Bonus_Lab3_Intro_Transformer

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```r
library(reticulate)
```

```
Warning: package 'reticulate' was built under R version 4.4.2
```

```r
use_condaenv("r-tensorflow", required = TRUE)
```

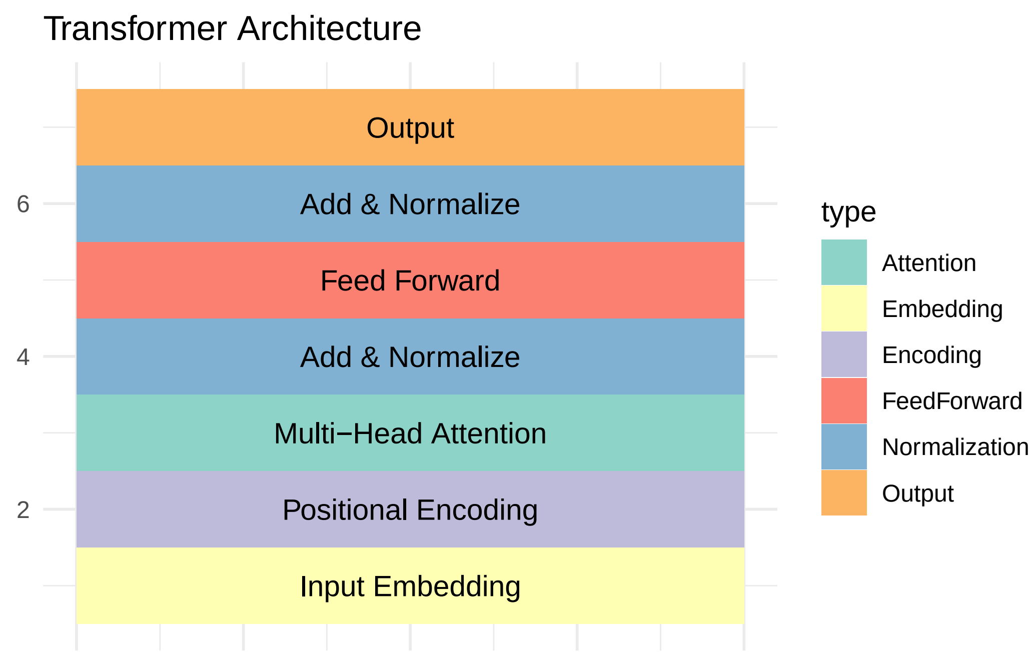
2.1 Exercise 1: Understanding the Transformer Architecture in R

```r
library(keras)
library(tensorflow)
library(tidyverse)
```

```
Warning: package 'tidyverse' was built under R version 4.4.2
```

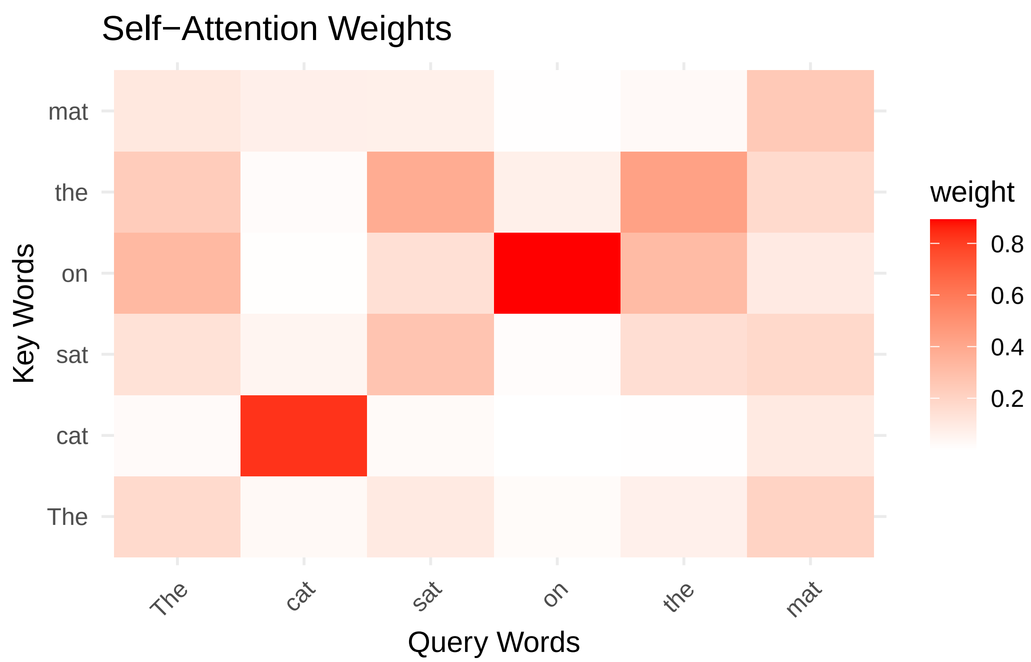
```
-- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
v dplyr     1.1.4     v readr     2.1.5
v forcats   1.0.0     v stringr   1.5.1
v ggplot2   3.5.1     v tibble    3.2.1
v lubridate 1.9.3     v tidyr     1.3.1
v purrr     1.0.2
-- Conflicts ------------------------------------------ tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
x dplyr::lag()    masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to becom
```

