



# Applying HPC and AI/ML Capabilities for Stockpile Stewardship Mission



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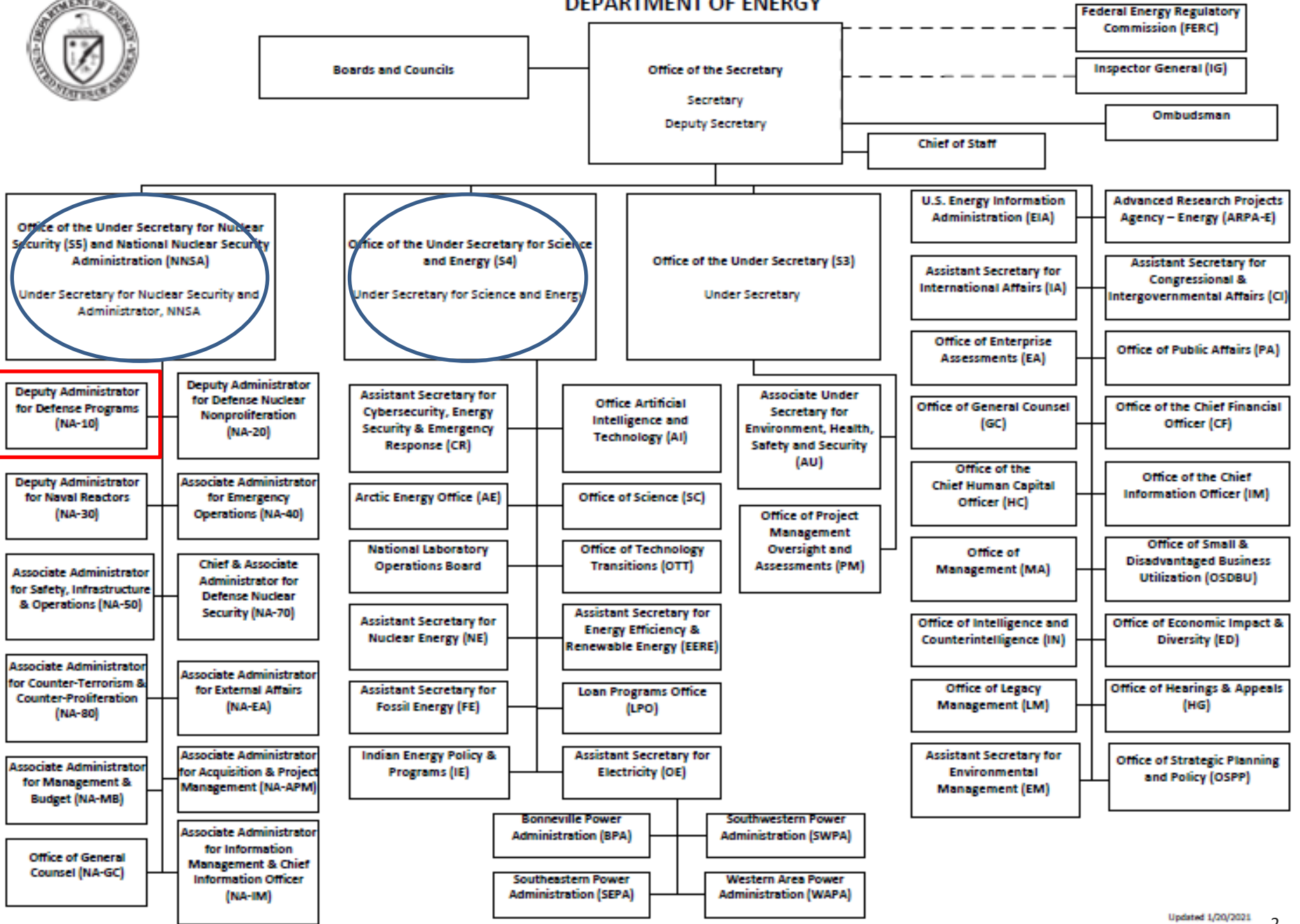
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NATIONAL NUCLEAR SECURITY ADMINISTRATION OFFICE OF DEFENSE PROGRAMS



