DeLighT: Very Deep and Light-weight Transformer

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Source code: https://github.com/sacmehta/delight

Abstract

We introduce a very deep and light-weight transformer, DeLighT, that delivers similar or better performance than transformer-based models with significantly fewer parameters. DeLighT more efficiently allocates parameters both (1) within each Transformer block using DExTra, a deep and light-weight transformation and (2) across blocks using block-wise scaling, that allows for shallower and narrower DeLighT blocks near the input and wider and deeper DeLighT blocks near the output. Overall, DeLighT networks are 2.5 to 4 times deeper than standard transformer models and yet have fewer parameters and operations. Experiments on machine translation and language modeling tasks show that DeLighT matches the performance of baseline Transformers with significantly fewer parameters. On the WMT’14 En-Fr high resource dataset, DeLighT requires 1.8 times fewer parameters and 2 times fewer operations and achieves better performance (+0.4 BLEU score) than baseline transformers. On the WMT’16 En-Ro low resource dataset, DeLighT delivers similar performance with 2.8 times fewer parameters than baseline transformers.

1 Introduction

Attention-based transformer networks [1] are widely used for sequence modeling tasks, including language modeling and machine translation. To improve performance, models are often scaled to be either wider by increasing the dimension of hidden layers (e.g., T5 [2] uses a dimension of 65K) or deeper by stacking more transformer blocks (e.g., GPT-3 [3] uses 96 transformer blocks). However, such scaling increases the number of network parameters significantly (e.g., T5 and GPT-3 have 11 billion and 175 billion parameters), and complicates learning (i.e. requiring very large training sets [2,3] or careful regularization [6,9]). In this paper, we introduce a new parameter-efficient attention-based architecture that can be easily scaled to be both very wide and deep.

Our very Deep and Light-weight Transformer architecture (DeLighT) extends the transformer architecture of Vaswani et al. [1] and delivers similar or better performance with significantly fewer parameters. At the heart of DeLighT is the DExTra transformation that uses group linear transformations [10] with an expand-reduce strategy for varying the width and depth of the DeLighT block efficiently. Since these transformations are local by nature, DExTra uses feature shuffling (analogous to channel shuffling [11] in convolutional networks) to share information between different groups. Such wide and deep representations facilitate replacing the multi-head attention and feed-forward lay-
ers in transformers with single headed attention and light-weight feed-forward layers, reducing total
networks parameters. Importantly, unlike transformers, D ExTra blocks can be scaled independent of
the input size. This allows us to allocate parameters more efficiently across blocks by using shallower
and narrower DeLighT blocks near the input and deeper and wider DeLighT blocks near the output.

We demonstrate that DeLighT models achieve similar or better performance than transformer models
with significantly fewer parameters and operations, on two common sequence modeling tasks, (i)
machine translation and (ii) language modeling. On the low resource WMT’16 En-Ro machine trans-
lation dataset, DeLighT attains transformer performance using 2.8× fewer parameters. On the high
resource WMT’14 En-Fr dataset, DeLighT delivers better performance (+0.4 BLEU score) with 1.8×
fewer parameters than baseline transformers. Similarly, on language modeling, DeLighT matches the
performance of the state-of-the-art transformer-based language model, Transformer-XL [9], with 52
million fewer parameters and 1.3× smaller context length on the WikiText-103 dataset.

2 Related Work

Improving transformers: Several methods have been introduced to improve the transformer ar-
chitecture. The first line of research addresses the computational challenge of modeling long input
sequences, that arises due to the self-attention operation (e.g., [12–14]). These methods can be
combined with our architecture to better represent long sequences. The second line of research
focuses on explaining multi-head attention (e.g., [15, 16]). They show that increasing the number
of transformer heads can lead to redundant representations [17, 18] and using fixed attention heads
with predefined patterns [19] or synthetic attention matrices [20] improves performance. These
results support our design choice of using single-head attention. The third line of research focuses
on improving transformers by learning better representations (e.g., [21–23]). These works aim
to improve the expressiveness of transformers using different transformations (e.g., convolutions
[21, 24] and gated linear units [25]) or multi-branch feature extractors (e.g., [22, 23]). Our work falls
into this category. Unlike previous work, we show that it is possible to efficiently allocate parameters
both at the block-level using D ExTra and across blocks using block-wise scaling. Our results show
that DeLighT delivers similar or better performance, with significantly fewer parameters.

Model scaling: Model scaling is a standard method to improve the performance of sequence models
[1–5, 26, 27]. Model dimensions are increased in width-wise scaling (e.g., [1–4]) while more blocks
(e.g., Transformer blocks) are stacked in depth-wise scaling (e.g., [3, 26]). In both cases (and their
combination), parameters inside each block of the network are the same, which may lead to a sub-
optimal solution. To further improve the performance of sequence models, this paper introduces
block-wise scaling that allows for variably-sized blocks and efficient allocation of parameters in
the network. Our results show that (1) shallower and narrower DeLighT blocks near the input and
deeper and wider DeLighT blocks near the output deliver the best performance, and (2) models
with block-wise scaling coupled with model scaling achieve better performance compared to model
scaling alone. We note that convolutional neural networks (CNNs) also learn shallower and narrower
representations near the input and deeper and wider representations near the output. Unlike CNNs
(e.g., ResNet [28]) that perform a fixed number of operations at each convolutional layer, the proposed
block-wise scaling uses a variable number of operations in each layer and block.

