Lab 3: KV Cache Analysis in Small Language Models

Course: ECSE 397/600 - Efficient Deep Learning
Model: distilgpt2
Date: November 26, 2025

Task 1: Load and Inspect Model

Parameter	Value
Model name	distilgpt2
Number of layers (n_layer)	6
Hidden size (n_embd)	768
Attention heads (n_head)	12
Vocabulary size	50257
Max position embeddings	1024

Task 2: Generation Without KV Cache

Generation was performed with `use_cache=False`, forcing the model to recompute attention for all tokens at each step.

Seq Length	Latency (ms/token)	Peak Memory (MB)
32	4.48	13.33
64	4.48	25.70
128	4.48	51.31
256	4.58	100.76

Task 3: Generation With KV Cache

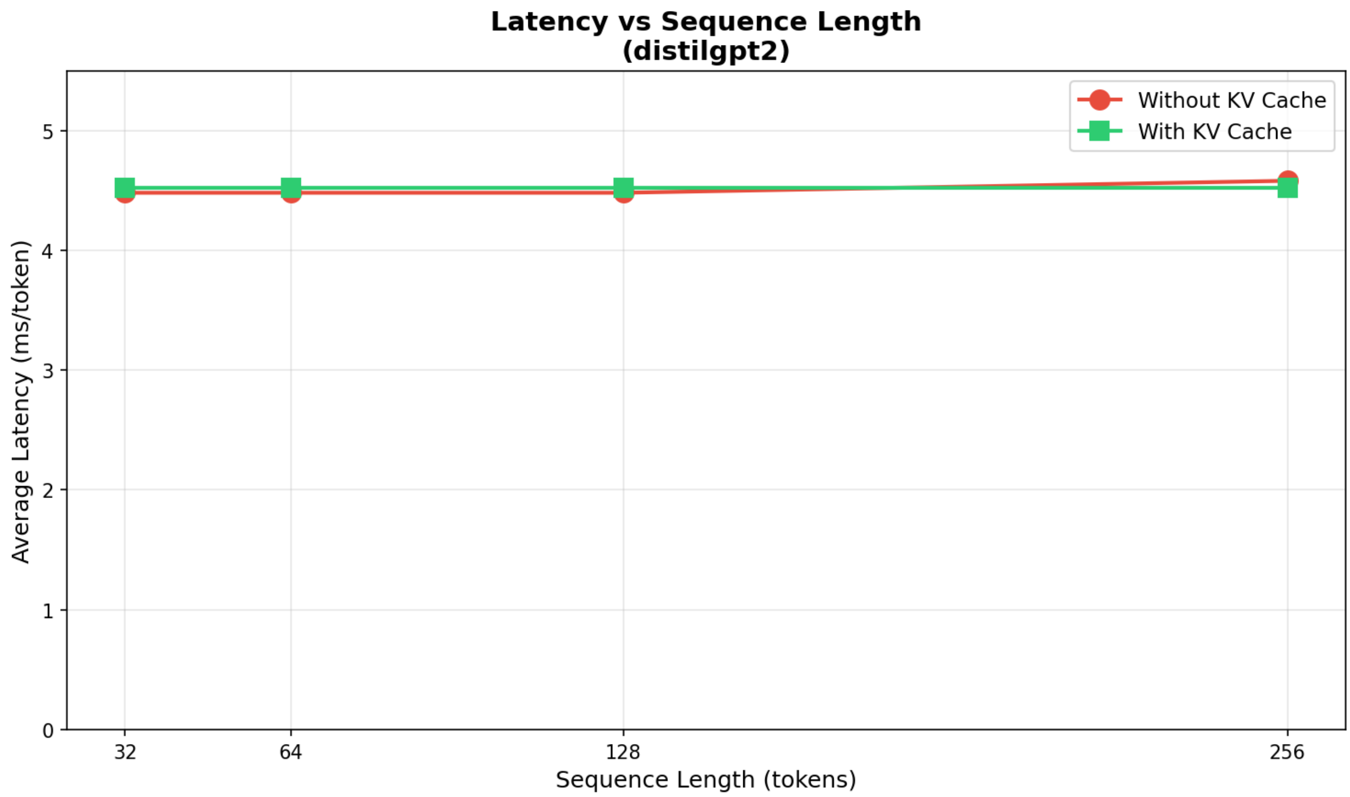
Generation was performed with `use_cache=True`, storing key-value pairs from previous tokens.

