AI Inferencing Storage IO Traffic Profiling and Analysis

Xiangyu Tang, Roy Leonard, Craig Lucero, Veera Saripalli, Chaman Saurav

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Agenda

1. AI Inferencing Steps and Performance Measurement in PCs
2. AI Inferencing Traffic
   a) Model Loading in AI Benchmarks
   b) Field Usage: Multi-model, Multi-modal, RAG
3. Uniqueness of AI Inferencing Traffic

AI Inferencing for PCs

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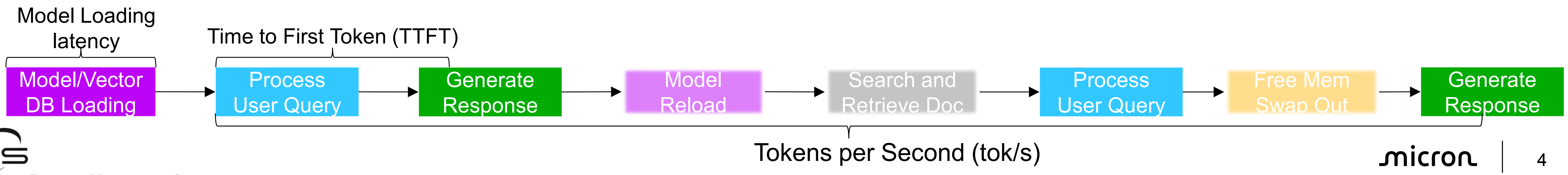
Inferencing on PCs

- AI Inferencing involves 3 main steps: loading the AI model, process user query, generate response
- Inferencing performance for LLM is measured using 3 main criteria
  1. AI model loading time: loading model weights to GPU
  2. Time to first token (TTFT): processing user query and prefill/initialize kv cache
  3. Tokens per second (Tok/s): measures inferencing performance after the first token
- Model loading time is dependent upon
  - SSD performance
  - AI framework (software stack, processor, etc)
  - Model (size, type, gen, etc)

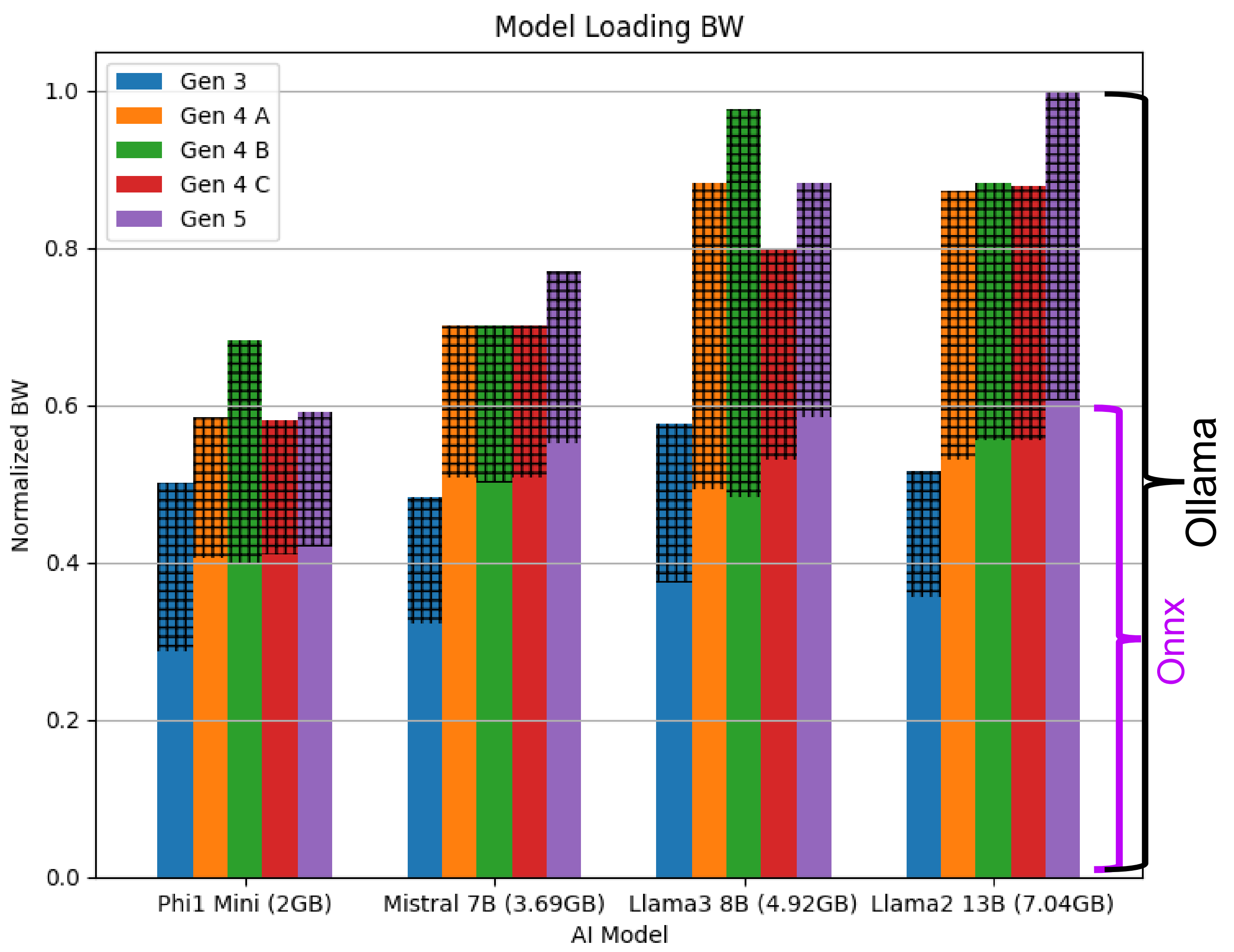
- TTFT is dependent on GPU processing power, since prefilling/initializing the kv matrix is compute intensive
- Tok/s is memory IO bound, dominated by kv cache read
- In many cases TTFT and Tok/s are also SSD performance bound
  - In multi-model scenarios, AI models in background could be discarded from memory to free space, and needs to be reloaded when user query arrives
  - In RAG scenarios, index searching for user query involves loading relevant index from disk to memory; data chunk retrieval needs to read data from disk
  - As KV matrix grows, may need to swap to disk



