Efficient Transformer for Mobile Application

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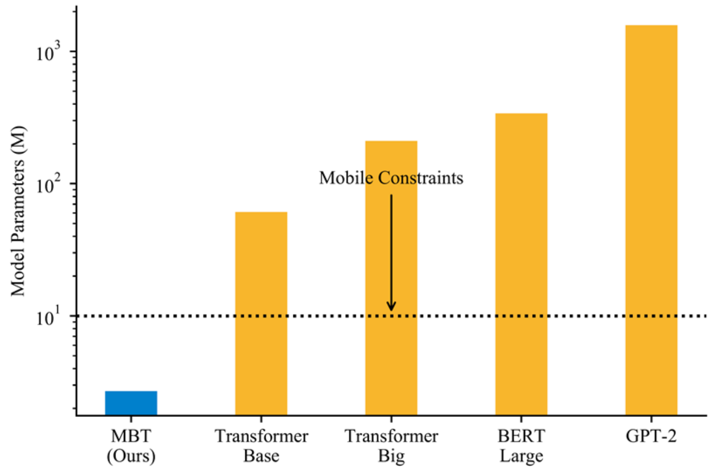
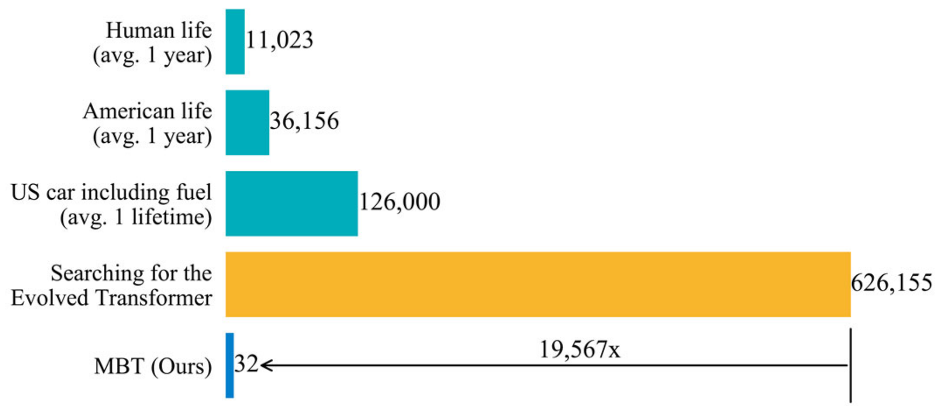
Modern NLP is EXPENSIVE



