

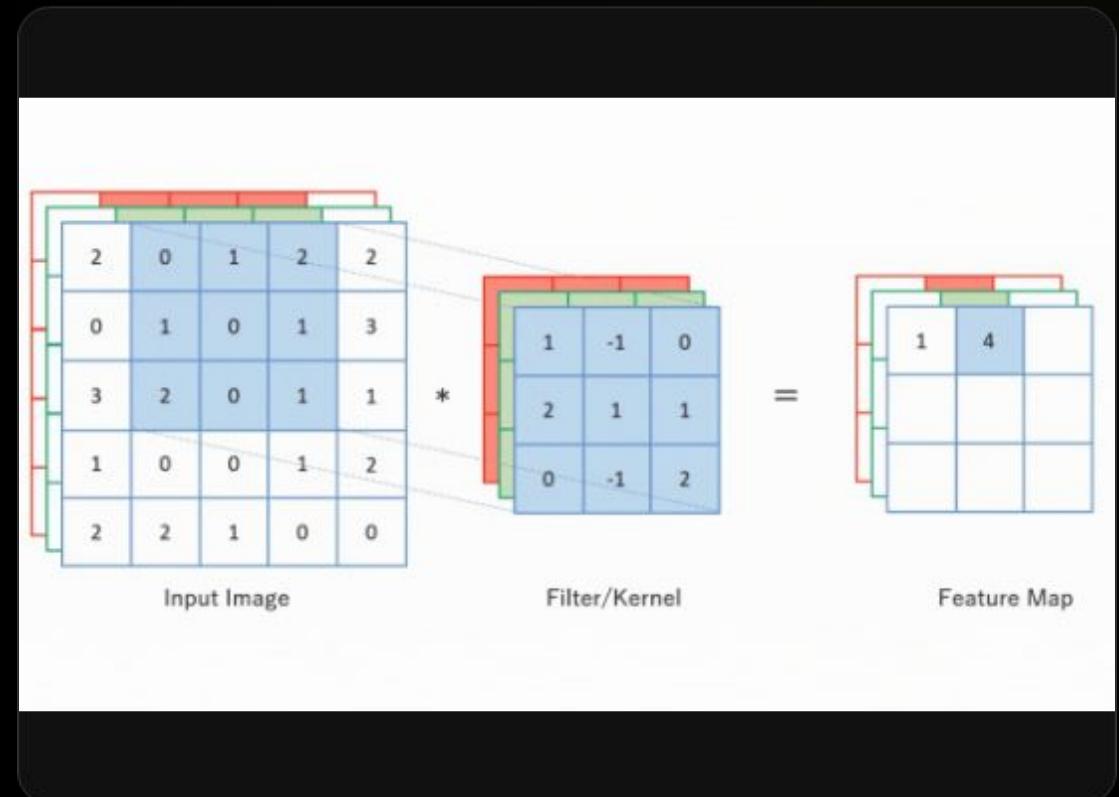
Parallel 2D Convolution for Deep Learning

