AI/ML and Simulation in the Context of Product Innovation

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Ansys

Ansys is the Simulation Leader

MISSION: Empower our customers to design and deliver transformational products

FOCUSED

This is all we do.
Leading product technologies in all physics areas. Largest development team focused on simulation

TRUSTED

97 of the **FORTUNE 100** industrials

More than **45,000** customers worldwide

ISO 9001 CERTIFIED

PROVEN

Nasdaq 100

Member of the prestigious STANDARD & POOR'S 500

$30B+ market capitalization

GLOBAL

4,500+ employees globally

75 offices in **40** countries

LARGEST

3x the size of our nearest competitor (revenue)

$1.5 Billion

INDEPENDENT

Long-term financial stability

CAD/PLM/IoT agnostic
Open Architecture

COMMITTED

Overall customer satisfaction globally is at **89%**

DRIVEN

Helping customers address new market challenges: **digitalization**, **5G**, **autonomy**, **electrification**, **additive** and **digital twins**

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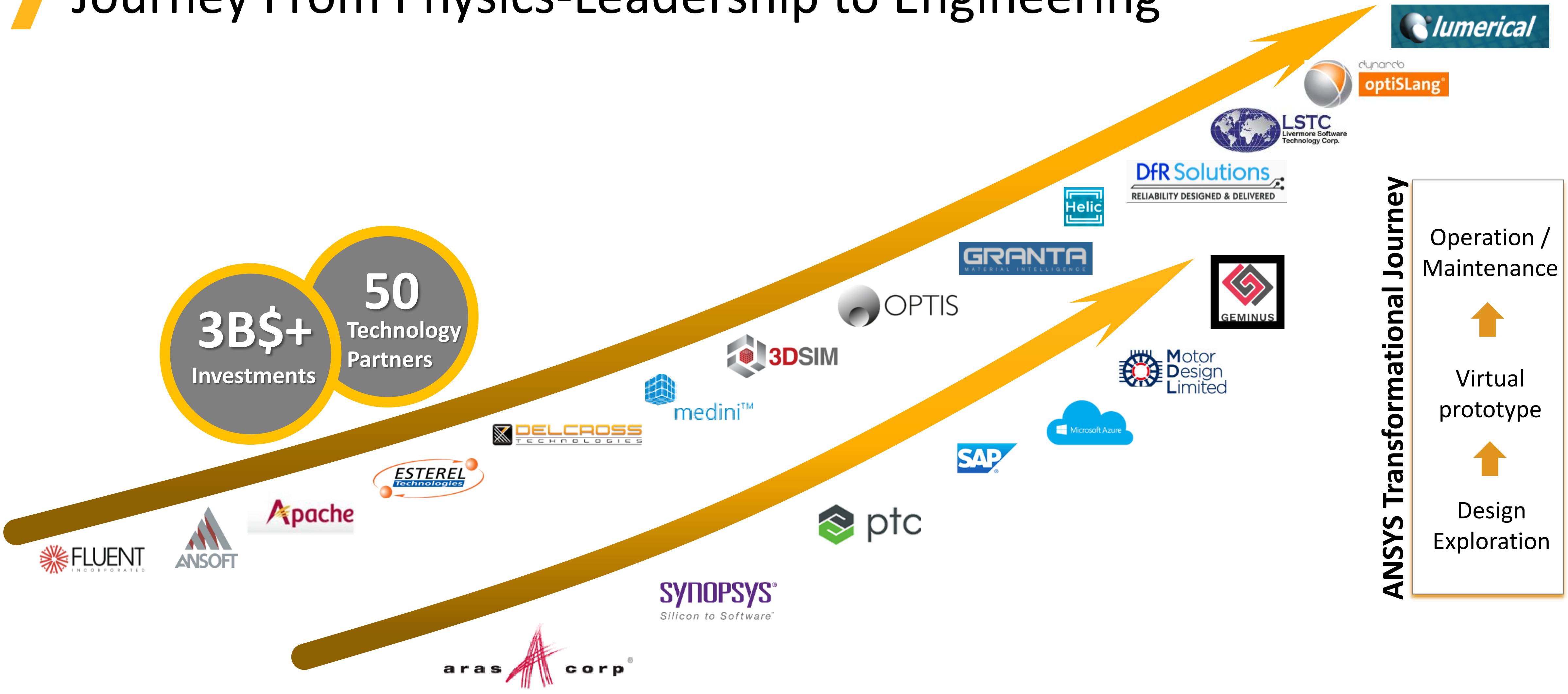
Journey From Physics-Leadership to Engineering



Physics | Process | Software | Controls | Engineering Analysis | Digital Technologies

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Ansys Offers the Only True Simulation Platform

COMPREHENSIVE SOLUTIONS: Autonomy / Electrification / 5G / IIot

Digital Twins

SYSTEMS & EMBEDDED SOFTWARE

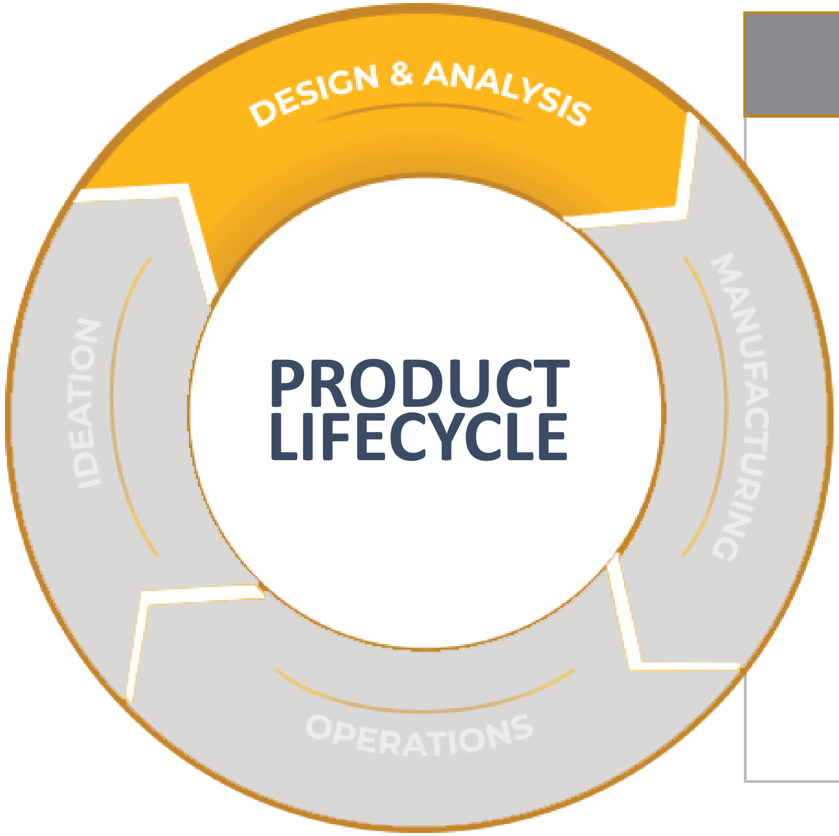
Embedded Software

Fluids | **Structures** | **Electromagnetics** | **Semiconductor** | **Design Exploration** | **Optical**

MATERIALS INFORMATION

PLATFORM AND CLOUD

Simulation Impacts Top-Line Growth And Bottom-Line Savings



Simulation impact

- Rapid innovation
- Lower cycle time
- Reduced risks
- Increased quality
- Manage complexity

