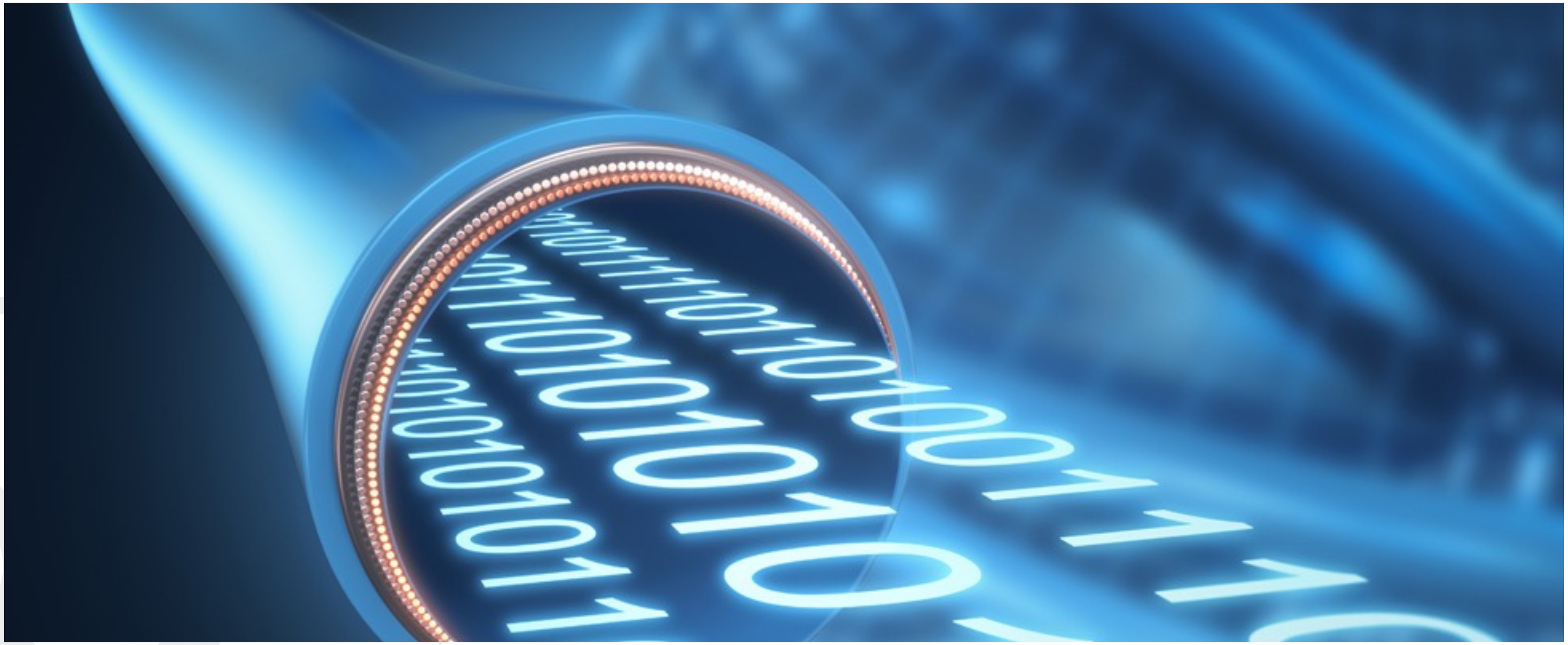
Computing Models for Processing Streaming Data from DOE Science



Graham Heyes – Jefferson Lab

What is this talk about?

- This is not a proposal for a computing model for ePIC. It is a short look at:
  - What streaming data is in the broadest sense
  - The opportunities and challenges for processing such data

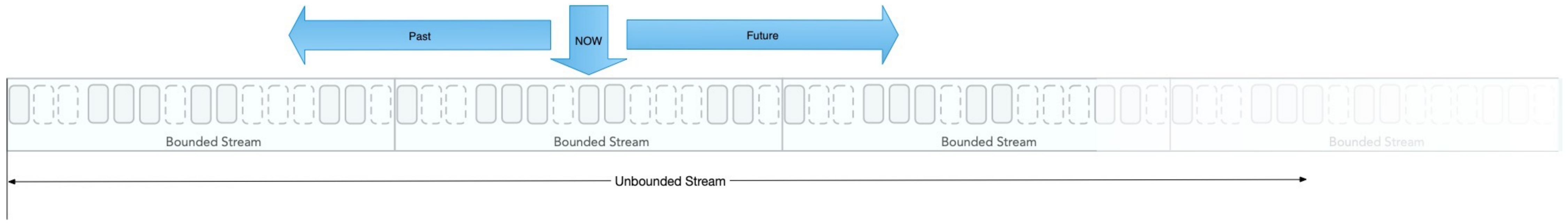
- Outline
  - Definition of streaming data
  - The current dominant data processing model
  - The need for a new approach
  - Data Streaming as a disruptive model
  - Science use cases
  - Computing models
  - Hardware architectures
  - Data steering
  - Summary

What is streaming data?

- For the purposes of this talk streaming data is:
  - Data that is generated continuously by many data sources, which typically send data records simultaneously in a time ordered sequence
  - Data that needs to be processed sequentially and incrementally on a record-by-record basis or over sliding time windows and used for a wide variety of analytics including correlations, aggregations, filtering, and sampling
  - Data that is typically considered to be “in motion” from a source through various processing stages
  - Data that typically has some time sensitivity or criticality requiring prompt processing
    - To prevent backup as new data arrives
    - To steer the data source
    - To respond to events in real-time
- Streaming data formats typically have a metadata wrapper for each record that contains
  - Data type, data source, position of the record in the stream

Bound an unbound data streams

- A bound data stream is finite stream where each record is well defined and the same format
  - Typically, bound data has a known ending point
  - A data taking run for an experiment is a bound stream of data
  - A YouTube clip is a bound stream of video frames
- Unbound data is unpredictable, infinite, and not always sequential. There is no concept of a run, the duration is effectively infinite
  - Example, continuous monitoring of a neutrino detector
    - The events occur at random
    - The events can be of randomly varying size.
    - A large event A could take longer to acquire or process than a small event B. The order in the stream becomes B then A where the order of occurrence was A then B
- An unbound stream of bounded streams is possible (binge watching YouTube)



- How does this data type fit into existing computing models? Is something different needed?

