Analyzing Word Translation of Transformer Layers

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Abstract

The Transformer translation model is popular for its effective parallelization and performance. Though a wide range of analysis about the Transformer has been conducted recently, the role of each Transformer layer in translation has not been studied to our knowledge. In this paper, we propose approaches to analyze the translation performed in encoder / decoder layers of the Transformer. How can we measure how translation evolves in transformer layers? One possibility that has not been investigated so far is word translation accuracy and this is what we focus on in this paper. Our approaches in general project the representations of an analyzed layer to the pretrained classifier and measure the word translation accuracy. For the analysis of encoder layers, our approach additionally learns a weight vector to merge multiple attention matrices into one and transform the source encoding to the target side with the merged alignment matrix to align source tokens with target translations while bridging different input - output lengths. While analyzing decoder layers, we additionally study the effects of the source context and the decoding history in word prediction through bypassing the corresponding selfattention or cross-attention sub-layers. Our analysis reveals that the translation starts at the very beginning of the "encoding" (specifically at the source word embedding layer), and shows how translation evolves during the forward computation of layers. Based on observations gained in our analysis, we propose that increasing encoder depth while removing the same number of decoder layers can simply but significantly boost the decoding speed. Furthermore, simply inserting a linear projection layer before the decoder classifier which shares the weight matrix with the embedding layer can effectively provide small but consistent and significant improvements in our experiments on the WMT 14 English-German,

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Figure 1: Example of Word Translations with the Transformer.

English-French and WMT 15 Czech-English translation tasks (+0.42, +0.37 and +0.47 respectively).

1 Introduction

Neural Machine Translation (NMT) has achieved great success in the last few years (Bahdanau et al., 2014; Gehring et al., 2017; Vaswani et al., 2017). The popular Transformer (Vaswani et al., 2017) model, which outperforms previous RNN/CNN based translation models (Bahdanau et al., 2014; Gehring et al., 2017), is based on multi-layer self-attention networks and can be paralleled effectively.

Recently, a wide range of analysises (Bisazza and Tump, 2018; Li et al., 2019a; Voita et al., 2019b; Yang et al., 2019; Tsai et al., 2019; Tang et al., 2019; He et al., 2019; Voita et al., 2019a) related to the Transformer have been conducted. For example, Bisazza and Tump (2018) perform a fine-grained analysis of how various source-side morphological features are captured at different levels of the NMT encoder, they find no correlation between the accuracy of source morphology encoding and translation quality, and morphological features only in context and only to the extent directly transferable to the target words are captured. Voita et al. (2019a) study how information flows across Transformer layers and find that representations differ significantly depending on the objectives (MT, LM and MLM). Tang et al. (2019) find that encoder hidden states outperform word embeddings significantly in word sense disambiguation. However, how the Transformer translation model transforms individual source tokens into corresponding target tokens (word translations, as shown in Figure 1), and specifically, what is the role of each Transformer layer in translation, at which layer a target word is translated has not been studied to our knowledge.

To detect roles of Transformer layers in translation, in this paper, we follow previous probing approaches (Adi et al., 2017; Hupkes et al., 2018; Conneau et al., 2018), and propose to measure the word translation accuracy of output representations of individual Transformer layers by probing corresponding target translation tokens in these representations. In addition to analyzing the role of each encoder / decoder layer, we also analyze the contribution of the source context and the decoding history in translation by testing the effects of the self-attention sub-layer and the cross-attention sub-layer in decoder layers.

Our analysis reveals that the translation already starts at the source embedding layer, which offers an explanation for Bisazza and Tump (2018). It also demonstrates how the word translation evolves across encoder / decoder layers and the effects of the source "encoding" and the decoding history on the translation of target tokens.

Based on the observations from our analysis, we find that: 1) the proper use of more encoder layers with fewer decoder layer can significantly boost decoding speed without harming quality; 2) inserting a linear projection layer before the decoder classifier can provide small but significant and consistent improvements in our experiments on the WMT 14 English-German, English-French and WMT 15 Czech-English news translation tasks (+0.42, +0.37 and +0.47 BLEU respectively).

2 Word Translation Accuracy Analysis

To analyze word translation accuracy of the Transformer, we first freeze a trained Transformer model so its behavior is consistent in how it performs in translation during our analysis, then we compute the forward pass and extract output representations of the layer analyzed. Finally, we apply a linear projection layer to extract and enhance features related to translation and feed projected representations to the frozen decoder classifier of the converged Transformer. The linear projection layer is the only module trained and updated on the training set with the original Transformer being frozen, thus it will

only transform between vector spaces without generating new features for the word translation. An illustration of our analysis approach for encoder / decoder layers is shown in Figure 2.

