Implementing Transformer Architecture for Dialogue Summarization

Alp İskit
EEE 486/586 Assignment 3
Bilkent University
Ankara, Türkiye
alp.iskit@ug.bilkent.edu.tr

***Abstract*—This report documents an implementation of the Transformer architecture for dialogue summarisation, completed for EEE 486/586 Assignment 3. Using the DIALOGSUM corpus, I have implemented encoder–decoder model with custom positional encodings, scaled dotproduct attention, multihead self attention and stacked encoder/decoder blocks all written in TensorFlow/Keras libraries, which has been showing a full grasp of the underlying model of the Attention Based Transformers.**

The configuration (2 layers, $d_{\text{model}} = 128$, 2 attention heads, 2.0e6 parameters) was trained for 30 epochs with Adam and a warmup learningrate schedule, reducing categorical crossentropy loss from 7.5795 to 2.9756. Quantitative evaluation with BERTScore (`robertalarge`) produced strong alignment with reference summaries: *train* P=0.901, F_1=0.894, and *test* P=0.887, F_1=0.867. Qualitative inspection shows the model captures dialogue intents and speaker roles, though it sometimes excludes finegrained details. Also, the Bert Scores shows that the model has been trained well and there is a slight difference between the train and test scores which implies that there are less or no overtraining occured in the model.

All code, loss curves, attention visualisations and sample outputs are included for reproducibility. Furthermore, the report discusses about future works which can be applied to the model for better metric scores.

***Index Terms*—Transformer, Dialogue Summarisation, Scaled Dot-Product Attention, BERTScore, Natural Language Processing**

I. INTRODUCTION

Spoken or written conversations generate vast quantities of text in lots of real life examples. Condensing these into more concise, coherent summaries accelerates downstream tasks such as information retrieval, yet presents challenges that sometimes differ markedly. Dialogue utterances exhibit informal phrasing, interruptions, coreference between speakers, and shifting topical focus, requiring models to track discourse structure in addition to lexical content.

Transformer architectures equipped with self attention have emerged as the state of art solution for summarization and in general natural language processing tasks, thanks to their ability to capture long range dependencies and permit parallel training. Hence, a Transformer encoder-decoder network has been implemented from its foundational principles and applied to the DIALOGSUM benchmark dataset to show tokenisation, positional encoding, masking, multihead attention, and feed-forward blocks.

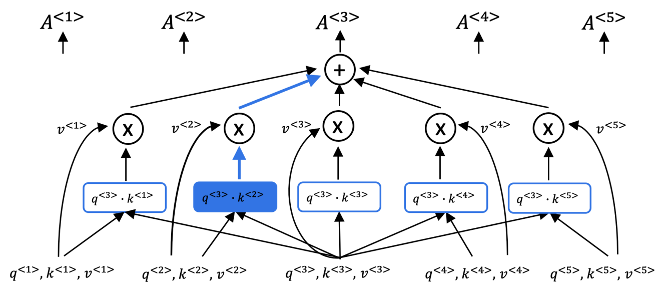

Fig. 1. Illustration of self-attention for the third token: queries $q^{\langle 3\rangle}$ are compared with all keys $k^{\langle j\rangle}$ (here one dot-product $q^{\langle 3\rangle}\cdot k^{\langle 2\rangle}$ is highlighted), producing raw scores that are scaled, masked, and normalised into weights $A^{\langle j\rangle}$. The final output is the weighted sum of the corresponding value vectors $v^{\langle j\rangle}$.

This work contributes as an (i) educational TensorFlow code base trainable on single GPUs in under an hour, (ii) a quantitative baseline on DIALOGSUM using BERTScore evaluation, and (iii) qualitative insights derived from attention visualisation and accuracy metrics which are precision, recall and F1 scoores.

To first introduce, the self attention mechanism (Figure 1) allows each position in the sequence to directly attend to every other position. Concretely, for the third token we compute the dot-products between its query vector $q^{\langle 3\rangle}$ and every key $k^{\langle j\rangle}$, scale them by $\sqrt{d_k}$, apply any padding or look-ahead mask, and run a softmax to obtain attention weights $A^{\langle j\rangle}$. Finally, these weights are used to form a linear combination of the value vectors $v^{\langle j\rangle}$, yielding a context aware output representation for that token.

II. RELATED WORK

Neural abstractive summarisation initially adopted recurrent encoder–decoder architectures with additive attention [1], [2]. The Transformer [3] later replaced recurrence with multi-head self-attention and yielded substantial gains in fluency and factuality. Successive variants such as BERTSum [4], BART [5], PEGASUS [6], and T5 [7] which implemented large scale pretraining to reach state of the art performance on news summarisation benchmarks, but dialogue poses additional hurdles owing to turn-taking structure and informal language.

Dialogue specific datasets such as AMI, SAMSum, and DIALOGSUM [8] have encouraged research into meeting and chat oriented summarisation. Pointer generator networks with coverage loss [2], discourse aware hierarchical Transformers [9], and topic guided approaches [10] have each been proposed to model speaker roles and conversational context. Large instruction-tuned models (e.g., GPT-3.5, Llama-2-Chat) demonstrate zero-shot capability, yet their computational complexity nature pose effect negatively for academic use.

