Yelp Reviews: Sentiment Analysis

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2026-01-30

1. Load and Prepare Data

```
yelp <- read_csv("Yelp Restaurant Reviews.csv")


yelp <- yelp %>%
  clean_names() %>%
  rename(
    url = yelp_url,
    text = review_text
  )


yelp <- yelp %>%
  mutate(
    sentiment = ifelse(rating >= 4, "Positive", "Negative"),
    sentiment = factor(sentiment, levels = c("Negative", "Positive"))
  )


cat("Dataset dimensions:", dim(yelp), "\n")
```

```
## Dataset dimensions: 19896 5
```

```
cat("\nSentiment distribution:\n")
```

```
##
## Sentiment distribution:
```

```
print(table(yelp$sentiment))
```

```
##
## Negative Positive
##     4566    15330
```

```
cat("\nProportions:\n")
```

```
##
## Proportions:
```

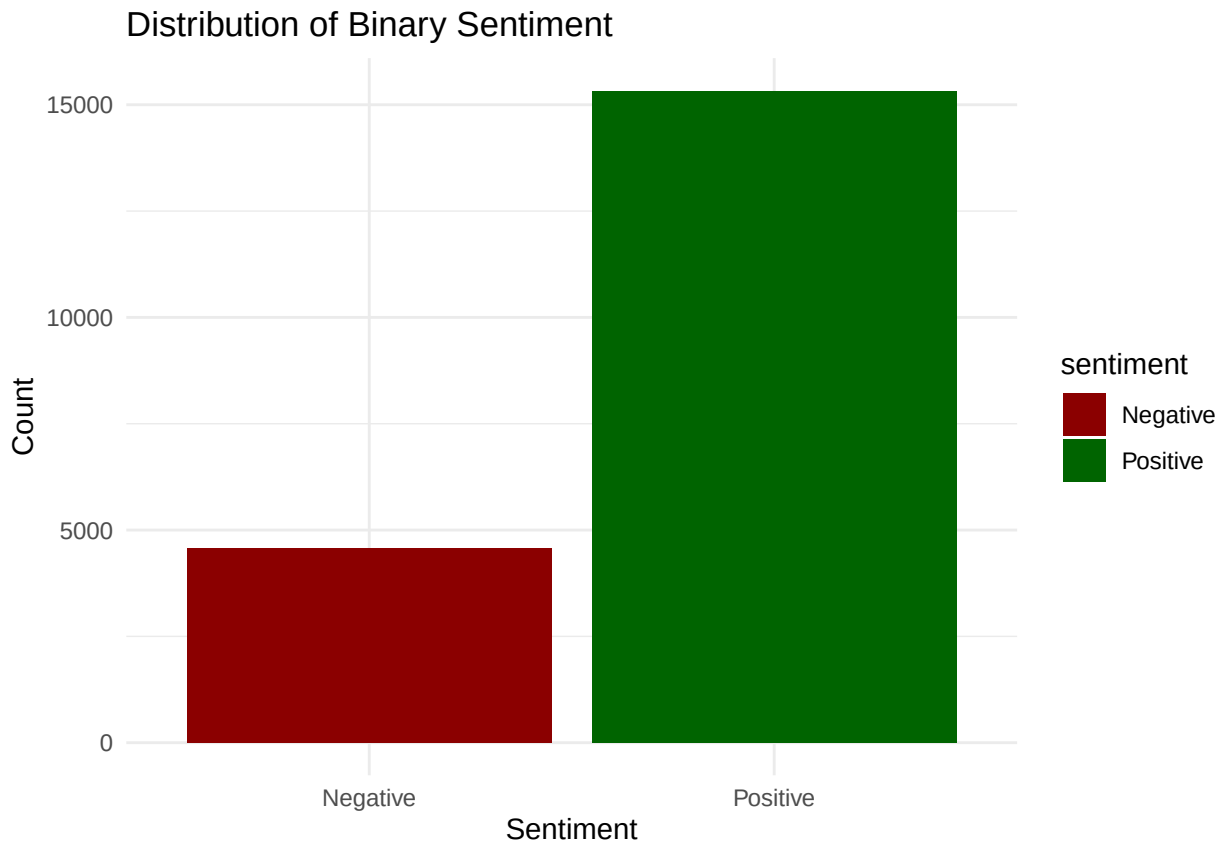
```r
print(prop.table(table(yelp$sentiment)))
```

```
##
##  Negative  Positive
## 0.2294934 0.7705066
```

