FACT: FFN-Attention Co-optimized Transformer Architecture with Eager Correlation Prediction

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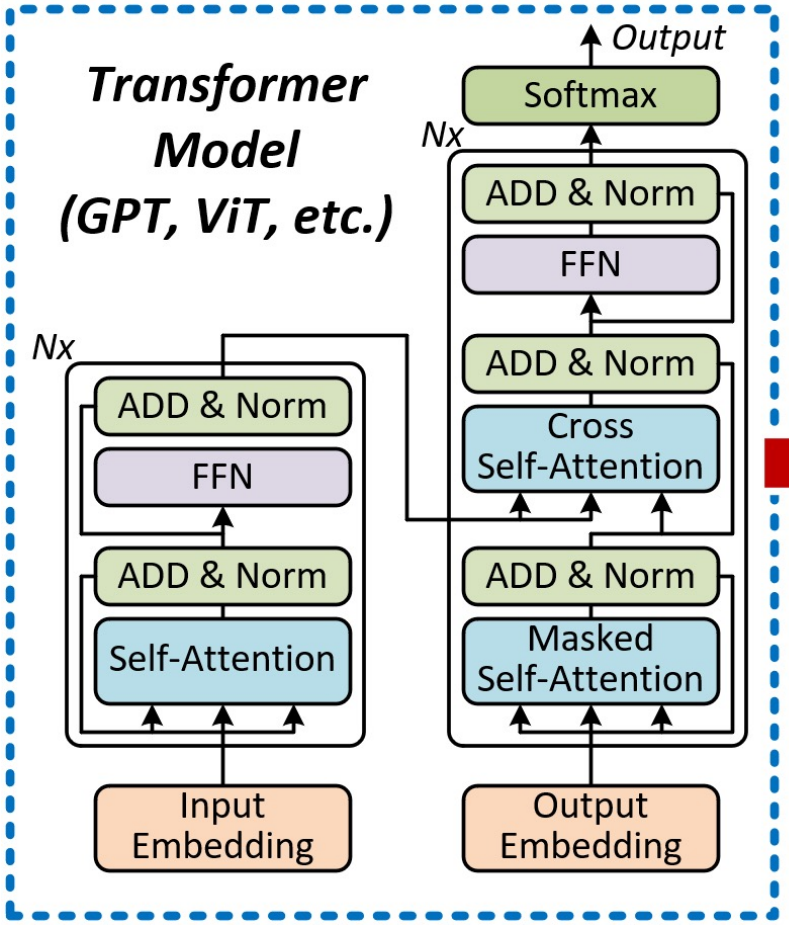
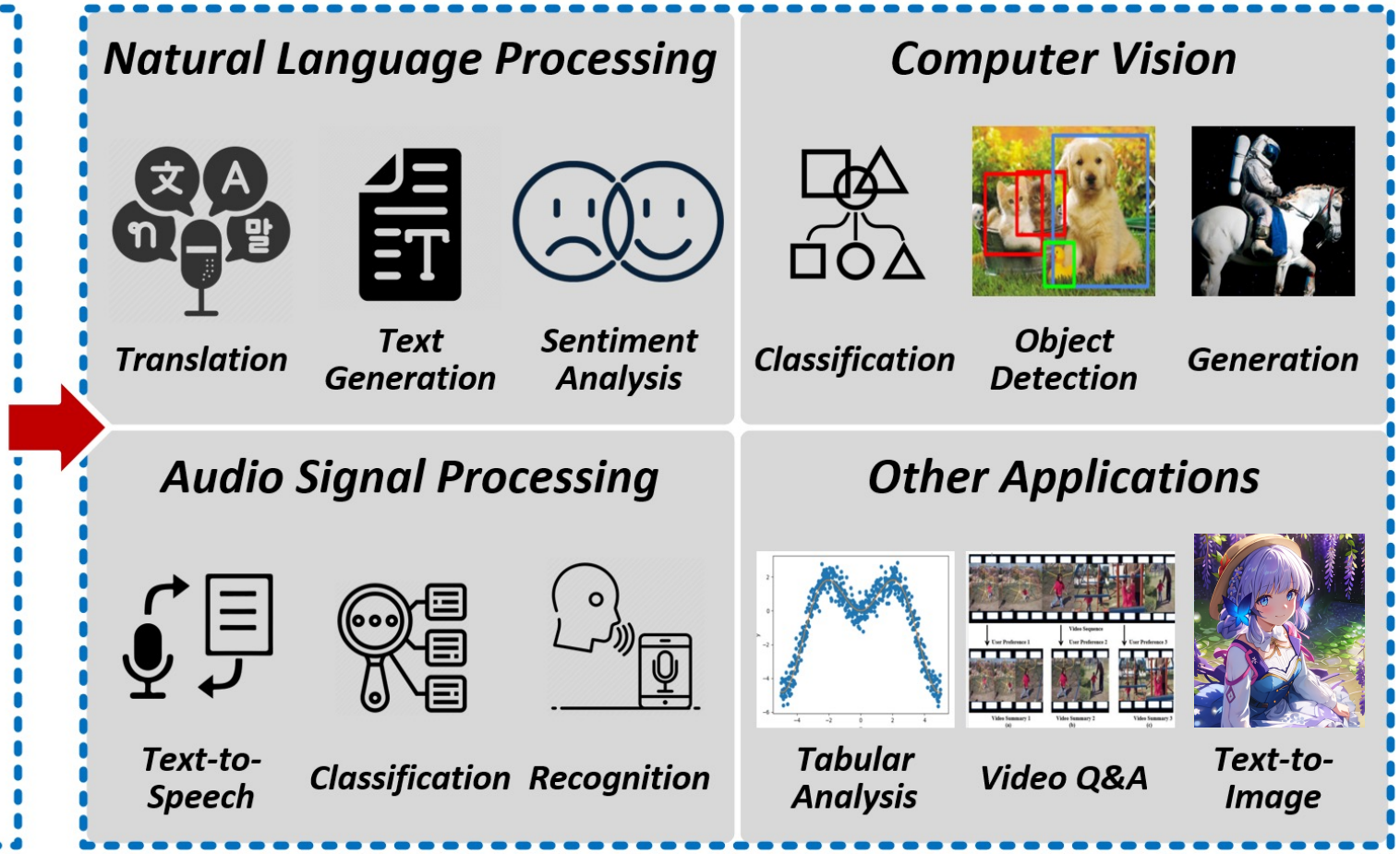
Outline

- **Background and Motivation**
- Eager Prediction Mechanism
- Hardware Innovation
- Evaluation

