

Streamlining Parameter Complexity of Transformer Architecture

*Dissertation submitted to
Visvesvaraya National Institute of Technology, Nagpur
in partial fulfillment of the requirements for the award of
the degree*

MASTER OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING

Submitted by

Lohith Ket
(Enrollment no. MT23MCS011)

Under the guidance of

Dr.Kumari Nidhi Lal

Assistant Professor



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

VISVESVARAYA NATIONAL INSTITUTE OF TECHNOLOGY

NAGPUR - 440010, MAHARASHTRA (INDIA)

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Declaration

I, **LOHITH KETI**, hereby declare that this dissertation titled "**Streamlining Parameter complexity of transformer architecture**" is carried out by me in the Department of Computer Science & Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier in whole or in part for the award of any degree at this or any other Institution.

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Certificate

This is to certify that the dissertation titled "**Streamlining Parameter complexity of transformer architecture**" is submitted by **LOHITH KETI** in partial fulfillment of the requirements for the award of the degree of **Master of Technology in Computer Science & Engineering**, VNIT Nagpur. The work is comprehensive, complete, and fit for final evaluation.

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ACKNOWLEDGEMENTS

At the outset, I would like to express my sincere gratitude to my supervisor, Dr. Nidhi Lal, for offering me the opportunity to work on the project titled “Streamlining Parameter complexity of Transformer Architecture” I am truly thankful for her constant guidance, valuable insights, and encouragement throughout the course of this work. Her support helped me navigate challenges, explore new ideas, and improve my research in this emerging area of Artificial Intelligence. I would also like to thank all the teaching and non-teaching staff of the Department of Computer Science and Engineering for their support and for providing essential resources that facilitated the successful completion of this project.

I would also like to express my gratitude to my family and friends for their unwavering support and encouragement throughout this journey. Their love, motivation, and belief in my abilities have been the driving force behind my accomplishments.

ABSTRACT

Transformer models have achieved exceptional results across numerous NLP tasks, including machine translation, language modeling, and question answering. However, their exceptional results are accompanied by substantial computational demands and high memory usage, largely driven by the extensive number of parameters. To address this issue, we propose a parameter-efficient variant of the Transformer architecture that reduces model complexity by sharing the FFN across all layers. Rather than instantiating a separate FFN for every block, we introduce a single global FFN module reused throughout the Transformer stack. This modification preserves the per-layer multi-head self-attention (MHSA) modules—essential for capturing layer-wise contextual dependencies—ensuring that representational diversity and modeling capacity remain intact. Our proposed design significantly decreases the number of learnable parameters and lowers memory consumption, without altering the self-attention mechanism. The result is a more compact and computationally efficient model, making it particularly well-suited for environments with limited resources, such as edge devices or real-time applications.

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Chapter 1

Introduction

Transformer architectures have become foundational to modern deep learning, excelling in fields like natural language processing (NLP), computer vision, and multi-modal tasks. Introduced in the groundbreaking paper “Attention is All You Need” by Vaswani et al., Transformers leverage their self-attention mechanism to effectively capture long-range dependencies and enable efficient parallel training. This has driven the success of large-scale models such as BERT, GPT, T5, and Vision Transformers (ViTs), establishing Transformers as a critical component in today’s advanced artificial intelligence systems.

However, this impressive performance comes at a substantial cost parameter complexity. As Transformer models scale in terms of depth (number of layers), width (hidden dimensionality), and sequence length, both their parameter count and computational demands increase significantly. This growth poses challenges for training efficiency, memory usage, and deployment, particularly in resource-constrained environments. requiring hundreds of gigabytes of memory and massive computational resources for both training and inference This parameter bloat not only limits accessibility to such models but also imposes significant barriers to deployment in real-time, low-power, and edge computing environments.

This paper targets the reduction of parameter complexity in standard Transformer architecture, proposing structural modifications that preserve model performance while significantly decreasing parameter count by reusing feed forward network layer in multiple layers. A major contributor to the high parameter count in Transformer models is the use of separate feed-forward network (FFN) layers in each Transformer block. In traditional Transformer architecture, each layer includes a separate FFN subnetwork, which significantly increases the total number of parameters.

The standard Transformer consists of multiple identical layers, each featuring two primary components: a Multi-Head Self-Attention (MHSA) mechanism and a

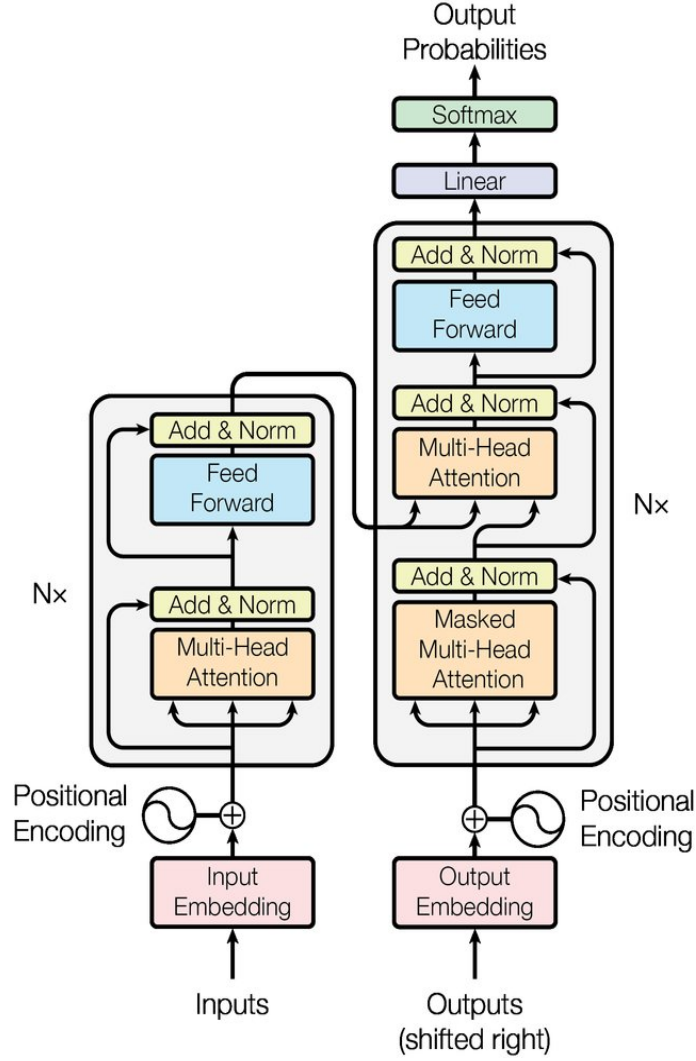


Figure 1.1: Standard Transformer Architecture.

Feed-Forward Network (FFN) sub-layer, followed by residual connections and layer normalization after each sub-component.

Each encoder layer is formally defined by the following components:

Multi-Head Self-Attention (MHSA): Models pairwise relationships between input tokens by projecting inputs into multiple attention heads, enabling simultaneous focus on diverse representation subspaces.

