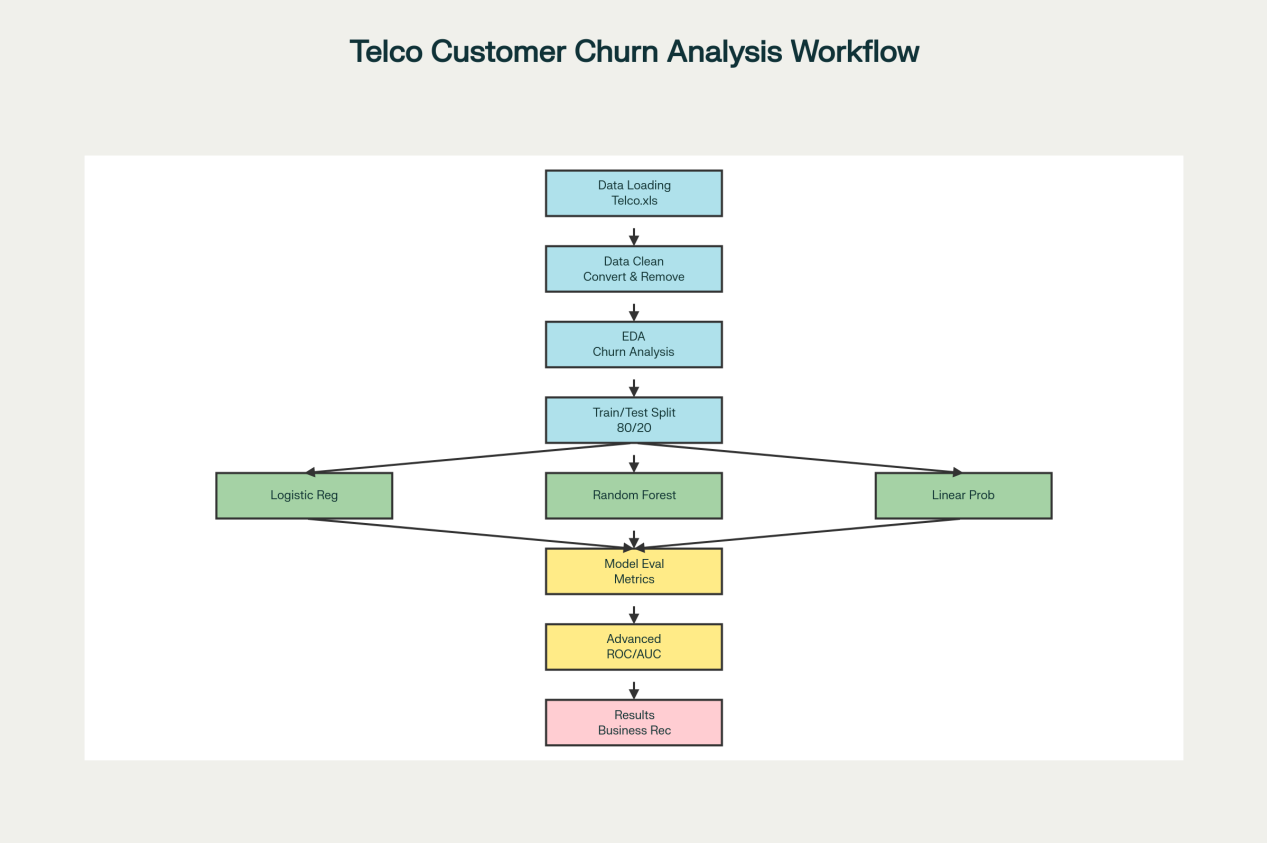
Professional Step-by-Step Guide: Telco Customer Churn Analysis in R

This comprehensive guide provides a professional, reproducible workflow for conducting end-to-end telco customer churn analysis using R, including data preprocessing, exploratory data analysis, machine learning modeling, and business insights generation.



