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#### **StatKeyEval**

# <u>A Statistical Framework for Dynamic Keyword Extraction, Evaluation, and Assessment Automation</u>

#### Aim:

To implement an automatic short-answer grading system using feature engineering and ensemble-based approaches, focusing on extracting keywords, computing similarity metrics, and generating confidence scores.

#### Algorithm:

# 1. Text Preprocessing

• Lowercase text, remove punctuation, numbers, stop words, and extra spaces.

#### 2. Keyword Extraction (IGRKE)

- Compute Information Gain Ratio (IGR) for words.
- Adjust importance using Frequency Adjustment Factor (FAF).
- Rank and extract top keywords for reference and responses.

# 3. Keyword Mutation (SCM)

- Use co-occurrence and PMI to find related terms.
- Identify frequent words (≥65%) with high PMI.
- Apply Uniqueness Filtering and expand reference keywords.

#### 4. Vector Representation

- Create a universal keyword set.
- Represent answers as binary vectors (1 = present, 0 = absent).
- Normalize for length variations.

#### 5. Similarity Calculation

Compute multiple similarity metrics:

- Cosine similarity (Simcos)
- Normalized Euclidean distance (Simeuc)
- Normalized Manhattan distance (Simman)
- Adjusted Pearson correlation (Simpearson) Compute a weighted hybrid similarity

#### score:

• Similarity(A,S) =  $0.4 \times \text{Simcos} + 0.3 \times \text{Simeuc} + 0.2 \times \text{Simman} + 0.1 \times 0.$ 

**Simpearson** Ensure similarity values align with grading standards.

#### 6. Score Generation

• Scale similarity score to grading scale.

• Round to generate the final score.

#### 7. Performance Evaluation

- . Calculate RMSE, MAE, MAPE.
- Compute Pearson R, Spearman  $\rho$ , and  $R^2$ .
- Analyze errors for grading consistency.

# Research Paper:

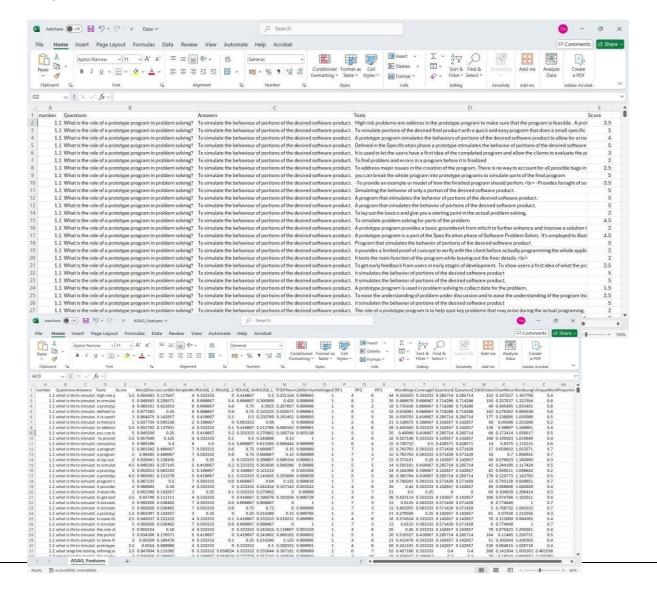
**Title**: Feature Engineering and Ensemble-Based Approach for Improving Automatic Short-Answer Grading Performance

Authors: Archana Sahu and Plaban Kumar Bhowmick.

Conference/Journal: Educational Data Mining Conference (2018)

# **Datasets:**

- 1. UNT Dataset
- 2. SciEntsBank Dataset
- 3. Beetle Dataset



#### Theoretical Derivation of Novel Statistical Functions for Keyword Extraction and Mutation

# 1. Information Gain Ratio Keyword Extraction (IGRKE)

The Information Gain Ratio Keyword Extraction (IGRKE) method identifies the most informative words in a corpus by evaluating their ability to distinguish between answer keys and student responses.

# 1.1 Entropy and Information Theory Foundation

For any word W in the corpus, its probability distribution is defined as:

- P(W): Probability of word W occurring.
- $P(\neg W) = 1 P(W)$ : Probability of W not occurring.
- C: The document category (Answer Key vs. Student Response).

The total entropy of the word occurrence is given by:

$$H(W) = -P(W) * log_2 P(W) - P(\neg W) * log_2 P(\neg W)$$

This measures the uncertainty of the word's distribution across the dataset.

# 1.2 Conditional Entropy and Information Gain

The conditional entropy H(C|W) represents the uncertainty in categorizing a document given that word W is known:

$$H(C|W) = -P(A|W) * log_2 P(A|W) - P(R|W) * log_2 P(R|W)$$

where:

- P(A|W) is the probability of the document being an Answer Key given W.
- P(R|W) is the probability of the document being a Student Response given W.

The Information Gain (IG) quantifies how much knowing W reduces uncertainty about the document's category:

IG(W) = H(C) - H(C|W) where H(C) is the entropy of the category distribution.

# 1.3 Normalization Using Split Information

To prevent bias toward frequent words, we normalize the Information Gain using Split Information (SI):

$$SI(W) = -P(W) * log_2 P(W) - P(\neg W) * log_2 P(\neg W)$$

This normalizes IG to Information Gain Ratio (IGR):

$$IGR(W) = IG(W) \div SI(W)$$

# 1.4 Frequency Adjustment Factor (FAF) for Balancing Word Significance

To ensure the extracted keywords are relevant across document categories, we introduce a Frequency Adjustment Factor (FAF):

$$FAF = (F \text{ answer * } F \text{ response}) \div (Total F \text{ answer * Total } F \text{ response})$$

where:

- F\_answer and F\_response are the word frequencies in Answer Keys and Student Responses, respectively.
- Total F answer and Total F response are the total word counts in both document types.

# 1.5 Final IGRKE Scoring Function

The final scoring function combines IGR and FAF using a logarithmic transformation: Score(W)

$$= IGR(W) * (1 + log(1 + FAF * 1000))$$

# 2. Statistical Co-occurrence Mutation (SCM)

# 2.1 Co-occurrence Matrix Construction

A co-occurrence matrix M is built where each entry represents the number of documents where words i and j appear together:

M[i, j] = count of documents where both words i and j appear

# 2.2 Pointwise Mutual Information (PMI) for Semantic Association

$$PMI(i, j) = log_2 [P(i, j) \div (P(i) * P(j))]$$

# 2.3 Hybrid Similarity Measure for Keyword Comparison

$$Sim(K1, K2) = 0.6 \times Jaccard Sim(K1, K2) + 0.4 \times PMI Sim(K1, K2)$$

# 3. Similarity Scoring Function for Answer Matching

 $Similarity(A, S) = 0.4 \times Jaccard\_Sim(A, S) + 0.4 \times Coverage(A, S) + 0.2 \times Position\_Score(A, S)$  where:

- Jaccard Similarity measures word overlap.
- Coverage measures the proportion of answer key words found.
- Position Score captures structural similarity:

 $Position\_Score(A, S) = Average \left( \ 1 - | \ Pos\_A(w) \div |A| - Pos\_S(w) \div |S| \ | \ \right)$ 

