

100-Day Roadmap: GPU Programming

Days 1–20: Core GPU & CUDA Foundations

Goal: Build a strong foundation in GPU architecture and CUDA programming, essential for optimizing AI models.

| Day | Topic | Hands-On / Mini-Project | Resources |
|-----|---|--|---|
| 1 | GPU vs CPU architecture | Diagram SMs, cores, memory hierarchy | PMPP Ch. 1; CS149 Lecture: "Why Parallelism? Why Efficiency?" (Sep 26) |
| 2 | Install CUDA toolkit, NVCC flags | "Hello GPU" kernel | PMPP Ch. 2; NVIDIA CUDA Toolkit Docs |
| 3 | Host vs Device code (<code>__global__</code> , etc.) | Vector addition (single block) | PMPP Ch. 3 |
| 4 | Thread hierarchy: grids, blocks, warps | Vector addition (multi-block) | PMPP Ch. 3; CS149 Lecture: "Multi-core Arch Part II + ISPC" (Oct 03) |
| 5 | Memory types: global vs shared vs registers | Vector copy with shared memory | PMPP Ch. 4 |
| 6 | Synchronization (<code>__syncthreads()</code>) | Tiled matrix multiply (naïve) | PMPP Ch. 5 |
| 7 | Host–device transfers (<code>cudaMemcpy</code>) | Benchmark copy bandwidth | PMPP Ch. 2 |
| 8 | Profiling intro: <code>nvprof</code> / Nsight Compute | Profile Day 6 kernel | NVIDIA Nsight Compute Docs |
| 9 | Warp divergence & branch control flow | Branchy kernel and divergence measurement | PMPP Ch. 6; CS149 Lecture: "GPU architecture and CUDA Programming" (Oct 17) |
| 10 | Occupancy & launch configuration | Tune block/thread sizes for Day 6 kernel | PMPP Ch. 6 |
| 11 | Atomic ops & race conditions | Parallel reduction with <code>atomicAdd</code> | PMPP Ch. 5 |
| 12 | Unified memory overview | Vector addition with <code>cudaMallocManaged</code> | PMPP Ch. 4 |
| 13 | Streams & asynchronous copies | Overlap compute + H→D copy in two streams | PMPP Ch. 7 |
| 14 | Events & timing | Precise timing of kernel + copy | PMPP Ch. 7 |
| 15 | Shared-memory bank conflicts | Experiment with conflicting vs. non-conflict indices | PMPP Ch. 4 |
| 16 | Constant & texture memory | Texture lookup kernel | PMPP Ch. 4 |
| 17 | Dynamic parallelism | Kernel that launches sub-kernels | PMPP Ch. 8 |
| 18 | CUDA Graphs basics | Capture and replay simple kernel sequence | NVIDIA CUDA Graphs Docs |
| 19 | Nsight Systems for end-to-end profiling | Profile host+kernel pipeline | NVIDIA Nsight Systems Docs |
| 20 | Capstone #1: Optimized Matrix Multiply | Shared memory + loop unrolling | PMPP Ch. 9; CS149 Assignment 1 (Oct 6) |

Days 21–40: Intermediate CUDA + Math-Heavy Kernels for AI

Goal: Develop optimized kernels (e.g., GEMM, convolutions) critical for AI workloads, including VLMs and LLMs.

| Day | Topic | Mini-Project | Resources |
|-----|---------------------------------------|-----------------------|------------|
| 21 | Tiled GEMM (shared + register tiling) | 64×64 matrix multiply | PMPP Ch. 9 |

