Predicting Machine Maintenance

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3/10/2019

The Problem Summary:

- Using data captured over a one year period, across a fleet of production machines, develop a model that will predict which machines will fail within the next 24 hours.

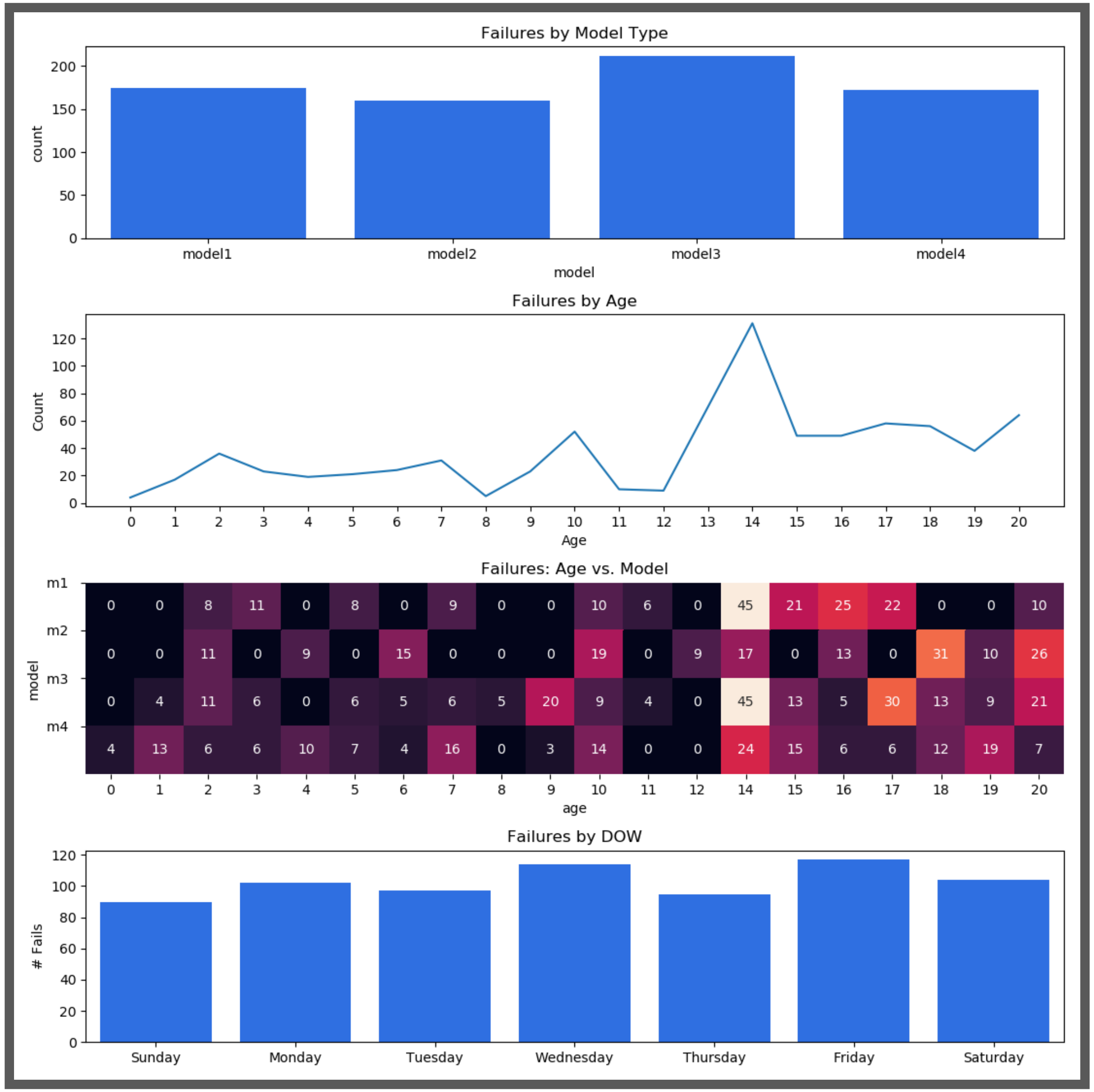
- Model should be extensible to predict maintenance costs and develop a proactive strategy to minimize costs

- Results: A random Forest model was created that was 97% effective in identifying machines due to fail. It would allow an efficient strategy to be developed, and significant savings (49%) to be achieved.

