CS4262/5462 Machine Learning Systems

Cloud systems & AI

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National University of Singapore
School of Computing

From LLMs to the cloud

Chef
(LLM)

Restaurant
(serving systems)

Disney world
(cloud systems)

From serving to cloud systems:

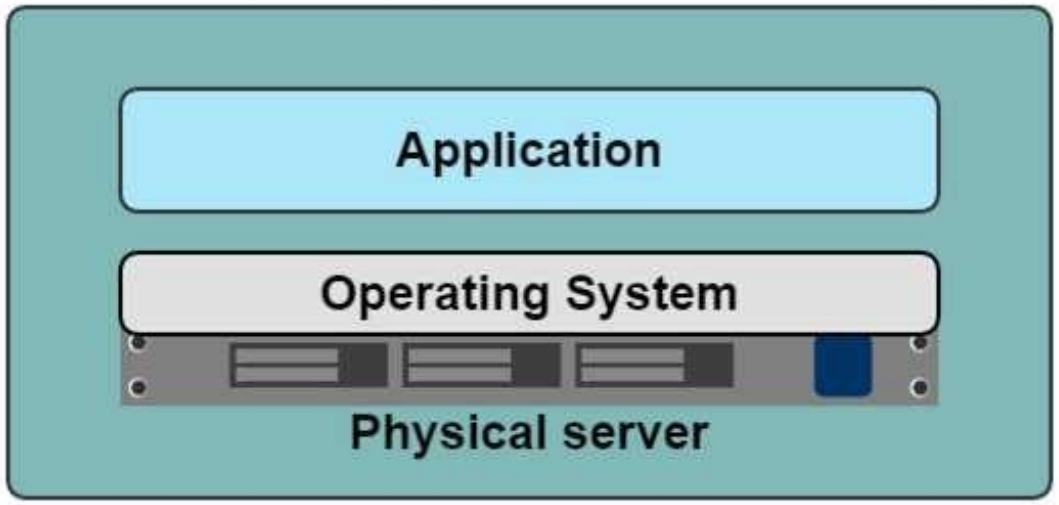
- **Multi-tenancy**: from scaling-up to scaling-out (models, users, applications, tasks etc.)
- **Operations of** large-scale, heterogeneous infrastructures

Outline

- Brief history of cloud computing
- Cloud native technologies
- Current practice and opportunities of AI on cloud

A history lesson

In the Dark Ages (1960s)

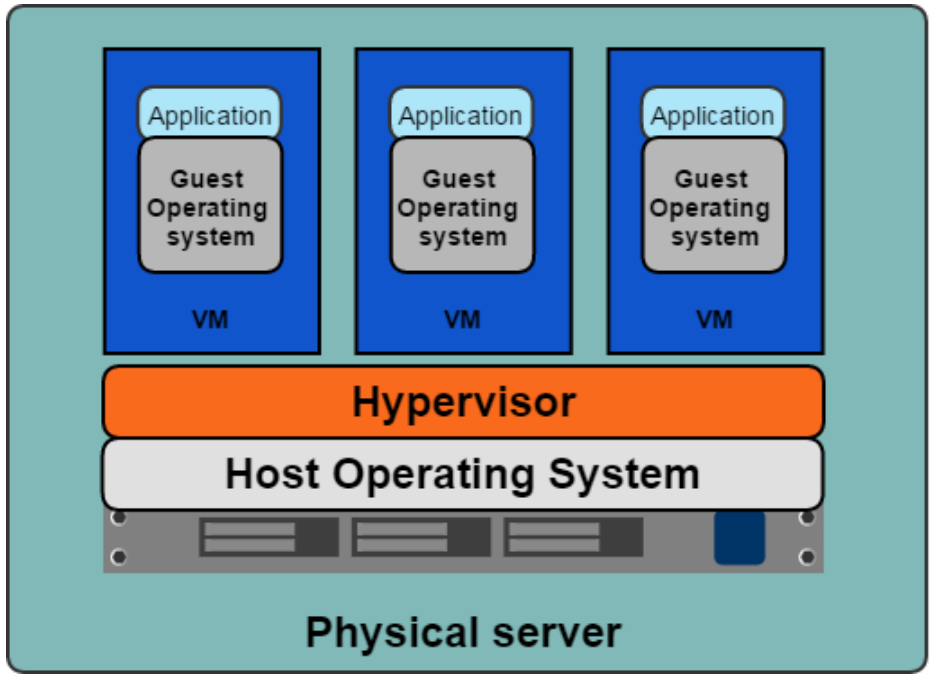


- Slow deployment times
- Huge costs & wasted resources
- Difficult to scale & migrate
- Vendor lock in

One application on one physical server

A history lesson

Hypervisor-based Virtualization (1970s)



- One physical server can contain multiple applications
- Each application runs in a virtual machine (VM)

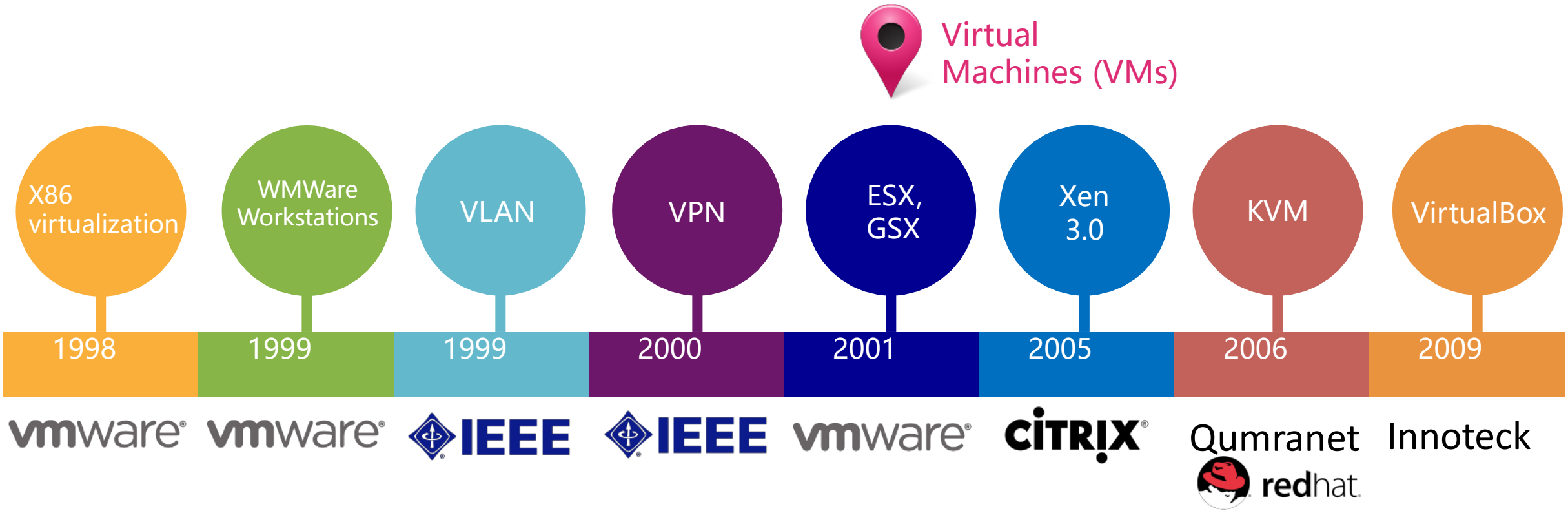
- Better resource pooling
  - One physical machine divided into multiple virtual machines
- Easier to scale
- VMs in the cloud
  - Rapid elasticity
  - Pay as you go model

