Probability of Recession

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Summary

Forecast the probability of a recession in the next 126 trading days using the following predictors:

1. Spread between 10Y CMT and Effective Federal Funds Rate
2. Spread between 10Y CMT and 3Mo TBill
3. Lags of the spreads
4. Adstock of the spreads
5. Moving averages of the spreads

There are between 250 and 253 trading days in a year. About 21 trading days in a month.

Extract Historical Data

Refer to this vignette for FRED data access.

```
library(tidyverse)
library(lubridate)
library(fredr)
library(car)
library(MLmetrics)
library(caret)
library(pdp)
library(gridExtra)
library(mboost)
library(gbm)
library(randomForest)
library(glmnet)
library(gtsummary)

randSeed <- 1983

startTestDate <- "1968-01-01"
startTrainDate <- "1978-01-01"
```

```
# series_id <- c("FEDFUNDS", "GS10", "USREC", "UNRATE", "CPIAUCSL")

series_id <- c("DFF", "DGS10", "DTB3")  # daily

response_id <- "USREC" # monthly
```

```r
full_data <- map_dfr(series_id, function(x) {
  fredr(
    series_id = x,
    observation_start = as.Date("1950-01-01"),
    observation_end = as.Date("2023-12-01")
  )
})

recession_dates <- map_dfr(response_id, function(x) {
  fredr(
    series_id = x,
    observation_start = as.Date("1950-01-01"),
    observation_end = as.Date("2023-12-01")
  )
})
```

Pivot Wider

```r
full_data_wide_raw <- full_data %>%
  arrange(date) %>%
  select(date, series_id, value) %>%
  pivot_wider(id_cols=date, names_from = series_id,
              values_from = value)%>%
  drop_na()
```

Calculate Features/Predictors

```r
full_data_wide_features <- full_data_wide_raw %>%
  arrange(date) %>%
  mutate(SPRD_10YCMT_FEDFUNDS = DGS10 - DFF,
         SPRD_10YCMT_3moTBill = DGS10 - DTB3,
         D_SPRD_FFR = SPRD_10YCMT_FEDFUNDS -
           lag(SPRD_10YCMT_FEDFUNDS, 5),
         D_SPRD_3mo = SPRD_10YCMT_3moTBill -
           lag(SPRD_10YCMT_3moTBill, 5)
         ) %>%
  mutate(across(
    .cols=c(SPRD_10YCMT_FEDFUNDS, SPRD_10YCMT_3moTBill),
    .fns=list(lag1d = ~lag(.x, 1),
         lag5d = ~lag(.x, 5),
         lag1m = ~lag(.x, 1*21),
         lag3m = ~lag(.x, 3*21),
         lag6m = ~lag(.x, 6*21),
         lag9m = ~lag(.x, 9*21),
         lag12m = ~lag(.x, 12*21)
         )
  )) %>%
  drop_na()
```

Calculate Adstock

The adstock transformation is an auto-regressive transformation of a time series. The transformation takes into account past values of the time series. The intuition is that past values of the time series has a contemporaneous effect on the outcome.

$$AdStock(x_t) = x_t + \theta AdStock(x_{t-1})$$

where

$$0 < \theta < 1$$

.

The parameters cannot be estimated easily with least squares or logistic regression. Instead, we assume a range of potential values.

```
full_data_wide_features_adstock <- full_data_wide_features %>%
  arrange(date) %>%
    mutate(across(
    .cols=c(SPRD_10YCMT_FEDFUNDS,
            SPRD_10YCMT_3moTBill,
            D_SPRD_FFR,
            D_SPRD_3mo
            ),
    .fns=list(adstk001 = ~stats::filter(.x,
                                     filter=0.001,
                                     method="recursive") ,
         adstk0001 = ~stats::filter(.x,
                                     filter=0.0001,
                                     method="recursive") ,
         adstk10 = ~stats::filter(.x,
                                     filter=0.10,
                                     method="recursive"),
         adstk40 = ~stats::filter(.x,
                                     filter=0.40,
                                     method="recursive"),
         adstk95 = ~stats::filter(.x,
                                     filter=0.95,
                                     method="recursive"),
         adstk98 = ~stats::filter(.x,
                                     filter=0.98,
                                     method="recursive")
  ))) %>%
  mutate(constant=1)
```

Calculate Moving Average

```
ma_fun <- function(k_param){
  rep(1/k_param, k_param)
}

full_data_wide_features_adstock <- full_data_wide_features_adstock %>%
```

```
  arrange(date) %>%
    mutate(across(
    .cols=c(SPRD_10YCMT_FEDFUNDS,
            SPRD_10YCMT_3moTBill,
            D_SPRD_FFR,
            D_SPRD_3mo),
    .fns=list(ma5d = ~stats::filter(.x,
                                     filter=ma_fun(5),
                                    method="convolution",
                                    sides=1) ,
         ma10d = ~stats::filter(.x,
                                    filter=ma_fun(10),
                                    method="convolution",
                                    sides=1) ,
         ma15d = ~stats::filter(.x,
                                     filter=ma_fun(15),
                                    method="convolution",
                                    sides=1),
         ma20d = ~stats::filter(.x,
                                      filter=ma_fun(20),
                                    method="convolution",
                                    sides=1),
         ma25d = ~stats::filter(.x,
                                     filter=ma_fun(25),
                                    method="convolution",
                                    sides=1),
         ma2m = ~stats::filter(.x,
                                      filter=ma_fun(2*21),
                                    method="convolution",
                                    sides=1),
         ma3m = ~stats::filter(.x,
                                      filter=ma_fun(3*21),
                                    method="convolution",
                                    sides=1),
         ma6m = ~stats::filter(.x,
                                      filter=ma_fun(6*21),
                                    method="convolution",
                                    sides=1),
         ma9m = ~stats::filter(.x,
                                      filter=ma_fun(9*21),
                                    method="convolution",
                                    sides=1),
         ma12m = ~stats::filter(.x,
                                      filter=ma_fun(12*21),
                                    method="convolution",
                                    sides=1)
  )))
```

Recession in next 6 months

```
full_data_wide <- full_data_wide_features_adstock %>%
  arrange(date) %>%
```

```
  mutate(date_month = month(date),
         date_year = year(date))

recession_df <- recession_dates %>%
  select(date, value) %>%
  arrange(date) %>%
  mutate(date_month = month(date),
         date_year = year(date))


full_data_wide <- full_data_wide %>%
  left_join(recession_df,
            by = c("date_month" = "date_month",
                   "date_year" = "date_year")) %>%
  mutate(USREC = value)


df_FUTREC = as.data.frame(
  data.table::shift(
    full_data_wide$USREC,
    n = 1:(6 * 21),
    type = "lead",
    give.names = TRUE,
    fill = NA
  )
) %>%
  rowwise() %>%
  mutate(FUTREC = max(c_across(V1_lead_1:V1_lead_126)))

full_data_wide$FUTREC <- df_FUTREC$FUTREC

full_data_wide <- full_data_wide %>%
  select(date=date.x, everything(), -date_month,
         -date_year, -date.y,
         -value)

full_data_wide$constant <- 1

full_data_wide_noUSREC <- full_data_wide %>%
  select(-USREC)
```

Remove the last 12 months of historical data

Since the NBER often dates recessions after they have already occurred (and sometimes ended), remove the last 12 months of historical data from both the training and test data sets.

```
recent_data <- tail(full_data_wide_noUSREC, 12*21)

train_test <- head(full_data_wide_noUSREC, -12*21) %>%
  drop_na()
```

Split Train/Test

```r
train_data <- train_test %>%
  filter(date >= startTrainDate)

test_data <- train_test %>%
  filter(date >= startTestDate) %>%
  filter(date < startTrainDate)

train_yes_no <- train_data %>%
  mutate(FUTREC = case_when(FUTREC == 1 ~ "yes",
                            TRUE ~ "no"))

train_yes_no$FUTREC <- factor(train_yes_no$FUTREC,
                              levels=c("yes","no"))



tbl_summary(train_data)
```

Characteristic	**N = 11,048**
date	1978-01-03 to 2022-03-15
DTB3	4.2 (0.9, 6.2)
DFF	4.6 (1.0, 6.9)
DGS10	5.4 (3.0, 8.2)
SPRD_10YCMT_FEDFUNDS	1.41 (0.35, 2.36)
SPRD_10YCMT_3moTBill	1.71 (0.80, 2.68)
D_SPRD_FFR	-0.01 (-0.13, 0.12)
D_SPRD_3mo	-0.01 (-0.09, 0.08)
SPRD_10YCMT_FEDFUNDS_lag1d	1.41 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_lag5d	1.41 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_lag1m	1.40 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_lag3m	1.39 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_lag6m	1.39 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_lag9m	1.41 (0.35, 2.37)
SPRD_10YCMT_FEDFUNDS_lag12m	1.41 (0.35, 2.39)
SPRD_10YCMT_3moTBill_lag1d	1.71 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag5d	1.71 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag1m	1.72 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag3m	1.72 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag6m	1.73 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag9m	1.75 (0.80, 2.68)
SPRD_10YCMT_3moTBill_lag12m	1.77 (0.80, 2.69)
SPRD_10YCMT_FEDFUNDS_adstk001	1.41 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_adstk0001	1.41 (0.35, 2.36)
SPRD_10YCMT_FEDFUNDS_adstk10	1.57 (0.39, 2.62)
SPRD_10YCMT_FEDFUNDS_adstk40	2.34 (0.58, 3.92)
SPRD_10YCMT_FEDFUNDS_adstk95	28 (7, 47)
SPRD_10YCMT_FEDFUNDS_adstk98	68 (17, 119)
SPRD_10YCMT_3moTBill_adstk001	1.71 (0.80, 2.68)
SPRD_10YCMT_3moTBill_adstk0001	1.71 (0.80, 2.68)

Characteristic	N = 11,048
SPRD__10YCMT__3moTBill__adstk10	1.90 (0.89, 2.98)
SPRD__10YCMT__3moTBill__adstk40	2.85 (1.33, 4.47)
SPRD__10YCMT__3moTBill__adstk95	34 (16, 54)
SPRD__10YCMT__3moTBill__adstk98	84 (41, 134)
D__SPRD__FFR__adstk001	-0.01 (-0.13, 0.12)
D__SPRD__FFR__adstk0001	-0.01 (-0.13, 0.12)
D__SPRD__FFR__adstk10	-0.01 (-0.14, 0.13)
D__SPRD__FFR__adstk40	-0.01 (-0.19, 0.18)
D__SPRD__FFR__adstk95	-0.06 (-0.80, 0.72)
D__SPRD__FFR__adstk98	-0.12 (-1.34, 1.21)
D__SPRD__3mo__adstk001	-0.01 (-0.09, 0.08)
D__SPRD__3mo__adstk0001	-0.01 (-0.09, 0.08)
D__SPRD__3mo__adstk10	-0.01 (-0.10, 0.09)
D__SPRD__3mo__adstk40	-0.01 (-0.14, 0.12)
D__SPRD__3mo__adstk95	-0.09 (-0.64, 0.58)
D__SPRD__3mo__adstk98	-0.16 (-1.16, 0.97)
constant	11,048 (100%)
SPRD__10YCMT__FEDFUNDS__ma5d	1.40 (0.35, 2.35)
SPRD__10YCMT__FEDFUNDS__ma10d	1.40 (0.34, 2.33)
SPRD__10YCMT__FEDFUNDS__ma15d	1.40 (0.33, 2.33)
SPRD__10YCMT__FEDFUNDS__ma20d	1.40 (0.32, 2.34)
SPRD__10YCMT__FEDFUNDS__ma25d	1.40 (0.32, 2.34)
SPRD__10YCMT__FEDFUNDS__ma2m	1.40 (0.36, 2.35)
SPRD__10YCMT__FEDFUNDS__ma3m	1.39 (0.39, 2.37)
SPRD__10YCMT__FEDFUNDS__ma6m	1.36 (0.35, 2.37)
SPRD__10YCMT__FEDFUNDS__ma9m	1.33 (0.38, 2.35)
SPRD__10YCMT__FEDFUNDS__ma12m	1.36 (0.41, 2.35)
SPRD__10YCMT__3moTBill__ma5d	1.71 (0.80, 2.68)
SPRD__10YCMT__3moTBill__ma10d	1.71 (0.80, 2.68)
SPRD__10YCMT__3moTBill__ma15d	1.71 (0.79, 2.68)
SPRD__10YCMT__3moTBill__ma20d	1.70 (0.80, 2.68)
SPRD__10YCMT__3moTBill__ma25d	1.70 (0.80, 2.68)
SPRD__10YCMT__3moTBill__ma2m	1.70 (0.81, 2.68)
SPRD__10YCMT__3moTBill__ma3m	1.71 (0.85, 2.68)
SPRD__10YCMT__3moTBill__ma6m	1.70 (0.82, 2.69)
SPRD__10YCMT__3moTBill__ma9m	1.68 (0.81, 2.70)
SPRD__10YCMT__3moTBill__ma12m	1.71 (0.84, 2.69)
D__SPRD__FFR__ma5d	-0.01 (-0.10, 0.10)
D__SPRD__FFR__ma10d	-0.01 (-0.07, 0.06)
D__SPRD__FFR__ma15d	-0.01 (-0.06, 0.06)
D__SPRD__FFR__ma20d	-0.01 (-0.05, 0.05)
D__SPRD__FFR__ma25d	0.00 (-0.05, 0.04)
D__SPRD__FFR__ma2m	-0.01 (-0.04, 0.03)
D__SPRD__FFR__ma3m	0.00 (-0.03, 0.03)
D__SPRD__FFR__ma6m	0.00 (-0.02, 0.02)
D__SPRD__FFR__ma9m	0.00 (-0.02, 0.02)
D__SPRD__FFR__ma12m	-0.003 (-0.020, 0.019)
D__SPRD__3mo__ma5d	-0.01 (-0.08, 0.07)
D__SPRD__3mo__ma10d	-0.01 (-0.06, 0.05)
D__SPRD__3mo__ma15d	0.00 (-0.05, 0.05)
D__SPRD__3mo__ma20d	0.00 (-0.04, 0.04)
D__SPRD__3mo__ma25d	0.00 (-0.04, 0.04)

Characteristic	N = 11,048
D_SPRD_3mo_ma2m	0.00 (-0.03, 0.03)
D_SPRD_3mo_ma3m	0.00 (-0.03, 0.02)
D_SPRD_3mo_ma6m	0.00 (-0.02, 0.02)
D_SPRD_3mo_ma9m	-0.001 (-0.020, 0.017)
D_SPRD_3mo_ma12m	-0.003 (-0.018, 0.017)
FUTREC	1,953 (18%)

