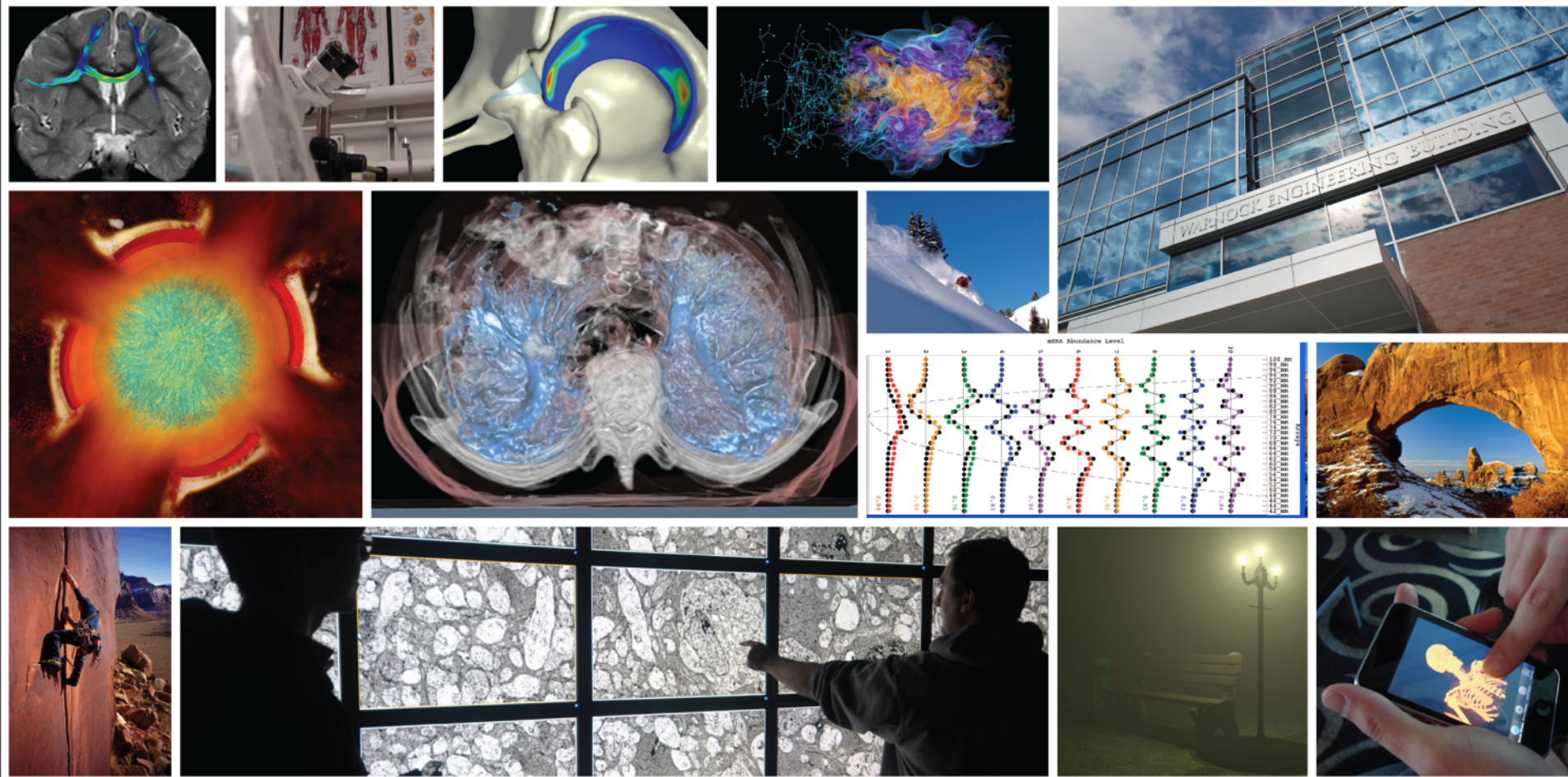
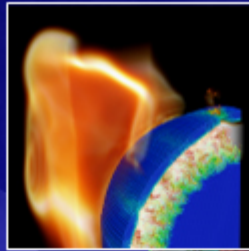


Big Data: A Scientific Visualization Perspective

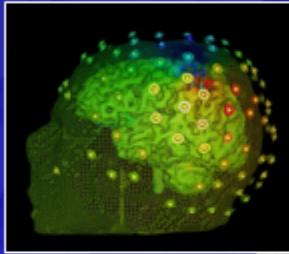


Chuck Hansen
Scientific Computing and Imaging Institute
University of Utah

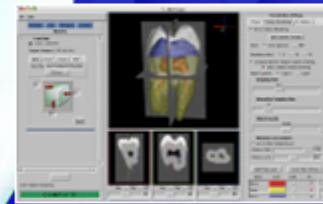
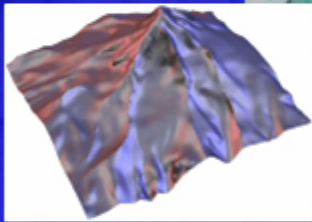
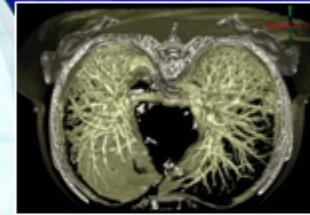
COMPUTING



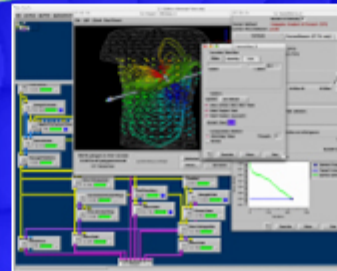
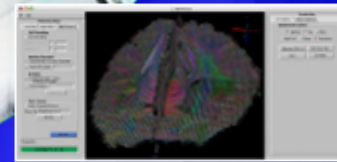
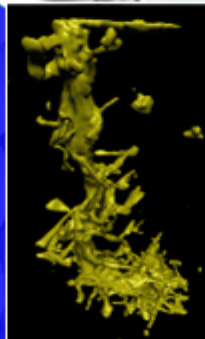
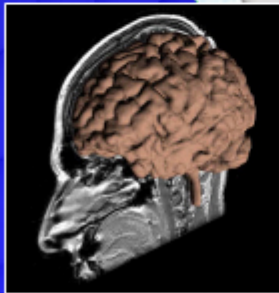
VISUALIZATION



