EDA_and_modelling_5oct

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```r
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.4     v readr     2.1.5
## v forcats   1.0.0     v stringr   1.5.2
## v ggplot2   4.0.0     v tibble    3.3.0
## v lubridate 1.9.4     v tidyr     1.3.1
## v purrr     1.1.0
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(glmnet)
```

```
## Loading required package: Matrix
##
## Attaching package: 'Matrix'
##
## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack
##
## Loaded glmnet 4.1-10
```

```r
library(randomForest)
```

```
## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
##
## The following object is masked from 'package:dplyr':
##
##     combine
##
## The following object is masked from 'package:ggplot2':
##
##     margin
```

```r
library(xgboost)
```

```
##
## Attaching package: 'xgboost'
##
## The following object is masked from 'package:dplyr':
##
##     slice
```

```r
library(MASS)
```

```
##
## Attaching package: 'MASS'
##
## The following object is masked from 'package:dplyr':
##
##     select
```

```r
library(caret)
```

```
## Loading required package: lattice
##
## Attaching package: 'caret'
##
## The following object is masked from 'package:purrr':
##
##     lift
```

```r
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
##
## Attaching package: 'pROC'
##
## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```r
select <- dplyr::select

df <- read_csv('/Users/michaelwang/Desktop/unsw/unsw\ actl/4305/Assignment/standardised_freely_quote_da
```

```
## Rows: 70000 Columns: 77
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr   (7): destinations, traveller_ages, platform, discount, convert, quote_...
## dbl  (45): quote_price, extra_cancellation, quote_hour, trip_length, lead_le...
## lgl   (5): has_child_U12, has_teen_O13, has_adult_O18, has_senior_O65, is_fa...
## dttm  (1): quote_create_time
## date (19): trip_start_date, trip_end_date, boost_1_start_date, boost_1_end_d...
```

```
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
crime_indices <- read_csv('/Users/michaelwang/Desktop/unsw/unsw actl/4305/Assignment/cleaned_crime_indi
```

```
## Rows: 70000 Columns: 2
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (1): crime_index
## dbl (1): quote_id
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
df_trim <- df %>%
  select(-destinations, -traveller_ages, -quote_create_time, -matches("^boost_.*_date$"))

df_clean <- df_trim %>%
  mutate(
    across(starts_with("boost_"), ~ if_else(is.na(.x), 0, .x)),
    quote_hour = if_else(quote_hour > 23, 24, quote_hour)
    )

any(is.na(df_clean))
```

```
## [1] FALSE
```

```r
df_discount <- df_clean %>%
  mutate(
    discount = as.numeric(str_extract(discount, "^[0-9]*"))
  )


character_colnames <- names(df_discount)[sapply(df_discount, is.character)]

df_factors <- df_discount %>%
  mutate(
    across(all_of(character_colnames), ~ as.factor(.x))
  )

df_crime_scores <- df_factors %>%
  mutate(quote_id = row_number()) %>%
  left_join(crime_indices, by = "quote_id") %>%
  select(-quote_id)

df_crime_scores <- df_crime_scores %>%
  rowwise() %>%
  mutate(
    median_crime_index = median(as.numeric(unlist(strsplit(crime_index, ", "))))
  ) %>%
  ungroup %>%
```

```
  select(-crime_index)

df_clean_quote_hour <- df_crime_scores %>%
  mutate(quote_hour = if_else(quote_hour > 23, 24, quote_hour))

df_extra_cancellation <- df_clean_quote_hour %>%
  mutate(
    extra_cancel_tier = case_when(
      extra_cancellation == 0 ~ 0,
      extra_cancellation <= 5000 ~ 1,
      extra_cancellation > 5000 ~ 2,
      TRUE ~ 1
    )
  ) %>%
    select(-extra_cancellation)

df_final <- df_extra_cancellation %>%
  select(-quote_time)


df_eda <- df_final


df_large_quote_price <- df_eda[df_eda$quote_price > 5000,]
df_large_lengths <- df_eda[df_eda$trip_length > 365,]

df_capped <- df_eda

cap_trip_len <- quantile(df_capped$trip_length, 0.99)
df_capped$trip_length_capped <- pmin(df_capped$trip_length, cap_trip_len)

cap_price <- quantile(df_capped$quote_price, 0.99)
df_capped$quote_price_capped <- pmin(df_capped$quote_price, cap_price)

cap_lead_len <- quantile(df_capped$lead_length, 0.99)
df_capped$lead_length_capped <- pmin(df_capped$lead_length, cap_lead_len)

boost_cols_1_2 <- paste0("boost_", 1:2, "_length")
for (col in boost_cols_1_2) {
  cap_val <- quantile(df_capped[[col]], 0.99)
  df_capped[[col]] <- pmin(df_capped[[col]], cap_val)
}

boost_cols_3_4_5 <- paste0("boost_", 3:5, "_length")
for (col in boost_cols_3_4_5) {
  cap_val <- quantile(df_capped[[col]], 0.999)
  df_capped[[col]] <- pmin(df_capped[[col]], cap_val)
}

boost_cols_6_7_8 <- paste0("boost_", 6:8, "_length")
for (col in boost_cols_6_7_8) {
  cap_val <- quantile(df_capped[[col]], 0.999)
  df_capped[[col]] <- pmin(df_capped[[col]], cap_val)
```

```
}

cap_age_range <- quantile(df_capped$age_range, 0.99)
df_capped$age_range_capped <- pmin(df_capped$age_range, cap_age_range)

df_capped <- df_capped %>%
  select(-trip_length, -quote_price, -lead_length, -age_range)

df_correlation <- df_capped %>%
  select(-median_age, -min_age, -max_age)

df_correlation <- df_correlation %>%
  select(-generations, -age_range_capped, -boost_4_length, -boost_5_length, -boost_6_length, -boost_7_le

df_pretransform_modelling <- df_correlation

df_transformations <- df_correlation

box_cox_cols <- c(
  "mean_age",
  "trip_length_capped",
  "quote_price_capped",
  "lead_length_capped",
  paste0("boost_", 1:3, "_length")
)

small <- 1e-6
for (col in box_cox_cols) {
  zero_flag <- min(df_transformations[[col]])
  if (zero_flag <= 0) {
    df_transformations[[col]] <- df_transformations[[col]] + small
  }
}