Improving sequence models: There is also significant recent work on other related methods for
improving sequence models, including (1) techniques for improving accuracy using better token-level
representations (e.g., BPE [29], adaptive inputs [30] and outputs [31], and DeFINE [32]) or (2) for
improving efficiency (compression [33–35], pruning [36–37], and distillation [38–39]). The closest to
our work is the DeFINE unit, which also learns representations using an expand-reduce strategy. The
key difference between the DeFINE unit (Figure 1a) and D ExTra (Figure 1b) is that D ExTra more
efficiently allocates parameters within expansion and reduction layers. Unlike DeFINE, which uses
fewer groups in group linear transformations to learn wider representations, D ExTra uses more
groups to learn wider representations with fewer parameters. Our results show that D ExTra achieves
comparable performance to the DeFINE unit but with significantly fewer parameters.
A standard approach to increase the expressivity and capacity of transformers is to increase the input dimensions, linearly using \( m \) and \( \text{operations} \) in the FFN are reduced by \( D \times 3 \). DExTra: Very Deep and Light-weight Transformer

extends the transformer architecture by introducing (1) DExTra (Section 3.1), a deep and light-weight expand-reduce transformation that enables learning wider representations efficiently and enables replacing multi-head attention and feed forward network (FFN) layers with single-head attention and a light-weight FFN (Section 3.2); (2) block-wise scaling that enables efficient allocation of parameters across DeLighT blocks to train deep and light-weight networks (Section 3.3).

3 DeLighT: Very Deep and Light-weight Transformer

DeLighT extends the transformer architecture by introducing (1) DExTra (Section 3.1), a deep and light-weight expand-reduce transformation that enables learning wider representations efficiently and enables replacing multi-head attention and feed forward network (FFN) layers with single-head attention and a light-weight FFN (Section 3.2), (2) block-wise scaling that enables efficient allocation of parameters across DeLighT blocks to train deep and light-weight networks (Section 3.3).

3.1 DExTra: Deep and Light-weight Expand-reduce Transformation

DExTra maps a \( d_m \) dimensional input vector into a high dimensional space (expansion) and then reduces it down to a \( d_o \) dimensional output vector (reduction) using \( N \) layers of group linear transformations (Figure 1). During these expansion and reduction phases, DExTra uses group linear transformations because they learn local representations by deriving the output from a specific part of the input and are more efficient than linear transformations. To learn global representations, DExTra shares information between different groups in the group linear transformation using feature shuffling. A standard approach to increase the expressivity and capacity of transformers is to increase the input dimensions, \( d_m \) (1) depth \( N \), (2) width multiplier \( m_w \), (3) input dimension \( d_m \), (4) output dimension \( d_o \), and (5) maximum groups \( g_{max} \) in a group linear transformation. In the expansion phase, DExTra projects the \( d_m \)-dimensional input to a high-dimensional space, \( d_{max} = m_w d_m \), linearly using \( \lceil \frac{N}{2} \rceil \) layers. In the reduction phase, DExTra projects the \( d_{max} \)-dimensional vector to a \( d_o \)-dimensional space using the remaining \( N - \lceil \frac{N}{2} \rceil \) layers. Mathematically, we define the output \( \mathbf{Y} \) at each layer \( l \) as:

\[
\mathbf{Y}^l = \begin{cases} 
F \left( \mathbf{X}, \mathbf{W}^l, \mathbf{b}^l, g_l^l \right), & l = 1 \\
F \left( H \left( \mathbf{Y}^{l-1} \right), \mathbf{W}^l, \mathbf{b}^l, g_l^l \right), & \text{Otherwise}
\end{cases}
\]

Figure 1: (a, b) compares the DeFINE unit with DExTra. Compared to the DeFINE unit, DExTra uses group linear transformations with more groups to learn wider representations with fewer parameters. Different colors are used to show groups in group linear transformations. For simplicity, we have not shown feature shuffling in (b). (c, d) Block-wise comparison between the standard transformer block and the DeLighT block. With DExTra, the number of operations in computing attention are reduced by half while the number of parameters (and operations) in the FFN are reduced by 16×. Layers with learnable parameters (Linear and DExTra) are shown in color. The shape of linear layers indicate their operation (expansion, reduction, etc.).
where the number of groups at each layer \( l \) are computed as:

\[
g^l = \begin{cases} 
\min(2^{l-1}, g_{\text{max}}), & 1 \leq l \leq \lceil N/2 \rceil \\
g^{N-l}, & \text{Otherwise}
\end{cases}
\]  

In the above equations, \( \mathcal{F} \) is a group linear transformation function. The function \( \mathcal{F} \) takes the input \( X \) or \( \mathcal{H}(X, Y^{l-1}) \), splits it into \( g^l \) groups, and then applies a linear transformation with learnable parameters \( \mathbf{W}^l \) and bias \( \mathbf{b}^l \) to each group independently. The outputs of each group are then concatenated to produce the final output \( Y^l \). The function \( \mathcal{H} \) first shuffles the output of each group in \( Y^{l-1} \) and then combines it with the input \( X \) using an input mixer connection \( \mathbf{F} \).

