Long Text Sequences

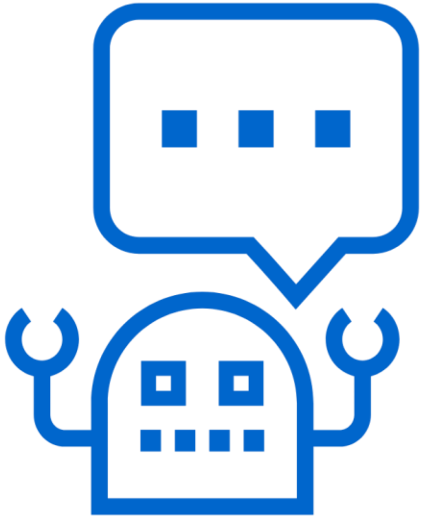
Tasks In NLP:

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.



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 10Mops/s)

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

Attention Complexity

- Attention: softmax(QK^T)V
- Q, K, V are all [L, d_model]
- QKT 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

LSH Attention

- What does Attention do?
  - Select Nearest Neighbors (K,Q) and return corresponding V

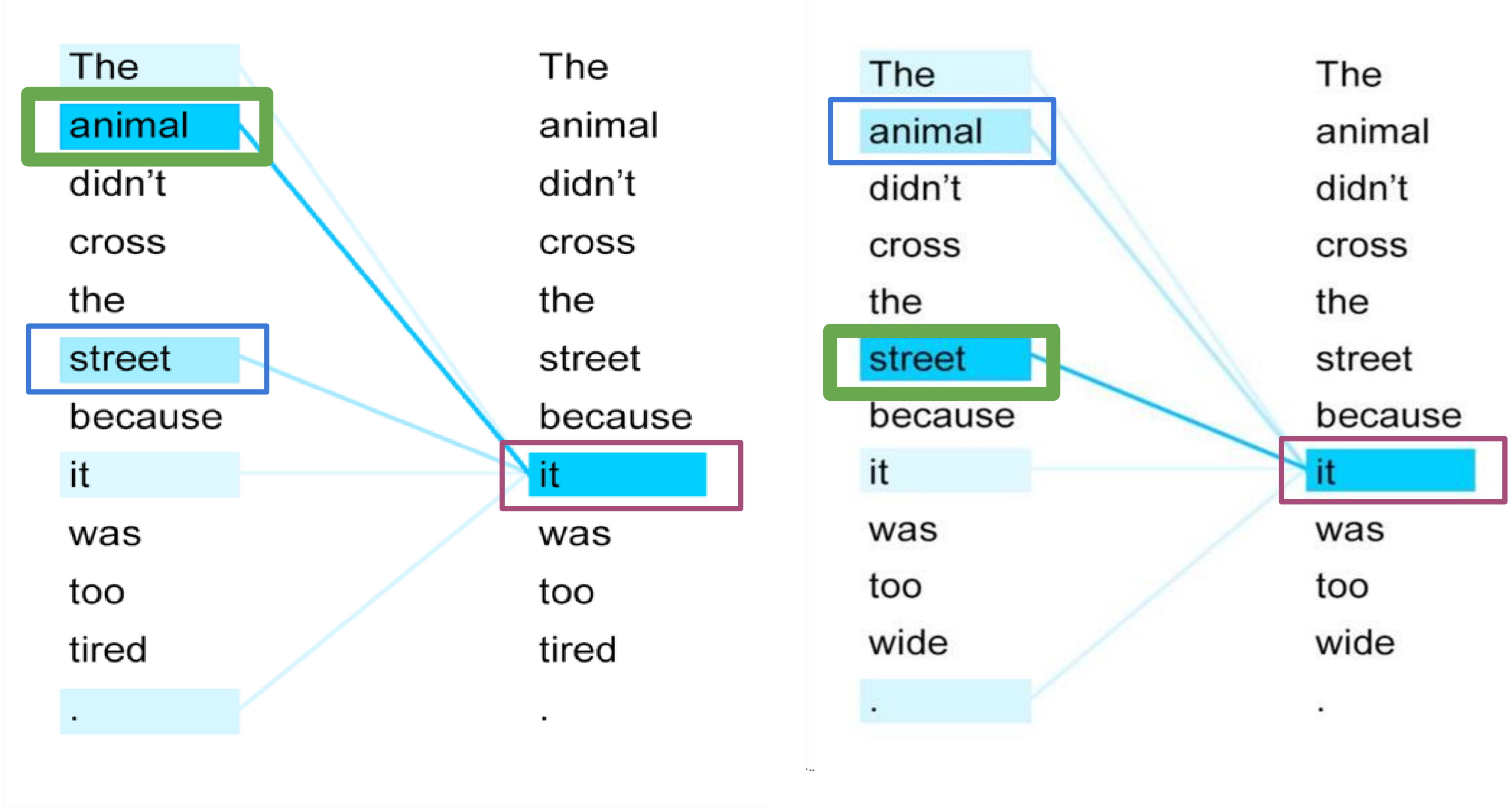


image © [(Transformer: A Novel Neural Network Architecture for Language Understanding.)]

