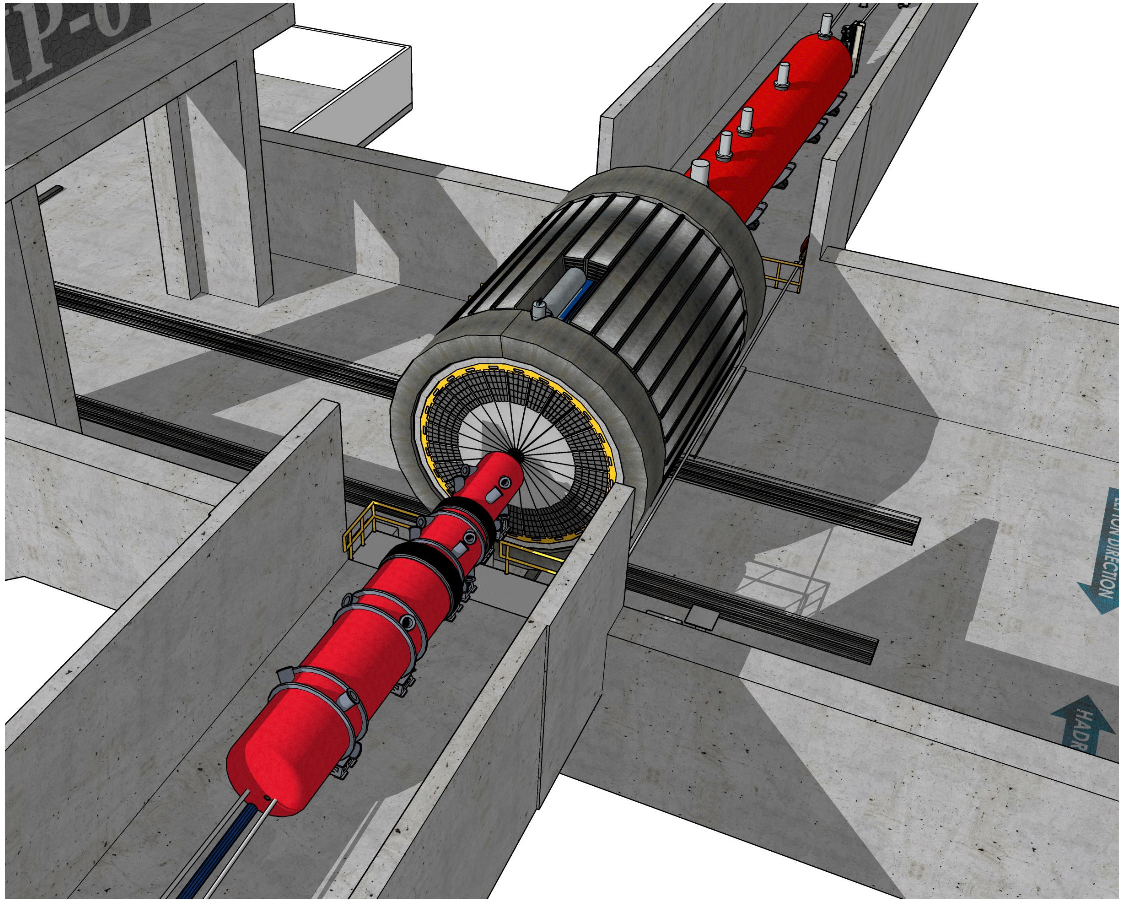
Markus Diefenthaler (Jefferson Lab)

ePIC Computing Model

The Highly-Integrated ePIC Experiment

Integrated Interaction and Detector Region (90 m)
Get close to full acceptance for all final state particles, and measure them with good resolution. All particles count!



Compute-Detector Integration
Seamless data processing from detector readout to analysis using streaming readout and streaming computing.

Definition of Streaming Readout
- Data is digitized at a fixed rate with thresholds and zero suppression applied locally.
- Data is read out in continuous parallel streams that are encoded with information about when and where the data was taken.
- Event building, filtering, monitoring, and other data processing is deferred to computing.

