StatKeyEval

A Statistical Framework for Dynamic Keyword Extraction, Evaluation, and Assessment Automation

The study employs a diverse range of text similarity features, grouped into categories to capture various aspects of similarity. While a total of 36 features are used, only a subset is explicitly discussed. Here's an exploration of these categories and the features they contain:

Semantic Similarity Features

Semantic features assess how closely the meanings of words or phrases align. Examples include:

- **PATH**: A measure based on the shortest path between two concepts in a semantic network.
- LCH: Leacock-Chodorow similarity, which scales path length logarithmically.
- WUP: Wu-Palmer similarity, which considers shared depth and individual depths of concepts.
- **RES**: Resnik similarity, derived from shared information content.
- JCN: Jiang-Conrath similarity, balancing shared and individual information.
- Lesk: A dictionary-based similarity using word definitions.
- **HSO**: Hirst-St-Onge measure of semantic relatedness.
- LSA: Latent Semantic Analysis, a technique based on matrix factorization of termdocument relationships.
- **CBOW/Skip-gram**: Neural word embeddings capturing word relationships.

Lexical Overlap Features

These features evaluate textual similarity based on word overlap:

- **Jaccard Similarity**: Measures the ratio of shared words to the total unique words in two texts.
- Word Overlap: Counts exact word matches.
- **IDF Overlap**: Weights overlaps using inverse document frequency.
- Phrasal Overlap: Captures matches at the phrase level.
- **ROUGE Metrics**: Includes ROUGE-1, ROUGE-2, ROUGE-L, and ROUGE-W for sequence-based comparisons.

Novel Features

Innovative and domain-specific features are introduced in this category:

- **TF-IDF Novelty**: Quantifies how novel a term is in a given text compared to the dataset.
- **Topical Features**: Techniques like **LDA** and **BTM** extract topic distributions for comparison.

- Relevance Feedback Features:
 - o **RF-I**: Feedback influenced by the top-ranked scorer. o **RFII**: Feedback based on the least-ranked scorer.
 - o **RF-III**: Feedback considering all scorers collectively.
- **IDF-Based Overlap**: A refined overlap measure using term frequency statistics.

Alignment-Based Features

These features align text elements to gauge similarity more granularly:

- Word-to-Word Alignment: Aligns individual words for direct comparison.
- Coverage: Quantifies the proportion of aligned content.
- Question-Demoted Alignment: Alignments adjusted to ignore question-related terms.

While the study highlights 22 distinct features, the remaining ones are likely derivatives or combinations tailored to specific tasks.

Regression Techniques Used in the Study

To analyze and predict outcomes, the study employs several regression techniques, each tailored to handle different types of data and relationships. Here's an overview of the models and their unique capabilities:

1. Support Vector Regression (SVR)

- Overview: A robust model that uses kernels to capture complex relationships in data.
- **Key Hyperparameters**: o Kernel type (e.g., RBF, linear). o c for regularization.
 - o Gamma for kernel width.

2. Kernel Ridge Regression (KRR)

- Overview: Combines ridge regression with kernel methods for non-linear regression.
- Key Hyperparameters:
 - o Alpha for regularization. o Kernel type (e.g., polynomial, RBF). o Gamma for kernel scaling.

3. Linear Regression (LR)

• Overview: A straightforward approach assuming linear relationships between input features and output.

4. LASSO Regression

- Overview: Incorporates L1 regularization to encourage sparsity in feature selection.
- Key Hyperparameter: o Alpha for controlling regularization strength.

5. Elastic Net Regression

- Overview: Blends L1 (LASSO) and L2 (ridge) penalties for improved flexibility.
- Key Hyperparameters:
 - o Alpha for regularization.
 - o L1 Ratio to balance L1 and L2 contributions.

6. Decision Tree Regression (TREE)

- Overview: Uses tree structures to split data hierarchically based on feature thresholds.
- Key Hyperparameters:
 - o Max_Depth for controlling tree depth. o Min_Samples_Split for minimum data points required to split nodes. o Min_Samples_Leaf for minimum data per leaf node.

7. Bagging Regressor

- Overview: An ensemble approach combining multiple decision trees trained on bootstrap samples.
- Key Hyperparameters:
 - o N Estimators for the number of trees.
 - Max_Features for features considered per split. o Max_Depth for individual tree depth.

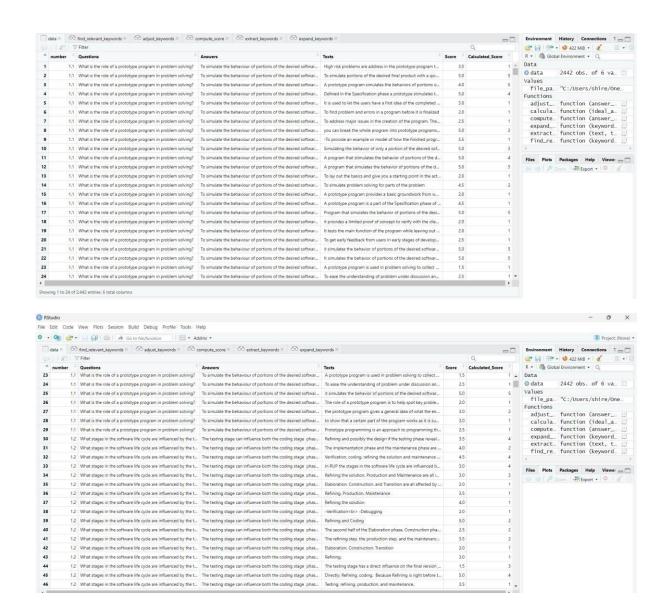
8. Gradient Boosting Regression

- Overview: Builds trees sequentially to correct errors of previous iterations.
- Key Hyperparameters:
 - Learning_Rate for step size. o N_Estimators for number of trees. o
 Max_Depth for tree complexity.

Code for getting correct updated score:

```
library(dplyr) library(tm) library(stringr)
file_path <- "C:/Users/shire/OneDrive/Desktop/Data.csv" data
<- read.csv(file_path, stringsAsFactors = FALSE)
extract_keywords <- function(text, top_n = 5) { corpus <-</pre>
Corpus(VectorSource(text)) corpus <- tm_map(corpus,</pre>
content_transformer(tolower)) corpus <- tm_map(corpus,</pre>
removePunctuation) corpus <- tm_map(corpus, removeNumbers)</pre>
corpus <- tm_map(corpus, removeWords, stopwords("english"))</pre>
tdm <- TermDocumentMatrix(corpus) freq <-
sort(rowSums(as.matrix(tdm)), decreasing = TRUE) keywords <-
names(freq)[1:min(top_n, length(freq))] return(keywords)
}
calculate_relevance_score <- function(ideal_answer, student_answer, top_n = 5) {</pre>
keywords <- extract_keywords(ideal_answer, top_n) matches <-
sum(str_detect(tolower(student_answer), keywords)) return(min((matches / top_n)
* 5 + 1, 5))
data <- data %>% rowwise()
%>% mutate(
Calculated_Score =
```

calculate_relevance	_sco			
re(Answers, Texts)				
) %>% ungroup()				
write.csv(data, "C:/ row.names = FALSE	Jsers/shire/OneDrive/Deskt head(data)	op/Updated_Data_Calo	culated_Scores_Plus_On	e.csv",
Output:				



New File link:

Load required libraries

https://drive.google.com/file/d/1WAEidulTo 8tokumGAYPnM8mB nB4 kK/view?usp=sharing

Code:

)

```
if (!require("pacman")) install.packages("pacman") pacman::p_load( dplyr, tm, text2vec, stringr, tidytext, topicmodels, proxy, textreuse, tokenizers, caret, data.table, wordnet
```

