Probability of Recession

William Chiu

2022-11-26

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"
```

```
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.

```
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

```
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_size <- nrow(full_data_wide)

test_size <- floor(full_size*0.5)

test_id <- seq.int(1,test_size,1)

full_data_wide$constant <- 1

train_data <- full_data_wide[-test_id,]
test_data <- full_data_wide[test_id,]

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

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



tbl_summary(train_data)
```

Characteristic	**N = 384**
date	1989-05-01 to 2021-04-01
USREC	36 (9.4%)
UNRATE	5.50 (4.70, 6.80)
GS10	4.30 (2.58, 6.00)
FEDFUNDS	2.40 (0.22, 5.25)
SPRD_10YCMT_FEDFUNDS	1.53 (0.54, 2.62)
D_UNRATE	-0.30 (-0.60, 0.30)
G_CPIU	2.47 (1.69, 3.12)
D_EFFR	-0.02 (-0.80, 0.53)
D_GS10	-0.32 (-0.87, 0.33)
SPRD_10YCMT_FEDFUNDS_lag1	1.52 (0.53, 2.62)
SPRD_10YCMT_FEDFUNDS_lag3	1.50 (0.51, 2.62)
SPRD_10YCMT_FEDFUNDS_lag6	1.50 (0.43, 2.62)
SPRD_10YCMT_FEDFUNDS_lag9	1.50 (0.43, 2.62)
SPRD_10YCMT_FEDFUNDS_lag12	1.52 (0.43, 2.62)
D_UNRATE_lag1	-0.30 (-0.60, 0.30)
D_UNRATE_lag3	-0.30 (-0.60, 0.30)
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, 0.20)
G_CPIU_lag1	2.47 (1.69, 3.12)
G_CPIU_lag3	2.49 (1.69, 3.14)
G_CPIU_lag6	2.52 (1.69, 3.16)
G_CPIU_lag9	2.54 (1.71, 3.19)
G_CPIU_lag12	2.55 (1.73, 3.21)
D_EFFR_lag1	-0.02 (-0.80, 0.54)
D_EFFR_lag3	-0.01 (-0.78, 0.57)
D_EFFR_lag6	0.01 (-0.75, 0.61)
D_EFFR_lag9	0.01 (-0.74, 0.68)
D_EFFR_lag12	0.01 (-0.74, 0.72)
GS10_lag1	4.32 (2.60, 6.03)
GS10_lag3	4.38 (2.64, 6.04)
GS10_lag6	4.46 (2.71, 6.10)
GS10_lag9	4.51 (2.72, 6.20)
GS10_lag12	4.54 (2.76, 6.23)
D_GS10_lag1	-0.32 (-0.87, 0.33)
D_GS10_lag3	-0.32 (-0.87, 0.34)
D_GS10_lag6	-0.31 (-0.86, 0.34)
D_GS10_lag9	-0.31 (-0.85, 0.35)
D_GS10_lag12	-0.30 (-0.84, 0.37)
UNRATE_adstk85	37 (32, 46)
UNRATE_adstk91	62 (54, 75)
UNRATE_adstk92	70 (61, 83)
UNRATE_adstk93	80 (70, 95)

Characteristic	N = 384
UNRATE_adstk94	94 (83, 110)
UNRATE_adstk95	113 (100, 132)
UNRATE_adstk99	614 (557, 650)
GS10_adstk85	29 (17, 41)
GS10_adstk91	49 (28, 71)
GS10_adstk92	55 (32, 80)
GS10_adstk93	63 (36, 93)
GS10_adstk94	75 (42, 109)
GS10_adstk95	91 (51, 132)
GS10_adstk99	597 (425, 775)
FEDFUNDS_adstk85	18 (4, 34)
FEDFUNDS_adstk91	33 (9, 58)
FEDFUNDS_adstk92	38 (10, 65)
FEDFUNDS_adstk93	44 (12, 74)
FEDFUNDS_adstk94	53 (16, 86)
FEDFUNDS_adstk95	65 (20, 103)
FEDFUNDS_adstk99	448 (253, 639)
SPRD_10YCMT_FEDFUNDS_adstk85	10 (3, 17)
SPRD_10YCMT_FEDFUNDS_adstk91	17 (6, 26)
SPRD_10YCMT_FEDFUNDS_adstk92	19 (7, 29)
SPRD_10YCMT_FEDFUNDS_adstk93	22 (9, 33)
SPRD_10YCMT_FEDFUNDS_adstk94	26 (11, 38)
SPRD_10YCMT_FEDFUNDS_adstk95	31 (15, 44)
SPRD_10YCMT_FEDFUNDS_adstk99	138 (114, 164)
D_UNRATE_adstk85	-2 (-3, 3)
D_UNRATE_adstk91	-4 (-5, 4)
D_UNRATE_adstk92	-4 (-6, 5)
D_UNRATE_adstk93	-4 (-7, 6)
D_UNRATE_adstk94	-5 (-7, 6)
D_UNRATE_adstk95	-5 (-8, 7)
D_UNRATE_adstk99	-8 (-17, 5)
G_CPIU_adstk85	16 (12, 20)
G_CPIU_adstk91	27 (21, 33)
G_CPIU_adstk92	30 (24, 37)
G_CPIU_adstk93	34 (28, 43)
G_CPIU_adstk94	40 (32, 49)
G_CPIU_adstk95	48 (38, 60)
G_CPIU_adstk99	309 (257, 402)
D_EFFR_adstk85	0 (-5, 3)
D_EFFR_adstk91	0 (-9, 5)
D_EFFR_adstk92	-1 (-10, 5)
D_EFFR_adstk93	-1 (-11, 6)
D_EFFR_adstk94	-1 (-13, 6)
D_EFFR_adstk95	-2 (-14, 6)
D_EFFR_adstk99	-18 (-37, -8)
D_GS10_adstk85	-1.9 (-4.6, 1.0)
D_GS10_adstk91	-2.7 (-6.2, 0.7)
D_GS10_adstk92	-2.9 (-6.6, 0.4)
D_GS10_adstk93	-3.1 (-7.1, 0.1)
D_GS10_adstk94	-3.7 (-7.7, -0.2)
D_GS10_adstk95	-4.4 (-8.6, -0.8)
D_GS10_adstk99	-20 (-23, -14)

Characteristic	N = 384
constant	384 (100%)
SPRD_10YCMT_FEDFUNDS_ma2m	1.51 (0.52, 2.59)
SPRD_10YCMT_FEDFUNDS_ma3m	1.50 (0.49, 2.60)
SPRD_10YCMT_FEDFUNDS_ma6m	1.51 (0.50, 2.62)
SPRD_10YCMT_FEDFUNDS_ma9m	1.49 (0.47, 2.64)
SPRD_10YCMT_FEDFUNDS_ma12m	1.48 (0.48, 2.62)
FUTREC	56 (15%)

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.
## "1957-06-01" "1965-05-16" "1973-05-01" "1973-05-01" "1981-04-16" "1989-04-01"
```

