# Transformer-based model compression

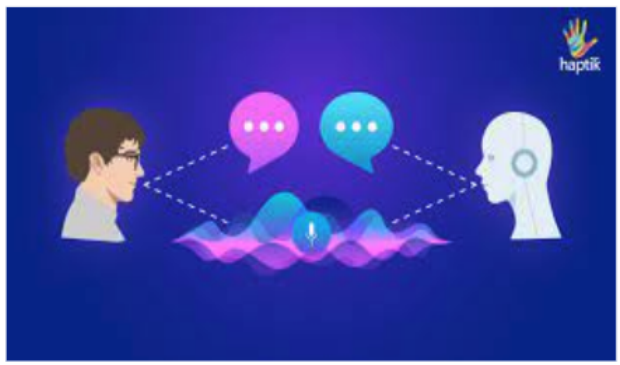
December 7, 2023

# Plan

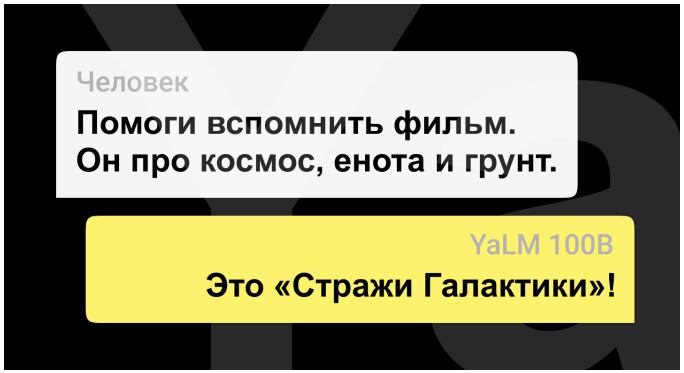
# The relevance of large Transformer models

Examples of applications where Transformers language models are successfully used

- Automatic completion of phrases in email
- Summarization of documents
- Program code generation, creation of new drugs formulas
- Few-shot and zero-shot tasks.
- Example: A GPT-3 model is asked to answer the question: "How many is two plus six?" or offer to play a game. The model answer is correct.




# Models, based on Transformer architecture



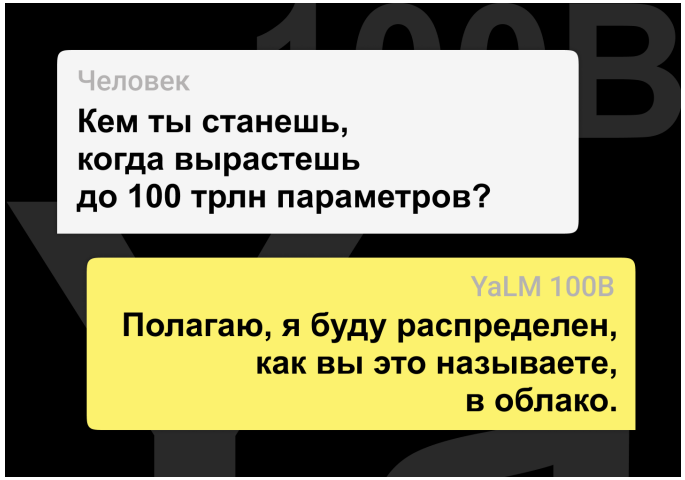




Table: Sizes of big Transformer-based models

| Model | GPT-3 | YaLM | mGPT | GPT-4 |
|---|---|---|---|---|
| Number of parameters | $175 \cdot 10^9$ | $100 \cdot 10^9$ | $1.3 \cdot 10^9$ | $100 \cdot 10^{12}$ |

# Models, based on Transformer architecture

## Training cost [1]

**Актуальность снижения затрат на тренировку и выбросов в атмосферу**

Энергия: 190 МВатт*час → Выбросы $CO_2$ в атмосферу: 85 тонн


Тренировка GPT-3

Отопление 126 домов в Дании

Поездка до Луны

[1] source: Sber-Skoltech project GreenAI

# The main "bottlenecks" in Transformers model

- **Embedding layer** (vocabulary_size $\times$ embedding_size $\approx$ $35 \cdot 10^3 \times 1024$)
- **Attention (Self-Attention) layer** (input_sequence $\times$ input_sequence, $1024 \times 1024$)
- **MLP** (GPT2-Medium $1024 \times 4096 \times 2 \times 24$)

Table: Size of the different blocks in Transformers, MB

| Layer-Model | GPT-2 small | GPT-2 medium | GPT-2 large |
|---|---|---|---|
| Attention | 9.01 | 16.02 | 25.02 |
| MLP | 18.01 | 32.02 | 50.02 |

# Transformers model

## Goal

To reach acceptable quality under a constrained resources (on a model with fixed number of parameters)

## Size reduction approaches

- **Efficient attention** - provide methods to accelerate the computation of attention vector and make attention matrix more sparse.
- **Parameters' size reduction** - in one way or another, reduces the amount of memory required for storing model parameters without change of configuration.
- **LA structures: SVD, Kronecker, Tensor/Matrix Representation** - reduces the number of parameters by representing a model layers as a products of decomposition.

