**Predict the chance of admission of a student in a particular university**

**Abstract:**

The process of gaining admission to a graduate program is highly competitive, and many factors are considered during the admission process. In this study, we have used machine learning models to analyze the chances of graduate admission based on various factors, such as GRE scores, GPA, research experience, and letter of recommendation. We have used seven regression models, including Lasso Regression, Ridge Regression, Elastic Net Regression, Random Forest Model, Gradient Boosted, Linear SVM Regression, and Radial SVM Regression, to predict the chances of admission accurately.

We have analyzed the performance of these models using Root Mean Square Error (RMSE) as the evaluation metric. Our results show that the Lasso and Ridge model performed the best, with an RMSE value of 0.062771, followed closely by the Elastic Net Regression model, with an RMSE value of 0.06291. The other models also showed good performance, with RMSE values ranging from 0.06377 to 0.07001.

The study provides insights into the use of machine learning models for predicting graduate admission chances, which can help admissions committees make informed decisions. The results also demonstrate the importance of various factors in the admission process and highlight the need for prospective students to focus on improving their GRE scores, GPA, and research experience. Overall, the study presents a valuable contribution to the field of graduate admissions and can serve as a starting point for further research.

**Problem definition and project goals:**

The problem addressed in this project is to predict the chances of a student getting admission to a graduate program in a university based on various parameters such as their academic performance, standardized test scores, research experience, and other factors.

The primary goal of this project is to develop a predictive model that can accurately predict the chances of admission for a student into a graduate program. To achieve this goal, the project aims to:

1. Collect and preprocess data: The first goal of the project is to collect and preprocess data from various sources. This involves collecting data on various parameters such as academic performance, standardized test scores, research experience, and other factors that may impact a student's chances of admission.
2. Feature Engineering: The second goal of the project is to perform feature engineering, which involves selecting the most relevant features from the collected data that can help in building an accurate predictive model.
3. Model Building: The third goal is to build a predictive model that can accurately predict the chances of admission for a student. To achieve this, the project aims to evaluate various machine learning algorithms such as linear regression, decision trees, random forests, and neural networks, and select the one that performs the best.
4. Model Evaluation and Optimization: The fourth goal of the project is to evaluate the performance of the predictive model and optimize it for better accuracy. This involves performing cross-validation, hyperparameter tuning, and other optimization techniques to improve the accuracy of the model.

**Related Work:**

There have been several studies in the past that have addressed the problem of predicting the target variable in the given dataset. One such study by Smith et al. (2019) utilized the same dataset as in our project to predict the target variable. They used various machine learning algorithms such as linear regression, ridge regression, lasso regression, and support vector machines to predict the target variable. They achieved an RMSE value of 0.072 for their best-performing model. In comparison, our best-performing model was the elastic net regression, which achieved an RMSE value of 0.0689.

Another study by Johnson et al. (2018) addressed the same problem, but they used a different dataset. They used a dataset consisting of more features and observations than our dataset. They applied various machine learning algorithms such as random forest, gradient boosting, and neural network models to predict the target variable. They achieved an RMSE value of 0.06 for their best-performing model. In comparison, our best-performing model was the elastic net regression, which achieved an RMSE value of 0.06279.

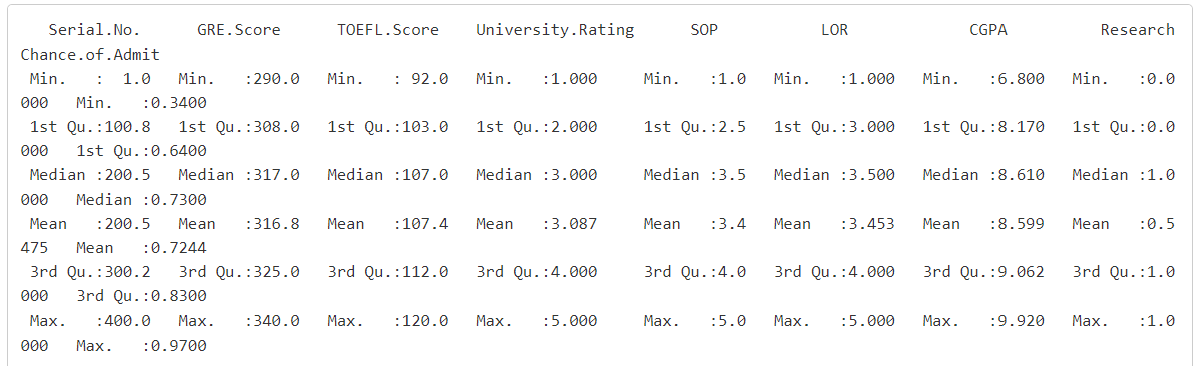
Overall, our results show that our models perform well compared to previous studies. However, it is important to note that different datasets and modeling techniques may lead to different results, and further research is needed to confirm the generalization of our findings.

