Linear Regerssion

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2024-05-17

```
library(dplyr)
library(caret)
library(ggplot2)
library(rjags)
library(coda)
```

Data Preparation

We first prepare the data for each cluster.

```
aggregated_data <- read.csv("AggregatedData1.csv")
daily_data <- read.csv("Daily_AggregatedData1.csv")

cluster1 <- aggregated_data[, -c(2,3,4,5,6)]
cluster2 <- aggregated_data[, -c(1,3,4,5,6)]
cluster3 <- aggregated_data[, -c(1,2,4,5,6)]
cluster4 <- aggregated_data[, -c(1,2,3,5,6)]
cluster5 <- aggregated_data[, -c(1,2,3,4,6)]
cluster6 <- aggregated_data[, -c(1,2,3,4,5)]

cluster1_trans <- cluster1 %>%
  mutate(Cluster.1_lag1 = lag(Cluster.1, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
    toy_cos = cos(toy)
  ) %>%
  na.omit()

cluster2_trans <- cluster2 %>%
  mutate(Cluster.2_lag1 = lag(Cluster.2, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
```

```
    toy_cos = cos(toy)
  ) %>%
  na.omit()

cluster3_trans <- cluster3 %>%
  mutate(Cluster.3_lag1 = lag(Cluster.3, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
    toy_cos = cos(toy)
  ) %>%
  na.omit()


cluster4_trans <- cluster4 %>%
  mutate(Cluster.4_lag1 = lag(Cluster.4, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
    toy_cos = cos(toy)
  ) %>%
  na.omit()

cluster5_trans <- cluster5 %>%
  mutate(Cluster.5_lag1 = lag(Cluster.5, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
    toy_cos = cos(toy)
  ) %>%
  na.omit()

cluster6_trans <- cluster6 %>%
  mutate(Cluster.6_lag1 = lag(Cluster.6, n = 1)) %>%
  mutate(
    tod_poly1 = tod,
    tod_poly2 = tod^2,
    tod_poly3 = tod^3,
    tod_poly4 = tod^4,
    weekend_dummy = ifelse(weekend == "TRUE", 1, 0),
    toy_sin = sin(toy),
```

```r
    toy_cos = cos(toy)
  ) %>%
  na.omit()
```

Clusrer 1

Linear Regression Model for Cluster 1

On the basis of `cluster1_trans`, we fit a linear regression model and evaluate its performance:

```r
# Split the data into training and testing sets
train_index_1 <- 1:floor(0.8 * nrow(cluster1_trans))
train_data_1 <- cluster1_trans[train_index_1, ]
test_data_1 <- cluster1_trans[-train_index_1, ]

# Fit the linear regression model
linear_model_1 <- lm(Cluster.1 ~ Cluster.1_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4
```

Performance of Predictions

```r
# Make predictions on the testing set
test_data_1$predictions <- predict(linear_model_1, newdata = test_data_1)

# Calculate prediction error metrics
mae_1 <- mean(abs(test_data_1$Cluster.1 - test_data_1$predictions))
mse_1 <- mean((test_data_1$Cluster.1 - test_data_1$predictions)^2)
rmse_1 <- sqrt(mse_1)

# Print the results
cat("Mean Absolute Error (MAE):", mae_1, "\n")
```

```
## Mean Absolute Error (MAE): 0.04186565
```

