SpAtten: Efficient Sparse Attention Architecture with Cascade Token and Head Pruning

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MIT HAN Lab
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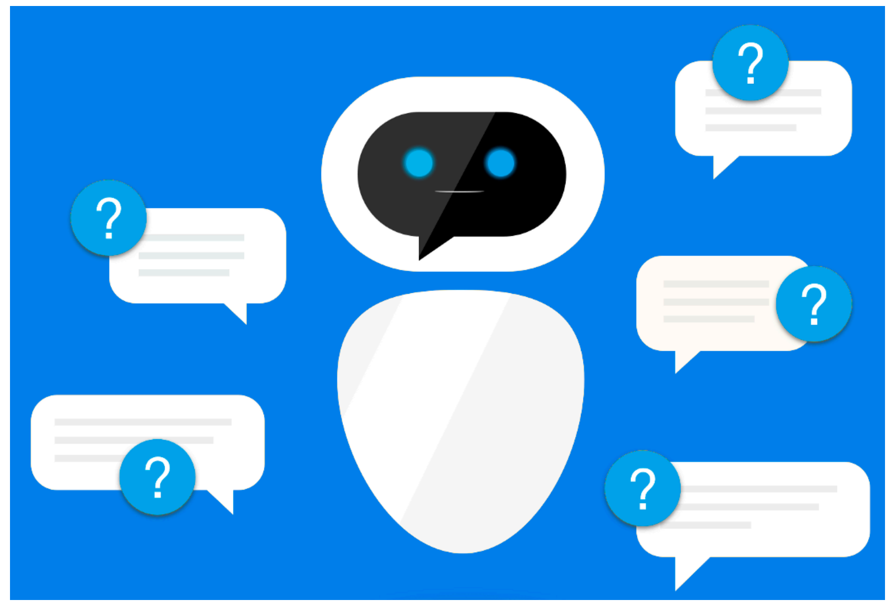
HPCA 2021

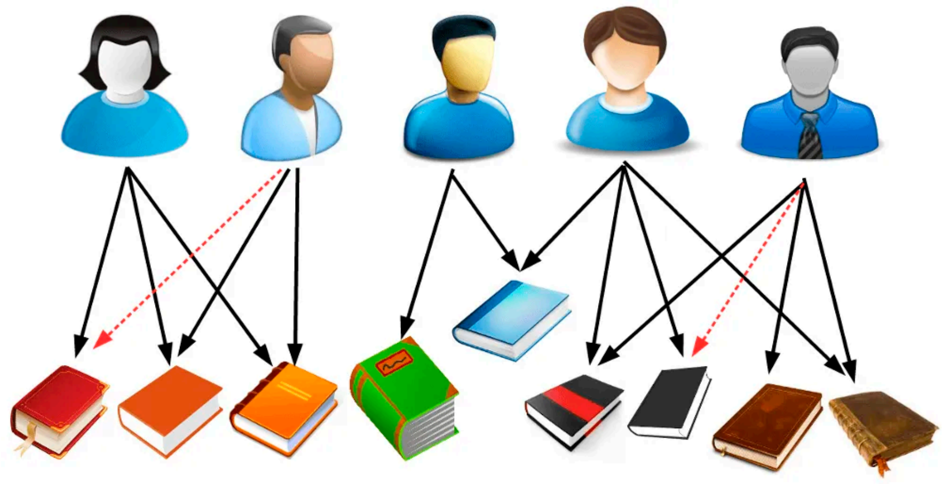
NLP is Ubiquitous

- NLP techniques are widely used



Chat Bots

Grammar Checking



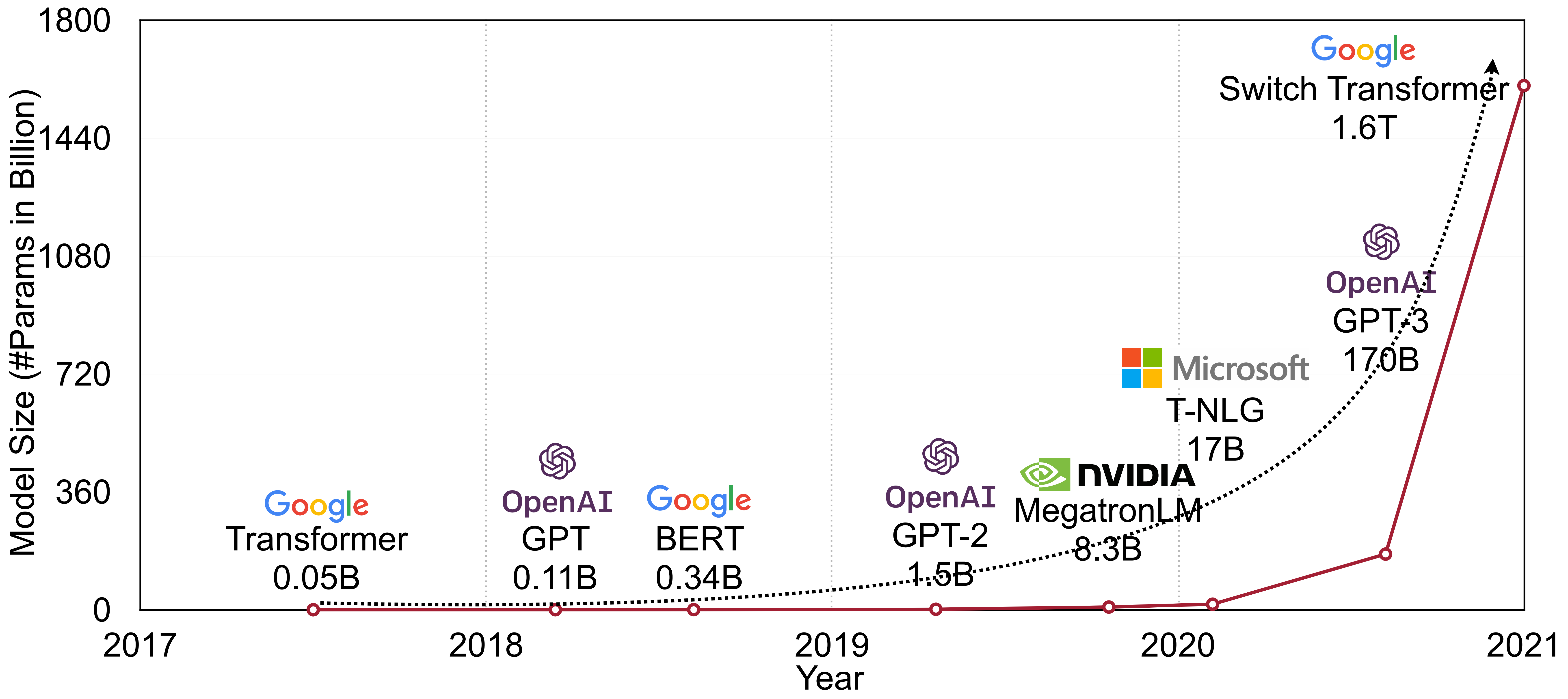
Recommender System

Machine Translation

medium.com/voice-tech-podcast/build-a-chatbot-using-c-and-dialogflow-93b50be39d7c
grammarly.com
translate.google.com
thedatascientist.com/right-way-recommender-system-startup

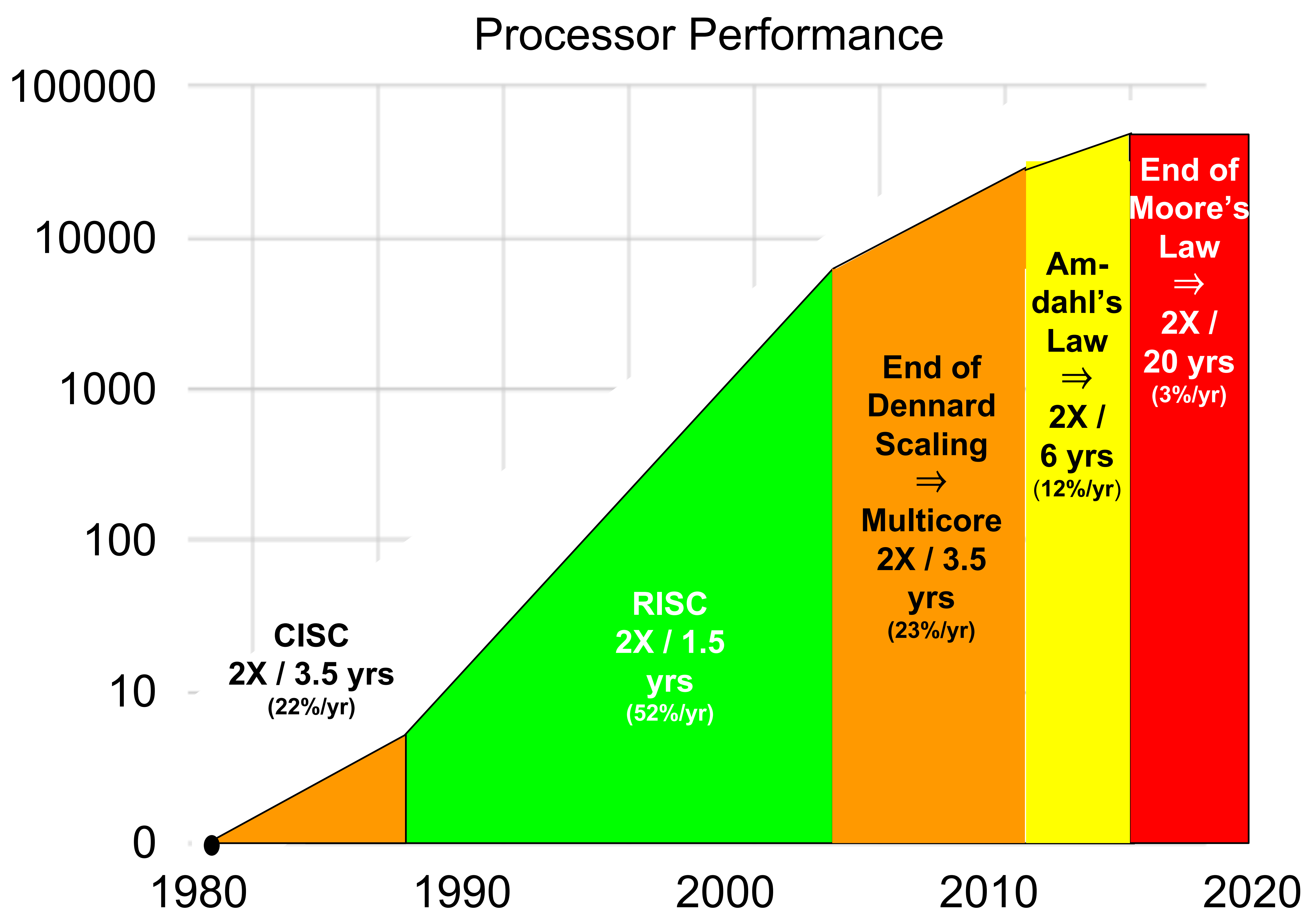
Efficient NLP is Important

- NLP model size and computation are increasing exponentially



Efficient NLP is Important

- End of Moore's Law
- Need specialized **efficient NLP algorithm-hardware co-design**



John Hennessy and David Patterson, Computer Architecture: A Quantitative Approach

Outline

- Quick Overview
- Background
- Algorithmic Optimizations
- Hardware Architecture
- Evaluation
- Conclusion

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Quick Overview —
Cascade Token/Head Pruning

`As a visual treat, the film is almost perfect.`

11 Tokens ↓ 8 Heads

- Intuition: human language contains high **redundancy**, remove unimportant tokens and heads

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BERT Layer 1 (100% Computation & Memory Access)

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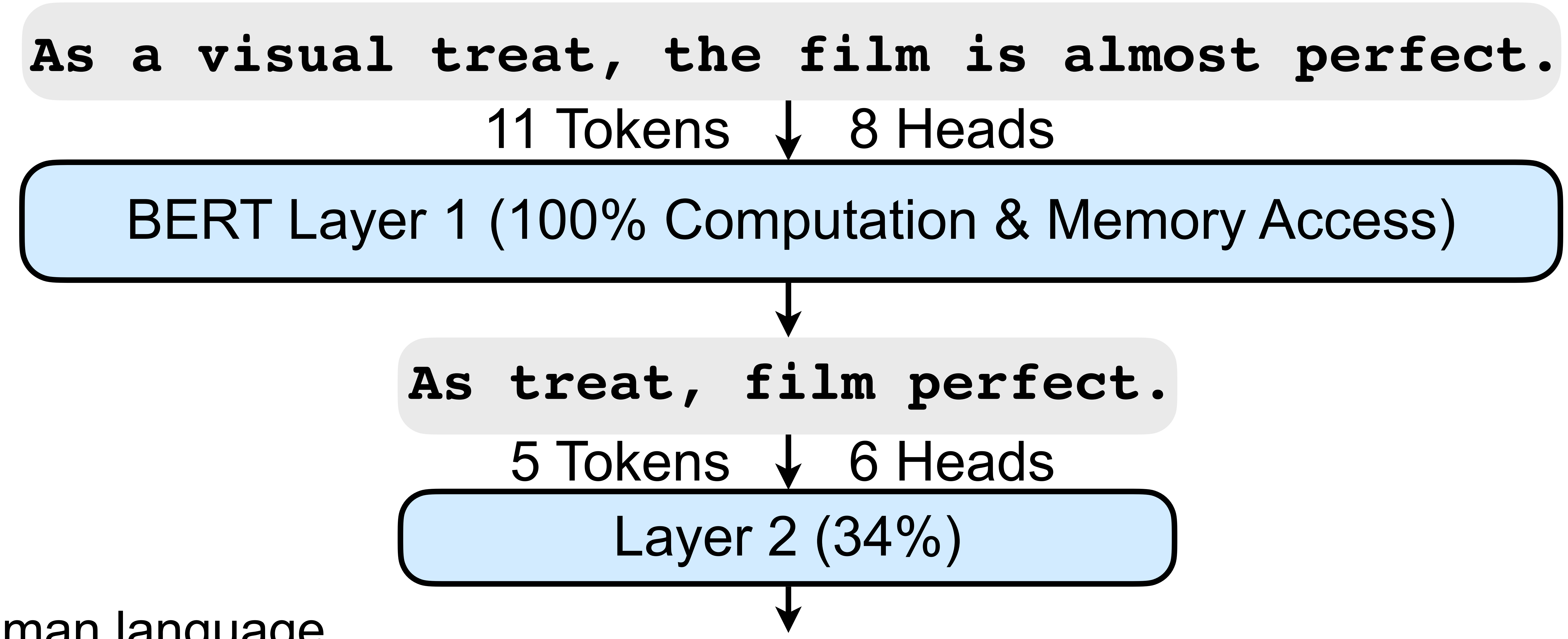

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Layer 2 (34%)

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film perfect

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`film perfect`

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Layer 3 (9%)

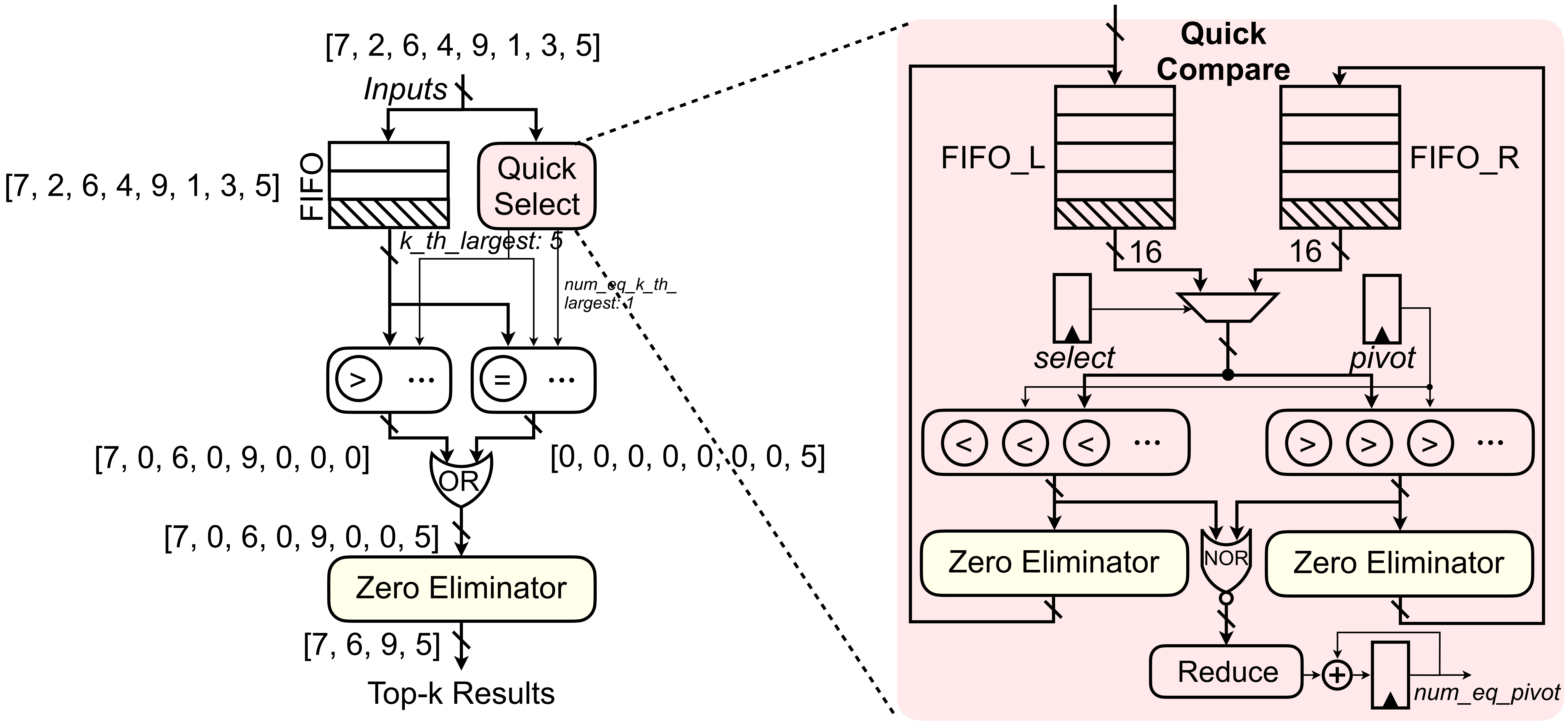
↓

Sentiment Classification: Positive ✅

- Intuition: human language contains high **redundancy**, remove unimportant tokens and heads

Quick Overview — Top-k Engine

- To support the fast selection of which tokens and heads to prune



Quick Overview — Progressive Quantization

- Reduce the DRAM access: eagerly fetch MSB; lazily fetch LSB
- An intuitive analogy:

Information in DRAM	MSB fetched to On-chip	Confidence	Need to fetch LSB?
“This is my favorite computer program”	“Ths is my favrit cmptr prog”	High	No
“I like the great visual treat"	“I lk te gt vl trt"	Low	Yes

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Attention-Based NLP Models

- Discriminative Model
  - BERT
    - Summarization Stage
- Generative Model
  - GPT-2
    - Summarization Stage
    - Generation Stage

Summarization Stage

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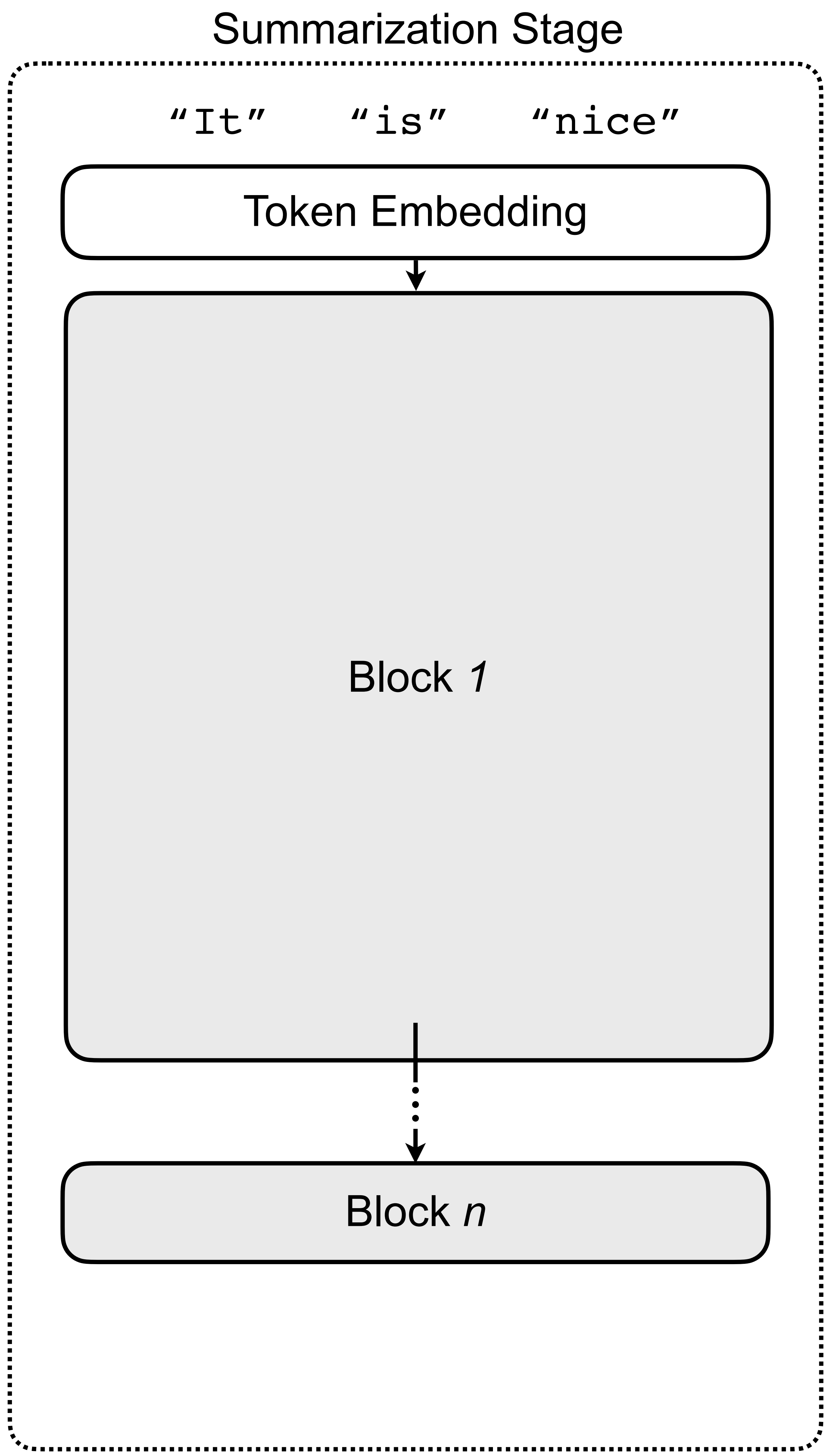

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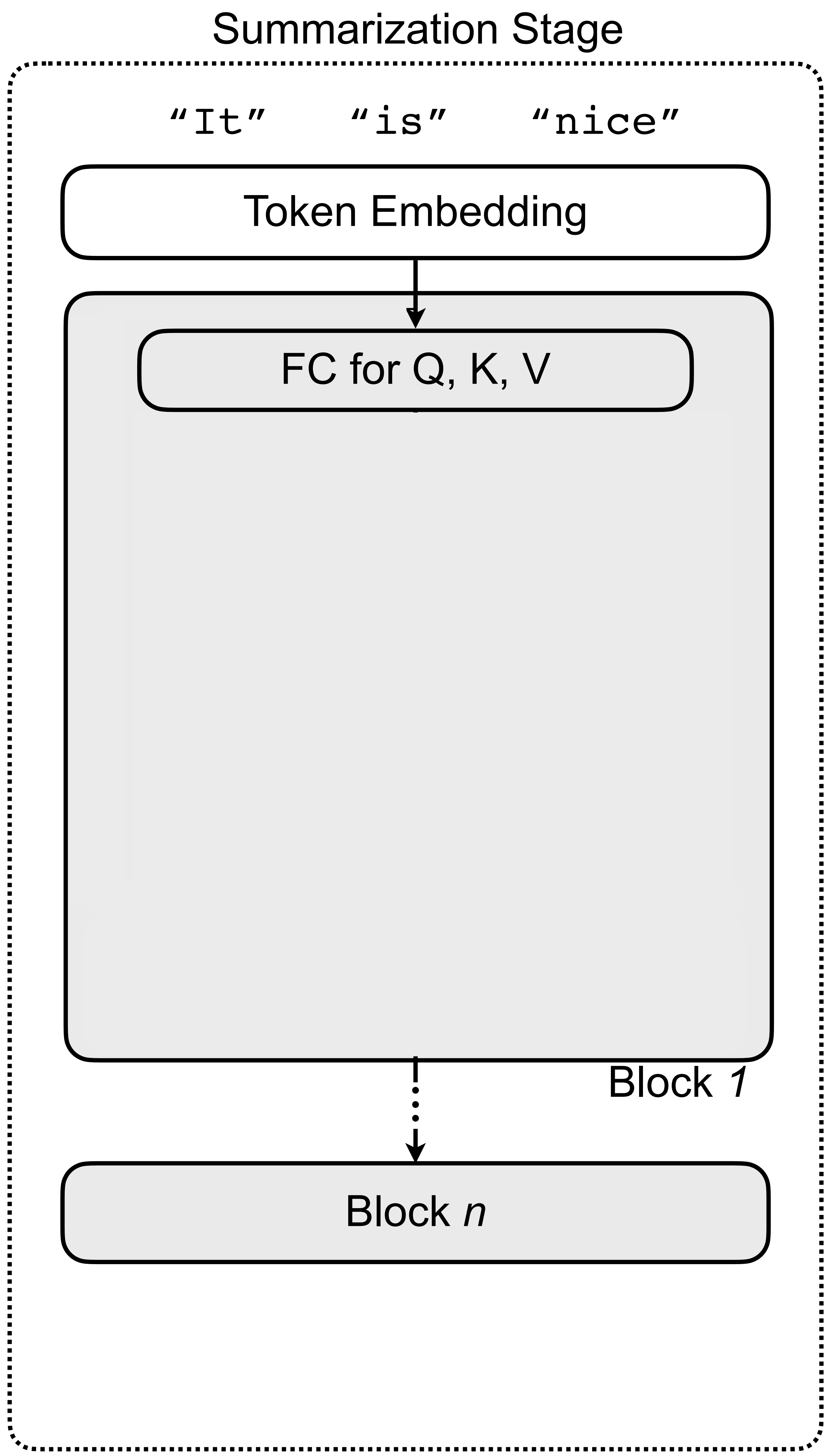

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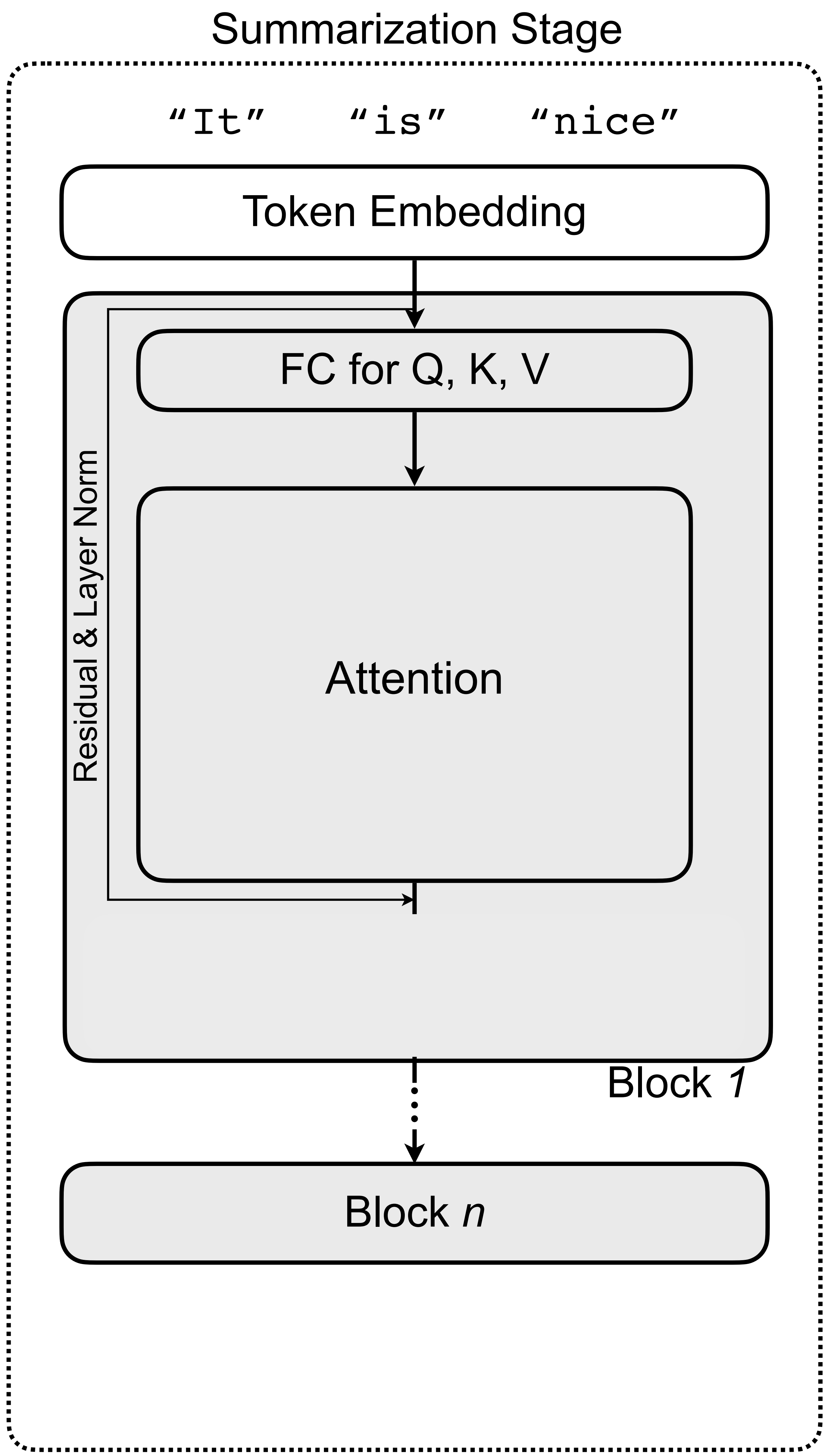

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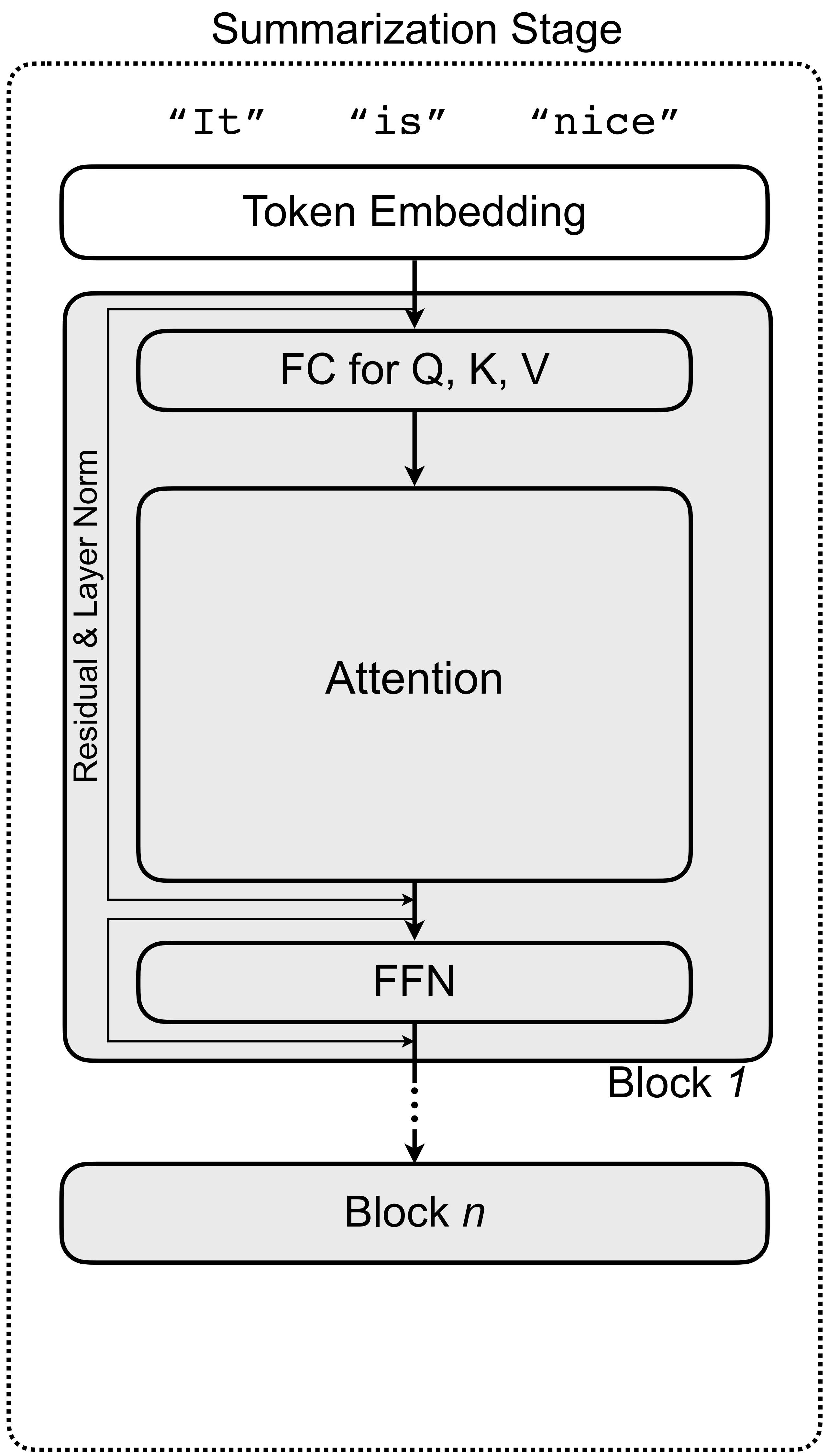

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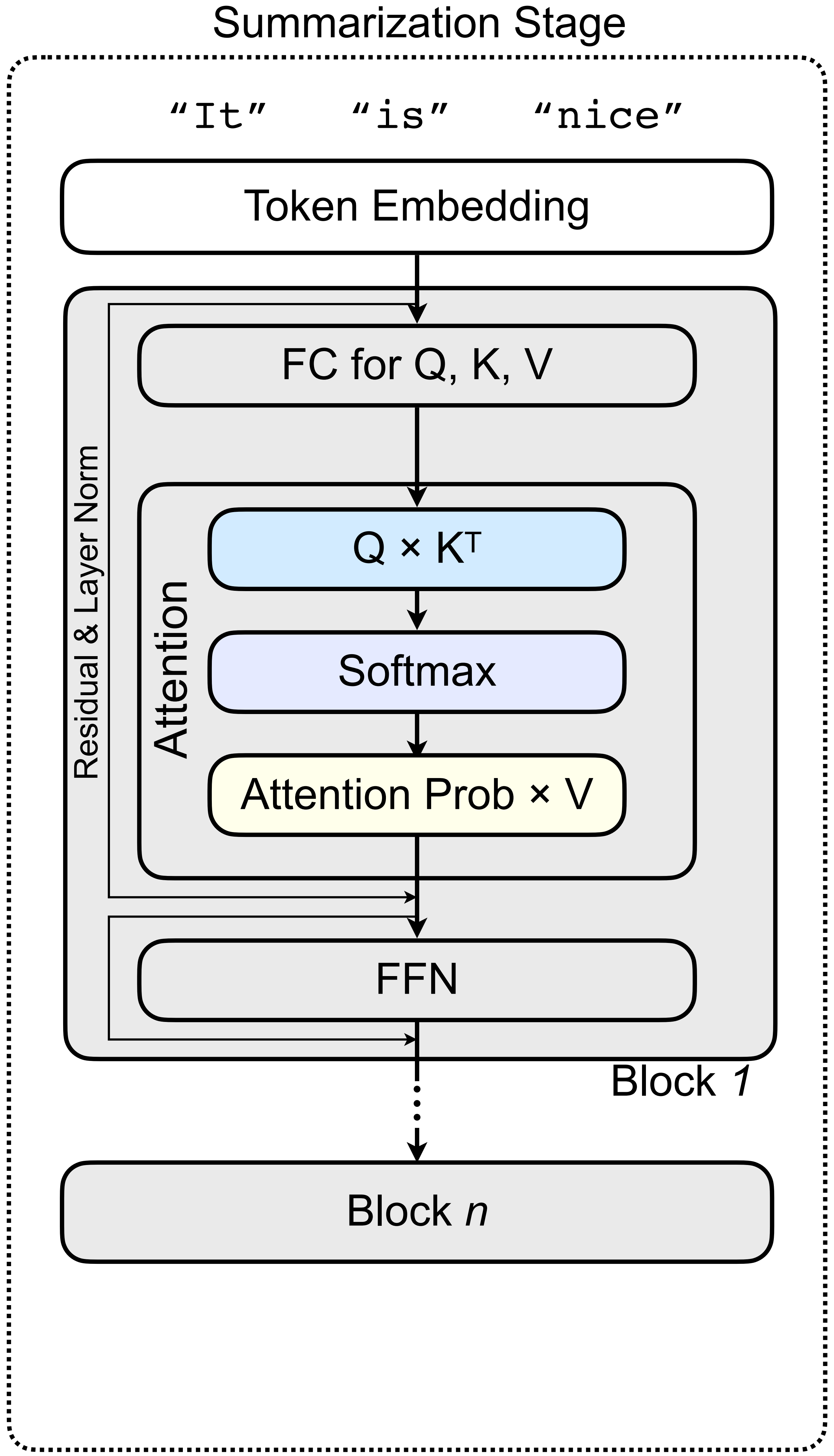

Q, K, V are all **matrices** in **summarization** stage

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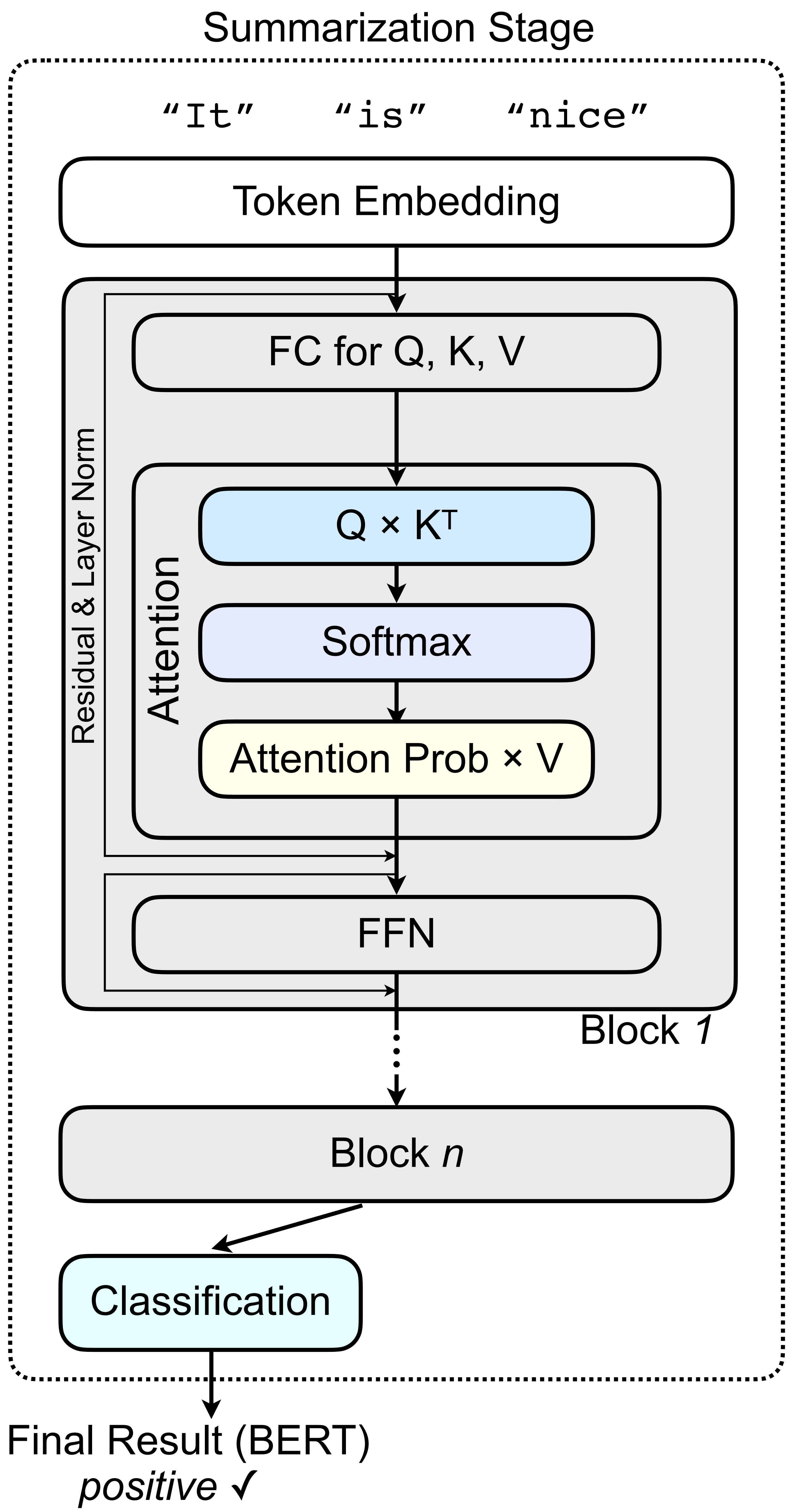

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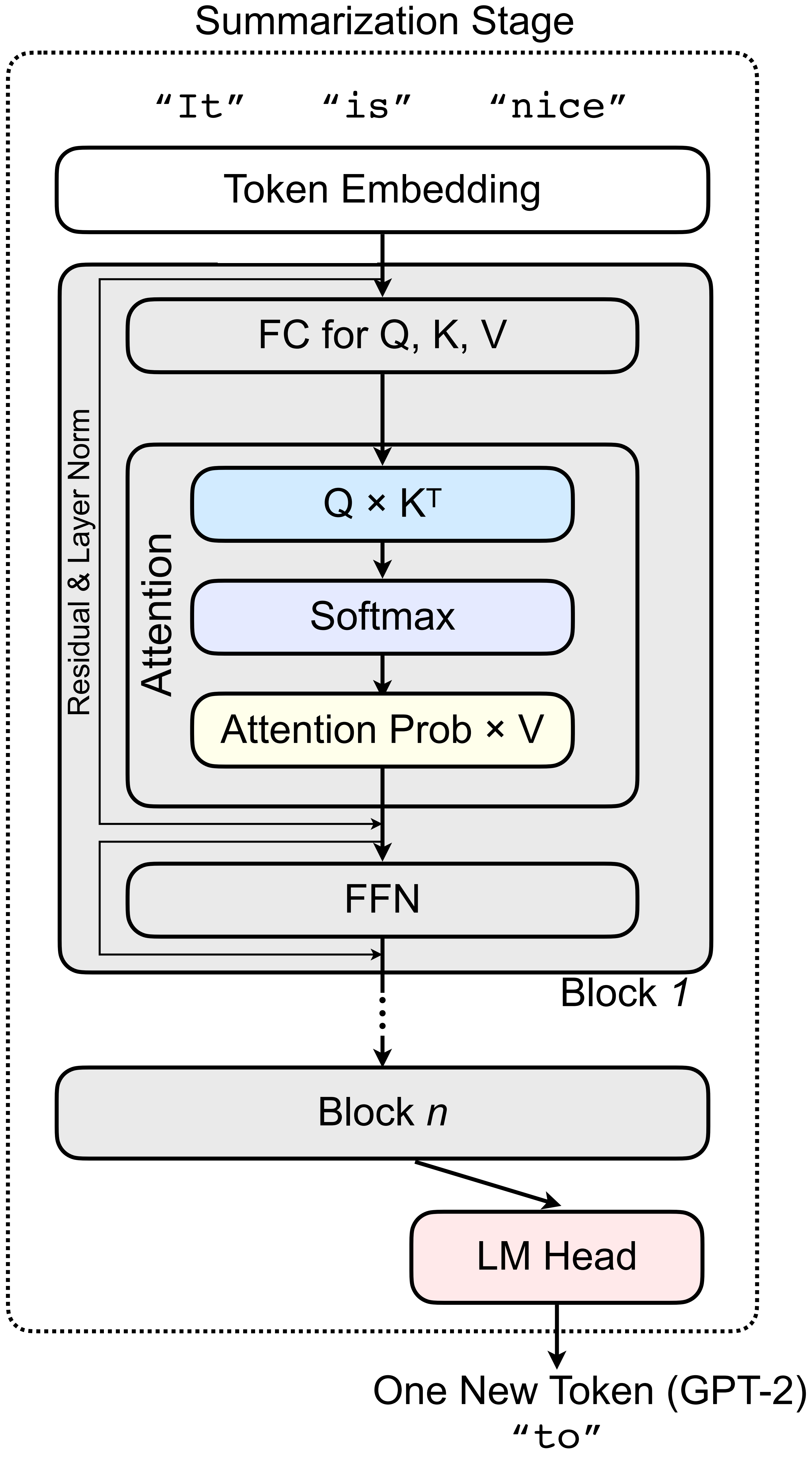

Generation Stage

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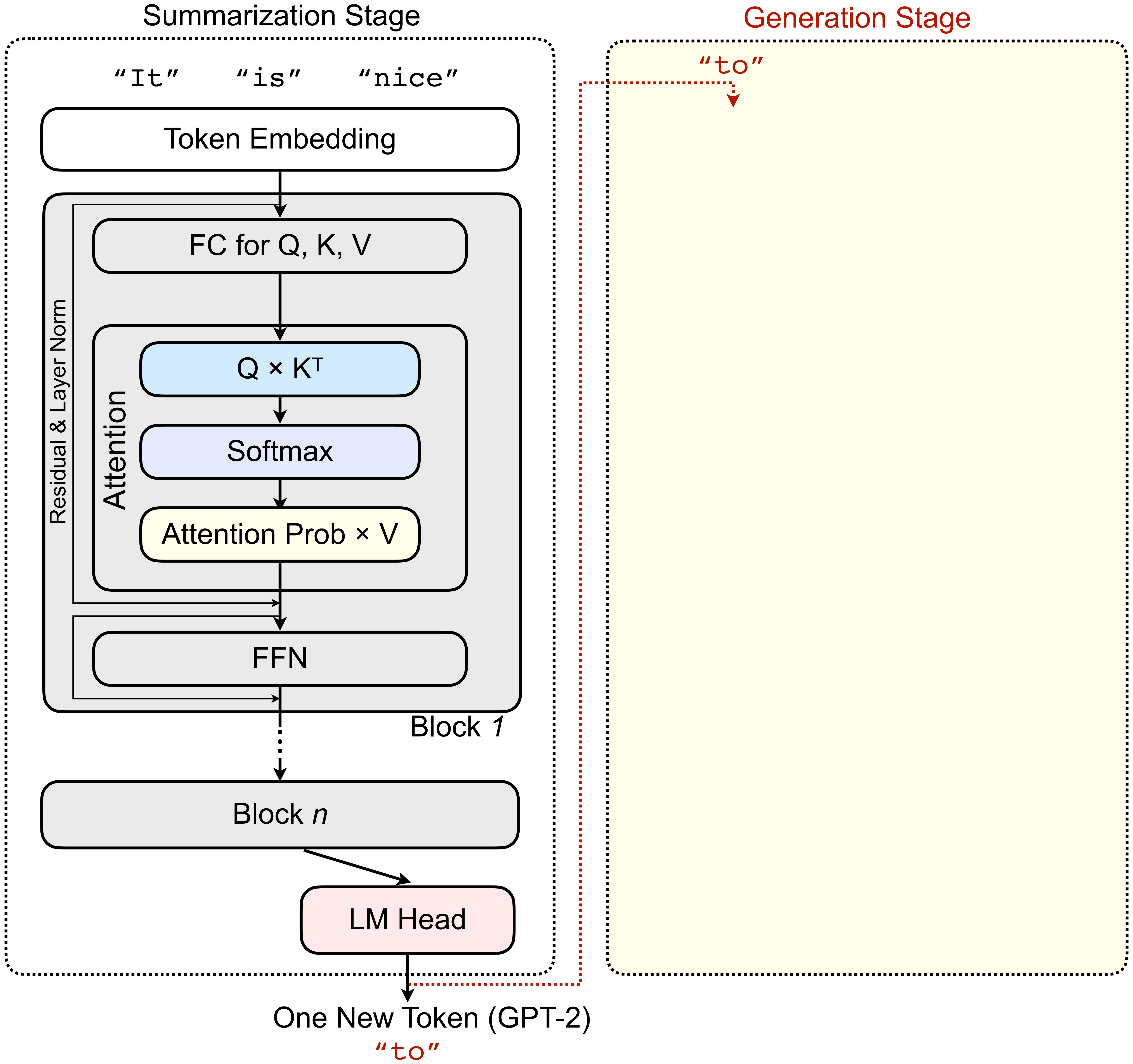

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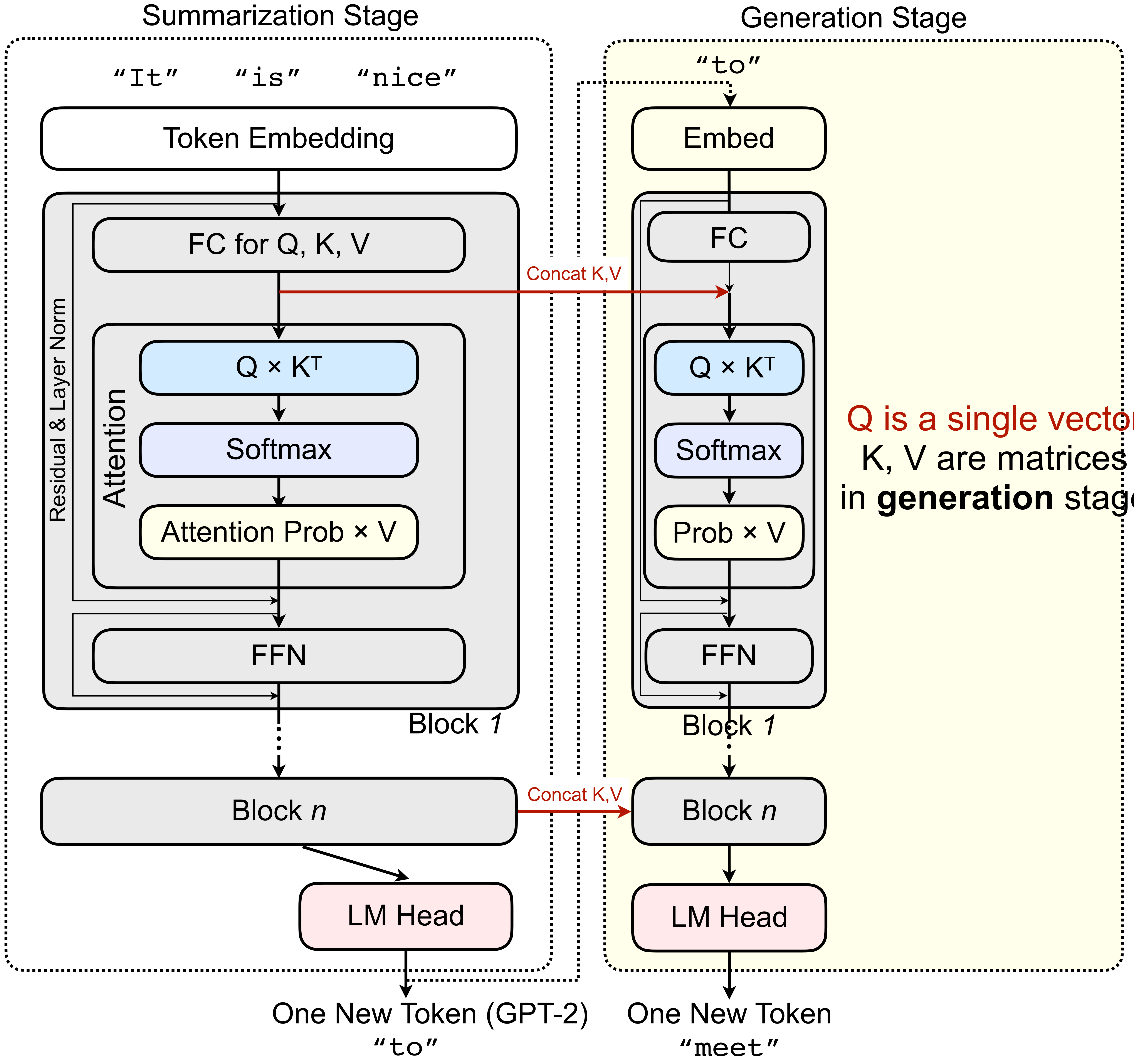

