# Probability of Recession

William Chiu

2022-12-03

## 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. Lags of the spread
3. Adstock transformations of the spread

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

## Extract Historical Data

Refer to this vignette for FRED data access.

```r
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"
```

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

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

response_id <- "USREC" # monthly

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

```
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

```
full_data_wide_features <- full_data_wide_raw %>%
  arrange(date) %>%
  mutate(SPRD_10YCMT_FEDFUNDS = DGS10 - DFF
         ) %>%
  mutate(across(
    .cols=c(SPRD_10YCMT_FEDFUNDS),
    .fns=list(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),
         lag5d = ~lag(.x, 5),
         lag10d = ~lag(.x, 10),
         lag15d = ~lag(.x, 15)
         )
  )) %>%
  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),
    .fns=list(adstk001 = ~stats::filter(.x,
                                         filter=0.001,
                                         method="recursive") ,
         adstk10 = ~stats::filter(.x,
                                         filter=0.10,
                                         method="recursive") ,
         adstk20 = ~stats::filter(.x,
                                         filter=0.20,
                                         method="recursive"),
         adstk40 = ~stats::filter(.x,
                                         filter=0.40,
                                         method="recursive"),
         adstk75 = ~stats::filter(.x,
                                         filter=0.75,
                                         method="recursive"),
         adstk95 = ~stats::filter(.x,
                                         filter=0.95,
                                         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(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,
```

```r
            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) %>%
  drop_na()

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.

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

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

## 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 = 8,357** |
|---|---|
| date | 1988-01-04 to 2021-05-26 |
| DFF | 2.72 (0.36, 5.29) |
| DGS10 | 4.48 (2.64, 6.21) |
| SPRD_10YCMT_FEDFUNDS | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag1m | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag3m | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag6m | 1.52 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag9m | 1.54 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag12m | 1.54 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag5d | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag10d | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_lag15d | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_adstk001 | 1.49 (0.48, 2.53) |
| SPRD_10YCMT_FEDFUNDS_adstk10 | 1.65 (0.54, 2.81) |
| SPRD_10YCMT_FEDFUNDS_adstk20 | 1.86 (0.60, 3.16) |
| SPRD_10YCMT_FEDFUNDS_adstk40 | 2.48 (0.80, 4.22) |
| SPRD_10YCMT_FEDFUNDS_adstk75 | 5.9 (2.0, 10.1) |
| SPRD_10YCMT_FEDFUNDS_adstk95 | 30 (10, 51) |
| constant | 8,357 (100%) |
| SPRD_10YCMT_FEDFUNDS_ma5d | 1.48 (0.49, 2.53) |
| SPRD_10YCMT_FEDFUNDS_ma10d | 1.47 (0.50, 2.53) |
| SPRD_10YCMT_FEDFUNDS_ma15d | 1.47 (0.50, 2.53) |
| SPRD_10YCMT_FEDFUNDS_ma20d | 1.47 (0.50, 2.54) |
| SPRD_10YCMT_FEDFUNDS_ma25d | 1.47 (0.51, 2.54) |
| SPRD_10YCMT_FEDFUNDS_ma2m | 1.47 (0.50, 2.56) |
| SPRD_10YCMT_FEDFUNDS_ma3m | 1.48 (0.47, 2.55) |
| SPRD_10YCMT_FEDFUNDS_ma6m | 1.51 (0.48, 2.57) |
| SPRD_10YCMT_FEDFUNDS_ma9m | 1.51 (0.48, 2.60) |
| SPRD_10YCMT_FEDFUNDS_ma12m | 1.49 (0.50, 2.60) |
| FUTREC | 1,248 (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.
## "1978-01-03" "1980-07-02" "1983-01-04" "1983-01-01" "1985-07-02" "1987-12-31"
```

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

summary(test_data$date)
```

```
##         Min.      1st Qu.       Median         Mean      3rd Qu.         Max.
## "1978-01-03" "1980-07-02" "1983-01-04" "1983-01-01" "1985-07-02" "1987-12-31"
```