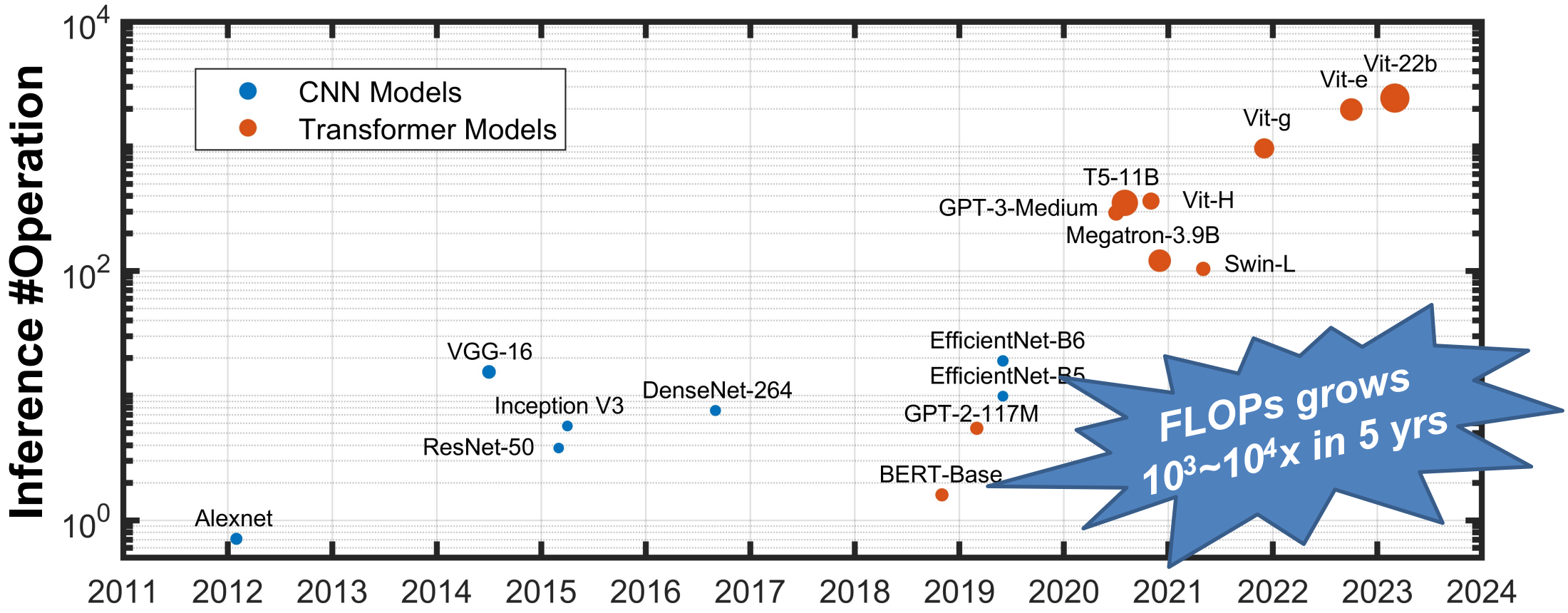
The Outstanding Transformer Model





Transformers beat traditional models in various fields.

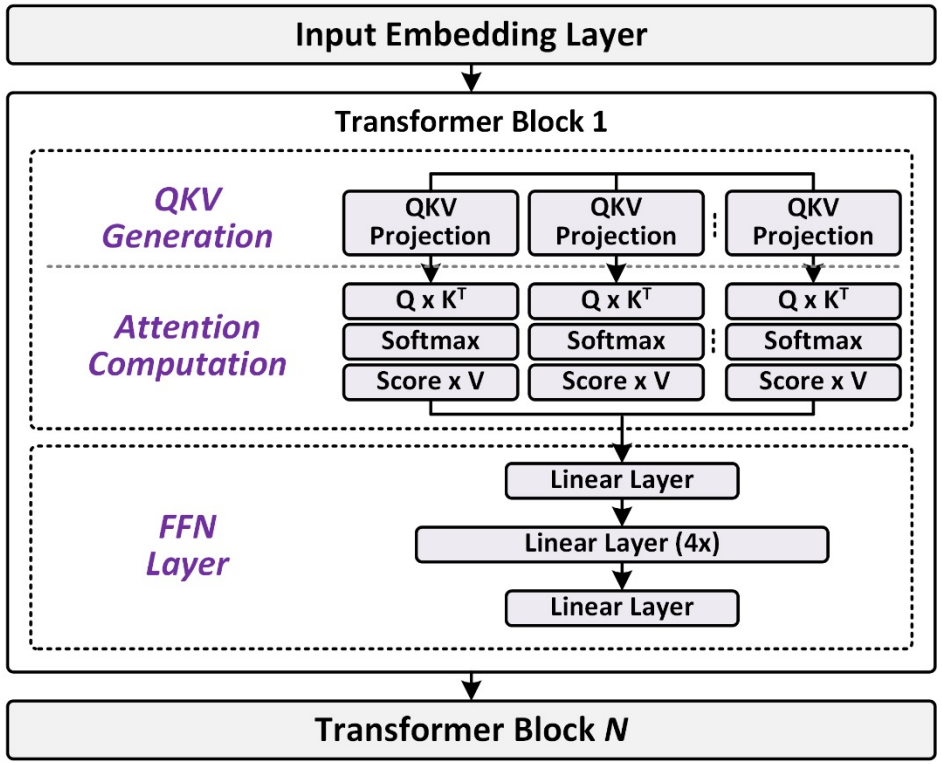
The Outstanding Transformer Model

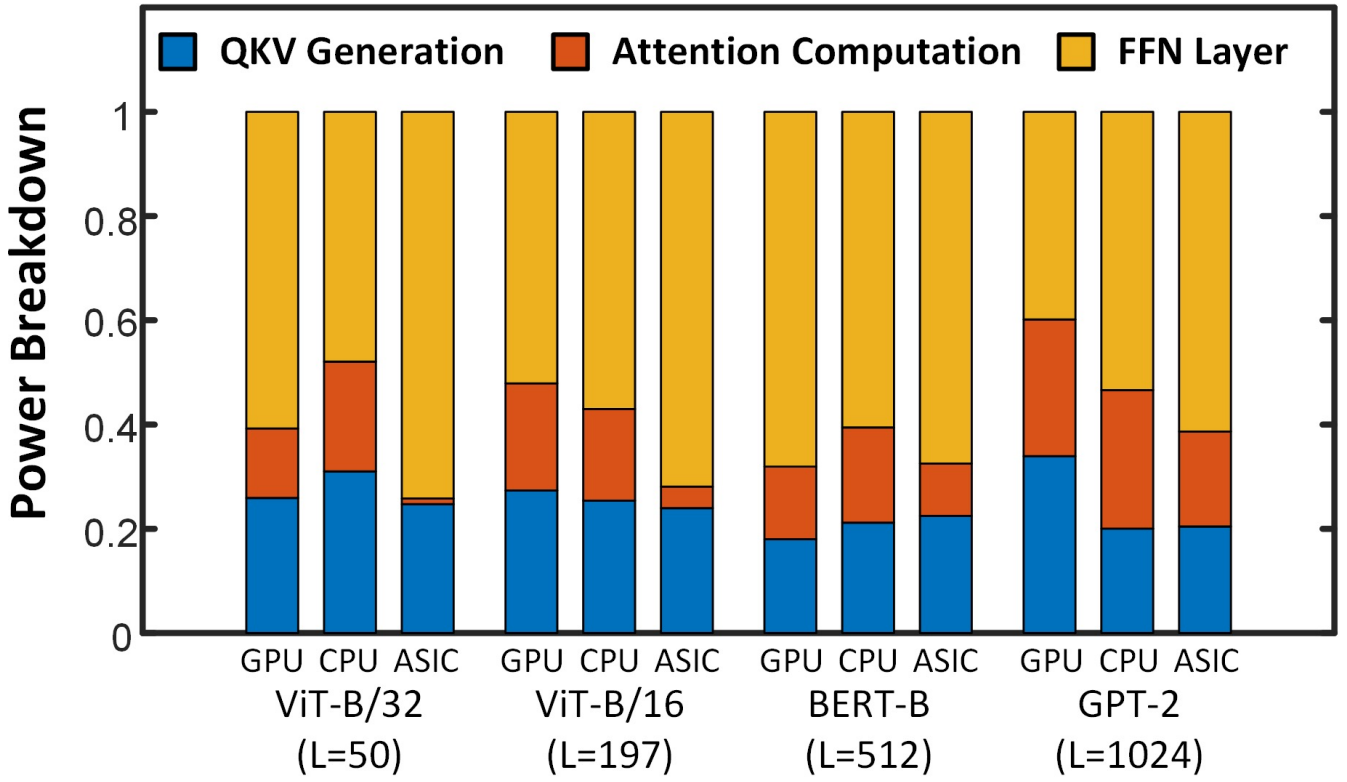


At the cost of explosive computation power

Power Breakdown of Transformer

- The power consumption of linear layer cannot be ignored!

