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*”.

Workflow: Adapted from OSEMN

EDA

This phase is geared toward a detailed understanding of all features, including their data-types and special concerns with the specific goal of producing the set of all applicable preprocessing options.

The output of this phase is used as input to the Dynamic Programming algorithm used in the Preprocessing phase.

Preprocessing

This phase executes a Dynamic Programming algorithm to optimize (the “best”) selection of

- Features
- Transformations thereof

… in order to produce models with the highest validation accuracy.

This phase consumes the configuration of applicable preprocessing options discovered in EDA.

The output of this phase is used as input for final transformations used for model building.

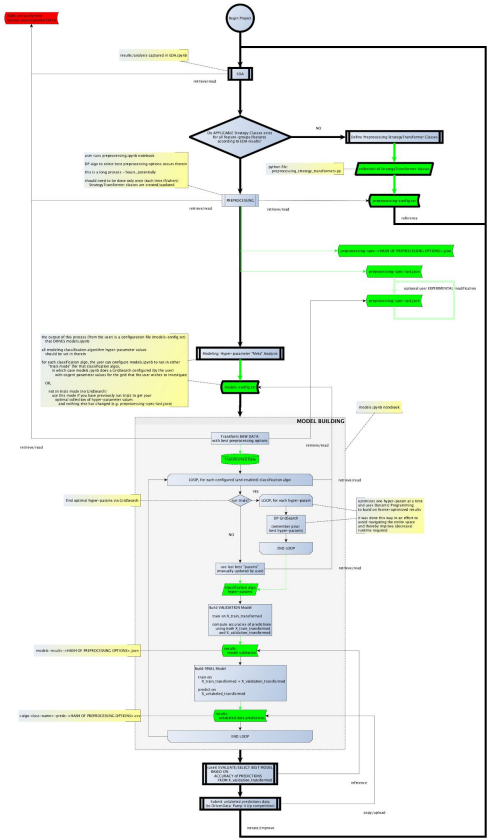
Model Building

This phase focuses on:

- Building an array of models using various classification algorithms
- Optimizing validation accuracy via parameter-tuning
- Building output (CSV) files containing unlabeled predictions produced from those models; these are the deliverables that are submitted to the competition for scoring

This phase consumes the output of the optimized (“best”) selection of features and transformation options output from the Preprocessing phase in order to produce the final transformed data used in model building.

Visualization: Workflow



View the diagram in your browser here.

Solution

Ensemble (`VotingClassifier`) of classification algorithms:

`RandomForestClassifier` and `CatboostClassifier`

Competition Leaderboard:

- *Model Accuracy*: **81.87%**
- *Competition Rank*: **837/9751**
- *Competition Percentile*: **> 91st**

Implementation

ALL PHASES PLAYED EQUALLY IMPORTANT ROLES!

