# Nonlinear

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### Import the train dataset

```
train = read_csv("./train.csv")

y = train$transformed_value
options(na.action = 'na.pass')
x = model.matrix(transformed_value ~ ., train)[,-1]
```

### Set a random seed

```
set.seed(2)
```

### Generallized additive model (GAM)

#### Use caret package

```
ctrl1 <- trainControl(method = "cv", number = 10)
gam.fit = train(x, y,
                preProcess = "medianImpute",
                method = "gam",
                tuneGrid = data.frame(method = "GCV.Cp",
                                      select = c(TRUE,FALSE)),
                trControl = ctrl1)

save(gam.fit, file = "./gam_fit.rda")
```

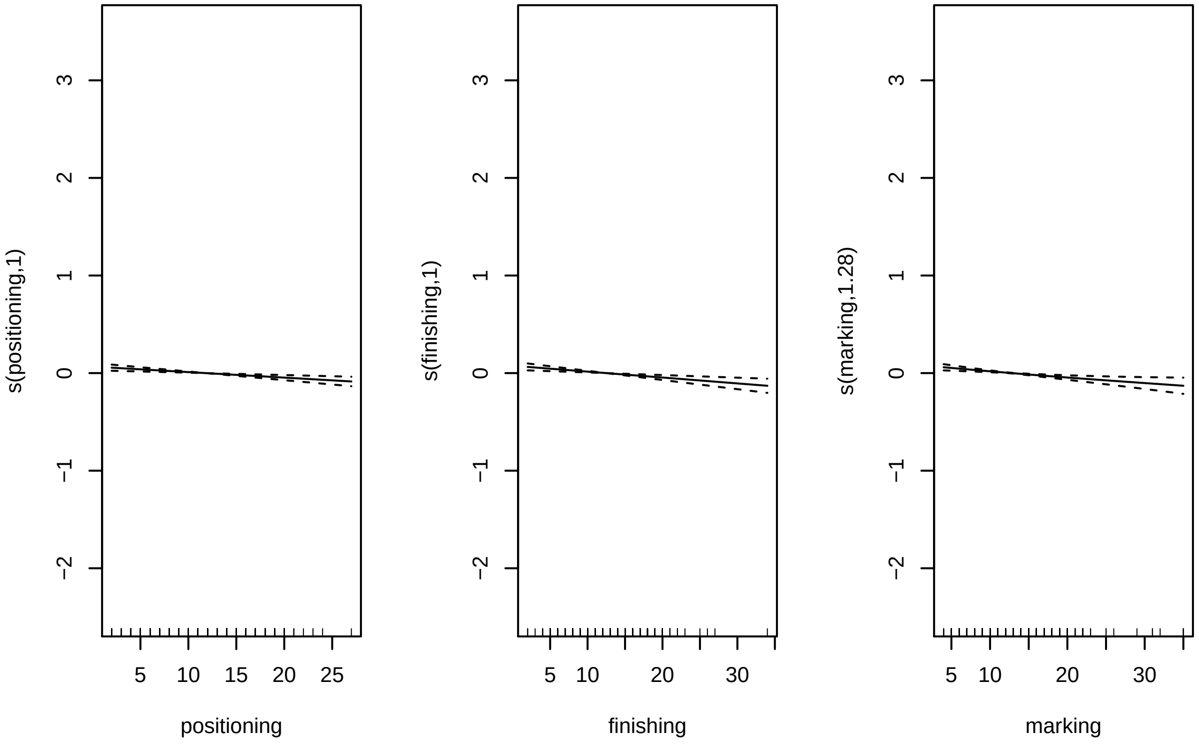
```
load(file = "./gam_fit.rda")
gam.fit$bestTune
```

