Cisco Silicon for Al – Capabilities, Designs, and Results

CISCO Live

Peter Jones
Distinguished Engineer

Dave Zacks
Distinguished Engineer

Hardware Cisco Silicon for AI Capabilities, Designs, and Results

Peter Jones
Distinguished Engineer

Dave Zacks
Distinguished Engineer



Cisco Webex App

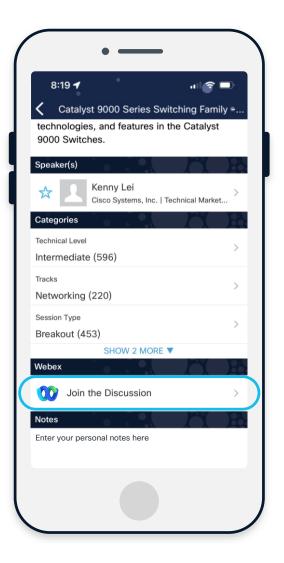
Questions?

Use Cisco Webex App to chat with the speaker after the session

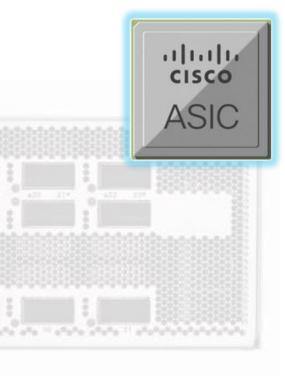
How

- 1 Find this session in the Cisco Live Mobile App
- 2 Click "Join the Discussion"
- 3 Install the Webex App or go directly to the Webex space
- 4 Enter messages/questions in the Webex space

Webex spaces will be moderated by the speaker until June 13, 2025.



Agenda





O1 Introduction
AI/ML, Generative AI,
Neural Networks, Transformers ...

O2 Al in Cisco
Using Al/ML in Solutions

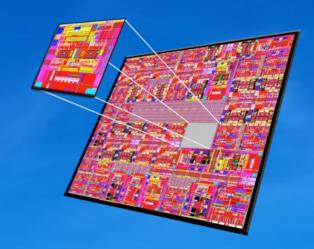


3 Al on Cisco
Building Networks for AI/ML

04 Summary and Wrap-Up

alialia

By Way of Introduction ...



I am a **Distinguished Engineer** in the Cisco Security Innovations CTO team, and have been with Cisco for 25 years.

I work primarily with large, high-performance Enterprise network architectures, designs, and systems. I have over 30 years of experience with designing, implementing, and supporting solutions with many diverse network technologies.

I have a strong background in, and focus on, customer requirements, and integrating these into the products and solutions Cisco builds.

I have a special interest in Flexible Hardware, Fabrics, Assurance and ML/AL.

Dave ZacksDistinguished Engineer

Email: dzacks@cisco.com
Bluesky: davezacks.bsky.social
Linkedln: ln/dave-zacks-43677474/



By Way of Introduction ...



I am a **Distinguished Engineer** in the Cisco Networking Hardware team and have been with Cisco since 2005.

I work on system architecture and standards strategy across the portfolio. I was a key figure in the development of the UADP switching ASIC architecture and the Catalyst switches that use it.

I work in defining and promoting new Ethernet standards in IEEE 802.3 and as Ethernet Alliance Chairman.

I am passionate about **Network Evolution, Adoptable Technology** and **Ethernet.**

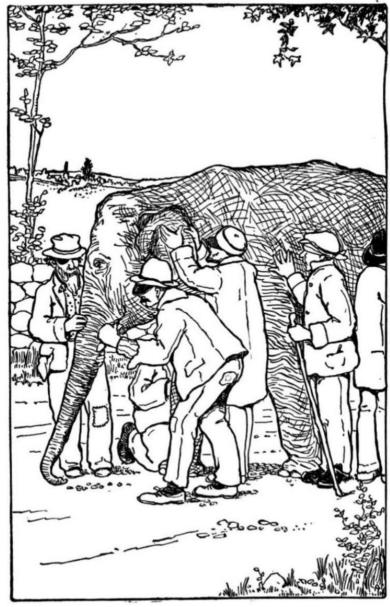
Peter Jones

Distinguished Engineer

Email: petejone@cisco.com Bluesky: petergjones.bsky.social

LinkedIn: in/petergiones/

What's this Al thing?



Wikipedia: Blind men and an elephant



The Breakdown of Artificial Intelligence

Artificial Intelligence

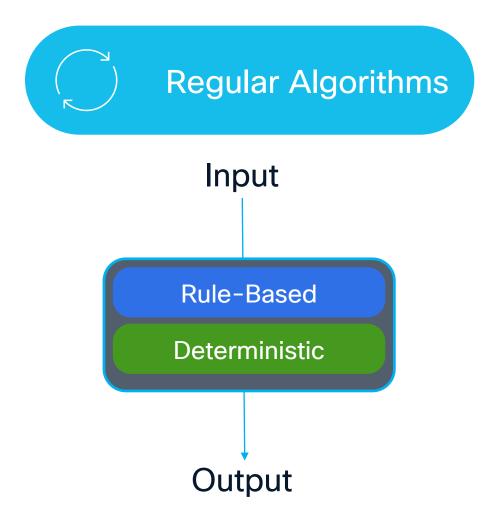
Machine Learning

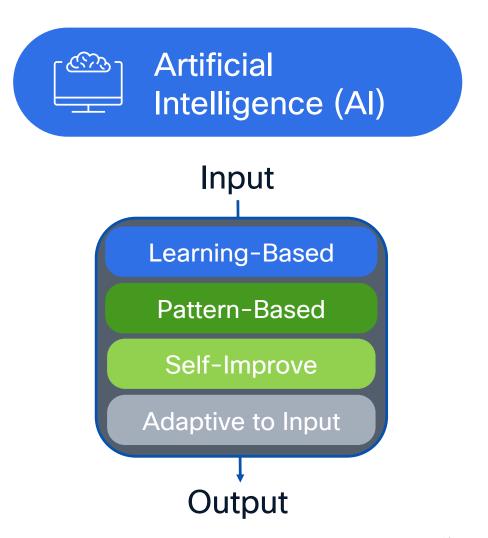
Deep Learning

Generative Al

Al that produces content

How Is Al Different From Regular Algorithms?





Supervised Learning

Supervised Learning

Using past "labeled" data to predict future trends

- Spam email identifier
- Stock price prediction
- Sales forecast

Note: Labeled data is data that has been tagged with the correct answer or output

Scenario: Predicting if an Email is Spam Email 2 Email 1 To/From To/From Subject Subject Content Content Email 4 **Email 3** To/From To/From Subject Subject Content Content Spam Not Spam Labels

Unsupervised Learning

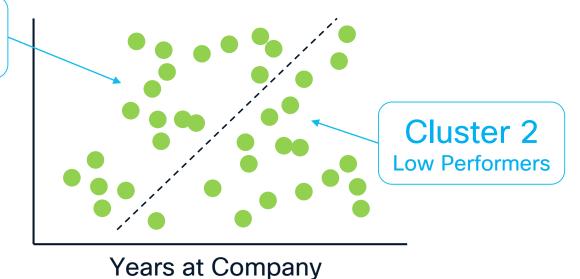
Unsupervised Learning

Using "Unlabeled" data to learn patterns

- User segmentation
- Anomaly detection
- Image/Video analysis

Scenario: Predicting if an employee is going to be a top performer

Cluster 1
High Performers



Note: Unlabeled data refers to data that does not have predefined categories or outputs

Unlabeled Data

Employee Data

Reinforcement Learning

Reinforcement Learning

Trained on reward or penalty feedback loop based on its actions during simulations.

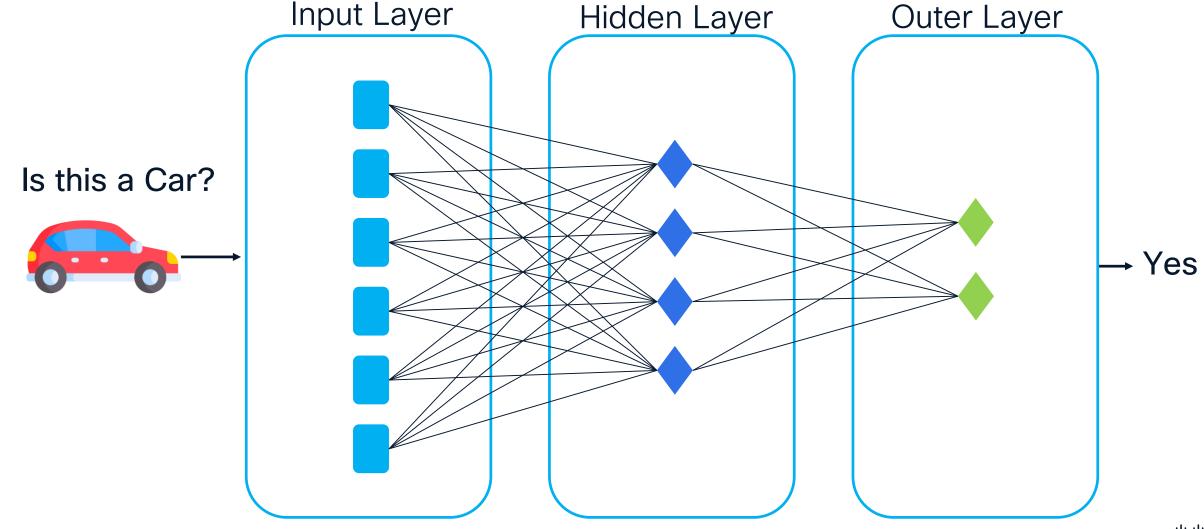
- Autonomous vehicles
- Robotics

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Resource management



Neural Networks – Identify Patterns with Deep Learning Divide and conquer large amounts of complex data



Large Language Models and Diffusion Models

Large Language Models

Trained to create text content.

Ex: ChatGPT 4o

Diffusion Models

Trained to create image and video content.

