HEALTH INSURANCE COST PREDICTION

- Maganti. Manogna Venkata Sudha Anirudh

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Introduction

In the complex landscape of insurance pricing, the quest for precision and reliability in predicting costs has become increasingly vital. Yet, the conventional methods rooted in frequentist approaches reveal inherent limitations, relying heavily on rigid data assumptions and lacking the adaptability required in today's dynamic insurance ecosystem. Recognizing these constraints, there's a burgeoning interest in alternative modeling methodologies, particularly in the realms of Bayesian modeling and machine learning.

The significance of accurately predicting insurance costs cannot be overstated. It serves as a linchpin for individuals and businesses alike, enabling prudent financial planning and risk mitigation strategies. Moreover, for insurance companies, the ability to set fair premiums while remaining competitive is contingent upon robust predictive models.

This project embarks on a journey leveraging Bayesian methodology, specifically employing Markov Chain Monte Carlo (MCMC) techniques and computational tools, to model insurance prices. While recognizing the importance of traditional regression models like Linear Regression, Ridge Regression, Lasso Regression, Decision Tree Regressor, Random Forest Regressor, and XGBoost Regressor, this study seeks to expand the horizon by delving deeper into the Bayesian approach.

The focus here extends beyond conventional approaches by embracing Bayesian Linear Regression and Bayesian Multiple Linear Regression. The intent is to compare and contrast these Bayesian models against the aforementioned regression models, gauging their efficacy based on metrics like R Square and RMSE. By doing so, we aim to uncover the strengths and advantages of Bayesian modeling in predicting insurance costs, potentially offering a more nuanced and accurate understanding that transcends the limitations of traditional frequentist techniques.

Data Description

The dataset comprises of several crucial features. It includes the **age** of insured individuals, their **gender** ('female' or 'male'), their **Body Mass Index (BMI)**, which serves as a metric for assessing body weight, the **number of children** or dependents they have, their **smoking status** (categorized as 'yes' for smokers and 'no' for non-smokers), the **geographic region** to which they belong (with categories like 'southwest,' 'southeast,' 'northeast,' and 'northwest'). The final column, "**charges**," quantifies the health insurance costs for each policyholder, serving as the target variable for predictive modeling.

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

[1338 rows x 7 columns]

Exploratory Data Analysis (EDA)

❑ Exploratory Data Analysis Overview

In the initial phase of exploration, a dataset of dimensions 1338x7 was loaded,

revealing no missing values across the entirety of the dataset.

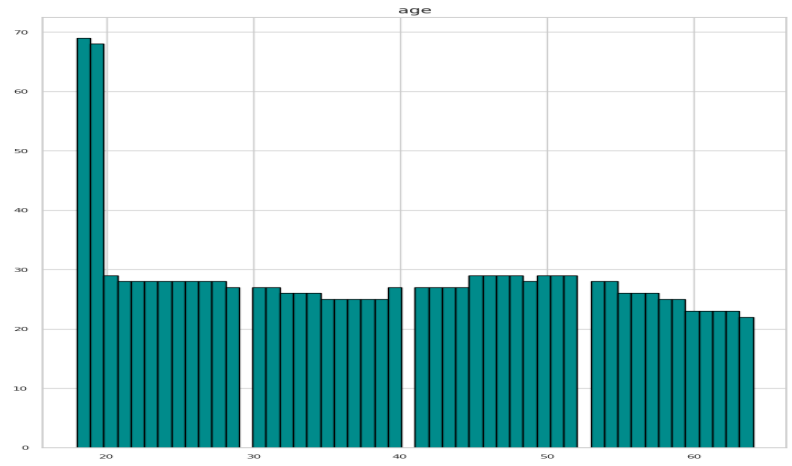
❑ Numerical Features Analysis (I.2)

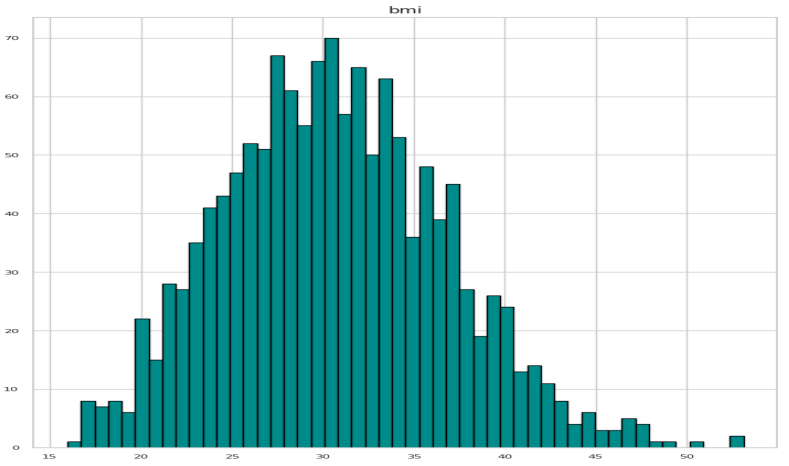
Extraction and examination of numerical features:

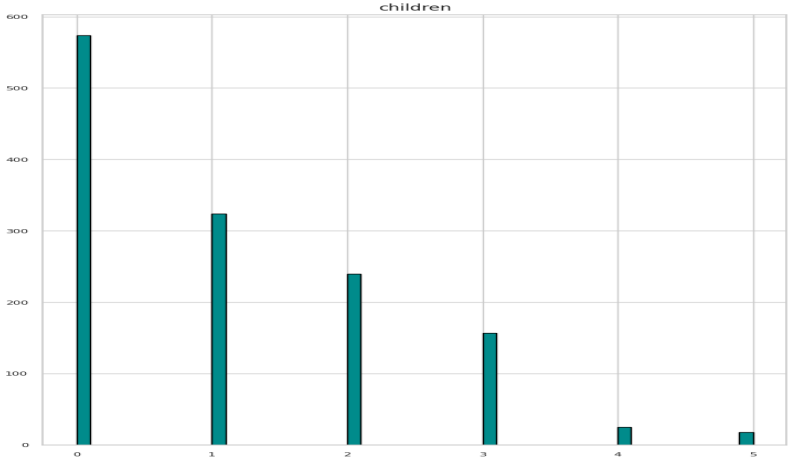
	age	bmi	children	charges
0	19	27.900	0	16884.92400
1	18	33.770	1	1725.55230
2	28	33.000	3	4449.46200
3	33	22.705	0	21984.47061
4	32	28.880	0	3866.85520

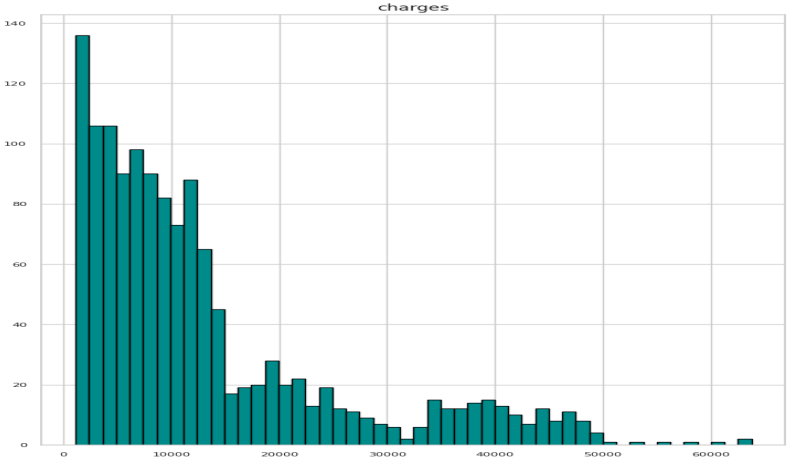
Exploratory Data Analysis (EDA)

- Features distribution:



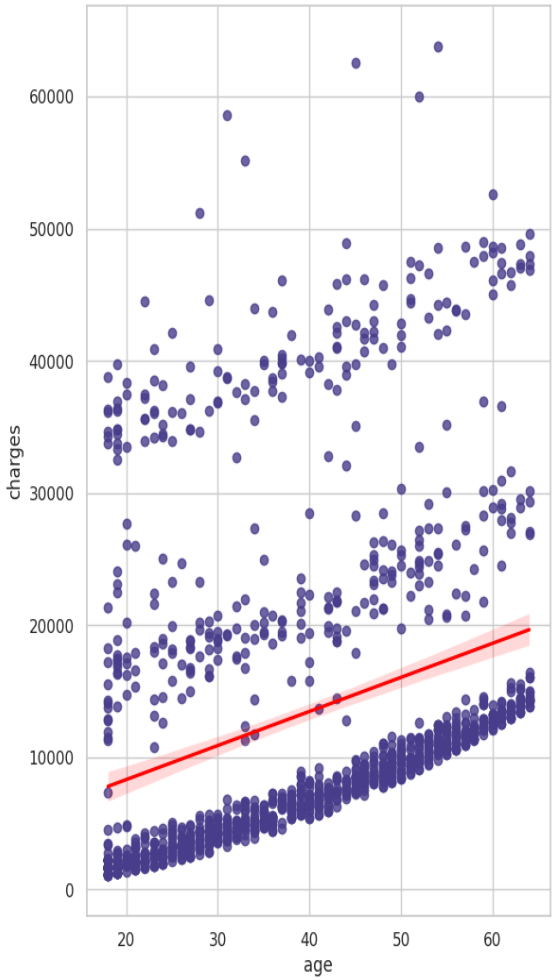


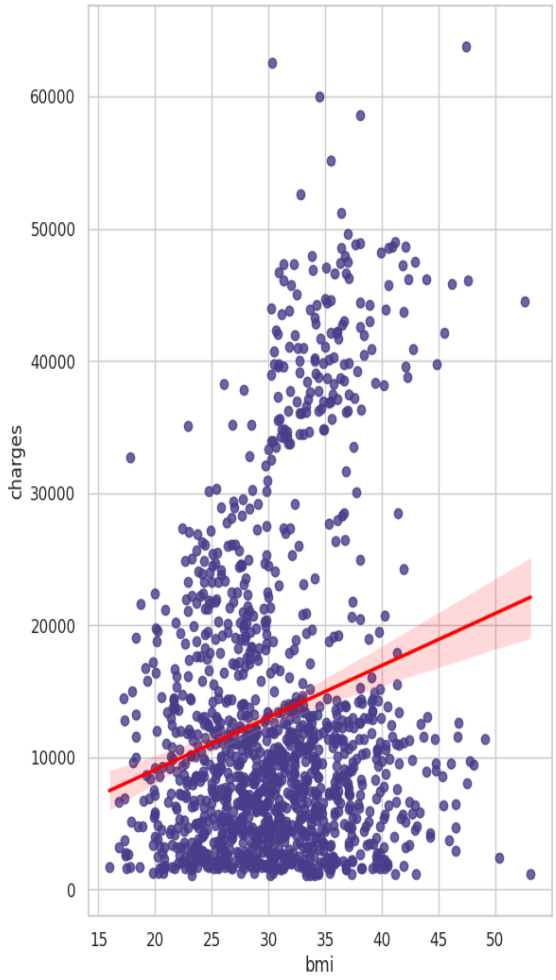


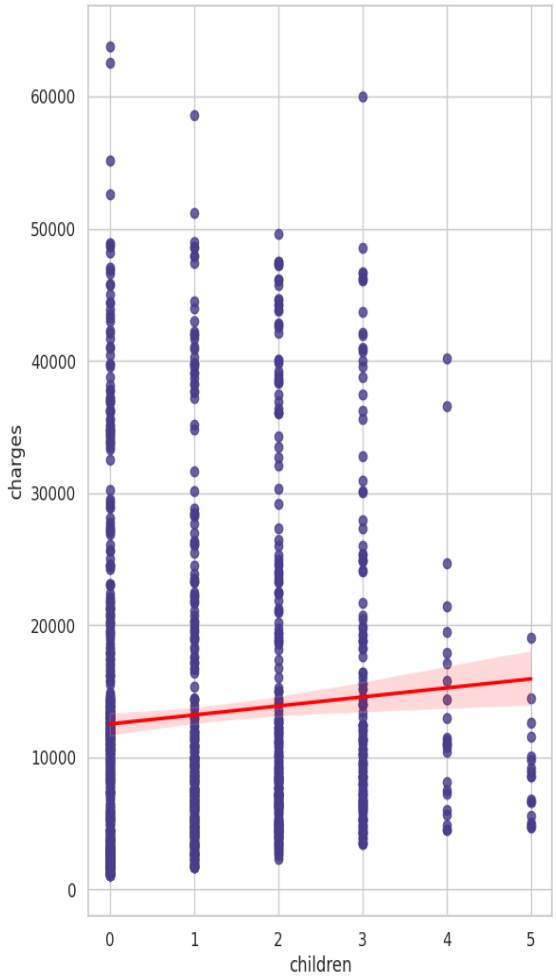


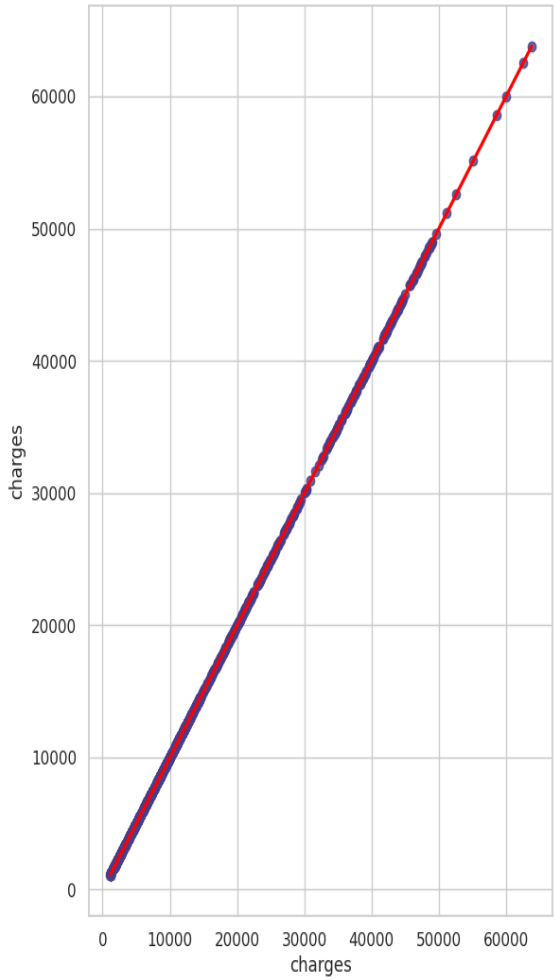
Exploratory Data Analysis (EDA)

- Scatterplot & Relationship Assessment:





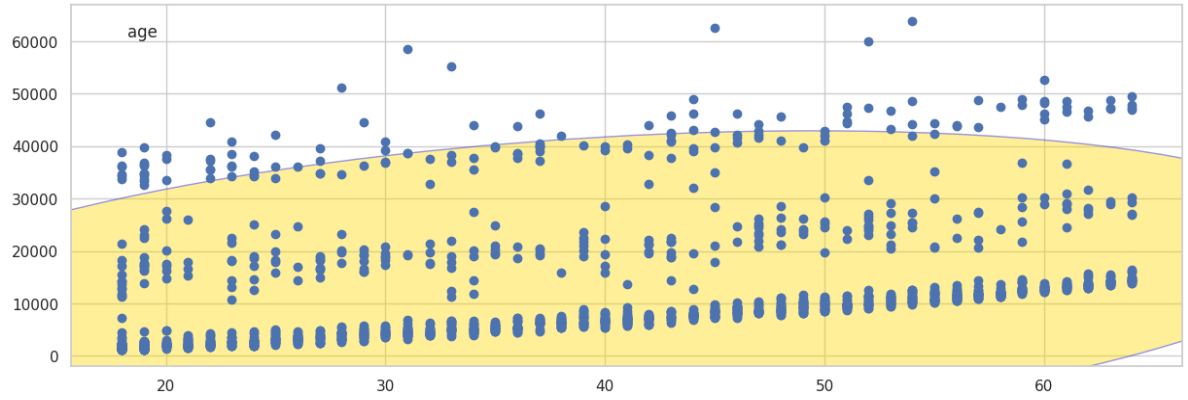


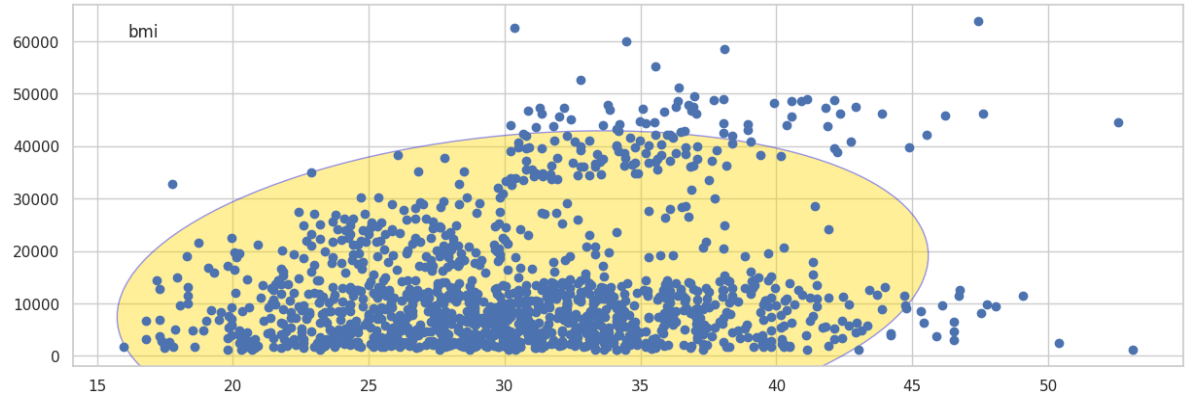


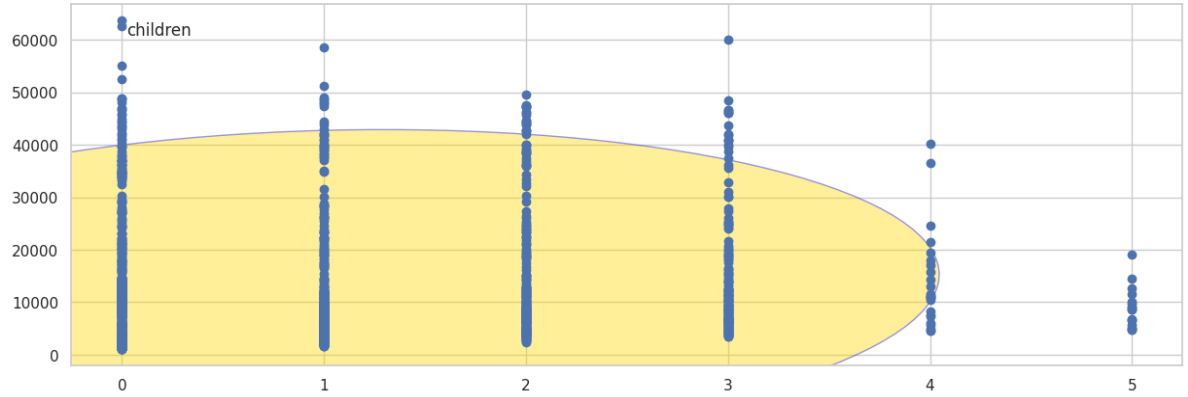
Exploratory Data Analysis (EDA)

❑ Bivariate Outliers detection Using Mahalanobis Distance:

Mahalanobis Distance (MD) is an effective distance metric that finds the distance between the point and the distribution. It works quite effectively on multivariate data because it uses a covariance matrix of variables to find the distance between data points and the center. This means that MD detects outliers based on the distribution pattern of data points, unlike the Euclidean distance.







Exploratory Data Analysis (EDA)

❑ Categorical Features Analysis (I.3)

Extracting Categorical Features:

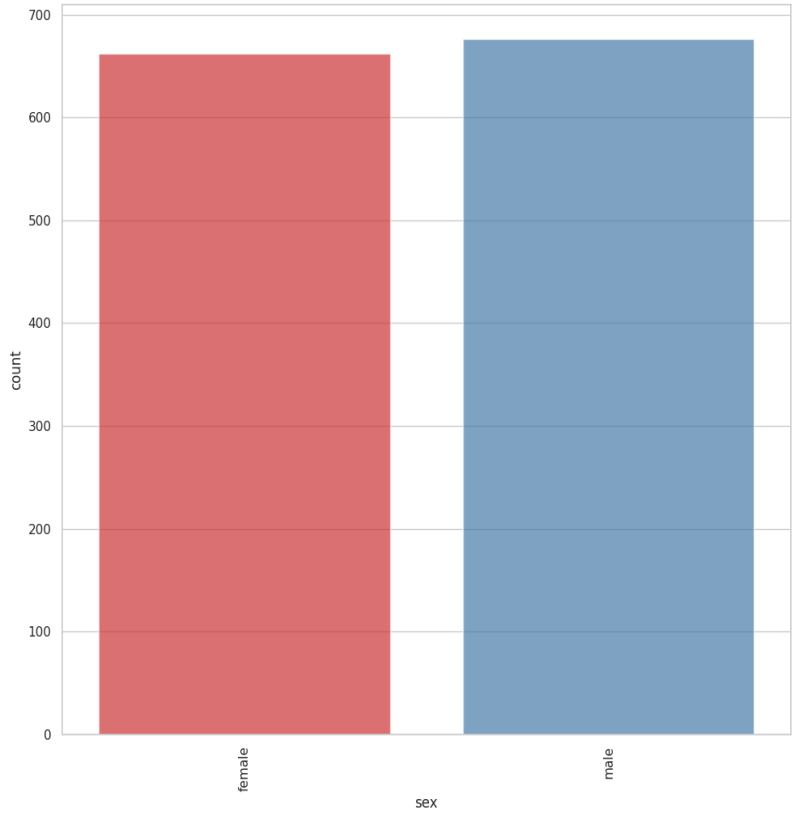
	sex	smoker	region	charges
0	female	yes	southwest	16,884.92
1	male	no	southeast	1,725.55
2	male	no	southeast	4,449.46
3	male	no	northwest	21,984.47
4	male	no	northwest	3,866.86
...	...	...	...	...
1333	male	no	northwest	10,600.55
1334	female	no	northeast	2,205.98
1335	female	no	southeast	1,629.83
1336	female	no	southwest	2,007.94
1337	female	yes	northwest	29,141.36

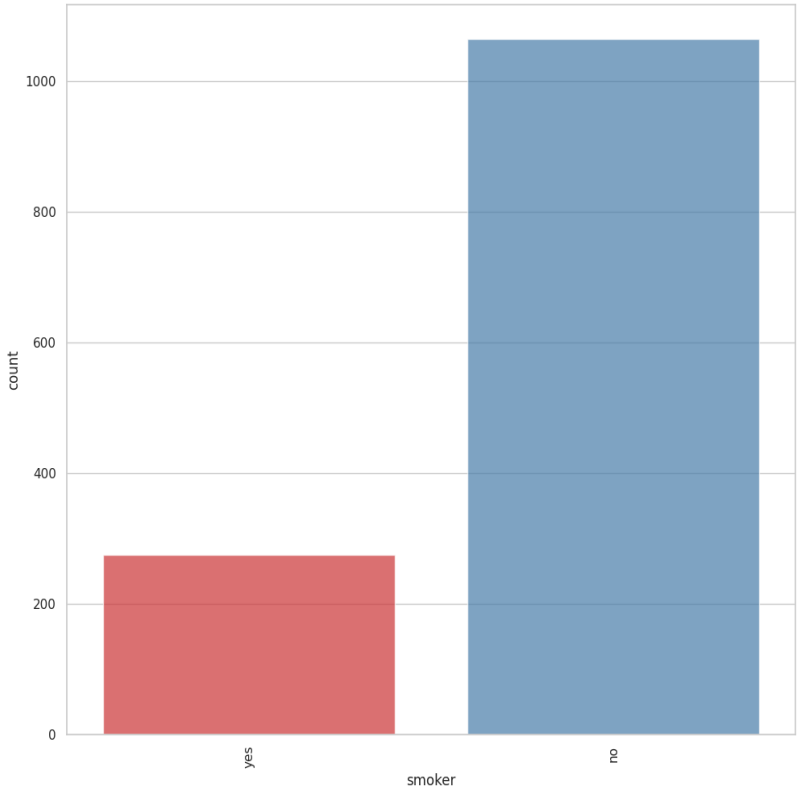
[1338 rows x 4 columns]