Microsoft Azure

amazon web services™

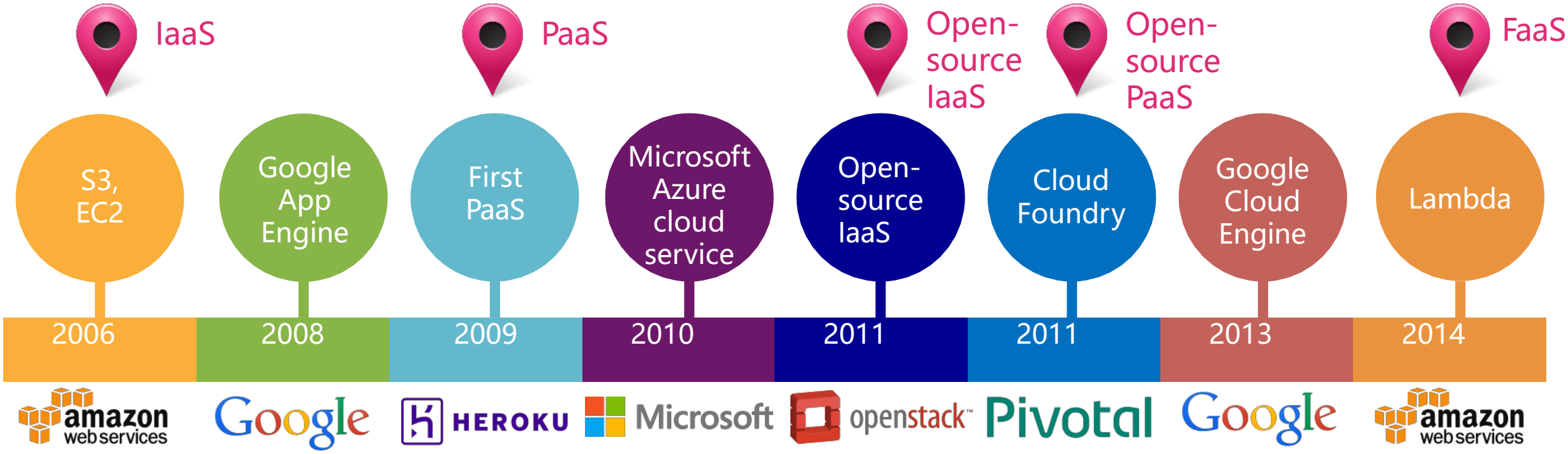
vmware®

Brief history of cloud computing



Mature of virtualization: no.1 important technology

Cloud computing offerings



2005

$5,000,000

Team of engineers

Months of development

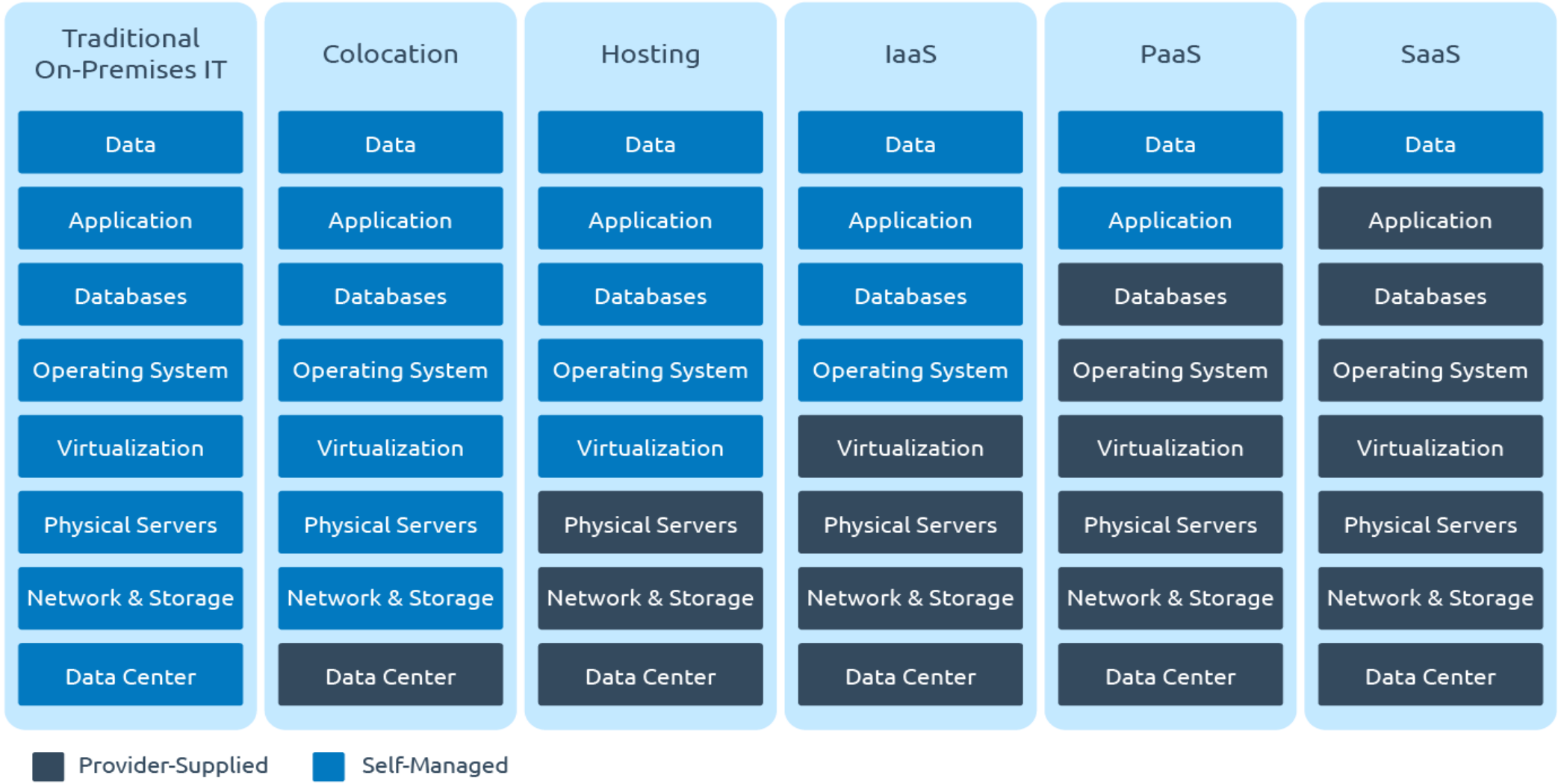
2017

$5,000

An engineer

Weeks development

Cloud computing offerings



However,

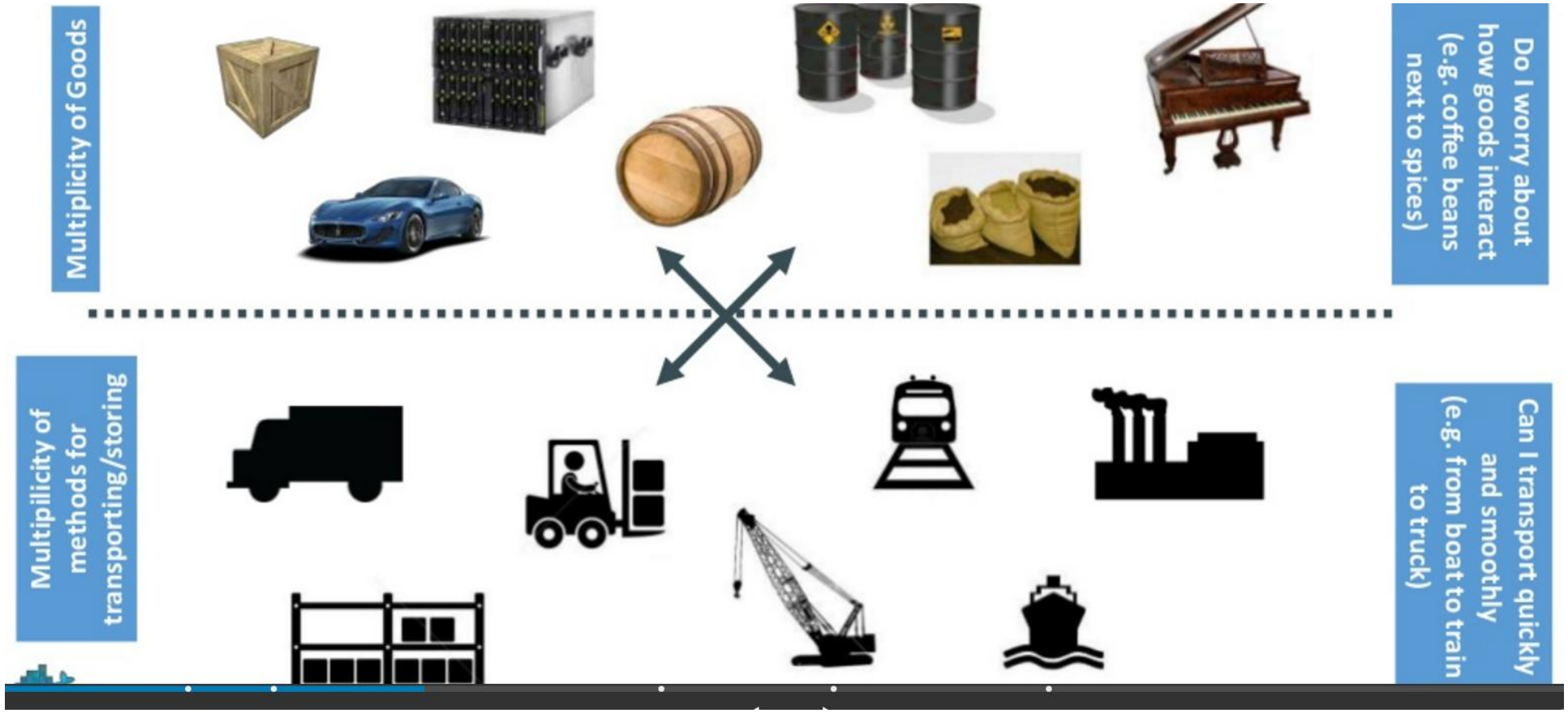
- Each VM stills requires
  - CPU allocation
  - Storage
  - RAM
  - An entire guest operating system
- The more VMs you run, the more resources you need
- Guest OS means wasted resources
- Application portability not guaranteed

Looking for all kinds of solutions…

	Development VM	QA Server	Single Prod Server	Onsite Cluster	Public Cloud	Contributor's laptop	Customer Servers
Static website	?	?	?	?	?	?	?
Web frontend	?	?	?	?	?	?	?
Background workers	?	?	?	?	?	?	?
User DB	?	?	?	?	?	?	?
Analytics DB	?	?	?	?	?	?	?
Queue	?	?	?	?	?	?	?