# Quantization: Overview

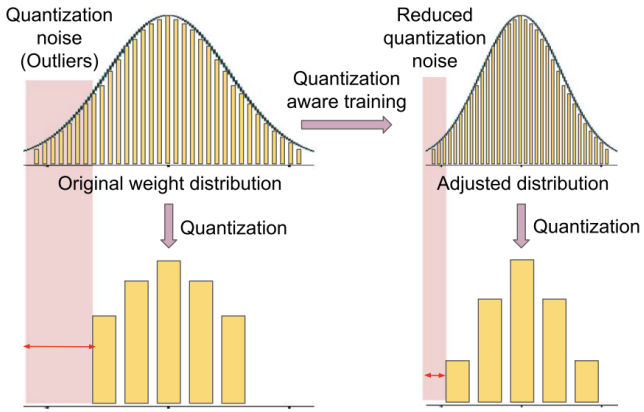
Quantization compresses the network by reducing the number of bits required to represent each weight. It can be applied to Embedding, Fully-connected layers, Attention layers (some layers are quantization friendly, some not - i didn't find a criterion).

- Fixed-point scalar quantization: change float32 weight to **8-bit** int or **4-bit** int (in initial work [2] to 1-bit or 2-bit).
- Groups quantization: split parameter matrix to blocks and replace every element of given block to one digit. Solution is found by finding the minimum of norm between real and quantized matrix [3].

[2] Quantized Neural Networks

[3] Training with Quantization Noise for Extreme Model Compression

# Quantization: Overview

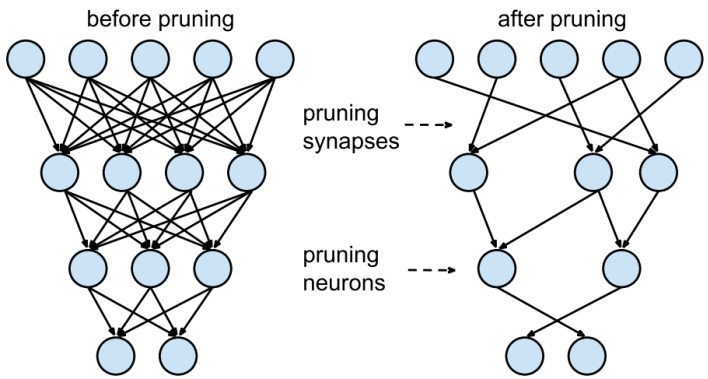



- Simple truncating leads to sizable drop in accuracy
- Tips:
  - Provide quantization while training.
  - Split weight in matrix to ones that match distribution ( 98%) and quantise it, and outlier set in rest.

**Pluses**: Easy to employ (**FP16** in PyTorch)
**Drawbacks**: The Naive methods lead to a performance decrease. For all methods, it is rather difficult to account for the effect of quantization in the resulting loss.

# Pruning: Overview

## The lottery ticket hypothesis



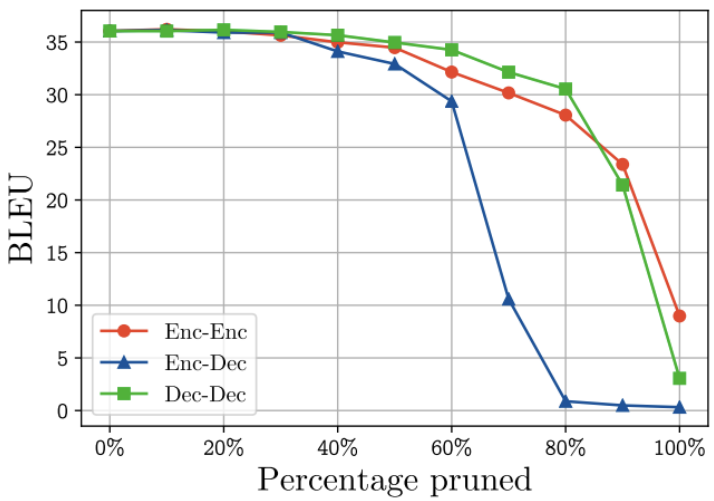

- Initialize weights
- Train
- Evaluate
- Remove weights close to zero, with gradients being close to zero
- Reset rest weights to initial state
- Train again

# Pruning: Overview

## Pruning types:

- Unstructured - remove weights from set of unimportant weights (Relative to gradient or other criteria)
- Structured - remove block of weights
  - **Prune L** - number of encoder blocks
  - **Prune H** - embedding size
  - **Prune A** - number of attention heads.