Revenue growth

- Offer more products
- Launch right products
- Faster time to market

Cost savings

- Improved R&D efficiency
- Fewer physical prototypes
- Lower warranty costs

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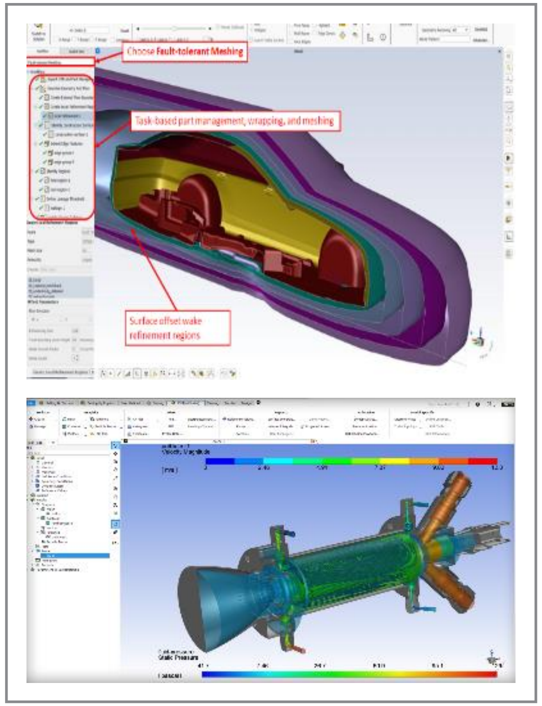
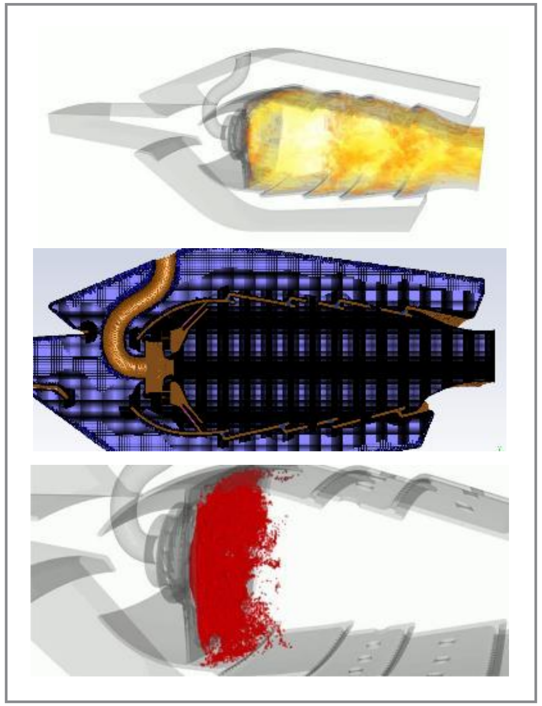
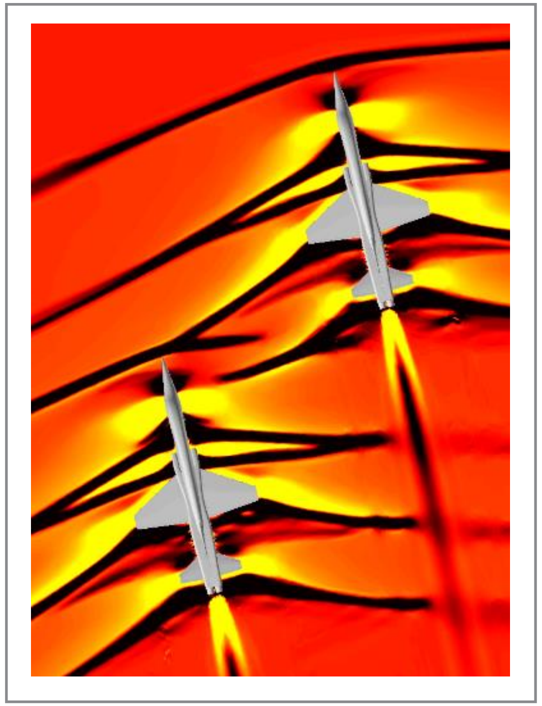
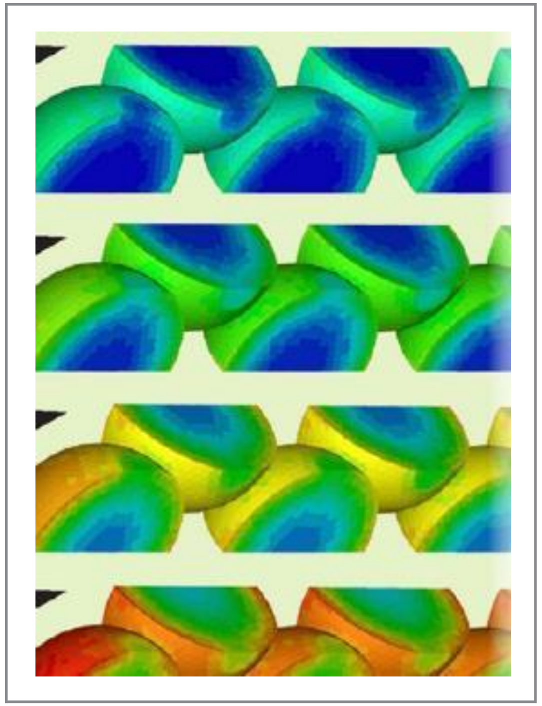
Fluids R&D directions









PRODUCTIVITY
- Workflows
- Customer driven
- Speed and robustness
- GPU based post processing
- Usability and repeatability

GAS TURBINES
- Combustion physics
- Numerics
- Spray physics
- Turbulence
- Best practices

EXTERNAL AERODYNAMICS
- Speed
- Accuracy
- Robustness
- Hypersonic physics
- Multiphase flows

ELECTRIFICATION
- Conjugate Heat Transfer
  Electro-Chemistry
- Battery Life
- Capacity fade
- Process and Chemical Industries

Structures R&D Directions

APPLICATION SPECIFIC
- Medical Initiative: heart simulation
- Electrophysiology, Incompressible flow, FSI, Adv. Mat.
- Additive Manufacturing
- Machine learning for faster thermal solutions
- Microstructure & property predictions
- Battery modeling in crash analysis

MATERIALS
- Multiscale – Data Driven framework, Short fibers
- Crystal plasticity
- Elastomers fatigue, inelastic fracture
- Thermo mechanical fatigue with damage
- ICME

EQUATION SOLVERS
- Data driven means to assess resource needs
- Low Rank meth. for acoustic wave equations
- Efficient scheduling for HPC performance

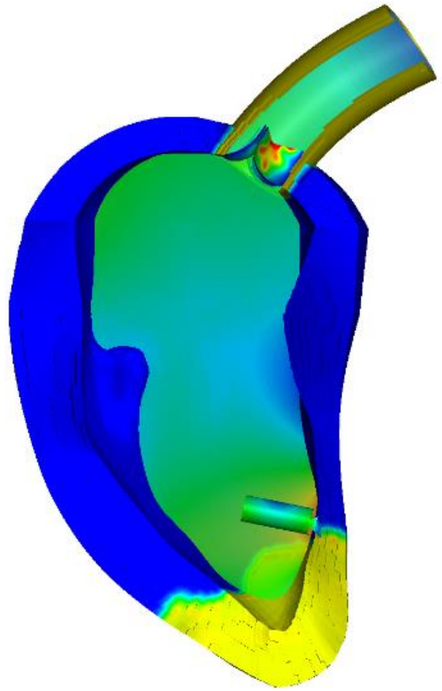
AUTOMOTIVE APPLICATIONS
- Streamlined Welding for Automotive Chassis
- New Meshing and geometry Enable Optimization Workflows

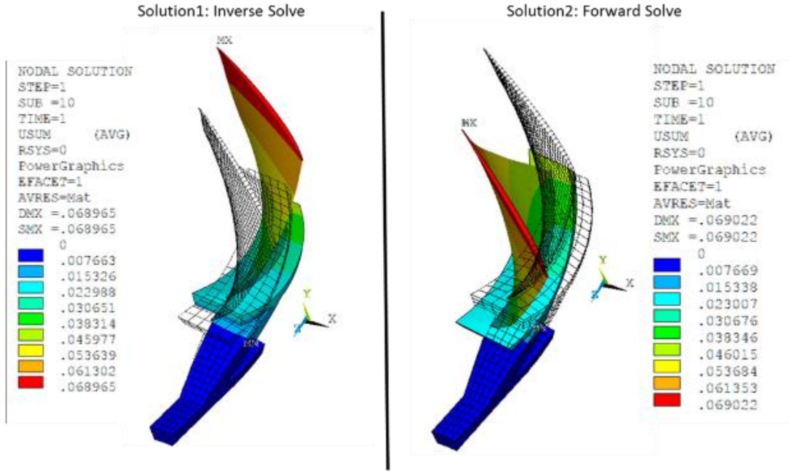
ELECTRONICS RELIABILITY
- Best-in-class pre-processing for seamless model exchange
- Coupling Ansys Mechanical and Sherlock

MORPHING-BASED OPTIMIZATION
- Better topology optimization
- Automatic creation of clean CAD

SOLVER METHODS
- Iso Geometric Analysis (IGA)
- Inverse methods
- Dual Lagrange Multiplier methods for contact
- Manufacturing constraints in Topo Optimization

SOFTWARE
- DCS:
- Distributed Log Service
- HPC 2.0 – HPC on demand
- System Coupling for multi-physics





Electromagnetics R&D Directions

AUTOMATION AND PERFORMANCE

- Streamlined electronics workflows for package and board
- Integration with thermo-mechanical for new applications

ANTENNA

- Advances in phased array antenna analysis with scalable HPC.