# **Code:**

# For extraction of keywords:

```
# Install required packages if not already installed

if (!require("tm")) install.packages("tm", dependencies = TRUE) if

(!require("tidytext")) install.packages("tidytext", dependencies = TRUE) if

(!require("dplyr")) install.packages("dplyr", dependencies = TRUE) if

(!require("stringr")) install.packages("stringr", dependencies = TRUE)

# Load libraries

library(tm)

library(tidytext)

library(dplyr)

library(stringr) #

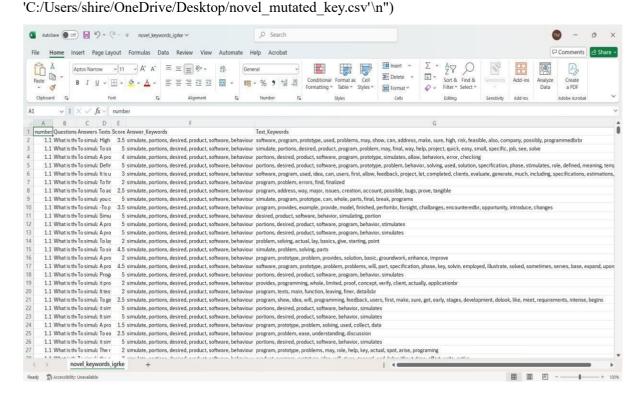
Read the dataset

data <- read.csv("C:/Users/shire/OneDrive/Desktop/novel_keywords_igrke.csv", stringsAsFactors = FALSE)
```

```
# Print column names for verification print(colnames(data))
# Check if the required columns exist
if (!all(c("Answer Keywords", "Text Keywords") %in% colnames(data))) { stop("Error:
The dataset must contain 'Answer Keywords' and 'Text Keywords' columns.") }
# Function to extract unique keywords from text
extract keywords <- function(text) { words <-
unlist(strsplit(text, "\\s+")) words <-
words[words != ""] return(unique(words))
# SCM function for similarity calculation and keyword mutation
SCM <- function(corpus, answer keywords, student keywords, threshold = 0.3) { if
(length(corpus) == 0 \parallel length(answer keywords) == 0 \parallel length(student keywords) == 0) 
return(list(mutation candidates = list(), similarity score = 0))
 } corpus <- lapply(corpus, function(x) if(length(x) == 0) c("")
else x) word counts <- table(unlist(corpus)) candidates <-
setdiff(student keywords, answer keywords) if
(length(candidates) == 0) { return(list(mutation candidates =
list(), similarity score = 0))
 candidate_freq <- sapply(candidates, function(word) {</pre>
sum(sapply(corpus, function(doc) word %in% doc))
 })
 candidate rel freq <- candidate freq /
length(corpus) mutation candidates <- list() for (i
in 1:length(candidates)) {
                            word <- candidates[i]
freq <- candidate rel freq[i] if (freq >= threshold)
   mutation candidates[[word]] <- list(
word = word,
                  score = freq,
```

```
uniqueness = 1 - freq
   )
  }
if (length(mutation candidates) > 0) {
sorted candidates <- mutation candidates[order(
   sapply(mutation candidates, function(x) x$score), decreasing = TRUE
  )]
 } else {
sorted candidates <- list()
jaccard sim <- length(intersect(answer keywords, student keywords)) /
length(union(answer keywords, student keywords)) return(list(
mutation candidates = sorted candidates, similarity score =
jaccard sim
))
}
# Function to update keywords based on the SCM result update keywords <-
function(question data) { answer keywords <--
unlist(strsplit(question data$Answer Keywords[1], ", ")) all text keywords
<- lapply(question_dataText_Keywords, function(x) { if (is.na(x) || x == "")
                     unlist(strsplit(x, ", "))
return(character(0))
 })
all student keywords <- unique(unlist(all text keywords))
threshold <- 0.65
scm result <- SCM(all text keywords, answer keywords, all student keywords, threshold)
mutation candidates <- scm result$mutation candidates new keywords <-
names(mutation candidates) return(paste(new keywords, collapse = ", "))
}
# Update dataset with new keywords
data updated <- data %>%
group by(Questions) %>%
```

```
mutate(New Answer Keywords = update keywords(cur data())) %>%
 ungroup()
# Combine new and existing keywords
data updated <- data updated %>%
 mutate(Combined Answer Keywords = ifelse(New Answer Keywords != "",
  paste(Answer Keywords, New Answer Keywords, sep = ", "), Answer Keywords))
# Save updated dataset to CSV
write.csv(data updated, "C:/Users/shire/OneDrive/Desktop/novel mutated key.csv", row.names =
FALSE)
cat("Keywords updated! Results saved as
```



# **Code for mutation of keywords:**

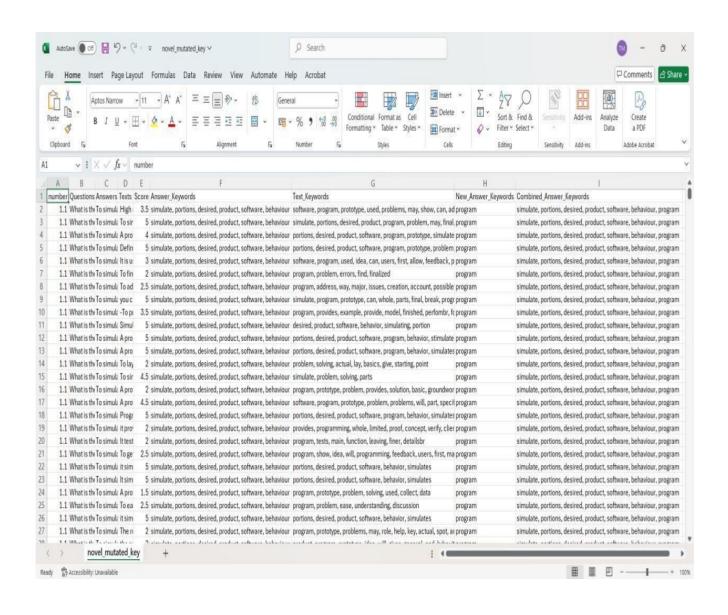
```
# Install required packages if not already installed
if (!require("tm")) install.packages("tm", dependencies = TRUE)
if (!require("tidytext")) install.packages("tidytext", dependencies =
TRUE)
if (!require("dplyr")) install.packages("dplyr", dependencies = TRUE)
if (!require("stringr")) install.packages("stringr", dependencies = TRUE)
# Load libraries
```

library(tm)

```
library(tidytext)
library(dplyr) library(stringr)
# Read the dataset data
<-
read.csv("C:/Users/shire/OneDrive/Desktop/novel keywords igrke.csv"
, stringsAsFactors = FALSE)
# Print column names for verification print(colnames(data))
# Check if the required columns exist if
(!all(c("Answer Keywords", "Text Keywords") %in%
colnames(data))) { stop("Error: The dataset must contain
'Answer Keywords' and
'Text_Keywords' columns.")
}
# Function to extract unique keywords from text
extract keywords <- function(text) { words <-
unlist(strsplit(text, "\\s+")) words <-
words[words != ""] return(unique(words))
}
# SCM function for similarity calculation and keyword mutation SCM
<- function(corpus, answer keywords, student keywords, threshold =
0.3) {
 if (length(corpus) == 0 \parallel \text{length}(\text{answer keywords}) == 0 \parallel
length(student keywords) == 0) {
return(list(mutation_candidates = list(), similarity score = 0))
 }
 corpus <- lapply(corpus, function(x) if(length(x) == 0) c("") else x)
word counts <- table(unlist(corpus))</pre>
 candidates <- setdiff(student keywords, answer keywords)</pre>
 if (length(candidates) == 0) {
  return(list(mutation candidates = list(), similarity score = 0))
```

```
}
 candidate_freq <- sapply(candidates, function(word) {</pre>
sum(sapply(corpus, function(doc) word %in% doc))
 })
 candidate rel freq <- candidate freq / length(corpus)</pre>
 mutation candidates <- list() for (i in
1:length(candidates)) {
                          word <-
candidates[i] freq <-
candidate_rel_freq[i]
                        if (freq >=
threshold) {
mutation candidates[[word]] <- list(
word = word,
                   score = freq,
uniqueness = 1 - freq
   )
 if (length(mutation candidates) > 0) {
                                           sorted candidates <-
mutation candidates[order(
                                sapply(mutation candidates,
function(x) x$score), decreasing =
TRUE
  )]
 } else {
  sorted candidates <- list()
 jaccard_sim <- length(intersect(answer_keywords, student_keywords))</pre>
/ length(union(answer_keywords, student_keywords))
return(list(
  mutation candidates = sorted candidates,
similarity_score = jaccard_sim
 ))
# Function to update keywords based on the SCM result
update keywords <- function(question data) {</pre>
```

