Different Models

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1. Packages

```
library(tidyverse)
library(modelr)
library(caret)
library(ROSE)
library(randomForest)
library(glmnet)
library(rpart)
```

2. Data pre-processing

(1) Read data

```
df <- read_csv("./tidy.csv", col_types = cols(.default = col_character())) %>%
  type_convert()
```

(2) Specify factors

```
df_format <- df %>%
  mutate(TMC = factor(TMC), Severity = factor(Severity), Year = factor(Year), Wday = factor(Wday)) %>%
  mutate_if(is.logical, factor) %>%
  mutate_if(is.character, factor)
```

(3) Narrow down to one State

```
df_format %>% count(State) %>% arrange(desc(n))
```

```
## # A tibble: 49 x 2
##    State      n
##    <fct>  <int>
##  1 CA    650285
##  2 TX    291281
##  3 FL    221148
##  4 SC    143606
##  5 NC    141397
##  6 NY    136288
##  7 PA     89120
##  8 MI     88488
```

```
##  9 IL     86105
## 10 GA     82547
## # ... with 39 more rows
```

```
# choose TX as the target State
df_TX <- df_format %>% filter(State == "TX") %>% select(-State)
```

(4) Remove unuseful variables

```
# remove variables with only 1 distinct value
df_TX %>% summarise_all(~ n_distinct(.)) %>%
  pivot_longer(everything(), names_to = "variable", values_to = "n") %>% filter(n == 1)
```

```
## # A tibble: 1 x 2
##   variable         n
##   <chr>        <int>
## 1 Turning_Loop     1
```

```
df_TX <- df_TX %>% select(-Turning_Loop)
```

(5) Drop weather condition/TMC levels

```
# some Weather_Condition levels only have a few observations
# which can be a problem when we try to build a model
df_TX %>% count(Weather_Condition) %>% filter(n < 20) %>% select(Weather_Condition)
```

```
## # A tibble: 18 x 1
##    Weather_Condition
##    <fct>
##  1 Blowing Dust
##  2 Drizzle and Fog
##  3 Haze / Windy
##  4 Heavy Drizzle
##  5 Heavy T-Storm / Windy
##  6 Light Drizzle / Windy
##  7 Light Freezing Fog
##  8 Light Haze
##  9 Light Ice Pellets
## 10 Light Rain Showers
## 11 Light Snow / Windy
## 12 N/A Precipitation
## 13 Rain Showers
## 14 Sand
## 15 Showers in the Vicinity
## 16 Smoke
## 17 Thunder / Windy
## 18 Wintry Mix
```

```
drop_weather <- df_TX %>% count(Weather_Condition) %>% filter(n < 20) %>% select(Weather_Condition)
drop_weather <- drop_weather$Weather_Condition %>% unlist()
df_TX <- df_TX %>% filter(!(Weather_Condition %in% drop_weather))
df_TX <- df_TX %>% mutate(Weather_Condition = factor(Weather_Condition))

# it's the same to TMC
df_TX %>% count(TMC) %>% filter(n < 10)
```

```
## # A tibble: 5 x 2
##   TMC       n
##   <fct> <int>
## 1 200       1
## 2 239       3
## 3 248       4
## 4 336       1
## 5 339       9
```

```
drop_TMC <- df_TX %>% count(TMC) %>% filter(n < 10) %>% select(TMC)
drop_TMC <- drop_TMC$TMC %>% unlist()
df_TX <- df_TX %>% filter(!TMC %in% drop_TMC) %>% mutate(TMC = factor(TMC))
```

(6) Add new labels

```
# group level 3 and 4 together, as "Severe"
# group level 1 and 2 together, as "Not Severe"
df_label <- df_TX %>%
  mutate("Status" = factor(ifelse(Severity == "3" | Severity == "4", "Severe", "Not Severe"),
                           levels = c("Not Severe", "Severe")))
df_label %>% select(Severity, Status)
```

```
## # A tibble: 291,138 x 2
##    Severity Status
##    <fct>    <fct>
##  1 2        Not Severe
##  2 2        Not Severe
##  3 2        Not Severe
##  4 2        Not Severe
##  5 3        Severe
##  6 2        Not Severe
##  7 2        Not Severe
##  8 3        Severe
##  9 3        Severe
## 10 2        Not Severe
## # ... with 291,128 more rows
```