SEMICONDUCTORS

- RaptorH combines Helic's RaptorX with Ansys HFSS,
- Gold standard verification for sensitive 5G integrated circuits

ELECTRIFICATION – RELIABILITY AND NVH

- New thermal and vibrational analysis coupled with Maxwell

ANSYS HFSS

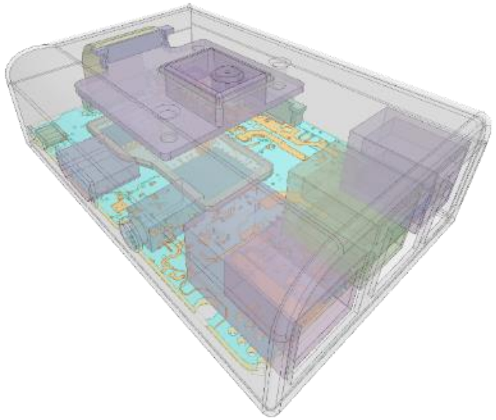
- Enhanced distributed direct matrix solver available on Cloud.
- Significantly reduced memory
- Scales to 100's of cores.

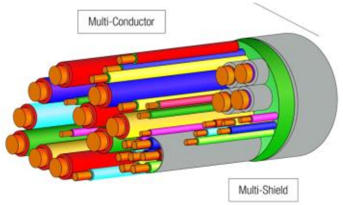
NEW ANSYS EMA 3D PRODUCT

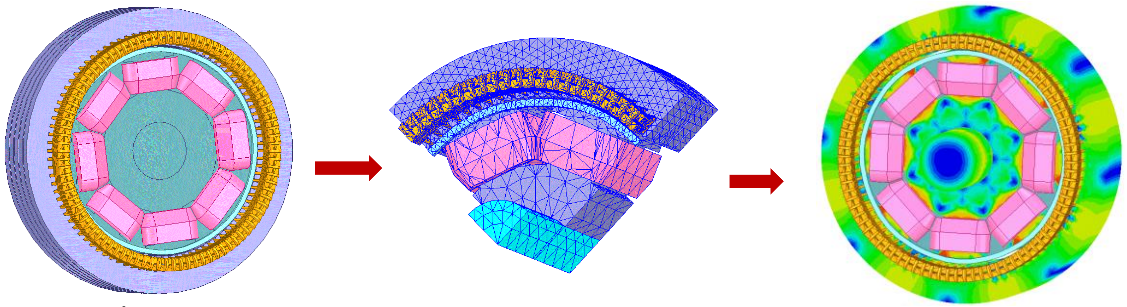
- Models EMI/EMC between complex cables

NEW CAPABILITIES IN ANSYS MAXWELL

- Speeds simulation by creating/solving model for rotating machines.







Setup in full model
Solved by partial model
Visualized in full model

Ansys Long-Term Technology Strategy Dimensions

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING
- Simulation used to train AI methods
- AI used to improve simulation

PLATFORM FOR MULTIPHYSICS SIMULATION
- Robust Multiphysics, Multi-disciplinary Optimization
- Micro-services for simulation

HYPERSCALE SIMULATION, COLLABORATION ON CLOUD
- GPU, SMP, MPI, task based
- Quantum computing

PREDICTIVE AND ROBUST DESIGN
- High accuracy, adaptive numerical methods
- Materials variation and uncertainties

DIGITAL AND PHYSICAL WORLDS
- AR/VR for Simulation brings digital world to physical
- IOT and Connectedness brings physical world to digital

DIGITAL TRANSFORMATION
- Digital Threads, Digital Continuity, Digital Twins
- Model Based Systems Engineering

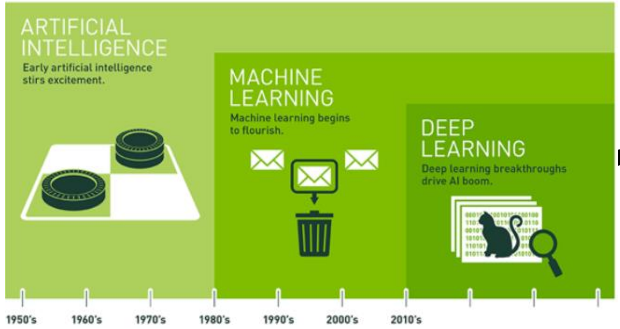
COMPUTATIONAL METHODS IN NEW AREAS
- Integrated Computational Materials Engineering
- Computational Chemistry, Biology, Healthcare, Photonic IC

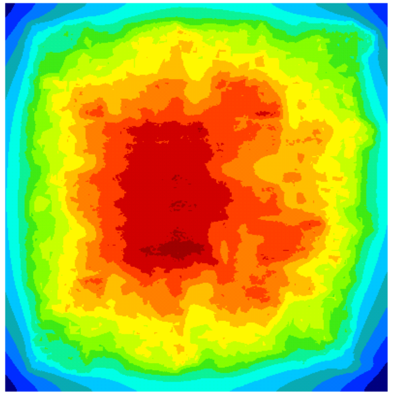
FUTURE OF SIMULATION
- ML based PDE -Solver, generative design
- Integrated synthesis and verification
- Automated mixed mode (0D-4D), MF, MS simulation

AI/Machine Learning and Simulation

Machine Learning, defined by Arthur Samuel, 1959:

"Field of study that gives computers the ability to learn without being explicitly programmed".





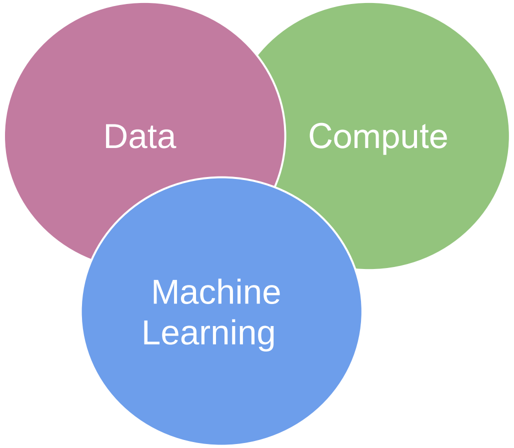
Machine Learning Methods
- Supervised Learning
- Unsupervised Learning
- Semi-supervised Learning
- Reinforcement Learning

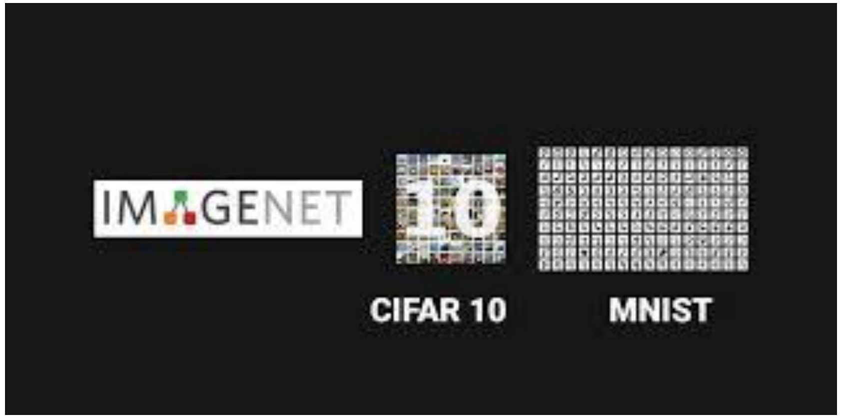
AI/ML Use Cases
- Customer Productivity
- Augmented Simulation
- Engineering Design
- Business Intelligence

Engg. Simulation Methods
- Geometry/Meshing
- 3D/4D Finite Element/Volume
- Physical/Math Models
- Reduced Order & System Models, Digital Twins
- Postprocessing/Visualization

Why is Machine Learning Relevant today?