Advantages of Streaming Readout
- Simplification of readout (no custom trigger hardware and firmware) and increased flexibility.
- Event building from holistic detector information.
- Continuous data flow provides detailed knowledge of backgrounds and enhances control over systematics.

Compute-Detector Integration to Maximize Science

Broad ePIC Science Program:
- Plethora of observables, with less distinct topologies where every event is significant.
- High-precision measurements: Control of systematic uncertainties of paramount importance.

Streaming Readout Capability Due to Moderate Signal Rate:
- **Capture every collision signal**, including background.
- Event selection using all available detector data for **holistic reconstruction**:
  - **Eliminate trigger bias** and provide accurate estimation of uncertainties during event selection.
- Streaming background estimates ideal to **reduce background** and related systematic uncertainties.

	EIC	RHIC	LHC → HL-LHC
Collision species	$\vec{e}+\vec{p}, \vec{e}+A$	$\vec{p}+\vec{p}/A, A+A$	$p+p/A, A+A$
Top x-N C.M. energy	140 GeV	510 GeV	13 TeV
Peak x-N luminosity	10^{34} cm^{-2} s^{-1}	10^{32} cm^{-2} s^{-1}	$10^{34} \rightarrow 10^{35}$ cm^{-2} s^{-1}
x-N cross section	**50 µb**	**40 mb**	**80 mb**
Top collision rate	500 kHz	10 MHz	1-6 GHz
$dN_{ch}/d\eta$	0.1-Few	~3	~6
Charged particle rate	**4M N_{ch}/s**	**60M N_{ch}/s**	**30G+ N_{ch}/s**

Compute-Detector Integration to Accelerate Science

- **Problem** Data for physics analyses and the resulting publications available after O(1year) due to complexity of NP experiments (and their organization).
  - Alignment and calibration of detector as well as reconstruction and validation of events time-consuming.
- **Goal** **Rapid turnaround of 2-3 weeks for data for physics analyses**.
  - Timeline driven by alignment and calibrations.
  - Preliminary information from detector groups indicates that 2-3 weeks are realistic.
- **Solution** Compute-detector integration using:

Streaming readout for continuous data flow of the full detector information.

AI for autonomous alignment and calibration as well as autonomous validation for rapid processing.

Heterogeneous computing for acceleration (CPU, GPU).

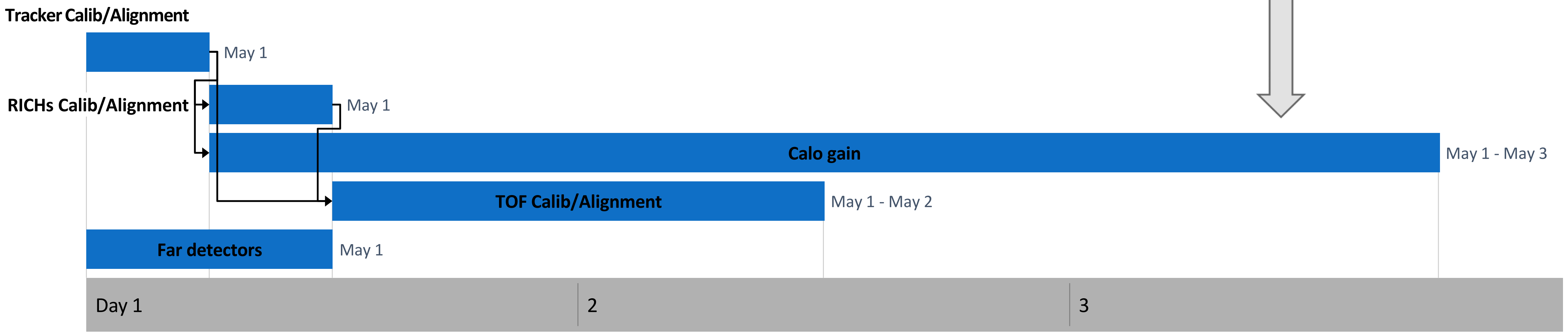
Alignment and Calibration Planning

[Spreadsheet](#)