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

summary(test_data$date)
```

```
##          Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1978-01-01" "1980-10-24" "1983-08-16" "1983-08-16" "1986-06-08" "1989-04-01"
```

Setup Parallel Processing

```
library(doParallel)

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

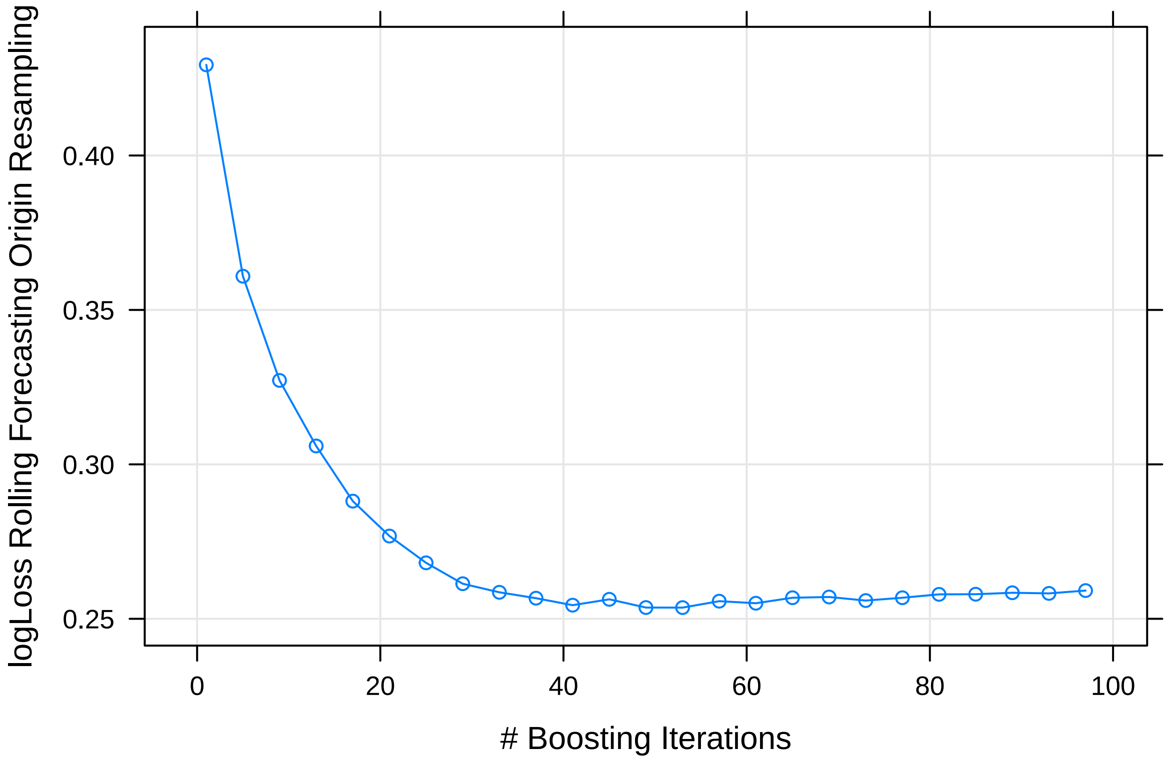
Cross-Validation Framework

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

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

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 - USREC - constant,
  data = train_yes_no,
  method = "gamboost",
  trControl = fitControl_oneSE,
  metric = "logLoss",
  tuneGrid = grid_gam,
  family = Binomial()
)

