Lab 8

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I want to make some use of my CART package. Everyone please try to run the following:

```
if (!pacman::p_isinstalled(YARF)){
  pacman::p_install_gh("kapelner/YARF/YARFJARs", ref = "dev")
  pacman::p_install_gh("kapelner/YARF/YARF", ref = "dev", force = TRUE)
}
options(java.parameters = "-Xmx4000m")
pacman::p_load(YARF)
```

```
## YARF can now make use of 11 cores.
```

For many of you it will not work. That's okay.

Throughout this part of this assignment you can use either the `tidyverse` package suite or `data.table` to answer but not base R. You can mix `data.table` with `magrittr` piping if you wish but don't go back and forth between `tbl_df`'s and `data.table` objects.

```
pacman::p_load(tidyverse, magrittr, data.table)
```

We will be using the `storms` dataset from the `dplyr` package. Filter this dataset on all storms that have no missing measurements for the two diameter variables, "ts_diameter" and "hu_diameter".

```
data(storms)

storms2 = storms %>%
  filter(!is.na(ts_diameter) & !is.na(hu_diameter) & ts_diameter > 0 & hu_diameter > 0)

storms2
```

```
## # A tibble: 1,022 x 13
##    name   year month   day  hour   lat  long status    category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>     <ord>    <int>    <int>
##  1 Alex   2004     8     3     6  33   -77.4 hurricane 1           70      983
##  2 Alex   2004     8     3    12  34.2 -76.4 hurricane 2           85      974
##  3 Alex   2004     8     3    18  35.3 -75.2 hurricane 2           85      972
##  4 Alex   2004     8     4     0  36   -73.7 hurricane 1           80      974
##  5 Alex   2004     8     4     6  36.8 -72.1 hurricane 1           80      973
##  6 Alex   2004     8     4    12  37.3 -70.2 hurricane 2           85      973
##  7 Alex   2004     8     4    18  37.8 -68.3 hurricane 2           95      965
##  8 Alex   2004     8     5     0  38.5 -66   hurricane 3          105      957
```

```
## 9 Alex   2004     8      5      6  39.5 -63.1 hurricane 3          105      957
## 10 Alex   2004     8      5     12  40.8 -59.6 hurricane 3          100      962
## # ... with 1,012 more rows, and 2 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>
```

From this subset, create a data frame that only has storm, observation period number for each storm (i.e., 1, 2, . . . , T) and the "ts_diameter" and "hu_diameter" metrics.

```
storms2 = storms2 %>%
  select(name, ts_diameter, hu_diameter) %>%
  group_by(name) %>%
  mutate(period = row_number())

storms2
```

```
## # A tibble: 1,022 x 4
## # Groups:   name [63]
##    name  ts_diameter hu_diameter period
##    <chr>       <dbl>       <dbl>  <int>
##  1 Alex         150.        46.0      1
##  2 Alex         150.        46.0      2
##  3 Alex         190.        57.5      3
##  4 Alex         178.        63.3      4
##  5 Alex         224.        74.8      5
##  6 Alex         224.        74.8      6
##  7 Alex         259.        74.8      7
##  8 Alex         259.        80.6      8
##  9 Alex         345.        80.6      9
## 10 Alex         437.        80.6     10
## # ... with 1,012 more rows
```