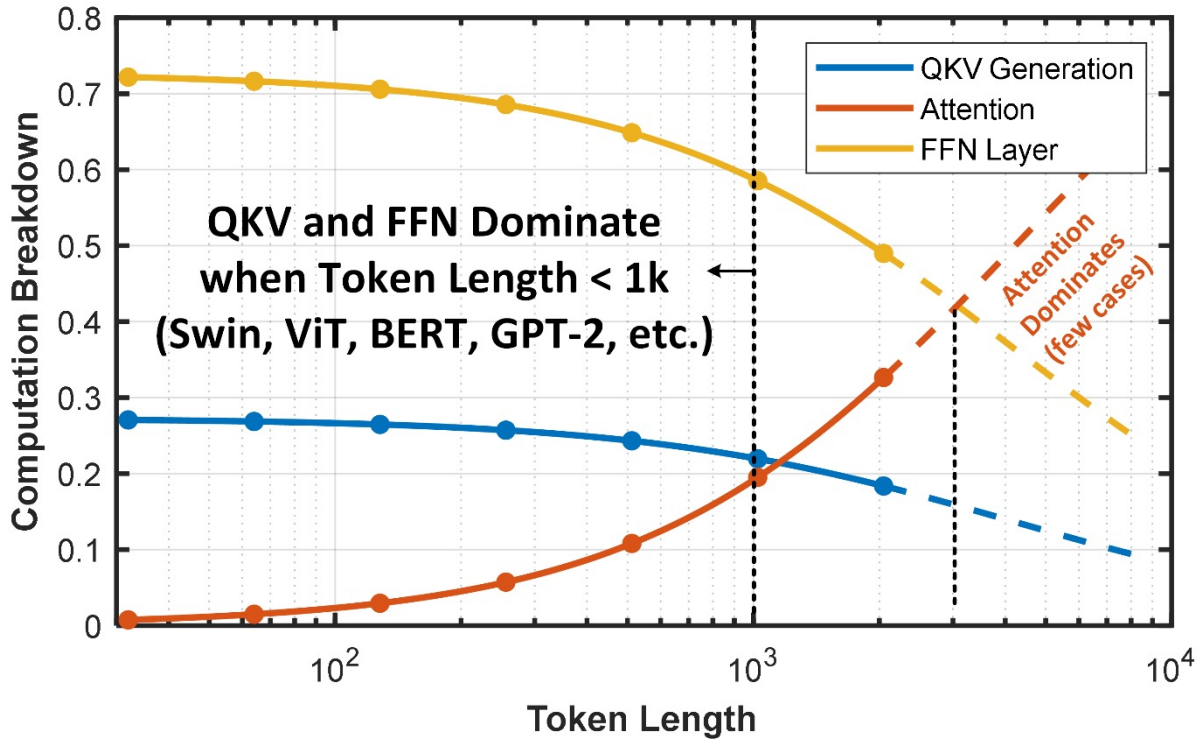




Power Breakdown of Transformer

- **Attention dominates only for very long token length**
- **The optimization of FFN and QKV is a must for most cases**

Layer Type	Num of Operation
Embedding	$4n_{token}d_{model}$
QKV Generation	$6n_{layer}n_{token}d_{model}^2$
Attention	$4n_{layer}n_{token}^2d_{model}$
Feed Forward	$18n_{layer}n_{token}d_{model}^2$
De-embedding	$2n_{token}d_{model}n_{vocab}$



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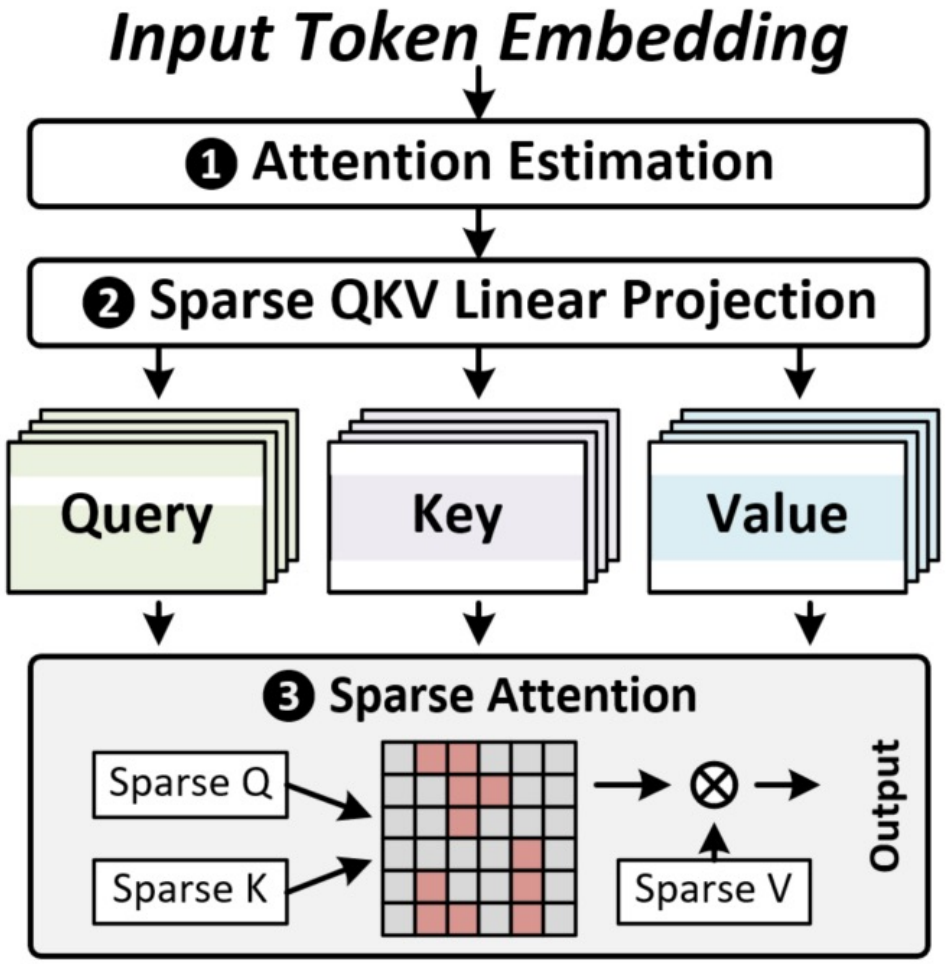
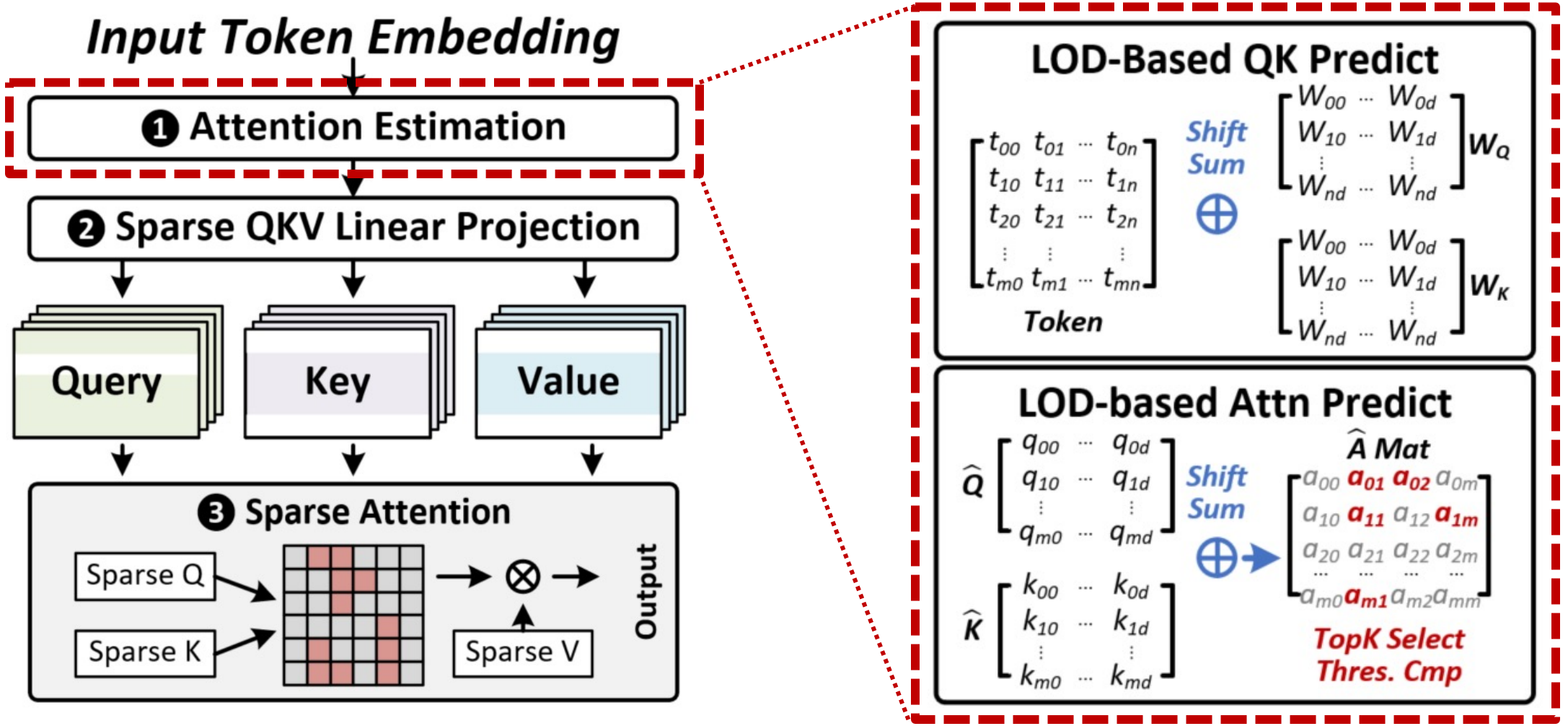
Eager Prediction – Procedure



