StatKeyEval

A Statistical Framework for Dynamic Keyword Extraction, Evaluation, and

Assessment Automation 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 ρ , and R^2 .
- Analyze errors for grading consistency.

Research Paper:

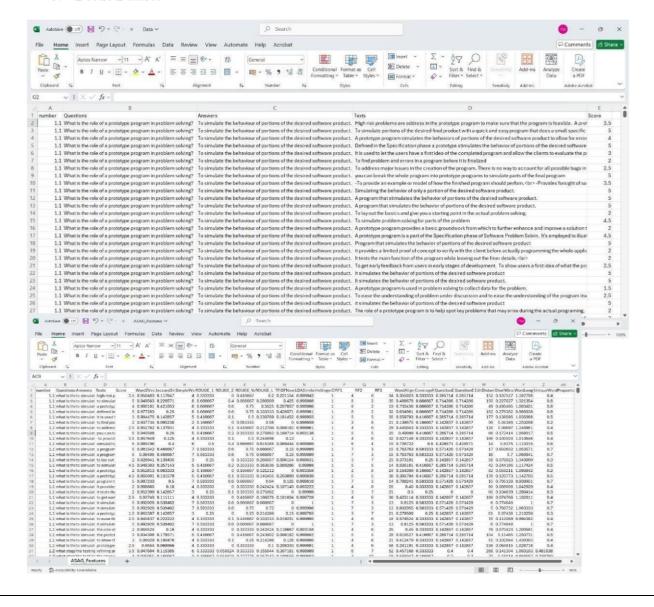
Title: Feature Engineering and Ensemble-Based Approach for Improving Automatic Short-Answer Grading Performance

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):