2. Exploratory Data Analysis

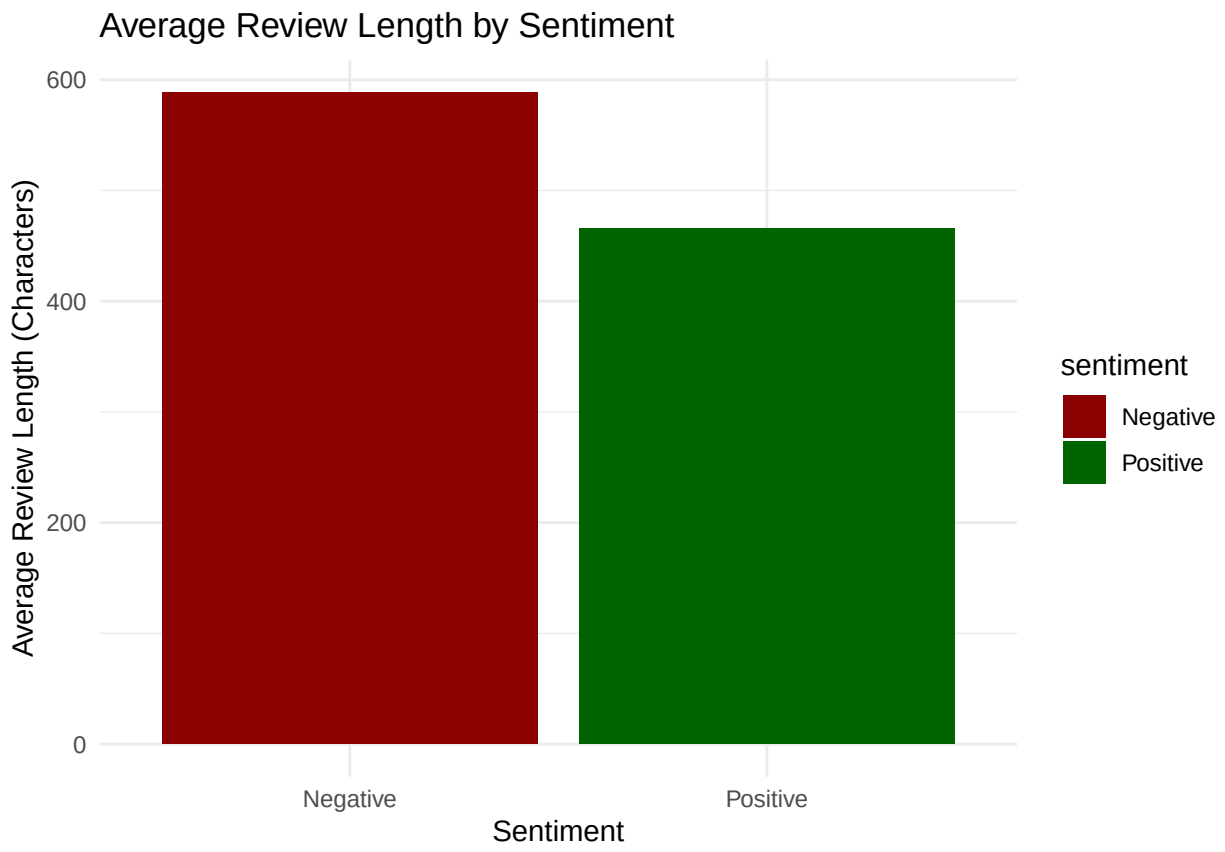
Distribution of Binary Sentiment

```r
ggplot(yelp, aes(x = sentiment, fill = sentiment)) +
  geom_bar() +
  scale_fill_manual(values = c("Negative" = "darkred", "Positive" = "darkgreen")) +
  labs(title = "Distribution of Binary Sentiment",
       x = "Sentiment",
       y = "Count") +
  theme_minimal()
```



Review Length by Sentiment

```r
yelp <- yelp %>%
  mutate(review_length = nchar(text))

yelp %>%
  group_by(sentiment) %>%
  summarise(
    avg_length = mean(review_length),
    median_length = median(review_length)
  ) %>%
  ggplot(aes(x = sentiment, y = avg_length, fill = sentiment)) +
  geom_col() +
  scale_fill_manual(values = c("Negative" = "darkred", "Positive" = "darkgreen")) +
  labs(title = "Average Review Length by Sentiment",
       x = "Sentiment",
       y = "Average Review Length (Characters)") +
  theme_minimal()
```



3. Text Preprocessing and Feature Engineering

```r
preprocess_text <- function(text_vector) {
  text_clean <- text_vector %>%
    tolower() %>%
    str_replace_all("http\\S+|www\\S+", "") %>%
```

```
    str_replace_all("\\S+@\\S+", "") %>%
    str_replace_all("[[:punct:]]", " ") %>%
    str_replace_all("[[:digit:]]+", "") %>%
    str_replace_all("\\s+", " ") %>%
    str_trim()

  return(text_clean)
}


yelp <- yelp %>%
  mutate(
    text_clean = preprocess_text(text),
    review_id = row_number()
  )
```

Create TF-IDF Features

```
food_stopwords <- tibble(word = c(
  "ice", "cream", "chocolate", "vanilla", "cookie", "cookies",
  "cake", "cakes", "flavor", "flavors", "bakery", "donut", "donuts"
))


tfidf_data <- yelp %>%
  select(review_id, sentiment, text_clean) %>%
  unnest_tokens(word, text_clean) %>%
  anti_join(stop_words, by = "word") %>%
  anti_join(food_stopwords, by = "word") %>%
  count(review_id, word) %>%
  bind_tf_idf(word, review_id, n)


discriminative_words <- tfidf_data %>%
  left_join(yelp %>% select(review_id, sentiment), by = "review_id") %>%
  group_by(word, sentiment) %>%
  summarise(
    total_tfidf = sum(tf_idf),
    count = n(),
    .groups = "drop"
  ) %>%
  pivot_wider(names_from = sentiment, values_from = c(total_tfidf, count), values_fill = 0) %>%
  mutate(
    total_count = count_Negative + count_Positive,

    discriminative_score = abs(total_tfidf_Positive - total_tfidf_Negative)
  ) %>%
  filter(total_count >= 10) %>%
  arrange(desc(discriminative_score)) %>%
  slice_head(n = 150) %>%
  select(word)
```

```r
dtm_wide <- tfidf_data %>%
  semi_join(discriminative_words, by = "word") %>%
  select(review_id, word, tf_idf) %>%
  pivot_wider(names_from = word, values_from = tf_idf, values_fill = 0)


features_final <- yelp %>%
  select(review_id, sentiment, review_length) %>%
  left_join(dtm_wide, by = "review_id")


features_final[is.na(features_final)] <- 0

cat("Features matrix dimensions:", dim(features_final), "\n")
```

```
## Features matrix dimensions: 19896 153
```

```r
cat("Number of discriminative features:", ncol(dtm_wide) - 1, "\n")
```

```
## Number of discriminative features: 150
```

4. Train-Test Split

```r
set.seed(42)


train_index <- createDataPartition(features_final$sentiment, p = 0.8, list = FALSE)

train_data <- features_final[train_index, ]
test_data <- features_final[-train_index, ]


X_train <- train_data %>% select(-review_id, -sentiment)
y_train <- train_data$sentiment

X_test <- test_data %>% select(-review_id, -sentiment)
y_test <- test_data$sentiment

cat("Training set distribution:\n")
```

```
## Training set distribution:
```

```r
print(table(y_train))
```

```
## y_train
## Negative Positive
##     3653    12264
```

```r
cat("\nTest set distribution:\n")
```

```
##
## Test set distribution:
```

```r
print(table(y_test))
```

```
## y_test
## Negative Positive
##      913     3066
```

```r
cat("\nNumber of features:", ncol(X_train), "\n")
```

```
##
## Number of features: 151
```

