ECE 277: GPU Programming Final Project Presentation

CUDA-Accelerated GPT-2 Inference Optimization

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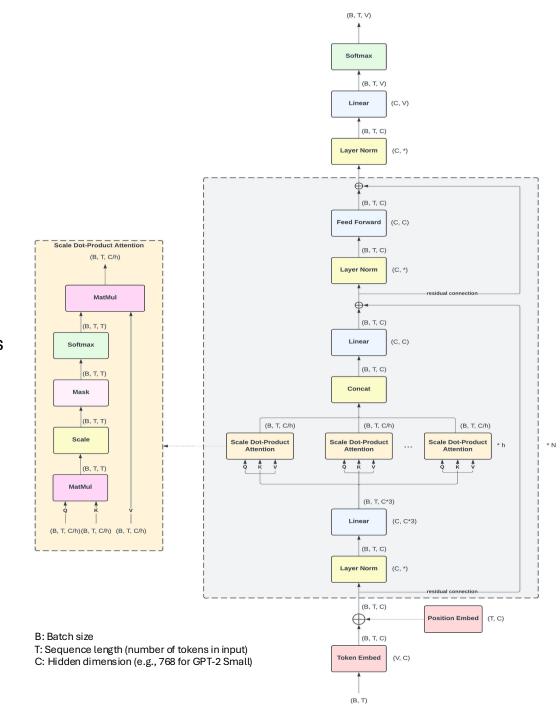
Problem statement

What is GPT-2?

- A transformer-based language model for natural language processing tasks.
- It is used for text generation, summarization and other NLP tasks
- GPT-2 inference is computationally expensive operation.
- Latency issues for real-time applications.

• Goal:

- Accelerate key computations with GPU for real-time performance.
- Focus on optimizing performance-critical components:
 - 1. Layer Norm
 - Softmax
 - 3. Attention



1.Layer Norm

A technique that normalizes the inputs across the feature dimension within a layer to stabilize training and improve convergence.

Each thread processes a subset of the array.

```
global
void layernorm kernel(float* out, float* x, float* w, float* b, int C){
int idx = threadIdx.x; //Thread indexing
float mean = 0;
shared float s mean[256]; //Shared memory allocation
shared float s var[256]; //Shared memory allocation
s mean[idx] = 0.0f;
s var[idx] = 0.0f;
syncthreads();
for(int i = idx;i<C;i+=blockDim.x){</pre>
s_mean[idx] += x[i];
syncthreads();
if(idx == 0){
float m = 0;
for(int i = 0;i<blockDim.x;i++){</pre>
m += s mean[i];
m /= C;
s mean[0] = m;
syncthreads();
```

Each thread accumulates partial sums for mean and stores them in shared memory(s_mean).

These partial sums are reduced to compute the overall mean.

```
	ext{LayerNorm}[x] = rac{x - 	ext{E}[x]}{\sqrt{	ext{Var}[x] + \epsilon}} * \gamma + eta,
```

