Probability of Recession

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Summary

Forecast the probability of a recession in the next 6 months using the following predictors:

1. Spread between 10Y CMT and Effective Federal Funds Rate
2. YOY change in Unemployment Rate
3. YOY growth in CPI-U
4. YOY change in Effective Federal Funds Rate
5. Adstock transformations of predictors

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 <- "1978-01-01"
startTrainDate <- "1988-01-01"
```

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

full_data <- map_dfr(series_id, function(x) {
  fredr(
    series_id = x,
    observation_start = as.Date("1950-01-01"),
    observation_end = as.Date("2022-12-01")
```

```
  )
})
```

Pivot Wider

```
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)
```

Calculate Features/Predictors

```
full_data_wide_features <- full_data_wide_raw %>%
  arrange(date) %>%
  mutate(SPRD_10YCMT_FEDFUNDS = GS10 - FEDFUNDS,
         D_UNRATE = UNRATE - lag(UNRATE, 12),
         G_CPIU = (CPIAUCSL / lag(CPIAUCSL, 12) - 1) * 100,
         D_EFFR = FEDFUNDS - lag(FEDFUNDS, 12),
         D_GS10 = GS10 - lag(GS10, 12)
         ) %>%
  mutate(across(
    .cols=c(SPRD_10YCMT_FEDFUNDS, D_UNRATE,
              G_CPIU, D_EFFR, GS10, D_GS10),
    .fns=list(lag1 = ~lag(.x, 1),
         lag3 = ~lag(.x, 3),
         lag6 = ~lag(.x, 6),
         lag9 = ~lag(.x, 9),
         lag12 = ~lag(.x, 12))
  )) %>%
  select(-CPIAUCSL) %>% ## index rises with time
  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 between 0.05 and 1.

```r
full_data_wide_features_adstock <- full_data_wide_features %>%
  arrange(date) %>%
    mutate(across(
    .cols=c(UNRATE:D_GS10),
    .fns=list(adstk85 = ~stats::filter(.x,
                                        filter=0.85,
                                        method="recursive") ,
         adstk91 = ~stats::filter(.x,
                                        filter=0.91,
                                        method="recursive") ,
         adstk92 = ~stats::filter(.x,
                                        filter=0.92,
                                        method="recursive"),
         adstk93 = ~stats::filter(.x,
                                        filter=0.93,
                                        method="recursive"),
         adstk94 = ~stats::filter(.x,
                                        filter=0.94,
                                        method="recursive"),
         adstk95 = ~stats::filter(.x,
                                        filter=0.95,
                                        method="recursive"),
         adstk99 = ~stats::filter(.x,
                                        filter=0.99,
                                        method="recursive")
  ))) %>%
  mutate(constant=1)
```

Calculate Moving Average

```r
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),
    .fns=list(
         ma2m = ~stats::filter(.x,
                                         filter=ma_fun(2),
                                       method="convolution",
                                       sides=1),
         ma3m = ~stats::filter(.x,
                                         filter=ma_fun(3),
                                       method="convolution",
                                       sides=1),
         ma6m = ~stats::filter(.x,
                                         filter=ma_fun(6),
                                       method="convolution",
                                       sides=1),
```

```
        ma9m = ~stats::filter(.x,
                                  filter=ma_fun(9),
                                method="convolution",
                                sides=1),
        ma12m = ~stats::filter(.x,
                                  filter=ma_fun(12),
                                method="convolution",
                                sides=1)
  )))
```

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_features_adstock, 12)

train_test <- head(full_data_wide_features_adstock, -12)
```

Recession in next 6 months

```
full_data_wide <- train_test %>%
  arrange(date) %>%
  mutate(USREC_LEAD1 = lead(USREC, 1),
         USREC_LEAD2 = lead(USREC, 2),
         USREC_LEAD3 = lead(USREC, 3),
         USREC_LEAD4 = lead(USREC, 4),
         USREC_LEAD5 = lead(USREC, 5),
         USREC_LEAD6 = lead(USREC, 6),
         FUTREC = pmax(USREC_LEAD1, USREC_LEAD2, USREC_LEAD3,
                              USREC_LEAD4, USREC_LEAD5, USREC_LEAD6)) %>%
  drop_na() %>%
  select( -USREC_LEAD1, -USREC_LEAD2, -USREC_LEAD3,
         -USREC_LEAD4, -USREC_LEAD5, -USREC_LEAD6)
```

