11868 LLM Systems

Accelerating Transformer Training and Inference

Lei Li

Project Team Formation

- https://forms.gle/gCggBdC6LEAuQEnh7
- Project proposal: Feb. 28th 23:59 ET
- Mid-term report: April 1st 23:59 ET
- Final Report: April 30th 23:59 ET

Paper Presentation

- Each group needs to turn in slides (and code example if available) one week in advance (hard deadline)
- We will give feedbacks
- All team member will prepare and present the work in 45~50mins
- 25-30 mins for group discussion
- We will give in-class quiz problems

LightSeq: A High Performance Inference Library for Transformers

NAACL 2021

Xiaohui Wang, Ying Xiong, Yang Wei, Mingxuan Wang, Lei Li

TurboTransformers: An Efficient GPU Serving System For Transformer Models

PPoPP 2021

Jiarui Fang, Yang Yu, Chengduo Zhao, Jie Zhou

LightSeq2: Accelerated Training for Transformer-based Models on GPUs

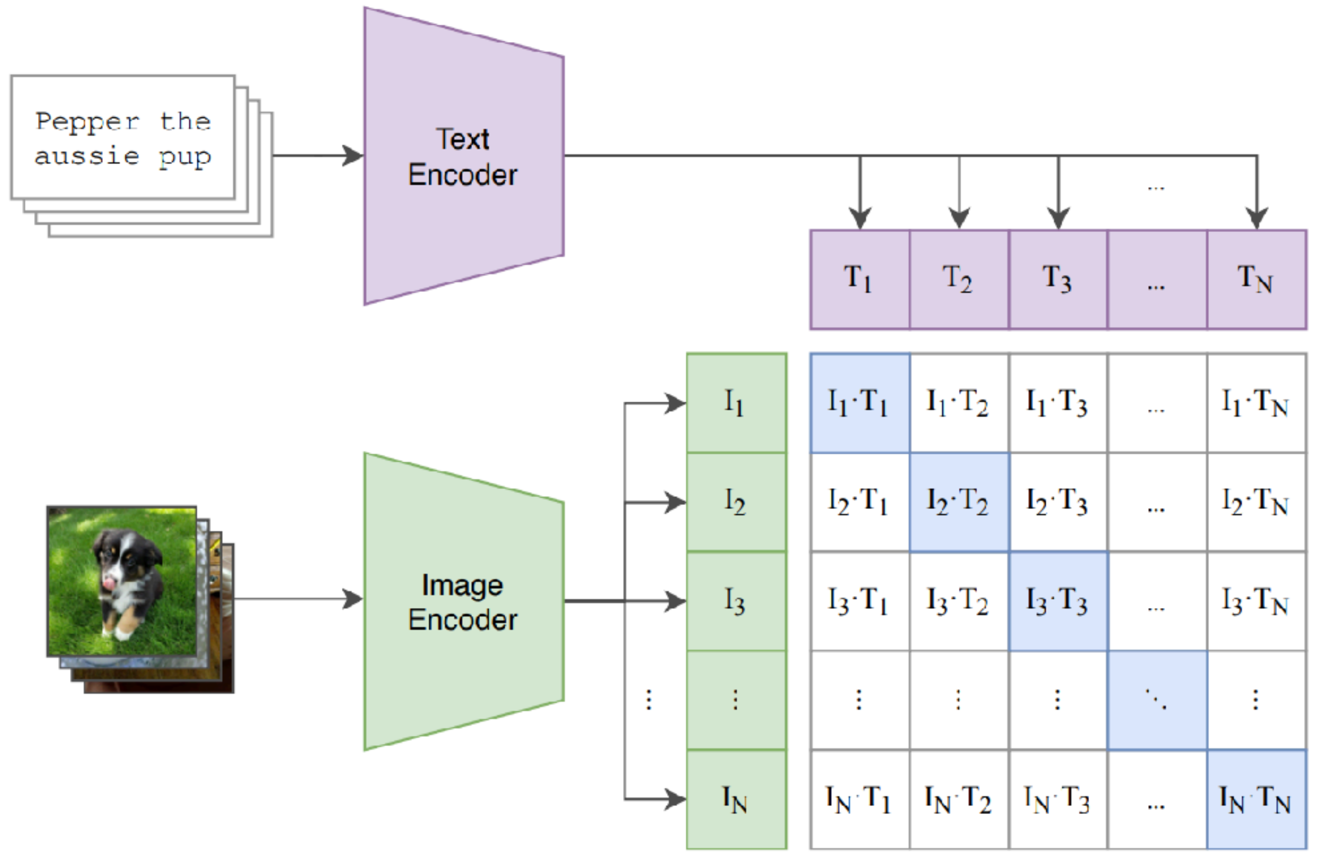
SC22 Dallas, TX hpc accelerates.

Xiaohui Wang, Wei Yang, Ying Xiong, Guyue Huang, Xian Qian, Yufei Ding, Mingxuan Wang, Lei Li

TensorRT-LLM (FasterTransformer)

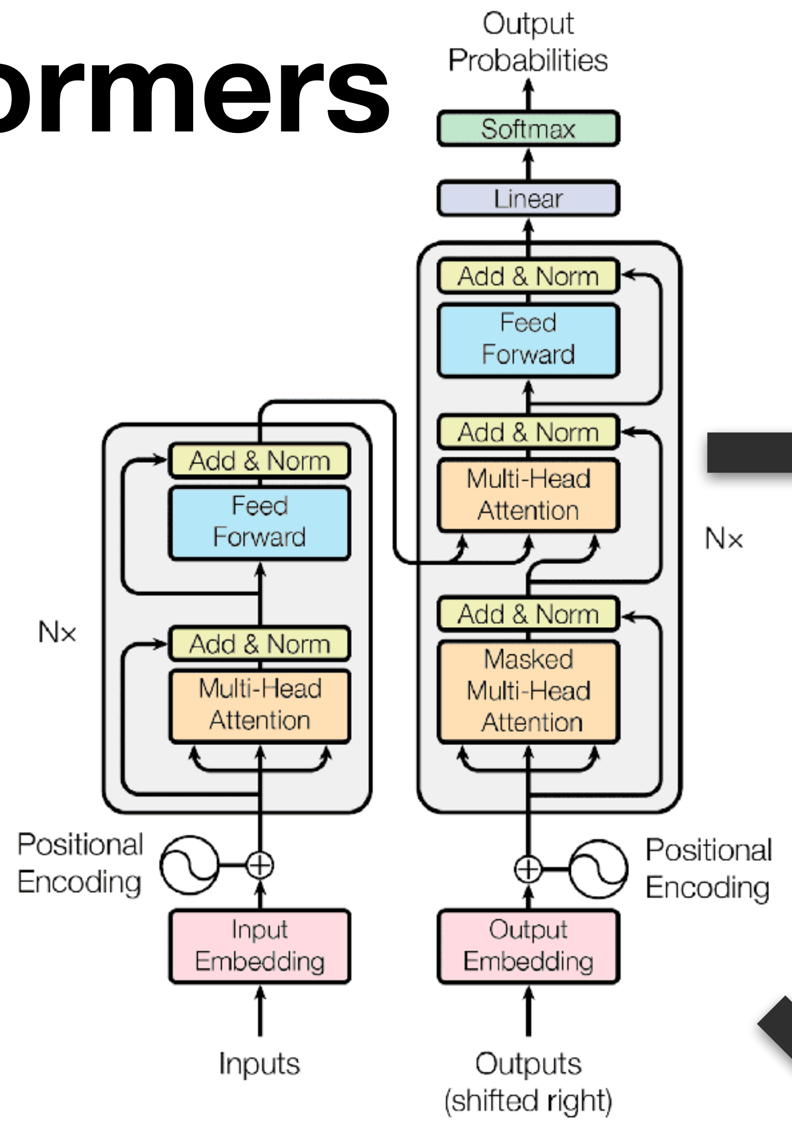
nvidia team

Transformer Models as universal architecture



Natural Language Supervision for Vision (CLIP)

Transformers



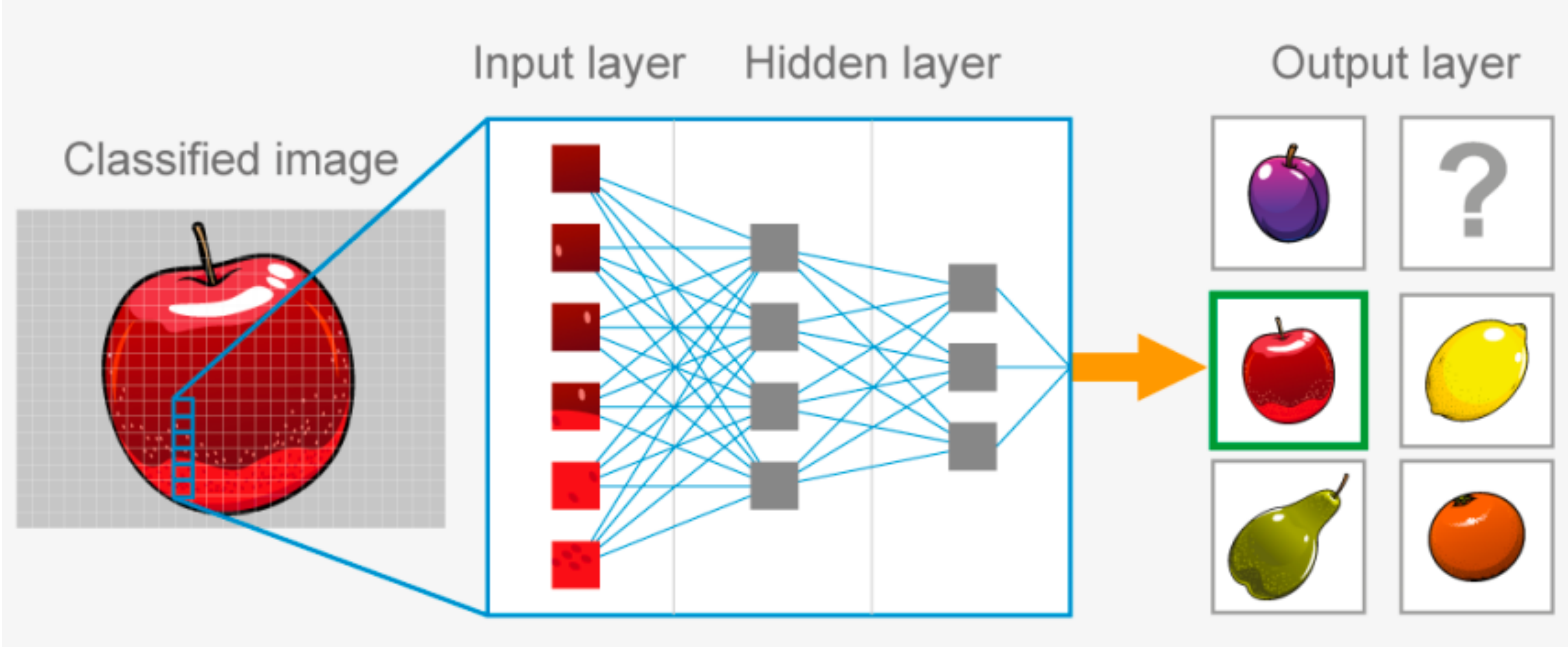
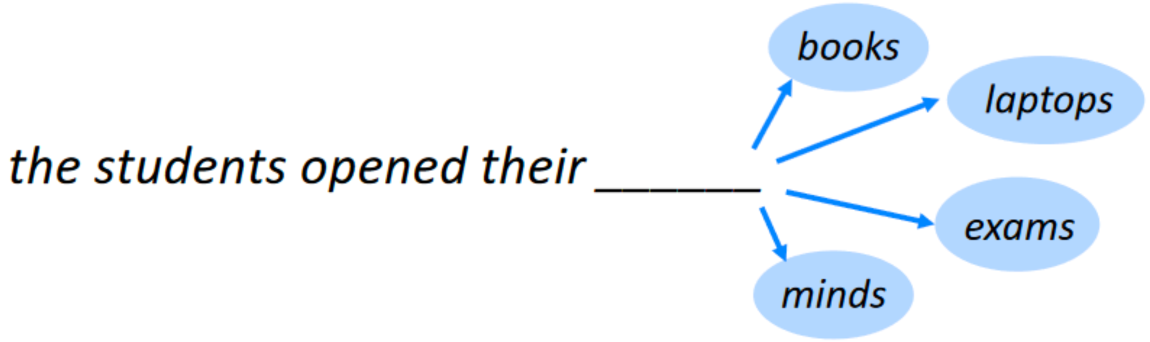


Image Classification (Vision Transformer, Swin-Transformer)

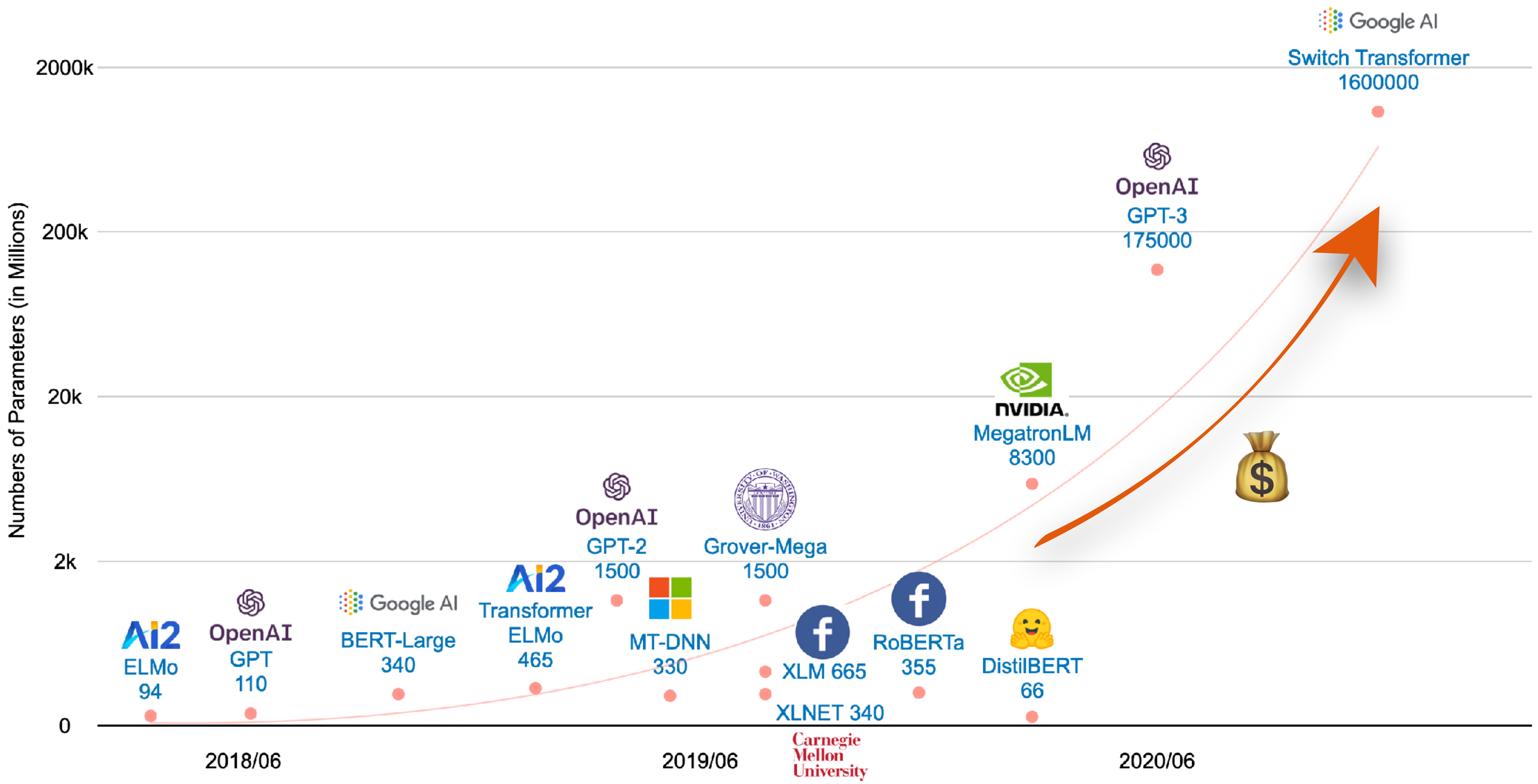


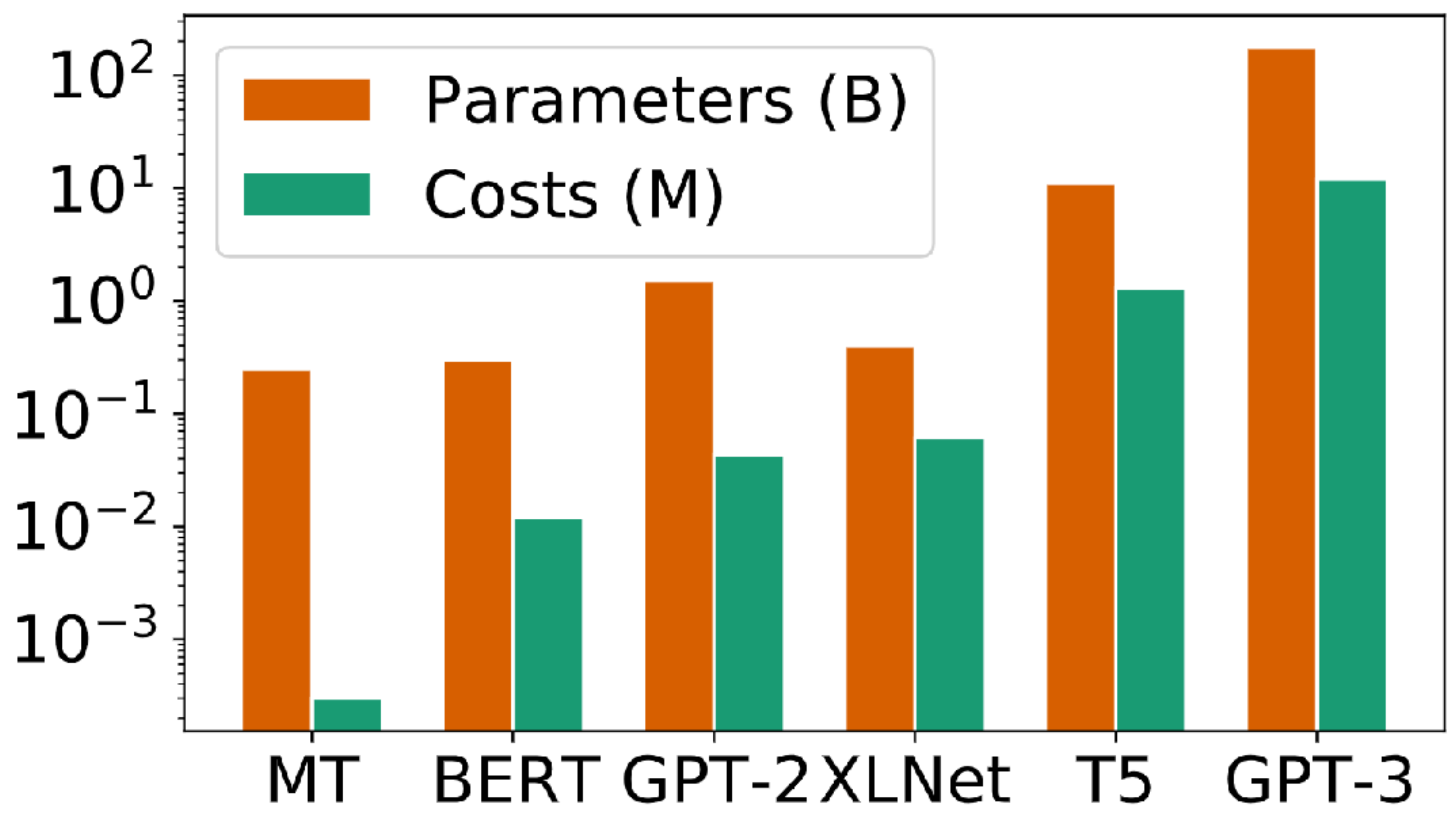
Language Model (BERT, T5, GPT3/4)

Text to Image (Stable Diffision)

Speech Recognition (wav2vec, HuBERT)

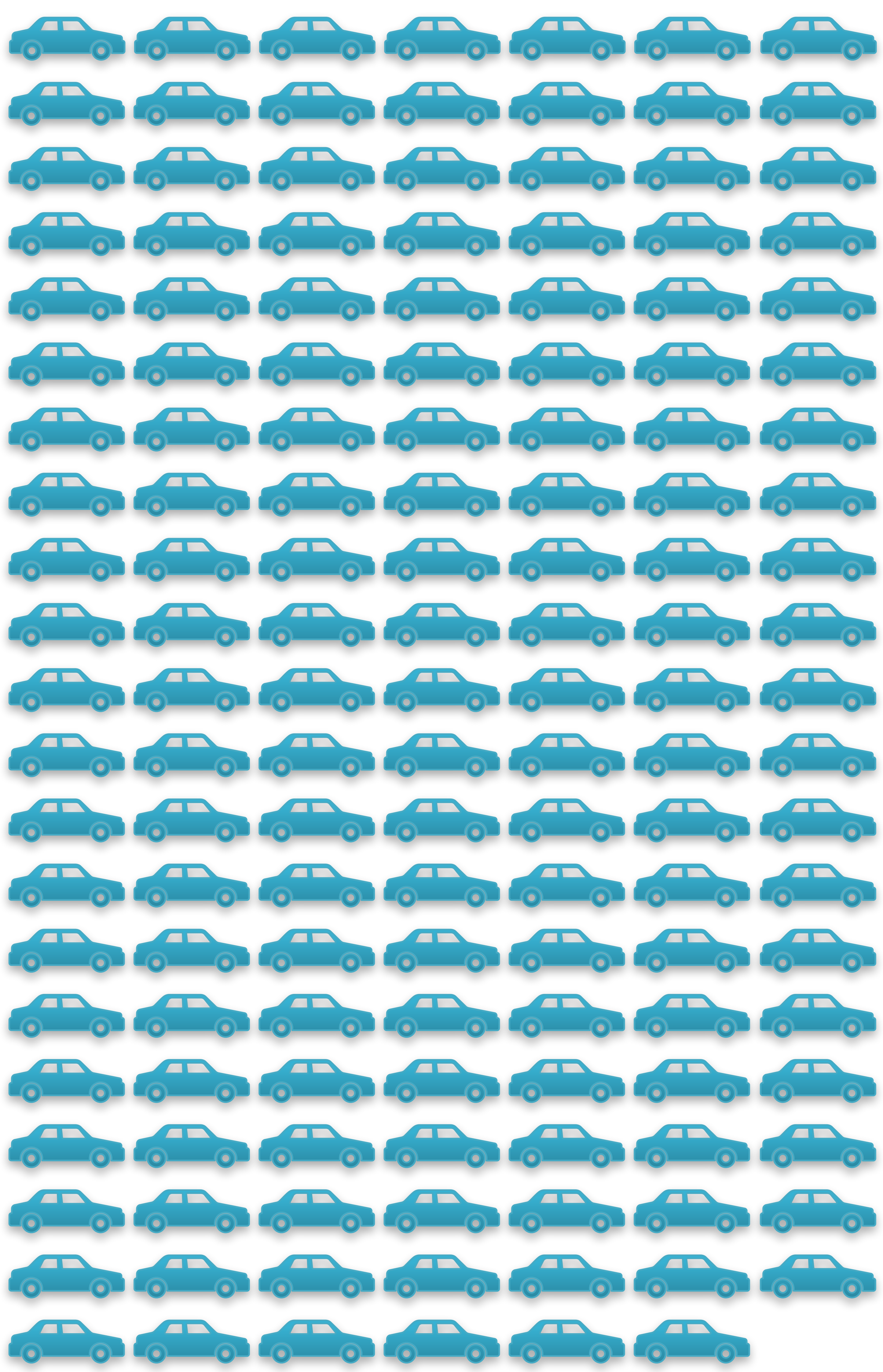
Training Large Models Are Expensive!



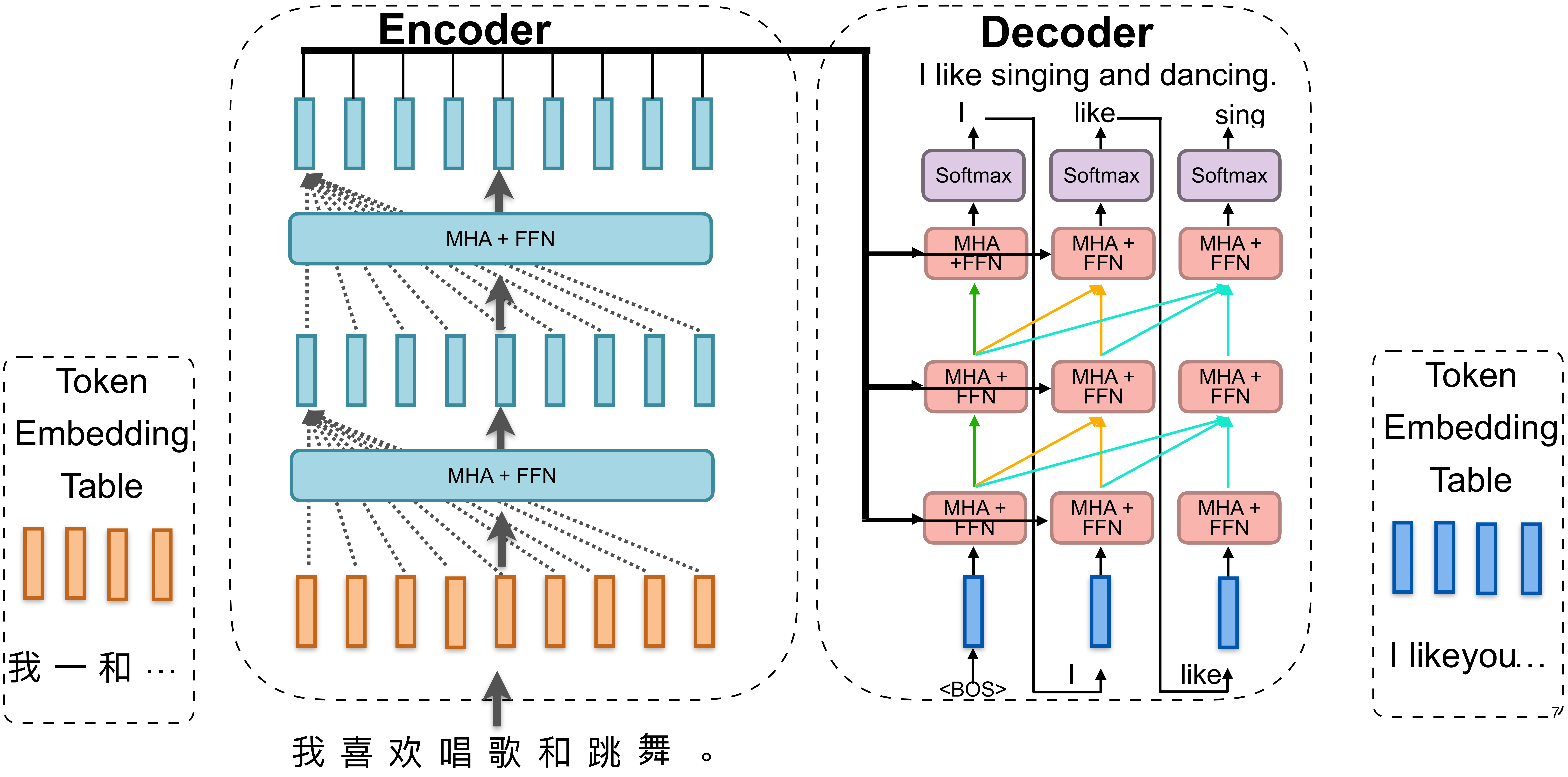


Carbon footprint: Training GPT3 = driving a car for 146 years!

