Artificial Intelligence: Infrastructure Matters

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Kelly Schlamb Executive IT Specialist, IBM Cognitive Systems

kschlamb@ca.ibm.com
@KSchlamb



"Al promises to unlock the value of your data – in totally new ways"

MTSIoan

270%

increase in Enterprise Al adoption over the past 4 years

91%

expect new business value from Al implementations in next 5 years



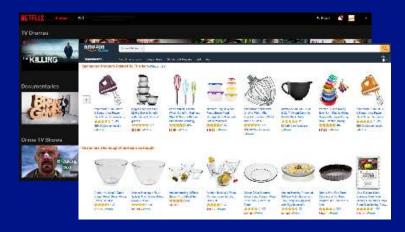
\$13.5B

2019 market for AI software platforms and AI applications

47% CAGR over next 5 years Software is largest & fastest growing Al tech category

Common AI Use Cases (but the possibilities are limitless)

Hyper or Radical Personalization



Price and Product Optimization



Predictions and Classifications



Resource Allocation and Strategic Planning



Discover Patterns, Anomalies and Trends



Natural Language Processing





Data Science

The practice of applying various scientific and statistical methods, algorithms, approaches and processes...

using programming languages and software frameworks...

to extract knowledge, insights and recommendations from data...

and deliver them to business users and consumers in consumable applications. Artificial Intelligence – System that mimics human intelligence (very broad ranging applications, methods and supporting technologies)

Machine Learning – Enable machines to learn from data and make accurate predictions, without being explicitly programmed to do so

Deep Learning – Perform complex tasks (like speech and image recognition) by exposing multilayered neural networks to vast amounts of data

Infrastructure [in-fruh-struhk-cher]

noun

The system of hardware, software, facilities and service components that support the delivery of business systems and IT-enabled processes.



didn't put **BLOCKBUSTER** out of business, ridiculous late fees did



<u>É MUSIC</u>

didn't force change on the industry, being forced to buy full length albums did



isn't hurting the TAXI business, limited access & fare control are



isn't hurting the HOTEL business, limited availability & pricing are

TECHNOLOGY itself is not the disruptor

Not being CUSTOMER-CENTRIC is the biggest threat to any business

Technology is an ENABLER

Al is a Science

Machine learning, deep learning, neural networks, predictive analytics, prescriptive analytics, etc. are all technologies that enable AI.

Al is an Enabler

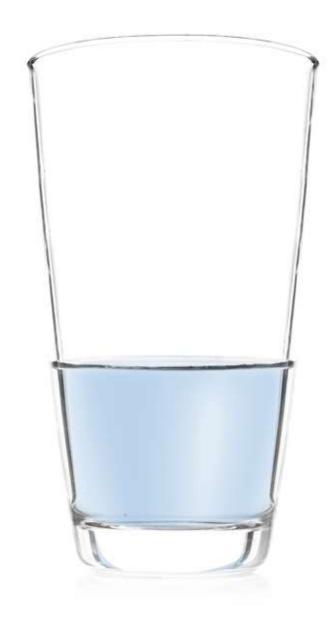
It helps domain experts make faster decisions to drive business outcomes more quickly. Al doesn't replace experts, it enables them.

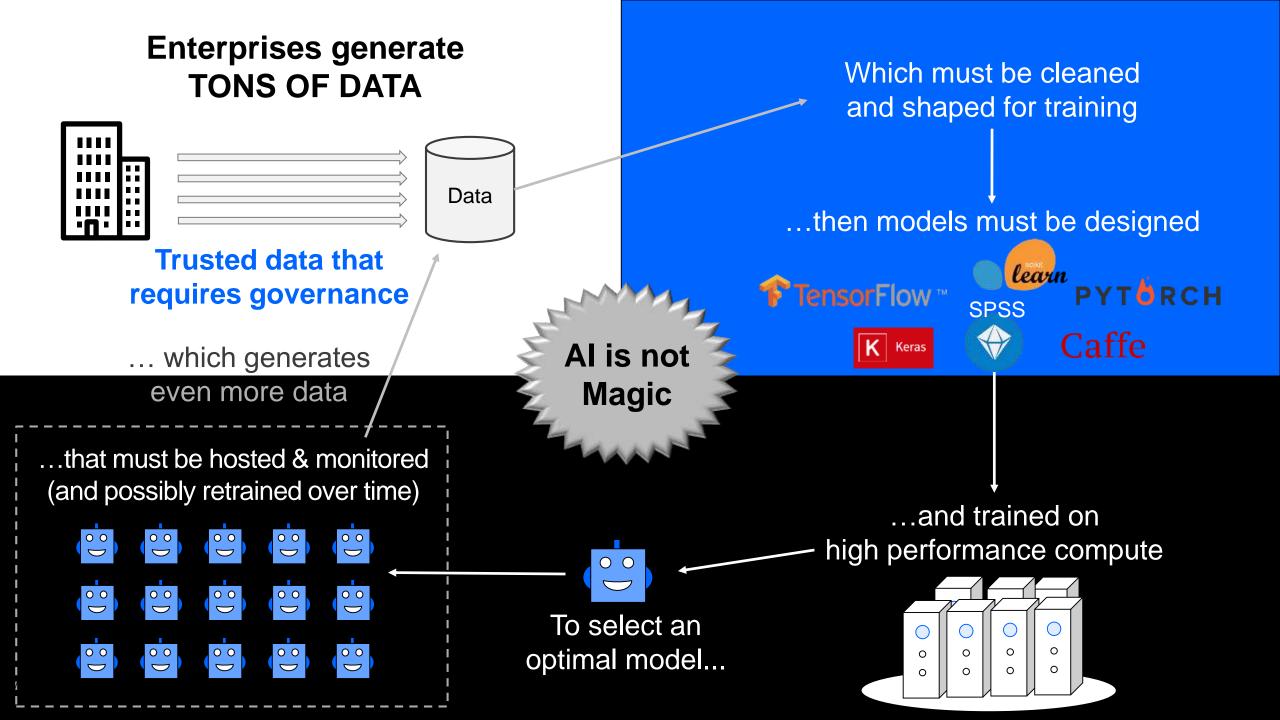


99% say their firms are trying to become insights-driven,

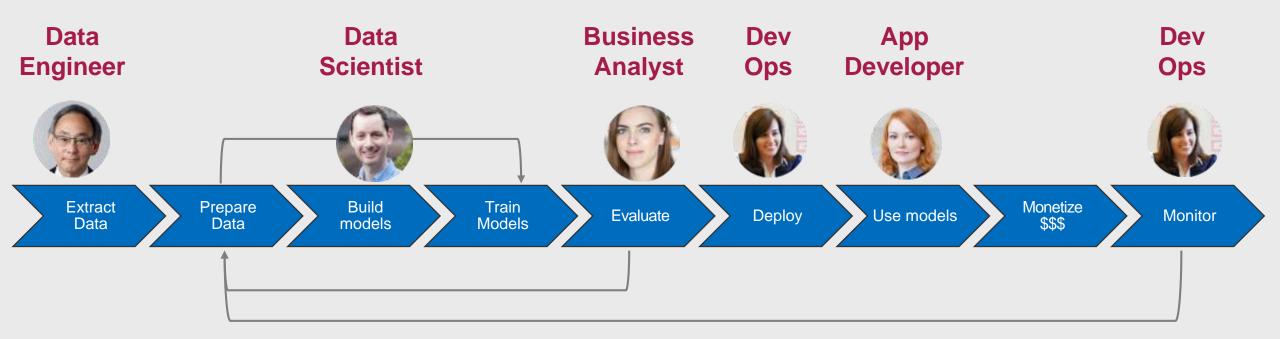
but only one-third report succeeding

NewVantage Partners, "Big Data Executive Survey 2018 Executive Summary of Findings"





Data Science and AI is a Team Sport



Building cognitive applications using ML and DL requires multiple skillsets and collaboration

What are the impediments of progress? **1. Data Explosion 2. Self-Service Bottleneck 3. Lack of Compliance & Visibility** 4. Lack of Skills, Availability & Collaboration **5. Inability to Monetize Insights**

Assembling the building blocks of a data and analytics platform is complex, risky and time-consuming

| CAPTURE | SECURE • | | – ANALYZE –––– | (| OPERATIONALIZE |
|--|--|---|---|---|---|
| Collect, Connect, and Access Data | Govern, Search, and Find Data | Understand and Prepare Data for Analysis | Build Descriptive, Predictive, and Prescriptive Models | Model Management and Deployment | Create Analytics Applications |
| Connect and discover content from multiple data sources across your organization. Provision databases and virtualized data access. | Grant user access levels and enforce business policies . Index for search, visualize consumers and producers of assets with lineage , metrics, and quality profiles . | Understand, cleanse and prepare your data to create data preparation pipelines visually. Use popular open source libraries to prepare structured and unstructured data. | Create Machine Learning, Deep Learning, Optimization, and other advanced mathematical models. Tools to design your models programmatically or visually. | Manage your models across dev, test, staging, and prod. Deploy your models and scale automatically for online, batch or streaming use cases with SLAs. | Incorporate trusted and governed models into applications, dashboards, and operational systems. |
| | Find data and analytics assets in the Enterprise Catalog. | | Train at scale with support for distributed compute and GPUs . | Monitor model performance and automatically trigger retraining and redeployment as rolling | |

upgrades.