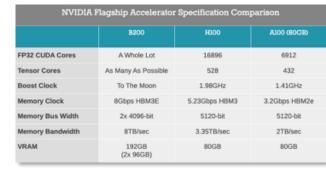
Ex: DALL-E 3

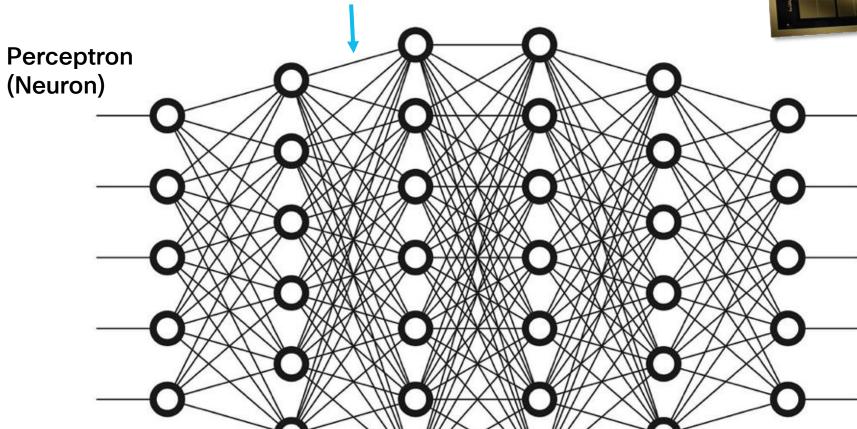
Why is this happening now?





Advances in Silicon – High-density, High-performance GPUs





Parameter

(Synapses)

Geoffrey Hinton - the "Godfather" of Deep Learning

Attention Is All You Need

Ashish Vaswani* Google Brain avaswani@google.com Noam Shazeer* Google Brain

Niki Parmar* Google Research Jakob Uszkoreit* Google Research

Google Brain Google Research Google noam@google.com nikip@google.com usz@g

usz@google.com

Llion Jones*
Google Research
llion@google.com

Aidan N. Gomez* † University of Toronto Łukasz Kaiser* Google Brain

aidan@cs.toronto.edu

lukaszkaiser@google.com

Illia Polosukhin* ‡

illia.polosukhin@gmail.com

arXiv:1706.03762 [cs.CL]

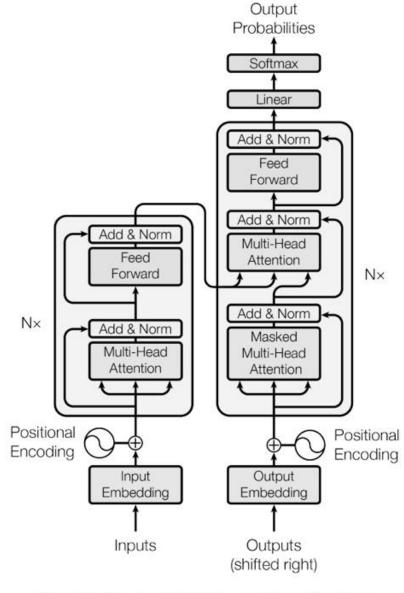


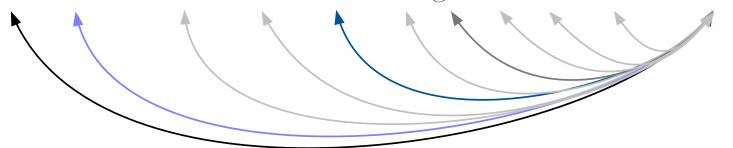
Figure 1: The Transformer - model architecture.

You have no problem interpreting "bank" in the following sentence:

"I swam across the river to get to the other bank."

A machine needs some help...

I swam across the river to get to the other bank.



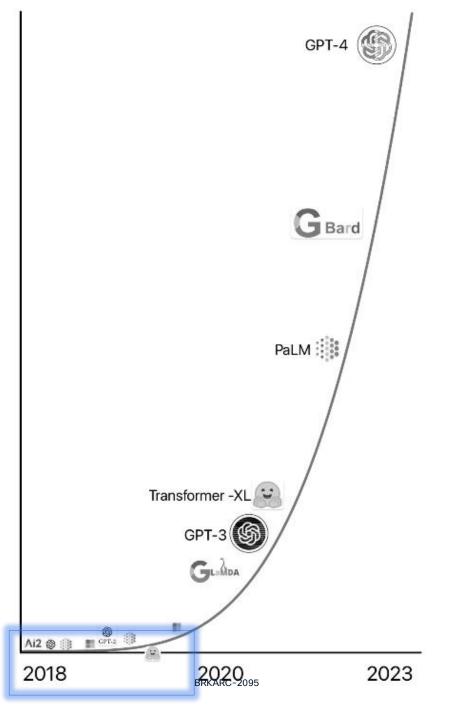
The goal of the attention mechanism is to add **contextual information** to words in a sentence.

"Cambrian Explosion" of Models **Open Source Closed Source Mistral** Llama Claude Gemma Dolphin Phi **Mixtral** Gemini Zephyr Chat **GPT** Vicuna Orca **Wizard**

Models - Various types, sizes, focus, ...

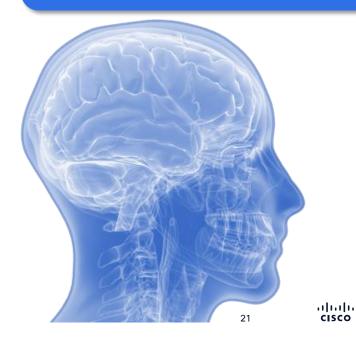
From Billions to Trillions of Parameters ...

500,000,000,000



FUN FACT!

The human brain contains
86 billion neurons, and over
100 trillion synaptic connections



How are LLMs Trained for Text and Code?

Step 1: Data Collection (Feeding Knowledge)

Step 2: Tokenization (Breaking It Down)

Step 3: Parameter Learning (Storing Knowledge)

Step 4: Fine-Tuning (Specialized Learning)

Step 1: Data Collection (Feeding Knowledge)

What Happens?

 LLMs are trained on massive amounts of text data – books, articles, websites, and more.

Analogy:

• Giving a child access to a library of books, the more they read, the more they learn.



Fun Fact: GPT-4 was trained on terabytes of text, equivalent to hundreds of millions of books.

Step 2: Tokenization and Vectorization Breaking it Down

How It Works:

- The text is split into tokens
 (words, subwords, or characters)
 so the model can process it.
- Tokens are further split into vectors (numerical values)

Analogy:

 Teaching a child to break down sentences into words & letters.

Raw Text

```
"My name is Dave"
```

Tokenized Text

```
["My", "name", "is", "Dave"]
```

Vectorized Tokens

```
"My" -> [0.12, -0.43, 0.33, 0.85, -0.17]
"name"-> [0.52, 0.10, -0.21, 0.44, -0.09]
"is" -> [0.09, -0.15, 0.47, 0.13, 0.56]
"Richard" -> [0.67, -0.25, -0.33, 0.78, 0.45]
```

Step 3: Parameters Learning (Storing Knowledge)

What Happens?

 Vectors flow through neural networks; parameters learn token relationships.

Analogy:

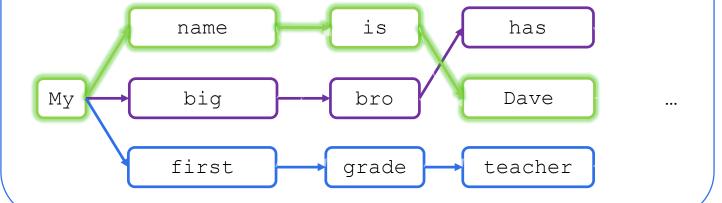
 A child learns how words fit together to form sentences.

Vectorized Text

```
"My" -> [0.12, -0.43, 0.33, 0.85, -0.17]
"name"-> [0.52, 0.10, -0.21, 0.44, -0.09]
"is" -> [0.09, -0.15, 0.47, 0.13, 0.56]
"Dave" -> [0.67, -0.25, -0.33, 0.78, 0.45]
```

Neural Network

Parameters store relationships between tokens to predict next words.



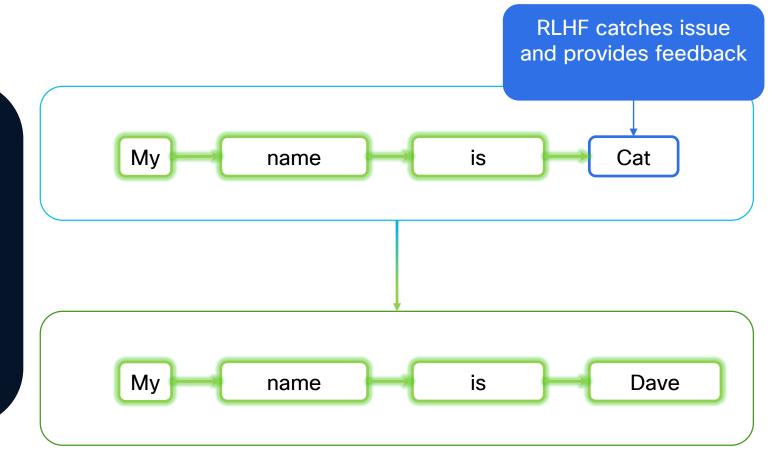
Step 4: Fine-Tuning the Model (Optimizing Predictions)

What happens?

- Parameters are adjusted to minimize prediction errors.
- The model improves by learning from its mistakes

Analogy:

A child practices speaking by receiving feedback & adjusting.



A Foundational Generative Al Model!

Jack of All Trades Model:

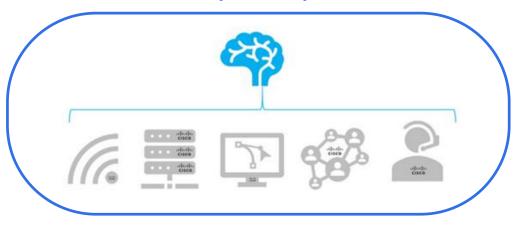
- Pre-trained on vast datasets including text, images, code, etc.
- Can handle a broad array of questions across domains.