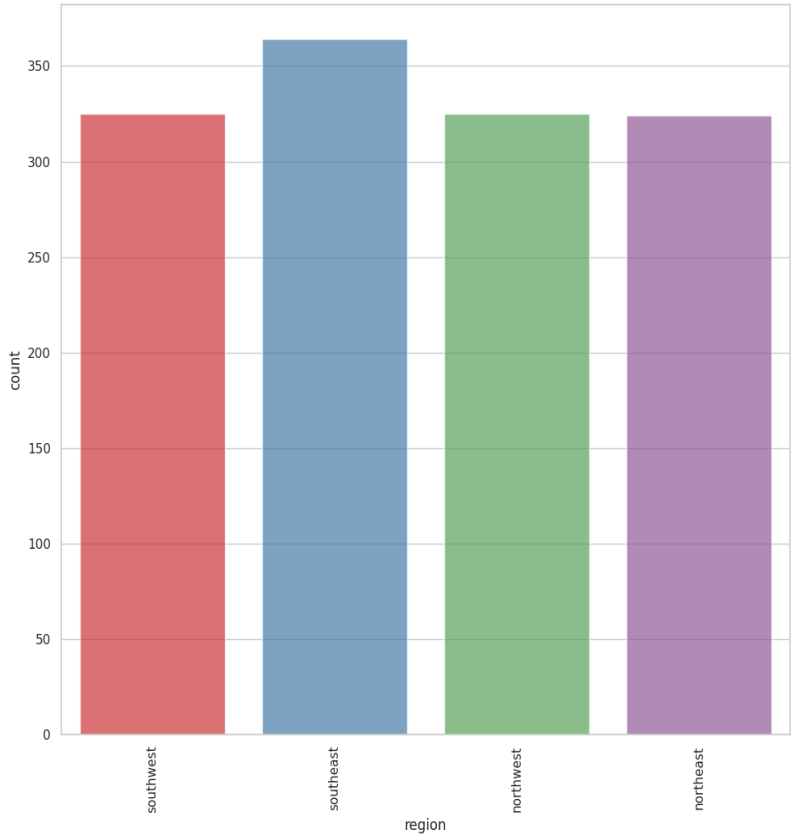
Exploratory Data Analysis (EDA)

❑ Counter Plots:

A count plot can be thought of as a histogram across a categorical, instead of quantitative variable. As a result, we don't want those predictors with a prevalent outcome such as smoker for instance because they don't contribute significantly to training our model.



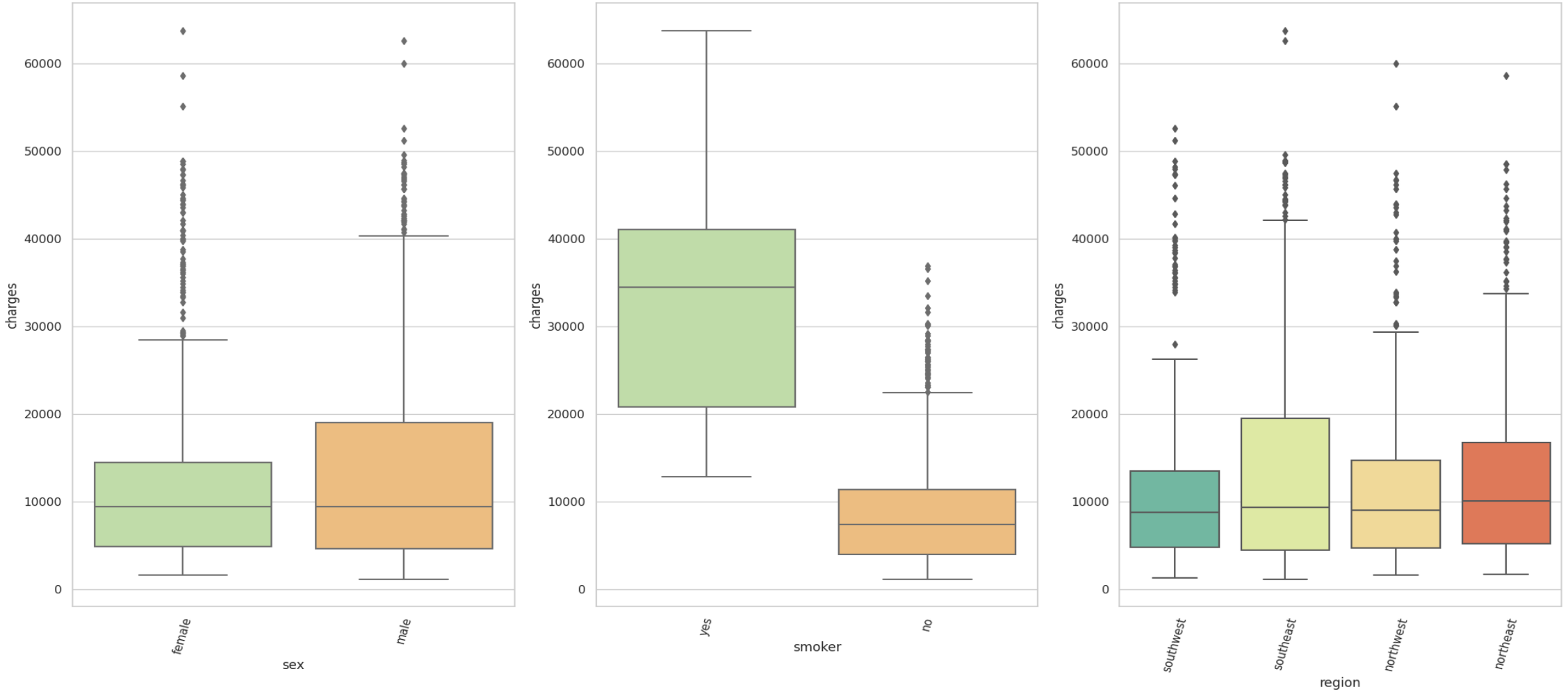




Exploratory Data Analysis (EDA)

❑ Box Plot:

Secondly, it's worth a look at the variation of the target variable with respect to each categorical feature.



Exploratory Data Analysis (EDA)

- Transform Categorical features into Binary features & Merge numerical and binary features into one data set :

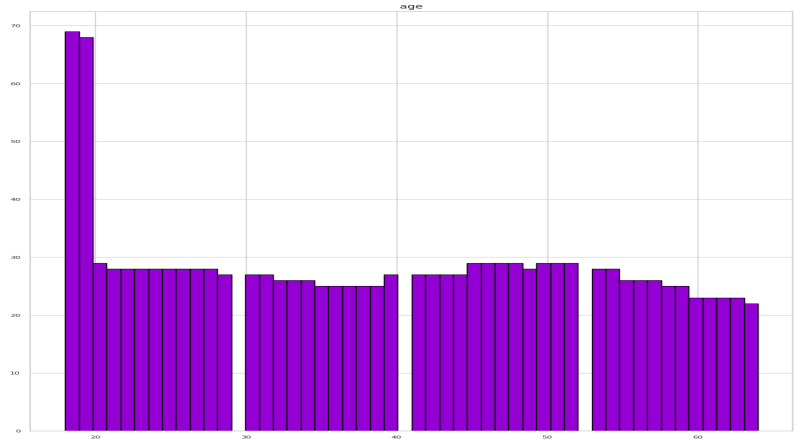
	age	bmi	children	charges	sex_male	smoker_yes	region_northwest	region_southeast	region_southwest
0	19	27.90	0	16,884.92	0	1	0	0	1
1	18	33.77	1	1,725.55	1	0	0	1	0
2	28	33.00	3	4,449.46	1	0	0	1	0
3	33	22.70	0	21,984.47	1	0	1	0	0
4	32	28.88	0	3,866.86	1	0	1	0	0
...	...	...	...	...	...	...	...	...	...
1333	50	30.97	3	10,600.55	1	0	1	0	0
1334	18	31.92	0	2,205.98	0	0	0	0	0
1335	18	36.85	0	1,629.83	0	0	0	1	0
1336	21	25.80	0	2,007.94	0	0	0	0	1
1337	61	29.07	0	29,141.36	0	1	1	0	0

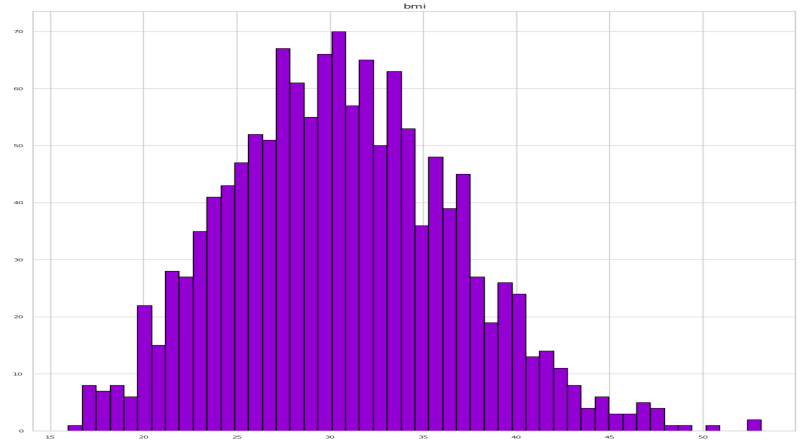
1338 rows × 9 columns

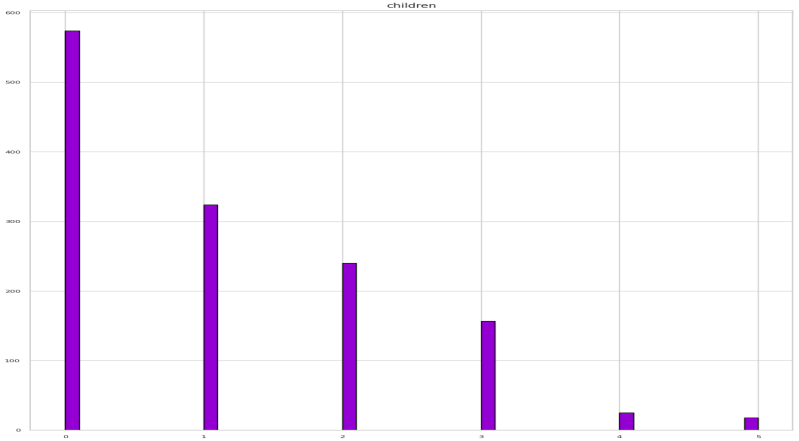
Train set: (1338, 9)

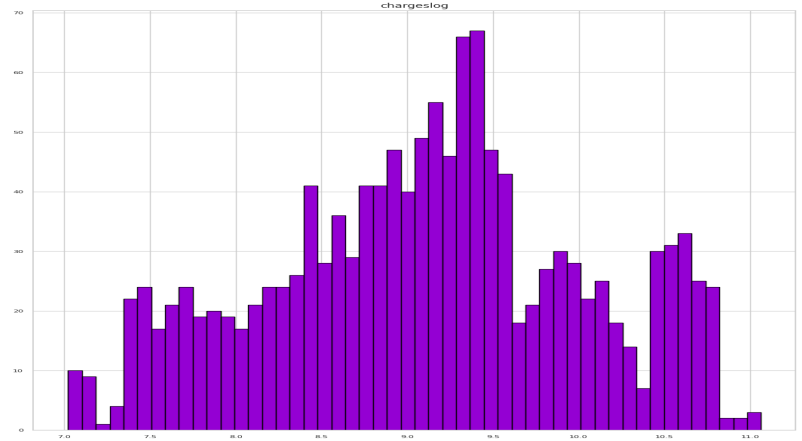
Exploratory Data Analysis (EDA)

Looking at the distribution of the numerical features right from the beginning, we can notice that "charges" is skewed as well. To help normalize this variable, a log transformation will be applied to "charges".