```r
# Function to visualize transformer architecture
plot_transformer_architecture <- function() {
  # Create data for visualization
  architecture_data <- tibble(
    component = c("Input Embedding", "Positional Encoding",
                  "Multi-Head Attention", "Add & Normalize",
                  "Feed Forward", "Add & Normalize",
                  "Output"),
    level = 1:7,
    type = c("Embedding", "Encoding", "Attention", "Normalization",
             "FeedForward", "Normalization", "Output")
  )

  # Plot the transformer architecture
  ggplot(architecture_data, aes(x = 1, y = level, fill = type)) +
    geom_tile(width = 0.8) +
    geom_text(aes(label = component)) +
    theme_minimal() +
    theme(axis.text.x = element_blank(),
          axis.title = element_blank()) +
    scale_fill_brewer(palette = "Set3") +
    labs(title = "Transformer Architecture")
}

# Call the function to plot
plot_transformer_architecture()
```




```r
# Add necessary libraries
library(keras)
library(tensorflow)

# Define softmax function if not using keras/tensorflow version
manual_softmax <- function(x) {
  exp_x <- exp(x - max(x))  # Subtract max for numerical stability
  exp_x / sum(exp_x)
}

# Modified calculate_attention function with proper softmax
calculate_attention <- function(query, key, value) {
  # Scaled dot-product attention
  attention_scores <- query %*% t(key) / sqrt(ncol(key))

  # Option 1: Using manual softmax
  attention_weights <- t(apply(attention_scores, 1, manual_softmax))

  # Option 2: Alternative using tensorflow if you prefer
  # attention_weights <- tf$nn$softmax(attention_scores)$numpy()

  # Compute attention output
  attention_output <- attention_weights %*% value
```

```r
  # Return attention scores, weights, and output
  list(
    scores = attention_scores,
    weights = attention_weights,
    output = attention_output
  )
}

# Example usage
text <- "The cat sat on the mat"
words <- strsplit(text, " ")[[1]]

# Create simple embeddings for demonstration
word_vectors <- matrix(rnorm(length(words) * 4),
                       nrow = length(words),
                       ncol = 4)

# Calculate attention result
attention_result <- calculate_attention(word_vectors, word_vectors, word_vectors)

# Visualization remains the same
plot_attention_matrix <- function(attention_weights, words) {
  attention_df <- expand.grid(
    word1 = factor(words, levels = words),
    word2 = factor(words, levels = words)
  )
  attention_df$weight <- as.vector(attention_weights)

  ggplot(attention_df, aes(x = word1, y = word2, fill = weight)) +
    geom_tile() +
    scale_fill_gradient(low = "white", high = "red") +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    labs(title = "Self-Attention Weights",
         x = "Query Words",
         y = "Key Words")
}

# Plot the attention matrix
plot_attention_matrix(attention_result$weights, words)
```



2.3 Exercise 1: Using Hugging Face Transformers in R

```r
library(keras)
library(tensorflow)
library(reticulate)
library(tidyverse)
library(gridExtra)
```

```
Warning: package 'gridExtra' was built under R version 4.4.2


Attaching package: 'gridExtra'

The following object is masked from 'package:dplyr':

    combine
```

```r
# Import necessary libraries
library(reticulate)
library(ggplot2)
library(gridExtra)

# Import transformers library (Python package)
transformers <- reticulate::import("transformers")

# Define the modified inspection function with safer tensor handling
inspect_attention_weights <- function(text) {
  # Initialize tokenizer and model
  tokenizer <- transformers$BertTokenizer$from_pretrained('bert-base-uncased')
  model <- transformers$TFBertModel$from_pretrained('bert-base-uncased')