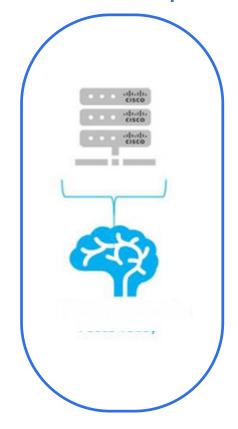


Artificial Intelligence and Cisco

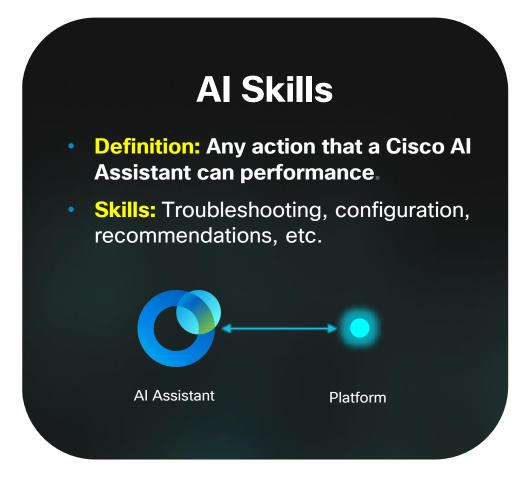
Al in Cisco –
Al to improve products



Al on Cisco – Products to improve Al



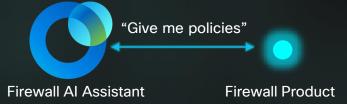
Al Assistants Have "Skills", Not Features



Al Assistants Native Skills Enhance Intra-Product Experience

Native Skills

 Definition: Capabilities of an Al Assistant for the local product it's integrated with



Documentation Summarization

Answers to questions about a product sourced from its documentation.

Optimization

Recommendations into how a user could better fully utilize their product.

Troubleshooting

Insights into issues and guided resolution for accelerated remediation.

Configuration

Guided workflows helping users to configure what they need to optimally.

Native Skills Across Products Examples



- Connection & Security logs
- 2. Policy inquiry
- 3. Policy creation



- 1. SPL generation
- 2. SPL querying
- 3. Data summarization



- 1. User activity timeline
 - . Device info & compliance
- 3. Authentication logs



- 1. Client troubleshooting
- 2. Device troubleshooting
- 3. App troubleshooting



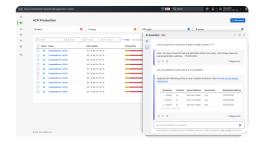
- Internet outages
- 2. Network events
- User to app troubleshooting



- 1. TAC case management
- 2. Field notices
- 3. Vulnerability & PSIRTs

Cisco Security's Suite of Al Assistants

Firewall



Block any outbound exfiltration to the IP address identified from the C&C

Secure Access



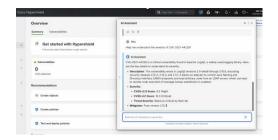
Ensure users access only resources they need securely

Duo



Lock affected user out of critical applications

Hypershield



Autonomous segmentation and exploit protection

Identity Service Engine



Enforces identity-based access policies, ensuring secure network access and compliance

Security Cloud Control



Manage all security products in a single place

Cisco Networking's Suite of Al Assistants



Cloud-managed networking with security, visibility, and device control



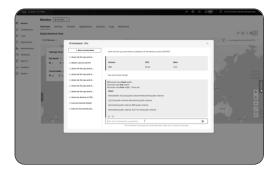
On-prem network management for automation, policy, security & assurance



Monitors network and application performance across the internet



identity-based access policies, ensuring secure network access and compliance



Optimizes WAN traffic and security across remote sites



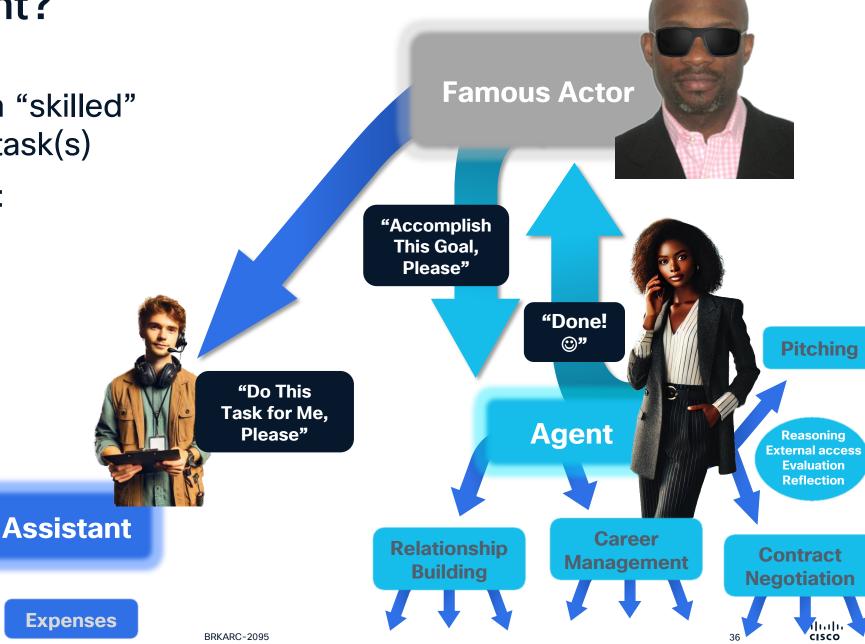
Optimizes WAN traffic and security across remote sites

Individual Al Assistants Are Integrated Across Cisco

| Security | Firewall, Secure Access, Hypershield, Duo, Identity Intelligence, Splunk Enterprise Security, IS |
|-----------------|--|
| Network | wing Meraki, Catalyst Center, Catalyst SD-WAN, ThousandEyes, Intersight, Mobility Services |
| Observa | ability Splunk Observability (Cloud, ITSI, AppDynamics) |
| Data | Splunk Platform |
| Collabor | ration Webex Control Hub |
| Service (| Ops Customer Experience |

What is an Al Agent?

- An Autonomous system "skilled" to accomplish specific task(s)
- LLM accompanied with:
 - Tools / Functions
 - Memory
- Core capabilities:
 - Planning and Reasoning

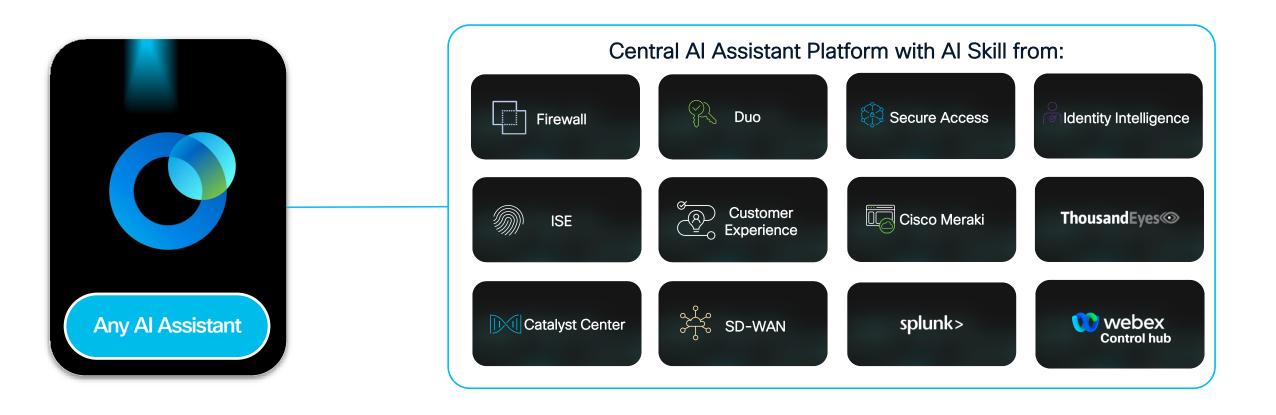


Scheduling

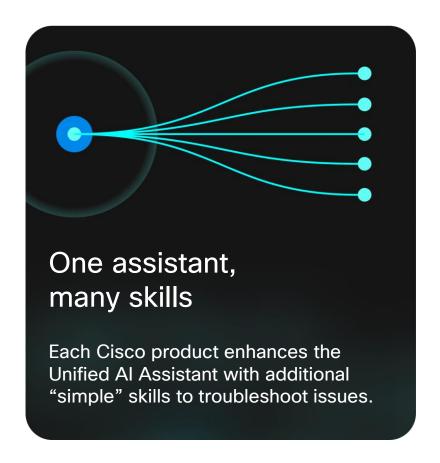
Errands

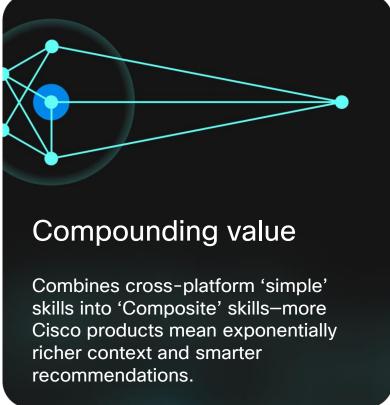
Expenses

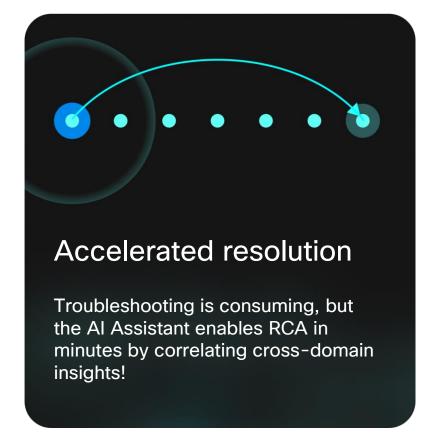
Unify Cisco Al Assistants to enable a network of Al Agents that can use cross-product Al Skills