## Setup Parallel Processing

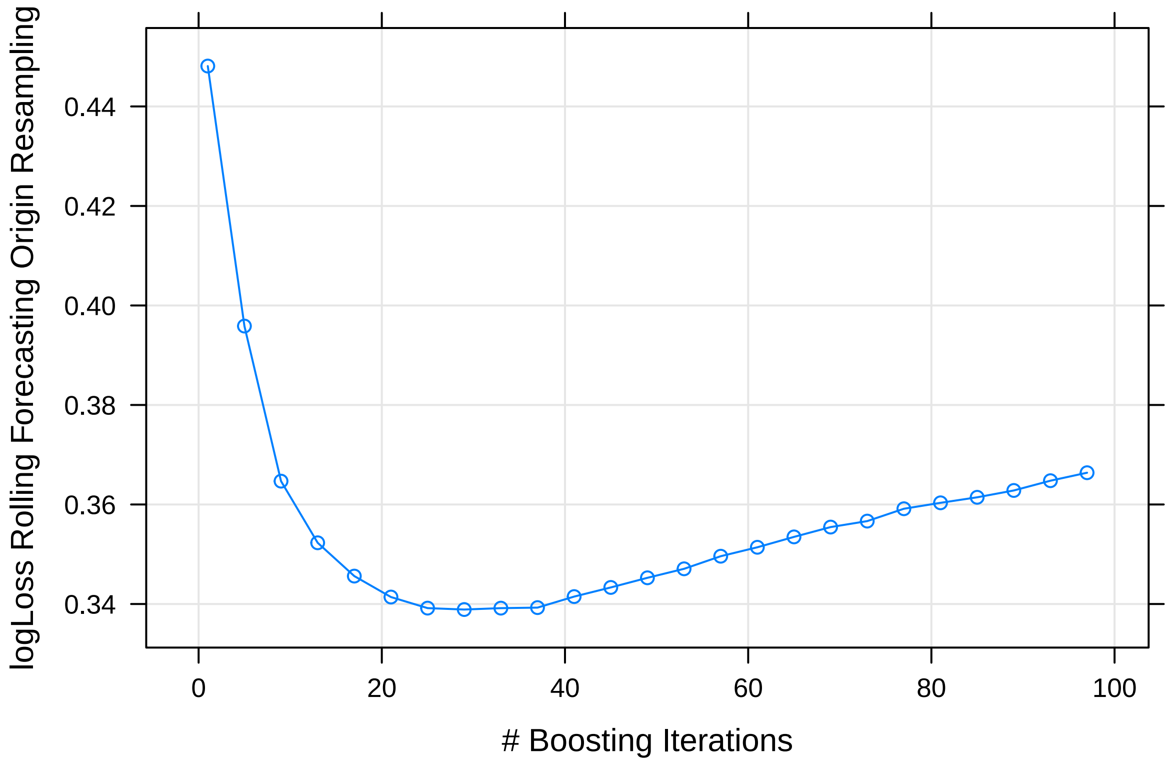
```r
library(doParallel)

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

## Cross-Validation Framework

```r
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)
```

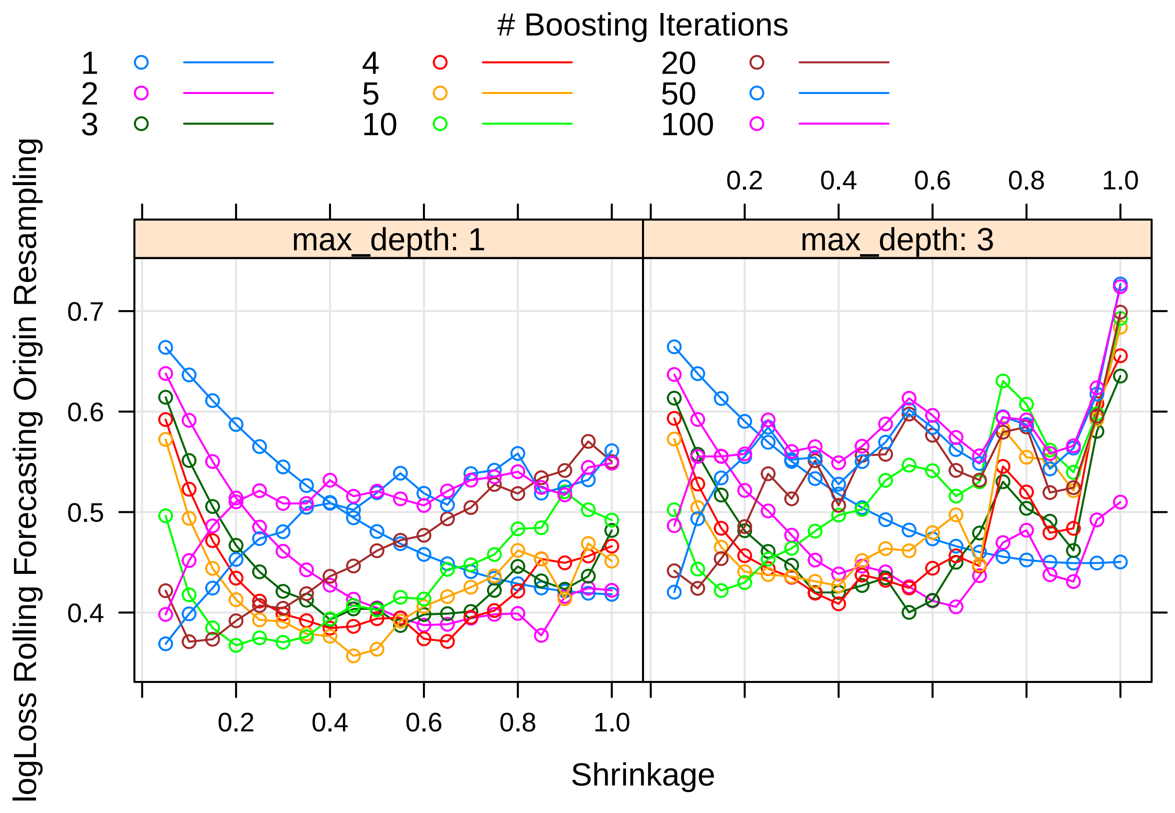


