Big Data Clusters

Building the Best Infrastructure Platform for Big Data Workloads

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Introduction

Using big data analytics and capitalizing on the benefits of automating predictive analytics through deep learning (DL), are essential strategies to make smarter, more informed decisions. But these tactics are not simple to execute.

Not only do you have to unite your data, organize it in a scalable and efficient manner, and determine how best to utilize it in your competitive landscape, but you also must build the hardware infrastructure to achieve these goals. Awareness of the technical nuances of the infrastructure, and designing for scalability, will help you take advantage of big data analytics and DL much more effectively.

Designing for big data workloads means understanding the differences in infrastructure required for each process. For example, training and inference in DL have different requirements based on their different workload objectives, with training absolutely requiring the ability to process huge quantities of data.

There are several key factors to consider when designing and building an environment for big data workloads.

- Storage solutions must be optimized, and you must decide whether cloud or on-premises storage will be most cost-effective.
- Servers and network hardware must have the necessary processing power and throughput to handle massive quantities of data in real-time.
- A simplified, software-defined approach to storage administration that can access and manage data at scale more easily.
- The system must be scalable and capable of expansion at any point.

Without a properly designed infrastructure, bottlenecks in storage media, scalability issues, and slow network performance can become huge impediments to success. Though building a big data analytics environment is not simple, it certainly isn't impossible. This technology guide will outline key components administrators and purchasing organizations should be aware of as they seek to build a big data cluster ideal for extracting value from massive data sets and eliminating compute bottlenecks and poor performance.

It will also show how the **Silicon Mechanics Triton Big Data Cluster™** reference architecture addresses these challenges and can be the big data analytics and DL training solution blueprint many organizations need to start their big data infrastructure journey.

The guide is for a technical person, especially those who might be a system admin in government, research, financial services, life sciences, oil and gas, or a similarly compute-intensive field. This individual may be tasked with making the organization's big data strategic initiatives a reality by enabling efficient, scalable access to data and finding ways to extend the value of their IT investment while still meeting computing needs.

> The Silicon Mechanics Triton Big Data Cluster™ reference architecture can be your big data analytics and DL solution blueprint, because it is custom-designed and tested for extracting value from massive data sets while eliminating compute bottlenecks and poor performance.

Key Components for Big Data Analytics and Deep Learning

It's essential to understand the infrastructure needs for each workload in your big data initiatives. These can be broken down into several basic categories and necessary elements.

COMPUTE

For compute, you'll need fast GPU interconnects, high-performance CPUs with balanced memory, and a configurable GPU topology to accommodate varied workloads.

NETWORKING

For networking, you'll need multiple fabrics, InfiniBand and Ethernet, to prevent latency-related bottlenecks in performance.

STORAGE

Your storage must avoid bottlenecks found in traditional scale-out storage appliances. This is where specific types of software-defined storage can become an exciting option for your big data infrastructure.

SOFTWARE-DEFINED STORAGE (SDS)

Understanding the storage requirements for big data analytics and DL workloads can be challenging. It's difficult to fully anticipate the application profiles, the I/O patterns, or the predicted data sizes before ever actually experiencing them in a real-world scenario. That's why infrastructure performance for compute and storage can be the difference between success and failure for big data analytics and DL builds.

Software-defined storage (SDS) is a technology used in data storage management that intentionally separates the functions responsible for provisioning capacity, protecting data, and controlling data placement from the physical hardware on which data is stored. SDS enables more efficiency and faster scalability by allowing storage hardware to be easily replaced, upgraded, and expanded without changing operational functionality.

This simple and efficient scaling of performance and capacity delivers file performance at low latency, while not compromising on features that ensure data security and availability. The Triton Big Data Cluster uses SDS from Weka, namely the WekaFS.