## Prune A




We can prune up to 20 to 40% of attention heads without increasing the performance [a]. BLEU when incrementally pruning heads from each attention type in the WMT model.

[a] Are Sixteen Heads Really Better than One?

# Pruning: modules selection [4]

- Method: Layer-wise relevance propagation (LRP)
- LRP describes the relative contribution of neurons at one point in a network to neurons at another. They evaluate the contribution of different heads to the Top-1 predicted logit.

| | **attention heads** (e/d/d-e) | **BLEU** from trained | from scratch |
|---|---|---|---|
| **WMT, 2.5m** | | | |
| baseline | 48/48/48 | **29.6** | |
| sparse heads | 14/31/30 | 29.62 | 29.47 |
| | 12/21/25 | 29.36 | 28.95 |
| | 8/13/15 | 29.06 | 28.56 |
| | 5/9/12 | 28.90 | 28.41 |

[4] Voita at al. Analyzing Multi-Head Self-Attention: Specialized Heads Do the Heavy Lifting, the Rest Can Be Pruned

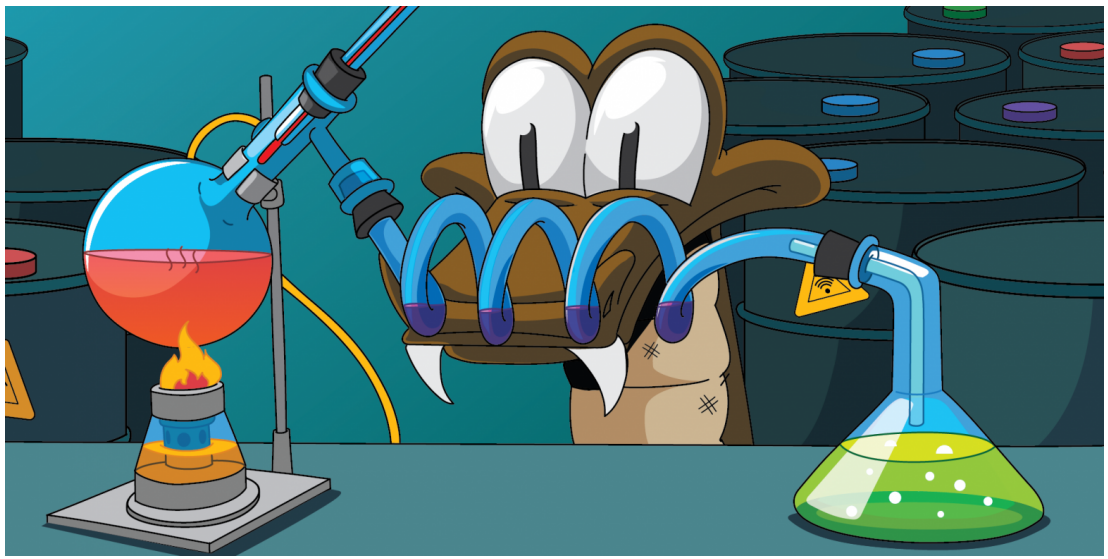
# Pruning: Overview

**Pros**: To prune part of a model is technically easy
**Drawbacks**: To select the proper part for pruning is not so easy (pruning is tedious)

- High resulting performance requires manual setup of criteria and requires additional hyper-parameter (in case of sparse attention we should vary the radius of interaction and select the most effective one).
- Pruning requires more iterations to converge than general methods.

# Distillation

- We have a big pre-trained language model (**Teacher**).
- This model fine-tunes on a small task i.e text classification, predicting labels for text objects.
- At the same time, the smaller model (**Student**) also is learned from scratch to predict labels w.r.t. teacher softmax outputs. It learns to imitate the teacher's answers.
- The Loss function of a common task splits into two: real prediction loss and teacher-student matching loss



# Distillation

## Distillation types

- **Offline distillation**: the knowledge is transferred from a pre-trained teacher model into a student model.
- **Online distillation**: both the teacher model and the student model are updated simultaneously, and the whole knowledge distillation framework is end-to-end trainable.
- **Self-distillation**: the same networks are used for the teacher and the student models, and can be regarded as a special case of online distillation.