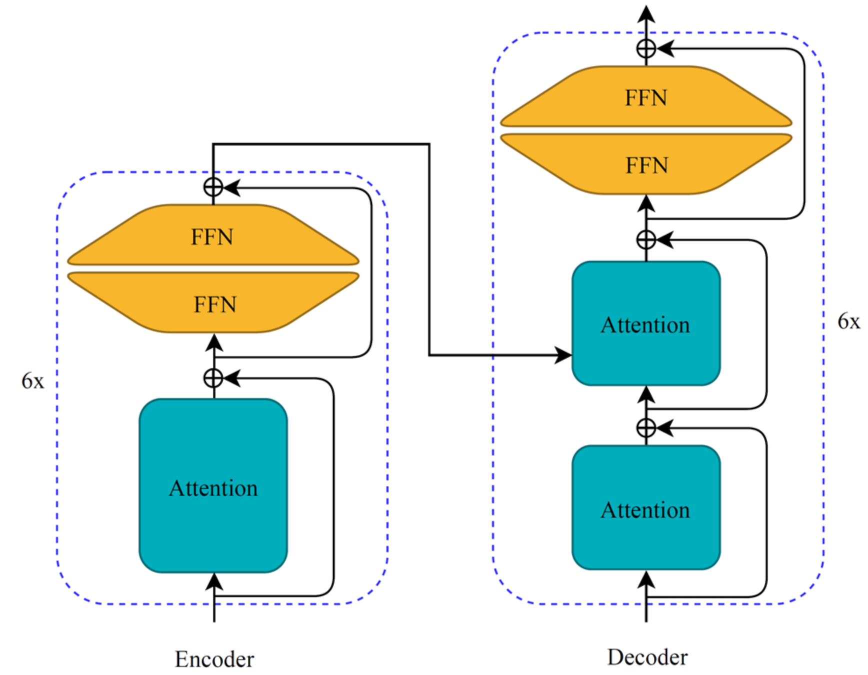
(a) Model sizes of modern NLP models



(b) The design cost measured in pounds of CO_2 emission

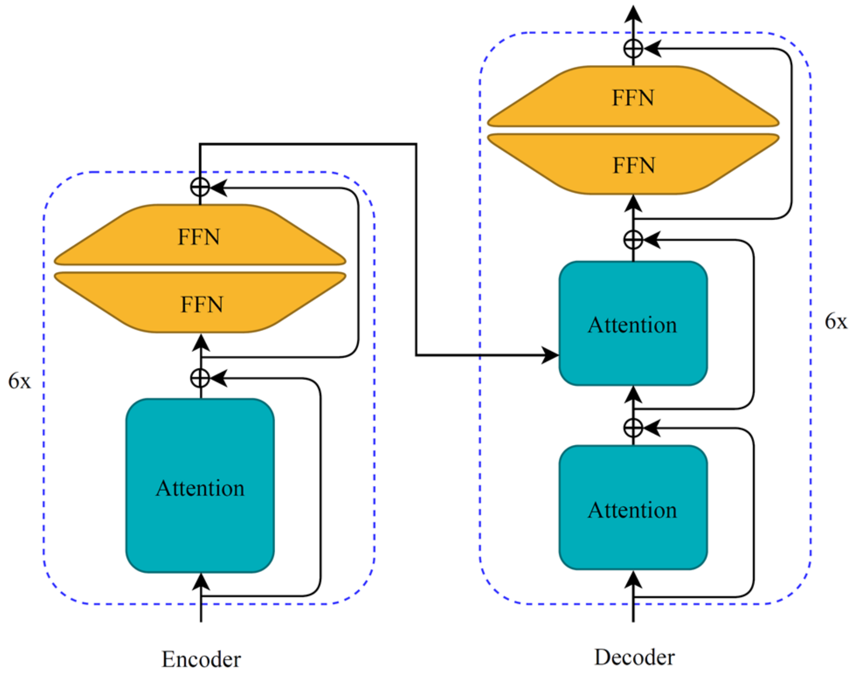
- NLP models are huge — much larger than mobile settings (a);
- Neural Architecture Search is a choice for finding an efficient model, but the massive searching cost raises much concerns (b).

Transformer Framework



Basic transformer architecture for translation

Transformer Framework



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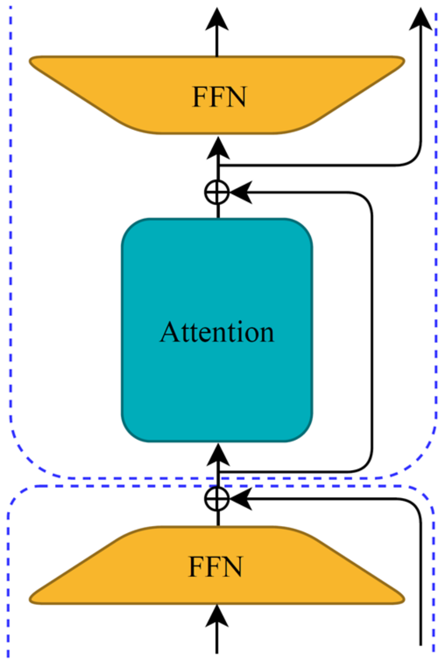
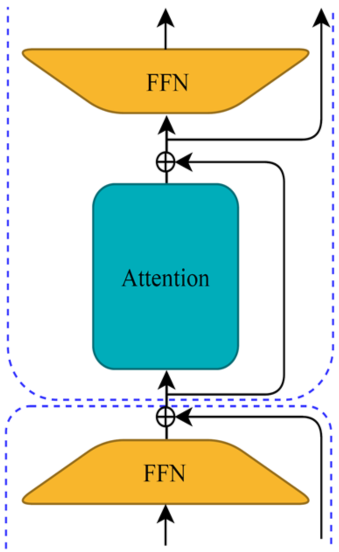


A different view for transformer block

Is Bottleneck Effective for 1-D Attention?