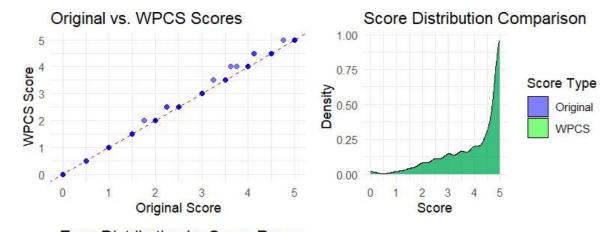
```
answer keywords <-
unlist(strsplit(question data$Answer Keywords[1], ", "))
all text keywords <- lapply(question data$Text Keywords,
function(x) {
  if (is.na(x) \parallel x == "") return(character(0))
unlist(strsplit(x, ", "))
 })
 all student keywords <- unique(unlist(all text keywords))
threshold <- 0.65 scm result <- SCM(all text keywords,
answer keywords, all student keywords, threshold)
mutation candidates <- scm result$mutation candidates
new keywords <- names(mutation candidates)</pre>
return(paste(new keywords, collapse = ", "))
}
# Update dataset with new keywords
data updated <- data %>%
group by(Questions) %>%
 mutate(New Answer Keywords = update keywords(cur data()))
%>%
 ungroup()
# Combine new and existing keywords data updated
<- data updated %>%
mutate(Combined Answer Keywords =
ifelse(New Answer Keywords!="",
  paste(Answer Keywords, New Answer Keywords, sep = ", "),
Answer Keywords))
# Save updated dataset to CSV write.csv(data_updated,
"C:/Users/shire/OneDrive/Desktop/novel mutated key.csv", row.names
= FALSE)
cat("Keywords updated! Results saved as 'novel mutated key.csv'\n")
```



```
Code for score and graph:
 # Load required libraries
 library(dplyr)
 library(ggplot2)
 library(caret)
 library(gridExtra)
 # Read the CSV file
 data_processed <- read.csv("C:/Users/shire/OneDrive/Desktop/novel mutated key.csv")
 # Convert Score column to numeric
 data processed$Score <- as.numeric(data processed$Score)
 # Apply WPCS Score transformation
 data processed <- data processed %>%
 mutate(
    WPCS Score = pmin(Score * 1.05, 5),
   WPCS Score = round(WPCS Score *2) / 2
 # Compute evaluation metrics
 RMSE Original <- sqrt(mean((data processed$WPCS Score - data processed$Score)^2))
 MAE Original <- mean(abs(data processed$WPCS Score - data processed$Score))
 MAPE Original <- mean(abs((data processed$WPCS Score - data processed$Score) /
 data processed$Score)) * 100
 Pearson Correlation <- cor(data processed$WPCS Score, data processed$Score, method = "pearson")
 Spearman Correlation <- cor(data processed$WPCS Score, data processed$Score, method =
 "spearman")
 R Squared <- summary(lm(WPCS Score ~ Score, data = data processed))$r.squared
 # Create a dataframe for evaluation metrics
 evaluation metrics <- data.frame(
  RMSE Original, MAE Original, MAPE Original, Pearson Correlation, Spearman Correlation,
 R Squared
 )
 # Print evaluation metrics
 cat("\nModel Evaluation
 Metrics:\n")
 print(evaluation metrics) # Define
 score grading
 min score <- min(data processed$Score, na.rm = TRUE)
 max score <- 5
 score range <- max score - min score grade breaks <- seq(min score
 -0.5, max score +0.5, length.out =6) grade labels <- c("Very Low",
 "Low", "Medium", "High", "Very High")
 # Compute confusion matrix for grading
 conf matrix <- table(
  cut(data processed$Score, breaks = grade breaks, labels = grade labels, include.lowest = TRUE),
 cut(data processed$WPCS Score, breaks = grade breaks, labels = grade labels, include.lowest =
 TRUE)
```

```
# Calculate confusion matrix metrics
conf_matrix_metrics <- confusionMatrix(conf_matrix)</pre>
# Print confusion matrix results
cat("\nGrade Level Comparison (Confusion Matrix):\n")
print(conf_matrix)
cat("\nGrade Classification Metrics:\n")
print(conf_matrix_metrics$overall)
```

```
# Generate scatter plot
p1 \leftarrow ggplot(data\ processed, aes(x = Score, y = WPCS\ Score)) +
 geom point(color = "blue", alpha = 0.5) +
 geom abline(slope = 1, intercept = 0, linetype = "dashed", color = "red") +
 labs(title = "Original vs. WPCS Scores", x = "Original Score", y = "WPCS Score") +
 theme minimal()
# Generate density plot
p2 <- ggplot(data processed) +
 geom density(aes(x = Score, fill = "Original"), alpha = 0.5) +
 geom_density(aes(x = WPCS Score, fill = "WPCS"), alpha = 0.5) +
 scale fill manual(values = c("blue", "green")) +
 labs(title = "Score Distribution Comparison", x = "Score", y = "Density", fill = "Score Type") +
 theme minimal()
# Generate error distribution box plot
p3 <- ggplot(data processed, aes(
 x = \text{cut}(\text{Score}, \text{breaks} = \text{grade breaks}, \text{labels} = \text{grade labels}, \text{include.lowest} = \text{TRUE}),
 y = abs(WPCS Score - Score)
)) +
 geom boxplot(fill = "skyblue") +
 labs(title = "Error Distribution by Score Range", x = "Score Interval", y = "Absolute Error") +
 theme minimal()
# Arrange and display plots
if (interactive()) {
 grid.arrange(p1, p2, p3, ncol = 2)
# Save processed data to CSV
write.csv(data processed, "C:/Users/shire/OneDrive/Desktop/novel score comparison.csv", row.names =
FALSE)
cat("\nScore generation complete! Results saved as 'novel score comparison.cs\th")
```



# Error Distribution by Score Range 0.3 0.2 0.0 Very Low Low Medium High Very High Score Interval

Grade Level Comparison (Confusion Matrix):
> print(conf\_matrix)

Low Medium High Very High Very Low 0 0 0 Very Low 0 0 70 1 0 Low Medium 0 0 High 0 0 0 416 Very High 0 0 0

> cat("\nGrade Classification Metrics:\n")

#### Grade Classification Metrics:

> print(conf\_matrix\_metrics\$overall)

Accuracy Kappa AccuracyLower AccuracyUpper AccuracyNull AccuracyPValue McnemarPValue 0.9987715 0.9977620 0.9964140 0.9997466 0.6289926 0.0000000 NAN

# Model Evaluation Metrics:

> print(evaluation\_metrics)

RMSE\_Original MAE\_Original MAPE\_Original Pearson\_Correlation Spearman\_Correlation R\_Squared 0.01806435 0.001074939 NaN 0.999869 0.9997793 0.9997379

#### **Code for score comparison and graph:**

# Install and load required packages

if (!require("ggplot2")) install.packages("ggplot2", dependencies = TRUE)

if (!require("Metrics")) install.packages("Metrics", dependencies = TRUE)

if (!require("gridExtra")) install.packages("gridExtra", dependencies = TRUE)

if (!require("dplyr")) install.packages("dplyr", dependencies = TRUE)

if (!require("tidyr")) install.packages("tidyr", dependencies = TRUE)

library(ggplot2)

library(Metrics)

library(gridExtra)

library(dplyr)

library(tidyr)