Nearest Neighbors

Course:

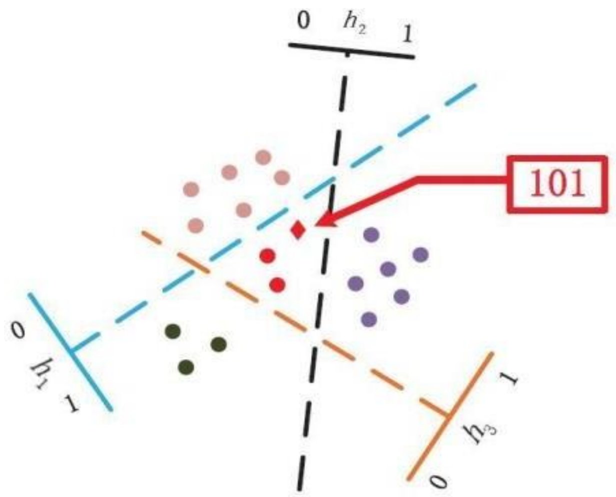
Natural Language Processing with Classification and Vector Spaces

Lessons:

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

Nearest Neighbors

- Compute the nearest neighbor to q among vectors $\{k_1, \ldots, k_n\}$
  - 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, _bins]
- n_hash

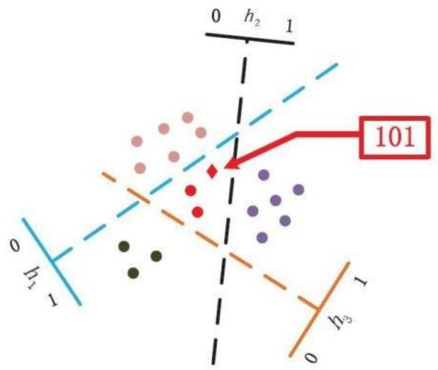


LSH Attention

- 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



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

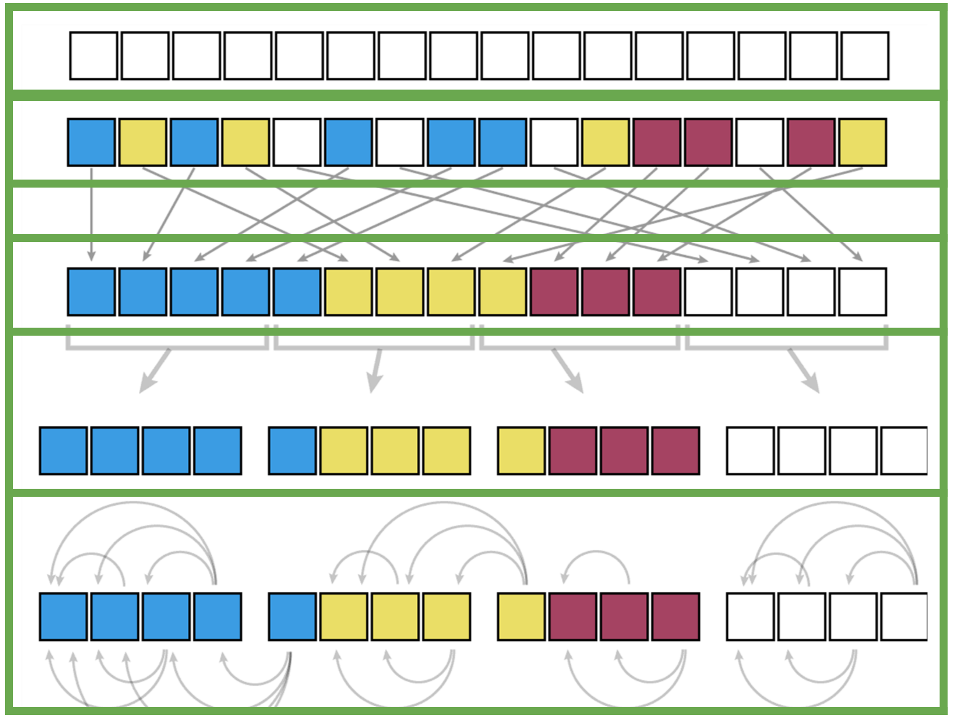


image © (Reformer: The Efficient Transformer)