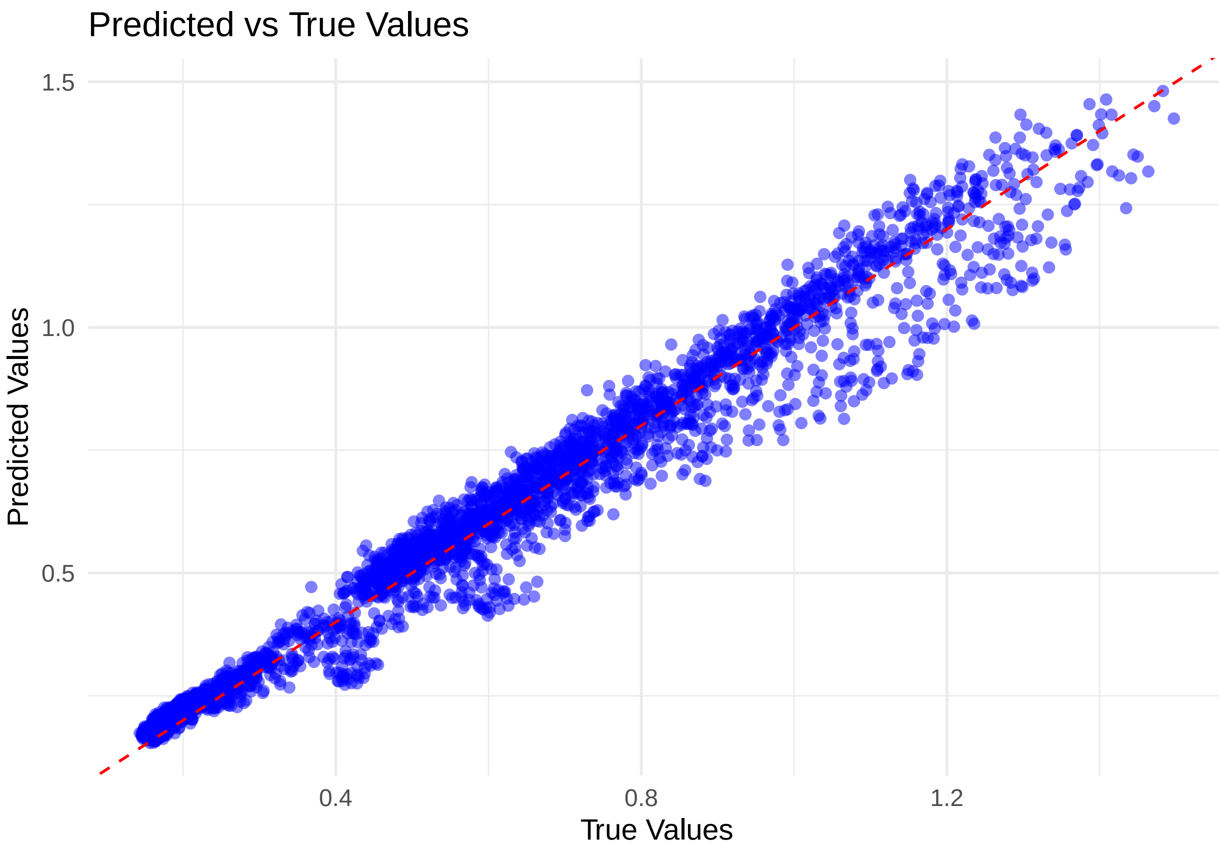
```r
cat("Mean Squared Error (MSE):", mse_1, "\n")
```

```
## Mean Squared Error (MSE): 0.003343571
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_1, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.05782362
```

```r
# Plot predicted vs true values
ggplot(test_data_1, aes(x = Cluster.1, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```



Linear Regression Model Summary

```r
summary(linear_model_1)
```

```
##
## Call:
## lm(formula = Cluster.1 ~ Cluster.1_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_1)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.165153 -0.026932 -0.008028  0.017576  0.300232
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -3.660e-02  1.999e-02  -1.831   0.0671 .
## Cluster.1_lag1  9.265e-01  3.346e-03 276.867  < 2e-16 ***
## temp           -9.932e-04  1.286e-04  -7.725  1.2e-14 ***
## tod_poly1       2.293e-02  6.069e-04  37.780  < 2e-16 ***
## tod_poly2      -1.602e-03  5.276e-05 -30.367  < 2e-16 ***
## tod_poly3       5.057e-05  1.632e-06  30.989  < 2e-16 ***
## tod_poly4      -5.649e-07  1.682e-08 -33.597  < 2e-16 ***
## weekend_dummy   1.519e-03  9.309e-04   1.632   0.1027
## toy_sin        -9.073e-03  9.531e-03  -0.952   0.3411
## toy_cos        -3.571e-02  1.860e-02  -1.920   0.0549 .
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.048 on 13428 degrees of freedom
## Multiple R-squared:  0.9653, Adjusted R-squared:  0.9652
## F-statistic: 4.145e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Analysis

- **Coefficients**:
  - `Cluster.1_lag1`: The coefficient is very high and significant, indicating a strong autocorrelation in the data.
  - `temp`: The negative coefficient suggests that an increase in temperature slightly decreases `Cluster.1`.
  - `tod_poly1`, `tod_poly2`, `tod_poly3`, and `tod_poly4`: These terms capture the non-linear effect of the time of day. Significant coefficients indicate a polynomial relationship with `Cluster.1`.
  - `weekend_dummy`: The positive and significant coefficient indicates that `Cluster.1` is higher on weekends compared to weekdays.
  - `toy_sin` and `toy_cos`: These coefficients are not significant, suggesting that the trigonometric transformation of the time of year might not be a strong predictor for `Cluster.1`.
- **Model Fit**:
  - The R-squared value of 0.9623 indicates that the model explains 96.23% of the variance in `Cluster.1`, which suggests a very good fit.

