Text Summarization using BiLSTM, Encoder-Decoder Architecture and Bert Transformer

Authors of the Project:

Vaishnav Naik

Yashaurya Soni

Piyush Borakhade

Problem Statement

Customer reviews can be lengthy and detailed. Manually analysing these reviews, as you might guess, takes a long time. This is where ATML can be put to use to develop a short summary for lengthy reviews.

Our objective here is to generate a summary for the "Amazon Fine Food reviews" using BiLSTM Encoder-Decoder

Project Pipeline

1. Understanding Text Summarization
2. Text pre-processing
3. Abstractive Text Summarization using BiLSTM, ENCODER-DECODER architecture and Bert Transformer

```
  import kagglehub
import pandas as pd
import os
import re
import numpy as np
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, LSTM, Bidirectional, Embedding, Dense
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
import seaborn as sns


# Download dataset
path = kagglehub.dataset_download("snap/amazon-fine-food-reviews")
dataset_files = os.listdir(path)
csv_file = [file for file in dataset_files if file.endswith(".csv")][0]
data = pd.read_csv(os.path.join(path, csv_file))
```

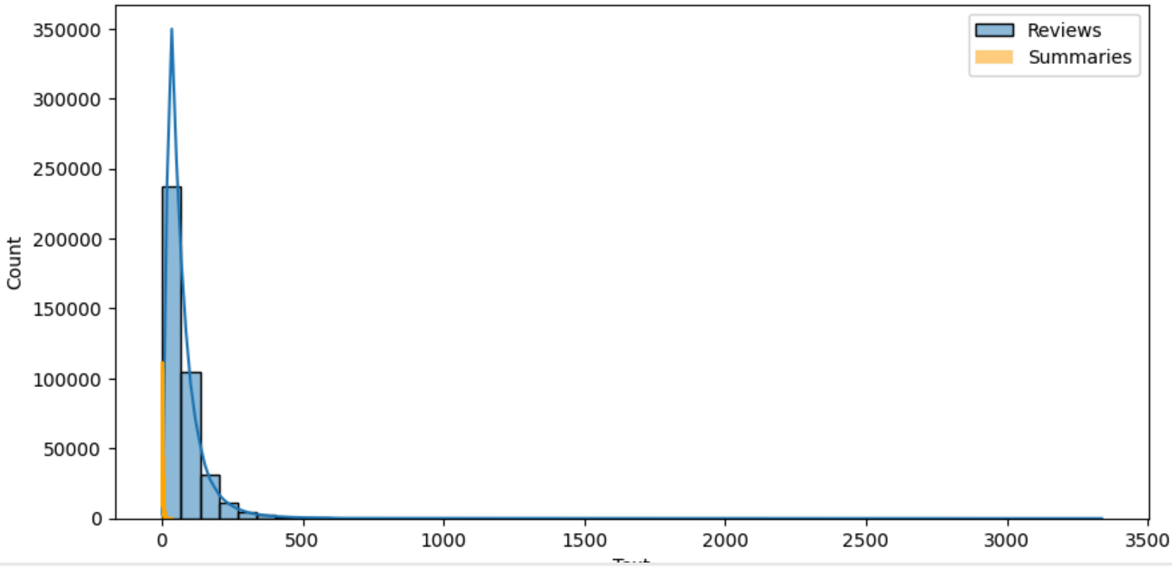
Text Preprocessing

Tokenized text and summary fields. Padded sequences to uniform lengths.