(7) Near Zero-Variance Predictors

```
# these variable may become zero-variance when the data are split into subsets
# remove them
nzv <- nearZeroVar(df_label, saveMetrics = T)
nzv[nzv$nzv,]
```

```
##                freqRatio percentUnique zeroVar  nzv
## Visibility      21.90824  0.0151131079   FALSE TRUE
## Amenity         52.04026  0.0006869594   FALSE TRUE
## Bump          5597.80769  0.0006869594   FALSE TRUE
## Give_Way       176.09124  0.0006869594   FALSE TRUE
## No_Exit        969.46000  0.0006869594   FALSE TRUE
## Railway        106.70921  0.0006869594   FALSE TRUE
## Roundabout   26466.09091  0.0006869594   FALSE TRUE
## Station         62.63672  0.0006869594   FALSE TRUE
## Stop            66.12889  0.0006869594   FALSE TRUE
```

```
## Traffic_Calming  2598.44643  0.0006869594   FALSE TRUE
```

```r
nzv_cols <- rownames(nzv[nzv$nzv,])
df_label <- df_label %>%
  select(-nzv_cols)
```

(8) Partition

```r
set.seed(1)
df_parts <- resample_partition(df_label, c(train = 0.6, valid = 0.2, test = 0.2))
train <- as_tibble(df_parts$train)
valid <- as_tibble(df_parts$valid)
test <- as_tibble(df_parts$test)
# check Weather_Condition levels / TMC levels
# train should have more levels than valid and test
tr <- train %>% select(Weather_Condition) %>% distinct()
va <- valid %>% select(Weather_Condition) %>% distinct()
te <- test %>% select(Weather_Condition) %>% distinct()
setdiff(va, tr)
```

```
## # A tibble: 0 x 1
## # ... with 1 variable: Weather_Condition <fct>
```

```r
setdiff(te, tr)
```

```
## # A tibble: 0 x 1
## # ... with 1 variable: Weather_Condition <fct>
```

```r
tr <- train %>% select(TMC) %>% distinct()
va <- valid %>% select(TMC) %>% distinct()
te <- test %>% select(TMC) %>% distinct()
setdiff(va, tr)
```

```
## # A tibble: 0 x 1
## # ... with 1 variable: TMC <fct>
```

```r
setdiff(te, tr)
```

```
## # A tibble: 0 x 1
## # ... with 1 variable: TMC <fct>
```

(9) Sampling

```r
new_train <- ovun.sample(Status ~ .,
                         data = train %>% select(-Severity),
                         method = "both", p = 0.5, N = 90000)$data %>% as_tibble()
table(new_train$Status)
```

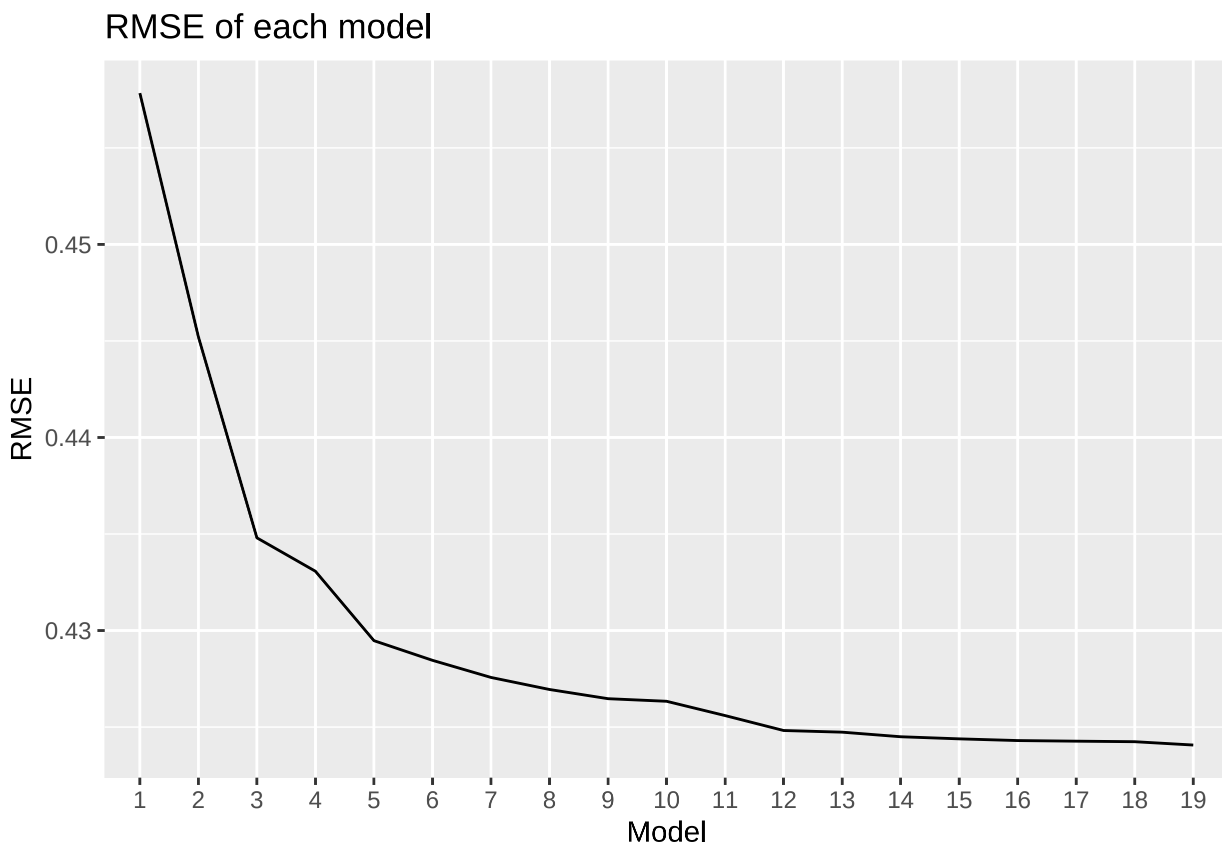
```
##
## Not Severe     Severe
##      44981      45019
```

