

# Future Technologies in 2030 and beyond

## A biased Perspective

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Technology Solution Professional

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HPC and Big Compute Switzerland

Microsoft

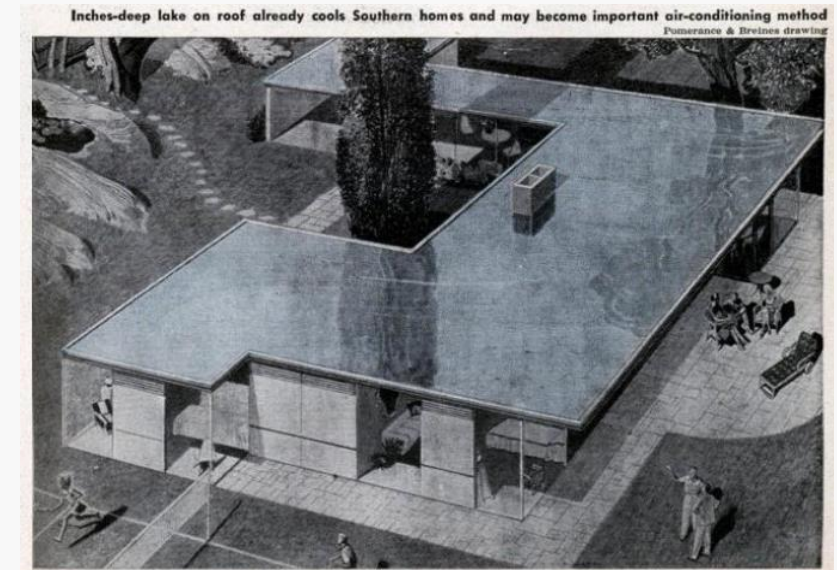
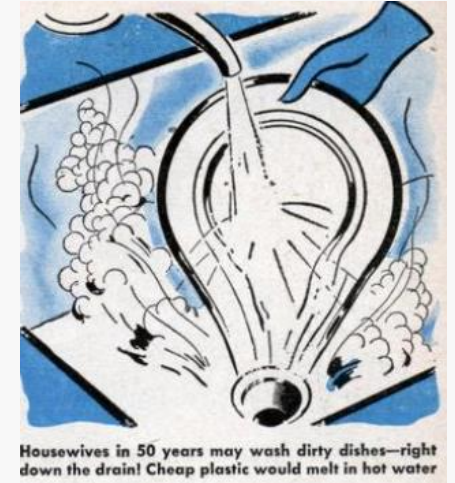
<http://microsoft.com/hpc>



eWIS-FutureTech, WMO, Geneva, March 2019



# Predictions are (quite often) biased



(...) before a hurricane has a chance to gather much strength and speed, **oil is spread over the sea and ignited**. There is an updraft. Air from the surrounding region, which includes the developing hurricane, rushes in to fill the void. The rising air condenses so that some of the water in the whirling mass falls as rain.

Miracles You'll see in next 50 years.  
Popular Mechanics, Feb. 1950

# Technical Advances come (often) unexpected

## ImageNet Classification with Deep Convolutional Neural Networks

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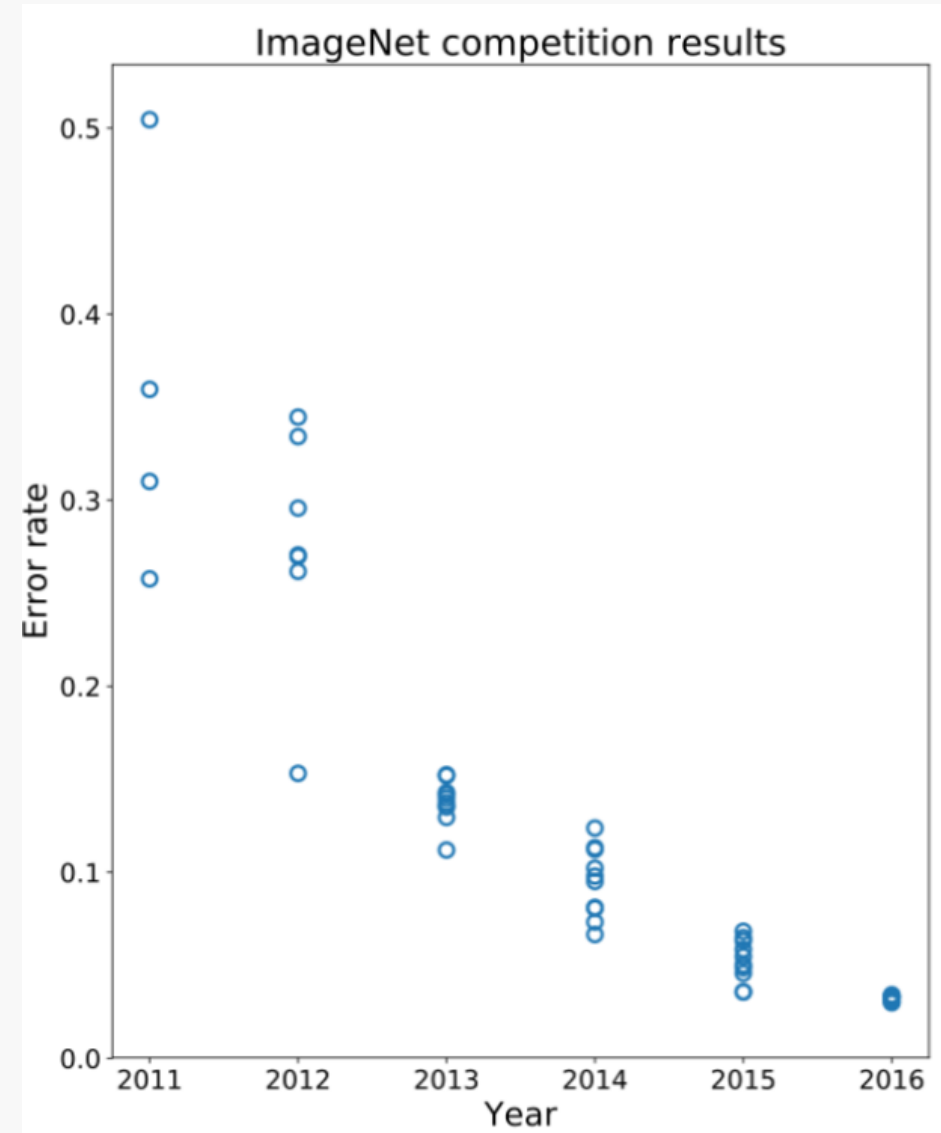
**Ilya Sutskever**  
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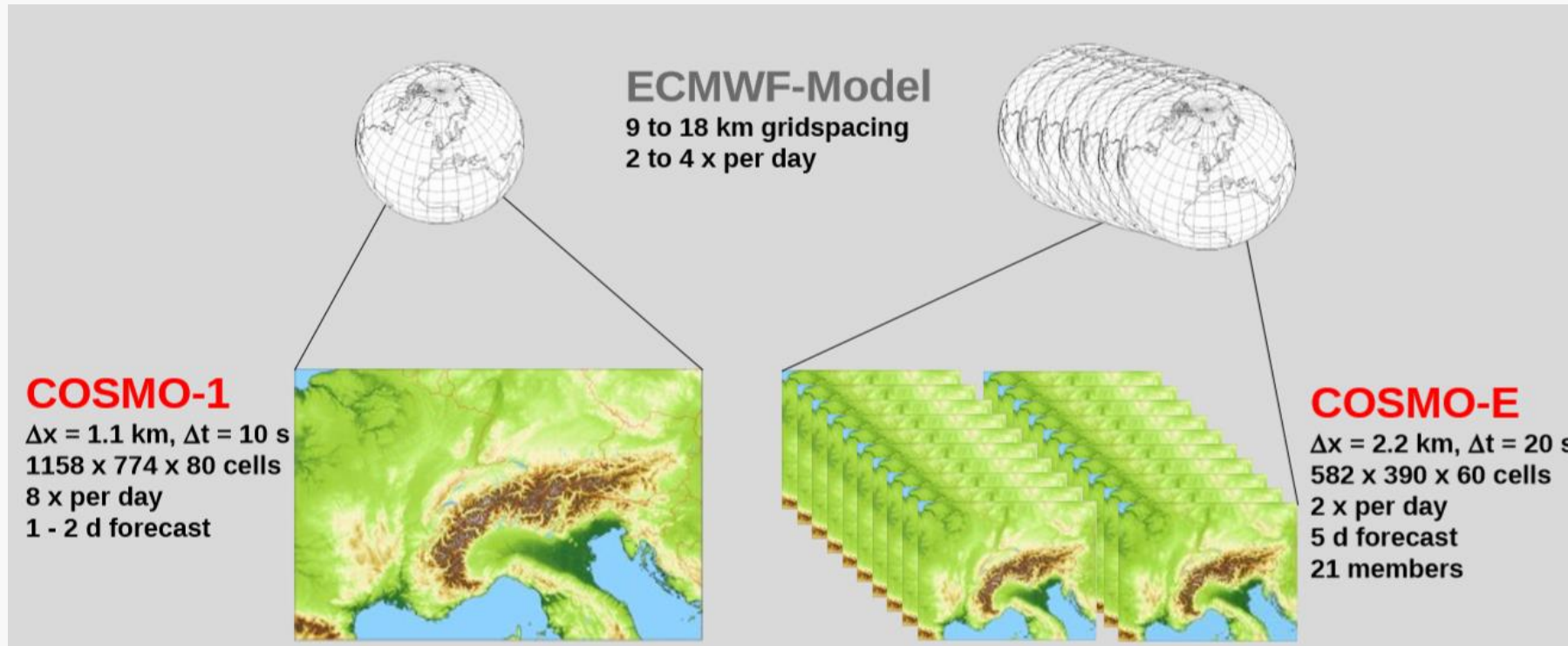
### Abstract

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make training faster, we used non-saturating neurons and a very efficient GPU implementation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called “dropout” that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

"**Suddenly** people started to pay attention to Deep Neural Networks, not just within the AI community but across the technology industry as a whole." (The Economist, 25 June 2016)



# Challenge #1: Growing HPC demands



Source: C. Osuna et al., Designs for Efficient Weather and Climate Models , ENES HPC Workshop

1km resolution requires:

- 97M node hours  
840 simulation days
- 68m CHF
  
- 22GWh
- 3800 tons CO<sub>2</sub>

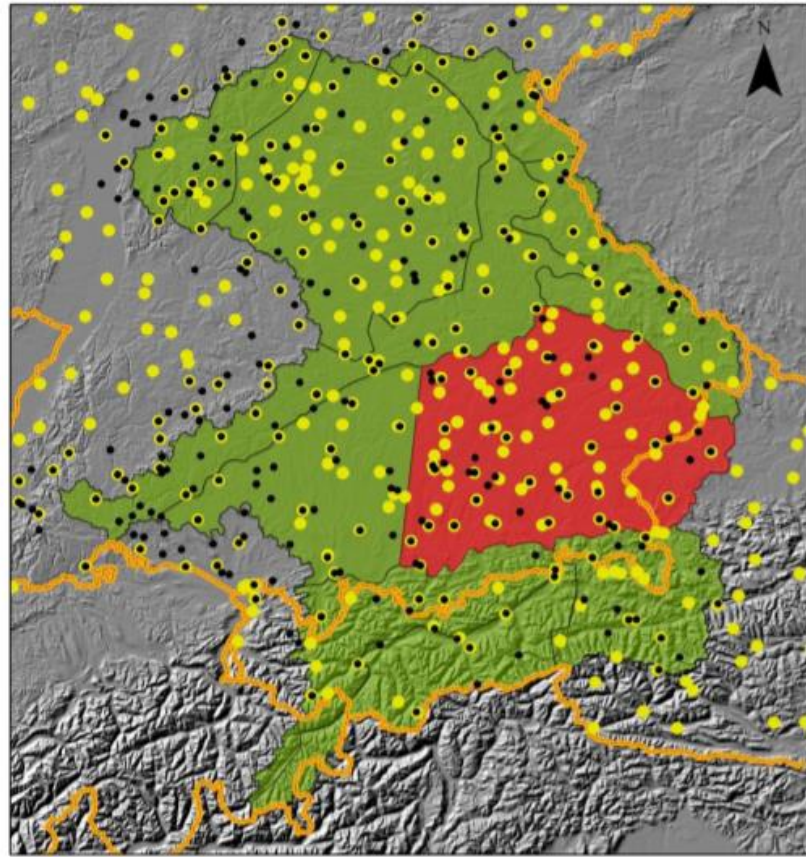
Source: PASC 2018

Need for km-scale global climate simulations

2x resolution increase -> 8x computational effort

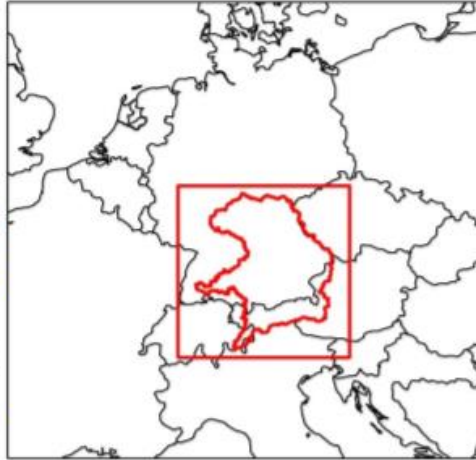
# Challenge #1: Growing HPC demands

The hydrological Bavaria: ~100.000 km<sup>2</sup>



Kilometers  
0 25 50 100 150 200

 ClimEx



- Disaggregated daily climate stations
- Reference hourly climate stations
- Eastern Alpine Foreland
- Country borders

ClimEx: modeling the effects of climate change on meteorological and hydrological extreme events in Bavaria and Québec

Model: CanESM2 (ca. 200 km resolution) integrated with CRCM5 (ca. 11km resolution)

50 transient runs x 150 years -> 7500 years of modeled climate

Data: +500 TB

HPC: Leibniz Supercomputer Center

# Challenge #2: Heterogeneity



- Sharing climate models and data
  - Different clusters based on different hardware
  - Hard maintenance: multiple branches, complex dev test procedures
  - Data movement/sharing challenge, portability challenge

What is your data strategy?

What are the challenges in such heterogenic and diverse ecosystem?

How do you expose/publish your models across Europe and the globe?

Where the models/data are located physically?

# Challenge #3: Reproducibility

“14 percent of published research is false because data analysis was inaccurate or misinterpreted.” [1]

In 2011 Bayer conducted its own reproducibility tests on 67 published experiments and failed to get similar results on 53.



More than **70% of researchers** have tried and **failed** to reproduce another scientist's experiments, and more than half have failed to reproduce their own experiments [2,3].

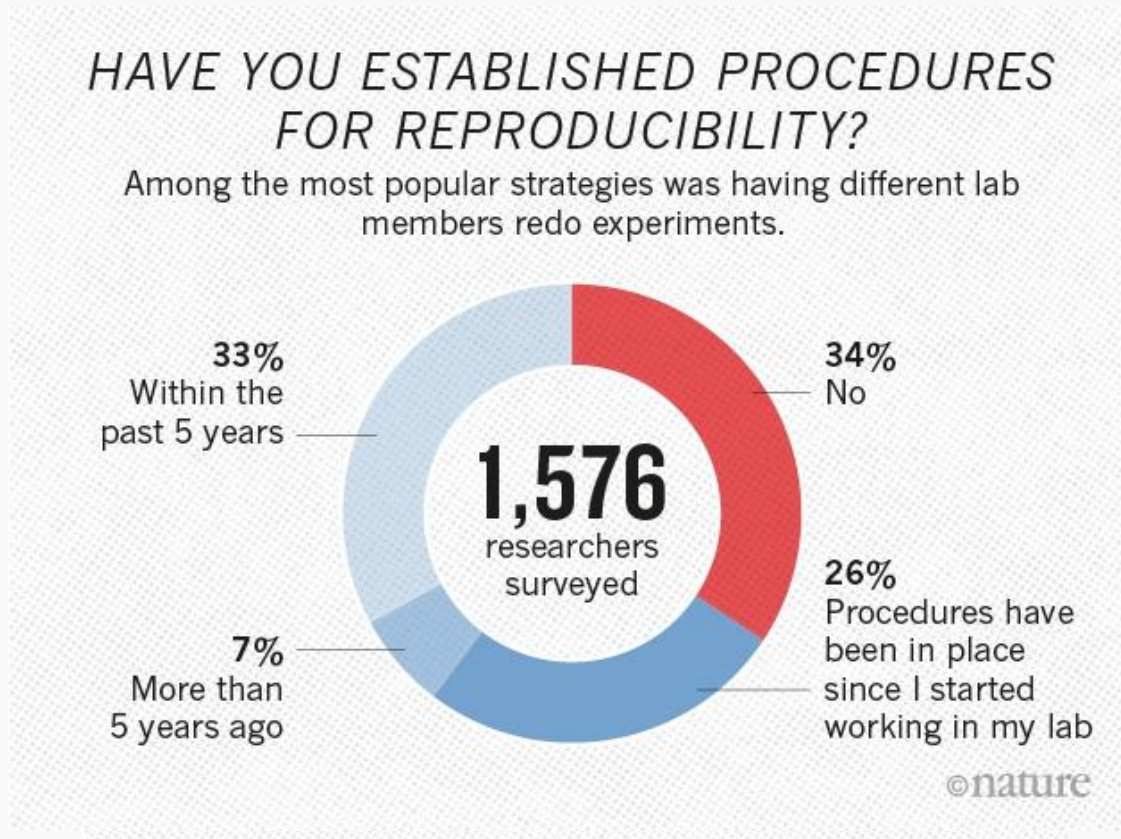
“We need to archive, store and secure these data so that the steps taken in each experiment are traceable.”  
—Alex Kolodkin, chair of the Task Force on Research Reproducibility at Johns Hopkins Hospital.

[1] Could you Repeat That? [Hopkins Medicine Magazine](#), Fall 2017.

[2] Scientific Rigour and Reproducibility, Special Edition, Nature, May 2017.

[3] 1,500 scientists lift the lid on reproducibility, Nature Survey, May 2016.

# Challenge #3: Reproducibility



## The Recomputation Manifesto

1. Computational experiments should be recomputable for all time [4]
2. Recomputation of recomputable experiments should be very easy
3. It should be easier to make experiments recomputable than not to
4. Tools and repositories can help recomputation become standard
5. **The only way** to ensure recomputability is to provide **virtual machines**
6. Runtime performance is a secondary issue

[3] 1,500 scientists lift the lid on reproducibility, Nature Survey, May 2016.

[4] Recomputation Initiative

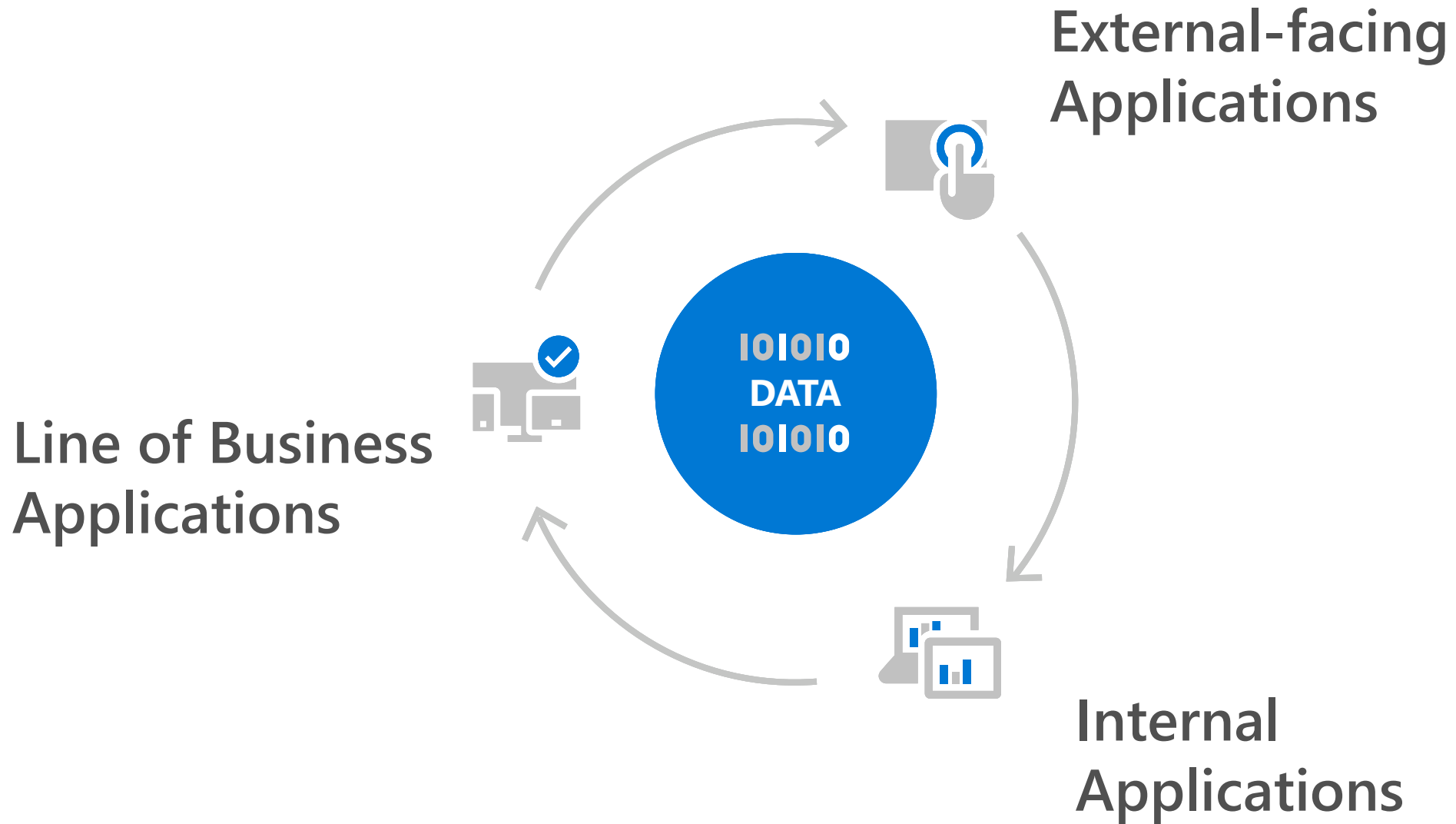
# What is "The Cloud"?