Remove stale data from test set

Exclude historical data prior to 1968-01-01 because the economy changed dramatically (due to computational innovation).

```
summary(test_data$date)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1968-01-02" "1970-06-30" "1972-12-28" "1972-12-30" "1975-07-01" "1977-12-30"
```

```
test_data <- test_data %>%
  filter(date >= startTestDate)

summary(test_data$date)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1968-01-02" "1970-06-30" "1972-12-28" "1972-12-30" "1975-07-01" "1977-12-30"
```

Setup Parallel Processing

```
library(doParallel)

cl <- makePSOCKcluster(3)
registerDoParallel(cl)
```

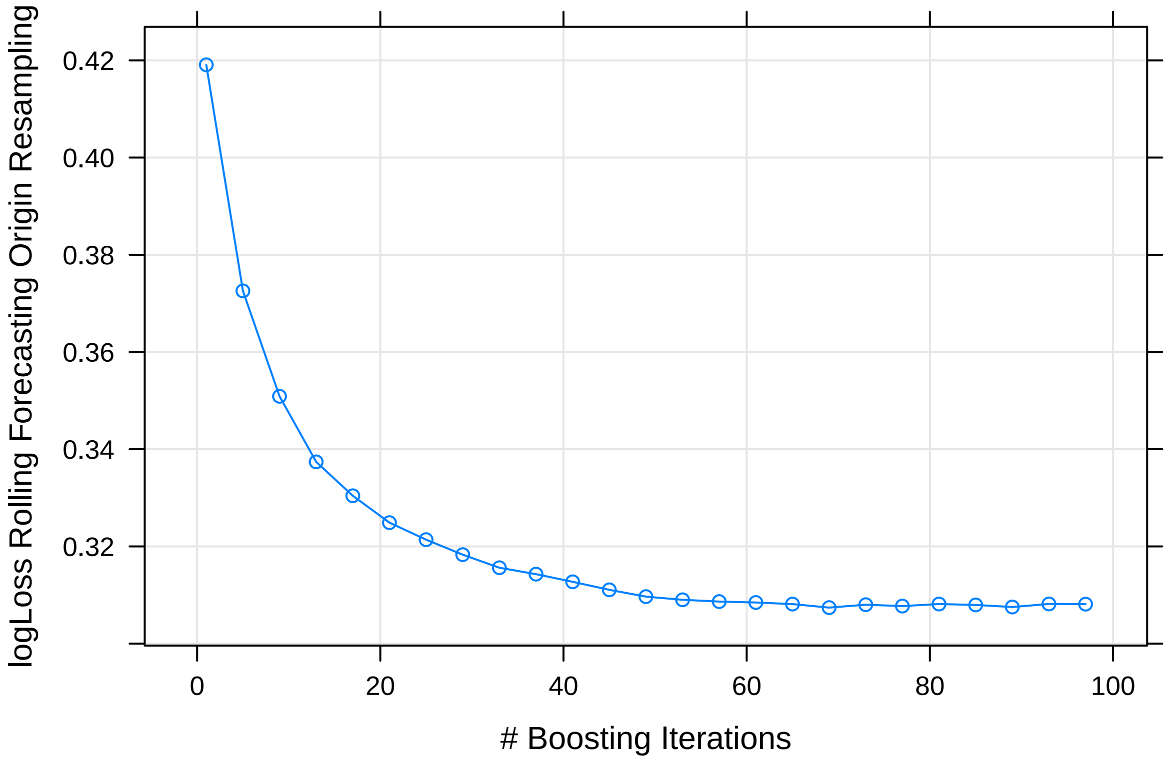
Cross-Validation Framework

```
fcstHorizon <- 6*21
initWindow <- 120*21
param_skip <- fcstHorizon - 1

if(initWindow < 100){
  stop("Too few observations.")
}

fitControl_oneSE <- trainControl(method = "timeslice",
                           initialWindow=initWindow,
                           horizon=fcstHorizon,
```

```
                           fixedWindow=FALSE,
                           skip=param_skip,
                           ## Estimate class probabilities
                           classProbs = TRUE,
                           ## Evaluate performance using
                           ## the following function
                           summaryFunction = mnLogLoss,
                           selectionFunction="oneSE")

fitControl_best <- trainControl(method = "timeslice",
                           initialWindow=initWindow,
                           horizon=fcstHorizon,
                           fixedWindow=FALSE,
                           skip=param_skip,
                           ## Estimate class probabilities
                           classProbs = TRUE,
                           ## Evaluate performance using
                           ## the following function
                           summaryFunction = mnLogLoss,
                           selectionFunction="best")
```

Gradient Boosting for Additive Models

```
grid_gam <- expand.grid(mstop=seq(1,100,4),
                        prune="no")

set.seed(randSeed)

gam_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
  method = "gamboost",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneGrid = grid_gam,
  family = Binomial(),
  dfbase =3

)

plot(gam_mod)
```



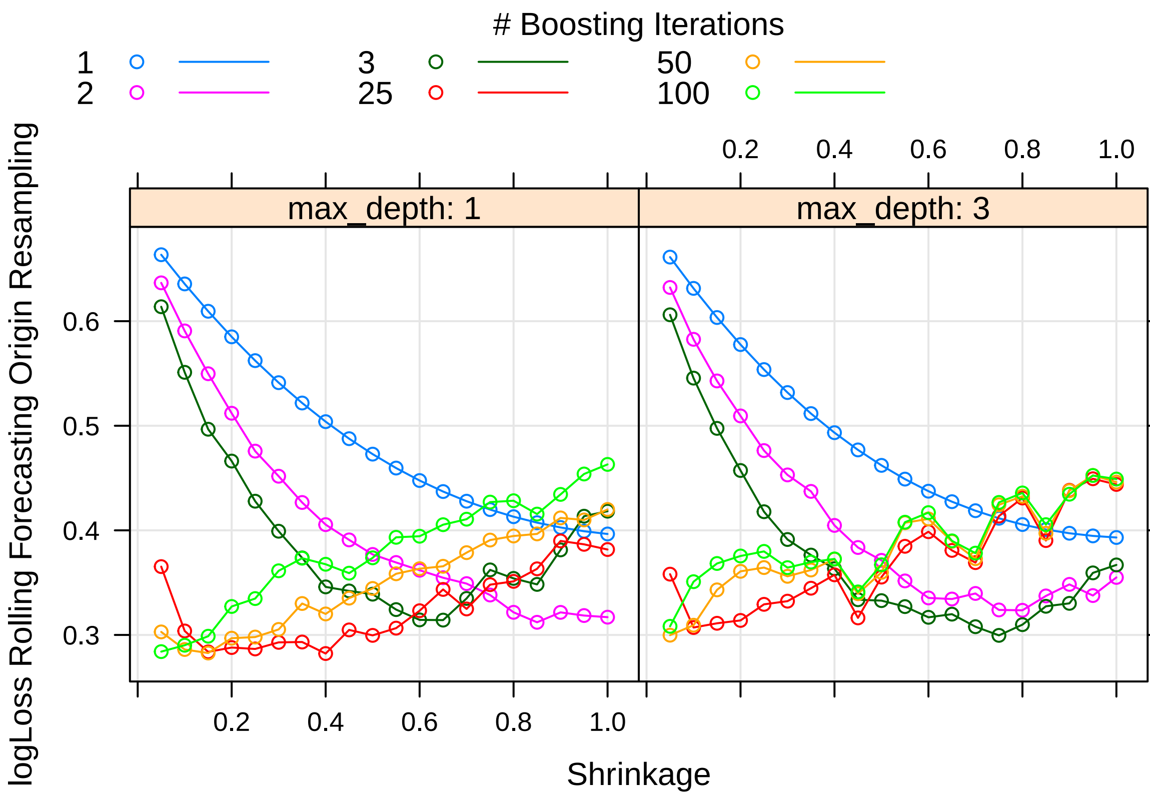

```
gam_mod$bestTune
```

```
##   mstop prune
## 3     9    no
```

eXtreme Gradient Boosting Trees

```
grid_xgb <- expand.grid(nrounds=c(1,2,3,25,
                                  50,100),
                        max_depth=c(1,3),
                        eta=seq(0.05,1,0.05),
                        gamma=0,
                        colsample_bytree=1,
                        min_child_weight=10,
                        subsample=1
                        )

set.seed(randSeed)

xgb_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
  method = "xgbTree",
```

```
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneGrid = grid_xgb,
  objective  = "binary:logistic"
)

plot(xgb_mod)
```



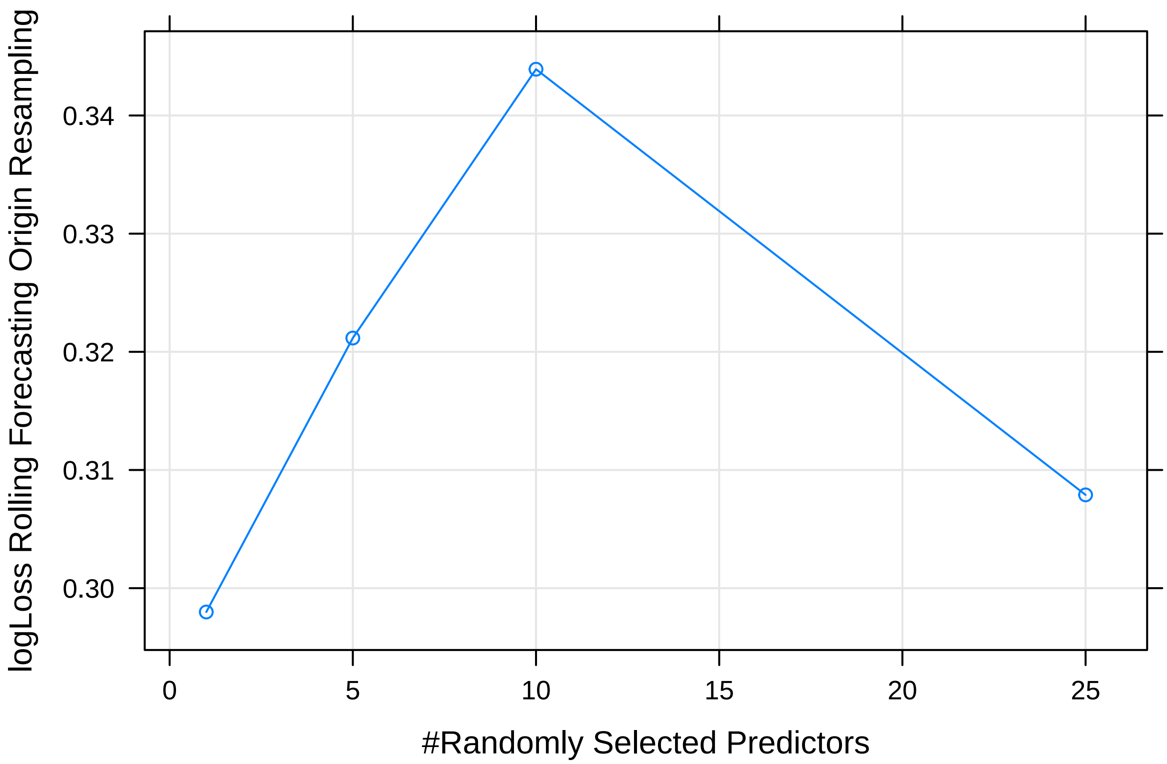

```
xgb_mod$bestTune
```

```
##     nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
## 170       2         1 0.75     0                1               10         1
```

Random Forest

```
grid_rf <- data.frame(mtry=c(1, 5, 10, 25))

set.seed(randSeed)

rf_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
```

```
  method = "rf",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneGrid = grid_rf,
  importance = TRUE
)

plot(rf_mod)
```




```
rf_mod$bestTune
```

```
##   mtry
## 1    1
```

Stepwise Regression

The `glmStepAIC` method uses the `glm()` function from the `stats` package. The documentation for `glm()` says:

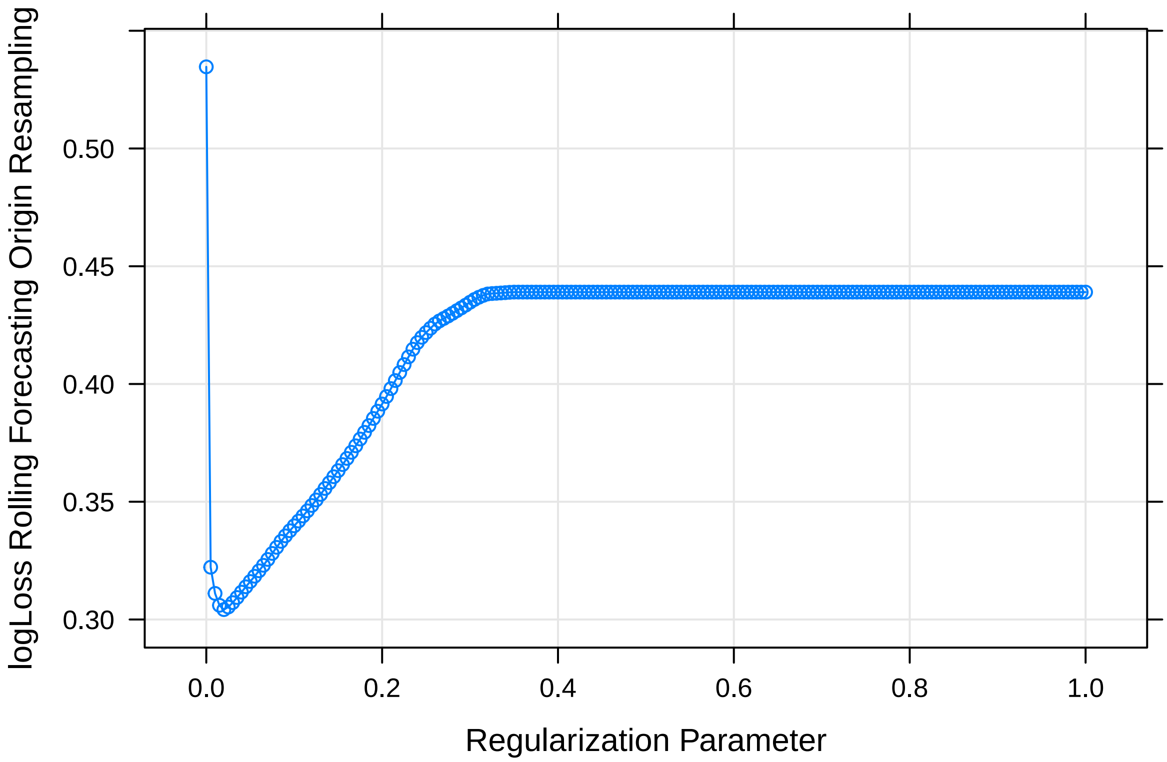
> For binomial and quasibinomial families the response can also be specified as a factor (when the first level denotes failure and all others success) or as a two-column matrix with the columns giving the numbers of successes and failures.