X <- as.data.frame(df_transformations[, box_cox_cols])

preprocess_boxcox <- preProcess(X, method = "BoxCox")
X_boxcox  <- predict(preprocess_boxcox, X)

df_transformations[paste0(names(X_boxcox), "_boxcox")] <- X_boxcox

z_cols <- paste0(box_cox_cols, "_boxcox")
X <- as.data.frame(df_transformations[, z_cols])
preprocess_z <- preProcess(X, method = c("center", "scale"))
X_z <- predict(preprocess_z, X)

df_transformations[paste0(box_cox_cols, "_boxcox_z")] <- X_z

df_transformations <- df_transformations %>%
  select(-ends_with("_boxcox"), -all_of(box_cox_cols))

df_transformations_1 <- df_transformations
```

```r
remaining_z_cols <- c(
  "median_crime_index",
  "num_adults",
  "boost_num",
  "num_travellers",
  "discount"
)

small <- 1e-6
for (col in remaining_z_cols) {
  zero_flag <- min(df_transformations_1[[col]])
  if (zero_flag <= 0) {
    df_transformations_1[[col]] <- df_transformations_1[[col]] + small
  }
}

X_z_df <- as.data.frame(df_transformations_1[, remaining_z_cols])
preprocess_z <- preProcess(X_z_df, method = c("center", "scale"))
X_z <- predict(preprocess_z, X_z_df)
df_transformations_1[paste0(remaining_z_cols, "_z")] <- X_z

df_transformations_1 <- df_transformations_1 %>%
  select(-all_of(remaining_z_cols))

df_modelling <- df_transformations_1
```

No imb data proc

Train/Test/Val

```r
# model.matrix converts to numeric matrix to run regression, [, -1] removes convert column
X <- model.matrix(convert ~ ., df_modelling)[, -1]
y <- ifelse(df_modelling$convert == "YES", 1, 0)

set.seed(111)
# regular sampling:
# train_index <- sample(seq_len(nrow(X)), 0.8 * nrow(X))

# stratified sampling to make sure test and train have equal proportions of converted and non-converted
train_index <- createDataPartition(y, p = 0.8, list = FALSE)
# 0.25 of 0.8 is 0.2 of total

X_train <- X[train_index,]
y_train <- y[train_index]

validation_index <- createDataPartition(y_train, p = 0.25, list = FALSE)
X_val <- X_train[validation_index,]
y_val <- y_train[validation_index]
X_train_inner <- X_train[-validation_index, ]
y_train_inner <- y_train[-validation_index]
```

```r
X_test <- X[-train_index,]
y_test <- y[-train_index]

# length(y_train_inner) / length(y)
# length(y_val) / length(y)
# length(y_test) / length(y)

Train_Data <- df_modelling[train_index,]
# validation_index_df <- createDataPartition(Train_Data$convert, p = 0.25, list = FALSE)
# Validation_Data <- Train_Data[validation_index_df, ]
# Train_Data_inner<- Train_Data[-validation_index_df, ]
Validation_Data <- Train_Data[validation_index, ]
Train_Data_inner<- Train_Data[-validation_index, ]
Test_Data <- df_modelling[-train_index,]
y_test_glm <- ifelse(Test_Data$convert == "YES", 1, 0)
y_validation_glm <- ifelse(Validation_Data$convert == "YES", 1, 0)
```

GLM/Shrinkage

```r
glm_basic <- glm(convert ~ ., data = Train_Data, family = binomial)
# summary(glm_basic)
```

```r
# ridge (alpha = 0), lasso (alpha = 1), elastic Net (0 < alpha < 1)
# then check best one. At the same time, also runs default 10 fold cv on training data to pick best lam
# hyperparameter for shrinkage to control degree of penalty applied.
cv_lasso <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 1)
cv_ridge <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 0)
cv_enet <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 0.5)
```

```r
# # cv_lasso, etc. are cv.glmnet objects - running coef on them returns a sparse coeff matrix with one
# # fitted coeffecients, with intercept in first row. This is with the best lambda, stored in the cv.gl
coef_lasso <- coef(cv_lasso, s = "lambda.min")
# coef_ridge <- coef(cv_ridge, s = "lambda.min")
# coef_enet <- coef(cv_enet, s = "lambda.min")

# # this extracts that column of coeffecients, keeps only the non 0 ones, and keeps it as a matrix (dro
# prevent dropping into a vector); then returns top 20.
lasso_nonzero <- coef_lasso[coef_lasso[,1] != 0, , drop = FALSE]
sort(lasso_nonzero[,1], decreasing = TRUE)[1:20]
```

```
##                    (Intercept)                     Antarctica
##                     51.9998897                      0.7423665
##                     discount_z    trip_length_capped_boxcox_z
##                      0.6093428                      0.6016991
##                has_child_U12TRUE                  South_America
##                      0.5882245                      0.5609581
##                  North_America        group_typesingle_old_O60
##                      0.4973767                      0.4836544
## group_typeolder_parents_family                         Africa
##                      0.4073433                      0.3744716
```

```
##                  boost_num_z                   gadget_cover
##                    0.3408810                      0.3398086
##                   snowsports                   Central_Asia
##                    0.3185885                      0.3177019
##                  Middle_East    group_typesingle_middle_U60
##                    0.2988412                      0.2614825
##     group_typesingle_young_U30                 has_teen_013TRUE
##                    0.2526183                      0.2312086
##             motorcycle_cover                Domestic_Cruise
##                    0.2247859                      0.2224792
```

```r
# ridge_nonzero <- coef_ridge[coef_ridge[,1] != 0, , drop = FALSE]
# sort(ridge_nonzero[,1], decreasing = TRUE)[1:20]

# enet_nonzero <- coef_enet[coef_enet[,1] != 0, , drop = FALSE]
# sort(enet_nonzero[,1], decreasing = TRUE)[1:20]

# # cv error vs log(lambda)
# plot(cv_lasso)
# plot(cv_ridge)
# plot(cv_enet)
```

```r
# type = response means to give probabilities for logistic reg instead of values for normal regression
# predict() as a universal apply data to model base r function

# idea of using dataframe for glm prediction and matrix for shrinkage prediction i think is because of
# the glm model saw the original data, so it was the test data in the same form to help process. The sh
# saw the data frame only a matrix rep, so thus it wants it in the same format.

pred_glm <- predict(glm_basic, newdata = Test_Data, type = "response")
pred_lasso <- predict(cv_lasso, newx = X_test, type = "response", s = "lambda.min")
pred_ridge <- predict(cv_ridge, newx = X_test, type = "response", s = "lambda.min")
pred_enet <- predict(cv_enet, newx = X_test, type = "response", s = "lambda.min")

glm_class <- ifelse(pred_glm > 0.5, 1, 0)
lasso_class <- ifelse(pred_lasso > 0.5, 1, 0)
ridge_class <- ifelse(pred_ridge > 0.5, 1, 0)
enet_class <- ifelse(pred_enet > 0.5, 1, 0)

acc_glm <- mean(glm_class == y_test_glm)
acc_lasso <- mean(lasso_class == y_test)
acc_ridge <- mean(ridge_class == y_test)
acc_enet <- mean(enet_class == y_test)

c(glm = acc_glm, Lasso = acc_lasso, Ridge = acc_ridge, ElasticNet = acc_enet)
```