# DEPARTMENT OF ENERGY



# Defense Programs is Structured to Support the United States Nuclear Deterrent

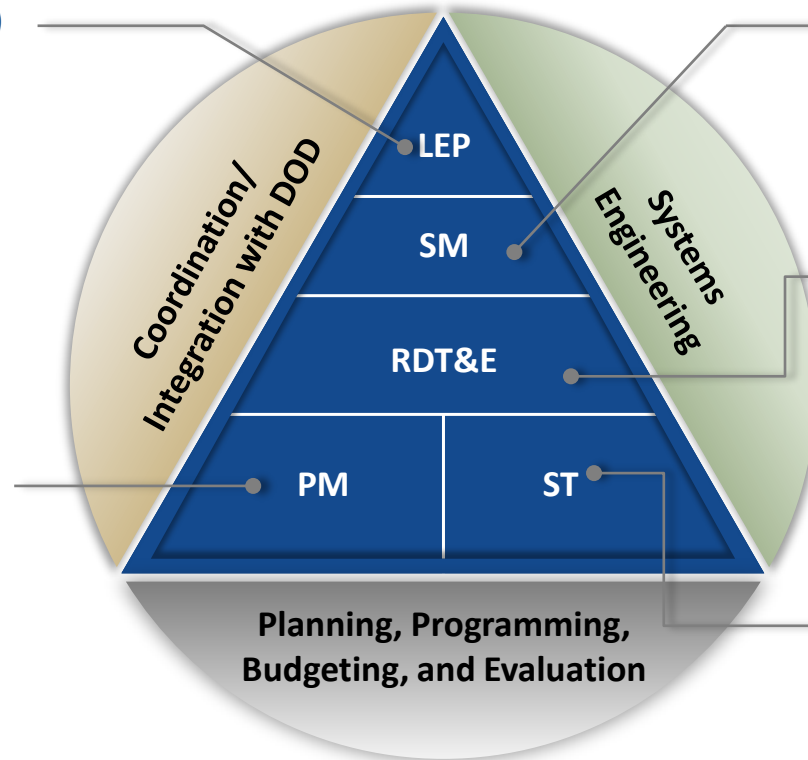
Maintain the Current Stockpile

Deliver LEPs

Prepare for the Future

**Life Extension Programs (LEPs)** prevent operational gaps while enhancing safety, security, and use control.

**Production Modernization** provides strategic investments to modernize infrastructure and manufacturing capabilities.



**Stockpile Management** sustains the Nation's nuclear weapon stockpile.

**Research, Development, Test, and Evaluation** provides tools and capabilities for stockpile assessment and certification, including the development of predictive capabilities.

**ASC Program is in RDT&E**

**Secure Transportation** provides safe and secure shipment of nuclear weapons, weapons components, and special nuclear material.

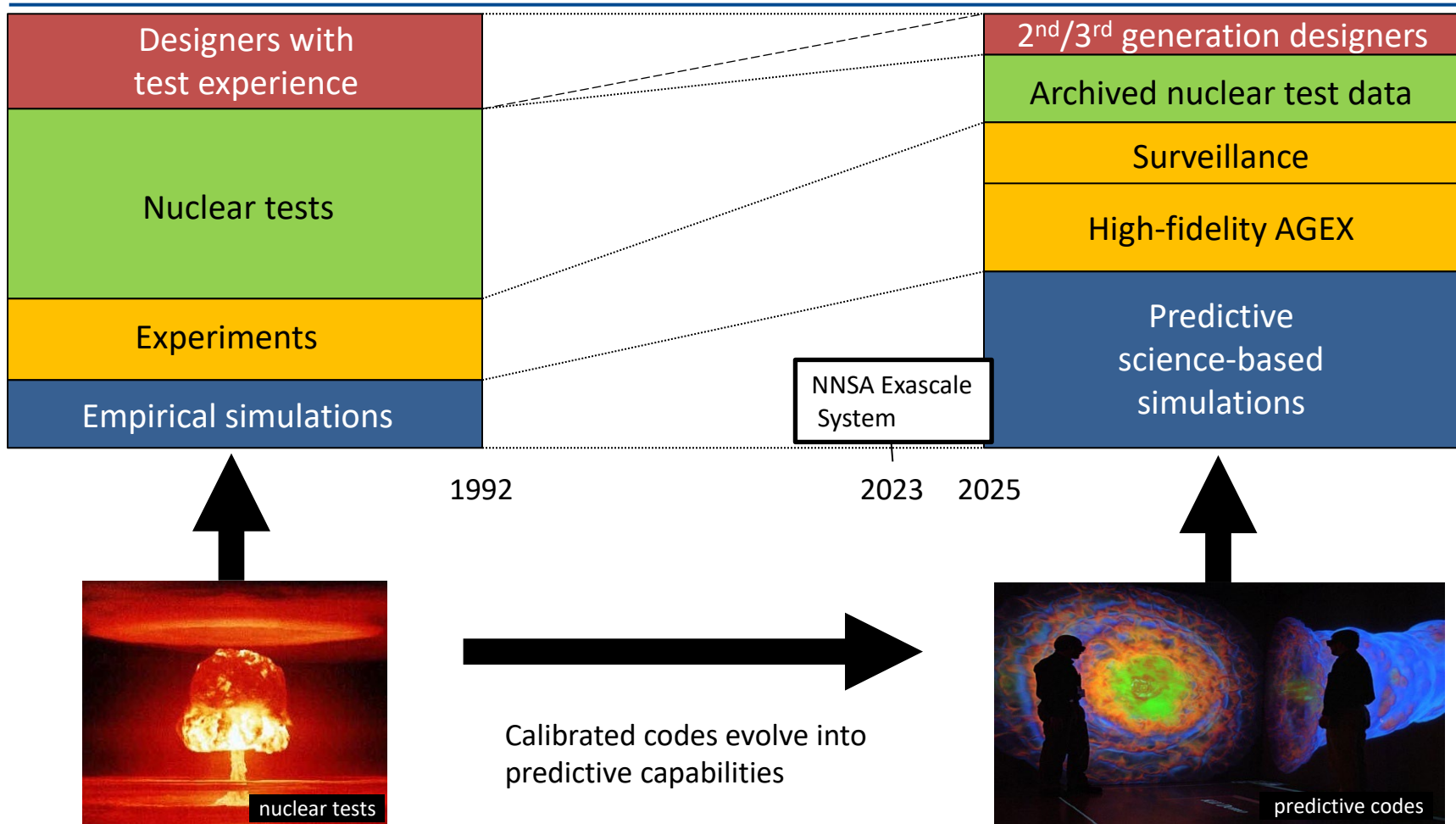
# Advanced Simulation and Computing (ASC)

ASC is predictive science through simulation: the people, state-of-the-art computational platforms, and simulation tools used in the annual certification of nuclear weapons stockpile:

- **Prediction Through Simulation.** Deliver verified and validated physics and engineering codes to enable simulations and risk-informed decisions of nuclear weapons performance, safety, and reliability.
- **Robust Tools.** Develop robust models, codes, and computational techniques to support stockpile needs such as Significant Finding Investigations, Life Extension Programs, annual assessments, as well as evolving future requirements.
- **Balanced Operational Infrastructure.** Implement a balanced computing strategy of platform acquisition and operational infrastructure to meet Directed Stockpile Work and Stockpile Stewardship Program needs for production and advanced simulation capabilities.