Feed-Forward Network (FFN): A position-wise network featuring two linear transformations with a non-linear activation (typically ReLU or GELU) applied between them.

Each decoder layer comprises:

Masked Multi-Head Self-Attention (Masked MHSA): Restricts attention to prior positions only, ensuring predictions at a given position depend solely on earlier

sequence elements. Inputs are projected into multiple attention heads to capture varied representation subspaces.

Cross-Attention: Allows the decoder to attend to the encoder’s output representations, selectively focusing on relevant parts of the input sequence during target token generation.

Feed-Forward Network (FFN): A position-wise, fully connected network with two linear transformations separated by a non-linear activation function (typically ReLU or GELU), applied independently to each sequence position.

1.0.1 Multi Head Attention

In the multi-head attention mechanism, the queries, keys, and values are each linearly transformed multiple times—specifically, h times—using different learned weight matrices. Each set of transformed vectors is processed through its own attention operation, resulting in h distinct attention outputs. These outputs are then concatenated and passed through one final linear layer to yield the final output. the

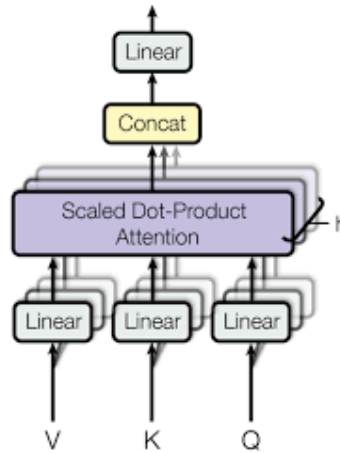


Figure 1.2: Multi Head Attention.

projections are computed as:

$$\mathbf{Q}_i = \mathbf{Q}\mathbf{W}_i^Q, \quad \mathbf{K}_i = \mathbf{K}\mathbf{W}_i^K, \quad \mathbf{V}_i = \mathbf{V}\mathbf{W}_i^V$$

where $\mathbf{W}_i^Q$, $\mathbf{W}_i^K$, and $\mathbf{W}_i^V$ are the learnable projection matrices.

Each attention head independently applies scaled dot-product attention, which starts by calculating the dot product between the transformed queries and keys. This result is then scaled by the inverse square root of the key dimension, $\sqrt{d_k}$, followed by

applying a softmax function to generate attention weights. These weights are used to compute a weighted sum of the corresponding value vectors, effectively capturing interactions between positions within the sequence.

After all heads have completed this process, their outputs are concatenated and passed through a final linear transformation using a learned matrix $\mathbf{W}^O$. This step merges the information gathered by each head into a unified representation. Utilizing multiple attention heads enables the model to attend to different types of contextual relationships in parallel, enriching its overall understanding of the input sequence.

1.0.2 Scaled Dot Product Attention

Scaled Dot-Product Attention serves as the core operation within each attention head in a Transformer. It takes three inputs—queries ($\mathbf{Q}$), keys ($\mathbf{K}$), and values ($\mathbf{V}$)—which are obtained by applying learned linear transformations to the input embeddings. To assess how much focus each token should receive, the mechanism calculates the dot product between the queries and keys, reflecting their pairwise similarity. This result is divided by $\sqrt{d_k}$, where d_k is the dimensionality of the keys, to prevent the dot product values from becoming excessively large, which can cause the softmax function to produce extremely small gradients. The scaled scores are then passed through a softmax to produce attention weights, which are applied to the value vectors to generate a context-sensitive weighted sum.

The complete formula for scaled dot-product attention is:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^\top}{\sqrt{d_k}}\right) \mathbf{V}$$

This process allows the model to emphasize the most significant elements in the input sequence by assigning greater attention weights to tokens that are more relevant when constructing each token’s representation.

1.1 Background and Motivation

Introduced by Vaswani et al. [1], the Transformer has established itself as a cornerstone in sequence modeling tasks, owing to its capacity to capture long-range dependencies through self-attention and its highly parallelizable structure.

This architecture has demonstrated scalability and robustness in numerous domains. However, as models grow deeper (e.g., 12 to 96 layers in modern architectures), this layer-wise replication of both attention and FFN blocks contributes

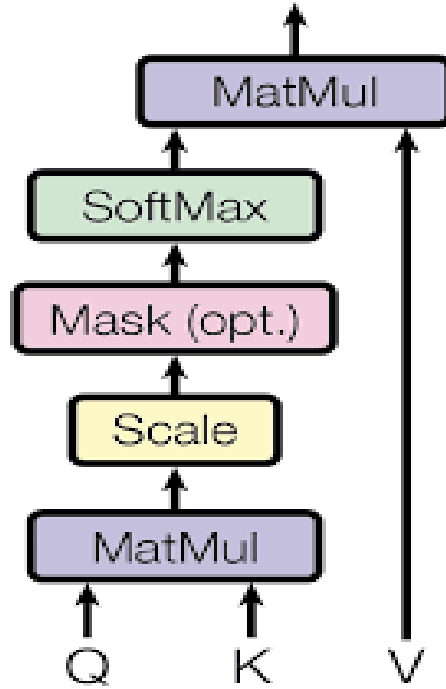


Figure 1.3: Scaled Dot Product Attention.

heavily to the total parameter count. While MHSA is often emphasized as the key to performance, empirical studies have shown that FFN layers typically account for a disproportionately large fraction of the total parameters.

Motivation stems from these limitations. I hypothesize that a more granular and selective sharing strategy, particularly targeting the FFN sub-component, can yield similar reductions in parameter complexity while preserving the flexibility of learning layer-wise attention dynamics. Since FFNs are structurally identical across layers and primarily perform token-wise transformations, they are strong candidates for sharing. In contrast, the attention layers—which capture positional and contextual relationships—benefit from being distinct to model diverse interactions at each layer depth.

To mitigate this, I explore the concept of reusing a shared FFN layer across multiple Transformer layers, thereby reducing the number of unique parameters without sacrificing depth or expressiveness. This strategy draws inspiration from parameter-sharing paradigms like those seen in ALBERT, but extends the idea to a more fine-grained level by selectively sharing only the FFN component while allowing other parts of the model, such as attention layers or normalization mechanisms, to remain the same. Hypothesis is that FFNs, being structurally similar across layers and primarily responsible for non-linear transformations.

1.2 Objectives of the Study

FFN layers across different Transformer layers are structurally identical and operate independently on each token, this study hypothesizes that the FFN is a suitable candidate for parameter sharing. Therefore, the core objective is to investigate the impact of sharing a single FFN module across all layers of the Transformer while preserving the layer-specific MHSA components, which are crucial for capturing diverse positional and contextual relationships throughout the depth of the model.