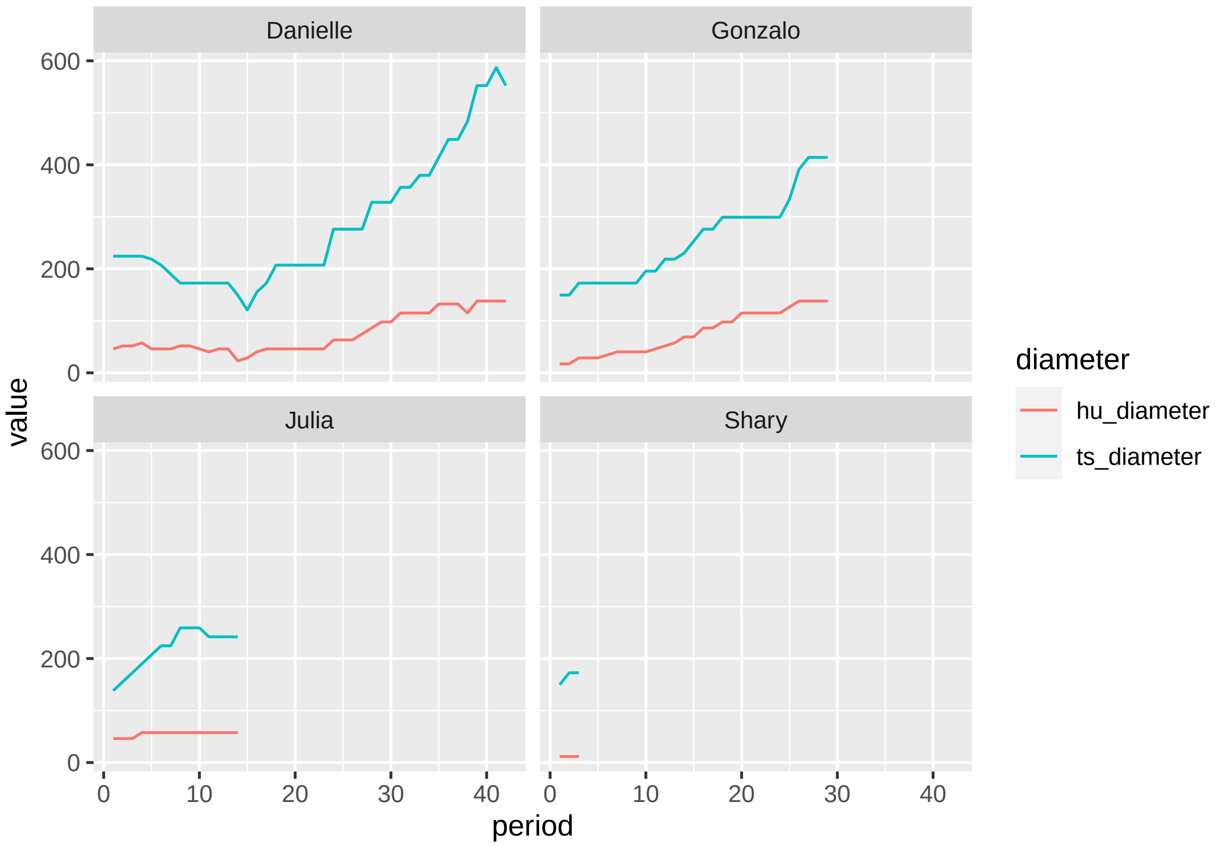
Create a data frame in long format with columns "diameter" for the measurement and "diameter_type" which will be categorical taking on the values "hu" or "ts".

```
storms_long = pivot_longer(storms2, cols = matches("diameter"), names_to = "diameter")

storms_long
```

```
## # A tibble: 2,044 x 4
## # Groups:   name [63]
##    name  period diameter    value
##    <chr>  <int> <chr>       <dbl>
##  1 Alex       1 ts_diameter 150.
##  2 Alex       1 hu_diameter  46.0
##  3 Alex       2 ts_diameter 150.
##  4 Alex       2 hu_diameter  46.0
##  5 Alex       3 ts_diameter 190.
##  6 Alex       3 hu_diameter  57.5
##  7 Alex       4 ts_diameter 178.
##  8 Alex       4 hu_diameter  63.3
##  9 Alex       5 ts_diameter 224.
## 10 Alex       5 hu_diameter  74.8
## # ... with 2,034 more rows
```

Using this long-formatted data frame, use a line plot to illustrate both "ts_diameter" and "hu_diameter" metrics by observation period for four random storms using a 2x2 faceting. The two diameters should appear in two different colors and there should be an appropriate legend.

```
storms_sample = sample(unique(storms2$name), 4)

ggplot(storms_long %>% filter(name %in% storms_sample)) +
  geom_line(aes(x = period, y = value, col = diameter)) +
  facet_wrap(name ~ ., nrow = 2)
```