```
##        glm      Lasso      Ridge ElasticNet
##  0.8824286  0.8822857  0.8806429  0.8823571
```

```r
calculate_metrics <- function(predictions, actual) {
  tp <- sum(predictions == 1 & actual == 1)
  tn <- sum(predictions == 0 & actual == 0)
  fp <- sum(predictions == 1 & actual == 0)
```

```r
  fn <- sum(predictions == 0 & actual == 1)

  accuracy <- (tp + tn) / (tp + tn + fp + fn)
  precision <- tp / (tp + fp)
  recall <- tp / (tp + fn)
  specificity <- tn / (tn + fp)
  f1 <- 2 * precision * recall / (precision + recall)

  return(c(
    Accuracy = accuracy,
    Precision = precision,
    Recall = recall,
    Specificity = specificity,
    F1_Score = f1
  ))
}

metrics_glm <- calculate_metrics(glm_class, y_test_glm)
metrics_lasso <- calculate_metrics(lasso_class, y_test)
metrics_ridge <- calculate_metrics(ridge_class, y_test)
metrics_enet  <- calculate_metrics(enet_class, y_test)

comparison_table <- data.frame(
  GLM = metrics_glm,
  Lasso = metrics_lasso,
  Ridge = metrics_ridge,
  ElasticNet = metrics_enet
)

print(round(comparison_table, 4))
```

```
##                GLM  Lasso  Ridge ElasticNet
## Accuracy    0.8824 0.8823 0.8806     0.8824
## Precision   0.6159 0.6147 0.6238     0.6161
## Recall      0.1550 0.1533 0.1110     0.1533
## Specificity 0.9862 0.9863 0.9905     0.9864
## F1_Score    0.2477 0.2454 0.1884     0.2455
```

```r
library(pROC)
roc_glm <- roc(y_test_glm, as.vector(pred_glm))
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```r
roc_lasso <- roc(y_test, as.vector(pred_lasso))
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
roc_ridge <- roc(y_test, as.vector(pred_ridge))
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
roc_enet <- roc(y_test, as.vector(pred_enet))
```

```
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

```r
auc(roc_glm)
```

```
## Area under the curve: 0.8047
```

```r
auc(roc_lasso)
```

```
## Area under the curve: 0.8046
```

```r
auc(roc_ridge)
```

```
## Area under the curve: 0.8011
```

```r
auc(roc_enet)
```

```
## Area under the curve: 0.8045
```

LASSO for more interpretability (feature selection)

ENET for slightly more stable coeffecients

HORRENDOUS F1 SCORE when not treating any imbalanced data stuff.

RF

```r
df_tree_modelling <- df_eda %>%
  select(-median_age, -min_age, -max_age, -generations, -age_range)
```

```r
set.seed(111)
# df_tree_modelling$convert <- factor(df_tree_modelling$convert, , levels = c("NO","YES"))
df_tree_modelling$convert <- factor(df_tree_modelling$convert)

y_tree <- df_tree_modelling$convert
train_index <- createDataPartition(y_tree, p = 0.8, list = FALSE)

y_train_tree <- y_tree[train_index]
validation_index <- createDataPartition(y_train_tree, p = 0.25, list = FALSE)
```

```r
tree_train <- df_tree_modelling[train_index, ]
tree_train_inner <- tree_train[-validation_index, ]
tree_val <- tree_train[validation_index, ]
tree_test <- df_tree_modelling[-train_index, ]
y_val_tree <- as.numeric(ifelse(tree_val$convert == "YES", 1, 0))
y_test_tree <- as.numeric(ifelse(tree_test$convert == "YES", 1, 0))
```

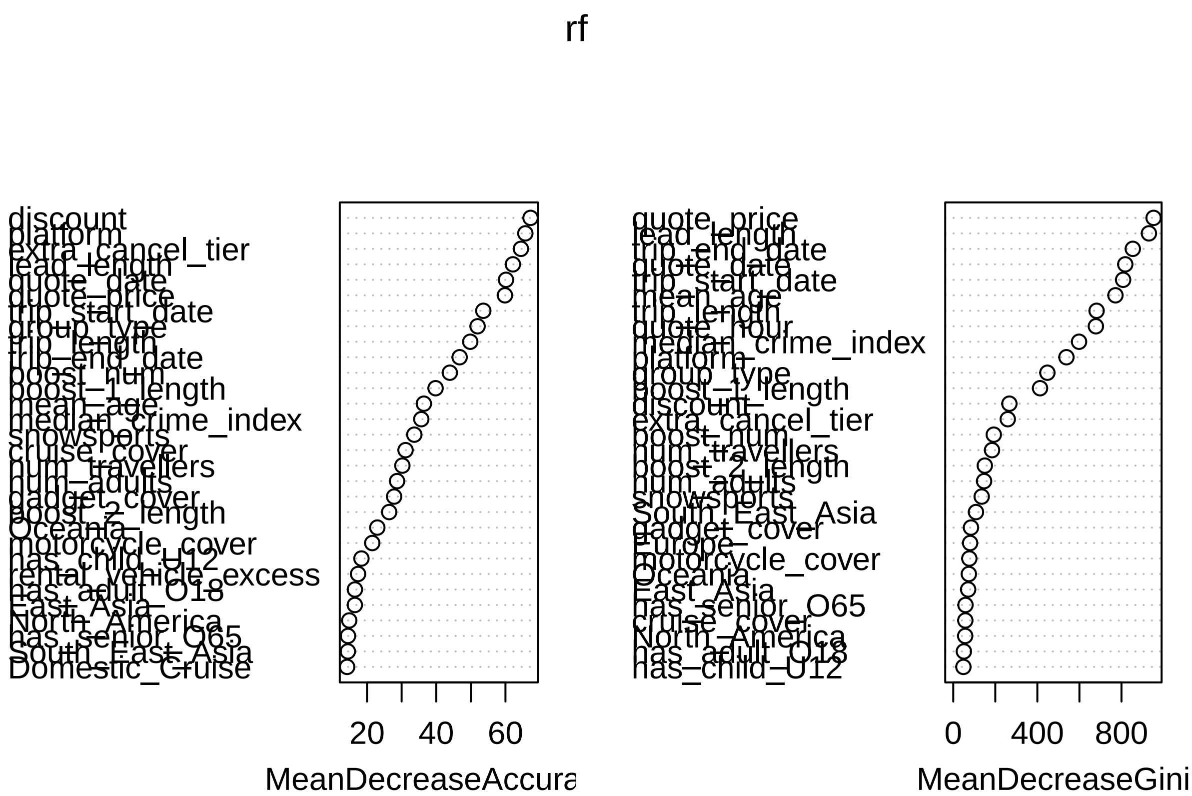
```r
set.seed(222)
rf <- randomForest(
  convert ~ .,
  data = tree_train,
  ntree = 500,
  mtry = floor(sqrt(ncol(tree_train) - 1)),
  importance = TRUE
)

# type = prob returns probabilities instead of class labels. This is for several reasons,
# first is calculating metrics like ROC or just probability in general, and second for
# later decision threshold tuning. [, "YES"] means we select the YES probability column.
pred_test <- predict(rf, tree_test, type = "prob")[, "YES"]
pred_class <- ifelse(pred_test >= 0.5, 1, 0)
rf_metrics <- calculate_metrics(pred_class, y_test_tree)

# RUN THESE ONLY
rf_metrics
```

```
##    Accuracy   Precision      Recall Specificity    F1_Score
##   0.8703479   0.4836601   0.1233333   0.9805722   0.1965471
```

```r
print(rf)
```

```
##
## Call:
##  randomForest(formula = convert ~ ., data = tree_train, ntree = 500,      mtry = floor(sqrt(ncol(tre
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 7
##
##         OOB estimate of  error rate: 12.86%
## Confusion matrix:
##        NO YES class.error
## NO  47906 894  0.01831967
## YES  6309 892  0.87612832
```

```r
varImpPlot(rf)
```