High-Performance Computing using MPI

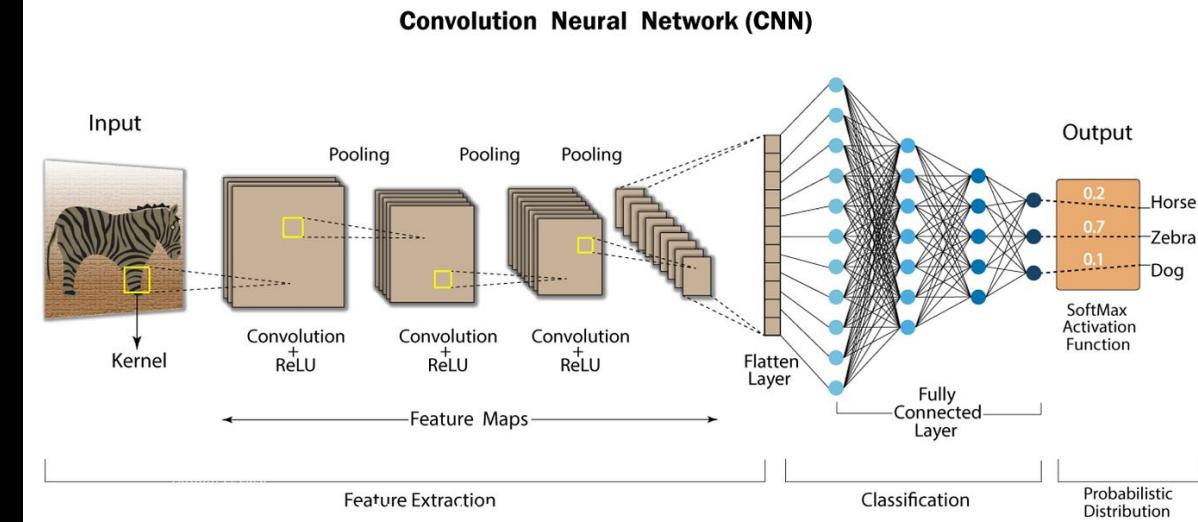
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The Computational Bottleneck

- **Massive Workload:** Convolutional Neural Networks (CNNs) rely on sliding thousands of filters over high-resolution images.
- **Serial Latency:** Standard CPU execution performs these operations sequentially, leading to $O(N^2)$ complexity.
- **Training Delay:** This bottleneck makes training large modern AI models prohibitively slow on single nodes.



What I did :)



The Bottleneck: Training modern AI models using CNNs is slow because the math operation behind it is a 2D Convolution which takes massive computing power and runs often $O(N^2)$ time, creating a major time bottleneck

The Solution: I implemented a Filter Parallelism using MPI message passing interface to divide the workload across multiple computers in the hpc cluster instead of relying on a single processor to do the task

The Strategy: Instead of splitting the image into parts, I distributed the thousands of *filters* so each processor works separately which eliminated more communication overhead during the computing task

The Result: By utilizing my strategy and solution I achieved a 3.5x speedup on the Nova cluster. THis proves that this method effectively scales deep learning tasks across distributed memory systems

MPI Strategy: Filter Parallelism



1. Distribute

The root process uses **`MPI Bcast`** to send the full image and **`MPI Scatterv`** to divide the 128 filters among workers



2. Compute

Each worker then computes the convolution on its own subset of filters separately



3. Collect

Root process uses **`MPI Gatherv`** to assemble the resulting feature maps into the final output tensor

Implementation Details

Language: C++ (Compiled with mpic++)

Optimization: I used flat 1D arrays to maximize the cache locality and memory throughout

Verification: I implemented a verification step that compares the parallel outputs that I run against a serial baseline to ensure that it runs accurately