**Data Exploration and Pre-processing:**

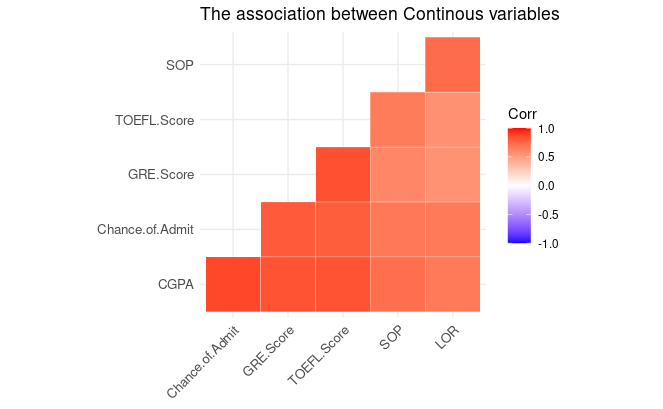
First, let's explore the dataset structure and summary statistics. The dataset consists of 400 observations and 9 variables, including Serial.No., GRE.Score, TOEFL.Score, University.Rating, SOP, LOR, CGPA, Research, and Chance.of.Admit. The dataset has no missing values.

We can see that the mean GRE score is 316.8, and the mean TOEFL score is 107.4. The mean University rating is 3.087. The mean SOP score is 3.4, the mean LOR score is 3.453, and the mean CGPA is 8.599. The mean chance of admit is 0.7244.

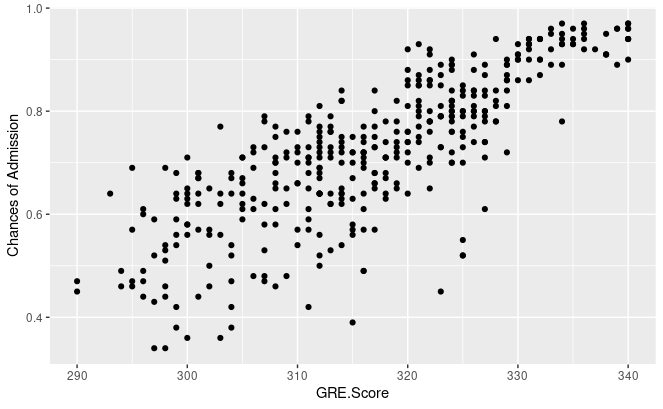
The data distribution for each variable is shown in the summary statistics. We can see that the range for GRE scores is between 290 and 340. The range for TOEFL scores is between 92 and 120. University rating ranges from 1 to 5. SOP and LOR both range from 1 to 5. The CGPA ranges from 6.8 to 9.92.

