

## Group 9 - Data-Driven Optimisation of Supply Chain Management

### Model Comparison

The analysis Logistic Regression and Decision Tree, to compare their performance in terms of accuracy, precision, recall, F1 score, and AUC.

```
# Load necessary Libraries
library(readxl)
library(dplyr)
library(lubridate)
library(ggplot2)
library(reshape2)
library(corrplot)
library(reshape2)
library(rpart)
library(caret)
library(lattice)
library(randomForest)
library(forecast)
library(pROC)
library(tidyr)
library(rpart.plot)

#data
data <- read_excel("D:/data mining data/incom2024_delay_example_dataset1.xlsx",
                  sheet = 'incom2024_delay_example_dataset')

#Data processing
data<- na.omit(data)
data <- unique(data)
data<- data[data$customer_state != '91732', ]

data <- data %>%
  mutate(label = ifelse(label %in% c(-1, 0), 0, label)) %>%
  mutate(label = case_when(
    label == 0 ~ "Not Delayed",
    label == 1 ~ "Delayed",
    TRUE ~ as.character(label)
  ))
data$label <- as.factor(data$label)

#Data processing
data <- data %>%mutate(across(where(is.character), as.factor))
data <- data %>% filter(customer_state != "OK")

# Split the data into training , testing sets and validation sets
set.seed(42)
train_index <- createDataPartition(data$label, p = 0.4, list = FALSE)
train_data <- data[train_index, ]
temp_data <- data[-train_index, ]
```

```
valid_index <- createDataPartition(temp_data$label, p = 0.5, list = FALSE)
valid_data <- temp_data[valid_index, ]
test_data <- temp_data[-valid_index, ]
```

*#Logistic regression model*

```
logistic_model <- glm(label ~ shipping_mode + order_region + category_name
                      + order_item_total_amount + customer_state
                      + customer_segment + department_name
                      + payment_type,
                      data = train_data, family = "binomial")
print(summary(logistic_model))
```

```
##
## Call:
## glm(formula = label ~ shipping_mode + order_region + category_name +
##      order_item_total_amount + customer_state + customer_segment +
##      department_name + payment_type, family = "binomial", data = train_data)
##
## Coefficients:
##
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      1.008e+01  8.827e+02   0.011   0.9909
## shipping_modeSame Day      4.484e+00  3.151e-01  14.230 <2e-16 ***
## shipping_modeSecond Class   3.178e+00  2.987e-01  10.639 <2e-16 ***
## shipping_modeStandard Class  4.793e+00  2.935e-01  16.328 <2e-16 ***
## order_regionCaribbean      -1.630e-01  4.950e-01  -0.329   0.7419
##
## order_regionCentral Africa  -1.140e-01  5.718e-01  -0.199   0.8420
## order_regionCentral America -1.602e-01  4.812e-01  -0.333   0.7392
## order_regionCentral Asia    3.638e-01  1.323e+00   0.275   0.7833
## order_regionEast Africa     1.039e-01  5.321e-01   0.195   0.8452
## order_regionEast of USA     -1.419e-01  4.975e-01  -0.285   0.7754
## order_regionEastern Asia    -1.156e-01  4.966e-01  -0.233   0.8159
## order_regionEastern Europe   1.406e-01  5.233e-01   0.269   0.7881
## order_regionNorth Africa    -5.857e-01  5.285e-01  -1.108   0.2678
## order_regionNorthern Europe -2.102e-02  4.903e-01  -0.043   0.9658
## order_regionOceania         5.131e-02  4.907e-01   0.105   0.9167
## order_regionSouth America    2.887e-02  4.877e-01   0.059   0.952
## order_regionSouth Asia       6.932e-02  4.999e-01   0.139   0.8897
## order_regionSouth of USA     1.072e-01  5.196e-01   0.206   0.8365
## order_regionSoutheast Asia  -1.046e-01  4.922e-01  -0.212   0.8317
## order_regionSouthern Africa  -2.441e-01  6.545e-01  -0.373   0.7092
## order_regionSouthern Europe  1.943e-02  4.917e-01   0.040   0.9685
## order_regionUS Center       -1.132e-01  5.086e-01  -0.223   0.8239
## order_regionWest Africa      1.176e-01  5.220e-01   0.225   0.8217
## order_regionWest Asia        2.889e-01  5.004e-01   0.577   0.5637
## order_regionWest of USA     -1.505e-01  4.982e-01  -0.302   0.7626
## order_regionWestern Europe  -1.623e-02  4.812e-01  -0.034   0.9731
## category_nameAs Seen on TV!  1.245e+00  2.769e+00   0.450   0.6529
## category_nameBaby           -1.207e-01  8.383e-01  -0.144   0.8855
## category_nameBaseball & Softball 8.463e-02  9.207e-01   0.092   0.9268
## category_nameBasketball      2.841e-01  1.498e+00   0.190   0.8496
```