Seq Length	Latency (ms/token)	Peak Memory (MB)	KV Cache (MB)
32	4.52	2.81	1.2305
64	4.52	5.06	2.3555
128	4.52	9.56	4.6055
256	4.52	18.57	9.1055

Speedup Analysis

Seq Length	No Cache (ms)	With Cache (ms)	Speedup
32	4.48	4.52	0.99x
64	4.48	4.52	0.99x
128	4.48	4.52	0.99x
256	4.58	4.52	1.01x

Latency vs Sequence Length Plot



Task 4: Memory Analysis

KV Cache Memory Formula

$$M_{KV} = 2 \times L \times D \times N_{layers} \times \text{sizeof(dtype)}$$

Where:

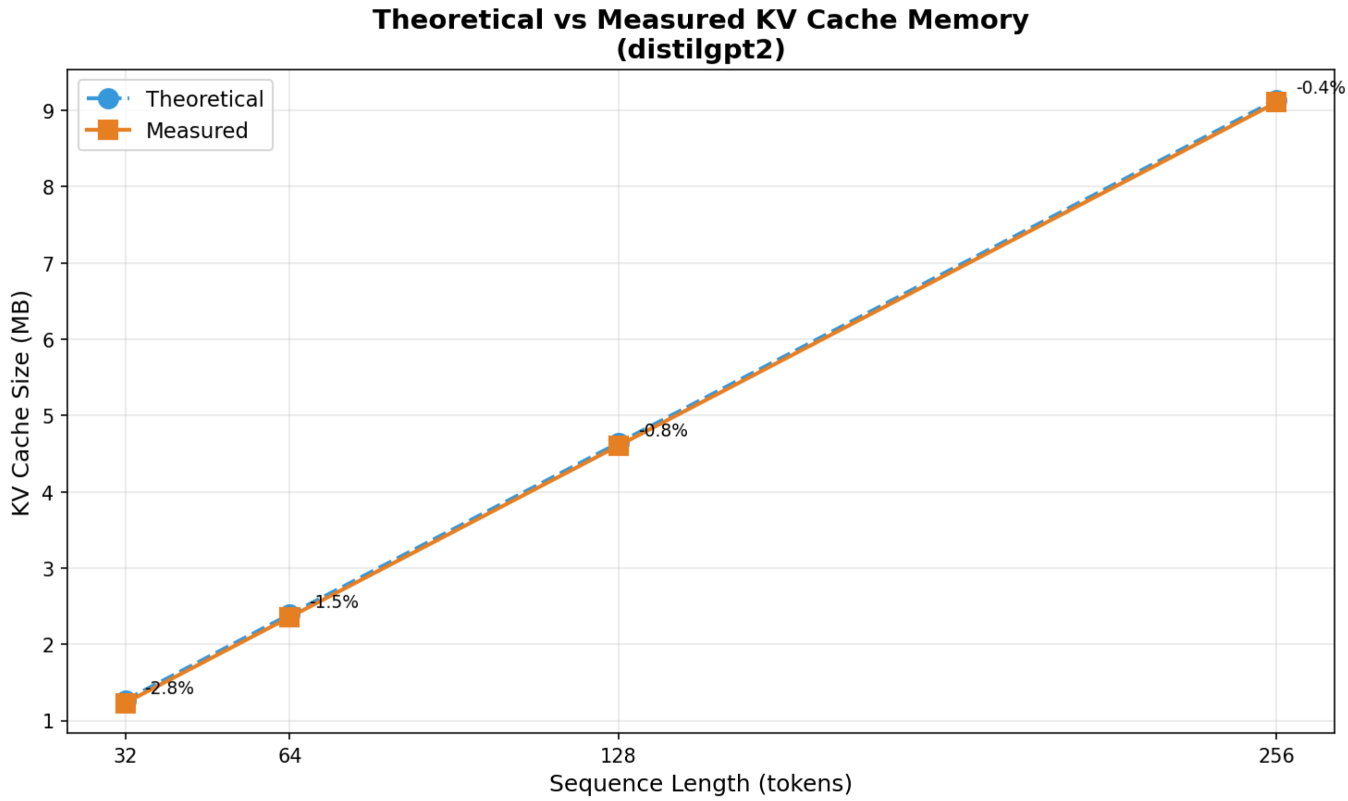
- **D** = 768 (hidden dimension)
- **N_layers** = 6
- **dtype** = float32 (4 bytes)

