Scalable Workflow System for Whole Slide Microscopy Analyses Using Neural Networks

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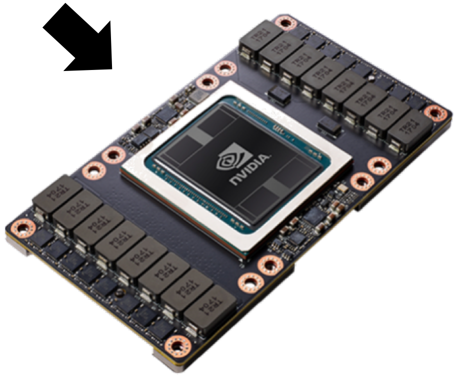
Outline

- Part I – Specific Application
  - Microscope Image Acquisition
    - In-Situ Image Based Measurements
  - Data Motion
    - Triggers from Acquisition Software
  - Scalable Data Processing
    - HTGS, Fast Image



- Part II – Generalization
  - How to write software to scale with hardware
  - Problem Decomposition
  - Software developer efficiency

Motivating Problem

- Image-based measurements via Automated Microscopy
  - Automation increases data generation rate
- Microscopes can produce 100's of whole slide images per day
  - 5 gigapixel whole slide images
  - 100000 x 50000 pixels at 10x magnification
  - 5 minutes to acquire each image
- Acquisition rate defines the compute budget for performing image-based measurements.

Zeiss AxioScan Z1 Microscope

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Whole Slide Image Analysis Problem

- Find all 100^2 pixel objects of interest within each 100,000 x 50,000 pixel slide

Example Slide

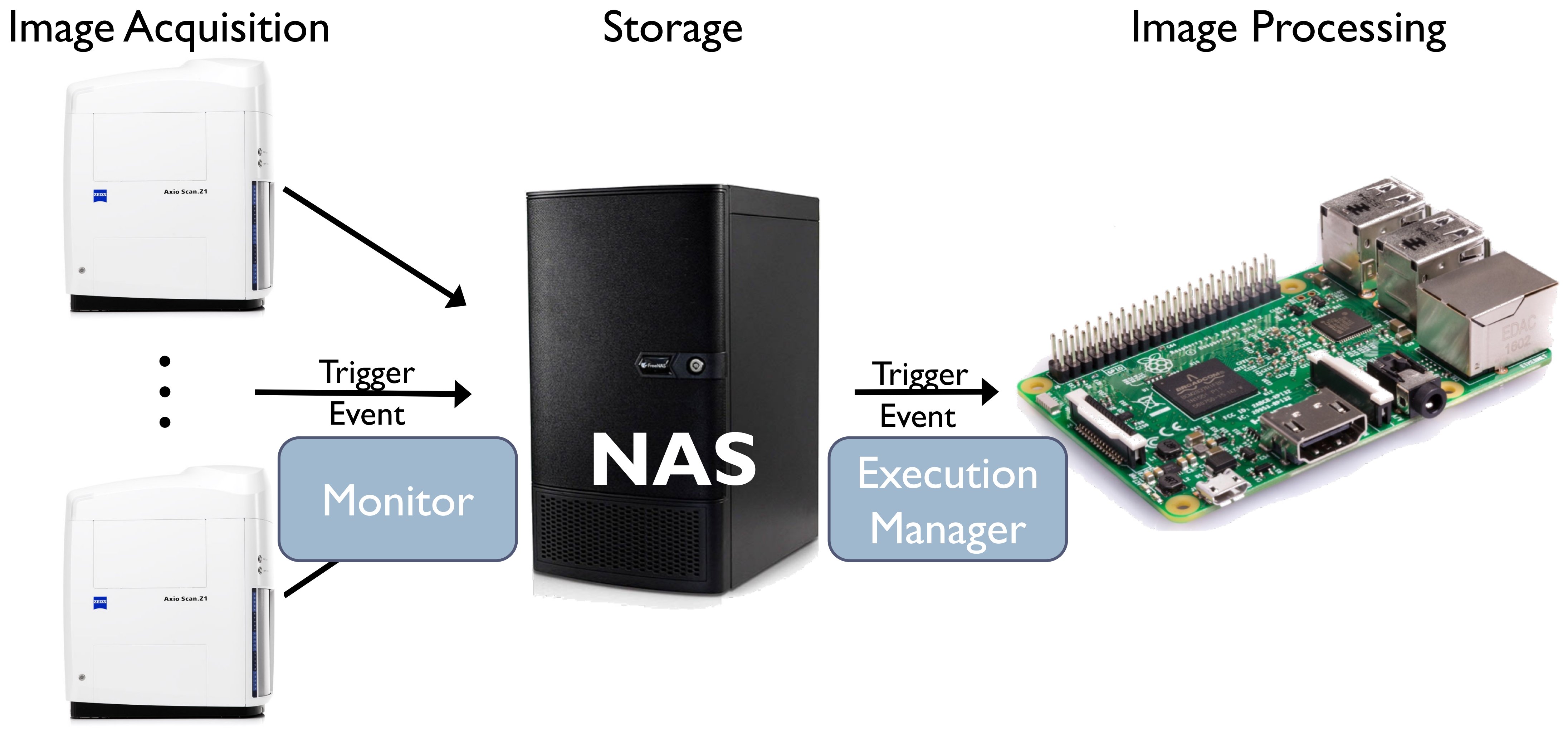
Goal:
Automate tedious,
error prone tasks

In Situ Image Analysis

- Perform analysis in semi-real-time while the next image is being acquired
- Brings image analysis into the wet-lab, providing immediate feedback/results

- Challenges
  - System must be robust and stable
  - Microscope acquisition time defines compute budget
- Benefits
  - End to end solution, user scanned image results are available 90 seconds later
    - Concurrent image acquisition and image processing
  - Data management
    - Integration with Zeiss Microscope to automatically copy image file to storage NAS
    - Processing computation initiated automatically when copy completes

Data Workflow



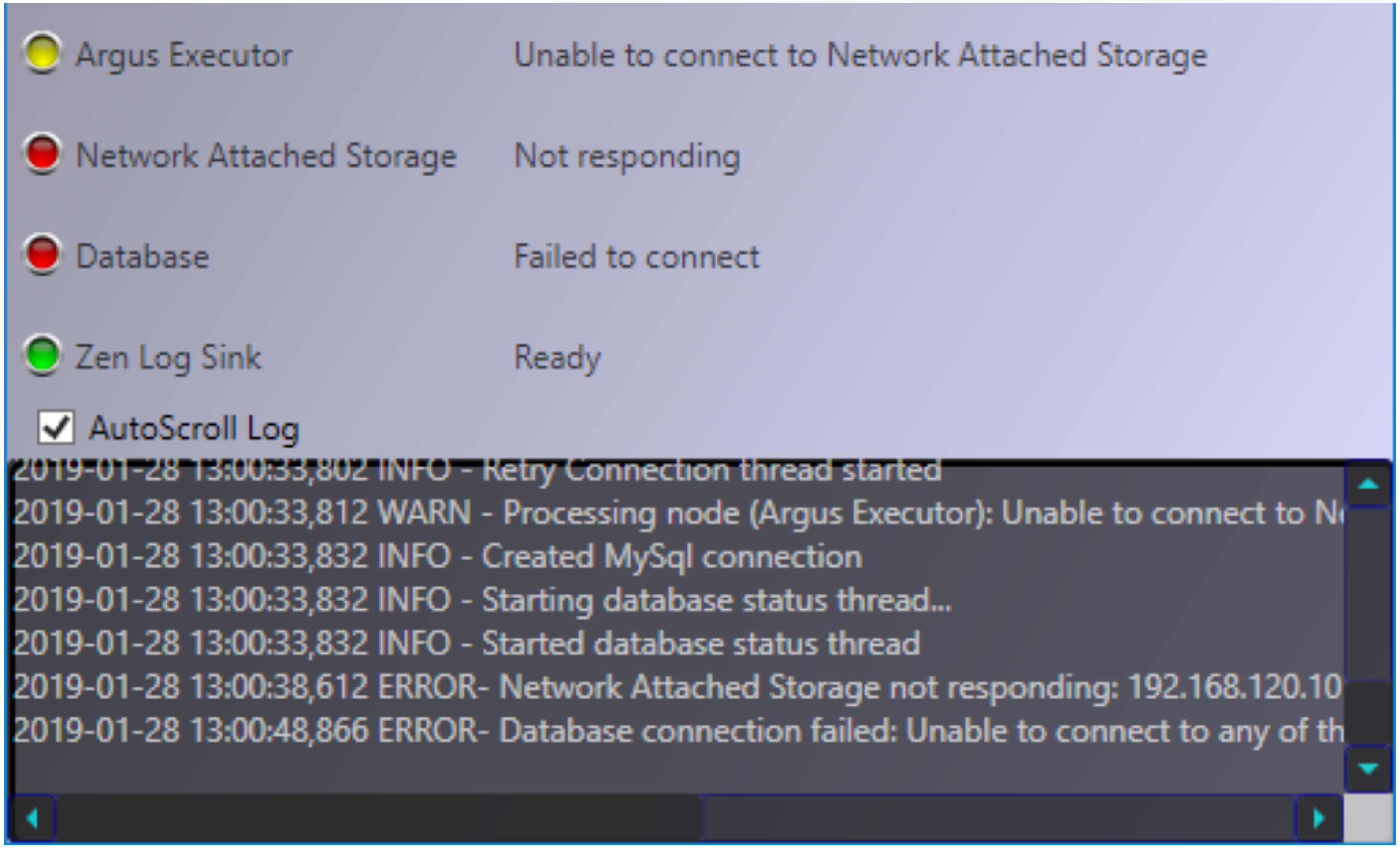
Microscope Acquisition System

- Queue up to 150 slides to be scanned
- AxioScan Z1 is driven from an attached computer
- Zeiss software scans images one at a time
- Images saved locally
- No local compute is allowed
- Lightweight program monitors scan status