AI Inferencing Traffic Patterns and IO BW

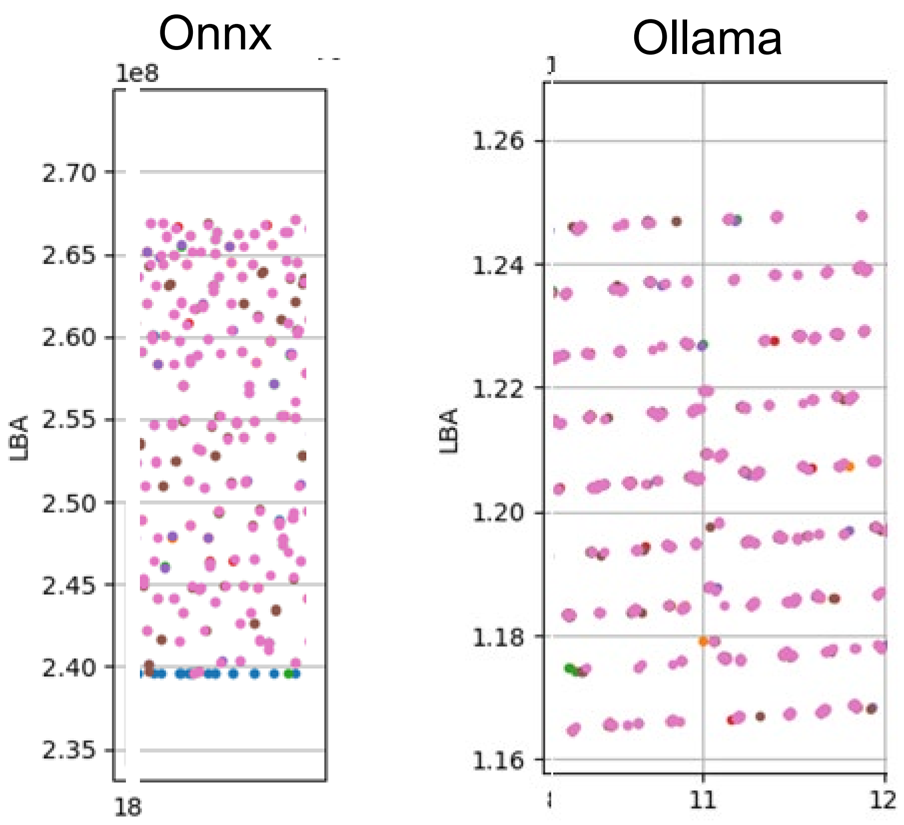
Model load time Disk Read BW

- Model loading BW is affected by
  1. SSD BW and optimizations
  2. AI model
  3. Run time framework



Llama and Ollama Model Loading Patterns

Disk Read Pattern



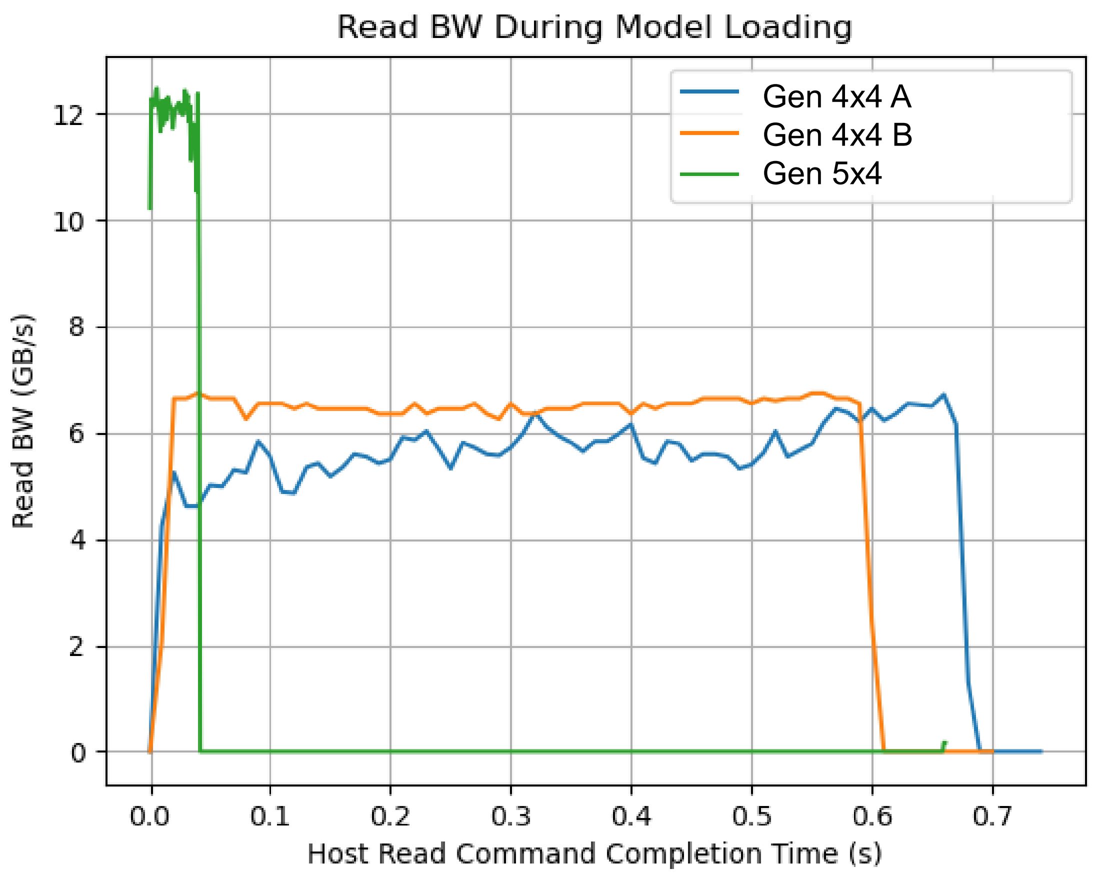
- Onnx run time (ORT) is less optimized than Ollama when loading models
  - Onnx model loading exhibits **random** read patterns, instead of Ollama's **multi-stream sequential** read patterns