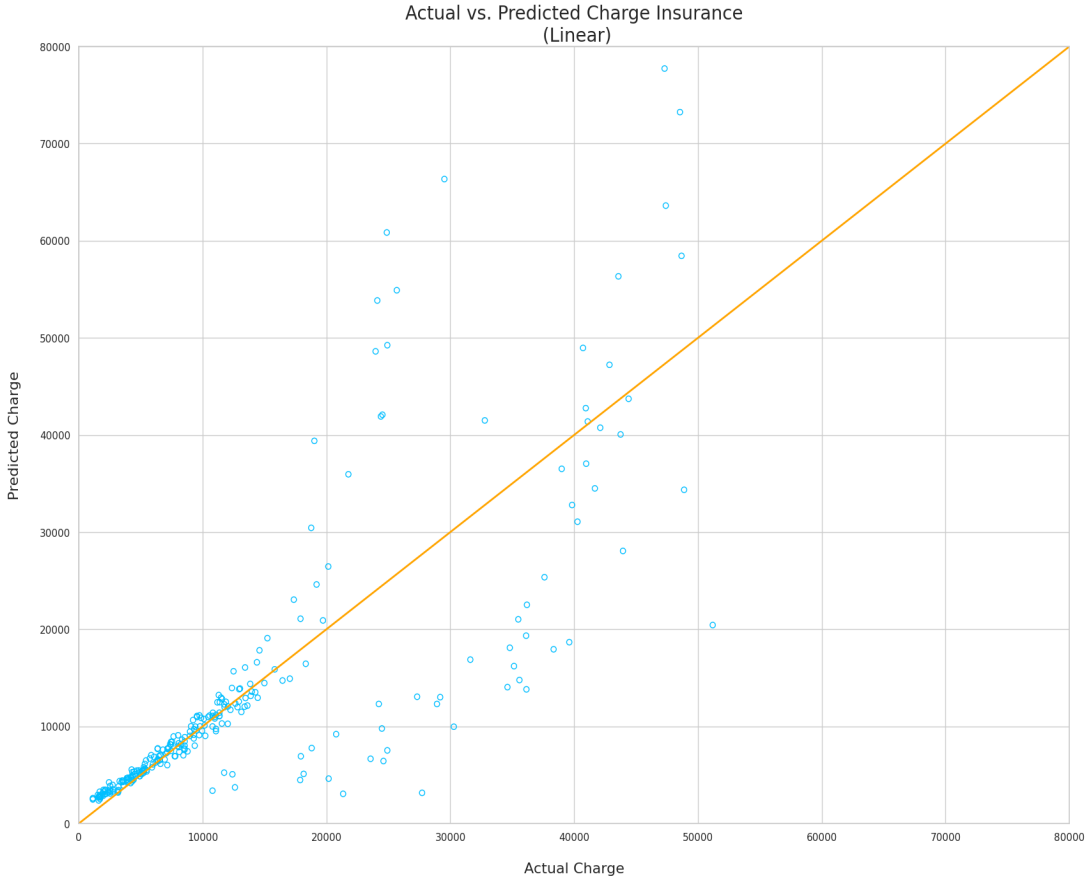
Modeling Overview

- Linear Regression
- Ridge Regression
- Lasso Regression
- Random Forest Regressor
- XGBoost Regressor

To measure model performance and their predictions the RMSE and R^{2} scores will be used.

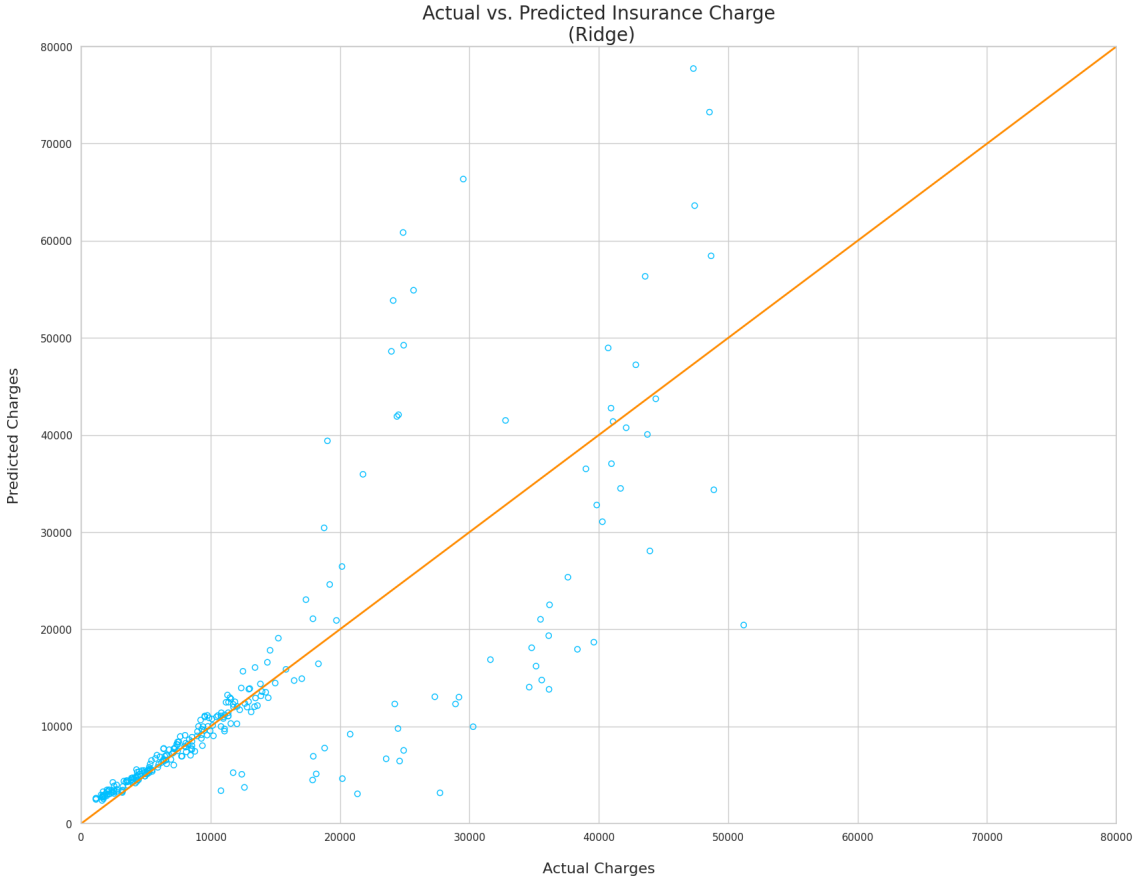
Modeling Overview

Linear Regression:




```
**** Regressor: Linear ****
R²: 0.7583042098055544
RMSE: 0.44680911669956613
```

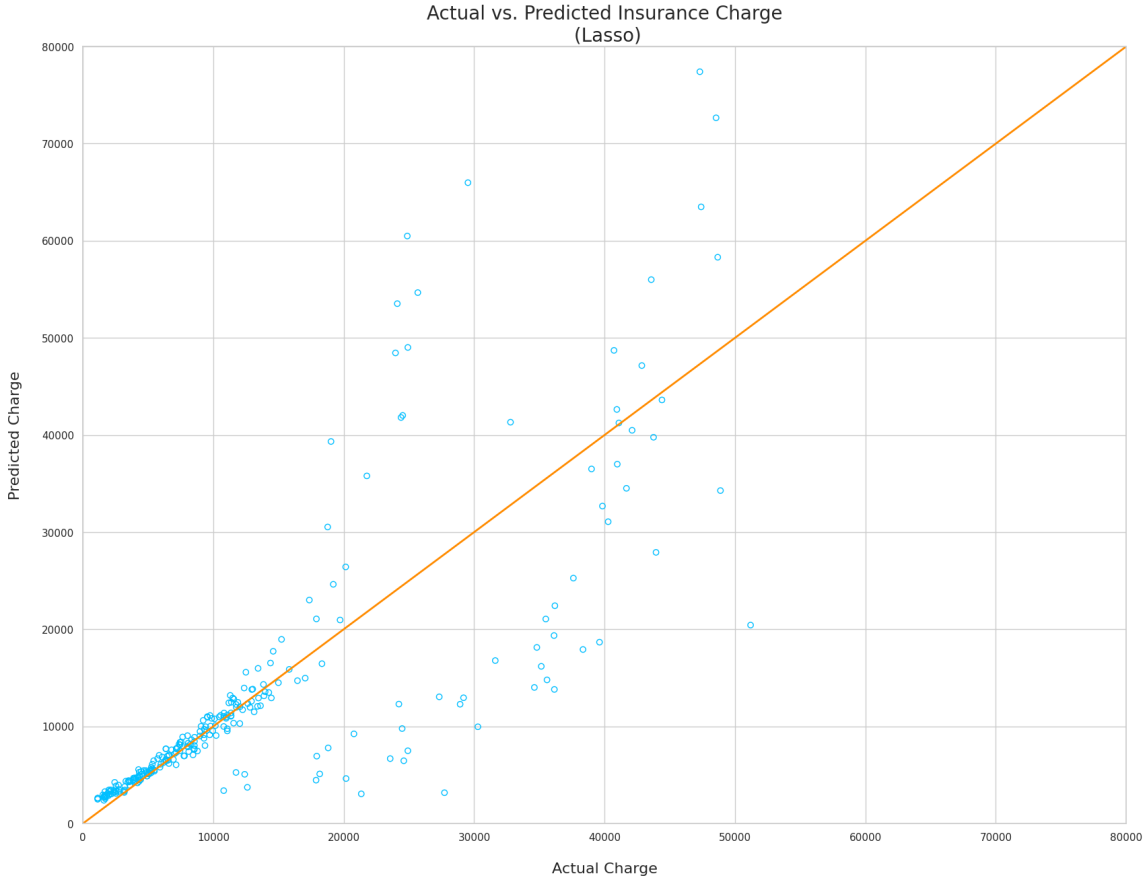
Ridge Regression:




```
**** Regressor: Ridge ****
R²: 0.7583042175563077
RMSE: 0.4468091095353794
```

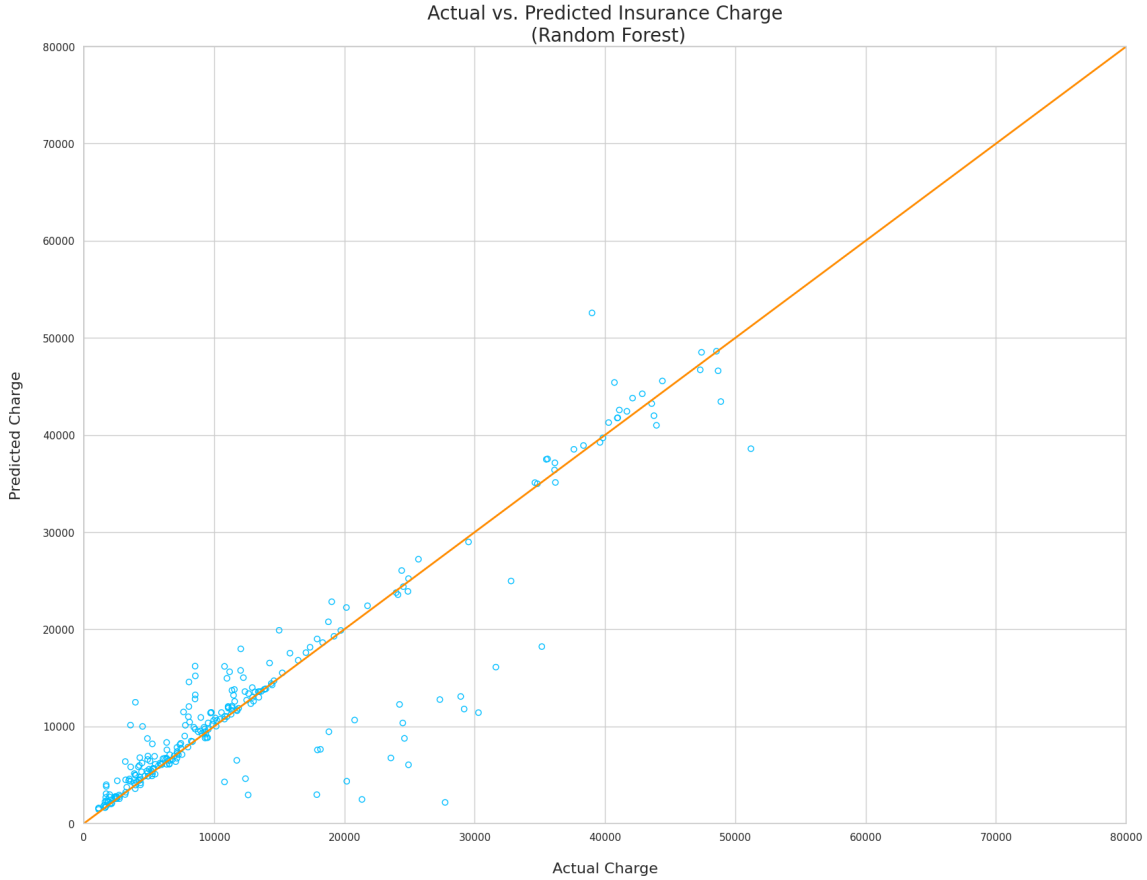
Modeling Overview

Lasso Regression:




```
**** Regressor: Lasso ****
R²: 0.7584416589307031
RMSE: 0.44668205148280593
```

