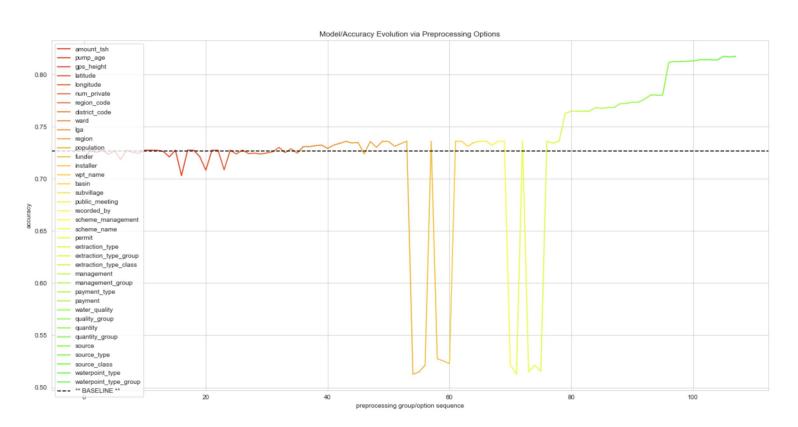
- Github Repo: <a href="https://github.com/sacontreras/dsc-mod-3-project-v2-1-online-ds-sp-000">https://github.com/sacontreras/dsc-mod-3-project-v2-1-online-ds-sp-000</a>
- Blog: <a href="https://sacontreras.github.io/my">https://sacontreras.github.io/my</a> first data science competition

## Workflow: Adapted from OSEMN

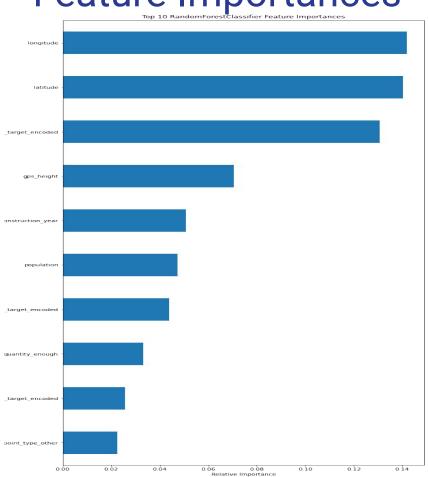


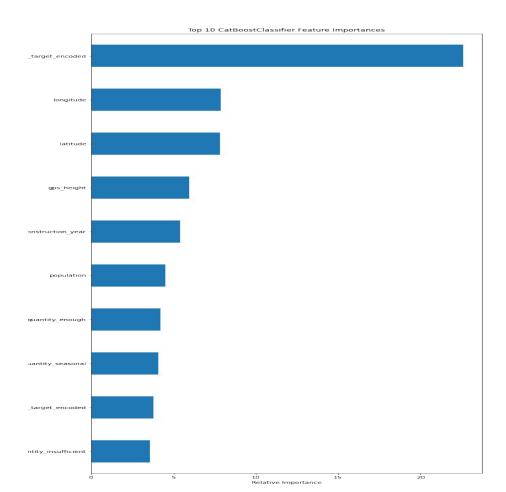
View the diagram in your browser here.

# Preprocessing (Optimization)



## Feature Importances





### Interpretation and Recommendations

- 1. Geographic Location (*ward*, *gps-coordinates*) features are the most important predictors: focus routine maintenance in locations with current greatest occurrence of *functional needs repair* status in order to preempt (avoid) this status in the future. The same rationale applies to those pumps with greater relative *population* as well as relatively older pumps.
- 2. For pumps/wells with greater *gps\_height* values and with status *non functional* or *functional needs repair* statuses, consider refitting with more powerful/robust pump-motor installation (and related components).
- 3. Water *quantity* and *amount\_tsh* ("Total static head (amount water available to waterpoint)") i.e. **flow** is a factor; for those pumps falling into the *quantity\_insufficient* or quantity\_seasonal categories, consider reducing power to the pump as a response to lower flow in order to address *functional needs repair* status or prevent *non functional* status.

### Conclusion and Future Work Consideration

Thank you so much for your time!

I really enjoyed this project and I learned MANY new and powerful techniques.

#### **Possible Future Work:**

- Preprocessing algorithm identified missing preprocessing options low-cardinality categoricals below threshold should be one-hot encoded (vs. current anomalous target encoding)... correct this for further increase to leadboard accuracy
- More advanced ensemble techniques:
  - Stacking
  - Blending
- Use a different classification algorithm (e.g. CatboostClassifier) for baselining within the preprocessing.ipynb notebook for comparison
- Experiment more with RandomizedSearchCV for better resolution of hyper-parameter tuning candidate
  values with, for example, RandomForestClassifier which may lead to even higher competition accuracy

### Supplemental: The Future is Now!

The result of switching low-cardinality categoricals below threshold to OneHot Encoding (previously Target Encoded):

### Competition Leaderboard:

• Model Accuracy: 81.99%

• Competition Rank: **719/9857** 

• Competition Percentile: **Top 8%**