



AI for Science

Jeff Nichols, ORNL

Rick Stevens, ANL

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Science

Why AI? What can it do for Science?



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Data Analytics via Supervised Deep Learning

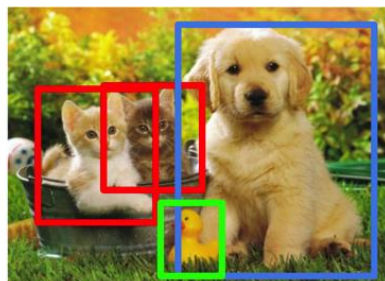
Classification



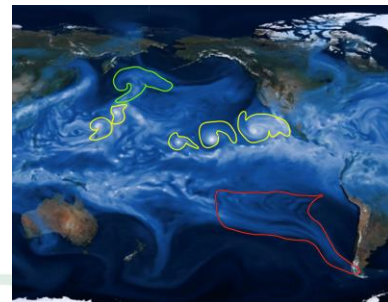
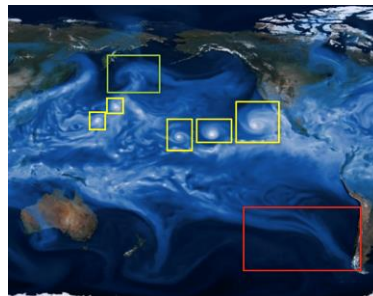
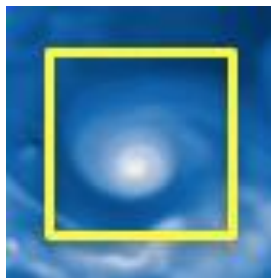
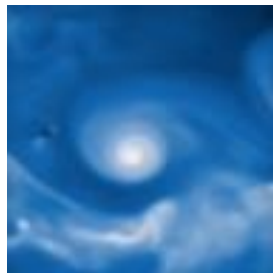
**Classification
+ Localization**



Object Detection



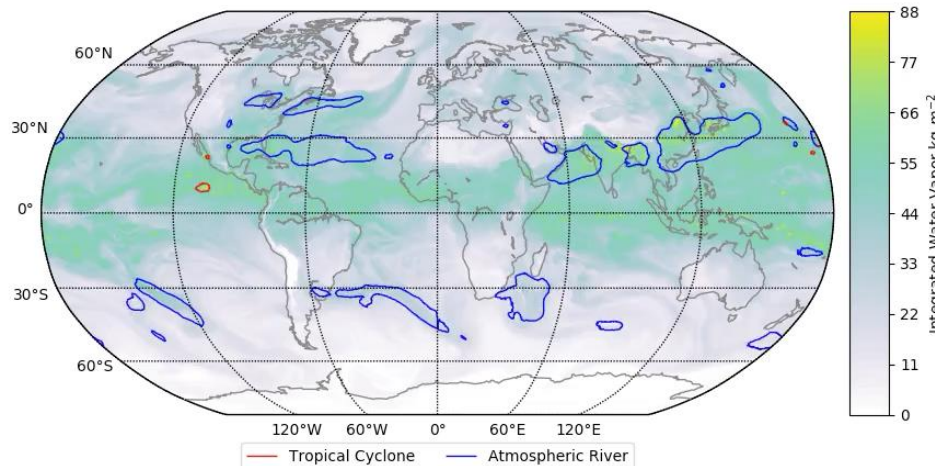
**Instance
Segmentation**



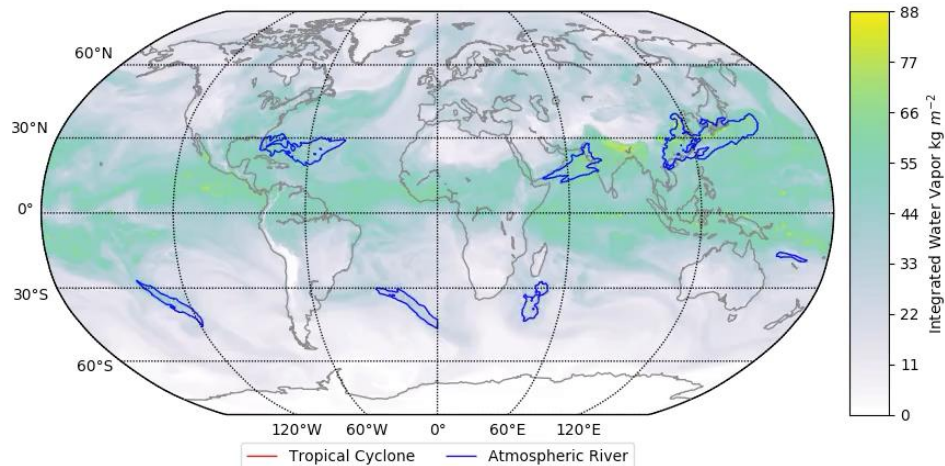
Extending image-based methods to complex, 3D, scientific data sets is non-trivial!

Big Data, Big Model, and Big Iron

Predicted Extreme Weather



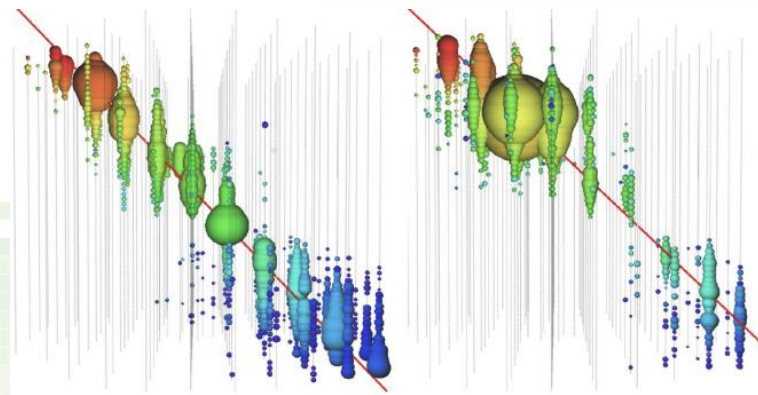
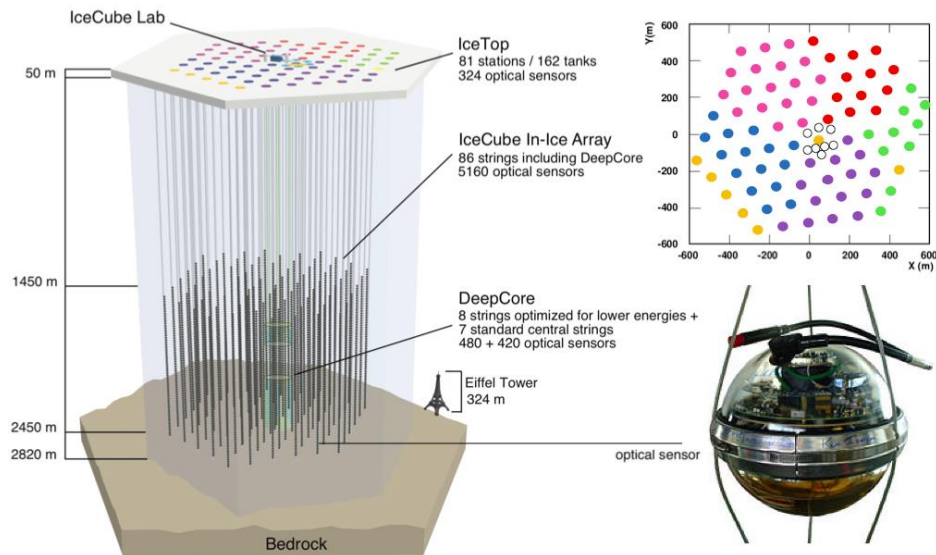
Ground Truth Extreme Weather



- Deep learning results are smoother than heuristic labels
- Achieved over 1 EF peak on OLCF Summit: Gordon Bell Prize in 2018

Graph NNs to Classify Neutrinos

- Apply graph convolutions to irregular, 3D detector grid
- Increase sensitivity of IceCube detector: 6.3x more events
- And improve Signal-to-Noise ratio by 3x



Light deposition for muons bundles

Stochastic light emission from a single high-energy muon

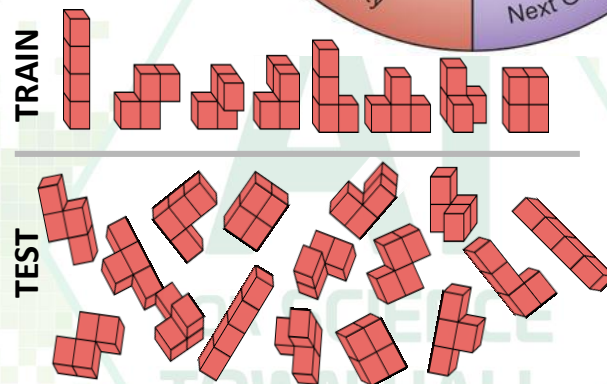
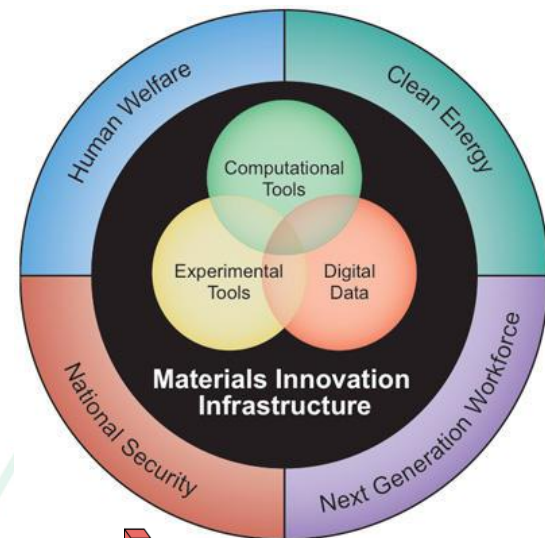