Research at SCI

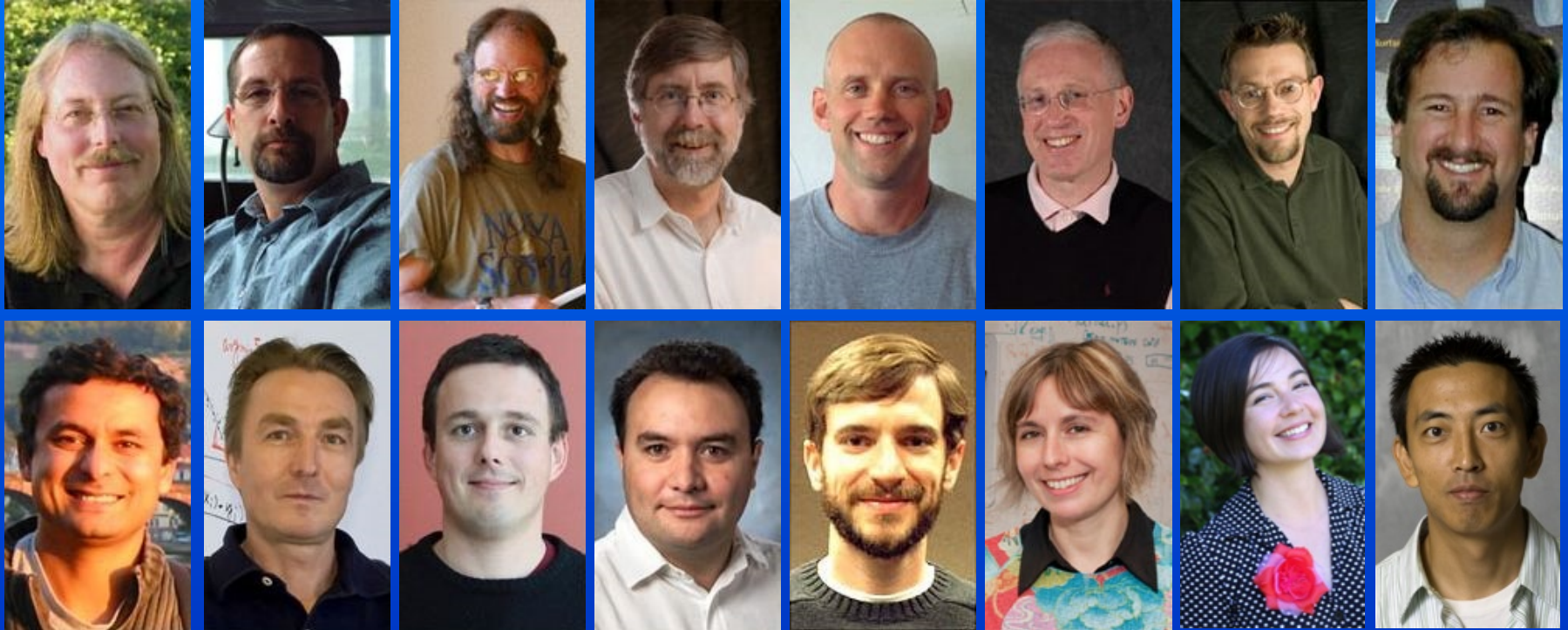


IMAGING



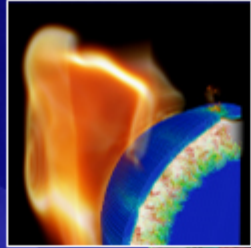
APPLICATIONS

SCI Institute Faculty

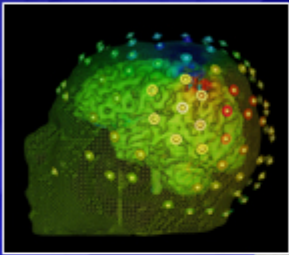




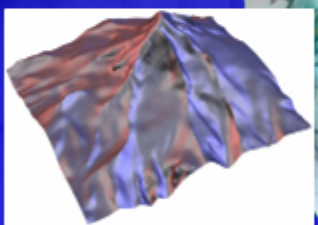
COMPUTING



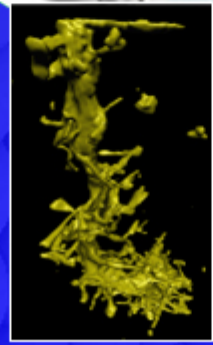
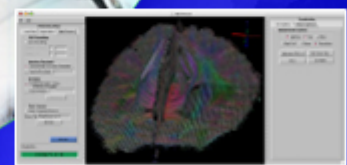
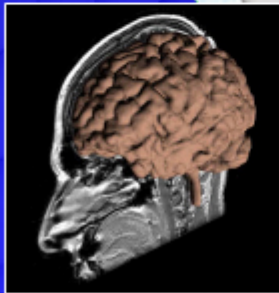
VISUALIZATION



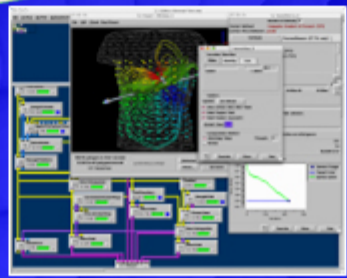
Research at SCI



IMAGING



APPLICATIONS

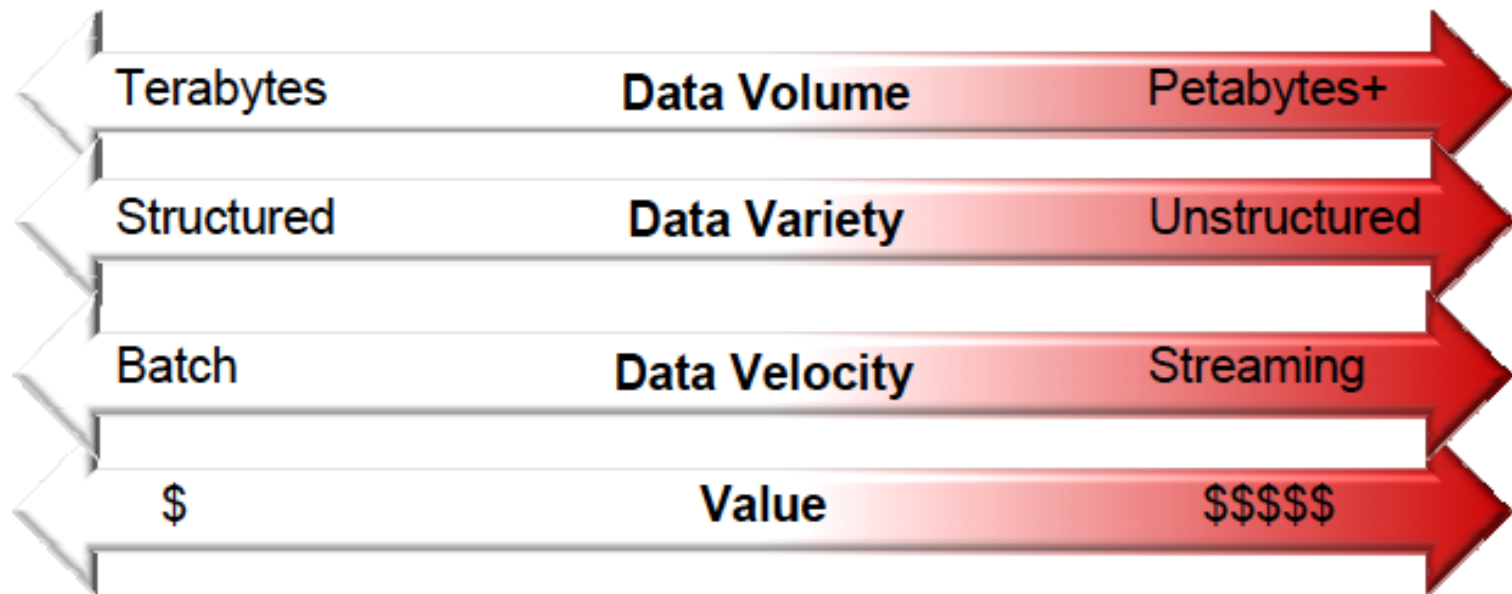


Emerging Technologies Hype Cycle 2012



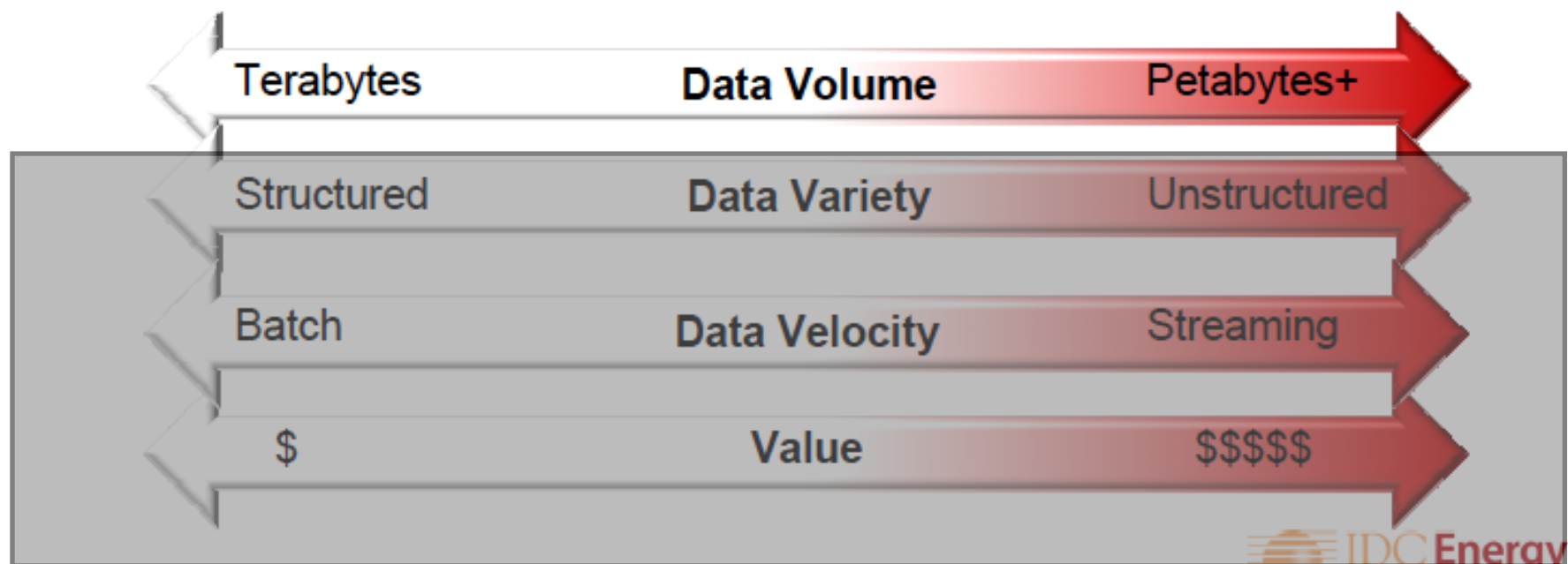
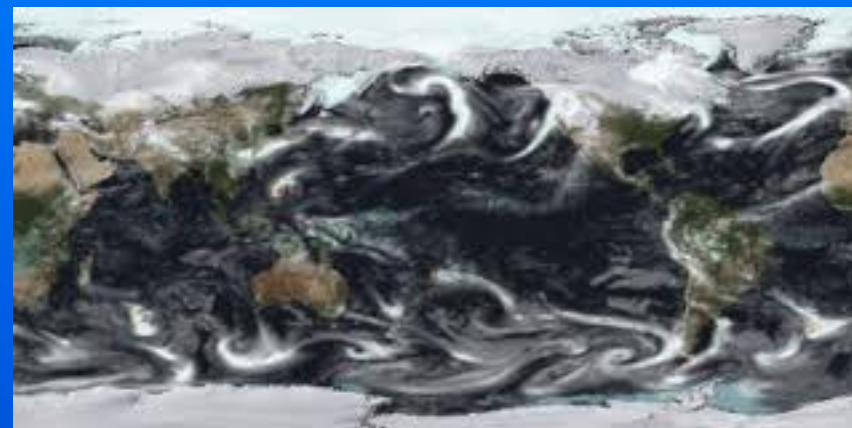
Gartner