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| 22 | Loop unrolling & software pipelining | Unroll inner loops of Day 21 kernel | PMPP Ch. 6 |
| 23 | Warp-level primitives (<code>__shfl*</code>) | Warp-wide reduce | NVIDIA CUDA Programming Guide |
| 24 | Prefix sum (scan) | Parallel scan via Blelloch algorithm | PMPP Ch. 10; CS149 Lecture: "Data-Parallel Thinking" (Oct 19) |
| 25 | Histogram & binning | Atomic vs. shared memory approach | PMPP Ch. 11 |
| 26 | 2D convolution in CUDA | Image filter (edge detect) | PMPP Ch. 12; CS149 Lecture: "Efficiently Evaluating DNNs on GPUs" (Oct 26) |
| 27 | cuBLAS intro & tuning | Compare against Day 21 custom GEMM | NVIDIA cuBLAS Docs |
| 28 | cuFFT intro | 1D FFT on sample signal | NVIDIA cuFFT Docs |
| 29 | Thrust library for high-level ops | Sort large array + reduction | NVIDIA Thrust Docs |
| 30 | Streaming large datasets | Double buffering with 3 streams | PMPP Ch. 7 |
| 31 | Pinned vs pageable memory | Copy throughput benchmark | PMPP Ch. 4 |
| 32 | Mixed precision (FP16) kernels | FP16 GEMM on Tensor Cores (WMMA) | NVIDIA Mixed Precision Docs |
| 33 | Tensor cores deep dive | WMMA API micro-benchmark | NVIDIA Tensor Core Programming Guide |
| 34 | CUDA Graphs advanced | Parameterized graph with loops | NVIDIA CUDA Graphs Docs |
| 35 | Multi-GPU peer-to-peer (P2P) copies | P2P memcopy between two GPUs | NVIDIA Multi-GPU Programming Docs |
| 36 | Cooperative groups | Grid-level sync reduce | NVIDIA Cooperative Groups Docs |
| 37 | Memory pools & <code>cudaMallocAsync</code> | Pool allocator micro-benchmark | NVIDIA CUDA Memory Management Docs |
| 38 | Profiling large kernels | Nsight Compute metrics analysis | NVIDIA Nsight Compute Docs |
| 39 | Kernel fusion techniques | Fuse GEMM + activation | Research papers on kernel fusion (e.g., arXiv) |
| 40 | Capstone #2: High-Throughput Convolution | Multi-stream + optimized memory | PMPP Ch. 12; CS149 Assignment 3 (Nov 8) |

Days 41–60: Deep Learning Framework Internals + Multimodal AI

Goal: Extend frameworks like PyTorch with custom CUDA ops, focusing on components of VLMs and multimodal models.

| Day | Topic | Mini-Project | Resources |
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| 41 | PyTorch extension scaffold (<code>cpp_extension</code>) | Hello from C++ + CUDA into Python | PyTorch C++ Extension Docs |
| 42 | Custom CUDA op: ReLU / GELU | Integrate and test in a PyTorch model | PyTorch Custom Ops Tutorial |
| 43 | <code>autograd.Function</code> for custom backward | GELU with custom backward | PyTorch Autograd Docs |
| 44 | Softmax kernel + numerical stability | Log-sum-exp trick | Research papers on stable softmax (e.g., arXiv) |
| 45 | LayerNorm kernel | Batch vs. layer norm | Research papers on Layer Normalization |
| 46 | Attention (QKV) CUDA kernel | Single-head scaled dot-product | Research papers on Attention; CS149 Lecture: "Efficiently Evaluating DNNs" |
| 47 | Multi-head attention & grouping | Merge heads + optimize memory reuse | Research papers on Multi-head Attention |
| 48 | FlashAttention techniques | Tiled attention with shared memory | FlashAttention paper (arXiv:2205.14135) |

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| 49 | Profile end-to-end transformer block | Combine Day 46+Day 45 kernels | NVIDIA Nsight Systems Docs |
| 50 | TensorRT integration & custom plugins | Export small model + optimize | NVIDIA TensorRT Docs |
| 51 | ONNX export & quant-aware graph | Convert PyTorch model → ONNX → TensorRT | ONNX Docs |
| 52 | Triton (OpenAI) intro | Write simple matmul in Triton | OpenAI Triton Docs |
| 53 | Compare Triton vs. CUDA kernel | Perf benchmark on small GEMM | Benchmarking Triton and CUDA |
| 54 | TVM or XLA auto-tuning overview | Try simple schedule on a kernel | Apache TVM Docs |
| 55 | JIT compilation in PyTorch 2.0 | torch.compile on custom op | PyTorch 2.0 Docs |
| 56 | Profiling frameworks (TensorBoard Profiler) | Trace and visualize ML pipeline | TensorBoard Profiler Docs |
| 57 | Memory fragmentation & defragmentation | Simulate large tensor allocations | Research papers on memory management |
| 58 | Data-loader bottlenecks (pin_memory) | Optimize DataLoader + prefetch | PyTorch DataLoader Docs |
| 59 | Mixed-precision training with AMP | Train small CNN with autocast | NVIDIA AMP Docs |
| 60 | Capstone #3: End-to-end multimodal block (e.g., CLIP) | Integrate vision + language in PyTorch | Research papers on CLIP (arXiv:2103.00020) |

Days 61–80: Model Compression & Quantization for Large Models

Goal: Master techniques to compress VLMs, LLMs, and multimodal models (e.g., pruning, quantization).

