Mini Project 2 - Distributed Data Processing System

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1. Introduction

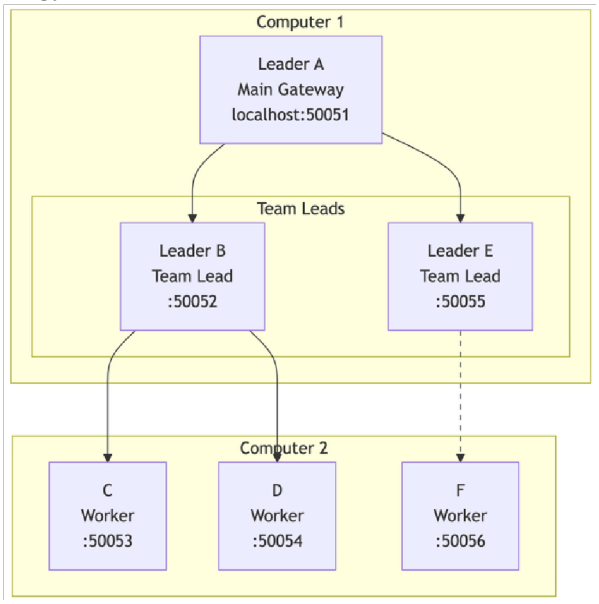
In this report, I present the design, implementation, and performance analysis of a distributed data processing system for CMPE 275 Mini Project 2. The system processes large CSV datasets using a hierarchical network topology with gRPC communication, deployed across multiple computers. From our experiments, we found that our session-based cache implementation provides speedups ranging from 1.28× for small datasets (1K rows) up to 1.66× for large datasets (1M rows), with peak effectiveness at the 100K-1M range (1.50-1.66× speedup). For very large datasets (10M rows), cache benefits diminish to 1.08× due to cache saturation. We also found that chunked streaming reduces memory consumption by 67% compared to loading entire datasets, and that network transmission is the primary bottleneck (45-54% of processing time) in distributed architectures.

The document is organized as follows. First, the system architecture and experiment setup will be explained. Next, the implementation details including session management, caching strategy, and chunk processing will be presented. Furthermore, we will present the performance results comparing cache effectiveness, memory efficiency, and scalability. Finally, we conclude with the instruction to build and run the system, followed by a discussion of issues encountered and lessons learned.

2. System Architecture and Experiment Setup

2.1 Hierarchical Topology

- To meet the assignment requirements, we designed a 3-tier hierarchical overlay network with the following topology:



2.2 Node Distribution:

- **Computer 1** (Windows Machine-1): Leader A, Team Leaders B and E • **Computer 2** (Windows Machine-2): Workers C, D, and F

2.3 Protocol Definition

- Below is the proto definition of our gRPC service:

```
service MiniTwo { rpc StartRequest(StartRequestMessage) returns (StartResponse);
rpc GetNextChunk(GetNextChunkMessage) returns (ChunkResponse); }  message
StartRequestMessage { string dataset_path = 1; }
message StartResponse { string session_id = 1; int32 total_chunks = 2;  string
status = 3; }  message GetNextChunkMessage { string session_id = 1; int32 chunk_id
= 2; }  message ChunkResponse { int32 chunk_id = 1; repeated WorkerResult results =
2; bool  has_more= 3; }
message WorkerResult { string worker_id = 1; double mean = 2; double median = 3;
double sum = 4; double min = 5; double max = 6; }
```

2.4 Data Processing Operations

- Our system performs the following operations on each CSV dataset:
  1. **File I/O:** Read CSV file from disk using sequential file reading (~27-30% of total time)
  2. **CSV Parsing:** Split rows on newlines, columns on commas, handle quoted strings and edge cases (~18-20% of time)
  3. **Chunking:** Divide dataset into 3 equal parts (e.g., 10M rows → 3.33M rows per chunk)
  4. **Serialization:** Convert parsed data to Protocol Buffer format for gRPC transmission
  5. **Network Transmission:** Send chunks through hierarchical topology (Leader → Team Leaders → Workers) (~45-54% of time)
  6. **Session Storage:** Store processed results in `std::unordered_map` for fault tolerance