Environment: I tested and benchmarked it on the nova HPC cluster like we have done in class.

```
1 #include <iostream>
2 #include <vector>
3 #include <chrono>
4 #include <cmath>
5 #include <random>
6 #include <mpi.h>
7
8 //different sizes to test with
9 const int IMAGE_HEIGHT = 1024;
10 const int IMAGE_WIDTH = 1024;
11 //the total number of filters
12 const int K_FILTERS = 128;
13 const int FILTER_HEIGHT = 5;
14 const int FILTER_WIDTH = 5;
15
16 //this calculates the sizes output sizes along with the image and filter size
17 const int OUTPUT_HEIGHT = IMAGE_HEIGHT - FILTER_HEIGHT + 1;
18 const int OUTPUT_WIDTH = IMAGE_WIDTH - FILTER_WIDTH + 1;
19 const int IMAGE_SIZE = IMAGE_HEIGHT * IMAGE_WIDTH;
20 const int FILTER_SIZE = FILTER_HEIGHT * FILTER_WIDTH;
21 const int OUTPUT_MAP_SIZE = OUTPUT_HEIGHT * OUTPUT_WIDTH;
22
23
24 //this performs a 2D convolution on one image with one filter. All data is in flat 1D vectors for the performance
25
26 std::vector<double> serial_convolution_single(const std::vector<double>& image,
27                                                 const std::vector<double>& filter)
28 {
29     std::vector<double> output_map(OUTPUT_MAP_SIZE);
30
31     //This loops over output map rows
32     for (int y = 0; y < OUTPUT_HEIGHT; ++y) {
33         //This loops over output map cols
34         for (int x = 0; x < OUTPUT_WIDTH; ++x) {
35
36             double sum = 0.0;
37             //This loops over filter rows
38             for (int j = 0; j < FILTER_HEIGHT; ++j) {
39                 //This loops over filter cols
40                 for (int i = 0; i < FILTER_WIDTH; ++i) {
41
42                     sum += image[y * IMAGE_WIDTH + j] * filter[i * FILTER_SIZE + j];
43
44                 }
45             }
46
47             output_map[y * OUTPUT_WIDTH + x] = sum;
48         }
49     }
50
51     //this stops the timer and verify
52     MPI_Barrier(MPI_COMM_WORLD);
53     double p_end = MPI_Wtime();
54
55     if (world_rank == 0) {
56         double parallel_time = p_end - p_start;
57         double serial_time = std::chrono::duration<double>{
58             std::chrono::high_resolution_clock::now() -
59             std::chrono::high_resolution_clock::now()
60         }.count();
61
62         //this gets serial time
63         auto start = std::chrono::high_resolution_clock::now();
64     }
65
66     //printing out for the terminal for verification
67     if (world_rank == 0) {
68         double parallel_time = p_end - p_start;
69         std::cout << "\nParallel Run Time: " << parallel_time << " seconds." << std::endl;
70
71         std::cout << "\nVerifying results..." << std::endl;
72         if (verify(serial_output, parallel_output)) {
73             std::cout << "Verification: SUCCESS! Serial and Parallel outputs match." << std::endl;
74         } else {
75             std::cout << "Verification: FAILED! Outputs do not match." << std::endl;
76         }
77     }
78
79     MPI_Finalize();
80     return 0;
81 }
```

Code Snippets

I implement the 2D convolution algorithm in which I use nested loops to slide a single filter over the image and calculate the dot product for each pixel

Than I establish a performance benchmark by running all convolutions sequentially on the root processor and timing the process to see how long it takes without parallelization

Than I sets up the parallel environment by broadcasting the image data to all cores ensuring every worker has the necessary input to perform its task

I also calculate how to divide the filters among the available cores load balancing determining exactly which chunk of filters each specific processor will be responsible for computing

```
133 //this is parallel execution
134 //this starts timer for parallel run
135 MPI_Barrier(MPI_COMM_WORLD);
136 double p_start = MPI_Wtime();
137
138 //this is the broadcast image and the non root process has to allocate the space before the broadcast
139 if (world_rank != 0) {
140     | image.resize(IMAGE_SIZE);
141 }
142 MPI_Bcast(image.data(), IMAGE_SIZE, MPI_DOUBLE, 0, MPI_COMM_WORLD);
143
144 //this is how many filters each rank gets
145 std::vector<int> counts(world_size);
146 std::vector<int> displs(world_size);
147
148 int base_chunk = K_FILTERS / world_size;
149 int remainder = K_FILTERS % world_size;
150 int current_displ = 0;
151
152 for (int i = 0; i < world_size; ++i) {
153     counts[i] = base_chunk + (i < remainder ? 1 : 0);
154     displs[i] = current_displ;
155     current_displ += counts[i];
156 }
157
158 //each of the ranks needs to know their local number of filters
159 int local_k = counts[world_rank];
160
161 std::vector<int> counts_bytes(world_size);
162 std::vector<int> displs_bytes(world_size);
163
164 //for scattering the filters
165 for (int i = 0; i < world_size; ++i) {
166     counts_bytes[i] = counts[i] * FILTER_SIZE;
167     displs_bytes[i] = displs[i] * FILTER_SIZE;
168 }
169
170
171 //this is serial baseline so it runs on the root
172 if (world_rank == 0) {
173     std::cout << "\nRunning serial baseline on root..." << std::endl;
174     auto start = std::chrono::high_resolution_clock::now();
175
176     std::vector<double> current_filter(FILTER_SIZE);
177
178     for (int k = 0; k < K_FILTERS; ++k) {
179         //this copies the k th filter from the flat array
180         std::copy(all_filters.begin() + k * FILTER_SIZE,
181                  all_filters.begin() + (k + 1) * FILTER_SIZE,
182                  current_filter.begin());
183
184         //this runs convolution for this single filter
185         std::vector<double> one_map = serial_convolution_single(image, current_filter);
186
187         //this copies the result into the full serial output tensor
188         std::copy(one_map.begin(), one_map.end(),
189                  serial_output.begin() + k * OUTPUT_MAP_SIZE);
190     }
191
192     auto end = std::chrono::high_resolution_clock::now();
193     std::chrono::duration<double> diff = end - start;
194     std::cout << "Serial Baseline Time: " << diff.count() << " seconds." << std::endl;
195 }
```