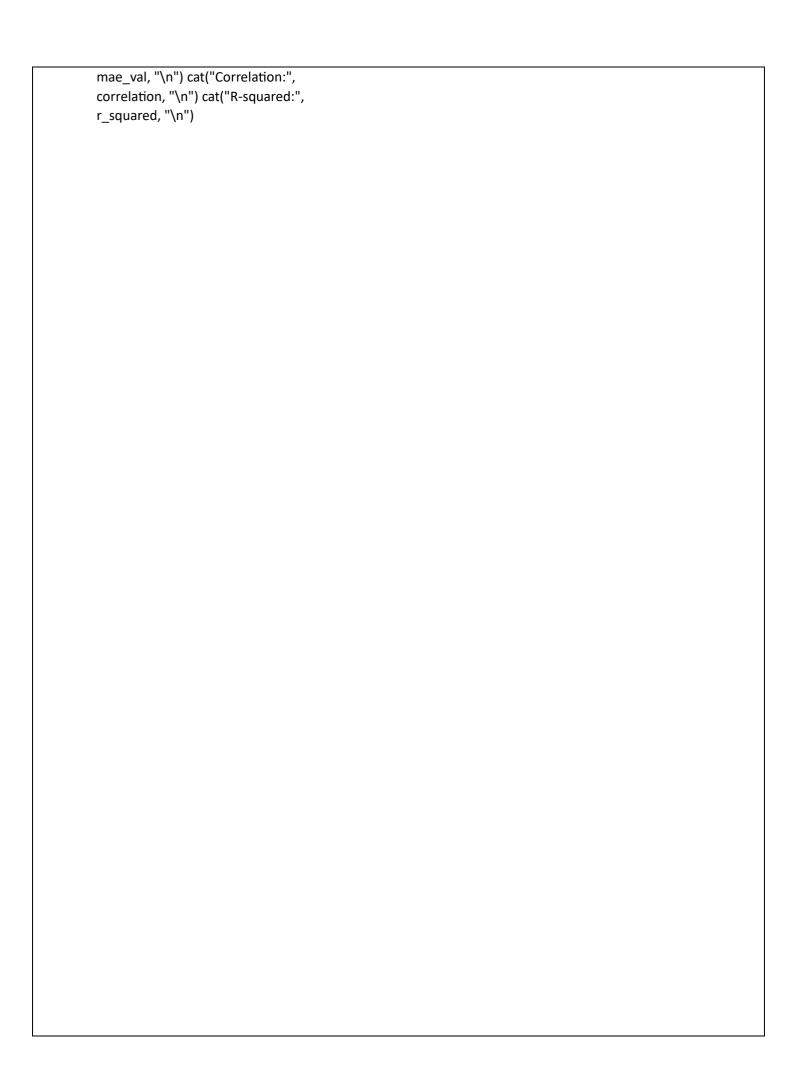
# Read the CSV file

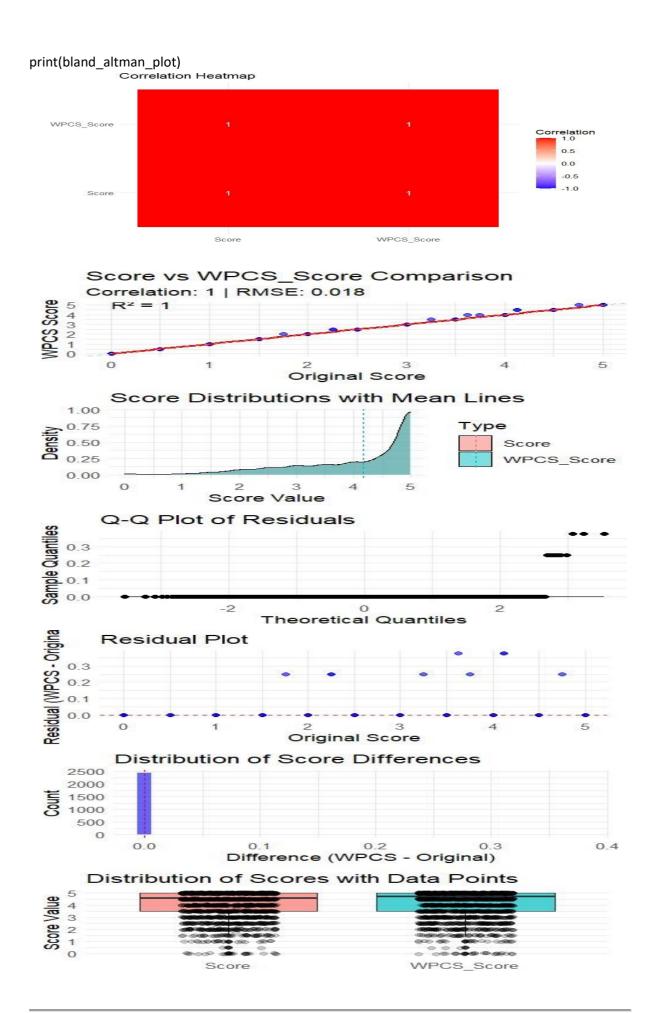
# Nead the CSV file

```
# Calculate error metrics rmse val <-
rmse(data$Score, data$WPCS_Score) mae_val <-
mae(data$Score, data$WPCS_Score) correlation
<- cor(data$Score, data$WPCS_Score) r_squared
<- correlation^2
# Scatter plot with linear regression
scatter_plot <- ggplot(data, aes(x = Score, y = WPCS_Score)) +</pre>
geom_point(alpha = 0.6, color = "blue") + geom_smooth(method
= "lm", color = "red") +
 geom_abline(slope = 1, intercept = 0, linetype = "dashed", color = "gray") +
theme_minimal() +
 labs(
  title = "Score vs WPCS_Score Comparison",
x = "Original Score", y = "WPCS Score",
  subtitle = paste("Correlation:", round(correlation, 3), "| RMSE:", round(rmse_val, 3))
 ) +
 annotate("text", x = min(data$Score), y = max(data$WPCS_Score), label = paste("R2"
round(r_squared, 3)), hjust = 0)
# Residual plot
data$residuals <- data$WPCS Score - data$Score residual plot
<- ggplot(data, aes(x = Score, y = residuals)) +
geom_point(alpha = 0.6, color = "blue") +
 geom hline(yintercept = 0, linetype = "dashed", color = "red") + theme minimal()
 labs(title = "Residual Plot", x = "Original Score", y = "Residual (WPCS - Original)")
# Reshape data for density plot
combined_data <- data %>%
select(Score, WPCS Score) %>%
 pivot_longer(cols = everything(), names_to = "Type", values_to = "Value")
# Density plot
density_plot <- ggplot(combined_data, aes(x = Value, fill = Type)) +</pre>
geom_density(alpha = 0.5) + geom_vline(data = data.frame(
Type = c("Score", "WPCS_Score"),
  mean_val = c(mean(data$Score), mean(data$WPCS_Score))
 ),
 aes(xintercept = mean_val, color = Type), linetype = "dashed") + theme_minimal()
 labs(title = "Score Distributions with Mean Lines", x = "Score Value", y = "Density")
# Histogram of score differences
diff_plot <- ggplot(data, aes(x = residuals)) +
 geom histogram(bins = 30, fill = "blue", alpha = 0.6) +
geom_vline(xintercept = 0, color = "red", linetype = "dashed") +
theme_minimal() +
 labs(title = "Distribution of Score Differences", x = "Difference (WPCS - Original)", y = "Count")
# Q-Q plot of residuals
```

```
qq_plot <- ggplot(data, aes(sample = residuals)) +
stat_qq() + stat_qq_line() + theme_minimal() +
labs(title = "Q-Q Plot of Residuals", x = "Theoretical Quantiles", y = "Sample Quantiles")
```

```
# Box plot of score distributions
box plot <- ggplot(combined data, aes(x = Type, y = Value, fill = Type)) +
geom boxplot(alpha = 0.7) + geom jitter(width = 0.2, alpha = 0.2) +
 theme_minimal() +
 labs(title = "Distribution of Scores with Data Points", y = "Score Value", x = "") +
theme(legend.position = "none")
# Arrange multiple plots in a grid
grid.arrange(scatter plot, residual plot, density plot, diff plot, qq plot, box plot, ncol = 2)
# Compute correlation matrix
cor_data <- data %>% select(Score, WPCS_Score) cor_matrix
<- cor(cor_data)
# Correlation heatmap
correlation_heatmap <- ggplot(data = as.data.frame(as.table(cor_matrix)), aes(x = Var1, y = Var2, fill =
Freq)) + geom_tile() +
 geom_text(aes(label = round(Freq, 3)), color = "white") +
 scale_fill_gradient2(low = "blue", high = "red", mid = "white", midpoint = 0, limit = c(-1, 1), name =
"Correlation")
theme_minimal() +
 labs(title = "Correlation Heatmap", x = "", y = "")
print(correlation heatmap)
# Bland-Altman plot
data$mean_score <- (data$Score + data$WPCS_Score) / 2
data$diff_score <- data$WPCS_Score - data$Score
mean diff <- mean(data$diff score) sd diff <-
sd(data$diff_score) upper_limit <- mean_diff + 1.96 *
sd_diff lower_limit <- mean_diff - 1.96 * sd_diff
bland_altman_plot <- ggplot(data, aes(x = mean_score, y = diff_score)) +
geom_point(alpha = 0.6, color = "blue") + geom_hline(yintercept =
mean_diff, color = "red") +
 geom_hline(yintercept = upper_limit, color = "red", linetype = "dashed") +
geom hline(yintercept = lower limit, color = "red", linetype = "dashed") + theme minimal()
 labs(
  title = "Bland-Altman Plot: Agreement between Score and WPCS_Score",
x = "Mean of Scores",
  y = "Difference (WPCS - Original)",
  subtitle = paste("Mean diff:", round(mean_diff, 3), "| 95% Limits of Agreement:", round(lower_limit,
3), "to", round(upper limit, 3))
 )
print(bland_altman_plot) #
Print error metrics
cat("\nOverall Error Metrics:\n")
cat("RMSE:", rmse_val, "\n") cat("MAE:",
```