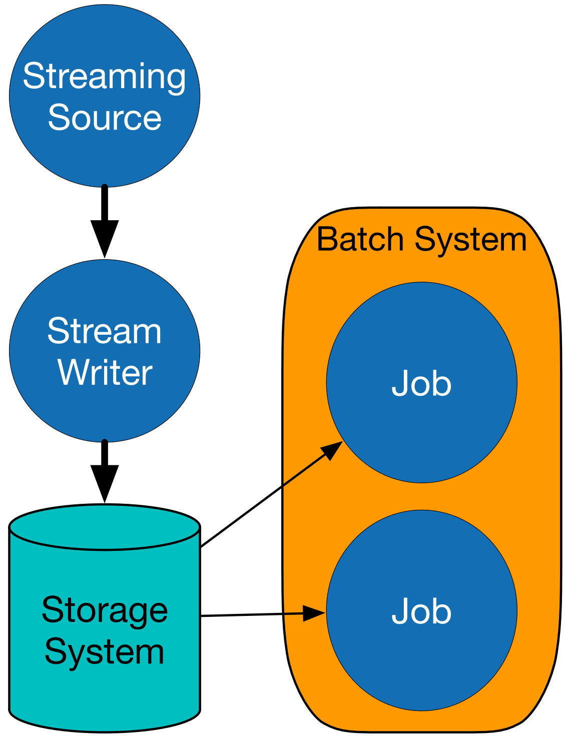
Current dominant data processing model for experimental science

- Data is acquired by online workflows and processed by offline workflows
  - These are usually decoupled with significant time period between acquisition and processing
- Between online and offline data is stored in a hierarchical storage system, typically files in a Posix filesystem
- The batch processing model dominates offline data processing, it relies on the need to repetitively process many thousands of files of data
  - Typically, a workflow manager retrieves files from storage and queues up jobs to process them
  - Jobs are managed by a batch system (SLURM) and executed when resources become available
- Advantages are
  - Automation of workflows – launch processing of thousands of files
  - Simplicity – each job is relatively independent of its peers
  - Efficient use of resources – jobs run when resources are available.
    - Assigning a range of priorities can keep a cluster busy without impact on high priority jobs

- Does this model fit streaming data? Statement: Batch processing is not a good fit

Scenario 1 – Write it to a file and sort it out later

- In this scenario the data streams terminate in a process that writes the records into one or more files
- Simple to set up but hard to manage and optimize if there are many parallel streams
  - One stream per file gives parallelism but potentially lots of small files
  - Aggregating streams and writing are potential bottlenecks
  - What does a file represent? – varies by use case
    - Unit of time?
    - Unit of data?
  - How to handle cases where data spans file boundaries?
  - File management – what deletes files so that the storage doesn't fill?
  - Batch system starts jobs when resources become available, this is non-deterministic.
    - Hard to implement real-time or even near-real-time processing
- This is a workable solution but making it work loses many benefits of streaming data



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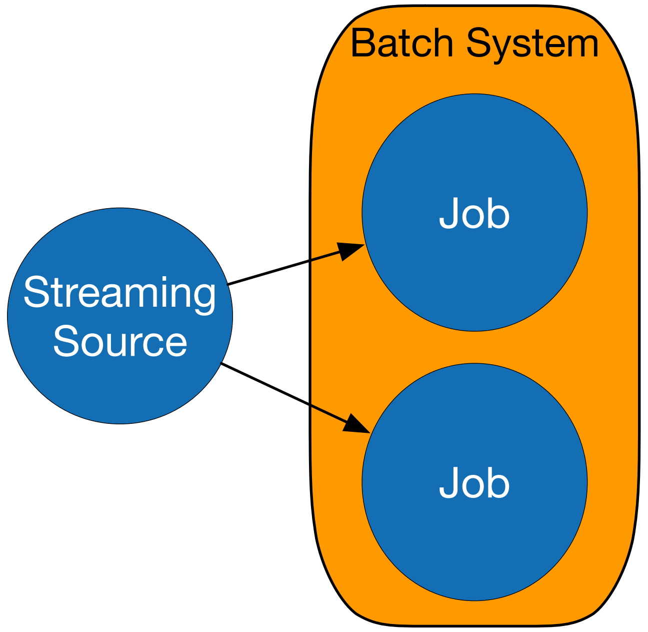
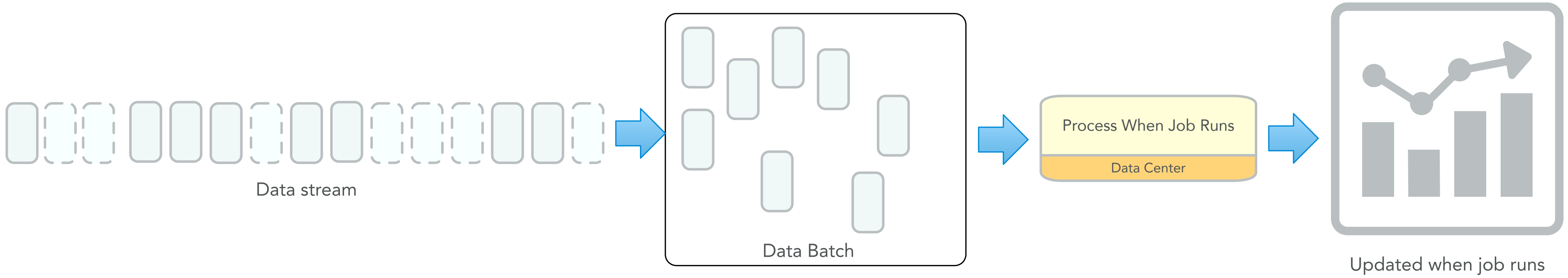
Scenario 2 – Start batch jobs that connect to streaming data sources

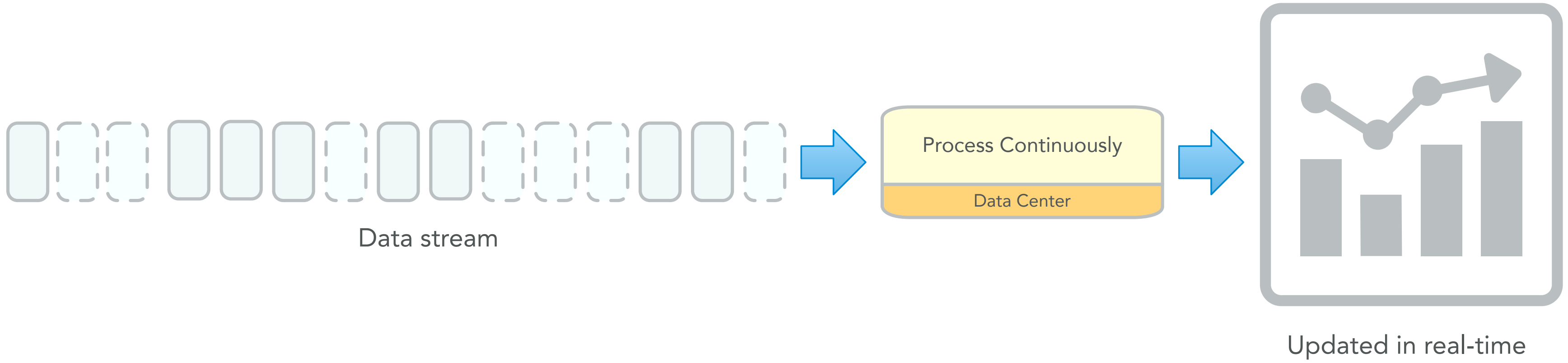
- In this scenario the data streams connect to jobs in the batch system directly. Streaming data all the way
  - The batch system starts the jobs when resources are available
  - These jobs must remain allocated for the duration of the experiment
  - Only works if the data is streaming over a network – otherwise need to target jobs to nodes with custom hardware
  - Needs an external orchestrator
    - Which nodes are running what?
    - Which data goes where?
    - Starting, stopping, monitoring, recovery
  - Unless running on a dedicated node the job has no control over what else is running on the node
    - Reliability?
    - Performance?
- This is a viable solution, but making it work efficiently requires sidelining the batch system except at initial startup
  - It doesn't meet the definition of batch processing



Summary comparison of batch processing and stream processing



Batch jobs only run when resources are available and, typically limited duration. Possible contention between jobs on the same node. Data is no longer streaming but sorted into batches. Results ready when job ends.



