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Tasks with Long Sequences

Long Text Sequences

Tasks In NLP:

Writing Books

Chatbots

Chatbots

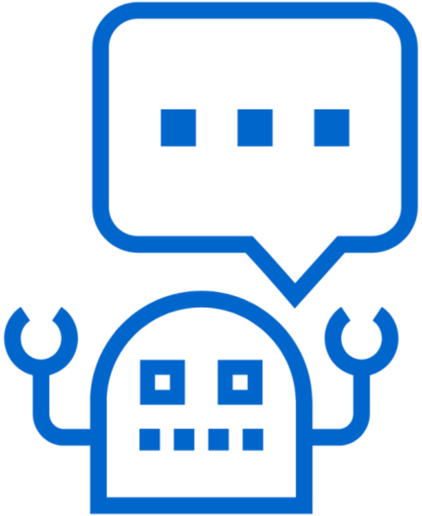
Context Windows:

User 1: What’s for dinner?

Chatbot: Who’s cooking, you or me?

User 1: Hey now chatbot.

Chatbot: I hope it’s not hay, that’s what horses eat.



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Transformer Complexity

Transformer Issues

- Attention on sequence of length L takes L^2 time and memory

  L=100 L^2 = 10K (0.001s at 10M ops/s)

  L=1000 L^2 = 1M (0.1s at 10M ops/s)

  L=10000 L^2 = 100M (10s at 10M ops/s)

  L=100000 L^2 = 10B (1000s at 10M ops/s)

- N layers take N times as much memory

  GPT-3 has 96 layers and new models will have more

Attention Complexity

- Attention: softmax(QK^T)V
- Q, K, V are all [L, d_model]
- QK^T is [L, L]
- Save compute by using area of interest for large L

Memory with N Layers

- Activations need to be stored for backprop
- Big models are getting bigger
- Compute vs memory tradeoff

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LSH Attention

What does Attention do?

Select Nearest Neighbors (K,Q) and return corresponding V

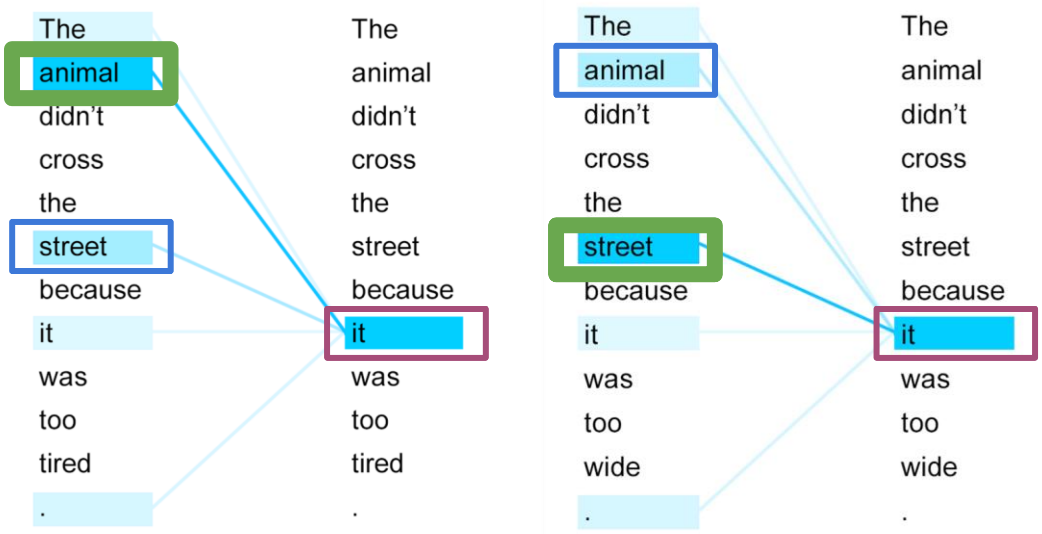


image © [(Transformer: A Novel Neural Network Architecture for Language Understanding.)]

Nearest Neighbors

Course:

Natural Language Processing with Classification and Vector Spaces

Lessons:

- KNN
- Hash Tables and Hash Functions
- Locality Sensitive Hashing
- Multiple Planes

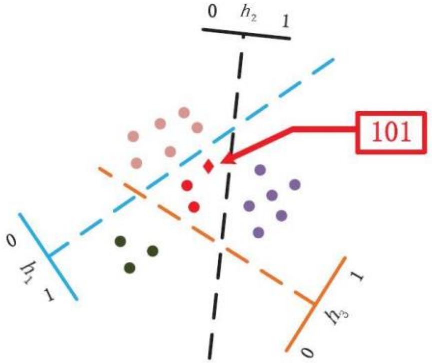
Nearest Neighbors

Compute the nearest neighbor to q among vectors $\{k_1, ..., k_n\}$

- Attention computes $d(q, k_i)$ for i from 1 to n which can be slow
- Faster *approximate* uses locality sensitive hashing (LSH)
- Locality sensitive: if q is close to k_i:

  $hash(q) == hash(k_i)$
- Achieve by randomly cutting space

  $hash(x) = sign(xR)$ R: [d, n_hash_



LSH Attention

Standard Attention:

$$A(Q, K, V) = \mathrm{softmax}(QK^T)V$$

LSH Attention:

- Hash Q and K
- Standard attention within same-hash bins
- Repeat a few times to increase probability of key in the same bin

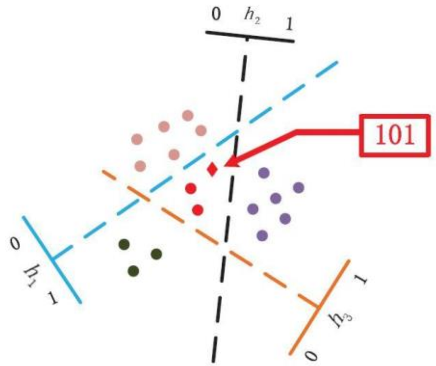


image ©
[(Reformer: The Efficient Transformer)]

LSH Attention

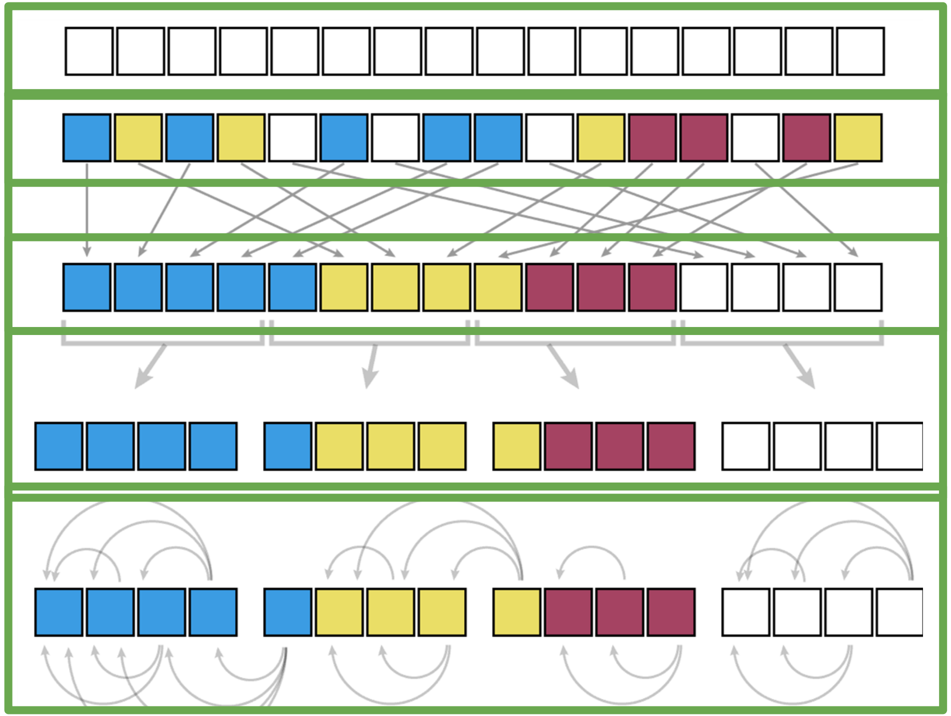
Sequence of Queries = Keys

LSH bucketing

Sort by LSH bucket

Chunk sorted sequence
to parallelize

Attend within same bucket of
own chunk and previous chunk



Motivation for Reversible Layers: Memory!

