Predictive Analysis of Recovery Time from Covid-19

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Introduction

This project aims to develop a prediction model for recovery time along with the identification of potential risk factors associated with a long recovery time from Covid-19. The data come from a combination of three cohort studies that collect information through questionnaires and medical records and tracked over several years.

Variables Summary

- ID: Participant ID
- Gender: 1 = Male, 0 = Female
- Race/ethnicity: 1 = White, 2 = Asian, 3 = Black, 4 = Hispanic
- Smoking: Smoking status; 0 = Never smoked, 1 = Former smoker, 2 = Current smoker
- Height: Height (in centimeters)
- Weight: Weight (in kilograms)
- BMI: Body Mass Index; BMI = weight (in kilograms) / height (in meters) squared
- Hypertension: 0 = No, 1 = Yes
- Diabetes: 0 = No, 1 = Yes
- Systolic blood pressure (SBP): Systolic blood pressure (in mm/Hg)
- LDL cholesterol: LDL (low-density lipoprotein) cholesterol (in mg/dL)
- Vaccine: Vaccination status at the time of infection - 0 = Not vaccinated, 1 = Vaccinated
- Severity: Severity of COVID-19 infection-0 = Not severe, 1= Severe
- Study: The study (A/B/C) that the participant belongs to
- Time to recovery: Time from COVID-19 infection to recovery in days

Exploratory analysis and data visualization

The scatterplots show that **SBP**, **LDL**, and **Age** are the continuous variables linearly correlated (small correlation coefficient though) to **Recovery_time** while no apparent discrepancy is found when finding the association between **Recovery_time** and the categorical variables of different levels. The correlation plot suggests that **SBP** is positively correlated to **Hypertension** while the correlation among **BMI**, **Weight**, and **Height** are foreseen. In short, there is no obvious collinearity among most of the covariates (none of them exceed the threshold of strong correlation 0.8).

Model Training

(Note: 5 times repeated 10 folds cross-validation is used across the training process)

- Ordinary Least square regression

While ordinary linear regression assumes linear relationship, normality of residuals, homoscedasticity, and independence of residual error terms, it can be seen from the diagnostic plots that the assumptions of normally distributed residuals and homoscedasticity are violated. Therefore, regularization methods and nonlinear methods should be introduced.

- Elastic net regression & Partial least squares

Since the assumptions of OLS are not met, parameter regularization/dimension reduction methods of the elastic net and partial least squares are used for model building. Through the process of cross-validation, the resulting elastic net model gives an alpha at 1, which is

equivalent to the Lasso model with penalty coefficient of 0.135. The partial least square model gives 14 components after cross-validation for best predictability.

- Generalized Additive Model (GAM)

For generalized additive model, the selected model after cross-validation has no penalty to each term, 6 out of 18 predictors get smooth terms while the rest of predictors are linearly related to the response variable.

- Multivariate adaptive regression spline model (MARS)

In the selected multivariate adaptive regression spline model after cross-validation, there is 10 terms with degree of 3. Within the 7 predictors in the model, `BMI` is of most significance as it is included in 9 out of 10 terms.

- K-Nearest Neighbors regression (KNN)

The selected KNN model has the tuning parameter k = 12 after cross-validation.

- Generalized Boosted Regression

The resulting generalized boosted regression model has 600 trees with 2 splits performed on a tree when the learning rate is specified as 0.02 based on size of training set and each terminal node has at least 10 observations.

Results

The generalized boosted regression model is selected as the final model for its best training performance with the lowest cross-validation root mean square error (23.66) among all models. This boosted regression model has a test mean squared error of 748.5. As shown by the final model, **BMI** is believed to be the most important predictor, which accounts for more than 63% of the reduction to the loss function given this set of predictors. **Height** and **Weight** are second and third most important predictors because of their mathematical relationship to **BMI**. A partial dependence plot shows that the recovery time is relatively short for individuals with a BMI between 23 and 30, whereas the obese patients with **BMI** greater than 30 tend to experience a remarkably long recovery period from Covid-19. **Vaccine**, another factor that draw the public attention, does help to slightly shorten the recovery time as shown by the partial dependence plot while the recovery time increases mildly as **Age** increases for the elderly over 50. On the other hand, the variables such as systolic blood pressure (**SBP**), **Race**, and **Diabetes** have little influence on the recovery time from Covid-19.

Conclusion

Based on the generalized boosted regression model with the best performance in predictions, BMI is the single most important factor that influences long recovery time (as well as weight and height due to their mathematical relationship to BMI). Obese patients with a BMI over 32 will experience a remarkably longer recovery period compared to patients with a lower BMI. Other common risk factors, such as symptom severity and age, do have a positive correlation with the length of recovery time, while vaccination does shorten the recovery period. However, there is no evidence to suggest that the aforementioned factors have an effect on the scenario of long recovery time as they only associate with a mild difference in recovery time.