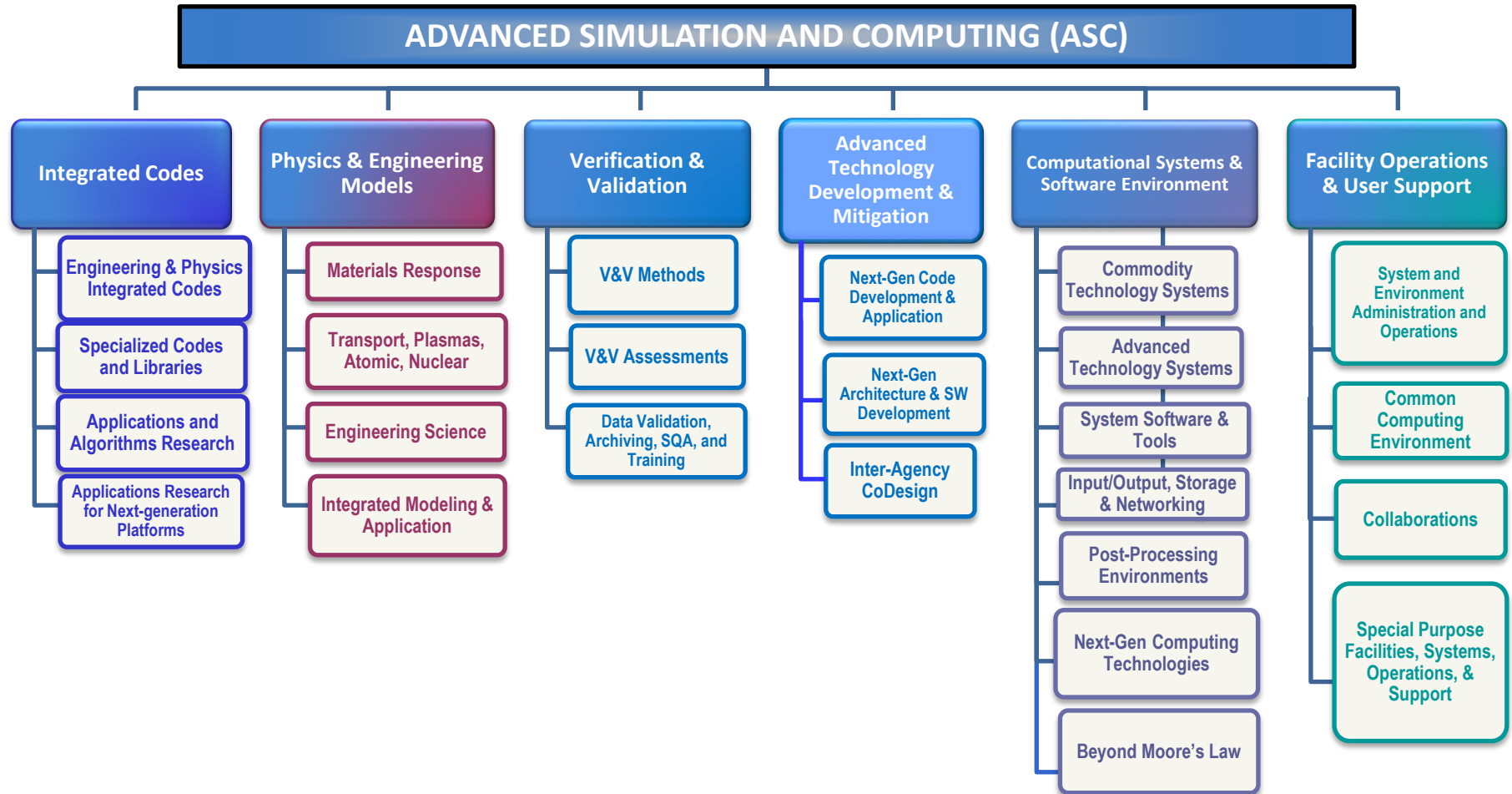


# Confidence in Stockpile Assessment Rests on Our People and Tools



Our confidence, once based on nuclear tests, now must be founded on improved physics understanding incorporated into predictive simulations validated against historic nuclear test data and focused experiments

# ASC Program National Work Breakdown Structure (nWBS)





## ASC Mod/Sim Capability is Unique Within National Security and Science Communities

- The suite of NNSA codes are the embodiment of all **our nuclear weapons knowledge** – captured in the data, models, phenomenology and expert staff.
- Simulation codes are tuned for **specific architectures to run in a reasonable time** (e.g., less than a year for large problems).
- Nuclear weapons codes are very large and complex and support very high consequence decisions:
  - Long life-time projects with >1 million lines of code, originally 15+ years of development by large teams and over \$1B investment
  - Transforming millions of lines of code to mitigate impact can take 3-5 years
- Tightly-coupled, multi-physics codes contain a set of distinguishing characteristics:
  - Mechanics, particle transport, nuclear reactions, thermodynamics, electromagnetics, multi-scales, etc.
  - Verification and validation, together with quantification of uncertainties, is essential & multiplying needs by ~1000X

Laboratory	Million Lines of Code*
LANL	16.5
LLNL	15.7
SNL	18.2
<b>Trilab Totals</b>	<b>50.4</b>