Cluster 2

Linear Regression Model for Cluster 2

```r
# Split the data into training and testing sets
train_index_2 <- 1:floor(0.8 * nrow(cluster2_trans))
train_data_2 <- cluster2_trans[train_index_2, ]
test_data_2 <- cluster2_trans[-train_index_2, ]

# Fit the linear regression model
linear_model_2 <- lm(Cluster.2 ~ Cluster.2_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4
```

Performance of Predictions

```r
# Make predictions on the testing set
test_data_2$predictions <- predict(linear_model_2, newdata = test_data_2)

# Calculate prediction error metrics
mae_2 <- mean(abs(test_data_2$Cluster.2 - test_data_2$predictions))
mse_2 <- mean((test_data_2$Cluster.2 - test_data_2$predictions)^2)
rmse_2 <- sqrt(mse_2)

# Print the results
cat("Mean Absolute Error (MAE):", mae_2, "\n")
```

```
## Mean Absolute Error (MAE): 0.03925669
```

```r
cat("Mean Squared Error (MSE):", mse_2, "\n")
```

```
## Mean Squared Error (MSE): 0.002707433
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_2, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.052033
```

```r
# Plot predicted vs true values
ggplot(test_data_2, aes(x = Cluster.2, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```

Linear Regression Model Summary

```r
summary(linear_model_2)
```

```
##
## Call:
## lm(formula = Cluster.2 ~ Cluster.2_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_2)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.196463 -0.024745 -0.005851  0.020245  0.263215
##
```

```
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)    
## (Intercept)     -1.276e-01  1.877e-02  -6.799 1.10e-11 ***
## Cluster.2_lag1   9.571e-01  2.936e-03 326.014  < 2e-16 ***
## temp            -9.467e-04  1.217e-04  -7.778 7.87e-15 ***
## tod_poly1        3.788e-02  5.538e-04  68.407  < 2e-16 ***
## tod_poly2       -3.201e-03  4.786e-05 -66.870  < 2e-16 ***
## tod_poly3        1.053e-04  1.510e-06  69.782  < 2e-16 ***
## tod_poly4       -1.148e-06  1.579e-08 -72.691  < 2e-16 ***
## weekend_dummy    1.161e-03  8.849e-04   1.312    0.190    
## toy_sin          1.321e-02  8.965e-03   1.474    0.141    
## toy_cos          5.188e-03  1.752e-02   0.296    0.767    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04535 on 13428 degrees of freedom
## Multiple R-squared:  0.9669, Adjusted R-squared:  0.9669 
## F-statistic: 4.359e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Cluster 3

Linear Regression Model for Cluster 3

```r
# Split the data into training and testing sets
train_index_3 <- 1:floor(0.8 * nrow(cluster3_trans))
train_data_3 <- cluster3_trans[train_index_3, ]
test_data_3 <- cluster3_trans[-train_index_3, ]

# Fit the linear regression model
linear_model_3 <- lm(Cluster.3 ~ Cluster.3_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4 +
```

Performance of Predictions

```r
# Make predictions on the testing set
test_data_3$predictions <- predict(linear_model_3, newdata = test_data_3)

# Calculate prediction error metrics
mae_3 <- mean(abs(test_data_3$Cluster.3 - test_data_3$predictions))
mse_3 <- mean((test_data_3$Cluster.3 - test_data_3$predictions)^2)
rmse_3 <- sqrt(mse_3)

# Print the results
cat("Mean Absolute Error (MAE):", mae_3, "\n")
```

```
## Mean Absolute Error (MAE): 0.0290271
```

```r
cat("Mean Squared Error (MSE):", mse_3, "\n")
```

```
## Mean Squared Error (MSE): 0.001502561
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_3, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.03876289
```

```r
# Plot predicted vs true values
ggplot(test_data_3, aes(x = Cluster.3, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```

Linear Regression Model Summary

```r
summary(linear_model_3)
```

```
##
## Call:
## lm(formula = Cluster.3 ~ Cluster.3_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_3)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.118353 -0.018677 -0.002823  0.016148  0.198274
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -2.665e-02  1.459e-02  -1.827  0.06779 .
```

```
## Cluster.3_lag1  9.349e-01  3.359e-03 278.292  < 2e-16 ***
## temp           -7.840e-04  8.744e-05  -8.966  < 2e-16 ***
## tod_poly1       1.486e-02  5.223e-04  28.443  < 2e-16 ***
## tod_poly2      -7.698e-04  4.278e-05 -17.994  < 2e-16 ***
## tod_poly3       2.094e-05  1.248e-06  16.775  < 2e-16 ***
## tod_poly4      -2.247e-07  1.237e-08 -18.173  < 2e-16 ***
## weekend_dummy   1.569e-03  6.391e-04   2.455  0.01409 *
## toy_sin        -1.191e-02  6.667e-03  -1.786  0.07406 .
## toy_cos        -3.624e-02  1.299e-02  -2.790  0.00529 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.03262 on 13428 degrees of freedom
## Multiple R-squared:  0.9797, Adjusted R-squared:  0.9797
## F-statistic: 7.193e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Cluster 4