In our experiments, we use \( g_{\text{max}} = \lfloor \frac{d}{2} \rfloor \) so that each group has at least 32 input elements. Note that (i) group linear transformations reduce to linear transformations when \( g^l = 1 \), and (ii) DExTra is equivalent to a multi-layer perceptron when \( g_{\text{max}} = 1 \).

### 3.2 DeLighT block

**Transformer block:** A standard transformer block (Figure 1c) comprises of multi-head attention that uses a query-key-value decomposition to model relationships between sequence tokens, and a feed forward network (FFN) to learn wider representations. Multi-head attention obtains query \( \mathbf{Q} \), key \( \mathbf{K} \), and value \( \mathbf{V} \) by applying three projections to the input, each consisting of \( h \) linear layers (or heads) that map the \( d_m \)-dimensional input into a \( d_h \)-dimensional space, where \( d_h = d_m/h \) is the head dimension. The FFN consists of two linear layers, where the first expands the dimensions from \( d_m \) to \( d_f \) and the second reduces the dimensions from \( d_f \) to \( d_m \). The number of parameters and operations are fixed within each block and scale linearly with the input dimension \( d_m \).

**DeLighT block:** Figure 1d shows how we integrate DExTra into the transformer block to improve its efficiency. The \( d_m \)-dimensional inputs are first fed to the DExTra transformation to produce \( d_o \)-dimensional outputs, where \( d_o < d_m \). These \( d_o \)-dimensional outputs are then fed into a single head attention, followed by a light-weight FFN to model their relationships.

**DExTra aware single head attention:** Let us assume we have a sequence of \( n \) input tokens, each of dimensionality \( d_m \). These \( n \), \( d_m \)-dimensional inputs are first fed to the DExTra transformation to produce \( n \), \( d_o \)-dimensional outputs, where \( d_o < d_m \). These \( n \), \( d_o \)-dimensional outputs are then projected simultaneously using three linear layers to produce \( d_o \)-dimensional queries \( \mathbf{Q} \), keys \( \mathbf{K} \), and values \( \mathbf{V} \). We then model contextual relationships between these \( n \) tokens using scaled dot-product attention (Eq. 3). To enable the use of residual connections \( \mathbf{F} \), the \( d_o \)-dimensional outputs of this attention operation are linearly projected into a \( d_m \)-dimensional space.

\[
\text{Attention}(\mathbf{K}, \mathbf{Q}, \mathbf{V}) = \text{softmax} \left( \frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_o}} \right) \mathbf{V}
\]

Since the DeLighT block learns wider representations of the input across different layers using DExTra, it enables us to replace multi-head attention with single-head attention. The computational costs for computing attention in the standard transformer and the DeLighT block are \( \mathcal{O}(d_m n^2) \) and \( \mathcal{O}(d_o n^2) \) respectively, where \( d_o < d_m \). Therefore, the DeLighT block reduces the cost for computing attention by a factor of \( d_m/d_o \). In our experiments, we used \( d_o = d_m/2 \), thus requiring \( 2 \times \) fewer multiplication-addition operations as compared to the transformer architecture.

**Light-weight FFN:** Similar to FFNs in transformers, this block also consists of two linear layers. Since the DeLighT block has already incorporated wider representations using the DExTra transformation, it allows us to invert the functionality of FFN layers in the transformer. The first layer reduces the dimensionality of the input from \( d_m \) to \( d_m/r \) while the second layer expands the dimensionality from \( d_m/r \) to \( d_m \), where \( r \) is the reduction factor (see Figure 1d). Our light-weight FFN reduces the number of parameters and operations in FFN by a factor of \( r d_f / d_m \). In the standard transformer, the FFN dimensions are expanded by a factor of 4. In our experiments, we reduce the dimensions by a factor of 4. Thus, the light-weight FFN reduces the number of parameters in the FFN by \( 16 \times \).

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1 Each neuron in layers with \( g^l=1 \) or \( g^{l+1}=1 \) has access to all input/output elements. Shuffling input/output features of such layers has no impact. Therefore, we replace \( \mathcal{H} \) with a concatenation function in such layers.
Figure 2: **Block-wise scaling** efficiently allocates parameters and operations across blocks, leading to shallower and narrower DeLighT blocks near the input and deeper and wider DeLighT blocks near the output. In (b), DeLighT networks with both uniform \((N=N_{\text{min}}=N_{\text{max}}=8)\) and block-wise \((N_{\text{min}}=4, N_{\text{max}}=8)\) scaling have about 16.7 million parameters and perform 3.5 billion operations (computed for a sequence length of \(n = 30\)), however, the DeLighT network with block-wise scaling delivered 2 points better perplexity. See Section 4.5 for more results.

### 3.3 Block-wise scaling

Standard methods for improving the performance of sequence models include increasing the model dimensions (width scaling), stacking more blocks (depth scaling), or both [1226]. However, such scaling is not very effective on small datasets. For example, when a Transformer-Base \((d_{\text{in}} = 512)\) network is replaced with Transformer-Large \((d_{\text{in}} = 1024)\) on the WMT’16 En-Ro corpus, the number of parameters increases by \(\sim 4 \times\) while the performance does not change appreciably (BLEU: 34.28 vs. 34.35). This is likely because scaling model width and depth uniformly allocates parameters across blocks, which may lead to learning redundant parameters. To create very deep and wide networks, we extend model scaling to the block level. The intuition is that some blocks benefit from increases in parameters more than others. Figure 2 compares uniform scaling with block-wise scaling.

