STAT 420 Final Data Analysis Project - Team KWS

Introduction

Life expectancy varies greatly across the world. Understanding the factors that influence life expectancy can provide insights for policymakers, healthcare providers, and individuals. This project aims to delve into the determinants of life expectancy.

The dataset used is from the World Health Organization (WHO) and United Nations, which provides a wealth of data related to life expectancy across 193 countries. The dataset, publicly available on Kaggle under the title “Life Expectancy (WHO)”, comprises 22 columns and 2,938 observations. Each observation represents the state of a given country in a particular year, with 20 predictor variables providing comprehensive information about various factors potentially impacting life expectancy.

The predictor variables span across a broad spectrum, including immunization-related factors, mortality factors, economic indicators, and social factors. Among these, we believe certain variables like the status of the country (developed vs developing), infant mortality rate, adult mortality rate, health expenditure, GDP, and average years of schooling may have significant importance in predicting life expectancy.

Our objective in this project is to create a model that can effectively predict life expectancy based on these predictors. We’re particularly interested in this dataset due to our curiosity about the factors influencing life expectancy and our desire to uncover the differences between countries that lead to a wide range of life expectancies. By building this model, we aim to provide insights that could potentially guide health policy and contribute to improvements in global health outcomes.

Methods

Loading Data

```
#read data
library(readr)
life_expectancy_data_full = read_csv("Life Expectancy Data.csv")
```

```
## Rows: 2938 Columns: 22
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr  (2): Country, Status
## dbl (20): Year, Life expectancy, Adult Mortality, infant deaths, Alcohol, pe...
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

We will remove rows with empty values to make analysis easier.

```
#remove rows with empty vals
life_expectancy_data = na.omit(life_expectancy_data_full)
View(life_expectancy_data)
```

For our analysis, we have chosen to convert the predictors Status and Country into factor variables, so that we can treat them as categories.

```
#convert Status (levels: Developing, Developed) to factor variable
life_expectancy_data$Status = as.factor(life_expectancy_data$Status)

#convert Country to factor variable
life_expectancy_data$Country = as.factor(life_expectancy_data$Country)
```

Exploratory Analysis

The pairs plot of all of the variables was very large, so we will display correlations between the numeric variables in the dataset with a Correlogram instead.

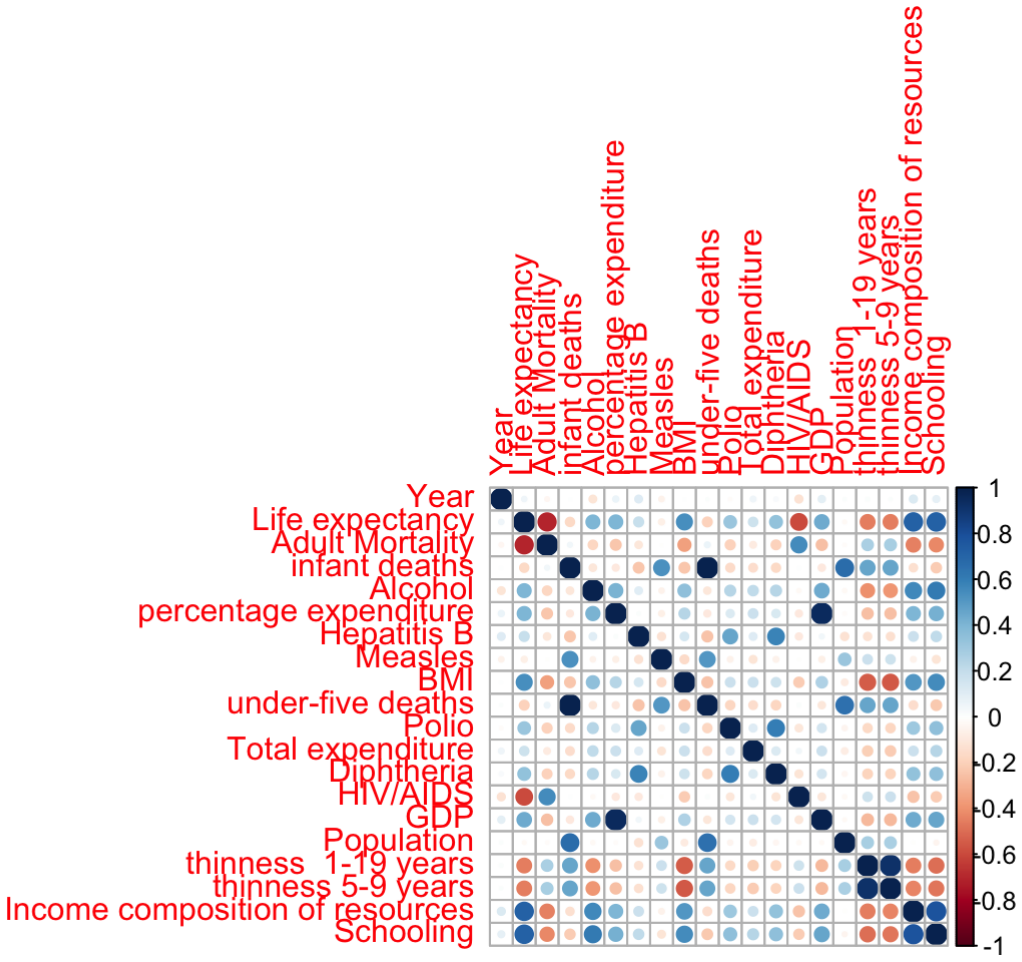
```
#pairs(life_expectancy_data)