Performance Results

```
--- Parallel 2D Convolution ---
```

```
Running with 16 processes.
```

```
Image: 1024x1024
```

```
Filters: 128 (5x5)
```

```
Running serial baseline on root...
```

```
Serial Baseline Time: 2.31388 seconds.
```

```
Parallel Run Time: 0.739325 seconds.
```

```
Verifying results...
```

```
Verification: SUCCESS! Serial and Parallel outputs match.
```

```
--- Parallel 2D Convolution ---
```

```
Running with 4 processes.
```

```
Image: 1024x1024
```

```
Filters: 128 (5x5)
```

```
Running serial baseline on root...
```

```
Serial Baseline Time: 1.93069 seconds.
```

```
Parallel Run Time: 1.03223 seconds.
```

```
--- Parallel 2D Convolution ---
```

```
Running with 1 processes.
```

```
Image: 1024x1024
```

```
Filters: 128 (5x5)
```

```
Running serial baseline on root...
```

```
Serial Baseline Time: 1.34274 seconds.
```

```
Parallel Run Time: 1.83391 seconds.
```

```
--- Parallel 2D Convolution ---
```

```
Running with 32 processes.
```

```
Image: 1024x1024
```

```
Filters: 128 (5x5)
```

```
Running serial baseline on root...
```

```
Serial Baseline Time: 1.57537 seconds.
```

```
Parallel Run Time: 0.520622 seconds.
```

```
Verifying results...
```

```
Verification: SUCCESS! Serial and Parallel outputs match.
```

- **Speedup:** The parallel implementation achieved a **3.5x speedup**, reducing the runtime from 1.83 seconds on a single core to just 0.52 seconds on 32 cores.
- **Scalability:** The performance graph shows a clear downward trend in execution time as the number of cores increases from 1 → 4 → 16 → 32, proving that the Filter Parallelism strategy effectively scales on the Nova cluster.
- **Overhead Analysis:** While the 1-core parallel run of 1.83 s was slightly slower than the serial baseline of 1.34s due to initial MPI communication overhead, this cost was quickly outweighed by the speed gains at 4 cores and beyond.
- **Accuracy:** Every parallel run that I did from 1 to 32 cores passed the verification step, producing results identical to the serial baseline within a certain tolerance to account for real world discrepancies.

Performance Results

As we can see the performance does a plateau which illustrates Amdahl's Law. In which the maximum speedup is constricted by the application's serial components and communication overhead. As core counts increase the non parallel bottlenecks prevent a linear scaling in performance which results in diminishing returns despite the additional hardware



*Achieved a **3.5x speedup**, reducing runtime from 1.83s to 0.52s by utilizing 32 cores.*

