Data Mining Project 3

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Contents

0.1 Introduction

The COVID-19 pandemic highlighted the importance of preparedness for infectious disease outbreaks. Anticipating which counties are at higher risk can enable early interventions, potentially saving lives and mitigating economic impacts. This project aims to classify U.S. counties into **high**, **medium**, or **low** risk categories for future pandemics based on historical COVID-19 data and other socioeconomic factors.

Following the CRISP-DM framework, we focus on:

- Data Preparation: Defining classes, cleaning data, feature engineering, and handling missing values.
- Modeling: Training and tuning multiple classification models.
- Evaluation: Assessing model performance and their utility to stakeholders.
-

0.2 Deployment: Discussing practical application and maintenance of the models.

0.3 1. Data Preparoation

```r
# Load required libraries
library(tidyverse)
library(lubridate)
library(caret)
library(rpart)  # Decision Tree
library(randomForest)  # Random Forest
library(e1071)  # SVM
library(DMwR2)
library(PRROC)
library(ggplot2)
library(gridExtra)
library(pROC)
library(xgboost)
library(class)
library(nnet)
library(iml)
```

0.3.1 Define Classes

- The classes are based on confirmed COVID-19 cases per 10,000 population per week:
  - **High Risk:** $\geq$ 50 cases.
  - **Medium Risk:** 10–49 cases.
  - **Low Risk:** $<$ 10 cases.
- These thresholds were chosen based on observed patterns in case severity and the need to trigger timely interventions.

```r
# Load mobility data
final_merged_dataset <- read_csv("data/final_merged_dataset.csv")

# Convert data from long to wide format
final_merged_dataset <- final_merged_dataset %>%
  pivot_wider(names_from = metric, values_from = count)
```

0.3.2 Data Preparation Steps

1. **Merge and Clean Data**: Ensure a single dataset with a class attribute.
2. **Select Predictive Features**: Extract features with potential predictive power.
3. **Handle Missing Data**: Use imputation or remove incomplete rows for models that cannot handle missing data.

```r
# Define risk levels
final_data <- final_merged_dataset %>%
  mutate(risk_level = case_when(
    confirmed_cases >= 50 ~ "high",
    confirmed_cases >= 10 ~ "medium",
    TRUE ~ "low"
  )) %>%
  mutate(risk_level = factor(risk_level, levels = c("low", "medium", "high")))

# Select relevant features
```

```r
classification_data <- final_data %>%
  select(retail_and_recreation_percent_change_from_baseline,
         grocery_and_pharmacy_percent_change_from_baseline,
         workplaces_percent_change_from_baseline,
         PC1, PC2, week, risk_level) %>%
  drop_na()

# Split data into training and testing
set.seed(123)
training_index <- sample(1:nrow(classification_data), 0.7 * nrow(classification_data))
training_data <- classification_data[training_index, ]
testing_data <- classification_data[-training_index, ]

# Balance training data
min_class_size <- min(table(training_data$risk_level))
balanced_training_data <- training_data %>%
  group_by(risk_level) %>%
  sample_n(min_class_size) %>%
  ungroup()
```

0.4 2. Modeling

0.4.1 Model 1: Decision Tree

- **Advantages**: Simple and interpretable.

```r
set.seed(123)
dt_model <- rpart(risk_level ~ ., data = balanced_training_data, method = "class",
                  control = rpart.control(cp = 0.05, maxdepth = 3))
```

0.4.2 Model 2: Random Forest

- **Advantages**: Handles large datasets and captures feature interactions.

```r
set.seed(123)
rf_model <- randomForest(risk_level ~ ., data = balanced_training_data, ntree = 100, mtry = 2)
```

0.4.3 Model 3: Support Vector Machine (SVM)

- **Advantages**: Effective for high-dimensional spaces.

```r
set.seed(123)
subsample_index <- sample(1:nrow(balanced_training_data), 0.01 * nrow(balanced_training_data))
subsample_data <- balanced_training_data[subsample_index, ]

svm_model <- svm(risk_level ~ ., data = subsample_data, cost = 0.1, gamma = 0.01, kernel = 'linear')
```

0.4.4 Model 4: Gradient Boosting

- **Advantages**:

```
# Prepare training features and labels
x_train <- model.matrix(risk_level ~ . - 1, data = balanced_training_data)  # Remove intercept and non-
y_train <- as.numeric(balanced_training_data$risk_level) - 1  # Convert factor to 0-indexed numeric

# Prepare testing features and labels
x_test <- model.matrix(risk_level ~ . - 1, data = testing_data)
y_test <- as.numeric(testing_data$risk_level) - 1

# Train the Gradient Boosting model
set.seed(123)
xgb_model <- xgboost(
  data = x_train,
  label = y_train,
  objective = "multi:softprob",  # Multiclass classification
  num_class = length(unique(balanced_training_data$risk_level)),  # Number of classes
  nrounds = 100,  # Number of boosting rounds
  eta = 0.1,      # Learning rate
  max_depth = 3,  # Tree depth
  verbose = 0     # Suppress training logs
)
```

0.4.5 Model 5: Logistic Regression

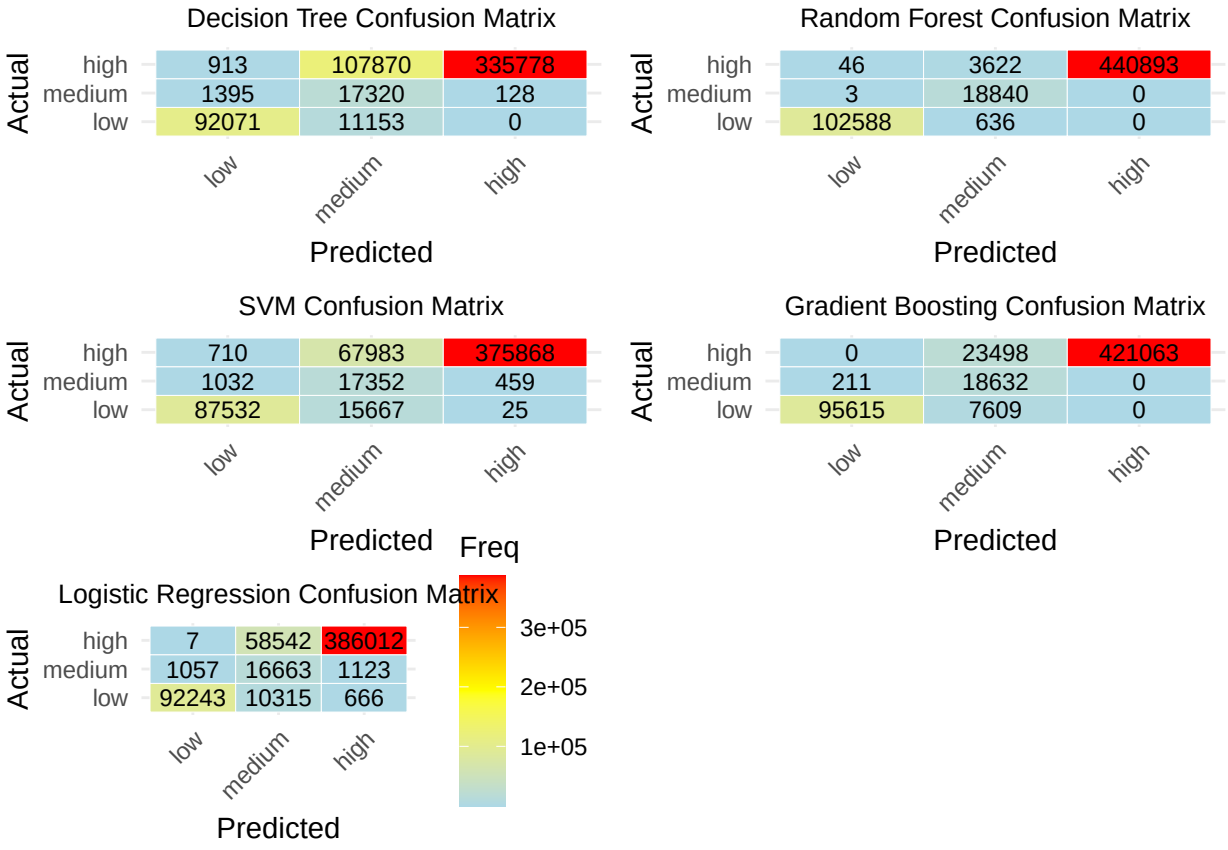
- **Advantages**:

```
# Train a multinomial logistic regression model
logistic_model <- multinom(risk_level ~ ., data = balanced_training_data)
```

```
## # weights:  24 (14 variable)
## initial  value 146546.090410
## iter  10 value 144726.645825
## iter  20 value 49159.376764
## iter  30 value 41823.952812
## iter  40 value 41660.518093
## iter  50 value 41296.754356
## final  value 40503.996163
## converged
```