#find pairwise correlations between all numeric variables in dataset
numeric_cols =  unlist(lapply(life_expectancy_data, is.numeric))
life_expectancy_data_numeric = life_expectancy_data[ , numeric_cols]
View(life_expectancy_data_numeric)

correlations = cor(life_expectancy_data_numeric)

#plot correlogram (positive correlations are blue, negative correlations are red)
library(corrplot)

corrplot(correlations)
```



We notice that there are a few variables with very high correlations, so we will attempt to address this issue in our modeling.

Initial Additive Model

First, we create a main effects model using all of the available predictors in the dataset to predict life expectancy.

```
additive_model = lm(life_expectancy_data$`Life expectancy` ~ ., data = life_expectancy_d
ata)
#summary(additive_model)
```

Analyze Model

```
#Calculate LOOCV RMSE
calc_loocv_rmse = function(model) {
  sqrt(mean((resid(model) / (1 - hatvalues(model))) ^ 2))
}

# Function to calculate model metrics

calc_model_metrics = function(model) {
  # Calculate adjusted R squared
  model_adjr2 = summary(model)$adj.r.squared

  # Calculate RMSE
  model_rmse = sqrt(mean(resid(model) ^ 2))

  # Calculate LOOCV RMSE
  model_loocv_rmse = sqrt(mean((resid(model) / (1 - hatvalues(model))) ^ 2))

  # Calculate AIC
  model_AIC = extractAIC(model)[2] # get only the AIC value, not the degrees of freedom

  # Return a list containing the calculated metrics
  list(Adj_R_Squared = model_adjr2, RMSE = model_rmse, LOOCV_RMSE = model_loocv_rmse, AI
C = model_AIC)
}

additive_model_metrics = as.data.frame(calc_model_metrics(additive_model))