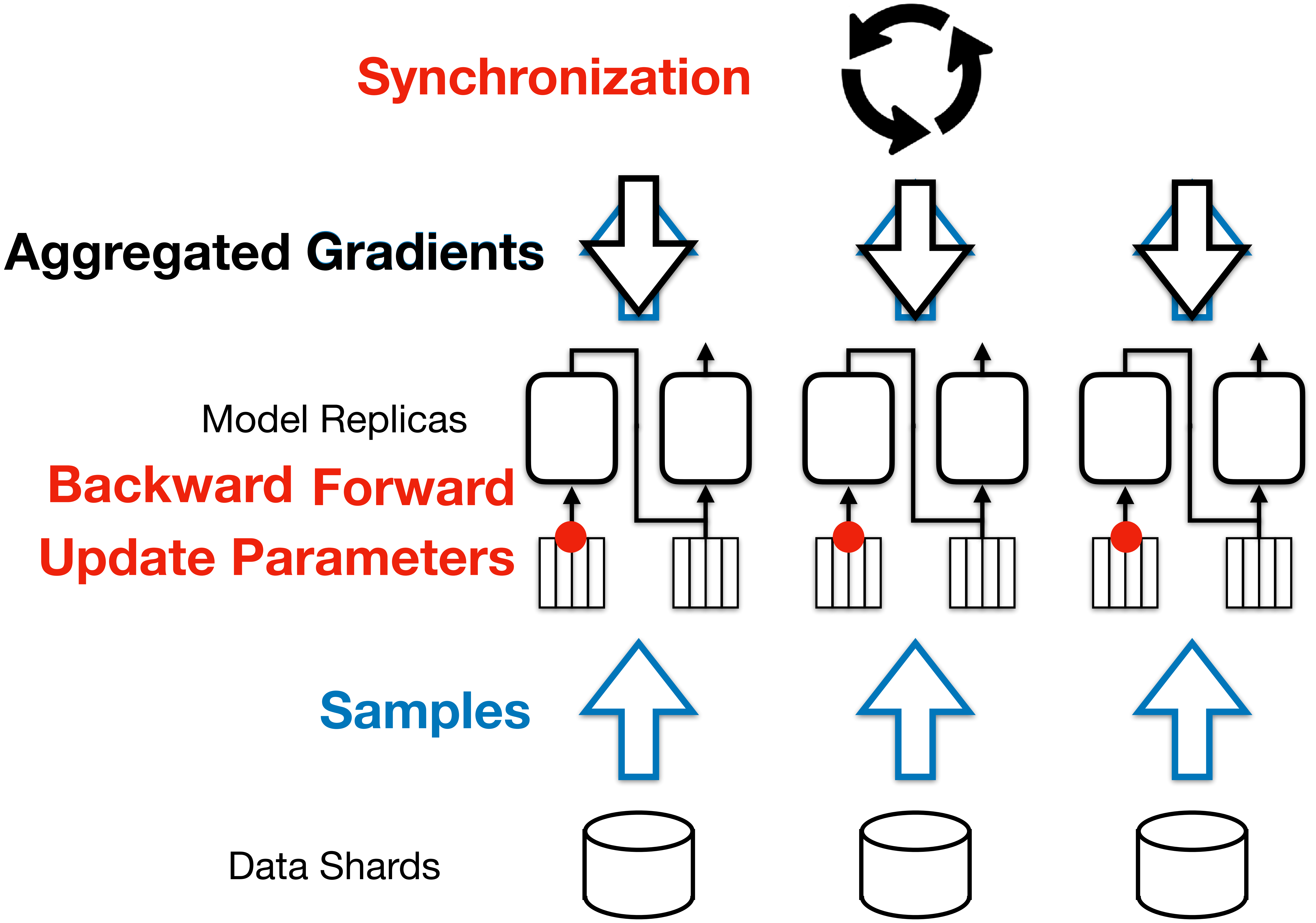
= 1 Car Year CO_2



Recap Transformer Architecture



Transformer Training Stages



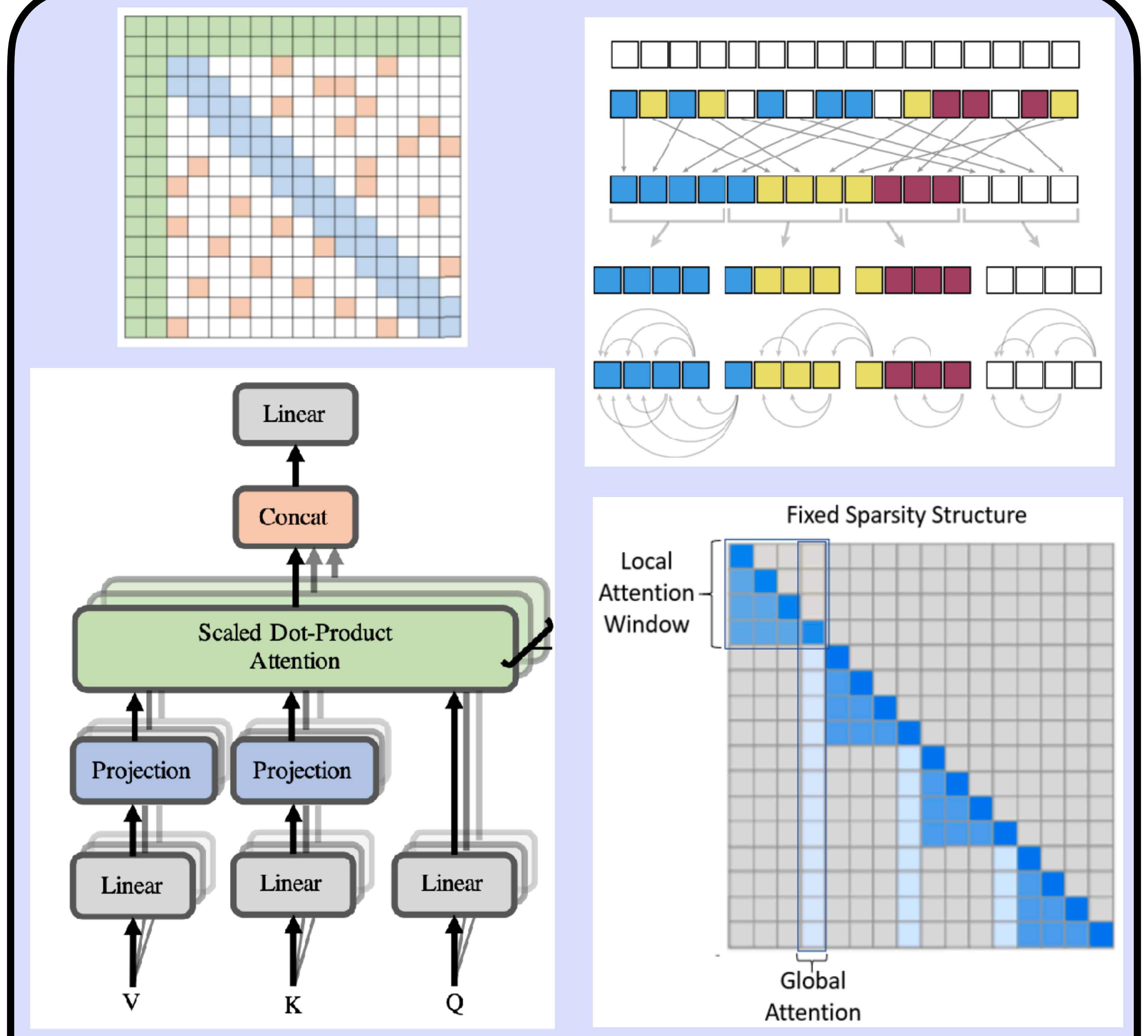
This Lecture
Accelerated GPU Computation for Transformer

Comparison of Acceleration Libraries for Transformers

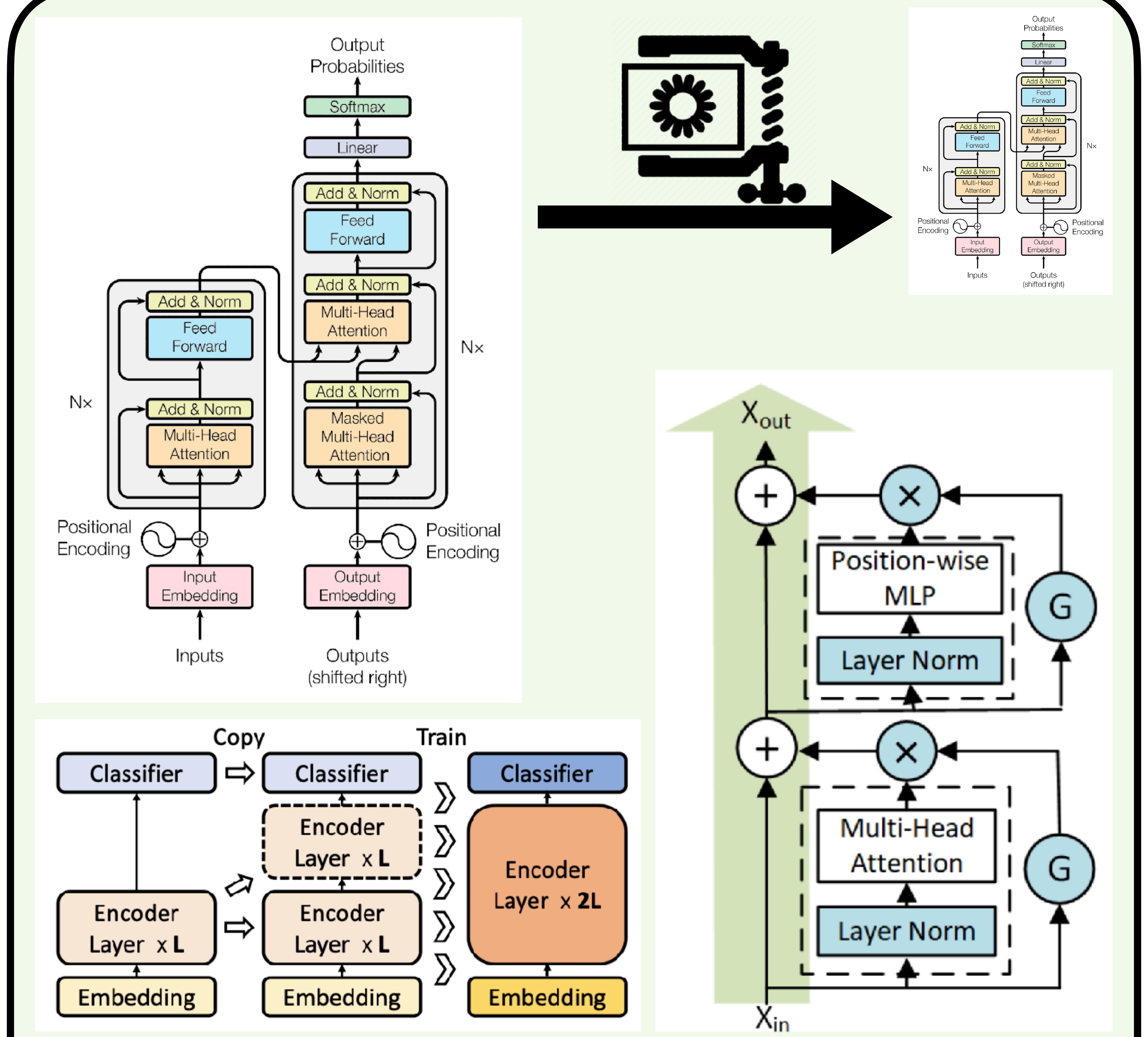
	Full Transformer	Training	Inference	PyTorch	Tensorflow
FasterTransformer	✔	✘	✔	✔	✔
TurboTransformers	✔	✘	✔	✔	?
DeepSpeed	✔*	✔	✔	✔	✘
LightSeq	✔	✔	✔	✔	✔

*DeepSpeed implemented Transformer Kernel in Oct 2022

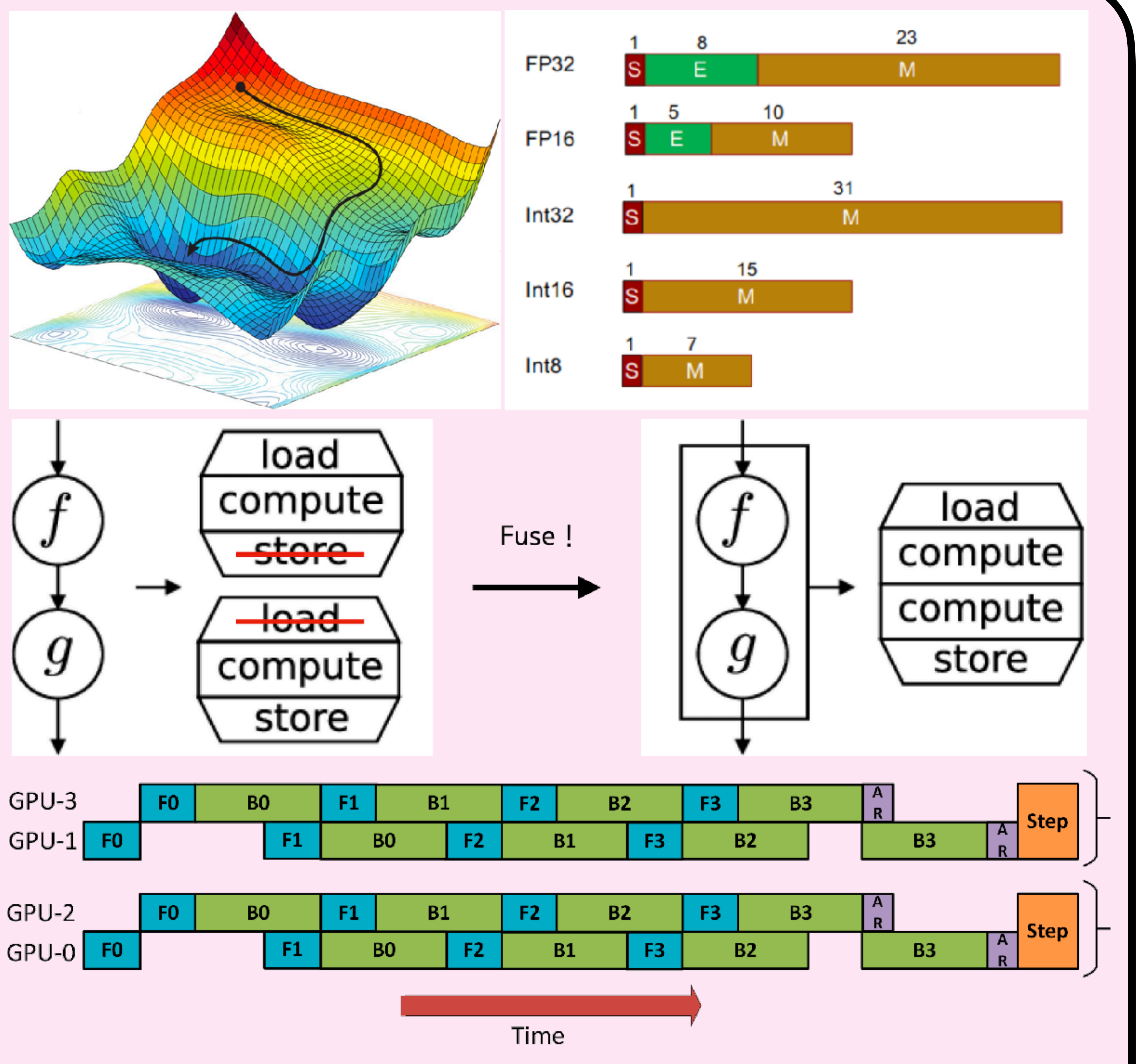
Other Approaches for Acceleration



Alternative Model Structures: Linformer, Reformer



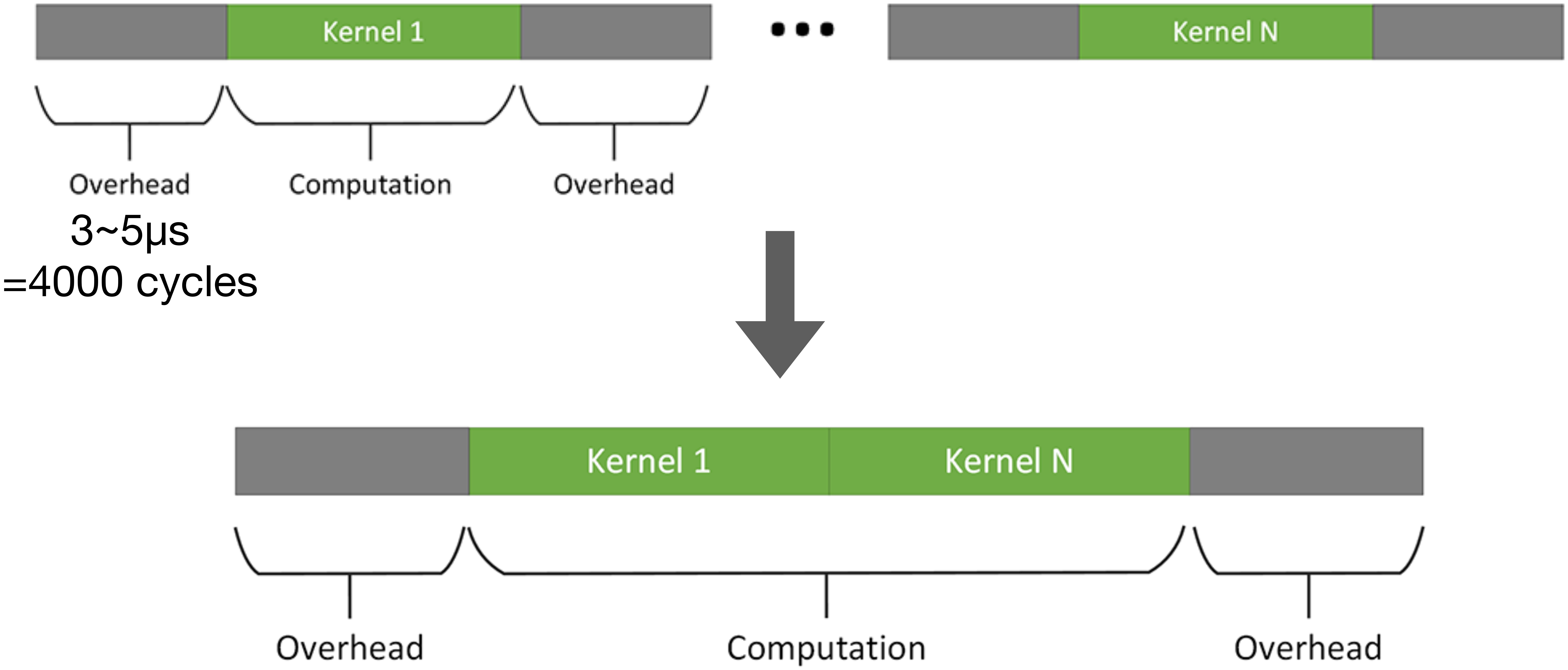
Training Strategy: Shallow to Deep, Layer Dropout



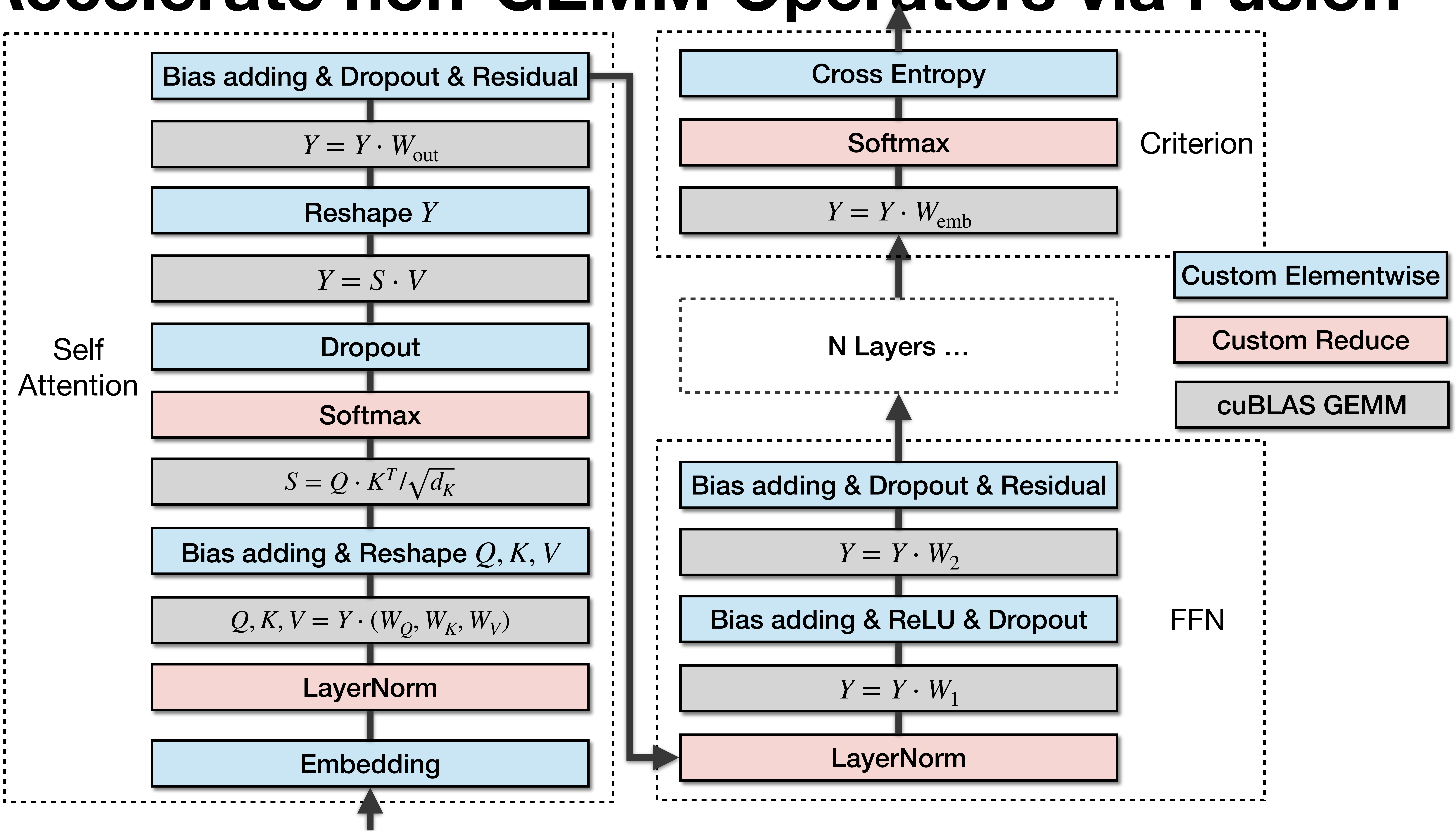
Efficient Computation: LAMB, Quantization, Hardware Optimization

LightSeq/LightSeq2 Optimization Overview

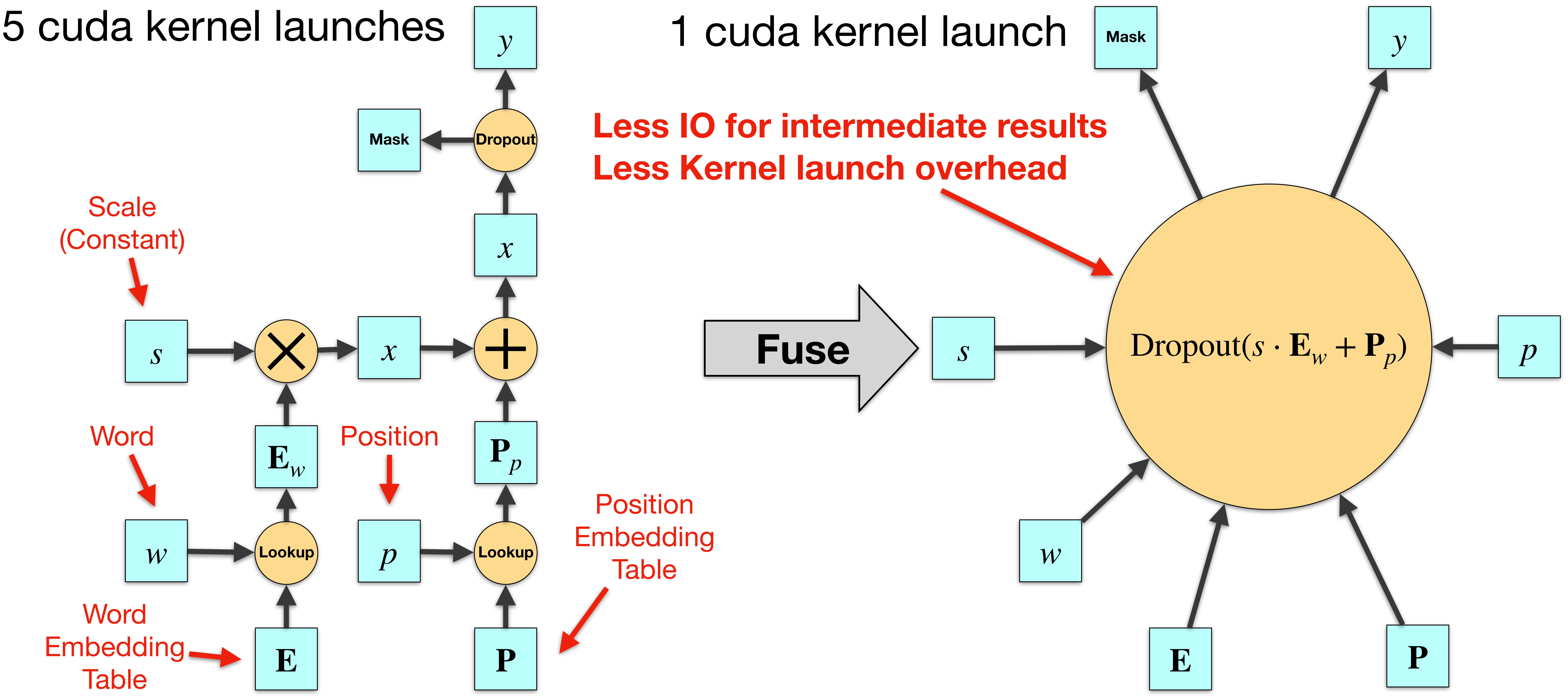
Idea1: Kernel Fusion



Accelerate non-GEMM Operators via Fusion



Fused Embedding Forward Operator



$$y = \mathrm{Dropout}(s \cdot \mathbf{E}_w + \mathbf{P}_p)$$

Code Example: Embedding Forward

```
__global__ void lookup_scale_pos_dropout<float>(
    float *output, const int *input, const int *tokens_position,
    const float *embeddings, const float *pos_embeddings, const float *cl
    uint8_t *dropout_mask, int seq_len, int embedding_dim, int padding_id
    float dropout_ratio, float emb_scale, int step, int seed) {
  int batch_id = blockIdx.x;
  int seq_id = blockIdx.y * blockDim.x + threadIdx.x;
  if (seq_id >= seq_len) return;

  int target_pos = batch_id * seq_len + seq_id;
  int start = target_pos * embedding_dim + threadIdx.y;
  int end = (target_pos + 1) * embedding_dim;
  int tid = input[target_pos];

  int token_pos_id = tokens_position[target_pos];
```

