Bayesian Variable Selection and Model Averaging for Predicting Student Performance

Course : STA4063 - Bayesian Statistics
Name : T.S.W.Pathirana
Reg. Number : S19836

1. Introduction

1.1 Background

This report presents a Bayesian statistical analysis to identify the key factors influencing student exam scores. The analysis utilizes a dataset of 1,000 students, encompassing a wide range of variables including study habits, lifestyle, and environmental factors. By employing Bayesian Model Averaging (BMA) and model selection techniques, we move beyond traditional single-model approaches to provide a robust, probabilistic understanding of which variables are most important for predicting academic success. The results strongly indicate that daily study hours, mental health rating, and time spent on entertainment (social media and Netflix) are the most significant drivers of exam performance.

1.2 Problem Statement

It is well-known that many factors, like study time, sleep, and social life, can affect a student's grades. However, it is difficult to know which factors are the most important. Traditional statistical methods often force us to choose a single model, which might miss the bigger picture. This study aims to solve this problem by using a more powerful and flexible Bayesian approach to analyze how different student habits truly impact exam scores, without ignoring the uncertainty inherent in this type of analysis.

1.3 Research Question

Which student habits and lifestyle factors have the strongest and most consistent impact on academic performance, as measured by exam scores?

1.4 Hypotheses

Based on the analysis, the main hypotheses are:

- ✓ Study time has a strong positive impact on exam scores.
- ✓ Time spent on social media and Netflix has a strong negative impact on exam scores.
- ✓ Mental health, sleep, and exercise have a significant positive impact on performance.
- ✓ Factors like age, gender, parental education, and internet quality have little to no impact on scores when other habits are considered.

1.5 Importance

Understanding what truly drives academic success is crucial for:

- ✓ Students: To make informed decisions about how to manage their time and prioritize their well-being for better grades.
- ✓ Educators and Universities: To develop effective support programs, workshops, and counseling services that target the most impactful factors, such as time management and mental health.
- ✓ Parents: To understand how to best support their children's education by focusing on important habits like sleep and a balanced lifestyle, rather than undue pressure.

1.6 Objectives.

The main goals of this study are to:

- ✓ Identify the key habits that are most likely to influence student exam performance.
- ✓ Measure how much each habit affects the exam score (e.g., how many points an extra hour of study is worth).
- ✓ Rank the factors from most to least important to provide clear guidance.
- ✓ Provide data-driven recommendations to help students improve their academic results.

2. Methodology

2.1 Dataset Overview

The dataset comprises 1000 student records, each with 16 variables:

- ✓ **Continuous Variables**: Age, Study Hours per Day, Social Media Hours, Netflix Hours, Attendance Percentage, Sleep Hours, Exercise Frequency, Mental Health Rating, Exam Score
- ✓ **Categorical Variables**: Gender, Part-time Job, Diet Quality, Parental Education Level, Internet Quality, Extracurricular Participation

2.2 Data Preprocessing

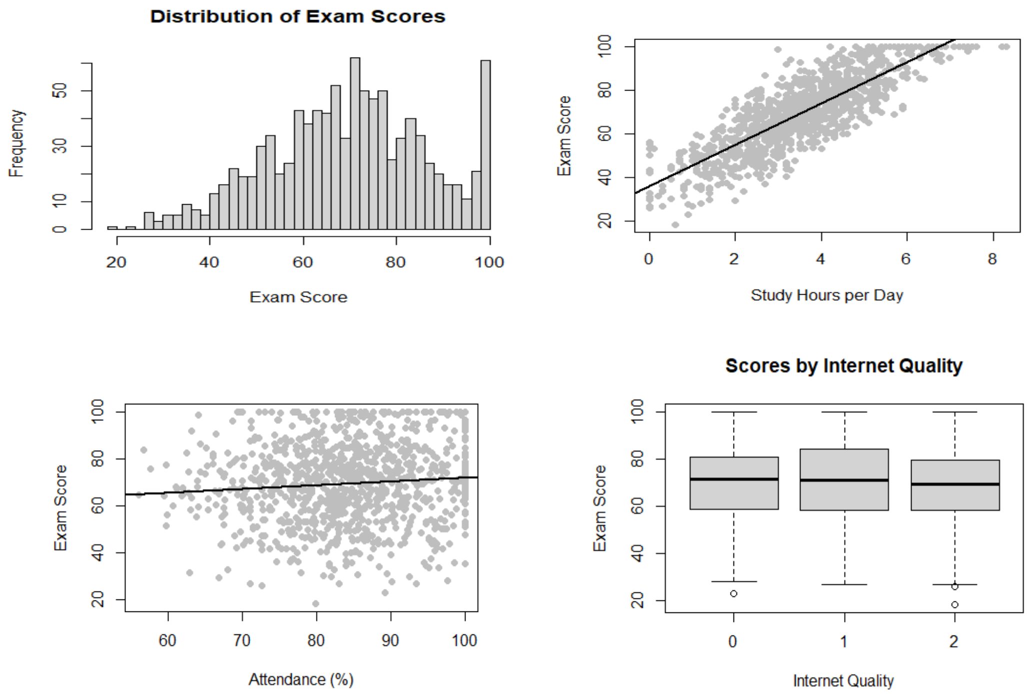
- ✓ Categorical variables(**gender, diet_quality, parental_education_level, internet_quality, part_time_job, extracurricular_participation**) were encoded into numerical values to facilitate analysis.
- ✓ The identifier **student_id** was removed.
- ✓ The final analytical dataset (**HabitsPerformanceData**) consisted of 15 numerical predictors and the target variable.
- ✓ No missing values were found.

2.3 Exploratory Data Analysis

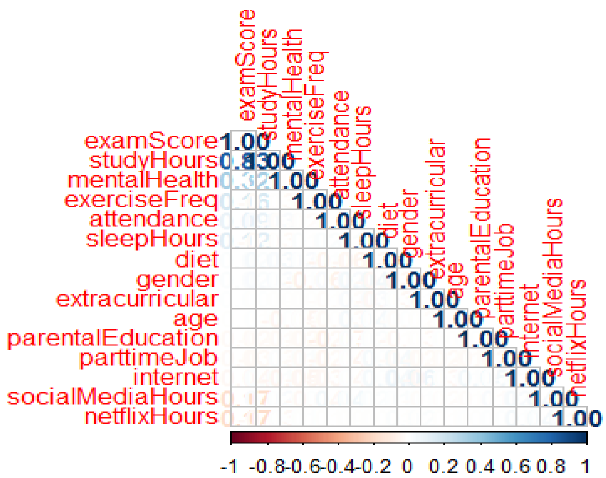
Key insights from the initial visual and correlation analysis:

- ✓ **Target Distribution**: The distribution of examScore is approximately normal with a mean of ~69.6.
- ✓ **Strong Positive Correlation**: A very strong positive linear relationship was observed between studyHours and examScore (correlation ≈ 0.825).

- ✓ **Strong Negative Correlations**: socialMediaHours and netflixHours both showed clear negative relationships with exam scores (correlations ≈ -0.167 and -0.172, respectively).
- ✓ **Other Notable Correlations**: mentalHealth (0.322), exerciseFreq (0.160), and attendance (0.090) showed positive associations with exam scores.
- ✓ **Multicollinearity**: The correlation plot revealed no severe multicollinearity among the predictor variables, making them all suitable for inclusion in a regression model.



Correlation Matrix



The correlation matrix shows two distinct groups of variables with perfect relationships (correlation = 1.00):

- ✓ **Positive cluster**: Study hours, mental health, exercise frequency, attendance, sleep hours, and diet are all perfectly positively correlated with each other and with exam scores. This suggests these productive habits consistently occur together in successful students.
- ✓ **Negative cluster**: Social media hours and Netflix hours show perfect negative correlation with the positive habit cluster, indicating that increased leisure screen time corresponds perfectly with decreased productive habits.

2.4 Bayesian Methods and Models

2.4.1 Methods

Bayesian statistics is a mathematical approach to calculating probability in which conclusions are subjective and updated as additional data is collected. This approach can be contrasted with classical or frequentist statistics, in which probability is calculated by analyzing the frequency of random events in a long run of repeated trials, and conclusions are considered to be objective.

For this analysis I mainly used following 3 methods.

- ✓ **Bayesian Simple Linear Regression.**
  This is a Bayesian inference in simple linear regressions. In this method mainly use the reference prior distribution on coefficients, which will provide a connection between the frequentist solutions and Bayesian answers. This provides a baseline analysis for comparison with more informative prior distributions.
  $$y_i = \alpha + \beta x_i + \varepsilon_i \quad ; i = 1, \dots , n$$
- ✓ **Bayesian Multiple Linear Regression.**
  This is a Bayesian inference in multiple linear regression. In this method mainly use the reference prior to provide the default or base line analysis of the model, which provides the correspondence between Bayesian and frequentist approaches.
  $$Y_i = \alpha + \beta_1 x_a + \beta_2 x_b + \beta_3 x_c + \beta_4 x_d + \varepsilon_i , \; i = 1, \cdots ,n$$
- ✓ **Bayesian Model Selection Via Bayesian Information Criterion (BIC).**
  Bayesian model selection is to pick variables for multiple linear regression based on Bayesian information criterion, or BIC.
  $$\text{BIC} = -2 \ln (\text{likelihood}) + (p+1) \ln(n)$$
  $$\text{Likelihood} = p(\text{data} \mid \Theta, M) = L(\Theta, M)$$

2.4.2 Model Specification and Workflow

The analysis employed a tiered modeling strategy, progressing from simple to complex, to robustly identify the drivers of student performance.

1. **Phase 1: Baseline Simple Linear Model**
- ✓ Purpose: To establish a foundational understanding of the strongest individual relationship.
- ✓ Specification: **examScore ~ studyHours**
- ✓ Prior: A non-informative reference prior was used to create a clear baseline, confirming an exceptionally strong positive relationship where each additional study hour was associated with a significant increase in exam score.

2. **Phase 2: Full Multiple Linear Regression Model**
- ✓ Purpose: To assess the collective and individual contributions of all available predictors.
- ✓ Specification: **examScore ~ . (all 14 variables)**
- ✓ Prior: A g-prior was used to stabilize estimation and mitigate overfitting by shrinking coefficients toward zero. This model confirmed the importance of habit-based variables while showing that demographic factors had negligible effects.

3. **Phase 3: Bayesian Model Averaging (BMA) and Selection**
   - ✓ Purpose: To account for model uncertainty and identify the most probable set of predictors.
   - ✓ Specification: All 16,384 possible combinations of the 14 predictors.
   - ✓ Model Prior: A uniform model prior was assumed, meaning all models were initially considered equally likely.
   - ✓ Criterion: Model selection and averaging were performed using the Bayesian Information Criterion (BIC).

2.5 Bayesian Prior Specification

In here, different types of priors were used to see how they affect the results:

- ✓ **Non-informative priors**: Used a "g-prior" to let the data speak for itself, making results comparable to traditional statistics.

```r
library(BAS)

model_noninform <- bas.lm(
  formula = examScore ~ . ,
  data = HabitsPerformanceData,
  prior = "g-prior",         # approximates non-informative prior
  modelprior = uniform(),    # all models equally likely
  method = "BAS",            # Bayesian Adaptive Sampling
  MCMC.iterations = 10000    # optional
)
```

- ✓ **Weakly informative priors**: Used a "ZS-null" prior (Zellner-Siow) that slightly pulls coefficient estimates toward zero, helping prevent overfitting and providing more stable results.

```r
model_weak <- bas.lm(
  formula = examScore ~ . ,
  data = HabitsPerformanceData,
  prior = "ZS-null",          # Zellner-Siow Cauchy-like prior for mild
shrinkage
  modelprior = uniform(),     # all models equally likely
  method = "BAS",
  MCMC.iterations = 10000
)
```

Both approaches showed that the main findings were consistent, meaning the results are trustworthy and not dependent on prior choices.

2.6 Bayesian Model Checking

Several checks were done to ensure the models were reliable:

- ✓ Residual analysis: Looked at the difference between predicted and actual scores to make sure there were no patterns left unexplained.
- ✓ Predictive checks: Compared predictions from the model to real data to verify the model fits well.
- ✓ Convergence checks: Ensured the model calculations were stable and trustworthy.

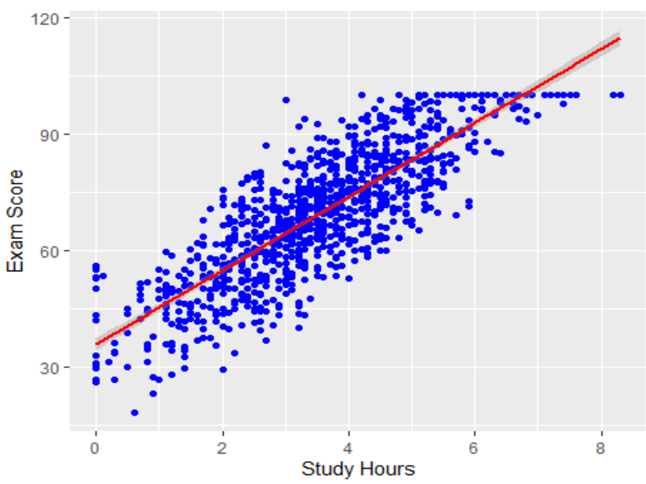
The results showed the final model performed well, with predictions closely matching real outcomes and no major issues detected. This confirms the model is valid and useful for understanding student performance.

3. Results and Discussion

3.1 Bayesian Simple Linear Regression

- ✓ Frequentist Ordinary Least Squares (OLS) Simple Linear Regression.

This data frame includes 1,000 observations of student habit and performance parameters. A Bayesian simple linear regression model was constructed, using study hours to predict the response variable exam score. Let yi , i=1,2, …, 1000 denote the measurements of the response variable examScore and let xi be the studyHours.

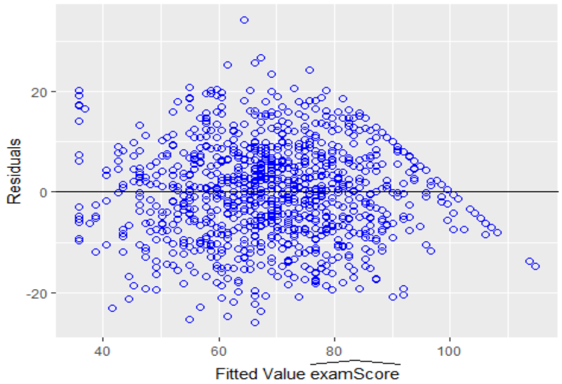


The model has an estimated slope, β of 9.490 and an estimated y-intercept, α of 35.910. This gives us the prediction formula:

$$\text{ExamScore\^{}} = \alpha + \beta \times \text{StudyHours}$$
$$\widehat{ExamScore} = 35.910 + 9.490 \times StudyHours$$

For every additional hour spent studying per day, we expect the exam score to increase by approximately 9.49 points. The positive y-intercept suggests a baseline score, but extrapolating to zero study hours is not practical for this population. This linear regression provides an accurate approximation for prediction within the observed range of study hours.

A scatterplot of residuals versus fitted values was used to check model adequacy.