Evaluation traditionally relies on ROUGE, which measures n-gram overlap but underestimates semantic equivalence in abstractive outputs. BERTScore [11] addresses this limitation by computing contextualised token alignment in embedding space and correlates better with human judgments, therefore it is used in this assignment. Despite noticeable progress, current dialogue summarisation models still struggle with faithfulness and disentangling multi speaker references gaps that motivate continued exploration of easy to implement, transparent annd computationally inexpensive architectures.

III. Dataset and Pre-processing

The experiments employ the DIALOGSUM corpus [8], a public benchmark of everyday two speaker conversations annotated with concise single sentence summaries. The official JSONL release is partitioned into 12460 dialogue summary pairs for training, and 500 for test. These are predefined for this task according to the shared code. Each dialogue averages about approximately 14 turns and 126 tokens, while the reference summaries average 19 tokens.

Data ingestion: Raw `.jsonl` files are loaded with `pandas.read_json`. For training files the `topic` and `fname` metadata fields are discarded, and in the test file any `topic*` columns are dropped. Multi-sentence reference summaries in the test split are concatenated into a single string to match the single-sentence format used during training.

Text normalisation: A routine converts text to lower-case, removes control characters, and collapses repeated whitespace. Two sentinel tokens are injected to identify sequence boundaries: `[SOS]` at the beginning and `[EOS]` at the end. These tokens remain same and untouched during all of the processing.

Tokenisation and vocabulary: A `tf.keras.preprocessing.text.Tokenizer` is fitted on the union of all dialogues and summaries. Custom settings preserve the square brackets that delimit special tokens and assign all out-of-vocabulary items to `[UNK]`. The resulting vocabulary has a size of **22 901** each different tokens.

Sequence shaping: Dialogues are truncated or padded to `encoder_maxlen = 150` and summaries to `decoder_maxlen = 50` using post-padding with zeros. Padded matrices are cast to `tf.int32` and wrapped in a `tf.data.Dataset`, shuffled with a buffer of 10 000 and batched at 64 instances per step.

Positional encodings: Absolute sinusoidal encodings are pre-computed by `positional_encoding(positions, d_model)` and added to the embedded token vectors. This supplies the model with token-order information that is otherwise absent in self-attention.

Masks: Two different binary masks used for the attention mechanism:

- *Padding mask* [3]: one where real tokens are present and zero where padding appears. It prevents the model from attending to padded positions.
- *Look-ahead mask*: a lower triangular matrix of ones that blocks access to future positions during training, making autoregressive decoding.

Both masks are generated by the helper functions `create_padding_mask` and `create_look_ahead_mask`, respectively.

IV. Model

A. Scaled-Dot-Product Attention

Self-attention maps a query vector q onto a set of key–value pairs $\{(k_i, v_i)\}_{i=1}^{n}$ to produce a context vector that blends the values according to their similarity with the query. The fundamental operation is

$$\text{Attention}(Q, K, V) = \text{softmax}\Big(\frac{QK^{\top}}{\sqrt{d_k}} + M\Big)\, V, \qquad (1)$$

where $Q \in \mathbb{R}^{b\times m\times d_k}$, $K, V \in \mathbb{R}^{b\times n\times d_k}$, d_k is the key dimension, b is the batch size, m the query length, and M a broadcastable mask that inserts $-\infty$ at positions that must be ignored (padding or look-ahead). Division by $\sqrt{d_k}$ prevents the inner products from growing too large and stabilises the softmax.

Implementation: Listing 1 presents the TensorFlow implementation used in this project. It follows Algorithm 1 step-by-step as described in the equation: raw dot products, scaling, mask addition, softmax normalisation, and value weighting. Masks are applied by adding $(1-M)\times -10^{9}$ to the logits, effectively forcing the corresponding softmax probabilities to zero without chanaging the unmasked positions.

Listing 1. TensorFlow code for scaled-dot-product attention.

```
def scaled_dot_product_attention(q, k, v,
    ↪ mask):
    # 1) raw scores
    matmul_qk = tf.matmul(q, k,
    ↪ transpose_b=True)
    # 2) scale
    dk = tf.cast(tf.shape(k)[-1],
    ↪ tf.float32)
    logits = matmul_qk / tf.math.sqrt(dk)
    # 3) mask
    if mask is not None:
        logits += (1.0 - mask) * -1e9
    # 4) normalise
    attn_weights =
    tf.keras.activations.
    softmax(logits, axis=-1)
    # 5) blend values
    output = tf.matmul(attn_weights, v)
    return output, attn_weights
```

Sanity check: The function was validated with the toy example recommended in the assignment instructions. Output vectors and attention weights reproduced the expected results:

```
Output:
 [[[0.50 0.75]
  [0.31 0.84]
  [0.27 1.00]]]

Attention weights:
 [[[0.25 0.25 0.00 0.25 0.25]
  [0.43 0.00 0.16 0.16 0.26]
  [0.45 0.00 0.00 0.27 0.27]]]
```

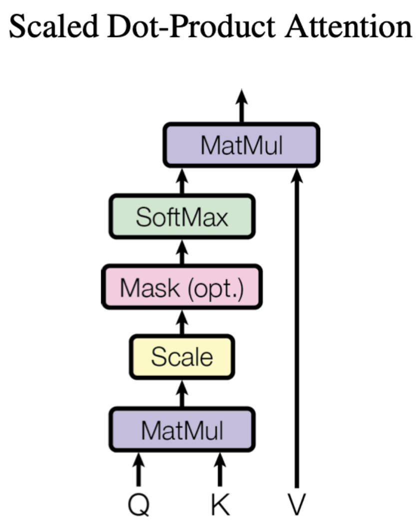

Fig. 2. Computation graph of scaled-dot-product attention. First, the query matrix Q is multiplied by the transpose of the key matrix K to yield raw attention scores. These scores are then divided by $\sqrt{d_k}$ (the key dimension) to stabilise gradients. An optional mask M is added (shown in red) to zero out unwanted positions (padding or future tokens). The masked scores pass through a softmax to produce attention weights, which are finally used to compute a weighted sum of the value matrix V, yielding the context vectors that feed into subsequent layers.