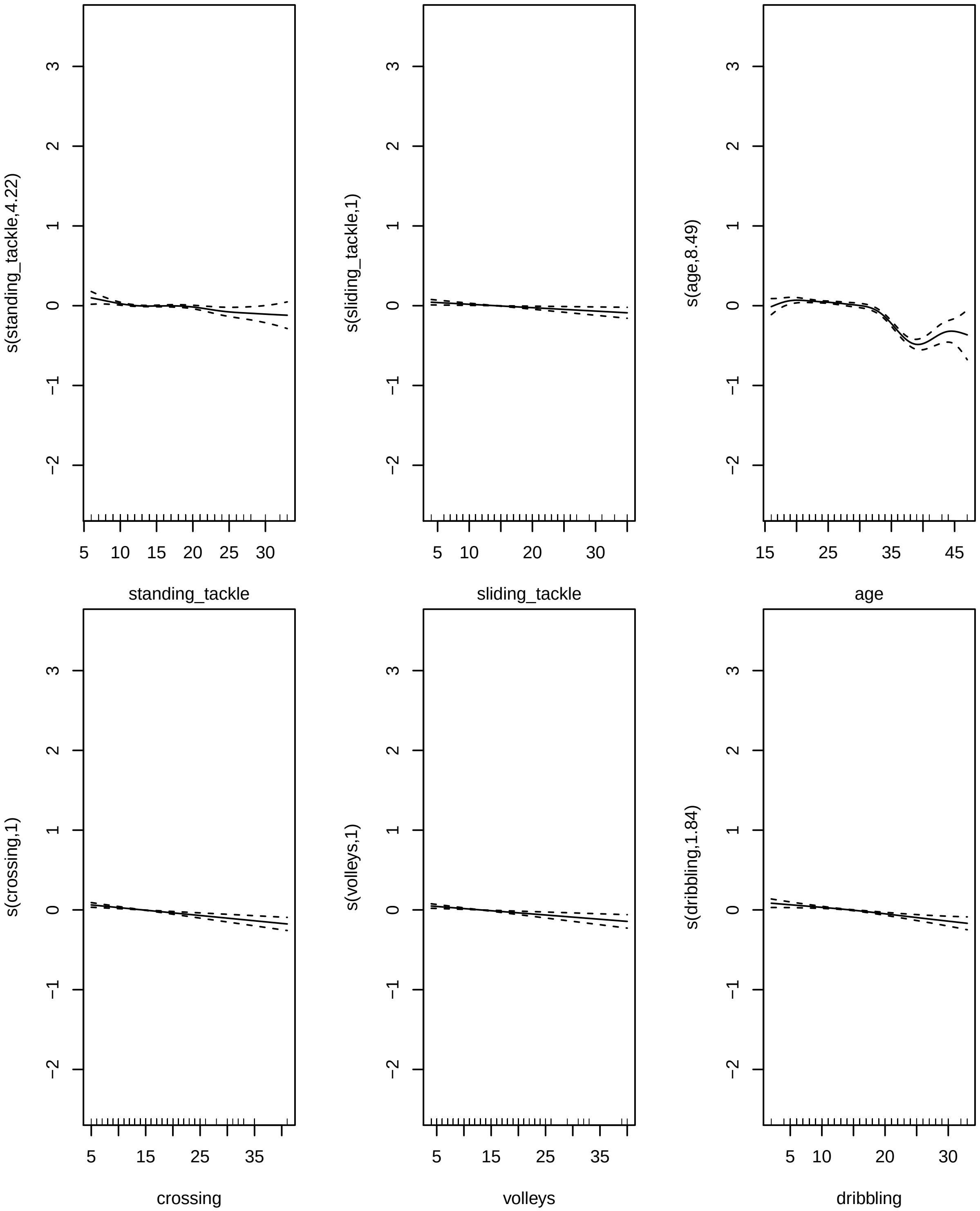
```
##   select method
## 1  FALSE GCV.Cp
```

