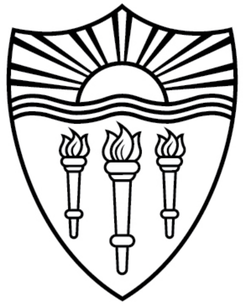
CSCI 544: Applied Natural Language Processing

Advanced Transformers

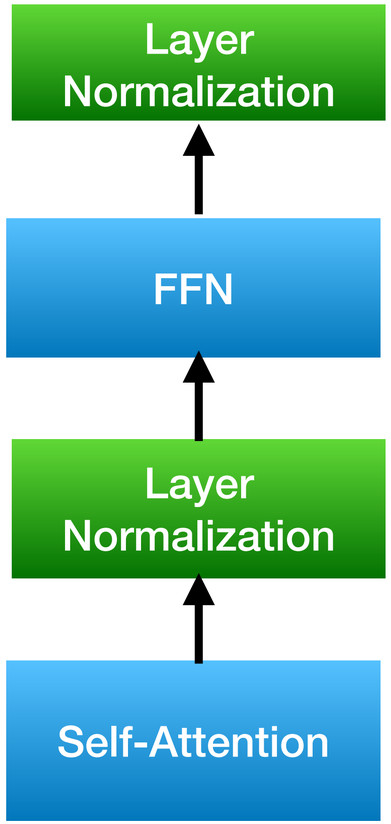
Xuezhe Ma (Max)



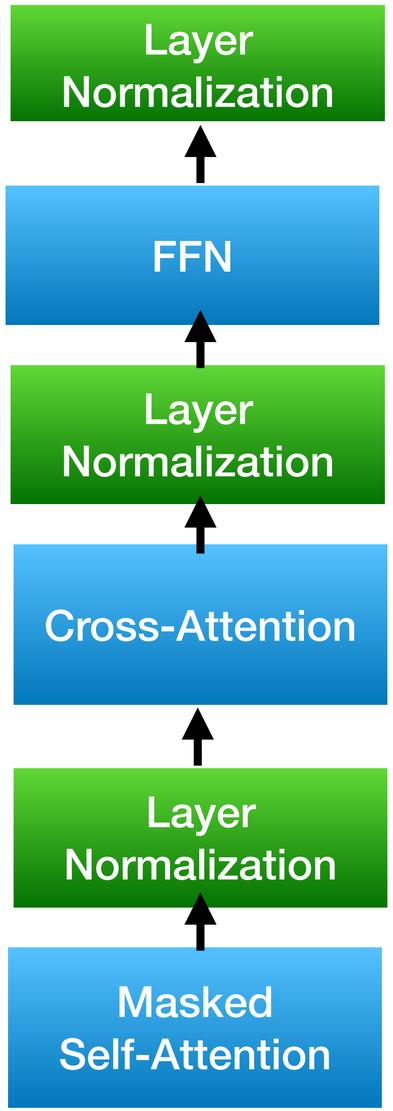
USC University of Southern California

Recap: Transformers

Transformer Encoder Block



Transformer Decoder Block



Attention

- **Easier to capture dependencies:** we draw attention between every pair of words!
- **Easier to parallelize:**

$$\text{MultiHead}(X) = \text{concat}(h_1, \ldots, h_k)W_O$$
$$h_i = \text{attn}(Q_i, K_i, V_i)$$
$$Q_i = (XW_Q)^i, K_i = (XW_K)^i, V_i = (XW_V)^i$$

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

Open Challenges in LLM Research

Aug 16, 2023 • Chip Huyen

Never before in my life had I seen so many smart people working on the same goal: making LLMs better. After talking to many people working in both industry and academia, I noticed the 10 major research directions that emerged. The first two directions, hallucinations and context learning, are probably the most talked about today. I'm the most excited about numbers 3 (multimodality), 5 (new architecture), and 6 (GPU alternatives).

Open challenges in LLM research

1. Reduce and measure hallucinations
2. Optimize context length and context construction
3. Incorporate other data modalities
4. Make LLMs faster and cheaper
5. Design a new model architecture
6. Develop GPU alternatives
7. Make agents usable
8. Improve learning from human preference
9. Improve the efficiency of the chat interface
10. Build LLMs for non-English languages

From Huyen's Blog

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Long Context Modeling

From Huyen's Blog

Why Long Context?

- **Longer Context = Higher Intelligence**
- **Long Context = Better Applications**
  - Book-level summarization
  - Doc-level translation
  - Customized assistant
  - High-resolution & long video generation
  - …

Pic from game of thrones

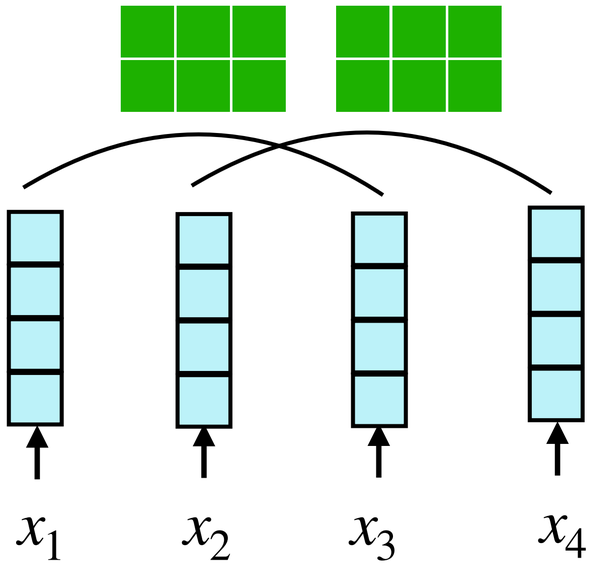
Long Context is hard for Transformer

- **Complexity**
  - Expensive: quadratic complexity
    - Both time and space
    - $O(hn^2)$: h heads and sequence length of n

- **Inductive Bias on Length Generalization**
  - Hard to be extended to longer contexts than pre-training
    - Almost no prior knowledge of dependency patterns (weak inductive bias)
    - Position information only from absolute/relative positional embeddings

Inductive Bias: CNN & RNN

CNN



- Local dependencies
  - Window size is usually small (e.g. 3 or 5)
- Time-invariant kernel

Inductive Bias: CNN & RNN

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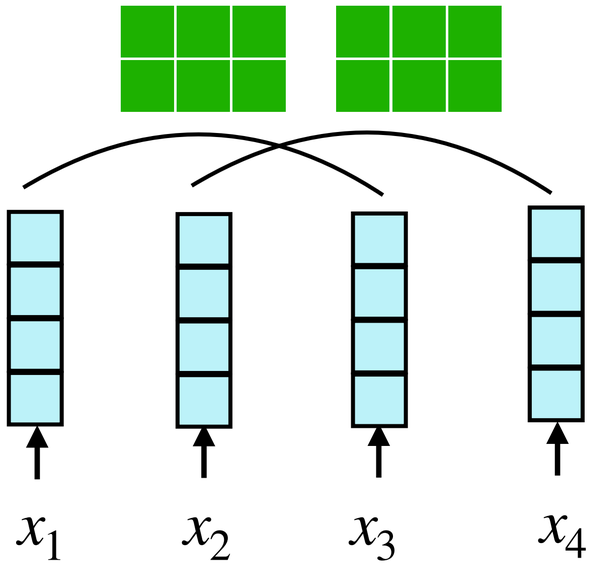

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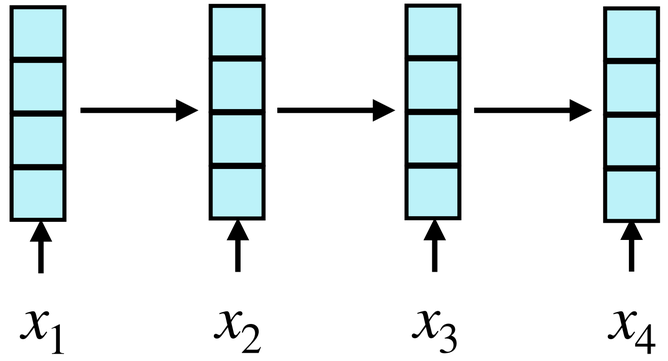
  - Window size is usually small (e.g. 3 or 5)
- Time-invariant kernel

RNN

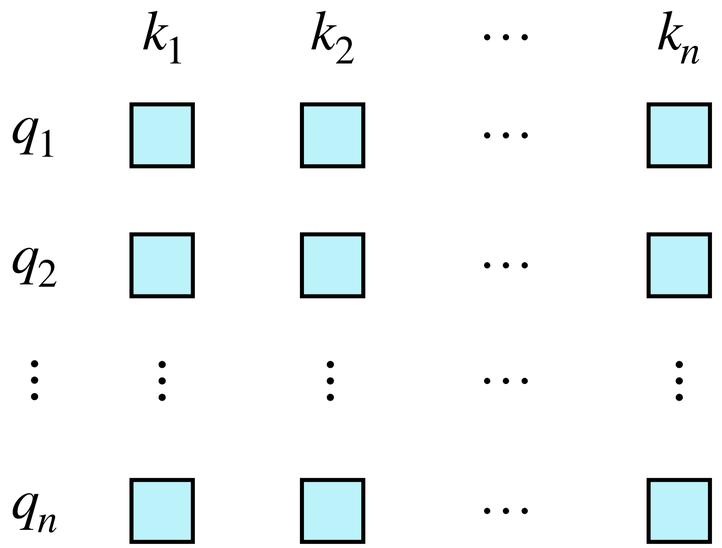


- Sequencial dependencies
- Time-invariant recurrence

Weak Inductive Bias on Length Generalization

- **Transformer Hard to be extended to longer contexts than pre-training**

Attention score $A \in \mathbb{R}^{n \times n}$



- Pair-wise interaction
- Order-invariant if no positional embeddings

Efficient Attention Mechanisms

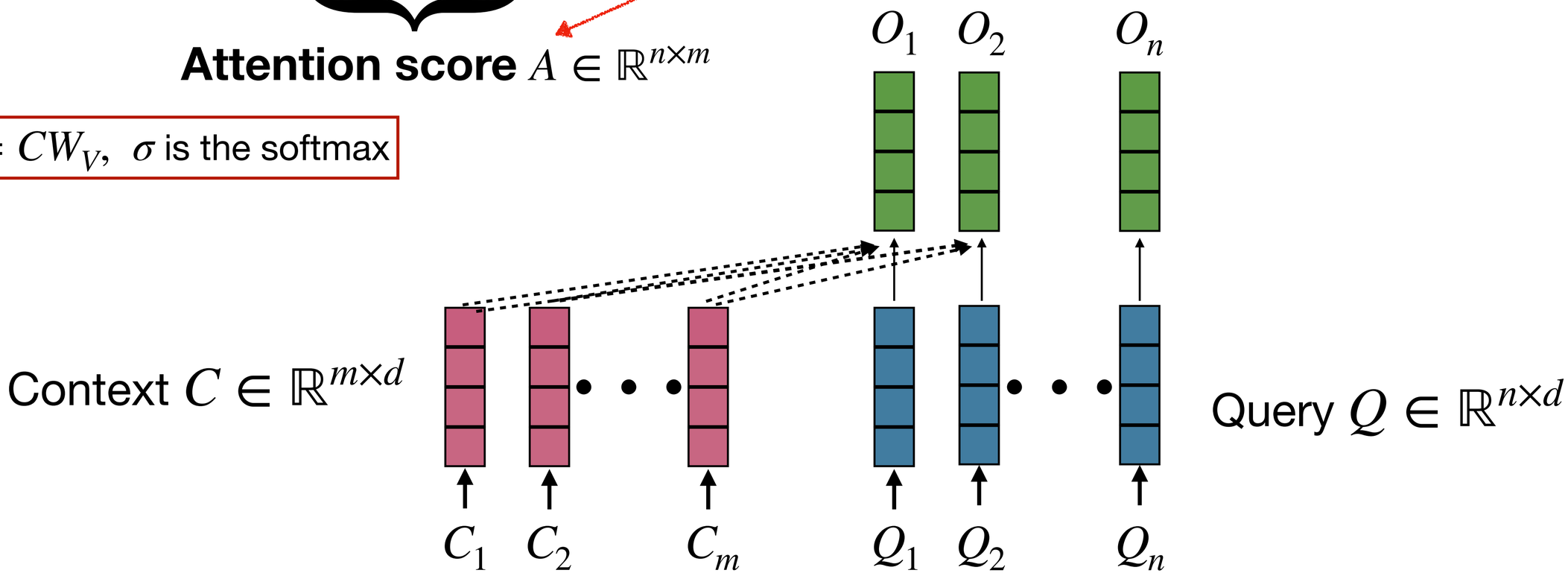
Attention Mechanism

Inputs: $Q \in \mathbb{R}^{n \times d}, \ C \in \mathbb{R}^{m \times d}$

Outputs: $O = Attn(Q, C) = \underbrace{\sigma\left(\frac{QK^T}{\sqrt{d}}\right)}_{\text{Attention score } A \in \mathbb{R}^{n \times m}} V$

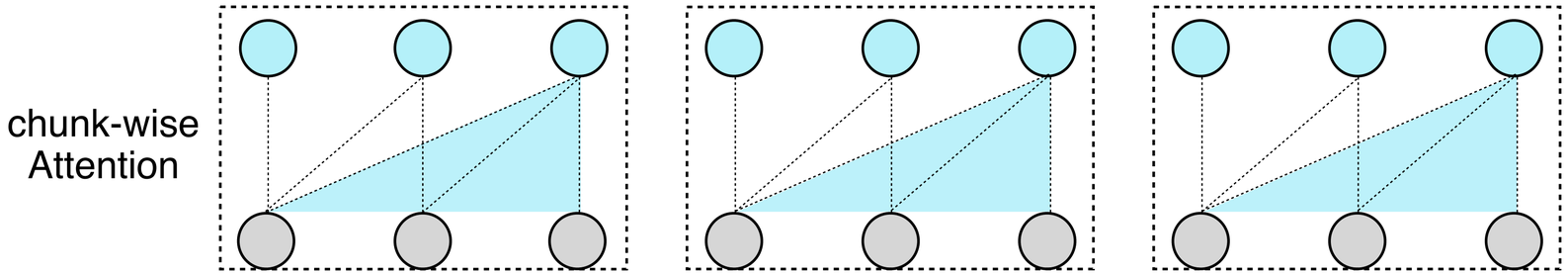
time and memory consuming

$K = CW_K, \ V = CW_V, \ \sigma$ is the softmax



Why not Chunk-wise Attention?