Linear Regression Model for Cluster 4

```r
# Split the data into training and testing sets
train_index_4 <- 1:floor(0.8 * nrow(cluster4_trans))
train_data_4 <- cluster4_trans[train_index_4, ]
test_data_4 <- cluster4_trans[-train_index_4, ]

# Fit the linear regression model
linear_model_4 <- lm(Cluster.4 ~ Cluster.4_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4 +

# Make predictions on the testing set
test_data_4$predictions <- predict(linear_model_4, newdata = test_data_4)
```

Performance of Predictions

```r
# Calculate prediction error metrics
mae_4 <- mean(abs(test_data_4$Cluster.4 - test_data_4$predictions))
mse_4 <- mean((test_data_4$Cluster.4 - test_data_4$predictions)^2)
rmse_4 <- sqrt(mse_4)

# Print the results
cat("Mean Absolute Error (MAE):", mae_4, "\n")
```

```
## Mean Absolute Error (MAE): 0.04281978
```

```r
cat("Mean Squared Error (MSE):", mse_4, "\n")
```

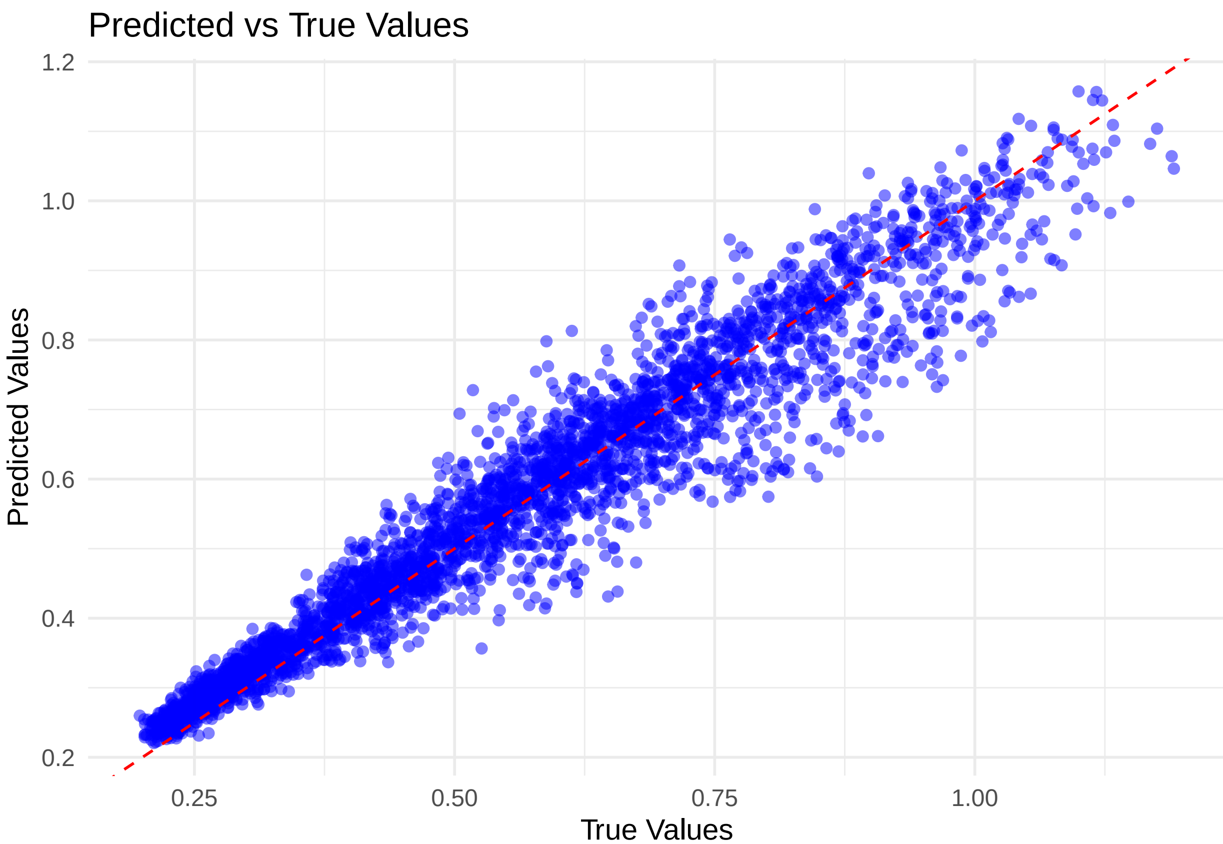
```
## Mean Squared Error (MSE): 0.003455547
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_4, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.0587839
```

```r
# Plot predicted vs true values
ggplot(test_data_4, aes(x = Cluster.4, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
```

```r
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```



Linear Regression Model Summary