Zeiss AxioScan Z1 Microscope

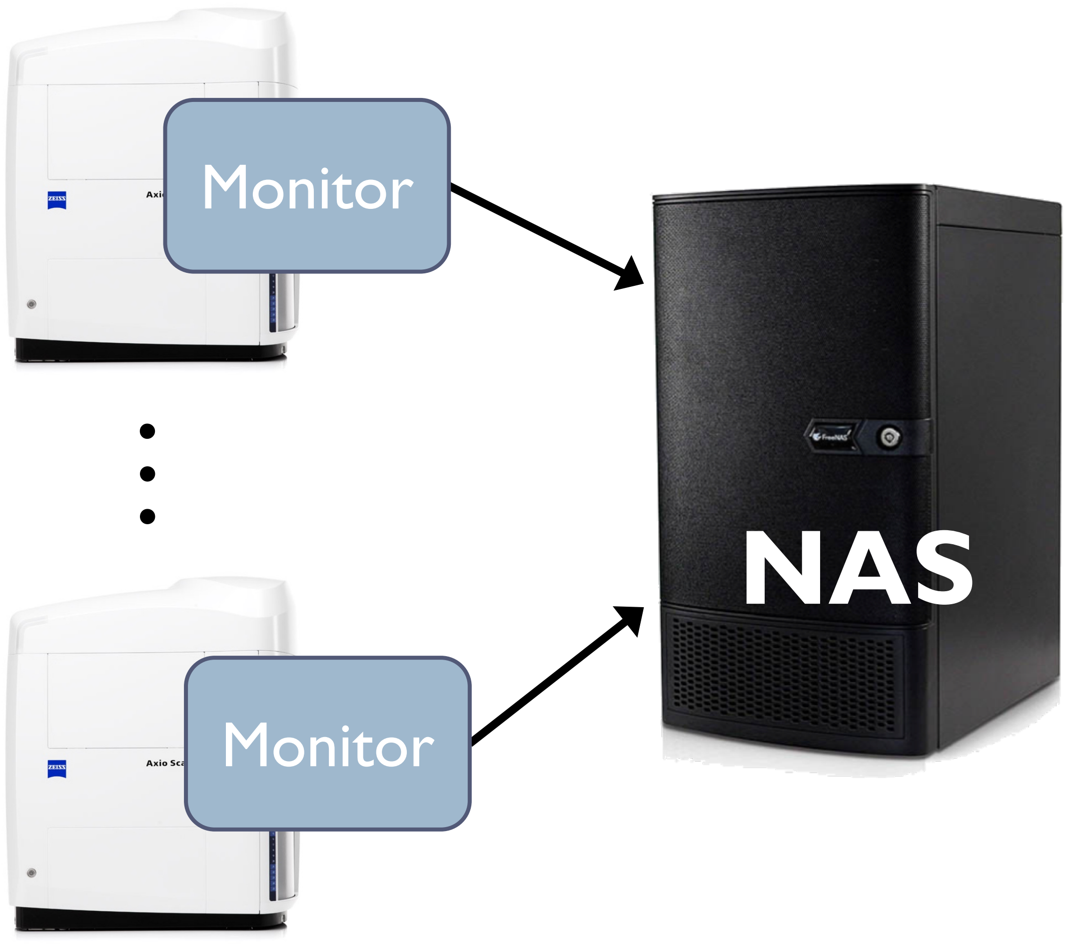
Acquisition Monitor

- Runs on Microscope Machine
- Two responsibilities
  - Showing System Status
  - Monitoring Zeiss log and copying completed scans to the NAS
- Green board means everything is up and running



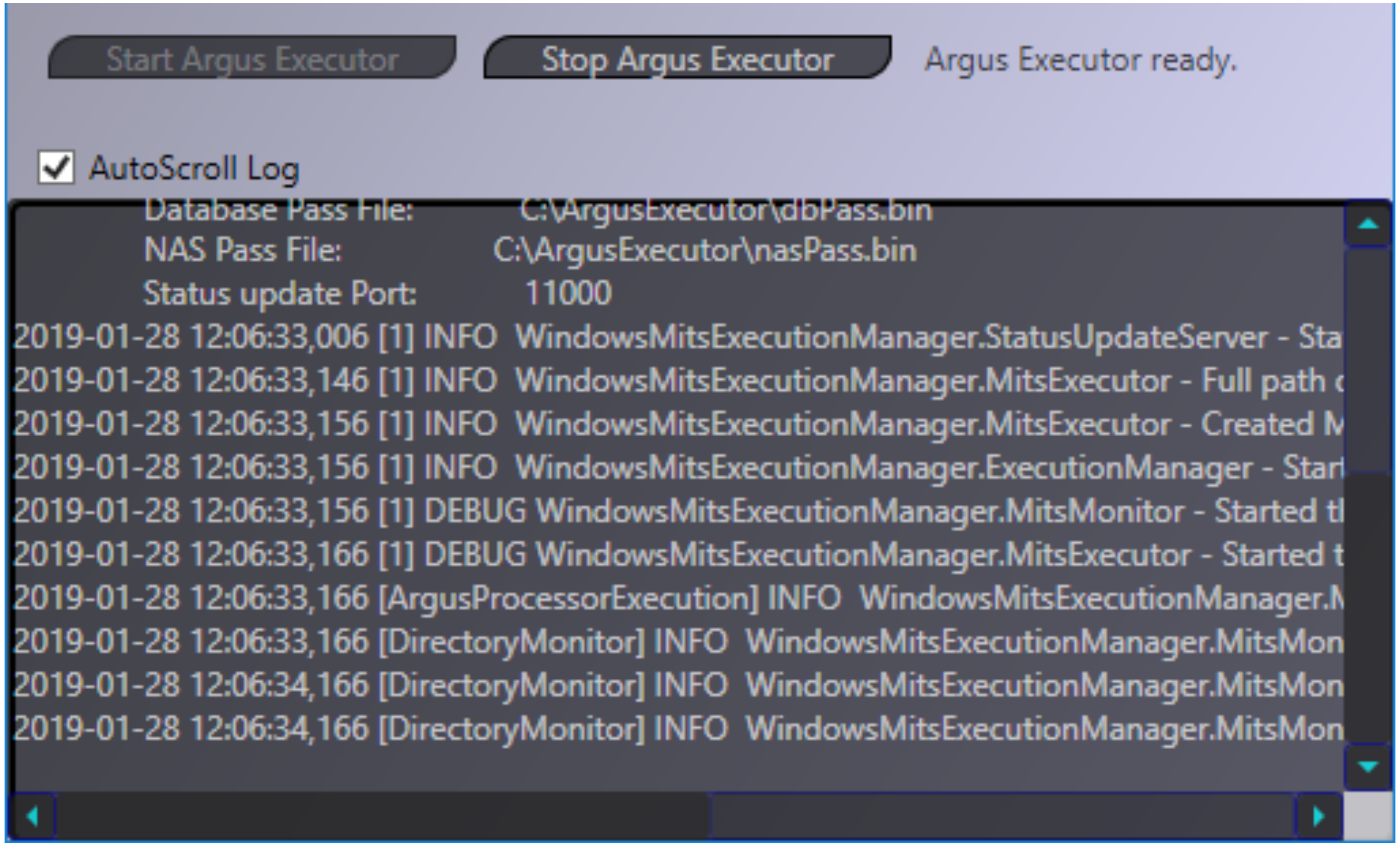
Acquisition Monitor

- Runs on each Microscope Machine
  - System supports N microscopes
  - Current hardware supports 4 microscopes
- Hooks to Zeiss event log
  - Watches for scan completed message
- Launches image copy to NAS
  - Able to recover if the network goes down
- Processing starts upon copy completion
- Copy & Processing decoupled from acquisition
  - Compute is overlapped with Acquisition