Split Train/Test

```
full_data_wide$constant <- 1

train_data <- full_data_wide %>%
  filter(date >= startTrainDate)

test_data <- full_data_wide %>%
  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 = 400
date	1988-01-01 to 2021-04-01
USREC	36 (9.0%)
UNRATE	5.50 (4.70, 6.70)
GS10	4.50 (2.67, 6.23)
FEDFUNDS	2.71 (0.37, 5.29)
SPRD_10YCMT_FEDFUNDS	1.48 (0.53, 2.56)
D_UNRATE	-0.30 (-0.60, 0.23)
G_CPIU	2.54 (1.69, 3.22)
D_EFFR	0.01 (-0.75, 0.63)
D_GS10	-0.30 (-0.85, 0.39)
SPRD_10YCMT_FEDFUNDS_lag1	1.48 (0.53, 2.56)
SPRD_10YCMT_FEDFUNDS_lag3	1.50 (0.53, 2.56)
SPRD_10YCMT_FEDFUNDS_lag6	1.54 (0.53, 2.56)
SPRD_10YCMT_FEDFUNDS_lag9	1.56 (0.53, 2.56)
SPRD_10YCMT_FEDFUNDS_lag12	1.56 (0.53, 2.56)
D_UNRATE_lag1	-0.30 (-0.60, 0.23)
D_UNRATE_lag3	-0.30 (-0.60, 0.20)
D_UNRATE_lag6	-0.30 (-0.60, 0.20)
D_UNRATE_lag9	-0.30 (-0.60, 0.20)
D_UNRATE_lag12	-0.30 (-0.60, 0.10)
G_CPIU_lag1	2.54 (1.69, 3.22)
G_CPIU_lag3	2.54 (1.70, 3.23)
G_CPIU_lag6	2.57 (1.72, 3.26)
G_CPIU_lag9	2.60 (1.73, 3.34)
G_CPIU_lag12	2.60 (1.74, 3.34)
D_EFFR_lag1	0.01 (-0.75, 0.63)
D_EFFR_lag3	0.01 (-0.75, 0.66)
D_EFFR_lag6	0.02 (-0.74, 0.68)
D_EFFR_lag9	0.02 (-0.73, 0.68)
D_EFFR_lag12	0.02 (-0.73, 0.68)
GS10_lag1	4.51 (2.70, 6.26)
GS10_lag3	4.53 (2.71, 6.27)
GS10_lag6	4.56 (2.72, 6.30)
GS10_lag9	4.58 (2.80, 6.42)
GS10_lag12	4.65 (2.84, 6.49)
D_GS10_lag1	-0.30 (-0.85, 0.39)
D_GS10_lag3	-0.30 (-0.85, 0.39)
D_GS10_lag6	-0.29 (-0.85, 0.41)
D_GS10_lag9	-0.27 (-0.83, 0.43)
D_GS10_lag12	-0.27 (-0.83, 0.43)
UNRATE_adstk85	37 (32, 45)
UNRATE_adstk91	62 (54, 74)

Characteristic	**N = 400**
UNRATE_adstk92	70 (61, 82)
UNRATE_adstk93	80 (71, 93)
UNRATE_adstk94	94 (83, 110)
UNRATE_adstk95	114 (101, 132)
UNRATE_adstk99	620 (557, 653)
GS10_adstk85	30 (17, 43)
GS10_adstk91	51 (29, 72)
GS10_adstk92	57 (33, 81)
GS10_adstk93	65 (37, 93)
GS10_adstk94	76 (43, 110)
GS10_adstk95	92 (51, 133)
GS10_adstk99	611 (434, 790)
FEDFUNDS_adstk85	21 (4, 36)
FEDFUNDS_adstk91	37 (9, 59)
FEDFUNDS_adstk92	43 (11, 66)
FEDFUNDS_adstk93	50 (14, 75)
FEDFUNDS_adstk94	59 (17, 87)
FEDFUNDS_adstk95	71 (21, 104)
FEDFUNDS_adstk99	457 (263, 652)
SPRD_10YCMT_FEDFUNDS_adstk85	10 (4, 17)
SPRD_10YCMT_FEDFUNDS_adstk91	17 (7, 26)
SPRD_10YCMT_FEDFUNDS_adstk92	19 (8, 29)
SPRD_10YCMT_FEDFUNDS_adstk93	22 (9, 32)
SPRD_10YCMT_FEDFUNDS_adstk94	26 (11, 37)
SPRD_10YCMT_FEDFUNDS_adstk95	31 (15, 44)
SPRD_10YCMT_FEDFUNDS_adstk99	137 (111, 161)
D_UNRATE_adstk85	-2 (-4, 2)
D_UNRATE_adstk91	-4 (-6, 4)
D_UNRATE_adstk92	-4 (-6, 4)
D_UNRATE_adstk93	-5 (-7, 5)
D_UNRATE_adstk94	-5 (-8, 6)
D_UNRATE_adstk95	-6 (-9, 6)
D_UNRATE_adstk99	-9 (-17, 5)
G_CPIU_adstk85	17 (12, 21)
G_CPIU_adstk91	28 (21, 35)
G_CPIU_adstk92	31 (24, 39)
G_CPIU_adstk93	35 (28, 44)
G_CPIU_adstk94	41 (32, 51)
G_CPIU_adstk95	49 (38, 61)
G_CPIU_adstk99	311 (261, 416)
D_EFFR_adstk85	0 (-5, 4)
D_EFFR_adstk91	0 (-9, 5)
D_EFFR_adstk92	-1 (-10, 5)
D_EFFR_adstk93	-1 (-11, 6)
D_EFFR_adstk94	-1 (-12, 6)
D_EFFR_adstk95	-2 (-13, 6)
D_EFFR_adstk99	-18 (-37, -8)
D_GS10_adstk85	-1.7 (-4.5, 1.4)
D_GS10_adstk91	-2.3 (-6.1, 1.2)
D_GS10_adstk92	-2.5 (-6.5, 1.0)
D_GS10_adstk93	-2.8 (-7.0, 0.6)
D_GS10_adstk94	-3.3 (-7.5, 0.1)

Characteristic	N = 400
D_GS10_adstk95	-4.2 (-8.4, -0.8)
D_GS10_adstk99	-20 (-23, -13)
constant	400 (100%)
SPRD_10YCMT_FEDFUNDS_ma2m	1.48 (0.48, 2.54)
SPRD_10YCMT_FEDFUNDS_ma3m	1.49 (0.49, 2.57)
SPRD_10YCMT_FEDFUNDS_ma6m	1.51 (0.50, 2.59)
SPRD_10YCMT_FEDFUNDS_ma9m	1.52 (0.49, 2.62)
SPRD_10YCMT_FEDFUNDS_ma12m	1.49 (0.50, 2.60)
FUTREC	56 (14%)

Remove stale data from test set

Exclude historical data prior to 1978-01-01 because the economy changed dramatically (due to computational innovation).

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

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1978-01-01" "1980-06-23" "1982-12-16" "1982-12-16" "1985-06-08" "1987-12-01"
```

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

summary(test_data$date)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1978-01-01" "1980-06-23" "1982-12-16" "1982-12-16" "1985-06-08" "1987-12-01"
```

Setup Parallel Processing

```
library(doParallel)