Materials Genome Initiative: generating data for learning



Rotated image

CNN filter output



Tensor field networks with 3D translation-
and 3D rotation-equivariance

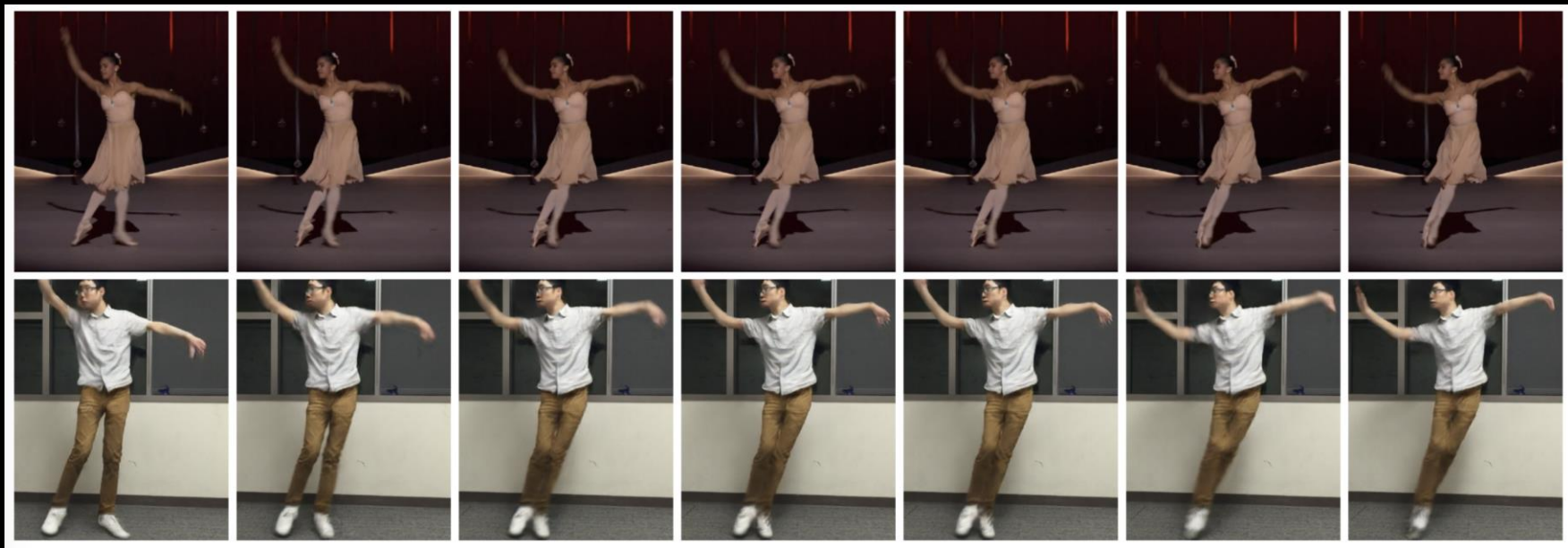
How to build next generation instruments and simulations with AI in mind?
(Smaller, faster, cheaper?)

Can we use existing data sets for new discoveries?

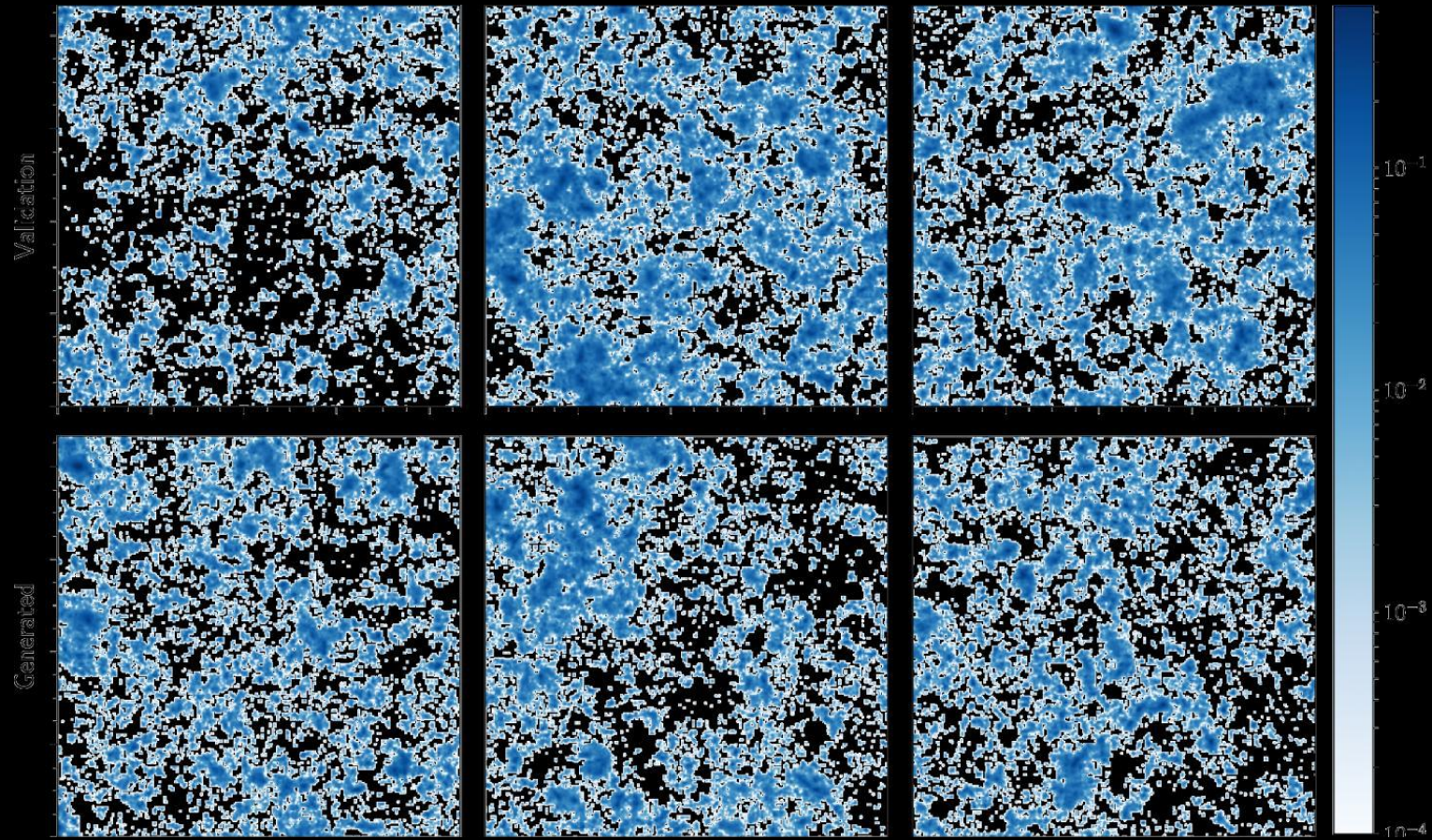
How will AI methods change?

Generative Adversarial Neural Nets make “Everybody Dance Now”

Caroline Chan, Shiry Ginosar, Tinghui Zhou, Alexei A. Efros, UC Berkeley



GANs to build convergence maps of weak gravitational lensing



CosmoGAN: Mustafa Mustafa, Deborah Bard, Wahid Bhimji, Zarija Lukić, Rami Al-Rfou, Jan M. Kratochvil

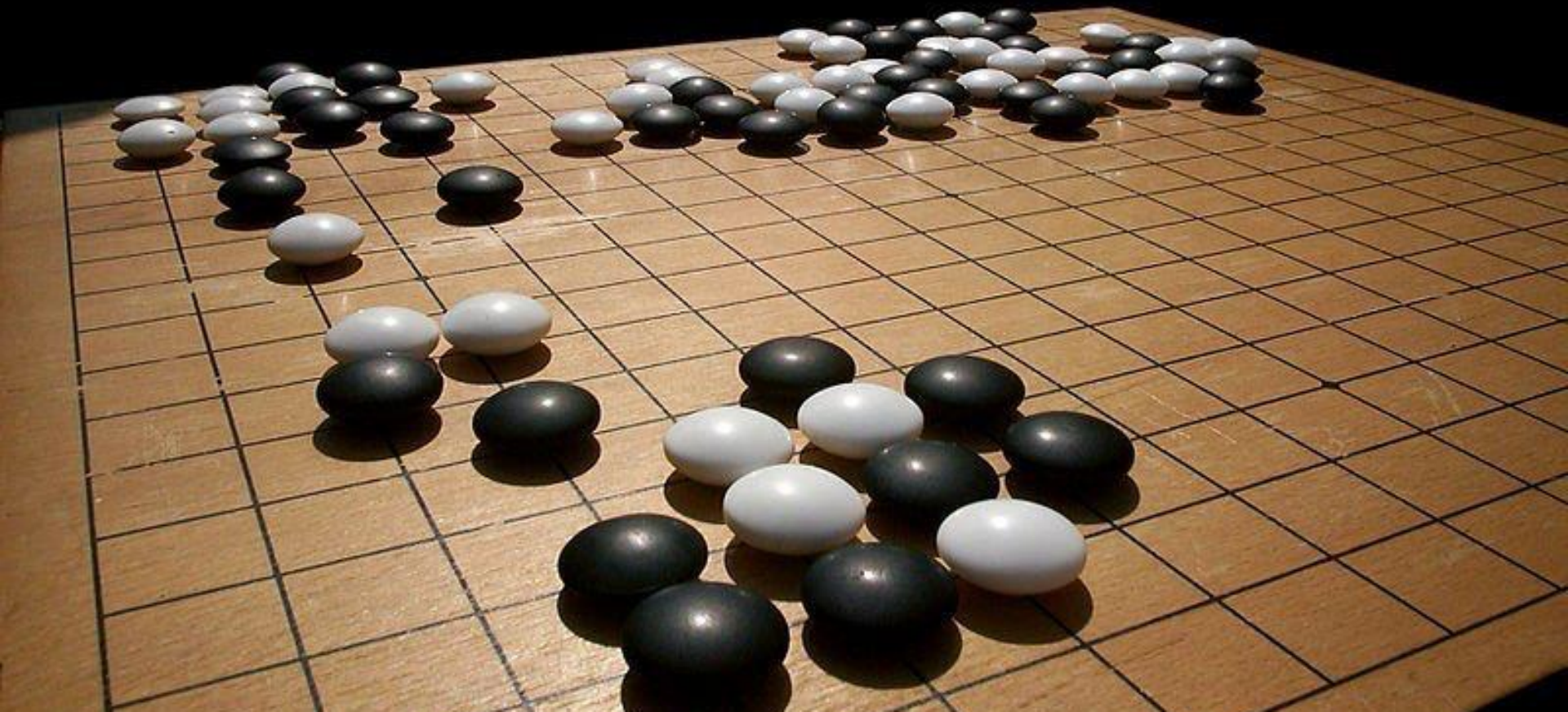
What scientific data sets can AI create?