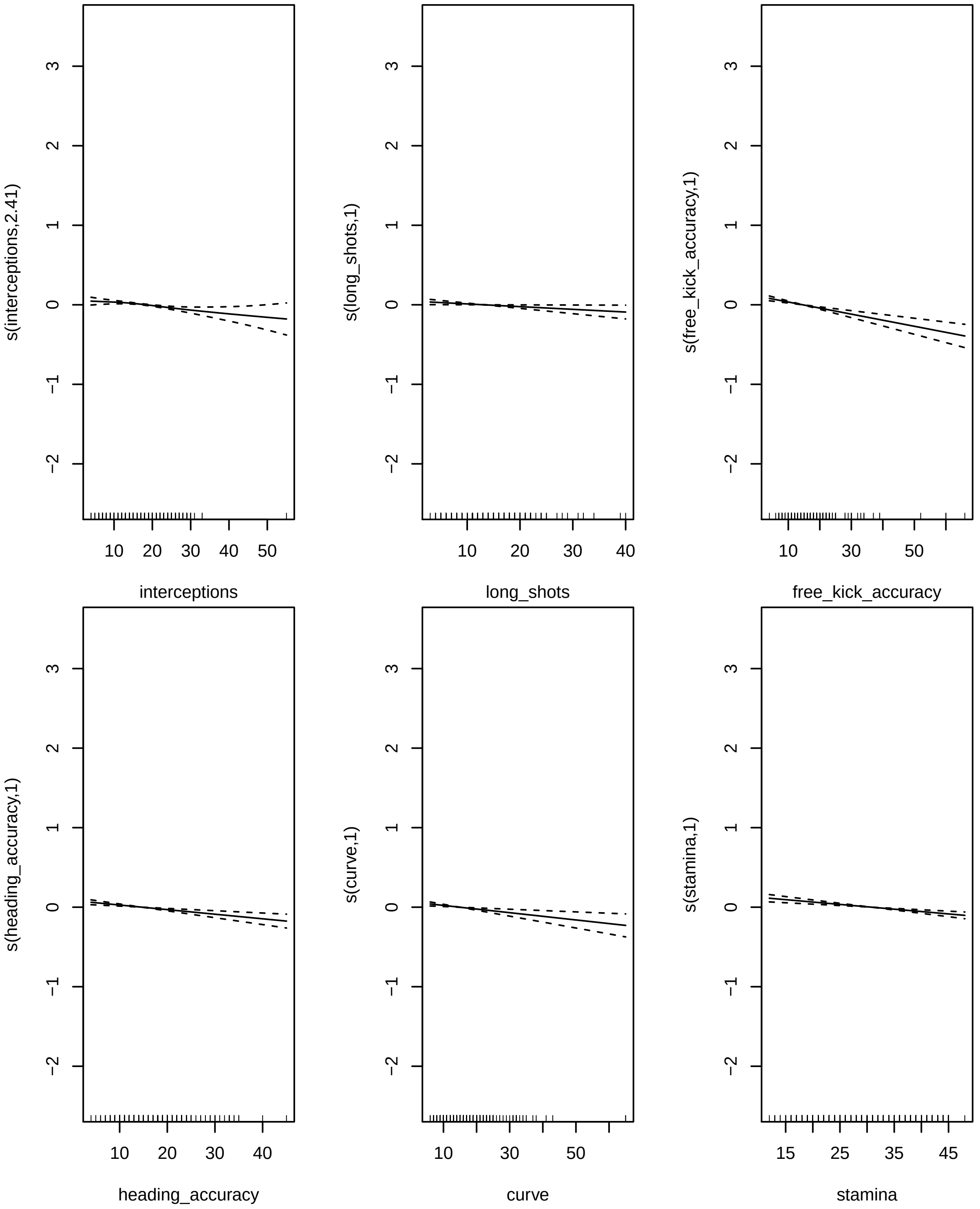
```
gam.fit$finalModel
```

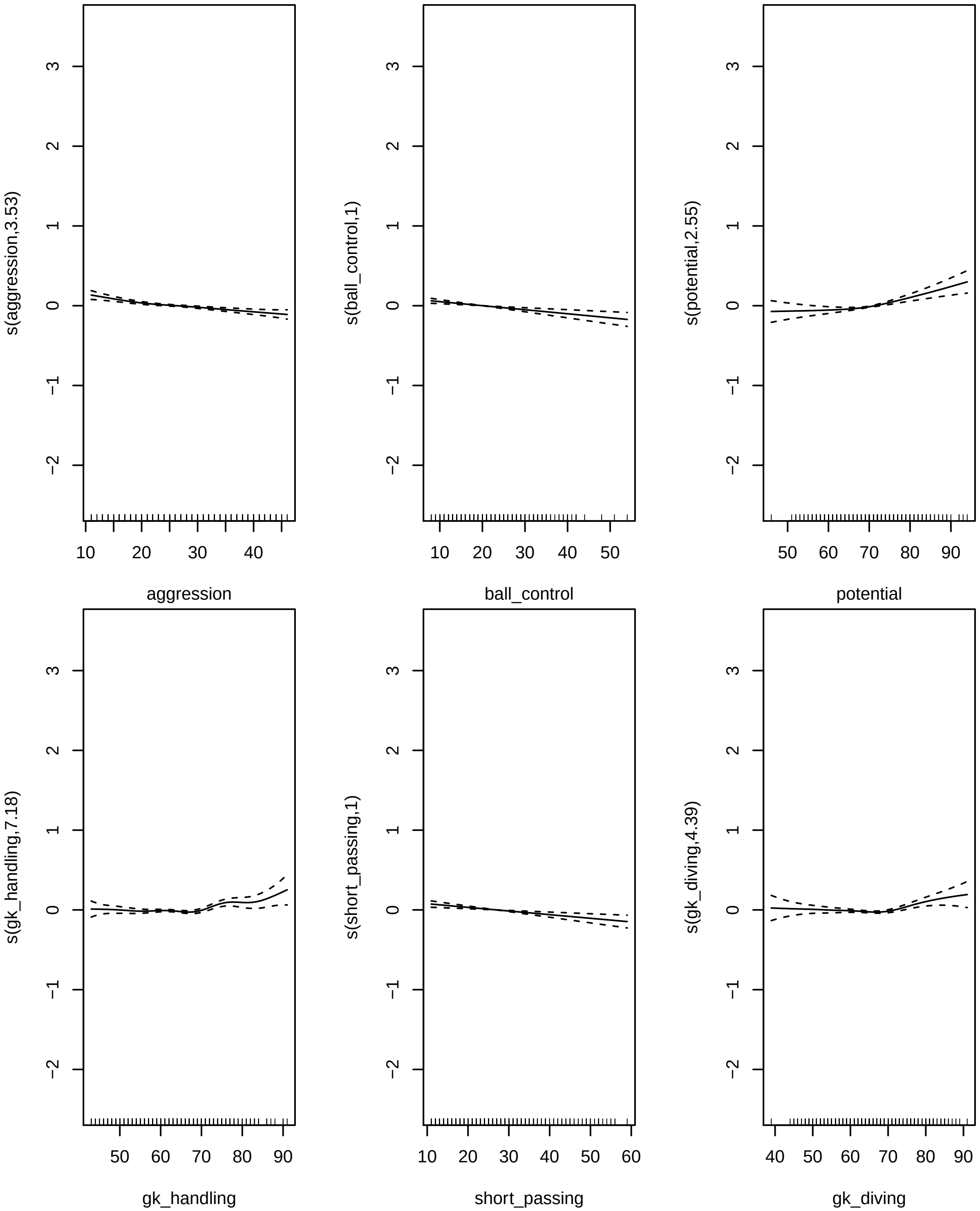
```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## .outcome ~ nationalityas + nationalityeu + nationalitysa + s(positioning) +
##     s(finishing) + s(marking) + s(standing_tackle) + s(sliding_tackle) +
##     s(age) + s(crossing) + s(volleys) + s(dribbling) + s(interceptions) +
##     s(long_shots) + s(free_kick_accuracy) + s(heading_accuracy) +
##     s(curve) + s(stamina) + s(aggression) + s(ball_control) +
##     s(potential) + s(gk_handling) + s(short_passing) + s(gk_diving) +
##     s(gk_reflexes) + s(penalties) + s(gk_kicking) + s(gk_positioning) +
##     s(long_passing) + s(shot_power) + s(acceleration) + s(sprint_speed) +
##     s(balance) + s(reactions) + s(agility) + s(composure) + s(strength) +
##     s(vision) + s(jumping) + s(special)
##
## Estimated degrees of freedom:
## 1.00 1.00 1.28 4.22 1.00 8.49 1.00
## 1.00 1.84 2.41 1.00 1.00 1.00 1.00
## 1.00 3.53 1.00 2.55 7.18 1.00 4.39
## 2.97 8.90 6.35 1.00 1.00 2.68 1.00
## 1.00 2.67 2.89 1.40 1.00 3.88 8.78
## 1.00 2.88  total = 101.29
##
## GCV score: 0.01923898
```