5. Model Training

Model 1: Logistic Regression

```r
class_weights <- 1 / table(y_train)
weights <- ifelse(y_train == "Negative",
                  class_weights["Negative"],
                  class_weights["Positive"])

weights <- weights / sum(weights) * length(weights)


logistic_model <- glm(
  sentiment ~ .,
  data = train_data %>% select(-review_id),
  family = binomial(link = "logit"),
  weights = weights
)


logistic_prob <- predict(logistic_model, newdata = X_test, type = "response")
logistic_pred <- factor(
  ifelse(logistic_prob > 0.5, "Positive", "Negative"),
  levels = c("Negative", "Positive")
)


logistic_accuracy <- mean(logistic_pred == y_test)
cat("Logistic Regression Test Accuracy:", round(logistic_accuracy * 100, 2), "%\n")
```

```
## Logistic Regression Test Accuracy: 74.49 %
```

Model 2: Random Forest

```
y_train <- factor(y_train, levels = c("Negative", "Positive"))
y_test <- factor(y_test, levels = c("Negative", "Positive"))


neg_count <- sum(y_train == "Negative")
pos_count <- sum(y_train == "Positive")


rf_model <- randomForest(
  x = X_train,
  y = y_train,
  ntree = 200,
  mtry = floor(sqrt(ncol(X_train))),
  sampsize = c("Negative" = neg_count, "Positive" = neg_count),  # Balance by sampling
  importance = TRUE
)


rf_pred <- predict(rf_model, newdata = X_test)
rf_pred <- factor(rf_pred, levels = c("Negative", "Positive"))


rf_accuracy <- mean(rf_pred == y_test)
cat("Random Forest Test Accuracy:", round(rf_accuracy * 100, 2), "%\n")
```

```
## Random Forest Test Accuracy: 78.56 %
```

6. Model Evaluation

Confusion Matrices

```
cat("=== Logistic Regression Confusion Matrix ===\n")
```

```
## === Logistic Regression Confusion Matrix ===
```

```
cm_logistic <- confusionMatrix(logistic_pred, y_test, positive = "Positive")
print(cm_logistic$table)
```

```
##           Reference
## Prediction Negative Positive
##   Negative      737      839
##   Positive      176     2227
```

```
cat("\n")
```

```r
print(cm_logistic$overall)
```

```
##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
##   7.449108e-01   4.251764e-01   7.310640e-01   7.583970e-01   7.705454e-01
## AccuracyPValue  McnemarPValue
##   9.999332e-01   6.701875e-96
```

```r
cat("\n=== Random Forest Confusion Matrix ===\n")
```

```
##
## === Random Forest Confusion Matrix ===
```

```r
cm_rf <- confusionMatrix(rf_pred, y_test, positive = "Positive")
print(cm_rf$table)
```

```
##           Reference
## Prediction Negative Positive
##   Negative      634      574
##   Positive      279     2492
```

```r
cat("\n")
```

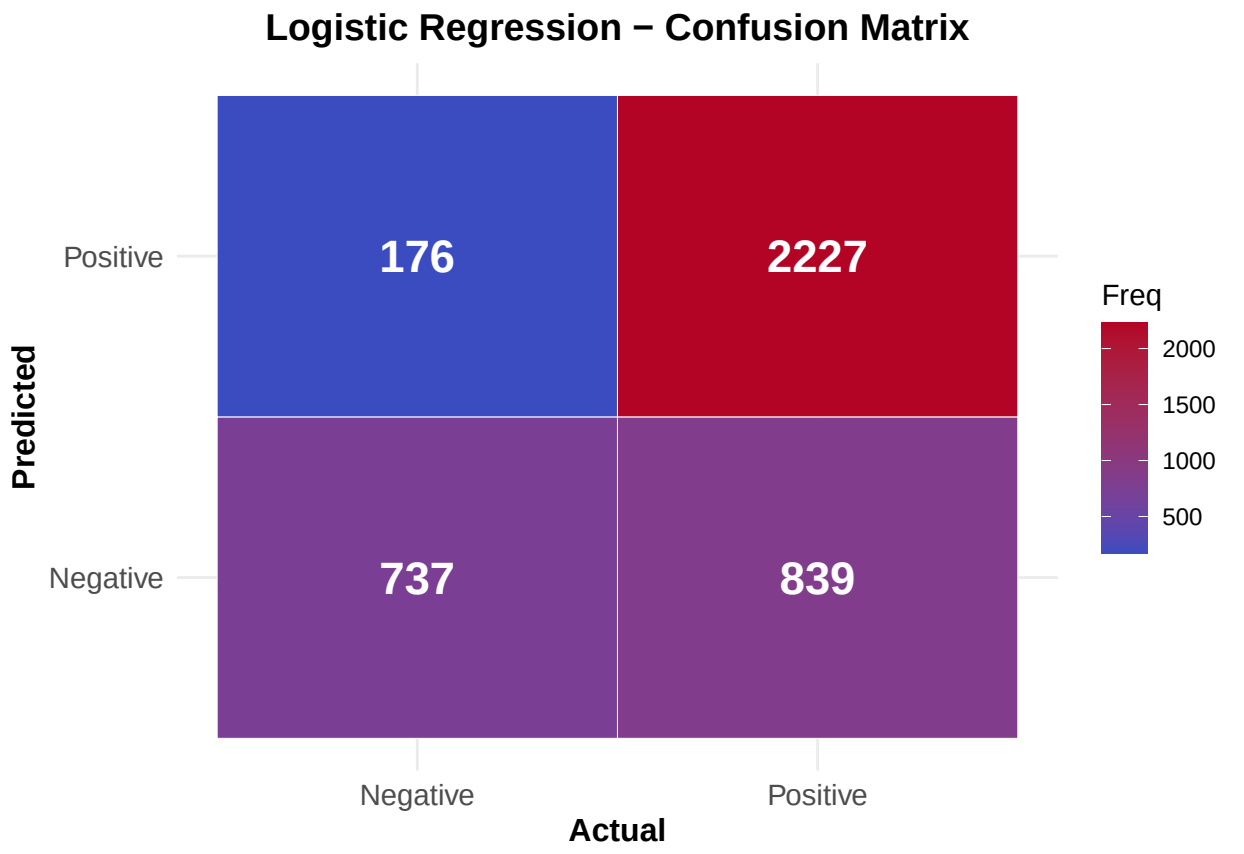
```r
print(cm_rf$overall)
```

```
##       Accuracy          Kappa  AccuracyLower  AccuracyUpper   AccuracyNull
##   7.856245e-01   4.555218e-01   7.725401e-01   7.982882e-01   7.705454e-01
## AccuracyPValue  McnemarPValue
##   1.198866e-02   7.779792e-24
```

