Predicting the number of O-Rings that experience thermal distress on a space shuttle flight

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Abstract

The following document presents two models for predicting the number of O-Rings in distress expected on a space shuttle flight. The models were trained on a dataset extracted from the UC Irvine ML Repository, which came to be because of the Challenger Launch disaster in 1986, where a shrinking of an O-Ring started a chain off event that ended with the destruction of the spacecraft.

O-Ring distress is conditioned by two dependent variables, temperature at launch and leak-check testing pressure. Our process included cleaning the dataset, an exploratory analysis of the data, and the training and testing of the models. Where we concluded that the likelihood of o-ring failure increases as launch temperature decreases and an increase in pressure will be accompanied by an increased likelihood of o-ring failure.

Keywords: logistic regression, linear regression, Challenger, O-Rings, Data Analysis

On January 28, 1986, tragedy unfolded as the Challenger Space Shuttle exploded 73 seconds into the flight. The seven astronauts on board were killed in the accident. After an exhaustive analysis of what went wrong, it was discovered that the shrinking of an O-Ring gasket, because of the cold temperatures at launch, allowed hot gas to leak out and melt one of the metal struts that held one of the solid rocket boosters in place.

The solid rocket booster, wiggling from the lower end, punched a hole in the fuel tank, with its pointy shape at the top. The fuel tank collapsed, and the space shuttle broke apart; a self-destruct command was then initiated for the loose free-falling components (Space Techie, 2020).

Before the mission, there had been a foregoing discussion regarding launch safety, where the probability of O-Ring failure was discussed (Draper, 1993). Given a temperature of 31 degrees Fahrenheit and data on the previous 23 flights, the aim of this investigation is to predict the number of o-rings that undergo thermal distress.

This technical report details the conclusions that can be determined based on the data analysis and model analysis performed.

Data Cleaning/Preparation

The possibility of failure revolved mainly around temperature at launch and the pressure at which safety testing of field join leaks was performed (although the effect of the pressure was unclear); where O-Ring failure could be caused by two distinct phenomena called erosion and blowby (Draper, 1993).

For our analysis we have a dataset, extracted from the UC Irvine ML Repository, of the previous 23 shuttle flights, their leak-check pressure, temperature, and information regarding the O-Ring status. This dataset consists of two databases: primary O-ring erosion and blow-by and primary O-ring erosion only. These databases are nearly identical, except for a difference in the 21st instance of the second attribute. The dataset contains five key attributes:

- *num_O_rings*. Number of O-Rings at risk per flight, integer. A shuttle is composed of two solid booster rockets, each with three field joints that individually include a primary and secondary O-Ring.
- *num_thermal_distress*. Number of O-rings experiencing thermal distress, integer.
- *launch_temp (F)*. Temperature, in degrees Fahrenheit at launch.
- *leak_check_pressure (psi)*. Pressure at which safety testing of field join leaks was performed.
- *Temporal order of flight*. Flight number.

To clean the dataset for exploratory analysis, both data sets were first transferred from their original text file form into Microsoft Excel sheets. This was done to try to alleviate any errors the computer could run into while reading the data. Next, all five columns of the datasets where unlabeled, so to improve the team's organization of this data, each column was labeled with its appropriate variable: num_Orings, num_thermaldistress, launch_temp, leak_check_psi, and temporal order.

Then, the team checked for null values in the data set. When the data was processed, it seemed that the computer detected three extra rows in the dataset not containing any values. Python code was utilized to trim these extra rows out so that they only included the 23 data points of interest. Next, Python code was utilized to figure out if there were any missing values in the dataset; fortunately, both data sets were found to be complete, so no action needed to be taken.

The next step was to determine the data types of each column. Every column in the erosion_only dataset was originally float variables, so they were converted into integers to make calculations easier. No changes were made to the other dataset because all the data points were already integers.

Lastly, various data frames were combined together and unique data was located to potentially improve processing. The temporal order column was removed from the dataset due to it not really containing any unique values. Also, the "count" sustained by this column is sufficiently covered by the actual index. Upon inspection, both datasets look virtually identical. To lessen the amount of data that needs to be processed, both dataframes (erosion and blowby) were combined together. The two columns containing data pertaining to the number of o-rings under thermal distress were renamed ThermalInitial and ThermalBlowby to indicate which dataset they came from for organizational purposes. Upon further inspection, the ThermalInitial and ThermalBlowby columns were also found to be almost identical save for one datapoint, so ThermalBlowby was chosen for the regression analysis.