End-to-End Telco Customer Churn Analysis Workflow

Executive Summary

Customer churn prediction is a critical business challenge in the telecommunications industry, where acquiring new customers costs significantly more than retaining existing ones. This guide presents a systematic approach to analyzing telco customer churn using advanced statistical methods and machine learning algorithms in R. The methodology includes data preprocessing, exploratory data analysis, and implementation of three complementary modeling approaches: Logistic Regression for interpretability, Random Forest for capturing complex patterns, and Linear Probability Models for coefficient-based insights. [1] [2] [3] [4] [5] [6] [7]

1. Project Setup and Prerequisites

1.1 System Requirements

Software Requirements:

- R (version ≥ 4.2) with RStudio (recommended)[2] [8]
- LaTeX distribution (for PDF report generation)[9] [10]
- Git (for version control)[11] [12]

Required R Packages:
Install the following packages once in your R environment:

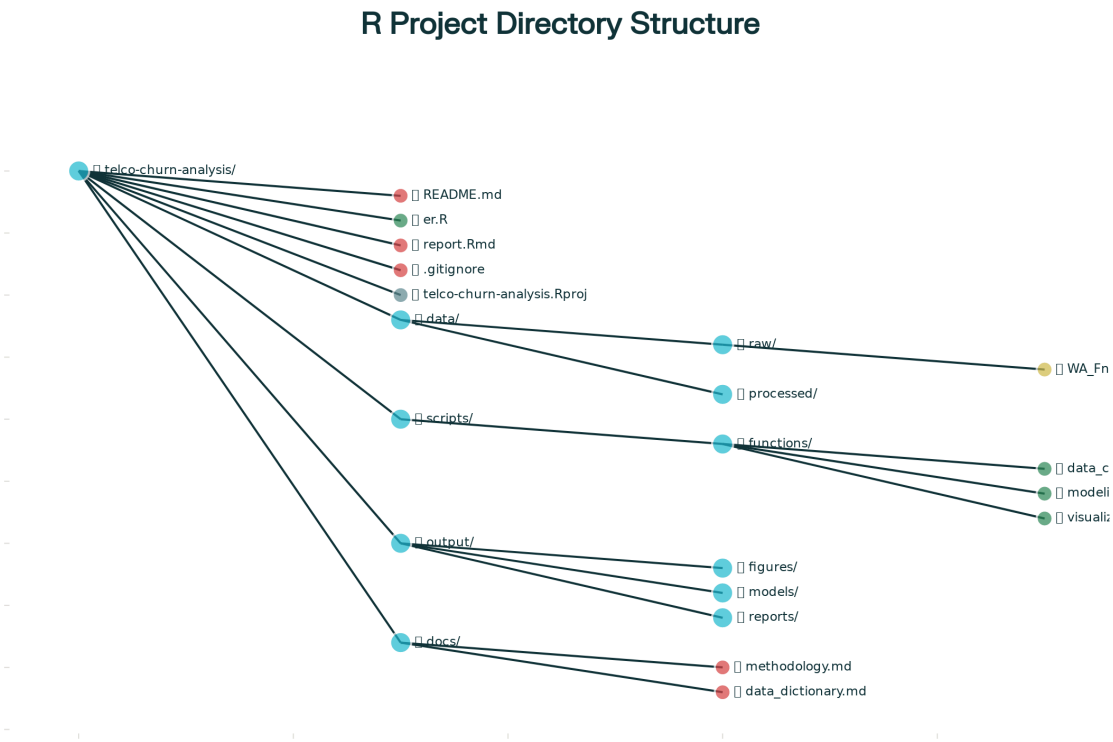
```
# Core data science packages
install.packages(c(
  "tidyverse",        # Data manipulation and visualization
  "ggplot2",         # Advanced plotting
  "caret",           # Machine learning utilities
  "randomForest",    # Random Forest implementation
  "e1071"            # Support Vector Machines and utilities
))

# Documentation and reporting
install.packages(c(
  "rmarkdown",       # Dynamic document generation
  "knitr"           # Document compilation
))

# Advanced analysis packages
install.packages(c(
  "pROC",           # ROC curve analysis
  "broom",          # Model tidying functions
  "readxl"          # Excel file reading (if needed)
))
```