| Day | Topic | Mini-Project | Resources |
|-----|---|---------------------------------------|--|
| 61 | Pruning theory: structured vs. unstructured | Magnitude pruning on small MLP | Research papers on pruning; CS149 Lecture: "Performance Optimization" (Oct 10) |
| 62 | Implement weight pruning kernel | Zero out pruned weights in CUDA | PyTorch Pruning Tutorial |
| 63 | Knowledge distillation overview | Train student from teacher model | Research papers on knowledge distillation (e.g., arXiv:1503.02531) |
| 64 | Implement distillation loss in CUDA | MSE + KL-divergence kernel | Custom loss function in PyTorch |
| 65 | PTQ workflow with BitsAndBytes | 8-bit quant of small BERT | BitsAndBytes Docs |
| 66 | Calibration & min-max vs. percentile | Compare calibration methods | Research papers on calibration |
| 67 | QAT workflow in PyTorch | Simulate quant noise in training | PyTorch Quantization Docs |
| 68 | 4-bit quant basics | Per-tensor vs. per-channel scaling | Research papers on 4-bit quantization (e.g., arXiv:2106.08295) |
| 69 | Build simple 4-bit linear kernel | Integrate into custom PyTorch op | Custom quantization kernel |
| 70 | Error analysis: activation vs. weight | Plot histograms + spikes | Research papers on quantization error |
| 71 | Dynamic quantization strategy (Unsloth style) | Layer-sensitivity measure + skip list | Unsloth Docs |
| 72 | Implement dynamic skip logic in your 4-bit kernel | Conditional bit-skipping | Custom kernel with skip logic |
| 73 | Mixed-bitwidth inference | 4-bit + 8-bit hybrid GEMM | Research papers on mixed precision |

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| 74 | Benchmark quantized vs. FP16/FP32 | Memory, latency, accuracy trade-offs | Benchmarking tools |
| 75 | Capstone #4: Dynamic 4-bit quantized VLM | Full forward pass + profiling | Combine previous days' work |
| 76 | Post-training accuracy recovery (fine-tuning) | QLoRA-style finetune on small LM | QLoRA paper (arXiv:2305.14314) |
| 77 | Mixed precision + quantization pipelining | Integrate AMP with quantized kernels | Research papers on mixed precision training |
| 78 | ONNX + TensorRT INT8/4 plugins | Export and serve quantized model | NVIDIA TensorRT Docs |
| 79 | Real-world benchmark (e.g., MMLU, GLUE, VQA) | Evaluate quantized VLM on tasks | Benchmark datasets (MMLU, GLUE, VQA) |
| 80 | Distillation + quantization hybrid | Tiny student model in 4-bit | Research papers on combined techniques |

Days 81–100: Distributed Training & Deployment for Large Models

Goal: Scale training/inference of VLMs and LLMs across GPUs and deploy efficiently.

| Day | Topic | Mini-Project | Resources |
|-----|---|---------------------------------------|---|
| 81 | Fundamentals of NCCL & MPI | All-reduce on two GPUs | NVIDIA NCCL Docs; MPI Docs |
| 82 | PyTorch DDP & FSDP | DataParallel vs. FullyShardedParallel | PyTorch Distributed Docs; CS149 Lecture: "Distributed Data-Parallel" (Oct 24) |
| 83 | DeepSpeed ZeRO & Offloading | Zero-offload config on small model | DeepSpeed Docs |
| 84 | Megatron-LM model parallelism | Split layers across 2 GPUs | Megatron-LM Docs |
| 85 | Gradient checkpointing | Save memory in long transformers | Research papers on gradient checkpointing |
| 86 | Horovod integration | Simple MNIST training across GPUs | Horovod Docs |
| 87 | Fault tolerance & elastic training | Simulate node failure with DDP | Research papers on fault tolerance |
| 88 | CUDA MPS & Multi-process service | Share GPU among CPU processes | NVIDIA MPS Docs |
| 89 | Kubernetes + GPU scheduling (intro) | Dockerfile + simple k8s GPU pod | Kubernetes GPU Scheduling Docs |
| 90 | CI/CD for ML (GitHub Actions + CUDA) | Build, test, deploy custom op | GitHub Actions Docs |
| 91 | Monitoring & telemetry (Prometheus, Grafana) | GPU metrics dashboard | Prometheus and Grafana Docs |
| 92 | Profiling distributed jobs | Nsight Systems on multi-GPU | NVIDIA Nsight Systems Docs |
| 93 | Serving inference at scale (TorchServe, Triton) | Dockerized Triton server | TorchServe and Triton Docs |
| 94 | A/B testing & canary deploys | Two versions of quantized model | Research papers on deployment strategies |
| 95 | Security: sandboxing CUDA kernels | User-code isolation | Research papers on kernel security |
| 96 | Optimizing latency vs. throughput | Batch size tuning | Research papers on optimization |
| 97 | Cost optimization on cloud GPUs | Spot instances, GPU families | Cloud provider docs (e.g., AWS, GCP) |
| 98 | Write technical blog series on your journey | Publish on Medium or personal blog | Blogging platforms (Medium, GitHub Pages) |
| 99 | Mock interviews: system design + CUDA trivia | Solve CUDA whiteboard questions | System design resources (e.g., "Designing Data-Intensive Applications") |