Benefits of the Unifying Al Assistants into a Network of Al Agents



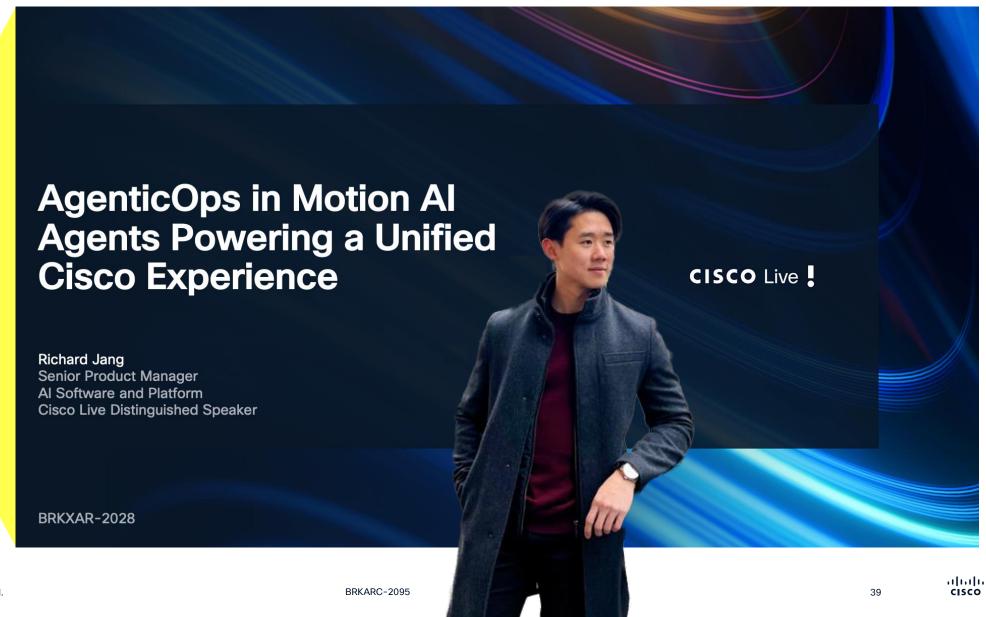




More about Cisco Assistants, GenAl, ...

Tuesday, June 10th

2:00 -3:30pm



Why Networking is Relevant to Al Deployments

LLMs are orders of magnitude more intensive than DLRM





Search, Feed ranking. Ads & content recommendation

Inference needs a few Gigaflops for 100ms TTFT

Narrower scope, domain specific

Training: ~100 Gigaflop/ sentence



Large Language Models

Intricacies of human language

Inference needs 10s of Petaflops for 1 sec TTFT

Generate intelligent, creative responses

Training: ~1 Petaflop/ sentence

An Improved user experience means a faster time to first token, making distributed inference an imperative



GenAl is upending the global IT spend.

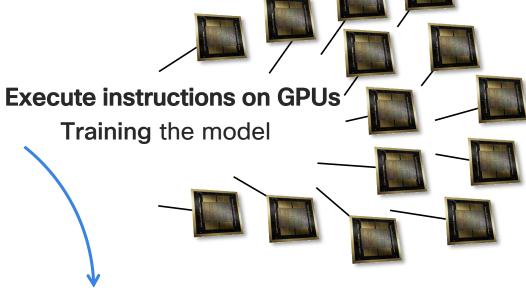
- The Hyperscalers spent ~\$180B in infrastructure alone in 2024¹.
- Al accelerator silicon revenue grew 130% in 3Q 2024².
- DC switching and NIC markets will double to >\$50B in 5 years³.
- A ChatGPT query takes ~10x the power of a Google search⁴.
- Nuclear power is becoming a *critical* DC energy source⁵.
- Goldman Sachs forecasts global DC power demand may increase
 165% by 2030⁶.
- 1) CIO Dive: Big tech on track to pour more than \$180B into data centers this year
- 2) Dell'Oro: US Hyperscalers Set to Deploy Over 5 Million Al Training-Capable Accelerators in 2024
- 3) Crehan Research: Ethernet switch and NIC market to reach \$50 Billion in the next five years
- 4) Kanoppi: Search Engines vs Al: energy consumption compared
- 5) Power: The SMR Gamble: Betting on Nuclear to Fuel the Data Center Boom
- 6) Goldman Sachs: Al to drive 165% increase in data center power demand by 2030

Why does the network matter for AI/ML?









Synchronise

Wait for everyone to complete

Job Completion Time (JCT) is based on the *worst-case tail latency*



Share results

Everyone sends to everyone



How do I get the most out of \$Bs of GPUs and Faculties









The network exists to enable the GPUs do *their work*

A *minute* occupied by the network is a *minute* the GPUs are idle

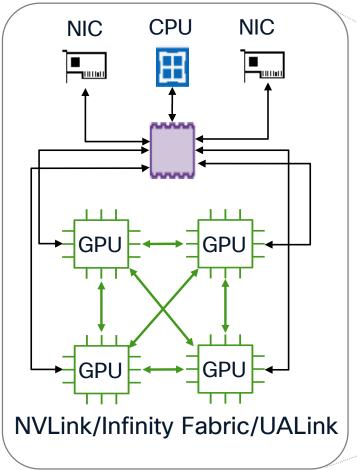
A *watt* spent on the network is a *watt* not spent on the GPUs

What matters?

Throughput under full load Reliability/Resilience Power



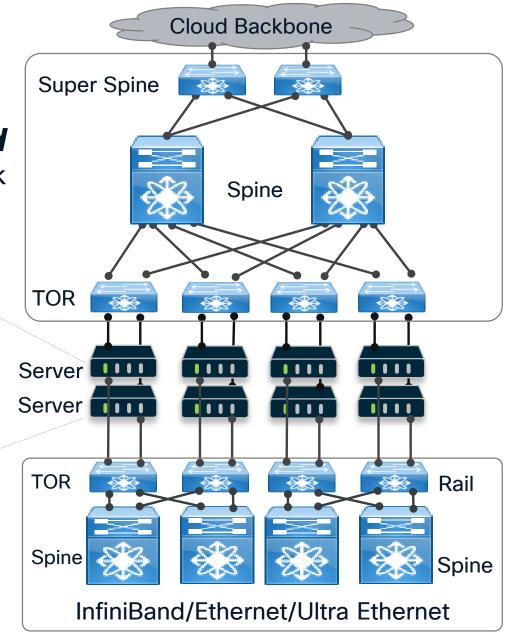
Al Network Fundamentals



Front-end Network

Back-end
Scale-up
Network

Back-end **Scale-out**Network



Ethernet vs InfiniBand

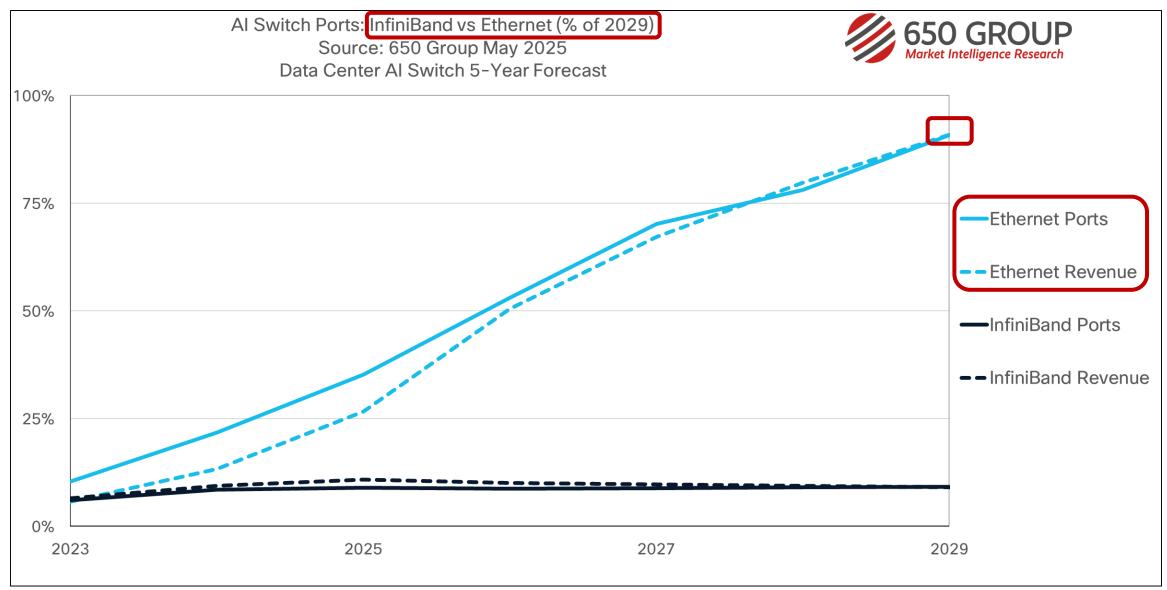
Google search "Ethernet InfiniBand benchmark" - Al Overview:

"In benchmarks, InfiniBand generally outperforms Ethernet in terms of latency and bandwidth, especially in HPC and AI environments. However, Ethernet is rapidly closing the gap, with newer standards like UltraEthernet offering substantial performance improvements. In some cases, especially with optimized Ethernet and larger, more complex workloads, **Ethernet** can even outperform InfiniBand."

- WWT: The Battle of Al Networking: Ethernet vs InfiniBand¹
 - Q: "is Ethernet good enough?"
 - A: "Across generative tests and OEMs, the performance delta between InfiniBand and Ethernet was **statistically insignificant** (< 0.03%)"
 - "WWT views Ethernet as a **wholly viable alternative** to InfiniBand for most generative and inference use cases"

1: https://www.wwt.com/blog/the-battle-of-ai-networking-ethernet-vs-infiniband

Ethernet vs InfiniBand - Al Backend Network Switch Ports



What's driving Ethernet?

Scale

• Hyperscalers are looking to build very large training clusters (300,000+) ¹, have clusters span multiple DCs¹, and InfiniBand has scaling limitations.