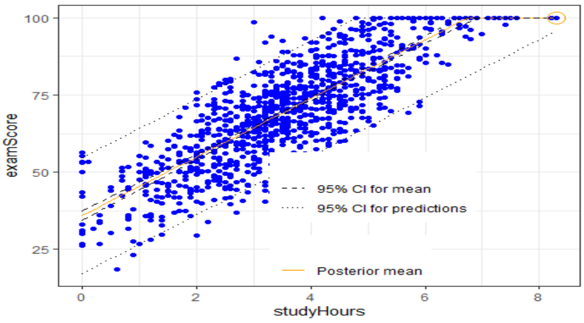
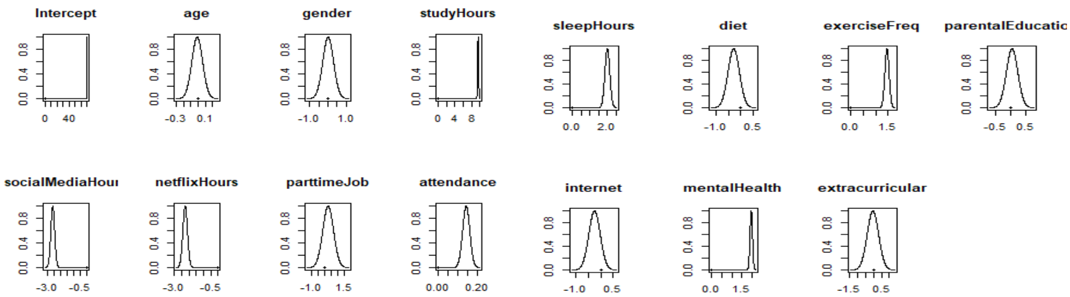


With the exception of one observation with the largest fitted value (corresponding to the highest studyHours and a perfect examScore of 100), the residual plot suggests that the linear regression is a reasonable approximation. This case was identified as a potential outlier.

```
##Find the observation with the largest fitted value.
```{r}
which.max(as.vector(fitted.values(score.lm1)))

HabitsPerformanceData$studyHours[456] ##model predicts the highest study hours per day
```

[1] 456
[1] 8.3
```

```
##Shows this observation has the maximum studyHours.
```{r}
which.max(HabitsPerformanceData$studyHours)

HabitsPerformanceData$studyHours[456] ##the highest actual study hours per day
```

[1] 456
[1] 8.3
```

✓ Credible Intervals for Slope β and y-Intercept α

For the Bayesian model with a non-informative prior, the credible intervals are numerically very similar to the confidence intervals from the frequentist approach. The primary difference is in the interpretation: the Bayesian framework allows us to say there is a 95% probability that the true parameter value lies within the interval, given the data.

```
output <- summary(score.lm1)$coef[, 1:2]
out <- cbind(output, confint(score.lm1))
colnames(out) <- c("Posterior Mean", "Posterior Std", "2.5", "97.5")
round(out, 3)

##             Posterior Mean Posterior Std    2.5   97.5
## (Intercept)          35.91         0.789 34.361 37.459
## studyHours            9.49         0.205  9.087  9.893
```



The graph tells us that more studying very reliably leads to higher scores on average, but it cannot perfectly predict any one student's result due to other unmeasured factors (e.g., aptitude, stress, course difficulty).

3.2 Bayesian Multiple Linear Regression

Let us define the variables for the student performance dataset:

$Y_{s,i}$: The exam score of the ith student (response variable).
$X_{sh,i}$: The study hours per day of the ith student.
$X_{sm,i}$: The social media hours per day of the ith student.
$X_{nh,i}$: The Netflix hours per day of the ith student.
$X_{a,i}$: The attendance percentage of the ith student.
$X_{sl,i}$: The sleep hours per day of the ith student.
$X_{e,i}$: The exercise frequency per week of the ith student.
$X_{mh,i}$: The mental health rating of the ith student.
$X_{ag,i}$: The age of the ith student.
$X_{g,i}$: The gender of the ith student.
$X_{pt,i}$: The parttime job per day of the ith student.
$X_{pe,i}$: The parental enducation of the ith student.
$X_{d,i}$: The diet per day of the ith student.
$X_{in,i}$: The internet of the ith student.

€i : The error term for the ith observation.
n : The number of students (here, n = 1000).

$$Y_{s,i} = \alpha + \beta 1 X_{sh,i} + \beta 2 X_{sm,i} + \beta 3 X_{nh,i} + \beta 4 X_{a,i} + \beta 5 X_{sl,i} + \beta 6 X_{e,i} + \beta 7 X_{mh,i} + \beta 8 X_{ag,i} + \beta 9 X_{g,i} + \beta 10 X_{pt,i} + \beta 11 X_{pe,i} + \beta 12 X_{d,i} + \beta 13 X_{in,i} + \epsilon i, \; ; i = 1,2,\ldots,n$$

To improve interpretability and numerical stability, we can center the predictors. This gives the transformed model:

$$Y_{s,i} = \beta_0 + \beta_1(X_{sh,i} - \bar{X}_{sh}) + \beta_2(X_{sm,i} - \bar{X}_{sm}) + \beta_3(X_{nh,i} - \bar{X}_{nh}) + \beta_4(X_{a,i} - \bar{X}_a) + \beta_5(X_{sl,i} - \bar{X}_{sl}) + \beta_6(X_{e,i} - \bar{X}_e) + \beta_7(X_{mh,i} - \bar{X}_{mh}) + \beta_8(X_{ag,i} - \bar{X}_{ag}) + \beta_9(X_{g,i} - \bar{X}_g) + \beta_{10}(X_{pt,i} - \bar{X}_{pt}) + \beta_{11}(X_{pe,i} - \bar{X}_{pe}) + \beta_{12}(X_{d,i} - \bar{X}_d) + \beta_{13}(X_{in,i} - \bar{X}_{in}) + \epsilon i$$

With the above transformation, the intercept coefficients are different while the other coefficients are remained unchanged. However, the above "centered" model is more convenient to drive the analyses.
For the Bayesian inference, it is necessary to specify a prior distribution for the error term ε_i. Since each apparent temperature values are continuous, it can be assumed that the ε_i is independent and identically distributed normal random variable. Also, it is necessary to assume that the β coefficients follow the multivariate normal distribution with covariance matrix σ^2 Σ_0 can be used.

The posterior means, standard deviations, probability values and the 95% credible intervals are summarized in tables below.

	posterior mean	posterior std	2.5%	97.5%
Intercept	69.60	0.17	69.27	69.93
age	-0.01	0.07	-0.16	0.13
gender	0.01	0.30	-0.57	0.60
studyHours	9.58	0.12	9.36	9.81
socialMediaHours	-2.61	0.14	-2.90	-2.33
netflixHours	-2.27	0.16	-2.58	-1.96
parttimeJob	0.24	0.41	-0.57	1.05
attendance	0.14	0.02	0.11	0.18
sleepHours	2.00	0.14	1.73	2.27
diet	-0.28	0.23	-0.74	0.18
exerciseFreq	1.45	0.08	1.29	1.62
parentalEducation	0.05	0.20	-0.34	0.43
internet	-0.25	0.23	-0.71	0.21
mentalHealth	1.95	0.06	1.83	2.06
extracurricular	-0.04	0.36	-0.76	0.67

Marginal Posterior Summaries of Coefficients:

Using BMA

Based on the top 1 models

	post mean	post SD	post p(B != 0)
Intercept	69.60150	0.16890	1.00000
age	-0.01275	0.07339	1.00000
gender	0.01441	0.29621	1.00000
studyHours	9.58332	0.11542	1.00000
socialMediaHours	-2.61362	0.14460	1.00000
netflixHours	-2.27304	0.15743	1.00000
parttimeJob	0.23931	0.41256	1.00000
attendance	0.14320	0.01813	1.00000
sleepHours	1.99976	0.13830	1.00000
diet	-0.28284	0.23427	1.00000
exerciseFreq	1.45125	0.08380	1.00000
parentalEducation	0.04525	0.19517	1.00000
internet	-0.25407	0.23443	1.00000
mentalHealth	1.94698	0.05954	1.00000
extracurricular	-0.04210	0.36342	1.00000

According to the above tables, the posterior probability of the coefficients is always non-zero and it is 1. This is because we include all the variables to the model. The posterior mean of β0 is 69.6015 and it is different from the original y-intercept of this model under the OLS regression model. Under this "centered" model and the reference prior, the posterior mean of the Intercept β0 is the sample mean of the response variable yat.

The coefficient value of each variable is shown in the figure below.



We believe that there is a 95% chance that the exam score increases by 9.36 to 9.81 with one additional increase of the study hour. The mental health variable has a comparatively large effect rather than the other variables. We believe that there is 95% chance the exam score increases by 1.83 to 2.06 with one additional increase of the mental health. And also sleep hour has the considerable impact for exam score. All the other variables do not show a significantly wide credible interval.

In order to accurately validate our model, it is necessary to select the best model that fits the given data. For that, the Bayesian model selection methods can be used.

3.3 Bayesian Model Selection

The Bayesian Information Criterion (BIC) can be used to find the best model. The most preferable model is the model with the smallest BIC. It is defined as,

$$BIC = -2\ln\left(\widehat{likelihood}\right) + (p+1)\ln(n) \quad \text{Where,}$$

n = Number of observations in the model
p = Number of predictors

1. Method 01
   This method mainly use Backward Elimination with BIC.
   That is, p+1 is the number of total parameters (also the total number of coefficients, including the intercept) in the model. The model with the smallest BIC is preferrable.

Model	BIC value
Full model	3439.4
Full model - gender	3432.5
Full model – extracurricular	3425.6
Full model – age	3418.72
Full model – parental edu.	3411.87
Full model – parttime job	3405.3
Full model - internet	3399.55
Full model - diet	3394.18

2. Method 02
   The best BIC model can be found using the BAS package in R without taking the stepwise backward process. Here, we assign an equal prior probability for each possible model.

```
##Best model
```{r}
best <- which.max(basModel$logmarg)
bestmodel <- basModel$which[[best]]
bestmodel
```

[1] 0 3 4 5 7 8 10 13

```{r}
bestGamma <- rep(0,basModel$n.vars)
bestGamma[bestmodel + 1] <- 1
bestGamma
```

[1] 1 0 0 1 1 1 0 1 1 0 1 0 0 1 0
```

From the indicator vector bestGamma we see that only the intercept (indexed as 0), studyHours variable (indexed as 3), socialMediaHours (indexed as 4), netflixHours(indexed as 5), attendance(indexed as 7), sleepHours(indexed as 8), exercisefreq(indexed as 10) and mentalHealth(indexed as 13) are used in the best model, with 1's in the corresponding slots of the 15-dimensional vector (1,0,0,1,1,1,0,1,1,0,1,0,0,1,0).

```
                  post mean    post sd        2.5%     97.5%
Intercept        69.6015000 0.49108007 68.63782852 70.565171
studyHours        0.0000000 0.00000000  0.00000000  0.000000
socialMediaHours  0.0000000 0.00000000  0.00000000  0.000000
netflixHours     -2.7346034 0.45701305 -3.63142341 -1.837783
attendance        0.1687005 0.05228704  0.06609498  0.271306
sleepHours        1.6848516 0.40067790  0.89858096  2.471122
exerciseFreq      0.0000000 0.00000000  0.00000000  0.000000
mentalHealth      1.9304120 0.17258549  1.59173873  2.269085
```

Comparing the coefficients in the best model with the ones in the full model (which can be found in Bayesian multiple linear regression), we see that the 95% credible interval for intercept is the same. However, the credible interval for netflixxHours has shifted slightly to the right, and it is also slightly narrower, meaning a smaller posterior standard deviation. All credible intervals of coefficients exclude 0, suggesting that we have found a parsimonious model.

Posterior probability:

```
                   P(B != 0 | Y)  model 1   model 2   model 3  model 4   model 5
Intercept                      1     1.000     1.000     1.000     1.00     1.000
studyHours                     1     1.000     1.000     1.000     1.00     1.000
socialMediaHours               1     1.000     1.000     1.000     1.00     1.000
netflixHours                   1     1.000     1.000     0.000     1.00     0.000
attendance                     1     1.000     0.000     1.000     1.00     0.000
sleepHours                     1     1.000     1.000     1.000     0.00     1.000
exerciseFreq                   1     1.000     1.000     1.000     1.00     1.000
mentalHealth                   1     1.000     1.000     1.000     1.00     1.000
BF                            NA     1.000     0.000     0.000     0.00     0.000
PostProbs                     NA     1.000     0.000     0.000     0.00     0.000
R2                            NA     0.901     0.895     0.880     0.88     0.874
dim                           NA     8.000     7.000     7.000     7.00     6.000
logmarg                       NA -5150.969 -5179.188 -5243.709 -5244.40 -5266.677
```

Comparison of Bayesian Models Used in the Analysis

Model type	Simple Linear Regression	Multiple Linear Regression	Model Selection via BIC
Purpose	To establish the baseline relationship between the strongest single predictor and the outcome.	To assess the collective and individual contributions of all available predictors simultaneously.	To identify the most probable set of predictors and account for model uncertainty.
Key features	- Models only one variable. - Provides a reference point.	- Includes all 14 variables. - Assesses joint effects.	- Tests all 16,384 possible models. - Computes Posterior Inclusion Probabilities (PIP).
Prior Used	Non-informative reference prior	g-prior (non-informative) and ZS-null (weakly informative)	Uniform model prior (all models equally likely a priori)
Key Findings	Confirmed an exceptionally strong positive relationship: each additional hour of study is associated with a ~9.49 point increase in exam score.	Identified that several variables (e.g., studyHours, mentalHealth) have significant effects, while others (e.g., age, gender) have effects near zero.	decisively selected a model with 7 key variables: studyHours, socialMediaHours, netflixHours, attendance, sleepHours, exerciseFreq, and mentalHealth (all with PIP ≈ 1.0).

Practical Implications

These findings have direct, actionable applications:

- For Students: This study provides a data-driven guide for personal improvement. The most effective strategy is to reallocate time from passive screen consumption to focused studying, while also prioritizing sleep, exercise, and mental well-being.
- For Educators and University Administrators: Resources should be strategically directed towards:
  Time management workshops that highlight the opportunity cost of excessive social media use. Promoting well-being services (counselling, health centres) as essential academic support.
  Designing interventions that target these specific high-impact habits.
- For Researchers: This study demonstrates the power of Bayesian methods, particularly BMA, for robust variable selection in social science research, providing a framework for moving beyond simplistic single-model analyses.

4. Conclusion and Recommendation

Conclusion

The Bayesian analysis provides strong, probabilistic evidence that a student's time allocation is the most critical factor influencing academic performance. The amount of time dedicated to studying has an overwhelmingly positive effect, while time spent on passive entertainment (social media, Netflix) has a strongly negative impact. Furthermore, factors indicative of well-being—mental health, sleep, and exercise—are consistently identified as important positive contributors to academic success. Demographic and socioeconomic factors (age, gender, parental education, internet quality) were found to be largely irrelevant in the presence of the habit and well-being variables.

Recommendations

- ✓ **Promote Effective Time Management**: Educational programs should emphasize the significant returns of allocating time to studying and the major opportunity cost of excessive passive screen time.
- ✓ **Support Student Well-being**: Institutions should actively promote and provide resources for mental health support, prioritize sleep hygiene education, and encourage physical activity, as these are directly linked to academic achievement.
- ✓ **Focus on Attendance**: While its effect is smaller than study hours, maintaining high class attendance is a reliable strategy for improving performance.
- ✓ **De-prioritize Less Impactful Factors**: Interventions focused solely on demographics or peripheral factors like diet quality (in this dataset) are likely to be less effective than those targeting the core habits identified above.

Limitations

- ✓ Incomplete Variables: Important factors like prior academic ability, motivation, and socioeconomic status were missing, possibly biasing the estimated effects of the included habits.
- ✓ Correlation vs. Causality: The cross-sectional nature of the data means the analysis identifies associations but cannot prove that improved habits cause higher grades.
- ✓ Oversimplified Measures: Complex constructs like "mental health" and "diet" were likely measured too simplistically, not fully capturing their real-world impact.