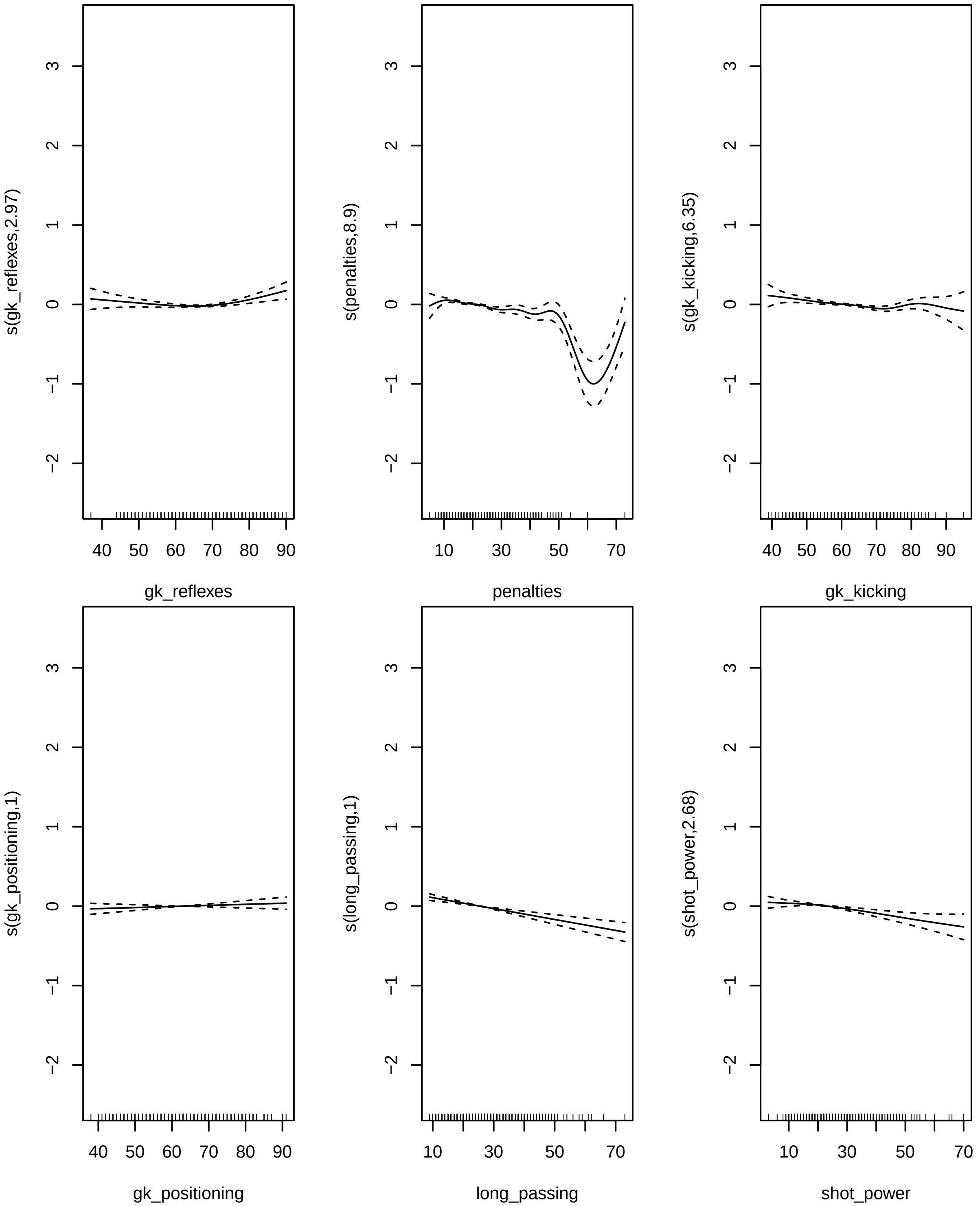
```
par(mfrow = c(1,3))
plot(gam.fit$finalModel)
```