(Test instruments, evaluate theories, approximate expensive simulations and experiments)

What level of confidence will we need in AI?



Deep Reinforcement Learning to play games of strategy



RL to control complex systems like traffic



Baseline Scenario



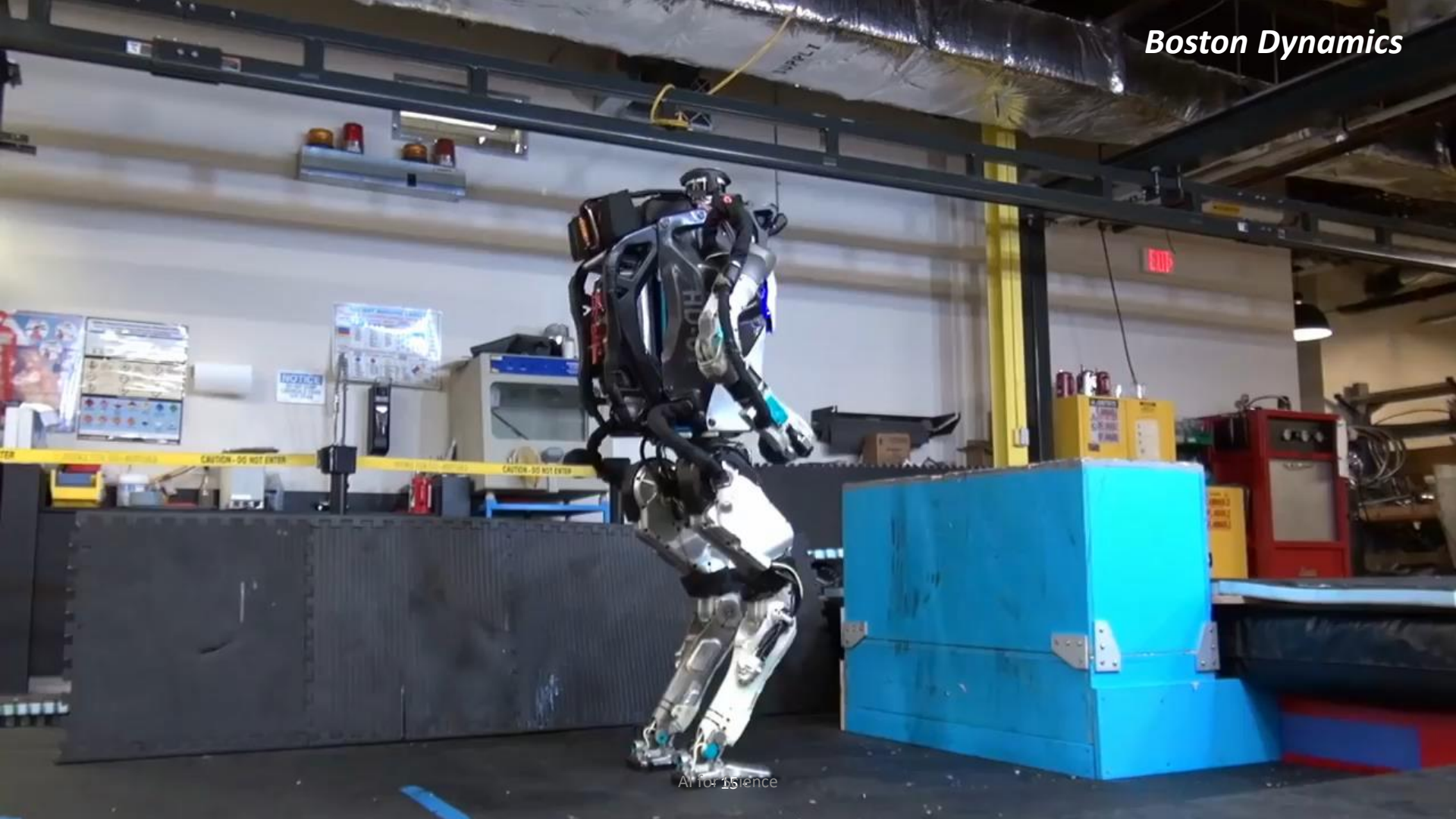
RL Vehicles

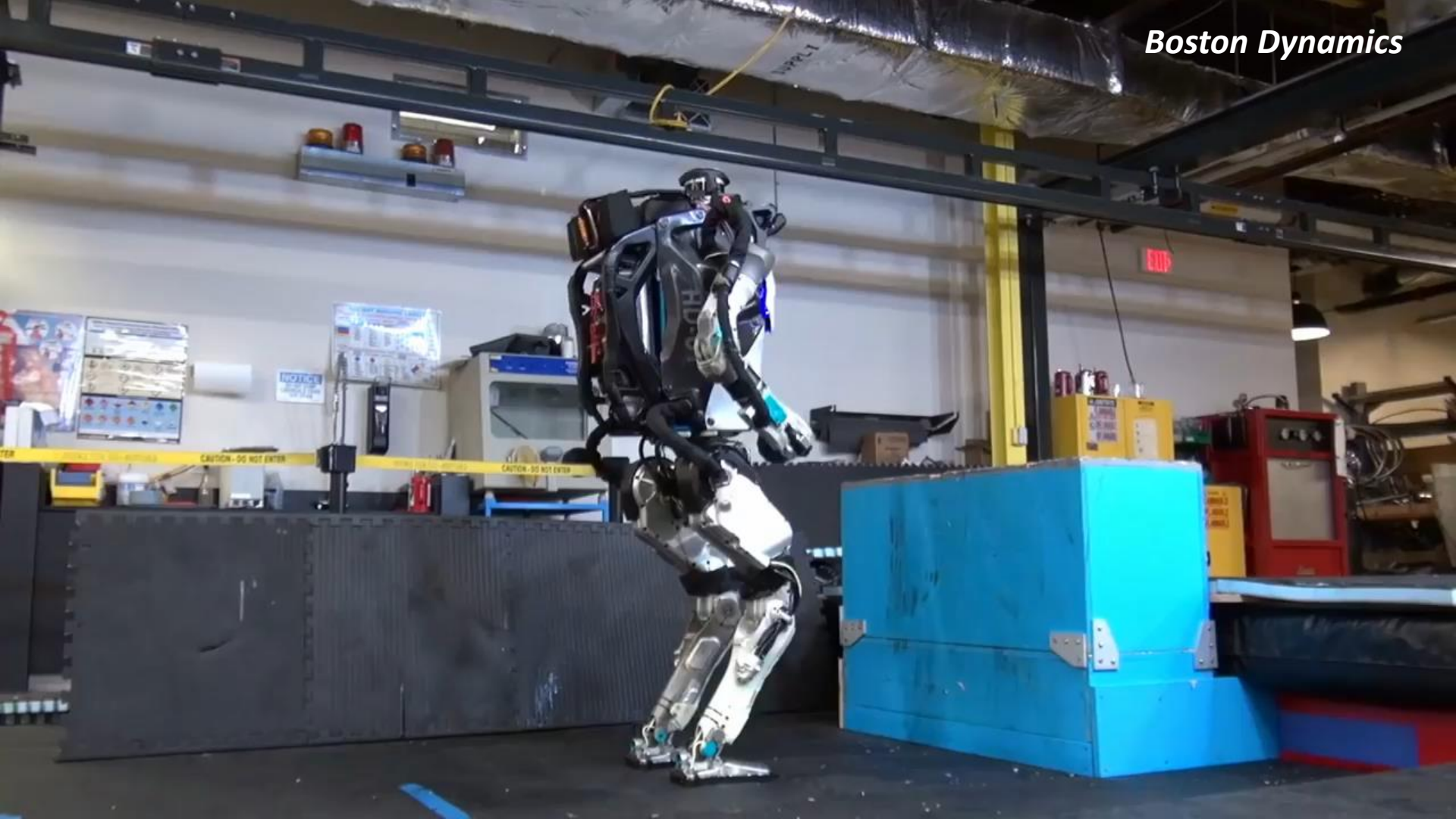
How can AI navigate complex spaces?

(Optimize energy systems, IT systems, find best path through space of experiments)

How do the systems need to change to support automation?