# Distillation

## **DistillBERT**(Offline) [5]

- Teacher - BERT
- Student - LSTM-based model or smaller version of BERT (remove polling layers and remover layers on the factors of 2).
- Loss = CrossEntropyLoss(student_logits, target) + alpha · KLDivLoss(student_logits, teacher_logits)

Table: Performance of Distillation

| Model name | BERT | DistillBERT |
|---|---|---|
| Number of parameters | $110 \cdot 10^6$ | $66 \cdot 10^6$ |
| Accuracy on IMBD | 93.4 | 92.8 |

[5] Paper about DistillBERT

# Distillation

## **TinyBERT**(Offline) Distilling BERT for Natural Language Understanding

6

- Teacher - BERT
- Student - BERT with 12 heads, number of layer 4, hidden size 312.

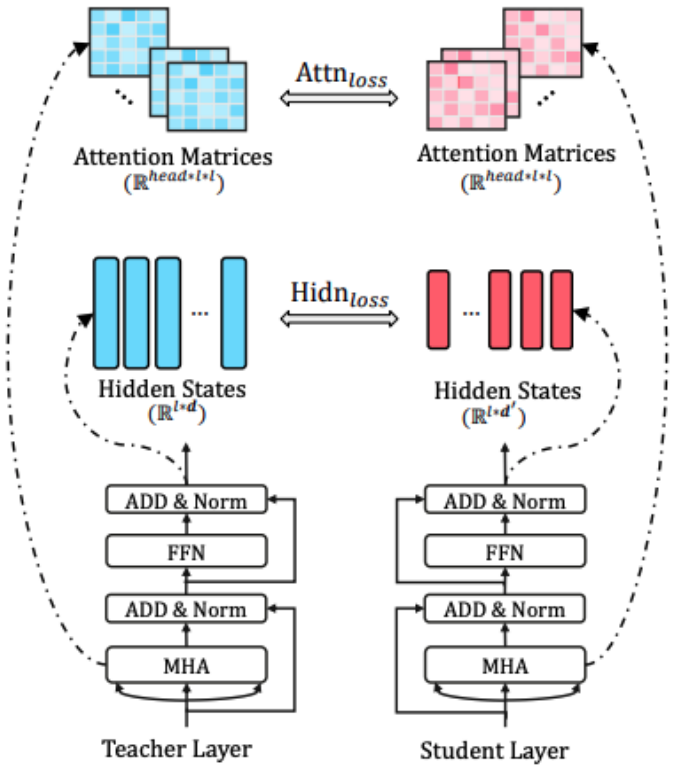
| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{BERT}_{\text{BASE}}$ (Teacher) | 109M | 22.5B | 1.0x | 83.9/83.4 | 71.1 | 90.9 | 93.4 | 52.8 | 85.2 | 87.5 | 67.0 | 79.5 |
| $\text{BERT}_{\text{TINY}}$ | 14.5M | 1.2B | 9.4x | 75.4/74.9 | 66.5 | 84.8 | 87.6 | 19.5 | 77.1 | 83.2 | 62.6 | 70.2 |
| $\text{BERT}_{\text{SMALL}}$ | 29.2M | 3.4B | 5.7x | 77.6/77.0 | 68.1 | 86.4 | 89.7 | 27.8 | 77.0 | 83.4 | 61.8 | 72.1 |
| $\text{BERT}_4$-PKD | 52.2M | 7.6B | 3.0x | 79.9/79.3 | 70.2 | 85.1 | 89.4 | 24.8 | 79.8 | 82.6 | 62.3 | 72.6 |
| $\text{DistilBERT}_4$ | 52.2M | 7.6B | 3.0x | 78.9/78.0 | 68.5 | 85.2 | 91.4 | 32.8 | 76.1 | 82.4 | 54.1 | 71.9 |
| $\text{MobileBERT}_{\text{TINY}}$† | 15.1M | 3.1B | - | 81.5/81.6 | 68.9 | **89.5** | 91.7 | **46.7** | 80.1 | **87.9** | 65.1 | **77.0** |
| $\text{TinyBERT}_4$ (ours) | 14.5M | 1.2B | 9.4x | **82.5/81.8** | **71.3** | 87.7 | **92.6** | 44.1 | **80.4** | 86.4 | **66.6** | **77.0** |

TinyBERT4 and BERT_TINY have ($M = 4, d = 312, di = 1200$). BERT_TINY means directly pretraining a small BERT, which has the same model architecture as TinyBERT.