There is no Al without an IA

(information architecture)

81%

do not understand the data required for Al 80%

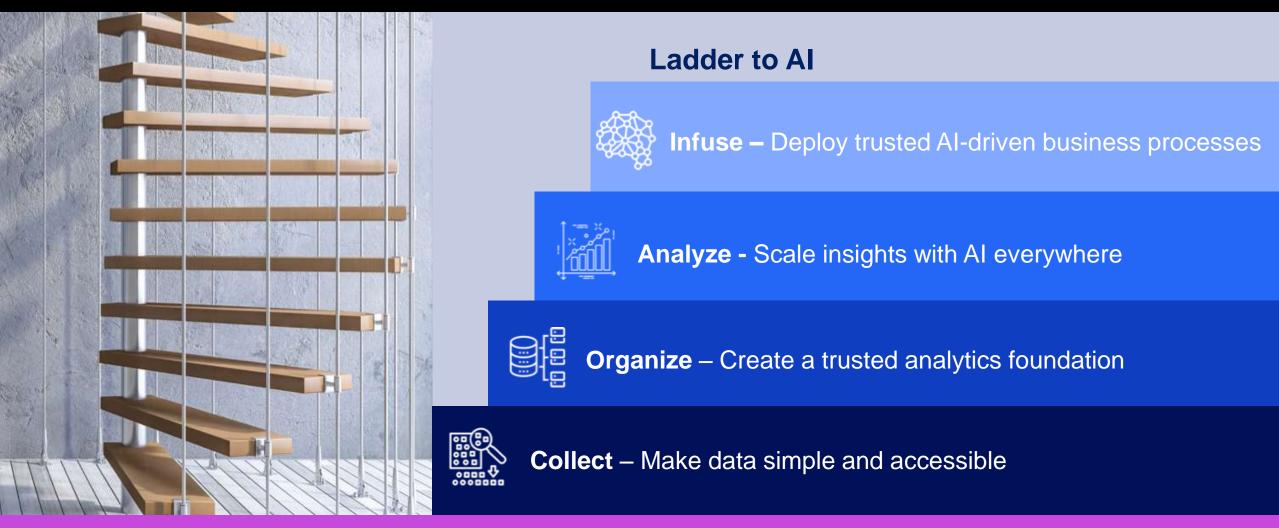
of data is either inaccessible, untrusted or unanalyzed

"No amount of AI algorithmic sophistication will overcome a lack of data [architecture]... bad data is simply paralyzing "

MITSIoan

The Al Ladder

A prescriptive, proven approach to accelerating the journey to Al



Requires a strong foundation that is built on a modern cloud-native architecture with underlying infrastructure that is highly performant, secure, reliable and cloud-ready

88% of Insight Leaders use a data science platform to overcome tool sprawl and put insights into action

Adoption of a single data science platform rising to 69% within next two years

Data Science Platform Market and Trends

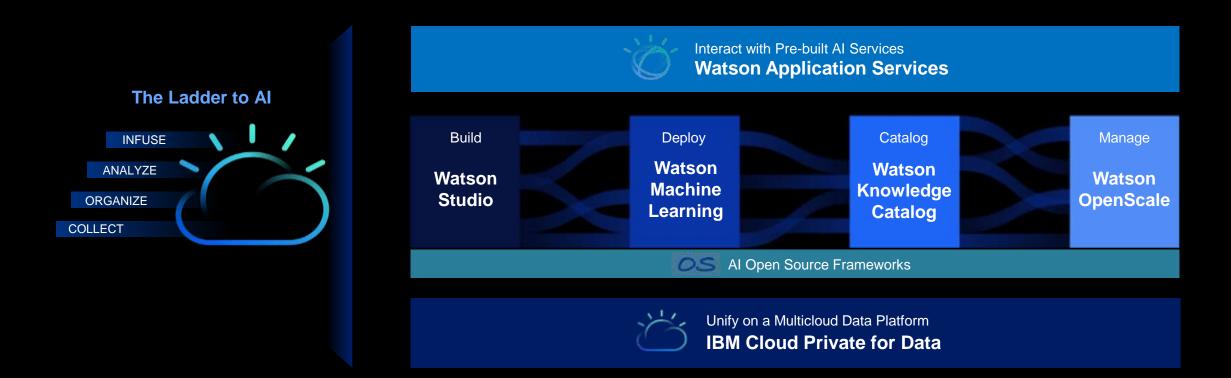


46% of organizations lack an integrated approach to their data science technology stack

> Data Science Platform market estimated to grow to \$128.21B by 2022 (CAGR 36.5%)

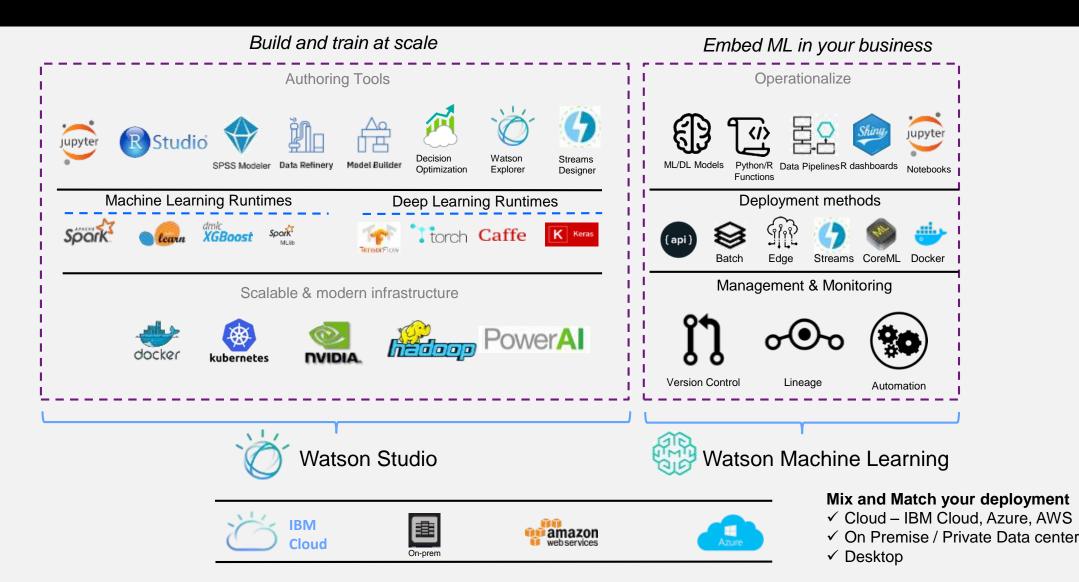
IBM's AI Portfolio

Everything you need for Enterprise AI, on any cloud



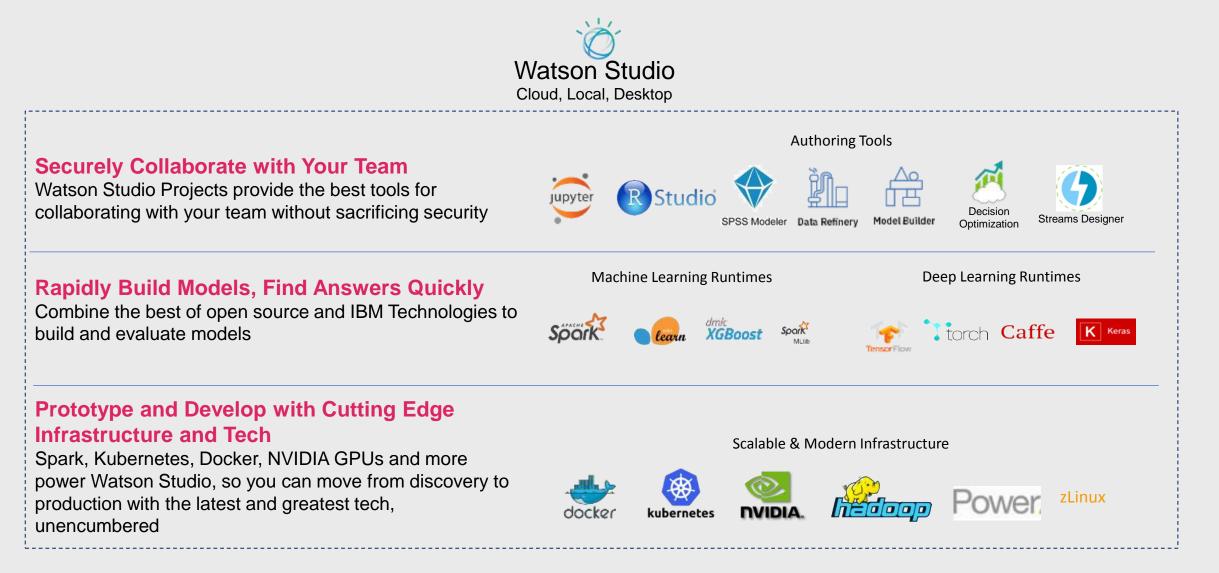


Watson Studio and Watson Machine Learning inject Al firepower into your business



Watson Studio

Solve your business problems by collaboratively working with data



Watson Machine Learning

Embed Machine Learning and Deep Learning into your business

Deploy and Manage Models

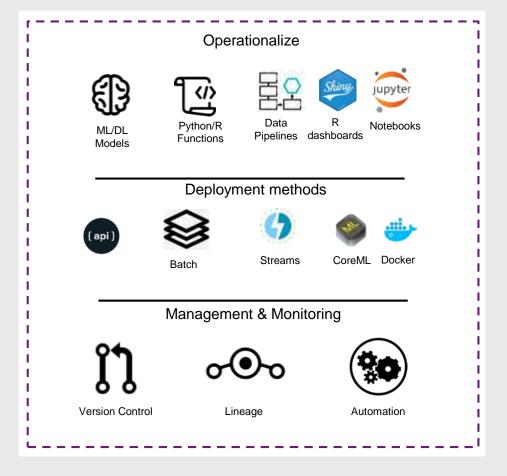
Move models to production, in an easy, secure, and compliant way

Intelligent Model Operations

Embed intelligent training services, with feedback loops that constantly learn from new data, regardless where it resides

Accelerate Compute Intensive Workloads

Distribute your deep learning training and Hadoop/Spark workloads with multi-tenant job scheduling



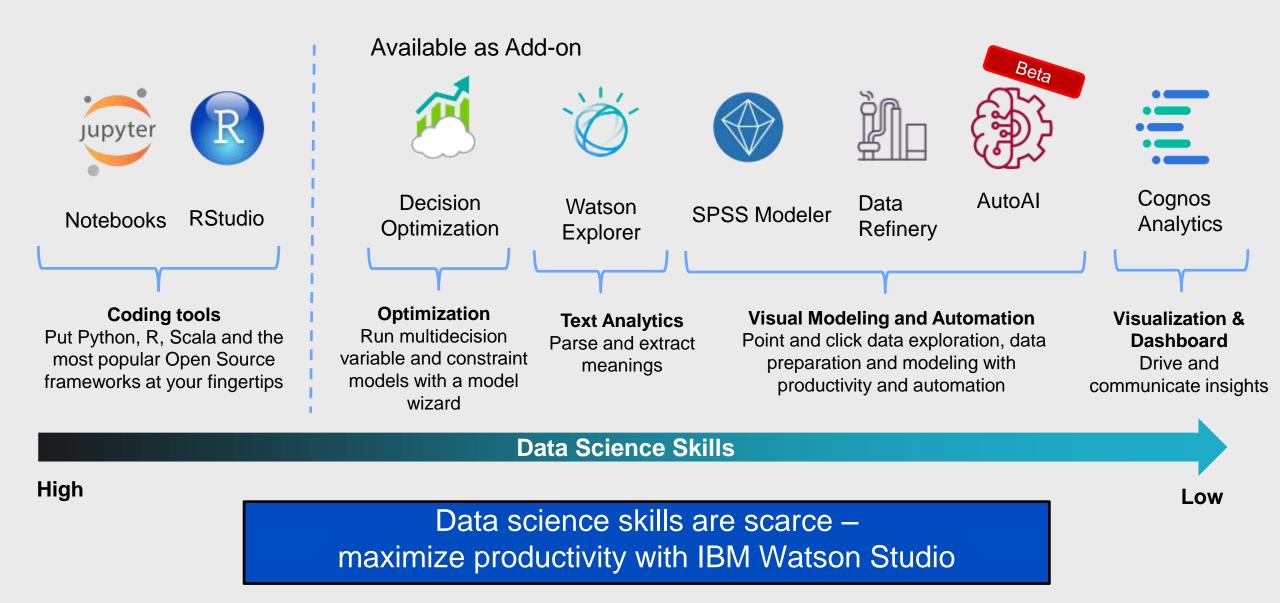
Mix and Match Watson Studio & Watson Machine Learning

across hybrid multi-cloud environments



Watson Studio and Watson Machine Learning Add-ons

More powerful and flexible tools built for teams



Watson Machine Learning Accelerator

Scaling deployment & management of ML, DL and AI models in a shared data science environment

