Fixed Encoder Self-Attention Patterns in Transformer-Based Machine Translation

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Abstract
Transformer-based models have brought a radical change to neural machine translation. A key feature of the Transformer architecture is the so-called multi-head attention mechanism, which allows the model to focus simultaneously on different parts of the input. However, recent works have shown that attention heads learn simple positional patterns which are often redundant. In this paper, we propose to replace all but one attention head of each encoder layer with fixed – non-learnable – attention patterns that are solely based on position and do not require any external knowledge. Our experiments show that fixing the attention heads on the encoder side of the Transformer at training time does not impact the translation quality and even increases BLEU scores by up to 3 points in low-resource scenarios.

1 Introduction
Models based on the Transformer architecture (Vaswani et al., 2017) have led to tremendous performance increases in a wide range of downstream tasks (Devlin et al., 2019). Despite these successes, the impact of the suggested parametrization choices, in particular the self-attention mechanism with its large number of attention heads distributed over several layers, has been the subject of many studies following two main lines of research.

The first line of research focuses on the interpretation of the network. A growing body of research is dedicated to the analyses of attention mechanisms and the interpretation of weights and connections (Raganato and Tiedemann, 2018; Tang et al., 2018; Mareček and Rosa, 2019; Voita et al., 2019a). The second line of research argues that Transformer networks are over-parametrized and learn redundant information that can be pruned in various ways. For example, Voita et al. (2019b) show that a few attention heads do the “heavy lifting” whereas others contribute very little or nothing at all. Similarly, Michel et al. (2019) raise the question whether 16 attention heads are really necessary to obtain competitive performance.

This study falls into the second category and is motivated by the observation that most self-attention patterns learned by the Transformer architecture merely reflect positional encoding of contextual information (Raganato and Tiedemann, 2018; Kovaleva et al., 2019; Voita et al., 2019a). Hence, we argue that most attentive connections in the encoder do not need to be learned at all, but can be replaced by simple predefined patterns. We suppose that such fixed patterns are especially attractive in low-resource scenarios, as they reduce the number of learnable parameters drastically without affecting the overall capacity of the network.

Our experiments with different language pairs and varying amounts of training data suggest that fixed self-attention patterns yield competitive results, at least for the task of machine translation. Our work shows that the encoder self-attention in Transformer-based machine translation can be simplified substantially, reducing the parameter footprint without loss of translation quality, and even improving quality in low-resource scenarios.

2 Methodology
In this section, we first briefly describe the Transformer architecture and its self-attention mechanism, and then introduce the fixed attention patterns used throughout the paper.

2.1 Self-attention in Transformers
The Transformer architecture follows the so-called encoder-decoder paradigm where the source sentence is encoded in a number of stacked encoder layers, and the target sentence is generated through a number of stacked decoder layers. Each layer of the encoder consists of two main components:
a multi-head attention mechanism and a feed-forward network. The multi-head attention mechanism computes the so-called scaled dot-product attention using three weight matrices: a query $Q$, a key $K$, and a value $V$:

$$\text{Attention}(Q, K, V) = \text{softmax}\left( \frac{QK^T}{\sqrt{d_k}} \right)V$$ (1)

with $d_k$ representing the dimension of the key $K$.

Query, key and value are linearly projected $h$ times (where $h$ is the number of heads, i.e. $0 \leq i < h$) to allow the model to jointly attend to information from different representations:

$$H_i = \text{Attention}(QW^Q_i, KW^K_i, VW^V_i)$$

and the results of the $h$ heads are then concatenated:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(H_1, \ldots, H_h)W^O$$

with parameter matrices $W^Q_i \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W^K_i \in \mathbb{R}^{d_{\text{model}} \times d_k}$, $W^V_i \in \mathbb{R}^{d_{\text{model}} \times d_v}$ and $W^O \in \mathbb{R}^{hd_k \times d_{\text{model}}}$.

The resulting MultiHead$(Q, K, V)$ is fed to a feed-forward network that consists of two linear layers with a ReLU activation in between. This multi-head attention is often called encoder self-attention, as it builds an attentive representation for the input sentence itself.