- Data storage is cheap
- Almost infinite compute capacity with rise in GPUs/TPUs





Open source datasets which accelerated the pace of research

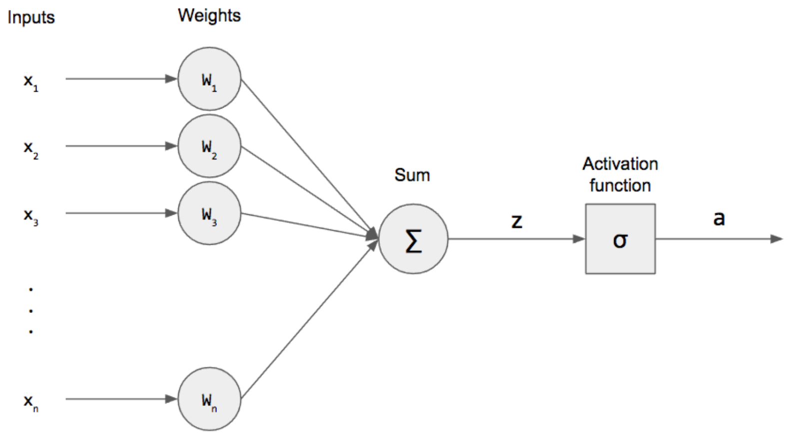
- Open source and ML Frameworks and datasets
- Growing community through top AI/ML conferences

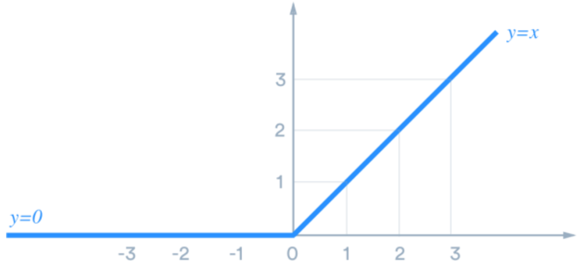
Top ML conferences

Open source ML frameworks that survived test of time

How does Deep Learning Work?

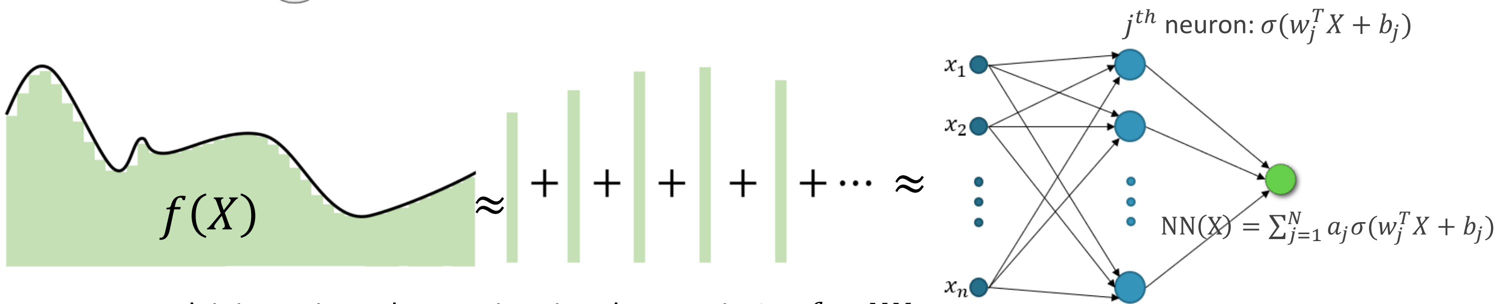
- Single neuron
  - Outputs an activation(a) of weighted sum of input (x)
  - Simplest activation: ReLU





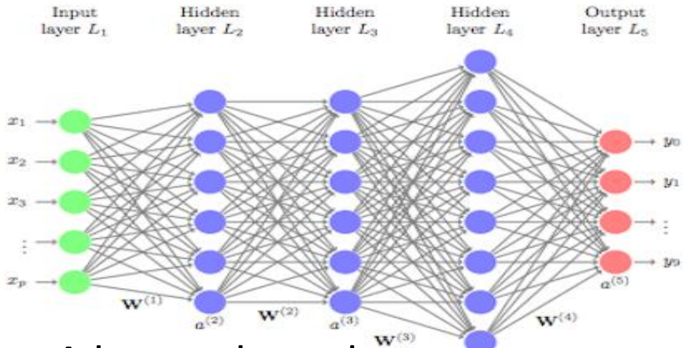
Activation Function: ReLU
(Rectified Linear activation)

- Universal Approximation Theorem (Cybenko, 1989):
  - A neural network with one hidden layer containing a finite number of neurons can approximate *any* continuous function to a reasonable accuracy.
  - >1D, no problem, but must increase neurons



Explaining universal approximation theorem in 1D: $f \approx NN$

- If we increase the numbers of layers
  - Can approximately represent many complex functions, say one function per layer
  - Can handle any non-linearity through ReLU
  - Why didn't we have perfect learning systems?



A deep neural network

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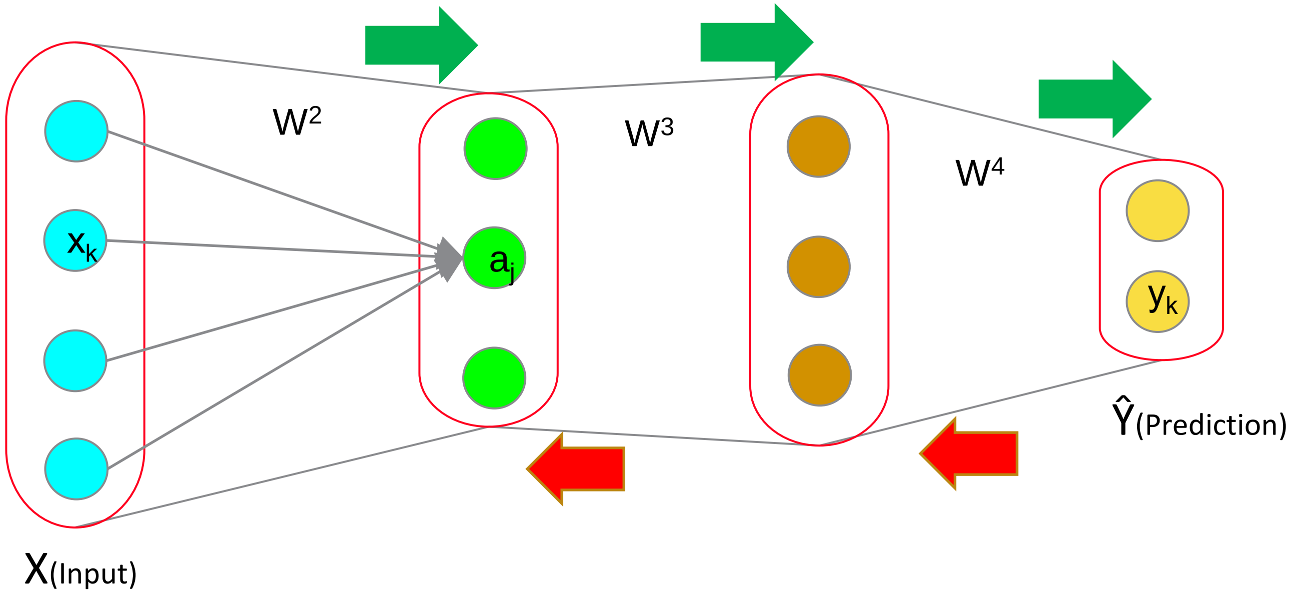
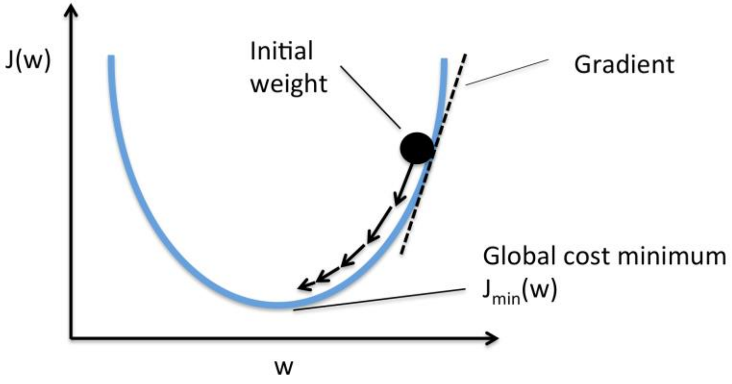
How does Deep Learning Work?