- To analyze the contribution of FFN layers to the overall parameter count in standard Transformer models and identify their role in model performance and redundancy.
- To design a modified Transformer architecture in which the FFN module is shared across all layers, thereby reducing parameter count while maintaining the model’s core computation pipeline.
- To preserve the uniqueness of MHSA layers across blocks, ensuring the model retains its ability to learn diverse attention patterns and context-dependent features at each depth level.
- To experimentally validate the proposed architecture on benchmark NLP tasks and compare its performance, and memory footprint with standard Transformer implementations.

1.3 Methodology

In the original design, each layer contains a unique FFN module and a layer-specific Multi-Head Self-Attention (MHSA) block. In proposed architecture, while the MHSA blocks remain layer-specific to preserve representational diversity, a single Feed-Forward Network (FFN) module is shared across all layers.

Model Design

FFN Sharing Strategy: A single shared Feed-Forward Network (FFN) module is instantiated and reused across all layers. This shared FFN replaces the per-layer FFNs traditionally present in the standard Transformer architecture, thereby reducing the overall parameter count significantly.

MHSA Layers Remain Distinct: To preserve the model’s representational flexibility and allow for diverse contextual learning at different depths, the Multi-Head Self-Attention (MHSA) components are kept unique for each layer.

The key idea in design is to instantiate the FFN module only once and reuse it across all layers. Instead of defining a separate FFN for each layer, a single FFN is created at the start of model construction and passed as a shared module to every block. During the forward pass, each layer invokes the shared FFN to process its intermediate representation before applying residual connections and layer normalization.

Feed-Forward Network (FFN) Weight Sharing

Formally, let

$$\text{FFN}(x) = \text{ReLU}(xW_1 + b_1)W_2 + b_2$$

be the feed-forward transformation. In the baseline Transformer architecture, a unique set of weights

$$(W_1^{(l)}, W_2^{(l)}, b_1^{(l)}, b_2^{(l)})$$

is learned for each layer l . In contrast, the proposed approach uses shared parameters

$$(W_1, W_2, b_1, b_2)$$

across all encoder layers $l = 1, \dots, N$ and decoder layers $l = 1, \dots, M$. This technique is inspired by the cross-layer parameter sharing strategy employed in models like ALBERT, although i apply it selectively to FFN layers only.

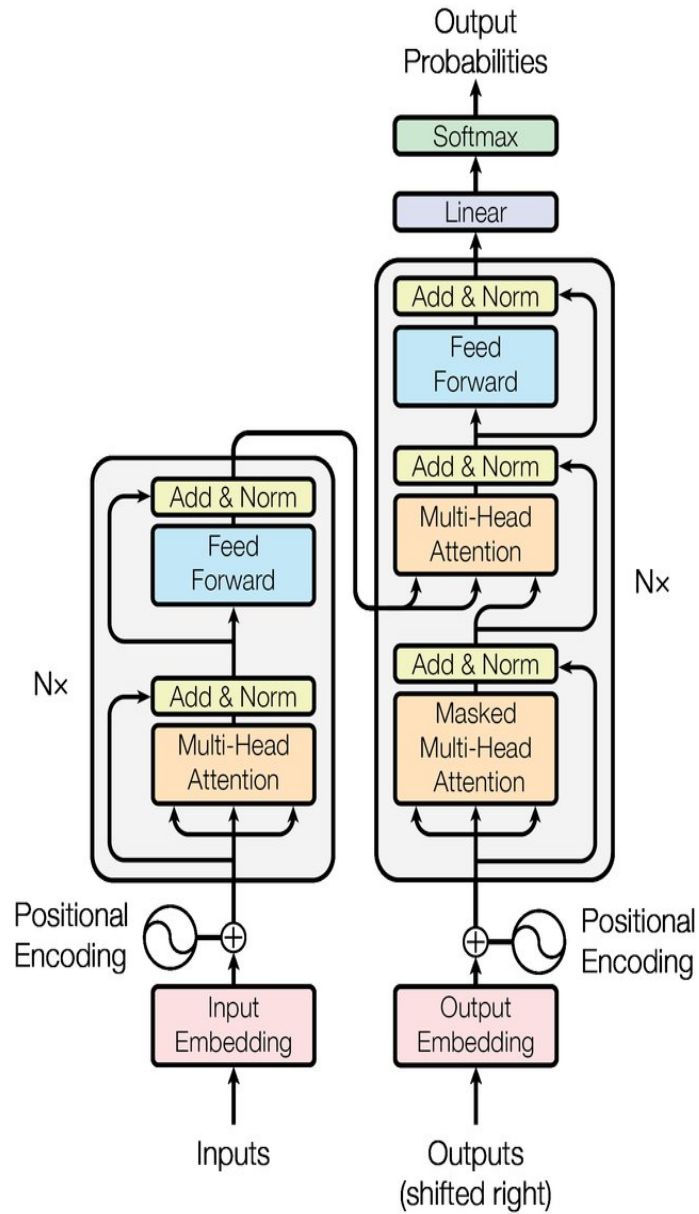


Figure 1.4: Standard Transformer Architecture.

In a standard Transformer, each layer has its own FFN sublayer, leading to a significant increase in parameter count as the number of layers increases. To address this, your approach:

- Instantiates a single Feed-Forward Network (FFN) module (i.e., creates it only once).
- Reuses (or shares) that same FFN across all layers.

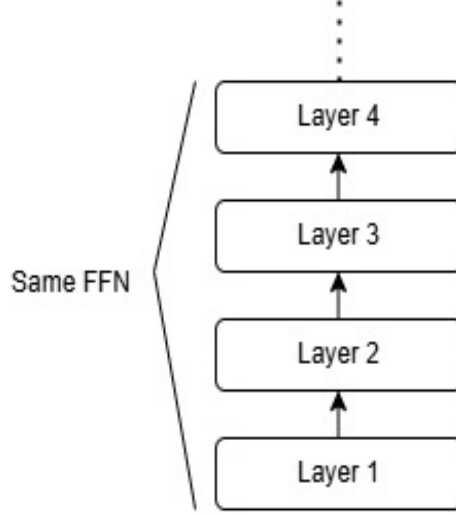


Figure 1.5: Shared Feed Forward Network across Layers.

1.4 Structure of the Thesis

- **Chapter 1: Introduction**

Provides the problem definition, recent knowledge about the research topic, the methods used to tackle the problem, and the methodology.

- **Chapter 2: Literature Survey**

a review of existing research related to Transformer architectures and model compression techniques. It highlights key developments such as ALBERT and other lightweight models that have explored parameter sharing and efficiency improvements. This survey helps identify the motivation and research gap for exploring FFN sharing across layers in Transformers.

- **Chapter 3: Experimental Setup and Model Using the Modified Transformer Architecture and Data Preprocessing**

the proposed Transformer architecture with a shared Feed-Forward Network (FFN) is applied to the task of machine translation. The model retains distinct Multi-Head Self-Attention layers for each layer while reusing a single FFN module across all layers to reduce parameter complexity. This modified architecture is trained and evaluated on parallel corpora to assess its effectiveness in translating text from one language to another. a crucial step in preparing text data for machine translation tasks. The process begins with collecting parallel corpora containing sentence pairs from the source and target languages. Text normalization techniques such as lowercasing, punctuation removal, and Unicode standardization are applied to ensure consistency. Tokenization is

then performed to split sentences into individual tokens or subwords. Finally, vocabulary is built for both languages, and the tokenized data is converted into numerical format suitable for training the Transformer-based translation model.