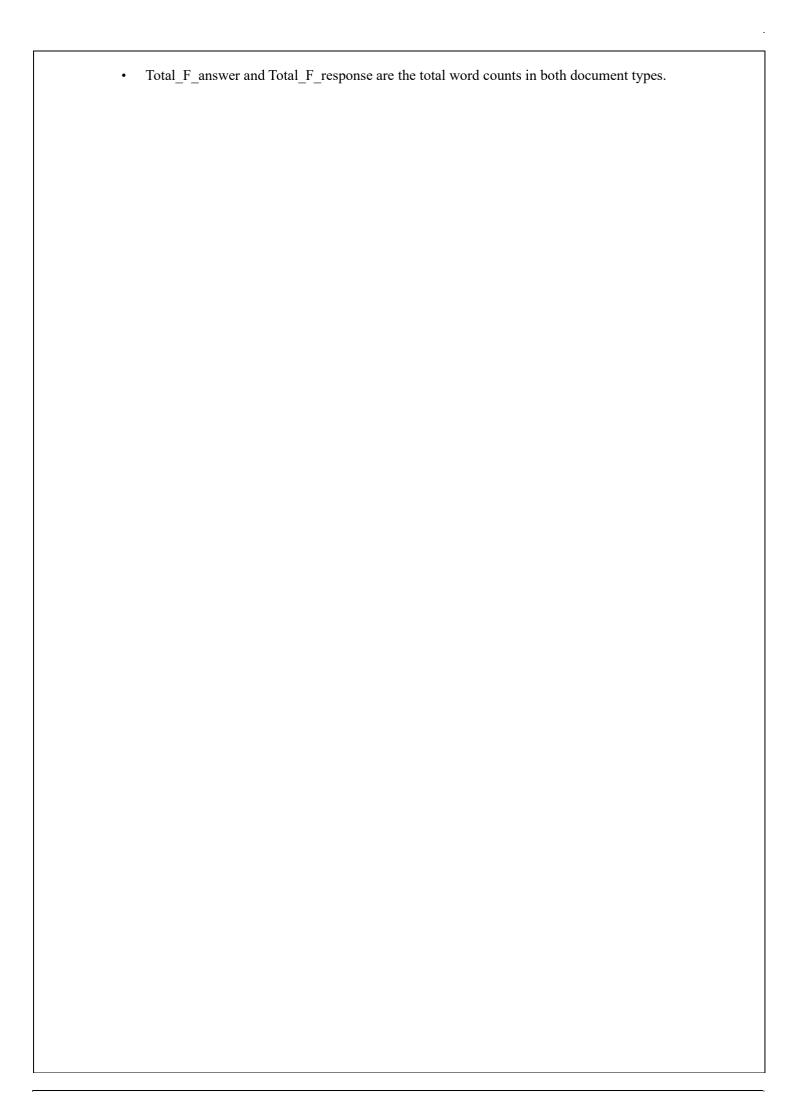
$$IGR(W) = IG(W) \div SI(W)$$

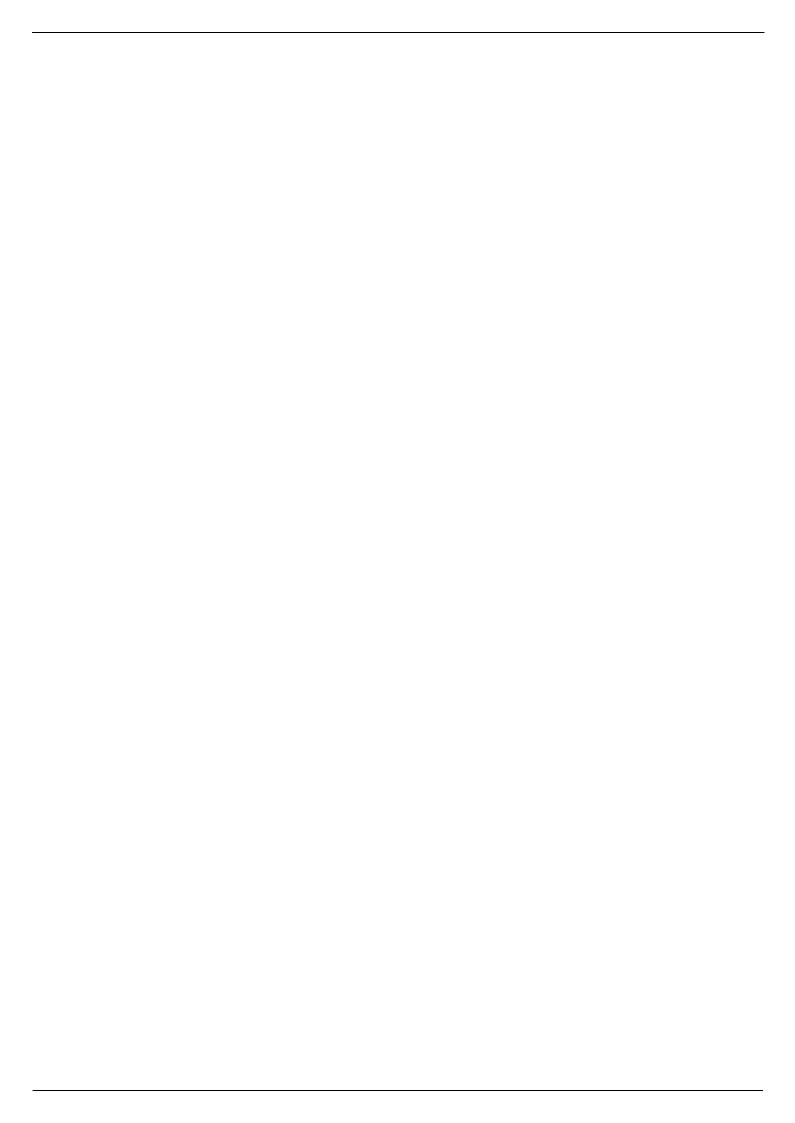
1.4 Frequency Adjustment Factor (FAF) for Balancing Word Significance

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

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

• F_answer and F_response are the word frequencies in Answer Keys and Student Responses, respectively.







