Random Forest (Ranger) Bicycle Model

Below is the code we used to tune the model. Once we ran this to get ballpark numbers, we fine tuned the 'mtry' and 'min.node.size' values. The size of our data set greatly influenced our tuning parameter values. Increasing trees used did not improve model fit.

```
df <- read_csv("daily_counts_aggregated.csv") %>%
  filter(qaqc_volume >= 0, user_type == "Bicycle", pass_fail == 1) %>%
  select(-user_type, -daily_volume, -maxhour, -maxday, -gap, -zero, -pass_fail, -weather_sta
  clean_names() %>%
  mutate(
    date = as.Date(date, format = "%m/%d/%Y"),
    is_holiday = if_else(date %in% us_holidays, 1, 0),
    is_weekend = if_else(weekdays(date) %in% c("Saturday", "Sunday"), 1, 0),
    counter_id = as.factor(counter_id),
    month = as.factor(format(date, "%m")),
    week = week(date),
    year = as.factor(lubridate::year(date)),
    day_of_year = yday(date),
    row_id = row_number()
  )

df_model <- df %>% drop_na()

# Stratified sampling (20% per month)
set.seed(42)
test_rows <- df_model %>%
  mutate(month_group = format(date, "%Y-%m")) %>%
  group_by(month_group) %>%
  sample_frac(0.2) %>%
  ungroup() %>%
  pull(row_id)

# Split data
```

```r
test_df <- df_model %>% filter(row_id %in% test_rows)
train_df <- df_model %>% filter(!row_id %in% test_rows)

train_df <- train_df %>% select(-date)
test_df  <- test_df %>% select(-date)
full_df  <- bind_rows(train_df, test_df)



#combine them for later complete test
full_df <- bind_rows(train_df, test_df)

# Step 6: TrainControl for caret
ctrl <- trainControl(
  method = "cv",        # cross-validation
  number = 5,           # 5-fold CV
  verboseIter = TRUE
)

# Step 7: Define hyperparameter grid
rf_grid <- expand.grid(
  mtry = c(40, 70, 86),         # Adjust depending on total # of predictors
  splitrule = "variance",     # for regression
  min.node.size = c(5, 20, 40, 80) #adjust depending on #obs
)

# Step 8: Train ranger model with caret
set.seed(123)
rf_tuned <- train(
  qaqc_volume ~ . - row_id,  # exclude row_id
  data = train_df,
  method = "ranger",
  trControl = ctrl,
  tuneGrid = rf_grid,
  num.trees = 100,
  importance = "impurity"
)

# Predict on the training set
train_preds <- predict(rf_tuned, newdata = train_df)

# Compute RMSE on training set
```

```r
train_rmse <- sqrt(mean((train_preds - train_df$qaqc_volume)^2))
cat("Training RMSE:", train_rmse, "\n")

# Step 9: Evaluate on Test
preds <- predict(rf_tuned, newdata = test_df)
rmse <- sqrt(mean((preds - test_df$qaqc_volume)^2))
cat("Test RMSE:", rmse, "\n")

#Test on entire dataset
preds <- predict(rf_tuned, newdata = full_df)
rmse <- sqrt(mean((preds - full_df$qaqc_volume)^2))
cat("Actual RMSE:", rmse, "\n")

#view mean on daily volume for context of RMSE
mean(full_df$qaqc_volume)
sd(full_df$qaqc_volume)

# Compute R^2 for full dataset
ss_total <- sum((full_df$qaqc_volume - mean(full_df$qaqc_volume))^2)
ss_res   <- sum((full_df$qaqc_volume - preds)^2)
r_squared <- 1 - (ss_res / ss_total)
cat("R-squared on full dataset:", r_squared, "\n")

# Get variable importance from caret::train model
vip_df <- varImp(rf_tuned)$importance %>%
  rownames_to_column("Variable") %>%
  arrange(desc(Overall)) %>%
  slice(1:20)  # top 20 variables

ggplot(vip_df, aes(x = reorder(Variable, Overall), y = Overall)) +
  geom_col(fill = "steelblue") +
  coord_flip() +
  labs(title = "Top 20 Variable Importances", x = "", y = "Importance")
```