Figures and outputs

Exploratory analysis and data visualization

Data summary

Name	Piped data
Number of rows	2000
Number of columns	16
_____	
Column type frequency:	
factor	8
numeric	8
_____	
Group variables	None

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
gender	0	1	FALSE	2	0: 1049, 1: 951
race	0	1	FALSE	4	1: 1304, 3: 406, 4: 197, 2: 93
smoking	0	1	FALSE	3	0: 1221, 1: 588, 2: 191
hypertension	0	1	FALSE	2	0: 1053, 1: 947
diabetes	0	1	FALSE	2	0: 1699, 1: 301
vaccine	0	1	FALSE	2	1: 1168, 0: 832
severity	0	1	FALSE	2	0: 1807, 1: 193
study	0	1	FALSE	3	B: 1229, A: 390, C: 381

Variable type: numeric

| skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
id	0	1	4995.42	2832.70	2.0	2603.25	4966.5	7424.5	9999.0	
age	0	1	60.16	4.47	45.0	57.00	60.0	63.0	79.0	
height	0	1	170.00	6.00	148.1	166.00	170.0	173.9	188.6	
weight	0	1	79.96	7.20	57.1	75.10	79.9	84.8	104.2	
bmi	0	1	27.73	2.82	19.6	25.80	27.6	29.5	38.4	
SBP	0	1	129.92	7.95	103.0	125.00	130.0	135.0	156.0	
LDL	0	1	110.19	19.80	32.0	97.00	110.0	124.0	172.0	
recovery_time	0	1	43.50	31.09	3.0	28.00	39.0	51.0	365.0	

