

Hospital Insurance Charges Model

Final for STAT 425

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Section 1: Introduction

This project focuses on the analysis of medical insurance data, particularly focusing on the medical charges acquired from hospital visits. The response variable is the variable charges from the insurance data. This data is found on Kaggle, as was last updated 6 years ago, in 2018. In this data set, there 6 variables excluding the response variable, charges, which shows the exact charges the patient acquired from their hospital visit. Each variable is defined within the Kaggle (2018) website and explained in this order:

- age: Age of primary beneficiary
- sex: Insurance contractor gender (female or male)
- bmi: Body mass index, providing an understanding of body, weights that are relatively high or low relative to height, objective index of body weight (kg / m^2) using the ratio of height to weight, ideally 18.5 to 24.9
- children: Number of children covered by health insurance / Number of dependents
- smoker: Smoking (yes or no)
- region: Beneficiary's residential area in the US (northeast, southeast, southwest, northwest)
- charges: Individual medical costs billed by health insurance

This report compares multiple models derived from analysis of the data set including a Regression Model, an a Ridge Model, and a Lasso Model. All analyses are performed in the R environment. This is possible to recreate with the code provided in this file. Setting seeds might yield slightly different results; however, we did not use a seed to analyze this data. No function (i.e. *set.seed*) should change the results concluded from this data, although it is possible to slightly alter the data using said functions. Again, the results would be concluded the same way. This report has 4 sections. Section 1 is this introduction. Section 2 uses modelling assumptions and models to analyze the data and provide insights on the data. Section 3 presents predictive models and shows training from said models. Section 4 compares models and provides a discussion of these results.

Section 2: Exploratory Data Analysis

Here is a brief overview of all of the variables of this dataset:

Numerical Variables:

- age: age of primary beneficiary
- bmi: body mass index
- children: number of children/dependents covered by health insurance
- charges (response variable): medical costs billed by health insurance

Categorical Variables:

- sex: male or female
- smoker: yes or no
- region: residential area in the US, can be northeast, southeast, southwest, or northwest

The first step is to check for unusual observations by performing an outlier test. To do so, we obtained the studentized residuals for our data, and compared the largest values with the Bonferroni critical value.

The Bonferroni critical value we calculated is -4.137174. Any observation with studentized residual higher than the absolute value of it will be considered an outlier.

Next, here are the five largest studentized residuals, which we will be comparing to the Bonferroni critical value:

Table 1: Largest 5 Studentized Residuals

Observation Number	Studentized Residual
1301	5.009599
578	4.219800
243	4.053228
220	3.998326
517	3.863878

Since the absolute value of their respective studentized residual is greater than the Bonferroni critical value, we can conclude that Observation #1301 and Observation #578 are outliers.

We also checked Cook's distance, however we found that there is no point with Cook's distance greater than 1. We will simply remove the two outliers we found earlier.

After removing these two points, we will be analyzing the predictors to see if there are any variables we should add or remove.