2.1 Analysis of Encoder Layers

Analyzing word translation accuracy of encoder layers requires us to align source tokens with corresponding target token. We use the alignment matrices computed by cross-attention sub-layers in decoder layers to align source tokens with target tokens. As there are multiple matrices produced by each sub-layer (due to the multi-head attention mechanism) and multiple decoder layers, we have to ensemble them into one matrix of high alignment accuracy using weights. Assume there are d decoder layers with h attention heads in each multihead attention sub-layer, which results in d * halignment matrices $A_1,...A_{d*h}$. We use a d*hdimension weight vector w to combine all these attention matrices. The weight vector is first normalized by softmax to a probability distribution

$$p_i = \frac{e^{w_i}}{\sum\limits_{j=1}^{d*h} e^{w_j}} \tag{1}$$

where i indicates the ith element in w.

Then we use p as the weights of corresponding attention matrices and merge them into 1 alignment matrix A.

$$A = \sum_{i=1}^{d*h} A_i * p_i \tag{2}$$

 \boldsymbol{w} can be trained during backpropagation together with the linear projection layer.

After we obtain the alignment matrix A, instead of selecting the target token with the highest alignment weight as the translation of a source token, we perform matrix multiplication between the encoded source representations E (size: source sentence length * input dimension) and the alignment matrix A (size: source sentence length * target sentence length) to transform / re-order source representations to the target side T_E :

$$T_E = A^T \times E \tag{3}$$

where A^T and \times indicate the transpose of A and matrix multiplication.

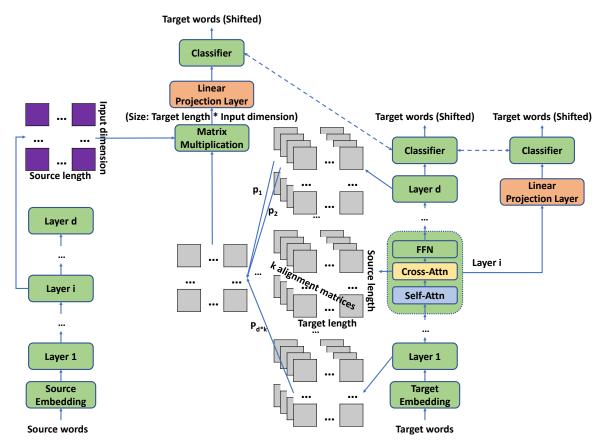


Figure 2: Analyzing Word Translations of Transformer Layers. Better viewed in color. Layers of the Trained Transformer Model (in green) for analysis are frozen. Parameters of the Linear Projection Layer (in orange) are trained on the training set. Dashed arrows indicate a shared module. When analyzes the effects of source contexts or decoding history in one decoder layer, the cross-attention sub-layer (in yellow) or the self-attention sub-layer (in blue) of the analyzing decoder layer are computed as a residual connection correspondingly. Layers are independently analyzed.

Thus T_E has the same length as the gold translation sequence, and the target sequence can be used directly as translations representing by T_E .

Though source representations are transformed to the target side, we suggest this does not involve any target side information as the pre-trained Transformer is frozen and the transformation does not introduce any representation from the decoder side. We do not retrieve target tokens with highest alignment score as word translations of corresponding source tokens because translation may involve one/none/multiple source token(s) to one/none/multiple target token(s) alignment, and we suggest that using a soft alignment (attention weights) may lead to more reliable gradients than the hard alignment.

2.2 Analysis of Decoder Layers

The analysis of predicting accuracy of the decoder is simpler than the encoder, as we can directly use the shifted target sequence without the requirement to bridge the different sequence length of the source sentence and the target while analyzing the encoder. We can simply use the output representations of the analyzed layer, and evaluate its prediction accuracy after projection.

However, as studied by Li et al. (2019a), the decoder involves 2 kinds of "translation", one (performed by the self-attention sub-layer) translates the history token sequence to the next token, another (performed by the cross-attention sub-layer) translates by attending source tokens. We additionally analyze the effects of these 2 kinds of translation on predicting accuracy by dropping the corresponding sub-layer of the analyzed decoder layer (i.e. we only compute the other sub-layer and the feed-forward layer with only the residual connection kept as the computation of the skipped sub-layer).