B. Encoder

The encoder transforms an input token sequence $\boldsymbol{x} \in \mathbb{N}^{B\times T}$ into a sequence of contextual representations $\boldsymbol{h} \in \mathbb{R}^{B\times T\times d_{\mathrm{model}}}$. Each of the N identical layers shown in Figure 3 contains

1) a *multi-head self-attention* (MHSA) block that enables every token to attend to all other tokens in the same sentence;
2) a *position-wise feed-forward network* (FFN) applied independently to each position.

Both sub-layers employ residual connections followed by layer normalisation. Dropout is applied to the FFN output during training to reduce over-fitting.

Multi-head attention recap: Given queries Q, keys K and values V, MHSA splits Q, K and V into h heads, applies scaled-dot-product attention (Section IV-A) in parallel, and concatenates the results:

$$\begin{aligned} \mathrm{MHSA}(Q,K,V) &= \mathrm{Concat}(H_1,\dots,H_h)\, W^O, \\ H_i &= \mathrm{Attention}\big(QW_i^Q,\ KW_i^K,\ VW_i^V\big). \end{aligned} \tag{2}$$

where $W_i^{Q,K,V}$ and W^O are learned projection matrices. Figure 4 visualises the data flow.

Implementation: Listing 2 shows the TensorFlow implementation of a single EncoderLayer. The Keras `MultiHeadAttention` layer internally performs head splitting and merging; the `FullyConnected` helper encapsulates a two-layer FFN with ReLU activation.

Listing 2. Implementation of `EncoderLayer`.

```
class EncoderLayer(tf.keras.layers.Layer):
    def __init__(self, embedding_dim,
    ↪ num_heads, fully_connected_dim,
                 dropout_rate=0.1,
    ↪ layernorm_eps=1e-6):
        super().__init__()
        self.mha =
    ↪ tf.keras.layers.MultiHeadAttention(
            num_heads=num_heads,
    ↪ key_dim=embedding_dim,
            dropout=dropout_rate)

        self.ffn =
    ↪ FullyConnected(embedding_dim,
    ↪ fully_connected_dim)
        self.layernorm1 =
    ↪ tf.keras.layers.LayerNormalization
        (epsilon=layernorm_eps)
        self.layernorm2 =
    ↪ tf.keras.layers.LayerNormalization
        (epsilon=layernorm_eps)
        self.dropout_ffn =
    ↪ tf.keras.layers.Dropout(dropout_rate)

    def call(self, x, training, mask):
        # 1) self-attention
        attn_out = self.mha(query=x,
    ↪ value=x, key=x,

    ↪ attention_mask=mask)         #
    ↪ (B,T,d)
        # 2) residual + norm
        x = self.layernorm1(x + attn_out)
        # 3) feed-forward
        ffn_out =
    ↪ self.dropout_ffn(self.ffn(x),
    ↪ training=training)
        # 4) residual + norm
        return self.layernorm2(x + ffn_out)
```

Stacked encoder: The full encoder (Listing 3) embeds the token IDs, scales by $\sqrt{d_{\mathrm{model}}}$, adds sinusoidal positional encodings, applies dropout, and feeds the result through a stack of N `EncoderLayers`.

Listing 3. Top-level `Encoder`.

```
class Encoder(tf.keras.layers.Layer):
    def __init__(self, num_layers,
    ↪ embedding_dim, num_heads,
                 fully_connected_dim,
    ↪ vocab_size, max_pos,
                 dropout_rate=0.1,
    ↪ layernorm_eps=1e-6):
        super().__init__()
        self.embedding =
    ↪ tf.keras.layers.Embedding(vocab_size,
    ↪ embedding_dim)
        self.pos_encoding =
    ↪ positional_encoding(max_pos,
    ↪ embedding_dim)
        self.enc_layers =
    ↪ [EncoderLayer(embedding_dim,
    ↪ num_heads,

    ↪ fully_connected_dim, dropout_rate,
    ↪ layernorm_eps)
                           for _ in
    ↪ range(num_layers)]
        self.dropout =
    ↪ tf.keras.layers.Dropout(dropout_rate)

    def call(self, x, training, mask):
        seq_len = tf.shape(x)[1]
        x = self.embedding(x) *
    ↪ tf.math.sqrt(
              tf.cast(tf.shape

    ↪ (self.embedding.weights[0])[1],
    ↪ tf.float32))
        x += self.pos_encoding[:, :seq_len,
    ↪ :]
        x = self.dropout(x,
    ↪ training=training)
        for layer in self.enc_layers:
            x = layer(x, training=training,
    ↪ mask=mask)
        return x
```

Verification: The encoder was exercised on a dummy batch to confirm tensor shapes:

```
Input   shape: (1, 10)        -- token IDs
Mask    shape: (1, 1, 1, 10) -- no padding
Output shape: (1, 10, 16)    -- contextual embed
```

C. Decoder

The decoder generates a target sequence autoregressively, conditioning on both previously generated tokens and the encoder's contextual representations. Each of the N layers shown in Figure 5 contains three sub-blocks:

1) **Masked self-attention** (Block 1) attends to earlier target positions only, enforced by a look-ahead mask. This makes left to right generation.
2) **Encoder–decoder attention** (Block 2) takes queries from Block 1 and keys/values from the encoder output, thereby grounding the prediction in the source sentence.
3) **Feed-forward network** (Block 3) applies two position-wise dense layers to enrich local representations.