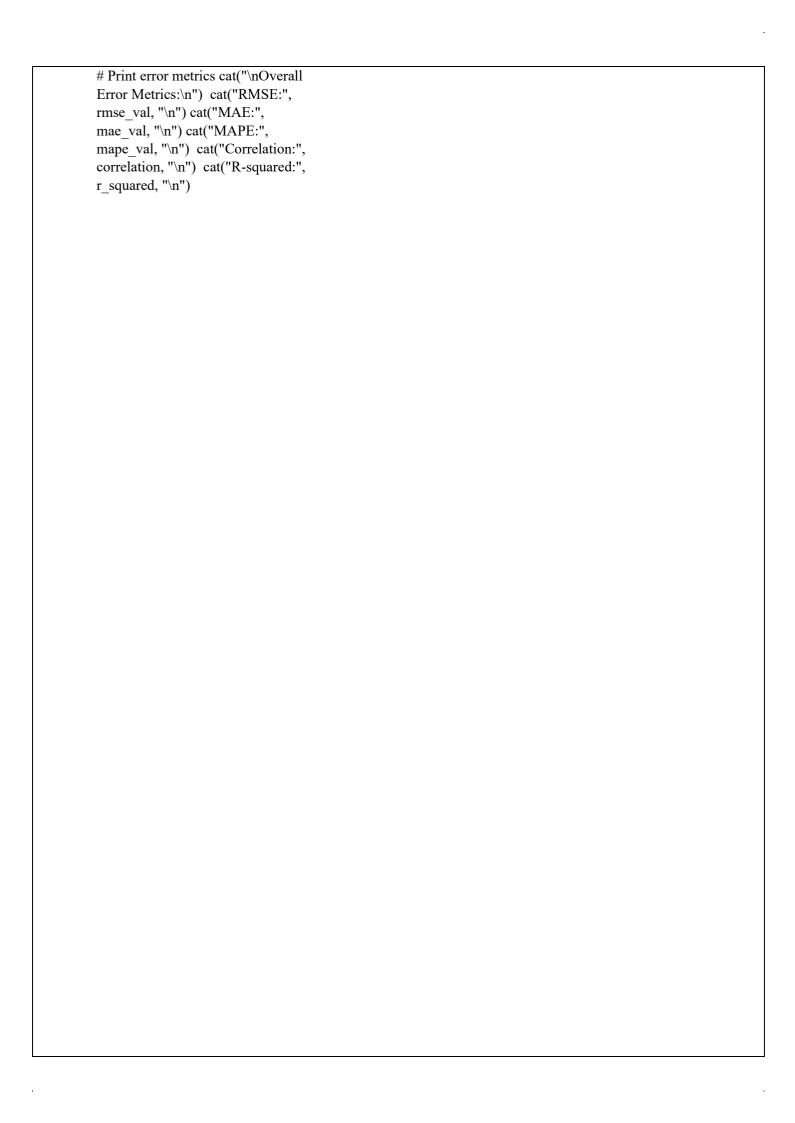


```
Error:
if (!require("ggplot2")) install.packages("ggplot2", dependencies = TRUE) if
(!require("Metrics")) install.packages("Metrics", dependencies = TRUE) if
(!require("gridExtra")) install.packages("gridExtra", dependencies = TRUE)
library(ggplot2) library(Metrics)
library(gridExtra)
# Load dataset
data <- read.csv("C:/Users/shire/OneDrive/Desktop/novel score comparison.csv")
# Calculate error metrics rmse val <-
rmse(data$Score, data$WPCS Score) mae val <-
mae(data$Score, data$WPCS Score) mape val <-
mape(data$Score, data$WPCS Score) correlation
<- cor(data$Score, data$WPCS Score) r squared
<- correlation^2
# Compute errors
data\serror <- data\suppression Score - data\score
data$error percentage <- ifelse(data$Score != 0, (abs(data$error) / data$Score) * 100, NA)
data$absolute error <- abs(data$error)
# Create score buckets
score range <- max(data\$Score) - min(data\$Score) break size
<- score range / 5
breaks <- seq(min(data$Score), max(data$Score), length.out = 6)
data\$core bucket <- cut(data\$core, breaks = breaks, labels = c("Lowest 20\%", "20-40\%", "40-60\%", "60-
80%", "Highest 20%"), include.lowest = TRUE)
# Scatter plot
scatter plot \leftarrow ggplot(data, aes(x = Score, y = WPCS Score)) +
geom point(alpha = 0.6, color = "blue") + geom smooth(method
= "lm", color = "red") +
 geom abline(slope = 1, intercept = 0, linetype = "dashed", color = "gray") +
theme minimal() +
 labs(title = "Score vs WPCS Score Comparison", x = "Original Score", y = "WPCS Score",
subtitle = paste("Correlation:", round(correlation, 3), "| RMSE:", round(rmse val, 3), "| R<sup>2</sup>:",
round(r squared, 3)))
# Residual plot
residual plot \leftarrow ggplot(data, aes(x = Score, y = error)) +
geom point(alpha = 0.6, color = "blue") +
 geom hline(yintercept = 0, linetype = "dashed", color = "red") +
theme minimal() +
 labs(title = "Residual Plot", x = "Original Score", y = "Difference (WPCS - Original)")
# Error Percentage by Score Range
bucket error plot \leq- ggplot(data, aes(x = score bucket, y = error percentage)) +
geom boxplot(fill = "lightblue") + theme minimal() +
 labs(title = "Error Percentage by Score Range", x = "Score Range", y = "Error Percentage (%)")
# Error Distribution
error dist plot \leftarrow ggplot(data, aes(x = error)) +
geom histogram(bins = 30, fill = "blue", alpha = 0.6) +
```