The decoder follows the same architecture as the encoder with multi-head attention mechanisms and feed-forward networks, with two main differences: i) an additional multi-head attention mechanism, called encoder-decoder attention connecting the last encoder layer to the first decoder layer, and ii) future positions are prevented from being attended to, by masking, in order to preserve the auto-regressive property of a left-to-right decoder.

The base version of the Transformer, the standard setting for machine translation, uses 6 layers for both encoder and decoder and 8 attention heads $h$ in each layer. In this work, we focus on the encoder self-attention and replace query $Q$ and key $K$ (or more precisely, the softmax operator and its input of Eq. 1) with fixed attentive patterns.

2.2 Fixed self-attention patterns

The inspection of encoder self-attention in standard MT models yields the somewhat surprising result that positional patterns, such as “current word” or “next word”, are key features across all layers and remain even after pruning most of the attention heads (Voita et al., 2019a,b). Instead of costly learning these trivial positional patterns using millions of sentences, we choose seven predefined patterns, each of which takes the place of an attention head (see Figure 1, upper row).

Given the $i$-th word within a sentence of length $n$, we determine the following patterns:

1. the current token, a fixed attention weight of 1.0 at position $i$,
2. the previous token, a fixed attention weight of 1.0 at position $i - 1$,
3. the next token, a fixed attention weight of 1.0 at position $i + 1$,
4. the larger left-hand context, a function $f$ over the positions 0 to $i - 2$,
5. the larger right-hand context, a function $f$ over the positions $i + 2$ to $n$,
6. the end of the sentence, a function $f$ over the positions 0 to $n$,
7. the start of the sentence, a function $f$ over the positions $n$ to 0.

We define $f$ as a normalized cubic function over...
the positions. Specifically, for each position $i$:

$$f(i) = \frac{(i + 1)^3}{\sum_{i=\text{start}}^{\text{end}}(i + 1)^3}$$

where \text{start} and \text{end} are defined by the respective fixed pattern.$^1$

These predefined attention heads are repeated over all layers of the encoder. The eighth attention head, instead, always remains learnable.

It is customary in NMT to split words into subword units and it can be assumed that learned attention patterns would treat split words differently. Therefore, we propose a second variant of the predefined attentive patterns that treat all parts of a word as a single token (see lower row of Figure 1).

3 Experiments

We perform a series of experiments to evaluate the fixed attentive encoder patterns, starting with a standard German $\leftrightarrow$ English translation setup (Section 3.1) and then extending the scope to low-resource and high-resource scenarios (Section 3.2).

3.1 Results: Standard scenario

To assess the general viability of the proposed approach and to quantify the effects of different numbers of encoder and decoder layers, we train models on a mid-sized dataset of 2.9M training sentences from the DE$\leftrightarrow$EN WMT19 news translation task, using Newstest2014 as test data. We compare against the reference using sacreBLEU (Papineni et al., 2002; Post, 2018).$^2$

We train four models: a standard Transformer in which all attention heads are learnable, one with fixed token-based attention patterns, one with fixed word-based attention patterns, and one with a single learnable attention head per layer. Each model is trained in 7 configurations: 6 encoder layers with 6 decoder layers, and 1 to 6 encoder layers coupled to 1 decoder layer. BLEU scores are shown in Figure 2.

Results for the most powerful model (6+6) show that the two fixed-attention models are almost indistinguishable from the standard model, whereas the single-head model yields slightly lower results. It could be argued that the 6-layer decoder is powerful enough to compensate for deficiencies due to fixed attention on the encoder side. The 6+1 configuration, which uses a single layer decoder, shows indeed a slight performance drop for DE$\rightarrow$EN, but no significant difference in the opposite direction. Overall translation quality drops significantly with three and less encoder layers, but the difference between fixed and learnable attention models is statistically insignificant in most cases. The fixed attention models always outperform the model with a single learnable head, which shows that the predefined patterns are indeed helpful. The (simpler) token-based approach seems to outperform the word-based one, but with higher numbers of layers the two variants are undistinguishable.