The data cleaning process helped indicate that the ThermalBlowby data is the target variable and is to be analyzed based on the pressure leaks and temperature data. The data cleaning process is also important because the later performance of regression analysis is highly dependent on the quality of the dataset being utilized. It was consummated on our 3 column x 23 row dataset; where only one of the two datasets were chosen, and certain variables were removed.

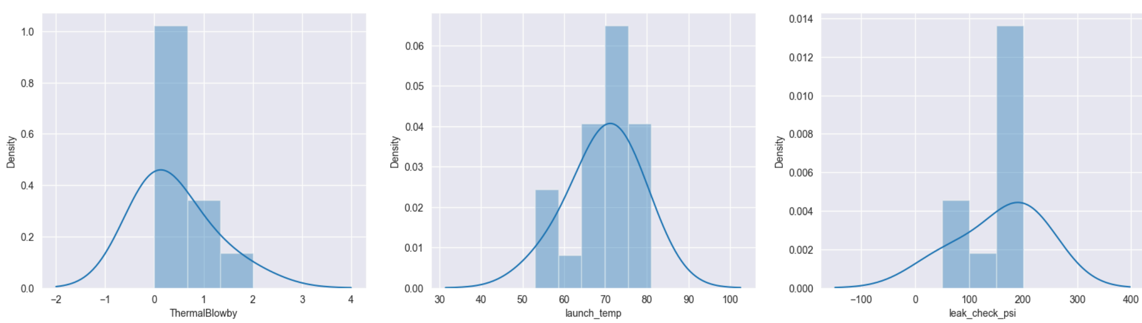
Exploratory Data Analysis

The exploratory data analysis (EDA) phase focused on understanding the relationships between the key features of the dataset, particularly the impact of launch temperature on O-ring failure. Histogram distribution plots, scatter plots, pair plots, and a heat map were all utilized to better visualize the data for analysis. These distributions indicate that the thermal rings under distress (ThermalBlowby) seem to correlate with the launch temperature and pressure leak data.

Regarding the distribution and behavior of the variables at the different shuttle launches as can be seen in Figure 1, we discovered that: the majority of shuttles experienced no O-Ring distress at all, occurred usually at relatively warm temperatures (mean 69.6 F), and conducted leak checks at a pressure of 200 psi. It is worth mentioning that no launch had ever occurred at such a low temperature, where the lowest recorded temperature had been observed at 53 F.

Figure 1

O-Rings, Temperature, and Pressure Distribution Plots



Note. The distribution plot is complemented by the descriptive statistics related to said variables, as can be seen in Figure 2.

Figure 2

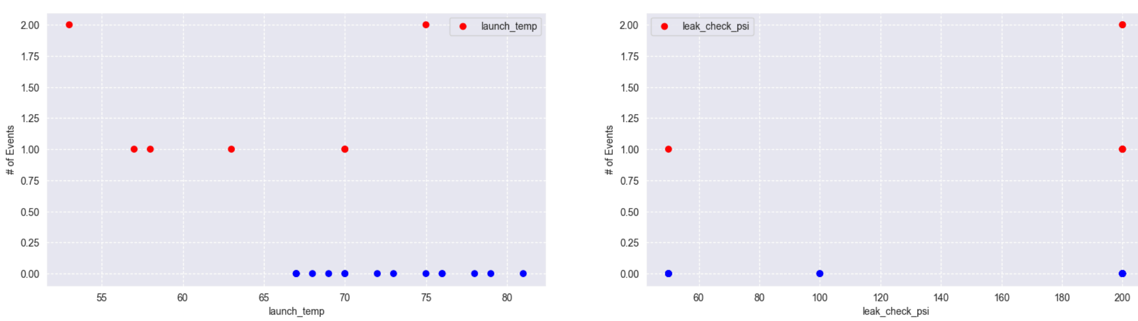
O-Rings, Temperature, and Pressure Statistics

mean	std	min	max	median
0.318182	0.567900	0.000000	2.000000	0.0
69.727273	7.179215	53.000000	81.000000	70.0
156.818182	66.000459	50.000000	200.000000	200.0

In relation to the interactions between Temperature-ORings and Pressure-ORings shown in Figure 3 below, it can be seen that O-Ring distress is experienced usually at lower temperatures; and accidents occurred at low and high psi.