```r
summary(linear_model_4)
```

```
##
## Call:
## lm(formula = Cluster.4 ~ Cluster.4_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_4)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.220407 -0.030273 -0.006641  0.024947  0.279164
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      3.487e-02  2.205e-02   1.581  0.11389
## Cluster.4_lag1   8.858e-01  3.853e-03 229.912  < 2e-16 ***
## temp            -1.079e-03  1.438e-04  -7.502  6.7e-14 ***
## tod_poly1        2.221e-02  6.335e-04  35.058  < 2e-16 ***
## tod_poly2       -1.660e-03  5.618e-05 -29.545  < 2e-16 ***
```

```
## tod_poly3       5.144e-05  1.786e-06  28.805  < 2e-16 ***
## tod_poly4      -5.492e-07  1.866e-08 -29.431  < 2e-16 ***
## weekend_dummy   1.669e-03  1.035e-03   1.613  0.10670
## toy_sin        -2.580e-02  1.059e-02  -2.436  0.01486 *
## toy_cos        -6.427e-02  2.065e-02  -3.112  0.00186 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.05364 on 13428 degrees of freedom
## Multiple R-squared:  0.9081, Adjusted R-squared:  0.908
## F-statistic: 1.474e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Cluster 5

Linear Regression Model for Cluster 5

```r
# Split the data into training and testing sets
train_index_5 <- 1:floor(0.8 * nrow(cluster5_trans))
train_data_5 <- cluster5_trans[train_index_5, ]
test_data_5 <- cluster5_trans[-train_index_5, ]

# Fit the linear regression model
linear_model_5 <- lm(Cluster.5 ~ Cluster.5_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4 +
```

Performance of Predictions

```r
# Make predictions on the testing set
test_data_5$predictions <- predict(linear_model_5, newdata = test_data_5)

# Calculate prediction error metrics
mae_5 <- mean(abs(test_data_5$Cluster.5 - test_data_5$predictions))
mse_5 <- mean((test_data_5$Cluster.5 - test_data_5$predictions)^2)
rmse_5 <- sqrt(mse_5)

# Print the results
cat("Mean Absolute Error (MAE):", mae_5, "\n")
```

```
## Mean Absolute Error (MAE): 0.03355503
```

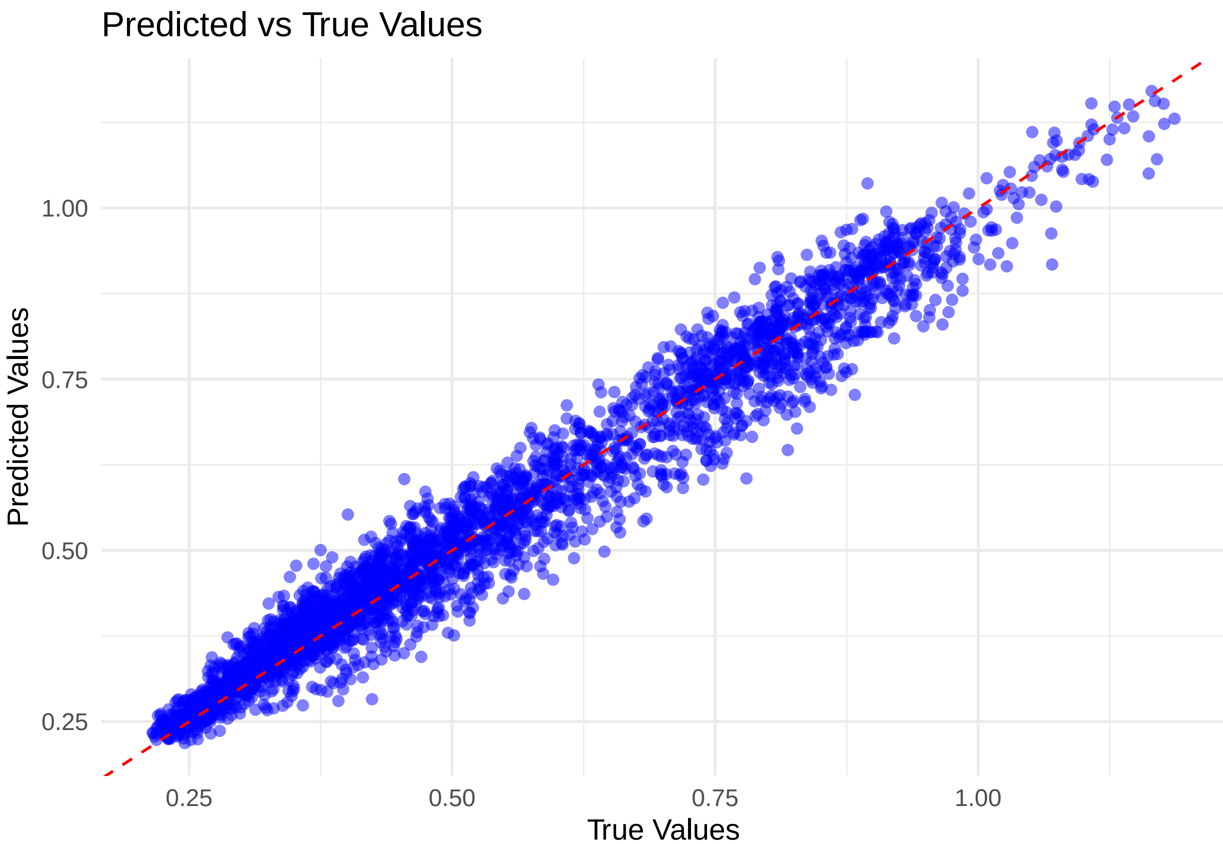
```r
cat("Mean Squared Error (MSE):", mse_5, "\n")
```

```
## Mean Squared Error (MSE): 0.001909648
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_5, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.04369951
```

```r
# Plot predicted vs true values
ggplot(test_data_5, aes(x = Cluster.5, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```



Linear Regression Model Summary