– Versions of Ollama can saturate NVMe BW when loading models

- Latest Onnx RT shows improvement in generating sequential read patterns and higher BW during model loading

Mistrallite Model Loading with Ollama

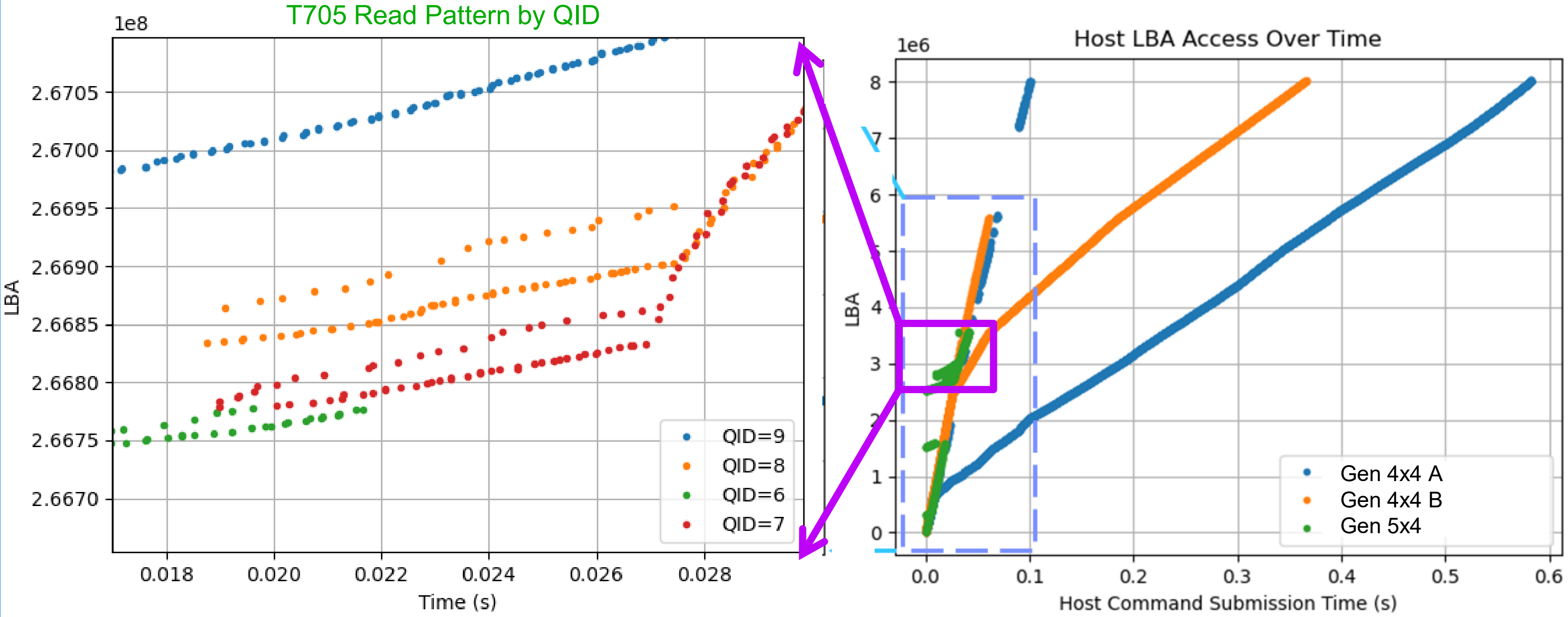
- Mistrallite NN model loaded with Ollama (v0.1.10)
  - About ~3.9GB is read
- Disk read saturates PCIe BW
- QD is high
- Read payload at MDTS
- Multiple stream sequential reads



