Midterm

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Load data

```
load("dat1.RData")
load("dat2.RData")

dat1 =
   dat1 |>
   select(-id)

dat2 =
   dat2 |>
   select(-id)
```

Explorey Data Analysis and Visualization

Summary statistics

```
summarize_cat = function(data, var_name) {
  var_label = deparse(substitute(var_name))
  out_df =
    data |>
    count({{ var_name }}) |>
    mutate(
      Percent = round(100 * n / sum(n), 1),
      Variable = var_label,
      Level = as.character({{ var_name }})
    ) |>
    rename(N = n) >
    select(Variable, Level, N, Percent)
  return(out_df)
gender <- summarize_cat(dat1, gender)</pre>
race <- summarize_cat(dat1, race)</pre>
smoking <- summarize_cat(dat1, smoking)</pre>
diabetes <- summarize_cat(dat1, diabetes)</pre>
```

```
hypertension <- summarize_cat(dat1, hypertension)
bind_rows(gender, race, smoking, diabetes, hypertension) %>%
knitr::kable()
```

Variable	Level	N	Percent
gender	0	2573	51.5
gender	1	2427	48.5
race	1	3221	64.4
race	2	278	5.6
race	3	1036	20.7
race	4	465	9.3
smoking	0	3010	60.2
smoking	1	1504	30.1
smoking	2	486	9.7
diabetes	0	4228	84.6
diabetes	1	772	15.4
hypertension	0	2702	54.0
hypertension	1	2298	46.0

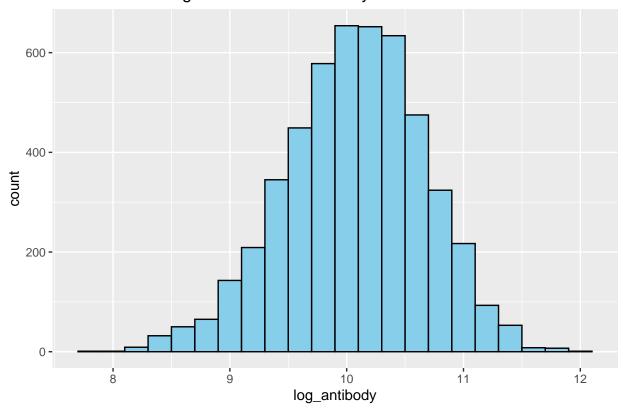
```
summarize_cont = function(data, var_name) {
  var_label = deparse(substitute(var_name))
  out_df =
    data |>
    summarize(
     Variable = var_label,
     Median = round(median({{ var_name }}, na.rm = TRUE), 1),
      Q1 = round(quantile({{ var_name }}, 0.25, na.rm = TRUE), 1),
      Q3 = round(quantile({{ var_name }}, 0.75, na.rm = TRUE), 1)
    ) |>
    mutate(
     IQR = paste0("[", Q1, ", ", Q3, "]")
    select(Variable, Median, IQR)
  return(out_df)
age = summarize_cont(dat1, age)
bmi = summarize_cont(dat1, bmi)
height = summarize_cont(dat1, height)
weight = summarize cont(dat1, weight)
SBP = summarize_cont(dat1, SBP)
LDL = summarize_cont(dat1, LDL)
log_anti = summarize_cont(dat1, log_antibody)
bind_rows(age, bmi, height, weight, SBP, LDL, log_anti) %>%
knitr::kable()
```

Variable	Median	IQR
age	60.0	[57, 63]
bmi	27.6	[25.8, 29.5]
height	170.1	[166.1, 174.2]
weight	80.1	[75.4, 84.9]
SBP	130.0	[124, 135]
LDL	110.0	[96, 124]
\log _antibody	10.1	[9.7, 10.5]