Data cleaning and model

Once the best tune has been determined, insert those parameters into the code below and the document will render much faster.

```r
# Load libraries
library(tidyverse)
```

```r
library(caret)
library(ranger)
library(ggplot2)
library(lubridate)
library(janitor)
library(timeDate)
library(reshape2)
library(knitr)

# Load and preprocess data
years <- unique(year(as.Date(read_csv("daily_counts_aggregated.csv")$date, format = "%m/%d/%Y
us_holidays <- as.Date(holidayNYSE(year = years))

df <- read_csv("daily_counts_aggregated.csv") %>%
  filter(qaqc_volume >= 0, user_type == "Bicycle", pass_fail == 1) %>%
  select(-user_type, -daily_volume, -maxhour, -maxday, -gap, -zero, -pass_fail, -weather_stat
  clean_names() %>%
  mutate(
    date = as.Date(date, format = "%m/%d/%Y"),
    is_holiday = if_else(date %in% us_holidays, 1, 0),
    is_weekend = if_else(weekdays(date) %in% c("Saturday", "Sunday"), 1, 0),
    counter_id = as.factor(counter_id),
    month = as.factor(format(date, "%m")),
    week = week(date),
    year = as.factor(lubridate::year(date)),
    day_of_year = yday(date),
    row_id = row_number()#,
  )

#print how many obs we have
nrow(df)
```

```
[1] 16744
```

```r
df_model <- df %>% drop_na()

#Print how many obs we have
nrow(df_model)
```

```
[1] 15108
```

```r
# Stratified sampling (20% per month)
set.seed(42)
test_rows <- df_model %>%
  mutate(month_group = format(date, "%Y-%m")) %>%
  group_by(month_group) %>%
  sample_frac(0.2) %>%
  ungroup() %>%
  pull(row_id)

# Split data
test_df <- df_model %>% filter(row_id %in% test_rows)
train_df <- df_model %>% filter(!row_id %in% test_rows)

train_df <- train_df %>% select(-date)
test_df  <- test_df %>% select(-date)
full_df  <- bind_rows(train_df, test_df)
nrow(train_df)
```

```
[1] 12089
```

```r
nrow(test_df)
```

```
[1] 3019
```

```r
# Train Random Forest model
set.seed(123)
rf_tuned <- ranger(
  formula = qaqc_volume ~ . - row_id,
  data = train_df,
  num.trees = 100,
  mtry = 70,
  min.node.size = 4,
  importance = "impurity"
)
```

RMSE

```r
# Evaluate performance
train_preds <- predict(rf_tuned, data = train_df)$predictions
test_preds  <- predict(rf_tuned, data = test_df)$predictions
full_preds <- predict(rf_tuned, data = full_df)$predictions
train_rmse <- sqrt(mean((train_preds - train_df$qaqc_volume)^2))
cat("Training RMSE:", train_rmse, "\n")
```

```
Training RMSE: 54.98756
```

```r
test_rmse <- sqrt(mean((test_preds - test_df$qaqc_volume)^2))
cat("Test RMSE:", test_rmse, "\n")
```

```
Test RMSE: 142.0085
```

```r
full_rmse <- sqrt(mean((full_preds - full_df$qaqc_volume)^2))
cat("Full Dataset RMSE:", full_rmse, "\n")
```

```
Full Dataset RMSE: 80.30713
```

```r
# Contextual stats
cat("Mean Volume:", mean(full_df$qaqc_volume), "\n")
```

```
Mean Volume: 105.5017
```

```r
cat("SD Volume:", sd(full_df$qaqc_volume), "\n")
```

```
SD Volume: 225.8497
```

```r
# Variable importance
vip_df <- as.data.frame(rf_tuned$variable.importance) %>%
  rownames_to_column("Variable") %>%
  setNames(c("Variable", "Importance")) %>%
  arrange(desc(Importance)) %>%
  slice(1:20)

#combined data r^2
ss_total <- sum((full_df$qaqc_volume - mean(full_df$qaqc_volume))^2)
ss_res   <- sum((full_df$qaqc_volume - full_preds)^2)
```

```
r_squared <- 1 - ss_res / ss_total
full_mean <- mean(full_df$qaqc_volume)
full_sd <- sd(full_df$qaqc_volume)

#test r^2
ss_total_test <- sum((test_df$qaqc_volume - mean(test_df$qaqc_volume))^2)
ss_res_test   <- sum((test_df$qaqc_volume - test_preds)^2)
r_squared_test <- 1 - ss_res_test / ss_total_test

#mean and sd
test_sd <- sd(test_df$qaqc_volume)
test_mean <- mean(test_df$qaqc_volume)
train_mean <- mean(train_df$qaqc_volume)
train_sd <- sd(train_df$qaqc_volume)

# Create long format tibble
summary_tbl <- tibble(
  Metric = c(
    "R Squared", "R Squared", "R Squared",
    "RMSE", "RMSE", "RMSE",
    "SD", "SD", "SD",
    "Mean", "Mean", "Mean"
  ),
  Set = c(
    "From Test Data", "From Both", "From Train Data",
    "From Test Data", "From Both", "From Train Data",
    "From Test Data", "From Both", "From Train Data",
    "From Test Data", "From Both", "From Train Data"
  ),
  Value = c(
    r_squared_test, r_squared, "High",
    test_rmse, full_rmse, train_rmse,
    test_sd, full_sd, train_sd,
    test_mean, full_mean, train_mean
  )
)

# Pivot to wide format
summary_tbl_wide <- summary_tbl %>%
  pivot_wider(
    names_from = Set,
    values_from = Value
```