Figure 3

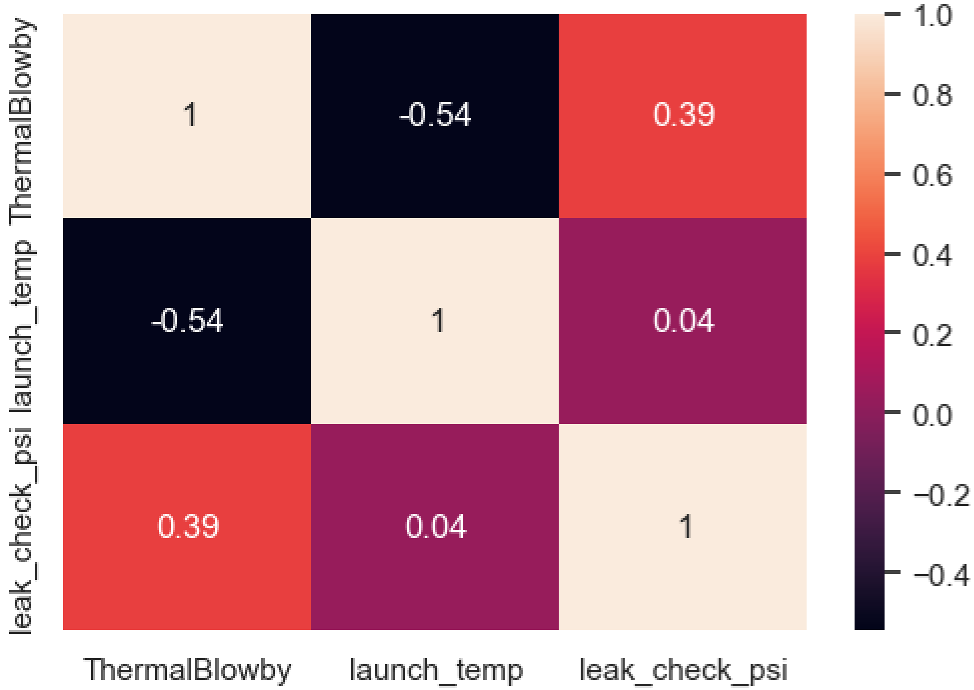
O-Rings, Temperature, and Pressure Scatterplots



According to the heat map (Figure 4), it appears that ThermalBlowby has more of a negative correlation with temperature (-.54). Meanwhile, ThermalBlowby appears to have more of a positive correlation with pressure(.39).

Figure 4

Correlation Heatmap between O-Rings (ThermalBlowby), Temperature, and Pressure



What can be hypothesized from this information is that, the likelihood of o-ring failure increases as launch temperature decreases. The positive correlation between leak check pressure and the o-ring failure leads to a hypothesis that may indicate that an increase in pressure will be accompanied by an increased likelihood of o-ring failure.

Model Selection

Two models were utilized for this data set: Linear Regression and Logistic Regression.