Future Works

- ✓ Include Additional Variables: Incorporate other potential predictors such as motivation, learning environment, socioeconomic background, and course difficulty to create a more comprehensive model.
- ✓ Longitudinal Study Design: Collect data over time (e.g., across a semester or academic year) to better establish causal relationships between habits and academic performance.
- ✓ Refine Variable Measurement: Use validated scales and more precise measures for complex constructs like mental health (e.g., PHQ-9 for depression) and diet quality (e.g., dietary logs) to improve accuracy.

5. References

- ✓ Zellner, A. (1986). On assessing prior distributions and Bayesian regression analysis.Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti,389–399.
- ✓ Liang, F., Paulo, R., Molina, G., Clyde, M. A., & Berger, J. O. (2008). Mixtures of g priors for Bayesian variable selection. Journal of the American Statistical Association, 103(481), 410–423.
- ✓ Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: A tutorial. Statistical Science, 14(4), 382–417.
- ✓ R Core Team. (2024). R: A language and environment for statistical computing (Version 4.x). R Foundation for Statistical Computing. https://www.R-project.org/

6. Appendices

- Dataset : https://www.kaggle.com/datasets/jayaantanaath/student-habits-vs-academic-performance

- R Codes :

STA4063 - Bayesian Statistics Project R codes

Thilina Pathirana

2025-08-28

Data & Preprocessing

##Load the data set.

```
studentHabitsPerformance <- read.csv("student_habits_performance.csv", hea
der = TRUE)
```

##Head of the data set.

```
head(studentHabitsPerformance)

##   student_id age gender study_hours_per_day social_media_hours netflix_
hours
## 1      S1000  23 Female                 0.0                1.2
1.1
## 2      S1001  20 Female                 6.9                2.8
2.3
## 3      S1002  21   Male                 1.4                3.1
1.3
## 4      S1003  23 Female                 1.0                3.9
```

```
1.0
## 5      S1004  19 Female                 5.0                4.4
0.5
## 6      S1005  24   Male                 7.2                1.3
0.0
##   part_time_job attendance_percentage sleep_hours diet_quality
## 1            No                  85.0         8.0         Fair
## 2            No                  97.3         4.6         Good
## 3            No                  94.8         8.0         Poor
## 4            No                  71.0         9.2         Poor
## 5            No                  90.9         4.9         Fair
## 6            No                  82.9         7.4         Fair
##   exercise_frequency parental_education_level internet_quality
## 1                  6                   Master          Average
## 2                  6              High School          Average
## 3                  1              High School             Poor
## 4                  4                   Master             Good
## 5                  3                   Master             Good
## 6                  1                   Master          Average
##   mental_health_rating extracurricular_participation exam_score
## 1                    8                           Yes       56.2
## 2                    8                            No      100.0
## 3                    1                            No       34.3
## 4                    1                           Yes       26.8
## 5                    1                            No       66.4
## 6                    4                            No      100.0
```

##Structure of the variables

```
str(studentHabitsPerformance)

## 'data.frame':    1000 obs. of  16 variables:
##  $ student_id                   : chr  "S1000" "S1001" "S1002" "S1003"
...
##  $ age                          : int  23 20 21 23 19 24 21 21 23 18 ..
.
##  $ gender                       : chr  "Female" "Female" "Male" "Female
" ...
##  $ study_hours_per_day          : num  0 6.9 1.4 1 5 7.2 5.6 4.3 4.4 4.
8 ...
##  $ social_media_hours           : num  1.2 2.8 3.1 3.9 4.4 1.3 1.5 1 2.
2 3.1 ...
##  $ netflix_hours                : num  1.1 2.3 1.3 1 0.5 0 1.4 2 1.7 1.
3 ...
##  $ part_time_job                : chr  "No" "No" "No" "No" ...
##  $ attendance_percentage        : num  85 97.3 94.8 71 90.9 82.9 85.8 7
7.7 100 95.4 ...
##  $ sleep_hours                  : num  8 4.6 8 9.2 4.9 7.4 6.5 4.6 7.1
7.5 ...
##  $ diet_quality                 : chr  "Fair" "Good" "Poor" "Poor" ...
##  $ exercise_frequency           : int  6 6 1 4 3 1 2 0 3 5 ...
##  $ parental_education_level     : chr  "Master" "High School" "High Sch
ool" "Master" ...
##  $ internet_quality             : chr  "Average" "Average" "Poor" "Good
```

```
" ...
##  $ mental_health_rating         : int  8 8 1 1 1 4 4 8 1 10 ...
##  $ extracurricular_participation: chr  "Yes" "No" "No" "Yes" ...
##  $ exam_score                   : num  56.2 100 34.3 26.8 66.4 100 89.8
72.6 78.9 100 ...
```

##Data Preprocessing

##Encode nominal and ordinal categorical variables

```
studentHabitsPerformance$part_time_job <- as.numeric(as.factor(studentHabi
tsPerformance$part_time_job))
studentHabitsPerformance$extracurricular_participation <- as.numeric(as.fa
ctor(studentHabitsPerformance$extracurricular_participation))
studentHabitsPerformance$gender <- as.numeric(ifelse(studentHabitsPerforma
nce$gender == "Male", 0, ifelse(studentHabitsPerformance$gender == "Female
", 1, 2)))
studentHabitsPerformance$diet_quality <- as.numeric(ifelse(studentHabitsPe
rformance$diet_quality == "Poor", 0,
                         ifelse(studentHabitsPerformance$diet_quality == "
Fair", 1, 2)))
studentHabitsPerformance$parental_education_level <- as.numeric(ifelse(stu
dentHabitsPerformance$parental_education_level == "None", 0,
                                                                       ife
lse(studentHabitsPerformance$parental_education_level == "High School", 1,
                                                                       ife
lse(studentHabitsPerformance$parental_education_level == "Bachelor", 2, 3)
)))
studentHabitsPerformance$internet_quality <- as.numeric(ifelse(studentHabi
tsPerformance$internet_quality == "Poor", 0,
                         ifelse(studentHabitsPerformance$internet_quality
== "Average", 1, 2)))
```

##Structure of the encoded and other variables

```
str(studentHabitsPerformance)

## 'data.frame':    1000 obs. of  16 variables:
##  $ student_id                   : chr  "S1000" "S1001" "S1002" "S1003"
...
##  $ age                          : int  23 20 21 23 19 24 21 21 23 18 ..
.
##  $ gender                       : num  1 1 0 1 1 0 1 1 1 1 ...
##  $ study_hours_per_day          : num  0 6.9 1.4 1 5 7.2 5.6 4.3 4.4 4.
8 ...
##  $ social_media_hours           : num  1.2 2.8 3.1 3.9 4.4 1.3 1.5 1 2.
2 3.1 ...
##  $ netflix_hours                : num  1.1 2.3 1.3 1 0.5 0 1.4 2 1.7 1.
3 ...
##  $ part_time_job                : num  1 1 1 1 1 1 2 2 1 1 ...
##  $ attendance_percentage        : num  85 97.3 94.8 71 90.9 82.9 85.8 7
7.7 100 95.4 ...
##  $ sleep_hours                  : num  8 4.6 8 9.2 4.9 7.4 6.5 4.6 7.1
7.5 ...
##  $ diet_quality                 : num  1 2 0 0 1 1 2 1 2 2 ...
```

```
## $ exercise_frequency          : int  6 6 1 4 3 1 2 0 3 5 ...
## $ parental_education_level    : num  3 1 1 3 3 3 3 2 2 2 ...
## $ internet_quality            : num  1 1 0 2 2 1 0 1 2 2 ...
## $ mental_health_rating        : int  8 8 1 1 1 4 4 8 1 10 ...
## $ extracurricular_participation: num  2 1 1 2 1 1 1 1 1 2 ...
## $ exam_score                  : num  56.2 100 34.3 26.8 66.4 100 89.8
72.6 78.9 100 ...
```

##Remove Identifiers and take all the numerical variables as a new data frame HabitsPerformanceData.

```
HabitsPerformanceData <- cbind(studentHabitsPerformance$age,studentHabitsP
erformance$gender, studentHabitsPerformance$study_hours_per_day, studentHa
bitsPerformance$social_media_hours, studentHabitsPerformance$netflix_hours
,studentHabitsPerformance$part_time_job,  studentHabitsPerformance$attenda
nce_percentage, studentHabitsPerformance$sleep_hours , studentHabitsPerfor
mance$diet_quality, studentHabitsPerformance$exercise_frequency, studentHa
bitsPerformance$parental_education_level , studentHabitsPerformance$intern
et_quality, studentHabitsPerformance$mental_health_rating, studentHabitsPe
rformance$extracurricular_participation, studentHabitsPerformance$exam_sco
re)

HabitsPerformanceData <- data.frame(HabitsPerformanceData)
```

##Rename the columns of the new data set.

```
names(HabitsPerformanceData) <- c("age","gender", "studyHours", "socialMed
iaHours", "netflixHours","parttimeJob", "attendance", "sleepHours", "diet"
,"exerciseFreq", "parentalEducation", "internet", "mentalHealth", "extracu
rricular", "examScore")
```

##Head of the new data set

```
head(HabitsPerformanceData)

##   age gender studyHours socialMediaHours netflixHours parttimeJob atten
dance
## 1  23      1        0.0              1.2          1.1           1
85.0
## 2  20      1        6.9              2.8          2.3           1
97.3
## 3  21      0        1.4              3.1          1.3           1
94.8
## 4  23      1        1.0              3.9          1.0           1
71.0
## 5  19      1        5.0              4.4          0.5           1
90.9
## 6  24      0        7.2              1.3          0.0           1
82.9
##   sleepHours diet exerciseFreq parentalEducation internet mentalHealth
## 1        8.0    1            6                 3        1            8
## 2        4.6    2            6                 1        1            8
## 3        8.0    0            1                 1        0            1
## 4        9.2    0            4                 3        2            1
## 5        4.9    1            3                 3        2            1
```

```
## 6        7.4    1            1                 3        1            4
##   extracurricular examScore
## 1               2      56.2
## 2               1     100.0
## 3               1      34.3
## 4               2      26.8
## 5               1      66.4
## 6               1     100.0
```

##Check whether, are there any missing observations in the new data frame.

```
sum(is.na(HabitsPerformanceData) == TRUE)

## [1] 0
```

##Get the summary output of the variables.

```
summary(HabitsPerformanceData)

##       age            gender        studyHours   socialMediaHours
##  Min.   :17.00   Min.   :0.000   Min.   :0.00   Min.   :0.000  
##  1st Qu.:18.75   1st Qu.:0.000   1st Qu.:2.60   1st Qu.:1.700  
##  Median :20.00   Median :1.000   Median :3.50   Median :2.500  
##  Mean   :20.50   Mean   :0.565   Mean   :3.55   Mean   :2.506  
##  3rd Qu.:23.00   3rd Qu.:1.000   3rd Qu.:4.50   3rd Qu.:3.300  
##  Max.   :24.00   Max.   :2.000   Max.   :8.30   Max.   :7.200  
##   netflixHours    parttimeJob      attendance        sleepHours   
##  Min.   :0.000   Min.   :1.000   Min.   : 56.00   Min.   : 3.20  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.: 78.00   1st Qu.: 5.60  
##  Median :1.800   Median :1.000   Median : 84.40   Median : 6.50  
##  Mean   :1.820   Mean   :1.215   Mean   : 84.13   Mean   : 6.47  
##  3rd Qu.:2.525   3rd Qu.:1.000   3rd Qu.: 91.03   3rd Qu.: 7.30  
##  Max.   :5.400   Max.   :2.000   Max.   :100.00   Max.   :10.00  
##       diet        exerciseFreq    parentalEducation    internet    
##  Min.   :0.000   Min.   :0.000   Min.   :0.000     Min.   :0.000  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000     1st Qu.:1.000  
##  Median :1.000   Median :3.000   Median :2.000     Median :1.000  
##  Mean   :1.193   Mean   :3.042   Mean   :1.593     Mean   :1.285  
##  3rd Qu.:2.000   3rd Qu.:5.000   3rd Qu.:2.000     3rd Qu.:2.000  
##  Max.   :2.000   Max.   :6.000   Max.   :3.000     Max.   :2.000  
##   mentalHealth    extracurricular   examScore     
##  Min.   : 1.000   Min.   :1.000   Min.   : 18.40  
##  1st Qu.: 3.000   1st Qu.:1.000   1st Qu.: 58.48  
##  Median : 5.000   Median :1.000   Median : 70.50  
##  Mean   : 5.438   Mean   :1.318   Mean   : 69.60  
##  3rd Qu.: 8.000   3rd Qu.:2.000   3rd Qu.: 81.33  
##  Max.   :10.000   Max.   :2.000   Max.   :100.00
```

##Standard deviations of each variable.

```
st_devs <- c(sd(HabitsPerformanceData$age), sd(HabitsPerformanceData$gende
r), sd(HabitsPerformanceData$studyHours), sd(HabitsPerformanceData$socialM
ediaHours), sd(HabitsPerformanceData$netflixHours), sd(HabitsPerformanceDa
ta$parttimeJob), sd(HabitsPerformanceData$attendance), sd(HabitsPerformanc
eData$sleepHours), sd(HabitsPerformanceData$diet), sd(HabitsPerformanceDat
```

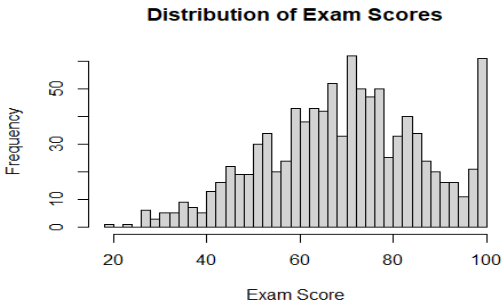
```
a$exerciseFreq), sd(HabitsPerformanceData$parentalEducation), sd(HabitsPer
formanceData$internet), sd(HabitsPerformanceData$mentalHealth), sd(HabitsP
erformanceData$extracurricular), sd(HabitsPerformanceData$examScore))

st_devs

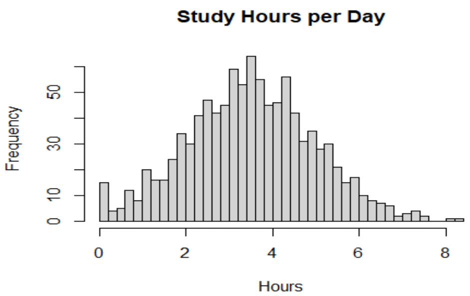
##  [1]  2.3080995  0.5745477  1.4688899  1.1724224  1.0751176  0.4110279
##  [7]  9.3992463  1.2263768  0.7254497  2.0254230  0.8706946  0.7268448
## [13]  2.8475014  0.4659325 16.8885639
```

Exploratory Data Analysis (EDA)

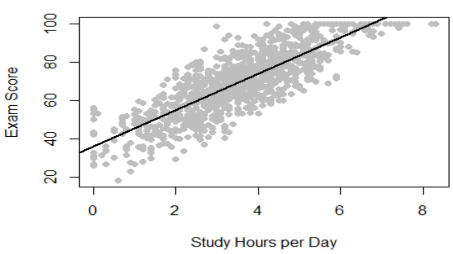
```
# Histograms
hist(HabitsPerformanceData$examScore, breaks = 30, main = "Distribution of
Exam Scores", xlab = "Exam Score")
```



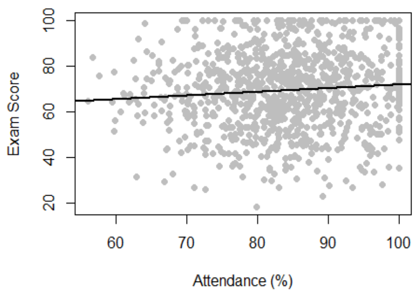

```
hist(HabitsPerformanceData$studyHours, breaks = 30, main = "Study Hours pe
r Day", xlab = "Hours")
```