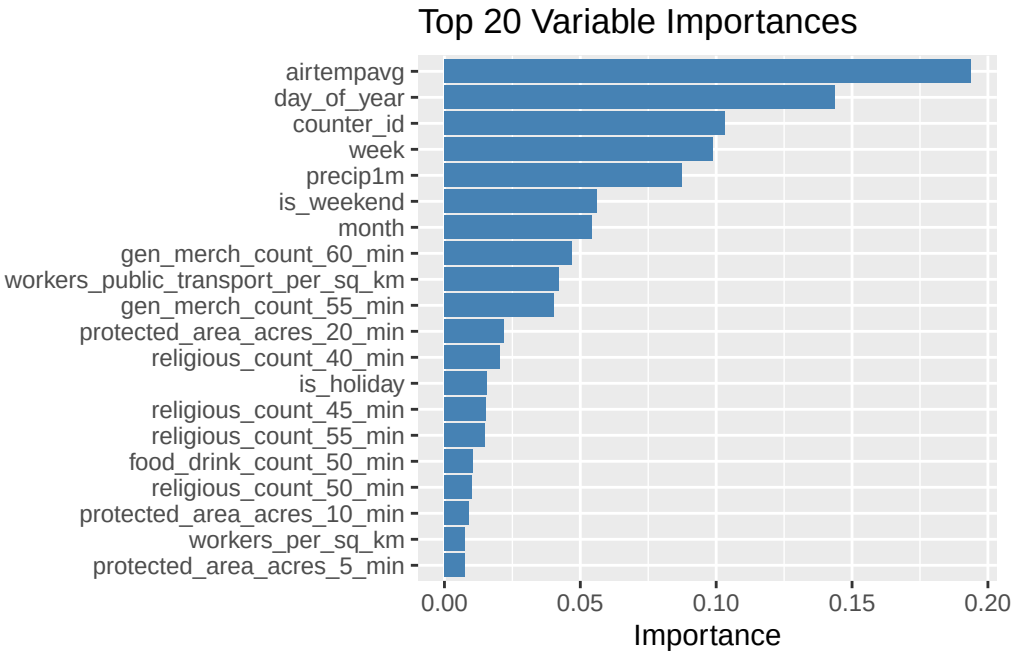
```
  )

summary_tbl_wide
```

```
# A tibble: 4 x 4
  Metric    `From Test Data`  `From Both`       `From Train Data`
  <chr>     <chr>             <chr>             <chr>
1 R Squared 0.742071475255157 0.873556053960595 High
2 RMSE      142.008461311511  80.307131762934   54.987555043458
3 SD        279.663941069486  225.849674031558  210.283995481852
4 Mean      107.270950645909  105.501720942547  105.059889155431
```

Plotting

This bar plot shows the top 20 variables ranked by importance from the trained random forest model. The most influential predictor is airtempavg (average air temperature), followed by non_workday, and workers_public_transport_per_sq_km. These indicate that weather and day type (e.g., weekend or holiday) strongly influence cyclist volume, as does the built environment (e.g., public transit density).

```
vip_df <- vip_df %>%
  mutate(Importance = Importance / sum(Importance),
         label = scales::percent(Importance, accuracy = 0.1))
ggplot(vip_df, aes(x = reorder(Variable, Importance), y = Importance)) +
  geom_col(fill = "steelblue") +
  coord_flip() +
  labs(title = "Top 20 Variable Importances", x = "", y = "Importance")
```