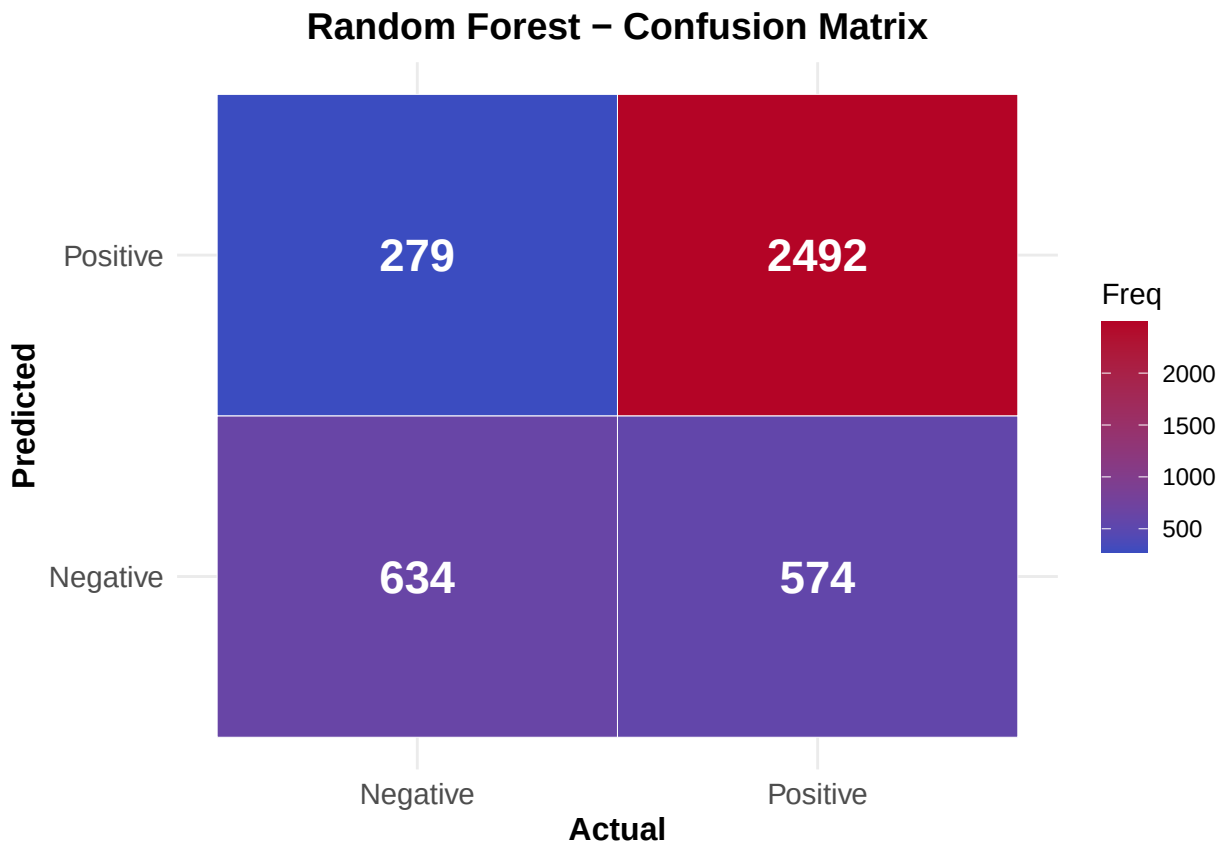
```r
library(ggplot2)
library(reshape2)
```

```r
plot_confusion_matrix <- function(cm, title) {
  cm_df <- as.data.frame(cm$table)
  colnames(cm_df) <- c("Prediction", "Reference", "Freq")


  ggplot(data = cm_df, aes(x = Reference, y = Prediction, fill = Freq)) +
    geom_tile(color = "white") +
    geom_text(aes(label = Freq), color = "white", size = 6, fontface = "bold") +
    scale_fill_gradient(low = "#3B4CC0", high = "#B40426") +
    labs(title = title,
         x = "Actual",
         y = "Predicted") +
    theme_minimal() +
    theme(plot.title = element_text(hjust = 0.5, size = 14, face = "bold"),
          axis.text = element_text(size = 11),
          axis.title = element_text(size = 12, face = "bold"),
          legend.position = "right")
}
```

```
plot_confusion_matrix(cm_logistic, "Logistic Regression - Confusion Matrix")
```




```
plot_confusion_matrix(cm_rf, "Random Forest - Confusion Matrix")
```



Performance Metrics Comparison

```
metrics_comparison <- data.frame(
  Model = c("Logistic Regression", "Random Forest"),
  Accuracy = c(cm_logistic$overall['Accuracy'], cm_rf$overall['Accuracy']),
  Precision = c(cm_logistic$byClass['Precision'], cm_rf$byClass['Precision']),
  Recall = c(cm_logistic$byClass['Recall'], cm_rf$byClass['Recall']),
  F1 = c(cm_logistic$byClass['F1'], cm_rf$byClass['F1'])
)

print(metrics_comparison)
```