“The Cloud” is a platform which allows you to

**Write, run and use** software

# Business is powered by applications

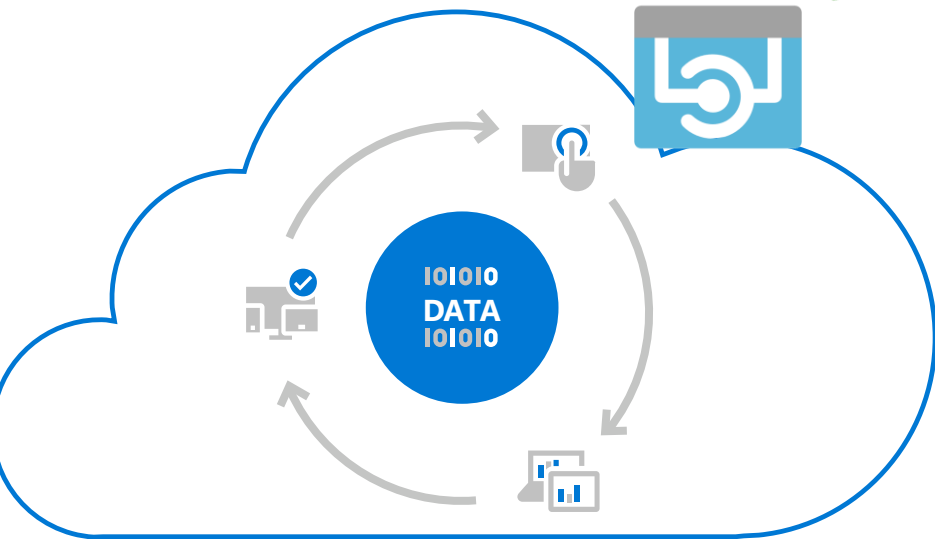
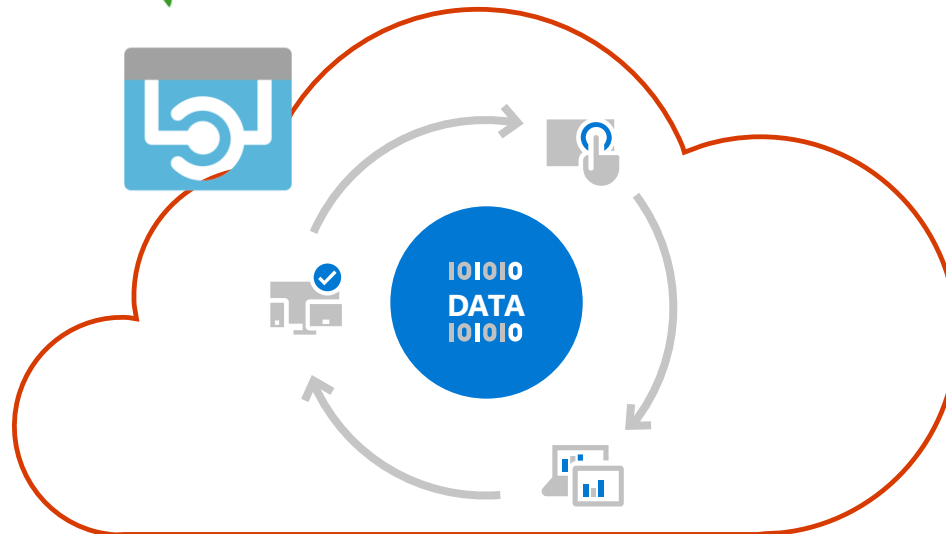
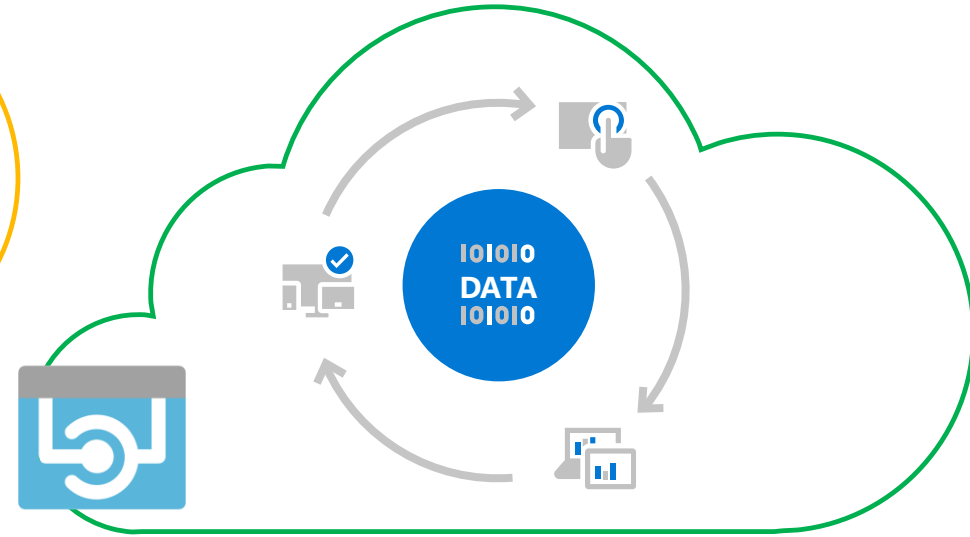