library(knitr)
knitr::kable(additive_model_metrics, caption = "Additive Model Summary", digits = 4)
```

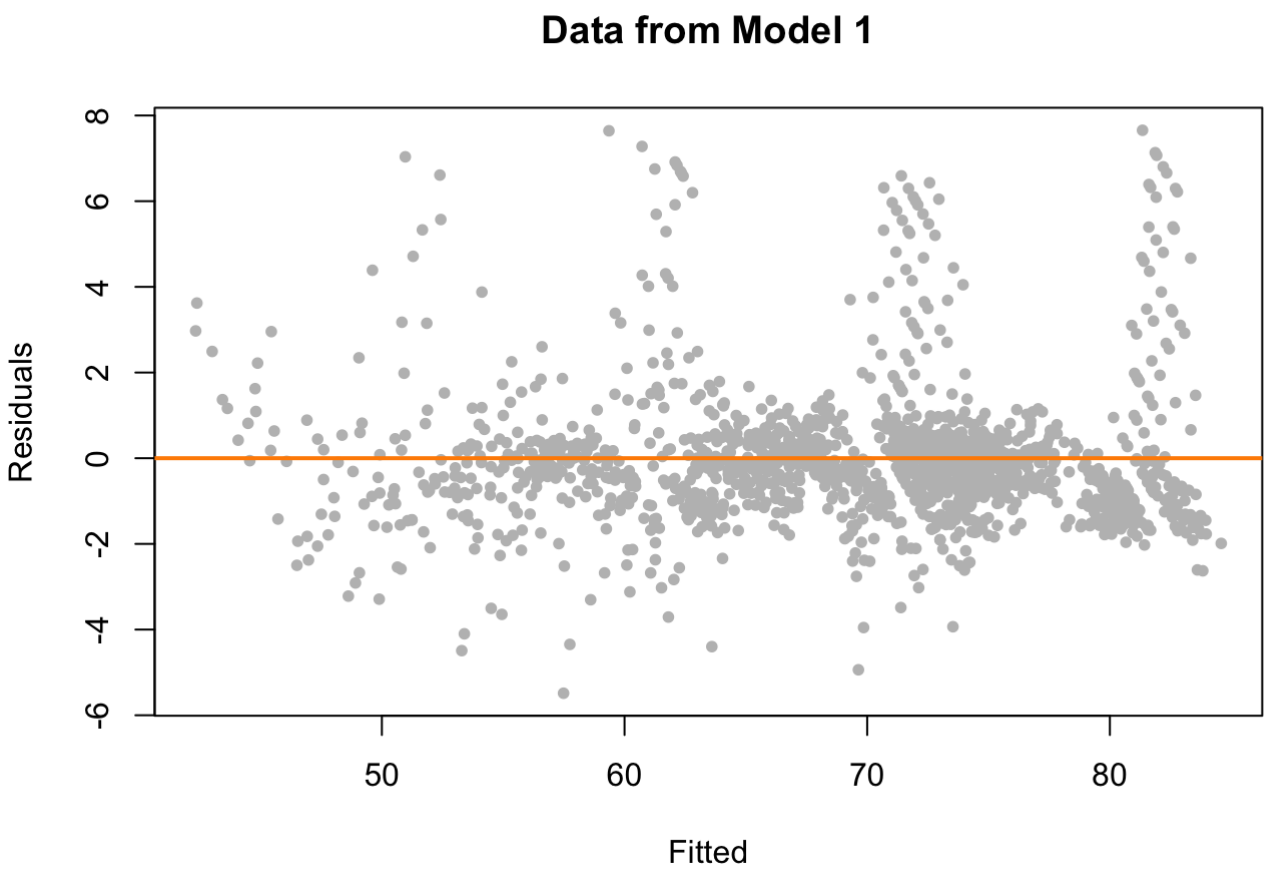
Additive Model Summary

