Kaggle Competition: Automated Essay Scoring

[Kaggle Overview]

The first automated essay scoring competition to tackle automated grading of student-written essays was twelve years ago. How far have we come from this initial competition? With an updated dataset and light years of new ideas we hope to see if we can get to the latest in automated grading to provide a real impact to overtaxed teachers who continue to have challenges with providing timely feedback, especially in underserved communities.

The goal of this competition is to train a model to score student essays. Your efforts are needed to reduce the high expense and time required to hand grade these essays. Reliable automated techniques could allow essays to be introduced in testing, a key indicator of student learning that is currently commonly avoided due to the challenges in grading.

Business Problem

The Educational Testing Industry is developing a tool to assist with evaluating student learning and performance on short answer responses and essays on standardized tests. Manual grading of essays is not only time-consuming but also resource-intensive, making it difficult for educators to provide timely feedback, especially in underserved communities. Automated Writing Evaluation (AWE) systems offer a solution by efficiently scoring essays and supplementing educators' efforts, allowing students to receive regular and prompt feedback on their writing.

This project supports the technical development team to explore several key model training and performance questions:

1. What are the optimal hyperparameters for the models tested?
2. How do different vectorization techniques (e.g., TF-IDF vs. BERT) impact the model's performance?
3. What is the effect of different model architectures on grading accuracy?

[Kaggle Data Understanding]

The competition dataset comprises about 24000 student-written argumentative essays. Each essay was scored on a scale of 1 to 6 (Link to the Holistic Scoring Rubric [rubric]). Your goal is to predict the score an essay received from its text.

File and Field Information

train.csv - Essays and scores to be used as training data.

essay_id - The unique ID of the essay

full_text - The full essay response

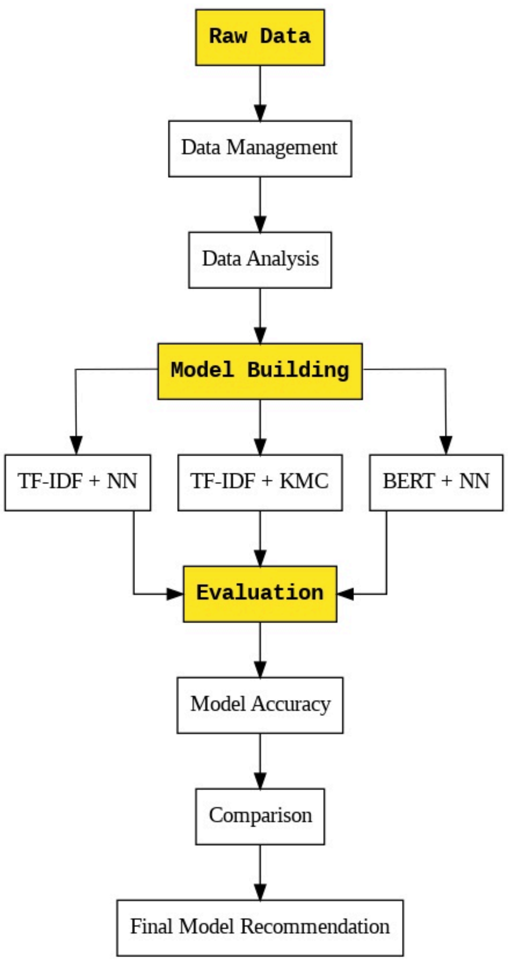
score - Holistic score of the essay on a 1-6 scale

test.csv - The essays to be used as test data. Contains the same fields as train.csv, aside from exclusion of score. (Note: The rerun test set has approximately 8k observations.)

sample_submission.csv - A submission file in the correct format.

essay_id - The unique ID of the essay score - The predicted holistic score of the essay on a 1-6 scale

General Project Roadmap



Import Libraries

```
%%capture

# Install necessary libraries
!pip install contractions
!pip install --upgrade keras-nlp
!pip install --upgrade keras
!pip install tensorflow==2.8.0
!pip install transformers==4.18.0
!pip install keras_tuner



#Import libraries for system operations and environment management
import sys
import os

# Print Python version to ensure compatibilitiy
print("Python version:")
print(sys.version)
print()


# Function to get the name of the virtual environment
def get_environment_name():
    """
    Retrieves the name of the current virtual environment, if one is active.

    Returns:
        str: The name of the virtual environment or a message indicating that no virtual environment is de
    """
    venv = os.getenv('VIRTUAL_ENV')
    if venv:
        return os.path.basename(venv)
    else:
        return "No virtual environment detected"

# Print environment name
print("Environment name:")
print(get_environment_name())
```

```
Python version:
3.10.12 (main, Nov 20 2023, 15:14:05) [GCC 11.4.0]

Environment name:
No virtual environment detected
```

Ensuring the correct execution environment in Google Colab is crucial for compatibility with required libraries and their versions. This setup verifies that the environment supports the versions of the libraries needed for this project.

```python
# Import Standard libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
from collections import Counter
import re

# 3D plotting
from mpl_toolkits.mplot3d import Axes3D

# Scikit-learn for machine learning
from sklearn.manifold import TSNE
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.cluster import KMeans

# TensorFlow and Keras for deep learning
import tensorflow as tf
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Input, Dense, Dropout, Embedding, LSTM
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.optimizers import Adam, RMSprop, SGD
import keras_tuner as kt

# Transformers and Keras NLP libraries
from transformers import BertTokenizer, TFBertModel
import keras_nlp
import keras.backend as K

# NLTK for natural language processing
import nltk
from nltk.tokenize import word_tokenize
import contractions

# WordCloud
from wordcloud import WordCloud

# Download necessary NLTK data
nltk.download('punkt', quiet=True)
nltk.download('stopwords', quiet=True)

# Initialize the inflect engine for converting numbers to words
import inflect
p = inflect.engine()

# Define Constants for feature extraction and modeling
MAX_FEATURES = 768
NUM_CLUSTERS = 5
NUM_CLASSES = 6
EPOCHS = 100
BATCH_SIZE = 32
SEED = 0

# Set colormap for visualizations
cmap = mpl.cm.get_cmap('viridis')

# Ensure reproducibility
np.random.seed(SEED)
```

```
<ipython-input-41-52486ae6319b>:59: MatplotlibDeprecationWarning: The get_cmap function was deprecated
  cmap = mpl.cm.get_cmap('viridis')
```

This code segment configures the backend engine for Keras, a high-level neural networks API, enhancing the computational efficiency of model training and execution. The available options include 'jax' for leveraging Google's JAX for autograd and XLA capabilities, 'tensorflow' for using TensorFlow's scaling and deployment features, and 'torch' for utilizing PyTorch's computation graphs and simple debugging.

Import Data

```
#Displaying the current working directory of the Colab notebook.
!pwd
```

```
/content
```

This information is crucial in a collaborative environment where multiple projects might be managed concurrently by different team members.

```
# Load the dataset from a CSV file into a Pandas DataFrame
essay_df = pd.read_csv('sample_data/train.csv')

# Select all 6000 rows from the dataset; optional adjustment based on RAM allowed
essay_df = essay_df.iloc[:6000]

# Display part of dataframe
essay_df.head()
```

	essay_id	full_text	score
0	000d118	Many people have car where they live. The thin...	3
1	000fe60	I am a scientist at NASA that is discussing th...	3
2	001ab80	People always wish they had the same technolog...	4
3	001bdc0	We all heard about Venus, the planet without a...	4
4	002ba53	Dear, State Senator\n\nThis is a letter to arg...	3

Next steps: Generate code with `essay_df` View recommended plots

Examining the data in tabular format to identify punctuation or textual characteristics that need to be addressed during preprocessing. While these steps are not directly relevant to running the program, they help establish a preprocessing roadmap, as demonstrated here.

Preproccessing

Utilizing the predefined roadmap, this section delineates functions designed to methodically preprocess each essay. Discrete words identified during subsequent analyses are removed using sets to ensure text cleanliness and relevance.