## category_nameBooks	-1.373e+01	4.839e+02	-0.028	0.9774
## category_nameBoxing & MMA	-1.016e+00	9.180e-01	-1.107	0.2683
## category_nameCameras	7.573e-02	8.928e-01	0.085	0.9324
## category_nameCamping & Hiking	6.549e-01	7.556e-01	0.867	0.3861
## category_nameCardio Equipment-	9.559e-01	5.718e-01	-1.672	0.0946
## category_nameCDs	-2.846e-01	1.133e+00	-0.251	0.8017
## category_nameChildren's Clothing	-1.383e-01	8.068e-01	-0.171	0.8639
## category_nameCleats	-1.603e-01	6.225e-01	-0.258	0.7968
## category_nameComputers	3.953e-01	1.158e+00	0.341	0.7328
## category_nameConsumer Electronics	-4.864e-01	1.159e+00	-0.420	0.674
## category_nameCrafts	-6.450e-01	5.441e-01	-1.185	0.2358
## category_nameDVDs	1.085e+00	1.085e+00	1.000	0.3172
## category_nameElectronics	-5.969e-01	4.557e-01	-1.310	0.1903
## category_nameFishing	5.402e-01	7.614e-01	0.709	0.4780
## category_nameFitness Accessories	-7.674e-01	8.978e-01	-0.855	0.3927
## category_nameGarden	-1.007e-01	8.514e-01	-0.118	0.9059
## category_nameGirls' Apparel	-6.610e-01	9.370e-01	-0.705	0.4806
## category_nameGolf Apparel	-8.053e-01	1.041e+00	-0.774	0.4390
## category_nameGolf Balls	-1.029e+00	4.823e-01	-2.133	0.0330
## category_nameGolf Gloves	-3.627e-01	5.031e-01	-0.721	0.4709
## category_nameGolf Shoes	-1.731e+00	6.918e-01	-2.503	0.0123
## category_nameHealth and Beauty	-1.848e-01	1.763e+00	-0.105	0.9166
## category_nameHockey	3.046e-01	9.720e-01	0.313	0.7540
## category_nameHunting & Shooting	4.755e-01	9.189e-01	0.517	0.6048
## category_nameIndoor/Outdoor Games	5.616e-01	7.559e-01	0.743	0.4575
## category_nameKids' Golf Clubs	-1.078e+01	6.242e+02	-0.017	0.986
## category_nameLacrosse	-4.908e-01	9.782e-01	-0.502	0.6159
## category_nameMen's Clothing	-2.439e-01	1.170e+00	-0.208	0.8349
## category_nameMen's Footwear	-1.469e-01	6.201e-01	-0.237	0.8127
## category_nameMen's Golf Clubs	-1.440e+01	2.792e+02	-0.052	0.9589
## category_nameMusic	1.327e-01	8.239e-01	0.161	0.8720
## category_namePet Supplies	-4.797e-01	9.516e-01	-0.504	0.6142
## category_nameShop By Sport	-2.401e-01	8.516e-01	-0.282	0.7780
## category_nameSoccer	-2.021e+00	8.974e-01	-2.252	0.0243
## category_nameSporting Goods	3.815e-01	1.296e+00	0.294	0.7684
## category_nameStrength Training.	-4.074e-01	1.424e+00	-0.286	0.7748
## category_nameTennis & Racquet	-8.551e-01	1.046e+00	-0.818	0.4135
## category_nameToys	1.260e-01	9.270e-01	0.136	0.8918
## category_nameTrade-In	-4.739e-01	6.045e-01	-0.784	0.4331
## category_nameVideo Games	1.500e-01	1.027e+00	0.146	0.8838
## category_nameWater Sports	5.587e-01	7.566e-01	0.738	0.4602
## category_nameWomen's Apparel	-2.010e-01	8.497e-01	-0.237	0.8130
## category_nameWomen's Clothing	8.224e-02	7.623e-01	0.108	0.9141
## category_nameWomen's Golf Clubs	9.944e-01	1.328e+00	0.749	0.4540
## order_item_total_amount	-3.769e-04	4.320e-04	-0.873	0.3829
## customer_stateAZ	-1.382e+01	8.827e+02	-0.016	0.9875
## customer_stateCA	-1.433e+01	8.827e+02	-0.016	0.9871
## customer_stateCO	-1.436e+01	8.827e+02	-0.016	0.9870
## customer_stateCT	-1.508e+01	8.827e+02	-0.017	0.9864
## customer_stateDC	-1.445e+01	8.827e+02	-0.016	0.9869
## customer_stateDE	-1.382e+01	8.827e+02	-0.016	0.9875
## customer_stateFL	-1.431e+01	8.827e+02	-0.016	0.9871
## customer_stateGA	-1.442e+01	8.827e+02	-0.016	0.9870

```

## customer_stateHI -1.463e+01 8.827e+02 -0.017 0.9868
## customer_stateIA 1.274e-01 1.248e+03 0.000 0.9999
## customer_stateID -1.428e+01 8.827e+02 -0.016 0.9871

## customer_stateIL -1.409e+01 8.827e+02 -0.016 0.9873
## customer_stateIN -1.439e+01 8.827e+02 -0.016 0.9870
## customer_stateKS -1.560e+01 8.827e+02 -0.018 0.9859
## customer_stateKY -1.438e+01 8.827e+02 -0.016 0.9870
## customer_stateLA -1.341e+01 8.827e+02 -0.015 0.9879
## customer_stateMA -1.357e+01 8.827e+02 -0.015 0.9877
## customer_stateMD -1.419e+01 8.827e+02 -0.016 0.9872
## customer_stateMI -1.438e+01 8.827e+02 -0.016 0.9870
## customer_stateMN -1.432e+01 8.827e+02 -0.016 0.9871
## customer_stateMO -1.466e+01 8.827e+02 -0.017 0.9867
## customer_stateMT -1.431e+01 8.827e+02 -0.016 0.9871
## customer_stateNC -1.444e+01 8.827e+02 -0.016 0.9869
## customer_stateND -1.298e+01 8.827e+02 -0.015 0.9883
## customer_stateNJ -1.443e+01 8.827e+02 -0.016 0.9870
## customer_stateNM -1.482e+01 8.827e+02 -0.017 0.9866
## customer_stateNV -1.431e+01 8.827e+02 -0.016 0.9871
## customer_stateNY -1.412e+01 8.827e+02 -0.016 0.9872
## customer_stateOH -1.425e+01 8.827e+02 -0.016 0.9871
## customer_stateOR -1.350e+01 8.827e+02 -0.015 0.9878
## customer_statePA -1.411e+01 8.827e+02 -0.016 0.9872
## customer_statePR -1.418e+01 8.827e+02 -0.016 0.9872
## customer_stateRI -1.454e+01 8.827e+02 -0.016 0.9869
## customer_stateSC -1.437e+01 8.827e+02 -0.016 0.9870
## customer_stateTN -1.427e+01 8.827e+02 -0.016 0.9871
## customer_stateTX -1.434e+01 8.827e+02 -0.016 0.9870
## customer_stateUT -1.338e+01 8.827e+02 -0.015 0.9879
## customer_stateVA -1.454e+01 8.827e+02 -0.016 0.9869
## customer_stateWA -1.379e+01 8.827e+02 -0.016 0.9875
## customer_stateWI -1.388e+01 8.827e+02 -0.016 0.9875
## customer_stateWV -1.489e+01 8.827e+02 -0.017 0.9865
## customer_segmentCorporate 2.643e-02 6.755e-02 0.391 0.6956
## customer_segmentHome Office 2.073e-02 8.350e-02 0.248 0.8039
## department_nameBook Shop 1.341e+01 4.839e+02 0.028 0.9779
## department_nameDiscs Shop 6.970e-03 8.985e-01 0.008 0.9938
## department_nameFan Shop -6.456e-01 6.646e-01 -0.971 0.3313
## department_nameFitness -2.146e-01 8.647e-01 -0.248 0.8040
## department_nameFootwear 7.507e-01 6.054e-01 1.240 0.2150
## department_nameGolf 1.140e-02 8.561e-01 0.013 0.9894
## department_nameHealth and Beauty -3.364e-02 1.776e+00 -0.019 0.9849
## department_nameOutdoors 3.413e-01 5.191e-01 0.658 0.5108
## department_namePet Shop 5.359e-01 1.179e+00 0.455 0.6494
## department_nameTechnology -1.821e-01 1.032e+00 -0.177 0.8599
## payment_typeDEBIT 1.810e-02 1.003e-01 0.180 0.8568
## payment_typePAYMENT -2.319e-02 1.065e-01 -0.218 0.8276
## payment_typeTRANSFER -4.988e-02 1.065e-01 -0.468 0.6396

## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)