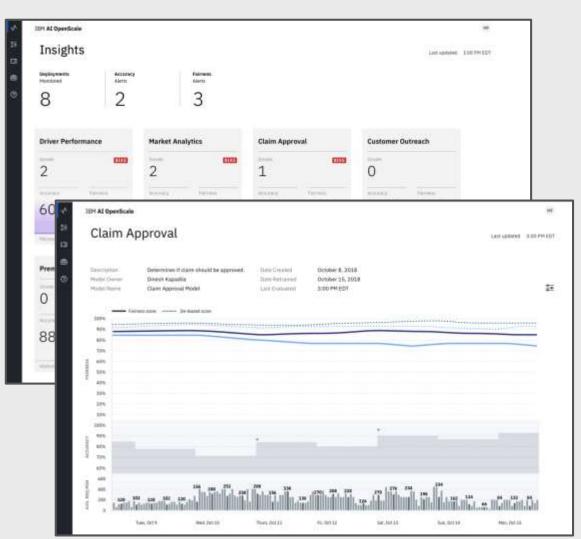
High Performance Clustering capability for Machine Learning & Deep Learning

| Accelerated analytics execution | Train and Deploy Al at Scale | Automate Deep Learning Workflows |
|---|---|---|
| Analytics, ML and DL acceleration for faster insights | Expand to distributed models and scale out inference | Drive higher accuracy through faster training iteration |
| Shared, Optimized Apache Spark Execution Accelerate training through transparent, Distributed & Elastic Deep Learning Enterprise Ready & Proven | Many models, across many users, supporting multi-tenancy at scale Optimized scheduling of model training across CPU/GPU Distributed & Elastic Inference | End to End Deep Learning Workflow Extend to Distributed/Parallel Hyperparameter Optimization Interactive Monitoring, Analysis of Training |

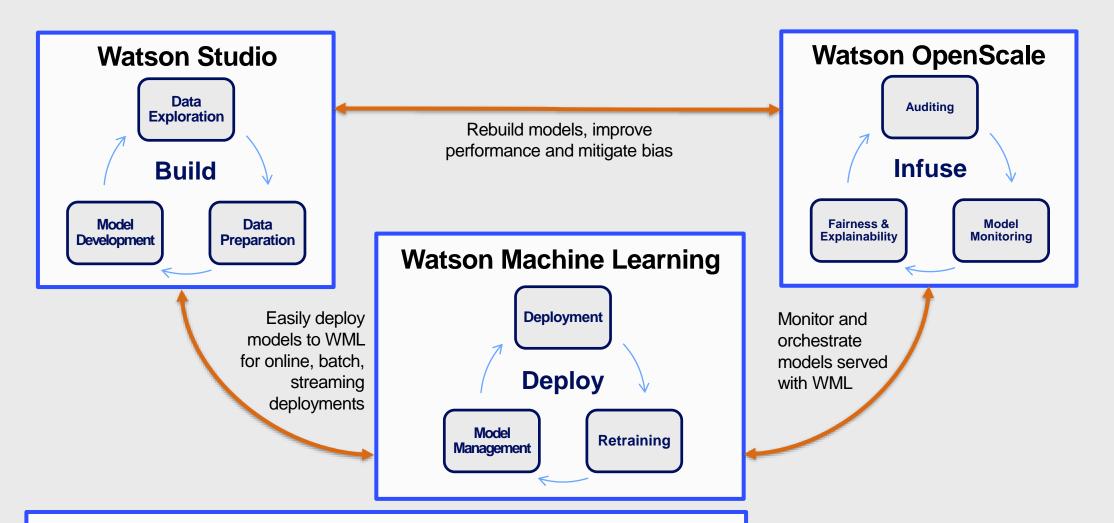
IBM Watson OpenScale

Automate and Operate AI at Scale

- Trust and Transparency
 - Intelligently delivers bias mitigation help
 - Provides traceability & auditability of AI predictions made in production applications
 - Tracks AI accuracy in applications
 - Explains an outcome in business terms
- Automation
 - Automatically detects and mitigates bias in model output, without affecting currently deployed model or outcomes
- Open by Design
 - Monitor and optimize models deployed on third party model serve engines
 - Deploy behind enterprise firewall or on laaS provider



Accelerate your data science lifecycle from discovery to production

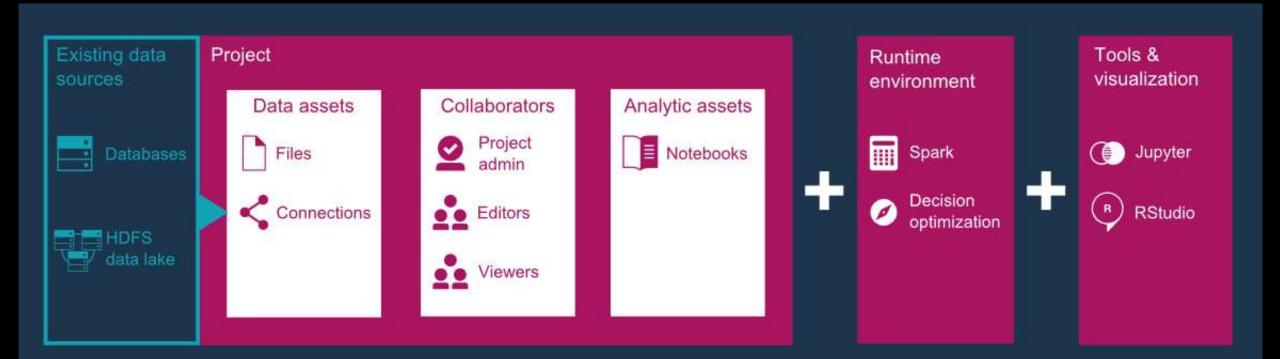


Watson Machine Learning Accelerator

Scalable, multitenant environment with automated tuning and parallel hyperparameter optimization supporting elastic, distributed training of ML & DL workloads

WSL / WML is a self-contained and extendable platform for developing and deploying analytics applications

WSL includes...



Collaborate Using Projects

| IBM Data Science Experience L | ocal | | | | ✓ 58 Trial Days Left |
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| > DSX_Local_Workshop_KG > All | | | | | |
| Notebooks RStudio Models | SPSS Modeler Stream | s Scripts Data Sets Other Files | Published Assets | | |
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| TeicoChurn_SparkML | 0 | | JI | JPYTER 03-19-2018 | : |
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Create Projects

A project is **how you organize your assets** to achieve a particular data analysis goal.

Your project assets can include:

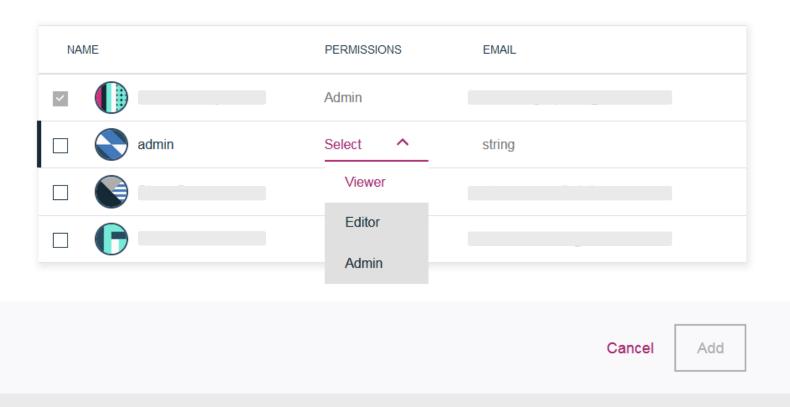
- Notebooks
- RStudio files
- Models
- SPSS Modeler Streams (add-on)
- Data sets (local files and remote data sets)
- Scripts
- Published assets

| IBM Data Science Experience | Lotal | | | v . | 57 Trial Days Left |
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Share, fork and reuse Project assets to increase your data science team's productivity

Add Collaborators



GitHub Integration

When starting a project you can:

- Create new project
- Import a project
- Connect to a project
 on GitHub

| | IBM Data Science Experience Local |
|-------|--|
| Proje | ects > Create Project |
| | Create Project |
| | Blank From File From Github |
| | Github Integrations Want to import your project from GitHub? Before you can import to GitHub, you need to create an access token. Visit GitHub personal access tokens, select repo scope and generate a token. Platform* • GitHub • GitHub Enterprise Access Token* |
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| | To change this token in the future, access the Integrations page in your profile Settings. |

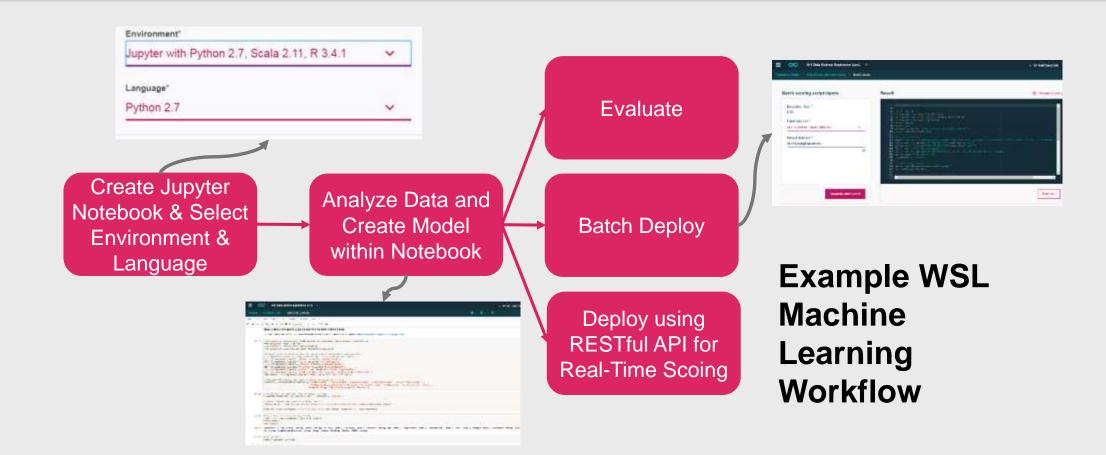
Integrated notebooks for interactive and collaborative environment – seamless Spark execution

| My Projects > | Testing notebooks | > Visualize car data with Brune | əl 🔬 🗠 | < | 0 | 1 | 0 | Ç | Q | 55 | 0 |
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What is a notebook?

A notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and explanatory text





IBM Watson Studio Local has R built into the experience thanks to our strategic partnership with RStudio

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Deploy, monitor and manage

- Monitor models through a dashboard
- Model versioning, evaluation history
- Publish versions of models, supporting dev/stage/production paradigm
- Monitor scalability through cluster dashboard
- Adapt scalability by redistributing compute/memory/disk resources

Accuracy

80%

- Watch it in action
 - <u>http://ibm.biz/WSL-Models</u>

| Dashboard Models Deployments | | | | | |
|--|--|--|--|---|------------------|
| Current Deployment Metrics | Recent Deployment Evalua | tions the Al Dighterrorits (13 | | | L. |
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Assembling the building blocks of a data and analytics platform is complex, risky and time-consuming

| CAPTURE | SECURE • | | – ANALYZE –––– | (| OPERATIONALIZE |
|--|--|---|---|---|---|
| Collect, Connect, and Access Data | Govern, Search, and Find Data | Understand and Prepare Data for Analysis | Build Descriptive, Predictive, and Prescriptive Models | Model Management and Deployment | Create Analytics Applications |
| Connect and discover content from multiple data sources across your organization. Provision databases and virtualized data access. | Grant user access levels and enforce business policies . Index for search, visualize consumers and producers of assets with lineage , metrics, and quality profiles . | Understand, cleanse and prepare your data to create data preparation pipelines visually. Use popular open source libraries to prepare structured and unstructured data. | Create Machine Learning, Deep Learning, Optimization, and other advanced mathematical models. Tools to design your models programmatically or visually. | Manage your models across dev, test, staging, and prod. Deploy your models and scale automatically for online, batch or streaming use cases with SLAs. | Incorporate trusted and governed models into applications, dashboards, and operational systems. |
| | Find data and analytics assets in the Enterprise Catalog. | | Train at scale with support for distributed compute and GPUs . | Monitor model performance and automatically trigger retraining and redeployment as rolling | |

upgrades.

Reality ("most information architectures")

Ideal State ("ICP for Data")



- Slow
- Siloed data and workflows
- Multiple disjunct stacks

- Fast
- Pre-integrated and governed
- Containerized

What is needed is a single, unified platform

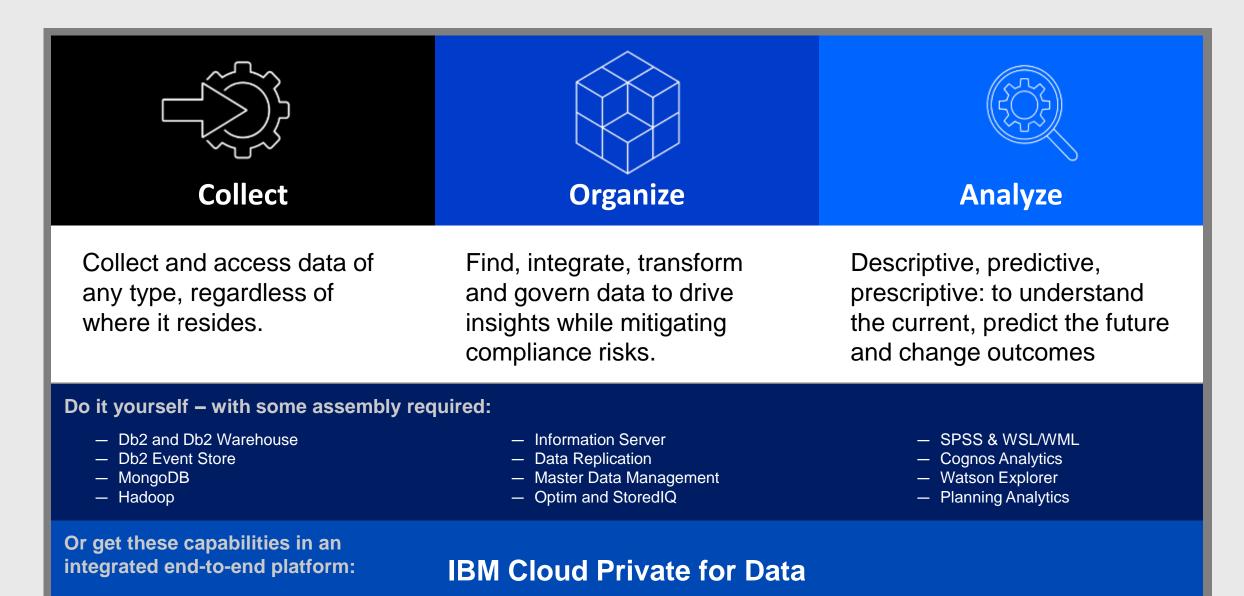
| CAPTURE | SECURE + | | – ANALYZE —— | → 0 | PERATIONALIZE |
|--------------------------------------|----------------------------------|--|--|------------------------------------|----------------------------------|
| Collect, Connect, and Access Data | Govern, Search, and Find Data | Understand and Prepare Data for Analysis | Build Descriptive, Predictive, and Prescriptive Models | Model Management and Deployment | Create Analytics Applications |

Single, Unified Platform

With Added Value:

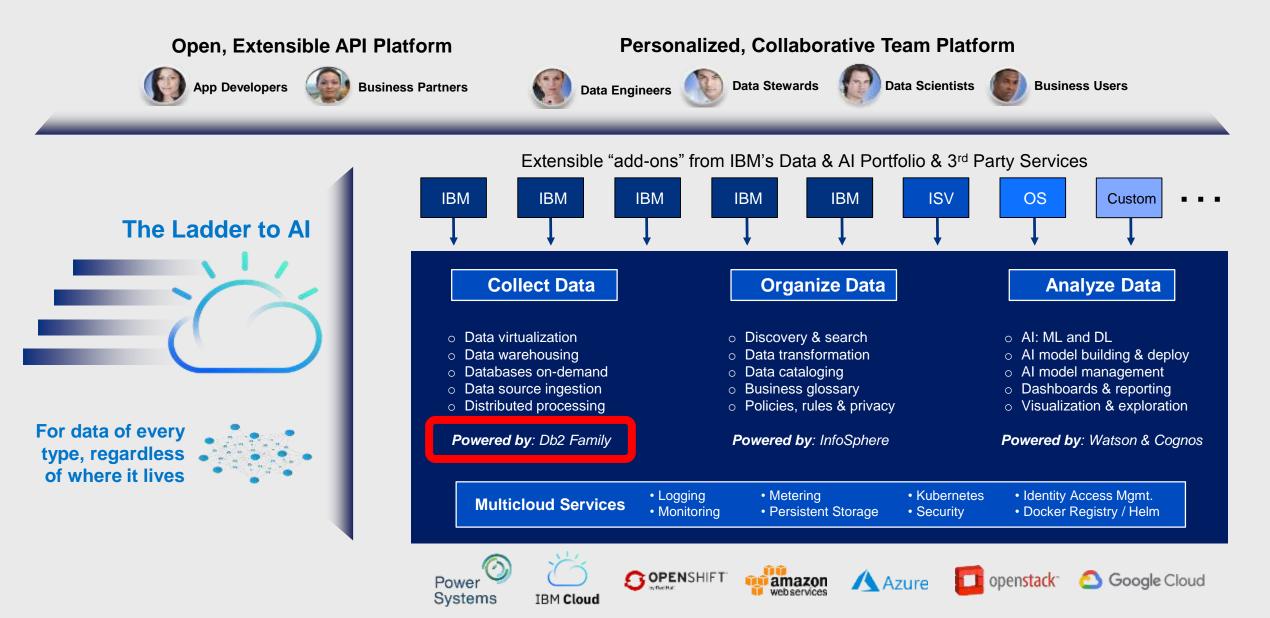
- Pre-Integrated
- Leverage Existing Investments
- Trusted, Business-Ready Foundation
- Built on Modern, Open Architecture
- Data Virtualization
- Ecosystem Management on a Single Pane