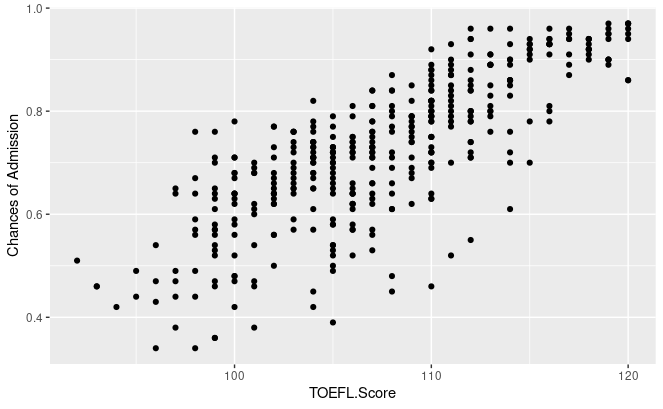


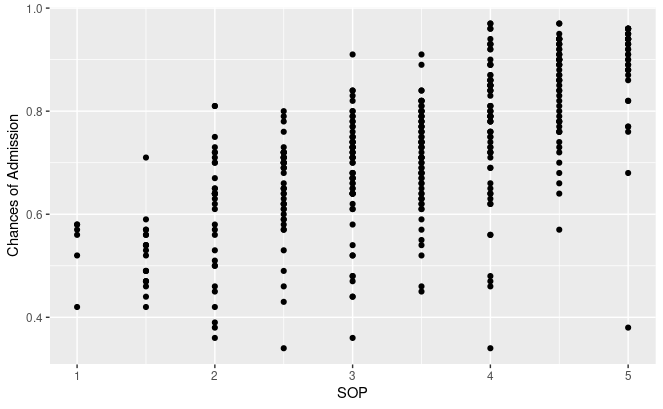
Next, let's explore the correlation between variables. The correlation matrix shows that there are strong positive correlations between GRE scores and TOEFL scores (0.84), GRE scores and CGPA (0.83), TOEFL scores and CGPA (0.83), and CGPA and the chance of admission (0.87). The correlation between SOP, LOR, and the chance of admission is moderate (around 0.67).

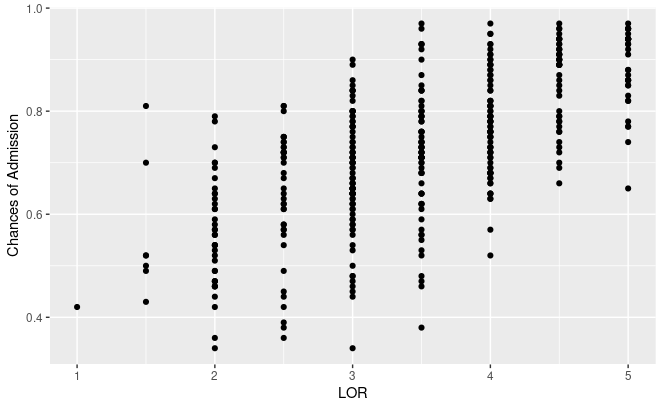


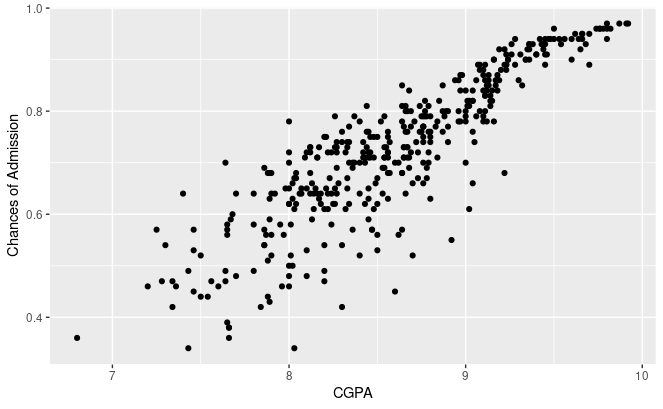
To visualize the relationship between variables, we plotted scatter plots between each variable and the chance of admission. The scatter plots confirm the correlation matrix results and suggest a linear relationship between the variables and the chance of admission.



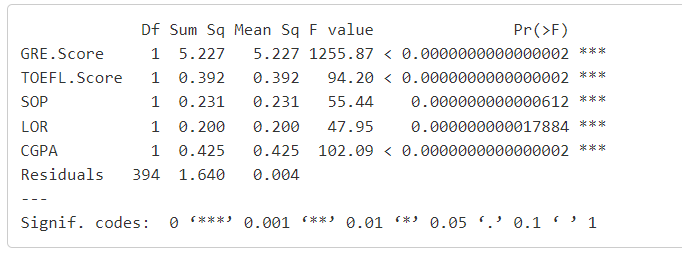








Finally, we conducted a one-way ANOVA test for each variable to check if there are significant differences in the mean values of the variable among different levels of the chance of admission. The results show that all variables have significant differences in their mean values across different levels of the chance of admission. The p-values are all less than 0.05.