**Scaling the DeLighT block**: The DeLighT block learns deep and wide representations using DExTra, whose depth and width are controlled by two configuration parameters: the number of group transformation layers \(N\) and the width multiplier \(m_w\) (Figure 2a). These configuration parameters allow us to increase the number of learnable parameters inside the DeLighT block independently of the input \(d_{\text{in}}\) and output \(d_{\text{out}}\) dimensions. Such calibration is not possible with the standard transformer block because their expressiveness and capacity are a function of the input (input dimension = number of heads x head dimension). Here, we introduce block-wise scaling that creates a network with variably-sized DeLighT blocks, allocating shallower and narrower DeLighT blocks near the input and deeper and wider DeLighT blocks near the output.

To do so, we introduce two network-wide configuration parameters: minimum depth \(N_{\text{min}}\) and maximum depth \(N_{\text{max}}\) of DExTra in the DeLighT network. We then compute the depth \(N^b\) and the width multiplier \(m_w^b\) of DExTra in each DeLighT block \(b\) using linear scaling (Eq. 4). With this scaling, each DeLighT block \(b\) has a different depth and width (Figure 2a).

\[
N^b = N_{\text{min}} + \frac{(N_{\text{max}} - N_{\text{min}}) b}{B - 1}, \quad m_w^b = m_w + \frac{(N_{\text{max}} - N_{\text{min}}) b}{N_{\text{min}}(B - 1)}, \quad 0 \leq b \leq B - 1 \quad (4)
\]

Here, \(B\) denotes the number of DeLighT blocks in the network. We also add superscript \(b\) to depth \(N\) and width multiplier \(m_w\) to indicate that these configuration parameters are for block \(b\). Note that setting \(N_{\text{max}} = N_{\text{min}} = N\) results in a network with a uniform parameter distribution. Our results in Section 4.5 show that block-wise scaling is more effective than uniform scaling.

**Network depth**: Each DeLighT block \(b\) stacks (i) a DExTra unit with \(N^b\) layers, (ii) three parallel linear layers for key, query, and value, (iii) a projection layer, and (iv) two linear layers of a lightweight FFN. Therefore, the depth of a DeLighT network with \(B\) blocks is \(\sum_{b=0}^{B-1} (N^b + 4)\). For the standard transformer network, the depth is \(4B\).
4 Experimental results

4.1 Datasets and Evaluation

**Machine translation:** To demonstrate the training of very deep and light-weight DeLighT models, we choose four standard corpora: (1) IWSLT’14 German-English (De-En) [40], (2) WMT’16 English-Romanian (En-Ro) [41], (3) WMT’14 English-German (En-De), and (4) WMT’14 English-French (En-Fr). The IWSLT’14 De-En dataset consists of about 160K/7K/7K sentence pairs for training, validation, and testing respectively and has a joint BPE vocabulary of about 10K tokens. The WMT’16 En-Ro dataset consists of 600K/2K/2K sentence pairs for training, validation, and testing respectively and has a joint BPE vocabulary of about 35K tokens. The WMT’14 En-De dataset has 3.9M/39K/3K sentence pairs for training, validation, and testing respectively and has a joint 44K BPE vocabulary. The WMT’14 En-Fr dataset has 36M/27K/3K sentence pairs for training, validation, and testing respectively and has a joint 44K BPE vocabulary. We measure performance in terms of BLEU [43] (higher is better) on the test set. We follow [21] for beam search related hyper-parameters.

**Language modeling:** We evaluate on the WikiText-103 dataset [44] that has 103M/217K/245K tokens for training, validation, and testing. It has a word-level vocabulary of about 260K tokens. Following [9, 30], we report performance in terms of perplexity (lower is better) on the test set.

4.2 Architecture

**Machine Translation:** We follow the encoder-decoder architecture [1] with both the encoder and the decoder networks having \( B \) DeLighT blocks. Decoder blocks are identical to the encoder blocks (Figure 1d), except that they have an additional source-target single-head attention unit before the light-weight FFN. In the source-target single-head attention unit, keys and values are projections over the encoder output (full details in Appendix A). In our experiments, we use \( m_w = 2, N_{min} = 4, \) and \( N_{max} = 8 \) for WMT’16 En-Ro, WMT’14 En-De, and WMT’14 En-Fr and \( m_w = 1, N_{min} = 3, \) and \( N_{max} = 9 \) for IWSLT’14 De-En. We scale \( d_m \) from 128 to 640 to increase network parameters. For simplicity, we set \( B = N_{max} \). We use a learnable look-up table that maps every token in the vocabulary to a 128-dimensional vector.

**Language modeling:** We use the transformer-based decoder architecture [30] with \( B \) DeLighT blocks. We use \( m_w = 2, N_{min} = 4, \) and \( N_{max} = 12 \). We scale \( d_m \) using values \{384, 512, 784, 1024\} for increasing network parameters. For simplicity, we set \( B = N_{max} \). Following standard practice, we use adaptive input [30] as a look-up table and adaptive output [31] as the classification layer with one head (head dimension is 128) and two tails (tail dimensions are 64 and 32). We also share weights between the input and the output layers [45, 46].