- Removed duplicate entries and NaN values.
- Converted all text to lowercase.
- Removed HTML tags and text within parentheses.
- Eliminated special characters, numbers, and extra spaces.
- Filtered out samples exceeding maximum sequence lengths.
- Added special tokens (sostok, eostok) to summaries.
- Tokenized text and summary fields.
- Padded sequences to uniform lengths.

```
# Data Cleaning
# Remove duplicates & NaN values
data.drop_duplicates(subset=['Text'], inplace=True)
data.dropna(axis=0, inplace=True)

def clean_text(text):
    text = text.lower()
```

```
    text = re.sub(r'<.*?>', '', text)  # Remove HTML tags
    text = re.sub(r"\'s", "", text)  # Remove ('s)
    text = re.sub(r'\([^)]*\)', '', text)  # Remove text inside parentheses
    text = re.sub(r'[^a-zA-Z]', ' ', text)  # Remove special characters & numbers
    text = re.sub(r'\s+', ' ', text).strip()  # Remove multiple spaces
    return text


# Apply cleaning to 'Text' and 'Summary' columns
data['Text'] = data['Text'].apply(clean_text)
data['Summary'] = data['Summary'].apply(clean_text)

# Drop empty rows after cleaning
data.replace('', np.nan, inplace=True)
data.dropna(axis=0, inplace=True)


# Sequence Length Analysis
text_lengths = data['Text'].apply(lambda x: len(x.split()))
summary_lengths = data['Summary'].apply(lambda x: len(x.split()))

plt.figure(figsize=(10,5))
sns.histplot(text_lengths, bins=50, kde=True, label='Reviews')
sns.histplot(summary_lengths, bins=50, kde=True, label='Summaries', color='orange')
plt.legend()
plt.show()
```




```
# Define max lengths
max_text_len = 30
max_summary_len = 8

data = data[data['Text'].apply(lambda x: len(x.split()) <= max_text_len)]
data = data[data['Summary'].apply(lambda x: len(x.split()) <= max_summary_len)]


# Add START & END tokens
data['Summary'] = data['Summary'].apply(lambda x: 'sostok ' + x + ' eostok')
```

```
<ipython-input-7-190f9a1da529>:2: 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.html#returning-a-
  data['Summary'] = data['Summary'].apply(lambda x: 'sostok ' + x + ' eostok')
```