The Building Blocks of Al

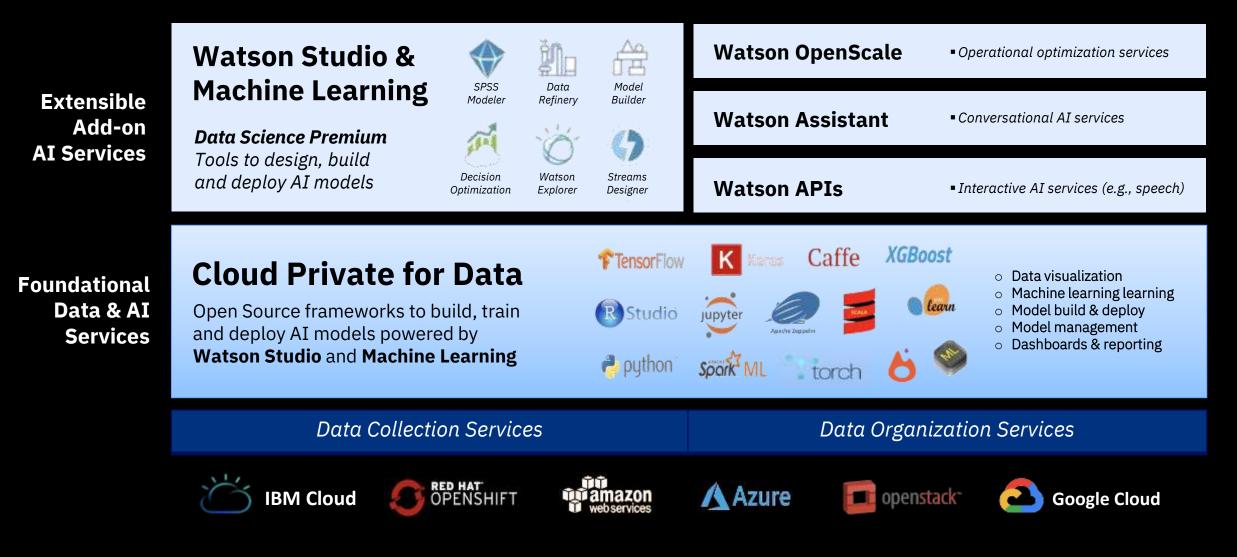


IBM Cloud Private for Data

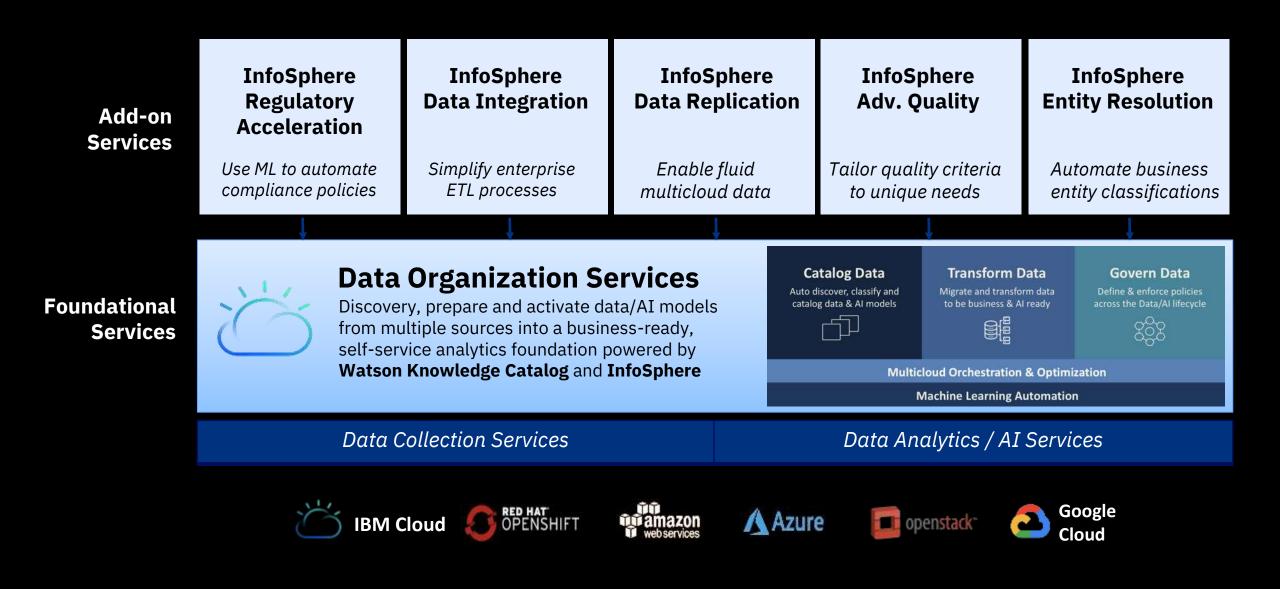
Unify on an open, multicloud Data & AI platform



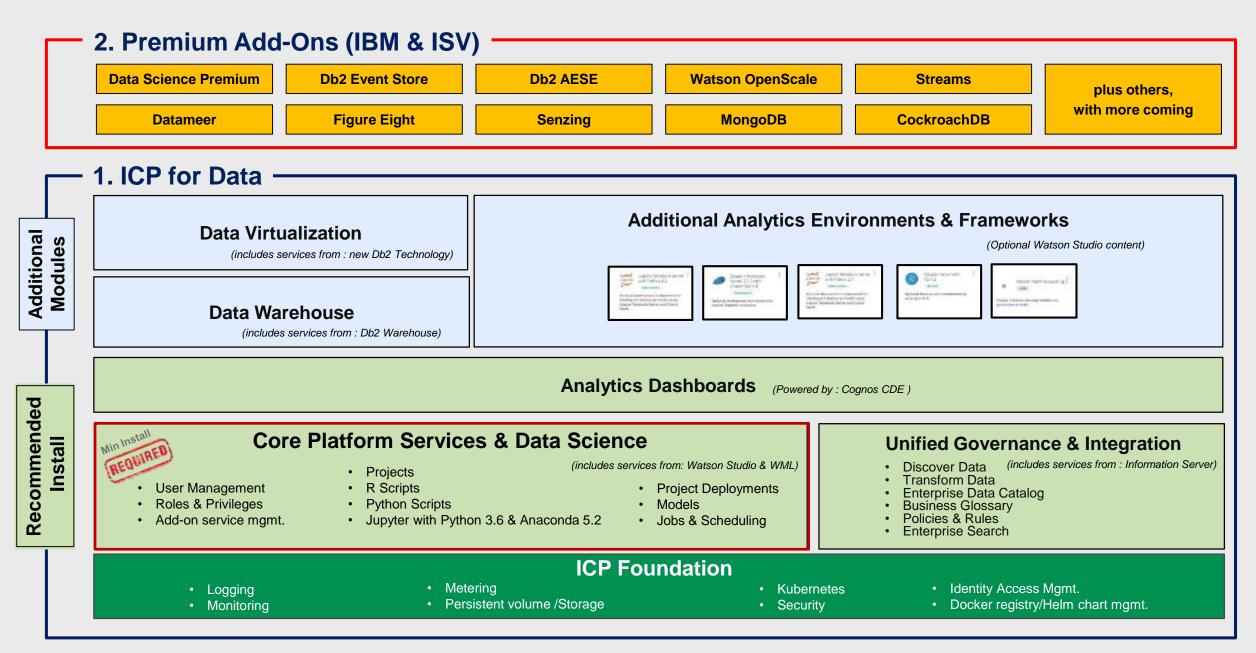
ICP for Data embeds Watson Studio providing open & extensible data science tooling



ICP for Data Embeds Unified Governance & Integration Capabilities



Modularized View of ICP for Data



IBM Cloud Private for Data Top Use Cases

| Accelerate Data & Analytics Monetization | من Operationalize Data Science & Al | Modernize to Next-gen Workloads | Smarter Governance |
|--|---|--|--|
| Capitalize on your data as a strategic asset - access all enterprise data regardless of location and speed . Analyze all data types at the source to accelerate insights and time to value. | Build, deploy, manage and govern models with trusted data at scale . Data scientists, developers, engineers, and business experts work collaboratively to accelerate innovation and improve business outcomes. | Benefit from a cloud native architecture while keeping your data where you want it. Build once and deploy anywhere , provision and scale in minutes, and achieve the agility you need to evolve your workloads with business needs, without the complexity. | Proactively adapt to comply with new or anticipated regulations through continuous visibility into your data landscape , universal oversight, and automated controls to prevent data misuse. |

IBM Cloud Private for Data Improving confidence in data-driven outcomes

Hear why GuideWell, a rapidly growing healthcare company, is excited about IBM Cloud Private for Data and its potential to help provide better outcomes to their customers: https://www.youtube.com/watch?y=R7P3Ee5n7MQ

"It's a very exciting product. You have a lot of things that a lot of different companies are doing, molded into one technology suite."

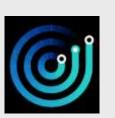
—James Wade, Director of Application Hosting, GuideWell





Collect Data

Collect data of every type, no matter where it lives, and achieve freedom from ever-changing data sources



Organize Data

Organize your data into a trusted, business-aligned source of truth to put data to work in new ways.



Analyze Data

Analyze your data in smarter ways, empowering all your teams with Machine Learning Everywhere



Modernize

Make your data ready for AI and the cloud

بناك قطر للتنامية QATAR DEVELOPMENT BANK "One of the key technologies that the Hub will deploy is IBM Cloud Private for Data. The exciting thing about IBM Cloud Private for Data is how quickly we will be able to drive new innovations in FinTech and SportsTech using the AI and ML microservices within the platform. What makes it especially attractive is that it enables us to develop and deploy new models quickly that brings AI to the data, rather than the other way around."

> — Abdulaziz Al Khalifa CEO, Qatar Development Bank

Qatar Development Bank (QDB) is a bank in Qatar offering financial services, banking and loans to the development of the industrial, tourism, educational, health care, agricultural, animal resources and fisheries sectors of the Qatari economy. It was created in 1997 by Emiri Decree No. 14 with the objective of diversifying Qatar's economy by promoting developmental projects.





Modernize

Make your data ready for AI and the cloud

Quote from blog : Trusting AI to save lives in India https://www.ibmbigdatahub.com/blog/trusting-ai-save-lives-ind

" IBM Cloud Private for Data facilitated the model development and deployment of a predictive model for cardiac care for iKure. IBM's Data Science Elite team demonstrated the model development process in ICP for Data via Watson Studio with multiple AWS data sources. It also proved model accuracy using patient clinical and demographic variables and physician feedback with the added benefits of rapid model development, publication and iteration."

— Sujay Santra CEO and Founder, iKure



iKure is an award-winning, tech-savvy, rapidly-growing, revenue-positive social enterprise that meets the primary health care and prevention needs through a unique combination of health outreach initiative, skills development, and technology intervention. The venture is poised to rapidly scale beyond its curative model, looking to the future of disease prevention and wellness for 840 million people in rural India. iKure's healthcare model has acquired extensive support and recognitions from across the world for being innovative, technologically advanced and sustainable.