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

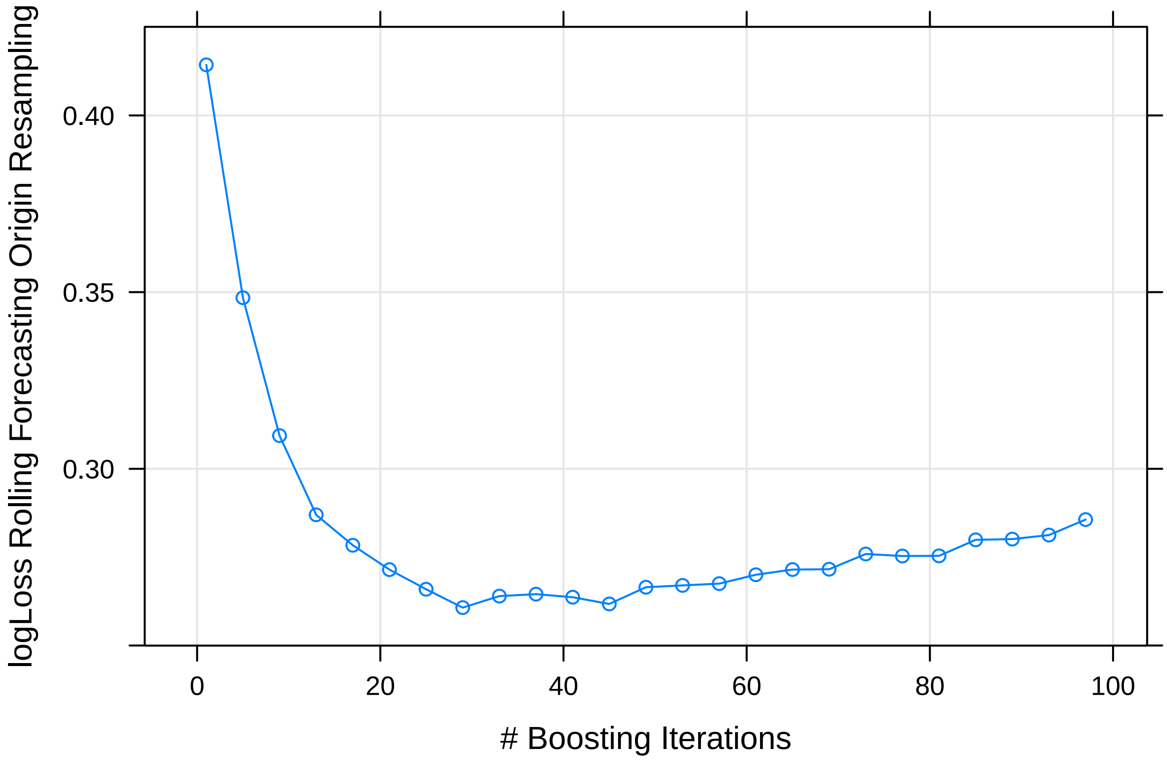
Cross-Validation Framework

```
fcstHorizon <- 3
initWindow <- 120
param_skip <- fcstHorizon - 1

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

```r
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

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

set.seed(randSeed)

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

plot(gam_mod)
```



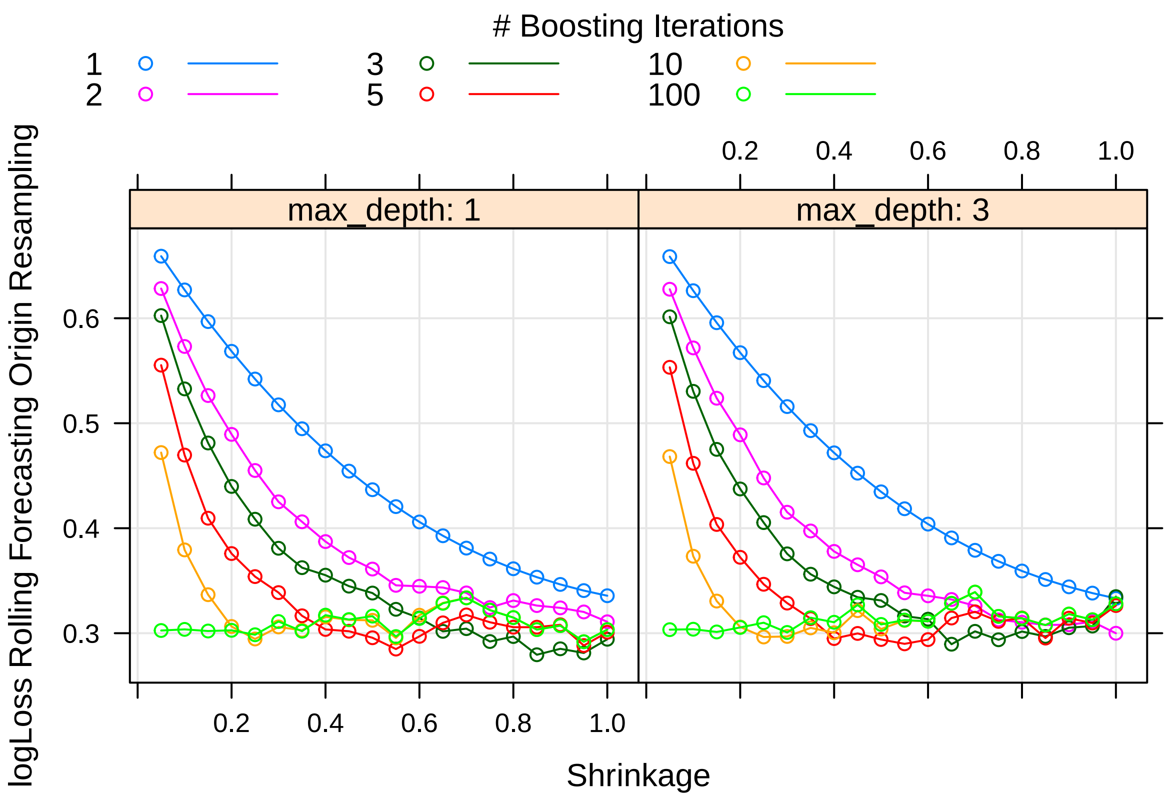

```
gam_mod$bestTune
```

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

eXtreme Gradient Boosting Trees

```
grid_xgb <- expand.grid(nrounds=c(1,2,3,5,10,100),
                        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 - USREC - constant,
  data = train_yes_no,
  method = "xgbTree",
  trControl = fitControl_oneSE,
```

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

plot(xgb_mod)
```