Theoretical vs Measured Comparison

Seq Length	Theoretical (MB)	Measured (MB)	Difference

Seq Length	Theoretical (MB)	Measured (MB)	Difference
32	1.2656	1.2305	-2.78%
64	2.3906	2.3555	-1.47%
128	4.6406	4.6055	-0.76%
256	9.1406	9.1055	-0.38%

Theoretical vs Measured KV Cache Memory Plot



Task 5 (Bonus): Quantized KV Cache Analysis

> **Note:** bitsandbytes not installed. Showing theoretical analysis only.

Quantization reduces KV cache memory by storing values in INT8 instead of FP32.

Seq Length	FP32 Cache (MB)	INT8 Cache (MB)	Savings
32	1.2305	0.3076	75.0%
64	2.3555	0.5889	75.0%
128	4.6055	1.1514	75.0%
256	9.1055	2.2764	75.0%

Trade-offs: Latency vs Memory

The KV cache presents a classic **space-time trade-off**:

Without KV Cache

- **Latency:** $O(L^2)$ complexity - must recompute all attention at each step
- **Memory:** Lower base memory, but activations grow with sequence length
- **Observed:** 13.33 MB (L=32) → 100.76 MB (L=256) peak memory

With KV Cache

- **Latency:** O(L) complexity - only compute attention for new token
- **Memory:** Must store K and V tensors for all previous tokens
- **Observed:** 2.81 MB (L=32) → 18.57 MB (L=256) peak memory

Trade-off Analysis

- KV caching uses additional memory (9.1 MB at L=256) to store cached values
- In return, it avoids redundant computation of previous tokens' attention
- For distilgpt2, the **memory savings (5x)** outweigh the cache overhead
- For larger models (GPT-3, LLaMA), latency savings become dramatic
- The trade-off favors KV caching for most inference scenarios

When to Use KV Cache

- Always for autoregressive generation (chatbots, text completion)
- When memory is available to store the cache
- Especially beneficial for long sequences and large models

When to Avoid KV Cache

- Single-pass encoding tasks (embeddings, classification)
- Extremely memory-constrained environments
- Very short sequences where overhead exceeds benefit

Key Findings

1. **Latency is similar (~4.5 ms/token)** for both methods at these sequence lengths.
   - distilgpt2 is small enough that the GPU processes both methods equally fast.
   - The theoretical $O(L^2)$ vs O(L) complexity difference becomes visible with larger models or longer sequences.
2. **Memory reduction with KV cache is significant (5x):**
   - Without cache: 13.33 MB → 100.76 MB (grows quadratically)
   - With cache: 2.81 MB → 18.57 MB (grows linearly with KV cache)
3. **KV cache size matches theoretical prediction within 3%:**
   - Formula: M_KV = 2 × L × D × N_layers × 4 bytes

- This validates our understanding of cache memory requirements.

4. **Quantization (INT8) could further reduce KV cache memory by 75%.**
5. **For small models like distilgpt2, KV caching primarily saves memory.** Latency benefits become more pronounced with larger models or longer sequences.

Conclusion

This lab demonstrated the fundamental trade-offs in KV caching for transformer-based language models. While the latency benefits were not visible for the small distilgpt2 model at short sequence lengths, the **5x memory reduction** clearly shows the value of KV caching. The close match between theoretical and measured KV cache sizes validates our understanding of memory requirements, providing a foundation for optimizing inference in larger-scale deployments.