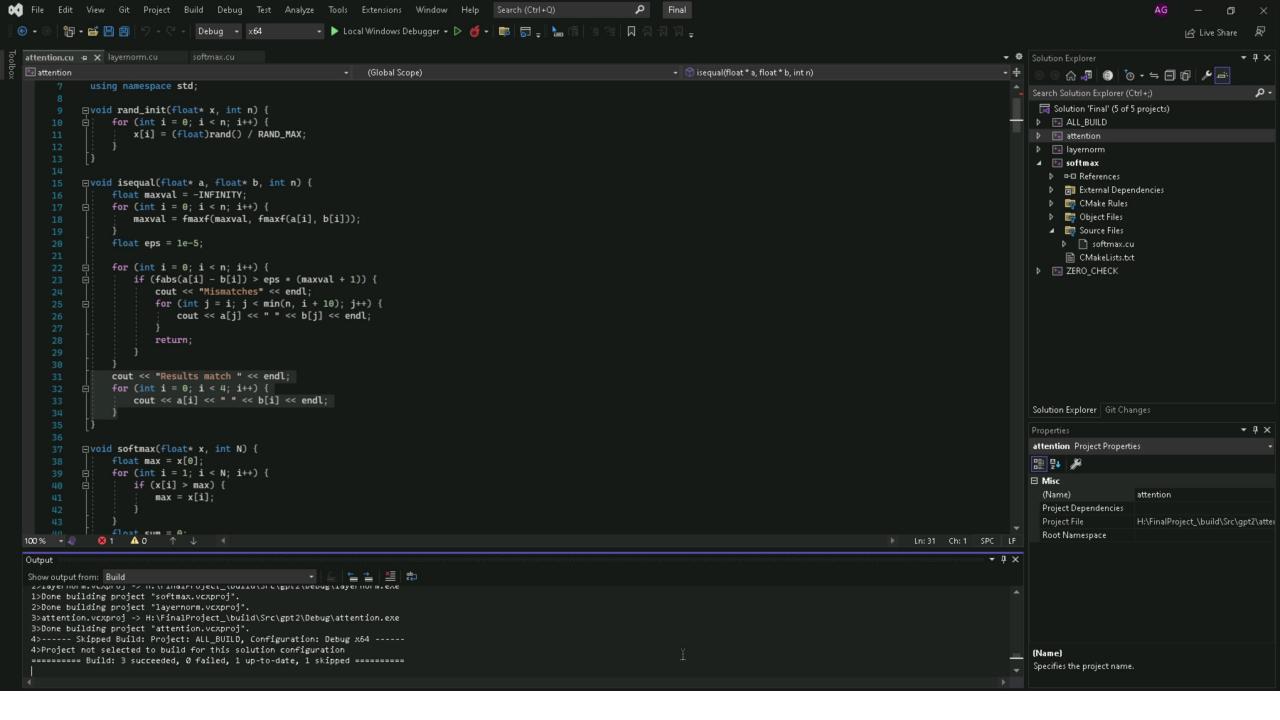
```
mean = s mean[0];
for(int i = idx;i<C;i+=blockDim.x){</pre>
float diff = x[i] - mean;
s var[idx] += diff * diff;
 syncthreads();
if(idx == 0){
float v = 0;
for(int i = 0;i<blockDim.x;i++){</pre>
v += s var[i];
v /= C;
s var[0] = v;
syncthreads();
float var = s var[0];
float scale = 1.0 / sgrt(var + 1e-6);
for(int i = idx;i<C;i+=blockDim.x){</pre>
out[i] = (x[i] - mean) * scale * w[i] + b[i];
```

Each thread accumulates partial variance for variance and stores them in shared memory(s_var).

These partial variance are reduced to compute the overall variance.

Each thread normalizes its portion of x, applies scaling (w), and adds the bias (b), writing the result to out.

```
void layernorm_gpu(float* out, float* x, float* w, float* b, int C){
int numThreads = 256;
int block = 1;
layernorm_kernel<<<block,numThreads>>>(out,x,w,b,C);
}
```



2.Softmax

Each thread processes a subset of the array.

```
__global__ void softmax kernel(float* x, int N) {
int idx = threadIdx.x; //Thread indexing
__shared__ float smax[1024]; //Shared memory allocation
__shared__ float ssum[1024]; //Shared memory allocation
smax[idx] = -FLT MAX;
ssum[idx] = 0.0f;
syncthreads();
for (int i = idx; i < N; i += blockDim.x) {
smax[idx] = fmaxf(smax[idx], x[i]);
syncthreads();
if (idx == 0) {
float maxval = -FLT MAX;
for (int i = 0; i < blockDim.x; i++) {
maxval = fmaxf(maxval, smax[i]);
smax[0] = maxval;
__syncthreads();
```

Each thread computes a partial maximum using **strided access** within the loop. And stores them in shared memory(**s_max**).

Reduction in shared memory for the global maximum.