- Is there a relationship between input X and observation Y?
- Yes, Given pairs(X,Y), Neural Network tries to fit a function $\mathcal{F}()$, which is parameterized by weights(w), such that : $\hat{Y} = \mathcal{F}(w, X)$.



- Key Steps
  - Initialize weights randomly or transfer from a previous learned task of a similar network
  - Feed Forward:
    - In this step NN predicts the Ŷ based on the current weights $\boldsymbol{w}$ and inputs.
    - Calculate Error($\mathcal{J}(w)$) = Norm of (Y- Ŷ)
  - Backpropagation:
    - Based on the Error($\mathcal{J}$), gradient of Error w.r.t. weights i.e. $\nabla(\mathcal{J}(\boldsymbol{w}))$ is calculated.
    - *Gradient Descent:* $w = w - \alpha . \nabla(\mathcal{J}(w))$, where α is learning rate



AI/Machine Learning at Ansys

Build internal expertise and support organic R&D

- Hired a small team of AI/ML software developers and leader in the Office of the CTO
- Working with a distributed team of AI/ML software developers in the Business Units
- Support, complement, accelerate BU projects short term
- Canonical customer use cases, drive results across BUs long term
  - Customer Productivity
  - Augmented Simulation
  - Engineering Design
  - Business Intelligence

Use partnerships to augment:

- Larger companies
- Startups
- Universities

AI/ML for Engineering Simulation

R&D Projects in BUs

CTO Office

- ML based PDE Solver (**Augmented simulation**)
- Physics Informed Neural Network (**Augmented sim**)
- Optimization for AMG Solver (**Customer productivity**)
- ML Framework as a service ((**Customer productivity)**

Mechanical BU

- Auto-identification of contacts (**Customer productivity**)
- Google: Reinforcement Learning with Py-ANSYS (**Customer productivity**)
- ML based surrogate modeling for VVUQ (**Augmented simulation**)

Fluids BU

- Geminus: Turbulence model tuning using ML (**Customer productivity**)
- AI/ML-enabled flow solver (**Augmented simulation**)

Electronics BU

- Runtime Predictor **(Business intelligence)**
- Auto-identify HFSS 3D regions in SIwave (**Customer productivity**)

Design BU

- Fast Topology Optimization (**Revolutionizing design**)

- **Materials BU**

- ML Analysis for Additive Manufacturing data (**Revolutionizing design**)
- ML methods in Granta Materials (**Customer productivity**)

Semiconductor BU

- Data-driven fast static/transient thermal solver (**Augmented simulation**)
- Nvidia: Physics Informed Neural Network Solvers (**Augmented simulation**)
- AutoML for SI and PI tools (**Customer productivity**)

System and Platform BU

- Automated ROM Creation for non-linear systems (**Augmented simulation**)
- Creation of Path Planners for autonomous vehicles (**Customer productivity)**
- Geminus: Augmented flow for Twinbuilder **(Augmented simulation)**

Cloud and Platform BU

- Resource prediction compute and storage on cloud (**Business intelligence)**

ACE

- Virtual Validation: Fusion modeling + less tests (**Augmented simulation)**
- Generative design for OEM Concept modeling (**Revolutionizing design**)

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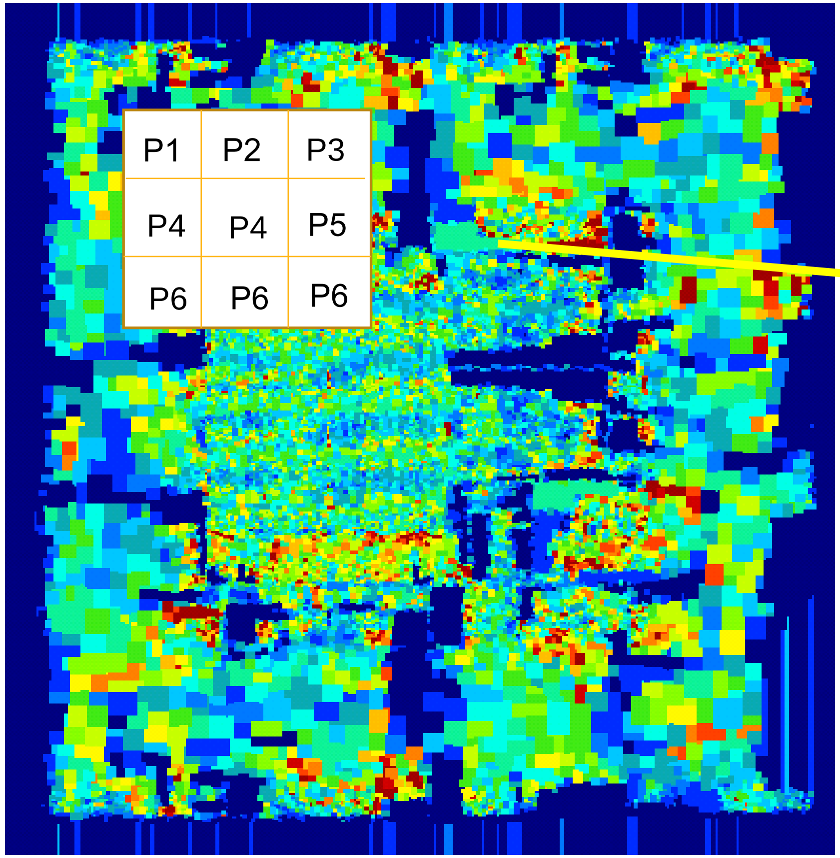
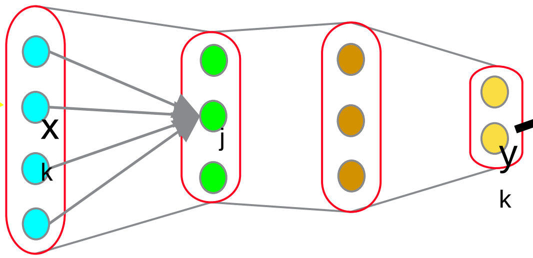
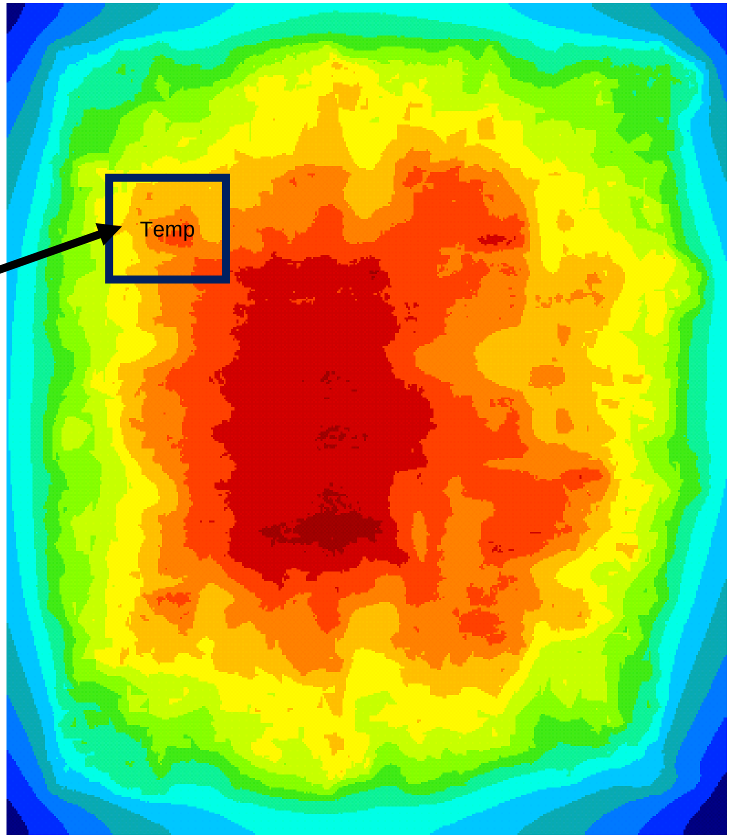
Augmented Simulation: Data-Driven Fast On-Chip Thermal Solver