Q is a single vector
K, V are matrices
in **generation** stage

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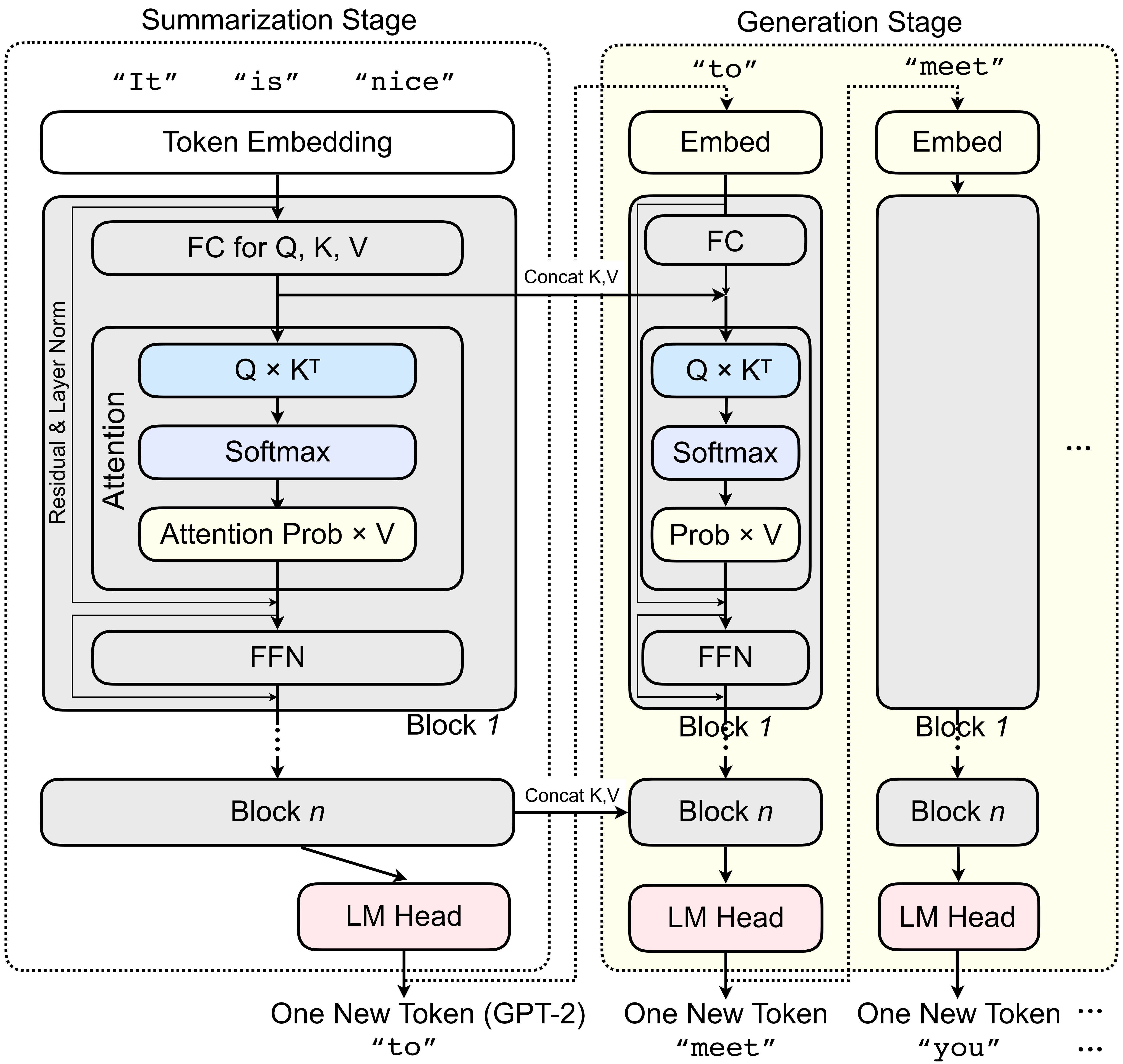

Generation Stage

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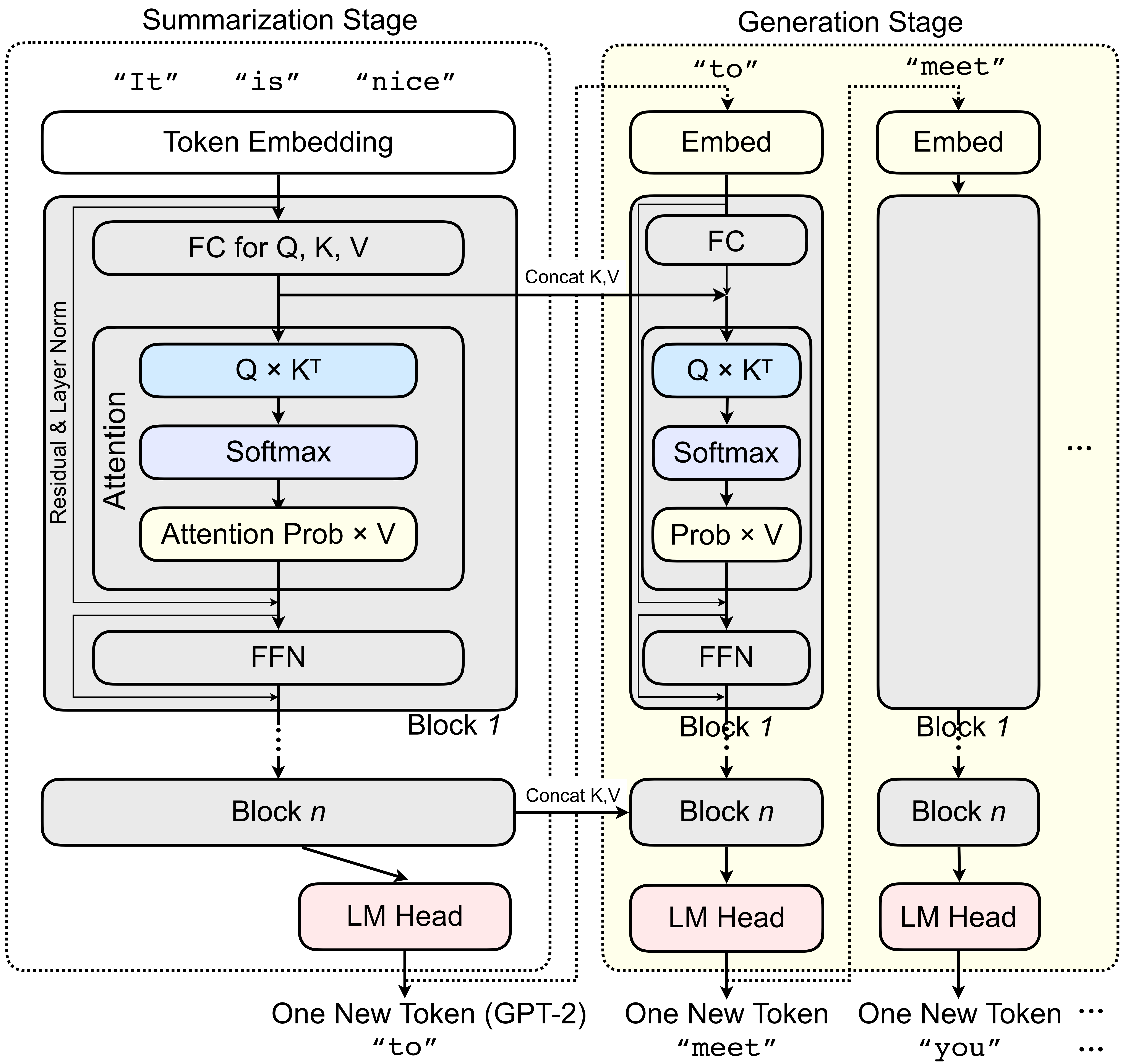
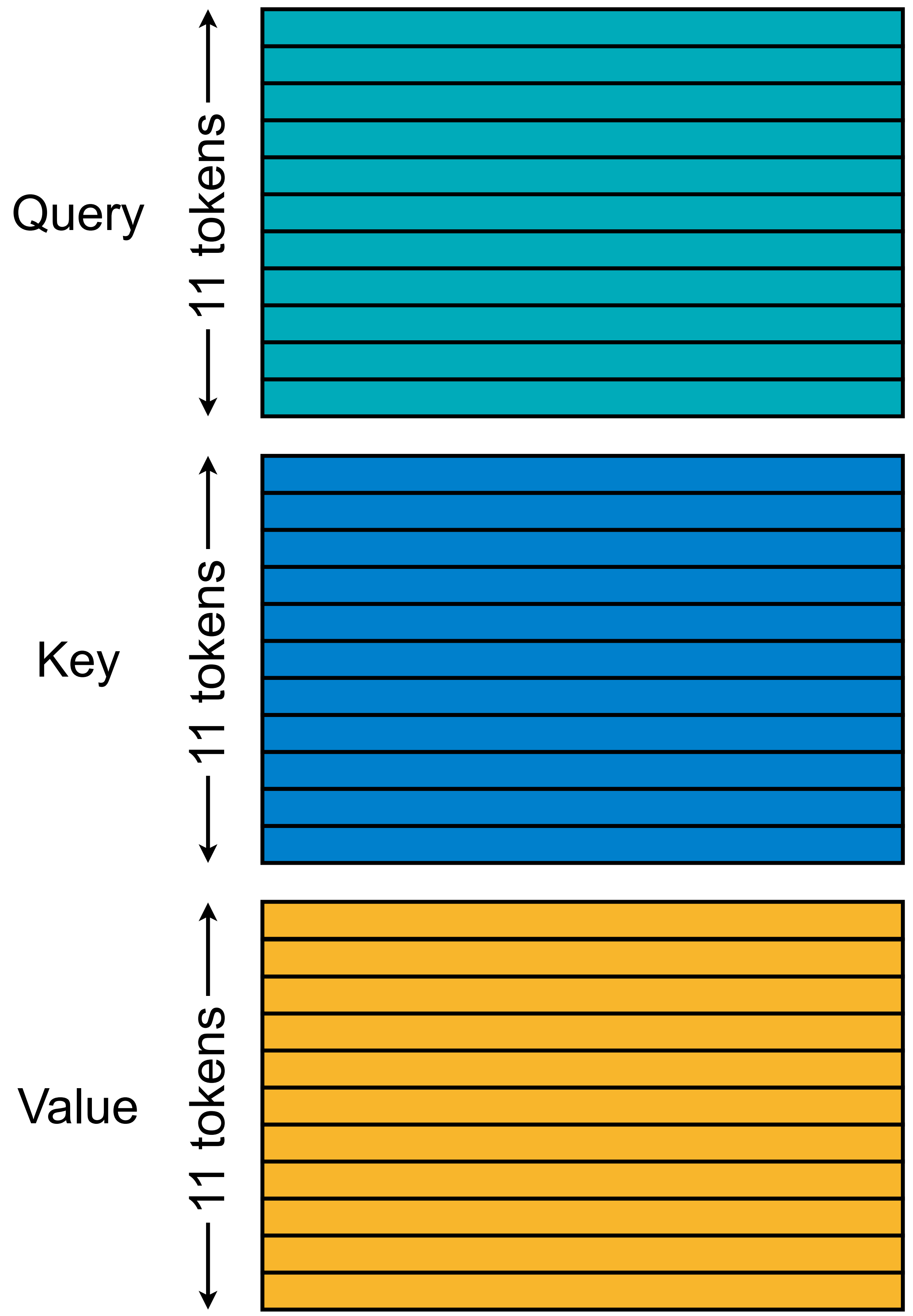
    - Generation Stage
- Block = Layer



Attention Layer - in Summarization Stage



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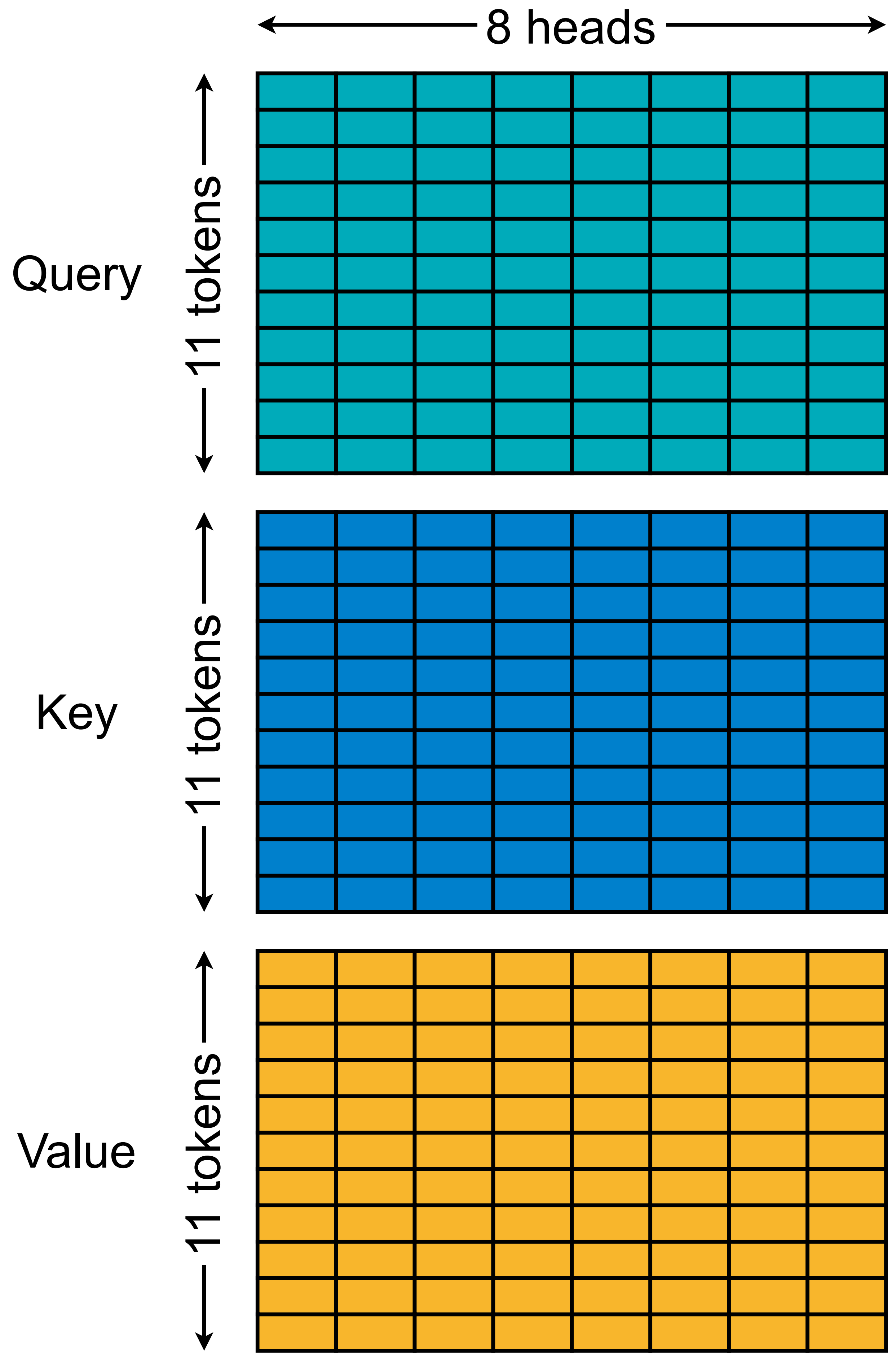

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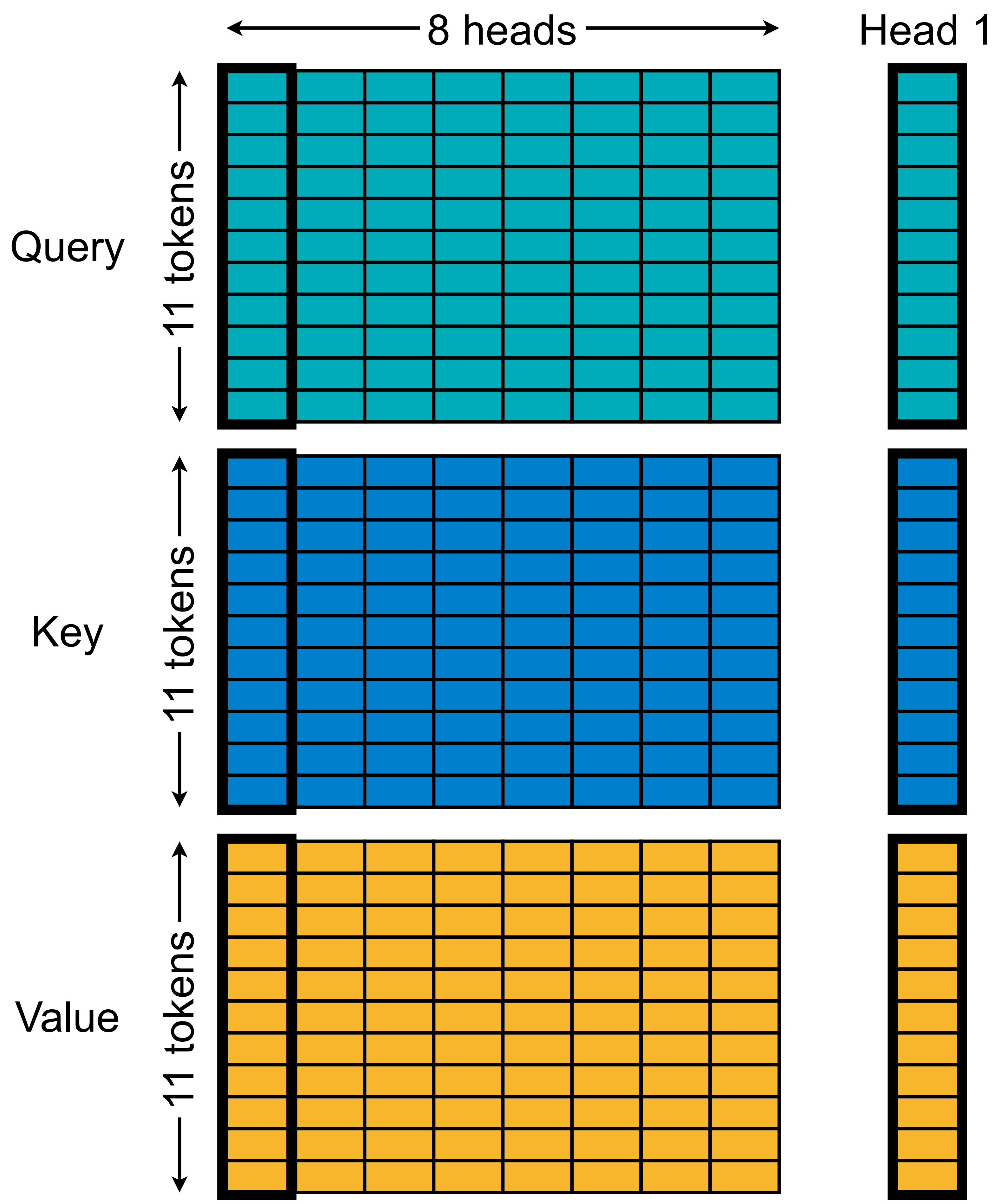
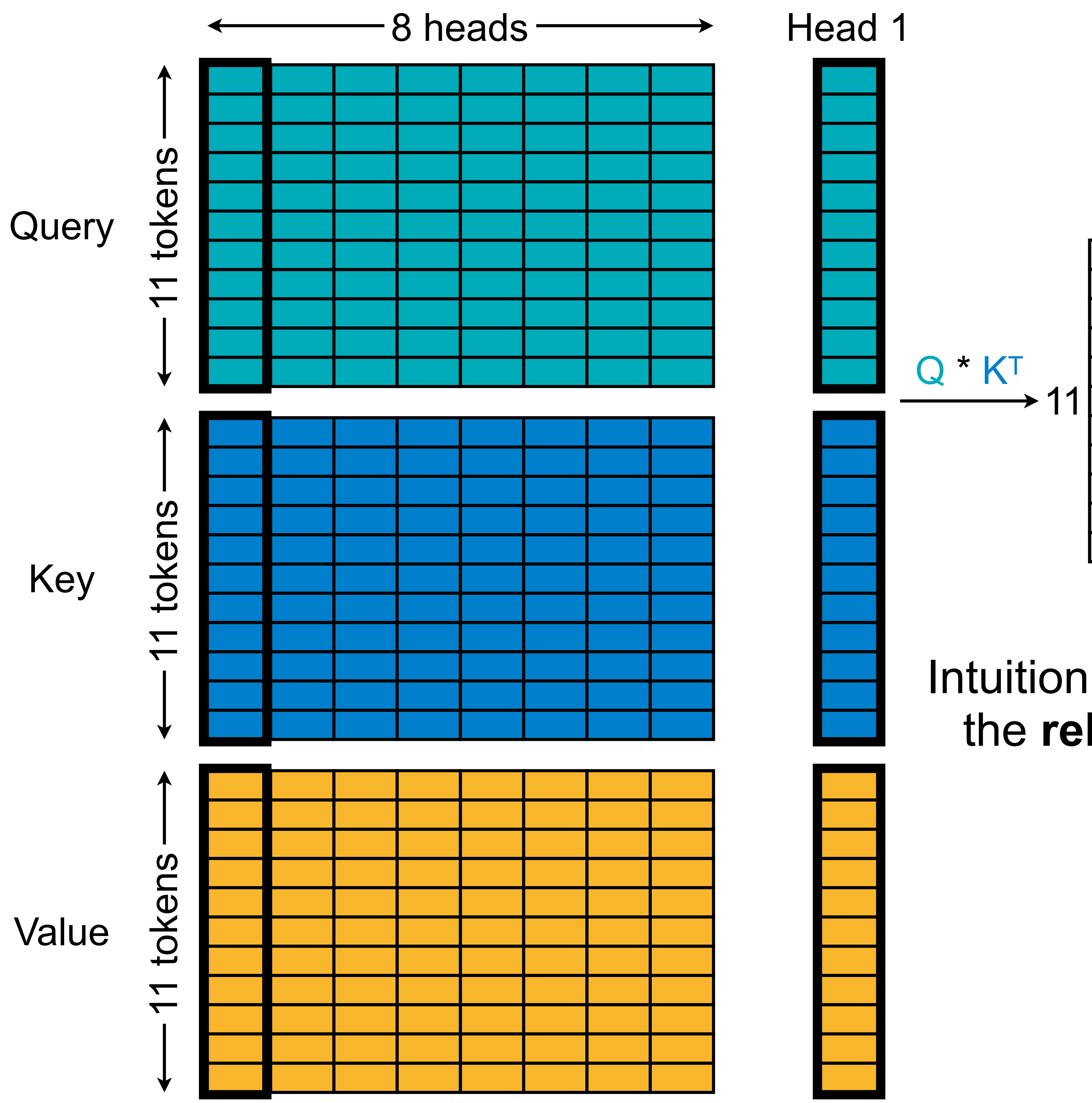
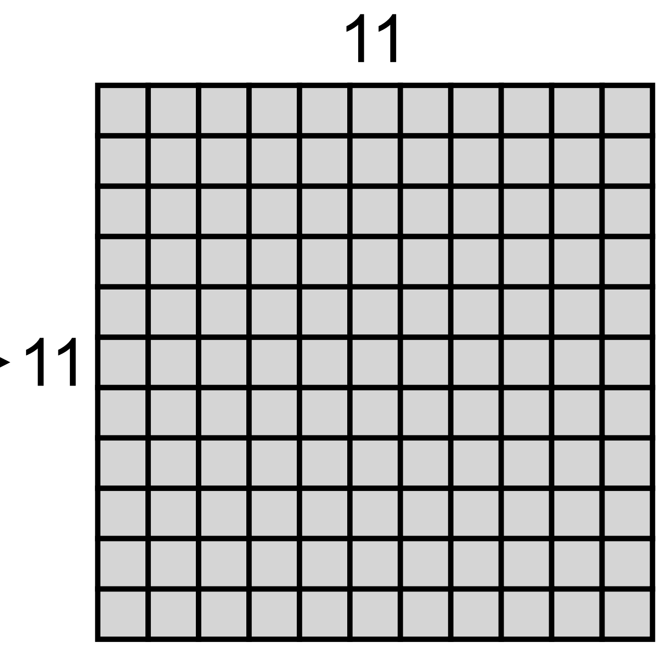


- Dimension of one head is typically 64

Attention Layer - in Summarization Stage

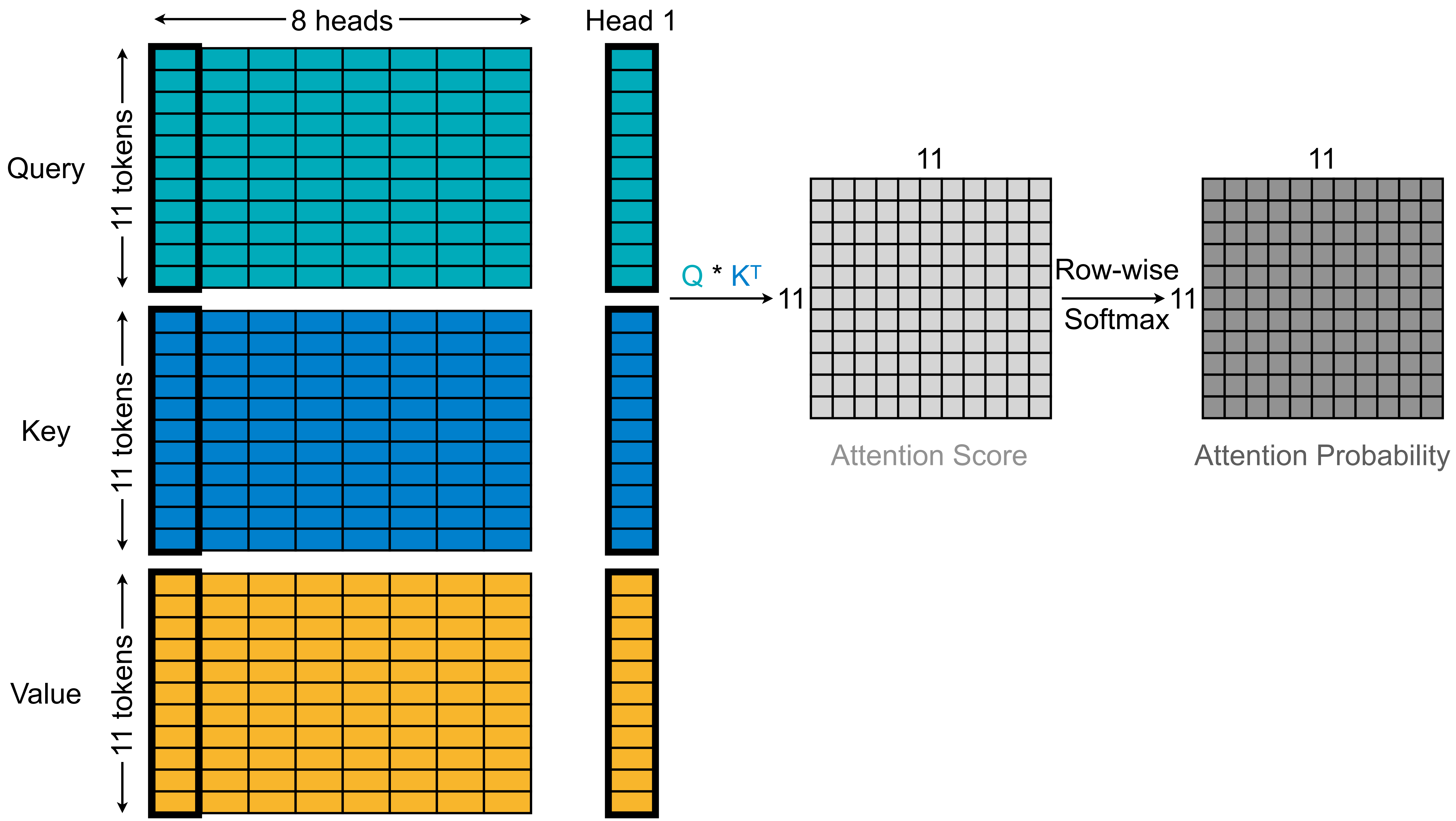




Attention Score

Intuition: each token is trying to assess the **relevance/importance** of other tokens to itself

Attention Layer - in Summarization Stage



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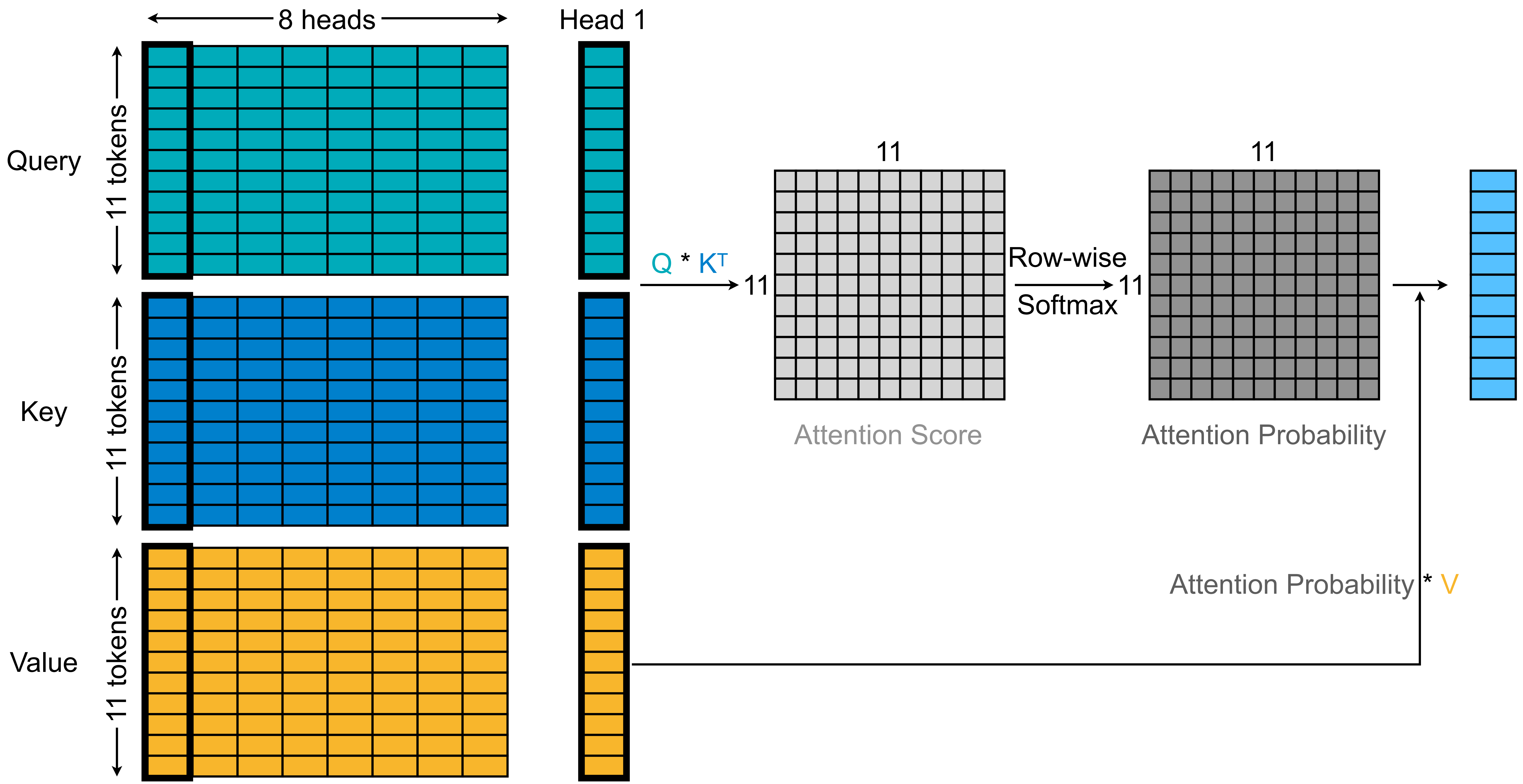

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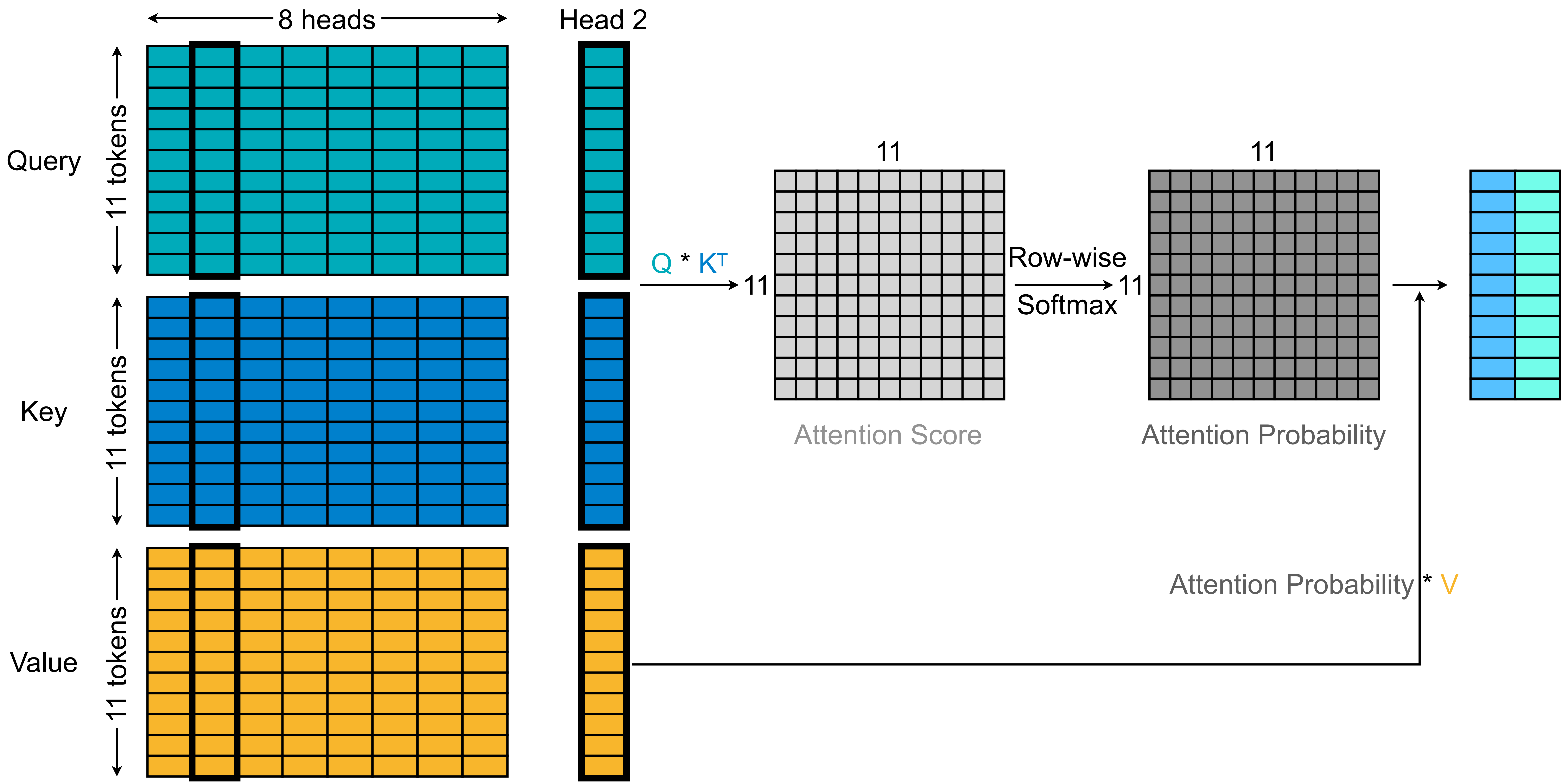

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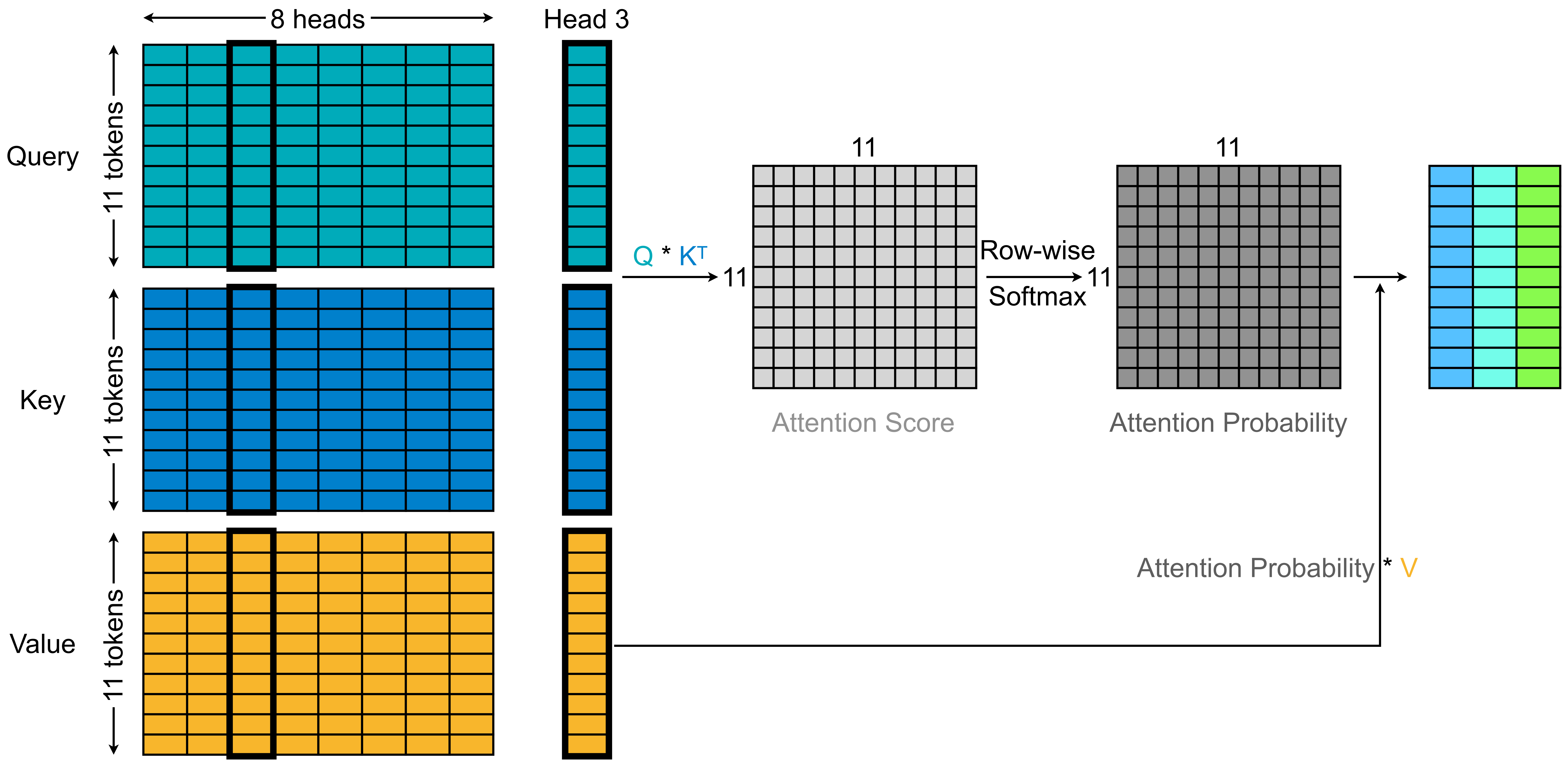

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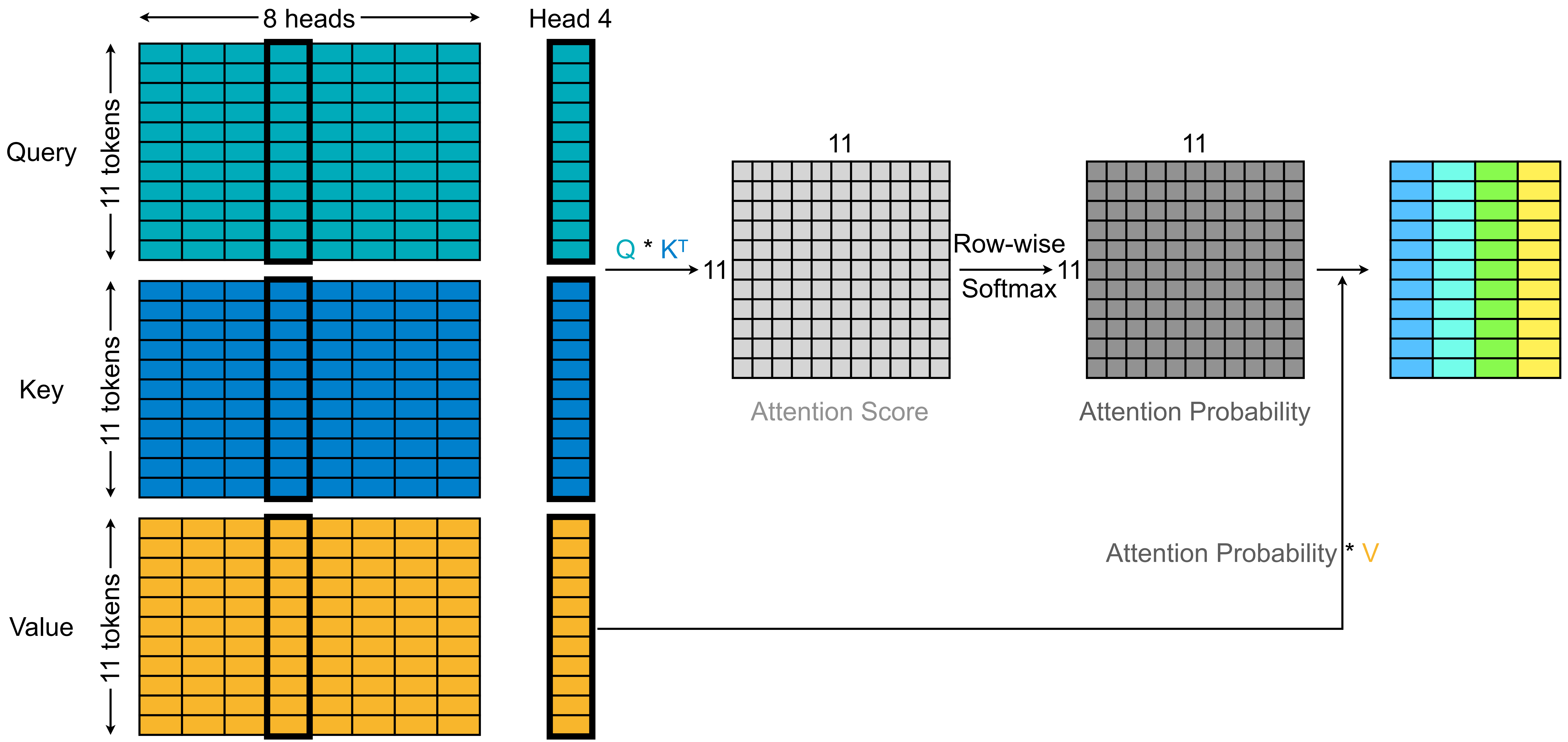

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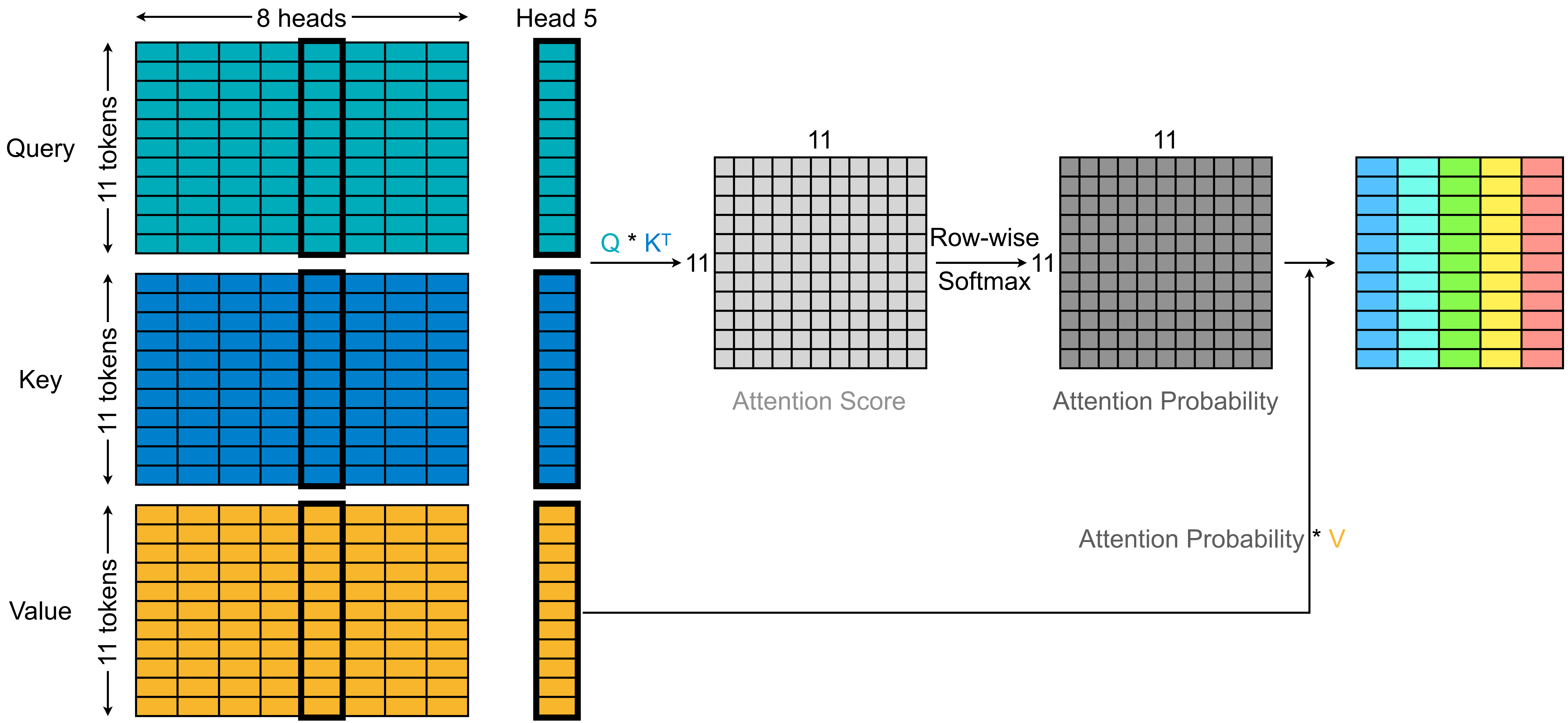

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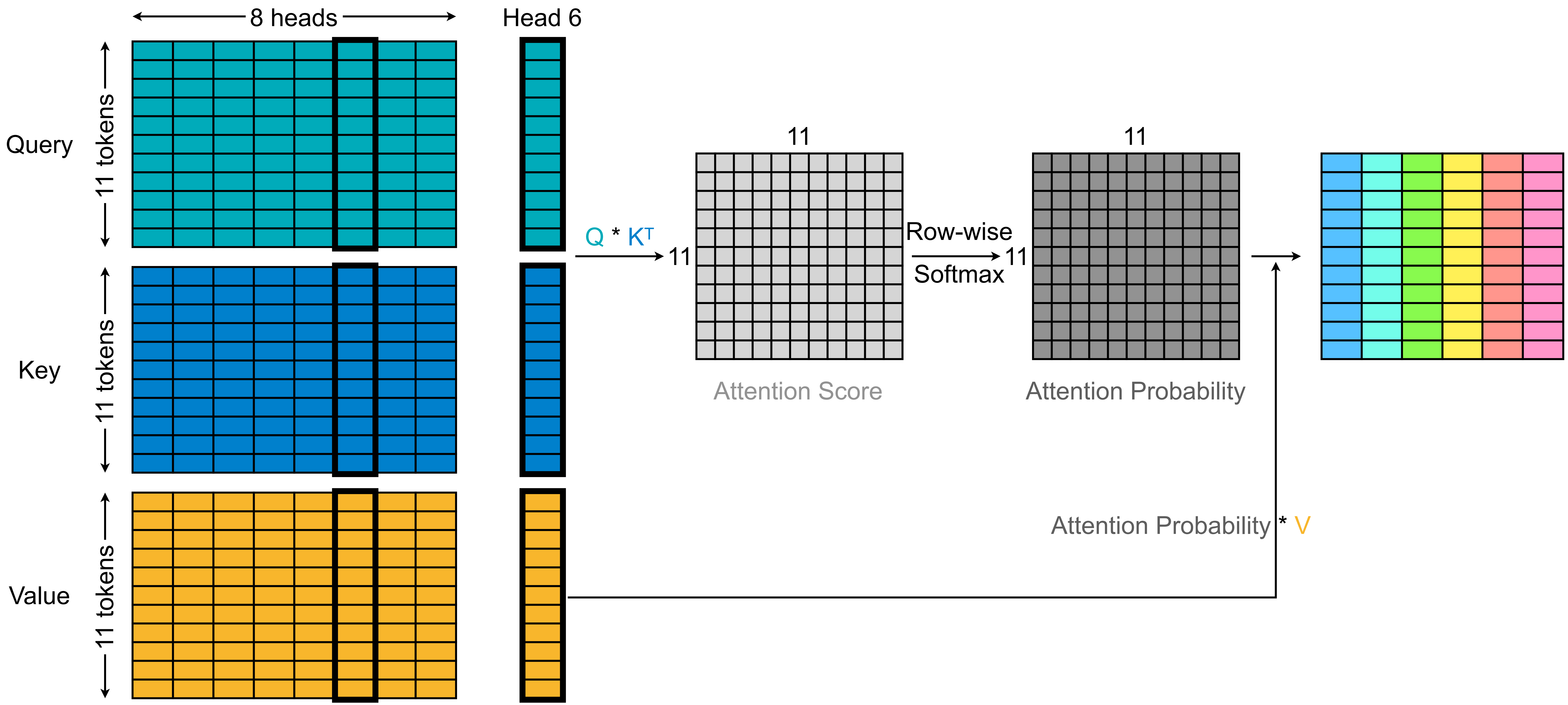