Mistrallite NN Model

Read Sequence

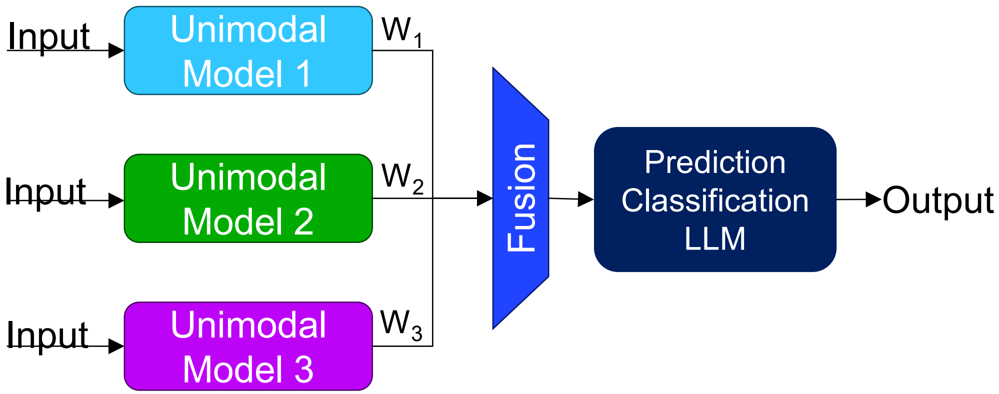
- Between 2 to 5 streams are used to read the entire file in a mostly sequential fashion
- Zooming in on Gen5 drives shows that one queue ID corresponds to one sequential stream



Multi-Modal NN

Model Architecture

- Multi-modal NN can have either multiple types of inputs, or multiple types of outputs, or both
- Tested Llava model which is a multi-modal NN with multiple types of input (image and text) and a text output
  - Combines a vision model (VTi) with Vicuna LLM (13B, 8GB) for general purpose visual and language understanding