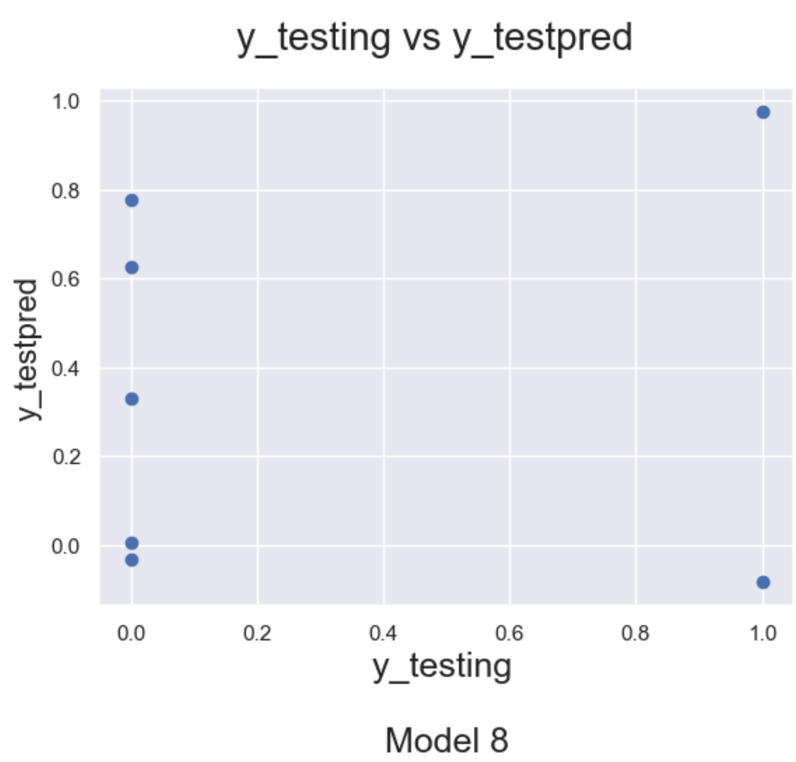
- The linear regression model, as can be seen at Figure 5, was utilized to create an equation that predicts the number of o-rings that fail given pressure values and the temperature of 31 degrees Fahrenheit, which was the temperature assigned in the original problem statement. When processed by Python code, the resulting equation was $y = 3.1525 - T * 0.0496 + P * 0.0047$. The pressure dataset consists of values of 50, 100, and 200, so given the dataset of [0, 50, 100, 200] and given a T value of 31, the predicted number of rings failing at 31 degrees Fahrenheit is as follows:

- 1 ring failing at 0 psi
- 1 ring failing at 50 psi
- 2 rings failing at 100 psi
- 2 rings failing at 200 psi

However, when comparing the prepared testing and training sets of data (Figure 7), the resulting figure indicates that linear regression may not be the best fit for this data.

Figure 7

O-Rings, Temperature, and Pressure Scatterplots



To improve on this, a logistic regression was chosen to investigate.

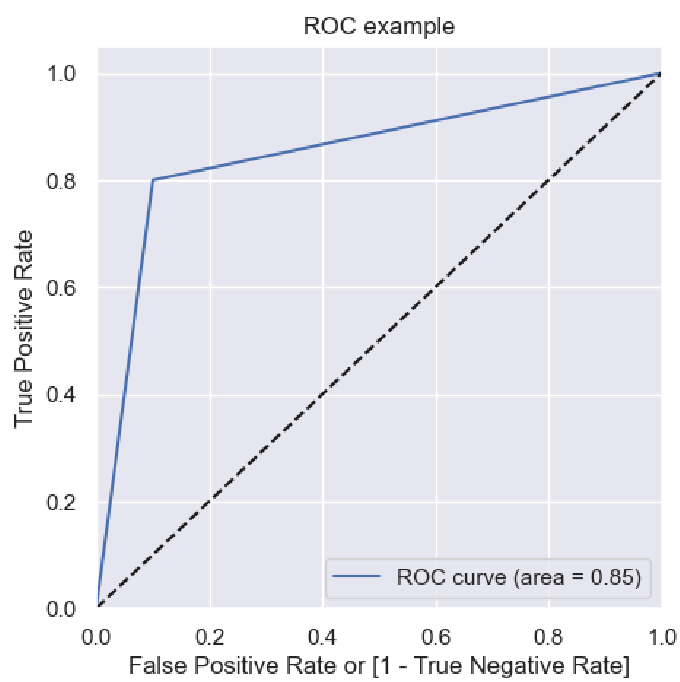
After a test set and training set was created in Python code for the logistic regression, the MinMaxScaler function from Python was utilized to normalize the datasets to improve processing.

Model Analysis

To analyze the data created by the logistic regression, an accuracy report was created with Python. The purpose of this report was to analyze true positives, true negatives, false positives, and false negatives so as to plot probability against accuracy, sensitivity, and specificity. The result of that plot, the point at which they all cross, indicates the optimal probability cutoff (.3). That is later utilized by the ROC curve to calculate the accuracy for the report. The calculated accuracy is found to be around 57% (Figure 8).