File paths

unt_dataset_path <- "C:/Users/shire/OneDrive/Desktop/Data.csv"

```
output_csv_path <- "C:/Users/shire/OneDrive/Desktop/ASAG_Features.csv" glove_file <-
"C:/Users/shire/OneDrive/Desktop/glove.6B.50d.txt"# Helper functions cosine_similarity
<- function(a, b) {         if (length(a) == 0 || length(b) == 0 ||
any(is.na(a)) || any(is.na(b))) { return(0)
 }
 similarity <- sum(a * b) / (sqrt(sum(a^2)) * sqrt(sum(b^2))) return(ifelse(is.na(similarity),
0, similarity))
}
jaccard_similarity <- function(a, b) {</pre>
if (length(a) == 0 | | length(b) == 0) { return(0)
 }
 intersection <- length(intersect(a, b)) union</pre>
<- length(union(a, b))
 return(ifelse(union == 0, 0, intersection / union))
}
# Load GloVe embeddings load_glove
<- function(filepath, dims) {
cat("Loading GloVe embeddings...\n") con <- file(filepath,
"r") embeddings <- new.env(hash =
TRUE)
 while (TRUE) { line <- readLines(con, n
= 1) if
(length(line) == 0) break
  values <- strsplit(line, " ")[[1]]</pre>
                                  word
<- values[1] vector <-
as.numeric(values[-1])
embeddings[[word]] <- vector
 }
 close(con)
return(embeddings)
}
get_glove_vector <- function(sentence, embeddings) { words</pre>
<- unlist(str_split(tolower(sentence), "\\W+")) words
<- words[words != ""] vectors <- matrix(0, ncol = 50) #
```

```
Assuming 50d embeddings count <- 0
 for (word in words) {    if (exists(word, envir = embeddings))
    vectors <- vectors + matrix(embeddings[[word]], nrow =</pre>
1)
     count <- count + 1
  }
 }
 if (count > 0) { return(vectors
/ count) } else
{ return(vectors)
}
}
# Read and preprocess data cat("Reading dataset...\n")
data <- read.csv(unt_dataset_path, stringsAsFactors =
FALSE)
data <- data %>% mutate(
Questions = tolower(Questions),
  Answers = tolower(Answers),
  Texts = tolower(Texts)
 )
# Load GloVe embeddings
if (file.exists(glove_file)) {
 glove_embeddings <- load_glove(glove_file, dims = 50)</pre>
} else {
 stop("GloVe file does not exist at the specified location!")
}
        Extract features cat("Extracting
features...\n")
features <-
                data
                        %>%
rowwise() %>% mutate(
Semantic similarity features
  CosineTFIDF = { corpus <-
```

```
Corpus(VectorSource(c(Answers, Texts))) dtm <- DocumentTermMatrix(corpus)
tfidf <- as.matrix(weightTfldf(dtm))
cosine similarity(tfidf[1,], tfidf[2,])
  },
  Word2VecSimilarity = {
   ref_vec <- get_glove_vector(Answers, glove_embeddings)</pre>
stu vec <- get glove vector(Texts, glove embeddings)
                                                          cosine similarity(ref vec, stu vec)
  },
  # Information retrieval feature TFIDFNovelty = {
                                                        dtm <-
DocumentTermMatrix(Corpus(VectorSource(c(Answers, Texts))))
                                                                    tfidf
<- as.matrix(weightTfldf(dtm))
                                  abs(sum(tfidf[1,]) - sum(tfidf[2,]))
  },
  # Lexical overlap features
  JaccardSimilarity = jaccard_similarity(
                                           unlist(str_split(Answers,
"\\W+")),
unlist(str_split(Texts, "\\W+"))
  ),
  SimpleWordOverlap = length(intersect(
                                             unlist(str_split(Answers,
"\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  # Modified ROUGE implementation
  ROUGE N
                        {
                                ref tokens
   unlist(str_split(Answers, "\\W+")) stu_tokens <- unlist(str_split(Texts,
   "\\W+"))
                ref bigrams <- tokenizers::tokenize ngrams(Answers, n
   2)[[1]]
                                                                stu_bigrams
                                                                                <-
   tokenizers::tokenize_ngrams(Texts, n = 2)[[1]]
   unigram_overlap <- length(intersect(ref_tokens, stu_tokens)) / max(1, length(ref_tokens))
bigram overlap <- length(intersect(ref bigrams, stu bigrams)) / max(1, length(ref bigrams))
(unigram_overlap + bigram_overlap) / 2
  },
  # Relevance feedback features RF1
= length(intersect(
unlist(str_split(Answers, "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  RF2 = length(setdiff(
```

```
unlist(str_split(Answers, "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  RF3 = length(union(
   unlist(str_split(Answers, "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  # Topical similarity features LDASimilarity = {
corpus <- Corpus(VectorSource(c(Answers, Texts)))</pre>
                                                       dtm
<- DocumentTermMatrix(corpus) # Handle
empty documents if (dim(dtm)[1] < 2 | | sum(dtm) ==
0) {
    0
   } else {
               tryCatch({
     Ida <- LDA(dtm, k = 2, control = list(seed = 1234))
topics
                   <-
                                  posterior(Ida)$topics
cosine_similarity(topics[1,], topics[2,])
                                             }, error =
function(e) 0)
   }
  },
  # Alignment-based features WordAlignment = {
                                                      ref_freq
<- table(unlist(str_split(Answers, "\\W+")))
                                                   stu_freq <-
table(unlist(str_split(Texts, "\\W+")))
                                                all_words <-
unique(c(names(ref_freq), names(stu_freq)))
                                                    ref_vec <-
numeric(length(all_words))
                                                  stu_vec <-
numeric(length(all_words))
                                 names(ref_vec) <- all_words
names(stu_vec) <- all_words</pre>
                                  ref_vec[names(ref_freq)] <-</pre>
                      stu_vec[names(stu_freq)] <- stu_freq</pre>
ref_freq
cosine_similarity(ref_vec, stu_vec) },
                                           Coverage = {
   ref tokens <- unlist(str split(Answers, "\\W+")) stu tokens <-
   unlist(str_split(Texts, "\\W+")) length(intersect(ref_tokens,
   stu_tokens)) / max(1, length(ref_tokens))
```

```
# Missing Semantic Similarity Features
KnowledgeBasedSimilarity = {
# Use WordNet or ConceptNet to calculate similarity (placeholder)
0
},
CorpusBasedSimilarity = {
# Use LSA or other corpus-based methods (placeholder)
0
},
SentenceSimilarityWeightedEmbedding = {
# Weighted average of word embeddings (using IDF) (placeholder)
0
},
WordMoversDistance = {
# Use Word Mover's Distance (placeholder)
0
},
MaximalMatchingSimilarity = {
# Placeholder for maximal matching similarity
0
},
# Missing Lexical Overlap Features
PhrasalOverlap = {
# Placeholder for phrasal overlap (placeholder)
0
ROUGE_W = {
# Placeholder for ROUGE-W (placeholder)
0
```