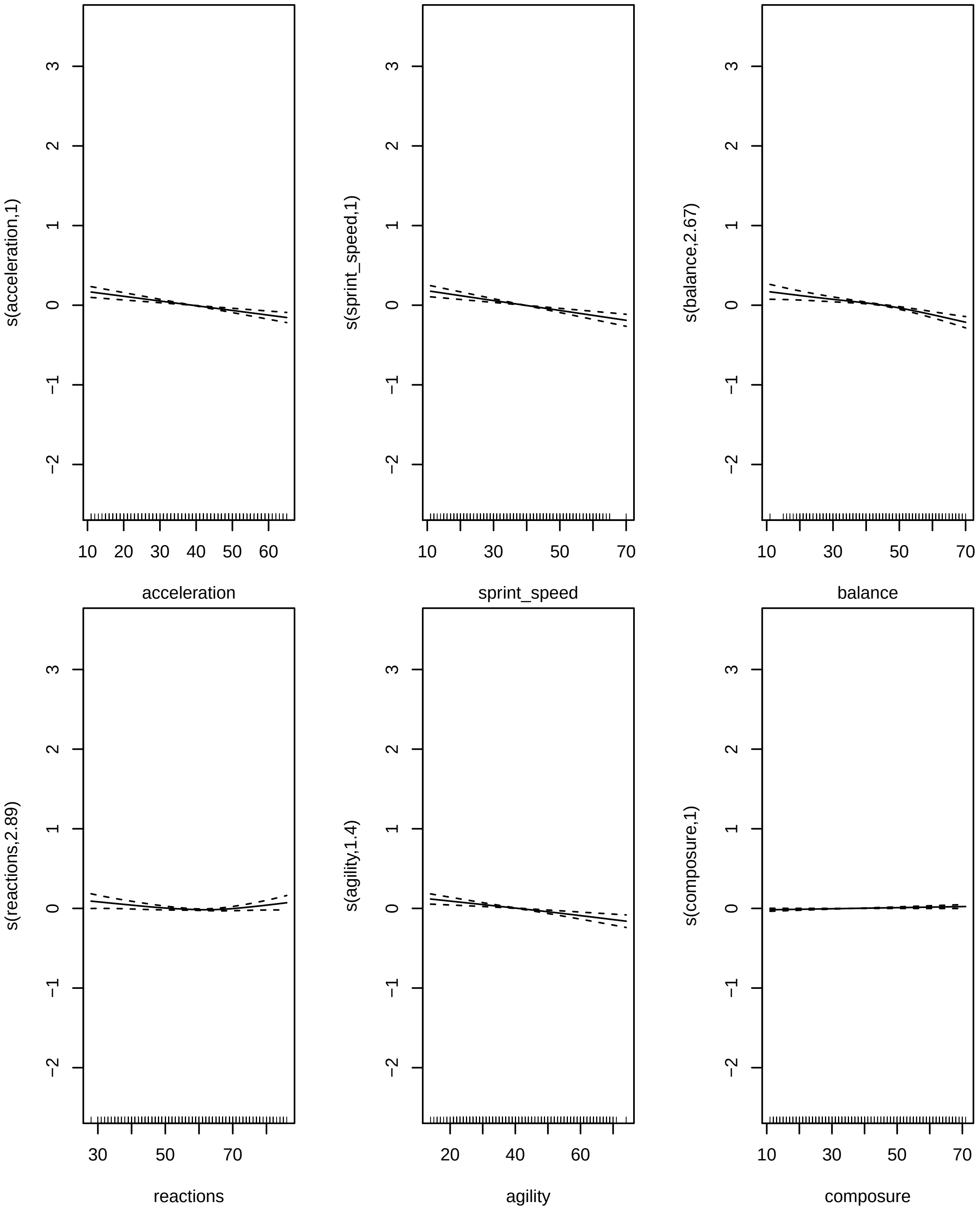


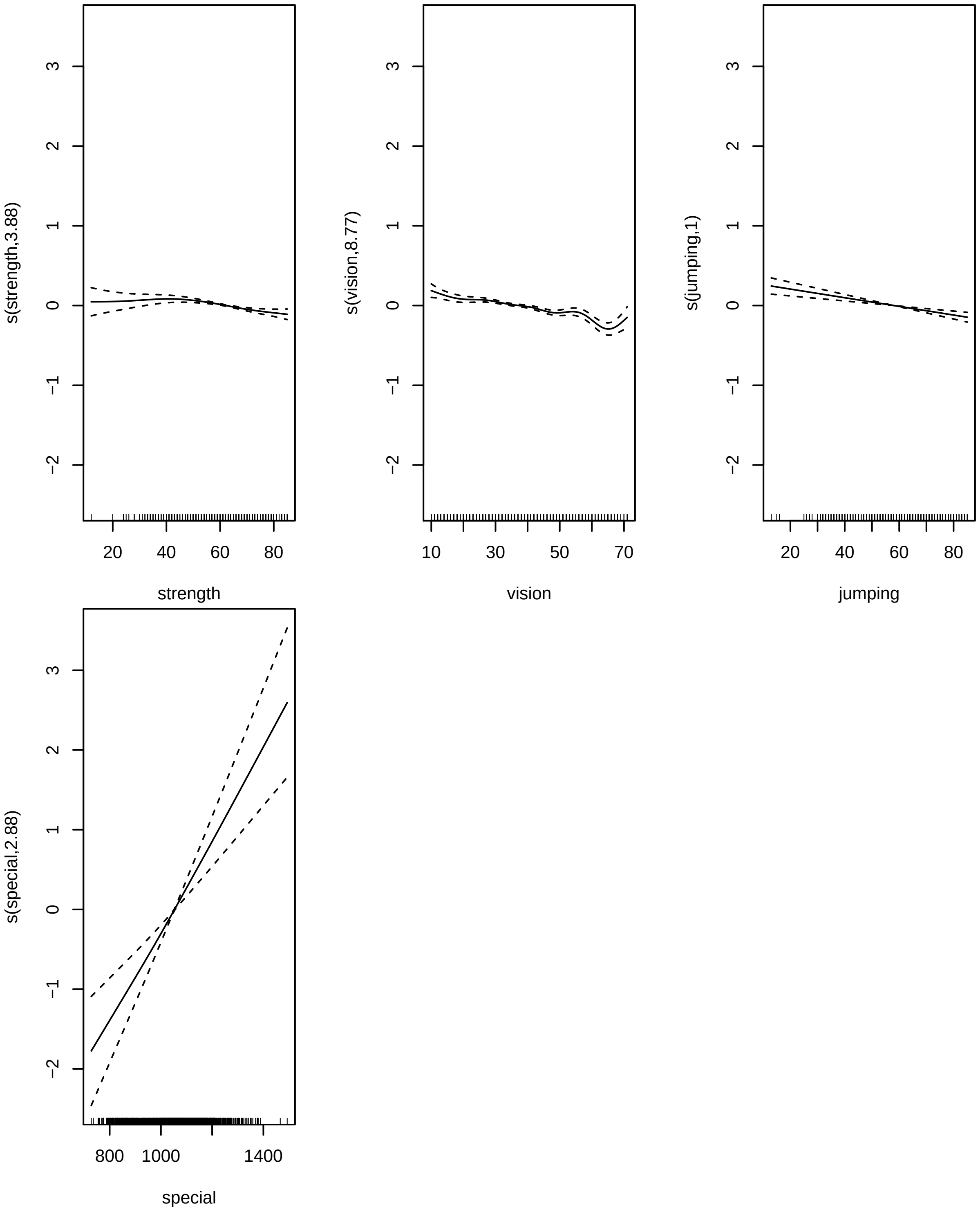

s(standing_tackle,4.22)
standing_tackle
5
10
15
20
25
30
s(sliding_tackle,1)
sliding_tackle
5
10
20
30
s(age,8.49)
age
15
25
35
45
s(crossing,1)
crossing
5
15
25
35
s(volleys,1)
volleys
5
15
25
35
s(dribbling,1.84)
dribbling
5
10
20
30
3
2
1
0
−1
−2


s(interceptions,2.41)
interceptions
10
20
30
40
50
s(long_shots,1)
long_shots
10
20
30
40
s(free_kick_accuracy,1)
free_kick_accuracy
10
30
50
s(heading_accuracy,1)
heading_accuracy
10
20
30
40
s(curve,1)
curve
10
30
50
s(stamina,1)
stamina
15
25
35
45
3
2
1
0
−1
−2


s(aggression,3.53)
aggression
10
20
30
40
s(ball_control,1)
ball_control
10
20
30
40
50
s(potential,2.55)
potential
50
60
70
80
90
s(gk_handling,7.18)
gk_handling
50
60
70
80
90
s(short_passing,1)
short_passing
10
20
30
40
50
60
s(gk_diving,4.39)
gk_diving
40
50
60
70
80
90
3
2
1
0
−1
−2


s(gk_reflexes,2.97)
gk_reflexes
40
50
60
70
80
90
s(penalties,8.9)
penalties
10
30
50
70
s(gk_kicking,6.35)
gk_kicking
40
50
60
70
80
90
s(gk_positioning,1)
gk_positioning
40
50
60
70
80
90
s(long_passing,1)
long_passing
10
30
50
70
s(shot_power,2.68)
shot_power
10
30
50
70
3
2
1
0
−1
−2


s(acceleration,1)
3
2
1
0
−1
−2
10
20
30
40
50
60
acceleration
s(sprint_speed,1)
3
2
1
0
−1
−2
10
30
50
70
sprint_speed
s(balance,2.67)
3
2
1
0
−1
−2
10
30
50
70
balance
s(reactions,2.89)
3
2
1
0
−1
−2
30
50
70
reactions
s(agility,1.4)
3
2
1
0
−1
−2
20
40
60
agility
s(composure,1)
3
2
1
0
−1
−2
10
30
50
70
composure



### Multivariate Adaptive Regression Splines (MARS)

```