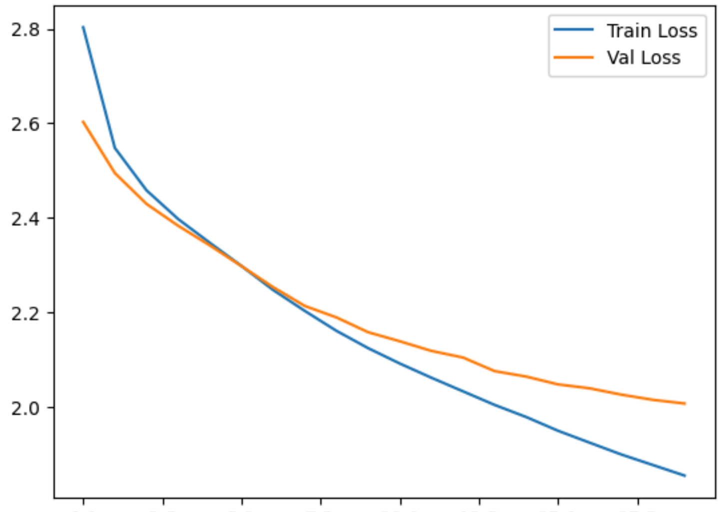
```
# Tokenization
text_tokenizer = Tokenizer()
text_tokenizer.fit_on_texts(data['Text'])
text_sequences = text_tokenizer.texts_to_sequences(data['Text'])
text_vocab_size = len(text_tokenizer.word_index) + 1

summary_tokenizer = Tokenizer()
summary_tokenizer.fit_on_texts(data['Summary'])
summary_sequences = summary_tokenizer.texts_to_sequences(data['Summary'])
summary_vocab_size = len(summary_tokenizer.word_index) + 1
```

```
# Padding
text_padded = pad_sequences(text_sequences, maxlen=max_text_len, padding='post')
summary_padded = pad_sequences(summary_sequences, maxlen=max_summary_len, padding='post')

# Train-Test Split
x_train, x_val, y_train, y_val = train_test_split(text_padded, summary_padded, test_size=0.1, random_state=42)


# Embedding Layer
embedding_dim = 300
encoder_inputs = Input(shape=(max_text_len,))
embedding_layer = Embedding(input_dim=text_vocab_size, output_dim=embedding_dim, trainable=True)(encoder_inputs)


# BiLSTM Encoder
encoder_lstm = Bidirectional(LSTM(300, return_state=True, dropout=0.4, recurrent_dropout=0.4))
encoder_outputs, forward_h, forward_c, backward_h, backward_c = encoder_lstm(embedding_layer)
state_h = tf.keras.layers.Concatenate()([forward_h, backward_h])
state_c = tf.keras.layers.Concatenate()([forward_c, backward_c])
encoder_states = [state_h, state_c]

# Decoder
decoder_inputs = Input(shape=(max_summary_len,))
decoder_embedding = Embedding(input_dim=summary_vocab_size, output_dim=embedding_dim, trainable=True)(decoder_inputs)
decoder_lstm = LSTM(600, return_sequences=True, return_state=True, dropout=0.4, recurrent_dropout=0.4)
decoder_outputs, _, _ = decoder_lstm(decoder_embedding, initial_state=encoder_states)
decoder_dense = Dense(summary_vocab_size, activation='softmax')
outputs = decoder_dense(decoder_outputs)

# Compile Model
model = Model([encoder_inputs, decoder_inputs], outputs)
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', metrics=['accuracy'])


# Early Stopping
early_stopping = EarlyStopping(monitor='val_loss', patience=5, verbose=1)


from tensorflow.keras.preprocessing.sequence import pad_sequences

# Define a proper max summary length
max_summary_len = 9

# Ensure padding before slicing
y_train_padded = pad_sequences(y_train, maxlen=max_summary_len, padding='post')
y_val_padded = pad_sequences(y_val, maxlen=max_summary_len, padding='post')

# Verify the shape before training
print("Encoder input shape:", x_train.shape)
print("Decoder input shape:", y_train_padded[:, :-1].shape)
print("Target output shape:", y_train_padded[:, 1:].shape)

# Explicitly build the model with a sample input
# This ensures all variables are created on the first call
dummy_encoder_input = np.zeros((1, max_text_len))
dummy_decoder_input = np.zeros((1, max_summary_len-1))
model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
model.build([(None, max_text_len), (None, max_summary_len-1)])

# Use tf.keras.backend.clear_session() to reset the session before training
tf.keras.backend.clear_session()

# Rebuild model (same architecture)
encoder_inputs = Input(shape=(max_text_len,))
embedding_layer = Embedding(input_dim=text_vocab_size, output_dim=embedding_dim, trainable=True)(encoder_inputs)

encoder_lstm = Bidirectional(LSTM(300, return_state=True, dropout=0.4, recurrent_dropout=0.4))
encoder_outputs, forward_h, forward_c, backward_h, backward_c = encoder_lstm(embedding_layer)
state_h = tf.keras.layers.Concatenate()([forward_h, backward_h])
state_c = tf.keras.layers.Concatenate()([forward_c, backward_c])
encoder_states = [state_h, state_c]

decoder_inputs = Input(shape=(max_summary_len-1,))
decoder_embedding = Embedding(input_dim=summary_vocab_size, output_dim=embedding_dim, trainable=True)(decoder_inputs)
decoder_lstm = LSTM(600, return_sequences=True, return_state=True, dropout=0.4, recurrent_dropout=0.4)
decoder_outputs, _, _ = decoder_lstm(decoder_embedding, initial_state=encoder_states)
decoder_dense = Dense(summary_vocab_size, activation='softmax')
outputs = decoder_dense(decoder_outputs)

# Create a new model instance with correct input/output shapes
fixed_model = Model([encoder_inputs, decoder_inputs], outputs)
fixed_model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
# Train model with corrected input shapes
history = fixed_model.fit(
    [x_train, y_train_padded[:, :-1]],  # Ensure decoder input is (None, 8)
    y_train_padded[:, 1:],  # Ensure target output is also (None, 8)
    epochs=20,
    batch_size=128,
    validation_data=([x_val, y_val_padded[:, :-1]], y_val_padded[:, 1:])
)
```

```
Encoder input shape: (71160, 30)
Decoder input shape: (71160, 8)
Target output shape: (71160, 8)
Epoch 1/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 187s 318ms/step - accuracy: 0.5885 - loss: 3.3095 - val_accuracy: 0.6459 - val_loss: 2.6027
Epoch 2/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 180s 323ms/step - accuracy: 0.6456 - loss: 2.5829 - val_accuracy: 0.6519 - val_loss: 2.4946
Epoch 3/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 324ms/step - accuracy: 0.6541 - loss: 2.4651 - val_accuracy: 0.6561 - val_loss: 2.4294
Epoch 4/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 324ms/step - accuracy: 0.6560 - loss: 2.4086 - val_accuracy: 0.6602 - val_loss: 2.3831
Epoch 5/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 201s 322ms/step - accuracy: 0.6601 - loss: 2.3530 - val_accuracy: 0.6621 - val_loss: 2.3416
Epoch 6/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 197s 314ms/step - accuracy: 0.6636 - loss: 2.3041 - val_accuracy: 0.6679 - val_loss: 2.2978
Epoch 7/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 179s 322ms/step - accuracy: 0.6683 - loss: 2.2497 - val_accuracy: 0.6708 - val_loss: 2.2533
Epoch 8/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 203s 323ms/step - accuracy: 0.6707 - loss: 2.2072 - val_accuracy: 0.6732 - val_loss: 2.2135