Adj_R_Squared	RMSE	LOOCV_RMSE	AIC
0.9642	1.5859	1.7559	1824.977

Check model assumptions

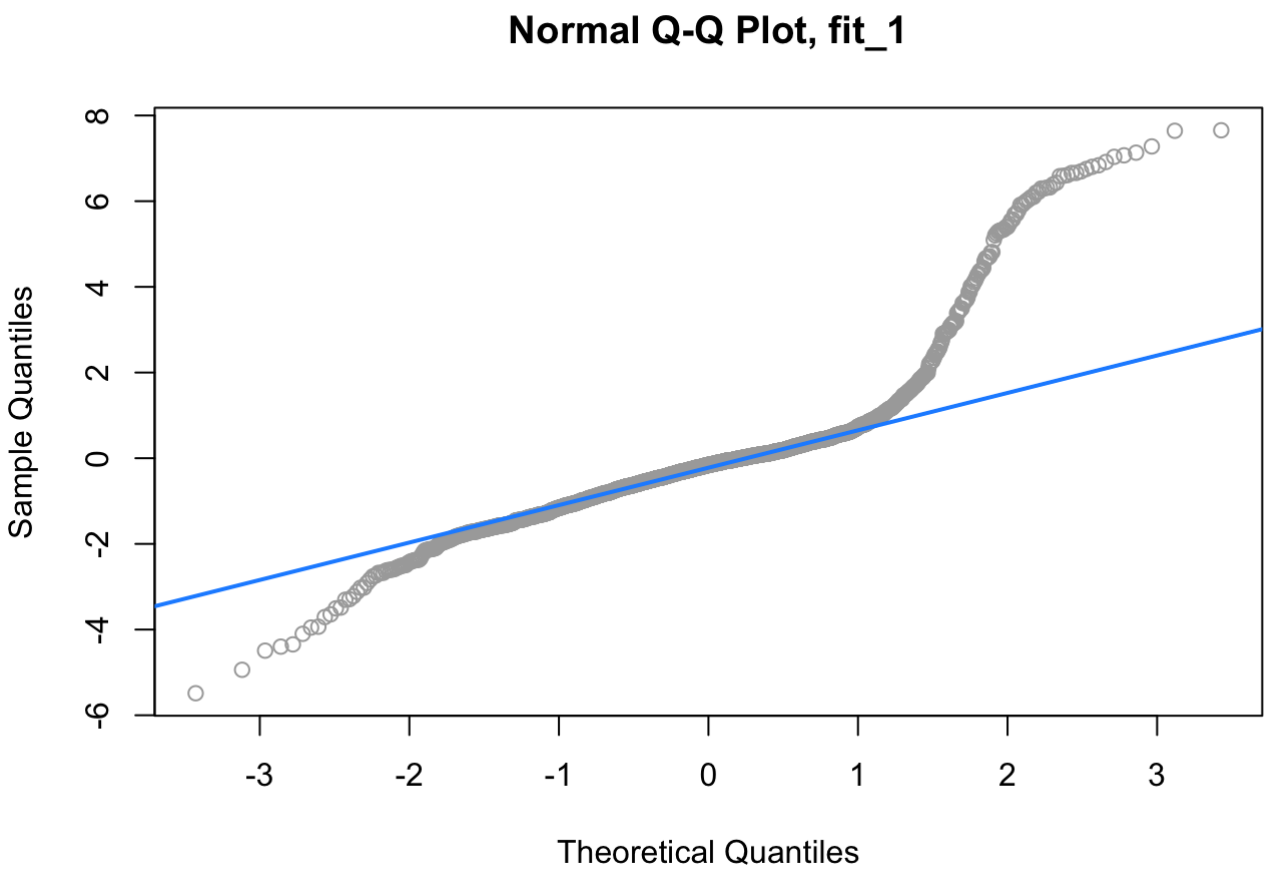
```
#Fitted vs Residuals Plot