Figure 8

Logistic regression ROC curve



Conclusions and Recommendations

In conclusion, the logistic regression equation can calculate the number of o-rings that experience thermal distress on a flight at 31 degrees Fahrenheit at about an accuracy of 57%. In the private industry under a different context, this may actually be an acceptable metric. However, by taking into account the context of the data, the lives of astronauts piloting a NASA shuttle depending on this statistic, it is prudent to make an improvement to this prediction statistics. Earlier in this investigation, it was mentioned that the performance of the regression would be dependent on the quality of the data being analyzed and processed. This point is key to further recommendations to improve this model. Firstly, it is noticeable that there are only five variables being presented in the initial data set. Of those five, only three of these can be counted as data with unique statistics. Given that this regression model is essentially being asked to perform a material's analysis of the rubber o-rings present on the Shuttle, it would improve the model if more relevant variables were available. Secondly, the pool of data to pull from is relatively shallow, given that it only takes into account 23 of the 135 Shuttle launches that occurred in the Shuttle program. Given that 135 is not a large data pool either in comparison to modern computer processes that may process datasets numbering in the thousands, including data from all 135 Shuttle launches would also help make the regression model more accurate.

Also, recommendations could also be extrapolated from the initial data visualization and data analysis. Given that it appears that the number of o-ring failures increases as temperature decreases and pressure increases, further analysis can take place when the data is actually taken into context with the engineering. Firstly, the o-rings are composed of some form of rubber, which is a material that breaks down under extreme heat and becomes brittle under extreme cold. Brittle materials tend to deface when they undergo huge increases in pressure, and unfortunately, the takeoff sequence of the Shuttle includes huge increases of pressure throughout and huge decreases in temperature as it reaches the upper atmosphere and vacuum of space, creating the perfect conditions for materials like rubber o-rings to grow brittle and deface.

More testing utilizing the variable related recommendations mentioned above would be needed to test this hypothesis, or a further recommendation based on this analysis would be to remove rubber o-rings from the design entirely. SpaceX rockets have less joints and moving parts to fracture under pressure and under extreme temperatures. They also are largely made of steel and are designed in such a way as to “breathe” to accommodate the extreme changes in temperature and pressure that go hand in hand with the vacuum of space. The use of this material as opposed to rubber is inherent to the design of the SpaceX rockets, because the new generation of rockets at SpaceX and NASA are meant to be reusable, meaning that they must resist multiple pressure and temperature changes in their vehicle lifetimes with minimal repairs needed. This change in design philosophy already occurred after the Shuttle program ended in 2011, so the use of a rubber o-ring may just be too brittle for the demands of modern aerospace engineering. However, this regression code can still be useful because at its core, it is essentially a model that tracks the limits of brittle materials under extreme pressure and temperature data. Given the extreme demands on materials entering and exiting Earth’s atmosphere, this model could easily be retrofitted for any material that needs to be tracked on the spacecraft like steel or ceramics.

References

Draper, D. (1993). Challenger USA Space Shuttle O-Ring [Dataset]. UCI Machine Learning Repository. https://doi.org/10.24432/C5PW2T.

Space Shuttle Challenger Disaster (1986). (2020, August 26). The Space Techie. https://www.thespacetechie.com/space-shuttle-challenger-disaster-1986/

Appendix A: Code Output

Figure 9

Loading and displaying "erosion_only" data

	num_Orings	num_thermaldistress	launch_temp	leak_check_psi	temporalorder
0	6.0	1.0	70.0	50	2.0
1	6.0	0.0	69.0	50	3.0
2	6.0	0.0	68.0	50	4.0
3	6.0	0.0	67.0	50	5.0
4	6.0	0.0	72.0	50	6.0
5	6.0	0.0	73.0	100	7.0
6	6.0	0.0	70.0	100	8.0
7	6.0	1.0	57.0	200	9.0
8	6.0	1.0	63.0	200	10.0
9	6.0	1.0	70.0	200	11.0
10	6.0	0.0	78.0	200	12.0
11	6.0	0.0	67.0	200	13.0
12	6.0	2.0	53.0	200	14.0
13	6.0	0.0	67.0	200	15.0
14	6.0	0.0	75.0	200	16.0
15	6.0	0.0	70.0	200	17.0
16	6.0	0.0	81.0	200	18.0
17	6.0	0.0	76.0	200	19.0
18	6.0	0.0	79.0	200	20.0
19	6.0	0.0	75.0	200	21.0
20	6.0	0.0	76.0	200	22.0
21	6.0	1.0	58.0	200	23.0
22	NaN	NaN	NaN	NaN	NaN