Batch system only used to start the processing. Must allocate resources for duration of experiment. Ideally data flow can't stop so guaranteed service quality is needed. Results update in real-time.

What models are a good fit?

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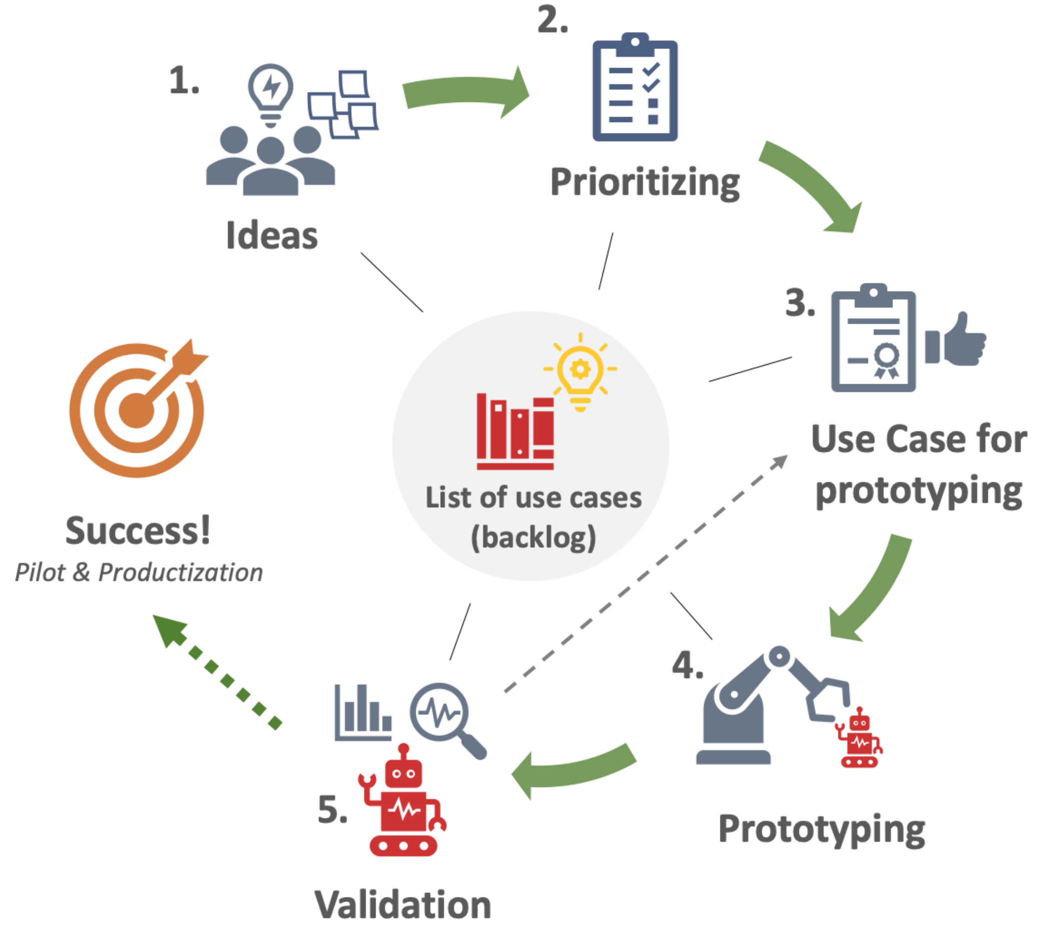
Data Streaming as a disruptive model

- Instead of trying to force streaming data processing to conform to a pre-existing model, like batch processing, treat it as a disruptive computing model in its own right.
  - Approach followed by Amazon, Google, Netflix, etc.
- Key components:
  - *Flexible data integration*: The ability to transport data in the format required, regardless of whether the data is structured or semi structured, direct or customized, static or changing
  - *Data inference*: Make it easy to map data and control how it is processed
  - *Code engines*: The ability to embed code to enrich and cleanse data, create alerts, and detect anomalies in stream in real time
  - *Live monitoring*: Real-time visibility into data streams for monitoring behavior, identifying potential discrepancies, and debugging data records – data level
  - *Pipeline transparency*: Provides continuous views of data in motion and notifications that allow users to view incoming events, monitor throughput and latency, and identify errors in real time – infrastructure level
  - *Agility:* The ability to dynamically expand or contract and migrate allocated resources.
  - *Support for heterogeneity:* The ability to allocate a tailored resource unconstrained by predefined hardware choices
- *How does it apply to science?*

Science use cases

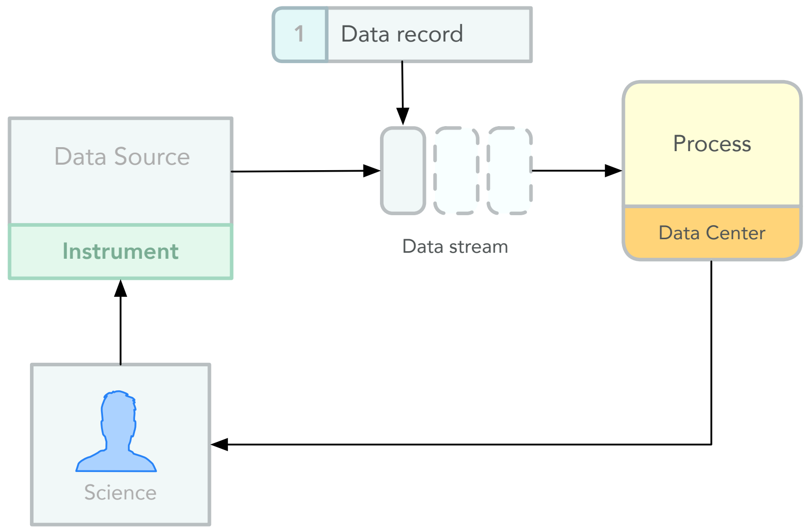
Any good computing model is driven by use cases that present challenges that it must solve. Here are four to consider

1. Time critical workflows
2. Data driven workloads
3. Distributed data sources
4. Complementary data sources



1) Time Critical Workflows

- Across a range of science programs, experiments follow time-critical use patterns
  - Success of the science depends upon data being processed within a specified time after acquisition
  - Examples:
    - Real time data filtering
    - Processing a data sample to inform instrument calibration stabilization
    - Data quality monitoring
    - Real time processing to
      - Reduce data archive requirements – smart data reduction
      - Steer experiments – set run conditions based on last run
      - Provide input to AI/ML, inference engines, digital twin models
- The key features to guarantee success are
  - timing of data delivery to compute resources
  - timing and continuity of compute resource availability
    - Uptime and quality of service
  - timing of real-time feedback delivery