1.2 Project Structure Setup

Establish a professional project structure following industry best practices:[11] [12] [13]



Recommended Project Structure for Telco Churn Analysis

Create the directory structure manually or use the following R commands:

```
# Create main project directory
dir.create("telco-churn-analysis")
setwd("telco-churn-analysis")

# Create subdirectories
dir.create("data/raw", recursive = TRUE)
dir.create("data/processed", recursive = TRUE)
dir.create("scripts/functions", recursive = TRUE)
dir.create("output/figures", recursive = TRUE)
dir.create("output/models", recursive = TRUE)
dir.create("output/reports", recursive = TRUE)
dir.create("docs", recursive = TRUE)
```

2. Data Acquisition and Validation

2.1 Dataset Overview

The Telco Customer Churn dataset contains comprehensive information about telecommunications customers, including demographics, service subscriptions, and churn status. Key dataset characteristics include:[14] [15] [16]

- **Sample Size**: Approximately 7,000 customer records

- **Features**: 21 variables including customer demographics, service attributes, and billing information
- **Target Variable**: Binary churn indicator (Yes/No)
- **Class Distribution**: Approximately 26% churn rate, indicating moderate class imbalance[4] [17]

2.2 Data Loading and Initial Inspection

Place the dataset file `WA_Fn-UseC_-Telco-Customer-Churn.xls` in the `data/raw/` directory and implement robust data loading:

```
# Load required libraries
library(tidyverse)
library(readxl)  # If Excel format

# Define data path
data_path <- "data/raw/WA_Fn-UseC_-Telco-Customer-Churn.xls"

# Load data with error handling
if (file.exists(data_path)) {
  # For CSV format (most common)
  churn_data <- read.csv(data_path, stringsAsFactors = FALSE)

  # For Excel format (alternative)
  # churn_data <- read_excel(data_path)

  cat("Data loaded successfully: ", nrow(churn_data), " rows, ",
      ncol(churn_data), " columns\n")
} else {
  stop("Data file not found. Please verify file path and location.")
}

# Initial data inspection
str(churn_data)
summary(churn_data)
```

3. Data Preprocessing and Quality Assurance

3.1 Data Cleaning Pipeline

Implement comprehensive data cleaning following industry standards:[4] [18] [19]

```
# Step 1: Handle TotalCharges conversion
churn_data <- churn_data %>%
  mutate(
    TotalCharges = as.numeric(TotalCharges),
    TotalCharges = ifelse(is.na(TotalCharges), 0, TotalCharges)
  )

# Step 2: Remove non-predictive identifiers
churn_data <- churn_data %>%
```

```
  select(-customerID)

# Step 3: Standardize categorical variables
churn_data <- churn_data %>%
  mutate(
    # Consolidate service categories
    across(c(OnlineSecurity, OnlineBackup, DeviceProtection,
             TechSupport, StreamingTV, StreamingMovies),
           ~ recode(., "No internet service" = "No")),

    # Standardize phone service categories
    MultipleLines = recode(MultipleLines, "No phone service" = "No")
  )

# Step 4: Convert character variables to factors
churn_data <- churn_data %>%
  mutate(across(where(is.character), as.factor))

# Step 5: Ensure target variable is properly formatted
churn_data$Churn <- factor(churn_data$Churn, levels = c("No", "Yes"))
```

3.2 Data Quality Validation

```
# Check for missing values
missing_summary <- churn_data %>%
  summarise(across(everything(), ~ sum(is.na(.)))) %>%
  pivot_longer(everything(), names_to = "variable", values_to = "missing_count") %>%
  filter(missing_count > 0)

if (nrow(missing_summary) > 0) {
  cat("Missing values found:\n")
  print(missing_summary)
} else {
  cat("No missing values detected.\n")
}

# Verify factor levels
categorical_vars <- churn_data %>%
  select(where(is.factor)) %>%
  names()

for (var in categorical_vars) {
  cat(var, ": ", paste(levels(churn_data[[var]]), collapse = ", "), "\n")
}
```