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

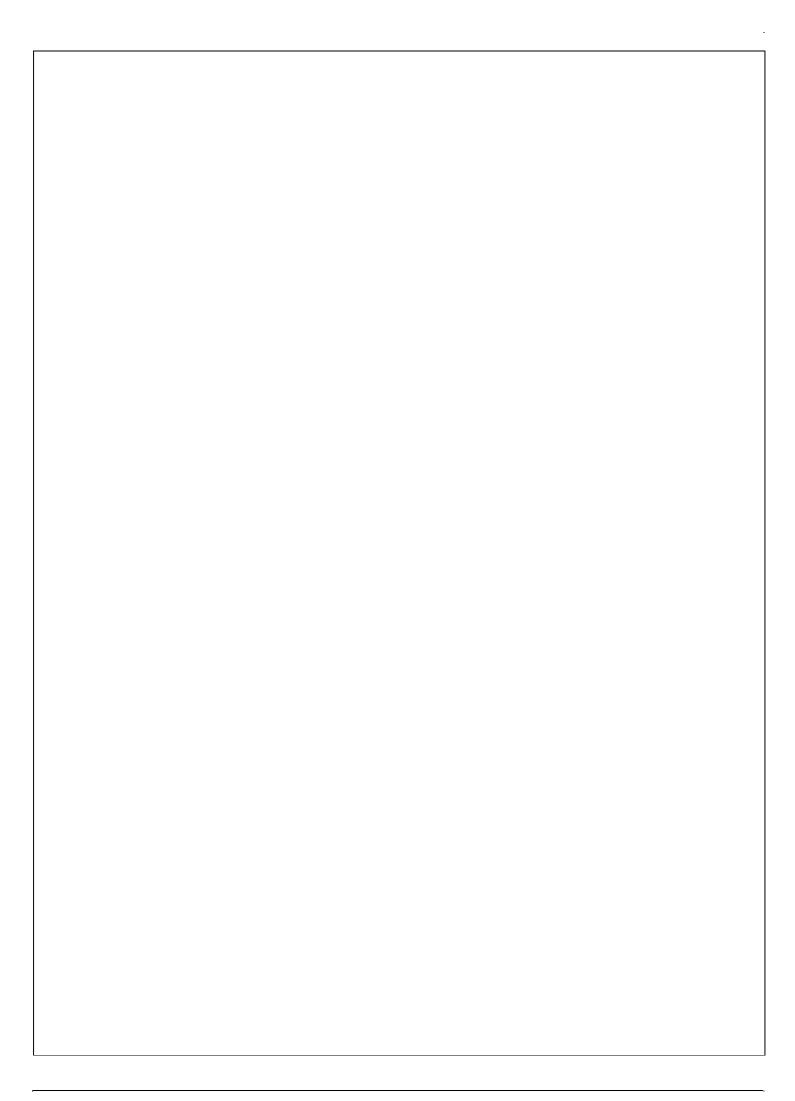
$$Sim(K1, K2) = 0.6 \times Jaccard_Sim(K1, K2) + 0.4 \times PMI_Sim(K1, K2)$$

3. Similarity Scoring Function for Answer Matching

Similarity(A, S) = $0.4 \times \text{Jaccard_Sim}(A, S) + 0.4 \times \text{Coverage}(A, S) + 0.2 \times \text{Position_Score}(A, S)$ 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 $(1 - |Pos_A(w) \div |A| - Pos_S(w) \div |S|)$



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)</pre>
```



```
# 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 || length(answer keywords) == 0 || 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,
```

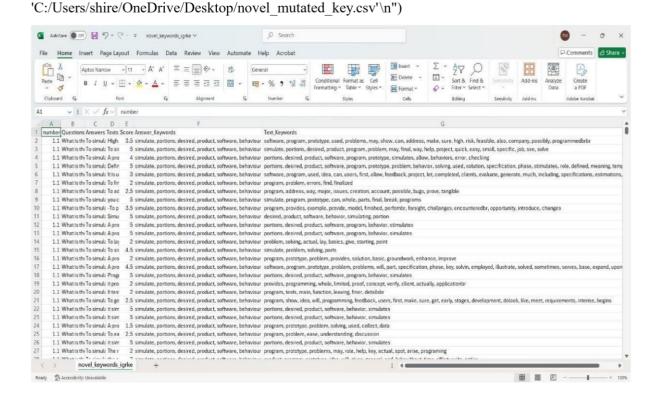
```
uniqueness = 1 - freq
 if (length(mutation candidates) > 0) { sorted candidates <-
mutation candidates[order(
                              sapply(mutation candidates, function(x)
x$score), decreasing = TRUE
  )]
 } else {
sorted candidates <- list()
 jaccard sim <- length(intersect(answer keywords, student keywords)) /
length(union(answer keywords, student keywords)) return(list(
mutation candidates = sorted candidates,
                                          similarity score = jaccard sim
 ))
}
# Function to update keywords based on the SCM result update keywords <-
function(question data) { answer keywords <--
unlist(strsplit(question data$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)