Providing Inferencing by Striding Templates with One Tile for Predicting Temperature at all Tile Locations

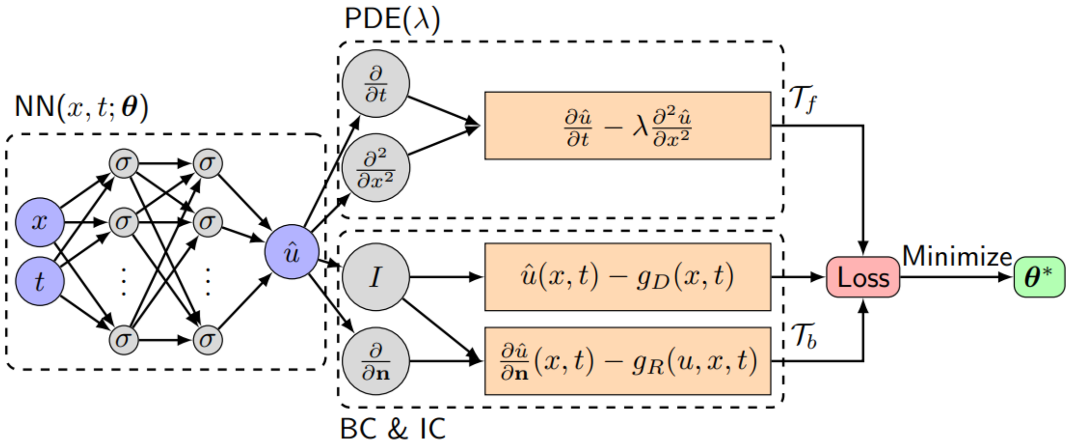




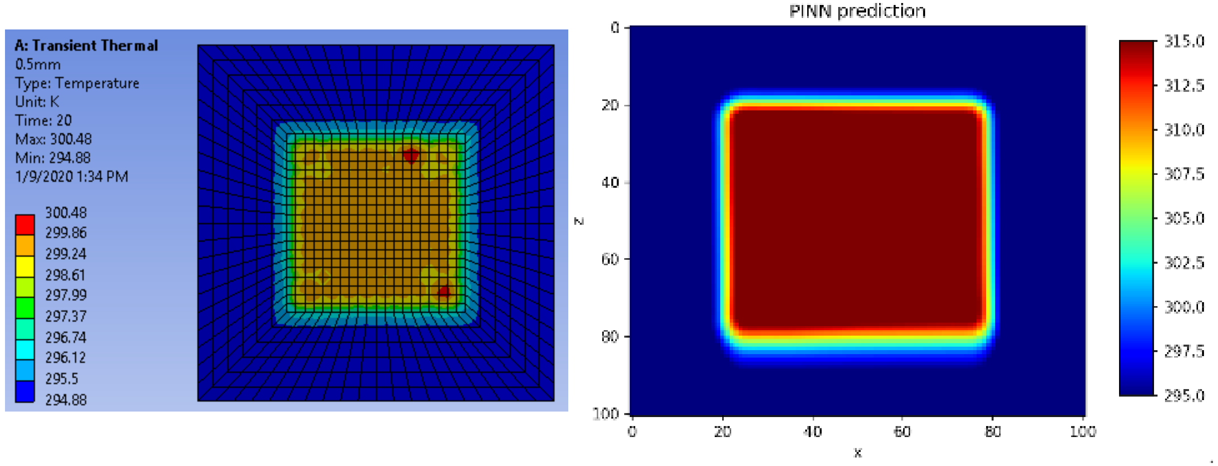


For each tile location, a set of tile powers and Theta-JA are input to the trained DeltaT Predictor to predict the temperature at the corresponding tile and added to the Temp from rough thermal profile

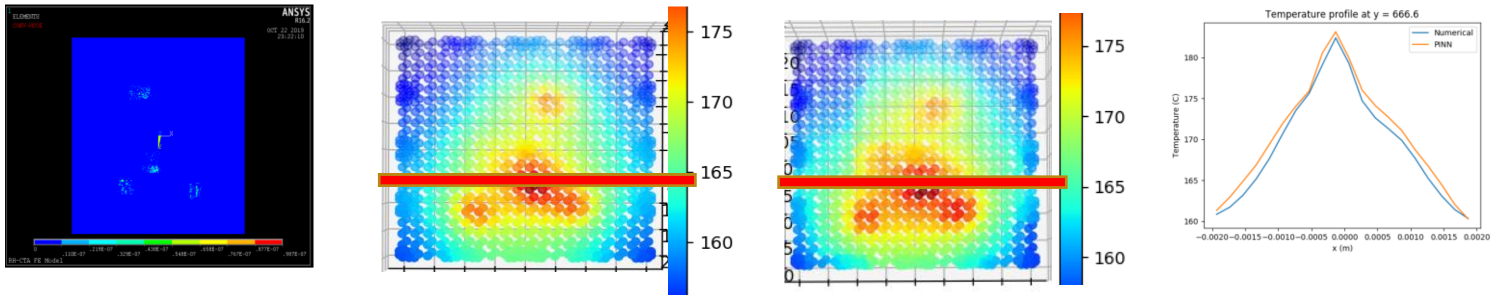
Augmented Simulation: Physics-Informed Neural Nets (PINN)