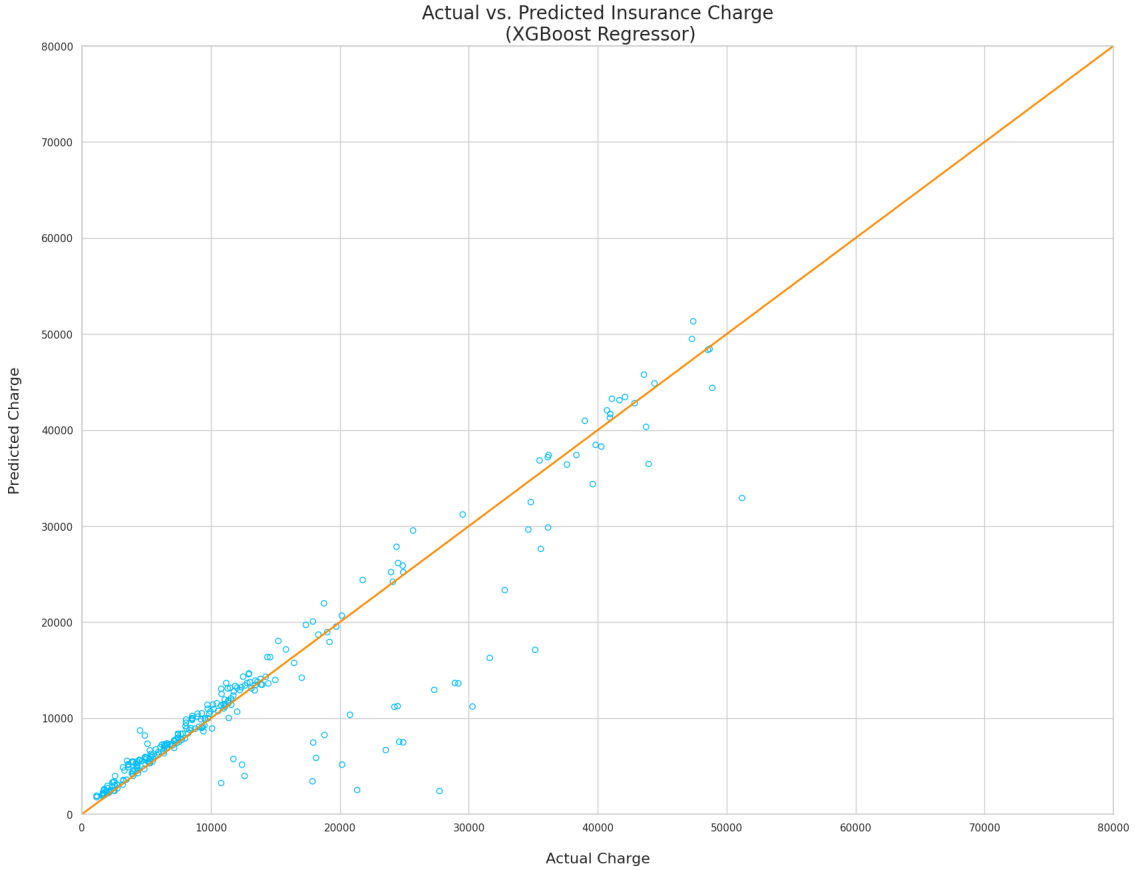
Random Forest Regressor:




```
**** Regressor: Random Forest ****
R²: 0.7932162588191821
RMSE: 0.4132812259195818
```

Modeling Overview

XGBoost Regression:




```
**** Regressor: XGBoost ****
R²: 0.8247486447824814
RMSE: 0.3804680349848538
```

Model	R^2	RMSE
LinearRegression	0.76	0.45
Ridge	0.76	0.45
Lasso	0.76	0.45
RandomForestRegressor	0.79	0.41
XGBRegressor	0.82	0.38

Bayesian Model - MCMC

The Bayesian approach, specifically using Markov Chain Monte Carlo (MCMC), is applied in this project for modeling health insurance costs. MCMC is used to estimate posterior distributions of model parameters(intercept & slope), allowing for uncertainty quantification and more robust predictions. The Bayesian approach contrasts with traditional frequentist methods by offering a comprehensive view of parameter uncertainty and incorporating prior knowledge.

Bayesian Methodology:

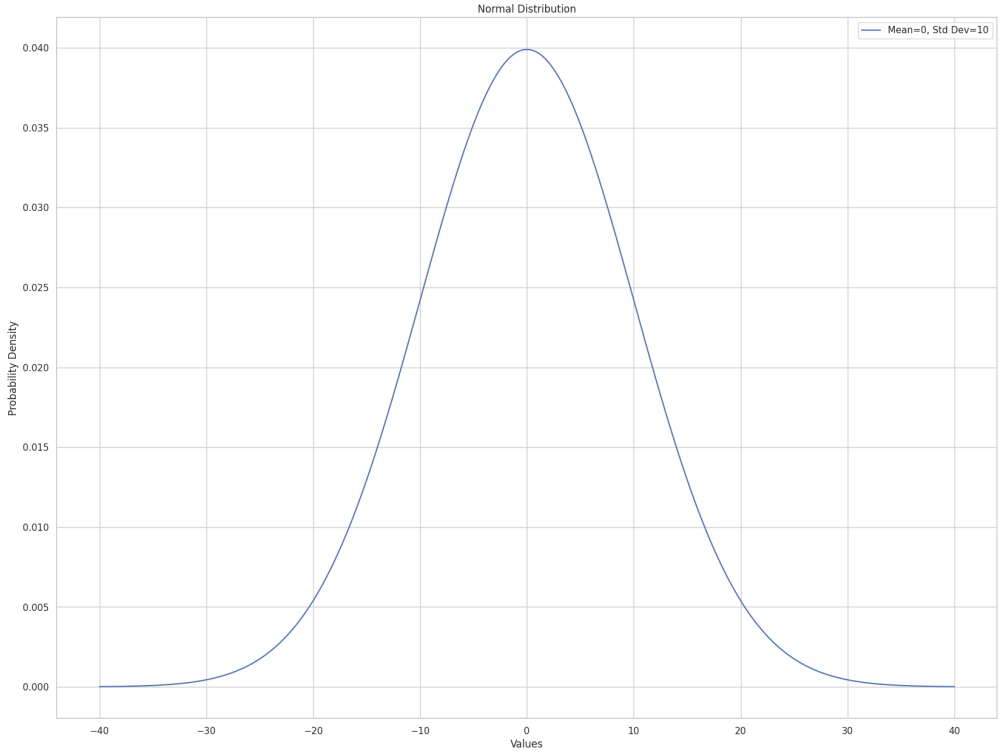
MCMC for Linear Regression Models:

Prior Probability (Prior):

Before seeing any medical charges data, the prior distributions express our uncertainty about the parameters

Here, the priors in our model are P(Intercept),P(beta)

These represent our initial beliefs about the intercept and slope (beta) parameters before observing the medical charges data. We are assuming normal distributions with mean 0 and standard deviation 10 as prior distributions for the intercept and beta parameters.



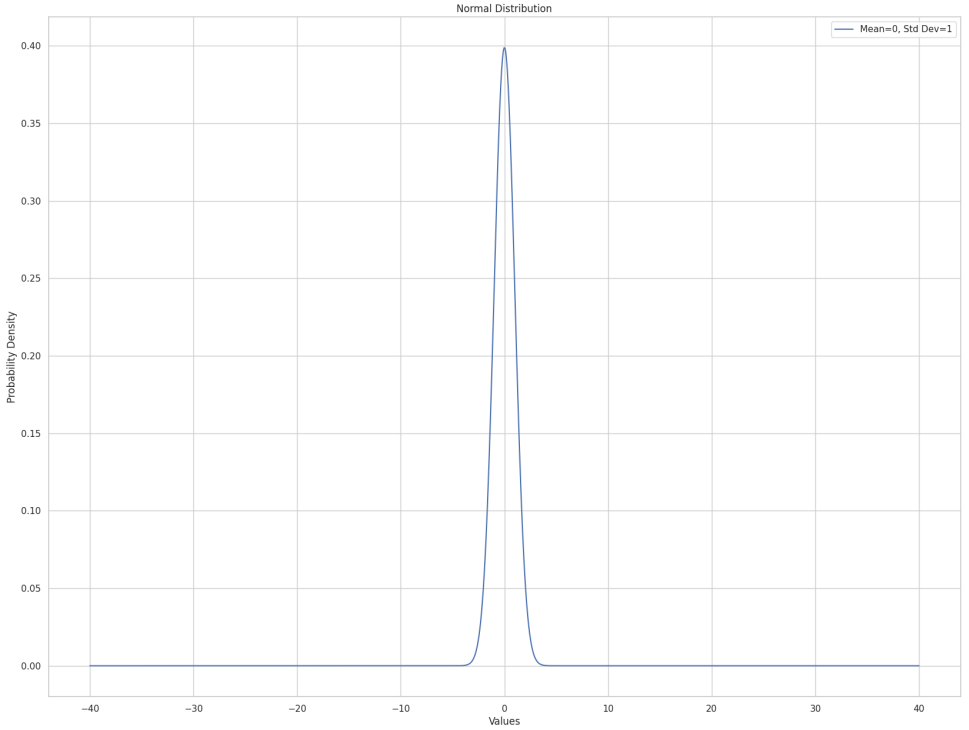
Bayesian Methodology:

Likelihood:

P(charges|Intercept,beta,BMI)

It quantifies how likely observed charges are for different combinations of intercept, slope, and BMI.

This represents the probability of observing the medical charges data given specific values of the intercept, slope, and BMI. We are considering a Normal likelihood assuming charges follow a Normal distribution around the predicted values based on the linear model, with a standard deviation of 1.



Bayesian Methodology:

Posterior Probability (Posterior):

$P(\text{Intercept,beta}|\text{charges,BMI})$

After analysing the medical charges data, the posterior distributions represent our updated understanding of the intercept and slope values.

This is our updated belief about the intercept and beta parameters after considering the observed medical charges data and BMI. It's a combination of the prior beliefs and what the data tells us about the parameters.

$$P(\text{Intercept, beta}|\text{charges, BMI}) = \frac{P(\text{charges}|\text{Intercept,beta,BMI}) \times P(\text{Intercept}) \times P(\text{beta})}{P(\text{charges})}$$

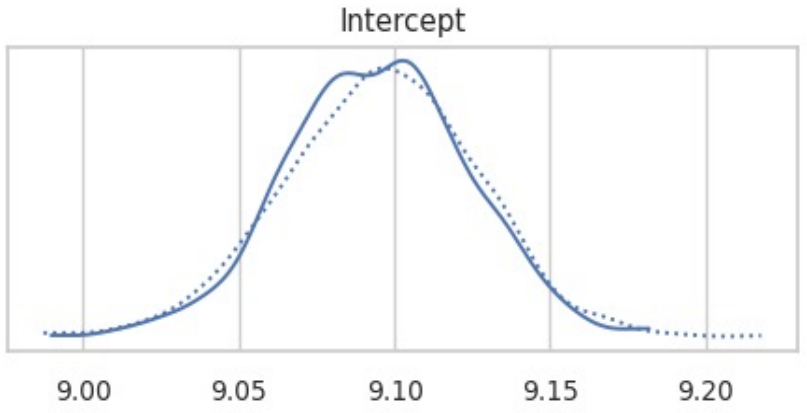
- **Prior** distributions express initial uncertainty about the intercept and slope parameters.