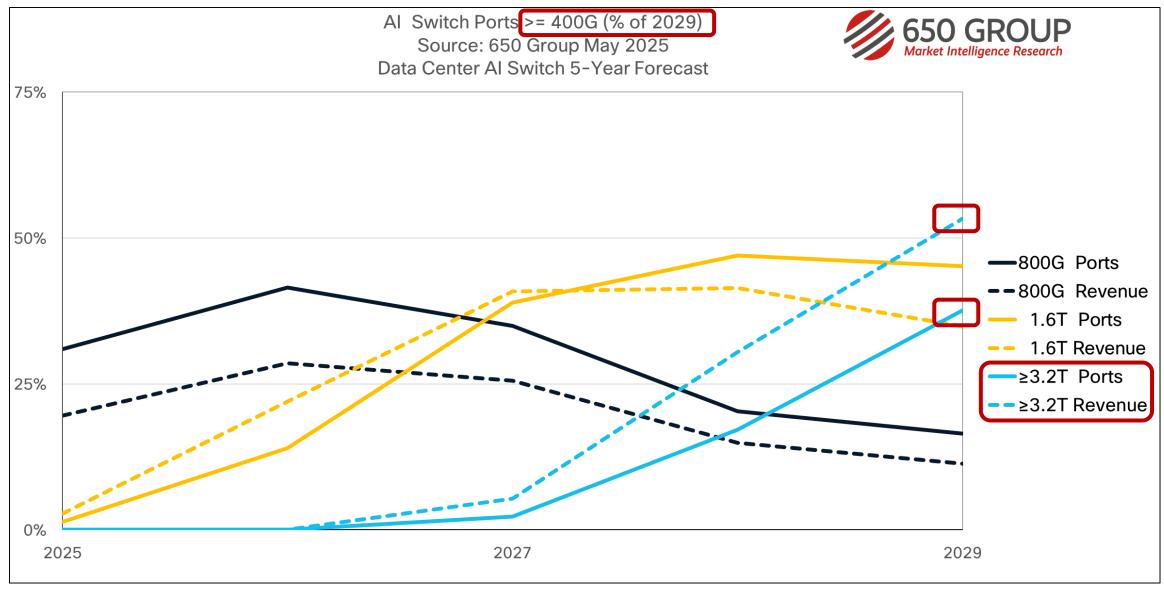
Supplier Diversity

Nvidia(Mellanox) dominates the InfiniBand market².

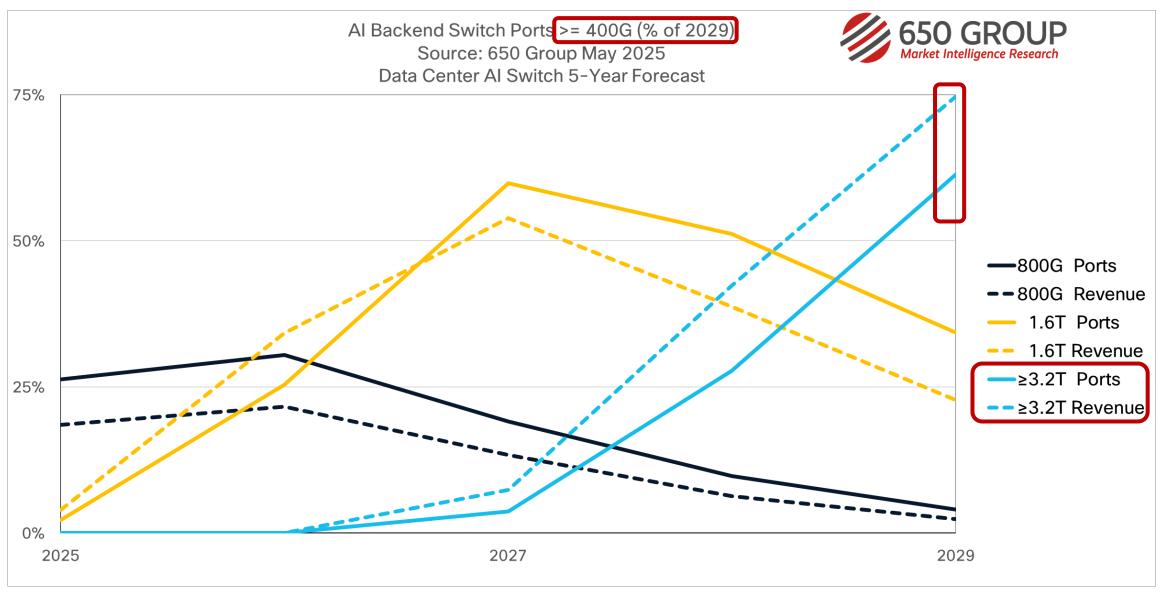
Cost of Operations

- History shows that Ethernet becomes less expensive to own and operate than the technologies it replaces.
- Everyone has Ethernet, using one technology reduces operational cost.
 - 1. SemiAnalysis: Multi-Datacenter Training: OpenAl's Ambitious Plan To Beat Google's Infrastructure
 - 2. NADDOD: Where to Buy Infiniband products

Ethernet Speed Trends - Al Network Switch Ports



Ethernet Speed Trends - Al Backend Network Switch Ports



RFC 1925: The Twelve Networking Truths

Network Working Group

Request for Comments: 1925

Category: Informational

Abstract

R. Callon, Editor
IOOF

1 April 1996

This memo documents the fundamental truths of networking for the Internet community. This memo does not specify a standard, except in the sense that all standards must implicitly follow the fundamental truths.

Acknowledgements

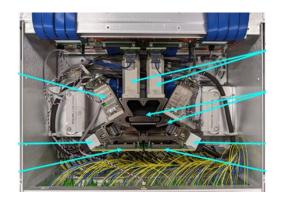
The truths described in this memo result from extensive study over an extended period of time by many people, some of whom did not intend to contribute to this work. The editor merely has collected these truths, and would like to thank the networking community for originally illuminating these truths.

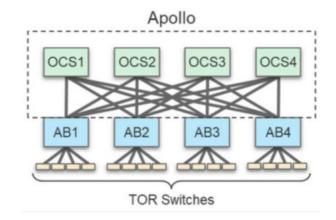
1. Introduction

This Request for Comments (RFC) provides information about the fundamental truths underlying all networking. These truths apply to networking in general, and are not limited to TCP/IP, the Internet, or any other subset of the networking community.

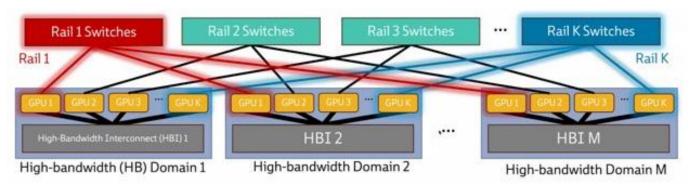
RFC 1925 rule 10 - "One size never fits all".

Google uses Custom Optical Switches¹ in its Jupiter network architecture².





Meta has a "Rail-only" design. 2



- 1. SemiAnalysis: Google OCS Apollo: The >\$3 Billion Game-Changer in Datacenter Networking
- 2. Google: Speed, scale and reliability: 25 years of Google data-center networking evolution
- NextPlatform: This Al Network Has No Spine And That's A Good Thing

Ethernet for Al Networks: Who's doing What

Ethernet Alliance

Building cross industry consensus, e.g., TEF 2024: Ethernet in the Age of Al

IEEE 802.3

IEEE P802.3dj is writing the 200G/lane standard

NEA investigating 400G/lane and Al bandwidth needs

Optical Internetworking Forum(OIF)

Exploring technology problems/solutions, e.g., 448Gbps Signaling for Al Workshop

Storage Networking Industry Alliance (SNIA)/Small Form Factor Committee (SFF)

Exploring technology problems/solutions, e.g., 400G Al Workshop

<u>Ultra Ethernet Consortium</u>(UEC)

Open standard for scale-out Ethernet networks

UE 1.0 specification expected soon

Adjacent: <u>Ultra Accelerator Link™</u> (UAL)

Open standard for scale-up Accelerator-to-Accelerator communication

UALink 1.0 defines 200G/lane for 1,024 accelerators within an Al pod

Ethernet for Al Networks: Who's doing What

Ethernet Alliance

Building cross industry consensus, e.g., TEF 2024: Ethernet in the Age of Al

IEEE 802.3

IEEE P802.3dj is writing the 200G/lane standard

NEA investigation

Optical Inter

Exploring to

Storage Net

Lots of Activity!

Exploring to

Ultra Ethern

Open standar

UE 1.0 specification expected soon

Adjacent: <u>Ultra Accelerator Link™</u> (UAL)

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Ethernet for Al Networks: Who's doing What

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Building cross industry consensus, e.g., TEF 2024: Ethernet in the Age of Al

IEEE 802.3

IEEE P802.3dj is writing the 200G/lane standard

NEA investigation

Optical Inter

Exploring to

Storage Net

Exploring to

Ultra Ethern

RFC 1925 rule 12:

"In protocol network design, perfection has been reached not when there is nothing left to add, but when there is nothing left to take away".

Open standar

UE 1.0 specification expected soon

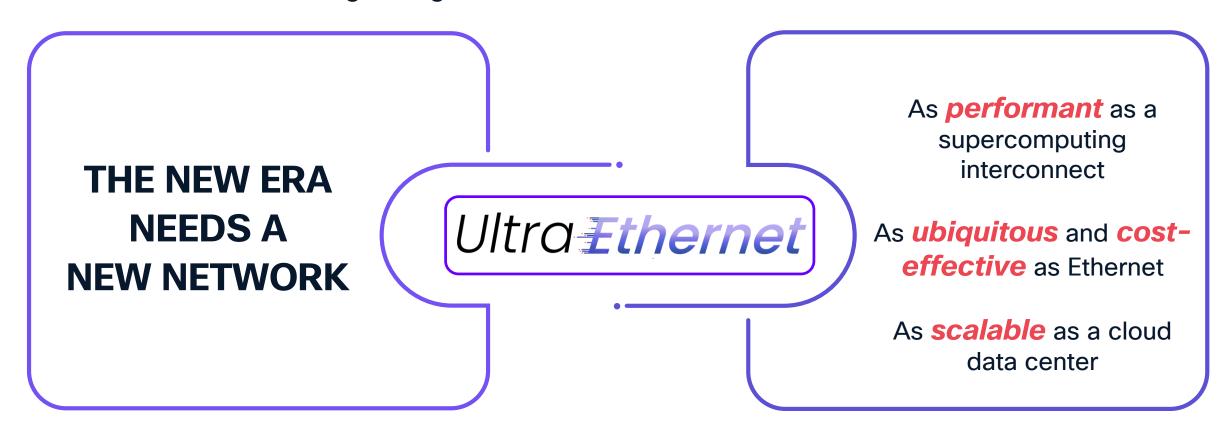
Adjacent: <u>Ultra Accelerator Link™</u> (UAL)