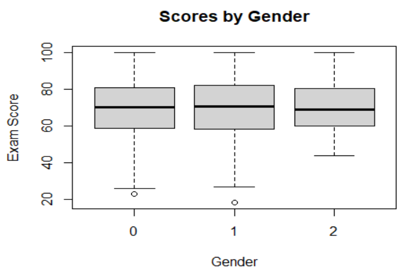

```
# Scatterplots with simple linear fit lines
plot(HabitsPerformanceData$studyHours, HabitsPerformanceData$examScore,
     xlab = "Study Hours per Day", ylab = "Exam Score", pch = 19, col = "g
rey")
abline(lm(examScore ~ studyHours, data = HabitsPerformanceData), lwd = 2)
```



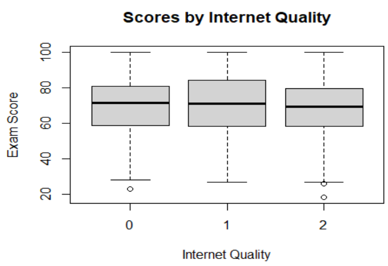
```r
plot(HabitsPerformanceData$attendance, HabitsPerformanceData$examScore,
     xlab = "Attendance (%)", ylab = "Exam Score", pch = 19, col = "grey")
abline(lm(examScore ~ attendance, data = HabitsPerformanceData), lwd = 2)
```




```r
# Boxplots by categories
boxplot(examScore ~ gender, data = HabitsPerformanceData, main = "Scores b
y Gender", xlab = "Gender", ylab = "Exam Score")
```



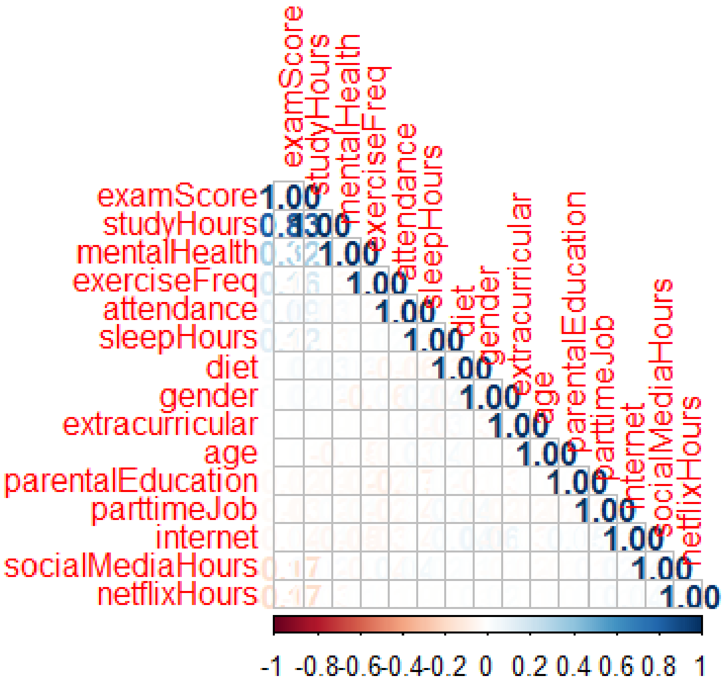

```r
boxplot(examScore ~ internet, data = HabitsPerformanceData, main = "Scores
by Internet Quality", xlab = "Internet Quality", ylab = "Exam Score")
```



Correlation & multicollinearity

##Correlation Coefficient

```r
library(corrplot)

## corrplot 0.95 loaded

corrplot(corr = cor(HabitsPerformanceData), method = "number" , order = 'F
PC', type = 'lower')
```




```
cor(HabitsPerformanceData)

##                            age       gender   studyHours socialMediaHou
rs
## age                1.000000000 -0.016885730  0.003971179    -0.0091511
99
## gender            -0.016885730  1.000000000  0.025374704     0.0097965
78
## studyHours         0.003971179  0.025374704  1.000000000     0.0202823
14
## socialMediaHours  -0.009151199  0.009796578  0.020282314     1.0000000
00
## netflixHours      -0.001174104  0.015345445 -0.031158347     0.0114765
64
## parttimeJob       -0.011680362 -0.023207117 -0.029132837     0.0212238
29
## attendance        -0.026055201  0.020554447  0.026264118     0.0404787
92
## sleepHours         0.037481916  0.041047303 -0.027757114     0.0182362
60
## diet               0.004116610 -0.033730504  0.033376571     0.0113436
43
## exerciseFreq      -0.003836236 -0.062561369 -0.028701192    -0.0373190
03
## parentalEducation  0.003330278 -0.032105708 -0.012686554    -0.0143768
24
## internet           0.007798551  0.062261888  0.014458732     0.0368047
42
## mentalHealth      -0.045101361  0.006442773 -0.003767826     0.0014964
91
## extracurricular   -0.004992818  0.008712470 -0.003264206    -0.0185973
```

```
32
## examScore         -0.008906872  0.016005692  0.825418509     -0.1667328
85
##                    netflixHours  parttimeJob   attendance    sleepHours
## age               -0.0011741040 -0.011680362 -0.026055201  0.0374819156
## gender             0.0153454448 -0.023207117  0.020554447  0.0410473031
## studyHours        -0.0311583466 -0.029132837  0.026264118 -0.0277571140
## socialMediaHours   0.0114765638  0.021223829  0.040478792  0.0182362596
## netflixHours       1.0000000000  0.009206920 -0.002091540 -0.0009345491
## parttimeJob        0.0092069199  1.000000000 -0.041771201  0.0016452496
## attendance        -0.0020915397 -0.041771201  1.000000000  0.0137560647
## sleepHours        -0.0009345491  0.001645250  0.013756065  1.0000000000
## diet              -0.0098850847  0.035265654 -0.058620993 -0.0347995298
## exerciseFreq      -0.0064482222 -0.021679197 -0.007857196  0.0197690236
## parentalEducation  0.0022647389 -0.023760782 -0.072177168  0.0192463551
## internet           0.0395632104  0.009130363 -0.039902718  0.0020454935
## mentalHealth       0.0080342346  0.013538800 -0.018744560 -0.0065079649
## extracurricular   -0.0051247795 -0.022841343 -0.017778281  0.0276930005
## examScore         -0.1717792385 -0.026608464  0.089835602  0.1216829106
##                           diet  exerciseFreq parentalEducation     inte
rnet
## age                0.004116610 -0.0038362359       0.003330278  0.00779
8551
## gender            -0.033730504 -0.0625613686      -0.032105708  0.06226
1888
## studyHours         0.033376571 -0.0287011920      -0.012686554  0.01445
8732
## socialMediaHours   0.011343643 -0.0373190028      -0.014376824  0.03680
4742
## netflixHours      -0.009885085 -0.0064482222       0.002264739  0.03956
3210
## parttimeJob        0.035265654 -0.0216791967      -0.023760782  0.00913
0363
## attendance        -0.058620993 -0.0078571964      -0.072177168 -0.03990
2718
## sleepHours        -0.034799530  0.0197690236       0.019246355  0.00204
5494
## diet               1.000000000  0.0053778488      -0.008635314  0.03795
8317
## exerciseFreq       0.005377849  1.0000000000      -0.023786422 -0.03465
7062
## parentalEducation -0.008635314 -0.0237864223       1.000000000  0.04586
1695
## internet           0.037958317 -0.0346570621       0.045861695  1.00000
0000
## mentalHealth       0.027362154 -0.0002422927      -0.022905940 -0.04828
2525
## extracurricular   -0.030722068 -0.0056811511      -0.003883742 -0.03141
9778
## examScore          0.015017747  0.1601074644      -0.021129195 -0.03629
8155
##                    mentalHealth extracurricular     examScore
## age               -0.0451013606   -0.0049928182 -0.0089068719
## gender             0.0064427728    0.0087124703  0.0160056917
```

```
## studyHours        -0.0037678263   -0.0032642058  0.8254185094
## socialMediaHours   0.0014964907   -0.0185973321 -0.1667328851
## netflixHours       0.0080342346   -0.0051247795 -0.1717792385
## parttimeJob        0.0135387998   -0.0228413428 -0.0266084640
## attendance        -0.0187445601   -0.0177782811  0.0898356018
## sleepHours        -0.0065079649    0.0276930005  0.1216829106
## diet               0.0273621537   -0.0307220678  0.0150177475
## exerciseFreq      -0.0002422927   -0.0056811511  0.1601074644
## parentalEducation -0.0229059396   -0.0038837421 -0.0211291951
## internet          -0.0482825248   -0.0314197778 -0.0362981551
## mentalHealth       1.0000000000   -0.0047411505  0.3215229307
## extracurricular   -0.0047411505    1.0000000000  0.0008806698
## examScore          0.3215229307    0.0008806698  1.0000000000
```

##Bayesian Analysis

Fit appropriate Bayesian models

##Model 1: Non-informative Priors

```
library(BAS)

model_noninform <- bas.lm(
  formula = examScore ~ . ,
  data = HabitsPerformanceData,
  prior = "g-prior",         # approximates non-informative prior
  modelprior = uniform(),    # all models equally likely
  method = "BAS",            # Bayesian Adaptive Sampling
  MCMC.iterations = 10000    # optional
)

summary(model_noninform)

##                   P(B != 0 | Y)   model 1       model 2      model 3
## Intercept            1.00000000    1.0000 1.000000e+00    1.0000000
## age                  0.03118669    0.0000 0.000000e+00    0.0000000
## gender               0.03064390    0.0000 0.000000e+00    0.0000000
## studyHours           1.00000000    1.0000 1.000000e+00    1.0000000
## socialMediaHours     1.00000000    1.0000 1.000000e+00    1.0000000
## netflixHours         1.00000000    1.0000 1.000000e+00    1.0000000
## parttimeJob          0.03516870    0.0000 0.000000e+00    0.0000000
## attendance           1.00000000    1.0000 1.000000e+00    1.0000000
## sleepHours           1.00000000    1.0000 1.000000e+00    1.0000000
## diet                 0.06321724    0.0000 1.000000e+00    0.0000000
## exerciseFreq         1.00000000    1.0000 1.000000e+00    1.0000000
## parentalEducation    0.03115783    0.0000 0.000000e+00    0.0000000
## internet             0.05540887    0.0000 0.000000e+00    1.0000000
## mentalHealth         1.00000000    1.0000 1.000000e+00    1.0000000
## extracurricular      0.03069762    0.0000 0.000000e+00    0.0000000
## BF                           NA    1.0000 6.760384e-02    0.0587999
## PostProbs                    NA    0.7529 5.090000e-02    0.0443000
## R2                           NA    0.9011 9.012000e-01    0.9012000
## dim                          NA    8.0000 9.000000e+00    9.0000000
## logmarg                      NA 1126.8143 1.124120e+03 1123.9807288
```

```
##                         model 4      model 5
## Intercept         1.000000e+00 1.000000e+00
## age               0.000000e+00 1.000000e+00
## gender            0.000000e+00 0.000000e+00
## studyHours        1.000000e+00 1.000000e+00
## socialMediaHours  1.000000e+00 1.000000e+00
## netflixHours      1.000000e+00 1.000000e+00
## parttimeJob       1.000000e+00 0.000000e+00
## attendance        1.000000e+00 1.000000e+00
## sleepHours        1.000000e+00 1.000000e+00
## diet              0.000000e+00 0.000000e+00
## exerciseFreq      1.000000e+00 1.000000e+00
## parentalEducation 0.000000e+00 0.000000e+00
## internet          0.000000e+00 0.000000e+00
## mentalHealth      1.000000e+00 1.000000e+00
## extracurricular   0.000000e+00 0.000000e+00
## BF                3.638702e-02 3.219593e-02
## PostProbs         2.740000e-02 2.420000e-02
## R2                9.011000e-01 9.011000e-01
## dim               9.000000e+00 9.000000e+00
## logmarg           1.123501e+03 1.123378e+03
```

##Model 2: Informative Priors

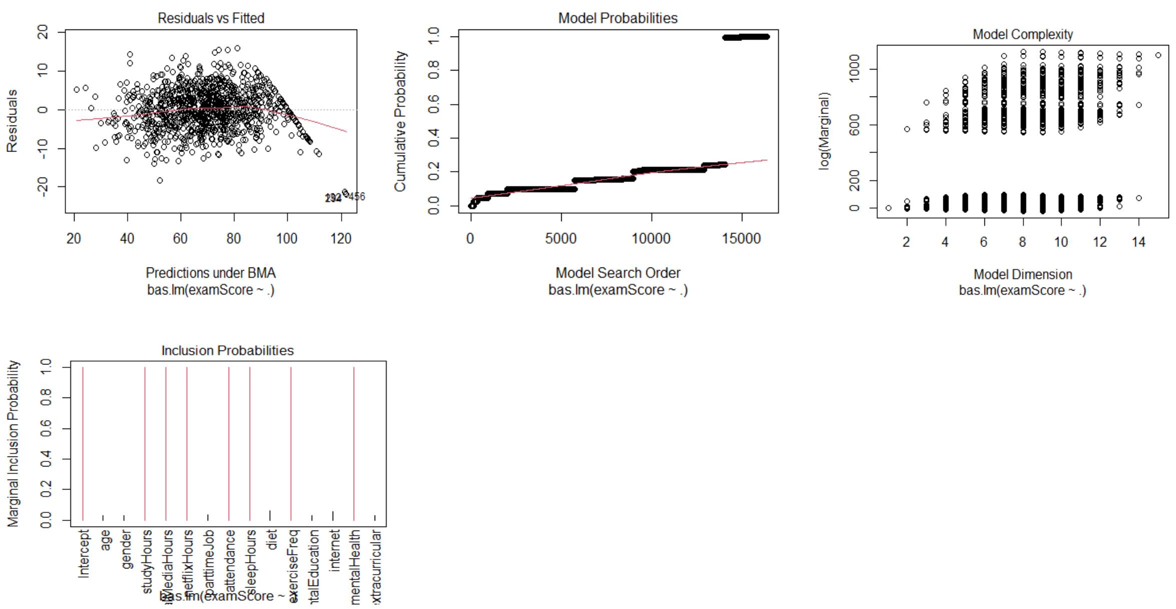
```
model_weak <- bas.lm(
  formula = examScore ~ . ,
  data = HabitsPerformanceData,
  prior = "ZS-null",         # Zellner-Siow Cauchy-like prior for mild shr
inkage
  modelprior = uniform(),    # all models equally likely
  method = "BAS",
  MCMC.iterations = 10000
)
summary(model_weak)
```

```
##                   P(B != 0 | Y)  model 1      model 2      model 3
## Intercept            1.00000000   1.0000 1.000000e+00 1.000000e+00
## age                  0.02813477   0.0000 0.000000e+00 0.000000e+00
## gender               0.02764352   0.0000 0.000000e+00 0.000000e+00
## studyHours           1.00000000   1.0000 1.000000e+00 1.000000e+00
## socialMediaHours     1.00000000   1.0000 1.000000e+00 1.000000e+00
## netflixHours         1.00000000   1.0000 1.000000e+00 1.000000e+00
## parttimeJob          0.03173350   0.0000 0.000000e+00 0.000000e+00
## attendance           1.00000000   1.0000 1.000000e+00 1.000000e+00
## sleepHours           1.00000000   1.0000 1.000000e+00 1.000000e+00
## diet                 0.05716285   0.0000 1.000000e+00 0.000000e+00
## exerciseFreq         1.00000000   1.0000 1.000000e+00 1.000000e+00
## parentalEducation    0.02810779   0.0000 0.000000e+00 0.000000e+00
## internet             0.05007748   0.0000 0.000000e+00 1.000000e+00
## mentalHealth         1.00000000   1.0000 1.000000e+00 1.000000e+00
## extracurricular      0.02769191   0.0000 0.000000e+00 0.000000e+00
## BF                           NA   1.0000 6.004999e-02 5.222226e-02
## PostProbs                    NA   0.7756 4.660000e-02 4.050000e-02
## R2                           NA   0.9011 9.012000e-01 9.012000e-01
```