Final Understanding

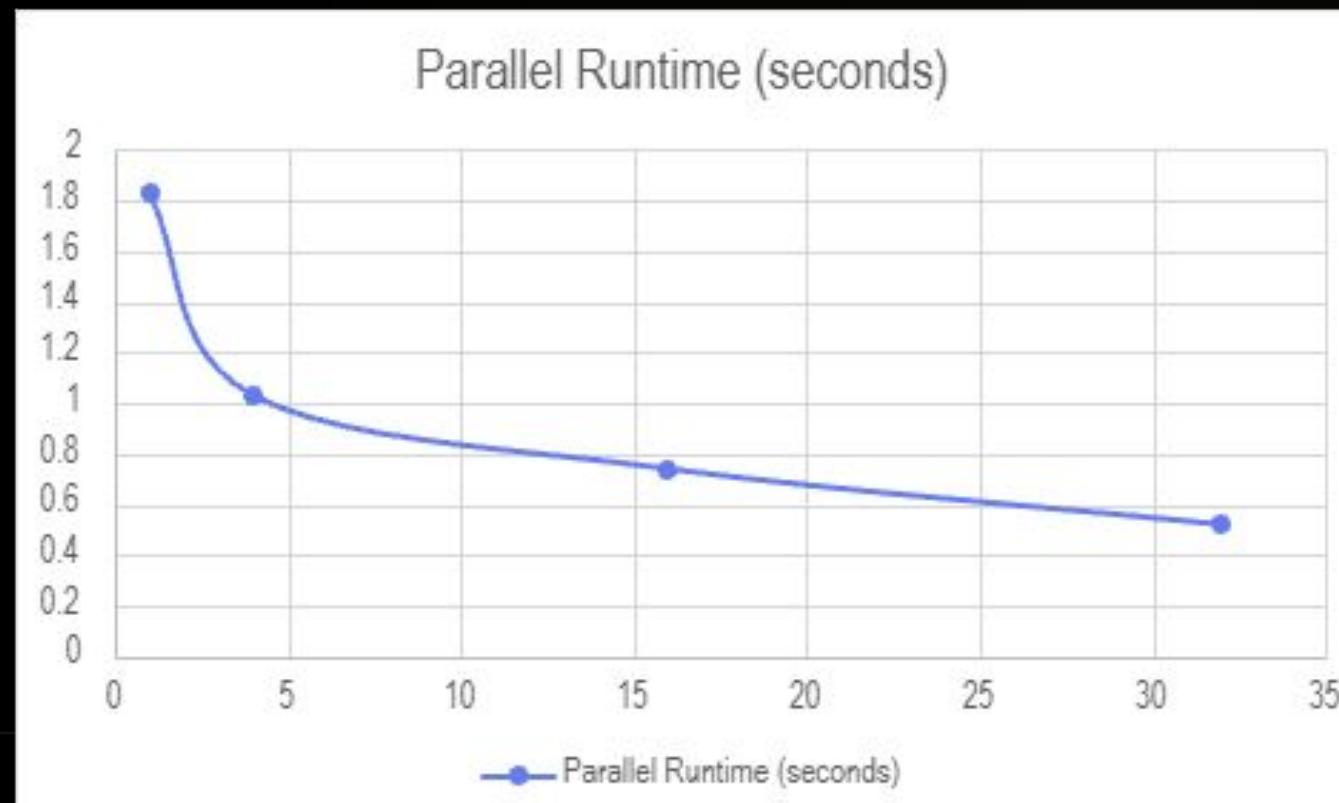
The data shows that as you increase the number of processor cores from 1 up to 32 the time it takes to complete the 2D Convolution task decreases significantly

The runtime drops from **1.83 seconds** using a single core down to **0.52 seconds** when using 32 cores.

While the process gets faster, it doesn't scale perfectly. Using 32 times the hardware (32 cores) results in a **3.52x speedup**, rather than being 32 times faster, likely due to the overhead of managing parallel tasks.

Diminishing Returns: The graph shows a steep drop in time initially between 1 and 4 cores, but the curve flattens out as you add more cores, meaning the efficiency gains become smaller at higher

Number of Cores	Parallel Runtime (seconds)	Speedup from Core 1
1	1.83	1x
4	1.03	1.77x
16	0.74	2.48x
32	0.52	3.52x



Questions?

Parallel 2D Convolution using MPI

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