- **Predict the QKV result, and then the attention matrix**
- **Compute the sparsity mask of attention**
- **Deduce the sparsity of QKV**

Eager Prediction – Procedure



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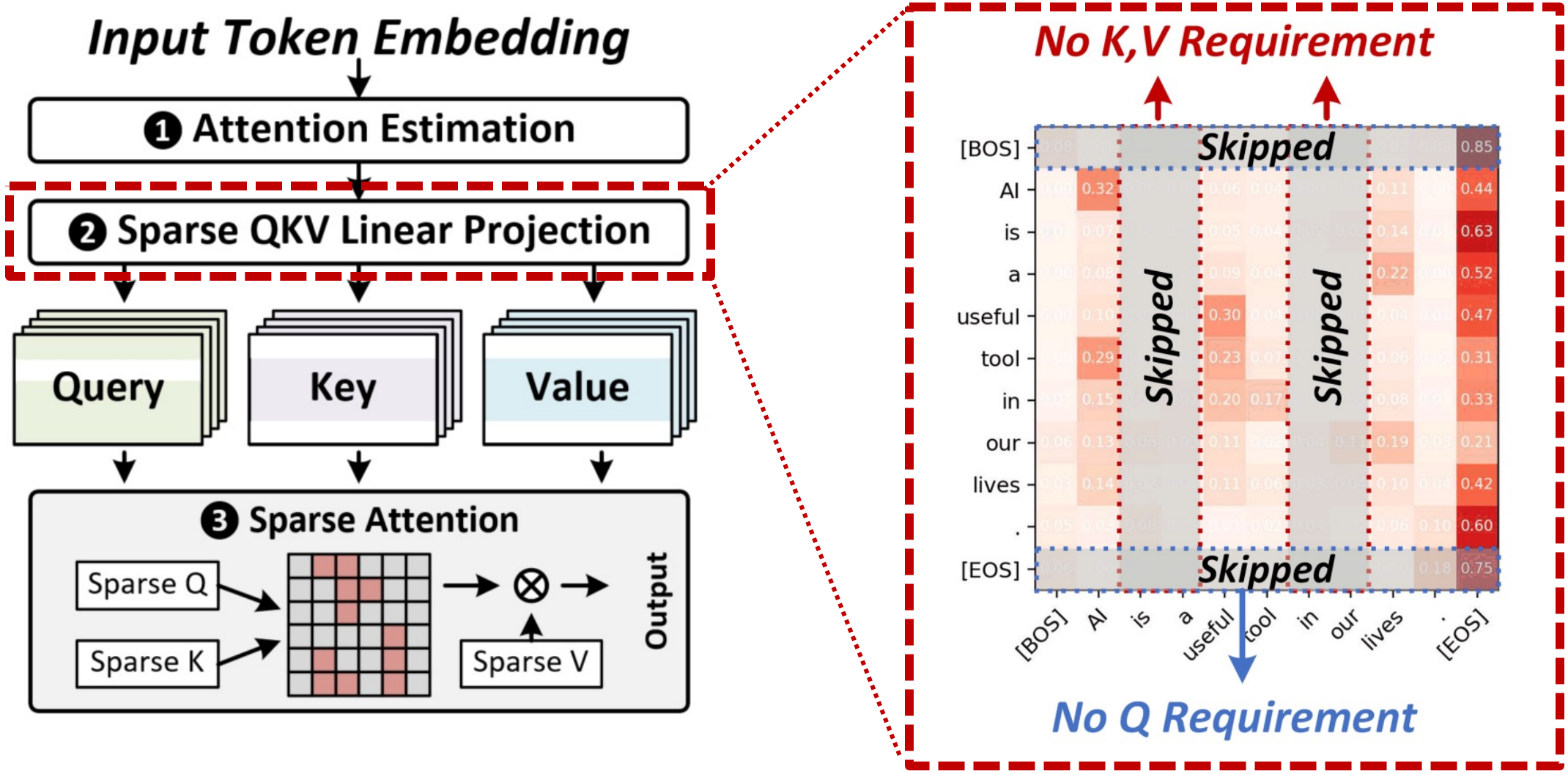
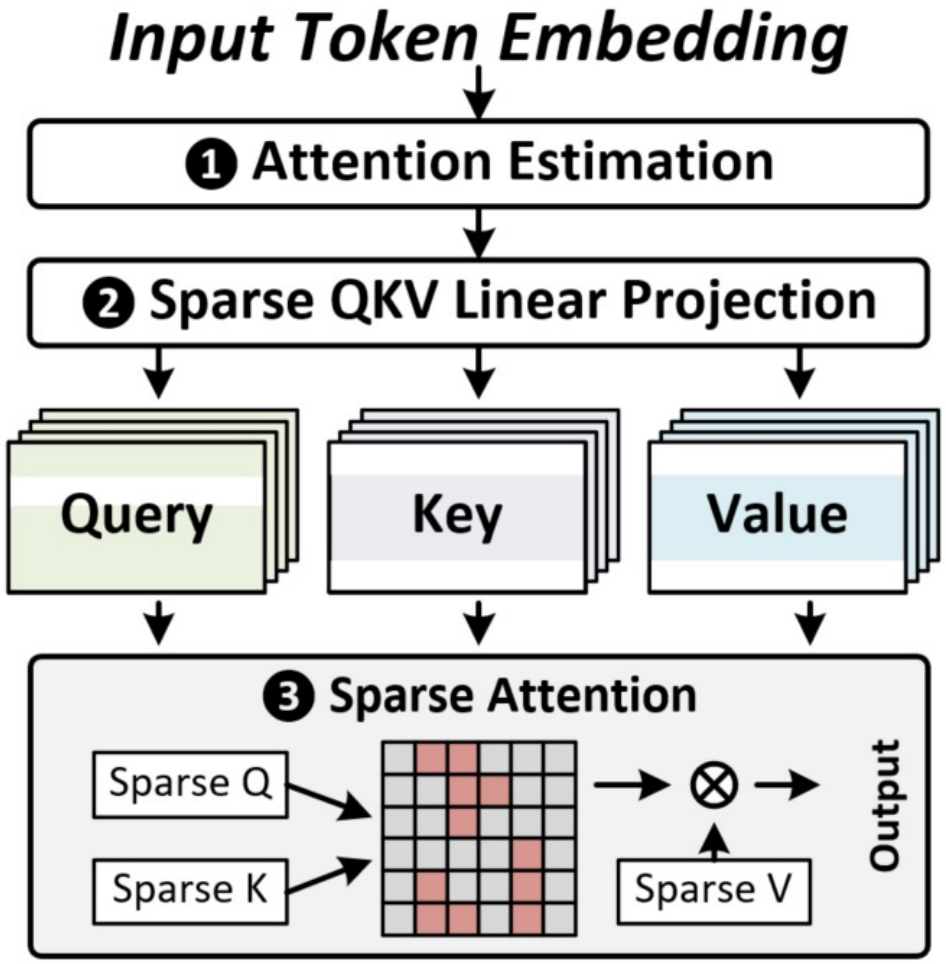