Figure 10

Locating the extra rows in "erosion_only" data

	num_Orings	num_thermaldistress	launch_temp	leak_check_psi	temporalorder
20	6.0	0.0	76.0	200	22.0
21	6.0	1.0	58.0	200	23.0
22	NaN	NaN	NaN	NaN	NaN
23	NaN	NaN	NaN	NaN	NaN
24	NaN	NaN	NaN	`	NaN

Figure 11

Output displaying the corrected 22 rows and 5 columns

```
(22, 5)
```

Figure 12

Loading and displaying the blowby data

	num_Orings	num_thermaldistress	launch_temp	leak_check_psi	temporalorder
0	6	1	70	50	2
1	6	0	69	50	3
2	6	0	68	50	4
3	6	0	67	50	5
4	6	0	72	50	6
5	6	0	73	100	7
6	6	0	70	100	8
7	6	1	57	200	9
8	6	1	63	200	10
9	6	1	70	200	11
10	6	0	78	200	12
11	6	0	67	200	13
12	6	2	53	200	14
13	6	0	67	200	15
14	6	0	75	200	16
15	6	0	70	200	17
16	6	0	81	200	18
17	6	0	76	200	19
18	6	0	79	200	20
19	6	2	75	200	21
20	6	0	76	200	22
21	6	1	58	200	23

Figure 13

No missing values for the "erosion_only" and "blowby" data

	0
num_Orings	0.0
num_thermaldistress	0.0
launch_temp	0.0
leak_check_psi	0.0
temporalorder	0.0

Figure 14

Checking the data types of the "erosion_only" data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22 entries, 0 to 21
Data columns (total 5 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   num_Orings           22 non-null     float64
 1   num_thermaldistress  22 non-null     float64
 2   launch_temp          22 non-null     float64
 3   leak_check_psi       22 non-null     object
 4   temporalorder        22 non-null     float64
dtypes: float64(4), object(1)
memory usage: 1008.0+ bytes
```

Figure 15

Output indicating the data type is now integer

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 22 entries, 0 to 21
Data columns (total 5 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   num_Orings           22 non-null     int64
 1   num_thermaldistress  22 non-null     int64
 2   launch_temp          22 non-null     int64
 3   leak_check_psi       22 non-null     int64
 4   temporalorder        22 non-null     int64
dtypes: int64(5)
memory usage: 1008.0 bytes
```

Figure 16

Output after removing non-unique data and merging data frames

	ThermalBlowby	launch_temp	leak_check_psi
0	1	70	50
1	0	69	50
2	0	68	50
3	0	67	50
4	0	72	50