# Interoperability?

APIs

API Management

Value added services



# Application layers



Code



Data + Intelligence



Infrastructure



# Challenges



Code



Data + Intelligence



Infrastructure

Application resiliency

Extensibility

Future proof

Data growth

Performance

Rising costs

Confidentiality

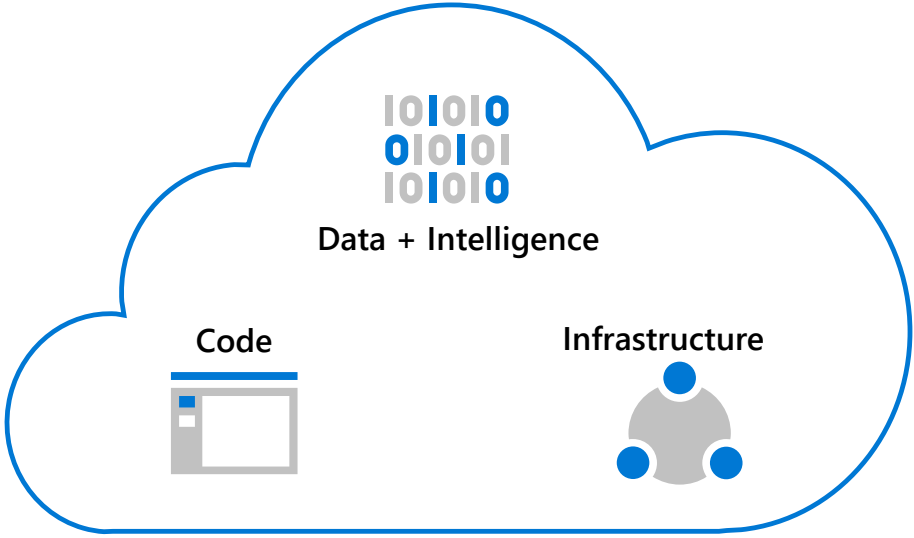
Hybrid/Global deployments

Security and management

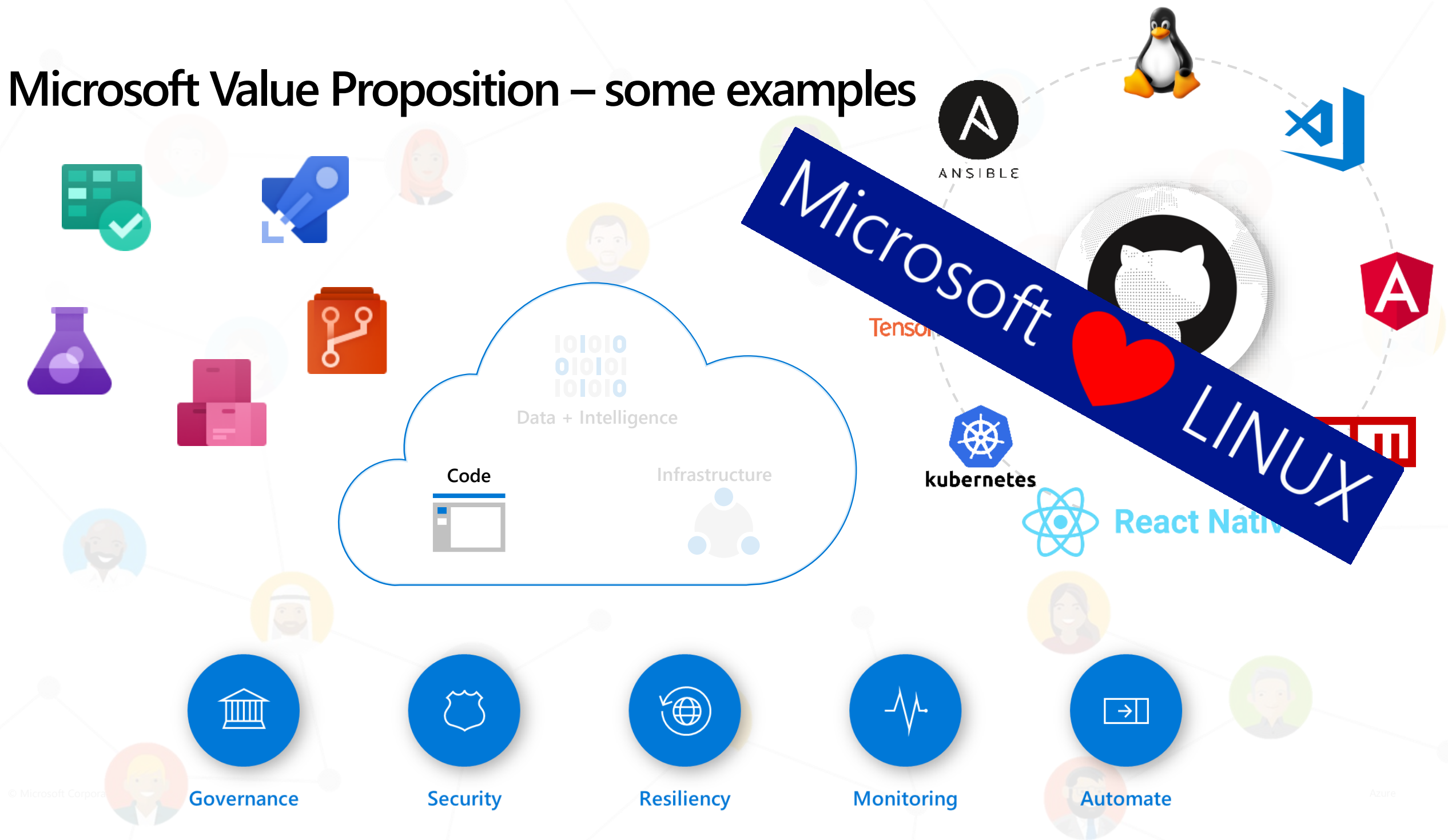
Continuous monitoring

Cost management

# Microsoft Value Proposition – some examples



# Microsoft Value Proposition – some examples



# Microsoft Value Proposition – some examples



IoT



Machine Learning

101010  
010101  
101010

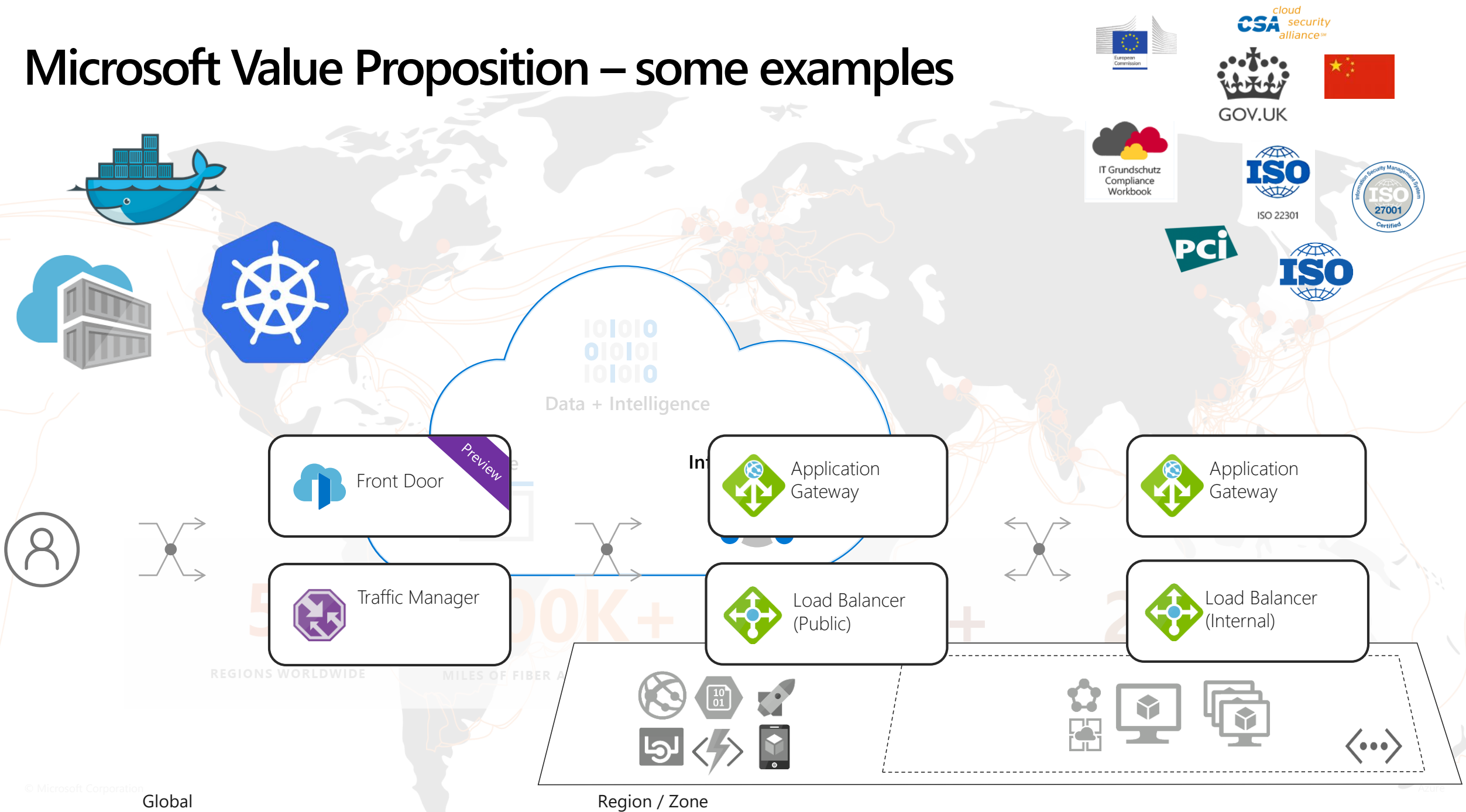
Data + Intelligence

1. The data volumes are exploding, **more data** has been created in the past two years than in the entire previous history of the human race.
2. Data is growing faster than ever before and by the year 2020, about **1.7 megabytes** of new information will be created every second for every human being on the planet.
3. By then, our accumulated digital universe of data will grow from 4.4 zettabytes today to around **44 zettabytes**, or 44 trillion gigabytes.
4. Every second we create new data. For example, we perform 40,000 search queries every second (on **Google alone**), which makes it 3.5 searches per day and 1.2 trillion searches per year.



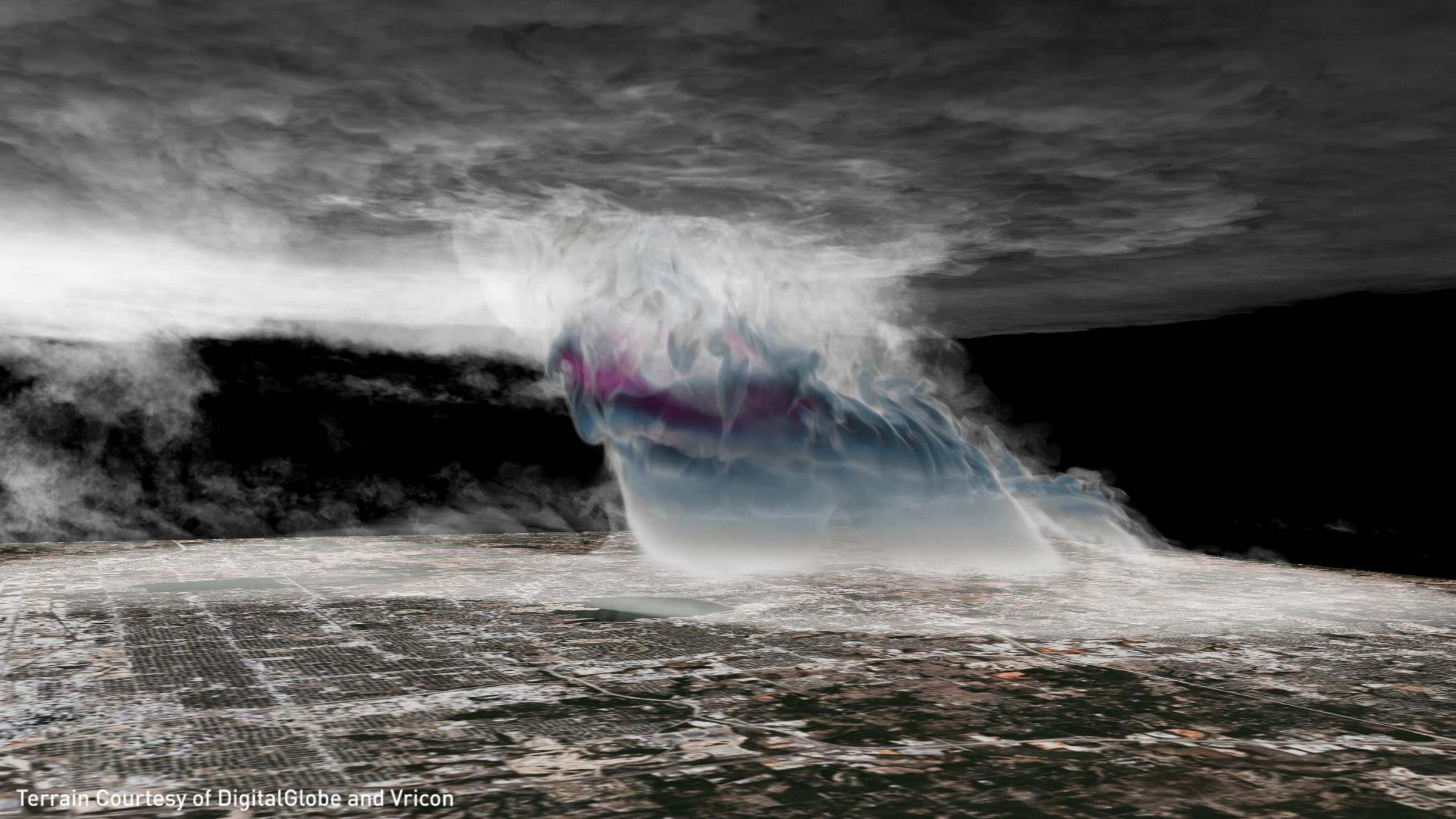
Microsoft Research  
Project Silica

# Microsoft Value Proposition – some examples



# Use Cases





Terrain Courtesy of DigitalGlobe and Vricon

## MeteoSwiss is interested in a failover and devtest infrastructure in the cloud

**Challenge:** MeteoSwiss needs a failover location with a specialized HPC architecture containing high-performance graphics processing units to enable weather simulations in a high availability mode.

**Solution:** We used ND40s with eight V100 to run a docker container with COSMO provided by NVIDIA. This setup simplified the GPUs were interconnected with NVLINK Kubernetes in Azure Container Service to handle back-end functions and increase the density of services running across compute nodes.

**Outcome:** With Azure, we managed to achieve very good performance. The simulation time is extremely close to the DGX1 system on prem with **2-3% variation**. MeteoSwiss engaged in follow up discussion on more workloads.

### Effort

5 commands, 1h work

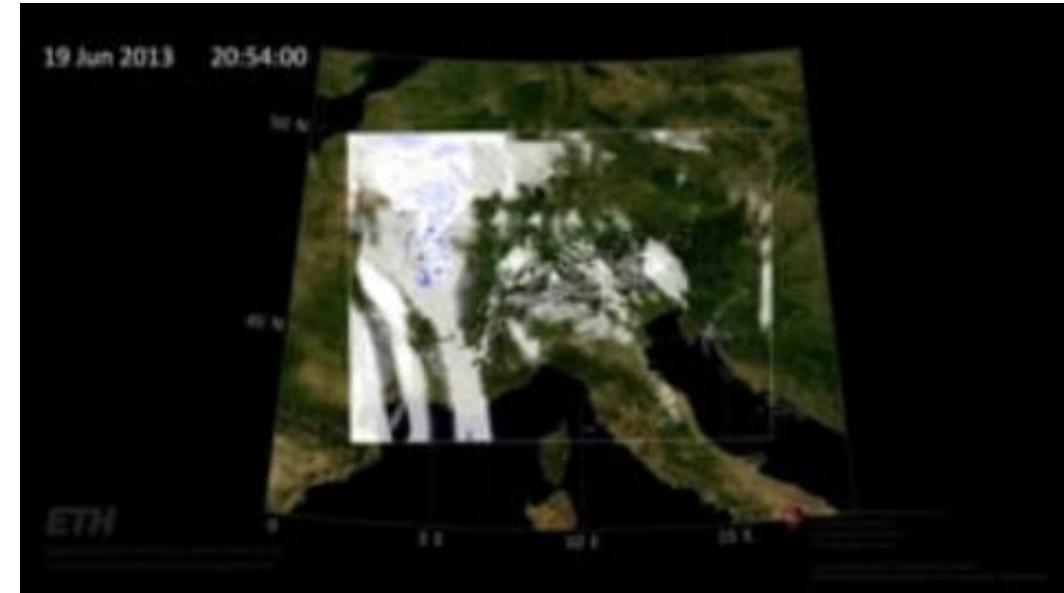


Fig. Visualization of COSMO-1 simulation.

# How Alaska outsmarts Mother Nature in the cloud

Alaskans are notoriously resilient people, and they don't want to be sidelined by the weather. To keep Alaska's highways open and safe during severe winter weather, the Alaska Department of Transportation & Public Facilities uses the Fathym WeatherCloud solution and Microsoft Azure IoT technologies to make better, hyper-local decisions about deploying road crews. By using the cloud to make better ground-level decisions, Alaska saves lives and significantly reduces road maintenance costs.