In this next first part of this lab, we will be joining three datasets in an effort to make a design matrix that predicts if a bill will be paid on time. Clean up and load up the three files. Then I'll rename a few features and then we can examine the data frames:

```
rm(list = ls())
pacman::p_load(tidyverse, magrittr, data.table, R.utils)
bills = fread("https://github.com/kapelner/QC_MATH_342W_Spring_2021/raw/master/labs/bills_dataset/bills
payments = fread("https://github.com/kapelner/QC_MATH_342W_Spring_2021/raw/master/labs/bills_dataset/pa
discounts = fread("https://github.com/kapelner/QC_MATH_342W_Spring_2021/raw/master/labs/bills_dataset/d
setnames(bills, "amount", "tot_amount")
setnames(payments, "amount", "paid_amount")
head(bills)
```

```
##          id   due_date invoice_date tot_amount customer_id discount_id
## 1: 15163811 2017-02-12   2017-01-13   99490.77    14290629     5693147
## 2: 17244832 2016-03-22   2016-02-21   99475.73    14663516     5693147
```

```
## 3: 16072776 2016-08-31   2016-07-17   99477.03    14569622     7302585
## 4: 15446684 2017-05-29   2017-05-29   99478.60    14488427     5693147
## 5: 16257142 2017-06-09   2017-05-10   99678.17    14497172     5693147
## 6: 17244880 2017-01-24   2017-01-24   99475.04    14663516     5693147
```

```
head(payments)
```

```
##          id paid_amount transaction_date  bill_id
## 1: 15272980    99165.60       2017-01-16 16571185
## 2: 15246935    99148.12       2017-01-03 16660000
## 3: 16596393    99158.06       2017-06-19 16985407
## 4: 16596651    99175.03       2017-06-19 17062491
## 5: 16687702    99148.20       2017-02-15 17184583
## 6: 16593510    99153.94       2017-06-11 16686215
```

```
head(discounts)
```

```
##         id num_days pct_off days_until_discount
## 1: 5000000       20      NA                  NA
## 2: 5693147       NA       2                  NA
## 3: 6098612       20      NA                  NA
## 4: 6386294      120      NA                  NA
## 5: 6609438       NA       1                   7
## 6: 6791759       31       1                  NA
```

```
bills = as_tibble(bills)
payments = as_tibble(payments)
discounts = as_tibble(discounts)
```

The unit we care about is the bill. The y metric we care about will be "paid in full" which is 1 if the company paid their total amount (we will generate this y metric later).

Since this is the response, we would like to construct the very best design matrix in order to predict y.

I will create the basic steps for you guys. First, join the three datasets in an intelligent way. You will need to examine the datasets beforehand.

```
bills_with_payments = left_join(bills, payments, by = c("id" = "bill_id"))
bills_with_payments
```

```
## # A tibble: 279,118 x 9
##          id due_date   invoice_date tot_amount customer_id discount_id     id.y
##       <dbl> <date>     <date>            <dbl>       <int>       <dbl>    <dbl>
##  1 15163811 2017-02-12 2017-01-13       99491.    14290629     5693147 14670862
##  2 17244832 2016-03-22 2016-02-21       99476.    14663516     5693147 16691206
##  3 16072776 2016-08-31 2016-07-17       99477.    14569622     7302585       NA
##  4 15446684 2017-05-29 2017-05-29       99479.    14488427     5693147 16591210
##  5 16257142 2017-06-09 2017-05-10       99678.    14497172     5693147 16538398
##  6 17244880 2017-01-24 2017-01-24       99475.    14663516     5693147 16691231
##  7 16214048 2017-03-08 2017-02-06       99475.    14679281     5693147 16845763
##  8 15579946 2016-06-13 2016-04-14       99476.    14450223     5693147 16593380
##  9 15264234 2014-06-06 2014-05-07       99480.    14532786     7708050 16957842
## 10 17031731 2017-01-12 2016-12-13       99476.    14658929     5693147       NA
## # ... with 279,108 more rows, and 2 more variables: paid_amount <dbl>,
## #   transaction_date <date>
```

```
bills_with_payments_with_discounts = left_join(bills_with_payments, discounts, by = c("discount_id" = "i
bills_with_payments_with_discounts
```

```
## # A tibble: 279,118 x 12
##          id due_date   invoice_date tot_amount customer_id discount_id     id.y
##       <dbl> <date>     <date>            <dbl>       <int>       <dbl>    <dbl>
##  1 15163811 2017-02-12 2017-01-13       99491.    14290629     5693147 14670862
##  2 17244832 2016-03-22 2016-02-21       99476.    14663516     5693147 16691206
##  3 16072776 2016-08-31 2016-07-17       99477.    14569622     7302585       NA
##  4 15446684 2017-05-29 2017-05-29       99479.    14488427     5693147 16591210
##  5 16257142 2017-06-09 2017-05-10       99678.    14497172     5693147 16538398
##  6 17244880 2017-01-24 2017-01-24       99475.    14663516     5693147 16691231
##  7 16214048 2017-03-08 2017-02-06       99475.    14679281     5693147 16845763
##  8 15579946 2016-06-13 2016-04-14       99476.    14450223     5693147 16593380
##  9 15264234 2014-06-06 2014-05-07       99480.    14532786     7708050 16957842
## 10 17031731 2017-01-12 2016-12-13       99476.    14658929     5693147       NA
## # ... with 279,108 more rows, and 5 more variables: paid_amount <dbl>,
## #   transaction_date <date>, num_days <int>, pct_off <dbl>,
## #   days_until_discount <int>
```