Word Embedding Lookup

Positional Embedding Lookup

```
  float4 *output4 = reinterpret_cast<float4 *>(output);
  const float4 *embeddings4 = reinterpret_cast<const float4 *>(embeddings
  const float4 *pos_embeddings4 =
      reinterpret_cast<const float4 *>(pos_embeddings);
  uint32_t *dropout_mask4 = reinterpret_cast<uint32_t *>(dropout_mask);

  // no need to calculate dropout_mask
  if (tid == padding_idx) {
    float4 zero4;
    zero4.x = zero4.y = zero4.z = zero4.w = 0.f;
    for (uint i = start; i < end; i += blockDim.y) {
      output4[i] = zero4;
    }
    return;
  }

  const float dropout_scale = 1.f / (1.f - dropout_ratio);
  float clip_max_val;
  if (clip_max) {
    clip_max_val = clip_max[0];
  }
  curandStatePhilox4_32_10_t state;
```

Dropout mask

```
  for (uint i = start; i < end; i += blockDim.y) {
    curand_init(seed, i, 0, &state);
    float4 rand4 = curand_uniform4(&state);
    uint8_t m[4];
    // dropout mask
    m[0] = (uint8_t)(rand4.x > dropout_ratio);
    m[1] = (uint8_t)(rand4.y > dropout_ratio);
    m[2] = (uint8_t)(rand4.z > dropout_ratio);
    m[3] = (uint8_t)(rand4.w > dropout_ratio);

    int offset = i - target_pos * embedding_dim;
    // step is non-zero only in inference
    float4 e4 = embeddings4[tid * embedding_dim + offset];
    float4 pe4 =
        pos_embeddings4[(token_pos_id + step) * embedding_dim + offset]
    float4 res4;
```

Apply dropout

```
    float scale_mask[4];
    scale_mask[0] = dropout_scale * m[0];
    scale_mask[1] = dropout_scale * m[1];
    scale_mask[2] = dropout_scale * m[2];
    scale_mask[3] = dropout_scale * m[3];

    uint8_t clip_mask[4];
    if (clip_max) {
      e4.x = fake_quantize(e4.x, clip_max_val, clip_mask[0], 2);
      e4.y = fake_quantize(e4.y, clip_max_val, clip_mask[1], 2);
      e4.z = fake_quantize(e4.z, clip_max_val, clip_mask[2], 2);
      e4.w = fake_quantize(e4.w, clip_max_val, clip_mask[3], 2);
    }
```

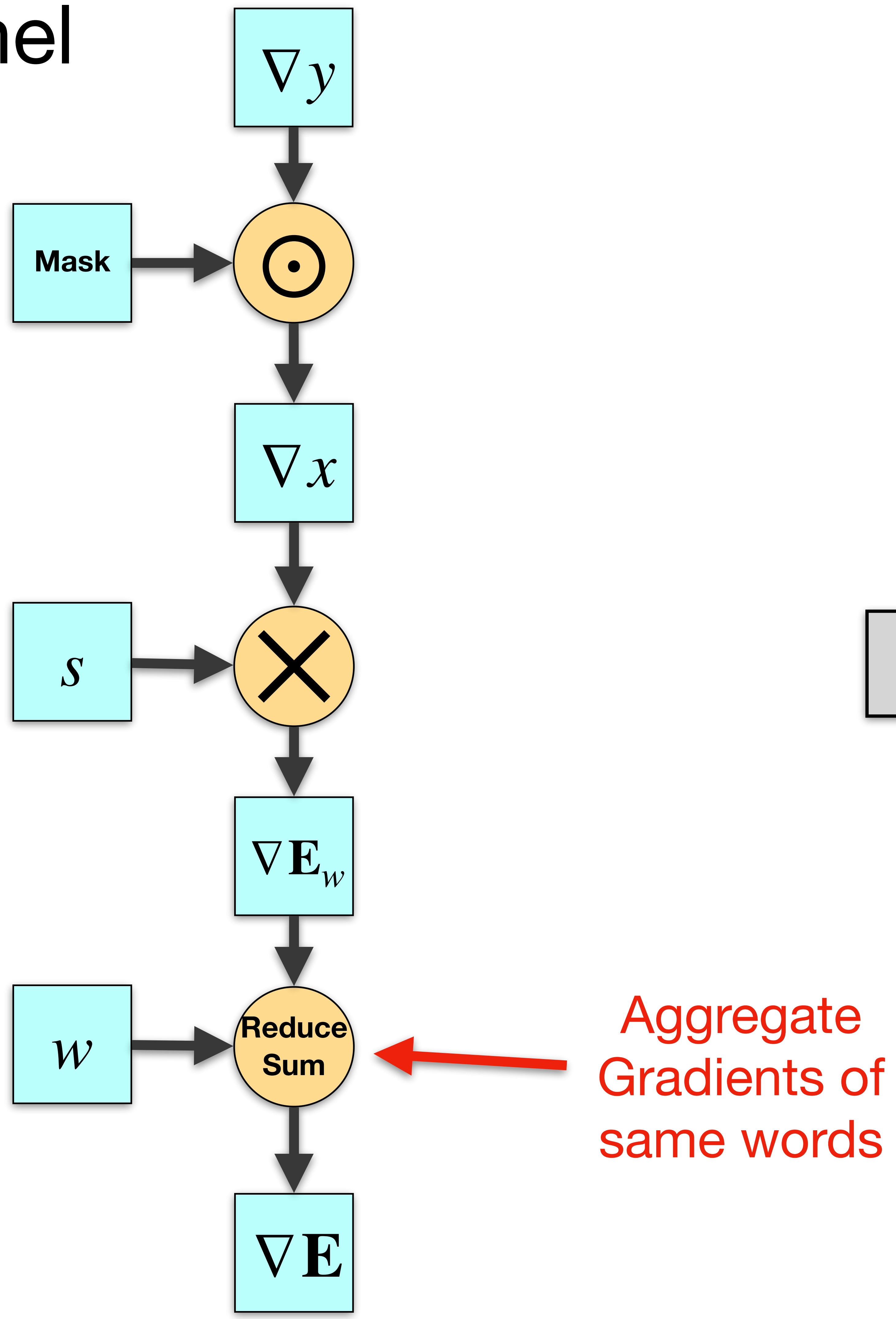
Scale

```
    res4.x = (emb_scale * e4.x + pe4.x) * scale_mask[0];
    res4.y = (emb_scale * e4.y + pe4.y) * scale_mask[1];
    res4.z = (emb_scale * e4.z + pe4.z) * scale_mask[2];
    res4.w = (emb_scale * e4.w + pe4.w) * scale_mask[3];

    output4[i] = res4;
    uint32_t *m4 = reinterpret_cast<uint32_t *>(m);
    if (clip_max) {
      m4[0] = m4[0] | reinterpret_cast<uint32_t *>(clip_mask)[0];
    }
    dropout_mask4[i] = m4[0];
  }
}
```

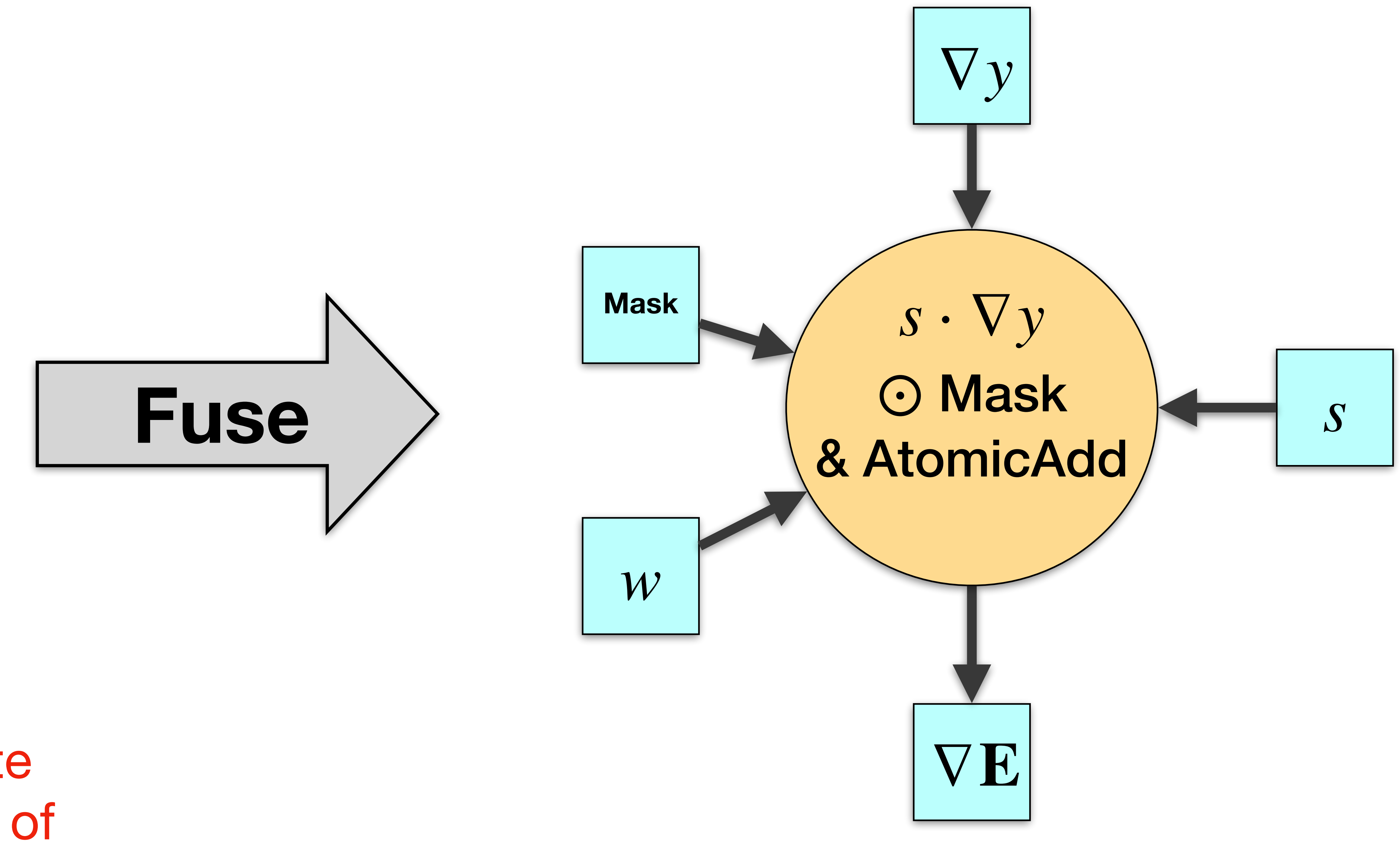
https://github.com/bytedance/lightseq/blob/master/lightseq/csrc/kernels/cuda/embedding_kernels.cu

Fused Embedding Backward Operator

3 cuda kernel launches



1 cuda kernel launch



$$\nabla \mathbf{E} = \mathrm{ReduceSum}(s \cdot \nabla y \odot \mathrm{Mask})$$

Code Example: Embedding Backward

```
__global__ void d_lookup_scale_pos_dropout<float>(
    float *grad_embeddings, float *grad_clip_max, const float *grad_output,
    const int *input, const uint8_t *dropout_mask, int seq_len,
    int embedding_dim, int padding_idx, float dropout_ratio, float emb_scale) {
  int batch_id = blockIdx.x;
  int seq_id = blockIdx.y * blockDim.x + threadIdx.x;
  if (seq_id >= seq_len) return;

  int target_pos = batch_id * seq_len + seq_id;
  int start = target_pos * embedding_dim + threadIdx.y;
  int end = (target_pos + 1) * embedding_dim;
  int tid = input[target_pos];

  if (tid == padding_idx) {
    return;
  }

  const float scale = 1.f / (1.f - dropout_ratio);
  const float4 *grad_output4 = reinterpret_cast<const float4 *>(grad_output);
  const uint32_t *dropout_mask4 =
      reinterpret_cast<const uint32_t *>(dropout_mask);
  // float block_g_clip_max = 0;
  float thread_cmax_grad = 0;
  float temp_cmax_grad = 0;
```

```
for (uint i = start; i < end; i += blockDim.y) {
  float4 go4 = grad_output4[i];
  uint32_t m4 = dropout_mask4[i];
  uint8_t *m4_ptr = reinterpret_cast<uint8_t *>(&m4);
  float4 res4;
  res4.x = emb_scale * go4.x * (m4_ptr[0] & 1) * scale;
  res4.y = emb_scale * go4.y * (m4_ptr[1] & 1) * scale;
  res4.z = emb_scale * go4.z * (m4_ptr[2] & 1) * scale;
  res4.w = emb_scale * go4.w * (m4_ptr[3] & 1) * scale;
  int offset = i - target_pos * embedding_dim;
  int idx = (tid * (embedding_dim) + offset) << 2;
  clip_bwd(res4.x, temp_cmax_grad, res4.x, m4_ptr[0], 2);
  thread_cmax_grad += temp_cmax_grad;
  clip_bwd(res4.y, temp_cmax_grad, res4.y, m4_ptr[1], 2);
  thread_cmax_grad += temp_cmax_grad;
  clip_bwd(res4.z, temp_cmax_grad, res4.z, m4_ptr[2], 2);
  thread_cmax_grad += temp_cmax_grad;
  clip_bwd(res4.w, temp_cmax_grad, res4.w, m4_ptr[3], 2);
  thread_cmax_grad += temp_cmax_grad;
  atomicAdd(grad_embeddings + idx, res4.x);
  atomicAdd(grad_embeddings + idx + 1, res4.y);
  atomicAdd(grad_embeddings + idx + 2, res4.z);
  atomicAdd(grad_embeddings + idx + 3, res4.w);
}

if (grad_clip_max) {
  __shared__ float block_cmax_grad;
  if (threadIdx.x == 0 && threadIdx.y == 0) {
    block_cmax_grad = 0;
  }
  __syncthreads();
  if (thread_cmax_grad != 0) {
    atomicAdd(&block_cmax_grad, thread_cmax_grad);
  }
  __syncthreads();
  if (threadIdx.x == 0 && threadIdx.y == 0) {
    if (block_cmax_grad != 0) {
      atomicAdd(&grad_clip_max[0], block_cmax_grad);
    }
  }
}
```

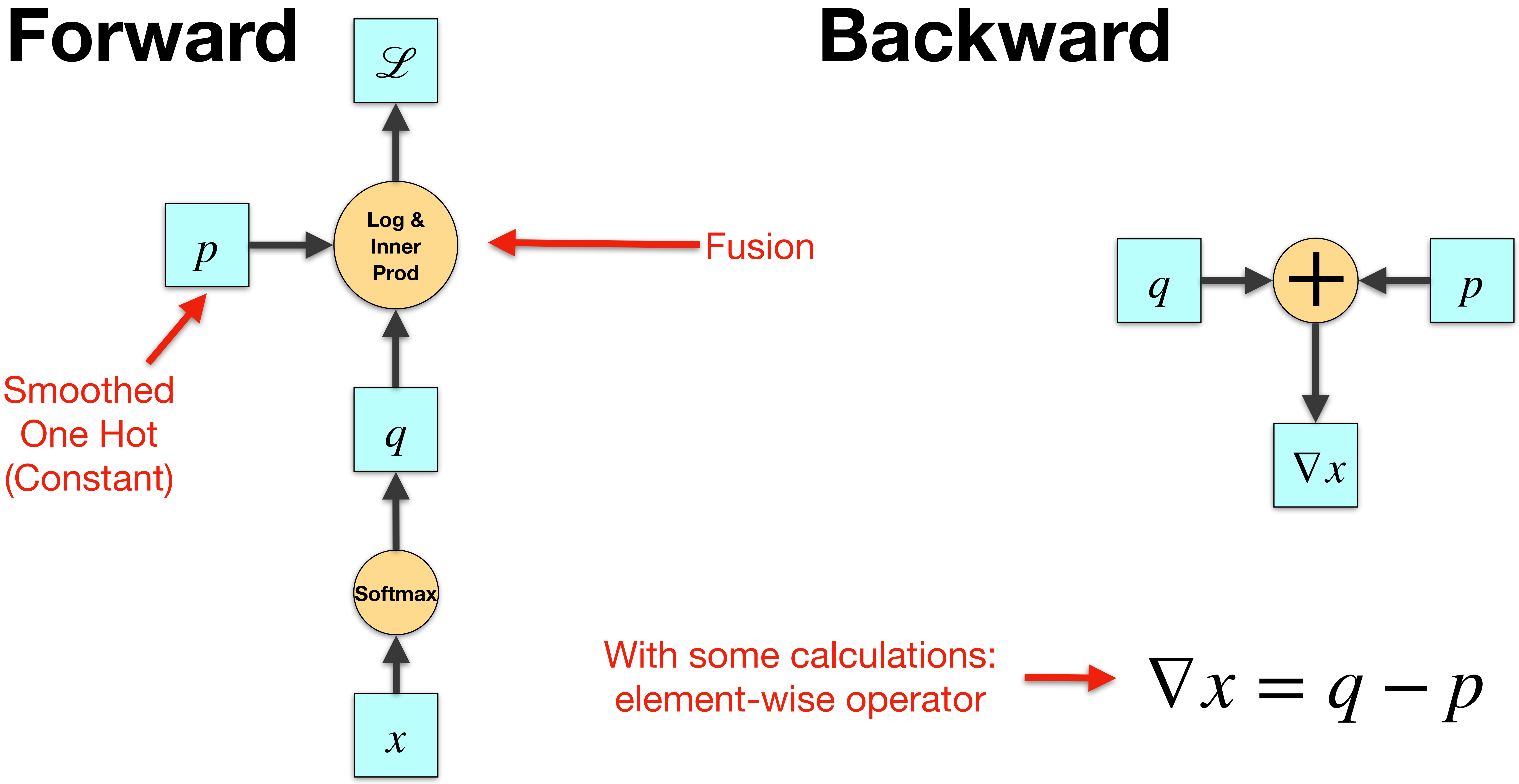
Dropout mask
Scale

Reduce sum

Gradient clipping
Gradient accumulation

https://github.com/bytedance/lightseq/blob/master/lightseq/csrc/kernels/cuda/embedding_kernels.cu

Fused Criterion Operator



$$\mathscr{L} = -\sum_i p_i \log(q_i)$$

Fused Criterion Operator

With some calculations:
element-wise operator

Smoothed one-hot ground truth

$$\mathbf{p} = (1-\alpha)\mathbf{y} + \frac{\alpha}{V}\cdot\mathbf{1}$$

α: smoothing parameter, 0< α < 1
V: vocabulary size, length of p, q

Softmax output

$$\mathbf{q} = \mathrm{Softmax}(\mathbf{h})$$

Gradient of Softmax

$$\frac{\partial \mathbf{q}_i}{\partial \mathbf{h}_j} = \begin{cases} -\mathbf{q}_i\mathbf{q}_j & i \neq j \\ \mathbf{q}_i(1-\mathbf{q}_i) & i = j \end{cases}$$

When i is equal to ground truth token index k:

$$\nabla \mathbf{h}_i = \frac{\partial \mathcal{L}}{\partial \mathbf{h}_i} = -\frac{\alpha}{V}\sum_{j\neq k}\frac{1}{\mathbf{q}_j}\cdot\frac{\partial \mathbf{q}_j}{\partial \mathbf{h}_k} - (1-\alpha+\frac{\alpha}{V})\cdot\frac{1}{\mathbf{q}_k}\cdot\frac{\partial \mathbf{q}_k}{\partial \mathbf{h}_k}$$
$$= \mathbf{q}_k - \frac{\alpha}{V} - 1 + \alpha$$

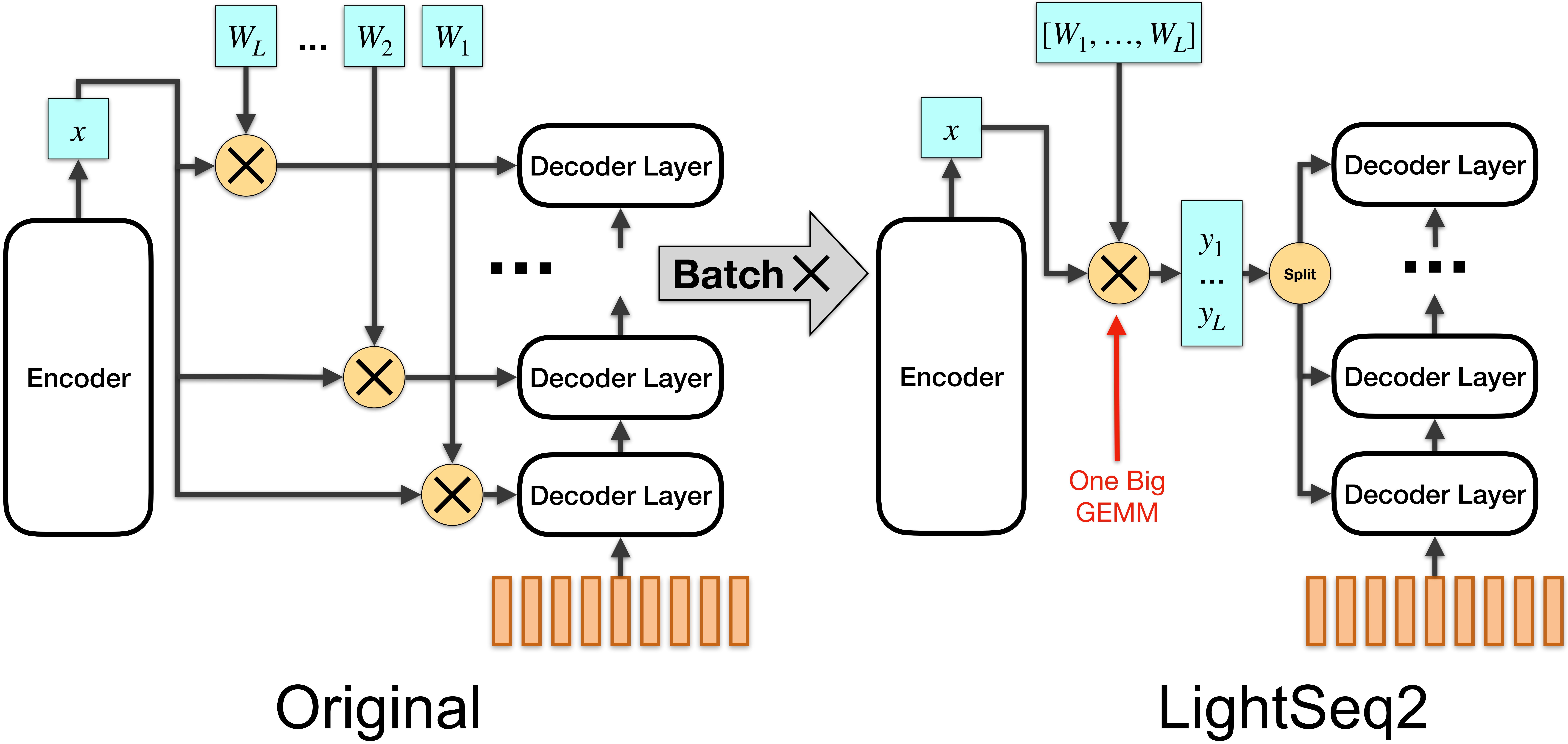
Otherwise

$$\nabla \mathbf{h}_i = \frac{\partial \mathcal{L}}{\partial \mathbf{h}_i} = -\frac{\alpha}{V}\sum_{j\neq k}\frac{1}{\mathbf{q}_j}\cdot\frac{\partial \mathbf{q}_j}{\partial \mathbf{h}_i} - (1-\alpha+\frac{\alpha}{V})\cdot\frac{1}{\mathbf{q}_k}\cdot\frac{\partial \mathbf{q}_k}{\partial \mathbf{h}_i}$$
$$= -\frac{\alpha}{V}\sum_{j\neq k, j\neq i}\frac{1}{\mathbf{q}_j}\cdot\frac{\partial \mathbf{q}_j}{\partial \mathbf{h}_i} - \frac{\alpha}{V}\cdot\frac{1}{\mathbf{q}_i}\cdot\frac{\partial \mathbf{q}_i}{\partial \mathbf{h}_i}$$
$$- (1-\alpha+\frac{\alpha}{V})\cdot\frac{1}{\mathbf{q}_k}\cdot\frac{\partial \mathbf{q}_k}{\partial \mathbf{h}_i} = \mathbf{q}_i - \frac{\alpha}{V}$$

Therefore

$$\nabla \mathbf{h}_i = \begin{cases} \mathbf{q}_i - \frac{\alpha}{V} - 1 + \alpha & \text{if token } i \text{ is the ground truth} \\ \mathbf{q}_i - \frac{\alpha}{V} & \text{otherwise} \end{cases}$$