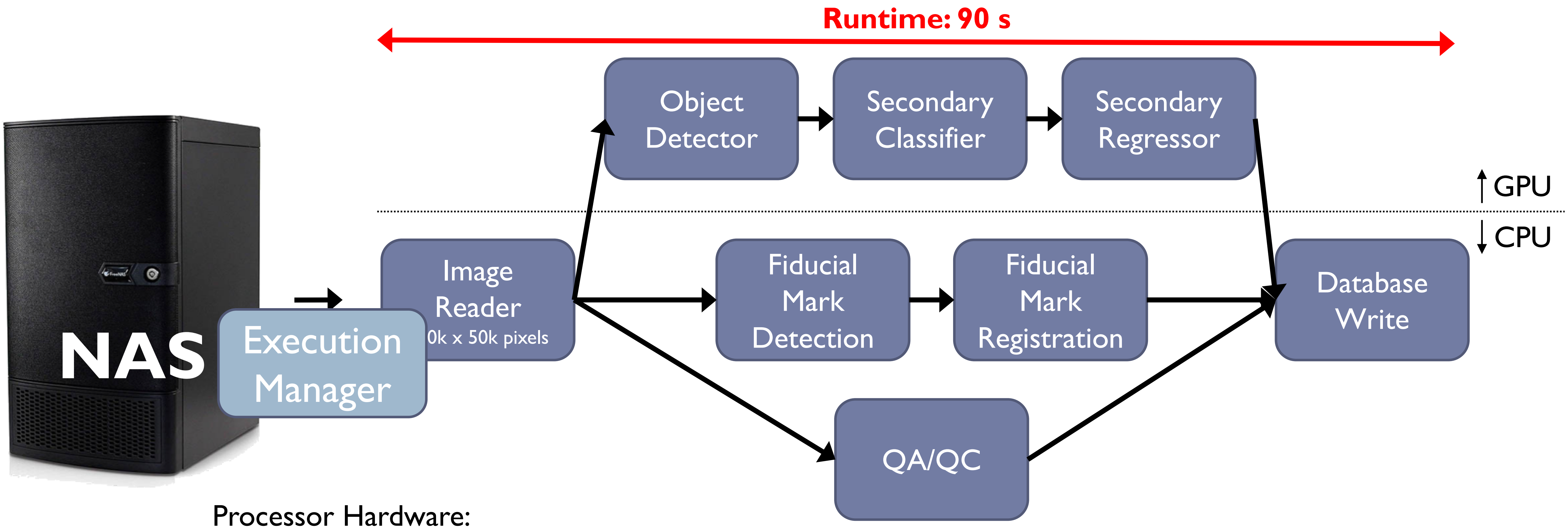


Execution Manager

- Runs on Processing Machine
- Launches Processing Workflow Per Image
  - Has an input queue of images
  - Monitor adds to that queue
- Displays Processing Log



Processing Workflow



Processor Hardware:

2x - Xeon Gold 5120 "Skylake" 14-core CPUs
2x - NVIDIA GTX Titan V graphics cards

Codebase: C++

Libraries: OpenCV, TensorRT, LibCZI, FastImage*, HTGS*

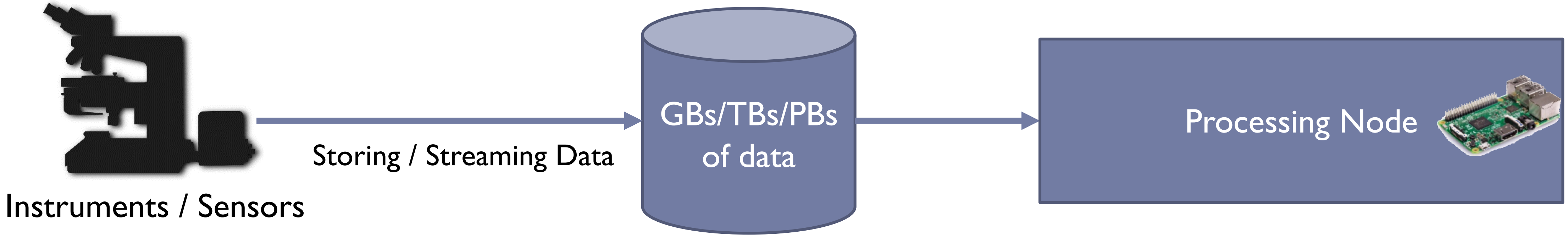
* NIST developed

Scalable Workflows

HTGS - Hybrid Task Graph Scheduler

Processing Workflow

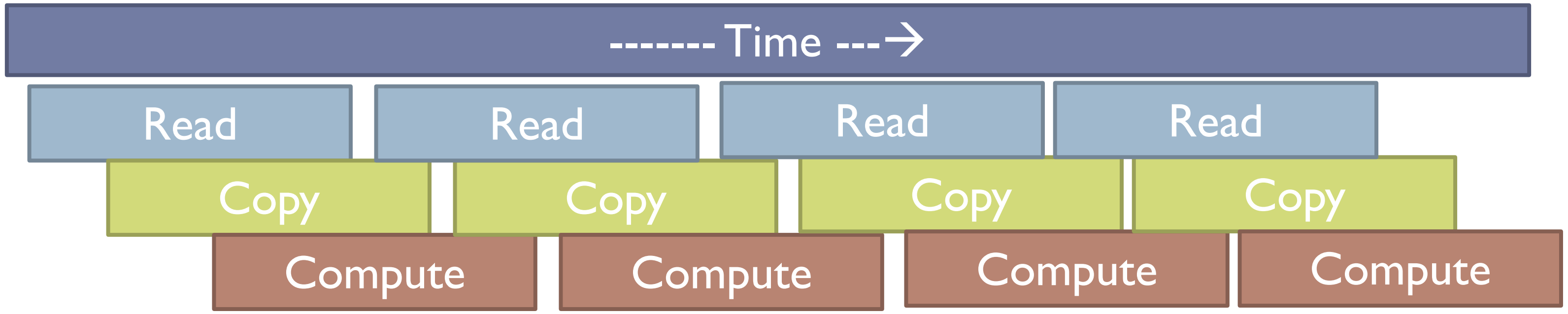
- Requirements
  - Meet time demands
  - Fully utilize processing hardware
  - Scales with increase to data rates
    - Multicore
    - Adding more GPUs to a machine
    - Additional processing nodes
- Approach
  - Asynchronous pipelined workflow
    - Effectively keeps processing resources busy
  - Appropriately size hardware
    - To deliver throughput



What is Pipelining

- Dictionary
  - A form of computer organization in which successive steps of an instruction sequence are executed in turn by a sequence of modules able to operate concurrently, so that another instruction can be begun before the previous one is finished.

- Applicable
  - Instruction pipelining: pre-fetching, branch prediction
  - Task pipelining: reading/writing data, copying, compute



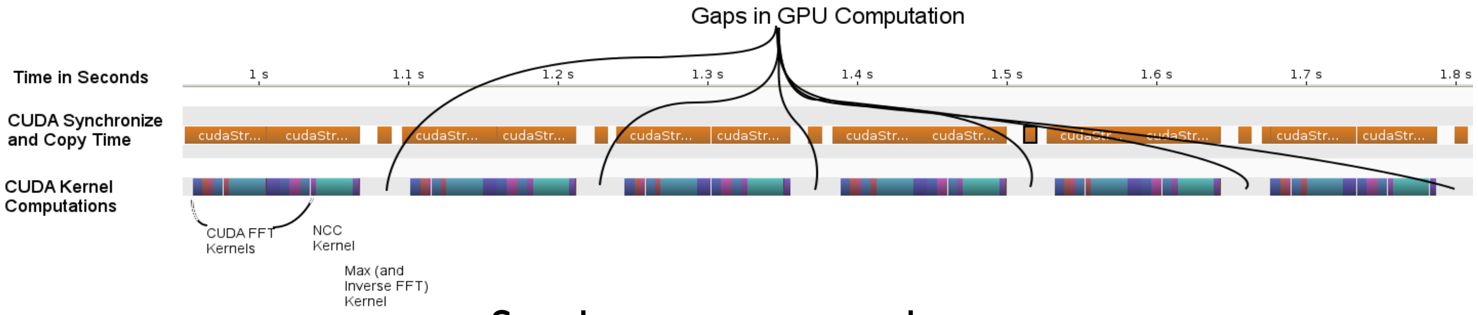
Example pipeline

Why Asynchronous Pipelined Workflow?

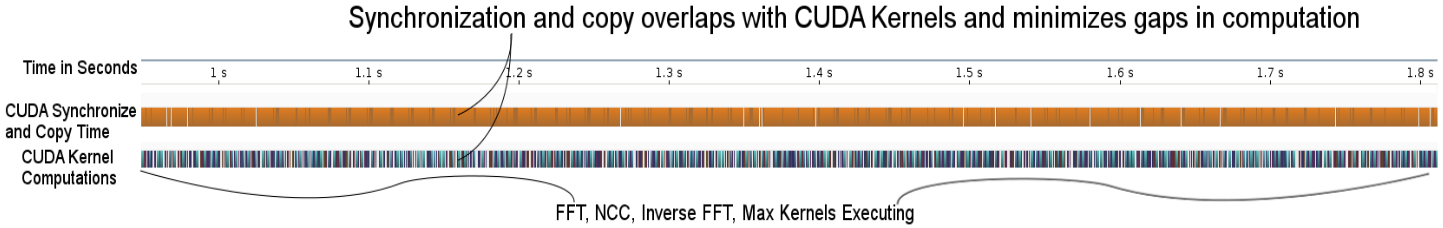
- Impacts on performance
  - Moving data between address spaces (CPU/GPU)
  - Disk I/O
  - Database updates