Big Data: The Vs



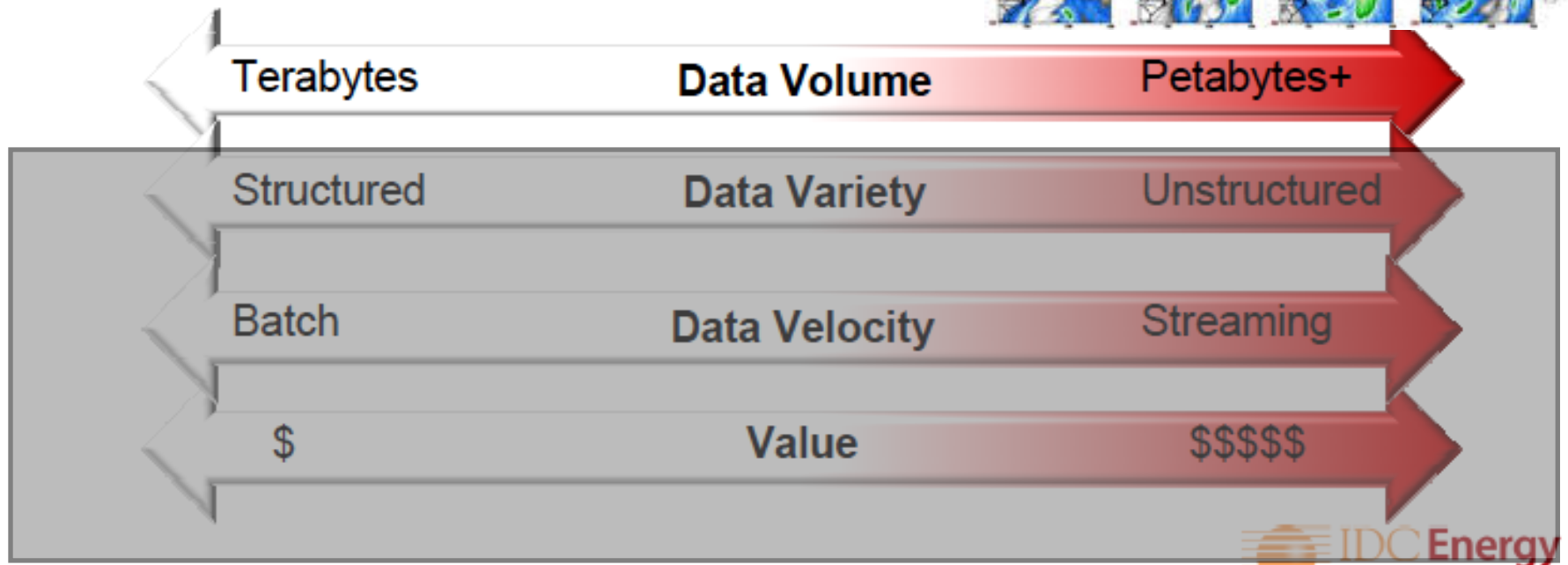
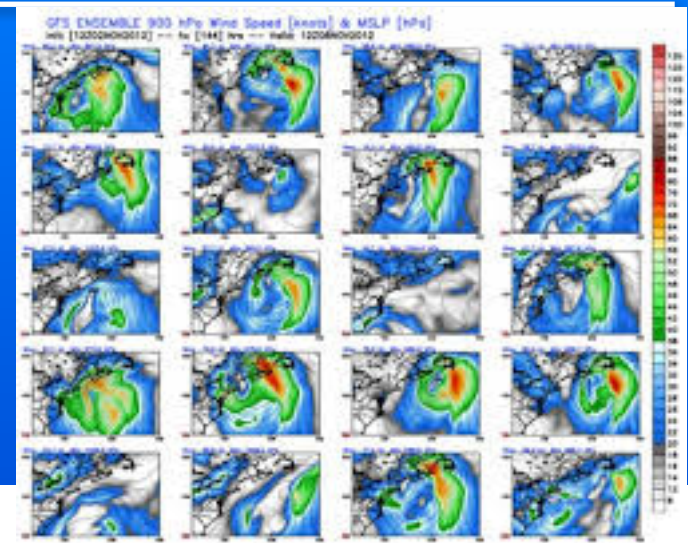
Big Data: The Vs

High Resolution Models



Big Data: The Vs

High Resolution Models Ensembles



Big Data: The V

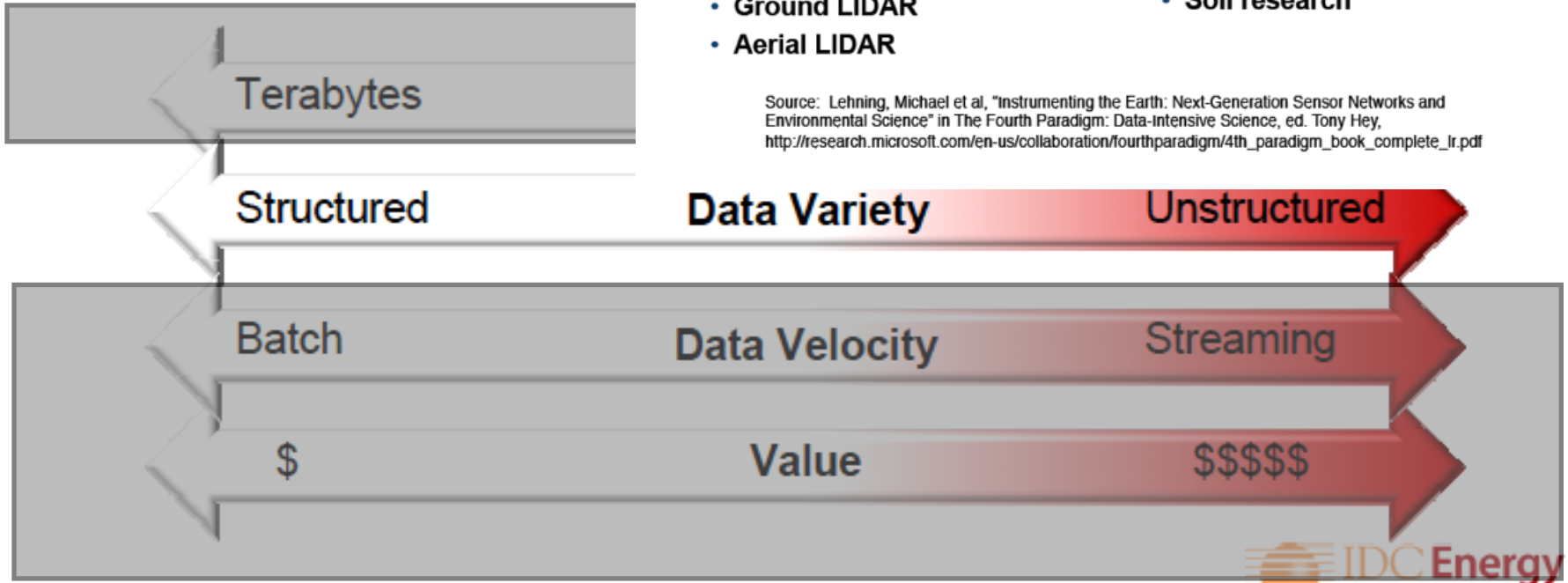
Heterogeneous Data: Environmental Science Example

Sensor data
Coupled models

- Mobile stations
- High-resolution weather stations
- Full-size snow/weather stations
- External weather stations
- Satellite imagery
- Weather radar
- Mobile weather radar
- Stream observations
- Citizen-supplied observations
- Ground LIDAR
- Aerial LIDAR
- Nitrogen/methane measures
- Snow hydrology & avalanche probes
- Seismic probes
- Distributed optical fiber temperature sensing
- Water quality sampling
- Stream gauging stations
- Rapid mass movements research
- Run-off stations
- Soil research