3. Use different models to fit the data

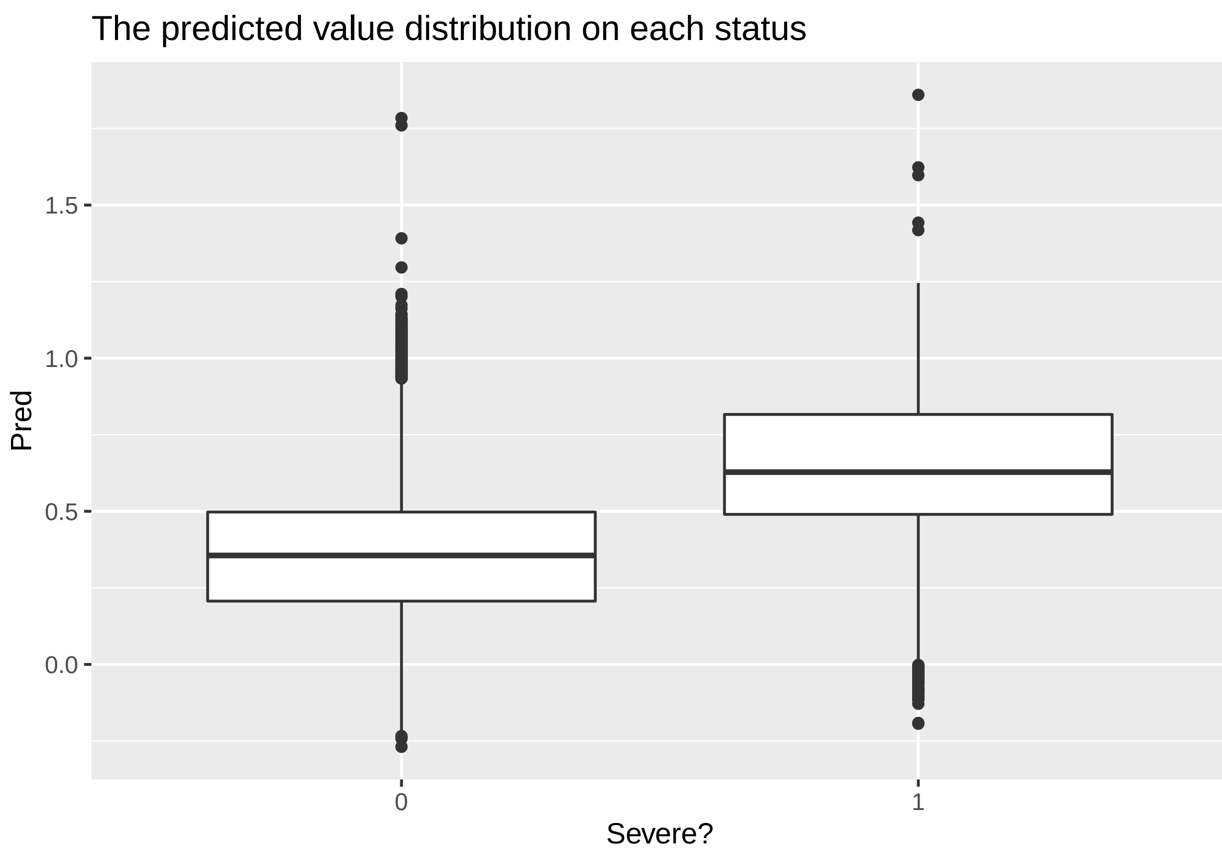
(1) Linear Regression

```
new_train_linear <- new_train %>%
  mutate(Status = as.numeric(recode(Status, "Not Severe" = 0, "Severe" = 1)))

# lm_total <- lm(Status ~ ., data = new_train_linear)
# step(lm_total)
# based on the result of step() function, build the models below
lm_ <- list()
lm_[[1]] <- lm(Status ~ TMC, data = new_train_linear)
lm_[[2]] <- lm(Status ~ TMC + Side, data = new_train_linear)
lm_[[3]] <- lm(Status ~ TMC + Side + Traffic_Signal, data = new_train_linear)
lm_[[4]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat, data = new_train_linear)
lm_[[5]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour, data = new_train_linear)
lm_[[6]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                 Junction, data = new_train_linear)
lm_[[7]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                 Junction + Wday, data = new_train_linear)
lm_[[8]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                 Junction + Wday + Distance, data = new_train_linear)
lm_[[9]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                 Junction + Wday + Distance + Crossing, data = new_train_linear)
lm_[[10]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration, data = new_train_linear)
lm_[[11]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year, data = new_train_linear)
lm_[[12]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng, data = new_train_linear)
lm_[[13]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure, data = new_train_linear)
lm_[[14]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition, data = new_train_linear)
lm_[[15]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition + Month, data = new_train_linear)
lm_[[16]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition + Month + Wind_Speed, data = new_train_linea
lm_[[17]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition + Month + Wind_Speed + Civil_Twilight, data =
lm_[[18]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition + Month + Wind_Speed + Civil_Twilight + Humi
lm_[[19]] <- lm(Status ~ TMC + Side + Traffic_Signal + Start_Lat + Hour +
                  Junction + Wday + Distance + Crossing + Duration + Year +
                  Start_Lng + Pressure + Weather_Condition + Month + Wind_Speed + Civil_Twilight + Humi

all_rmse = vector(length = 19)
```

```r
for (i in 1:19) {
  all_rmse[i] <- rmse(lm_[[i]], data = new_train_linear)
}

# choose 15th model as the best
ggplot(tibble(rmse = all_rmse)) +
  geom_line(aes(factor(1:19), rmse, group = 1)) +
  labs(x = "Model",
       y = "RMSE",
       title = "RMSE of each model")
```




```r
# get predictions on valid dataset
valid_pred_lm <- valid %>%
  mutate(Status = as.numeric(recode(Status, "Not Severe" = 0, "Severe" = 1))) %>%
  add_predictions(lm_[[15]])
# see the predicted value distribution
ggplot(valid_pred_lm) +
  geom_boxplot(aes(x = factor(Status), y = pred)) +
  labs(x = "Severe?",
       y = "Pred",
       title = "The predicted value distribution on each status")
```



