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BitOoda

BitOoda AI Research

Cloud Infrastructure for AI Workloads

Abstract

Access to services from Cloud Service Providers (CSPs) can relieve you of the need to maintain your own data centers. As competition among CSPs intensifies, companies—whether startups or large corporations new to AI—can opt for an asset-light approach by relying on cloud services. Beyond the sheer number of providers now offering cloud compute, there is also a wide variety of services available, which introduces a paradox of choice and can often lead to management making suboptimal decisions for their AI compute needs. This report will cover the various options available when using a CSP for AI compute workloads, diving deep into each type, its pros and cons, and the specific services you might consider.

Research

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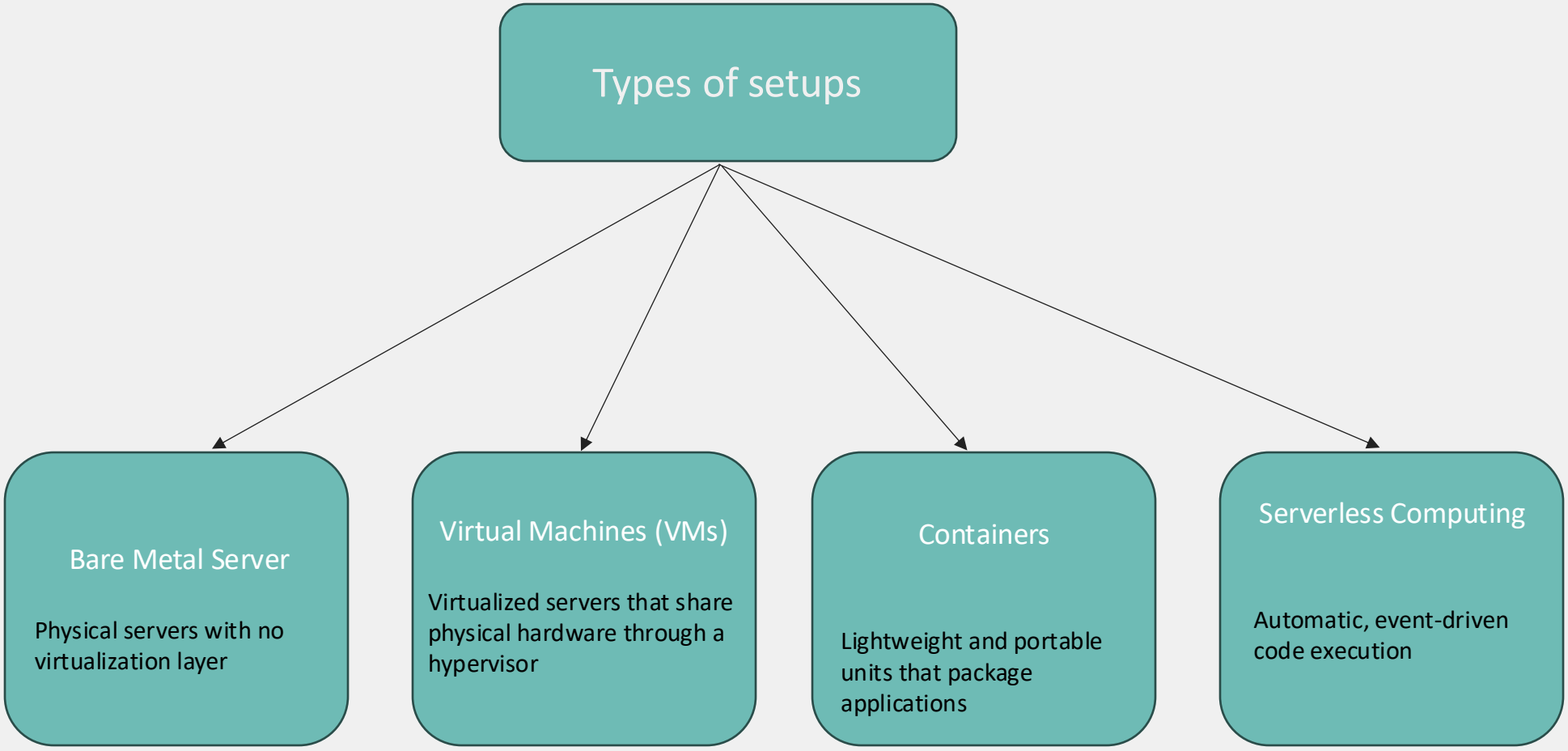
- What are the main compute resource setups for AI workloads and why are they important?
- What makes each setup—bare metal, virtual machines, containers, and serverless—unique in its approach to AI tasks?
- How do different setups impact performance, scalability, and cost for AI applications?
- What are the pros and cons of each compute setup, and which AI workloads are they best suited for?