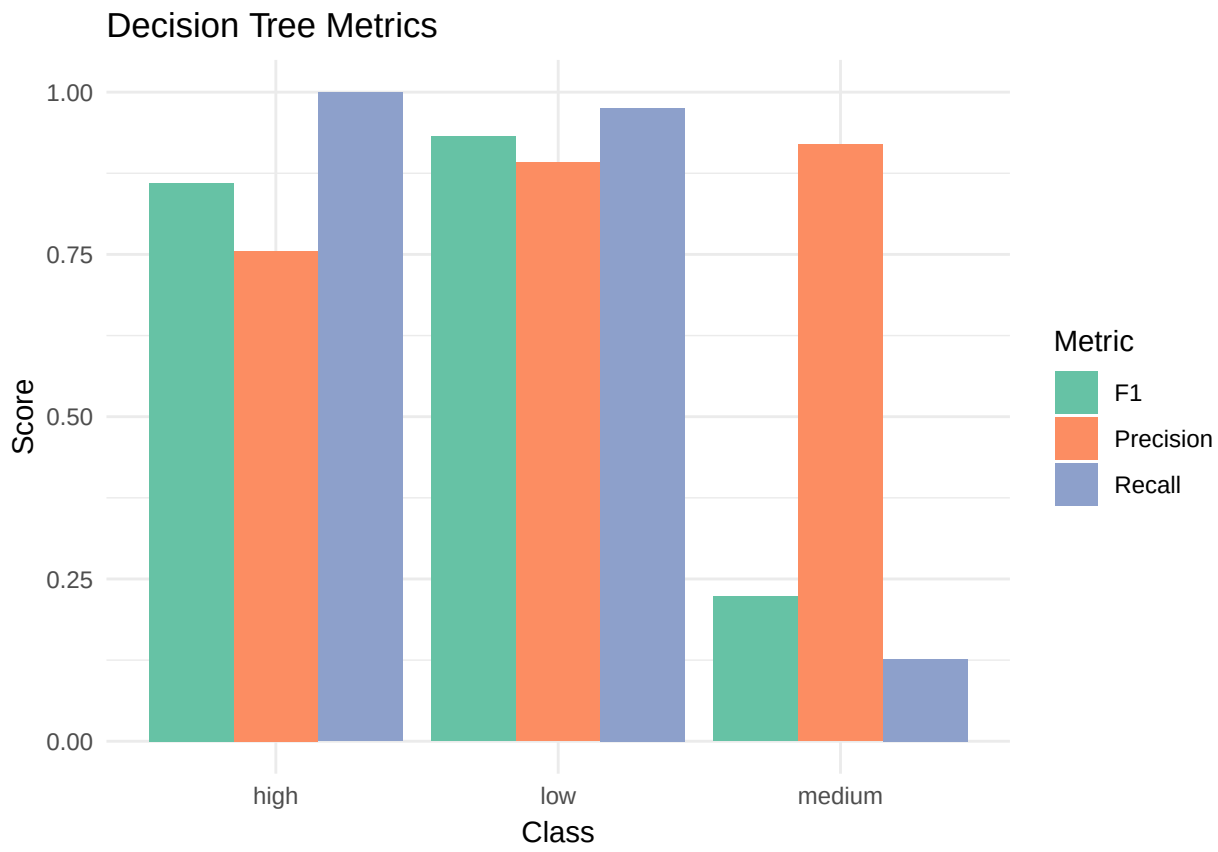
0.5 3. Evaluation

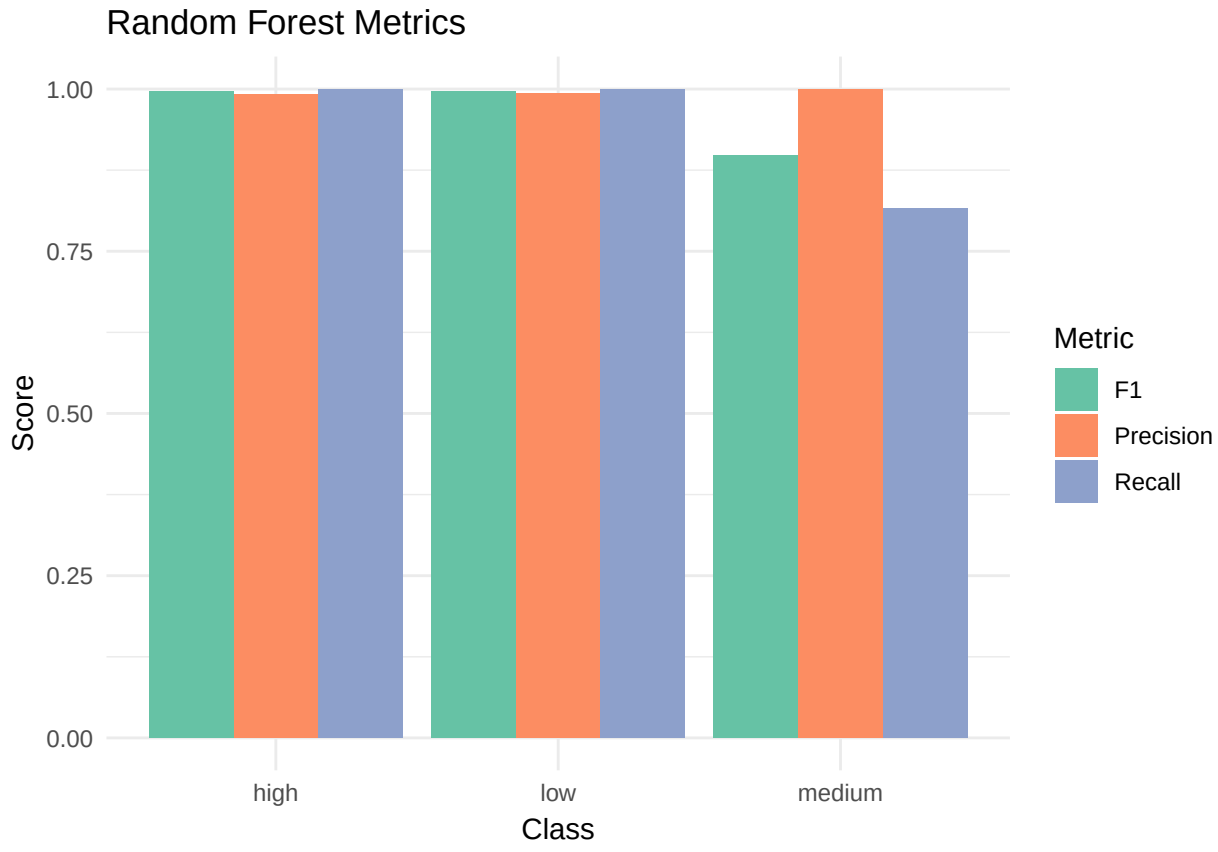
0.5.1 1. Confusion Matrix Heatmaps

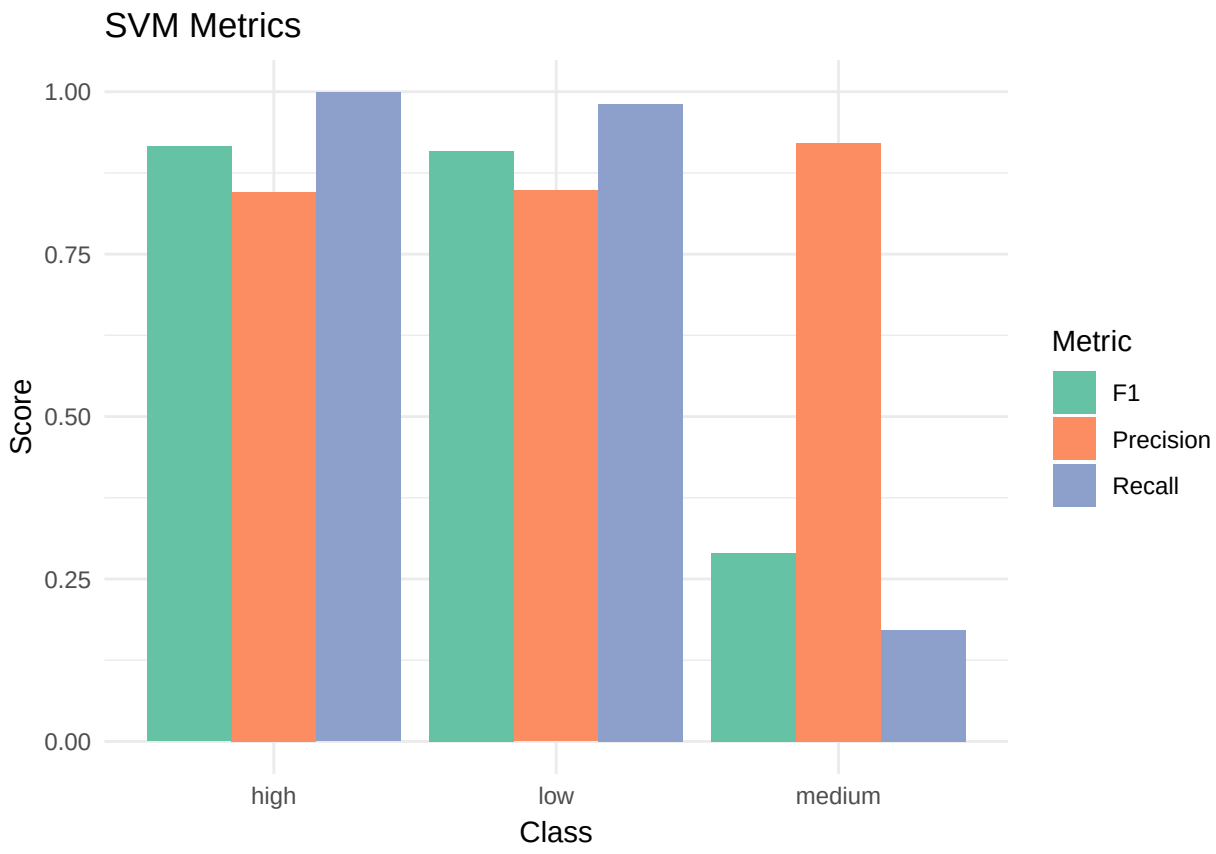


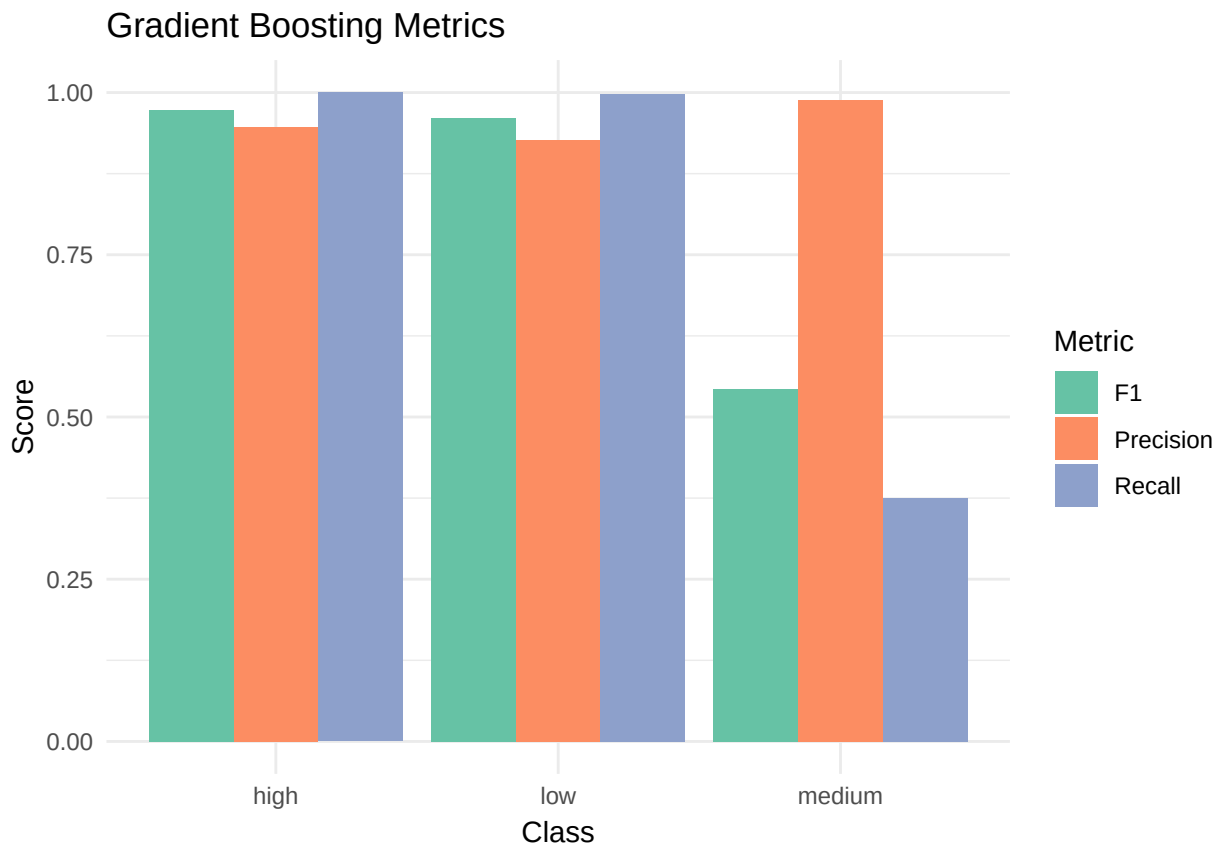
ALT

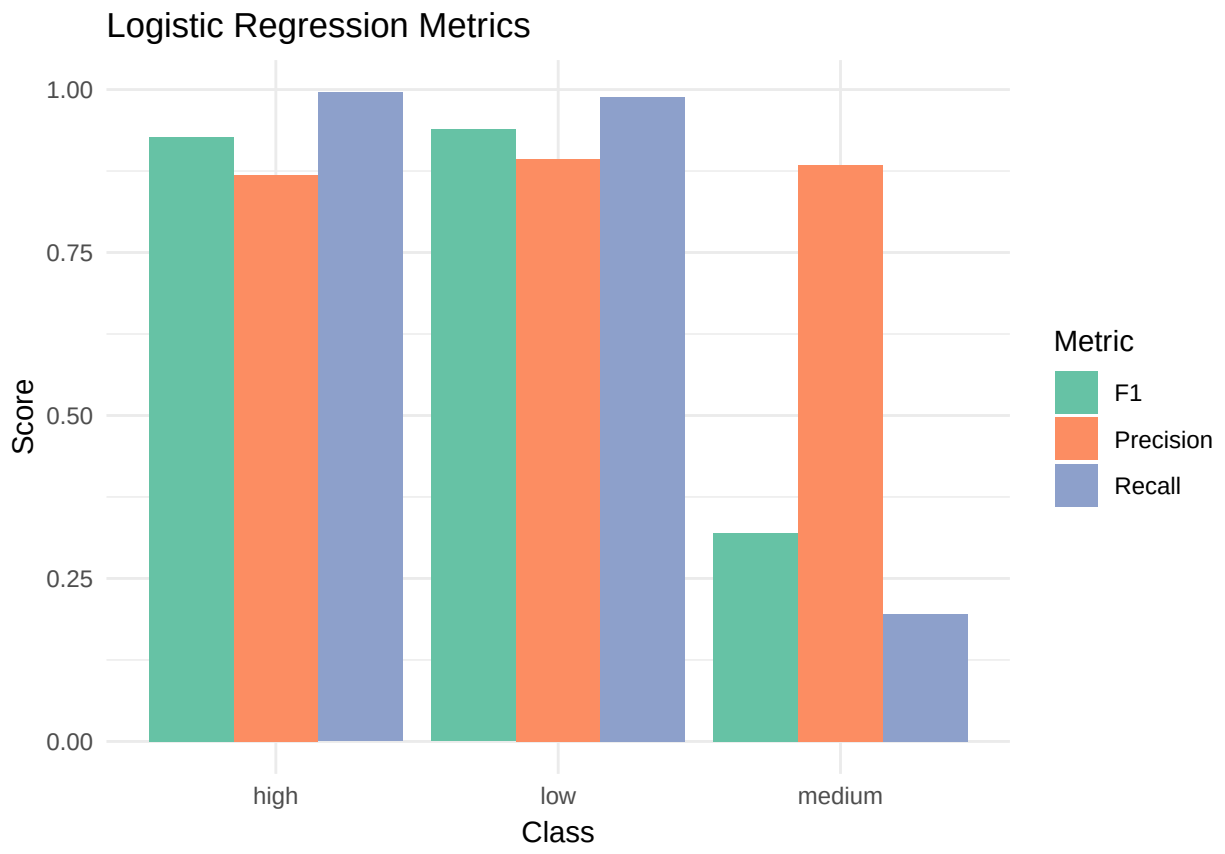
0.5.2 2. Precision, Recall and F1-score






SVM Metrics
1.00
0.75
0.50
0.25
0.00
Score
high
low
medium
Class
Metric
F1
Precision
Recall


Gradient Boosting Metrics
1.00
0.75
0.50
0.25
0.00
Score
high
low
medium
Class
Metric
F1
Precision
Recall



ALT

Table 1: Precision, Recall, and F1-Score for Each Model

	Model	Class	Precision	Recall	F1_Score