```
gam_mod$bestTune
```

```
##   mstop prune
## 2     5    no
```

## eXtreme Gradient Boosting Trees

```
grid_xgb <- expand.grid(nrounds=c(1,2,3,4,5,10,20,
                                  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)
```

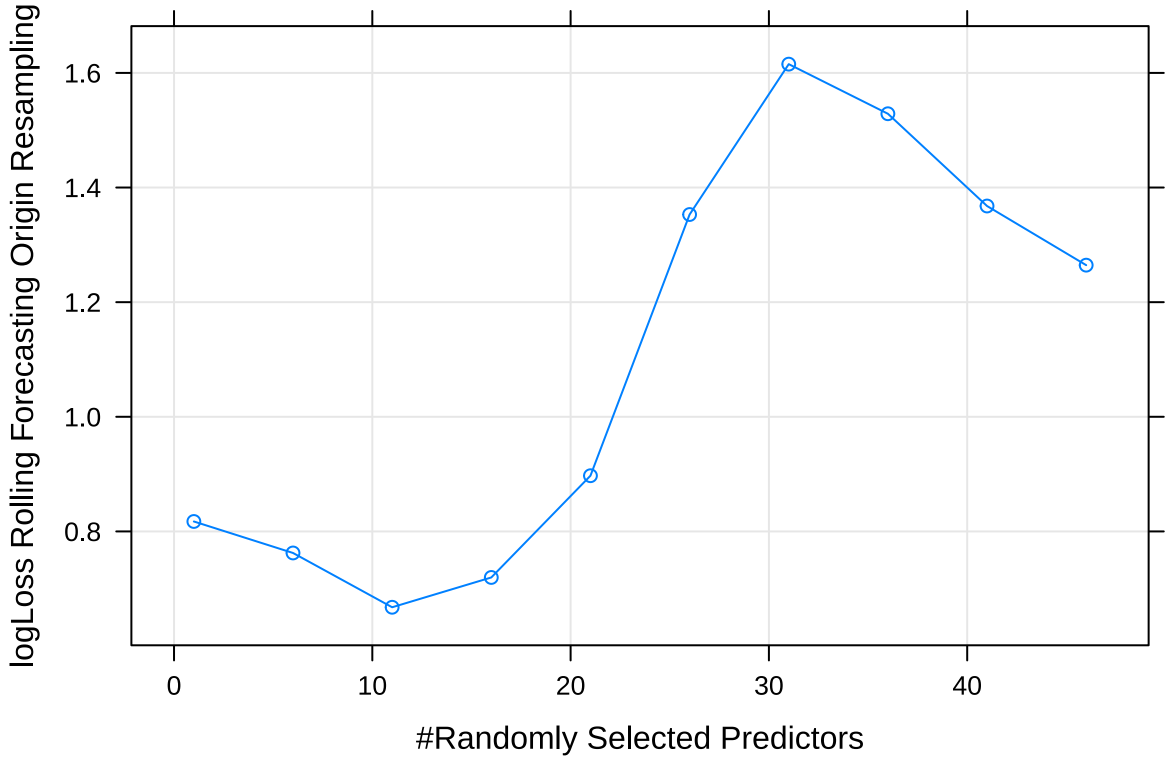


```
xgb_mod$bestTune
```

```
##     nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
## 271       1         1 0.8     0                1               10         1
```

### Random Forest

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

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:

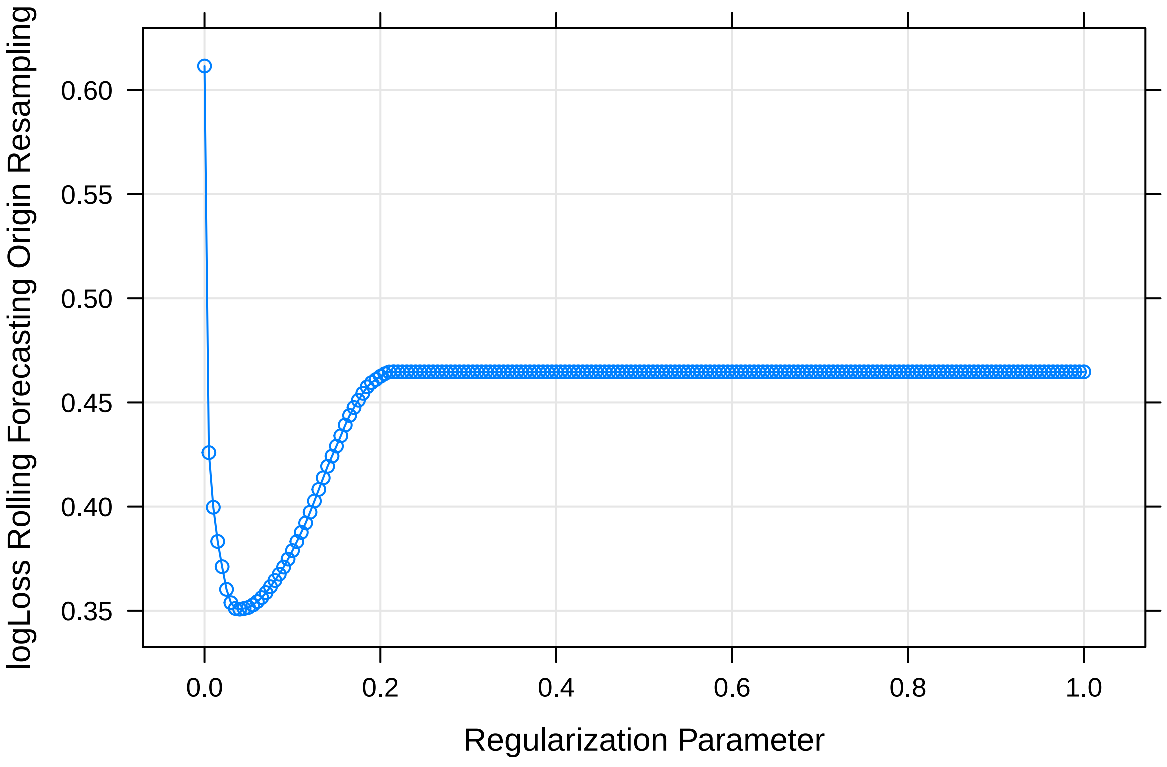
> For binomial and quasibinomial families the response can also be specified as a factor (when the first level denotes failure and all others success) or as a two-column matrix with the columns giving the numbers of successes and failures.

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)
```