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Memory Efficiency

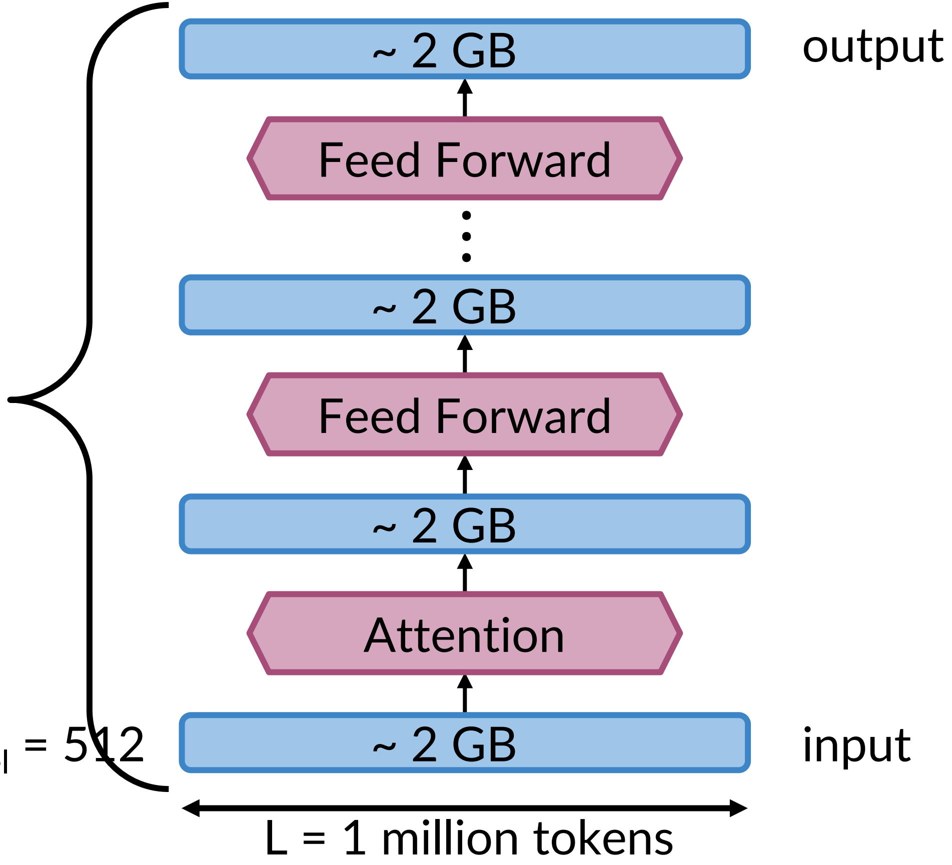
$d_{model} = 512$ ~ 2 GB input

L = 1 million tokens

Memory Efficiency

12 x Attention
12 x Feed-Forward

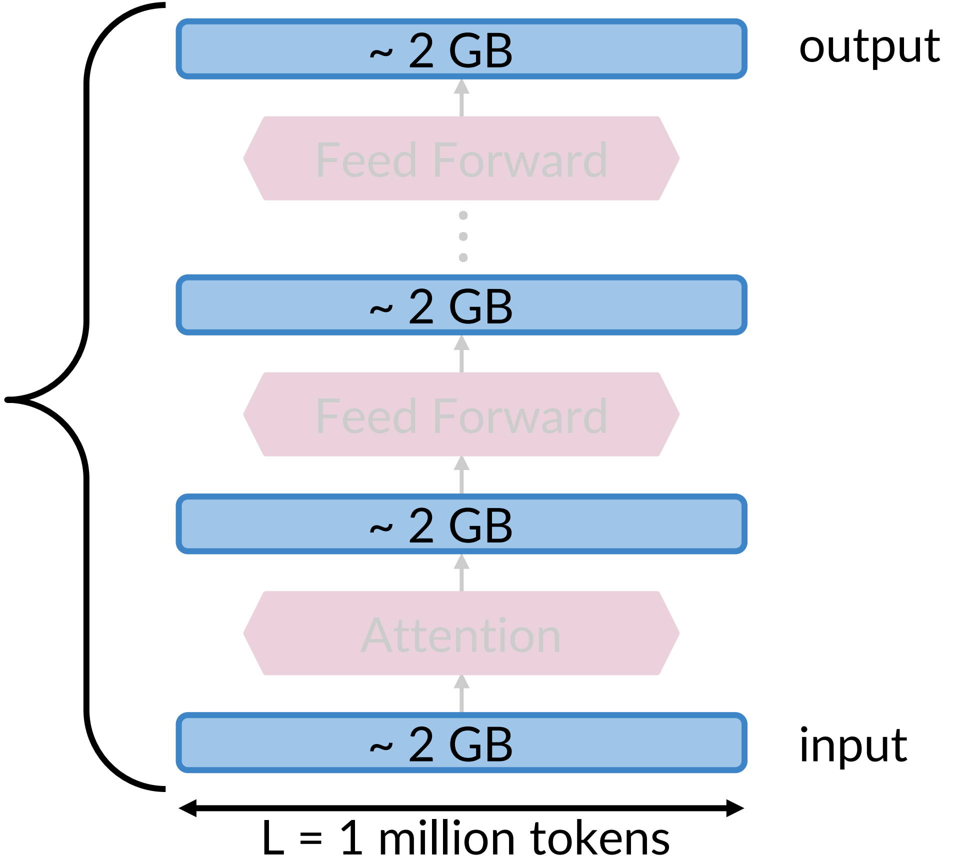