However, for most methods (that do not invoke `glm()`) in `train`, the first level denotes the success (the opposite of `glm()`). This behavior causes the coefficient signs to flip. Be highly suspicious when interpreting coefficients from models that are fit using `train`.

```
set.seed(randSeed)

stepwise_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
  method = "glmStepAIC",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneLength = 10,
  family = binomial,
  trace = 0,
  k = 10*log(nrow(train_yes_no)),
  direction = "forward"
)
```

Elastic Net (Lasso)

```
grid_glmnet <- expand.grid(
  alpha = 1,
  lambda = seq(0, 1, 0.005)
)

set.seed(randSeed)

glmnet_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
  method = "glmnet",
  trControl = fitControl_best,
  metric = "logLoss",
  tuneGrid = grid_glmnet,
  family = "binomial"
)

plot(glmnet_mod)
```

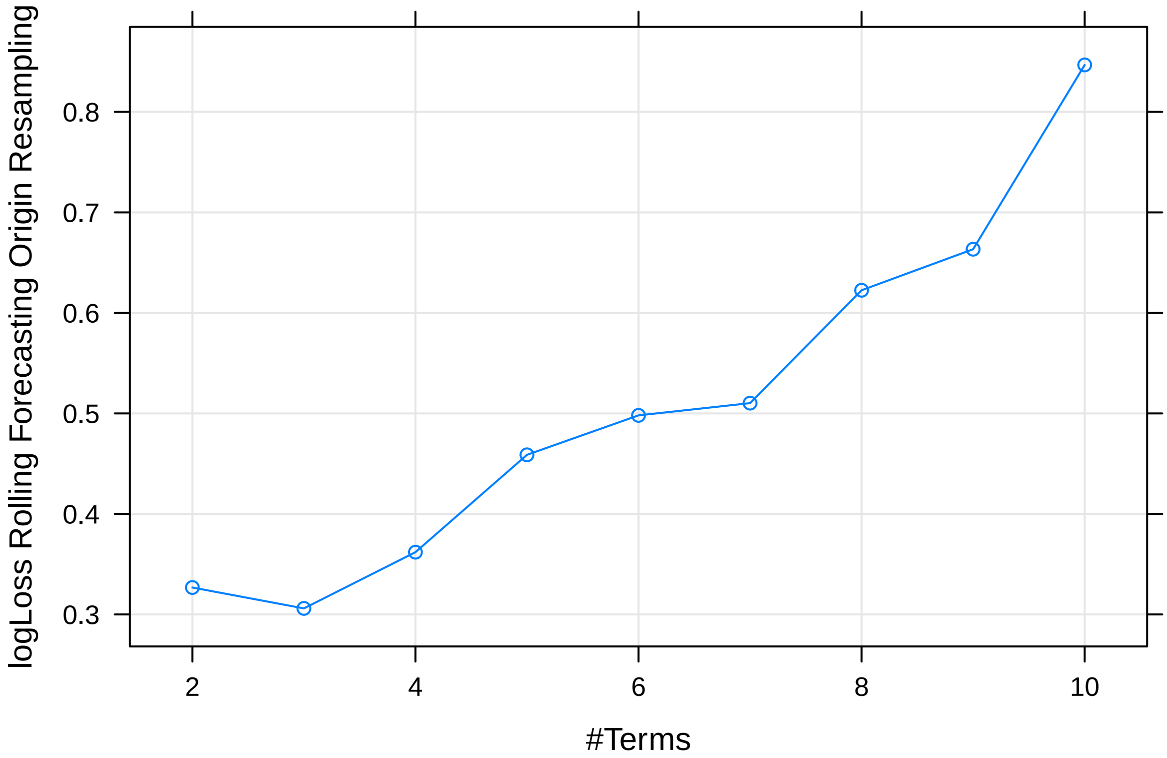



```
glmnet_mod$bestTune
```

```
##   alpha lambda
## 5     1   0.02
```

Multivariate Adaptive Regression Splines

```
grid_mars <- expand.grid(nprune=seq(2,10,1),
                         degree=1)

set.seed(randSeed)

earth_mod <- train(
  FUTREC ~ . - date - constant,
  data = train_yes_no,
  method = "earth",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneGrid = grid_mars,
  glm = list(family = binomial)
)

plot(earth_mod)
```




```
earth_mod$bestTune
```

```
##   nprune degree
## 1      2      1
```

Null Model: Intercept-only Model

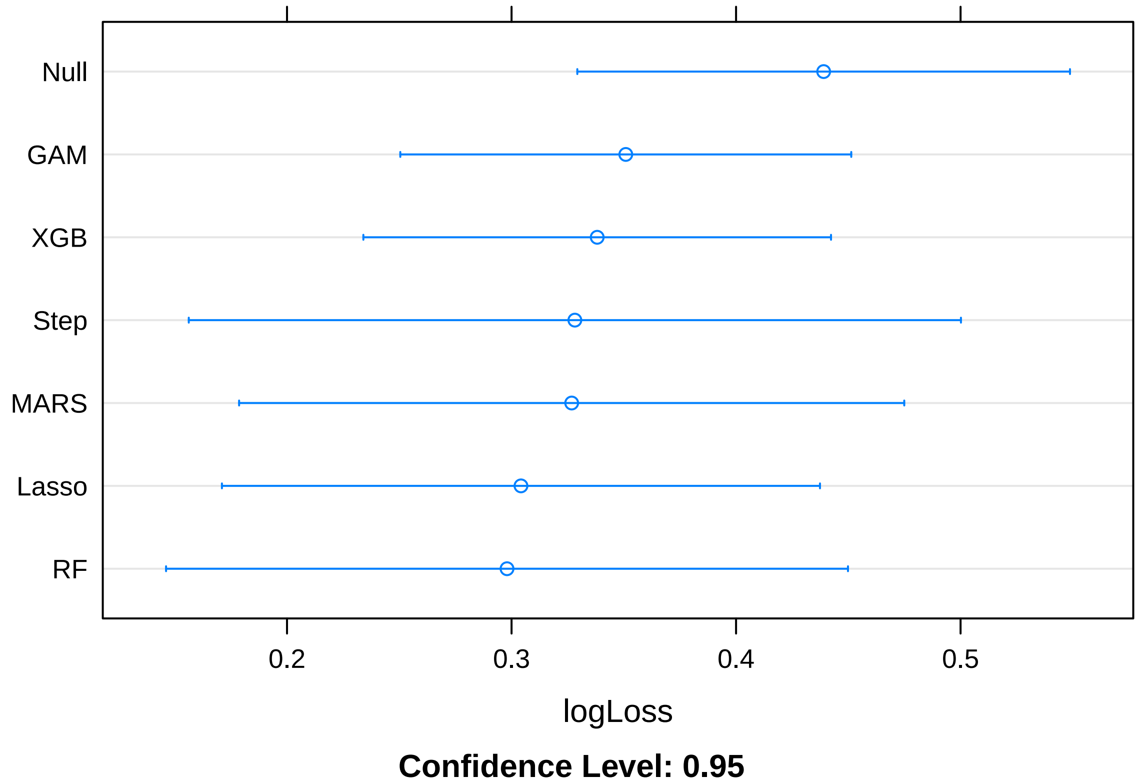
```
set.seed(randSeed)

null_mod <- train(
  FUTREC ~ constant,
  data = train_yes_no,
  method = "glm",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  family = binomial
)
```

Compare Models

```r
resamps <- resamples(list(XGB = xgb_mod,
                          GAM = gam_mod,
                          RF = rf_mod,
                          Step = stepwise_mod,
                          Lasso = glmnet_mod,
                          MARS = earth_mod,
                          Null = null_mod)
                     )
summary(resamps)
```

```
##
## Call:
## summary.resamples(object = resamps)
##
## Models: XGB, GAM, RF, Step, Lasso, MARS, Null
## Number of resamples: 67
##
## logLoss
##               Min.     1st Qu.     Median      Mean   3rd Qu.     Max. NA's
## XGB   9.706955e-02 0.120047610 0.12867821 0.3381515 0.4448383 2.149419    0
## GAM   7.187133e-02 0.109438944 0.17395687 0.3508842 0.3068812 1.847333    0
## RF    7.947642e-05 0.010990497 0.05843691 0.2979832 0.2965779 3.877775    0
## Step  1.695727e-04 0.005499925 0.04140367 0.3282011 0.3166599 3.973332    0
## Lasso 2.661618e-03 0.015462210 0.06859686 0.3041967 0.3168502 2.777522    0
## MARS  2.032118e-03 0.034840031 0.06235141 0.3267843 0.2633954 3.445667    0
## Null  1.922472e-01 0.210926202 0.23755031 0.4390169 0.3228349 1.705219    0
```

```r
dotplot(resamps, metric = "logLoss", conf.level=0.95)
```



Explore XGB Model

```
xgb_mod$bestTune
```

```
##     nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
## 170       2         1 0.75     0                1               10         1
```

```
df_imp <- varImp(xgb_mod)$importance %>%
  arrange(desc(Overall))

df_imp$variable <- rownames(df_imp)

df_imp <- df_imp %>%
  select(variable, Overall)

row.names(df_imp) <- NULL

knitr::kable(df_imp)
```

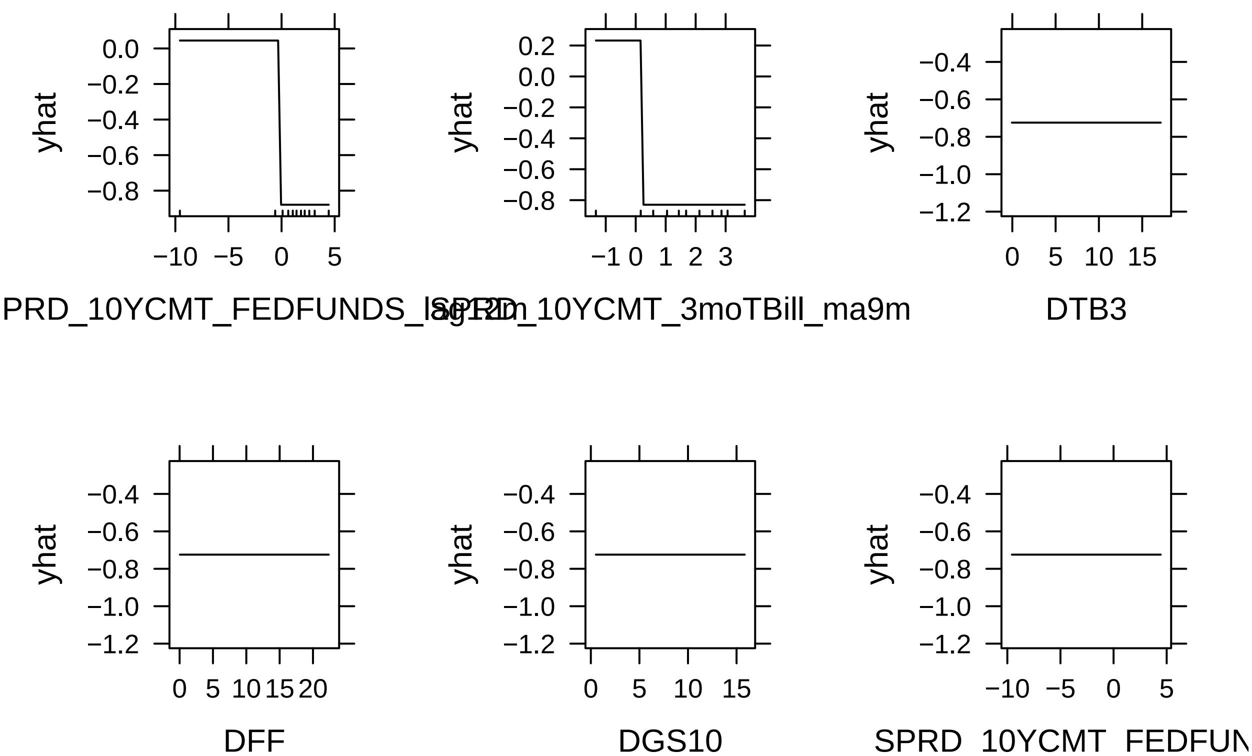
variable	Overall
SPRD_10YCMT_FEDFUNDS_lag12m	100.0000

variable	Overall
SPRD__10YCMT__3moTBill__ma9m	65.3285
DTB3	0.0000
DFF	0.0000
DGS10	0.0000
SPRD__10YCMT__FEDFUNDS	0.0000
SPRD__10YCMT__3moTBill	0.0000
D__SPRD__FFR	0.0000
D__SPRD__3mo	0.0000
SPRD__10YCMT__FEDFUNDS__lag1d	0.0000
SPRD__10YCMT__FEDFUNDS__lag5d	0.0000
SPRD__10YCMT__FEDFUNDS__lag1m	0.0000
SPRD__10YCMT__FEDFUNDS__lag3m	0.0000
SPRD__10YCMT__FEDFUNDS__lag6m	0.0000
SPRD__10YCMT__FEDFUNDS__lag9m	0.0000
SPRD__10YCMT__3moTBill__lag1d	0.0000
SPRD__10YCMT__3moTBill__lag5d	0.0000
SPRD__10YCMT__3moTBill__lag1m	0.0000
SPRD__10YCMT__3moTBill__lag3m	0.0000
SPRD__10YCMT__3moTBill__lag6m	0.0000
SPRD__10YCMT__3moTBill__lag9m	0.0000
SPRD__10YCMT__3moTBill__lag12m	0.0000
SPRD__10YCMT__FEDFUNDS__adstk001	0.0000
SPRD__10YCMT__FEDFUNDS__adstk0001	0.0000
SPRD__10YCMT__FEDFUNDS__adstk10	0.0000
SPRD__10YCMT__FEDFUNDS__adstk40	0.0000
SPRD__10YCMT__FEDFUNDS__adstk95	0.0000
SPRD__10YCMT__FEDFUNDS__adstk98	0.0000
SPRD__10YCMT__3moTBill__adstk001	0.0000
SPRD__10YCMT__3moTBill__adstk0001	0.0000
SPRD__10YCMT__3moTBill__adstk10	0.0000
SPRD__10YCMT__3moTBill__adstk40	0.0000
SPRD__10YCMT__3moTBill__adstk95	0.0000
SPRD__10YCMT__3moTBill__adstk98	0.0000
D__SPRD__FFR__adstk001	0.0000
D__SPRD__FFR__adstk0001	0.0000
D__SPRD__FFR__adstk10	0.0000
D__SPRD__FFR__adstk40	0.0000
D__SPRD__FFR__adstk95	0.0000
D__SPRD__FFR__adstk98	0.0000
D__SPRD__3mo__adstk001	0.0000
D__SPRD__3mo__adstk0001	0.0000
D__SPRD__3mo__adstk10	0.0000
D__SPRD__3mo__adstk40	0.0000
D__SPRD__3mo__adstk95	0.0000
D__SPRD__3mo__adstk98	0.0000
SPRD__10YCMT__FEDFUNDS__ma5d	0.0000
SPRD__10YCMT__FEDFUNDS__ma10d	0.0000
SPRD__10YCMT__FEDFUNDS__ma15d	0.0000
SPRD__10YCMT__FEDFUNDS__ma20d	0.0000
SPRD__10YCMT__FEDFUNDS__ma25d	0.0000
SPRD__10YCMT__FEDFUNDS__ma2m	0.0000
SPRD__10YCMT__FEDFUNDS__ma3m	0.0000