Too many to consider

An analogy: cargo transportation



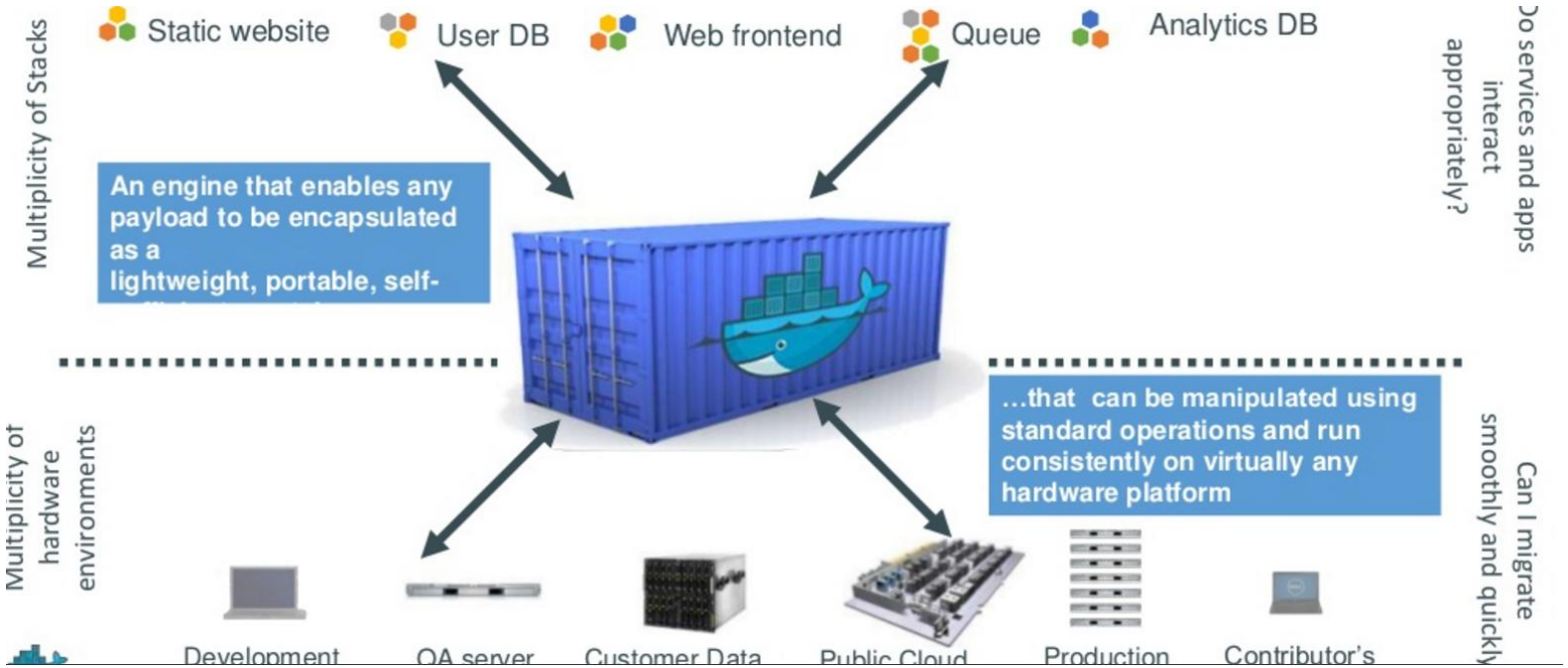
What are the possibilities

	?	?	?	?	?	?	?
	?	?	?	?	?	?	?
	?	?	?	?	?	?	?
	?	?	?	?	?	?	?
	?	?	?	?	?	?	?
	?	?	?	?	?	?	?
							

Any ideas?

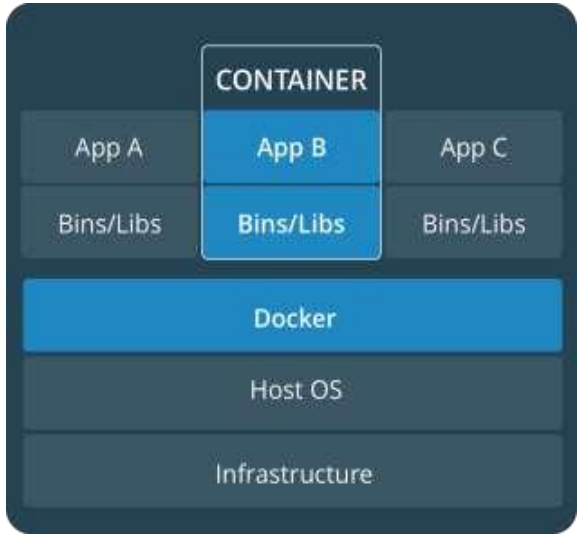
Shipping containers

Container for code?

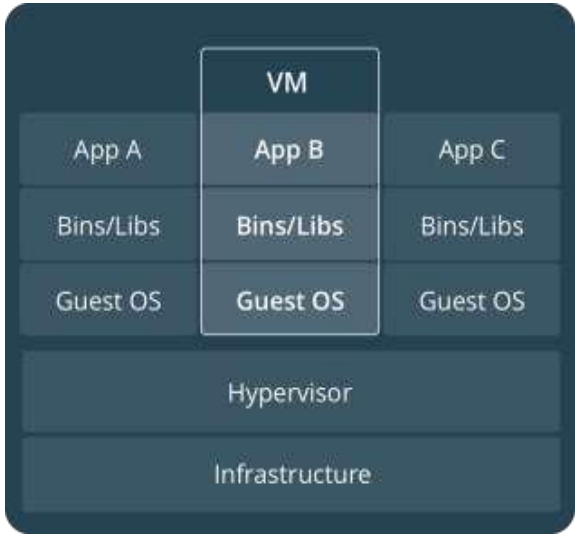


- **Speed:** share the same OS kernel. No OS to boot = applications online in seconds
- **Portability:** Standardized software packaging. Less dependencies between process layers = ability to move between infrastructure & OS
- **Efficiency:** Less OS overhead & improved VM density
- **Isolation:** Achieved by Linux namespace and Cgroups

Comparing containers and VMs

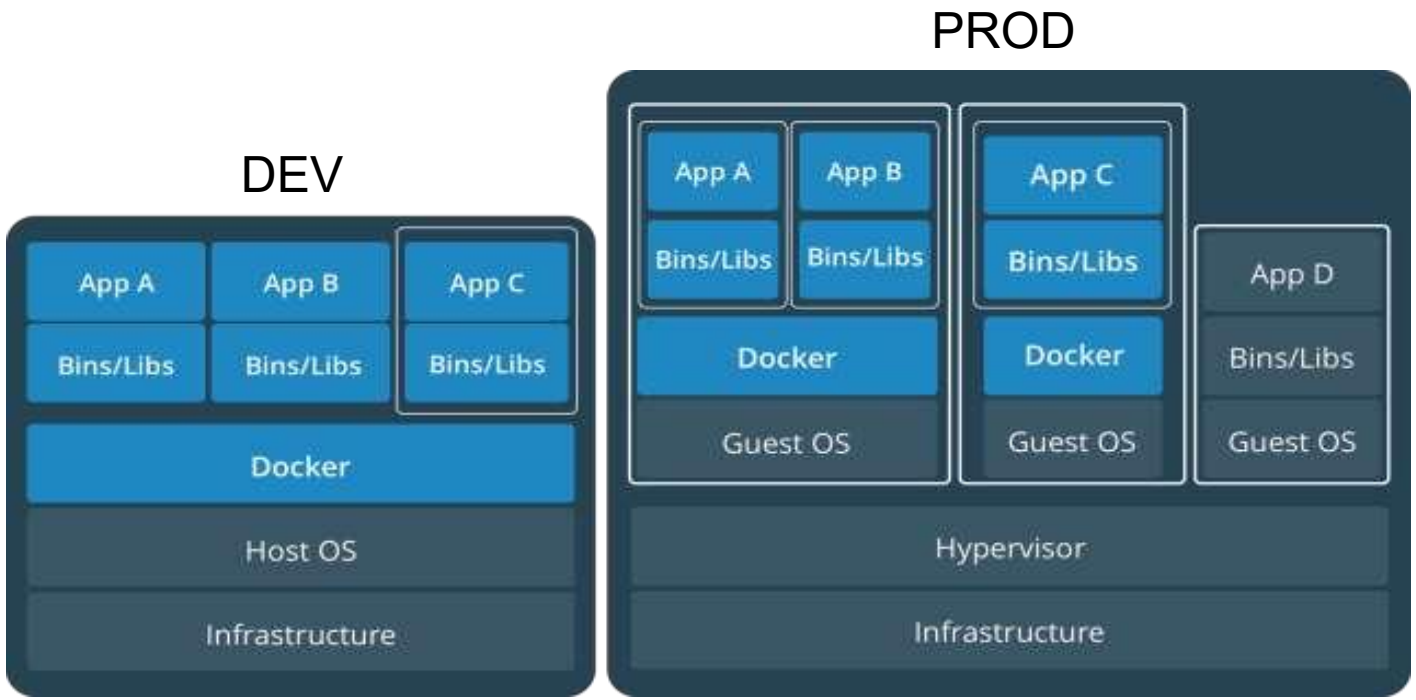


Containers are an app level construct



VMs are an infrastructure level construct to turn one machine into many servers

Containers and VMs together



Containers and VMs together provide a tremendous amount of flexibility for IT to optimally deploy and manage apps.

Cloud native technologies

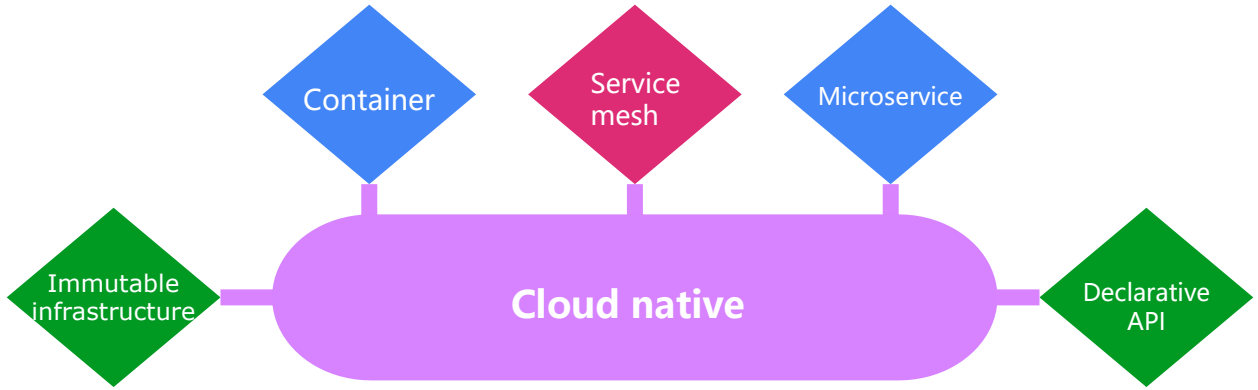
Definitions by Cloud Native Computing Foundation (CNCF) :