\* not including math libraries

\* not including new codes

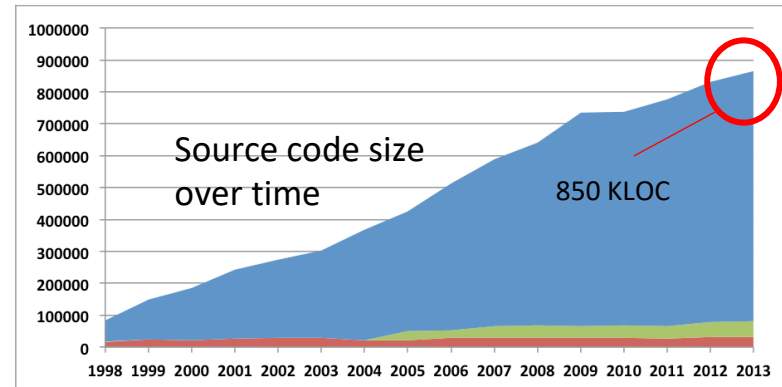
Typical single code's line count:

- Multi-physics: 1.3 million
- Engineering: 3.5 million
- Safety: 1.0 million

High-fidelity simulations are required to either establish or negate the need for return to underground testing

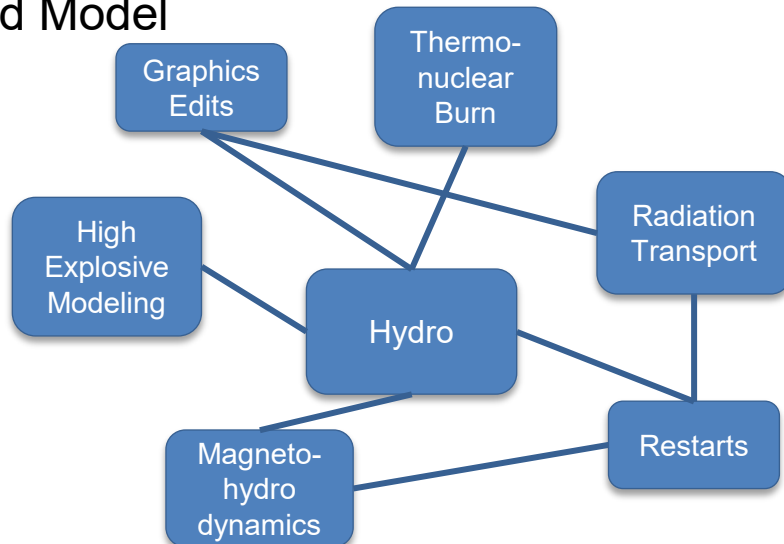
# Increasing code complexity, coupled with architecture uncertainty, is driving NNSA Labs to a new, modular approach

- Codes today are >5x larger than pre-ASCI (1995) codes
- Modular infrastructure can be reused by other codes
- Central Data Store allows individual components to be modified/rewritten independently

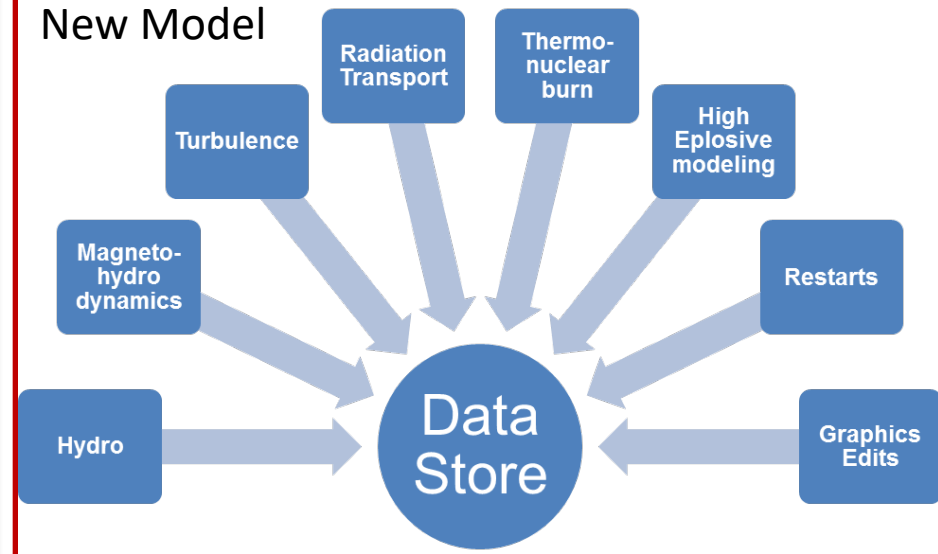


Average of 60K lines of code (KLOC) per year of additional code to support a representative integrated code

## Old Model



## New Model





# Current ASC Computing/Architecture Environment

## Sierra @ LLNL



### Compute Node

- 2 IBM POWER9 CPUs
- 4 NVIDIA Volta GPUs
- NVMe-compatible PCIe 1.6 TB SSD
- 256 GiB DDR4
- 16 GiB Globally addressable HBM2 associated with each GPU
- Coherent Shared Memory

### Compute Rack

- Standard 19"
- Warm water cooling

### Compute System

- 4320 nodes
- 1.29 PB Memory
- 240 Compute Racks
- 125 PFLOPS
- ~12 MW

### Components

#### IBM POWER9

- Gen2 NVLink



#### NVIDIA Volta

- 7 TFlop/s
- HBM2

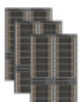
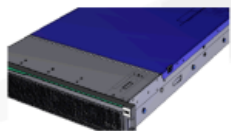