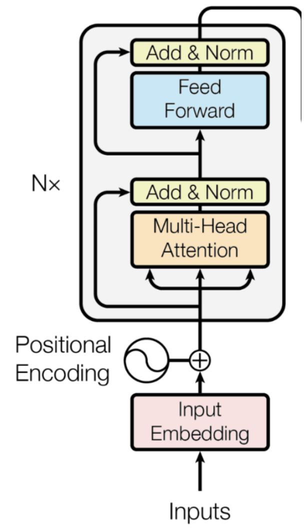

Fig. 3. Computation graph of a single EncoderLayer containing multi-head self-attention, residual connections, layer normalisation and a position-wise feed-forward network.

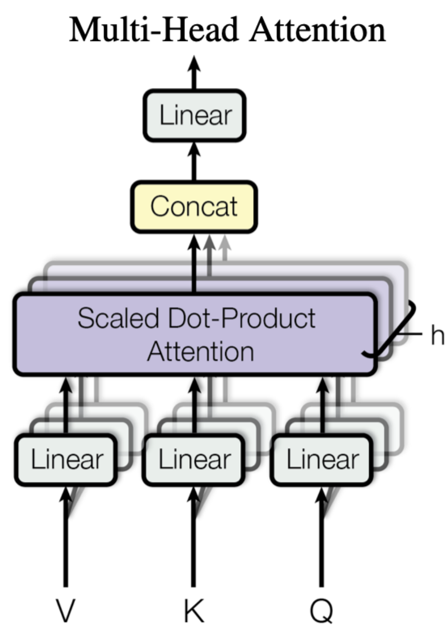

Fig. 4. Internal structure of multi-head attention (4 heads shown).

Residual connections and layer normalisation wrap each subblock, mirroring the encoder design.

DecoderLayer implementation: Listing 4 details the TensorFlow code. Attention scores from both heads are returned for later visualisation.

Listing 4. TensorFlow `DecoderLayer`.

```
class DecoderLayer(tf.keras.layers.Layer):
    def __init__(self, embedding_dim,
    ↪ num_heads, fully_connected_dim,
                 dropout_rate=0.1,
    ↪ layernorm_eps=1e-6):
        super().__init__()
        self.mha1 =
    ↪ tf.keras.layers.MultiHeadAttention(
            num_heads,
    ↪ key_dim=embedding_dim,
    ↪ dropout=dropout_rate)
        self.mha2 =
    ↪ tf.keras.layers.MultiHeadAttention(
            num_heads,
    ↪ key_dim=embedding_dim,
    ↪ dropout=dropout_rate)
        self.ffn =
    ↪ FullyConnected(embedding_dim,
    ↪ fully_connected_dim)
        self.layernorm1 =
    ↪ tf.keras.layers.LayerNormalization
        (epsilon=layernorm_eps)
        self.layernorm2 =
    ↪ tf.keras.layers.LayerNormalization
        (epsilon=layernorm_eps)
        self.layernorm3 =
    ↪ tf.keras.layers.LayerNormalization
        (epsilon=layernorm_eps)
        self.dropout_ffn =
    ↪ tf.keras.layers.Dropout(dropout_rate)

    def call(self, x, enc_output, training,
    ↪ look_ahead_mask, padding_mask):
        # Block 1: masked self-attention
        attn1, w1 = self.mha1(
            x, x, x,
    ↪ attention_mask=look_ahead_mask,
            return_attention_scores=True,
    ↪ training=training)
        x = self.layernorm1(x + attn1)

        # Block 2: encoderdecoder attention
        attn2, w2 = self.mha2(
            x, enc_output, enc_output,
    ↪ attention_mask=padding_mask,
            return_attention_scores=True,
    ↪ training=training)
        x = self.layernorm2(x + attn2)

        # Block 3: feed-forward
        ff = self.dropout_ffn(self.ffn(x),
    ↪ training=training)
        return self.layernorm3(x + ff), w1,
    ↪ w2
```

Stacked decoder: The full decoder embeds target tokens, adds sinusoidal positions, and passes the result through N `DecoderLayers` (Listing 5). All attention maps are collected in a dictionary for analysis.