CLOUD NATIVE COMPUTING FOUNDATION

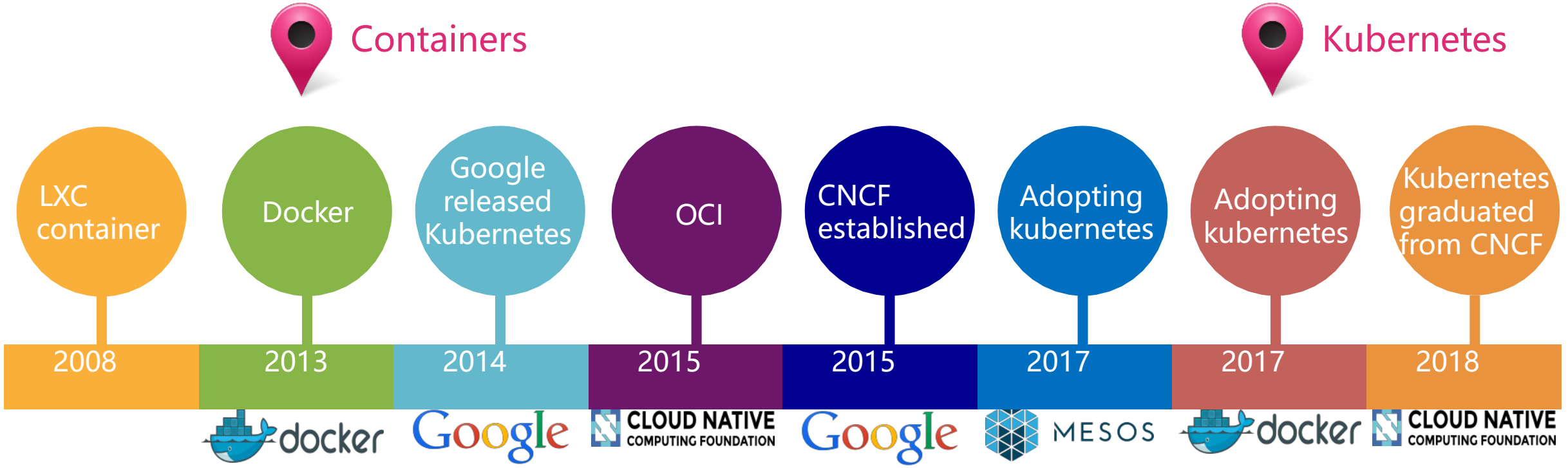
- Cloud native practices empower organizations to develop, build, and deploy workloads in computing environments (public, private, hybrid cloud) to meet their organizational needs at scale in a programmatic and repeatable manner. It **is characterized by loosely coupled systems that interoperate in a manner that is secure, resilient, manageable, sustainable, and observable.**

- Cloud native technologies and architectures typically consist of some combination of containers, service meshes, multi-tenancy, microservices, immutable infrastructure, serverless, declarative APIs etc.

- Combined with robust automation, cloud native practices allow organizations to make high-impact changes frequently, predictably, with minimal toil and clear separation of concerns.

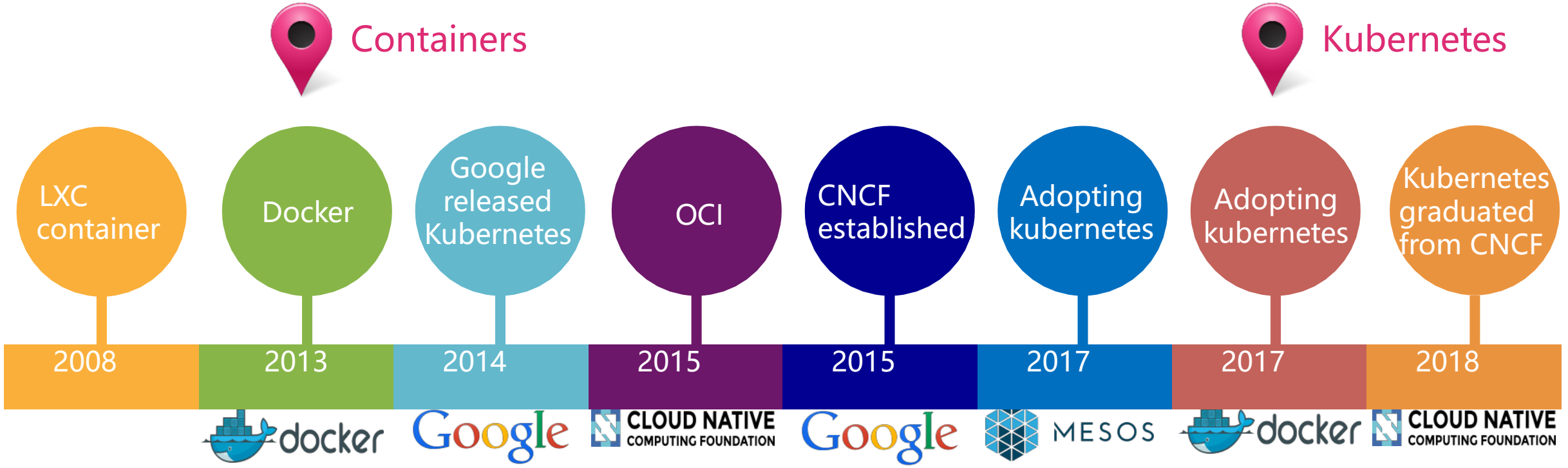


Rise of containers and Kubernetes (K8s)



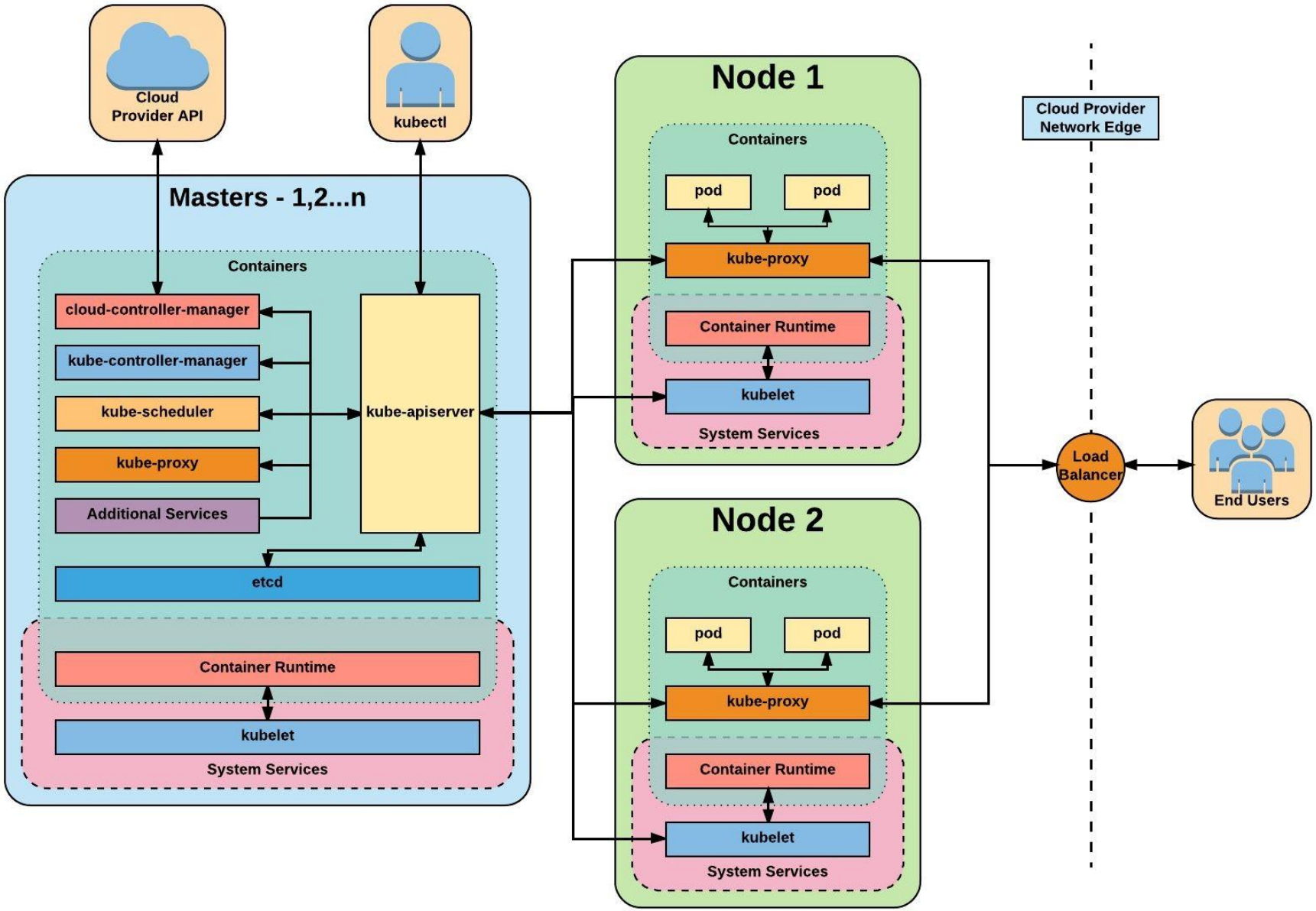
Kubernetes or **K8s** is a project spun out of Google as an open source next-gen container scheduler

Rise of containers and Kubernetes (K8s)

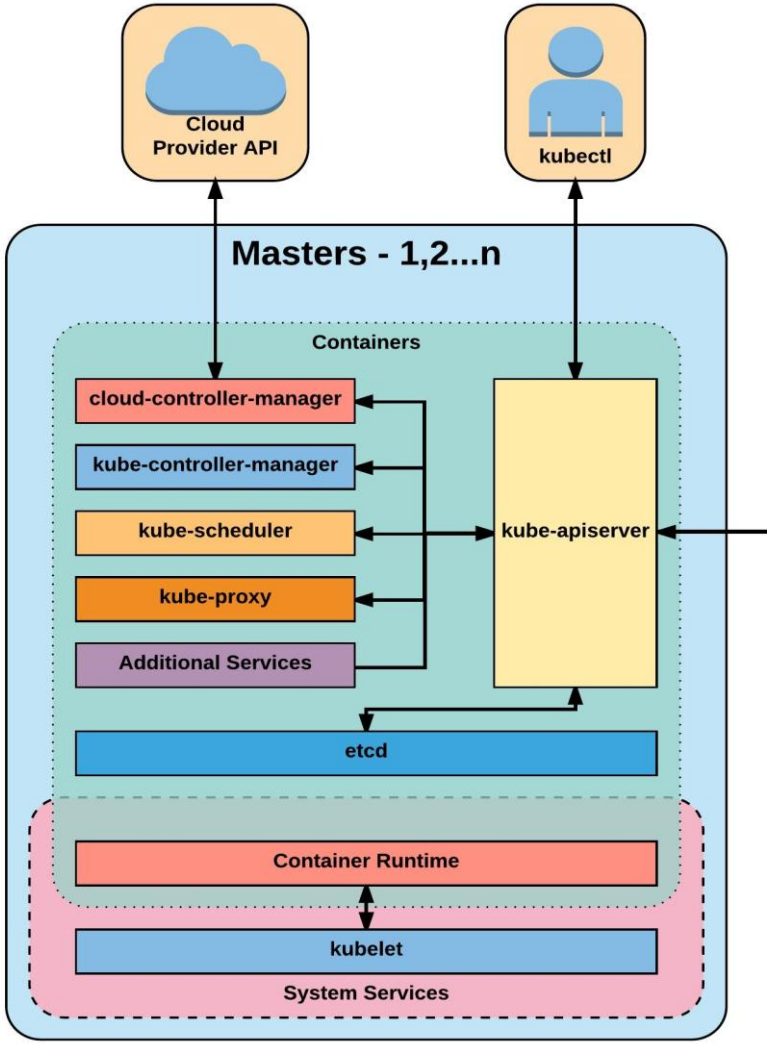


- K8s is an orchestration tool for managing distributed services or containerized applications across a distributed cluster of nodes.
- K8s follows a **client-server architecture with a master and worker nodes**. Core concepts in Kubernetes include pods, services (logical pods with a stable IP address) and deployments (a definition of the desired state for a pod or replica set).
- K8s **users define rules** for how container management should occur, and then K8s handles the rest