	Encoder		Decoder					
_					-Self attention		-Cross attention	
Layer	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ
0	40.73		13.72					
1	41.85	1.12	20.52	6.80	17.46	-3.06	16.47	-4.05
2	43.75	1.90	26.06	5.54	21.03	-5.03	22.91	-3.15
3	45.49	1.74	34.13	8.07	26.68	-7.45	27.79	-6.34
4	47.14	1.65	55.00	20.87	39.43	-15.57	35.32	-19.68
5	48.35	1.21	66.14	11.14	62.60	-3.54	55.84	-10.30
6	49.22	0.87	70.80	4.66	70.13	-0.67	69.03	-1.77

Table 1: Word Translation Accuracy of Transformer Layers.

3 Analysis Experiments

3.1 Settings

We conducted experiments based on the Neutron implementation of the Transformer (Xu and Liu, 2019). We first trained a Transformer base model for our analysis following all settings of Vaswani et al. (2017) on the WMT 14 English to German news translation task. The input dimension of the model and the hidden dimension of the feedforward sub-layer were 512 and 2, 048 respectively. We employed a 512 * 512 parameter matrix as the linear projection layer. The source embedding matrix, the target embedding matrix and the weight of the classifier were bound.

We applied joint Byte-Pair Encoding (BPE) (Sennrich et al., 2016) with 32k merge operations to address the unknown word issue. We only kept sentences with a maximum of 256 sub-word to-kens for training. We removed repeated data in the training set, and the training set was randomly shuffled in every training epoch. The concatenation of newstest 2012 and newstest 2013 was used for validation and newstest 2014 as the test set.

The number of warm-up steps was set to $8k^{-1}$. Each training batch contained at least 25k target tokens, and the model was trained for 100k training steps. The large batch size is achieved by gradient accumulation. We used a dropout of 0.1 and employed a label smoothing (Szegedy et al., 2016) value of 0.1. We used the Adam optimizer (Kingma and Ba, 2015) with 0.9, 0.98 and 10^{-9} as β_1 , β_2 and ϵ . Parameters were uniformly initialized under the Lipschitz constraint (Xu et al., 2019).

We averaged the last 5 checkpoints saved with an

interval of 1,500 training steps. For decoding, we used a beam size of 4, and evaluated tokenized casesensitive BLEU 2 . The averaged model achieved a BLEU score of 27.96 on the test set.

The linear projection layer and the weight vector w of 48 elements for alignment during the analysis of encoder layers were trained on the training set. We monitored the accuracy on the development set during their training, and reported results on the test set.

3.2 Analysis

The analysis results of the trained Transformer are shown in Table 1. Layer 0 stands for the embedding layer. "Acc" indicates the prediction accuracy. "-Self attention" and "-Cross attention" in the decoder layer analysis mean bypassing the computation of the self-attention sub-layer and the cross-attention sub-layer respectively of the analyzed decoder layer. In layer analysis of the encoder and decoder, " Δ " indicates improvements in word translation accuracy of the analyzed layer over the previous layer. While analyzing the self-attention and cross-attention sub-layers, " Δ " is the accuracy loss when we remove the computation of the corresponding sub-layer.

The results of encoder layers in Table 1 shows that: 1) surprisingly but reasonably the translation already starts at the embedding layer, and an amazingly sound word translation accuracy is obtained at the source embedding layer! This indicates that the translation already begins at the very beginning of "encoding" (specifically, the source embedding layer) instead of at the decoder. 2) With the stacking of encoder layers, the word translation accuracy

https://github.com/tensorflow/
tensor2tensor/blob/v1.15.4/
tensor2tensor/models/transformer.py#
L1818.

²https://github.com/moses-smt/
mosesdecoder/blob/master/scripts/
generic/multi-bleu.perl.

Layer	BLEU1	Δ	BLEU	Δ
0	33.1		7.92	
1	35.7	2.6	8.99	1.07
2	41.0	5.3	11.05	2.06
3	43.3	2.3	11.89	0.84
4	46.8	3.5	13.13	1.24
5	48.1	1.3	13.34	0.21
6	48.6	0.5	13.45	0.11
FULL	62.0	13.4	33.26	19.81

Table 2: Translation Performance of Encoder Layers.

improves (i.e. encoder layers gradually fix word translations of the source embedding layer), and improvements brought by different layers are relatively similar.