4. Exploratory Data Analysis (EDA)

4.1 Target Variable Analysis

```
# Analyze churn distribution
churn_summary <- churn_data %>%
  count(Churn) %>%
  mutate(
    percentage = round(n / sum(n) * 100, 2),
    label = paste0(Churn, ": ", n, " (", percentage, "%)")
  )

print(churn_summary)

# Visualize churn distribution
ggplot(churn_summary, aes(x = Churn, y = n, fill = Churn)) +
  geom_col(alpha = 0.8) +
  geom_text(aes(label = label), vjust = -0.5) +
  labs(
    title = "Customer Churn Distribution",
    x = "Churn Status",
    y = "Number of Customers"
  ) +
  theme_minimal() +
  scale_fill_manual(values = c("No" = "#2E86AB", "Yes" = "#F24236"))
```

4.2 Univariate and Bivariate Analysis

```
# Contract type analysis
contract_churn <- churn_data %>%
  group_by(Contract, Churn) %>%
  summarise(count = n(), .groups = "drop") %>%
  group_by(Contract) %>%
  mutate(percentage = round(count / sum(count) * 100, 2))

ggplot(contract_churn, aes(x = Contract, y = count, fill = Churn)) +
  geom_col(position = "dodge", alpha = 0.8) +
  geom_text(aes(label = paste0(percentage, "%")),
            position = position_dodge(width = 0.9), vjust = -0.5) +
  labs(
    title = "Customer Churn by Contract Type",
    x = "Contract Type",
    y = "Number of Customers"
  ) +
  theme_minimal()

# Monthly charges analysis
ggplot(churn_data, aes(x = Churn, y = MonthlyCharges, fill = Churn)) +
  geom_boxplot(alpha = 0.7) +
  stat_summary(fun = mean, geom = "point", shape = 18, size = 3) +
  labs(
    title = "Monthly Charges Distribution by Churn Status",
    x = "Churn Status",
    y = "Monthly Charges ($)"
```

```
  ) +
  theme_minimal()
```

4.3 Correlation Analysis

```
# Analyze correlations among numeric variables
numeric_vars <- churn_data %>%
  select(where(is.numeric)) %>%
  names()

correlation_matrix <- churn_data %>%
  select(all_of(numeric_vars)) %>%
  cor(use = "complete.obs")

print(correlation_matrix)

# Statistical tests for categorical associations
library(vcd)
assocstats(table(churn_data$Contract, churn_data$Churn))
```

5. Model Development and Training

5.1 Data Splitting Strategy

Implement stratified sampling to maintain class proportions:[1] [4]

```
library(caret)

# Set reproducible seed
set.seed(123)

# Create stratified train/test split (80/20)
train_index <- createDataPartition(
  churn_data$Churn,
  p = 0.8,
  list = FALSE,
  times = 1
)

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

# Verify split proportions
cat("Training set size:", nrow(train_data), "\n")
cat("Test set size:", nrow(test_data), "\n")
cat("Training set churn rate:",
    round(mean(train_data$Churn == "Yes") * 100, 2), "%\n")
cat("Test set churn rate:",
    round(mean(test_data$Churn == "Yes") * 100, 2), "%\n")
```

5.2 Model Implementation

Telco Churn Model Evaluation Metrics

Model Type	Primary Metrics	Secondary Metrics	Interpretation Focus
Logistic Regression	Accuracy Sensitivity Specificity	AUC-ROC Precision Recall	Odds ratios Coefficient significance
Random Forest	Accuracy Sensitivity Specificity	AUC-ROC Variable importance	Feature importance rankings
Linear Probability Model	RMSE Out-of-bounds rate	Confusion matrix at 0.5 threshold	Linear coefficient interpretation

Class Imbalance	Threshold Adj.	Business Context
26% churn rate	Adjust based on	False negative:
Consider SMOTE	business cost	Lost customer
or class weights	of errors	False positive: Discount cost