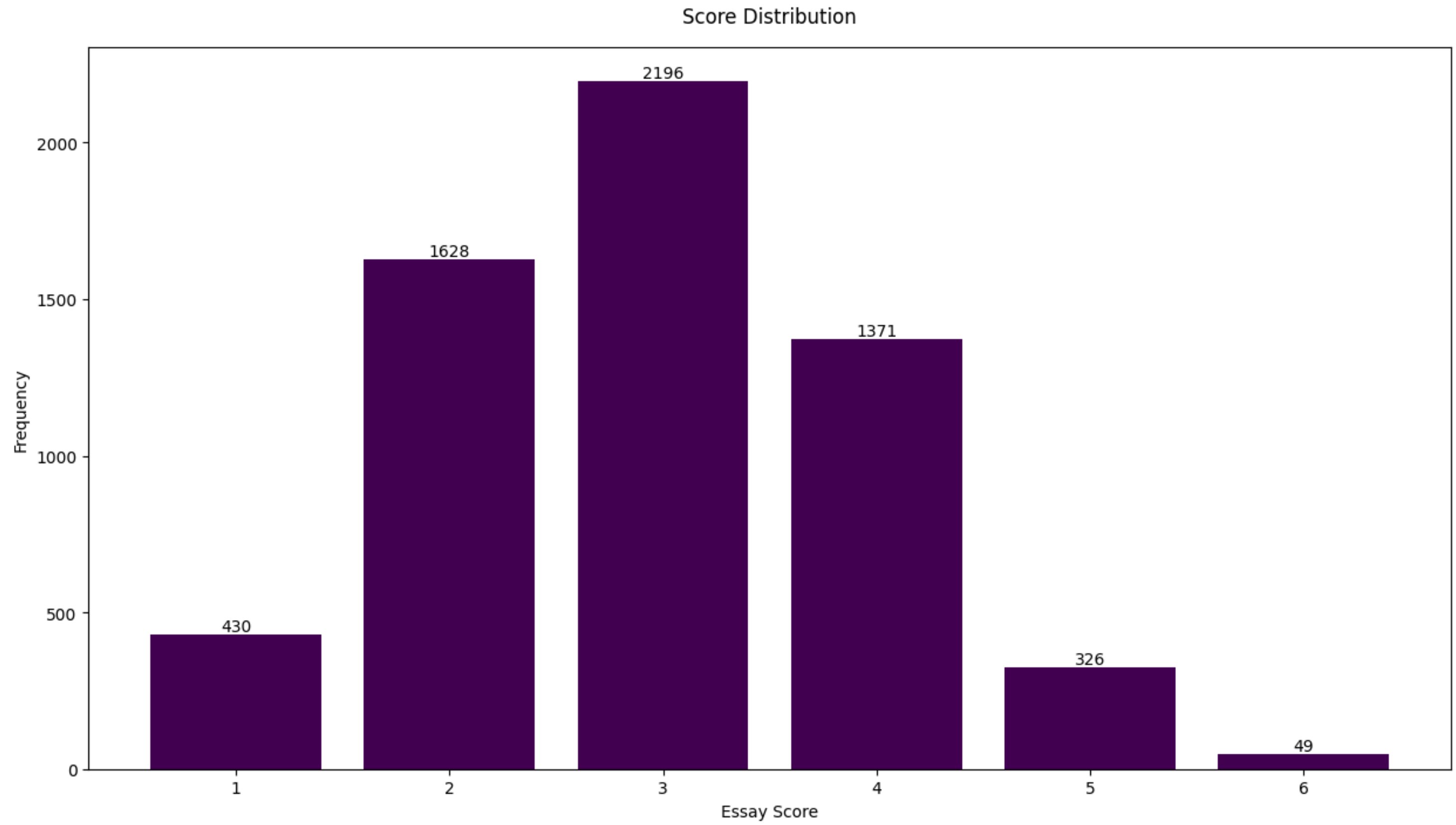
```
def contains_numeric(token):
  """
    Check if the token contains any numeric characters.

    Parameters:
    token (str): The token to check.

    Returns:
    bool: True if the token contains digits, False otherwise.
    """
  return any(char.isdigit() for char in token)


def convert_numbers_to_words(token):
  """
    Convert numbers within a token to words if the token contains numeric characters.

    Parameters:
    token (str): The token to process.

    Returns:
    list: A list of words after converting numbers to words and tokenization.
    """
  if contains_numeric(token):
    # Keeps alphanumeric, whitespace, and "."s, remove anything else
    token = re.sub(r'[^\w\s.]', '', token) # Remove punctuation for conversion

    wordString = p.number_to_words(token).replace(" ", "-")

    #wordString = wordString.replace("-", " ")

    # Tokenize the wordString
    tokens = word_tokenize(wordString)

    return tokens # Return the flat list of tokens instead of a list of lists
  else:
    return [token] # Return the token as a list

# Takes in a raw essay - just a long string
# Outputs a cleaned up list of tokens

def preprocess(rawEssay):
  """
    Preprocess the raw essay text into a cleaned list of tokens.

    Parameters:
    raw_essay (str): The essay text to preprocess.

    Returns:
    list: A list of cleaned, processed tokens from the essay.
    """
  # Step 1: replace hypens with spaces
  rawEssay = rawEssay.replace("-", " ")

  # Step 2: replace % with the word percent
  rawEssay = rawEssay.replace("%", "percent")

  # Put any other future single character manipulations here

  # Step 3: expand contractions ex: I'm -> I am
  essayExpanded = contractions.fix(rawEssay)

  # Step 4: take the big long string and turn it into tokens (individual strings)
  tokens = word_tokenize(essayExpanded) # just splitting on spaces
```

```
  # Step 5: convert the numeric tokens to one or more word tokens
  # ex: 10% -> ['ten', 'percent'] or 1.00 -> ['one', 'point', 'zero', 'zero']
  # use a new array to preserve the order of the tokens
  processedTokens = []

  # leaves non-numeric tokens alone
  for token in tokens:
    processedTokens.extend(convert_numbers_to_words(token))

  # Step 6: remove non-alphabet tokens and lowercase everything
  essayTokens = [word.lower() for word in processedTokens if word.isalpha()]

  # Step 7: remove stop words (common words like 'the', 'and', etc.)
  stop_words = set(nltk.corpus.stopwords.words('english'))
  additional_stop_words = {'would', 'could', 'should'}
  stop_words.update(additional_stop_words)

  essayTokensClean = [word for word in essayTokens if word not in stop_words]

  return essayTokensClean
```

Normalization of the target variable (y) is imperative as neural networks generally achieve better performance when output values lie within a 0-1 range.

Visualizing the dataset's score distribution to understand its spread and frequency of each score category.

```python
def essay_score_dist(essay_df):
    """
    Create a bar plot displaying the frequency of each score in the dataset.

    Parameters:
    essay_df (DataFrame): DataFrame containing essay scores.

    Returns:
    None: Displays a matplotlib bar plot.
    """
    # Create a Counter of scores from the available data
    score_bins = Counter(essay_df['score'])

    # Define all bins to display
    all_bins = [1, 2, 3, 4, 5, 6]

    # Create counts for all bins, filling missing bins with zero counts
    counts_per_bin = {bins: score_bins.get(bins, 0) for bins in all_bins}

    # Plot the count of different scores
    plt.figure(figsize=(15, 8))
    bars = plt.bar(counts_per_bin.keys(), counts_per_bin.values(), color='#440154')

    plt.ylabel('Frequency')
    plt.xlabel('Essay Score')
    plt.title('Score Distribution', y=1.02)

    # Show the counts on top of the bars
    for bar in bars:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, yval + 0.1, int(yval), ha='center', va='bottom')

    plt.show()

# View dataframe
essay_score_dist(essay_df)
```



Section Summary

This essay score distribution approximates a standard bell curve, with the majority of scores clustered around 1, 2, and 3. Notably, the score of 3 is the most frequently assigned in this skewed distribution. This prevalence increases the likelihood of the models assigning a score of 3, even when the input data is imperfect. Consequently, the probability of the models correctly assigning a score increases. However, it also raises the potential for the models to incorrectly learn and overfit to the score of 3, potentially compromising the accuracy of score assignments for essays that warrant different scores.