Distribution of antibody levels

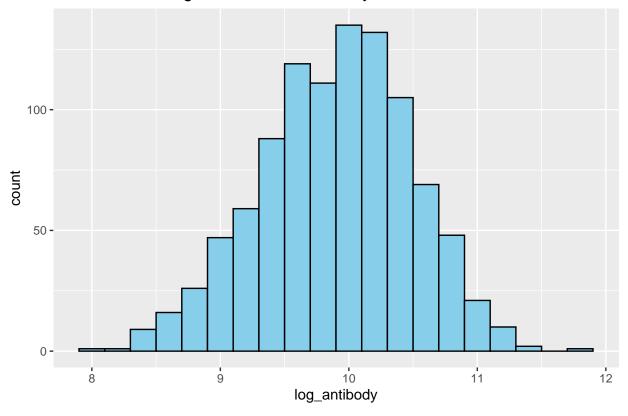
```
ggplot(dat1, aes(x = log_antibody)) +
geom_histogram(binwidth = 0.2, fill = 'skyblue', color = 'black') +
labs(title = "Distribution of Log-Transformed Antibody Levels")
```

Distribution of Log-Transformed Antibody Levels



```
ggplot(dat2, aes(x = log_antibody)) +
  geom_histogram(binwidth = 0.2, fill = 'skyblue', color = 'black') +
  labs(title = "Distribution of Log-Transformed Antibody Levels")
```

Distribution of Log-Transformed Antibody Levels

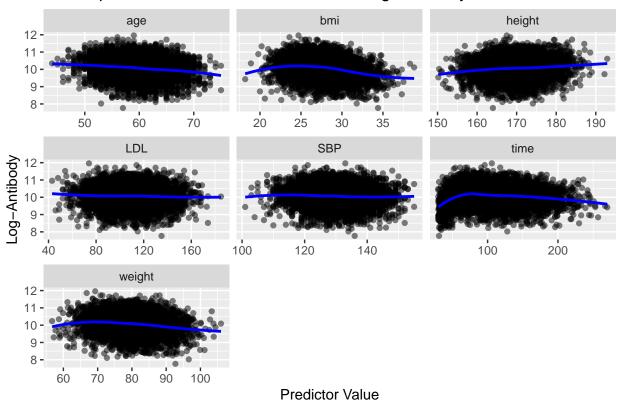


Scatterplots of Continuous Predictors vs. Log-Antibody

```
dat1 %>%
  select(age, height, weight, bmi, SBP, LDL, time, log_antibody) %>%
  pivot_longer(
    cols = c(age, height, weight, bmi, SBP, LDL, time),
    names_to = "predictor",
    values_to = "value"
) %>%
  ggplot(aes(x = value, y = log_antibody)) +
  geom_point(alpha = 0.5) +
  geom_smooth(method = "loess", se = FALSE, color = "blue") +
  facet_wrap(~ predictor, scales = "free_x") +
  labs(
    x = "Predictor Value",
    y = "Log-Antibody",
    title = "Scatterplots of Continuous Predictors vs. Log-Antibody"
)
```

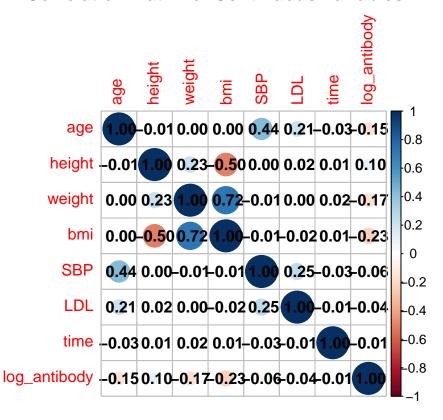
'geom_smooth()' using formula = 'y ~ x'