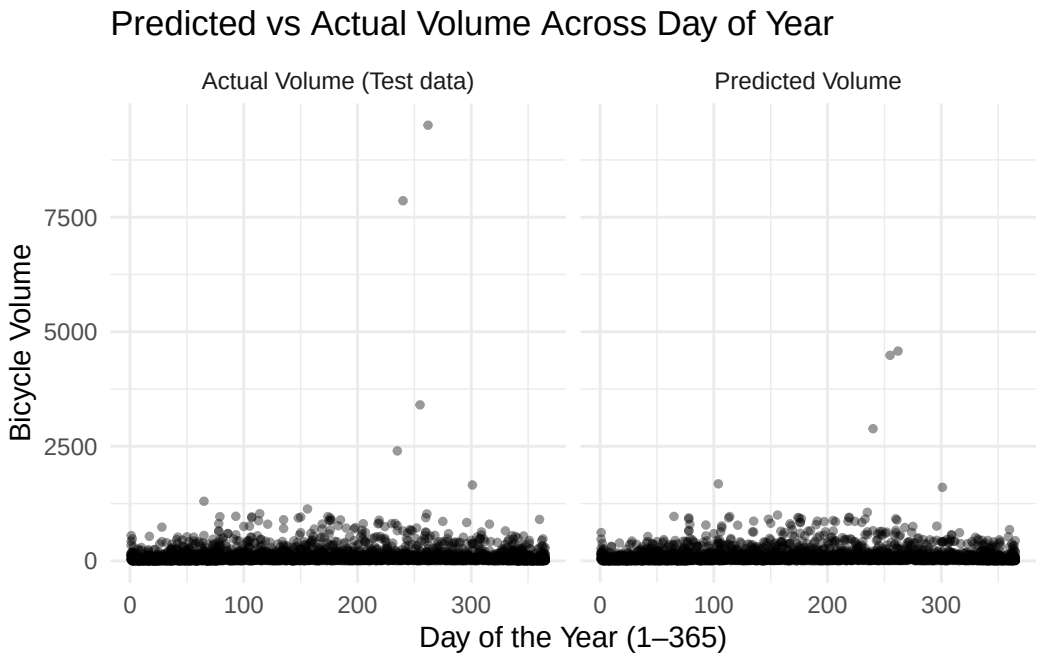



```
# Add predictions and residuals
plot_df <- test_df %>%
  mutate(
    predicted = test_preds,
    actual = qaqc_volume,
    residual = actual - predicted
  )
```

This plot shows that our model captures season variation, but fails to capture the full magnitude of those variations (spring (60-151), summer (152-243), and fall (244-334)).

```
# Prepare long format for faceting
plot_df_long <- plot_df %>%
  select(day_of_year, predicted, actual) %>%
  pivot_longer(cols = c(predicted, actual), names_to = "type", values_to = "volume")

# Facet plot
ggplot(plot_df_long, aes(x = day_of_year, y = volume)) +
  geom_point(alpha = 0.4, color = "black", size = 1) +
  facet_wrap(~type, ncol = 2, labeller = labeller(type = c(
    predicted = "Predicted Volume",
    actual = "Actual Volume (Test data)"
  ))) +
```

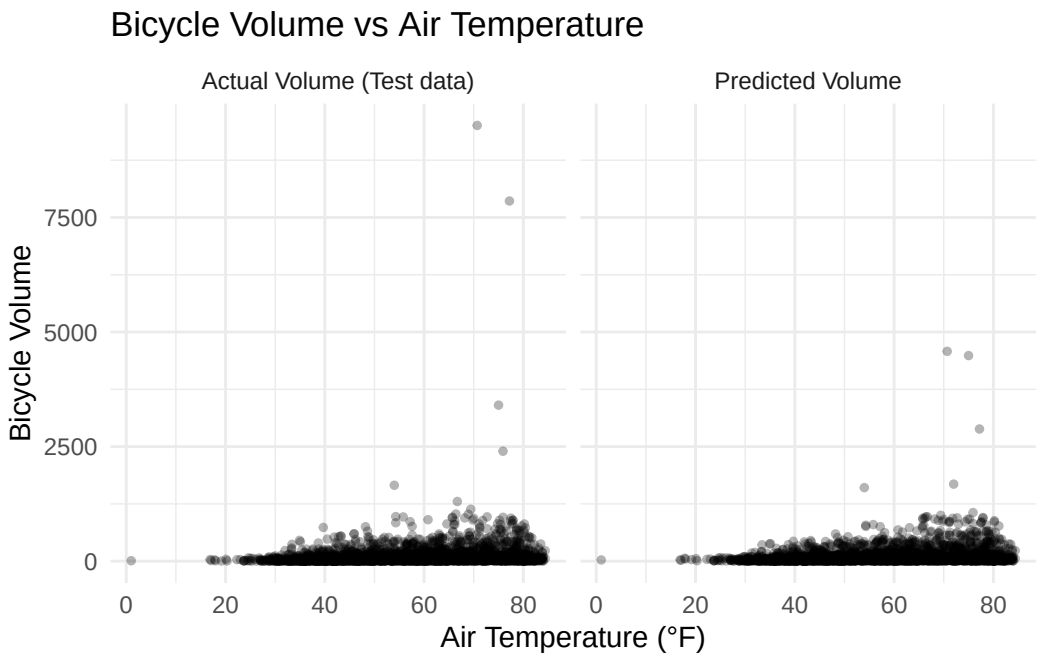
```
  labs(
    title = "Predicted vs Actual Volume Across Day of Year",
    x = "Day of the Year (1-365)",
    y = "Bicycle Volume"
  ) +
  theme_minimal()
```