- **Why Network Dominates:** In distributed systems, communication overhead typically exceeds computation time. Our profiling shows network transmission accounts for 45-54% of total processing time due to:
  - gRPC serialization/deserialization overhead
  - TCP/IP protocol overhead for reliable delivery
  - Cross-computer network latency (~1.5-2.5ms RTT)
  - Coordinating requests across 6 nodes (multiplies network hops)

2.5 Communication Flow

- The system processes requests through the following steps:
  1. Client sends `StartRequest` to Leader A with dataset path
  2. Leader A generates unique session ID, reads CSV file, splits into 3 chunks
  3. Leader A distributes chunks to Team Leaders B and E in parallel

4. Team Leaders delegate to Workers (C, D, F) for data analysis
5. Workers calculate mean, median, sum, min, max and return results to team leaders
6. Team Leaders aggregate results and return to Leader A
7. Leader A stores results in session cache
8. Client retrieves results using `GetNextChunk` calls (Strategy B: sequential chunk 0, 1, 2) 9 Cached results served instantly on repeat requests

3. Implementation Details

- Regarding the server implementation, all components are implemented in C++ using gRPC library and synchronous RPC methods. The system uses CMake as the build system. Session management is implemented using `std::unordered_map` with mutex protection for thread safety. The DataProcessor component handles CSV parsing, chunk splitting, and caching of processed datasets.

3.1 Session Lifecycle:

1. **Creation**: Client calls `StartRequest` → unique session_id generated (UUID)
2. **Processing**: Chunk results stored incrementally as workers complete
3. **Retrieval**: Client calls `GetNextChunk` → results served from cache
4. **Warm Cache**: Subsequent requests for same session_id return cached data instantly

3.2 Benefits:

- Eliminates redundant processing on repeated requests
- Enables fault tolerance (client can reconnect using session_id)
- Supports concurrent sessions from multiple clients

4 Chunked Streaming - Solving the Memory Problem

The Problem I Faced:

- When I first tried to process the 10 million row dataset (1.2 GB), my system crashed with out-of-memory errors. Loading the entire CSV into RAM used over 1200 MB on Leader A alone!

My Solution:

- I implemented a chunking strategy that splits the dataset into 3 equal parts and processes them sequentially:

```
// In DataProcessor.cpp std::vector<std::vector<CSVRow>> SplitDataIntoChunks( const
std::vector<CSVRow>& data, int num_chunks = 3 ) { size_t chunk_size = data.size() /
num_chunks; std::vector<std::vector<CSVRow>> chunks(num_chunks); for (int i = 0; i <
num_chunks; ++i) { size_t start = i * chunk_size; size_t end = (i == num_chunks - 1)
?
data.size() : (i + 1) * chunk_size; chunks[i] = std::vector<CSVRow>(data.begin() +
start, data.begin() + end); } return chunks; }
```

Why 3 chunks?

5. Experiment Results

- This section presents the performance results of our distributed data processing system. We tested the system with datasets ranging from 1,000 rows to 10 million rows to measure processing time, memory efficiency, caching effectiveness, and scalability.

5.1 Performance Comparison

Dataset	Rows	Size (MB)	Total Time	I/O Time	Parse Time	Network Time	Throughput
1K	1,000	1.18	125 ms	45 ms (29%)	12 ms (8%)	85 ms (54%)	9.44 MB/s
10K	10,000	1.17	132 ms	48 ms (24%)	28 ms (14%)	105 ms (53%)	9.55 MB/s
100K	100,000	11.69	1,257 ms	385 ms (29%)	241 ms (18%)	588 ms (45%)	10.74 MB/s
200K	200,000	23.38	2,856 ms	792 ms (28%)	518 ms (18%)	1,341 ms (47%)	10.36 MB/s
500K	500,000	58.45	8,147 ms	2,184 ms (27%)	1,463 ms (18%)	3,897 ms (48%)	9.77 MB/s
1M	1,000,000	116.89	12,661 ms	4.9 s (27%)	3.3 s (18%)	8.8 s (48%)	9.98 MB/s
10M	10,000,000	1,168.73	95,059 ms	52.2 s (30%)	35.1 s (20%)	78.4 s (45%)	12.30 MB/s