plot(gam_mod)
```



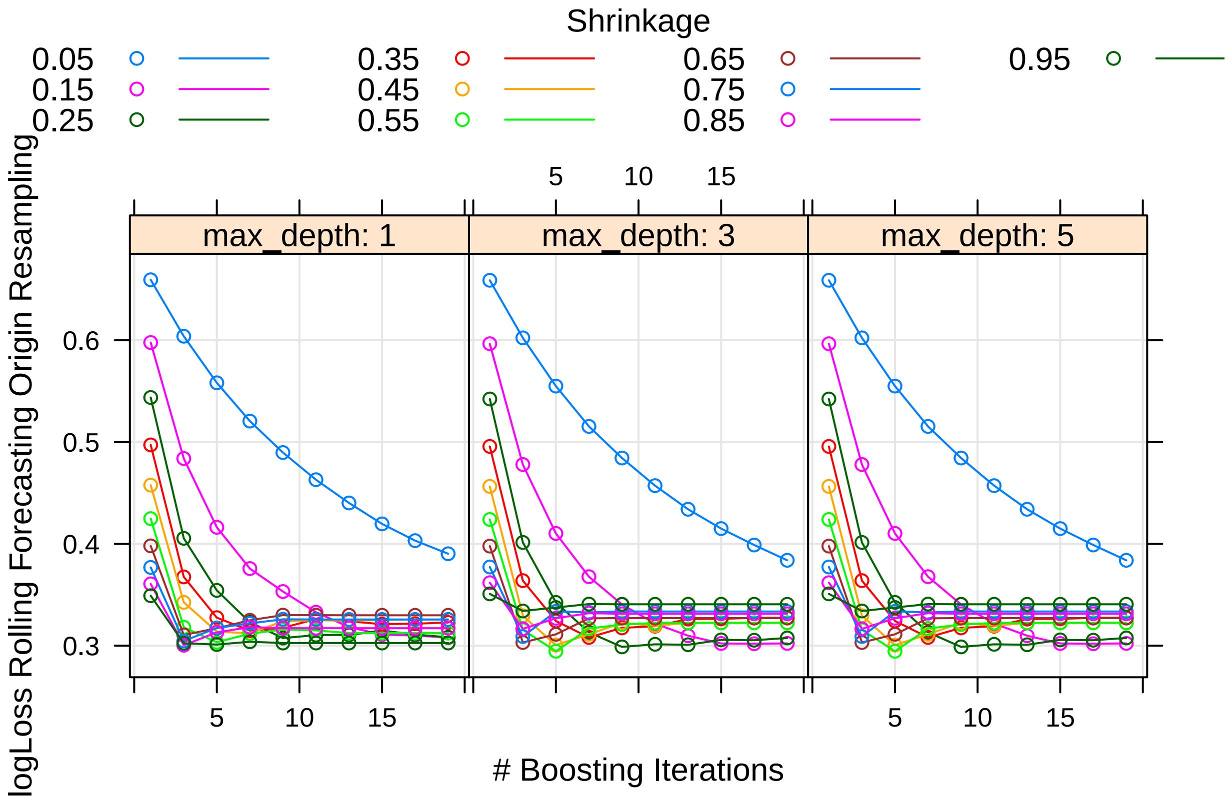

```
gam_mod$bestTune
```

```
##   mstop prune
## 5    17    no
```

eXtreme Gradient Boosting Trees

```
grid_xgb <- expand.grid(nrounds=seq(1, 20, 2),
                        max_depth=c(1,3,5),
                        eta=seq(0.05,1,0.1),
                        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)
```



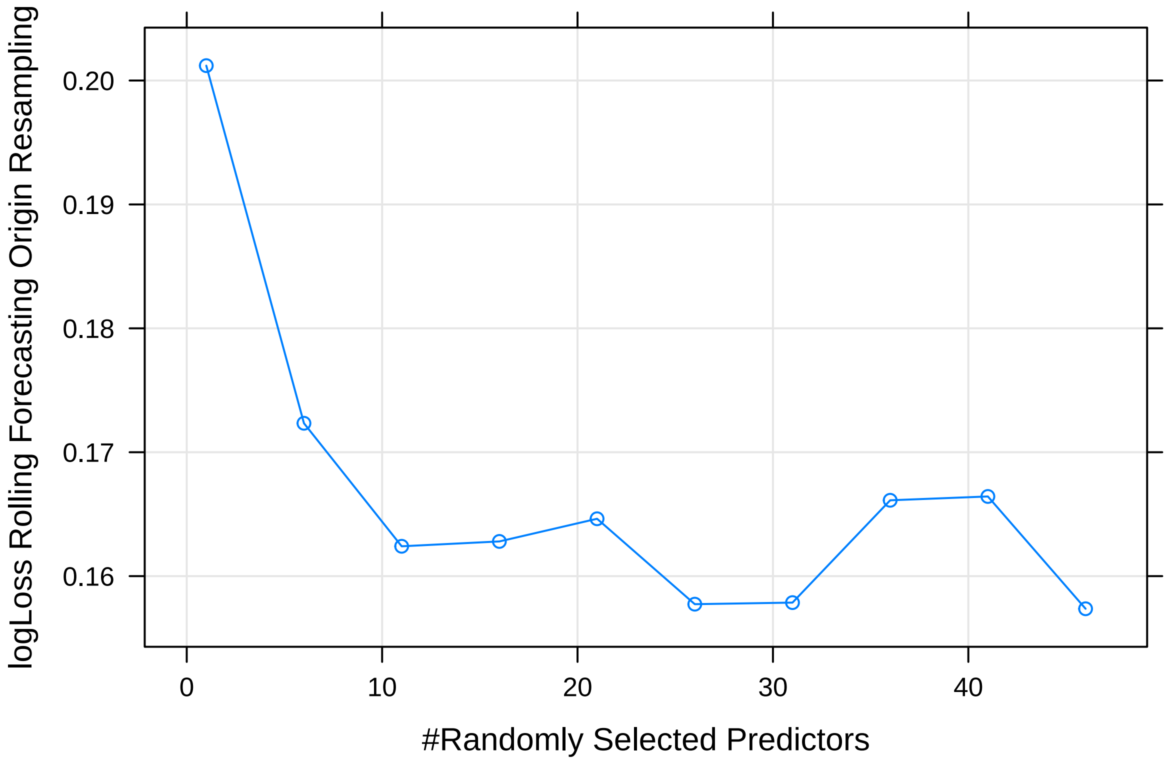