- Applying attention individually to each chunk with fixed length

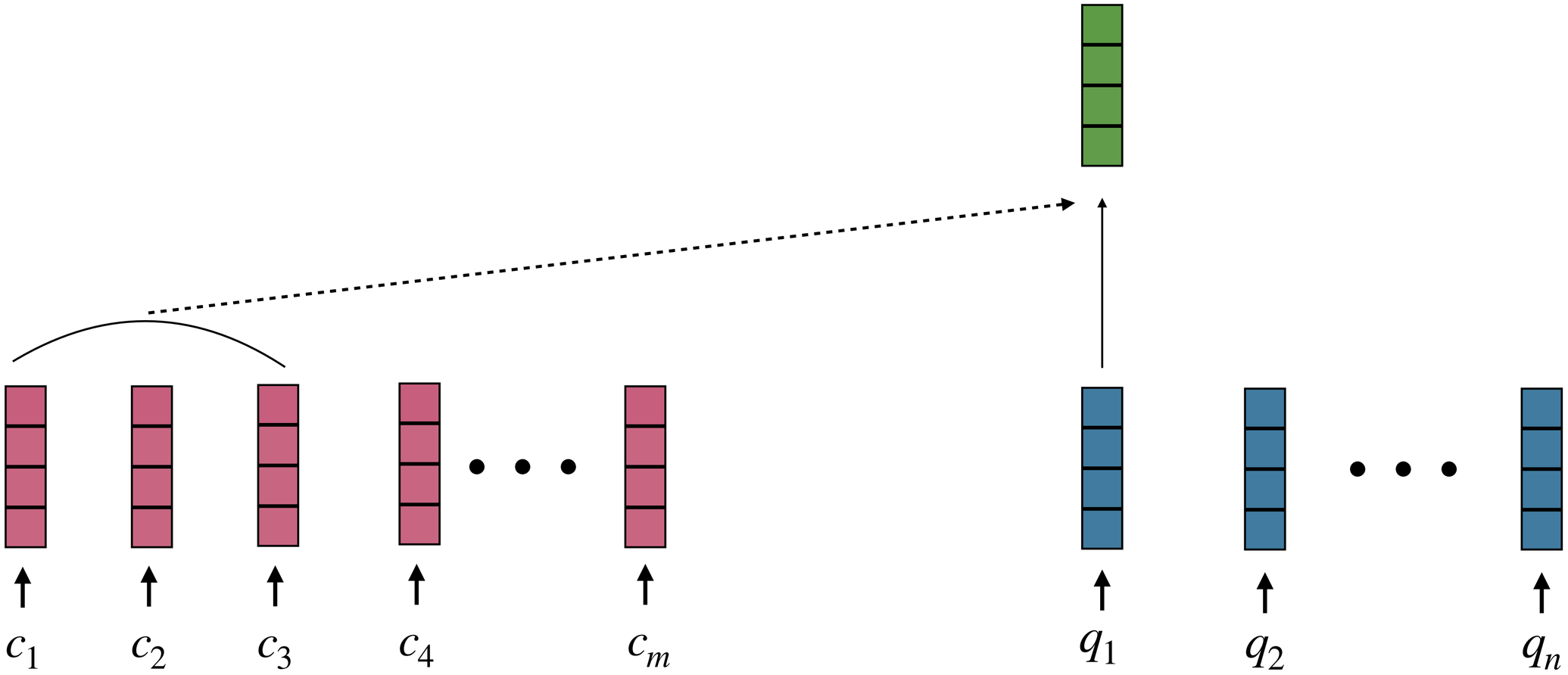


Previous Work: Efficient Attention

- **Sparse Attention**
  - Local attention
    - Image Transformer (Parmar et al., 2018)
  - Stride attention
    - Sparse Transformer (Child et al., 2019)
    - Longformer (Beltagy et al., 2020)
  - Attention with learnable patterns
    - Reformer (Kitaev et al., 2020)
    - Sinkhorn attention (Tay et al., 2020)

LongFormer

- **Sliding Window Attention**



LongFormer

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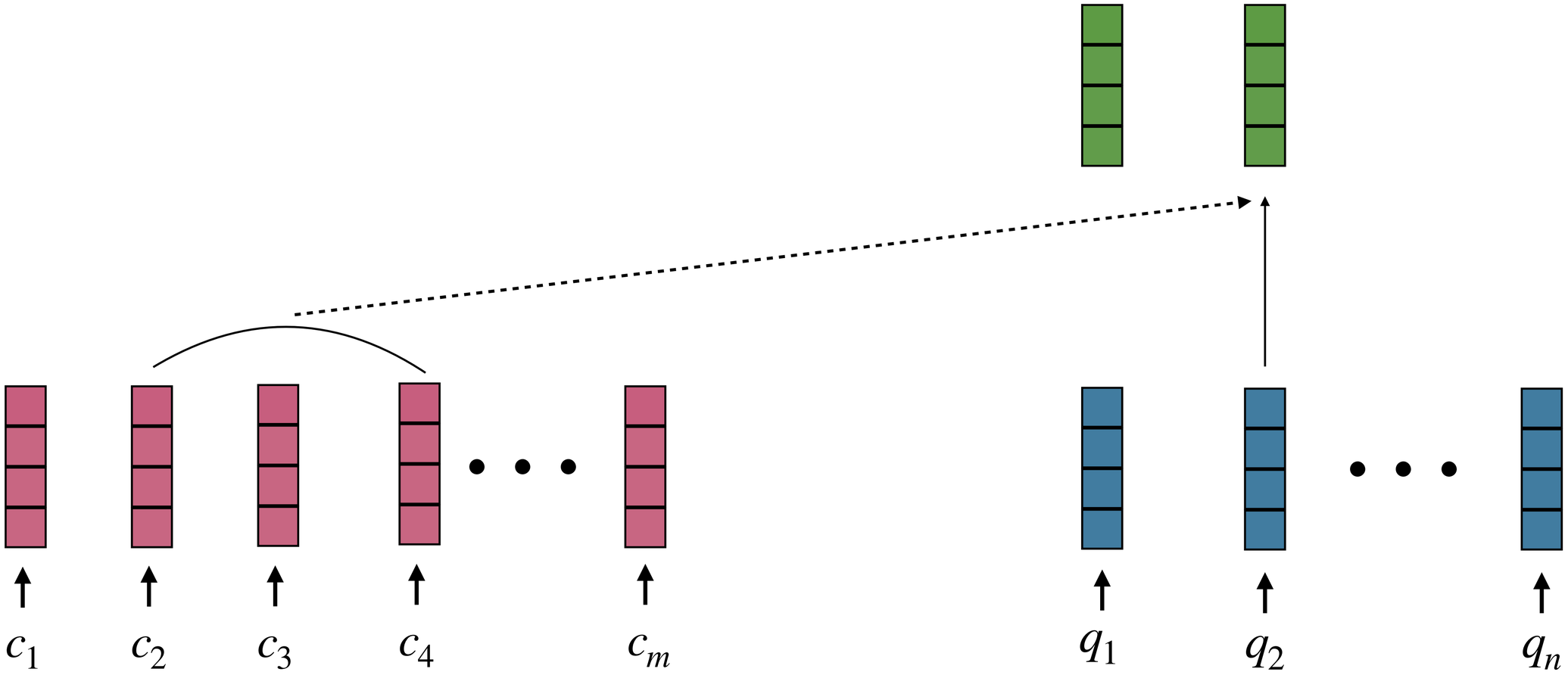
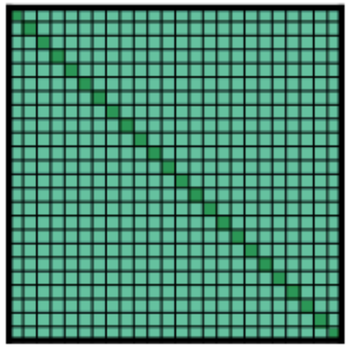
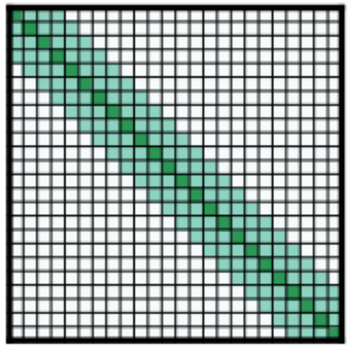


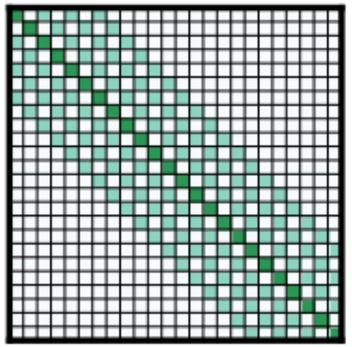
Sliding Window Attention



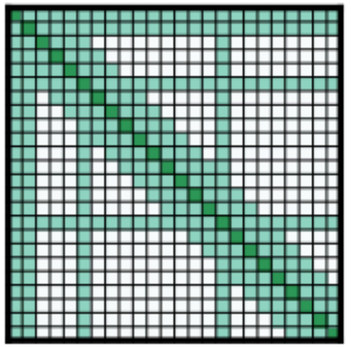
(a) Full n^2 attention



(b) Sliding window attention



(c) Dilated sliding window



(d) Global+sliding window

Implementation is NOT easy

Longformer (Beltagy, et al., 2020)

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- **Linear Attention: Decoupling Attention Matrix**
  - Lambda Network (Bello, et al., 2021)
  - Performer (Chor, et al., 2021)
  - Random Feature Attention (RFA) (Peng et al., 2021)
  - Recent works: H3, RetNet, RWKV, …

Linear Attention: Decoupling Attention Matrix

$$\sigma\left(\frac{QK^T}{\sqrt{d}}\right)V = \underbrace{A}_{n\times m} \times \underbrace{V}_{m\times d}$$

$$\approx \left(\underbrace{Q'}_{n\times k} \times \underbrace{(K')^T}_{k\times m}\right) \times \underbrace{V}_{m\times d}$$

$$\approx \underbrace{Q'}_{n\times k} \times \left(\underbrace{(K')^T}_{k\times m} \times \underbrace{V}_{m\times d}\right)$$

$$k \ll n, m$$

Decoupling Attention Matrix

- **Lambda Network** (Bello, 2021)

$$Q' = Q,\ (K')^T = \sigma\left(\frac{K^T}{\sqrt{d}}\right)$$

Decoupling Attention Matrix

- **Kernel Methods** (Chor, et al., 2021, Peng et al., 2021)

$$Q' = \phi(Q),\ \ (K')^T = \phi(K^T)$$

$$\phi(x) = \frac{1}{\sqrt{k}}\left[\sin(w_1^T x), \ldots, \sin(w_k^T x), \cos(w_1^T x), \ldots, \cos(w_k^T x)\right]$$

$$w_i \sim \mathcal{N}(0,\ \sigma^2 I)$$

$$\mathbb{E}_W\left[\phi(x)^T \phi(y)\right] = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$$

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- **Low-rank Approximation**
  - Linformer (Wang et al., 2020)
  - Luna (Ma et al., 2021)

Low-Rank Approximation

- **Motivation: projecting context C into a shorter length**

Linear Attention (Linformer, Wang et al., 2020)

$$\sigma\left(\frac{Q(EC)^T}{\sqrt{d}}\right)(FC)$$

$n \times l$ $\quad$ $l \times d$

$$l \ll n, m$$

$$E,\ F \in \mathbb{R}^{l \times m}$$

learnable parameters

Problems:

- Cannot model sequences with various lengths
- E and F do NOT contain contextual information

Linear Nested Attention: Pack & Unpack

- **Motivation: first packing context C into a shorter length, then unpacking with query Q**

Linear Attention

$$\underbrace{\sigma\left(\frac{Q(EC)^T}{\sqrt{d}}\right)}_{n\times l}\underbrace{(FC)}_{l\times d}$$

A nested attention

Pack Attention

$$C' = \underbrace{\sigma\left(\frac{PC^T}{\sqrt{d}}\right)}_{l\times m} \underbrace{C}_{m\times d}$$