- Overlap computation with data motion, disk I/O, and database updates

- May require decomposing problem into multiple sub-problems



Synchronous approach



Asynchronous pipelined workflow approach

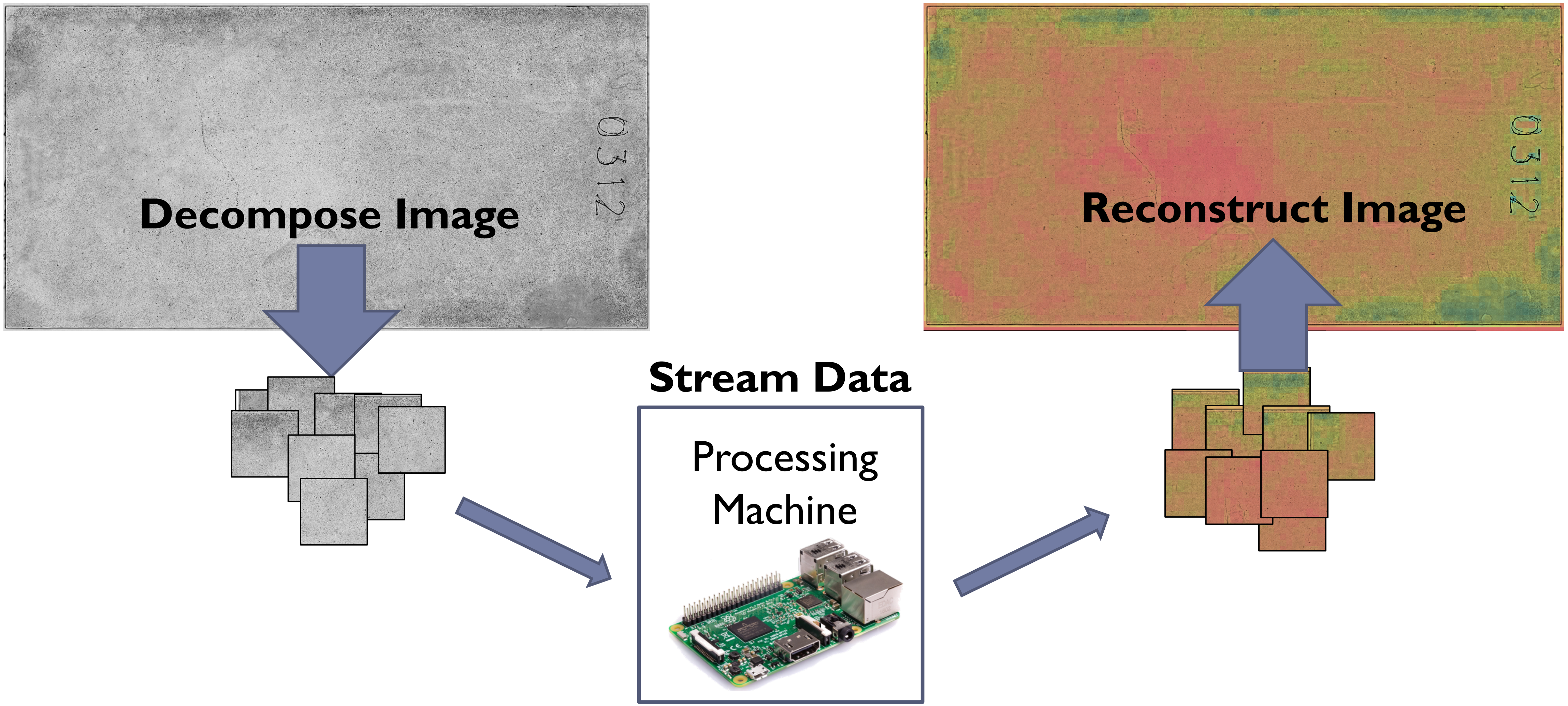
Challenges of Asynchronous Pipelining Workflows

- Legacy code often does not play well with pipelining
  - Restructuring and/or re-writing code may be necessary
    - Possibly algorithmic redesign
- Writing code that pipelines from scratch requires a lot of code structuring
  - Multi-threading
  - Thread safety
- Making sense of asynchronous behavior in an algorithm is not always obvious
- Solution: use existing frameworks … helps
  - Task libraries
    - StarPU, Legion, …
  - Hybrid Task Graph Scheduler (HTGS)

Hybrid Task Graph Scheduler

- Our approach for developing asynchronous pipeline workflows
- Application is a dataflow graph
  - Persists at runtime
  - Experimentation for performance
  - Debug, Profile, Visualize performance using the dataflow representation
- Targets powerful single nodes
  - Dual multicore CPUs & multiple GPUs
- Focus on
  - Separation of concerns
    - State maintenance versus computation
  - Coarse-grain parallelism
  - Hide latency of data motion
  - Memory management
- C++ Header API only

Streaming Tile Based Processing



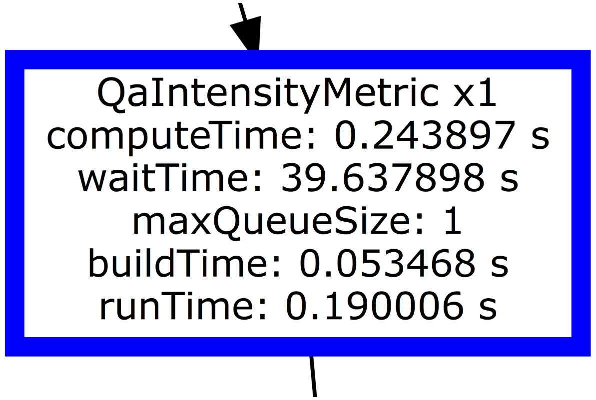
HTGS API

- Task interface
  - Templates define Input and Output
  - Execute(input)
    - Called when data is available for the task
  - addResult(output)
    - Called by user when output is ready to be sent to the next task
- Data is sent to the task
  - Each task holds a pool of threads
  - Extra data + multiple threads = parallelism

- Specialty tasks
  - Bookkeeper task
    - Manages complex data dependencies
    - Maintains state of computation
  - CUDA Task
    - Binds task to NVIDIA CUDA GPU
  - Execution Pipeline Task
    - Creates copies of a task graph
      - Each copy bound to a specified GPU
  - Memory Manager
    - Attaches memory edge to a task
      - getMemory("nameOfEdge")
      - Binds memory allocation to address space
        - CPU, GPU, etc.

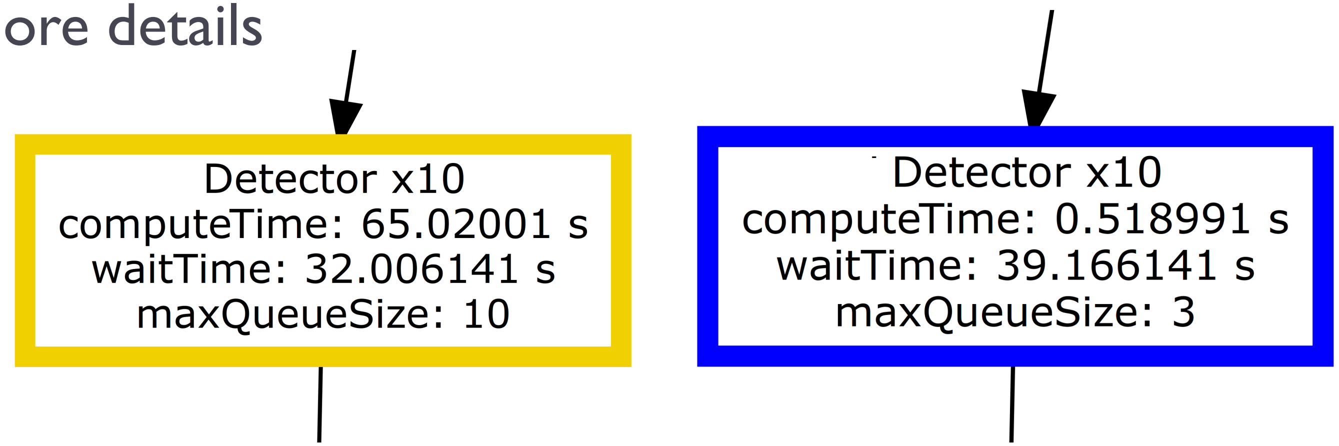
HTGS Profiling

- Zero overhead profiling
  - Profiling is gathered in both Release and Debug
    - Task level