```
xgb_mod$bestTune
```

```
##     nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
## 271       1         1 0.95     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",
```

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

plot(rf_mod)
```




```
rf_mod$bestTune
```

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

Stepwise Regression

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

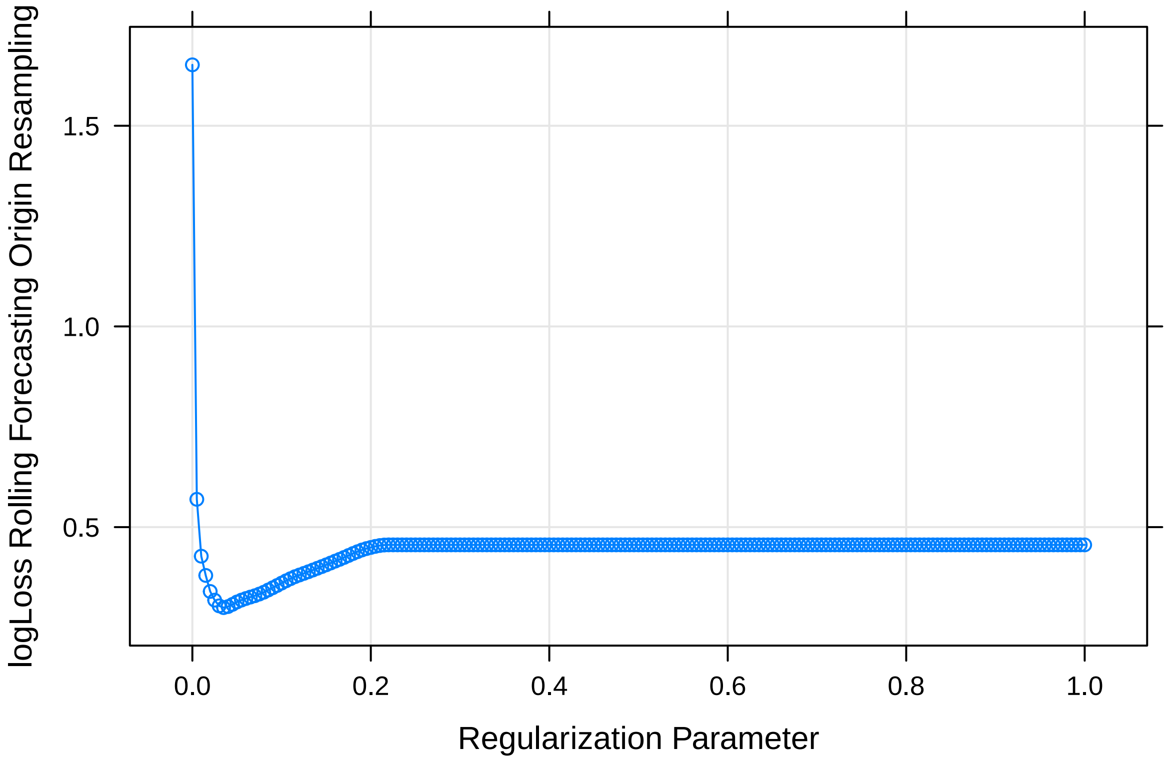
> For binomial and quasibinomial families the response can also be specified as a factor (when the first level denotes failure and all others success) or as a two-column matrix with the columns giving the numbers of successes and failures.