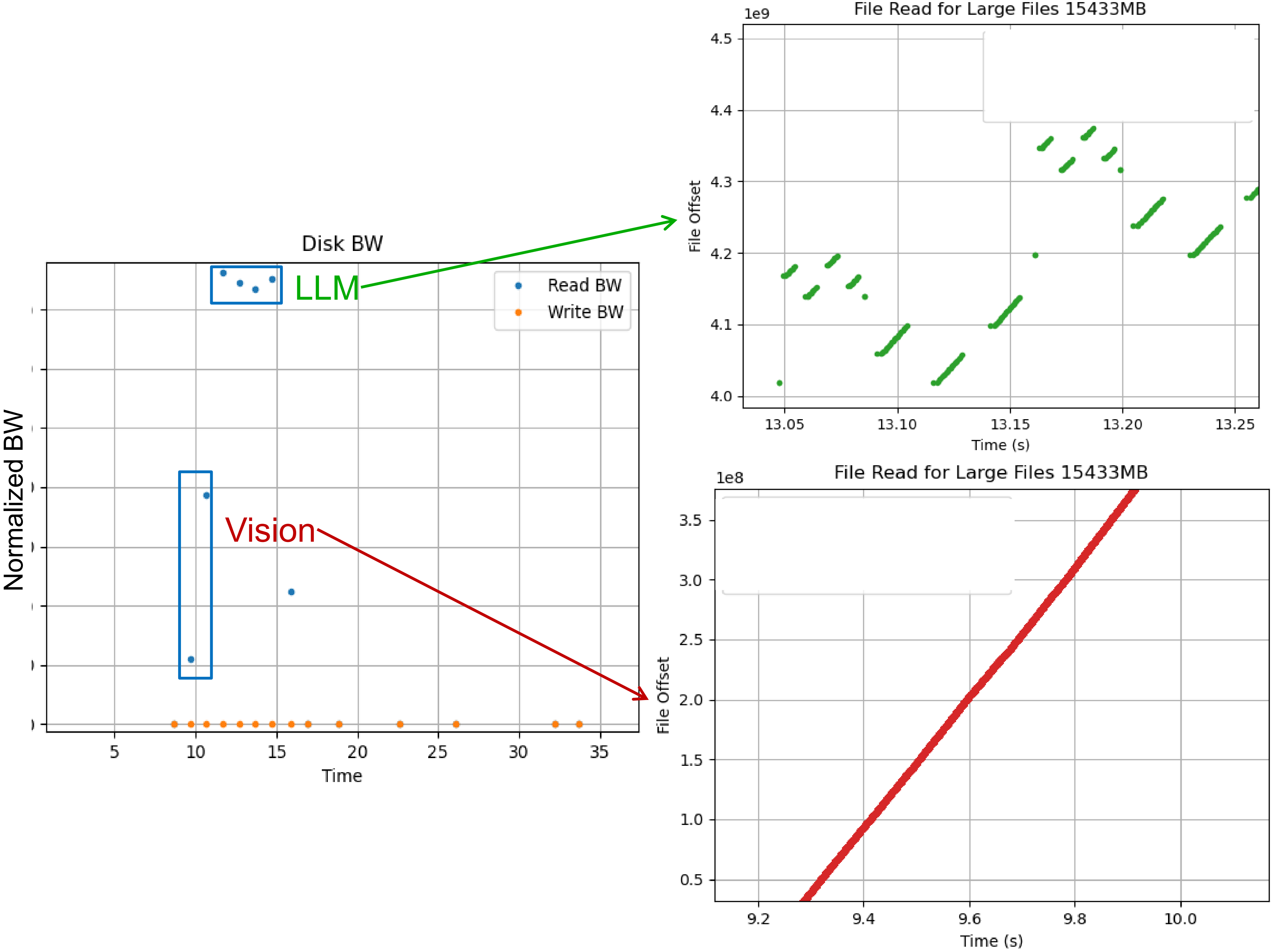


Query: What is the ending of this movie

Multi-Modal NN

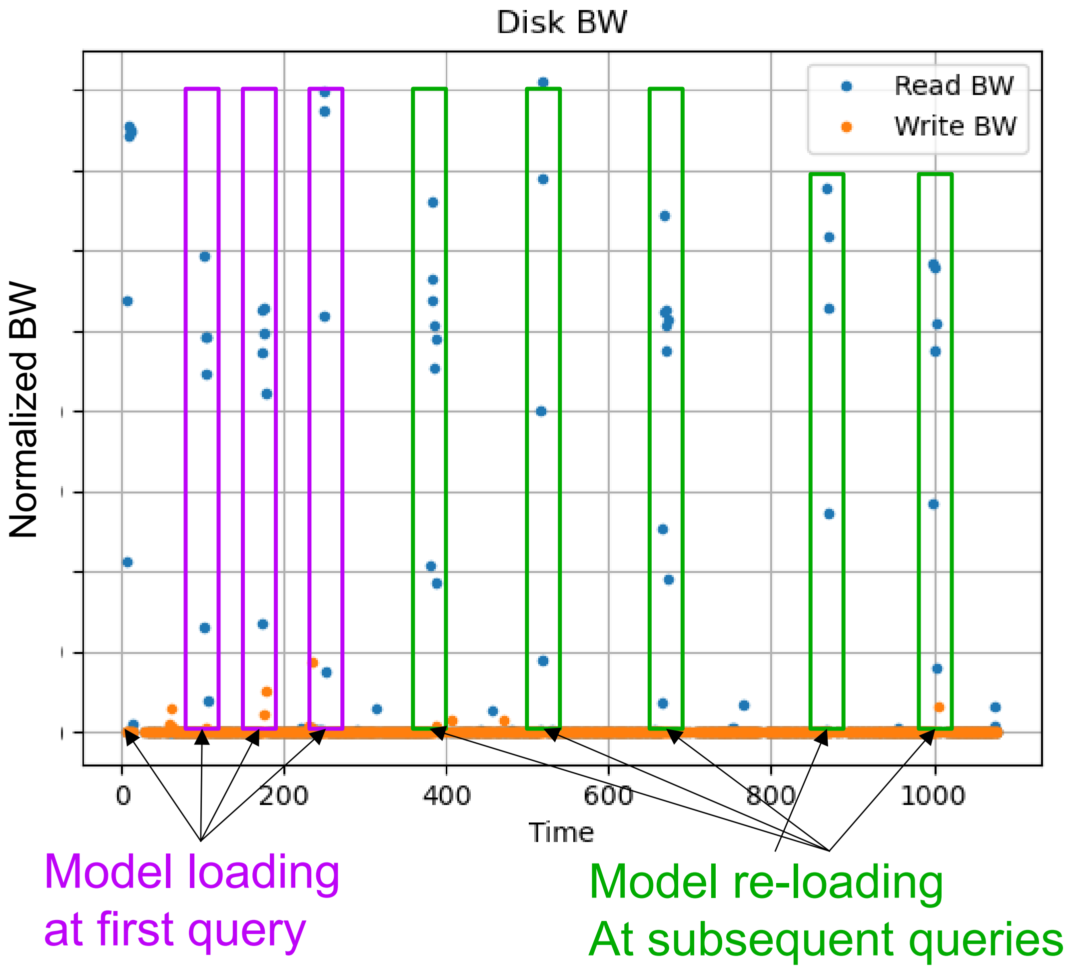
Llava Loading on Ollama

- Loading pattern is model dependent
  - Vision model: single stream sequential read, smaller payload size
  - LLM model: higher BW/QD, multiple stream sequential read, large payload size (MDTS)