ctrl1 <- trainControl(method = "cv", number = 10)
mars_grid = expand.grid(degree = 1:2,
                        nprune = 2:38)
```

```r
mars.fit = train(x, y,
                 method = "earth",
                 preProcess = "medianImpute",
                 tuneGrid = mars_grid,
                 trControl = ctrl1
                 )
save(mars.fit, file = "./earth.rda")
```

```r
load(file = "./earth.rda")
summary(mars.fit)
```

```
## Call: earth(x=matrix[1523,42], y=c(2.795,2.772,1...), keepxy=TRUE,
##             degree=1, nprune=18)
##
##                       coefficients
## (Intercept)             0.70326337
## nationalityeu           0.04077075
## h(age-29)              -0.02402008
## h(age-33)              -0.05729609
## h(age-39)               0.12757144
## h(71-potential)        -0.00539790
## h(potential-71)         0.01690058
## h(61-agility)          -0.00171512
## h(balance-47)          -0.00319876
## h(68-gk_diving)        -0.00717104
## h(gk_diving-68)         0.01607073
## h(67-gk_handling)      -0.00482717
## h(gk_handling-67)       0.01440001
## h(gk_kicking-72)        0.00936914
## h(gk_positioning-43)    0.00790612
## h(gk_reflexes-71)       0.01509622
## h(reactions-63)         0.01070404
## h(41-strength)         -0.01290410
##
## Selected 18 of 28 terms, and 12 of 42 predictors
## Termination condition: RSq changed by less than 0.001 at 28 terms
## Importance: gk_diving, age, gk_positioning, potential, reactions, ...
## Number of terms at each degree of interaction: 1 17 (additive model)
## GCV 0.02047396    RSS 29.76514    GRSq 0.8598615    RSq 0.8660527
```