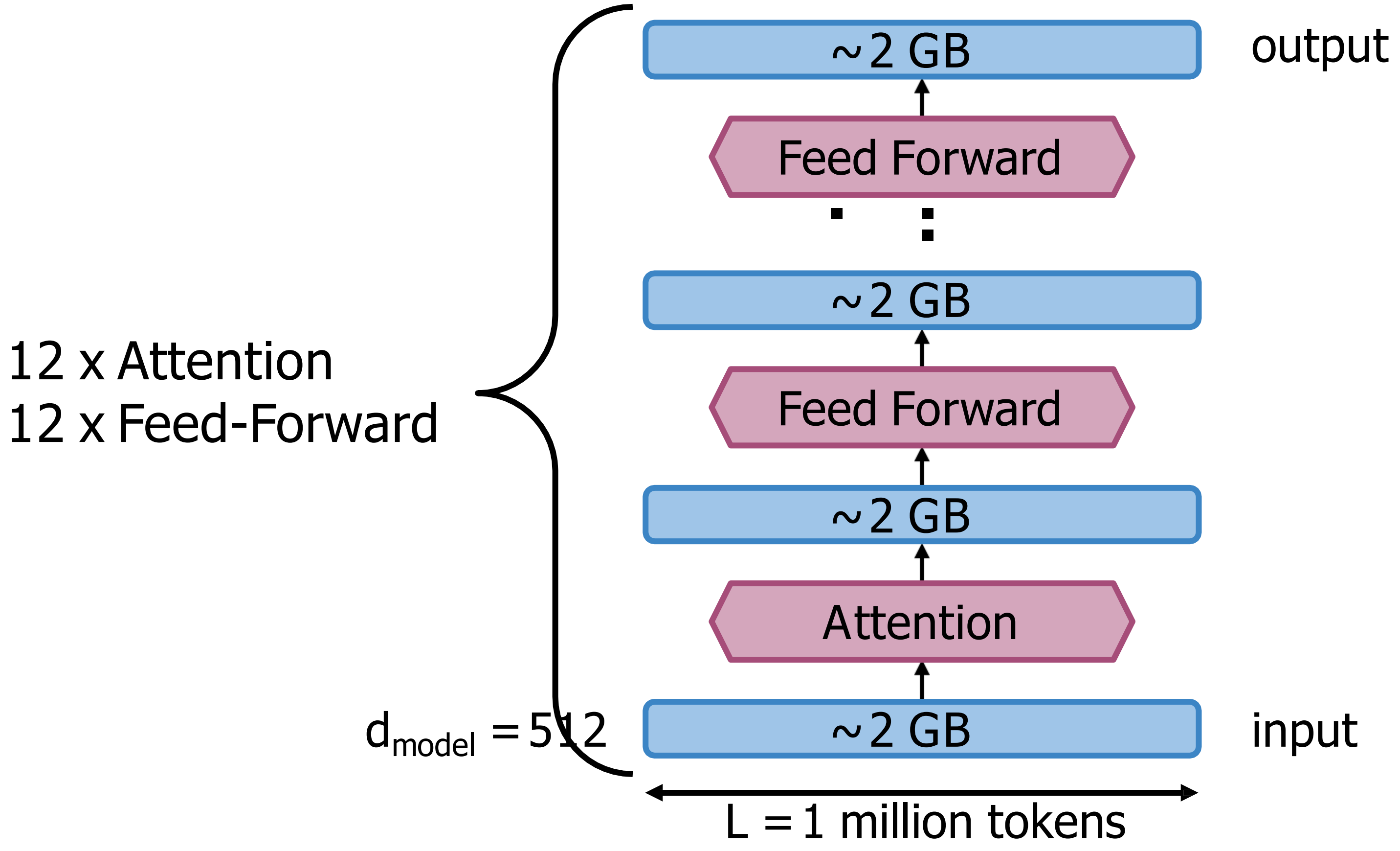
Motivation for Reversible Layers: Memory!