Open standard for scale-up Accelerator-to-Accelerator communication

UALink 1.0 defines 200G/lane for 1,024 accelerators within an Al pod

Ultra Ethernet Consortia (UEC)

Deliver an Ethernet based open, interoperable, high performance, full-communications stack architecture to meet the growing network demands of AI & HPC at scale



Al Ethernet Fabric Options

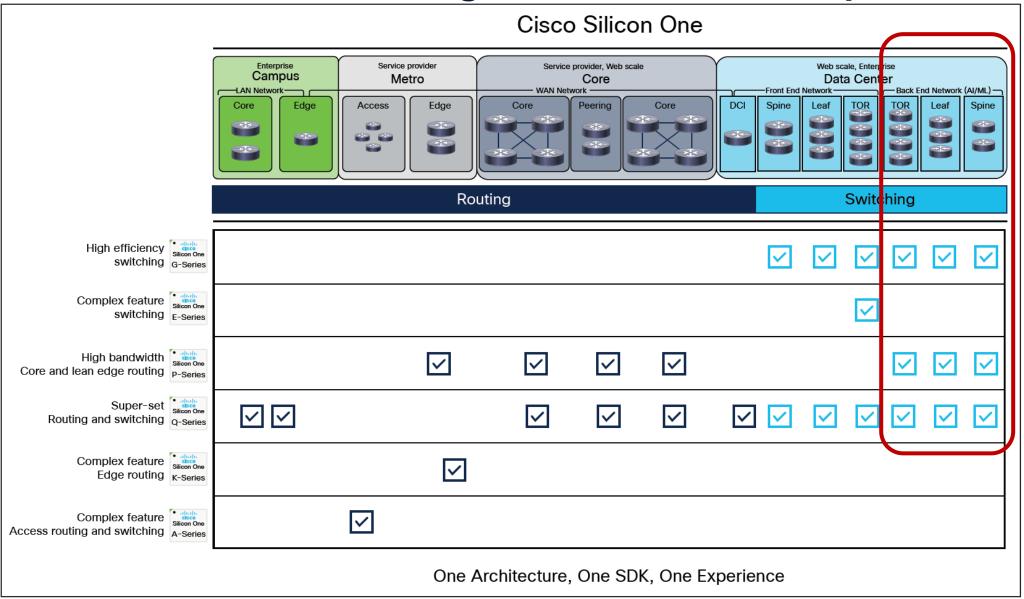
| | Ethernet | Enhanced Ethernet | | Ultra Ethernet | Scheduled Ethernet |
|--------------------------|----------------------------------|---|-------------------------------------|--|---------------------------------|
| Load Balance | Stateless ECMP | Stateful Flow/ Flowlet | Spray & Re- order in SmartNIC | Endpoint Controlled adaptive packet spraying | Spray & Re- order in leaf |
| Congestion Management | Congestion Reaction with ECN/PFC | Adjust distribution based on congestion | | Congestion Management | Congestion Avoidance |
| Link Failure | Software | Hardware | | Hardware | Hardware |
| JCT | Good | Better | | Even Better | Best |
| NIC and Fabric Coupled | No | No | Yes | Yes | No |
| Place in Network | Frontend, Backend | Frontend, Backend | | Backend | Frontend, Backend |

Performance *DEPENDENT* on Traffic Characteristics

Performance NOT DEPENDENT on Traffic Characteristics



Cisco Silicon One - Convergence without compromise



Silicon One in Al





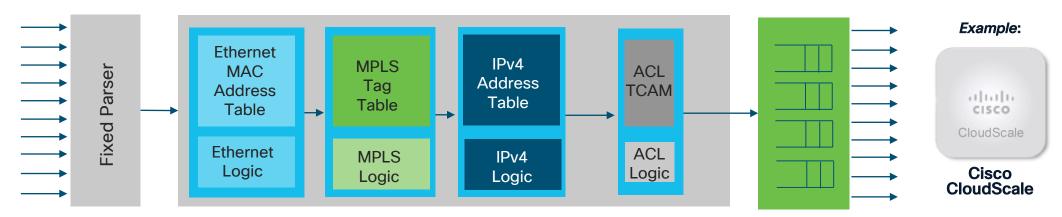




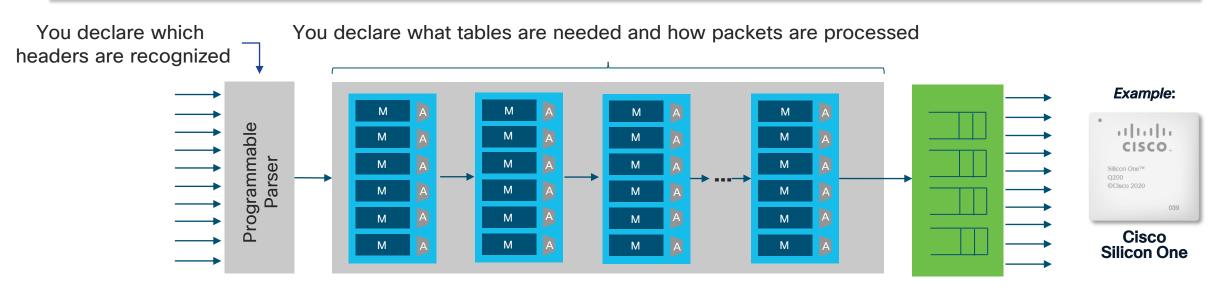


Q200L - 12.8T 32x400GE P100 - 19.2T 24x800GE G100 - 25.6T 24x800GE G202 - 25.6T 64x400GE G200 - 51.2T 64x800GE

Fixed vs. Programmable Packet Processing



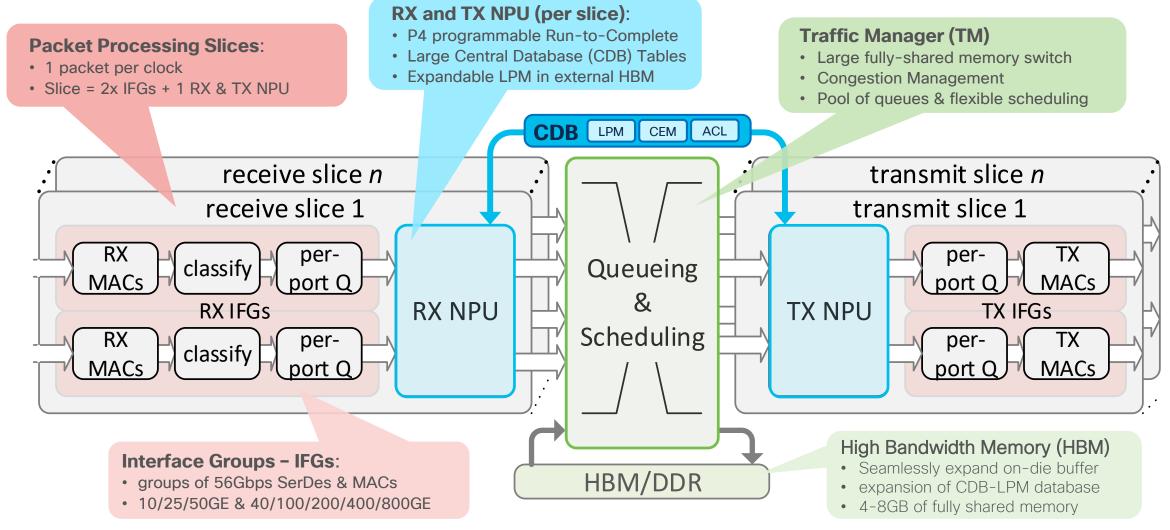
Fixed Pipeline: features and functionality are baked-in at design time



Programmable Pipeline: all stages identical, customer-defined match-action logic

Silicon One

Top Level



ECMP and Congestion

All-to-All flows

- smaller number of bigger flows
- low header entropy

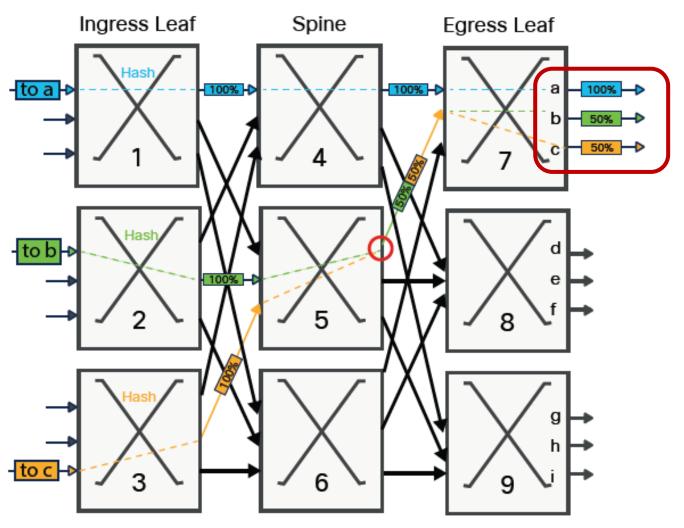
ECMP

- unaware of network load/congestion
- needs entropy in packer headers
- assumes most flows are short lived

Result

traffic/network inefficiency as flows "collide" in the network

Congested Links



https://www.cisco.com/c/en/us/solutions/collateral/silicon-one/evolve-ai-ml-network-silicon-one.html