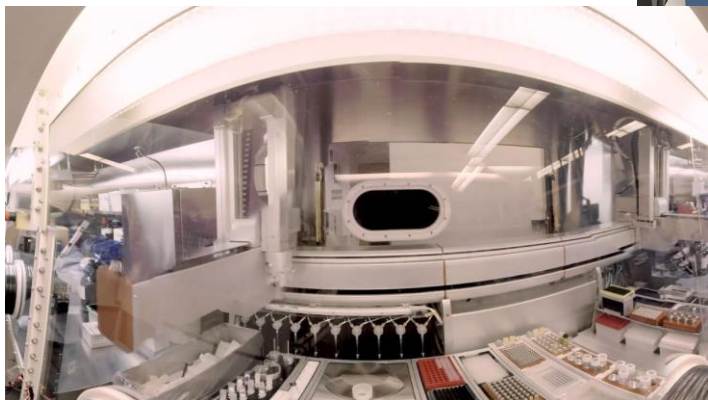




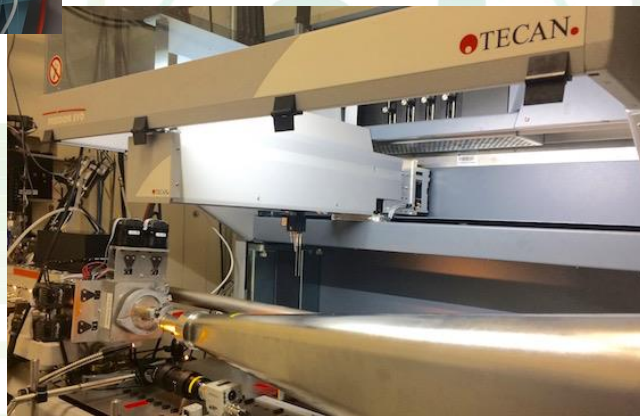
Robotics and precision control in science



MassSpec robot at JGI



Nanoparticle Robot at the Molecular Foundry



Robot at SYBLIS beamline at ALS

How will robotics and automation transform user facilities?

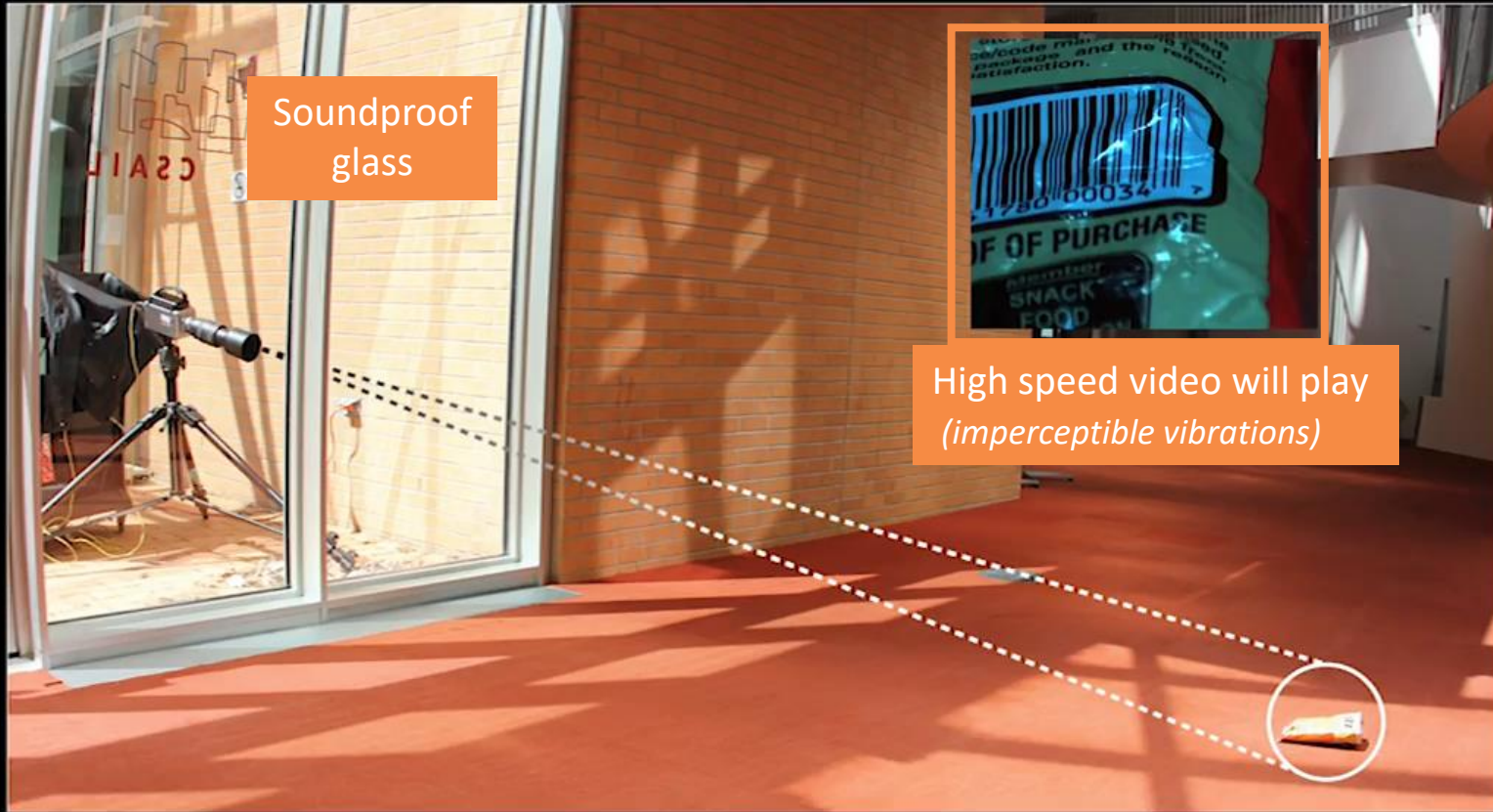
(Lab in the cloud, remote access, higher throughput)

How will AI-trained robots enable new instruments?

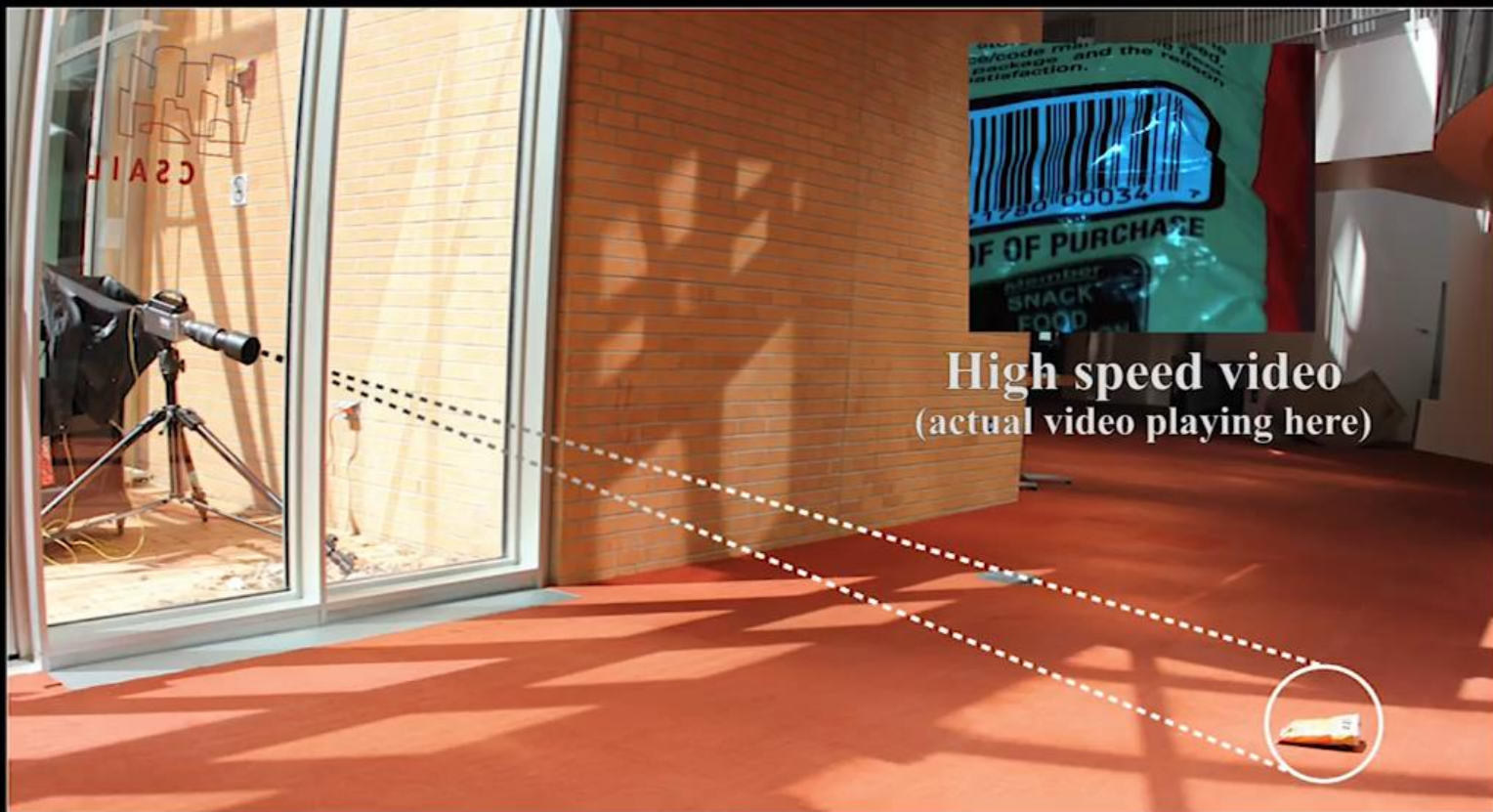
(Particle accelerators, fusion, etc.)

What level of confidence will we need in AI?