Now create the binary response metric `paid_in_full` as the last column and create the beginnings of a design matrix `bills_data`. Ensure the unit / observation is bill i.e. each row should be one bill!

```
bills_data = bills_with_payments_with_discounts %>%
  mutate(tot_amount = if_else(is.na(pct_off), tot_amount, tot_amount * (1 - pct_off / 100))) %>%
  group_by(id) %>%
  mutate(sum_of_payment_amount = sum(paid_amount)) %>%
  mutate(paid_in_full = if_else(sum_of_payment_amount >= tot_amount, 1, 0, missing = 0)) %>%
  slice(1) %>%
  ungroup()

table(bills_data$paid_in_full, useNA = "always")
```

```
##
##      0      1   <NA>
## 112664 113770      0
```

How should you add features from transformations (called "featurization")? What data type(s) should they be? Make some features below if you think of any useful ones. Name the columns appropriately so another data scientist can easily understand what information is in your variables.

```
pacman::p_load("lubridate")

bills_data = bills_data %>%
  select(-id, -id.y, -num_days, -transaction_date, -pct_off, -days_until_discount, -sum_of_payment_amour
  mutate(num_days_to_pay = as.integer(ymd(due_date) - ymd(invoice_date))) %>%
  select(-due_date, -invoice_date) %>%
  mutate(discount_id = as.factor(discount_id)) %>%
  group_by(customer_id) %>%
  mutate(bill_num = row_number()) %>%
  ungroup() %>%
  select(-customer_id, -paid_amount) %>%
  relocate(paid_in_full, .after = last_col())
```

Now let's do this exercise. Let's retain 25% of our data for test.

```
K = 4
test_indices = sample(1 : nrow(bills_data), round(nrow(bills_data) / K))
train_indices = setdiff(1 : nrow(bills_data), test_indices)
bills_data_test = bills_data[test_indices, ]
bills_data_train = bills_data[train_indices, ]
```

Now try to build a classification tree model for `paid_in_full` with the features (use the `Xy` parameter in `YARF`). If you cannot get `YARF` to install, use the package `rpart` (the standard R tree package) instead. You will need to install it and read through some documentation to find the correct syntax.

Warning: this data is highly anonymized and there is likely zero signal! So don't expect to get predictive accuracy. The value of the exercise is in the practice. I think this exercise (with the joining exercise above) may be one of the most useful exercises in the entire semester.

```
y_train = factor(bills_data_train$paid_in_full)
X_train = bills_data_train
X_train$paid_in_full = NULL


n_train = nrow(X_train)

y_test = factor(bills_data_test$paid_in_full)
X_test = bills_data_test
X_test$paid_in_full = NULL

tree_mod = YARFCART(X_train, y_train, calculate_oob_error = FALSE)
```

```
## YARF initializing with a fixed 1 trees...
## YARF factors created...
## YARF after data preprocessed... 36 total features...
## Beginning YARF classification model construction...done.
```

```
#tree_mod = YARFCART(Xy = bills_data_train, calculate_oob_error = FALSE)
bills_data_train
```

```
## # A tibble: 169,826 x 5
##    tot_amount discount_id num_days_to_pay bill_num paid_in_full
##         <dbl> <fct>                 <int>    <int>        <dbl>
##  1     99529. 7397895                  30        1            0
##  2     99477. 7397895                  11        1            0
##  3     99479. 7397895                   0        2            0
##  4     99477. 7397895                  30        1            0
##  5     99477. 7397895                   0        1            0
##  6     99477. 7397895                  30        2            0
##  7     99485. 7397895                  30        4            0
##  8     99477. 7397895                  30        2            0
##  9     99481. 7397895                  45        6            0
## 10     99475. <NA>                     30        1            0
## # ... with 169,816 more rows
```