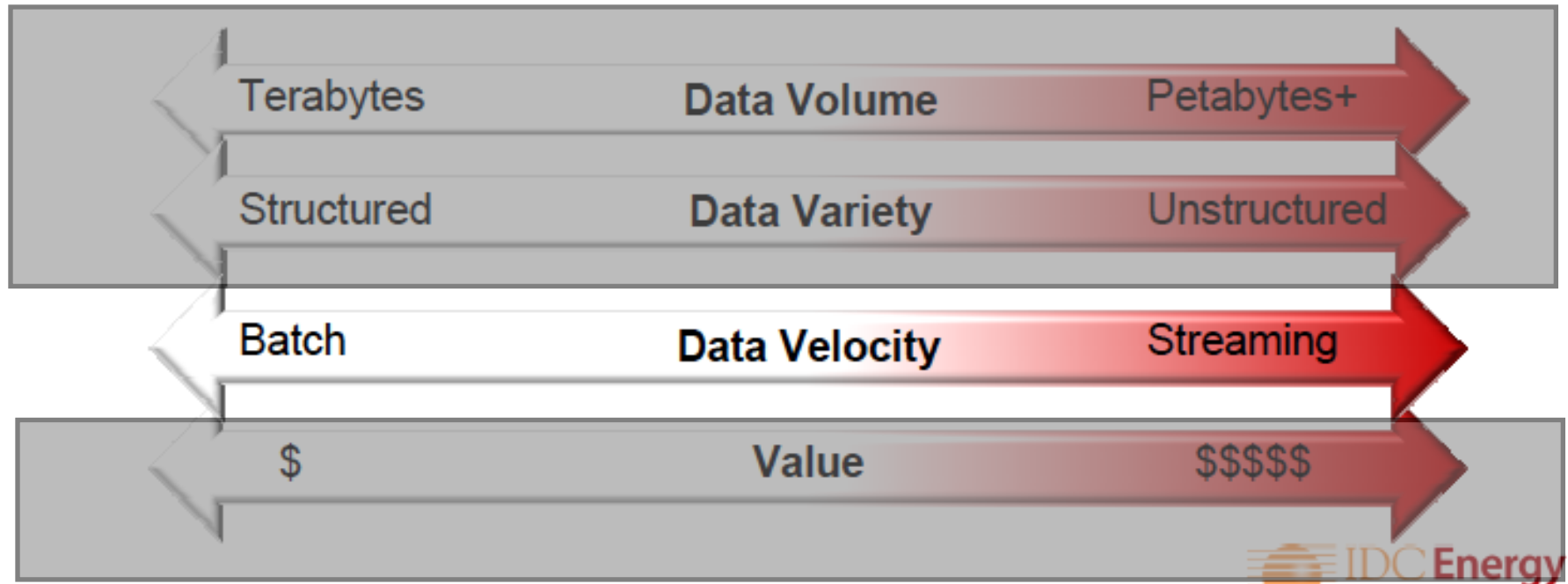
Source: Lehning, Michael et al, "Instrumenting the Earth: Next-Generation Sensor Networks and Environmental Science" in The Fourth Paradigm: Data-Intensive Science, ed. Tony Hey, http://research.microsoft.com/en-us/collaboration/fourthparadigm/4th_paradigm_book_complete_lr.pdf

14



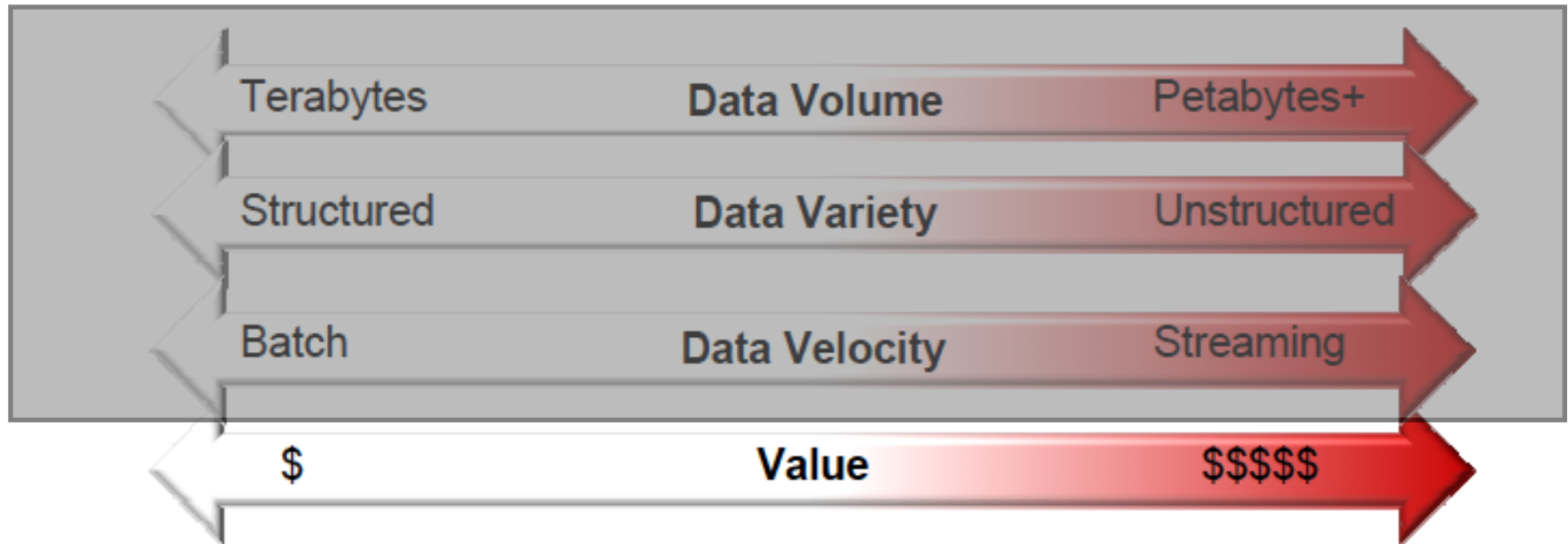
Big Data: The Vs

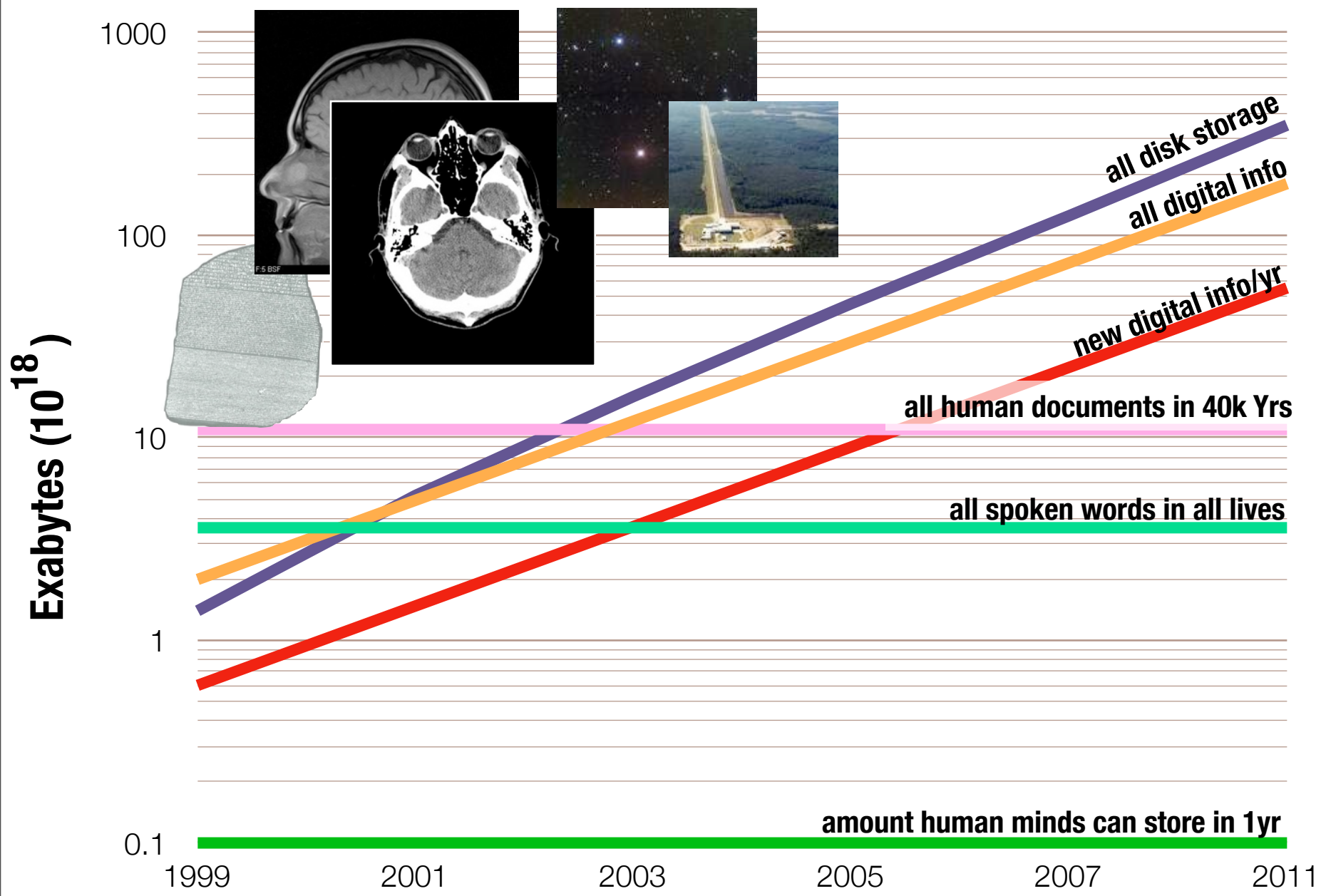
High-throughput Analysis
Real-time predictive models