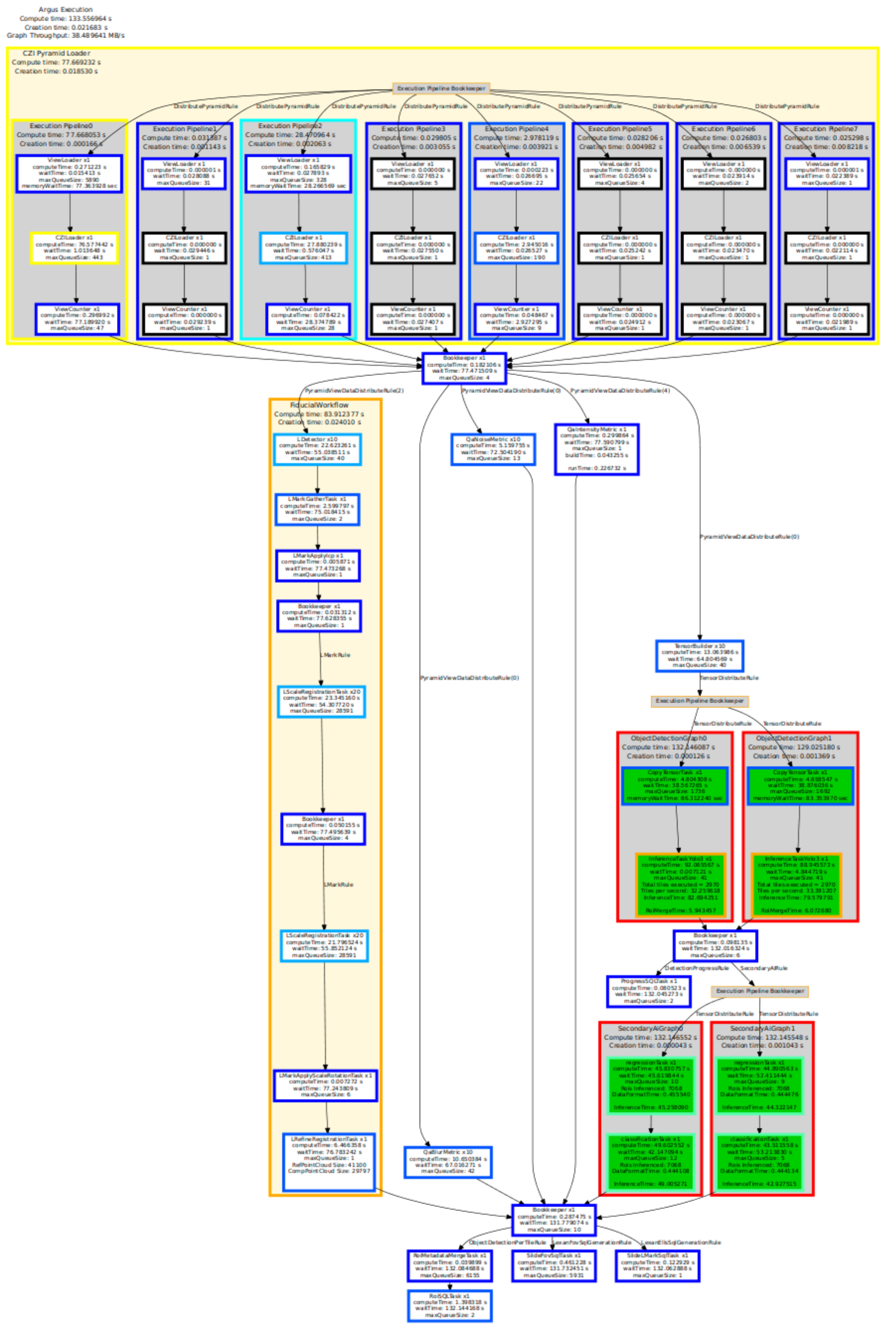
- Graph visualization report generated after every run
  - Immediately identify performance impacts per task
  - Customize task profiling to obtain more details

- Optimize per task
  - Find alternative methods



HTGS Software Engineering

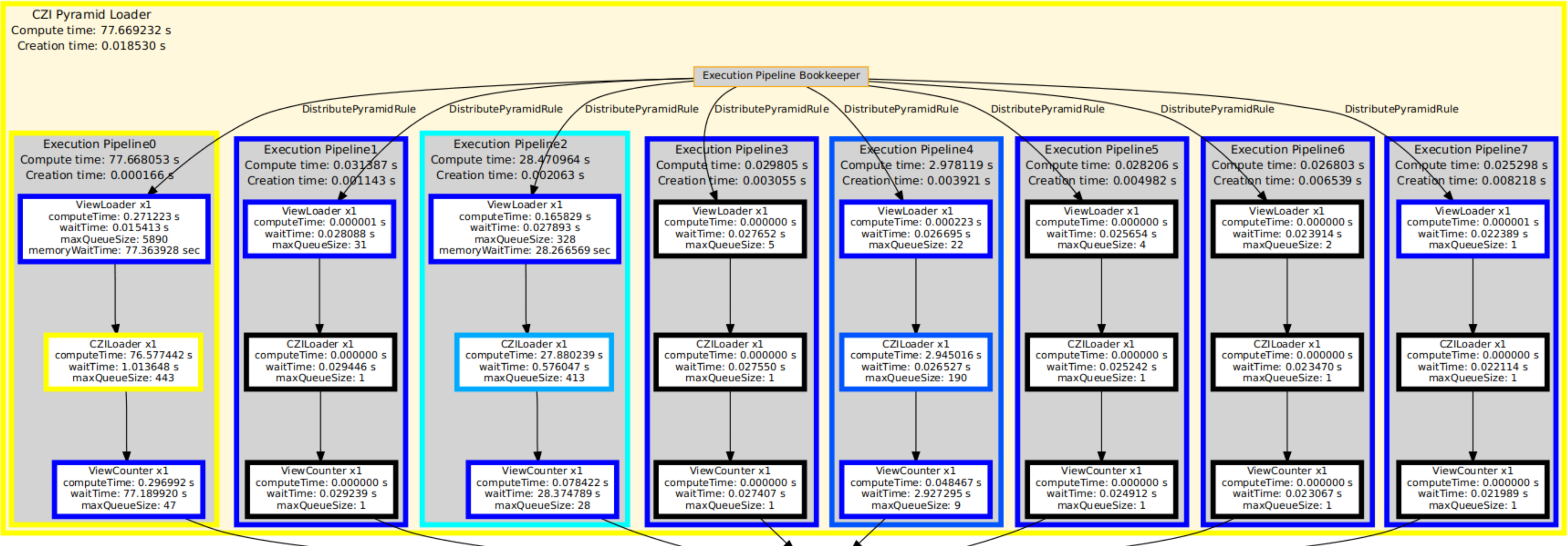
- Distribute tasks to developers
  - Narrow view of the world
    - Operate only on data sent as input and produce output
  - Difficult for developers to have code conflicts
    - Not impossible
- Maintains parallelism of the workflow
- Visual representation of critical path
  - Self-motivating to improve performance



Microscopy Analysis

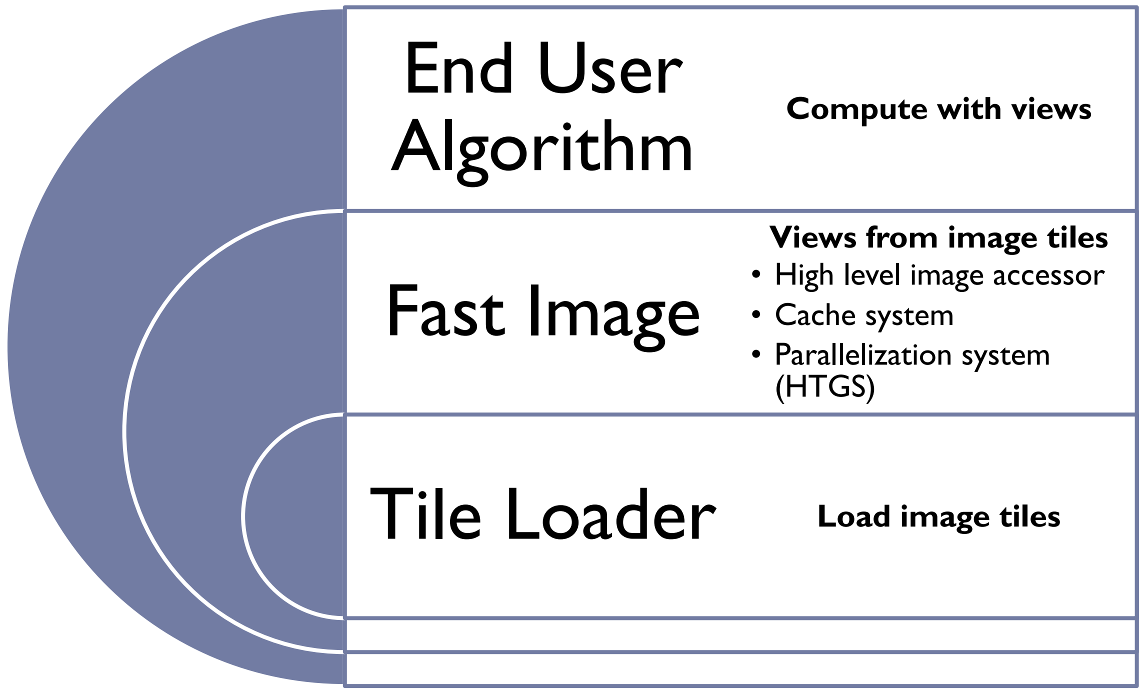
Image Reading

- Zeiss generates CZI images (pyramidal)
  - Tasks can operate at whatever pyramid they need to
  - Fiducial Detection happens at level 2 (25% resolution)
- Read all pyramid levels in parallel using FastImage