variable	Overall
SPRD__10YCMT__FEDFUNDS__ma6m	0.0000
SPRD__10YCMT__FEDFUNDS__ma9m	0.0000
SPRD__10YCMT__FEDFUNDS__ma12m	0.0000
SPRD__10YCMT__3moTBill__ma5d	0.0000
SPRD__10YCMT__3moTBill__ma10d	0.0000
SPRD__10YCMT__3moTBill__ma15d	0.0000
SPRD__10YCMT__3moTBill__ma20d	0.0000
SPRD__10YCMT__3moTBill__ma25d	0.0000
SPRD__10YCMT__3moTBill__ma2m	0.0000
SPRD__10YCMT__3moTBill__ma3m	0.0000
SPRD__10YCMT__3moTBill__ma6m	0.0000
SPRD__10YCMT__3moTBill__ma12m	0.0000
D__SPRD__FFR__ma5d	0.0000
D__SPRD__FFR__ma10d	0.0000
D__SPRD__FFR__ma15d	0.0000
D__SPRD__FFR__ma20d	0.0000
D__SPRD__FFR__ma25d	0.0000
D__SPRD__FFR__ma2m	0.0000
D__SPRD__FFR__ma3m	0.0000
D__SPRD__FFR__ma6m	0.0000
D__SPRD__FFR__ma9m	0.0000
D__SPRD__FFR__ma12m	0.0000
D__SPRD__3mo__ma5d	0.0000
D__SPRD__3mo__ma10d	0.0000
D__SPRD__3mo__ma15d	0.0000
D__SPRD__3mo__ma20d	0.0000
D__SPRD__3mo__ma25d	0.0000
D__SPRD__3mo__ma2m	0.0000
D__SPRD__3mo__ma3m	0.0000
D__SPRD__3mo__ma6m	0.0000
D__SPRD__3mo__ma9m	0.0000
D__SPRD__3mo__ma12m	0.0000

```
pdp.top1 <- partial(xgb_mod,
          pred.var = df_imp$variable[1],
          plot = TRUE,
          rug = TRUE)

pdp.top2 <- partial(xgb_mod,
          pred.var = df_imp$variable[2],
          plot = TRUE,
          rug = TRUE)

pdp.top3 <- partial(xgb_mod,
    pred.var = df_imp$variable[3],
    plot = TRUE,
    chull = TRUE
  )

pdp.top4 <- partial(xgb_mod,
    pred.var = df_imp$variable[4],
```

```r
    plot = TRUE,
    chull = TRUE
  )

pdp.top5 <- partial(xgb_mod,
    pred.var = df_imp$variable[5],
    plot = TRUE,
    chull = TRUE
  )

pdp.top6 <- partial(xgb_mod,
    pred.var = df_imp$variable[6],
    plot = TRUE,
    chull = TRUE
  )

grid.arrange(pdp.top1, pdp.top2, pdp.top3,
             pdp.top4, pdp.top5, pdp.top6, ncol = 3)
```



Peeking

Peeking means we use the insights from the automated models to choose variables in subsequent models. This is technically cheating and causes the cross-validation errors to be artificially low. This is addressed in the test set which does not have peeking bias.

```r
top_predictors <- head(df_imp$variable)

best_predictor <- head(top_predictors, 1)

top_fmla <- as.formula(paste0("FUTREC ~",
                              paste0(top_predictors,
                                     collapse=" + ")))

top1_fmla <- as.formula(paste0("FUTREC ~",
                              paste0(best_predictor,
                                     collapse=" + ")))
```

Logistic Regression (with peeking)

As mentioned early, `train` and `glm` treat the reference level differently for binary outcomes. Hence, the coefficients are flipped when training a logistic regression inside `train`.

```r
logit_mod <- train(
  top1_fmla,
  data = train_yes_no,
  method = "glm",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  family=binomial
)

summary(logit_mod)
```

```
##
## Call:
## NULL
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.0861   0.1219   0.2584   0.4773   4.6654
##
## Coefficients:
##                               Estimate Std. Error z value Pr(>|z|)
## (Intercept)                    0.67949    0.03293   20.63   <2e-16 ***
## SPRD_10YCMT_FEDFUNDS_lag12m  1.29334    0.03062   42.24   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 10307.0  on 11047  degrees of freedom
## Residual deviance:  6675.8  on 11046  degrees of freedom
## AIC: 6679.8
##
## Number of Fisher Scoring iterations: 6
```

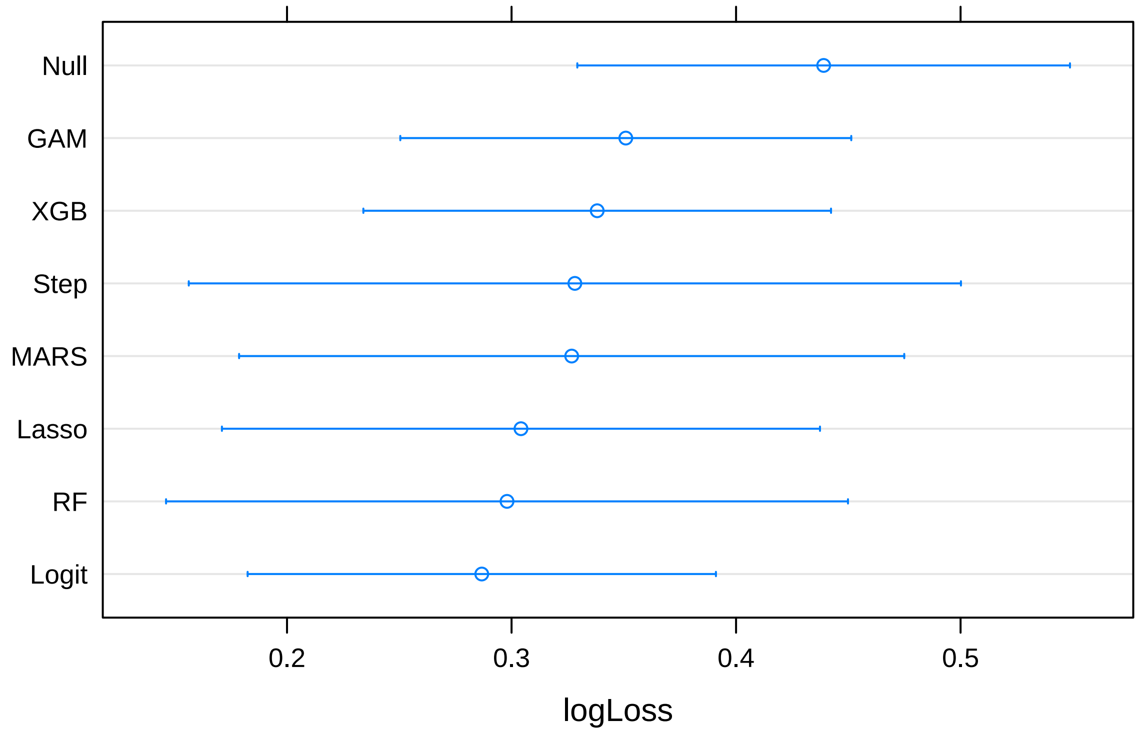
Compare Models

CV errors for models with peeking are misleadingly low. This will be addressed with a test set.

```
mymods <- list(XGB = xgb_mod,
                          GAM = gam_mod,
                          RF = rf_mod,
                          Step = stepwise_mod,
                          Lasso = glmnet_mod,
                          MARS = earth_mod,
                          Null = null_mod,
                          Logit = logit_mod)  ## peeking

resamps <- resamples(mymods)
summary(resamps)
```

```
##
## Call:
## summary.resamples(object = resamps)
##
## Models: XGB, GAM, RF, Step, Lasso, MARS, Null, Logit
## Number of resamples: 67
##
## logLoss
##               Min.     1st Qu.     Median      Mean   3rd Qu.     Max. NA's
## XGB   9.706955e-02 0.120047610 0.12867821 0.3381515 0.4448383 2.149419    0
## GAM   7.187133e-02 0.109438944 0.17395687 0.3508842 0.3068812 1.847333    0
## RF    7.947642e-05 0.010990497 0.05843691 0.2979832 0.2965779 3.877775    0
## Step  1.695727e-04 0.005499925 0.04140367 0.3282011 0.3166599 3.973332    0
## Lasso 2.661618e-03 0.015462210 0.06859686 0.3041967 0.3168502 2.777522    0
## MARS  2.032118e-03 0.034840031 0.06235141 0.3267843 0.2633954 3.445667    0
## Null  1.922472e-01 0.210926202 0.23755031 0.4390169 0.3228349 1.705219    0
## Logit 8.237872e-03 0.027319883 0.09623894 0.2867424 0.3318647 2.101194    0
```

```
dotplot(resamps, metric = "logLoss", conf.level=0.95)
```



Confidence Level: 0.95

Test Set Performance

```
perf <-
  function(lst_mods,
           f_metric = caTools::colAUC,
           metricname = "ROC-AUC",
           dat=test_data,
           response="FUTREC") {
    lst_preds <- map(
      .x = lst_mods,
      .f = function(x) {
        if (class(x)[1] != "train") {
          predict(x, newdata = dat, type = "response")
        } else
          (
            predict(x, newdata = dat, type = "prob")[, "yes"]

          )
      }
    )

    map_dfr(lst_preds, function(x) {
      f_metric(x, dat[,response, drop=TRUE])
    }) %>%
```

```
    pivot_longer(everything(), names_to = "model", values_to = metricname)
  }

perf(mymods, caTools::colAUC, "ROC-AUC") %>%
  arrange(desc(`ROC-AUC`)) %>%
      knitr::kable()
```

model	ROC-AUC
MARS	0.9704625
RF	0.9656495
GAM	0.9465486
Step	0.9105037
XGB	0.9022879
Lasso	0.9003905
Logit	0.7792215
Null	0.5000000

```
perf(mymods, MLmetrics::LogLoss, "LogLoss") %>%
  arrange(LogLoss) %>%
      knitr::kable()
```

model	LogLoss
MARS	0.2251296
RF	0.2610343
XGB	0.3669408
Step	0.3788840
GAM	0.3795383
Lasso	0.3800811
Logit	0.6867408
Null	0.6920835

Probability of Recession (Most Recent 12 months)

```
curr_data <- recent_data

curr_data$date
```

```
##   [1] "2022-03-16" "2022-03-17" "2022-03-18" "2022-03-21" "2022-03-22"
##   [6] "2022-03-23" "2022-03-24" "2022-03-25" "2022-03-28" "2022-03-29"
##  [11] "2022-03-30" "2022-03-31" "2022-04-01" "2022-04-04" "2022-04-05"
##  [16] "2022-04-06" "2022-04-07" "2022-04-08" "2022-04-11" "2022-04-12"
##  [21] "2022-04-13" "2022-04-14" "2022-04-18" "2022-04-19" "2022-04-20"
##  [26] "2022-04-21" "2022-04-22" "2022-04-25" "2022-04-26" "2022-04-27"
##  [31] "2022-04-28" "2022-04-29" "2022-05-02" "2022-05-03" "2022-05-04"
##  [36] "2022-05-05" "2022-05-06" "2022-05-09" "2022-05-10" "2022-05-11"
##  [41] "2022-05-12" "2022-05-13" "2022-05-16" "2022-05-17" "2022-05-18"
##  [46] "2022-05-19" "2022-05-20" "2022-05-23" "2022-05-24" "2022-05-25"
```

```
##  [51] "2022-05-26" "2022-05-27" "2022-05-31" "2022-06-01" "2022-06-02"
##  [56] "2022-06-03" "2022-06-06" "2022-06-07" "2022-06-08" "2022-06-09"
##  [61] "2022-06-10" "2022-06-13" "2022-06-14" "2022-06-15" "2022-06-16"
##  [66] "2022-06-17" "2022-06-21" "2022-06-22" "2022-06-23" "2022-06-24"
##  [71] "2022-06-27" "2022-06-28" "2022-06-29" "2022-06-30" "2022-07-01"
##  [76] "2022-07-05" "2022-07-06" "2022-07-07" "2022-07-08" "2022-07-11"
##  [81] "2022-07-12" "2022-07-13" "2022-07-14" "2022-07-15" "2022-07-18"
##  [86] "2022-07-19" "2022-07-20" "2022-07-21" "2022-07-22" "2022-07-25"
##  [91] "2022-07-26" "2022-07-27" "2022-07-28" "2022-07-29" "2022-08-01"
##  [96] "2022-08-02" "2022-08-03" "2022-08-04" "2022-08-05" "2022-08-08"
## [101] "2022-08-09" "2022-08-10" "2022-08-11" "2022-08-12" "2022-08-15"
## [106] "2022-08-16" "2022-08-17" "2022-08-18" "2022-08-19" "2022-08-22"
## [111] "2022-08-23" "2022-08-24" "2022-08-25" "2022-08-26" "2022-08-29"
## [116] "2022-08-30" "2022-08-31" "2022-09-01" "2022-09-02" "2022-09-06"
## [121] "2022-09-07" "2022-09-08" "2022-09-09" "2022-09-12" "2022-09-13"
## [126] "2022-09-14" "2022-09-15" "2022-09-16" "2022-09-19" "2022-09-20"
## [131] "2022-09-21" "2022-09-22" "2022-09-23" "2022-09-26" "2022-09-27"
## [136] "2022-09-28" "2022-09-29" "2022-09-30" "2022-10-03" "2022-10-04"
## [141] "2022-10-05" "2022-10-06" "2022-10-07" "2022-10-11" "2022-10-12"
## [146] "2022-10-13" "2022-10-14" "2022-10-17" "2022-10-18" "2022-10-19"
## [151] "2022-10-20" "2022-10-21" "2022-10-24" "2022-10-25" "2022-10-26"
## [156] "2022-10-27" "2022-10-28" "2022-10-31" "2022-11-01" "2022-11-02"
## [161] "2022-11-03" "2022-11-04" "2022-11-07" "2022-11-08" "2022-11-09"
## [166] "2022-11-10" "2022-11-14" "2022-11-15" "2022-11-16" "2022-11-17"
## [171] "2022-11-18" "2022-11-21" "2022-11-22" "2022-11-23" "2022-11-25"
## [176] "2022-11-28" "2022-11-29" "2022-11-30" "2022-12-01" "2022-12-02"
## [181] "2022-12-05" "2022-12-06" "2022-12-07" "2022-12-08" "2022-12-09"
## [186] "2022-12-12" "2022-12-13" "2022-12-14" "2022-12-15" "2022-12-16"
## [191] "2022-12-19" "2022-12-20" "2022-12-21" "2022-12-22" "2022-12-23"
## [196] "2022-12-27" "2022-12-28" "2022-12-29" "2022-12-30" "2023-01-03"
## [201] "2023-01-04" "2023-01-05" "2023-01-06" "2023-01-09" "2023-01-10"
## [206] "2023-01-11" "2023-01-12" "2023-01-13" "2023-01-17" "2023-01-18"
## [211] "2023-01-19" "2023-01-20" "2023-01-23" "2023-01-24" "2023-01-25"
## [216] "2023-01-26" "2023-01-27" "2023-01-30" "2023-01-31" "2023-02-01"
## [221] "2023-02-02" "2023-02-03" "2023-02-06" "2023-02-07" "2023-02-08"
## [226] "2023-02-09" "2023-02-10" "2023-02-13" "2023-02-14" "2023-02-15"
## [231] "2023-02-16" "2023-02-17" "2023-02-21" "2023-02-22" "2023-02-23"
## [236] "2023-02-24" "2023-02-27" "2023-02-28" "2023-03-01" "2023-03-02"
## [241] "2023-03-03" "2023-03-06" "2023-03-07" "2023-03-08" "2023-03-09"
## [246] "2023-03-10" "2023-03-13" "2023-03-14" "2023-03-15" "2023-03-16"
## [251] "2023-03-17" "2023-03-20"
```