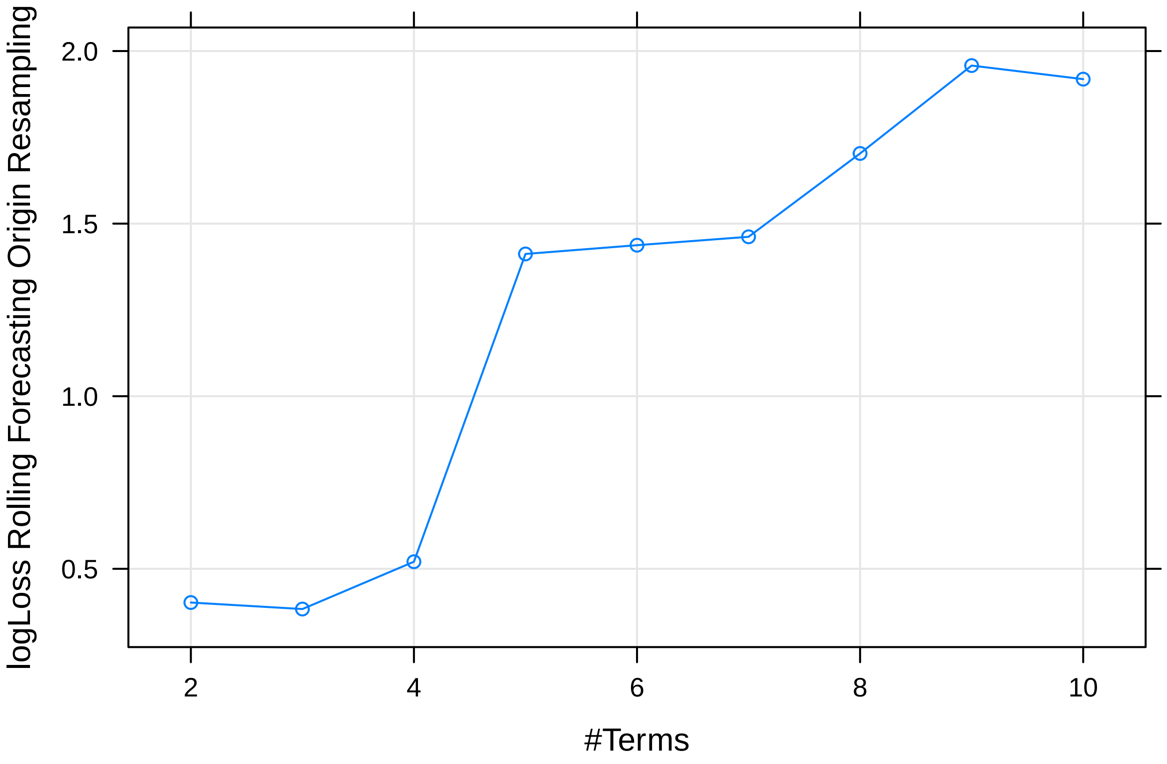


```
glmnet_mod$bestTune
```

```
##   alpha lambda
## 9     1   0.04
```