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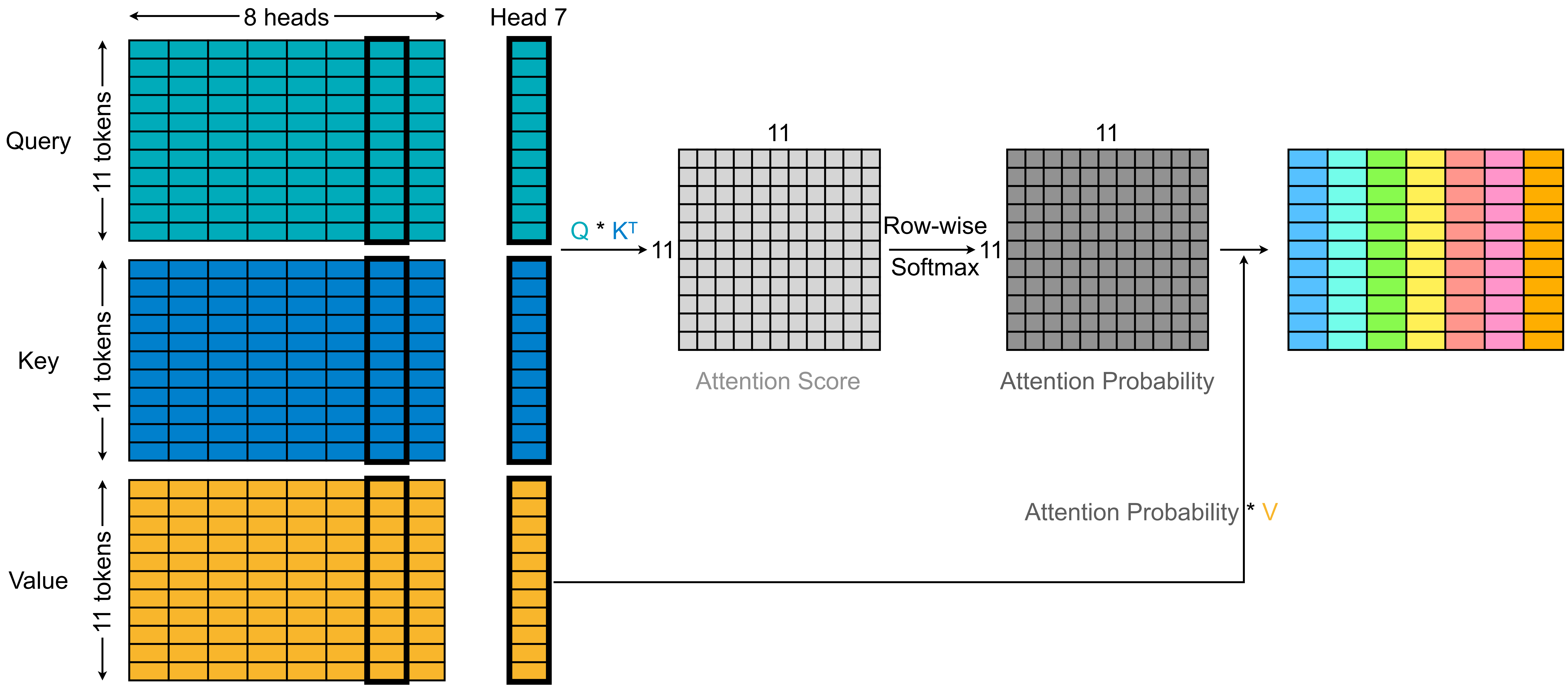

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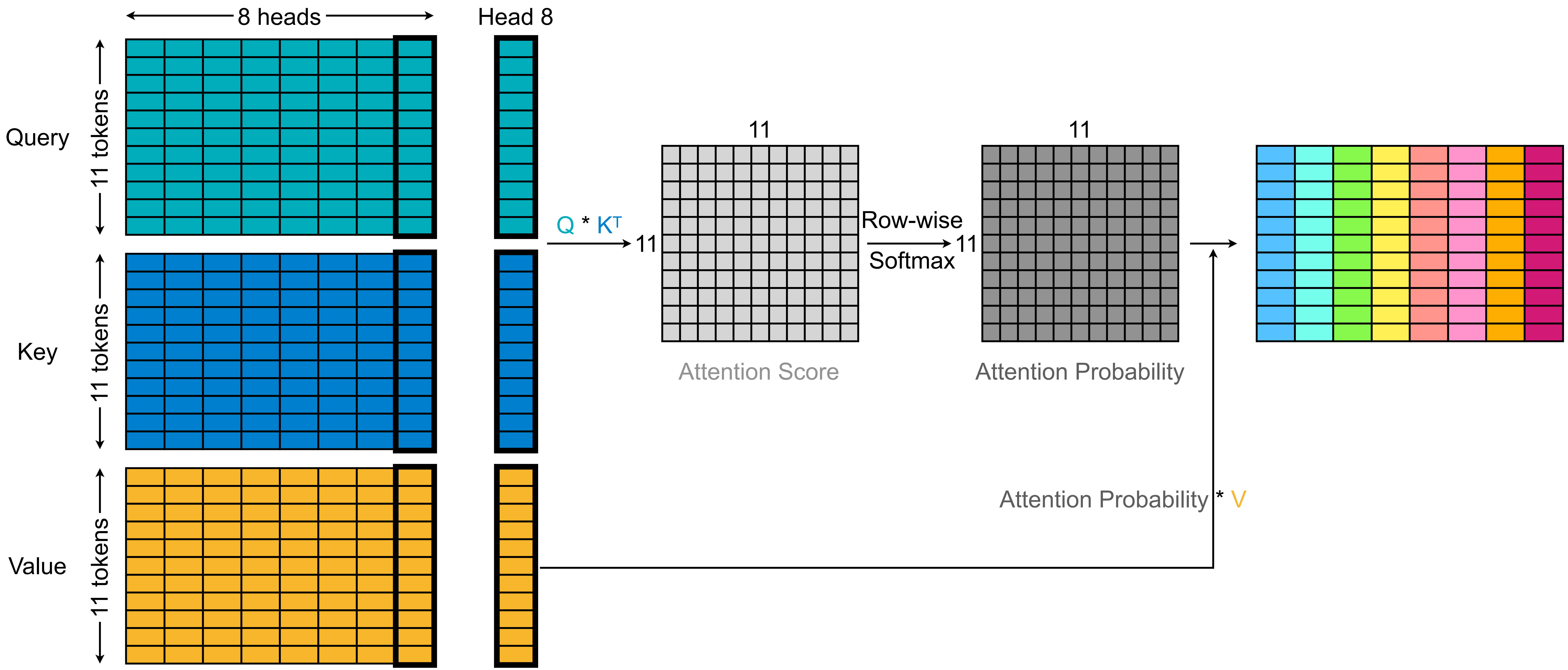
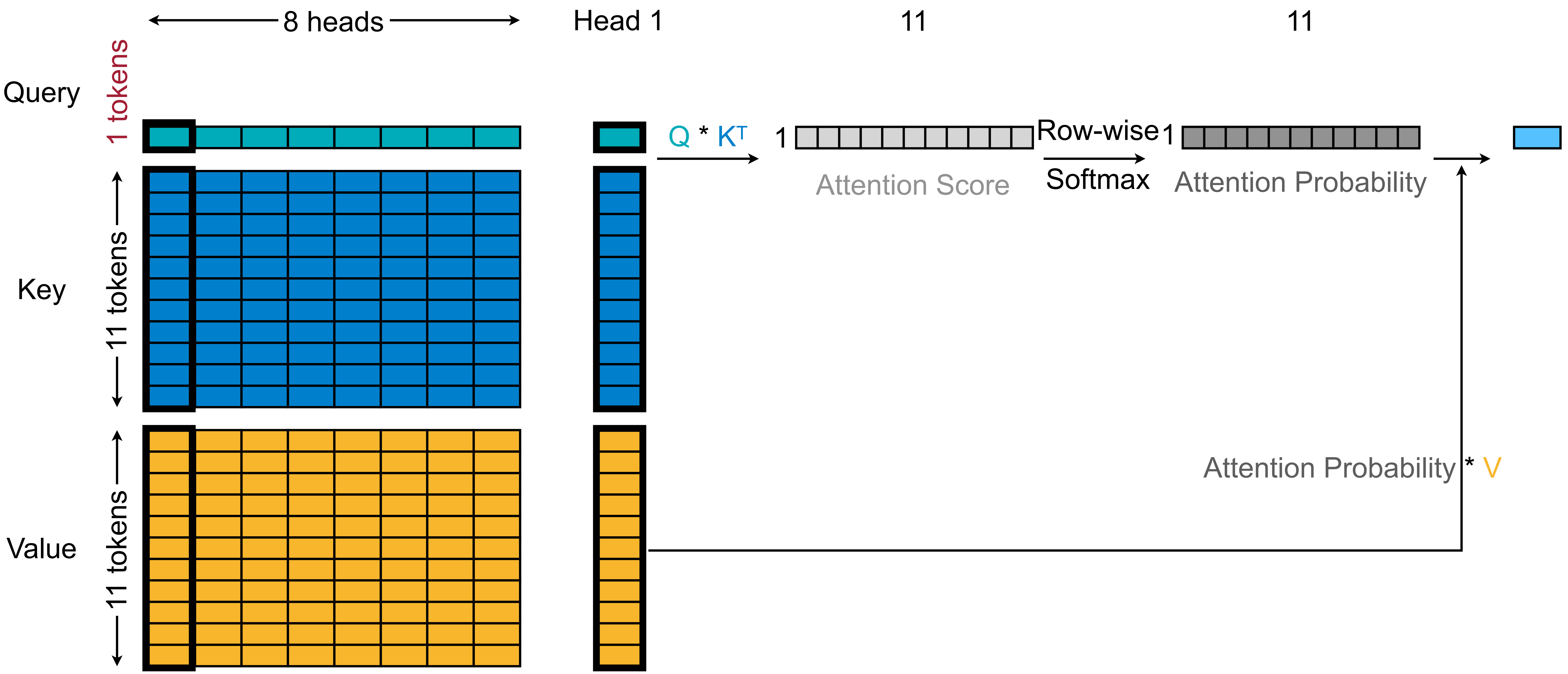


Attention Layer - in Generation Stage



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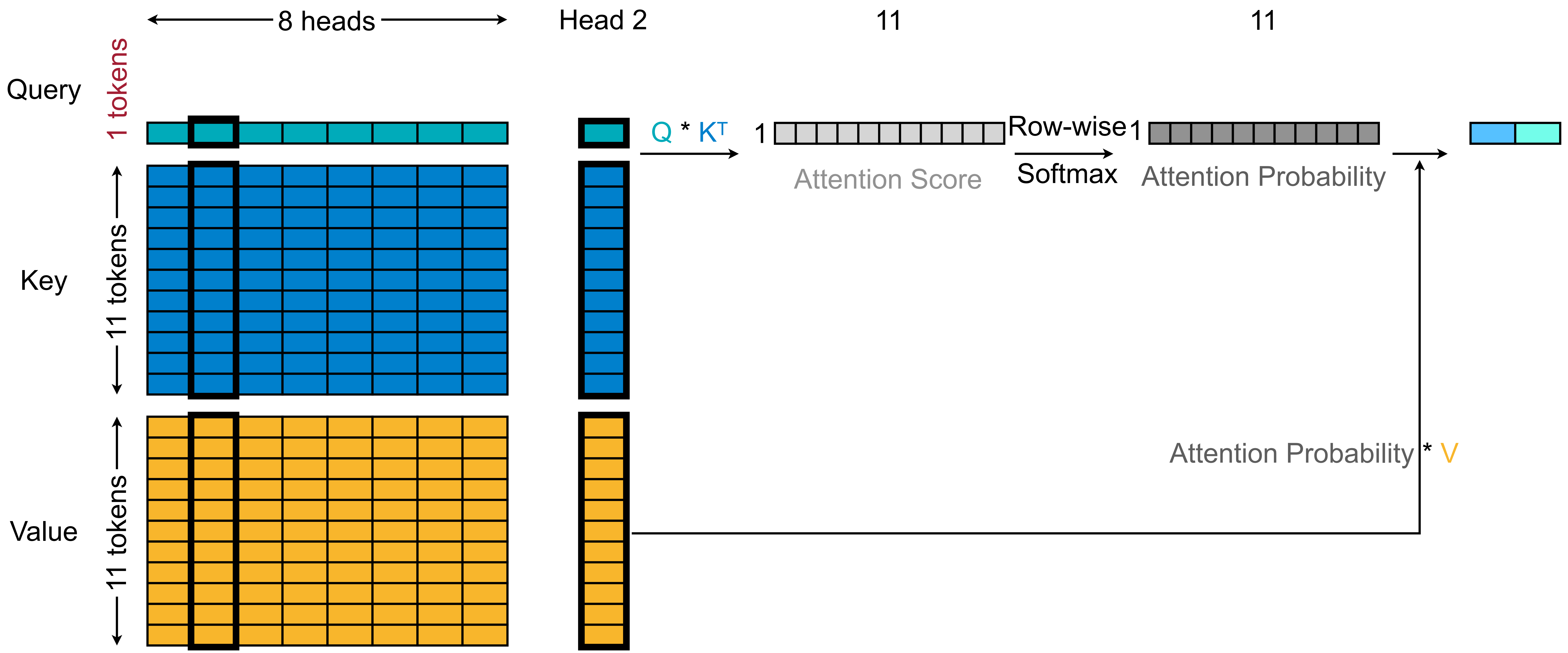

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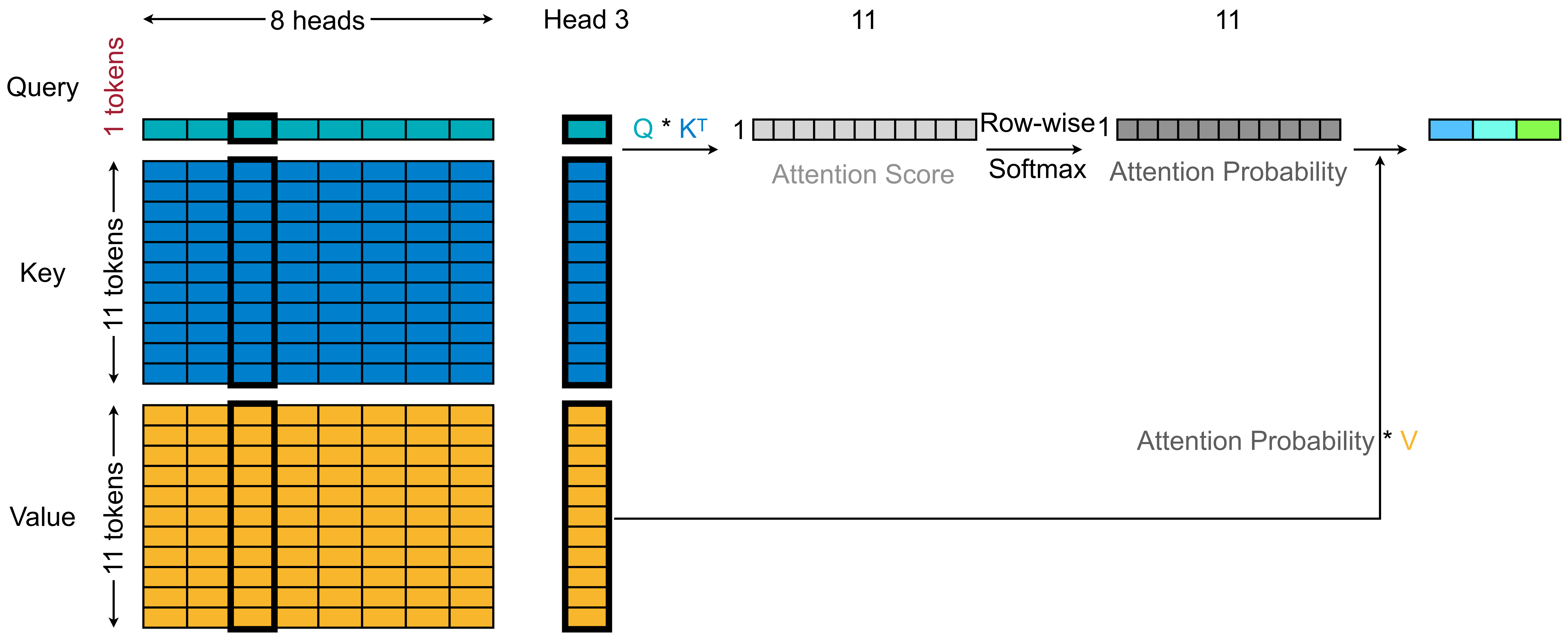

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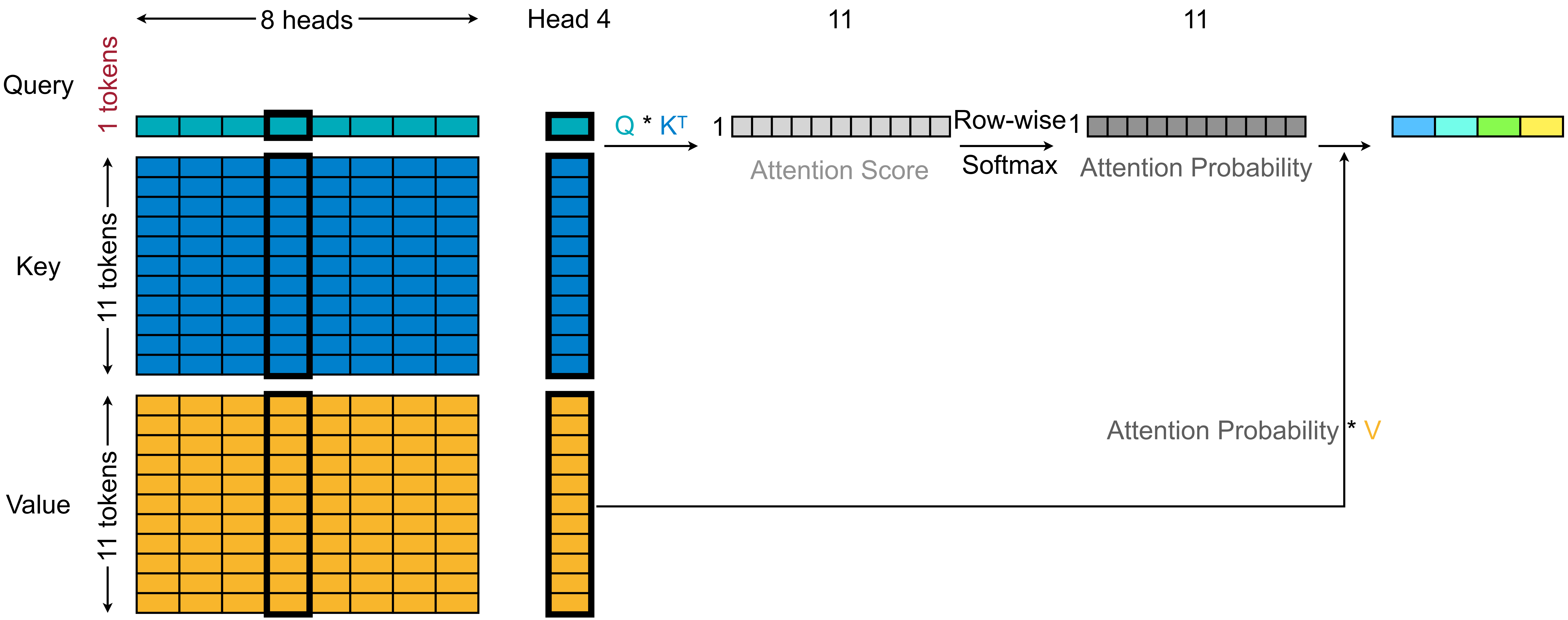

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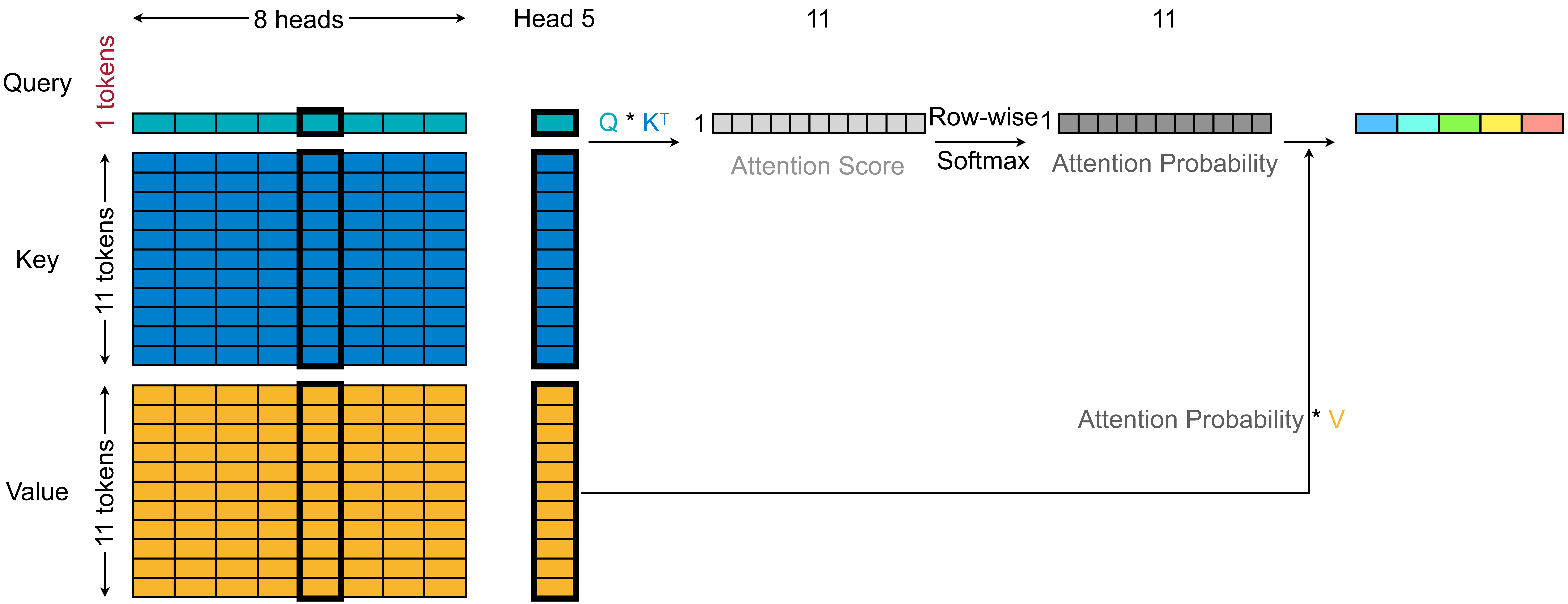

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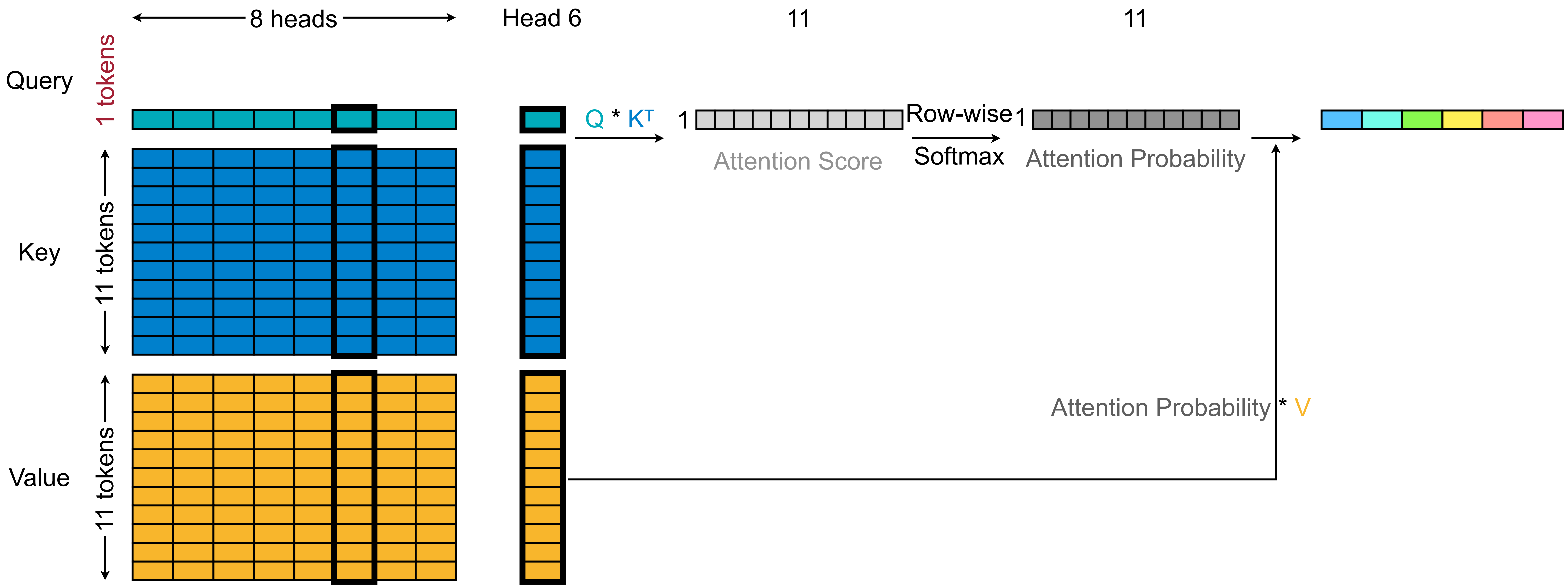

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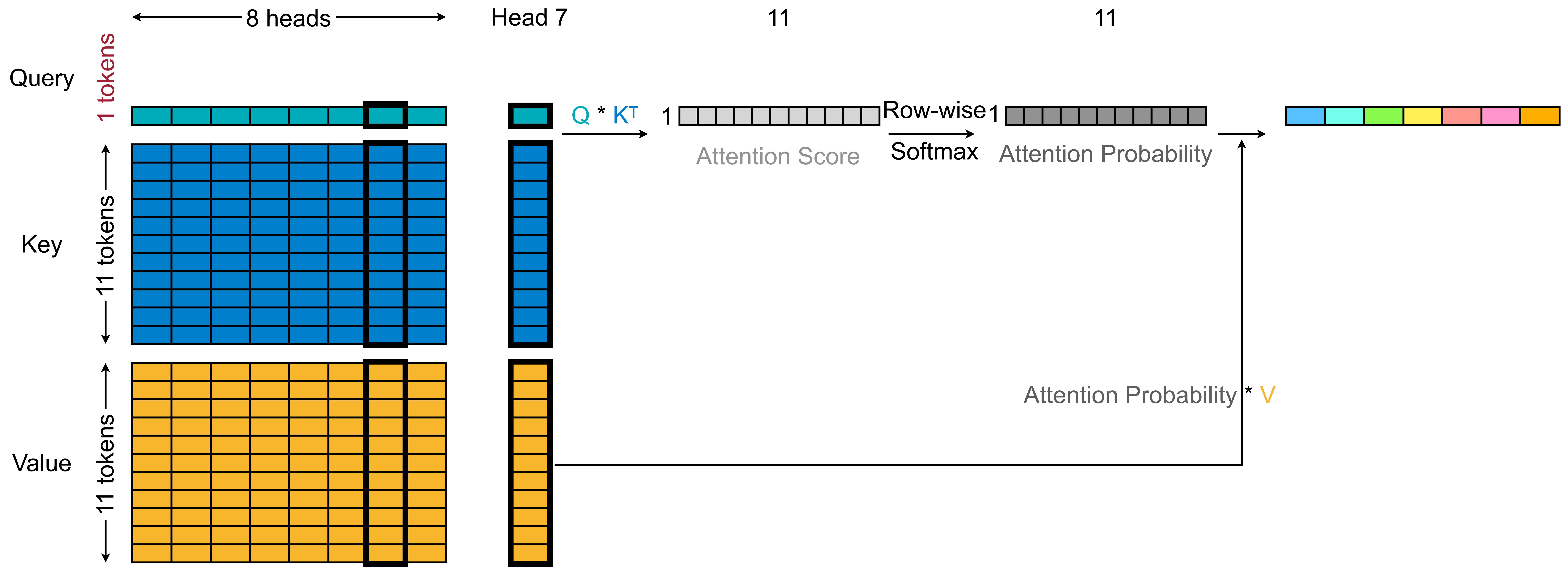

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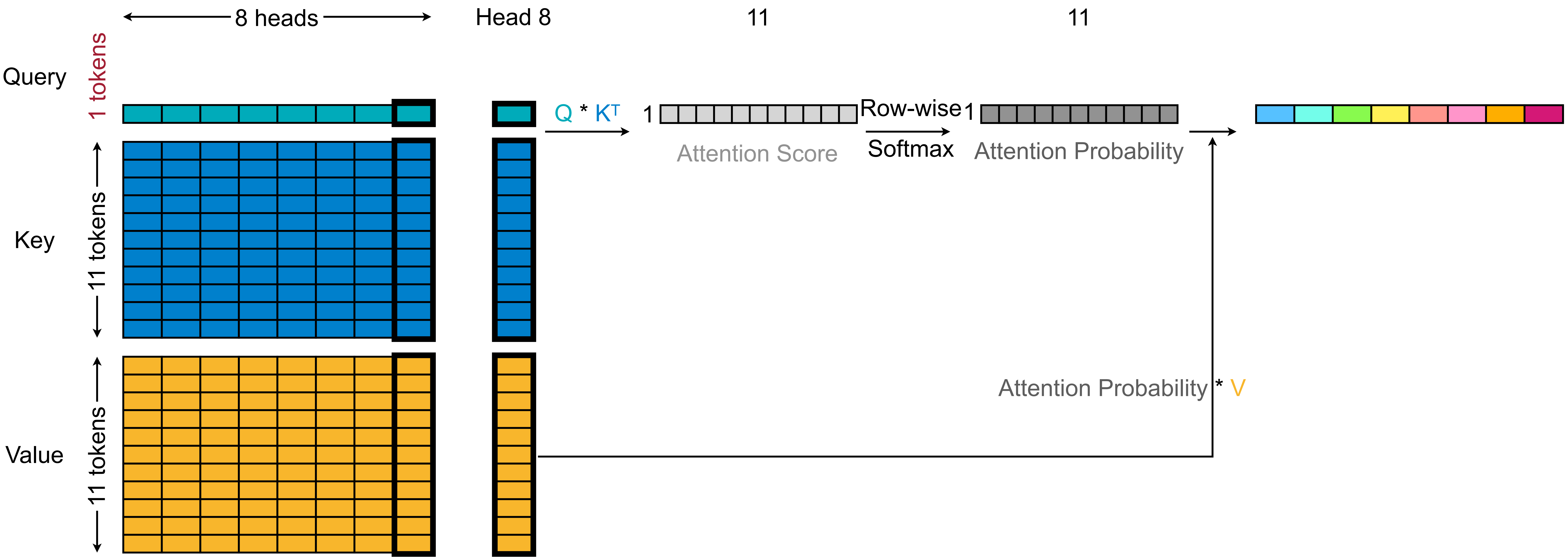
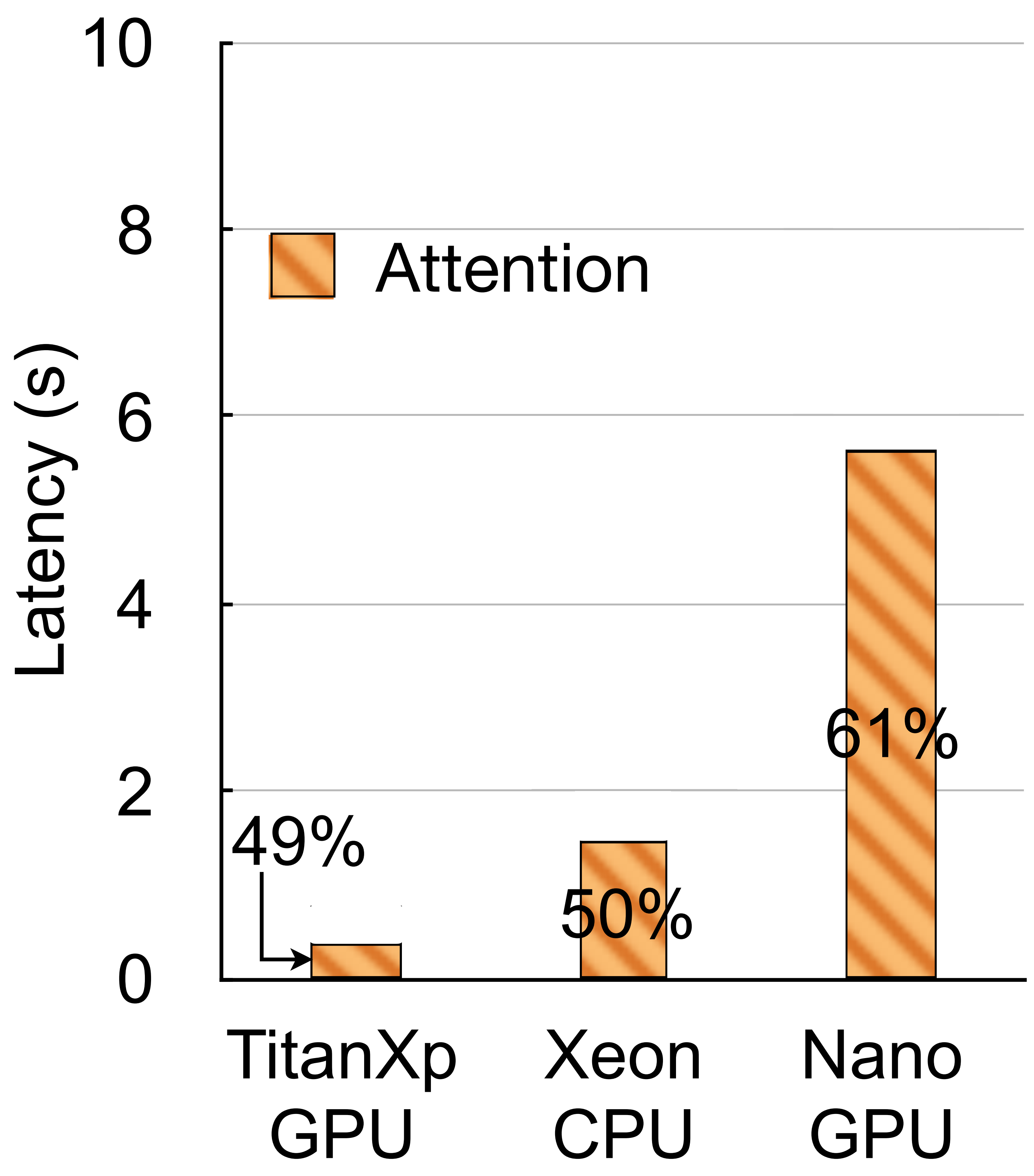


- Different from Convolution or FC:
  - Query, Key, Value are **activations**

Attention Runs Slow

- End-to-End GPT-2 latency breakdown



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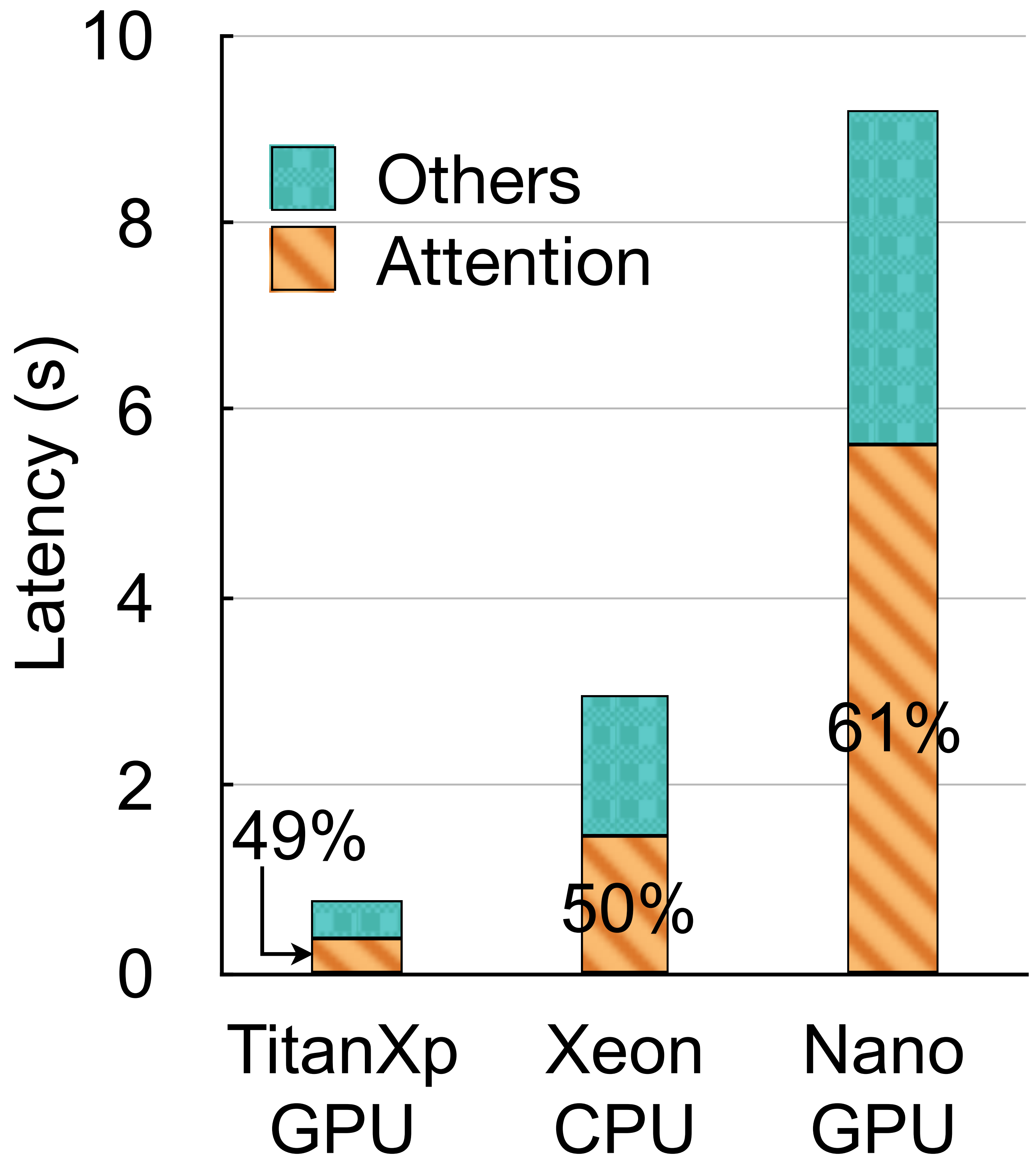

- Attention takes over 50% latency

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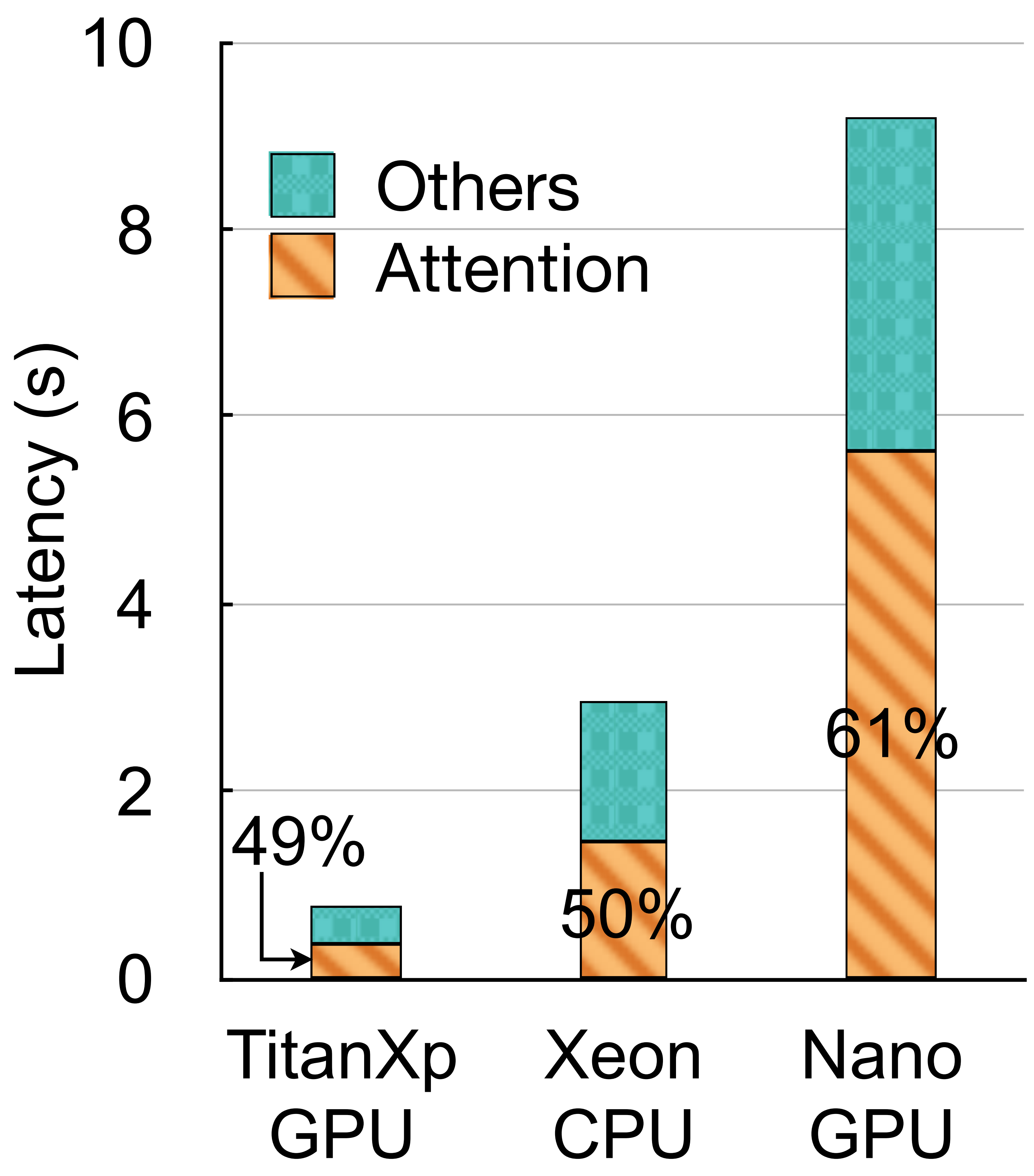

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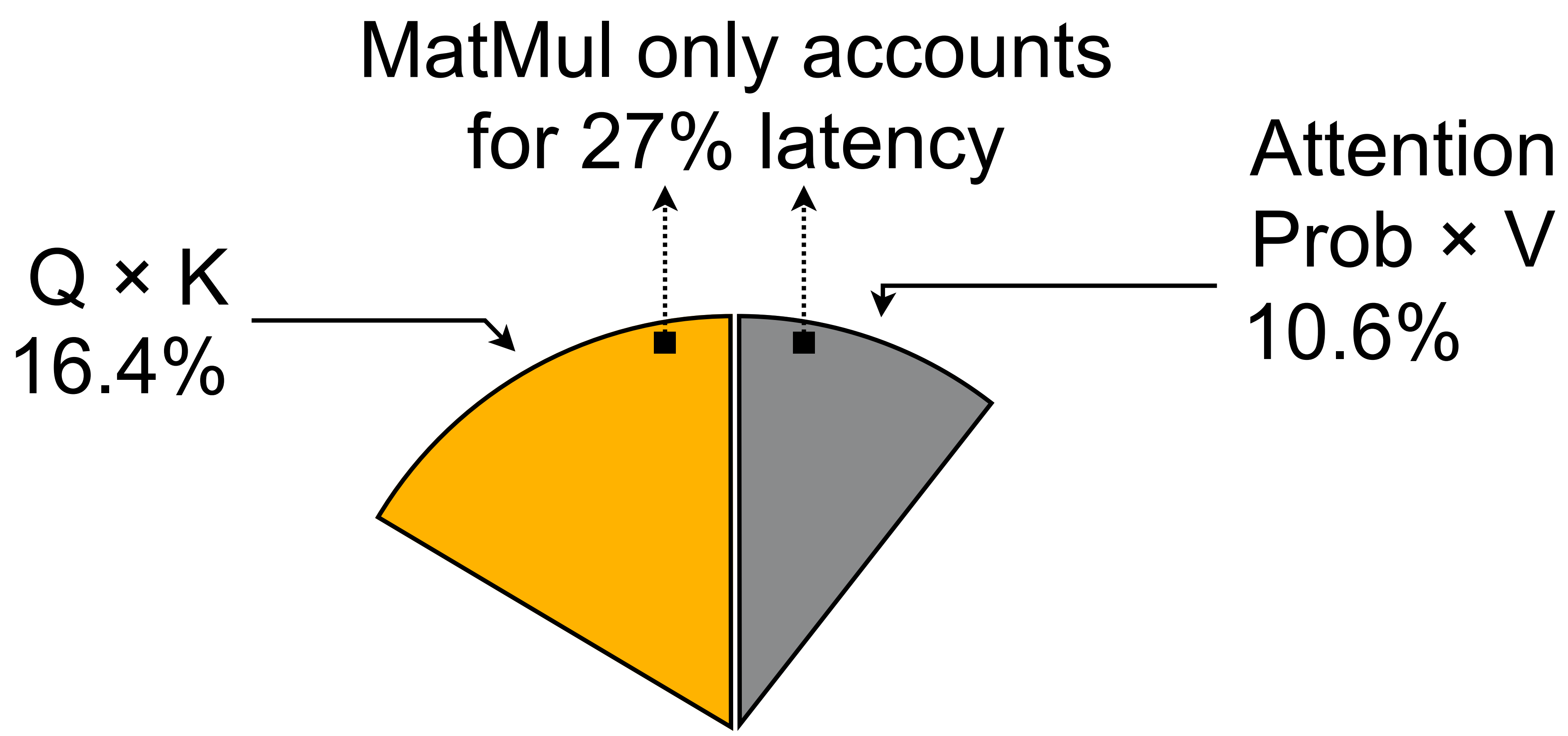

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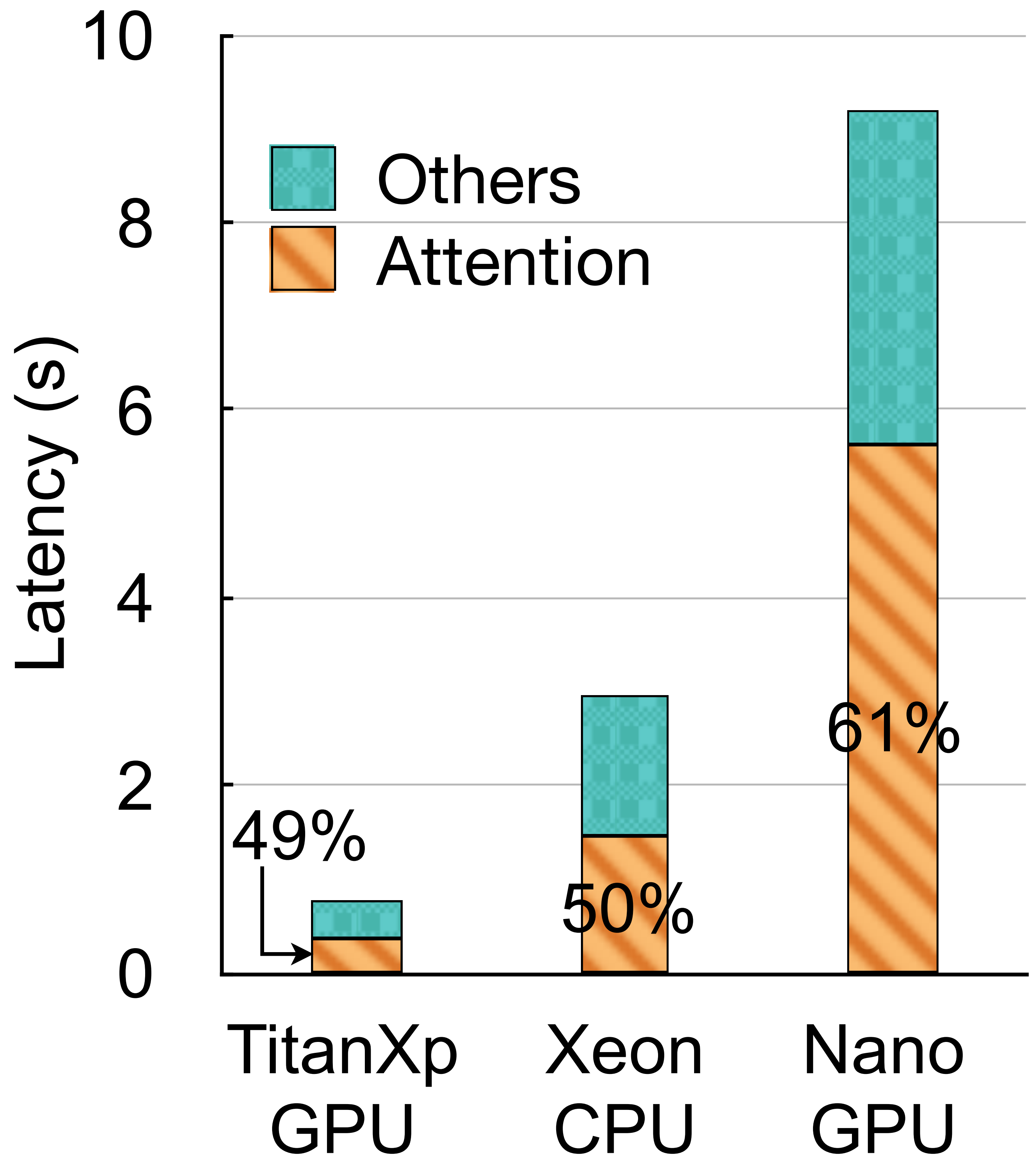