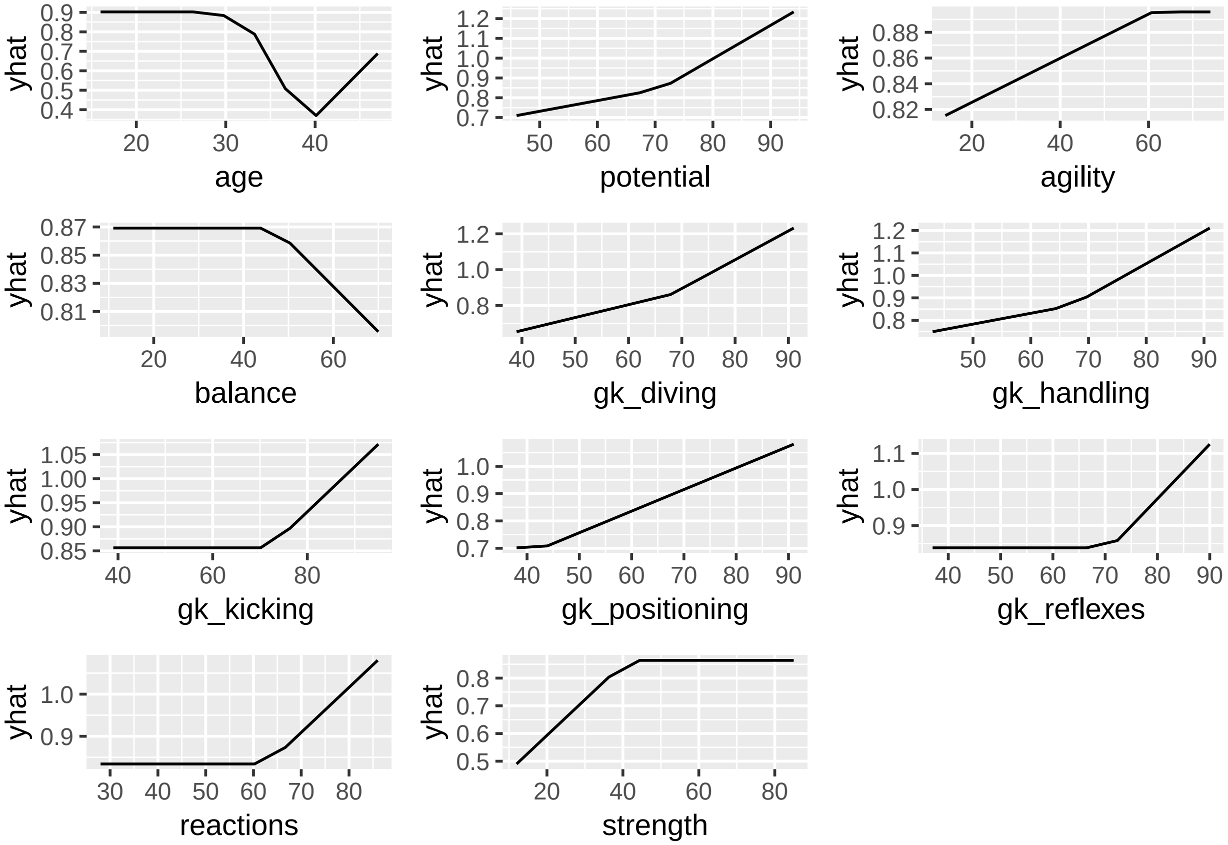
```r
mars.fit$bestTune
```

```
##    nprune degree
## 17     18      1
```

```r
p1 = partial(mars.fit, pred.var = c("age"), grid.resolution = 10) %>% autoplot()
p2 = partial(mars.fit, pred.var = c("potential"), grid.resolution = 10) %>% autoplot()
p3 = partial(mars.fit, pred.var =c("agility"), grid.resolution = 10) %>% autoplot()
p4 = partial(mars.fit, pred.var =c("balance"), grid.resolution = 10) %>% autoplot()
p5 = partial(mars.fit, pred.var =c("gk_diving"), grid.resolution = 10) %>% autoplot()
p6 = partial(mars.fit, pred.var =c("gk_handling"), grid.resolution = 10) %>% autoplot()
p7 = partial(mars.fit, pred.var =c("gk_kicking"), grid.resolution = 10) %>% autoplot()
p8 = partial(mars.fit, pred.var =c("gk_positioning"), grid.resolution = 10) %>% autoplot()
p9 = partial(mars.fit, pred.var =c("gk_reflexes"), grid.resolution = 10) %>% autoplot()
p10 = partial(mars.fit, pred.var =c("reactions"), grid.resolution = 10) %>% autoplot()
```

