# IE 7280 Statistical Methods in Engineering

## Final Project


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**Data Inspection:**

Preliminary analysis of the data shows that there are no missing values and that all of the independent features and the dependent variable are numerical.

```
data.describe(include='all')
```

| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | Y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **count** | 999.0 | 999.0 | 999.00 | 999.0 | 999.000 | 999.0 | 999 | 999.0000 | 999.00 | 999.00 | 999.0 | 999 |
| **unique** | 95.0 | 132.0 | 79.00 | 75.0 | 136.000 | 54.0 | 139 | 239.0000 | 85.00 | 88.00 | 49.0 | 6 |
| **top** | 7.8 | 0.5 | 0.49 | 2.0 | 0.084 | 6.0 | 15 | 0.9972 | 3.26 | 0.57 | 9.5 | 5 |
| **freq** | 37.0 | 31.0 | 65.00 | 92.0 | 40.000 | 96.0 | 24 | 35.0000 | 33.00 | 44.00 | 103.0 | 468 |

```
data.head()
```

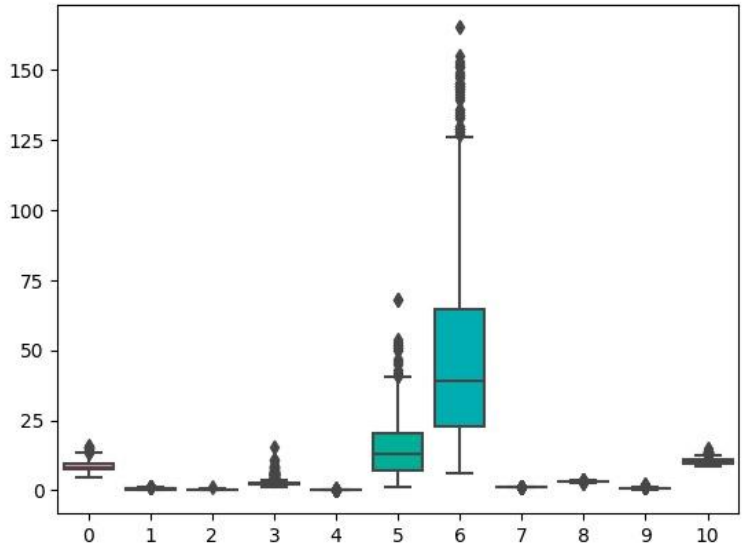
| | X1 | X2 | X3 | X4 | X5 | X6 | X7 | X8 | X9 | X10 | X11 | Y |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 7.4 | 0.7 | 0 | 1.9 | 0.076 | 11 | 34 | 0.9978 | 3.51 | 0.56 | 9.4 | 5 |
| **2** | 7.8 | 0.88 | 0 | 2.6 | 0.098 | 25 | 67 | 0.9968 | 3.2 | 0.68 | 9.8 | 5 |
| **3** | 7.8 | 0.76 | 0.04 | 2.3 | 0.092 | 15 | 54 | 0.997 | 3.26 | 0.65 | 9.8 | 5 |
| **4** | 11.2 | 0.28 | 0.56 | 1.9 | 0.075 | 17 | 60 | 0.998 | 3.16 | 0.58 | 9.8 | 6 |
| **5** | 7.4 | 0.7 | 0 | 1.9 | 0.076 | 11 | 34 | 0.9978 | 3.51 | 0.56 | 9.4 | 5 |