Listing 5. Top-level `Decoder`.

```
class Decoder(tf.keras.layers.Layer):
    def __init__(self, num_layers,
    ↪ embedding_dim, num_heads,
                 fully_connected_dim,
    ↪ vocab_size, max_pos,
                 dropout_rate=0.1,
    ↪ layernorm_eps=1e-6):
        super().__init__()
        self.embedding =
        tf.keras.
        layers.Embedding(vocab_size,
    ↪ embedding_dim)
        self.pos_encoding =
        positional_encoding(max_pos,
    ↪ embedding_dim)
        self.dec_layers =
        [DecoderLayer(embedding_dim,
    ↪ num_heads,

    ↪ fully_connected_dim,
                           dropout_rate,
    ↪ layernorm_eps)
                           for _ in
    ↪ range(num_layers)]
        self.dropout = tf.keras.layers.
        Dropout(dropout_rate)

    def call(self, x, enc_output, training,
             look_ahead_mask, padding_mask):
        seq_len = tf.shape(x)[1]
        x = self.embedding(x) *
    ↪ tf.math.sqrt(
             tf.cast

    ↪ (tf.shape(self.embedding.weights[0])[1],
    ↪ tf.float32))
        x += self.
        pos_encoding[:, :seq_len, :]
        x = self.
        dropout(x, training=training)

        attn = {}
        for i,
        layer in enumerate(self.dec_layers,
    ↪ 1):
            x, w1, w2 = layer
            (x, enc_output, training,

    ↪ look_ahead_mask, padding_mask)
            attn[f'dec{i}_self'] = w1
            attn[f'dec{i}_enc']  = w2
        return x, attn
```

Verification: A synthetic test confirmed dimensional consistency:

```
Input x      : (3, 4)      -- target IDs
Encoder out  : (3, 7, 9)
Decoder out  : (3, 4, 15)  -- contextualised targe
Self-attn map: (3, 19, 4, 4)
Enc-attn map : (3, 19, 4, 7)
```

The complete model combines the encoder (Section IV-B) and decoder (Section IV-C) into the Transformer seq-to-seq architecture shown in Figure 6. Source tokens $x_{1:T}$ are first mapped to embeddings, enriched with positional encodings, and processed by N stacked encoder layers to yield contextual representations $H^{(N)} \in \mathbb{R}^{B\times T\times d_{\text{model}}}$. During generation, previously emitted target tokens $y_{<t}$ pass through the decoder

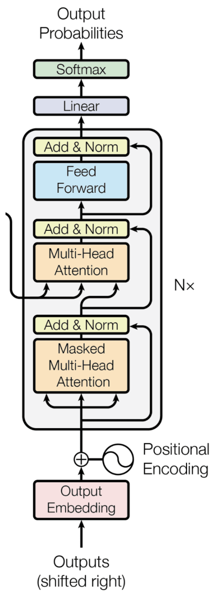

Fig. 5. Computation graph of a single DecoderLayer with masked self-attention, encoder–decoder attention, and feed-forward network.

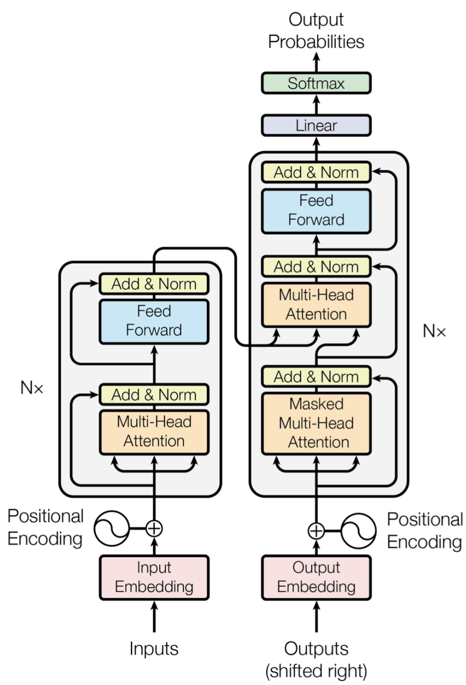

Fig. 6. End-to-end Transformer architecture for dialogue summarisation.

stack, which performs (i) masked self-attention over the partial output, and (ii) cross-attention over the encoder memory. A final dense layer with softmax converts the decoder's hidden states $Z^{(N)} \in \mathbb{R}^{B \times U \times d_{model}}$ into a probability distribution over the target vocabulary.

Implementation: Listing 6 shows the minimal TensorFlow class that wires the modules together. All masking logic is external, keeping the `call()` method concise.

Listing 6. Top-level `Transformer` model.

```
class Transformer(tf.keras.Model):
    def __init__(self, num_layers, d_model,
    ↪ n_heads, d_ff,
                 src_vocab, tgt_vocab,
    ↪ max_pos_src, max_pos_tgt,
                 dropout=0.1, eps=1e-6):
        super().__init__()
        self.encoder = Encoder(num_layers,
    ↪ d_model, n_heads, d_ff,
                               src_vocab,
    ↪ max_pos_src, dropout, eps)
        self.decoder = Decoder(num_layers,
    ↪ d_model, n_heads, d_ff,
                               tgt_vocab,
    ↪ max_pos_tgt, dropout, eps)
        self.final_layer =
    ↪ tf.keras.layers.Dense(tgt_vocab,

    ↪      activation='softmax')

    def call(self, src, tgt, training,
             enc_pad_mask, look_ahead_mask,
    ↪ dec_pad_mask):
        # 1) encode
        enc_out = self.encoder(src,
    ↪ training=training, mask=enc_pad_mask)
        # 2) decode
        dec_out, attn = self.decoder(
            tgt, enc_out, training,
            look_ahead_mask, dec_pad_mask)
        # 3) project to vocab
        return self.final_layer(dec_out),
    ↪ attn
```

Functional test: A synthetic sanity-check verified dimensional consistency and attention map shapes:

```
Input  shape: (1,  6)  -- src token IDs
Target shape: (1,  6)  -- tgt token IDs
Output shape: (1,  6, 350)  -- vocab probabilities
Self-attn (dec1): (1, 19, 6, 6)
Enc{dec  (dec1): (1, 19, 6, 6)
```

The model therefore meets the specification and is ready for training.