Visualize potential relationship between reponse variable and numeric predictors
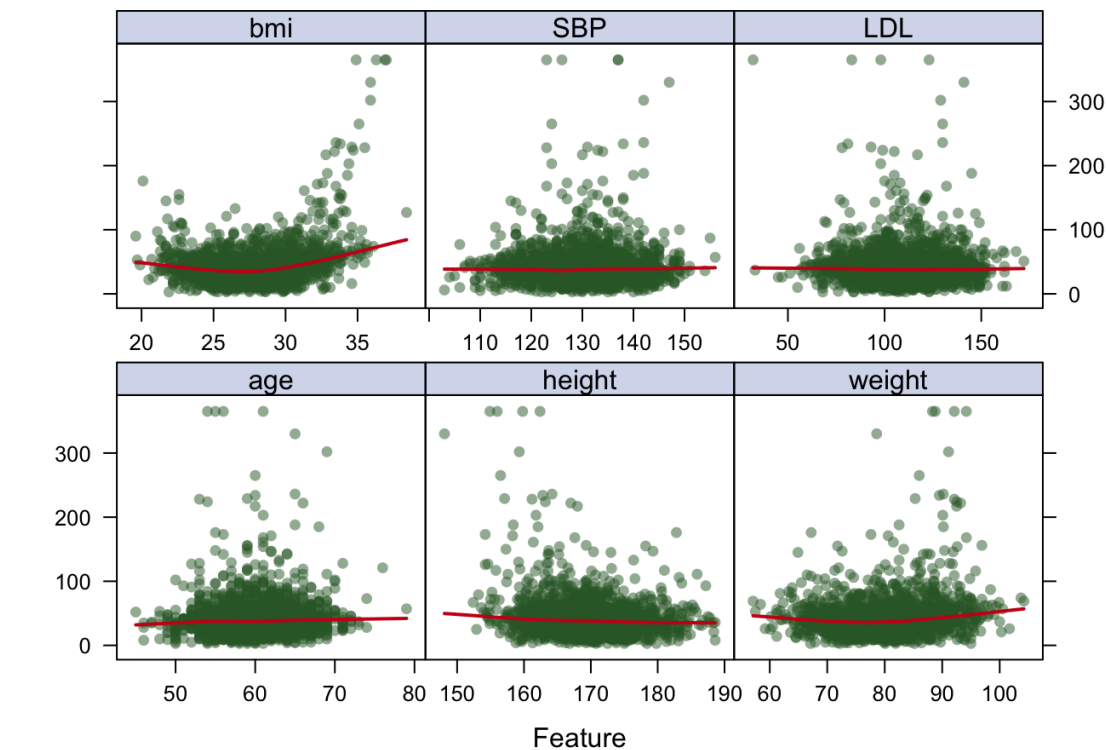
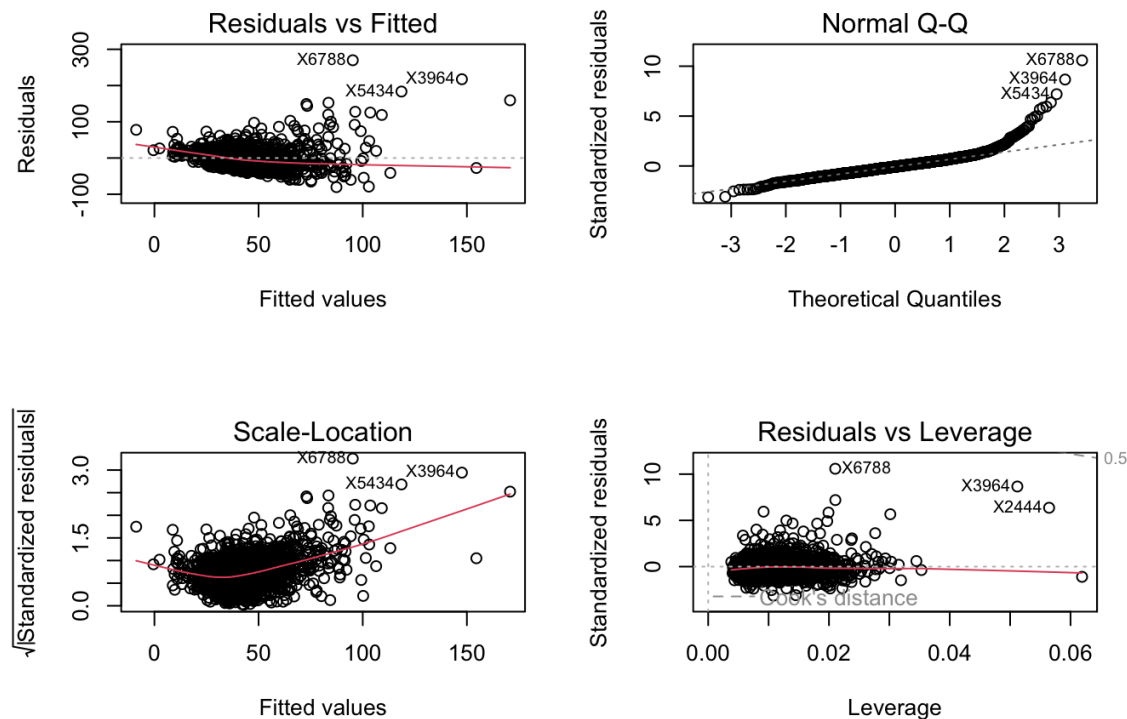# Visualize