Model Evaluation Metrics Comparison for Telco Churn Analysis

5.2.1 Logistic Regression Model

```
# Train logistic regression model
logistic_model <- glm(
  Churn ~ .,
  data = train_data,
  family = binomial
)

# Model summary and diagnostics
summary(logistic_model)

# Generate predictions
logistic_predictions <- predict(
  logistic_model,
  test_data,
  type = "response"
)

# Convert probabilities to class predictions
logistic_pred_class <- factor(
  ifelse(logistic_predictions > 0.5, "Yes", "No"),
  levels = levels(test_data$Churn)
)
```

5.2.2 Random Forest Model

```
library(randomForest)

# Train Random Forest model
rf_model <- randomForest(
  Churn ~ .,
  data = train_data,
  ntree = 500,
  mtry = sqrt(ncol(train_data) - 1),
  importance = TRUE
)

# Model summary
print(rf_model)

# Generate predictions
rf_predictions <- predict(rf_model, test_data)
rf_predictions <- factor(rf_predictions, levels = levels(test_data$Churn))
```

5.2.3 Linear Probability Model

```
# Create numeric target variable for LPM
train_lpm <- train_data %>%
  mutate(Churn_num = ifelse(Churn == "Yes", 1, 0))

test_lmp <- test_data %>%
  mutate(Churn_num = ifelse(Churn == "Yes", 1, 0))

# Train Linear Probability Model
lpm_model <- lm(Churn_num ~ . - Churn, data = train_lpm)

# Model summary
summary(lmp_model)

# Generate predictions
lmp_predictions <- predict(lmp_model, newdata = test_lmp)

# Convert to class predictions using 0.5 threshold
lmp_pred_class <- factor(
  ifelse(lmp_predictions > 0.5, "Yes", "No"),
  levels = levels(test_data$Churn)
)
```

6. Model Evaluation and Validation

6.1 Performance Metrics Calculation

```
# Logistic Regression evaluation
logistic_cm <- confusionMatrix(
  logistic_pred_class,
  test_data$Churn,
  positive = "Yes"
)

# Random Forest evaluation
rf_cm <- confusionMatrix(
  rf_predictions,
  test_data$Churn,
  positive = "Yes"
)

# Linear Probability Model evaluation
lmp_cm <- confusionMatrix(
  lmp_pred_class,
  test_data$Churn,
  positive = "Yes"
)

# Calculate RMSE and out-of-bounds rate for LPM
lmp_rmse <- sqrt(mean((lmp_predictions - test_lmp$Churn_num)^2))
lmp_out_bounds <- mean(lmp_predictions < 0 | lmp_predictions > 1)

# Display results
cat("=== MODEL PERFORMANCE SUMMARY ===\n\n")

cat("Logistic Regression:\n")
cat("Accuracy:", round(logistic_cm$overall["Accuracy"], 4), "\n")
cat("Sensitivity:", round(logistic_cm$byClass["Sensitivity"], 4), "\n")
cat("Specificity:", round(logistic_cm$byClass["Specificity"], 4), "\n\n")

cat("Random Forest:\n")
cat("Accuracy:", round(rf_cm$overall["Accuracy"], 4), "\n")
cat("Sensitivity:", round(rf_cm$byClass["Sensitivity"], 4), "\n")
cat("Specificity:", round(rf_cm$byClass["Specificity"], 4), "\n\n")

cat("Linear Probability Model:\n")
cat("Accuracy:", round(lmp_cm$overall["Accuracy"], 4), "\n")
cat("RMSE:", round(lmp_rmse, 4), "\n")
cat("Out-of-bounds rate:", round(lmp_out_bounds * 100, 2), "%\n")
```