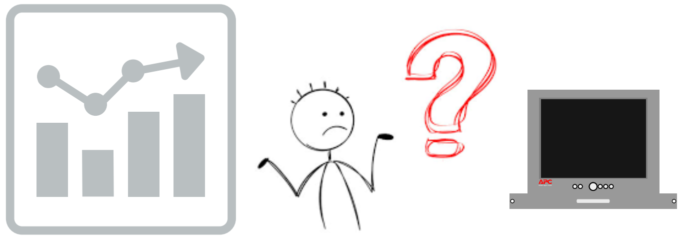


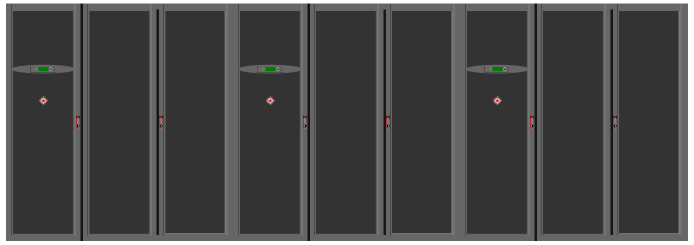
2) Data driven workload

- The scale of computing resource required for an experiment is driven by data rate and complexity
  - NP and HEP:
    - Processing time is a function of detector and event complexity as well as the science being studied
    - Scale of compute resource needed can vary depending on data taking conditions
      - It is frequently hard to guess in advance (overestimates are as bad as underestimates)
  - Light Sources:
    - Data complexity and rate varies between beamlines and, for individual beamlines, from sample to sample
    - Relatively simple sensors with high sample rates
      - Low complexity simplifies processing, but data rate is problematic
    - Complex sensors like high-rate cameras
      - Data is complex AND data rates are high

- Benefit is tiers of processing before storage to reduce data volume
- Key to success is an adaptive system that can expand or contract as the workload fluctuates.

Do I need a laptop or Supercomputer

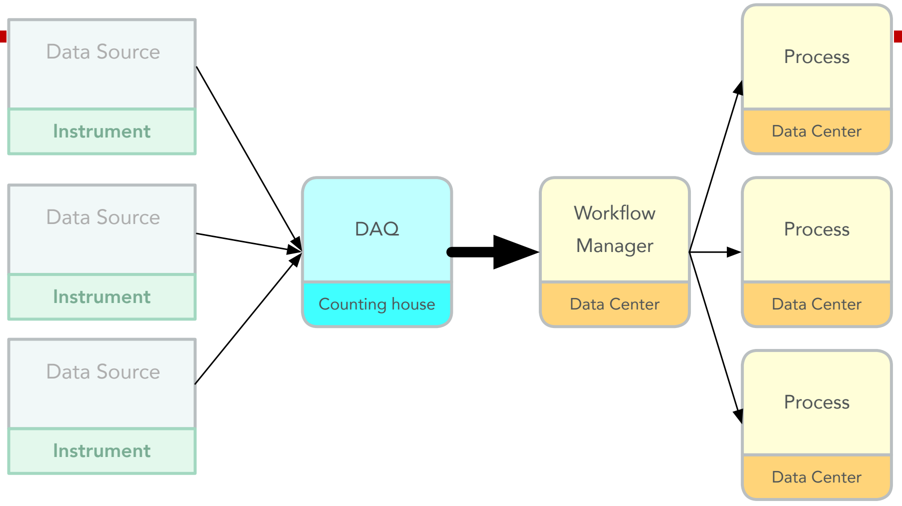


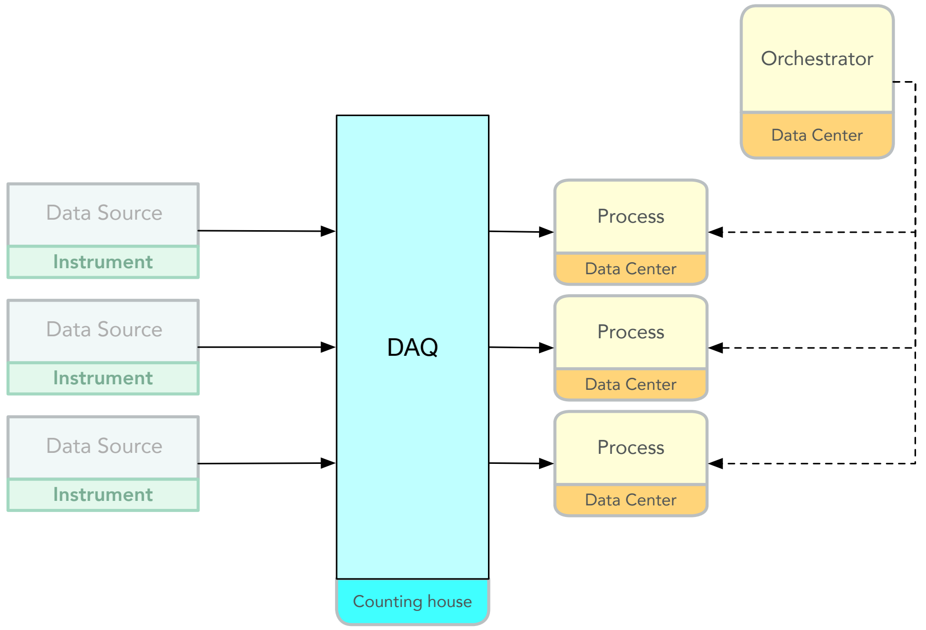


3) Distributed data sources – NP and HEP

- Very familiar to NP and HEP – detectors are composed of sub-detectors, that in turn are groupings of individual detector channels
  - Data sources are spread over a volume of space
  - Also fold in data from other sources, accelerator, beamline, etc.
- Typically, this is dealt with online by an "Event Builder" that combines data records from various detectors for the same interaction into an "event"
  - This can be a serious bottleneck and affect data flow stability
- Streaming data in parallel to a computing resource allows deferral event building until the data is in the data center.
  - Building can happen in parallel

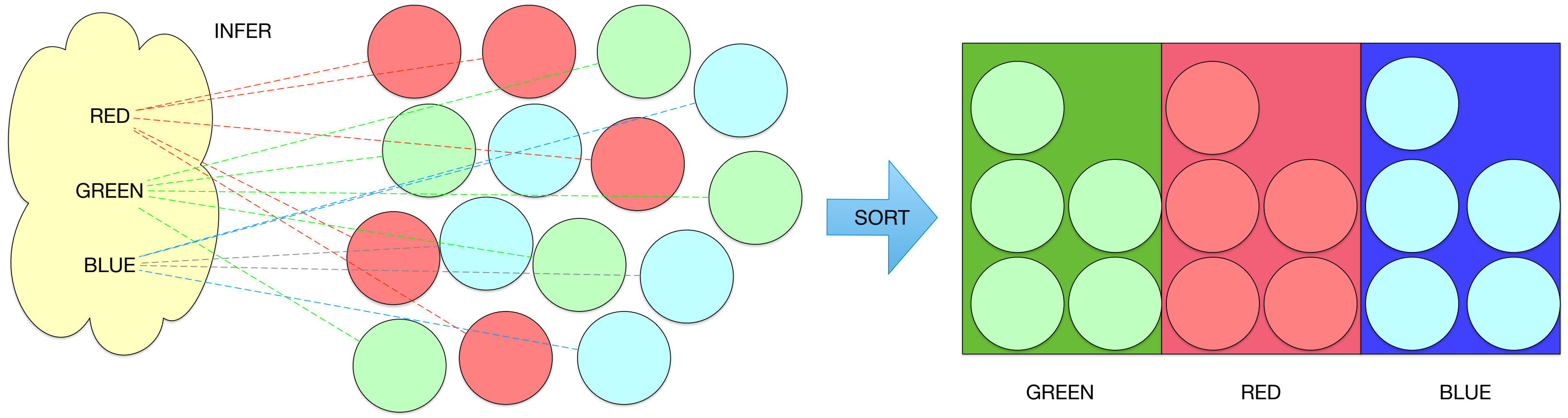
- Streaming data flows are parallel and determanistic
- Key takeaway is that streaming data processing is a natural fit, distributed is in the definition of streaming data





