Scaling Laws

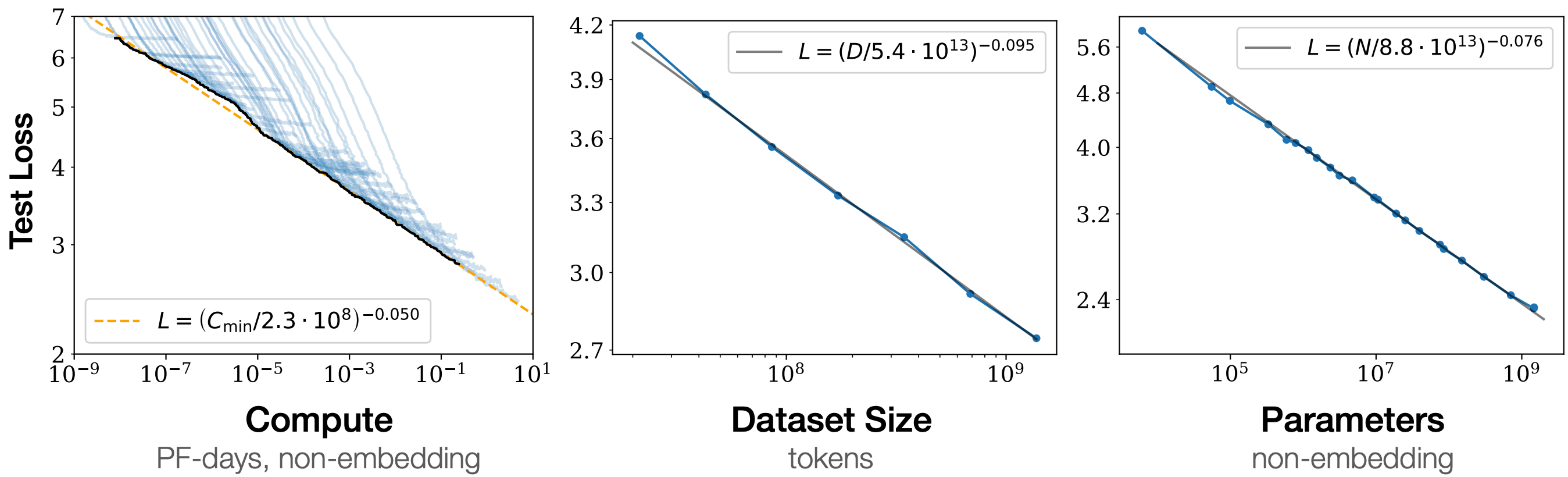


Figure 1 Language modeling performance improves smoothly as we increase the model size, datasetset size, and amount of compute[2] used for training. For optimal performance all three factors must be scaled up in tandem. Empirical performance has a power-law relationship with each individual factor when not bottlenecked by the other two.

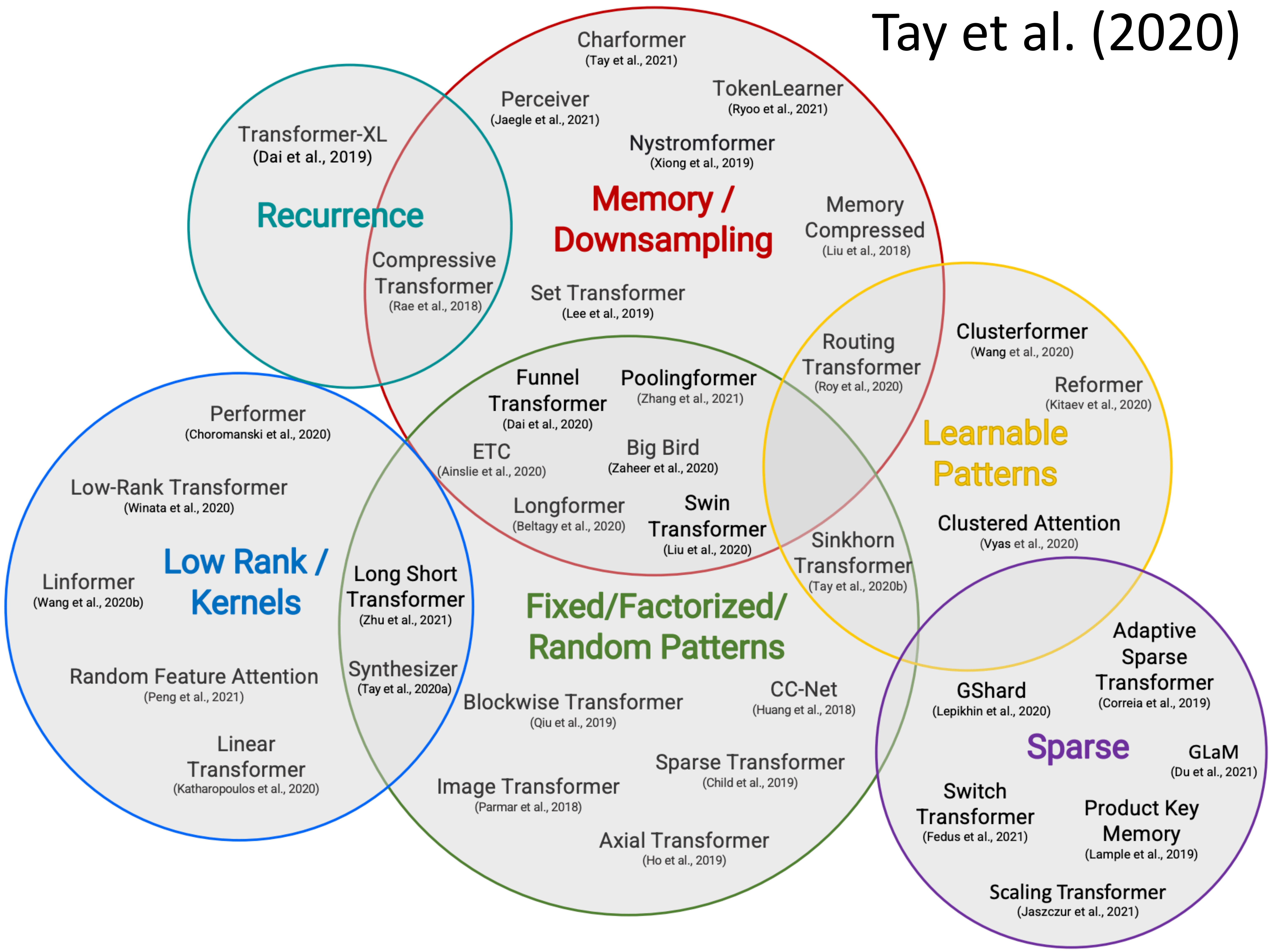
- Transformers scale really well!