$d_{model} = 512$



Memory Efficiency

12 x Attention
12 x Feed-Forward

50 GB total



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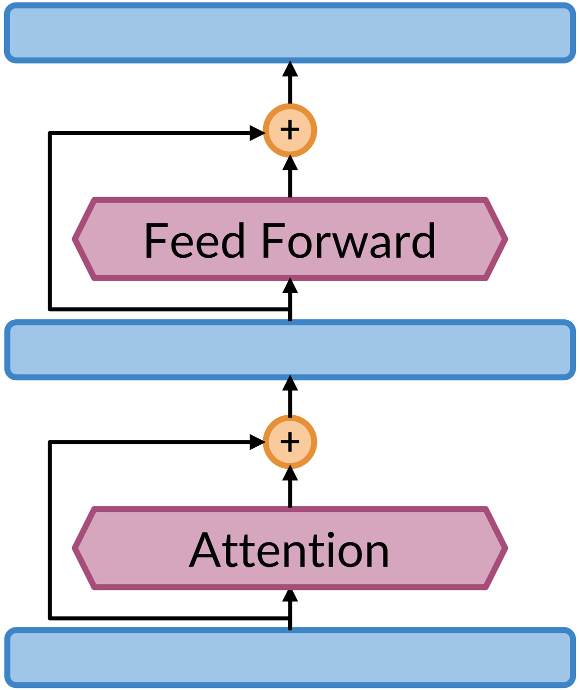
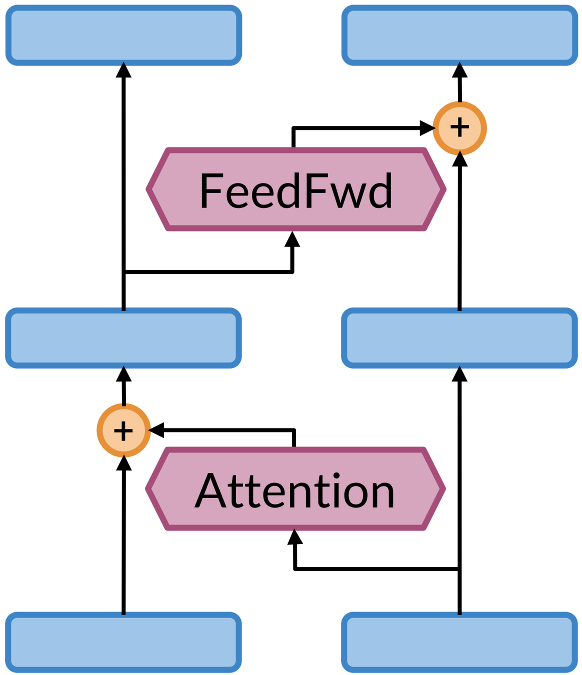
Reversible Residual Layers