Scatterplots of Continuous Predictors vs. Log-Antibody



Correlation Matrix of Continuous Variables

Correlation Matrix of Continuous Variables

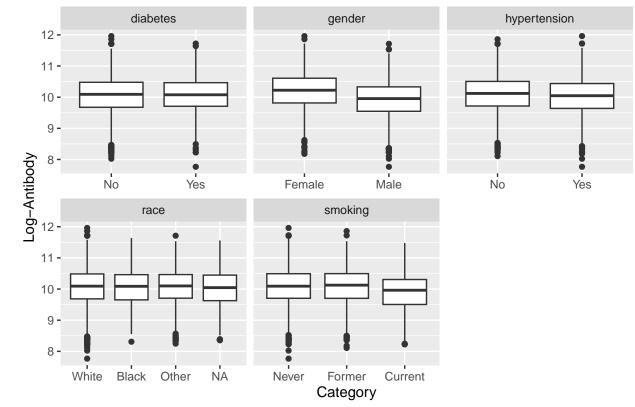


Boxplots of log_antibody by categorical variables

```
dat1 %>%
  select(log_antibody, gender, race, smoking, diabetes, hypertension) %>%
  mutate(
    gender = factor(dat1$gender,
                      levels = c(0, 1),
                      labels = c("Female", "Male")),
   race = factor(dat1$race,
                    levels = c(1, 2, 3),
                    labels = c("White", "Black", "Other")),
    smoking = factor(dat1$smoking,
                       levels = c(0, 1, 2),
                       labels = c("Never", "Former", "Current")),
   diabetes = factor(dat1$diabetes,
                        levels = c(0, 1),
                        labels = c("No", "Yes")),
   hypertension = factor(dat1$hypertension,
                            levels = c(0, 1),
                            labels = c("No", "Yes"))
  ) %>%
  pivot_longer(
   cols = c(gender, race, smoking, diabetes, hypertension),
   names_to = "predictor",
```

```
values_to = "category"
) %>%
ggplot(aes(x = category, y = log_antibody)) +
geom_boxplot() +
facet_wrap(~ predictor, scales = "free_x") +
labs(
    x = "Category",
    y = "Log-Antibody",
    title = "Boxplots of Log-Antibody by Categorical Predictors"
)
```

Boxplots of Log-Antibody by Categorical Predictors



Models Building

 ${\it cross-validation}$

```
set.seed(123)
ctrl = trainControl(method = "cv", number = 10)
```

LASSO

```
x <- model.matrix(log_antibody ~ . , data = dat1)[, -1]
y <- dat1$log_antibody

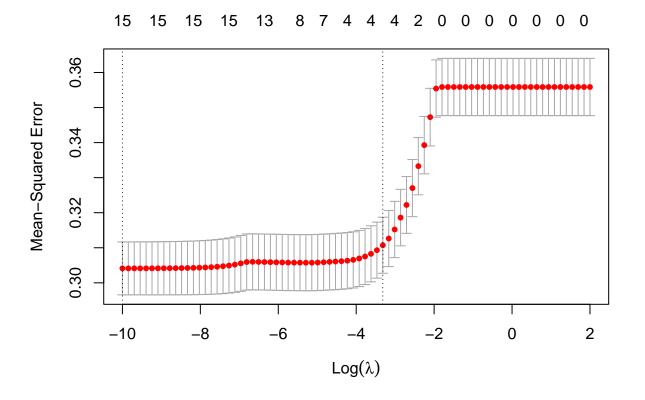
cv_lasso <- cv.glmnet(x, y, alpha = 1, lambda = exp(seq(2, -10, length = 80)))
cv_lasso$lambda.min

## [1] 4.539993e-05

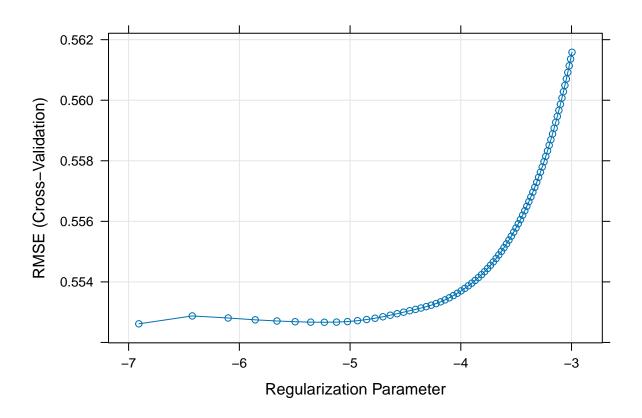
cv_lasso$lambda.1se

## [1] 0.0362812

plot(cv_lasso)</pre>
```



```
plot(model_lasso, xTrans = log)
```



model_lasso\$bestTune

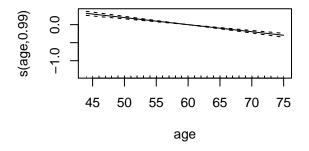
```
## alpha lambda
## 1 1 0.001
```

$\mathbf{G}\mathbf{A}\mathbf{M}$

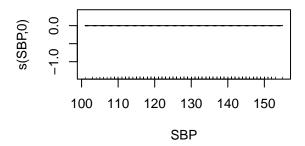
```
model_gam <- train(
  log_antibody ~ .,
  data = dat1,
  method = "gam",
  trControl = ctrl
)
model_gam$finalModel</pre>
```