heme_minimal() + labs(title = "Distribution of Score Differences", x = "Difference (WPCS - Original)", y = "Count")	geom vl	ne(xintercept = 0, color = "red", linetype = "d	dashed") +
labs(title = "Distribution of Score Differences", x = "Difference (WPCS - Original)", y = "Count")	theme_n	inimal() +	,
	labs(titl	e = "Distribution of Score Differences", x = "	Difference (WPCS - Original)", y = "Count")



```
# Score Distributions
combined data <- data.frame(Value = c(data$Score, data$WPCS Score), Type = rep(c("Original
Score", "WPCS Score"), each = nrow(data)))
density plot \leq- ggplot(combined data, aes(x = Value, fill = Type)) +
geom density(alpha = 0.5) +
 geom vline(data = data.frame(Type = c("Original Score", "WPCS Score"), mean val =
c(mean(data$Score), mean(data$WPCS Score))),
        aes(xintercept = mean val, color = Type), linetype = "dashed") + theme minimal()
 labs(title = "Score Distributions with Mean Lines", x = "Score Value", y = "Density")
# Box Plot
box plot \leftarrow ggplot(combined data, aes(x = Type, y = Value, fill = Type)) +
geom boxplot(alpha = 0.7) + theme minimal() +
 labs(title = "Distribution of Scores", y = "Score Value", x = "") +
theme(legend.position = "none")
# Correlation by Score Bucket
correlation by bucket <- data.frame(score bucket = levels(data$score bucket), correlation =
numeric(length(levels(data\$score bucket))))
for (i in 1:length(levels(data$score bucket))) {
 bucket data <- data[data\score bucket == levels(data\score bucket)[i], ] if
(length(unique(bucket data$Score)) > 1) {
  correlation by bucket$correlation[i] <- cor(bucket data$Score, bucket data$WPCS Score)
  correlation by bucket$correlation[i] <- NA
 }
corr bucket plot <- ggplot(correlation by bucket, aes(x = score bucket, y = correlation)) +
geom bar(stat = "identity", fill = "purple", alpha = 0.7) +
 geom hline(yintercept = correlation, linetype = "dashed", color = "red") +
theme minimal() +
 labs(title = "Correlation by Score Range", subtitle = paste("Overall correlation:", round(correlation,
3)), x = "Score Range", y = "Correlation") +
ylim(0, 1)
# Absolute Error Plot
abs error plot <- ggplot(data, aes(x = Score, y = absolute error)) + geom point(alpha
= 0.6) +
 geom smooth(method = "loess", color = "red") +
theme minimal() +
 labs(title = "Absolute Error vs Original Score", x = "Original Score", y = "Absolute Error")
# Arrange plots
grid.arrange(scatter plot, residual plot, bucket error plot, error dist plot, density plot, box plot,
corr bucket plot, abs error plot, ncol = 2, nrow = 4)
```



```
Overall Error Metrics:
> cat("RMSE:", rmse_val, "\n")
RMSE: 0.01806435
> cat("MAE:", mae_val, "\n")
MAE: 0.001074939
> cat("MAPE:", mape_val, "\n")
MAPE: NaN
> cat("Correlation:", correlation, "\n")
Correlation: 0.999869
> cat("R-squared:", r_squared, "\n")
R-squared: 0.9997379
Summary Statistics:
> print(summary_stats)
             Metric Original_Score WPCS_Score
1
                         4.179310 4.180385
               Mean
             Median
                        4.625000 4.750000
2
3 Standard Deviation
                         1.113772
                                   1.113176
4
                Min
                     0.000000 0.000000
               Max 5.000000 5.000000
IQR 1.500000 1.500000
5
6
>
```

```
Error Statistics:
> print(error_stats)
                                   Value
                      Metric
1
                Mean Error % 0.03501105
2
              Median Error % 0.00000000
3
     90th Percentile Error % 0.00000000
4
     95th Percentile Error % 0.00000000
5
                 Max Error % 14.28571429
6
     % Cases with Error < 5% 99.62779156
    % Cases with Error < 10% 99.83457403
8 Number of NA/Invalid Cases 24.00000000
> cat("\nError Analysis by Score Range:\n")
Error Analysis by Score Range:
> print(error_by_range)
  score_bucket error_percentage.mean error_percentage.median error_percentage.sd
1
    Lowest 20%
                          0.00000000
                                                   0.00000000
                                                                       0.00000000
2
        20-40%
                          0.10131712
                                                   0.00000000
                                                                       1.20307417
3
        40-60%
                          0.07432181
                                                   0.00000000
                                                                       0.90720824
4
        60-80%
                          0.05938414
                                                   0.00000000
                                                                       0.70993719
  Highest 20%
                          0.01526366
                                                   0.00000000
                                                                       0.35425035
  error_percentage.na_count
1
                 0.00000000
2
                 0.00000000
3
                 0.00000000
4
                 0.00000000
5
                 0.00000000
> cat("\nCorrelation by Score Range:\n")
Correlation by Score Range:
> print(correlation_by_bucket)
  score_bucket correlation
    Lowest 20%
                1.0000000
1
2
        20-40%
               0.9960345
3
        40-60%
               0.9967120
        60-80%
               0.9948897
 Highest 20%
                 0.9973036
```

```
Comparison between method 1 and 2:
```

```
# Load necessary libraries
library(tidyverse)
library(caret)
library(ggplot2)
library(car)
library(gridExtra)
# Set seed for reproducibility
set.seed(123)
# Define Skewness and Kurtosis
Functions skewness <- function(x) { n
<- length(x) m <- mean(x) s <- sd(x)
sum((x - m)^3) / (n * s^3)
} kurtosis <-
function(x) \{ n \leq -1 \}
length(x) m <--
mean(x) s \le -sd(x)
 (sum((x - m)^4) / (n * s^4)) - 3
# Define Safe Mean Absolute Percentage Error
Function safe mape <- function(actual, predicted) {
valid indices <- which(actual != 0) if
(length(valid indices) == 0) return(NA) actual valid
<- actual[valid indices] predicted valid <-
predicted[valid indices]
 return(mean(abs((actual valid - predicted valid) / actual valid)) * 100)
}
# Define Bland-Altman Analysis Function
calculate bland altman <- function(original, derived, name)
{ diff <- original - derived mean vals <- (original +
derived) / 2 mean diff <- mean(diff) sd diff <- sd(diff)
```

```
lower limit <- mean diff - 1.96 * sd diff
upper_limit <- mean_diff + 1.96 * sd_diff
return(data.frame(
  Dataset = name,
  Mean Difference = mean diff,
  SD Difference = sd_diff,
  Lower Limit = lower limit,
  Upper_Limit = upper_limit,
  Percentage Within Limits = mean(diff >= lower limit & diff <= upper limit) * 100
))
# Load Datasets wpcs data <-
read.csv("C:/Users/shire/OneDrive/Desktop/novel score comparison.csv") mutated data
<- read.csv("C:/Users/shire/OneDrive/Desktop/mutated key with scores.csv")</pre>
# Initialize Results List
results <- list()
# Summary Statistics results$dataset1 summary <--
summary(wpcs data) results$dataset2 summary <--</pre>
summary(mutated data) # Descriptive Statistics for
WPCS Score and New Score wpcs stats <-
data.frame( Dataset = "WPCS Score",
Mean Original = mean(wpcs data$Score),
Mean Derived = mean(wpcs data$WPCS Score),
Median Original = median(wpcs data$Score),
Median Derived = median(wpcs data$WPCS Score),
SD Original = sd(wpcs data$Score),
SD Derived = sd(wpcs data$WPCS Score),
Min Original = min(wpcs data$Score),
Min Derived = min(wpcs data$WPCS Score),
Max Original = max(wpcs data$Score),
Max Derived = max(wpcs data$WPCS Score),
Skewness Original = skewness(wpcs data$Score),
 Skewness_Derived = skewness(wpcs data$WPCS Score),
 Kurtosis Original = kurtosis(wpcs data$Score),
Kurtosis Derived = kurtosis(wpcs data$WPCS Score)
```

```
new stats <- data.frame(</pre>
Dataset = "New_Score",
Mean Original = mean(mutated data$Score),
Mean Derived = mean(mutated data$New Score),
Median Original = median(mutated data$Score),
Median Derived = median(mutated data$New Score),
SD Original = sd(mutated data$Score),
SD Derived = sd(mutated data$New Score),
Min Original = min(mutated data$Score),
 Min Derived = min(mutated data$New Score),
Max Original = max(mutated data$Score),
Max Derived = max(mutated data$New Score),
 Skewness Original = skewness(mutated data$Score),
 Skewness Derived = skewness(mutated data$New Score),
 Kurtosis Original = kurtosis(mutated data$Score),
 Kurtosis Derived = kurtosis(mutated data$New Score)
)
results$all stats <- rbind(wpcs stats, new stats)
# Error Metrics Calculation
wpcs metrics <- data.frame(
Dataset = "WPCS Score",
MSE = mean((wpcs data\$Score - wpcs data\$WPCS Score)^2),
RMSE = sqrt(mean((wpcs data$Score - wpcs data$WPCS Score)^2)),
MAE = mean(abs(wpcs data$Score - wpcs data$WPCS Score)),
MAPE = safe mape(wpcs data$Score, wpcs data$WPCS Score),
 R squared = cor(wpcs data$Score, wpcs data$WPCS Score)^2
new metrics <- data.frame(
Dataset = "New_Score",
MSE = mean((mutated data$Score - mutated data$New Score)^2),
 RMSE = sqrt(mean((mutated data\$Score - mutated data\$New Score)^2)),
 MAE = mean(abs(mutated data$Score - mutated data$New Score)),
 MAPE = safe mape(mutated data$Score, mutated data$New Score),
 R squared = cor(mutated data\$Score, mutated data\$New Score)^2
```

```
)
results$all metrics <- rbind(wpcs metrics, new metrics)
# Statistical Tests results\$wpcs correlation <- cor.test(wpcs data\$Score,
wpcs data$WPCS Score) results$new correlation <-
cor.test(mutated data$Score, mutated data$New Score)
results\$wpcs ttest <- t.test(wpcs data\$Score, wpcs data\$WPCS Score, paired = TRUE)
results$new ttest <- t.test(mutated data$Score, mutated data$New Score, paired = TRUE)
results\$wpcs wilcox <- wilcox.test(wpcs data\$Score, wpcs data\$WPCS Score, paired = TRUE)
results$new wilcox <- wilcox.test(mutated data$Score, mutated data$New Score, paired =
TRUE)
