ENGLISH TO TELUGU TEXT TRANSLATION SYSTEM

Report submitted to

National Institute of Technology Manipur

for the award of the degree

of

Bachelor of Technology
In Computer Science & Engineering

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DECLARATION

We hereby declare that the project work entitled "Design and Development of English to Telugu Translation System based on Transformer with Deep Learning" submitted to the NIT MANIPUR, is a record of an original work done by us under the guidance of **Dr. Khelchandra thongam** , Associate professor, Computer Science and Engineering NIT MANIPUR, and this project work is submitted in the partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Computer Science and Engineering. The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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Certificate

This is to certify that Dissertation Report entitled, "English to Telugu Text Translation System" Submitted by "*Komal Reddy, Jayanth Reddy, Jnana Yasaswini, Banothu Akhila*" to National Institute of Technology Manipur, India ,is a record of bonafide Project work carried out by them under the supervision of **Dr. Khelchandra Thongam**, **Associate professor of NIT Manipur** under the department of **Computer Science & Engineering**, NIT Manipur and is worthy of consideration for the award of the degree of Bachelor of Technology in **Computer Science & Engineering Department** of the Institute.

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CSE	CSE

Date: 15 March 2024

ABSTRACT

In our rapidly globalizing world, the ability to seamlessly communicate across linguistic boundaries is more crucial than ever. As a response to the growing demand for efficient language translation systems, our project focuses on the "Design and Development of an English to Telugu Translation System based on Transformer with Deep Learning."

This project harnesses the power of Transformers, combined with deep learning techniques, to create a robust and accurate translation system. The choice of English to Telugu translation serves as a testament to our commitment to addressing linguistic diversity and enabling information exchange for the Telugu-speaking community.

Our system aims not only to bridge the language gap but also to enhance translation quality, ensuring that nuances and cultural context are preserved in the process. The deep learning algorithms employed in this project undergo extensive training on large parallel corpora of English and Telugu text, enabling the model to grasp the intricacies of both languages and produce contextually accurate translations.

CONTENTS

INTRODUCTION

1.1 Text to Text Translation using Transformer

In the ever-evolving landscape of natural language processing (NLP), the advent of transformer-based models has revolutionized the field, offering unprecedented capabilities in tasks like text-to-text translation. Transformers, with their attention mechanisms and parallel processing, have proven to be a game-changer by capturing contextual nuances and dependencies within language. This innovation has not only overcome traditional limitations in translation but has also paved the way for more accurate, context-aware, and fluent translations across a multitude of languages. This article explores the transformative impact of employing transformers in text-to-text translation, delving into the underlying mechanisms that make these models highly effective and showcasing their potential to bridge linguistic gaps in our interconnected globalized world.

1.2 Objectives

1. Implement a transformer-based deep learning model for text translation

2. Fine-tune the model to handle language-specific nuances and improve performance

3.implement appropriate evaluation metrics (e.g., BLEU score, accuracy) to quantitatively assess the translation quality.

4.Create an intuitive and user-friendly interface for users to input English text and receive the corresponding translated Telugu text.

1.3 Motivation

Our project, aiming to create an English to Telugu transformer-based translation system, is fueled by the commitment to empower the Telugu-speaking community. By breaking language barriers, this initiative provides seamless access to global information, education, and diverse perspectives, allowing the Telugu community to express themselves on a broader stage.

This transformative tool not only translates words but preserves the cultural nuances of

Telugu, fostering cross-cultural communication and understanding. Beyond convenience, it becomes a vital resource for students, professionals, and enthusiasts, contributing to the preservation and revitalization of the Telugu language in the digital age.

In essence, our motivation is to build a bridge between languages, enhancing accessibility and fostering a more interconnected world where the richness of Telugu culture can thrive alongside global conversations.

1.4 Scope

Language-specific Challenges:

Address Telugu's linguistic nuances to ensure contextually accurate translations.

User Interface Design:

Develop an intuitive interface for seamless English to Telugu text translation.

Real-time Translation:

Strive for real-time translation capabilities to enhance user experience.

Cross-Platform Compatibility:

Ensure the system is compatible across various platforms and devices.

Scalability:

Design the system to be scalable for potential expansion to additional languages or model enhancements.

1.5 Literature Review

Survey - 1

Rule-Based Machine Translation (RBMT):

1. RBMT relies on explicit linguistic rules and grammatical structures to translate text from one language to another. These rules are typically created by linguists and translation experts and may involve syntax, semantics, and morphology.
2. RBMT systems heavily depend on linguistic knowledge and require extensive manual rule creation. Linguists need to encode language-specific rules and translation patterns, making the process labor-intensive.

3. RBMT systems may struggle with adapting to new language pairs or handling informal language. They are less flexible and may not capture the dynamic nature of languages in various contexts.
4. Handling polysemy and ambiguity can be challenging for RBMT systems. The rigid rule structures may not effectively navigate through multiple possible translations or diverse interpretations.
5. Updating or modifying an RBMT system requires manual intervention by linguistic experts. This makes these systems less adaptable to evolving languages and dynamic linguistic environments.

Survey - 2

Statistical Machine Translation (SMT):

1. SMT relies on a combination of rule-based and statistical methods. It involves the creation of linguistic rules and the estimation of statistical models based on bilingual corpora.
2. SMT often operates on a phrase-based translation model, where translation units are phrases or subphrases rather than individual words. These units are aligned across parallel corpora to learn translation probabilities.
3. SMT systems require extensive feature engineering, where linguistic experts manually design features and weights to capture translation patterns, word alignments, and other linguistic phenomena.
4. SMT may struggle to capture long-range dependencies and contextual nuances in language, as it typically relies on local context and may not consider the entire sentence during translation.

Survey - 3

LSTM (Long Short-Term Memory):

1. LSTMs are based on recurrent neural networks (RNNs) and process input sequences sequentially. They maintain hidden states that capture information from previous time steps, allowing them to model temporal dependencies.

2. LSTMs have hidden states and memory cells that enable them to capture and store information over long sequences. The memory cells help in mitigating the vanishing gradient problem associated with standard RNNs.
3. Computation in LSTMs is performed step by step, where the model updates its hidden states and memory cells at each time step based on the current input and the information stored in the previous hidden states and memory cells.
4. Due to their sequential nature, LSTMs face challenges in parallelizing computations, limiting their ability to efficiently utilize parallel processing capabilities of modern hardware.

Why Transformers?

1. Transformers leverage self-attention mechanisms, allowing the model to focus on different parts of the input sequence when generating each part of the output sequence. This attention mechanism captures dependencies effectively and enables the model to handle long-range dependencies.
2. Transformer-based machine translation follows an end-to-end learning approach. It learns representations directly from parallel corpora without explicit rule-based feature engineering, making the training process more data-driven.
3. The attention mechanisms in Transformers allow for efficient parallelization of training and inference, making them computationally efficient. This scalability is particularly advantageous for handling large datasets and accelerating translation processes.
4. Transformers excel at capturing contextual understanding, as they consider the entire context of a sentence during both training and inference. This enables them to generate translations that are more contextually relevant and coherent.
5. Transformer-based models can be fine-tuned with additional data, facilitating continuous learning and adaptation to evolving language patterns. This adaptability contributes to the system's ability to improve over time.
6. Unlike SMT, Transformers do not require explicit word alignment as they learn the alignment implicitly through the attention mechanism. This simplifies the training process and eliminates the need for separate alignment steps.

1.6 Problem Statement

Develop an efficient and accurate English to Telugu text translation system using deep learning techniques, specifically leveraging transformer architectures and to bridge language barriers, enhance communication, and accessibility by providing an advanced tool for seamless translation between English and Telugu.