- Memory Efficiency

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

L = 1 million tokens

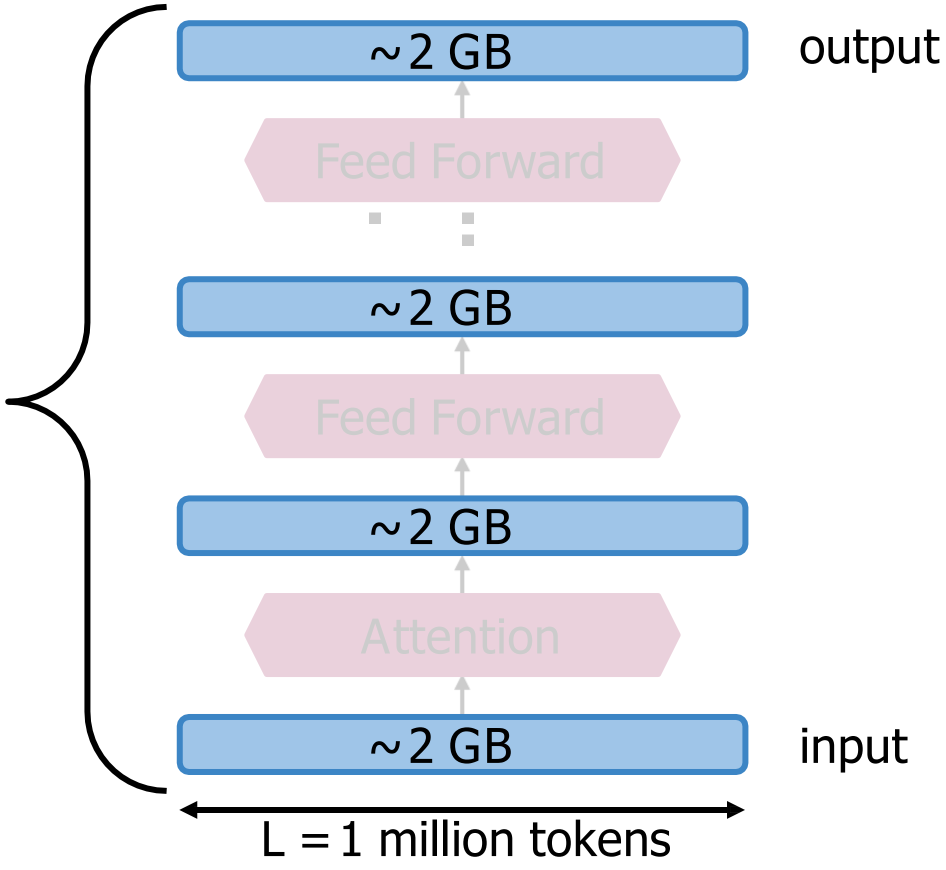
Memory Efficiency



Memory Efficiency

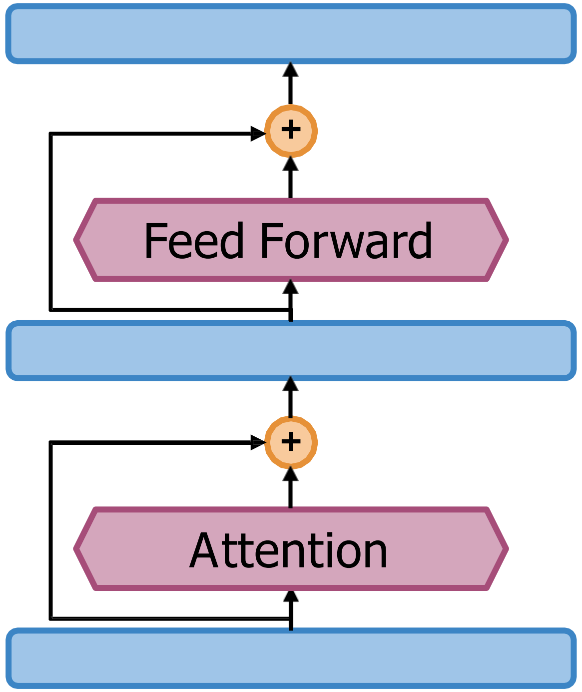
12 x Attention
12 x Feed-Forward

50 GB total

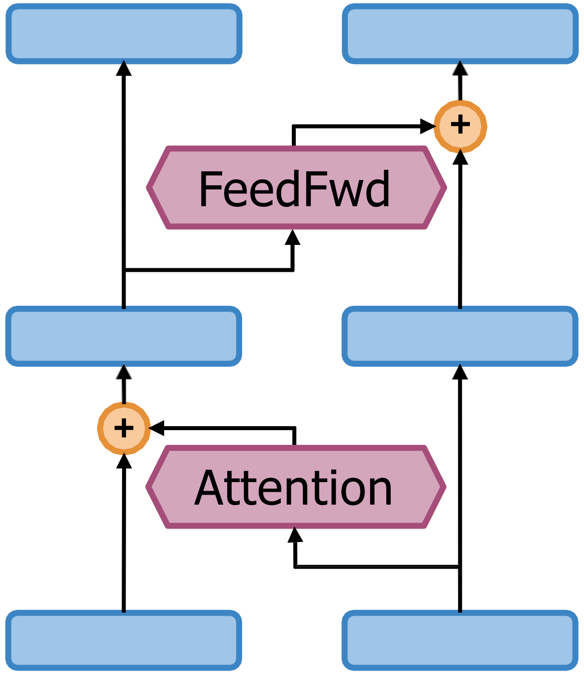


Reversible Residual Layers

- Residual Blocks in Transformer



Needs Ability To Reverse



Reversible layers equations

Standard Transformer:

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

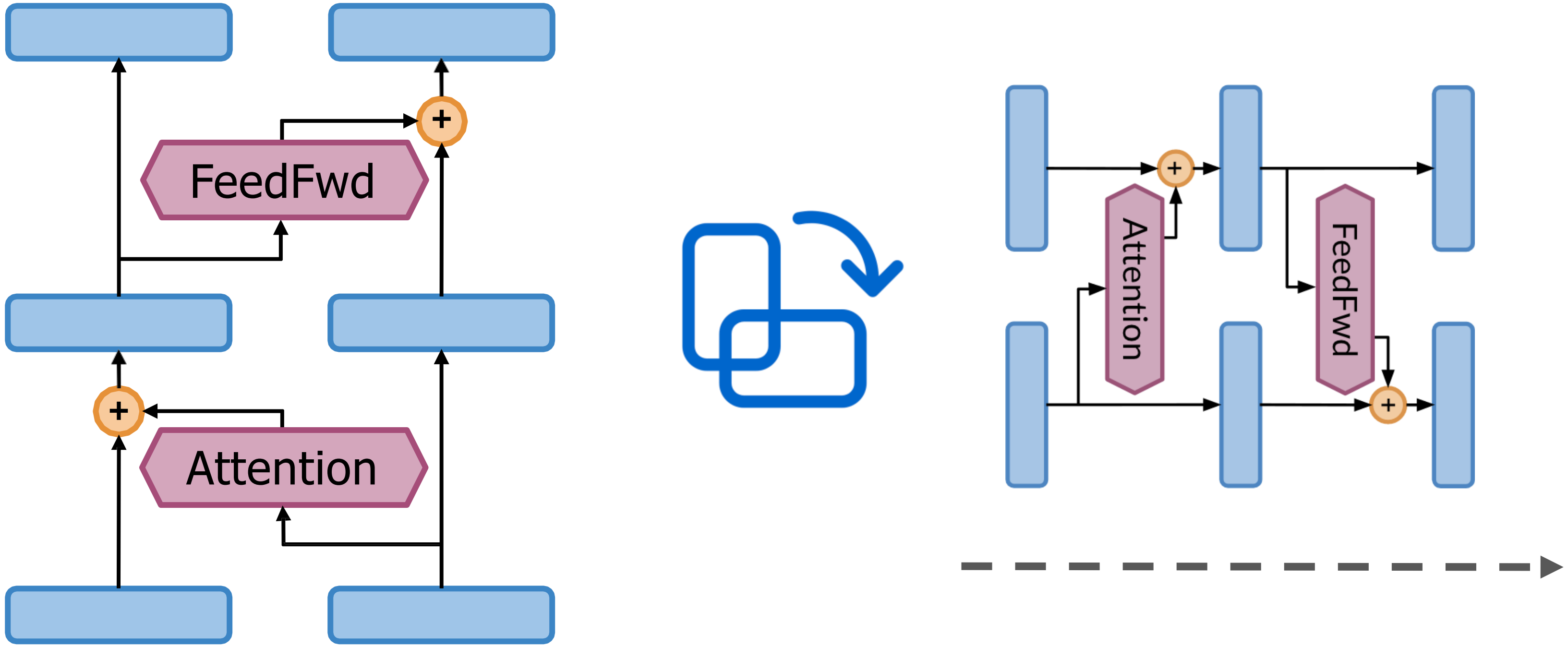
Reversible:

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

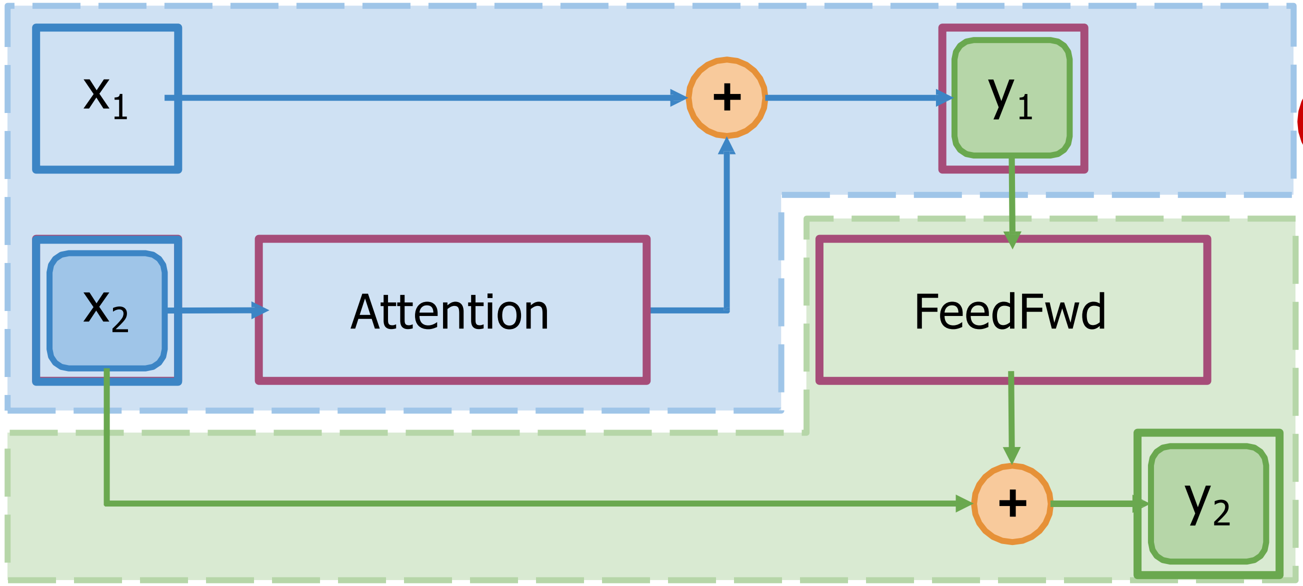
Recompute x_1, x_2 from y_1, y_2:

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

Reversible layers equations



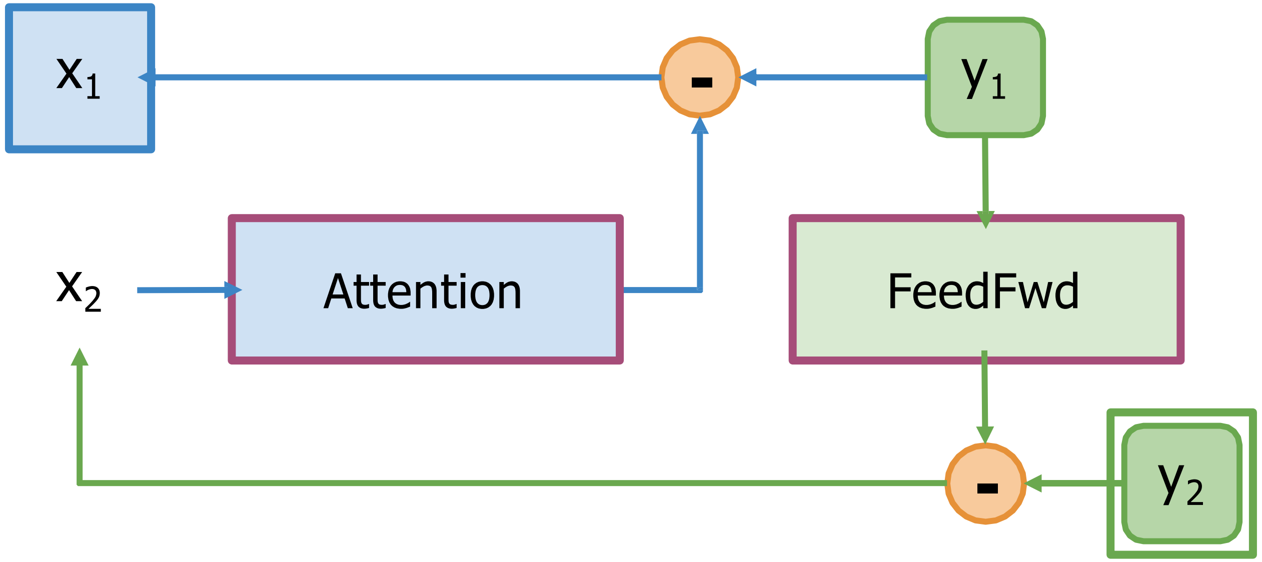
Reversible layers equations



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

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

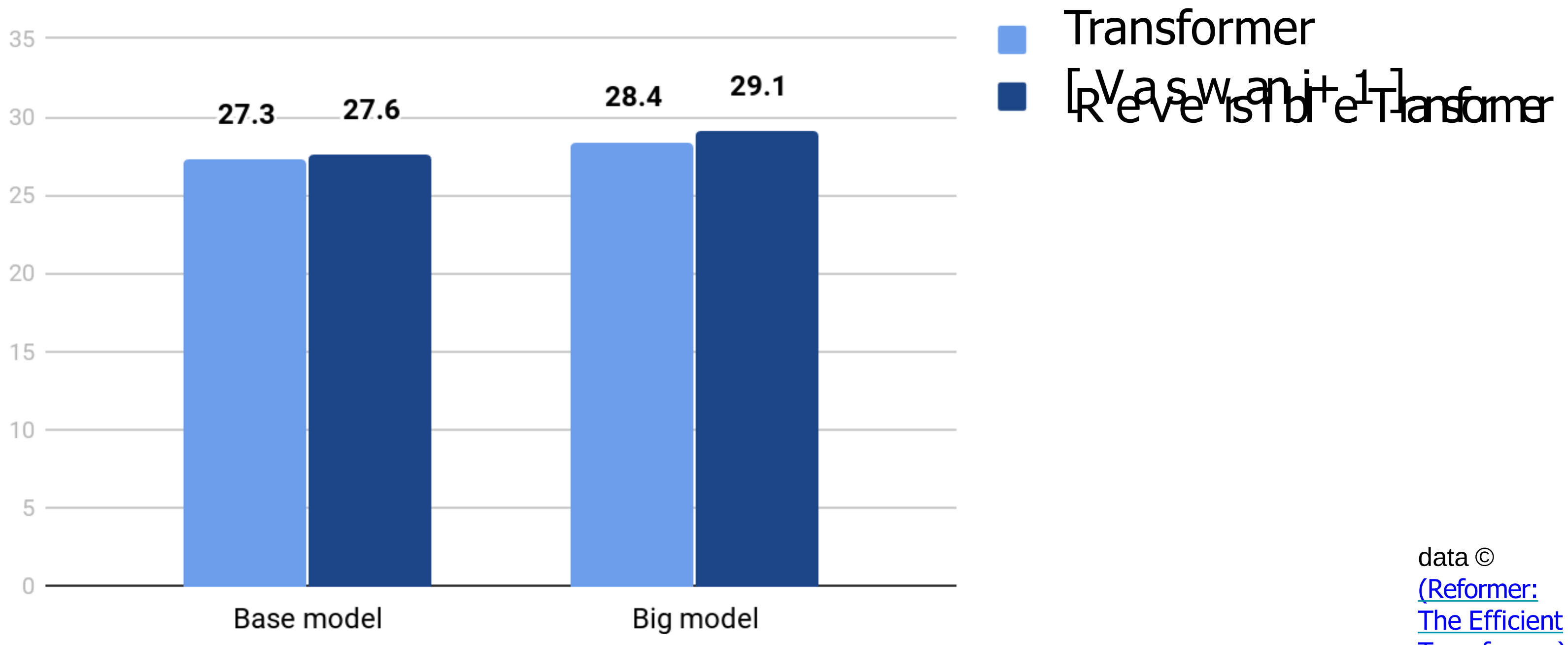
Reversible layers equations



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

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

Reversible Transformer: BLEU Scores



data © [(Reformer: The Efficient Transformer)]

Reformer

The Reversible Transformer

L = 1 million tokens

1 GPU

(16 GB)