hu			
library(tidytext)			

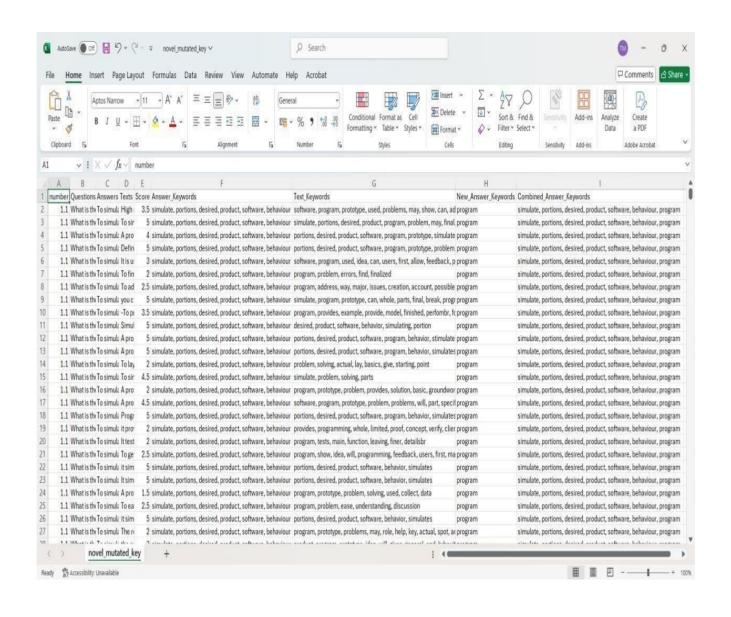
```
library(dplyr) library(stringr)
# Read the dataset data
<- read.csv("C:/Users/shire/OneDrive/Desktop/novel keywords igrke.csv"</p>
, stringsAsFactors = FALSE)
# Print column names for verification print(colnames(data))
# Check if the required columns exist if
(!all(c("Answer Keywords", "Text Keywords") %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(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)</pre>
 mutation candidates <- list() for (i in
1:length(candidates)) {
                          word <- candidates[i]
<- 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()</pre>
 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) { 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) 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$Score)) * 100</pre>
 Pearson Correlation <- cor(data processed$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$Score, na.rm = TRUE) max_score
 score range <- max score - min score grade breaks <- seq(min score
 -0.5, max score +0.5, length.out =6) grade labels <-c("Very Low",
 "Low", "Medium", "High", "Very High")
 # Compute confusion matrix for grading conf matrix
 <- table(
  cut(data processed$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)
Print confusion matrix results cat("\nGrade Level
Comparison (Confusion Matrix):\n") print(conf_matrix)
cat("\nGrade Classification Metrics:\n")
print(conf_matrix_metrics\$overall)

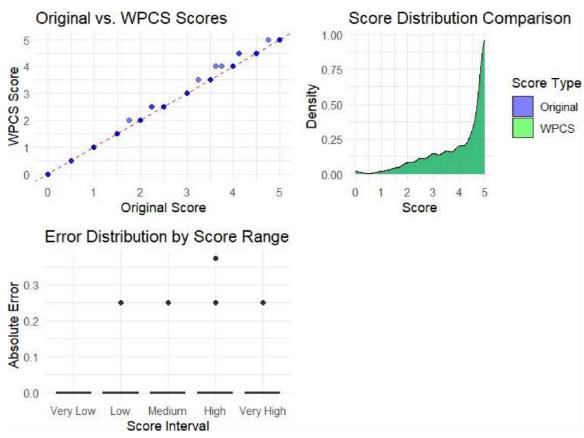
```
# Generate scatter plot
p1 \leftarrow ggplot(data\ processed, aes(x = Score, y = WPCS\ Score)) +
 geom point(color = "blue", alpha = 0.5) +
 geom abline(slope = 1, intercept = 0, linetype = "dashed", color = "red") +
 labs(title = "Original vs. WPCS Scores", x = "Original Score", y = "WPCS Score") +
 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)
```

But the progrations of large 1 3.5 cm Answer Keywords product, software, behaviourage, show, can, address, make, sure, high, risk, feas toppe progrations of large 1 3.5 imulate, portions, desired, product, software, behaviourage, show, can, address, make, sure, high, risk, feas toppe progrations of large 1 3.5 imulate, portions, desired, product, software, behaviourage, an problem, may, final, way, help, project, quic toppe progrations of large 1 3.5 