Road Weather Information System (IoT) data were transmitted to Decision Support System while mobile sensors placed on maintenance vehicles were transmitted to the cloud via mobile phones.



## Products and Services

Microsoft Azure  
Azure Data Lake Store  
Azure Event Hubs  
Azure IoT Hub  
Azure Stream Analytics

## Organization Size

3,100 Employees

## Industry

Government

## Country

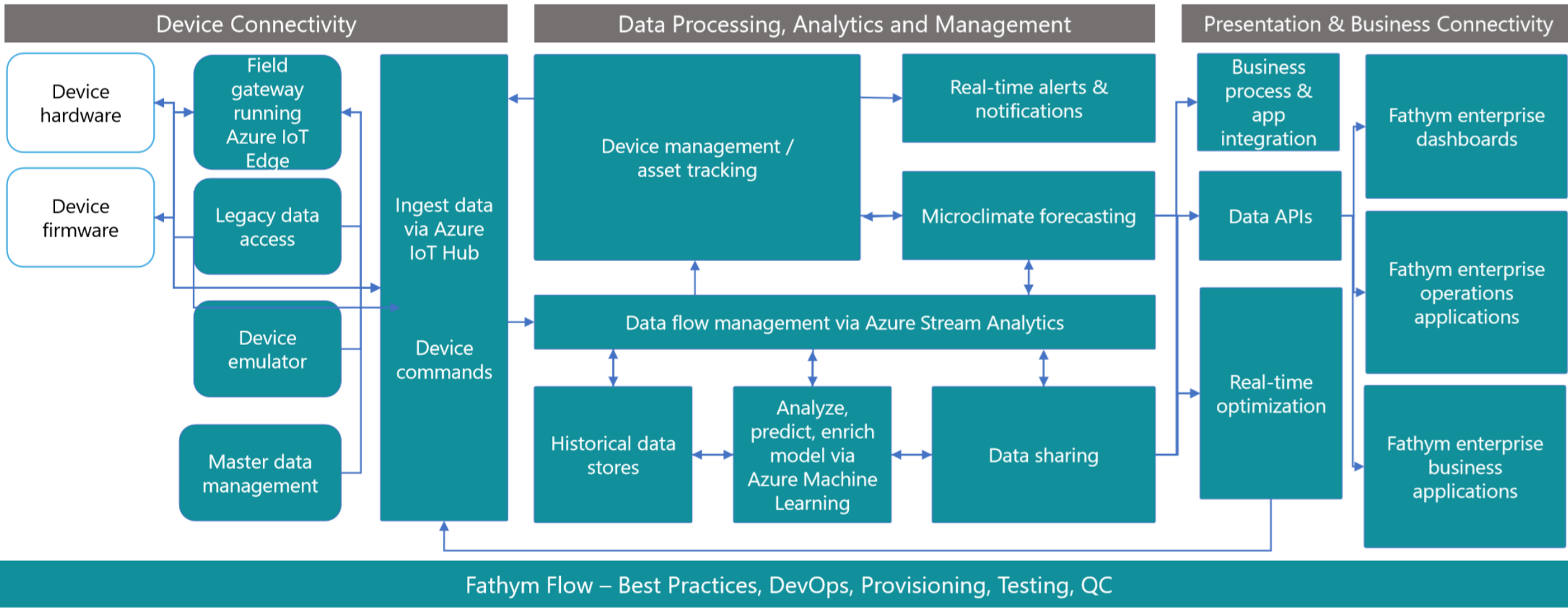
United States

## Partner

Fathym



# Architecture



# AI for Earth

AI for Earth puts Microsoft cloud and AI tools in the hands of those working to solve global environmental challenges.

## Areas of focus

AI for Earth awards grants to projects that use artificial intelligence to address four critical areas that are vital for building a sustainable future.

[Learn about AI for Earth grants](#) >



### Climate

The changing climate threatens human health, infrastructure, and natural systems. AI can give people more accurate climate predictions to help reduce the potential impacts.



### Agriculture

By 2050, farmers must produce more food, on less arable land, and with less environmental impact to feed the world's increasing population. AI can help people monitor the health of farms in real time.



### Biodiversity

Species are going extinct at an alarming rate. AI can help people accelerate the discovery, monitoring, and protection of biodiversity across our planet.



### Water

In the next two decades, demand for fresh water is predicted to dramatically outpace supply. AI can help people model Earth's water supply to help us conserve and protect fresh water.

# Land Cover Mapping

AI for Earth

Gallery

About

Browse through sample images from across the United States. Click on an image to view the land classification for that region.



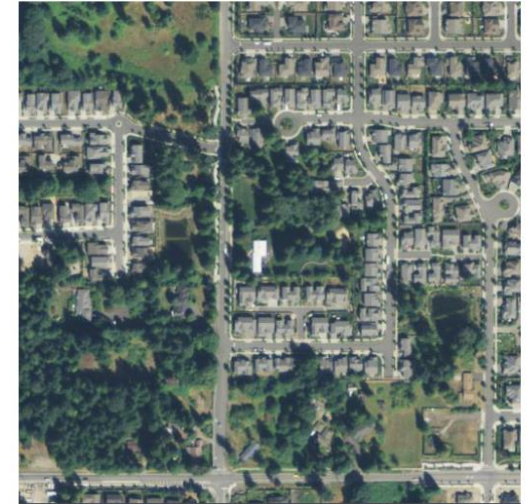
Location: kent island  
Year: 2011



Location: kent island  
Year: 2013



Location: kent island  
Year: 2015



Location: north redmond  
Year: 2011



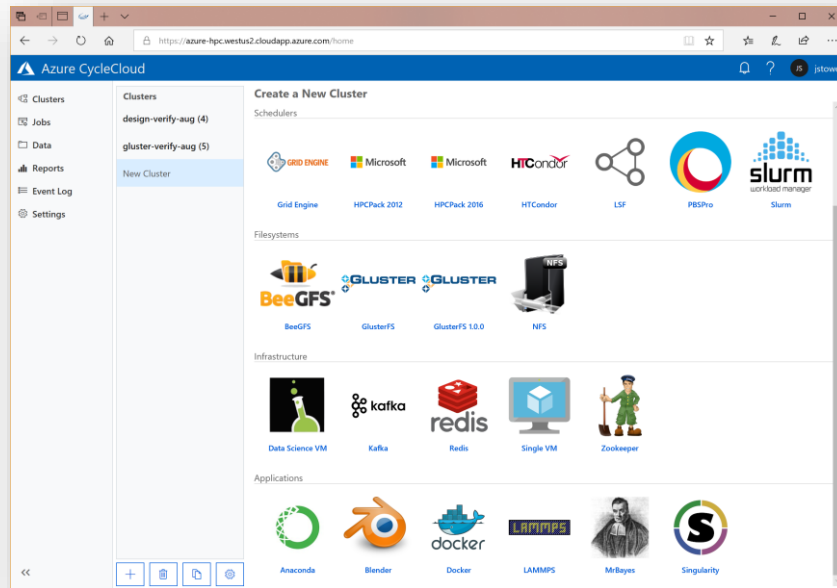


# Enabling Capabilities

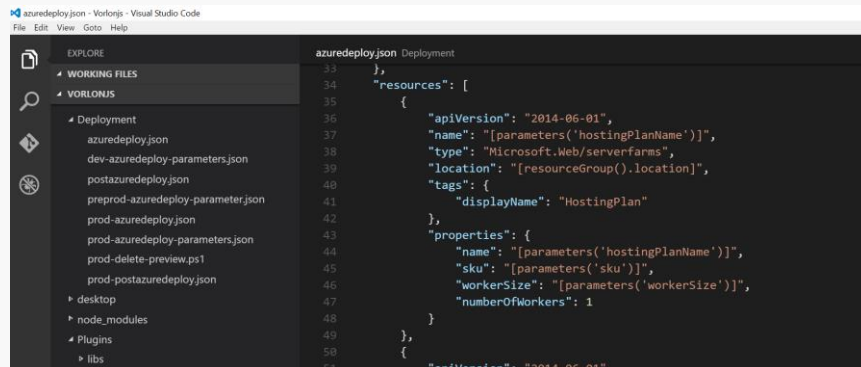


# Next Generation HPC

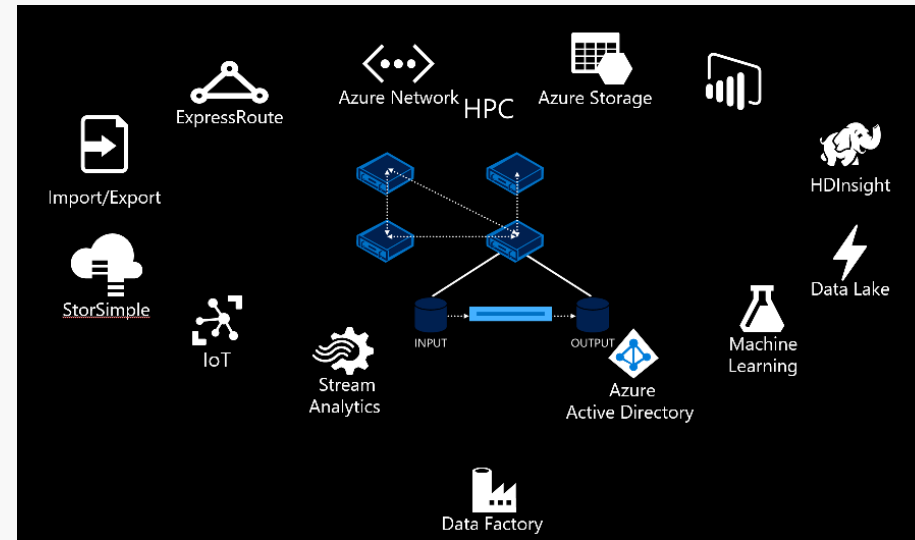
"A cluster (cloud!) for every HPC workload"



"HPC Infrastructure as code"



"HPC is one building block"









"AI, ML, Data Analytics"