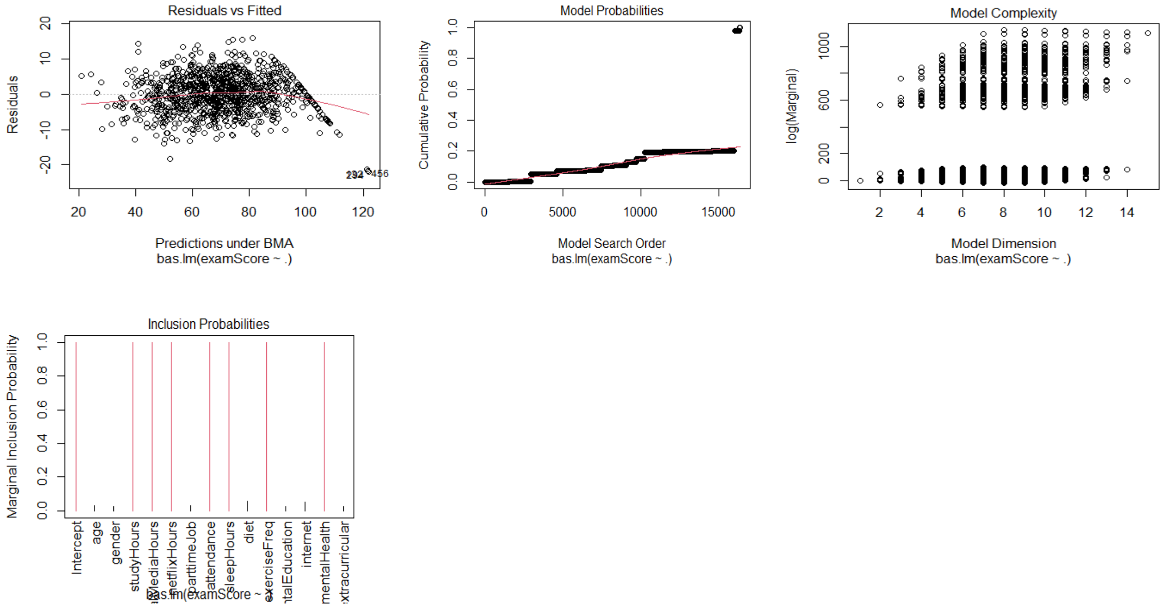
```
## dim                            NA    8.0000 9.000000e+00 9.000000e+00
## logmarg                        NA 1125.5152 1.122703e+03 1.122563e+03
##                         model 4      model 5
## Intercept             1.0000000 1.000000e+00
## age                   0.0000000 1.000000e+00
## gender                0.0000000 0.000000e+00
## studyHours            1.0000000 1.000000e+00
## socialMediaHours      1.0000000 1.000000e+00
## netflixHours          1.0000000 1.000000e+00
## parttimeJob           1.0000000 0.000000e+00
## attendance            1.0000000 1.000000e+00
## sleepHours            1.0000000 1.000000e+00
## diet                  0.0000000 0.000000e+00
## exerciseFreq          1.0000000 1.000000e+00
## parentalEducation     0.0000000 0.000000e+00
## internet              0.0000000 0.000000e+00
## mentalHealth          1.0000000 1.000000e+00
## extracurricular       0.0000000 0.000000e+00
## BF                    0.0323007 2.857671e-02
## PostProbs             0.0251000 2.220000e-02
## R2                    0.9011000 9.011000e-01
## dim                   9.0000000 9.000000e+00
## logmarg            1122.0825448 1.121960e+03
```

##Model Comparison and Selection

```
plot(model_noninform)
```




```
plot(model_weak)
```



##Posterior Summaries

Non-informative prior

```
coef_noninform <- coef(model_noninform)   # Extract posterior mean, SD
print(coef_noninform)

##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  BMA
##
##  Based on the top  16384 models
##                     post mean   post SD     post p(B != 0)
## Intercept           6.960e+01   1.686e-01   1.000e+00
## age                -4.370e-04   1.316e-02   3.119e-02
## gender              4.016e-05   5.159e-02   3.064e-02
## studyHours          9.565e+00   1.150e-01   1.000e+00
## socialMediaHours   -2.617e+00   1.441e-01   1.000e+00
## netflixHours       -2.275e+00   1.569e-01   1.000e+00
## parttimeJob         7.723e-03   8.706e-02   3.517e-02
## attendance          1.445e-01   1.797e-02   1.000e+00
## sleepHours          2.002e+00   1.376e-01   1.000e+00
## diet               -1.817e-02   9.125e-02   6.322e-02
## exerciseFreq        1.450e+00   8.335e-02   1.000e+00
## parentalEducation   1.126e-03   3.489e-02   3.116e-02
## internet           -1.436e-02   8.076e-02   5.541e-02
## mentalHealth        1.947e+00   5.923e-02   1.000e+00
## extracurricular    -6.875e-04   6.360e-02   3.070e-02
```

Weak-informative prior

```
coef_weak <- coef(model_weak)
print(coef_weak)
```

```
##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  BMA
##
##  Based on the top  16384 models
##                     post mean   post SD     post p(B != 0)
## Intercept            6.960e+01   1.686e-01   1.000e+00
## age                 -3.944e-04   1.250e-02   2.813e-02
## gender               3.554e-05   4.900e-02   2.764e-02
## studyHours           9.567e+00   1.150e-01   1.000e+00
## socialMediaHours    -2.617e+00   1.441e-01   1.000e+00
## netflixHours        -2.275e+00   1.569e-01   1.000e+00
## parttimeJob          6.967e-03   8.273e-02   3.173e-02
## attendance           1.445e-01   1.797e-02   1.000e+00
## sleepHours           2.003e+00   1.376e-01   1.000e+00
## diet                -1.643e-02   8.694e-02   5.716e-02
## exerciseFreq         1.451e+00   8.336e-02   1.000e+00
## parentalEducation    1.016e-03   3.314e-02   2.811e-02
## internet            -1.298e-02   7.691e-02   5.008e-02
## mentalHealth         1.947e+00   5.923e-02   1.000e+00
## extracurricular     -6.183e-04   6.041e-02   2.769e-02
```

WAIC/DIC Calculation for BAS Models

```
## Model Comparison using BAS
# Calculate log marginal likelihoods for model comparison
log_marginals <- c(model_noninform$logmarg[which.max(model_noninform$logma
rg)],
                   model_weak$logmarg[which.max(model_weak$logmarg)])

# Approximate Bayes Factor (using log marginal likelihoods)
bf <- exp(log_marginals[1] - log_marginals[2])
cat("Bayes Factor (Non-informative vs Weak):", round(bf, 3), "\n")

## Bayes Factor (Non-informative vs Weak): 3.666

# Model probabilities
cat("Model probabilities:\n")

## Model probabilities:

cat("Non-informative prior model:", round(exp(log_marginals[1])/sum(exp(lo
g_marginals)), 3), "\n")

## Non-informative prior model: NaN

cat("Weak prior model:", round(exp(log_marginals[2])/sum(exp(log_marginals
)), 3), "\n")

## Weak prior model: NaN
```

##Model Diagnostics Section

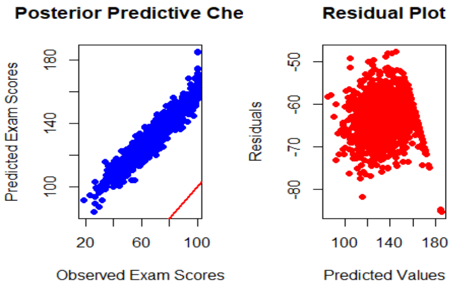
```
# Check variable inclusion probabilities
cat("\nVariable Inclusion Probabilities (Non-informative prior):\n")
```

```
##
## Variable Inclusion Probabilities (Non-informative prior):

print(model_noninform$probne0[-1])  # exclude intercept

##  [1] 0.03118669 0.03064390 1.00000000 1.00000000 1.00000000 0.03516870
##  [7] 1.00000000 1.00000000 0.06321724 1.00000000 0.03115783 0.05540887
## [13] 1.00000000 0.03069762

cat("\nVariable Inclusion Probabilities (Weak prior):\n")

##
## Variable Inclusion Probabilities (Weak prior):

print(model_weak$probne0[-1])

##  [1] 0.02813477 0.02764352 1.00000000 1.00000000 1.00000000 0.03173350
##  [7] 1.00000000 1.00000000 0.05716285 1.00000000 0.02810779 0.05007748
## [13] 1.00000000 0.02769191

# Check model size distribution
cat("\nModel Size Distribution:\n")

##
## Model Size Distribution:

table(model_noninform$size)

##
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14
15
##    1   14   91  364 1001 2002 3003 3432 3003 2002 1001  364   91   14
1
```

##Posterior Predictive Checks

```
## Posterior Predictive Checks - FIXED
# Simulate data from the best model and compare to observed
best_model_idx <- which.max(model_noninform$postprobs)
best_model_vars <- model_noninform$which[[best_model_idx]] + 1  # +1 to ac
count for intercept

# Extract the variables included in the best model (excluding intercept)
included_vars <- best_model_vars[-1] - 1  # -1 to adjust back to column in
dices
cat("Variables in best model:", colnames(HabitsPerformanceData)[included_v
ars], "\n")

## Variables in best model: studyHours socialMediaHours netflixHours atten
dance sleepHours exerciseFreq mentalHealth

# Create design matrix for the best model
if (length(included_vars) > 0) {
  X_best <- as.matrix(cbind(Intercept = 1, HabitsPerformanceData[, include
d_vars]))
} else {
  X_best <- matrix(1, nrow = nrow(HabitsPerformanceData), ncol = 1)  # Int
```

```
ercept only
}

# Get coefficient estimates - FIXED ACCESS METHOD
beta_hat <- model_noninform$mle[[best_model_idx]]  # This is already the c
oefficient vector
y_pred <- X_best %*% beta_hat

# Compare observed vs predicted
par(mfrow = c(1, 2))
plot(HabitsPerformanceData$examScore, y_pred,
     xlab = "Observed Exam Scores", ylab = "Predicted Exam Scores",
     main = "Posterior Predictive Check", pch = 19, col = "blue")
abline(0, 1, col = "red", lwd = 2)

# Residual plot
residuals <- HabitsPerformanceData$examScore - y_pred
plot(y_pred, residuals,
     xlab = "Predicted Values", ylab = "Residuals",
     main = "Residual Plot", pch = 19, col = "red")
abline(h = 0, col = "blue", lwd = 2)
```




```
# Add some diagnostic statistics
cat("\nPosterior Predictive Check Diagnostics:\n")

##
## Posterior Predictive Check Diagnostics:

cat("Mean Absolute Error:", mean(abs(residuals)), "\n")

## Mean Absolute Error: 63.44428

cat("Root Mean Squared Error:", sqrt(mean(residuals^2)), "\n")

## Root Mean Squared Error: 63.66605

cat("Correlation (Observed vs Predicted):", cor(HabitsPerformanceData$exam
Score, y_pred), "\n")

## Correlation (Observed vs Predicted): 0.9492476
```

##Formal Model Comparison Table

```
## ROBUST Model Comparison with Error Handling
model_comparison <- data.frame(
  Model = c("Non-informative Prior", "Weak Prior")
```

```r
)

# Safely extract values with error handling
safe_extract <- function(model, value_name) {
  tryCatch({
    if (value_name == "logmarg") {
      val <- max(model[[value_name]], na.rm = TRUE)
      if (is.infinite(val)) return(NA) else return(val)
    } else if (value_name == "BIC") {
      # Get BIC of the best model
      best_idx <- which.max(model$postprobs)
      return(model$BIC[best_idx])
    } else if (value_name == "size") {
      best_idx <- which.max(model$postprobs)
      return(model$size[best_idx])
    } else if (value_name == "postprob") {
      return(max(model$postprobs))
    }
  }, error = function(e) {
    return(NA)
  })
}

# Fill comparison table safely
model_comparison$Log_Marginal <- c(
  safe_extract(model_noninform, "logmarg"),
  safe_extract(model_weak, "logmarg")
)

model_comparison$BIC <- c(
  safe_extract(model_noninform, "BIC"),
  safe_extract(model_weak, "BIC")
)

model_comparison$Size <- c(
  safe_extract(model_noninform, "size"),
  safe_extract(model_weak, "size")
)

model_comparison$Posterior_Prob <- c(
  safe_extract(model_noninform, "postprob"),
  safe_extract(model_weak, "postprob")
)

cat("\n=== ROBUST MODEL COMPARISON TABLE ===\n")

##
## === ROBUST MODEL COMPARISON TABLE ===

print(model_comparison)

##                   Model Log_Marginal Size Posterior_Prob
## 1 Non-informative Prior     1126.814    8      0.7528962
## 2           Weak Prior      1125.515    8      0.7755590
```

```r
# Determine best model
if (!any(is.na(model_comparison$Log_Marginal))) {
  best_idx <- which.max(model_comparison$Log_Marginal)
  cat("\nBest model based on marginal likelihood:", model_comparison$Model
[best_idx], "\n")
} else if (!any(is.na(model_comparison$Posterior_Prob))) {
  best_idx <- which.max(model_comparison$Posterior_Prob)
  cat("\nBest model based on posterior probability:", model_comparison$Mod
el[best_idx], "\n")
} else if (!any(is.na(model_comparison$BIC))) {
  best_idx <- which.min(model_comparison$BIC)
  cat("\nBest model based on BIC:", model_comparison$Model[best_idx], "\n"
)
} else {
  cat("\nCannot determine best model due to missing values\n")
}

##
## Best model based on marginal likelihood: Non-informative Prior
```

##Frequentist linear regression(p-values and confidence intervals)

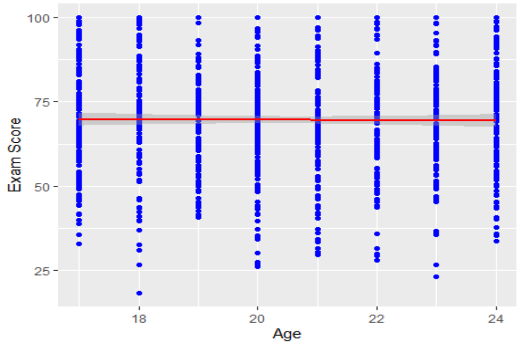
```r
lmScore <- lm(formula = examScore ~ . , data = HabitsPerformanceData)
summary(lmScore)

##
## Call:
## lm(formula = examScore ~ ., data = HabitsPerformanceData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.8035  -3.4559   0.0299   3.6161  15.5633
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          6.88566    2.64573   2.603  0.00939 **
## age                 -0.01275    0.07339  -0.174  0.86213
## gender               0.01441    0.29621   0.049  0.96121
## studyHours           9.58332    0.11542  83.027  < 2e-16 ***
## socialMediaHours    -2.61362    0.14460 -18.075  < 2e-16 ***
## netflixHours        -2.27304    0.15743 -14.438  < 2e-16 ***
## parttimeJob          0.23931    0.41256   0.580  0.56200
## attendance           0.14320    0.01813   7.900 7.41e-15 ***
## sleepHours           1.99976    0.13830  14.459  < 2e-16 ***
## diet                -0.28284    0.23427  -1.207  0.22760
## exerciseFreq         1.45125    0.08380  17.318  < 2e-16 ***
## parentalEducation    0.04525    0.19517   0.232  0.81669
## internet            -0.25407    0.23443  -1.084  0.27873
## mentalHealth         1.94698    0.05954  32.701  < 2e-16 ***
## extracurricular     -0.04210    0.36342  -0.116  0.90780
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.341 on 985 degrees of freedom
```

```
## Multiple R-squared:  0.9014, Adjusted R-squared:    0.9
## F-statistic: 643.1 on 14 and 985 DF,  p-value: < 2.2e-16
```

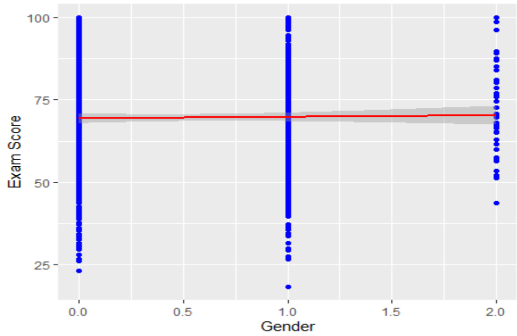
##The scatter plots and the fitted simple linear regression lines of the selected explanatory variables versus exam score variable

##Load ggplot2 library.