Architecture overview

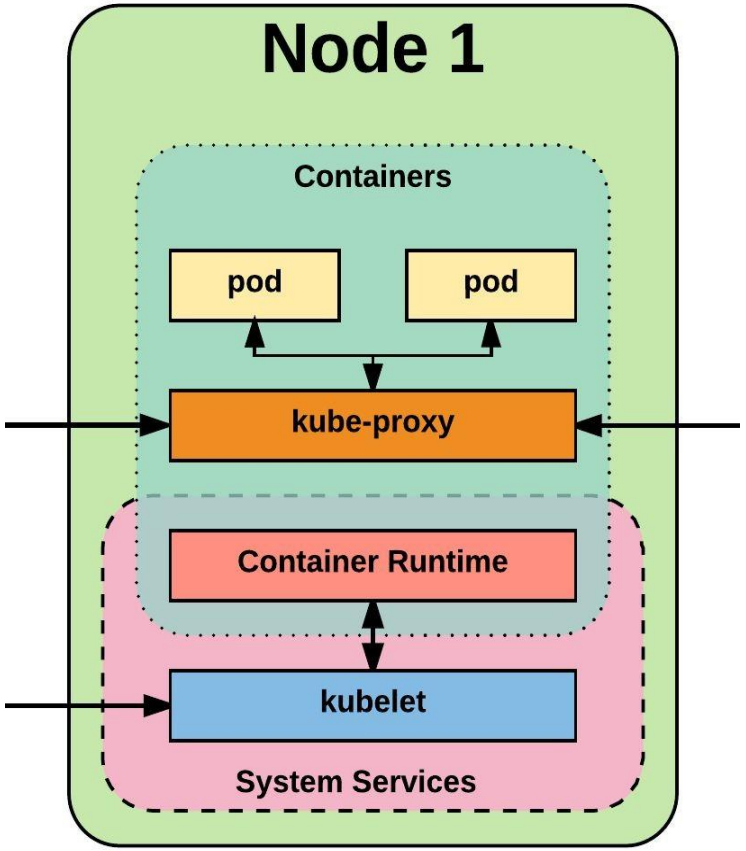


Master components



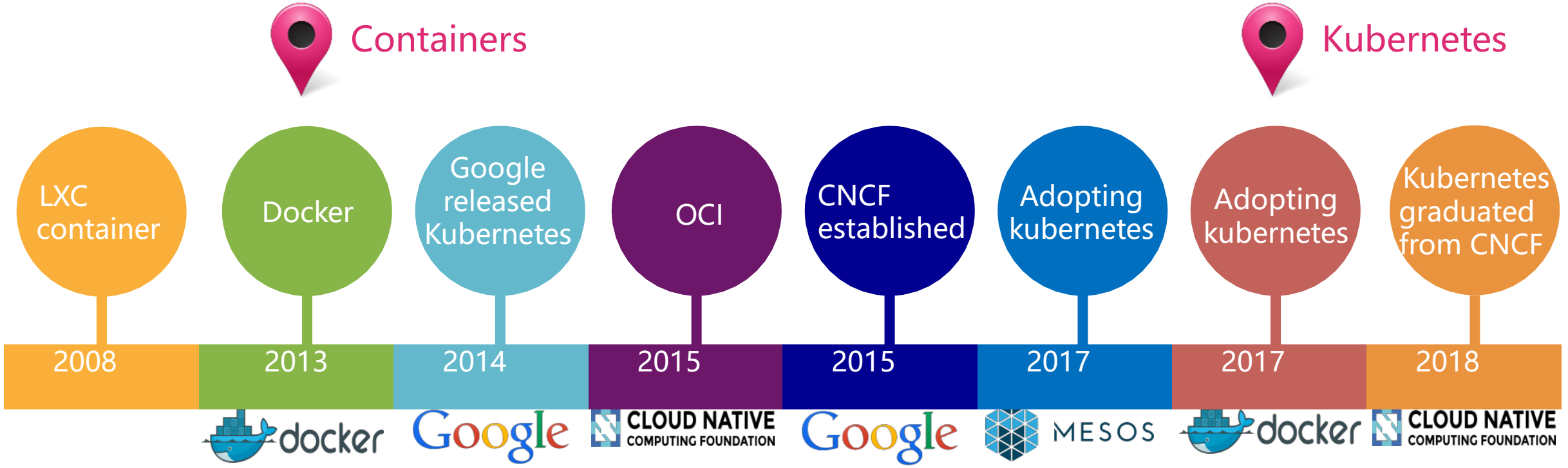
- **Kube-apiserver:** provides REST interface into the K8s control plane and datastore.
- **Etcd:** the cluster datastore; providing a strong, consistent and highly available key-value store used for persisting cluster state
- **Kube-controller-manager:** manages all core component control loops; monitors and steers the cluster towards the desired state.
- **Cloud-controller-manager:** provides cloud-provider specific knowledge and integration capability.
- **Kube-scheduler:** evaluates workload resource requirements and place it on a matching resource.

Node components



- **kubelet:** node agent for managing pod lifecycle on its host.
- **kube-proxy:** managing the network rules on each node and performs connection forwarding or load balancing.
- **container runtime:** executes and manages containers.

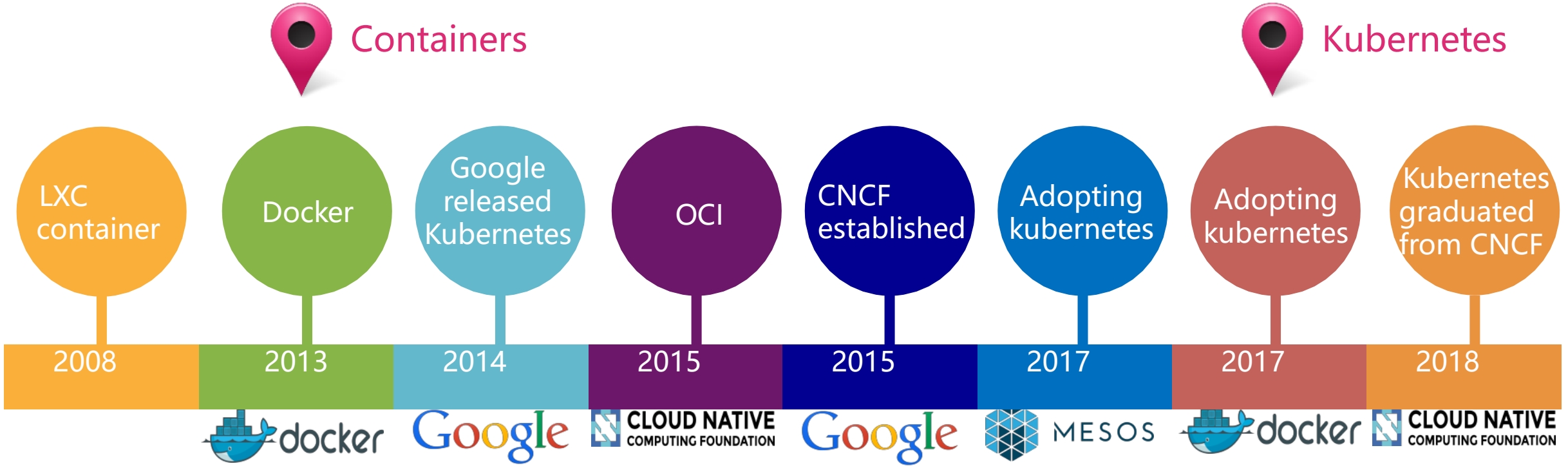
Rise of containers and Kubernetes (K8s)



Advantages of using K8s in reliable & efficient software deployment

- **Velocity:** fast to deploy while maintaining availability by immutable infrastructures & declarative configurations
- **Scaling:** fast and auto scaling of software and develop team
- **Infrastructure abstraction:** applications-infrastructure separation & portability
- **Efficiency:** lower costs of running a server, develop/deploy/test software

Rise of containers and Kubernetes (K8s)



Cloud evolvement in the last two decades

- From physical machines to virtual machines to containers
- Different offerings: IaaS, PaaS, SaaS, Caas, FaaS on Public /private / hybrid cloud
- Kubernetes becoming standard
- High-available service on low-available hardware

Outline

- Brief history of cloud computing
- Cloud native technologies (what can be the problems?)
- Current practice and opportunities of AI on cloud

Chef
(LLM)

Restaurant
(serving systems)

Disney world
(cloud systems)

Placement and load balancing (PLB)

Question: put 18KB into [A: 10KB | B: 20KB | C: 19KB | D: 25KB | E: 30KB]

- **Placement**

  The overall goal is to reduce violation to users' Service Level Agreements (SLAs), given that resource usages are **dynamic**.

