

Chatbot

- Video: Tasks with Long Sequences 2 min
- Reading: Tasks with Long Sequences 10 min
- Reading: Optional Al Storytelling 15 min
- Video: Transformer Complexity
- Reading: Transformer Complexity 10 min
- Video: LSH Attention
- Reading: LSH Attention 10 min
- Reading: Optional KNN & LSH Review 20 min
- Lab: Ungraded Lab: Reformer LSH
- Video: Motivation for Reversible Layers: Memory!
- Reading: Motivation for Reversible Layers: Memory! 10 min
- Video: Reversible Residual Layers 5 min
- Reading: Reversible Residual Layers
- Lab: Ungraded Lab: Revnet
- Video: Reformer
- Reading: Reformer 10 min
- Reading: Optional Transformers beyond NLP 20 min
- Reading: Acknowledgments 10 min

Heroes of NLP: Quoc Le

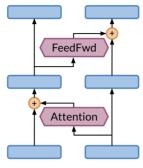
Assignment

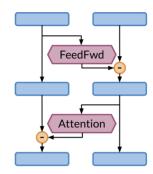
Course Resources

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Reversible Residual Layers

Reversible residual layers allow you to reconstruct the forward layer from the end of the network. Usually you have two similar branches in the network that you use to compute the network.





In the left picture, you have the forward propagation. One side of the network is used as input and the other is used for the attention. In the left side, the same thing is happening but in the opposite

Standard Transformer:

$$y_a = x + Attention(x)$$

$$y_b = y_a + FeedFwd(y_a)$$

Reversible:

$$y_{1} = x_{1} + Attention(x_{2})$$

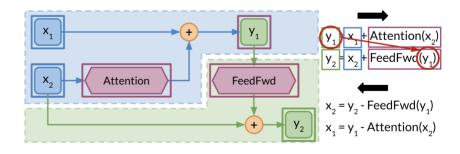
$$y_2 = x_2 + FeedFwd(y_1)$$

Recompute x_1, x_2 from y_1, y_2 :

$$x_1 = y_1 - Attention(x_2)$$

$$x_2 = y_2 - FeedFwd(y_1)$$

Take a few minutes and try to understand the equations above. You basically make use of the two branches of the network. When coming back for the back propagation, you only need the y's to compute x_2 and then you can use x_2 along with y_1 to compute x_1 . Pretty neat! Now you don't have to store the weights, because you can just compute them from scratch. This image shows you a visualization of what is happening.



Mark as completed