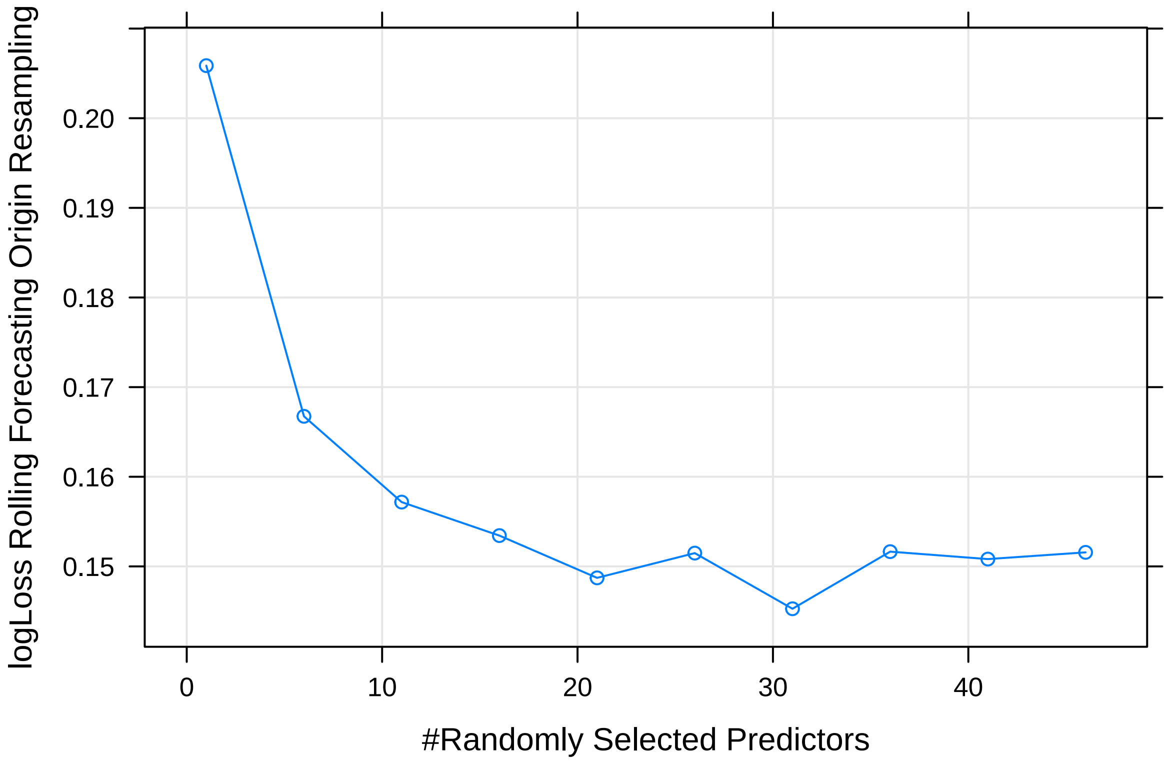

```
xgb_mod$bestTune
```

```
##     nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
## 229       1         1   1     0                1               10         1
```

Random Forest

```
grid_rf <- data.frame(mtry=seq.int(1,50,5))

set.seed(randSeed)

rf_mod <- train(
  FUTREC ~ . - date - USREC - constant,
  data = train_yes_no,
  method = "rf",
```

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

plot(rf_mod)
```




```r
rf_mod$bestTune
```

```
##   mtry
## 2    6
```

Stepwise Regression

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

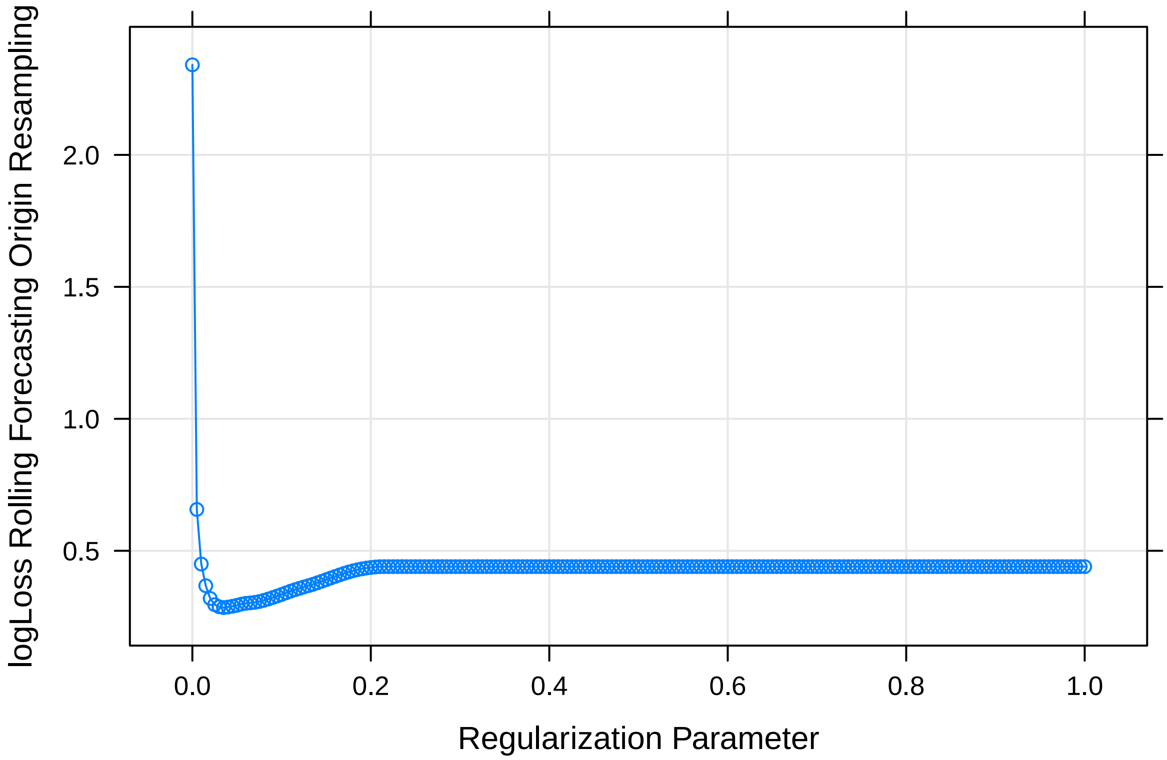
> For binomial and quasibinomial families the response can also be specified as a factor (when the first level denotes failure and all others success) or as a two-column matrix with the columns giving the numbers of successes and failures.

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`.

```r
set.seed(randSeed)

stepwise_mod <- train(
  FUTREC ~ . - date - USREC - 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)

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

set.seed(randSeed)