ABOUT THE WEKAFS

The WekaFS is a POSIX-compliant file system that is built from a clean-sheet design to use the power of flash technology. You get improvements in application performance, resulting in faster insights, shorter time to market, and better infrastructure

This SDS technology allows you to pool all your data and manage it through a global namespace. The software has been engineered so that no tuning is required for one workload or another. With this dramatically simplified administration of storage, the Triton cluster allows you to easily access and manage data at scale and deliver better outcomes.

- It can improve time to results by 10x and more.
- It is ideally suited for the challenges of mixed workloads, including large and small files, random and sequential access, structured and unstructured data.
- It eliminates infrastructure complexity by extending the file system namespace to include any S3 compatible object store (public or private). Your applications won't lose access to the data, and you can maintain working data sets on NVMe flash storage and use a data lake with hard disks for long term storage.
- WekaFS can be deployed on-premises and burst to the cloud for compute elasticity.

This new SDS approach provides exciting new capabilities. You can scale up and scale out your clusters with simple, pre-determined storage configurations.

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Key Infrastructure Elements for Big Data

Any infrastructure that supports big data must feature scalability, high-speed/low-latency capabilities, and parallel processing optimized for east-west traffic.

Scalability refers to the ability of your infrastructure to successfully handle increases in processing speed and data flow, and increased storage requirements. Considering scalability while in the planning stage of your big data architecture will make it much simpler to add processing and storage power when needed down the line, future-proofing your investment.

Latency refers to any delay in processing or data transfer. It's the amount of time any packet of data takes to travel from one point to another. High-speed, low-latency data flow is crucial to maximizing your analytics efforts. Moving terabytes to petabytes of information quickly enough to have real-time benefits to your organization is critical to success. This data flow ensures that CPU and GPU compute resources are being fully utilized, maximizing the ROI of your workflow.

Parallel processing entails having multiple processors handling separate parts of any computing task simultaneously. This allows your system to allocate your data so you can quickly access it at high speeds. Building your infrastructure optimized for east-west traffic, with data sharing from server to server, facilitates successful parallel processing capabilities. Parallel processing is also heavily affected by GPU acceleration, which divides up repetitive tasks withing the GPU, massively accelerating workloads.

When built correctly, your infrastructure will quickly maximize your big data workloads.

> Any infrastructure that facilitates your big data analytics must feature scalability, high-speed/low-latency capabilities, and parallel processing optimized for east-west traffic.

Challenges to Big Data Analytics

While the advantages of big data are undeniable, there can be some hurdles to implementing it in your organization. While every organization is different, all must address these challenges to ensure they reap all the benefits of big data analytics.

One challenge is that data can be siloed. Structured data, or quantitative data, is typically highly organized and easy to decipher. Unstructured data, or qualitative data, is not as easily gathered and analyzed. These two types of data are stored in separate places and must be accessed through different means.

This creates the challenge of tapping into structured and unstructured data in a unified data lake. Structured data is data that fits logically into fixed form fields in traditional databases and spreadsheets. It consists of information such as names, dates, addresses, credit card numbers, phone numbers, zip codes, etc.

Unstructured data, on the other hand, cannot be managed or analyzed using traditional tools or methods. Unstructured data consists of information such as text files, audio and video files, social media posts, mobile usage, satellite, or surveillance imagery, etc.

Unifying these two disparate sources of data is a huge impetus for big data analytics success, and it is the first step to ensuring your infrastructure will be capable of helping you reach your goals. A unified data lake, with both structured and unstructured data located together, allows all relevant data to be analyzed together in every query to maximize value and insight.

Your unified data leads to projects that tend to involve terabytes to petabytes of information. These massive amounts of data need infrastructure capable of moving, storing, and analyzing vast quantities of information quickly to maximize the effectiveness of big data initiatives.

The goal of your big data analytics is to fully utilize available data to get superior insights, act accordingly based on that information, and maximize benefits for all your employees in every facet of your organization. When done correctly, these analytics will fuel your day-to-day operations as well as your long-term strategies. Understanding these challenges will help you build the infrastructure you need.

