

ReneWind

ReneWind: Model Tuning

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Executive Summary



- The AdaBoost Classifier tuned using oversampled data has the best performance
- V30, V9 and V18 are most important features
 - They can be deciphered to determine and analyze the actual variables to understand their impact on the predictive task at hand
- This model can be further used to detect if a wind turbine will fail or not and this will help reduce the cost.
- We also saw that there might be few points near around the classification threshold (0.5 by default)
 which can be further studied by the engineer and a final call could be made.



Business Problem Overview and Solution Approach

- Renewable energy sources play an increasingly important role in the global energy mix, as the effort
 to reduce the environmental impact of energy production increases. Out of all the renewable energy
 alternatives, wind energy is one of the most developed technologies worldwide.
- Predictive maintenance uses sensor information and analysis methods to measure and predict
 degradation and future component capability. The idea behind predictive maintenance is that failure
 patterns are predictable and if component failure can be predicted accurately and the component is
 replaced before it fails, the costs of operation and maintenance will be much lower.
- The sensors fitted across different machines involved in the process of energy generation collect data related to various environmental factors (temperature, humidity, wind speed, etc.) and additional features related to various parts of the wind turbine (gearbox, tower, blades, break, etc.).
- ReneWind is a company working on improving the machinery/processes involved in the production of wind energy using machine learning and has collected data of generator failure of wind turbines using sensors.

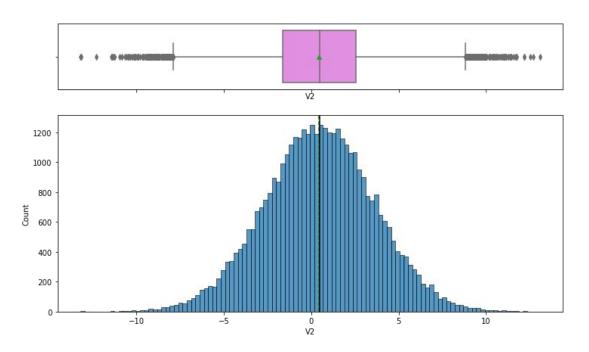


Business Problem Overview and Solution Approach

- The task at hand is to build various classification models, tune them, and find the best one that will help identify failures so that the generators could be repaired before failing/breaking to reduce the overall maintenance cost.
- The nature of predictions made by the classification model will translate as follows:
 - True positives (TP) are failures correctly predicted by the model. These will result in repairing costs.
 - False negatives (FN) are real failures where there is no detection by the model. These will result in replacement costs.
 - False positives (FP) are detections where there is no failure. These will result in inspection costs.
- It is given that the cost of repairing a generator is much less than the cost of replacing it, and the cost of inspection is less than the cost of repair

EDA Results





The distribution of all the variables are similar All the variables are close to normally distributed

Data Preprocessing



- The data shared is a ciphered version containing 20000 observations in the train set and 5000 in the test set
- The number of features provided is 40 but the data is ciphered hence, the column names are anonymous
- There were few missing values in V1 and V2, we imputed them using the median and to avoid data leakage we imputed missing values after splitting train data into train and validation sets.
- 94.5% of the observations are negative and only 5.5% observations are a positive representing failure. The dataset is highly imbalanced so we tried undersampling and oversampling techniques to balance the data.





Training Performance

	Gradient Boosting tuned with oversampled data	XGBoost tuned with oversampled data	AdaBoost tuned with oversampled data	Random forest tuned with undersampled data
Accuracy	0.993	0.978	0.992	0.961
Recall	0.992	1.000	0.988	0.933
Precision	0.994	0.959	0.995	0.989
F1	0.993	0.979	0.992	0.960
	Gradient Boosting tuned with oversampled data	XGBoost tuned with oversampled data	AdaBoost tuned with oversampled data	Random forest tuned with undersampled data
Accuracy				
Accuracy Recall	data	data	data	data
The second second second	0.969	data 0.938	0.979	0.938

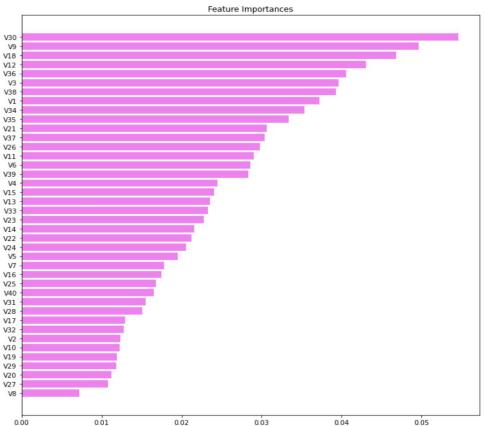
AdaBoost model trained with oversampled data has generalised performance, so let's considentifestime to be the performance by may an income only.