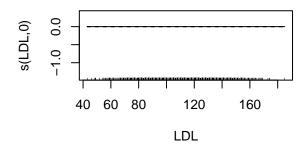
```
##
## Family: gaussian
## Link function: identity
##
```

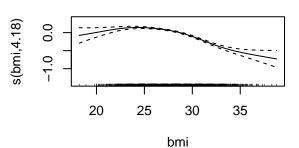
```
## Formula:
  .outcome ~ gender + race2 + race3 + race4 + smoking1 + smoking2 +
       diabetes + hypertension + s(age) + s(SBP) + s(LDL) + s(bmi) +
##
##
       s(time) + s(height) + s(weight)
## Estimated degrees of freedom:
## 0.991 0.000 0.000 4.179 7.892 1.234 0.000
  total = 23.3
##
## GCV score: 0.2786734
model_gam$bestTune
     select method
       TRUE GCV.Cp
## 2
par(mfrow = c(2,2))
```

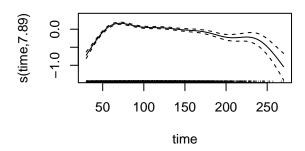


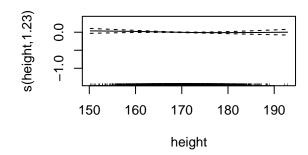
plot(model_gam\$finalModel)

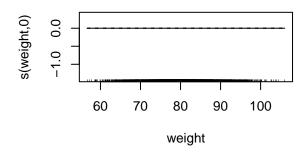






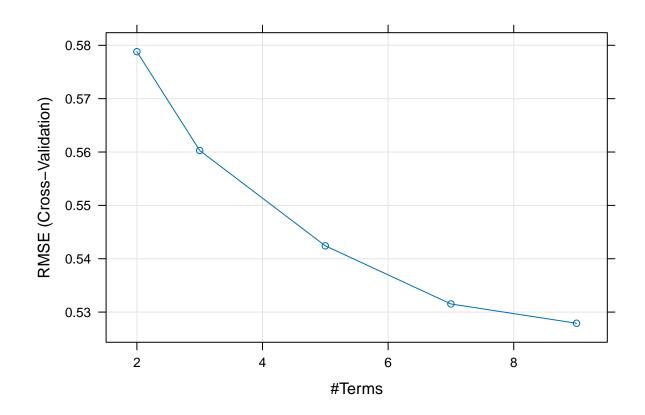






MARS

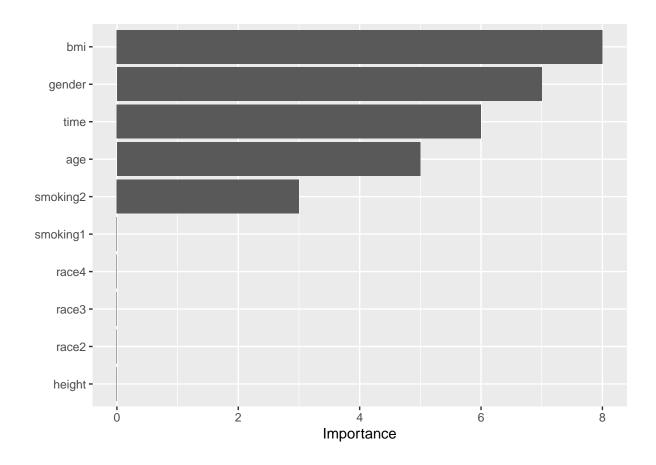
```
model_mars <- train(
  log_antibody ~ .,
  data = dat1,
  method = "earth",
  trControl = ctrl,
  tuneLength = 5
)</pre>
```