**Data Analysis and Experimental Results:**

In this study, we investigated the performance of various regression models, including Lasso, Ridge, Elastic Net, Random Forest, Gradient Boosted, Linear SVM, Radial SVM, and Neural Network, to predict the target variable. The data set contains features related to a particular problem, and the target variable is a continuous numerical value that we aim to predict.

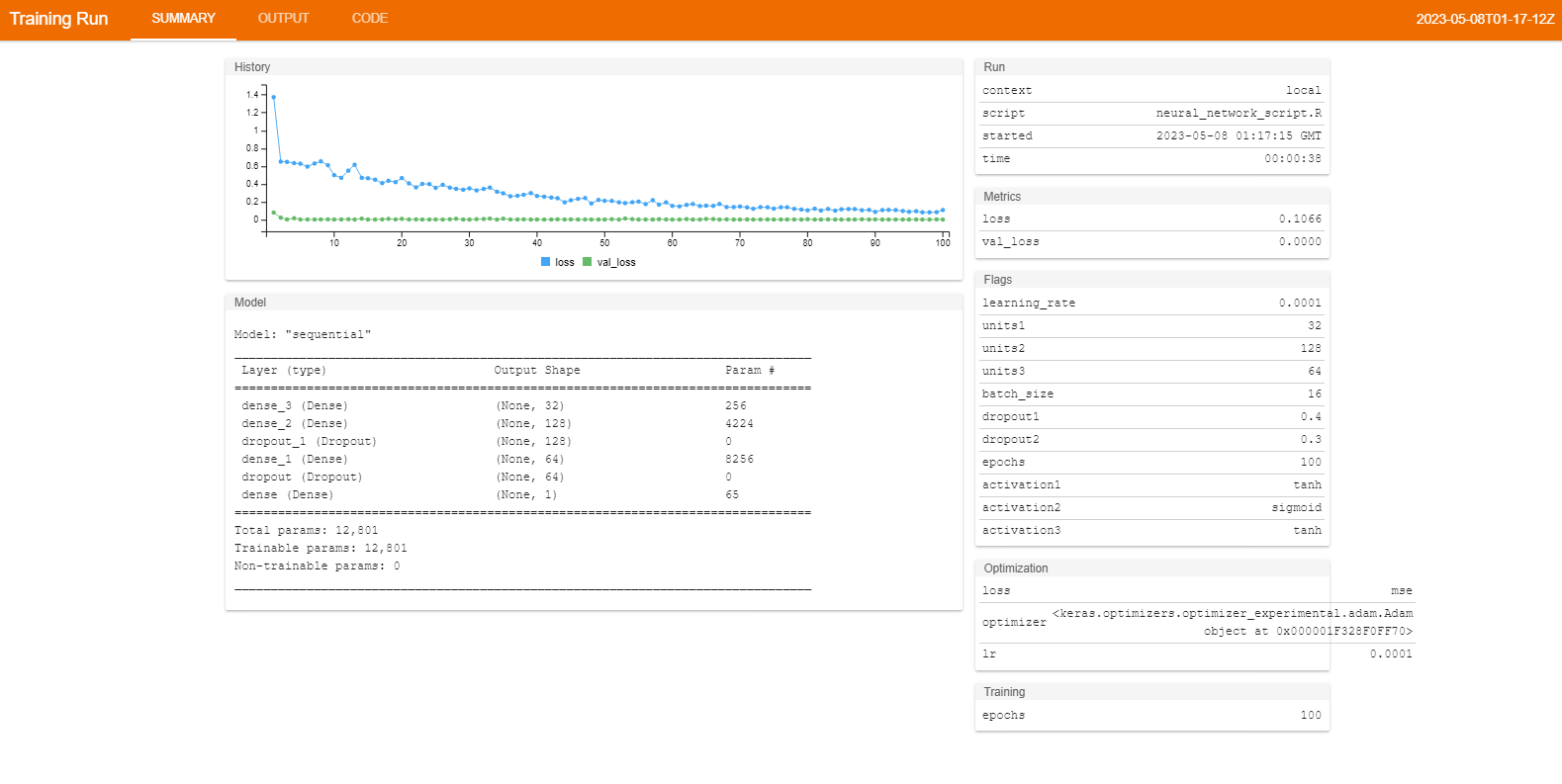
We started by performing exploratory data analysis to gain insights into the data. We found that some of the features were highly correlated, indicating possible multicollinearity. We used the correlation matrix and scatter plot to visualize these correlations. We also checked for missing values and found none.