Validation Performance

Final Model Feature Importance



 V30, V9 and V18 are most important features. They can be deciphered to determine and analyze the actual variables to understand their impact on the predictive task at hand



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Productionize and test the final model using pipelines

- We build the pipeline with the following components:
 - Simple Imputer for imputation
 - AdaBoost model with oversampled data
- AdaBoost model performed well on test data

Data	Accuracy	Recall	Precision	F1
Test	0.978	0.844	0.780	0.811



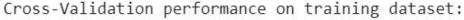
APPENDIX

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Model Performance Summary - Original data





Logistic regression: 0.4927566553639709

Bagging: 0.7210807301060529

Random forest: 0.7235192266070268

GBM: 0.7066661857008874

Adaboost: 0.6309140754635308 Xgboost: 0.7403217661063415

dtree: 0.6982829521679532

Validation Performance:

Logistic regression: 0.48201438848920863

Bagging: 0.7302158273381295

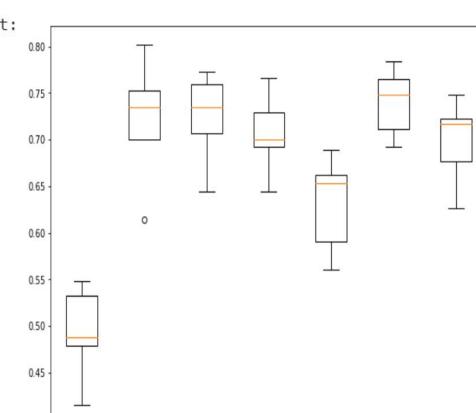
Random forest: 0.7266187050359713

GBM: 0.7230215827338129

Adaboost: 0.6762589928057554

Xgboost: 0.762589928057554

dtree: 0.7050359712230215 This file is meant for personal use by mayanipurva



Adaboost

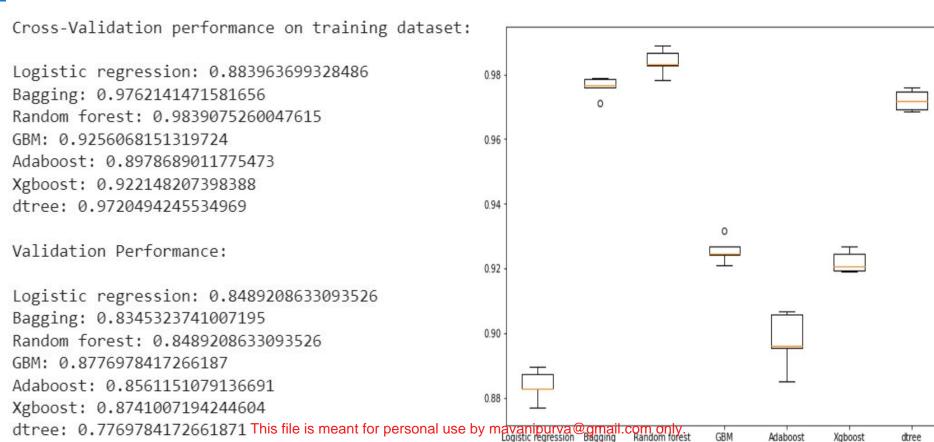
Xaboost

dtree

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Model Performance Summary - Oversampled data



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Model Performance Summary - Undersampled data

Cross-Validation performance on training dataset:

Logistic regression: 0.8726138085275232

Bagging: 0.8641945025611427

Random forest: 0.9038669648654498

GBM: 0.8990621167303946

Adaboost: 0.8666113556020489 Xgboost: 0.9002669360075031

dtree: 0.8617776495202367

Validation Performance:

Logistic regression: 0.8525179856115108

Bagging: 0.8705035971223022

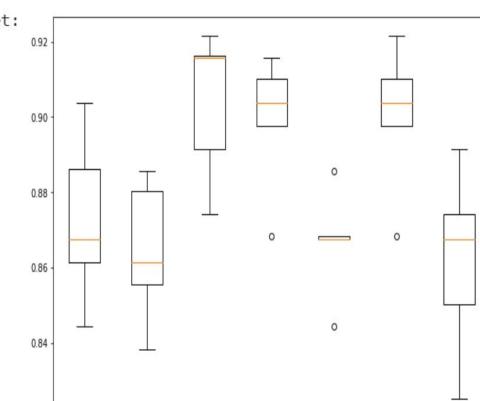
Random forest: 0.8920863309352518

GBM: 0.8884892086330936

Adaboost: 0.8489208633093526

Xgboost: 0.8884892086330936

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Adaboost

Xaboost

dtree

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