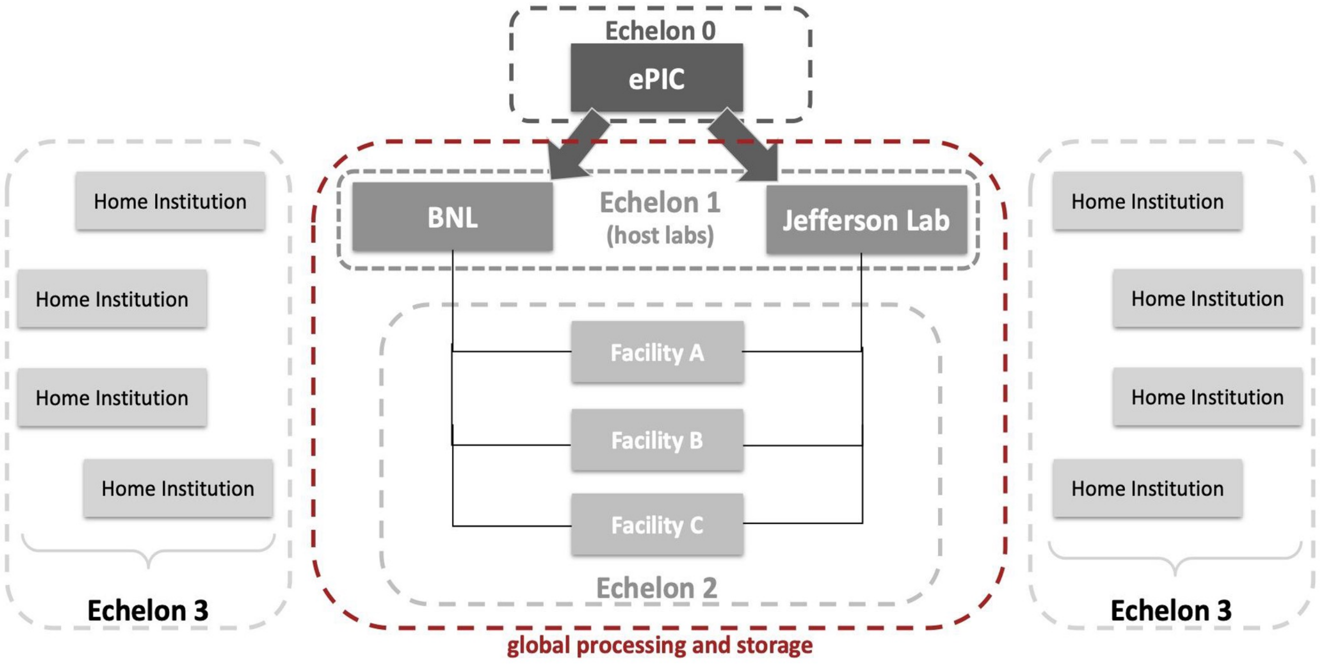
Alignment and Calibration of the ePIC Detector

- Series of meetings with detector experts to discuss alignment and calibration procedures and requirements for each detector subsystem.
- Summarized in a **spreadsheet outlining alignment and calibration workflows**.

