Twilight: Adaptive Attention Sparsity with Hierarchical Top-p Pruning

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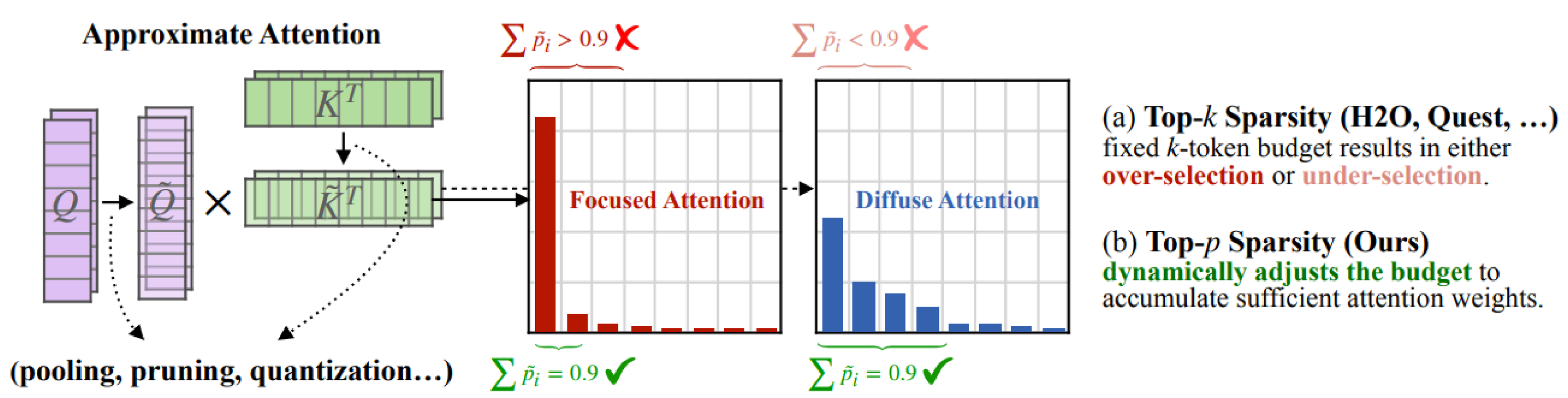
Introduction

- Top-k sparse attention accelerates long context LLM inference by saving memory loading costs.
- However, fixed budget can lead to over-selection or under-selection.
- We propose **Twilight**, a composable optimizer to accelerate any top-k sparse attention through hierarchical top-p pruning, making them efficient and budget-adaptive.



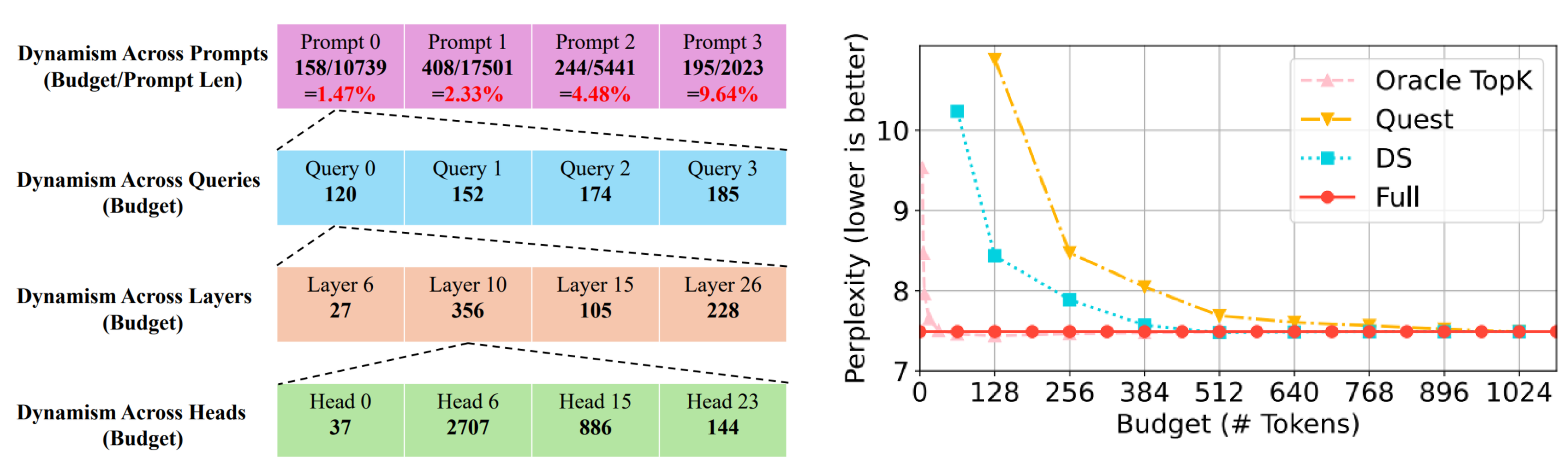
Top-k Sparse Attention for Long Context Large Language Model Inference

- For long context LLM inference, attention dominates the latency. Top-k sparse attention is proposed to save memory loading cost.