Decision Tree.low	Decision Tree	low	0.89	0.98	0.93
Decision Tree.medium	Decision Tree	medium	0.92	0.13	0.22
Decision Tree.high	Decision Tree	high	0.76	1.00	0.86
Random Forest.low	Random Forest	low	0.99	1.00	1.00
Random Forest.medium	Random Forest	medium	1.00	0.82	0.90
Random Forest.high	Random Forest	high	0.99	1.00	1.00
Logistic Regression.low	Logistic Regression	low	0.89	0.99	0.94
Logistic Regression.medium	Logistic Regression	medium	0.88	0.19	0.32
Logistic Regression.high	Logistic Regression	high	0.87	1.00	0.93

0.5.3 2. ROC Curves

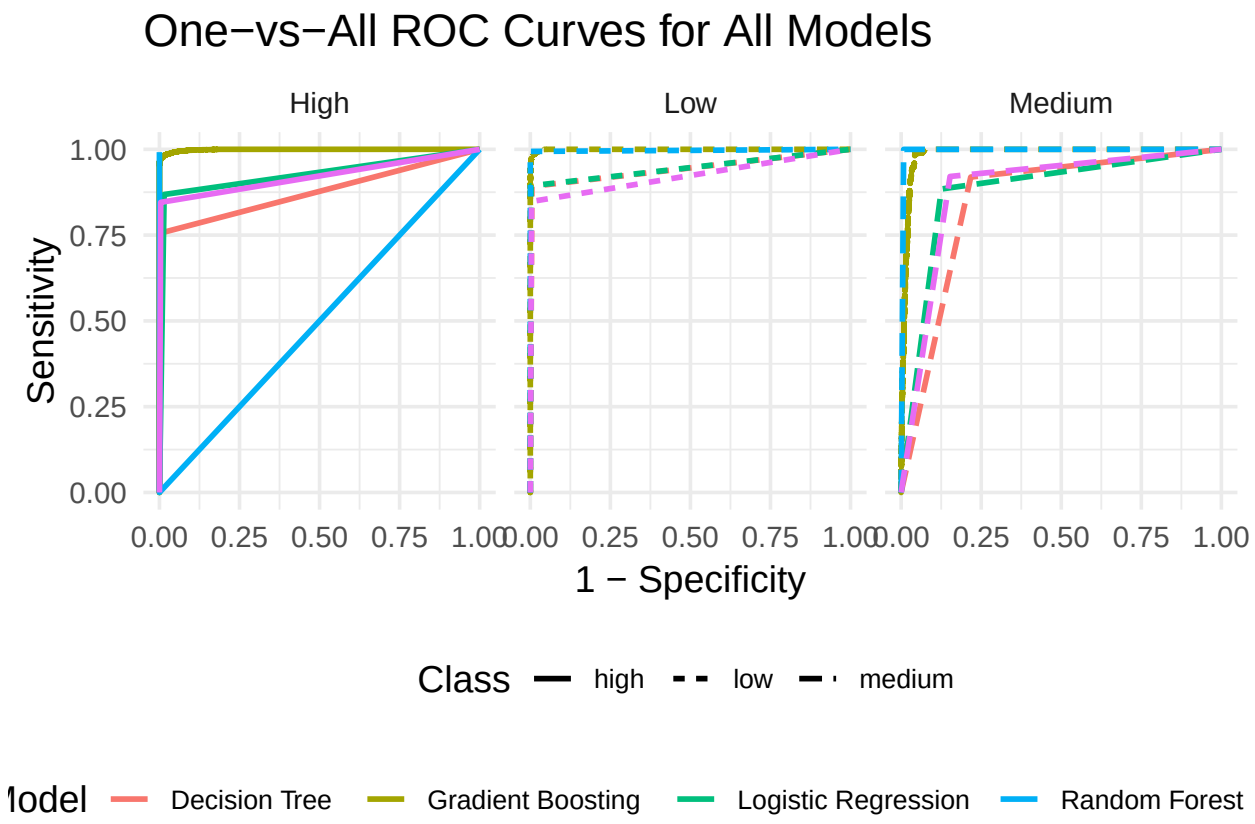
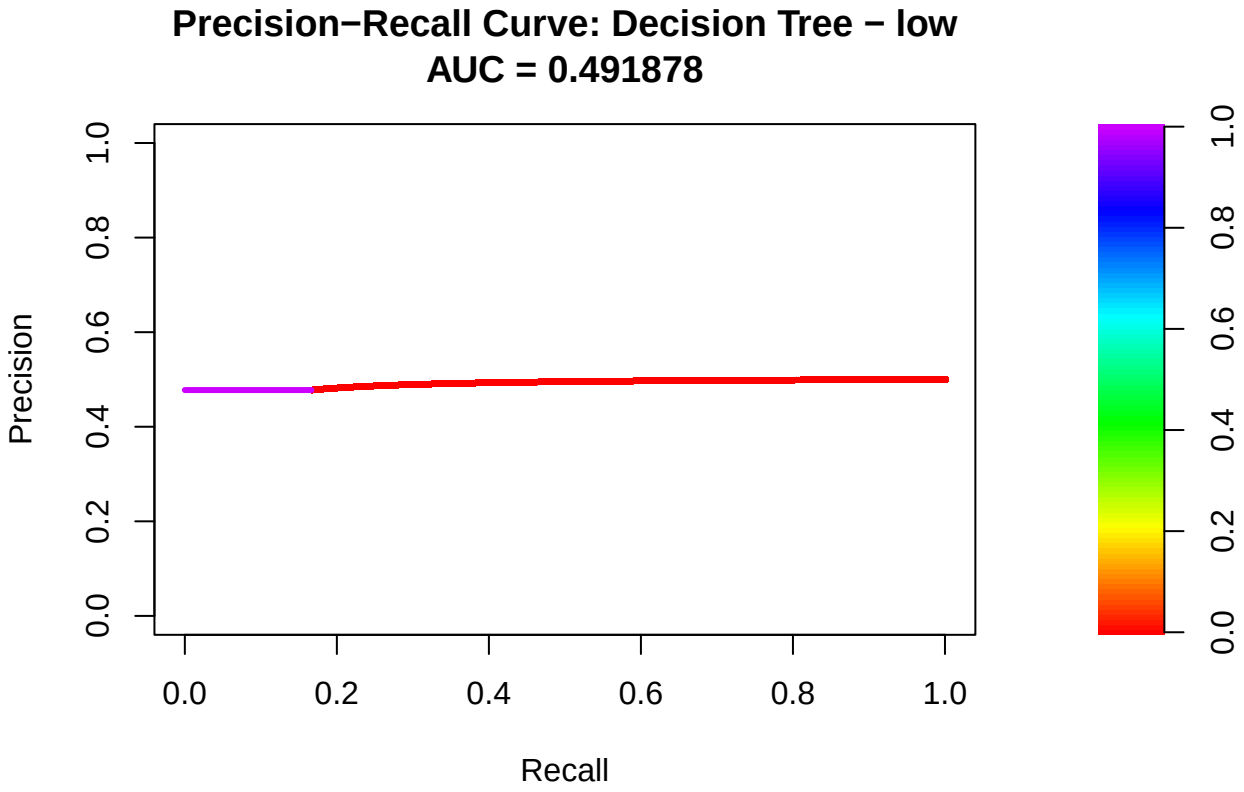
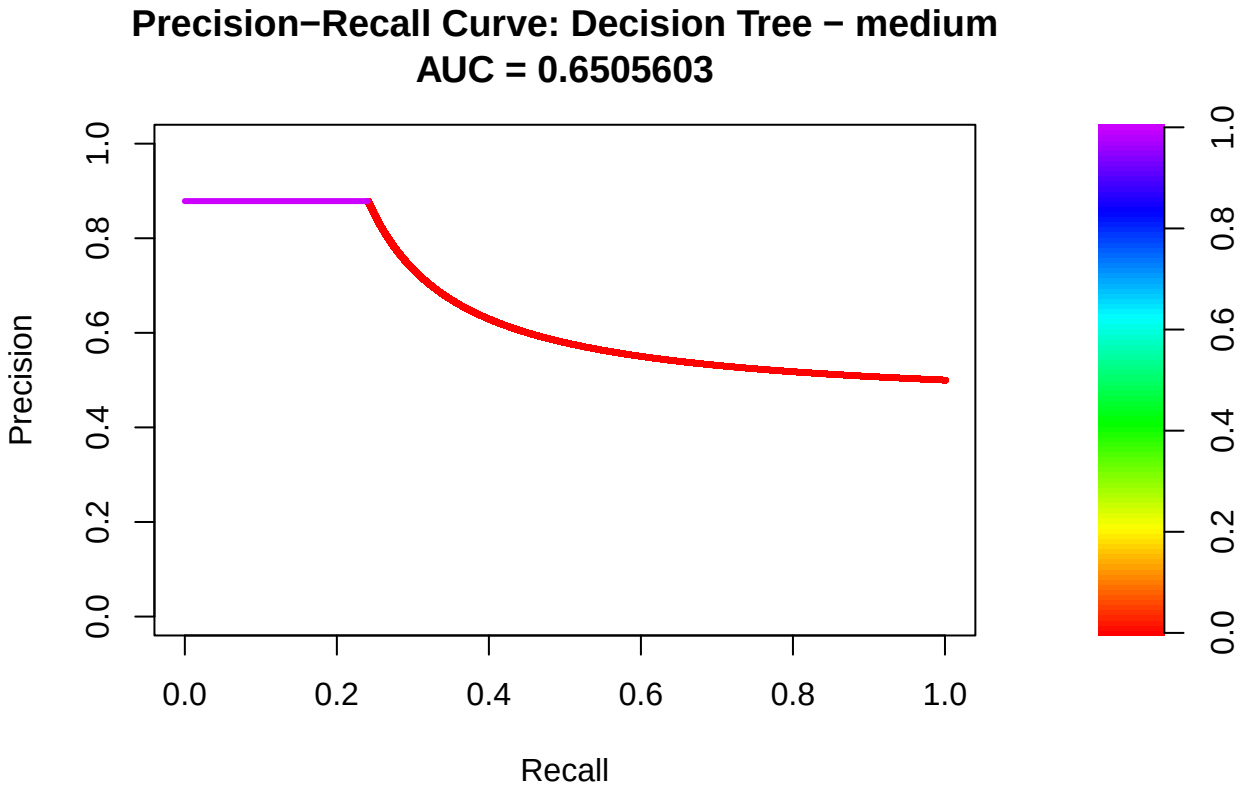