Imb data procs

GLM DTO

```
optimise_threshold <- function(predictions, actual, metric = "f1") {
  thresholds <- seq(0.1, 0.9, by = 0.01)
  results <- data.frame(
    threshold = thresholds,
    accuracy = NA,
    precision = NA,
    recall = NA,
    f1 = NA,
    specificity = NA
  )

  # quick logic for this loop: predictions is a numeric vector of probabilities. Use an if else to chan
  # into class labels 1 or 0 according to the new threshold. Scan across all the thresholds, calculate
  # neg, false pos and false neg. Then use these to calculate the diff metrics to eventually get to F1

  # At the end, we have a results data frame. Append each metric into the result data frame, such that
  # the result data frame is a list of the metrics for each threshold level.

  for (i in seq_along(thresholds)) {
```

```r
    threshold <- thresholds[i]
    pred_class <- ifelse(predictions > threshold, 1, 0)

    tp <- sum(pred_class == 1 & actual == 1)
    tn <- sum(pred_class == 0 & actual == 0)
    fp <- sum(pred_class == 1 & actual == 0)
    fn <- sum(pred_class == 0 & actual == 1)

    results$accuracy[i] <- (tp + tn) / (tp + tn + fp + fn)
    results$precision[i] <- tp / (tp + fp)
    results$recall[i] <- tp / (tp + fn)
    results$f1[i] <- 2 * results$precision[i] * results$recall[i] / (results$precision[i] + results$reca
    results$specificity[i] <- tn / (tn + fp)
  }

  # which picks out the index of the list which is the highest. We can decide which metric to use. Here
  # to F1 since its the best indicator overall esp for this imbalanced data.
  # then we extract the threshold that corresponds do it, and return everything.

  optimal_index <- which.max(results[[metric]])
  optimal_threshold <- results$threshold[optimal_index]

  return(list(
    optimal_threshold = optimal_threshold,
    all_results = results,
    best_metrics = results[optimal_index, ]
  ))
}
```

```r
glm_dt_opt <- glm(convert ~ ., data = Train_Data_inner, family = binomial)
cv_lasso_dt_opt <- cv.glmnet(X_train_inner, y_train_inner,
                             family = "binomial", alpha = 1)
cv_ridge_dt_opt <- cv.glmnet(X_train_inner, y_train_inner,
                             family = "binomial", alpha = 0)
cv_enet_dt_opt <- cv.glmnet(X_train_inner, y_train_inner,
                            family = "binomial", alpha = 0.5)

pred_glm_dt_opt_val <- predict(glm_dt_opt, newdata = Validation_Data, type = "response")
pred_lasso_dt_opt_val <- predict(cv_lasso_dt_opt, newx = X_val, type = "response",
                      s = "lambda.min")
pred_ridge_dt_opt_val <- predict(cv_ridge_dt_opt, newx = X_val, type = "response",
                      s = "lambda.min")
pred_enet_dt_opt_val <- predict(cv_enet_dt_opt,  newx = X_val, type = "response",
                     s = "lambda.min")

opt_glm_dt_opt <- optimise_threshold(pred_glm_dt_opt_val, y_validation_glm, metric = "f1")
opt_lasso_dt_opt <- optimise_threshold(pred_lasso_dt_opt_val, y_val, metric = "f1")
opt_ridge_dt_opt <- optimise_threshold(pred_ridge_dt_opt_val, y_val, metric = "f1")
opt_enet_dt_opt <- optimise_threshold(pred_enet_dt_opt_val, y_val, metric = "f1")
```

```r
res_lasso_dt_opt <- opt_lasso_dt_opt$all_results

ggplot(res_lasso_dt_opt, aes(x = threshold, y = f1)) +
```

```
  geom_line() +
  geom_vline(xintercept = opt_lasso_dt_opt$optimal_threshold, linetype = 2) +
  geom_point(data = subset(res_lasso_dt_opt,
                           threshold == opt_lasso_dt_opt$optimal_threshold),
             aes(x = threshold, y = f1), size = 2) +
  labs(title = "Decision Threshold Optimisation (F1)",
       subtitle = paste("Optimal threshold =",
                        round(opt_lasso_dt_opt$optimal_threshold, 3)),
       x = "Threshold", y = "F1 score") +
  theme_minimal()
```


```
# ValidatioN Results After Tuning Decision Threshold
res_glm_dt_opt <- opt_glm_dt_opt$all_results
res_ridge_dt_opt <- opt_ridge_dt_opt$all_results
res_enet_dt_opt <- opt_enet_dt_opt$all_results

res_glm_dt_opt[res_glm_dt_opt$threshold == opt_glm_dt_opt$optimal_threshold,]
```

```
##   threshold  accuracy precision    recall        f1 specificity
## 9      0.18 0.7981429 0.3526188 0.6232508 0.4504084   0.8249053
```

```
res_lasso_dt_opt[res_lasso_dt_opt$threshold == opt_lasso_dt_opt$optimal_threshold,]
```

```
##   threshold  accuracy precision    recall        f1 specificity
## 9      0.18 0.7970714 0.3510155 0.6232508 0.4490983   0.8236699
```

```r
res_ridge_dt_opt[res_ridge_dt_opt$threshold == opt_ridge_dt_opt$optimal_threshold,]
```

```
##   threshold  accuracy precision    recall        f1 specificity
## 8      0.17 0.7864286 0.3406532 0.6512379 0.4473198   0.8071158
```

```r
res_enet_dt_opt[res_enet_dt_opt$threshold == opt_enet_dt_opt$optimal_threshold,]
```

```
##   threshold  accuracy precision    recall        f1 specificity
## 9      0.18 0.7976429 0.3518687 0.6232508 0.4497961   0.8243288
```

```r
# Model Eval Using Test Set
pred_glm_dt_opt <- predict(glm_dt_opt, newdata = Test_Data, type = "response")
pred_lasso_dt_opt <- predict(cv_lasso_dt_opt, newx = X_test, type = "response",
                      s = "lambda.min")
pred_ridge_dt_opt <- predict(cv_ridge_dt_opt, newx = X_test, type = "response",
                      s = "lambda.min")
pred_enet_dt_opt <- predict(cv_enet_dt_opt,  newx = X_test, type = "response",
                     s = "lambda.min")

glm_class_dt_opt <- ifelse(pred_glm_dt_opt > opt_glm_dt_opt$optimal_threshold, 1, 0)
lasso_class_dt_opt <- ifelse(pred_lasso_dt_opt > opt_lasso_dt_opt$optimal_threshold,
                             1, 0)
ridge_class_dt_opt <- ifelse(pred_ridge_dt_opt > opt_ridge_dt_opt$optimal_threshold,
                             1, 0)
enet_class_dt_opt <- ifelse(pred_enet_dt_opt  > opt_enet_dt_opt$optimal_threshold, 1, 0)

metrics_glm_dt_opt <- calculate_metrics(glm_class_dt_opt, y_test_glm)
metrics_lasso_dt_opt <- calculate_metrics(lasso_class_dt_opt, y_test)
metrics_ridge_dt_opt <- calculate_metrics(ridge_class_dt_opt, y_test)
metrics_enet_dt_opt <- calculate_metrics(enet_class_dt_opt,  y_test)

comparison_table <- data.frame(
  GLM = metrics_glm_dt_opt,
  Lasso = metrics_lasso_dt_opt,
  Ridge = metrics_ridge_dt_opt,
  ElasticNet = metrics_enet_dt_opt
)
comparison_table
```

```
##                   GLM     Lasso     Ridge ElasticNet
## Accuracy    0.8024286 0.8014286 0.7905714  0.8012857
## Precision   0.3333333 0.3320312 0.3194021  0.3317057
## Recall      0.5823799 0.5835240 0.5989703  0.5829519
## Specificity 0.8338230 0.8325171 0.8179073  0.8324355
## F1_Score    0.4239900 0.4232365 0.4166335  0.4228216
```