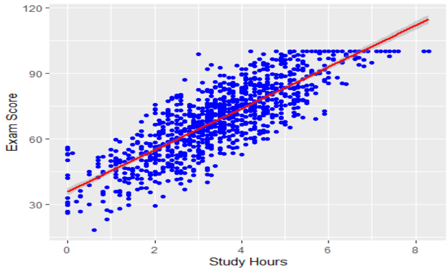
```
library(ggplot2)

scPlot1 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = age , y
= examScore)) + geom_point(color="blue") + xlab("Age") + ylab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot1

## `geom_smooth()` using formula = 'y ~ x'
```



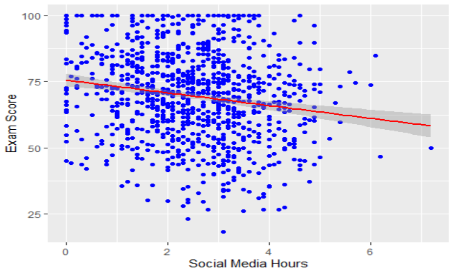

```
scPlot2 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = gender
, y = examScore)) + geom_point(color="blue") + xlab("Gender") + ylab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot2

## `geom_smooth()` using formula = 'y ~ x'
```



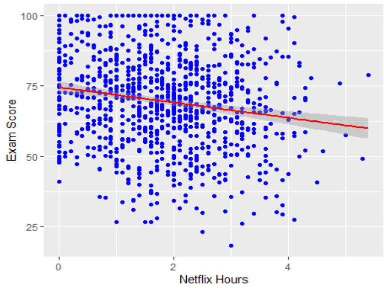

```
scPlot3 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = studyHo
urs , y = examScore)) + geom_point(color="blue") + xlab("Study Hours") + y
lab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot3

## `geom_smooth()` using formula = 'y ~ x'
```



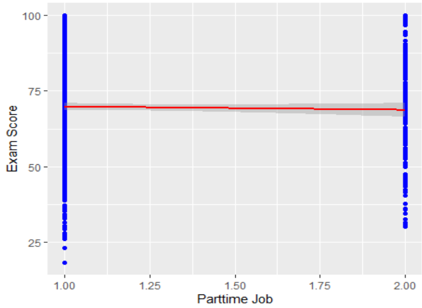

```
scPlot4 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = socialM
ediaHours , y = examScore)) + geom_point(color="blue") + xlab("Social Medi
a Hours") + ylab("Exam Score") + geom_smooth(method=lm, color="red")
scPlot4

## `geom_smooth()` using formula = 'y ~ x'
```



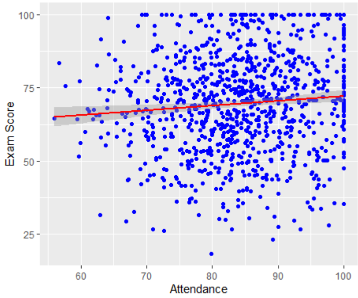

```
scPlot5 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = netflix
Hours , y = examScore)) + geom_point(color="blue") + xlab("Netflix Hours")
+ ylab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot5

## `geom_smooth()` using formula = 'y ~ x'
```



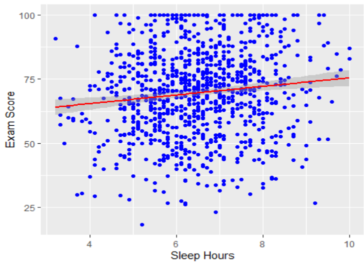

```
scPlot6 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = parttim
eJob , y = examScore)) + geom_point(color="blue") + xlab("Parttime Job") +
ylab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot6

## `geom_smooth()` using formula = 'y ~ x'
```



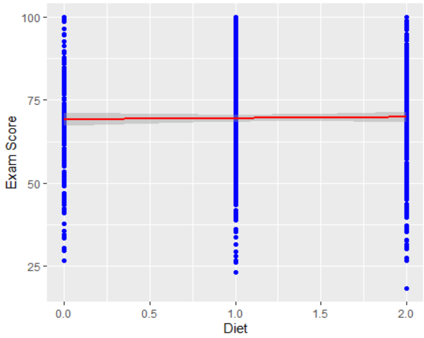

```
scPlot7 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = attenda
nce , y = examScore)) + geom_point(color="blue") + xlab("Attendance") + yl
ab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot7

## `geom_smooth()` using formula = 'y ~ x'
```



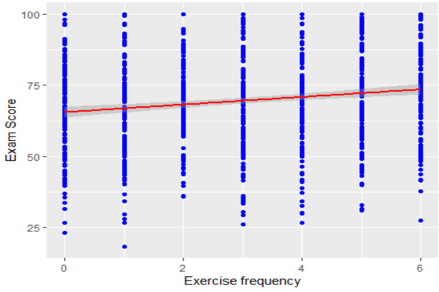

```
scPlot8 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = sleepHo
urs , y = examScore)) + geom_point(color="blue") + xlab("Sleep Hours") + y
lab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot8

## `geom_smooth()` using formula = 'y ~ x'
```



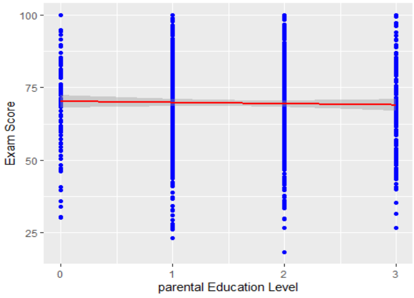

```
scPlot9 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = diet ,
y = examScore)) + geom_point(color="blue") + xlab("Diet") + ylab("
Exam Score") + geom_smooth(method=lm, color="red")
scPlot9

## `geom_smooth()` using formula = 'y ~ x'
```



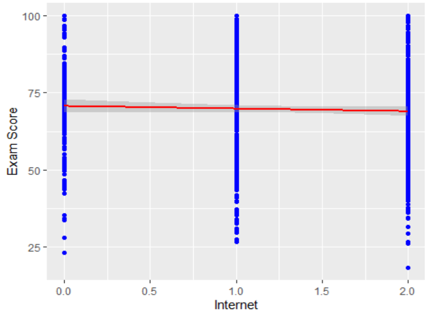

```
scPlot10 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = exerci
seFreq , y = examScore)) + geom_point(color="blue") + xlab("Exercise frequ
ency") + ylab("Exam Score") + geom_smooth(method=lm, color="red")
scPlot10

## `geom_smooth()` using formula = 'y ~ x'
```



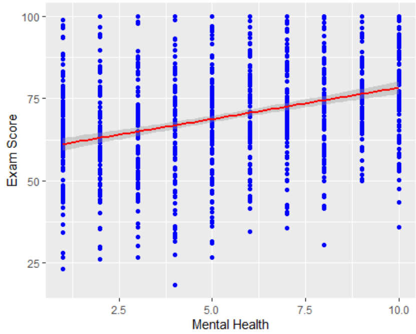

```
scPlot11 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = parent
alEducation , y = examScore)) + geom_point(color="blue") + xlab("parental
Education Level") + ylab("Exam Score") + geom_smooth(method=lm, color="red
")
scPlot11

## `geom_smooth()` using formula = 'y ~ x'
```



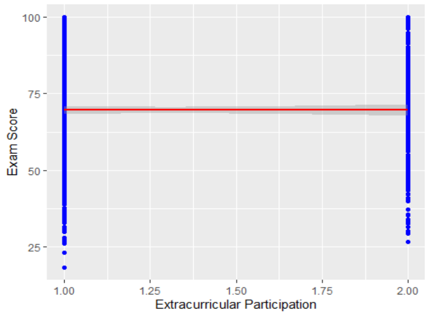

```
scPlot12 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = intern
et , y = examScore)) + geom_point(color="blue") + xlab("Internet") + ylab(
"Exam Score") + geom_smooth(method=lm, color="red")
scPlot12

## `geom_smooth()` using formula = 'y ~ x'
```




```
scPlot13 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = mental
Health , y = examScore)) + geom_point(color="blue") + xlab("Mental Health"
) + ylab("Exam Score") + geom_smooth(method=lm, color="red")
scPlot13

## `geom_smooth()` using formula = 'y ~ x'
```




```
scPlot14 <- ggplot(data = HabitsPerformanceData , mapping = aes(x = extrac
urricular , y = examScore)) + geom_point(color="blue") + xlab("Extracurric
ular Participation") + ylab("Exam Score") + geom_smooth(method=lm, color="
red")
scPlot14

## `geom_smooth()` using formula = 'y ~ x'
```



Bayesian Simple Linear Regression

We can also use the 'BAS' package to find the best BIC HabitsPerformanceData without taking the stepwise backward process.

##Load BAS Library

```
library(BAS)
```

##Get the summary output of the above HabitsPerformanceData.

```
score.lm1 <- bas.lm(formula = examScore ~ . , data = HabitsPerformanceData
, prior="BIC", modelprior=uniform())

# Coefficients averaged across models (Bayesian Model Averaging)
coef(score.lm1, estimator = "BMA")

##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  BMA
##
##  Based on the top  16384 models
##                      post mean   post SD     post p(B != 0)
## Intercept             6.960e+01   1.686e-01   1.000e+00
## age                  -4.378e-04   1.317e-02   3.121e-02
## gender                4.028e-05   5.163e-02   3.066e-02
## studyHours            9.575e+00   1.150e-01   1.000e+00
## socialMediaHours     -2.619e+00   1.442e-01   1.000e+00
## netflixHours         -2.277e+00   1.570e-01   1.000e+00
## parttimeJob           7.747e-03   8.721e-02   3.524e-02
## attendance            1.446e-01   1.798e-02   1.000e+00
## sleepHours            2.004e+00   1.377e-01   1.000e+00
## diet                 -1.834e-02   9.169e-02   6.375e-02
## exerciseFreq          1.452e+00   8.340e-02   1.000e+00
## parentalEducation     1.128e-03   3.492e-02   3.118e-02
## internet             -1.448e-02   8.110e-02   5.580e-02
## mentalHealth          1.949e+00   5.926e-02   1.000e+00
## extracurricular      -6.889e-04   6.365e-02   3.071e-02

# Coefficients from the single best model (highest posterior probability)
coef(score.lm1, estimator = "HPM")

##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  HPM
##
##  Based on the top  1 models
##                      post mean  post SD   post p(B != 0)
## Intercept            69.60150    0.16857   1.00000
## age                   0.00000    0.00000   0.03121
## gender                0.00000    0.00000   0.03066
## studyHours            9.57456    0.11503   1.00000
## socialMediaHours     -2.61978    0.14413   1.00000
## netflixHours         -2.27708    0.15697   1.00000
## parttimeJob           0.00000    0.00000   0.03524
## attendance            0.14473    0.01797   1.00000
## sleepHours            2.00462    0.13764   1.00000
## diet                  0.00000    0.00000   0.06375
## exerciseFreq          1.45187    0.08338   1.00000
## parentalEducation     0.00000    0.00000   0.03118
## internet              0.00000    0.00000   0.05580
```

```
## mentalHealth        1.94891    0.05924   1.00000
## extracurricular     0.00000    0.00000   0.03071
```

##Fit a simple linear regression HabitsPerformanceData of examScores versus studyHours.

```
score.lm1 <- lm(formula = examScore ~ studyHours , data = HabitsPerformanc
eData)
summary(score.lm1)

##
## Call:
## lm(formula = examScore ~ studyHours, data = HabitsPerformanceData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -25.979  -6.626   0.236   6.537  34.319
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  35.9102     0.7893   45.50   <2e-16 ***
## studyHours    9.4903     0.2055   46.19   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.539 on 998 degrees of freedom
## Multiple R-squared:  0.6813, Adjusted R-squared:  0.681
## F-statistic:  2134 on 1 and 998 DF,  p-value: < 2.2e-16
```

##Obtain residuals and n.(Residual analysis checks model accuracy and assumptions. A smaller MSE = better fit.)

```
resid <- residuals(score.lm1)
n <- length(resid)
n

## [1] 1000
```

##Calculate MSE

```
MSE <- 1/(n-2) * sum((resid ^ 2))
MSE

## [1] 90.98735
```

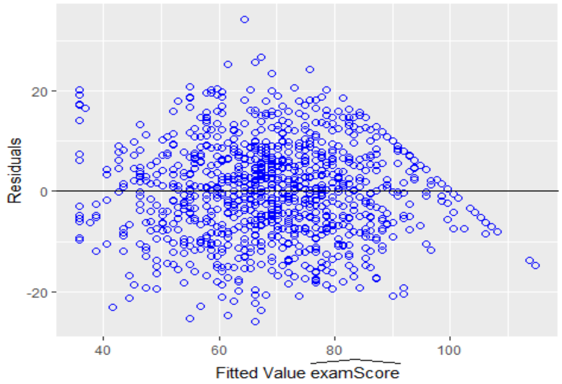
##Combine residuals and fitted values into a data frame.

```
result <- data.frame(fitted_values = fitted.values(score.lm1) , residuals
=   residuals(score.lm1))
```

##Load library and plot residuals versus fitted values.

```
library(ggplot2)
ggplot(data = result , aes(x = fitted_values , y = residuals)) + geom_poin
t(color = "blue" , pch = 1 , size = 2) + geom_abline(intercept = 0 , slope
```

```
= 0) + xlab(expression(paste("Fitted Value " , widehat(examScore)))) + yla
b("Residuals")
```



##Find the observation with the largest fitted value.