},

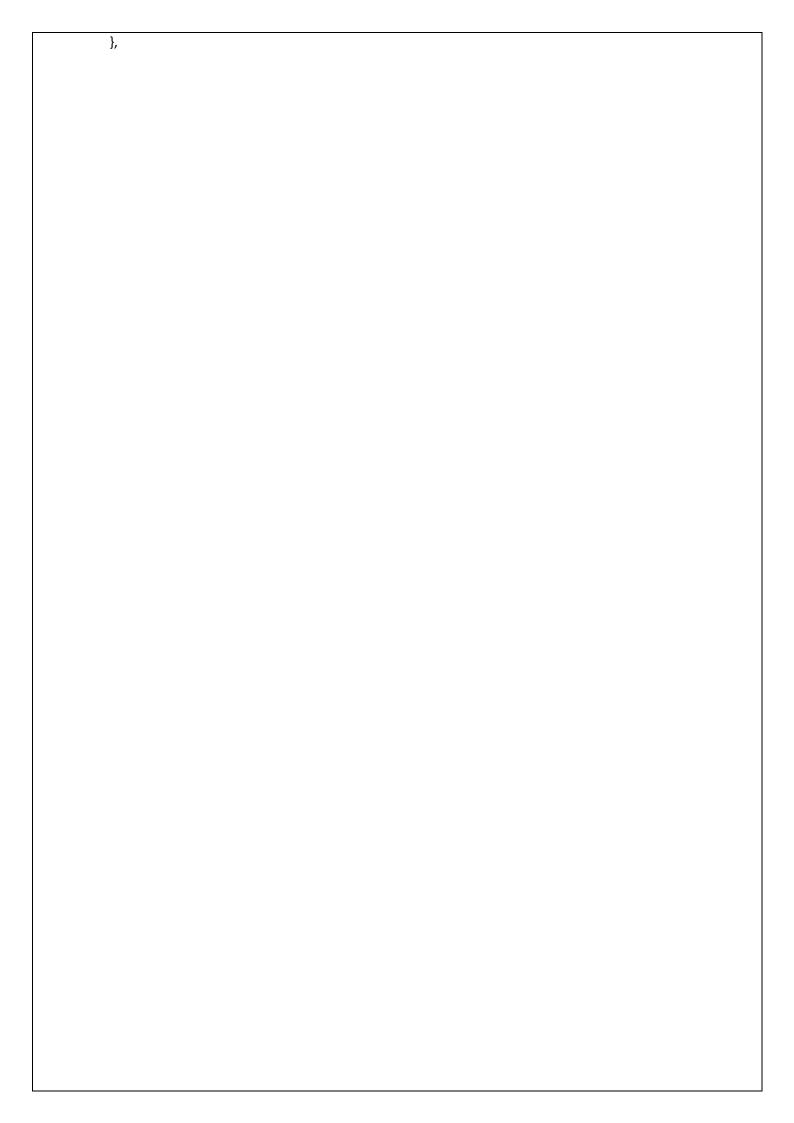
},

ROUGE_SU = {

```
# Placeholder for ROUGE-SU (placeholder)
   0
  },
  # Missing Topical Similarity Features
  BTM_Similarity = {
   # Placeholder for BTM Similarity (placeholder)
   0
  },
  TopicCoherence = {
   # Placeholder for topic coherence (placeholder)
   0
  },
  TopicRelevance = {
   # Placeholder for topic relevance (placeholder)
  0
  },
  # Missing Alignment-Based Features
WordToWordAlignment = {
   # Placeholder for word-to-word alignment (placeholder)
   0
  QuestionDemotedWordToWordAlignment = {
   # Placeholder for question-demoted word-to-word alignment
(placeholder)
   0
  },
  QuestionDemotedCoverage = {
   # Placeholder for question-demoted coverage (placeholder)
   0
  },
  AlignedPhraseSimilarity = {
   # Placeholder for aligned phrase similarity (placeholder)
   0
```

},

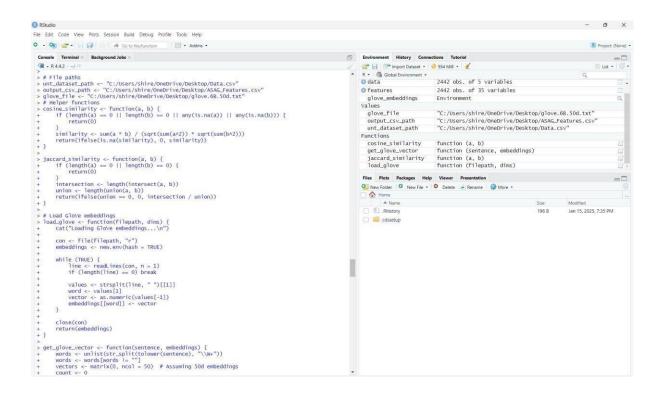
```
},
AlignmentNovelty = {
  # Placeholder for alignment novelty (placeholder)
  0
},
FineGrainedAlignment = {
  # Placeholder for fine-grained alignment (placeholder)
  0
},
PhraseLevelAlignmentSimilarity = {
  # Placeholder for phrase-level alignment similarity (placeholder)
  0
}
}%>%
```

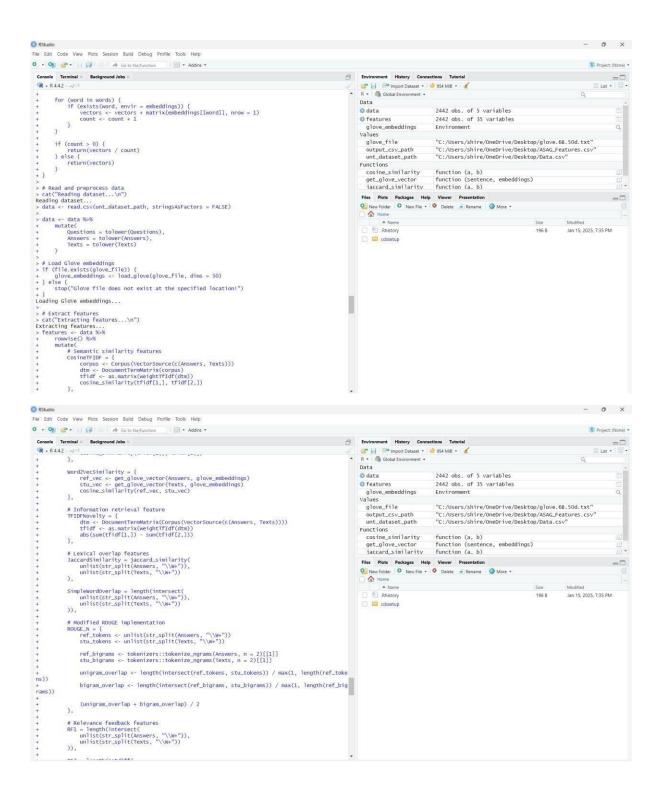


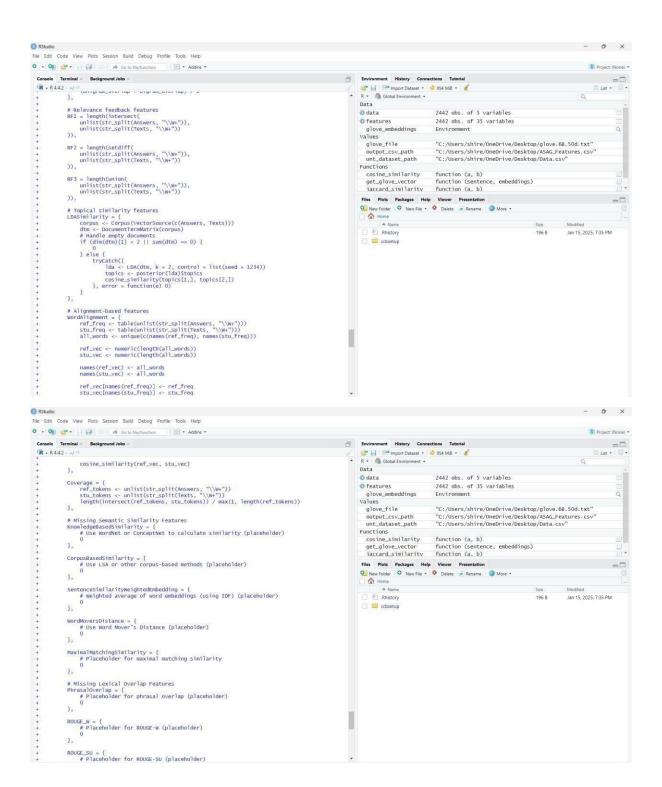
ungroup()