RF DTO

```r
set.seed(222)
rf_dto <- randomForest(
  convert ~ .,
  data = tree_train_inner,
  ntree = 500,
  mtry  = floor(sqrt(ncol(tree_train_inner) - 1)),
  importance = TRUE
)

pred_val <- predict(rf_dto, tree_val, type = "prob")[, "YES"]
opt_rf_dto <- optimise_threshold(pred_val, y_val_tree, metric = "f1")
res_opt_rf_dto <- opt_rf_dto$all_results
cat("Validation Results")
```

```
## Validation Results
```

```r
res_opt_rf_dto[res_opt_rf_dto$threshold == opt_rf_dto$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 11       0.2 0.7977287 0.3400558 0.6085508 0.4363057   0.8256557
```

```r
pred_test_dto <- predict(rf_dto, tree_test, type = "prob")[, "YES"]
rf_class_dt_opt <- ifelse(pred_test_dto > opt_rf_dto$optimal_threshold, 1, 0)
metrics_rf_dto <- calculate_metrics(rf_class_dt_opt, y_test_tree)
metrics_rf_dto
```

```
##    Accuracy   Precision      Recall Specificity    F1_Score
##   0.7995571   0.3447531   0.6205556   0.8259693   0.4432540
```

U/D Sampling

glmnet / cv.glmnet (logistic) - for family="binomial", glmnet expects a binary outcome. It accepts either numeric 0/1, or a 2-level factor (internally converted to 0/1 with the first level as 0). Turning it into numeric makes it simple and less error prone (0/1 encoding)

randomForest - in rf, the task is inferred from the type of y. if y is factor, it is classification forest (type="prob" gives class probs as mentioned earlier). if y is numeric, we will get a regression forest (continuous outputs; no type="prob").