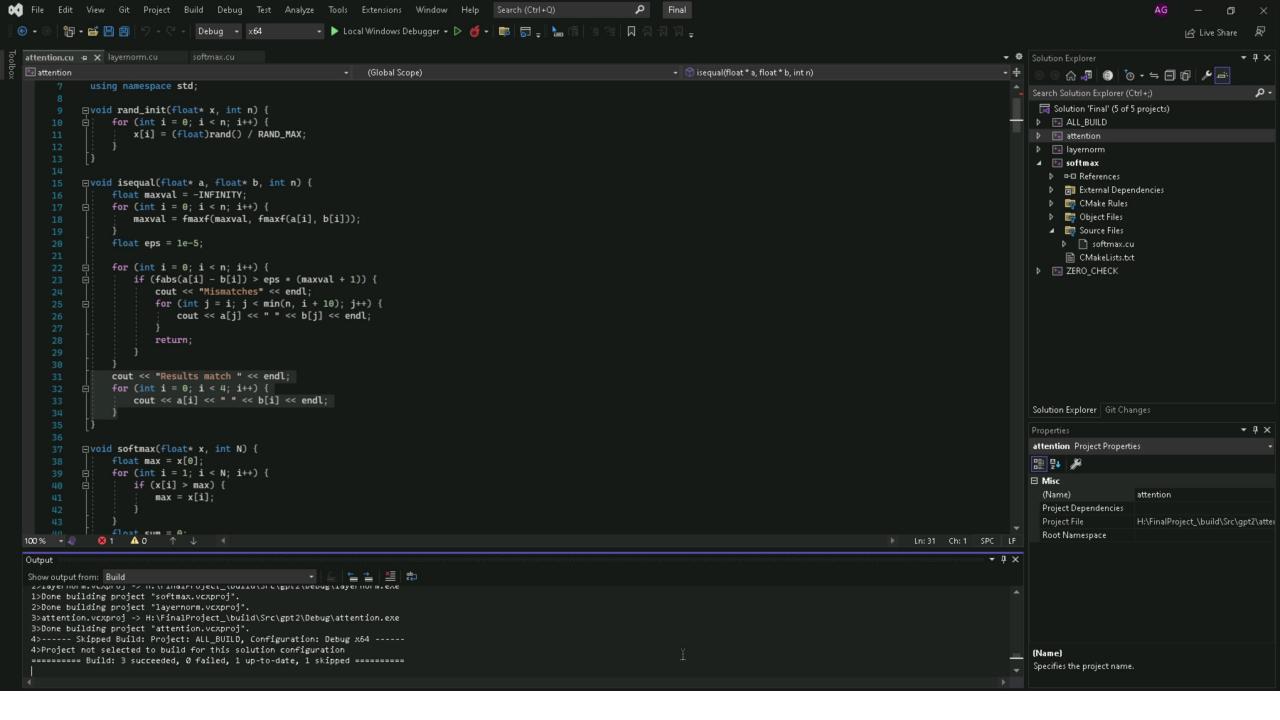
```
\operatorname{softmax}(x_i) = rac{e^{x_i}}{\sum_{j=1}^N e^{x_j}}
```

```
float maxval = smax[0];
float local sum = 0.0f;
for (int i = idx; i < N; i += blockDim.x) {</pre>
x[i] = expf(x[i] - maxval);
local sum += x[i];
ssum[idx] = local sum;
__syncthreads();
if (idx == 0) {
float sum = 0.0f;
for (int i = 0; i < blockDim.x; i++) {
sum += ssum[i];
ssum[0] = sum;
syncthreads();
float sum = ssum[0];
for (int i = idx; i < N; i += blockDim.x) {
x[i] /= sum;
void softmax gpu(float* x, int N) {
int numThreads = 1024;
softmax kernel<<<1, numThreads>>>(x, N);
```

Threads compute exp(x[i] - maxval) for their segment. Local sums stored in shared memory.

Thread 0 accumulates partial sums into the global sum.

Threads divide their computed exponentials by the global sum.



3. Attention Block

• The attention mechanism helps models focus on the most relevant parts of the input sequence when generating output.

1. Head Size Calculation:

• Compute head_size = C / NH to divide the total number of features (C) evenly across the attention heads (NH).

2. Key and Value Cache Population:

- The fill_cache kernel reorganizes keys and values from the qkv tensor into key_cache and value_cache.
- This cache is reshaped to ensure memory coalescing for subsequent attention calculations.

3. Attention Score Computation: $att = q * K^T$

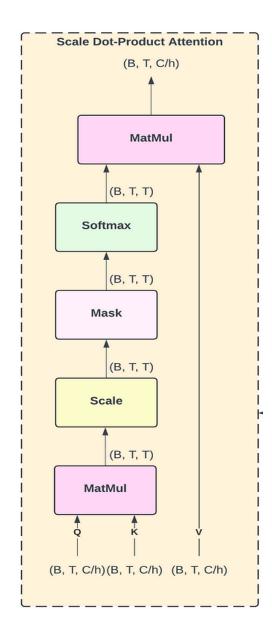
- The compute_att_kernel computes the dot product of the query vector (q) with the key matrix (K^T) for each head.
- Threads are parallelized across the time steps (T) and attention heads (NH).

4. Softmax Normalization:

- The softmax_kernel normalizes the attention scores in-place to ensure they sum to 1.
- Employs warp-level reductions (warpReduceMax and warpReduceSum) for efficient summation and normalization.