In both tasks, we encode token positions using sinusoidal position embeddings [1]. We implement our models using Fairseq [47] and use their scripts for pre-processing, training, and evaluation.

4.3 Training

**Machine translation:** For IWSLT’14 De-En models, we follow the training setup of [21] and train all our models for 50K iterations with a batch size of 4K tokens on a single NVIDIA GTX 1080 GPU. For WMT’16 En-Ro, we follow the training setup for transformer models in [48] and train models for 100K iterations on 16 NVIDIA Tesla V100 GPUs with an effective batch size of 64K tokens. For WMT’14 En-De and WMT’14 En-Fr, we follow the training set-up of [21, 22] and train our models on 16 V100 GPUs for 30K and 50K iterations, respectively. We minimize cross entropy loss with label smoothing of value 0.1 during training. For a fair comparison, we trained our baseline transformer models using the same training set-up. Note that our reproduced numbers are either the same or better than the ones reported by Vaswani et al. [1].

**Language modeling:** We follow the training setup of [30], except that we train our models on 8 NVIDIA Tesla V100 GPUs for 100K iterations with a context length of 512 and an effective batch

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2Unlike existing methods that use 4.5M/3K sentence pairs for training and validation, we use a smaller training and a larger validation split (as processed by the Fairseq library). Also, we use training and validation data that is compatible with the Tensor2Tensor library [42] in order to have fair comparisons with recent work, i.e., Evolved Transformer [23].
Figure 3: **Results on machine translation corpora.** Compared to baseline transformers, DeLighT models require significantly fewer parameters to achieve similar performance. Here, 1 and 2 indicate the best reported transformer baselines from [21] and [48], respectively. *These models share weights in each layer along the channel dimension inside convolutional layers to reduce network parameters. DeLighT does not employ such methods, yet it has fewer parameters. We believe that sharing weights across groups in group linear transformation would further reduce network parameters and such experiments are left for future studies.

Table 1: Comparison of machine translation models in terms of network depth, network parameters, number of multiplication-addition operations (MACs), and BLEU on the WMT’14 En-Fr dataset. DeLighT delivers state-of-the-art performance with significantly fewer parameters and operations. We used 20 source and 20 target tokens for computing MACs. The procedure for counting MACs is in Appendix B.

| Model                | WMT’16 En-Ro | WMT’14 En-De | WMT’14 En-Fr |
|----------------------|--------------|--------------|--------------|
| Parameters (in M)    | BLEU         | Parameters (in M) | BLEU         |
| Dynamic convolution  | 43 M         | 62 M         | 40 M         |
| Lite transformer*    | 17 M         | 67 M         | 62 M         |
| Evolved transformer   | 48 M         | 67 M         | 67 M         |
| Transformer (Baseline) [1] | 34.3        | 34.3        | 27.7         |
| Transformer (Ours)   | 14 M         | 22 M         | 37 M         |
| DeLighT (Ours)       | 30 M         | 53 M         | 54 M         |

(c) **Comparison with state-of-the-art methods**

4.4 Results

**Machine translation:** In Figure 3, we compare the performance of DeLighT on machine translation corpora with state-of-the-art methods (standard transformer [1], dynamic convolutions [21], and lite transformer [22]). Figure 3c shows that DeLighT delivers state-of-the-art performance, outperforming all other models with fewer parameters and operations. Specifically, compared to our baseline transformer model, DeLighT delivers similar performance but with significantly fewer parameters. On low-resource (WMT’16 En-Ro), medium resource (WMT’14 En-De) and high resource (WMT’14 En-Fr) datasets, DeLighT delivers similar or better performance with 2.8×, 1.8×, and 1.8× fewer parameters, respectively. In contrast to the transformer architecture, our models are 3.7 times deeper and have significantly fewer parameters and operations for similar or better performance (Table 1).

**Language modeling:** Table 2a compares the performance of DeLighT with previous methods, on WikiText-103. Table 2b plots the variation of perplexity with number of parameters for DeLighT and Transformer (base). For both tasks, we train all our models using Adam [49] with a learning rate warm-up strategy.
Table 2: Results on the WikiText-103 dataset. Compared to the baseline network (Transformer-XL [9]), DeLighT delivers better performance (lower perplexity) with a smaller context length and fewer parameters.

(a) Comparison with existing methods

| Method                  | Network Depth | Context Length | Parameters (in million) | Perplexity (Test) |
|-------------------------|---------------|----------------|-------------------------|-------------------|
| LSTM [50]               | –             | –              | –                       | 48.70             |
| LSTM + Neural Cache [50]| –             | –              | –                       | 40.80             |
| QRNN [51]               | –             | 151 M          | –                       | 33.00             |
| Transformer-XL (Baseline) [9] | 64          | 640            | 151 M                   | 24.03             |
| Transformer-XL (Our impl.) | 64          | 640            | 151 M                   | 24.34             |
| DeLighT (Ours)          | 158           | 480            | 99 M                    | 24.14             |

(b) DeLighT vs. Transformer-XL

Transformer-XL [9] – which outperforms other transformer-based implementations (e.g., [30]). Both tables show that DeLighT delivers better performance than state-of-the-art methods (including Transformer-XL) and it does this using a smaller context length and significantly fewer parameters, suggesting that deeper and wider representations learned using DeLighT help model strong contextual relationships.