Thus pass numeric into glm but factor into

```r
X_train_matrix <- as.data.frame(X_train)
y_train_fac <- as.factor(Train_Data$convert)

set.seed(123)
train_up <- upSample(x = X_train_matrix, y = y_train_fac, yname = "convert")
X_train_up <- data.matrix(subset(train_up, select = -convert))
y_train_up <- as.numeric(train_up$convert)

set.seed(123)
train_down <- downSample(x = X_train_matrix, y = y_train_fac, yname = "convert")
```

```r
X_train_down <- data.matrix(subset(train_down, select = -convert))
y_train_down <- as.numeric(train_down$convert)

Train_Data_up <- Train_Data
Train_Data_up$convert <- factor(Train_Data_up$convert, levels = c("NO","YES"))

set.seed(123)
up_train <- upSample(x = subset(Train_Data_up, select = -convert),
                     y = Train_Data_up$convert, yname = "convert")

Train_Data_down <- Train_Data
Train_Data_down$convert <- factor(Train_Data_down$convert, levels = c("NO","YES"))

set.seed(123)
down_train <- upSample(x = subset(Train_Data_down, select = -convert),
                     y = Train_Data_down$convert, yname = "convert")
# prop table is just table but in proportions
# prop.table(table(y_train))
# prop.table(table(y_train_up))
# prop.table(table(y_train_down))

X_train_inner_matrix <- as.data.frame(X_train_inner)
y_train_inner_fac <- droplevels(as.factor(y_train_inner))

set.seed(123)
train_up_inner <- upSample(x = X_train_inner_matrix, y = y_train_inner_fac, yname = "convert")
X_train_inner_up <- data.matrix(subset(train_up_inner, select = -convert))
y_train_inner_up <- as.numeric(as.character(train_up_inner$convert))

set.seed(123)
train_down_inner <- downSample(x = X_train_inner_matrix, y = y_train_inner_fac, yname = "convert")
X_train_inner_down <- data.matrix(subset(train_down_inner, select = -convert))
y_train_inner_down <- as.numeric(as.character(train_down_inner$convert))

Train_Data_inner_up <- Train_Data_inner
Train_Data_inner_up$convert <- factor(Train_Data_inner_up$convert, levels = c("NO","YES"))

set.seed(123)
up_train_inner <- upSample(x = subset(Train_Data_inner_up, select = -convert),
                     y = Train_Data_inner_up$convert, yname = "convert")

Train_Data_inner_down <- Train_Data_inner
Train_Data_inner_down$convert <- factor(Train_Data_inner_down$convert, levels = c("NO","YES"))

set.seed(123)
down_train_inner <- upSample(x = subset(Train_Data_inner_down, select = -convert),
                     y = Train_Data_inner_down$convert, yname = "convert")
```

```r
# set seed is a random number SEQUENCE setter - use it again before each random act to make sure each r
set.seed(111)
glm_up <- glm(convert ~ ., data = up_train, family = binomial)
cv_lasso_up  <- cv.glmnet(X_train_up, y_train_up, family = "binomial", alpha = 1)
cv_ridge_up  <- cv.glmnet(X_train_up, y_train_up, family = "binomial", alpha = 0)
```

```r
cv_enet_up   <- cv.glmnet(X_train_up, y_train_up, family = "binomial", alpha = 0.5)

set.seed(111)
glm_down <- glm(convert ~ ., data = down_train, family = binomial)
cv_lasso_down <- cv.glmnet(X_train_down, y_train_down, family = "binomial", alpha = 1)
cv_ridge_down <- cv.glmnet(X_train_down, y_train_down, family = "binomial", alpha = 0)
cv_enet_down <- cv.glmnet(X_train_down, y_train_down, family = "binomial", alpha = 0.5)
```

```r
pred_glm_up <- predict(glm_up, newdata = Test_Data, type = "response")
pred_lasso_up <- predict(cv_lasso_up, newx = X_test, type = "response", s = "lambda.min")
pred_ridge_up <- predict(cv_ridge_up, newx = X_test, type = "response", s = "lambda.min")
pred_enet_up  <- predict(cv_enet_up,  newx = X_test, type = "response", s = "lambda.min")

glm_class_up <- ifelse(pred_glm_up > 0.5, 1, 0)
lasso_class_up <- ifelse(pred_lasso_up > 0.5, 1, 0)
ridge_class_up <- ifelse(pred_ridge_up > 0.5, 1, 0)
enet_class_up  <- ifelse(pred_enet_up  > 0.5, 1, 0)

metrics_glm_up <- calculate_metrics(glm_class_up, y_test_glm)
metrics_lasso_up <- calculate_metrics(lasso_class_up, y_test)
metrics_ridge_up <- calculate_metrics(ridge_class_up, y_test)
metrics_enet_up  <- calculate_metrics(enet_class_up,  y_test)

comparison_table <- data.frame(
  GLM = metrics_glm_up,
  Lasso = metrics_lasso_up,
  Ridge = metrics_ridge_up,
  ElasticNet = metrics_enet_up
)

print(round(comparison_table, 4))
```

```
##                GLM  Lasso  Ridge ElasticNet
## Accuracy    0.7358 0.7356 0.7231     0.7356
## Precision   0.2836 0.2837 0.2731     0.2837
## Recall      0.7311 0.7328 0.7328     0.7328
## Specificity 0.7365 0.7360 0.7217     0.7360
## F1_Score    0.4086 0.4091 0.3979     0.4091
```

```r
pred_glm_down <- predict(glm_down, newdata = Test_Data, type = "response")
pred_lasso_down <- predict(cv_lasso_down, newx = X_test, type = "response",
                           s = "lambda.min")
pred_ridge_down <- predict(cv_ridge_down, newx = X_test, type = "response",
                           s = "lambda.min")
pred_enet_down <- predict(cv_enet_down, newx = X_test, type = "response",
                          s = "lambda.min")

glm_class_down <- ifelse(pred_glm_down > 0.5, 1, 0)
lasso_class_down <- ifelse(pred_lasso_down > 0.5, 1, 0)
ridge_class_down <- ifelse(pred_ridge_down > 0.5, 1, 0)
enet_class_down <- ifelse(pred_enet_down  > 0.5, 1, 0)
```

```r
metrics_glm_down <- calculate_metrics(glm_class_down, y_test_glm)
metrics_lasso_down <- calculate_metrics(lasso_class_down, y_test)
metrics_ridge_down <- calculate_metrics(ridge_class_down, y_test)
metrics_enet_down <- calculate_metrics(enet_class_down,  y_test)

comparison_table <- data.frame(
  GLM = metrics_glm_down,
  Lasso = metrics_lasso_down,
  Ridge = metrics_ridge_down,
  ElasticNet = metrics_enet_down
)
print(round(comparison_table, 4))
```

```
##                GLM  Lasso  Ridge ElasticNet
## Accuracy    0.7358 0.7314 0.7179     0.7314
## Precision   0.2836 0.2807 0.2710     0.2808
## Recall      0.7311 0.7368 0.7454     0.7374
## Specificity 0.7365 0.7306 0.7139     0.7306
## F1_Score    0.4086 0.4065 0.3975     0.4068
```