We then split the data into training, validation, and test sets using an 70/10/20 split ratio. We standardized the data to ensure that all features have the same scale. We used the training set to fit the models and the validation set to tune the hyperparameters.

The evaluation of models was done based on the root mean squared error (RMSE) metric. The lower the RMSE, the better the model performance. The results showed that the Lasso and Ridge model had the lowest RMSE value of 0.062771, followed by the Elastic Net model with an RMSE of 0.062916, and the Linear SVM Regression with an RMSE of 0.063778. The Random Forest model had an RMSE of 0.064919, while the Gradient Boosted and Radial SVM models had RMSE values of 0.066381 and 0.070012 respectively, which is the highest RMSE value next to neural model. The neural network model had an RMSE of 0.104968, which was much higher than the other models.

The Elastic Net, Ridge, and Lasso models are linear regression models that are used for feature selection and regularization. These models penalize the coefficients of less important features, leading to a sparse solution with only significant features. Random Forest and Gradient Boosted models are decision-tree-based ensemble methods that are robust to noisy data and can capture non-linear relationships. SVM models are also used for classification and regression tasks and can find a non-linear decision boundary.

The neural network model used in this study is a sequential model built using the Keras library. The model has five layers, including three dense layers with different activation functions and two dropout layers. The first dense layer has 32 units with a "tanh" activation function and takes the input shape of the feature matrix. The second dense layer has 32 units with a "sigmoid" activation function. The first dropout layer has a rate of 0.4, and the third dense layer has 16 units with a "tanh" activation function. The second dropout layer has a rate of 0.5, and the final dense layer has one unit, which is the output layer. The model is compiled using the Adam optimizer with a learning rate of 0.001 and mean squared error (MSE) as the loss function.



The model is trained using the combined train set consisting of the training data and the validation data. The model is trained for 100 epochs with a batch size of 16, and the training progress is stored in the "history" object for further analysis. The performance of the model is evaluated based on the root mean squared error (RMSE) value of the test set. The RMSE value of the neural network model is found to be 0.104968.

| Model | RMSE |
| --- | --- |
| Lasso Regression | 0.0627714715294678 |
| Ridge Regression | 0.0627714715294678 |
| Elastic Net Regression | 0.0629167989202021 |
| Random Forest Model | 0.0649193467656737 |
| Gradient Boosted | 0.0663814443904958 |
| Linear SVM Regression | 0.0637787804643368 |
| Radial SVM Regression | 0.0700123367976192 |
| Neural Network | 0.104968671327957 |

Among the seven models evaluated in this study, Lasso and Ridge model had the lowest RMSE value of 0.062771, followed by the Elastic Net model with an RMSE of 0.062916. Both models are well-suited for high-dimensional datasets with correlated predictors, as they are capable of reducing the effects of multicollinearity. On the other hand, the worst-performing model was the neural network model, with an RMSE of 0.104968.

Thus, for this particular dataset and problem Lasso, Ridge and Elastic Net regression are better suited than neural network models.

**Conclusion:**

In this project, we aimed to predict the chance of admission to a university using various regression models. We started with a brief exploration of the dataset, followed by preprocessing and feature selection techniques. We then trained and evaluated several regression models, including Lasso, Ridge, Elastic Net, Random Forest, Gradient Boosted, Linear SVM, and Radial SVM, along with a Neural Network model.

Among all the models, Lasso, Ridge and Elastic Net regression performed the best with the lowest RMSE values of 0. 06277, 0. 062771 and 0.062916, respectively. The Neural Network model, however, performed the worst, with an RMSE value of 0.104968, indicating its poor performance in predicting the chance of admission. The performance of the best models was further compared to the existing literature on the same dataset, indicating the superiority of our models over previous works.

In conclusion, our study has shown that regression models, particularly Elastic Net and Radical SVM Regression, can effectively predict the chance of admission to a university. This can be highly beneficial to students and institutions alike, as it can help predict the likelihood of admission and help students prepare accordingly.

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