While analyzing decoder layers, Table 1 shows that: 1) shallow decoder layers (0, 1, 2 and 3) perform significantly worse compared to corresponding encoder layers (until reaching the 4th decoder layer, where a word translation accuracy which surpasses the embedding layer of the encoder is achieved); 2) The improvements brought by different decoder layers are quite different. Specifically, layer 4 and 5 bring more improvements than the others.

While analyzing the effects of the source context (the self-attention sub-layer is responsible for the target language re-ordering, and "-Self attention" prevents using the decoding history in the analyzed decoder layer) and the decoding history ("-Cross attention" prevents copying translation from the source "encoding"), Table 1 shows that in shallow decoder layers (layer 1-3), the decoding history plays a similarly important role like the source "encoding", while in deep layers, the source "encoding" plays a more vital role than the decoding history. Thus, we suggest our comparison sheds light on the importance of translation performed by the encoder.

3.3 Translation from Encoder Layers

Since our approach extracts features for translation from output representations of encoder layers while analyzing them, is it possible to perform word translation with only these features from encoder layers without using the decoder?

To achieve this goal, we feed output representations from an encoder layer to the corresponding linear projection layer, and feed the output of the linear projection layer directly to the decoder classifier, and retrieve tokens with highest probabilities as "translations". Even though such "translations" from encoder layers have a same length and a same word-order as source sentences, individual source tokens are translated to the target language to some extent. We evaluated BPEized 3 case-insensitive BLEU and BLEU 1 (1-gram BLEU, indicates the word translation quality), and results are shown in Table 2. "FULL" is the performance of the whole Transformer model (decoding with a beam size of 4). " Δ " means the improvements obtained by the introduced layer (or the decoder for "FULL") over the previous layer.

Table 2 shows that though there is a significant gap in BLEU scores between encoder layers and the full Transformer, the gap in BLEU 1 is relatively smaller than in BLEU. It is reasonable that encoder layers achieve a comparably high BLEU 1 score while a low BLEU score, as they perform word translation in the same order as the source sentence without any word re-ordering of the target language. We suggest the BLEU 1 score achieved by only the source embedding layer (i.e. translating with only embeddings) surprising and worth noting.

4 Findings Based on Observations

4.1 Trade Decoder Layers for Encoder Layers

From our analysis of the 6-layer Transformer base model (Table 1), we find that in contrast to the improvements of the word translation accuracy with increasing depth on the encoder side, some decoder layers contribute significantly fewer improvements than the others (i.e. Layer 4 and 5 bring more word translation accuracy improvements than that from layer 1, 2, 3 and 6 in Table 1)⁴. We suggest there might be more "lazy" layers in the decoder than in the encoder, which means that it might be easier to compress the decoder than the encoder, and further conjecture that simply removing some decoder layers while adding the same number of

³Since there is no re-ordering of the target language performed, which makes the merging of translated sub-word units in the source sentence order pointless.

⁴Though the improvements of encoder layers are smaller compared to that of the decoder, we suggest it is unfair to directly compare the accuracy improvements between encoder layers and decoder layers, as the encoder has to perform word sense disambiguation with contexts and its evaluation suffers from wrong alignments, while cross-attention sub-layers in decoder layers can copy the translation results from the encoder which should be easier for boosting performance.

Approach	Acc
Analysis of Decoder Layer 6	70.80
Standard Transformer	70.56

Table 3: Word Translation Accuracy of Standard Transformer and the last Decoder layer.

encoder layers may improve the performance of the Transformer. The other motivations for doing so are:

- Each decoder layer has one more crossattention sub-layer than an encoder layer, and increasing encoder layers while decreasing the same number of decoder layers will reduce the number of parameters and computational cost;
- The decoder has to compute the forward pass for every decoding step (the decoding of each target token), and the acceleration of reducing decoder layers will be more significant in decoding, which is of productive value.

4.2 Linear Projection Layer before Classifier

We compare the word translation accuracy achieved by the last decoder layer (with the linear projection layer) during analysis and that of the pre-trained standard Transformer (without the projection layer before the decoder classifier), and results are shown in Table 3.