IBM Cloud Private for Data Cloud-Native by Design

Agility

Efficiency

Cost Savings

IBM Cloud Private for Data

Microservices



An architecture of loosely coupled data services, easily refactored to create containerized workloads

Containerized Workloads



Stand-alone workloads composed of microservices & data that are flexibly deployed, orchestrated and managed

Multicloud Provisioning



Agile provisioning of containerized workloads in multicloud environments and consumption of cloud services

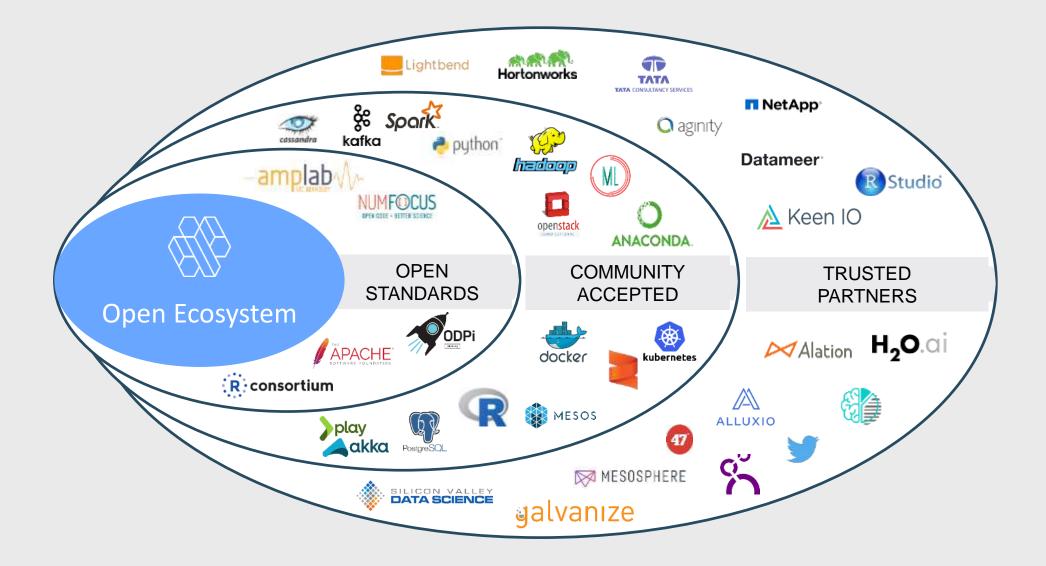






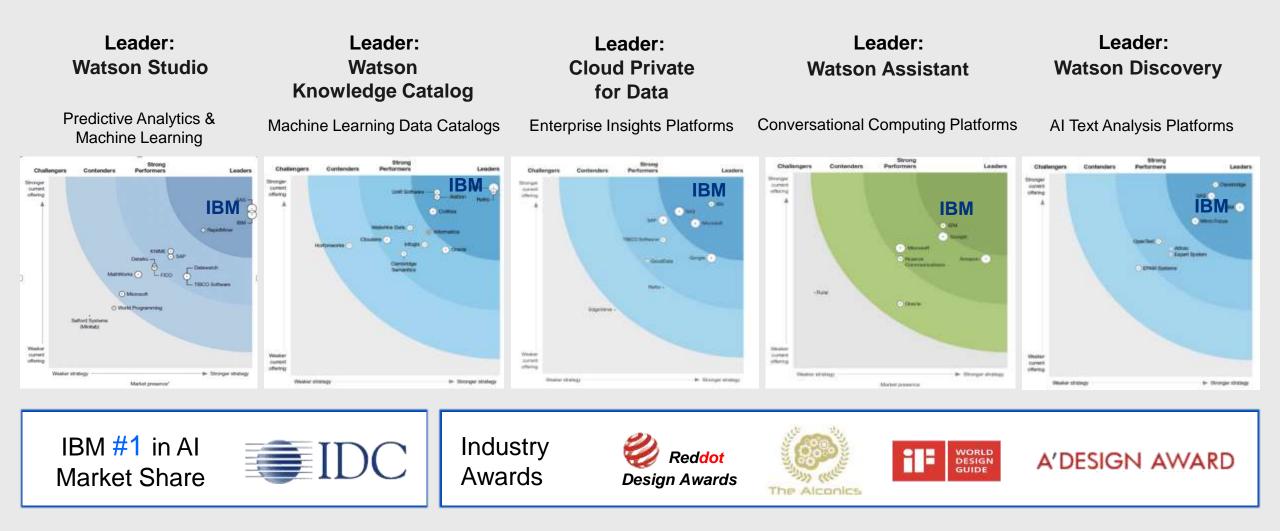


Underpinned by an Open Ecosystem Where we partner, co-create & lead



Integrating Industry Leading AI Technology

Forrester Wave[™] Reports



IBM Cloud Private for Data A new approach to Data Virtualization

Query anything, anywhere.

1

Query **many heterogenous data sources as one** across cloud, on-premise and mobile with advanced analytics using the most popular languages and tools

Simplicity and scalability.

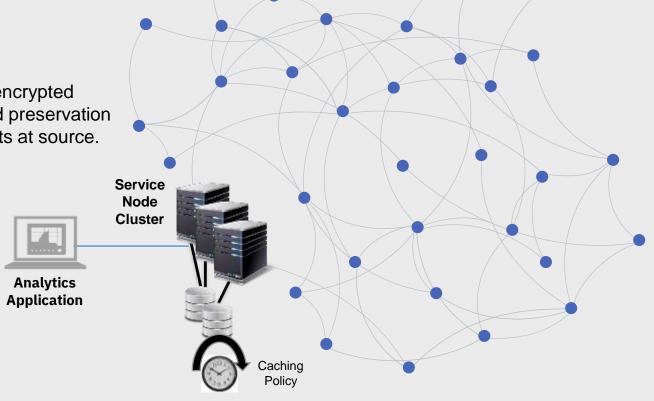
Automatically discover, and connect few to many devices and data stores into a single self balancing constellation. Avoid the complexity of centralized copies. Data only persists at the source.

Execution speedup.

Many times acceleration using the power of every device to compute and aggregate results.

Security.

Fully secure and encrypted communication and preservation of data access rights at source.



Constellation

Data Source Node

IBM Watson in Multicloud Environments Deploy "Watson Anywhere" with IBM Cloud Private for Data

I want to use Watson to build and deploy AI on the clouds of my choice:

- 1. Provision ICP/D which includes base Watson Studio, WML & Knowledge Catalog
- 2. Optionally provision the Data Science Premium add-on from ICP/D catalog to add premium features a well as optionally provision the Watson APIs add-on from the ICP/D catalog

Watson APIs

Data Science Premium

Cloud Private for Data

I want to use Watson Assistant on the clouds of my choice:

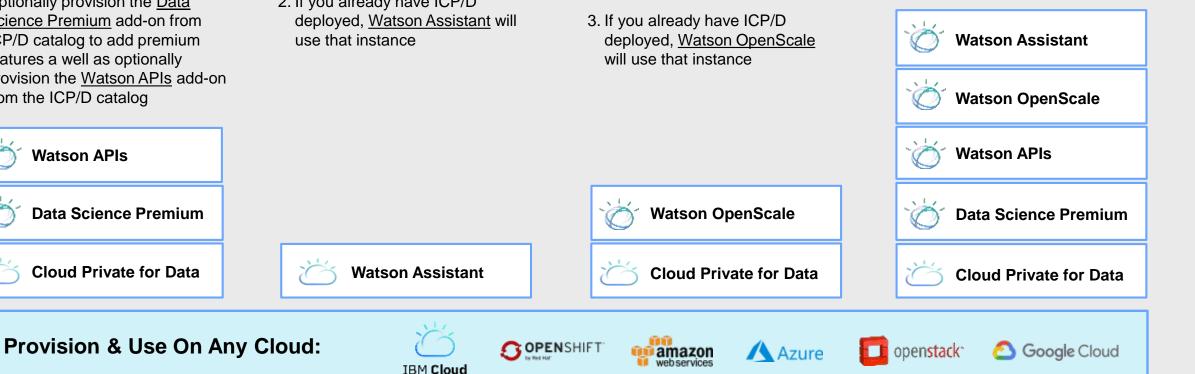
- 1. Provision Watson Assistant on the cloud which also provisions the embedded ICP/D platform
- 2. If you already have ICP/D deployed, Watson Assistant will use that instance

I want to use Watson **OpenScale on the clouds of** my choice:

- 1. Provision ICP/D on the cloud
- 2. Provision add-on from ICP/D catalog for Watson OpenScale

I want to progressively deploy the full Watson stack on the clouds of my choice

1. Starting with provisioning ICP/D, progressively provision the Watson offerings from the ICP/D add-ons catalog



Choose the Right Edition For Your Needs

Cloud Native Edition



Enterprise Edition

- All features are supported across both editions
- Cloud Native Edition has the following limits:
 - # of records in data set on which you can run automated discovery or data transformation jobs (1 million)
 - # of jobs that can run each day to transform data or assign terms (500)
 - # of accepted assets in the enterprise data catalog (3,000)
 - # of concurrently published data science model deployments (50)
 - # of concurrently running data science batch jobs (60)
 - # of concurrently running Shiny apps (40)
 - # of active nodes across all data warehouses (4)

IBM Cloud Private for Data enables you to:

- 1) Deploy an information architecture for AI
- 2) Modernize your data estate for a multicloud world
- 3) Make your data ready for AI
- 4) Infuse AI everywhere, with confidence
- 5) Put open source to work



ICP for Data: Additional Sources of Information



Resource Center: <u>https://docs-icpdata.mybluemix.net</u> Product Page: <u>https://www.ibm.com/products/cloud-private-for-data</u> Community: <u>http://ibm.biz/ICP4D-Community</u> Product Roadmap: <u>http://ibm.biz/ICP4D-Roadmap</u>



Product Walkthrough: <u>https://www.youtube.com/watch?v=TiYCZfCZx_o</u> Collect & Organize: <u>https://www.youtube.com/watch?v=vY3jPXwrhyE</u> Analyze: <u>https://www.youtube.com/watch?v=-Z4LAe5OkfU</u> Stock Trader Demo: <u>https://www.youtube.com/watch?v=aD4O3MMhlgo</u>



ICP for Data Experiences: <u>http://ibm.biz/experienceICP4D</u> DTE Assets: <u>http://ibm.biz/ICP4D-DTE</u>



IBM Cloud Garage & Systems Co-creation Workshops: http://ibm.com/cloud/garage

- Various engagement offerings available
- IBM Data Science Elite Team: <u>http://ibm.biz/DSEliteTeam</u>
 - 30 minute consult (free), 6 week kick-start (free), 12 week build (co-invest)

Infrastructure Matters for Private Clouds and Enterprise Al What do businesses need?



98% surveyed said that a single hour of downtime costs over \$100,000 (and much more for some)¹

Performance

Security

Enterprise-cloud ready

Cost-effectiveness

A top concern for CIOs – the average cost of a single data breach globally is \$3.86M²

Meet the most stringent application SLAs

and scale to handle growth over time

Agile with elastic growth and flexible consumption models

Make most efficient use of resources and do more with less (29% of organizations are reporting a decline in IT capital budgets for 2019 ³)

IBM Power Systems

When dataintensive and Al workloads are the bottom line

Enterprise cloud-ready

#1 in reliability

Industry-leading value and performance





Built-in PowerVM virtualization, IBM POWER9-based Power Systems are cloudready, enabling you to deploy the right cloud environment to meet your needs. Power Systems easily integrates into your organization's private or hybrid cloud strategy to handle flexible consumption models and changing customer needs. Ranked #1 in every major reliability category by ITIC, IBM Power Systems deliver the most reliable onpremises infrastructure to meet around-theclock customer demands. With Power Systems, clients can take advantage of superior core performance and memory bandwidth to deliver both performance and price-performance advantages.