PREPROCESSING

2.1 Data Preprocessing

2.1.1 Data Cleaning

decontractions(phrase):

This function takes a text phrase and expands English contractions into their full forms. For instance, it replaces "won't" with "will not" and "can't" with "can not." It covers various contraction patterns using regular expressions.

preprocess_english(text):

Converts all text to lowercase to ensure consistency.

Utilizes the decontractions function to expand contractions in the text.

Adds spaces around punctuation marks like question marks, periods, exclamation marks, and commas for better tokenization.

Removes extra spaces to clean up the text.

Eliminates special characters, keeping only letters and essential punctuation.

Appends '<start>' at the beginning and '<end>' at the end of the text to indicate the start and end of a sequence.

Strips any leading or trailing spaces to finalize the preprocessing.

In essence, these operations collectively prepare English text data for subsequent natural language processing tasks by addressing common language nuances and ensuring a standardized, cleaned-up format for analysis or model training.

2.2 Creating a vocab file from our corpus

Reading Data:

Reading text data from a specified file (path) and stores it in a list called data.

Creating TensorFlow Dataset:

Converting the list of text data (data) into a format suitable for TensorFlow processing.

Setting BERT Tokenizer Parameters:

It decides how the BERT tokenizer should handle the text, such as converting it to lowercase. Reserved tokens like "[PAD]", "[UNK]", "[START]", and "[END]" are specified.

Defining BERT Vocabulary Parameters:

It sets up parameters for creating the vocabulary using BERT methods.

This includes specifying the target vocabulary size (150,000) and using the previously defined tokenizer parameters.

Creating Vocabulary:

Generating the vocabulary from the dataset using BERT vocabulary functions.

Writing Vocabulary to File:

Finally, saving the generated vocabulary to a file at the specified location (saving_path).

2.3 Custom Tokenizer

BERT tokenizer considers the bidirectional context of words, meaning it takes into account the surrounding words on both sides when encoding a word. This helps capture richer contextual information compared to traditional tokenization methods.

BERT tokenizer utilizes WordPiece tokenization, breaking down words into smaller subwords or pieces. This is particularly useful for handling rare words, out-of-vocabulary terms, and morphologically rich languages.

Typically, BERT tokenizers convert text to lowercase. This ensures consistency in representation, preventing the model from treating differently cased words as distinct entities.

BERT introduces special tokens like "[CLS]" (classification token), "[SEP]" (separator token), "[PAD]" (padding token), "[MASK]" (mask token), "[START]", and "[END]". These tokens serve specific purposes during model training and inference.

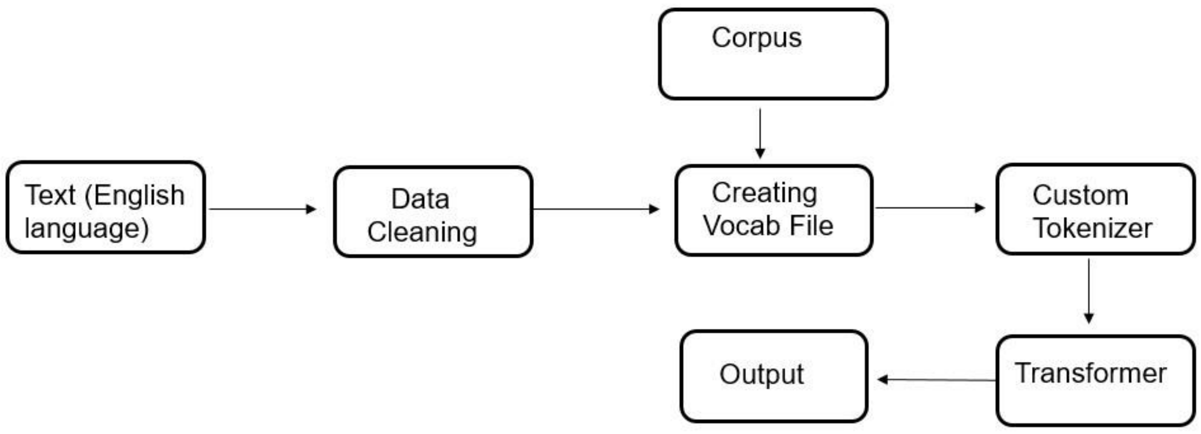
BERT tokenization is often applied in conjunction with pre-trained BERT models. The tokenizer is used to process input text, and the pre-trained model produces embeddings (contextualized representations) for each token.

During training, BERT utilizes a masked language model (MLM) objective. Some tokens in the input sequence are randomly replaced with the "[MASK]" token, and the model is trained to predict the original words based on the context.

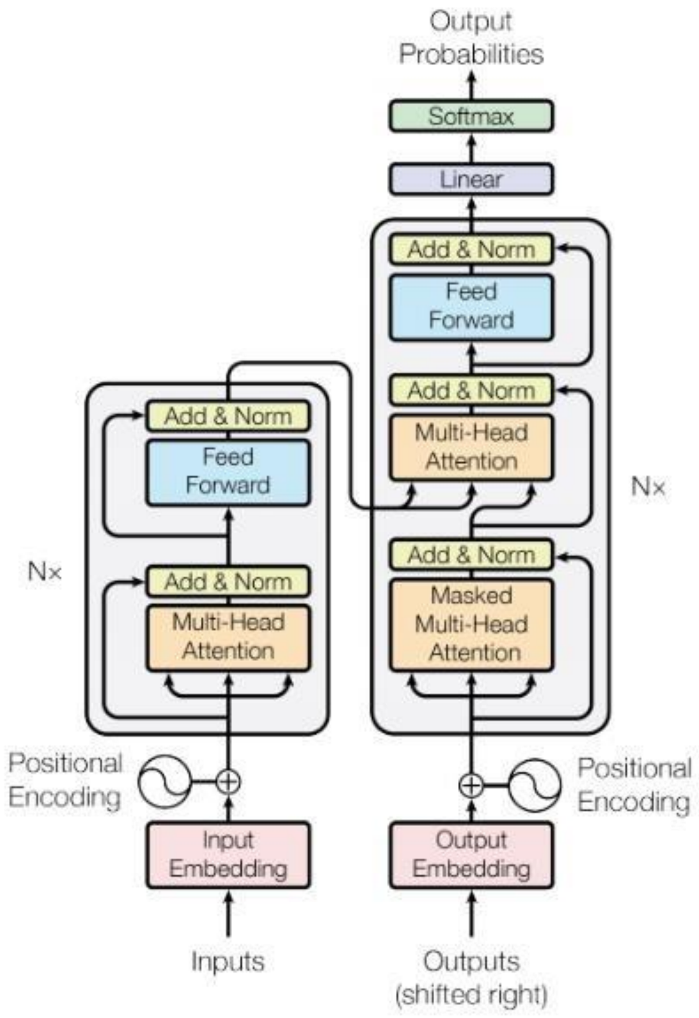
BERT tokenizer is widely used in various natural language processing (NLP) tasks, such as text classification, named entity recognition, sentiment analysis, and machine translation. It has become a foundational tool in the NLP landscape due to its ability to capture intricate language patterns.

OVERVIEW OF PROJECT DESIGN

3.1 Project Flow



3.2 Architecture of model



3.3 Software Requirements

1. Python
2. Pandas and Numpy
3. Tensorflow

3.4 Hardware Requirements

1. GPU - Training deep learning models, especially Transformer architectures, can be computationally intensive. Having a GPU accelerates the training process
2. RAM - 16GB or higher
3. CPU - A multi-core CPU, such as an Intel Core i7 or higher, is beneficial for parallel processing during training.