Extracting signals from noisy data: “Visual Microphone”

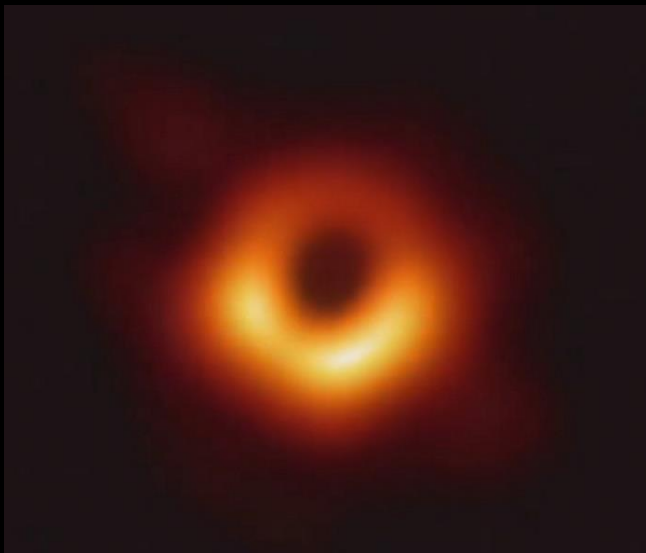


Abe Davis, M Rubinstein, N Wadhwa, GJ
Mysore, F Durand, WT Freeman, MIT AI for Science

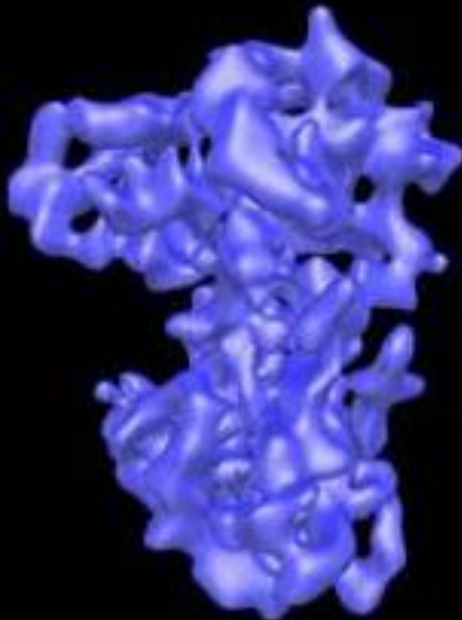


High speed video
(actual video playing here)

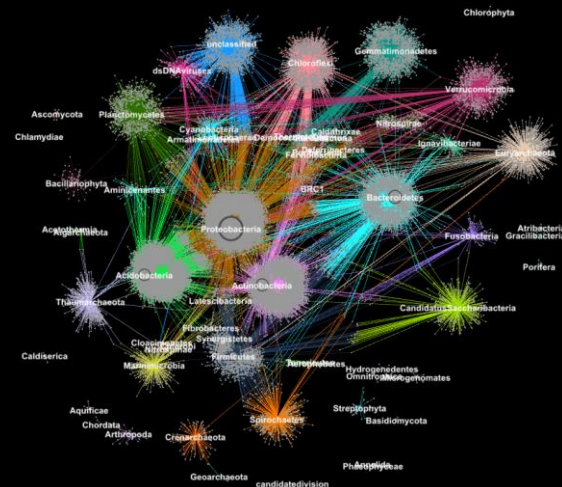
Finding Structure in Sparse, Noisy Data



First Image of a Black Hole



Retinoblastoma Protein



New protein clusters

Where can AI find smaller signals in noisier data?

How can AI learn physically realistic models and design processes?



How can AI help?

Data Analytics

Classification

Regression

Clustering

Dimensionality
Reduction

Inverse problems

Model
reconstruction

Parameter
estimation

Denoising

Surrogate models

Approximate
expensive
simulations

Approximate
experiments

Fill in missing
models in
simulations

Design and control

Optimize design of
experiments

Control
instruments

Navigate state
spaces

Learn from sparse
rewards

A Vision for the Future of AI in Science



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AI for Science Vision: 2020 \Rightarrow 2030

- AI will enable us to attack **new problems**
- AI becomes **equal partners** to modeling and simulation and data analysis
- AI will **enable experimentalists to harness the power of Exascale** computing
- AI will power **automated laboratories** and change the nature of experimental science
- AI will need **new computing architectures, new software environments, new policies** and create **new user communities** and new ways of dissemination
- AI **will improve how DOE laboratories operate** and how work is done

Things we can do in Science with AI now

Learn predictive models from data without relying upon theory or deep mechanistic understanding

Example: predicting materials and chemistry properties

Learn approximate solutions to inverse problems where we have data and models are not available or are inefficient

Example: phase retrieval in coherent x-ray imaging

Generate large collections of synthetic data that models real data

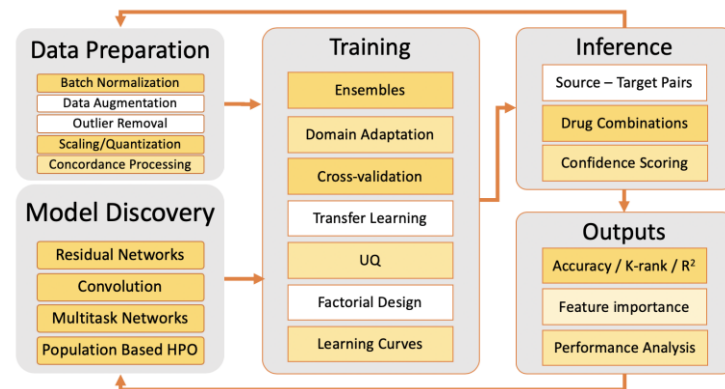
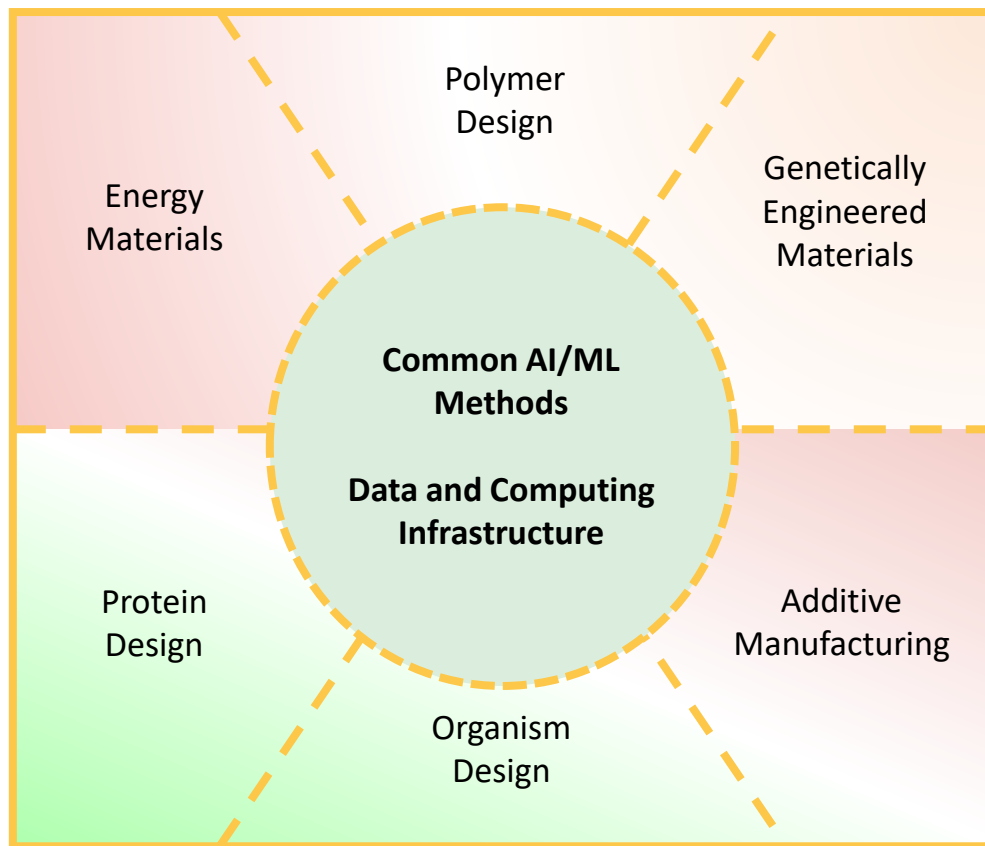
Example: synthetic sky in cosmology

In Ten Years...

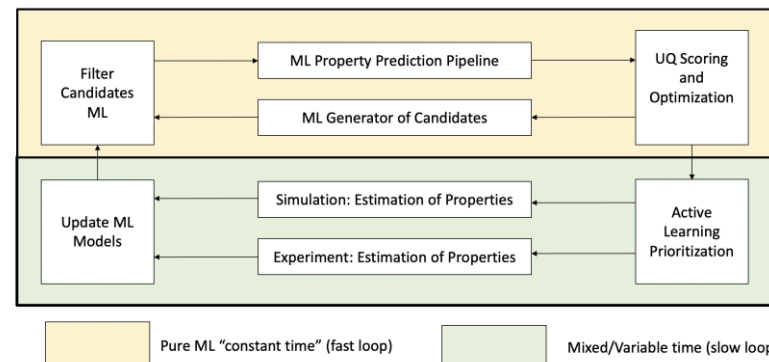
- **Learned Models Begin to Replace Data**
 - queryable, portable, pluggable, chainable, secure
- **Experimental Discovery Processes Dramatically Refactored**
 - models replace experiments, experiments improve models
- **Many Questions Pursued Semi-Autonomously at Scale**
 - searching for materials, molecules and pathways, new physics
- **Simulation and AI Approaches Merge**
 - deep integration of ML, numerical simulation and UQ
- **Theory Becomes Data for Next Generation AI**
 - AI begins to contribute to advancing theory
- **AI Becomes Common Part of Scientific Laboratory Activities**
 - Infuses scientific, engineering and operations