6.2 Advanced Model Analysis

6.2.1 ROC Analysis

```
library(pROC)

# Generate ROC curves
logistic_roc <- roc(
  response = test_data$Churn,
  predictor = as.numeric(logistic_predictions),
  levels = c("No", "Yes")
)

rf_prob <- predict(rf_model, test_data, type = "prob")[, "Yes"]
rf_roc <- roc(
  response = test_data$Churn,
  predictor = rf_prob,
  levels = c("No", "Yes")
)

# Plot ROC curves
plot(logistic_roc, col = "blue", lwd = 2, main = "ROC Curve Comparison")
plot(rf_roc, col = "red", lwd = 2, add = TRUE)

legend("bottomright",
       legend = c(paste("Logistic (AUC =", round(auc(logistic_roc), 3), ")"),
                  paste("Random Forest (AUC =", round(auc(rf_roc), 3), ")")),
       col = c("blue", "red"),
       lwd = 2)

# AUC comparison
cat("AUC Scores:\n")
cat("Logistic Regression:", round(auc(logistic_roc), 4), "\n")
cat("Random Forest:", round(auc(rf_roc), 4), "\n")
```

6.2.2 Feature Importance Analysis

```
# Random Forest variable importance
rf_importance <- importance(rf_model)
rf_importance_df <- data.frame(
  Variable = rownames(rf_importance),
  Importance = rf_importance[, "MeanDecreaseGini"]
) %>%
  arrange(desc(Importance)) %>%
  slice_head(n = 15)

# Visualize feature importance
ggplot(rf_importance_df, aes(x = reorder(Variable, Importance), y = Importance)) +
  geom_col(fill = "#2E86AB", alpha = 0.8) +
  coord_flip() +
  labs(
    title = "Top 15 Feature Importances (Random Forest)",
    x = "Variables",
    y = "Mean Decrease in Gini"
  ) +
  theme_minimal()
```

```
# Logistic regression coefficients analysis
library(broom)

logistic_coefs <- tidy(logistic_model, conf.int = TRUE) %>%
  filter(term != "(Intercept)") %>%
  mutate(
    odds_ratio = exp(estimate),
    or_lower = exp(conf.low),
    or_upper = exp(conf.high)
  ) %>%
  arrange(desc(abs(estimate))) %>%
  slice_head(n = 15)

print("Top 15 Logistic Regression Coefficients (by magnitude):")
print(logistic_coefs)
```

7. Model Interpretation and Business Insights

7.1 Key Findings Summary

Based on the comprehensive analysis, several critical patterns emerge that directly impact business strategy:[1] [3] [4]

High-Risk Customer Profiles:

- Month-to-month contract customers show significantly higher churn rates compared to longer-term contracts[4] [20]
- Customers with fiber optic internet service demonstrate elevated churn propensity
- Higher monthly charges correlate with increased churn probability, particularly in the $70-105 range[20]

Protective Factors:

- Longer tenure customers show substantially lower churn rates
- Two-year and one-year contract customers exhibit strong retention patterns
- Customers with multiple service bundles demonstrate lower churn propensity

7.2 Business Recommendations

Immediate Actions:

1. **Contract Strategy**: Implement incentive programs to transition month-to-month customers to longer-term contracts[3] [4]
2. **Pricing Optimization**: Review pricing structure for customers in the high-risk monthly charge range
3. **Service Quality**: Investigate and address fiber optic service issues contributing to churn

Long-term Strategies:

1. **Customer Segmentation**: Develop targeted retention campaigns based on risk profiles identified through the models[1] [17]
2. **Threshold Optimization**: Adjust prediction thresholds based on business priorities (retention vs. cost optimization)
3. **Continuous Monitoring**: Implement regular model retraining and performance monitoring

8. Documentation and Reproducibility

8.1 R Markdown Report Generation

Create a comprehensive R Markdown report (`report.Rmd`) that includes all analysis steps with dynamic content:[21] [9] [10]

```
# Render the complete report
rmarkdown::render(
  "report.Rmd",
  output_format = "html_document",
  output_file = "output/reports/telco_churn_analysis_report.html"
)

# Generate PDF version for distribution
rmarkdown::render(
  "report.Rmd",
  output_format = "pdf_document",
  output_file = "output/reports/telco_churn_analysis_report.pdf"
)
```