#### Mellanox Interconnect

- Single Plane EDR InfiniBand
- 2 to 1 Tapered Fat Tree

#### GPFS File System

- 154 PB usable storage
- 1.54 TB/s R/W bandwidth



## Trinity @ LANL

### Trinity Cray XC40 Specifications

Intel Xeon E5-2698v3 "Haswell"	Intel Xeon Phi 7250 "Knights Landing"
9436 nodes	9984 nodes
Dual socket, 16 cores/socket, 2.3 GHz	1 socket, 68 cores, 1.4 GHz, > 3 Tflops/KNL
128 GB DDR4	96 GB DDR4 + 16GB HBM
1.15 PB on-node memory	1.12 PB on-node memory
Aries "Dragonfly" interconnect	



### Trinity HSW

- 32 cores + HT [64]
- AVX 256-bit [4 doubles]

### Trinity KNL

- 68 cores + 4 HW [272]
- AVX-512 512-bit [8 doubles]

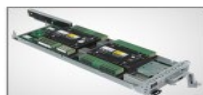


### Cray Sonexion Storage System

78 PB Usable, ~1.6 TB/s

**Cray DataWarp**  
 576 Burst Buffer Nodes  
 3.7 PB, ~3.3 TB/s

## Astra @ SNL



HPE Apollo 70 Cavium TX2 Node

HPE Apollo 70 Chassis: 4 nodes



HPE Apollo 70 Rack



18 chassis/rack

72 nodes/rack

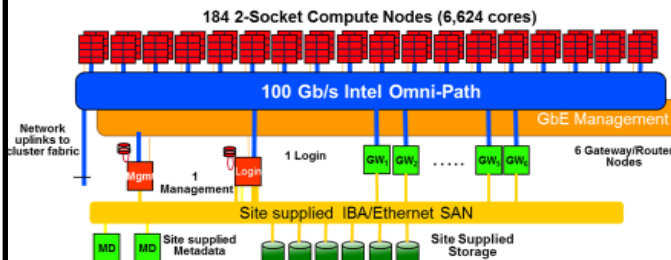
3 IB switches/rack (one 36-port switch per 6 chassis)

36 compute racks (9 scalable units, each 4 racks)

2592 compute nodes (5184 TX2 processors)



## Tri-lab CTS-1 Deployments



### ASC & Institutional Computing:

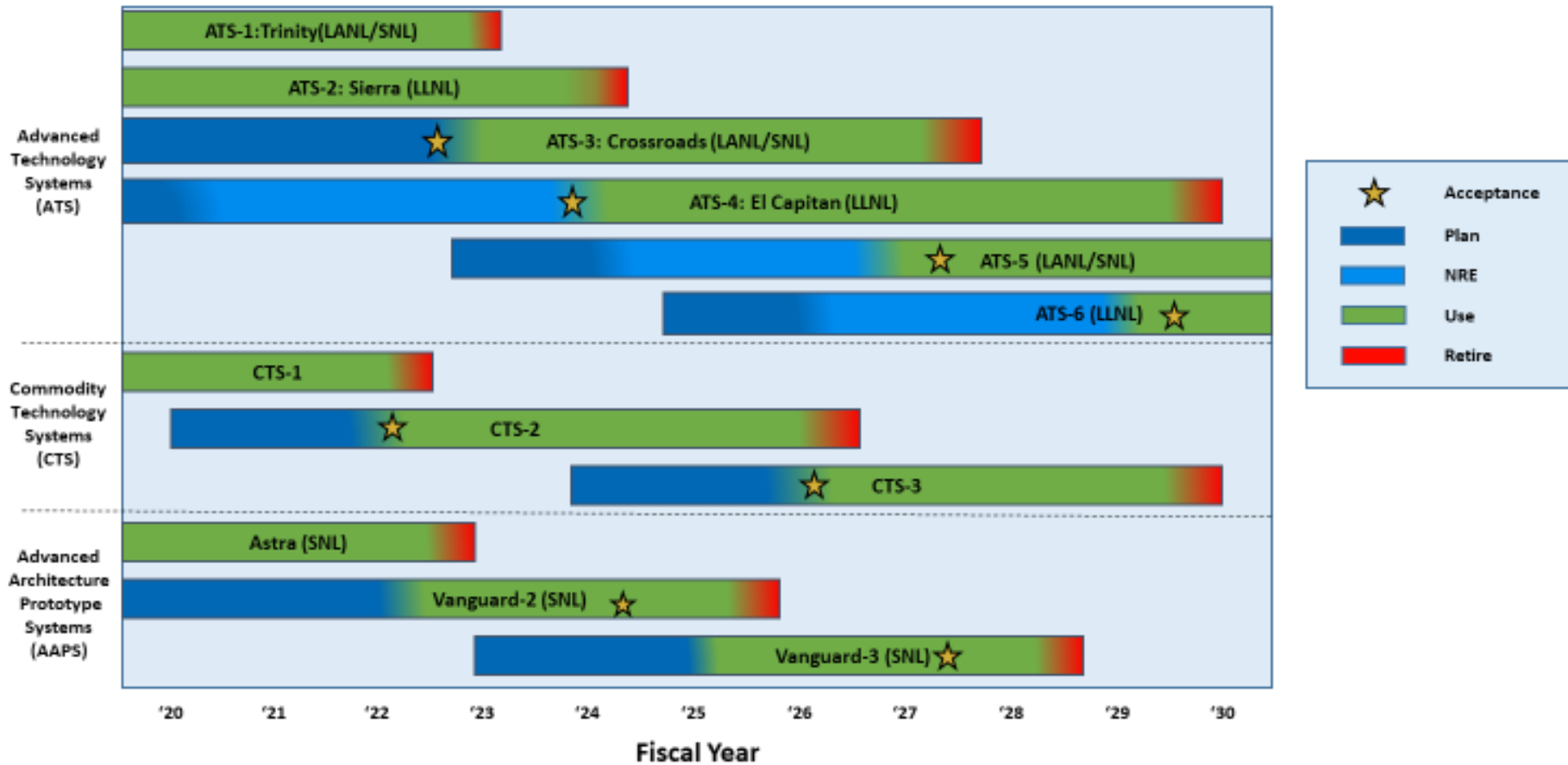
- LLNL- 52 SUs
- LANL- 37.5 SUs
- SNL- 34.5 SUs