3) Distributed data sources and streaming - generalized

- Event Building, on the previous slide, is an example of real time data sorting
  - In the diagram below colored counters are sorted into boxes
  - In Event Building the color represents the time that the data was taken, with counters from different data sources. The task is to sort data from the same time from different sources so they can be processed together
- An alternative is to use ML to recognize the ”color” and group by reference
  - In this simple case ML is not really needed but much more complex sorts could be imagined that do
- Streaming data formats provide access to rich metadata that is ideal for enabling rapid real time sorting or selection of data of interest – opportunities for innovation exist



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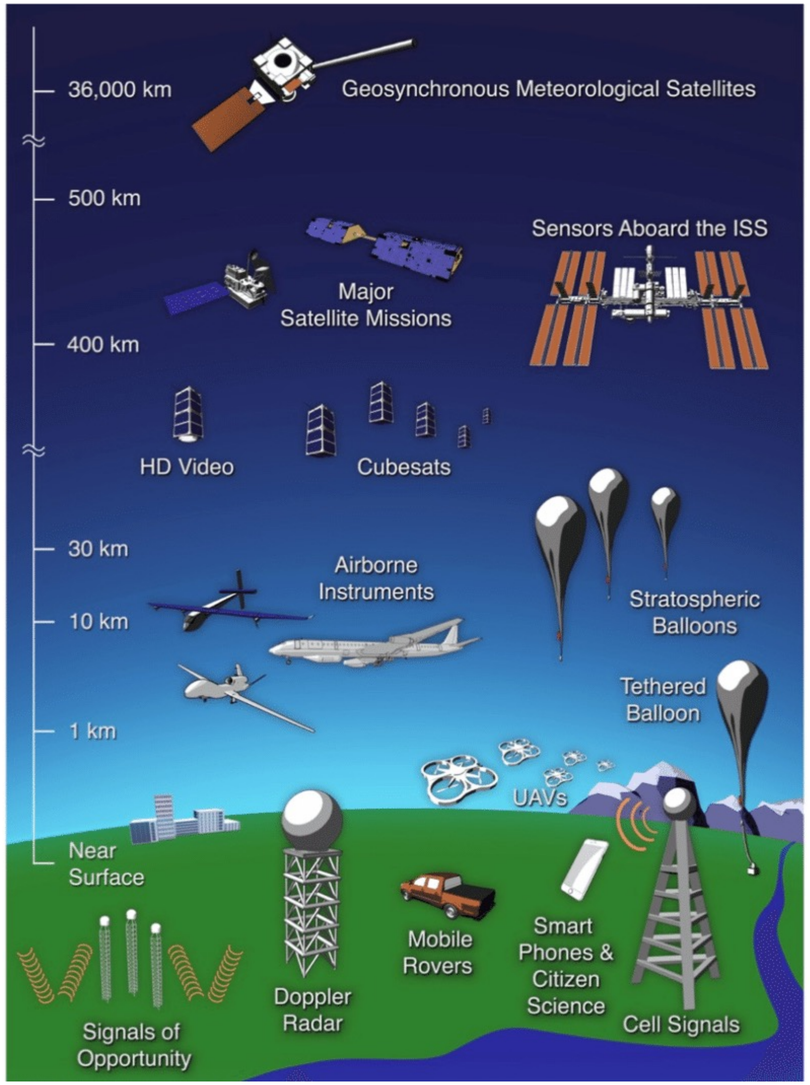
4) Complementary data sources

- In some fields observational or experimental data is combined from completely different but complementary sources
  - NASA and NOAA combine satellite data with ground radar, wind gauges, temperature sensors
  - Astronomy combines radio, optical and IR images
  - Light sources use data from one beamline to calculate configuration settings to simultaneously study the same material in another beamline
- There is also interest in running simulation in real-time using models informed by complementary measurements
  - Example, scan a sample to determine shape and structure, simulate interaction with beam using real shape and structure, compare with experiment in real time to inform next run
- Can generate overwhelming volumes of uninteresting data. Combining and processing incoming streams allows steered data reduction (what we call triggering)



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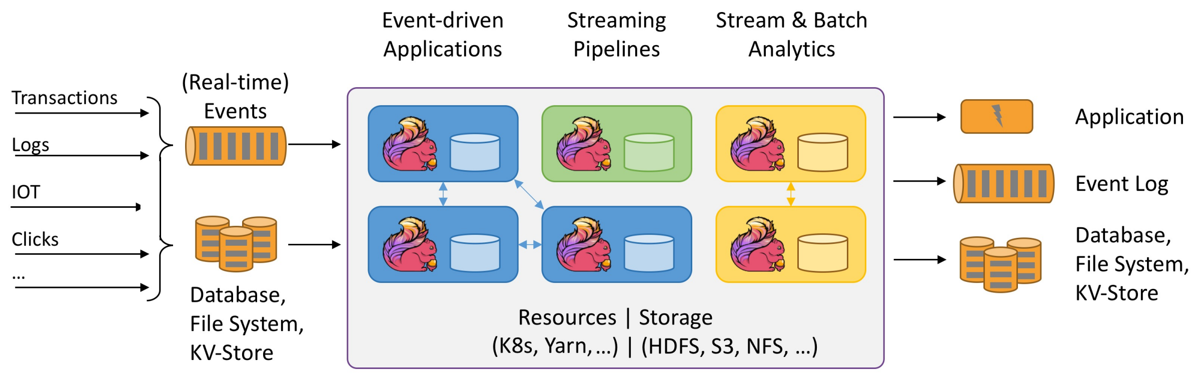
Frameworks implementing streaming data models

- Streaming data is a hot topic – commercial and open-source solutions exist
  - Amazon
    - Kenesis - ingest, buffer, and process streaming data in real-time
  - Apache
    - Flume - simple and flexible architecture based on streaming data flows, aimed at log data
    - Kafka - open-source distributed event streaming platform
    - Flink - A framework and distributed processing engines for stateful computations over *unbounded and bounded* data streams.
    - Apex - batch and stream processing using Hadoop's data-in-motion architecture by YARN.
  - ASCR – several initiatives, for example research in streaming data reduction
  - Also, highly tailored solutions from national labs, BNL sPHENIX ,CERN, etc
- Question: Innovate or integrate?
  - A little bit of both
  - Third-party products are evolving
  - Some likely never a good fit
  - Perfection is the enemy of good enough