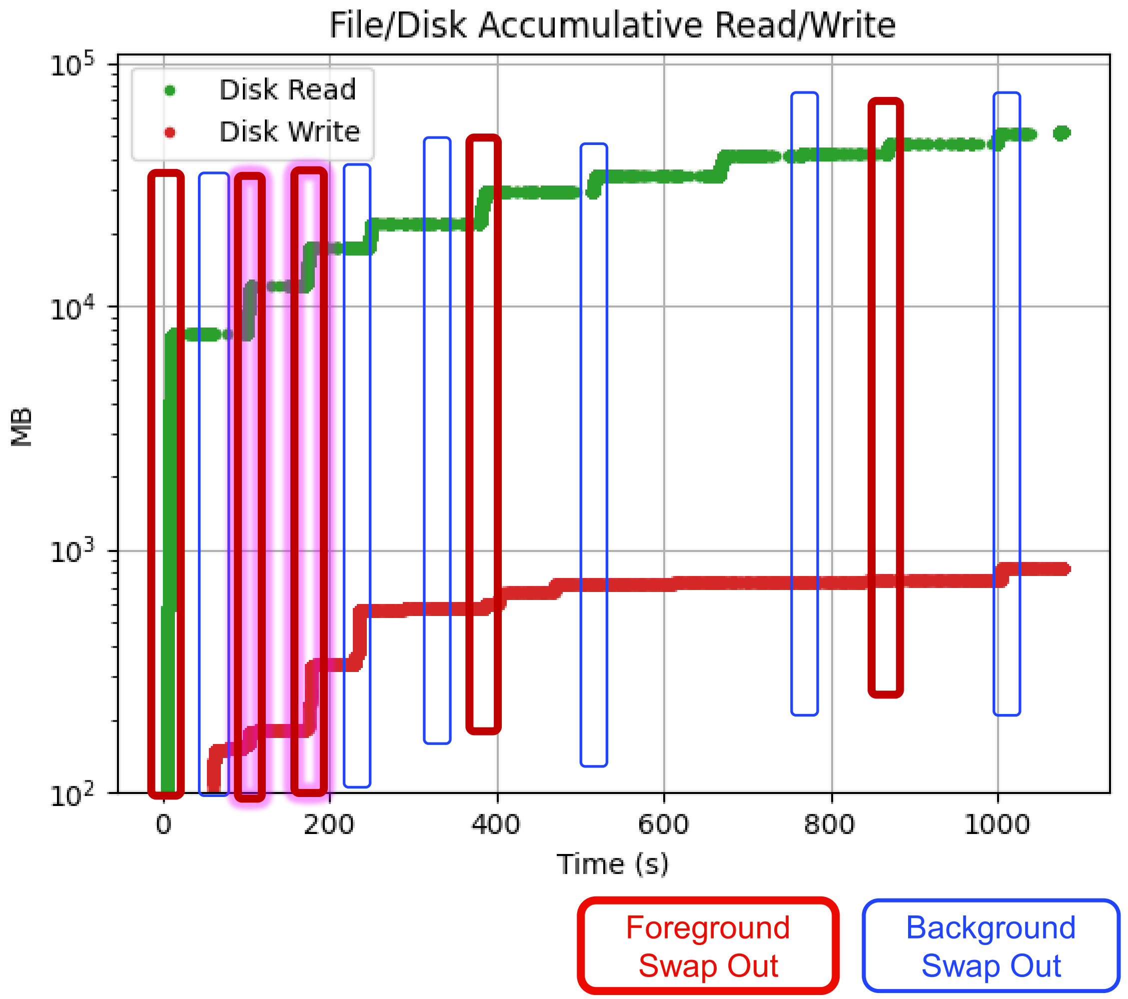


Multi-Model NN

- Multiple models (4) running concurrently in the same Ollama framework
  - Llava 13B(8GB), qwen2.5(4.7GB), gemma2(5.4GB), llama3.1(4.7B)
- Combined model size greater than physical memory capacity
  - Query only a single model at a time, rotate which model is queried
- Model weights and active user data are periodically swapped in/out, making SSD BW a gating factor
  - When memory is full, memory is freed by *discarding* existing models in memory, *not* by swapping out
  - When a model is needed again, it is reloaded from disk
  - Only ~500MB of live user data (not models) are swapped out to disk into virtual memory (pagefile.sys), 50% in foreground