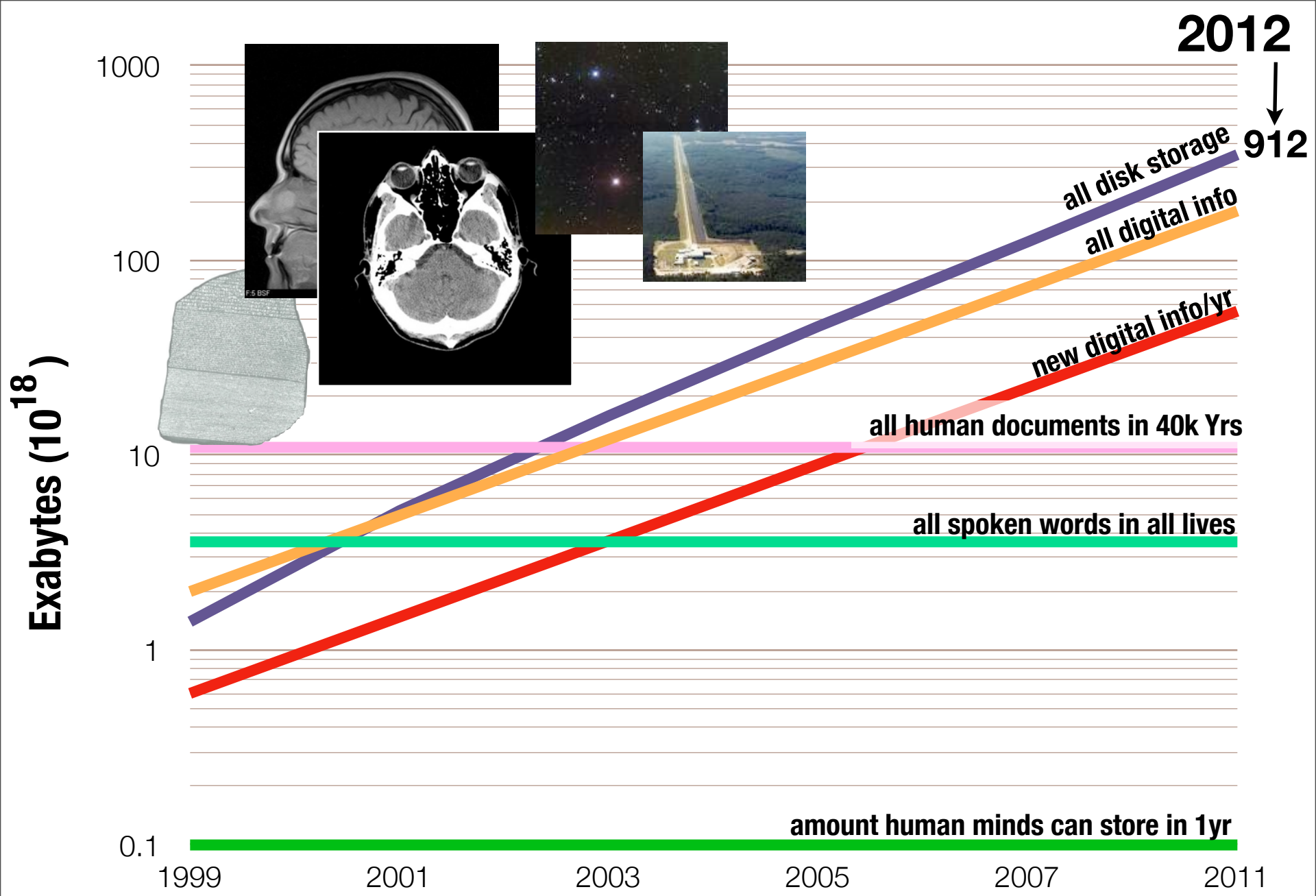
Big Data: The Vs

Climate Change
Clean Energy
Disaster Prediction

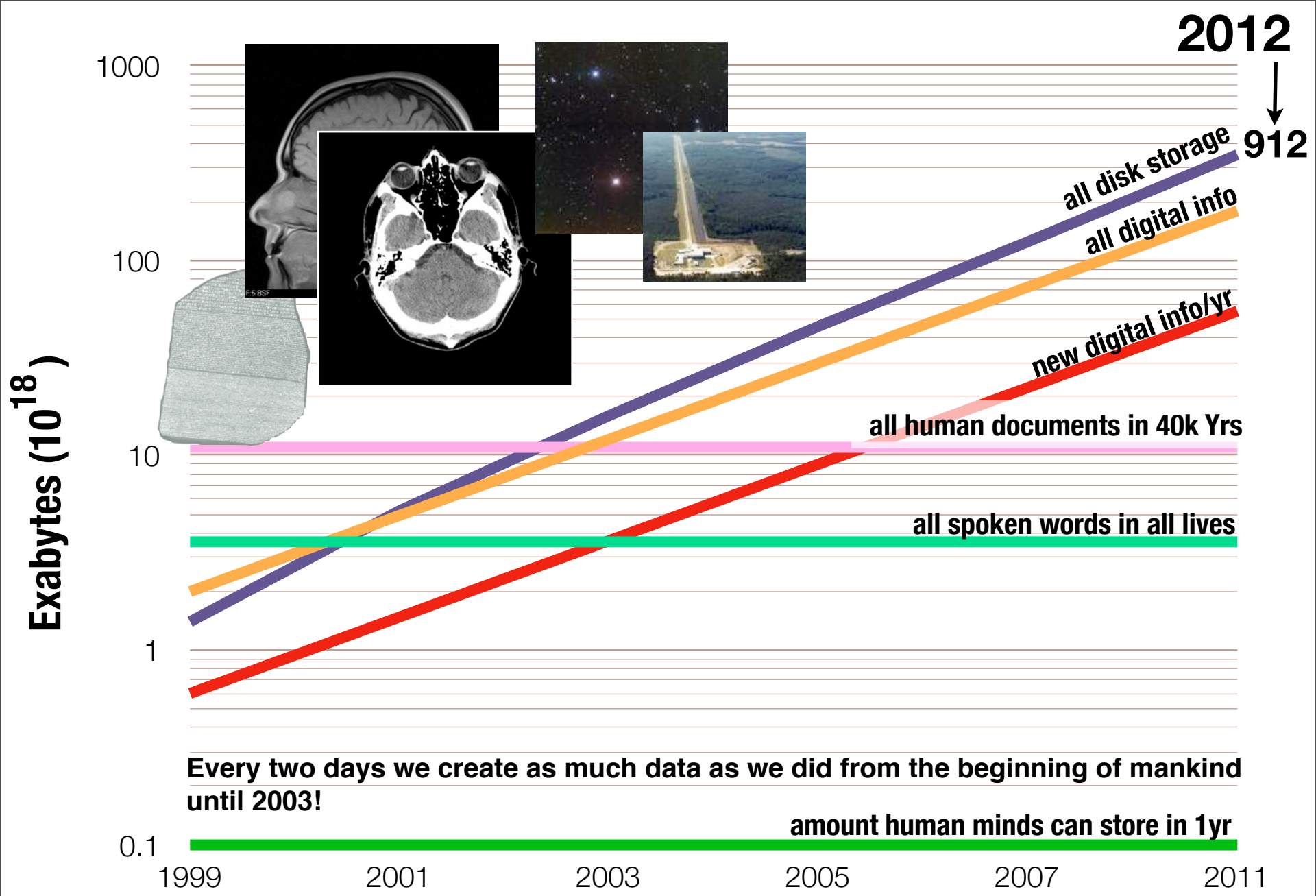




Sources: Lesk, Berkeley SIMS, Landauer, EMC, TechCrunch, Smart Planet



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How many trees does it take to print out an Exabyte?