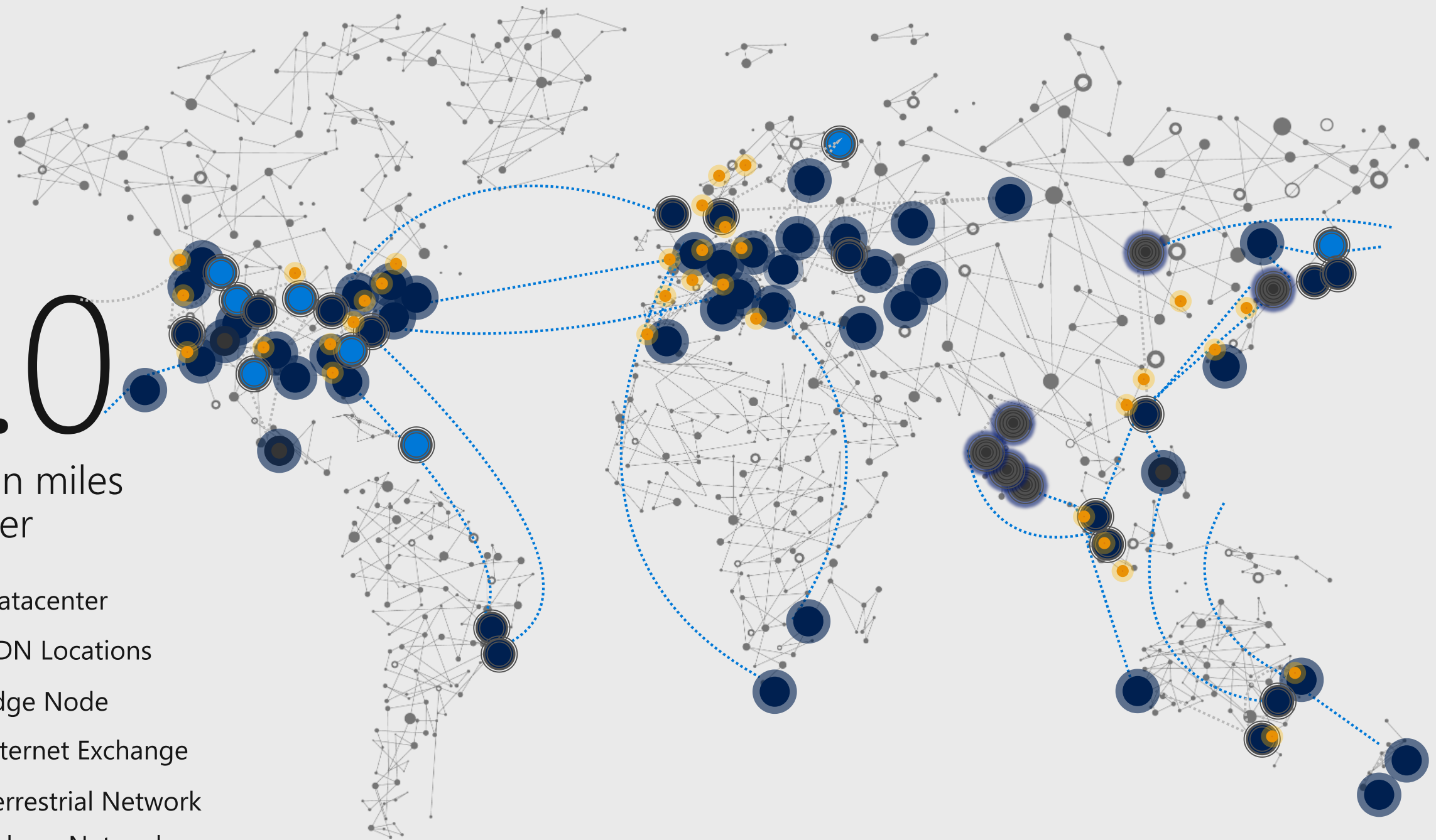


Databricks for distributed deep learning (Horovod)  
Tensorflow, Keras on Jupiter Notebooks

# 2.0

million miles  
of fiber

-  Datacenter
-  CDN Locations
-  Edge Node
-  Internet Exchange
-  Terrestrial Network
-  Subsea Network

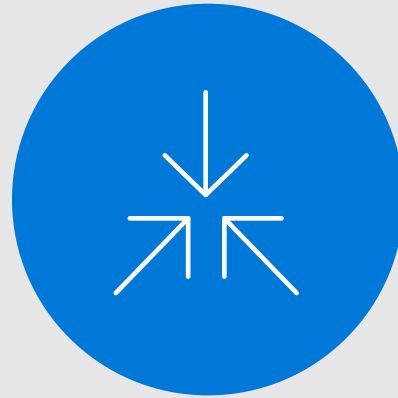


# HPC in Azure- Azure adds value to HPC workloads



Most performant infrastructure

- Fastest HPC and GPU instances in the Cloud
- Specialized instances for AI Training, Remote visualization, Accelerated Analytics
- Only cloud providing ultra-fast, low latency networking with RDMA and Infiniband
- Azure capabilities for easily deploying and managing scale for large, parallel jobs



Open & Integrated

Industry specific

Life Sciences

CYCLECOMPUTING BizData teradici Workspot rescale

Bright Computing

Finance

Willis Towers Watson IHS Markit kinetica excelian Milliman rescale ACTIVEVIAM

Manufacturing

Altair d3VIEW JSOL CORPORATION OpenFOAM CD-adapco ANSYS HALLIBURTON SIEMENS SIMULIA

PBS Works MSC Software

Schlumberger ANSYS HALLIBURTON SIEMENS SIMULIA

Software & Hardware

Languages

R node python Ruby Java php

Operating Systems

CentOS ubuntu redhat SUSE FreeBSD Windows Server

Infrastructure

excelian CYCLECOMPUTING rescale Fujitsu intel Mellanox Bright Computing teradici Workspot



Granular cost control & Governance

- Flexible consumption and cost savings with low-priority VMs on Azure
- Per-minute billing for VMs
- Granular insights into HPC usage & costs helping with workload optimization
- Built-in policy based governance for richer collaboration
- Largest global footprint & compliance portfolio of any cloud

# HPC in Azure: VMs with RDMA, GPU, FPGA + Cray



## Entry Level VMs

Dev/Test Workloads



## General Purpose VMs

Common Applications, Intel Haswell/Broadwell



## Compute Optimized VMs

Gaming, Analytics



## Large Memory VMs

Up to 128 vCPUs and 3.8 TB RAM



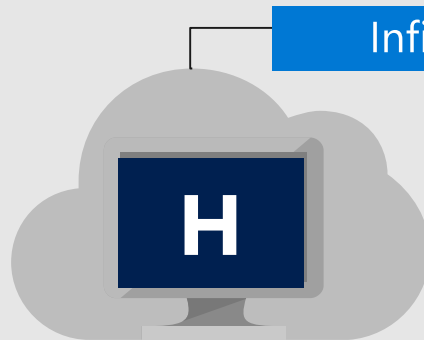
>80,000 IOPs  
Premium Storage

Low latency, high throughput apps



## Storage optimized VMs

No SQL Databases (Cassandra, MongoDB), High Disk Throughput and IO



## High Performance VMs

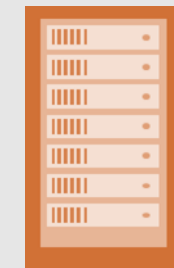
Batch processing, fluid dynamics, monte carlo simulation

Infiniband



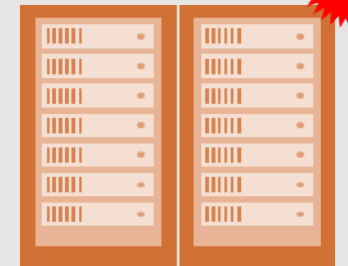
## GPU-enabled VMs

NV -Graphic based applications  
NC2 – Advanced Sim (P100-X)  
ND1 – AI Inferencing (P40)  
ND2\* – AI Training (V100/V100 SXM)



## FPGA\*

Virtual Machines – HPC  
FPGA Microservices – AI/Edge



## Cray in Azure

Aries Connected CPU/GPU/Storage available in cloud

NEW!

# Cray in Azure

- 1 A **dedicated** Cray XC or CS-Storm system with ClusterStor **built to your specifications**, running in an Azure data center, and delivered as managed service to **your virtual network**.
- 2 A **scalable** and powerful infrastructure to support the needs of the most demanding codes in engineering, climate, energy, and others in a way that **no other public cloud can approach**.
- 3 Use **Azure and Cray together**. This allows for smoother multi-stage **workflows** including dev/test, visualization, AI, analytics, and data commons.
- 4 Because the Azure Cray system is supported and maintained by **Cray specialists**, you receive expert support on both Azure and Cray resources.



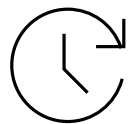
# Challenges with on-premises HPC



Finite resources do not scale with the business



Usage spikes creates inconsistent ROI that is challenging to forecast



Updating HW is time consuming and expensive



Regulations



AI

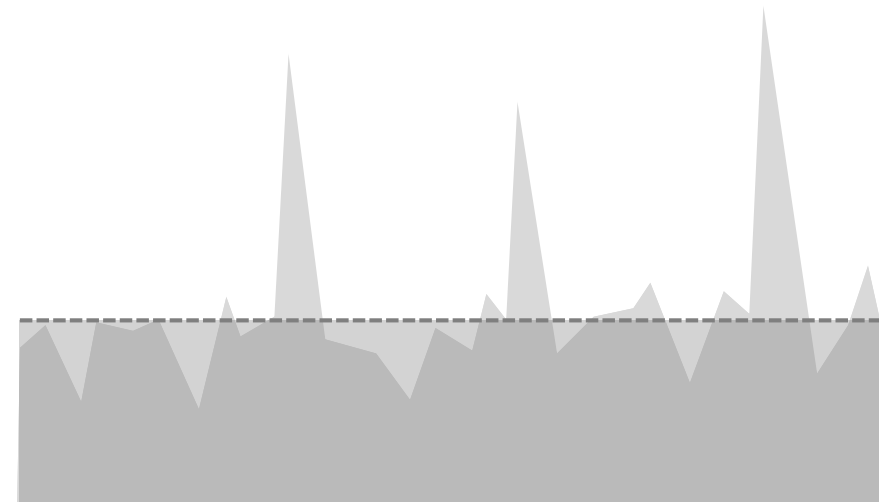


IoT



Data analytics

Random, unpredictable spikes in demand for HPC can come from any new or existing application workflow



Demand for HPC infrastructure



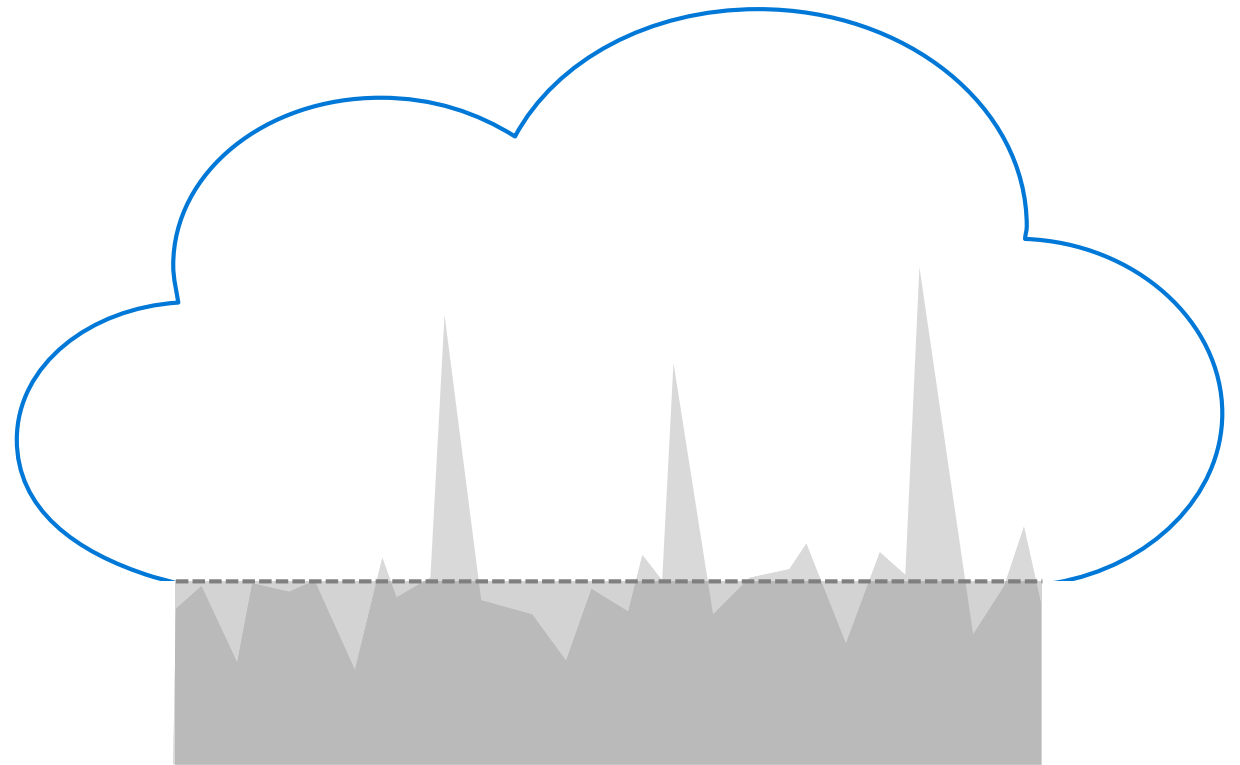
On-premises

# The HPC Cloud Opportunity

The **elasticity** of the cloud provides the perfect accommodation for variable demands of compute resources.