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

plot(glmnet_mod)
```

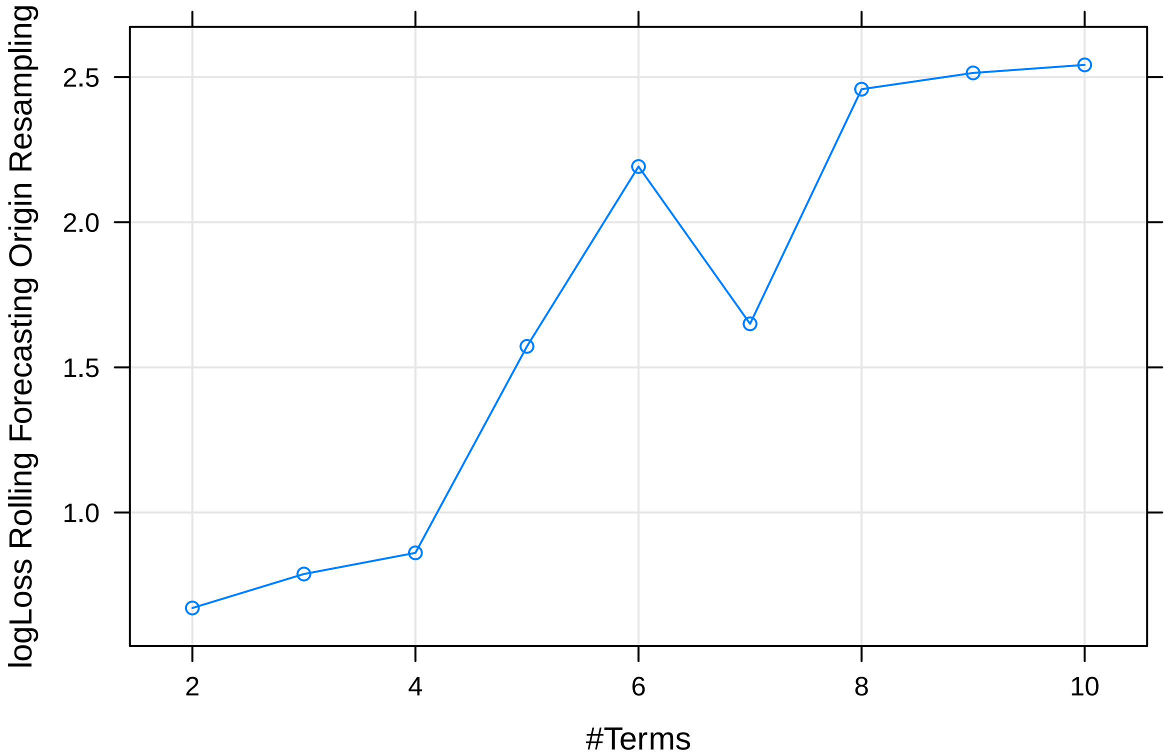



```
glmnet_mod$bestTune
```

```
##   alpha lambda
## 8     1  0.035
```

Multivariate Adaptive Regression Splines

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

set.seed(randSeed)

earth_mod <- train(
  FUTREC ~ . - date - USREC - 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

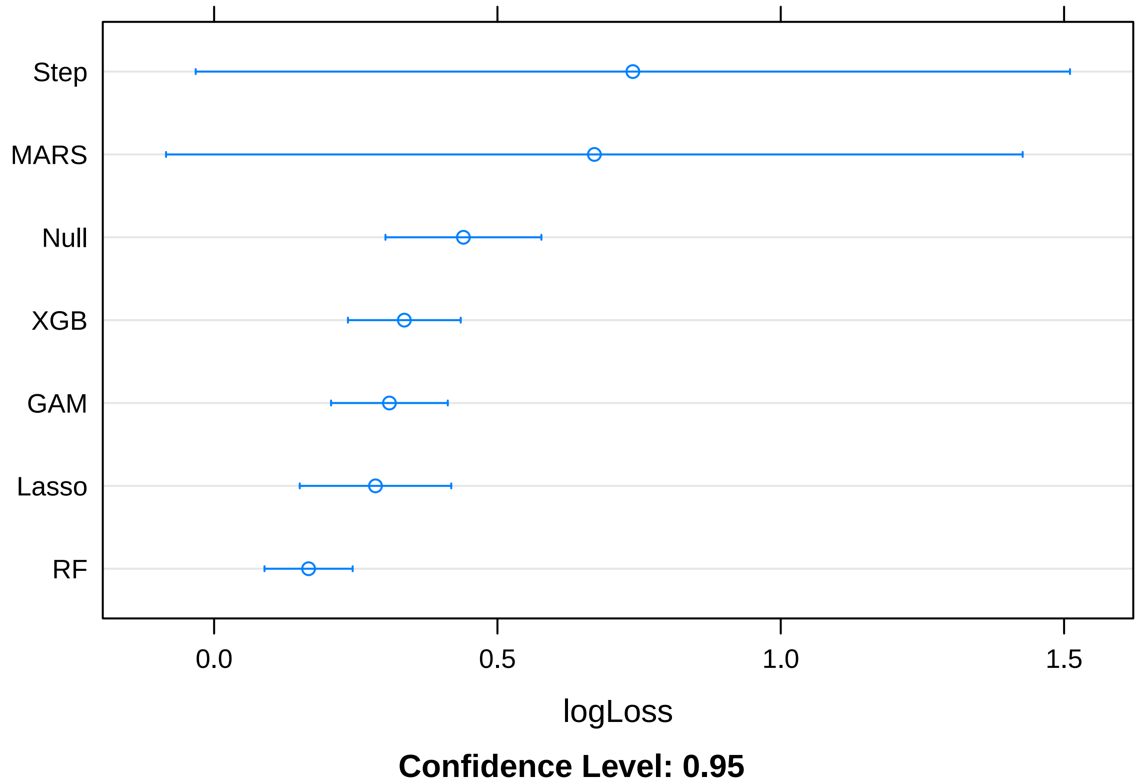
```
set.seed(randSeed)