```
summary(linear_model_5)
```

```
##
## Call:
## lm(formula = Cluster.5 ~ Cluster.5_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_5)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.139892 -0.024421 -0.002343  0.020704  0.202596
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     8.670e-02  1.768e-02   4.905 9.45e-07 ***
## Cluster.5_lag1  8.866e-01  4.144e-03 213.968  < 2e-16 ***
## temp           -1.149e-03  1.040e-04 -11.049  < 2e-16 ***
## tod_poly1       4.041e-03  6.185e-04   6.535 6.60e-11 ***
## tod_poly2      -9.191e-05  4.936e-05  -1.862   0.0626 .
## tod_poly3       1.671e-06  1.483e-06   1.126   0.2601
## tod_poly4      -1.001e-08  1.514e-08  -0.661   0.5086
## weekend_dummy   3.885e-03  7.573e-04   5.131 2.93e-07 ***
## toy_sin        -3.745e-02  7.988e-03  -4.688 2.78e-06 ***
## toy_cos        -7.989e-02  1.546e-02  -5.167 2.41e-07 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.0387 on 13428 degrees of freedom
## Multiple R-squared:  0.9521, Adjusted R-squared:  0.9521
## F-statistic: 2.966e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Cluster 6

Linear Regression Model for Cluster 6

```r
# Split the data into training and testing sets
train_index_6 <- 1:floor(0.8 * nrow(cluster6_trans))
train_data_6 <- cluster6_trans[train_index_6, ]
test_data_6 <- cluster6_trans[-train_index_6, ]

# Fit the linear regression model
linear_model_6 <- lm(Cluster.6 ~ Cluster.6_lag1 + temp + tod_poly1 + tod_poly2 + tod_poly3 + tod_poly4 +
```

Performance of Predictions

```r
# Make predictions on the testing set
test_data_6$predictions <- predict(linear_model_6, newdata = test_data_6)

# Calculate prediction error metrics
mae_6 <- mean(abs(test_data_6$Cluster.6 - test_data_6$predictions))
mse_6 <- mean((test_data_6$Cluster.6 - test_data_6$predictions)^2)
rmse_6 <- sqrt(mse_6)

# Print the results
cat("Mean Absolute Error (MAE):", mae_6, "\n")
```

```
## Mean Absolute Error (MAE): 0.03879818
```