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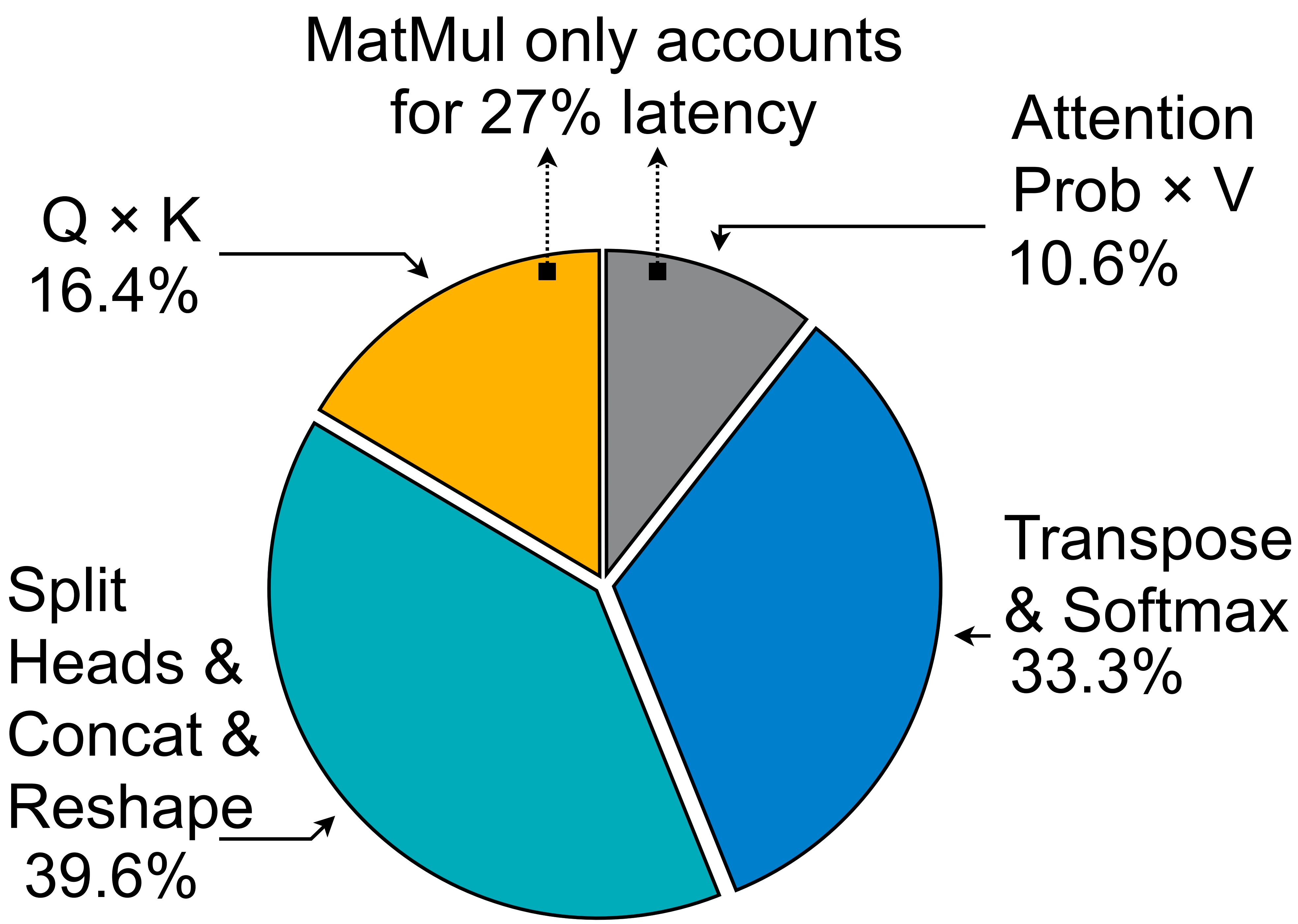
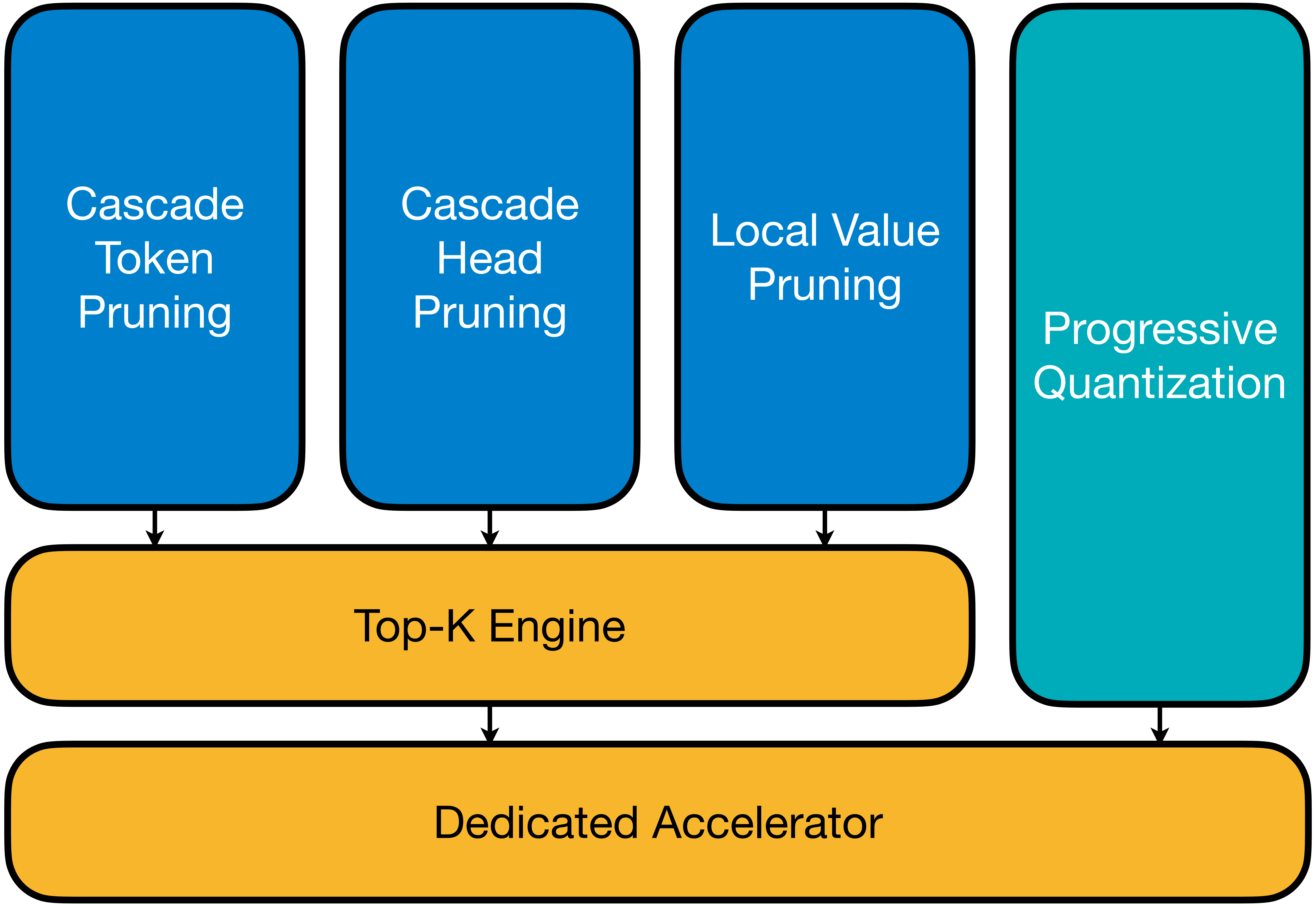


- Attention takes over 50% latency
- Memory operations take over 70% latency

Our Solution: SpAtten



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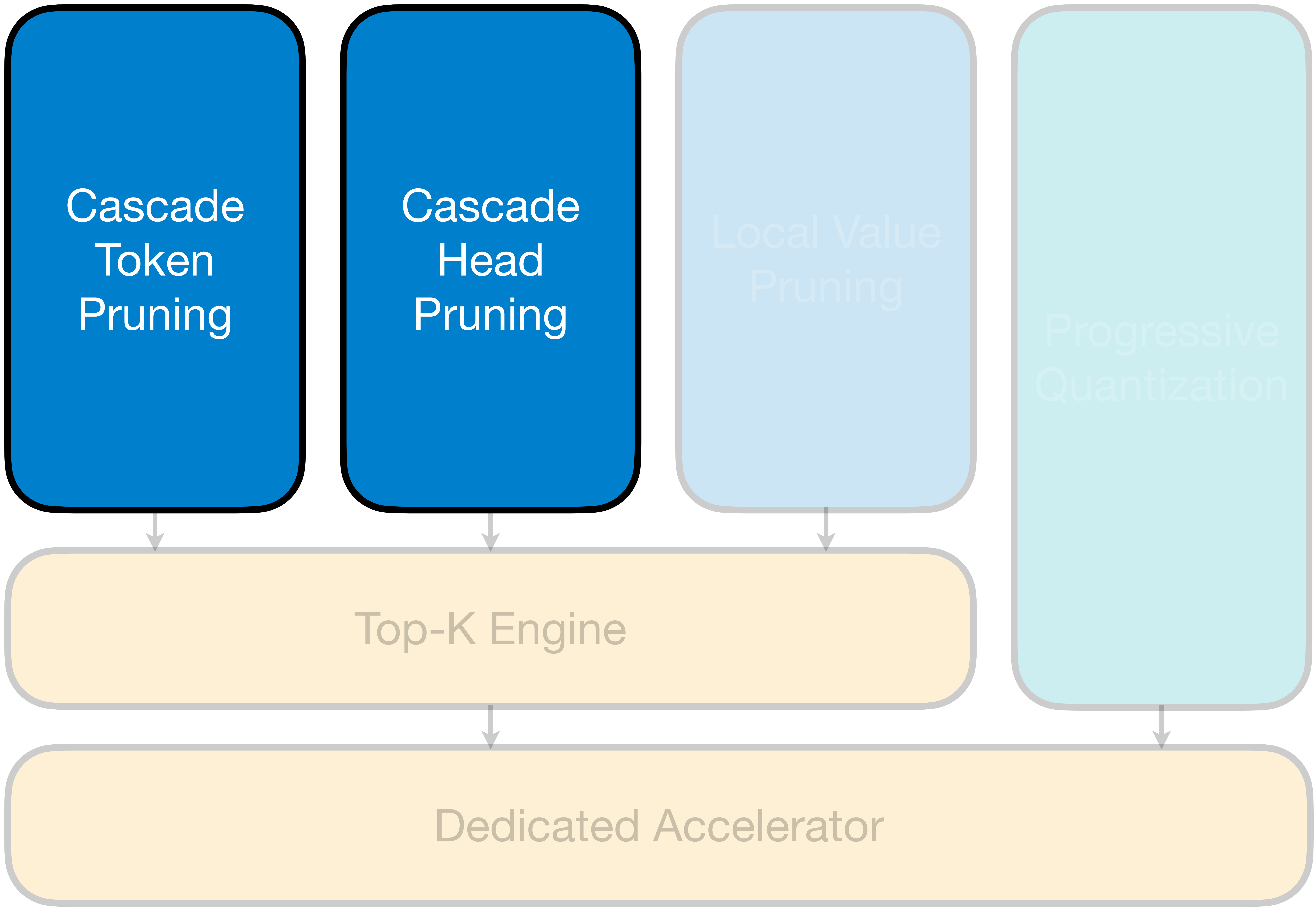
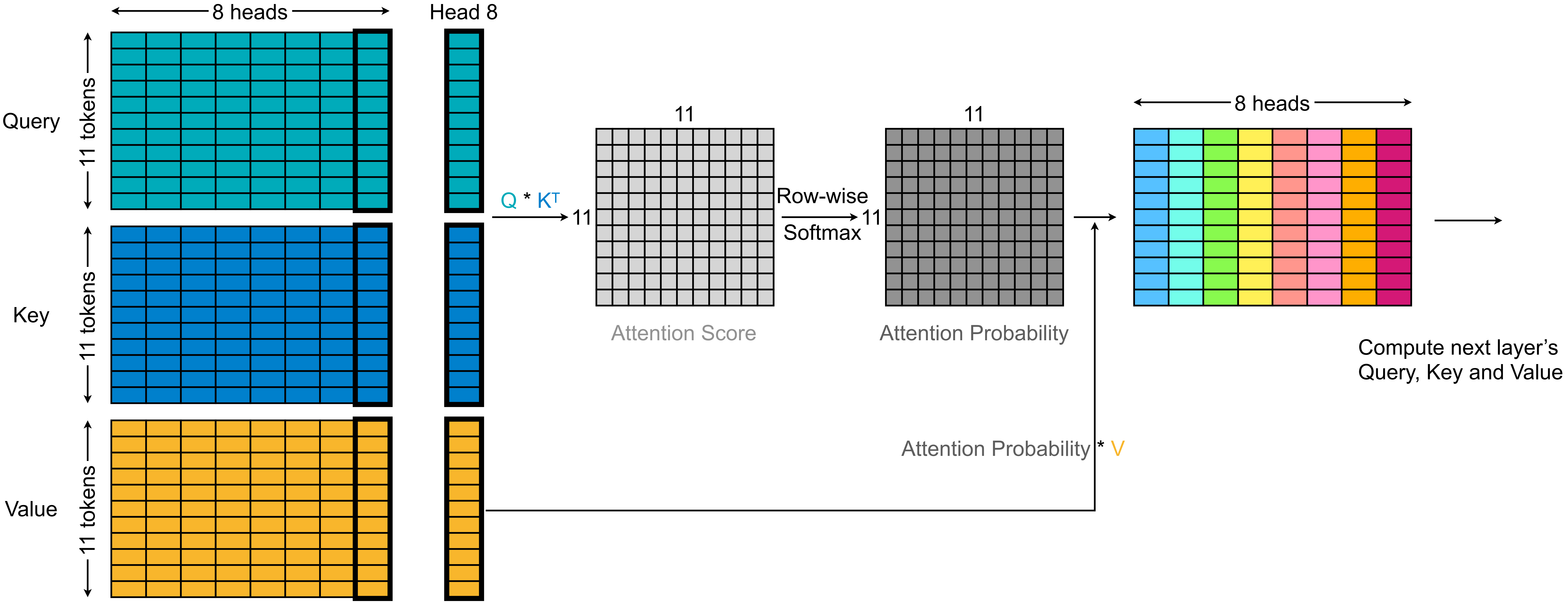


Cascade Token/Head Pruning



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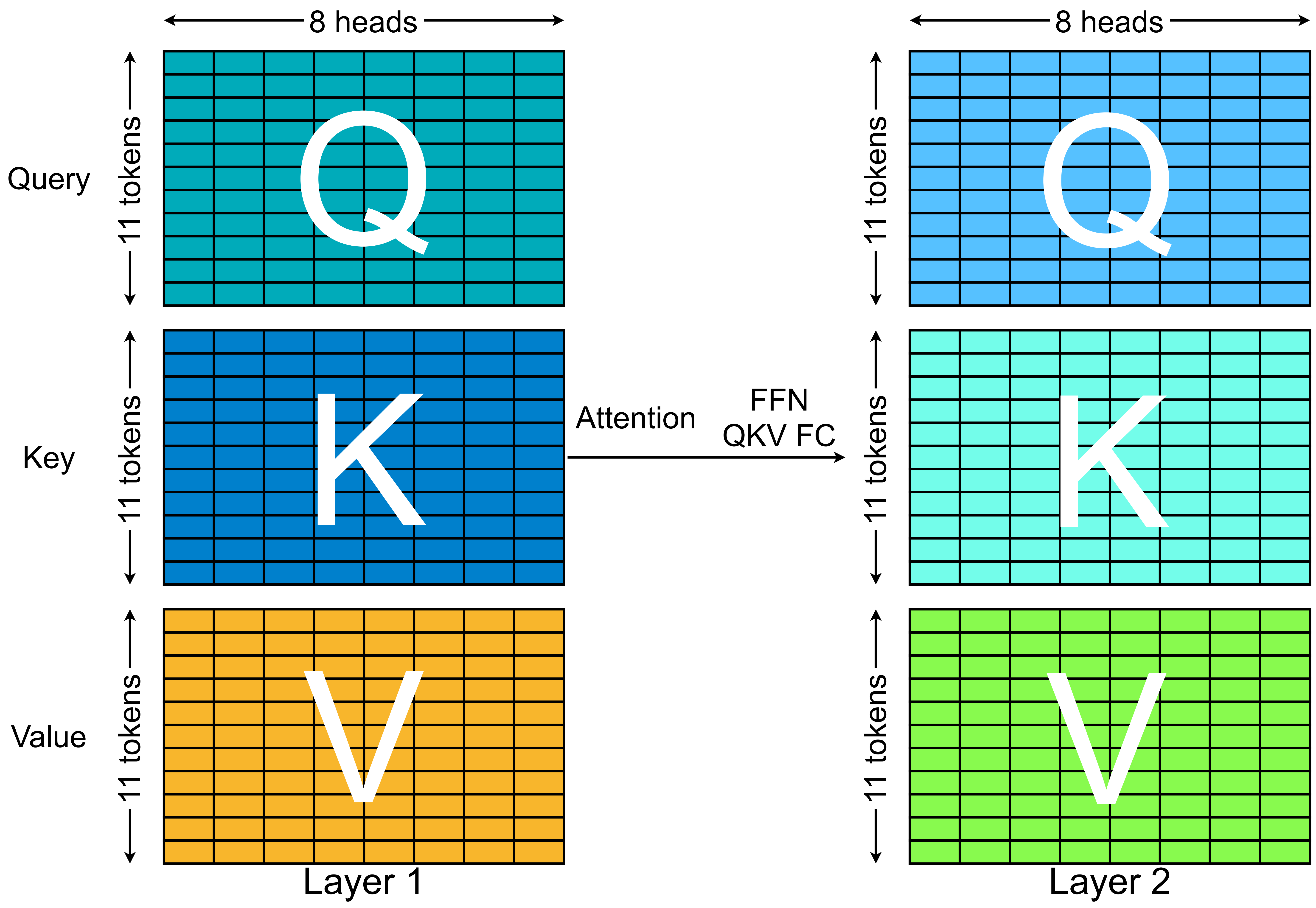

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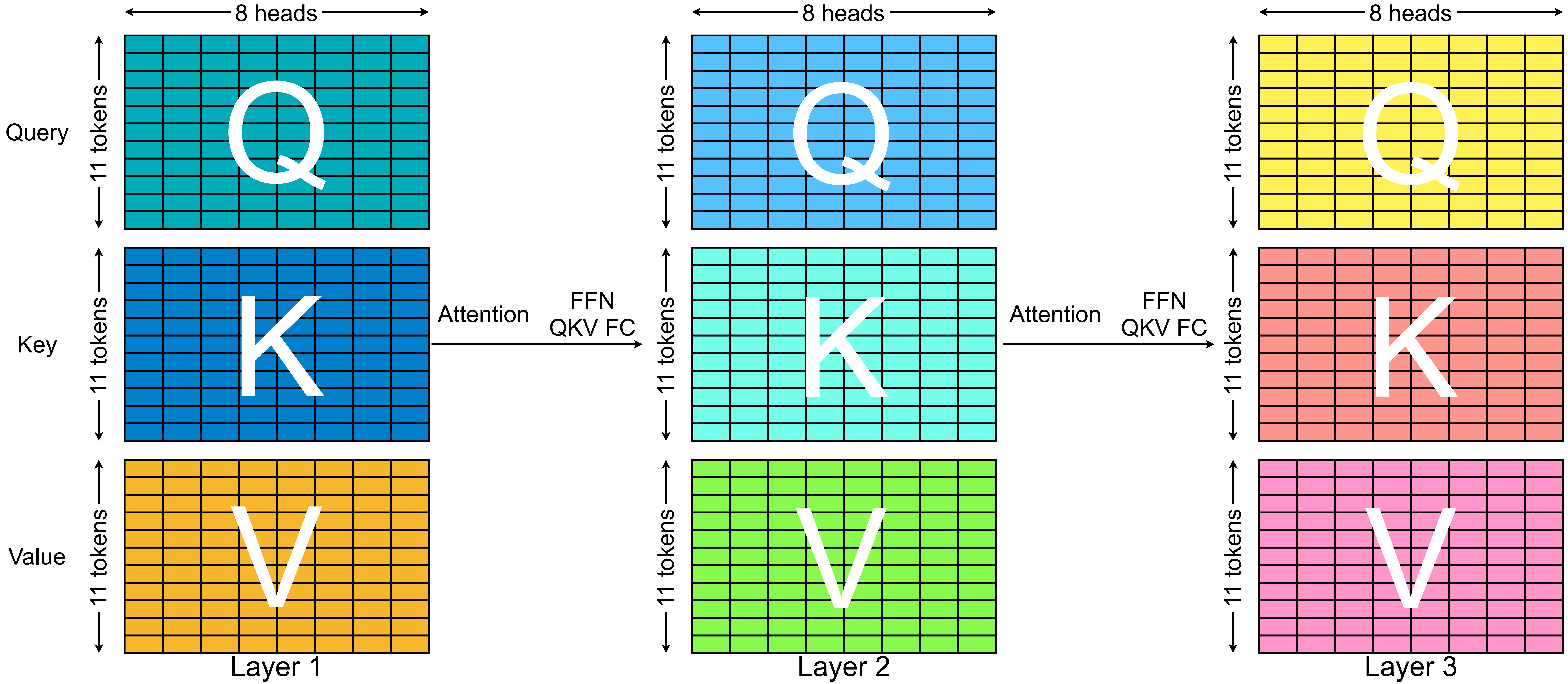
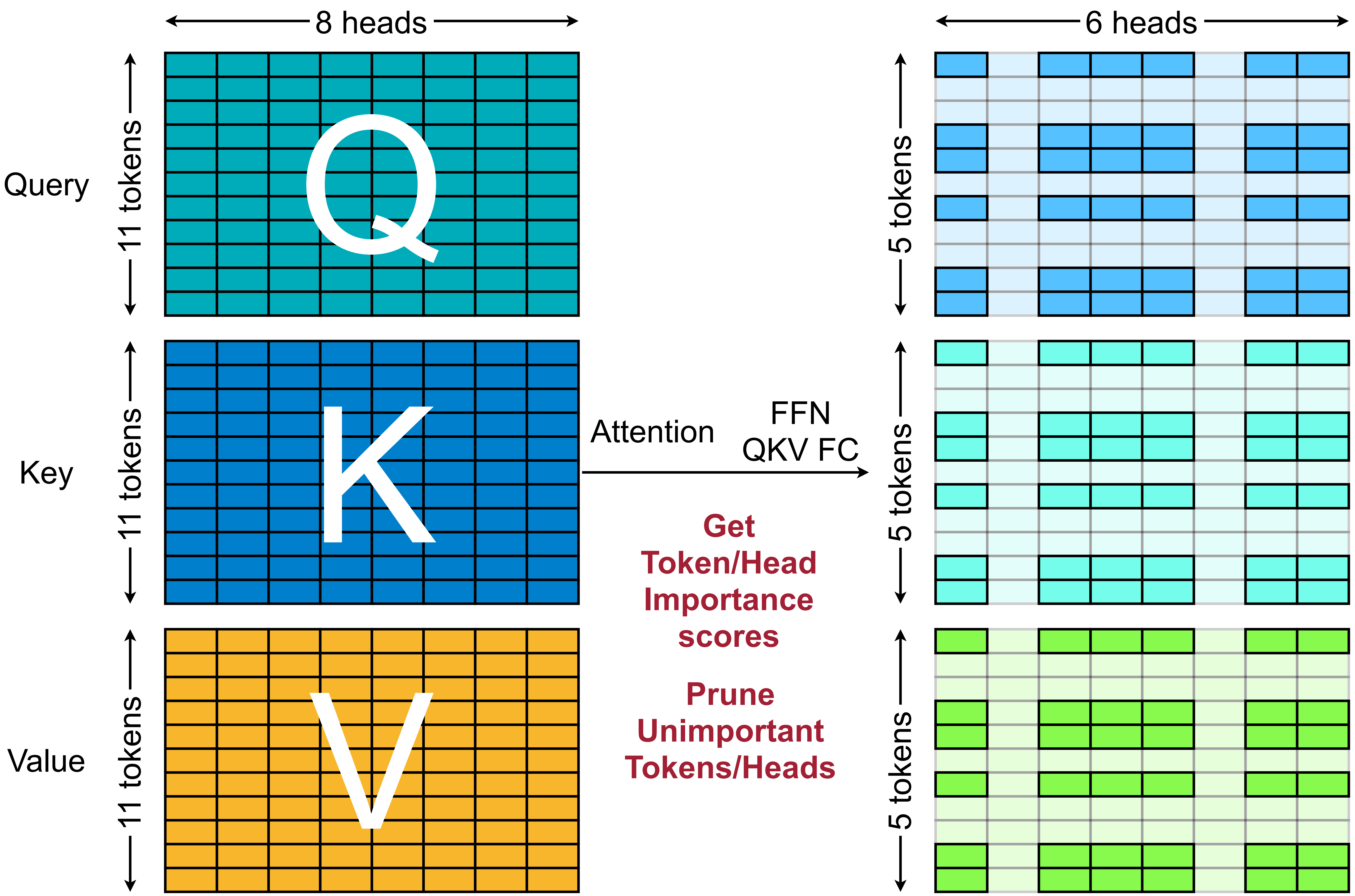


- Not all tokens/heads are created **equal**
- Find **unimportant** tokens and heads in **front** layers
- Remove them in **latter** layers

Cascade Token/Head Pruning



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"As a visual treat, the film is almost perfect."

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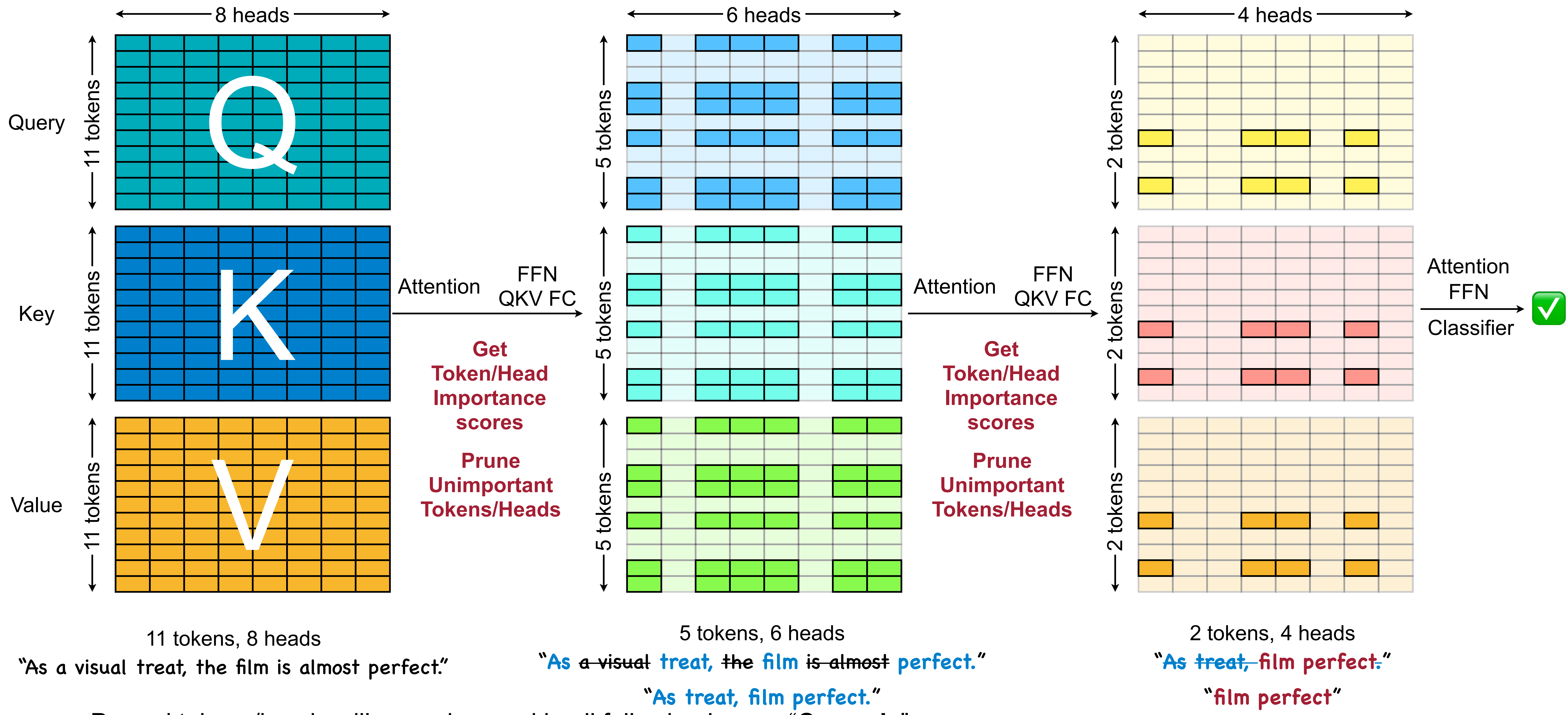
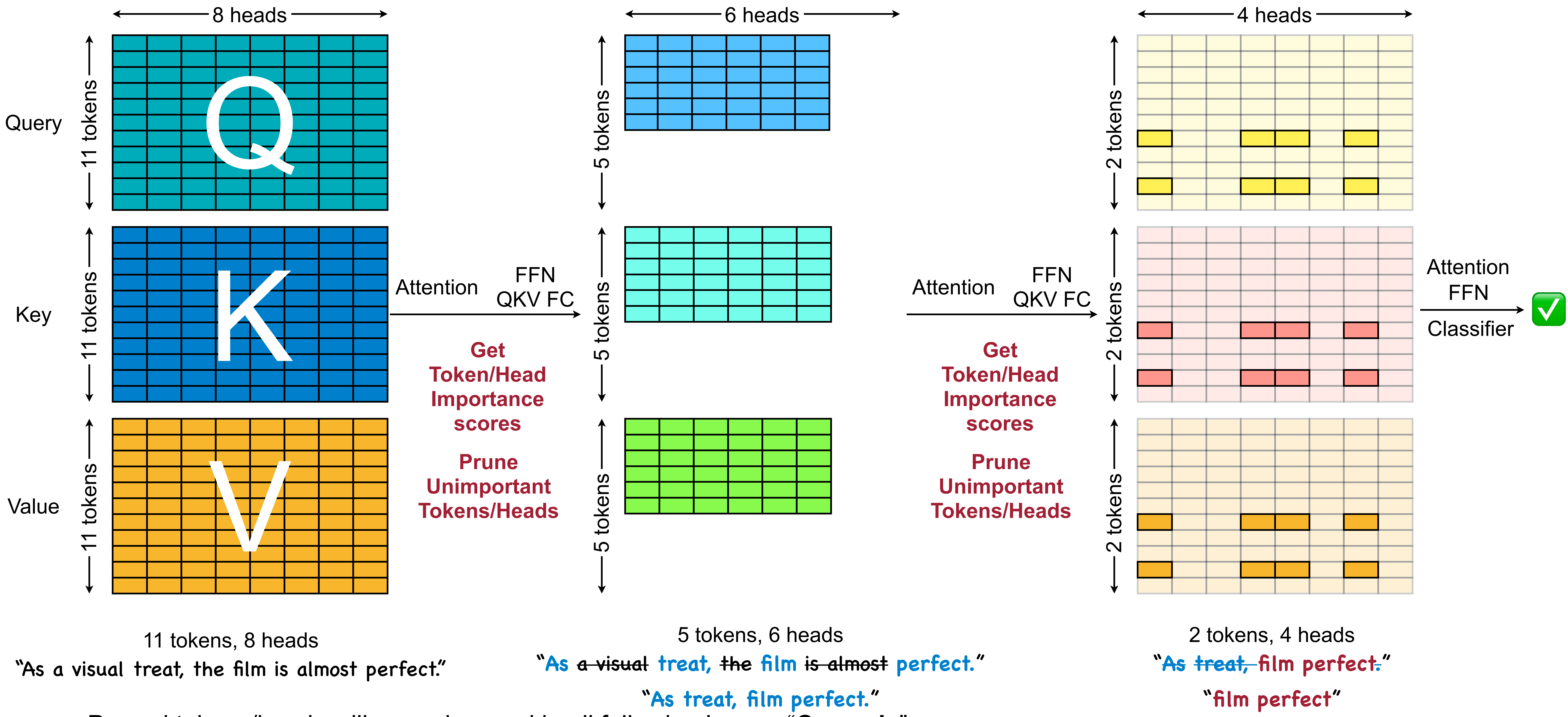
"As treat, film perfect."

Cascade Token/Head Pruning



- Pruned tokens/heads will never be used in all following layers: "**Cascade**"

Cascade Token/Head Pruning



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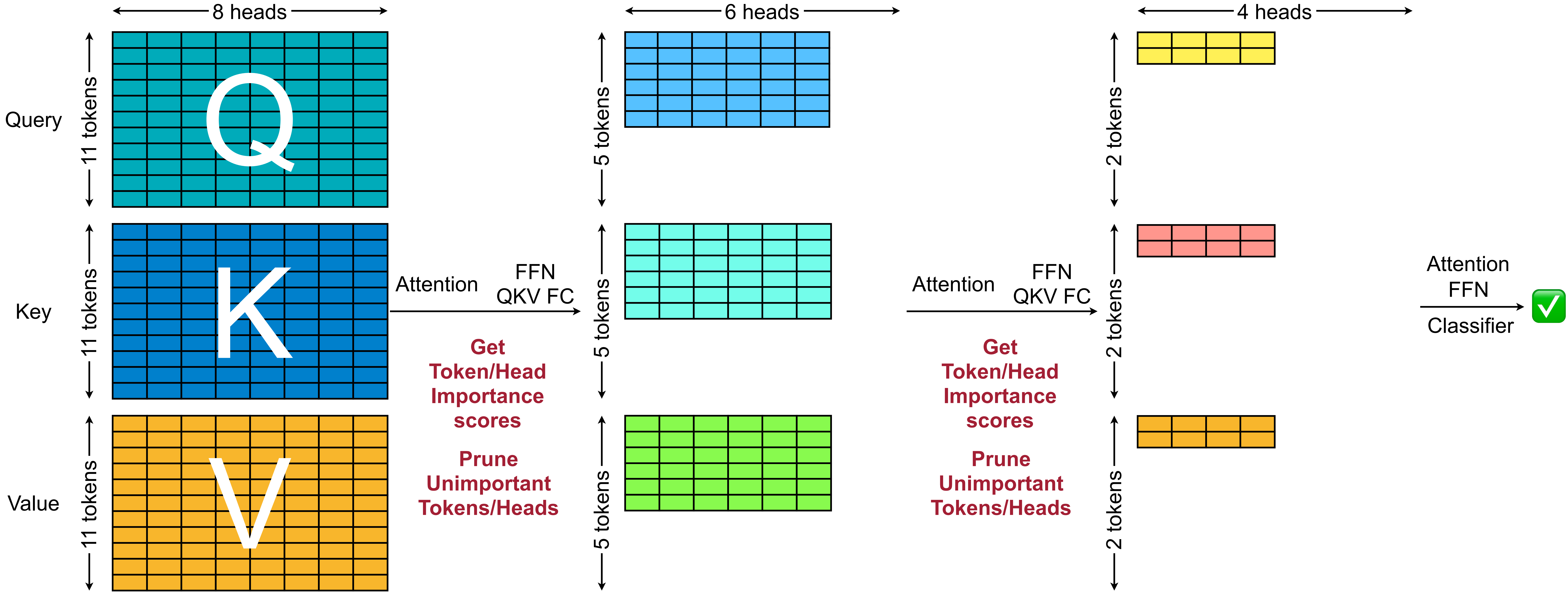

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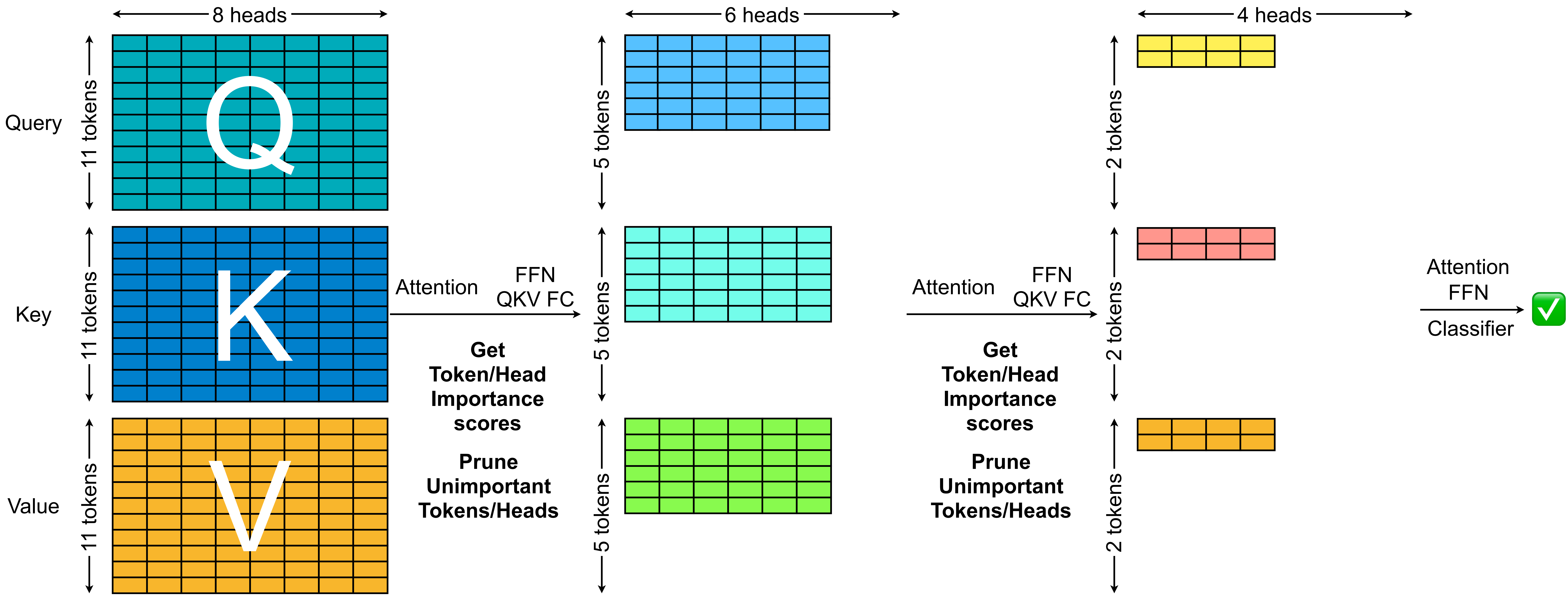
2 tokens, 4 heads

"~~As treat,~~ film perfect~~.~~"

"film perfect"

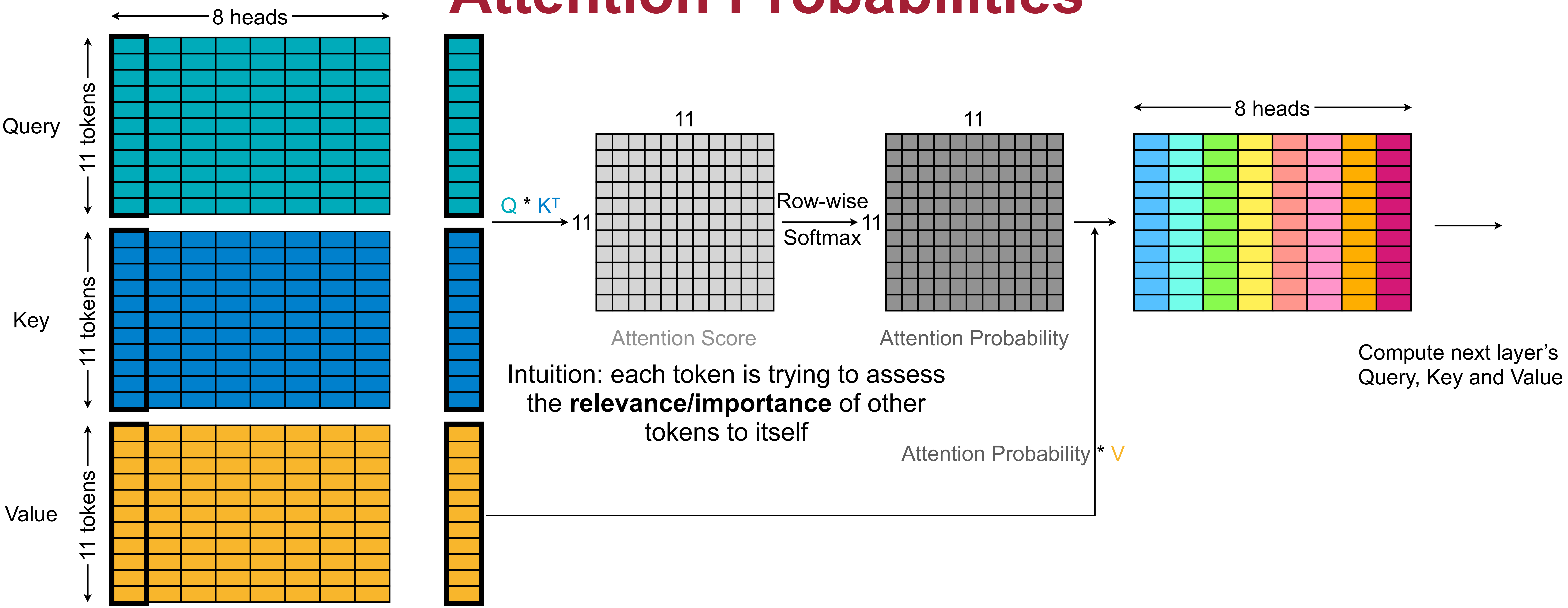
- Pruned tokens/heads will never be used in all following layers: "**Cascade**"

Cascade Token/Head Pruning



- Fundamentally **different** from weight pruning:
  - Query, Key, Value are **activations**
  - Pruned tokens/heads are **input-dependent**

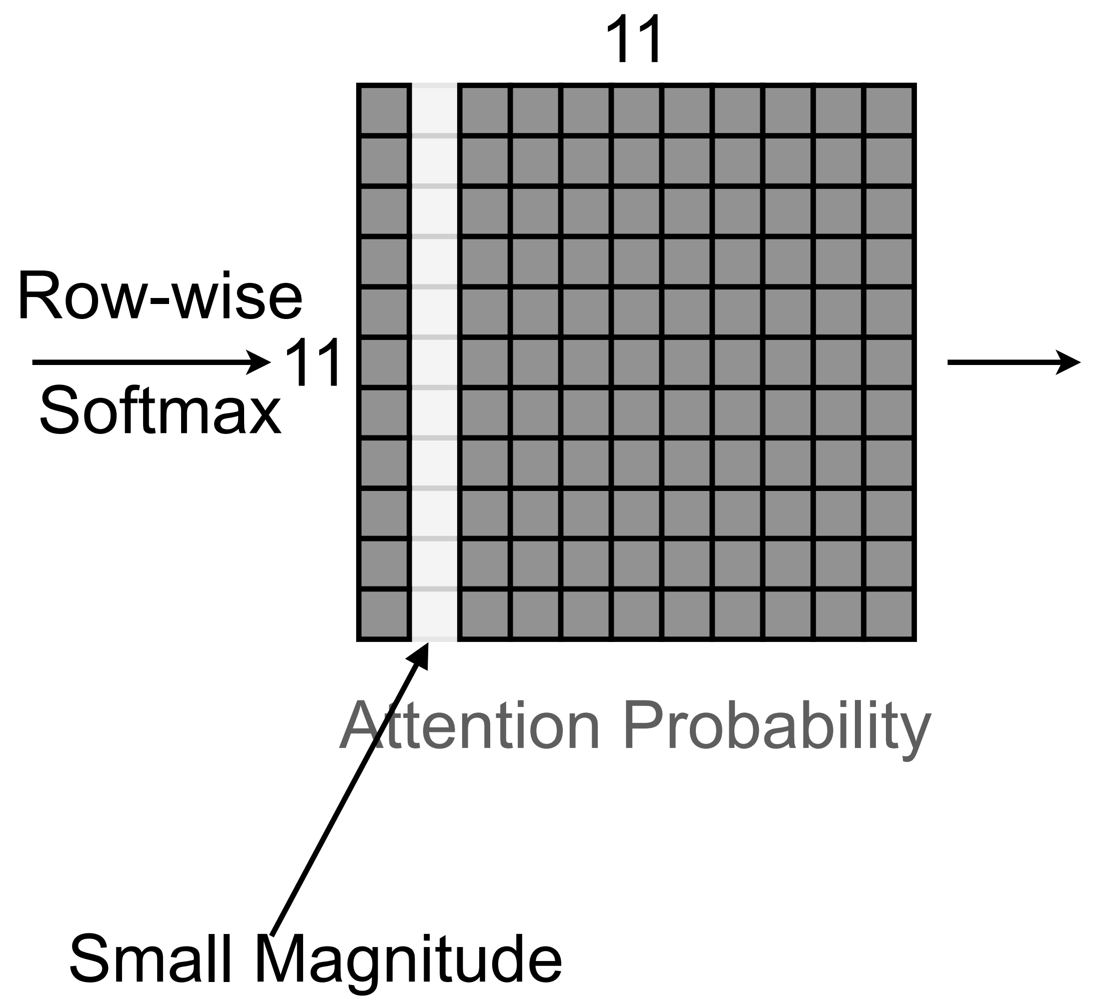
Find Unimportant Tokens with Attention Probabilities



Intuition: each token is trying to assess the **relevance/importance** of other tokens to itself

Find Unimportant Tokens with Attention Probabilities

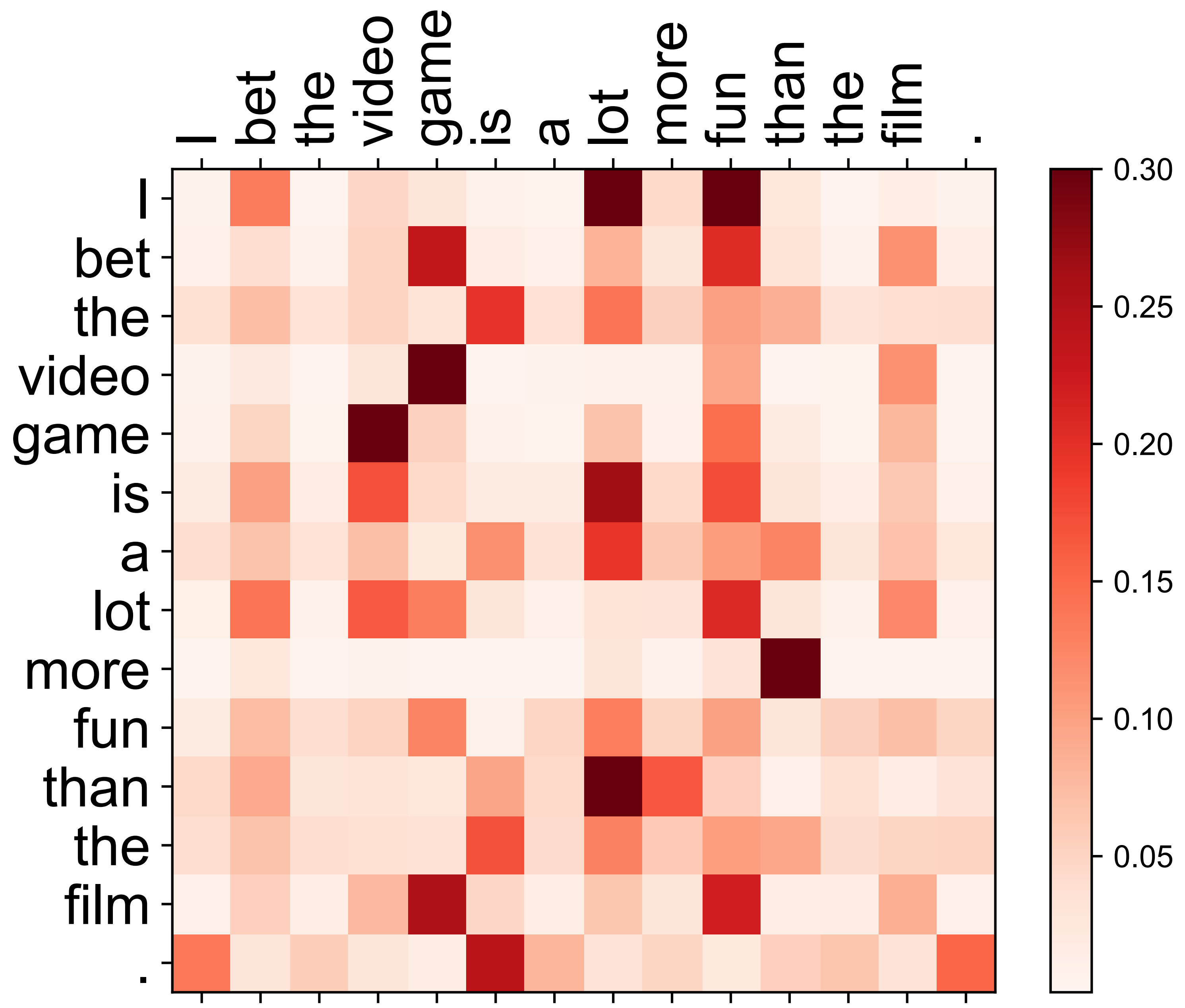
- If one column in attention probability is **small**: the token is **unimportant** to all other tokens



Find Unimportant Tokens with Attention Probabilities

- If one column in attention probability is **small**: the token is **unimportant** to all other tokens
- Maintain an **importance score** for each token

Row-wise
Softmax

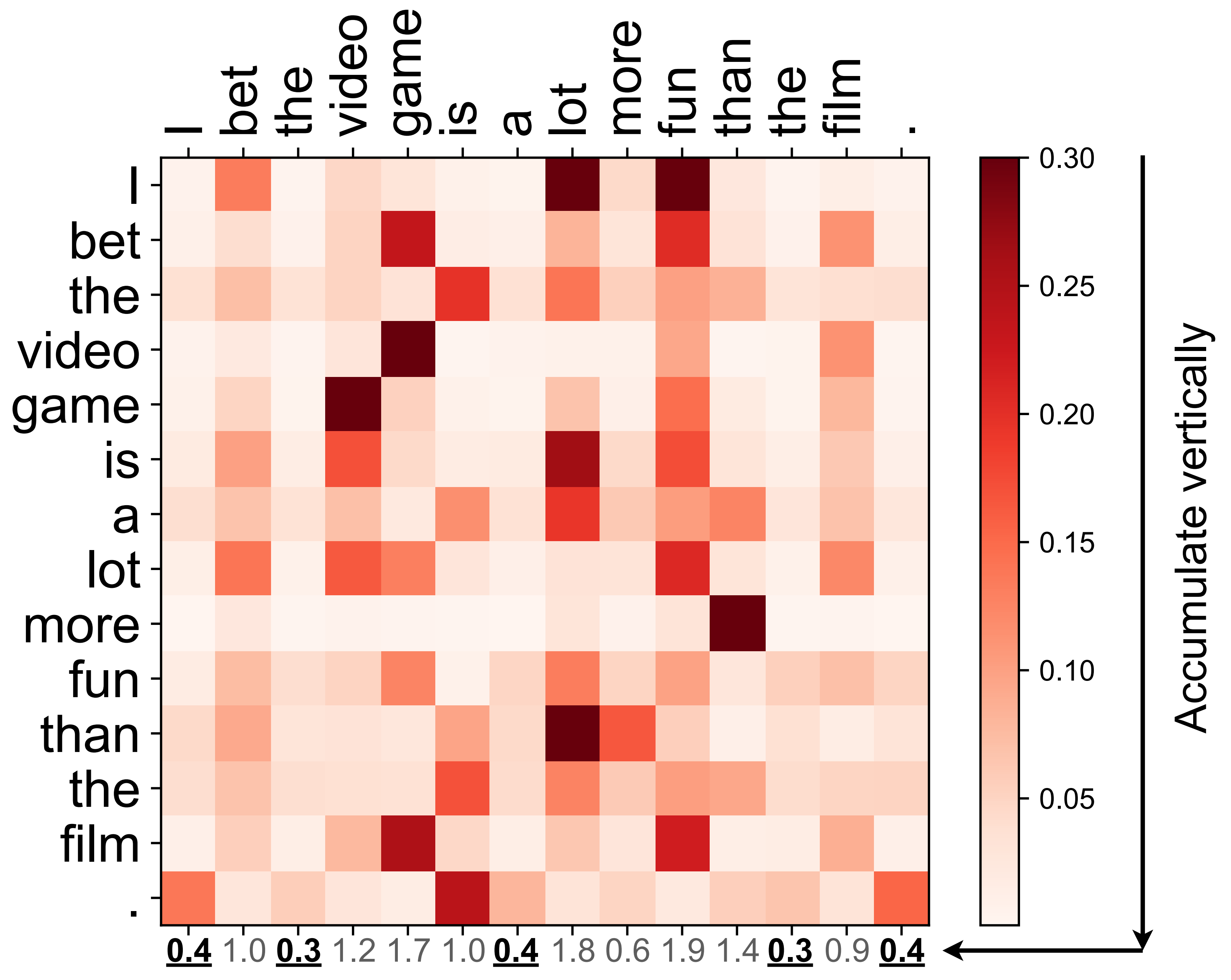


Attention Probability

Find Unimportant Tokens with Attention Probabilities

- If one column in attention probability is **small**: the token is **unimportant** to all other tokens
- Maintain an **importance score** for each token
- **Accumulate** attention probs to the importance scores