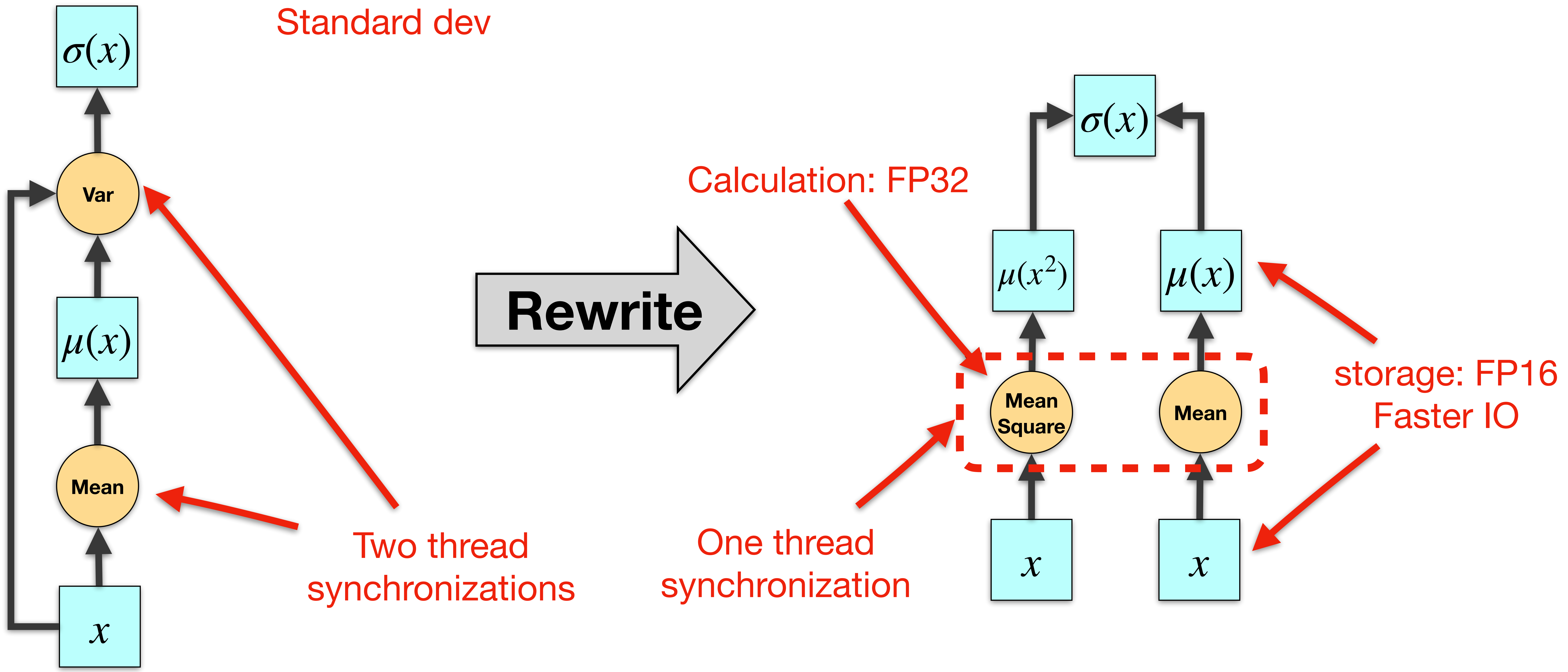
Layer-Batched Cross Attention



Idea 2: Reduce synchronization

Rewrite Reduction: LayerNorm Forward

LayerNorm: $y_i = w_i \frac{\overbrace{x_i - \mu(x)}^{\text{Mean}}}{\underbrace{\sigma(x)}_{\text{Standard dev}}} + b_i$ rescales input for stability



$$\sigma(x) = \sqrt{\frac{1}{N}\sum_i \left(x_i - \mu(x)_i\right)^2}$$

$$\sigma(x) = \sqrt{\mu(x^2) - \mu(x)^2}$$

Rewrite Reduction: LayerNorm Backward

Before:

$$\nabla \mathbf{x}_i = \frac{\mathbf{w}_i \nabla \mathbf{y}_i}{\sigma(\mathbf{x})} - \frac{1}{m\sigma(\mathbf{x})}\left(\sum_j \nabla \mathbf{y}_j \mathbf{w}_j + \hat{\mathbf{x}}_i \sum_j \nabla \mathbf{y}_j \mathbf{w}_j \hat{\mathbf{x}}_j\right)$$

Rearrange:

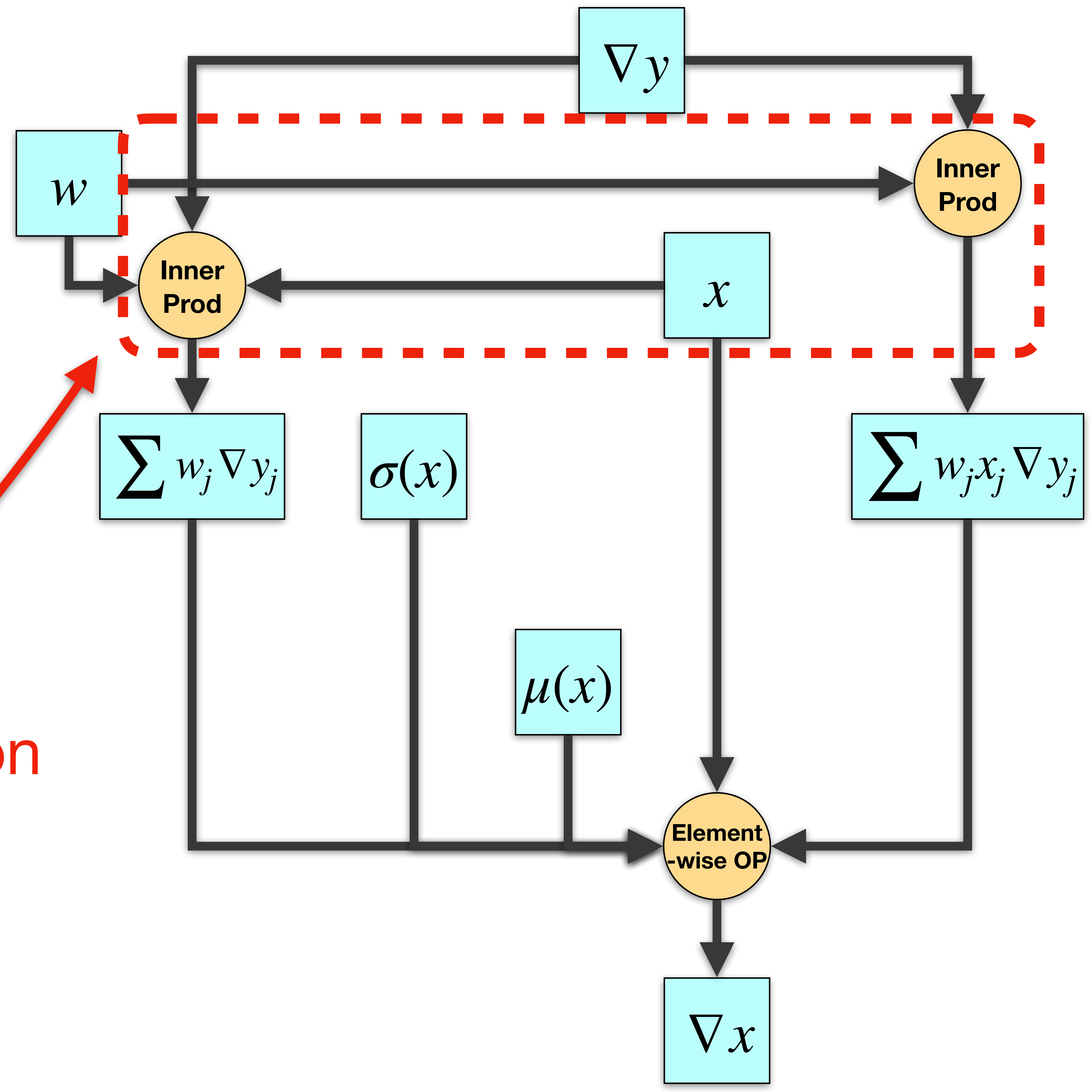
$$\nabla x_i = \frac{w_i \nabla y_i}{\sigma(x)} + \alpha \cdot \sum_j w_j \nabla y_j + \beta \cdot \sum_j w_j \nabla y_j x_j$$

where
$$\alpha = \frac{[x_i - \mu(x)]\mu(x) - \sigma(x)}{m\sigma(x)^3}$$

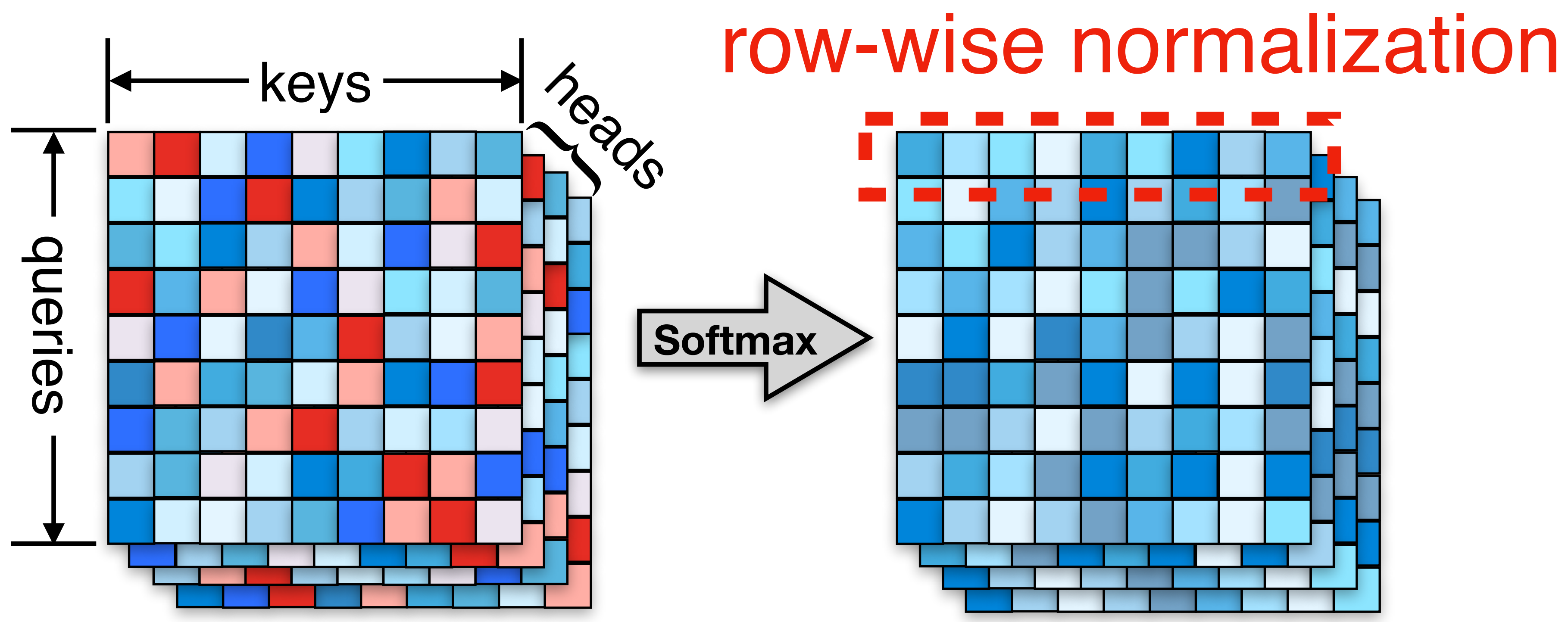
$$\beta = \frac{\mu(x) - x_i}{m\sigma(x)^3}$$

You will implement LayerNorm in assignment3!

One thread synchronization



Rewrite Reduction: Softmax Forward

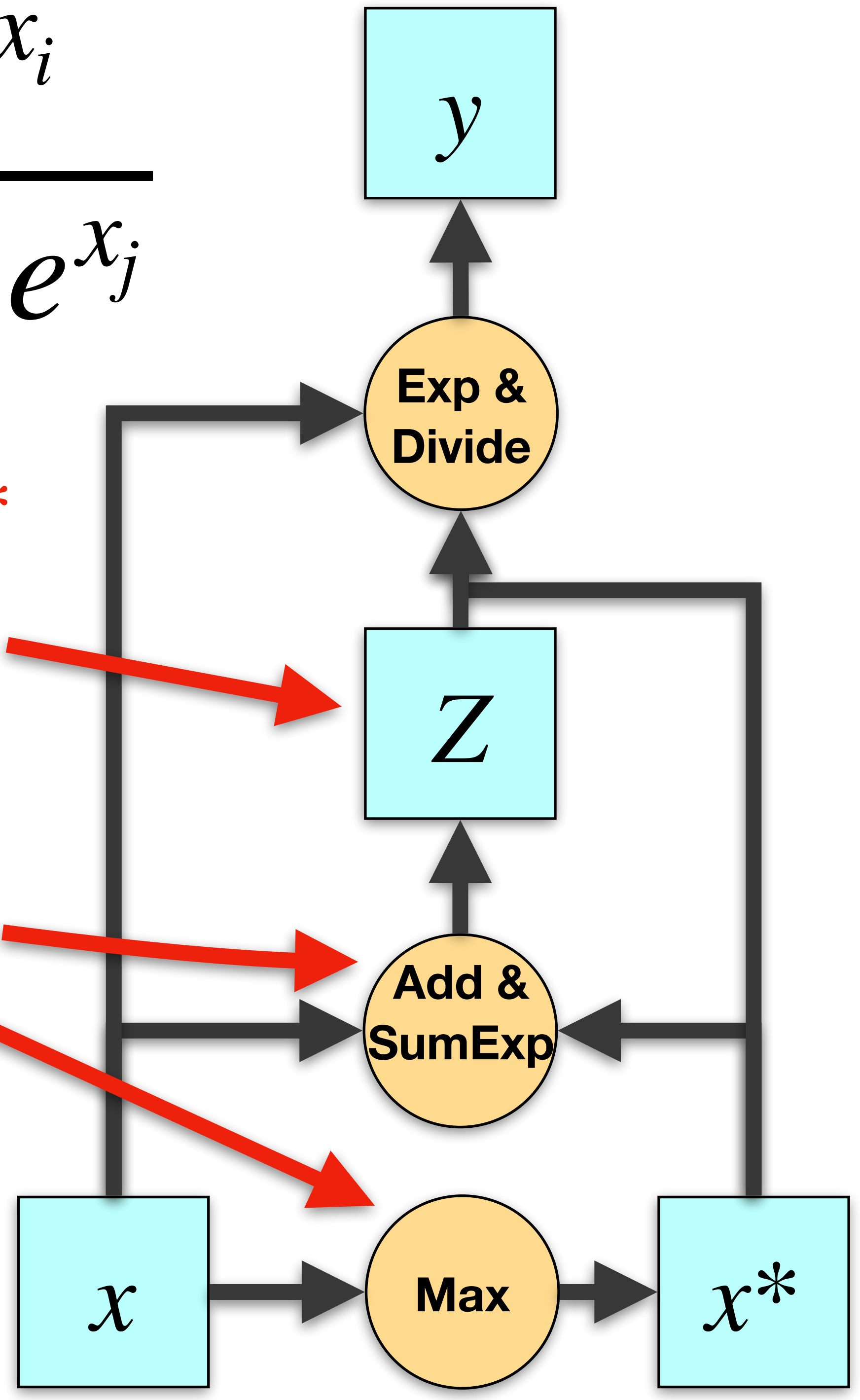


$$y_i = \frac{e^{x_i}}{\sum e^{x_j}}$$

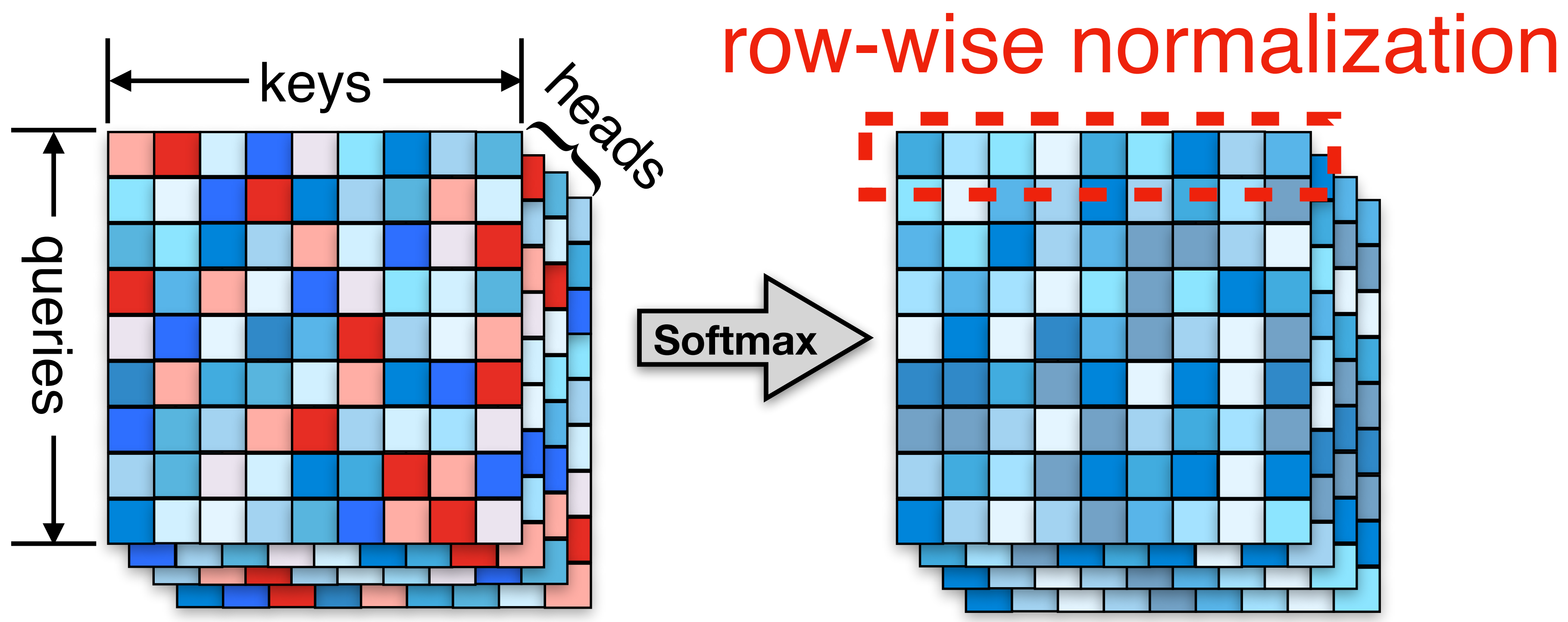
$$Z = \sum_i e^{x_i - x^*}$$

Two thread synchronizations

Two reduce: Costly!



Rewrite Reduction: Softmax Forward

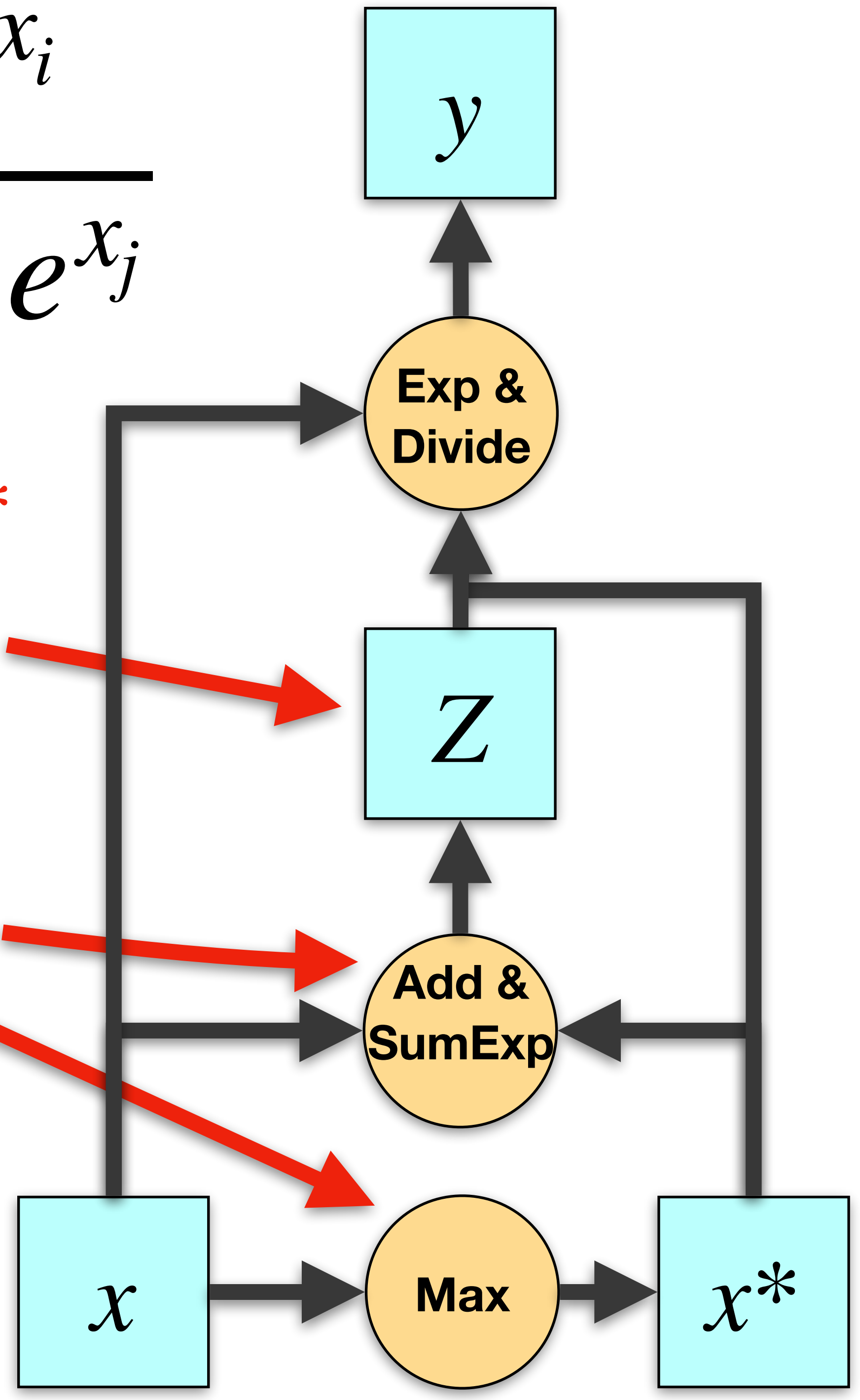


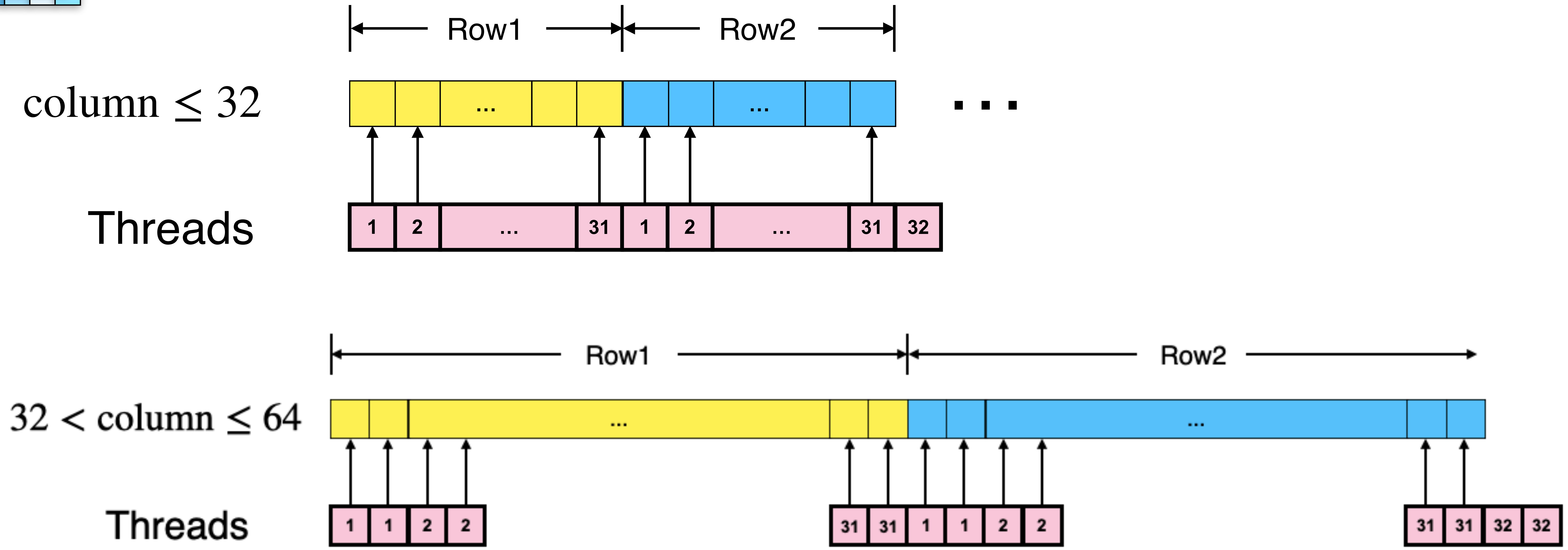
Parameters (e.g. # of blocks, warps per block) are shape dependent for maximal speedup

$$y_i = \frac{e^{x_i}}{\sum e^{x_j}}$$

$$Z = \sum_i e^{x_i - x^*}$$

Two thread synchronizations





And Other Shapes …

You will implement Softmax in assignment3!