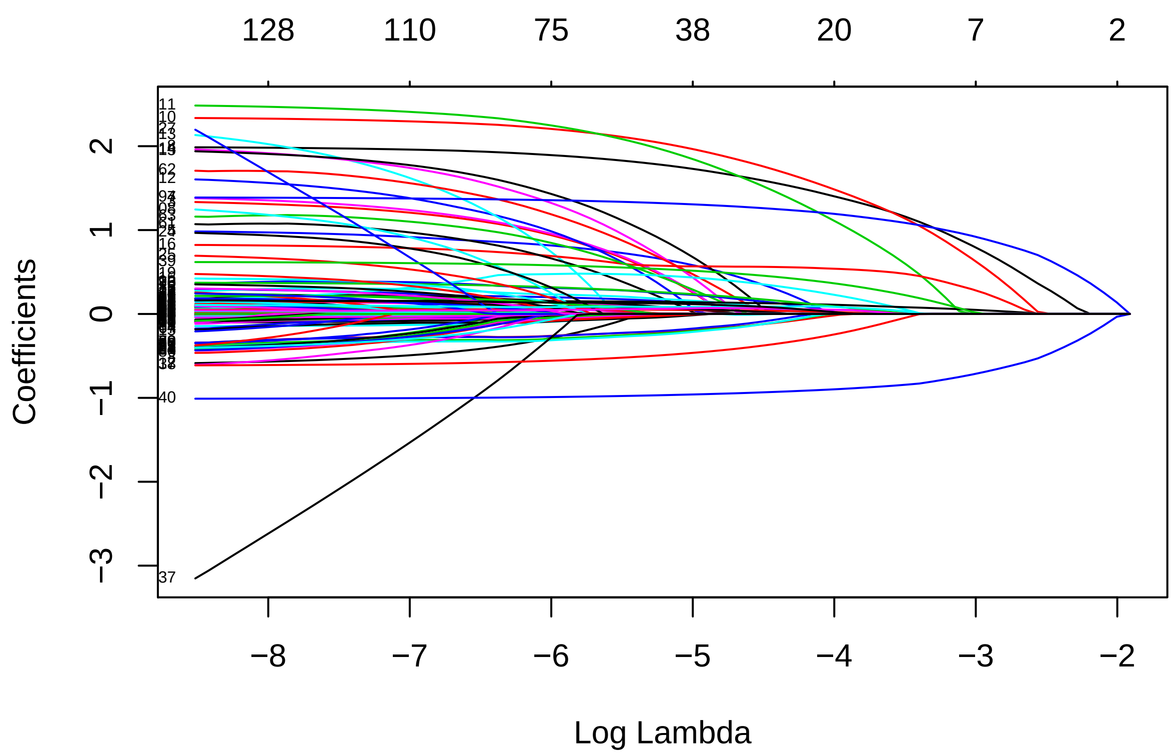

```r
# choose 0.5 as the boundary

valid_pred_lm <- valid_pred_lm %>%
  mutate(pred_status = ifelse(pred > 0.5, 1, 0))
# accuracy
confusionMatrix(table(valid_pred_lm$Status, valid_pred_lm$pred_status))
```

```
## Confusion Matrix and Statistics
##
##
##           0     1
##    0 31614 10308
##    1  4369 11937
##
##                Accuracy : 0.7479
##                  95% CI : (0.7444, 0.7515)
##     No Information Rate : 0.618
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4375