Table 3 shows that feeding the representations from the last decoder layer after the linear projection to the decoder classifier leads to slightly higher word prediction accuracy than feeding them directly to the classifier. We conjecture potential reasons might be:

- We follow Vaswani et al. (2017) binding the weight matrix of the classifier with the embedding matrix. Processing the inserted linear projection layer followed by the classifier is equivalent to using only a classifier but with a new weight matrix (equivalent to the matrix multiplication of the linear projection layer's weight matrix and the embedding matrix), which indirectly detaches the classifier weight matrix with the embedding matrix;
- As described in our analysis approach, the linear projection layer is expected to enhance the
 part of its input representations which relates
 to the classification while fading the other

parts irrelevant to the word prediction, which may benefit the performance.

Thus, we suggest that inserting a linear projection layer which simply performs matrix multiplication between input representations and a weight matrix before the decoder classifier may help improve the word translation accuracy and further lead to improved translation quality.

4.3 Results and Analysis

4.3.1 Effects of Encoder/Decoder Depth

We examine the effects of reducing decoder depth while adding corresponding numbers of encoder layers, and results are shown in Table 4. The decoding speed is measured on the test set which contains 3,003 sentences with a beam size of 4. "Speed up" stands for the decoding acceleration compared to the 6-layer Transformer.

Table 4 shows that while the acceleration of trading decoder layers for encoding layers in training is small, in decoding is significant. Specifically, the Transformer with 10 encoder layers and 2 decoder layers is 2.32 times as fast as the 6-layer Transformer while achieving a slightly higher BLEU.

Though the Transformer with 11 encoder layers and only 1 decoder layer fails to achieve a comparable performance comparing with the 6-layer Transformer, our results still suggest that using more encoder layers with fewer but sufficient decoder layers can significantly boost the decoding speed, which is simple but effective and valuable for production applications.

We demonstrate the word accuracy analysis results of the 10 encoder layer 2 decoder layer Transformer in Table 5.

Comparing Table 5 with Table 1, we find that: 1) The differences in improvements (1.17 vs. 0.11) brought by individual layers of the 10-layer encoder are larger than those of the 6-layer encoder (1.90 vs. 0.87), indicating that there might be some "lazy" layers in the 10-layer encoder; 2) Decreasing the depth of the decoder removes those "lazy" decoder layers in the 6-layer decoder and makes decoder layers rely more on the source "encoding" (by comparing the effects of skipping the self-attention sub-layer and cross-attention sub-layer on performance).

4.3.2 Effects of the Projection Layer

To study the effects of the linear projection layer on performance, we conducted experiments on the

De	pth		Time				
Encoder	Decoder	BLEU	Train	Decode (/s)	Speed up		
6	6	27.96	33h33min	44	1.00		
7	5	28.07	32h17min	38	1.16		
8	4	28.61	31h26min	31	1.42		
9	3	28.53	30h29min	25	1.76		
10	2	28.47	30h11min	19	2.32		
11	1	27.02	29h27min	13	3.38		

Table 4: Effects of Encoder / Decoder Depth.

	Enco	Encoder			Decoder			
_					-Self attention		-Cross attention	
Layer	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ
0	40.48		14.04					
1	41.29	0.81	37.42	23.38	25.56	-11.86	20.40	-17.02
2	43.00	1.71	68.77	31.35	62.01	-6.76	40.67	-28.10
3	44.07	1.07						
4	45.86	1.79						
5	46.54	0.68						
6	47.46	0.92						
7	48.92	1.46						
8	49.58	0.66						
9	50.24	0.66						
10	50.35	0.11						

Table 5: Word Accuracy Analysis.

	En-De	En-Fr	Cs-En
Transformer	27.96	39.54	28.78
+ Linear Proj.	28.38 [†]	39.91 [‡]	29.25 [†]

Table 6: Effects of the Linear Projection Layer. "+ Linear Proj." indicates inserting the linear projection layer before the decoder classifier. \dagger and \ddagger indicate p < 0.01 and p < 0.05.

WMT 14 English-French and WMT 15 Czech-English news translation tasks in addition to the WMT 14 English-German task. We also conducted significance tests (Koehn, 2004). Results are tested on newstest 2014 and 2015 respectively and shown in Table 6.

Table 6 shows that the linear projection layer is able to provide small but consistent and significant improvements in all 3 tasks.