  # Tokenize the input text
  inputs <- tokenizer$encode_plus(
    text,
    return_tensors = "tf",
    add_special_tokens = TRUE,
    return_attention_mask = TRUE
  )

  # Convert inputs to tensorflow tensors explicitly
  input_ids <- inputs$input_ids
  attention_mask <- inputs$attention_mask

  # Get model outputs
  outputs <- model(
    list(
      input_ids = input_ids,
      attention_mask = attention_mask
    ),
    output_attentions = TRUE
  )

  # Safely convert attention weights to R
  attention_weights <- lapply(outputs$attentions, function(x) {
    # Convert TensorFlow tensor to numpy array, then to R array
    as.array(x$numpy())
  })

  # Print structure information
```

```r
  cat("Number of layers:", length(attention_weights), "\n")
  cat("Shape of attention weights for first layer:\n")
  print(dim(attention_weights[[1]]))

  # Get tokens
  tokens <- tokenizer$convert_ids_to_tokens(input_ids[1,])
  cat("\nTokens:\n")
  print(tokens)

  return(list(
    attention_weights = attention_weights,
    tokens = tokens
  ))
}

# Define the modified visualization function for a single layer's attention
plot_single_layer_attention <- function(result, layer_num) {
  # Get attention weights and tokens
  attention_weights <- result$attention_weights
  tokens <- result$tokens

  # Get attention weights for the specific layer
  layer_attention <- attention_weights[[layer_num]]

  # Average across attention heads
  avg_attention <- apply(layer_attention[1,,,], c(2,3), mean)

  # Create data frame for plotting
  attention_df <- expand.grid(
    token1 = factor(tokens, levels = tokens),
    token2 = factor(tokens, levels = tokens)
  )
  attention_df$weight <- as.vector(avg_attention)

  # Create plot
  ggplot(attention_df, aes(x = token1, y = token2, fill = weight)) +
    geom_tile() +
    scale_fill_gradient(low = "white", high = "red") +
    theme_minimal() +
    theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
    labs(title = paste("Layer", layer_num, "Attention"),
         x = "Token",
```

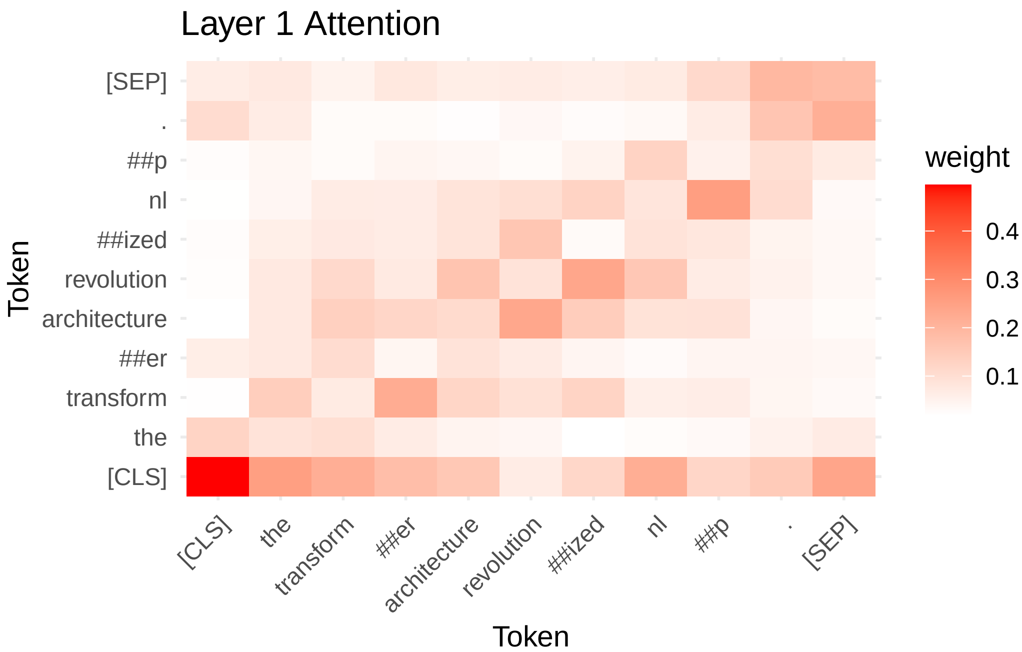
```
        y = "Token")
}

