

Production Line Performance



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Agenda

- ❏ Introduction
- ❏ Feature Selection and Engineering
- ❏ Modeling and Evaluation
- ❏ Further Improvement



Data Source

- Kaggle competition: <https://www.kaggle.com/c/bosch-production-line-performance/overview>
- Predict internal failures using thousands of measurements and tests made for each component along the assembly line
- Features represent measurements of parts as moving through production lines
- Target is to predict which parts (ID) will fail quality control
- An extremely large number of anonymized features with information of production line, station, and feature number
- Features separated into 3 files: numerical, categorical, and date



Target and Tools

- Target: predict which parts (ID) will fail quality control
- Tools we use:
 - Loading Data with Amazon S3 bucket
 - Exploratory Analysis: **Spark** SQL, **Spark** Dataframe
 - Feature Selection and Engineering: **Spark** SQL, **Spark** Dataframe, UDF in Pandas, visualization with matplotlib
 - Modeling: **Spark** ML (Logistic Regression, Random Forest, Gradient Boosted Tree), XGBoost



Biggest Challenges

...

- 4,265 features in the dataset
- Extremely **imbalanced** data

```
In [12]: cat.printSchema()
```

```
root
|-- Id: integer (nullable = true)
|-- L0_S1_F25: string (nullable = true)
|-- L0_S1_F27: string (nullable = true)
|-- L0_S1_F29: string (nullable = true)
|-- L0_S1_F31: string (nullable = true)
|-- L0_S2_F33: string (nullable = true)
|-- L0_S2_F35: string (nullable = true)
|-- L0_S2_F37: string (nullable = true)
|-- L0_S2_F39: string (nullable = true)
|-- L0_S2_F41: string (nullable = true)
|-- L0_S2_F43: string (nullable = true)
|-- L0_S2_F45: string (nullable = true)
|-- L0_S2_F47: string (nullable = true)
|-- L0_S2_F49: string (nullable = true)
|-- L0_S2_F51: string (nullable = true)
|-- L0_S2_F53: string (nullable = true)
|-- L0_S2_F55: string (nullable = true)
|-- L0_S2_F57: string (nullable = true)
```