$P \in \mathbb{R}^{l\times d}$

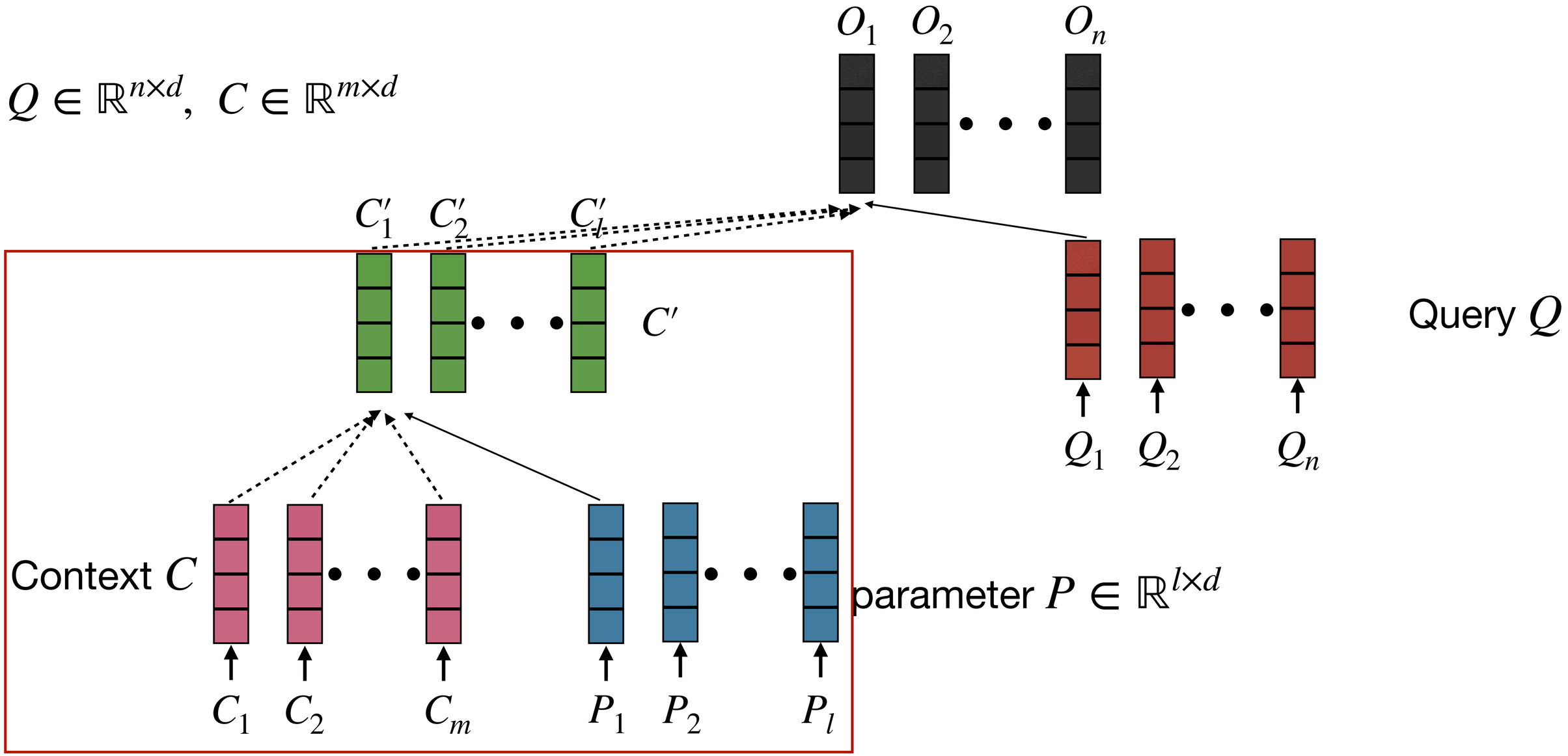
learnable parameters

Unpack Attention

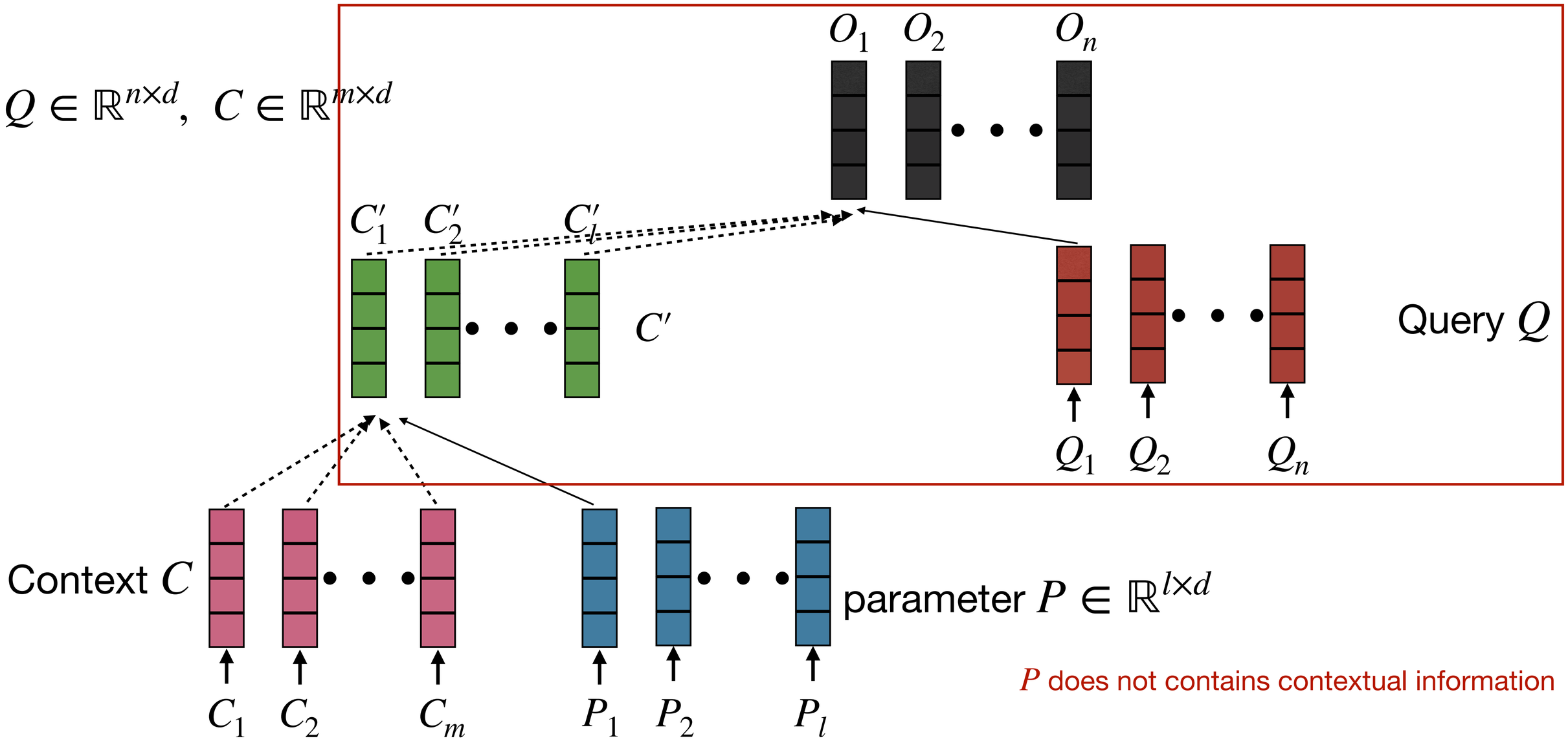
$$O = \underbrace{\sigma\left(\frac{Q(C')^T}{\sqrt{d}}\right)}_{n\times l} \underbrace{C'}_{l\times d}$$

Linear Nested Attention: Pack & Unpack

$Q \in \mathbb{R}^{n \times d},\ C \in \mathbb{R}^{m \times d}$



Linear Nested Attention: Pack & Unpack



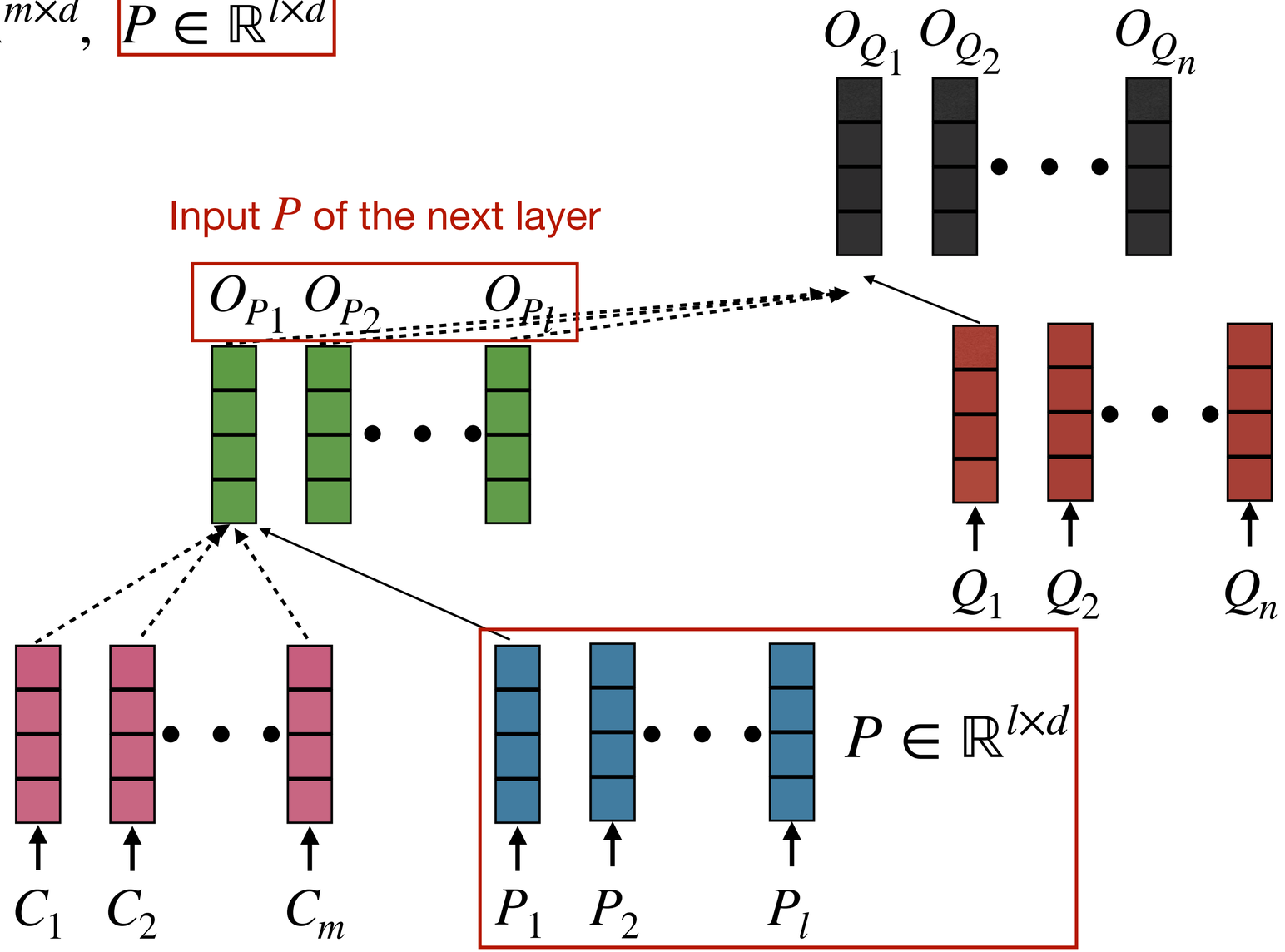
Luna: Linear Unified Nested Attention (Ma, et al., 2021)

Inputs: $Q \in \mathbb{R}^{n \times d}$, $C \in \mathbb{R}^{m \times d}$, $P \in \mathbb{R}^{l \times d}$

Outputs:

$$O_P = C' = \sigma\left(\frac{PC^T}{\sqrt{d}}\right)C$$

$$O_Q = \sigma\left(\frac{Q(C')^T}{\sqrt{d}}\right)C'$$

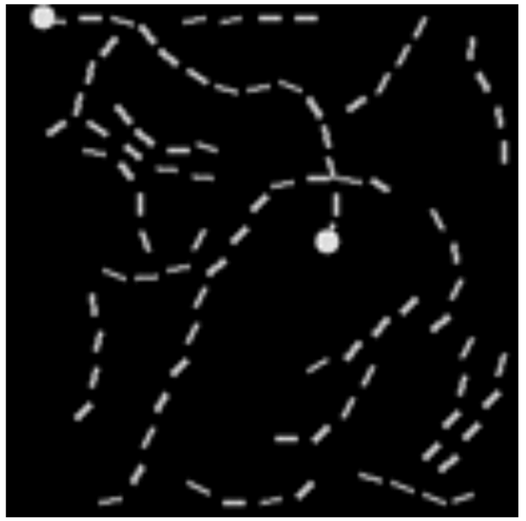


LRA: Long Range Arena

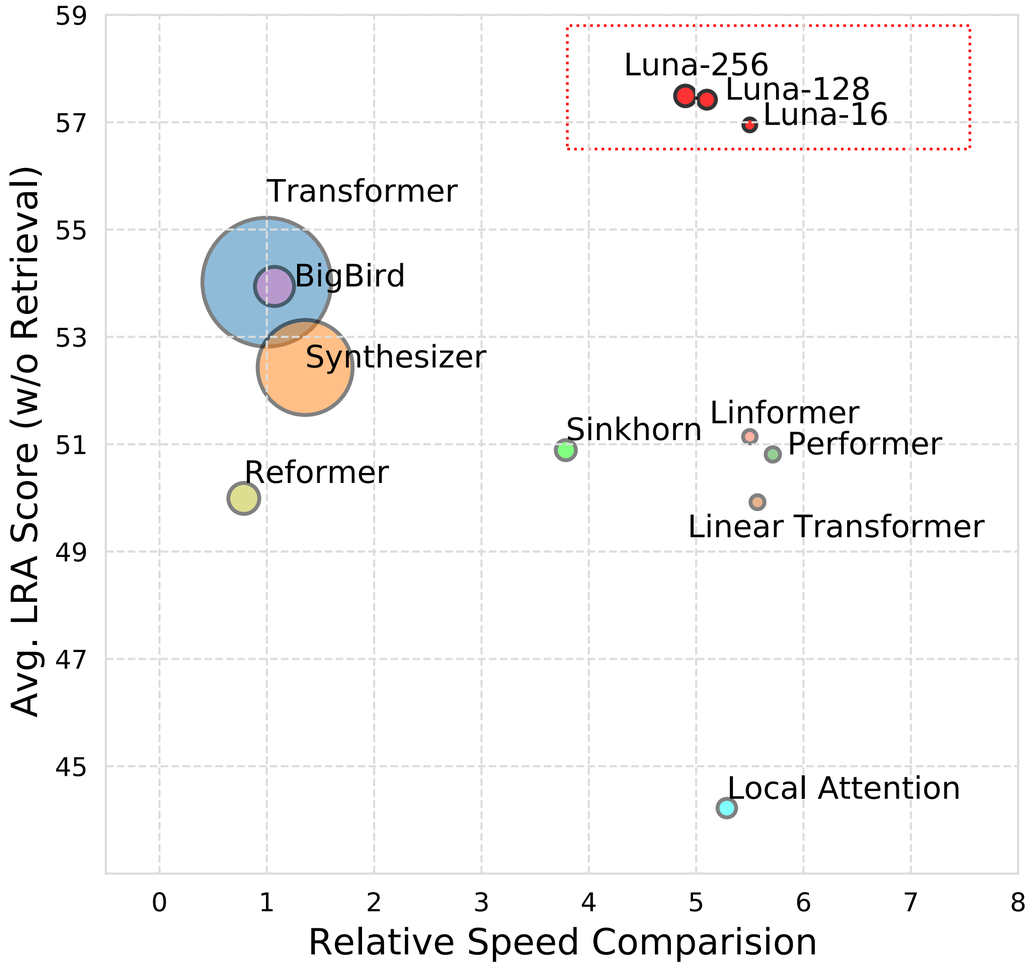
- **A benchmark of 6 tasks for long-range sequence modeling**
  - Intentionally designed to be challenging
- **Tasks**
  - Long ListOpts:

    INPUT: `[MAX 4 3 [MIN 2 3 ] 1 0 [MEDIAN 1 5 8 9, 2]]` **OUTPUT:** `5`

  - Byte-level text classification on IMDB (> 4k tokens)
  - Byte-level document retrieval on ACL Anthology Network (ANN) (> 2k tokens)
  - Pixel-level image classification on CIFAR-10 (32x32 = 1024 token
  - PathFinder (32x32 = 1024 tokens)
  - Path-X (Extreme Length: 128x128 = 16,384 tokens)

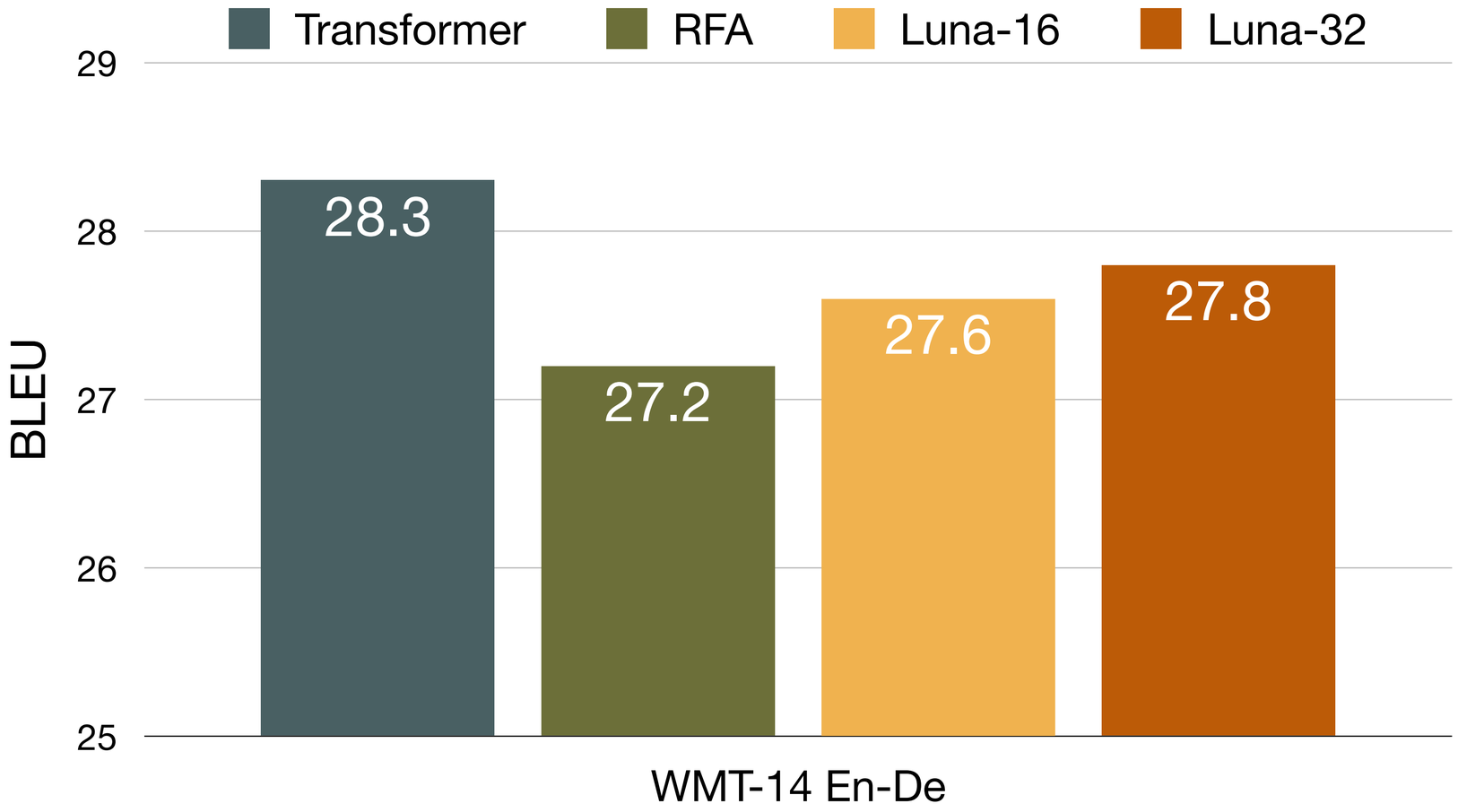


Performance on LRA



Trade-off between accuracy (y-axis), speed (x-axis) and memory (circle-radius)

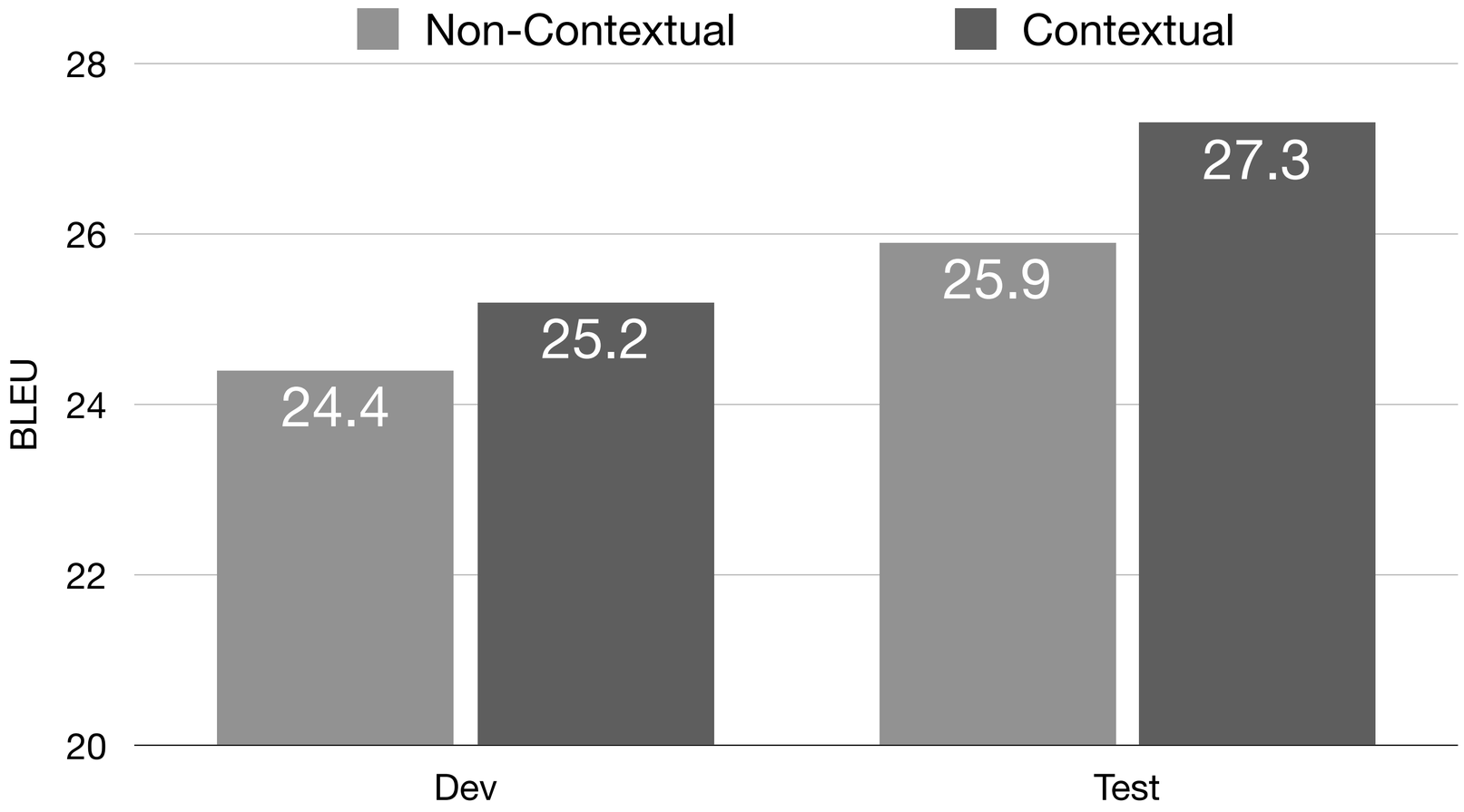
Results: Machine Translation



RFA: random feature attention (Peng et al., 2021)

All models were optimized with Apollo (Ma 2020)

Effect of Contextual P



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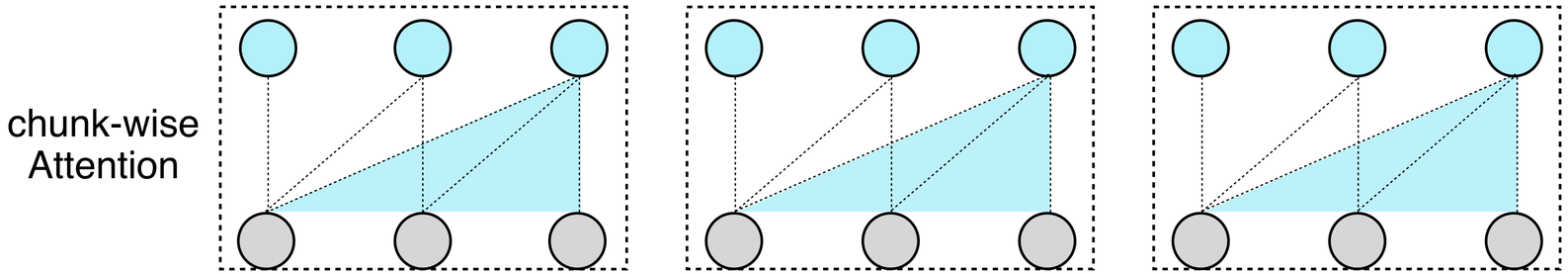
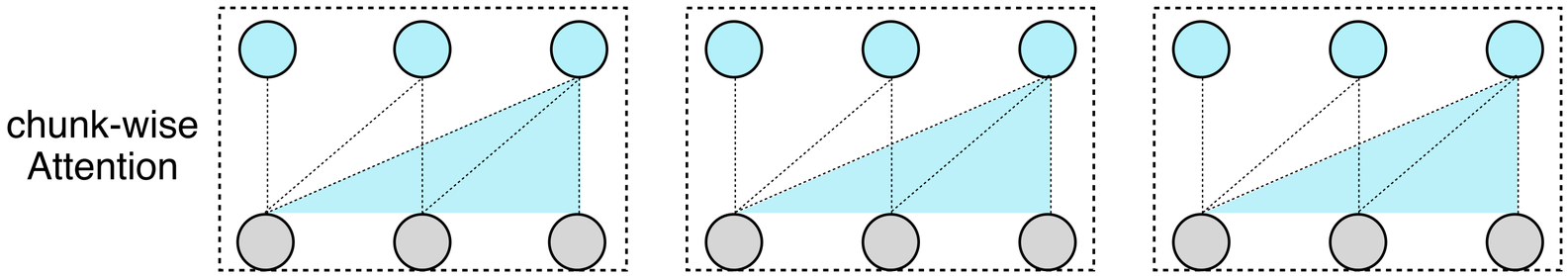
Why not Chunk-wise Attention?