Code Example: Softmax Forward

Parameters tuning by using templates

```
template <typename T, int block_dim, int ele_per_thread>
__global__ void ker_attn_softmax(T *inp, const T *attn_mask, int from_len,
                                 int to_len, bool mask_future) {
```

```
template <typename T, int block_dim, int ele_per_thread>
__global__ void ker_attn_softmax_lt32(T *inp, const T *attn_mask, int from_len,
                                      int to_len, bool mask_future) {
```

https://github.com/bytedance/lightseq/blob/master/lightseq/csrc/kernels/cuda/softmax_kernels.cu

Code Example: Softmax Forward

Parameters tuning by using templates

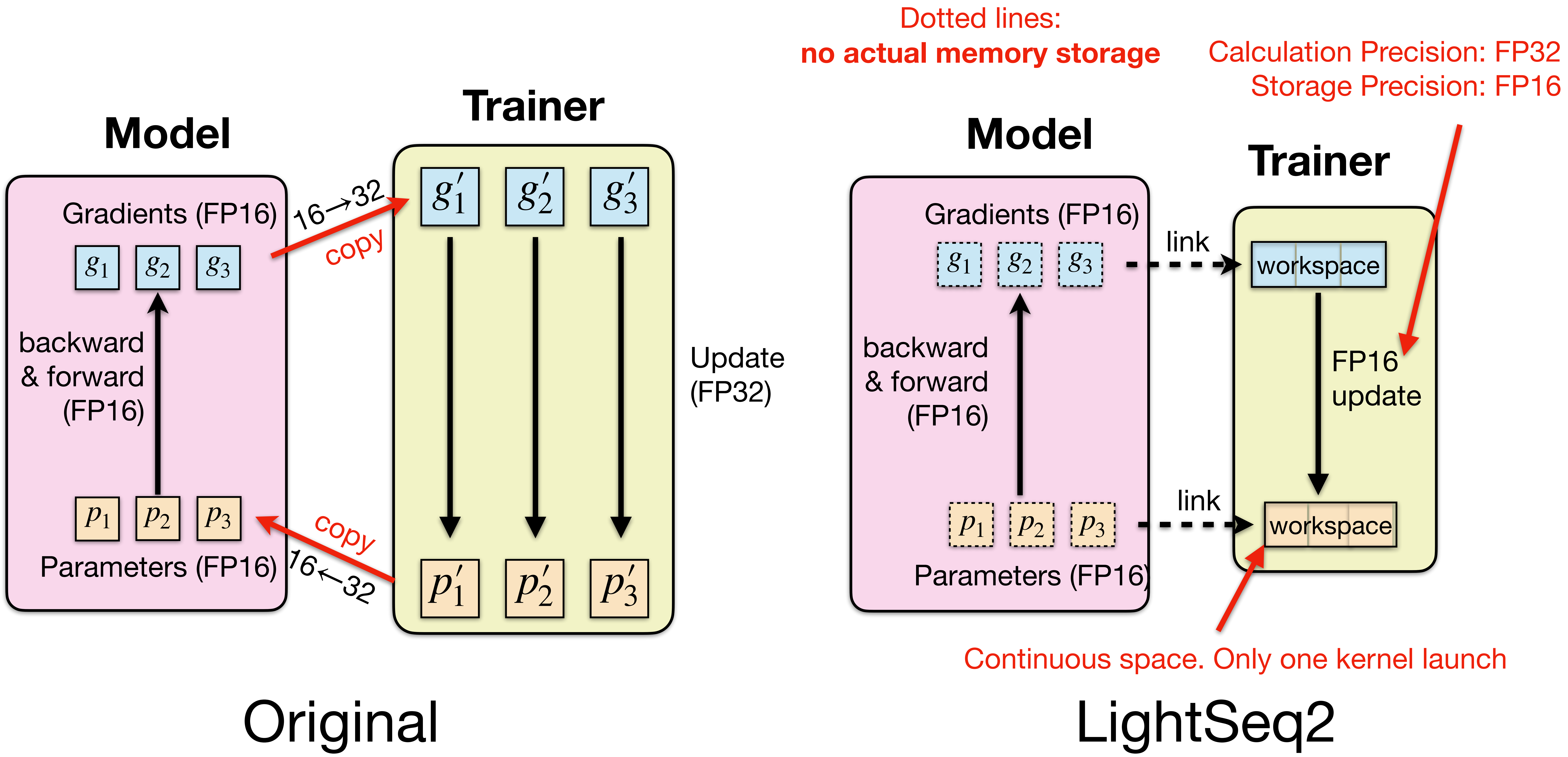
```
template <typename T, int block_dim, int ele_per_thread>
__global__ void ker_attn_softmax(T *inp, const T *attn_mask, int from_len,
                                 int to_len, bool mask_future) {

template <typename T, int block_dim, int ele_per_thread>
__global__ void ker_attn_softmax_lt32(T *inp, const T *attn_mask, int from_len,
                                      int to_len, bool mask_future) {
```

Then call with parameters in launch

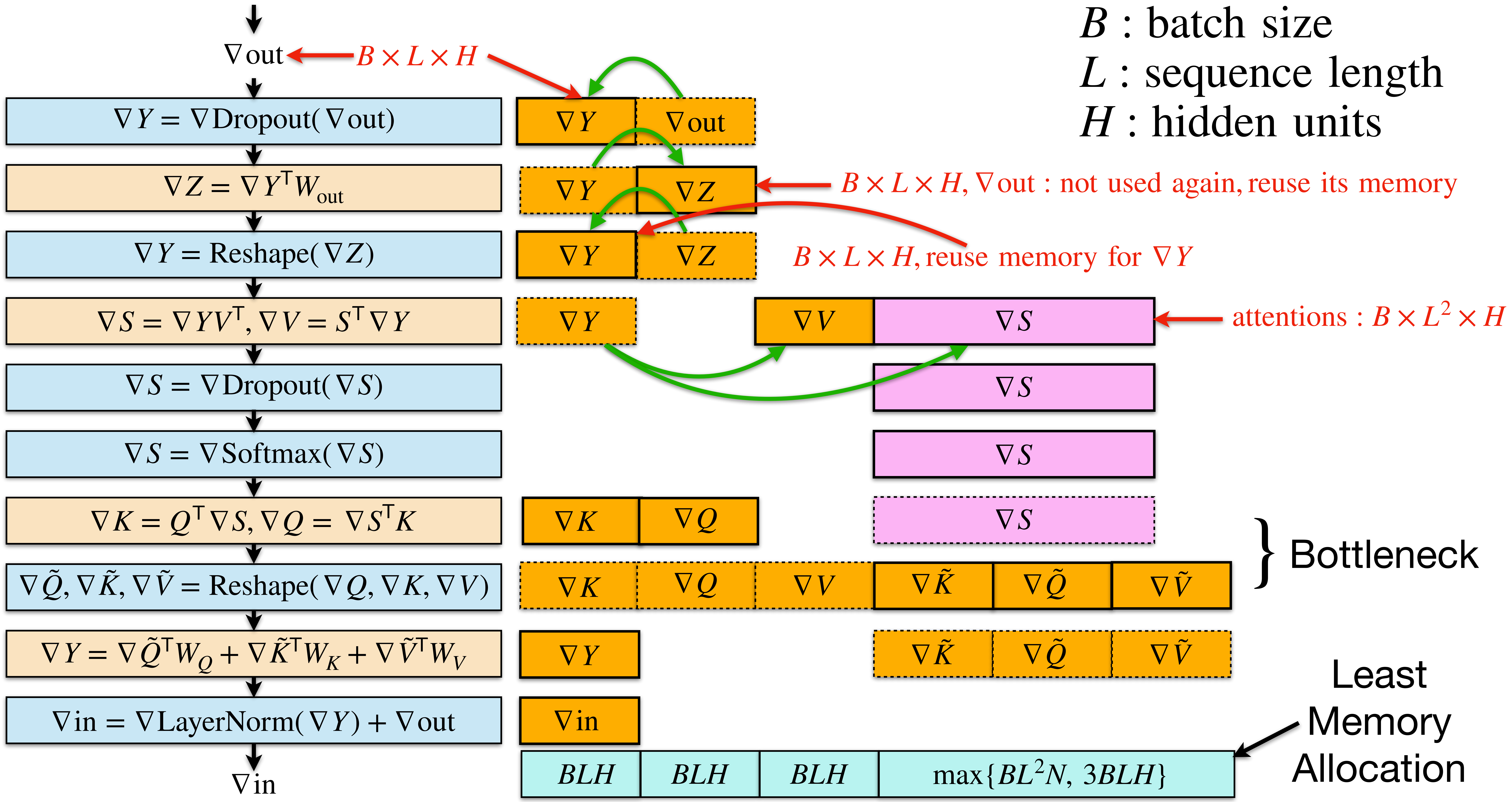
```
void launch_attn_softmax<float>(float *inp, const float *attn_mask,
                                int batch_size, int nhead, int from_len
                                int to_len, bool mask_future,
                                cudaStream_t stream) {
  dim3 grid_dim(1, batch_size, nhead);
  if (to_len <= 32) {
    ker_attn_softmax_lt32<float, 32, 1><<<grid_dim, 32, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else if (to_len <= 64) {
    ker_attn_softmax_lt32<float, 32, 2><<<grid_dim, 32, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else if (to_len <= 128) {
    grid_dim.x = 16;
    ker_attn_softmax<float, 64, 2><<<grid_dim, 64, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else if (to_len <= 256) {
    grid_dim.x = 32;
    ker_attn_softmax<float, 128, 2><<<grid_dim, 128, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else if (to_len <= 512) {
    grid_dim.x = 64;
    ker_attn_softmax<float, 256, 2><<<grid_dim, 256, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else if (to_len <= 1024) {
    grid_dim.x = 128;
    ker_attn_softmax<float, 512, 2><<<grid_dim, 512, 0, stream>>>(
        inp, attn_mask, from_len, to_len, mask_future);
  } else {
    throw std::runtime_error(
        "Sequence length greater than 512 is currently not supported");
  }
}
```

https://github.com/bytedance/lightseq/blob/master/lightseq/csrc/kernels/cuda/softmax_kernels.cu

Accelerated Mixed-Precision Update

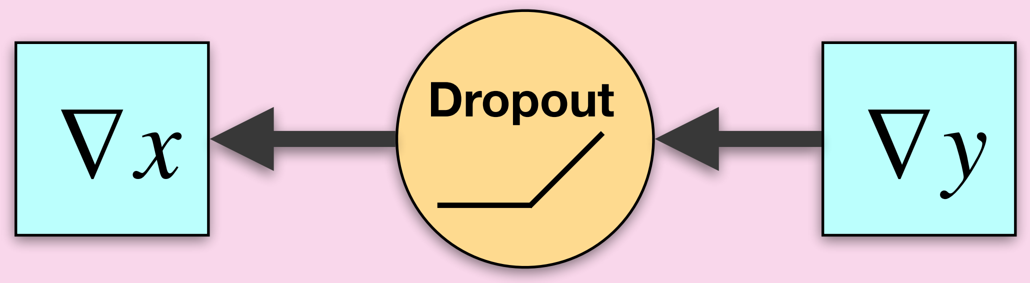


Memory Management: Self Attention Backward Example



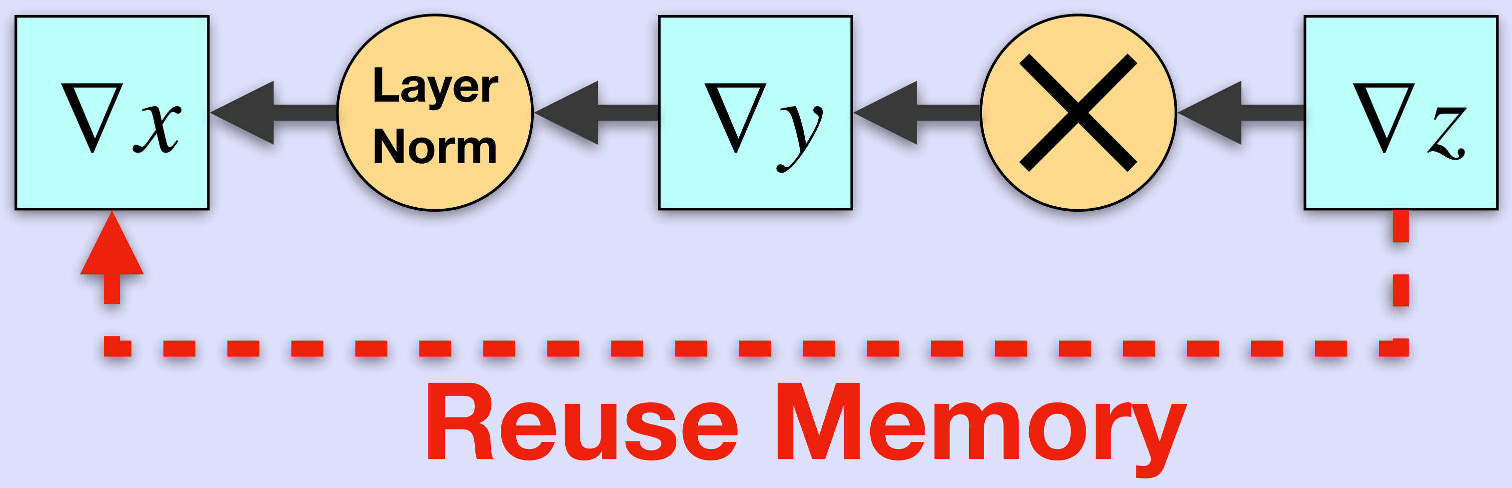
Summary for Accelerating Transformer Training

High performance Kernels for Forward and Backward



Efficient Parameter Update

Memory Management



key techniques

- Kernel Fusion: merge kernels other than matmul
- Algebraic Transformation: reduce sync
- Mix-precision calculation (use half precision whenever possible)
- Memory reuse (dependent on architecture)

Fast Inference for Transformer

LightSeq: A High Performance Inference Library for Transformers

Xiaohui Wang, Ying Xiong, Yang Wei, Mingxuan Wang, Lei Li

NAACL 2021

TurboTransformers: An Efficient GPU Serving System For Transformer Models

Jiarui Fang, Yang Yu, Chengduo Zhao, Jie Zhou

PPoPP 2021

Inference: Beam Search

argmax_y P(Y|X)

1. start with empty S

2. at each step, keep k best partial sequences

3. expand them with one more forward generation

4. collect new partial results and keep top-k

Code Example

```
# 1.compute next token log probability
log_token_prob = tf.nn.log_softmax(logit) # [batch_size, beam_size, vocab_size]
log_seq_prob += log_token_prob # [batch_size, beam_size, vocab_size]
log_seq_prob = tf.reshape(log_seq_prob, [-1, beam_size * vocab_size])
# 2. compute the top k sequence probability for each batch sequence
topk_log_probs, topk_indices = tf.nn.top_k(log_seq_prob, k=K)
# 3. refresh the cache (decoder key and values) based on beam id
refresh_cache(cache, topk_indices)
```

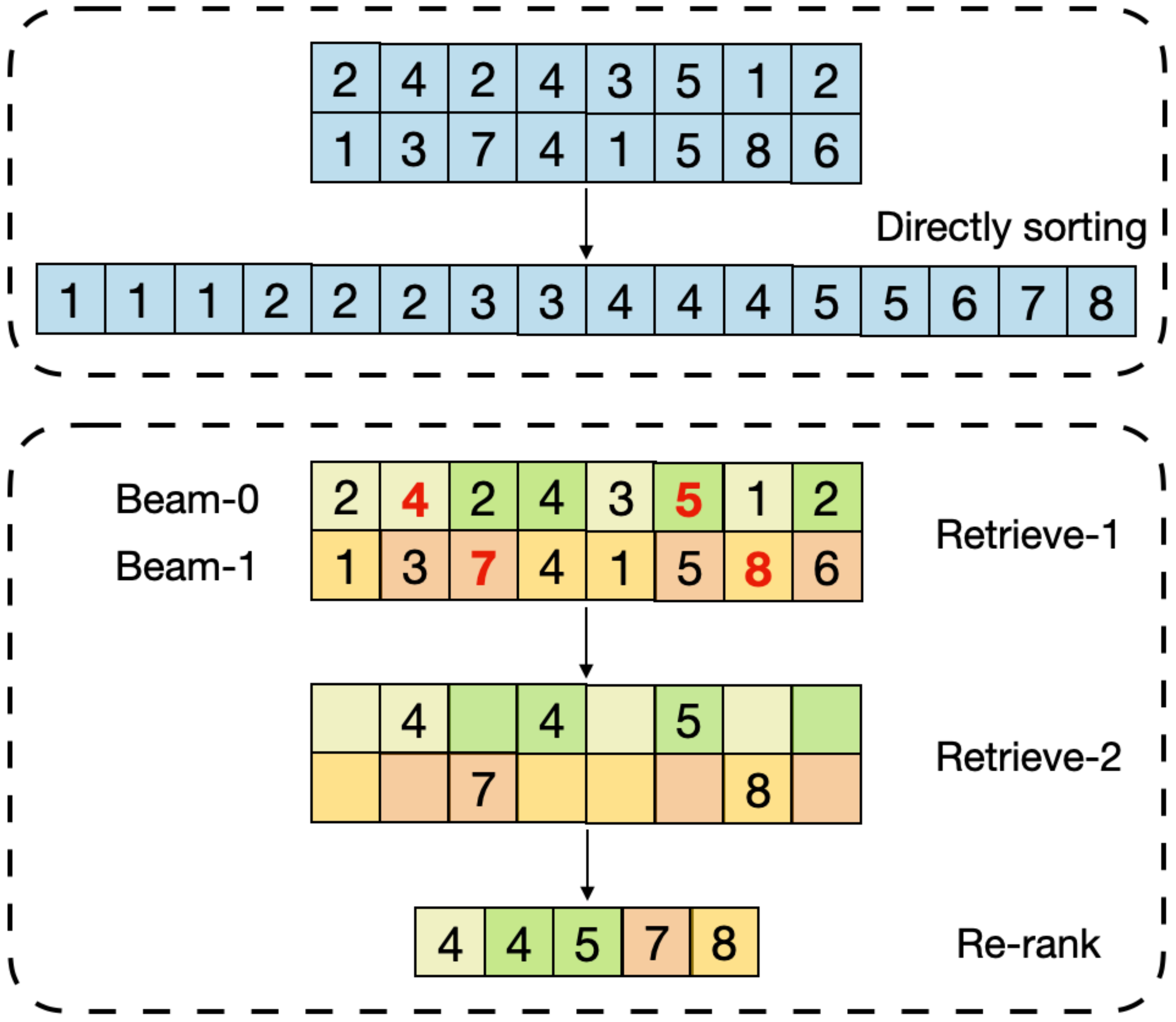
Hierarchical Auto Regressive Search for decoding

- Two calculations are needed in one step of beam search:
  - Compute the conditional probability of each token in vocab using Softmax
  - Select the top-k beams by sequential probability.
    - need sorting k*V elements!

- retrieve and re-rank to reduce complexity

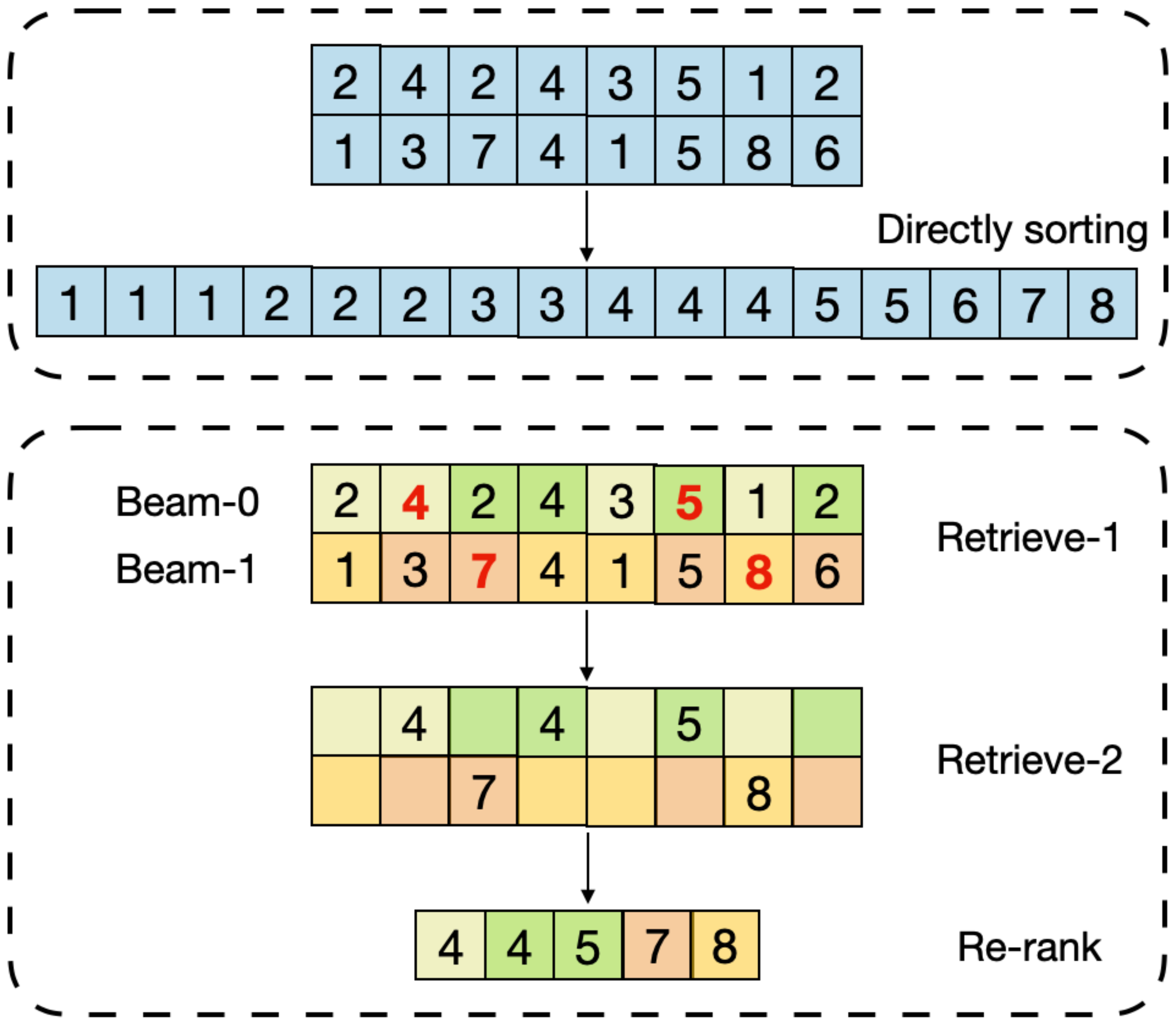
Retrieve

- Divide logits into k groups.
- Calculate the maximum of group i, denoted as m_i, marked red
- Calculate the minimum of m_i in each beam, denoted as rough top-kth logit $\mathscr{R}$.
- Select logits larger than $\mathscr{R}$ and write them into GPU memory.



Re-rank

- Re-rank on candidate logits



Example

- Original logits, with Beam size = 2 and Vocab size = 8.

2	4	2	4	3	5	1	2
1	3	7	4	1	5	8	6

Example

- For each beam, divide the eight logits into two groups.

2	4	2	4	3	5	1	2
1	3	7	4	1	5	8	6

Example

- Calculate the *maximum* of each group.

2	**4**	2	4	3	**5**	1	2
1	3	**7**	4	1	5	**8**	6

Example

- For each beam, calculate the *minimum* of each group's maximum.

2	**4**	2	4	3	5	1	2
1	3	**7**	4	1	5	8	6

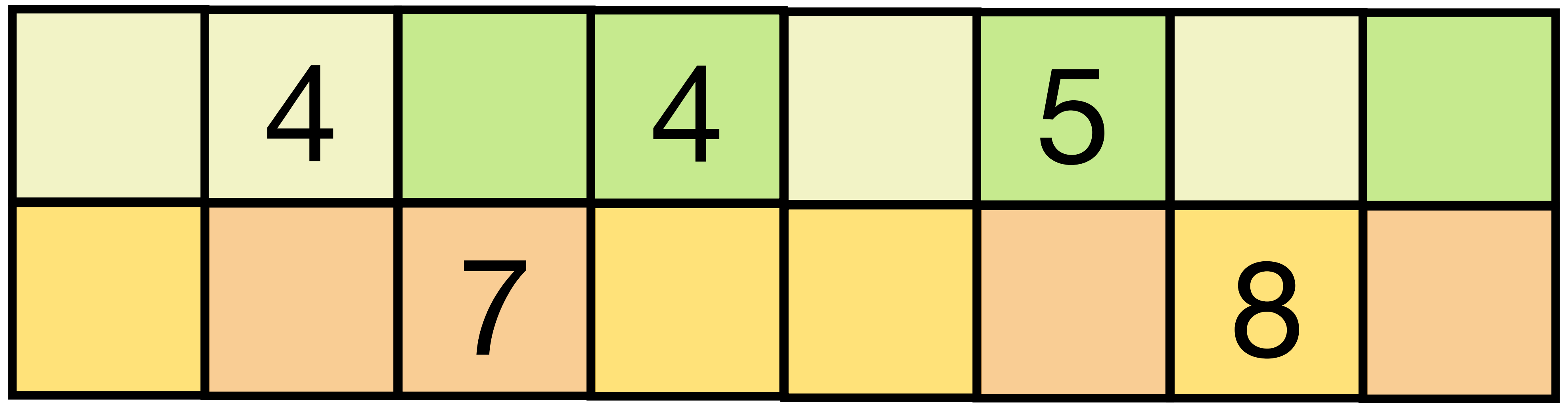
Example

- For each beam, select logits larger than the minimum in previous step.

2	**4**	2	**4**	3	**5**	1	2
1	3	**7**	4	1	5	**8**	6

Example

- For each beam, select logits larger than the minimum in previous step.