Compute Resource Allocation Options

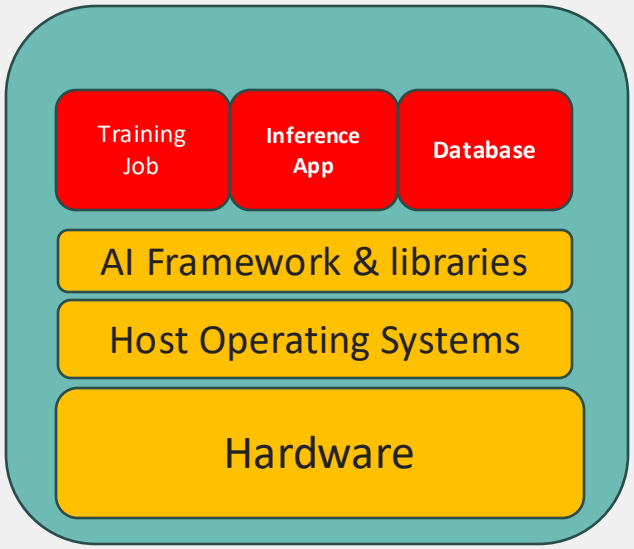
Types of Compute Resource Setups

When choosing infrastructure for AI workloads, one of the first considerations is how resources are allocated. Here are the main types of compute resource setups



Types of Compute Resource Setups

Bare Metal Servers



Bare metal servers are physical servers dedicated to a **single tenant** without any virtualization layer. They provide direct access to hardware resources.

In a bare metal setup, applications like training, inference, and databases run directly on dedicated hardware without virtualization, providing high-performance, **direct access to resources**. This setup is ideal for intensive AI tasks, such as l**arge scale LLM training**, requiring maximum processing power, customization, and low latency.

Pros:

- **High Performance:** Direct hardware access, no overhead.
- **Customizable:** Tailored configurations for AI tasks.
- **Low Latency:** Ideal for real-time applications.

Cons:

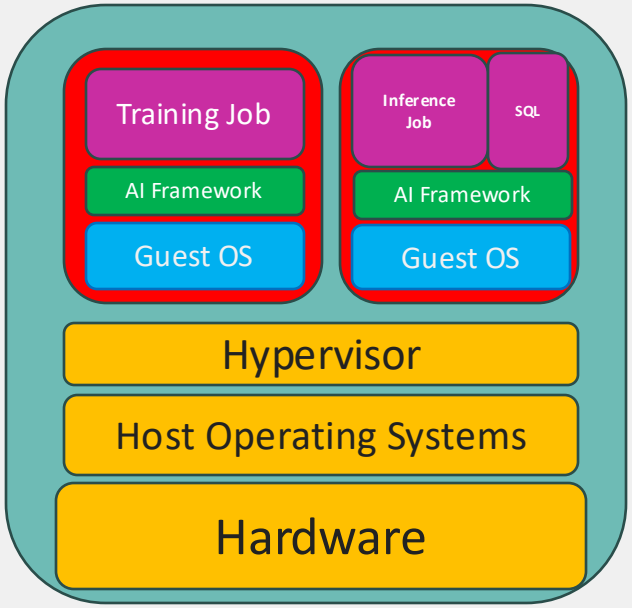
- **Costly:** Higher expense for dedicated resources.
- **Limited Scalability:** Slower to scale compared to virtual solutions.
- **More Maintenance:** Requires manual management and updates.

Options you could consider:

- **Oracle Cloud Infrastructure (OCI)**: Offers bare metal instances with NVIDIA GPUs (H100, L40S, A100) tailored for AI and machine learning, with plans to add H200 and Blackwell GPUs, as well as AMD Instinct MI300X GPUs.
- **NVIDIA GH200 Superchip**: Oracle provides the NVIDIA GH200 Grace Hopper Superchip for efficient large language model (LLM) inference.
- **IBM Cloud**: Provides customizable bare metal servers with NVIDIA GPUs and Intel/AMD CPUs, allowing specific GPU selection and integration with IBM Watson for enhanced AI capabilities.

Types of Compute Resource Setups

Virtual Machine



Virtualized servers run on a **hypervisor**, allowing multiple virtual machines (VMs) to share the **same physical hardware.**

A hypervisor is software that creates and manages virtual machines by **allowing multiple operating systems** to share a single physical host's hardware resources.