Subsystem	Region	Pre-physics-operation calibrations (Cosmic, no-beam calibration, commissioning)	Steady State calibrations: aim to produce final reconstruction-ready calibration within few days of physics data taking in a conti							
			Task	Human intervention ?	Data Needed	Dependecy	T0 + 12hr	T0 + 24hr	T0 + 36hr	T0 + 48
MAPS	Barrel+Disk	Threshold Scan / ALICE=20min Fake rate scan/noisy pixel masking	(See Alignment)							
MPGD	Barrel+Disk	?	?							
bTOF, eTOF (ac-lgad)	Barrel/Forward	Bias voltage determination ASIC baseline, noise, threshold Clock sync Time walk calibration	Gain calibration TDC bin width determination Clock offset calibration Hit position dependency (intrinsic and c-by-c)	QA	High p tracks ~1hr of production data?	Tracking, pfRICH	Data Acc. Dependen	Dependen	Processin	Proces
Central Detector Tracker Alignment		Initial alignment	Alignment Check/Update (if needed)	QA	Prodcution data		Processing			
pfRICH	Backward	Thresholds (noise dependent), dynamic range adjustments, timing offsets, synchronization Initial alignment	Alignment Check/Update (if needed) Time dependencies (Aerogel transparency, mirror reflectivity, Gas pressure)	?	Prodcution data		Data Acc.	Processing		
DIRC	Barrel	Laser data?	?	?						
dRICH	Forward	Bunch timing offset scan Threshold scan Noise masking	Track based alignment	?	High p tracks ~1hr of of production data?	Tracking	Data Acc. Dependen	Processin	Processing	
bEMC	Backward	Cosmic and LED for the initial gain balancing	DIS Electron Pi0->gg events energy scale	QA	DIS electron Pi0 di-photon resonance ~1 day of production data	Tracking	Data Acc. Dependen	Data Acc.	Processin	Proces
AstroPix	Barrel									
ScifiPb	Barrel		SiPM gain		?					
fEMC	Forward	IV Scan	Pi0, eta->gg events energy scale Second iteration pi0 (if needed)	QA	Pi0 di-photon resonance ~1 day of production data		Data Acc.	Data Acc.	Processin	Proces
bHCAL	Backward	LED	?							
cHCAL	Barrel	MIP calibration Gain calibration	(See hadronic e-scale calib)							
fHCAL	Forward									
fHCAL insert	Forward									
Hadronic energy scale calibration		?	Set full calo stack energy scale for hadroinc shower and jets	?	High energy hadronic showers and jets	Tracking h-PID	Data Acc. Dependen	Data Acc. Dependen	Data Acc. Dependen	?
low Q2 Tagger	Far Backward	Alignment?								
low Q2 Tagger (CAL)	Far Backward									



The ePIC Streaming Computing Model



Echelon 0: ePIC Streaming DAQ.

Echelon 1: Two host labs, two primary ePIC computing facilities.

Echelon 2: Global contributions leveraging commitments to ePIC computing from labs and universities, domestically and internationally.

Echelon 3: Supporting the analysis community *where they are* at their home institutes, primarily via services hosted at Echelon 1 and 2.

Computing Use Cases and Their Echelon Distribution

Use Case	Echelon 0	Echelon 1	Echelon 2	Echelon 3
Streaming Data Storage and Monitoring	✓	✓		
Alignment and Calibration		✓	✓	
Prompt Reconstruction		✓		
First Full Reconstruction		✓	✓	
Reprocessing		✓	✓	
Simulation		✓	✓	
Physics Analysis		✓	✓	✓
AI Modeling and Digital Twin		✓	✓	

Prompt := rapid low-latency processing.

Prompt processing of newly acquired data typically begins in seconds, not tens of minutes or longer.

Assumed Fraction of Use Case Done Outside Echelon 1	
Alignment and Calibration	50%
First Full Reconstruction	40%
Reprocessing	60%
Simulation	75%

- **Echelon 1** sites uniquely perform the **low-latency streaming workflows** consuming the data stream from Echelon 0:
  - Archiving and monitoring of the streaming data, prompt reconstruction and rapid diagnostics.
- Apart from low-latency, Echelon 2 sites fully participate in use cases:
  - Tentative resource requirements model assumes a **substantial role for Echelon 2**.