3.2 Results: Low-resource and high-resource scenarios

We assume that fixed attentive patterns are especially useful in low-resource scenarios since the number of parameters to be learned is drastically reduced, without losing key attentive patterns. For instance, a fixed-attention model saves 2.7M parameters compared to a fully learnable one. We test this assumption on four translation tasks: $^3$

- German $\rightarrow$ English, using the data from the IWSLT 2014 shared task (Cettolo et al., 2014) (159 000 training sentences),
- Korean $\rightarrow$ English, using the dataset described in Sennrich and Zhang (2019) (90 000 training sentences),
- Vietnamese $\leftrightarrow$ English, using the data from the IWSLT 2015 shared task (Cettolo et al., 2015) (133 000 training sentences).

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$^1$Pattern 5 and 7 are the flipped version of pattern 4 and 6, respectively.

$^2$Signature: BLEU+case.lc+#.1+s.exp+tok.13a+v.1.2.11.
Table 1: BLEU scores obtained for the low-resource scenarios with 6+6 layer configurations. Results marked with † are taken from Sennrich and Zhang (2019), those marked with ⊎ from Kudo (2018).

| Model                  | DE–EN | KO–EN | EN–VI | VI–EN |
|------------------------|-------|-------|-------|-------|
| All learned            | 26.57 | 6.67  | 29.85 | 26.15 |
| Fixed (word)           | 28.08 | **8.70** | **31.15** | 28.90 |
| Fixed (token)          | **28.38** | 8.43  | 31.05 | **29.16** |
| Single-head            | 26.15 | 6.14  | 28.67 | 25.03 |
| Prior work             | † 33.60 | † 10.37 | † 27.71 | † 26.15 |

Table 2: BLEU scores obtained for the high-resource scenario with 6+6 layer configurations.

| Model                  | EN–DE | DE–EN |
|------------------------|-------|-------|
| All learned            | 26.75 | **34.10** |
| Fixed (word-based)     | **26.92** | 33.17 |
| Fixed (token-based)    | 26.52 | 33.50 |
| Single-head learned    | 26.26 | 32.91 |

Low-resource scenarios can be sensible to the choice of hyperparameters (Sennrich and Zhang, 2019). Hence, we apply three mainstream adaptations: reduced batch size (4k → 1k tokens), increased dropout (0.1 → 0.3), and tied embeddings.

Results of the 6+6 layer configurations are shown in Table 1.³ The models using fixed attention consistently outperform the models using learned attention, by up to 3 points BLEU. No clear winner between token-based and word-based fixed attention can be distinguished though.

Our English ↔ Vietnamese models outperform prior work based on an RNN architecture by a large margin, but the DE↔EN and KO↔EN models are below the heavily optimized models of Sennrich and Zhang (2019). Both types of optimization are independent of each other and could be combined.

Finally, we also evaluate a high-resource scenario for German ↔ English with 11.5M training sentences. Table 2 shows that the results of the fixed attention models do not degrade even when abundant training data allow all attention heads to be learned accurately.

### 3.3 Ablation study

We perform an ablation study to assess the contribution of each attention head separately. For this, we mask one attention pattern across encoder layers at test time. Table 3 shows the degradations compared to the full model, on the mid-sized German ↔ English and on the Vietnamese ↔ English models, both in the 6+1 and 6+6 configurations.

We find that heads 2, 3 and 4 (previous word, next word, previous context) are particularly important, whereas the impact of the remaining context heads is small. Head 1 is not useful in the token-based model, but shows slightly larger numbers in the word-based setting.

The most interesting results concern the eighth, learned head. Its impact is significant, but in most cases lower than the three main heads listed above. Interestingly, disabling it causes much lower degradation in the 6+6 configurations, which suggests that a more powerful decoder can compensate the absence of learned encoder representations.

### 4 Conclusion

In this work, we simplify encoder self-attention of Transformer-based NMT models by replacing all but one attention head with fixed positional attentive patterns that require neither training nor external knowledge.

The following points summarize our findings:

i) The proposed fixed patterns improve translation quality in low-resource settings thanks to the strong injected prior knowledge about positional attention.

ii) The reduction in translation quality in mid-sized...
and high-resource settings is mostly insignificant. iii) If the number of decoder layers is sufficient, even the trainable encoder head can be disabled without hampering translation quality. iv) The integration of subword splitting information in the fixed patterns does not yield conclusive improvements.

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