# Full visualization function for BERT's attention across all layers
visualize_bert_attention <- function(text) {
  # Get attention weights and tokens
  result <- inspect_attention_weights(text)
  attention_weights <- result$attention_weights
  tokens <- result$tokens

  # Create plots for each layer
  plots <- list()
  for(layer in seq_along(attention_weights)) {
    # Average attention weights across heads for this layer
    layer_attention <- attention_weights[[layer]]
    avg_attention <- apply(layer_attention[1,,,], c(2,3), mean)

    # Create data frame for plotting
    attention_df <- expand.grid(
      token1 = factor(tokens, levels = tokens),
      token2 = factor(tokens, levels = tokens)
    )
    attention_df$weight <- as.vector(avg_attention)

    # Create plot
    p <- ggplot(attention_df, aes(x = token1, y = token2, fill = weight)) +
      geom_tile() +
      scale_fill_gradient(low = "white", high = "red") +
      theme_minimal() +
      theme(axis.text.x = element_text(angle = 45, hjust = 1),
            axis.text.y = element_text(angle = 0)) +
      labs(title = paste("Layer", layer, "Attention"),
           x = "Token",
           y = "Token") +
      coord_fixed()

    # Add the plot to the list of plots
    plots[[layer]] <- p
  }

  # Arrange plots in a grid and display
  do.call(grid.arrange, c(plots, ncol = 3))
```

```r
}

# Example text for inspection and visualization
texts <- c(
  "The transformer architecture revolutionized NLP.",
  "Attention mechanisms help models focus on relevant parts.",
  "BERT learns contextual word representations."
)

# Try the inspection first with one text
result <- inspect_attention_weights(texts[1])
```

```
Number of layers: 12
Shape of attention weights for first layer:
[1]  1 12 11 11

Tokens:
 [1] "[CLS]"         "the"           "transform"     "##er"          "architecture"
 [6] "revolution"    "##ized"        "nl"            "##p"           "."
[11] "[SEP]"
```

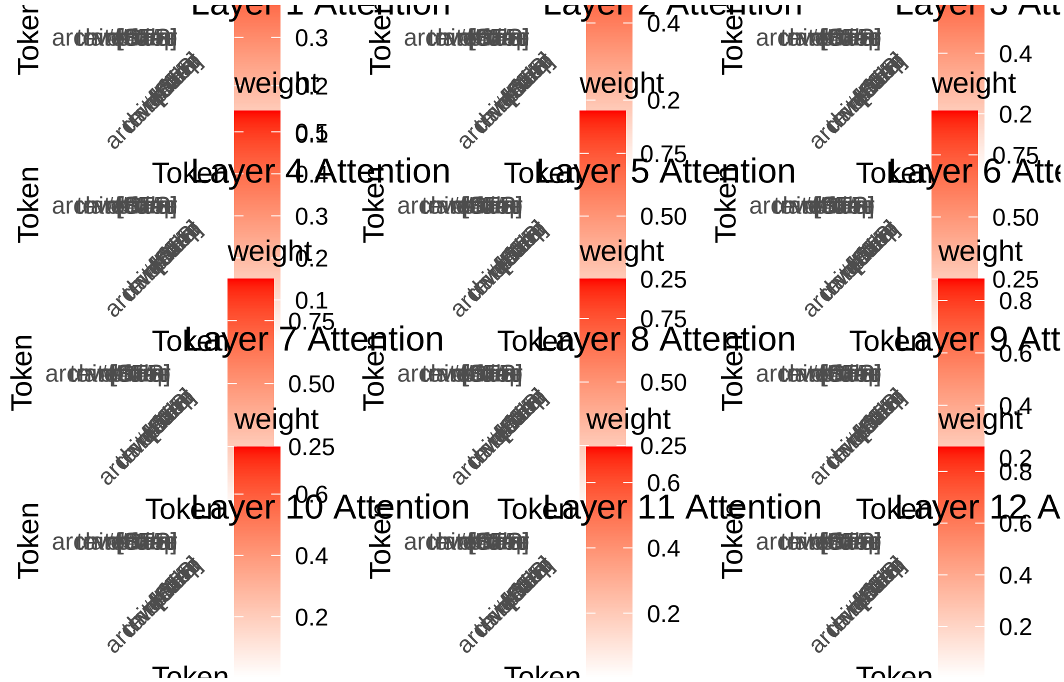
Plotting a single laye