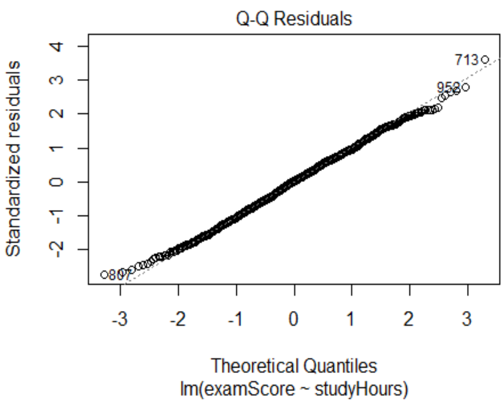
```
which.max(as.vector(fitted.values(score.lm1)))

## [1] 456

HabitsPerformanceData$studyHours[456] ##model predicts the highest study h
ours per day

## [1] 8.3
```

##Shows this observation has the maximum studyHours.

```
which.max(HabitsPerformanceData$studyHours)

## [1] 456

HabitsPerformanceData$studyHours[456] ##the highest actual study hours per
day

## [1] 8.3
```

##Normal probability plot of the residuals.(to check normality assumption)

```
plot(score.lm1, which = 2)
```



##Credible Intervals for Slope Beta and y-Intercept alpha.

```
output <- summary(score.lm1)$coef[, 1:2]
out <- cbind(output, confint(score.lm1))
colnames(out) <- c("Posterior Mean", "Posterior Std", "2.5", "97.5")
round(out, 3)

##             Posterior Mean Posterior Std    2.5   97.5
## (Intercept)          35.91         0.789 34.361 37.459
## studyHours            9.49         0.205  9.087  9.893

library(ggplot2)
```

##Construct current prediction.

```
alpha <- score.lm1$coefficients[1]
alpha

## (Intercept)
##    35.91016

beta <- score.lm1$coefficients[2]
beta

## studyHours
##    9.49025

new_x <- seq(min(HabitsPerformanceData$studyHours) , max(HabitsPerformance
Data$studyHours) , length.out = 100)
y_hat <- alpha + beta*new_x
```

##Get lower and upper bounds for mean.

```
ymean <- data.frame(predict(score.lm1 , newdata = data.frame(studyHours =
new_x) , interval = "confidence" , level = 0.95))
```

##Get lower and upper bounds for prediction.

```
ypred <- data.frame(predict(score.lm1 , newdata = data.frame(studyHours =
new_x) , interval = "prediction" , level = 0.95))

output <- data.frame(x = new_x ,
                     y_hat     = pmin(pmax(y_hat, 0), 100),
                     ymean_lwr = pmin(pmax(ymean$lwr, 0), 100),
                     ymean_upr = pmin(pmax(ymean$upr, 0), 100),
                     ypred_lwr = pmin(pmax(ypred$lwr, 0), 100),
                     ypred_upr = pmin(pmax(ypred$upr, 0), 100))
output

##              x    y_hat ymean_lwr ymean_upr ypred_lwr ypred_upr
## 1   0.00000000 35.91016  34.36128  37.45904  17.12792  54.69240
## 2   0.08383838 36.70581  35.18811  38.22351  17.92612  55.48550
## 3   0.16767677 37.50146  36.01482  38.98809  18.72425  56.27867
## 4   0.25151515 38.29710  36.84142  39.75279  19.52232  57.07189
## 5   0.33535354 39.09275  37.66788  40.51762  20.32033  57.86517
## 6   0.41919192 39.88840  38.49420  41.28260  21.11828  58.65852
## 7   0.50303030 40.68405  39.32038  42.04771  21.91617  59.45192
## 8   0.58686869 41.47969  40.14639  42.81299  22.71400  60.24538
## 9   0.67070707 42.27534  40.97224  43.57844  23.51177  61.03891
```

```
## 10  0.75454545  43.07099  41.79791  44.34406  24.30948  61.83250
## 11  0.83838384  43.86663  42.62338  45.10988  25.10713  62.62614
## 12  0.92222222  44.66228  43.44865  45.87591  25.90471  63.41985
## 13  1.00606061  45.45793  44.27369  46.64217  26.70224  64.21362
## 14  1.08989899  46.25358  45.09849  47.40866  27.49970  65.00745
## 15  1.17373737  47.04922  45.92303  48.17542  28.29711  65.80134
## 16  1.25757576  47.84487  46.74729  48.94245  29.09445  66.59529
## 17  1.34141414  48.64052  47.57125  49.70979  29.89174  67.38930
## 18  1.42525253  49.43617  48.39488  50.47745  30.68896  68.18337
## 19  1.50909091  50.23181  49.21815  51.24548  31.48612  68.97751
## 20  1.59292929  51.02746  50.04104  52.01388  32.28322  69.77170
## 21  1.67676768  51.82311  50.86351  52.78270  33.08026  70.56595
## 22  1.76060606  52.61875  51.68553  53.55198  33.87724  71.36027
## 23  1.84444444  53.41440  52.50706  54.32175  34.67416  72.15465
## 24  1.92828283  54.21005  53.32805  55.09205  35.47101  72.94908
## 25  2.01212121  55.00570  54.14845  55.86294  36.26781  73.74358
## 26  2.09595960  55.80134  54.96822  56.63446  37.06455  74.53814
## 27  2.17979798  56.59699  55.78730  57.40668  37.86122  75.33276
## 28  2.26363636  57.39264  56.60562  58.17965  38.65783  76.12744
## 29  2.34747475  58.18829  57.42312  58.95345  39.45439  76.92218
## 30  2.43131313  58.98393  58.23973  59.72813  40.25088  77.71699
## 31  2.51515152  59.77958  59.05537  60.50379  41.04731  78.51185
## 32  2.59898990  60.57523  59.86995  61.28051  41.84368  79.30678
## 33  2.68282828  61.37087  60.68339  62.05836  42.63999  80.10176
## 34  2.76666667  62.16652  61.49560  62.83745  43.43623  80.89681
## 35  2.85050505  62.96217  62.30648  63.61786  44.23242  81.69192
## 36  2.93434343  63.75782  63.11594  64.39969  45.02855  82.48708
## 37  3.01818182  64.55346  63.92389  65.18304  45.82461  83.28231
## 38  3.10202020  65.34911  64.73023  65.96799  46.62062  84.07761
## 39  3.18585859  66.14476  65.53489  66.75463  47.41656  84.87296
## 40  3.26969697  66.94041  66.33778  67.54303  48.21244  85.66837
## 41  3.35353535  67.73605  67.13885  68.33326  49.00826  86.46384
## 42  3.43737374  68.53170  67.93803  69.12537  49.80402  87.25938
## 43  3.52121212  69.32735  68.73531  69.91938  50.59972  88.05497
## 44  3.60505051  70.12299  69.53066  70.71533  51.39536  88.85063
## 45  3.68888889  70.91864  70.32408  71.51320  52.19093  89.64635
## 46  3.77272727  71.71429  71.11560  72.31298  52.98645  90.44213
## 47  3.85656566  72.50994  71.90525  73.11462  53.78190  91.23797
## 48  3.94040404  73.30558  72.69310  73.91807  54.57730  92.03387
## 49  4.02424242  74.10123  73.47920  74.72326  55.37263  92.82983
## 50  4.10808081  74.89688  74.26365  75.53011  56.16790  93.62585
## 51  4.19191919  75.69252  75.04651  76.33854  56.96311  94.42194
## 52  4.27575758  76.48817  75.82789  77.14845  57.75826  95.21808
## 53  4.35959596  77.28382  76.60788  77.95976  58.55335  96.01429
## 54  4.44343434  78.07947  77.38658  78.77236  59.34838  96.81055
## 55  4.52727273  78.87511  78.16407  79.58616  60.14335  97.60688
## 56  4.61111111  79.67076  78.94044  80.40108  60.93825  98.40327
## 57  4.69494949  80.46641  79.71579  81.21702  61.73310  99.19972
## 58  4.77878788  81.26206  80.49019  82.03392  62.52788  99.99623
## 59  4.86262626  82.05770  81.26372  82.85168  63.32260 100.00000
## 60  4.94646465  82.85335  82.03645  83.67025  64.11727 100.00000
## 61  5.03030303  83.64900  82.80845  84.48955  64.91187 100.00000
## 62  5.11414141  84.44464  83.57977  85.30952  65.70641 100.00000
## 63  5.19797980  85.24029  84.35047  86.13011  66.50089 100.00000
```

```
## 64  5.28181818  86.03594  85.12061  86.95127  67.29531 100.00000
## 65  5.36565657  86.83159  85.89022  87.77296  68.08966 100.00000
## 66  5.44949495  87.62723  86.65935  88.59512  68.88396 100.00000
## 67  5.53333333  88.42288  87.42804  89.41773  69.67820 100.00000
## 68  5.61717172  89.21853  88.19632  90.24074  70.47237 100.00000
## 69  5.70101010  90.01418  88.96422  91.06413  71.26648 100.00000
## 70  5.78484848  90.80982  89.73179  91.88786  72.06054 100.00000
## 71  5.86868687  91.60547  90.49903  92.71191  72.85453 100.00000
## 72  5.95252525  92.40112  91.26597  93.53626  73.64846 100.00000
## 73  6.03636364  93.19676  92.03264  94.36089  74.44233 100.00000
## 74  6.12020202  93.99241  92.79906  95.18576  75.23614 100.00000
## 75  6.20404040  94.78806  93.56524  96.01087  76.02989 100.00000
## 76  6.28787879  95.58371  94.33121  96.83621  76.82358 100.00000
## 77  6.37171717  96.37935  95.09697  97.66174  77.61721 100.00000
## 78  6.45555556  97.17500  95.86253  98.48747  78.41078 100.00000
## 79  6.53939394  97.97065  96.62793  99.31337  79.20428 100.00000
## 80  6.62323232  98.76630  97.39315 100.00000  79.99773 100.00000
## 81  6.70707071  99.56194  98.15822 100.00000  80.79112 100.00000
## 82  6.79090909 100.00000  98.92315 100.00000  81.58444 100.00000
## 83  6.87474747 100.00000  99.68794 100.00000  82.37771 100.00000
## 84  6.95858586 100.00000 100.00000 100.00000  83.17091 100.00000
## 85  7.04242424 100.00000 100.00000 100.00000  83.96405 100.00000
## 86  7.12626263 100.00000 100.00000 100.00000  84.75714 100.00000
## 87  7.21010101 100.00000 100.00000 100.00000  85.55016 100.00000
## 88  7.29393939 100.00000 100.00000 100.00000  86.34312 100.00000
## 89  7.37777778 100.00000 100.00000 100.00000  87.13602 100.00000
## 90  7.46161616 100.00000 100.00000 100.00000  87.92886 100.00000
## 91  7.54545455 100.00000 100.00000 100.00000  88.72164 100.00000
## 92  7.62929293 100.00000 100.00000 100.00000  89.51436 100.00000
## 93  7.71313131 100.00000 100.00000 100.00000  90.30702 100.00000
## 94  7.79696970 100.00000 100.00000 100.00000  91.09962 100.00000
## 95  7.88080808 100.00000 100.00000 100.00000  91.89216 100.00000
## 96  7.96464646 100.00000 100.00000 100.00000  92.68464 100.00000
## 97  8.04848485 100.00000 100.00000 100.00000  93.47706 100.00000
## 98  8.13232323 100.00000 100.00000 100.00000  94.26942 100.00000
## 99  8.21616162 100.00000 100.00000 100.00000  95.06172 100.00000
## 100 8.30000000 100.00000 100.00000 100.00000  95.85396 100.00000
```

##Extract potential outlier data point.

```
outlier <- data.frame(x = HabitsPerformanceData$studyHours[456] , y = Habi
tsPerformanceData$examScore[456])
outlier

##     x   y
## 1 8.3 100
```

##Scatter plot of original.

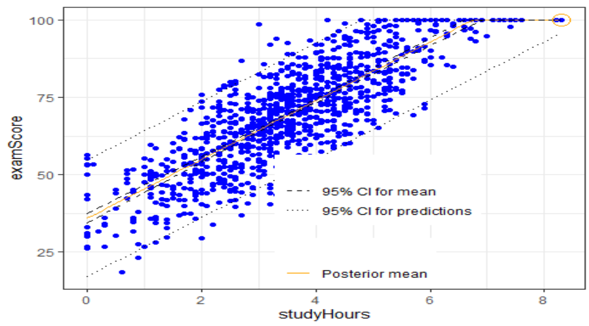
```
plot1 <- ggplot(data = HabitsPerformanceData , aes(x = studyHours , y = ex
amScore)) + geom_point(color = "blue")
```

##Add bounds of mean and prediction.

```
plot2 <- plot1 +
  geom_line(data = output , aes(x = new_x , y = y_hat , color = "first") ,
lty = 1) +
  geom_line(data = output , aes(x = new_x , y = ymean_lwr , lty = "second"
)) +
  geom_line(data = output , aes(x = new_x , y = ymean_upr , lty = "second"
)) +
  geom_line(data = output , aes(x = new_x , y = ypred_upr , lty = "third")
) +
  geom_line(data = output , aes(x = new_x , y = ypred_lwr , lty = "third")
) +
  scale_colour_manual(values = c("orange") , labels = "Posterior mean" , n
ame = "") +
  scale_linetype_manual(values = c(2,3) , labels = c("95% CI for mean" , "
95% CI for predictions") , name = "") +
  theme_bw() + theme(legend.position = c(1,0) , legend.justification = c(1
.5,0))

## Warning: A numeric `legend.position` argument in `theme()` was deprecat
ed in ggplot2
## 3.5.0.
## ℹ Please use the `legend.position.inside` argument of `theme()` instead
.
## This warning is displayed once every 8 hours.
## Call `lifecycle::last_lifecycle_warnings()` to see where this warning w
as
## generated.
```

##Identify potential outlier.

```
plot2 + geom_point(data = outlier , aes(x = x , y = y) , color = "orange"
, pch = 1 , cex = 5)
```



Bayesian Multiple Linear Regression

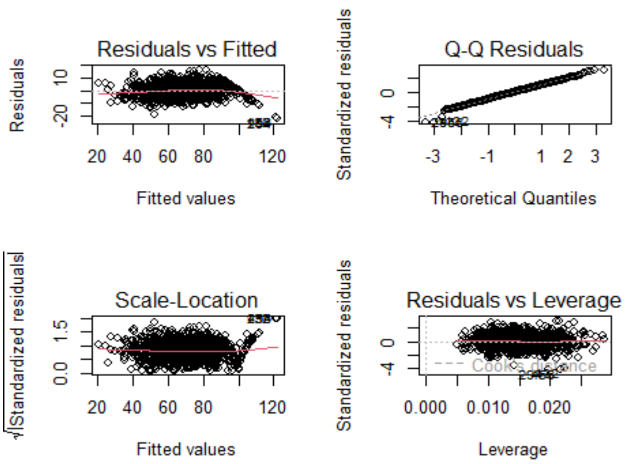
##Import library.

```
library(BAS)
```

##Use *bas.lm* to run regression HabitsPerformanceData.

```
score.bas = lm(examScore ~ . , data =  HabitsPerformanceData)
summary(score.bas)
```

```
##
## Call:
## lm(formula = examScore ~ ., data = HabitsPerformanceData)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -21.8035  -3.4559   0.0299   3.6161  15.5633
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)          6.88566    2.64573   2.603  0.00939 **
## age                 -0.01275    0.07339  -0.174  0.86213
## gender               0.01441    0.29621   0.049  0.96121
## studyHours           9.58332    0.11542  83.027  < 2e-16 ***
## socialMediaHours    -2.61362    0.14460 -18.075  < 2e-16 ***
## netflixHours        -2.27304    0.15743 -14.438  < 2e-16 ***
## parttimeJob          0.23931    0.41256   0.580  0.56200
## attendance           0.14320    0.01813   7.900 7.41e-15 ***
## sleepHours           1.99976    0.13830  14.459  < 2e-16 ***
## diet                -0.28284    0.23427  -1.207  0.22760
## exerciseFreq         1.45125    0.08380  17.318  < 2e-16 ***
## parentalEducation    0.04525    0.19517   0.232  0.81669
## internet            -0.25407    0.23443  -1.084  0.27873
## mentalHealth         1.94698    0.05954  32.701  < 2e-16 ***
## extracurricular     -0.04210    0.36342  -0.116  0.90780
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.341 on 985 degrees of freedom
## Multiple R-squared:  0.9014, Adjusted R-squared:    0.9
## F-statistic: 643.1 on 14 and 985 DF,  p-value: < 2.2e-16

par(mfrow = c(2,2))
plot(score.bas)
```



##Use *bas.lm* to run regression HabitsPerformanceData.