null_mod <- train(
  FUTREC ~ constant,
  data = train_yes_no,
  method = "glm",
  trControl = fitControl_best,
  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: 93
##
## logLoss
##               Min.      1st Qu.       Median      Mean     3rd Qu.      Max.
## XGB   1.319869e-01 1.366067e-01 1.539588e-01 0.3357008 0.161339671  2.066952
## GAM   6.477267e-02 8.776182e-02 9.701278e-02 0.3093973 0.180938950  2.786303
## RF    9.992007e-16 6.711129e-03 2.362709e-02 0.1667428 0.119006715  2.818110
## Step  9.992007e-16 9.992007e-16 1.114294e-13 0.7389759 0.001166015 34.538776
## Lasso 1.047675e-03 4.119648e-03 1.967613e-02 0.2847785 0.133543781  3.185871
## MARS  9.992007e-16 4.302611e-03 3.877078e-02 0.6710615 0.050065756 34.538776
## Null  9.065437e-02 1.407726e-01 1.576289e-01 0.4399853 0.193132473  2.465489
##       NA's
## XGB      0
## GAM      0
## RF       0
## Step     0
## Lasso    0
## MARS     0
## Null     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
## 229       1         1   1     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)
```

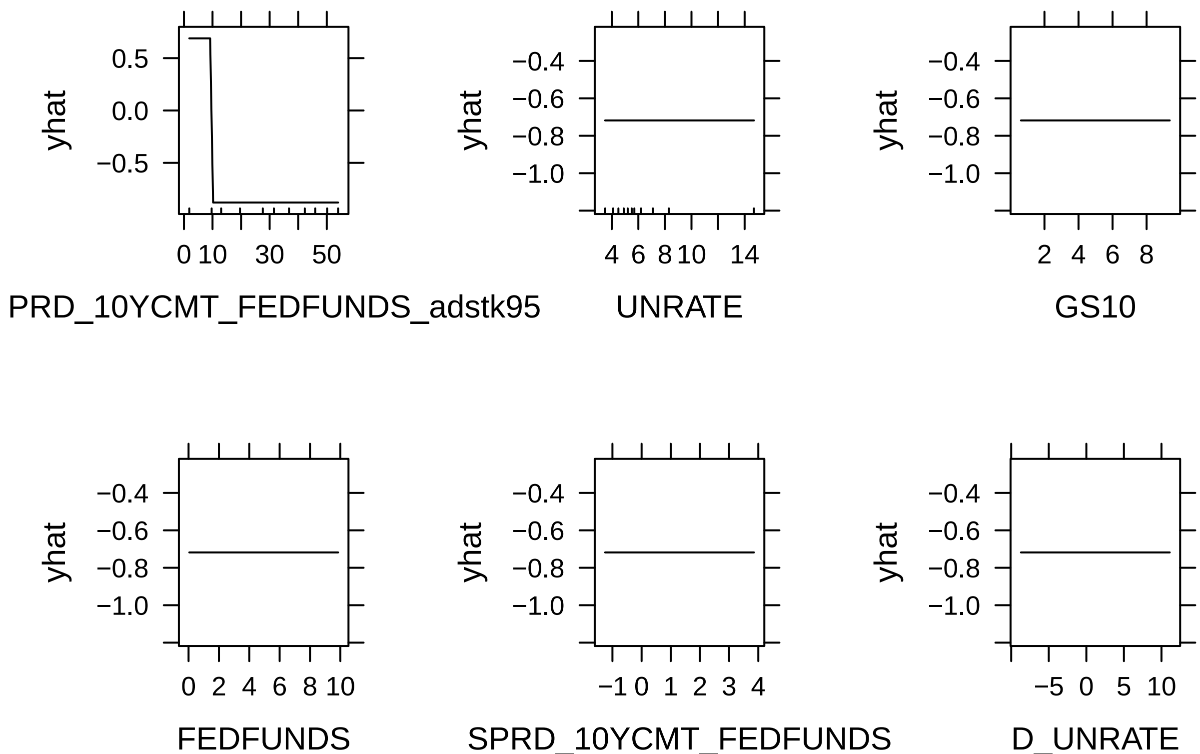
variable	Overall
SPRD_10YCMT_FEDFUNDS_adstk95	100

variable	Overall
UNRATE	0
GS10	0
FEDFUNDS	0
SPRD__10YCMT__FEDFUNDS	0
D__UNRATE	0
G__CPIU	0
D__EFFR	0
D__GS10	0
SPRD__10YCMT__FEDFUNDS__lag1	0
SPRD__10YCMT__FEDFUNDS__lag3	0
SPRD__10YCMT__FEDFUNDS__lag6	0
SPRD__10YCMT__FEDFUNDS__lag9	0
SPRD__10YCMT__FEDFUNDS__lag12	0
D__UNRATE__lag1	0
D__UNRATE__lag3	0
D__UNRATE__lag6	0
D__UNRATE__lag9	0
D__UNRATE__lag12	0
G__CPIU__lag1	0
G__CPIU__lag3	0
G__CPIU__lag6	0
G__CPIU__lag9	0
G__CPIU__lag12	0
D__EFFR__lag1	0
D__EFFR__lag3	0
D__EFFR__lag6	0
D__EFFR__lag9	0
D__EFFR__lag12	0
GS10__lag1	0
GS10__lag3	0
GS10__lag6	0
GS10__lag9	0
GS10__lag12	0
D__GS10__lag1	0
D__GS10__lag3	0
D__GS10__lag6	0
D__GS10__lag9	0
D__GS10__lag12	0
UNRATE__adstk85	0
UNRATE__adstk91	0
UNRATE__adstk92	0
UNRATE__adstk93	0
UNRATE__adstk94	0
UNRATE__adstk95	0
UNRATE__adstk99	0
GS10__adstk85	0
GS10__adstk91	0
GS10__adstk92	0
GS10__adstk93	0
GS10__adstk94	0
GS10__adstk95	0
GS10__adstk99	0

variable	Overall
FEDFUNDS__adstk85	0
FEDFUNDS__adstk91	0
FEDFUNDS__adstk92	0
FEDFUNDS__adstk93	0
FEDFUNDS__adstk94	0
FEDFUNDS__adstk95	0
FEDFUNDS__adstk99	0
SPRD__10YCMT__FEDFUNDS__adstk85	0
SPRD__10YCMT__FEDFUNDS__adstk91	0
SPRD__10YCMT__FEDFUNDS__adstk92	0
SPRD__10YCMT__FEDFUNDS__adstk93	0
SPRD__10YCMT__FEDFUNDS__adstk94	0
SPRD__10YCMT__FEDFUNDS__adstk99	0
D__UNRATE__adstk85	0
D__UNRATE__adstk91	0
D__UNRATE__adstk92	0
D__UNRATE__adstk93	0
D__UNRATE__adstk94	0
D__UNRATE__adstk95	0
D__UNRATE__adstk99	0
G__CPIU__adstk85	0
G__CPIU__adstk91	0
G__CPIU__adstk92	0
G__CPIU__adstk93	0
G__CPIU__adstk94	0
G__CPIU__adstk95	0
G__CPIU__adstk99	0
D__EFFR__adstk85	0
D__EFFR__adstk91	0
D__EFFR__adstk92	0
D__EFFR__adstk93	0
D__EFFR__adstk94	0
D__EFFR__adstk95	0
D__EFFR__adstk99	0
D__GS10__adstk85	0
D__GS10__adstk91	0
D__GS10__adstk92	0
D__GS10__adstk93	0
D__GS10__adstk94	0
D__GS10__adstk95	0
D__GS10__adstk99	0
SPRD__10YCMT__FEDFUNDS__ma2m	0
SPRD__10YCMT__FEDFUNDS__ma3m	0
SPRD__10YCMT__FEDFUNDS__ma6m	0
SPRD__10YCMT__FEDFUNDS__ma9m	0
SPRD__10YCMT__FEDFUNDS__ma12m	0

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