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)
```

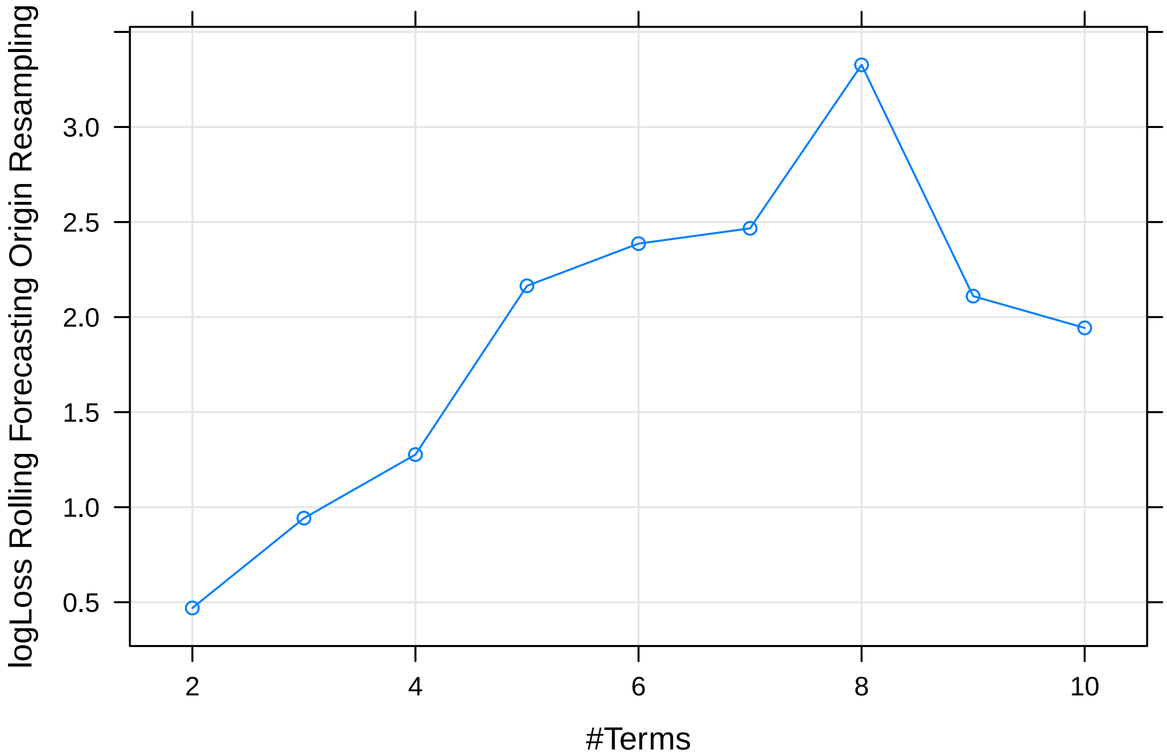



```
glmnet_mod$bestTune
```

```
##   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

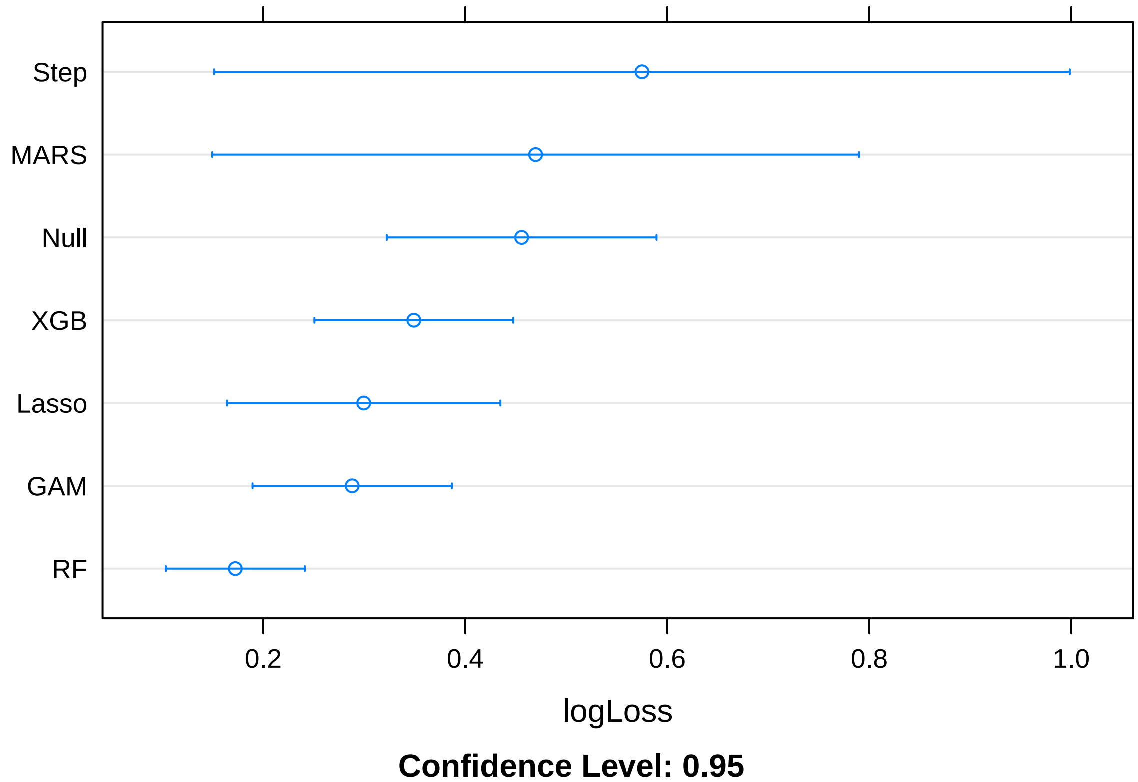
```
set.seed(randSeed)

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: 88
##
## logLoss
##               Min.      1st Qu.       Median      Mean     3rd Qu.       Max.
## XGB   1.450788e-01 1.496156e-01 1.690907e-01 0.3491106 0.177098549  1.976725
## GAM   4.483755e-02 6.743569e-02 7.411663e-02 0.2880962 0.220368103  2.158609
## RF    9.992007e-16 4.685443e-03 2.538823e-02 0.1723374 0.113094297  1.832739
## Step  9.992007e-16 9.992007e-16 1.275443e-12 0.5749372 0.006473728 11.512925
## Lasso 1.036515e-03 4.824572e-03 2.376865e-02 0.2994578 0.181316668  3.444482
## MARS  9.992007e-16 5.107155e-03 4.255252e-02 0.4696355 0.055218492 11.512925
## Null  1.036784e-01 1.542887e-01 1.735843e-01 0.4557812 0.211315844  2.288196
##       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