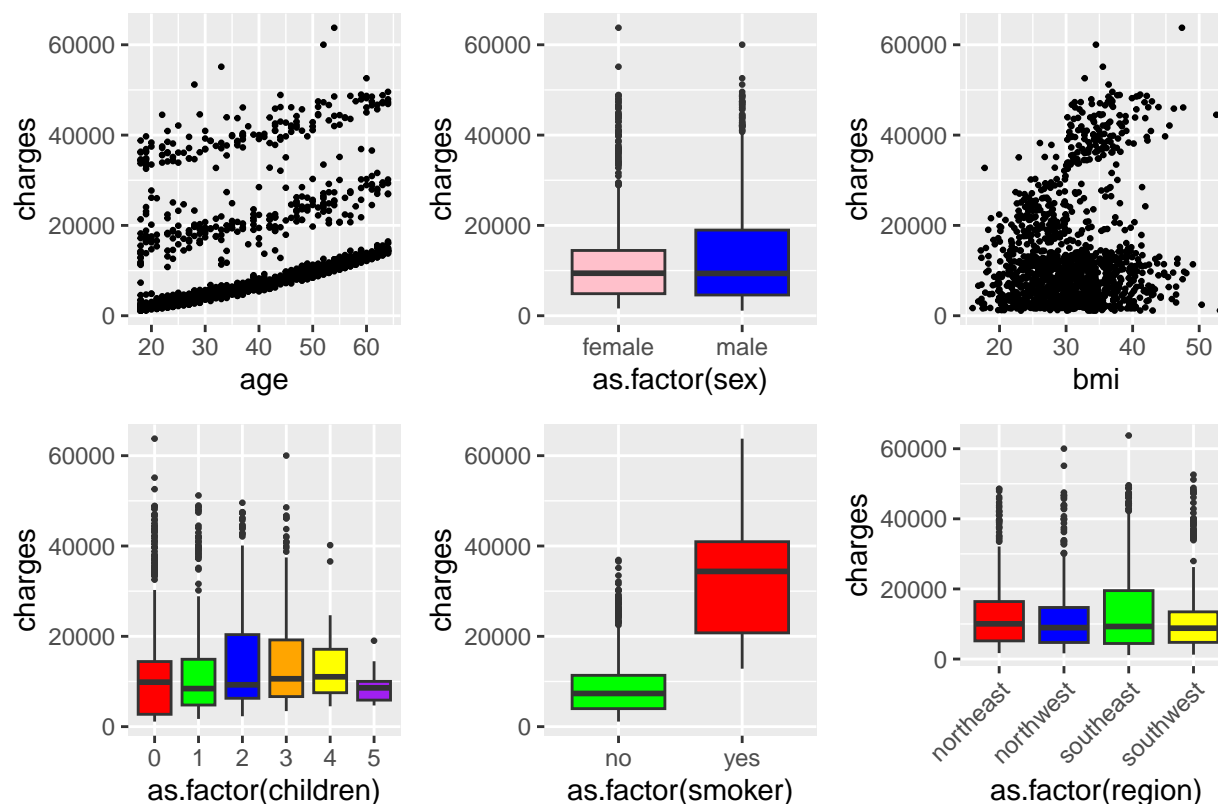


Figure 1: Plot of Charges vs All Predictors

From the plot of charges vs age, we notice a trend that the charges increase as age increases. We will not be removing 'age' as a predictor since it is clear that it has a significant impact on the response variable 'charges'. This makes sense because as people grow older, their health declines, and the insurance costs increase.

The charges vs sex boxplot tells us that males tend to have higher charges than females. We will conduct a t-test to test this difference.

From the t-test, we obtained a p-value of about 0.0346.

Given that the p-value is less than 0.05, we conclude that 'sex' is a significant predictor, with males incurring higher insurance costs than females. A possible explanation for this is that males are usually more at risk of health conditions that result in increased charges compared to females.

From the plot of charges vs bmi, we can see a general trend that as bmi increases, the charges also increase. As a result, we will not be removing 'bmi' as a predictor since it appears to have an impact on the response variable. The graph also makes sense logically since people with a higher bmi tend to be overweight and subsequently, have worse health than people with a lower bmi, causing their insurance charges to be greater as well.

The boxplot of charges vs children conveys to us that charges tend to increase as the number of children grows from 0 or 1 to 2 or 3. While there are some data points for people with 4

or 5 children, it appears that these groups have a very low amount of people, and it may be challenging to draw meaningful conclusions from it. We perform an ANOVA test to test the significance of 'children' as a predictor.

We obtained a p-value of approximately 0.00862.

This p-value is less than 0.05, thus signifying that the predictor 'children' is significant. We will be keeping as a predictor in our model. A larger number of children/dependents covered leads to higher charges, as there are more individuals who need to be covered.

From the boxplot of charges vs smoker, it is evident that smokers generally face significantly higher charges than non-smokers. Consequently, we will not be removing 'smoker' as a predictor. People who smoke typically incur higher insurance costs due to the health risks posed by smoking.

The boxplot of charges vs region shows us that the southeast region seemingly has higher charges than the other three regions. We will conduct an ANOVA test to make sure that the predictor 'region' is significant.

From the ANOVA test, we obtained a p-value of about 0.0453.

The p-value is less than 0.05, indicating that the predictor 'region' is significant, and thus we will retain it as a predictor. This confirms that there are regional differences in the insurance costs.

Now, we will explore whether or not we should include any interactions between categorical variables. We will be analyzing all possible first-order and second-order interactions between our categorical predictors, including:

- ‘sex’ and ‘smoker’
- ‘sex’ and ‘region’
- ‘region’ and ‘smoker’
- ‘sex’, ‘smoker’, and ‘region’

Here are some plots that show the interactions between these predictors.