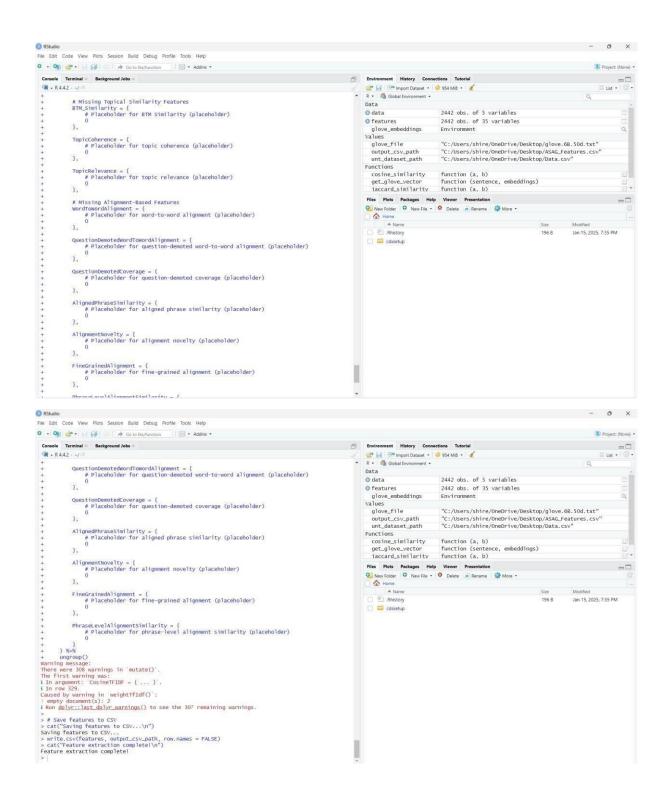
Save features to CSV cat("Saving features to CSV...\n")

write.csv(features, output_csv_path, row.names = FALSE) cat("Feature extraction
complete!\n")









Regression Code: # Load

necessary libraries

library(caret)

library(dplyr)

library(e1071)

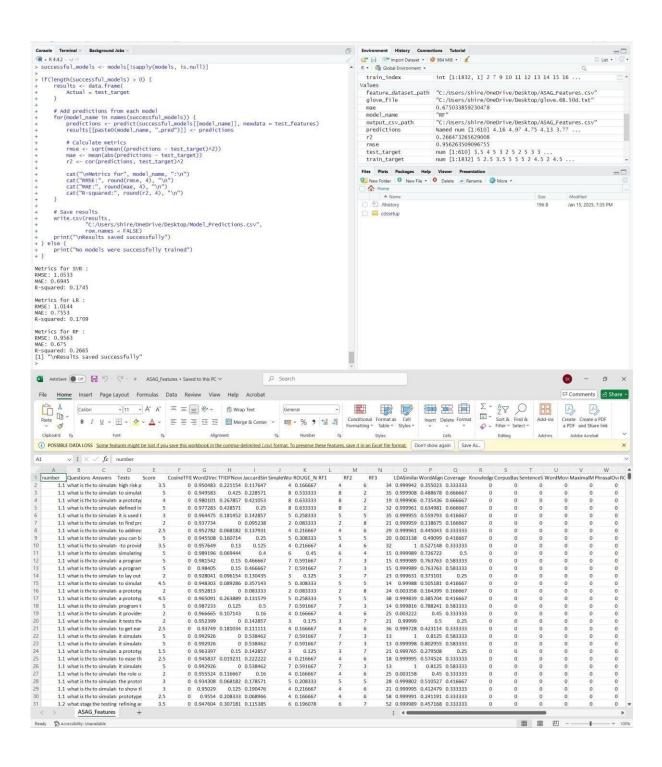
library(glmnet)

library(randomForest)

```
library(xgboost)
library(tidyr)
library(readr)
# Load dataset
feature_dataset_path <- "C:/Users/shire/OneDrive/Desktop/ASAG_Features.csv" data <-
read.csv(feature dataset path, stringsAsFactors = FALSE)
# Print initial data dimensions
print(paste("Initial data dimensions:", dim(data)[1], "rows,", dim(data)[2], "columns"))
# Improved prepare_data function prepare_data
<- function(df) {
  # List of columns to keep (add or remove columns as needed based on your dataset)
numeric features <- c(
    "Score", "CosineTFIDF", "Word2VecSimilarity", "TFIDFNovelty",
    "JaccardSimilarity", "SimpleWordOverlap", "ROUGE_N", "RF1",
    "RF2", "RF3", "LDASimilarity", "WordAlignment", "Coverage",
    "KnowledgeBasedSimilarity", "CorpusBasedSimilarity",
    "SentenceSimilarityWeightedEmbedding", "WordMoversDistance",
    "MaximalMatchingSimilarity", "PhrasalOverlap", "ROUGE_W",
    "ROUGE_SU", "BTM_Similarity", "TopicCoherence", "TopicRelevance",
    "WordToWordAlignment", "QuestionDemotedWordToWordAlignment",
    "QuestionDemotedCoverage", "AlignedPhraseSimilarity",
    "AlignmentNovelty", "FineGrainedAlignment",
    "PhraseLevelAlignmentSimilarity"
  )
  # Select only the numeric feature columns
df_selected <- df[, numeric_features]</pre>
Convert all columns to numeric
  df_numeric <- as.data.frame(lapply(df_selected, as.numeric))</pre>
  # Remove rows with any NA values
df clean <- na.omit(df numeric)</pre>
Print dimensions after cleaning
  print(paste("Dimensions after cleaning:", dim(df_clean)[1], "rows,", dim(df_clean)[2], "columns"))
return(df_clean)
}
# Create train-test split first set.seed(123)
```

```
train_index <- createDataPartition(data$Score, p = 0.75, list = FALSE)
train_data <- data[train_index, ] test_data <- data[-train_index, ] #</pre>
Prepare the data
train_data_numeric <- prepare_data(train_data) test_data_numeric <- prepare_data(test_data)
# Verify data preparation print("Training data
summary:")
print(summary(train_data_numeric$Score)) #
Prepare features and target for modeling
train_features <- train_data_numeric[, !colnames(train_data_numeric) %in% "Score", drop = FALSE]
train_target <- train_data_numeric$Score</pre>
test_features <- test_data_numeric[, !colnames(test_data_numeric) %in% "Score", drop = FALSE]
test_target <- test_data_numeric$Score</pre>
# Define training control ctrl
<- trainControl( method =
"cv",
  number = 5, # Reduced from 10 for faster training
                                                       verboselter
= TRUE
)
# Initialize models list models
<- list()
# Train Support Vector Regression (SVR)
tryCatch({ models$SVR <- train(</pre>
= train_features,
                     y = train_target,
method = "svmRadial",
                            trControl =
         preProcess = c("center",
ctrl,
"scale")
  )
  print("SVR model trained successfully")
}, error = function(e) {          print(paste("SVR
Error:", e$message))
})
# Train Linear Regression tryCatch({
models$LR <- train(
                        x = train_features,
                    method = "lm",
y = train_target,
trControl = ctrl,
                    preProcess =
c("center", "scale") )
  print("Linear Regression trained successfully")
}, error = function(e) {
  print(paste("LR Error:", e$message))
})
# Train Random Forest
```

```
tryCatch({ models$RF
<- train(
            x =
train_features,
                   y =
train_target,
method = "rf",
trControl = ctrl,
ntree
= 100.
    preProcess = c("center", "scale")
  )
  print("Random Forest trained successfully")
}, error = function(e) {
  print(paste("RF Error:", e$message))
})
# Get predictions and evaluate models successful_models
<- models[!sapply(models, is.null)] if(length(successful_models)</pre>
> 0) {
results <- data.frame(
    Actual = test_target
  )
  # Add predictions from each model for(model_name
in names(successful models)) {
    predictions <- predict(successful_models[[model_name]], newdata = test_features)</pre>
results[[paste0(model_name, "_pred")]] <- predictions</pre>
    # Calculate metrics
    rmse <- sqrt(mean((predictions - test_target)^2))
                                                          mae <-
mean(abs(predictions - test_target)) r2 <- cor(predictions,
test_target)^2
    cat("\nMetrics for", model name, ":\n")
cat("RMSE:", round(rmse, 4), "\n")
                                       cat("MAE:",
round(mae, 4), "\n") cat("R-squared:",
round(r2, 4), "\n")
  }
  # Save results write.csv(results,
       "C:/Users/shire/OneDrive/Desktop/Model Predictions.csv",
                                                                            row.names =
FALSE) print("\nResults saved successfully")
} else {
  print("No models were successfully trained")
}
```