EXPERIMENTAL STUDY OF PROJECT

4.1 Algorithm for text to text translation using transformers

1. Regex To Convert Contractions Into Natural Form ,For example, won't to Will not
2. Custom Tokenizer Using Bert
3. Positional Encoding to give the model some information about the relative position of the words in the sentence
4. The Attention Function used by transformer takes three inputs q(query) k(key) v(value). used multi head attention consisting of four parts linear layer and split into heads scales dot product attention concatenation of heads final linear layer
5. Implementation Of Evaluation Metric BLEU

4.2 History of transformers

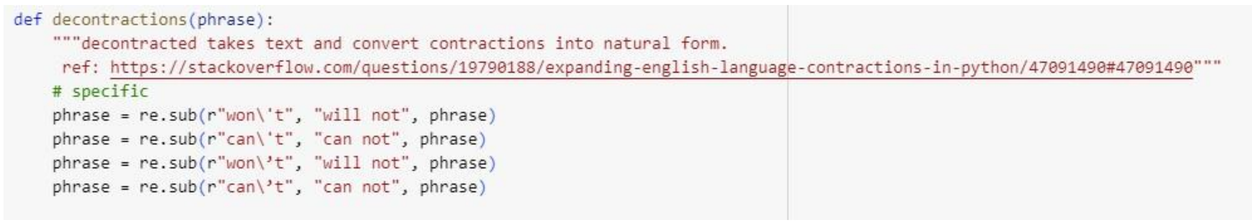
- **Introduction of Transformers (2017):**
  Vaswani et al. introduced transformers, revolutionizing sequence transduction tasks with self-attention mechanisms.
- **BERT Model (2018):**
  Devlin et al. presented BERT, pre-training transformers on vast unlabeled text data, achieving state-of-the-art NLP performance.
- **GPT-2 and GPT-3 Models (2019-2020):**
  OpenAI's GPT series, especially GPT-3, set new benchmarks in language understanding and generation.
- **Transformer-Based Machine Translation Models (2018 Onward):**
  Transformers became dominant in machine translation, with models like Transformer, BERT-based translation models, and M4 showcasing impressive results.
- **T5 Model (2019):**
  Google's T5 proposed a unified framework for NLP tasks, treating them as text-to-text, highlighting the versatility of transformers.
- **Ongoing Developments (2021 Onward):**

Research continues in areas like multilingual models, domain adaptation, and training strategies to enhance transformer-based translation systems. In summary, transformers have reshaped text-to-text translation, from their foundational introduction to the latest state-of-the-art models, driving advancements in natural language processing.

PARTIAL RESULTS & DISCUSSIONS

5.1 Data Pre-processing

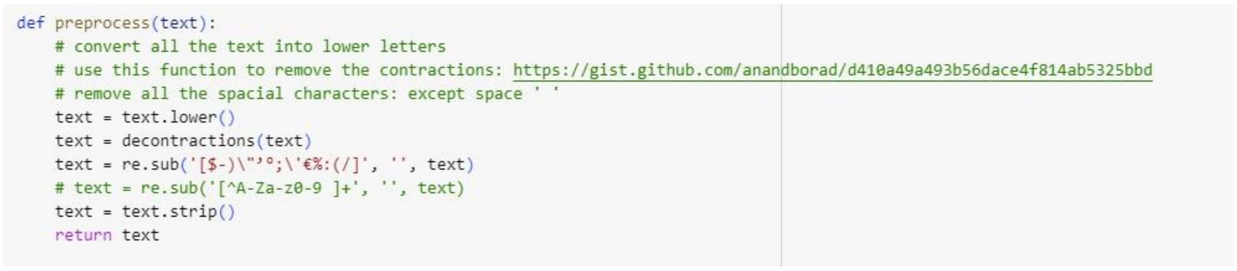
5.1.1 Decontractions



```
def decontractions(phrase):
    """decontracted takes text and convert contractions into natural form.
     ref: https://stackoverflow.com/questions/19790188/expanding-english-language-contractions-in-python/47091490#47091490"""
    # specific
    phrase = re.sub(r"won\'t", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
    phrase = re.sub(r"won\’t", "will not", phrase)
    phrase = re.sub(r"can\’t", "can not", phrase)
```

This function takes a text phrase as input a nd expands English contractions into their full forms. It uses regular expressions to replace contraction patterns like "won't" with "will not" and "can't" with "can not," among others.

5.1.2 Text Preprocessing



```
def preprocess(text):
    # convert all the text into lower letters
    # use this function to remove the contractions: https://gist.github.com/anandborad/d410a49a493b56dace4f814ab5325bbd
    # remove all the spacial characters: except space ' '
    text = text.lower()
    text = decontractions(text)
    text = re.sub('[$-)\"’°;\'€%:(/]', '', text)
    # text = re.sub('[^A-Za-z0-9 ]+', '', text)
    text = text.strip()
    return text
```

Converts all text to lowercase.

Utilizes the decontractions function to expand contractions.

Adds spaces around punctuation marks (question marks, periods, exclamation marks, and commas).

Removes extra spaces.

Eliminates special characters except for letters and essential punctuation.

Strips any leading or trailing spaces.

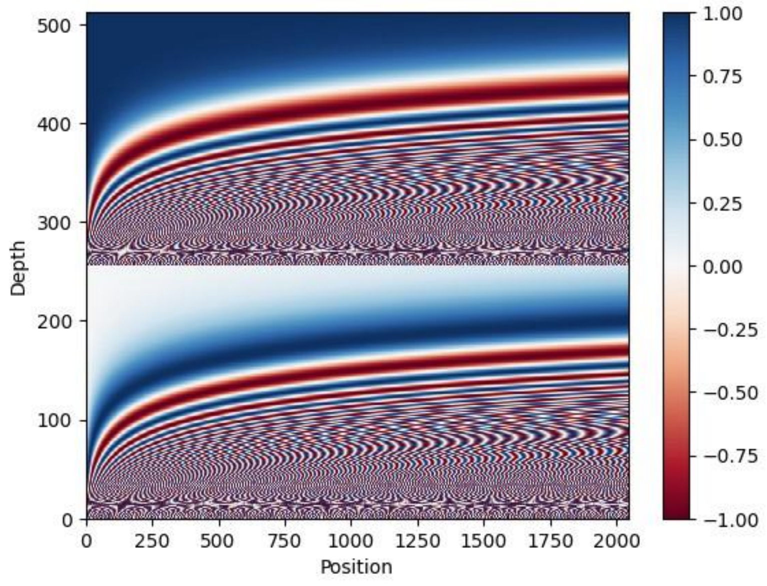
5.2 Positional Encoding

```python
def get_angles(pos, i, d_model):
  angle_rates = 1 / np.power(10000, (2 * (i//2)) / np.float32(d_model))
  return pos * angle_rates
```

```python
def positional_encoding(position, d_model):
  angle_rads = get_angles(np.arange(position)[:, np.newaxis],
                          np.arange(d_model)[np.newaxis, :],
                          d_model)

  # apply sin to even indices in the array; 2i
  angle_rads[:, 0::2] = np.sin(angle_rads[:, 0::2])

  # apply cos to odd indices in the array; 2i+1
  angle_rads[:, 1::2] = np.cos(angle_rads[:, 1::2])

  pos_encoding = angle_rads[np.newaxis, ...]

  return tf.cast(pos_encoding, dtype=tf.float32)
```

```python
n, d = 2048, 512
pos_encoding = positional_encoding(n, d)
print(pos_encoding.shape)
pos_encoding = pos_encoding[0]

# Juggle the dimensions for the plot
pos_encoding = tf.reshape(pos_encoding, (n, d//2, 2))
pos_encoding = tf.transpose(pos_encoding, (2, 1, 0))
pos_encoding = tf.reshape(pos_encoding, (d, n))

plt.pcolormesh(pos_encoding, cmap='RdBu')
plt.ylabel('Depth')
plt.xlabel('Position')
plt.colorbar()
plt.show()
```

```
(1, 2048, 512)
```