```r
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],
    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.

```
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
## -2.85885   0.01615   0.05089   0.21740   1.44457
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -2.35475    0.47256  -4.983 6.26e-07 ***
## SPRD_10YCMT_FEDFUNDS_adstk95  0.22758    0.03434   6.627 3.43e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 323.97  on 399  degrees of freedom
## Residual deviance: 169.43  on 398  degrees of freedom
## AIC: 173.43
##
## Number of Fisher Scoring iterations: 8
```

Compare Models

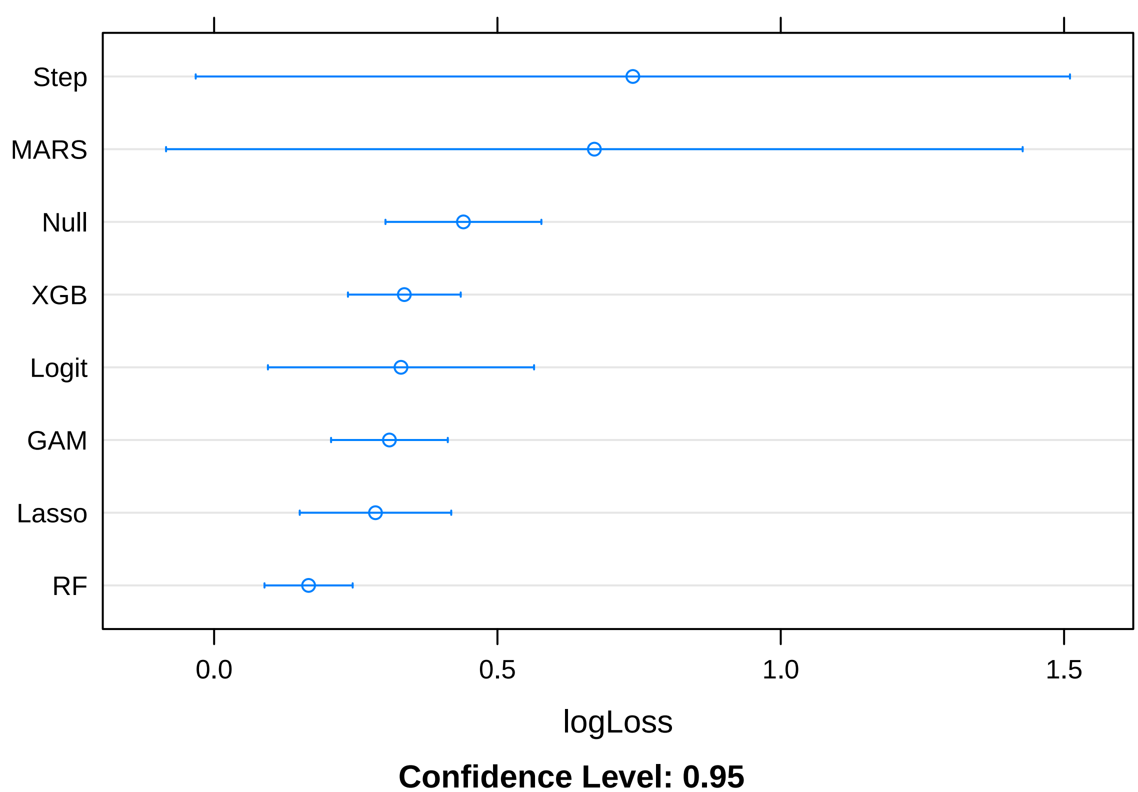
CV errors for models with peeking are misleadingly low. This will be addressed with a test set.

```r
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: 93
##
## logLoss
##               Min.      1st Qu.       Median      Mean     3rd Qu.       Max.
## XGB   1.319869e-01 1.366067e-01 1.539588e-01 0.3357008 0.161339671  2.066952
## GAM   6.477267e-02 8.776182e-02 9.701278e-02 0.3093973 0.180938950  2.786303
## RF    9.992007e-16 6.711129e-03 2.362709e-02 0.1667428 0.119006715  2.818110
## Step  9.992007e-16 9.992007e-16 1.114294e-13 0.7389759 0.001166015 34.538776
## Lasso 1.047675e-03 4.119648e-03 1.967613e-02 0.2847785 0.133543781  3.185871
## MARS  9.992007e-16 4.302611e-03 3.877078e-02 0.6710615 0.050065756 34.538776
## Null  9.065437e-02 1.407726e-01 1.576289e-01 0.4399853 0.193132473  2.465489
## Logit 9.992007e-16 1.213044e-04 9.481820e-04 0.3297987 0.036391729  7.139040
##       NA's
## XGB      0
## GAM      0
## RF       0
## Step     0
## Lasso    0
## MARS     0
## Null     0
## Logit    0
```

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



Test Set Performance

```r
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
Step	0.9634233
Logit	0.9634233
GAM	0.9616477
MARS	0.9595170
Lasso	0.9460227
XGB	0.8863636
RF	0.8370028
Null	0.5000000

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

model	LogLoss
XGB	0.4172260
GAM	0.4181043
RF	0.4559358

model	LogLoss
Lasso	0.5220408
Null	0.6349002
Step	0.6771614
Logit	0.6771614
MARS	2.7799214

Probability of Recession (Most Recent Month)

```
curr_data <- tail(full_data_wide_features_adstock, 1)