```

```

##
## Null deviance: 8472.3 on 6218 degrees of freedom
## Residual deviance: 6781.6 on 6088 degrees of freedom
## AIC: 7043.6
##
## Number of Fisher Scoring iterations: 13

logistic_predictions <- predict(logistic_model, test_data, type = "response")
logistic_predictions <- ifelse(logistic_predictions > 0.5, "Delayed", "Not Delayed")
conf_matrix <- confusionMatrix(as.factor(logistic_predictions), as.factor(test_data$label))

# valid
valid_predictions <- predict(logistic_model, newdata = valid_data, type = "response")
valid_pred_labels <- ifelse(valid_predictions > 0.5, "Delayed", "Not Delayed")

# test
test_predictions <- predict(logistic_model, newdata = test_data, type = "response")
test_pred_labels <- ifelse(test_predictions > 0.5, "Delayed", "Not Delayed")

# calculate valid metrics
valid_conf_matrix <- confusionMatrix(as.factor(valid_pred_labels), as.factor(valid_data$label))
valid_accuracy <- valid_conf_matrix$overall["Accuracy"]
valid_precision <- valid_conf_matrix$byClass["Precision"]
valid_recall <- valid_conf_matrix$byClass["Recall"]
valid_F1 <- valid_conf_matrix$byClass["F1"]
valid_auc <- auc(valid_data$label, valid_predictions)

# print valid results
cat("Accuracy: ", valid_accuracy, "\n")
## Accuracy: 0.3262594
cat("Precision: ", valid_precision, "\n")
## Precision: 0.4183007
cat("Recall: ", valid_recall, "\n")
## Recall: 0.4277757
cat("F1 Score: ", valid_F1, "\n")
## F1 Score: 0.4229851
cat("AUC: ", valid_auc, "\n")
## AUC: 0.7255645

# calculate test metrics
test_conf_matrix <- confusionMatrix(as.factor(test_pred_labels), as.factor(test_data$label))
test_accuracy <- test_conf_matrix$overall["Accuracy"]
test_precision <- test_conf_matrix$byClass["Precision"]
test_recall <- test_conf_matrix$byClass["Recall"]