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| 100 | Final Capstone: End-to-end pipeline for VLM/LLM | Train → Quantize → Serve a multimodal API | Combine all learned skills; CS149 Assignment 4 (Dec 4) |
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Additional Resources & Tips

- **PMPP Book:** Use as your primary reference for GPU programming (chapters listed above).
- **CS149 Lectures & Assignments:** Follow the Fall 2023 schedule and assignments for parallel computing insights (specific dates provided).
- **Research Papers:** Access via arXiv or Google Scholar for cutting-edge techniques (e.g., FlashAttention, QLoRA, CLIP).
- **NVIDIA Documentation:** Essential for CUDA, TensorRT, Nsight, and other tools (links provided).
- **PyTorch Ecosystem:** Leverage official docs for extensions, quantization, and distributed training.

Youtube playlists

GPU Mode <https://www.youtube.com/@gpumode>

Notes <https://christianjmills.com/series/notes/cuda-mode-notes.html>

codes <https://github.com/gpu-mode/lectures/tree/main/>

for intuition

<https://youtube.com/playlist?list=PL5XwKDZZlwaY7t0M5OLprpkJUlrF8Lc9j>

https://www.youtube.com/playlist?list=PLU0zjpa44nPXddA_hWV1U8oO7AevFgXnT

<https://www.youtube.com/playlist?list=PLRRuQYjFhpmubuwX-w8X964ofVkw1T8O4>

Complete course

CS149 Course <https://gfxcourses.stanford.edu/cs149/fall23> <https://www.youtube.com/playlist?list=PLoROMvodv4rMp7MTFr4hQsDEcX7Bx6Qdp>

George Hotz(American Hacker) Youtube channel(Have so much stuff Like MOE Transformers tiny grad)

Deep learning Course which may assist in flash attention transformers etc <https://course.fast.ai/>

Github Repo links

Learning GPU Programming (30 days plan)(Have good ML Tiny exercises)

<https://github.com/hkproj/100-days-of-gpu/blob/main/CUDA.md>

Leaderboard of discord server(Post your github code link daily they will add you to the leaderboard)

<https://github.com/hkproj/100-days-of-gpu/blob/main/CUDA.md>

<https://github.com/rkinas/cuda-learning?tab=readme-ov-file>(Have Many Resources Including exceptional optimization)

A-hamdi the man who completed 100 days of GPU Programming <https://github.com/a-hamdi/GPU>

Some other guys

<https://github.com/1y33/100Days>

<https://github.com/JungHoyoun/100days-gpu-challenge>

For who wanted to get into HPC

<https://github.com/AdepojuJeremy/CUDA-120-DAYS--CHALLENGE>



Andrej Karpathy The man Behind the Tesla and OpenAI Dont know pytorch wrote entire LLM Training on C
<https://github.com/karpathy/llm.c>

Similarly another guy wrote a script llama.cpp to run an large LLM locally on phone or laptop
<https://andrewkchan.dev/posts/yalm.html> <https://github.com/ggml-org/llama.cpp>

<https://github.com/kmohan321/LLMs/tree/master> Have implementation of bert llm etc

Blogs

<https://salykova.github.io/sgemm-gpu/>(This guy Beating cuBLAS in Single-Precision General Matrix Multiplication)

<https://minami.bearblog.dev/gpu/?s=09>

Follow <https://unsloth.ai/blog/>(the guys behind every LLM VLM Quantization) <https://github.com/unslothai>

Challenges Unsloth

<https://colab.research.google.com/drive/1JqKqA1XWeLHvnYAc0wzrR4JBCnq43H>

Codes by different LLMs benchmark (Have max every code)

<https://scalingintelligence.stanford.edu/KernelBenchLeaderboard/>

Platform to code

<https://leetgpu.com/>

Leetcode for GPU programming

<https://tensara.org/problems>

This guy is like god of kernels

<https://github.com/youkaichao>

Principal engineer at apple writes so much about GPU programming

https://www.linkedin.com/in/yidewang?trk=public_post_feed-actor-name

Training LLM on GPU Kernels

https://huggingface.co/spaces/nanotron/ultrascale-playbook?section=first_steps:training_on_one_gpu