Code:

Feature extraction: # Load

required libraries

if (!require("pacman")) install.packages("pacman") pacman::p_load(dplyr, tm, text2vec, stringr, tidytext, topicmodels, proxy, textreuse, tokenizers, caret, data.table, wordnet

```
)
# File paths unt_dataset_path <-
"C:/Users/shire/OneDrive/Desktop/Data.csv" glove_file <-
"C:/Users/shire/OneDrive/Desktop/glove.6B.50d.txt" output_csv_path <-
"C:/Users/shire/OneDrive/Desktop/ASAG_Features.csv
# Helper functions cosine similarity <- function(a, b) { if (length(a)
== 0 || length(b) == 0 || any(is.na(a)) || any(is.na(b))) { return(0)
 similarity <- sum(a * b) / (sqrt(sum(a^2)) * sqrt(sum(b^2))) return(ifelse(is.na(similarity),
0, similarity))
jaccard_similarity <- function(a, b) { if</pre>
(length(a) == 0 | length(b) == 0) {
return(0)
 }
 intersection <- length(intersect(a, b)) union <-
length(union(a, b)) return(ifelse(union == 0, 0,
intersection / union))
}
# Load GloVe embeddings load_glove
<- function(filepath, dims) {
cat("Loading GloVe embeddings...\n")
con <- file(filepath, "r") embeddings</pre>
<- new.env(hash = TRUE) while
(TRUE) { line <- readLines(con, n = 1)
if (length(line) == 0) break values <-
strsplit(line, " ")[[1]] word <-
values[1] vector <-
as.numeric(values[-1])
embeddings[[word]] <- vector
 close(con) return(embeddings)
get_glove_vector <- function(sentence, embeddings) {  words</pre>
<- unlist(str_split(tolower(sentence), "\\W+")) words <-
words[words != ""] vectors <- matrix(0, ncol = 50) #</pre>
Assuming 50d embeddings count <- 0 for (word in words) {
if (exists(word, envir = embeddings)) {     vectors <- vectors</pre>
+ matrix(embeddings[[word]], nrow = 1) count <- count +
```

```
1
  }
 if (count > 0) { return(vectors
/ count)
} else {
return(vectors)
}
}
# Read and preprocess data cat("Reading dataset...\n") data
<- read.csv(unt_dataset_path, stringsAsFactors = FALSE) data</pre>
<- data %>% mutate(
  Questions = tolower(Questions),
  Answers = tolower(Answers),
  Texts = tolower(Texts)
# Load GloVe embeddings if
(file.exists(glove_file)) { glove_embeddings <-</pre>
load_glove(glove_file, dims = 50)
} else { stop("GloVe file does not exist at the specified location!")
}
       Extract
                     features
cat("Extracting features...\n")
features <-
                data
                       %>%
rowwise() %>% mutate(
  # Semantic similarity features
                                  CosineTFIDF = {
corpus <- Corpus(VectorSource(c(Answers, Texts)))</pre>
dtm <- DocumentTermMatrix(corpus)</pre>
                                            tfidf <-
as.matrix(weightTfldf(dtm))
cosine_similarity(tfidf[1,], tfidf[2,])
  },
  Word2VecSimilarity = {
                             ref_vec <-
get_glove_vector(Answers, glove_embeddings)
                                                   stu_vec
<- get_glove_vector(Texts, glove_embeddings)
cosine_similarity(ref_vec, stu_vec)
  },
  # Lexical overlap features
```

```
JaccardSimilarity = jaccard_similarity(
unlist(str_split(Answers,
                                                                                "\\W+")),
unlist(str_split(Texts, "\\W+"))
    ),
     SimpleWordOverlap = length(intersect(
                                                                                "\\W+")),
unlist(str_split(Answers,
unlist(str_split(Texts, "\\W+"))
    )),
     # ROUGE implementation ROUGE_1 = {
                                                                                                                     ref_tokens <-
unlist(str_split(Answers, "\\W+")) stu_tokens <- unlist(str_split(Texts,
"\\W+"))
                              length(intersect(ref_tokens, stu_tokens)) / max(1,
length(ref_tokens))
    },
     ROUGE_2 = {
                                              ref_bigrams <- tokenizers::tokenize_ngrams(Answers, n = 2)[[1]]</pre>
stu_bigrams <- tokenizers::tokenize_ngrams(Texts, n = 2)[[1]]
length(intersect(ref_bigrams, stu_bigrams)) / max(1, length(ref_bigrams))
    },
     ROUGE_W = {
                                                                                         ref_tokens <-
unlist(str_split(Answers, "\\W+"))
                                                                                       stu_tokens <-
unlist(str_split(Texts, "\\W+"))
                                                                                                 # Calculate
                                                                        weighted_overlap <-
weighted overlap
function(ref, stu) {
                                                            n <- length(ref)
length(stu)
                                        dp \leftarrow matrix(0, nrow = n + 1, ncol = n + 1,
m + 1
                         for (i in 1:n) {
                                                                       for (j in 1:m) {
(ref[i] == stu[j]) {
                                                            dp[i + 1, j + 1] \leftarrow dp[i, j] + 1
               } else {
                  dp[i + 1, j + 1] < -max(dp[i + 1, j], dp[i, j + 1])
               }
            }
          }
          # Compute weighted ROUGE
                                                                                           max_weighted_overlap <- dp[n +
1, m + 1]
                                 weight <- 1 # Assign a weight to consecutive matches (can
be tuned)
          (max_weighted_overlap * weight) / max(1, length(ref))
       }
          weighted_overlap(ref_tokens, stu_tokens)
    },
   ROUGE_L
                                                           {
                                                                               ref_tokens
unlist(str_split(Answers, "\\W+"))
                                                                                            stu_tokens <-
```