Experiment Sections

Tokenizing step used in multiple expeiments.

```
# Tokenize the essays by applying preprocessing and then join tokens back to a single string
essay_df['preprocessed'] = essay_df['full_text'].apply(preprocess) # Apply preprocessing to each essay
essay_df['preprocessed_str'] = essay_df['preprocessed'].apply(lambda x: ' '.join(x)) # Convert list of wor

# Normalize scores
def min_max_normalization(score):
  """
    Normalize the score to a range between 0 and 1.

    Parameters:
    score (int): The original score of the essay.

    Returns:
    float: Normalized score.
    """
  return (score - 1) / (6-1)

essay_df['normalized_score'] = essay_df.apply(lambda row: min_max_normalization(row['score']), axis=1)

# Print the first few rows of the DataFrame
essay_df.head()
```

	essay_id	full_text	score	preprocessed	preprocessed_str	normalized_score
0	000d118	Many people have car where they live. The thin...	3	[many, people, car, live, thing, know, use, ca...	many people car live thing know use car alot t...	0.4
1	000fe60	I am a scientist at NASA that is discussing th...	3	[scientist, nasa, discussing, face, mars, expl...	scientist nasa discussing face mars explaining...	0.4
2	001ab80	People always wish they had the same technolog...	4	[people, always, wish, technology, seen, movie...	people always wish technology seen movies best...	0.6
3	001bdc0	We all heard about Venus, the planet without a...	4	[heard, venus, planet, without, almost, oxygen...	heard venus planet without almost oxygen earth...	0.6

Next steps: Generate code with `essay_df` View recommended plots

Experiment 1: TF-IDF Vector with Neural Net Model

Experiment 1 involves a basic approach using the TF-IDF vectorization combined with a neural network model. This represents a foundational, straightforward model utilizing default parameters, which should be effective in predicting essay grades.

Model Preparation

```
# Initialize the TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=768)  # Adjust max_features as needed

# Fit and transform the text data
X = tfidf_vectorizer.fit_transform(essay_df['preprocessed_str']).toarray()
```

```
# Set the seed for reproducibility
np.random.seed(42)

# Generate 5 random indices for data inspection
random_indices = np.random.choice(essay_df.index, size=1, replace=False) #change size to output as many es

# Print the full text and preprocessed text for each random row
# verify processing
for index in random_indices:
  print("Row Index:", index)
  print("Full Text:")
  print(essay_df.loc[index, 'full_text'])
  print("\nPreprocessed Text:")
  print(essay_df.loc[index, 'preprocessed'])
  print("\n" + "="*50 + "\n") # add a separator between rows for readability
```

```
Row Index: 1782
Full Text:
Car alarms, car horns, and engines are basically the only thing people hear nowadays. The number of ca

Citizens all around the world, we all should really try to limit the amount of time that we are spendi

If you really take a moment to think about it, this could honestly turn out to be a really good thing.

Cars are not neccisarily a need, they are a want. I can undertand if you are going to be traveling a f

Limiting car usage is very important. Most families tend to spend about about $20-50.00 on gas a week.

" "

When I had a car I was always tense. I'm much happier this way" " People who have decided to limit the

One advantage to limiting the use of cars is that the air would become much more fresh and clean, and

" "

Its a good oppertunity to take away stress and lower air pollution," said a busiinessman Carlos Arturo

Most people that have decided to stop using cars or have significantly limited their car usuage, have

If more people became aware that not spending so much time driving was a good thing, and simply limite

A former citizen has shared with us that one advantage to limiting car usgae for her is that her child

"... organized their summer jobs and social life around where they can walk or take public transportat

Driving your car is not intirely a bad thing, but simply limiting your car usage is a wonderfull thing

If you decide to park your car in the garage and put away the keys, you'd really be able to see how ni

Preprocessed Text:
['car', 'alarms', 'car', 'horns', 'engines', 'basically', 'thing', 'people', 'hear', 'nowadays', 'numb

==================================================
```

This step ensures the preprocessing is effective by visually comparing the original and the processed texts, which should reflect the expected transformation into a list of cleaned, lowercased strings, without numerical values and special characters.

```
# Prepare target labels
y = essay_df['score'].values

# One-hot encode the target labels
# The probability predictions need a map to the essay grade/score otherwise the
# neural net output is undetermined and doesn't make sense. This is needed for
# compatibility with the neural net.

# categorical data (score/grade)
## One-hot encode the target labels to map probability predictions to the essay grade/score
# Step 1: Convert grade to integer labels
label_encoder = LabelEncoder()
integer_encoded = label_encoder.fit_transform(y)

# Step 2: Reshape the data to be a 2D array as required by OneHotEncoder
integer_encoded = integer_encoded.reshape(-1, 1)

# Step 3: Apply OneHotEncoder to transform the integer encoded labels to one-hot encoded labels
onehot_encoder = OneHotEncoder(sparse=False)
y_one_hot_encoded = onehot_encoder.fit_transform(integer_encoded)

# Print the results
print("Original Categories:", y)
print("Integer Encoded:", integer_encoded.ravel())
print("One-Hot Encoded:\n", y_one_hot_encoded)
#.unique

# Split the data into training and testing sets, ensuring an 80-20 split with a fixed random state for rep
X_train, X_test, y_train, y_test = train_test_split(X, y_one_hot_encoded, test_size=0.2, random_state=42)
```

```
Original Categories: [3 3 4 ... 4 4 4]
Integer Encoded: [2 2 3 ... 3 3 3]
One-Hot Encoded:
 [[0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 ...
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]]
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse`
  warnings.warn(
```

```
# Build and compile the multiclass classification model
input_dim = X_train.shape[1] #number of features
#dimensionality of the vectors is specified [1] chooses which feature in the set


#Number of classes
num_classes = y_one_hot_encoded.shape[1] #number of classes


# Build and compile a simple Keras model for multiclass classification
#like specifying how each split decision is made in a decision tree
inputs = Input(shape=(input_dim,)) #input layer; shape 768 dimensions; setting up an empty framework
x = Dense(128, activation='relu')(inputs) # x=hidden layer; each input gets an additional hidden layer add
x = Dropout(0.5)(x)
x = Dense(64, activation='relu')(x)
x = Dropout(0.5)(x)
outputs = Dense(num_classes, activation='softmax')(x)  # Softmax activation for multiclass classification


model = Model(inputs=inputs, outputs=outputs)

#multiclass
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])


model.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_3 (InputLayer)        [(None, 768)]             0         
                                                                 
 dense_10 (Dense)            (None, 128)               98432     
                                                                 
 dropout_44 (Dropout)        (None, 128)               0         
                                                                 
 dense_11 (Dense)            (None, 64)                8256      
                                                                 
 dropout_45 (Dropout)        (None, 64)                0         
                                                                 
 dense_12 (Dense)            (None, 6)                 390       
                                                                 
=================================================================
Total params: 107,078
Trainable params: 107,078
Non-trainable params: 0
_________________________________________________________________
```

Model Training

```
# step 4: Build and Train the Neural Network
# Train the Keras model
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=50, batch_size=32, validati

# Predictions on training and test data
#predictions are probabilities of which class (grade) the essay will be placed in
y_train_pred = model.predict(X_train)
y_test_pred = model.predict(X_test)

#print (y_train_pred) #to view the output data
#print (y_test_pred)  #to view the output data
```

```
# Convert probabilities to class predictions
y_train_pred_classes = np.argmax(y_train_pred, axis=1)
y_test_pred_classes = np.argmax(y_test_pred, axis=1)

print(y_train_pred_classes)
print(y_test_pred_classes)
print(y)
print(y_one_hot_encoded)
```

```
[2 2 1 ... 2 1 1]
[2 2 0 ... 3 0 1]
[3 3 4 ... 4 4 4]
[[0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 ...
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]]
```

```
# Convert integer labels to original categories
predicted_categories_train = label_encoder.inverse_transform(y_train_pred_classes)
predicted_categories_test = label_encoder.inverse_transform(y_test_pred_classes)
print(predicted_categories_train)
print(predicted_categories_test)
```

```
[3 3 2 ... 3 2 2]
[3 3 1 ... 4 1 2]
```

```
# Calculate accuracy
train_accuracy = accuracy_score(np.argmax(y_train, axis=1), y_train_pred_classes)
test_accuracy = accuracy_score(np.argmax(y_test, axis=1), y_test_pred_classes)

print("Train Accuracy:", train_accuracy)
print("Test Accuracy:", test_accuracy)
```