Now lets do the same side by side lot for air temperature, which shows us a similar trend.

```
plot_df_long <- plot_df %>%
  select(airtempavg, predicted, actual) %>%
  pivot_longer(cols = c(predicted, actual), names_to = "type", values_to = "volume")
# Plot side-by-side (faceted)
ggplot(plot_df_long, aes(x = airtempavg, y = volume)) +
  geom_point(alpha = 0.3, color = "black", size = 1) +
  facet_wrap(~type, ncol = 2, labeller = labeller(type = c(
    predicted = "Predicted Volume",
    actual = "Actual Volume (Test data)"
  ))) +
  labs(
    title = "Bicycle Volume vs Air Temperature",
    x = "Air Temperature (°F)",
    y = "Bicycle Volume"
```

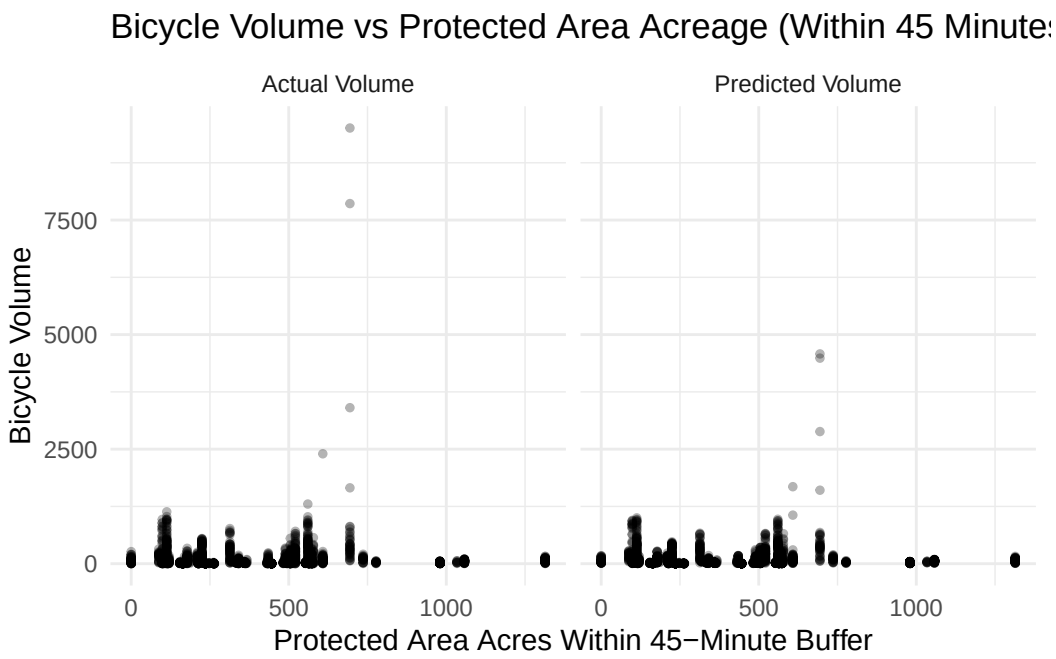
```
  ) +
  theme_minimal()
```



Same thing, but with protect land within 45 minutes. We see our model consistently fails to capture the real world variation.

```
# Convert to long format for facet plotting
plot_df_long <- plot_df %>%
  select(protected_area_acres_45_min, predicted, actual) %>%
  pivot_longer(cols = c(predicted, actual), names_to = "type", values_to = "volume")

# Create side-by-side facet plot
ggplot(plot_df_long, aes(x = protected_area_acres_45_min, y = volume)) +
  geom_point(alpha = 0.3, color = "black", size = 1) +
  facet_wrap(~type, ncol = 2, labeller = labeller(type = c(
    predicted = "Predicted Volume",
    actual = "Actual Volume"
  ))) +
  labs(
    title = "Bicycle Volume vs Protected Area Acreage (Within 45 Minutes)",
    x = "Protected Area Acres Within 45-Minute Buffer",
    y = "Bicycle Volume"
```