Eager Prediction – Algorithm



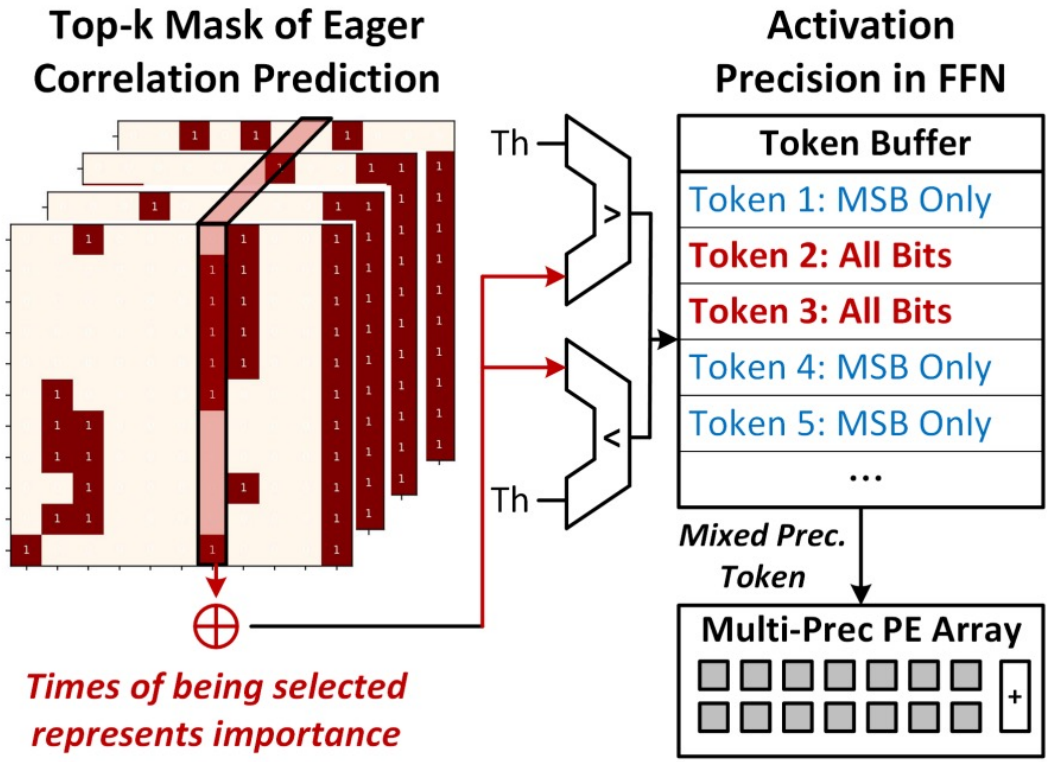
Algorithm Eager Prediction with Correlation Estimation

Input: $Token(T), Weight(W_Q, W_K, W_V)$
Input: k, r ▷ Top-K ratio and FFN threshold
Output: M^A, M^Q, M^{KV} ▷ Sparsity mask
Output: M^{FFN} ▷ Low precision mask for FFN

1: $E^T \leftarrow LOD(T)$
2: $E^{WQ} \leftarrow LOD(W_Q)$
3: $E^{WK} \leftarrow LOD(W_K)$
4: $\hat{Q_{i,j}} \leftarrow \sum_k Sgn(T_{i,k}W^Q_{k,j}) << (E^T_{i,k} + E^{WQ}_{k,j})$
5: $\hat{K_{i,j}} \leftarrow \sum_k Sgn(T_{i,k}W^K_{k,j}) << (E^T_{i,k} + E^{WK}_{k,j})$
6: $\hat{A_{i,j}} \leftarrow \sum_k Sgn(\hat{Q_{i,k}}\hat{K^T_{k,j}}) << (\hat{Q_{i,k}} + \hat{K^T_{k,j}})$
7: $M^A \leftarrow \hat{A_i} \geq top\_k(\hat{A_i}, k)$
8: $M^Q \leftarrow max(\hat{A_i}) - 2^{nd}\_max(\hat{A_i}) \leq Thr$
9: $M^{KV} \leftarrow \prod_k M^{EA}_{k,i}$
10: $M^{FFN} \leftarrow \sum M^{EA} \leq L \times C \times k \times r$

Eager Prediction – FFN Acceleration

- Adaptively reduces FFN precision according to the token's appearance in the top-k result



- A token's key's being selected by top-k means the token's content is crucial to the query.
- The more times being selected by top-k, the more important the token is.
- EP only assigns high FFN precision to important tokens.