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 999 entries, 1 to 999
Data columns (total 12 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   X1      999 non-null    object
 1   X2      999 non-null    object
 2   X3      999 non-null    object
 3   X4      999 non-null    object
 4   X5      999 non-null    object
 5   X6      999 non-null    object
 6   X7      999 non-null    object
 7   X8      999 non-null    object
 8   X9      999 non-null    object
 9   X10     999 non-null    object
 10  X11     999 non-null    object
 11  Y       999 non-null    object
dtypes: object(12)
memory usage: 93.8+ KB
```

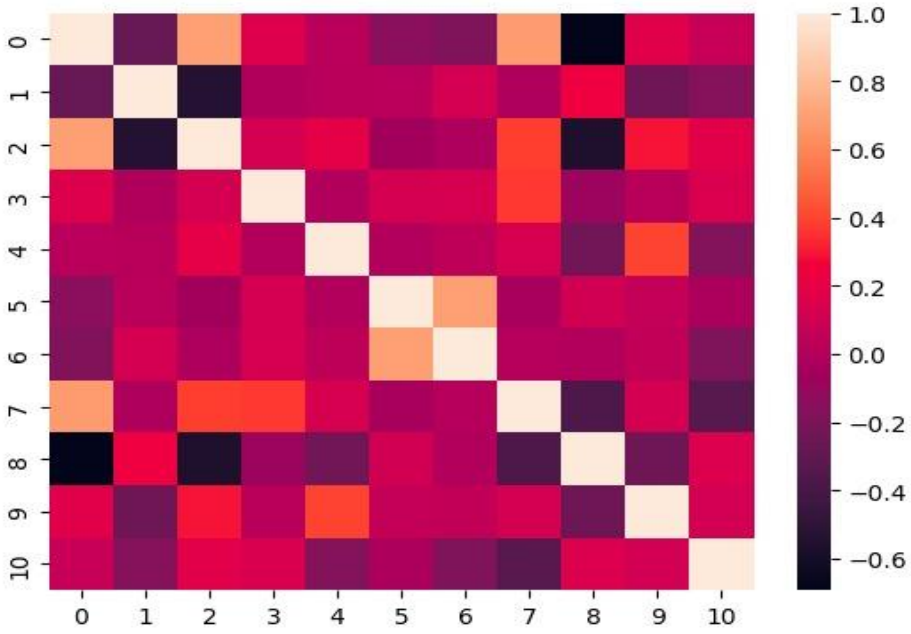
**Outlier Detection and Correlation Check:**

We used a boxplot to determine whether our data contains any outliers. The linear correlations between all the pairs of independent features can be discovered using heat maps.




Outliers can significantly affect the regression model by skewing the results and reducing the accuracy of the model. As we can see, the data set observes outliers for variables X5 and X6. It is also important to note that the removal of outliers should be done with caution, as removing too many or important observations can lead to an incorrect model fit and poor predictions. We

assume that the outlier won't significantly impact the model's performance hence we are moving forward.




From the plot, we can infer the following

1) Highly correlated feature pairs: (X6, X7), (X1, X8), (X1, X3)
2) Weakly correlated feature pairs: (X1, X9), (X2, X3), (X3, X9)

**Data Modelling:**

In our models, we have analyzed the following metrics:

1. Mean Squared Error (MSE): The average squared difference between the expected and actual values are represented by the mean squared error (MSE) measure. Better model performance is indicated by lower MSE values.
2. Sum of Squared Errors (SSE): The total of the squared deviations between the predicted and actual values is this metric. SSE should be reduced because it indicates the entire inaccuracy in the model.
3. R-squared (R2): This statistic shows the percentage of the dependent variable's variance that can be accounted for by the independent variable (s). Better model fit and data explainability are indicated by higher R2 values.
4. Adjusted R-squared: This statistic is comparable to R2 but accounts for the number of predictors included in the model. The model is penalized for adding pointless predictors by the adjusted R2, which could lead to a higher R2. Better model performance is indicated by higher adjusted R2 values.

In our model selection - we have decided to evaluate using R2, Adjusted R2, and MSE.
The lower the MSE, the better the model's performance, and a value of 0 indicates a perfect fit to the data (although this is often not achievable in practice).
R-squared is the proportion of the variance and ranges from 0 to 1, where 0 means the model does not explain any variation in the dependent variable and 1 means the model perfectly explains all the variation in the dependent variable. However, R-squared alone can be misleading when the number of independent variables in the model is large. In this case, the adjusted R-squared is used. In summary, R-squared tells you how well the model fits the data, while adjusted R-squared tells you how well the model fits the data while taking into account the number of independent variables, and Mean square error (MSE) is the average of the square of the errors.

**a) Polynomial regression**

Polynomial Regression is a type of regression analysis used to model the relationship between a dependent variable and one or more independent variables by fitting a polynomial equation to the data. The degree of the polynomial equation is chosen based on the complexity of the data and the desired level of accuracy. For example, a quadratic equation (degree 2) would fit a parabolic curve to the data, while a cubic equation (degree 3) would fit a more complex curve.
It is often used when the relationship between the dependent and independent variables is not linear and cannot be adequately modeled by linear regression.

Evaluation Metrics for Model 1 - Polynomial Regression

**Mean Squared Error:** 0.28134867534589914
**Sum of Squared Errors:** 281.06732667055326
**R-squared:** 0.7186513246541009
**Adjusted R-squared:** 0.7155157264486247

**b) Random forest regressor:**
Random Forest Regressor is a machine learning algorithm that uses an ensemble of decision trees to make predictions on a continuous target variable. The algorithm is based on the concept of bagging, where multiple models are trained on different subsets of the data to reduce the variance of the predictions.

Evaluation Metrics for Model 2 - Random Forest Regressor

**Mean Squared Error:** 0.045092992992993
**SSE:** 45.047900000000006
**R-squared:** 0.9292101898947827
**Adjusted R-squared:** 0.9284212457092129

**c) XGBoost:**

XGBoost is a popular machine-learning algorithm that uses an ensemble of decision trees to make predictions on a target variable. The algorithm is based on the gradient boosting framework, which involves iterative fitting weak models to the residuals of the previous models in the ensemble. It is robust to outliers and can handle high-dimensional data, as well as missing and non-linear relationships between the input features and the target variable. XGBoost also provides insights into the importance of individual input features in making predictions, which can be useful for feature selection and interpretation.

Evaluation Metrics for Model 3 - Gradient Boost

**Mean Squared Error:** 0.01602389180335345
**SSE:** 16.007867911550097
**R-squared:** 0.9839600521928356
**Adjusted R-squared:** 0.9837812888434143

**Model Comparison and Selection:**

Polynomial Regression, as indicated by the relatively high mean squared error (MSE) of 0.281 and the lower R-squared and adjusted R-squared values compared to the other two models. These metrics suggest that the model may be fitting the training data too closely and may not generalize well to new data. In contrast, Models 2 and 3 - Random Forest Regressor and Gradient Boost, respectively, appear to have better generalization performance and do not show any clear signs of overfitting based on the evaluation metrics.

Based on the evaluation metrics, Model 3 - Gradient Boost appears to be the best model to use for testing. This is because it has the lowest mean squared error (MSE) of 0.0160 and the highest R-squared value of 0.9839, indicating a better fit for the data. The adjusted R-squared values for all three models are relatively close, but Model 3 still has the highest value of 0.983, indicating that it is the best fit for the data while also being the most parsimonious. Therefore, We would recommend using Model 3 - Gradient Boost for testing.