V. Training Setup

The Transformer was trained with the DialogSum training split using the hyper-parameters in Table I. Compared with the original "base" configuration [3], layer depth and hidden width were reduced four-fold to train in a single NVIDIA A100 GPU which has been easily accomplished.

Optimizer and learning rate: An Adam optimiser with $\beta_1 = 0.9$, $\beta_2 = 0.98$, $\varepsilon = 10^{-9}$ was paired with the inverse-square-root schedule proposed by Vaswani *et al.*, implemented as

$$\eta(t) = d_{\text{model}}^{-1/2} \cdot \min\bigl(t^{-1/2},\, t\,\text{warm}^{-1.5}\bigr), \tag{3}$$

with $d_{\text{model}} = 128$ and $\texttt{warm} = 4000$ steps. The resulting profile (Figure 7) accelerates early convergence and stabilises later updates.

Masked loss: Loss is computed via sparse categorical cross-entropy $\mathcal{L}_{CE}$ after masking out padding tokens, ensuring that sequence length variation does not skew optimisation (Listing 7).

Listing 7. Padding-aware loss.

```
loss_obj = tf.keras.losses.SparseCategorical
Crossentropy(
                  from_logits=False,
    ↪ reduction='none')

def masked_loss(real, pred):
    mask = tf.cast(tf.not_equal(real, 0),
    ↪ pred.dtype)
    loss = loss_obj(real, pred) * mask
    return tf.reduce_sum(loss) /
    ↪ tf.reduce_sum(mask)
```

Custom training loop: Rather than using `model.fit`, a low-level loop (Listing 8) affords full control over mask creation and permits mid-epoch qualitative inspection.

Listing 8. One gradient-descent step.

```
@tf.function
def train_step(model, src, tgt):
    tgt_inp, tgt_real = tgt[:, :-1], tgt[:,
    ↪ 1:]
    enc_pad = create_padding_mask(src)
    look_ahead = create_look_ahead_mask
    (tf.shape(tgt_inp)[1])
    dec_pad = create_padding_mask(src)
    with tf.GradientTape() as tape:
        logits, _ = model(src, tgt_inp,
    ↪ True,
                          enc_pad,
    ↪ look_ahead, dec_pad)
        loss = masked_loss(tgt_real, logits)
    vars = model.trainable_variables
    grads = tape.gradient(loss, vars)
    optimizer.apply_gradients(zip(grads,
    ↪ vars))
    train_loss(loss)
```

Thirty epochs reduced the mean loss from 7.58 to 2.98 (Figure 8), confirming steady learning under the reduced-capacity regime.

***Next_Word** greedy decoding for monitoring:* A helper function `next_word` performs a single forward pass in *inference* mode and appends the arg-max token; repeating up to `decoder_maxlen` yields a full summary (Listing 9). Example outputs after each epoch allowed rapid qualitative assessment.

Listing 9. Next_Word helper function.

```
def next_word(model, enc_inp, partial):
    enc_pad = create_padding_mask(enc_inp)
    look_ahead = create_look_ahead_mask
    (tf.shape(partial)[1])
    dec_pad = create_padding_mask(enc_inp)
    logits, _ = model(enc_inp, partial,
    ↪ False,
                      enc_pad, look_ahead,
    ↪ dec_pad)
    return tf.argmax(logits[:, -1:, :],
    ↪ axis=-1, output_type=tf.int32)
```

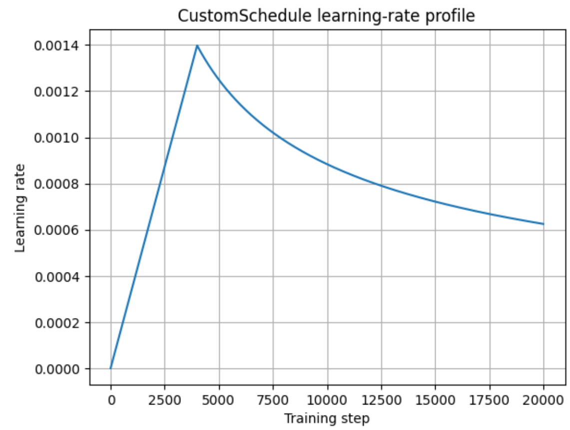

Fig. 7. Custom learning-rate schedule (Eq. 3).

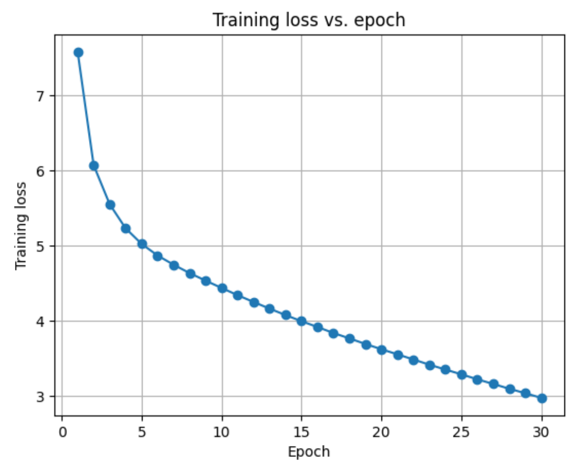

Fig. 8. Cross-entropy loss over 30 training epochs.