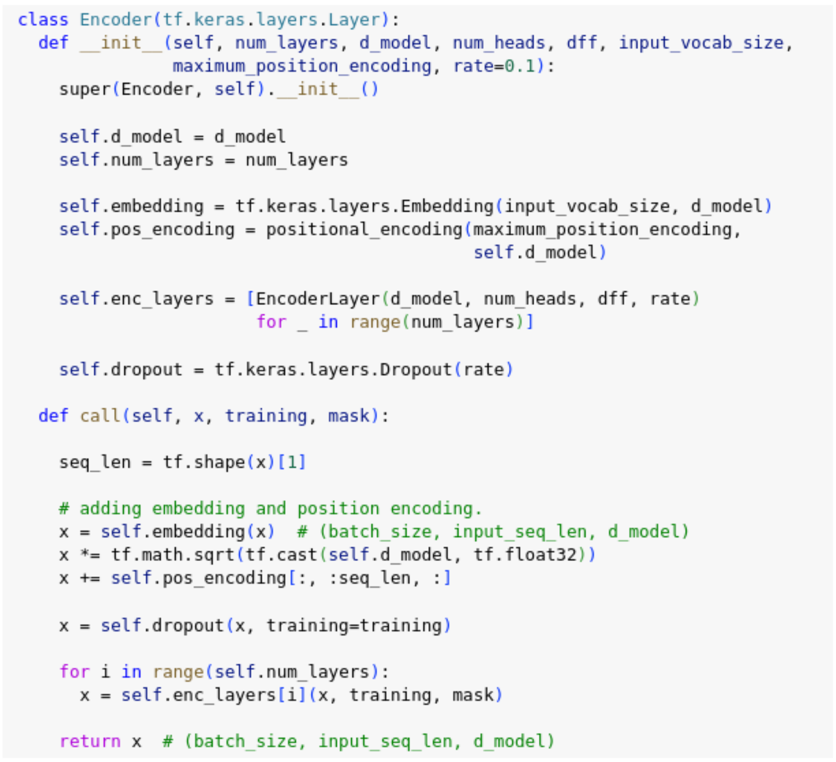
Since this model doesn't contain any recurrence or convolution, positional encoding is added to give the model some information about the relative position of the words in the sentence. The positional encoding vector is added to the embedding vector. Embedding represent a token in a d-dimensional space where tokens with similar meaning will be closer to each other. But the embedding do not encode the relative position of words in a sentence. So, after adding the positional encoding, words will be closer to each other based on the similarity of their meaning and their position in the sentence, in the d-dimensional space. The formula for calculating the positional encoding is as follows:

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

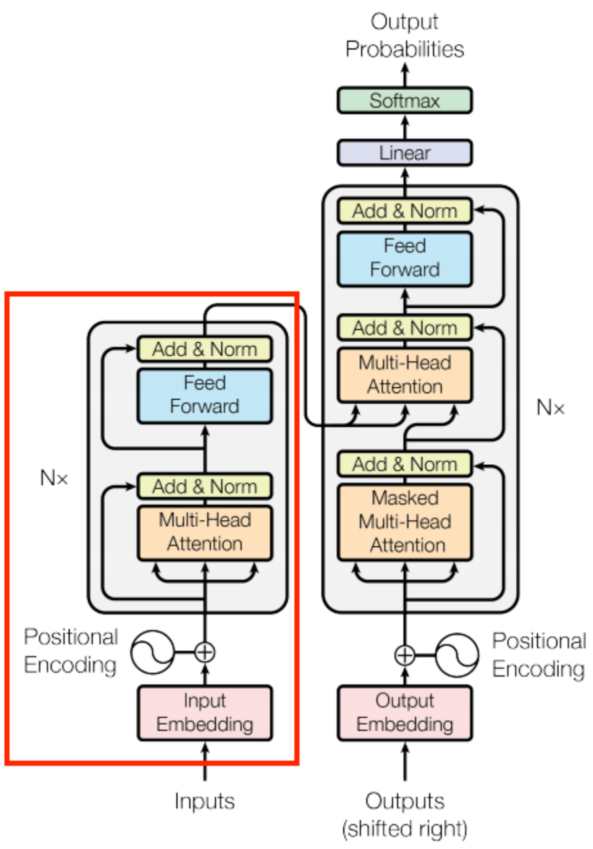
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

5.3 Transfomer

5.3.1 Encoder



```
class Encoder(tf.keras.layers.Layer):
  def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
               maximum_position_encoding, rate=0.1):
    super(Encoder, self).__init__()

    self.d_model = d_model
    self.num_layers = num_layers

    self.embedding = tf.keras.layers.Embedding(input_vocab_size, d_model)
    self.pos_encoding = positional_encoding(maximum_position_encoding,
                                            self.d_model)

    self.enc_layers = [EncoderLayer(d_model, num_heads, dff, rate)
                       for _ in range(num_layers)]

    self.dropout = tf.keras.layers.Dropout(rate)

  def call(self, x, training, mask):

    seq_len = tf.shape(x)[1]

    # adding embedding and position encoding.
    x = self.embedding(x)  # (batch_size, input_seq_len, d_model)
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x += self.pos_encoding[:, :seq_len, :]

    x = self.dropout(x, training=training)

    for i in range(self.num_layers):
      x = self.enc_layers[i](x, training, mask)

    return x  # (batch_size, input_seq_len, d_model)
```



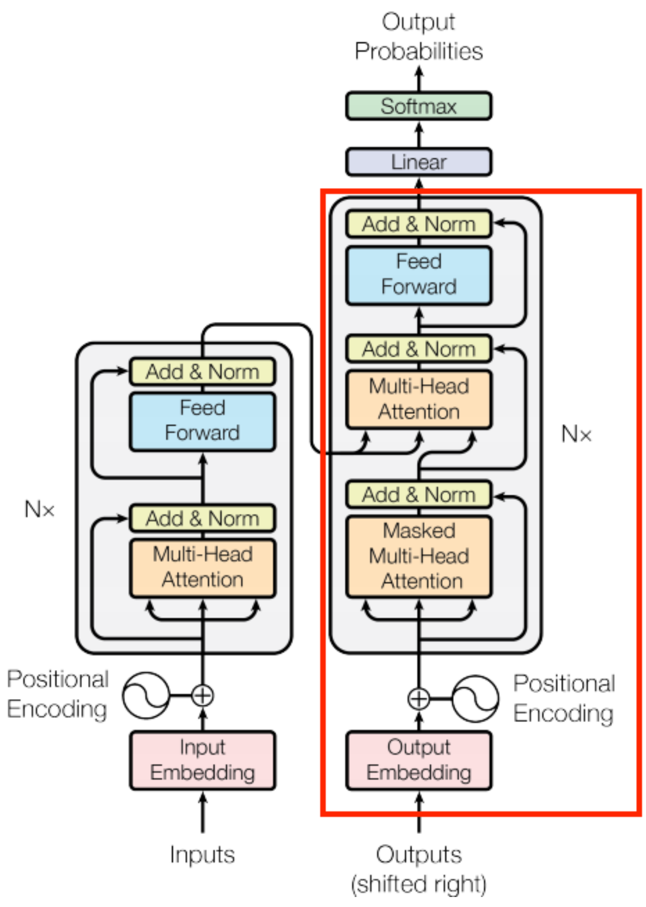
The encoder consists of:

- A PositionalEmbedding layer at the input.
- A stack of EncoderLayer layers.