Computing Resource Needs and Their Implications

Processing by Use Case [cores]	Echelon 1	Echelon 2
Streaming Data Storage and Monitoring	-	-
Alignment and Calibration	6,004	6,004
Prompt Reconstruction	60,037	-
First Full Reconstruction	72,045	48,030
Reprocessing	144,089	216,134
Simulation	123,326	369,979
Total estimate processing	**405,501**	**640,147**

Storage Estimates by Use Case [PB]	Echelon 1	Echelon 2
Streaming Data Storage and Monitoring	71	35
Alignment and Calibration	1.8	1.8
Prompt Reconstruction	4.4	-
First Full Reconstruction	8.9	3.0
Reprocessing	9	9
Simulation	107	107
Total estimate storage	**201**	**156**

Computing Resource Needs in 2034 for EIC Phase I

O(1M) core-years to process a year of data:

- Optimistic scaling of constant-dollar performance gains would reduce the numbers about 5x:
  - Based on current LHC measure of 15% per year.
  - But the trend is towards lower gains per year.
- Whatever the gains over time, processing scale is substantial!
- Motivates attention to leveraging distributed and opportunistic resources from the beginning.

~350 PB to store data of one year.

ePIC is compute intensive experiment, must ensure ePIC is not compute-limited in its science.

Technology Choices and Evolution

- **Modularity is Key**: We will have a modular software design with structures robust against changes in the computing environment so that changes in underlying code can be handled without an entire overhaul of the structure.
- **Lessons Learned from the NHEP Community** informed the ePIC Streaming Computing Model:
  - Our software is deployed via containers.
  - Our containers are distributed via CernVM-FS.
  - We run large-scale simulation campaigns on the Open Science Grid.
  - Access to our simulations is facilitated through XRootD.
  - We are in the process of deploying Rucio for distributed data management, improving access for collaborators to specific simulation files.
- **Engagement in Advanced Scientific Computing Discussions,** including:
  - DOE SC ASCR's Integrated Research Infrastructure (IRI) program. Data-integration-intensive and time-sensitive patterns highly relevant for ePIC.
  - DOE SC ASCR's High Performance Data Facility (HPDF) project, not only enabling these patterns but also potential partnership on data and analysis preservation.
  - HEP Software Foundation's discussions on analysis facilities, analysis use cases, and analysis infrastructure.
- **Software Stewardship by the NHEP Community**:
  - Participation in workshop committee for the *"Software Infrastructure for Advanced Nuclear Physics Computing."*
  - Engaging in discussions about HSF Affiliated Projects and Software.
- **Data and AI**:
  - AI has a strong presence in ePIC. We are integrating existing AI solutions into our production workflows.
  - We will help with guiding the DOE SC Round Table on *"Transformational Science Enabled by Artificial Intelligence,"* which will shape ePIC's approach to leveraging AI.

The Role of AI

- **Compute-detector integration** using**:**

Streaming readout for continuous data flow of the full detector information.

AI for autonomous alignment and calibration as well as reconstruction and validation for rapid processing.

Heterogeneous computing for acceleration.

- AI will **empower the data processing** at the EIC.
  - Rapid turnaround of data relies on autonomous alignment and calibration as all as autonomous validation.

- AI will also **empower autonomous experimentation and control** beyond data processing:
  - Vision for a responsive, cognizant detector system, .e.g., adjusting thresholds according to background rates.
  - Enabled by access to full detector information via streaming readout.

Streaming DAQ and Computing Milestones

Streaming DAQ Release Schedule:

PicoDAQ FY26Q1
- Readout test setups

MicroDAQ: FY26Q4
- Readout detector data in test stand using engineering articles

MiniDAQ: FY28Q1
- Readout detector data using full hardware and timing chain

Full DAQ-v1: FY29Q2
- Full functionality DAQ ready for full system integration & testing

Production DAQ: FY31Q3
- Ready for cosmics

Streaming Computing Milestones:

Start development of streaming orchestration, including workflow and workload management system tool.
Start streaming and processing streamed data between BNL, Jefferson, DRAC Canada, and other sites.
Support of test-beam measurements, using variety of electronics and DAQ setups:
- Digitization developments will allow detailed comparisons between simulations and test-beam data.
- Track progress of the alignment and calibration software developed for detector prototypes.
- Various JANA2 plugins for reading test-beam data required. Work started on an example.

Establish autonomous alignment and calibration workflows that allows for validation by experts.

Analysis challenges exercising end-to-end workflows from (simulated) raw data.