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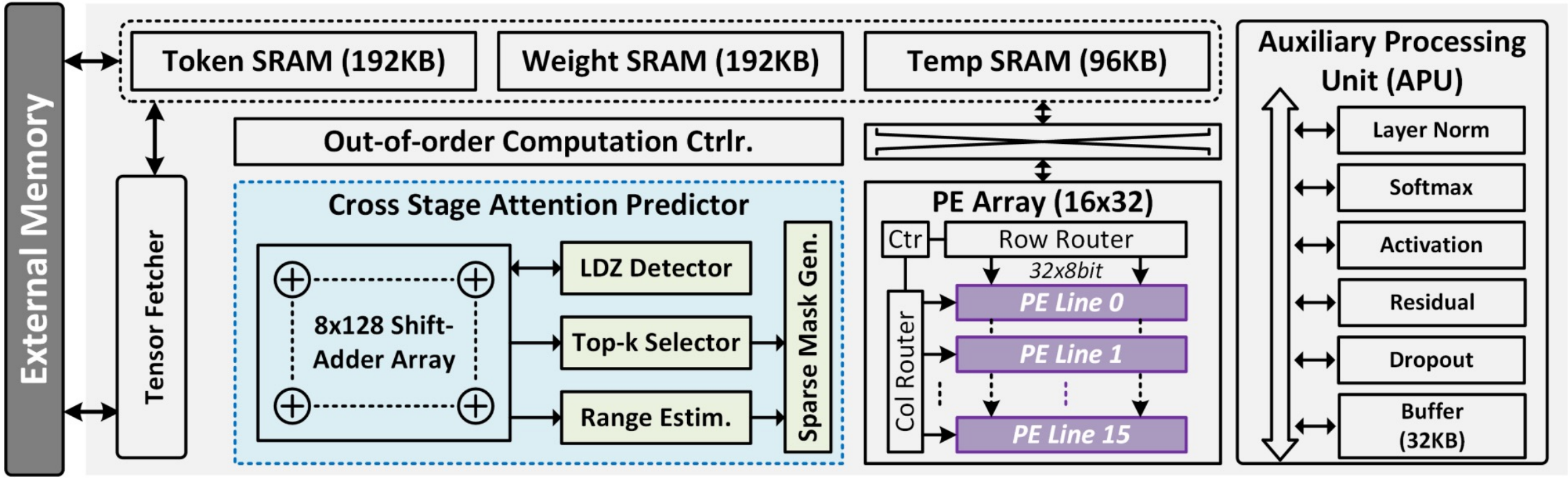
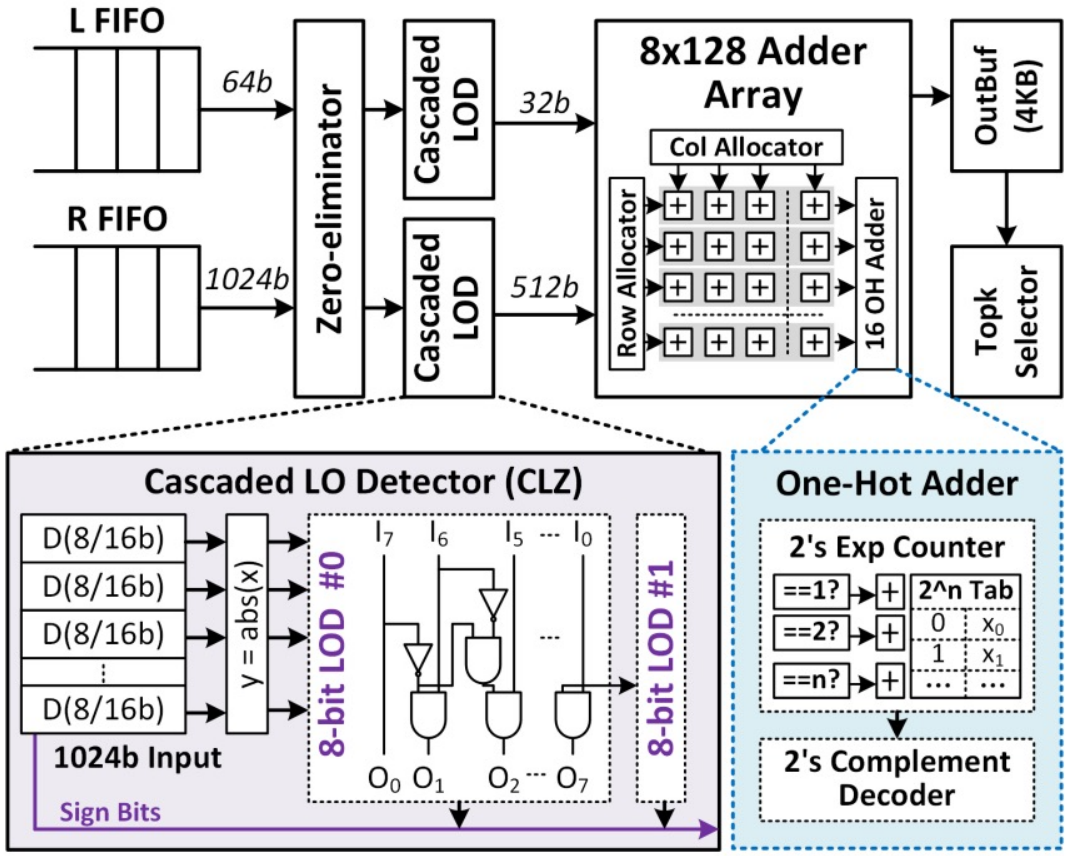
Overall Architecture

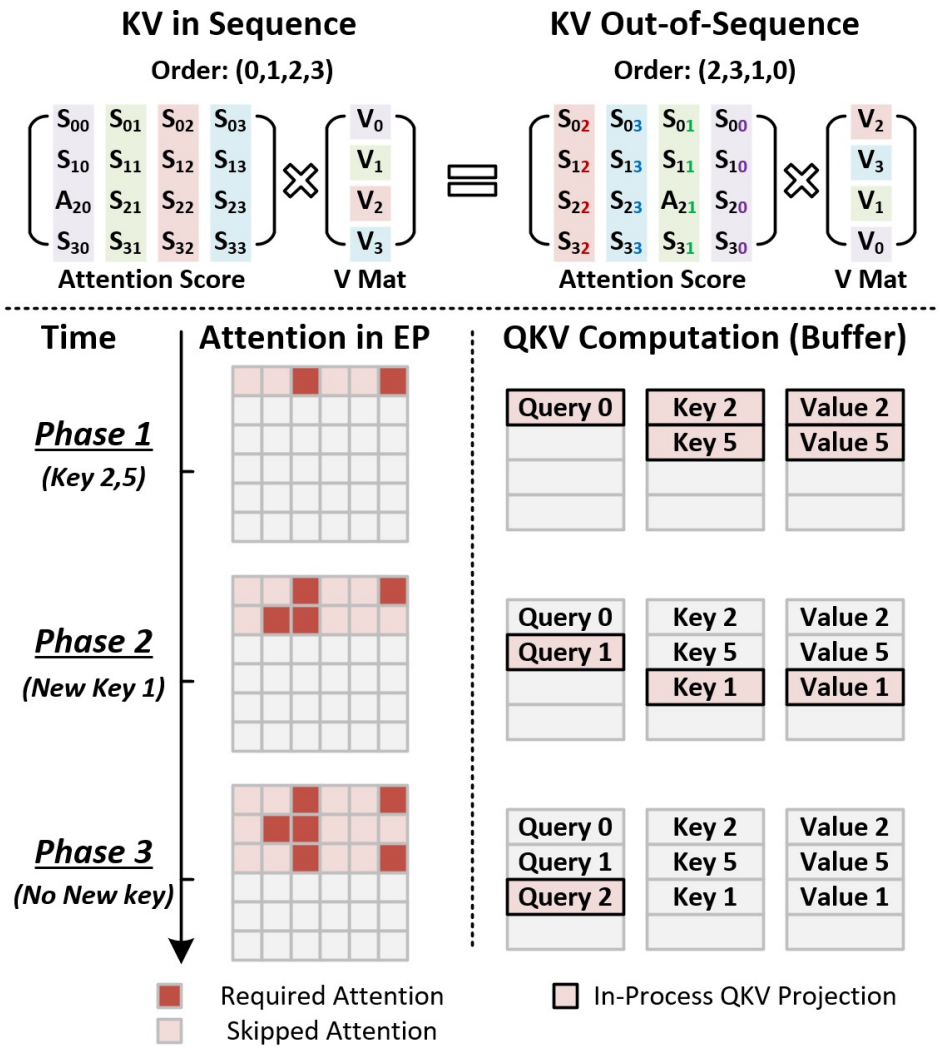


Multiplication-free EP Unit



- Using leading-one detector (LOD) for MM prediction
- FIFO stores MM input matrix, with sparse data eliminated
- Cascaded LOD can be applied to INT16/INT8 input datatype
- One-hot adder tree adds up the position of LOD result