Epoch 9/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 201s 323ms/step - accuracy: 0.6725 - loss: 2.1732 - val_accuracy: 0.6755 - val_loss: 2.1893
Epoch 10/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 322ms/step - accuracy: 0.6755 - loss: 2.1269 - val_accuracy: 0.6772 - val_loss: 2.1580
Epoch 11/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 322ms/step - accuracy: 0.6798 - loss: 2.0792 - val_accuracy: 0.6803 - val_loss: 2.1388
Epoch 12/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 323ms/step - accuracy: 0.6809 - loss: 2.0557 - val_accuracy: 0.6826 - val_loss: 2.1184
Epoch 13/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 201s 321ms/step - accuracy: 0.6820 - loss: 2.0375 - val_accuracy: 0.6804 - val_loss: 2.1044
Epoch 14/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 197s 313ms/step - accuracy: 0.6836 - loss: 2.0027 - val_accuracy: 0.6856 - val_loss: 2.0756
Epoch 15/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 312ms/step - accuracy: 0.6854 - loss: 1.9809 - val_accuracy: 0.6861 - val_loss: 2.0640
Epoch 16/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 207s 321ms/step - accuracy: 0.6882 - loss: 1.9439 - val_accuracy: 0.6880 - val_loss: 2.0476
Epoch 17/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 198s 313ms/step - accuracy: 0.6890 - loss: 1.9240 - val_accuracy: 0.6888 - val_loss: 2.0393
Epoch 18/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 201s 312ms/step - accuracy: 0.6905 - loss: 1.8976 - val_accuracy: 0.6879 - val_loss: 2.0259
Epoch 19/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 179s 321ms/step - accuracy: 0.6910 - loss: 1.8834 - val_accuracy: 0.6898 - val_loss: 2.0149
Epoch 20/20
556/556 ━━━━━━━━━━━━━━━━━━━━ 202s 321ms/step - accuracy: 0.6932 - loss: 1.8520 - val_accuracy: 0.6913 - val_loss: 2.0071
```

```
# Diagnostic Plot
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.legend()
plt.show()
```



```
# Inference Setup
encoder_model = Model(encoder_inputs, encoder_states)

decoder_state_input_h = Input(shape=(600,))
decoder_state_input_c = Input(shape=(600,))
decoder_states_inputs = [decoder_state_input_h, decoder_state_input_c]

decoder_outputs, state_h, state_c = decoder_lstm(decoder_embedding, initial_state=decoder_states_inputs)
decoder_states = [state_h, state_c]
decoder_outputs = decoder_dense(decoder_outputs)

decoder_model = Model([decoder_inputs] + decoder_states_inputs, [decoder_outputs] + decoder_states)

def decode_sequence(input_seq):
    states_value = encoder_model.predict(input_seq)
    target_seq = np.zeros((1,1))
    target_seq[0, 0] = summary_tokenizer.word_index['sostok']
    stop_condition = False
    decoded_sentence = ''
    while not stop_condition:
        output_tokens, h, c = decoder_model.predict([target_seq] + states_value)
        sampled_token_index = np.argmax(output_tokens[0, -1, :])
        sampled_word = summary_tokenizer.index_word.get(sampled_token_index, '')
        decoded_sentence += ' ' + sampled_word
        if sampled_word == 'eostok' or len(decoded_sentence.split()) > max_summary_len:
            stop_condition = True
        target_seq[0, 0] = sampled_token_index
        states_value = [h, c]
    return decoded_sentence

print("Model ready for inference!")
```

```
Model ready for inference!
```

```
sample_text = "The food was great and the service was excellent. Highly recommended!"
sequence = text_tokenizer.texts_to_sequences([sample_text])
padded_sequence = pad_sequences(sequence, maxlen=max_text_len, padding='post')

# Generate summary
generated_summary = decode_sequence(padded_sequence)
print("Generated Summary:", generated_summary)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 725ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 546ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 92ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 69ms/step
Generated Summary:  great product eostok
```

```
# Sample lengthy review text
sample_text = """I recently purchased this organic green tea, and I must say, I am thoroughly impressed.
From the moment I opened the package, I was greeted with a fresh and aromatic scent that was inviting.
Upon brewing, the tea had a beautiful golden hue and a rich flavor that wasn't overpowering but had just the right balance c
I have tried many brands in the past, but this one stands out because of its smoothness and lack of bitterness.
Additionally, the packaging is eco-friendly, which is a huge plus for me.
The tea bags are made from biodegradable material, and the resealable pouch keeps the tea fresh for a long time.
I drink this tea every morning, and it gives me a calming start to my day.
Highly recommended for anyone who loves a good quality tea that's both organic and delicious!"""

# Preprocess the input text
sequence = text_tokenizer.texts_to_sequences([sample_text])
padded_sequence = pad_sequences(sequence, maxlen=max_text_len, padding='post')

# Generate summary
generated_summary = decode_sequence(padded_sequence)
print("Generated Summary:", generated_summary)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 92ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 33ms/step
Generated Summary:  great tea eostok
```

```
# Sample lengthy review text
sample_text = """I ordered this product hoping for a good experience, but it turned out to be a complete disaster. The packa

# Preprocess the input text
sequence = text_tokenizer.texts_to_sequences([sample_text])
padded_sequence = pad_sequences(sequence, maxlen=max_text_len, padding='post')

# Generate summary
```

```
generated_summary = decode_sequence(padded_sequence)
print("Generated Summary:", generated_summary)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 60ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
Generated Summary:  not what i expected eostok
```