Probability of Recession (the 12 most recent months)

```r
curr_data <- recent_data

curr_data$date
```

```
##   [1] "2022-03-16" "2022-03-17" "2022-03-18" "2022-03-21" "2022-03-22"
##   [6] "2022-03-23" "2022-03-24" "2022-03-25" "2022-03-28" "2022-03-29"
##  [11] "2022-03-30" "2022-03-31" "2022-04-01" "2022-04-04" "2022-04-05"
##  [16] "2022-04-06" "2022-04-07" "2022-04-08" "2022-04-11" "2022-04-12"
```

```
##  [21] "2022-04-13" "2022-04-14" "2022-04-18" "2022-04-19" "2022-04-20"
##  [26] "2022-04-21" "2022-04-22" "2022-04-25" "2022-04-26" "2022-04-27"
##  [31] "2022-04-28" "2022-04-29" "2022-05-02" "2022-05-03" "2022-05-04"
##  [36] "2022-05-05" "2022-05-06" "2022-05-09" "2022-05-10" "2022-05-11"
##  [41] "2022-05-12" "2022-05-13" "2022-05-16" "2022-05-17" "2022-05-18"
##  [46] "2022-05-19" "2022-05-20" "2022-05-23" "2022-05-24" "2022-05-25"
##  [51] "2022-05-26" "2022-05-27" "2022-05-31" "2022-06-01" "2022-06-02"
##  [56] "2022-06-03" "2022-06-06" "2022-06-07" "2022-06-08" "2022-06-09"
##  [61] "2022-06-10" "2022-06-13" "2022-06-14" "2022-06-15" "2022-06-16"
##  [66] "2022-06-17" "2022-06-21" "2022-06-22" "2022-06-23" "2022-06-24"
##  [71] "2022-06-27" "2022-06-28" "2022-06-29" "2022-06-30" "2022-07-01"
##  [76] "2022-07-05" "2022-07-06" "2022-07-07" "2022-07-08" "2022-07-11"
##  [81] "2022-07-12" "2022-07-13" "2022-07-14" "2022-07-15" "2022-07-18"
##  [86] "2022-07-19" "2022-07-20" "2022-07-21" "2022-07-22" "2022-07-25"
##  [91] "2022-07-26" "2022-07-27" "2022-07-28" "2022-07-29" "2022-08-01"
##  [96] "2022-08-02" "2022-08-03" "2022-08-04" "2022-08-05" "2022-08-08"
## [101] "2022-08-09" "2022-08-10" "2022-08-11" "2022-08-12" "2022-08-15"
## [106] "2022-08-16" "2022-08-17" "2022-08-18" "2022-08-19" "2022-08-22"
## [111] "2022-08-23" "2022-08-24" "2022-08-25" "2022-08-26" "2022-08-29"
## [116] "2022-08-30" "2022-08-31" "2022-09-01" "2022-09-02" "2022-09-06"
## [121] "2022-09-07" "2022-09-08" "2022-09-09" "2022-09-12" "2022-09-13"
## [126] "2022-09-14" "2022-09-15" "2022-09-16" "2022-09-19" "2022-09-20"
## [131] "2022-09-21" "2022-09-22" "2022-09-23" "2022-09-26" "2022-09-27"
## [136] "2022-09-28" "2022-09-29" "2022-09-30" "2022-10-03" "2022-10-04"
## [141] "2022-10-05" "2022-10-06" "2022-10-07" "2022-10-11" "2022-10-12"
## [146] "2022-10-13" "2022-10-14" "2022-10-17" "2022-10-18" "2022-10-19"
## [151] "2022-10-20" "2022-10-21" "2022-10-24" "2022-10-25" "2022-10-26"
## [156] "2022-10-27" "2022-10-28" "2022-10-31" "2022-11-01" "2022-11-02"
## [161] "2022-11-03" "2022-11-04" "2022-11-07" "2022-11-08" "2022-11-09"
## [166] "2022-11-10" "2022-11-14" "2022-11-15" "2022-11-16" "2022-11-17"
## [171] "2022-11-18" "2022-11-21" "2022-11-22" "2022-11-23" "2022-11-25"
## [176] "2022-11-28" "2022-11-29" "2022-11-30" "2022-12-01" "2022-12-02"
## [181] "2022-12-05" "2022-12-06" "2022-12-07" "2022-12-08" "2022-12-09"
## [186] "2022-12-12" "2022-12-13" "2022-12-14" "2022-12-15" "2022-12-16"
## [191] "2022-12-19" "2022-12-20" "2022-12-21" "2022-12-22" "2022-12-23"
## [196] "2022-12-27" "2022-12-28" "2022-12-29" "2022-12-30" "2023-01-03"
## [201] "2023-01-04" "2023-01-05" "2023-01-06" "2023-01-09" "2023-01-10"
## [206] "2023-01-11" "2023-01-12" "2023-01-13" "2023-01-17" "2023-01-18"
## [211] "2023-01-19" "2023-01-20" "2023-01-23" "2023-01-24" "2023-01-25"
## [216] "2023-01-26" "2023-01-27" "2023-01-30" "2023-01-31" "2023-02-01"
## [221] "2023-02-02" "2023-02-03" "2023-02-06" "2023-02-07" "2023-02-08"
## [226] "2023-02-09" "2023-02-10" "2023-02-13" "2023-02-14" "2023-02-15"
## [231] "2023-02-16" "2023-02-17" "2023-02-21" "2023-02-22" "2023-02-23"
## [236] "2023-02-24" "2023-02-27" "2023-02-28" "2023-03-01" "2023-03-02"
## [241] "2023-03-03" "2023-03-06" "2023-03-07" "2023-03-08" "2023-03-09"
## [246] "2023-03-10" "2023-03-13" "2023-03-14" "2023-03-15" "2023-03-16"
## [251] "2023-03-17" "2023-03-20"
```

```r
score_fun <- function(mods, dat) {
  output <- map_dfc(.x = mods, .f = function(x) {
    if(class(x)[1] != "train"){
      predict(x, newdata = dat, type = "response")
    } else(
       predict(x, newdata = dat, type = "prob")[,"yes"]
```

```r
    )

  })

  output$date <- dat$date


  output <- output %>%
    pivot_longer(-date, names_to = "model",
                 values_to = "prob_rec")

  return(output)
}


recent_prob <- score_fun(mymods, curr_data)

knitr::kable(recent_prob %>% filter(
  date >= "2022-10-01"
))
```

date	model	prob_rec
2022-10-03	XGB	0.1225104
2022-10-03	GAM	0.1374255
2022-10-03	RF	0.0160000
2022-10-03	Step	0.0105017
2022-10-03	Lasso	0.0368705
2022-10-03	MARS	0.0451622
2022-10-03	Null	0.1767741
2022-10-03	Logit	0.0703915
2022-10-04	XGB	0.1225104
2022-10-04	GAM	0.1377551
2022-10-04	RF	0.0340000
2022-10-04	Step	0.0099211
2022-10-04	Lasso	0.0357219
2022-10-04	MARS	0.0451622
2022-10-04	Null	0.1767741
2022-10-04	Logit	0.0712426
2022-10-05	XGB	0.1225104
2022-10-05	GAM	0.1389941
2022-10-05	RF	0.0020000
2022-10-05	Step	0.0103759
2022-10-05	Lasso	0.0374447
2022-10-05	MARS	0.0451622
2022-10-05	Null	0.1767741
2022-10-05	Logit	0.0765511
2022-10-06	XGB	0.1225104
2022-10-06	GAM	0.1389094
2022-10-06	RF	0.0020000
2022-10-06	Step	0.0106752
2022-10-06	Lasso	0.0377035
2022-10-06	MARS	0.0451622

date	model	prob_rec
2022-10-06	Null	0.1767741
2022-10-06	Logit	0.0756418
2022-10-07	XGB	0.1225104
2022-10-07	GAM	0.1380737
2022-10-07	RF	0.0080000
2022-10-07	Step	0.0112643
2022-10-07	Lasso	0.0375414
2022-10-07	MARS	0.0451622
2022-10-07	Null	0.1767741
2022-10-07	Logit	0.0712426
2022-10-11	XGB	0.1225104
2022-10-11	GAM	0.1383550
2022-10-11	RF	0.0100000
2022-10-11	Step	0.0118508
2022-10-11	Lasso	0.0385448
2022-10-11	MARS	0.0451622
2022-10-11	Null	0.1767741
2022-10-11	Logit	0.0721031
2022-10-12	XGB	0.1225104
2022-10-12	GAM	0.1375308
2022-10-12	RF	0.0140000
2022-10-12	Step	0.0129945
2022-10-12	Lasso	0.0391492
2022-10-12	MARS	0.0451622
2022-10-12	Null	0.1767741
2022-10-12	Logit	0.0678945
2022-10-13	XGB	0.1225104
2022-10-13	GAM	0.1370788
2022-10-13	RF	0.0140000
2022-10-13	Step	0.0135517
2022-10-13	Lasso	0.0392876
2022-10-13	MARS	0.0451622
2022-10-13	Null	0.1767741
2022-10-13	Logit	0.0654799
2022-10-14	XGB	0.1225104
2022-10-14	GAM	0.1375396
2022-10-14	RF	0.0160000
2022-10-14	Step	0.0140739
2022-10-14	Lasso	0.0401418
2022-10-14	MARS	0.0451622
2022-10-14	Null	0.1767741
2022-10-14	Logit	0.0670806
2022-10-17	XGB	0.1225104
2022-10-17	GAM	0.1381808
2022-10-17	RF	0.0300000
2022-10-17	Step	0.0134419
2022-10-17	Lasso	0.0391378
2022-10-17	MARS	0.0451622
2022-10-17	Null	0.1767741
2022-10-17	Logit	0.0695499
2022-10-18	XGB	0.1225104
2022-10-18	GAM	0.1390101

date	model	prob_rec
2022-10-18	RF	0.0120000
2022-10-18	Step	0.0130427
2022-10-18	Lasso	0.0388368
2022-10-18	MARS	0.0451622
2022-10-18	Null	0.1767741
2022-10-18	Logit	0.0729732
2022-10-19	XGB	0.1225104
2022-10-19	GAM	0.1377762
2022-10-19	RF	0.0220000
2022-10-19	Step	0.0126112
2022-10-19	Lasso	0.0369051
2022-10-19	MARS	0.0451622
2022-10-19	Null	0.1767741
2022-10-19	Logit	0.0670806
2022-10-20	XGB	0.1225104
2022-10-20	GAM	0.1378316
2022-10-20	RF	0.0200000
2022-10-20	Step	0.0129281
2022-10-20	Lasso	0.0373098
2022-10-20	MARS	0.0451622
2022-10-20	Null	0.1767741
2022-10-20	Logit	0.0670806
2022-10-21	XGB	0.1225104
2022-10-21	GAM	0.1367999
2022-10-21	RF	0.0200000
2022-10-21	Step	0.0133081
2022-10-21	Lasso	0.0367781
2022-10-21	MARS	0.0451622
2022-10-21	Null	0.1767741
2022-10-21	Logit	0.0623845
2022-10-24	XGB	0.1225104
2022-10-24	GAM	0.1368629
2022-10-24	RF	0.0280000
2022-10-24	Step	0.0139566
2022-10-24	Lasso	0.0378632
2022-10-24	MARS	0.0451622
2022-10-24	Null	0.1767741
2022-10-24	Logit	0.0623845
2022-10-25	XGB	0.1225104
2022-10-25	GAM	0.1364095
2022-10-25	RF	0.0300000
2022-10-25	Step	0.0143097
2022-10-25	Lasso	0.0383115
2022-10-25	MARS	0.0451622
2022-10-25	Null	0.1767741
2022-10-25	Logit	0.0601531
2022-10-26	XGB	0.1225104
2022-10-26	GAM	0.1368700
2022-10-26	RF	0.0300000
2022-10-26	Step	0.0142055
2022-10-26	Lasso	0.0386929
2022-10-26	MARS	0.0451622