### 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

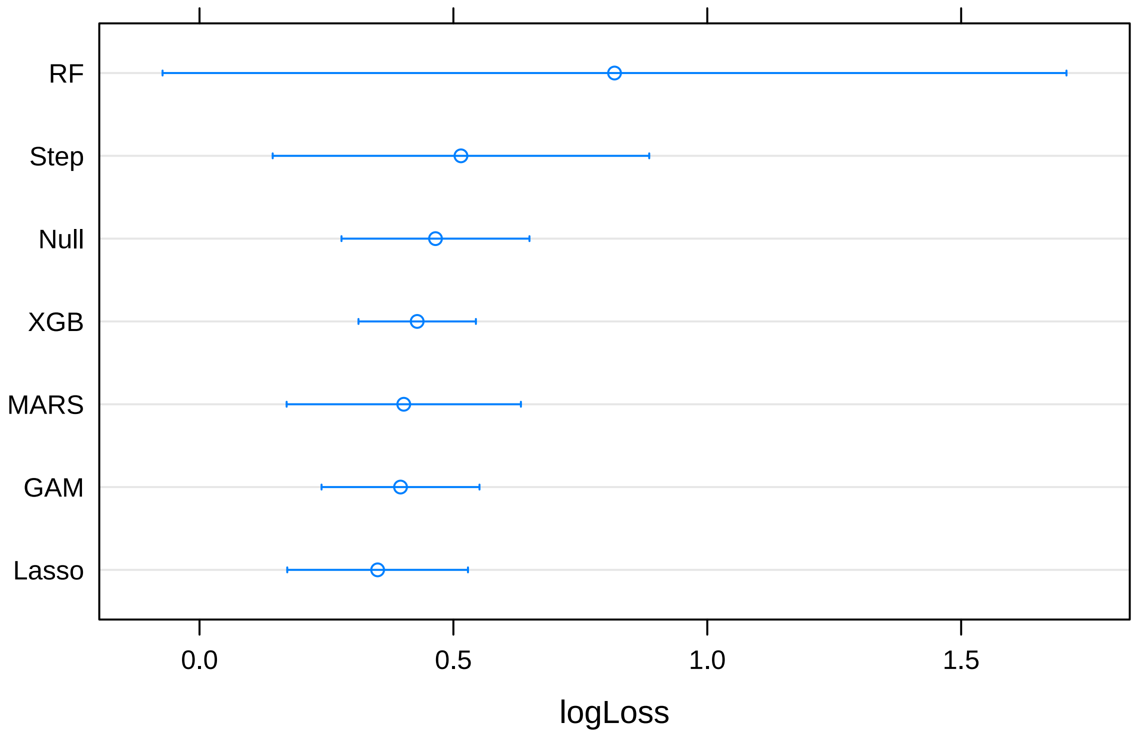
```
set.seed(randSeed)

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

## Compare Models

```
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: 46
##
## logLoss
##               Min.     1st Qu.     Median      Mean   3rd Qu.       Max. NA's
## XGB   2.010778e-01 0.217319219 0.22510756 0.4286741 0.4253161  1.649584    0
## GAM   9.649594e-02 0.125957153 0.14820984 0.3958571 0.2270635  1.762089    0
## RF    9.536533e-05 0.037201063 0.11551094 0.8173299 0.4148020 19.946658    0
## Step  3.228520e-06 0.004524957 0.03375977 0.5148946 0.3415982  6.880424    0
## Lasso 5.687156e-03 0.033942492 0.07558526 0.3507532 0.3453562  2.541241    0
## MARS  7.184630e-04 0.056736427 0.06736552 0.4022505 0.3873593  3.418330    0
## Null  1.004490e-01 0.154440199 0.17462598 0.4647126 0.2209028  2.167452    0
```

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



**Confidence Level: 0.95**

### Explore XGB Model