Row-wise
Softmax



Attention Probability

Find Unimportant Tokens with Attention Probabilities

- If one column in attention probability is **small**: the token is **unimportant** to all other tokens
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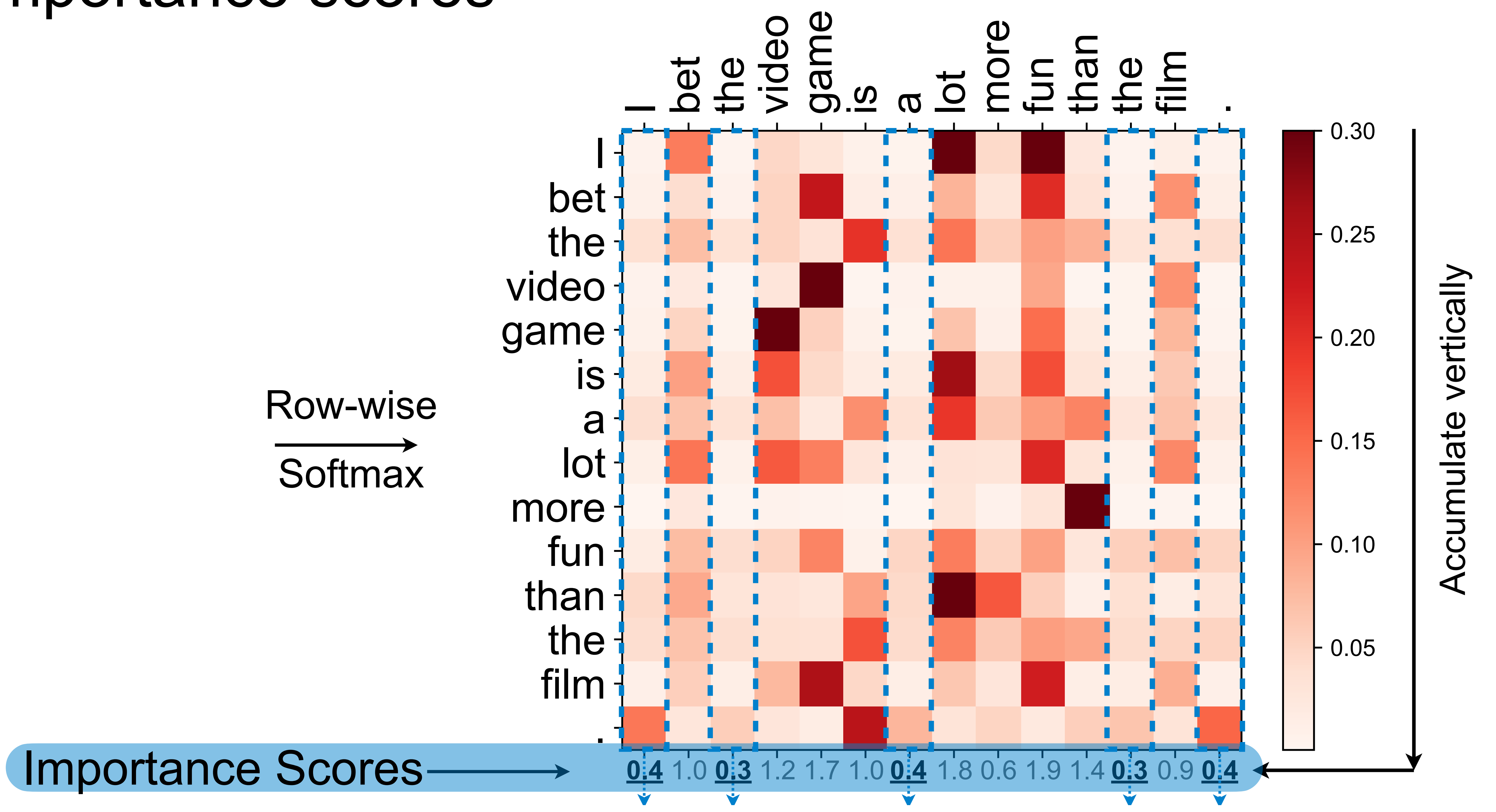
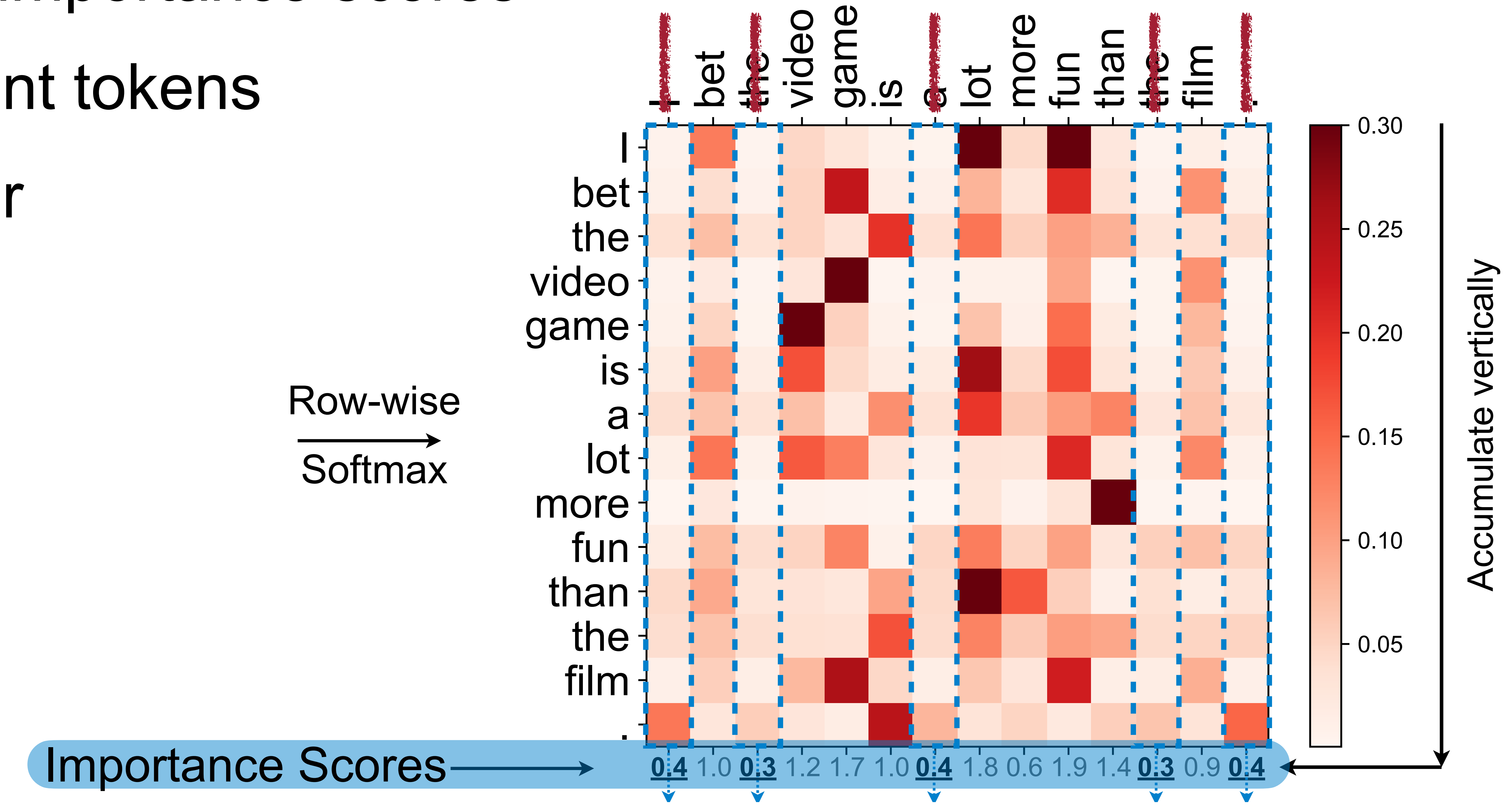


Attention Probability

Find Unimportant Tokens with Attention Probabilities

- If one column in attention probability is **small**: the token is **unimportant** to all other tokens
- Maintain an **importance score** for each token
- **Accumulate** attention probs to the importance scores
- **Top-k** scores indicate top-k important tokens
    - Pruning ratio is a hyperparameter

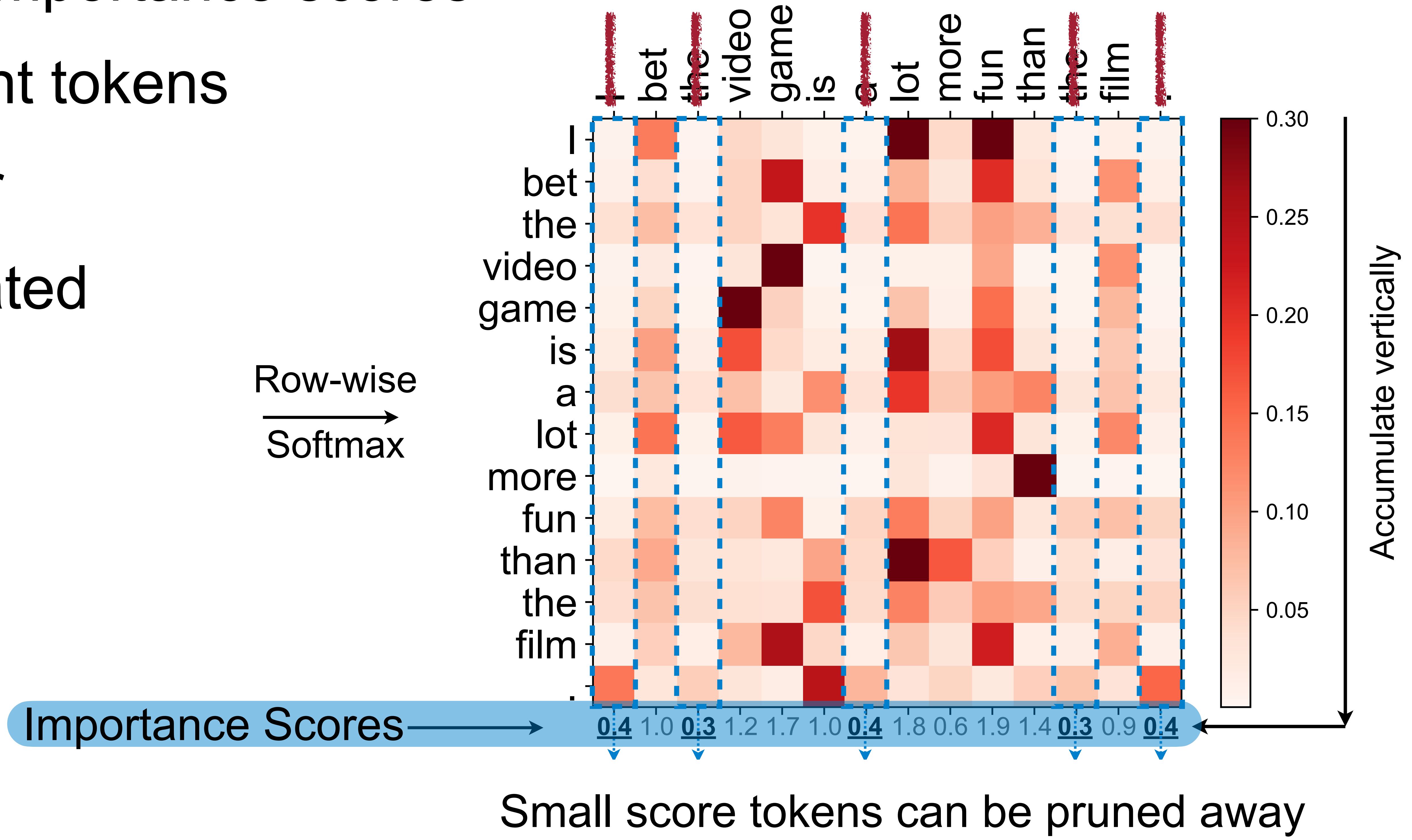


Small score tokens can be pruned away

Attention Probability

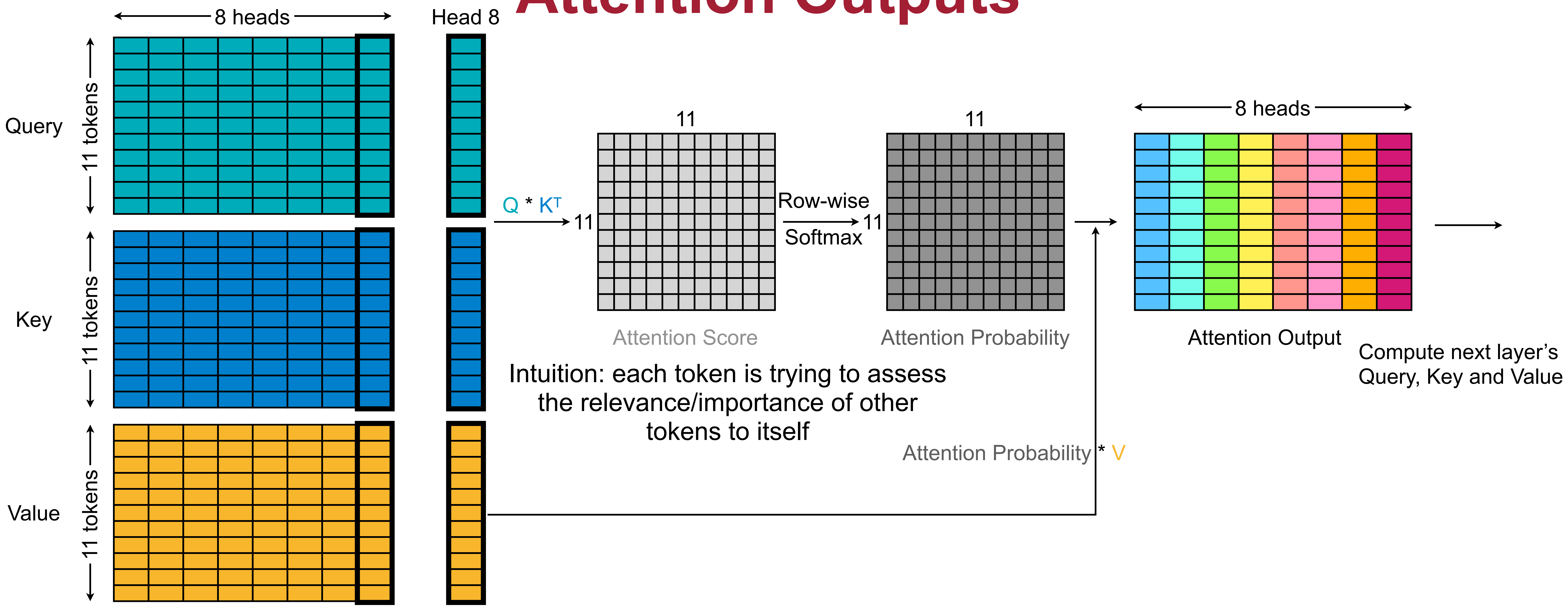
Find Unimportant Tokens with Attention Probabilities

- If one column in attention probability is **small**: the token is **unimportant** to all other tokens
- Maintain an **importance score** for each token
- **Accumulate** attention probs to the importance scores
- **Top-k** scores indicate top-k important tokens
  - Pruning ratio is a hyperparameter
- Importance scores can be accumulated **across** heads and layers



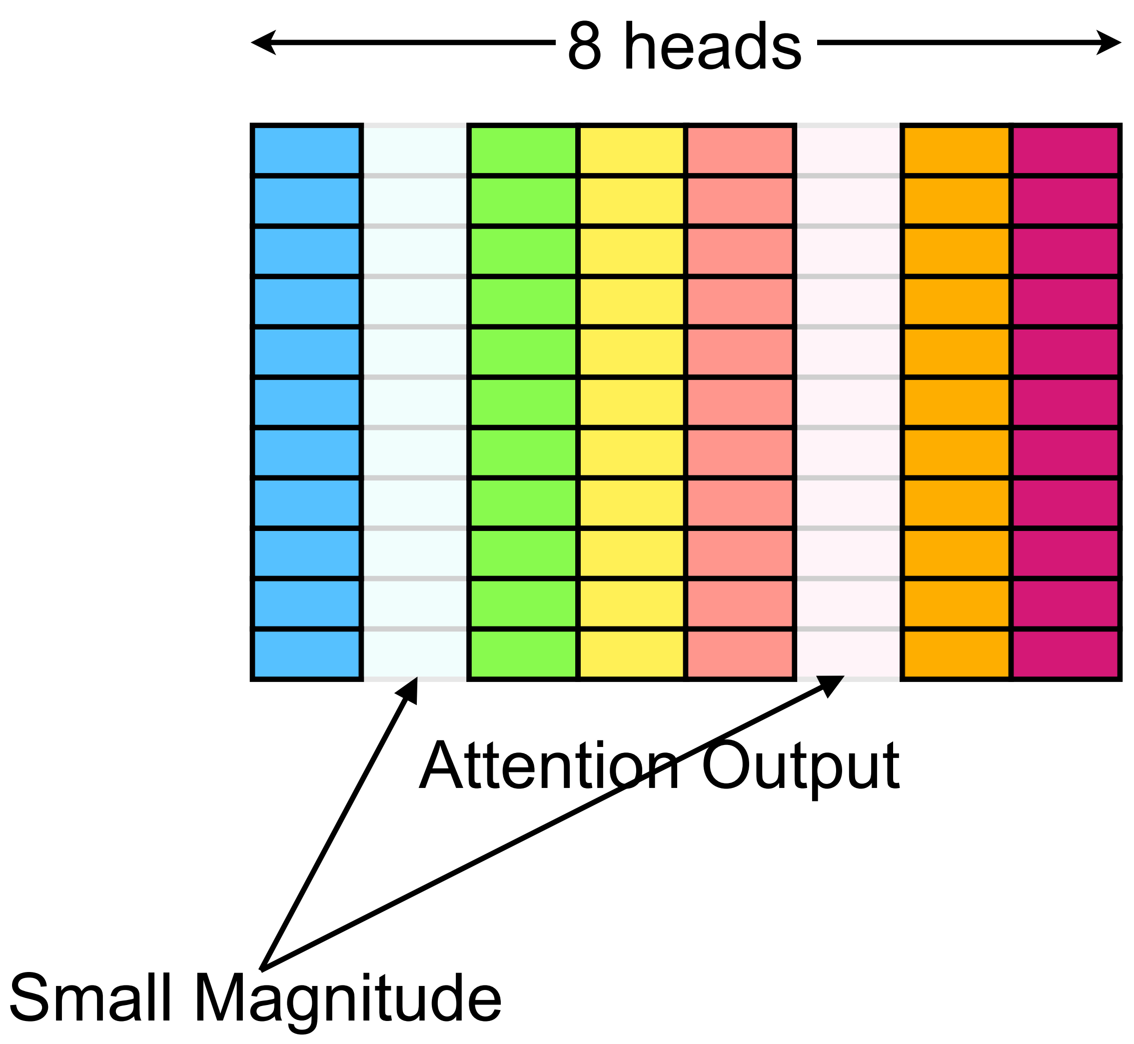
Attention Probability

Find Unimportant Heads with Attention Outputs

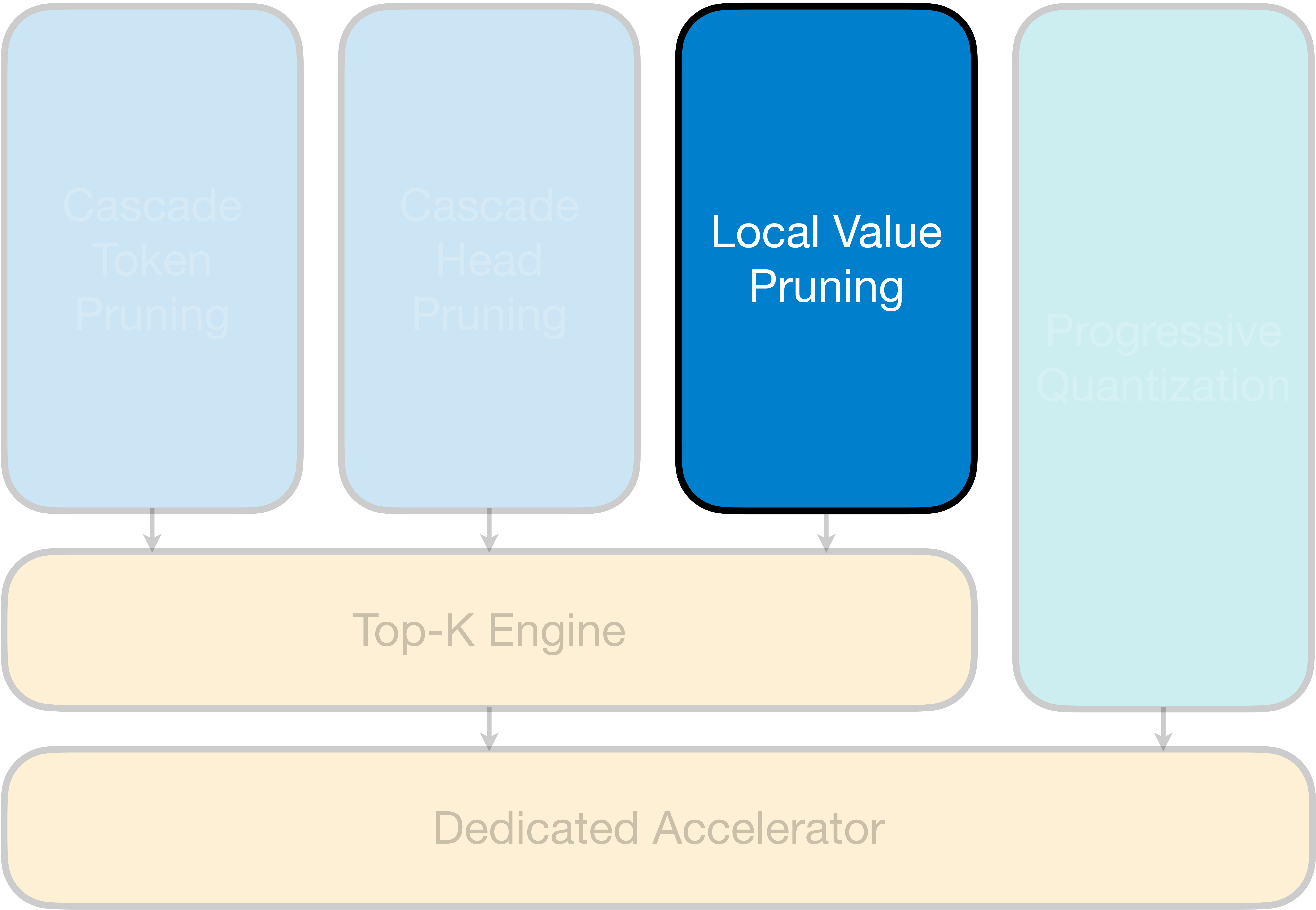


Find Unimportant Heads with Attention Outputs

- If one head output is **small**: the head is **unimportant** to latter layers
- Maintain an **importance score** for each head
- **Accumulate** attention output magnitude to the importance scores
- **Top-k** scores indicate top-k important heads
- Importance scores can be accumulated **across** layers

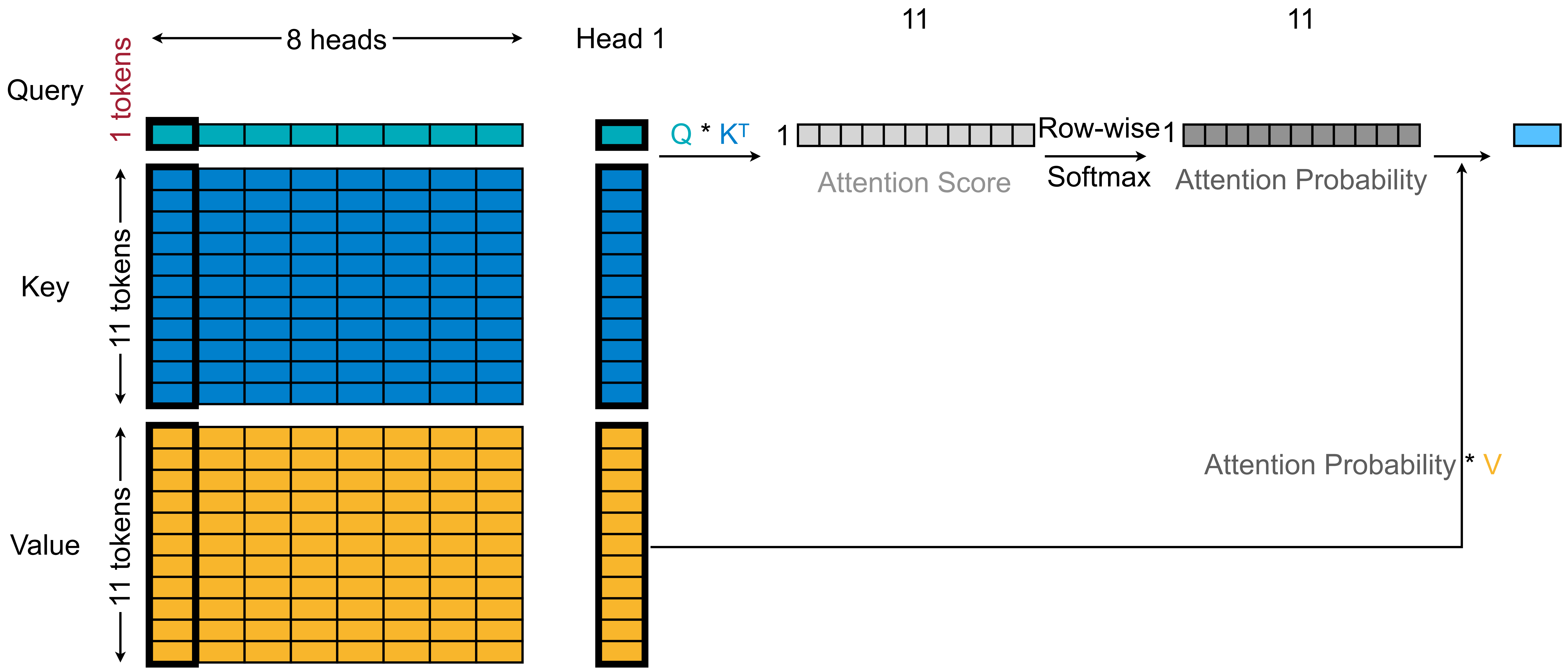


Our Solution: SpAtten



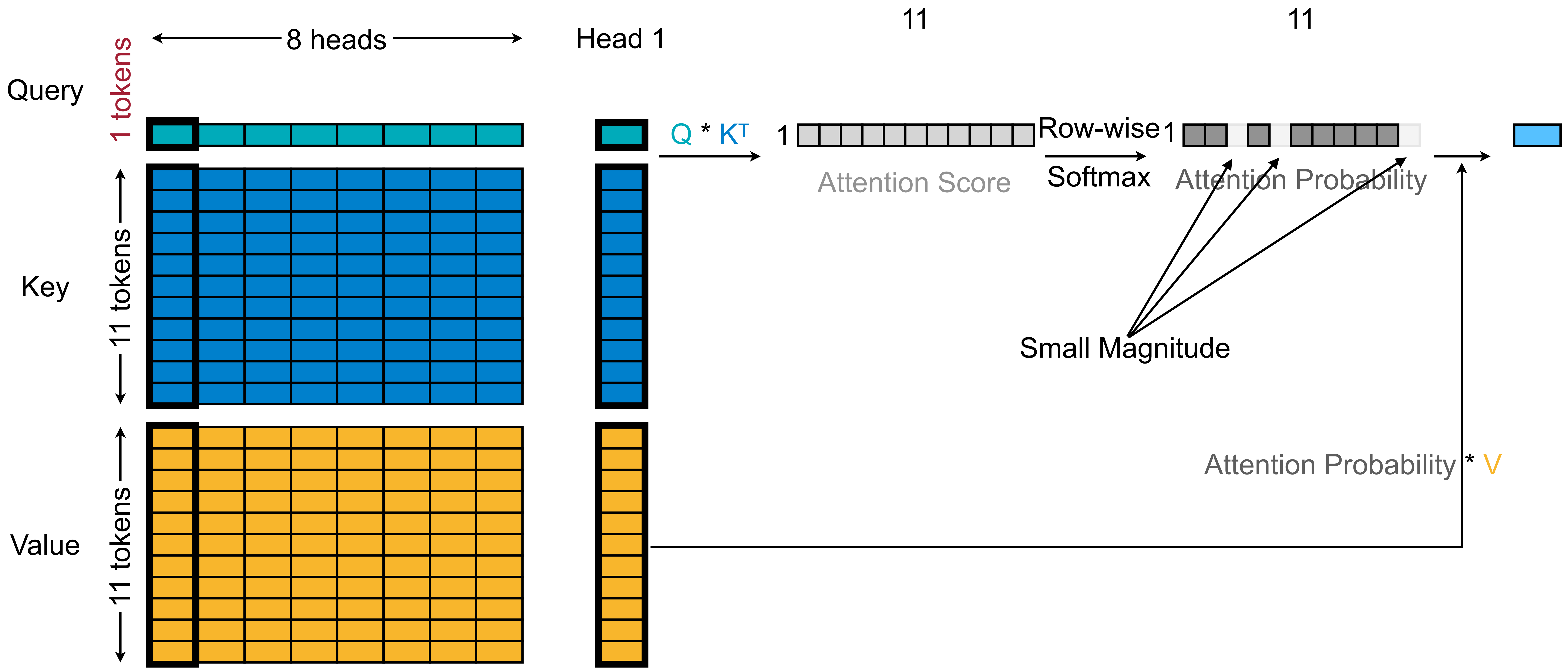
Local Value Pruning

- Cascade token/head pruning find unimportant token/head in **current** layer, prune in **next** layer
- Local value pruning find unimportant Value in **current** layer, prune in **current** layer



Local Value Pruning

- Cascade token/head pruning find unimportant token/head in **current** layer, prune in **next** layer
- Local value pruning find unimportant Value in **current** layer, prune in **current** layer
- **Directly** rank top-k attention probabilities and only fetch their Value vectors



Local Value Pruning

- Cascade token/head pruning find unimportant token/head in **current** layer, prune in **next** layer
- Local value pruning find unimportant Value in **current** layer, prune in **current** layer
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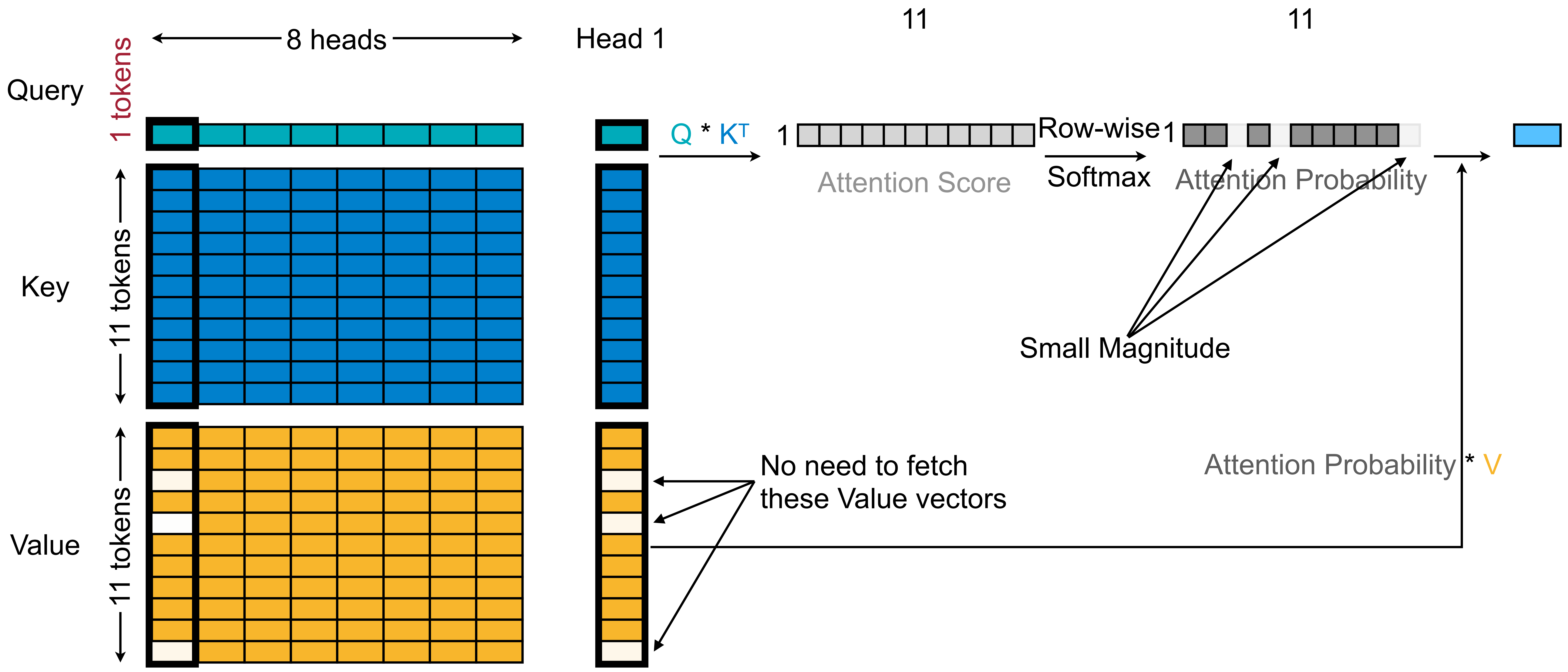
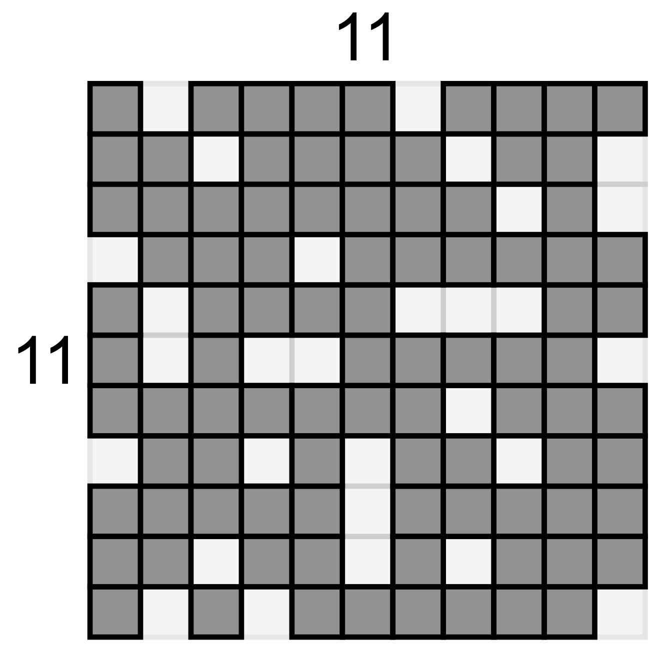


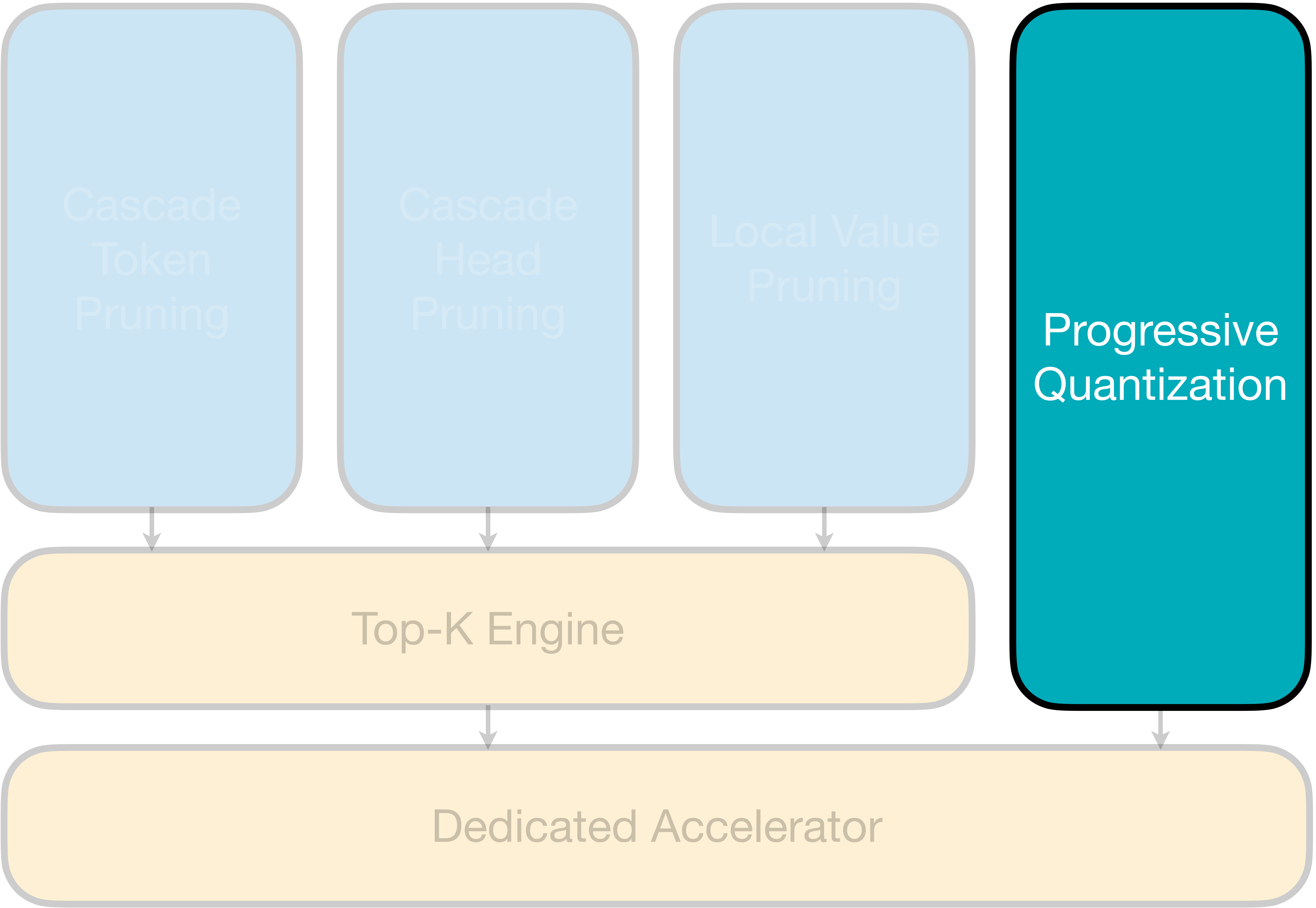
Local Value Pruning

- Cascade token/head pruning find unimportant token/head in **current** layer, prune in **next** layer
- Local value pruning find unimportant Value in **current** layer, prune in **current** layer
- **Directly** rank top-k attention probabilities and only fetch their value vectors
- Only for **generation** stage
  - Because in summarization, small attention probs have different locations in different rows



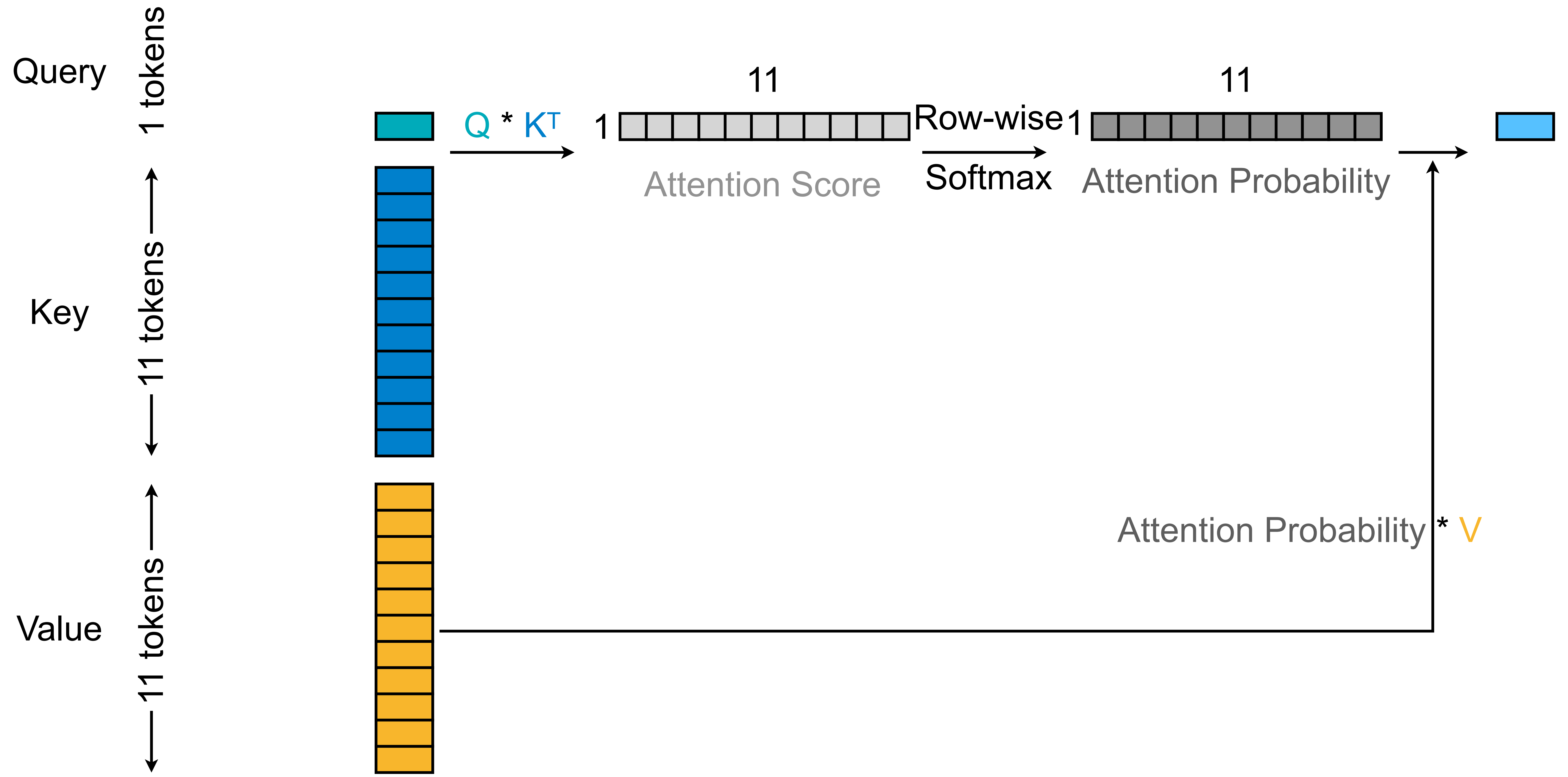
Attention Probability

Our Solution: SpAtten



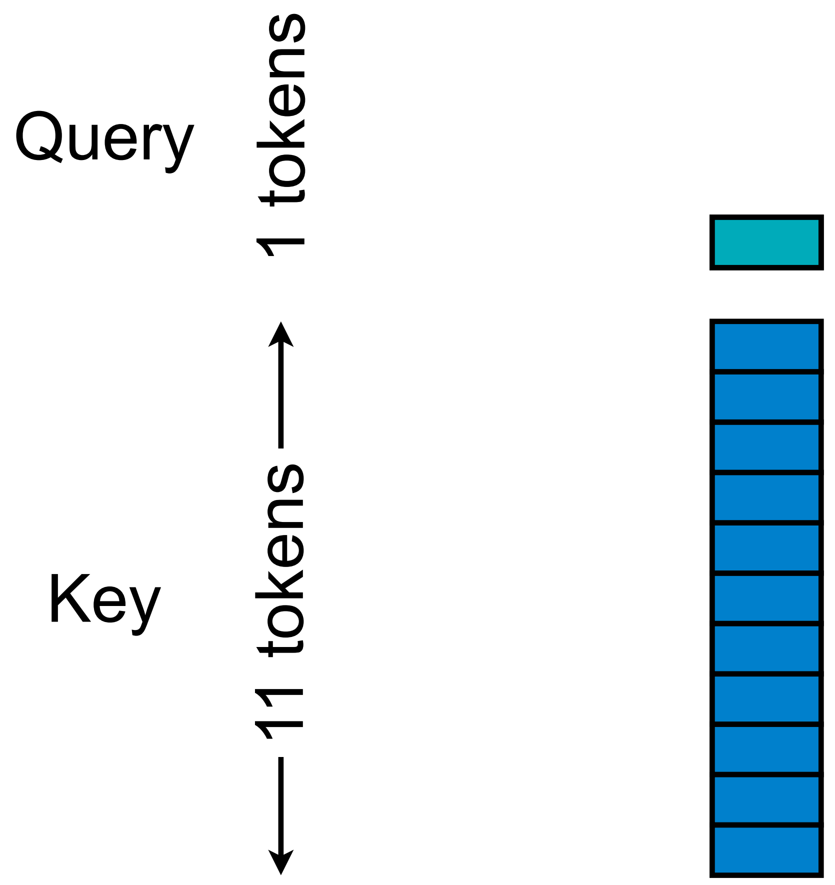
Progressive Quantization

- Generation stage is **memory-bounded** because of matrix vector multiplication
  - Need to fetch Key and Value from DRAM
- **Static** quantization: quantizes Key, Value to reduce DRAM access



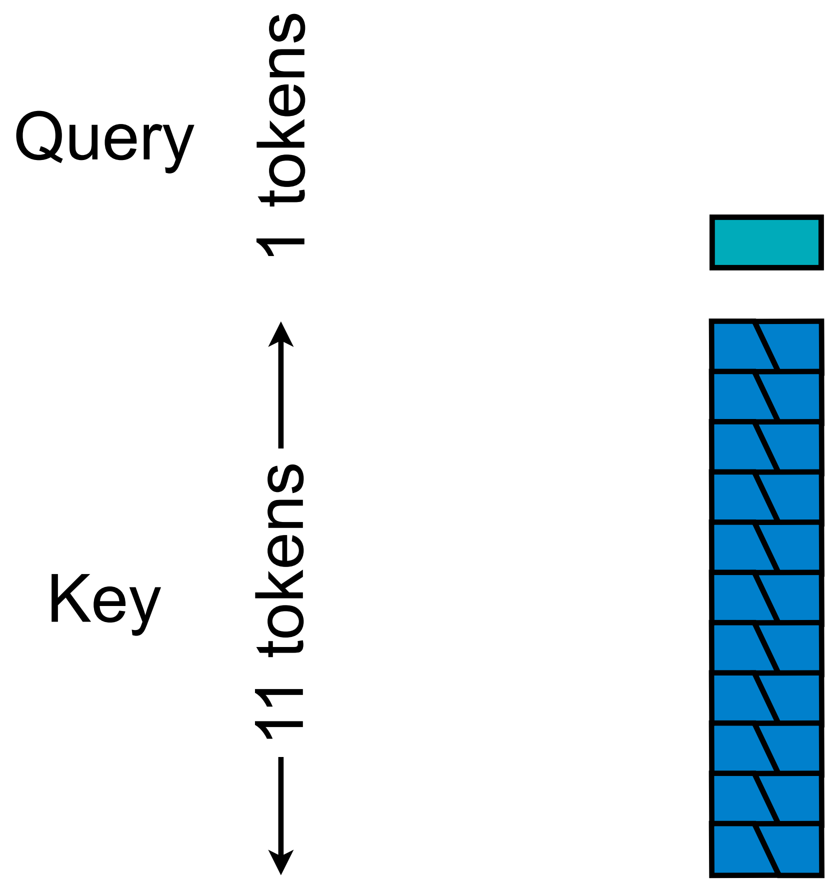
Progressive Quantization

- Generation stage is **memory-bounded** because of matrix vector multiplication
  - Need to fetch Key and Value from DRAM
- **Static** quantization: quantizes Key, Value to reduce DRAM access
- **Progressive** quantization on Key to further **trade more computation to less DRAM access**