date	model	prob_rec
2022-10-26	Null	0.1767741
2022-10-26	Logit	0.0616322
2022-10-27	XGB	0.1225104
2022-10-27	GAM	0.1373425
2022-10-27	RF	0.0400000
2022-10-27	Step	0.0133961
2022-10-27	Lasso	0.0376886
2022-10-27	MARS	0.0451622
2022-10-27	Null	0.1767741
2022-10-27	Logit	0.0631453
2022-10-28	XGB	0.1225104
2022-10-28	GAM	0.1376225
2022-10-28	RF	0.0280000
2022-10-28	Step	0.0125735
2022-10-28	Lasso	0.0364448
2022-10-28	MARS	0.0451622
2022-10-28	Null	0.1767741
2022-10-28	Logit	0.0639147
2022-10-31	XGB	0.1225104
2022-10-31	GAM	0.1393647
2022-10-31	RF	0.0340000
2022-10-31	Step	0.0123476
2022-10-31	Lasso	0.0372050
2022-10-31	MARS	0.0451622
2022-10-31	Null	0.1767741
2022-10-31	Logit	0.0712426
2022-11-01	XGB	0.1225104
2022-11-01	GAM	0.1388831
2022-11-01	RF	0.0280000
2022-11-01	Step	0.0122584
2022-11-01	Lasso	0.0361121
2022-11-01	MARS	0.0451622
2022-11-01	Null	0.1767741
2022-11-01	Logit	0.0687176
2022-11-02	XGB	0.1225104
2022-11-02	GAM	0.1391438
2022-11-02	RF	0.0300000
2022-11-02	Step	0.0125378
2022-11-02	Lasso	0.0363825
2022-11-02	MARS	0.0451622
2022-11-02	Null	0.1767741
2022-11-02	Logit	0.0695499
2022-11-03	XGB	0.1225104
2022-11-03	GAM	0.1389615
2022-11-03	RF	0.0340000
2022-11-03	Step	0.0130773
2022-11-03	Lasso	0.0368649
2022-11-03	MARS	0.0451622
2022-11-03	Null	0.1767741
2022-11-03	Logit	0.0678945
2022-11-04	XGB	0.1225104
2022-11-04	GAM	0.1395193

date	model	prob_rec
2022-11-04	RF	0.0280000
2022-11-04	Step	0.0136608
2022-11-04	Lasso	0.0380081
2022-11-04	MARS	0.0451622
2022-11-04	Null	0.1767741
2022-11-04	Logit	0.0695499
2022-11-07	XGB	0.1225104
2022-11-07	GAM	0.1389548
2022-11-07	RF	0.0280000
2022-11-07	Step	0.0137075
2022-11-07	Lasso	0.0375495
2022-11-07	MARS	0.0451622
2022-11-07	Null	0.1767741
2022-11-07	Logit	0.0662757
2022-11-08	XGB	0.1225104
2022-11-08	GAM	0.1404535
2022-11-08	RF	0.0400000
2022-11-08	Step	0.0140691
2022-11-08	Lasso	0.0393124
2022-11-08	MARS	0.0451622
2022-11-08	Null	0.1767741
2022-11-08	Logit	0.0721031
2022-11-09	XGB	0.1225104
2022-11-09	GAM	0.1421627
2022-11-09	RF	0.0380000
2022-11-09	Step	0.0142971
2022-11-09	Lasso	0.0408468
2022-11-09	MARS	0.0451622
2022-11-09	Null	0.1767741
2022-11-09	Logit	0.0793394
2022-11-10	XGB	0.1225104
2022-11-10	GAM	0.1412467
2022-11-10	RF	0.0400000
2022-11-10	Step	0.0130862
2022-11-10	Lasso	0.0376583
2022-11-10	MARS	0.0451622
2022-11-10	Null	0.1767741
2022-11-10	Logit	0.0738530
2022-11-14	XGB	0.1225104
2022-11-14	GAM	0.1424278
2022-11-14	RF	0.0560000
2022-11-14	Step	0.0119507
2022-11-14	Lasso	0.0365705
2022-11-14	MARS	0.0451622
2022-11-14	Null	0.1767741
2022-11-14	Logit	0.0783998
2022-11-15	XGB	0.1225104
2022-11-15	GAM	0.1407647
2022-11-15	RF	0.0500000
2022-11-15	Step	0.0108361
2022-11-15	Lasso	0.0332035
2022-11-15	MARS	0.0451622

date	model	prob_rec
2022-11-15	Null	0.1767741
2022-11-15	Logit	0.0695499
2022-11-16	XGB	0.1225104
2022-11-16	GAM	0.1406613
2022-11-16	RF	0.1640000
2022-11-16	Step	0.0095184
2022-11-16	Lasso	0.0308221
2022-11-16	MARS	0.0451622
2022-11-16	Null	0.1767741
2022-11-16	Logit	0.0678945
2022-11-17	XGB	0.1225104
2022-11-17	GAM	0.1399906
2022-11-17	RF	0.0740000
2022-11-17	Step	0.0084238
2022-11-17	Lasso	0.0286188
2022-11-17	MARS	0.0451622
2022-11-17	Null	0.1767741
2022-11-17	Logit	0.0639147
2022-11-18	XGB	0.1225104
2022-11-18	GAM	0.1402484
2022-11-18	RF	0.0440000
2022-11-18	Step	0.0083625
2022-11-18	Lasso	0.0289166
2022-11-18	MARS	0.0451622
2022-11-18	Null	0.1767741
2022-11-18	Logit	0.0639147
2022-11-21	XGB	0.1225104
2022-11-21	GAM	0.1410632
2022-11-21	RF	0.0400000
2022-11-21	Step	0.0080229
2022-11-21	Lasso	0.0290625
2022-11-21	MARS	0.0451622
2022-11-21	Null	0.1767741
2022-11-21	Logit	0.0662757
2022-11-22	XGB	0.1225104
2022-11-22	GAM	0.1415160
2022-11-22	RF	0.1540000
2022-11-22	Step	0.0076839
2022-11-22	Lasso	0.0288585
2022-11-22	MARS	0.0451622
2022-11-22	Null	0.1767741
2022-11-22	Logit	0.0670806
2022-11-23	XGB	0.1225104
2022-11-23	GAM	0.1427342
2022-11-23	RF	0.2100000
2022-11-23	Step	0.0075798
2022-11-23	Lasso	0.0294686
2022-11-23	MARS	0.0451622
2022-11-23	Null	0.1767741
2022-11-23	Logit	0.0712426
2022-11-25	XGB	0.1225104
2022-11-25	GAM	0.1413137

date	model	prob_rec
2022-11-25	RF	0.2260000
2022-11-25	Step	0.0072099
2022-11-25	Lasso	0.0277819
2022-11-25	MARS	0.0451622
2022-11-25	Null	0.1767741
2022-11-25	Logit	0.0639147
2022-11-28	XGB	0.1225104
2022-11-28	GAM	0.1408573
2022-11-28	RF	0.2340000
2022-11-28	Step	0.0067604
2022-11-28	Lasso	0.0264967
2022-11-28	MARS	0.0451622
2022-11-28	Null	0.1767741
2022-11-28	Logit	0.0608885
2022-11-29	XGB	0.1225104
2022-11-29	GAM	0.1416954
2022-11-29	RF	0.2480000
2022-11-29	Step	0.0066804
2022-11-29	Lasso	0.0268634
2022-11-29	MARS	0.0451622
2022-11-29	Null	0.1767741
2022-11-29	Logit	0.0631453
2022-11-30	XGB	0.1225104
2022-11-30	GAM	0.1450316
2022-11-30	RF	0.2700000
2022-11-30	Step	0.0066511
2022-11-30	Lasso	0.0287366
2022-11-30	MARS	0.0451622
2022-11-30	Null	0.1767741
2022-11-30	Logit	0.0765511
2022-12-01	XGB	0.1225104
2022-12-01	GAM	0.1445527
2022-12-01	RF	0.2640000
2022-12-01	Step	0.0065276
2022-12-01	Lasso	0.0279259
2022-12-01	MARS	0.0451622
2022-12-01	Null	0.1767741
2022-12-01	Logit	0.0729732
2022-12-02	XGB	0.1225104
2022-12-02	GAM	0.1464178
2022-12-02	RF	0.2940000
2022-12-02	Step	0.0065516
2022-12-02	Lasso	0.0285902
2022-12-02	MARS	0.0451622
2022-12-02	Null	0.1767741
2022-12-02	Logit	0.0802893
2022-12-05	XGB	0.1225104
2022-12-05	GAM	0.1468952
2022-12-05	RF	0.2960000
2022-12-05	Step	0.0065551
2022-12-05	Lasso	0.0284557
2022-12-05	MARS	0.0451622

date	model	prob_rec
2022-12-05	Null	0.1767741
2022-12-05	Logit	0.0812495
2022-12-06	XGB	0.1225104
2022-12-06	GAM	0.1469931
2022-12-06	RF	0.2900000
2022-12-06	Step	0.0062548
2022-12-06	Lasso	0.0272995
2022-12-06	MARS	0.0451622
2022-12-06	Null	0.1767741
2022-12-06	Logit	0.0802893
2022-12-07	XGB	0.1225104
2022-12-07	GAM	0.1491087
2022-12-07	RF	0.3060000
2022-12-07	Step	0.0059614
2022-12-07	Lasso	0.0275328
2022-12-07	MARS	0.0451622
2022-12-07	Null	0.1767741
2022-12-07	Logit	0.0893154
2022-12-08	XGB	0.1225104
2022-12-08	GAM	0.1477948
2022-12-08	RF	0.3220000
2022-12-08	Step	0.0060341
2022-12-08	Lasso	0.0267648
2022-12-08	MARS	0.0451622
2022-12-08	Null	0.1767741
2022-12-08	Logit	0.0812495
2022-12-09	XGB	0.1225104
2022-12-09	GAM	0.1470948
2022-12-09	RF	0.3260000
2022-12-09	Step	0.0061869
2022-12-09	Lasso	0.0268534
2022-12-09	MARS	0.0451622
2022-12-09	Null	0.1767741
2022-12-09	Logit	0.0765511
2022-12-12	XGB	0.1225104
2022-12-12	GAM	0.1466017
2022-12-12	RF	0.3400000
2022-12-12	Step	0.0062151
2022-12-12	Lasso	0.0267068
2022-12-12	MARS	0.0451622
2022-12-12	Null	0.1767741
2022-12-12	Logit	0.0729732
2022-12-13	XGB	0.1225104
2022-12-13	GAM	0.1475046
2022-12-13	RF	0.3680000
2022-12-13	Step	0.0063492
2022-12-13	Lasso	0.0275667
2022-12-13	MARS	0.0451622
2022-12-13	Null	0.1767741
2022-12-13	Logit	0.0756418
2022-12-14	XGB	0.1225104
2022-12-14	GAM	0.1480178

date	model	prob_rec
2022-12-14	RF	0.3780000
2022-12-14	Step	0.0065472
2022-12-14	Lasso	0.0285399
2022-12-14	MARS	0.0451622
2022-12-14	Null	0.1767741
2022-12-14	Logit	0.0765511
2022-12-15	XGB	0.1225104
2022-12-15	GAM	0.1496306
2022-12-15	RF	0.4020000
2022-12-15	Step	0.0065084
2022-12-15	Lasso	0.0293457
2022-12-15	MARS	0.0451622
2022-12-15	Null	0.1767741
2022-12-15	Logit	0.0822202
2022-12-16	XGB	0.1225104
2022-12-16	GAM	0.1496315
2022-12-16	RF	0.4280000
2022-12-16	Step	0.0064419
2022-12-16	Lasso	0.0290792
2022-12-16	MARS	0.0451622
2022-12-16	Null	0.1767741
2022-12-16	Logit	0.0802893
2022-12-19	XGB	0.1225104
2022-12-19	GAM	0.1494225
2022-12-19	RF	0.4020000
2022-12-19	Step	0.0065137
2022-12-19	Lasso	0.0289553
2022-12-19	MARS	0.0451622
2022-12-19	Null	0.1767741
2022-12-19	Logit	0.0774704
2022-12-20	XGB	0.1225104
2022-12-20	GAM	0.1503994
2022-12-20	RF	0.4060000
2022-12-20	Step	0.0070749
2022-12-20	Lasso	0.0309777
2022-12-20	MARS	0.0451622
2022-12-20	Null	0.1767741
2022-12-20	Logit	0.0802893
2022-12-21	XGB	0.1225104
2022-12-21	GAM	0.1513815
2022-12-21	RF	0.4260000
2022-12-21	Step	0.0075260
2022-12-21	Lasso	0.0327817
2022-12-21	MARS	0.0451622
2022-12-21	Null	0.1767741
2022-12-21	Logit	0.0832014
2022-12-22	XGB	0.1225104
2022-12-22	GAM	0.1513497
2022-12-22	RF	0.4520000
2022-12-22	Step	0.0080486
2022-12-22	Lasso	0.0340987
2022-12-22	MARS	0.0451622

date	model	prob_rec
2022-12-22	Null	0.1767741
2022-12-22	Logit	0.0812495
2022-12-23	XGB	0.1225104
2022-12-23	GAM	0.1507053
2022-12-23	RF	0.4620000
2022-12-23	Step	0.0084418
2022-12-23	Lasso	0.0348215
2022-12-23	MARS	0.0451622
2022-12-23	Null	0.1767741
2022-12-23	Logit	0.0765511
2022-12-27	XGB	0.1225104
2022-12-27	GAM	0.1514643
2022-12-27	RF	0.4880000
2022-12-27	Step	0.0087448
2022-12-27	Lasso	0.0364654
2022-12-27	MARS	0.0451622
2022-12-27	Null	0.1767741
2022-12-27	Logit	0.0783998
2022-12-28	XGB	0.1225104
2022-12-28	GAM	0.1510071
2022-12-28	RF	0.5000000
2022-12-28	Step	0.0085132
2022-12-28	Lasso	0.0360434
2022-12-28	MARS	0.0451622
2022-12-28	Null	0.1767741
2022-12-28	Logit	0.0747425
2022-12-29	XGB	0.1225104
2022-12-29	GAM	0.1517741
2022-12-29	RF	0.5040000
2022-12-29	Step	0.0081023
2022-12-29	Lasso	0.0361671
2022-12-29	MARS	0.0451622
2022-12-29	Null	0.1767741
2022-12-29	Logit	0.0765511
2022-12-30	XGB	0.1225104
2022-12-30	GAM	0.1519264
2022-12-30	RF	0.4480000
2022-12-30	Step	0.0083064
2022-12-30	Lasso	0.0371924
2022-12-30	MARS	0.0451622
2022-12-30	Null	0.1767741
2022-12-30	Logit	0.0756418
2023-01-03	XGB	0.1225104
2023-01-03	GAM	0.1510990
2023-01-03	RF	0.4960000
2023-01-03	Step	0.0080613
2023-01-03	Lasso	0.0359832
2023-01-03	MARS	0.0451622
2023-01-03	Null	0.1767741
2023-01-03	Logit	0.0703915
2023-01-04	XGB	0.1225104
2023-01-04	GAM	0.1521039