For those of you who installed `YARF`, what are the number of nodes and depth of the tree?

```
get_tree_num_nodes_leaves_max_depths(tree_mod)
```

```
## $num_nodes
## [1] 69855
##
## $num_leaves
## [1] 34928
##
## $max_depth
## [1] 129
```

For those of you who installed `YARF`, print out an image of the tree.

```
illustrate_trees(tree_mod, max_depth = 5, length_in_px_per_half_split = 30, open_file = TRUE)
```

Predict on the test set and compute a confusion matrix.

```
y_hat_test = predict(tree_mod, X_test)

oos_conf_table = table(y_test, y_hat_test)
oos_conf_table
```

```
##       y_hat_test
## y_test     0     1
##      0 21926  6319
##      1  6517 21846
```

Report the following error metrics: misclassifcation error, precision, recall, F1, FDR, FOR.

```
n = sum(oos_conf_table)
fp = oos_conf_table[1, 2]
fn = oos_conf_table[2, 1]
tp = oos_conf_table[2, 2]
tn = oos_conf_table[1, 1]
num_pred_pos = sum(oos_conf_table[, 2])
num_pred_neg = sum(oos_conf_table[, 1])
num_pos = sum(oos_conf_table[2, ])
num_neg = sum(oos_conf_table[1, ])

misclassification_error = (fn + fp) / n

cat("misclassification_error", round(misclassification_error * 100, 2), "%\n")
```

```
## misclassification_error 22.68 %
```

```
precision = tp / num_pred_pos
cat("precision", round(precision * 100, 2), "%\n")
```

```
## precision 77.56 %
```

```r
recall = tp / num_pos

cat("recall", round(recall * 100, 2), "%\n")
```

```
## recall 77.02 %
```

```r
false_discovery_rate = 1 - precision

cat("false_discovery_rate", round(false_discovery_rate * 100, 2), "%\n")
```

```
## false_discovery_rate 22.44 %
```

```r
false_omission_rate = fn / num_pred_neg

cat("false_omission_rate", round(false_omission_rate * 100, 2), "%\n")
```

```
## false_omission_rate 22.91 %
```

Is this a good model? (yes/no and explain).

This is a good model, there is not much misclassification, precision is high (70%~ of positive predictions are correct) and recall is also high (70%~ of positives were located). This means that FDR and FOR will be low, since there are less false discoveries and less omissions.

There are probability asymmetric costs to the two types of errors. Assign the costs below and calculate oos total cost.

```r
c_fp = 100
c_fn = 25

oos_total_cost = fp * c_fp + fn * c_fn
oos_total_cost
```

```
## [1] 794825
```

We now wish to do asymmetric cost classification. Fit a logistic regression model to this data.

```r
logistic_mod = glm(paid_in_full ~ ., bills_data_train, family = "binomial")
p_hats_train = predict(logistic_mod, bills_data_train, type = "response")
p_hats_test = predict(logistic_mod, bills_data_test, type = "response")
y_hats_train = ifelse(p_hats_train >= 0.5, 1, 0)
```