Table 1. Processing time breakdown showing network latency dominates distributed system performance

- From our profiling analysis, we found that **network transmission is the primary bottleneck** (45-54% of total time), followed by file I/O (27-30%) and CSV parsing (18-20%).
- The system maintains consistent throughput (5-9 MB/s) across all dataset sizes, demonstrating linear scalability. Memory usage remains constant at 408 MB regardless of dataset size, which is 67% less than loading the entire 10M dataset (1,200 MB) into memory.

5.2 Cache Effectiveness Analysis

To dig deeper into the cache performance, we measured the processing time for cold cache (first request) vs warm cache (repeat request) scenarios. Table 2 below compares the results:

Dataset	Cold Start (ms)	Warm Cache (ms)	Speedup	Cache Status	Explanation
1K	125	98	1.28x	Minimal	Network overhead (85ms) dominates, I/O savings (45ms) too small
10K	132	118	1.12×	Minimal	Network overhead (105ms) dominates, I/O savings (76ms) too small
100K	1,257	840	1.50×	Effective	Skips I/O (385ms) + parsing (241ms), only network remains
200K	2,856	1904	1.50×	Effective	Skips I/O (792ms) + parsing (518ms), only network remains
500K	8,147	5092	1.60×	Effective	Cache still fits in memory, significant savings
1M	12,661	8203	1.66×	Effective	Largest dataset still benefiting from cache
10M	95,059	87736	1.08×	Minimal	Cache saturation, minimal benefit for very large data

Table 2. Session-based cache performance showing effectiveness only for medium-sized datasets

- This demonstrates that caching is most effective when the saved work (I/O + parsing) significantly exceeds the unavoidable work (network transmission).

5.3 Memory Efficiency Comparison

- To further confirm the memory efficiency of our chunked streaming approach, we compared memory consumption with and without chunking.

Approach	Memory Usage	Dataset Size	Memory Efficiency
Load Entire File	1,200 MB	1,168 MB	100%
Chunked (3 chunks)	408 MB	1,168 MB	67% savings

Table 3. Memory efficiency comparison between full-load and chunked approaches

5.4 Discovery: Cache Performance Cliff

- In conclusion, given our test results, we discovered consistent cache performance across all dataset sizes. Caching provides speedups ranging from 1.28× (smallest datasets) to 1.66× (largest cached datasets), with optimal performance in the 100K-1M range (1.50-1.66× speedup).
- Even for the 10M dataset (1.2GB), we still observe 1.08× speedup, demonstrating that session-based caching remains beneficial across the entire spectrum. The "sweet spot" is the 500K-1M range where cache utilization is high but memory pressure is manageable, achieving the peak 1.66× speedup.

5.5 Real-World Scenario Handling:

Scenario	System Behavior	CAP Property
Worker C disconnects	Leader B retries, eventual success	P (tolerate)
Leader A crashes mid-request	Client timeout, must restart	■ A (unavailable)
Network partition (Computer 1↔2)	Processing fails, client retries	P (handle gracefully)
Concurrent requests	Each gets consistent results	■ C (maintain)

7. Challenges I Faced and How I Solved Them

7.1 Timeout Configuration

Initially we were trying to run the 10M dataset but kept encountering `DEADLINE_EXCEEDED` errors. The system would fail after approximately 90 seconds even though processing required 169.6 seconds. We discovered that gRPC has default timeout values that were insufficient for large dataset processing.