This setup provides a balance between performance, flexibility, and cost-effectiveness, making it suitable for a **wide range of AI workloads.** Virtualized environments offer isolation between applications while enabling flexible resource allocation, ideal for tasks like **inference** or **moderate-scale model training.**

Pros:

- **Flexible Scaling:** VMs can easily be resized or added to meet changing AI workload demands.
- **Cost-Effective:** Shared hardware reduces costs
- **Isolation for Multi-Tenancy:** VMs provide isolation, allowing multiple AI applications to run securely

Cons:

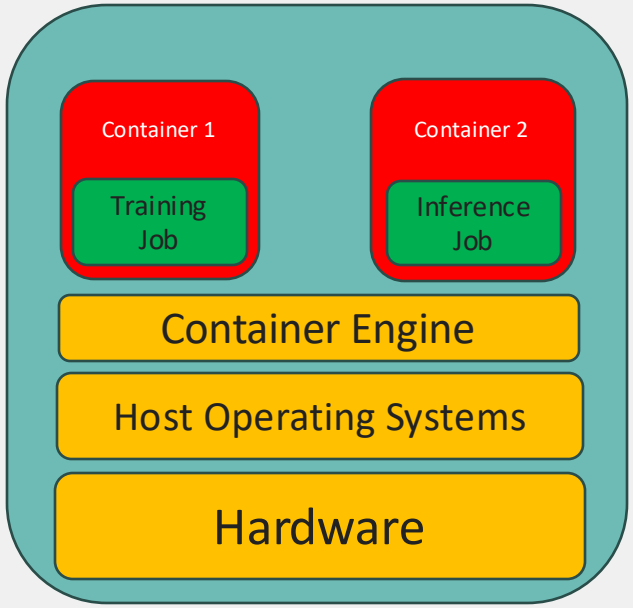
- **Performance Overhead**: Virtualization introduces latency
- **Resource Contention**: Shared resources can cause performance issues due to other VMs.
- **Complex Management**: Running multiple VMs for AI workloads demands careful monitoring.

Options you could consider:

- **Amazon EC2:** Provides a variety of GPU-optimized VM types, suitable for both training and inference AI tasks.
- **Microsoft Azure Virtual Machines:** Supports GPU-accelerated VMs for high-performance AI applications, offering both Linux and Windows environments.
- **Google Compute Engine:** Offers customizable VMs with GPU support, ideal for scaling AI inference and moderate model training.

Types of Compute Resource Setups

Containers



Containers bundle applications and everything they **need to run in small, separate units.** This setup makes it easy to **deploy and scale** AI models quickly and reliably across different environments. Containers work especially well for systems with multiple small tasks (microservices) and for running AI tasks, as they use resources efficiently and can scale up or down quickly.

Containers run applications (like training and inference jobs) in isolated units on shared hardware. A **Container Engine** manages these containers on top of the **Host Operating System**, enabling efficient and consistent operation across multiple environments.

Pros:

- **Portability:** Ensures consistent environments across development, testing, and production.
- **Efficient Resource Use:** Shares the host OS, reducing overhead and making containers lightweight.
- **Rapid Scaling:** Ideal for quickly scaling AI inference to meet demand.

Cons:

- **Security Risks:** Shared host OS kernel can introduce vulnerabilities.
- **Orchestration Complexity:** Requires tools like Kubernetes, adding management overhead.
- **Limited for Long Training:** Best for short-lived or inference tasks, not long-running training jobs.

Options you could consider:
Managed Kubernetes services like **Amazon EKS (Elastic Kubernetes Service), Azure Kubernetes Service,** and **Google Kubernetes Engine** offer scalable container orchestration with AI integration, supporting GPU-based inference and machine learning model deployment.

Next Slide:
Some services provide ML-specific, container-based offerings, tailored for the unique demands of AI workloads.

Types of Compute Resource Setups

Managed AI Platforms for AI Workloads (Containers – 2)

When selecting infrastructure for AI workloads, it's crucial to consider how resources are allocated. Managed AI platforms **offer end-to-end environments** for building, training, and deploying machine learning models, **leveraging containers behind the scenes** to provide a fully managed experience. This approach allows organizations to focus on AI development without the burden of managing underlying infrastructure.

Pros:

- **End-to-End Solution:** Supports the entire machine learning workflow, from data preparation to model deployment.
- **Scalability:** Automatically scales compute resources based on training and inference needs, optimizing costs and performance.
- **Ease of Use:** Managed services reduce infrastructure setup, allowing data scientists to focus on model development and experimentation.

Cons

- **Vendor Lock-In:** Heavy reliance on a single cloud service provider's ecosystem, which can limit flexibility and portability.
- **Higher Cost at Scale:** Managed services can be more expensive, especially for large-scale training or deployment.
- **Limited Customization:** Less control over underlying infrastructure compared to DIY container solutions.

Options you could consider:

- **AWS SageMaker:** Provides tools for building, training, tuning, and deploying machine learning models. It includes SageMaker Studio, SageMaker Autopilot for AutoML, and support for custom containers.
- **Google Vertex AI:** Offers a unified platform for AI development with tools for data labeling, model training, and deployment. Vertex AI integrates with Google's Tensor Processing Units (TPUs) for accelerated training.
- **Azure Machine Learning:** Provides an integrated workspace for managing machine learning workflows, with tools for automated ML, responsible AI, and deployment to various environments, including Kubernetes.