Fully Scheduled Network

All-to-All flows

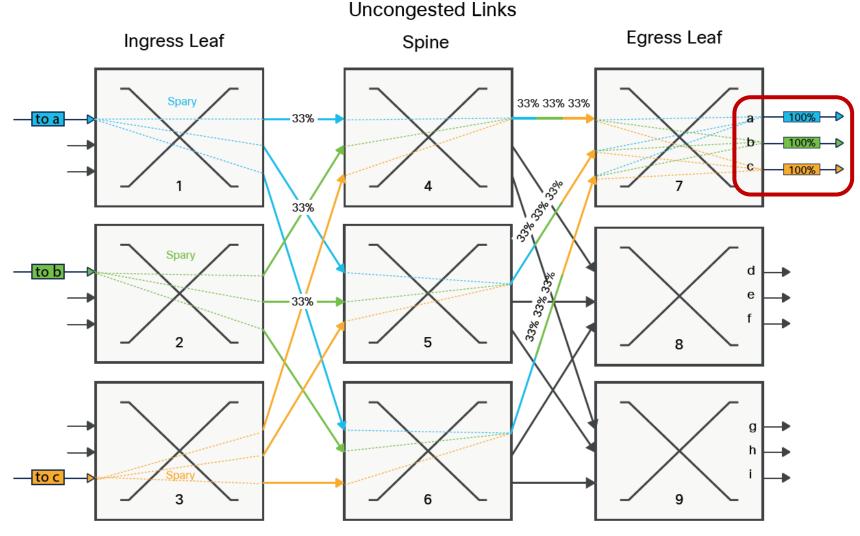
- smaller number of bigger flows toal
- low header entropy

Distributed Switch Model

- VoQs in ingress leaf
- active congestion control
- re-ordering at egress

Result

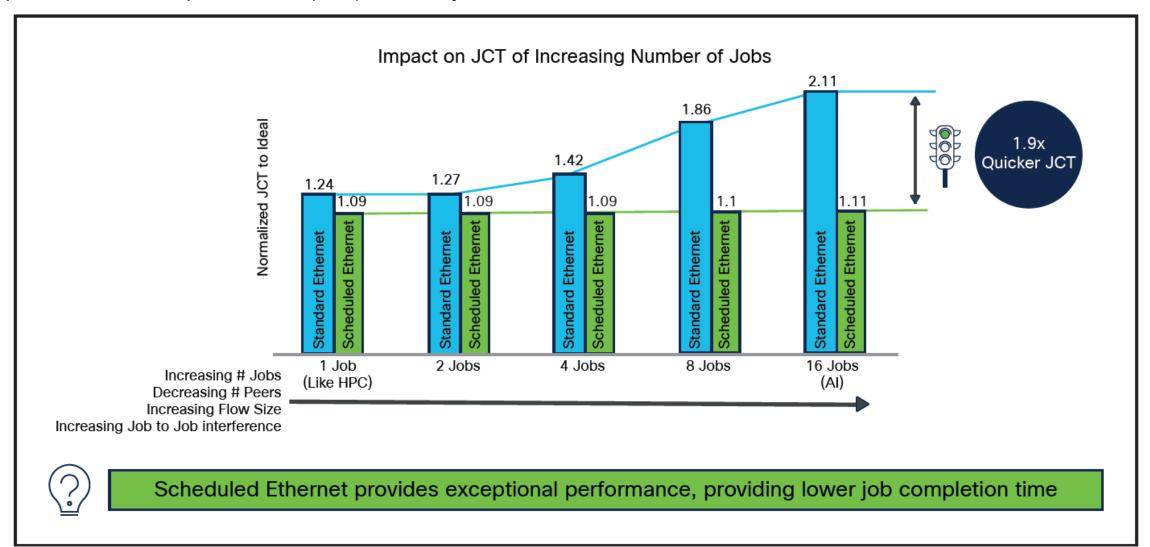
optimal network performance

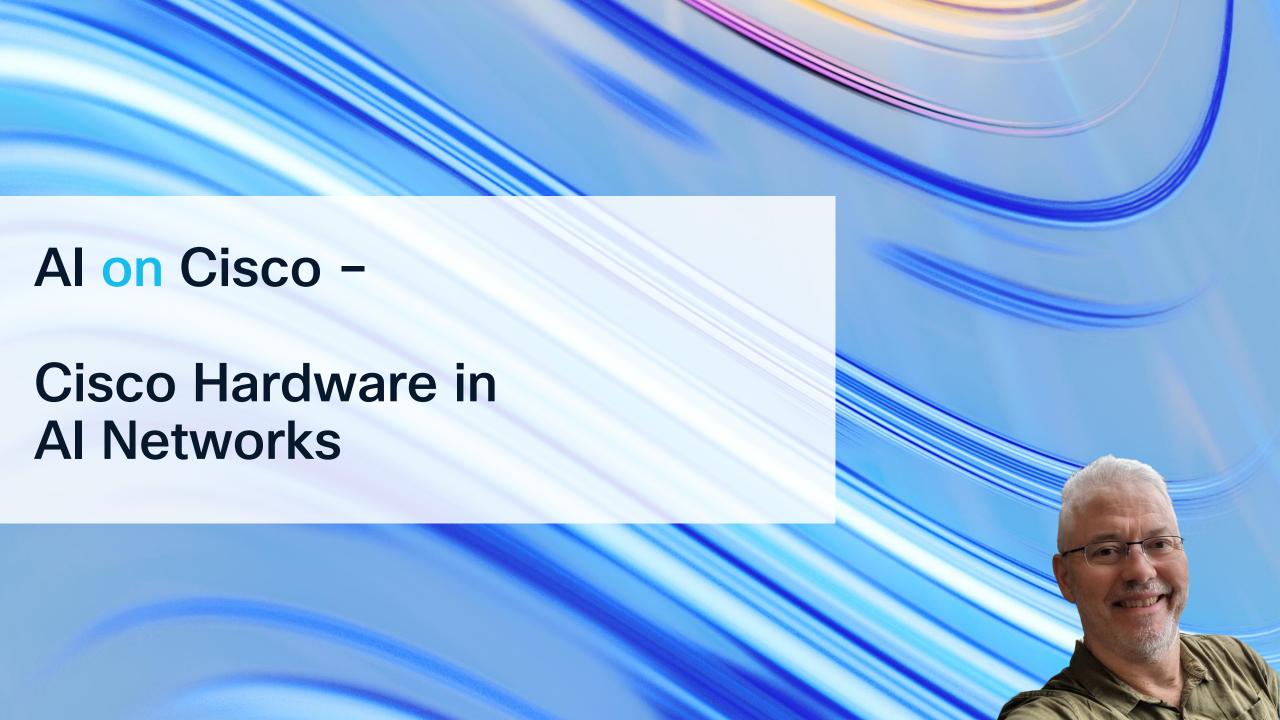


https://www.cisco.com/c/en/us/solutions/collateral/silicon-one/evolve-ai-ml-network-silicon-one.html

Building Networks for ML/AI Workloads

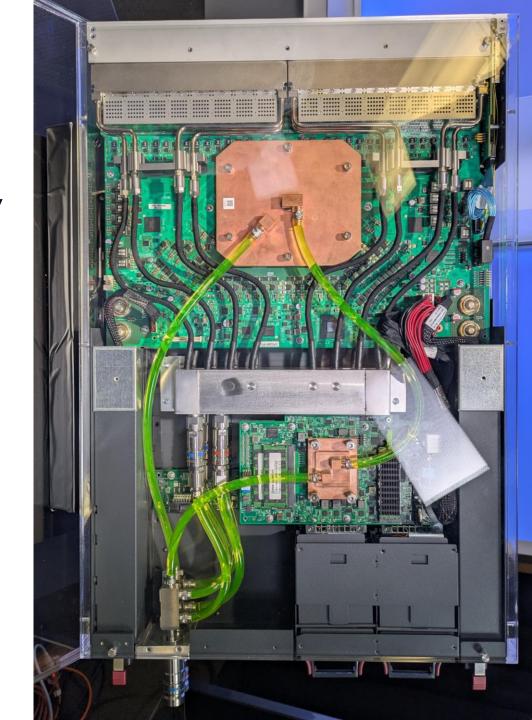
Optimized Job Completion Time(JCT) with Fully Scheduled Fabric





Cold Plate Liquid Cooling

- Power density/cooling is becoming the limiting constraint
- NVIDIA GB200 NVL72 is ~1.2kW per GPU and ~120kW per rack¹
- Microsoft and Meta Mount Diablo design uses 400Vdc² into the rack
- Google is planning for racks up to 1MW³
- Power savings
 - ~10-15% from system fans
 - ~60% facility power (chillers etc)
- Improves Power Usage Effectiveness(PUE)⁴ ~20%
- 1. NVIDIA GB200 NVL72: https://training.continuumlabs.ai/infrastructure/servers-and-chips/nvidia-gb200-nvl72
- 2. Mount Diablo: https://www.datacenterdynamics.com/en/news/microsoft-and-meta-reveal-open-ai-rack-design-with-separate-power-and-compute-cabinets/
- 3. Google 1MW rack plans: https://cloud.google.com/blog/topics/systems/enabling-1-mw-it-racks-and-liquid-cooling-at-ocp-emea-summit
- 4. Power usage effectiveness: https://en.wikipedia.org/wiki/Power_usage_effectiveness

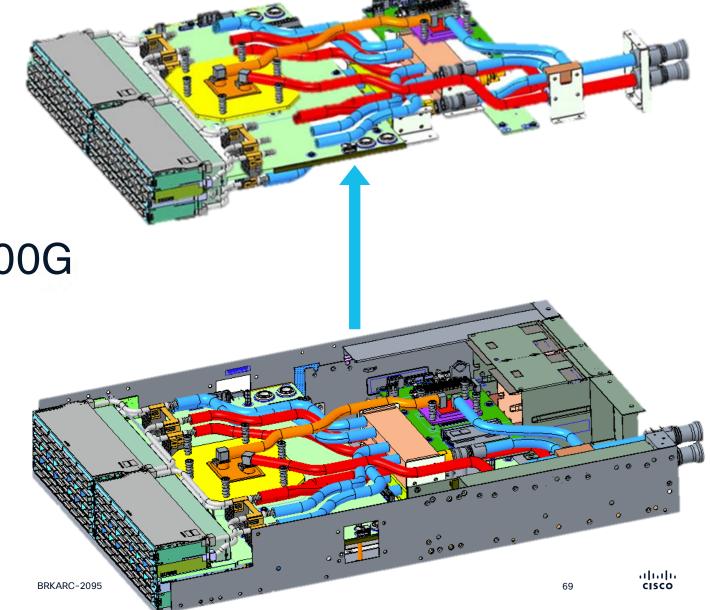


Liquid Cooling 51.2T Switch Technology Demonstration

Liquid cooled components:

ASIC, CPU, 64 x OSFP 800G

Liquid Cooling removes up to 80% of system heat



25.6T Co-Packaged Optics(CPO) at OFC 2023

Retimed optics

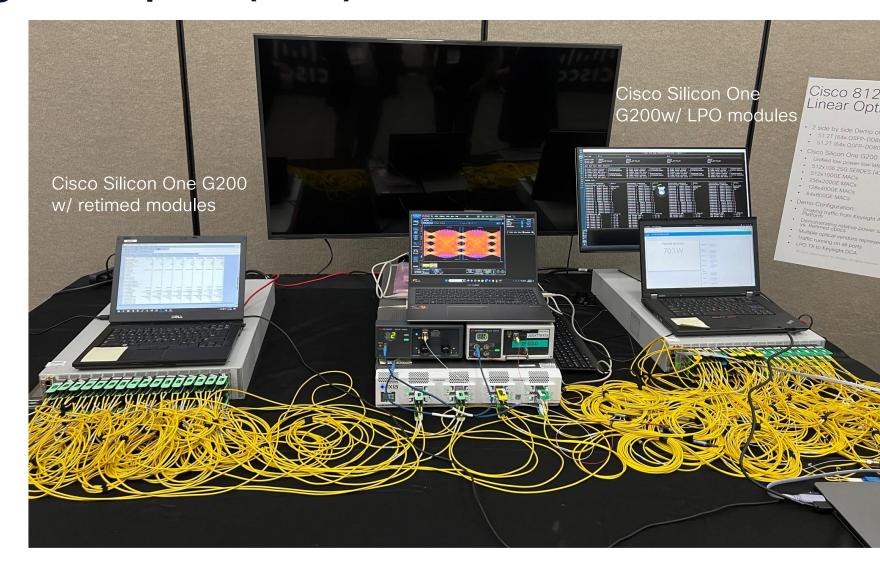
CPO

CPO power reduction: ~270W

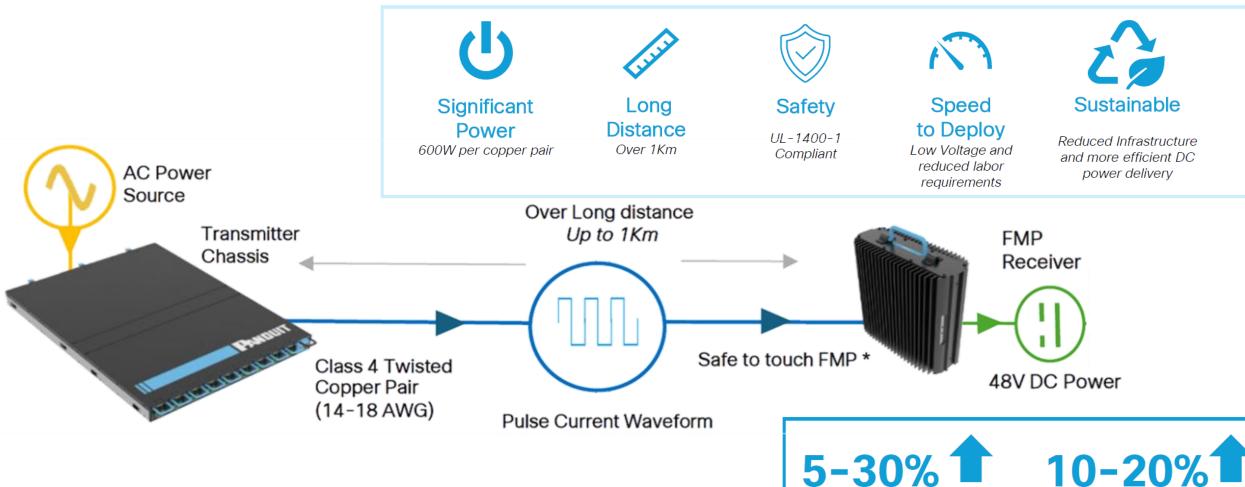


51.2T Linear Pluggable Optics(LPO) at OFC 2024

LPO power reduction: ~700W



Fault Managed Power: Touch Safe High Voltage DC

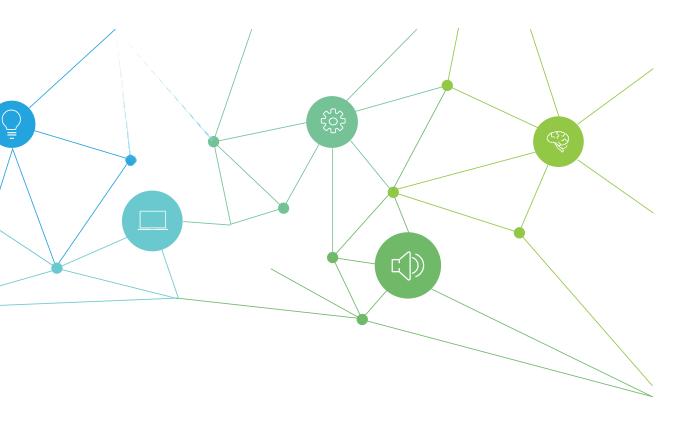


https://www.panduit.com/en/products/featured-products/panduit-fault-managed-power-system.html https://www.cisco.com/c/en/us/td/docs/engineering alliances/panduit fmps and cisco implementation guide.html increase in energy savings in buildings with widespread adoption of DC power **US Dept Energy**

10-20% increase in energy efficiency by eliminating AC to DC conversion www.energv.gov

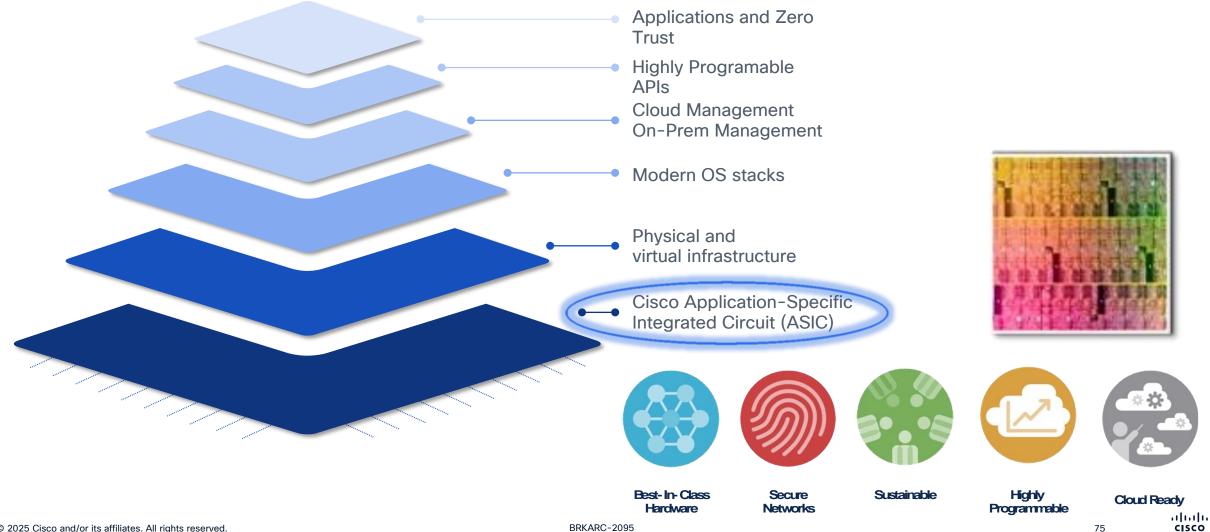
Summary -*Hardware*Cisco Silicon for Al

Cisco and Al



- Cisco is investing in Al capabilities
- We have a focus on creating Al solutions for use by customers
- We have a focus on creating solutions that support Al workloads

Cisco Silicon Hardware for Al Foundational Elements to Support Al Growth



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How Did We Do?

Cisco Silicon Hardware for Al

Do You Have a Better Understanding ...





... what Cisco is doing in Al and why it matters?

... of why Hardware Functionality and Flexibility are Key for Al Solutions ...

... and how You can Leverage
Cisco's Latest Flexible
Hardware and Advanced
Capabilities in Your Own
Network Designs?



Complete your session evaluations



Complete a minimum of 4 session surveys and the Overall Event Survey to be entered in a drawing to win 1 of 5 full conference passes to Cisco Live 2026.



Earn 100 points per survey completed and compete on the Cisco Live Challenge leaderboard.



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Contact us at: email: dzacks@cisco.com

bluesky: petergjones.bsky.social

What else to see

- Silicon One
 - Networking for AI DEMCPA-09
 - Networking for Al | Silicon One -DEMAIDC-04
 - Redefine your AI/ML networks with Silicon One - PSODCN-1005
 - Redefine your AI/ML networks with Silicon One - AIHUB-1004
 - SILICON ONE & ULTRA ETHERNET FOR AI INFRASTRUCTURE -BRKNWT-2508
 - Preparing for AI-Ready Infrastructure with Silicon One -ITLGEN-2065
 - Silicon One DEMCPA-10
 - Ethernet Fabrics for Al clusters –
 Silicon One and Nexus ultra high performance, scalable & non–

- blocking ethernet fabric. BRKCOC-3005
- Liquid Cooling
 - WoS demonstration Sustainability Booth
 - Integrated Rack Design | Liquid Cooling for Networking, Linear Pluggable Optics, and Rack System Cooling - DEMAIDC-02
 - The Al-Revolution Cooling Technologies for the Data Center & Edge – WOSGEN-2100
 - Improving Power Usage Effectiveness | Immersion Cooling and Energy Management -DEMAIDC-06
 - Next generation power and cooling technologies in the datacenter -IBOCOM-2101

Optics

- Optics for Al Infrastructure WOSGEN-2102
- Optics for Al Connectivity DEMSGC-03
- Integrated Rack Design | Liquid Cooling for Networking, Linear Pluggable Optics, and Rack System Cooling - DEMAIDC-02
- 400G, 800G, and Terabit Pluggable Optics: What You Need to Know -BRKOPT-2699



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