Residual Blocks in Transformer

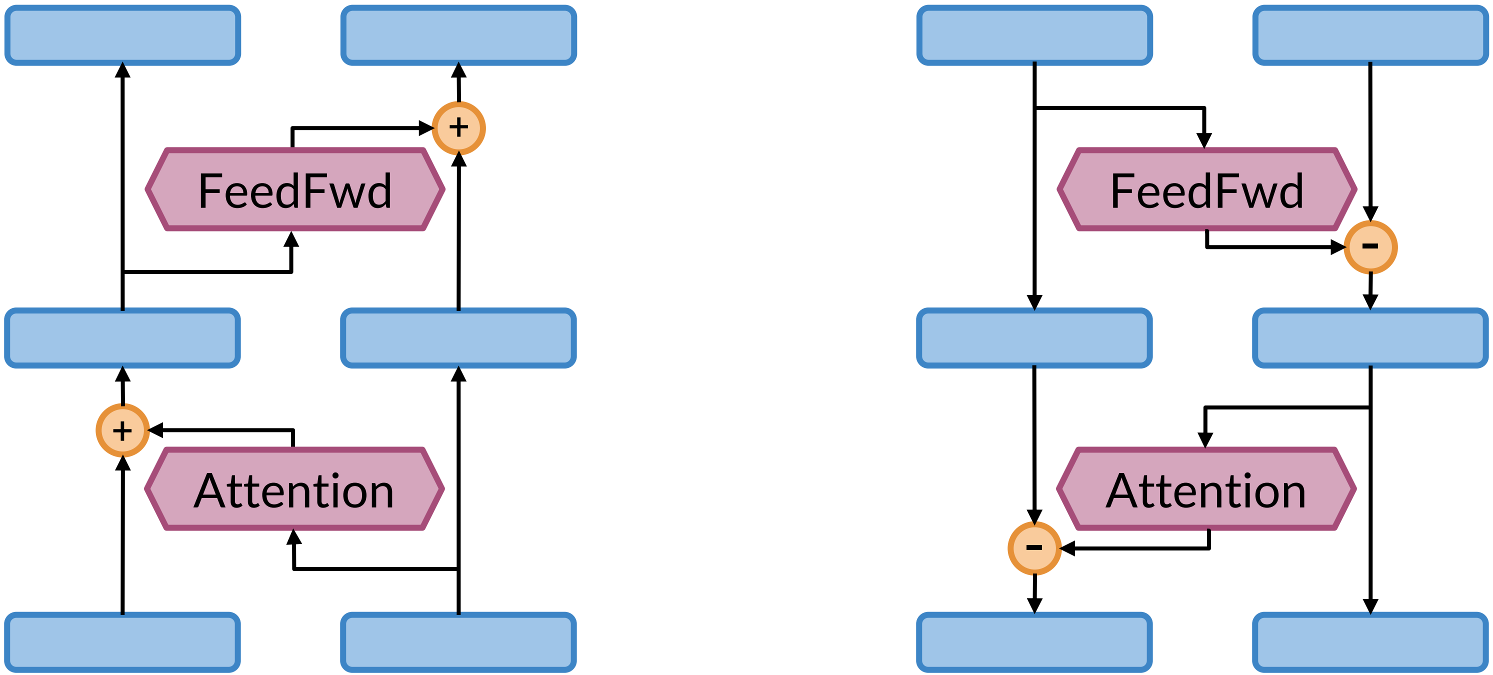


Needs
Ability
To
Reverse

Reversible Residual Blocks



Reversible layers



Reversible layers equations

Standard Transformer:

$y_a = x + \text{Attention}(x)$ $\qquad$ $y_b = y_a + \text{FeedFwd}(y_a)$

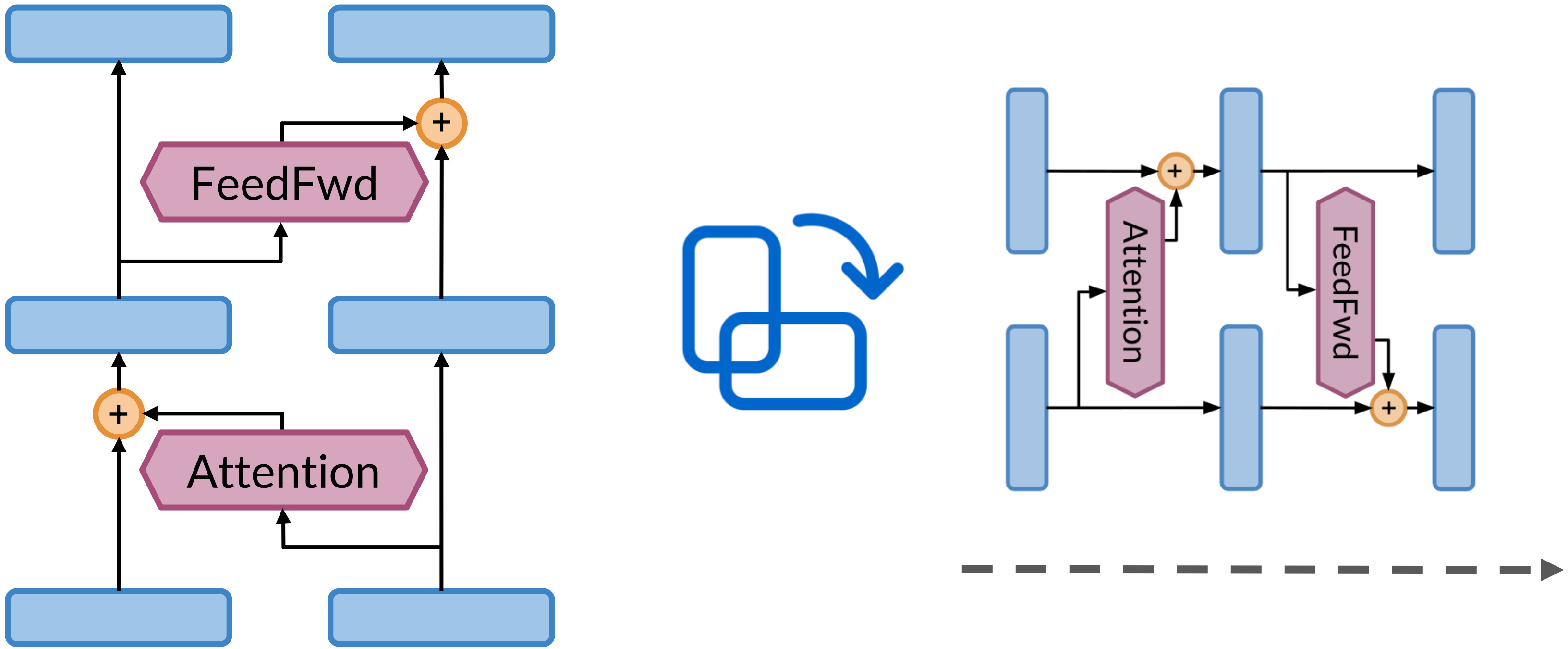
Reversible:

$y_1 = x_1 + \text{Attention}(x_2)$ $\qquad$ $y_2 = x_2 + \text{FeedFwd}(y_1)$

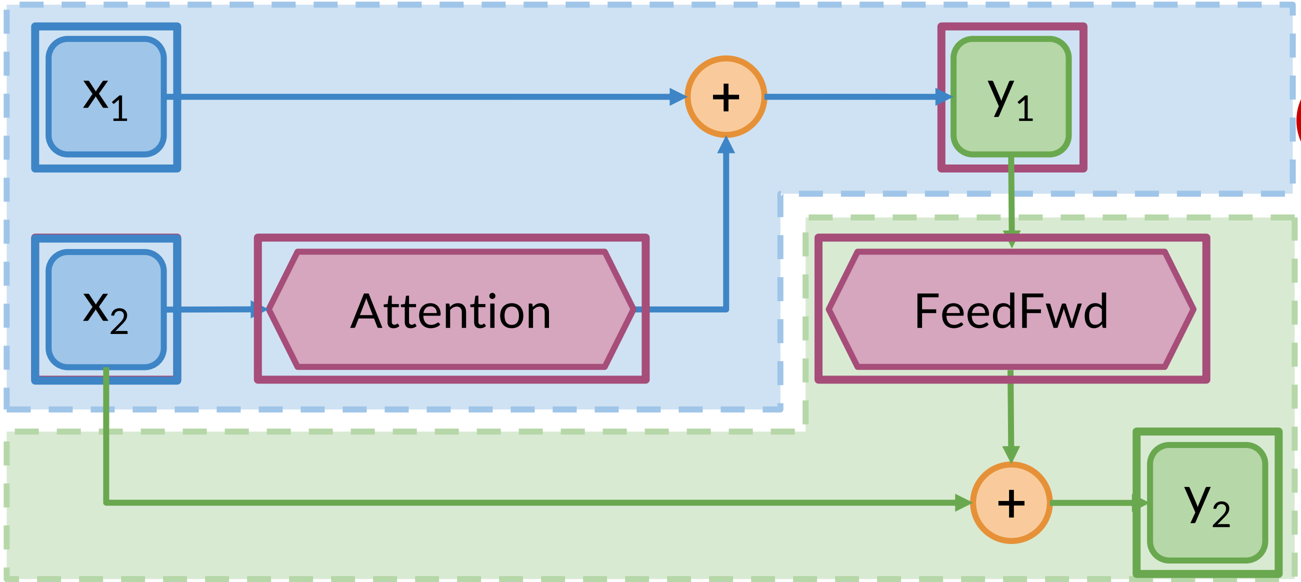
Recompute x_1, x_2 from y_1, y_2:

$x_1 = y_1 - \text{Attention}(x_2)$ $\qquad$ $x_2 = y_2 - \text{FeedFwd}(y_1)$

Reversible layers equations



Reversible layers equations



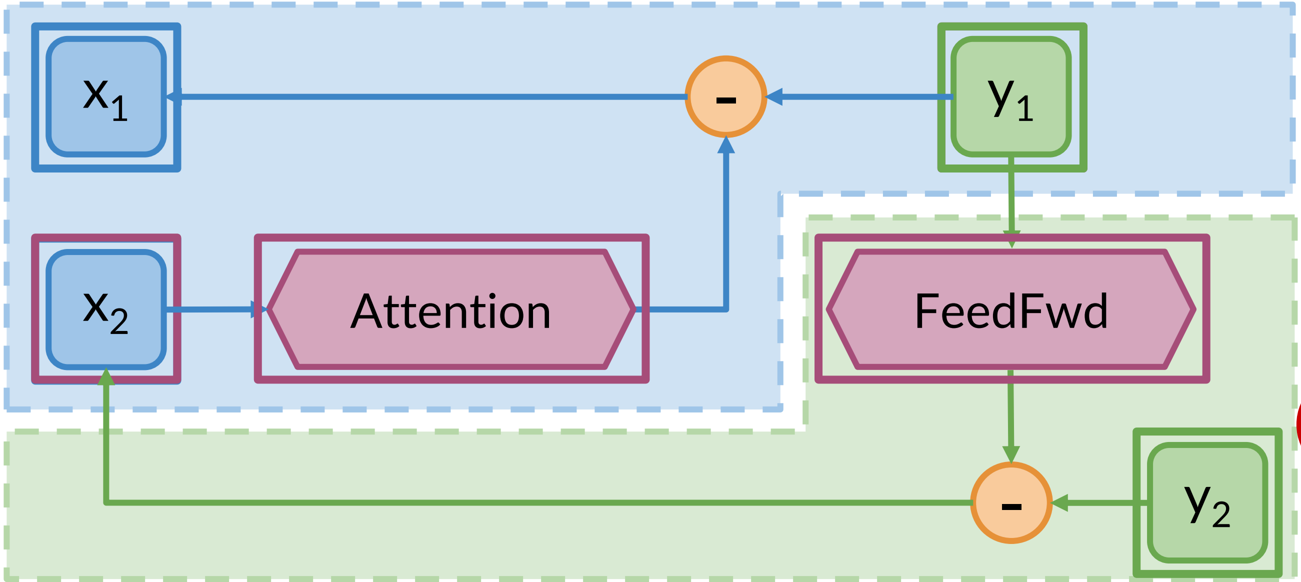
$y_1 = x_1 + \text{Attention}(x_2)$

$y_2 = x_2 + \text{FeedFwd}(y_1)$

$x_2 = y_2 - \text{FeedFwd}(y_1)$

$x_1 = y_1 - \text{Attention}(x_2)$

Reversible layers equations



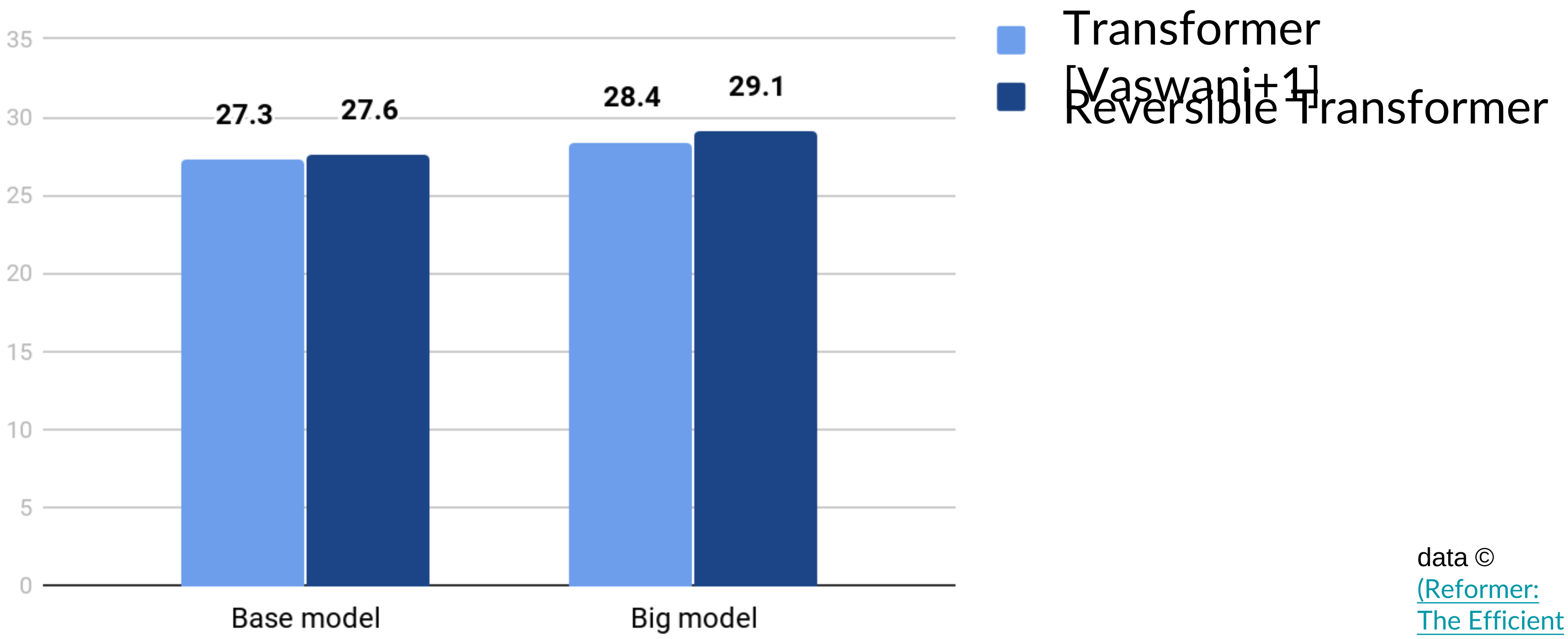
$y_1 = x_1 + \text{Attention}(x_2)$

$y_2 = x_2 + \text{FeedFwd}(y_1)$

$x_2 = y_2 - \text{FeedFwd}(y_1)$

$x_1 = y_1 - \text{Attention}(x_2)$

Reversible Transformer: BLEU Scores



data © [(Reformer: The Efficient Transformer)]