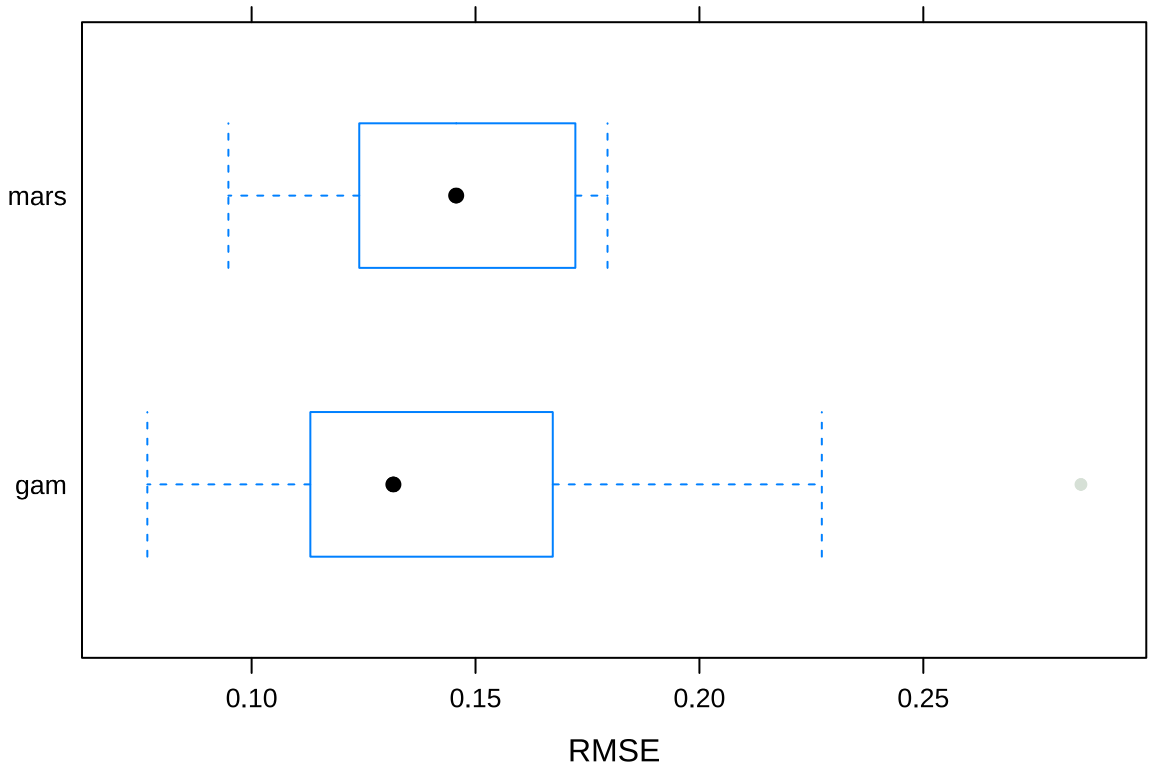
```
p11 = partial(mars.fit, pred.var =c("strength"), grid.resolution = 10) %>% autoplot()

grid.arrange(p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, ncol = 3, nrow = 4)
```



### Compare those models

```
bwplot(resamples(list(mars = mars.fit,gam = gam.fit)),
       metric = "RMSE")
```



### Importance

```
varImp(mars.fit)
```

```
## earth variable importance
##
##   only 20 most important variables shown (out of 42)
##
##                  Overall
## gk_diving        100.000
## age               44.619
## gk_positioning    44.619
## gk_reflexes       32.682
## potential         30.563
## reactions         24.640
## gk_handling       18.626
## strength          14.856
## nationalityeu     10.442
## gk_kicking         7.197
## balance            3.178
## agility            3.178
## stamina            0.000
## interceptions      0.000
## nationalityoc      0.000
## sprint_speed       0.000
## short_passing      0.000
## marking            0.000
## standing_tackle    0.000
## crossing          0.000
```

```
varImp(gam.fit)
```

```
## gam variable importance
##
##   only 20 most important variables shown (out of 40)
##
##                     Overall
## age                 100.000
## vision                9.209
## penalties             7.638
## balance               7.021
## long_passing          6.349
## special               6.112
## free_kick_accuracy    6.105
## sprint_speed          5.358
## potential             5.107
## stamina               5.073
## acceleration          5.070
## jumping               4.968
## dribbling             4.891
## strength              4.882
## gk_handling           4.527
## aggression            4.331
## crossing              3.954
## gk_diving             3.585
## heading_accuracy      3.500
## ball_control          3.362
```

## Questions

1. As we can't use the test dataset to choose our final model, do we need to calculate test error for each model or just our final model.

Do we write (linear -> nonlinear, if we know it is nonlinear why we try linear firstly)

depend on oursevles

2. How to know our model is good or not, just with a train error and a test error. (close and both small -> good, train << test overfitted, both large underfitted) However, how do we know it is small or large (MSE also depends on y)

can't

3. Which variables are important? Different models have different important variables. Do we only use the result of our final model?
4. how do we present our model in the report (coefficients? tunning parameter? plot?)
5. Model assumptions and limitations

*linear* Multi linear: model linear in parameter (error term mean 0 constant variance uncorrelated)

lasso and ridge: linear (Anything else? Multicollinearity?)

pcr: linear (Anything else? Multicollinearity?)

*non-linear* gam: Nonlinear relationship (Anything else?) mars: Nonlinear relationship (Anything else)

6. How to choose tunning parameters? like we try lambda from (eˆ-10, eˆ10), then we choose the best lambda by 10-fold cross vaildation.

7.How do we know model is enough flexible? How do we make prediction?