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Sources: <http://www.whatsabyte.com/> and <http://wiki.answers.com>

Brain Information Bandwidth (Velocity)

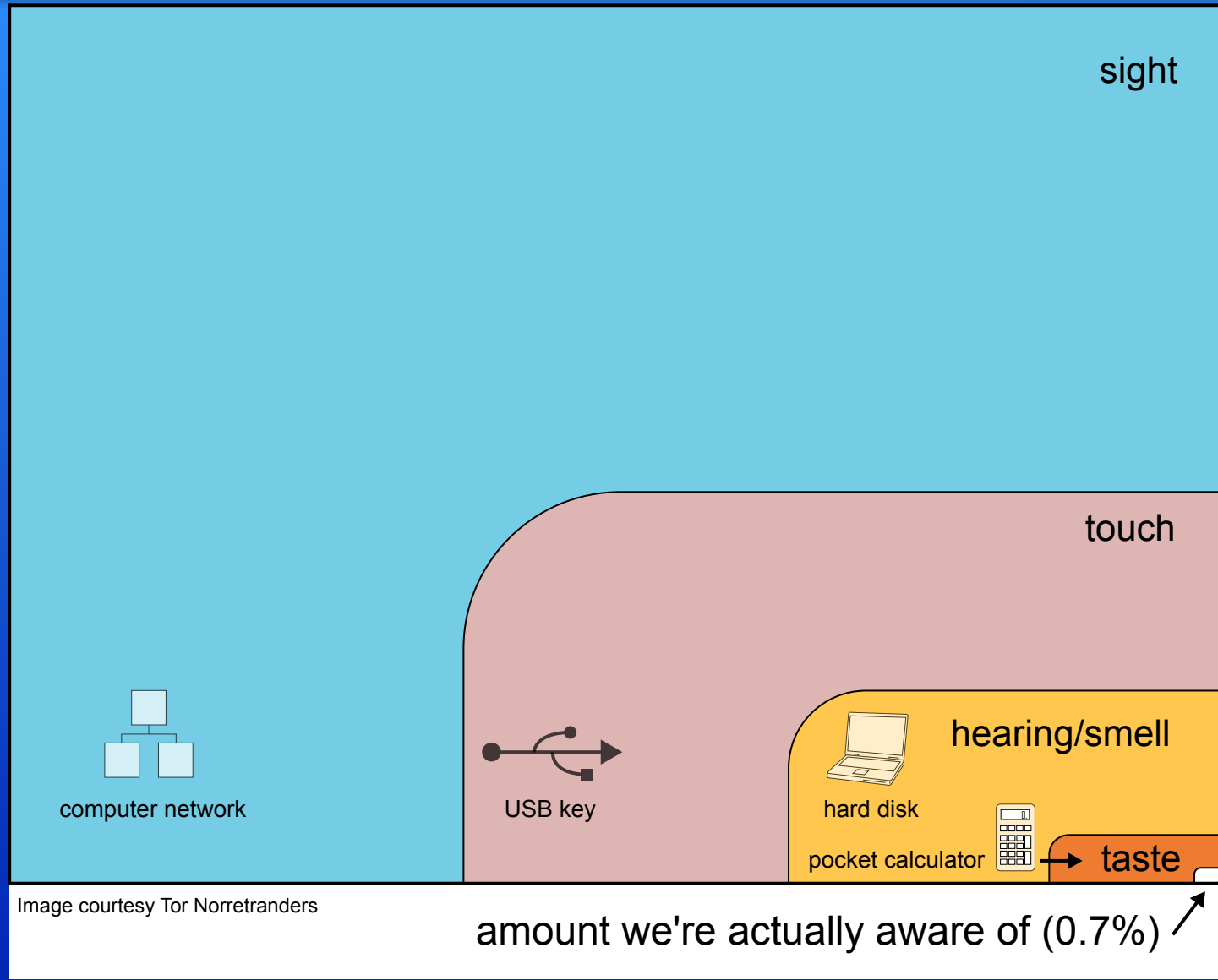


Image courtesy Tor Norretranders

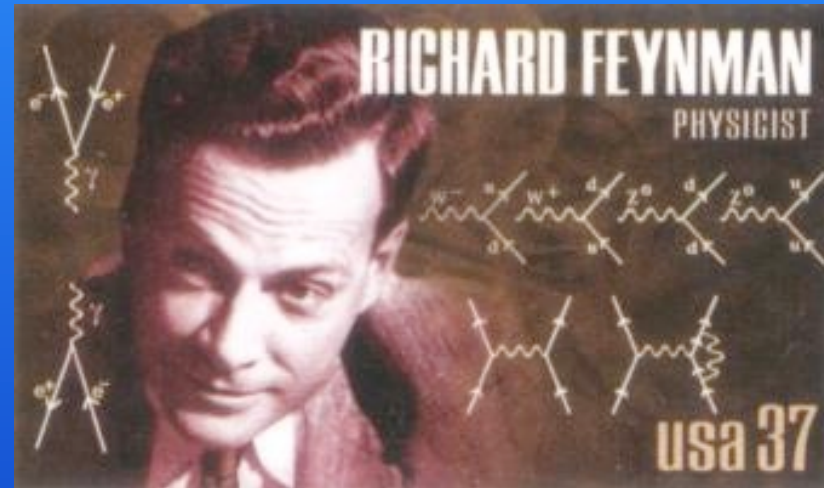
Feynman Diagrams (Data Analytics)

Drawing Theories Apart

The Dispersion of
FEYNMAN DIAGRAMS
in Postwar Physics



DAVID KAISER



Feynman: “What I am really try to do is bring birth to clarity, which is really a half-assedly thought-out-pictorial semi-vision thing. I would see the jiggle-jiggle-jiggle or the wiggle of the path. Even now when I talk about the influence functional, I see the coupling and I take this turn - like as if there was a big bag of stuff - and try to collect it in away and to push it. It's all visual. It's hard to explain.”

James Gleick, *The Life and Science of Richard Feynman*, Vintage Books, New York, 1992.