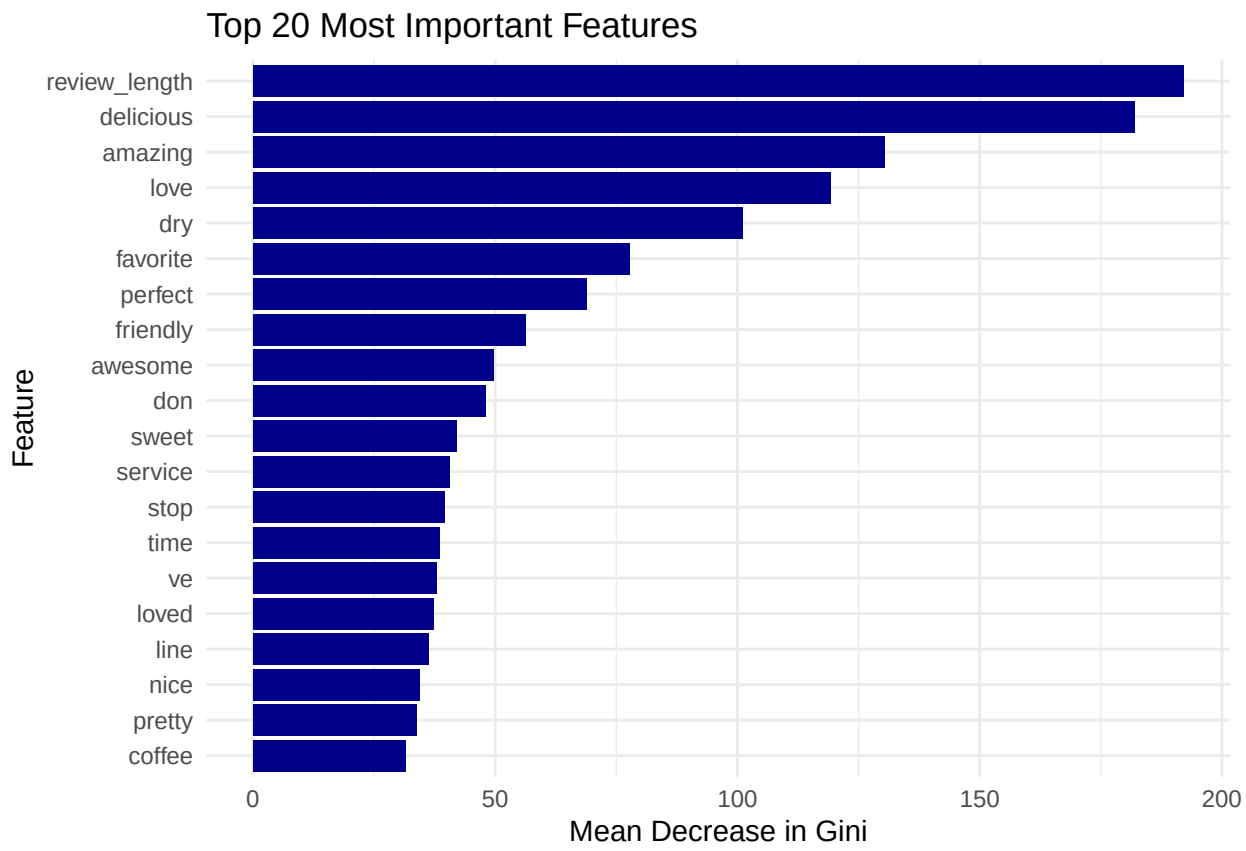
```
##                 Model  Accuracy Precision    Recall        F1
## 1 Logistic Regression 0.7449108 0.9267582 0.7263536 0.8144085
## 2       Random Forest 0.7856245 0.8993143 0.8127854 0.8538633
```

```
metrics_comparison %>%
  pivot_longer(cols = c(Accuracy, Precision, Recall, F1),
               names_to = "Metric",
               values_to = "Score") %>%
  ggplot(aes(x = Metric, y = Score, fill = Model)) +
  geom_col(position = "dodge") +
  scale_y_continuous(limits = c(0, 1), labels = scales::percent) +
```

```
  labs(title = "Model Performance Comparison",
       y = "Score") +
  theme_minimal()
```

Feature Importance

```
importance_df <- as.data.frame(importance(rf_model))
importance_df$feature <- rownames(importance_df)

top_20_features <- importance_df %>%
  arrange(desc(MeanDecreaseGini)) %>%
  head(20)


ggplot(top_20_features, aes(x = reorder(feature, MeanDecreaseGini), y = MeanDecreaseGini)) +
  geom_col(fill = "darkblue") +
  coord_flip() +
  labs(title = "Top 20 Most Important Features",
       x = "Feature",
       y = "Mean Decrease in Gini") +
  theme_minimal()
```