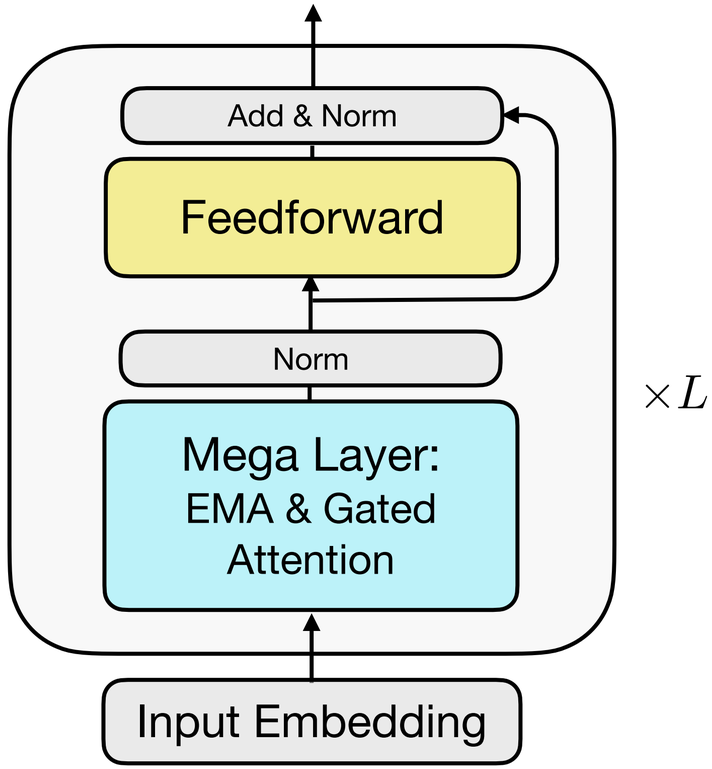
- Applying attention individually to each chunk with fixed length



Mega: Executive Summary

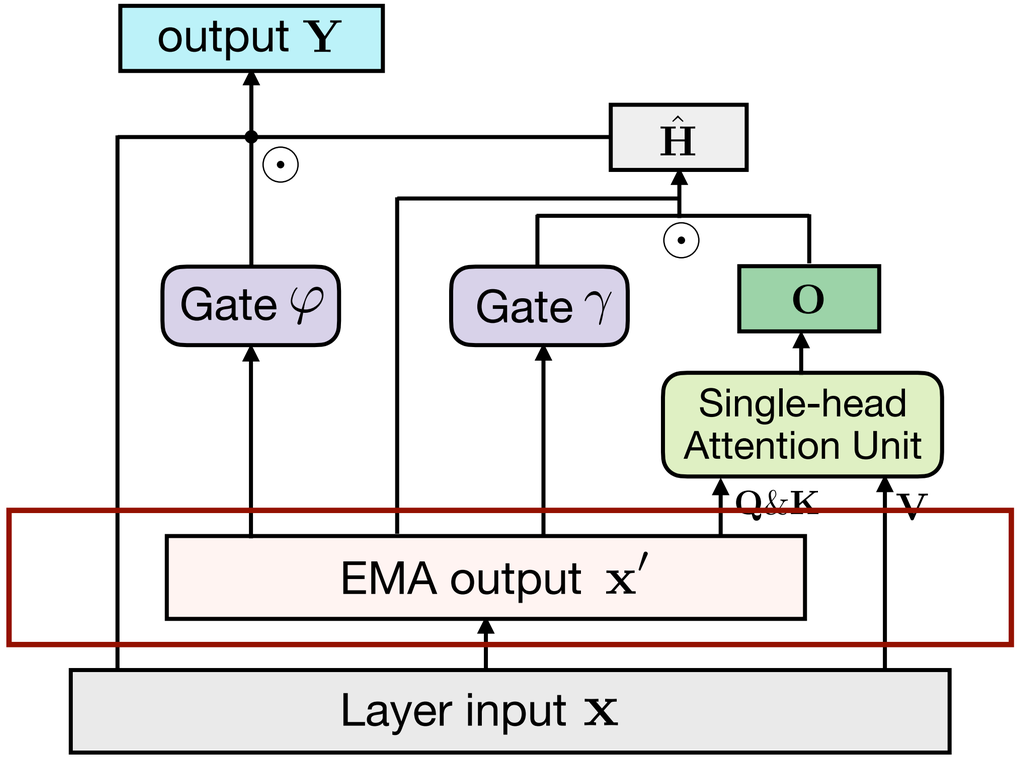
- **Effective and efficient drop-in replacement of attention for long sequence modeling**
  - Outstanding results on various types of data
    - text, images and audios
  - Exponential Moving Average (EMA)
  - Mega-chunk: linear complexity of time and space





Mega Architecture: Outline

- **Exponential Moving Average (EMA)**
  - Local dependencies that decaying exponentially over time



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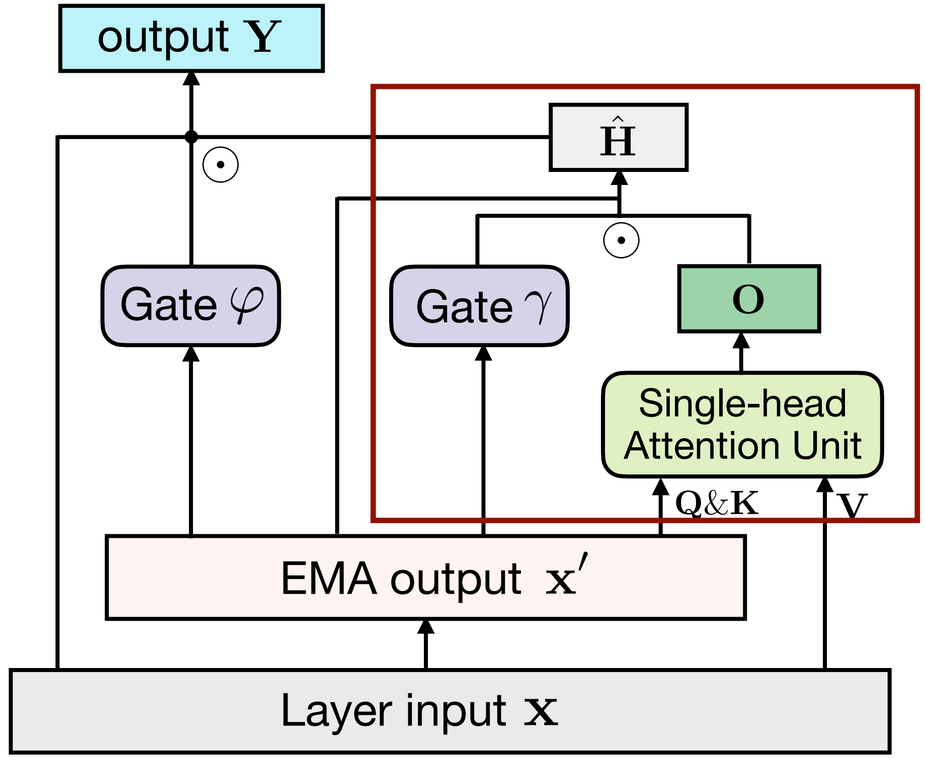
  - Adding a reset gate to the attention output
  - Theoretically proving that single-head gated attention is as expressive as multi-head one



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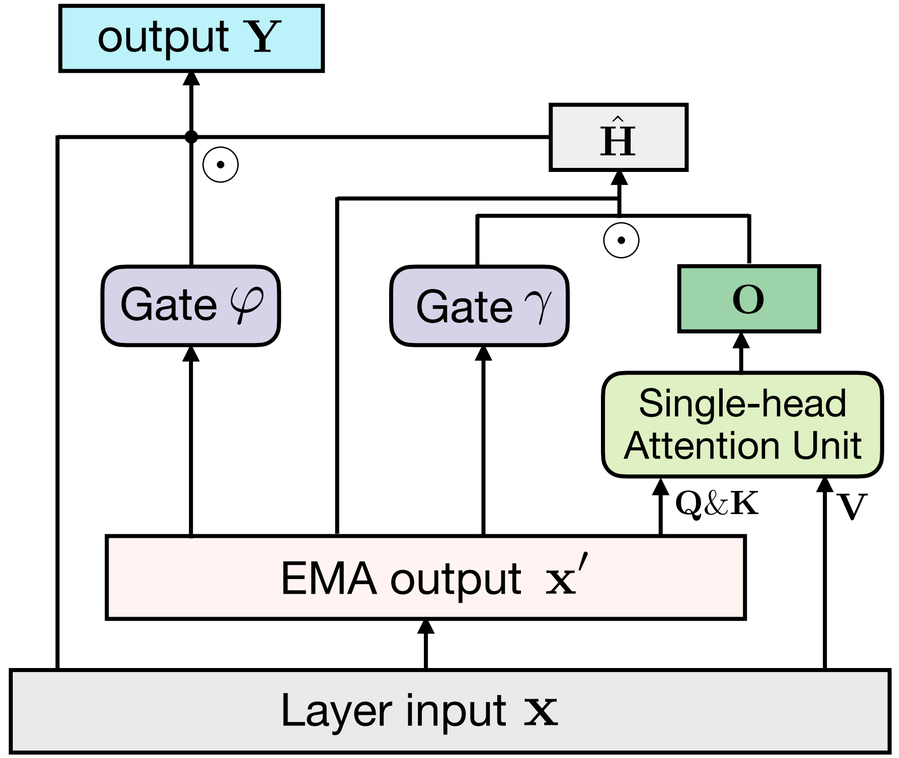
- **Mega-Chunk**
  - Applying attention to local chunks of fixed length
  - Reducing quadratic complexity to linear



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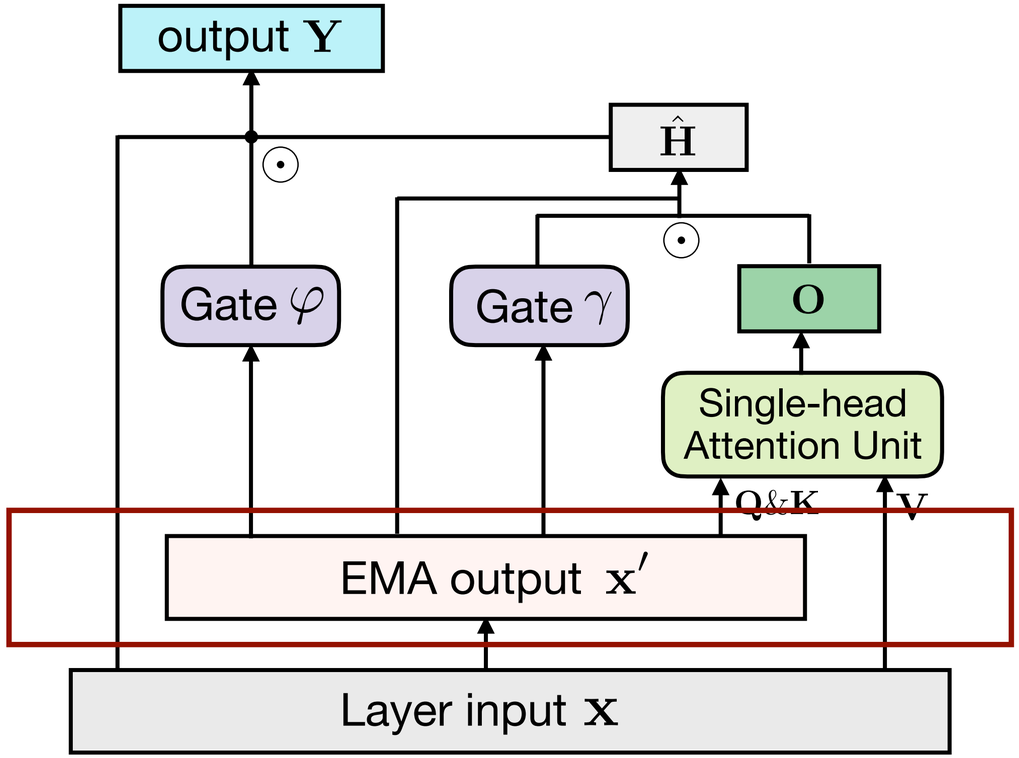
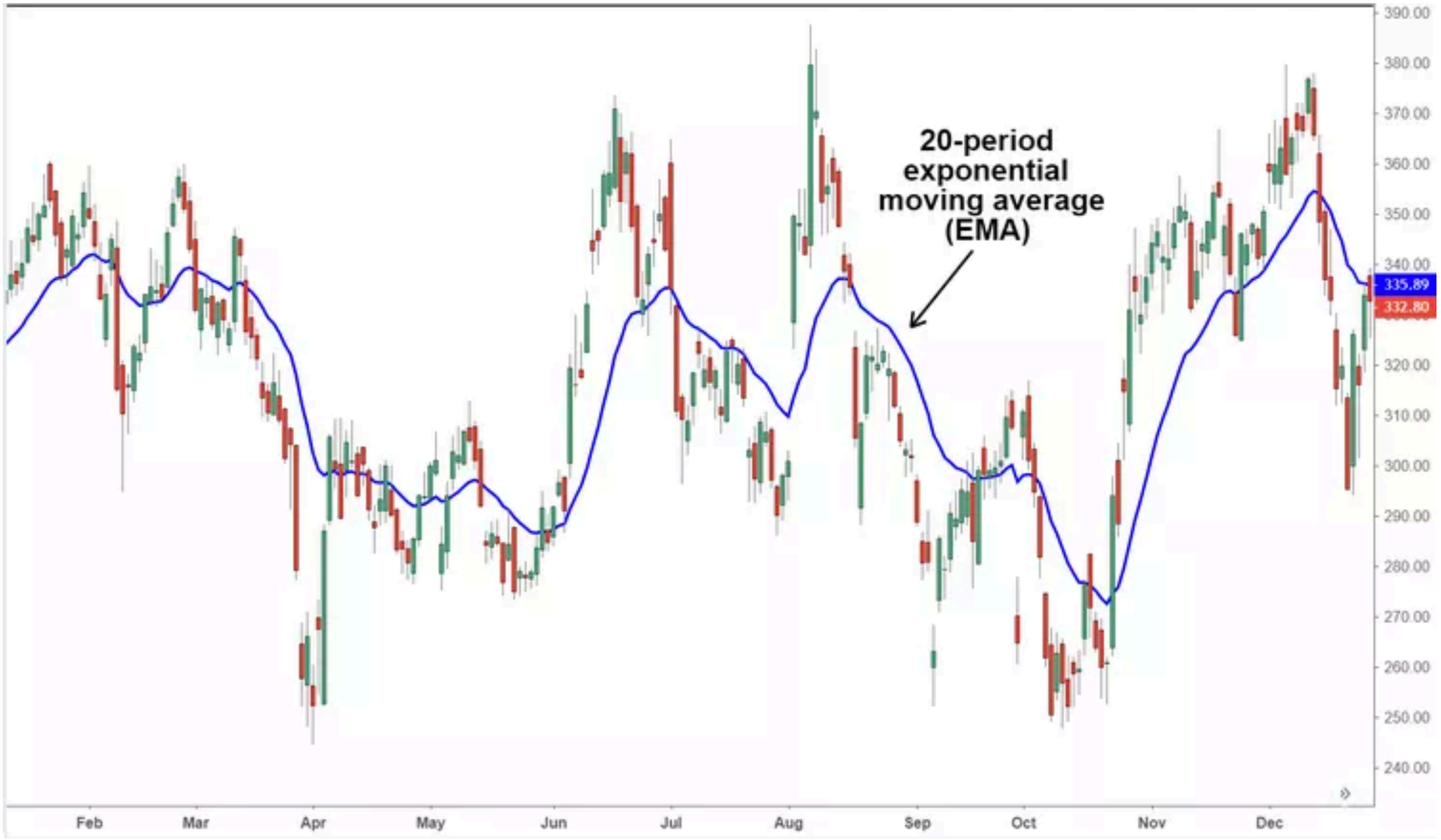