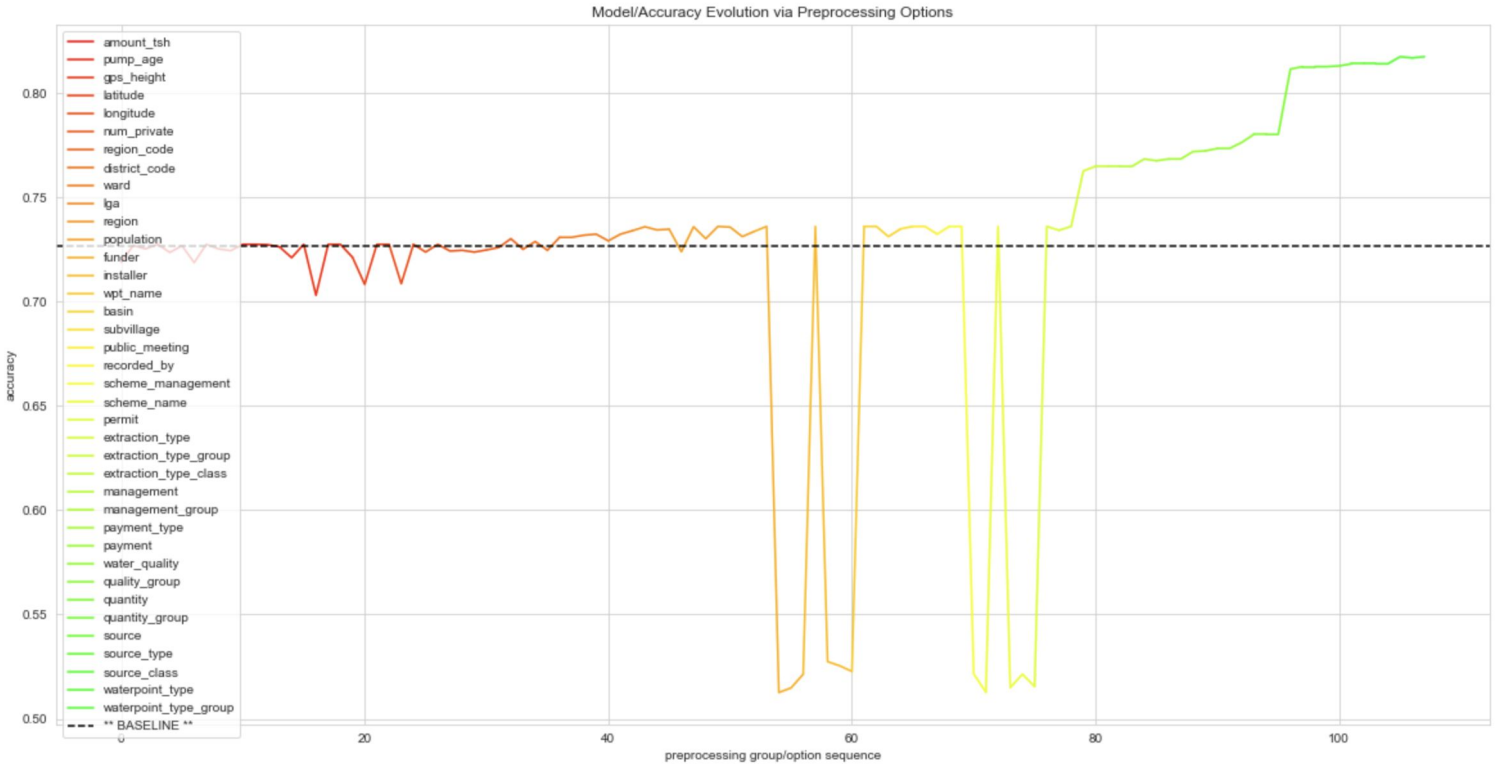
Phase Detail: EDA

- **Start with 38 “raw” features that are VERY messy!**
- **Foundation and dependency of subsequent phases**
- **Purity of goal**: complete and thorough investigation of EACH feature AND related features (by description… the “kind” of feature… not data type though) to **uncover ALL possible and applicable transformations**; *this required resisting the urge to pollute the EDA process with actual, applied preprocessing and transformations that might be used in final model building*
- Required the **Development and Incorporation of Advanced Techniques for handling High-Cardinality categorical features** (e.g. containing 2000+ “unique” categories)
  - *Target-Encoding*
  - NLP Techniques
    - *TF-IDF Vectorization*
    - Experimental Technique: unsupervised *KMeans Clustering* classification on top of *TF-IDF Vectorization*

Phase Detail: Preprocessing

- **Dynamic Programming algorithm that optimizes feature selection AND the best preprocessing transformation to use**
- **Depends on building a baseline model with a flexible classification algorithm:** XGBClassifier was used for baseline model
- **The best results (optimized set of preprocessing options) depend on a COMPLETE set of applicable transformations for a given feature;** note that this necessitated considering that dropping the feature or “leaving it as is” could be the best option
- **Complexity (big “O”) falls between linear and exponential** (but is not intractable - i.e. VASTLY improves on NP-Hard brute-force) **when there is more than one feature in a feature-group** (related by “kind” of data it represents, provided by feature description) **but is otherwise linear**; thus, **it is imperative to be thorough and at the same time careful to not include extraneous/unnecessary preprocessing options for a given feature**
- **Basis for evaluation: evolution/improvement of validation-set accuracy of baseline model while isolating candidate preprocessing/transformation option**

Visualization: Preprocessing (Optimization)



Phase Detail: Model-Building

- **Algorithms considered:**
  - `DecisionTreeClassifier`, `RandomForestClassifier`, `XGBClassifier`, `CatboostClassifier`, `SVM.SVC`(RBF Kernel)
  - Ensemble (`VotingClassifier`) of: `RandomForestClassifier`, `SVM.SVC`(RBF Kernel), and `CatboostClassifier`
- **Hyper-Parameter Tuning:** In some cases `RandomizedSearchCV` (vs. `GridSearchCV`) is preferred since it can search a continuous distribution (vs. only discrete lists in the `GridSearchCV` case - in order to overcome the potential flaw “did I not include an important possible value?”)
- **Experimentation: ensembling can “squeeze out” even more accuracy**
- **Produces unlabeled predictions used in competition scoring**

Best Competition Model: Summary

- **Algorithms used:** Ensemble (`VotingClassifier`) of: `RandomForestClassifier` and `CatboostClassifier`
  - “soft” voting results in greater accuracy than “hard” voting
  - the model from this ensemble results in greater leaderboard accuracy than either classification algorithm by itself
- **Leaderboard Stats:**