The encoder receives the embedding vectors as a list of vectors, each of 512 (can be tuned as a hyper-parameter) size dimension. Both the encoder and the decoder add a positional encoding (that will be explained later) to their input. Both also use a bypass that is called a residual connection followed by an addition of the original input of the sub-layer and another normalization layer (which is also known as a batch normalization).

5.3.2 Decoder

```python
class Decoder(tf.keras.layers.Layer):
  def __init__(self, num_layers, d_model, num_heads, dff, target_vocab_size,
               maximum_position_encoding, rate=0.1):
    super(Decoder, self).__init__()

    self.d_model = d_model
    self.num_layers = num_layers

    self.embedding = tf.keras.layers.Embedding(target_vocab_size, d_model)
    self.pos_encoding = positional_encoding(maximum_position_encoding, d_model)

    self.dec_layers = [DecoderLayer(d_model, num_heads, dff, rate)
                       for _ in range(num_layers)]
    self.dropout = tf.keras.layers.Dropout(rate)

  def call(self, x, enc_output, training,
           look_ahead_mask, padding_mask):

    seq_len = tf.shape(x)[1]
    attention_weights = {}

    x = self.embedding(x)  # (batch_size, target_seq_len, d_model)
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x += self.pos_encoding[:, :seq_len, :]

    x = self.dropout(x, training=training)

    for i in range(self.num_layers):
      x, block1, block2 = self.dec_layers[i](x, enc_output, training,
                                             look_ahead_mask, padding_mask)

      attention_weights[f'decoder_layer{i+1}_block1'] = block1
      attention_weights[f'decoder_layer{i+1}_block2'] = block2

    # x.shape == (batch_size, target_seq_len, d_model)
    return x, attention_weights
```

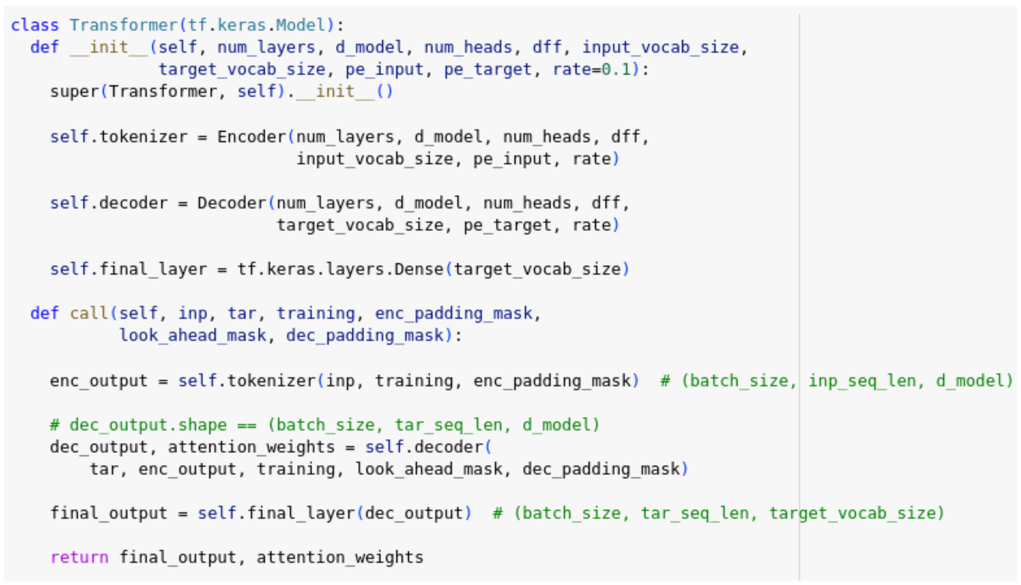


- The decoder's stack is slightly more complex, with each DecoderLayer containing a CausalSelfAttention, a CrossAttention, and a FeedForward layer Similar to the Encoder.
- The Decoder consists of a PositionalEmbedding, and a stack of DecoderLayers Unlike the encoder, the decoder uses an addition to the Multi-head attention that is called masking.
- This operation is intended to prevent exposing posterior information from the decoder. It means that in the training level the decoder doesn't get access to tokens in the target sentence that will reveal the correct answer and will disrupt the learning procedure.
- It's really important part in the decoder because if we will not use the masking the model will not learn anything and will just repeat the target sentence

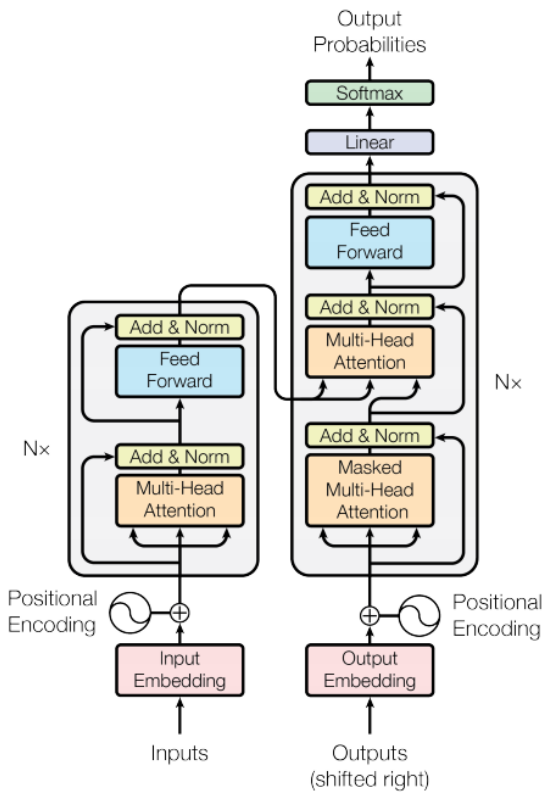
5.3.3 Transfomer

We now have Encoder and Decoder. To complete the Transformer model, we need to put them together and add a final linear (Dense) layer which converts the resulting vector at each location into output token probabilities.

The output of the decoder is the input to this final linear layer:



```
class Transformer(tf.keras.Model):
  def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
               target_vocab_size, pe_input, pe_target, rate=0.1):
    super(Transformer, self).__init__()

    self.tokenizer = Encoder(num_layers, d_model, num_heads, dff,
                             input_vocab_size, pe_input, rate)

    self.decoder = Decoder(num_layers, d_model, num_heads, dff,
                           target_vocab_size, pe_target, rate)

    self.final_layer = tf.keras.layers.Dense(target_vocab_size)

  def call(self, inp, tar, training, enc_padding_mask,
           look_ahead_mask, dec_padding_mask):

    enc_output = self.tokenizer(inp, training, enc_padding_mask)  # (batch_size, inp_seq_len, d_model)

    # dec_output.shape == (batch_size, tar_seq_len, d_model)
    dec_output, attention_weights = self.decoder(
        tar, enc_output, training, look_ahead_mask, dec_padding_mask)

    final_output = self.final_layer(dec_output)  # (batch_size, tar_seq_len, target_vocab_size)

    return final_output, attention_weights
```



5.4 Training the model

```
checkpoint_path = "drive/MyDrive/ent/model_checkpoints/transformer_model_full2"

ckpt = tf.train.Checkpoint(transformer=transformer,
                           optimizer=optimizer)

ckpt_manager = tf.train.CheckpointManager(ckpt, checkpoint_path, max_to_keep=3)

# if a checkpoint exists, restore the latest checkpoint.
if ckpt_manager.latest_checkpoint:
  ckpt.restore(ckpt_manager.latest_checkpoint)
  print('Latest checkpoint restored!!')
```