Kaplan et al. (2020)

Transformer Runtime

- Even though most parameters and FLOPs are in feedforward layers, Transformers are still limited by quadratic complexity of self-attention
- Many ways proposed to handle this

Tay et al. (2020)



Performers

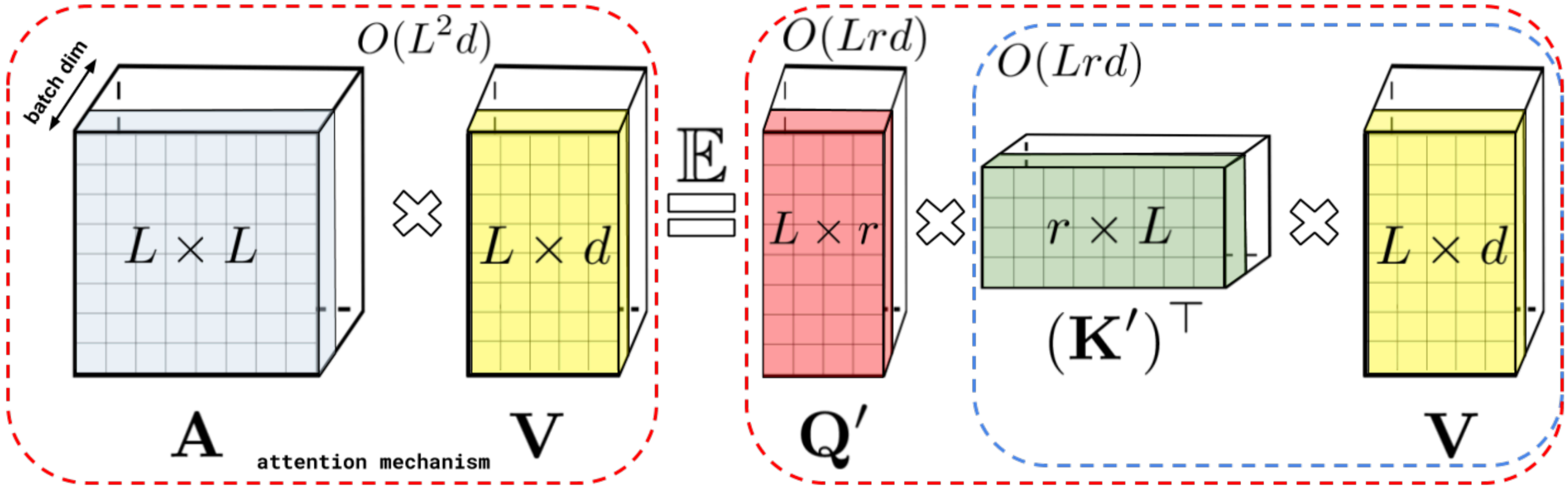
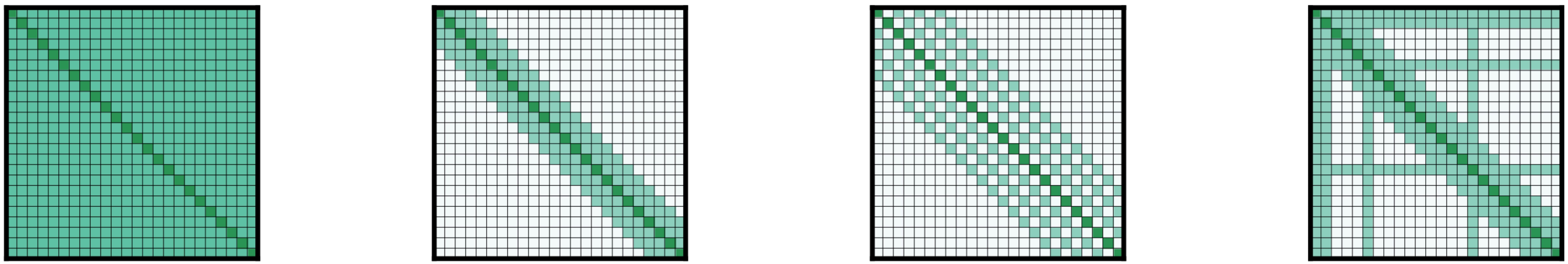