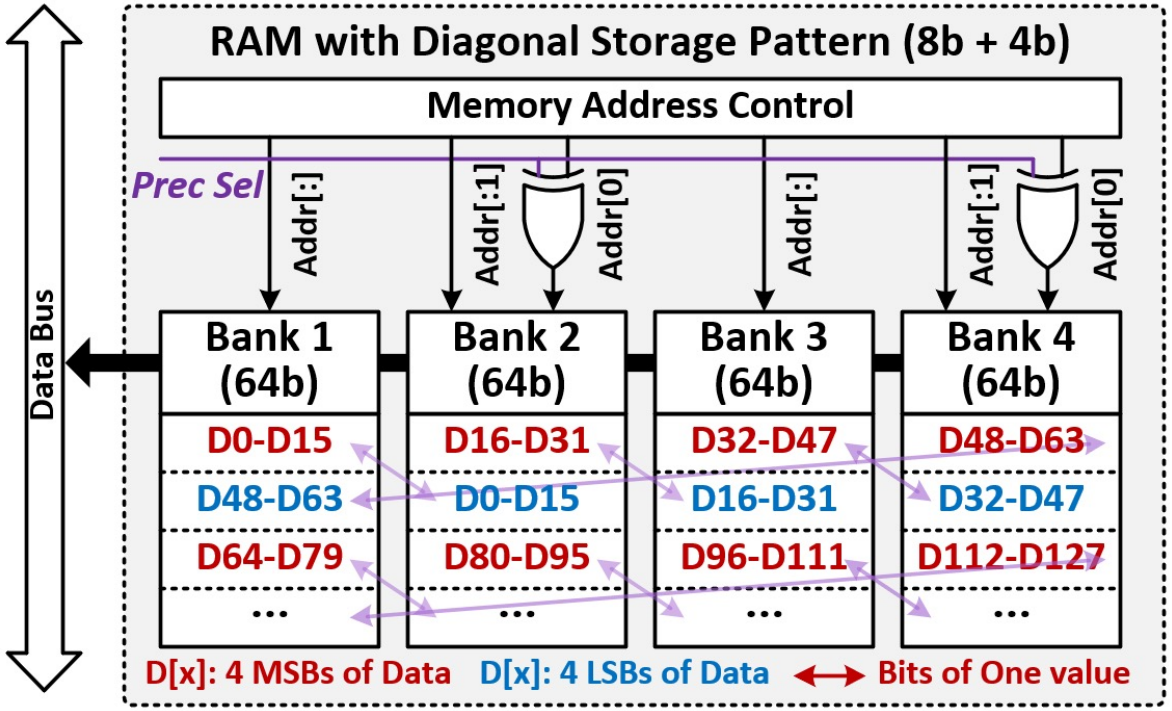
Out-of-order QKV Scheduler

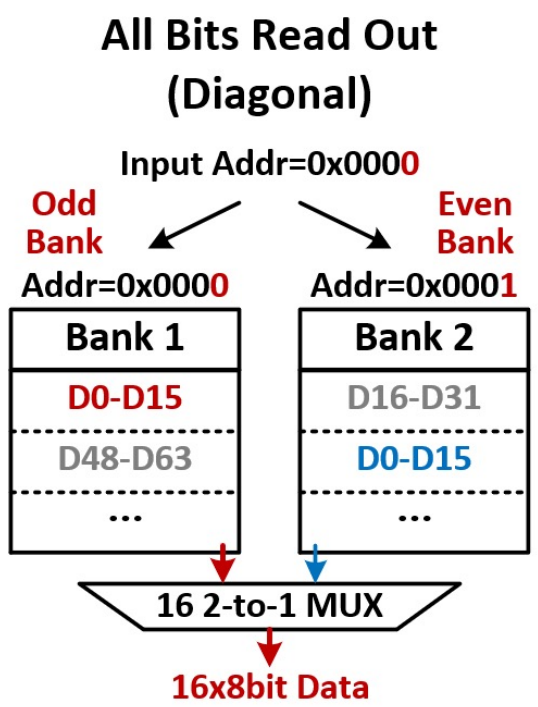


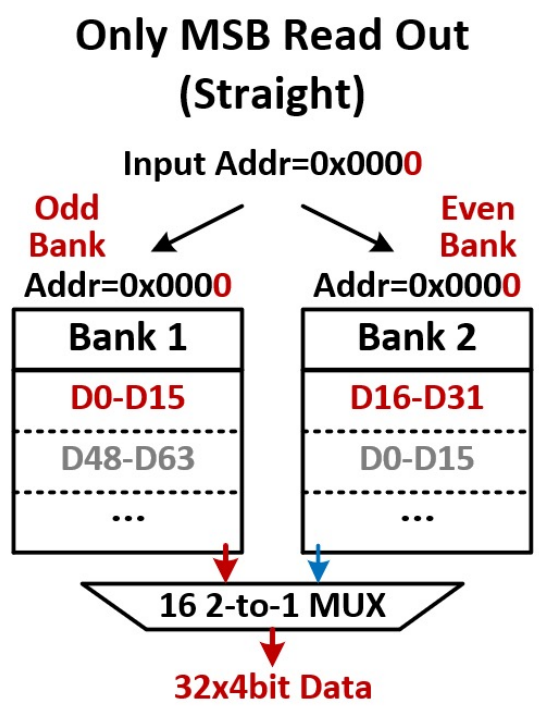
- Reorder the Key and Value matrix to minimize the memory footprint
- Only load additional required KV for new query, unused ones skipped
- Reorder the order of query to maximize data reuse of KV
- If a new query needs the same KV as the last one, it has high priority

Diagonal Storage Pattern

- **Store MSB parts and LSB parts with periodic shift**
  Ensure readout for MSB-only and full data with no waste







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Experimental Setup

Software:

- Model build and finetune with PyTorch
  - BERT-base, BERT-large for GLUE, SQuAD and Wiki-2
  - ViT/B-32, ViT/B-16 for ImageNet-1k classification

Hardware:

- RTL design with Synopsys Design Compiler with 28nm 1P8M CMOS
- Placement and routing with DCG and ICC
- Post-layout simulation with VCS and PT

Processor Layout and Specification

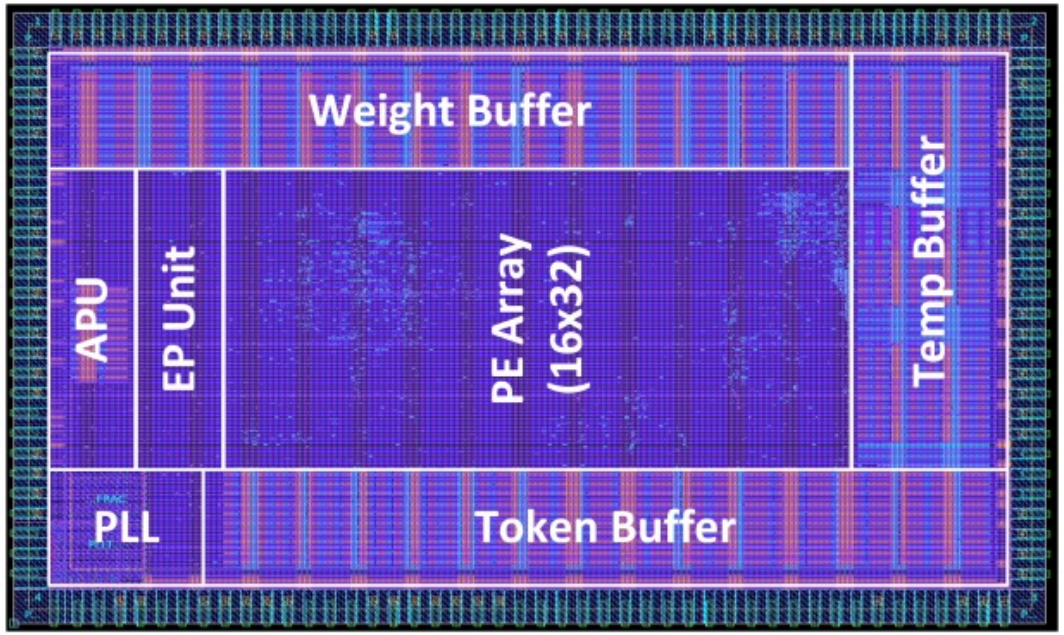
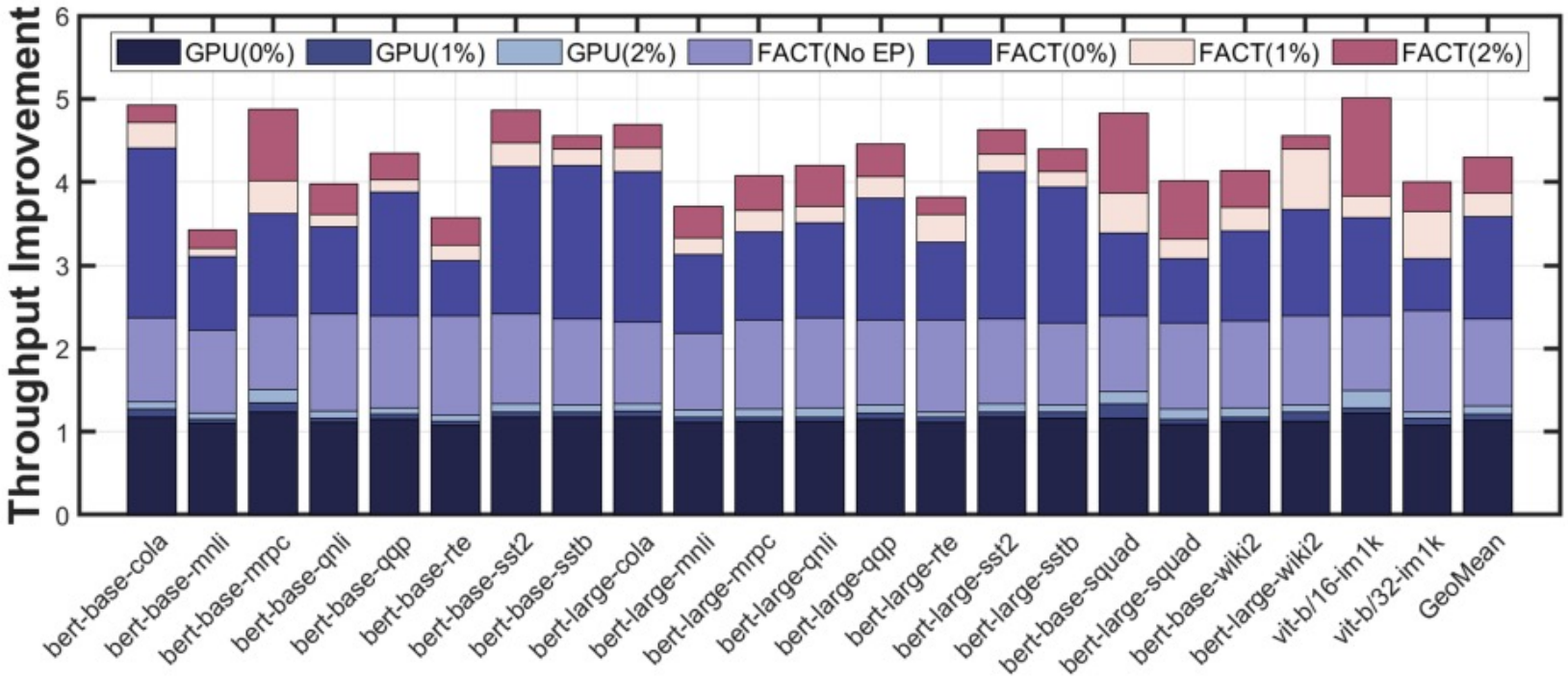