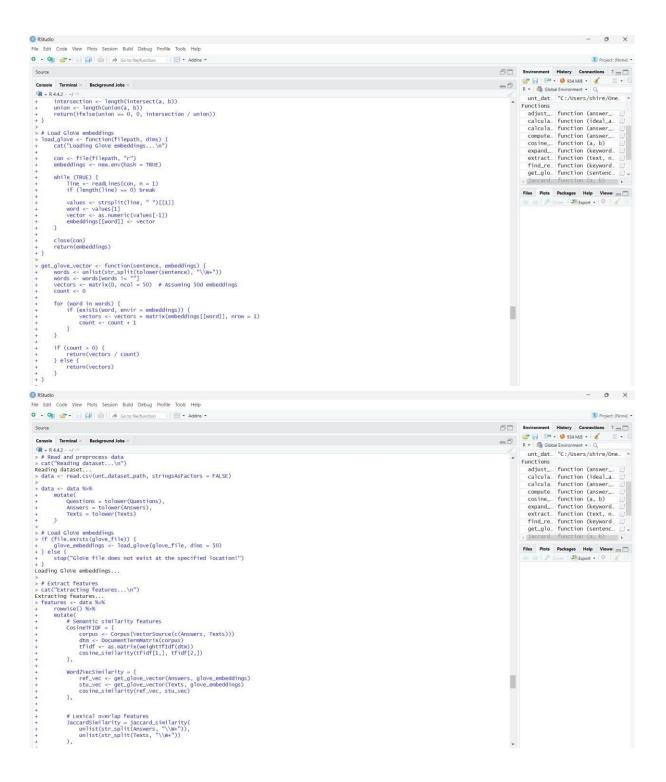
```
unlist(str_split(Texts, "\\W+"))
                                    # Function to
calculate LCS
                 lcs <- function(x, y) {</pre>
                                            n <-
length(x)
              m <- length(y)
                                 dp <- matrix(0,
nrow = n + 1, ncol = m + 1)
                                 for (i in 1:n) {
for (j in 1:m) {
                   if(x[i] == y[j]) {
                                              dp[i+
1, j
+ 1] <- dp[i, j] + 1
      } else {
                      dp[i + 1, j + 1] < -max(dp[i + 1, j],
dp[i, j + 1]
       }
     }
    }
    return(dp[n + 1, m + 1])
   lcs_length <- lcs(ref_tokens, stu_tokens)</pre>
                                                 precision
                                               recall <-
<- lcs_length / max(1, length(stu_tokens))
lcs_length / max(1, length(ref_tokens))
                                            if
(precision + recall == 0) {
    0
   } else {
    (2 * precision * recall) / (precision + recall)
   }
  },
  # Information retrieval feature
  TFIDFNovelty = {
                       dtm <-
DocumentTermMatrix(Corpus(VectorSource(c(Answers, Texts)))) tfidf <- as.matrix(weightTfldf(dtm))
abs(sum(tfidf[1,]) - sum(tfidf[2,]))
  },
  # Topical similarity features LDASimilarity = {
corpus <- Corpus(VectorSource(c(Answers, Texts)))</pre>
dtm <- DocumentTermMatrix(corpus)</pre>
                                           if
(dim(dtm)[1] < 2 \mid | sum(dtm) == 0) {
    0
   } else {
               tryCatch({
                                Ida <- LDA(dtm, k = 2, control
= list(seed = 1234))
                          topics <- posterior(lda)$topics
cosine_similarity(topics[1,
], topics[2, ])
    }, error = function(e) 0)
   }
  },
```

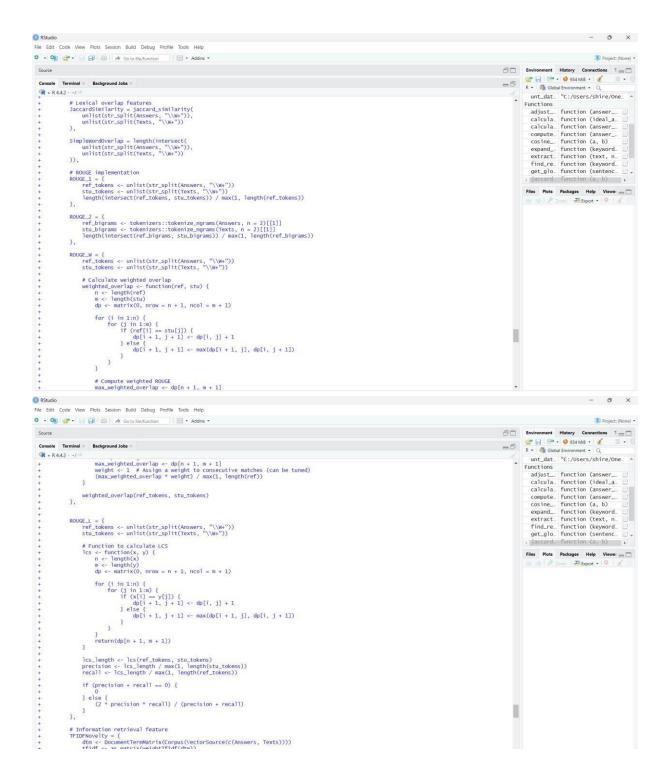
```
HellingerDistance = {
                           corpus <-
Corpus(VectorSource(c(Answers, Texts)))
                                             dtm <-
DocumentTermMatrix(corpus)
                                   if (dim(dtm)[1] < 2
| | sum(dtm) == 0) {
                         1 # Max dissimilarity for
empty distributions
                                Ida \leftarrow LDA(dtm, k = 2,
   } else {
               tryCatch({
control = list(seed = 1234))
                                  topics <-
posterior(lda)$topics
hellinger_distance(topics[1, ], topics[2, ])
    }, error = function(e) 1)
   }
  },
  # Relevance feedback features RF1
= length(intersect(
unlist(str_split(Answers, "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  RF2
                        length(setdiff(
unlist(str_split(Answers,
                                 "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  RF3
                        length(union(
unlist(str_split(Answers,
                                 "\\W+")),
unlist(str_split(Texts, "\\W+"))
  )),
  #Alignment based features WordAlignment = {
ref_freq <- table(unlist(str_split(Answers, "\\W+")))</pre>
stu_freq <- table(unlist(str_split(Texts, "\\W+")))</pre>
all words <- unique(c(names(ref freq), names(stu freq)))
ref_vec <- numeric(length(all_words))</pre>
                                           stu_vec <-
numeric(length(all_words))
                               names(ref_vec) <- all_words
names(stu_vec) <- all_words ref_vec[names(ref_freq)] <-</pre>
            stu_vec[names(stu_freq)] <- stu_freq</pre>
cosine_similarity(ref_vec, stu_vec)
  },
                          ref_tokens <- unlist(str_split(Answers, "\\W+"))
  CoverageFeature = {
stu_tokens <- unlist(str_split(Texts, "\\W+"))
length(intersect(ref_tokens, stu_tokens)) / max(1, length(ref_tokens))
},
```

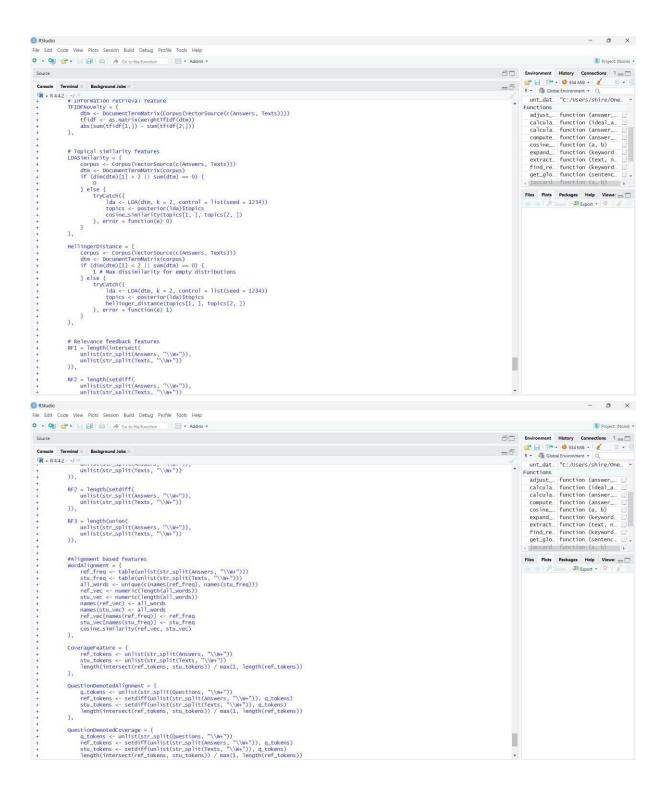
```
QuestionDemotedAlignment = { q_tokens <- unlist(str_split(Questions,
"\\W+"))
            ref_tokens <- setdiff(unlist(str_split(Answers, "\\W+")),</pre>
             stu_tokens <- setdiff(unlist(str_split(Texts, "\\W+")),</pre>
q_tokens)
q_tokens)
             length(intersect(ref_tokens, stu_tokens)) / max(1,
length(ref_tokens))
  },
  QuestionDemotedCoverage = { q_tokens <- unlist(str_split(Questions,
"\\W+"))
            ref_tokens <- setdiff(unlist(str_split(Answers, "\\W+")),
q_tokens) stu_tokens <- setdiff(unlist(str_split(Texts, "\\W+")),</pre>
             length(intersect(ref_tokens, stu_tokens)) / max(1,
q_tokens)
length(ref_tokens))
 },
) %>% ungroup() # Save features
to CSV cat("Saving features to
CSV...\n") write.csv(features,
output_csv_path, row.names =
FALSE) cat("Feature extraction
complete!\n")
```