Definition 3.2 (Oracle Top-k Sparse Attention). Given the budget B,

$$\mathcal{I} = \arg\max_{\mathcal{I}} \sum_{i \in \mathcal{I}} \mathbf{W}[i] \quad \text{s.t. } |\mathcal{I}| = B$$

- However, the best budget (a.k.a, k) choices are dynamic.
- The main challenge of top-k sparse attention is to find a universally applicable budget to all scenarios.



The best budget choices vary dynamically across different levels.

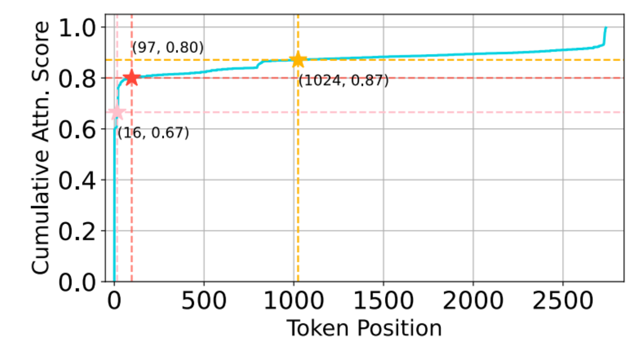
Bringing Top-p Sampling to Sparse Attention

- The core reason for budget dynamism is the dynamic nature of the attention weight distributions at runtime.
- Inspired by nucleus sampling, we propose **top-p sparse attention**.

Definition 3.3 (Oracle Top-p Sparse Attention). Given the threshold p,

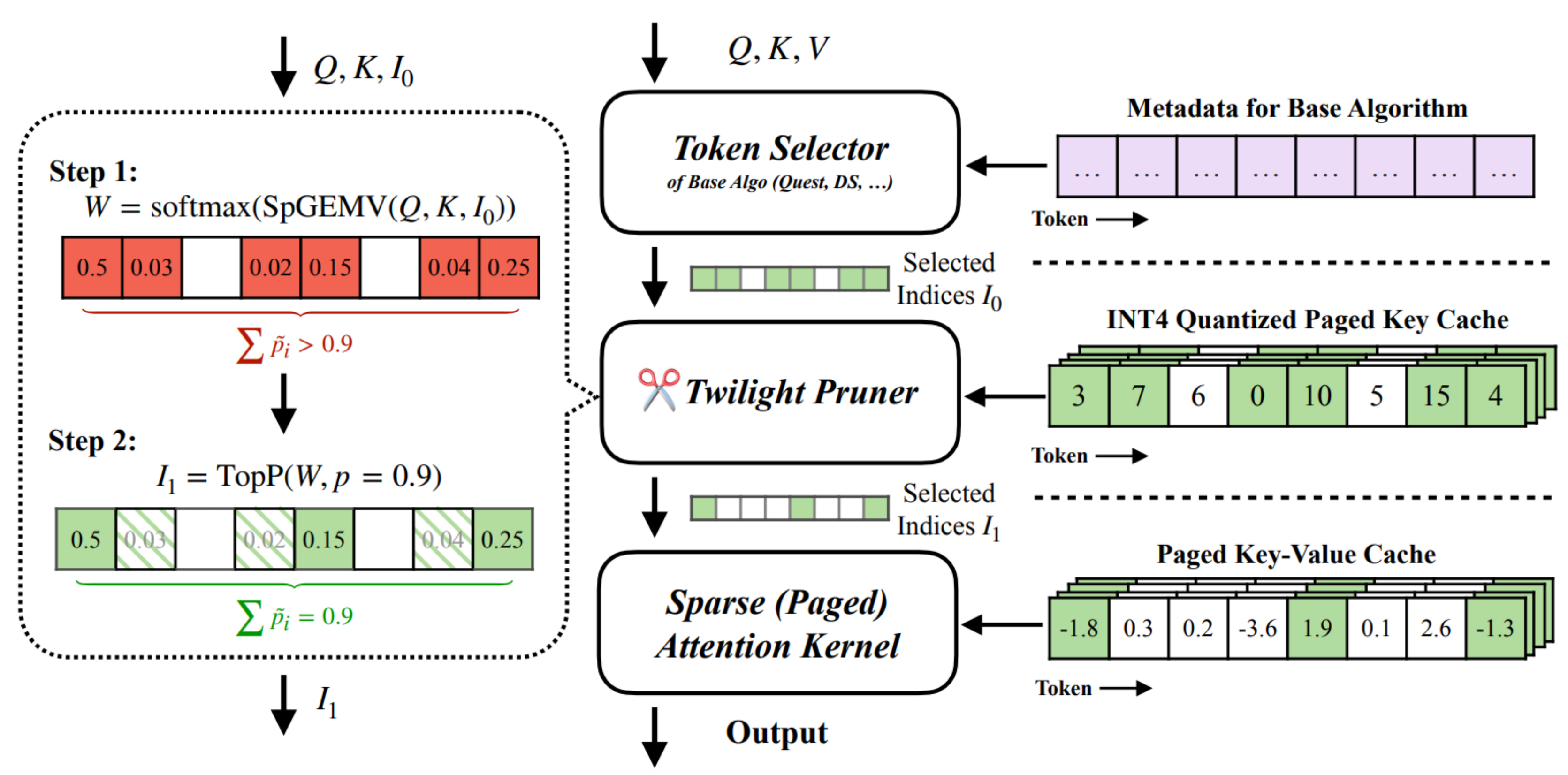
$$\mathcal{I} = \arg\min_{\mathcal{I}} |\mathcal{I}| \quad \text{s.t. } \sum_{i \in \mathcal{I}} \mathbf{W}[i] \geq p$$