potential relationship between reponse variable and categorical predictors
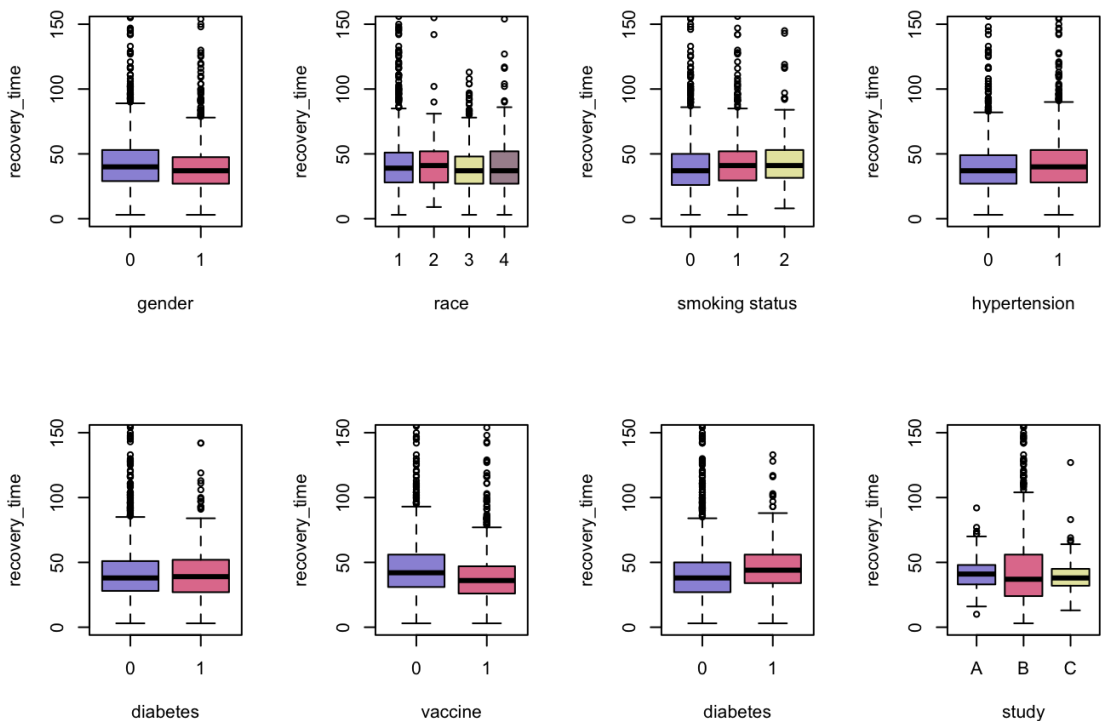
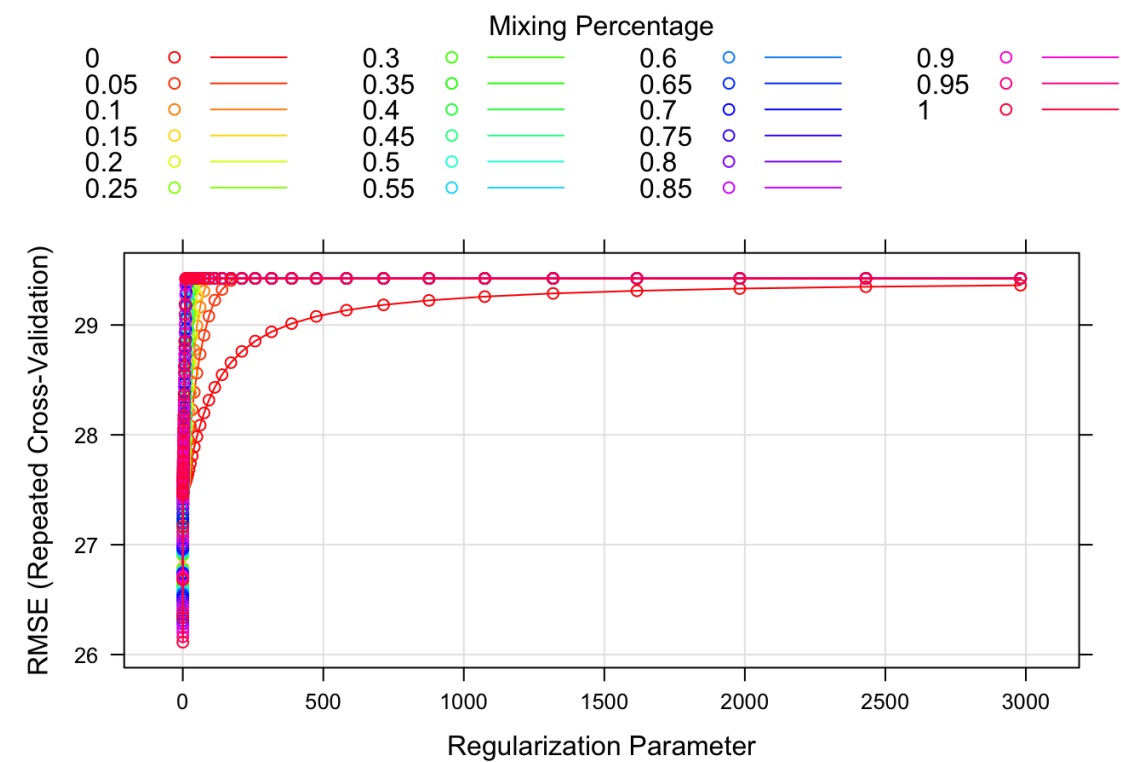# Correlation