Variable demand

Fixed demand



Demand for HPC infrastructure



On-premises

# The HPC Cloud Opportunity

A fully native, cloud-based HPC environment ensures **optimized business agility** by accommodating an on-demand usage model for compute resources

On demand compute



Demand for HPC infrastructure



On-premises

# Azure Big Compute Platform

HPC End-users, IT Staff, Line of Business

Developers

App Users

Cluster templates to run existing, on-prem HPC applications, schedulers

SaaS / Client Solution

Azure Batch AI

Parallel R

VFX Plug-Ins



Azure CycleCloud

Hybrid & Cluster Manager for HPC/AI



Azure Batch

VM Management & Job Scheduling

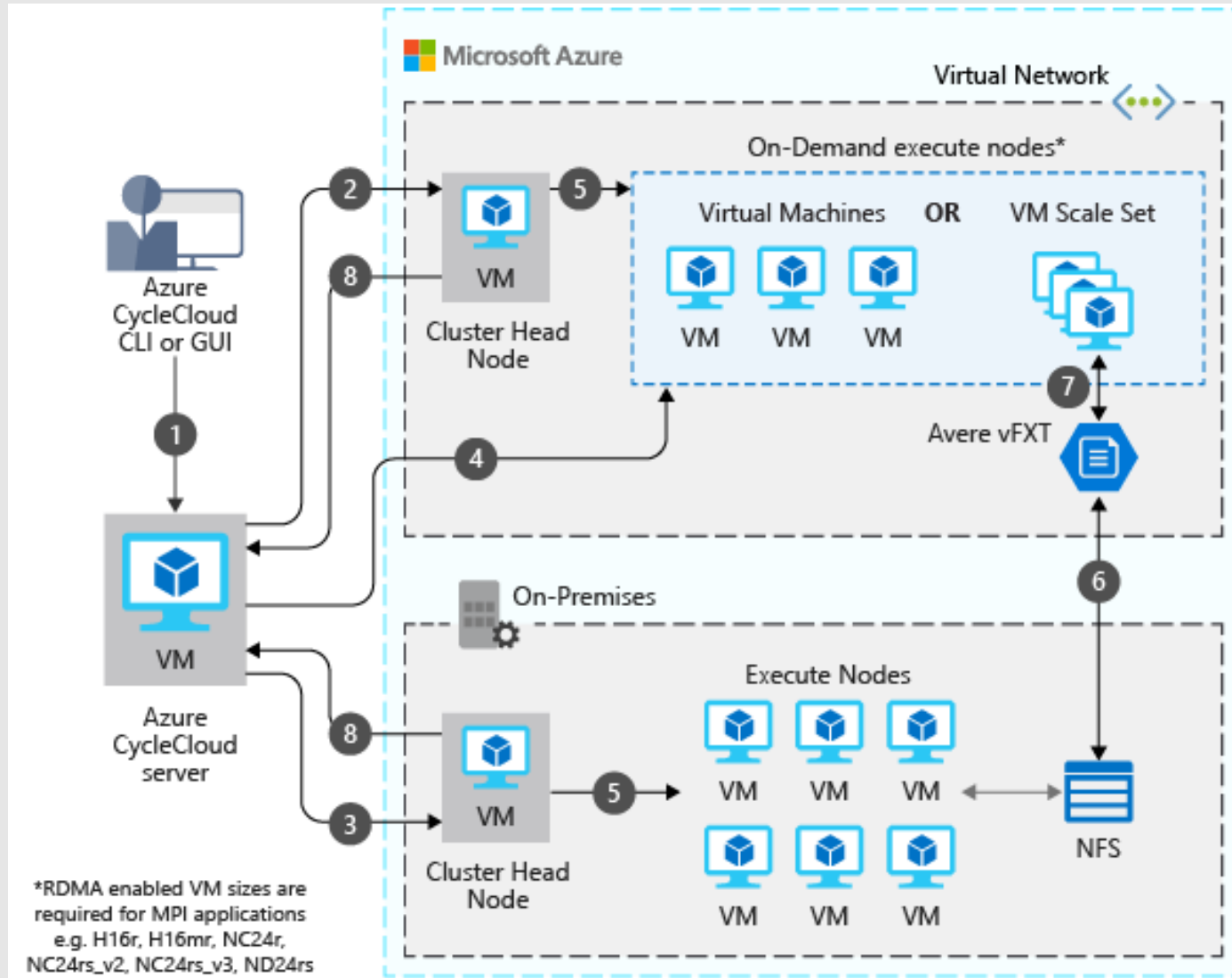


Cloud Services,  
VMs, VMSS



Hardware

# Architecture



1. Connect to the Azure CycleCloud server to configure the cluster.

2. Configure and create the cluster head node, using RDMA enabled machines for MPI.

3. Add and configure the on-premises head node.

4. Autoscaling

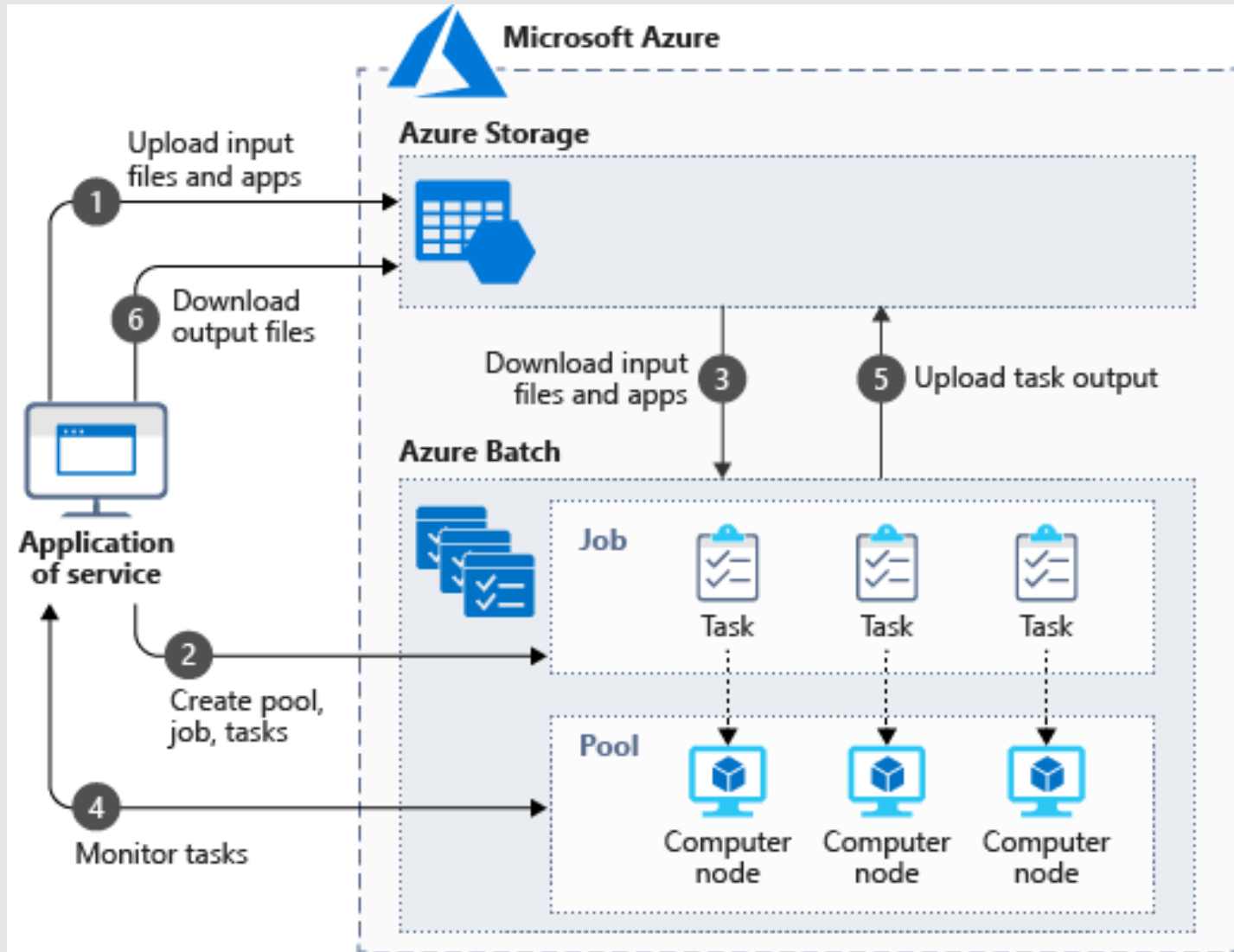
5. Tasks allocated to the execute nodes.