plot(fitted(additive_model), resid(additive_model), col = "grey", pch = 20,
     xlab = "Fitted", ylab = "Residuals", main = "Data from Model 1")
abline(h = 0, col = "darkorange", lwd = 2)
```




```
#Q-Q Plot

qqnorm(resid(additive_model), main = "Normal Q-Q Plot, fit_1", col = "darkgrey")
qqline(resid(additive_model), col = "dodgerblue", lwd = 2)
```



The fitted vs residuals plot and Q-Q plot suggest issues with this model's assumptions, which we will confirm via more formal tests.

```
library(lmtest)
bptest(additive_model)
```

```
##
##  studentized Breusch-Pagan test
##
## data:  additive_model
## BP = 283.35, df = 151, p-value = 4.012e-10
```

```
shapiro.test(resid(additive_model))
```

```
##
##  Shapiro-Wilk normality test
##
## data:  resid(additive_model)
## W = 0.82427, p-value < 2.2e-16
```

The results of the Breusch-Pagan test and the Shapiro-Wilk test confirm that this model violates both the constant variance assumption and the normality assumption. We will attempt to improve these issues below.

Model Improvement: Removing Highly Correlated Variables

We will attempt to fix these issues by removing highly correlated predictors. In particular, the variables `thinness 1-19 years` and `thinness 5-9 years` had a correlation of 0.997. In addition, the variables `under 5 death` and `infant death` had a correlation of 0.928. We'll remove one from each of the above pairs of predictors and reassess the model.

```
#---------- Next step ------------------------------

#Removing infant deaths and thinness 1-19 years
corr_removed_data_1 = life_expectancy_data[ , !(names(life_expectancy_data) %in% c('infa
nt deaths', 'thinness 1-19 years'))]
corr_removed_model_1 = lm(`Life expectancy` ~ ., data = corr_removed_data_1)
corr_removed_metrics_1 = calc_model_metrics(corr_removed_model_1)


#Removing infant deaths and thinness 5-9 years
corr_removed_data_2 = life_expectancy_data[ , !(names(life_expectancy_data) %in% c('infa
nt deaths', 'thinness 5-9 years'))]
corr_removed_model_2 = lm(`Life expectancy` ~ ., data = corr_removed_data_2)
corr_removed_metrics_2 = calc_model_metrics(corr_removed_model_2)


#Removing under 5 deaths and thinness 1-19 years
corr_removed_data_3 = life_expectancy_data[ , !(names(life_expectancy_data) %in% c('unde
r 5 death', 'thinness 1-19 years'))]
corr_removed_model_3 = lm(`Life expectancy` ~ ., data = corr_removed_data_3)
corr_removed_metrics_3 = calc_model_metrics(corr_removed_model_3)

#Removing under 5 deaths and thinness 5-9 years
corr_removed_data_4 = life_expectancy_data[ , !(names(life_expectancy_data) %in% c('unde
r 5 death', 'thinness 5-9 years'))]
corr_removed_model_4 = lm(`Life expectancy` ~ ., data = corr_removed_data_4)
corr_removed_metrics_4 = calc_model_metrics(corr_removed_model_4)

# Create a data frame summarizing the model metrics
model_summary = data.frame(
  Variables_Removed = c("infant deaths + thinness 1-19", "infant deaths + thinness 5-9",
"under 5 deaths + thinness 1-19", "under 5 deaths + thinness 5-9 years"),
  Adjusted_R_Squared = c(corr_removed_metrics_1$Adj_R_Squared, corr_removed_metrics_2$Ad
j_R_Squared, corr_removed_metrics_3$Adj_R_Squared, corr_removed_metrics_4$Adj_R_Square
d),
  RMSE = c(corr_removed_metrics_1$RMSE, corr_removed_metrics_2$RMSE, corr_removed_metric
s_3$RMSE, corr_removed_metrics_4$RMSE),
  LOOCV_RMSE = c(corr_removed_metrics_1$LOOCV_RMSE, corr_removed_metrics_2$LOOCV_RMSE, c
orr_removed_metrics_3$LOOCV_RMSE, corr_removed_metrics_4$LOOCV_RMSE),
  AIC = c(corr_removed_metrics_1$AIC, corr_removed_metrics_2$AIC, corr_removed_metrics_3
$AIC, corr_removed_metrics_4$AIC)
)

library(knitr)
knitr::kable(model_summary, caption = "Model Summary", digits = 4)
```

Model Summary

Variables_Removed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
infant deaths + thinness 1-19	0.9640	1.5914	1.7576	1834.247

Variables_Removed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
infant deaths + thinness 5-9	0.9639	1.5937	1.7590	1837.088
under 5 deaths + thinness 1-19	0.9642	1.5859	1.7559	1824.977
under 5 deaths + thinness 5-9 years	0.9641	1.5883	1.7572	1827.939

Our analysis suggests that removing the variables `under 5 deaths` and `thinness 1-19` results in the most model improvement. However, the resulting AIC of this model is still large, so we need to further improve the model.

Model Improvement: Log Transformation of Predictor Variables

We will attempt to further improve the model by log transforming certain predictor variables (`Population` and `GDP`).