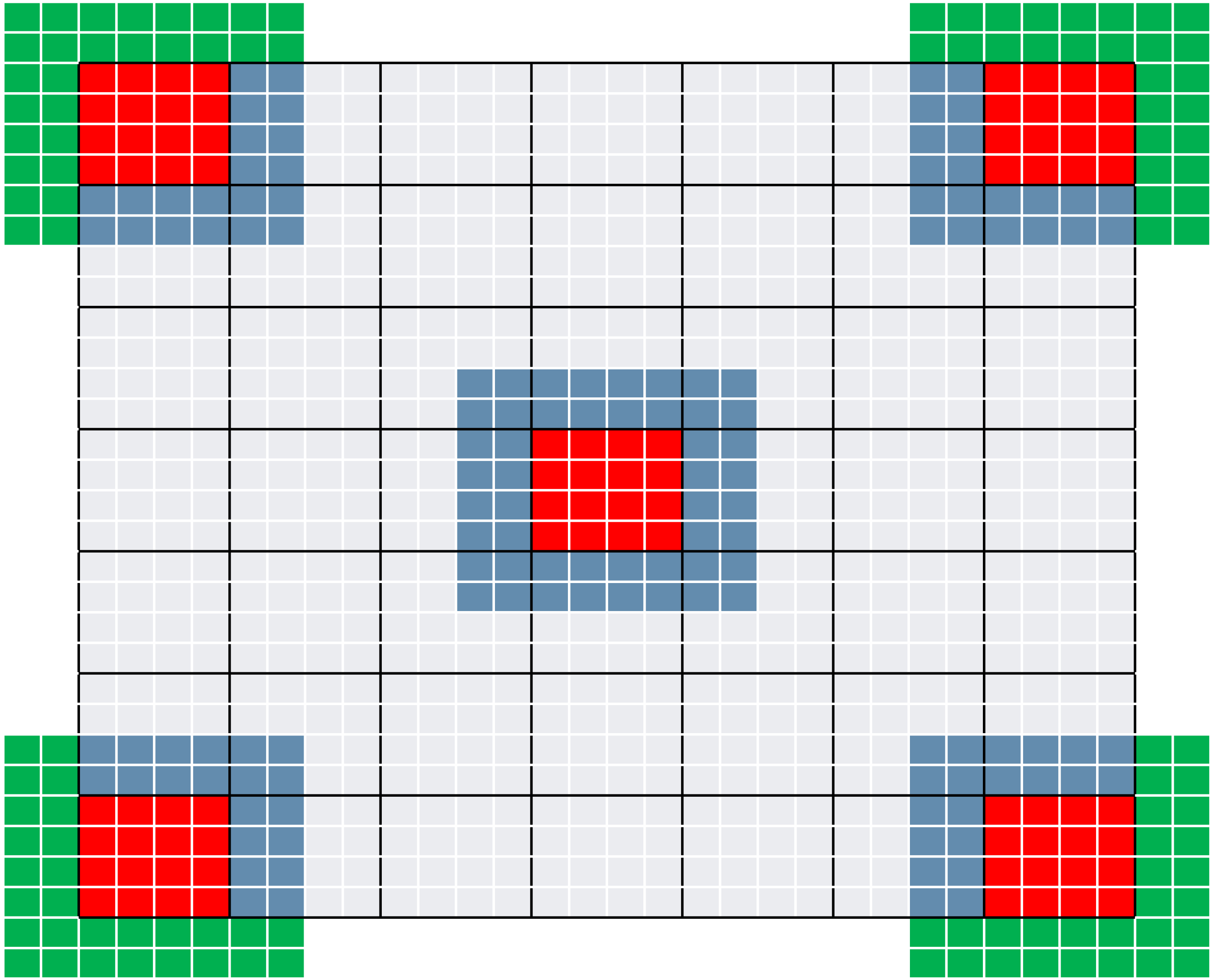


Fast Image

- C++ Library based on HTGS
- High level API to access an image
  - Or part of it
- Only access interesting views in an image
- https://github.com/usnistgov/FastImage



Views and Tiles



Tile

- Part of the image (here 28x28 pixels) given by the image loader

View

- Center tile (here 4x4 pixels)
- Neighboring pixels within a radius (here 2 pixels)
- Ghost (halo) values

Advantages

- Reduce memory footprint
- Enable tile caching & parallelism

Problem Decomposition into Tasks

Task Graph

- Traditional CV Tasks
  - Quality Analysis/Quality Control
  - Fiducial Mark Detection and Registration
    - Pipeline of subtasks
- AI Tasks
  - Object Detection
  - Secondary Classification/Regression