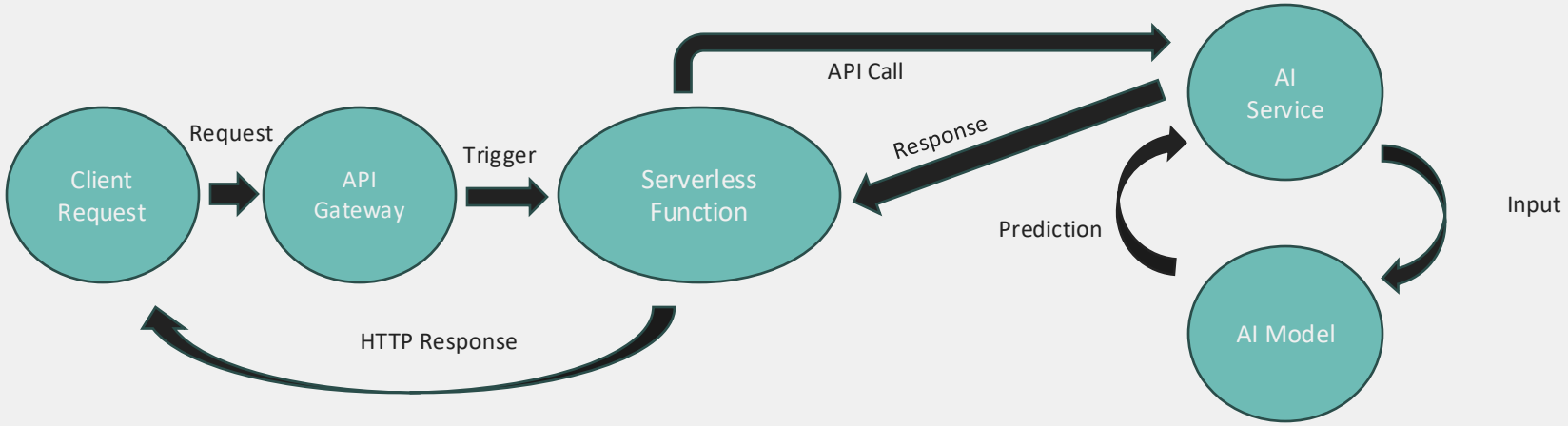
Types of Compute Resource Setups

Serverless Compute

Serverless computing offers an **event-driven, on-demand approach** where compute resources are allocated automatically in response to workload needs. This setup allows developers to run code **without managing servers**, making it ideal for lightweight, burstable AI tasks such as **inference, data preprocessing, or real-time processing.**

Options you could consider:

- **Amazon SageMaker Serverless Inference:** Allows serverless deployment and scaling of ML models, with automatic compute resource management.
- **Azure Functions:** Microsoft's serverless service supports deploying AI models for inference, integrated within Azure's AI offerings.
- **Hugging Face NVIDIA NIM API:** Offers serverless inference for enterprise users on Hugging Face, using NVIDIA DGX Cloud for accelerated compute.
- **OpenAI API:** Provides serverless access to language models and AI capabilities through an easy-to-use API.



Sample Serverless Workflow:

- Client makes an HTTP request
- API Gateway triggers the serverless function and function makes an API call to the AI service
- AI service sends input to the model
- Model returns its prediction
- Results flow back as responses

Summarizing the Services

What's best for you?

Compute Setup	Compute Platform	Scaling	Applications	Unique Features	Examples of Services
Bare Metal	Physical, dedicated servers	Manual scaling	High-performance AI training, HPC applications	Maximum performance, full hardware control	IBM Cloud Bare Metal, Oracle Bare Metal, Packet
Virtual Machines (VMs)	Hypervisor-based VMs	Flexible with auto-scaling	Flexible AI workloads, multi-tenancy	Cost-effective with shared hardware, isolated environment	Amazon EC2, Google Compute Engine, Azure VMs
Containers	Docker/ Kubernetes clusters	Rapid horizontal scaling	Scalable AI inference, microservices	Lightweight, portable, and consistent across environments	Amazon EKS, Azure AKS, Google GKE
Serverless	Cloud provider functions	Automatic scaling	Event-driven AI tasks, burstable workloads	Cost-effective, pay-as-you-go, minimal management	AWS Lambda, Google Cloud Functions, Azure Functions

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Analyst Certification

Niraj Yagnik and Dhyay Bhatt, the primary research analysts of this report, hereby certifies that all of the views expressed in this report accurately reflect their personal views, which have not been influenced by considerations of the firm's business or client relationships.

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