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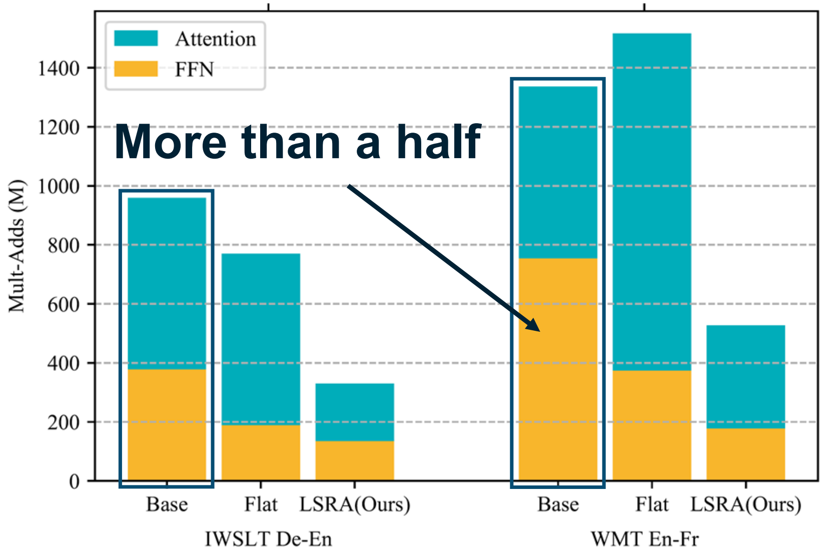
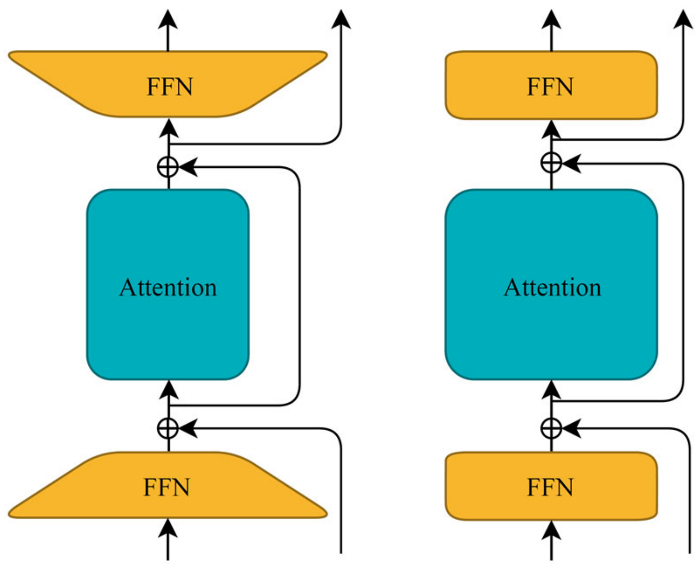


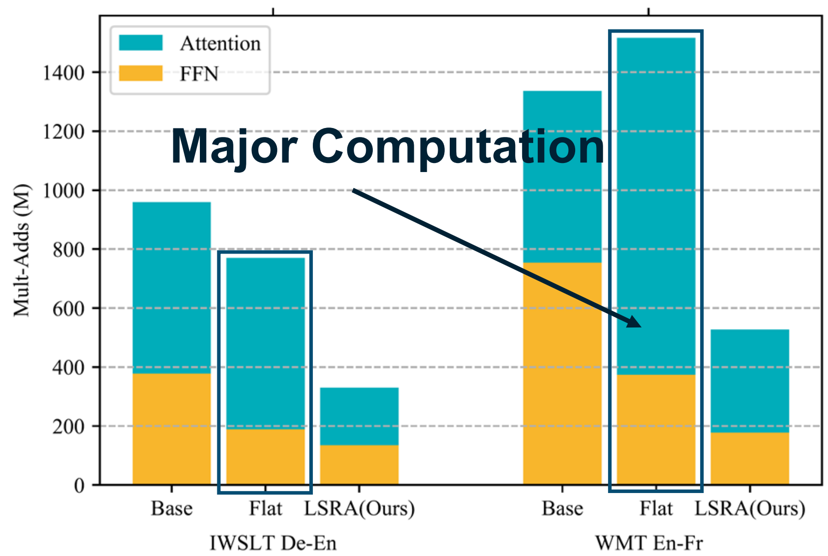
Mult-Adds breakdown for attention and FFN

- Original bottleneck design cannot significantly reduce the computation, also harms the capacity of attention layer due to smaller dimension.