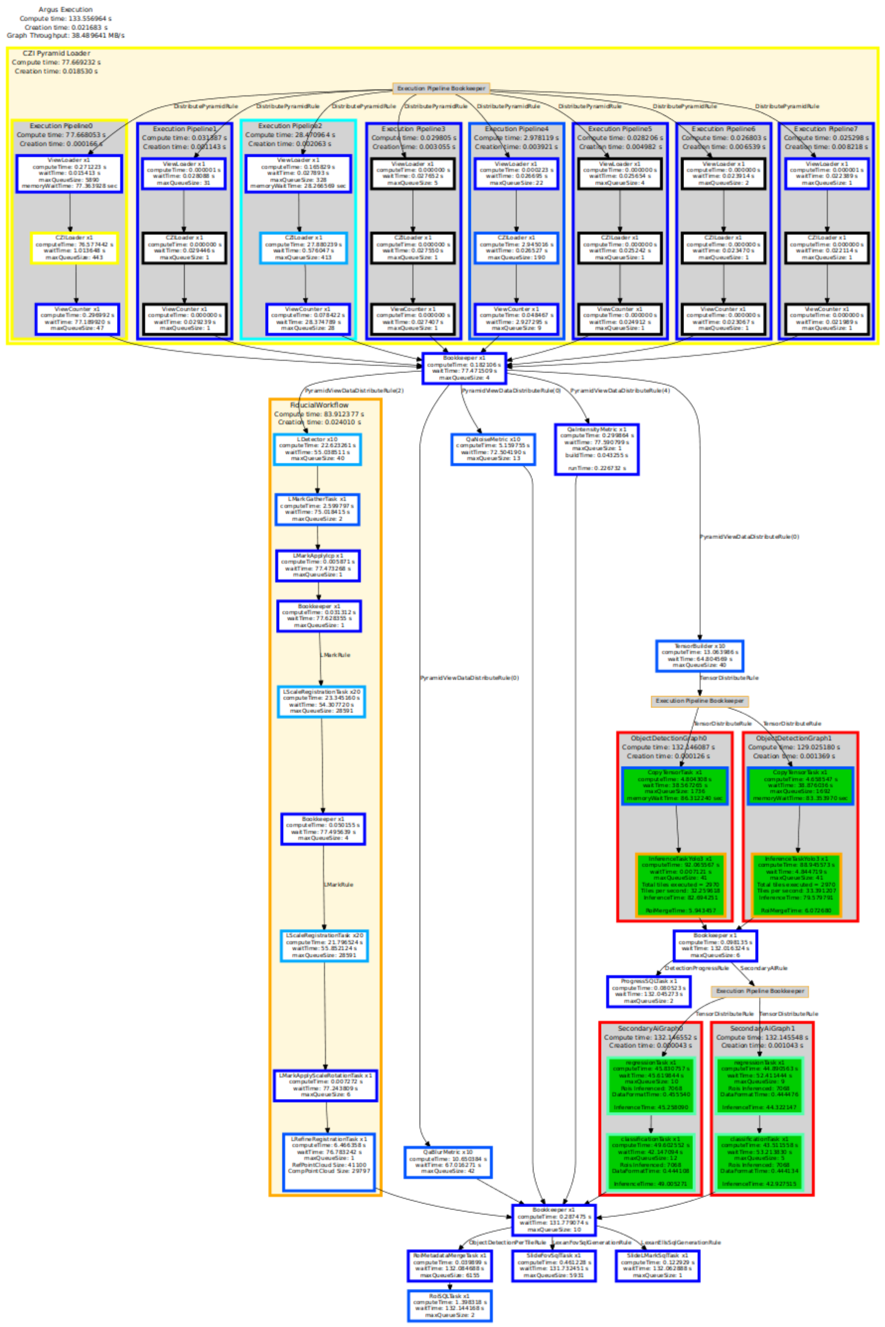
Relative Compute Time

Less More

Image Readers

Processing Workflow

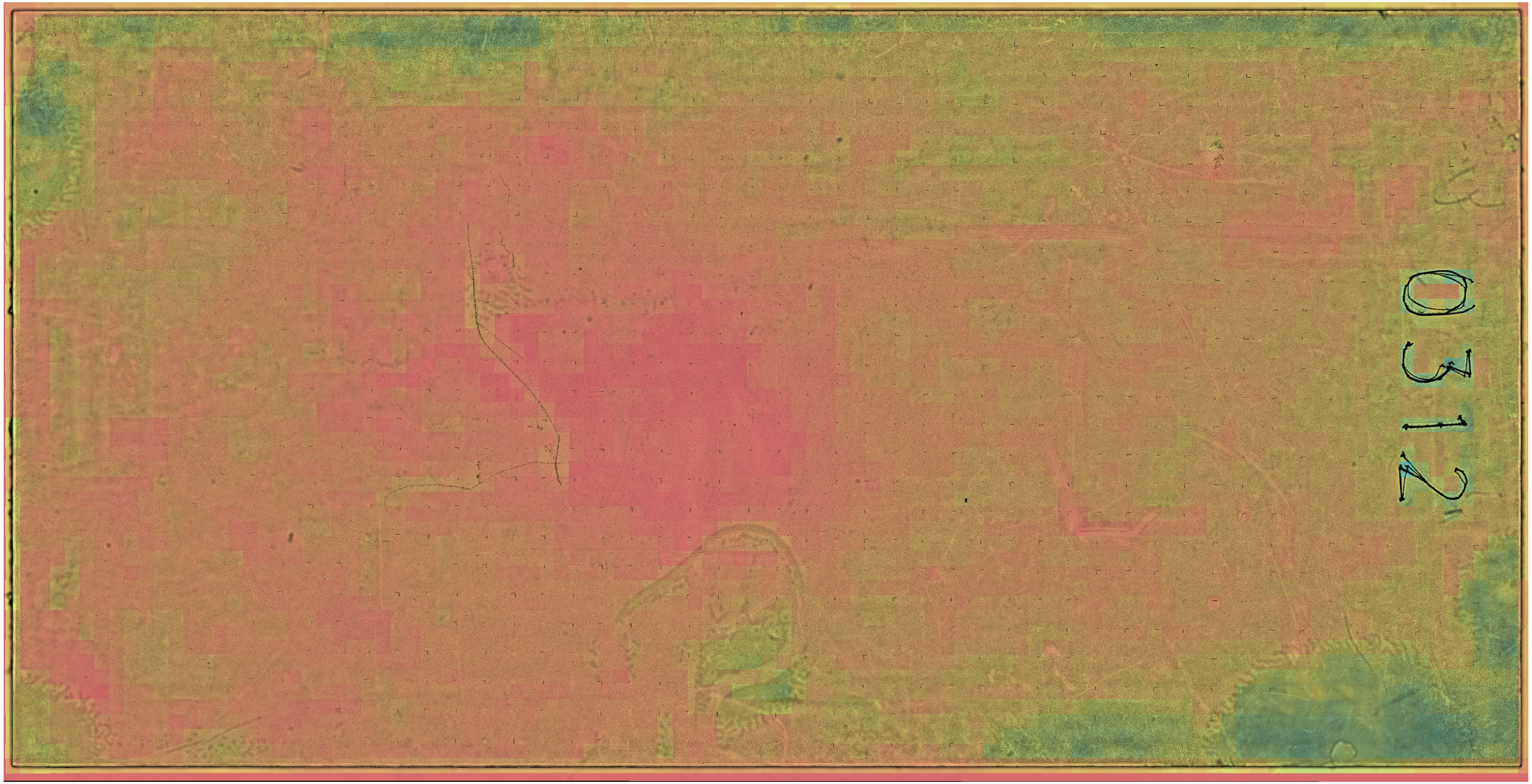
Database Transactions



QA/QC

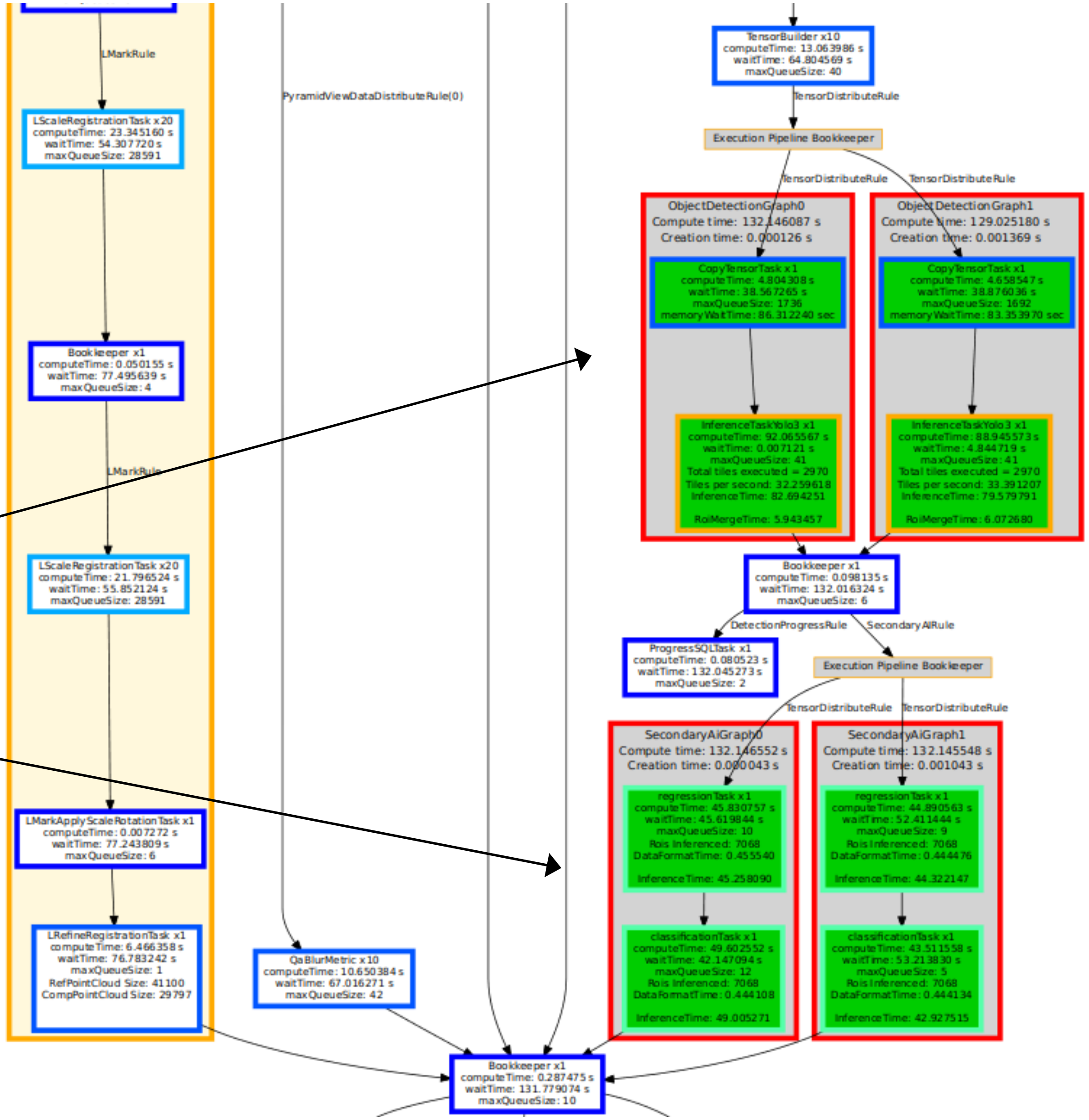
- Input: whole slide image coming directly from microscope
- No guarantees the image was
  - acquired correctly
    - contains the expected content
- Need to verify that the input image is within quality specifications for
  - Focus (image blur)
  - Background noise
  - Image brightness
- Each QA/QC item is a task in the HTGS system
  - Leverages OpenCV

QA/QC – Quality Heatmap



AI Tasks

- Traditional Computer Vision Tasks
  - Quality Analysis/Quality Control
  - Fiducial Mark Detection/Registration
    - Pipeline of subtasks
- AI Tasks
  - Object Detection
  - Secondary Classification/Regression



Relative Compute Time

Less More

AI Tasks

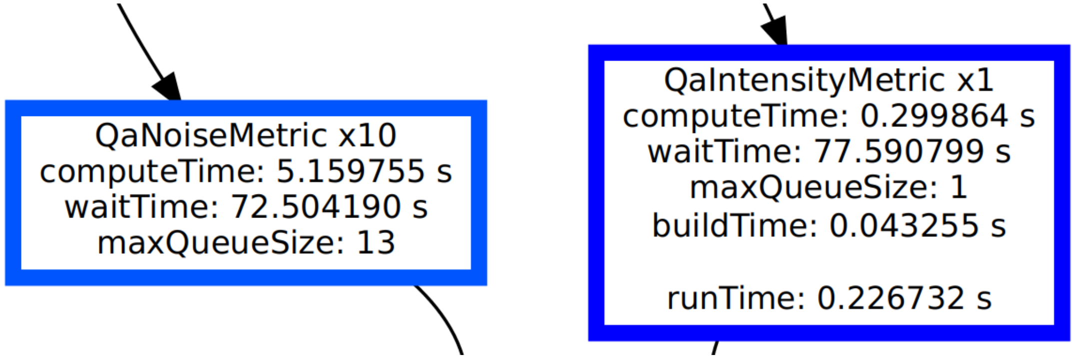
- Object Detection
  - Yolo v3 model
- Secondary Feature Categorization/Regression
  - Pair of ResNet50 models