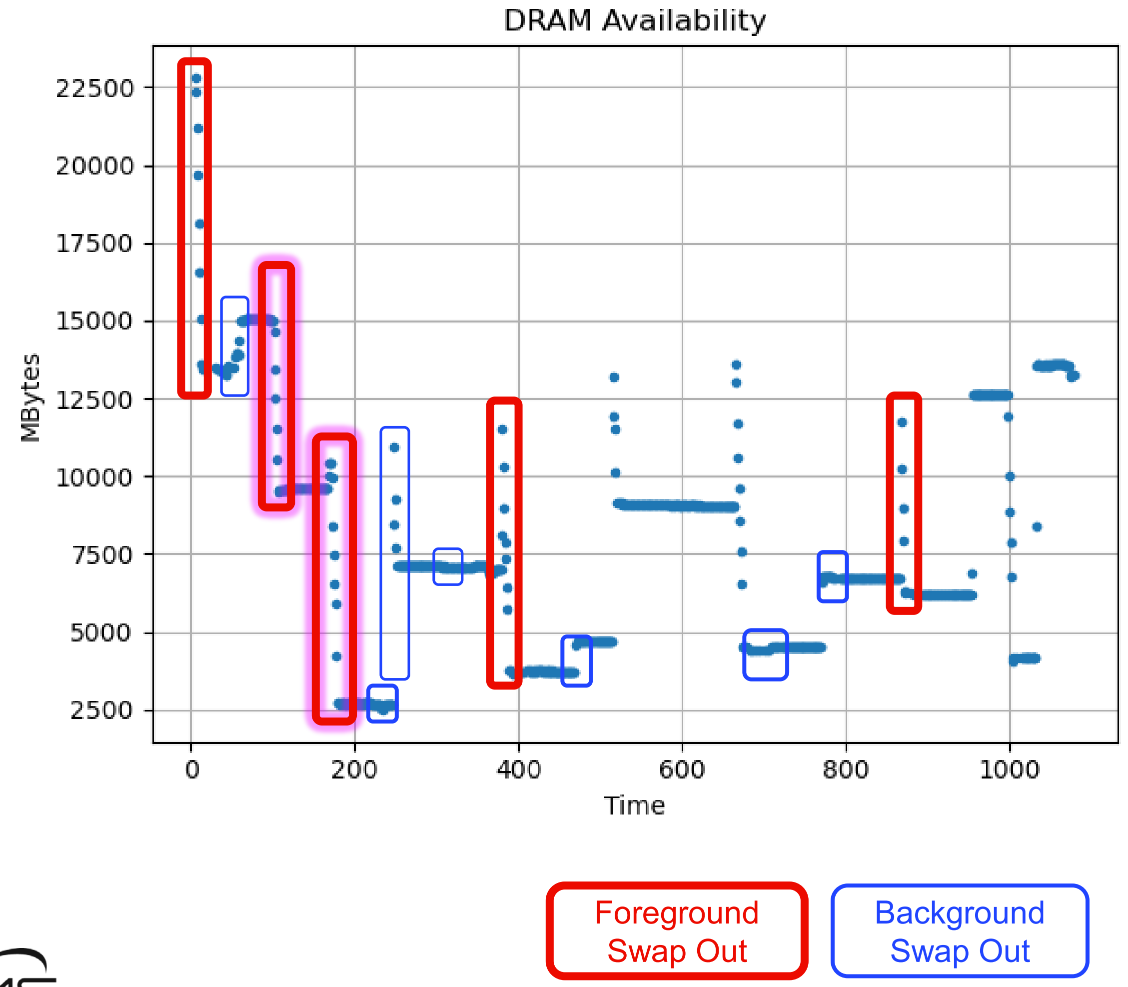


Multi-Model NN



- Models are reloaded from disk during user query in multi-model scenario
  - This gates query response time
- A significant portion of swap-outs occur during model reload (250MB out of 500MB)
  - SSD write BW gates model reload and thus query response time
- Disk swap outs are large sequential writes
- Sequential reads and mixed read/writes can impact Tokens-per-Second

Physical Memory Availability



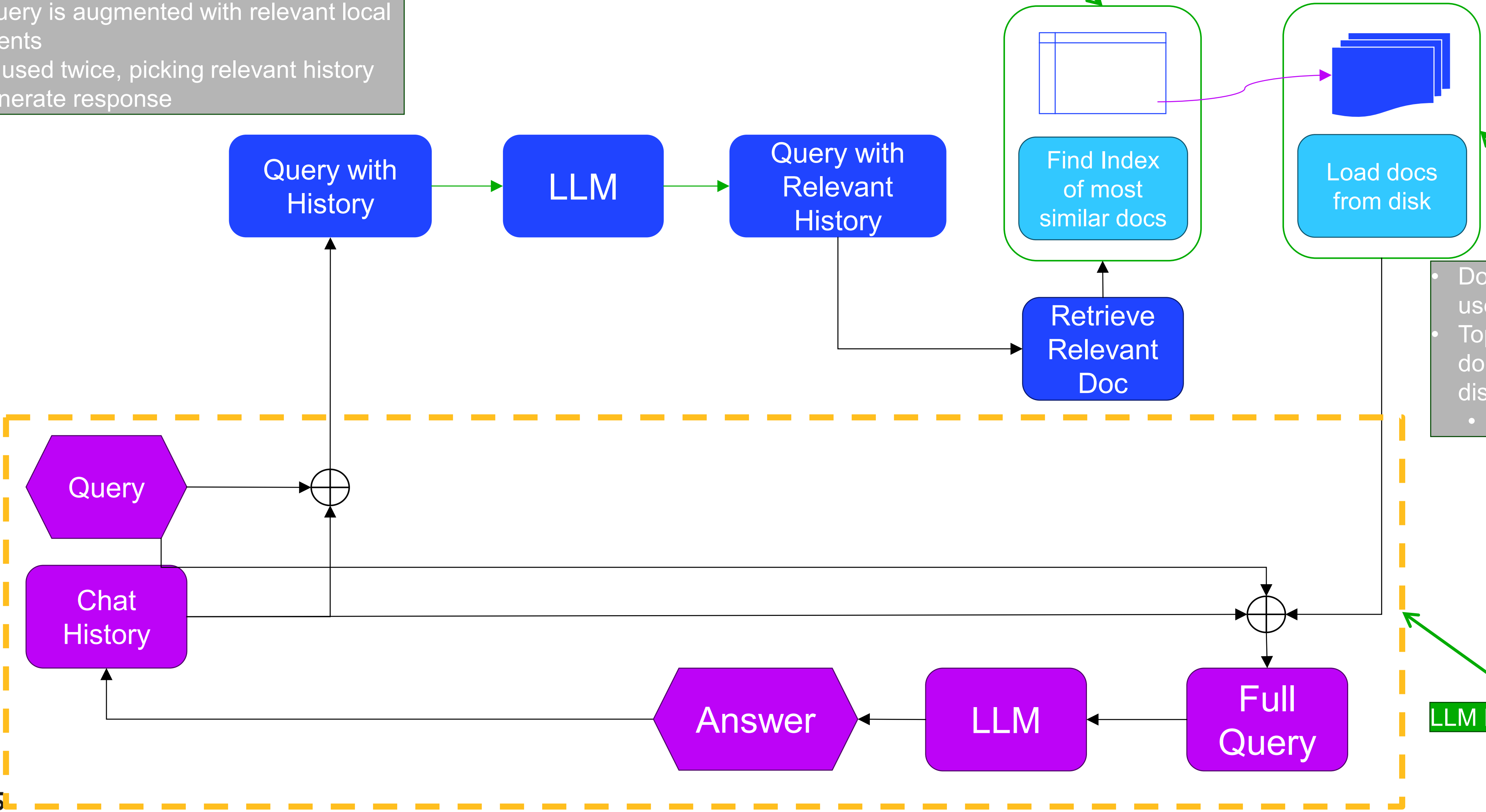
- Majority of memory reclamation comes from discards
- Swap-out writes to virtual memory is an order of magnitude smaller than reading from disk
  - 500MB total
- Conjecture:
  - Live user data from other non-AI apps are swapped out to disk, in order to free memory to load models
  - Models are simply discarded from memory if more space is needed
  - KV cache will eventually be swapped out to disk