Reformer

- LSH Attention
- Reversible Layers

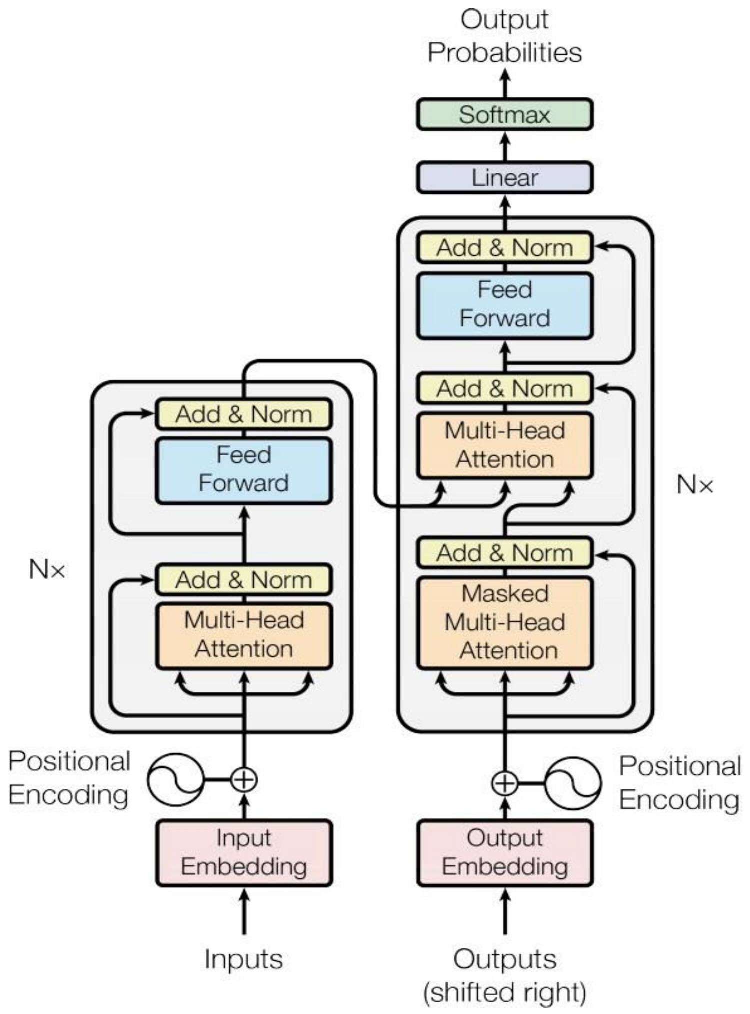
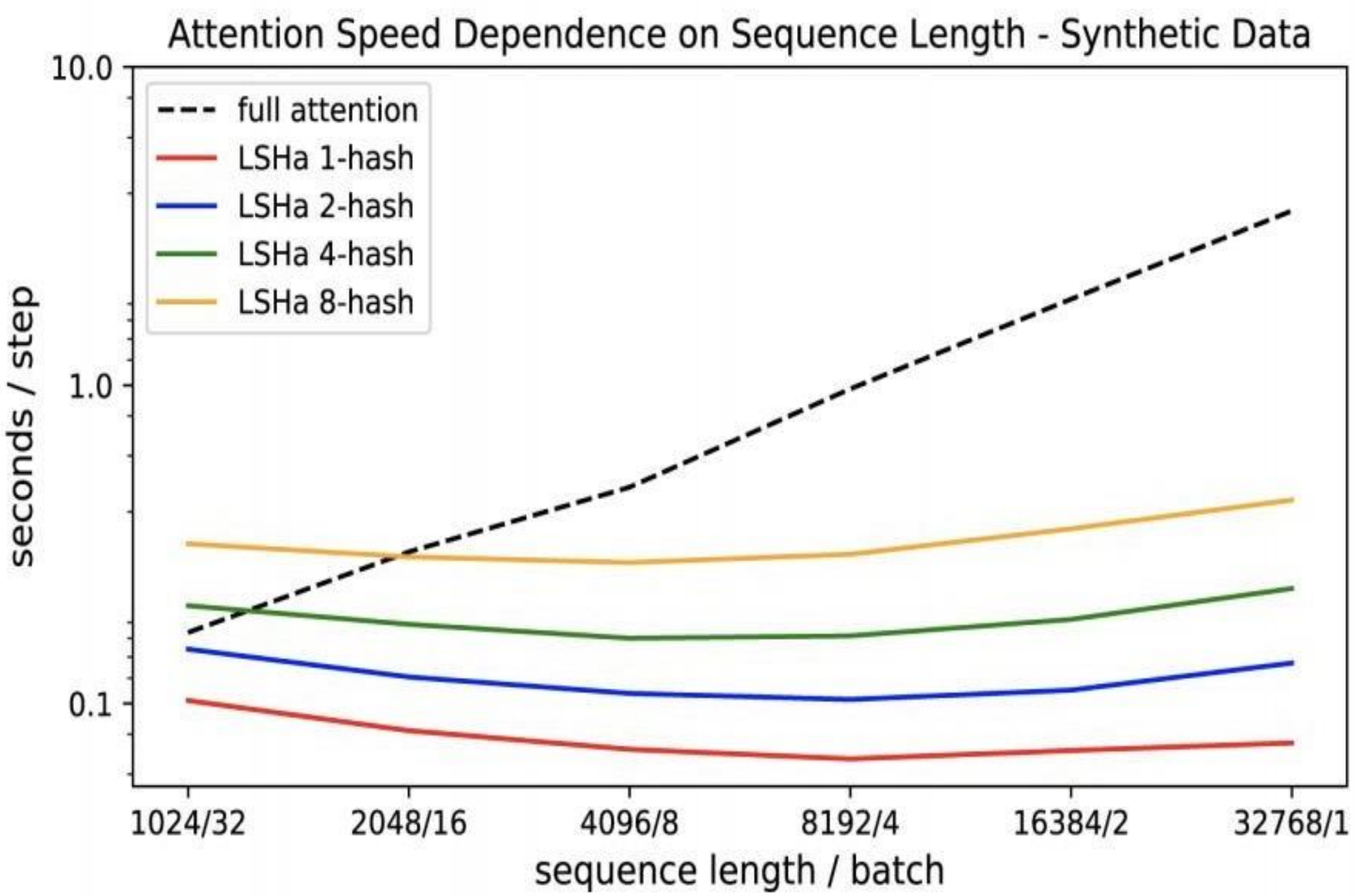


image © [(Attention Is All You _Need)]

Reformer



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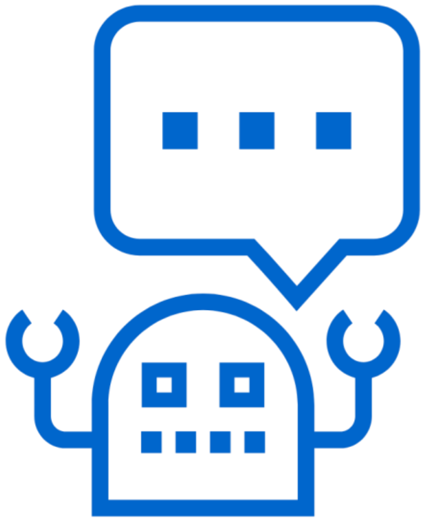
Chatbot



- Reformer
- MulitiWOZ dataset
- Trax