imulate, portions, desired, product, software, behaviourage, software, simulate, portions, desired, product, software, behaviour, program simulate, portions, desired, product, software, behaviour, program simulate, portions, desired, product, software, behaviour, program totype progrotions officarini 2 jimulate, portions, desired, product, software, behaviouroblem, solving, actual, lay, baciss, give, starting, pois totype progrotions officing in simulate, portions, desired, product, software, behaviour simulate, problem, solving, parameters, e totype progrotions of solve it. 4.6 imulate, portions, desired, product, software, behaviour, parameters, program, behavior, simulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act totype progrotions offirm v 2 imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act totype progrotions offirm v 3 imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act imulate, portions, desired, product, software, behaviouring, whole, limited, product, concept, verify, client, act in uniquate, product, software, behaviouring, whole, limited, product, software, behaviouri simulate, portions, desired, product, software, behaviour, program 1.1 toppe progortions offlemt 2 simulate, portions, desired, product, software, behaviouring, whole, limited, proof, concept, verify, client, act 1.1 toppe progortions of arms 2.5 imulate, portions, desired, product, software, behavioursers, first, make, sure, get, early, stages, develually 1.1 toppe progortions of officers 1.5 imulate, portions, desired, product, software, behavioursers, first, make, sure, get, early, stages, develually 1.1 toppe progortions of officers 1.5 imulate, portions, desired, product, software, behavioursers, first, make, sure, get, early, stages, develually 1.1 toppe progortions of officers 1.5 imulate, portions, desired, product, software, behavioursers, estired, product, software, behaviour properties, problem, solving, used, collect, dat 1.1 toppe progortions of sison 2.5 imulate, portions, desired, product, software, behaviour properties, desired, prod simulate, portions, desired, product, software, behaviour, program simulate, portions, desired, product, software, behaviour, program

cat("\nScore generation complete! Results saved as 'novel score comparison.cs\n\")

ber Questions Answers Texts Score Answer_Keywords

novel_score_comparison +