```r
xgb_mod$bestTune
```

```
##     nrounds max_depth  eta gamma colsample_bytree min_child_weight subsample
## 271       1         1 0.95     0                1               10         1
```

```r
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)
```

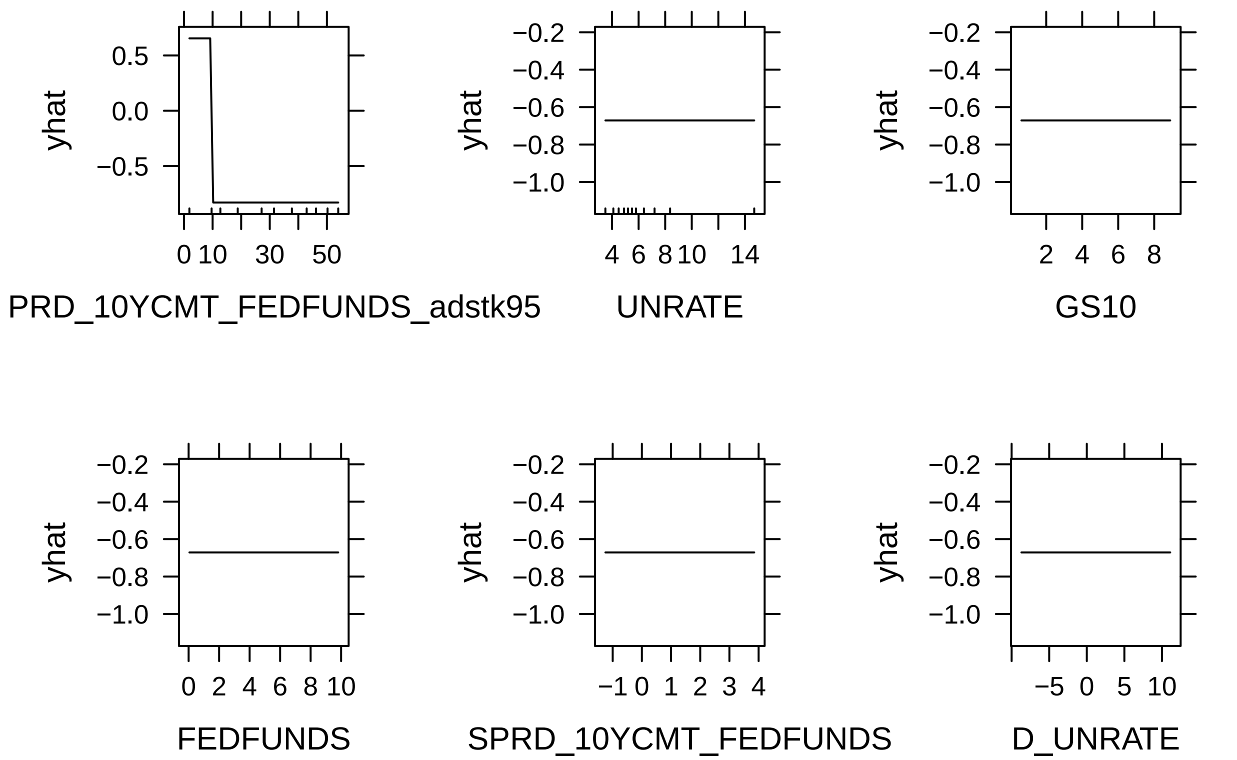
variable	Overall
SPRD_10YCMT_FEDFUNDS_adstk95	100

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)
```

```
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
## -2.83000   0.01675   0.04716   0.22745   1.43896
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -2.30643    0.47314  -4.875 1.09e-06 ***
## SPRD_10YCMT_FEDFUNDS_adstk95  0.22291    0.03453   6.455 1.08e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 319.04  on 383  degrees of freedom
## Residual deviance: 168.84  on 382  degrees of freedom
## AIC: 172.84
##
## Number of Fisher Scoring iterations: 8
```