Is Bottleneck Effective for 1-D Attention?



Vanilla and flattened transformer block



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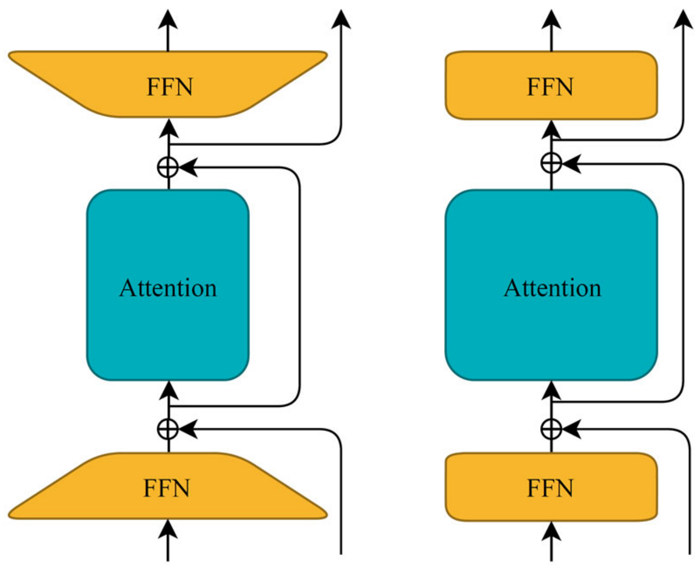

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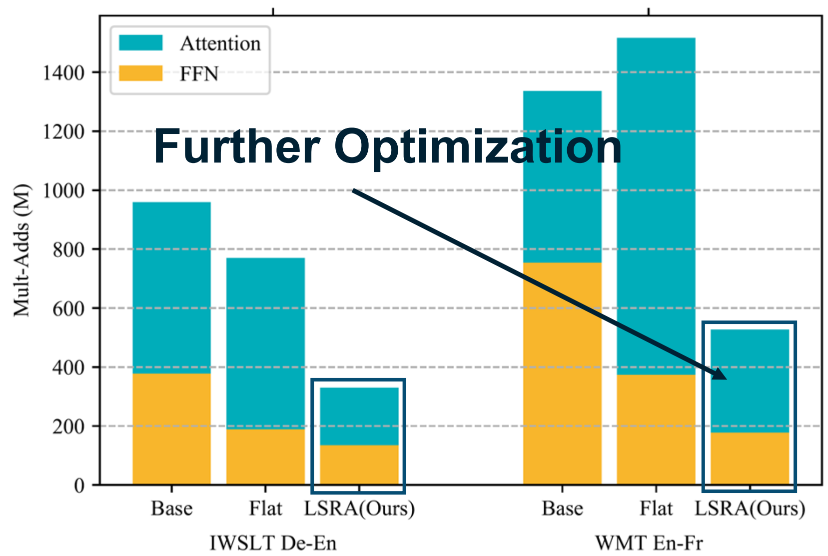


Mult-Adds breakdown for attention and FFN

- Original bottleneck design cannot significantly reduce the computation, also harms the capacity of attention layer due to smaller dimension.
- Flatten the transformer leaves larger space for further optimization.