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8786
##             Specificity : 0.5366
##          Pos Pred Value : 0.7541
```

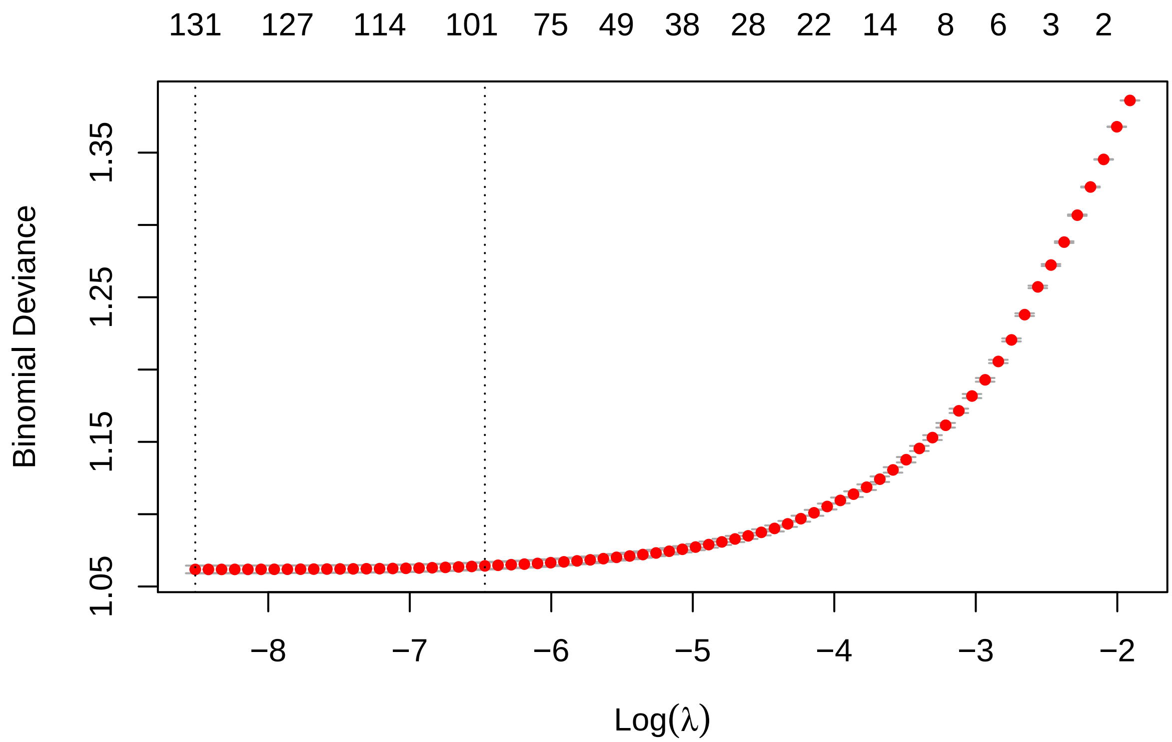
```
##          Neg Pred Value : 0.7321
##              Prevalence : 0.6180
##          Detection Rate : 0.5429
##    Detection Prevalence : 0.7200
##       Balanced Accuracy : 0.7076
##
##        'Positive' Class : 0
##
```