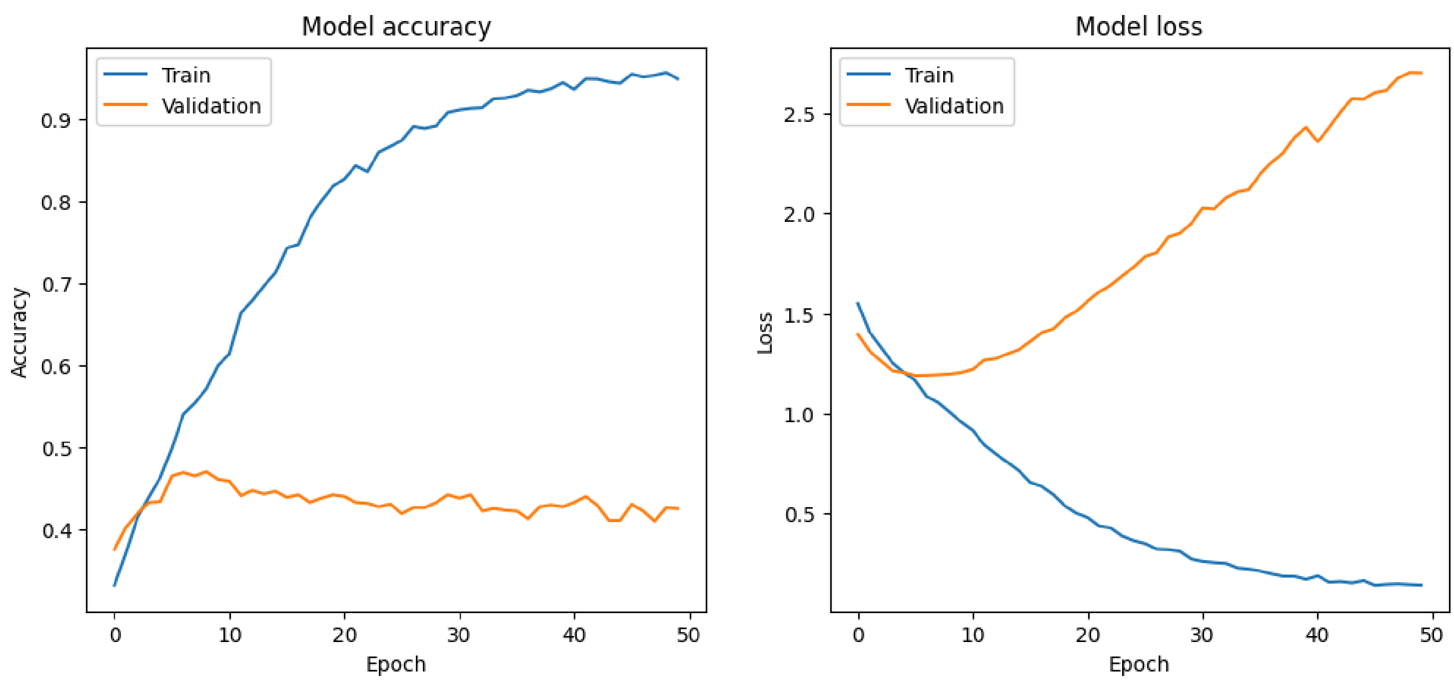
```
Train Accuracy: 0.8829166666666667
Test Accuracy: 0.4275
```

These results establish a solid baseline for model performance. The accuracy scores serve as a benchmark for comparing subsequent, more complex modeling approaches.

Final Evaluation

```
# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f'Test Loss: {test_loss}')
print(f'Test Accuracy: {test_accuracy}')

# Plot the training and validation accuracy/loss over epochs
plt.figure(figsize=(12, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.show()
```

```
38/38 [==============================] - 0s 3ms/step - loss: 2.8953 - accuracy: 0.4275
Test Loss: 2.8953473567962646
Test Accuracy: 0.42750000953674316
```



Section Summary

The observed data indicates inconsistency in model performance. Despite the accuracy graph not reaching high values, the loss graph demonstrates an optimal point with a minimal value. To address this, adding more layers and nodes may potentially enhance the model's performance.

An increasing loss over epochs without corresponding improvements in accuracy suggests the model may be overfitting. However, there is a segment of the loss curve with a downward trend, indicating potential for improvement. Exploring ways to extend this downward trend could help refine the model's effectiveness and reduce overfitting.

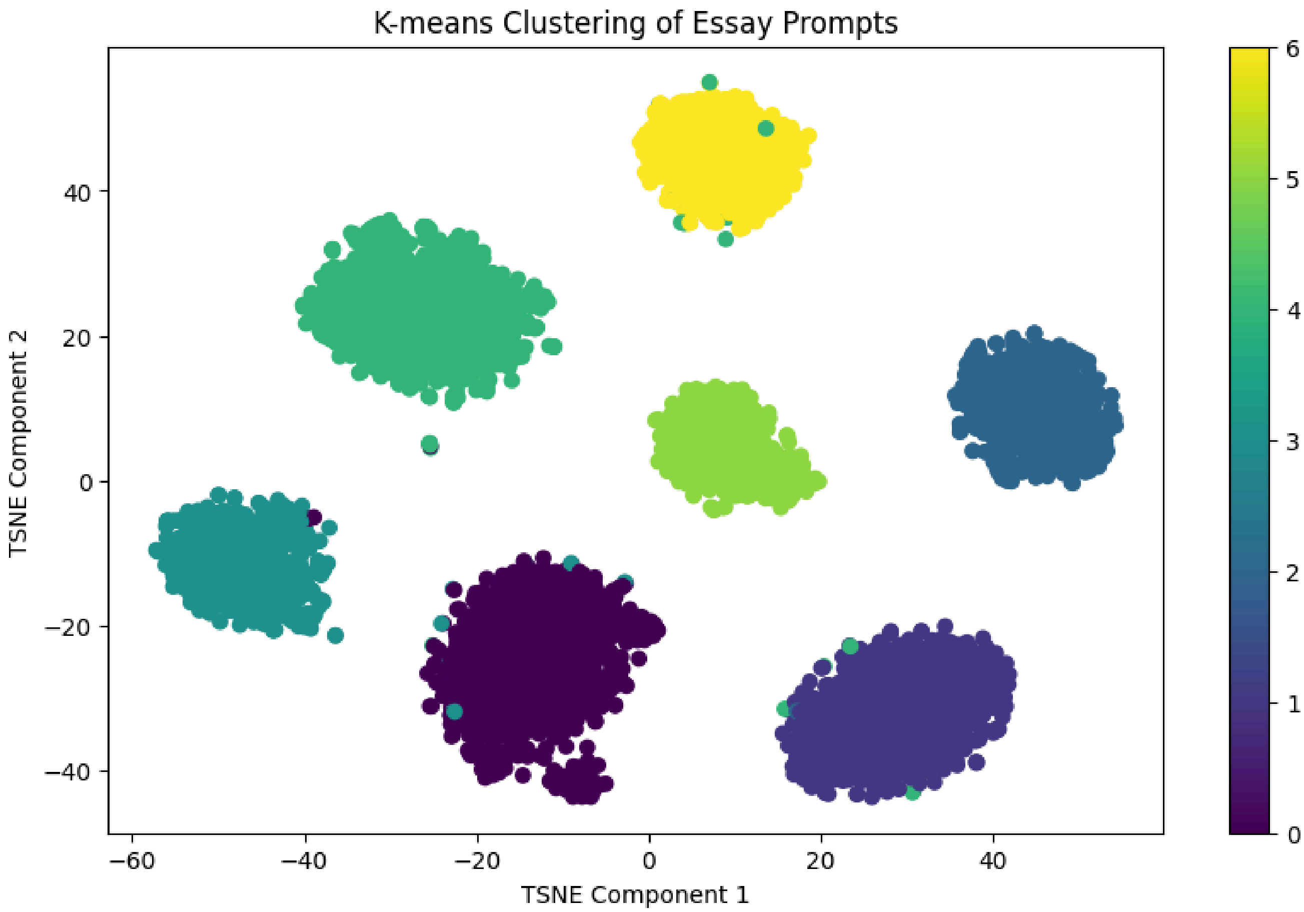
Experiment 2: TF-IDF Vector with K-Means Model

This model is designed to effectively predict clustering categories related to essay content, rather than directly assessing the grades of the essays.