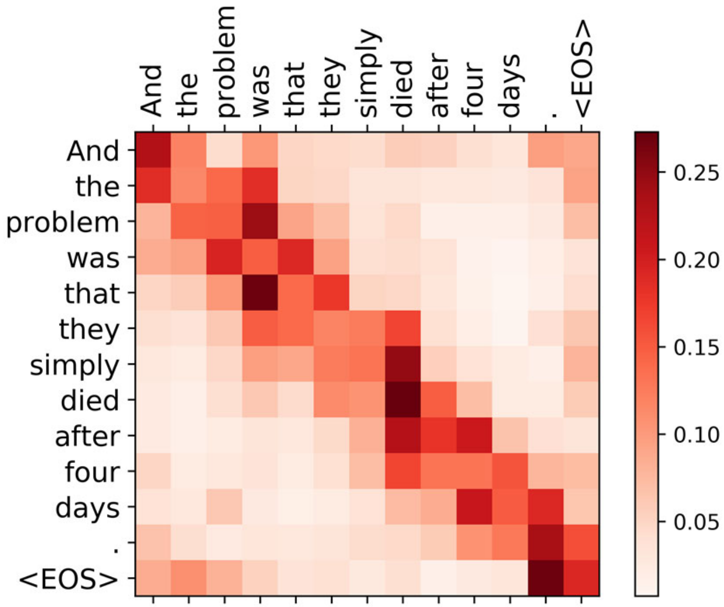
Flatten the Transformer

	IWSLT De-En			WMT En-De				WMT En-Fr
	Embedding	Mult-Adds	BLEU	Embedding	Mult-Adds	Attention	BLEU	BLEU
Vaswani et al. (2017)	512-1024	959M	34.4	512-2048	1.3G	44%	27.3	38.1
So et al. (2019)	–	–	–	512-2048	1.3G	44%	27.7	40.0
Our Reimplementation	512-1024	959M	34.5	512-2048	1.3G	44%	27.7	39.9
Transformer (*Flat*)	512-512	460M	**34.5**	720-720	1.5G	75%	**27.8**	**41.0**

- With the 'flat' version of transformer, the attention part now takes up the major computation.
- 'Flat' transformer can achieve comparable BLEU with the original transformer (slightly increase the computation, when necessary).

What does Attention Learn?

- Strong pattern for the attention: sparse points, vertical lines and diagonal groups
- The former two as "global" information and the latter one as "local" correlation.



Self Attention

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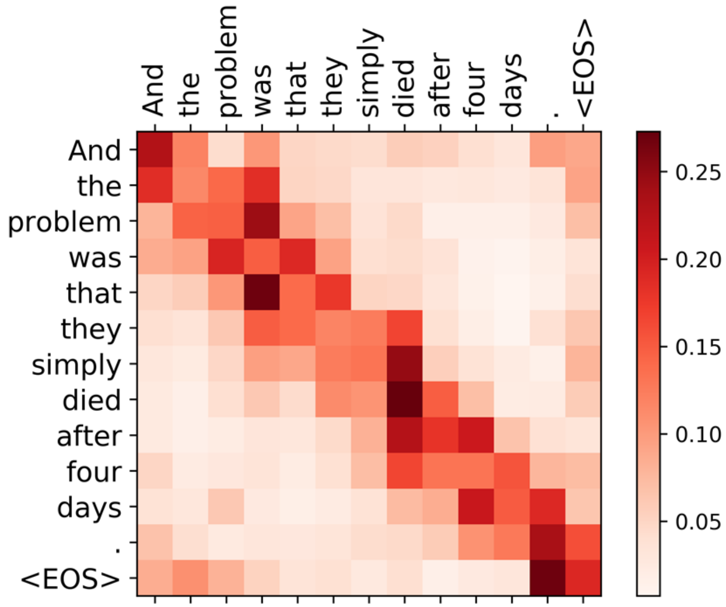
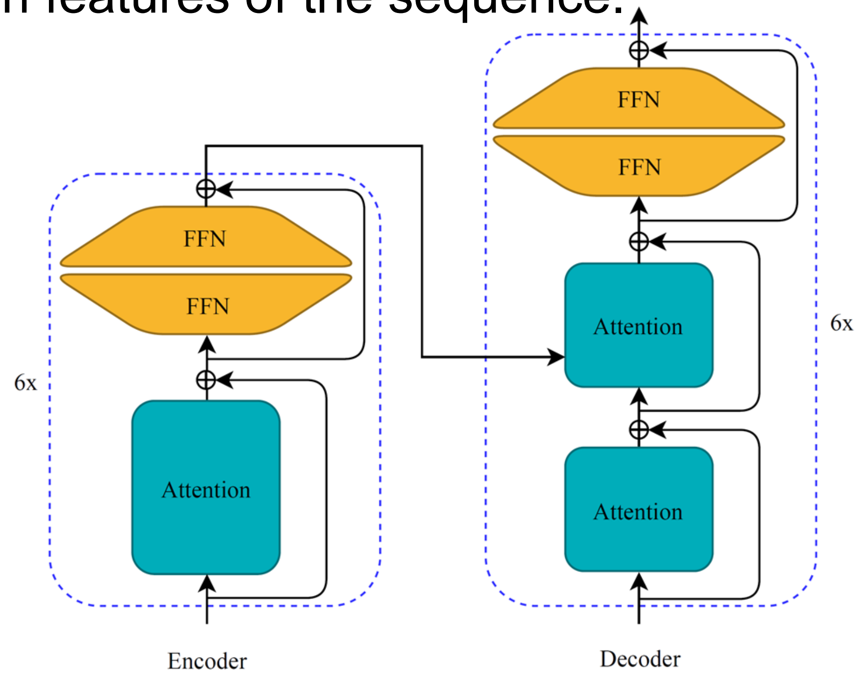
What does Attention Learn?