- Top-p efficiently uses minimal budget to achieve the error requirement, thus achieving adaptive sparsity.



Twilight Design

- Twilight adopts a hierarchical **Select-then-Prune** architecture to accelerate existing sparse attention methods.



- Three **key kernel optimizations** to accelerate Twilight Pruner:
  1) Efficient SpGEMV with 4-bit Quantization of Key Cache.
  2) Efficient Sorting-Free Top-p via Binary Search.
  3) Load Balancing Attention Kernel with Awareness of Head Dynamism and GQA adaption.

Accuracy Evaluation

- Twilight achieves nearly no accuracy loss on three medium-context benchmarks and two long-context benchmarks (LongBench, RULER).

Table 2: Average scores on 12 different tasks from Longbench. We report relative error changes (improvement or degradation) when integrating Twilight with each base algorithm. Detailed results are in Table 5 in Appendix C.

	Budget	Longchat-7B -v1.5-32k	LLaMA-3.1-8B -Instruct
Full	32k	36.78	52.01
	Twilight	38.52 (+4.7%)	51.64 (-0.7%)
MagicPIG	K=8, L=75	-	51.70
	K=10, L=150	-	51.32
Quest	256	31.26	38.20
	1024	36.85	47.79
	4096	37.33	50.79
	8192	37.10	51.44
	Twilight	38.04 (+2.5%)	51.57 (+0.3%)
DS	256	35.32	45.74
	1024	35.96	49.43
	4096	36.31	50.98
	8192	36.62	51.14
	Twilight	**38.71** (+5.7%)	**51.73** (+1.2%)

Table 3: Average scores on RULER.

	Budget	16k	32k	64k	96k	Avg.
Full	100%	92.88	89.42	85.17	85.23	88.18
	Twilight	93.13	89.10	84.64	83.10	87.49
MagicPIG	K=8, L=75	92.22	**89.37**	84.07	82.58	87.06
	K=10, L=150	91.38	88.20	83.34	82.02	86.23
Quest	4%	79.35	79.8	78.64	73.22	77.75
	8%	87.31	83.06	80.82	75.28	81.62
	Twilight	91.53	87.97	84.12	**82.96**	86.65
DS	4%	92.04	88.11	84.43	82.56	86.79
	8%	92.89	88.70	84.39	82.72	87.18
	Twilight	**93.54**	89.24	**85.91**	82.81	**87.88**

Table 4: Results on 3 medium-context benchmarks.

	GSM8K(flexible/strict)↑	COQA(em/f1)↑	PG-19 Perplexity↓
	LLaMA-2-7B-Chat		
Full	0.2290/0.2282	0.5935/0.7511	7.503
Quest	0.0523/0.0508	0.5710/0.7425	14.15
DS	0.2191/0.2190	0.5855/0.7401	7.622
Twilight	**0.2153/0.2115**	**0.6088/0.7642**	**7.600**
(Twilight Avg. Budget)	90.82	91.86	102.58
	LLaMA-3.1-8B-Instruct		
Full	0.7726/0.7475	0.6363/0.7882	7.490
Quest	0.3639/0.3533	0.6007/0.7554	19.00
DS	0.6194/0.6027	**0.6455/0.7964**	7.967
Twilight	**0.7771/0.7604**	0.6325/0.7869	**7.529**
(Twilight Avg. Budget)	112.40	86.85	110.98

Efficiency Evaluation

- Speedup on self-attention operator compared to FlashInfer and Quest without Twilight.