Example

- Re-rank only on five logits

4	4	5	7	8

Details in Implementation

- share tensor memory across layers
- mixed precision computation, mostly using FP16 for computation
- Using `float4 and half2 to increase bandwidth`
- No need to keep intermediate results and gradients during infernece, similar to `with torch.no_grad()`

LightSeq Software Architecture

API Example: HuggingFace BERT

```
from lightseq.training import LSTransformerEncoderLayer

config = LSTransformerEncoderLayer.get_config(
            model="bert-base",
            max_batch_tokens=4096,
            max_seq_len=512,
            fp16=True,
            local_rank=0)

ls_layer = LSTransformerEncoderLayer(config)

# replace the 1st Hugging Face layer with LightSeq2
bert_model.layer[0] = ls_layer
```

Step 1: import LightSeq

Step 2: Config and define your model/layer

Step 3: Replace HuggingFace Layer

LightSeq + Fairseq Integration

```
lightseq-train DATA_SET \
    --task translation \
    --arch ls_transformer_wmt_en_de_big_t2t \
    --optimizer ls_adam \
    --criterion ls_label_smoothed_cross_entropy \
    --OTHER_PARAMS
```

- LightSeq can be seamlessly used with Fairseq
  - Training: `lightseq-train`, using prefix `ls_`

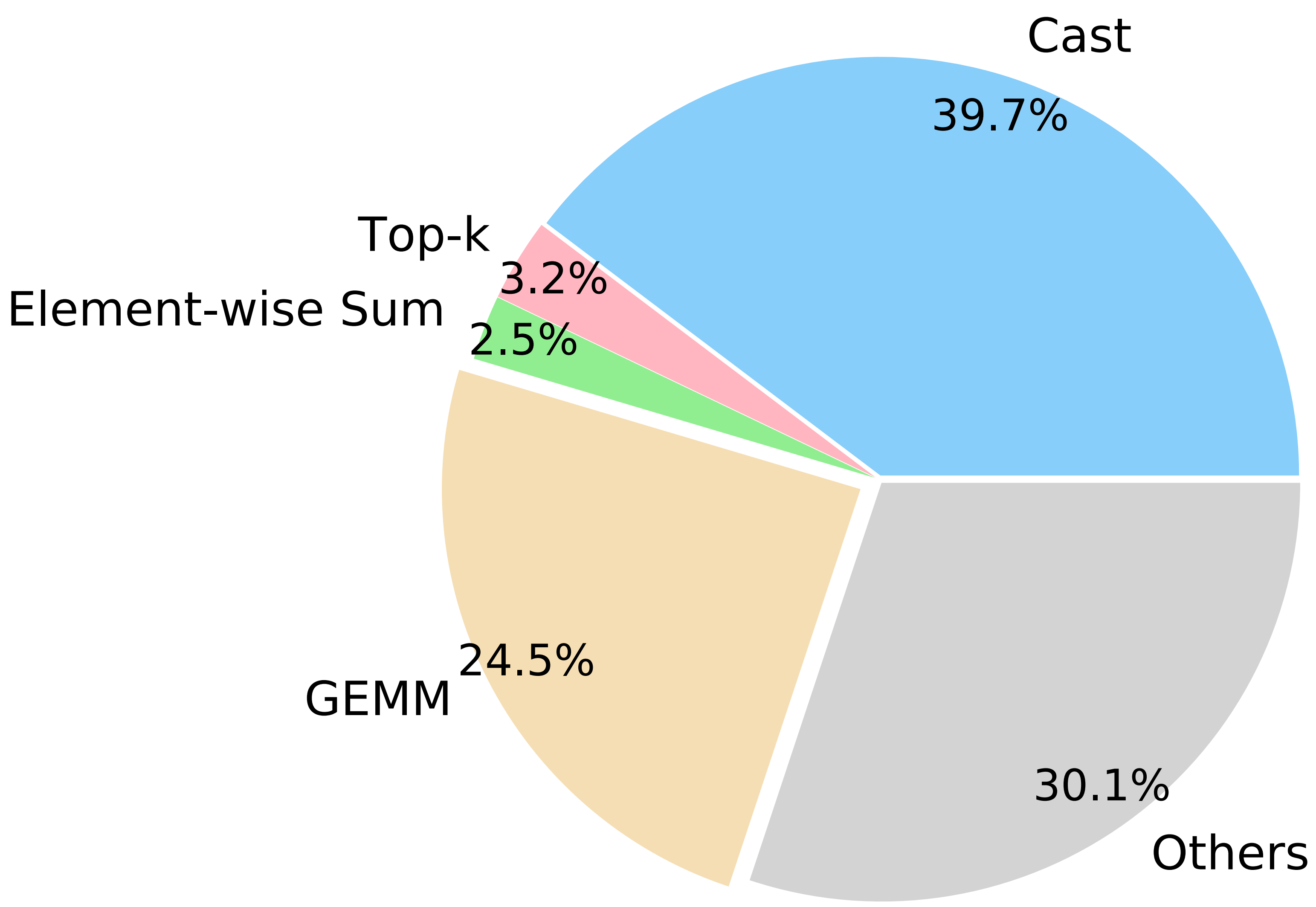
LightSeq + Fairseq Integration

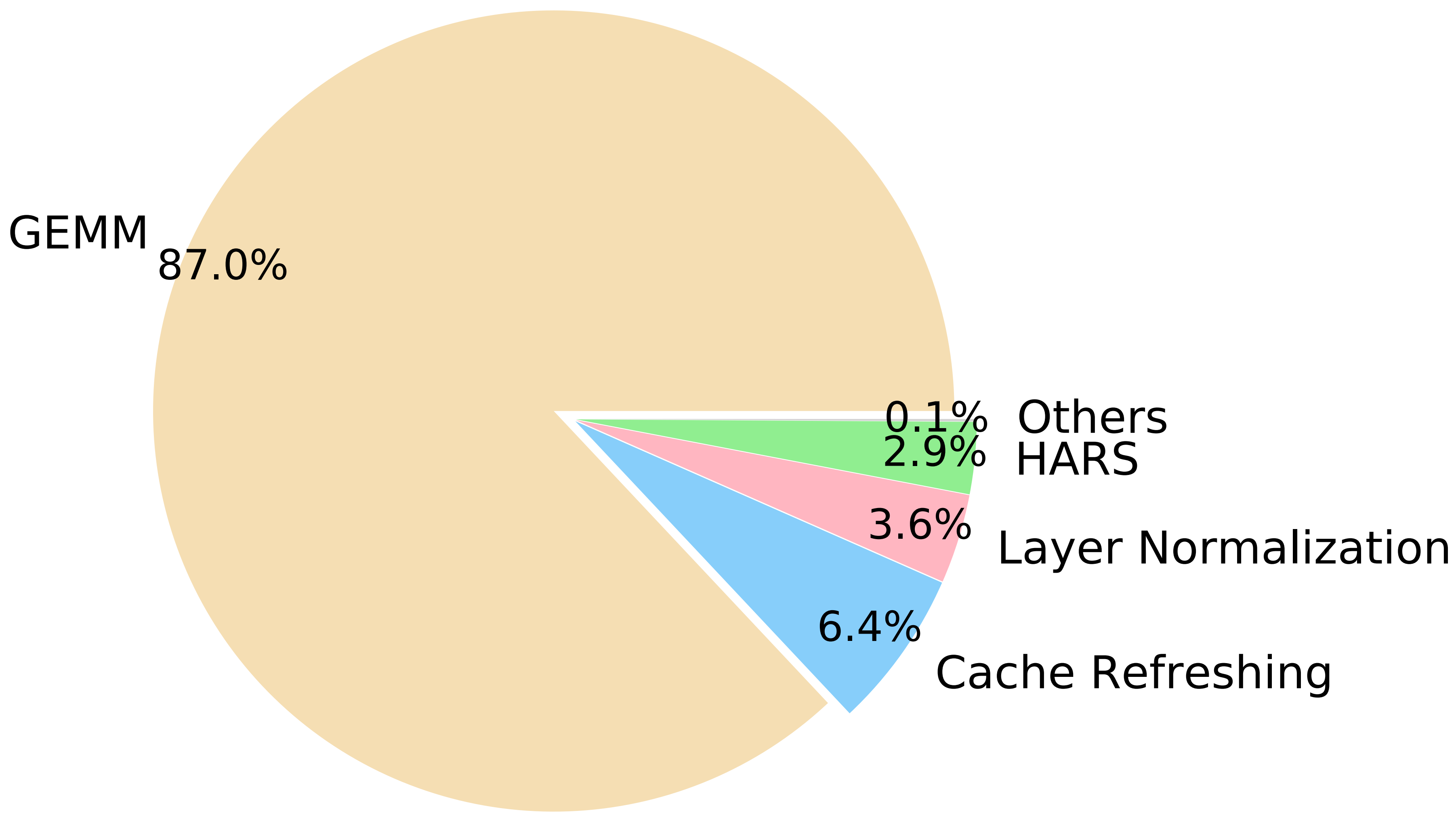
- LightSeq accelerated Transformer embedding / encoder / decoder、Adam and cross entropy for Fairseq
- LightSeq is compatible with Fairseq cache and reorder
- LightSeq is compatible with Apex and DeepSpeed together with Fairseq。

```
deepspeed ds_fairseq.py DATA_SET \
    --user-dir fs_modules \
    --deepspeed_config deepspeed_config.json \
    --task translation \
    --arch ls_transformer_wmt_en_de_big_t2t \
    --optimizer ls_adam \
    --criterion ls_label_smoothed_cross_entropy \
    --OTHER_PARAMS
```

GPU Occupation

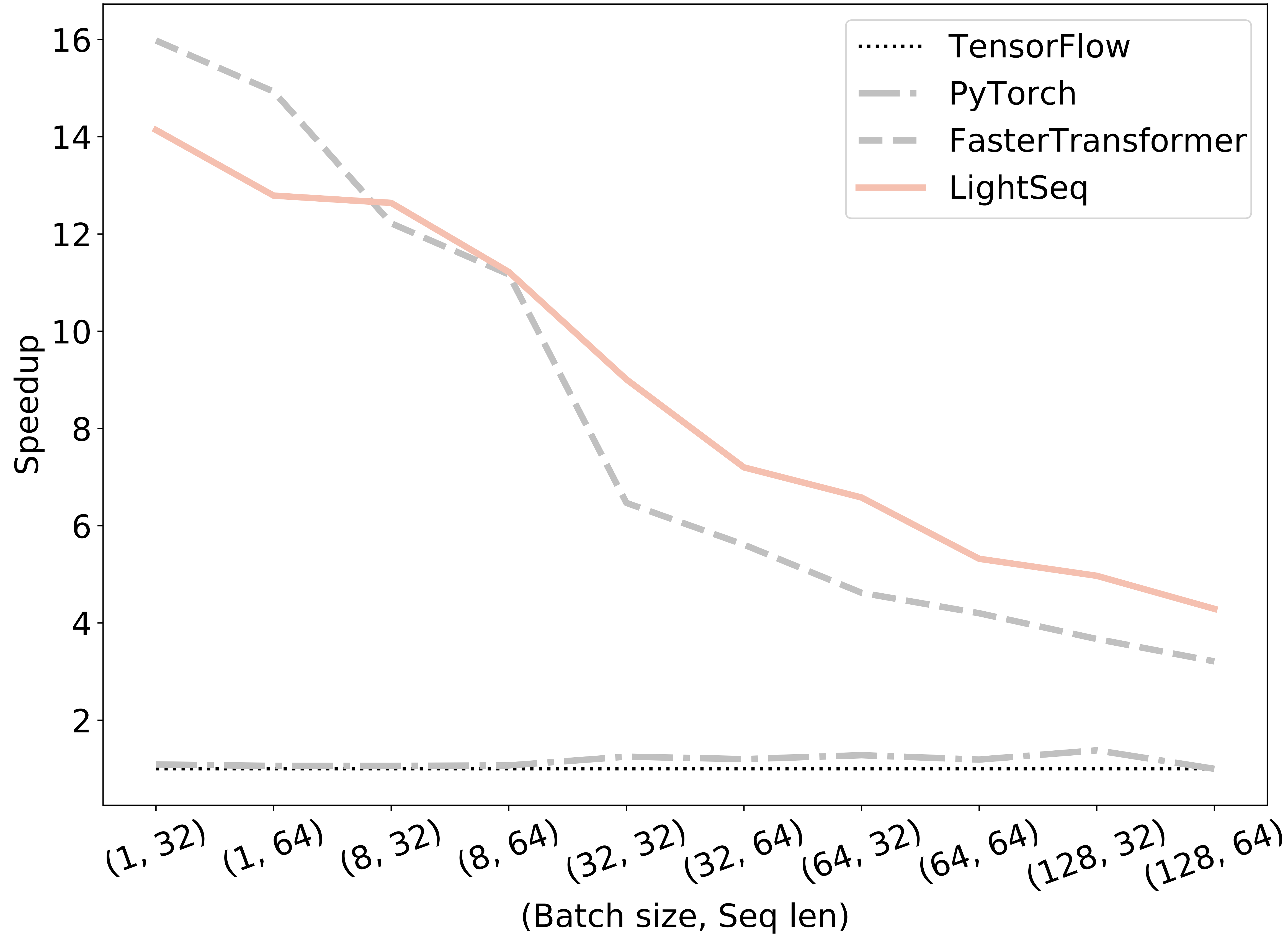
- LightSeq greatly reduces the proportion of kernels other than GEMM.





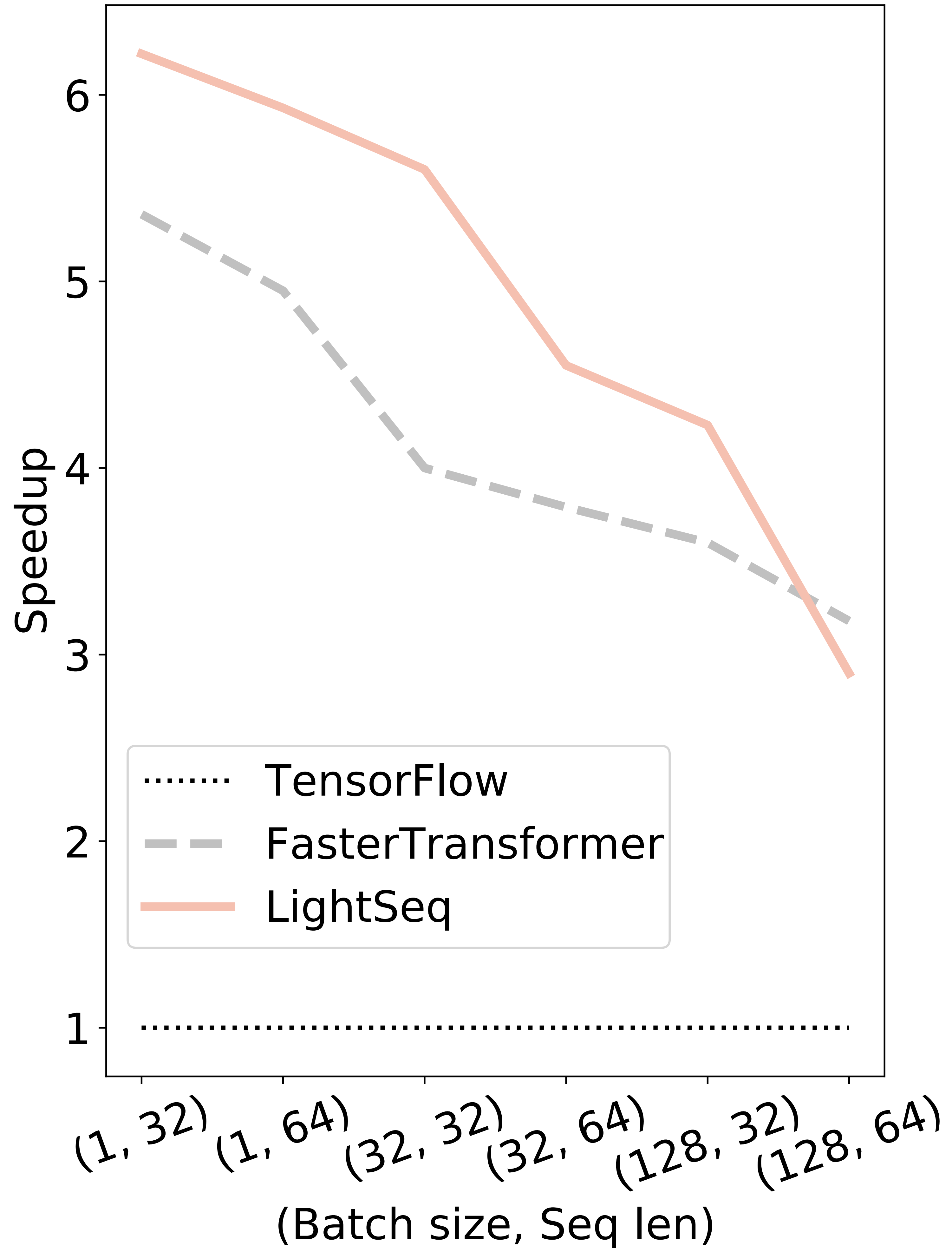
Machine Translation Inference: 14x speedup

- LightSeq outperforms others in most cases, especially in large batch size.

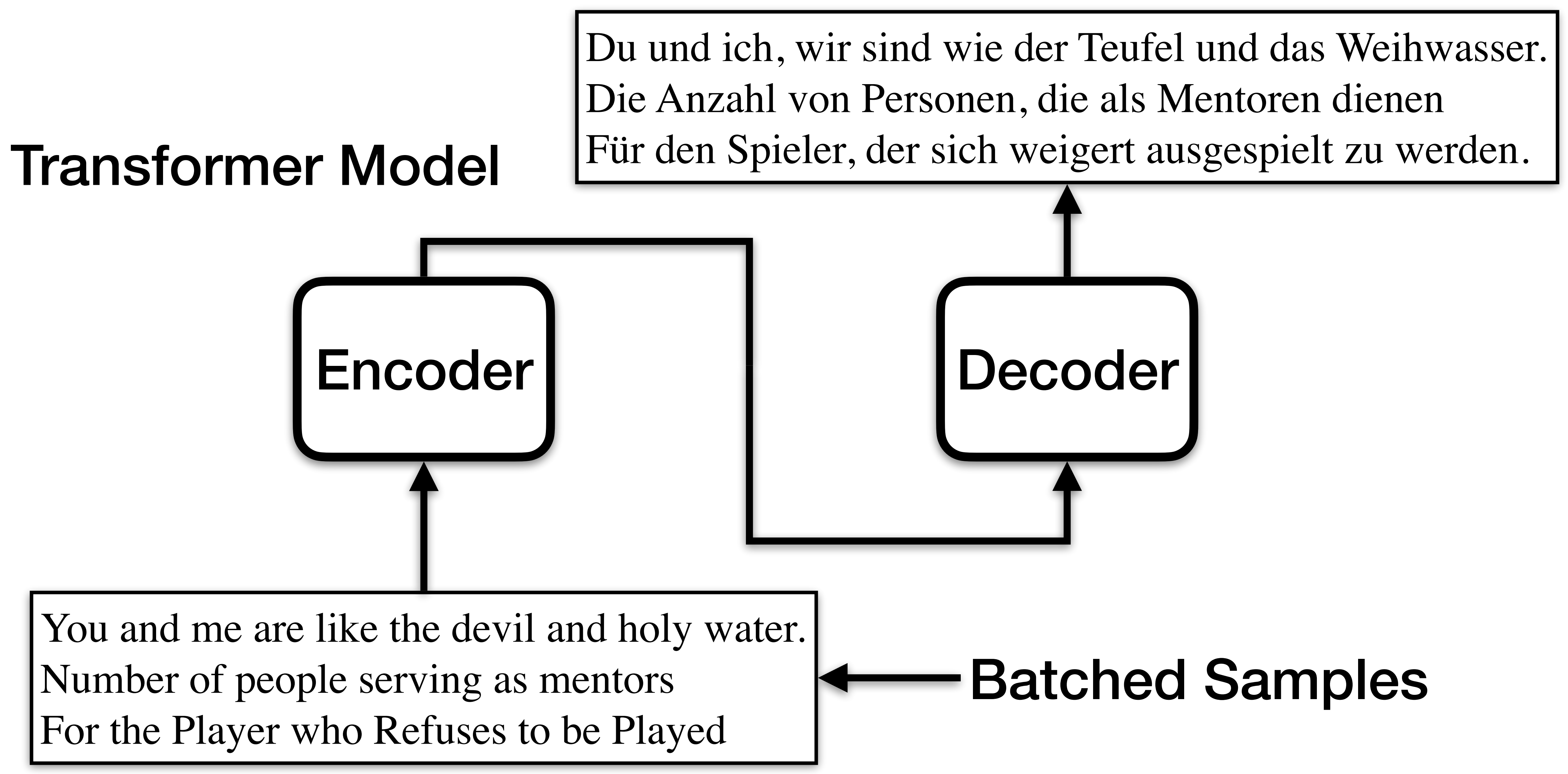


GPT2 Inference: 6x speedup

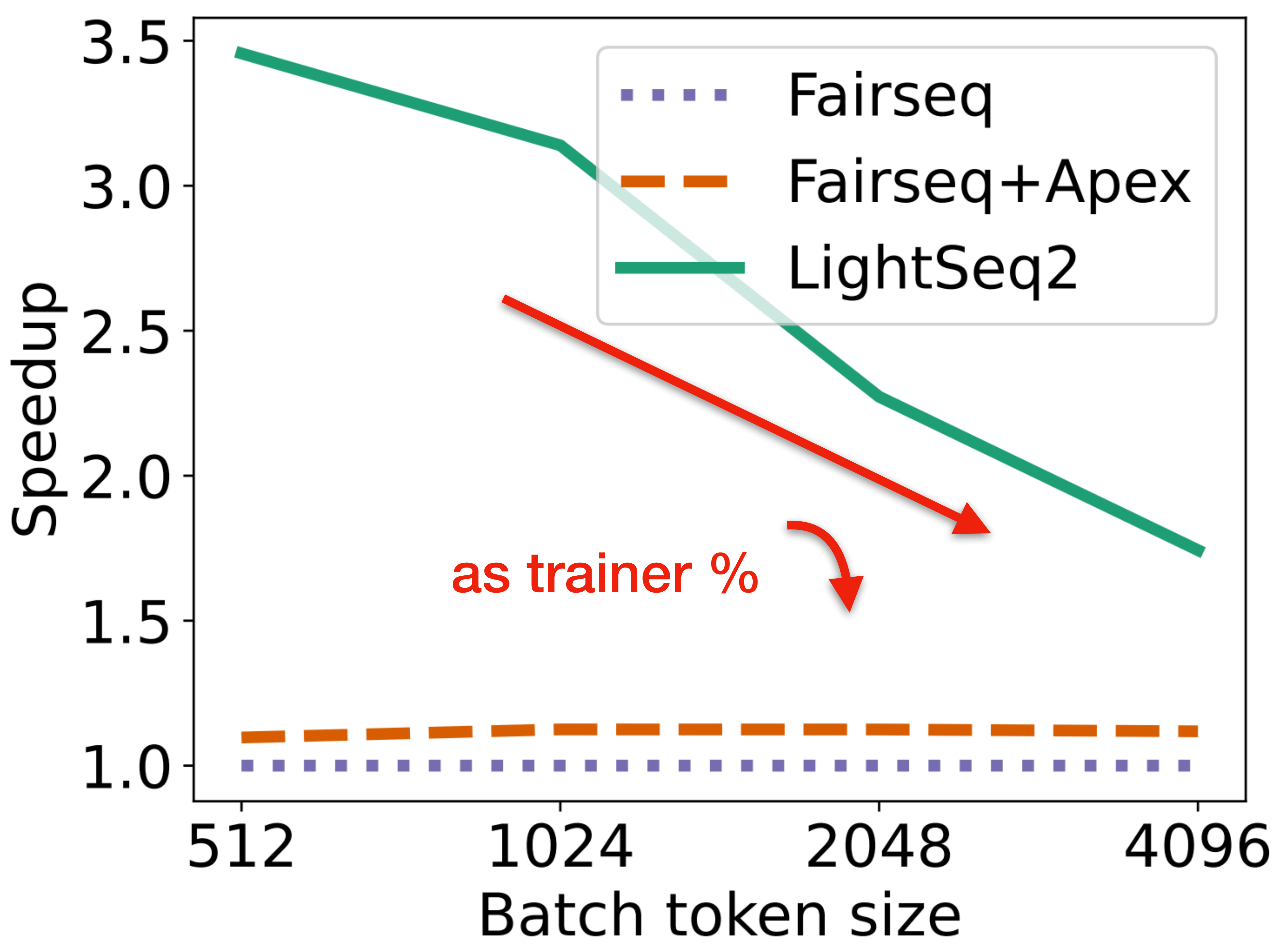
- LightSeq outperforms others in most cases



Machine Translation Training: 1.4-3.5x Speedup



DataSet	WMT14 English-German Machine Translation
Model	Transformer: 24 encoder layers + 24 decoder layers
Hardware	1 Worker with 8x A100
Baseline	FairSeq (PyTorch) + Apex (optimized operators)



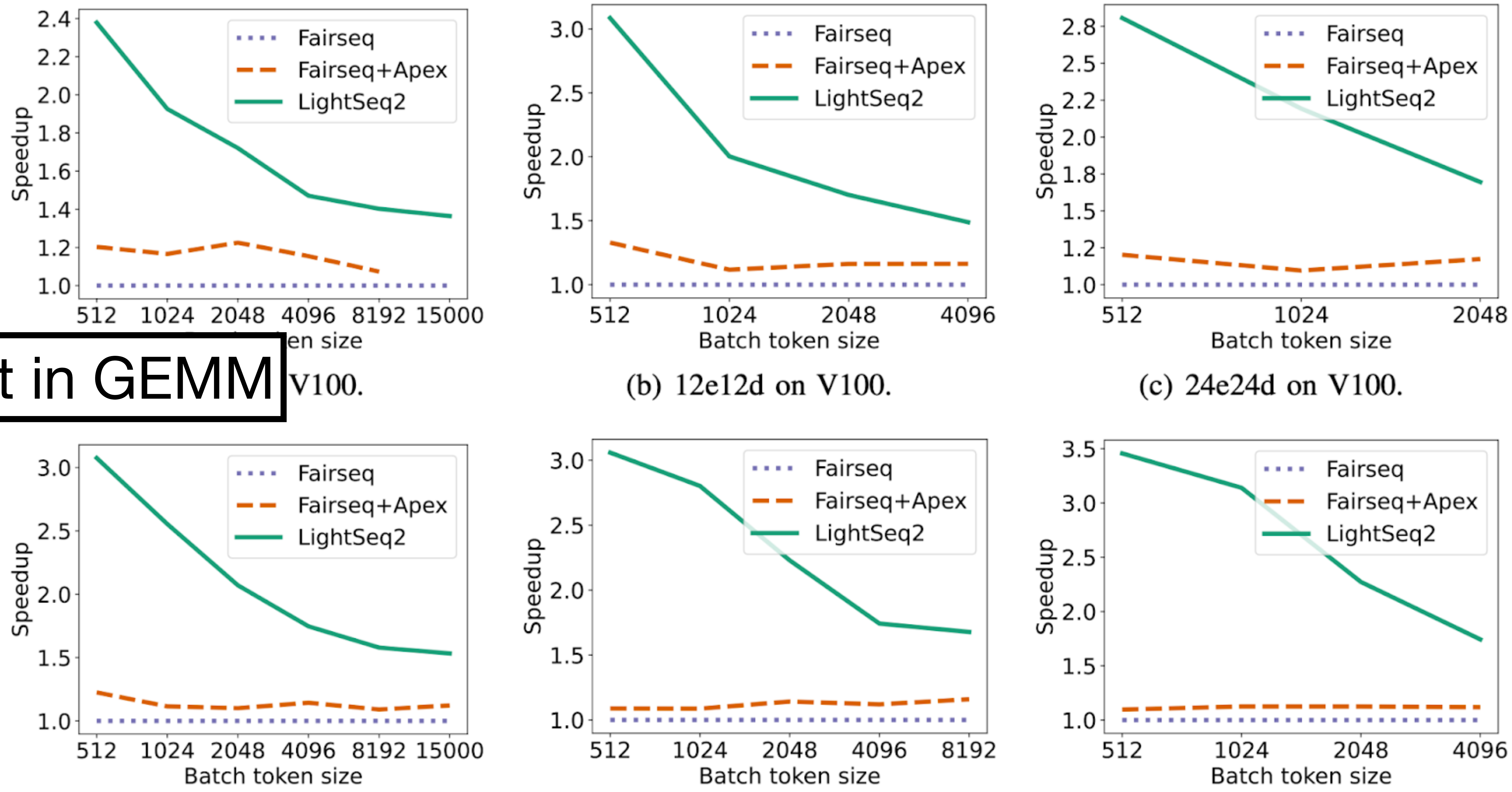
Experiment with different batch sizes

Machine Translation Training: 1.4-3.5x Speedup

V100: 1.4-2.8x →

A100: 1.5-3.5x →

A100 is more efficient in GEMM



V100.