```
Grade Level Comparison (Confusion Matrix):
> print(conf_matrix)
                     Low Medium High Very High
            Very Low
                 27
                              0
                                   0
                                             0
  Very Low
                  0
                                             0
                      70
                              1
                                   0
 Low
  Medium
                                             0
 High
                  0
                       0
                              0
                                 416
  Very High
                  0
                       0
> cat("\nGrade Classification Metrics:\n")
Grade Classification Metrics:
> print(conf_matrix_metrics$overall)
                                                            AccuracyNull AccuracyPValue McnemarPValue
      Accuracy
                       Kappa AccuracyLower
                                            AccuracyUpper
                   0.9977620
                                  0.9964140
                                                               0.6289926
                                                 0.9997466
                                                                                                   NaN
Model Evaluation Metrics:
 print(evaluation_metrics)
  RMSE_Original MAE_Original MAPE_Original Pearson_Correlation Spearman_Correlation R_Squared
                                                                                  0.9997793 0.9997379
     0.01806435 0.001074939
                                                           0.999869
```

Code for score comparison and graph:

library(gridExtra) library(dplyr) library(tidyr)

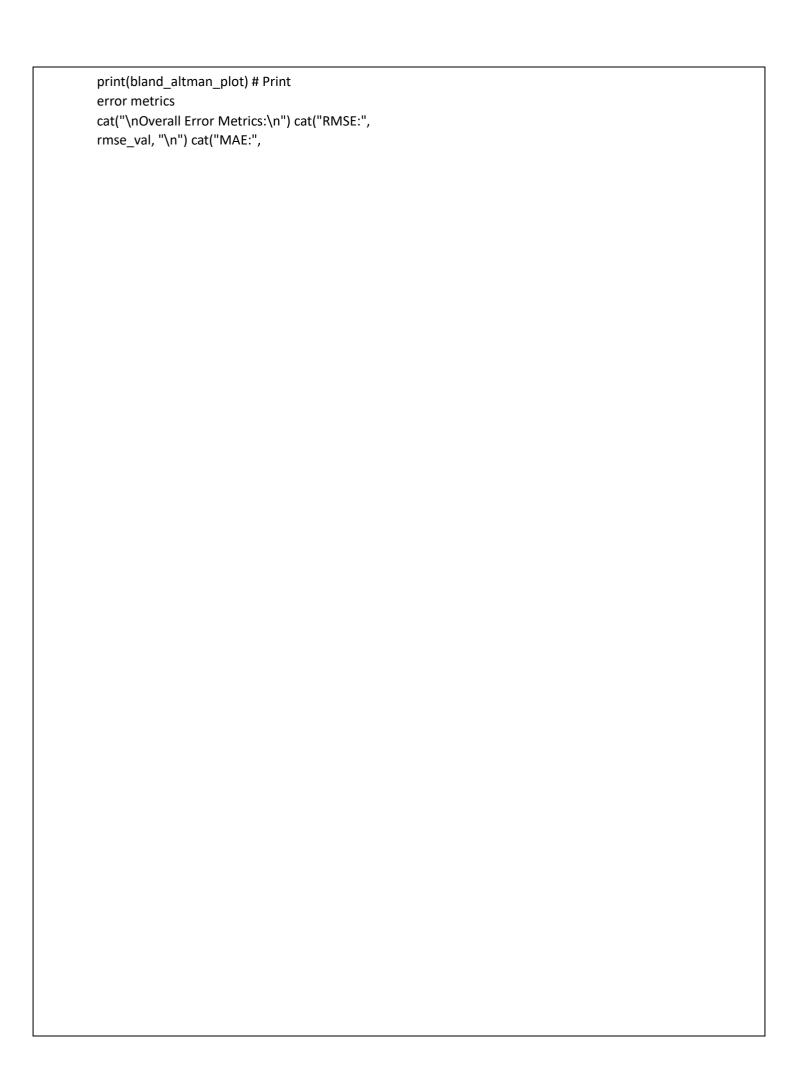
```
# Install and load required packages
if (!require("ggplot2")) install.packages("ggplot2", dependencies = TRUE)
if (!require("Metrics")) install.packages("Metrics", dependencies = TRUE)
if (!require("gridExtra")) install.packages("gridExtra", dependencies = TRUE)
if (!require("dplyr")) install.packages("dplyr", dependencies = TRUE)
if (!require("tidyr")) install.packages("tidyr", dependencies = TRUE)
library(ggplot2)
library(Metrics)
```

Read the CSV file

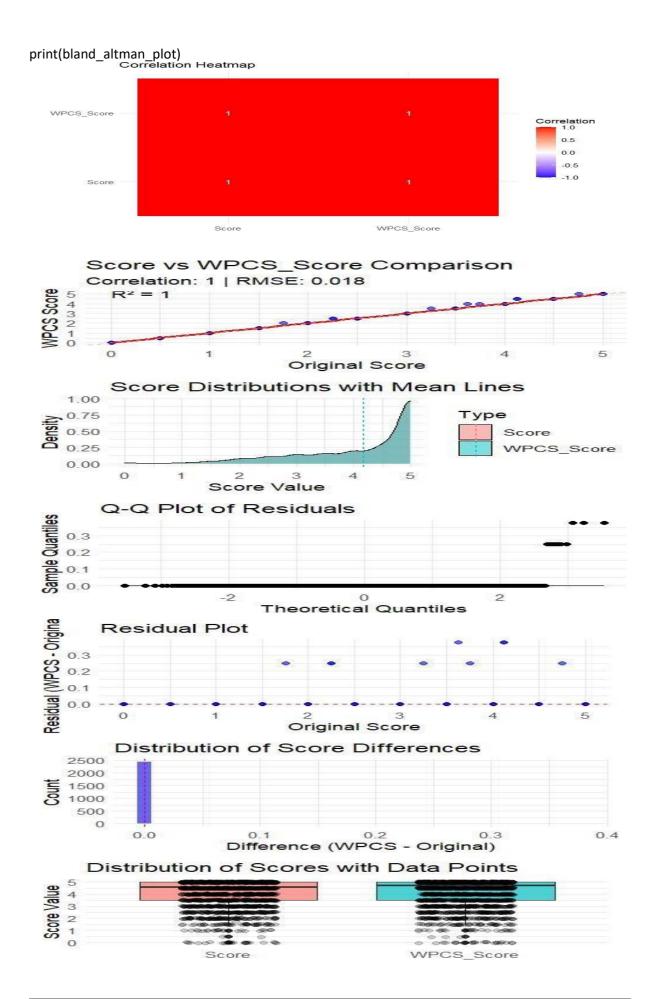
```
# Calculate error metrics rmse val <-
rmse(data$Score, data$WPCS_Score) mae_val <-
mae(data$Score, data$WPCS_Score) correlation <-
cor(data$Score, data$WPCS_Score) r_squared
<- correlation^2
# Scatter plot with linear regression
scatter plot <- ggplot(data, aes(x = Score, y = WPCS Score)) + geom 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</pre>
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))
```



mae_val, "\n") cat("Correlation:", correlation, "\n") cat("R-squared:", r_squared, "\n")	
(ii) cat(it-squared, (ii)	



