# Transformer

# Efficient Transformers

### Learning goals

- Understand the efficiency problems and shortcomings of transformer-based models
- Learn about some strategies to alleviate them

# THE $\mathcal{O}(N^2)$ PROBLEM

**Quadratic time & memory complexity of Self-Attention**

- *Inductive bias of Transformer models:*
  Connect all tokens in a sequence to each other
- **Pro:** Can (theoretically) learn contexts of arbitrary length
- **Con:** Bad scalability limiting (feasible) context size

**Resulting Problems:**

- Several tasks require models to consume longer sequences
- *Efficiency:* Are there more efficient modifications which achieve similar or even better performance?

# EFFICIENT TRANSFORMERS

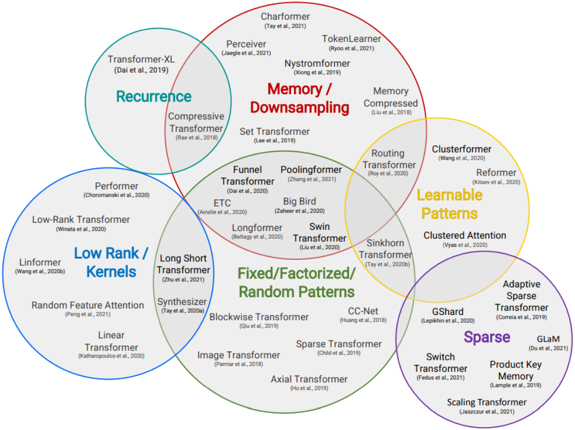
**Broad overview on so-called "X-formers"** ▸ Tay et al., 2020

- Efficient & fast Transformer-based models
  $\rightarrow$ Reduce complexity from $\mathcal{O}(n^2)$ to (up to) $\mathcal{O}(n)$
- Claim on-par (or even) superior performance
- Different techniques used:
  - Fixed/Factorized/Random Patterns
  - Learnable Patterns (extension of the above)
  - Low-Rank approximations or Kernels
  - Recurrence (see e.g. ▸ Dai et al., 2019)
  - Memory modules

**Side note:**

- Most Benchmark data sets not explicitly designed for evaluating long-range abilities of the models.
- Recently proposed: *Longe Range Arena: A benchmark for efficient transformers* ▸ Tay et al., 2020

# EFFICIENT TRANSFORMERS



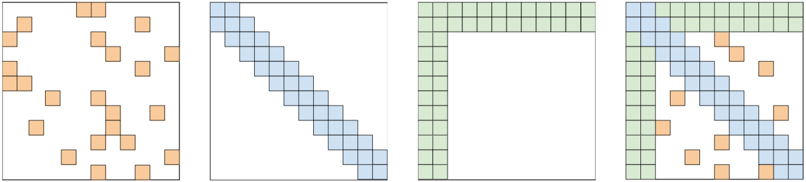

▸ Tay et al., 2020

# ATTENTION PATTERNS

## Reasoning:

- Making every token attend to every other token might be unnecessary
- Introduce sparsity in the commonly dense attention matrix

## Example:



(a) Random attention (b) Window attention (c) Global Attention (d) BIGBIRD

Figure 1: Building blocks of the attention mechanism used in BIGBIRD. White color indicates absence of attention. (a) random attention with $r = 2$, (b) sliding window attention with $w = 3$ (c) global attention with $g = 2$. (d) the combined BIGBIRD model.

▸ Source: Zaheer et al. (2020)

# TBD

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