(b) 12e12d on V100.

(c) 24e24d on V100.

(d) 6e6d on A100.

(e) 12e12d on A100.

(f) 24e24d on A100.

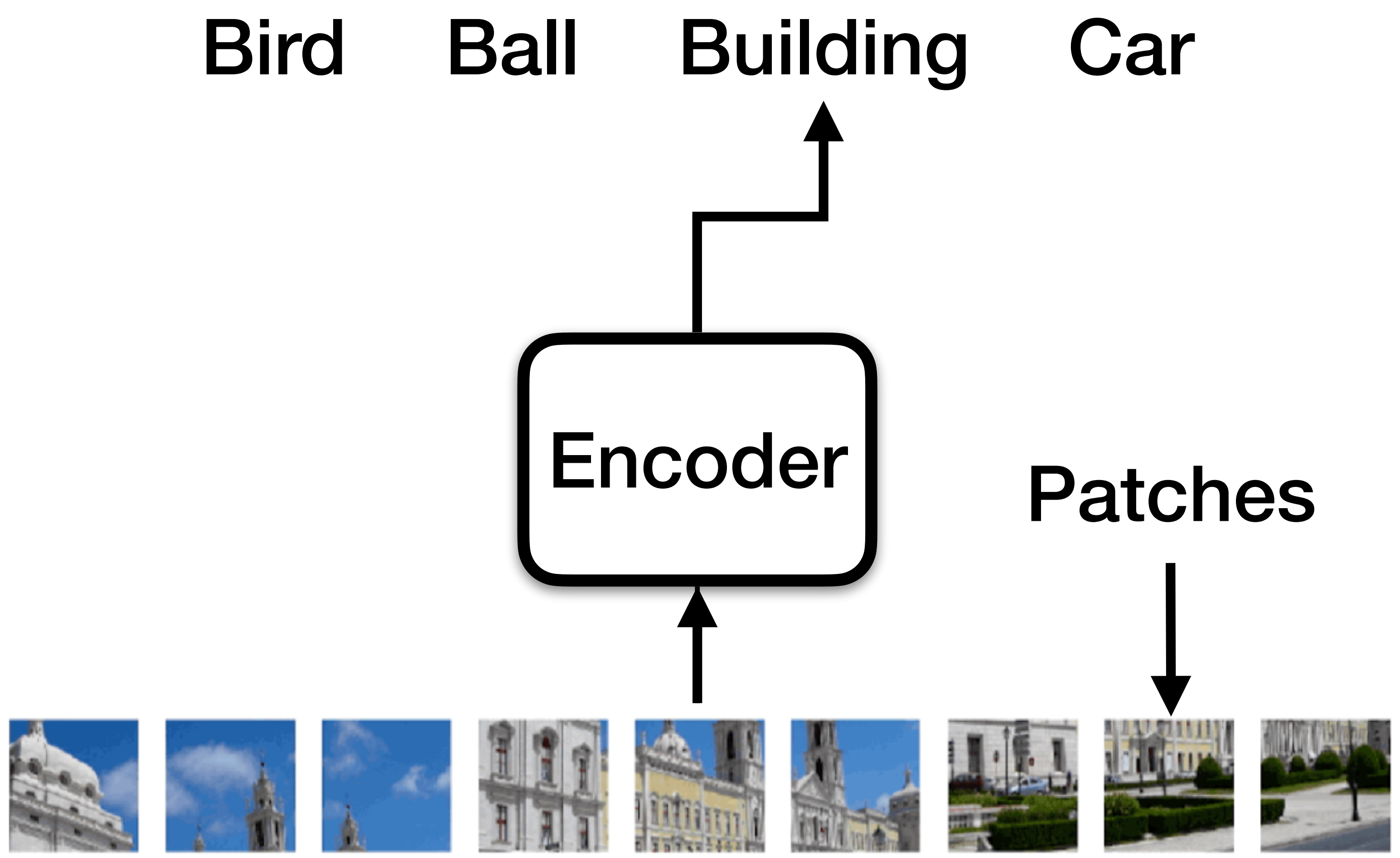
Model Size ↑ ⇒ Speedup ↑

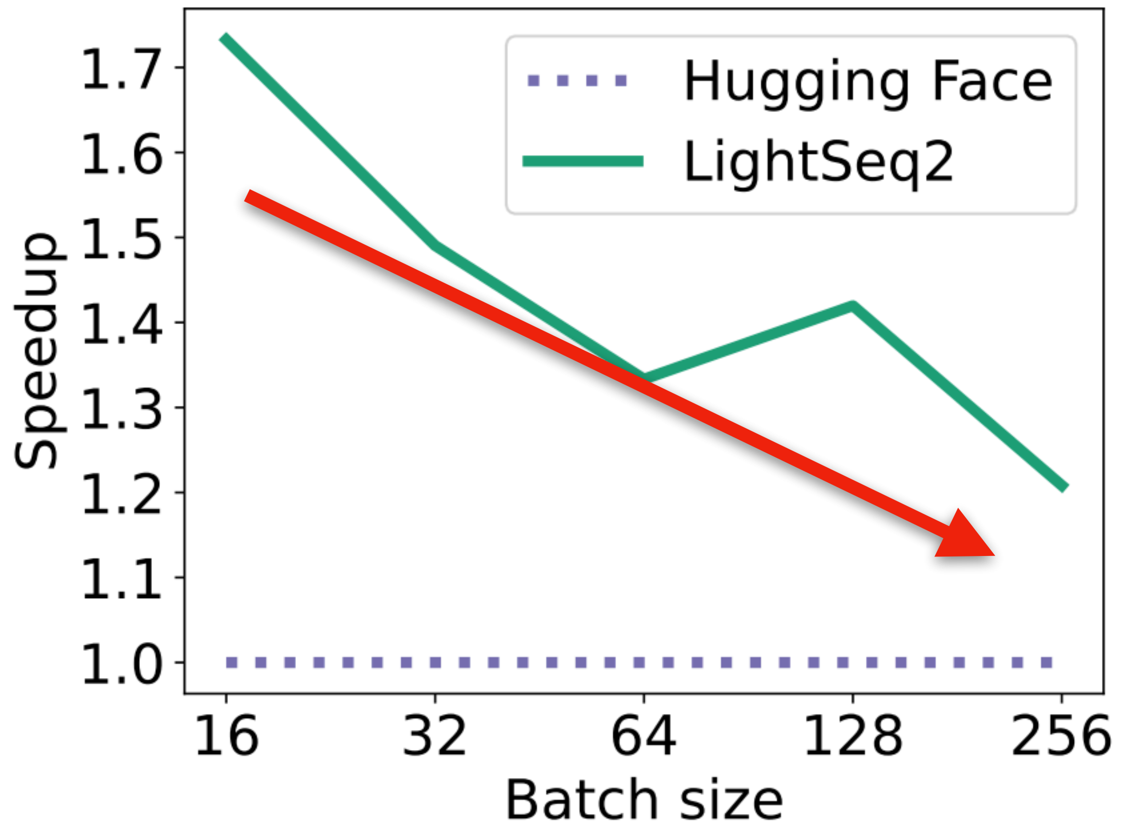
Visualization of Training on GPU

Image Classification: Vision Transformer (ViT)

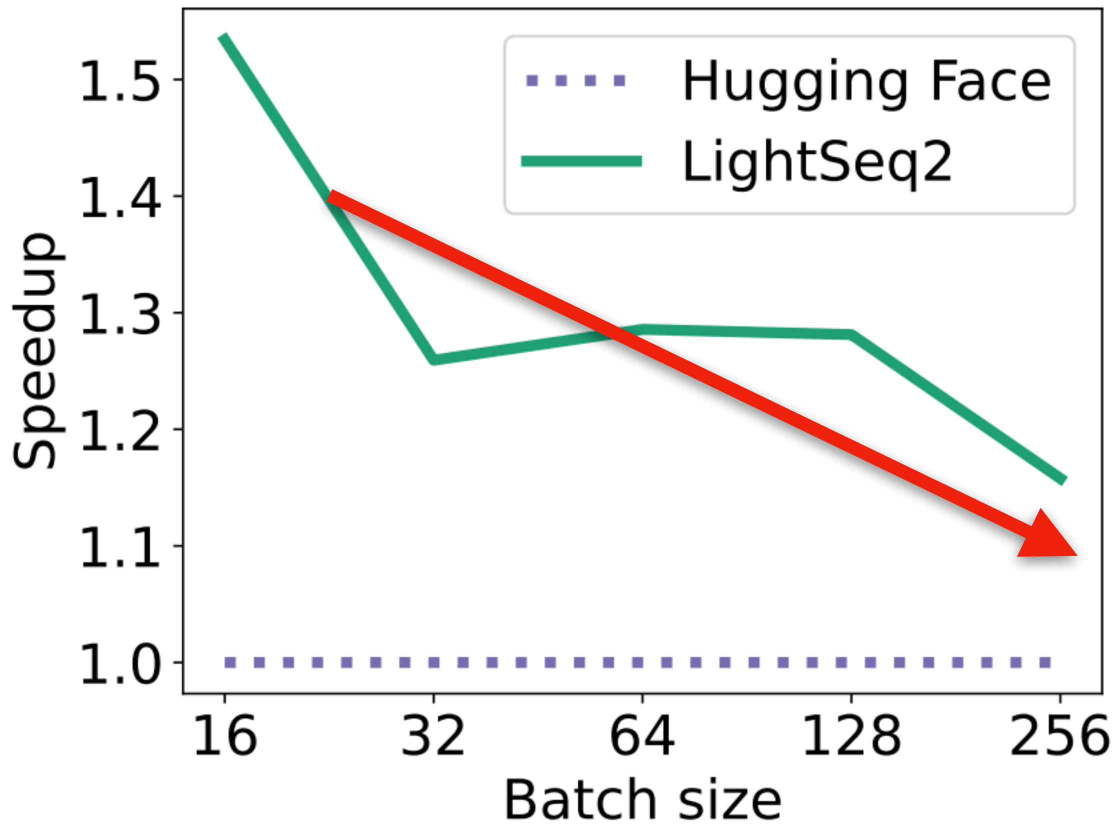
Vision Transformer for Image classification from google AI blog

Image Classification: 1.2-1.7x Speedup





Vit Base

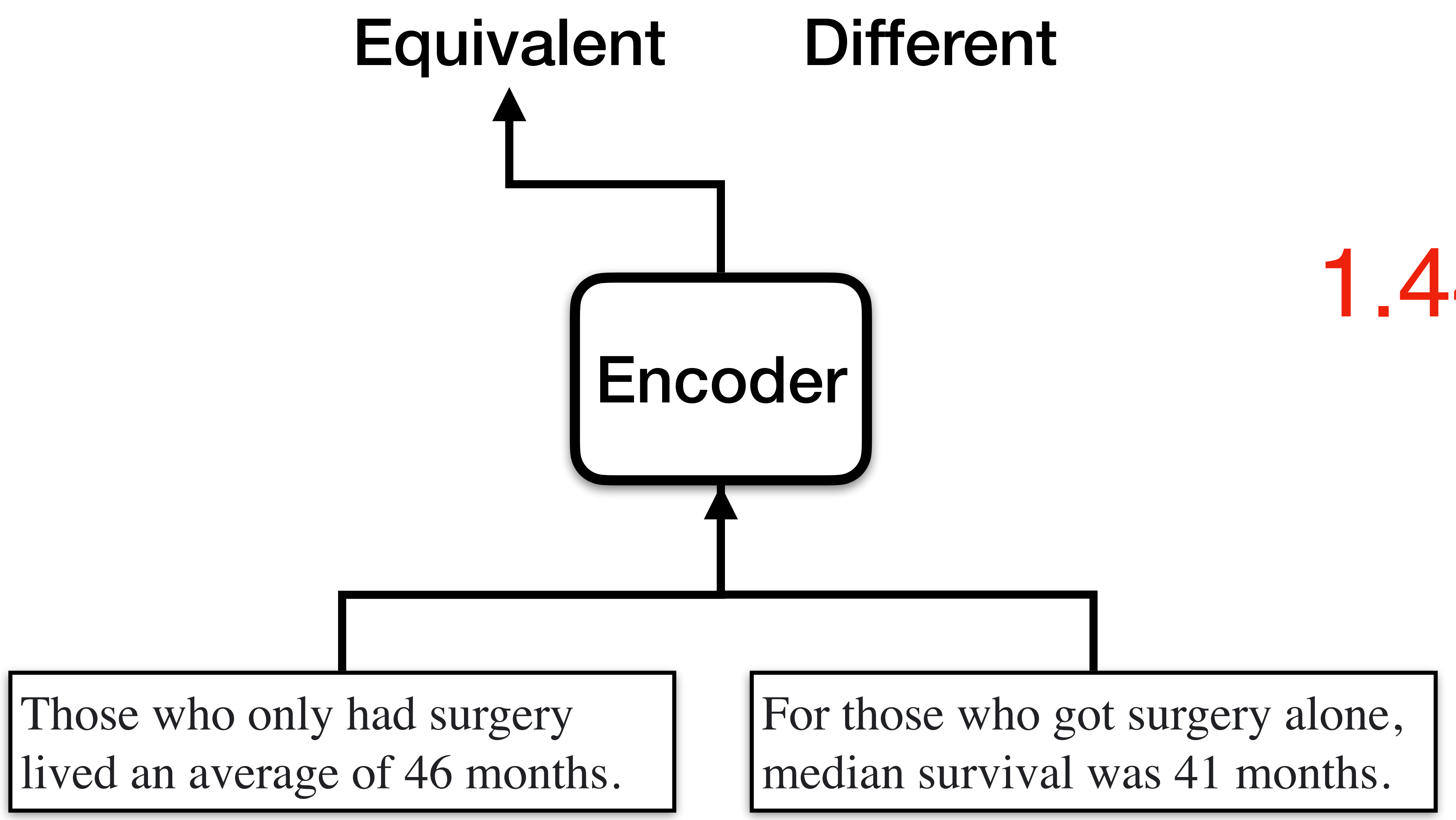


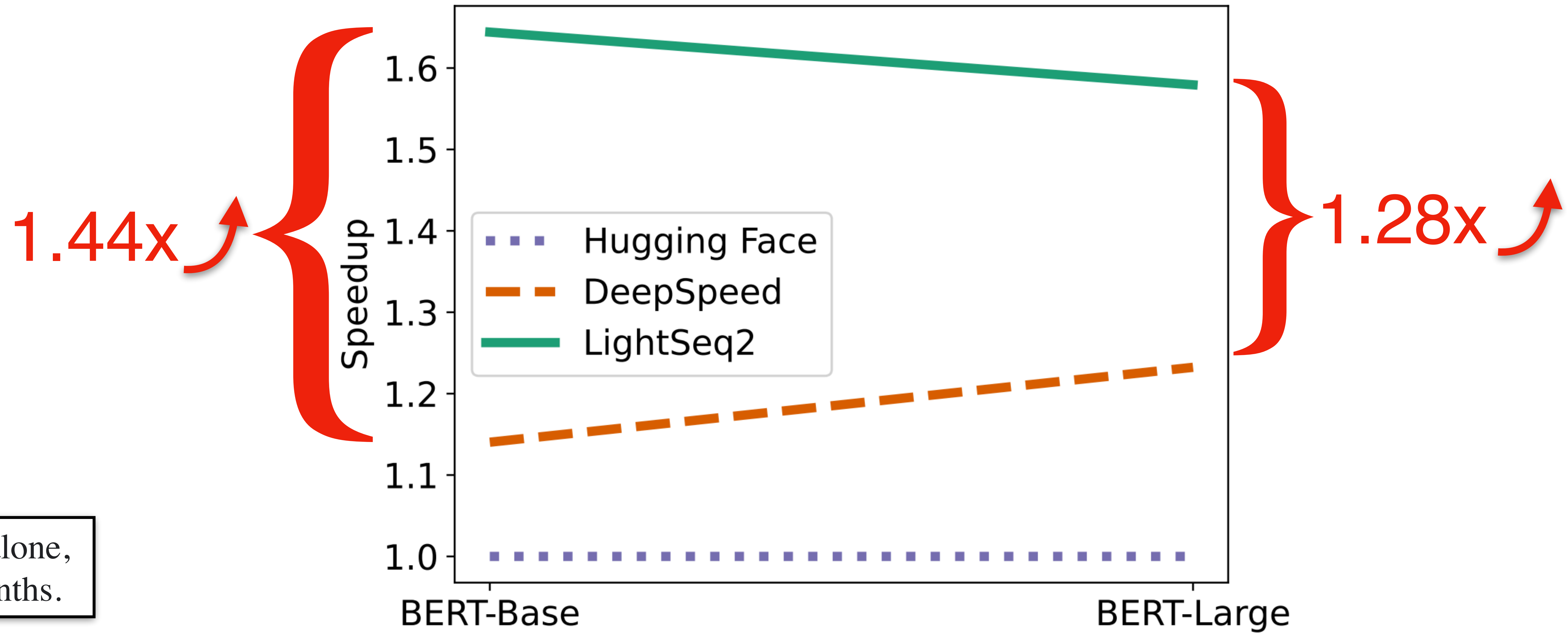
Vit Large

DataSet	CIFAR-10
Model	Vision Transformer (ViT)
Hardware	1 Worker with 8x V100
Baseline	Hugging Face (PyTorch)

Batch Size (#Patches) ⇨ Speedup

Paraphrase Identification: 1.28-1.44x Speedup



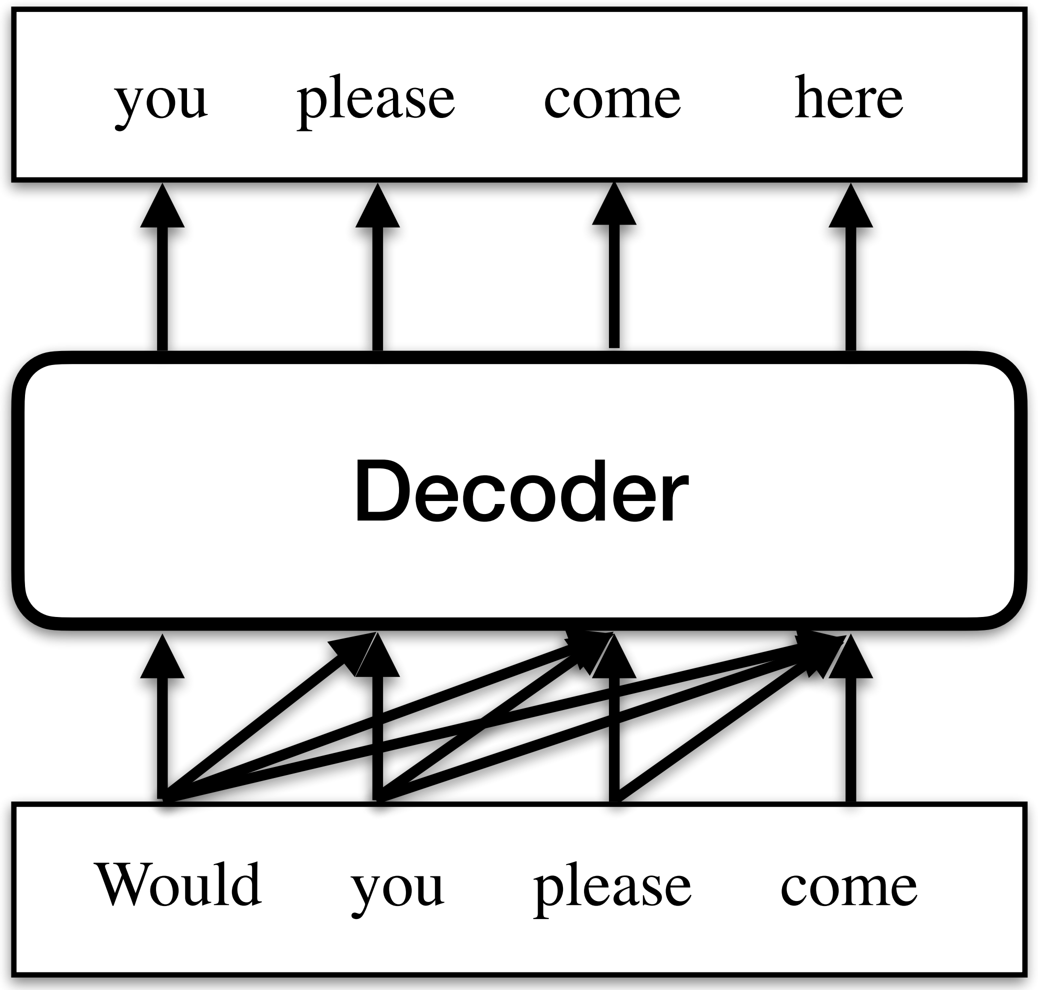


DataSet	Microsoft Research Paraphrase Corpus
Model	BERT
Hardware	1 Worker with 8x V100
Baseline	Hugging Face (PyTorch) DeepSpeed (Kernel Fusion)

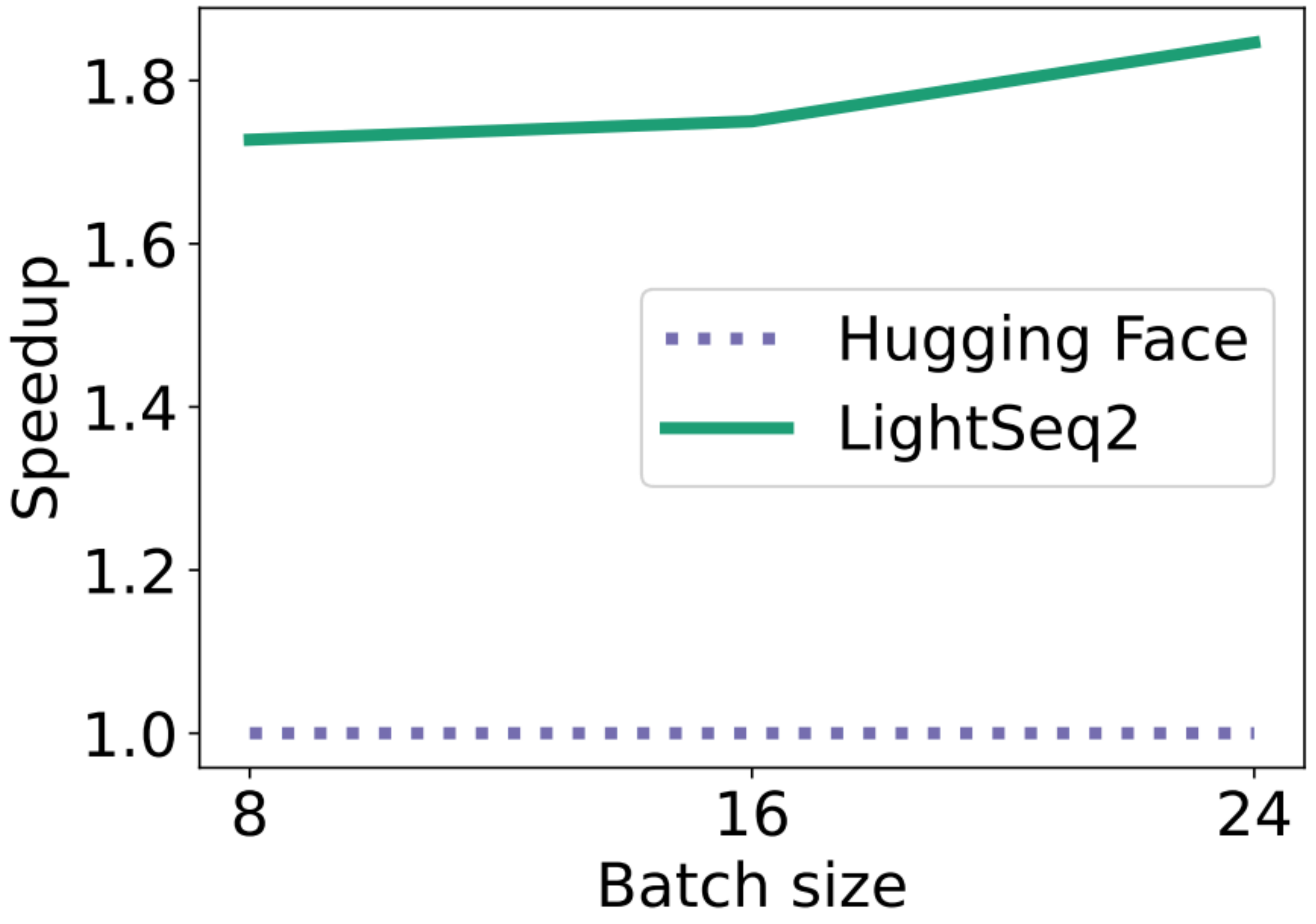
Library	Criterion	Embedding	Trainer
DeepSpeed	✘	✘	✘
LightSeq 2	✔	✔	✔