plot to check collinearity between covariates (based on training data)
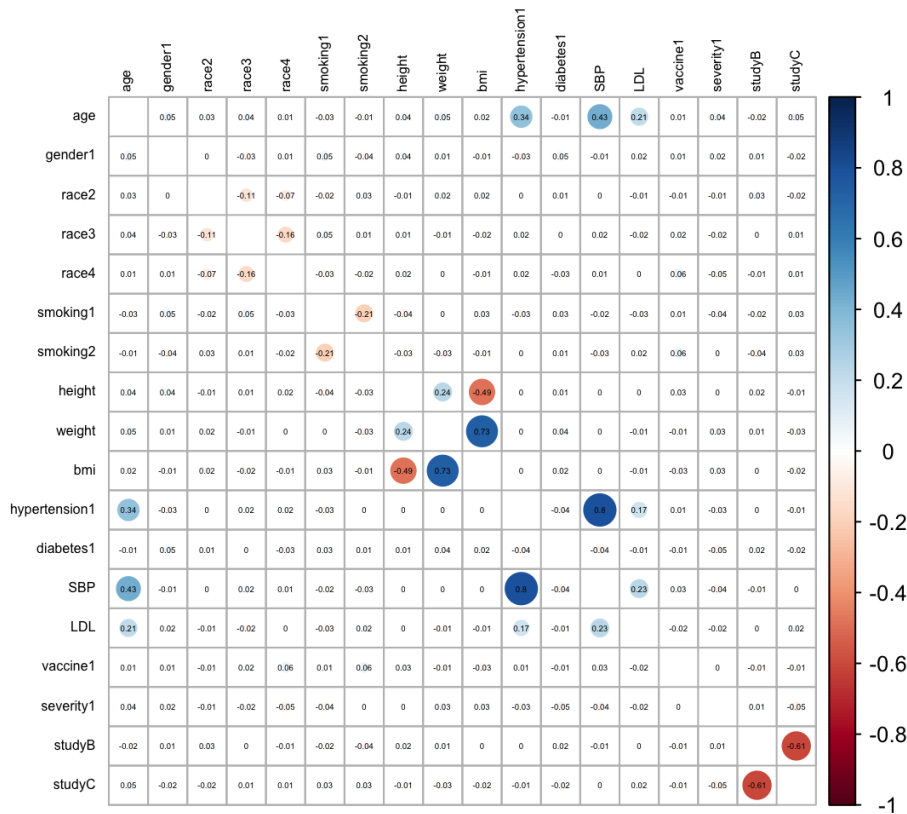
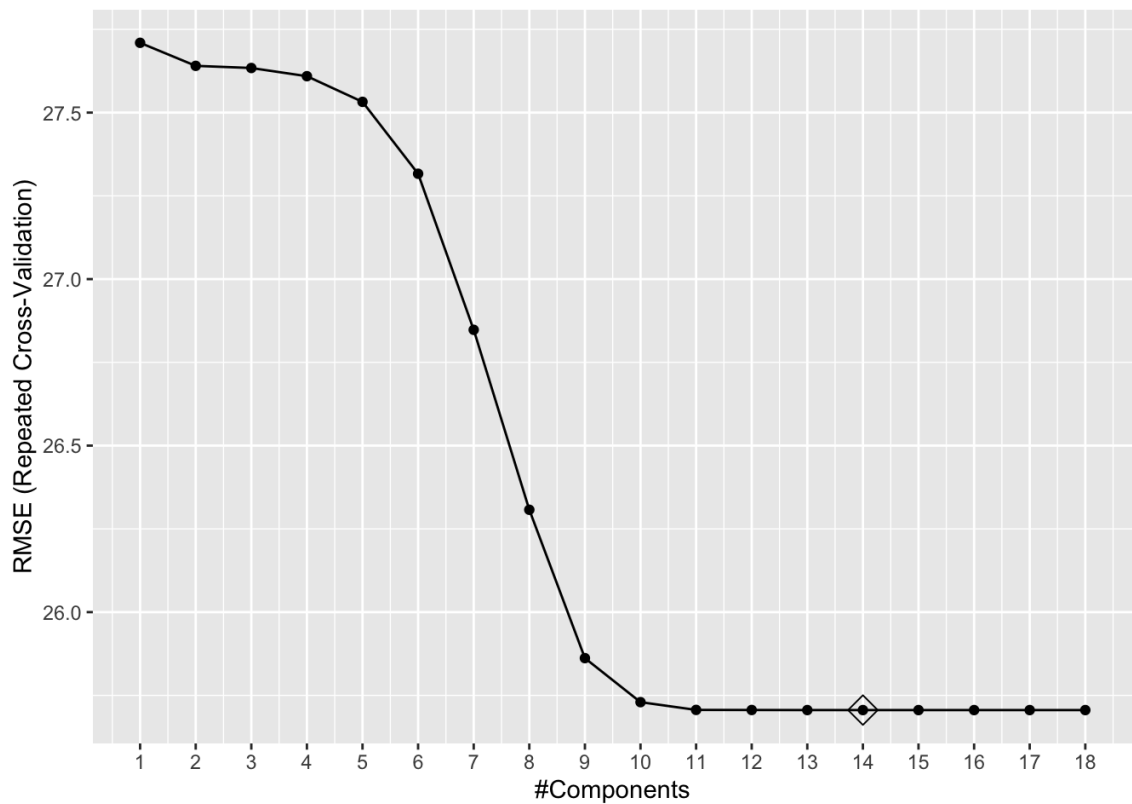# Model Training