```
#---------- Next step ------------------------------

log_transform_1 = lm(`Life expectancy` ~ . + log(Population) + log(GDP), data = life_exp
ectancy_data)
log_transformed_metrics_1 = calc_model_metrics(log_transform_1)

log_transform_2 = lm(`Life expectancy` ~ . + log(GDP), data = life_expectancy_data)
log_transformed_metrics_2 = calc_model_metrics(log_transform_2)

log_transform_3 = lm(`Life expectancy` ~ . + log(Population), data = life_expectancy_dat
a)
log_transformed_metrics_3 = calc_model_metrics(log_transform_3)


log_model_summary = data.frame(
  Variables_Log_Transformed = c("Population + GDP", "GDP", "Population"),
  Adjusted_R_Squared = c(log_transformed_metrics_1$Adj_R_Squared, log_transformed_metric
s_2$Adj_R_Squared, log_transformed_metrics_3$Adj_R_Squared),
  RMSE = c(log_transformed_metrics_1$RMSE, log_transformed_metrics_2$RMSE, log_transform
ed_metrics_3$RMSE),
  LOOCV_RMSE = c(log_transformed_metrics_1$LOOCV_RMSE, log_transformed_metrics_2$LOOCV_R
MSE, log_transformed_metrics_3$LOOCV_RMSE),
  AIC = c(log_transformed_metrics_1$AIC, log_transformed_metrics_2$AIC, log_transformed_
metrics_3$AIC)
)

knitr::kable(log_model_summary, caption = "Log Transformed Model Summary", digits = 4)
```

Log Transformed Model Summary

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
Population + GDP	0.9642	1.5853	1.7583	1827.612
GDP	0.9642	1.5853	1.7569	1825.613

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
Population	0.9642	1.5859	1.7574	1826.977

Experimenting with various log transformations of the predictor variables `Population` and `GDP` suggests that log transformation of `GDP` resulted in a minimal improvement in AIC.

```
n = length(resid(additive_model))
```

```
#---------- Next step --------------------------------

#We will use AIC and BIC backwards search to attempt to further improve the model

#AIC and BIC for additive models
additive_mod_back_aic = step(additive_model, direction = "backward", trace = 0)
additive_mod_back_bic = step(additive_model, direction = "backward", k = log(n), trace =
0)

metrics_additive_mod_back_aic = calc_model_metrics(additive_mod_back_aic)
metrics_additive_mod_back_bic = calc_model_metrics(additive_mod_back_bic)
```

```
# AIC and BIC for models without highly corelated features
corr_mod_1_back_aic = step(corr_removed_model_1, direction = "backward", trace = 0)
corr_mod_2_back_aic = step(corr_removed_model_2, direction = "backward", trace = 0)
corr_mod_3_back_aic = step(corr_removed_model_3, direction = "backward", trace = 0)

corr_mod_1_back_bic = step(corr_removed_model_1, direction = "backward", k = log(n), tra
ce = 0)
corr_mod_2_back_bic = step(corr_removed_model_2, direction = "backward", k = log(n), tra
ce = 0)
corr_mod_3_back_bic = step(corr_removed_model_3, direction = "backward", k = log(n), tra
ce = 0)

metrics_corr_mod_1_back_aic = calc_model_metrics(corr_mod_1_back_aic)
metrics_corr_mod_2_back_aic = calc_model_metrics(corr_mod_2_back_aic)
metrics_corr_mod_3_back_aic = calc_model_metrics(corr_mod_3_back_aic)

metrics_corr_mod_1_back_bic = calc_model_metrics(corr_mod_1_back_bic)
metrics_corr_mod_2_back_bic = calc_model_metrics(corr_mod_2_back_bic)
metrics_corr_mod_3_back_bic = calc_model_metrics(corr_mod_3_back_bic)
```