LightSeq2 vs DeepSpeed Major Differences

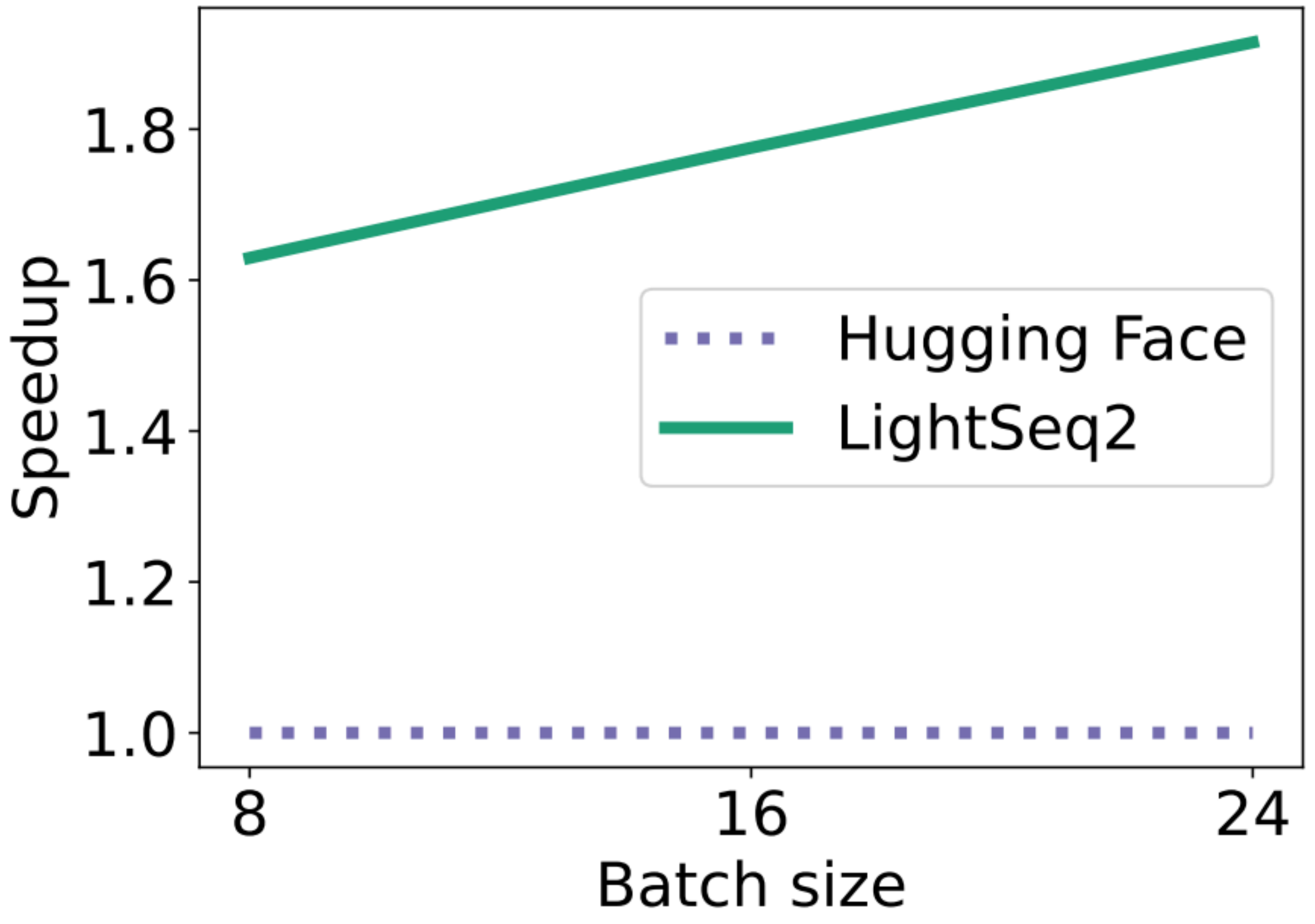
GPT2 Training: 1.6-1.9x Speedup



DataSet	WikiText
Model	GPT2
Hardware	1 Worker with 8x V100/A100
Baseline	Hugging Face (PyTorch)



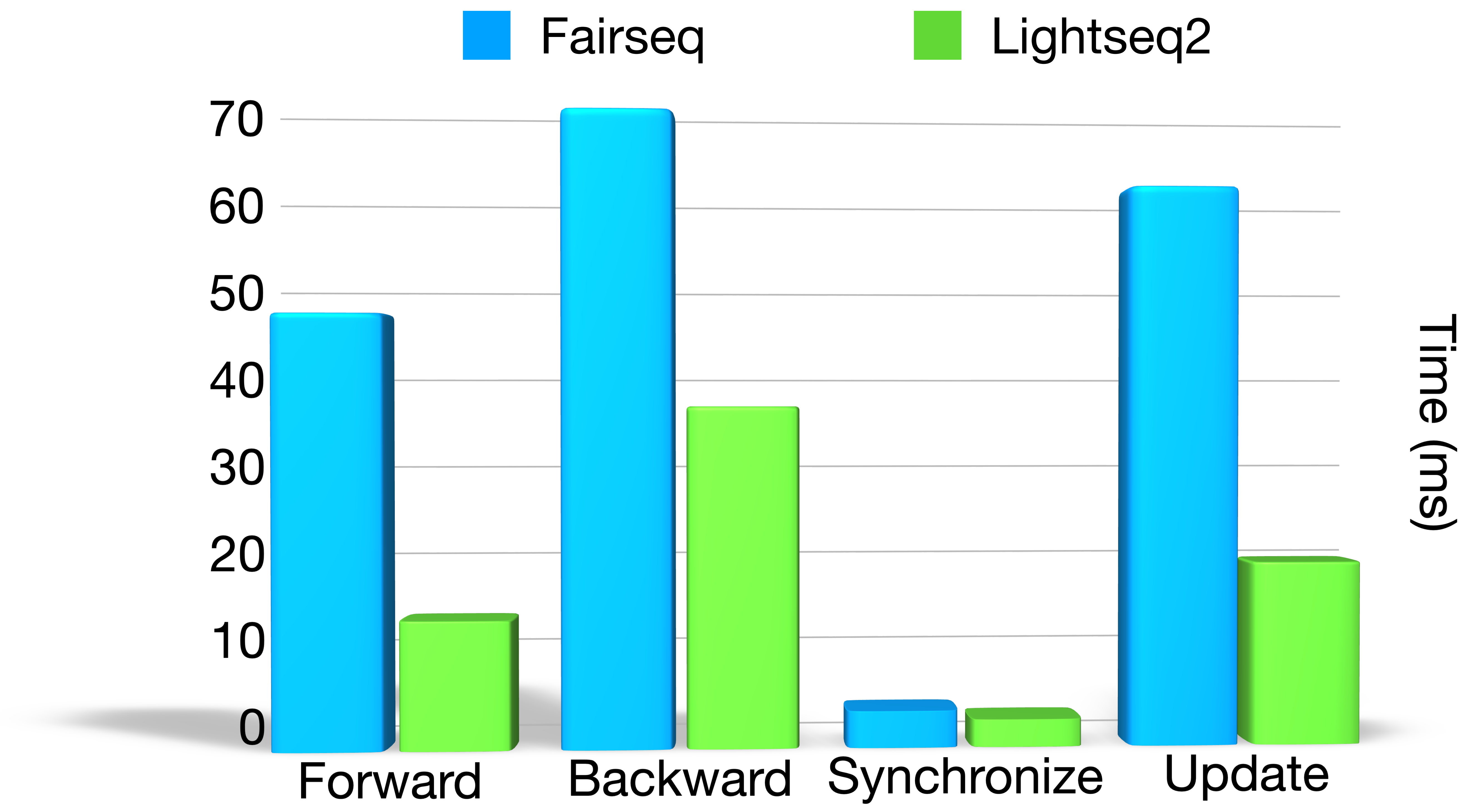
GPT2 Large trained on V100, 1.7-1.8x Speedup



GPT2 Large trained on A100, 1.6-1.9x Speedup

Training Speedup Breakdown

Task: WMT14 Engish German Machine Translation
(same for rest pages)

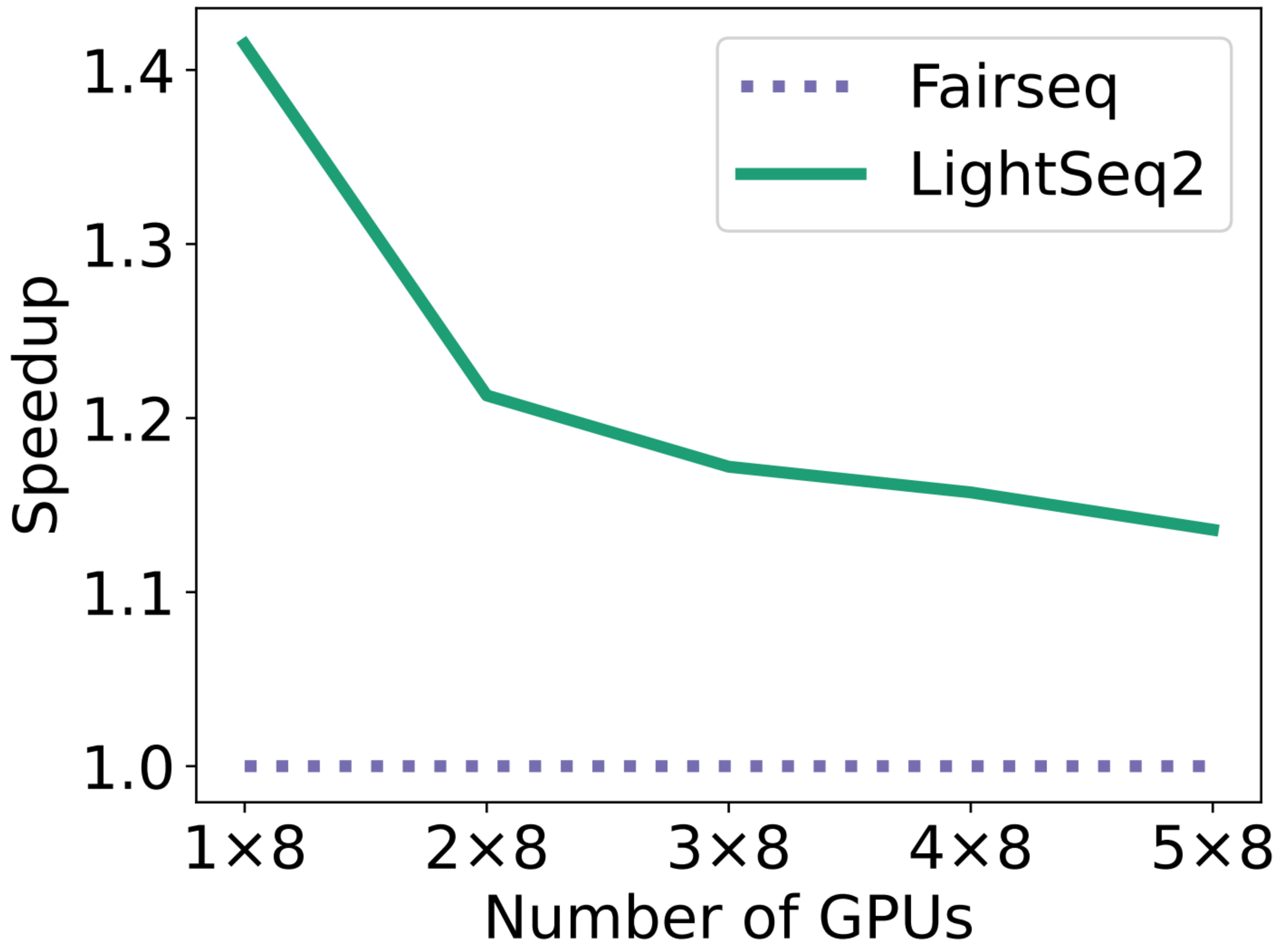


Time cost for each training stages

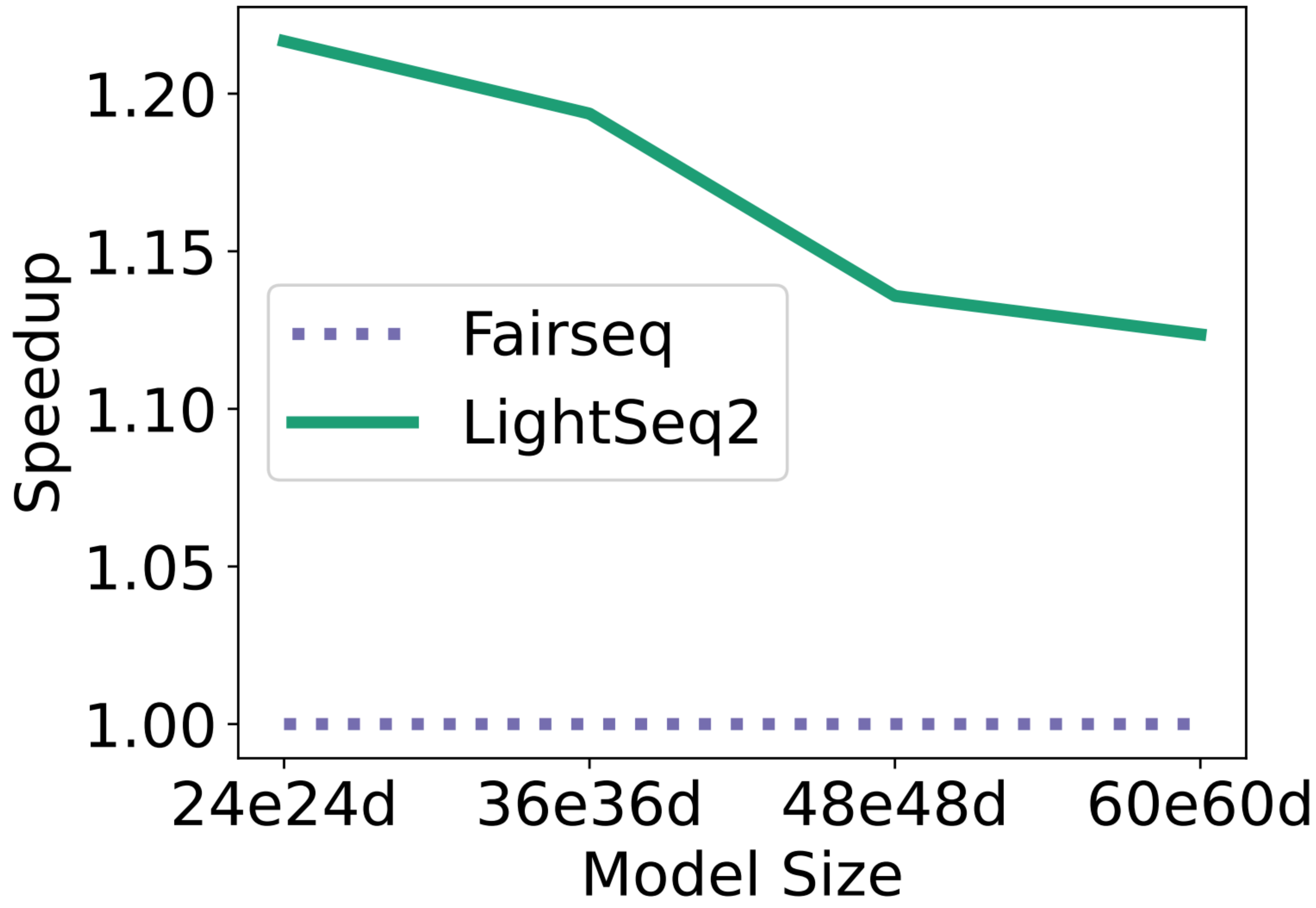
Operator	Speedup
LayerNorm	4x
Softmax	2.5-3.4x
Dropout	1.1-2.5x
Trainer	2.3x

Operator Speedup

Scalability: 1.12-1.41x Speedup

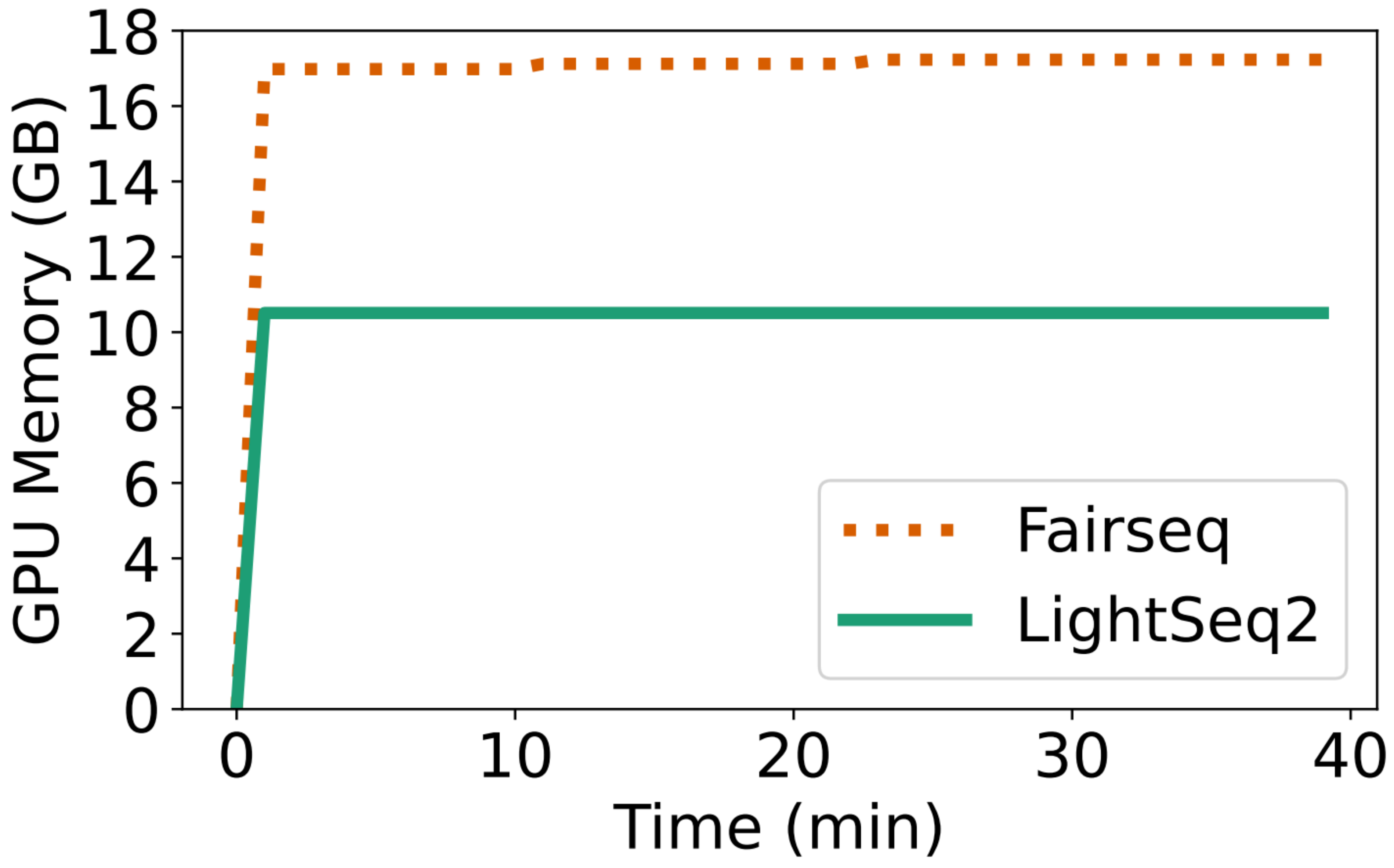


Speedup on 1 to 5 workers, each has 8x A100

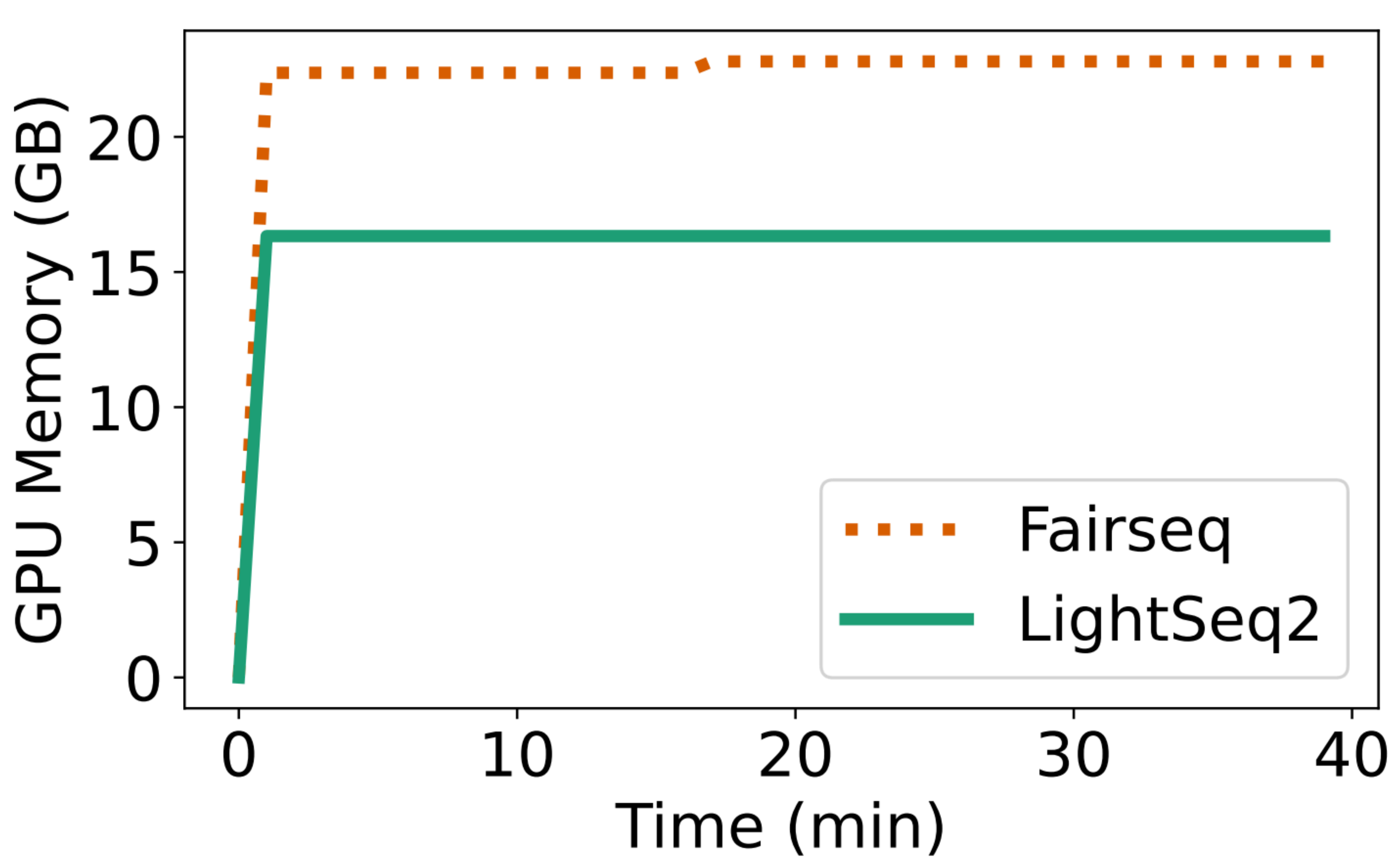


Speedup of Models with different layers

Training Memory Cost: 6G less



Transformer Base

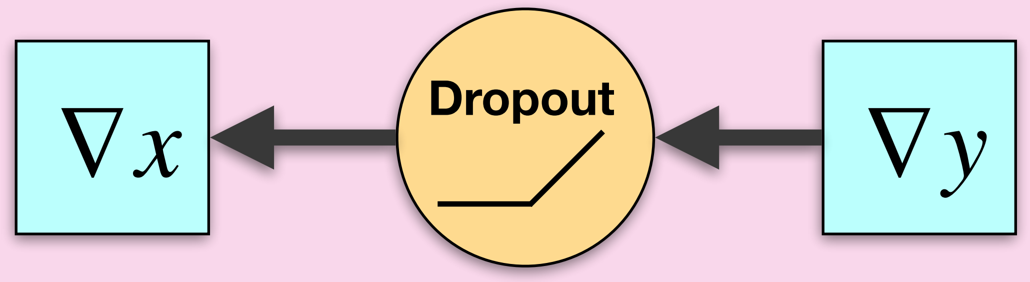


Transformer Large

Summary

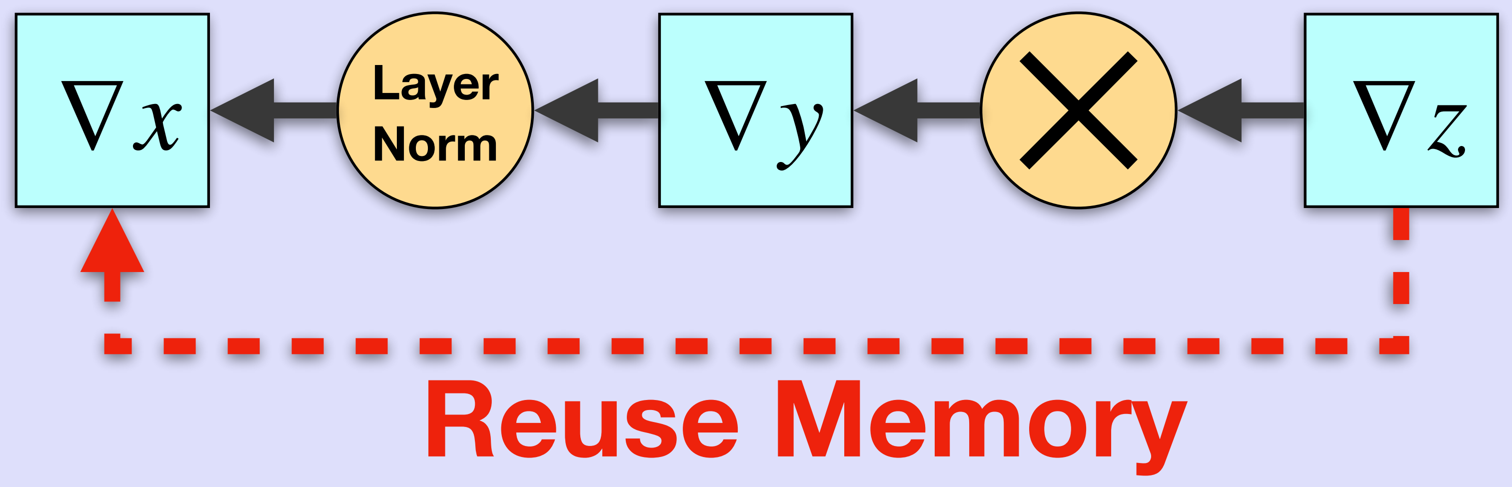
We optimize the training process from 3 aspects

High performance Kernels for Forward and Backward via Fusion & Algebra trick



Efficient Parameter Update via mixed precision

Memory Management



Operators that can be reused in Other Networks:
Dropout, LayerNorm, Softmax, Cross Entropy

code is available at

https://github.com/bytedance/lightseq

Early Course Feedback

What do students agree?

- Code walkthroughs
- The topic and assignments of the course are relevant to the current trends in the field.
  - Assignments are closely related to what’s useful to job market.
  - Good for student to help their research.
- The course is well-prepared. It starts from easy to hard.
- Slides and reading material are made available before class.

Early Course Feedback

Suggestions/Feedback

- Homework write-ups may need improved clarity on expectations, pseudo code, examples, to help students do what is required.
- Releasing example solutions could help students grow between assignments.
  - you may come to office hour to review code.
- Pace
  - The individual classes are a bit dense.
  - Lecture sometimes fast, while sometimes a bit slow.
- More Explanation about CUDA kernels

Reading for Next

- PyTorch Distributed: Experiences on Accelerating Data Parallel Training
- PyTorch FSDP: Experiences on Scaling Fully Sharded Data Parallel