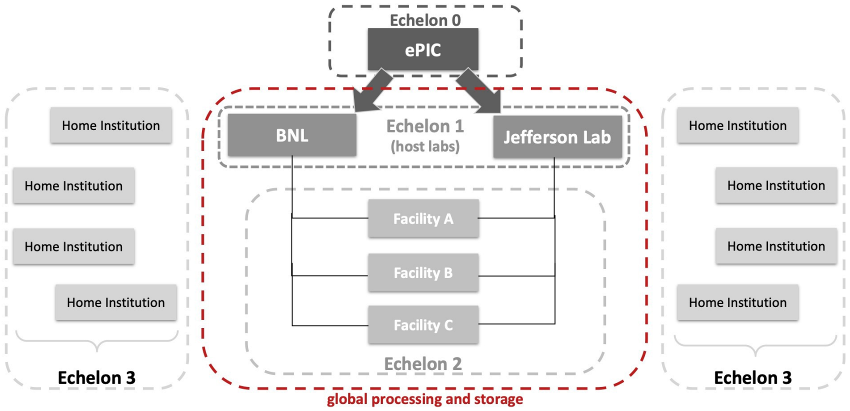
Streaming challenges exercising the streaming workflows from DAQ through offline reconstruction, and the Echelon 0 and Echelon 1 computing and connectivity.
Analysis challenges exercising autonomous alignment and calibrations.

Data challenges exercising scaling and capability tests as distributed ePIC computing resources at substantial scale reach the floor, including exercising the functional roles of the Echelon tiers, particularly Echelon 2, the globally distributed resources essential to meeting computing requirements of ePIC.

Summary

- **Streaming Readout of the ePIC Detector to maximize and accelerate science:**
  - ePIC aims for **rapid turnaround of 2-3 weeks for data for physics analyses**.
  - Timeline driven by alignment and calibration.

- **Four tiers of the ePIC Streaming Computing Model computing fabric:**
  - **Echelon 0**: ePIC Streaming DAQ.
  - **Echelon 1**: Crucial and innovative partnership between host labs.
  - **Echelon 2**: Global contributions.
  - **Echelon 3**: Full support of the analysis community.



- **High level milestones** ensure that the agile development process is continuously confronted with real world exercising of the software and the developing realization of the computing model:
  - Priority always given to meeting near-term needs. ePIC leverages monthly production campaigns, CI-driven benchmarks, and timeline-based prioritization to **ensure timely completion of the simulation studies for the TDR**.
  - **Longer range timeline progressively exercising the streaming computing** model to deliver for the needs of the CD process, for specific applications, e.g. test beams, for scaling and capability challenges, and ultimately for the phases of data taking.

Backup

Streaming Data Processing

Traditional Workflow Characteristics in NP and HEP Experiments:
- Data is acquired in online workflows.
- Data is stored as large files in hierarchical storage.
- Offline workflows process the data, often with substantial latency.
- Batch queue-based resource provisioning is typical.
- Key features: discrete, coarse-grained processing units (files and datasets) and decoupling from real-time data acquisition.

ePIC Streaming Data Processing Characteristics

- Quasi-continuous flow of fine-grained data.
- Dynamic flexibility to match real-time data inflow.
- Prompt processing is crucial for data quality and detector integrity.
- Processing full data set quickly to minimize time for detector calibration and deliver analysis-ready data.

Challenging Characteristics of Streaming Data Processing:
- **Time critical**, proceeding in near real time.
- **Data driven**, consuming a fine-grained and quasi-continuous data flow across parallel streams.
- **Adaptive and highly automated**, in being flexible and robust against dynamic changes in data-taking patterns, resource availability and faults.
- **Inherently distributed** in its data sources and its processing resources.

Assumptions for Infrastructure:
- Existing batch-style processing likely to remain.
- Dynamic processing, e.g. Kubernetes, may displace the batch model.
- Design the system for both batch and dynamic processing to ensure resilience against technology evolution.
- Accommodate but effectively hide these underlying infrastructure characteristics.