[6] Paper about TinyBERT

# Distillation

The Transformer-layer distillation includes the attention based distillation and hidden states based distillation:




$$\mathcal{L}_{\text{layer}} = \begin{cases} \mathcal{L}_{\text{embd}}, & m = 0 \\ \mathcal{L}_{\text{hidn}} + \mathcal{L}_{\text{attn}}, & M \geq m > 0 \\ \mathcal{L}_{\text{pred}}, & m = M + 1 \end{cases}$$

- $L_{attn} = \frac{1}{h} \sum_i^h MSE(A_i^s, A_i^t)$
- $L_{hiddn} - MSE(h_s W_h, h_t)$
- $L_{emb} - MSE(e_s, e_t)$
- $L_{pred} - CE(z_t, z_s)$

# Distillation

## **FastBERT**(Self-distillation) [7]

This work uses the same model for teacher and student models:

- We have classic BERT model as encoder with h =12 layers
- On the top of every layer we have light weight **Teacher classifier** $p_t = TC(h_{L-1})$, L- number of transformer layers
- On the top of every layer we also have light weight **Student classifier** $p_{cl} = SC(h_l)$
- Loss $(p_{c0} \dots p_{cL}) = \sum_i^{L-1} KL(p_{ci}, p_t)$

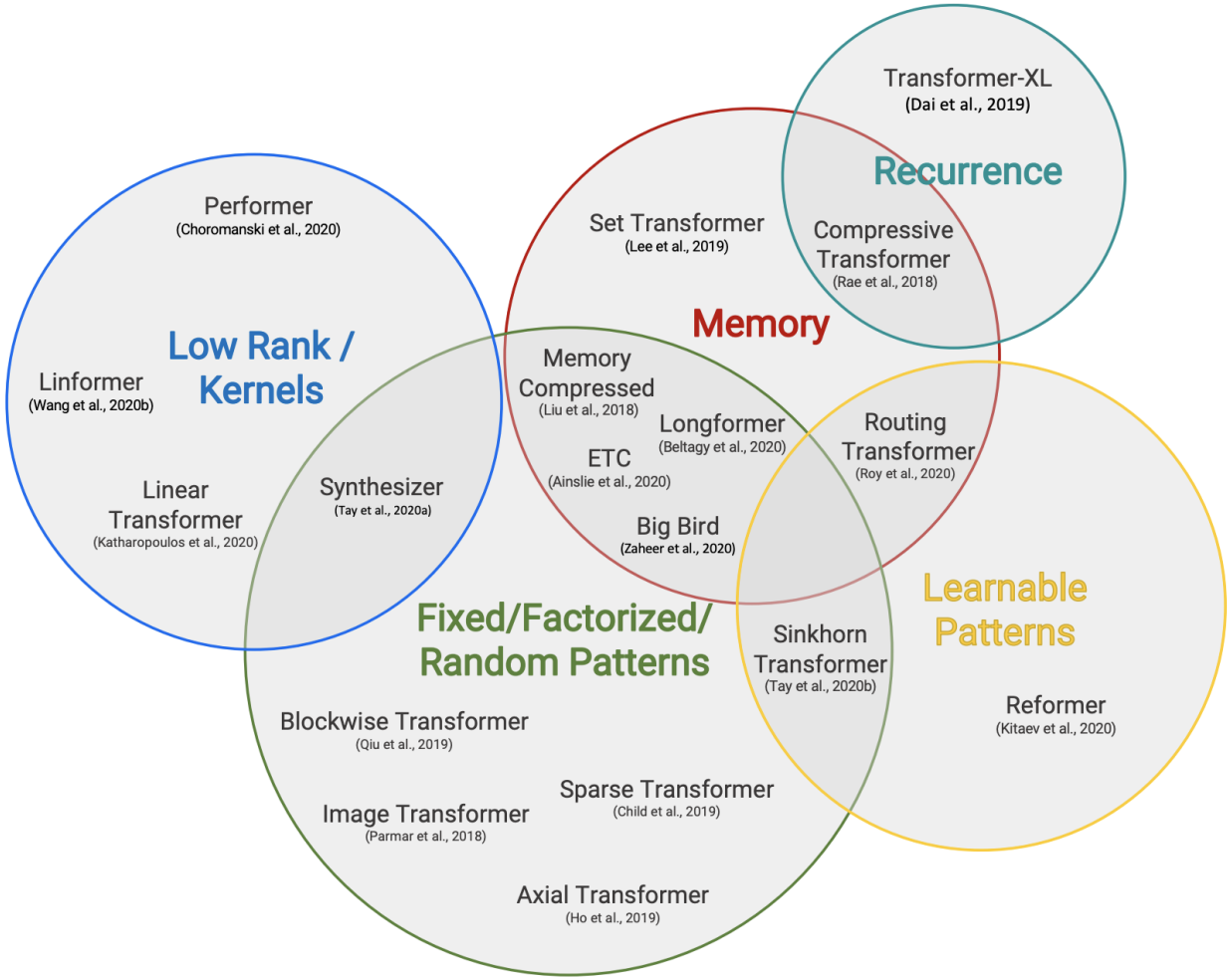
[7] Paper about FastBERT

# Distillation

**Pros**: Method can archive a good compression without drop in the performance **Drawbacks**:

- The approach gives a solution only to a particular problem and is not generalizable
- Needs accurate parameters fine tuning to obtain a good results

# Efficient Attention [8]




[8] Efficient Transformers: A Survey

# Efficient Attention: Kernel methods

## Linear Transformer

Improves the complexity of self-attention from quadratic to linear by using a kernel function. **Kernel trick**: we can map function to other space by $\phi$, where we can split variables.

$$attn(Q, K, V) = softmax(\frac{Q, K^T}{\sqrt{(d)}})V,$$

$$\text{attn}(\text{Q}, \text{K}_i, V_i) = \frac{\sum_{j=1}^{p} sim(Q_i, K_j)V_j}{\sum_{j=1}^{p} sim(Q_i, K_j)},$$

$$sim(q, k) = \exp\left(q^T k/\sqrt{d}\right) = sim(q, k) = \phi(q)^T \phi(k)$$

than:

$$attn(Q, K_i, V_i) = \frac{\phi(Q_i)^T \sum_{j=1}^{p} \phi(K_j)V_j}{\phi(Q_i) \sum_{j=1}^{p} \phi(K_j)}$$

In original paper (ELU - Exponential Linaer Unit):

$$\phi(x) = elu(x) + 1$$

.

# Efficient Attention: Kernel methods

## Linformer [9]

Key and value matrix maps to low-rank space using trainable matrix $R \in \mathrm{R}^{b \times N}$

$$K' = RK, V' = RV$$

| $n$ | Model | SST-2 | IMDB | QNLI | QQP | Average |
|---|---|---|---|---|---|---|
| 512 | Liu et al. (2019), RoBERTa-base | 93.1 | 94.1 | 90.9 | **90.9** | 92.25 |
| | Linformer, 128 | 92.4 | 94.0 | 90.4 | 90.2 | 91.75 |
| | Linformer, 128, shared kv | **93.4** | 93.4 | 90.3 | 90.3 | 91.85 |
| | Linformer, 128, shared kv, layer | 93.2 | 93.8 | 90.1 | 90.2 | 91.83 |
| | Linformer, 256 | 93.2 | 94.0 | 90.6 | 90.5 | 92.08 |
| | Linformer, 256, shared kv | 93.3 | 93.6 | 90.6 | 90.6 | 92.03 |
| | Linformer, 256, shared kv, layer | 93.1 | 94.1 | **91.2** | 90.8 | **92.30** |
| 512 | Devlin et al. (2019), BERT-base | 92.7 | 93.5 | 91.8 | 89.6 | 91.90 |
| 512 | Sanh et al. (2019), Distilled BERT | 91.3 | 92.8 | 89.2 | 88.5 | 90.45 |

[9] Linformer

# Efficient Attention: Trainable Patterns

## Reformer [10]

Attention is used inside groups of elements with the same hash function, i.e. if *query* is close to *key* $h(q_i) = h(k_j)$. Locality sensitive hashing

$$h(x) = \text{argmax}[xR, -xR], R - \text{random matrix}$$

## Routing transformer [11]

The K-Means clustering for splitting input sequence to attention groups is used. Query and keys matrices are projected into a new space using a trainable matrix, K-Means clustering is used to split the resulting vectors into groups.

[10] Reformer

[11] Routing transformer

# Efficient Attention: Fixed Patterns [12]

Fixed Patterns (or "Sparse Attention") is most simple to realize and intuitively understandable. At the same time, they are effective, so they are most widely used.