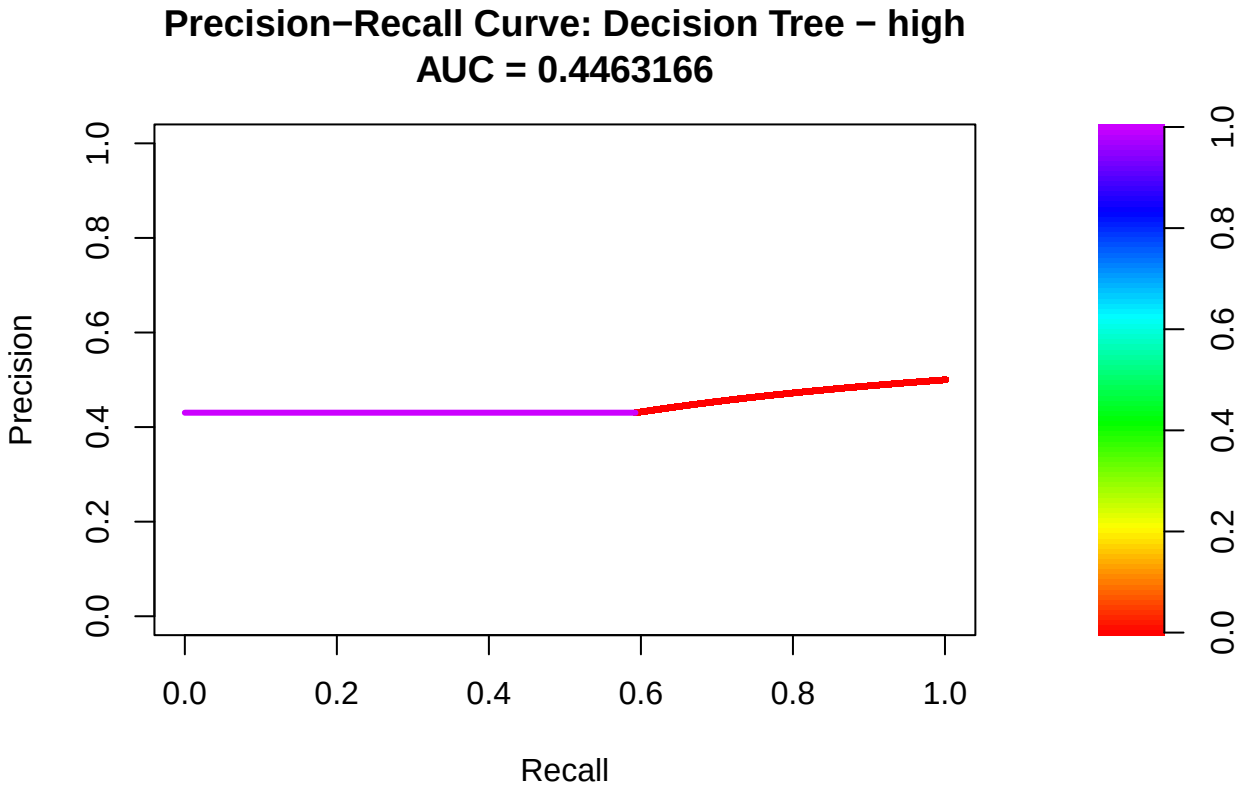
Table 2: AUC Values for Each Model and Class

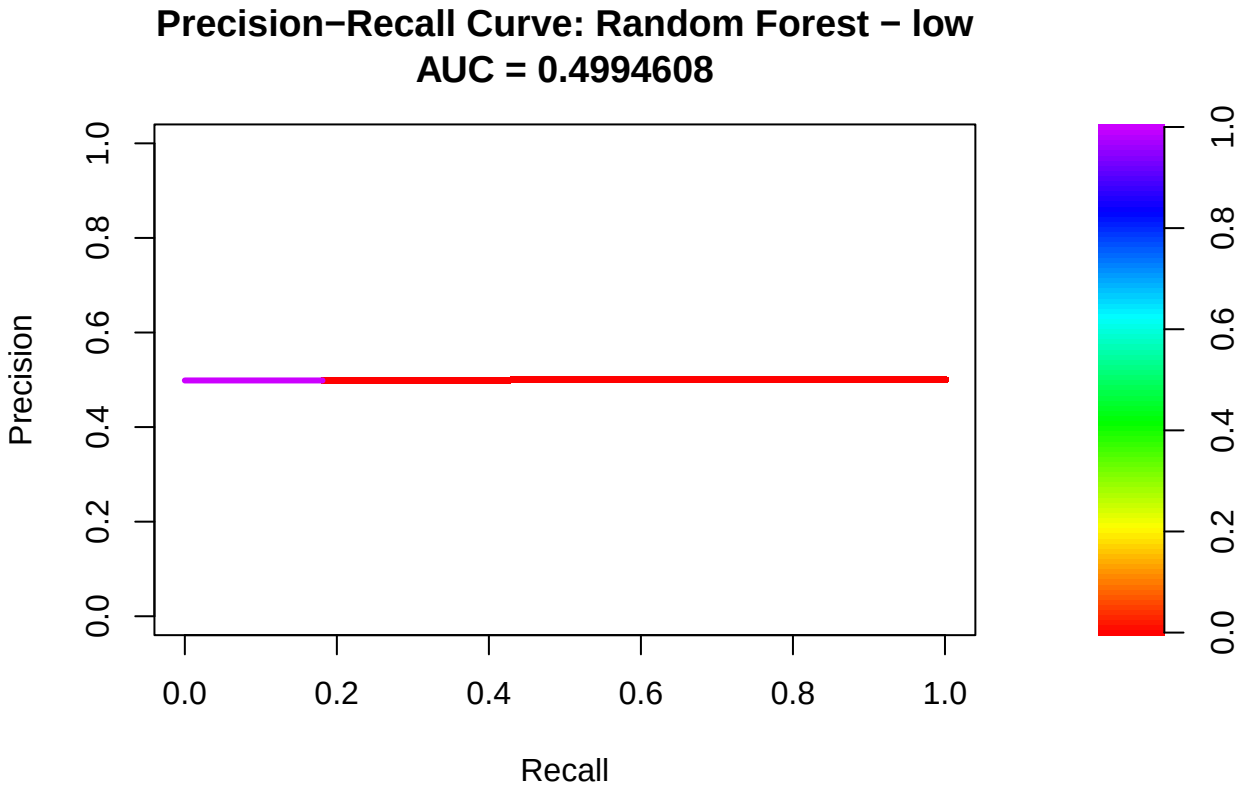
	Model	Class	AUC
Decision Tree.low	Decision Tree	low	0.9434864
Decision Tree.medium	Decision Tree	medium	0.8509469
Decision Tree.high	Decision Tree	high	0.8771269
Random Forest.low	Random Forest	low	0.9968821
Random Forest.medium	Random Forest	medium	0.9960430
Random Forest.high	Random Forest	high	0.9958836
Logistic Regression.low	Logistic Regression	low	0.9456618
Logistic Regression.medium	Logistic Regression	medium	0.8793032
Logistic Regression.high	Logistic Regression	high	0.9268217