### Scalable Unit (SU) Parameters: 192 nodes; 232 TF/s; 24.5 TB DRAM

- 184 dual socket compute nodes; 128 GB DDR4-2400 SDRAM
- HPC 100 Gb/s network fabric; scalable to 4K+ end points
- Compute and Gateway nodes remote boot from Management nodes
- Site supplied parallel storage and SAN
- Options for on node PCIe accelerators and NVRAM
- Base for building multi-SU clusters

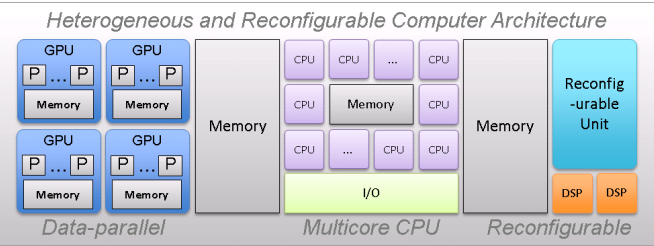
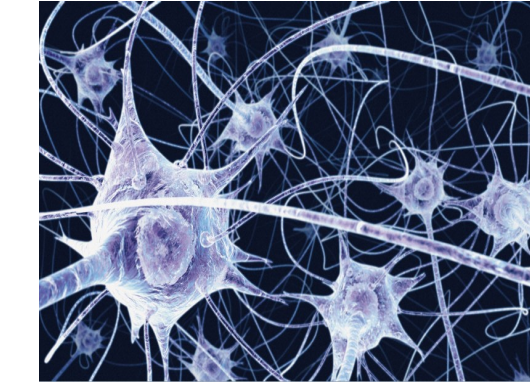
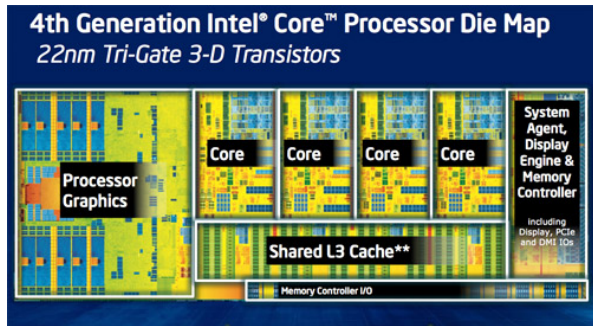


# ASC Platform Timeline



February 2021

# We Must Keep Up with Evolving Architectures to Meet Mission Needs



Neuromorphic systems



Homogeneous Many-Core & Heterogeneous Architectures

The computing landscape will continue to evolve; we must capitalize on future technologies

# SNL Project on Credibility for Scientific Machine Learning: Data Verification & Model Qualification

## Problem

- High-consequence ND workflows require rigorous V&V and UQ
- Need evidence-based credibility for scientific machine learning when used in ND workflows.

## Technical Approach

- Rigorously assess ML models using Predictive Capability Maturity Model (PCMM) workflow
  - Statistical properties of input features when training a ML model
  - Examine associated sources of noise, e.g., measurement noise.
- Exemplar: Stronglink Aging Classification
  - Predict health of devices using waveforms collected using non-destructive tests.
  - Identify key input features in time or Fourier domains, assess the quality of training datasets, and decompose uncertainty into its aleatoric and epistemic components.

## Deployment:

- A standalone implementation and integration with Dakota.

### Characteristics of PCMM Elements

#### Representation and Geometric Fidelity

What features are neglected because of simplifications or stylizations?

#### Physics and Material Model Fidelity

How fundamental are the physics and material models and what is the level of model calibration?

#### Code Verification

Are algorithm deficiencies, software errors, and poor SQE practices corrupting the simulation results?

#### Solution Verification

Are numerical solution errors and human procedural errors corrupting the simulation results?

#### Model Validation

How carefully is the accuracy of the simulation and experimental results assessed at various tiers in a validation hierarchy?

#### Uncertainty Quantification and Sensitivity Analysis

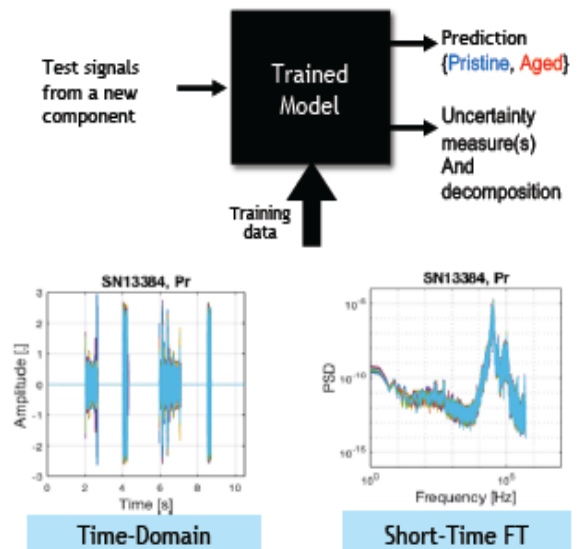
How thoroughly are uncertainties and sensitivities characterized and propagated?