Use the function from class to calculate all the error metrics for the values of the probability threshold being 0.001, 0.002, . . . , 0.999 in a data frame.

```r
#' Computes performance metrics for a binary probabilistic classifer
#'
#' Each row of the result will represent one of the many models and its elements record the performance
#'
#' @param p_hats  The probability estimates for n predictions
#' @param y_true  The true observed responses
```

```r
#' @param res      The resolution to use for the grid of threshold values (defaults to 1e-3)
#'
#' @return         The matrix of all performance results
compute_metrics_prob_classifier = function(p_hats, y_true, res = 0.001){
  #we first make the grid of all prob thresholds
  p_thresholds = seq(0 + res, 1 - res, by = res) #values of 0 or 1 are trivial

  #now we create a matrix which will house all of our results
  performance_metrics = matrix(NA, nrow = length(p_thresholds), ncol = 12)
  colnames(performance_metrics) = c(
    "p_th",
    "TN",
    "FP",
    "FN",
    "TP",
    "miscl_err",
    "precision",
    "recall",
    "FDR",
    "FPR",
    "FOR",
    "miss_rate"
  )

  #now we iterate through each p_th and calculate all metrics about the classifier and save
  n = length(y_true)
  for (i in 1 : length(p_thresholds)){
    p_th = p_thresholds[i]
    y_hats = factor(ifelse(p_hats >= p_th, 1, 0))
    confusion_table = table(
      factor(y_true, levels = c(0, 1)),
      factor(y_hats, levels = c(0, 1))
    )

    fp = confusion_table[1, 2]
    fn = confusion_table[2, 1]
    tp = confusion_table[2, 2]
    tn = confusion_table[1, 1]
    npp = sum(confusion_table[, 2])
    npn = sum(confusion_table[, 1])
    np = sum(confusion_table[2, ])
    nn = sum(confusion_table[1, ])

    performance_metrics[i, ] = c(
      p_th,
      tn,
      fp,
      fn,
      tp,
      (fp + fn) / n,
      tp / npp, #precision
      tp / np,  #recall
      fp / npp, #false discovery rate (FDR)
```

```r
      fp / nn,  #false positive rate (FPR)
      fn / npn, #false omission rate (FOR)
      fn / np   #miss rate
    )
  }

  #finally return the matrix
  performance_metrics
}
```

```r
#performance_metrics_out_of_sample = compute_metrics_prob_classifier(p_hats_test, y_test) %>% data.tabl
#performance_metrics_out_of_sample

performance_metrics_in_sample = compute_metrics_prob_classifier(p_hats_train, y_train) %>% data.table
performance_metrics_in_sample
```

```
##       p_th    TN    FP    FN    TP miscl_err precision       recall       FDR
##   1: 0.001 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   2: 0.002 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   3: 0.003 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   4: 0.004 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   5: 0.005 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##  ---
## 995: 0.995 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 996: 0.996 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 997: 0.997 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 998: 0.998 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 999: 0.999 83452     4 85383     2 0.5027911 0.3333333 2.342332e-05 0.6666667
##               FPR          FOR    miss_rate
##   1: 8.742451e-01 9.527439e-05 1.171166e-05
##   2: 8.742451e-01 9.527439e-05 1.171166e-05
##   3: 8.742451e-01 9.527439e-05 1.171166e-05
##   4: 8.742451e-01 9.527439e-05 1.171166e-05
##   5: 8.742451e-01 9.527439e-05 1.171166e-05
##  ---
## 995: 4.792945e-05 5.057157e-01 9.999649e-01
## 996: 4.792945e-05 5.057157e-01 9.999649e-01
## 997: 4.792945e-05 5.057157e-01 9.999649e-01
## 998: 4.792945e-05 5.057157e-01 9.999649e-01
## 999: 4.792945e-05 5.057186e-01 9.999766e-01
```

Calculate the column `total_cost` and append it to this data frame.

```r
#performance_metrics_out_of_sample %<>%
#  mutate(total_cost = c_fn * FN + c_fp * FP)

#performance_metrics_out_of_sample

performance_metrics_in_sample %<>%
  mutate(total_cost = c_fn * FN + c_fp * FP)

performance_metrics_in_sample
```

```
##       p_th    TN    FP    FN    TP miscl_err precision       recall       FDR
##   1: 0.001 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   2: 0.002 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   3: 0.003 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   4: 0.004 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##   5: 0.005 10495 72961     1 85384 0.4296280 0.5392276 9.999883e-01 0.4607724
##  ---
## 995: 0.995 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 996: 0.996 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 997: 0.997 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 998: 0.998 83452     4 85382     3 0.5027852 0.4285714 3.513498e-05 0.5714286
## 999: 0.999 83452     4 85383     2 0.5027911 0.3333333 2.342332e-05 0.6666667
##               FPR          FOR    miss_rate total_cost
##   1: 8.742451e-01 9.527439e-05 1.171166e-05    7296125
##   2: 8.742451e-01 9.527439e-05 1.171166e-05    7296125
##   3: 8.742451e-01 9.527439e-05 1.171166e-05    7296125
##   4: 8.742451e-01 9.527439e-05 1.171166e-05    7296125
##   5: 8.742451e-01 9.527439e-05 1.171166e-05    7296125
##  ---
## 995: 4.792945e-05 5.057157e-01 9.999649e-01    2134950
## 996: 4.792945e-05 5.057157e-01 9.999649e-01    2134950
## 997: 4.792945e-05 5.057157e-01 9.999649e-01    2134950
## 998: 4.792945e-05 5.057157e-01 9.999649e-01    2134950
## 999: 4.792945e-05 5.057186e-01 9.999766e-01    2134975
```