The Data

Dataset contains:

- **100 Machines**
  - 4 Models
  - Ages 0-20 years
  - Differing failure profiles
- **Hourly Sensor Data:**
  - Vibration, Rotation, Pressure, Voltage
- **5 Different Error Codes**
- **Daily Failure Data**



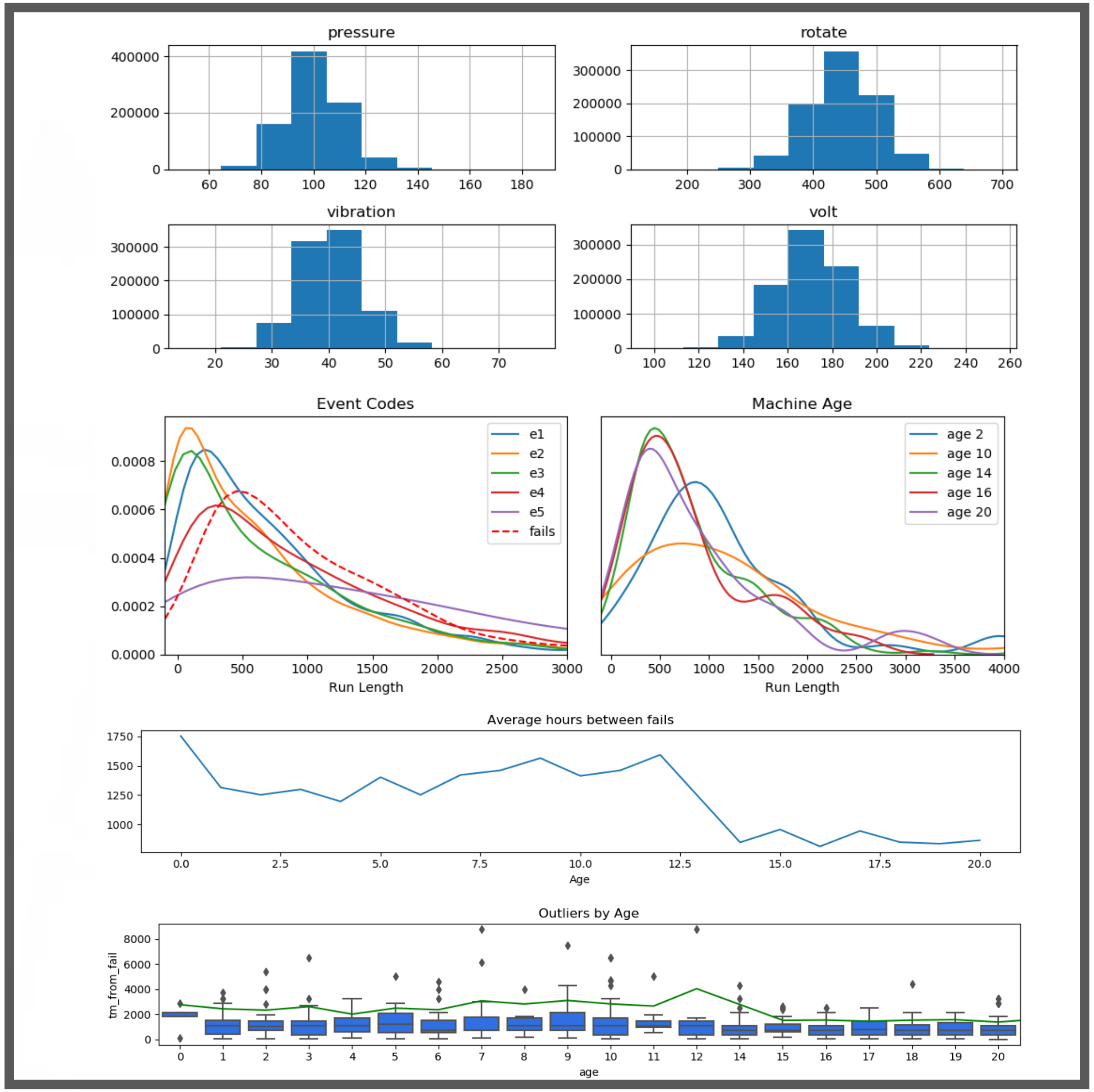
The Data (contd)