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Challenges to Deep Learning Infrastructure

Designing an infrastructure for DL creates its own set of unique challenges. You typically want to run a proof of concept (POC) for the training phase of the project and a separate one for the inference portion, as the requirements for each are different.

SCALABILITY

The hardware-related steps required to stand up a DL cluster each have unique challenges. Moving from POC to production often results in failure, due to additional scale, complexity, user adoption, and other issues. You need to design scalability into the hardware at the start.

CUSTOMIZED WORKLOADS

Specific workloads require specific customizations. You can run ML on a non-GPU-accelerated cluster, but DL typically requires GPU-based systems. And training requires the ability to support ingest, egress, and processing of massive datasets.

OPTIMIZE WORKLOAD PERFORMANCE

One of the most crucial factors of your hardware build is optimizing performance for your workload. Your cluster should be a modular design, allowing customization to meet your key concerns, such as networking speed, processing power, etc. This build can grow with you and your workloads and adapt as new technologies or needs arise.

Infrastructure Needs for DL Processes

Training an artificial neural network requires you to curate huge quantities of data into a designated structure, then feed that massive training dataset into a DL framework. Once the DL framework is trained, it can leverage this training when exposed to new data and make inferences about the new data. But each of these processes features different infrastructure requirements for optimal performance.

TRAINING

Training is the process of learning a new capability from existing data based on exposure to related data, usually in very large quantities. These factors should be considered in your training infrastructure:

- Get as much raw compute power and as many nodes as you can allocate. You should employ multi-core processors and GPUs because accurately training your AI model is the most critical issue you'll face. It may take a long time to get there but the more nodes and the more mathematical accuracy you can build into your cluster, the faster and more accurate your training will be.
- Training often requires incremental addition of new data sets that remain clean and well-structured. That means these resources cannot be shared with others in the datacenter. You should focus on optimization for this workload to have better performance and more accurate training. Don't try to make a general-

purpose compute cluster with the assumption that it can take on other jobs in its free time.

- Huge training datasets require massive networking and storage capabilities to hold and transfer the data, especially if your data is image-based or heterogeneous. Plan for adequate networking and storage capacity, not just for strong computing.
- The greatest challenge in designing hardware for neural network training is scaling. Doubling the amount of training data doesn't mean doubling the number of resources used to process it. It means expanding exponentially.

INFERENCE

Inference is the application of what has been learned to new data (usually via an application or service) and making an informed decision regarding the data and its attributes. Once your framework is trained, it can then make educated assumptions about new data based on the training it has received. These factors should be considered in your inference infrastructure:

- Inference clusters should be optimized for performance using simpler hardware with less power than the training cluster but with the lowest latency possible.
- Throughput is critical to inference. The process requires high I/O bandwidth and enough memory to hold both the required training model(s) and the input data without having to make calls back to the storage components of the cluster.
- Datacenter resource requirements for inference are typically not as great for a single instance compared to training needs. This is because the amount of data or number of users an inference platform can support is limited to the performance of the platform and the application requirements. Think of speech recognition software, which can only operate when there is one clear input stream. More than one input stream renders the application inoperable. It's the same with inference input streams.

INFERENCE ON THE EDGE

There are several special considerations for inference on the edge:

- Edge-based computers are significantly less powerful than the massive compute power available in data centers and the cloud. But this still works because inference requires much less processing power than training clusters.
- If you have hundreds or thousands of instances of the neural network model to support, though, remember that each of these multiple incoming data sources needs sufficient resources to process the data.
- Normally, you want your storage and memory as close to the processor as possible, to reduce latency. But when you have edge devices, the memory is sometimes nowhere near the processing and storage components of the system. This means you either need a device that supports GPU or FPGA compute and storage at the edge, and/or access to a high-performance, low-latency network.
- You could also use a hybrid model, where the edge device gathers data but sends it to the cloud, where the inference model is applied to the new data. If the inherent latency of moving data to the cloud is acceptable (it is not in some real-time applications, such as self-driving cars), this could work for you.