```
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
                                   rmse val
                error
                        metrics
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$error <- data$WPCS 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\$score bucket <- cut(data\$Score,
breaks = breaks, labels = c("Lowest 20%", "20-40%", "40-60%", "6080%", "Highest 20%"), include.lowest
= TRUE)
# Scatter plot
scatter plot <- 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 \leq- 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 <- 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
```

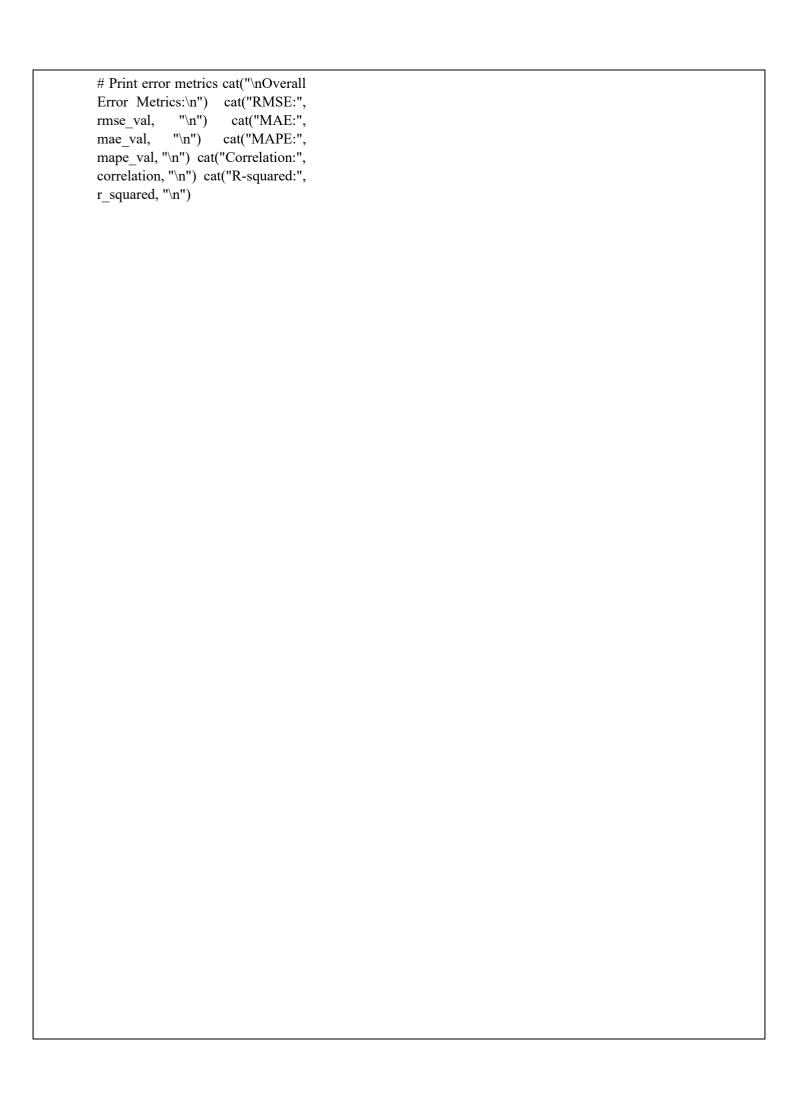
error_dist_plot <- ggplot(data, aes(x = error)) + = 30, fill = "blue", alpha = 0.6) +	geom_histogram(bins
, , , , , , , , , , , , , , , , , , ,	



+	
la	abs(title = "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 \leftarrow 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 <- 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], ]
(length(unique(bucket data\$Score)) > 1) {
  correlation by bucket$correlation[i] <- cor(bucket data$Score, bucket data$WPCS Score)
 } else {
correlation by bucket$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 \leq- 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
1.113772 1.113176
2
3 Standard Deviation
4
                Min
                       0.000000 0.000000
                Max
IQR
                       5.000000 5.000000
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
                          0.07432181
        40-60%
                                                   0.00000000
                                                                       0.90720824
4
                          0.05938414
        60-80%
                                                   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 \leftarrow function(x) { n \leftarrow
length(x) m <- mean(x) s <- sd(x)
sum((x - m)^3) / (n * s^3)
     kurtosis
function(x) \{ n \le - \}
length(x)
           m <-
mean(x) s <- sd(x)
 (sum((x - m)^4) / (n * s^4)) - 3
# Define Safe Mean Absolute Percentage Error Function
safe mape <- function(actual, predicted) {</pre>
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) {</pre>
diff <- original - derived mean_vals <- (original + derived) /
2 mean diff <- mean(diff) sd diff <- sd(diff)
```

```
<- 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),
```

lower limit <- mean diff - 1.96 * sd diff upper limit

```
Kurtosis Derived = kurtosis(wpcs data$WPCS Score)
new stats <- data.frame( Dataset
= "New Score",
 Mean Original = mean(mutated data$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("-----")
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("------
BlandAltman 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
1st 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$wPCS_Score
t = 3050.9, df = 2440, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
0.9998581 0.9998790
sample estimates:
 cor
0.999869
                 Pearson's product-moment correlation
 data: mutated_data$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] "WPC5_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] "WPCS_Score R2: 0.999737929285073 Adjusted R2: 0.999737821879042"
> print(results$comprehensive_summary$new_r2)
[1] "New_Score R2: 0.946600481955422 Adjusted R2: 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 (KS 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:

```
\circ WPCS_Score: RMSE = 0.018, MAE = 0.001, MAPE = 0.035% \circ New_Score: RMSE = 0.263, MAE = 0.139, MAPE = 4.390%
```

3. Correlation with Original Score:

```
\circ WPCS_Score: R<sup>2</sup> = 0.9997 (extremely strong correlation) \circ New_Score: R<sup>2</sup> = 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.