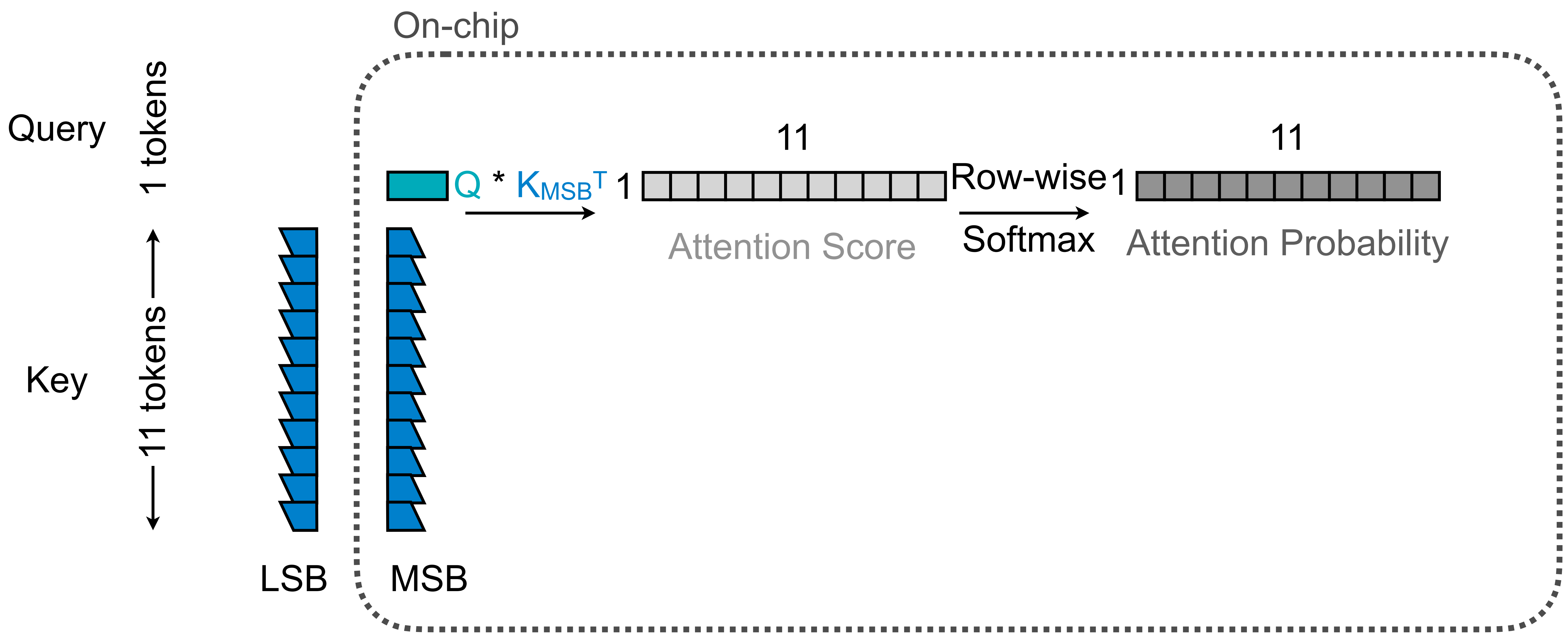
Progressive Quantization

- **Separate** Key to LSB part and MSB part



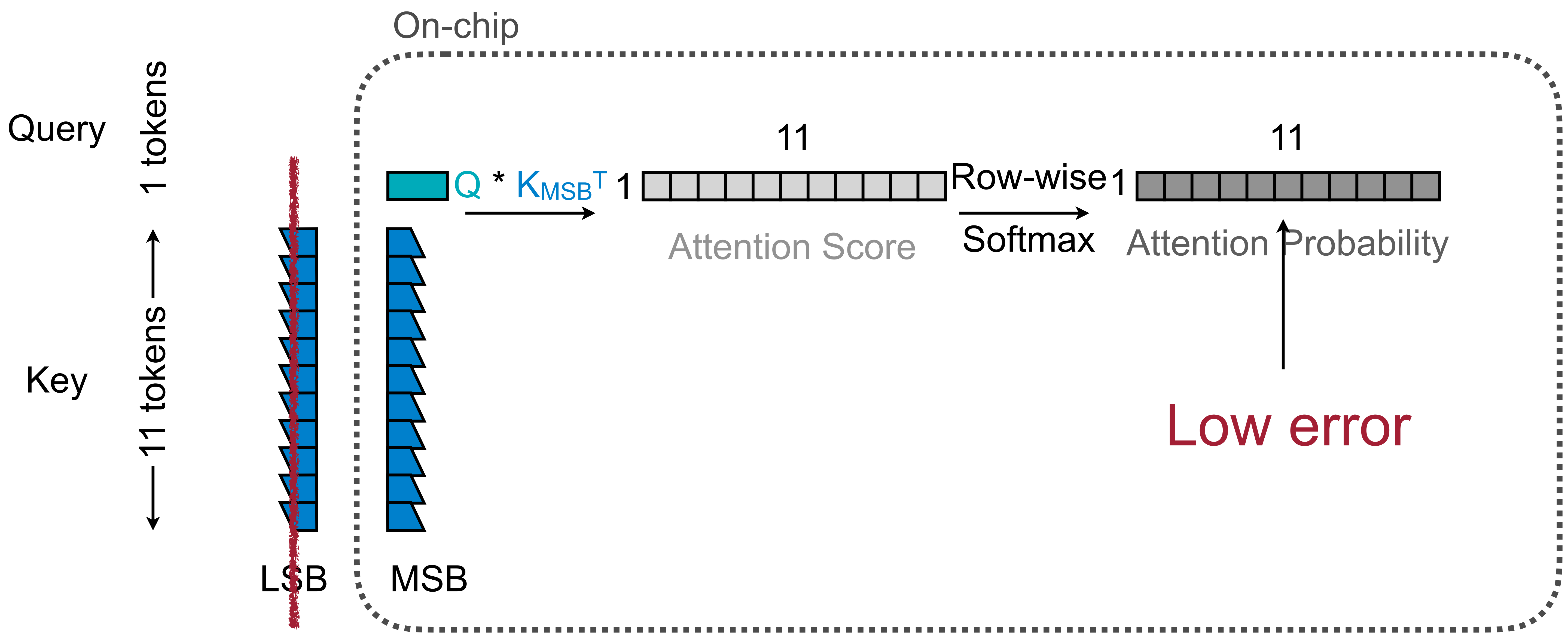
Progressive Quantization

- **Separate** Key to LSB part and MSB part
- **Only fetch MSB** from DRAM to on-chip, and compute attention probability



Progressive Quantization

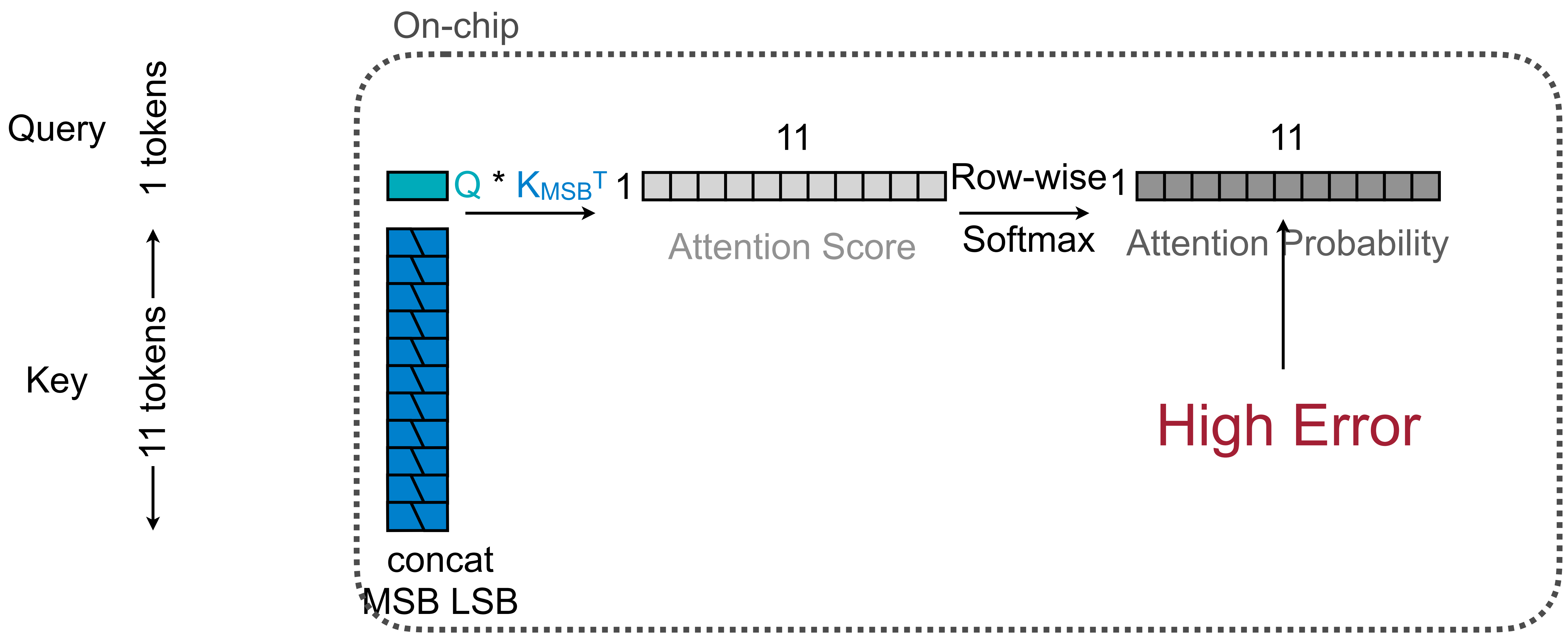
- **Separate** Key to LSB part and MSB part
- **Only fetch MSB** from DRAM to on-chip, and compute attention probability
- If attention probability has low error:



No need to fetch LSB

Progressive Quantization

- **Separate** Key to LSB part and MSB part
- **Only fetch MSB** from DRAM to on-chip, and compute attention probability
- If attention probability has high error:

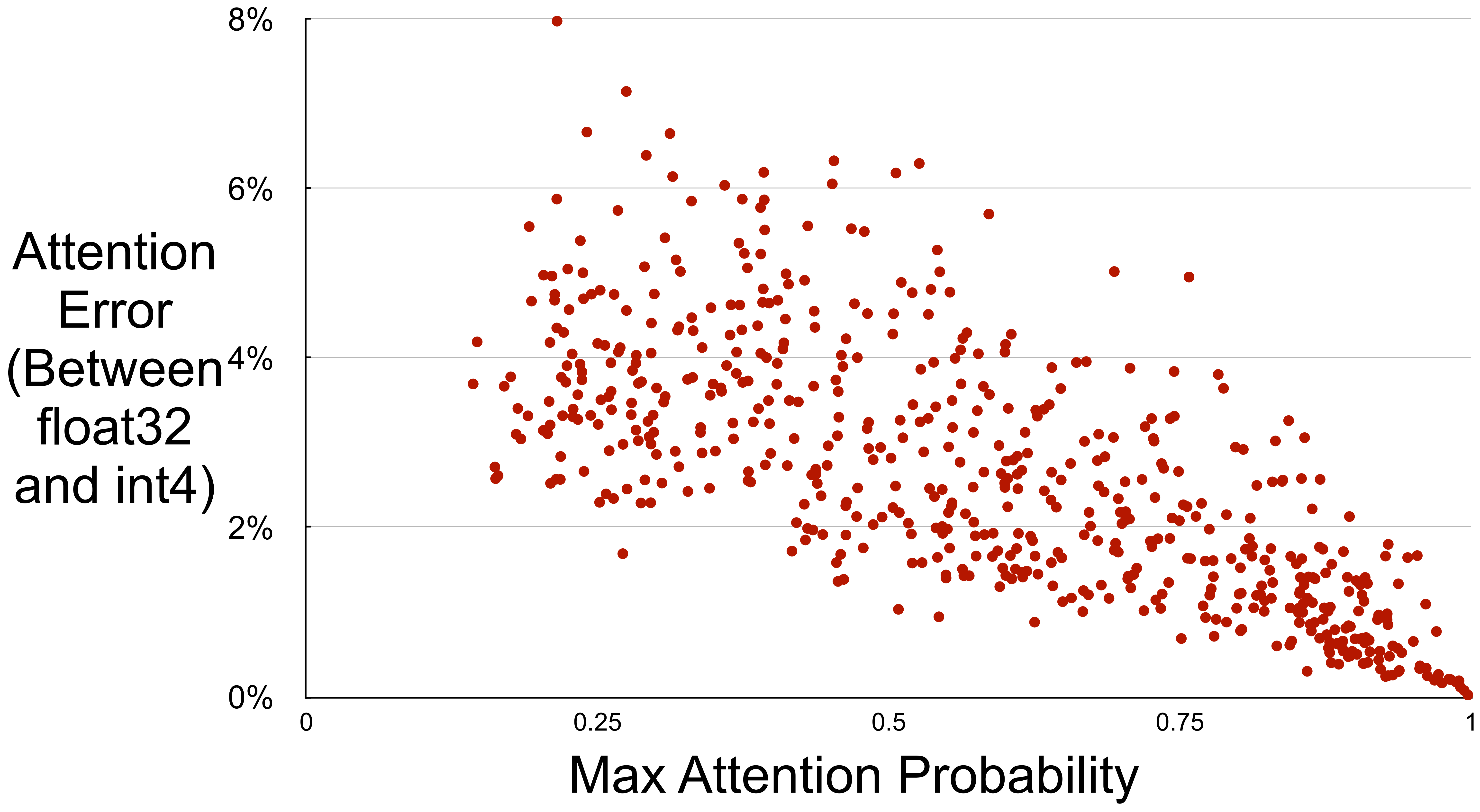


Need to fetch LSB and
recompute attention probability

- **Eagerly** fetch MSB, **lazily** fetch LSB: reduce the average bitwidth

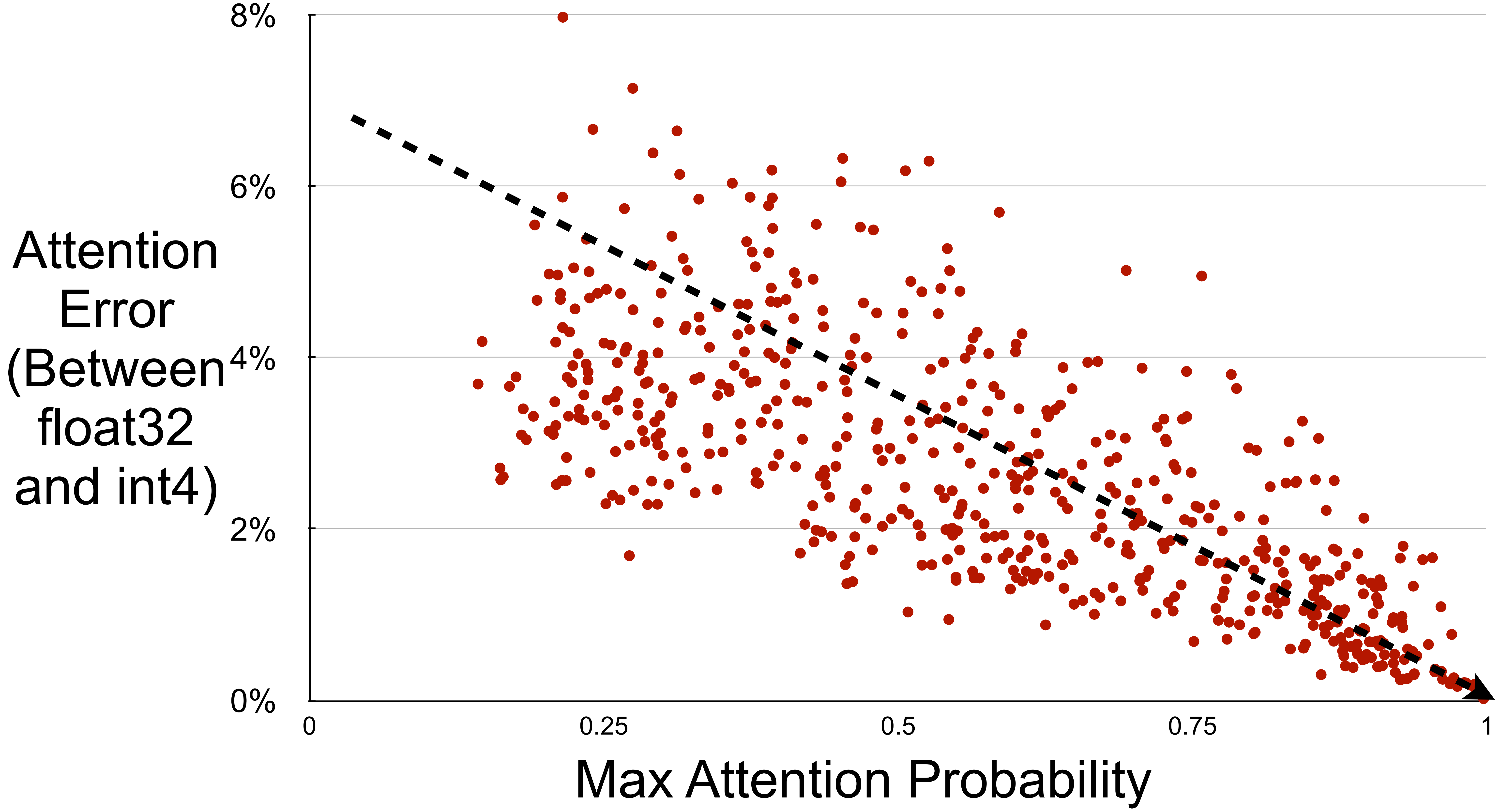
Determine Attention Error with Attention Probability

- How to check whether error is high?



Determine Attention Error with Attention Probability

- How to check whether error is high?
- The **larger** the max attention probability, the **smaller** the attention error



Determine Attention Error with Attention Probability

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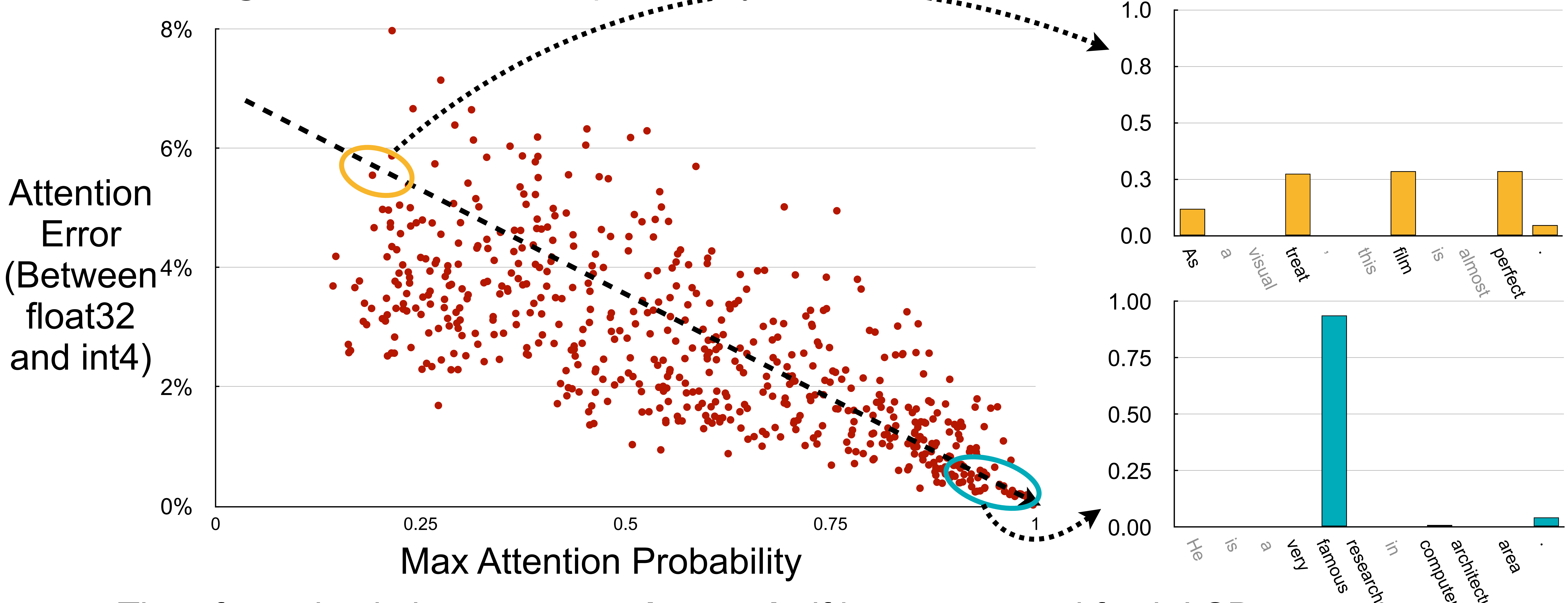
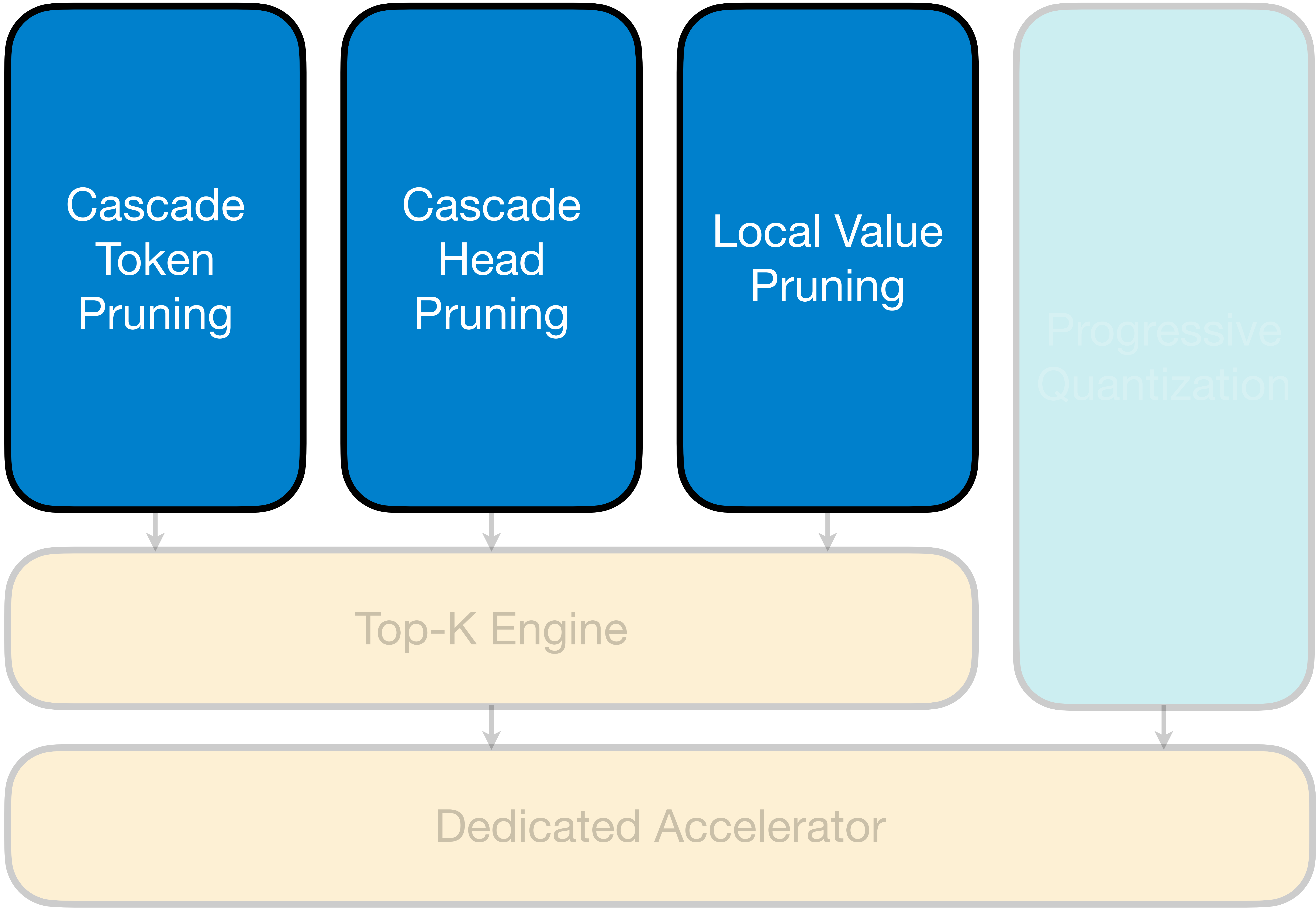


- Therefore, check the **max attention prob**, if large, not need fetch LSB.

Outline

- Quick Overview
- Background
- Algorithmic Optimizations
- Hardware Architecture
- Evaluation
- Conclusion

Our Solution: SpAtten



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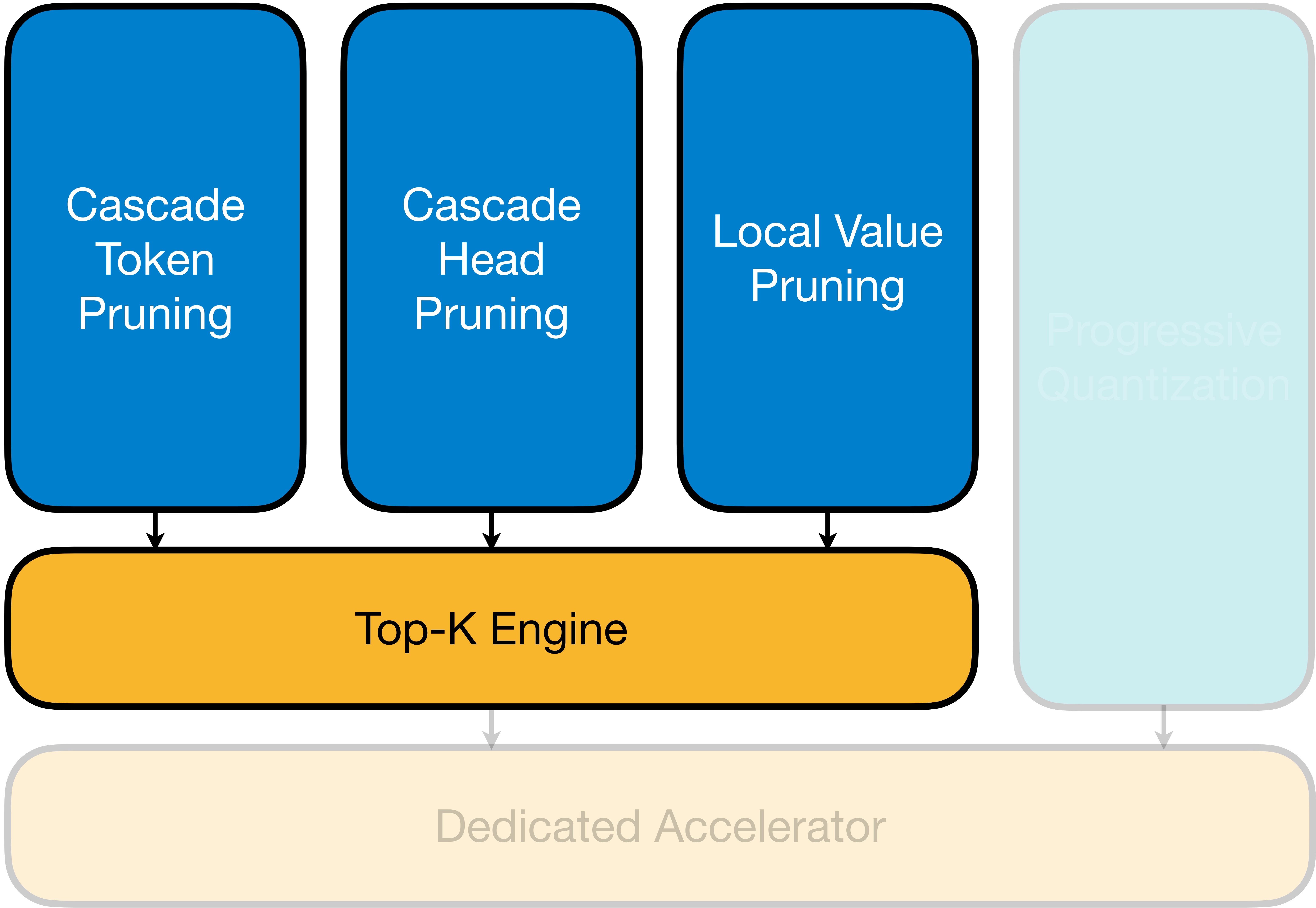

Top-k Engine

- Top-k engine supports cascade token/head pruning and local value pruning
- Example: find top 4 elements from [7, 2, 6, 4, 9, 1, 3, 5]
  - Find the **4^{th} largest**: 5
  - Filter the input, **preserve** those ≥ 4^{th} largest: [7, 6, 9, 5]

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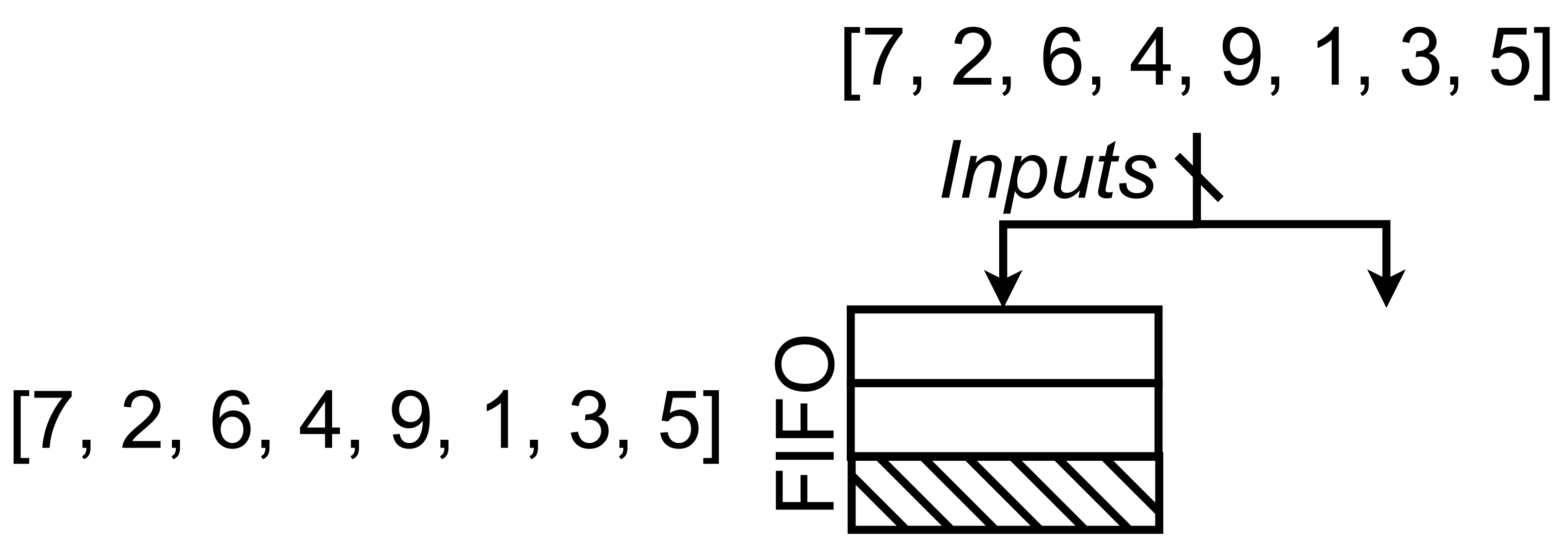

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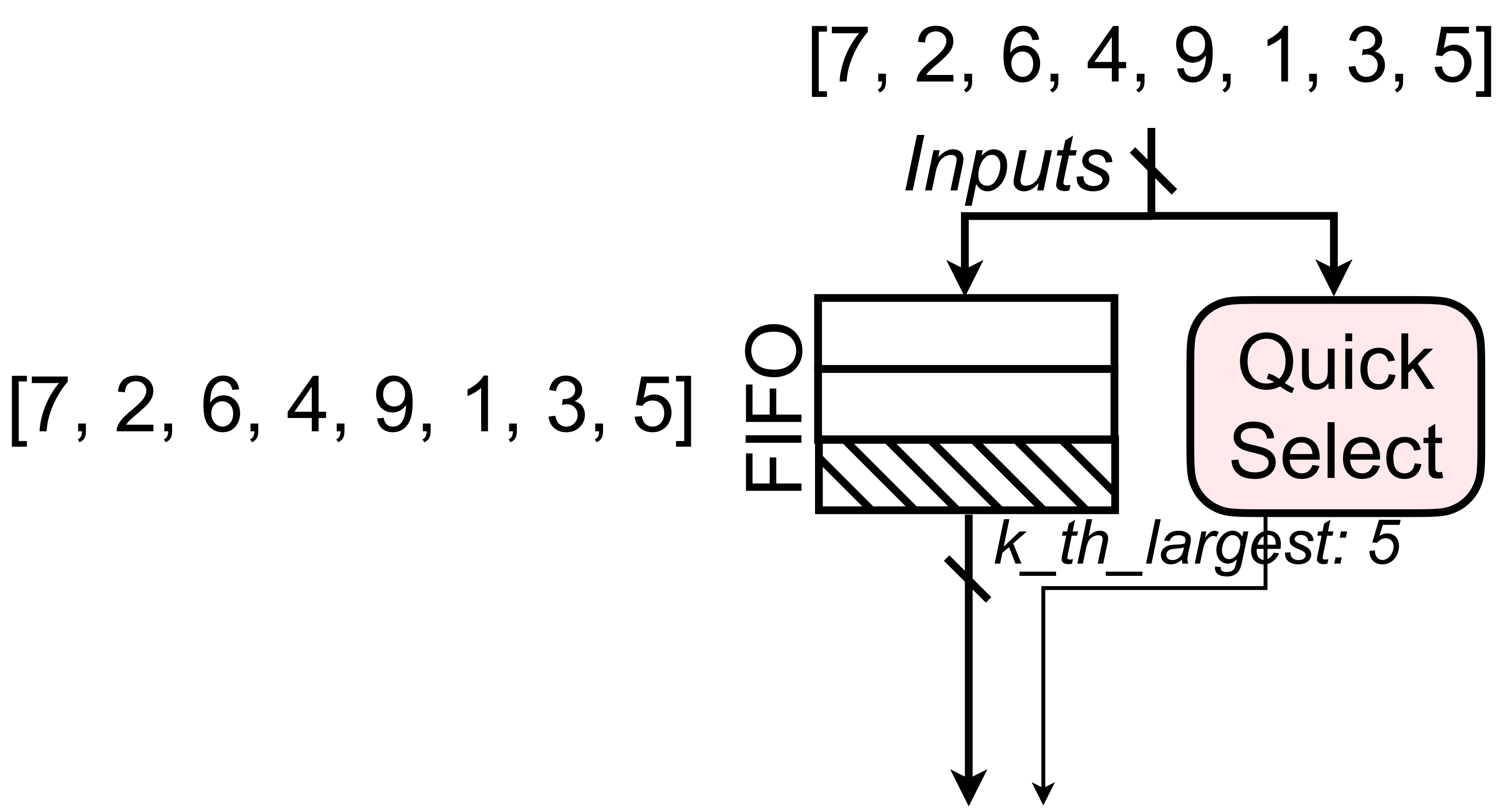

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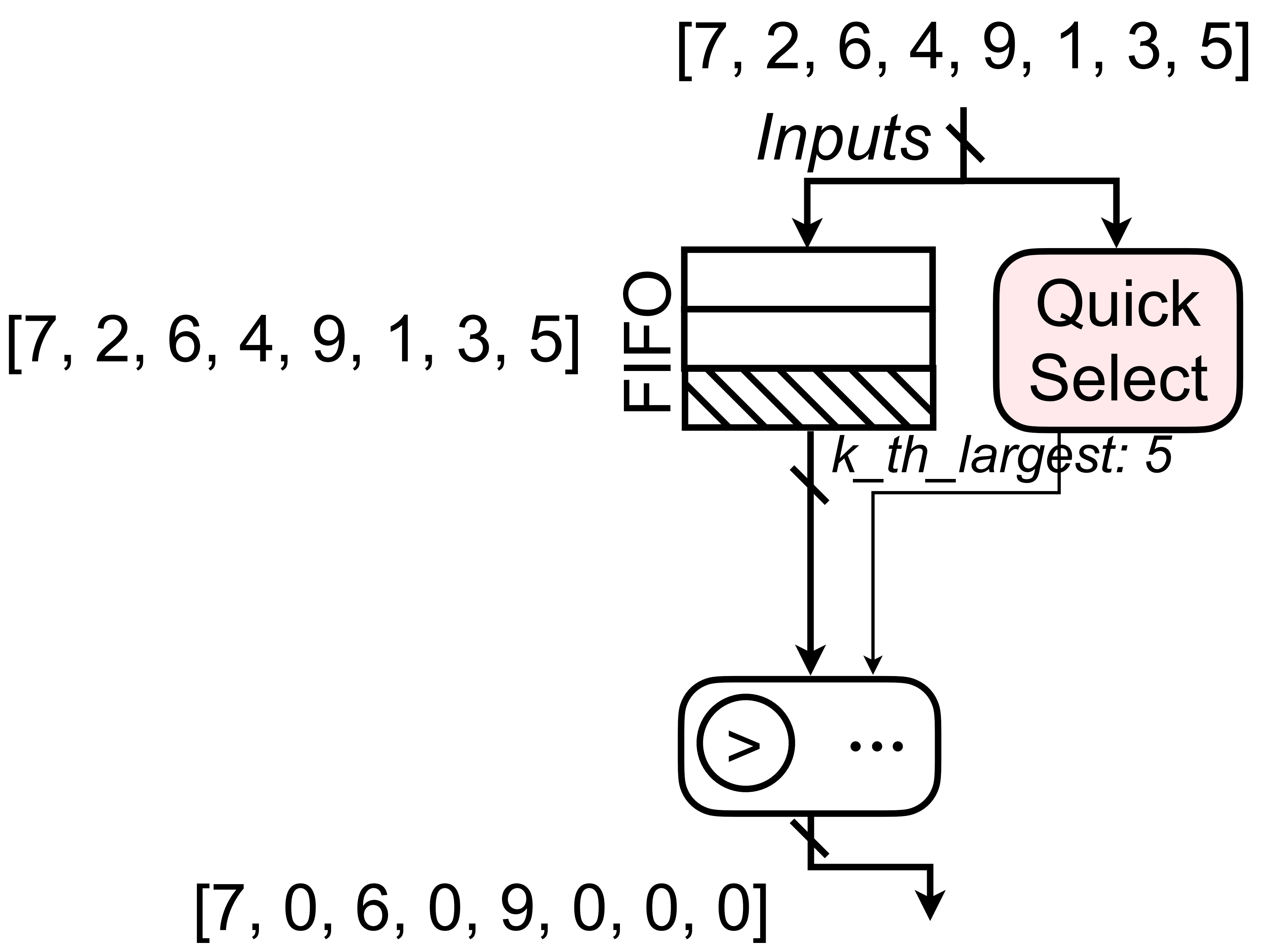

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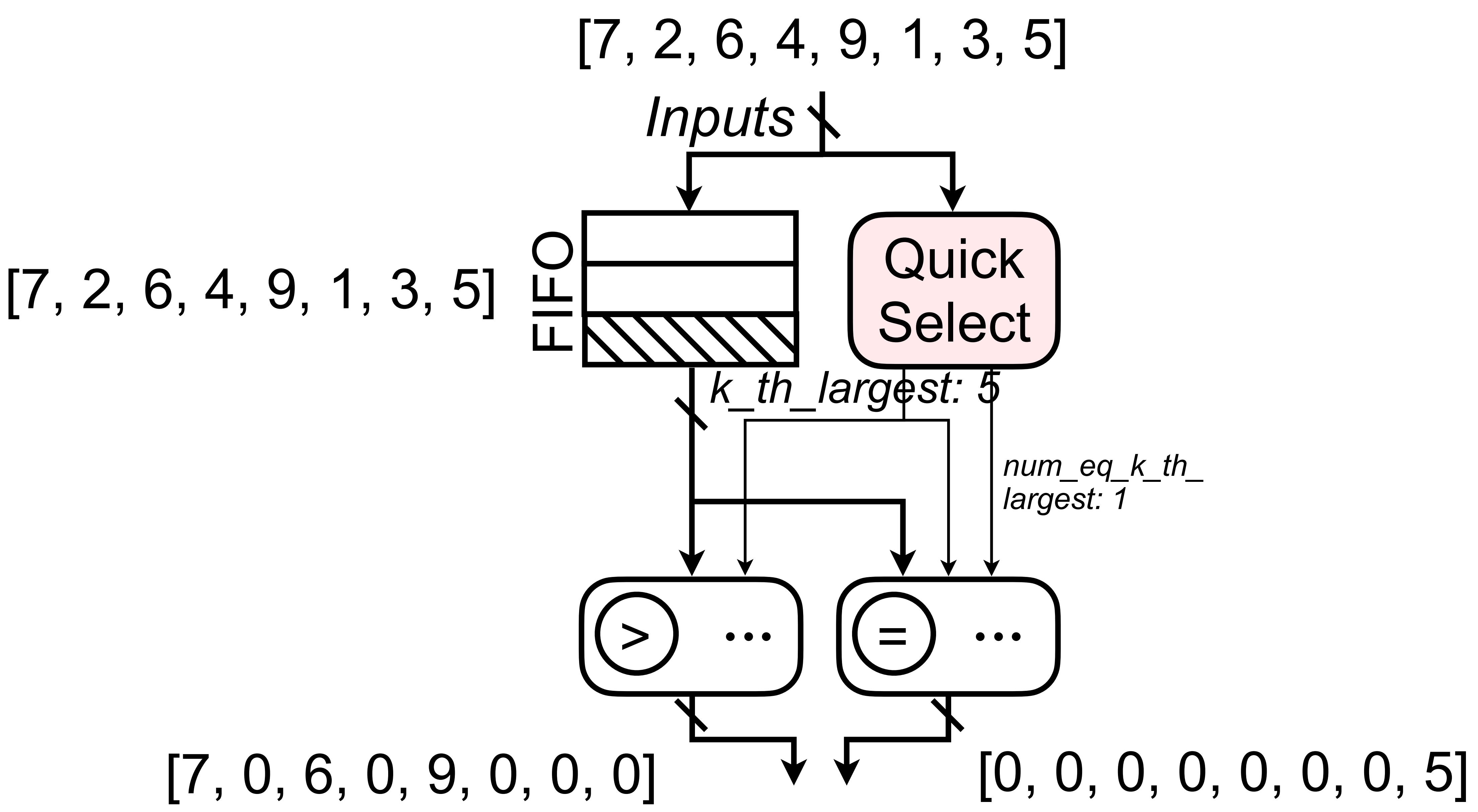

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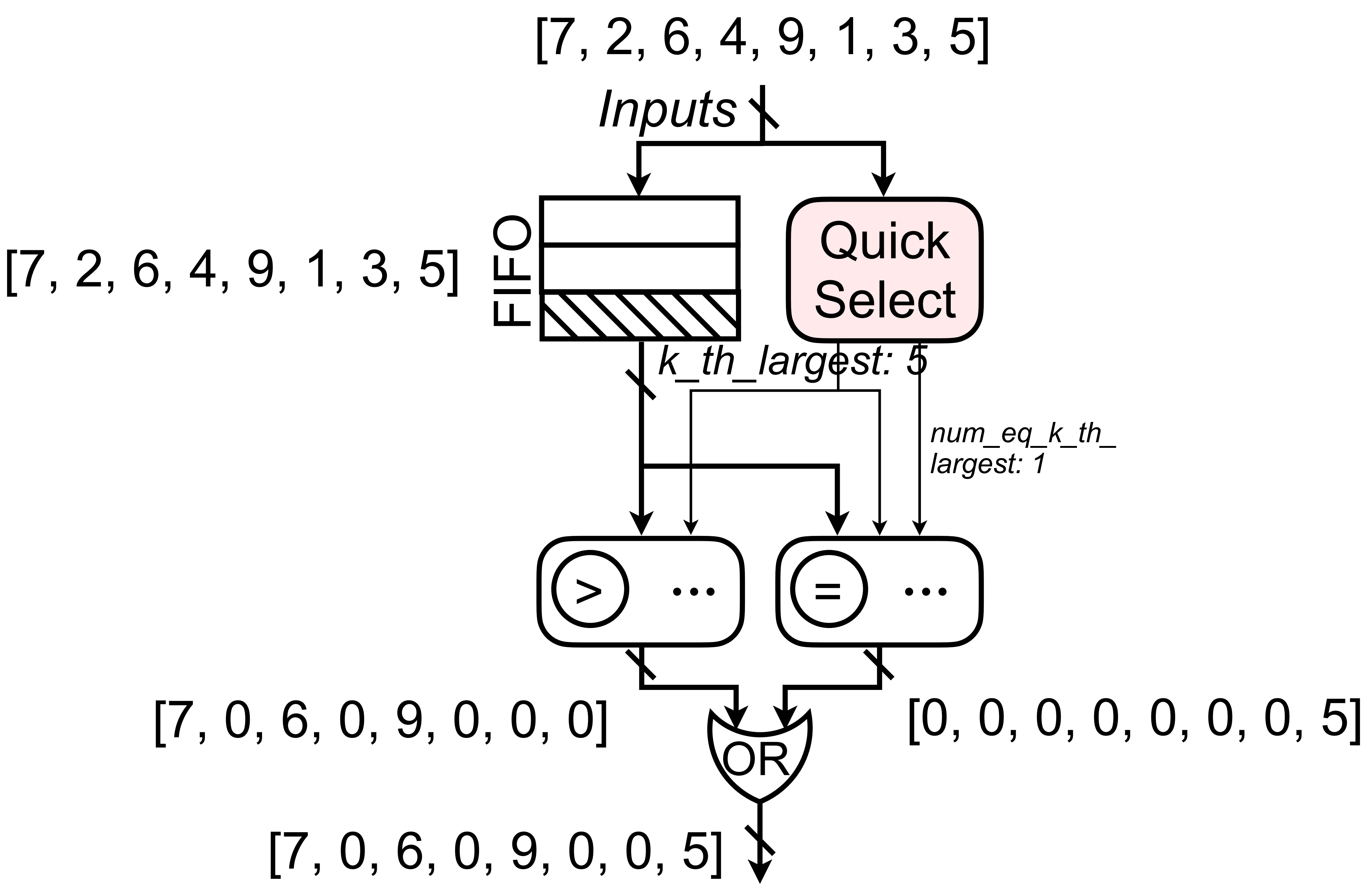

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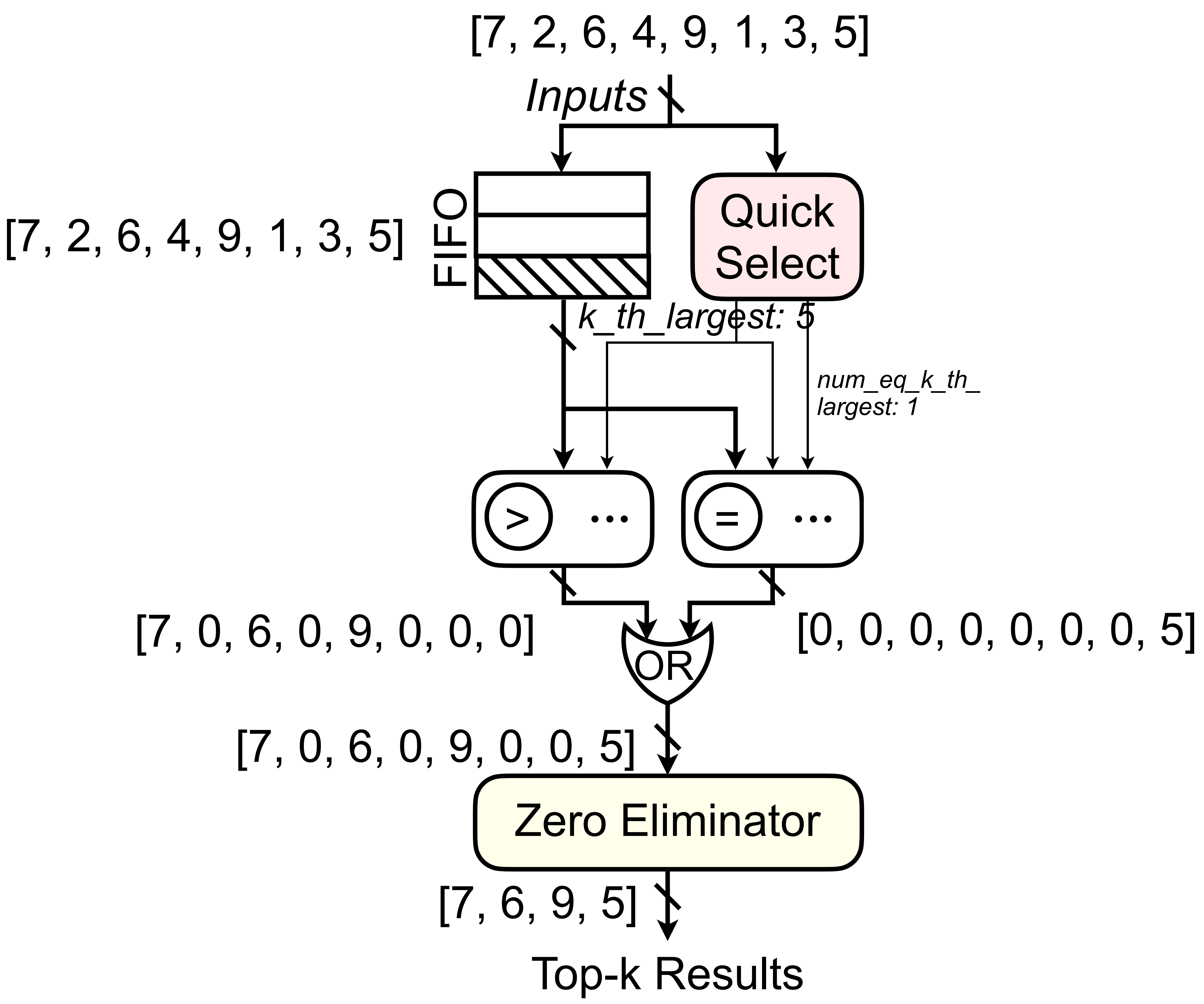


Quick Select

- Quick Select module selects the kth largest element
- Example: selects the 4th largest from [7, 2, 6, 4, 9, 1, 3, 5]

Random pivot

[7, 2, 6, 4, 9, 1, 3, 5] Find the 4th largest

smaller elements / larger elements

[1] [7, 6, 4, 9, 3, 5] Find the 4th largest

smaller elements / larger elements

Find the 1st largest [4, 3, 5] [7, 9]

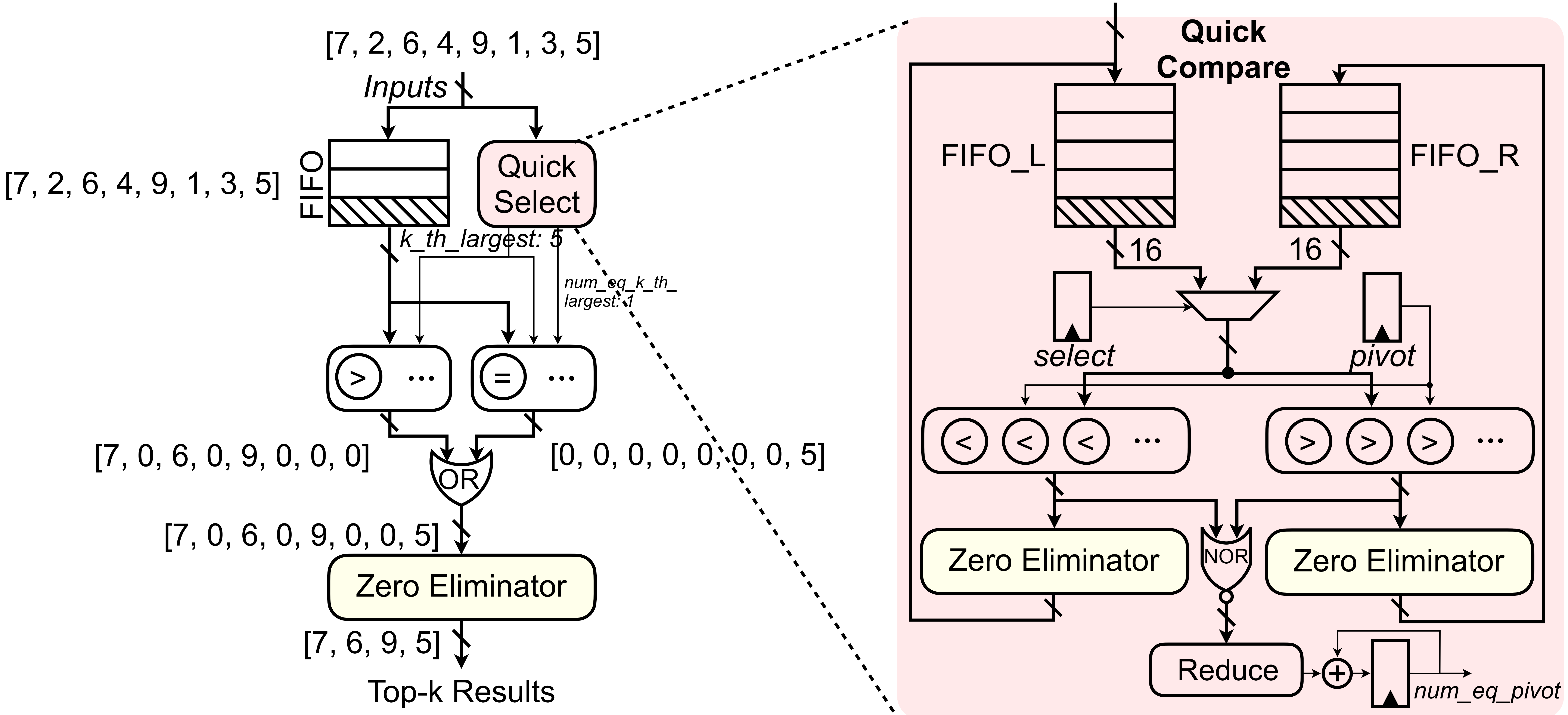
smaller elements / larger elements

[3] [5] Find the 1st largest

[5]