```r
xgb_mod$bestTune
```

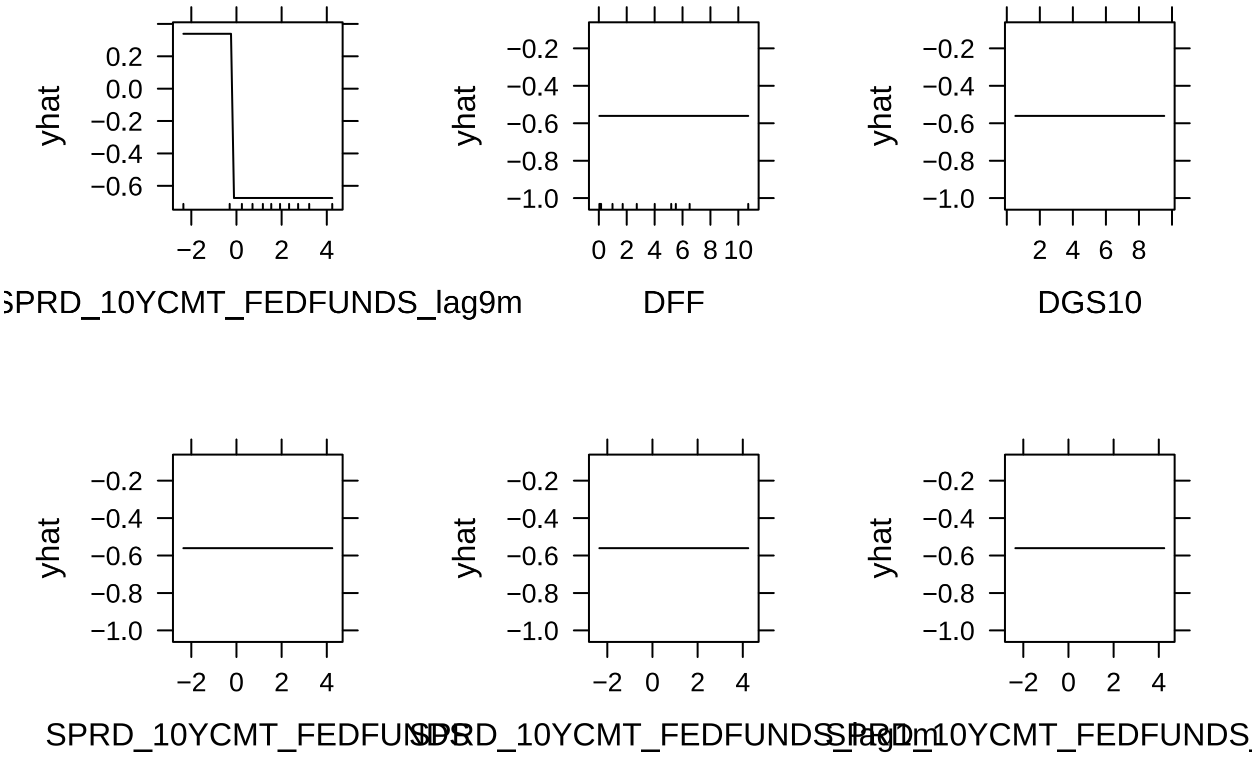
```
##     nrounds max_depth eta gamma colsample_bytree min_child_weight subsample
## 271       1         1 0.8     0                1               10         1
```

```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_lag9m | 100 |

| variable | Overall |
|---|---:|
| DFF | 0 |
| DGS10 | 0 |
| SPRD_10YCMT_FEDFUNDS | 0 |
| SPRD_10YCMT_FEDFUNDS_lag1m | 0 |
| SPRD_10YCMT_FEDFUNDS_lag3m | 0 |
| SPRD_10YCMT_FEDFUNDS_lag6m | 0 |
| SPRD_10YCMT_FEDFUNDS_lag12m | 0 |
| SPRD_10YCMT_FEDFUNDS_lag5d | 0 |
| SPRD_10YCMT_FEDFUNDS_lag10d | 0 |
| SPRD_10YCMT_FEDFUNDS_lag15d | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk001 | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk10 | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk20 | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk40 | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk75 | 0 |
| SPRD_10YCMT_FEDFUNDS_adstk95 | 0 |
| SPRD_10YCMT_FEDFUNDS_ma5d | 0 |
| SPRD_10YCMT_FEDFUNDS_ma10d | 0 |
| SPRD_10YCMT_FEDFUNDS_ma15d | 0 |
| SPRD_10YCMT_FEDFUNDS_ma20d | 0 |
| SPRD_10YCMT_FEDFUNDS_ma25d | 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 |

```r
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`.

```
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
## -3.15979   0.06882   0.17978   0.42060   2.70315
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   0.4533     0.0402   11.28   <2e-16 ***
## SPRD_10YCMT_FEDFUNDS_lag9m    1.7364     0.0481   36.10   <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: 7045.9  on 8356  degrees of freedom
## Residual deviance: 4452.8  on 8355  degrees of freedom
## AIC: 4456.8
##
## Number of Fisher Scoring iterations: 6
```

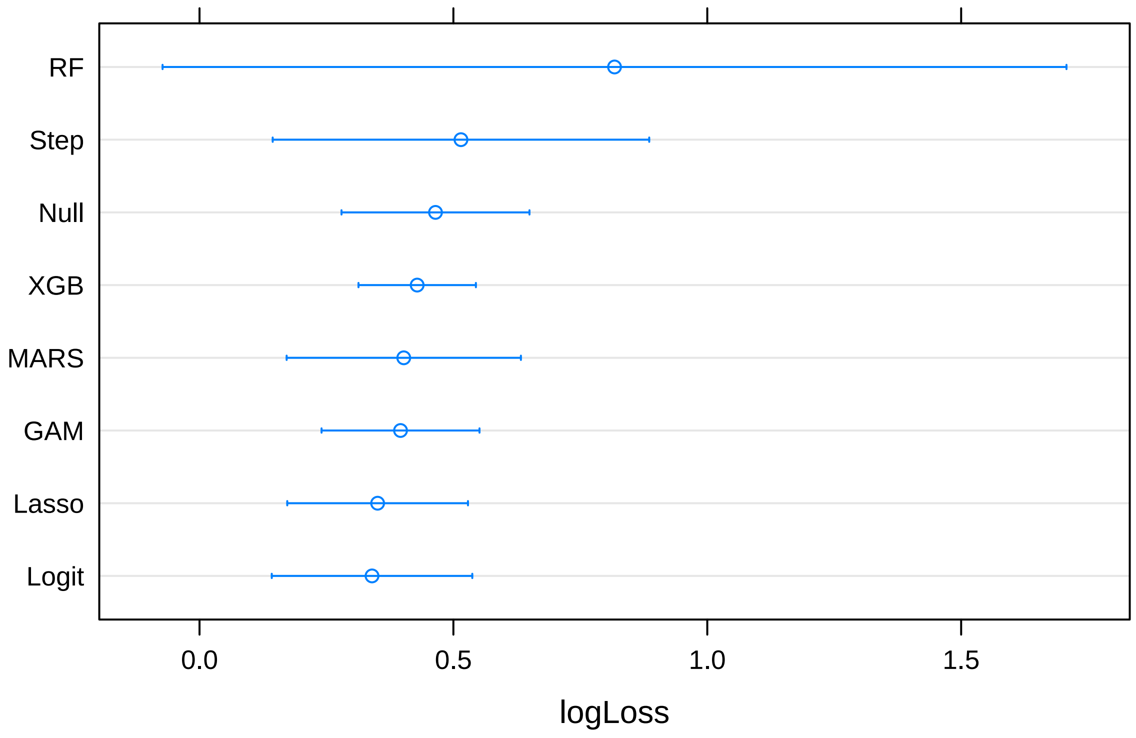
## Compare Models

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