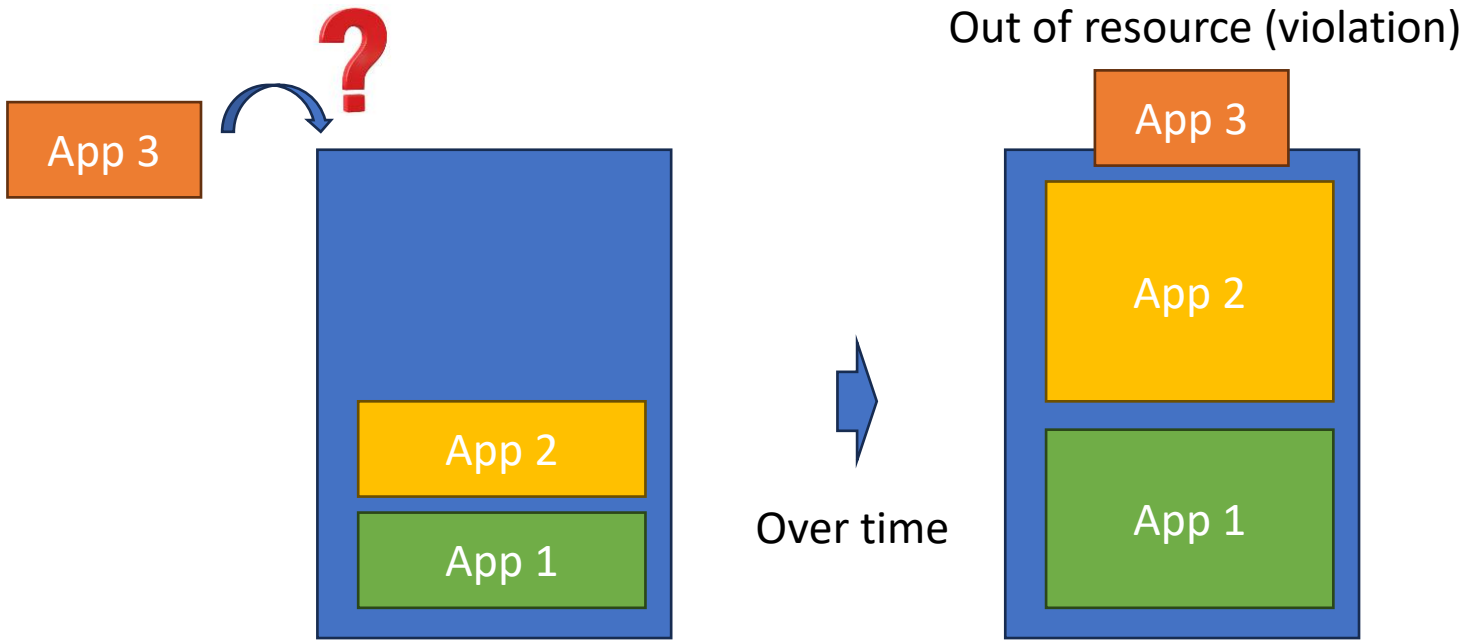
  What can be the placement strategies?

  - **First Fit:** the first one that fits → B: 20KB
  - **Best Fit:** the one that just fits → C: 19KB
  - **Worst first:** the one that has the most resource → E: 30KB

  - **More advanced:**
    - **Multi-resource:** memory, disk, CPU, etc. [TETRIS, SIGCOMM 2014]
    - **More complex policies:** constrains, leave-one-out, leave-two-out and so on

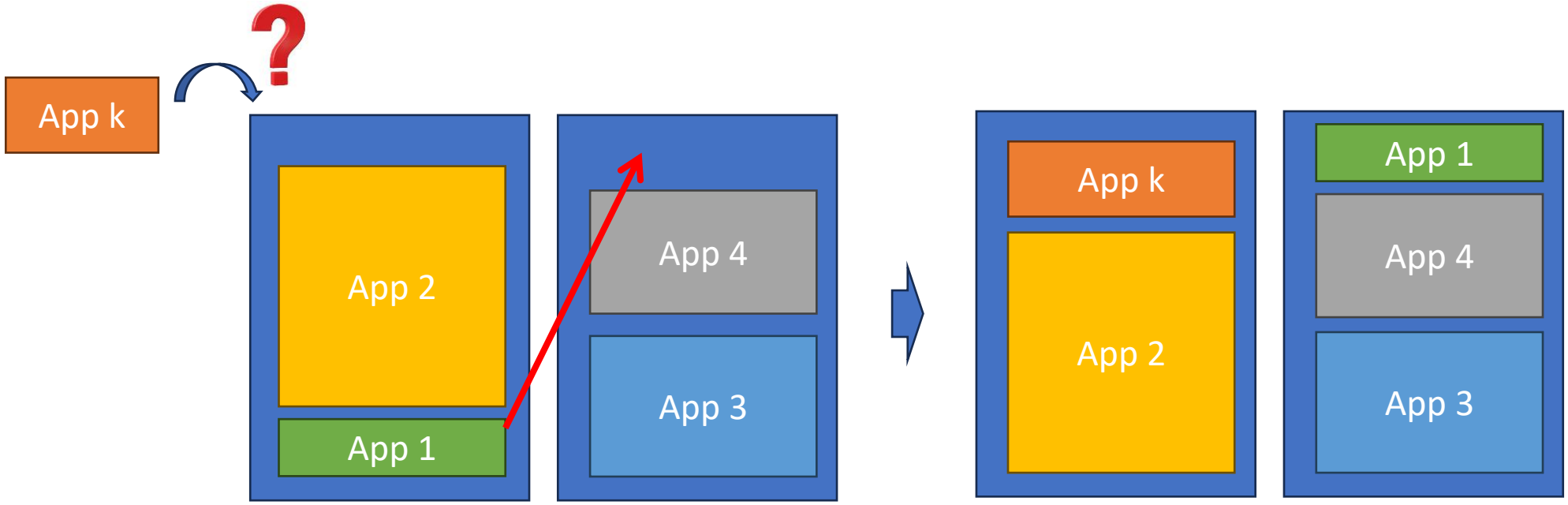
Placement and load balancing (PLB)

- **The real problem:** usages can change → no theoretical guarantee for optimal placement, since everything is data-driven



Placement and load balancing (PLB)

- **Load balancing:** migrate to “make” some room

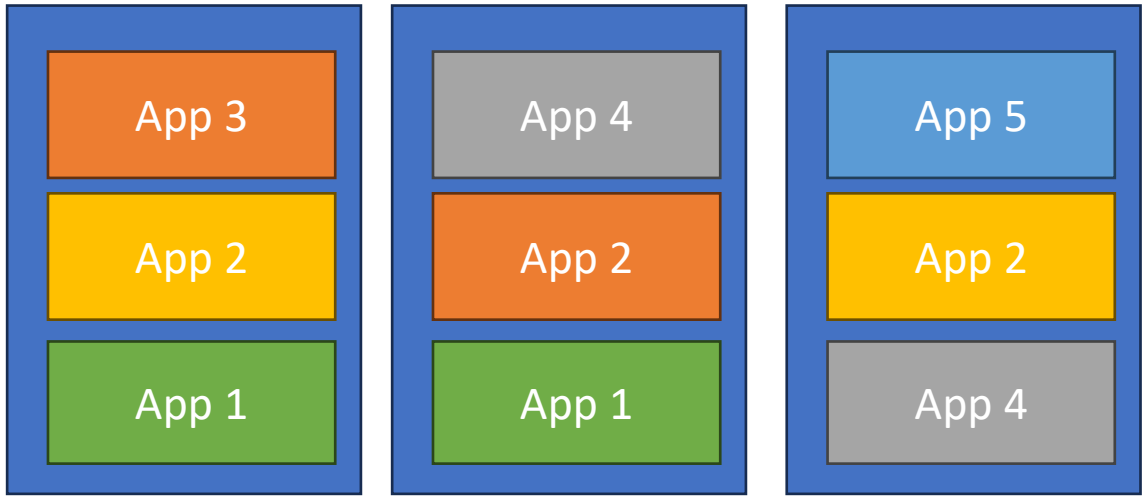


But migration is not free, often very expensive: stateful VMs, DBs, etc.

- Better migration mechanisms: cache compression, disaggregated memory etc.
- Resource usage prediction: placement & balancing based on predicted usages

Failovers

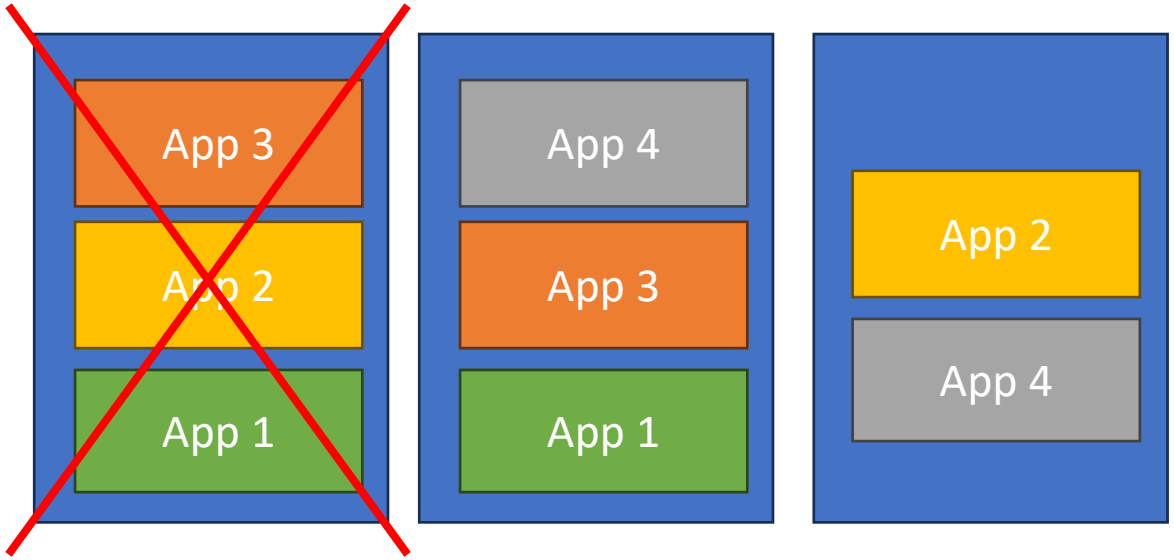
- Failovers ensure a robust & highly available service
  - Duplica on independent resources to avoid simultaneous failure



- Failovers are useful for hot software patching / updates
- Failovers can co-exist with PLB which makes it a lot more complex

Failovers

- **A fast failover** involves efficient context switch & recovery



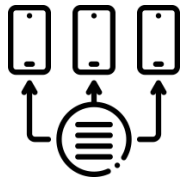
- Route requests to duplica
- Recover main from duplica
  - Reinstate using logs
  - Live migration

Failover due to:

- Unexpected: software/hardware failure
- Scheduled: Software update

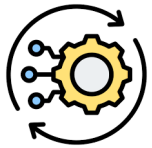
Serverless computing

- Some “rewrap” of ideas, but many cloud-native techniques are the same underneath



No servers to provision or manage. User describes application; system finds out best provision.