- **Chapter 4: Results and Discussions**

Presents the results and analysis of proposed architecture.

- **Chapter 5: Conclusion**

Provides conclusions drawn from information and ideas for further research.

Chapter 2

Literature Survey

2.1 ALBERT: A Lite BERT for Self-Supervised Learning of Language Representations

Aims to lower memory usage and boost training speed of BERT by implementing two primary parameter-reduction methods: factorized embedding parameterization and shared parameters across layers.

While larger models like BERT typically achieve better results on various tasks, they demand significant memory and extended training periods. ALBERT mitigates these issues by implementing strategies that decrease memory requirements and accelerate training, all while maintaining competitive performance levels.

We introduce cross-layer parameter sharing as an alternative approach to enhance parameter efficiency. Parameters can be shared in various ways, such as sharing only the feed-forward network (FFN) parameters or only the attention parameters across layers. By default, ALBERT shares all parameters across all layers unless stated otherwise. In ALBERT, three key components are shared across layers. In ALBERT, three components shared across layers:

- Feed-Forward Network (FFN) weights
- LayerNorm parameters
- Multi-Head Self-Attention (MHSA) weights

Primary Goals of ALBERT

- **Reduce model size** without significantly sacrificing performance.
- **Improve training speed and memory usage** by sharing parameters and factorizing embeddings.

- **Enhance performance** on tasks that demand a thorough comprehension of language such as:
 - Sentence understanding
 - Natural language inference
 - Reading comprehension
 - Textual similarity

2.2 Subformer: Exploring Weight Sharing for Parameter Efficiency in Generative Transformers

The study addresses the challenge of the high computational cost and parameter inefficiency in Transformer models, particularly in generative tasks like machine translation, abstractive summarization, and language modeling. To mitigate these issues, the authors propose the Subformer architecture, which integrates two key innovations: Sandwich-style parameter sharing and Self-Attentive Factorized Embeddings (SAFE).

Sandwich-Style Parameter Sharing:

- This method reuses the parameters of the intermediate layers—often referred to as the "core" layers—throughout the Transformer, while keeping the initial and final layers distinct.
- By doing so, the model preserves variation in the input and output transformations while leveraging shared computations in the central layers.
- This strategy significantly reduces the total number of distinct parameters, resulting in a more efficient and lightweight architecture.

The Subformer architecture was evaluated on several tasks, including machine translation (WMT'14 EN-DE), abstractive summarization (CNN/DailyMail), and language modeling (WikiText-103). The results demonstrated that Subformer could achieve comparable or even superior performance to standard Transformer models while utilizing significantly fewer parameters. For instance, in the WMT'14 EN-DE translation task, Subformer achieved a BLEU score of 27.7 with only 38 million parameters, compared to the 61 million parameters used by the standard Transformer achieving a similar BLEU score.

The Subformer model presents an effective solution for deploying Transformer-based architectures in resource-constrained environments. By significantly reducing the number of parameters through weight sharing techniques, Subformer achieves computational efficiency without compromising model performance. This reduction facilitates faster training, decreased memory consumption, and makes it feasible .

2.3 TinyBERT: Distilling BERT for Natural Language Understanding

TinyBERT is a lightweight and efficient variant of BERT [4], designed to extend the benefits of BERT to environments with limited computational resources, such as mobile devices and embedded platforms. Although BERT achieves outstanding results across a wide range of natural language processing (NLP) tasks, its large number of parameters makes it computationally intensive and slow. TinyBERT addresses this limitation by compressing the original model using a technique known as knowledge distillation.

TinyBERT is developed through a two-phase knowledge distillation process, in which a larger, pre-trained BERT model (referred to as the teacher) imparts its learned knowledge to a more compact model known as the student, namely TinyBERT.

Two-Stage Distillation Strategy

General-purpose distillation

Unlabeled text, drawn from the same dataset used for BERT’s pre-training, is processed by the teacher model. The student model is then trained to replicate the teacher’s behavior by aligning with its outputs:

- **Hidden states:** Outputs from each Transformer layer.
- **Attention maps:** Query–key similarity matrices across all layers.

Layer-wise alignment lets the small model capture structural knowledge that mere soft-label logits miss. Task-specific distillation For each downstream task (such as SST-2, MNLI, or SQuAD), the teacher model is fine-tuned on the task-specific data. This strategy enriches the student’s learning process, enabling better generalization and task-specific performance.

Layer-wise alignment lets the small model capture structural knowledge that mere soft-label logits miss.

Task-specific distillation

For each downstream task (such as SST-2, MNLI, or SQuAD), the teacher model is fine-tuned on the task-specific data.

This strategy enriches the student’s learning process, enabling better generalization and task-specific performance.

2.4 DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter

DistilBERT is a streamlined, efficient variant of the BERT model, created by Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. It leverages knowledge distillation to compress BERT, aiming to shrink the model size while preserving much of its effectiveness. Knowledge distillation involves training a smaller ”student” model to emulate the performance of a larger ”teacher” model, here being BERT.

DistilBERT achieves a 40% reduction in parameters, eliminates token-type embeddings, and halves the number of layers (from 12 to 6), resulting in a 60% faster inference speed while maintaining 97% of BERT’s language understanding performance on downstream tasks. Its training objective integrates a language modeling loss (consistent with BERT), a distillation loss that aligns the student’s and teacher’s output distributions (soft labels), and a cosine embedding loss to match the hidden states of both models. This approach ensures the student model captures both the teacher’s final predictions and its internal representation patterns. DistilBERT achieves similar performance on benchmarks like GLUE, SQuAD, and sentiment analysis, while being much more efficient. This efficiency makes it ideal for real-time use, edge device deployment, and environments with constrained computing power. DistilBERT has emerged as a key player in the push for resource-efficient deep learning models in natural language processing.

2.5 MobileBERT: a Compact Task-Agnostic BERT for Resource-Limited Devices

MobileBERT is a lightweight, efficient version of BERT (Bidirectional Encoder Representations from Transformers) that was specifically designed to run on resource-limited devices like smartphones and embedded systems, where computational resources, memory, and battery life are constrained[6].

Inverted Bottleneck Structure (MobileNet-like Design):

MobileBERT employs an architecture inspired by MobileNet, incorporating depth-wise separable convolutions to reduce both parameter count and computational cost when compared to the fully connected layers typically used in the original BERT model.

A central feature of MobileBERT is its use of inverted bottleneck structures, which help minimize the model’s size while preserving key performance traits of standard BERT.