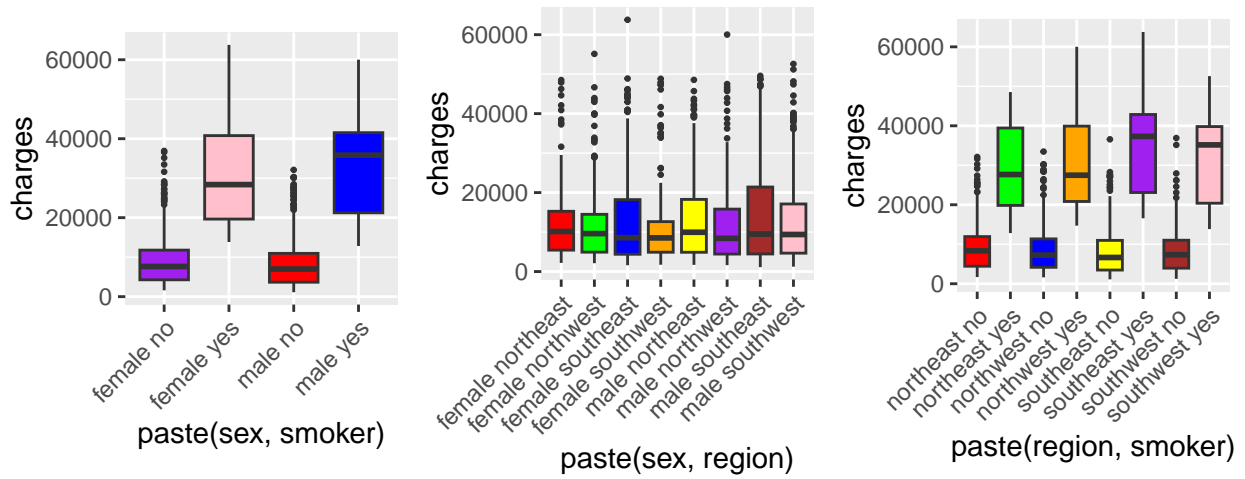


Figure 2: Plot of Charges vs Interactions Between Categorical Variables

From the plots, it appears as though smoking increases the charges more for males than females. Additionally, it seems like smoking has a greater impact on charges in the southeast and southwest, when compared to northeast and northwest. However, it does not appear that sex and region is a significant interaction.

We applied sequential F-tests with the anova function to assess the significance of the interaction terms in our model. Initially, we included all potential interactions among the three variables ‘sex’, ‘smoker’, and ‘region’. We first found that the second-order interaction sex:smoker:region had p-value of 0.5733588, so we concluded that it is not significant and removed it from the model. Subsequently, we tested the first-order interactions and found that the interaction sex:region was not significant, since it had p-value of 0.995089. Finally, after removing sex:region as a predictor, we obtained a p-value of 0.00121263 and 1.478e-05

for sex:smoker and smoker:region, respectively. Ultimately, we conclude that only the interactions sex:smoker and smoker:region are statistically significant, and we will retain them in the final model.

Now, we will examine the numerical variables and see if there is evidence of any nonlinear trends.