AI Driven Autonomous Laboratory Cluster



Layered workflow combining AI, HPC and HTS



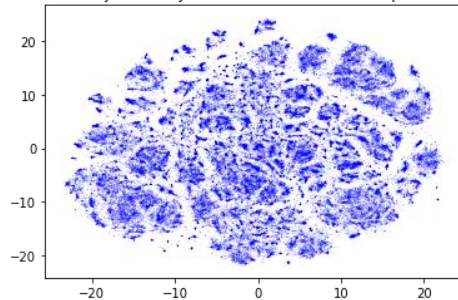
Connecting HPC and AI

In addition to partnerships in AI applications, there are considerable opportunities in foundational methods development, software and software infrastructure for AI workflows and advanced hardware architectures for AI, below we highlight some ideas in the HPC + AI space

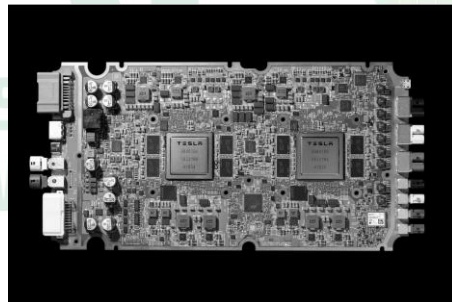
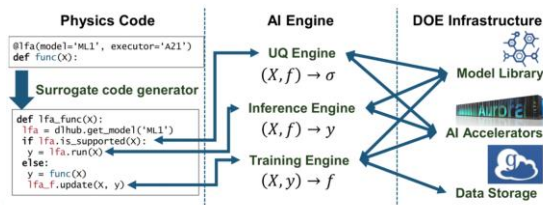
- Steering of simulations
- Embedding ML to simulation methods
- Customized computational kernels
- Tuning applications parameters
- Generative models to compare with simulation
- Student (AI) Teacher (Sim) models \Rightarrow learned functions
- Guided search through parameter spaces
- Hybrid architectures HPC + Neuromorphic
- Many, many more

Generative Models

Projection of Junction Tree autoencoder space



Learned Function Accelerators



The Landscape of AI Research and Applications



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AI: a fundamental shift in the economic and military landscape

- Executive Order brings focus to national strategy and government engagement
- Industry focuses on developing AI-based products for business, especially social, financial, health and security
- Universities focus on basic research and education
- DOE has a unique role
 - Mission-driven development and application of AI/ML, i.e., innovation in, for example
 - Science
 - Energy
 - National security
 - Build on its HPC mission
 - Large-scale scientific data for research
 - Talent development



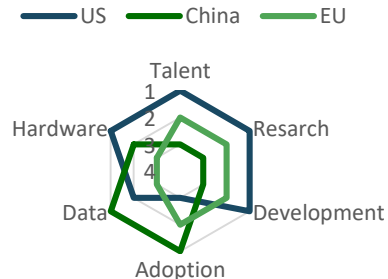
Vision: Transform DOE into a world-leading AI enterprise by accelerating the research, development, delivery, and adoption of AI.

Observations on the international AI landscape

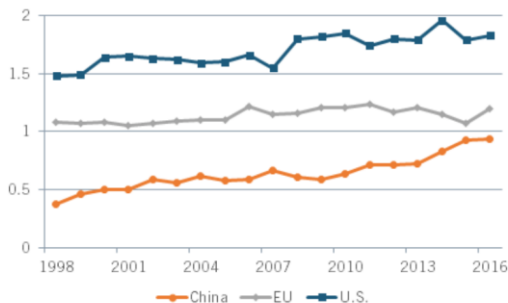
Of the 35 countries that have AI strategies, only three stand out, the U.S., the E.U. and China.

- The U.S.
 - Leads in research, development and talent (education)
 - Based on historical investments in education, laboratories and the business environment
- China
 - Leads in overall adoption of AI and the collection and use of data
 - Is investing heavily
 - Quality and development is increasing rapidly
- The E.U.
 - Has the most researchers
 - Does not translate this into innovation effectively

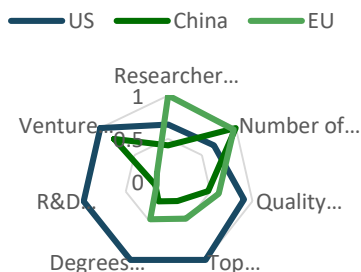
Relative ranking of US, EU and China



Field-weighted Citation Index Trends



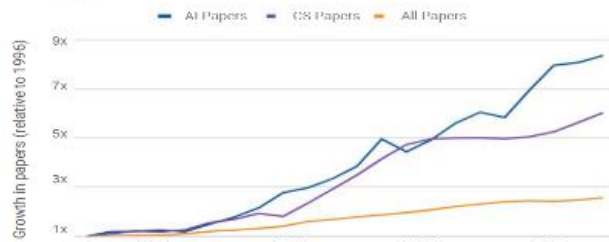
Research metrics (normalized)



The AI/ML Research Landscape (Measured by Publications)

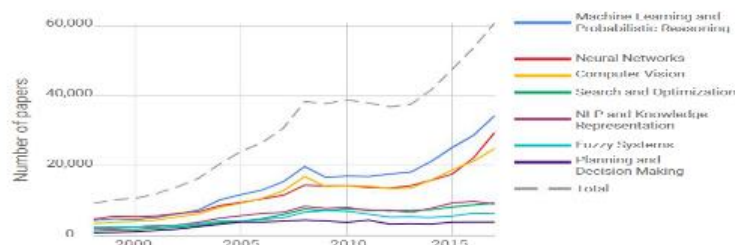
Growth of annually published papers by topic (1996–2017)

Source: Scopus

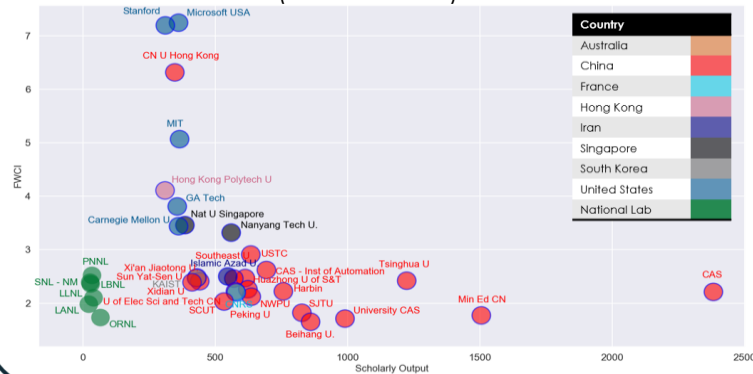


Number of AI papers on Scopus by subcategory (1998–2017)

Source: Elsevier



Neural Network Publications
(2016 – Present)



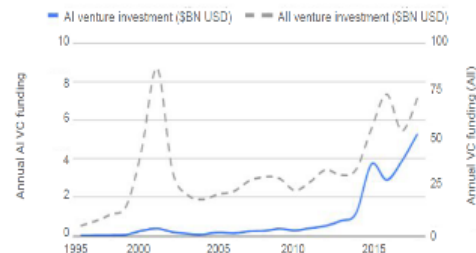
Machine Learning Publications
(2016 – Present)



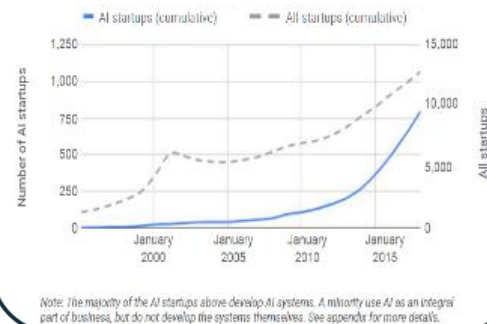
The Business Landscape

- Business must incorporate AI
 - The “Big 9” dominate, but don’t discount traditional business
 - \$7.4B in start-up investments in 488 deals in 2019/Q2 (over \$12B in the past 6 months)
 - \$803M in “AI for cybersecurity” VC in last six months
- Barriers to insertion
 - Understanding: 37% of executive feel their employees understand the importance of data
 - Trust:
 - 49% of U.S. consumers would trust AI-generated advice for retail,
 - 38% would trust AI-generated advice for hospitality, while only
 - 20% would trust AI-generated advice for healthcare and
 - 19% for financial services
 - Example: 33% of US and 85% of Chinese healthcare professionals have implemented AI into their practice, compared to a 5-country average of 46%.
- Need a consistent approach to regulatory (data and sensitive technologies)

Annual VC funding of AI startups (U.S., 1995 – 2017)
Source: Sand Hill Econometrics



AI startups (U.S., January 1995 – January 2018)
Source: Sand Hill Econometrics



DOE is building on a record of success delivering HPC capabilities

Pre-exascale systems

First exascale systems

2012

2016

2018

2020

2021-2023



Titan

ORNL
Cray/NVIDIA



Mira

ANL
IBM BG/Q



Theta

ANL
Cray/Intel KNL



Edison

LBNL
Cray/Intel Xeon



Cori

Cray/Intel Xeon/KNL

LBNL



Summit

ORNL
IBM/NVIDIA



Perlmutter

Cray/AMD/NVIDIA

LBNL



Aurora

ANL
Intel/Cray



FRONTIER

ORNL
Cray/AMD



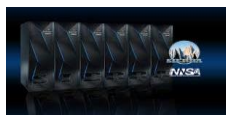
Sequoia

LLNL
IBM BG/Q



Trinity

LANL/SNL
Cray/Intel Xeon/KNL



LLNL
IBM/NVIDIA



LANL/SNL
TBD



LLNL
Cray

Dramatically increasing AI/ML capabilities

DOE NNSA ASC Computing

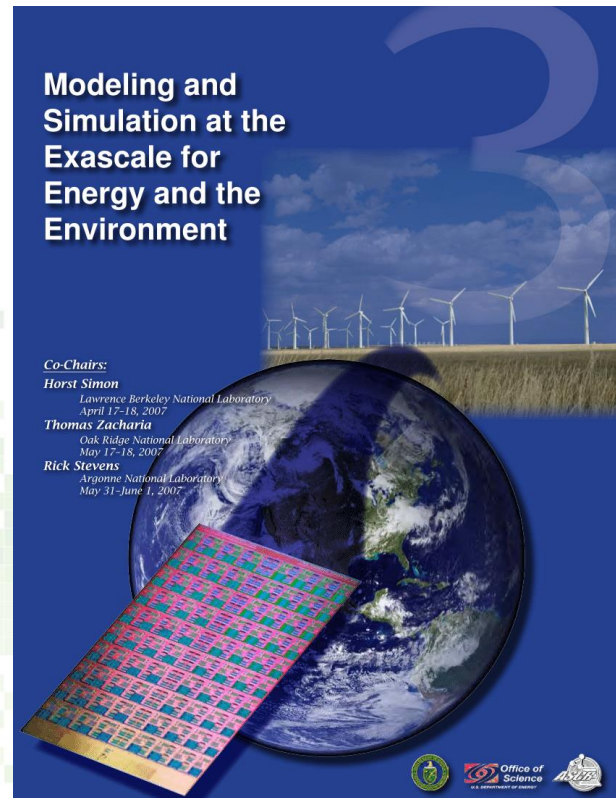
Washington DC Town Hall
October 22-23



Science

Why Are We Here?