Modernization To Private Cloud with IBM Power Systems

Simplifies Cloud Application Deployment

Over **50% faster** to deploy applications versus traditional infrastructure ¹

And is **27% less** expensive than the public cloud to run a typical workload mix²

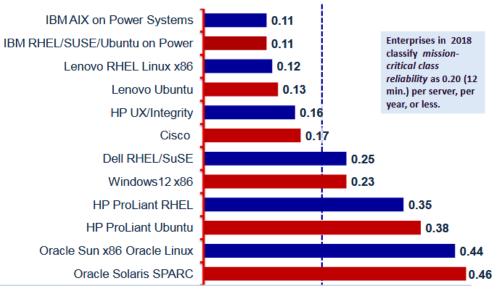
With **88% more** containers per core supported on Power versus x86 ³

Ranked Number 1 in every major reliability category by ITIC

Unplanned Downtime in 2017 - 2018 (Hours per Year)

HIGH

ME



"IBM POWER8-based processor systems and the latest POWER9 servers provide several key feature/function advantages that advance reliability and enable customers to lower Total Cost of Ownership (TCO) and achieve near-immediate ROI."

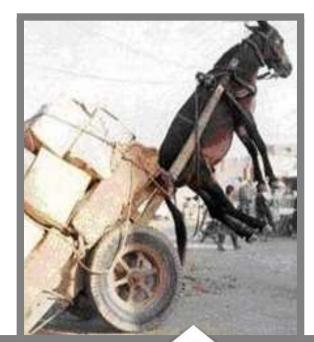
Modern Infrastructure For Modern Data Workloads

2X Price/Performance Leader versus x86

For data-intensive, scale-out databases and analytics workloads such as MongoDB, EDB Postgres and IBM Db2

Accelerate your Al Journey

Train machine learning & deep learning models faster and accelerate the data science workflow



In a MongoDB benchmark running on IBM Cloud Private (with open-source Docker on Linux), IBM Power Systems outperformed a comparable Intel system by having...

Power

Systems

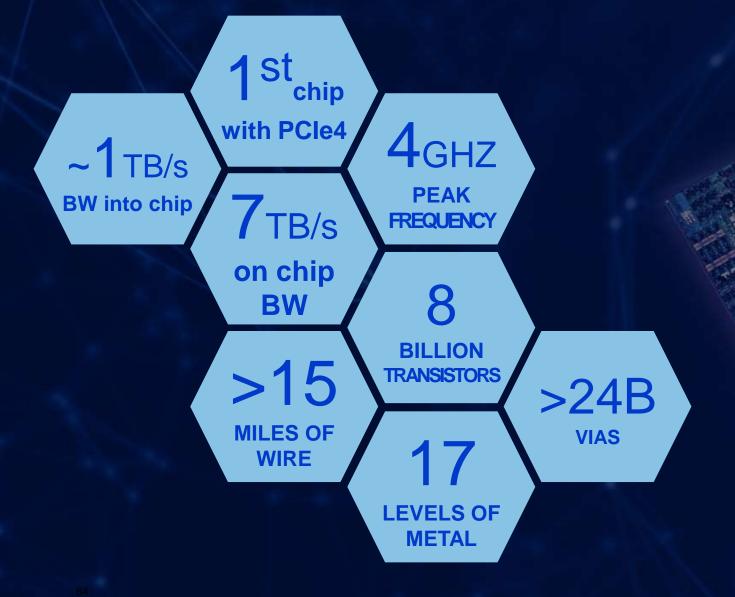
3.6X more containers/core

3.3x better price-performance



Industry leading container and VM density

POWER9 processor



POWER9 vs. x86 Xeon SP (Skylake)

2x¹

performance per core

2.6x²

more RAM per socket

1.8X³ memory bandwidth per socket

POWER9 with NVLink vs. x86 Xeon

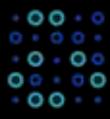
9.5X⁴ CPU to accelerator bandwidth

IBM POWER SYSTEMS for AI



An Acceleration Superhighway

Unleash state of the art IO and accelerated computing potential in the post "CPU-only" era



Designed for the AI Era

Architected for the modern analytics and AI workloads that fuel insights



Delivering Enterprise-Class Al

Flatten the time to AI value curve by accelerating the journey to build, train, and infer deep neural networks



IBM Power Systems LC922 & LC921

For the Analytics that feed Enterprise AI

The IBM Power Systems LC922 enhances the LC product line's open heritage while delivering superior performance in a cost optimized design needed in today's AI Era.

2x

Price performance advantage for data intensive applications such as MongoDB

59%

Improved Spark priceperformance for efficiency across the AI data leveraging the P9 thread density for large amounts of concurrent Spark queries

2X

more data scientists on a single server at FASTER RESPONSE TIMES with Watson Studio Local (WSL)

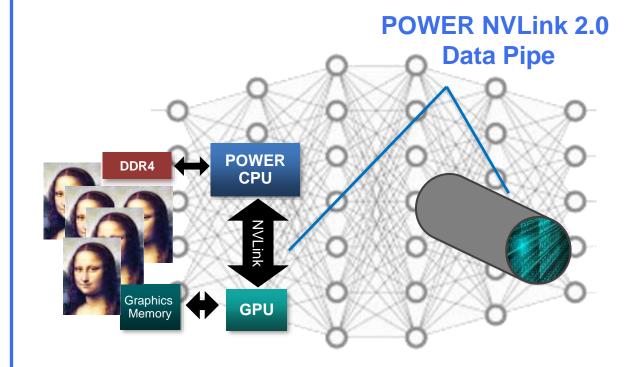
Train larger more complex models with WML-A and AC922