Sensor data has predominantly normal distributions

Error Codes map to varying run length

Machine age Matters:

- Age maps to different run lengths, with a visible change at 12 years
- “Outliers” (machines that have long TBF) are more prevalent in the younger machines



The Data (contd)

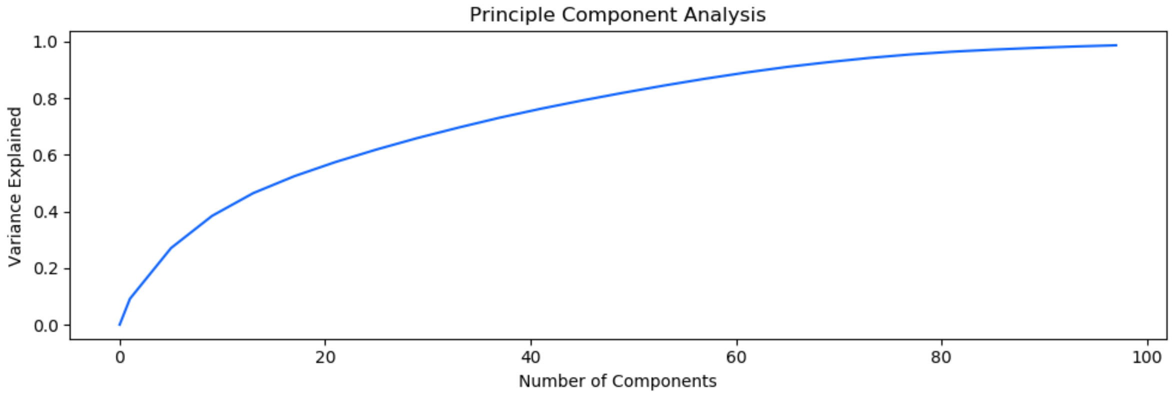
Lag features:

- 3 and 24 hour periods created
- Surprisingly low correlation to “fails’. Makes sense given multiple failures modes likely have different physical profiles.

PCA:

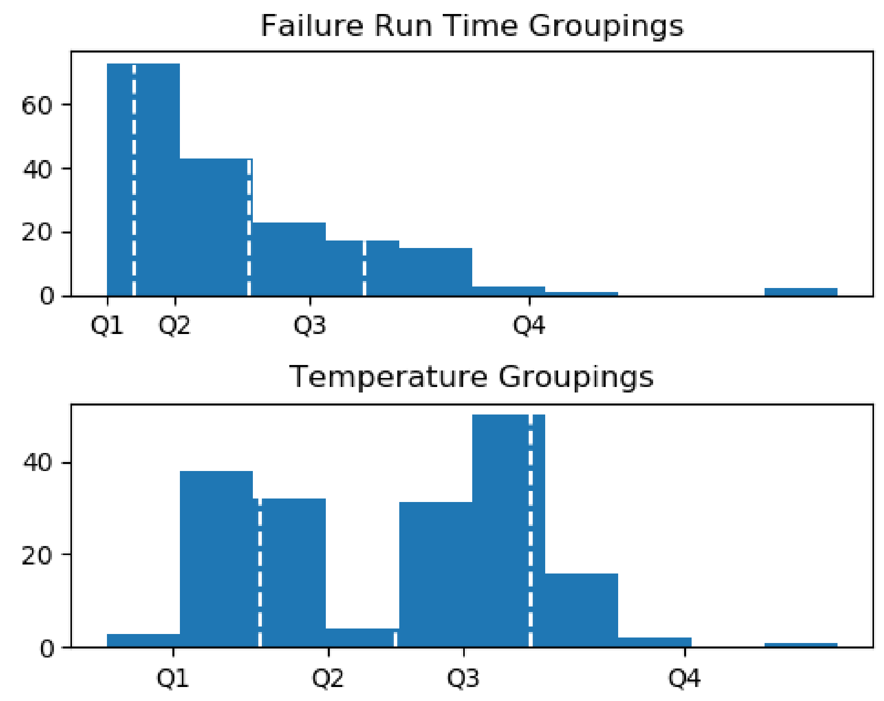
- Many features required to absorb variance.
- No clear ‘knee’ supports low correlation of sensors to fails