```r
# Try plotting a single layer
plot_single_layer_attention(result, 1)
```




```r
# If that works, try the full visualization
visualize_bert_attention(texts[1])
```

```
Number of layers: 12
Shape of attention weights for first layer:
[1]  1 12 11 11

Tokens:
 [1] "[CLS]"         "the"           "transform"     "##er"          "architecture"
 [6] "revolution"    "##ized"        "nl"            "##p"           "."
[11] "[SEP]"
```




```
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from transformers import BertTokenizer, TFBertModel
import pandas as pd
from sklearn.manifold import TSNE

# Part 1: Transformer Architecture Visualization
def plot_transformer_architecture():
    """Visualize basic transformer architecture"""
    components = ['Input Embedding', 'Positional Encoding', 'Multi-Head Attention',
                  'Add & Normalize', 'Feed Forward', 'Add & Normalize', 'Output']
    types = ['Embedding', 'Encoding', 'Attention', 'Normalization', 'FeedForward',
             'Normalization', 'Output']

    fig, ax = plt.subplots(figsize=(10, 8))
    y_positions = np.arange(len(components))

    # Create colored boxes
    for i, (component, type_) in enumerate(zip(components, types)):
        ax.add_patch(plt.Rectangle((0.2, i-0.4), 0.6, 0.8, facecolor=plt.cm.Set3(i/len(compon
        ax.text(0.5, i, component, ha='center', va='center')
```

```
    ax.set_ylim(-0.5, len(components)-0.5)
    ax.set_xlim(0, 1)
    ax.axis('off')
    plt.title('Transformer Architecture')
    plt.tight_layout()
    plt.show()

# Part 2: Self-Attention Visualization
def calculate_attention(query, key, value):
    """Calculate attention scores and weights"""
    attention_scores = np.dot(query, key.T) / np.sqrt(key.shape[1])
    attention_weights = tf.nn.softmax(attention_scores, axis=-1).numpy()
    attention_output = np.dot(attention_weights, value)
    return attention_scores, attention_weights, attention_output

def plot_attention_matrix(attention_weights, words):
    """Visualize attention weights between words"""
    fig, ax = plt.subplots(figsize=(10, 8))
    sns.heatmap(attention_weights, xticklabels=words, yticklabels=words, cmap='YlOrRd', anno
    plt.title('Self-Attention Weights')
    plt.xlabel('Key Words')
    plt.ylabel('Query Words')
    plt.tight_layout()
    plt.show()

# Part 3: BERT Implementation
class BertVisualizer:
    def __init__(self):
        self.tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
        self.model = TFBertModel.from_pretrained('bert-base-uncased')

    def visualize_tokenization(self, text):
        """Visualize BERT tokenization"""
        # Tokenize text
        tokens = self.tokenizer.encode(text, add_special_tokens=True)
        token_words = self.tokenizer.convert_ids_to_tokens(tokens)

        # Create visualization
        fig, ax = plt.subplots(figsize=(15, 2))
        for i, token in enumerate(token_words):
            color = 'pink' if token in ['[CLS]', '[SEP]'] else 'lightblue'
            ax.add_patch(plt.Rectangle((i, 0), 1, 1, facecolor=color))
```

```
            ax.text(i+0.5, 0.5, token, ha='center', va='center')

        ax.set_xlim(0, len(token_words))
        ax.set_ylim(0, 1)
        ax.axis('off')
        plt.title(f'BERT Tokenization: "{text}"')
        plt.tight_layout()
        plt.show()

    def visualize_attention_layers(self, text):
        """Visualize attention patterns across BERT layers"""
        # Encode text and get attention
        inputs = self.tokenizer(text, return_tensors="tf", add_special_tokens=True)
        outputs = self.model(inputs, output_attentions=True)
        attention_weights = outputs.attentions

        # Convert to numpy and average across heads
        attention_array = np.array([att.numpy() for att in attention_weights])
        avg_attention = np.mean(attention_array, axis=2)  # Average across heads