Ordinary Least square
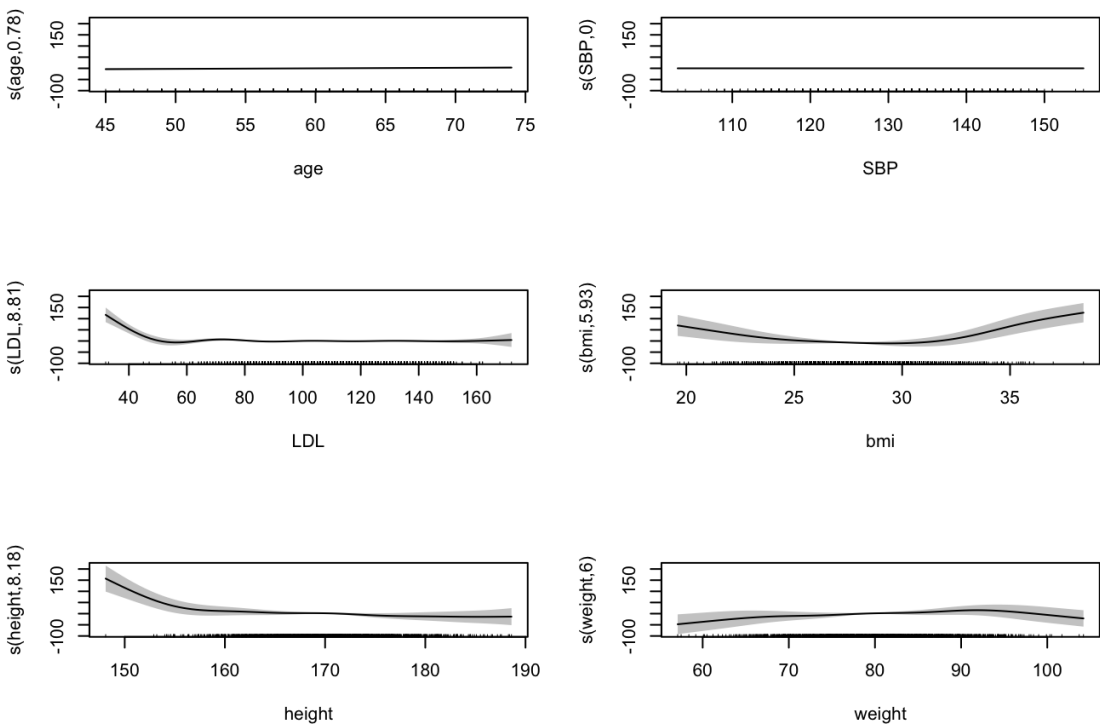
Elastic net regression


```
##      alpha    lambda
## 1001     1 0.1353353
```
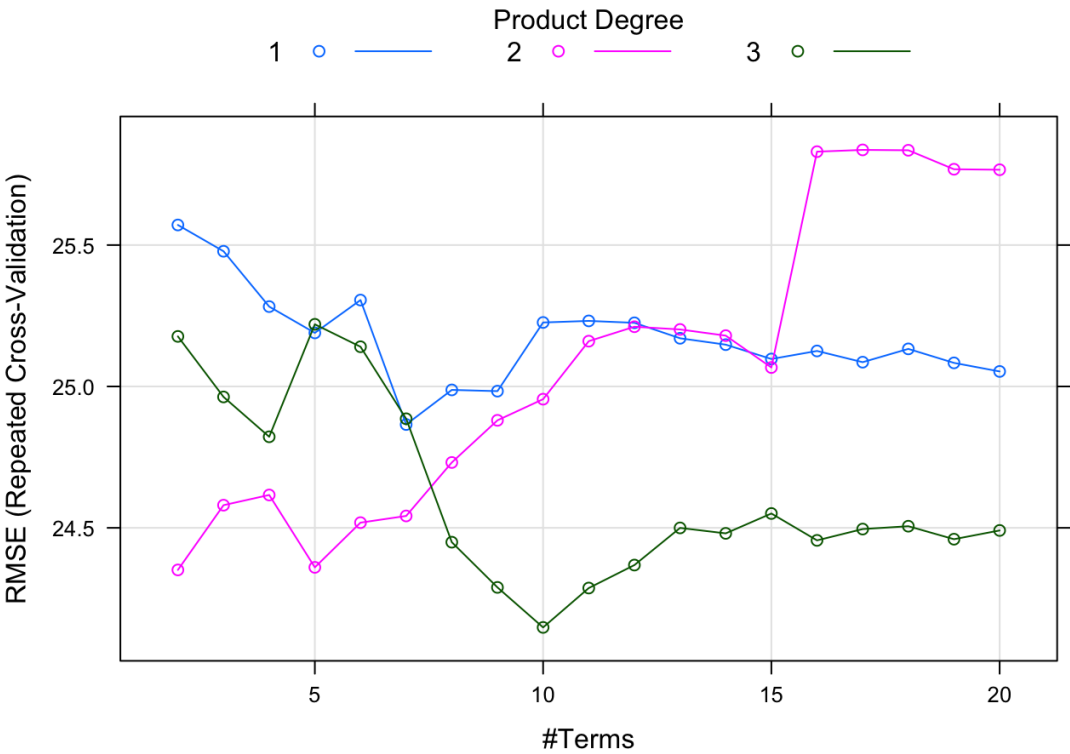
Partial least squares
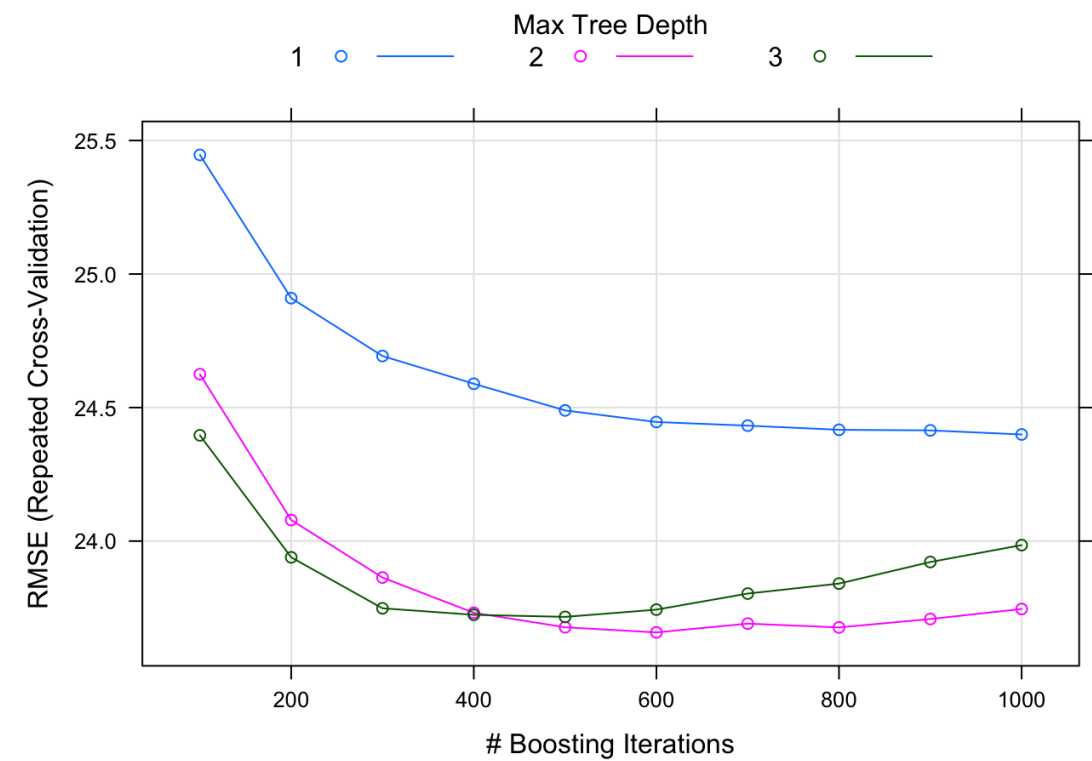
Generalized Additive Models (GAM)