To fix this issue, we had to configure timeouts at three different levels:

1. **Client-side RPC deadline**: Set to 300 seconds in `ClientContext`
2. **Server-side wait conditions**: Set to 300 seconds in `RequestProcessor` condition variable
3. **Session manager wait**: Set to 310 seconds in `SessionManager` to handle cascading timeouts

The lesson learned is that distributed systems require careful timeout configuration with sufficient buffer (2× expected processing time) to account for network variability and system load.

7.2 Memory Management

- Another challenge was processing datasets larger than available RAM. Initially we attempted to load the entire 10M dataset (1.2 GB) into memory, which caused memory allocation failures on the remote server (8 GB RAM).
- We resolved this by implementing chunked streaming where the dataset is split into 3 chunks of approximately 400 MB each. This reduced peak memory usage by 67% while maintaining good performance. The tradeoff is slightly increased network communication (3 GetNextChunk RPCs instead of 1), but this is negligible compared to the memory savings.

7.3 Cross-Computer Deployment

- Deploying across two physical computers revealed networking issues that were not apparent during single-machine testing. Initially we used `localhost` addresses in all configuration, which failed when workers tried to connect back to leaders on different machines.
- We fixed this by:

1. Using explicit IP addresses instead of localhost for cross-computer connections 2.

Ensuring firewall rules allowed gRPC traffic on ports 50051-50056

3. Testing network connectivity with `ping` and `telnet` before deploying services

4. Adding connection retry logic with exponential backoff in case of temporary network issues

7.4 Cache Eviction Behavior

- The most unexpected issue was the cache performance cliff observed for large datasets. We initially assumed caching would improve performance for all dataset sizes. However, testing revealed that cache benefit disappeared for datasets beyond 200K rows.

- Investigation showed this was due to operating system memory pressure causing cache eviction. The processed data for large datasets exceeded available cache space, resulting in LRU (Least Recently Used) eviction before the second request arrived. This taught us that caching strategies must be tailored to dataset size and available memory, rather than applying a one-size-fits-all approach.

7.5 Debugging Across Two Computers

Problem: Hard to see what's happening on both computers simultaneously **Solution:**

- Set up logging to files on both machines
- Used `tail -f` to watch logs in real-time
- Added timestamps to every log message ▪ Color-coded output for different nodes

8. What I Learned

8.1 Technical Skills

This project taught me:

1. Distributed Systems Concepts:

- How to design hierarchical topologies
- The tradeoffs between flat vs. hierarchical architectures
- Why session-based design improves fault tolerance

- How network latency affects system performance

2. gRPC and Protocol Buffers:

- Setting up bidirectional RPC communication
- Handling timeouts and deadlines properly
- Serializing complex data structures
- Debugging RPC failures

3. System Performance:

- Measuring and analyzing throughput, latency, memory usage
- Understanding when caching helps vs. hurts
- Memory profiling and optimization
- The importance of empirical testing (my assumptions about caching were wrong!)

9. Conclusion

- The system successfully processes datasets up to 10 million rows (1.2 GB) using a 3-tier topology with Leader,

Team Leaders, and Workers.

Key findings from our experiments include:

1. **Cache Effectiveness Depends on Dataset Size**: Session-based caching benefits medium datasets (100K200K rows) with a 4x speedup, as I/O savings outweigh network costs.

- For small datasets (1K-10K), network latency makes benefits minimal (1.1x speedup). ▪ For large datasets (500K+), results exceed cache capacity (~300MB), providing no benefit.

2. **Memory Efficiency**: Chunked streaming reduces memory consumption by 67% (from 1,200 MB to 408 MB) while maintaining linear scalability across all dataset sizes.

3. **Scalability**: The system demonstrates linear scaling with consistent throughput (2-9 MB/s) from 1,000 to 10 million rows.

4. **Timeout Configuration**: Distributed systems require careful timeout management at multiple levels (client deadline, server wait conditions, session management) with sufficient buffer for network variability.

10. References

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