Scientific Computing and Imaging Institute, University of Utah

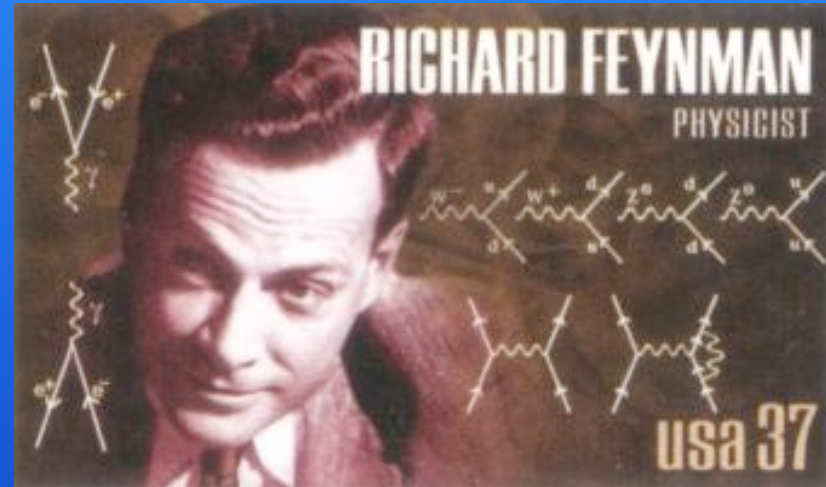
Feynman Diagrams

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DAVID KAISER

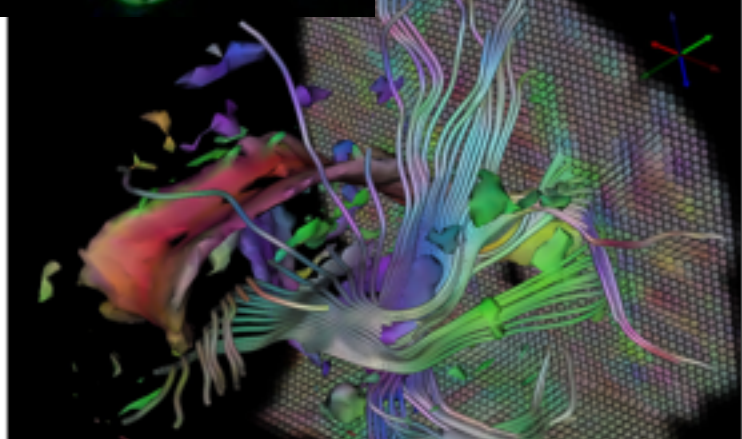
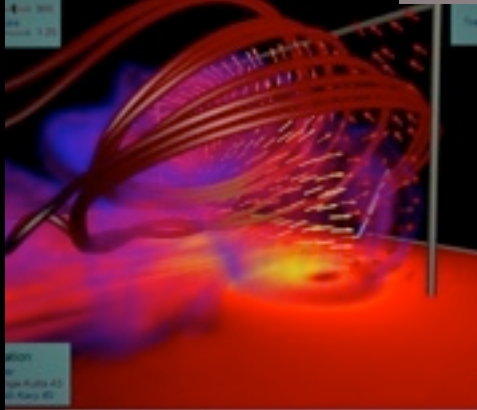
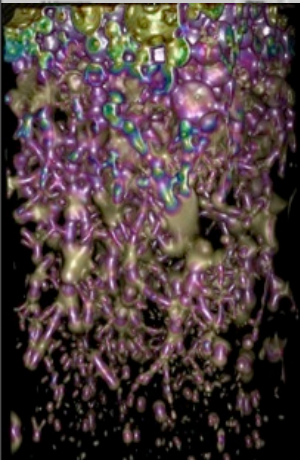
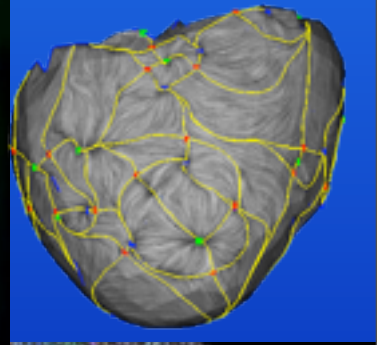
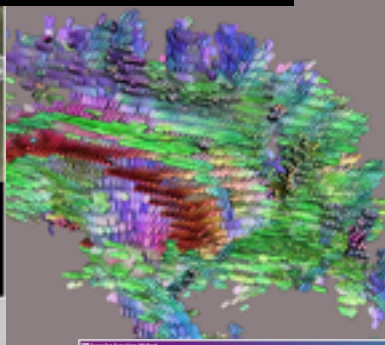
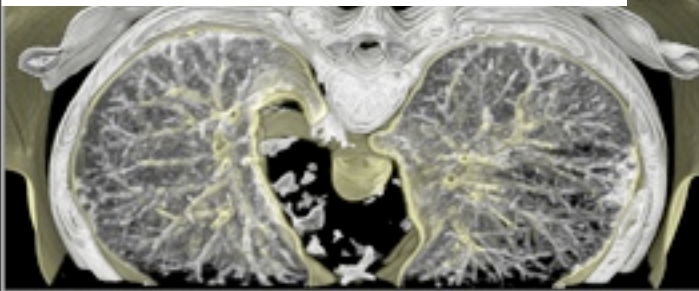
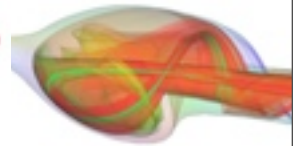
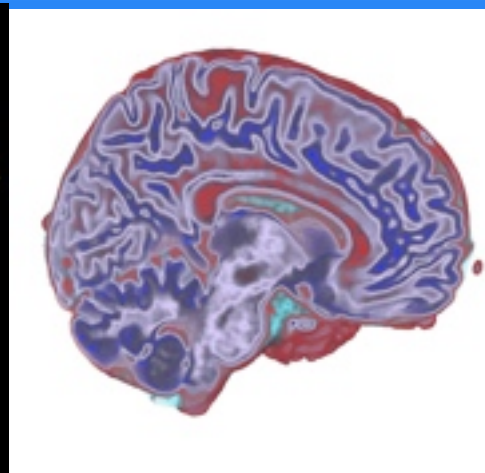
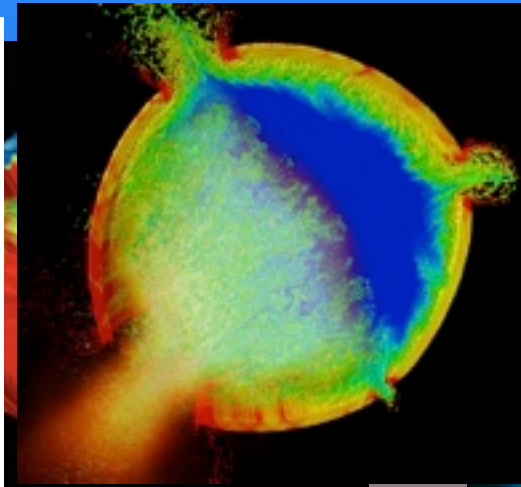
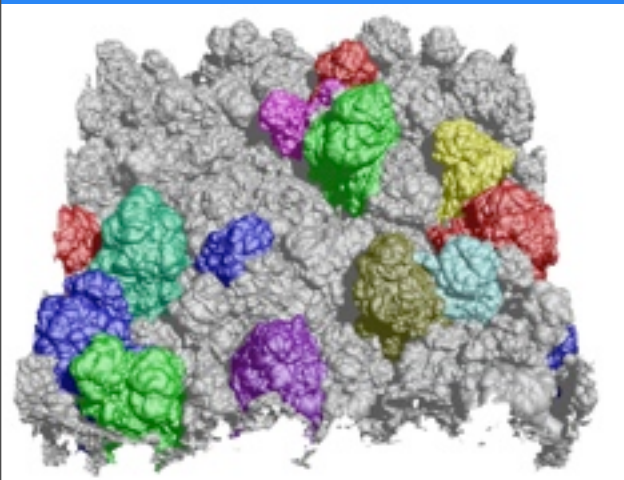


Feynman: "In certain particular problems that I have done it was necessary to continue the development of the picture as the method before the mathematics could be really done."

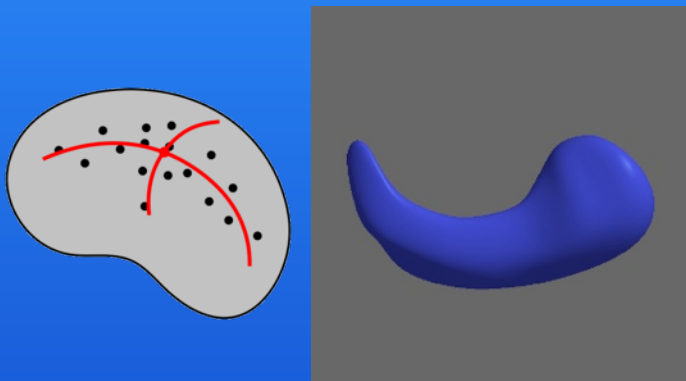
James Gleick, *The Life and Science of Richard Feynman*, Vintage Books, New York, 1992.

Scientific Computing and Imaging Institute, University of Utah

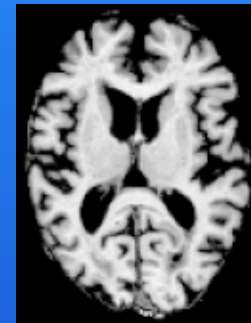
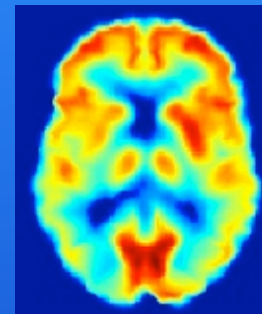
New Visual Analysis Techniques



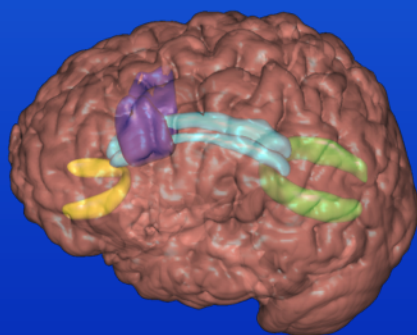
Big Data in Imaging Research



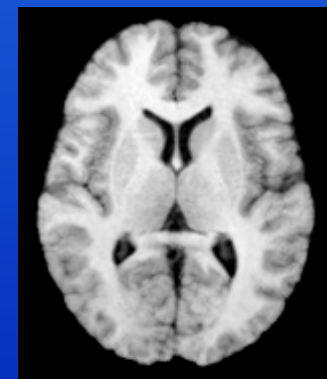
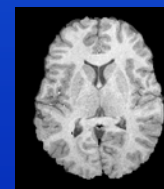
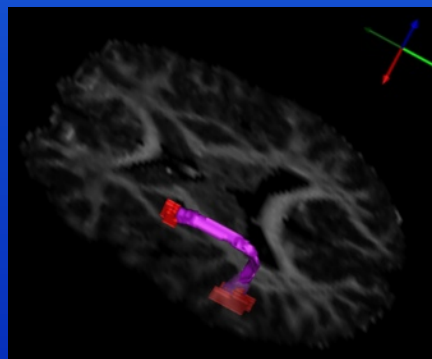
**Computational Statistics
in Nonlinear Spaces**