(2) Sparse Logistic regression

```r
x <- model.matrix(Status ~ ., data = new_train)
model_total <- glmnet(x, new_train$Status, family = "binomial")
plot(model_total, xvar = "lambda", label = T)
```




```r
model_lambda <- cv.glmnet(x, new_train$Status, family = "binomial")
plot(model_lambda)
```




```r
# use the best lambda
valid_pred <- valid %>%
  mutate("pred" = predict(model_lambda,
                          newx = model.matrix(Status ~ ., data = valid %>% select(-Severity)),
                          s = "lambda.min", type = "response")[,1]) %>%
  mutate("pred" = ifelse(pred > 0.5, "Severe", "Not Severe"))
valid_pred %>% select(Status, pred)
```

```
## # A tibble: 58,228 x 2
##    Status     pred
##    <fct>      <chr>
##  1 Not Severe Not Severe
##  2 Not Severe Not Severe
##  3 Not Severe Not Severe
##  4 Severe     Severe
##  5 Severe     Severe
##  6 Not Severe Not Severe
##  7 Not Severe Not Severe
##  8 Not Severe Not Severe
##  9 Not Severe Not Severe
## 10 Not Severe Not Severe
## # ... with 58,218 more rows
```

```r
table(valid$Status)
```

```
##
## Not Severe     Severe
```

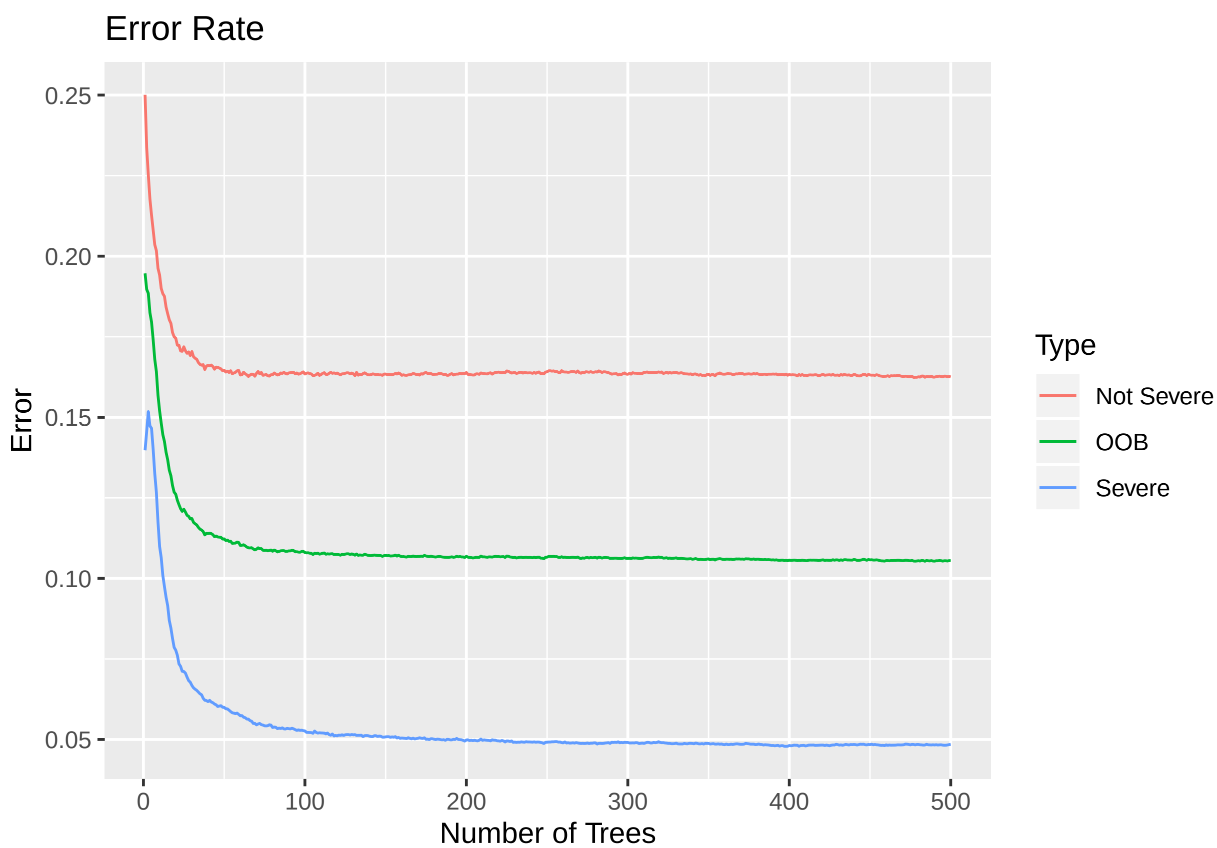
```
##      41922      16306
```

```r
confusionMatrix(table(valid_pred$Status, valid_pred$pred))
```