Exponential Moving Average (EMA)



Exponential Moving Average (EMA)

Notations: Assuming 1-dim input sequence $\mathbf{x} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\}$, $\mathbf{x}_t \in \mathbb{R}$

EMA

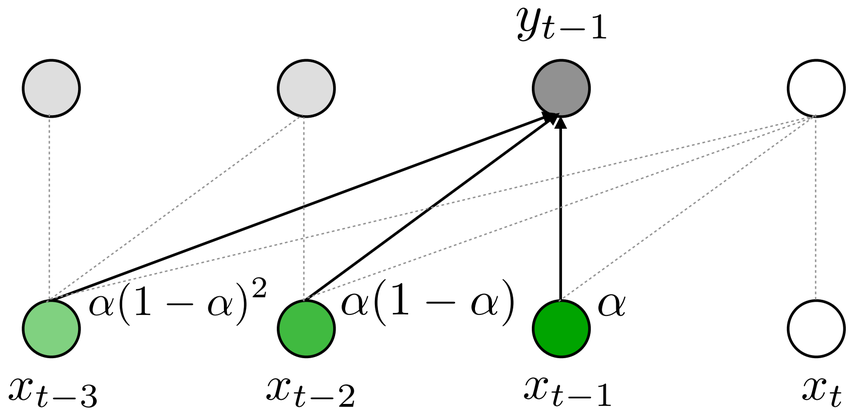
$$\mathbf{y}_t = \boldsymbol{\alpha} \odot \mathbf{x}_t + (1 - \boldsymbol{\alpha}) \odot \mathbf{y}_{t-1}, \quad \boldsymbol{\alpha} \in (0, 1)$$

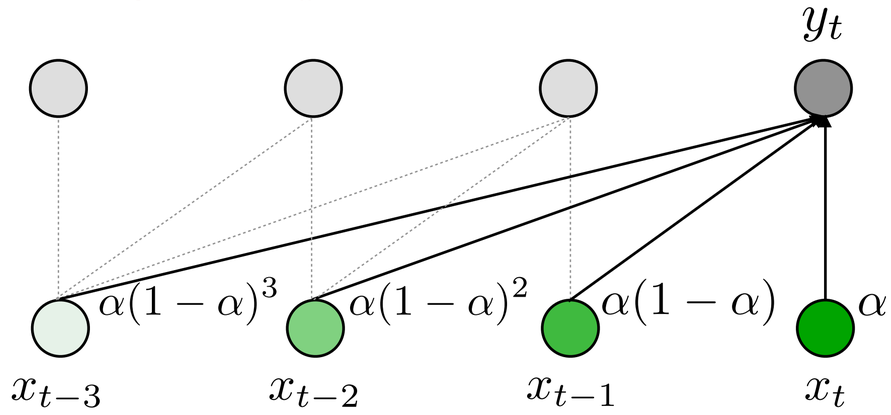
Damped EMA

$$\mathbf{y}_t = \boldsymbol{\alpha} \odot \mathbf{x}_t + (1 - \boldsymbol{\alpha} \odot \boldsymbol{\delta}) \odot \mathbf{y}_{t-1}, \quad \boldsymbol{\delta} \in (0,1)$$

Learnable Parameters

Relaxing the coupled weights



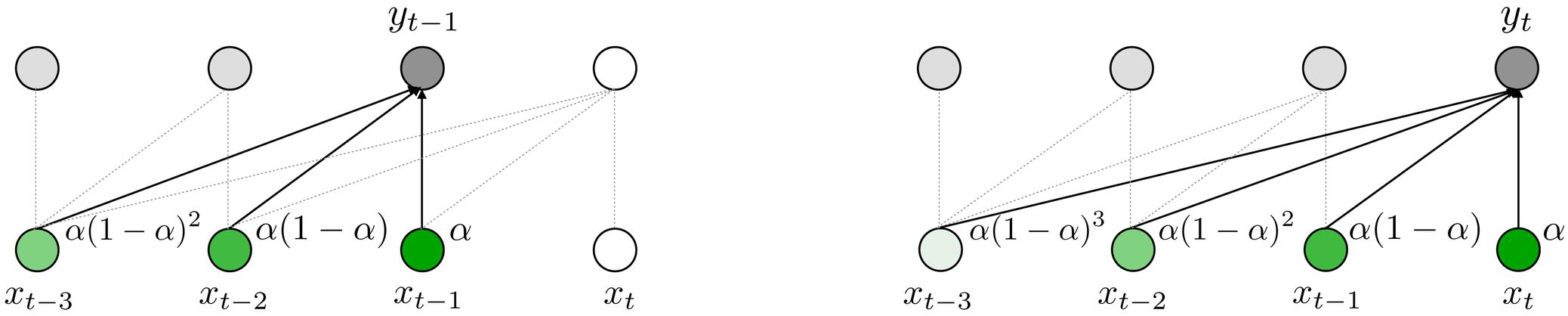


Efficient Algorithm for EMA

- **Efficiently compute EMA outputs of all tokens in parallel**

$$\mathbf{y}_t = \boxed{\boldsymbol{\alpha}} \odot \mathbf{x}_t + \boxed{(1 - \boldsymbol{\alpha} \odot \boldsymbol{\delta})} \odot \mathbf{y}_{t-1}$$

EMA weights are input independent



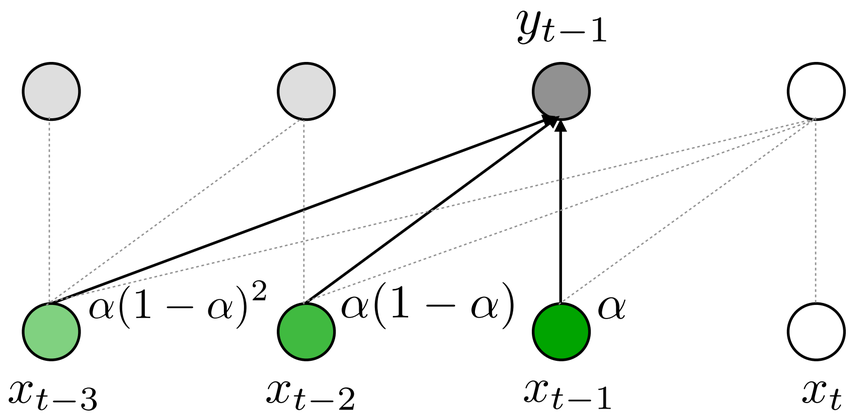
We can compute the weights for each input tokens in advance and compute EMA with FFTs.

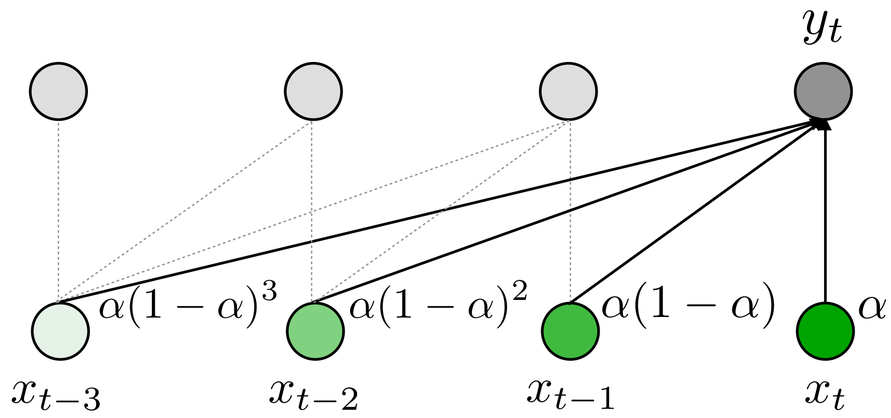
Extending EMA to Multi-dimensional Input

- **How to apply EMA to vector input $\mathbf{X}_t \in \mathbb{R}^d$**
  - Stacking d individual EMA layers
  - Dimension-independent: no interactions across different dimensions
  - Implementation via vectorization

EMA: Summary

- **Strong Inductive Bias**
  - Favors recent, local contexts
  - In principle, can peek unbounded context history
- **Efficient to compute and easy to learn**
  - Parallel computation
  - Less parameters & capacity
  - Extremely simplified state space model



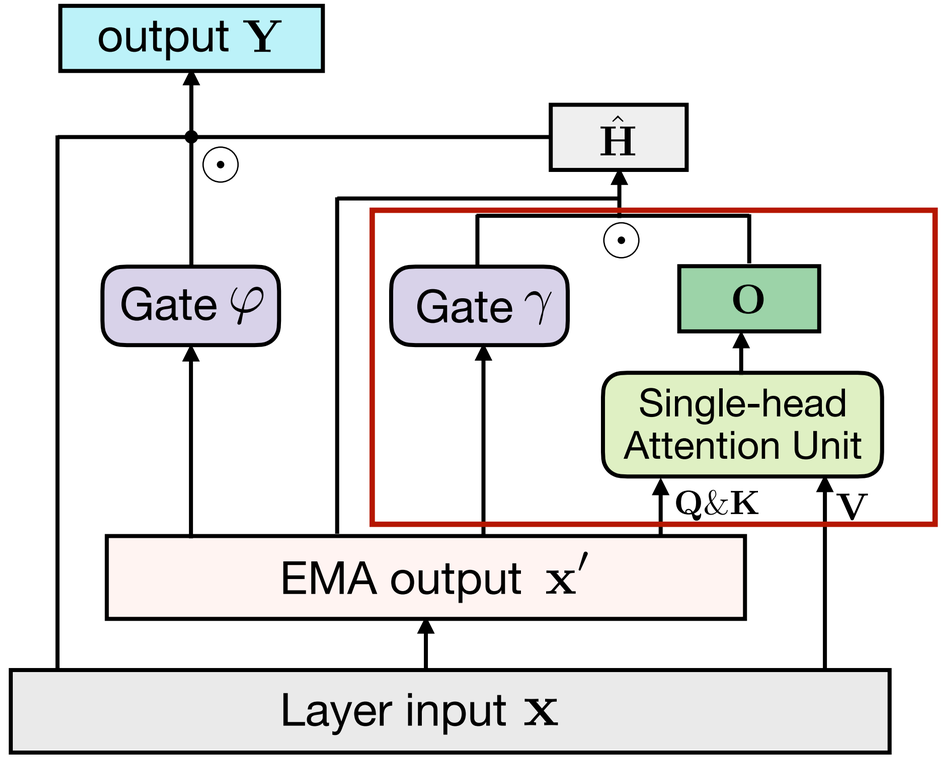


Mega Architecture: Outline

- Exponential Moving Average (EMA)
  - Local dependencies that decaying exponentially over time
  - Connection with State Space Models (e.g S4)

- **Single-head Gated Attention**
  - Adding a reset gate to the attention output
  - Theoretically proving that single-head gated attention is as expressive as multi-head one