- Original self attention in the transformer captures both local and global information, since the FFN does not learn features of the sequence.



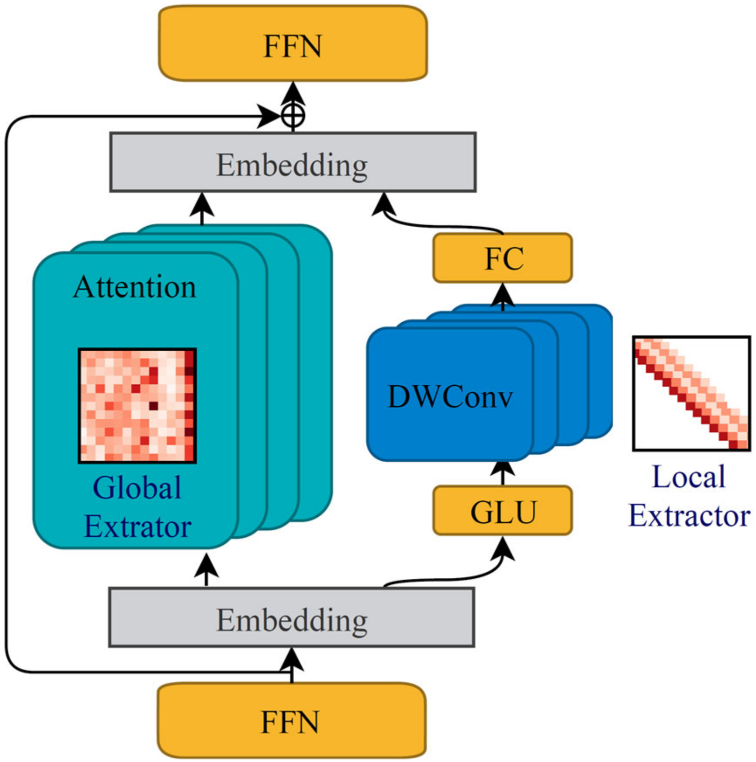
Self Attention



Basic transformer architecture for translation

Long-Short Range Attention (LSRA)

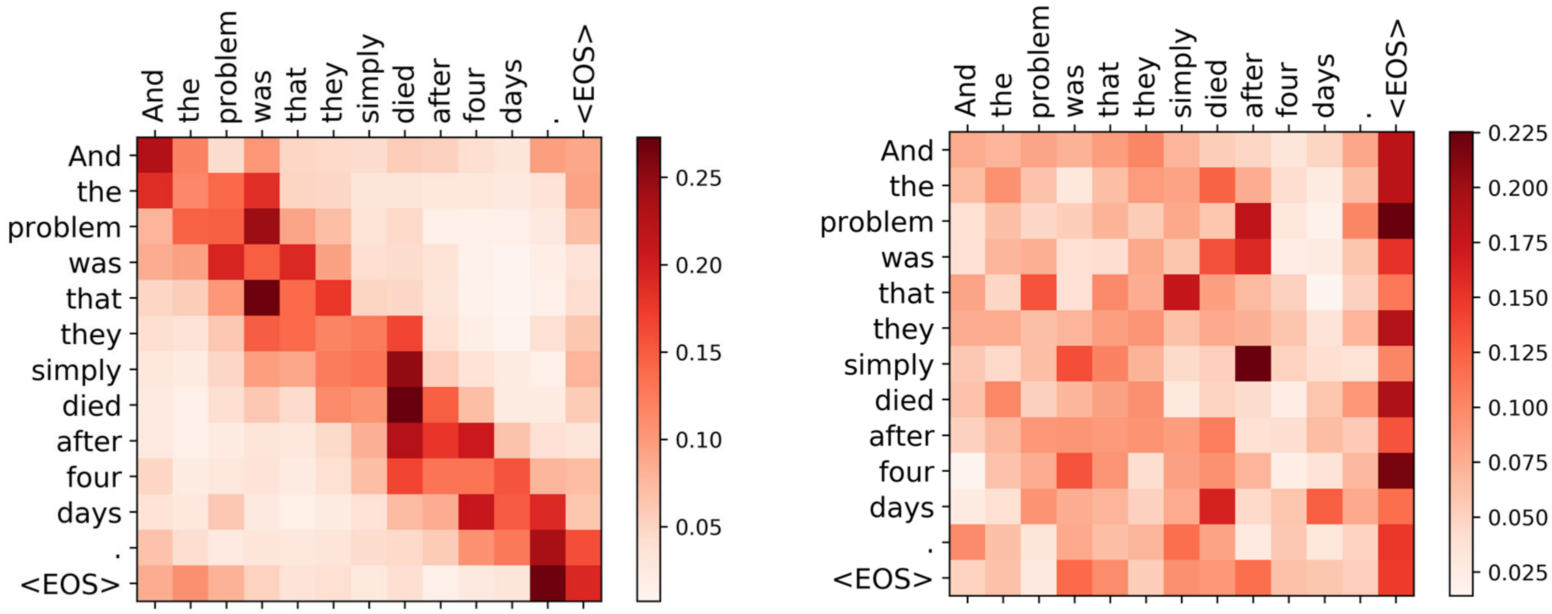
- Motivation: original attention modules must extract all the features with the same architecture, requiring a large capacity.
- Specialization works great in hardware design when the resources are limited.
- LSRA follows a specialized two-branch design: left for global context, right for local information