5 Related Work

Analysis of NMT Models. Li et al. (2019a) analyze the word alignment quality in NMT with prediction difference, and further analyze the effect

of alignment errors on translation errors, which demonstrates that NMT captures good word alignment for those words mostly contributed from source, while their word alignment is much worse for those words mostly contributed from target. Voita et al. (2019b) evaluate the contribution of individual attention heads to the overall performance of the model and analyze the roles played by them in the encoder. Yang et al. (2019) propose a word reordering detection task to quantify how well the word order information is learned by Self-Attention Networks (SAN) and RNN, and reveal that although recurrence structure makes the model more universally-effective on learning word order, learning objectives matter more in the downstream tasks such as machine translation. Tsai et al. (2019) regard attention as applying a kernel smoother over the inputs with the kernel scores being the similarities between inputs, and analyze individual components of the Transformers attention with the new formulation via the lens of the kernel. Tang et al. (2019) find that encoder hidden states outperform word embeddings significantly in word sense disambiguation. He et al. (2019) measure the word importance by attributing the NMT output to every input word and reveal that words of certain syntactic categories have higher importance while the categories vary across language pairs. Voita et al. (2019a) use canonical correlation analysis and mutual information estimators to study how information flows across Transformer layers and find that representations differ significantly depending on the objectives (MT, LM and MLM). An early work (Bisazza and Tump, 2018) performs a fine-grained analysis of how various source-side morphological features are captured at different levels of the NMT encoder. While they are unable to find any correlation between the accuracy of source morphology encoding and translation quality, they discover that morphological features are only captured in context and only to the extent that they are directly transferable to the target words, thus they suggest encoder layers are "lazy", while our analysis offers an explanation for their results as the translation already starts at the source embedding layer, and possibly source embeddings already represent linguistic features of their translations more than those of themselves.

Analysis of BERT. BERT (Devlin et al., 2019) uses the Transformer encoder, and analysis of BERT may provide valuable references for analyzing the Transformer. Jawahar et al. (2019) provide novel support that BERT networks capture structural information, and perform a series of experiments to unpack the elements of English language structure learned by BERT. Tenney et al. (2019) employ the edge probing task suite to explore how the different layers of the BERT network can resolve syntactic and semantic structure within a sentence, and find that the model represents the steps of the traditional NLP pipeline in an interpretable and localizable way, and that the regions responsible for each step appear in the expected sequence: POS tagging, parsing, NER, semantic roles, then coreference. Pires et al. (2019) present a large number of probing experiments, and show that Multilingual-BERTs robust ability to generalize cross-lingually is underpinned by a multilingual representation.

Accelerating Decoding. Zhang et al. (2018a) propose average attention as an alternative to the self-attention network in the Transformer decoder to accelerate its decoding. Wu et al. (2019) introduce lightweight convolution and dynamic convo-

lutions which are simpler and more efficient than self-attention. The number of operations required by their approach scales linearly in the input length, whereas self-attention is quadratic. Zhang et al. (2018b) apply cube pruning into neural machine translation to speed up the translation. Zhang et al. (2018c) propose to adapt an n-gram suffix based equivalence function into beam search decoding, which obtains similar translation quality with a smaller beam size, making NMT decoding more efficient. Non-Autoregressive Translation (NAT) (Gu et al., 2018; Libovický and Helcl, 2018; Wei et al., 2019; Shao et al., 2019; Li et al., 2019b; Wang et al., 2019; Guo et al., 2019) enables parallelized decoding, while there is still a significant quality drop compared to traditional autoregressive beam search, our findings on using more encoder layers might also be adapted to the NAT.

6 Conclusion

We propose approaches for the analysis of word translation accuracy of Transformer layers to investigate how translation is performed. To measure word translation accuracy, our approaches train a linear projection layer which bridges representations from the analyzing layer and the pre-trained classifier. While analyzing encoder layers, our approach additionally learns a weight vector to merge multiple attention matrices into one, and transforms the source "encoding" to the target shape by multiplying the merged alignment matrix. For the analysis of decoder layers, we additionally analyze the effects of the source context and the decoding history in word prediction through bypassing the corresponding sub-layers.

Two main findings of our analysis are: 1) the translation starts at the very beginning of "encoding" (specifically at the source word embedding layer), and evolves further with the forward computation of layers; 2) translation performed by the encoder is very important for the evolution of word translation of decoder layers, especially for Transformers with few decoder layers.

Based on our analysis, we propose to increase encoder depth while removing the same number of decoder layers to boost the decoding speed. We further show that simply inserting a linear projection layer before the decoder classifier which shares the weight matrix with the embedding layer can effectively provide small but consistent and significant improvements.

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