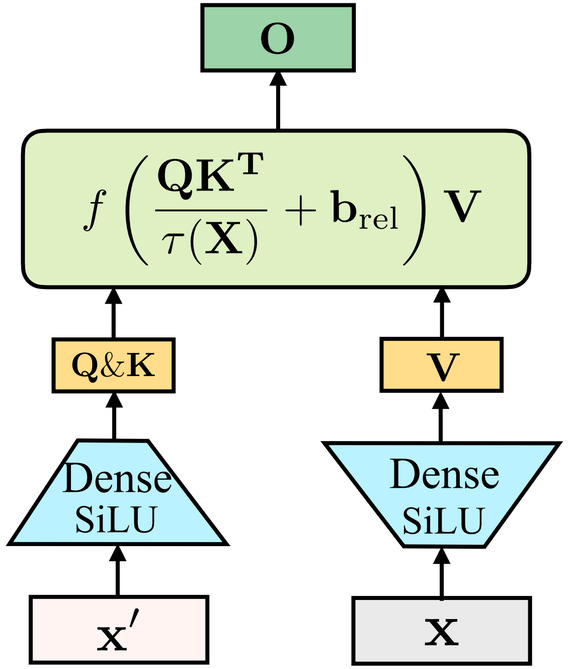
- Mega-Chunk
  - Applying attention to local chunks of fixed length
  - Reducing quadratic complexity to linear



Single-head Gated Attention

- **Adding a reset gate to the attention output**

Attention: $$O = \text{softmax}\left(\frac{QK^T}{\tau(X)} + b_{\text{rel}}\right)V$$



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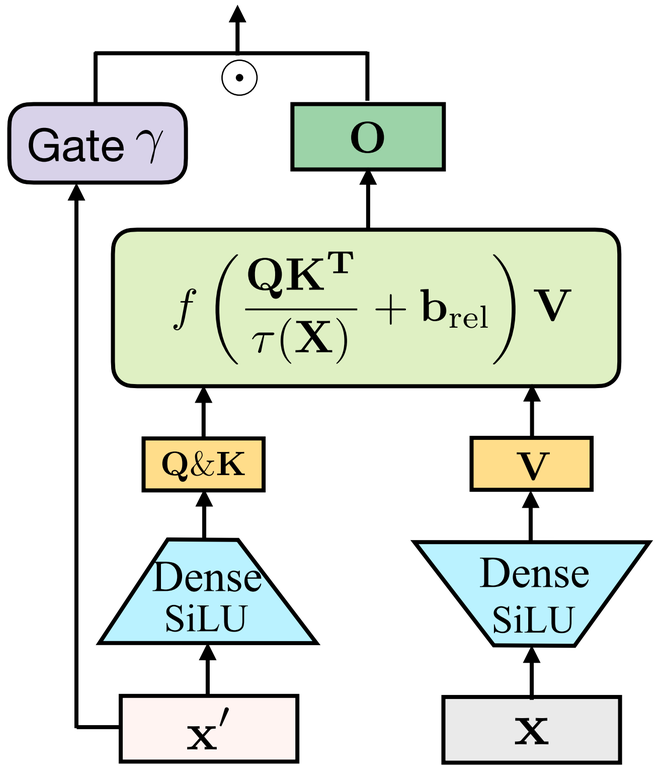
Gated Attention: $$\gamma = \mathcal{G}(X)$$

$$O_{\text{SHGA}} = O \odot \gamma$$

$\mathcal{G}()$ is a transform, e.g. an MLP



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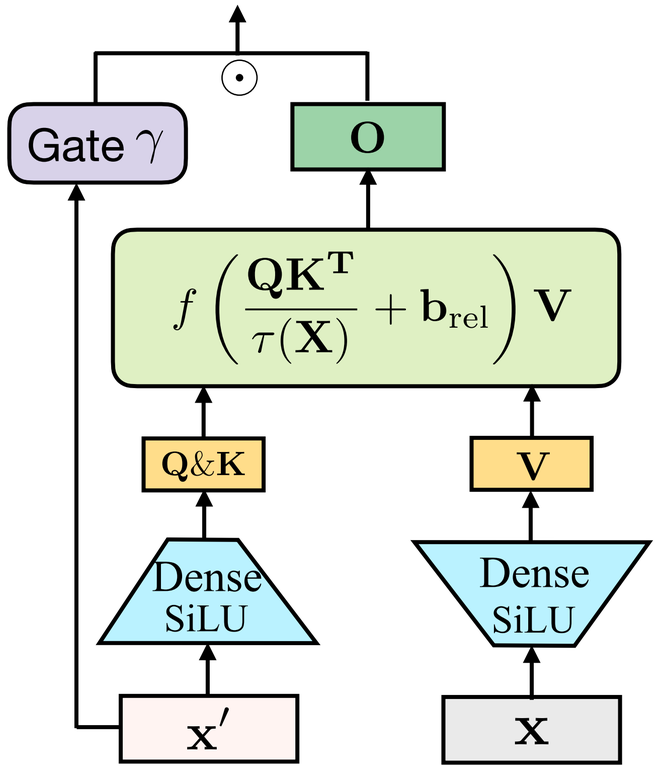

- **Single-head gated attention is as expressive as multi-head one**

Theorem: *Suppose the transformation $\mathcal{G}$ is a universal function approximator. Then, for each $\boldsymbol{X}$ there exists $\boldsymbol{\gamma} = \mathcal{G}(\boldsymbol{X})$ such that* $\boldsymbol{O}_{\text{SHGA}} = \boldsymbol{O}_{\text{MHA}}$

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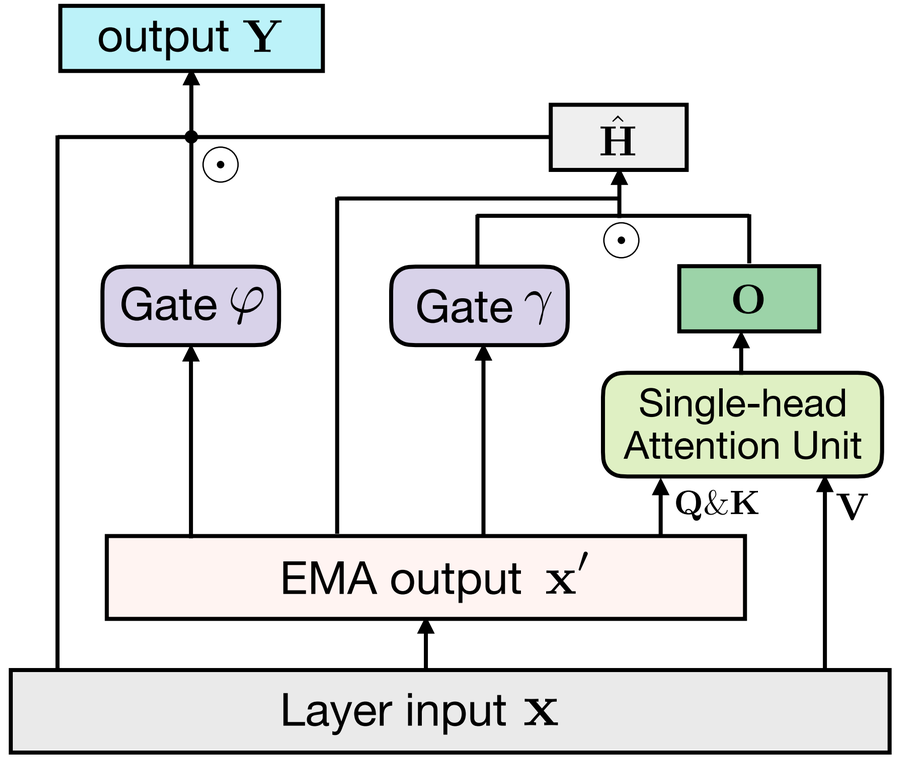
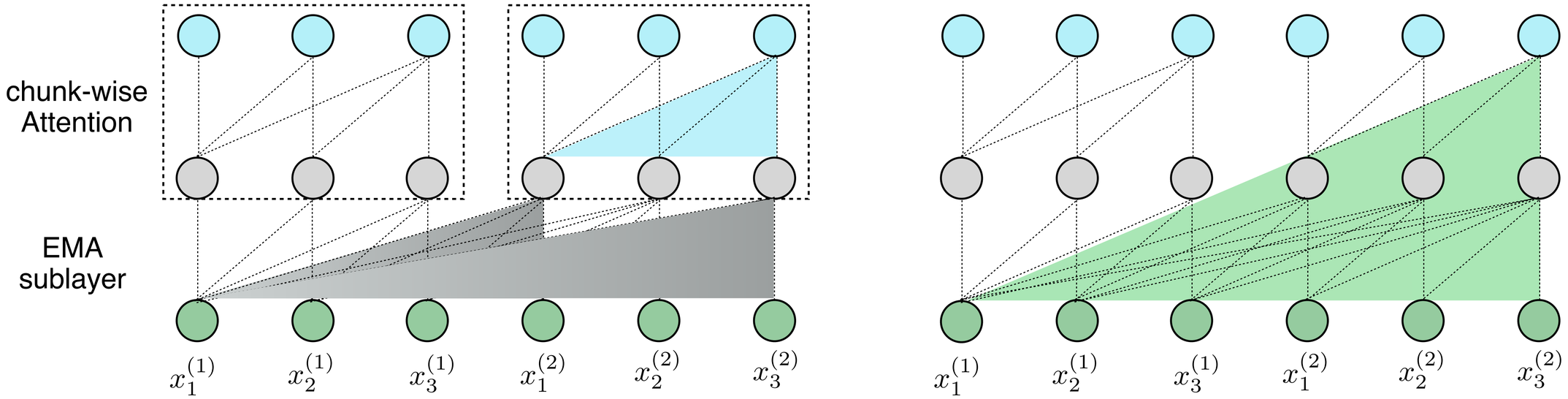


- **Mega-Chunk**
  - Applying attention to local chunks of fixed length
  - Reducing quadratic complexity to linear

Mega-Chunk: Efficient Mega

- Split input sequences into multiple chunks with fixed length
- Applying attention individually to each chunk
  - Linear complexity & easy implementation
  - Losing contextual information between chunks
  - Fortunately, EMA preserves the loss of information from previous chunks



Experiments

- **Long Range Arena (LRA)**
  - 3 tasks on byte-level text classification
  - 3 tasks on pixel-level image classification
- **Language Modeling**
  - Enwiki8 (character-level)
  - WikiText-103 (Word-level)
- **Machine Translation**
  - WMT'14 English - German
- **Image Classification**
  - ImageNet-1K
- **Raw Speech Classification**
  - Speech Commands

Experimental Results

	LRA	WMT'14	WikiText-103	ImageNet	Raw-SC
XFM	59.24	27.68	18.66	81.80	31.24
S4	85.86	—	20.95	—	**97.50**
Mega	**88.21**	**29.01**	**18.07**	**82.35**	97.30

Analysis on LRA: Accuracy & Efficiency

Models	ListOps	Text	Retrieval	Image	Pathfinder	Path-X	Avg.	Speed	Mem.
XFM	36.37	64.27	57.46	42.44	71.40	✗	54.39	–	–
XFM‡	37.11	65.21	79.14	42.94	71.83	✗	59.24	1×	1×
Reformer	37.27	56.10	53.40	38.07	68.50	✗	50.67	0.8×	0.24×
Linformer	35.70	53.94	52.27	38.56	76.34	✗	51.36	5.5×	0.10×
BigBird	36.05	64.02	59.29	40.83	74.87	✗	55.01	1.1×	0.30×
Performer	18.01	65.40	53.82	42.77	77.05	✗	51.41	**5.7**×	**0.11**×
Luna-256	37.98	65.78	79.56	47.86	78.55	✗	61.95	4.9×	0.16×
S4-v1	58.35	76.02	87.09	87.26	86.05	88.10	80.48	–	–
S4-v2	59.60	86.82	90.90	88.65	94.20	96.35	86.09	–	–
S4-v2‡	59.10	86.53	90.94	88.48	94.01	96.07	85.86	4.8×	0.14×
MEGA	**63.14**	**90.43**	**91.25**	**90.44**	**96.01**	**97.98**	**88.21**	2.9×	0.31×
MEGA-chunk	58.76	90.19	90.97	85.80	94.41	93.81	85.66	5.5×	0.13×

Limitations of Mega

- **Mode Capacity vs. Full Attention**
  - Limited capacity of EMA sub-layer
    - Mega-chunk fails behind Mega w. full attention

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  - Limited capacity of EMA sub-layer
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- **Architectural Divergence on Difference Data Modalities**
  - Not only for Mega, but for almost all architectures
  - Different normalization layers on different positions
    - Batch Norm vs. Layer Norm vs. RMS Norm vs Scale Norm vs. …
    - Pre-Norm vs. Post-Norm vs. QK-Norm vs. …
  - Different attention functions
    - Softmax vs. ReLU2 vs. Laplace vs …
  - …

Unified Architecture for Multi-Modality

- **Why a Unified Architecture Important for Multi-modality?**
  - A unified foundation model learning from various types of signals

Limitations of Mega

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  - Different attention functions
    - Softmax vs. ReLU2 vs. Laplace vs …
  - …
- **No Evidences or Results for Mega's Scalability**
  - Large-scale pretraining with Mega?