Quick Select

- Top-k Engine has **high-parallelism**
  - 16 ‘<’ comparators and 16 ‘>’ comparators in Quick Select
  - Compare the elements with pivot **in parallel**



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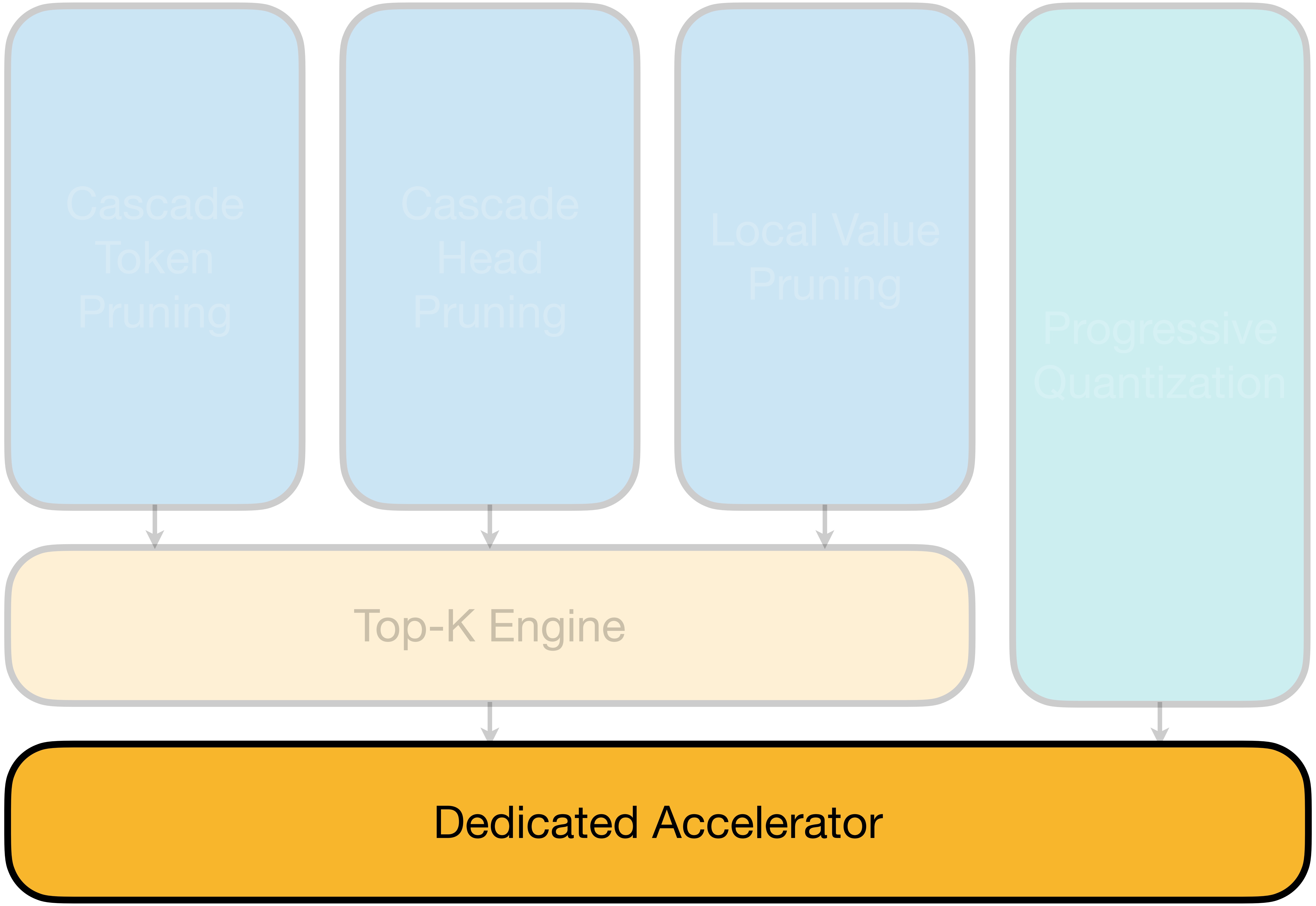
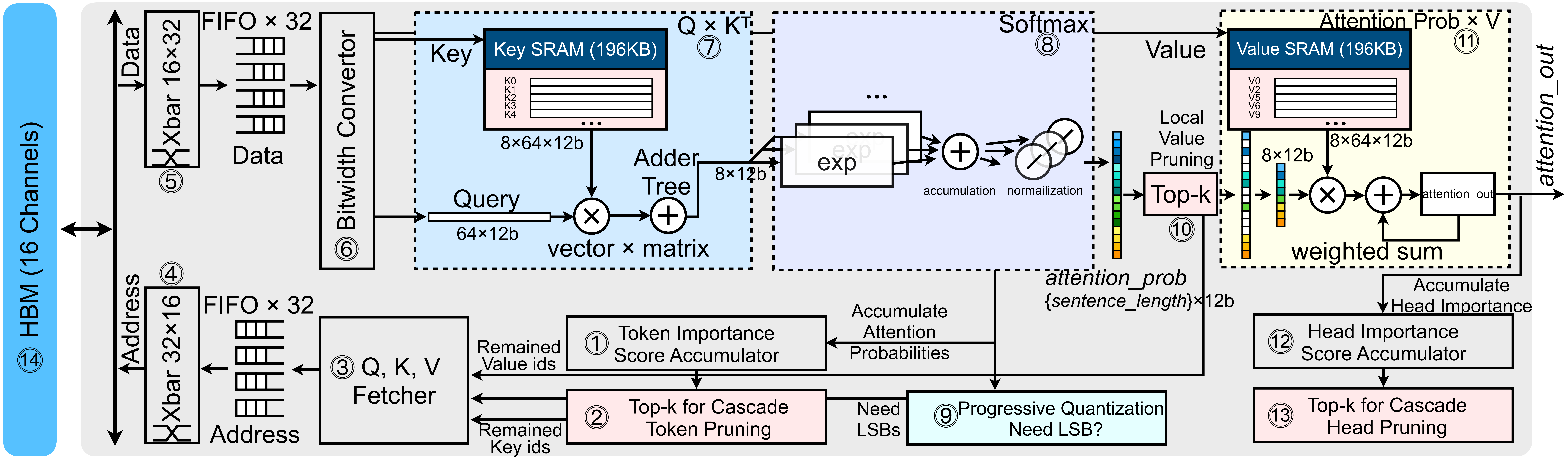


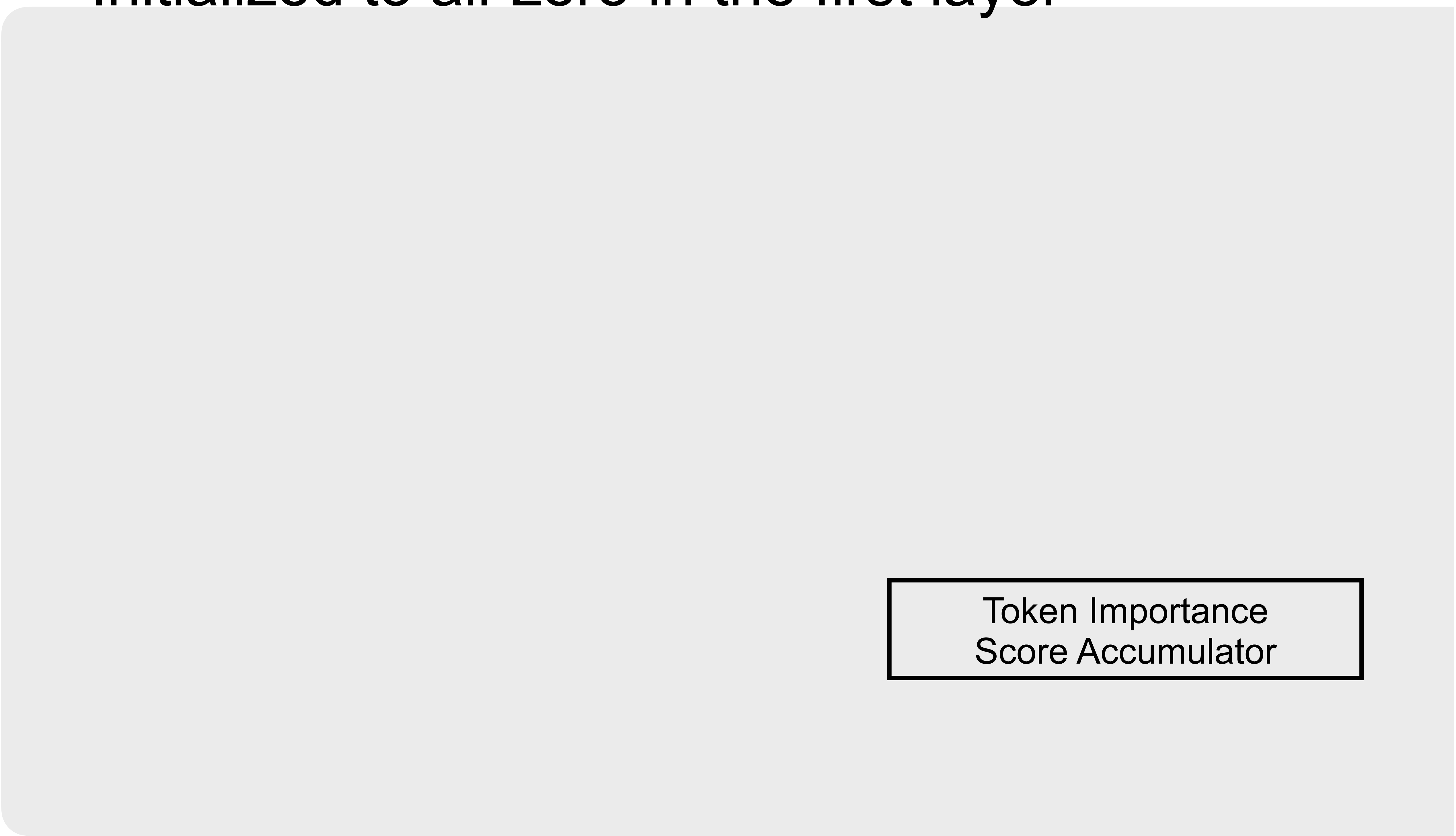
Dedicated Accelerator

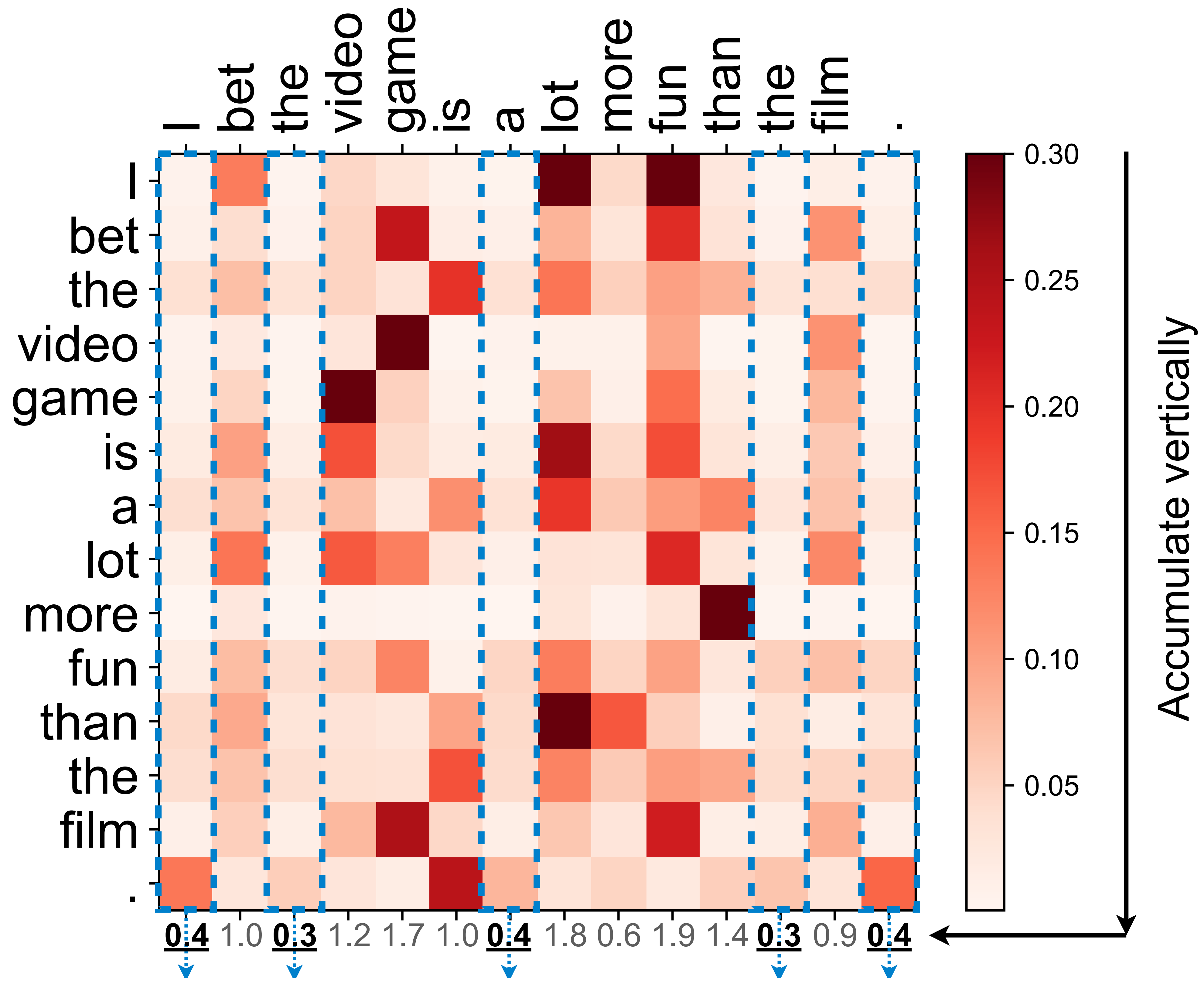
- Pipelined architecture to improve the throughput



Dedicated Accelerator

- The **token importance score accumulator module** stores scores across layers
  - Initialized to all-zero in the first layer





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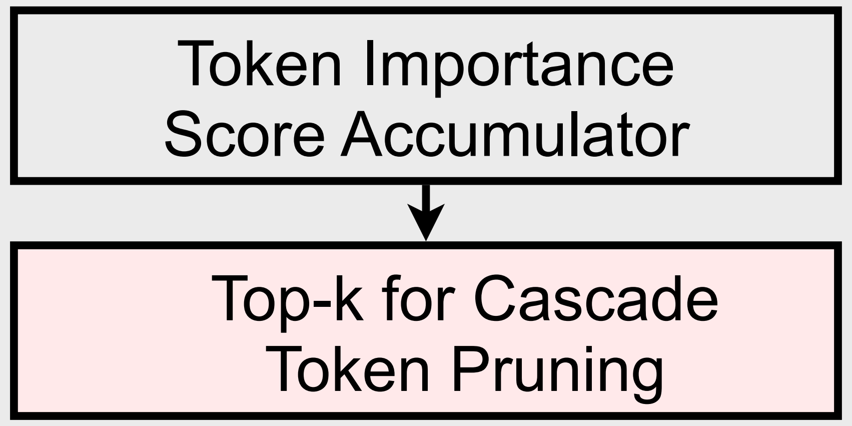

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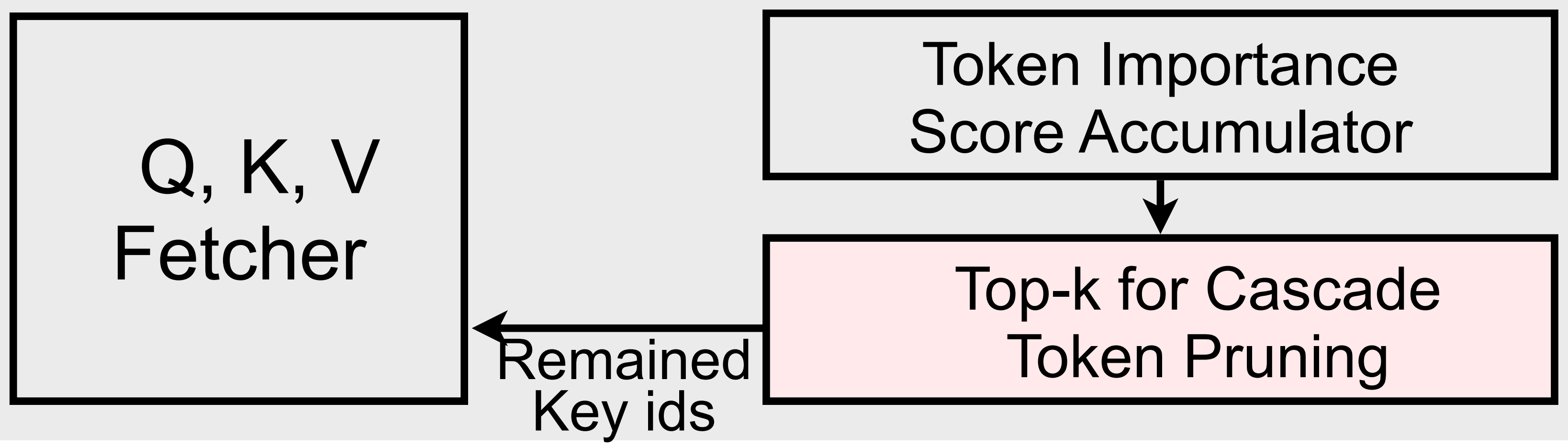

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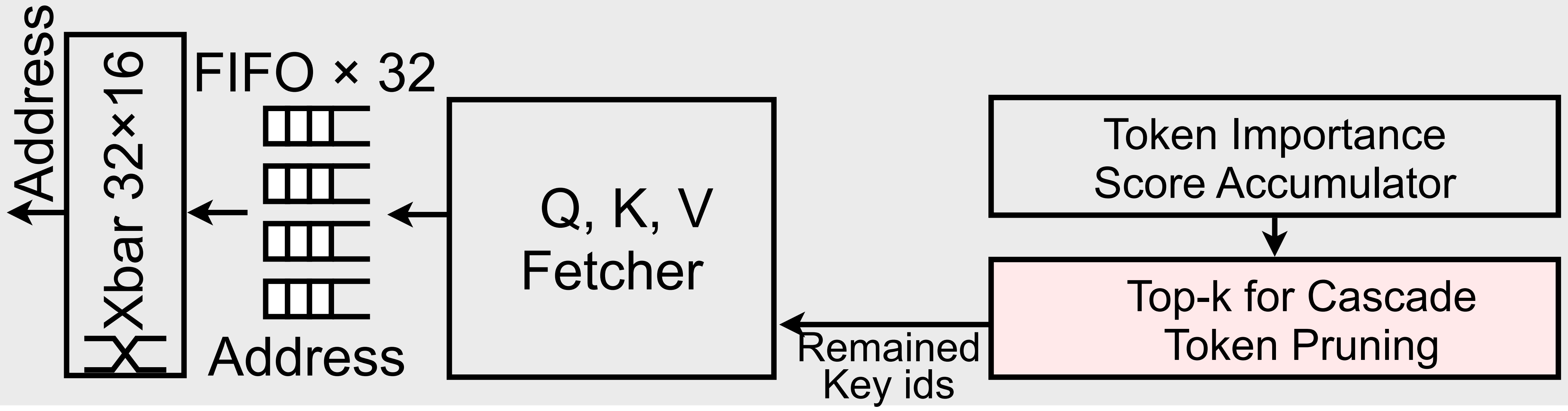

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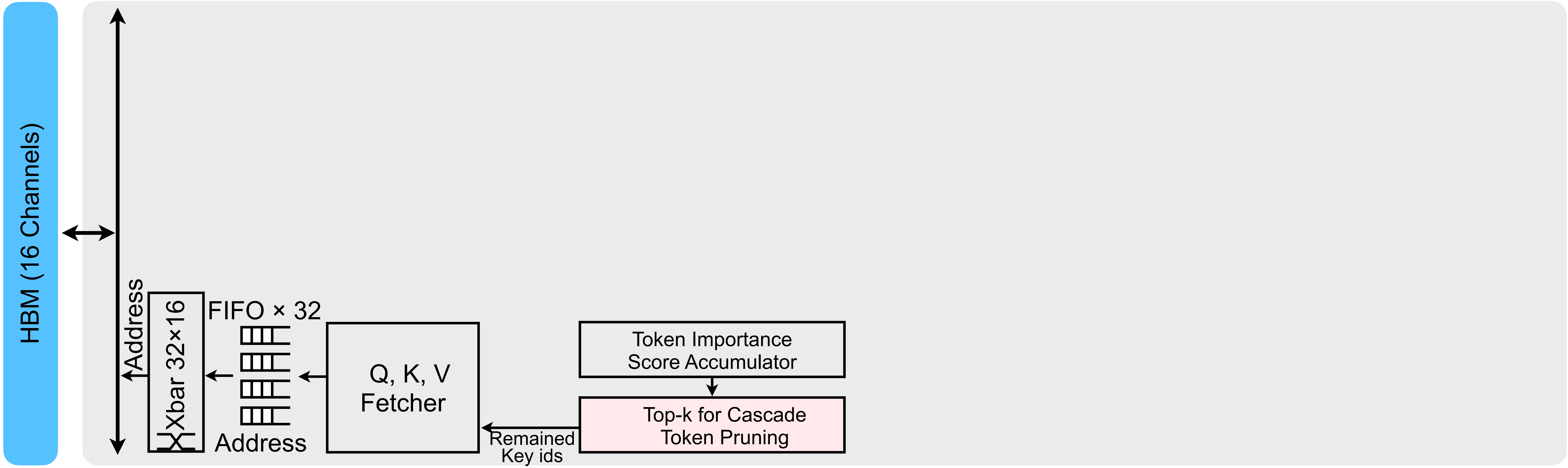
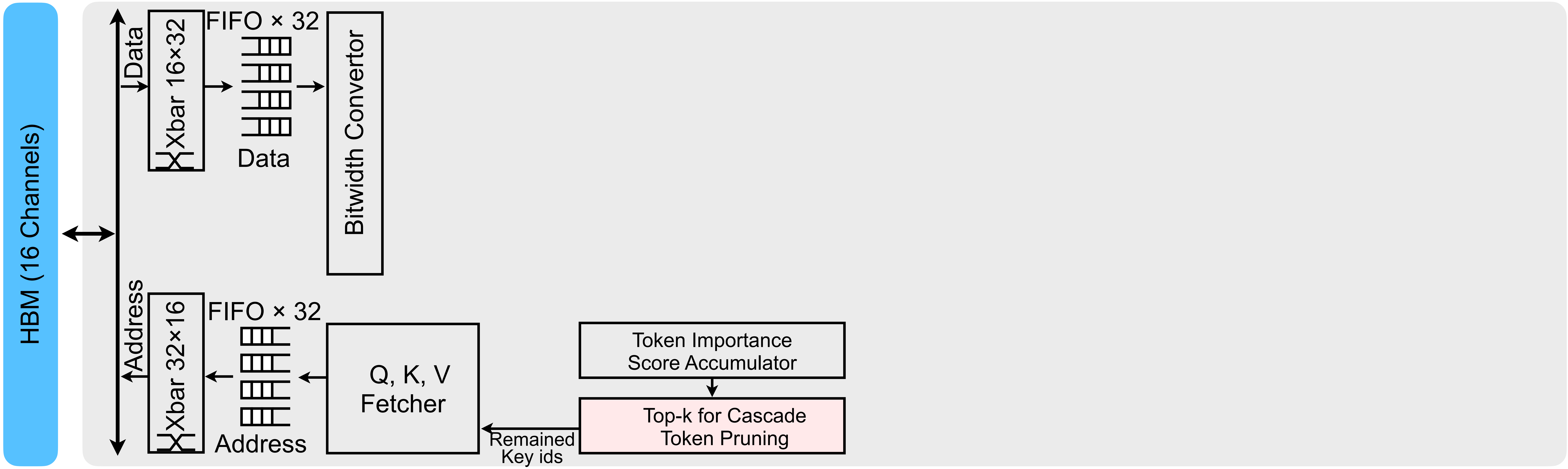


- The consecutive Key/Value vectors are stored in **different HBM channels** to leverage HBM bandwidth

Dedicated Accelerator



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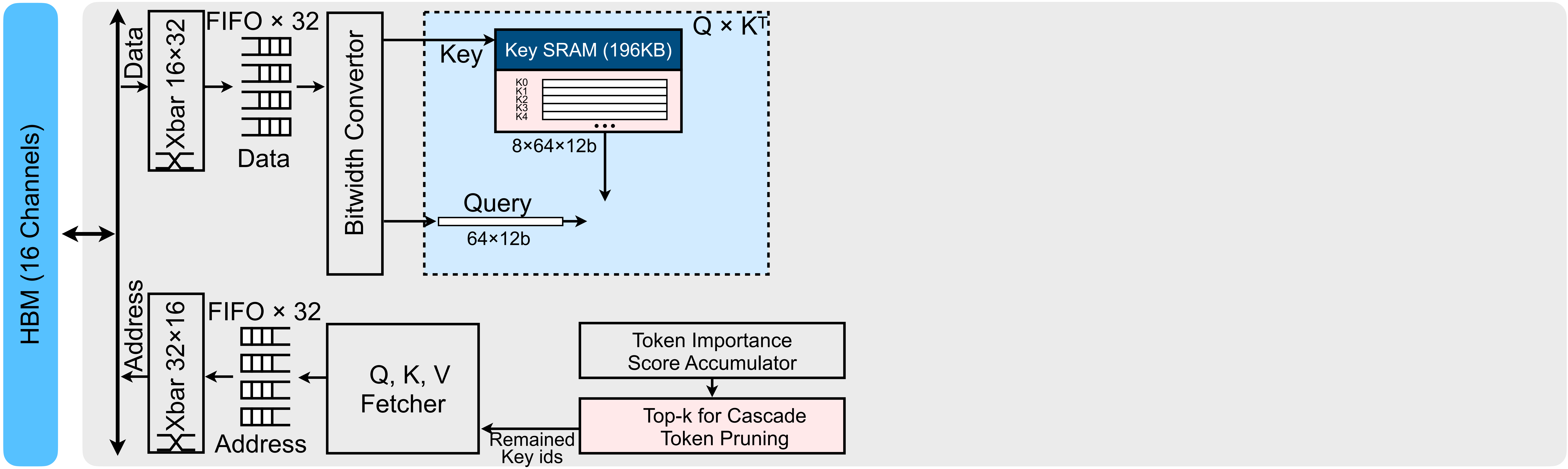

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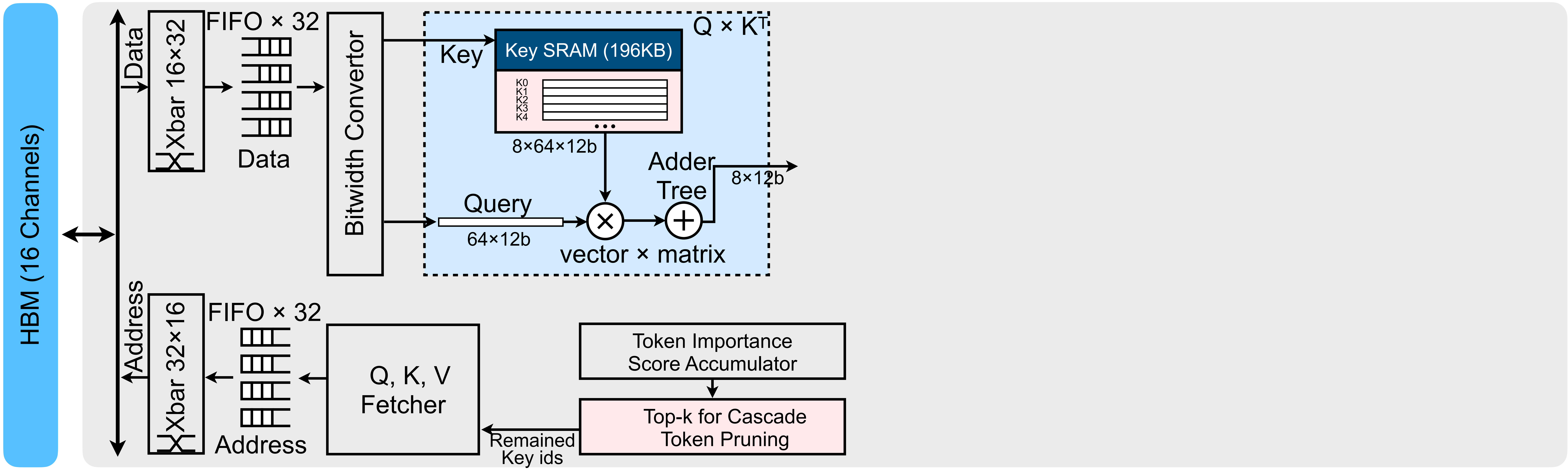
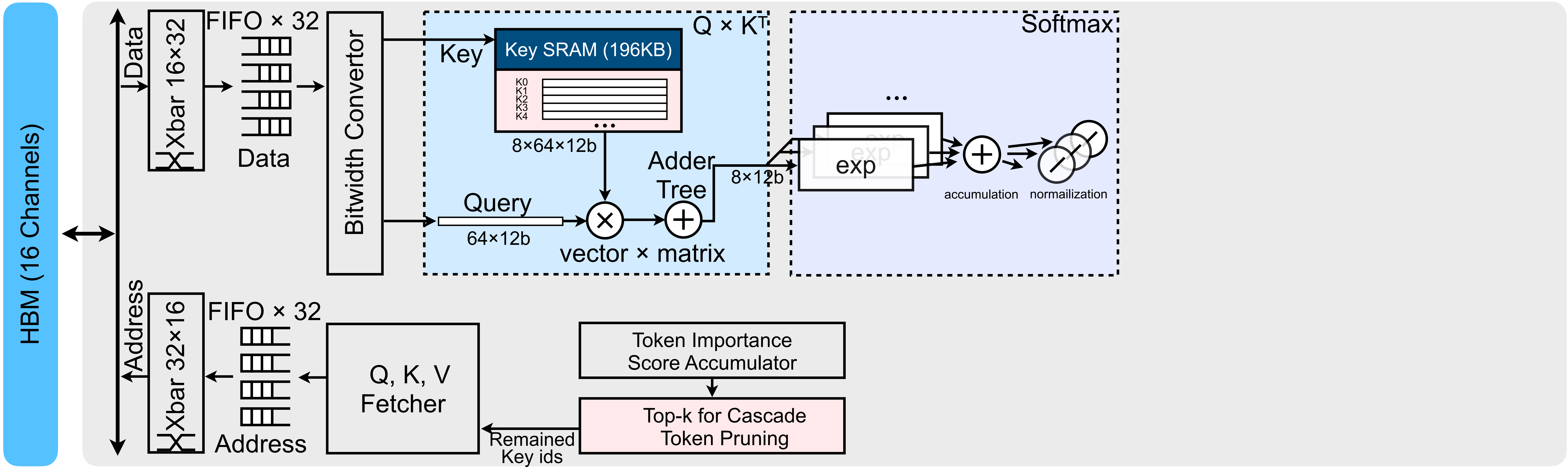


Dedicated Accelerator



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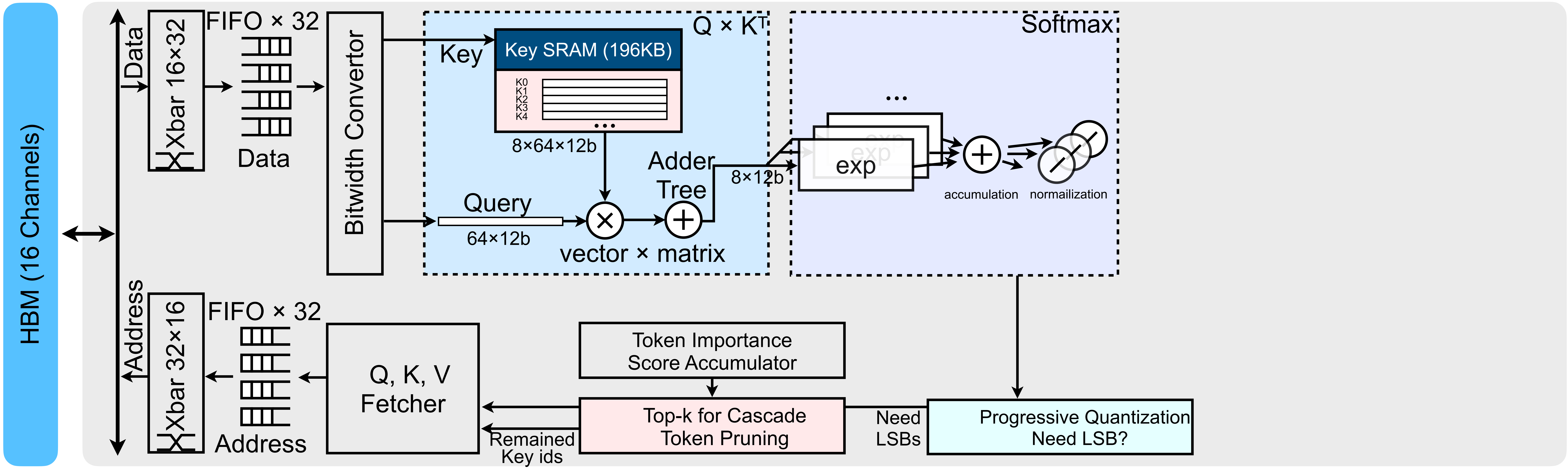

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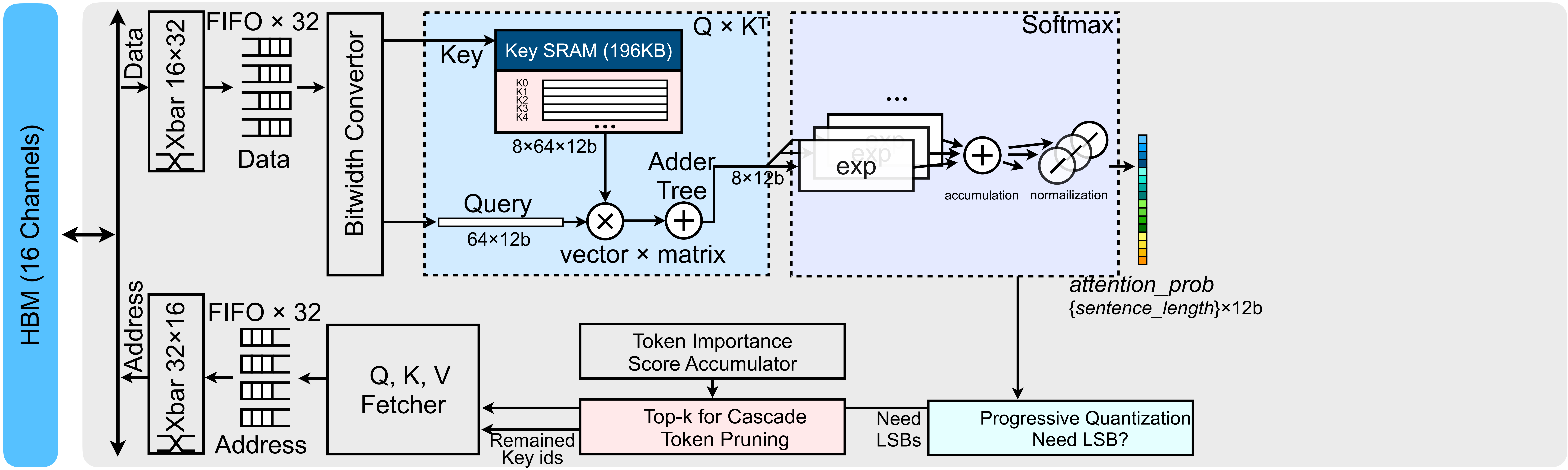

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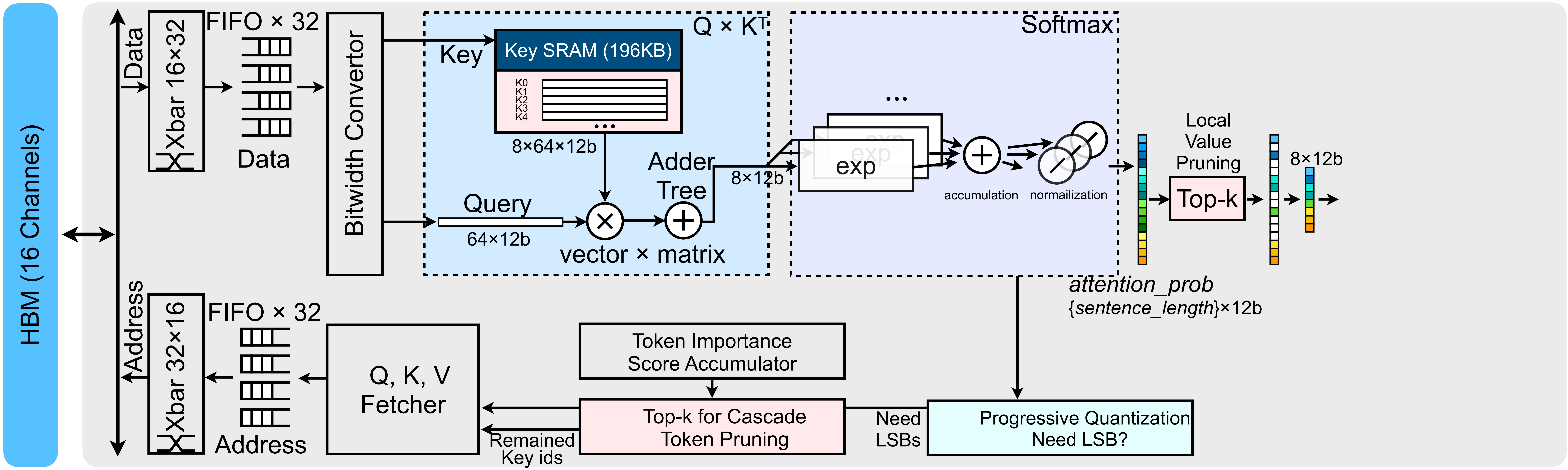

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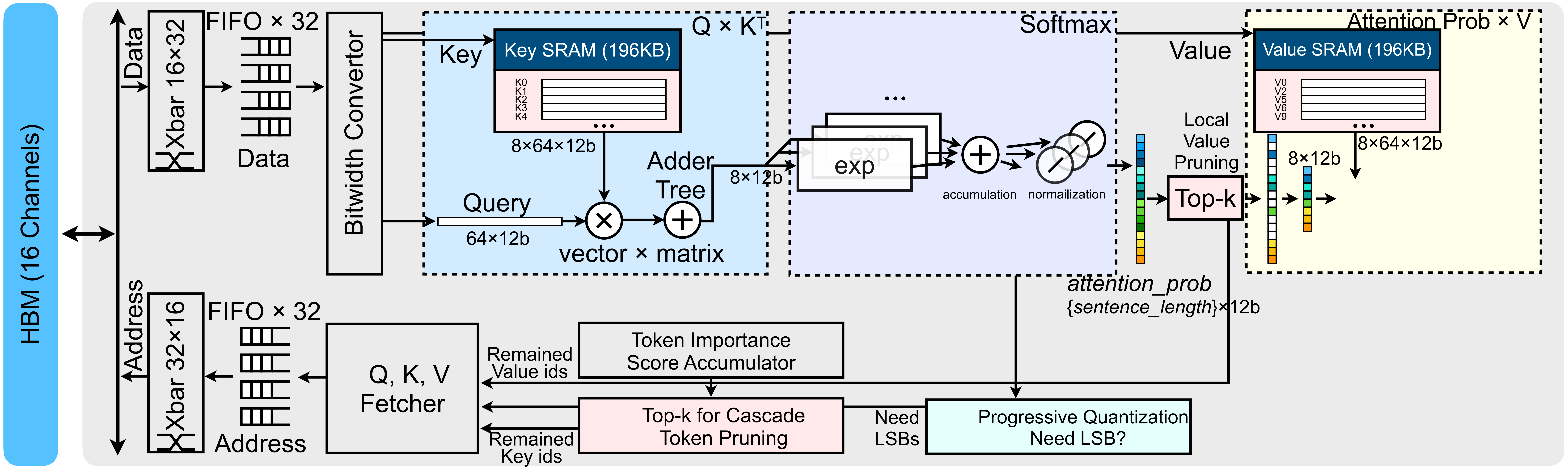

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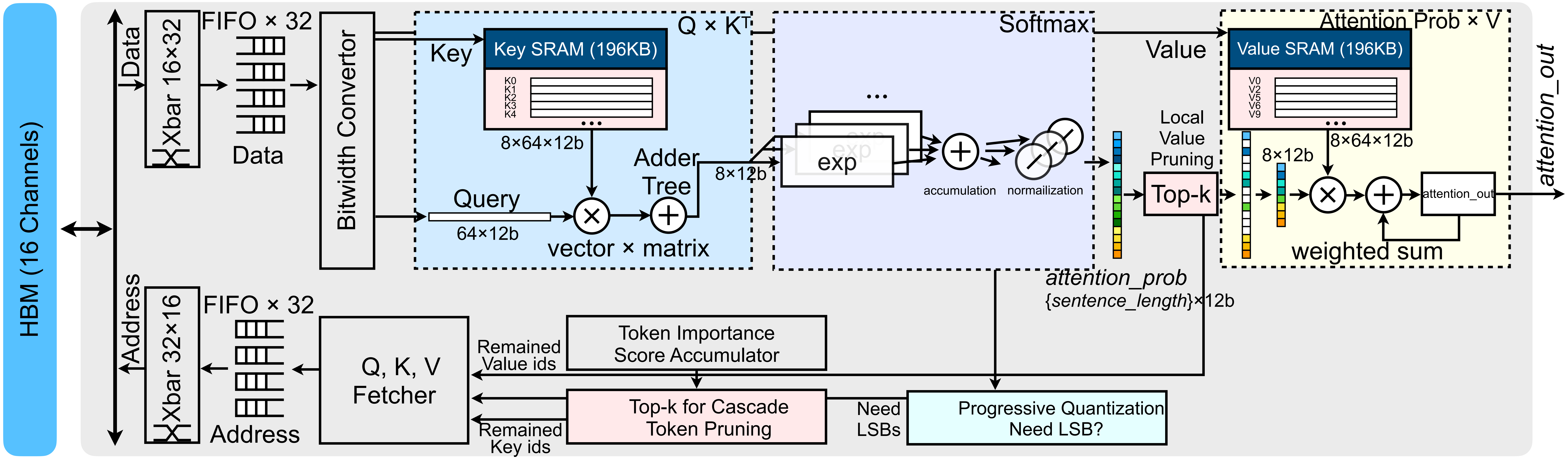

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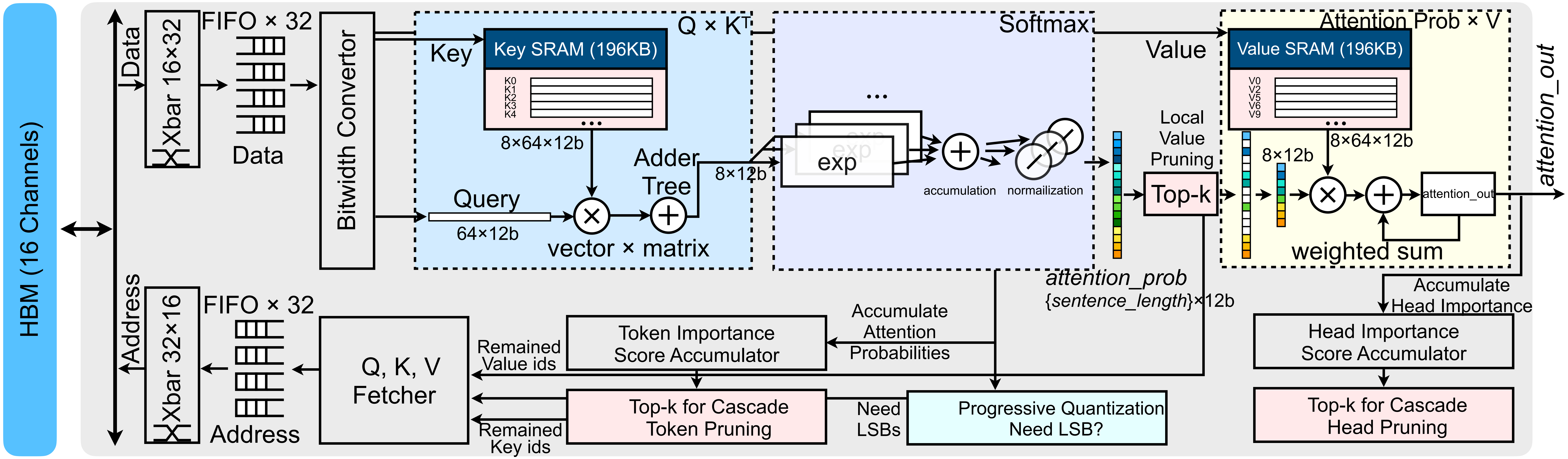

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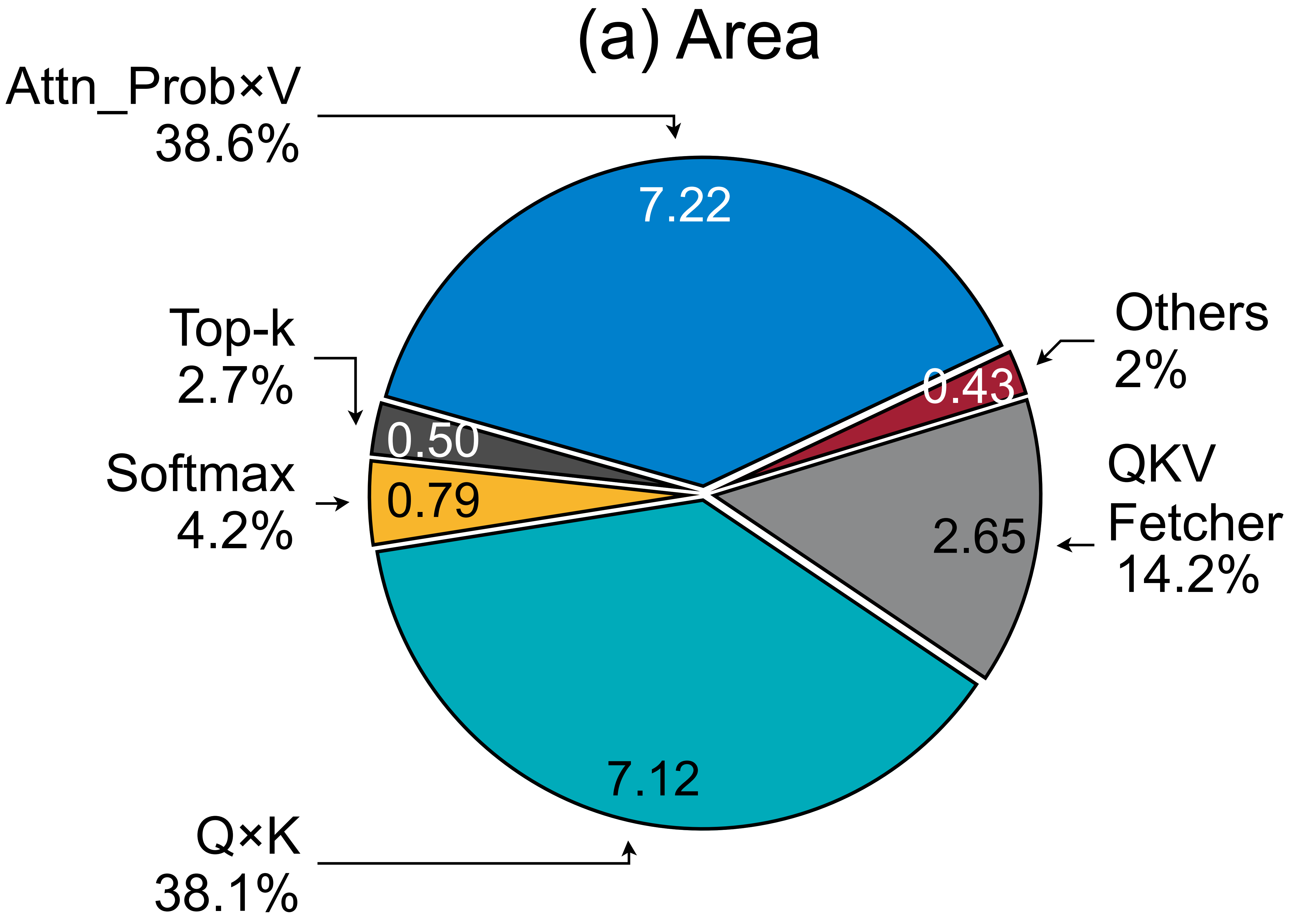
Evaluation

- Hardware Implementation

Technology	TSMC 40nm
Area (w/o DRAM)	18.71mm^2
Power (w/ DRAM)	8.30W
Multipliers	1024
SRAM	392KB
DRAM	HBM2 16 Channels, each @ 32GB/s
Performance on Summarization Stage	1.61TFLOPS
Performance on Generation Stage	0.43TFLOPS