	volt__roll24	pressure__roll24	rotate__roll24	vibration__roll24	fails
volt__roll24	1.000000	-0.087151	0.102392	-0.129977	0.044354
pressure__roll24	-0.087151	1.000000	0.066487	-0.090076	0.039598
rotate__roll24	0.102392	0.066487	1.000000	0.074266	-0.055014
vibration__roll24	-0.129977	-0.090076	0.074266	1.000000	0.044072
fails	0.044354	0.039598	-0.055014	0.044072	1.000000



The Model Features: 8 given, 168 derived, 176 total

Type	Source	Derived	Groups
Time Series Run Length	Sensor, Error Codes, Model	max, min, std, roll3, roll24, Q1-4	Age, Model Type,
Time Series	Time from fail	delta	MachineID
Run Number	Error Codes Fails	Delta	MachineID
Categorical	DOW, Model	One hot encode	



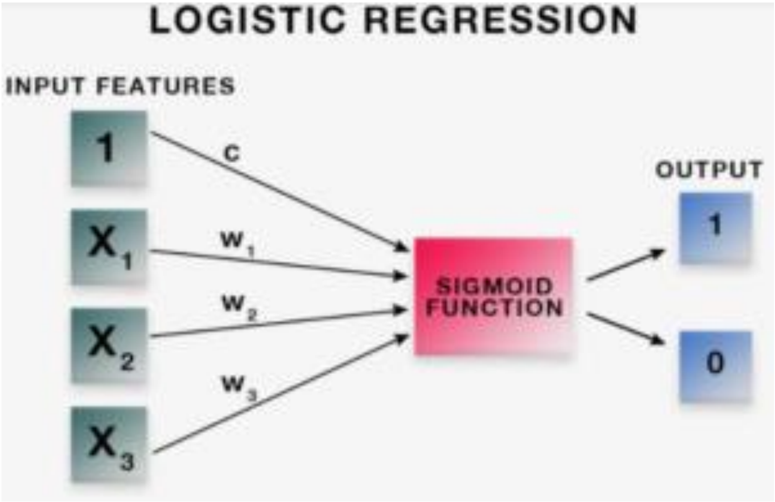
The Model

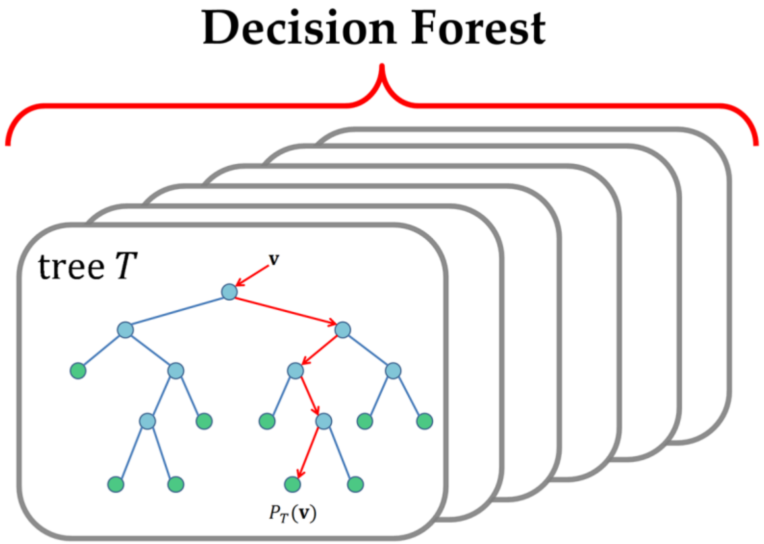
Considerations / Decisions

Single Daily Fail Point / Develop “Fail w/in 24hr” target class –Binary Classification