Megalodon: An Improved Version of Mega

- **Complex Exponential Moving Average**
  - Extending EMA to the Complex Field
- **Timestep Normalization**
  - Auto-regressive group normalization across sequential dimension
- **Numerical Stability**
  - Normalized Attention
  - Pre-Norm w. Top-hop Residual

Megalodon: Results on Small-Scale Benchmarks

	LRA	SC	ImageNet	Enwiki8	WT103
S4	85.86	97.50	—	—	20.95
XFM	59.24	xx	81.8	1.08	18.66
Mega-chunk	85.66	96.92	—	1.02	18.07
Mega	88.21	—	82.35	—	—
Megalodon-chunk	**87.62**	**98.14**	**—**	**1.00**	**17.23**
Megalodon	**88.63**	**—**	**83.12**	**—**	**—**

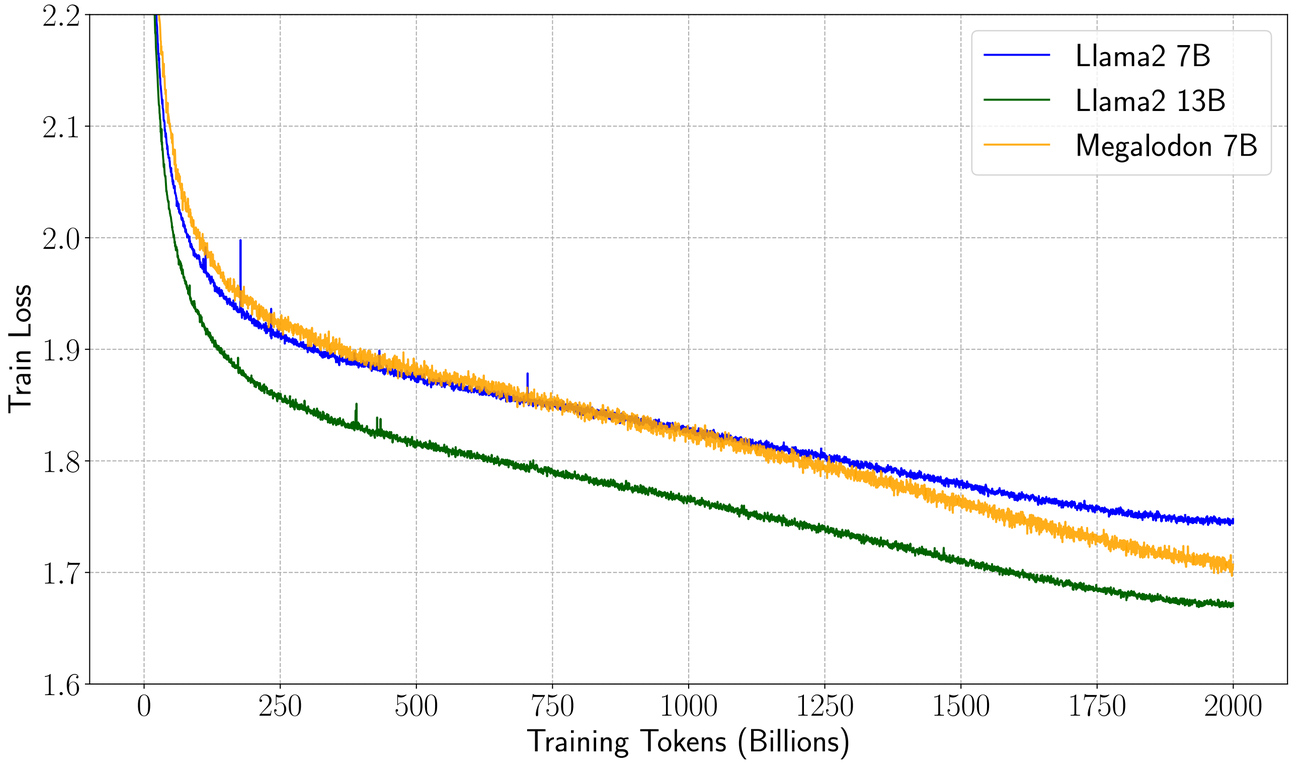
Importantly! All the experiments were conducted using exactly the same architecture!

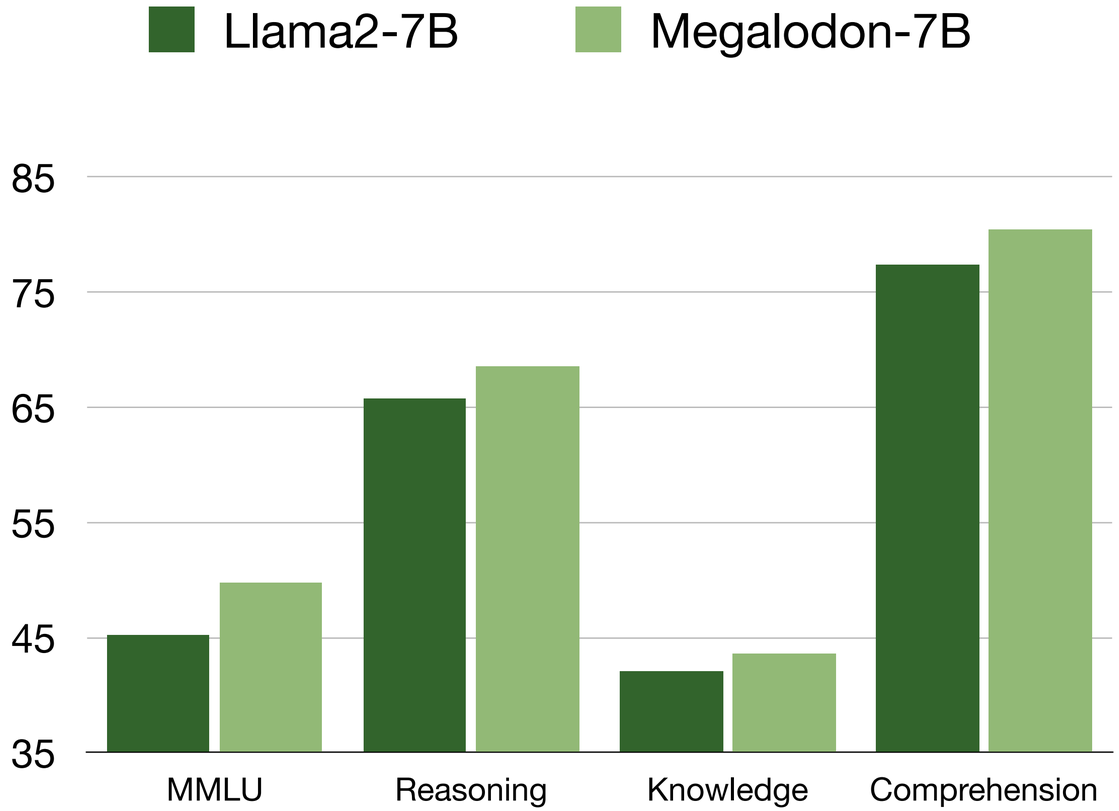
Megalodon on LLM Pretraining

- **Pretraining Data**
  - 2 trillion tokens
  - Exactly the same with Llama2 for head-to-head comparison
- **Architecture Hyperparameters**
  - Closely following Llama2
    - 7B parameters
    - 32 blocks, model dimension 4096
    - Rotary positional embedding (RoPE)
  - Differences
    - 4 attention heads (32 in Llama2)
    - 32K context length w. 4K attention chunk size (4K full attention in Llama2)

Efficiency of Megalodon-7B

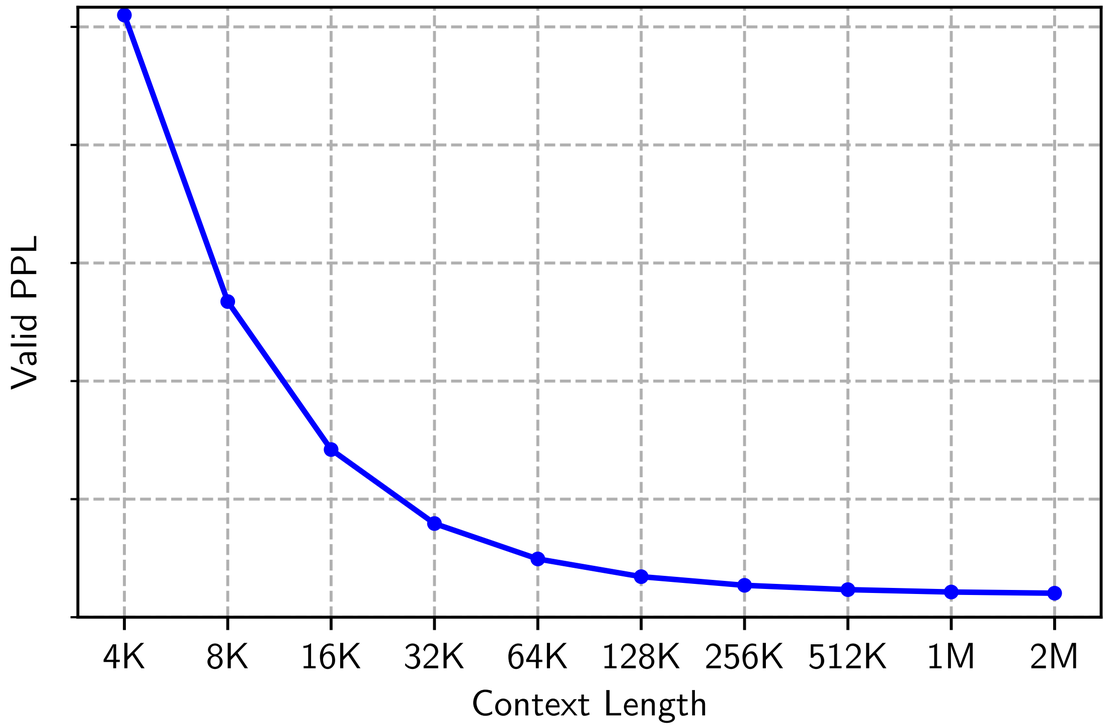
- **Data Efficiency**





Long-Context Modeling

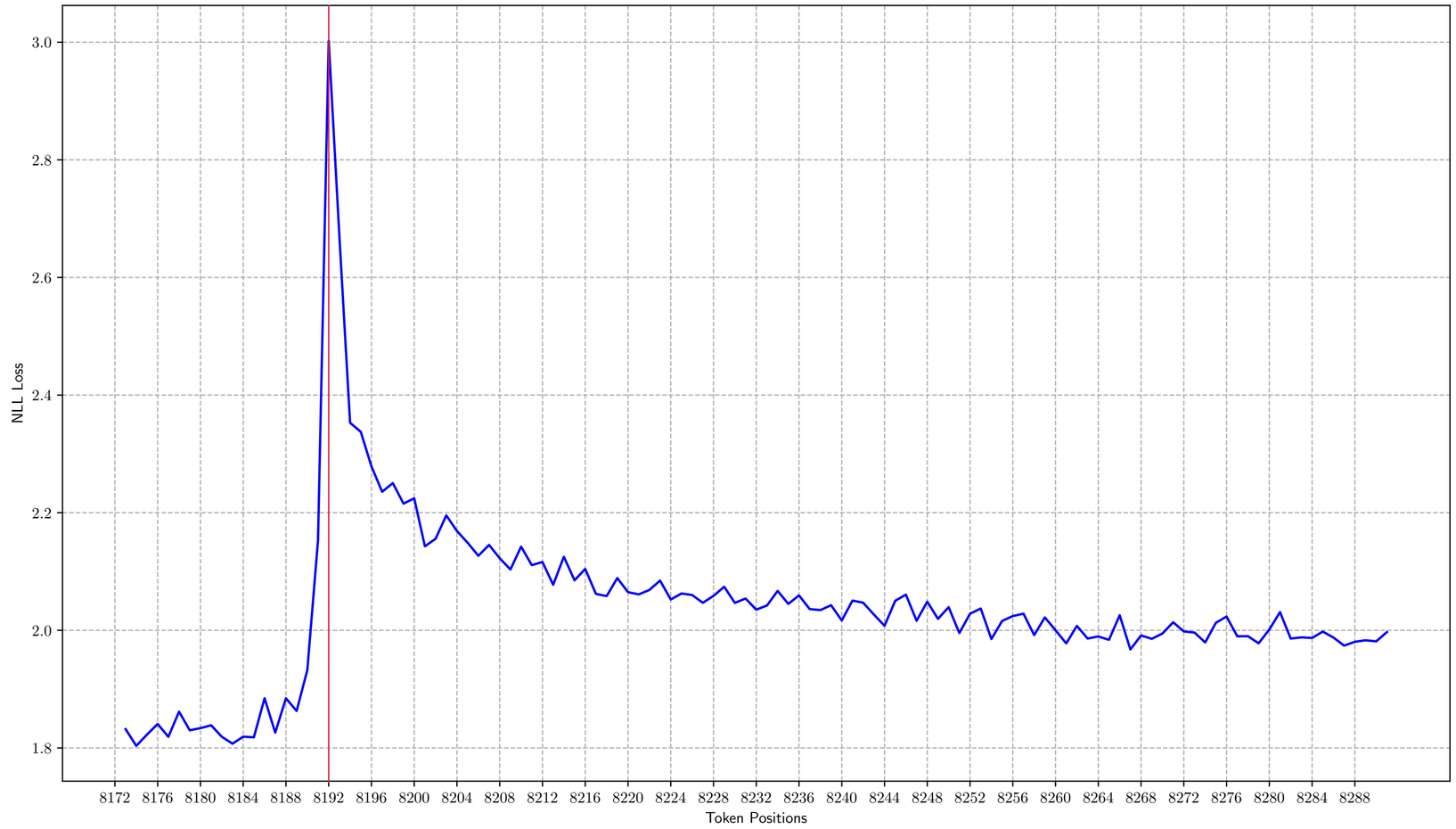
- **Long-Context Evaluation of Megalodon-7B**
  - Perplexity w. various context lengths
  - Long-context QA tasks in Scrolls



Model	NaQA	Qasper	QMSum
Xgen	17.4	20.5	6.8
MPT	18.8	24.7	8.8
Yarn	20.9	26.2	11.4
LLAMA2	18.8	19.8	10.1
LLAMA2-L*	23.5	**28.3**	**14.5**
MEGALODON	**23.9**	28.0	13.1

Existing Problems of Megalodon

- Validation losses on positions before and after chunk boundaries increase significantly



Thanks!
Q&A