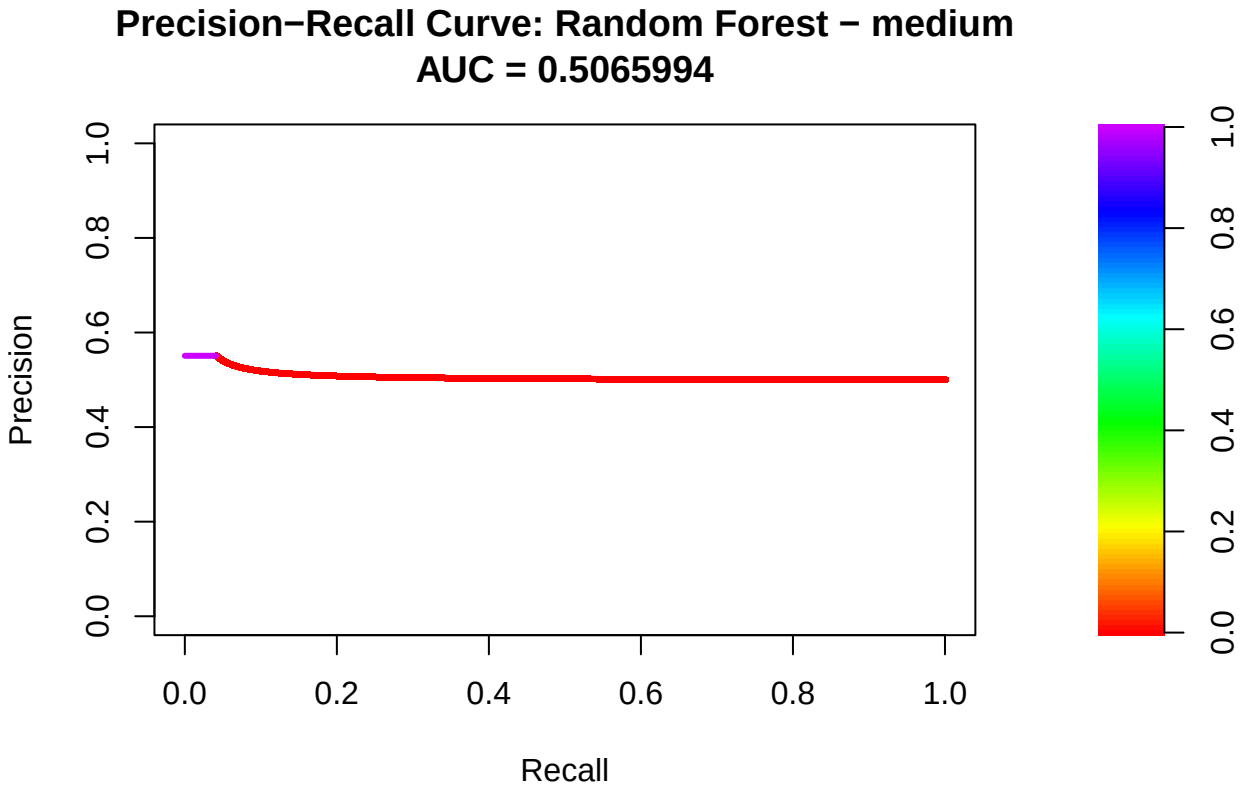
0.5.4 3. Precision-Recall Curves

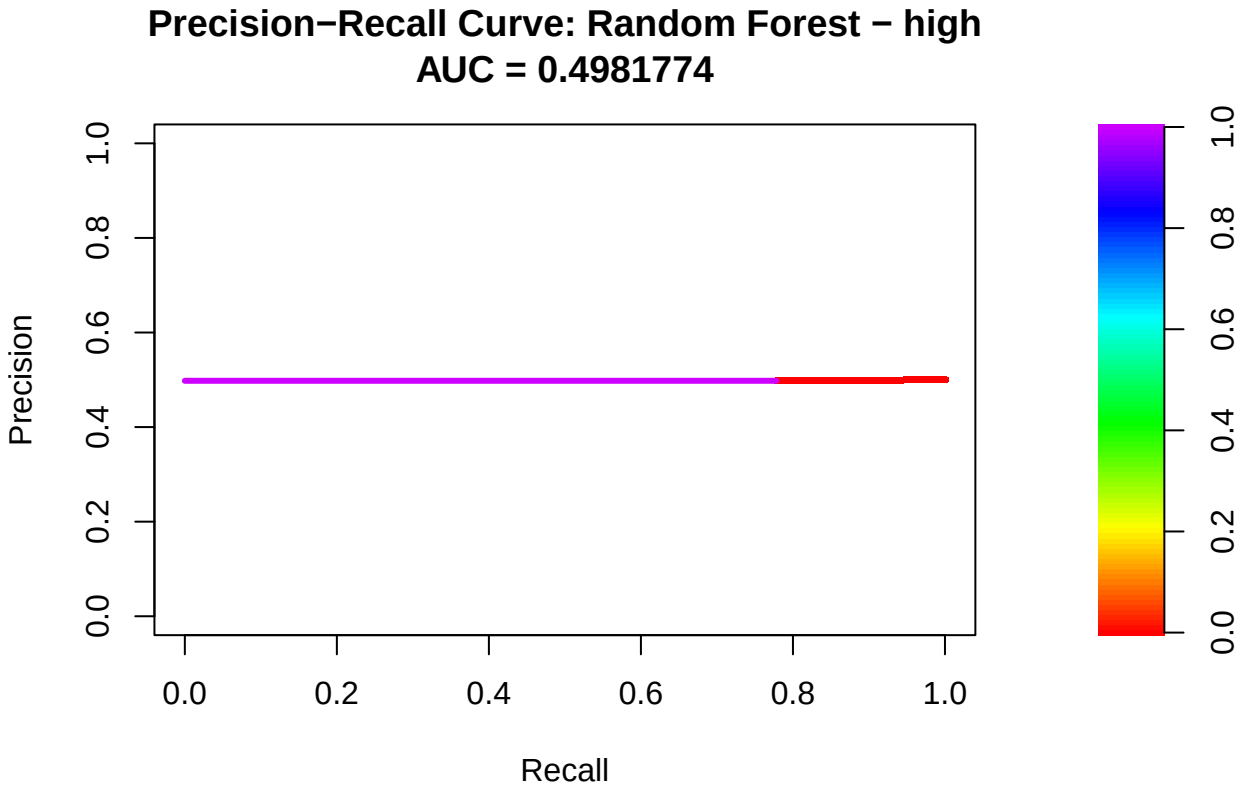


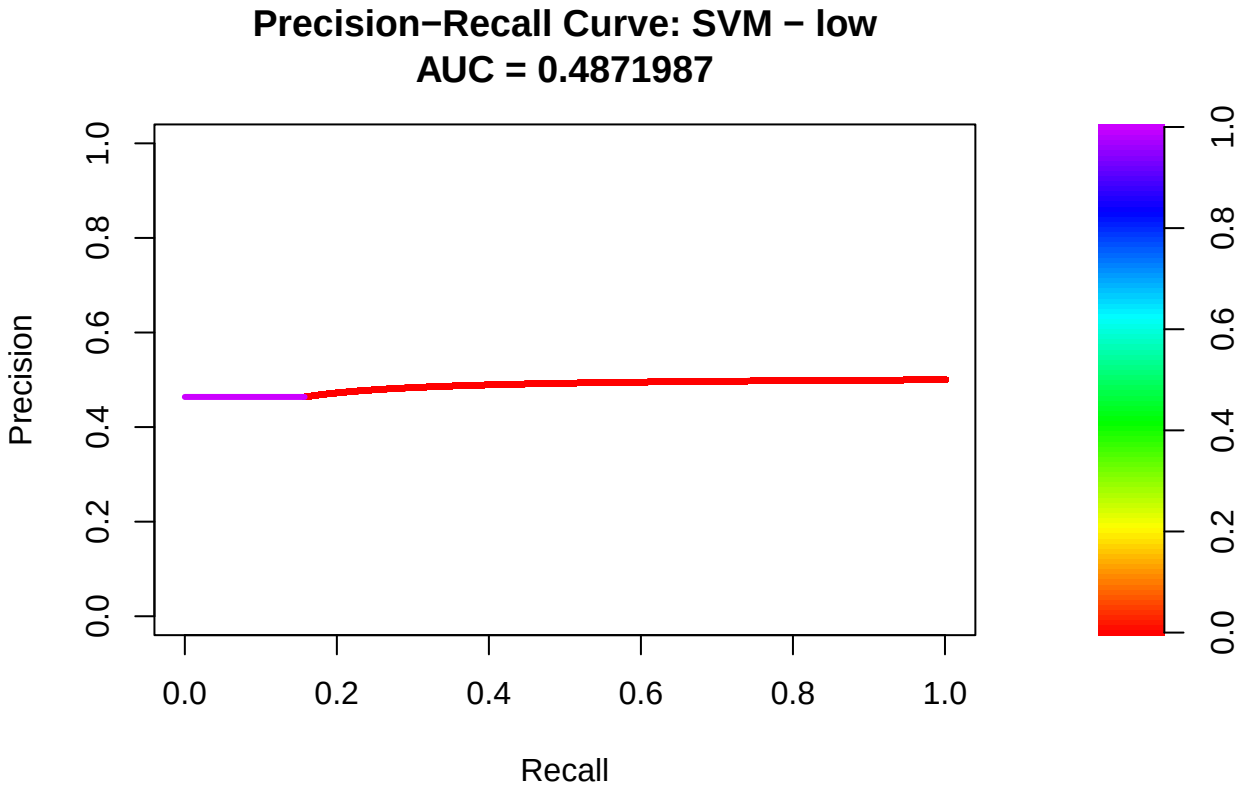


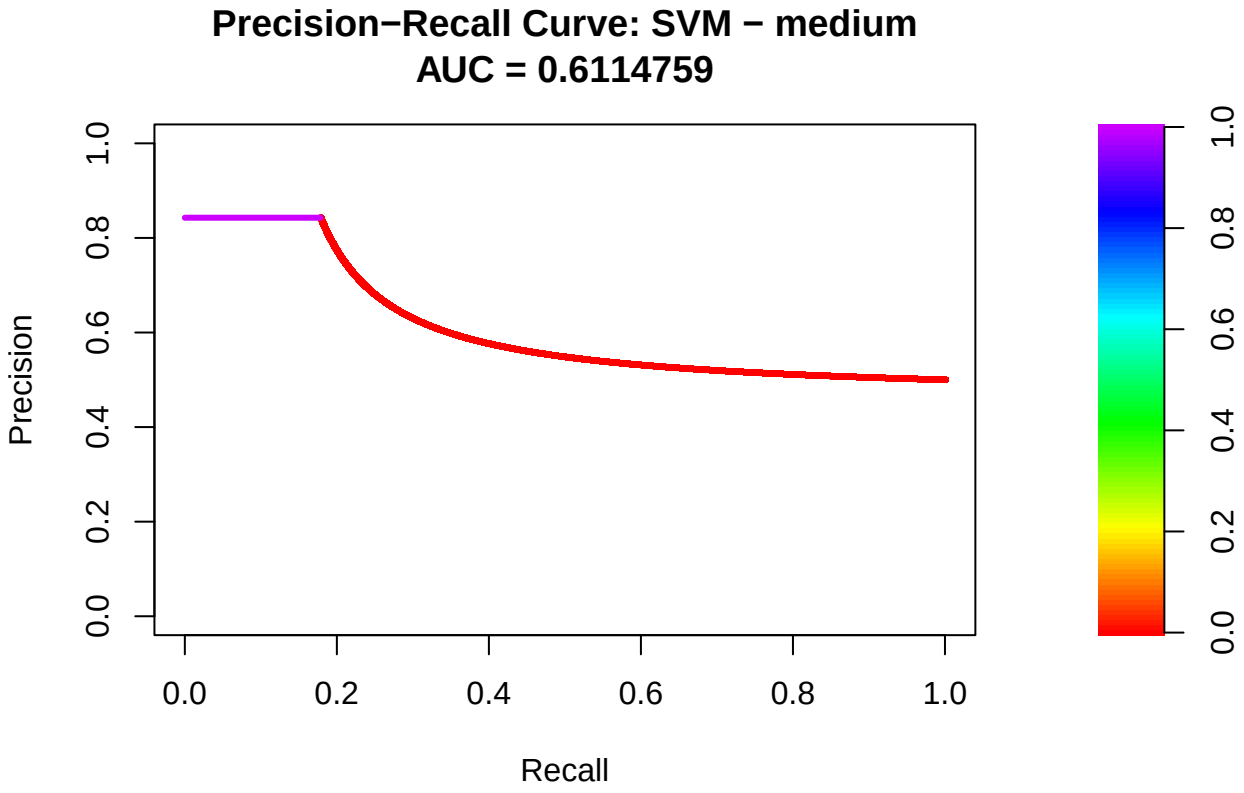

Precision−Recall Curve: Decision Tree − high
AUC = 0.4463166
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