5. Weighted Sum (Attention * Value):

• The compute_out_kernel computes the weighted sum of the values (V) based on the normalized attention scores (att) to produce the output tensor (out).



Cuda optimization techniques used

Memory Coalescing

- Fill Cache Kernel: Rearranges keys and values into a layout that enables coalesced memory access during attention computation.
- Access patterns are aligned for efficient global memory reads and writes.

Parallelism

- Each CUDA block handles one attention head.
- Threads within a block handle computations for time steps (TTT) or head size (HSHSHS).

Warp-Level Primitives

- Softmax Kernel: Utilizes __shfl_sync for warp-level reductions to compute max and sum values efficiently.
- Reduces latency for operations like summation and normalization.

Shared Memory Usage

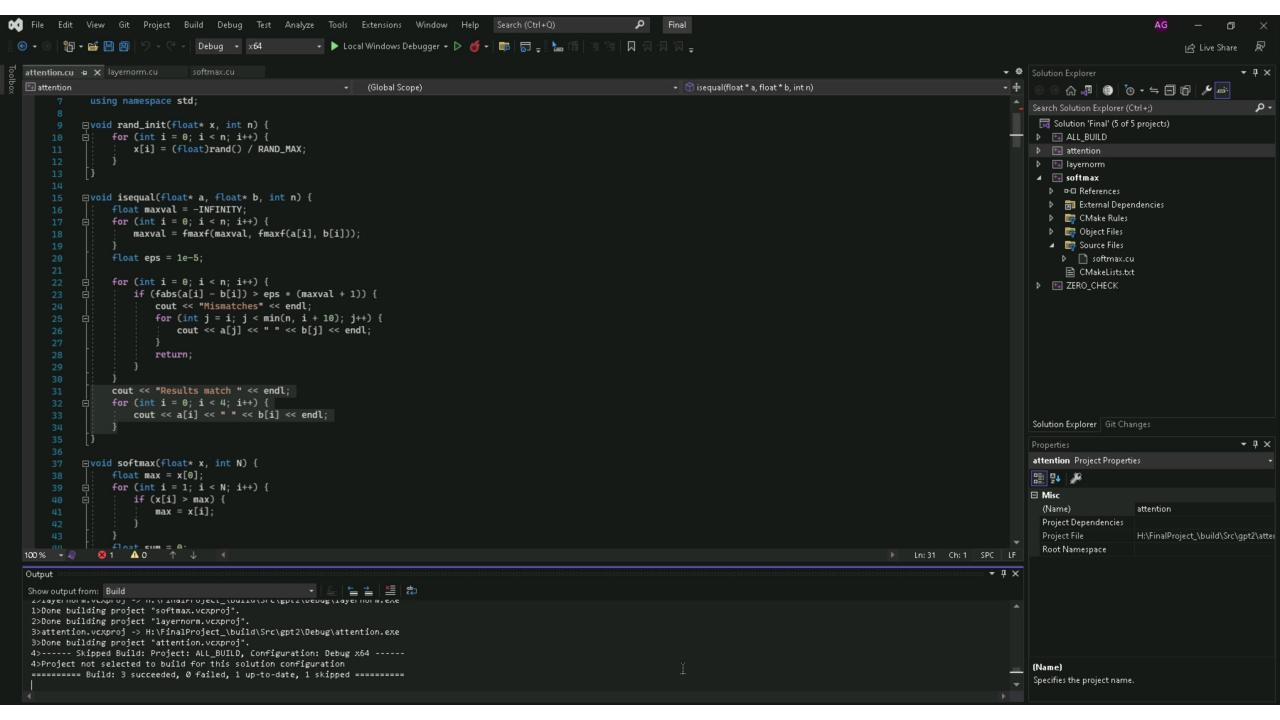
- Softmax Kernel: Uses shared memory for intermediate storage of max and sum values.
- Reduces global memory transactions, improving speed.

Loop Unrolling

 Dot Product and Weighted Sum Kernels: Loops over head size and sequence positions are unrolled to maximize instruction-level parallelism.

Thread Count Management

- Caps threads per block at 1024 to comply with hardware constraints.
- Dynamically adjusts the number of threads for sequence positions (pos) and head size (HS).



Performance Bench Marking

	Layer-Norm	Softmax	Attention
CPU	0.0072ms	2.1551ms	5.4209ms
GPU	0.3502ms	1.6969ms	1.4694ms

Thank you!

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