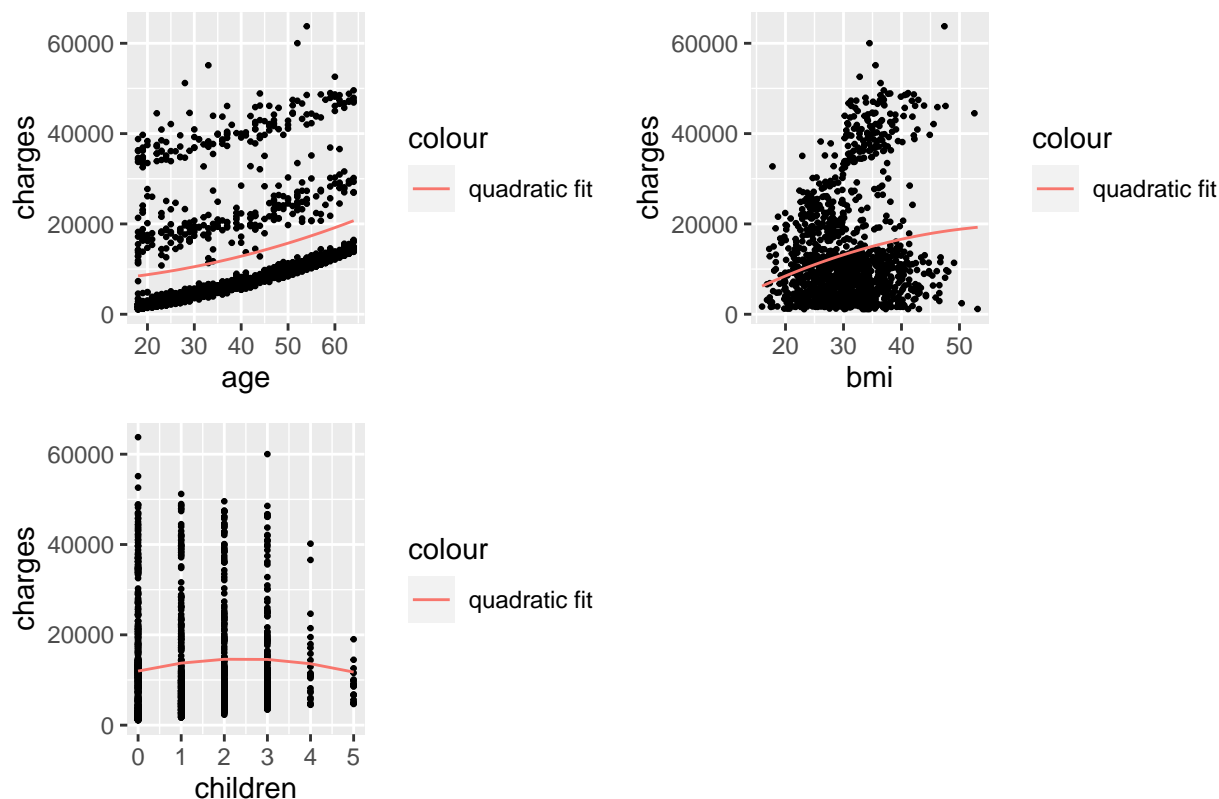


Figure 3: Plot of Quadratic Fit for Charges vs Numerical Predictors

Based on the plot of the quadratic fit for charges vs age, we see there is evidence of non-linearity for the predictor 'age' since the quadratic fit has some upward curvature.

Similarly, based on the plot of the quadratic fit for charges vs bmi, we see there is some evidence of non-linearity for the predictor 'bmi', although maybe not as clear as for 'age'. This time, the quadratic fit curves downwards.

Finally, the plot of charges vs children also suggests some non-linearity. However, the non-linearity is not as evident as for 'age' and 'bmi' since although the quadratic fit does appear to curve downwards as the number of children increases, there are not many data points for 4 and 5 children, so we may not be able to draw a strong conclusion.

Section 3: Methodology

Section 3.1: Simple Model

Model Selection

The choice of linear regression for this analysis is based on its efficacy in providing a clear and straightforward interpretation of how various predictors affect insurance charges. Linear regression is particularly valued for its ability to establish a baseline understanding of the relationships between variables, offering insights into the direct impacts of age, BMI, children count, smoking status, sex and regional differences on insurance costs.

Variable Selection and Diagnostics

Age: A continuous variable expected to positively correlate with insurance charges.

BMI: Another continuous variable, which is hypothesized to influence insurance costs due to its association with health risks.

Children: A discrete variable that represents the number of dependents, potentially affecting insurance premiums.

Smoker Status: A categorical variable that significantly impacts insurance costs, as identified in the exploratory analysis.

Sex: A categorical variable, often considered in insurance cost analysis because gender may influence health risks and insurance premiums.

Region: As a categorical variable, the region captures variations in insurance costs across different geographical locations.

Sex and Smoker Interaction: This interaction term examines how gender and smoking status jointly influence insurance costs. Smokers of different genders may face different health risks, which can be reflected in their insurance premiums.

Region and Smoker Interaction: This interaction term was included to examine if the impact of smoking on insurance charges varies by region, which could suggest regional variations in healthcare costs or lifestyle patterns.