```
# AIC and BIC for models with log transformations
tranform_mod_1_back_aic = step(log_transform_1, direction = "backward", trace = 0)
tranform_mod_2_back_aic = step(log_transform_2, direction = "backward", trace = 0)
tranform_mod_3_back_aic = step(log_transform_3, direction = "backward", trace = 0)

tranform_mod_1_back_bic = step(log_transform_1, direction = "backward", k = log(n), trac
e = 0)
tranform_mod_2_back_bic = step(log_transform_2, direction = "backward", k = log(n), trac
e = 0)
tranform_mod_3_back_bic = step(log_transform_3, direction = "backward", k = log(n), trac
e = 0)

metrics_tranform_mod_1_back_aic = calc_model_metrics(tranform_mod_1_back_aic)
metrics_tranform_mod_2_back_aic = calc_model_metrics(tranform_mod_2_back_aic)
metrics_tranform_mod_3_back_aic = calc_model_metrics(tranform_mod_3_back_aic)


metrics_tranform_mod_1_back_bic = calc_model_metrics(tranform_mod_1_back_bic)
metrics_tranform_mod_2_back_bic = calc_model_metrics(tranform_mod_2_back_bic)
metrics_tranform_mod_3_back_bic = calc_model_metrics(tranform_mod_3_back_bic)
```

```
additive_model_summary = data.frame(
  Variables_Log_Transformed = c("additive AIC", "Additive BIC"),

  Adjusted_R_Squared =
  c(metrics_additive_mod_back_aic$Adj_R_Squared, metrics_additive_mod_back_bic$Adj_R_Squ
ared),

  RMSE = c(metrics_additive_mod_back_aic$RMSE, metrics_additive_mod_back_bic$RMSE),

  LOOCV_RMSE =
    c(metrics_additive_mod_back_aic$LOOCV_RMSE, metrics_additive_mod_back_bic$LOOCV_RMS
E),

  AIC = c(metrics_additive_mod_back_aic$AIC, metrics_additive_mod_back_bic$AIC)

)

knitr::kable(additive_model_summary, caption = "Additive model AIC and BIC Summary", dig
its = 4)
```

Additive model AIC and BIC Summary

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
additive AIC	0.9643	1.5882	1.7430	1809.740
Additive BIC	0.9642	1.5932	1.7455	1814.022

```
corr_model_summary = data.frame(
  Variables_Log_Transformed = c("corr AIC model 1", "corr AIC model 2", "corr AIC model
3",
                                "corr BIC model 1","corr BIC model 2", "corr BIC model 3"
),

  Adjusted_R_Squared =
  c(metrics_corr_mod_1_back_aic$Adj_R_Squared, metrics_corr_mod_2_back_aic$Adj_R_Square
d,
    metrics_corr_mod_3_back_aic$Adj_R_Squared,
    metrics_corr_mod_1_back_bic$Adj_R_Squared, metrics_corr_mod_2_back_bic$Adj_R_Square
d,
    metrics_corr_mod_3_back_bic$Adj_R_Squared
    ),

  RMSE =
      c(metrics_corr_mod_1_back_aic$RMSE, metrics_corr_mod_2_back_aic$RMSE,
    metrics_corr_mod_3_back_aic$RMSE,
    metrics_corr_mod_1_back_bic$RMSE, metrics_corr_mod_2_back_bic$RMSE,
    metrics_corr_mod_3_back_bic$RMSE
    ),
  LOOCV_RMSE =
    c(metrics_corr_mod_1_back_aic$LOOCV_RMSE, metrics_corr_mod_2_back_aic$LOOCV_RMSE,
    metrics_corr_mod_3_back_aic$LOOCV_RMSE,
    metrics_corr_mod_1_back_bic$LOOCV_RMSE, metrics_corr_mod_2_back_bic$LOOCV_RMSE,
    metrics_corr_mod_3_back_bic$LOOCV_RMSE
    ),