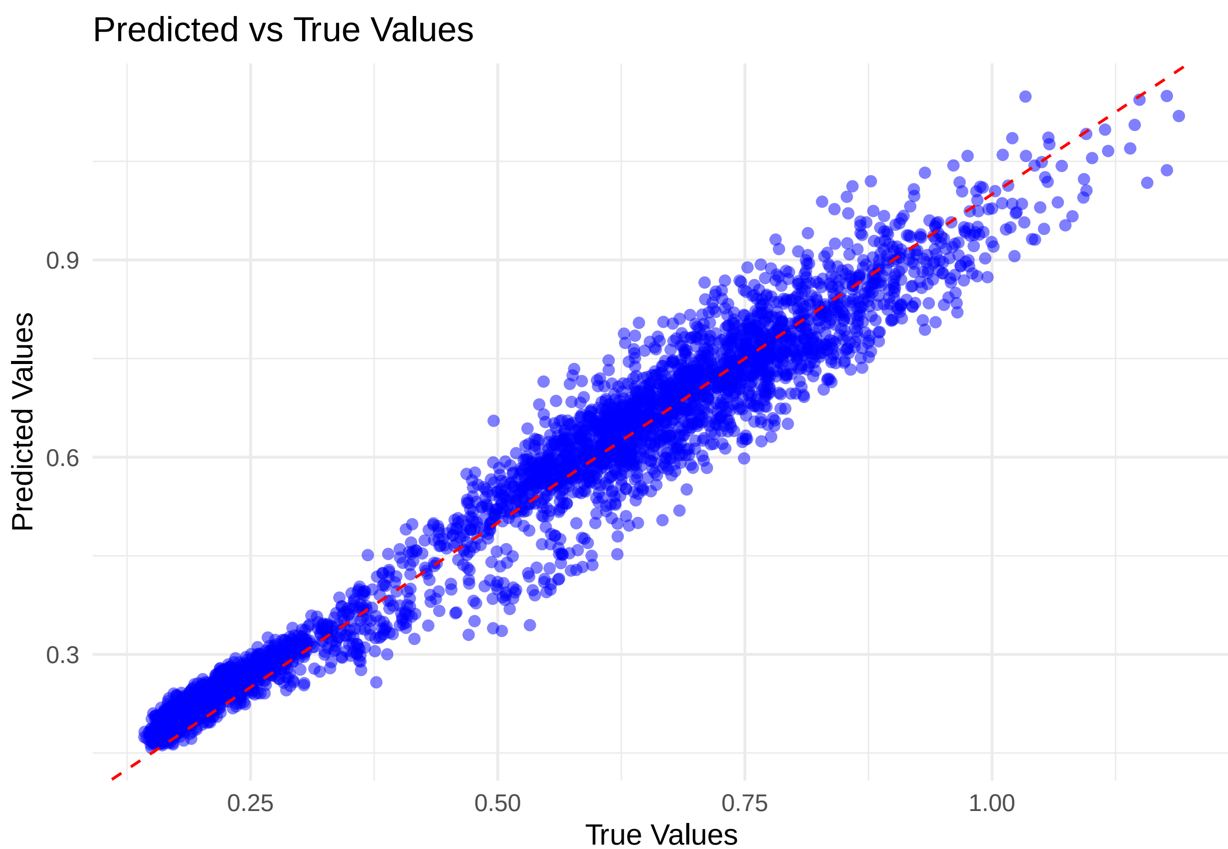
```r
cat("Mean Squared Error (MSE):", mse_6, "\n")
```

```
## Mean Squared Error (MSE): 0.002503867
```

```r
cat("Root Mean Squared Error (RMSE):", rmse_6, "\n")
```

```
## Root Mean Squared Error (RMSE): 0.05003866
```

```r
# Plot predicted vs true values
ggplot(test_data_6, aes(x = Cluster.6, y = predictions)) +
  geom_point(color = 'blue', alpha = 0.5) +
  geom_abline(intercept = 0, slope = 1, color = 'red', linetype = "dashed") +
  labs(title = "Predicted vs True Values",
       x = "True Values",
       y = "Predicted Values") +
  theme_minimal()
```



Linear Regression Model Summary

```r
summary(linear_model_6)
```

```
##
## Call:
## lm(formula = Cluster.6 ~ Cluster.6_lag1 + temp + tod_poly1 +
##     tod_poly2 + tod_poly3 + tod_poly4 + weekend_dummy + toy_sin +
##     toy_cos, data = train_data_6)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.213397 -0.027366 -0.004184  0.025137  0.239803
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)     3.241e-02  2.120e-02   1.529 0.126388
## Cluster.6_lag1  8.936e-01  4.408e-03 202.700  < 2e-16 ***
## temp           -1.131e-03  1.308e-04  -8.649  < 2e-16 ***
## tod_poly1       1.288e-02  7.602e-04  16.943  < 2e-16 ***
## tod_poly2      -4.028e-04  7.078e-05  -5.692 1.28e-08 ***
## tod_poly3       4.116e-06  2.202e-06   1.870 0.061538 .
## tod_poly4      -1.317e-08  2.220e-08  -0.593 0.553046
## weekend_dummy   1.425e-03  9.487e-04   1.502 0.133196
## toy_sin        -2.796e-02  9.974e-03  -2.803 0.005074 **
## toy_cos        -6.734e-02  1.937e-02  -3.476 0.000511 ***
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04909 on 13428 degrees of freedom
## Multiple R-squared:  0.9454, Adjusted R-squared:  0.9453
## F-statistic: 2.582e+04 on 9 and 13428 DF,  p-value: < 2.2e-16
```