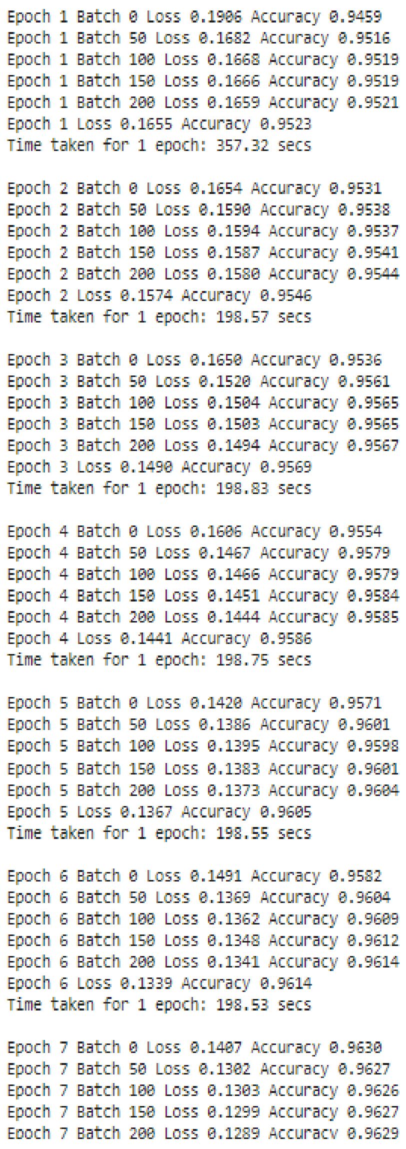
```
Latest checkpoint restored!!
```

```
EPOCHS = 30
```

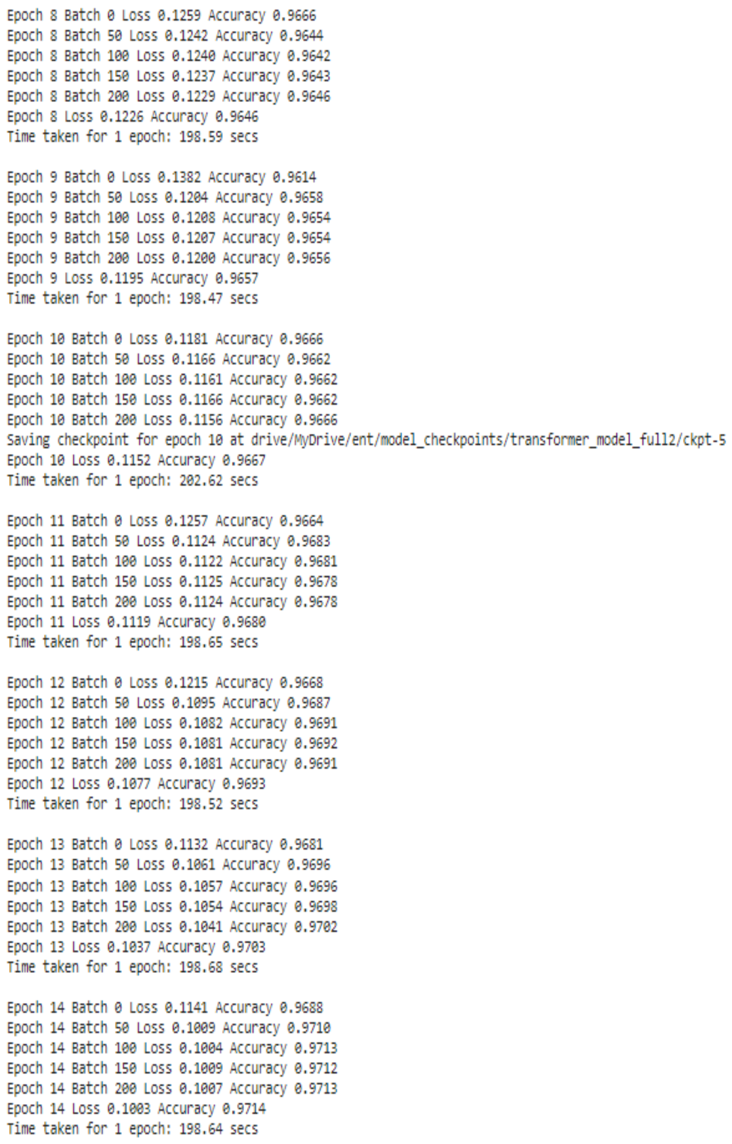
```
# The @tf.function trace-compiles train_step into a TF graph for faster
# execution. The function specializes to the precise shape of the argument
# tensors. To avoid re-tracing due to the variable sequence lengths or variable
# batch sizes (the last batch is smaller), use input_signature to specify
# more generic shapes.

train_step_signature = [
    tf.TensorSpec(shape=(None, None), dtype=tf.int64),
    tf.TensorSpec(shape=(None, None), dtype=tf.int64),
]


@tf.function(input_signature=train_step_signature)
def train_step(inp, tar):
  tar_inp = tar[:, :-1]
  tar_real = tar[:, 1:]

  enc_padding_mask, combined_mask, dec_padding_mask = create_masks(inp, tar_inp)

  with tf.GradientTape() as tape:
    predictions, _ = transformer(inp, tar_inp,
                                 True,
                                 enc_padding_mask,
                                 combined_mask,
                                 dec_padding_mask)
    loss = loss_function(tar_real, predictions)

  gradients = tape.gradient(loss, transformer.trainable_variables)
  optimizer.apply_gradients(zip(gradients, transformer.trainable_variables))

  train_loss(loss)
  train_accuracy(accuracy_function(tar_real, predictions))
```

```
for epoch in range(EPOCHS):
  start = time.time()

  train_loss.reset_states()
  train_accuracy.reset_states()

  # inp -> english, tar -> telugu
  for (batch, (inp, tar)) in enumerate(train_batches):
    train_step(inp, tar)

    if batch % 50 == 0:
      print(f'Epoch {epoch + 1} Batch {batch} Loss {train_loss.result():.4f} Accuracy {train_accuracy.result():.4f}')

  if (epoch + 1) % 10 == 0:
    ckpt_save_path = ckpt_manager.save()
    print(f'Saving checkpoint for epoch {epoch+1} at {ckpt_save_path}')

  print(f'Epoch {epoch + 1} Loss {train_loss.result():.4f} Accuracy {train_accuracy.result():.4f}')

  print(f'Time taken for 1 epoch: {time.time() - start:.2f} secs\n')
```