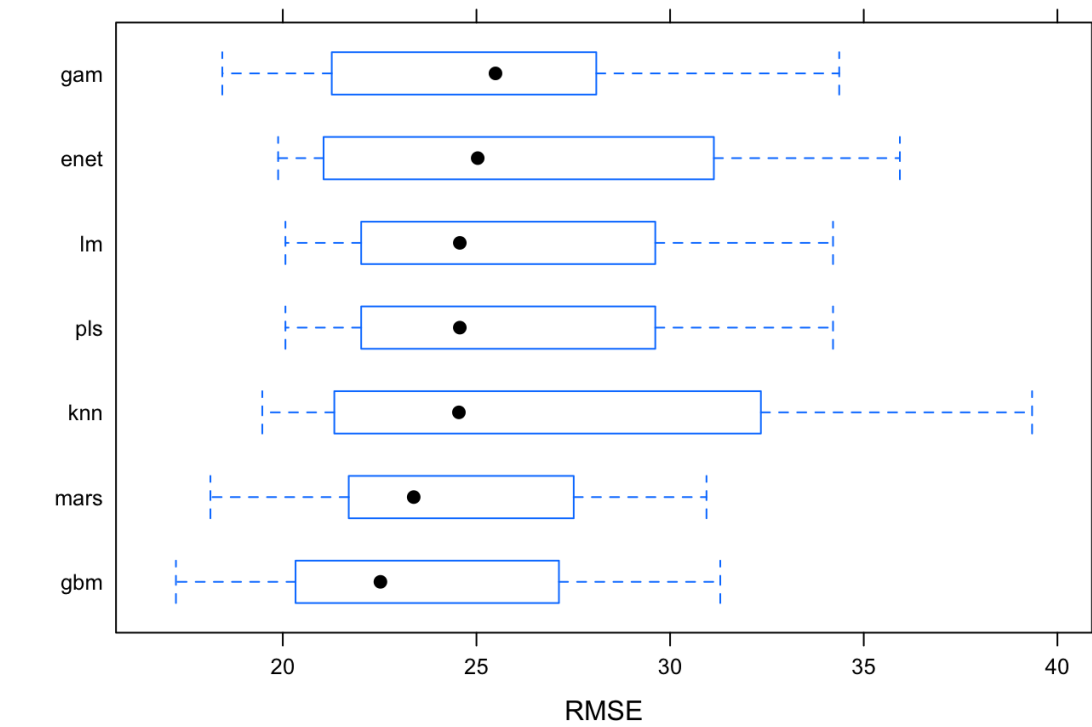# Multivariate adaptive regression spline model (MARS)