  AIC = c(metrics_corr_mod_1_back_aic$AIC, metrics_corr_mod_2_back_aic$AIC,
    metrics_corr_mod_3_back_aic$AIC,
    metrics_corr_mod_1_back_bic$AIC, metrics_corr_mod_2_back_bic$AIC,
    metrics_corr_mod_3_back_bic$AIC
    )
)

knitr::kable(corr_model_summary, caption = "correlation transformed model AIC and BIC Su
mmary", digits = 4)
```

correlation transformed model AIC and BIC Summary

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
corr AIC model 1	0.9641	1.5935	1.7457	1818.552
corr AIC model 2	0.9640	1.5958	1.7484	1823.343
corr AIC model 3	0.9643	1.5882	1.7430	1809.740
corr BIC model 1	0.9639	1.6003	1.7497	1824.704
corr BIC model 2	0.9638	1.6043	1.7531	1830.836
corr BIC model 3	0.9642	1.5932	1.7455	1814.022

```
transform_model_summary = data.frame(
  Variables_Log_Transformed = c("Log transform AIC model 1", "Log transform AIC model
2", "Log transform AIC model 3",
                                "Log transform BIC model 1","Log transformBIC model 2",
"Log transform BIC model 3" ),

  Adjusted_R_Squared =
  c(metrics_tranform_mod_1_back_aic$Adj_R_Squared, metrics_tranform_mod_2_back_aic$Adj_R
_Squared, metrics_tranform_mod_3_back_aic$Adj_R_Squared,

    metrics_tranform_mod_1_back_bic$Adj_R_Squared, metrics_tranform_mod_2_back_bic$Adj_R
_Squared, metrics_tranform_mod_3_back_bic$Adj_R_Squared
    ),

  RMSE =
      c(metrics_tranform_mod_1_back_aic$RMSE, metrics_tranform_mod_2_back_aic$RMSE,
    metrics_tranform_mod_3_back_aic$RMSE,
    metrics_tranform_mod_1_back_bic$RMSE, metrics_tranform_mod_2_back_bic$RMSE,
    metrics_tranform_mod_3_back_bic$RMSE
    ),
  LOOCV_RMSE =
    c(metrics_tranform_mod_1_back_aic$LOOCV_RMSE, metrics_tranform_mod_2_back_aic$LOOCV_
RMSE,
    metrics_tranform_mod_3_back_aic$LOOCV_RMSE,
    metrics_tranform_mod_1_back_bic$LOOCV_RMSE, metrics_tranform_mod_2_back_bic$LOOCV_RM
SE,
    metrics_tranform_mod_3_back_bic$LOOCV_RMSE
    ),

  AIC = c(metrics_tranform_mod_1_back_aic$AIC, metrics_tranform_mod_2_back_aic$AIC,
    metrics_tranform_mod_3_back_aic$AIC,
    metrics_tranform_mod_1_back_bic$AIC, metrics_tranform_mod_2_back_bic$AIC,
    metrics_tranform_mod_3_back_bic$AIC
    )
)

knitr::kable(transform_model_summary, caption = "log transformation model AIC and BIC Su
mmary", digits = 4)
```

log transformation model AIC and BIC Summary

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
Log transform AIC model 1	0.9643	1.5882	1.7430	1809.740
Log transform AIC model 2	0.9643	1.5882	1.7430	1809.740
Log transform AIC model 3	0.9643	1.5882	1.7430	1809.740
Log transform BIC model 1	0.9642	1.5932	1.7455	1814.022
Log transformBIC model 2	0.9642	1.5932	1.7455	1814.022

Variables_Log_Transformed	Adjusted_R_Squared	RMSE	LOOCV_RMSE	AIC
Log transform BIC model 3	0.9642	1.5932	1.7455	1814.022

Results

Discussions

Appendix

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