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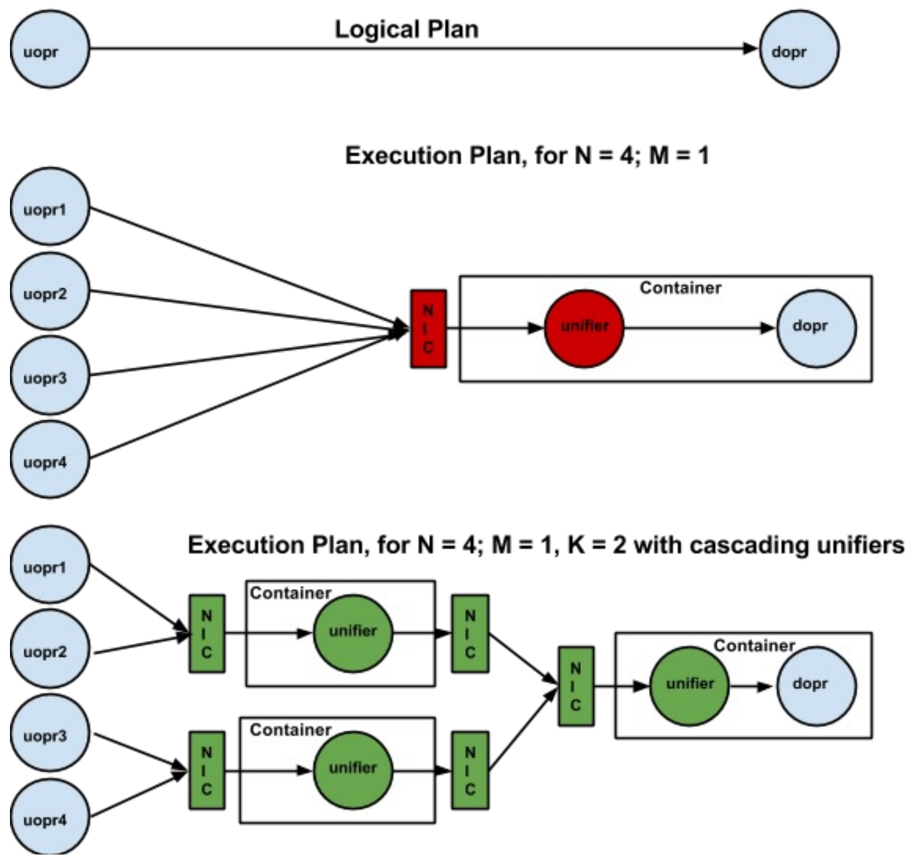
Processing models

- Most of the solutions are fundamentally similar and based on a distributed parallel model
  - Event driven data processing engines are networked by data pipelines and data lakes
    - Data between engines is “in flight” as much as possible but data lakes allow unstructured “pools” of data
      - Provide temporary buffering of data to rate match application components
      - Time sync streaming data to allow cross stream data queries – earlier slide on sorting
- A Directed Acyclic Graph (DAG) can be thought of as a blueprint of how engines, pipes, and lakes are laid out to implement an application
- Stream processing engines are built on top of runtime libraries which help developers focus on algorithmic code without dealing with lower-level streaming mechanics.
- There are two major types of processing engines.
  - Compositional Engines
  - Managed Declarative Engines

Compositional Engines

- In compositional stream processing engines, developers define the Directed Acyclic Graph (DAG) in advance and then process the data. This may simplify code, but also means developers need to plan their architecture carefully to avoid inefficient processing.
  - In the diagram the simple logical plan becomes complicated by multiple data sources and bottlenecks
- **Challenges:** Compositional stream processing are considered the “first generation” of stream processing and can be complex and difficult to manage.
- **Examples:** Compositional engines include Samza, Apex, and Apache Storm.
- Developer builds the application from a kit of parts according to a plan



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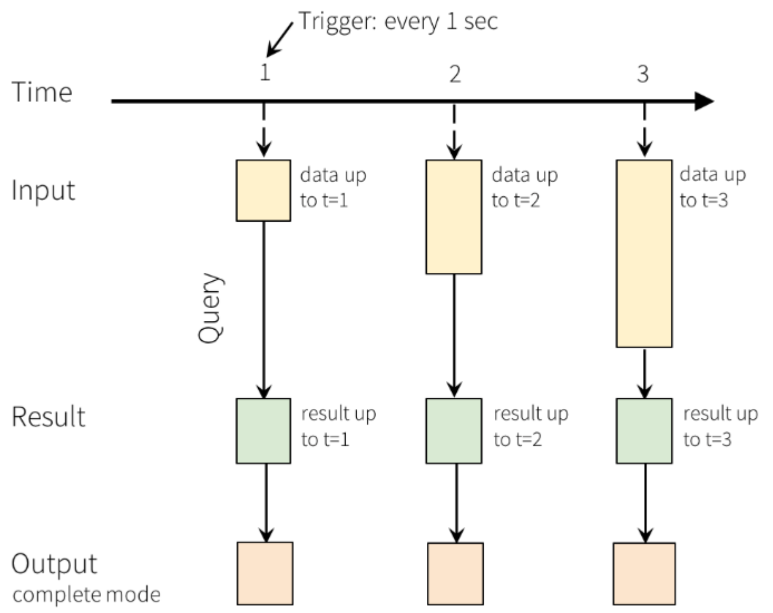
Declarative Engines

- Developers use declarative engines to chain stream processing functions. The engine calculates the DAG as it ingests the data. Developers can specify the DAG explicitly in their code, and the engine optimizes it on the fly.
- **Challenges:** While declarative engines are easier to manage, and have readily-available managed service options, they still require major investments in data engineering to set up the data pipeline, from source to eventual storage and analysis.
- **Examples:** Declarative engines include Apache Spark Streaming and Flink.

- The engine assembles the network based on incoming data or optimizes an existing net

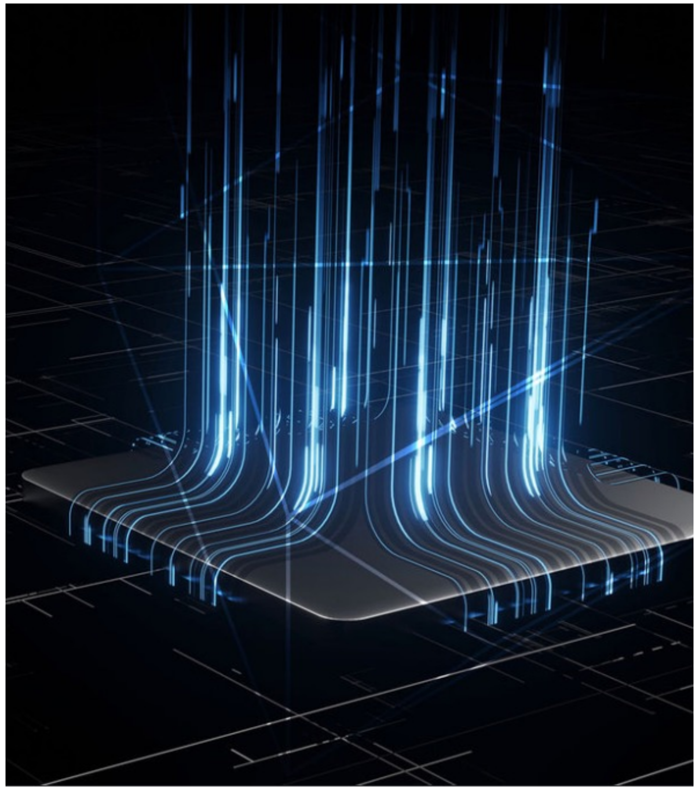
```
spark
  .readStream
  .select($"value".cast("string").alias("jsonData"))
  .select(from_json($"jsonData",jsonSchema).alias("payload"))
  .writeStream
  .trigger("1 seconds")
  .start()
```