        # Plot attention for each layer
        n_layers = avg_attention.shape[0]
        fig, axes = plt.subplots(3, 4, figsize=(20, 15))
        axes = axes.ravel()
        tokens = self.tokenizer.convert_ids_to_tokens(inputs['input_ids'][0].numpy())

        for i in range(n_layers):
            sns.heatmap(avg_attention[i, 0], xticklabels=tokens, yticklabels=tokens, ax=axes
            axes[i].set_title(f'Layer {i+1}')
            axes[i].tick_params(axis='both', rotation=90)

        plt.tight_layout()
        plt.show()

    def visualize_embeddings(self, text):
        """Visualize word embeddings using t-SNE"""
        # Get embeddings
        inputs = self.tokenizer(text, return_tensors="tf", add_special_tokens=True)
        outputs = self.model(inputs)
        embeddings = outputs.last_hidden_state[0].numpy()

        # Perform t-SNE
```

```
        tsne = TSNE(n_components=2, perplexity=5, random_state=42)
        embeddings_2d = tsne.fit_transform(embeddings)

        # Get tokens
        tokens = self.tokenizer.convert_ids_to_tokens(inputs['input_ids'][0].numpy())

        # Plot
        plt.figure(figsize=(12, 8))
        plt.scatter(embeddings_2d[:, 0], embeddings_2d[:, 1], alpha=0.5)

        for i, token in enumerate(tokens):
            plt.annotate(token, (embeddings_2d[i, 0], embeddings_2d[i, 1]), xytext=(5, 5), t

        plt.title('Word Embeddings Visualization (t-SNE)')
        plt.tight_layout()
        plt.show()

# Example Usage
# Initialize BERT visualizer
bert_viz = BertVisualizer()

# Example texts
texts = [
    "The transformer architecture revolutionized NLP.",
    "Attention mechanisms help models focus on relevant parts.",
    "BERT learns contextual word representations."
]

# Demonstrate visualizations
def demonstrate_transformer_visualizations(texts):
    # Show architecture
    plot_transformer_architecture()

    # Show tokenization for each text
    for text in texts:
        bert_viz.visualize_tokenization(text)

    # Show attention patterns
    bert_viz.visualize_attention_layers(texts[0])

    # Show embeddings
    bert_viz.visualize_embeddings(texts[0])
```

```
    # Demonstrate simple self-attention
    # Create dummy embeddings for demonstration
    words = texts[0].split()
    word_vectors = np.random.randn(len(words), 4)
    _, attention_weights, _ = calculate_attention(word_vectors, word_vectors, word_vectors)
    plot_attention_matrix(attention_weights, words)

# Additional Analysis Functions
def analyze_attention_patterns(text, bert_viz):
    """Analyze how attention changes across layers"""
    inputs = bert_viz.tokenizer(text, return_tensors="tf", add_special_tokens=True)
    outputs = bert_viz.model(inputs, output_attentions=True)
    attention_weights = outputs.attentions

    # Analyze attention to [CLS] token
    cls_attention = np.array([att.numpy()[0, :, 0, :] for att in attention_weights])

    # Plot attention to [CLS] across layers
    plt.figure(figsize=(12, 6))
    sns.heatmap(cls_attention.mean(axis=1), xticklabels=bert_viz.tokenizer.convert_ids_to_tok
                ytickslabels=range(1, cls_attention.shape[0] + 1), cmap='YlOrRd')
    plt.title('Attention to [CLS] Token Across Layers')
    plt.xlabel('Tokens')
    plt.ylabel('Layer')
    plt.tight_layout()
    plt.show()

def visualize_layer_similarities(text, bert_viz):
    """Visualize similarities between layer representations"""
    inputs = bert_viz.tokenizer(text, return_tensors="tf", add_special_tokens=True)
    outputs = bert_viz.model(inputs, output_hidden_states=True)
    hidden_states = outputs.hidden_states

    # Calculate similarities between layers
    n_layers = len(hidden_states)
    similarities = np.zeros((n_layers, n_layers))

    for i in range(n_layers):
        for j in range(n_layers):
            hi = hidden_states[i].numpy()
            hj = hidden_states[j].numpy()
            similarity = np.corrcoef(hi.flatten(), hj.flatten())[0, 1]
```

```
        similarities[i, j] = similarity

# Plot similarities
plt.figure(figsize=(10, 8))
sns.heatmap(similarities, xticklabels=range(n_layers), yticklabels=range(n_layers), cmap=
plt.title('Layer Representation Similarities')
plt.xlabel('Layer')
plt.ylabel('Layer')
plt.tight_layout()
plt.show()
```