4.5 Ablations on the WikiText-103 dataset

Table 3a studies the impact of DeLighT block parameters, namely (1) minimum depth $N_{min}$, (2) maximum depth $N_{max}$, (3) width multiplier $m_w$, and (4) model dimension $d_m$ (see Figure 1d). Table 3c-3b shows the impact of the DExTra transformation, feature shuffling, and the light-weight FFN.

DeLighT block: Overall, Table 3 shows that scaling depth and width using DExTra and block-wise scaling improves performance. We make following observations:

a) Block-wise scaling (R4, R5) delivers better performance compared to uniform scaling (R1-R3). For instance, DeLighT with $N_{min} = 4$ and $N_{max} = 8$ (R4) is $1.25 \times$ shallower than DeLighT with $N_{min} = 8$ and $N_{max} = 8$ (R2), but delivers better performance with a similar number of parameters and operations. Scaling $m_w$ improves performance (R2 vs. R3), however, the improvement is significantly lower than for the model with block-wise scaling (R3 vs. R5). This suggests that non-uniform distribution of parameters across blocks allows the network to learn better representations.

b) Different ratios between $N_{max}$ and $N_{min}$ yields different results. We observe significant performance improvements when the ratio is greater than or equal to two. For example, when we scale $N_{max}/N_{min}$ from 2 to 3 (R6 vs. R8), the perplexity improves by $\sim 5$ points with only a moderate increase in network parameters. On the other hand, when the $N_{max}/N_{min}$ is close to 1 (R6 vs. R7), performance does not change appreciably. This is likely because the allocation of parameters across blocks is close to uniform (Eq. 4). This is consistent with our previous observation.

c) Learning shallower and narrower representations near the input and deeper and wider representations near the output achieves better performance. For example, when we scaled $N_{max}$ from 8 to 12 for $N_{min} = 4$ (R6, R8), DeLighT delivered better performance with a similar number of parameters compared to a model with $N_{min} = 6$ (R7, R9). This is likely because the ratio of $N_{max}$ and $N_{min}$ is higher when $N_{min} = 4$, which helps allocate parameters per block more effectively. We also observe that deeper and wider representations near the input and shallower and narrower representations near the output hurts performance (R13 vs. R16).

d) Scaling width using $m_w$ and $d_m$ improves performance (R10-R15), however, their impact is different. For example, when we scale $m_w$ and $d_m$ by two, the rate of increase in number of parameters and operations is more rapid with $d_m$ compared to $m_w$. DeLighT’s ability to learn wider representations in different ways may be useful in selecting application specific models.

This work investigates relationships between $N_{min}$, $N_{max}$, $m_w$, and $d_m$, manually. We believe that a more principled approach (e.g., [27]) that establishes relationships between these parameters would produce more efficient and accurate models. We will explore such methods in the future.
Table 3: Ablations on the Wikitext-103 validation set. In (a), we ablate on different aspects of the DeLighT block, including uniform vs. block-wise scaling, depth scaling, and width scaling. Rows partially highlighted in color have the same configuration (repeated for illustrating results). In (b), we study the effect of feature shuffling. (c) studies the impact of reduction factor $r$ in the light-weight FFN. (d) studies the impact of different transformation functions in the DeLighT block. Our experimental setup is similar to Section 4 except that we train our models for 50K iterations. Multiplication and addition operations (MACs) are computed for 20 time steps. Additional results at different settings are included in Appendix C.

(a)

| Row # | $N_{min}$ | $N_{max}$ | $m_w$ | $d_m$ | Depth | Parameters (in million) | MACs | Perplexity |
|-------|-----------|-----------|-------|-------|-------|--------------------------|------|------------|
| R1    | 4         | 4         | 2     | 256   | 43    | 14.1 M                   | 2.96 B | 56.19      |
| R2    | 8         | 8         | 2     | 256   | 115   | 16.6 M                   | 3.49 B | 48.58      |
| R3    | 8         | 8         | 4     | 256   | 115   | 22.1 M                   | 4.64 B | 45.10      |
| R4    | 4         | 8         | 2     | 256   | 92    | 16.7 M                   | 3.51 B | 46.30      |
| R5    | 4         | 12        | 2     | 256   | 158   | 21.0 M                   | 4.41 B | 41.18      |

Varying depth ($N_{min}$ and $N_{max}$ (Eq. 4))

| Row # | $N_{min}$ | $N_{max}$ | $m_w$ | $d_m$ | Depth | Parameters (in million) | MACs | Perplexity |
|-------|-----------|-----------|-------|-------|-------|--------------------------|------|------------|
| R6    | 4         | 8         | 2     | 256   | 92    | 16.7 M                   | 3.51 B | 46.30      |
| R7    | 6         | 8         | 2     | 256   | 102   | 16.5 M                   | 3.46 B | 46.68      |
| R8    | 4         | 12        | 2     | 256   | 158   | 21.0 M                   | 4.41 B | 41.18      |
| R9    | 6         | 12        | 2     | 256   | 172   | 20.0 M                   | 4.20 B | 42.26      |