Scales with usage. System expanse and shrinks automatically with actual usage.



Build-in availability and fault tolerance. System also provides safety belts at no cost to the users.

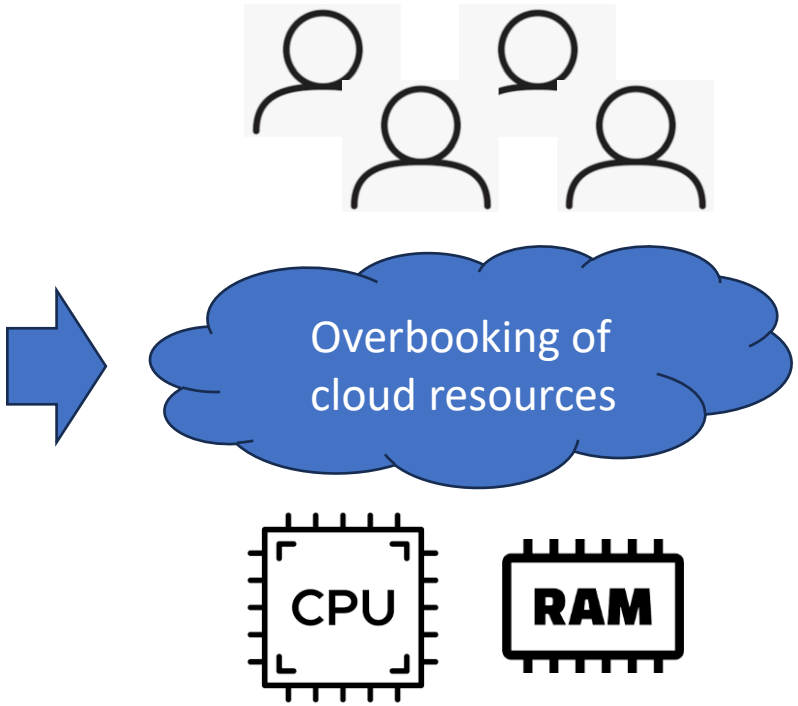
No pay for idle. Billing model – user pays only for actual usage; financial risks at the operator.

Containers & orchestrators

(New) Serverless functions & overscriptions

Resource oversubscription

100 seats, sell 105 tickets



- (Almost) direct revenue boost , given the base at **$100B!**
- But still, new technologies needed

Resource oversubscription

- **Technology prerequisites:**
  - Virtualization to cut CPU/disk/memory into fine granularity
  - Quick allocation / migration
  - Multi-tenancy over shared resources

- **Key problem for oversubscription:**
  - Increase oversubscription rate, while reduce/prevent violations w/ user SLAs
    SLA can be latency of query, service availability, etc.

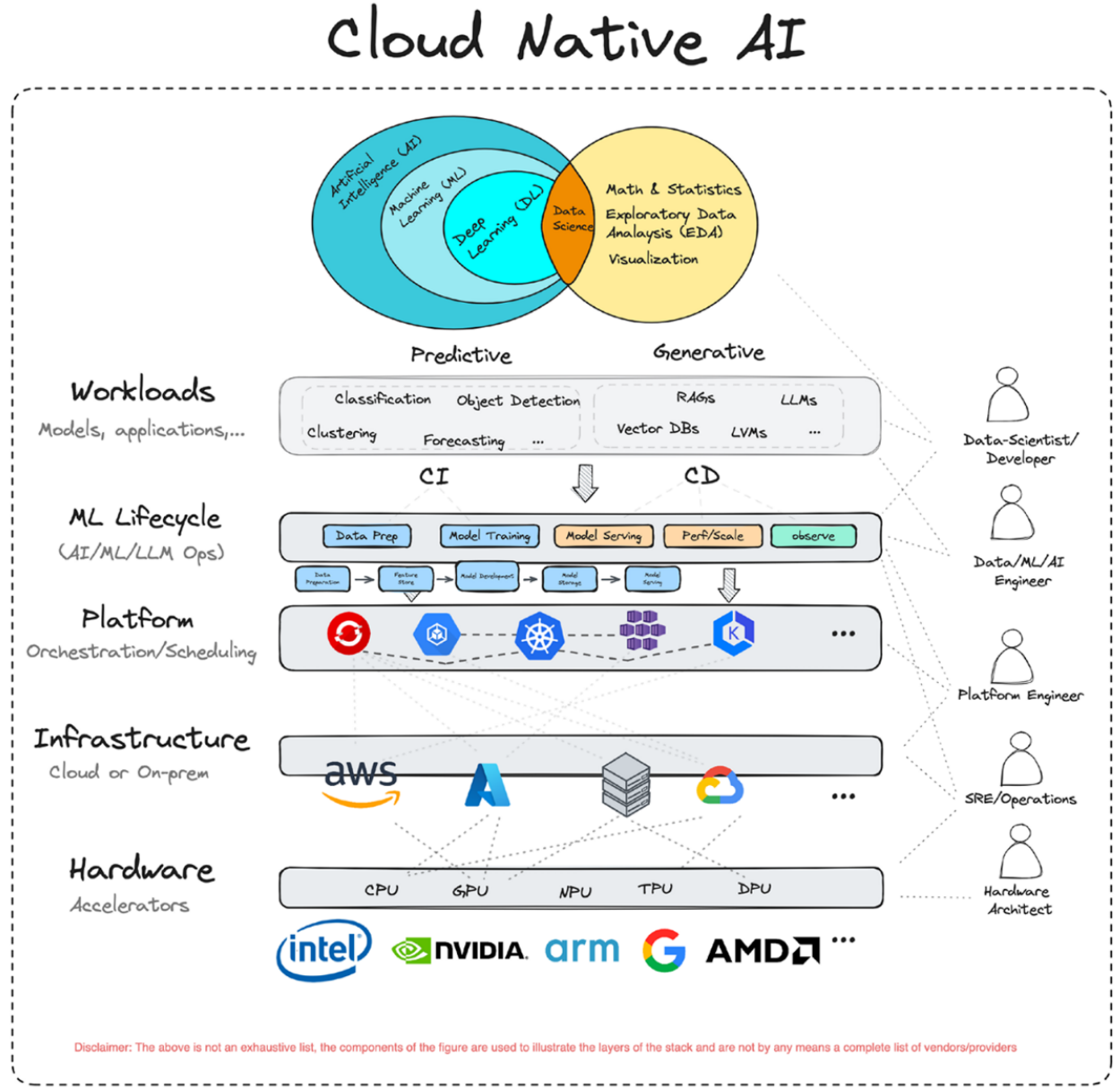
- **Mechanisms for an oversubscribed system:**
  - Similar PLB but at high resource usages

Outline

- Brief history of cloud computing
- Cloud native technologies
- Current practice and opportunities of AI on cloud

Practice and opportunities of AI on GPU cloud

- Cloud native technologies are open-box solutions for may AI use cases
- **Key idea:** containerizing your models

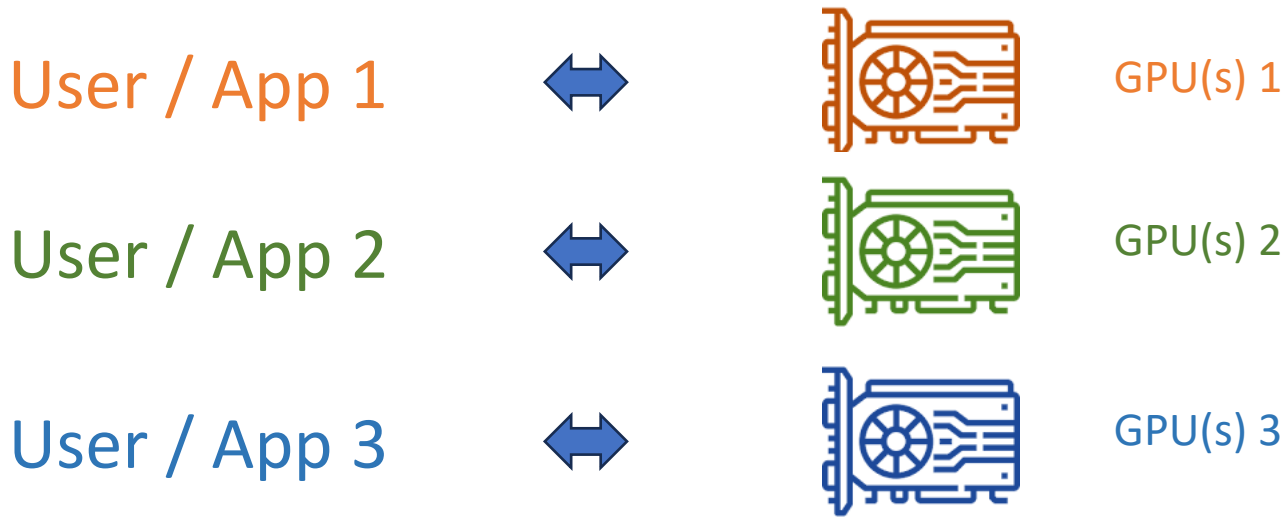


https://www.cncf.io/wp-content/uploads/2024/03/cloud_native_ai24_031424a-2.pdf

Practice and opportunities of AI on GPU cloud

- But, some cloud-native ideas couldn’t be applied
  - GPU virtualization and oversubscription
  - Fine-grained scheduling and operations
    - Each container is a big black-box

