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Abstract · Simple network architecture · · · Transformer · based solely on attention mechanisms! · Experiments (machine translation):

- superior in quality
- move parallelizable
- require significantly less time to train
- · WMT 2014, best BLEV
- · generalizes well!
 - Constituency parsing

1. Introduction

(Recurrent models)

- typically factor Computation along the symbol position of the input and output sequences.
- Aligning the positions to steps in computation time, they generate a sequence of hidden states ht, as
 - · a function of previous hidden state ht-1
 - · input for position t.

preclude parallelization within training examples, Critical at longer sequence lengths!

(improvements: factorization tricks & conditional computation)

- Attention mechanism
 - : allow modeling of dependencies without regard to their distance in the input or output sentences.

(Transformer

- rely entirely on an attention mechanism to draw global dependencies between input & output
- more parallelization
- SOTA in translation quality
- 12 hrs training with 8 P100 GPUs.

2. Background to reduce sequential computation; CNN Extented Neural GPU · ByteNet Conv S2S the number of operations required to relate signals from two arbitrary input or output positions grows in the distance between positions. - linearly for Comus25 - logarithmically for ByteNet * Transformer - reduced to a constant number of operations, - reduced effective resolution due to averaging attention - weighted positions counteract with Multi-Head Attention - Self - Attention