```

```

test_F1 <- test_conf_matrix$byClass["F1"]
test_auc <- auc(test_data$label, test_predictions)

## Setting levels: control = Delayed, case = Not Delayed
## Setting direction: controls < cases

# print test results
cat("Accuracy: ", test_accuracy, "\n")
## Accuracy: 0.3158911
cat("Precision: ", test_precision, "\n")
## Precision: 0.4097172
cat("Recall: ", test_recall, "\n")
## Recall: 0.4197623
cat("F1 Score: ", test_F1, "\n")
## F1 Score: 0.4146789
cat("AUC: ", test_auc, "\n")
## AUC: 0.733879

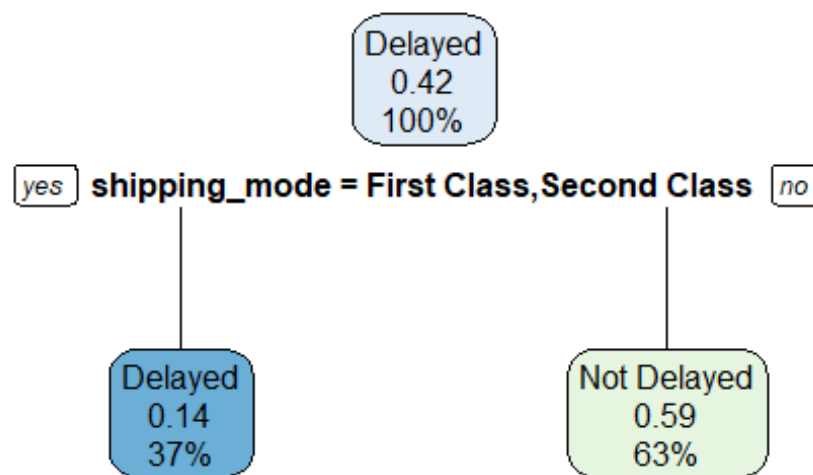
# decision tree model
decision_tree_model <- rpart(label ~ shipping_mode + order_region + category_name
                             + order_item_total_amount + customer_state
                             + customer_segment + department_name
                             + payment_type,
                             data = train_data, method = "class")

print(decision_tree_model)

## n= 6219
##
## node), split, n, loss, yval, (yprob)
##      * denotes terminal node
##
## 1) root 6219 2629 Delayed (0.5772632 0.4227368)
##   2) shipping_mode=First Class,Second Class 2303 324 Delayed (0.859313
##     9 0.1406861) *
##   3) shipping_mode=Same Day,Standard Class 3916 1611 Not Delayed (0.411
##     3892 0.5886108) *

# plot the decision tree
rpart.plot(decision_tree_model)