3D transient heat transfer with source



2D heat transfer on a chip with nonlinear power map



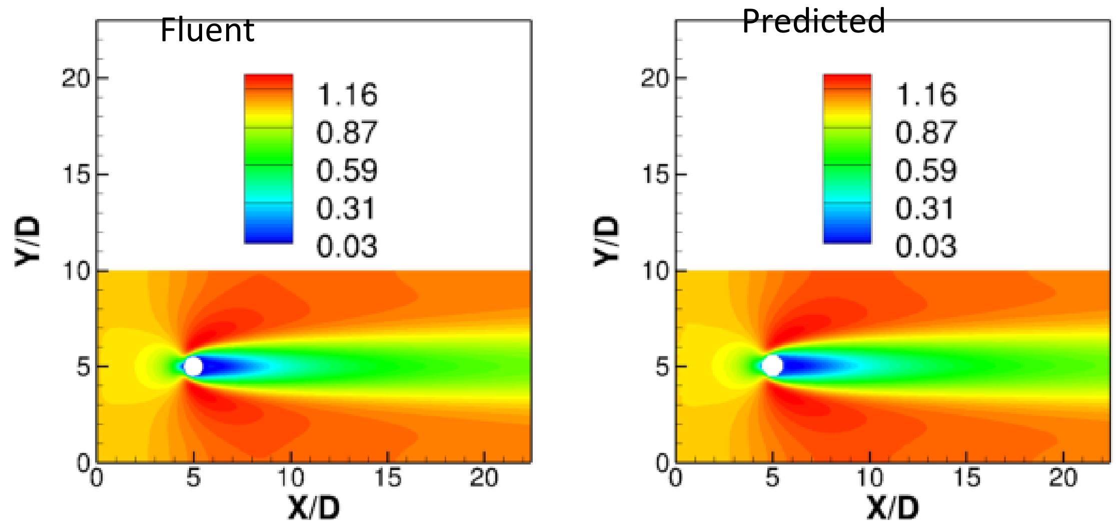
Power map Numerical PINN Comparison

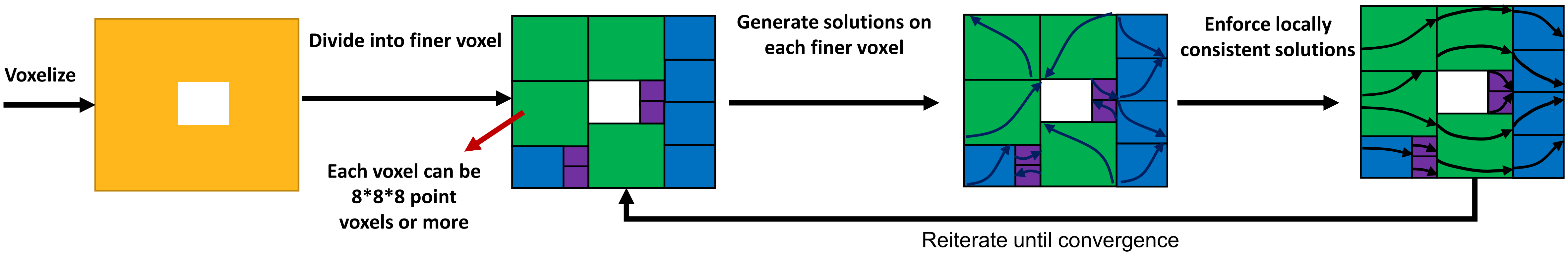
- **PINN uses upfront inference modeling**
- **Runtimes in fractions of seconds (100X)**

Augmented Simulation: ML-Based Partial Differential Equation Solver

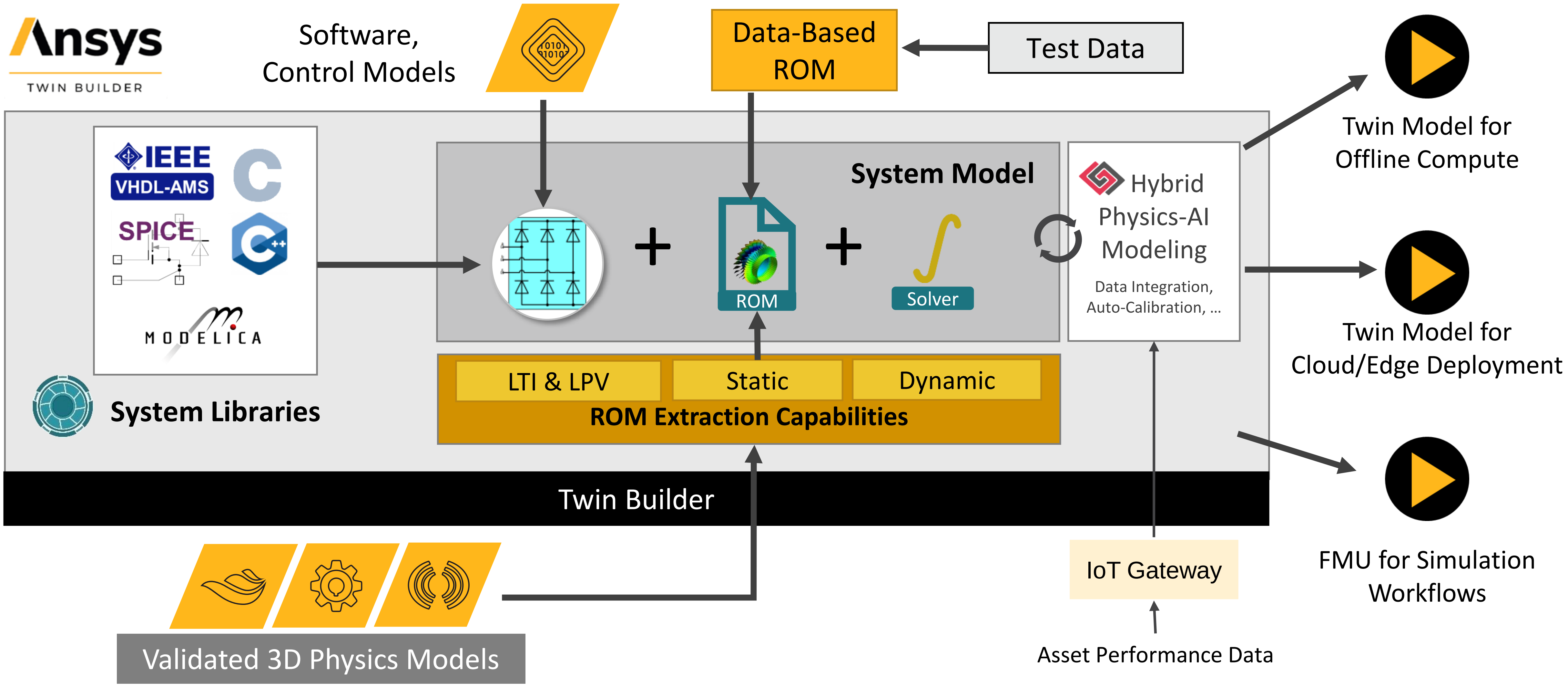
- **Motivation:**
  - Geometries and physics have lots of patterns.
  - Do we need to solve from scratch?
    - No! Create solution instances on patches using a generative network
- **Key insights:**
  - Take a general domain and voxelize into patches
  - Decide boundary conditions for each patch
  - "Solve" for the latent vectors on each patch.
  - Requires learning a consistency condition between adjacent patches
  - More than 100X speedup in time to solution

Example Results: Flow over cylinder: Velocity





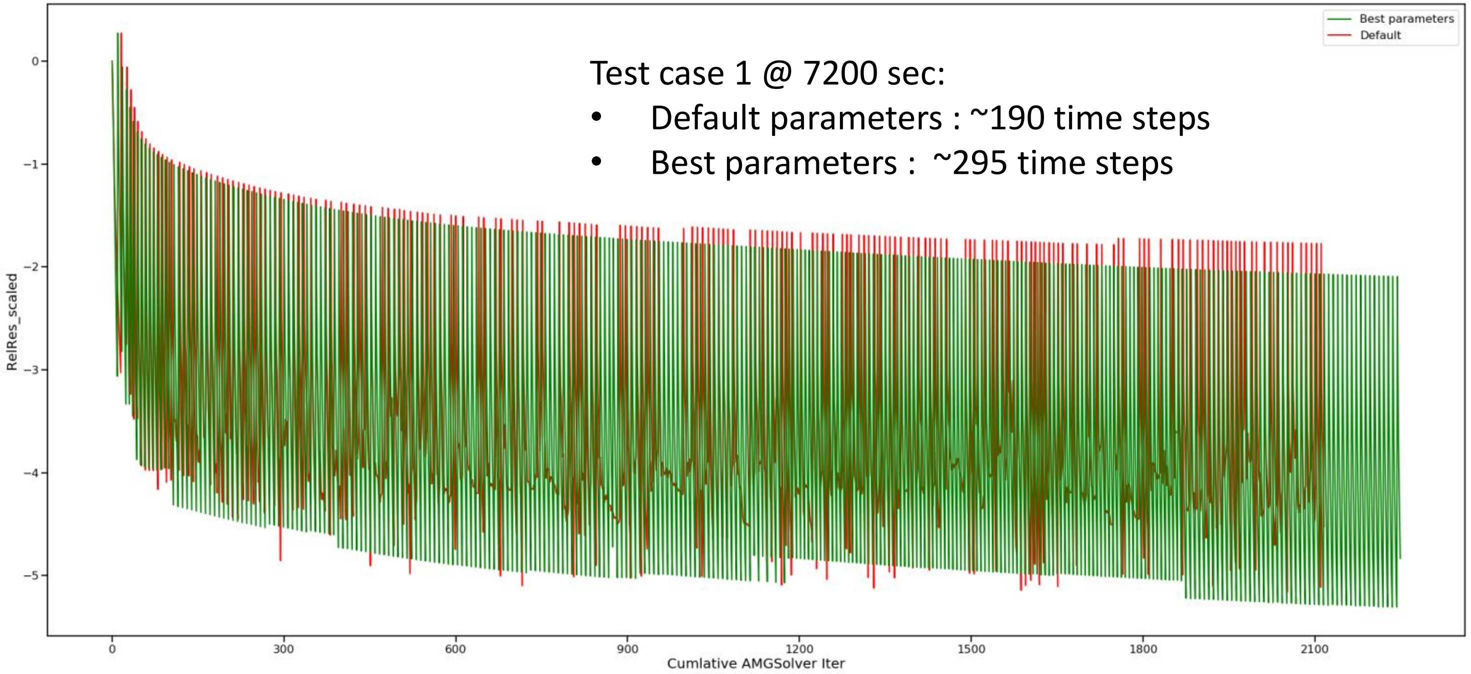
Augmented Simulation: Hybrid Physics AI Digital Twin Architecture and Workflow