- Exascale Town Halls in 2007
- Led to many other workshops (>10)
- ASCAC engagement
- NSCI
- And the Exascale Computing Initiative
 - ECP: Exascale Computing Project
 - Exascale systems
 - Application efforts across DOE
- Ideas for the next big thing, complementing exascale
- 4 Town Halls organized by the Labs
 - 4th is in DC, October 22-23

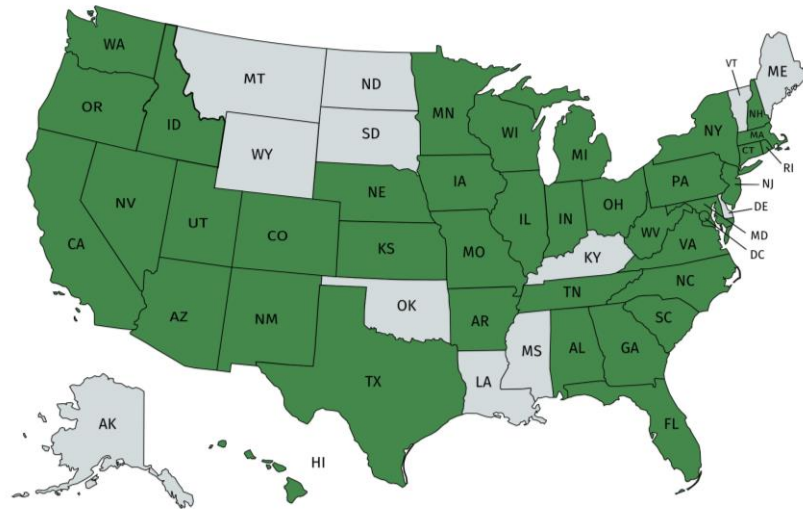


The AI for Science Town Halls so far

- Over 1000 registrations across 4 Town Halls

ANL	357	
ORNL	330	
LBNL	349	+100 online
DC	273	+ ?
Totals	1309	

- All 17 DOE National Laboratories
- 39 Companies from large and small
- Over 90 different universities
- 6 DOE/SC Offices + EERE and NNSA