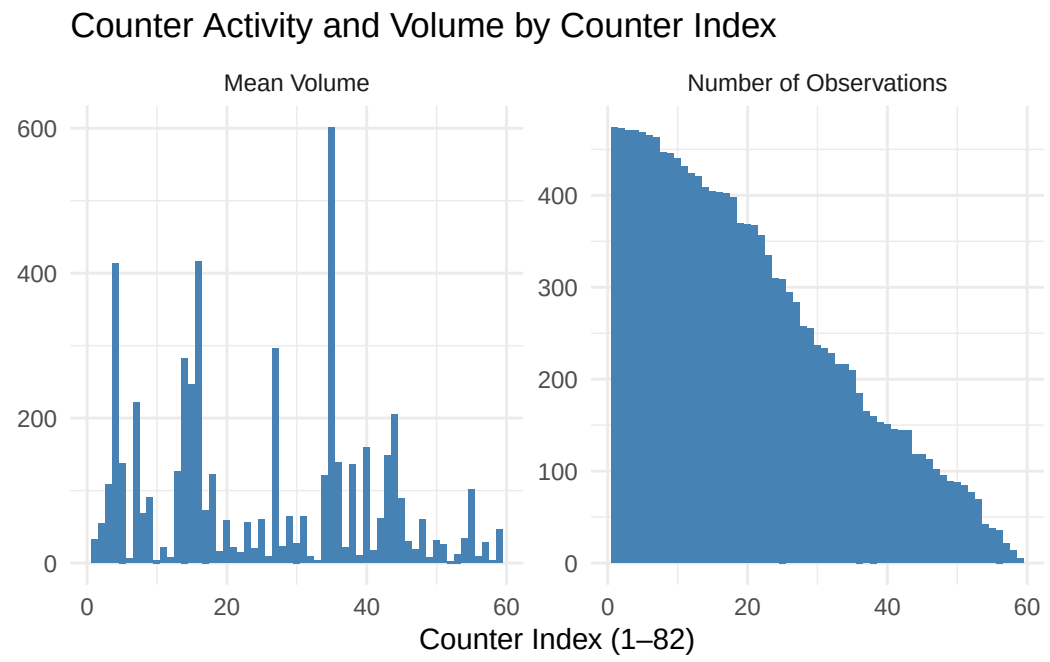
```
  ) +
  theme_minimal()
```



Now let's see how many observations each counter is contributing to our dataset.

```
# Summarize data by counter_id
summary_df <- df_model %>%
  group_by(counter_id) %>%
  summarise(
    n_obs = n(),
    total_volume = sum(qaqc_volume, na.rm = TRUE),
    mean_volume = mean(qaqc_volume, na.rm = TRUE)
  ) %>%
  arrange(desc(n_obs)) %>%
  mutate(counter_index = row_number())  # 1 to 82

# Reshape for faceting
plot_df_long <- summary_df %>%
  select(counter_index, n_obs, mean_volume) %>%
  pivot_longer(cols = c(n_obs, mean_volume),
               names_to = "metric",
               values_to = "value")
```

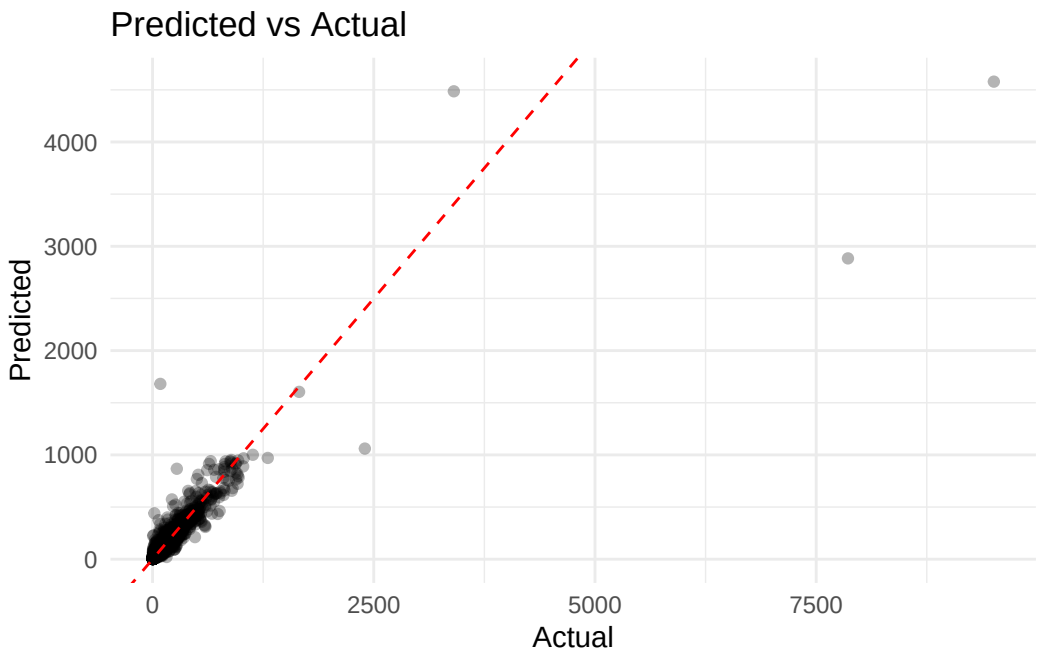
```
# Faceted bar plot
ggplot(plot_df_long, aes(x = counter_index, y = value)) +
  geom_bar(stat = "identity", fill = "steelblue") +
  facet_wrap(~metric, scales = "free_y", labeller = labeller(
    metric = c(n_obs = "Number of Observations", mean_volume = "Mean Volume")
  )) +
  labs(
    title = "Counter Activity and Volume by Counter Index",
    x = "Counter Index (1-82)",
    y = NULL
  ) +
  theme_minimal()
```