Model Preparation

```
# Initialize the TF-IDF Vectorizer
tfidf_vectorizer = TfidfVectorizer(max_features=768)  # Adjust max_features as needed

# Fit and transform the text data to TF-IDF features
X = tfidf_vectorizer.fit_transform(essay_df['preprocessed_str']).toarray()

# Apply k-means clustering
num_clusters = 7 #specify the number of clusters
kmeans = KMeans(n_clusters=num_clusters, random_state=42)
essay_df['cluster'] = kmeans.fit_predict(X)

# Visualize the clusters using tsne for dimensionality reduction
tsne = TSNE(n_components=2, random_state=42)
X_tsne = tsne.fit_transform(X)

plt.figure(figsize=(10, 6))
scatter = plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=essay_df['cluster'], cmap='viridis')
plt.colorbar(scatter)
plt.title('K-means Clustering of Essay Prompts')
plt.xlabel('TSNE Component 1')
plt.ylabel('TSNE Component 2')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default valu
  warnings.warn(
```



In the visualization of the clustered essay assignments, some inconsistencies, referred to as 'noise', are observed which might explain a few instances of misclassification. Since the visualization involves reducing the dimensionality of vector data through techniques like t-SNE, certain artifacts might emerge that potentially influence the accuracy of the clustering. Notably, the visualization reveals a purple cluster that appears to be bifurcated into two closely situated subclusters. This phenomenon might suggest the essays within this cluster address a topic that inherently presents a dichotomy, such as an issue with distinct 'agree' or 'disagree' positions, thereby causing a natural division within the cluster.

The max_features parameter represents the upper limit of words considered in the corpus, focusing on the most impactful terms. Systematic optimization for determining this parameter could be explored further. Additionally, clustering by essay prompts has been empirically set to 7 from an initial 5 clusters. Future work might involve more systematic methods to optimize the number of clusters for better model performance.

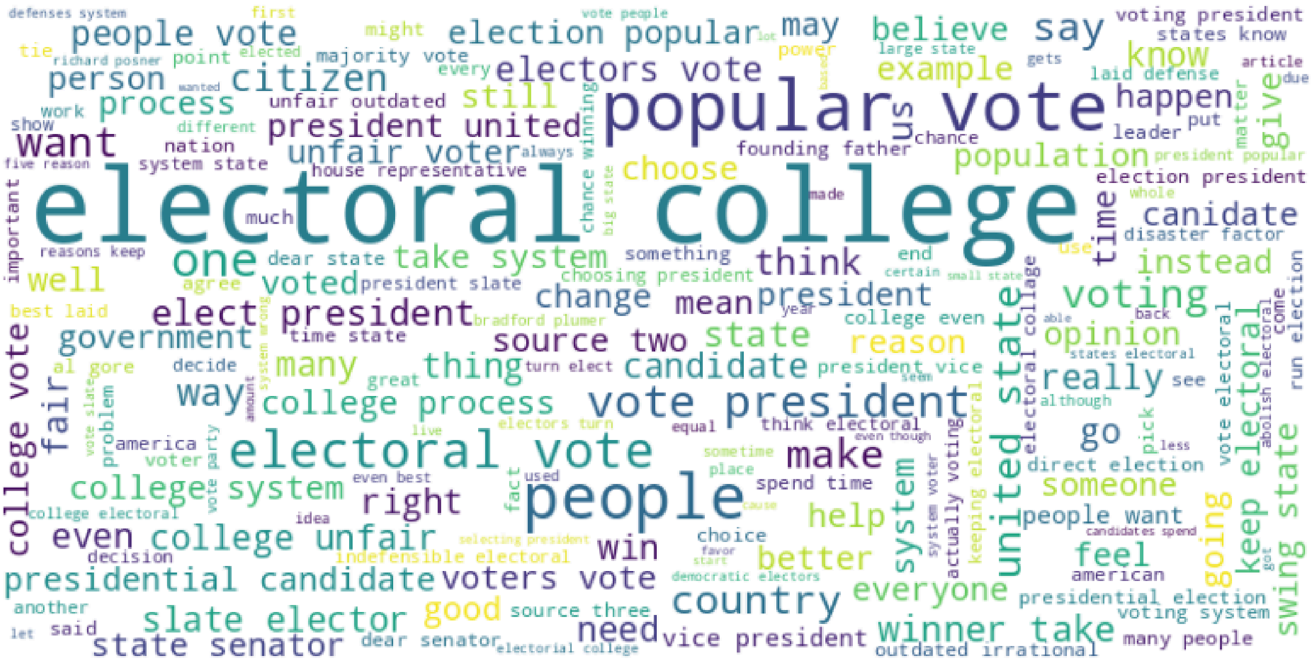
```python
def generate_word_cloud(text, num_cluster):
    """
    Generates and displays a word cloud for a given text and cluster number.

    Args:
        text (str): The input text to generate the word cloud from.
        num_cluster (int): The cluster number for which the word cloud is generated.

    Returns:
        None
    """
    wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')
    plt.title('Topic: {}'.format(num_cluster +1))
    plt.show()

def generate_bar_plot(text, num_cluster):
    """
    Generates and displays a bar plot of the top 5 most common words in a given text and cluster number.

    Args:
        text (str): The input text to generate the bar plot from.
        num_cluster (int): The cluster number for which the bar plot is generated.

    Returns:
        None
    """
    # Preprocess the text to remove non-alphabetic characters and convert to lower case
    words = re.findall(r'\b\w+\b', text.lower())

    # Count the frequency of each word
    word_counts = Counter(words)

    # Get the 5 most common words and their frequencies
    most_common_words = word_counts.most_common(5)

    # Separate the words and their frequencies for plotting
    words, frequencies = zip(*most_common_words)

    # Get colors from colormap
    #colors = [cmap(i / len(words)) for i in range(len(words))]

    # Get colors from colormap
    colors = cmap(num_cluster/6)

    # Create the bar plot
    plt.figure(figsize=(10, 5))
    bars = plt.bar(words, frequencies, color=colors)

    # Add title and labels
    plt.title('Top 5 Words in Topic: {}'.format(num_cluster +1), fontsize=15)
    plt.xlabel('Words', labelpad=15, fontsize=15)
    plt.ylabel('Frequency', labelpad=15, fontsize=15)

    # Show the counts on top of the bars
    for bar in bars:
        yval = bar.get_height()
        plt.text(bar.get_x() + bar.get_width()/2, yval + 0.1, int(yval), ha='center', va='bottom')

    # Display the plot
    plt.show()
```

The previous functions generate visualizations to analyze the content of clustered essay assignments. The generate_word_cloud function creates a word cloud to visually represent the most frequent words in a given cluster. The generate_bar_plot function generates a bar plot to display the top five most common words and their frequencies within a cluster. These visualizations help identify predominant topics and terms in each cluster.