### DATASHEETS

Verification of training datasets: documenting composition, collection process, preprocessing, cleaning, labeling, uses, distribution, and maintenance.

### EXEMPLAR

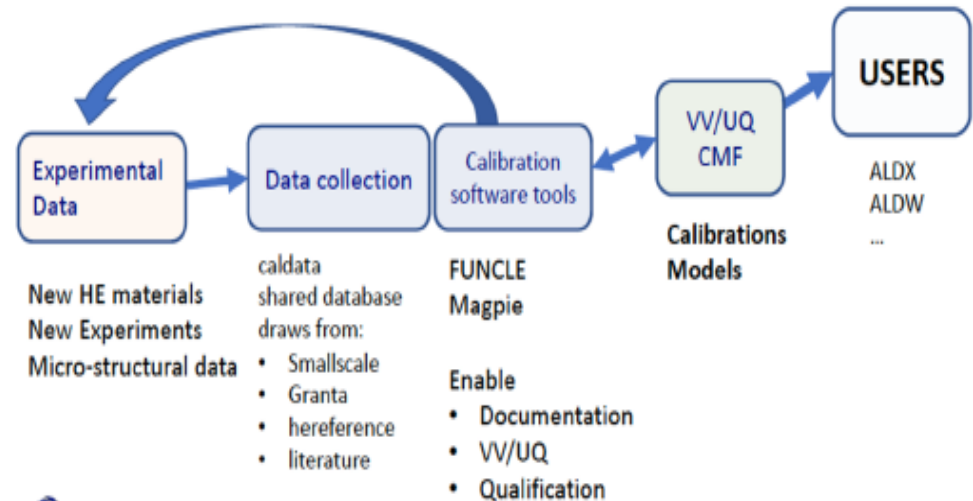
#### Stronglink Component Aging Classification



# LANL High Explosive Calibration Workflow

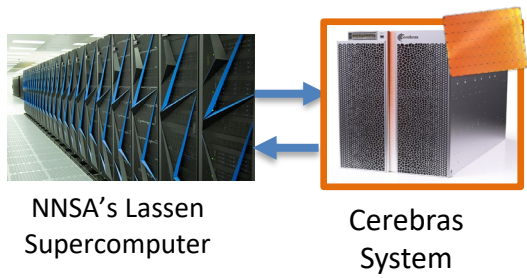
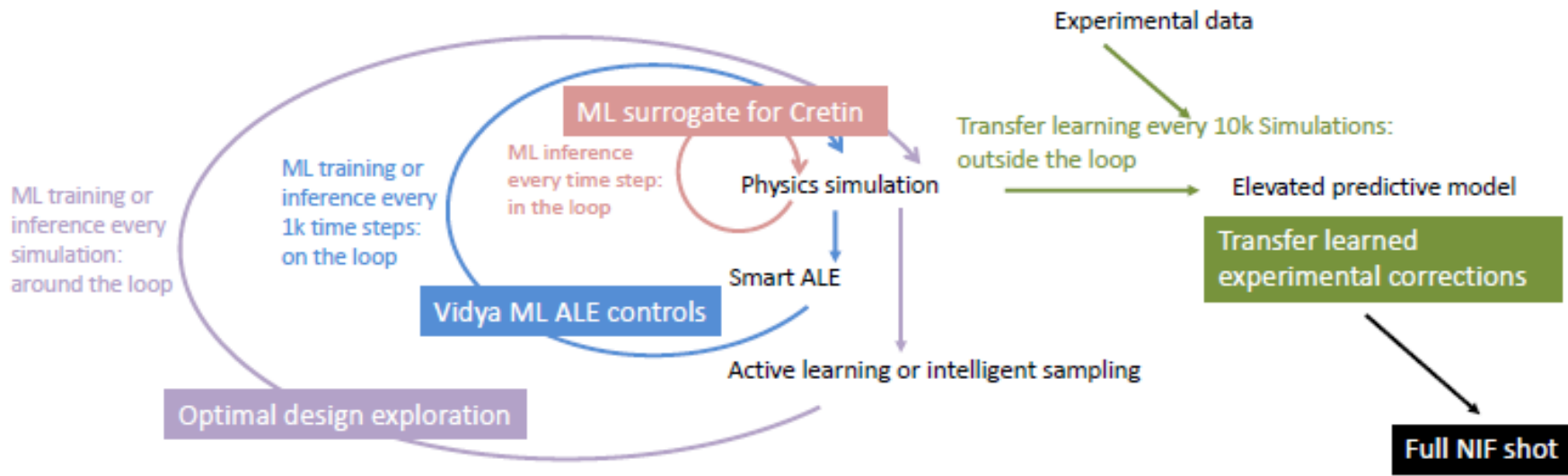
- **Goal:** Create a ML-based workflow for agile HE model calibration and development.
- **Method:** Both experimental and simulation data are used in training and validation. Multiple ML optimization efforts and database work to transform HE analysis.
- **Key result:** Workflow for HE calibrations is working based on CalData database and ML tool for calibration based on FUNCLE and Magpie.