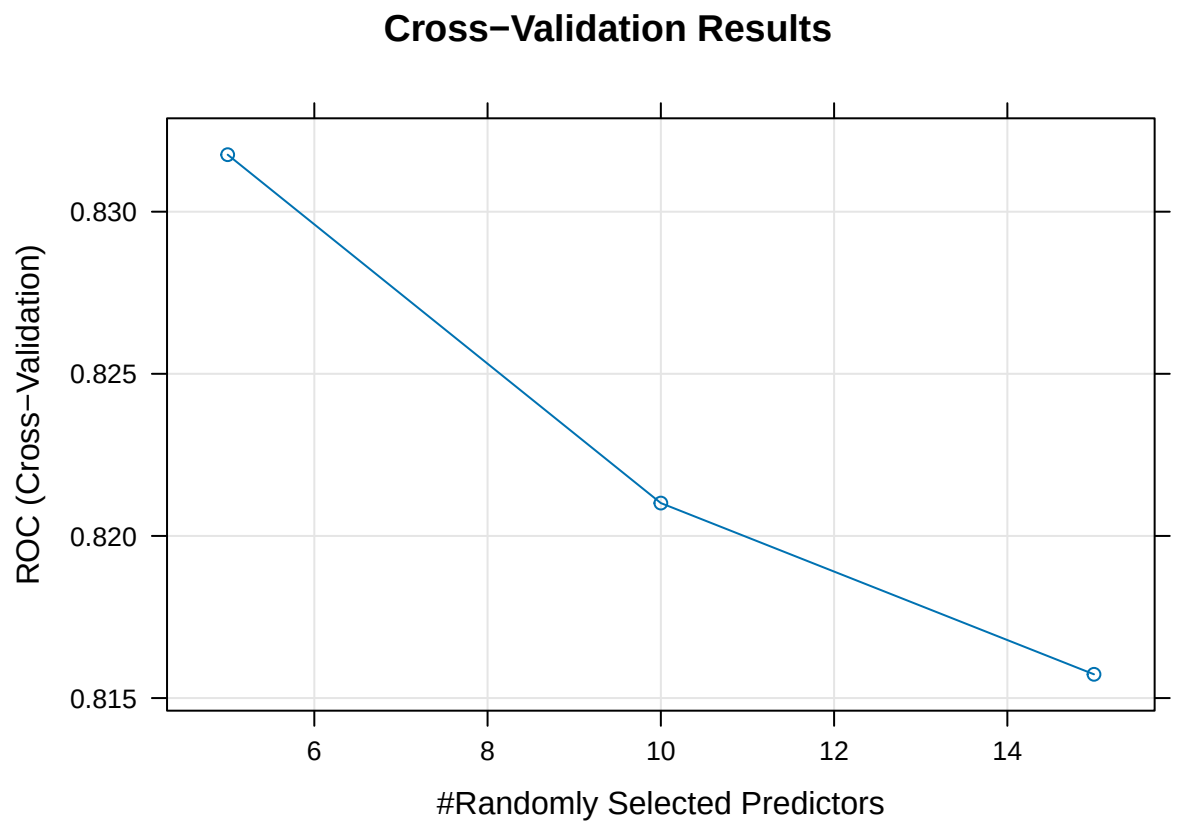
7. Cross-Validation

```
train_control <- trainControl(
  method = "cv",
  number = 5,
  classProbs = TRUE,
  summaryFunction = twoClassSummary
)


cv_rf <- train(
  x = X_train,
  y = y_train,
  method = "rf",
  trControl = train_control,
  tuneGrid = data.frame(mtry = c(5, 10, 15)),
  ntree = 200,
  metric = "ROC"
)

print(cv_rf)
```

```
## Random Forest
```

```
##
## 15917 samples
##   151 predictor
##     2 classes: 'Negative', 'Positive'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 12734, 12733, 12735, 12733, 12733
## Resampling results across tuning parameters:
##
##   mtry  ROC        Sens       Spec
##    5    0.8317581  0.3375249  0.9664872
##   10    0.8210130  0.3739325  0.9526254
##   15    0.8157327  0.3909079  0.9467548
##
## ROC was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 5.
```

```
plot(cv_rf, main = "Cross-Validation Results")
```



8. Bias-Variance Analysis

Calculate Training Performance

```
logistic_train_prob <- predict(logistic_model, newdata = X_train, type = "response")
logistic_train_pred <- factor(
  ifelse(logistic_train_prob > 0.5, "Positive", "Negative"),
  levels = c("Negative", "Positive")
)

rf_train_pred <- predict(rf_model, newdata = X_train)


logistic_train_acc <- mean(logistic_train_pred == y_train)
rf_train_acc <- mean(rf_train_pred == y_train)

cat("Logistic Regression Training Accuracy:", round(logistic_train_acc * 100, 2), "%\n")
```

```
## Logistic Regression Training Accuracy: 76.13 %
```

```
cat("Random Forest Training Accuracy:", round(rf_train_acc * 100, 2), "%\n")
```

```
## Random Forest Training Accuracy: 93.06 %
```