Figure 1: Approximation of the regular attention mechanism **AV** (before $\mathbf{D}^{-1}$-renormalization) via (random) feature maps. Dashed-blocks indicate order of computation with corresponding time complexities attached.

- No more len² term, but we are fundamentally approximating the self-attention mechanism (cannot form **A** and take the softmax)

Choromanski et al. (2020)

Longformer



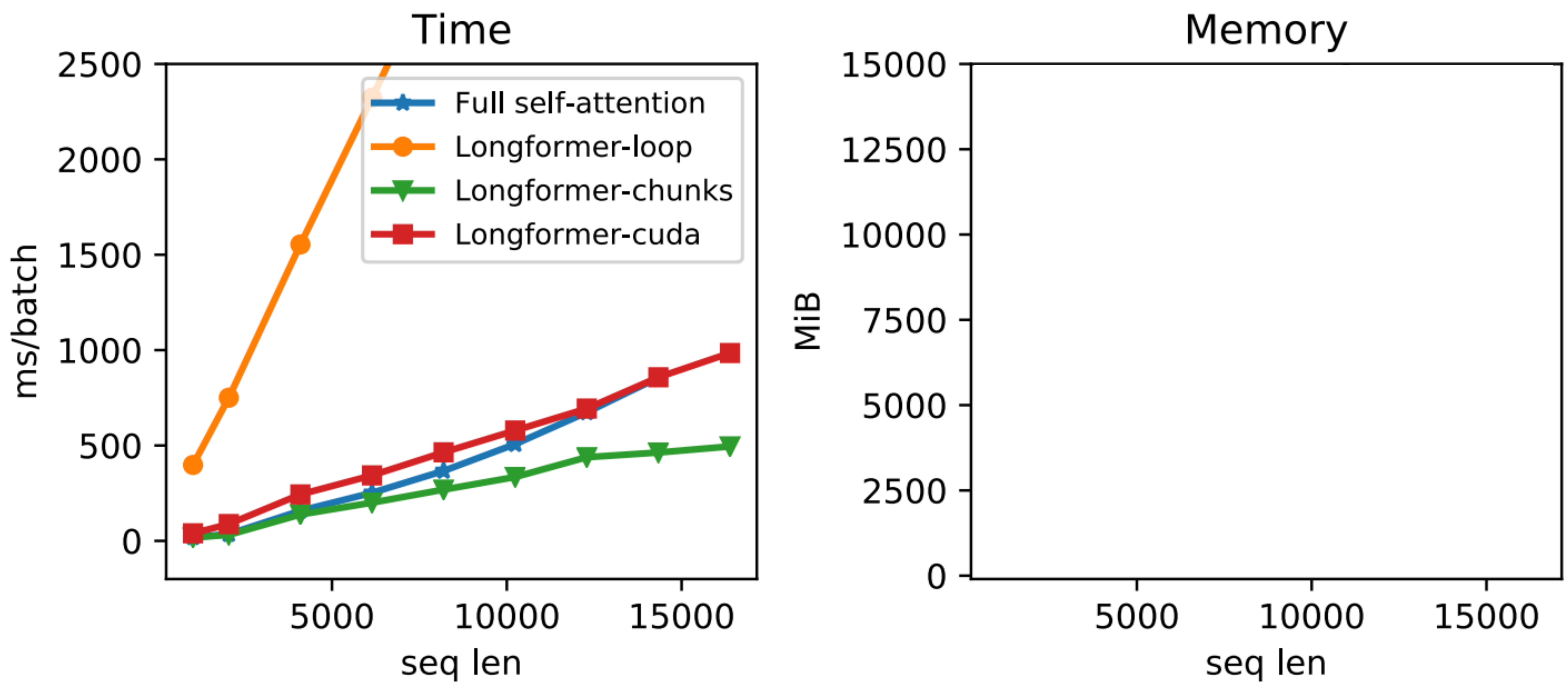
(a) Full n^2 attention (b) Sliding window attention (c) Dilated sliding window (d) Global+sliding window

Figure 2: Comparing the full self-attention pattern and the configuration of attention patterns in our Longformer.

- Use several pre-specified self-attention patterns that limit the number of operations while still allowing for attention over a reasonable set of things
- Scales to 4096-length sequences

Beltagy et al. (2021)

Attention Maps



- Loop = non-vectorized version
- What will the memory profile look like?

Beltagy et al. (2021)