6. Data cached in Azure from on-premises NFS server.

7. Data read in from the Avere vFXT for Azure cache.

8. Job and task information relayed to the Azure CycleCloud server.

# Architecture



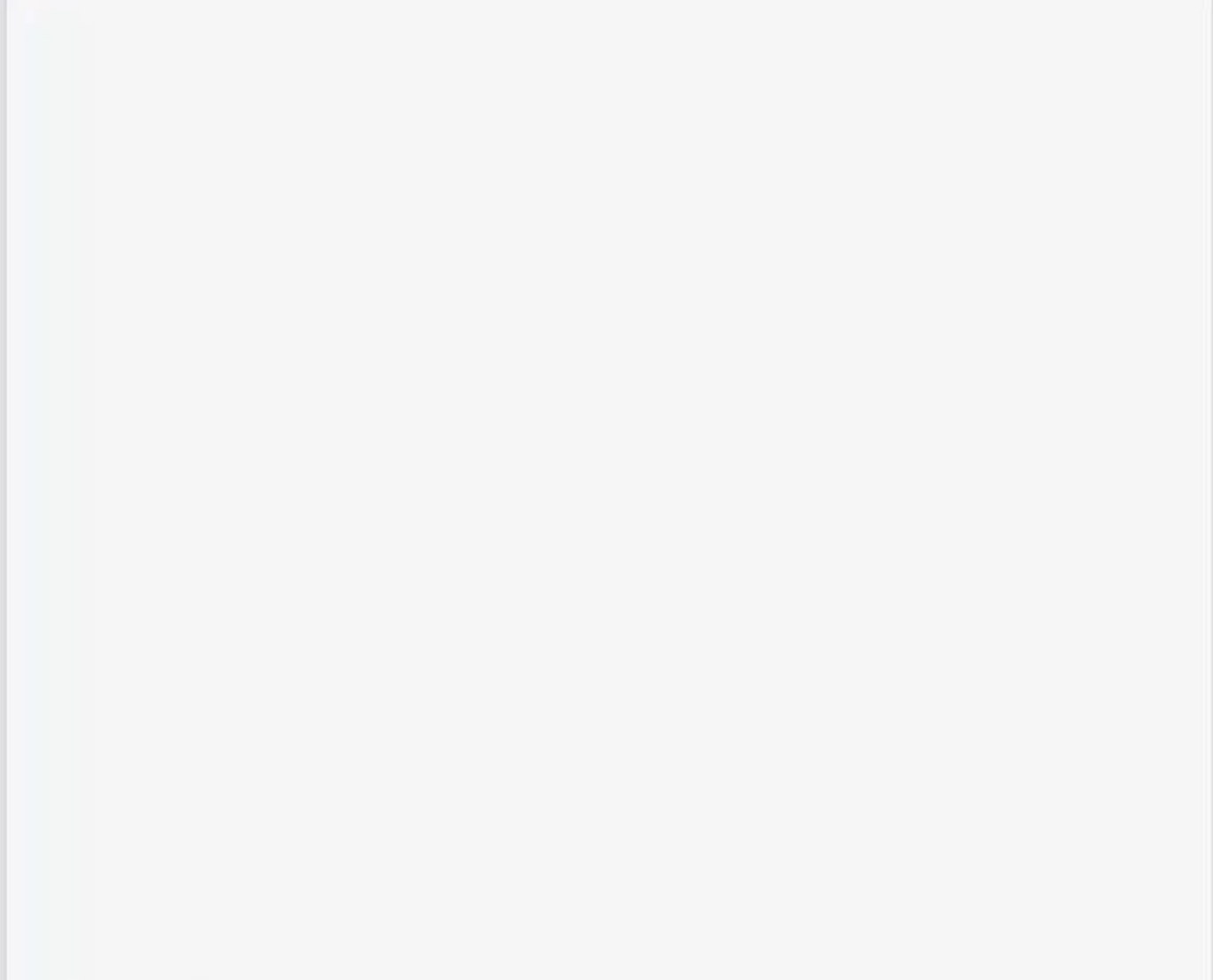
1. Upload input files and the applications to process those files to your Azure Storage account.
2. Create a Batch pool of compute nodes in your Batch account, a job to run the workload on the pool, and tasks in the job.
3. Download input files and the applications to Batch.
4. Monitor task execution.
5. Upload task output.
6. Download output files.

Summary

Pool Name:	SoakTestPool_F56F156F-093A-4D41-93B0-38E489A21E58	Allocation State:	Resizing
VM Size:	small	Target Number VM's:	16000
Max Tasks Per VM:	1	Current Number VM's:	0
Running Tasks:	0	Schedulable VM's:	0



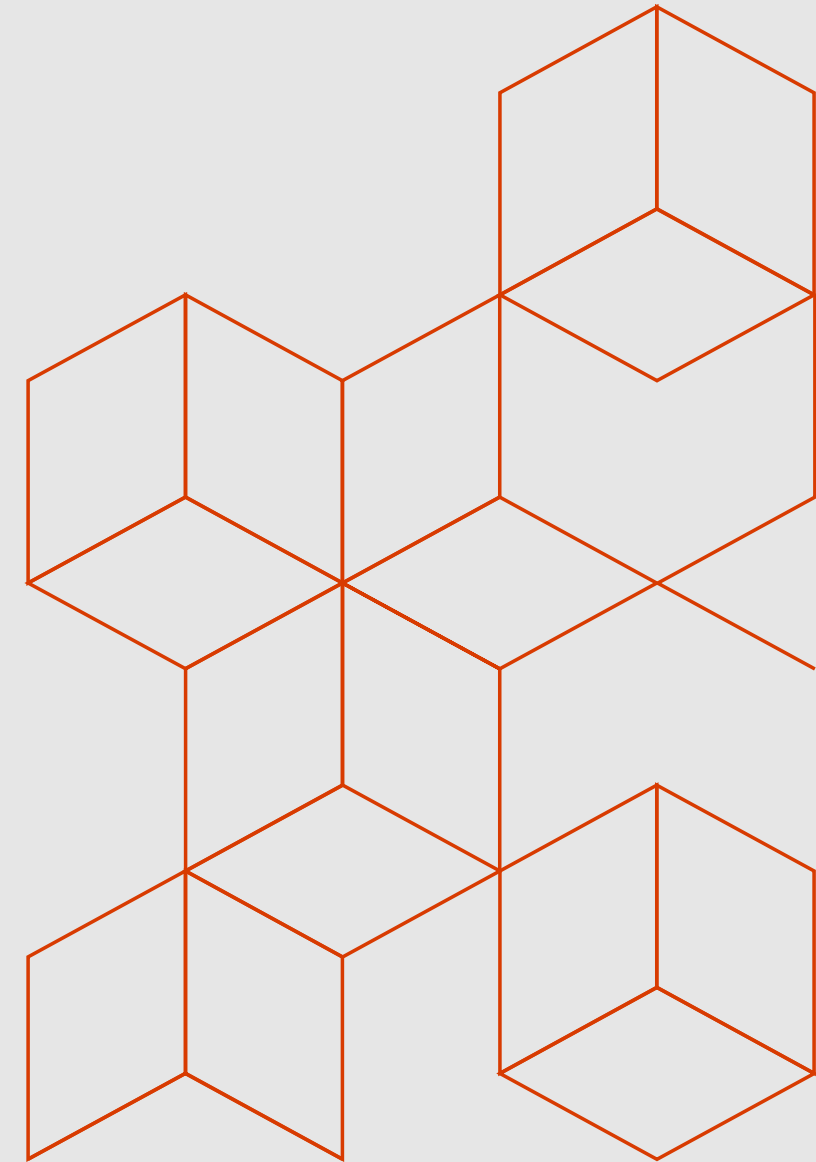
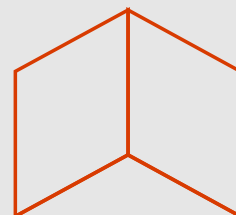
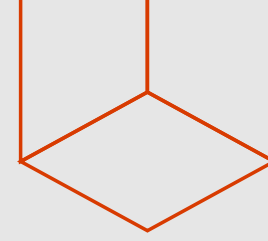
Heatmap



Legend:  Idle  Running  Transitioning  Error

Refresh Interval (seconds): 15

# Conclusion



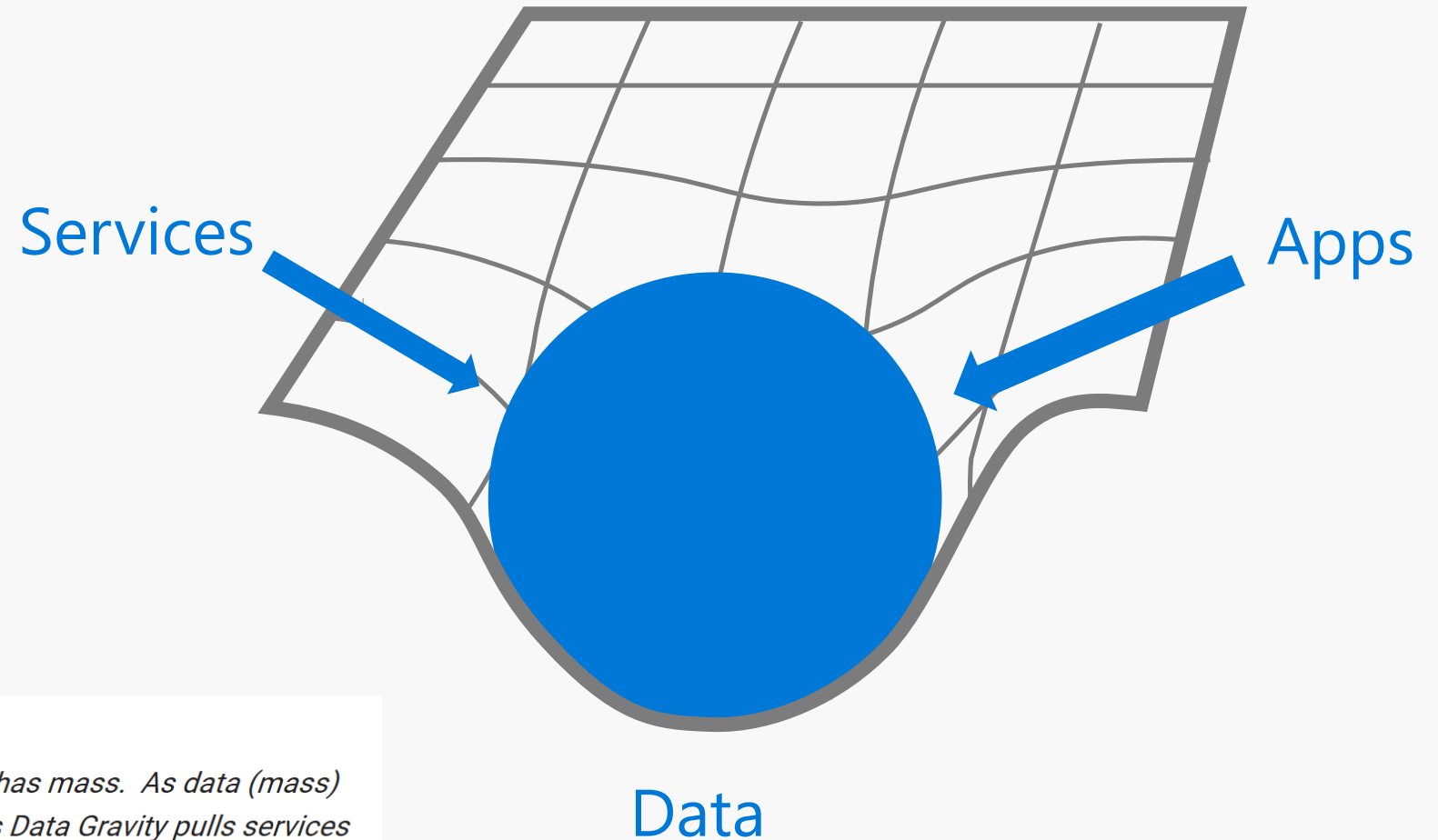
# The concept of data gravity

$$\text{Data Gravity} = \frac{\left( \text{Data Mass} \times \text{Application Mass} \right) \times \text{Number of Requests per second}}{\left( \text{Latency in seconds} + \left( \frac{\text{Average Request Size in MBs}}{\text{Bandwidth in MBs per second}} \right) \right)^2}$$

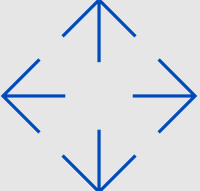
## McCrary's Original Equation

“

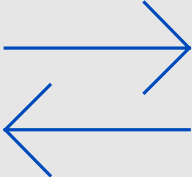
*Data Gravity is a theory around which data has mass. As data (mass) accumulates, it begins to have gravity. This Data Gravity pulls services and applications closer to the data. This attraction (gravitational force) is caused by the need for services and applications to have higher bandwidth and/or lower latency access to the data.*



# Cloud Value for Weather Modeling



Scale



Elasticity



Pay for use



Reach & locality



Hardware selection



No infrastructure



Known costs