U/D Samp+DTO

```r
# attempt for u/d sampling with earlier optimal decision threshold
# up:
glm_class_up <- ifelse(pred_glm_up > opt_glm_dt_opt$optimal_threshold, 1, 0)
lasso_class_up <- ifelse(pred_lasso_up > opt_lasso_dt_opt$optimal_threshold, 1, 0)
ridge_class_up <- ifelse(pred_ridge_up > opt_ridge_dt_opt$optimal_threshold, 1, 0)
enet_class_up <- ifelse(pred_enet_up > opt_enet_dt_opt$optimal_threshold, 1, 0)

metrics_glm_up <- calculate_metrics(glm_class_up, y_test_glm)
metrics_lasso_up <- calculate_metrics(lasso_class_up, y_test)
metrics_ridge_up <- calculate_metrics(ridge_class_up, y_test)
metrics_enet_up <- calculate_metrics(enet_class_up, y_test)

comparison_table <- data.frame(
  GLM = metrics_glm_up,
  Lasso = metrics_lasso_up,
  Ridge = metrics_ridge_up,
  ElasticNet = metrics_enet_up
)

print(round(comparison_table, 4))
```

```
##                GLM  Lasso  Ridge ElasticNet
## Accuracy    0.3866 0.3845 0.3203     0.3843
## Precision   0.1652 0.1648 0.1530     0.1648
## Recall      0.9657 0.9662 0.9794     0.9662
## Specificity 0.3040 0.3015 0.2262     0.3013
## F1_Score    0.2822 0.2816 0.2646     0.2815
```

```r
glm_class_down <- ifelse(pred_glm_down > opt_glm_dt_opt$optimal_threshold, 1, 0)
lasso_class_down <- ifelse(pred_lasso_down > opt_lasso_dt_opt$optimal_threshold, 1, 0)
ridge_class_down <- ifelse(pred_ridge_down > opt_ridge_dt_opt$optimal_threshold, 1, 0)
enet_class_down <- ifelse(pred_enet_down > opt_enet_dt_opt$optimal_threshold, 1, 0)

metrics_glm_down <- calculate_metrics(glm_class_down, y_test_glm)
metrics_lasso_down <- calculate_metrics(lasso_class_down, y_test)
metrics_ridge_down <- calculate_metrics(ridge_class_down, y_test)
metrics_enet_down <- calculate_metrics(enet_class_down, y_test)

comparison_table <- data.frame(
  GLM = metrics_glm_down,
  Lasso = metrics_lasso_down,
  Ridge = metrics_ridge_down,
  ElasticNet = metrics_enet_down
)
print(round(comparison_table, 4))
```

```
##                GLM  Lasso  Ridge ElasticNet
## Accuracy    0.3866 0.3872 0.3210     0.3872
## Precision   0.1652 0.1654 0.1532     0.1654
## Recall      0.9657 0.9657 0.9805     0.9657
## Specificity 0.3040 0.3047 0.2269     0.3047
## F1_Score    0.2822 0.2824 0.2650     0.2824
```

```r
# Actual optimisation:
set.seed(111)
glm_up_inner <- glm(convert ~ ., data = up_train_inner, family = binomial)
cv_lasso_up_inner <- cv.glmnet(X_train_inner_up, y_train_inner_up,
                          family = "binomial", alpha = 1)
cv_ridge_up_inner <- cv.glmnet(X_train_inner_up, y_train_inner_up,
                          family = "binomial", alpha = 0)
cv_enet_up_inner <- cv.glmnet(X_train_inner_up, y_train_inner_up,
                          family = "binomial", alpha = 0.5)

set.seed(111)
glm_down_inner <- glm(convert ~ ., data = down_train_inner, family = binomial)
cv_lasso_down_inner <- cv.glmnet(X_train_inner_down, y_train_inner_down,
                                 family = "binomial", alpha = 1)
cv_ridge_down_inner <- cv.glmnet(X_train_inner_down, y_train_inner_down,
                                 family = "binomial", alpha = 0)
cv_enet_down_inner <- cv.glmnet(X_train_inner_down, y_train_inner_down,
                                family = "binomial", alpha = 0.5)
```

```r
set.seed(111)
pred_glm_up_inner <- predict(glm_up_inner, newdata = Validation_Data, type = "response")
pred_lasso_up_inner <- predict(cv_lasso_up_inner, newx = X_val, type = "response", s = "lambda.min")
pred_ridge_up_inner <- predict(cv_ridge_up_inner, newx = X_val, type = "response", s = "lambda.min")
pred_enet_up_inner <- predict(cv_enet_up_inner,  newx = X_val, type = "response", s = "lambda.min")

pred_glm_down_inner <- predict(glm_down_inner, newdata = Validation_Data,
                               type = "response")
pred_lasso_down_inner <- predict(cv_lasso_down_inner, newx = X_val, type = "response", s = "lambda.min"
```

```r
pred_ridge_down_inner <- predict(cv_ridge_down_inner, newx = X_val, type = "response", s = "lambda.min"
pred_enet_down_inner <- predict(cv_enet_down_inner,  newx = X_val, type = "response", s = "lambda.min")
```

```r
# up
set.seed(111)
opt_glm_up_inner <- optimise_threshold(pred_glm_up_inner,
                                       y_validation_glm, metric = "f1")
opt_lasso_up_inner <- optimise_threshold(pred_lasso_up_inner, y_val, metric = "f1")
opt_ridge_up_inner <- optimise_threshold(pred_ridge_up_inner, y_val, metric = "f1")
opt_enet_up_inner <- optimise_threshold(pred_enet_up_inner, y_val, metric = "f1")

res_glm_up_inner <- opt_glm_up_inner$all_results
res_lasso_up_inner <- opt_lasso_up_inner$all_results
res_ridge_up_inner <- opt_ridge_up_inner$all_results
res_enet_up_inner <- opt_enet_up_inner$all_results

res_glm_up_inner[res_glm_up_inner$threshold == opt_glm_up_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 51       0.6 0.7973571 0.3498927 0.6141012 0.4457902   0.8253994
```

```r
res_lasso_up_inner[res_lasso_up_inner$threshold == opt_lasso_up_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 51       0.6 0.7979286 0.3504774 0.6124865 0.4458374   0.8263054
```

```r
res_ridge_up_inner[res_ridge_up_inner$threshold == opt_ridge_up_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 49      0.58 0.7879286   0.33959 0.6329386 0.4420222   0.8116455
```

```r
res_enet_up_inner[res_enet_up_inner$threshold == opt_enet_up_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 51       0.6 0.7977857 0.3502616 0.6124865 0.4456628   0.8261407
```

```r
# down
opt_glm_down_inner <- optimise_threshold(pred_glm_down_inner,
                                         y_validation_glm, metric = "f1")
opt_lasso_down_inner <- optimise_threshold(pred_lasso_down_inner, y_val, metric = "f1")
opt_ridge_down_inner <- optimise_threshold(pred_ridge_down_inner, y_val, metric = "f1")
opt_enet_down_inner <- optimise_threshold(pred_enet_down_inner, y_val, metric = "f1")

res_glm_down_inner <- opt_glm_down_inner$all_results
res_lasso_down_inner <- opt_lasso_down_inner$all_results
res_ridge_down_inner <- opt_ridge_down_inner$all_results
res_enet_down_inner <- opt_enet_down_inner$all_results
res_glm_down_inner[res_glm_down_inner$threshold == opt_glm_down_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 51       0.6 0.7973571 0.3498927 0.6141012 0.4457902   0.8253994
```

```r
res_lasso_down_inner[res_lasso_down_inner$threshold ==
                       opt_lasso_down_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 53      0.62 0.8046429 0.3563708 0.5855759 0.4430869    0.838165
```

```r
res_ridge_down_inner[res_ridge_down_inner$threshold ==
                       opt_ridge_down_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall        f1 specificity
## 51       0.6 0.7992857 0.3500315 0.5979548 0.4415739   0.8300939
```

```r
res_enet_down_inner[res_enet_down_inner$threshold ==
                      opt_enet_down_inner$optimal_threshold,]
```

```
##    threshold  accuracy precision    recall       f1 specificity
## 53      0.62 0.8057857 0.3580613 0.5844995 0.444081   0.8396475
```

```r
# test set
# up
pred_glm_up_inner <- predict(glm_up_inner, newdata = Test_Data, type = "response")
pred_lasso_up_inner <- predict(cv_lasso_up_inner, newx = X_test, type = "response",
                      s = "lambda.min")
pred_ridge_up_inner <- predict(cv_ridge_up_inner, newx = X_test, type = "response",
                      s = "lambda.min")
pred_enet_up_inner <- predict(cv_enet_up_inner,  newx = X_test, type = "response",
                     s = "lambda.min")

glm_class_up_inner <- ifelse(pred_glm_up_inner >
                               opt_glm_up_inner$optimal_threshold, 1, 0)
lasso_class_up_inner <- ifelse(pred_lasso_up_inner >
                                 opt_lasso_up_inner$optimal_threshold, 1, 0)
ridge_class_up_inner <- ifelse(pred_ridge_up_inner >
                                 opt_ridge_up_inner$optimal_threshold, 1, 0)
enet_class_up_inner  <- ifelse(pred_enet_up_inner  >
                                 opt_enet_up_inner$optimal_threshold, 1, 0)

metrics_glm_up_inner <- calculate_metrics(glm_class_up_inner, y_test_glm)
metrics_lasso_up_inner <- calculate_metrics(lasso_class_up_inner, y_test)
metrics_ridge_up_inner <- calculate_metrics(ridge_class_up_inner, y_test)
metrics_enet_up_inner <- calculate_metrics(enet_class_up_inner, y_test)

comparison_table_up_inner <- data.frame(
  GLM = metrics_glm_up_inner,
  Lasso = metrics_lasso_up_inner,
  Ridge = metrics_ridge_up_inner,
  ElasticNet = metrics_enet_up_inner
)
comparison_table_up_inner
```

```
##                     GLM     Lasso     Ridge ElasticNet
```

```
## Accuracy    0.8016429 0.8016429 0.7951429  0.8015000
## Precision   0.3288992 0.3286713 0.3234552  0.3282239
## Recall      0.5657895 0.5646453 0.5869565  0.5635011
## Specificity 0.8352922 0.8354554 0.8248449  0.8354554
## F1_Score    0.4159832 0.4154915 0.4170732  0.4148242
```

```r
# down

pred_glm_down_inner <- predict(glm_down_inner, newdata = Test_Data, type = "response")
pred_lasso_down_inner <- predict(cv_lasso_down_inner, newx = X_test, type = "response",
                      s = "lambda.min")
pred_ridge_down_inner <- predict(cv_ridge_down_inner, newx = X_test, type = "response",
                      s = "lambda.min")
pred_enet_down_inner <- predict(cv_enet_down_inner,  newx = X_test, type = "response",
                     s = "lambda.min")

glm_class_down_inner <- ifelse(pred_glm_down_inner >
                                 opt_glm_down_inner$optimal_threshold, 1, 0)
lasso_class_down_inner <- ifelse(pred_lasso_down_inner >
                                   opt_lasso_down_inner$optimal_threshold, 1, 0)
ridge_class_down_inner <- ifelse(pred_ridge_down_inner >
                                   opt_ridge_down_inner$optimal_threshold, 1, 0)
enet_class_down_inner  <- ifelse(pred_enet_down_inner >
                                   opt_enet_down_inner$optimal_threshold, 1, 0)

glm_class_up_inner <- ifelse(pred_glm_up_inner > 0.5, 1, 0)
lasso_class_up_inner <- ifelse(pred_lasso_up_inner > 0.5, 1, 0)
ridge_class_up_inner <- ifelse(pred_ridge_up_inner > 0.5, 1, 0)
enet_class_up_inner  <- ifelse(pred_enet_up_inner > 0.5, 1, 0)

metrics_glm_down_inner <- calculate_metrics(glm_class_down_inner, y_test_glm)
metrics_lasso_down_inner <- calculate_metrics(lasso_class_down_inner, y_test)
metrics_ridge_down_inner <- calculate_metrics(ridge_class_down_inner, y_test)
metrics_enet_down_inner <- calculate_metrics(enet_class_down_inner, y_test)

comparison_table_down_inner <- data.frame(
  GLM = metrics_glm_down_inner,
  Lasso = metrics_lasso_down_inner,
  Ridge = metrics_ridge_down_inner,
  ElasticNet = metrics_enet_down_inner
)
comparison_table_down_inner
```

```
##                   GLM     Lasso     Ridge ElasticNet
## Accuracy    0.8016429 0.8090000 0.8040714  0.8095714
## Precision   0.3288992 0.3366267 0.3301468  0.3368870
## Recall      0.5657895 0.5457666 0.5532037  0.5423341
## Specificity 0.8352922 0.8465557 0.8398629  0.8476983
## F1_Score    0.4159832 0.4164120 0.4135129  0.4156072
```