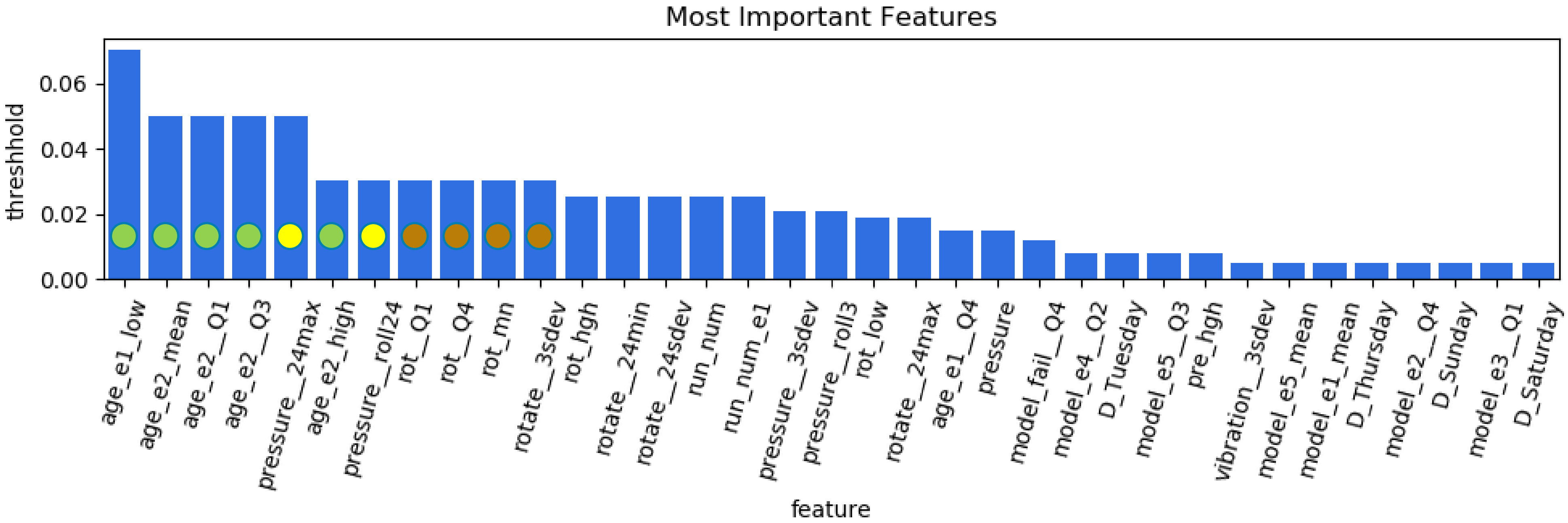
Unbalanced Data / Keep All Fail24 Class, Subsample Normal Class

PCA indicates need for high # features / Keep all features, try both logistic regression and Random forest as a first pass





Feature Importance (rf model)



- Machine age interacting with error code# and runtime
- Max Pressure over past 24 hours
- Rotation Performance

Judging Criteria:

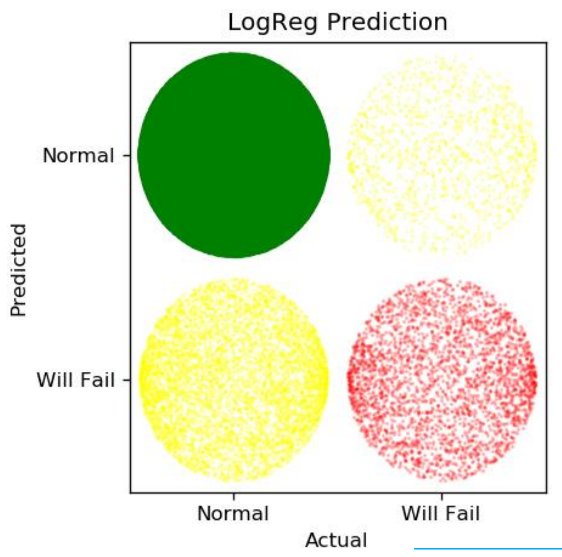
- Maintenance cost = $f(correctly\ predicted\ failures) +$
  $f(incorrectly\ predicted\ failures) +$
  $f(false\ failure\ service\ calls)$

- We don't know the actual costs, but we need a mechanism to judge the model. For exercise purposes:

- $f(correctly\ predicted\ failures)$ = True Positives = $500 (min down time, mini repair cost)
- $f(incorrectly\ predicted\ failures)$= False Negatives = $1,000 (maximum down time, max repair cost)
- $f(false\ failure\ service\ calls)$ = False Positives = $250 (0 downtime, unnecessary repair call)