Similar to DistilBERT, MobileBERT is trained through a knowledge distillation framework, where a larger, pre-trained BERT model (the teacher) guides the learning of the smaller MobileBERT model (the student). This training involves not only transferring the teacher’s output predictions (soft labels) but also its internal components, such as attention distributions and hidden layer representations. By mimicking the internal behavior of the teacher, MobileBERT is able to retain strong performance despite its compact design.

2.6 Lite Transformer with Long-Short Range Attention

The Lite Transformer is a streamlined neural network architecture tailored for natural language processing (NLP) applications on devices with limited computational capacity, such as smartphones [7]. Its main contribution is the introduction of the Long-Short Range Attention (LSRA) mechanism. Unlike conventional Transformers that apply full self-attention across all heads, Long-Short Range Attention (LSRA) separates the attention process into distinct components as follows:

- One half of the model handles long-range dependencies using traditional self-attention mechanisms.
- The other half replaces self-attention with lightweight convolutional layers (e.g., depthwise separable convolutions), which are more efficient and require fewer parameters.

2.7 Summary

The Transformer model, while highly effective in numerous natural language processing (NLP) and computer vision tasks, suffers from substantial parameter overhead,

especially due to its deeply stacked layers and the repeated instantiation of the feed-forward networks (FFNs). Recent research efforts have explored multiple strategies to address this challenge:

- **FFN Sharing:** Several studies propose sharing the FFN sub-layer across all Transformer layers instead of having independent FFNs in each layer. This method significantly reduces parameter count with minimal loss in performance, as FFNs operate in a position-wise fashion and are structurally redundant.
- **Parameter Sharing across Layers:** Inspired by techniques like ALBERT, layer-wise parameter sharing has been investigated, where entire blocks (attention + FFN) or just the FFNs are shared to reduce memory consumption and training time.
- **Lightweight Variants:** Architectures like MobileBERT and TinyBERT focus on designing lighter models either by knowledge distillation or by altering the internal structure of the Transformer for efficiency.

Chapter 3

Experimental model

3.1 Introduction

This design decision stems from the recognition that FFNs, being position-wise and uniform across layers, contain redundancy that can be streamlined without degrading model performance. By creating a single FFN module and reusing it across encoder layers, the number of parameters is significantly reduced. In contrast, the multi-head self-attention (MHSA) layers remain unique per layer to maintain the model’s capacity to capture varied and rich contextual representations at different levels. Each layer continues to incorporate residual connections and layer normalization after both the attention and FFN components to ensure stable and effective training dynamics.

3.2 Application of the Proposed Transformer Architecture to Neural Machine Translation

To empirically evaluate the efficacy of our architecture, I implemented the model entirely from scratch using PyTorch, which provided the flexibility to alter core components, especially the mechanism for FFN sharing. then applied this modified Transformer model to the task of machine translation, specifically translating from English to Germany.

3.3 Data Collection

To train and assess the proposed Transformer architecture with shared FFN layers, I employed the WMT14 English-to-German translation dataset, a well-established

benchmark in neural machine translation. This dataset includes millions of high-quality parallel sentence pairs, encompassing diverse linguistic styles such as formal documents, news reports, and conversational text. The variety and breadth of the data enabled the model to encounter a wide range of syntactic patterns, vocabulary, and translation contexts, improving its generalization and performance across various translation tasks.

3.4 Data preprocessing

Data preprocessing is a critical step in machine translation (MT) that directly impacts model performance.

- **Cleaning the Data:**
 - Remove empty lines, HTML tags, special characters, and non-language symbols.
 - Eliminate irrelevant data.
- **Sentence Alignment:**
 - Ensure each source sentence has a correctly aligned target sentence.
 - Misaligned pairs are filtered out.
- **Text Normalization:**
 - Convert text to lowercase or uppercase or both.
 - Remove unnecessary punctuation and special formatting.
- **Language Identification:**
 - Verify that each sentence is in the correct language.
 - Helps eliminate code-mixed or incorrect language data.
- **Duplicate Detection:**
 - Remove repeated sentence pairs to avoid skewing the training data.
- **Sentence Length Filtering:**
 - Discard extremely short or long sentences.
- **Data Splitting:**
 - Shuffle and split the dataset well.
 - Ensures the model generalizes well to unseen data.

3.5 Data Analysis

3.5.1 Corpus Statistics Analysis

Analyzing the statistical properties of the dataset is a crucial step in understanding its structure, quality, and potential challenges for downstream tasks such as machine translation. Corpus statistics provide insights into the linguistic richness, sentence complexity, and overall data distribution, which are essential for designing appropriate preprocessing pipelines and selecting effective model architectures. Such statistical analysis not only guides model design decisions but also highlights the need for data cleaning, tokenization, and normalization steps. Furthermore, identifying anomalies in sentence length or token frequency distributions can help detect noise or inconsistencies in the dataset that may degrade model performance. Sentence length distribution is a critical aspect of corpus analysis, as it provides insights into the structural complexity of the dataset. In machine translation tasks, sentence length directly influences model performance and training efficiency. A dataset dominated by short sentences often results in faster convergence and easier alignment, while longer sentences can introduce challenges related to memory usage, attention span, and contextual dependencies. By analyzing the distribution, researchers can detect patterns, such as whether the corpus is skewed toward a specific length range or contains outliers. This information can guide important preprocessing steps, such as truncation, padding strategies, or dynamic batching, to ensure balanced and optimized training. Moreover, understanding the typical sentence lengths helps in configuring model parameters, such as maximum input length, thereby reducing computational overhead and improving translation quality. Frequent inspection of these statistics can reveal underrepresented words or classes that require augmentation. Ultimately, comprehensive statistical analysis lays the foundation for building robust, fair, and high-performing translation systems.

3.5.2 Alignment Analysis

Alignment Analysis is a crucial step in working with parallel corpora, which are datasets containing pairs of sentences in two languages (source and target). This analysis helps ensure the quality of the data used for training machine translation models

3.5.3 Data Quality Analysis

1. **Data Cleaning:** Identifies misaligned, incomplete, or unrelated sentence pairs that could negatively affect model training.