date	model	prob_rec
2023-01-04	RF	0.5300000
2023-01-04	Step	0.0075979
2023-01-04	Lasso	0.0357408
2023-01-04	MARS	0.0451622
2023-01-04	Null	0.1767741
2023-01-04	Logit	0.0729732
2023-01-05	XGB	0.1225104
2023-01-05	GAM	0.1523016
2023-01-05	RF	0.5220000
2023-01-05	Step	0.0073007
2023-01-05	Lasso	0.0350750
2023-01-05	MARS	0.0451622
2023-01-05	Null	0.1767741
2023-01-05	Logit	0.0721031
2023-01-06	XGB	0.1225104
2023-01-06	GAM	0.1507491
2023-01-06	RF	0.4900000
2023-01-06	Step	0.0069164
2023-01-06	Lasso	0.0326628
2023-01-06	MARS	0.0451622
2023-01-06	Null	0.1767741
2023-01-06	Logit	0.0639147
2023-01-09	XGB	0.1225104
2023-01-09	GAM	0.1506163
2023-01-09	RF	0.4540000
2023-01-09	Step	0.0058728
2023-01-09	Lasso	0.0297142
2023-01-09	MARS	0.0451622
2023-01-09	Null	0.1767741
2023-01-09	Logit	0.0616322
2023-01-10	XGB	0.1225104
2023-01-10	GAM	0.1500911
2023-01-10	RF	0.4700000
2023-01-10	Step	0.0053452
2023-01-10	Lasso	0.0278437
2023-01-10	MARS	0.0454700
2023-01-10	Null	0.1767741
2023-01-10	Logit	0.0579966
2023-01-11	XGB	0.1225104
2023-01-11	GAM	0.1501751
2023-01-11	RF	0.4960000
2023-01-11	Step	0.0049307
2023-01-11	Lasso	0.0268835
2023-01-11	MARS	0.0462782
2023-01-11	Null	0.1767741
2023-01-11	Logit	0.0565995
2023-01-12	XGB	0.1225104
2023-01-12	GAM	0.1500956
2023-01-12	RF	0.5080000
2023-01-12	Step	0.0045090
2023-01-12	Lasso	0.0257130
2023-01-12	MARS	0.0471477

date	model	prob_rec
2023-01-12	Null	0.1767741
2023-01-12	Logit	0.0545630
2023-01-13	XGB	0.1225104
2023-01-13	GAM	0.1502058
2023-01-13	RF	0.5380000
2023-01-13	Step	0.0044232
2023-01-13	Lasso	0.0258840
2023-01-13	MARS	0.0480188
2023-01-13	Null	0.1767741
2023-01-13	Logit	0.0532439
2023-01-17	XGB	0.1225104
2023-01-17	GAM	0.1512750
2023-01-17	RF	0.5520000
2023-01-17	Step	0.0045339
2023-01-17	Lasso	0.0271362
2023-01-17	MARS	0.0488805
2023-01-17	Null	0.1767741
2023-01-17	Logit	0.0552341
2023-01-18	XGB	0.1225104
2023-01-18	GAM	0.1519915
2023-01-18	RF	0.5620000
2023-01-18	Step	0.0044730
2023-01-18	Lasso	0.0274141
2023-01-18	MARS	0.0498107
2023-01-18	Null	0.1767741
2023-01-18	Logit	0.0559129
2023-01-19	XGB	0.1225104
2023-01-19	GAM	0.1532951
2023-01-19	RF	0.5660000
2023-01-19	Step	0.0046966
2023-01-19	Lasso	0.0287091
2023-01-19	MARS	0.0507357
2023-01-19	Null	0.1767741
2023-01-19	Logit	0.0587073
2023-01-20	XGB	0.1225104
2023-01-20	GAM	0.1522331
2023-01-20	RF	0.5880000
2023-01-20	Step	0.0049777
2023-01-20	Lasso	0.0287344
2023-01-20	MARS	0.0516732
2023-01-20	Null	0.1767741
2023-01-20	Logit	0.0532439
2023-01-23	XGB	0.1225104
2023-01-23	GAM	0.1510162
2023-01-23	RF	0.5840000
2023-01-23	Step	0.0050815
2023-01-23	Lasso	0.0280171
2023-01-23	MARS	0.0526459
2023-01-23	Null	0.1767741
2023-01-23	Logit	0.0476723
2023-01-24	XGB	0.1225104
2023-01-24	GAM	0.1523160

date	model	prob_rec
2023-01-24	RF	0.5860000
2023-01-24	Step	0.0050454
2023-01-24	Lasso	0.0286739
2023-01-24	MARS	0.0536437
2023-01-24	Null	0.1767741
2023-01-24	Logit	0.0500767
2023-01-25	XGB	0.1225104
2023-01-25	GAM	0.1528501
2023-01-25	RF	0.5780000
2023-01-25	Step	0.0052520
2023-01-25	Lasso	0.0297658
2023-01-25	MARS	0.0546592
2023-01-25	Null	0.1767741
2023-01-25	Logit	0.0500767
2023-01-26	XGB	0.1225104
2023-01-26	GAM	0.1549411
2023-01-26	RF	0.5980000
2023-01-26	Step	0.0054470
2023-01-26	Lasso	0.0319734
2023-01-26	MARS	0.0556491
2023-01-26	Null	0.1767741
2023-01-26	Logit	0.0552341
2023-01-27	XGB	0.1225104
2023-01-27	GAM	0.1554576
2023-01-27	RF	0.5880000
2023-01-27	Step	0.0056553
2023-01-27	Lasso	0.0328243
2023-01-27	MARS	0.0566437
2023-01-27	Null	0.1767741
2023-01-27	Logit	0.0552341
2023-01-30	XGB	0.1225104
2023-01-30	GAM	0.1553794
2023-01-30	RF	0.5880000
2023-01-30	Step	0.0059854
2023-01-30	Lasso	0.0334043
2023-01-30	MARS	0.0576549
2023-01-30	Null	0.1767741
2023-01-30	Logit	0.0532439
2023-01-31	XGB	0.1225104
2023-01-31	GAM	0.1545402
2023-01-31	RF	0.6020000
2023-01-31	Step	0.0065006
2023-01-31	Lasso	0.0339713
2023-01-31	MARS	0.0587250
2023-01-31	Null	0.1767741
2023-01-31	Logit	0.0488605
2023-02-01	XGB	0.1225104
2023-02-01	GAM	0.1558903
2023-02-01	RF	0.6080000
2023-02-01	Step	0.0068616
2023-02-01	Lasso	0.0354655
2023-02-01	MARS	0.0598519

date	model	prob_rec
2023-02-01	Null	0.1767741
2023-02-01	Logit	0.0513216
2023-02-02	XGB	0.1225104
2023-02-02	GAM	0.1571014
2023-02-02	RF	0.6120000
2023-02-02	Step	0.0070935
2023-02-02	Lasso	0.0367022
2023-02-02	MARS	0.0610902
2023-02-02	Null	0.1767741
2023-02-02	Logit	0.0532439
2023-02-03	XGB	0.1225104
2023-02-03	GAM	0.1574935
2023-02-03	RF	0.6160000
2023-02-03	Step	0.0073894
2023-02-03	Lasso	0.0374804
2023-02-03	MARS	0.0622993
2023-02-03	Null	0.1767741
2023-02-03	Logit	0.0525957
2023-02-06	XGB	0.1225104
2023-02-06	GAM	0.1576714
2023-02-06	RF	0.6100000
2023-02-06	Step	0.0077153
2023-02-06	Lasso	0.0383978
2023-02-06	MARS	0.0634947
2023-02-06	Null	0.1767741
2023-02-06	Logit	0.0513216
2023-02-07	XGB	0.1225104
2023-02-07	GAM	0.1588421
2023-02-07	RF	0.6140000
2023-02-07	Step	0.0081404
2023-02-07	Lasso	0.0402567
2023-02-07	MARS	0.0646794
2023-02-07	Null	0.1767741
2023-02-07	Logit	0.0532439
2023-02-08	XGB	0.1225104
2023-02-08	GAM	0.1586248
2023-02-08	RF	0.6080000
2023-02-08	Step	0.0085648
2023-02-08	Lasso	0.0410082
2023-02-08	MARS	0.0659219
2023-02-08	Null	0.1767741
2023-02-08	Logit	0.0506956
2023-02-09	XGB	0.1225104
2023-02-09	GAM	0.1570447
2023-02-09	RF	0.6140000
2023-02-09	Step	0.0089178
2023-02-09	Lasso	0.0403622
2023-02-09	MARS	0.0672151
2023-02-09	Null	0.1767741
2023-02-09	Logit	0.0442704
2023-02-10	XGB	0.1225104
2023-02-10	GAM	0.1578280

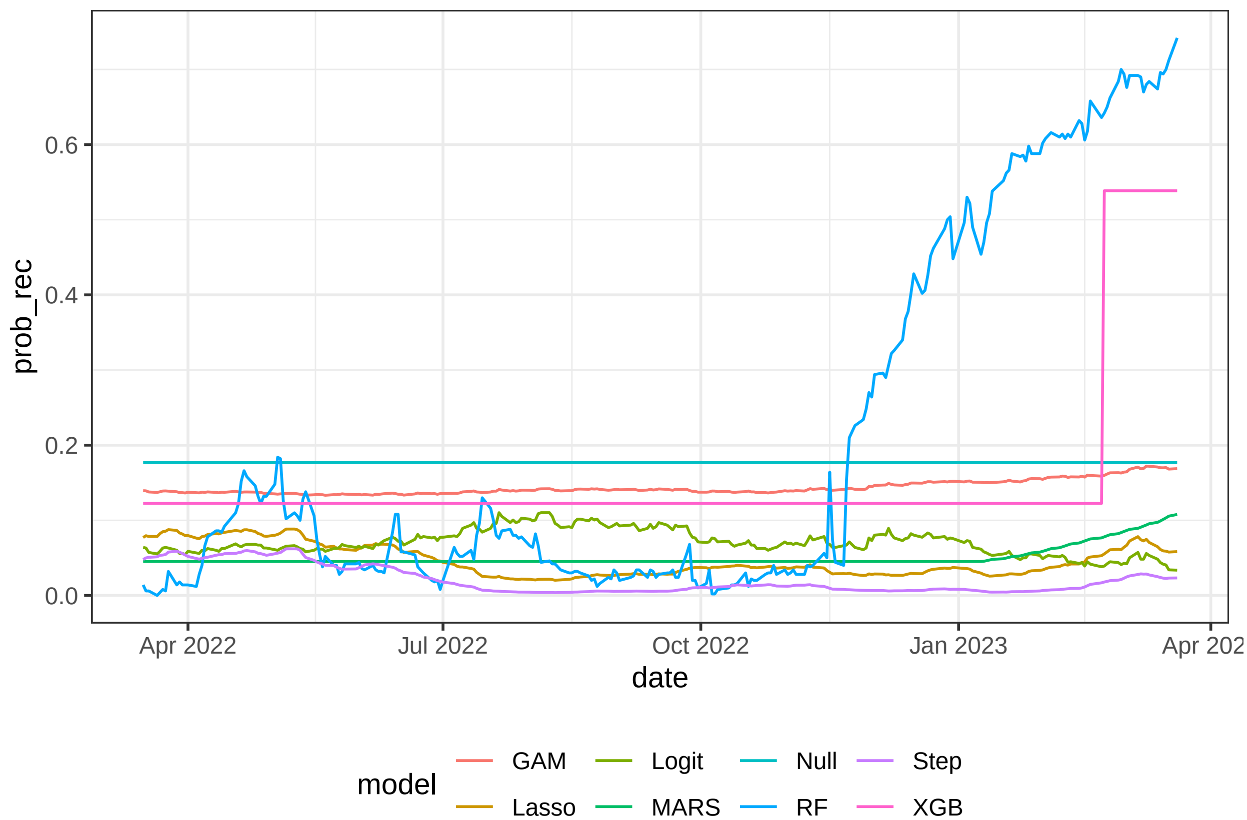
date	model	prob_rec
2023-02-10	RF	0.6100000
2023-02-10	Step	0.0092454
2023-02-10	Lasso	0.0418605
2023-02-10	MARS	0.0684979
2023-02-10	Null	0.1767741
2023-02-10	Logit	0.0448209
2023-02-13	XGB	0.1225104
2023-02-13	GAM	0.1576460
2023-02-13	RF	0.6320000
2023-02-13	Step	0.0094118
2023-02-13	Lasso	0.0418523
2023-02-13	MARS	0.0698329
2023-02-13	Null	0.1767741
2023-02-13	Logit	0.0426575
2023-02-14	XGB	0.1225104
2023-02-14	GAM	0.1586300
2023-02-14	RF	0.6280000
2023-02-14	Step	0.0100896
2023-02-14	Lasso	0.0437824
2023-02-14	MARS	0.0711569
2023-02-14	Null	0.1767741
2023-02-14	Logit	0.0437264
2023-02-15	XGB	0.1225104
2023-02-15	GAM	0.1574761
2023-02-15	RF	0.6060000
2023-02-15	Step	0.0113287
2023-02-15	Lasso	0.0446360
2023-02-15	MARS	0.0725295
2023-02-15	Null	0.1767741
2023-02-15	Logit	0.0391096
2023-02-16	XGB	0.1225104
2023-02-16	GAM	0.1602099
2023-02-16	RF	0.6180000
2023-02-16	Step	0.0130227
2023-02-16	Lasso	0.0499108
2023-02-16	MARS	0.0738436
2023-02-16	Null	0.1767741
2023-02-16	Logit	0.0448209
2023-02-17	XGB	0.1225104
2023-02-17	GAM	0.1596216
2023-02-17	RF	0.6580000
2023-02-17	Step	0.0147154
2023-02-17	Lasso	0.0511581
2023-02-17	MARS	0.0752322
2023-02-17	Null	0.1767741
2023-02-17	Logit	0.0416136
2023-02-21	XGB	0.1225104
2023-02-21	GAM	0.1588390
2023-02-21	RF	0.6360000
2023-02-21	Step	0.0168105
2023-02-21	Lasso	0.0528725
2023-02-21	MARS	0.0766126