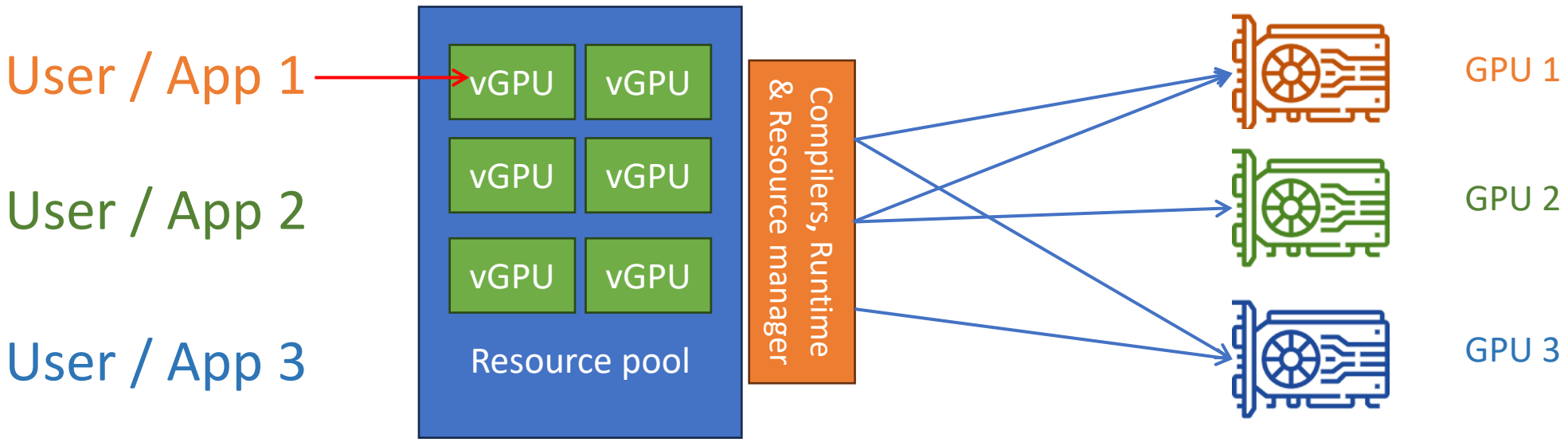
Resource oversubscription for GPUs?



Tight coupling between
resource specification and allocation

This means it's hard to switch context / allocation, even when the resource is in idle.

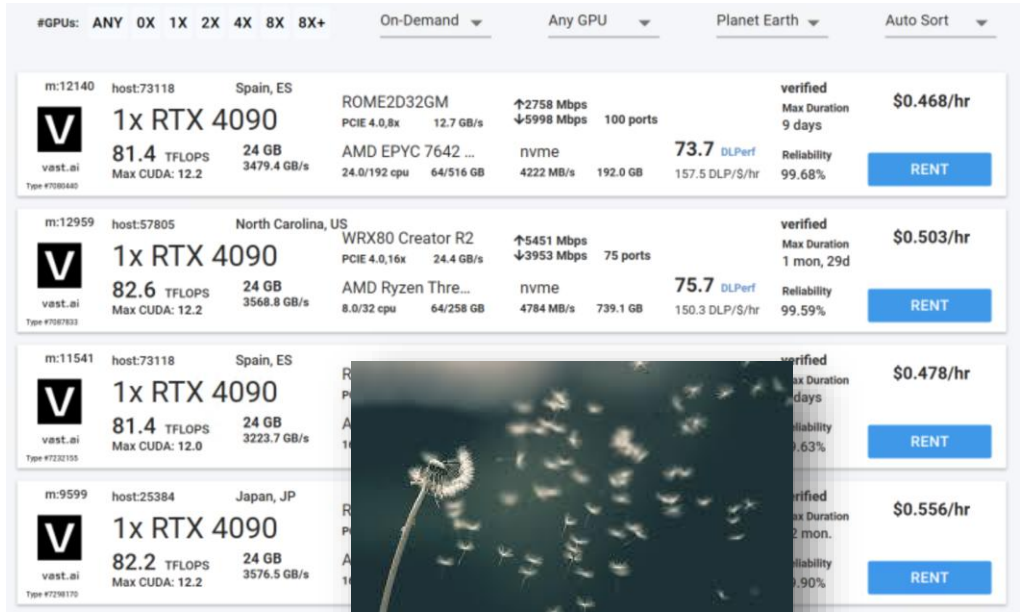
Breaking the tight coupling between apps & allocation



"Virtulizating" GPUs into thread and memory blocks,
But, big engineering challenges

Looking forward

- New opportunities in cloud AI
  - **New cloud** with heterogeneous, ephemeral infra
    spot instances, intermittent/green power
  - **New services:** RL, agentic workflows, etc.
  - **New hardware & architecture:** RISC-V AI chips, AISC chips
  - **New applications:** AI-for-X



Looking forward

- Agentic infrastructures & systems
  - Agent in, agent out, system is a “skill”
  - Data analytics
  - “Knowledge”

LUMILAKE: An Agentic Analytics Engine for AI4Science

Zhengyuan Su, Noppanat Wadlom, Junyi Shen, Peisong Zhang, Ran Luo, Dianbo Liu, Yi Hou, Yicong Huang*, Wentao Wu+, Yao Lu
National University of Singapore, Databricks*, Microsoft Research+

ABSTRACT

In the emerging *agentic analytics*, the fundamental unit of computation is no longer a SQL query or a Python script but an *agentic workflow*: a DAG of agent operations, each defined by a template that may compose sub-operations such as SQL queries, object fetches, model invocations, or multi-round subagent interactions. These workflows are computationally explosive – a single input triggers cascades of agent and subagent calls that quickly overwhelm the modest, fragmented GPU resources typical of research groups; yet existing serving systems treat each call in isolation.

We present LUMILAKE, an agentic analytics engine that models

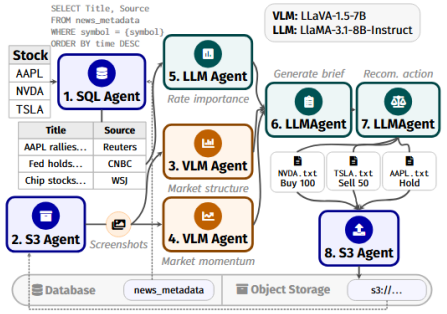


Figure 1: An agentic analytics workflow that combines SQL query, object fetch, and LLM invocations.

Just as the transition from hand-written queries to cost-based optimizers transformed relational analytics, the transition from human-authored scripts to agent-authored pipelines demands a new engine design: one that understands, optimizes, and governs agentic workflows as first-class objects.

This shift is already visible in AI4Science [16, 33] [1]. A clinical decision-support workflow chains a data-retrieval agent that issues SQL over patient records to six specialist agents, each prompted with distinct clinical guidelines, which follow a debate template of three pro/con rounds before a final arbiter synthesizes the diagnosis [3]. A materials-spectroscopy workflow dispatches three parallel expert agents, each following a template with two analyst subagents using different guided prompts, then orchestrates cross-branch critique through iterative rebuttal rounds [5]. A financial-analysis

FLOWMESH: A SERVICE FABRIC FOR COMPOSABLE LLM WORKFLOWS

Junyi Shen [1] Noppanat Wadlom [1] Lingfeng Zhou [2] Dequan Wang [2] Xu Miao [3] Lei Fang [3] Yao Lu [1]

ABSTRACT

AI deployment increasingly resembles a pipeline of data transformation, fine-tuning, and agent interactions rather than a monolithic LLM job; recent examples include RLHF/RLAIF training and agentic workflows. To cope with this shift, we propose FlowMesh, a multi-tenant service fabric that executes and optimizes these workloads as one shared service instead of isolated pipelines. It decomposes workflows into fine-grained operators with recorded lineage, enabling de-duplication of work across users and batching requests on the same hardware while preserving per-workflow provenance. A global control plane maintains a cluster-wide pool of ready operators and uses a single utility function to pick both the batch and the worker, balancing throughput, cost, and data locality on heterogeneous GPUs. The data plane is an elastic fleet of stateless workers
store, enabling rapid, automatic scale-out, safe retry after preemption, and po
such as Kubernetes and geo-distributed GPU marketplaces such as Vast.ai. C
FlowMesh achieves up to 3.8× cost reduction and 2.0× lower energy usage, p
profile, and remains efficient under dynamic and failure-prone conditions.

1 INTRODUCTION

The dominant paradigm in applied machine learning is undergoing a significant transformation, shifting from monolithic, single-shot model training and inference to the orchestration of complex, multi-stage post-training workflows. These workflows, encompassing method-

et al., 2015; Zaharia
understanding of th
any form of cross-jo
connect gives rise to
hinder efficiency, s
GPU cluster or network:

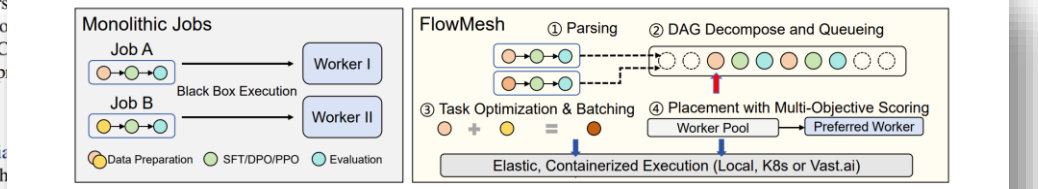


Figure 1. FlowMesh decomposes multi-stage LLM workflows into fine-grained, tasks and dispatch them among distributed workers.

What we have covered & not covered

- MLsys foundations
- Automatic differentiation
- Hardware acceleration
- Parallelism and training techniques
- Transformers, attention and optimizations
- Serving LLMs
- Fine-tuning and alignment techniques
- Application systems & AI agents
- LLM safety
- ML Operations
- Data & Cloud systems for AI

Covered

- Compute graph optimization
- Serving multi-modal models
- Serving mixture-of-experts models
- Many more..

Not covered

Logistics for next week

- LLM benchmark – Leaderboard: submit your result before next Wednesday

- In-person presentation
  - 1 Slide briefing + Demo (project 2,3), present to other students
  - TA & I will grade also

- Peer review & voting
  - Review 3 other groups' projects
  - Submit a short description for how another project can help in yours

- Reflection
  - In which way your solution can be improved by others' ideas.

- Final report
  - Research style: background, motivation, solution, evaluation, analysis.
  - Review + reflect + demo (project 2,3)