Composite

RAG

- RAG used to optimize LLM with private and updated user data
  - Eg, Itinerary, Perfect Shot, Recall
- User query is augmented with relevant local documents
- LLM is used twice, picking relevant history and generate response

- Vector DB (>7x expansion) is multi-level and is too large to be stored entirely in memory, split into level-0 and SQL and stored on disk
  - Level-0 loaded along with LLM from disk into memory (sequential read, low QD)
  - Similarity search loads SQL DB OTF from disk for every “cold” query, gates query latency
    - Sub-512B of index generates 4kB payload



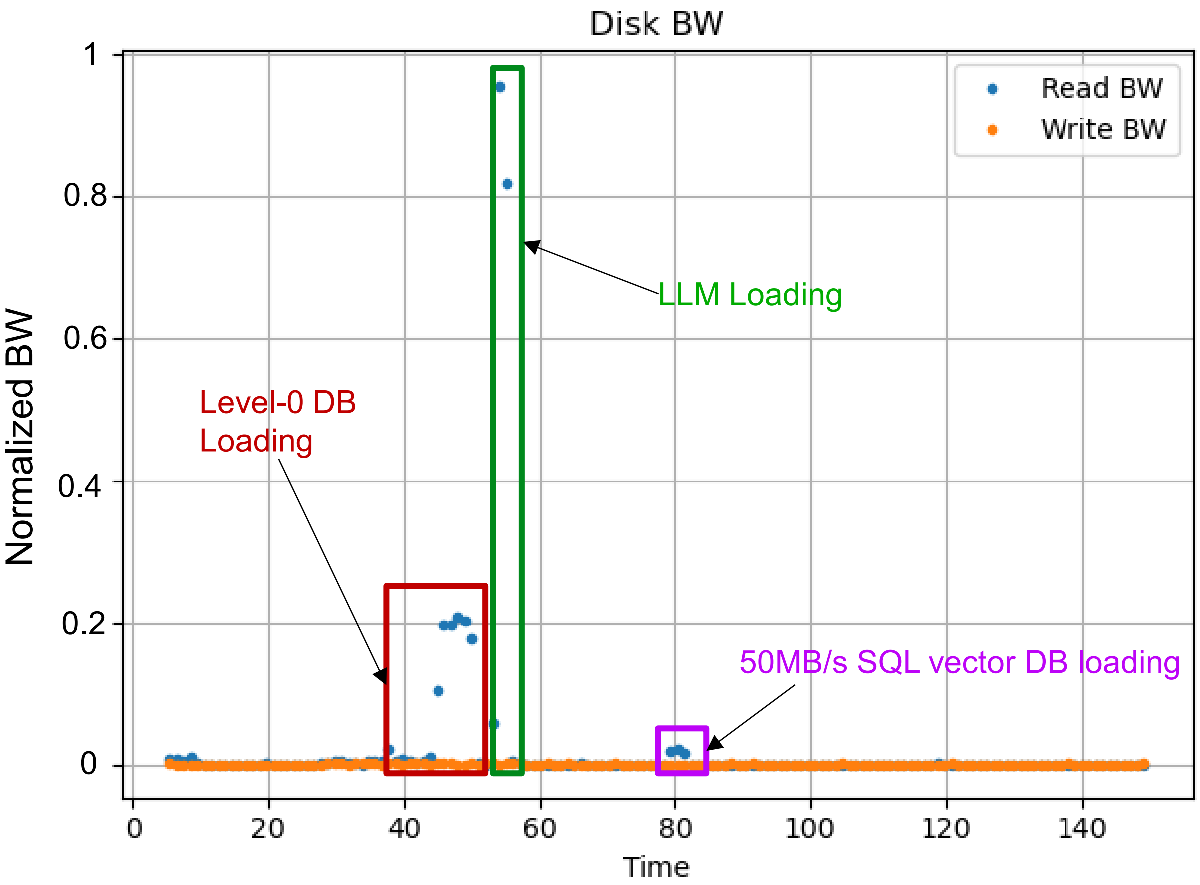
- Docustore is a DB of chunks of user documents (3x expansion)
- Top ~10 most relevant document chunks are read from disk
  - Small 4k random reads

LLM Inferencing

Rag

Model and Database Loading

- Loading sequence:
  1. Level-0 index (2.5GB) loaded at first
     - Small sized single stream sequential read, lower QD, 500MB/s
  2. LLM model (5GB) loaded next
     - Large sized multiple stream sequential read, higher QD, 2.5GB/s
  3. After user query, portion of SQL DB (150MB/6GB) loaded for similarity search
     - 4kB random read, QD 1, 50MB/s
     - 100k 4k reads into ~150MB of LBA range for single query, many cache hits
  4. Document chunk loaded (several 4kB)
     - 4kB random read, low QD
  5. SQL DB loaded for every "***cold***" query



Unique Characteristics of AI Inferencing Traffic

Summary

- Uniqueness of AI traffic affords opportunity to target these traffic for performance improvements
  1. Multi-stream sequential reads
  2. Large volume (GB levels) of continuous read operations
  3. Mixed read/write patterns:
     - SR+SW for memory swapping