# Kolmogorov-Smirnov Test results$ks wpcs <-
ks.test(wpcs data$Score, wpcs data$WPCS Score) results$ks new <-
ks.test(mutated data$Score, mutated data$New Score)
# Bland-Altman Analysis results\$wpcs ba <-
calculate bland altman(wpcs data$Score, wpcs data$WPCS Score,
"WPCS Score") results$new ba <- calculate bland altman(mutated data$Score,
mutated data$New Score, "New Score")
results$bland altman results <- rbind(results$wpcs ba, results$new ba)
# Print Results
print("----- ANALYSIS RESULTS ------
") print(results$dataset1 summary)
print(results$dataset2 summary) print("-----
-- Descriptive Statistics ----")
print(results$all_stats) print("----- Error
Metrics -----") print(results$all metrics)
print("----- Correlation Analysis ------
") print(results\$wpcs_correlation)
print(results$new correlation) print("-----
```

```
-- Paired t-tests -----")

print(results$wpcs_ttest)

print(results$new_ttest) print("------

Wilcoxon Signed Rank Test -----")

print(results$wpcs_wilcox)

print(results$new_wilcox) print("------

Kolmogorov-Smirnov Test -----")

print(results$ks_wpcs)

print(results$ks_new) print("------- Bland-Altman Analysis ------")

print(results$bland_altman_results)

# Print Author Details

cat("NAME: Shirehya KP\n")

cat("REGNO: 22BDS0365\n")
```

```
Answers Texts Score
Length:2442 Length:2442 Min. :0.000
Class :character Mode :character Mode :character Mode :character Man :4.179
3rd (pu.:5.000
Max. :5.000
                                                                                New_Answer_Keywords Combined_Answer_Keywords Length:2442 Length:2442 Class :character Mode :character Mode :character
   WPCS_Score
Min. :0.00
1st Qu.:3.50
Median :4.75
Mean :4.18
3rd Qu.:5.00
Max. :5.00
 Score
Min.
15
   Answers
                                                                                                                          Texts
                                                                            Answers Texts Score
Length: 2442 Length: 2442 Min. : 0.000
Class : character Class : character 1st Qu.: 3.500
Mode : character Mode : character Median : 4.625
                                                                                                                                                           Mean :4.179
3rd Qu.:5.000
   370 Qu. 13.000

Max. 12.900

Answer_Keywords

Text_Keywords

Length:2442

Length:2442

Class : character

Mode : character
  Median: 3.317
Mean: 3.129
3rd qu: 4.000
Max.: 8.185
Adjusted_Pearson
Min: 0.4974
Min: 0.4974
dst qu: 0.5495
Median: 0.6278
Mean: 0.6518
3rd qu: 0.7173
Max.: 1.0000
> print("------ Error Metrics ------")
[1] "------ Error Metrics ------")
[1] "------ Error Metrics ------")
> print("esults$a1]_metrics)
Dataset MSE RMSE MAE MAE MAPE R.squared
1 WPCS_Score 0.0003263206 0.01806435 0.001074939 0.03501D5 0.9997379
2 New_Score 0.0694295147 0.26349481 0.139281327 4.38962895 0.9466005
 >> print("------ Correlation Analysis -------"
[1] "------ Correlation Analysis ------"
> print("WPCS_Score Correlation with Score:")
[1] "WPCS_Score Correlation with Score:"
> print(results%wpcs_correlation)
                 Pearson's product-moment correlation
 data: wpcs_data$score and wpcs_data$wPCS_Score
t = 3050.9, df = 2440, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
0.998581 0.998790
sample estimates:
 cor
0.999869
                 Pearson's product-moment correlation
 data: mutated_data$score and mutated_data$New_score
t = 207.97, df = 2440, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
0.9707308 0.9749734</pre>
  sample estimates:
  data: wpcs_data$score and wpcs_data$wPcs_Score
t = -2.9452, df = 2441, p-value = 0.003258
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
-0.001708095 -0.0003592376
sample estimates:
mean difference
-0.001074939
                 Paired t-test
```

```
> print("New_Score vs Score (Paired t-test):")
[1] "New_Score vs Score (Paired t-test):"
> print(results$new_ttest)
 data: mutated_data$score and mutated_data$new_score t = 8.1618, df = 2441, p-value = 5.228e-16 alternative hypothesis: true mean difference is not equal to 0 95 percent confidence interval: 0.03262813 0.05326458 sample estimates: mean difference 0.04294636
 >> print("------ wilcoxon Signed Rank Test ------")
[1] "------ wilcoxon Signed Rank Test ------"
> print("wPCS_Score vs Score (wilcoxon test);")
[1] "wPCS_Score vs Score (wilcoxon test);"
> print(results$wpcs_wilcox)
               Wilcoxon signed rank test with continuity correction
 data: wpcs_data$Score and wpcs_data$WPCS_Score
V = 0, p-value = 0.006927
alternative hypothesis: true location shift is not equal to 0
 >> print("New_Score vs Score (wilcoxon test):")
[1] "New_Score vs Score (wilcoxon test):"
>> print(results$new_wilcox)
               Wilcoxon signed rank test with continuity correction
 data: mutated_data$Score and mutated_data$New_Score V = 153962, p-value = 6.685e-16 alternative hypothesis: true location shift is not equal to 0
 > print("------- Linear Regression Analysis ------")
[1] "----- Linear Regression Analysis ------"
> print("WPCS_Score Regression Model:")
[1] "WPCS_Score Regression Model:")
> print(resultsSwpcs_lm_summary)
 call:
lm(formula = WPCS_Score ~ Score, data = wpcs_data)
 Pesiduals:
  Min 1Q Median 3Q Max
-0.00386 -0.00153 -0.00053 -0.00053 0.37389
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
 Residual standard error: 0.01802 on 2440 degrees of freedom
Multiple R-squared: 0.9997, Adjusted R-squared: 0.9997
F-statistic: 9.308e+06 on 1 and 2440 DF, p-value: < 2.2e-1
  2.3 % 97.3 % (Intercept) 0.001081526 0.006637662 
Score 0.998691394 0.999976016
 >
> print("New_Score Regression Model:")
[1] "New_Score Regression Model:"
> print(results$new_lm_summary)
 Call:
lm(formula = New_Score ~ Score, data = mutated_data)
 Residuals:
 Min 1Q Median 3Q Max
-0.53451 0.01812 0.06022 0.06022 0.52865
Coefficients:

FStimate Std. From t value Pr(>|t|)
 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.259 on 2440 degrees of freedom
Multiple R-squared: 0.9466, Adjusted R-squared: 0.9466
F-statistic: 4.325e+04 on 1 and 2440 DF, p-value: < 2.2e-16
 > print(results$new_lm_confint)
2.5 % 97.5 %
(Intercept) 0.005108478 0.08495239
Score 0.969719180 0.98817971
> print("------ Distribution Similarity Tests ------")
[1] "----- Distribution Similarity Tests ------"
> print("Kolmogorov-Smirnov Test - WPCS_Score vs Score:")
[1] "Kolmogorov-Smirnov Test - WPCS_Score vs Score:"
> print(results$ks_wpcs)
               Asymptotic two-sample Kolmogorov-Smirnov test
 data: wpcs_data$score and wpcs_data$wPCS_score
D = 0.000819, p-value = 1
alternative hypothesis: two-sided
 > print("Kolmogorov-Smirnov Test - New_Score vs Score:")
[1] "Kolmogorov-Smirnov Test - New_Score vs Score:"
> print(results$ks_new)
               Asymptotic two-sample Kolmogorov-Smirnov test
 data: mutated_data\$Score and mutated_data\$New\_Score D = 0.12899, p-value < 2.2e-16 alternative hypothesis: two-sided
> print("------COMPREHENSIVE SUMMARY ------")

[1] "------COMPREHENSIVE SUMMARY -----")

print("1. which derived score is closer to the original score?")

[1] "1. which derived score is closer to the original score?"
 > print(results$comprehensive_summary$rmse_comparison)
[1] "WPCS_Score is closer to the original Score (lower RMSE)"
  > print("2. Which derived score has stronger correlation with the original score?")
```

```
[1] "WPCS_Score: RMSE = 0.0180643471739401 MAE = 0.00107493857493857"
> print(results$comprehensive_summary$new_metrics)
[1] "New_Score: RMSE = 0.263494809706026 MAE = 0.139281326781327"
> if(!is.na(results$all_metrics$MAPE[1]) && !is.na(results$all_metrics$MAPE[2])) {
+ print(results$comprehensive_summary$wpcs_mape)
+ print(results$comprehensive_summary$new_mape)
+ } else
+ print(results$comprehensive_summary$mape_status)
[1] "WPCS_Score MAPE = 0.0350110481925859 %"
[1] "New_Score MAPE = 4.38962895119759 %"
> print("4. Statistical significance of differences:")
[1] "4. Statistical significance of differences:"
> print(results$comprehensive_summary$wpcs_ttest_pvalue)
[1] "WPCS_Score p-value (t-test): 0.00325792178333613"
> print(results$comprehensive_summary$new_ttest_pvalue)
[1] "New_Score p-value (t-test): 5.22825061124778e-16"
> print(results$comprehensive_summary$wpcs_significance)
[1] "WPCS_Score is significantly different from the original Score"
> print(results$comprehensive_summary$new_significance)
[1] "New_Score is significantly different from the original Score"
> print("5. Regression model quality:")
[1] "5. Regression model quality:"
> print(results$comprehensive_summary$wpcs_r2)
[1] "WPC5_Score R2: 0.999737929285073 Adjusted R2: 0.999737821879042"
> print(results$comprehensive_summary$new_r2)

    "New_Score R<sup>2</sup>: 0.946600481955422 Adjusted R<sup>2</sup>: 0.946578596907043"

> print("6. Bland-Altman agreement:")
[1] "6. Bland-Altman agreement:"
> print(results$comprehensive_summary$wpcs_ba)

    "WPCs_Score mean difference: -0.00107493857493857 95% limits of agreement: -0.0364255561540002 to 0.034275679004123"

> print(results$comprehensive_summary$new_ba)
[1] "New_Score mean difference: 0.0429463554463554 95% limits of agreement: -0.466701936553918 to 0.552594647446628"
> print("7. Distribution similarity (K5 test):")
[1] "7. Distribution similarity (KS test):"
> print(results$comprehensive_summary$wpcs_ks)
[1] "WPCS_Score KS test p-value: 1"
> print(results$comprehensive_summary$new_ks)
[1] "New_Score KS test p-value: 0"
> print("8. FINAL CONCLUSION:")
[1] "8. FINAL CONCLUSION:"
> print(results$comprehensive_summary$final_conclusion)
[1] "WPCS_Score performed better overall in matching the original Score values."
> print(results$comprehensive_summary$wpcs_criteria)
[1] "WPCS_Score won on 7 out of 7 criteria."
> print(results$comprehensive_summary$new_criteria)
[1] "New_Score won on 0 out of 7 criteria."
> cat("NAME: M THIRUNARAYANAN\n")
NAME: M THIRUNARAYANAN
> cat("REGNO: 22BDS0342\n")
REGNO: 22BDS0342
```