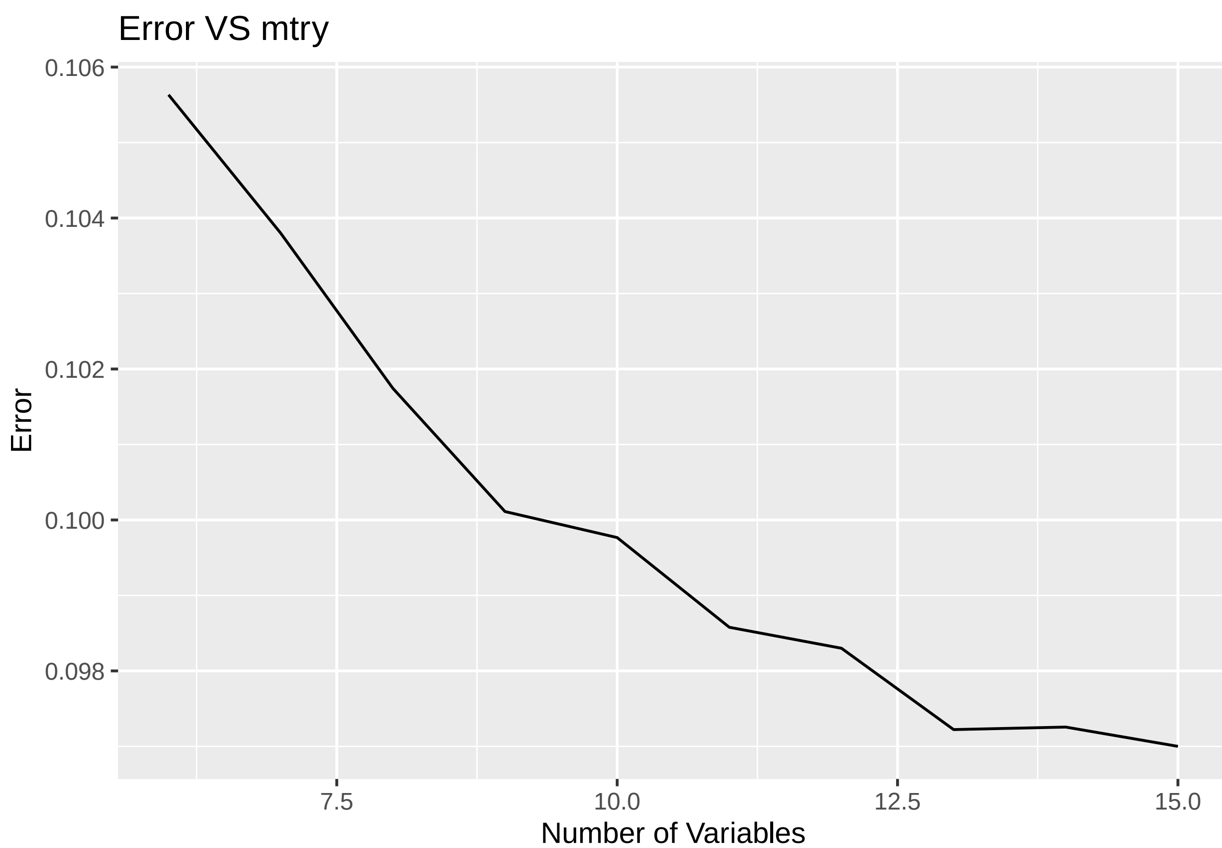
```
## Confusion Matrix and Statistics
##
##
##                Not Severe Severe
##   Not Severe      31305  10617
##   Severe           4212  12094
##
##                  Accuracy : 0.7453
##                    95% CI : (0.7418, 0.7489)
##     No Information Rate : 0.61
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                     Kappa : 0.4361
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##               Sensitivity : 0.8814
##               Specificity : 0.5325
##            Pos Pred Value : 0.7467
##            Neg Pred Value : 0.7417
##                Prevalence : 0.6100
##            Detection Rate : 0.5376
##      Detection Prevalence : 0.7200
##         Balanced Accuracy : 0.7070
##
##        'Positive' Class : Not Severe
##
```