Varying DExTra’s width $m_w$ (Eq. 4)

| Row # | $N_{min}$ | $N_{max}$ | $m_w$ | $d_m$ | Depth | Parameters (in million) | MACs | Perplexity |
|-------|-----------|-----------|-------|-------|-------|--------------------------|------|------------|
| R10   | 4         | 12        | 2     | 256   | 158   | 21.0 M                   | 4.41 B | 41.18      |
| R11   | 4         | 12        | 3     | 256   | 158   | 23.8 M                   | 4.99 B | 39.92      |
| R12   | 4         | 12        | 4     | 256   | 158   | 27.1 M                   | 5.69 B | 39.10      |

Varying model width $d_m$

| Row # | $N_{min}$ | $N_{max}$ | $m_w$ | $d_m$ | Depth | Parameters (in million) | MACs | Perplexity |
|-------|-----------|-----------|-------|-------|-------|--------------------------|------|------------|
| R13   | 4         | 12        | 2     | 256   | 158   | 21.0 M                   | 4.41 B | 41.18      |
| R14   | 4         | 12        | 2     | 384   | 158   | 29.9 M                   | 6.28 B | 35.14      |
| R15   | 4         | 12        | 2     | 512   | 158   | 43.8 M                   | 9.20 B | 30.81      |

Deeper and wider near the Input

| Row # | $N_{min}$ | $N_{max}$ | $m_w$ | $d_m$ | Depth | Parameters (in million) | MACs | Perplexity |
|-------|-----------|-----------|-------|-------|-------|--------------------------|------|------------|
| R16   | 12        | 4         | 2     | 256   | 158   | 21.0 M                   | 4.41 B | 43.10      |

Impact of DExTra: We replace DExTra in the DeLighT block (Figure 1d) with the DeFINE unit and a stack of linear layers. Table 3d shows that DExTra delivers similar performance with significantly fewer parameters compared to the DeFINE unit and linear layers. In these experiments, the settings are the same as R13-R15 (Table 3), except, $N_{max} = 8$, because models with a stack of linear layers learn too many parameters.

Feature shuffling: Table 3c shows that feature shuffling improves the performance of DeLighT by 1-2 perplexity points. Here, we use the same settings as in R13-R15 (Table 3).

Light-weight FFN: Table 3d shows the impact of varying the reduction factor $r$ in the light-weight FFN. We use the same settings as in R13 (Table 3). We did not observe any significant drop in performance until $r = 4$. Beyond $r = 4$, we see a drop in performance (perplexity increases by $\sim 2$ points). In such cases, the inner dimensions of the light-weight FFN are very small and hurt performance. Notably, the light-weight FFN with $r = 2^2$ delivered the same performance as $r = 2^{-2}$, but with $1.28 \times$ fewer network parameters. At $r = 2^{-2}$, the light-weight FFN is the same as the FFN in [11]. This suggests that the ability of DExTra to learn representations in high-dimensional spaces efficiently allows us to reduce the computational burden on the FFN.

5 Conclusion

This paper introduces a very deep and light-weight transformer architecture, DeLighT, that efficiently allocates parameters both within the DeLighT block and across DeLighT blocks. Compared to state-of-the-art Transformer models, DeLighT models are (1) very deep and light-weight and (2) deliver similar or better performance. In the future, we plan to apply DeLighT to other tasks, including language model pre-training, question answering, and language generation. Also, existing deep learning frameworks (e.g., PyTorch) do not have efficient implementations of group linear
transformations and single-head attention. Similar to dedicated CUDA kernels for the Transformer, we expect a dedicated CUDA kernel for DeLighT units to be much more efficient, both in terms of speed as well as memory during forward and backward passes.

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Broader Impact

Deep neural networks have led to a series of breakthroughs across different fields, including computer vision and sequence modeling. However, training very deep neural networks for sequence modeling tasks is still challenging because such models learn millions of parameters and require large amounts of labeled training data. This paper provides insights into creating very deep neural networks for sequence modeling tasks and shows how to train such models with fewer parameters. We hope that our work will make research in deep learning accessible with a more modest computation budget, especially on low resource settings where it is still difficult to train. Otherwise, we expect that it will have the same broader impact, both positive and negative, as the field as a whole.

A DeLighT Architectures for Language Modeling and Machine Translation

DeLighT architectures for language modeling and machine translation are shown in Figure 4. For language modeling, we follow the architecture in [30] while for machine translation, we follow the architecture in [1].

Language modeling: Figure 4a shows the architecture for language modeling. The architecture stacks B DeLighT blocks, the configuration of each block is determined using block-wise scaling. Each block has three sub-layers. The first layer is a DExTra unit that learns representations in high-dimensional space. The second layer is single-head attention that encodes contextual relationships. The third layer is a position-wise light-weight feed-forward network. Similar to [1], we employ a residual connections [28]. Similar to previous works [9, 30], we use tied adaptive input [30] and adaptive softmax [31] to map tokens to vectors and vectors to tokens, respectively.