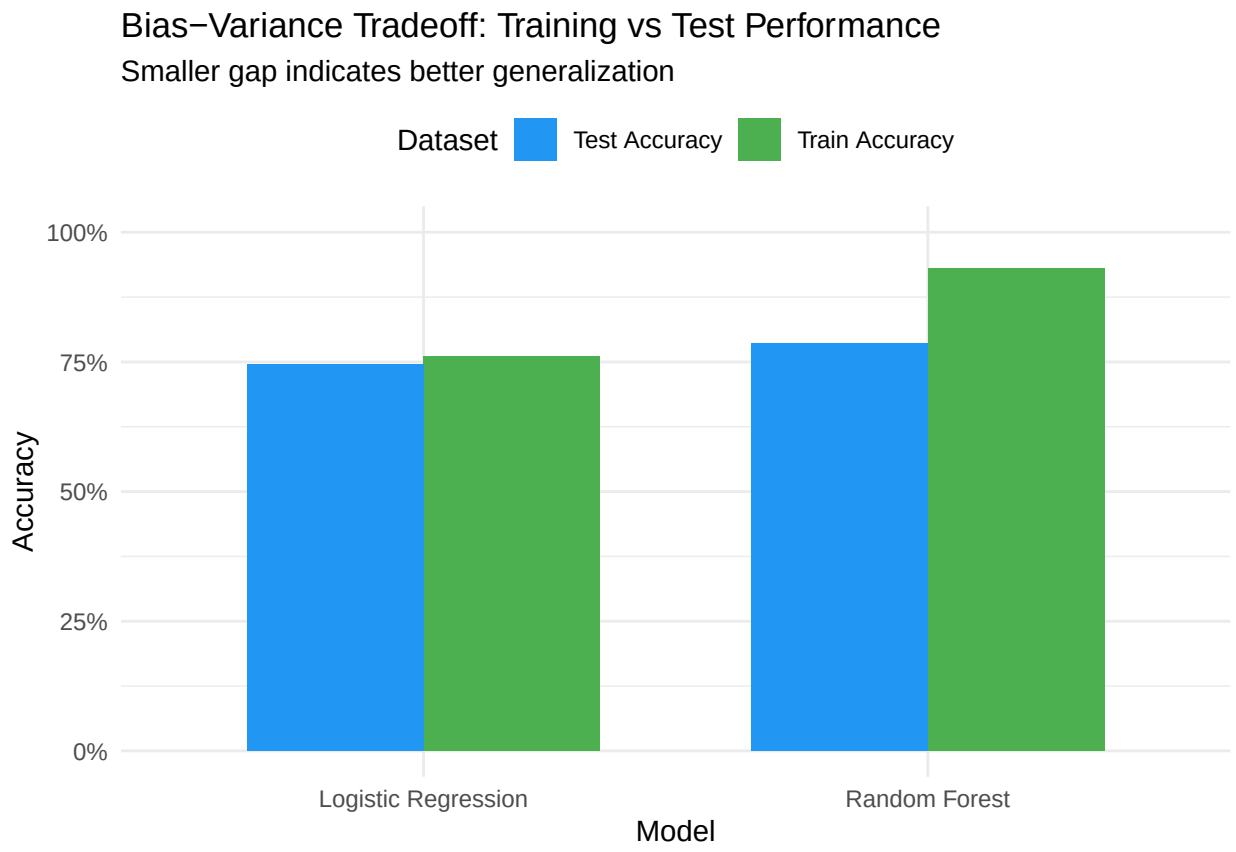
Bias-Variance Tradeoff Comparison

```
bias_variance_table <- data.frame(
  Model = c("Logistic Regression", "Random Forest"),
  Train_Accuracy = c(logistic_train_acc, rf_train_acc),
  Test_Accuracy = c(logistic_accuracy, rf_accuracy),
  Gap = c(logistic_train_acc - logistic_accuracy,
          rf_train_acc - rf_accuracy)
)

print(bias_variance_table)
```

```
##                 Model Train_Accuracy Test_Accuracy        Gap
## 1 Logistic Regression      0.7612615     0.7449108 0.01635076
## 2       Random Forest      0.9306402     0.7856245 0.14501567
```

```
bias_variance_table %>%
  select(Model, Train_Accuracy, Test_Accuracy) %>%
  pivot_longer(cols = c(Train_Accuracy, Test_Accuracy),
               names_to = "Dataset",
               values_to = "Accuracy") %>%
  mutate(Dataset = str_replace(Dataset, "_", " ")) %>%
  ggplot(aes(x = Model, y = Accuracy, fill = Dataset)) +
  geom_col(position = "dodge", width = 0.7) +
  scale_y_continuous(limits = c(0, 1), labels = scales::percent) +
```

```
  scale_fill_manual(values = c("Train Accuracy" = "#4CAF50",
                               "Test Accuracy" = "#2196F3")) +
  labs(title = "Bias-Variance Tradeoff: Training vs Test Performance",
       subtitle = "Smaller gap indicates better generalization",
       y = "Accuracy",
       x = "Model") +
  theme_minimal() +
  theme(legend.position = "top")
```



Interpretation

Logistic Regression: - Train-Test Gap: 1.64 % - Interpretation: Low variance, good generalization

Random Forest: - Train-Test Gap: 14.5 % - Interpretation: Potential overfitting

Overall Assessment: - Random Forest shows larger train-test gap, suggesting higher variance - However, RF still achieves better test performance overall

Cross-Validation Stability Analysis

```
cv_results <- cv_rf$resample

cat("\n=== Cross-Validation Stability ===\n\n")
```

```
##
## === Cross-Validation Stability ===
```

```
cat("ROC AUC across folds:\n")
```

```
## ROC AUC across folds:
```

```
print(summary(cv_results$ROC))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.8250  0.8281  0.8310  0.8318  0.8346  0.8401
```

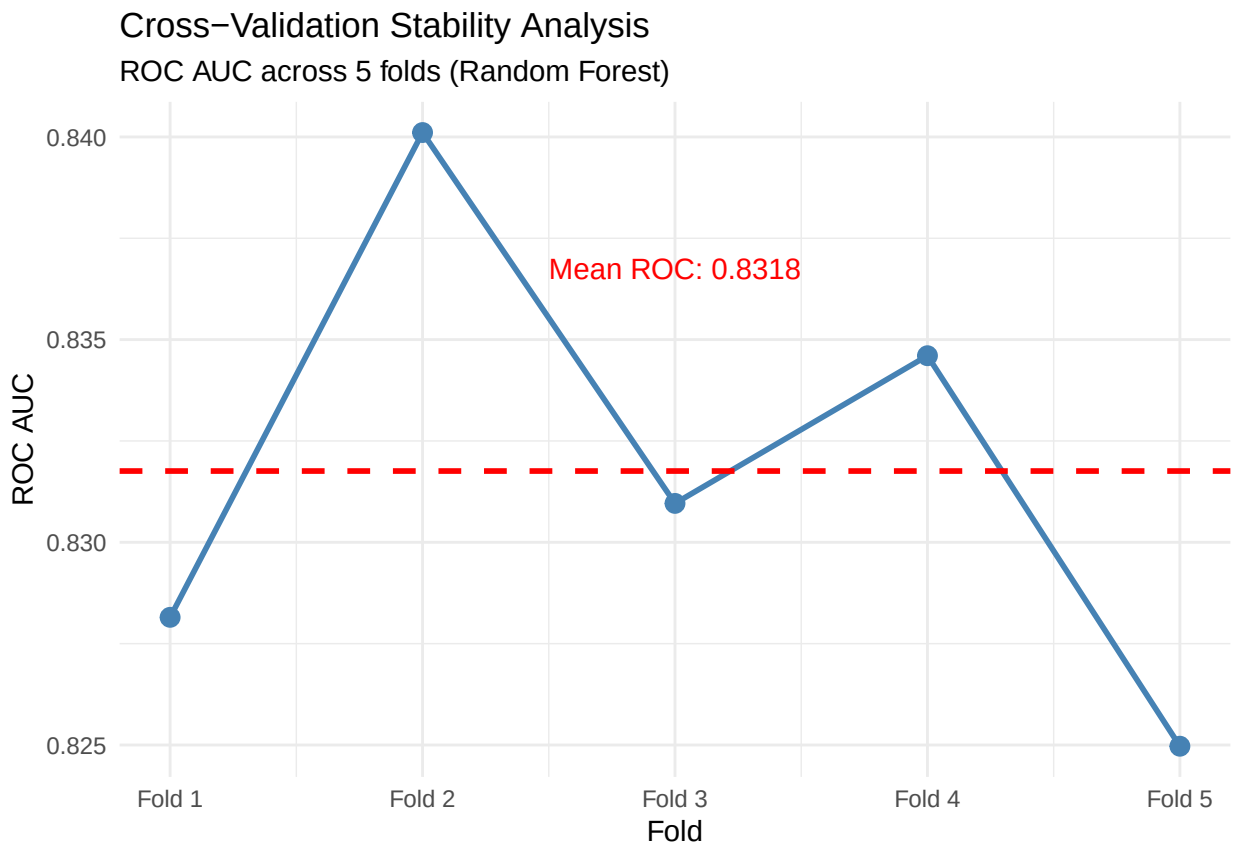
```
cat("\nStandard Deviation:", round(sd(cv_results$ROC), 4), "\n")
```

```
##
## Standard Deviation: 0.0059
```

```
cat("Coefficient of Variation:", round(sd(cv_results$ROC) / mean(cv_results$ROC) * 100, 2), "%\n")
```

```
## Coefficient of Variation: 0.71 %
```

```
ggplot(cv_results, aes(x = 1:nrow(cv_results), y = ROC)) +
  geom_line(color = "steelblue", size = 1) +
  geom_point(color = "steelblue", size = 3) +
  geom_hline(yintercept = mean(cv_results$ROC),
             linetype = "dashed", color = "red", size = 1) +
  annotate("text", x = 3, y = mean(cv_results$ROC) + 0.005,
           label = paste("Mean ROC:", round(mean(cv_results$ROC), 4)),
           color = "red") +
  scale_x_continuous(breaks = 1:5, labels = paste("Fold", 1:5)) +
  labs(title = "Cross-Validation Stability Analysis",
       subtitle = "ROC AUC across 5 folds (Random Forest)",
       x = "Fold",
       y = "ROC AUC") +
  theme_minimal()
```