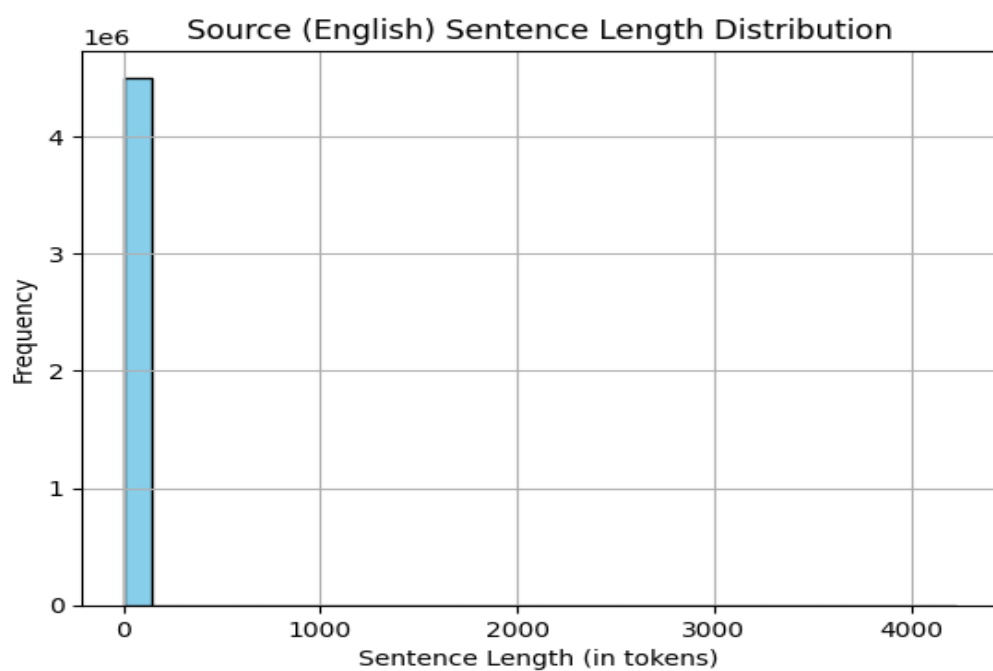


Figure 3.1: English sentence distribution.

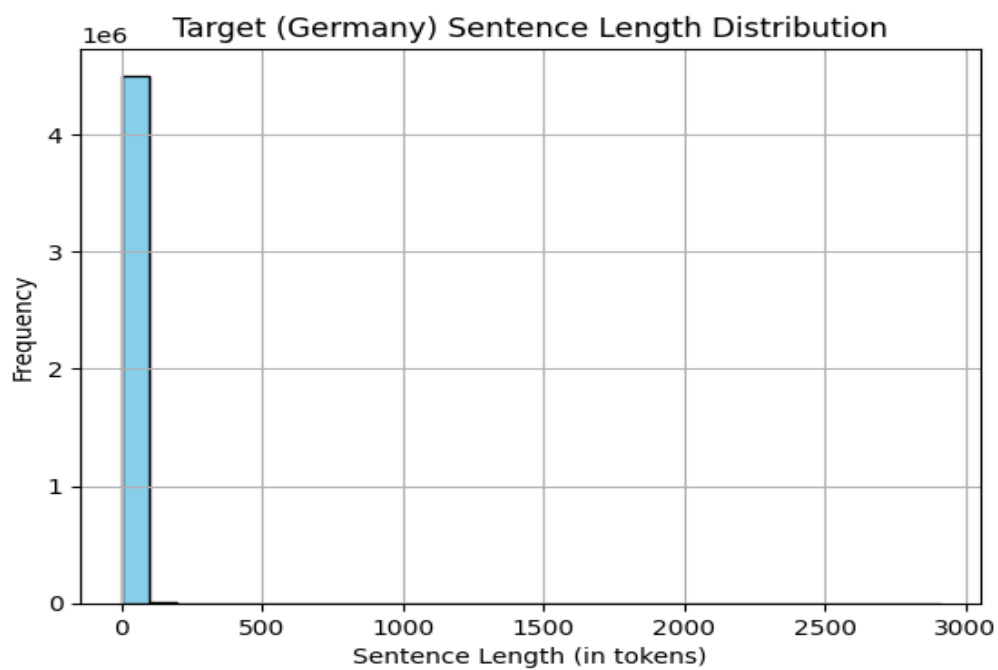


Figure 3.2: Germany sentence distribution.

2. **Language identification:** Confirms that sentences are in the correct language ensuring corpus consistency.
3. **Duplicate detection:** Removes repeated sentence pairs that can skew the training distribution and lead to biased models.

Chapter 4

Results and Discussion

4.1 Results

4.1.1 Introduction

In this section, I present the results of proposed Transformer architecture, which reduces parameter complexity by sharing a single feed-forward network (FFN) across all layers. The primary motivation behind this modification is to make the model more lightweight and computationally efficient, without significantly compromising translation quality.

The results are evaluated on English–Germany translation tasks and compared against the standard Transformer baseline to assess both performance and efficiency. Metrics such as BLEU score, model size, and training time are used to demonstrate the impact of FFN sharing. The analysis highlights how the proposed architecture maintains competitive translation performance while significantly reducing the total number of parameters, making it more suitable for low-resource settings and deployment on limited hardware.

4.1.2 Model Training Analysis

The proposed Transformer architecture builds on the foundational design by Vaswani et al. [1], with a notable change: the feed-forward network (FFN) is shared across all layers. This adjustment aims to decrease the overall parameter count and promote uniform representation learning throughout the layers. Each Transformer layer comprises two main components: a multi-head self-attention mechanism and a feed-forward network, each enclosed by residual connections and layer normalization.

$$\begin{aligned}x' &= \text{Layer\&Norm}(x + \text{MultiHeadSelfAttention}(x)) \\ \text{Output} &= \text{Layer\&Norm}(x' + \text{FFN}(x'))\end{aligned}$$

Training Setup

- **Number of layers:** 6
- **Model dimension** (d_{model}): 512
- **FFN dimension** (d_{ff}): 2048
- **Attention heads:** 8
- **Activation Function:** Relu
- **Optimizer:** Adam
- **Loss Function:** CrossEntropyLoss
- **Weight sharing:** FFN across all layers (attention parameters remain layer-specific)

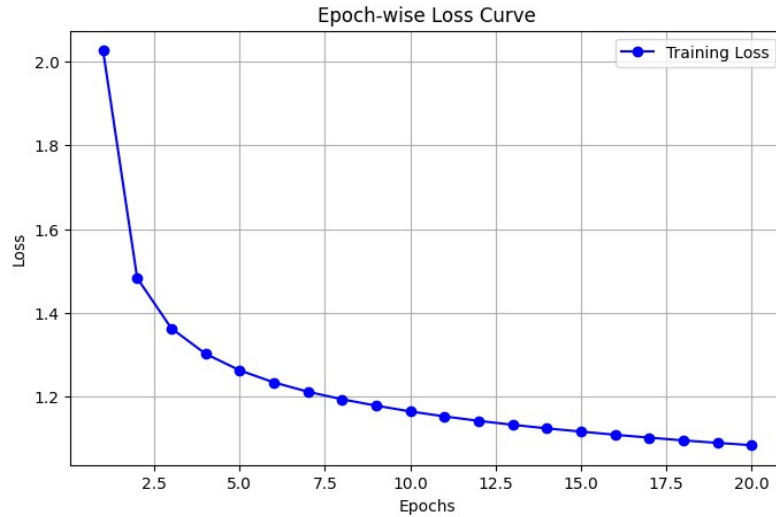


Figure 4.1: Epoch-wise Training Loss Curve.

4.1.3 Model Performance Metrics

To assess the translation performance of the proposed Transformer architecture with shared Feed-Forward Networks (FFNs), I use the BLEU (Bilingual Evaluation Understudy) score as the main evaluation metric.