Machine translation: Figure 4b shows the architecture for machine translation. The encoder stacks B DeLighT blocks, the configuration of each block is determined using block-wise scaling. Similar to language modeling, each encoder block has three sub-layers. The first layer is a DExTra unit that learns representations in high-dimensional space. The second layer is single-head attention that encodes contextual relationships. The third layer is a position-wise light-weight feed-forward network. Similar to [1], we employ a residual connections [28]. Similar to [1], we use learnable look-up table to map tokens to vectors.

Similar to the encoder, the decoder also stacks B blocks. Decoder blocks are identical to encoder blocks, except that they have an additional source-target single-head attention unit before the light-weight FFN. Keys and values in source-target single-head attention unit are projections over the encoder output. We use standard learnable look-up table to map tokens to vectors and linear classification layer to map vectors to tokens.

Implementation: We implement DeLighT using Fairseq [47]. We note that existing libraries, such as PyTorch, do not have efficient implementation of group linear transformation. In our experiments, we use a solution that reshapes and transposes the input tensor and then perform a batch matrix multiplication. Reshaping and transposing operations in high-dimensional spaces are computationally very expensive. A dedicated CUDA kernel (similar to multi-head attention) may improve the computational efficiency of DeLighT.
B Multiplication-Addition Operations in DeLighT

The DeLighT block is built using linear transformations, group linear transformations, and scaled dot-product attention. Total number of multiplication-addition operations (MACs) in a network is an accumulation of these individual operations.

Let $n$ denotes the number of source tokens, $m$ denotes the number of target tokens, $d_m$ denotes the input dimension, $d_o$ denotes the output dimension, and $g$ denotes the number of groups in group linear transformation. The procedure for counting MACs for each of these operations is described below.

**Group linear transformation:** Group linear transformation $F$ splits a $d_m$-dimensional input $X$ into $g$ non-overlapping groups such that $X = \text{Concat}(X_1, \cdots, X_g)$, where $X_i$ is a $\frac{d_m}{g}$-dimensional vector. $X_i$’s are then simultaneously transformed using $g$ linear transforms $W_i \in \mathbb{R}^{\frac{d_m}{g} \times \frac{d_o}{g}}$ to produce $g$ outputs $Y_i = X_iW_i$. $Y_i$’s are then concatenated to produce the final $d_o$-dimensional output $Y = \text{Concat}(Y_1, \cdots, Y_g)$.

Group linear transformation $F$ has $g$ learnable matrices $W_i \in \mathbb{R}^{\frac{d_m}{g} \times \frac{d_o}{g}}$. Therefore, group linear transformation learns $\frac{d_md_o}{g}$ parameters and performs $\frac{d_md_od_o}{g}$ MACs to transform $d_m$-dimensional input to $d_o$-dimensional output. Following a standard practice (e.g., ResNet [28]), we count addition
and multiplication as one operation instead of two because these operations can be fused in recent hardwares.

Importantly, when $g = 1$, the group linear transformation is the same as linear transformation.

**Self-attention in DeLighT:** The scaled dot-product self-attention in DeLighT is defined as:

$$\text{Attention}(K, Q, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_o}} \right) V$$

(5)

where $Q \in \mathbb{R}^{n \times d_o}$, $K \in \mathbb{R}^{n \times d_o}$, $V \in \mathbb{R}^{n \times d_o}$ denotes query, key, and value, respectively.

The attention operation involves two dot-products. The first dot product between $Q$ and $K$ while the second dot product is between the output of first dot product and $V$. Both dot products require $d_o n^2$ MACs. Therefore, total number of MACs in computing scaled dot-product self-attention are $2d_o n^2$.

In case of a source-target attention (as in machine translation), $K$’s and $V$’s are from the source (encoder) and $Q$’s are incrementally decoded (one token at a time). Therefore, the number of MACs required to decode $m$ target tokens given $n$ source tokens are $\sum_{k=1}^{m} 2knd_o$.

### C Additional Results

#### C.1 Uniform vs. block-wise scaling

Figure 5 compares the performance of DeLighT with uniform and block-wise scaling. For a given model dimension $d_m$, DeLighT models with block-wise scaling delivers better performance.

![Uniform vs. block-wise scaling](image)

Figure 5: Uniform vs. block-wise scaling. (a) contrasts the uniform and block-wise scaling methods. (b) compares the results of DeLighT with uniform and block-wise scaling methods on the WikiText-103 dataset. DeLighT networks with block-wise scaling delivers better performance across different settings.

#### C.2 Scaling up DeLighT

The DeLighT network is specified using following configuration parameters: (1) minimum depth $N_{min}$, (2) maximum depth $N_{max}$, (3) width multiplier $m_w$, and (4) model dimension $d_m$. Figure 6 shows the results obtained after varying these parameters ($N_{min} = \{4, 6\}$, $N_{max} = \{8, 12\}$, $m_w = \{2, 3, 4\}$, and $d_m = \{256, 384, 512\}$). We can see that scaling one configuration parameter (e.g., $d_m$) while keeping other configuration parameters constant (e.g., $N_{min}$, $N_{max}$, and $m_w$) consistently improves performance.
Figure 6: Scaling up DeLighT. Scaling one configuration parameter (e.g., $d_m$) while keeping other configuration parameters constant (e.g., $N_{\text{min}}$, $N_{\text{max}}$, and $m_w$) consistently improves performance. The numbers on top of each bar represents network parameters (in million).

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