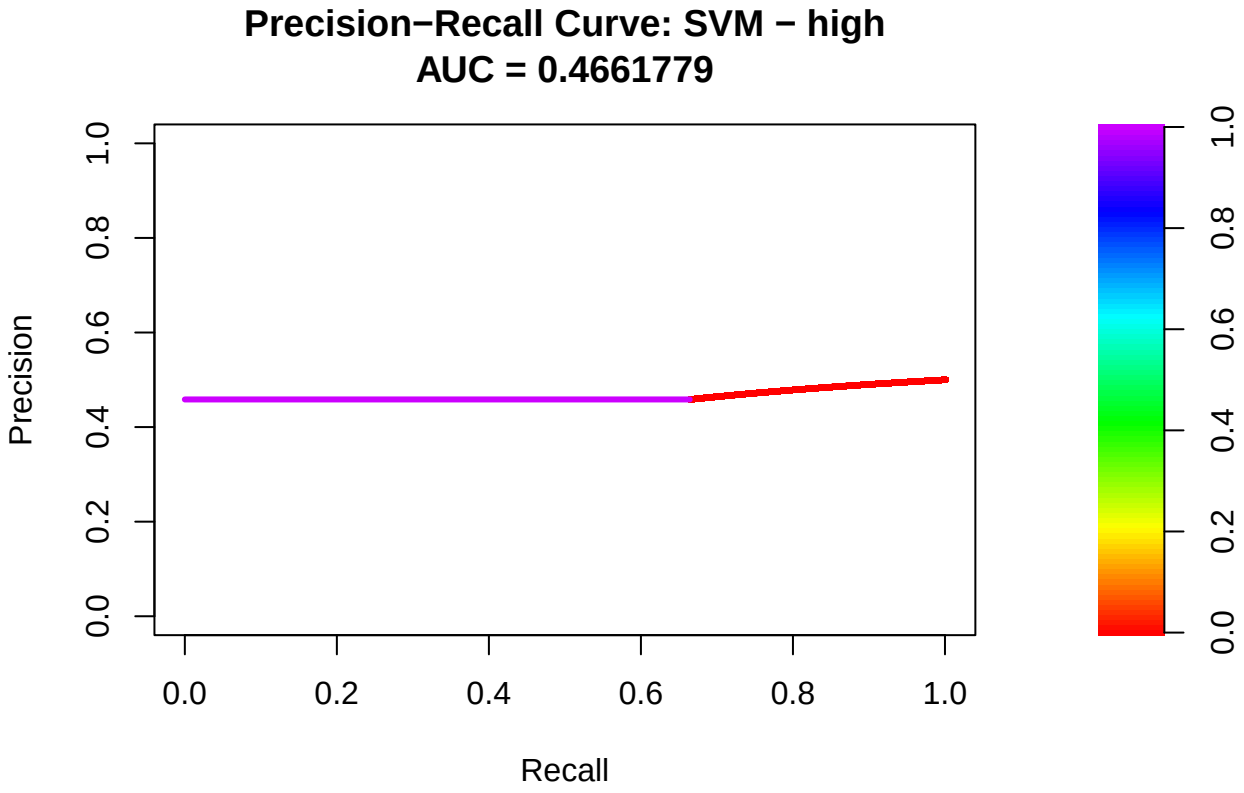

Precision−Recall Curve: Random Forest − low
AUC = 0.4994608
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
0.0
0.2
0.4
0.6
0.8
1.0

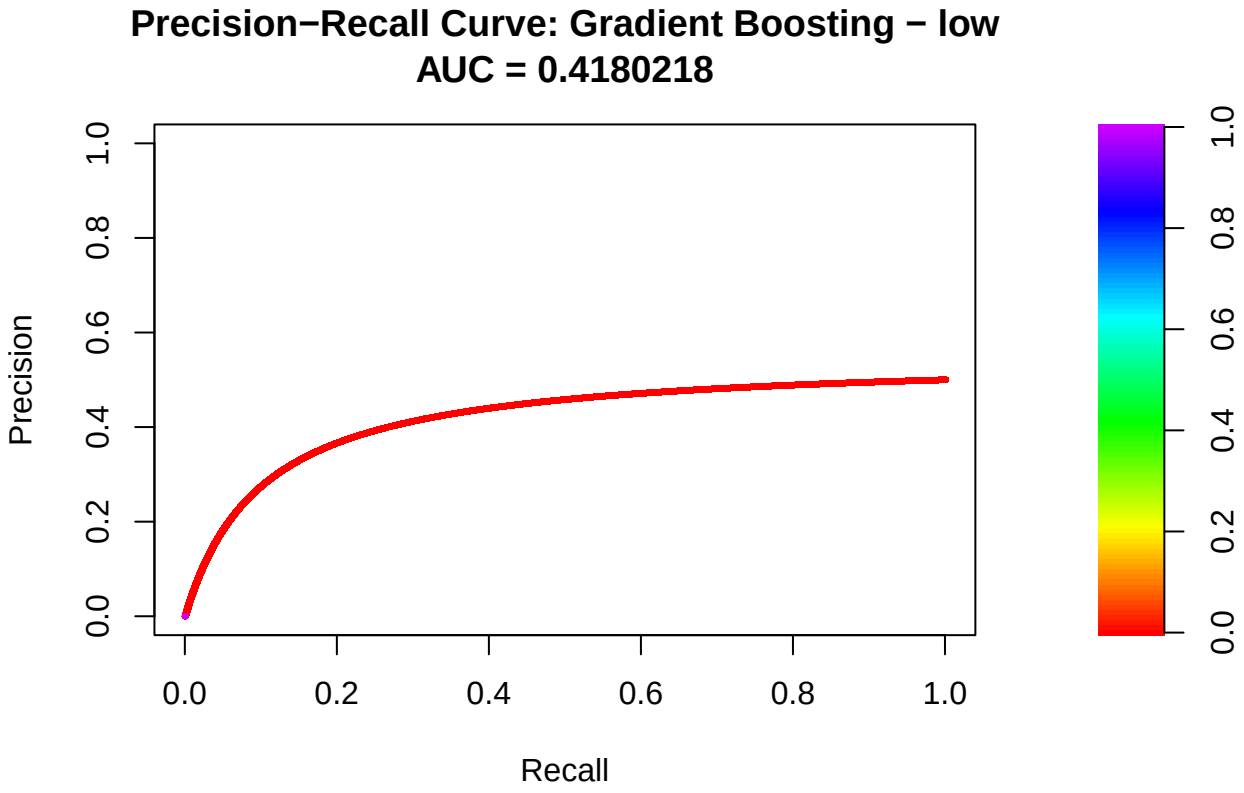

Precision−Recall Curve: Random Forest − medium
AUC = 0.5065994
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

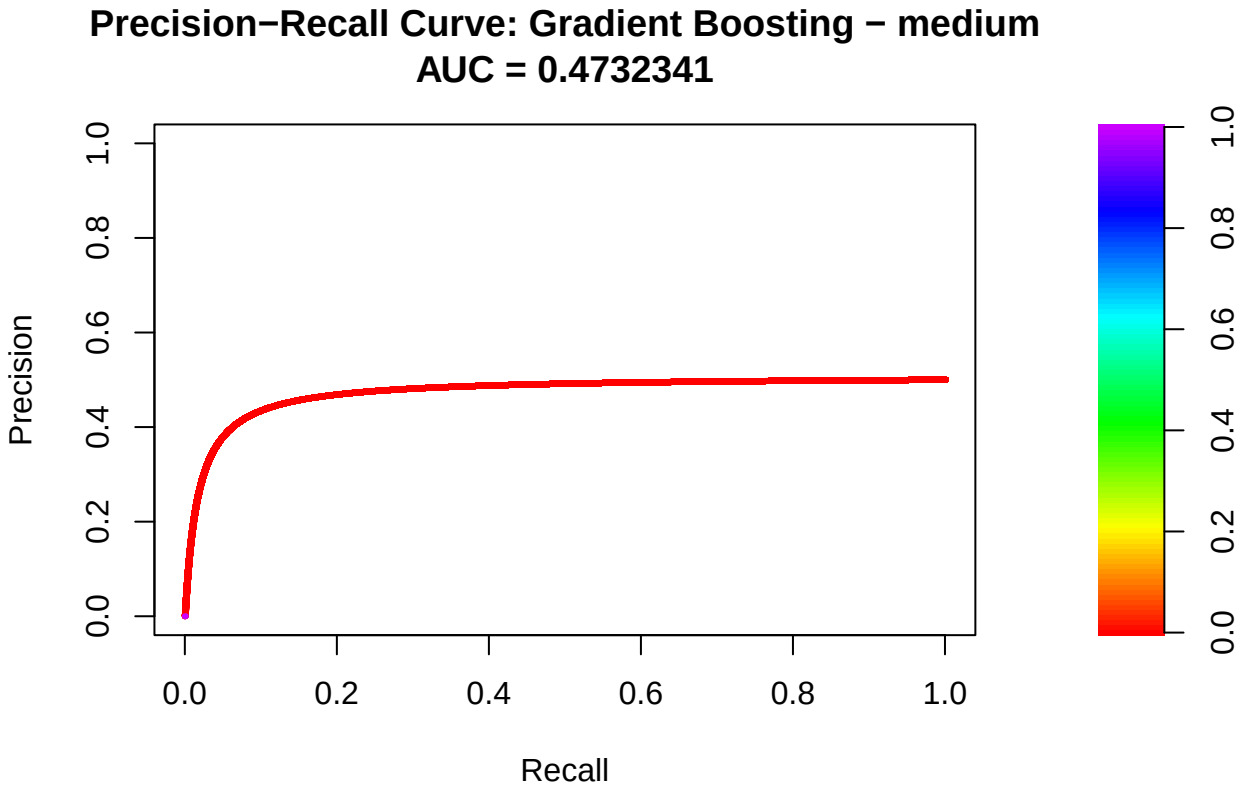

Precision−Recall Curve: Random Forest − high
AUC = 0.4981774
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

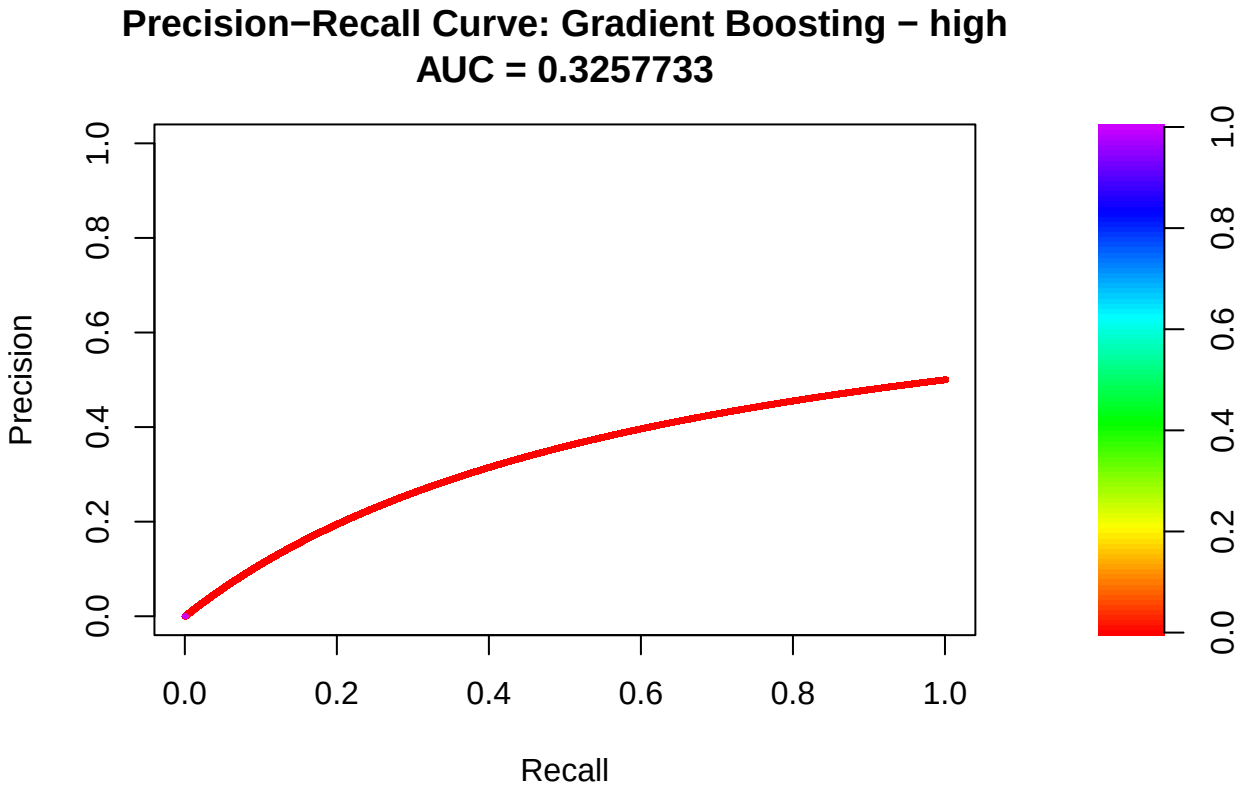

Precision−Recall Curve: SVM − low
AUC = 0.4871987
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
0.0
0.2
0.4
0.6
0.8
1.0