curr_data$date
```

```
## [1] "2022-10-01"
```

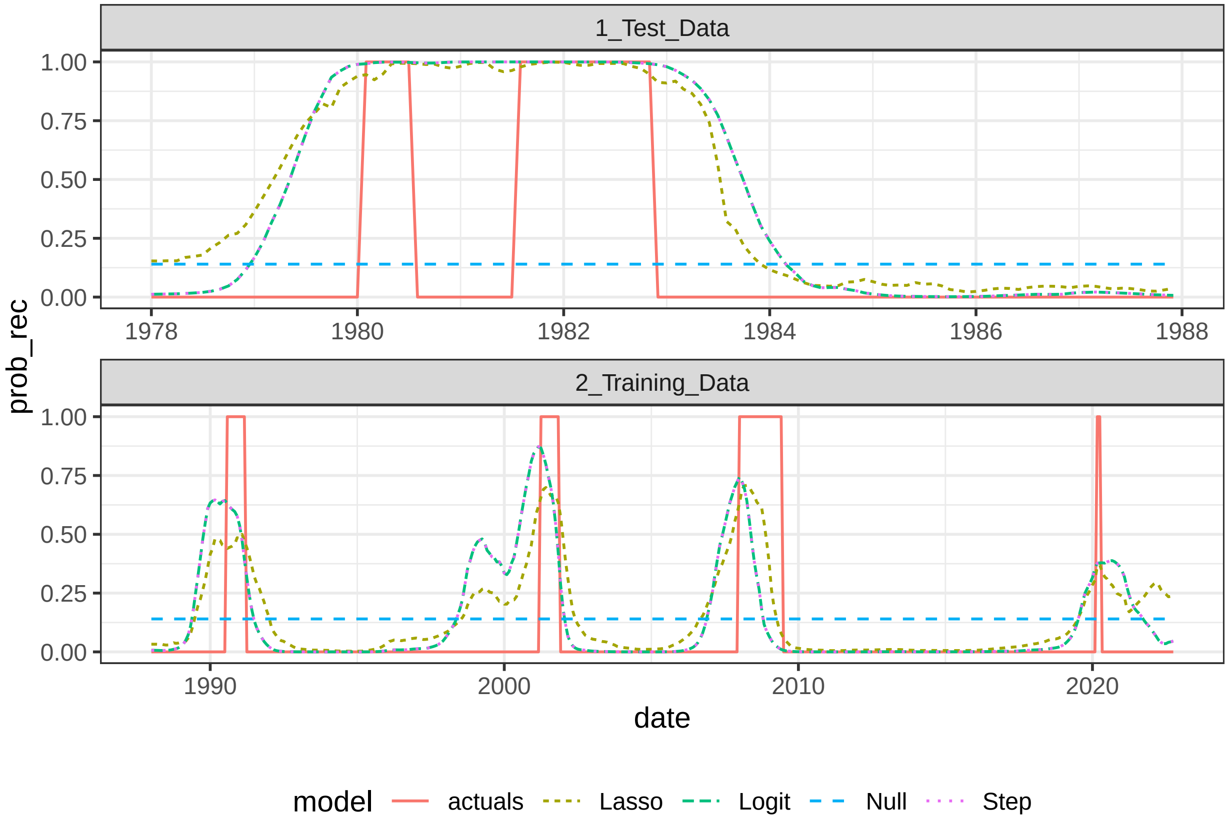
```
score_fun <- function(mods, dat) {
  output <- map_dfc(.x = mods, .f = function(x) {
    if(class(x)[1] != "train"){
      predict(x, newdata = dat, type = "response")
    } else(
       predict(x, newdata = dat, type = "prob")[,"yes"]

    )

  }) %>%
    pivot_longer(everything(), names_to = "model",
                 values_to = "prob_rec")

  output$prob_rec <- scales::percent(output$prob_rec)

  return(output)
}


knitr::kable(score_fun(mymods, curr_data))
```

model	prob_rec
XGB	14.71%
GAM	11.58%
RF	31.60%
Step	4.58%
Lasso	22.04%
MARS	5.15%
Null	14.00%
Logit	4.58%

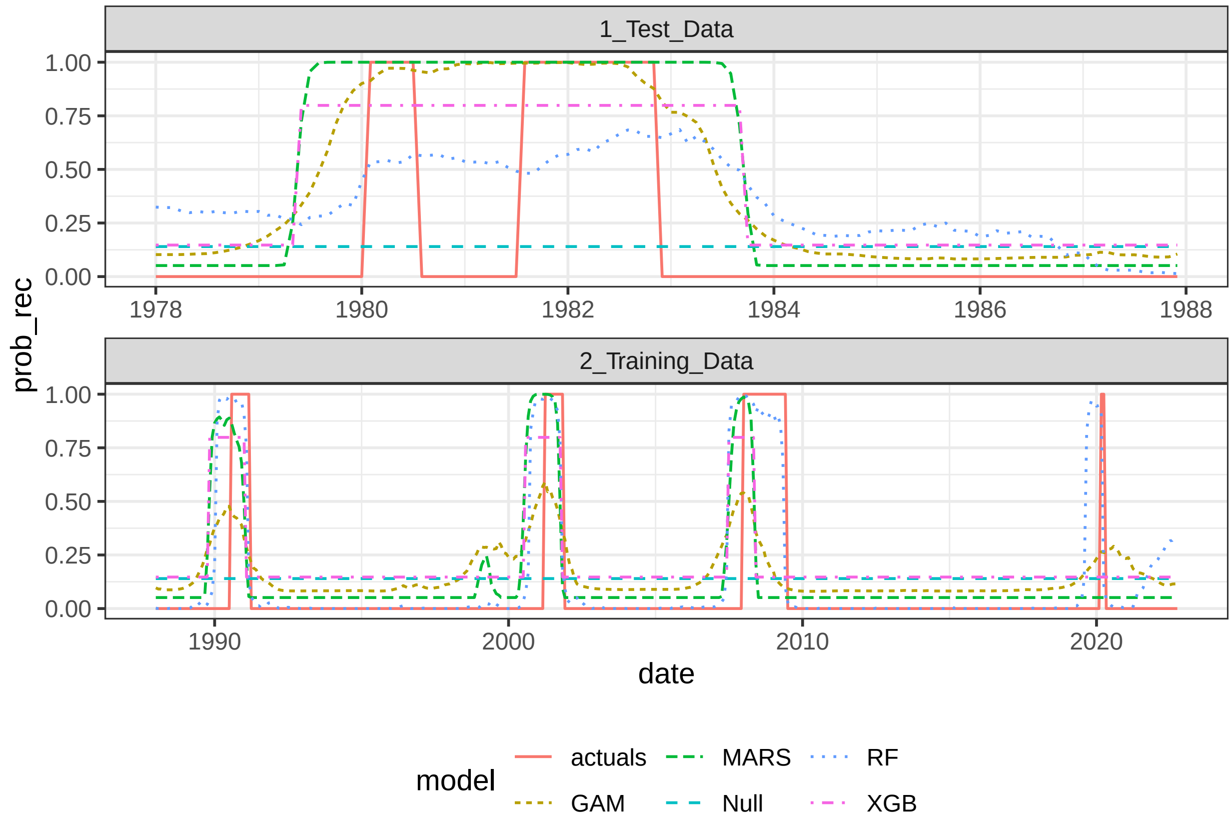
Backtesting

```
full_data_bktst <- full_data_wide_features_adstock %>%
  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'))
```

```r
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)
```




```r
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)
```