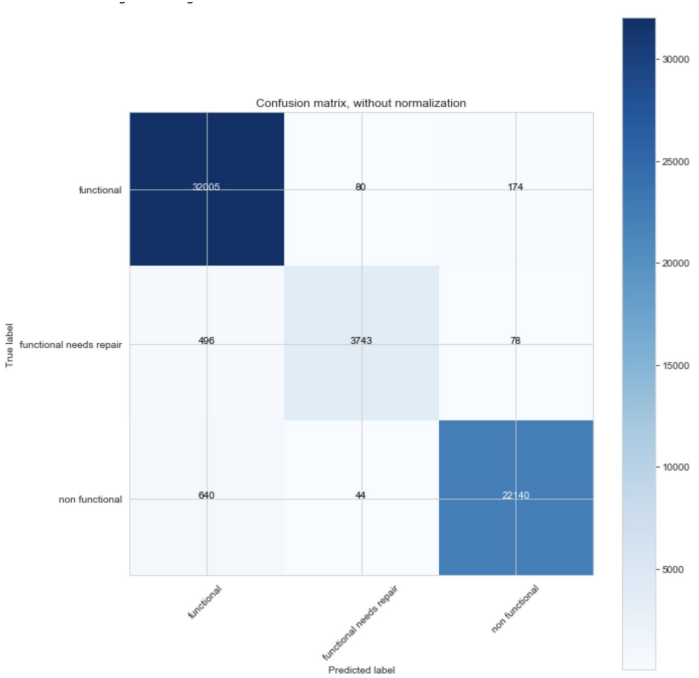
Submissions

BEST	CURRENT RANK	# COMPETITORS	SUBS. MADE
0.8187	837	9751	2 of 3

Best Competition Model: Summary: Part 2

- **Accuracy:**
  - All-labeled (Train + Validation): 97.45%
- **Classification Report:**

	precision	recall	f1-score	support
functional	0.97	0.99	0.98	32259
functional needs repair	0.97	0.87	0.91	4317
non functional	0.99	0.97	0.98	22824
accuracy			0.97	59400
macro avg	0.97	0.94	0.96	59400
weighted avg	0.97	0.97	0.97	59400



Best Competition Model: Feature Importances: 0

`VotingClassifier` **does not itself support feature importances, so we consider feature importances of each base classifier within the ensemble.**

Best Competition Model: Feature Importances: 1

`RandomForestClassifier` **feature importances (ordered segment):**

('longitude', 0.1419938300000846),
('latitude', 0.1408485505887231),
('ward_target_encoded', 0.13300125845632754),
('gps_height', 0.07072012309118425),
('construction_year', 0.05129212504533979),
('population', 0.047929559853772334),
('waterpoint_type_target_encoded', 0.04523917965056266),
('lga_target_encoded', 0.043926103105620604),
('quantity_enough', 0.03280674663306963),
('region_code_target_encoded', 0.026483118450123147),
('extraction_type_other', 0.021280819083445587),
('management_target_encoded', 0.021228146094434134),
('quantity_insufficient', 0.02076935581412387),
('amount_tsh', 0.01674554733198661),
('quantity_seasonal', 0.011250677364134225),
…

(from here, specific/individual one-hot encoded features determine importance)

Best Competition Model: Feature Importances: 2

`CatboostClassifier` **feature importances:**

('ward_target_encoded', 22.41649207493856),
('longitude', 7.689541298355761),
('latitude', 7.5612363143697205),
('waterpoint_type_target_encoded', 6.783655095530763),
('gps_height', 5.963876290835135),
('construction_year', 5.590341595095007),
('population', 4.475029132086664),
('quantity_enough', 4.085805641935429),
('quantity_seasonal', 4.032185134327176),
('lga_target_encoded', 3.9554054760800943),
('quantity_insufficient', 3.7031852130628846),
('region_code_target_encoded', 2.488859587057985),
('management_target_encoded', 2.196357543701259),
('amount_tsh', 1.8572530354537147),
…

(from here, specific/individual one-hot encoded features determine importance)

Feature Importances: High-level Analysis

Though the feature-importance coefficients of the `RandomForestClassifier` and `CatboostClassifier` components of the final ensemble model differ, the feature-importance orderings of each are still rather close.

The similarity of feature-importance orderings provides a high-level overview of "final" feature-importance:

- ward_target_encoded
- longitude
- latitude
- waterpoint_type_target_encoded
- gps_height
- construction_year
- population
- lga_target_encoded
- region_code_target_encoded
- management_target_encoded
- amount_tsh

It is also very interesting that both classifiers in the ensemble agree on particular (one-hot encoded) categories that are of great importance in classifying the target:

- 'quantity_enough'
- 'quantity_seasonal'
- 'quantity_insufficient'

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:

- **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**