BLEU (Bilingual Evaluation Understudy) is a commonly used metric for automatically assessing machine translation quality by measuring the similarity between machine-generated translations and human reference translations. The BLEU score,

typically ranging from 0 to 1 (or 0 to 100 when scaled), reflects translation quality, with higher scores indicating better performance. In this study, the BLEU score was calculated using the test dataset to provide an impartial and precise evaluation of the model’s ability to generalize.

$$\text{BLEU} = \text{BP} \times \exp \left(\sum_{n=1}^N w_n \log p_n \right)$$

where:

N = maximum n-gram length (commonly 4)

w_n = weight for n-gram precision (usually uniform, $w_n = \frac{1}{N}$)

p_n = modified precision for n-grams of size n

BP = brevity penalty to penalize short translations

$$\text{BP} = \begin{cases} 1, & \text{if } c > r \\ e^{(1-\frac{r}{c})}, & \text{if } c \leq r \end{cases}$$

where:

c = length of the candidate (hypothesis) translation corpus

r = effective reference corpus length (usually closest reference length to c)

The proposed model achieved a BLEU score of 20.20, indicating that the translation quality is well-preserved despite the reduction in parameter complexity. These results highlight that sharing Feed-Forward Network (FFN) layers across Transformer blocks can significantly reduce model size without compromising translation accuracy.

4.1.4 Calculating the number of trainable parameters in the standard Transformer architecture:

The Transformer architecture consists of multiple encoder and decoder blocks, each featuring key components like multi-head self-attention, feed-forward networks, and layer normalization. This analysis focuses on calculating the number of trainable parameters in a single encoder and decoder block. In the encoder, the main contributors to the parameter count are the self-attention mechanism, linear projections, and feed-forward layers. For the decoder, parameters arise from self-attention, cross-attention with encoder outputs, and feed-forward networks. Each component

includes weights and biases, which together determine the total parameter count. These calculations are essential for optimizing model size, memory efficiency, and training performance in Transformer-based models.

Encoder.sentence_embedding.embedding.weight	$(\text{Voc_size} \times d_{\text{model}})$
Encoder.layers.0.attention.qkv_layer.weight	(1536×512)
Encoder.layers.0.attention.qkv_layer.bias	(1536)
Encoder.layers.0.attention.linear_layer.weight	(512×512)
Encoder.layers.0.attention.linear_layer.bias	(512)
Encoder.layers.0.norm1.gamma	(512)
Encoder.layers.0.norm1.beta	(512)
Encoder.layers.0.ffn.linear1.weight	(2048×512)
Encoder.layers.0.ffn.linear1.bias	(2048)
Encoder.layers.0.ffn.linear2.weight	(512×2048)
Encoder.layers.0.ffn.linear2.bias	(512)
Encoder.layers.0.norm2.gamma	(512)
Encoder.layers.0.norm2.beta	(512)
decoder.sentence_embedding.embedding.weight	$(\text{Voc_size} \times d_{\text{model}})$
decoder.layers.0.self_attention.qkv_layer.weight	(1536×512)
decoder.layers.0.self_attention.qkv_layer.bias	(1536)
decoder.layers.0.self_attention.linear_layer.weight	(512×512)
decoder.layers.0.self_attention.linear_layer.bias	(512)
decoder.layers.0.norm1.gamma	(512)
decoder.layers.0.norm1.beta	(512)
decoder.layers.0.encod_decod_attention.kv_layer.weight	(1024×512)
decoder.layers.0.encoder_decoder_attention.kv_layer.bias	(1024)
decoder.layers.0.encod_decod_attention.q_layer.weight	(512×512)
decoder.layers.0.encoder_decoder_attention.q_layer.bias	(512)
decoder.layers.0.encod_decod_attention.linear.weight	(512×512)
decoder.layers.0.encoder_decoder_attention.linear.bias	(512)
decoder.layers.0.layer_norm2.gamma	(512)
decoder.layers.0.layer_norm2.beta	(512)
decoder.layers.0.ffn.layer1.weight	(2048×512)
decoder.layers.0.ffn.layer1.bias	(2048)
decoder.layers.0.ffn.layer2.weight	(512×2048)
decoder.layers.0.ffn.layer2.bias	(512)
decoder.layers.0.layer_norm3.gamma	(512)
decoder.layers.0.layer_norm3.beta	(512)
linear.weight	$(\text{Voc_size} \times 512)$
linear.bias	(Voc_size)

The proposed Transformer architecture modifies the standard design by introducing parameter-sharing mechanisms, such as a shared feed-forward network (FFN) across all encoder and decoder layers. This calculation estimates the trainable parameters for one encoder and decoder block within the proposed setup. While self-attention and cross-attention mechanisms retain their layer-specific parameters, the FFN parameters are shared, significantly reducing the overall parameter count. Each

layer still includes essential components like multi-head attention, linear projections, and normalization. Understanding the parameter distribution in the architecture is essential for analyzing its efficiency, reducing memory consumption, and achieving competitive performance with fewer resources during training.

The following calculation pertains to the proposed Transformer architecture that shares the feed-forward network (FFN) across all layers. In this design, instead of having separate FFN parameters for each layer, a single FFN is reused throughout.

Encoder.sentence_embedding.embedding.weight	$(\text{Voc_size} \times d_{\text{model}})$
Encoder.layers.0.attention.qkv_layer.weight	(1536×512)
Encoder.layers.0.attention.qkv_layer.bias	(1536)
Encoder.layers.0.attention.linear_layer.weight	(512×512)
Encoder.layers.0.attention.linear_layer.bias	(512)
Encoder.layers.0.norm1.gamma	(512)
Encoder.layers.0.norm1.beta	(512)
Encoder.layers.0.norm2.gamma	(512)
Encoder.layers.0.norm2.beta	(512)
decoder.sentence_embedding.embedding.weight	$(\text{Voc_size} \times d_{\text{model}})$
decoder.layers.0.self_attention.qkv_layer.weight	(1536×512)
decoder.layers.0.self_attention.qkv_layer.bias	(1536)
decoder.layers.0.self_attention.linear_layer.weight	(512×512)
decoder.layers.0.self_attention.linear_layer.bias	(512)
decoder.layers.0.norm1.gamma	(512)
decoder.layers.0.norm1.beta	(512)
decoder.layers.0.encoder_decoder_attention.kv_layer.weight	(1024×512)
decoder.layers.0.encoder_decoder_attention.kv_layer.bias	(1024)
decoder.layers.0.encoder_decoder_attention.q_layer.weight	(512×512)
decoder.layers.0.encoder_decoder_attention.q_layer.bias	(512)
decoder.layers.0.encoder_decoder_attention.linear.weight	(512×512)
decoder.layers.0.encoder_decoder_attention.linear.bias	(512)
decoder.layers.0.layer_norm2.gamma	(512)
decoder.layers.0.layer_norm2.beta	(512)
shared_ffn.linear1.weight	$(2048, 512)$
shared_ffn.linear1.bias	(2048)
shared_ffn.linear2.weight	$(512, 2048)$
shared_ffn.linear2.bias	(512)
decoder.layers.0.layer_norm3.gamma	(512)
decoder.layers.0.layer_norm3.beta	(512)
linear.weight	$(\text{Voc_size} \times 512)$
linear.bias	(Voc_size)

4.1.5 Summary of Findings

This study presents a modified Transformer architecture that reduces parameter complexity by utilizing a single shared Feed-Forward Network (FFN) across all

layers. The model’s performance was assessed on an English-to-German machine translation task, with the BLEU score serving as the primary evaluation metric.