This scatterplot compares predicted values to actual observations. Ideally, points should fall along the red 45-degree line. We see that while the model performs reasonably well, there is noticeable scatter — especially at higher volumes — suggesting underprediction in high-traffic scenarios and possibly some heteroskedasticity.

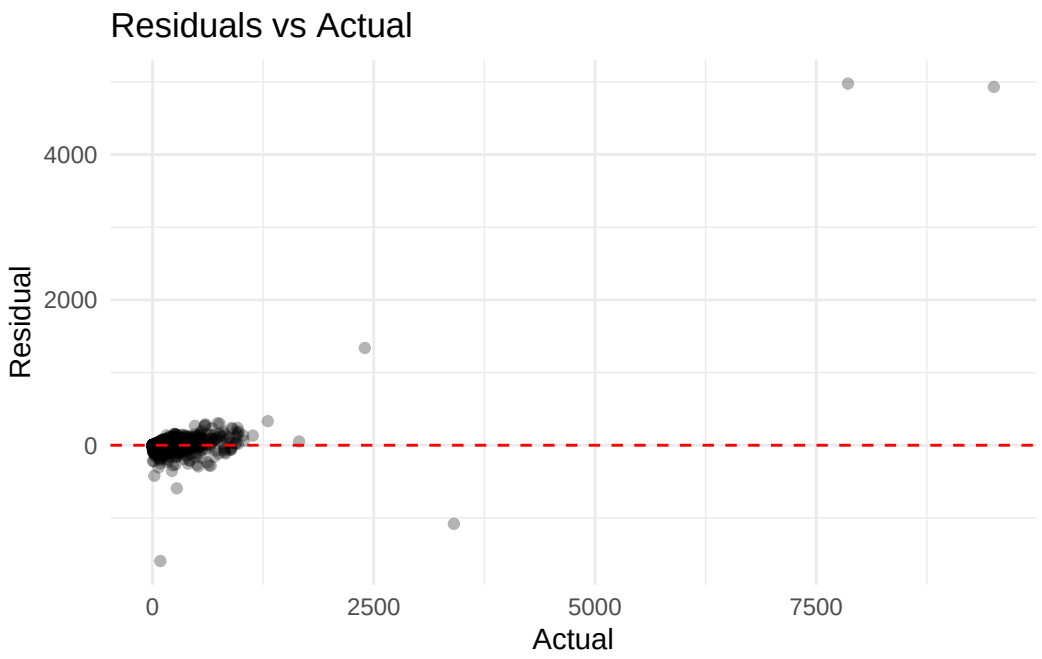
```
# Basic diagnostic plots
ggplot(plot_df, aes(x = actual, y = predicted)) +
  geom_point(alpha = 0.3) +
  geom_abline(slope = 1, intercept = 0, color = "red", linetype = "dashed") +
```

```
  labs(title = "Predicted vs Actual", x = "Actual", y = "Predicted") +
  theme_minimal()
```



This diagnostic plot shows the residuals (predicted minus actual) against actual values. A well-fitted model should show residuals randomly distributed around zero. Here, we observe that residual spread increases with actual volume, again indicating the model struggles with large counts. Our model also seems to undercount low volumes.