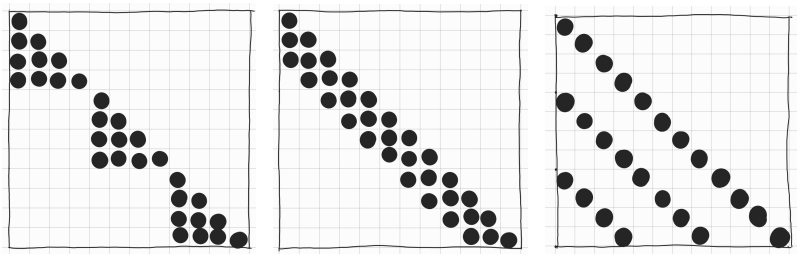


Figure: (a) – **Block Local Attention**, (b) – **Fixed Radius Local Attention**, (c) – **Block Strided Attention**.

- Block Local Attention
  The issue is grouping consecutive elements in the input sequence into blocks. Attention is calculated for elements within each block, elements from different groups do not interact.

$$A_{ij} = \begin{cases} Q_i K_j^T, & \text{if } \lfloor i/k \rfloor = \lfloor j/k \rfloor \\ 0, & \text{else} \end{cases}$$

[12] Generating Long Sequences with Sparse Transformers

# Efficient Attention: Fixed Patterns

- Block Strided Attention Similar to block local attention, blocks consist of elements that are departed from each other for a fixed destination $d$:

$$A_{ij} = \begin{cases} Q_i K_j^T & \text{if} i \equiv j \pmod{k} \\ 0, & \text{else} \end{cases}$$

  In original article, stride $= 128$.

- Fixed Radius Local Attention attention is zero for elements stating apart on distance more than $d$:

$$A_{ij} = \begin{cases} Q_i K_j^T, & \text{if} |i-j| \leq k \\ 0, & \text{else.} \end{cases} \tag{1}$$

# Efficient Attention: Memory [13]

- Regular attention ($\approx n^2$):

$$\begin{aligned} MHA(X, Y) &= \text{Multihead}(\text{Queries} = X, \text{Keys} = Y, \text{Values} = Y), \\ H &= \text{LayerNorm}(X + MHA(X, Y, Y)), \\ MAB(X, Y) &= LayerNorm(H + rFF(H)), \\ SAB &= MAB(X, X) \end{aligned}$$

- Induced point in self-attention ($\approx 2nk$):

$$\begin{aligned} ISAB_m(X) &= MAB(X, IP_m), \\ IP_m &= MAB(I_m, X) \end{aligned}$$

[13] Set Transformer

# Efficient Attention: Memory [14]

- $I_m$ - trainable parameter, which part of X choose for attention calculating. We choose to catch more informative parts of input for final task. Proposed operation are *permutation invariant*, in means that $I_m$ - fixed set of indexes, on which every semantic meaning can stand for different sentence (negotiation, definition, ...).
- Overall:

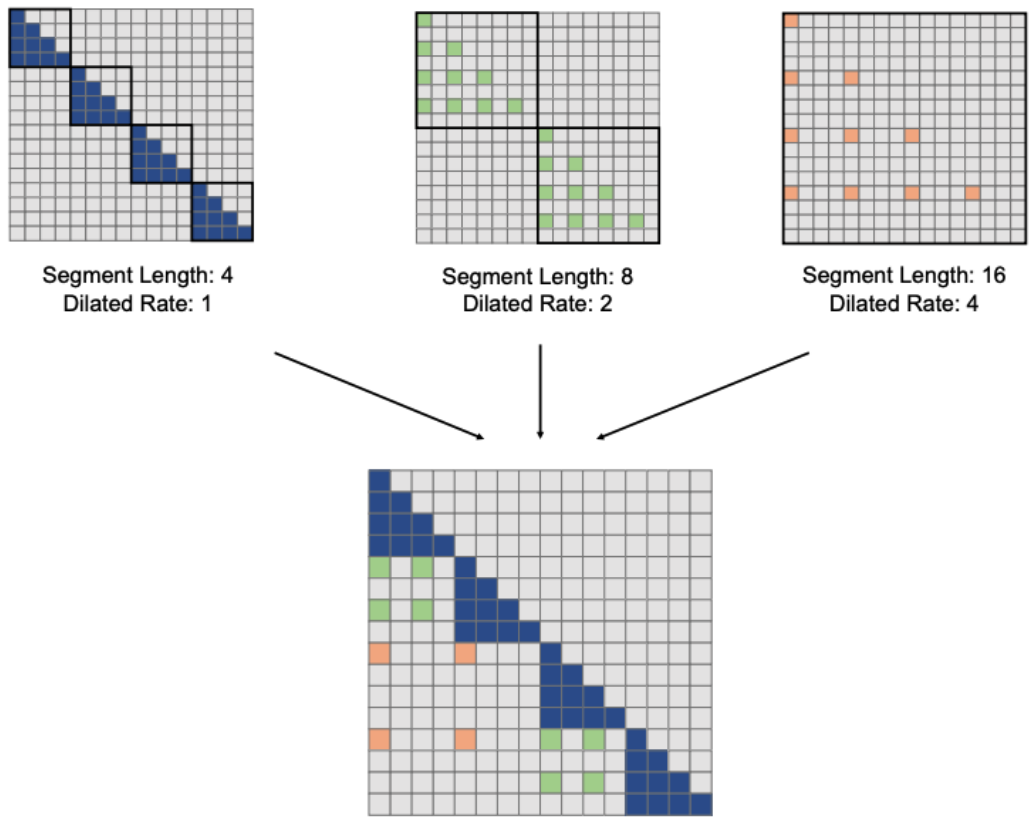
$$\begin{aligned} X - input, \\ Z = Encoder(X) = ISAB_m(X), \\ Y = Decoder(Z) = MAB(S, rFF(Z)), \end{aligned}$$

