

Depth Growing for Neural Machine Translation

¹Lijun Wu, ²Yiren Wang, ³Yingce Xia, ³Fei Tian, ³Fei Gao, ³Tao Qin, ¹Jianhuang Lai and ³Tie-Yan Liu



¹Sun Yat-sen University; ²University of Illinois at Urbana-Champaign; ³Microsoft Research Asia

1. Motivation

- Training *deep networks* has been widely adopted and has *shown effectiveness* in image recognition, QA and text classification.
- Very deep and effective model training still *remains* challenging for NMT.



4. Two-stage Training

- Stage-1: The bottom modules (*enc*₁ and *dec*₁) are trained and subsequently fixed.
- Stage-2: Only the top modules (enc_2 and dec_2) are trained and optimized.

Discussion:

- Training complexity is reduced compared with jointly training, which eases optimization difficulty.
- We only have a "single" model grown to be a well-trained deeper one, which outperforms the "ensemble" models.



 Instead of working on RNN/CNN structures, we propose a novel approach to construct and train *deeper NMT models based on Transformer*.



5. Experiments

Overall Results

– WMT14 En \rightarrow De and WMT14 En \rightarrow Fr

The test performances of WMT14 En \rightarrow De and En \rightarrow Fr.

Model	En→De	En→Fr
Transformer (6B) [†]	28.40	41.80
Transformer (6B)	28.91	42.69
Transformer (8B)	28.75	42.63
Transformer (10B)	28.63	42.73
Transparent Attn (16B) [†]	28.04	
Ours (8B)	29.92	43.27

dagger: results reported in previous works

- We achieve **30.07** BLEU score on $En \rightarrow De$ with 10 blocks (10B).

Analysis

- Directly Stacking (DS): extend the 6-block baseline to 8-block by directly stacking 2 blocks.
- Ensemble Learning (Ensemble): separately train 2 models and ensemble their decoding results.



• [1] Cross-module residual connections

• [2] Hierarchical encoder-decoder attention