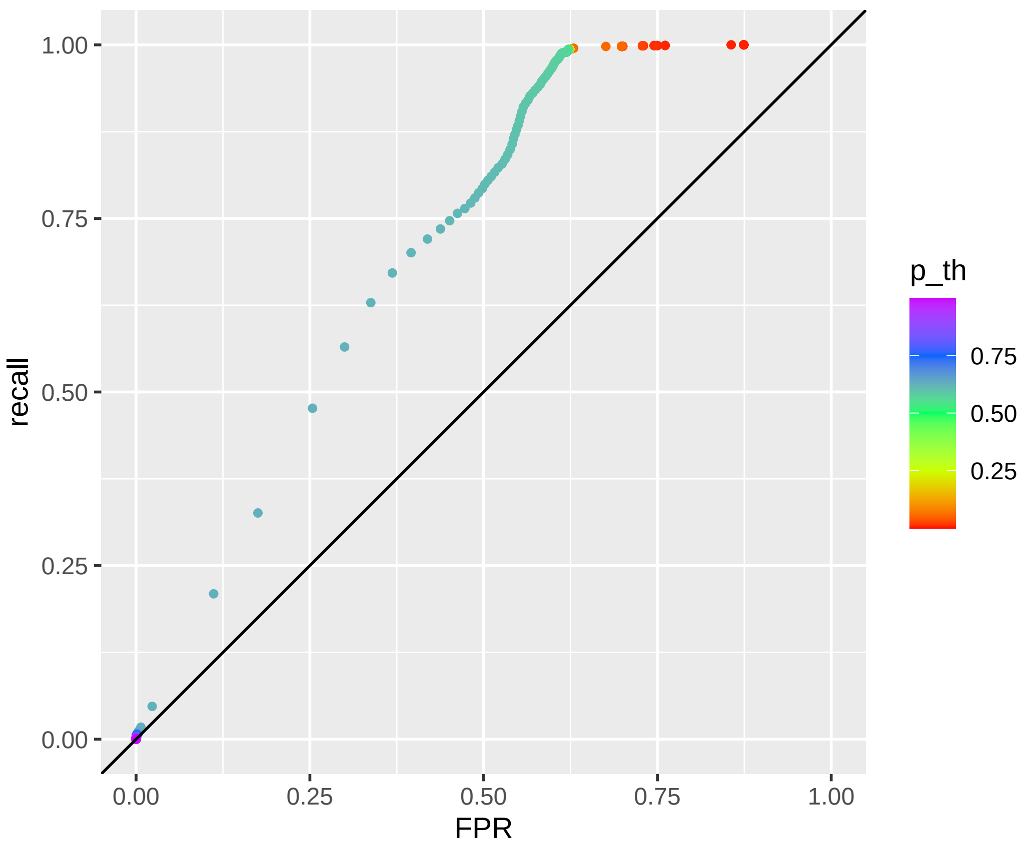
Which is the winning probability threshold value and the total cost at that threshold?

```r
#performance_metrics_out_of_sample %>%
#  arrange(total_cost) %>%
#  slice(1) %>%
#  select(p_th, total_cost)

performance_metrics_in_sample %>%
  arrange(total_cost) %>%
  slice(1) %>%
  select(p_th, total_cost)
```

```
##     p_th total_cost
## 1: 0.728    2128000
```