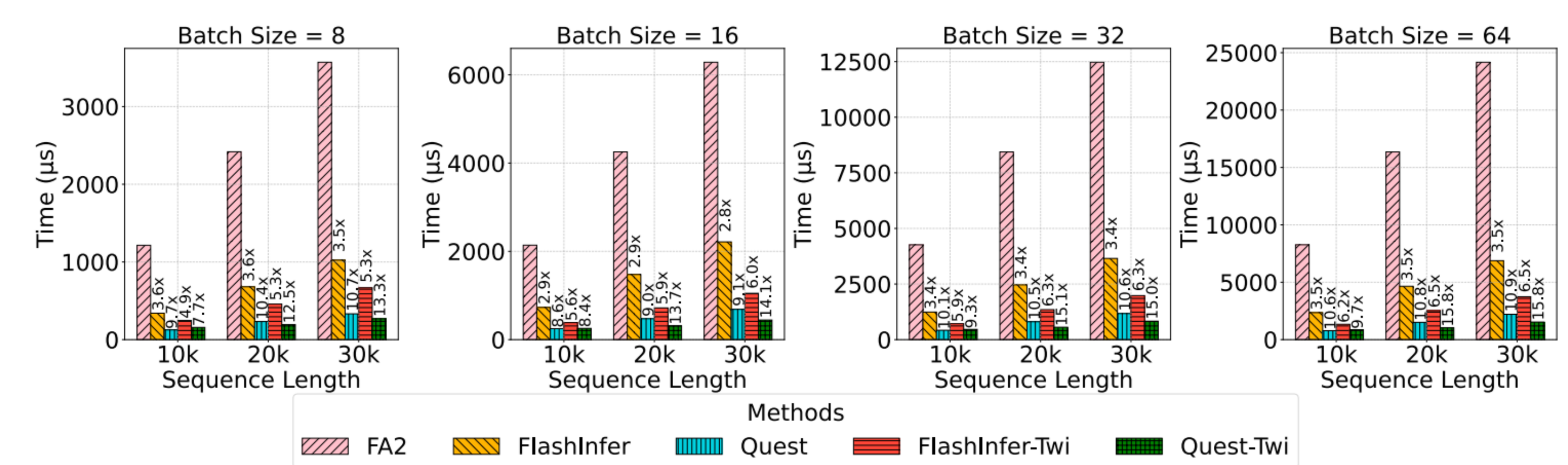
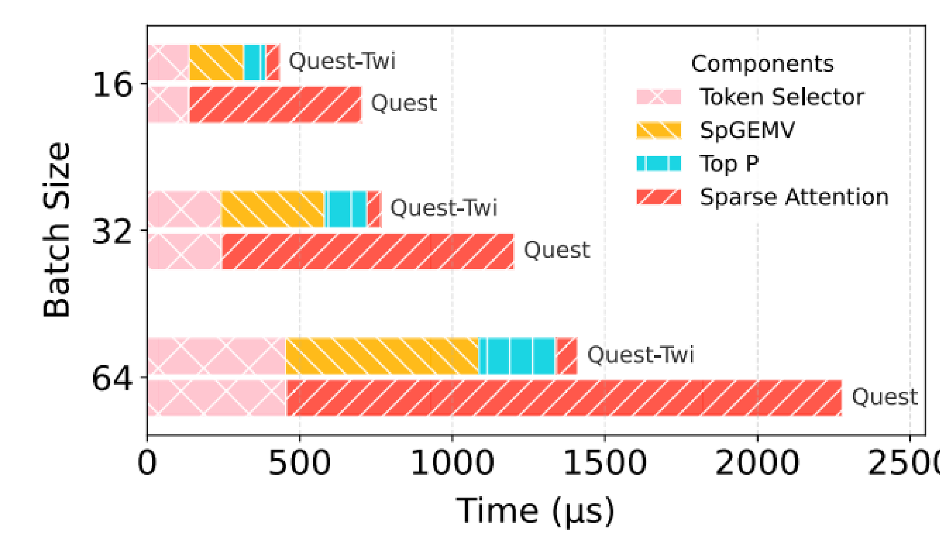


Figure 7: Latencies and speedups of self-attention at different sequence lengths and batch sizes.

- Latency breakdown of Quest with Twilight.



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