Screenshots:

```
-5 R → 1
 Console Terminal × Background Jobs ×
  R • R 4.4.2 · ~/
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 Functior
adjust
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                                                                                                                                                                                                                                                                                                            calcul
                                                                                                                                                                                                                                                                                                            comput
+)
Installing package into 'C:/Users/shire/AppData/Local/R/win-library/4.4'
(as 'lib' is unspecified)
Warning: unable to access index for repository http://www.stats.ox.ac.uk/pub/RWin/bin/windows/contrib/4.4:
cannot open URL 'http://www.stats.ox.ac.uk/pub/RWin/bin/windows/contrib/4.4/PACKAGES'
trying URL 'https://cran.rstudio.com/bin/windows/contrib/4.4/wordnet_0.1-17.zip'
Content type 'application/zip' length 120495 bytes (117 KB)
downloaded 117 KB
                                                                                                                                                                                                                                                                                                            cosine
                                                                                                                                                                                                                                                                                                            expand
                                                                                                                                                                                                                                                                                                           find r
                                                                                                                                                                                                                                                                                                        get_gl
 package 'wordnet' successfully unpacked and MDS sums checked
 The downloaded binary packages are in C:\Users\shire\AppData\Local\Temp\Rtmpw1oal3\downloaded_packages
wordnet installed warning message: In pacman::p_load(dplyr, tm, text2vec, stringr, tidytext, topicmodels, : Failed to install/load: wordnet
  > # File paths
 > # File paths
- unt_dataset_path <- "C:/Users/shire/OneDrive/Desktop/Data.csv"
> glove_file <- "C:/Users/shire/OneDrive/Desktop/glove.68.50d.txt"
> output_csv_path <- "C:/Users/shire/OneDrive/Desktop/ASAG_Features.csv"</pre>
 > # Helper functions
> cosine_similarity <- function(a, b) {
+ if (length(a) == 0 || length(b) == 0 || any(is.na(a)) || any(is.na(b))) {
+ return(0)
          similarity <- sum(a * b) / (sqrt(sum(a^2)) * sqrt(sum(b^2)))
return(ifelse(is.na(similarity), 0, similarity))</pre>
 > jaccard_similarity <- function(a, b) {
+    if (length(a) == 0 || length(b) == 0) {
+       return(0)</pre>
           intersection <- length(intersect(a, b))
```







```
stu_vec[names(stu_freq)] <- stu_freq</pre>
                    cosine_similarity(ref_vec, stu_vec)
              }.
              CoverageFeature = {
                   ref_tokens <- unlist(str_split(Answers, "\\W+"))
stu_tokens <- unlist(str_split(Texts, "\\W+"))
                    length(intersect(ref_tokens, stu_tokens)) / max(1, length(ref_tokens))
             QuestionDemotedAlignment = {
                    tionDemotedAlignment = {
q_tokens <- unlist(str_split(Questions, "\\\\")), q_tokens)
cotdiff(unlist(str_split(Answers, "\\\\\")), q_tokens)</pre>
                    ref_tokens <- setdiff(unlist(str_split(Answers, "\\W+")), q_token
stu_tokens <- setdiff(unlist(str_split(Texts, "\\W+")), q_tokens)
                    length(intersect(ref_tokens, stu_tokens)) / max(1, length(ref_tokens))
              QuestionDemotedCoverage = {
                   q_tokens <- unlist(str_split(Questions, "\\W+"))
ref_tokens <- setdiff(unlist(str_split(Answers, "\\W+")), q_tokens)
stu_tokens <- setdiff(unlist(str_split(Texts, "\\W+")), q_tokens)</pre>
                    length(intersect(ref_tokens, stu_tokens)) / max(1, length(ref_tokens))
        ) %>%
        ungroup()
Warning message:
There were 308 warnings in `mutate()`.
The first warning was:
i In argument: `CosineTFIDF = { ... }`.
i In row 329.
Caused by warning in `weightTfIdf()`:
   empty document(s): 2
i Run dplyr::last_dplyr_warnings() to see the 307 remaining warnings.
> # Save features to CSV
> cat("Saving features to CSV...\n") Saving features to CSV...
> write.csv(features, output_csv_path, row.names = FALSE)
> cat("Feature extraction complete!\n")
Feature extraction complete!
```

Code:

```
# Load necessary libraries library(randomForest) library(ggplot2)
# Step 1: Load dataset (using the built-in iris dataset) data(iris)
# Step 2: Train a Random Forest model

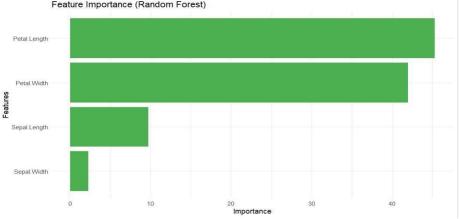
rf_model <- randomForest(Species ~ ., data = iris, importance = TRUE)

# Step 3: Extract feature importance and convert it to a data frame rf_importance_df <- data.frame(
Feature = rownames(importance(rf_model)),

Importance = importance(rf_model)[, "MeanDecreaseGini"] # Using MeanDecreaseGini for importance
)

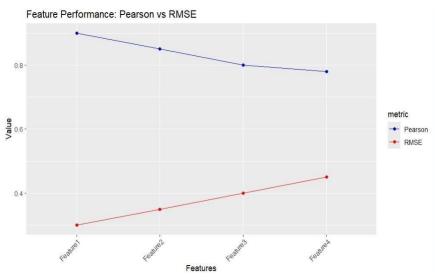
# Step 4: Plot feature importance
ggplot(rf_importance_df, aes(x = reorder(Feature, Importance), y = Importance)) + geom_bar(stat = "identity", fill = "#4CAF50") + # Green bar color coord_flip() + labs(title = "Feature Importance (Random
```