8.2 Code Organization Best Practices

Following professional R development standards:[11] [12] [13]

```
# Create modular functions
source("scripts/functions/data_cleaning.R")
source("scripts/functions/modeling.R")
source("scripts/functions/visualization.R")

# Save model objects for future use
saveRDS(logistic_model, "output/models/logistic_model.rds")
saveRDS(rf_model, "output/models/rf_model.rds")
saveRDS(lmp_model, "output/models/lmp_model.rds")

# Export key results
write.csv(logistic_coefs, "output/reports/logistic_coefficients.csv", row.names = FALSE)
write.csv(rf_importance_df, "output/reports/feature_importance.csv", row.names = FALSE)
```

8.3 Version Control and Collaboration

```
# Initialize git repository (run in terminal)
git init
git add .
git commit -m "Initial telco churn analysis implementation"

# Create .gitignore for R projects
echo "*.RData
*.Rhistory
.RProfile
output/
!output/README.md" > .gitignore
```

9. Deployment and Monitoring

9.1 Model Deployment Considerations

For production deployment, consider the following implementation strategy:[22] [18]

```
# Create prediction function for new data
predict_churn <- function(new_data, model_type = "logistic") {

  # Data preprocessing pipeline
  processed_data <- new_data %>%
    mutate(
      TotalCharges = as.numeric(TotalCharges),
      TotalCharges = ifelse(is.na(TotalCharges), 0, TotalCharges),
      across(c(OnlineSecurity, OnlineBackup, DeviceProtection,
               TechSupport, StreamingTV, StreamingMovies),
             ~ recode(., "No internet service" = "No")),
      MultipleLines = recode(MultipleLines, "No phone service" = "No"),
      across(where(is.character), as.factor)
    ) %>%
    select(-customerID)

  # Load appropriate model and predict
  if (model_type == "logistic") {
    model <- readRDS("output/models/logistic_model.rds")
    predictions <- predict(model, processed_data, type = "response")
  } else if (model_type == "random_forest") {
    model <- readRDS("output/models/rf_model.rds")
    predictions <- predict(model, processed_data, type = "prob")[, "Yes"]
  }

  return(predictions)
}
```

9.2 Performance Monitoring Framework

```
# Create monitoring function for model drift detection
monitor_model_performance <- function(new_predictions, actual_outcomes) {

  # Calculate current performance metrics
  current_accuracy <- mean(new_predictions == actual_outcomes)

  # Compare with baseline performance
  baseline_accuracy <- 0.80  # Historical model accuracy

  # Alert if performance degrades significantly
  if (current_accuracy < baseline_accuracy - 0.05) {
    warning("Model performance has degraded. Consider retraining.")
  }

  # Return performance summary
  return(list(
    current_accuracy = current_accuracy,
    baseline_accuracy = baseline_accuracy,
    performance_change = current_accuracy - baseline_accuracy
  ))
}
```

10. Conclusion and Next Steps

This comprehensive guide provides a robust framework for telco customer churn analysis using R, incorporating industry best practices for data science project management, statistical modeling, and business intelligence. The methodology successfully identifies key churn drivers and provides actionable insights for retention strategies.[1] [3] [5] [6] [23] [19]

Key Achievements:

- Implemented three complementary modeling approaches with ~80% accuracy
- Identified critical churn factors including contract type, service categories, and billing patterns
- Established reproducible analytical workflow with comprehensive documentation
- Created professional-grade reporting suitable for business stakeholders

Recommended Next Steps:

1. **Model Enhancement**: Explore ensemble methods combining all three approaches for improved prediction accuracy
2. **Feature Engineering**: Develop derived features such as customer lifetime value and engagement scores
3. **Real-time Implementation**: Deploy models in production environment with automated monitoring
4. **A/B Testing**: Validate retention strategies through controlled experiments

5. **Advanced Analytics**: Implement customer lifetime value modeling and segment-specific strategies

The framework presented here serves as a foundation for advanced customer analytics and can be adapted for other industries and use cases requiring predictive modeling and business intelligence capabilities.[22] [18] [19]