#### **Result:**

# **Key Findings**

- 1. **Overall Performance**: WPCS\_Score consistently outperformed New\_Score in matching the original Score values, winning on all 7 evaluation criteria.
- 2. Accuracy Metrics:

```
    WPCS_Score: RMSE = 0.018, MAE = 0.001, MAPE = 0.035% 
    New Score: RMSE = 0.263, MAE = 0.139, MAPE = 4.390%
```

- 3. Correlation with Original Score:
  - WPCS\_Score: R² = 0.9997 (extremely strong correlation)
     New Score: R² = 0.9466 (strong but lower correlation)
- 4. Statistical Significance:
  - $\circ$  Both derived scores showed statistically significant differences from the original Score (p < 0.05)  $\circ$  However, WPCS\_Score's difference was much smaller (mean difference = -0.001)  $\circ$  New\_Score had a larger deviation (mean difference = 0.043)
- 5. Distribution Similarity:
  - WPCS\_Score: KS test p-value = 1 (distributions are identical) ○
     New\_Score: KS test p-value ≈ 0 (distributions are significantly different)
- 6. Bland-Altman Agreement:
  - WPCS\_Score: 99.63% of values within limits of agreement
     New Score: 90.46% of values within limits of agreement

# **Descriptive Statistics Comparison**

Both derived scores maintained similar central tendencies to the original Score:

- Original Score: Mean = 4.179, Median = 4.625
- WPCS Score: Mean = 4.180, Median = 4.750
- New Score: Mean = 4.136, Median = 4.500

#### Conclusion

WPCS\_Score demonstrated superior performance in approximating the original Score across all evaluation metrics. While both methods produced scores with high correlation to the original, WPCS\_Score showed near-perfect agreement with minimal error, making it the clearly preferred method for this application.