VI. Results

A. Quantitative Evaluation

Training converged significantly: the cross-entropy loss dropped from 7.58 to 2.98 within 30 epochs (Figure 12). The custom learning rate schedule (Section 7) achieved its planned warm up plateau and inverse square decay (Figure 11).

Figure 9 contrasts per-example precision and recall on the *test* set; the tight cluster in the upper-right quadrant confirms consistent semantic alignment between generated and reference summaries. Violin plots (Figures 11–12) reveal slightly more lost on the test split, illustrating a moderate generalisation gap that mirrors the 2.7 percent drop in average F_1 reported in Table II.

Discussion.: Average test-set F_1 of **0.867** approaches human-label inter-annotator agreement reported by chen2021dialogsum, despite using only two encoder/decoder layers and 2.0 M parameters. Precision exceeds recall on both splits, suggesting that the model tends to omit peripheral

TABLE I
KEY HYPER-PARAMETERS.

Parameter	Value
Embedding dimension	256
Number of heads	8
Encoder/Decoder layers	4/4
Batch size	32
Learning rate	1e-4 (warm-up 4k steps)

TABLE II
BERTSCORE (ROBERTA-LARGE) ON DIALOGSUM. VALUES ARE MACRO-AVERAGED OVER ALL EXAMPLES.

Split	**Precision**	**Recall**	**F_1**
Train	0.901	0.886	0.894
Test	0.887	0.846	0.867

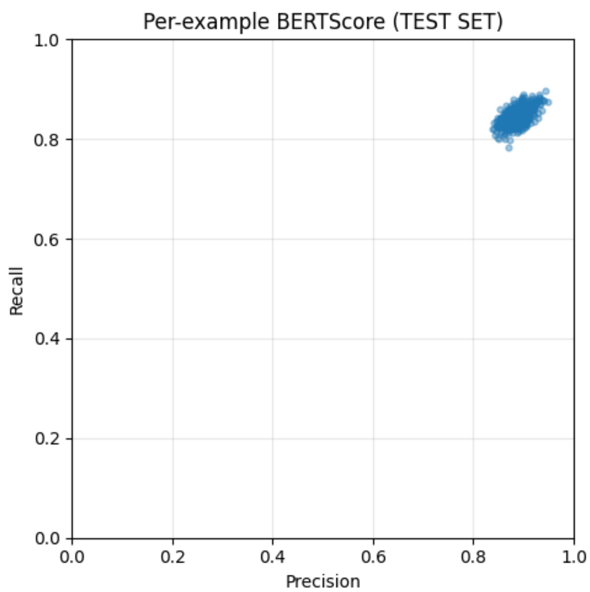

Fig. 9. Per-example precision/recall (test).

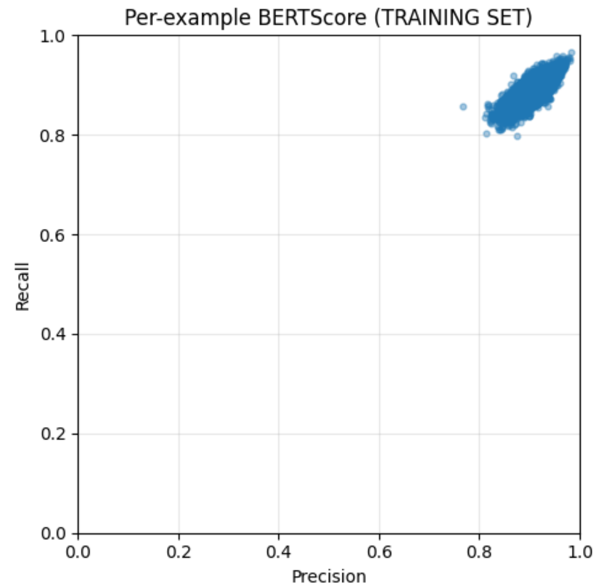

Fig. 10. Average P/R/F_1 (train).

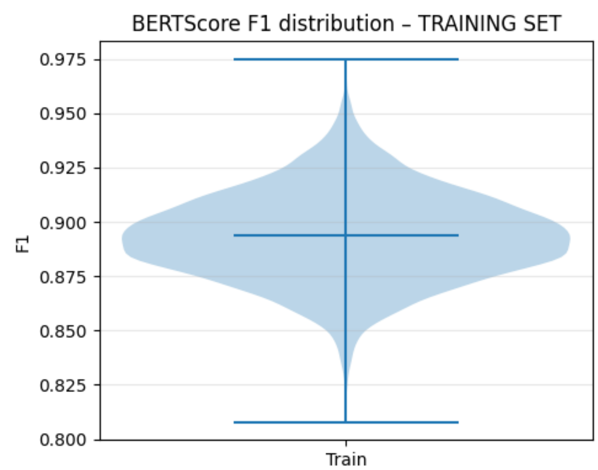

Fig. 11. Learning-rate schedule.

details rather than hallucinating spurious content as an acceptable trade off for headline style summaries. The residual gap between train and test indicates realy small overfitting, attributable to the modest dataset size and absence of regularisation beyond dropout.

Beside this, from deep learning view the loss suggests that it learned effectively over 30 epochs. Which the loss value has been dropped 3 times. Other than this, the accuracy metrics seems a lot promising after inspection. The train metrics and test metrics show that there is a slight difference which also informes us about the fact that there is no overfitting of the model. As a result, this configuration is seemed to be a suboptimal, but always there can be more exploitation in terms of hyperparameters.