- Baseline: 4,053 failures * $1,000/unpredicted failure = $4.05M maintenance cost

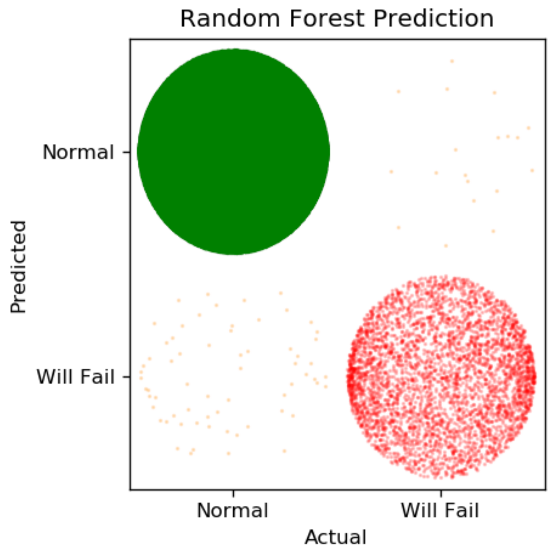
Model Results



Logistic Regression

- True Failures = 2,875 $1,437,500
- Unpredicted Failures = 1,178 $1,178,000
- Falsely Predicted Failures = 5,481 $1,370,250
- ______
- Baseline $4,053,000 $3,990,525
- Savings: $ 62,475

1.5% Savings



Random Forest

- True Failures = 4,034 $2,017,000
- Unpredicted Failures = 19 $ 38,000
- Falsely Predicted Failures = 65 $ 16,250
- ______
- $2,071,250
- Savings: $ 1,981,750

49% Savings

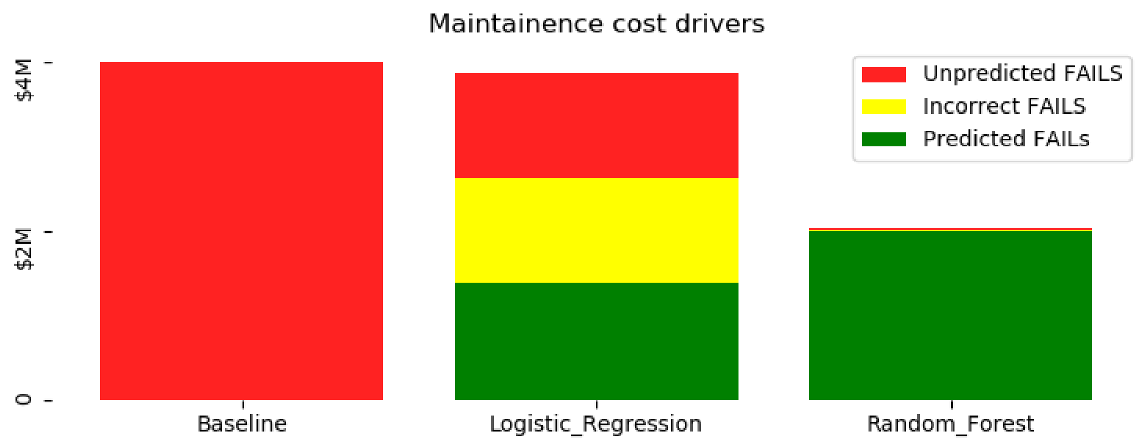
The Model (results)

The Logistic Regression Model:

- Some predictive value
- The economic penalties of the incorrect predictions make that model almost worthless.

The Random Forest Model:

- 97% accuracy in predictions
- Economic Impact Clear



From a pragmatic standpoint it is not worth expending any additional effort on the LR model.

Summary

- Across a dataset with 100 machines, all with different failure profiles, basic sensor, errorcode and failure rates were analyzed.
- A model was developed that is 97% accurate in terms of predicting machines that will fail within 24 hours
  - Key indicators: error codes run times in model and age contexts (5/top 11)
  - Pressure and Rotation Sensor outputs over past 24 hours (6/top 11)
- Using reasonable assumptions, the best model was able to save nearly 50% of the maintenance cost. A poor model saved only 1.5%