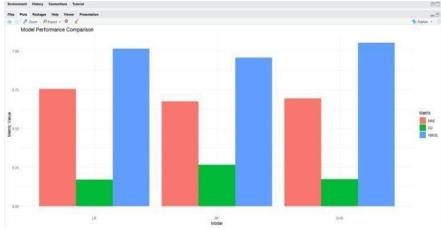
```
Forest)",
            x = "Features",
                               y = "Importance") + theme_minimal()
Graph: # Load necessary libraries library(randomForest)
library(ggplot2)
# Step 1: Load dataset (using the built-in iris dataset) data(iris)
# Step 2: Train a Random Forest model
rf_model <- randomForest(Species ~ ., data = iris, importance = TRUE)
# Step 3: Extract feature importance and convert it to a data frame rf_importance_df <- data.frame(
 Feature = rownames(importance(rf_model)),
 Importance = importance(rf_model)[, "MeanDecreaseGini"] # Using MeanDecreaseGini for
importance
)
# Step 4: Plot feature importance
ggplot(rf importance df, aes(x = reorder(Feature, Importance)), y = Importance)) +
geom bar(stat = "identity", fill = "#4CAF50") + # Green bar color coord flip() +
labs(title = "Feature Importance (Random Forest)",
                                                      x = "Features", y =
"Importance") + theme minimal()
             Feature Importance (Random Forest)
```

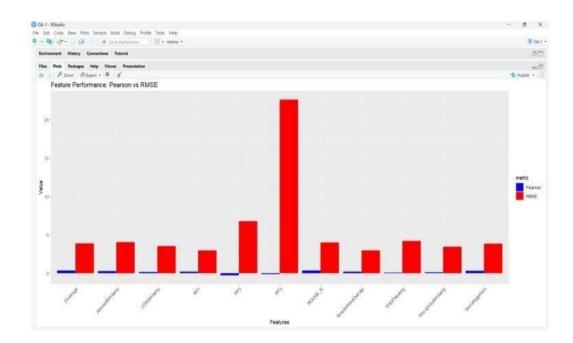


Code:

```
title = "Feature Performance: Pearson vs RMSE",
x = "Features", y = "Value"
) +
theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
scale_color_manual(values = c("Pearson" = "blue", "RMSE" = "red"))
```







Regression Code:

```
library(caret) library(dplyr)
```

library(e1071)

library(glmnet)

library(randomForest)

library(xgboost)

library(tidyr) library(readr)

feature_dataset_path <- "C:/Users/shire/OneDrive/Desktop/ASAG_Features.csv" data

<- read.csv(feature_dataset_path, stringsAsFactors = FALSE)</pre>

print(paste("Initial data dimensions:", dim(data)[1], "rows,", dim(data)[2], "columns")) prepare_data

"Score", "CosineTFIDF", "Word2VecSimilarity", "TFIDFNovelty",

"JaccardSimilarity", "SimpleWordOverlap", "ROUGE_N", "RF1",

"RF2", "RF3", "LDASimilarity", "WordAlignment", "Coverage",

"KnowledgeBasedSimilarity", "CorpusBasedSimilarity",

"SentenceSimilarityWeightedEmbedding", "WordMoversDistance",

"MaximalMatchingSimilarity", "PhrasalOverlap", "ROUGE_W",

"ROUGE_SU", "BTM_Similarity", "TopicCoherence", "TopicRelevance",

"WordToWordAlignment", "QuestionDemotedWordToWordAlignment",

```
"QuestionDemotedCoverage", "AlignedPhraseSimilarity",
    "AlignmentNovelty", "FineGrainedAlignment",
    "PhraseLevelAlignmentSimilarity"
  )
  df_selected <- df[, numeric_features]</pre>
  <- na.omit(df_numeric)
  print(paste("Dimensions after cleaning:", dim(df_clean)[1], "rows,", dim(df_clean)[2], "columns"))
return(df_clean)
}
set.seed(123)
train_index <- createDataPartition(data$Score, p = 0.75, list = FALSE) train_data
<- data[train_index, ] test_data <- data[-train_index, ] train_data_numeric <-
prepare_data(train_data) test_data_numeric
<- prepare_data(test_data)</pre>
train_features <- train_data_numeric[, !colnames(train_data_numeric) %in% "Score", drop = FALSE]
train_target <- train_data_numeric$Score</pre>
test_features <- test_data_numeric[, !colnames(test_data_numeric) %in% "Score", drop = FALSE]
test_target <- test_data_numeric$Score
train_data_combined <- cbind(train_features, Score = train_target) ctrl</pre>
<- trainControl(method = "cv", number = 5, verboseIter = TRUE)
models <- list() tryCatch({    models$SVR <- train(</pre>
train_features,
                  y = train_target,
                                       method = "svmRadial",
trControl = ctrl,
    preProcess = c("center", "scale")
  )
  print("SVR model trained successfully")
}, error = function(e) {
  print(paste("SVR Error:", e$message))
})
tryCatch({ models$LR
<- train(
    Score ~ .,
```

```
data = train_data_combined,
method = "lm",
                    trControl =
ctrl,
    preProcess = c("center", "scale")
  )
  print("Linear Regression model trained successfully")
}, error = function(e) {
  print(paste("LR Error:", e$message))
})
tryCatch({ models$RF
<- train(
    Score ~ .,
    data = train_data_combined,
method = "rf",
                   trControl =
         ntree = 100,
ctrl,
    preProcess = c("center", "scale")
  print("Random Forest model trained successfully")
}, error = function(e) {
  print(paste("RF Error:", e$message))
})
successful_models <- models[!sapply(models, is.null)]</pre>
if(length(successful_models) > 0) { results <-
data.frame(Actual = test_target) for(model_name
in names(successful_models)) {
    predictions <- predict(successful_models[[model_name]], newdata = test_features)</pre>
results[[paste0(model_name, "_pred")]] <- predictions
                                                            rmse <-
sqrt(mean((predictions - test_target)^2))
                                            mae <- mean(abs(predictions -
                 r2 <- cor(predictions, test_target)^2
                                                         cat("\nMetrics for",
test target))
                        cat("RMSE:", round(rmse, 4), "\n") cat("MAE:",
model name, ":\n")
round(mae, 4),
"\n")
          cat("R-squared:", round(r2, 4), "\n")
  }
```

```
write.csv(results, "C:/Users/shire/OneDrive/Desktop/Model_Predictions.csv", row.names = FALSE)
print("\nResults saved successfully")
} else {
  print("No models were successfully trained")
}
library(caret) library(gbm)
data <- read.csv("C:/Users/shire/OneDrive/Desktop/ASAG Features.csv", stringsAsFactors = FALSE)
dependent_variable <- "Score"</pre>
if (!(dependent_variable %in% colnames(data))) {
 stop("Ensure the target variable column is present in your dataset!")
}
numerical_features <- c("Word2VecSimilarity", "JaccardSimilarity", "SimpleWordOverlap",
             "ROUGE_1", "ROUGE_2", "ROUGE_W", "ROUGE_L", "TFIDFNovelty", "LDASimilarity",
             "HellingerDistance", "RF1", "RF2", "RF3", "WordAlignment", "CoverageFeature",
             "QuestionDemotedAlignment", "QuestionDemotedCoverage") features
<- data[, numerical_features] target <- data[[dependent_variable]] set.seed(123)
train_index <- createDataPartition(target, p = 0.8, list = FALSE)</pre>
train_data <- data[train_index, ] test_data <- data[train_index,</pre>
] for (col_name in colnames(train_data)) {    if
(is.factor(train_data[[col_name]])) {
  levels(test_data[[col_name]]) <- levels(train_data[[col_name]])</pre>
 }
train_x <- as.matrix(train_data[, numerical_features])</pre>
train_y <- train_data[[dependent_variable]] test_x <-</pre>
as.matrix(test_data[, numerical_features]) test_y <-
test_data[[dependent_variable]] evaluate_model <-
function(predictions, actuals) {
                                           rmse <-
sqrt(mean((predictions - actuals)^2))
                                               r2 <-
cor(predictions, actuals)^2 return(data.frame(RMSE
= rmse, R2 = r2)
}
boosting_tree_model <- gbm(train_y ~ ., data = train_data[, numerical_features], distribution =
"gaussian", n.trees = 100)
```