Figure 17

Pair Plot Data Visualization

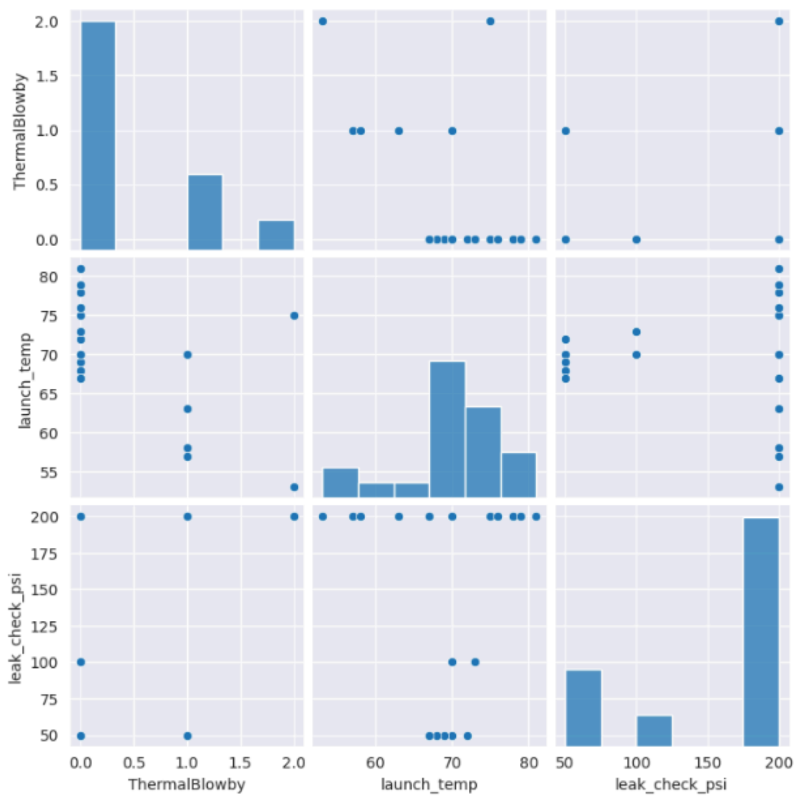


Figure 18

Output of Linear Regression Summary

OLS Regression Results

Dep. Variable:	ThermalBlowby	**R-squared:**	0.460
Model:	OLS	**Adj. R-squared:**	0.370
Method:	Least Squares	**F-statistic:**	5.105
Date:	Sun, 20 Oct 2024	**Prob (F-statistic):**	0.0249
Time:	18:37:59	**Log-Likelihood:**	-11.698
No. Observations:	15	**AIC:**	29.40
Df Residuals:	12	**BIC:**	31.52
Df Model:	2		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	3.1525	1.369	2.302	0.040	0.169	6.136
launch_temp	-0.0496	0.019	-2.629	0.022	-0.091	-0.008
leak_check_psi	0.0047	0.002	1.922	0.079	-0.001	0.010

Omnibus:	16.877	**Durbin-Watson:**	2.337
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	14.712
Skew:	1.747	**Prob(JB):**	0.000639
Kurtosis:	6.366	**Cond. No.**	1.68e+03

Figure 19

Output of Linear Regression Equation Predictions

```
# of rings failing at 31 F at 0 psi = 1
# of rings failing at 31 F at 50 psi = 1
# of rings failing at 31 F at 100 psi = 2
# of rings failing at 31 F at 200 psi = 2
```

Figure 20

Output of Logistic Regression Summary

Dep. Variable:	ThermalBlowby	**No. Observations:**	15
Model:	GLM	**Df Residuals:**	12
Model Family:	Binomial	**Df Model:**	2
Link Function:	Logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-4.1750
Date:	Sun, 20 Oct 2024	**Deviance:**	8.3500
Time:	19:04:56	**Pearson chi2:**	7.53
No. Iterations:	21	**Pseudo R-squ. (CS):**	0.5115
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-26.6871	2.76e+04	-0.001	0.999	-5.41e+04	5.41e+04
launch_temp	-7.0547	4.155	-1.698	0.089	-15.197	1.088
leak_check_psi	30.9880	2.76e+04	0.001	0.999	-5.41e+04	5.41e+04

Figure 21

Plotting Optimal Probability Cutoff

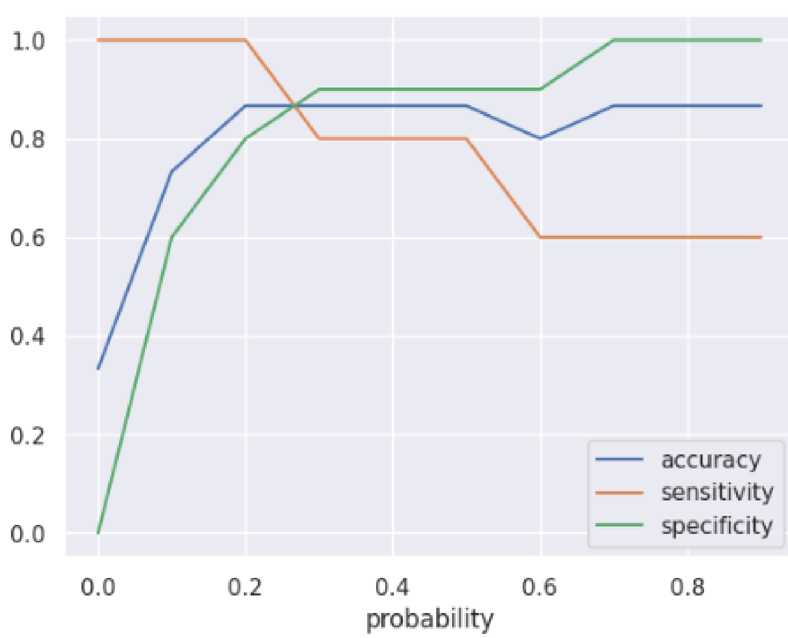


Figure 22

Output of Logistic Regression Prediction Accuracy

```
Accuracy #:  0.5714285714285714
How many failed O-Rings correctly predicted):  0.5
How much of the failed dataset was correctly predicted):  0.3333333333333333
```