```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: 46
##
## logLoss
##               Min.     1st Qu.     Median      Mean   3rd Qu.      Max. NA's
## XGB   2.010778e-01 0.217319219 0.22510756 0.4286741 0.4253161  1.649584    0
## GAM   9.649594e-02 0.125957153 0.14820984 0.3958571 0.2270635  1.762089    0
## RF    9.536533e-05 0.037201063 0.11551094 0.8173299 0.4148020 19.946658    0
## Step  3.228520e-06 0.004524957 0.03375977 0.5148946 0.3415982  6.880424    0
## Lasso 5.687156e-03 0.033942492 0.07558526 0.3507532 0.3453562  2.541241    0
## MARS  7.184630e-04 0.056736427 0.06736552 0.4022505 0.3873593  3.418330    0
## Null  1.004490e-01 0.154440199 0.17462598 0.4647126 0.2209028  2.167452    0
## Logit 4.929317e-04 0.011633527 0.04909710 0.3397412 0.3670520  2.966334    0
```

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



**Confidence 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 | 0.9230727 |
| Lasso | 0.9229897 |
| GAM | 0.9033686 |
| Logit | 0.8677480 |
| MARS | 0.8381275 |
| RF | 0.8333087 |
| XGB | 0.8227510 |
| Null | 0.5000000 |

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

| model | LogLoss |
|---|---|
| Lasso | 0.3750170 |
| XGB | 0.4313091 |
| GAM | 0.4366629 |
| Step | 0.4695585 |
| RF | 0.4789201 |
| Logit | 0.5909993 |
| Null | 0.6541396 |
| MARS | 0.8957176 |

## Probability of Recession (Most Recent Trading Day)

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

curr_data$date
```

```
## [1] "2022-12-01"
```

```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"]

    )
  }) %>%
    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))
```

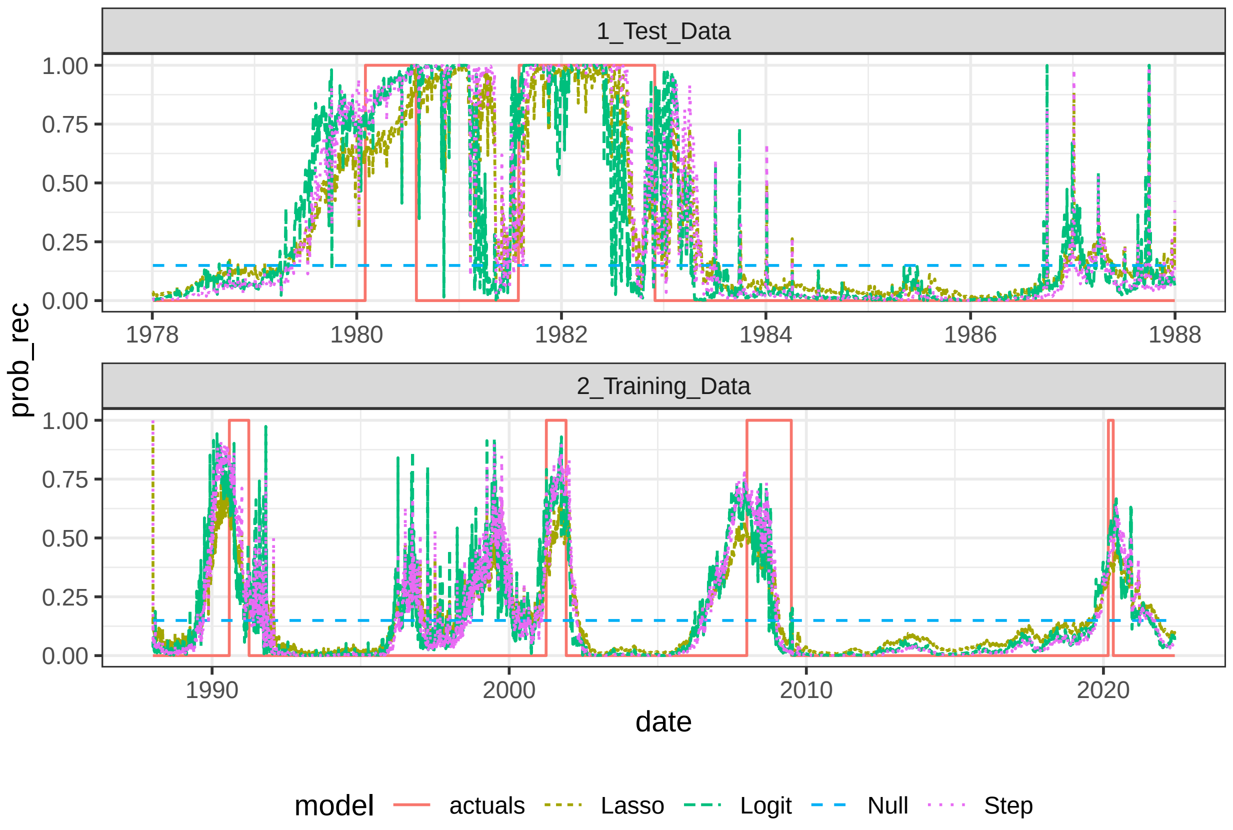
| model | prob_rec |
|---|---|
| XGB | 20.56% |
| GAM | 12.87% |
| RF | 3.00% |
| Step | 3.34% |
| Lasso | 8.16% |
| MARS | 5.26% |
| Null | 14.93% |
| Logit | 3.55% |