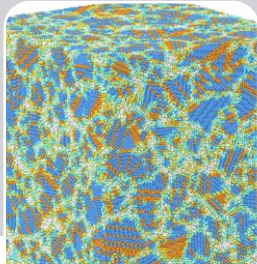
The AI for Science Town Halls so far

Argonne



Cosmology

Salman Habib



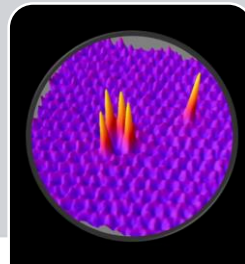
Materials

Ian Foster



Climate

Rao Kotamarthi



Microscopy

Sergei Kalinin

Oak Ridge



Manufacturing

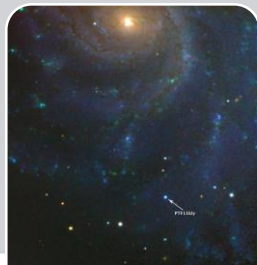
Tom Kurfess



Health

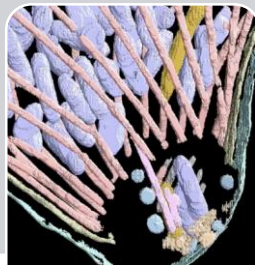
Gina Tourassi

Berkeley



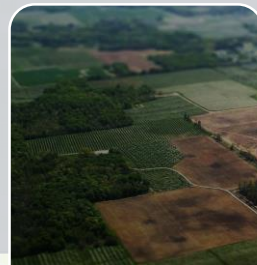
Astrophysics

Josh Bloom



User Facilities

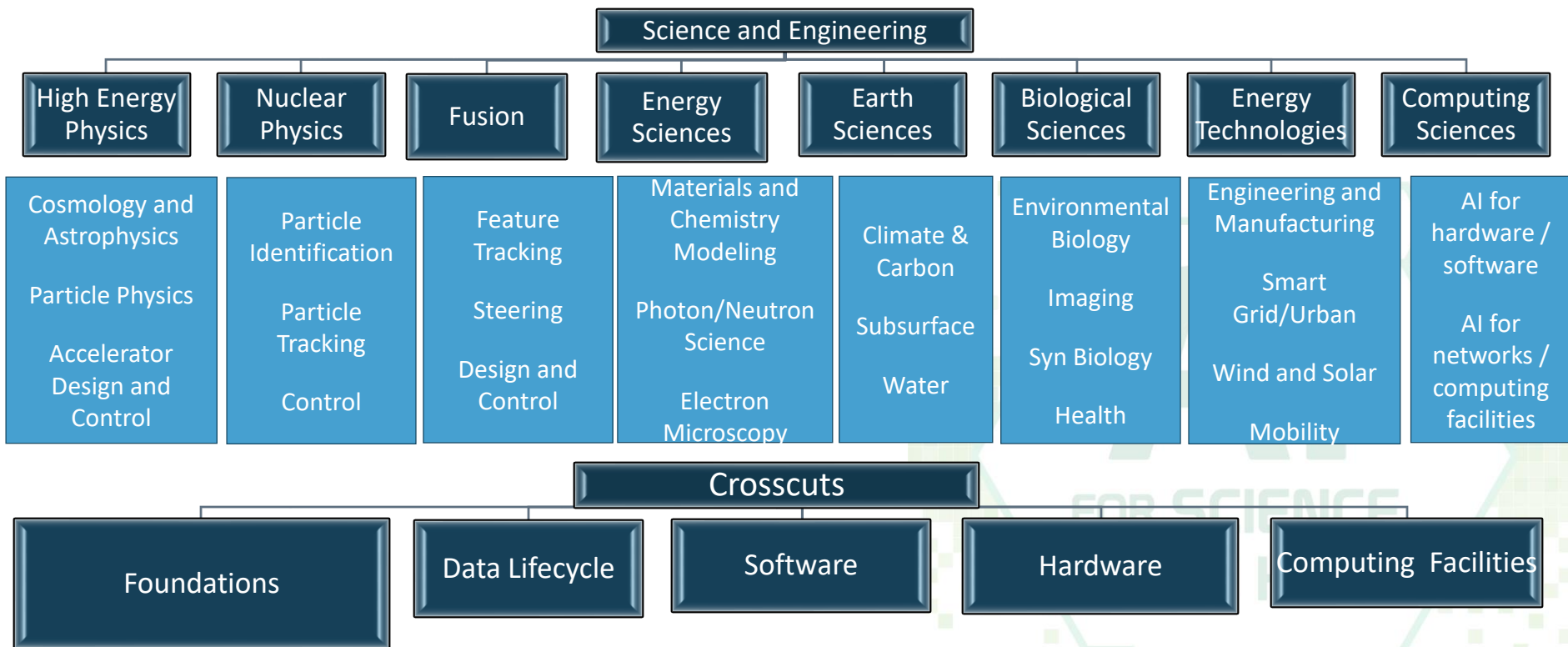
James Sethian



Biology

Ben Brown

Breakouts and Subtopics



AI Hardware Technology and Industry

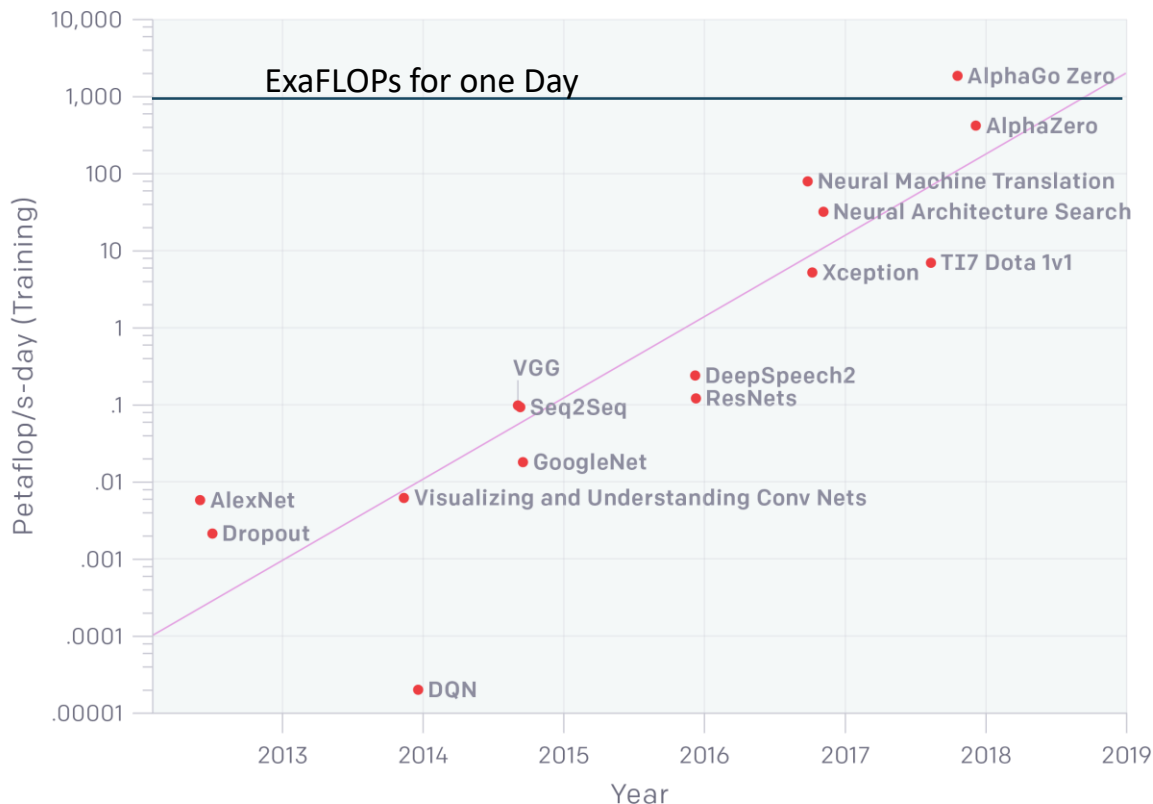


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Deep Learning Needs High Performance Computing

AlexNet to AlphaGo Zero: A 300,000x Increase in Compute



**Specialized hardware is emerging that will be
10x – 100x the performance of
general purpose CPU and GPU designs for AI**

**US VCs investing >\$4B in startups
for AI acceleration**

Which platforms will be good for science?

AI Chip Landscape

More on <https://basicmi.github.io/AI-Chip/>

Tech Giants/Systems

Google

Microsoft

aws IBM

facebook

Apple

HUAWEI 百度

Alibaba Group
阿里巴巴集团

FUJITSU NOKIA

TOSHIBA

Hewlett Pack
Enterprise

DELL

IC Vender/Fabless

intel

SAMSUNG

NVIDIA

QUALCOMM

AMD

NXP ST

XILINX

MEDIATEK

BROADCOM

MARVELL

Rockchip
瑞芯微电子

IP/Design Service

arm

SYNOPSYS

Imagination

cadence

CEVA

VeriSilicon

SiFive

ARTERIS IP

alchip GUC

FARADAY

eSilicon

Startup in China

Cambricon
寒武纪科技

地平线
Horizon Robotics

BITMAIN

intel fusion
云天励飞

ChipIntelli

Think Force

Canaan

云和声
Unisound Rokid

AISPEECH 思必驰
专注人性化的智能语音

瞻微电子
NextVPU

Enflame

亿智科技
清微智能
TSING MICRO

Startup Worldwide

cerebras

WAVE
COMPUTING

Graphcore

habana

thinci

SambaNova
SYSTEMS

KALRAY

LIGHT
INTELLIGENCE

HAILO
Empowering Intelligence

Esperanto
TECHNOLOGIES

Tenstorrent

MYTHIC

Preferred
Networks

brainchip

PEZY Computing

GREENWAVES
TECHNOLOGIES

AMOTIVE

KONIKU

Tachyum

flexlogix

SYNTIANT

gyrfalcon
technology

NOVUMIND

groq



扫码访问AI芯片文章

Compiler

XRT

GLOW

tvm

NVIDIA TensorRT

ONNX



nGraph Compiler stack (Beta)

plaidML

Benchmarks

MLPerf

AI - Benchmark

AI Matrix.

中国人工智能产业联盟
China Artificial Intelligence Industry Alliance

AI Across Government Agencies



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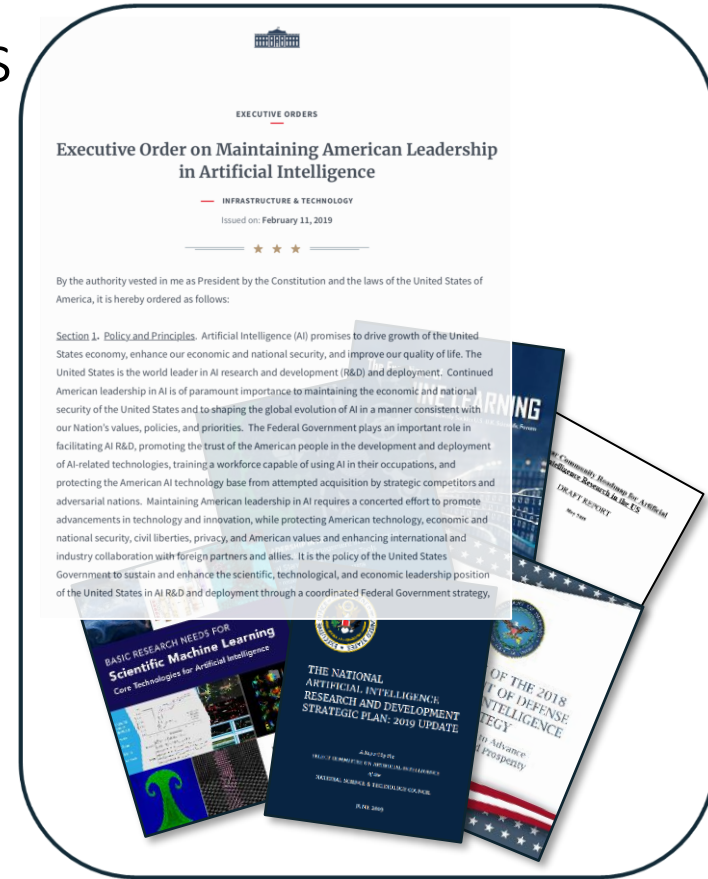
Development and Application of AI Critical For All Government Agencies

- Executive Order on AI

Policy Statement: Artificial Intelligence (AI) promises to drive growth of the United States economy, enhance our economic and national security, and improve our quality of life.

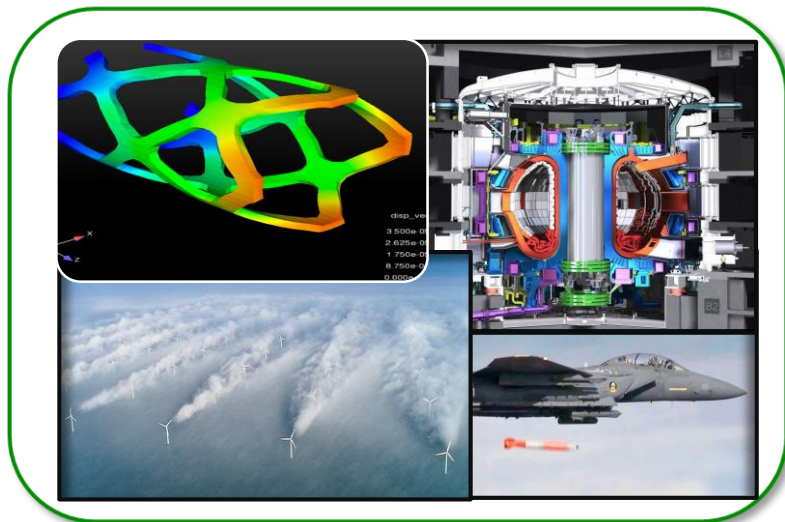
... leadership requires a concerted effort to promote advancements in technology and innovation, while protecting American technology, economic and national security, civil liberties, privacy, and American values and enhancing international and industry collaboration with foreign partners and allies.

- Supported by multiple agency strategies and programs



DOE builds on historical missions and touches all areas

- The U.S. AI strategy includes
 - 1. Long-term investment in research**
 2. Effective methods for human-AI collaboration
 3. Address ethical, legal and social implications
 - 4. Ensure the safety and security of AI Systems**
 - 5. Develop shared datasets and environments**
 6. Standards and benchmarks
 7. Understand the AI workforce
 8. Expand public-private partnerships
- DOE will play a key role in AI for science and engineering
 - AI Technology office
 - Research and talent development
 - Data to support science and engineering research



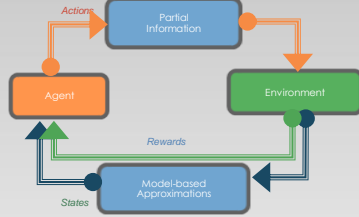
DOE research challenges touch all areas of AI

Data



- Experimental design
- Data curation and validation
- Compressed sensing
- Facilities operation and control

Learning



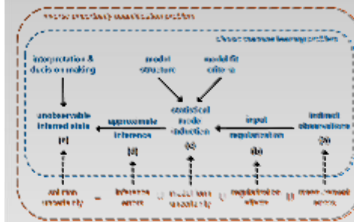
- Physics informed
- Reinforcement learning
- Adversarial networks
- Representation learning and multi-modal data
- “Foundational math” of learning

Scalability



- Algorithms, complexity and convergence
- Levels of parallelization
- Mixed precision arithmetic
- Communication
- Implementations on accelerated-node hardware

Assurance



- Uncertainty quantification
- Explainability and interpretability
- Validation and verification
- Causal inference

Workflow



- Edge computing
- Compression
- Online learning
- Federated learning
- Infrastructure
- Augmented intelligence
- Human-computer interface

AI Revolution

- **Learned Models Replace Data**
- **Experimental Discovery Refactored**
- **Questions Pursued Semi-Autonomously**
- **Simulation and AI Merge**
- **Theory Becomes Data**
- **AI Laboratories**