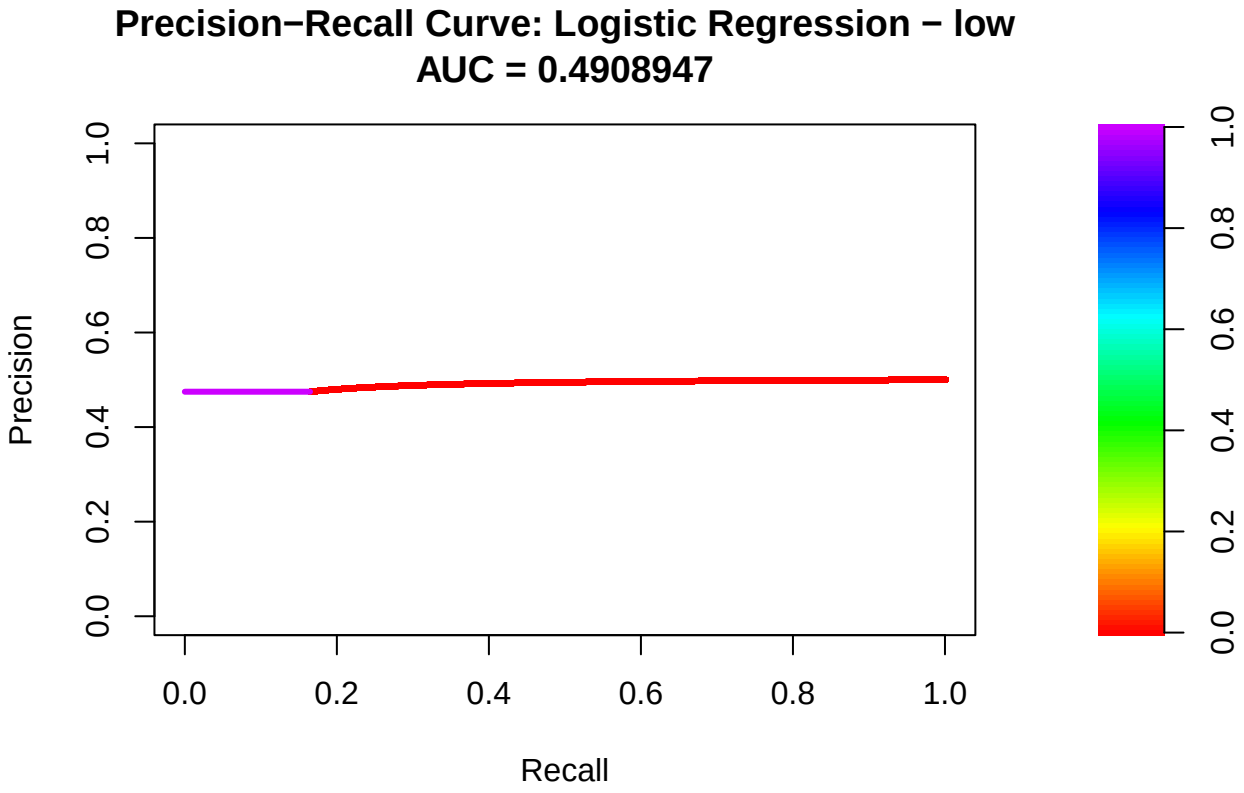

Precision−Recall Curve: SVM − medium
AUC = 0.6114759
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

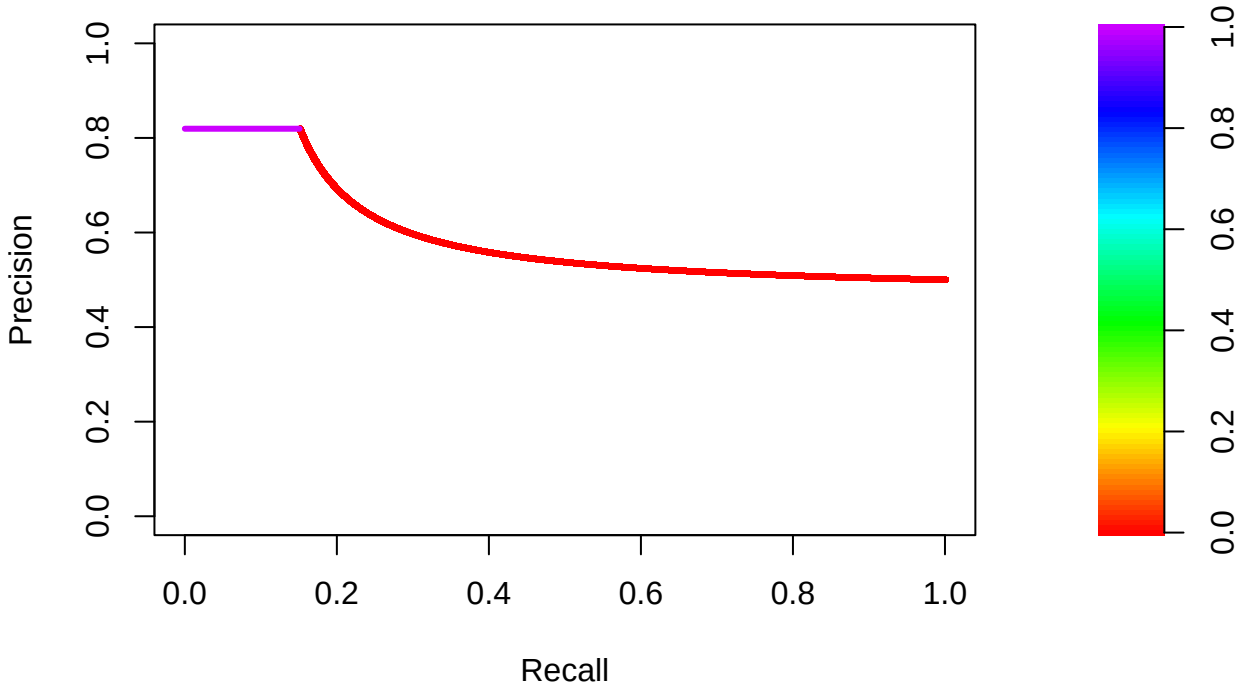

Precision−Recall Curve: SVM − high
AUC = 0.4661779
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

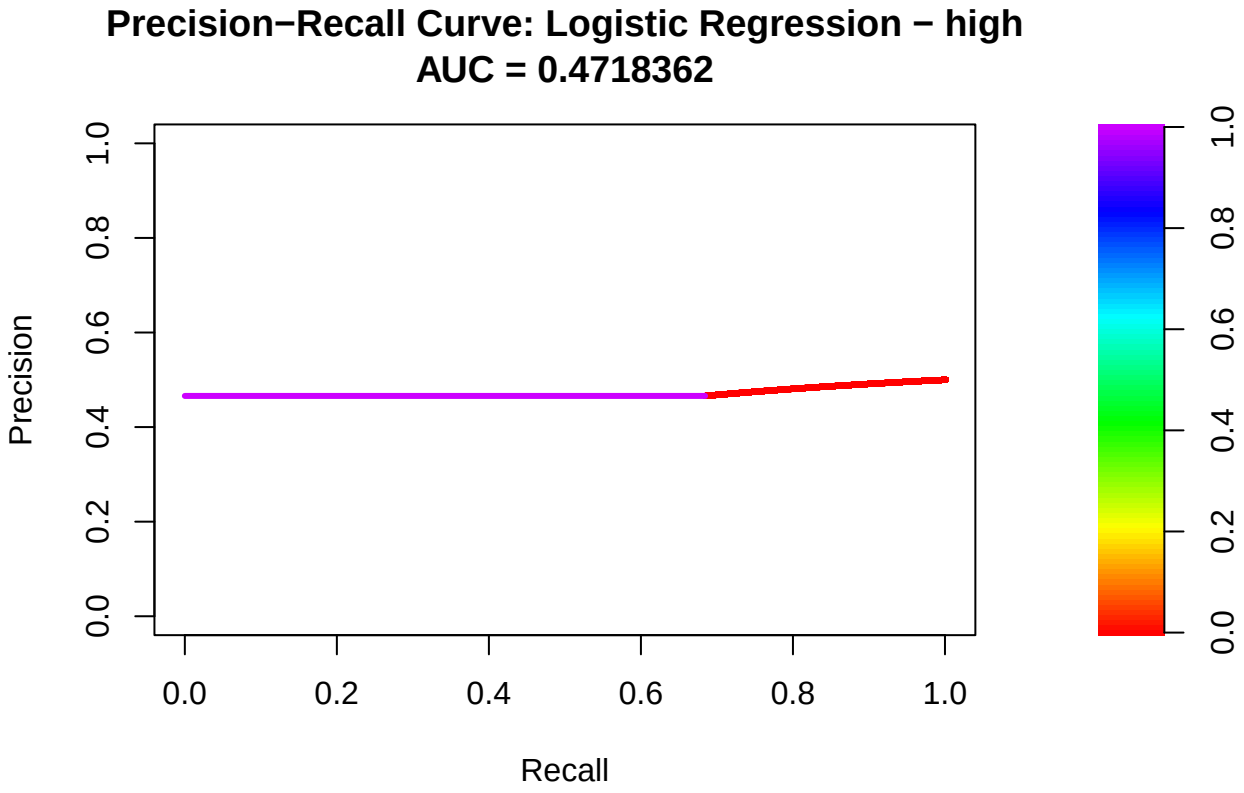

Precision−Recall Curve: Gradient Boosting − low
AUC = 0.4180218
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0


Precision−Recall Curve: Gradient Boosting − medium
AUC = 0.4732341
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