seems like overall performace is better without up or down sampling maybe? need to think about what metrics we really want to be using.

Next Steps - tuning, feature selection, weights, analysis of error and residuals

To do: - tune hyper parameters - do better feature selection —> hybrid/forward/backward subset feature selection - try the weights 4 to 1 thing for lasso/enet after optimising decision boundary - check if under or overfitting by comparing pure train and test error

```
cv_lasso <- cv.glmnet(X_train, y_train, family = "binomial", alpha = 1)
train_preds <- predict(cv_lasso, newx = X_train, s = "lambda.min", type = "response")
test_preds <- predict(cv_lasso, newx = X_test, s = "lambda.min", type = "response")

opt_threshold <- opt_lasso_dt_opt$optimal_threshold
train_class <- ifelse(train_preds > opt_threshold, 1, 0)
test_class <- ifelse(test_preds > opt_threshold, 1, 0)

train_error <- mean(train_class != y_train)
test_error <- mean(test_class != y_test)

cat("Training error:", round(train_error, 3), "\n")
```

```
## Training error: 0.203
```

```
cat("Test error:", round(test_error, 3))
```

```
## Test error: 0.198
```

underfitting? maybe a discuss for next week.

```
# step_model <- stepAIC(glm_basic, direction = "both", trace = FALSE)
# summary(step_model)
# formula(step_model)
```

- stratified samplied didn't do much, the original sampling was already relatively well split between train and test for the target variable.
- tested model with more significant predictors, didn't change model too much
- tested using weights in cv.glmnet, worse overall than decision threshold optimisation

To Do:

- loads of testing with different models, with different params, before and after box cox or z scaling
- loads of testing to do with hyperparams
- try rf with up/down sampling, check why rf with optimised decision threshold has such good performance.