Mobile Transformer Block (LSRA)

Mobile Transformer with LSRA

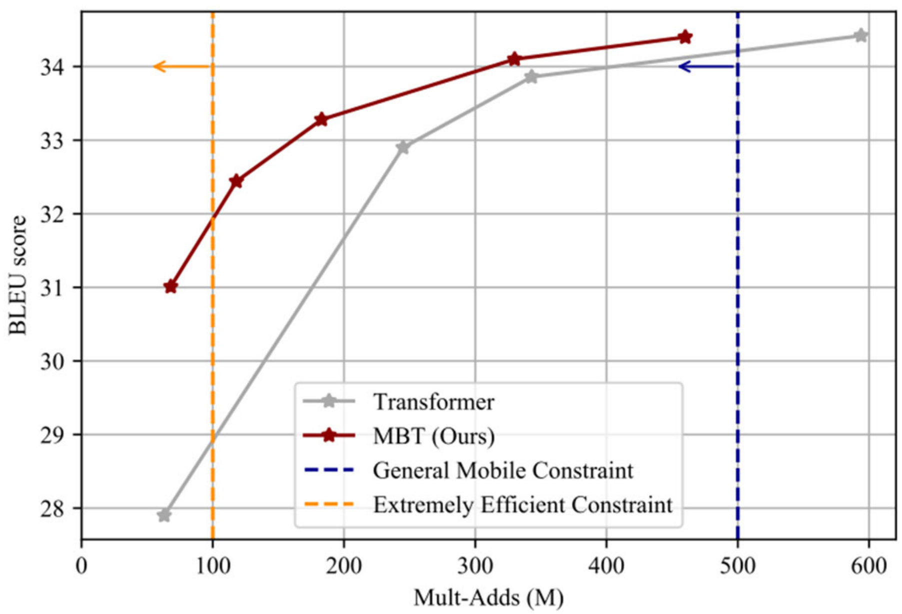
- Original self attention in original transformer needs to capture both local and global information (a).
- With LSRA, the attention branch only captures global contexts (b).