Power & Area Breakdown

- On-chip power and area breakdown



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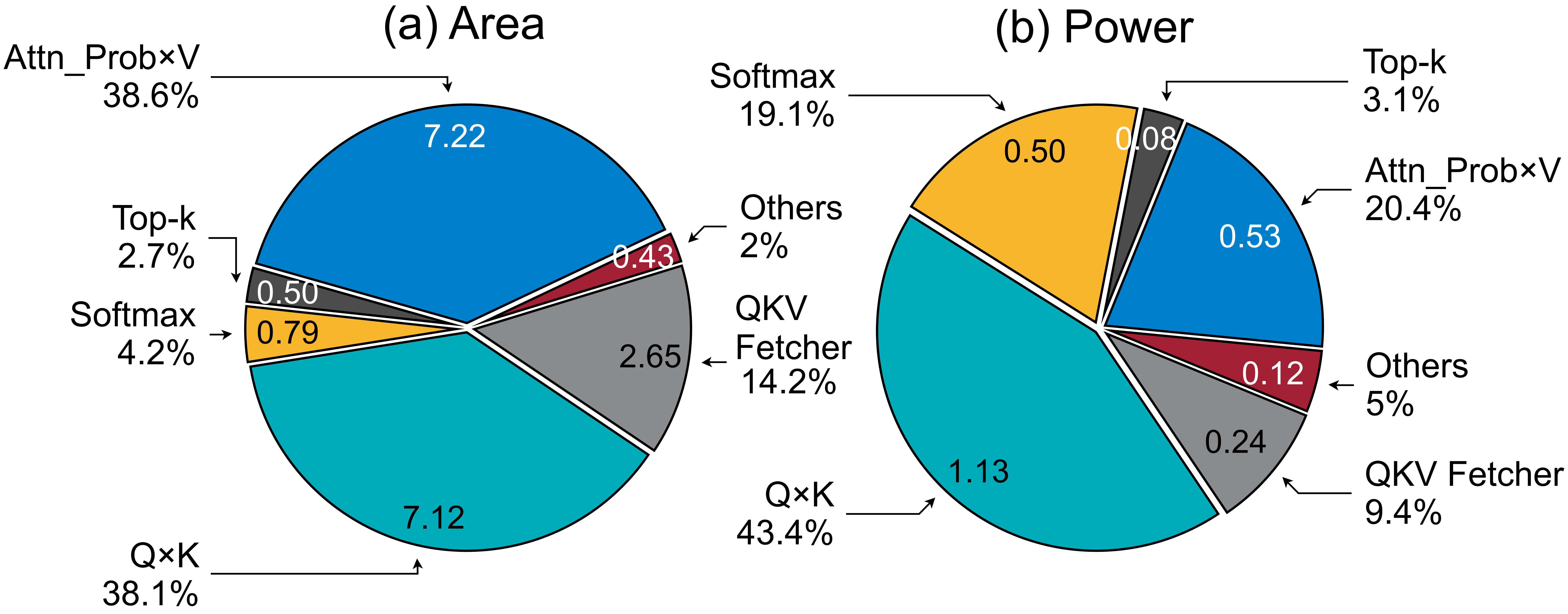


30 Benchmarks

- Model Architecture
  - BERT-Base, BERT-Large, GPT-2-Small, GPT-2-Medium
- Task:
  - Discriminative: GLUE (9 tasks), SQuAD-V1, SQuAD-V2
  - Generative: Language modeling on Wikitext-103, Wikitext-2, Pen-tree Bank, Google One Billion Words

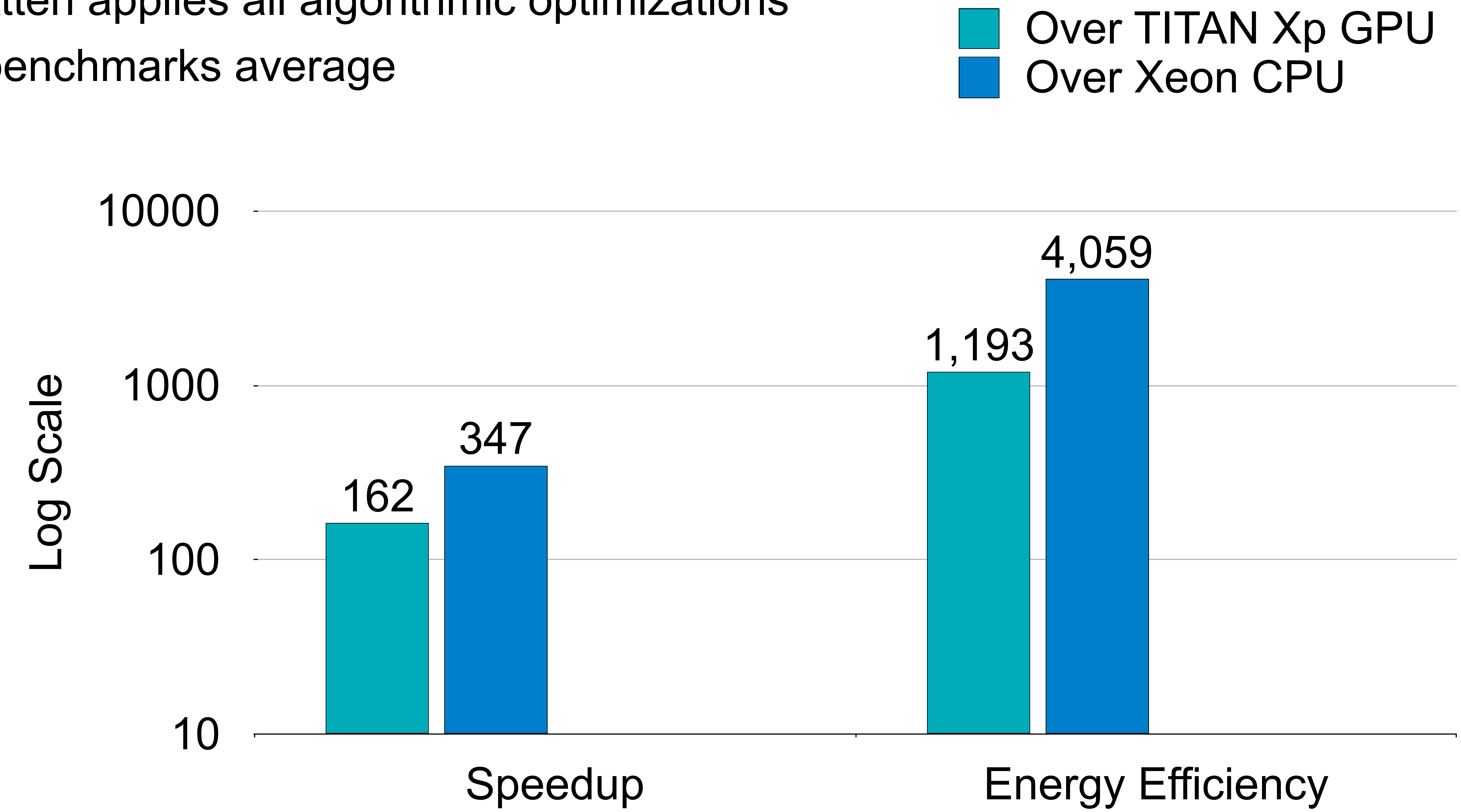
Pruning and Quantization Results

- Pruning ratio is **highly dependent** on sentence length
  - For long sentence (1000 in LM with GPT-2), can prune more than **70%** tokens
  - For short sentence (12 in CoLA with BERT), can prune less than **15%** tokens
- Under same performance (<2% loss on several BERT models), 30 benchmarks average:

Cascade Token Pruning	Prune away 35% (ranging 10%~75%)
Cascade Head Pruning	Prune away 10%
Progressive Quantization Effective Bitwidth	7.8 bits
Local Value Pruning (on top of cascade token pruning)	Prune away 63% (Value)

Performance Comparisons

- Over general-purpose CPUs/GPUs on attention layers
  - SpAtten applies all algorithmic optimizations
  - 30 benchmarks average



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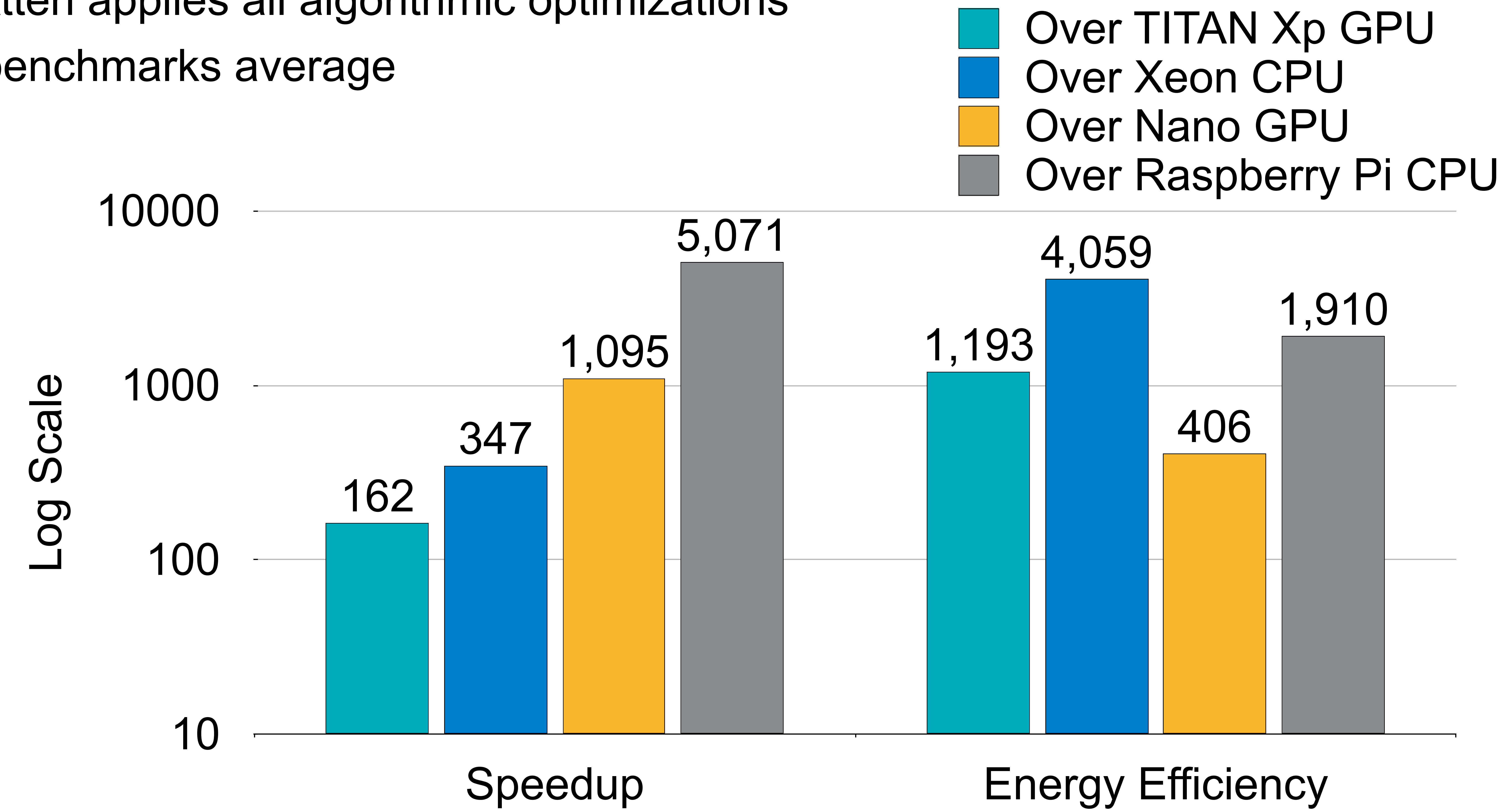
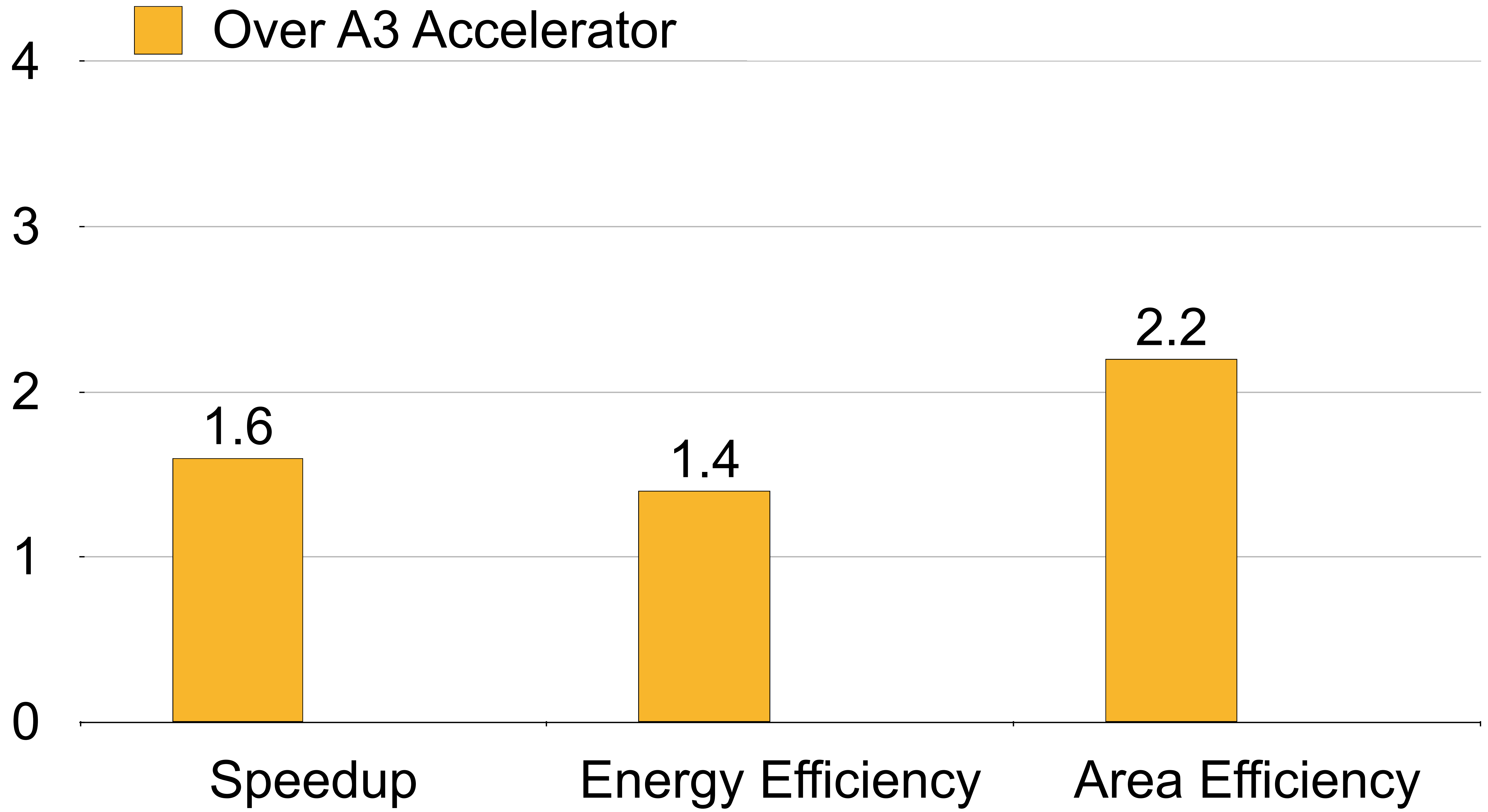


Performance Comparisons

- Over state-of-the-art attention accelerators
  - A3 (ASIC) supports local key/value pruning
  - MNNFast (FPGA) supports local value pruning



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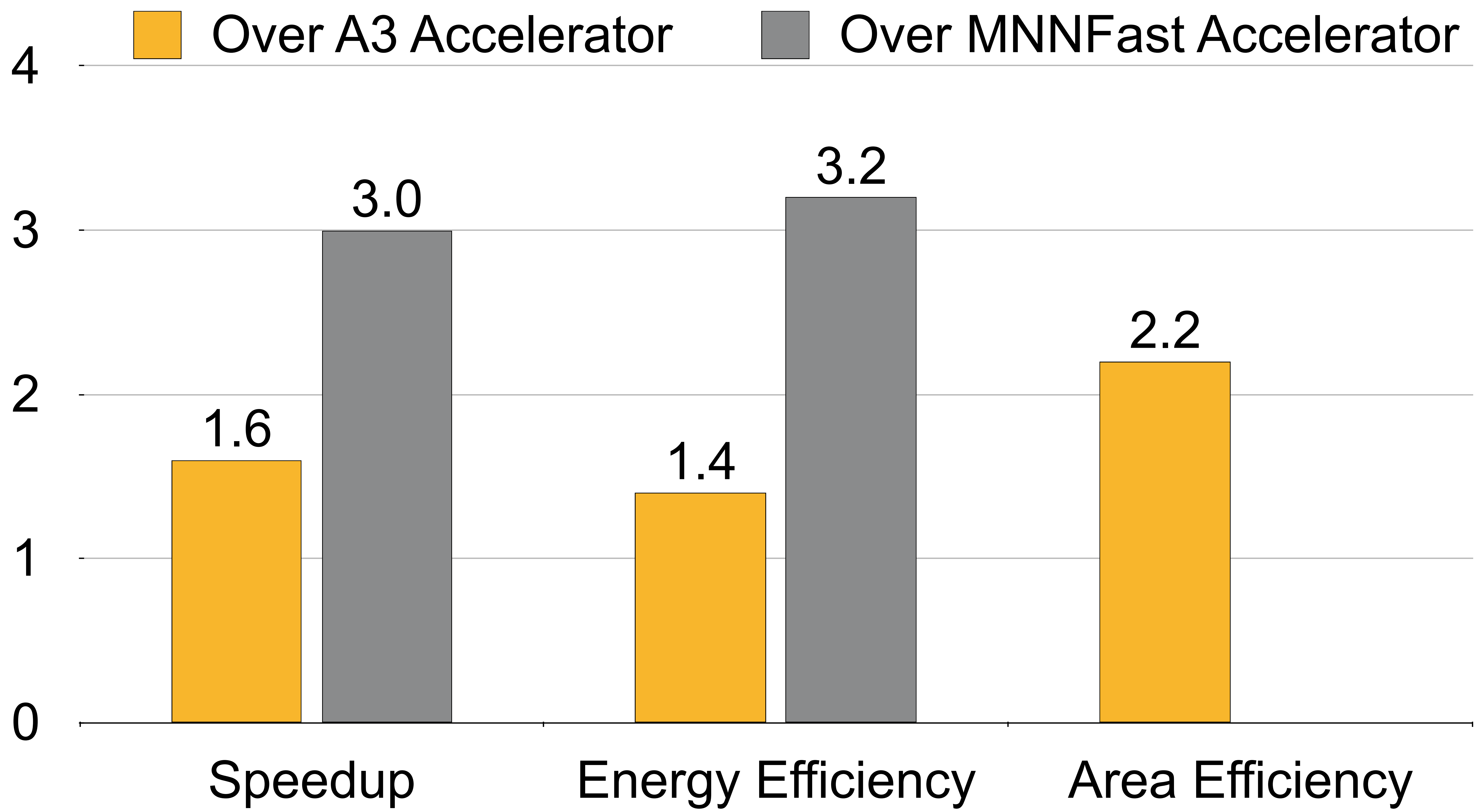
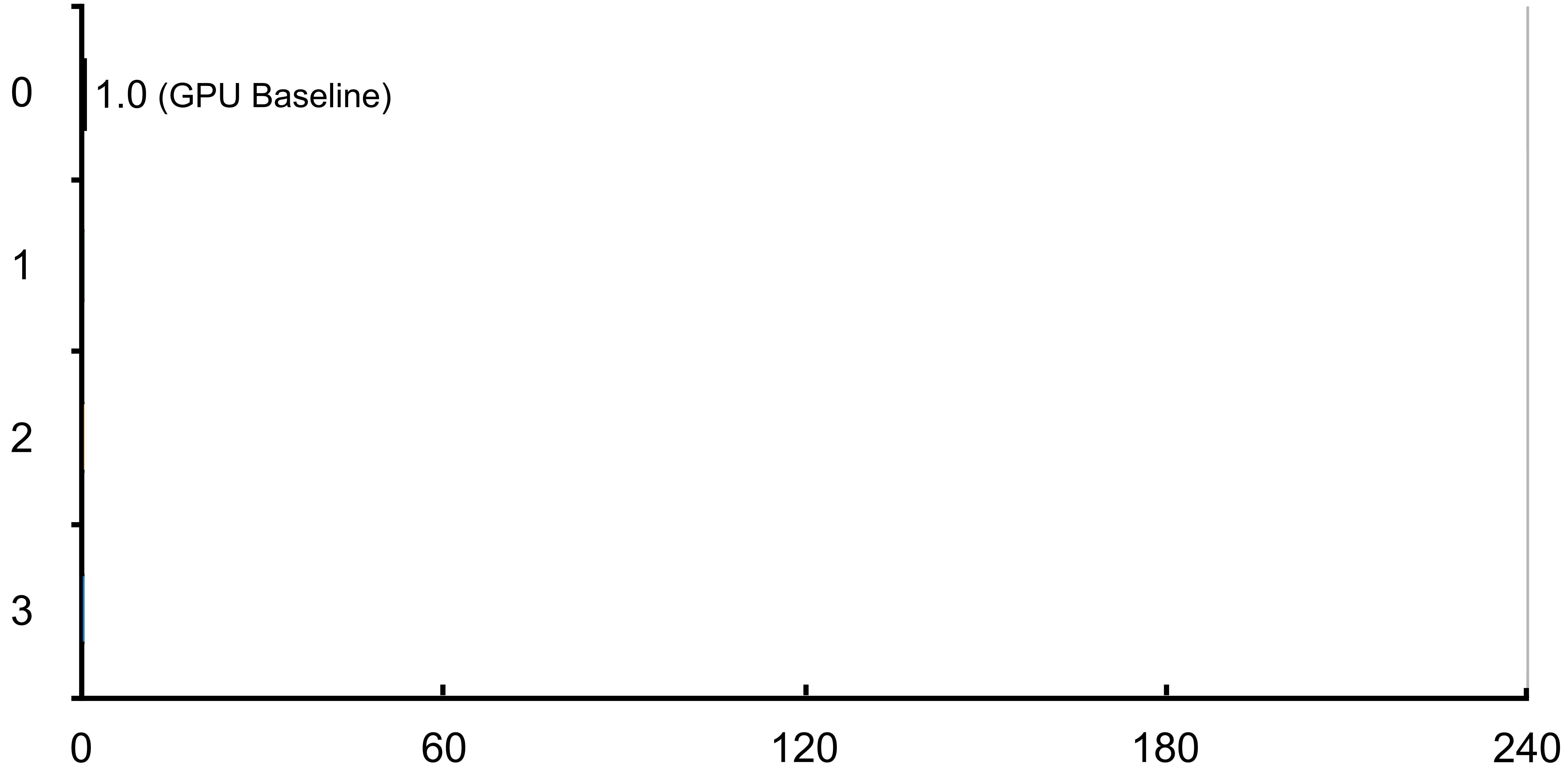


Speedup Breakdown

- Speedup breakdown on GPT-2 Models over TITAN Xp GPU



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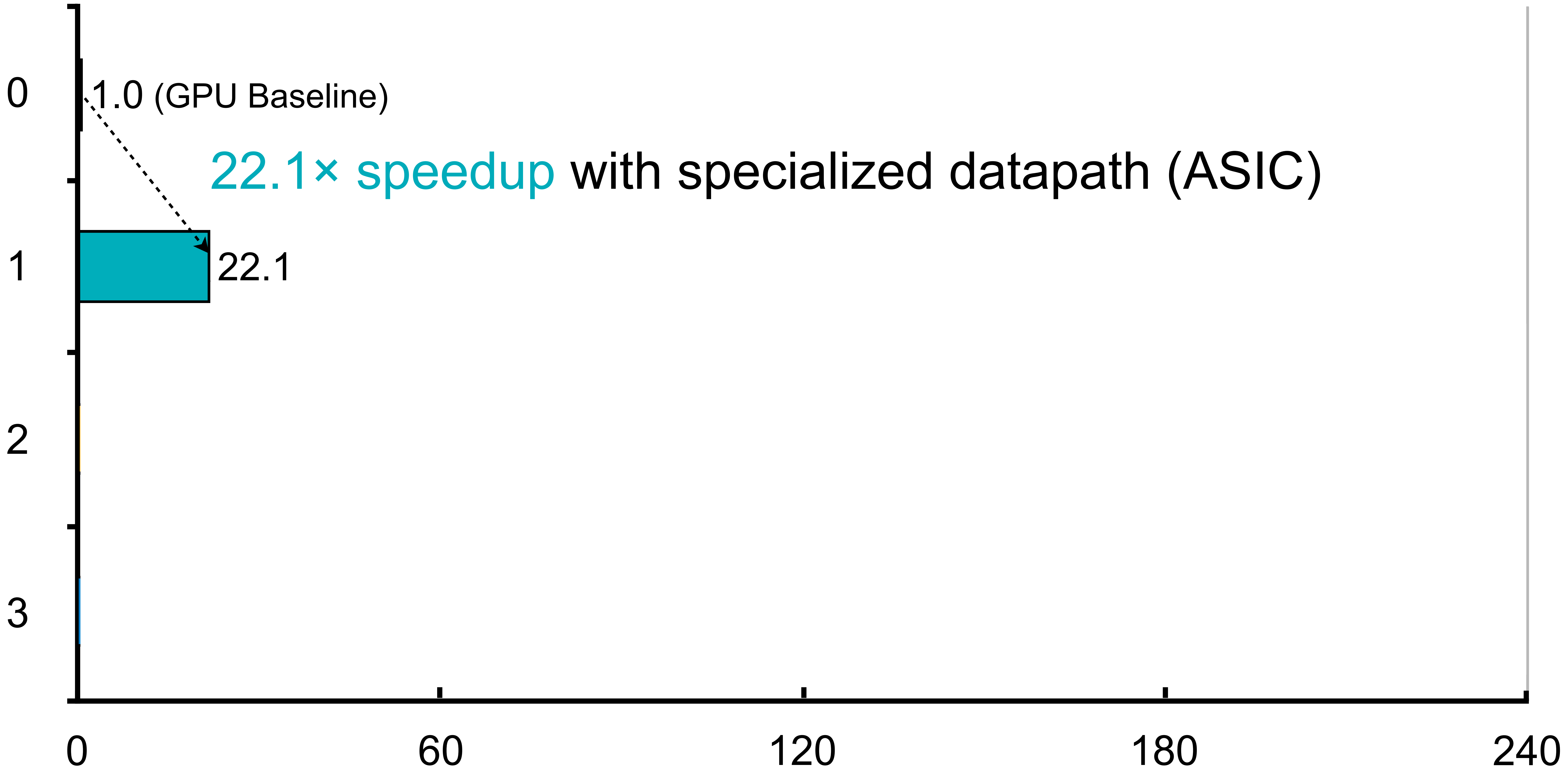

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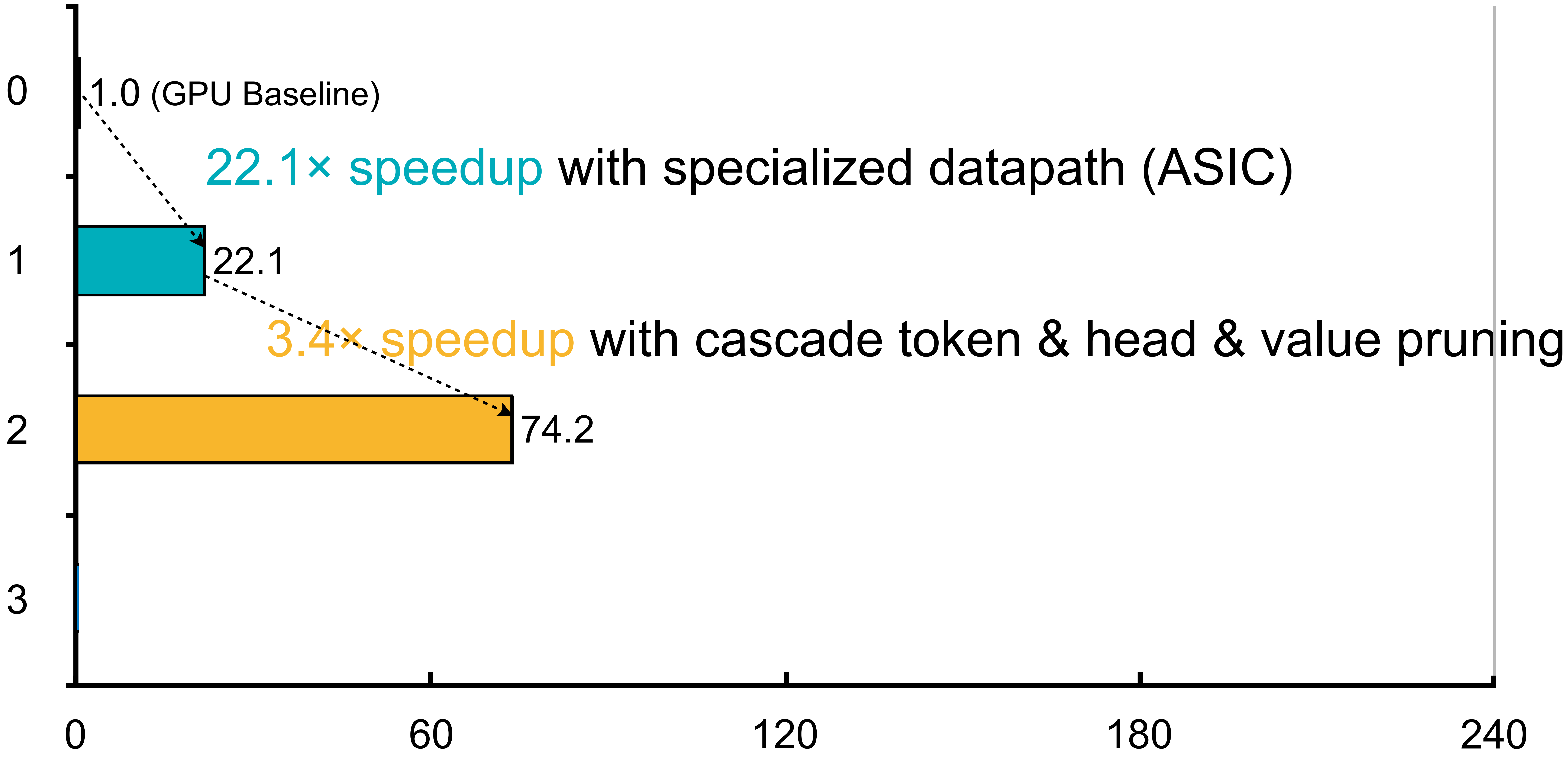

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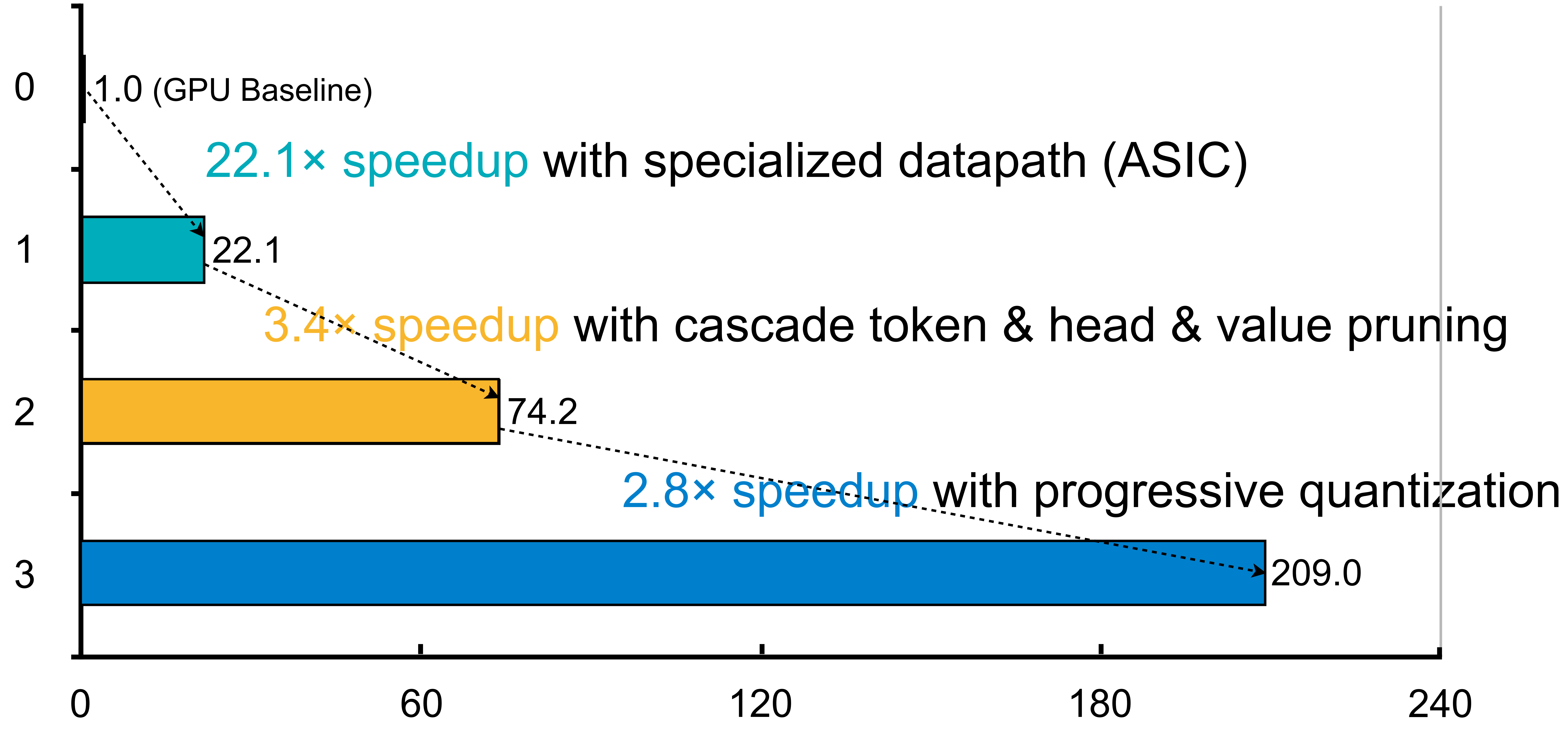

More Examples

- BERT sentence classification: (Film sentiment classification result: *positive*)

A wonderful movie, ~~I am~~ sure ~~that~~ you will remember ~~it,~~ you admire ~~its~~ conception and ~~are~~ able ~~to~~ resolve ~~some of the~~ confusions you had while watching ~~it.~~

More Examples

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sure remember admire resolve confusions

More Examples

- GPT-2 for language modeling: (‘**English**’ is the generated token.)

Du ~~Fu was a great~~ poet ~~of the~~ Tang dynasty. Recently ~~a variety of~~ styles ~~have been used~~ in efforts to translate the work of Du Fu into English

More Examples

- GPT-2 for language modeling: ('**English**' is the generated token.)

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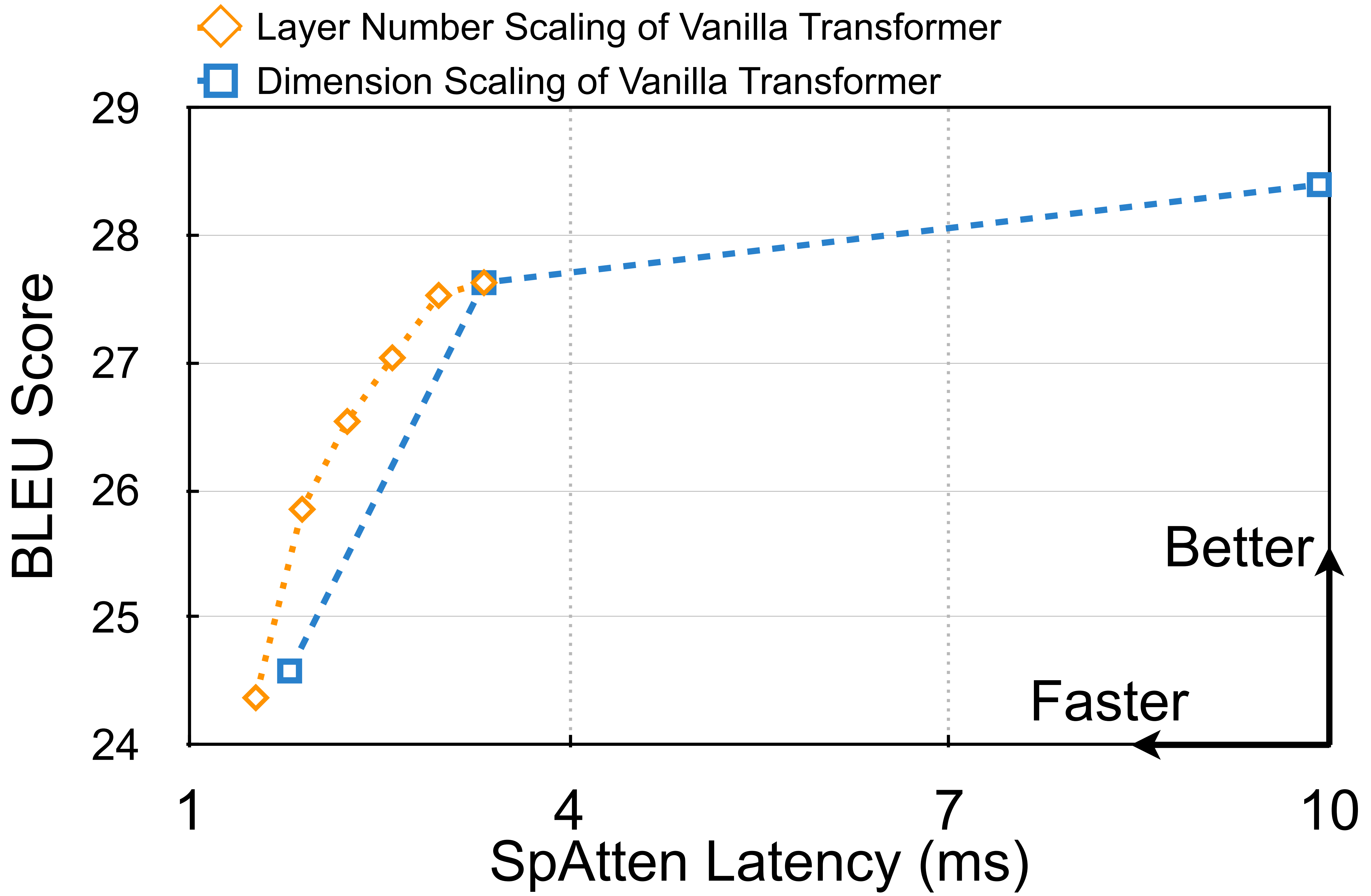
Du translate into → English

Specialized Model for SpAtten with HAT: Hardware-Aware Transformer NAS

- HAT: Hardware-Aware Transformer NAS is a framework to search for most suitable model for a target hardware



*Hanrui Wang, et al. "HAT: Hardware-aware transformers for efficient natural language processing." *ACL*, 2020.

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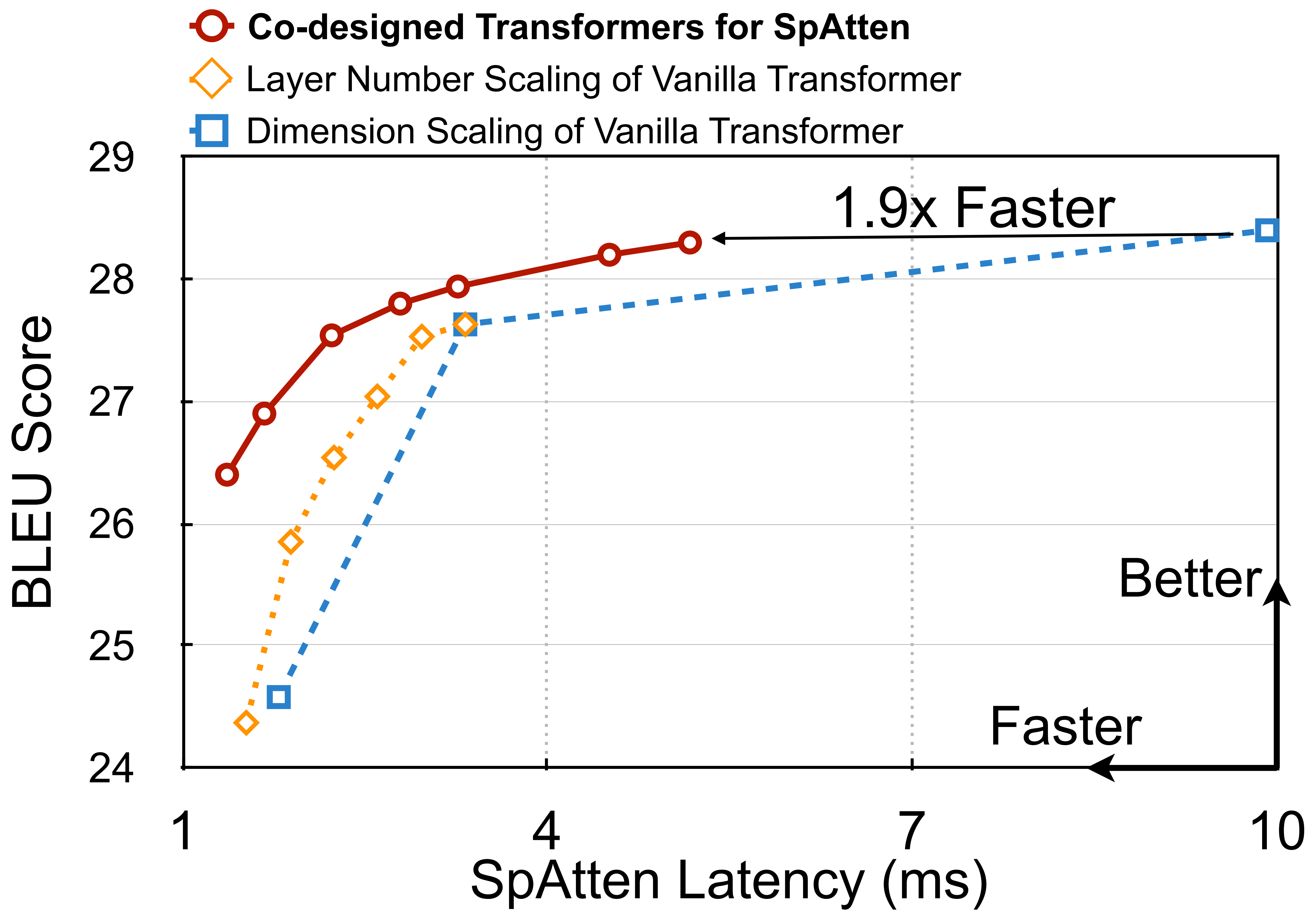

- The co-designed specialized model for SpAtten can be **1.9x faster** than vanilla model

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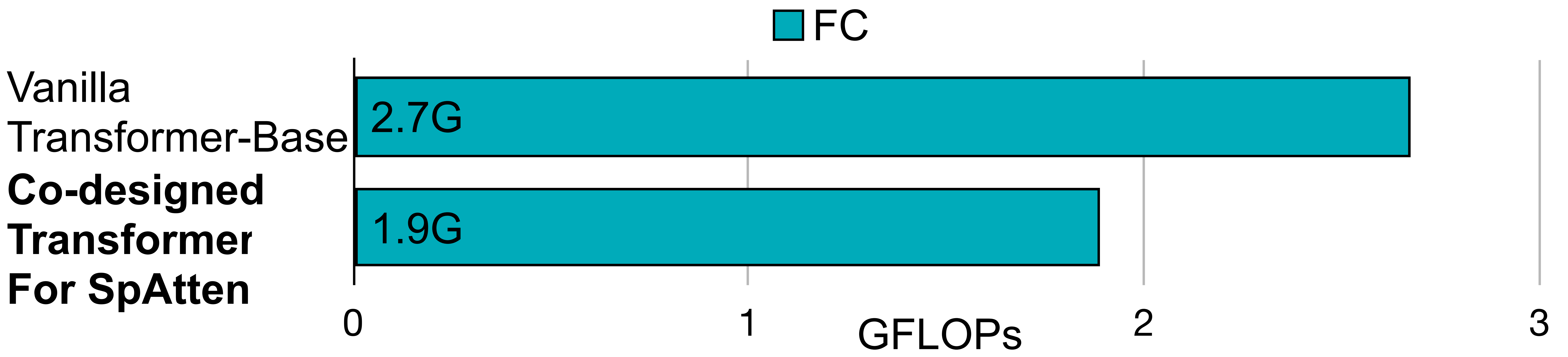

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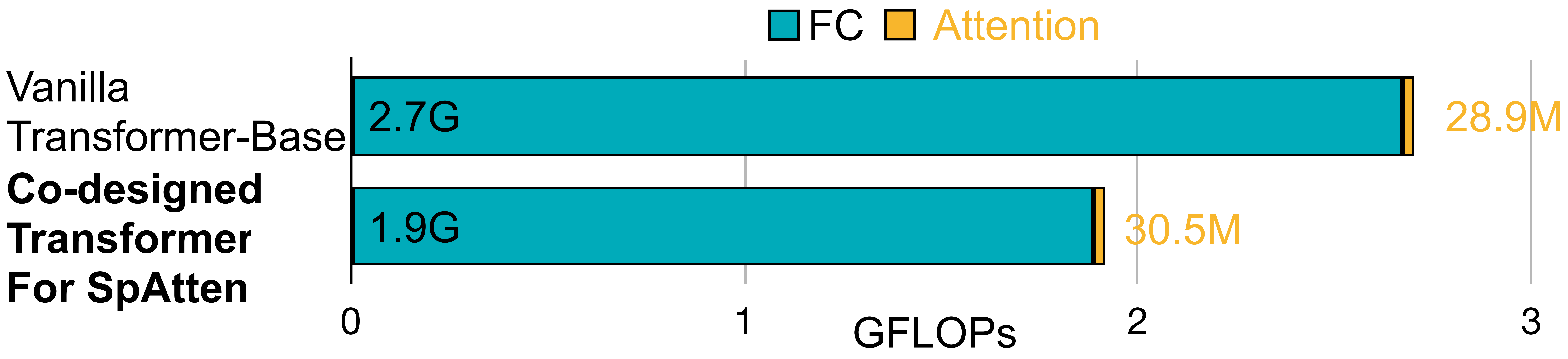

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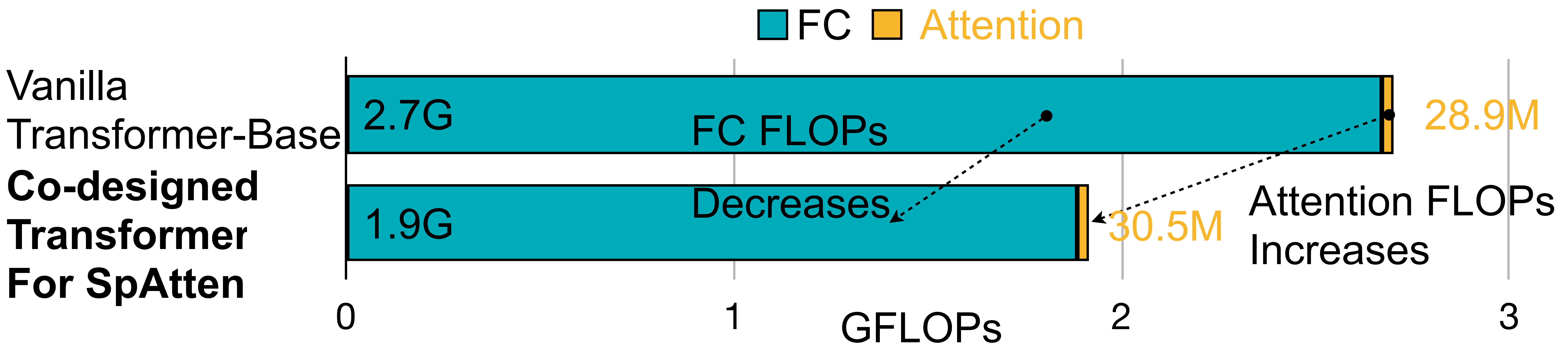

- SpAtten is good at processing attention layers

*Hanrui Wang, et al. "HAT: Hardware-aware transformers for efficient natural language processing." *ACL*, 2020.

Outline

- Quick Overview
- Background
- Algorithmic Optimizations
- Hardware Architecture
- Evaluation
- Conclusion

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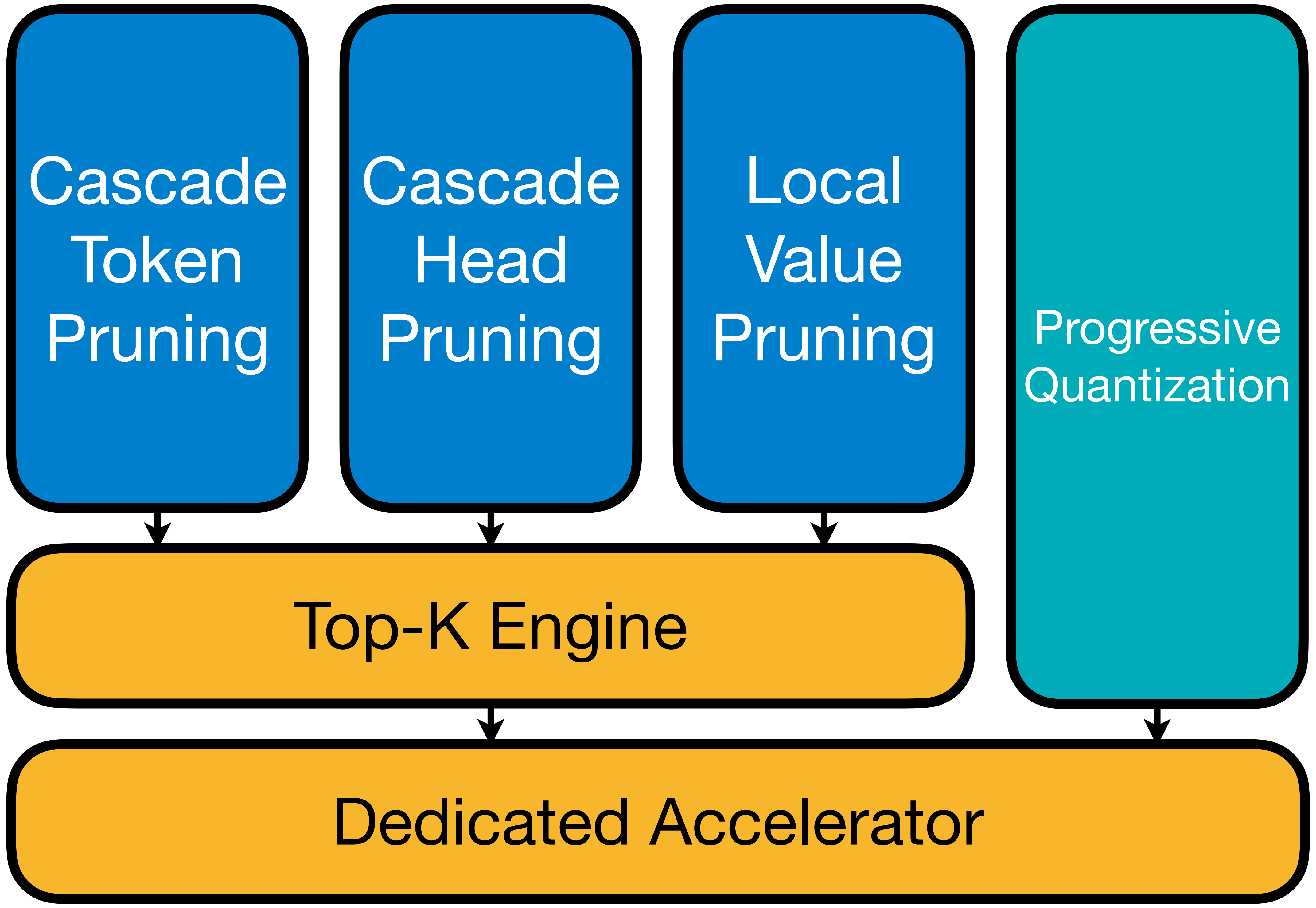
SpAtten: Sparse Attention Architecture

Pushing the frontier of Green AI and Tiny AI

- SpAtten accelerates NLP by removing **human language redundancy**
  - Cascade token/head pruning
  - Local value pruning
  - Progressive quantization
- Hardware accelerator
  - High-Parallelism Top-k engine
  - Specialized data path and operators



HPCA 2021 Live Q&A:
Session 1B
Mon. March 1, 10:40 EST

Thank you!