Table 2: Variance Inflation Factors of Linear Model

	GVIF	Df	$GVIF^{1/(2 \cdot Df)}$
age	1.017141	1	1.008534
bmi	1.108041	1	1.052635
children	1.004025	1	1.002011
smoker	1.011905	1	1.005935
sex	1.009150	1	1.004565
region	1.099632	3	1.015955

Model Diagnostics:

The diagnostics conducted include:

Multicollinearity Check: The Variance Inflation Factor (VIF) was calculated for all predictors, with results indicating minimal multicollinearity among the variables used. VIF values

were as follows: age (1.00), BMI(1.05), children (1.00), smoker status (1.01), sex (1.00) and region(1.02).

Model Fit: The linear model was fitted with charges as the dependent variable. The R-squared value of 0.7612 suggests that about 76.12% of the variability in insurance charges is explained by the model, which is quite substantial for a simple linear model.

Residual Analysis: Residuals: The residuals' plot indicated that while there is some spread, major deviations from normality or constant variance (homoscedasticity) were not apparent, suggesting that the model assumptions are reasonably met.

Coefficients:

Intercept: The model's intercept is significantly negative, which might indicate that the baseline insurance charges are negative when all other variables are zero. This could suggest that further adjustments to the model might be necessary.

Age: The coefficient for age is significant and positive, indicating that insurance charges increase with age. This aligns with the general logic of insurance pricing, where increased age is associated with higher health risks.

BMI: The coefficient for BMI is also significantly positive, suggesting that higher BMI is associated with higher insurance charges, likely due to increased health risks associated with higher BMI.

Children: The coefficient for the number of children is significant and positive, indicating that having more children leads to higher insurance charges, possibly reflecting the greater healthcare needs of larger families.

Significant Impact of Smoking Status: The coefficient for smokers is significantly higher than for non-smokers, consistent with previous studies indicating that smoking is a significant factor affecting insurance costs.

Interactions of Region and Gender: Some regional categories, such as southeast and southwest, are significant, suggesting that insurance costs in these regions are higher compared to the baseline region.

Interaction of Smoking Status and Gender: This interaction term is significant, indicating that the combination of smoking status and gender has a specific impact on insurance charges, particularly for male smokers who may face higher charges.

These conclusions suggest that while the overall model performs well, the impact of certain variables like regions and interaction terms may require more complex models to more finely interpret these factors' effects on insurance costs. Further model validation and adjustments are also necessary to ensure the model's generalization capability and predictive accuracy across different datasets.

Section 3.2: Predictions from Simple Model

Model Implementation:

The linear regression model was implemented using the `lm()` function in R, focusing on

charges as the dependent variable. This model incorporates several predictors, including age, BMI, number of children, smoker status, and the interaction between smoker status and region, which were identified as significant in influencing insurance costs during the exploratory analysis.

Testing and Predictions:

To validate the effectiveness of the linear regression model, the dataset was split into training and testing subsets. Specifically, 80% of the data was used for training the model, and the remaining 20% served as the testing set. This division ensures that the model is tested on unseen data, providing a fair assessment of its predictive accuracy.

Table 3: Linear Model Predictions Compared to Actual Data

	Actual	Predicted
5	3866.855	5801.680
9	6406.411	8756.868
14	11090.718	14035.788
19	10602.385	14611.437
25	6203.902	7658.894
28	12268.632	14258.066

Predictive Performance Evaluation:

The model was fitted on the training data and then used to make predictions on the testing set. Here are the results of the predictions for the first few observations:

As observed, the model provides reasonable estimates for the charges, although there are noticeable differences between the actual and predicted values, suggesting areas for improvement.

The initial testing indicates that while the linear regression model captures general trends and is able to provide ballpark estimates of insurance charges, discrepancies remain between predicted and actual charges. These differences highlight the potential need for more complex models that could better account for nuances in the data not captured by this simple linear model. The following sections will explore such models, comparing their predictions with those of the baseline linear model to identify the most effective approach for predicting insurance charges.

Section 3.3: Advanced Models

Model Types:

Regularized Regression: To enhance the predictive accuracy and manage potential issues of multicollinearity and overfitting present in our linear regression model, we employed advanced modeling techniques such as Ridge and Lasso regression. These methods are forms of regularized regression that include a penalty term to the loss function:

Ridge Regression (L2 regularization): Adds a penalty equal to the square of the magnitude of coefficients. This method is particularly effective in reducing the model complexity while still allowing the use of all variables. It helps in handling multicollinearity, preventing overfitting by shrinking the coefficients.