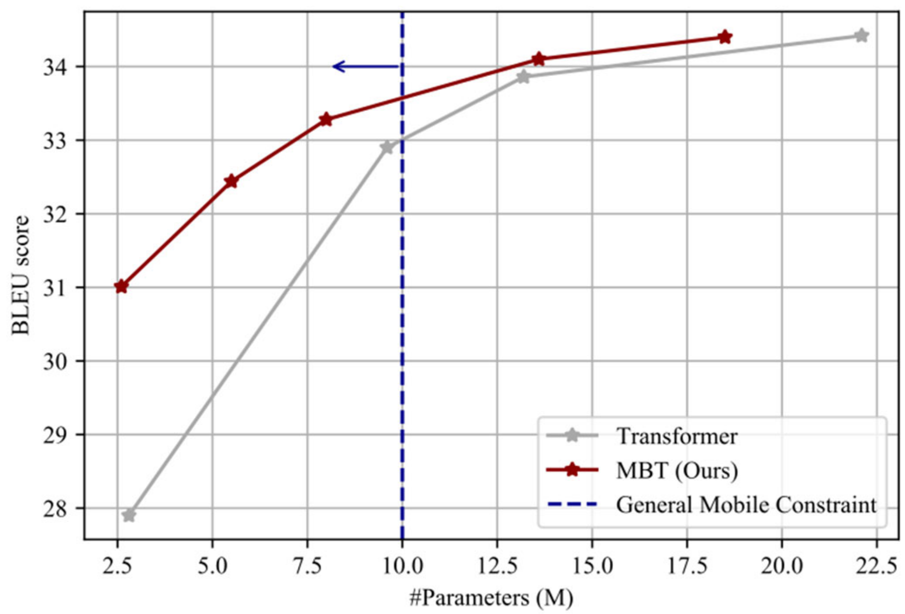
(a) Self Attention **(b) LSRA**

Mobile Transformer

- Our mobile transformer (MBT) with LSRA outperforms the basic transformer.
- On IWSLT'14 De-En dataset with better trade-off for both Mult-Adds and the number of parameters.



(a) IWSLT'14 De-En BLEU vs. Mult-Adds



(b) IWSLT'14 De-En BLEU vs. #Parameters

Mobile Transformer

- Our mobile transformer (MBT) also outperforms the basic transformer on both WMT'14 En-De and WMT'14 En-Fr dataset on mobile settings.
- Specialization is more effective with tighter resource constraints.

	#Parameters	Mult-Adds	WMT'14 En-De BLEU	WMT'14 En-De ΔBLEU	WMT'14 En-Fr BLEU	WMT'14 En-Fr ΔBLEU
Transformer (Vaswani et al., 2017)	2.8M	87M	21.3	–	33.6	–
Mobile Transformer (Ours)	2.9M	90M	**22.5**	**+1.2**	**34.9**	**+1.3**
Transformer (Vaswani et al., 2017)	11.1M	338M	25.1	–	37.6	–
Mobile Transformer (Ours)	11.7M	360M	**25.8**	**+0.7**	**38.7**	**+1.1**
Transformer (Vaswani et al., 2017)	17.3M	527M	26.1	–	38.4	–
Mobile Transformer (Ours)	17.3M	527M	**26.5**	**+0.4**	**39.6**	**+1.2**

Mobile Transformer

- Even compared to Neural Architecture Search-based Evolved Transformer (ET) [1], MBT offers 0.5 and 0.4 more BLEU score under the 100M and 400M mobile settings.
- It saves the design cost by 20000× in CO2 emission and the 250 GPU years of searching.

	#Parameters	Mult-Adds	BLEU	GPU Hours	CO_2e (lbs)	Cloud Computation Cost
Transformer	2.8M	87M	21.3	8×12	26	\$68 - \$227
ET (So et al., 2019)	3.0M	94M	22.0	8×274K	626K	\$1.6M - \$5.5M
Mobile Transformer (Ours)	2.9M	90M	**22.5**	8×14	32	\$83 - \$278
Transformer	11.1M	338M	25.1	8× 16	36	\$93.9 - \$315
ET (So et al., 2019)	11.8M	364M	25.4	8× 274K	626K	\$1.6M - \$5.5M
Mobile Transformer (Ours)	11.7M	360M	**25.8**	8 × 19	43	\$112 - \$376

[1] So, David, Quoc Le, and Chen Liang. "The Evolved Transformer." ICML, 2019.

Summary

- We analyze the computation bottleneck structure and argue that the bottleneck design is not optimal for 1-D attention.
- We propose a novel specialized multi-branch feature extractor, Long-Short Range Attention (LSRA) and a Mobile Transformer (MBT) based on LSRA.
- It alerts us to rethink the practicality of AutoML in terms of design cost.
- The efficient natural language processing designed for mobile settings is vital for the deployment of language related applications, such as machine translation on the edge devices.

Thank you!

Hardware, **A**I and **N**eural-nets

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