- S - trainable set of k seed vectors

[14] Set Transformer

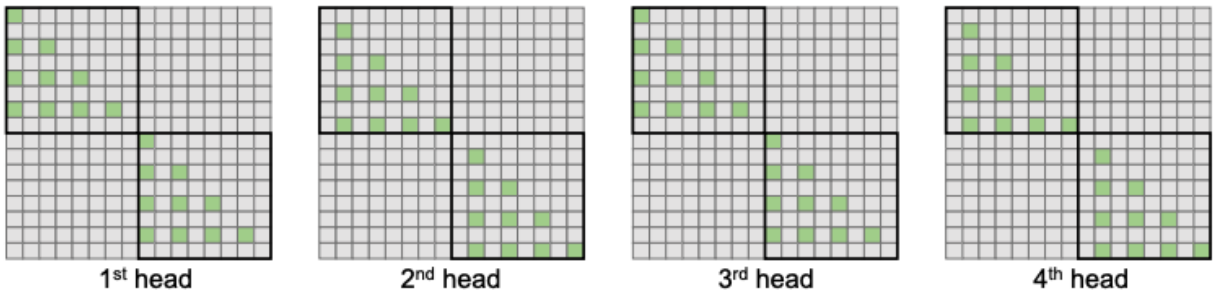
# Efficient Attention: Dilated Attention

LONGNET: Scaling Transformers to 1,000,000,000 Tokens [15]
Dilated Attention: Attention Allocation decreases exponentially as the distance between tokens grows.




[15] https://arxiv.org/pdf/2307.02486.pdf

# Efficient Attention: Dilated Attention




| Model | Length | Batch | Github 2K | Github 8K | Github 32K |
|---|---|---|---|---|---|
| Transformer [VSP+17] | 2K | 256 | 4.24 | 5.07 | 11.29 |
| Sparse Transformer [CGRS19] | 8K | 64 | 4.39 | 3.35 | 8.79 |
| **LONGNET (ours)** | | | 4.23 | 3.24 | 3.36 |
| Sparse Transformer [CGRS19] | 16K | 32 | 4.85 | 3.73 | 19.77 |
| **LONGNET (ours)** | | | 4.27 | 3.26 | 3.31 |
| Sparse Transformer [CGRS19] | 32K | 16 | 5.15 | 4.00 | 3.64 |
| **LONGNET (ours)** | | | 4.37 | 3.33 | 3.01 |

Table 2: Perplexity of language models for LONGNET and the baselines.

# Efficient Attention: Overview

Computational Efficiency

| Model | Complexity | Class |
|---|---|---|
| Linear Transformer | $\mathcal{O}(n)$ | Kernel |
| Linformer | $\mathcal{O}(n)$ | Kernel |
| Transformer XL | $\mathcal{O}(nk)$ | Recur |
| Reformer | $\mathcal{O}(n \log n)$ | TP |
| Routing transformer | $\mathcal{O}(n\sqrt{n})$ | TP |
| Sparse transformer | $\mathcal{O}(n\sqrt{n})$ | FP |
| Set transformer | $\mathcal{O}(nk)$ | Memory |
| Dilated Attention | $\mathcal{O}(n)$ | FP |

$n$ is sequence length, $d$ - hidden dimention, $k$ - size of block

Thank you for your attention =)