## HE data and modeling workflow PEM-HE point of view

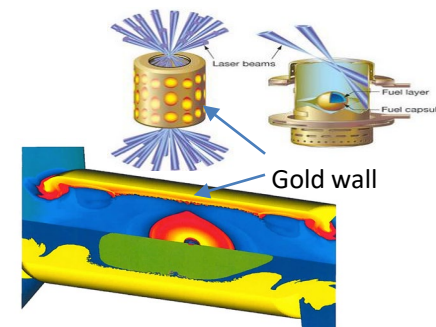


Calibration workflow starts with experimental data. This work develops CalData database which houses curated data. Using these data, EOS and rate law calibrations are made with Magpie and FUNCLE. Long term vision for this tool set is to enable VV/UQ and qualification work.

## AI-driven hierarchical simulation for optimal design



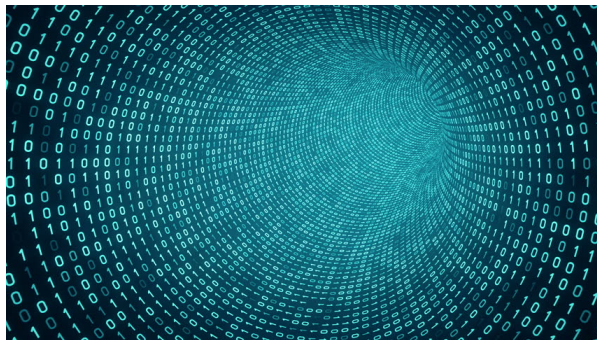
- Radiation opacities near gold wall requires complex calculations
- These calculations can consume 90% of the runtime
- A Deep Neural Network, trained offline, has demonstrated 10X speedups relative to inline opacity calculations



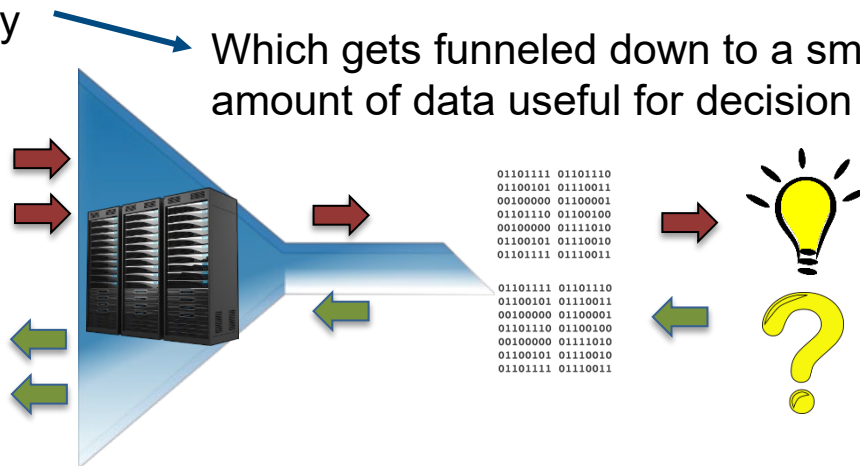
We have demonstrated another ~20X speedup with AI optimized hardware, with >100X possible

## AI-based Computing

AI and machine learning is driven by large amounts of training data



Which gets funneled down to a small amount of data useful for decision analysis



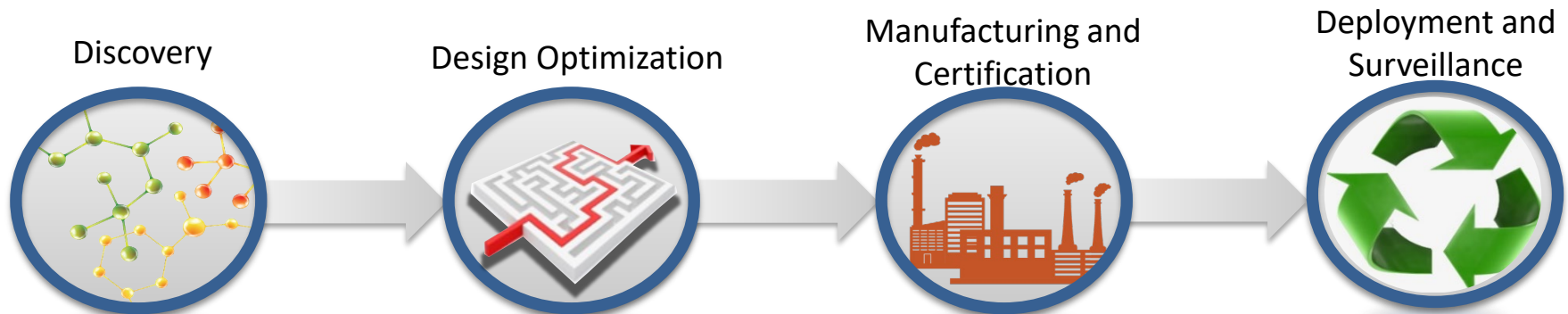
HPC generates huge amounts of data suitable for AI training

HPC simulation starts with a small amount of data as initial conditions

## HPC-based Simulation

Courtesy: Jim Brase, LLNL

- AI-driven methods for designing, manufacturing and deploying products have the potential to revolutionize NNSA workflows:



- High-performance computing (HPC) will continue to be the computing technology foundation for NNSA stockpile stewardship, plus other advanced architectures:
  - Surrogate models generated by powerful accelerator-based HPC systems provide faster models for many-query applications.
  - Current “exascale computing” technology allows ensemble calculations to be possible, with the latter being the nucleus of Uncertainty Quantification.

**Full engagement and true collaborations as public-private partnerships between government, industry, and academia continue to be necessary**





# Thank you