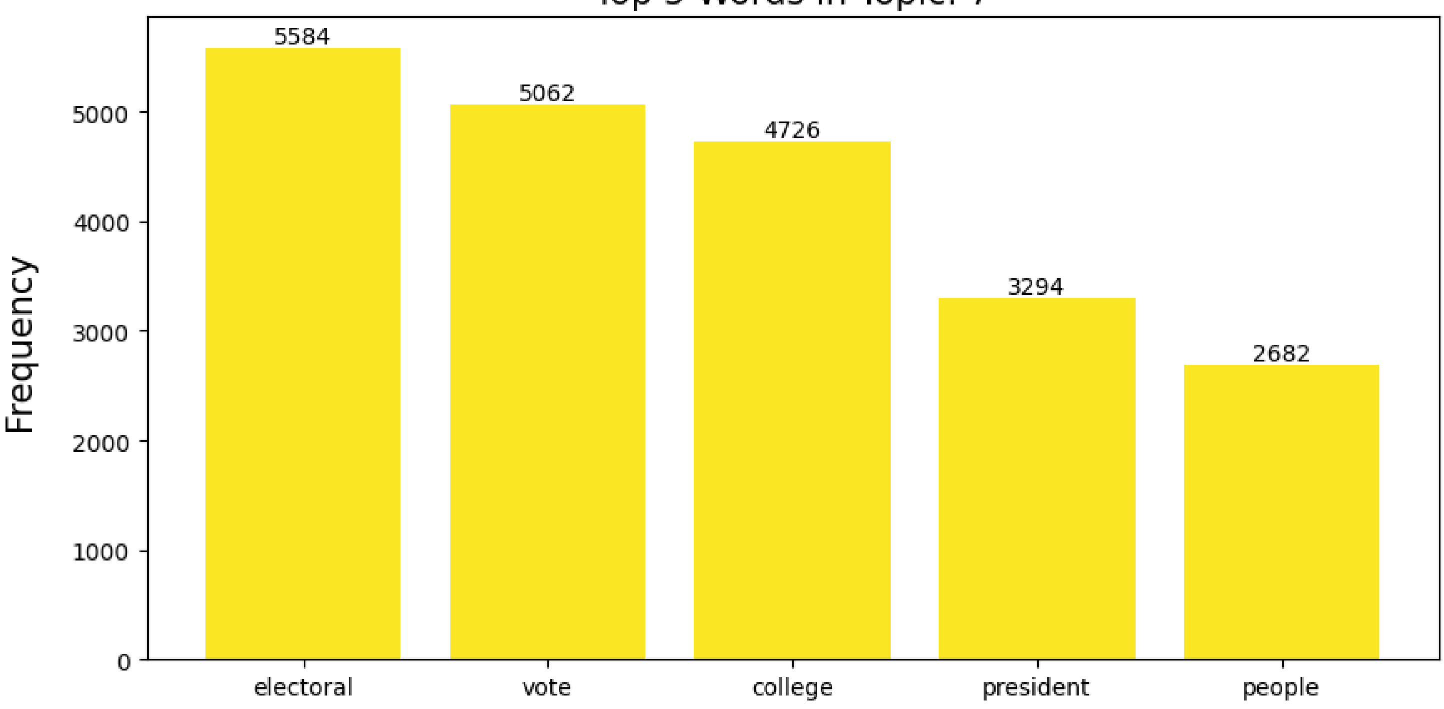
```
essay_df['cluster']

for i in range (num_clusters):
 cluster_lists = ' '.join(essay_df[essay_df['cluster'] == i]['preprocessed_str'])
# Generate and display the word cloud
 generate_word_cloud(cluster_lists, i)
# Generate a ranked bar plot of words
 generate_bar_plot(cluster_lists, i)
```

Words

Topic: 7



Top 5 Words in Topic: 7



Words

The bar charts revealed the most probable essay question topic prompts based on term frequency. These are as follows:

Topic 1: *This essay prompt might ask students to discuss the impact of driverless cars on society.*
Topic 2: *This essay prompt could be a comparative analysis of Venus and Earth.*
Topic 3: *This essay prompt could be asking students to analyze different aspects of Mars exploration.*
Topic 4: *This essay prompt could ask students to consider the impact of car usage on society and the environment.*
Topic 5: *This essay prompt may be asking about the role of technology in helping students manage emotions.*
Topic 6: *This essay prompt may ask students to analyze the interplay of seagoing adventures and western cowboy culture in literature and media.*
Topic 7: *This essay topic perhaps asks students to explore the Electoral College and its impact on presidential elections.*

Now, at this stage, it is smart to spot-check the data that will be utilized for neural network training. This involves verifying the preprocessing steps by comparing the full text of the essays with their preprocessed versions. The goal is to ensure that the preprocessing has been performed correctly and the preprocessed text is a list of strings, as expected.

```
# Set the seed for reproducibility
np.random.seed(42)

# Generate 5 random indices for data inspection
random_indices = np.random.choice(essay_df.index, size=1, replace=False) #change size to output as many es

# Print the full text and preprocessed text for each randomly selected essay
for index in random_indices:
    print("Row Index:", index) # Print the index of the essay
    print("Full Text:") # Print the label for the full text
    print(essay_df.loc[index, 'full_text']) # Print the full text of the essay
    print("\nPreprocessed Text:") # Print the label for the preprocessed text
    print(essay_df.loc[index, 'preprocessed']) # Print the preprocessed text of the essay
    print("\nTopic:", essay_df.loc[index, 'cluster'])
    print("\n" + "=" * 50 + "\n")  # add a separator between rows
```

```
Row Index: 1782
Full Text:
Car alarms, car horns, and engines are basically the only thing people hear nowadays. The number of ca

Citizens all around the world, we all should really try to limit the amount of time that we are spendi

If you really take a moment to think about it, this could honestly turn out to be a really good thing.

Cars are not neccisarily a need, they are a want. I can undertand if you are going to be traveling a f
```

```
Limiting car usage is very important. Most families tend to spend about about $20-50.00 on gas a week.

" "

When I had a car I was always tense. I'm much happier this way" " People who have decided to limit the

One advantage to limiting the use of cars is that the air would become much more fresh and clean, and i

" "

Its a good oppertunity to take away stress and lower air pollution," said a busiinessman Carlos Arturo

Most people that have decided to stop using cars or have significantly limited their car usuage, have r

If more people became aware that not spending so much time driving was a good thing, and simply limited

A former citizen has shared with us that one advantage to limiting car usgae for her is that her childr

"... organized their summer jobs and social life around where they can walk or take public transportati

Driving your car is not intirely a bad thing, but simply limiting your car usage is a wonderfull thing,

If you decide to park your car in the garage and put away the keys, you'd really be able to see how nic

Preprocessed Text:
['car', 'alarms', 'car', 'horns', 'engines', 'basically', 'thing', 'people', 'hear', 'nowadays', 'numbe

Topic: 3

==================================================
```

One-hot encoding the target labels is necessary because the output is categorical. Probability predictions require a mapping to the essay grade/score; otherwise, the neural network output is ambiguous and can lead to incorrect data.

```
# Prepare target labels
y = essay_df['score'].values

# categorical data (score/grade)
## One-hot encode the target labels to map probability predictions to the essay grade/score
# Step 1: Convert grade to integer labels
label_encoder = LabelEncoder()
integer_encoded = label_encoder.fit_transform(y)

# Step 2: Reshape the data to be a 2D array as required by OneHotEncoder
integer_encoded = integer_encoded.reshape(-1, 1)

# Step 3: Apply OneHotEncoder to transform the integer encoded labels to one-hot encoded labels
onehot_encoder = OneHotEncoder(sparse=False)
y_one_hot_encoded = onehot_encoder.fit_transform(integer_encoded)

# Print the results
print("Original Categories:", y)
print("Integer Encoded:", integer_encoded.ravel())
print("One-Hot Encoded:\n", y_one_hot_encoded)
#.unique

# Split the data into training and testing sets, ensuring an 80-20 split with a fixed random state for rep
X_train, X_test, y_train, y_test = train_test_split(X, y_one_hot_encoded, test_size=0.2, random_state=42)
```

```
Original Categories: [3 3 4 ... 4 4 4]
Integer Encoded: [2 2 3 ... 3 3 3]
One-Hot Encoded:
 [[0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
```

```
 ...
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0. 0.]]
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse`
  warnings.warn(
```

Keras Tuner's RandomSearch (explores different hyperparameters randomly until it finds the optimal set, which is useful because doesn't get stcuk in local minimums where other algorithms can), BayesianOptimization (seeks the best parameters similar to gradient descent), and Hyperband are search methods to find the optimal hyperparameters.
When determining the optimal hyperparameters for a neural network, consider the impact of the number of hidden layers, the number of units in each layer, the dropout rates, and the optimizer used. These hyperparameters can significantly influence the model's performance, including its ability to generalize without overfitting or underfitting.