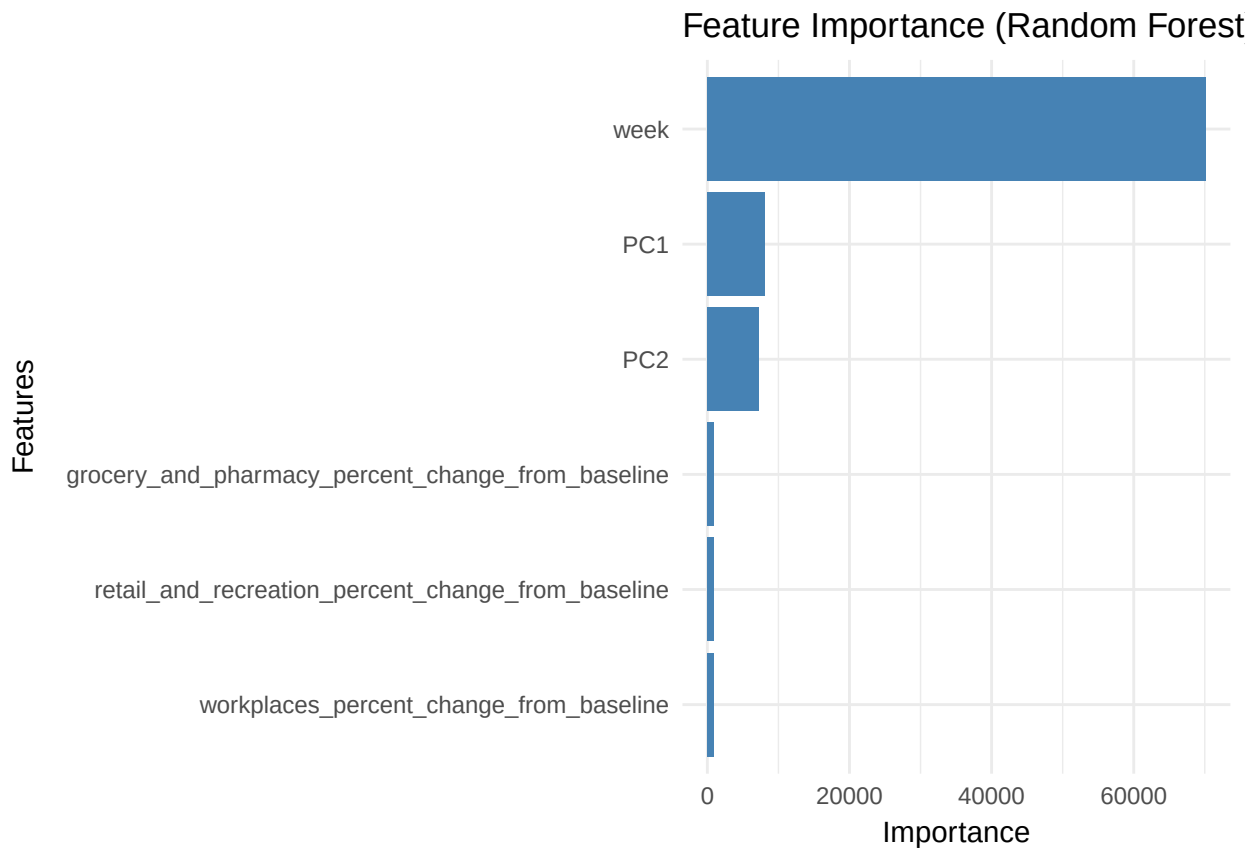

Precision−Recall Curve: Gradient Boosting − high
AUC = 0.3257733
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

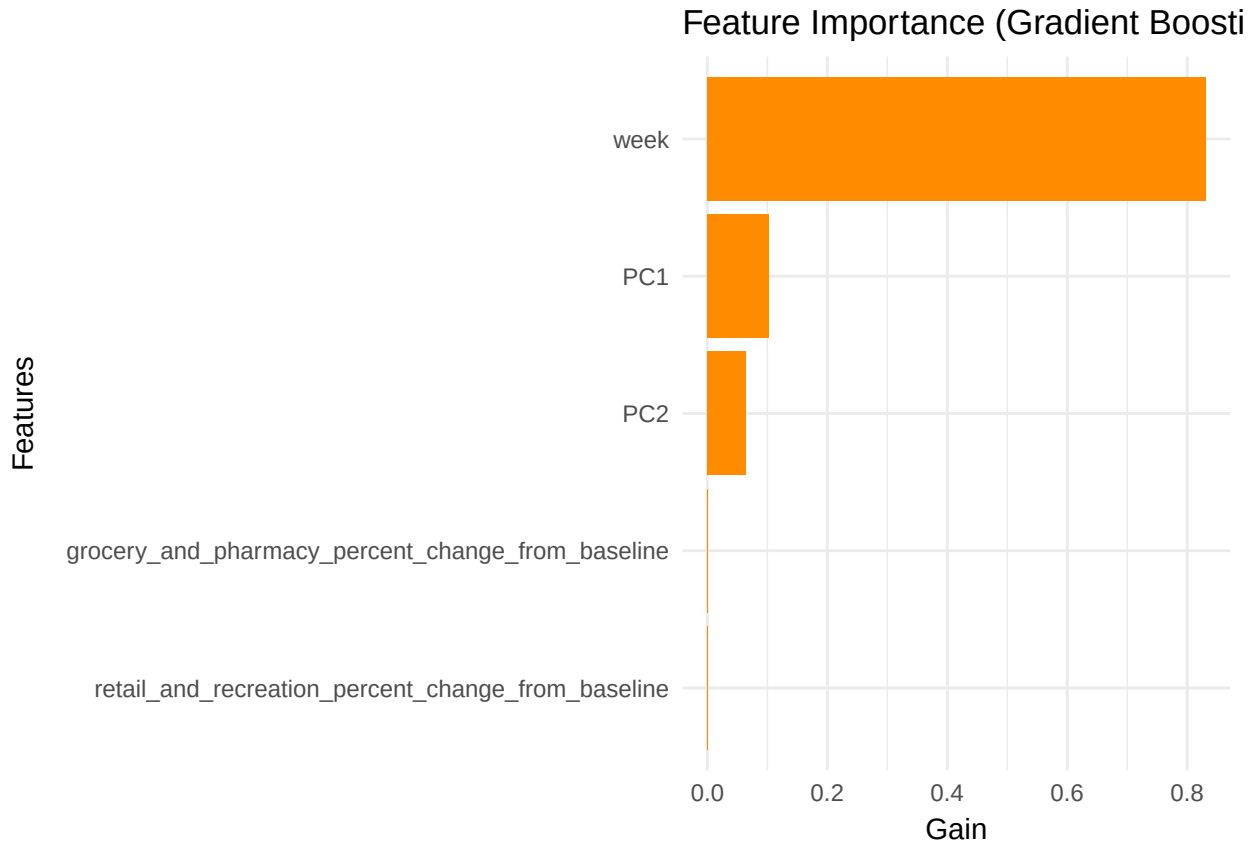

Precision−Recall Curve: Logistic Regression − low
AUC = 0.4908947
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0


Precision−Recall Curve: Logistic Regression − medium
AUC = 0.5929723
Precision
Recall
0.0
0.2
0.4
0.6
0.8
1.0

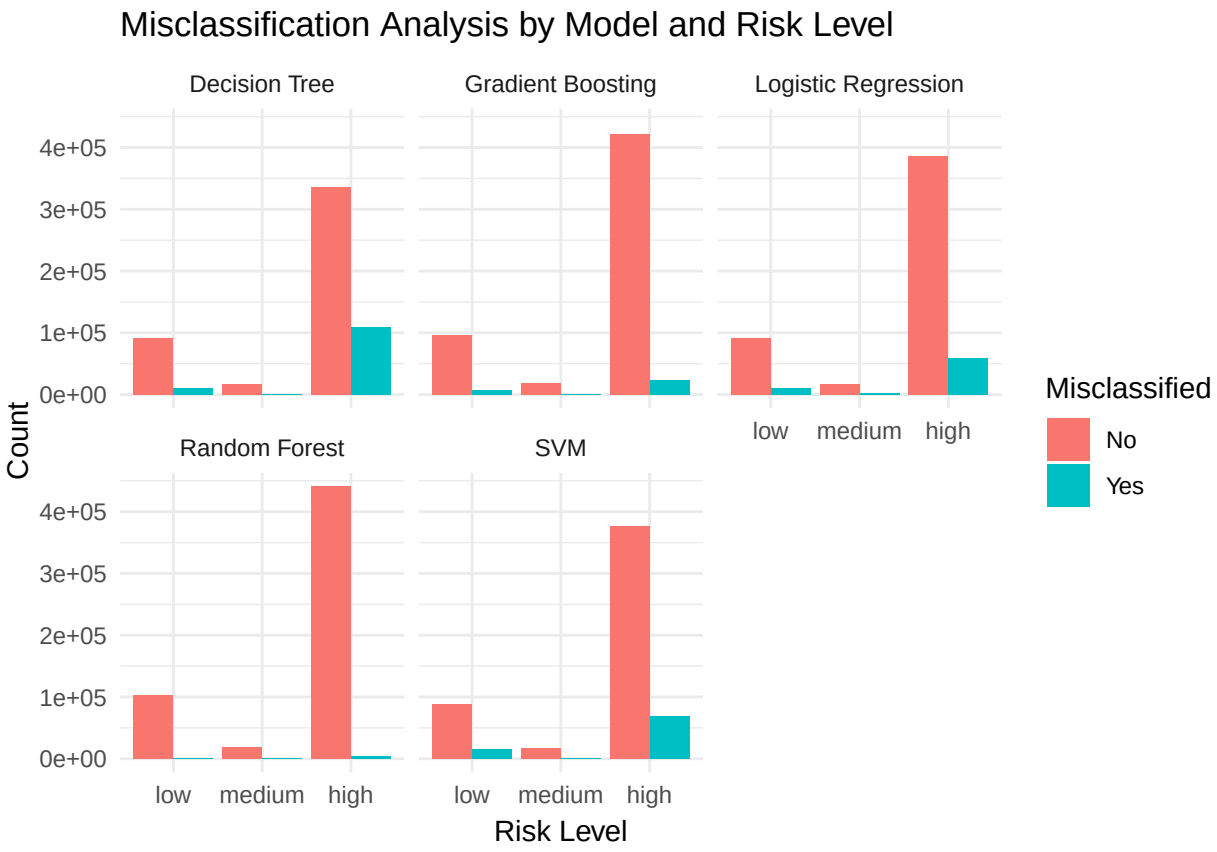

Precision−Recall Curve: Logistic Regression − high
AUC = 0.4718362
Precision
0.0
0.2
0.4
0.6
0.8
1.0
Recall
0.0
0.2
0.4
0.6
0.8
1.0

0.5.5 4. Feature Importance





0.5.6 5. Misclassification Analysis



0.5.7 Conclusion

These visuals provide insights into the models' performance and help stakeholders understand the trade-offs between accuracy, precision, and recall for each classification method. They also highlight areas for improvement, such as addressing misclassifications.

0.6 4. Deployment

- **Practical Use**: The model can guide early interventions (e.g., mask mandates, closures).
- **Update Frequency**: Weekly updates based on new data.
- **Integration**: Stakeholders can incorporate model predictions into decision-making frameworks.

```
# Save all models
save_model(dt_model, "dt_model_balanced.rds")
```

```
## Model saved to: dt_model_balanced.rds
```

```
save_model(rf_model, "rf_model_balanced.rds")
```

```
## Model saved to: rf_model_balanced.rds
```

```
save_model(svm_model, "svm_model_balanced.rds")
```

```
## Model saved to: svm_model_balanced.rds
```

```
save_model(xgb_model, "xgb_model_balanced.rds")
```

```
## Model saved to: xgb_model_balanced.rds
```

```
save_model(logistic_model, "logistic_model_balanced.rds")
```

```
## Model saved to: logistic_model_balanced.rds
```

```
# Load all models
loaded_dt_model <- load_model("dt_model_balanced.rds")
```

```
## Model loaded from: dt_model_balanced.rds
```

```
loaded_rf_model <- load_model("rf_model_balanced.rds")
```

```
## Model loaded from: rf_model_balanced.rds
```

```
loaded_svm_model <- load_model("svm_model_balanced.rds")
```

```
## Model loaded from: svm_model_balanced.rds
```

```
loaded_xgb_model <- load_model("xgb_model_balanced.rds")
```

```
## Model loaded from: xgb_model_balanced.rds
```

```
loaded_logistic_model <- load_model("logistic_model_balanced.rds")
```

```
## Model loaded from: logistic_model_balanced.rds
```

0.7 Appendix

- **Team Contributions**:
  - Olivia Hofmann: Lead on data preparation and feature engineering.
  - Michael Perkins: Lead on modeling and evaluation.
- **Graduate Work**:
  - Additional models: Gradient Boosting and k-Nearest Neighbors (to be implemented).