Streaming optimized hardware architecture

- The software architectures discussed in the last few slides allow the creation of managed streaming applications
  - Developers provide code to plug into event driven engines
  - Engines are assembled into an application using network graphs
  - A management layer optimizes data flow and performance on the fly

- What sort of hardware architecture would optimally support these applications?
  - It must support
    - Guaranteed uptime, performance and service quality
    - Data flow optimization on the fly
    - Applications of (somewhat) arbitrary scale on heterogenous hardware
    - Integration of AI/ML and other data science techniques
    - Integration of novel technologies (adapt to future needs)



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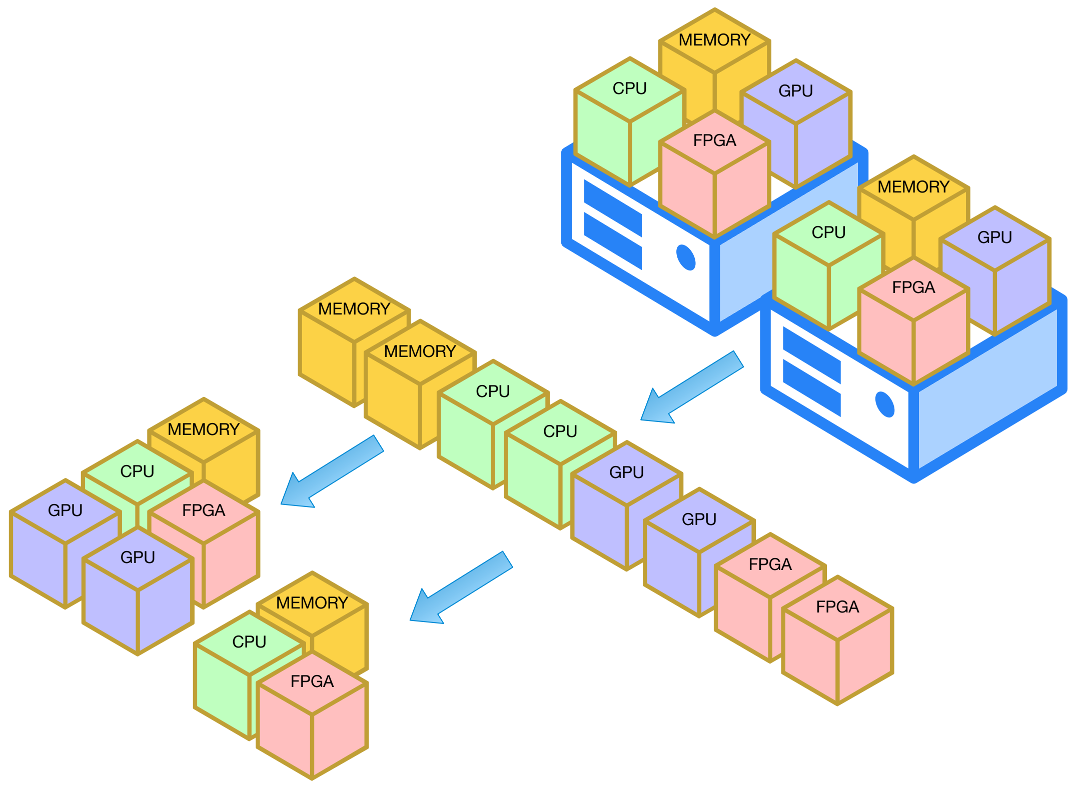
Disaggregation and reassembly

- Imagine a computing resource with all the right parts for a particular streaming application but not necessarily in the right configuration
- What if we could disaggregate individual nodes into a network of parts and reassemble something that is a better match to our application?
- Technology roadmaps from silicon vendors show inter CPU and GPU networking with coherent memory is either coming or already here
- This would allow adaptive tailoring of a hardware architecture to match a streaming application

- How do you reconfigure hardware in a running application?



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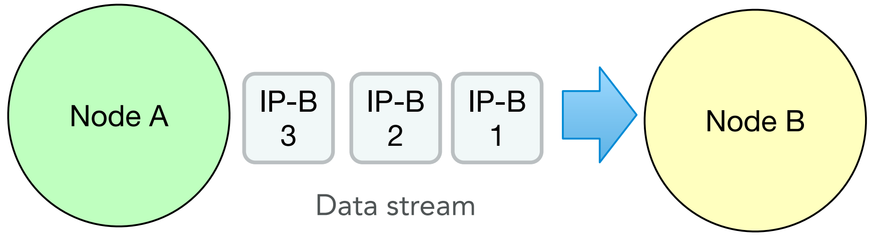
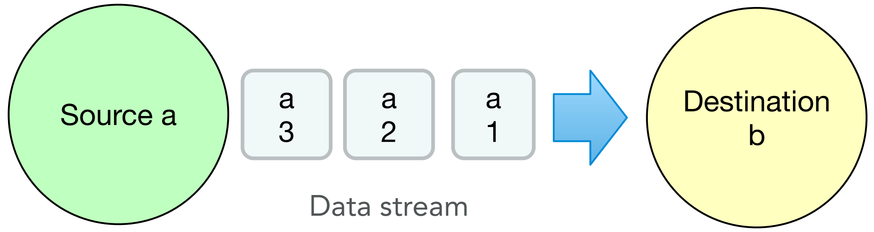
Data flow steering

- An adaptive dynamic architecture must be able to:
  - Reroute data that is in flight when the system architecture reconfigures
  - Allow remote data sources to be agnostic of the destination hardware configuration
  - Provide robustness while preserving agility and performance
- IP based networking identifies hardware endpoints via IP addresses. Data is routed according to *where* it needs to go
- Ideally a streaming data application routes data according to *what kind* of data it is and *where it came from*.
- This complements the Declarative Engine approach
  - The sender has zero knowledge of where physically the data is going, the destination selects the data it needs using metadata



- Packets are sent to the address of B
- A and B are IP addresses



- Packets are routed to “b” based-on source (a), data type and, (optionally) sequence number
- “a” and “b” are logical identifiers not IP addresses

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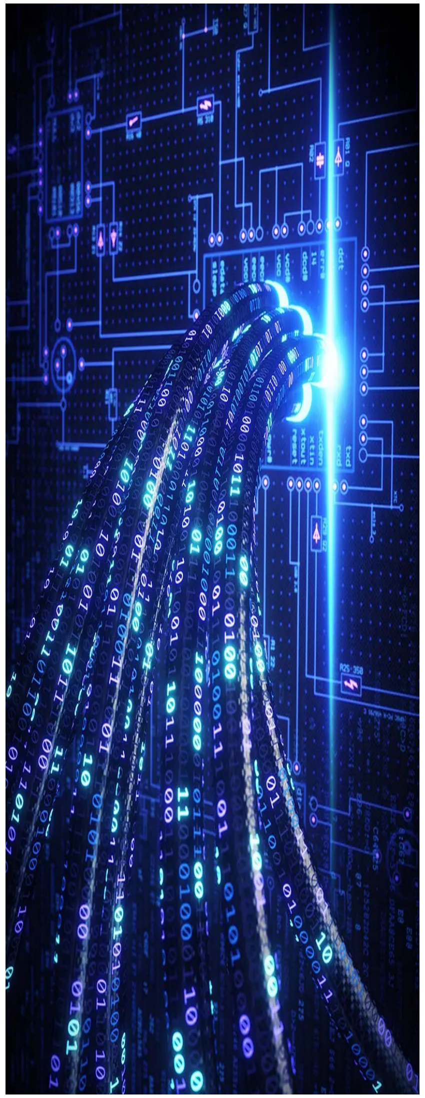
I have no crystal ball, but…