```



```

# predict on train set
train_predictions <- predict(decision_tree_model, newdata = train_data, type = "class")

# predict on validation set
test_predictions <- predict(decision_tree_model, newdata = test_data, type = "class")

# caculate train metrics
train_conf_matrix <- confusionMatrix(factor(train_predictions), factor(train_data$label))

train_accuracy <- train_conf_matrix$overall["Accuracy"]
train_precision <- train_conf_matrix$byClass["Precision"]
train_recall <- train_conf_matrix$byClass["Recall"]
train_F1 <- train_conf_matrix$byClass["F1"]

# caculate train AUC
train_roc <- roc(train_data$label, as.numeric(train_predictions))

## Setting levels: control = Delayed, case = Not Delayed
## Setting direction: controls < cases

train_AUC <- train_roc$auc

# print train results
cat("Accuracy: ", train_accuracy, "\n")
## Accuracy: 0.6888567
cat("Precision: ", train_precision, "\n")
## Precision: 0.8593139

```

```

cat("Recall: ", train_recall, "\n")
## Recall: 0.5512535
cat("F1 Score: ", train_F1, "\n")
## F1 Score: 0.6716443
cat("AUC: ", train_AUC, "\n")
## AUC: 0.7140064

# caculate test metrics
test_conf_matrix <- confusionMatrix(factor(test_predictions), factor(test_
data$label))

test_accuracy <- test_conf_matrix$overall["Accuracy"]
test_precision <- test_conf_matrix$byClass["Precision"]
test_recall <- test_conf_matrix$byClass["Recall"]
test_F1 <- test_conf_matrix$byClass["F1"]

# caculate test AUC
test_roc <- roc(test_data$label, as.numeric(test_predictions))

## Setting levels: control = Delayed, case = Not Delayed
## Setting direction: controls < cases

test_AUC <- test_roc$auc

# print test results
cat("Accuracy: ", test_accuracy, "\n")
## Accuracy: 0.6849668
cat("Precision: ", test_precision, "\n")
## Precision: 0.8611931
cat("Recall: ", test_recall, "\n")
## Recall: 0.5416048
cat("F1 Score: ", test_F1, "\n")
## F1 Score: 0.6649943
cat("AUC: ", test_AUC, "\n")
## AUC: 0.711188

```