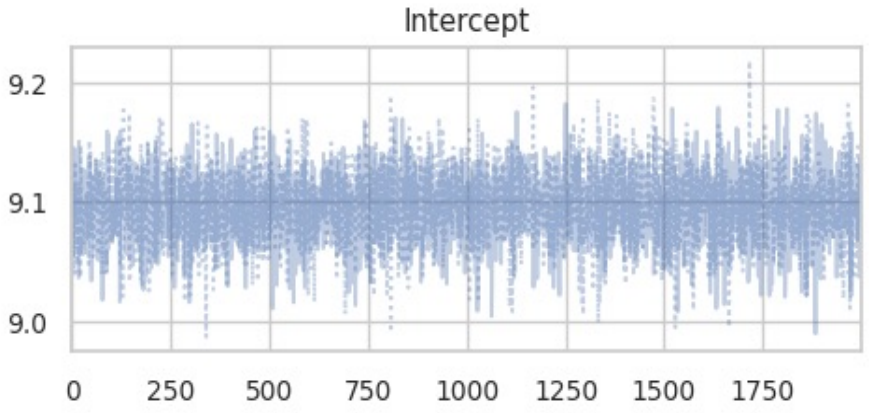
- **Likelihood** calculates the probability of observing charges given specific intercept, slope, and BMI values.

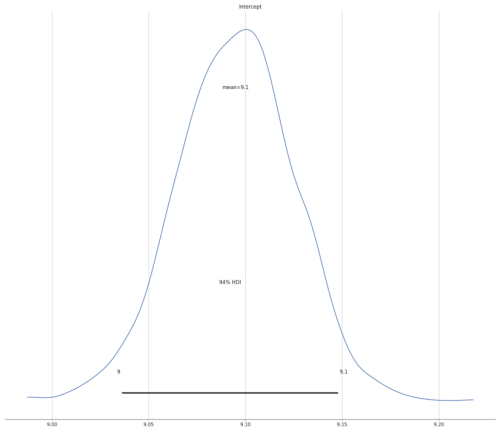
- **Posterior** distributions represent updated beliefs about the intercept and slope parameters after observing medical charges data and BMI, combining prior knowledge with observed evidence.

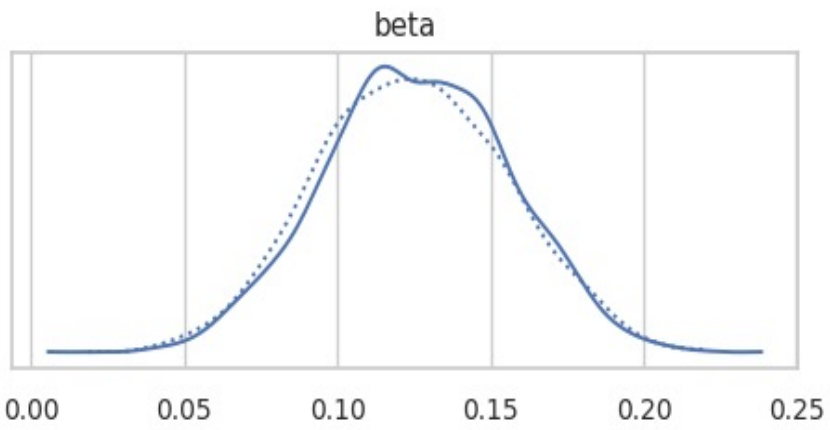
Bayesian Linear Regression:

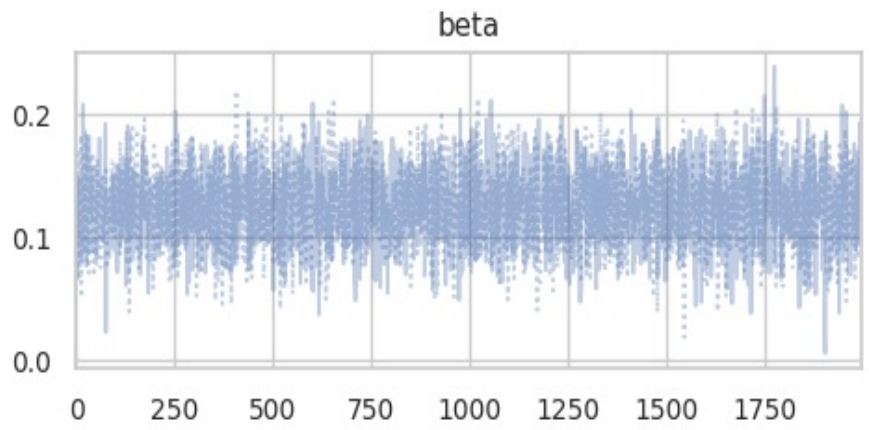
MCMC for Linear Regression Models:

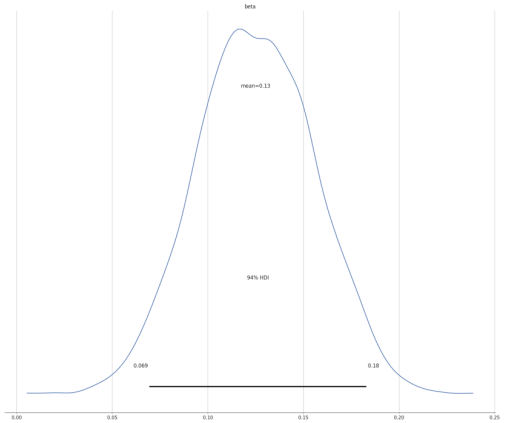












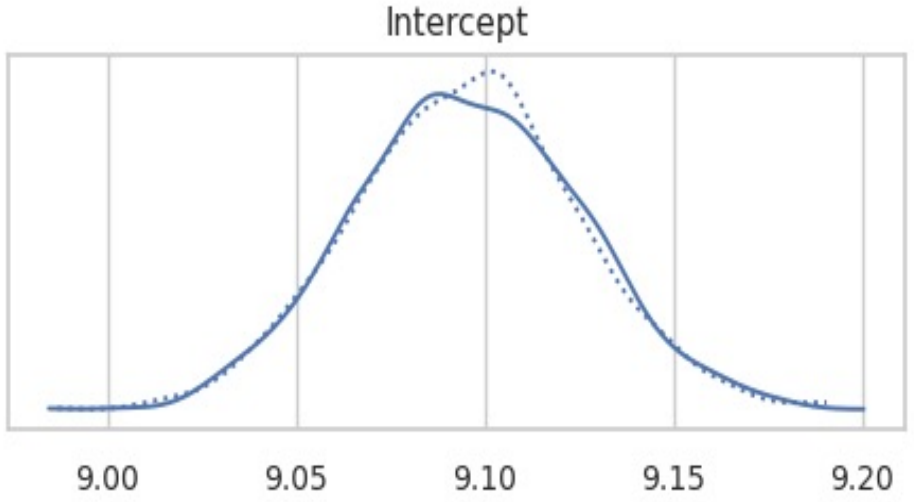
```
Mean squared error: 0.82
```

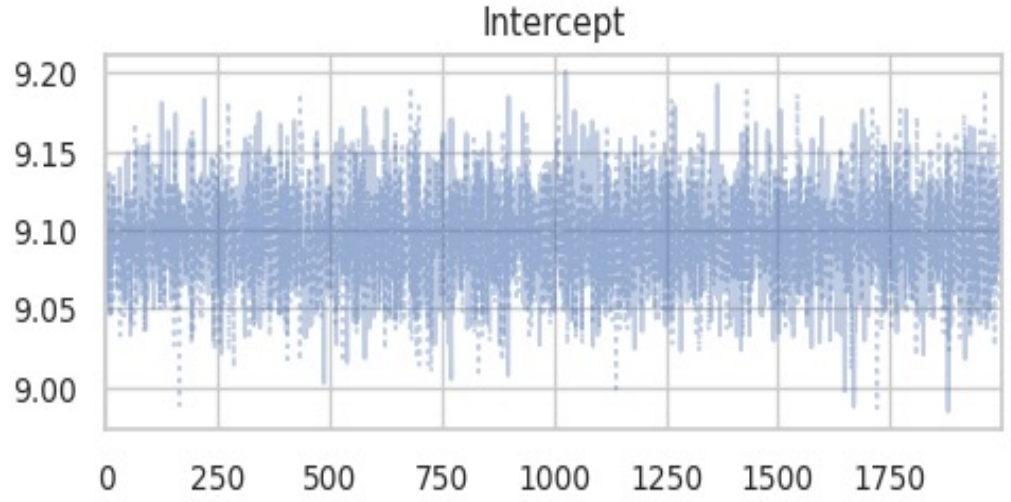
Bayesian Linear Regression:

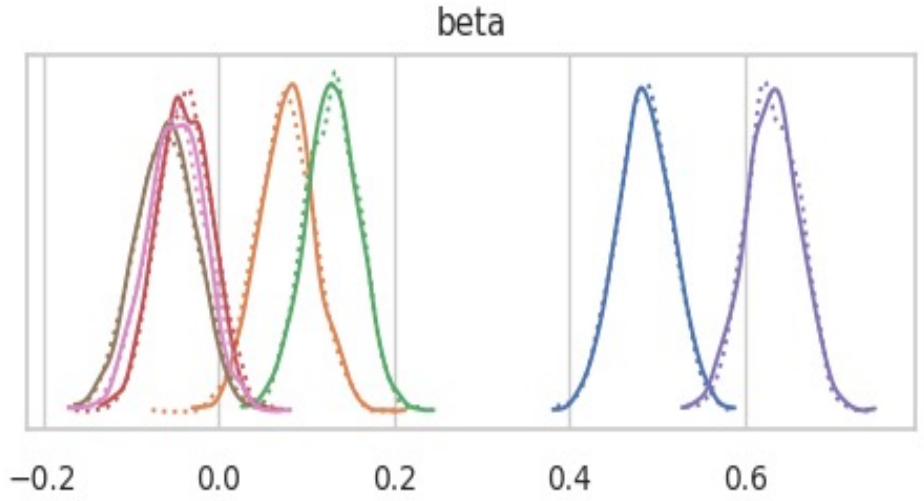
	train_x	y_train	y_pred
0	0.36	8.79	8.96
1	-0.30	8.38	9.05
2	-0.06	11.04	9.11
3	-1.08	7.70	9.01
4	-1.46	9.38	9.03
5	1.48	7.92	8.98
6	0.26	9.17	9.23
7	-1.29	8.99	9.17
8	-0.89	9.04	9.19
9	0.49	9.09	8.99

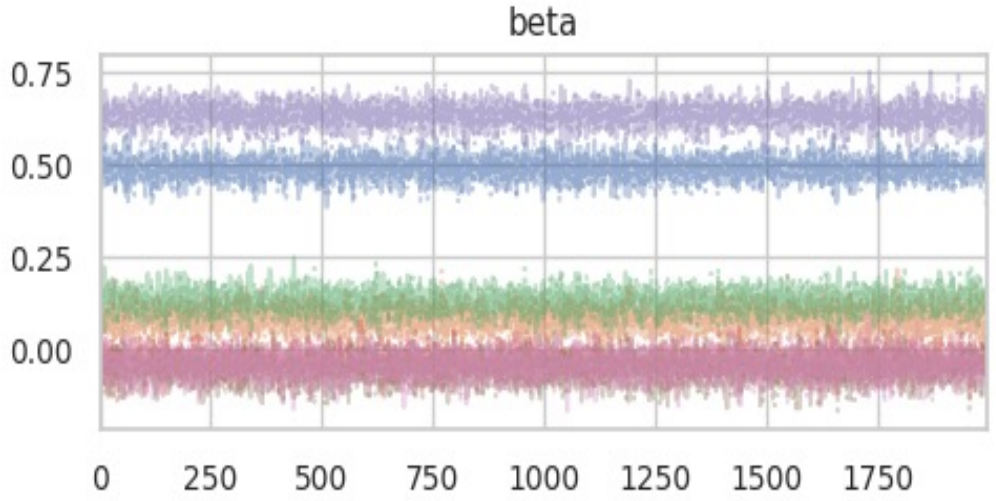
Bayesian Multiple Linear Regression:

- Results on Train(1070, 7) data:



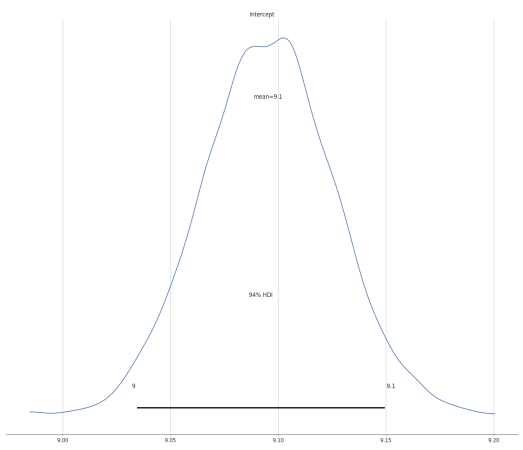


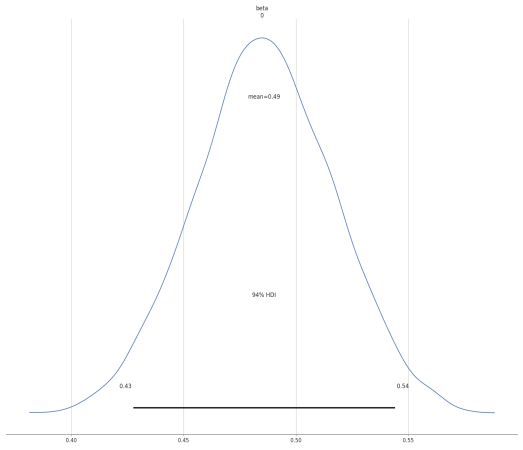


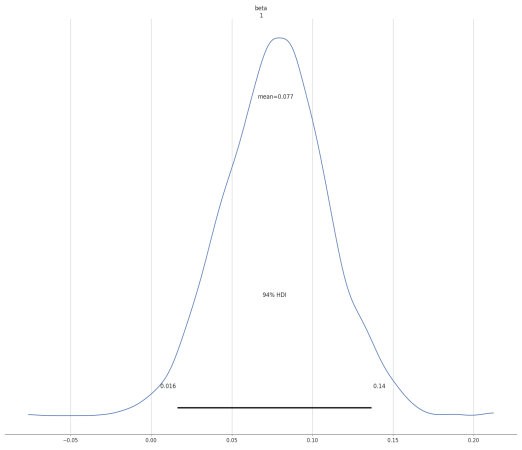


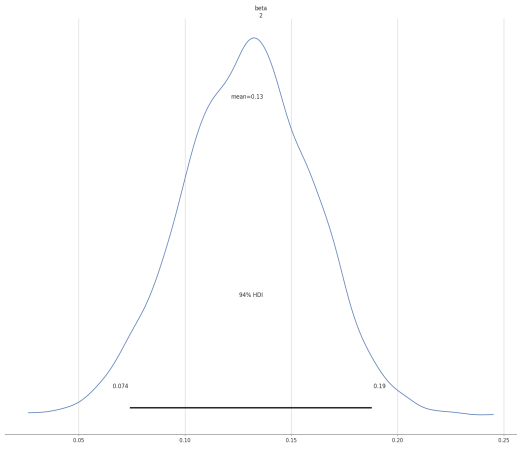
Bayesian Multiple Linear Regression:

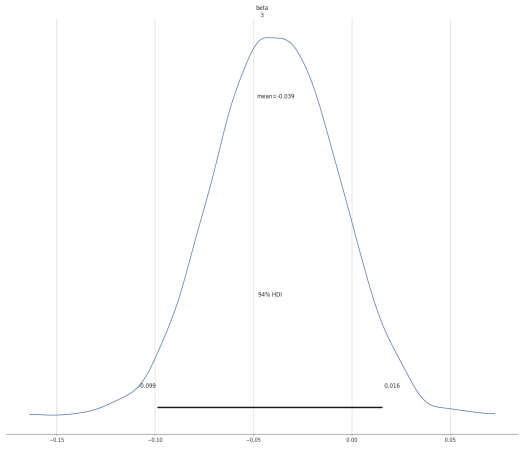
- Results on Train(1070, 7) data:

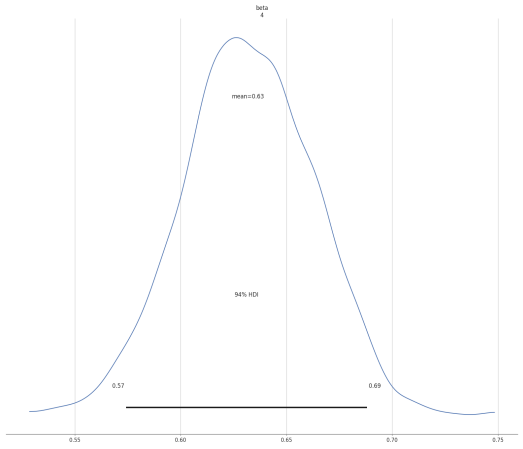


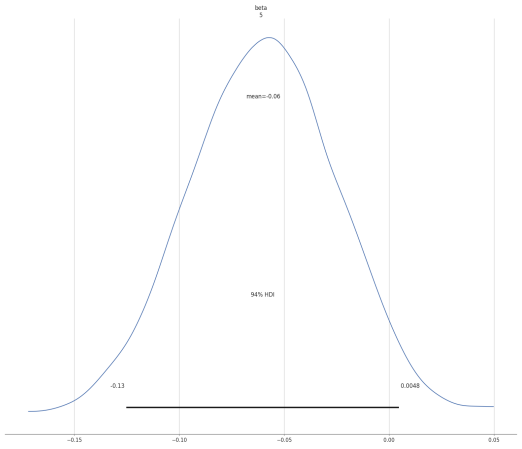


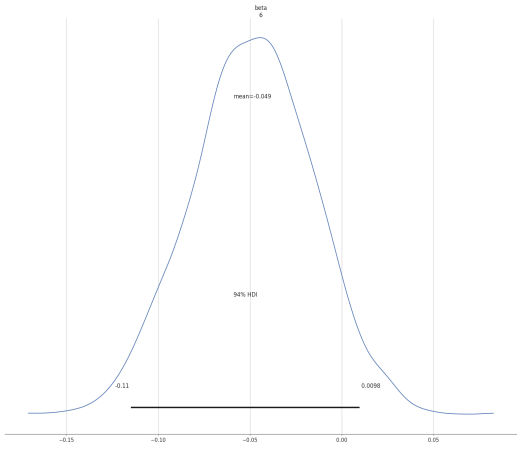






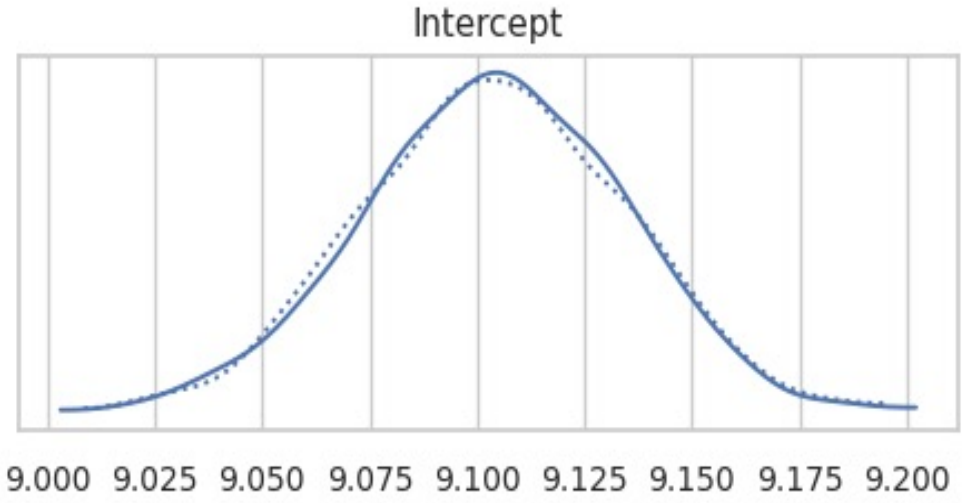


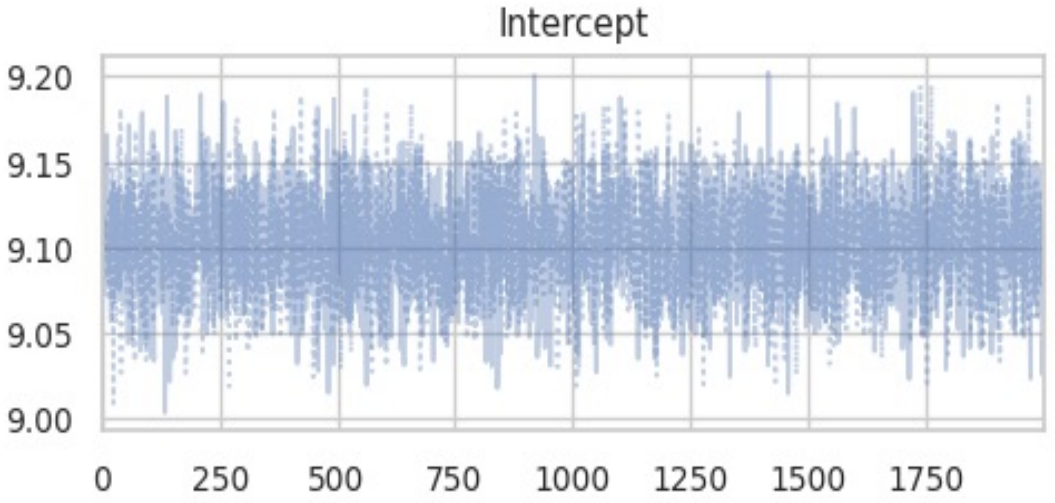


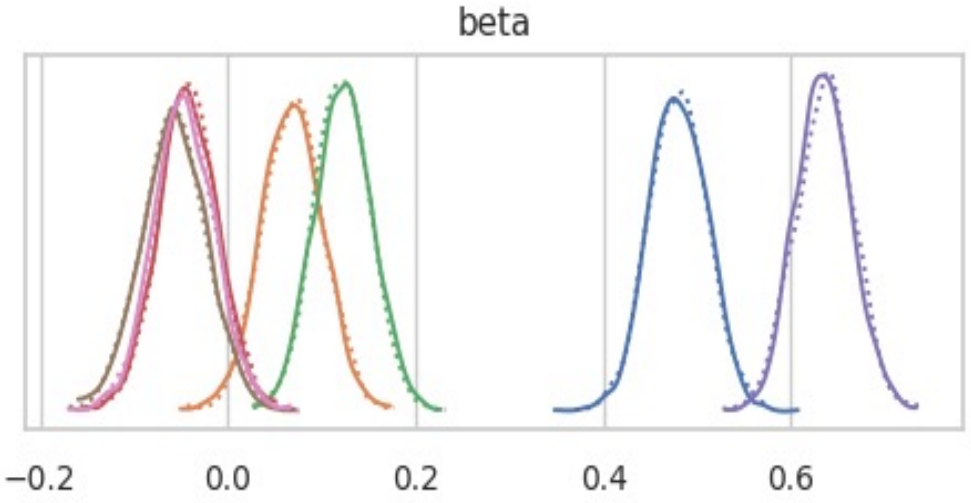


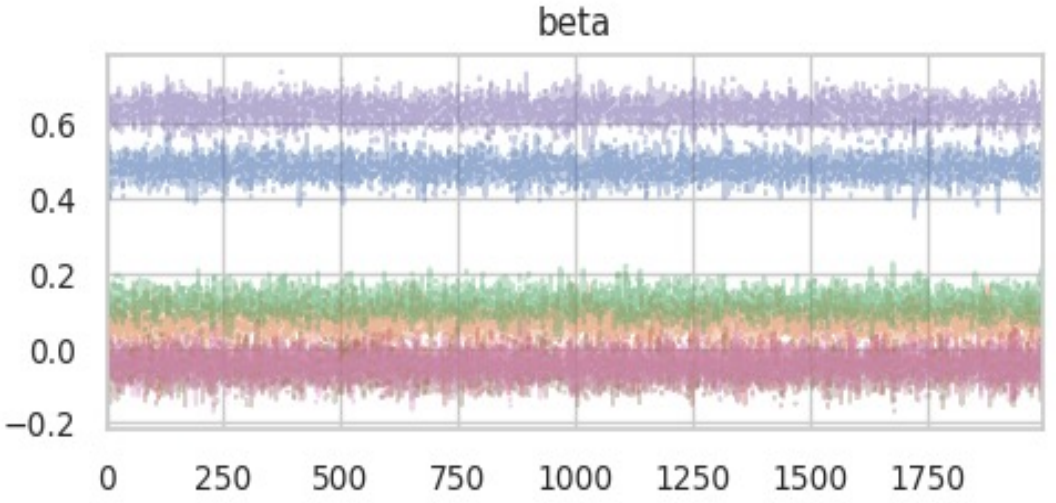
Bayesian Multiple Linear Regression:

- Results on Test(268, 7) data:



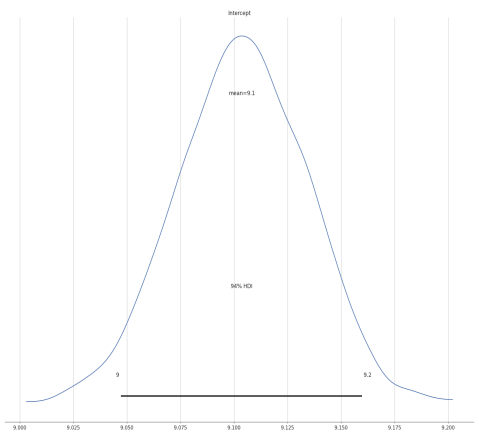


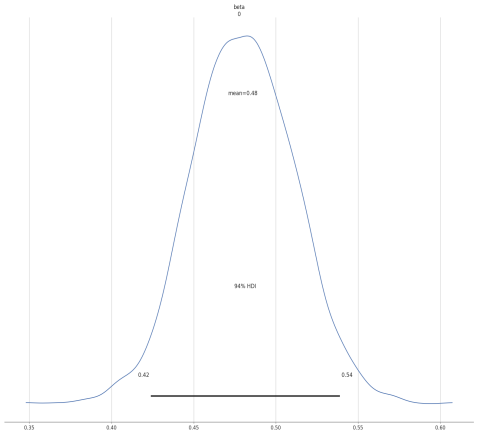


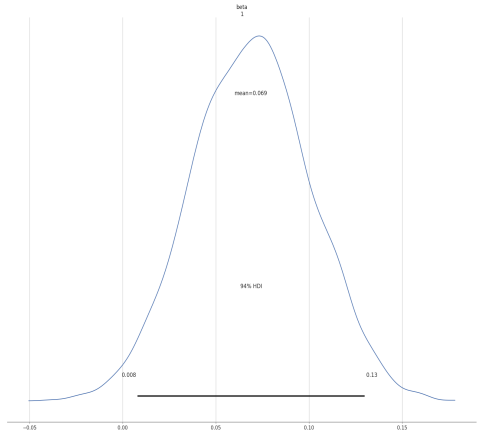


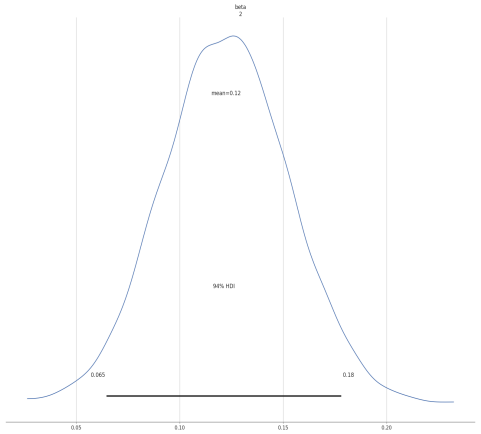
Bayesian Multiple Linear Regression:

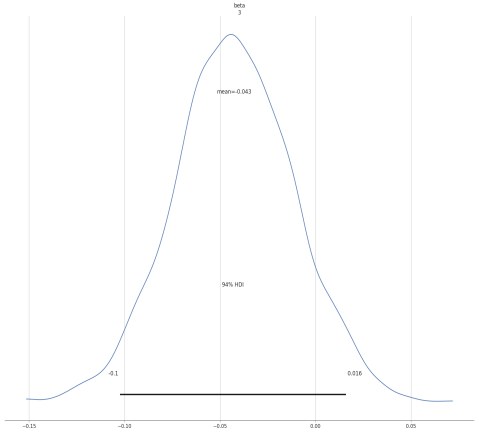
- Results on Test(268, 7) data:

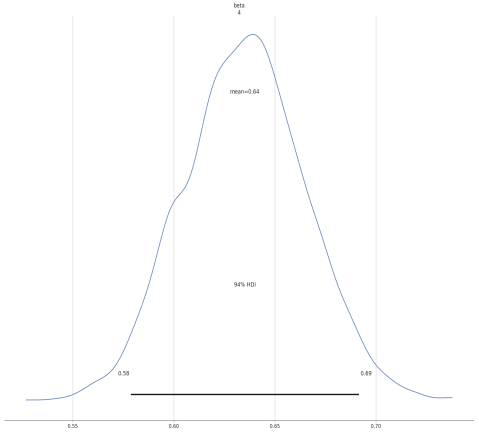


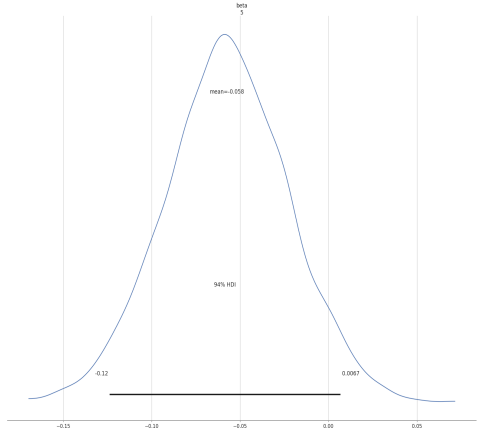


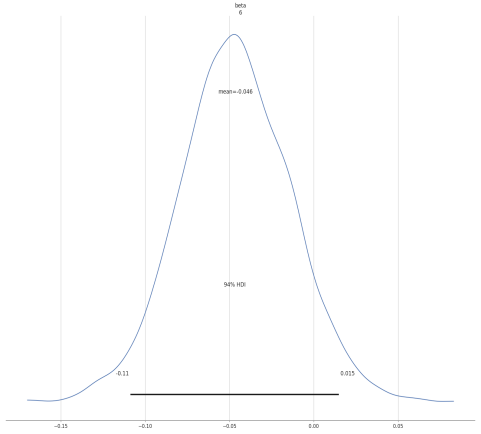












Bayesian Multiple Linear Regression:

- Results on Test(268, 7) data:

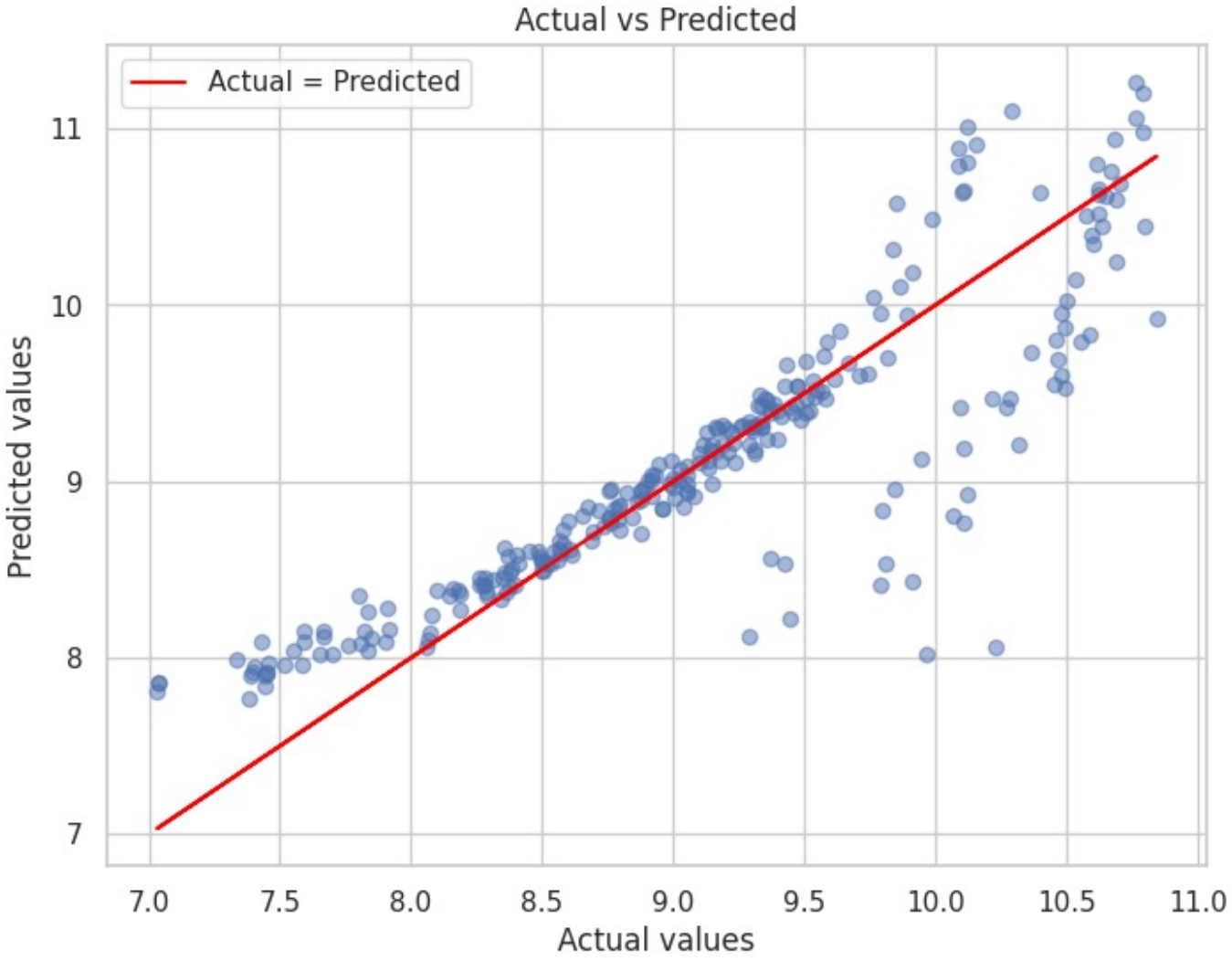
```
Mean squared error: 0.17
Intercept    9.10
beta[0]      0.48
beta[1]      0.07
beta[2]      0.12
beta[3]     -0.04
beta[4]      0.64
beta[5]     -0.06
beta[6]     -0.05
Name: mean, dtype: float64
Coefficients:
 [ 9.10331276  0.48029169  0.06890278  0.12280198 -0.04199448  0.63518322
 -0.05770177 -0.04635644]
```

y_pred = beta[0]x1+ beta[1]x2+ beta[2]x3+ beta[3]x4+ beta[4]x5+ beta[5]x6+ beta[6]x7+Intercept

y_pred = 0.48(age)+ 0.07(bmi)+ 0.12(children)- 0.04(sex_male)+ 0.64 smoker_yes)
- 0.06(region_southeast)- 0.05(region_southwest)+9.10

Bayesian Multiple Linear Regression:

Results on Test(268,7) data:



	y_test	y_pred
0	9.29	9.13
1	10.10	10.67
2	8.26	8.44
3	8.69	8.60
4	10.09	10.78
5	8.46	8.48
6	9.56	9.72
7	8.88	8.97
8	10.65	10.57
9	7.44	7.88

y_pred shape = (268, 2000)

R-squared: 0.8940

RMSE: 0.4604

Model Performance Comparison:

Without Bayesian:

Model	R^2	RMSE
LinearRegression	0.76	0.45
Ridge	0.76	0.45
Lasso	0.76	0.45
RandomForestRegressor	0.79	0.41
XGBRegressor	0.82	0.38

With Bayesian:

	Model	R^2	RMSE
0	Bayesian Multi Linear Regression	0.89	0.46

Conclusion:

The Bayesian linear regression may have a smaller mean squared error compared to the least squares linear regression due to the uncertainty estimates provided by the Bayesian model. In Bayesian linear regression, we estimate the posterior distribution of the model parameters given the data, which allows us to obtain a range of plausible values for the parameters, instead of a single point estimate as in least squares regression.

This uncertainty estimate can be particularly helpful in situations where we have limited data or when the data is noisy or has outliers. The uncertainty estimates can help to regularize the model and reduce overfitting. Additionally, Bayesian models allow for the incorporation of prior knowledge, which can be useful in situations where we have some prior knowledge about the relationship between the variables.

Therefore, the Bayesian approach may provide a more robust estimate of the parameters, resulting in better predictions and a smaller mean squared error compared to the least squares approach.

Thank You !