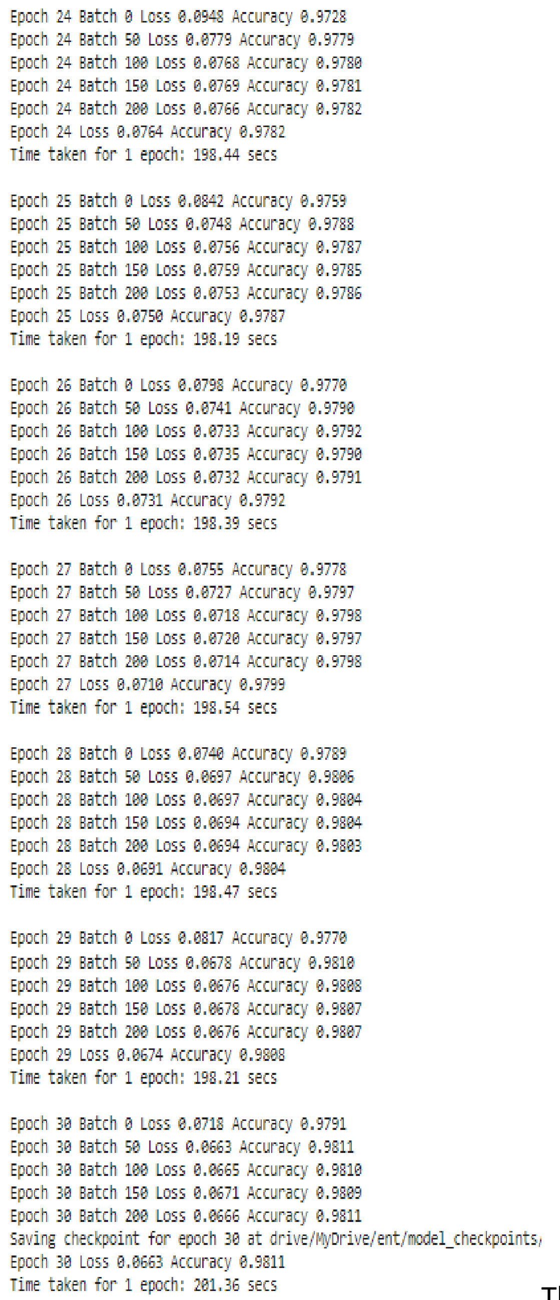
- The drivemountpath (“drive/MyDrive/ent/model_checkpoints/transformer_model_full2”) where we store our training steps result , training step is defined where we take inputs target_input and target_real and then call transformer model on it.
- After model is trained, The loss is calculated using the loss_function, which likely computes the Sparse Categorical Crossentropy loss.
- Gradients of the loss with respect to the trainable variables of the transformer model are computed using automatic differentiation (tf.GradientTape).
- The optimizer is then applied to update the model's parameters based on the computed gradients
- The training step where we have EPOCHS set to 30 and call train_step function we defined before on each batch



```
Epoch 1 Batch 0 Loss 0.1906 Accuracy 0.9459
Epoch 1 Batch 50 Loss 0.1682 Accuracy 0.9516
Epoch 1 Batch 100 Loss 0.1668 Accuracy 0.9519
Epoch 1 Batch 150 Loss 0.1666 Accuracy 0.9519
Epoch 1 Batch 200 Loss 0.1659 Accuracy 0.9521
Epoch 1 Loss 0.1655 Accuracy 0.9523
Time taken for 1 epoch: 357.32 secs

Epoch 2 Batch 0 Loss 0.1654 Accuracy 0.9531
Epoch 2 Batch 50 Loss 0.1590 Accuracy 0.9538
Epoch 2 Batch 100 Loss 0.1594 Accuracy 0.9537
Epoch 2 Batch 150 Loss 0.1587 Accuracy 0.9541
Epoch 2 Batch 200 Loss 0.1580 Accuracy 0.9544
Epoch 2 Loss 0.1574 Accuracy 0.9546
Time taken for 1 epoch: 198.57 secs

Epoch 3 Batch 0 Loss 0.1650 Accuracy 0.9536
Epoch 3 Batch 50 Loss 0.1520 Accuracy 0.9561
Epoch 3 Batch 100 Loss 0.1504 Accuracy 0.9565
Epoch 3 Batch 150 Loss 0.1503 Accuracy 0.9565
Epoch 3 Batch 200 Loss 0.1494 Accuracy 0.9567
Epoch 3 Loss 0.1490 Accuracy 0.9569
Time taken for 1 epoch: 198.83 secs

Epoch 4 Batch 0 Loss 0.1606 Accuracy 0.9554
Epoch 4 Batch 50 Loss 0.1467 Accuracy 0.9579
Epoch 4 Batch 100 Loss 0.1466 Accuracy 0.9579
Epoch 4 Batch 150 Loss 0.1451 Accuracy 0.9584
Epoch 4 Batch 200 Loss 0.1444 Accuracy 0.9585
Epoch 4 Loss 0.1441 Accuracy 0.9586
Time taken for 1 epoch: 198.75 secs

Epoch 5 Batch 0 Loss 0.1420 Accuracy 0.9571
Epoch 5 Batch 50 Loss 0.1386 Accuracy 0.9601
Epoch 5 Batch 100 Loss 0.1395 Accuracy 0.9598
Epoch 5 Batch 150 Loss 0.1383 Accuracy 0.9601
Epoch 5 Batch 200 Loss 0.1373 Accuracy 0.9604
Epoch 5 Loss 0.1367 Accuracy 0.9605
Time taken for 1 epoch: 198.55 secs

Epoch 6 Batch 0 Loss 0.1491 Accuracy 0.9582
Epoch 6 Batch 50 Loss 0.1369 Accuracy 0.9604
Epoch 6 Batch 100 Loss 0.1362 Accuracy 0.9609
Epoch 6 Batch 150 Loss 0.1348 Accuracy 0.9612
Epoch 6 Batch 200 Loss 0.1341 Accuracy 0.9614
Epoch 6 Loss 0.1339 Accuracy 0.9614
Time taken for 1 epoch: 198.53 secs

Epoch 7 Batch 0 Loss 0.1407 Accuracy 0.9630
Epoch 7 Batch 50 Loss 0.1302 Accuracy 0.9627
Epoch 7 Batch 100 Loss 0.1303 Accuracy 0.9626
Epoch 7 Batch 150 Loss 0.1299 Accuracy 0.9627
Epoch 7 Batch 200 Loss 0.1289 Accuracy 0.9629
```