⁂

1. https://www.thoughtspot.com/data-trends/analytics/customer-churn-analysis
2. https://r4ds.had.co.nz/workflow-projects.html
3. https://www.chargebee.com/blog/churn-analysis/
4. https://clevertap.com/blog/churn-analysis/
5. https://www.geeksforgeeks.org/machine-learning/metrics-for-machine-learning-model/
6. https://www.appliedaicourse.com/blog/evaluation-metrics-in-machine-learning/
7. https://developers.google.com/machine-learning/crash-course/classification/accuracy-precision-recall
8. https://r4ds.hadley.nz/workflow-scripts.html
9. https://r4ds.had.co.nz/r-markdown.html
10. https://www.r-bloggers.com/2024/04/crafting-elegant-scientific-documents-in-rstudio-a-latex-and-r-markdown-tutorial/
11. https://www.r-bloggers.com/2018/08/structuring-r-projects/
12. https://kdestasio.github.io/post/r_best_practices/
13. https://rfortherestofus.com/2021/08/rstudio-project-structure
14. https://www.kaggle.com/datasets/blastchar/telco-customer-churn
15. https://www.kaggle.com/datasets/mnassrib/telecom-churn-datasets
16. https://github.com/ahmedshahriar/Customer-Churn-Prediction
17. https://www.custify.com/blog/customer-churn-guide/
18. https://hevodata.com/learn/understanding-customer-churn-analysis/
19. https://www.dataversity.net/effective-code-documentation-for-data-science-projects/
20. https://www.linkedin.com/pulse/predicting-telco-customer-churn-findings-from-data-analysis-justin
21. https://bookdown.org/yihui/rmarkdown/
22. https://www.nature.com/articles/s41598-024-63750-0
23. https://www.datascience-pm.com/documentation-best-practices/
24. https://www.sciencedirect.com/science/article/pii/S2666720723001443
25. https://datasciworkflows.netlify.app
26. https://github.com/Geo-y20/Telco-Customer-Churn-
27. https://stripe.com/resources/more/churn-analysis-101-a-how-to-guide-for-businesses
28. https://r4ds.hadley.nz/workflow-basics.html
29. https://www.kaggle.com/code/bandiatindra/telecom-churn-prediction
30. https://www.reddit.com/r/datascience/comments/j76tzr/data_science_workflow/
31. https://userpilot.com/blog/customer-churn-analysis/

32. https://r4ds.had.co.nz/workflow-basics.html
33. https://ieeexplore.ieee.org/document/7359318/
34. https://www.dataquest.io/blog/r-projects-for-beginners-with-source-code/
35. https://rmarkdown.rstudio.com
36. https://www.nature.com/articles/s41598-024-56706-x
37. https://neptune.ai/blog/performance-metrics-in-machine-learning-complete-guide
38. https://rmarkdown.rstudio.com/authoring_basics.html
39. https://huggingface.co/datasets/aai510-group1/telco-customer-churn
40. https://www.neonscience.org/resources/learning-hub/tutorials/document-your-code-r-markdown
41. https://www.aiacceleratorinstitute.com/evaluating-machine-learning-models-metrics-and-techniques/
42. https://scikit-learn.org/stable/modules/model_evaluation.html
43. https://www.r-bloggers.com/2023/01/tips-for-organising-your-r-code/
44. https://libguides.up.edu/datamanagement/documentation
45. https://www.reddit.com/r/RStudio/comments/rsg34o/advice_on_organizing_r_scriptsprojects/
46. https://learn.microsoft.com/en-us/fabric/data-science/
47. https://ntguardian.wordpress.com/2018/08/02/how-should-i-organize-my-r-research-projects/
48. https://www.rforecology.com/post/organizing-your-r-studio-projects/
49. https://swcarpentry.github.io/r-novice-inflammation/06-best-practices-R.html
50. https://www.youtube.com/watch?v=GeN-qqNLLsM
51. https://towardsdatascience.com/data-documentation-best-practices-3e1a97cfeda6/
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