## Backtesting

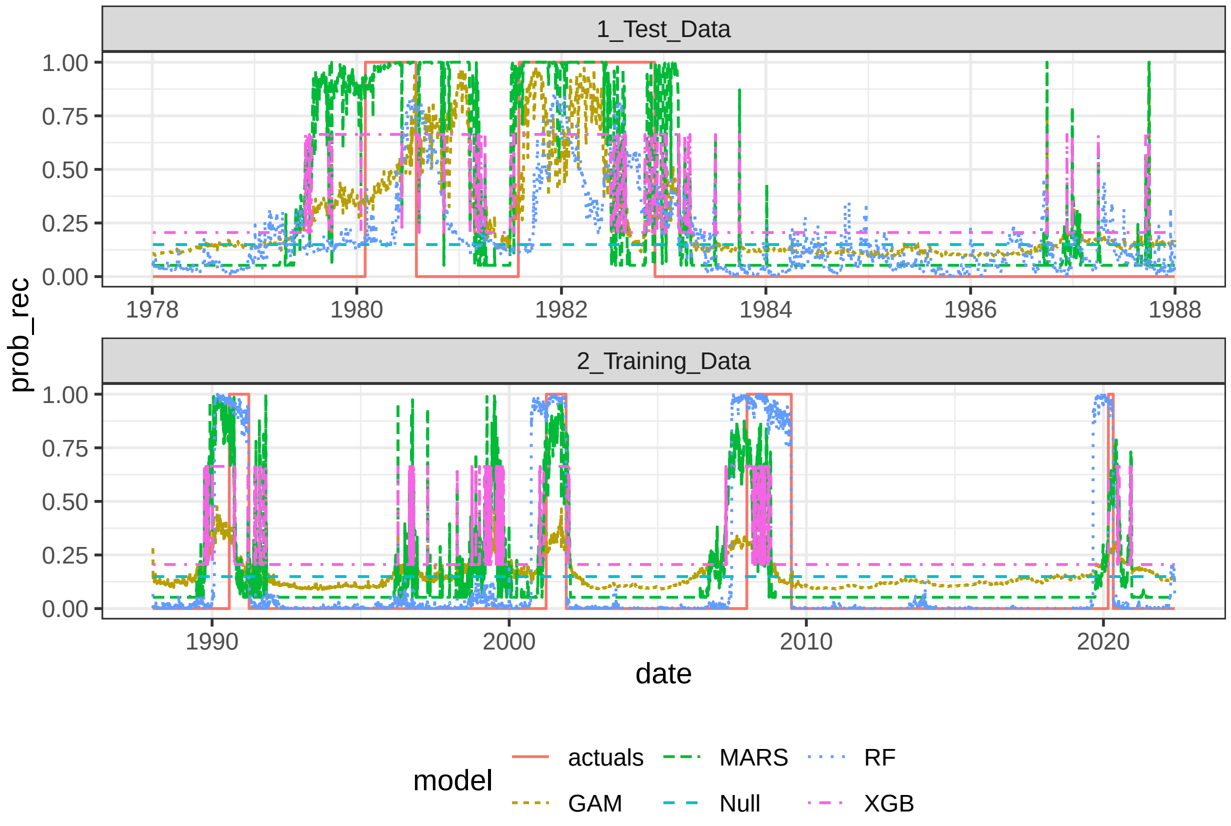
```
full_data_bktst <- full_data_wide %>%
  filter(date >= startTestDate)

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)
```

```r
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)
```



```
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)
```