Compare Models

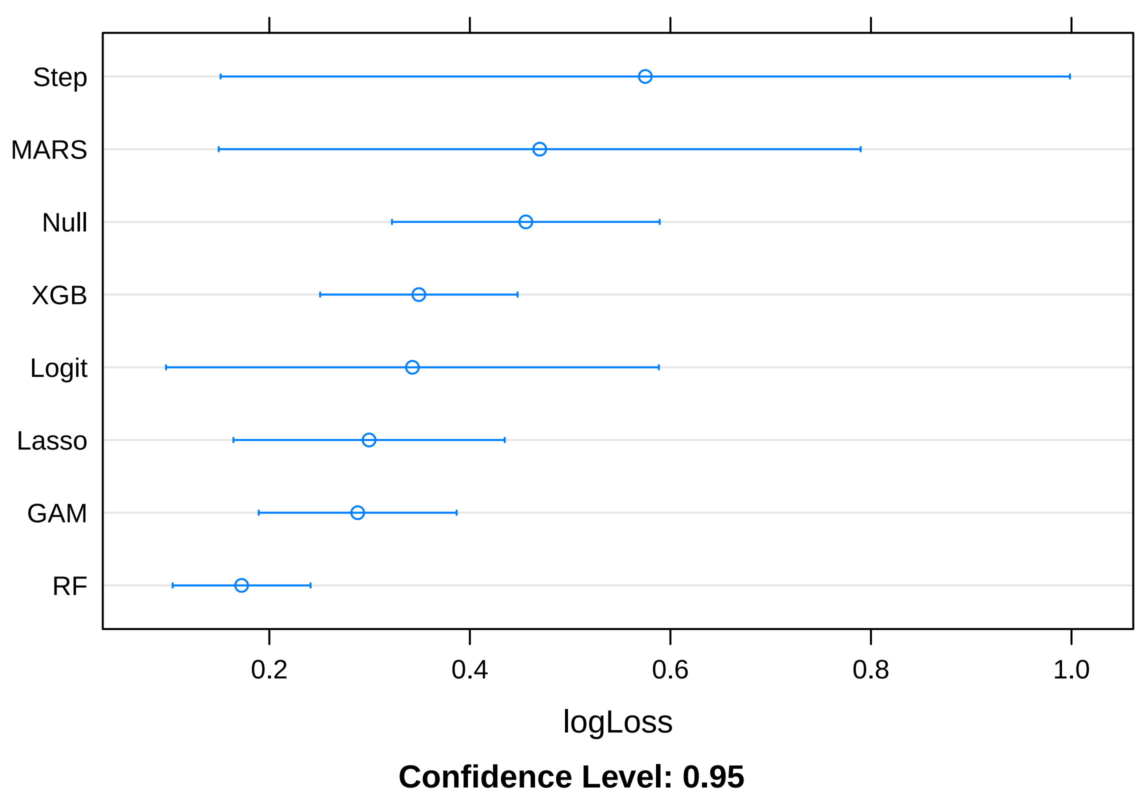
CV errors for models with peeking are misleadingly low. This will be addressed with a test set.

```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: 88
##
## logLoss
##               Min.      1st Qu.       Median      Mean      3rd Qu.      Max.
## XGB   1.450788e-01 1.496156e-01 1.690907e-01 0.3491106 0.177098549  1.976725
## GAM   4.483755e-02 6.743569e-02 7.411663e-02 0.2880962 0.220368103  2.158609
## RF    9.992007e-16 4.685443e-03 2.538823e-02 0.1723374 0.113094297  1.832739
## Step  9.992007e-16 9.992007e-16 1.275443e-12 0.5749372 0.006473728 11.512925
## Lasso 1.036515e-03 4.824572e-03 2.376865e-02 0.2994578 0.181316668  3.444482
## MARS  9.992007e-16 5.107155e-03 4.255252e-02 0.4696355 0.055218492 11.512925
## Null  1.036784e-01 1.542887e-01 1.735843e-01 0.4557812 0.211315844  2.288196
## Logit 9.992007e-16 1.341124e-04 1.173229e-03 0.3427265 0.023668275  6.875513
##       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

```
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
GAM	0.9708534
Step	0.9690505
Logit	0.9690505
MARS	0.9660457
Lasso	0.9546274
XGB	0.9038462
RF	0.8668870
Null	0.5000000

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

model	LogLoss
XGB	0.3915135
RF	0.4248122
Lasso	0.4967863

model	LogLoss
GAM	0.5492307
Null	0.5735494
Step	0.5902273
Logit	0.5902273
MARS	2.4815290

Probability of Recession (Most Recent Month)

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

curr_data$date
```

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

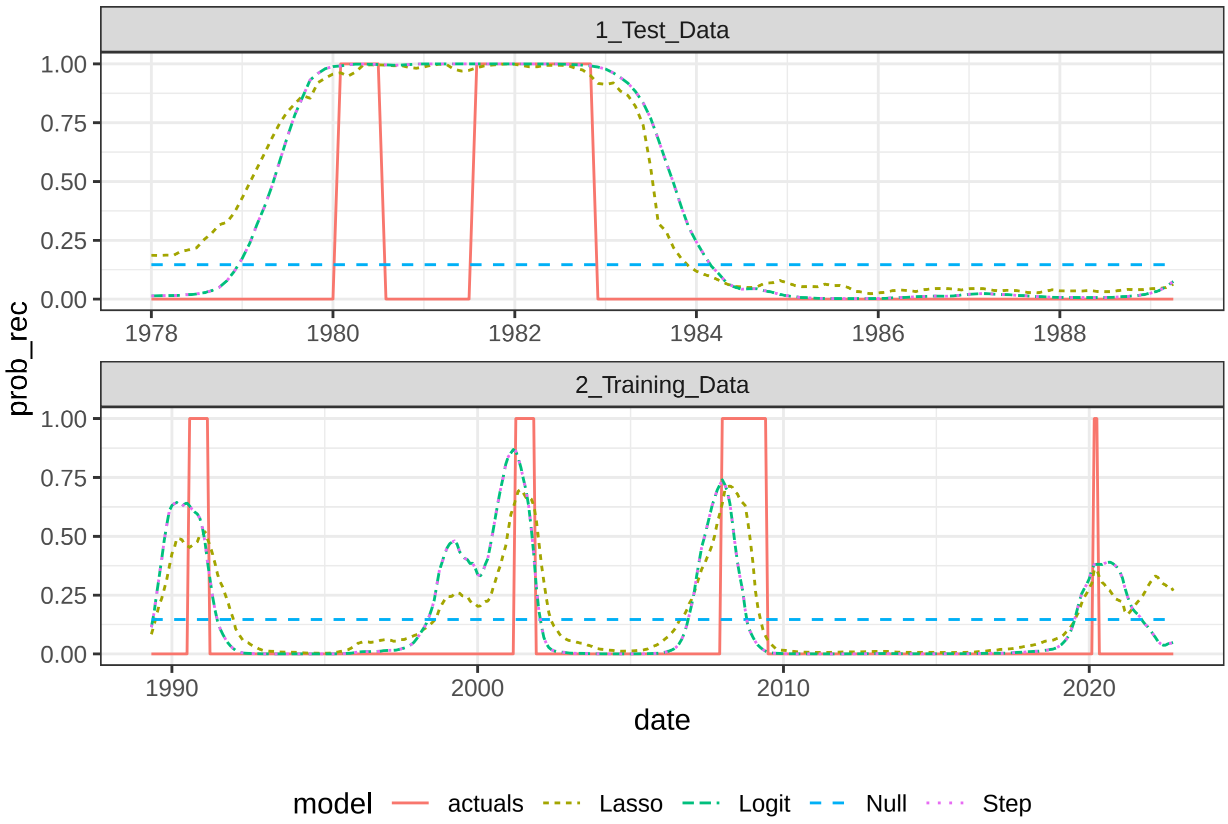
```
score_fun <- function(mods, dat) {
  output <- map_dfc(.x = mods, .f = function(x) {
    if(class(x)[1] != "train"){
      predict(x, newdata = dat, type = "response")
    } else(
       predict(x, newdata = dat, type = "prob")[,"yes"]