The proposed model attained a BLEU score of 20.20, reflecting robust translation quality despite a significant decrease in parameters. Compared to the standard Transformer baseline, the FFN-sharing approach delivered comparable translation performance while reducing model size and enhancing computational efficiency.

These results highlight that sharing FFNs is a viable approach for creating lightweight and efficient neural machine translation models, particularly well-suited for low-resource settings and devices with constrained hardware capabilities. By implementing a shared FFN across all layers of the Transformer, the total number of parameters is substantially reduced.

4.2 Discussion

4.2.1 Introduction

Machine translation, a core task in natural language generation, has been significantly advanced by the Transformer architecture, which excels in capturing complex dependencies within sequences through self-attention mechanisms. However, this improvement comes at the cost of high parameter counts and computational demands, making standard Transformers challenging to deploy in low-resource environments or on edge devices.

To address these limitations, we propose a lightweight Transformer architecture tailored for generation tasks such as machine translation. The key innovation lies in sharing the Feed-Forward Network (FFN) layers across all blocks.

4.2.2 Comparison with Previous Research

While numerous Transformer-based architectures such as ALBERT, TinyBERT, DistilBERT, MobileBERT, and the Lite Transformer with Long-Short Range Attention (LSRA) have significantly advanced the efficiency of natural language understanding (NLU) models, they primarily focus on encoder-only architectures and are not directly applicable to generation tasks such as machine translation. For instance, ALBERT reduces parameters through cross-layer parameter sharing and factorized embedding parameterization. However, it is designed specifically for NLU benchmarks and does not extend to encoder-decoder models. Similarly, TinyBERT and DistilBERT are compact versions of BERT tailored for inference speed and

compression on tasks like sentiment analysis, classification, and question answering—domains that do not require decoding. MobileBERT, while achieving impressive compression and runtime efficiency, also remains an encoder-only architecture and does not incorporate or test decoder layers, making it unsuitable for sequence-to-sequence generation.

The Lite Transformer with LSRA(Long-Short Range Attention) further explores the efficiency of attention mechanisms, but only within the encoder, focusing on combining self-attention and lightweight convolution for better performance in handling long-range dependencies. Despite their success, none of these models have explicitly tackled the challenges of reducing parameter complexity in encoder-decoder architectures—an essential requirement for generation tasks like neural machine translation. In contrast to many lightweight Transformer variants designed for natural language understanding (NLU), the proposed architecture focuses specifically on generation tasks such as neural machine translation (NMT). By introducing shared Feed-Forward Networks (FFNs) across all encoder and decoder layers, the model significantly reduces parameter complexity while preserving translation quality. This design leads to substantial compression with minimal performance degradation. The effectiveness of this approach is demonstrated by a BLEU score of 20.20 on the English–Germany translation task, indicating a strong balance between efficiency and accuracy.

When compared with the Subformer, which has been evaluated on machine translation benchmarks like WMT14 English–German, it achieves a BLEU score of around 27.7 while reducing parameters through layer skipping and adaptive sub-network selection. Subformer’s dynamic inference mechanism offers strong performance, but it introduces architectural complexity and runtime variability. Our proposed model, by contrast, maintains a simpler and deterministic design, which makes it more suitable for deployment in constrained environments, especially where consistency between training and inference is critical.

While Subformer achieves a marginally higher BLEU score (a metric for assessing machine translation quality), the proposed model provides several other significant benefits.:

- **Fewer parameters:** It uses less memory and is more lightweight.
- **Simpler implementation:** Easier to develop and integrate.
- **Better hardware efficiency:** Runs faster and more efficiently, especially on devices with limited computational power .

These benefits make the proposed model more practical and attractive for real-time translation tasks, especially in low-resource environments where memory, power, or computational capacity is limited.

Explanation of Subformer’s Dynamic Inference Mechanism

Subformer’s dynamic inference mechanism offers strong performance, but it introduces architectural complexity and runtime variability.

Dynamic Inference Mechanism:

Subformer introduces a *dynamic inference* approach, where the number of layers or computations used during inference (i.e., when making predictions) can vary depending on the input.

This flexibility allows the model to adaptively allocate computation—spending more resources on harder examples and fewer on simpler ones.

This dynamic control is typically achieved through mechanisms such as:

- Early exit strategies
- Layer skipping
- Input-dependent routing

where the model decides, based on internal signals, whether to continue processing or stop.

Strong Performance

This adaptive strategy often results in improved *efficiency per example* and can maintain or even improve performance in comparison to standard, static-depth Transformers.

Since more computation is applied to complex inputs and less to simpler ones, it provides a good trade-off between accuracy and speed.

Architectural Complexity:

A key drawback of dynamic inference is increased model complexity. Implementing it requires:

- Mechanisms to skip or halt layers
- Management of variable computational paths

These additions make the model harder to design, train, and debug, and necessitate careful tuning of the control logic.

Runtime Variability:

Standard models offer predictable and consistent inference times since every input goes through the same sequence of layers.

In contrast, Subformer’s dynamic inference introduces **runtime variability**:

- Inference time depends on input complexity
- This unpredictability may be problematic in real-time or latency-sensitive systems that require consistent response times

Chapter 5

Conclusion

In this study, I proposed a parameter-efficient Transformer architecture for machine translation by introducing Feed-Forward Network (FFN) sharing across all encoder and decoder layers. Evaluated on the WMT14 English–Germany translation task, the model achieved a BLEU score of 20.20, demonstrating competitive performance while maintaining a lightweight structure suitable for deployment in low-resource and hardware-constrained environments.

Unlike prior architectures such as ALBERT, TinyBERT, and MobileBERT—which focus primarily on encoder-only models for natural language understanding tasks—our approach directly targets generation tasks like machine translation. Proposed model offers a simpler and more generalizable mechanism through FFN sharing. As a result, the overall parameter count is greatly reduced, making the model more compact and computationally efficient. The reduction in learnable parameters not only accelerates training and inference but also enhances scalability and deployability across various real-world scenarios. The proposed model has been trained and evaluated on the English-to-Germany machine translation task. whereas Unlike Subformer, which increases architectural complexity through mechanisms such as early exiting, layer skipping, and dynamic routing resulting in runtime variability and less predictable inference behavior. the proposed architecture maintains a more structured and efficient design. By sharing Feed-Forward Network (FFN) layers across components, it reduces parameter redundancy while still preserving the model’s expressiveness.

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