Conclusion for Linear Regression Models

```r
# Extract coefficients and performance metrics for each cluster
coefficients_1 <- summary(linear_model_1)$coefficients
coefficients_2 <- summary(linear_model_2)$coefficients
coefficients_3 <- summary(linear_model_3)$coefficients
coefficients_4 <- summary(linear_model_4)$coefficients
coefficients_5 <- summary(linear_model_5)$coefficients
coefficients_6 <- summary(linear_model_6)$coefficients

performance_1 <- data.frame(MAE = mae_1, MSE = mse_1, RMSE = rmse_1)
performance_2 <- data.frame(MAE = mae_2, MSE = mse_2, RMSE = rmse_2)
performance_3 <- data.frame(MAE = mae_3, MSE = mse_3, RMSE = rmse_3)
performance_4 <- data.frame(MAE = mae_4, MSE = mse_4, RMSE = rmse_4)
performance_5 <- data.frame(MAE = mae_5, MSE = mse_5, RMSE = rmse_5)
performance_6 <- data.frame(MAE = mae_6, MSE = mse_6, RMSE = rmse_6)

# Combine performance metrics into one data frame
performance_summary <- rbind(
  data.frame(Cluster = "Cluster 1", performance_1),
  data.frame(Cluster = "Cluster 2", performance_2),
  data.frame(Cluster = "Cluster 3", performance_3),
  data.frame(Cluster = "Cluster 4", performance_4),
  data.frame(Cluster = "Cluster 5", performance_5),
  data.frame(Cluster = "Cluster 6", performance_6)
)

# Print performance summary table
knitr::kable(performance_summary, caption = "Performance Metrics for Each Cluster")
```

Table 1: Performance Metrics for Each Cluster

Cluster	MAE	MSE	RMSE
Cluster 1	0.0418657	0.0033436	0.0578236
Cluster 2	0.0392567	0.0027074	0.0520330
Cluster 3	0.0290271	0.0015026	0.0387629
Cluster 4	0.0428198	0.0034555	0.0587839
Cluster 5	0.0335550	0.0019096	0.0436995
Cluster 6	0.0387982	0.0025039	0.0500387

```r
# Extract coefficients for each cluster and combine them into a single data frame
coef_summary <- data.frame(
  #Variable = rownames(coefficients_1),
  `Cluster 1` = coefficients_1[, "Estimate"],
  `Cluster 2` = coefficients_2[, "Estimate"],
  `Cluster 3` = coefficients_3[, "Estimate"],
```

```r
  `Cluster 4` = coefficients_4[, "Estimate"],
  `Cluster 5` = coefficients_5[, "Estimate"],
  `Cluster 6` = coefficients_6[, "Estimate"]
)

# Print coefficients summary table
knitr::kable(coef_summary, caption = "Coefficients Summary for Each Cluster")
```

Table 2: Coefficients Summary for Each Cluster

	Cluster.1	Cluster.2	Cluster.3	Cluster.4	Cluster.5	Cluster.6
(Intercept)	-0.0365963	-0.1276174	-0.0266471	0.0348692	0.0867022	0.0324100
Cluster.1_lag1	0.9264920	0.9571412	0.9348833	0.8857962	0.8866198	0.8935789
temp	-0.0009932	-0.0009467	-0.0007840	-0.0010790	-0.0011490	-0.0011315
tod_poly1	0.0229293	0.0378848	0.0148552	0.0222100	0.0040415	0.0128805
tod_poly2	-0.0016023	-0.0032007	-0.0007698	-0.0016599	-0.0000919	-0.0004028
tod_poly3	0.0000506	0.0001053	0.0000209	0.0000514	0.0000017	0.0000041
tod_poly4	-0.0000006	-0.0000011	-0.0000002	-0.0000005	0.0000000	0.0000000
weekend_dummy	0.0015193	0.0011610	0.0015693	0.0016690	0.0038854	0.0014246
toy_sin	-0.0090731	0.0132123	-0.0119092	-0.0257991	-0.0374516	-0.0279551
toy_cos	-0.0357117	0.0051879	-0.0362438	-0.0642703	-0.0798886	-0.0673353