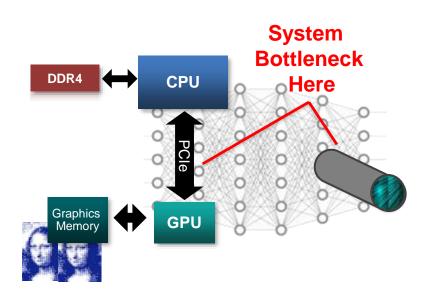
Traditional Model Support

Limited memory on GPU forces tradeoff in model size / data resolution

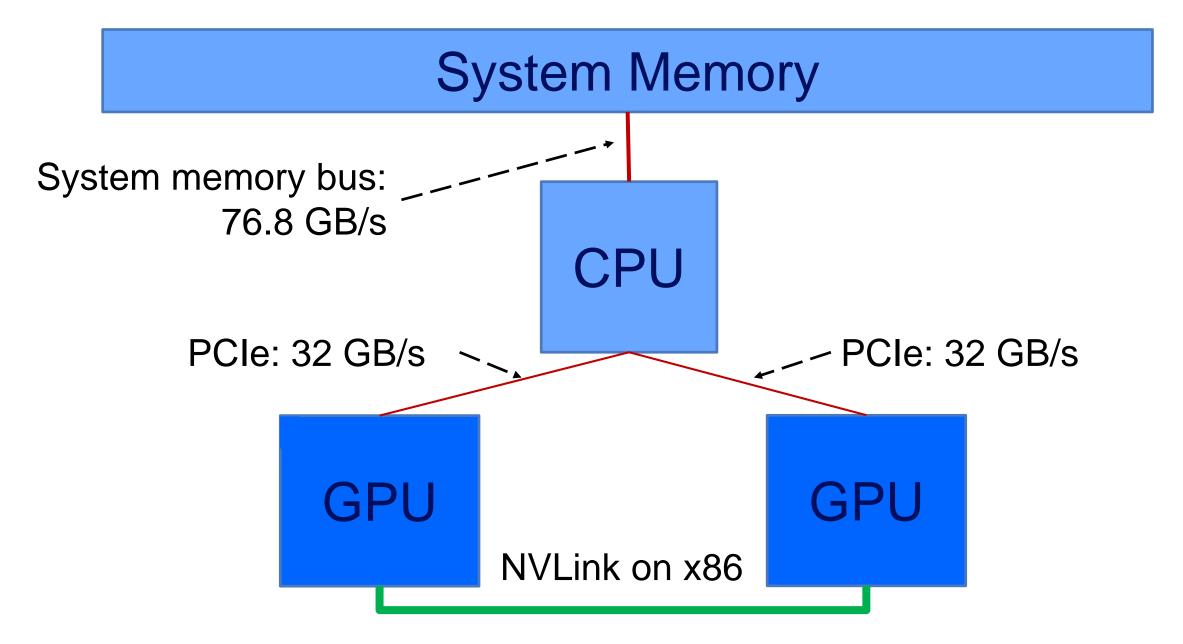
Large Model Support

Use system memory and GPU to support more complex and higher resolution data

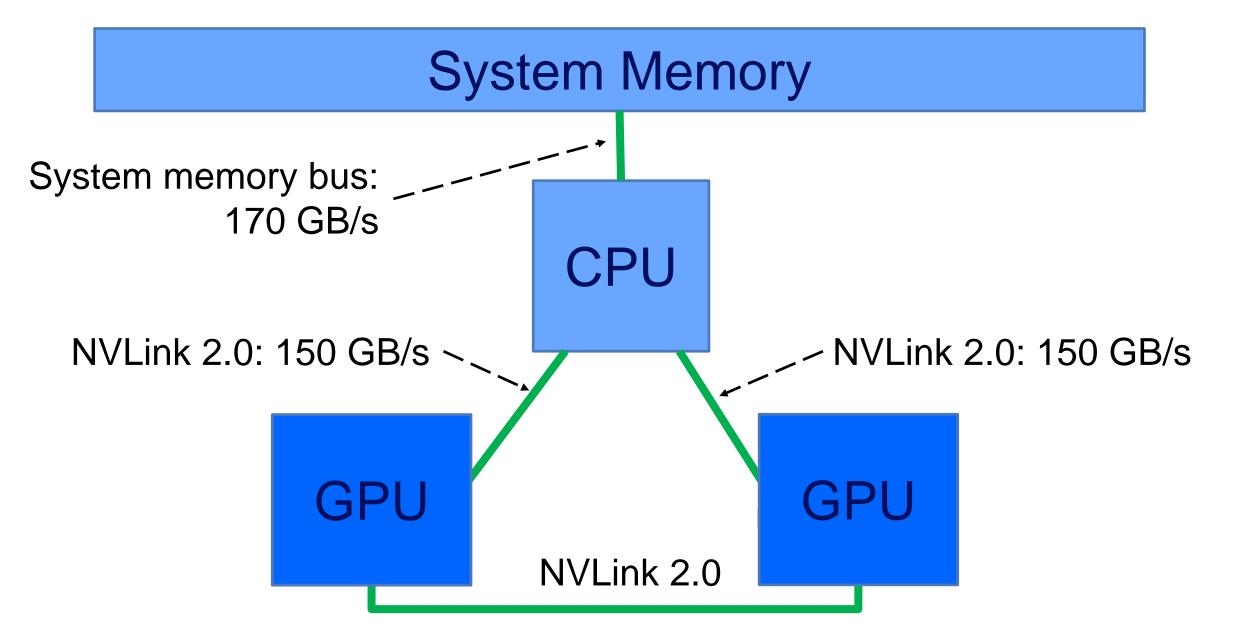




Typical GPU connectivity



NVLink CPU to GPU connectivity only on POWER9

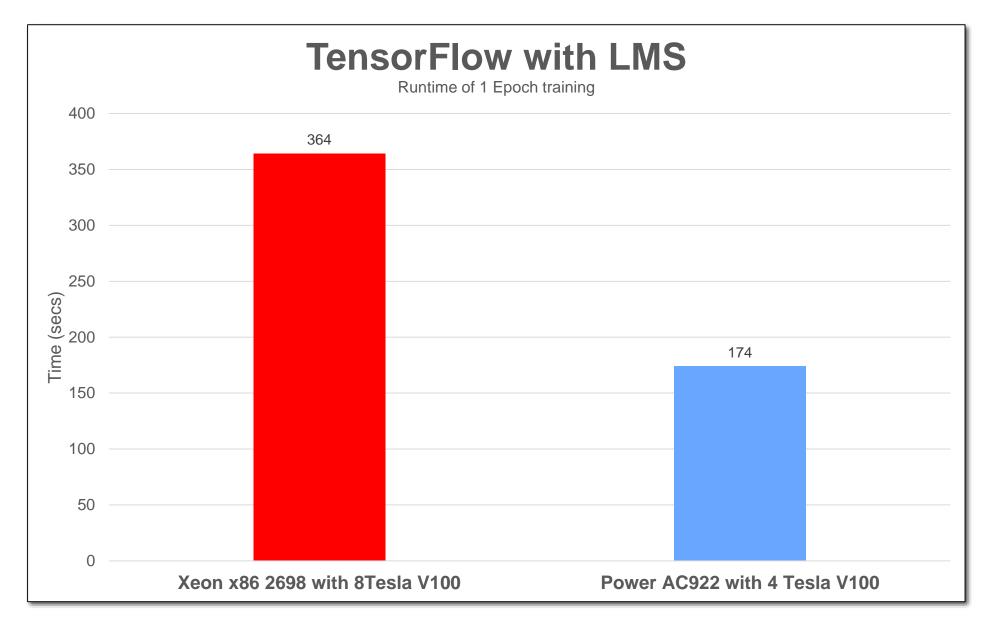


Effects of NVLink 2.0 on Large Model Support (LMS)

DGX1: PCIe connected GPU training one high res 3D MRI with large model support



POWER9 with 4 GPUs is 2.1x faster than x86 with 8 GPUs



Distributed Deep Learning (DDL)

Deep learning training takes days to weeks

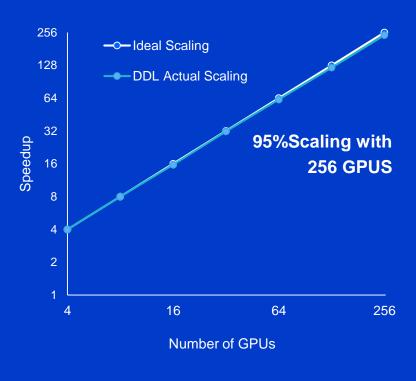
Limited scaling to multiple x86 servers

WML with DDL enables scaling to 100s of GPUs

16 Days Down to 7 Hours 58x Faster 16 Days 7 Hours 1 System 64 Systems

ResNet-101, ImageNet-22K

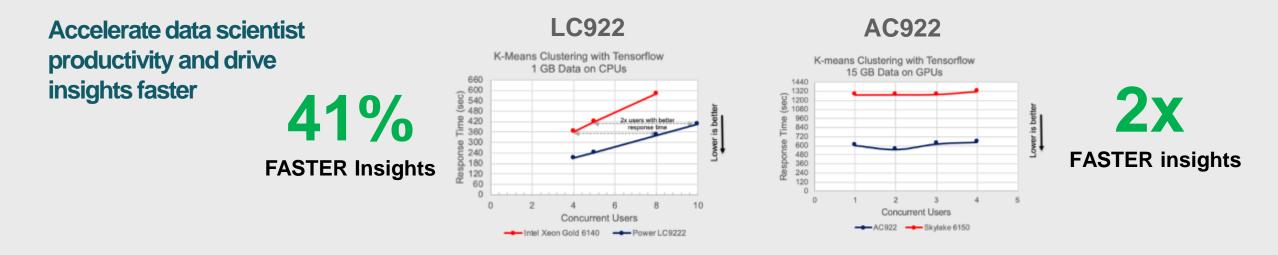
Near Ideal Scaling to 256 GPUs



ResNet-50, ImageNet-1K

Caffe with WML DDL, Running on Minsky (S822LC) Power System

Power Systems Value for Data and AI Workloads



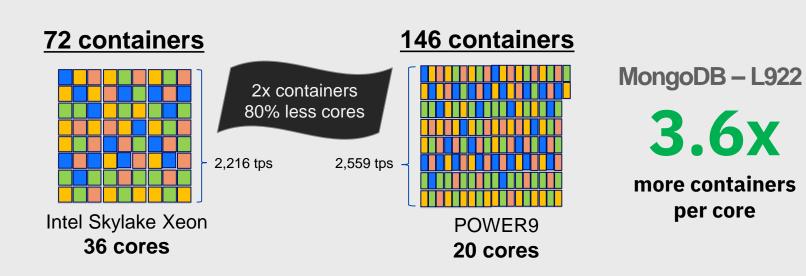
Higher performance for data management workloads

Db2 Warehouse – L922

2.54x

per core performance

Greater container density



IBM Power Systems

The high-performing, reliable and secure foundation for Enterprise AI & ICP for Data

True Cognitive Systems are about co-optimized



which *just work* for machine learning, deep learning and artificial intelligence



Infuse – Deploy trusted AI-driven business processes



Analyze - Scale insights with AI everywhere



Organize – Create a trusted analytics foundation



Collect – Make data simple & accessible



Modern infrastructure for cutting-edge data & Al workloads

- Enterprise-cloud ready
- #1 in reliability
- Secure to the core
- Unparalleled container density
- Industry leading value & performance

Power Systems: The bedrock supporting the AI ladder

Simplified Multicloud

IBM Power Systems enable the most data intensive and mission critical workloads in private and hybrid cloud environments.



Scale Performance Affordably

IBM POWER9 processor drives the world's fastest supercomputers and is ready to accelerate your enterprise.





Delivered with Security

IBM Power Systems have security built-in at all layers, from processor to the OS, designed to deliver end-to-end security.



Proven Reliable

IBM Power Systems ranked the most reliable for the 10th straight year delivering 99.9996% uptime.

Watson Machine Learning Community Edition

Curated, tested and pre-compiled binary **software distribution** that enables enterprises to quickly and easily deploy deep learning for their data science and analytics development

• Order it from IBM (support available for a fee)

- Download it from here: <u>http://ibm.biz/download-powerai</u>
- Get Docker container here: <u>https://hub.docker.com/r/ibmcom/powerai/</u>

Includes all of these frameworks:

Caffe Caffe Caffe 2

BVLC Caffe IBM Enhanced Caffe Caffe2



TensorFlow TensorFlow Probability TensorBoard TensorFlow-Keras





NNX

IBM Spectrum MPI

Free !!

ML

HDF5

Snap



Available for: POWER9 With GPUs X86 64-bit

Baze

H2O Driverless AI Delivers Automatic ML for the Enterprise



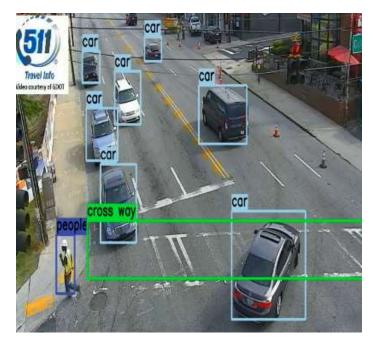
- Performs the function of an expert data scientist
- Create models quickly with GPUs and Machine Learning automation
- Delivers insights and interpretability
- Created and supported by world renowned AI experts from H2O.ai
- Award-winning software



21 day free trial for Driverless AI

PowerAl Vision: "Point-and-Click" Al for Images & Video

Label Image or Video Data





My DL Tasks / Create Task New DL Task - Build Image Classifier **Build Model Deploy And Test** Choose Dataset Select or create dataset Deploy trained model and run test Build model based on selected cataset Name of Image Classifier. Test1 Select dataset: Room Create a New Dataset 01 Build Model Cancel Latest Status: training 🔅 -O- Train Loss -O- Test Loss -O- Accuracy Train Iteration: 101 Train Loss: 0.62105 Test Iteration: 100 Test Loss: 0.47246 Accurary: 0.81771 1 5 9 1317212529333741454953576165697377818389 25 100 Estimated left time: 0 seconds

Package & Deploy AI Model













Total: 102, Page Count: 17



Upload pictures (jpg / png) by dropping them here Or Select some



Power Non techies ... can

- upload training data from on-site video or cameras
- create detection categories to match the safety use case using business domain expertise
- label data using acquired business domain expertise
- build model & expose it as a RESTful API endpoint for hybrid cloud consumption

use the model

Watson Machine Learning for z/OS, V2.1

WHAT

An end to end machine learning platform to build, deploy and monitor predictive models

HOW

Integrates and operationalizes AI / machine learning models within transactional systems

WHY

To ensure the lowest latency and the highest performance, security and resiliency to deliver real-time business insight and automation



Watson Machine Learning for z/OS V2.1 Key Features



Flexible model development

Build, train, and evaluate models using your IDE of choice or the WMLz extensive model building features based on enterprise-grade open source software.

Improved productivity

Optimize data science productivity through extensive model building features/modes including notebooks, visual builders, wizards, and enhanced intelligence

Enterprise-ready AI model deployment

Operationalize predictive models within transactional applications, without significant overhead, enabling real-time insight at the point of interaction.

Enhanced model accuracy

Enable data scientists and engineers to schedule periodic reevaluations of new data to monitor model accuracy over time and be alerted when performance deteriorates. Automatically refresh models to maintain model accuracy with confidence.

Production-ready machine learning

Deliver essential model versioning, auditing and monitoring as well as high availability, high performance, low latency, and machine learning model automation (ML as-a-Service).

Quick-start solution templates

Offer essential foundational templates for common business requirements to bootstrap your machine learning efforts and add value to key business areas including fraud detection, loan approval and IT Operational Analytics (ITOA).

Adopt and Expand Al Shorten Time to Value with IBM Storage