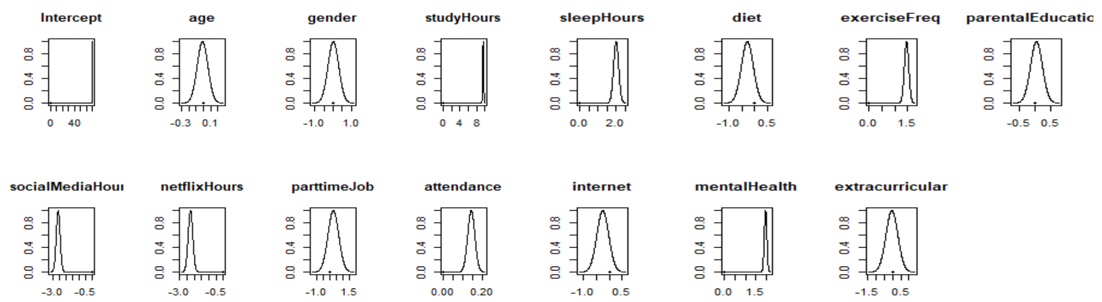
```
score.bas2 <- bas.lm(examScore ~ . , data =  HabitsPerformanceData ,
                     prior = "BIC" ,
```

```
                          modelprior = Bernoulli(1) ,
                          include.always = ~ . ,
                          n.models = 1)

##Posterior Means and Posterior Standard Deviations.
score.coef = coef(score.bas2)
score.coef
```

```
##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  BMA
##
##  Based on the top  1 models
##                     post mean  post SD   post p(B != 0)
## Intercept           69.60150    0.16890   1.00000
## age                 -0.01275    0.07339   1.00000
## gender               0.01441    0.29621   1.00000
## studyHours           9.58332    0.11542   1.00000
## socialMediaHours    -2.61362    0.14460   1.00000
## netflixHours        -2.27304    0.15743   1.00000
## parttimeJob          0.23931    0.41256   1.00000
## attendance           0.14320    0.01813   1.00000
## sleepHours           1.99976    0.13830   1.00000
## diet                -0.28284    0.23427   1.00000
## exerciseFreq         1.45125    0.08380   1.00000
## parentalEducation    0.04525    0.19517   1.00000
## internet            -0.25407    0.23443   1.00000
## mentalHealth         1.94698    0.05954   1.00000
## extracurricular     -0.04210    0.36342   1.00000
```

##visualization of the coefficients.

```
par(mfrow = c(2, 4))
plot(score.coef , ask = F)
```



##Summary Table.

```
out <- confint(score.coef)[, 1:2]
## Extract the upper and lower bounds of the credible intervals

names = c("posterior mean", "posterior std", colnames(out))
out = cbind(score.coef$postmean, score.coef$postsd, out)
colnames(out) = names
```

```r
round(out, 2)

##                     posterior mean posterior std  2.5% 97.5%
## Intercept                    69.60          0.17 69.27 69.93
## age                          -0.01          0.07 -0.16  0.13
## gender                        0.01          0.30 -0.57  0.60
## studyHours                    9.58          0.12  9.36  9.81
## socialMediaHours             -2.61          0.14 -2.90 -2.33
## netflixHours                 -2.27          0.16 -2.58 -1.96
## parttimeJob                   0.24          0.41 -0.57  1.05
## attendance                    0.14          0.02  0.11  0.18
## sleepHours                    2.00          0.14  1.73  2.27
## diet                         -0.28          0.23 -0.74  0.18
## exerciseFreq                  1.45          0.08  1.29  1.62
## parentalEducation             0.05          0.20 -0.34  0.43
## internet                     -0.25          0.23 -0.71  0.21
## mentalHealth                  1.95          0.06  1.83  2.06
## extracurricular              -0.04          0.36 -0.76  0.67
```

Bayesian Model Selection

```r
# Total num of observations
n <- nrow(HabitsPerformanceData)
n

## [1] 1000

sco.lm1 <- lm(examScore ~ . , data = HabitsPerformanceData)
sco.step <- step(sco.lm1, k = log(n))

## Start:  AIC=3439.4
## examScore ~ age + gender + studyHours + socialMediaHours + netflixHours
+
##     parttimeJob + attendance + sleepHours + diet + exerciseFreq +
##     parentalEducation + internet + mentalHealth + extracurricular
##
##                     Df Sum of Sq    RSS    AIC
## - gender             1         0  28100 3432.5
## - extracurricular    1         0  28101 3432.5
## - age                1         1  28101 3432.5
## - parentalEducation  1         2  28102 3432.5
## - parttimeJob        1        10  28110 3432.8
## - internet           1        34  28134 3433.7
## - diet               1        42  28142 3434.0
## <none>                            28100 3439.4
## - attendance         1      1781  29881 3493.9
## - netflixHours       1      5947  34048 3624.5
## - sleepHours         1      5965  34065 3625.0
## - exerciseFreq       1      8556  36656 3698.3
## - socialMediaHours   1      9321  37421 3718.9
## - mentalHealth       1     30507  58607 4167.6
## - studyHours         1    196658 224759 5511.7
##
## Step:  AIC=3432.5
```

```
## examScore ~ age + studyHours + socialMediaHours + netflixHours +
##     parttimeJob + attendance + sleepHours + diet + exerciseFreq +
##     parentalEducation + internet + mentalHealth + extracurricular
##
##                     Df Sum of Sq    RSS    AIC
## - extracurricular    1         0  28101 3425.6
## - age                1         1  28101 3425.6
## - parentalEducation  1         2  28102 3425.6
## - parttimeJob        1        10  28110 3425.9
## - internet           1        33  28134 3426.8
## - diet               1        42  28142 3427.1
## <none>                            28100 3432.5
## - attendance         1      1781  29882 3487.1
## - netflixHours       1      5948  34048 3617.6
## - sleepHours         1      5977  34078 3618.4
## - exerciseFreq       1      8585  36686 3692.2
## - socialMediaHours   1      9321  37421 3712.0
## - mentalHealth       1     30511  58611 4160.7
## - studyHours         1    196777 224878 5505.4
##
## Step:  AIC=3425.6
## examScore ~ age + studyHours + socialMediaHours + netflixHours +
##     parttimeJob + attendance + sleepHours + diet + exerciseFreq +
##     parentalEducation + internet + mentalHealth
##
##                     Df Sum of Sq    RSS    AIC
## - age                1         1  28102 3418.7
## - parentalEducation  1         2  28102 3418.7
## - parttimeJob        1        10  28111 3419.0
## - internet           1        33  28134 3419.9
## - diet               1        42  28142 3420.2
## <none>                            28101 3425.6
## - attendance         1      1783  29884 3480.2
## - netflixHours       1      5947  34048 3610.7
## - sleepHours         1      5979  34080 3611.6
## - exerciseFreq       1      8587  36688 3685.3
## - socialMediaHours   1      9321  37422 3705.2
## - mentalHealth       1     30513  58614 4153.9
## - studyHours         1    196778 224879 5498.5
##
## Step:  AIC=3418.72
## examScore ~ studyHours + socialMediaHours + netflixHours + parttimeJob
+
##     attendance + sleepHours + diet + exerciseFreq + parentalEducation +
##     internet + mentalHealth
##
##                     Df Sum of Sq    RSS    AIC
## - parentalEducation  1         2  28103 3411.9
## - parttimeJob        1        10  28111 3412.2
## - internet           1        33  28135 3413.0
## - diet               1        42  28143 3413.3
## <none>                            28102 3418.7
## - attendance         1      1787  29889 3473.5
## - netflixHours       1      5947  34049 3603.8
```

```
## - sleepHours         1      5982  34084 3604.8
## - exerciseFreq       1      8588  36690 3678.5
## - socialMediaHours   1      9320  37422 3698.2
## - mentalHealth       1     30590  58691 4148.3
## - studyHours         1    196779 224881 5491.6
##
## Step:  AIC=3411.87
## examScore ~ studyHours + socialMediaHours + netflixHours + parttimeJob
+
##     attendance + sleepHours + diet + exerciseFreq + internet +
##     mentalHealth
##
##                    Df Sum of Sq    RSS    AIC
## - parttimeJob       1        10  28113 3405.3
## - internet          1        33  28136 3406.1
## - diet              1        42  28145 3406.4
## <none>                           28103 3411.9
## - attendance        1      1789  29892 3466.7
## - netflixHours      1      5947  34050 3596.9
## - sleepHours        1      5989  34092 3598.1
## - exerciseFreq      1      8588  36691 3671.6
## - socialMediaHours  1      9325  37428 3691.5
## - mentalHealth      1     30595  58698 4141.5
## - studyHours        1    196793 224896 5484.7
##
## Step:  AIC=3405.3
## examScore ~ studyHours + socialMediaHours + netflixHours + attendance +
##     sleepHours + diet + exerciseFreq + internet + mentalHealth
##
##                    Df Sum of Sq    RSS    AIC
## - internet          1        33  28145 3399.6
## - diet              1        41  28153 3399.8
## <none>                           28113 3405.3
## - attendance        1      1781  29894 3459.8
## - netflixHours      1      5944  34057 3590.2
## - sleepHours        1      5990  34103 3591.5
## - exerciseFreq      1      8579  36692 3664.7
## - socialMediaHours  1      9317  37429 3684.6
## - mentalHealth      1     30612  58725 4135.0
## - studyHours        1    196888 225001 5478.3
##
## Step:  AIC=3399.55
## examScore ~ studyHours + socialMediaHours + netflixHours + attendance +
##     sleepHours + diet + exerciseFreq + mentalHealth
##
##                    Df Sum of Sq    RSS    AIC
## - diet              1        43  28189 3394.2
## <none>                           28145 3399.6
## - attendance        1      1804  29949 3454.8
## - sleepHours        1      5987  34132 3585.5
## - netflixHours      1      5989  34134 3585.6
## - exerciseFreq      1      8624  36770 3659.9
## - socialMediaHours  1      9369  37514 3680.0
## - mentalHealth      1     30791  58937 4131.7
```

```
## - studyHours        1    196856 225001 5471.4
##
## Step:  AIC=3394.18
## examScore ~ studyHours + socialMediaHours + netflixHours + attendance +
##     sleepHours + exerciseFreq + mentalHealth
##
##                    Df Sum of Sq    RSS    AIC
## <none>                           28189 3394.2
## - attendance        1      1843  30032 3450.6
## - netflixHours      1      5980  34169 3579.7
## - sleepHours        1      6027  34216 3581.0
## - exerciseFreq      1      8616  36805 3654.0
## - socialMediaHours  1      9388  37577 3674.7
## - mentalHealth      1     30752  58941 4124.9
## - studyHours        1    196883 225072 5464.8
```

`

```
library(BAS)
```

##Model

```
basModel <- bas.lm(formula = examScore ~ . , data = HabitsPerformanceData
, prior = "BIC" , modelprior  = uniform()) # equal prior to the model
```

##bas_model

```
basCoeff <- coef(basModel)
basCoeff

##
##  Marginal Posterior Summaries of Coefficients:
##
##  Using  BMA
##
##  Based on the top  16384 models
##                    post mean   post SD     post p(B != 0)
## Intercept          6.960e+01   1.686e-01   1.000e+00
## age               -4.378e-04   1.317e-02   3.121e-02
## gender             4.028e-05   5.163e-02   3.066e-02
## studyHours         9.575e+00   1.150e-01   1.000e+00
## socialMediaHours  -2.619e+00   1.442e-01   1.000e+00
## netflixHours      -2.277e+00   1.570e-01   1.000e+00
## parttimeJob        7.747e-03   8.721e-02   3.524e-02
## attendance         1.446e-01   1.798e-02   1.000e+00
## sleepHours         2.004e+00   1.377e-01   1.000e+00
## diet              -1.834e-02   9.169e-02   6.375e-02
## exerciseFreq       1.452e+00   8.340e-02   1.000e+00
## parentalEducation  1.128e-03   3.492e-02   3.118e-02
## internet          -1.448e-02   8.110e-02   5.580e-02
## mentalHealth       1.949e+00   5.926e-02   1.000e+00
## extracurricular   -6.889e-04   6.365e-02   3.071e-02
```

##Best model

```
best <- which.max(basModel$logmarg)
bestmodel <- basModel$which[[best]]
bestmodel

## [1]  0  3  4  5  7  8 10 13

bestGamma <- rep(0,basModel$n.vars)
bestGamma[bestmodel + 1] <- 1
bestGamma

##  [1] 1 0 0 1 1 1 0 1 1 0 1 0 0 1 0
```

##Fit the best BIC model by imposing which variables to be used using the indicators.

```
bas_bestmodel <- bas.lm(examScore ~ studyHours+socialMediaHours+netflixHou
rs+attendance+sleepHours+exerciseFreq+mentalHealth , data = HabitsPerforma
nceData,
 prior = "BIC", n.models = 1, bestmodel = bestGamma,
 modelprior = uniform())
```

Coefficient Estimates Under Reference Prior for Best BIC model

##Retreat coefficients information.

```
score.coeff <- coef(bas_bestmodel)
```

##Retreat bounds of credible intervals.

```
out <- confint(score.coeff)[,1:2]
```

##Combine results and construct summary table.

```
basSummary <- cbind(score.coeff$postmean , score.coeff$postsd , out)
names <- c("post mean" , "post sd" , colnames(out))
colnames(basSummary) <- names
basSummary

##                   post mean    post sd        2.5%     97.5%
## Intercept        69.6015000 0.49108007 68.63782852 70.565171
## studyHours        0.0000000 0.00000000  0.00000000  0.000000
## socialMediaHours  0.0000000 0.00000000  0.00000000  0.000000
## netflixHours     -2.7346034 0.45701305 -3.63142341 -1.837783
## attendance        0.1687005 0.05228704  0.06609498  0.271306
## sleepHours        1.6848516 0.40067790  0.89858096  2.471122
## exerciseFreq      0.0000000 0.00000000  0.00000000  0.000000
## mentalHealth      1.9304120 0.17258549  1.59173873  2.269085
```

Calculating Posterior Probability

##Use ‘bas.lm’ for regression

```
basModel <- bas.lm(examScore ~ studyHours + socialMediaHours +  netflixHou
rs +  attendance  +  sleepHours + exerciseFreq + mentalHealth , data = Hab
itsPerformanceData , prior = "BIC" , modelprior = uniform())

round(summary(basModel) , 3)
```

```
##                  P(B != 0 | Y)   model 1   model 2   model 3  model 4 
model 5
## Intercept                    1     1.000     1.000     1.000     1.00 
1.000
## studyHours                   1     1.000     1.000     1.000     1.00 
1.000
## socialMediaHours             1     1.000     1.000     1.000     1.00 
1.000
## netflixHours                 1     1.000     1.000     0.000     1.00 
0.000
## attendance                   1     1.000     0.000     1.000     1.00 
0.000
## sleepHours                   1     1.000     1.000     1.000     0.00 
1.000
## exerciseFreq                 1     1.000     1.000     1.000     1.00 
1.000
## mentalHealth                 1     1.000     1.000     1.000     1.00 
1.000
## BF                          NA     1.000     0.000     0.000     0.00 
0.000
## PostProbs                   NA     1.000     0.000     0.000     0.00 
0.000
## R2                          NA     0.901     0.895     0.880     0.88 
0.874
## dim                         NA     8.000     7.000     7.000     7.00 
6.000
## logmarg                     NA -5150.969 -5179.188 -5243.709 -5244.40 -
5266.677
```

The marginal posterior inclusion probability (pip)

```
print(basModel)
```

```
## 
## Call:
## bas.lm(formula = examScore ~ studyHours + socialMediaHours + 
##     netflixHours + attendance + sleepHours + exerciseFreq + 
mentalHealth, 
##     data = HabitsPerformanceData, prior = "BIC", modelprior = 
uniform())
## 
## 
##  Marginal Posterior Inclusion Probabilities: 
##        Intercept        studyHours  socialMediaHours      
netflixHours  
##                1                 1                 1                 
1  
##       attendance        sleepHours      exerciseFreq      
mentalHealth  
##                1                 1
```