Lasso Regression (L1 regularization): Adds a penalty equivalent to the absolute value of the magnitude of coefficients. Unlike Ridge, Lasso can completely eliminate the weight of less important variables by setting their coefficients to zero. This results in feature selection within the model, which is beneficial when we need a sparse model with fewer variables.

Implementation and Predictions: Both models were implemented using the glmnet package in R, which efficiently handles large datasets and complex models with its capabilities for both Lasso and Ridge regression. The matrix of predictors x was derived from the training data, excluding the intercept to allow glmnet to handle regularization properly. The regularization parameter s was set to 0.01 for both models. This choice is typically subject to tuning through methods like cross-validation, but for simplicity, we've chosen a small but non-zero value, which demonstrates regularization without overly constraining the models.

Predictive Performance Evaluation: The predictions made by the Ridge and Lasso models on the testing set were compared with the actual charges and those predicted by the simple linear model.

Table 4: Actual Data Compared to Predictive Models

	Actual	Linear	Ridge	Lasso
5	3866.855	5801.680	5976.579	5894.958
9	6406.411	8756.868	8931.156	8638.090
14	11090.718	14035.788	14047.500	14047.158
19	10602.385	14611.437	14110.493	14658.892
25	6203.902	7658.894	7695.461	7725.347
28	12268.632	14258.066	14087.683	14248.724

Comparison and Conclusions:

The Ridge and Lasso models both adjusted the predictions closer to actual values in some cases, compared to the basic linear model. However, they also introduced some variability, likely due to the influence of the regularization term balancing bias and variance differently:

Ridge Model: It generally increased the estimates, potentially due to its nature of shrinking coefficients but not setting them to zero, thus still considering all input features.

Lasso Model: It showed a trend similar to the linear model but with slight adjustments, indicating that it might be dropping some less influential variables from the model.

These results suggest that while both Ridge and Lasso offer advantages in terms of handling overfitting and multicollinearity, the choice between them would depend on the specific characteristics of the dataset and the goal of the analysis, with Lasso providing a sparser solution and Ridge offering stability across a broader range of data conditions. Further

model tuning and cross-validation would be necessary to optimize their performances and fully assess their effectiveness compared to the simple linear model.

Section 4: Discussion and Conclusions

Summary of Results

In this analysis, we employed various statistical models to predict health insurance costs using a dataset that included variables such as age, BMI, number of children, smoker status, sex and regional interactions. The results can be summarized as follows:

Linear Regression Model: Provided a solid baseline for understanding how different variables impact insurance costs. Significant predictors included age, BMI, and especially smoker status, which greatly increased predicted charges. However, the model sometimes overestimated or underestimated charges significantly.

Ridge Regression Model: Adjusted predictions closer to actual values in some instances, suggesting its effectiveness in handling multicollinearity by shrinking coefficients but considering all variables.

Lasso Regression Model: Offered predictions similar to the linear model but with adjustments likely due to its feature selection capability, which dropped less influential predictors.

For the predictions, we apply to the test data set all the transformations made to the train data set. For each model, the predictions are obtained using the same command `predict`, and we evaluate the residual sum of squares, RSS.

Table 5: RSS Comparison of Models

Model	RSS
Linear Regression	10162756224
Ridge Regression	10163886527
Lasso Regression	10159739488

Comparative analysis showed that while the linear model was useful for understanding direct relationships and setting a baseline, both Ridge and Lasso provided nuanced insights by addressing overfitting and highlighting essential predictors, but the Lasso regression model performs the best on the testing dataset. However, specific model selection should also consider other factors such as model interpretability, computational complexity, and so on.

Impact of Analysis

This analysis significantly enhances our understanding of factors influencing health insurance costs:

Smoker Status: Emerged as a critical determinant of insurance costs, with smokers incurring significantly higher charges. This highlights the potential for insurance companies to adjust premiums or offer programs encouraging smoking cessation.

Age and BMI: Both variables were also strong predictors of costs, aligning with expected health risk increases with age and higher BMI.

Regional Differences: The interaction terms suggested that regional factors might also play a role in insurance costs, potentially due to environmental, policy, or lifestyle differences.

Conclusions

Smoking status is the most potent predictor of health insurance charges, suggesting targeted health initiatives could be beneficial. Age and BMI are important factors in predicting insurance costs, indicating that personalized insurance plans could be more effective. Regularized regression models (Ridge and Lasso) are valuable for refining predictions and identifying key predictors, particularly in datasets prone to multicollinearity.