Plot an ROC curve and interpret.

```r
pacman::p_load(ggplot2)

ggplot(performance_metrics_in_sample) +
  geom_point(aes(x = FPR, y = recall, col = p_th), size = 1) +
  geom_abline(intercept = 0, slope = 1) +
  coord_fixed() + xlim(0, 1) + ylim(0, 1) +
  scale_colour_gradientn(colours = rainbow(5))
```




```
#ggplot(performance_metrics_out_of_sample) +
#  geom_point(aes(x = FPR, y = recall, col = p_th), size = 1) +
#  geom_abline(intercept = 0, slope = 1) +
#  coord_fixed() + xlim(0, 1) + ylim(0, 1) +
#  scale_colour_gradientn(colours = rainbow(5))
```

When there is low FPR (high specificity), the recall is also low. When FPR is high (low specificity), the recall is high. So when there is low false positive rate, there is also low recall, which means the model did not locate many of the positives. When specificity is low, recall is high.

Calculate AUC and interpret.

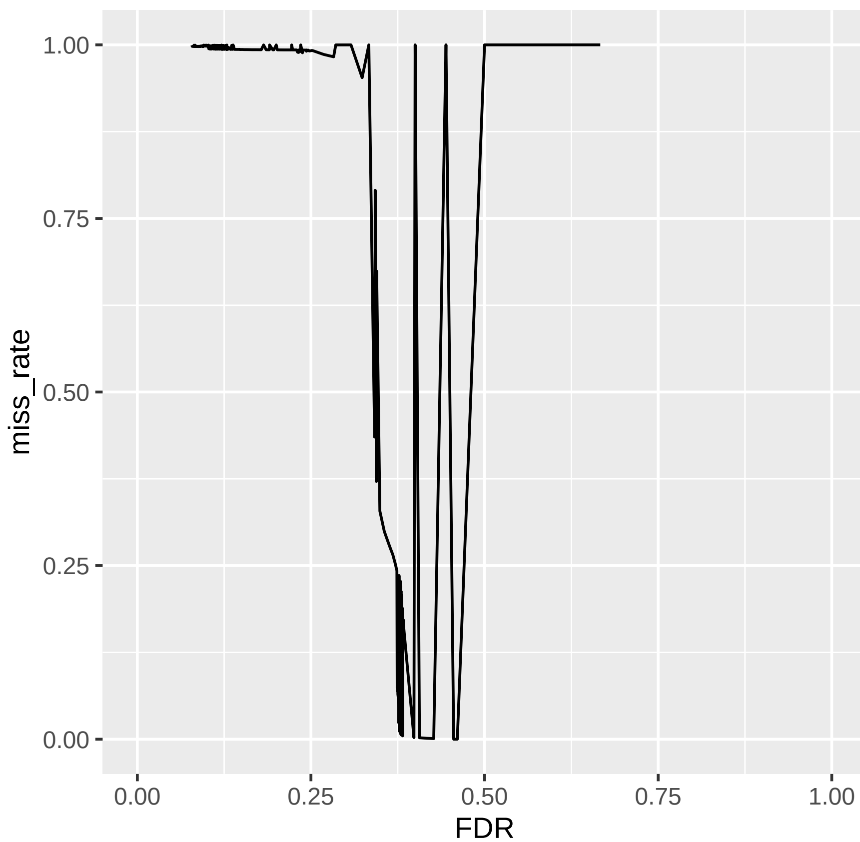
```
pacman::p_load(pracma)
#-trapz(performance_metrics_out_of_sample$FPR, performance_metrics_out_of_sample$recall)
-trapz(performance_metrics_in_sample$FPR, performance_metrics_in_sample$recall)
```

```
## [1] 0.5852239
```

AUC is around 50% which is just okay, there isn't much distinguished between 1 and 0 classifications. Typically AUC should be above 50% for a model to have predictive power.

Plot a DET curve and interpret.

```
ggplot(performance_metrics_in_sample) +
  geom_line(aes(x = FDR, y = miss_rate)) +
  coord_fixed() + xlim(0, 1) + ylim(0, 1)
```



When FDR is around 40-45% the miss rate is 0%. When the miss rate is 100% then the FDR is either around 10-25% or 50+%