Customer Productivity : Using AI/ML to Improve Convergence

- Problem:
  - Solution convergence takes a lot of time and applicable to all solvers
  - Can we learn from the history of convergence to find the ideal control parameters?
- Solution:
  - We applied Bayesian optimization to a linear solver such as AMG
  - Results shown below

	Test case 1	Test case 2	Test case 3
Default parameters	**11280 (sec)**	**11934**	**29323**
Learned Parameters	**8260**	**9658**	**23416**
	-27%	**-19%**	**-20%**



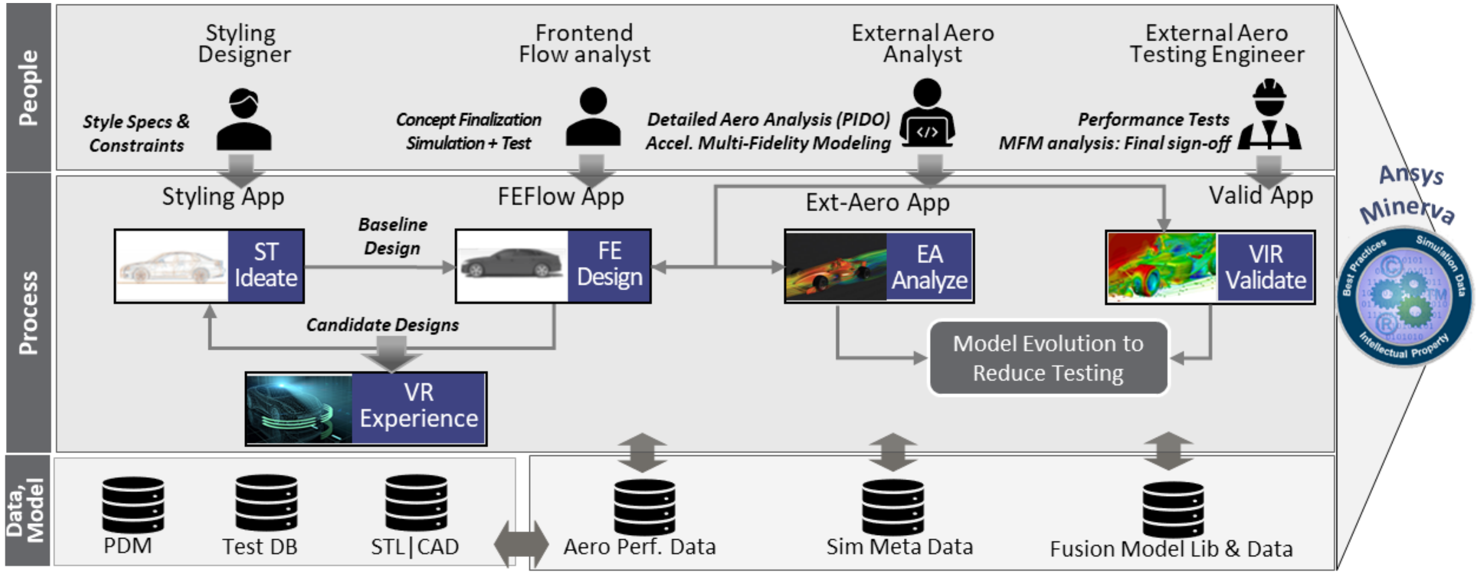
Engineering Design: Machine Learning-Driven Generative Design

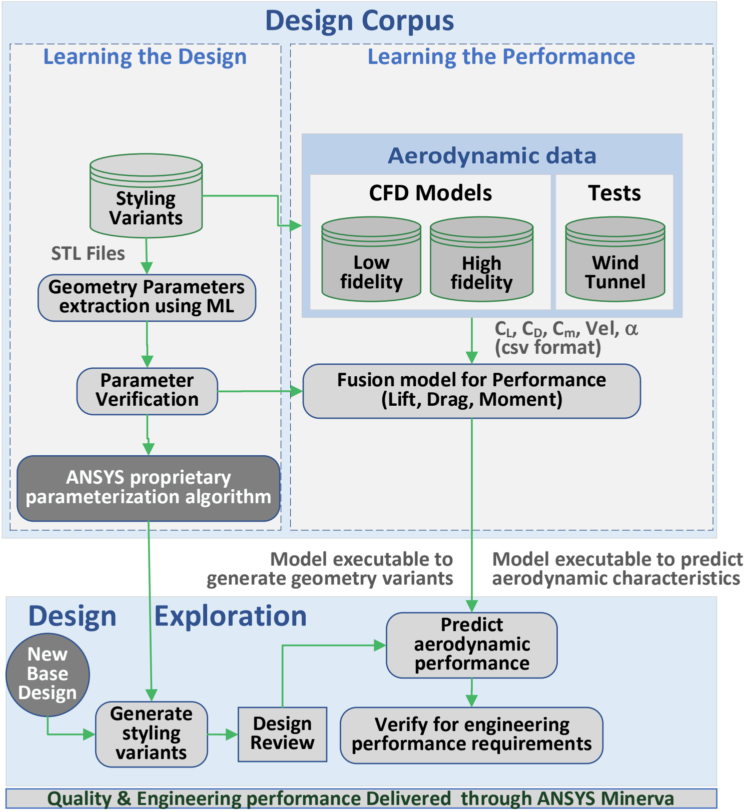
Learning the Designs

- *Embeddings:* Prior designs are parameterized
- Future design style changes embodied in parametric design space
- Variant designs are constructed from the parametrized model

Learning the Performance

- Using Fusion Modeling technique, prior CAE and test data are fused to fast and accurate surrogate model
- Surrogate models are used for rapid evaluation of design variants





Summary

- Engineering simulation solves laws of physics in our world
  - Physics captured by equations (Navier Stokes' equations for fluids, Maxwell's equations for electro-magnetics)
  - Equations solved using numerical methods such as finite element analysis and finite difference
- Artificial Intelligence has progressed from Expert Systems to Machine Learning to Deep Learning
- Discussed the use of AI/ML to improve engineering simulation around four use cases:
  - Improving Customer Productivity
  - Augmented Simulation
  - Revolutionizing engineering design
  - Business Intelligence.
- Highlighted six AI/ML applications in engineering simulation
  - Data-driven thermal solver
  - Physics informed neural network for simulation
  - Machine learning based PDE solvers
  - Hybrid AI and Physics based Digital Twins
  - Using AI/ML to Improve Convergence
  - ML based Generative networks

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