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Reformer

Reformer

The Reversible Transformer

L = 1 million tokens

1 GPU
(16 GB)

Reformer

- LSH Attention
- Reversible Layers

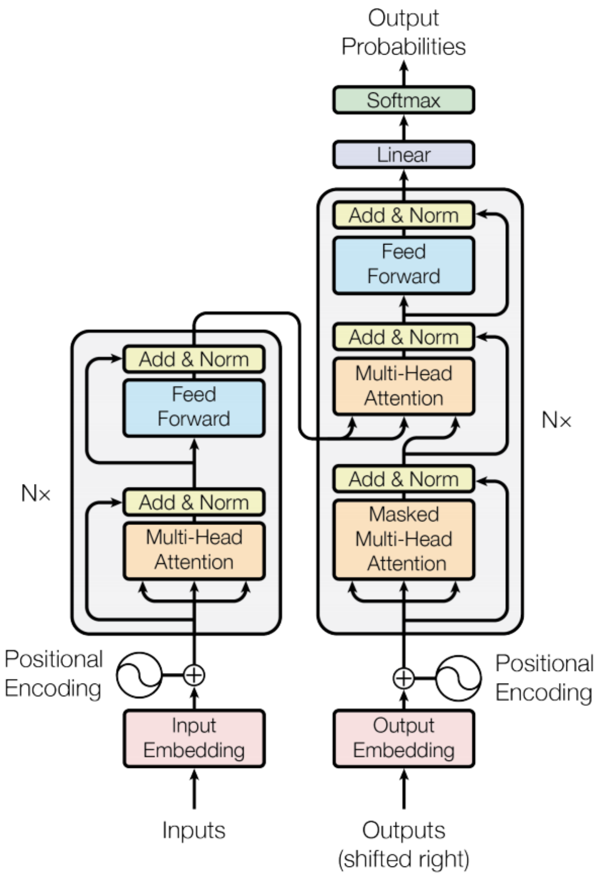
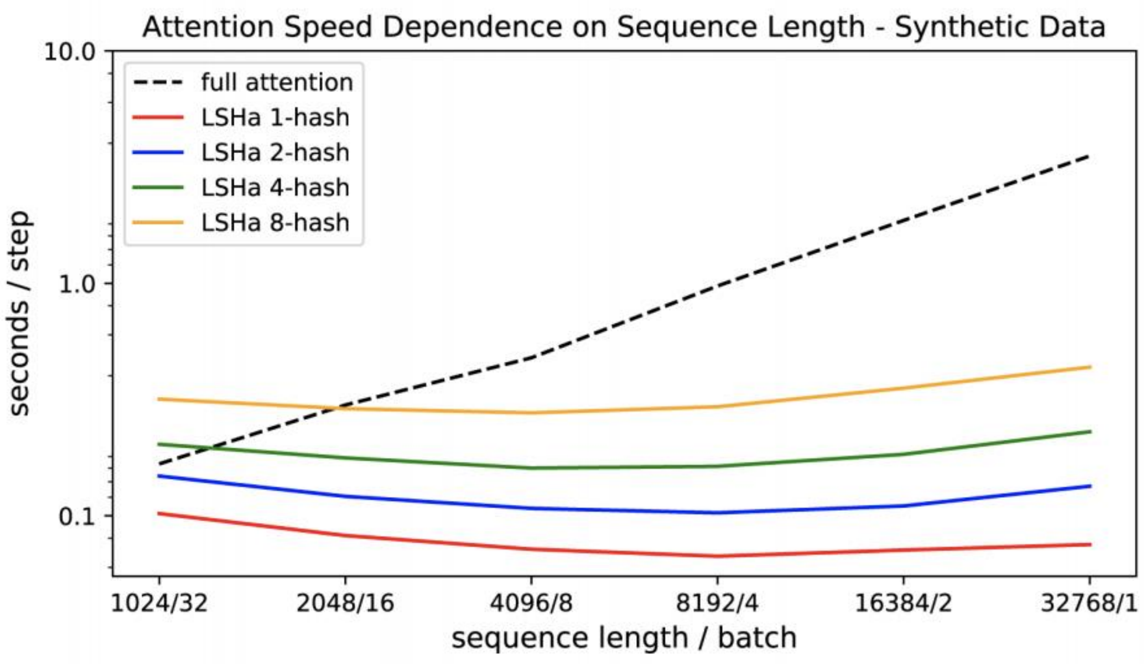


image © [(Attention Is All You Need)]

Reformer



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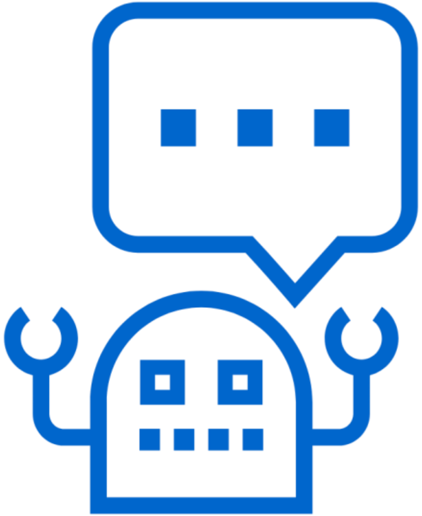
Chatbot



- Reformer
- MulitiWOZ dataset
- Trax