Hugging Face Transformers (BART model)

```
from transformers import pipeline

# Load pre-trained summarization pipeline
summarizer = pipeline("summarization", model="facebook/bart-large-cnn")

def generate_summary(text, max_length=50, min_length=20):
    """Generates a summary using a pretrained transformer model."""
    summary = summarizer(text, max_length=max_length, min_length=min_length, do_sample=False)
    return summary[0]['summary_text']

# ✅ Sample Positive Review
positive_review = """I recently purchased this organic green tea, and I must say, I am thoroughly impressed.
From the moment I opened the package, I was greeted with a fresh and aromatic scent that was inviting.
Upon brewing, the tea had a beautiful golden hue and a rich flavor that wasn't overpowering but had just the right balance c
I have tried many brands in the past, but this one stands out because of its smoothness and lack of bitterness.
Additionally, the packaging is eco-friendly, which is a huge plus for me.
The tea bags are made from biodegradable material, and the resealable pouch keeps the tea fresh for a long time.
I drink this tea every morning, and it gives me a calming start to my day.
Highly recommended for anyone who loves a good quality tea that's both organic and delicious!"""

# ✅ Sample Negative Review
negative_review = """I ordered this product hoping for a good experience, but it turned out to be a complete disaster.
The packaging was damaged when it arrived, and the product itself was stale. It had a weird smell, and the taste was awful.
I tried contacting customer support, but they were extremely unhelpful and rude.
They refused to replace or refund my order, making this a terrible shopping experience.
I would not recommend this to anyone, and I will never buy from this brand again!"""

# 🔥 Generate Summaries
print("🔹 Positive Review Summary:", generate_summary(positive_review))
print("🔹 Negative Review Summary:", generate_summary(negative_review))
```

```
/usr/local/lib/python3.11/dist-packages/huggingface_hub/utils/_auth.py:94: UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab (https://huggingface.co/settings/tokens),
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access public models or datasets.
  warnings.warn(
config.json: 100%   1.58k/1.58k [00:00<00:00, 159kB/s]
model.safetensors: 100%   1.63G/1.63G [00:06<00:00, 254MB/s]
generation_config.json: 100%   363/363 [00:00<00:00, 41.9kB/s]
vocab.json: 100%   899k/899k [00:00<00:00, 1.58MB/s]
merges.txt: 100%   456k/456k [00:00<00:00, 3.66MB/s]
tokenizer.json: 100%   1.36M/1.36M [00:00<00:00, 6.72MB/s]
Device set to use cuda:0
🔹 Positive Review Summary: I drink this tea every morning, and it gives me a calming start to my day. The tea bags are
🔹 Negative Review Summary: The packaging was damaged when it arrived, and the product itself was stale. I tried contact
```