Figure: Chip layout after placement

Table: Area and Power breakdown @500MHz

Module	Area [mm^2]	Power [mW]
PE Array	2.76	162.93
EP Unit - Adder	0.23	16.04
EP Unit - Others	0.02	1.59
APU	0.56	23.95
SRAM	2.23	110.28
Others	0.22	22.28
Total	**6.03**	**337.07**

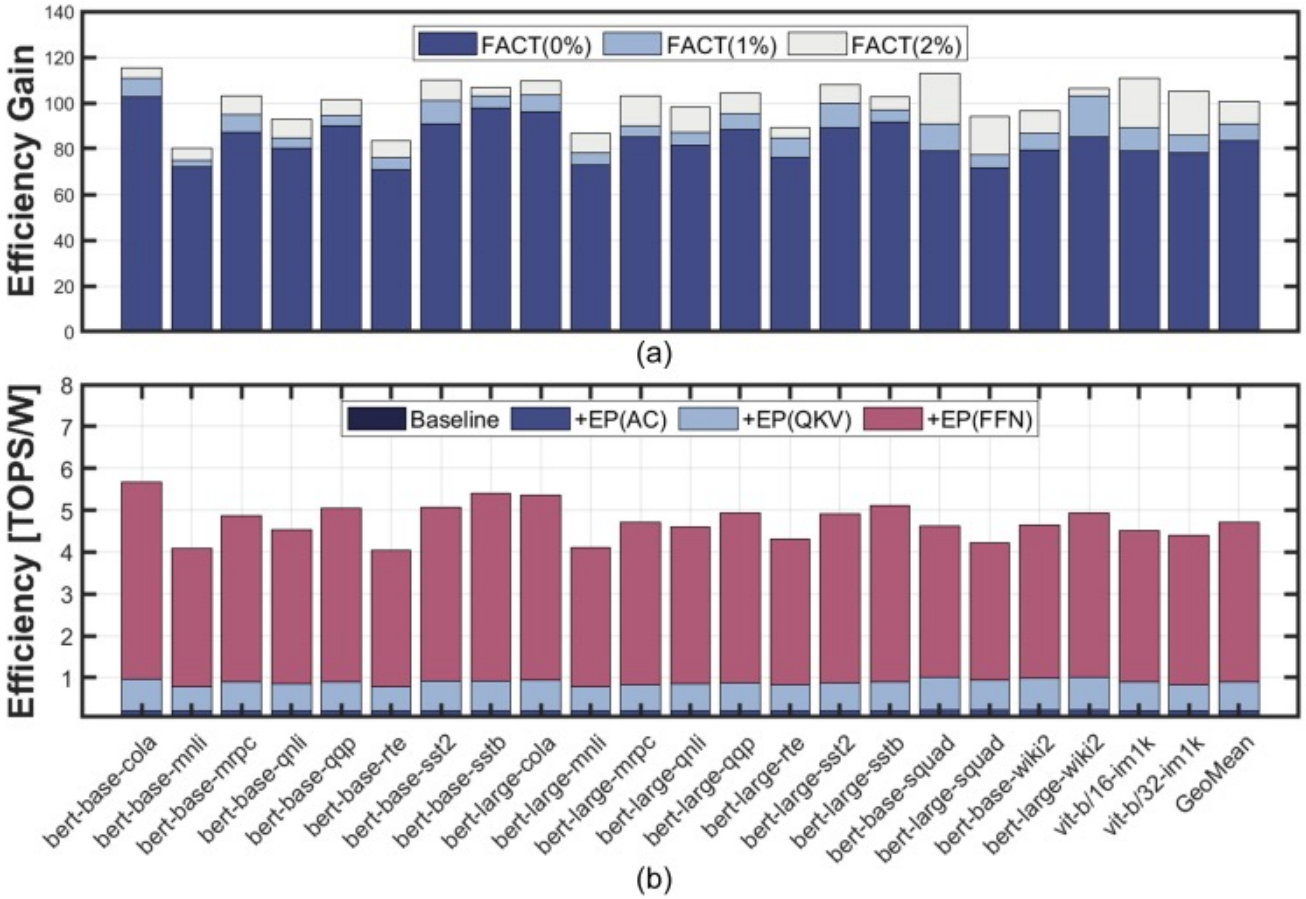
Evaluation – Throughput and Efficiency



FACT accelerates the whole model inference process by 3.59x/3.87x/4.30x on geomean average of 22 tasks, within 0%/1%/2% accuracy degradation

Specifications	
Acceleration for	QKV, Attention, FFN
Frequency [MHz]	500
Area [mm^2]	6.03
Throughput [GOPS]	928
Area Efficiency [GOPS/mm2]	153.9
Energy Efficiency [GOPS/W]	4388

Evaluation – Throughput and Efficiency



- **83.4x higher energy efficiency compared to V100 GPU**
- **Optimizing the QKV and FFN layers yields 22.9x efficiency gain**

Conclusion

- **An energy-efficient Transformer inference design with:**
  - Eager correlation prediction algorithm
    - √ Reduces computation of all the main blocks of Transformer
  - Multiplication-free eager prediction unit
    - √ Ensure neglectable sparsity prediction overhead
  - Out-of-order QKV Scheduler
    - √ Maximizes data reuse for sparse attention computation
  - Diagonal data storage pattern
    - √ Avoids unnecessary memory footprint for mix-precision FFN

Thank you

Any Questions?