- The number of rows in cat:
1,183,747
- The number of columns in cat:
2,141



0.58%

v.s

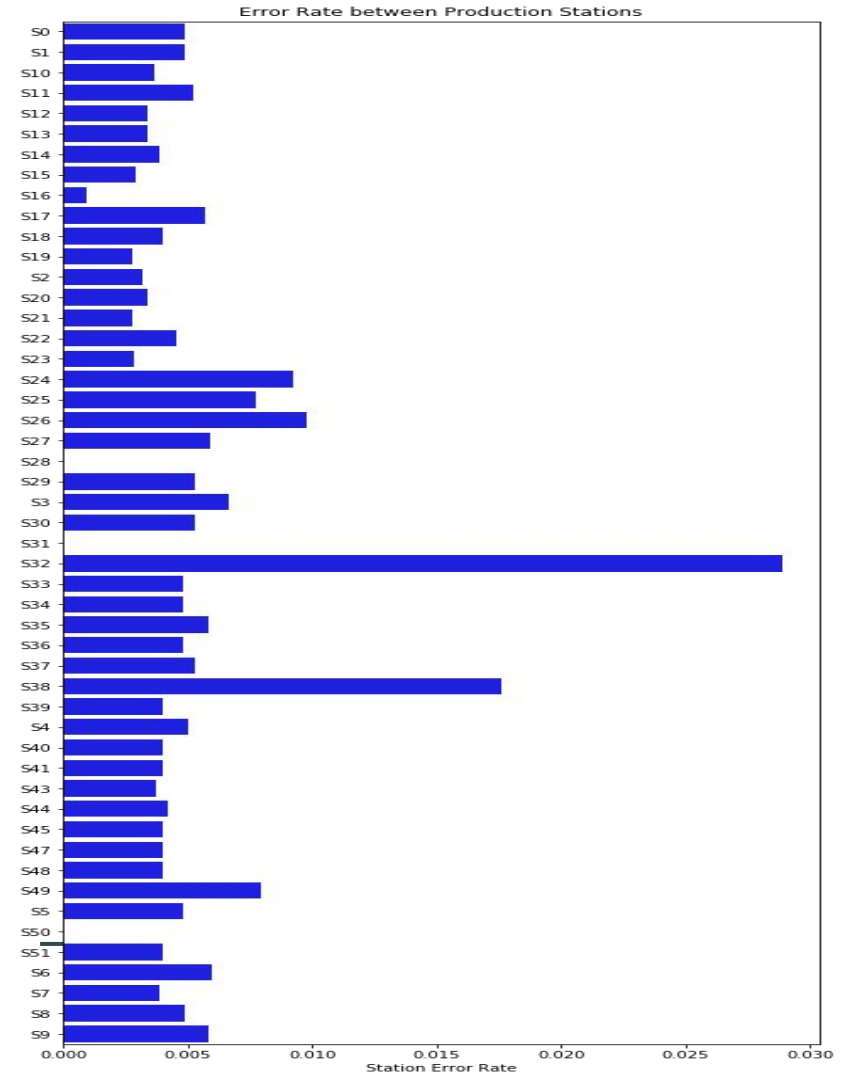
Success Rate=99.42%

Failure rate at different stations

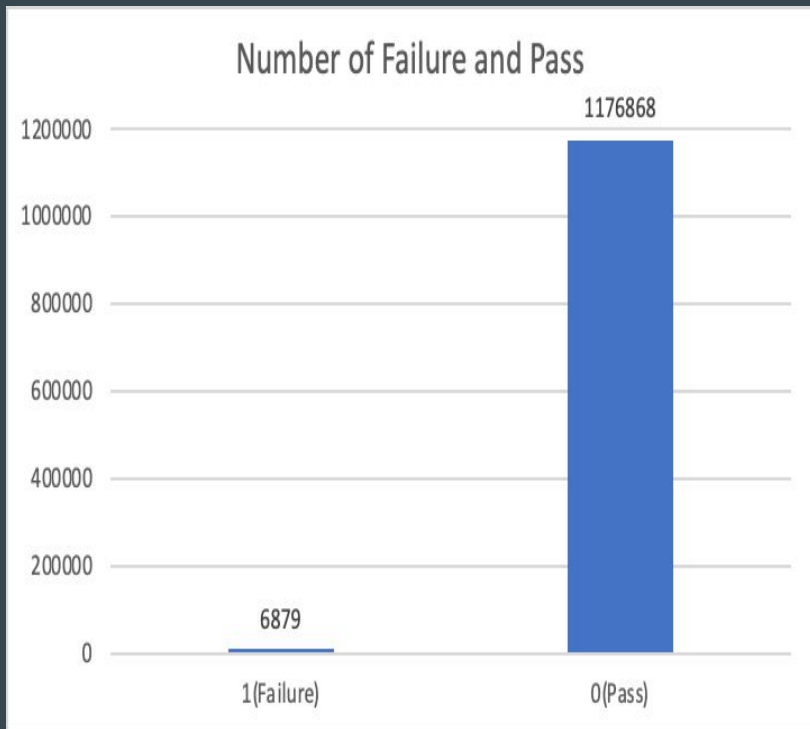
Top 1: S32

Top 2: S38

Top 3: S26



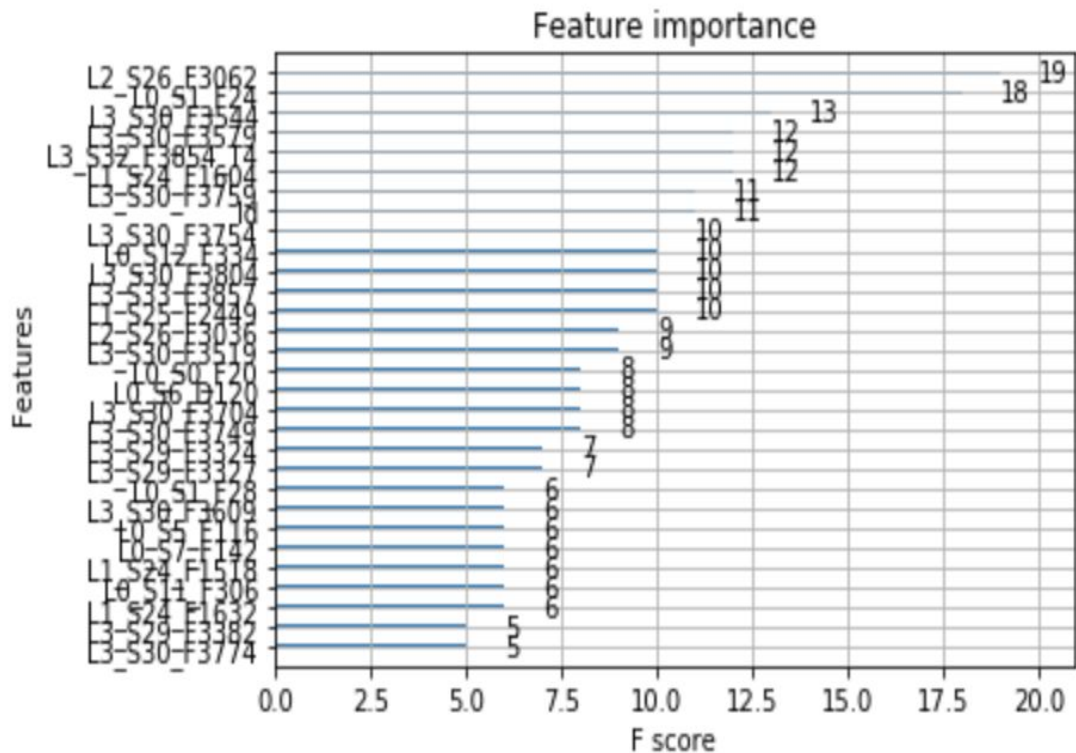
Imbalanced Response



- Data Preparation:
Oversampling (SMOTE)
- Model Evaluation:
Matthews correlation coefficient (MCC)

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Feature Selection --- XGBoost



Feature Engineering

01

Numeric Features

- Failure rate differs based on stations
- Generate Features for each station

02

Categorical Features

- Type of features has most NaN
(Only two have missing values less than 900k.)
- Pick columns with largest variance

03

Date Features

- A lot of duplicate columns for each station
(Prob. for station to have the same values: 0.98)
- Observations are unique for station Id pair



Modeling & Evaluation

Model	MCC Score
Random Forest	0
Logistic Regression	0.019
Gradient Boosted Tree	0.097
XGBoost	0.15



Further Improvement

- Alternative methods to deal with imbalanced, sparse data
- Hyperparameters tuning



EVERYTHING
IS UNDER
CTRL

Thank you

Q & A