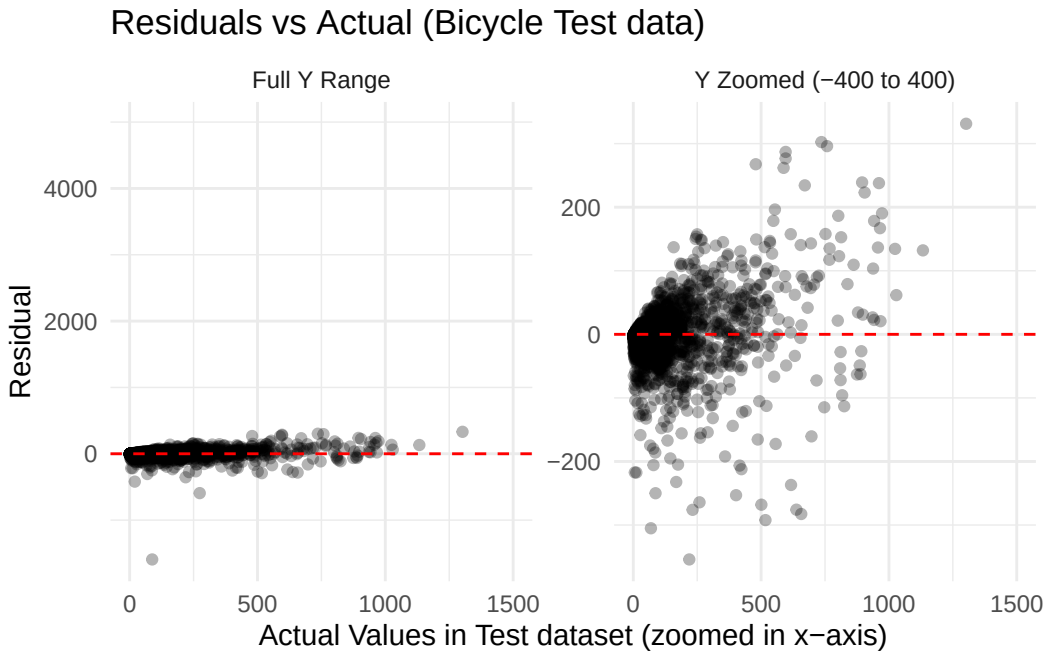
```
ggplot(plot_df, aes(x = actual, y = residual)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red", linetype = "dashed") +
  labs(title = "Residuals vs Actual", x = "Actual", y = "Residual") +
  theme_minimal()
```



Since our residual plot is very zoomed out due to a few outliers, let's create a residual plot that is zoomed in. Now we will be able to see what the residuals look like for most of our data points.

```
# RESIDUALS One version: zoomed-in y
plot_df_zoomed <- plot_df %>%
  filter(residual >= -400, residual <= 400) %>%
  mutate(view = "Y Zoomed (-400 to 400)")

# One version: full y-range
plot_df_full <- plot_df %>%
  mutate(view = "Full Y Range")

# Combine for faceting
plot_df_facet <- bind_rows(plot_df_zoomed, plot_df_full)

# Plot with facet
ggplot(plot_df_facet, aes(x = actual, y = residual)) +
  geom_point(alpha = 0.3) +
  geom_hline(yintercept = 0, color = "red", linetype = "dashed") +
  labs(
    title = "Residuals vs Actual (Bicycle Test data)",
    x = "Actual Values in Test dataset (zoomed in x-axis)",
```

```
    y = "Residual"
  ) +
  coord_cartesian(xlim = c(0, 1500)) +
  facet_wrap(~view, scales = "free_y") +  # this allows separate y-axes
  theme_minimal()
```



In general, the model performs well, though it struggles to predict high volume days.

```
summary_stats <- summary(plot_df[c("actual", "predicted", "workers_public_transport_per_sq_km
kable(summary_stats, caption = "Summary Statistics for Selected Variables")
```

Table 1: Summary Statistics for Selected Variables

actual	predicted	workers_public_transport_per_sq_km
Min. : 0.0	Min. : 1.218	Min. : 0.000
1st Qu.: 14.0	1st Qu.: 16.776	1st Qu.: 0.000
Median : 40.0	Median : 45.201	Median : 5.113
Mean : 107.3	Mean : 106.488	Mean : 13.388
3rd Qu.: 115.0	3rd Qu.: 119.514	3rd Qu.: 9.276
Max. :9508.0	Max. :4578.562	Max. :194.787

This scatterplot with a smoothed line shows a nonlinear relationship between predicted cyclist volume and public transit worker density. Cyclist volume is moderately high at low levels of transit density, dips slightly in the middle range (approximately 25–100 workers per sq. km), and then increases again at high density levels. The upward trend at higher densities may reflect dense urban environments where both cycling and transit are viable, co-located transportation modes. The dip in the middle could correspond to suburban areas where neither transit nor cycling is heavily used, or it may reflect the influence of other unmeasured factors such as road infrastructure or land use.

```
ggplot(plot_df, aes(x = workers_public_transport_per_sq_km, y = predicted)) +
  geom_point(alpha = 0.3) +
  geom_smooth(se = FALSE, color = "darkgreen") +
  labs(title = "Predicted Volume vs Public Transit Density",
       x = "Transit Density", y = "Predicted Volume") +
  theme_minimal()
```

```
`geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```