(3) Random forest

```r
model <- randomForest(Status ~ ., data = new_train, mtry = 6, ntree = 500)

# see if ntree = 500 is enough
error_data <- model$err.rate %>%
  as_tibble() %>%
  mutate("Trees" = seq_along(OOB)) %>%
  pivot_longer(cols = 1:3, names_to = "Type", values_to = "Error")

ggplot(error_data, aes(Trees, Error, color = Type)) +
  geom_line() +
  labs(x = "Number of Trees",
       title = "Error Rate")
```




```r
# try different mtry
oob_values <- vector(length = 10)
for (i in 1:10) {
  temp_model <- randomForest(Status ~ ., data = new_train, mtry = (i + 5))
  oob_values[i] <- temp_model$err.rate[nrow(temp_model$err.rate), 1]
}
ggplot(tibble("Error" = oob_values), aes(x = 6:15, y = Error)) +
  geom_line(aes(group = 1)) +
  labs(x = "Number of Variables",
       title = "Error VS mtry")
```




```r
# choose mtry = 13 as the best model
best_model <- randomForest(Status ~ ., data = new_train, mtry = 13, ntree = 500)

valid_pred_rf <- valid %>%
  add_predictions(best_model)
table(valid_pred_rf$Status)
```

```
##
## Not Severe     Severe
##      41922      16306
```

```r
confusionMatrix(valid_pred_rf$Status, valid_pred_rf$pred)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   Not Severe Severe
##   Not Severe      33167   8755
##   Severe           2175  14131
##
##                Accuracy : 0.8123
##                  95% CI : (0.8091, 0.8155)
##     No Information Rate : 0.607
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5856
##
```

```
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.9385
##             Specificity : 0.6175
##          Pos Pred Value : 0.7912
##          Neg Pred Value : 0.8666
##              Prevalence : 0.6070
##          Detection Rate : 0.5696
##    Detection Prevalence : 0.7200
##       Balanced Accuracy : 0.7780
##
##        'Positive' Class : Not Severe
##
```

(4) Decision tree

```r
model_decision <- rpart(Status ~ ., data = new_train, method = "class")

valid_pred_dc <- valid %>%
  mutate(pred = predict(model_decision, valid, type = "class"))
confusionMatrix(table(valid_pred_dc$Status, valid_pred_dc$pred))
```

```
## Confusion Matrix and Statistics
##
##
##               Not Severe Severe
##   Not Severe      30990  10932
##   Severe           4044  12262
##
##                Accuracy : 0.7428
##                  95% CI : (0.7392, 0.7464)
##     No Information Rate : 0.6017
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.4351
##
##  Mcnemar's Test P-Value : < 2.2e-16
##
##             Sensitivity : 0.8846
##             Specificity : 0.5287
##          Pos Pred Value : 0.7392
##          Neg Pred Value : 0.7520
##              Prevalence : 0.6017
##          Detection Rate : 0.5322
##    Detection Prevalence : 0.7200
##       Balanced Accuracy : 0.7066
##
##        'Positive' Class : Not Severe
##
```