This notebook uses the following approach to accomplish this:
1. Extraction: Extract the number of layers, units per layer, dropout rates per layer, and the optimizer used from the best hyperparameters.
2. Informative Print Statements: Provide insights into the optimal architecture found by the tuner.
3. Retraining: Retrains the model with the best hyperparameters to see the final performance, which is useful for verification purposes.

This neural network model fine-tunes the number of layers based on the best hyperparameters determined from Bayesian optimization.

```python
# Number of classes
num_classes = y_one_hot_encoded.shape[1]  # number of classes

def build_model(hp):
    """
    Build and compile a Keras model with hyperparameters.

    Parameters:
    hp : keras_tuner.HyperParameters
        Hyperparameters object for tuning.

    Returns:
    model : tensorflow.keras.Model
        Compiled Keras model.
    """
    model = Sequential()
    # Input layer with variable units
    model.add(Dense(units=hp.Int('units_input', min_value=32, max_value=1024, step=16),
                    activation='relu', input_shape=(X_train.shape[1],)))
    model.add(Dropout(hp.Float('dropout_input', min_value=0.2, max_value=0.5, step=0.1)))

    # Variable number of hidden layers
    for i in range(hp.Int('num_layers', 1, 3)):
        model.add(Dense(units=hp.Int(f'units_{i}', min_value=32, max_value=1024, step=16),
                        activation='relu'))
        model.add(Dropout(hp.Float(f'dropout_{i}', min_value=0.2, max_value=0.5, step=0.1)))

    # Output layer with softmax activation for multiclass classification
    model.add(Dense(num_classes, activation='softmax'))

    # Compile model with selected optimizer
    model.compile(optimizer=hp.Choice('optimizer', ['adam', 'rmsprop', 'sgd']),
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    return model

# Using Bayesian Optimization for hyperparameter tuning
tuner = kt.BayesianOptimization(
    hypermodel=build_model,
    objective='val_accuracy',
    max_trials=10,
    num_initial_points=None,
    alpha=0.0001,
    beta=2.6,
    seed=42,
    hyperparameters=None,
    tune_new_entries=True,
    allow_new_entries=True,
    max_retries_per_trial=0,
    max_consecutive_failed_trials=3
)

# Search for the best hyperparameters
tuner.search(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

# Retrieve the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]

# Gather details about the best hyperparameters
num_layers = best_hps.get('num_layers')
layer_units = [best_hps.get(f'units_{i}') for i in range(num_layers)]
dropout_rates = [best_hps.get(f'dropout_{i}') for i in range(num_layers)]
optimizer = best_hps.get('optimizer')
```

```
print(f"""
The hyperparameter search is complete. The optimal hyperparameters are:
- Units in the input layer: {best_hps.get('units_input')}
- Number of hidden layers: {num_layers}
- Dropout rate for input layer: {best_hps.get('dropout_input')}
- Optimizer: {optimizer}
""")

for i in range(num_layers):
    print(f"""
    Hidden Layer {i + 1}:
    - Units: {layer_units[i]}
    - Dropout rate: {dropout_rates[i]}
    """)
# step 4: Build the model with the best hyperparameters and train it
# Retrain the model with the best hyperparameters
model = tuner.hypermodel.build(best_hps)
history = model.fit(X_train, y_train, epochs=100, validation_data=(X_test, y_test), batch_size=32, validat
```

```
Reloading Tuner from ./untitled_project/tuner0.json

The hyperparameter search is complete. The optimal hyperparameters are:
- Units in the input layer: 576
- Number of hidden layers: 2
- Dropout rate for input layer: 0.2
- Optimizer: rmsprop


    Hidden Layer 1:
    - Units: 272
    - Dropout rate: 0.4


    Hidden Layer 2:
    - Units: 944
    - Dropout rate: 0.2
```

Model Training

```
# Calculate accuracy
train_accuracy = model.evaluate(X_train, y_train)
print(f'Train Accuracy: {train_accuracy}')
test_accuracy = model.evaluate(X_test, y_test)
print(f'Test Accuracy: {test_accuracy}')
```

```
150/150 [==============================] - 1s 5ms/step - loss: 2.5803 - accuracy: 0.8825
Train Accuracy: [2.5803444385528564, 0.8824999928474426]
38/38 [==============================] - 0s 5ms/step - loss: 14.6321 - accuracy: 0.4050
Test Accuracy: [14.632088661193848, 0.4050000011920929]
```

The training accuracy score is significantly higher than the testing accuracy score, indicating that the model is overfitting. This means the model is memorizing the training data rather than generalizing well to unseen data.

Several strategies could potentially reduce overfitting:

1. Tweaking the model parameters (reducing the number of epochs, adjusting the optimizer, etc.).

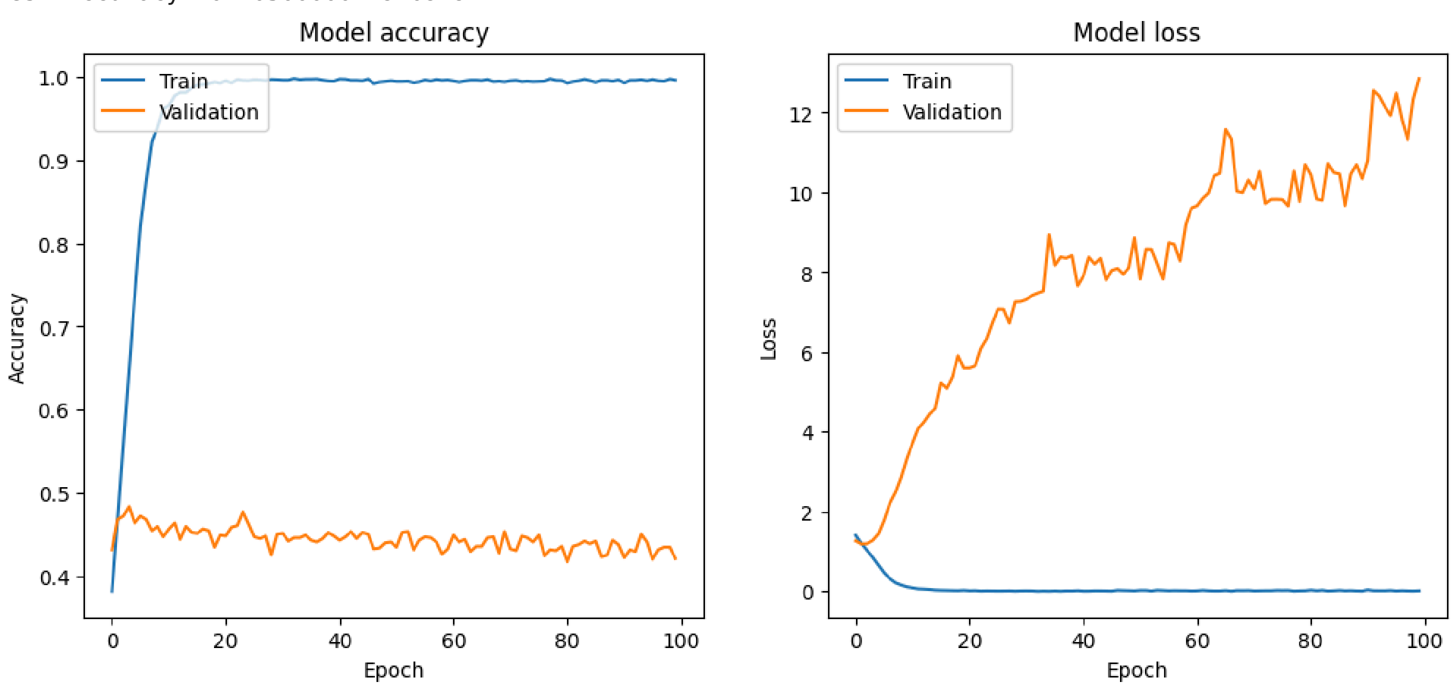
2. Experimenting with adding more layers or increasing the dimensions might help mitigate overfitting.