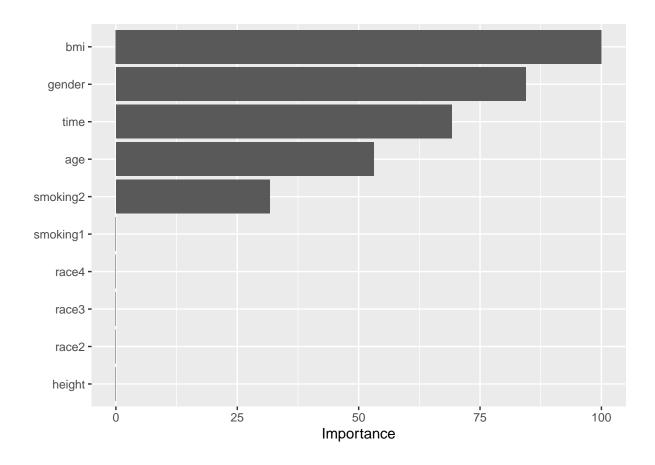
coef(model_mars\$finalModel)

```
## (Intercept) h(27.8-bmi) h(time-57) h(57-time) gender h(age-59)
## 10.847446930 -0.061997354 -0.002254182 -0.033529326 -0.296290451 -0.022957648
## h(59-age) smoking2 h(bmi-23.7)
## 0.016138468 -0.205126851 -0.084380175
```

vip(model_mars\$finalModel, type = "nsubsets")



vip(model_mars\$finalModel, type = "rss")



Predictions and Model Evaluation

```
pred_lasso <- predict(model_lasso, newdata = dat2)</pre>
pred_mars <- predict(model_mars, newdata = dat2)</pre>
          <- predict(model_gam, newdata = dat2)</pre>
pred_gam
resample = resamples(list(lasso = model_lasso, gam = model_gam, mars = model_mars))
summary(resample)
##
## Call:
## summary.resamples(object = resample)
##
## Models: lasso, gam, mars
## Number of resamples: 10
##
## MAE
##
              Min.
                      1st Qu.
                                 Median
                                              Mean
                                                     3rd Qu.
## lasso 0.4302898 0.4347903 0.4384044 0.4402713 0.4443131 0.4543854
         0.4075818 0.4191554 0.4252307 0.4228909 0.4269059 0.4340199
                                                                           0
## mars 0.3998365 0.4142026 0.4225842 0.4225721 0.4296486 0.4466906
##
## RMSE
```

```
1st Qu.
                                Median
                                            Mean
                                                   3rd Qu.
## lasso 0.5419531 0.5451779 0.5484308 0.5526149 0.5607064 0.5679933
        0.5114329 0.5250503 0.5291679 0.5284976 0.5310636 0.5503925
## mars 0.4983898 0.5196328 0.5275137 0.5279091 0.5352447 0.5623342
                                                                        0
## Rsquared
                     1st Qu.
                                Median
                                            Mean
                                                   3rd Qu.
              Min.
## lasso 0.1174197 0.1295564 0.1442448 0.1419938 0.1558283 0.1614893
         0.1640261 0.1884887 0.2122991 0.2157631 0.2358544 0.2821440
                                                                        0
## mars 0.1850330 0.2027610 0.2069534 0.2167496 0.2415450 0.2521676
```

GAM

##

```
pred_gam \leftarrow predict(gam.fit\finalModel, newdata = dat2) \ sqrt(mean((pred_gam - y2)^2))
```

Antibody level and time

Multiple R-squared: 0.05771,

```
library(splines)
model_spline <- lm(log_antibody ~ ns(time, df = 4), data = dat1)</pre>
summary(model_spline)
##
## lm(formula = log_antibody ~ ns(time, df = 4), data = dat1)
##
## Residuals:
##
       Min
                 1Q
                      Median
                                   3Q
                                            Max
## -2.03592 -0.36964 0.01735 0.40630 1.86009
## Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)
                     9.47141
                                0.03945 240.066 < 2e-16 ***
## ns(time, df = 4)1 0.55828
                                0.04100 13.616 < 2e-16 ***
## ns(time, df = 4)2 0.28006
                                          5.525 3.46e-08 ***
                                0.05069
## ns(time, df = 4)3 1.16159
                                0.10205 11.383 < 2e-16 ***
## ns(time, df = 4)4 - 0.44128
                                0.11083 -3.981 6.95e-05 ***
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
```

Residual standard error: 0.5792 on 4995 degrees of freedom

F-statistic: 76.48 on 4 and 4995 DF, p-value: < 2.2e-16

Adjusted R-squared: 0.05695