9. Results Summary

Classification Task:

- Binary (Negative vs. Positive)
  - Negative: 1-3 star ratings
  - Positive: 4-5 star ratings

Model Performance:

- Logistic Regression:
  - - Accuracy: 74.49 %
  - - Precision: 92.68 %
  - - Recall: 72.64 %
  - - F1 Score: 81.44 %
- Random Forest:
  - - Accuracy: 78.56 %
  - - Precision: 89.93 %
  - - Recall: 81.28 %

  - - F1 Score: 85.39 %

- Cross-Validated Random Forest:
  - * ROC AUC: 0.832

Top 5 Most Important Features:

1. review_length
2. delicious
3. amazing
4. love
5. dry

```
sessionInfo()
```

```
## R version 4.4.3 (2025-02-28)
## Platform: aarch64-apple-darwin20
## Running under: macOS Sonoma 14.6
##
## Matrix products: default
## BLAS:   /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRlapack.dylib;  LAPACK v
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## time zone: America/New_York
## tzcode source: internal
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] reshape2_1.4.4       caret_7.0-1          lattice_0.22-6
##  [4] randomForest_4.7-1.2 janitor_2.2.1        tidytext_0.4.3
##  [7] lubridate_1.9.4      forcats_1.0.0        stringr_1.5.1
## [10] dplyr_1.1.4          purrr_1.0.4          readr_2.1.5
## [13] tidyr_1.3.1          tibble_3.2.1         ggplot2_3.5.2
## [16] tidyverse_2.0.0
##
## loaded via a namespace (and not attached):
##  [1] tidyselect_1.2.1     timeDate_4041.110    farver_2.1.2
##  [4] fastmap_1.2.0        janeaustenr_1.0.0    pROC_1.19.0.1
##  [7] digest_0.6.37        rpart_4.1.24         timechange_0.3.0
## [10] lifecycle_1.0.4      tokenizers_0.3.0     survival_3.8-3
## [13] magrittr_2.0.3       compiler_4.4.3       rlang_1.1.5
## [16] tools_4.4.3          yaml_2.3.10          data.table_1.17.0
## [19] knitr_1.49           labeling_0.4.3       bit_4.6.0
## [22] plyr_1.8.9           withr_3.0.2          nnet_7.3-20
## [25] grid_4.4.3           stats4_4.4.3         e1071_1.7-16
```

```
## [28] colorspace_2.1-1     future_1.67.0        globals_0.18.0
## [31] scales_1.3.0         iterators_1.0.14     MASS_7.3-65
## [34] cli_3.6.4            crayon_1.5.3         rmarkdown_2.29
## [37] generics_0.1.3       rstudioapi_0.17.1    future.apply_1.20.0
## [40] tzdb_0.5.0           proxy_0.4-27         splines_4.4.3
## [43] parallel_4.4.3       vctrs_0.6.5          hardhat_1.4.2
## [46] Matrix_1.7-2         hms_1.1.3            bit64_4.6.0-1
## [49] listenv_0.9.1        foreach_1.5.2        gower_1.0.2
## [52] recipes_1.3.1        glue_1.8.0           parallelly_1.45.1
## [55] codetools_0.2-20     stringi_1.8.4        gtable_0.3.6
## [58] munsell_0.5.1        pillar_1.10.1        htmltools_0.5.8.1
## [61] ipred_0.9-15         lava_1.8.1           R6_2.6.1
## [64] vroom_1.6.5          evaluate_1.0.3       SnowballC_0.7.1
## [67] snakecase_0.11.1     class_7.3-23         Rcpp_1.0.14
## [70] nlme_3.1-167         prodlim_2025.04.28   xfun_0.51
## [73] pkgconfig_2.0.3      ModelMetrics_1.2.2.2
```