> Both training and inference feature different infrastructure requirements for optimal performance.

Advantages of the Triton Big Data Cluster Solution

Your goals for your big data analytics and DL initiatives are to accelerate business decisions, make smarter, more informed decisions, and to ultimately drive more positive business outcomes based on data. That's why Silicon Mechanics created the Triton Big Data Cluster reference architecture for analytics workloads.

Silicon Mechanics is an engineering firm providing custom solutions in HPC/AI, storage, and networking; delivering best-in-class solutions based on open standards, the latest technologies, and achieving maximum value with a consultative approach to every opportunity. The Triton Big Data Cluster is the result of hours of engineering, testing, and optimization geared toward creating a best fit solution for your big data analytics implementations.

Triton allows you to seamlessly extract value from massive data sets. It alleviates bottleneck issues via a shared pool of NVMe over fabric (NVMeOF) that enables jobs to run up to 10x faster.

The solution features S3-compliant storage allowing you to control costs. Plus, it comes available with EDSFF drives, a cutting-edge storage form factor that consolidates the overall physical footprint of your storage, reducing TCO and supporting data and application growth.

Inside the Triton Big Data Cluster

COMPUTE

- AMD EPYC™ processors with PCIe 4.0 support – The world's highest performing x86 server processors. AMD EPYC processors deliver the highest per-core performance to ensure fast time-to-value for your organization.

NETWORKING

- NVIDIA HDR 200Gb/s InfiniBand Switches – These high-end switches provide high-bandwidth performance and low power consumption. At 200Gb/s, InfiniBand is a staple in supercomputers and leading HPC and AI environments, due to its high relative bandwidth compared to other networking options. In a big data analytics cluster, NVIDIA HDR switches are used for the most demanding, densely configured workflows to ensure peak performance.
- NVIDIA Spectrum Ethernet Switches – Ethernet Switches are the backbone of data centers around the world, providing plenty of bandwidth for general-purpose or even some high-end workloads. For a big data system, NVIDIA Spectrum Ethernet is the standard networking option, and is used when the added bandwidth of InfiniBand is not needed to maximize performance.

STORAGE

- 425TB of capacity per node
- Software-defined storage using Weka.io file system (WekaFS), optimized for large datasets
- High-speed, low-latency NVIDIA adapters

BENEFITS OF TRITON

- Software-defined architecture based on massively scalable, parallel WekaFS file system (via NVMe over fabric)
- Optional S3 Compliant Tier
- Scale-up and scale-out with simple, pre-defined storage building blocks (6+ server configuration)
- Ideal for HPC with large datasets or for AI training (which requires large datasets)
- Storage in new enterprise & data center SSD form factor (EDSFF)

USE CASES

The Triton reference architecture is ideal for such big data objectives as business intelligence, real-time HPC analytics, DL training and inference, predictive analytics, data visualization, and more. It's also ideal for any compute-intensive field like oil and gas, financial services, life sciences, media and entertainment, aerospace and defense, and others.

Triton saves you time and focus because it was designed to meet the specific workloads and organizational needs of your big data analytics initiatives. It is constructed explicitly to avoid computing bottlenecks and performance issues that can derail any big data project.

Conclusion

Getting the benefits of big data analytics can be challenging, but it is a necessary endeavor for any organization to succeed going forward. Understanding the challenges to maximizing big data analytics and DL, and how to overcome them, is crucial. Determining your expectations up front, and carefully orchestrating your infrastructure build, will allow you to construct an architecture that is scalable and prepared for the demands big data applications will place on it.

The Silicon Mechanics Triton Big Data Cluster can help make your big data analytics goals a reality. This reference architecture delivers a flexible, scalable platform that is robust enough to meet your high-speed data processing needs while ultimately reducing TCO.