K-Nearest Neighbors (KNN)

```
##    k
## 6 12
```

Generalized Boosted Regression
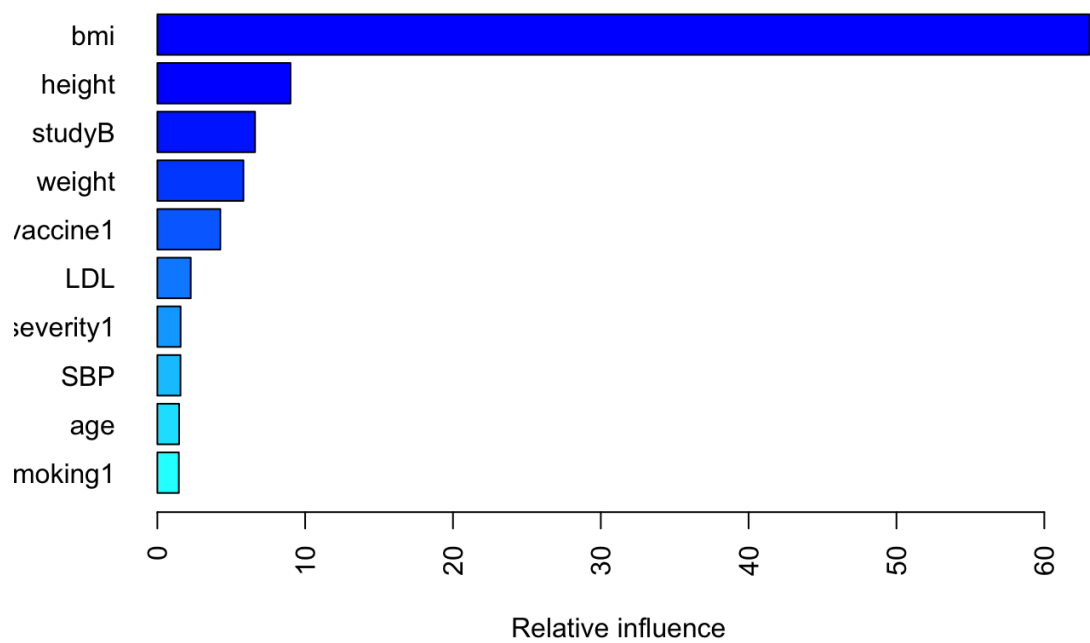
Models comparsion based on cross validation error

Results

Test Mean Squared Error

```
## [1] 748.4655
```

Variable importance plots

	rel.inf
bmi	63.0493226
height	9.0091073
studyB	6.6109336
weight	5.8246237
vaccine1	4.2622552
LDL	2.2613620
severity1	1.5747687
SBP	1.5669913
age	1.4736886
smoking1	1.4541593
gender1	1.4338109
smoking2	0.6074393
hypertension1	0.5483854
race2	0.2682331
diabetes1	0.0341425
race4	0.0207763
race3	0.0000000
studyC	0.0000000

Partial dependance plots