3. Utilizing deeper learning architectures with potentially hundreds of layers could be explored.

Final Evaluation

```
# Evaluate the model on the test set
test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f'Test Loss: {test_loss}')
print(f'Test Accuracy: {test_accuracy}')

# Plot the training and validation accuracy/loss over epochs
plt.figure(figsize=(12, 5))

# Plot training & validation accuracy values
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.show()
```

```
38/38 [==============================] - 0s 5ms/step - loss: 14.6321 - accuracy: 0.4050
Test Loss: 14.632088661193848
Test Accuracy: 0.4050000011920929
```



Section Summary

These graphs are the main take away of the training process. The validation scores are pretty flat. That correlates with the increase in validation on loss graph basically saying that the training isn't making it any better and so the 'loss' of resources continues to increase.

A potential improvement could be to attepmt a different vectorization technique that could encode more information from each essay.

Test Accuracy = Validation

Experiment 3: BERT Vector and Model

This model should improve grade prediction accuracy compared to previous models. High accuracy scores can be challenging to achieve but this experiment will nevertheless serve as a good comparison between models. Given the complexity of the data, BERT is expected to provide better vector representations than TF-IDF. The comparison between these vectorizers will help us understand their effectiveness.

Model Preparation

Here a Bert Tokenizer is used. The Bert (Bidirectional Encoder Representations from Transformers) is a pre-trained transformer-based model for natural language understanding tasks, trained on large amounts of text data.

Transformer-based models (like BERT), can capture intricate nuances in language usage, context, and semantics. BERT excels in understanding the relationships between different parts of the text and can provide nuanced assessments aligned with the criteria of the rubric. Additionally, the bidirectional nature allows BERT to consider the entire context of the essay when making scoring decisions.

```
# Load BERT tokenizer and model
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
bert_model = TFBertModel.from_pretrained('bert-base-uncased')

def bert_vectorizer(text):
    """
    Vectorizes input text using BERT model.

    Parameters:
    text : str
        The input text to be vectorized.

    Returns:
    np.ndarray
        The BERT vector representation of the input text.
    """
    inputs = tokenizer(text, return_tensors='tf', truncation=True, padding=True)
    outputs = bert_model(inputs)
    return tf.reduce_mean(outputs.last_hidden_state, axis=1).numpy().squeeze()
```

```
Some layers from the model checkpoint at bert-base-uncased were not used when initializing TFBertModel:
- This IS expected if you are initializing TFBertModel from the checkpoint of a model trained on anothe
- This IS NOT expected if you are initializing TFBertModel from the checkpoint of a model that you expe
All the layers of TFBertModel were initialized from the model checkpoint at bert-base-uncased.
If your task is similar to the task the model of the checkpoint was trained on, you can already use TFE
```

The above message is informational and does not indicate an error. Since I will be fine-tuning, I'll ignore and continue.

```
# just the first 2000 rows from the data: due to size of RAM needed
#this is where the shared and BERT data frame split
essay_df_BERT = essay_df.iloc[:2000]

# Apply BERT vectorization to the DataFrame
essay_df_BERT['bert_embeddings'] = essay_df_BERT['preprocessed_str'].apply(bert_vectorizer)
```

```
<ipython-input-65-837411ab93d9>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.
  essay_df_BERT['bert_embeddings'] = essay_df_BERT['preprocessed_str'].apply(bert_vectorizer)
```

```
# View data frame
essay_df.head()
```

	essay_id	full_text	score	preprocessed	preprocessed_str	normalized_score	cluster
0	000d118	Many people have car where they live. The thin...	3	[many, people, car, live, thing, know, use, ca...	many people car live thing know use car alot t...	0.4	3
1	000fe60	I am a scientist at NASA that is discussing th...	3	[scientist, nasa, discussing, face, mars, expl...	scientist nasa discussing face mars explaining...	0.4	2
2	001ab80	People always wish they had the same technolog...	4	[people, always, wish, technology, seen, movie...	people always wish technology seen movies best...	0.6	0
3	001bdc0	We all heard about Venus, the planet without a...	4	[heard, venus, planet, without, almost, oxygen...	heard venus planet without almost oxygen earth...	0.6	1

Next steps: Generate code with `essay_df` View recommended plots

Code check, the verification of the BERT embedding for the first essay will be performed. The preprocessing output will be compared with the BERT embedding data to ensure they meet the expected criteria. Specifically, the BERT output dimensions will be checked to confirm they are 768-dimensional vectors, as anticipated.

```
# Print the full content of the 'bert_embeddings' column for the first row
bert_embeddings = essay_df_BERT.loc[0, 'bert_embeddings']
#print(bert_embeddings) #this code can be uncommented to check the BERT encodings
print(len(bert_embeddings))
```

```
768
```

looks good - one vector with 768 dimensions. This is what the function was expected to output.

```
# Set the seed for reproducibility
np.random.seed(42)

# Generate 5 random indices for data inspection
random_indices = np.random.choice(essay_df_BERT.index, size=1, replace=False) #change size to output as ma

# Print the full text and preprocessed text for each randomly selected essay
for index in random_indices:
  print("Row Index:", index) # Print the index of the essay
  print("Full Text:") # Print the label for the full text
  print(essay_df_BERT.loc[index, 'full_text']) # Print the full text of the essay
  print("\nPreprocessed Text:") # Print the label for the preprocessed text
  print(essay_df_BERT.loc[index, 'preprocessed']) # Print the preprocessed text of the essay
  print("\n" + "="*50 + "\n") # add a separator between rows
```

```
Row Index: 1860
Full Text:
Many people have different opinions about what happens on the planet Mars. During a recent discovery ma

On May 24th NASA's Viking 1 spacecraft was on Mars. The spacecraft was going about it's regular missio

While many people do have different opinions about certain things, sometimes those opinions can chhang

Preprocessed Text:
['many', 'people', 'different', 'opinions', 'happens', 'planet', 'mars', 'recent', 'discovery', 'many',

==================================================
```

This verification includes a check to ensure that the preprocessing worked correctly. The full text of the essays is compared with the preprocessed text to confirm that the preprocessing has produced the expected list of strings.

```
# Prepare the data for Keras model
X = np.stack(essay_df_BERT['bert_embeddings'].values)
y = essay_df_BERT['score'].values

# categorical data (score/grade)
## One-hot encode the target labels to map probability predictions to the essay grade/score
# Step 1: Convert grade to integer labels
label_encoder = LabelEncoder()
integer_encoded = label_encoder.fit_transform(y)

# Step 2: Reshape the data to be a 2D array as required by OneHotEncoder
integer_encoded = integer_encoded.reshape(-1, 1)

# Step 3: Apply OneHotEncoder to transform the integer encoded labels to one-hot encoded labels
onehot_encoder = OneHotEncoder(sparse=False)
y_one_hot_encoded = onehot_encoder.fit_transform(integer_encoded)

# Print the results
print("Original Categories:", y)
print("Integer Encoded:", integer_encoded.ravel())
print("One-Hot Encoded:\n", y_one_hot_encoded)
#.unique

# Split the data into training and testing sets, ensuring an 80-20 split with a fixed random state for rep
X_train, X_test, y_train, y_test = train_test_split(X, y_one_hot_encoded, test_size=0.2, random_state=42)
```

```
Original Categories: [3 3 4 ... 4 2 3]
Integer Encoded: [2 2 3 ... 3 1 2]
One-Hot Encoded:
 [[0. 0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0.]
```