- All the pieces are emerging for adaptive, data driven, processing of streams of data.
  - Hardware architectures that dynamically reconfigure for fault tolerance and load balancing
  - Software architectures that are:
    - Based on graph representations of processing applications
    - Self optimizing
    - Tailored to support streaming data use cases
  - Network protocols that:
    - Complement stream processing paradigms
    - Support dynamic reconfiguration of the application graph
    - Have enhanced tolerance to faults while data is in flight (which streaming data always is)
  - AI/ML techniques that can drive an intelligent self optimizing data center

- These are being driven by "hyper scale" computing, Amazon, Google, Microsoft, etc., and many open-source products exist



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Summary

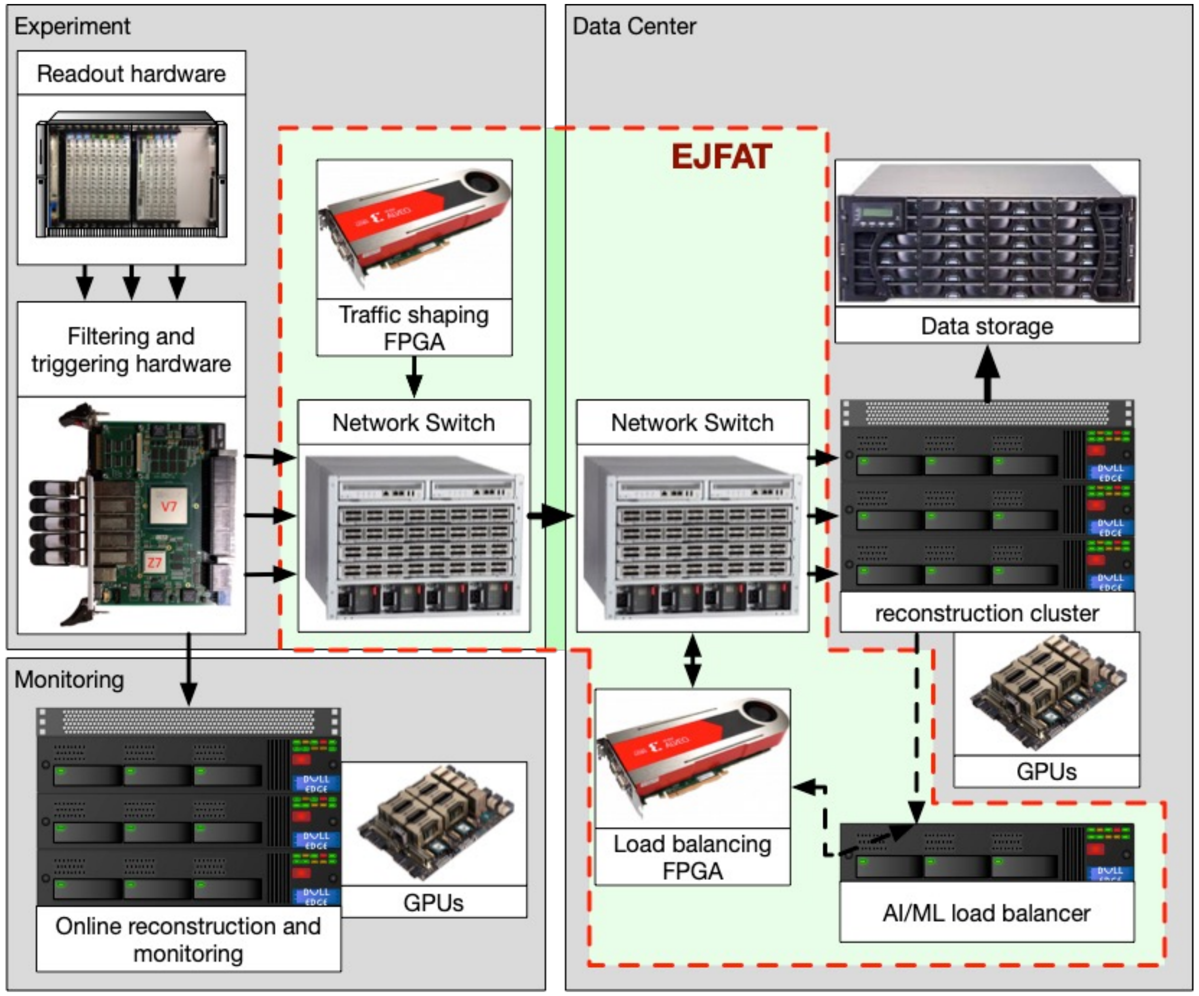
- In this talk topics were outlined, and questions asked:
  - Definition of streaming data
    - Does it fit into existing computing models? Is something different needed?
  - The dominant data processing model for experimental science
    - Does that model fit streaming data?
  - Use of the batch model to process streaming data
    - Workable but not a good fit
    - What models are a good fit?
  - Data Streaming as a disruptive model
    - *How does it apply to science?*
    - *Example use cases*
  - Software frameworks implementing streaming data models
  - Streaming optimized hardware architecture
    - How do you reconfigure hardware in a running application?
    - Data flow steering

THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

- Processing streaming data is a “hot topic” in industry, computer science research, as well as DOE funded science
- As with all “hot topics” the right balance must be found between innovation and implementation – there’s a lot out there when you start to look!
- I strongly suggest that you look at opportunities and carefully weigh risk vs gain

Prototype dynamic steering of streaming data

- The ESnet Jlab FPGA Accelerated Transport project is an example
  - Streaming data format contains metadata describing the data
  - Using standard IP based network all traffic is directed to an FPGA device
  - Firmware modifies IP packet headers to reroute the data based on what kind of data it is and what kind of destination it should stream to
- Initial implementation has static translation tables to implement data distribution schemes
  - Round robin, sorting by time or source
- Goal is dynamic intelligent steering



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Why is Jefferson Lab giving this talk?

- We have many years of experience handling data from a diverse and sometimes rapidly changing set of experiments
- Nuclear physics experiments at JLab are transitioning to a streaming data acquisition model
- The EIC project, in partnership with BNL, will use streaming data acquisition
- We have real problems to solve, and it is of greatest benefit to the broad DOE science community to try to develop solutions that can be shared
- We now have ASCR funding for a follow-on project to EJFAT to extend towards the instrument at the data source end and closer to the silicon at the data center
- We have an LDRD to investigate multi-site workflows
- Partnerships with NERSC, BNL, and SLAC
  - BNL for EIC but also NSLS-II
  - SLAC for light source data
  - NERSC for workflow transition between data centers