date	model	prob_rec
2023-02-21	Null	0.1767741
2023-02-21	Logit	0.0381491
2023-02-22	XGB	0.5385929
2023-02-22	GAM	0.1598190
2023-02-22	RF	0.6420000
2023-02-22	Step	0.0178991
2023-02-22	Lasso	0.0553287
2023-02-22	MARS	0.0780162
2023-02-22	Null	0.1767741
2023-02-22	Logit	0.0391096
2023-02-23	XGB	0.5385929
2023-02-23	GAM	0.1615981
2023-02-23	RF	0.6500000
2023-02-23	Step	0.0187070
2023-02-23	Lasso	0.0580018
2023-02-23	MARS	0.0794378
2023-02-23	Null	0.1767741
2023-02-23	Logit	0.0421324
2023-02-24	XGB	0.5385929
2023-02-24	GAM	0.1631751
2023-02-24	RF	0.6620000
2023-02-24	Step	0.0196803
2023-02-24	Lasso	0.0607888
2023-02-24	MARS	0.0808156
2023-02-24	Null	0.1767741
2023-02-24	Logit	0.0448209
2023-02-27	XGB	0.5385929
2023-02-27	GAM	0.1633574
2023-02-27	RF	0.6840000
2023-02-27	Step	0.0203940
2023-02-27	Lasso	0.0613568
2023-02-27	MARS	0.0822379
2023-02-27	Null	0.1767741
2023-02-27	Logit	0.0437264
2023-02-28	XGB	0.5385929
2023-02-28	GAM	0.1629523
2023-02-28	RF	0.7000000
2023-02-28	Step	0.0212009
2023-02-28	Lasso	0.0608975
2023-02-28	MARS	0.0837121
2023-02-28	Null	0.1767741
2023-02-28	Logit	0.0411008
2023-03-01	XGB	0.5385929
2023-03-01	GAM	0.1641327
2023-03-01	RF	0.6940000
2023-03-01	Step	0.0229175
2023-03-01	Lasso	0.0640859
2023-03-01	MARS	0.0851453
2023-03-01	Null	0.1767741
2023-03-01	Logit	0.0426575
2023-03-02	XGB	0.5385929
2023-03-02	GAM	0.1644951

date	model	prob_rec
2023-03-02	RF	0.6760000
2023-03-02	Step	0.0247263
2023-03-02	Lasso	0.0668527
2023-03-02	MARS	0.0865588
2023-03-02	Null	0.1767741
2023-03-02	Logit	0.0421324
2023-03-03	XGB	0.5385929
2023-03-03	GAM	0.1679432
2023-03-03	RF	0.6920000
2023-03-03	Step	0.0259910
2023-03-03	Lasso	0.0724499
2023-03-03	MARS	0.0879754
2023-03-03	Null	0.1767741
2023-03-03	Logit	0.0500767
2023-03-06	XGB	0.5385929
2023-03-06	GAM	0.1708319
2023-03-06	RF	0.6920000
2023-03-06	Step	0.0279277
2023-03-06	Lasso	0.0782828
2023-03-06	MARS	0.0893389
2023-03-06	Null	0.1767741
2023-03-06	Logit	0.0572941
2023-03-07	XGB	0.5385929
2023-03-07	GAM	0.1684368
2023-03-07	RF	0.6900000
2023-03-07	Step	0.0286906
2023-03-07	Lasso	0.0741420
2023-03-07	MARS	0.0908152
2023-03-07	Null	0.1767741
2023-03-07	Logit	0.0482630
2023-03-08	XGB	0.5385929
2023-03-08	GAM	0.1690180
2023-03-08	RF	0.6700000
2023-03-08	Step	0.0284077
2023-03-08	Lasso	0.0725779
2023-03-08	MARS	0.0923070
2023-03-08	Null	0.1767741
2023-03-08	Logit	0.0482630
2023-03-09	XGB	0.5385929
2023-03-09	GAM	0.1721498
2023-03-09	RF	0.6800000
2023-03-09	Step	0.0285134
2023-03-09	Lasso	0.0746973
2023-03-09	MARS	0.0937758
2023-03-09	Null	0.1767741
2023-03-09	Logit	0.0559129
2023-03-10	XGB	0.5385929
2023-03-10	GAM	0.1719289
2023-03-10	RF	0.6840000
2023-03-10	Step	0.0273360
2023-03-10	Lasso	0.0705689
2023-03-10	MARS	0.0954418

date	model	prob_rec
2023-03-10	Null	0.1767741
2023-03-10	Logit	0.0532439
2023-03-13	XGB	0.5385929
2023-03-13	GAM	0.1709240
2023-03-13	RF	0.6740000
2023-03-13	Step	0.0249669
2023-03-13	Lasso	0.0648233
2023-03-13	MARS	0.0972936
2023-03-13	Null	0.1767741
2023-03-13	Logit	0.0482630
2023-03-14	XGB	0.5385929
2023-03-14	GAM	0.1699439
2023-03-14	RF	0.6960000
2023-03-14	Step	0.0238933
2023-03-14	Lasso	0.0611908
2023-03-14	MARS	0.0991706
2023-03-14	Null	0.1767741
2023-03-14	Logit	0.0437264
2023-03-15	XGB	0.5385929
2023-03-15	GAM	0.1698569
2023-03-15	RF	0.6940000
2023-03-15	Step	0.0230508
2023-03-15	Lasso	0.0593118
2023-03-15	MARS	0.1011967
2023-03-15	Null	0.1767741
2023-03-15	Logit	0.0416136
2023-03-16	XGB	0.5385929
2023-03-16	GAM	0.1701825
2023-03-16	RF	0.7000000
2023-03-16	Step	0.0225397
2023-03-16	Lasso	0.0589438
2023-03-16	MARS	0.1032385
2023-03-16	Null	0.1767741
2023-03-16	Logit	0.0405941
2023-03-17	XGB	0.5385929
2023-03-17	GAM	0.1681451
2023-03-17	RF	0.7120000
2023-03-17	Step	0.0231465
2023-03-17	Lasso	0.0577392
2023-03-17	MARS	0.1055379
2023-03-17	Null	0.1767741
2023-03-17	Logit	0.0341001
2023-03-20	XGB	0.5385929
2023-03-20	GAM	0.1687438
2023-03-20	RF	0.7420000
2023-03-20	Step	0.0233032
2023-03-20	Lasso	0.0583324
2023-03-20	MARS	0.1078314
2023-03-20	Null	0.1767741
2023-03-20	Logit	0.0336767

```
ggplot(recent_prob, aes(x=date, y=prob_rec,
                        group=model, color=model)) +
  geom_line() + theme_bw() +
  theme(legend.position = "bottom")
```

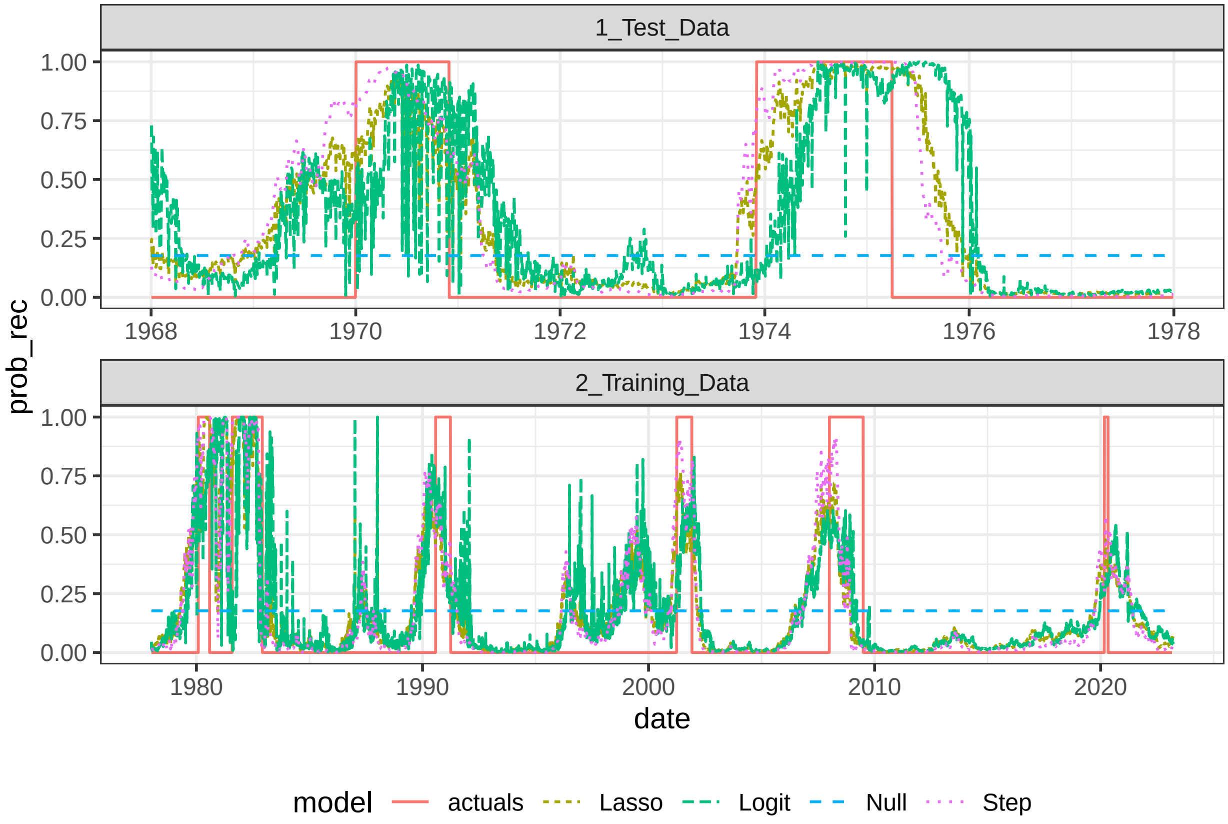


Backtesting

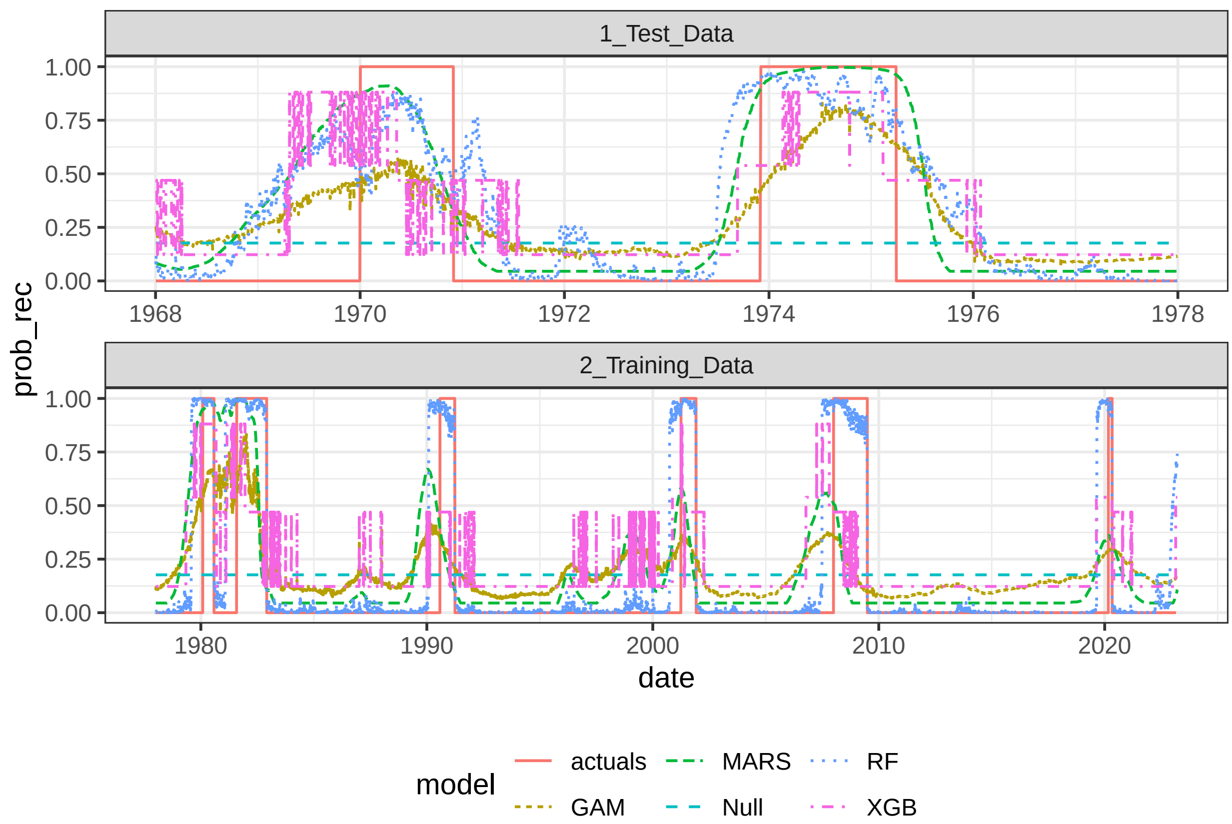
```
full_data_bktst <- full_data_wide %>%
  filter(date >= startTestDate)

bkst_fun <- function(mods, dat) {
  output <- map_dfc(.x = mods, .f = function(x) {
    if(class(x)[1] != "train"){
      predict(x, newdata = dat, type = "response")
    } else(
       predict(x, newdata = dat, type = "prob")[,"yes"]

    )

  })

  output$date <- dat$date
```

```
  output <- output%>%
    pivot_longer(-date, names_to = "model",
                 values_to = "prob_rec")

  return(output)
}

df_plot <- bkst_fun(mymods, full_data_bktst)

actuals <- full_data_bktst %>%
  mutate(model="actuals") %>%
  select(date, model, prob_rec=USREC)

df_plot_final <- bind_rows(df_plot, actuals)

end_test_date <- max(test_data$date)

df_plot_final <- df_plot_final %>%
  mutate(epoc = case_when(date <= end_test_date ~ "1_Test_Data",
                          TRUE ~ "2_Training_Data")
  )

df_plot_logit_scam <- df_plot_final %>%
  filter(model %in% c('actuals', 'Null',
                      'Logit', 'Step', 'Lasso',
                      'LogitKnot'))

df_plot_knots_gbm <- df_plot_final %>%
  filter(model %in% c('actuals', 'Null',
                      'XGB', 'RF',
                      'GAM',
                      'MARS'))
```

```
ggplot(df_plot_logit_scam, aes(x=date, y=prob_rec, group=model,
                          linetype=model, color=model)) +
  geom_line() +
  theme_bw() +
  theme(legend.position = "bottom") +
  facet_wrap(vars(epoc), scales="free", nrow=2)
```




```
ggplot(df_plot_knots_gbm, aes(x=date, y=prob_rec, group=model,
                              linetype=model, color=model)) +
  geom_line() +
  theme_bw() +
  theme(legend.position = "bottom") +
  facet_wrap(vars(epoc), scales="free", nrow=2)
```




```
stopCluster(cl)
```