Sample Efficient Text Summarization Using a Single Pre-Trained Transformer

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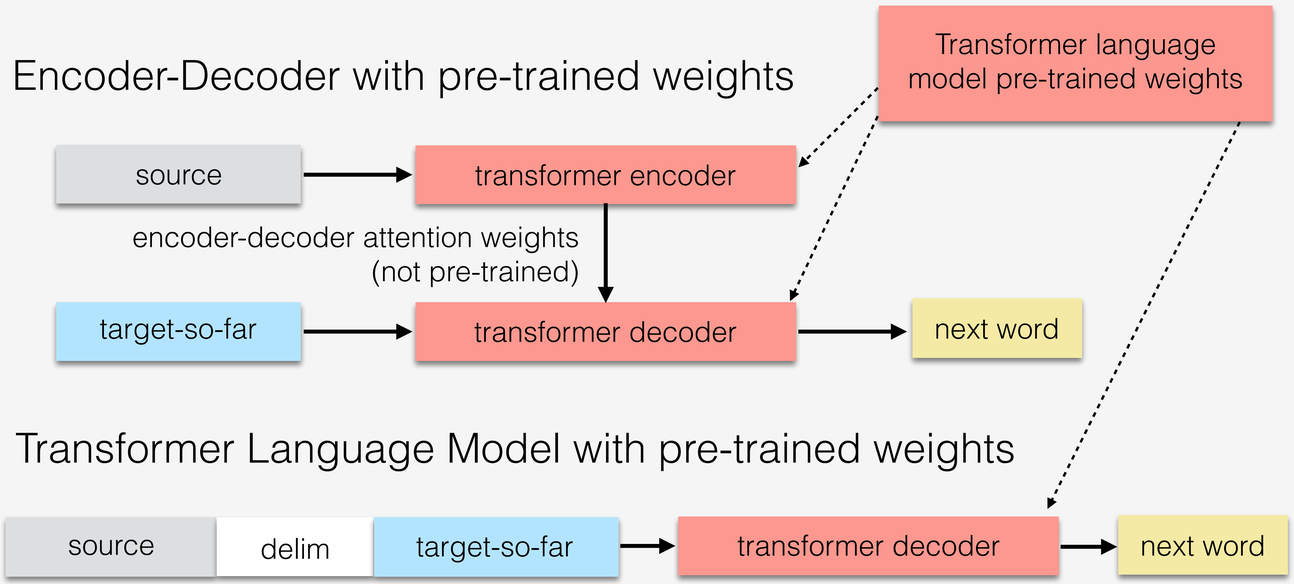
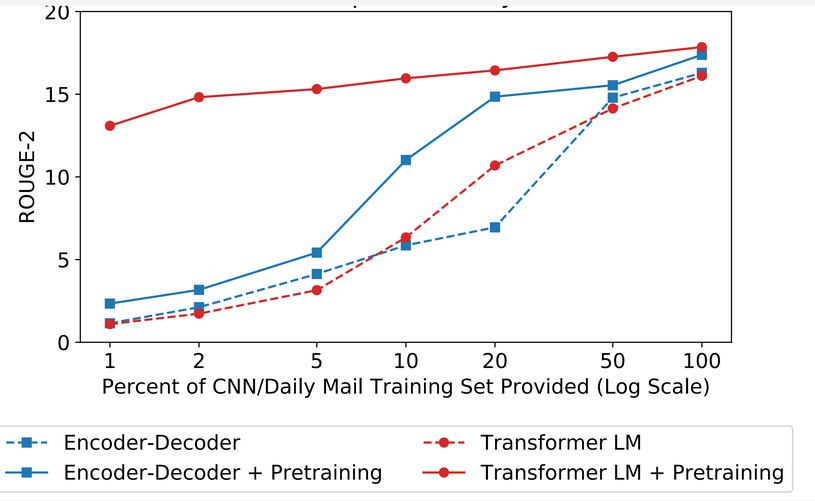
Given the pre-trained weights of a Transformer language model, replacing the Transformer encoder-decoder with a Transformer decoder only model for fine-tuning on text summarization is highly sample efficient since there are no more non-pre-trained encoder-decoder attention weights.

Fine-tuning on Text Summarization



Simpler model, fewer parameters and no non-pre-trained attention weights

Sample Efficiency



Outputs from models fine-tuned on 1% data

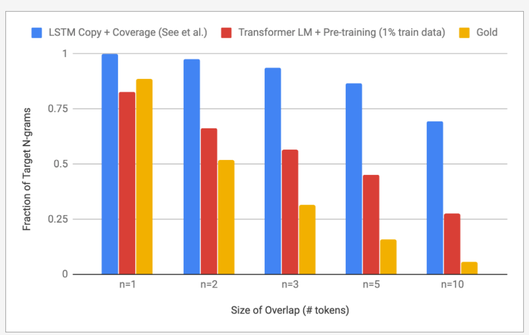
Ground truth: *A man in suburban Boston is selling snow online to customers in warmer states. For $89, he will ship 6 pounds of snow in an insulated Styrofoam box.*

Encoder-Decoder + Pre-training: *NEW: A snowfall of is forecast for New England. NEW: The Massachusetts-based company hopes to sell more than 30,000 bottles of snow. The company says it will use snow from as far as Canada.*

Transformer LM + Pre-training: *Kyle Waring will ship you 6 pounds of Boston-area snow in an insulated Styrofoam box – enough for 10 to 15 snowballs, he says. But not if you live in New England or surrounding states.*

The Transformer LM fine-tuned on 1% data successfully extracts facts from the source, while the encoder-decoder hallucinates facts/ generates gibberish.

How much of the sample efficiency is due to copying?



This Transformer LM is more abstractive (copies less) than the Pointer-Generator model, likely due to lack of the copy mechanism.
A drawback of this abstractiveness is subtle factual inaccuracies!

References
[1] Peter J Liu, et al. 2018. *Generating Wikipedia by summarizing long sequences.* In ICLR.
[2] Alec Radford et al. 2018. *Improving language understanding by generative pre-training.*
[3] Abigail See et al. 2017. *Get to the point: Summarization with pointer-generator networks.* In ACL.

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Code: https://github.com/tensorflow/tensor2tensor