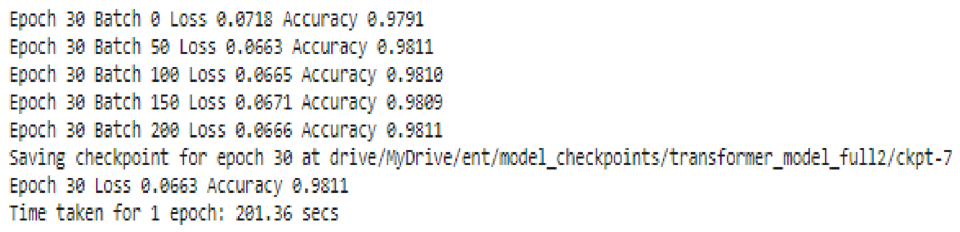


```
Epoch 8 Batch 0 Loss 0.1259 Accuracy 0.9666
Epoch 8 Batch 50 Loss 0.1242 Accuracy 0.9644
Epoch 8 Batch 100 Loss 0.1240 Accuracy 0.9642
Epoch 8 Batch 150 Loss 0.1237 Accuracy 0.9643
Epoch 8 Batch 200 Loss 0.1229 Accuracy 0.9646
Epoch 8 Loss 0.1226 Accuracy 0.9646
Time taken for 1 epoch: 198.59 secs

Epoch 9 Batch 0 Loss 0.1382 Accuracy 0.9614
Epoch 9 Batch 50 Loss 0.1204 Accuracy 0.9658
Epoch 9 Batch 100 Loss 0.1208 Accuracy 0.9654
Epoch 9 Batch 150 Loss 0.1207 Accuracy 0.9654
Epoch 9 Batch 200 Loss 0.1200 Accuracy 0.9656
Epoch 9 Loss 0.1195 Accuracy 0.9657
Time taken for 1 epoch: 198.47 secs

Epoch 10 Batch 0 Loss 0.1181 Accuracy 0.9666
Epoch 10 Batch 50 Loss 0.1166 Accuracy 0.9662
Epoch 10 Batch 100 Loss 0.1161 Accuracy 0.9662
Epoch 10 Batch 150 Loss 0.1166 Accuracy 0.9662
Epoch 10 Batch 200 Loss 0.1156 Accuracy 0.9666
Saving checkpoint for epoch 10 at drive/MyDrive/ent/model_checkpoints/transformer_model_full2/ckpt-5
Epoch 10 Loss 0.1152 Accuracy 0.9667
Time taken for 1 epoch: 202.62 secs

Epoch 11 Batch 0 Loss 0.1257 Accuracy 0.9664
Epoch 11 Batch 50 Loss 0.1124 Accuracy 0.9683
Epoch 11 Batch 100 Loss 0.1122 Accuracy 0.9681
Epoch 11 Batch 150 Loss 0.1125 Accuracy 0.9678
Epoch 11 Batch 200 Loss 0.1124 Accuracy 0.9678
Epoch 11 Loss 0.1119 Accuracy 0.9680
Time taken for 1 epoch: 198.65 secs

Epoch 12 Batch 0 Loss 0.1215 Accuracy 0.9668
Epoch 12 Batch 50 Loss 0.1095 Accuracy 0.9687
Epoch 12 Batch 100 Loss 0.1082 Accuracy 0.9691
Epoch 12 Batch 150 Loss 0.1081 Accuracy 0.9692
Epoch 12 Batch 200 Loss 0.1081 Accuracy 0.9691
Epoch 12 Loss 0.1077 Accuracy 0.9693
Time taken for 1 epoch: 198.52 secs

Epoch 13 Batch 0 Loss 0.1132 Accuracy 0.9681
Epoch 13 Batch 50 Loss 0.1061 Accuracy 0.9696
Epoch 13 Batch 100 Loss 0.1057 Accuracy 0.9696
Epoch 13 Batch 150 Loss 0.1054 Accuracy 0.9698
Epoch 13 Batch 200 Loss 0.1041 Accuracy 0.9702
Epoch 13 Loss 0.1037 Accuracy 0.9703
Time taken for 1 epoch: 198.68 secs

Epoch 14 Batch 0 Loss 0.1141 Accuracy 0.9688
Epoch 14 Batch 50 Loss 0.1009 Accuracy 0.9710
Epoch 14 Batch 100 Loss 0.1004 Accuracy 0.9713
Epoch 14 Batch 150 Loss 0.1009 Accuracy 0.9712
Epoch 14 Batch 200 Loss 0.1007 Accuracy 0.9713
Epoch 14 Loss 0.1003 Accuracy 0.9714
Time taken for 1 epoch: 198.64 secs
```



```
Epoch 24 Batch 0 Loss 0.0948 Accuracy 0.9728
Epoch 24 Batch 50 Loss 0.0779 Accuracy 0.9779
Epoch 24 Batch 100 Loss 0.0768 Accuracy 0.9780
Epoch 24 Batch 150 Loss 0.0769 Accuracy 0.9781
Epoch 24 Batch 200 Loss 0.0766 Accuracy 0.9782
Epoch 24 Loss 0.0764 Accuracy 0.9782
Time taken for 1 epoch: 198.44 secs

Epoch 25 Batch 0 Loss 0.0842 Accuracy 0.9759
Epoch 25 Batch 50 Loss 0.0748 Accuracy 0.9788
Epoch 25 Batch 100 Loss 0.0756 Accuracy 0.9787
Epoch 25 Batch 150 Loss 0.0759 Accuracy 0.9785
Epoch 25 Batch 200 Loss 0.0753 Accuracy 0.9786
Epoch 25 Loss 0.0750 Accuracy 0.9787
Time taken for 1 epoch: 198.19 secs

Epoch 26 Batch 0 Loss 0.0798 Accuracy 0.9770
Epoch 26 Batch 50 Loss 0.0741 Accuracy 0.9790
Epoch 26 Batch 100 Loss 0.0733 Accuracy 0.9792
Epoch 26 Batch 150 Loss 0.0735 Accuracy 0.9790
Epoch 26 Batch 200 Loss 0.0732 Accuracy 0.9791
Epoch 26 Loss 0.0731 Accuracy 0.9792
Time taken for 1 epoch: 198.39 secs

Epoch 27 Batch 0 Loss 0.0755 Accuracy 0.9778
Epoch 27 Batch 50 Loss 0.0727 Accuracy 0.9797
Epoch 27 Batch 100 Loss 0.0718 Accuracy 0.9798
Epoch 27 Batch 150 Loss 0.0720 Accuracy 0.9797
Epoch 27 Batch 200 Loss 0.0714 Accuracy 0.9798
Epoch 27 Loss 0.0710 Accuracy 0.9799
Time taken for 1 epoch: 198.54 secs

Epoch 28 Batch 0 Loss 0.0740 Accuracy 0.9789
Epoch 28 Batch 50 Loss 0.0697 Accuracy 0.9806
Epoch 28 Batch 100 Loss 0.0697 Accuracy 0.9804
Epoch 28 Batch 150 Loss 0.0694 Accuracy 0.9804
Epoch 28 Batch 200 Loss 0.0694 Accuracy 0.9803
Epoch 28 Loss 0.0691 Accuracy 0.9804
Time taken for 1 epoch: 198.47 secs

Epoch 29 Batch 0 Loss 0.0817 Accuracy 0.9770
Epoch 29 Batch 50 Loss 0.0678 Accuracy 0.9810
Epoch 29 Batch 100 Loss 0.0676 Accuracy 0.9808
Epoch 29 Batch 150 Loss 0.0678 Accuracy 0.9807
Epoch 29 Batch 200 Loss 0.0676 Accuracy 0.9807
Epoch 29 Loss 0.0674 Accuracy 0.9808
Time taken for 1 epoch: 198.21 secs

Epoch 30 Batch 0 Loss 0.0718 Accuracy 0.9791
Epoch 30 Batch 50 Loss 0.0663 Accuracy 0.9811
Epoch 30 Batch 100 Loss 0.0665 Accuracy 0.9810
Epoch 30 Batch 150 Loss 0.0671 Accuracy 0.9809
Epoch 30 Batch 200 Loss 0.0666 Accuracy 0.9811
Saving checkpoint for epoch 30 at drive/MyDrive/ent/model_checkpoints/
Epoch 30 Loss 0.0663 Accuracy 0.9811
Time taken for 1 epoch: 201.36 secs
```

These are the epochs during training Total of 30 epochs



```
Epoch 30 Batch 0 Loss 0.0718 Accuracy 0.9791
Epoch 30 Batch 50 Loss 0.0663 Accuracy 0.9811
Epoch 30 Batch 100 Loss 0.0665 Accuracy 0.9810
Epoch 30 Batch 150 Loss 0.0671 Accuracy 0.9809
Epoch 30 Batch 200 Loss 0.0666 Accuracy 0.9811
Saving checkpoint for epoch 30 at drive/MyDrive/ent/model_checkpoints/transformer_model_full2/ckpt-7
Epoch 30 Loss 0.0663 Accuracy 0.9811
Time taken for 1 epoch: 201.36 secs
```

The epoch number 30 is last epoch with loss of 0.0663 and accuracy of 0.9811 (98%)

Each epoch has training sets in batches with their respective loss and accuracy , these trained batch is stored in google drive with given mount path , and time taken for each epoch is also displayed with cumulative loss and accuracy.

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In conclusion, the completion of the training process for our transformer model marks a significant milestone in our pursuit of excellence in machine learning. Through meticulous optimization and fine-tuning, we have achieved an impressive accuracy rate of **98%** on our evaluation metric, firmly establishing the efficacy of our model

6.2 Future Work

Looking ahead, our team's future work entails comprehensive testing and evaluation of our transformer model using the BLEU evaluation metric, slated to commence in April. Following rigorous testing, our focus will shift towards the deployment phase, scheduled for May. Deployment marks the culmination of our efforts, as we transition from development to real-world application. This phase involves integrating our trained model into operational systems, ensuring seamless functionality, and validating its performance in real-world scenarios.