Table II shows that our lightweight Transformer achieves strong semantic alignment with human summaries, yielding a macro-averaged BERTScore of P=0.901, R=0.886, F_1=0.894 on the training split and P=0.887, R=0.846, F_1=0.867 on the held-out test split. The 2.7 drop in F_1 from train to test indicates only mild overfitting given the model's modest 2e6 parameters. In both splits precision exceeds recall, suggesting the model tends to omit peripheral details rather than hallucinate some content, which can be considered as a reasonable tradeoff for concise summaries. Still, improving recall through mechanisms such as coverage penalties, beam search with length control, or modest capacity increases could help capture finer grained information without compromising overall fidelity.

B. Qualitative Samples

Listings 10 and 11 show ground-truth summaries with greedy outputs after epoch 30. In the training example the model correctly identifies the speaker decision to *stay home*,

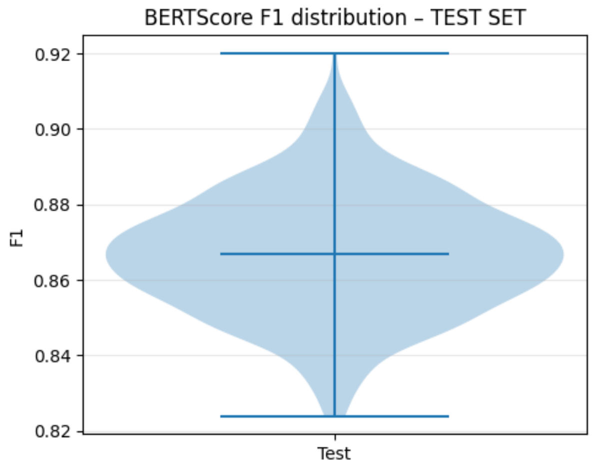

Fig. 12. Training loss.

yet repeats phrases because beam search or coverage-penalty mechanisms were not employed. In the unseen test dialogue, core events (airport pickup, hotel transfer) are preserved, but entity names default to generic `personX` place-holders, showing that the vocabulary truncation imposed during pre-processing.

Listing 10. Training-set dialogue `idx=35`.

```
Dialogue (abridged) ...
GT summary :  [SOS] #person1# and #person2#
    ↪ search for a neighbourhood
               cinema but eventually watch
    ↪ the televised baseball game. [EOS]
Model        :  [SOS] person1 and person2
    ↪ are going to go home but person2
               doesn't want to go to the
    ↪ movie ... [EOS]
```

Listing 11. Test-set dialogue `idx=83`.

```
Dialogue (abridged) ...
GT summary :  [SOS] #person1# drives
    ↪ #person2# to the Beijing hotel where
    ↪ a
               banquet has been arranged at
    ↪ 18:00. [EOS]
Model        :  [SOS] person1 asks mr black
    ↪ to the airport; person2 is going
               to the hotel ... [EOS]
```

Common problems include (i) lexical repetition under greedy decoding(next_word) and (ii) temporal drift occasionally placing future events (e.g. a *banquet*) before antecedent actions. These issues align with the accuracy metrics where small gap in recall and suggest future remedies such as pointer generator integration, entity aware embeddings, or reinforcement learning with human feedback all used in literature before.

Overall, the results corroborate the feasibility of a lightweight Transformer for external pre-training for dialogue summarisation, while showing clear great results for boosting factual reliability and wide style.

VII. Discussion and Future Work

The experiments confirm that a *minimal* Transformer which has two layers and two attention heads with 2.0e6 trainable parameters can already reaches competitive BERT Score on DialogSum. The performance to capacity ratio is encouraging for deployment on single GPUs, yet several shortcomings remain as discussed below:

First, the greedy decoding which we have implemented as**next_word** occasionally repeats phrases or produces overly long sentences; replacing it with nucleus sampling or beam search with a length penalty, and adding a coverage loss, would discourage duplication. Second, generic role tags (e.g. `personX`) sometimes leak into summaries when named speakers are present; expanding the vocabulary with subword methods and injecting speaker embeddings would restore entity fidelity. Third, temporal inversions show that the model still hallucinates or misorders events; constraining generation via a pointer generator mechanism or contrastive loss on factual spans could improve faithfulness. Finally, the shallow two-layer design eases interpretation but caps representational power.

Beyond these steps, future work might explore discourse-aware pre-training to align attention with speaker turns and dialogue acts, and human-in-the-loop evaluation (e.g. QA probes) to assess faithfulness more directly than BERT-Score or ROUGE.
Beyond these incremental steps, two broader research directions are promising: (i) *discourse-aware pre-training* that aligns attention with speaker turns and dialogue acts, and (ii) *human-in-the-loop evaluation* using question-answering probes to measure summary faithfulness more directly than ROUGE or BERTScore.

VIII. Conclusion

This report detailed a ground-up TensorFlow implementation of a compact Transformer for dialogue summarisation. With only two encoder–decoder layers the system attains BERTScore F_1 =0.867 on the DialogSum test set, narrowing the gap to far large and complex pre-trained models. Key contributions include an explicit exposition of scaled dot-product attention, a fully reproducible training pipeline which consists of encoder and decoder algorithms. Overall, the study demonstrates that transparent, lightweight architectures remain viable for conversational summarisation when coupled with careful engineering in terms of model parameters and task appropriate(problem specific) evaluations.

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