    )

  }) %>%
    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	15.99%
GAM	20.70%
RF	31.60%
Step	4.86%
Lasso	26.88%
MARS	5.42%
Null	14.58%
Logit	4.86%

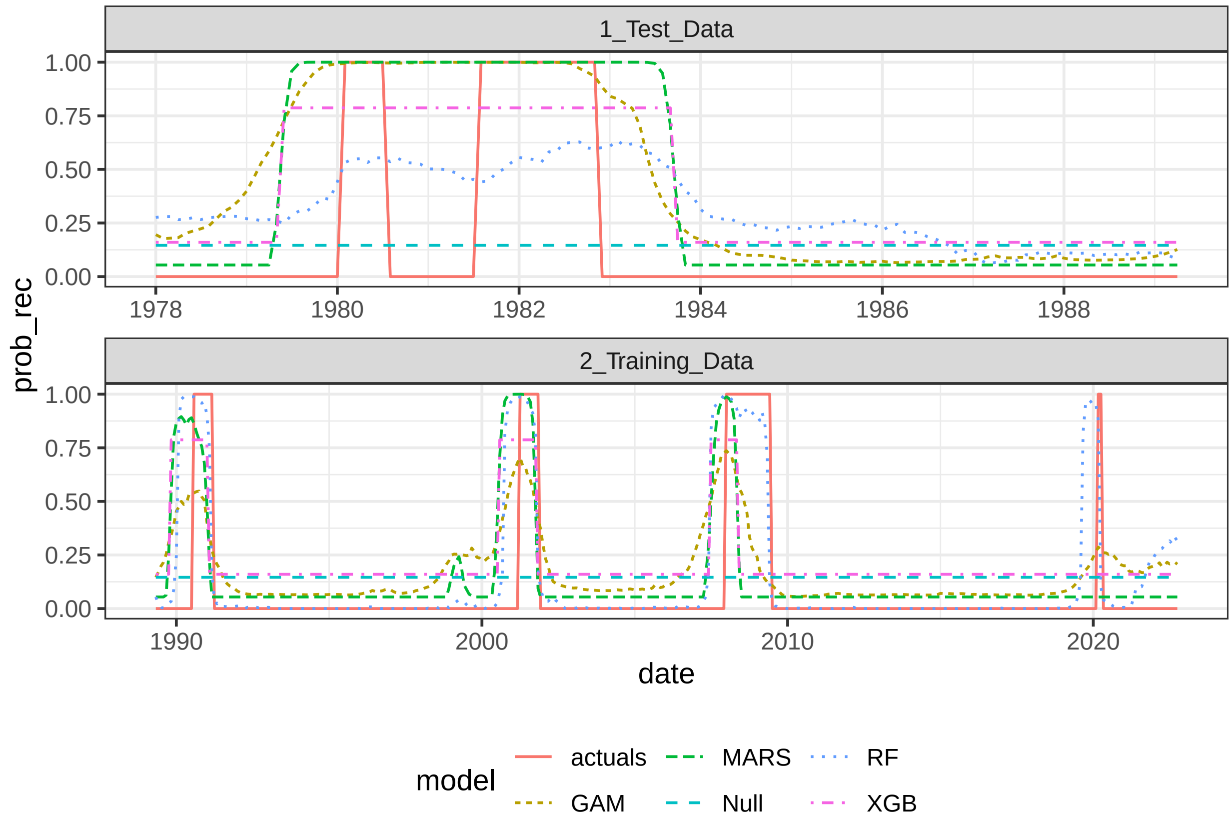
Backtesting

```
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)
```