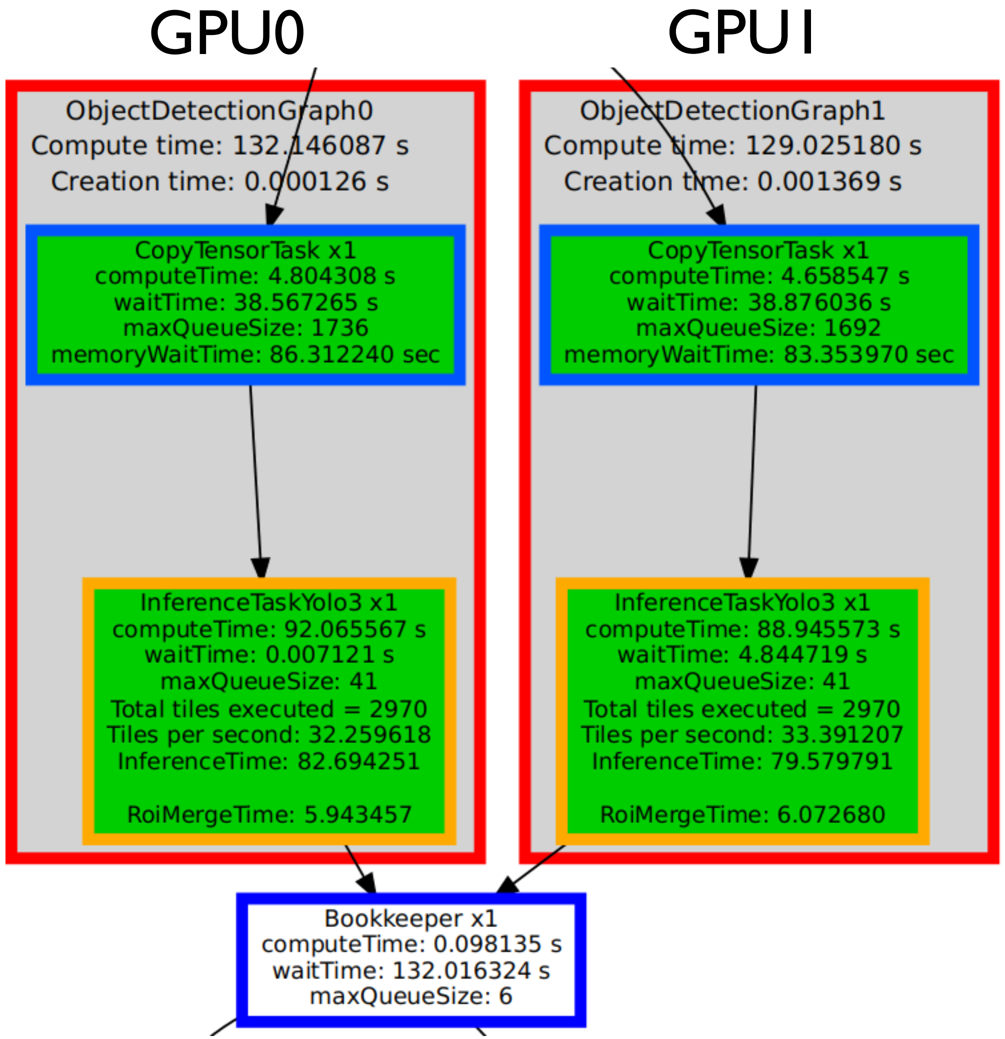
- Object detector extracts Regions of Interest (ROIs)

- ROIs are streamed to secondary AI models
    - As soon as the detector task generates an ROI output
  - Classification and regression tasks are run sequentially per ROI
  - Each task adds a new metadata value to an ROI as it flows through the compute graph

Task Scalability

- Specify thread count per task to control task's processing
  - Fiducial mark detection is expensive
    - 40 threads
  - QA is cheap
    - 1-10 threads
- AI tasks utilize all available GPUs





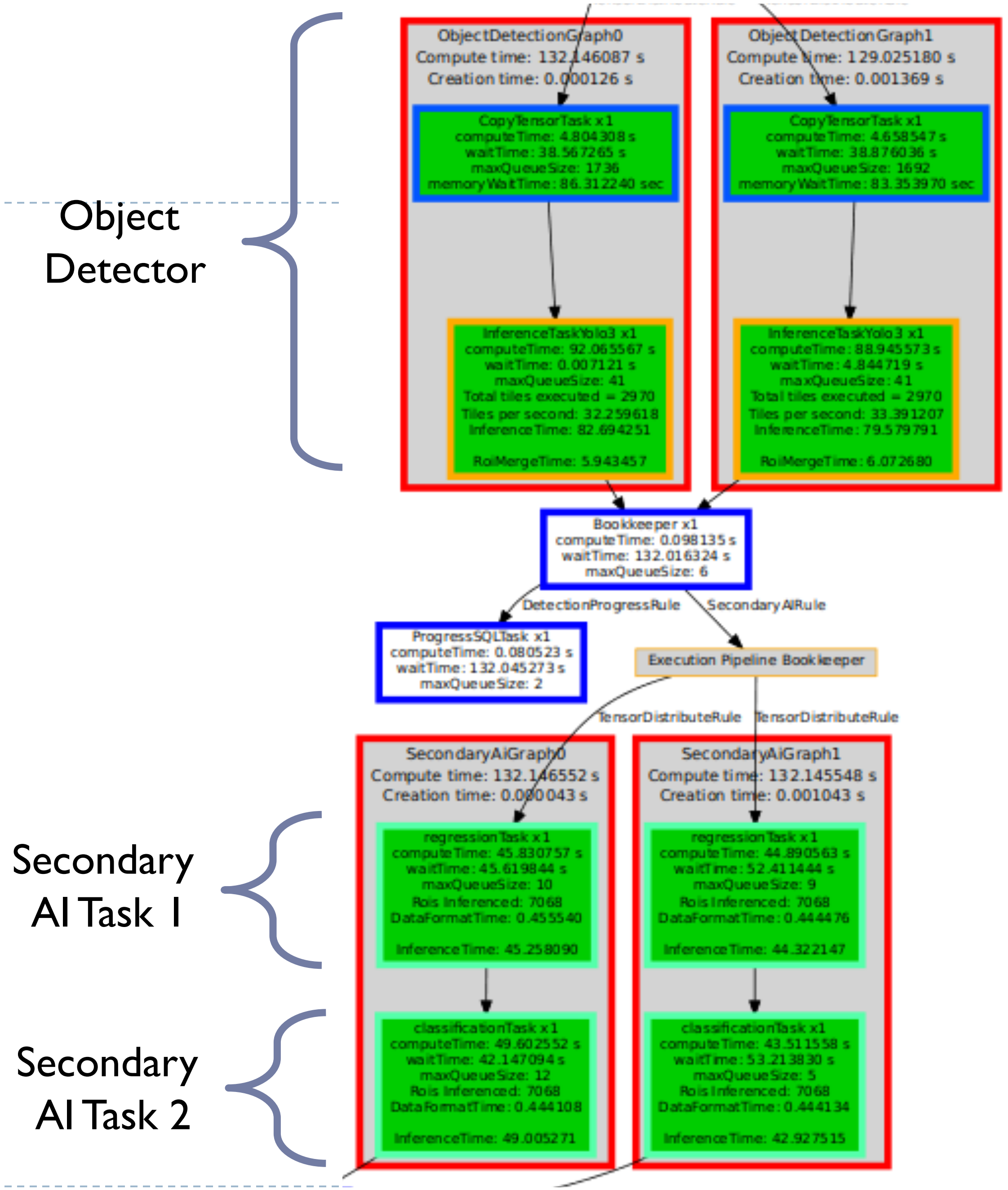
TensorRT

TensorRT

- AI models trained in Tensorflow on Power9 with V100s
  - Trained models saved in UFF format
- Deploy AI in TensorRT
  - Enables FP16 inference using Titan V tensor cores
  - Translate from UFF to TRT
- Processor detects what UFF/TRT models exist
  - Auto-generates new optimized TRT when UFF is newer than existing TRT
  - TRT creation time is amortized over many runs
  - Generate TRT on deployment hardware to have models optimized for platform of interest

TensorRT Engine

- TensorRT engine initialization
  - Loads serialized TRT model
- One TRT Engine per AI task
  - AI tasks duplicate: one per GPU using HTGS execution pipeline
- Example with 2 Titan V GPUs used for inferencing on 3 separate TRT models
  - Each red box is a sub-workflow per GPU
- Progress updates sent to database
  - Real-time visualization of progress



Workflow Scalability

- Codebase is designed for scalability
  - Auto detects the number of GPUs
  - Initializes one AI workflow, per model, per GPU
- Add another GPU if AI tasks are the bottleneck
  - AI tasks will duplicate
- CPU tasks specify the number of threads to use
  - Allocation of threads distinct from what to compute
  - Specifying thread count controls speed of task completion
  - Allows for load balancing between different tasks
    - Fiducial mark registration is CPU-bound and uses 40 threads
    - QA is fairly cheap and gets 1 thread only.

Programming Scalability

- Software developers write HTGS tasks
  - Tasks are constrained so that they can scale arbitrarily if needed
- Once dev decomposes the problem into a data streaming task based processing, tasks become the logical unit of thinking
- For example, whole image is never passed through the GPU for inference.
  - Too large to fit in GPU memory
  - Inference happens per 1024 x 1024 tile managed by Fast Image
- Developers incur upfront cost of learning curve
  - Enables parallel development & testing at task level
  - Simplifies obtaining performance-oriented software

Summary

Requirements for Realtime Microscope Processing

- Hardware:
  - Microscope with event hooks to enable automation
  - Storage for images
  - Processing machine
    - Same as acquisition machine or on LAN

- Software
  - Fixed analysis pipeline which needs to be applied to every image coming off the microscope
  - Task based, data streaming processing model
  - Workflow system to orchestrate compute in a scalable manner

Future Work

- Hedgehog: next generation of HTGS
  - Hedgehog simplifies graph design
    - Each task can have multiple input types and broadcast outputs
  - Hedgehog implementation of FastImage
    - Generalization beyond image data → serialized matrices data
  - Available now
- Shift from UFF AI model format to ONNX

Thank You

- Questions?

- Code
  - HTGS: github.com/usnistgov/HTGS
  - Hedgehog: github.com/usnistgov/hedgehog
  - FastImage: github.com/usnistgov/FastImage
  - HedgehogFastImage: soon

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