**Combined PET + MRI analysis
Alzheimer's disease project**

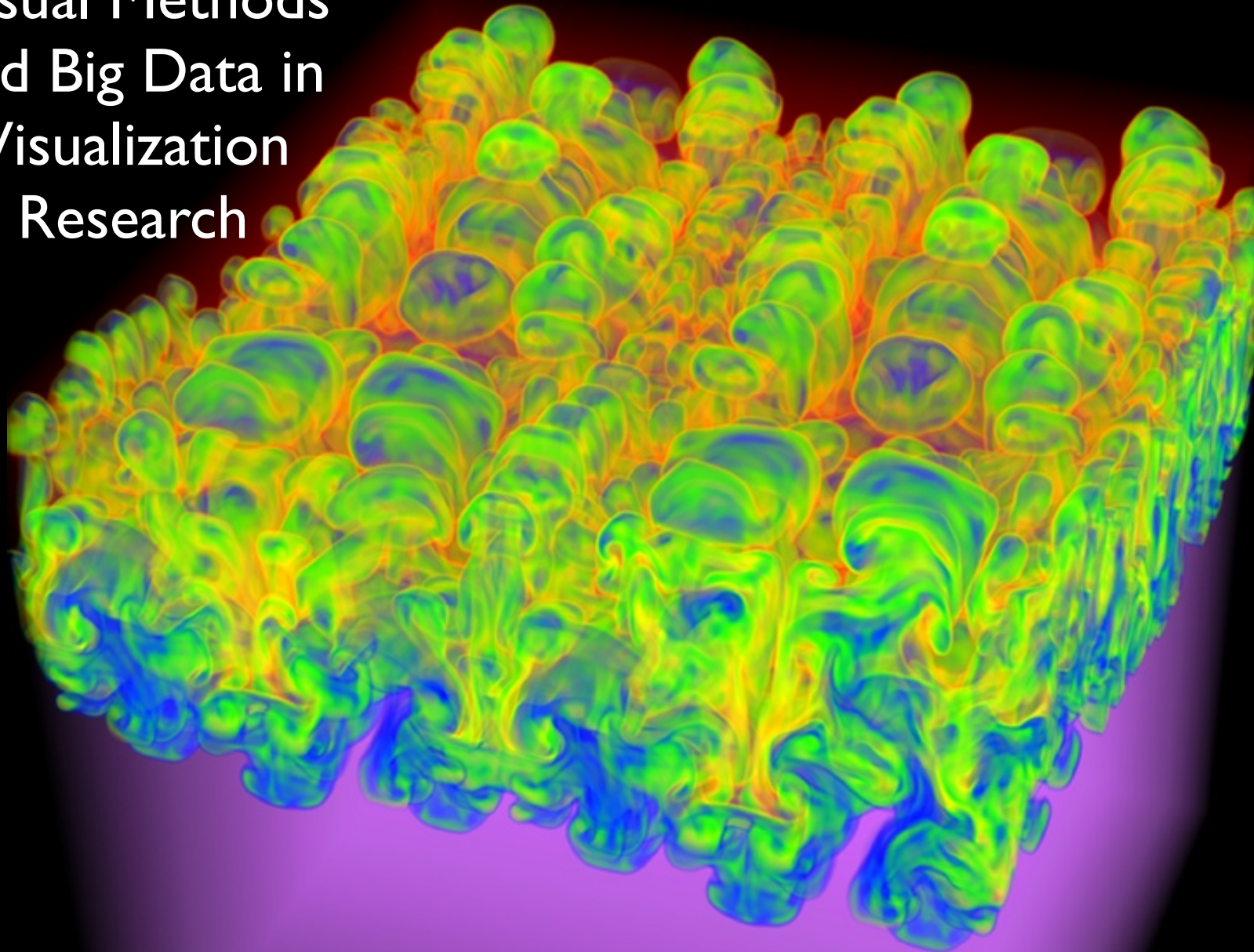


**Diffusion Tensor Image Analysis
Autism project**



**Anatomical shape averaging
and variability**

Visual Methods and Big Data in Visualization Research



Perceptual Cues for Shading



Jim Blinn:

“Lighting models... there's something that always bothered me about lighting models. Bui Tuong Phong is[was] a great guy and he did wonderful work ...

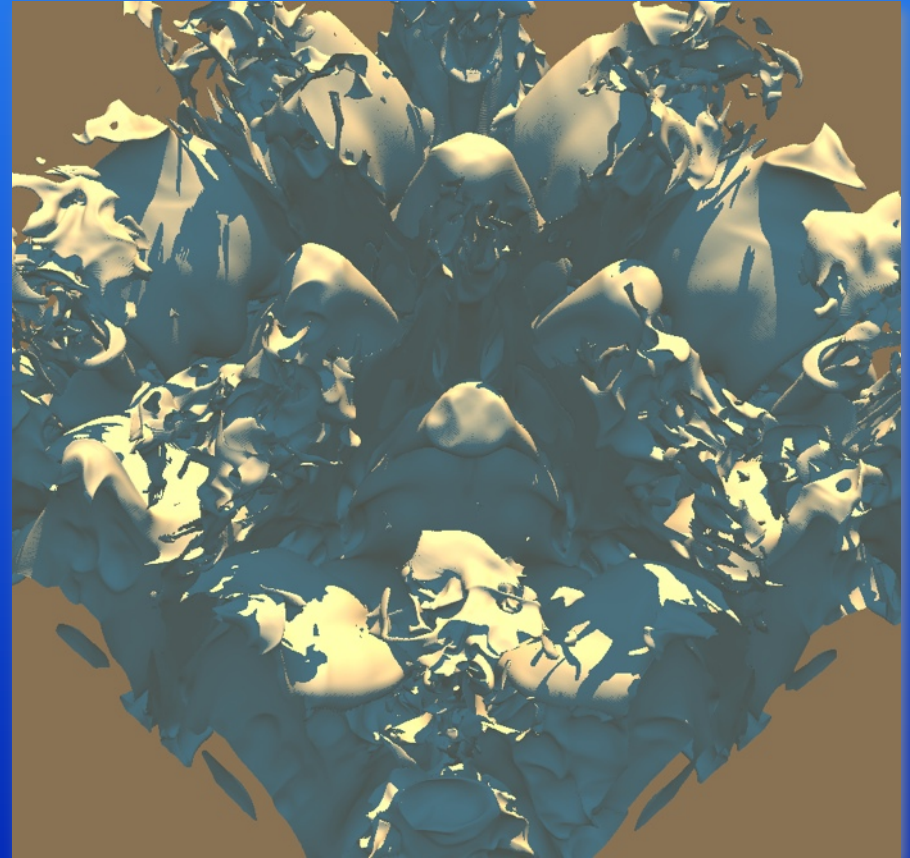
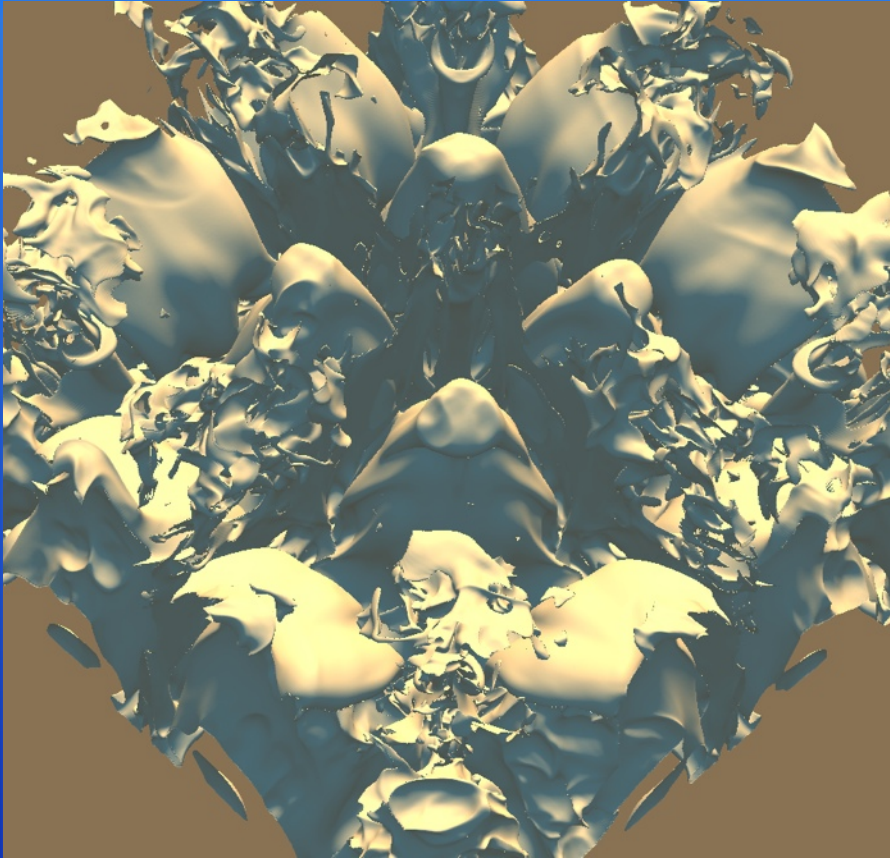
The thing is, this has no physical basis whatsoever ...

I'd like to see cosine power retired and better approximations being done.”

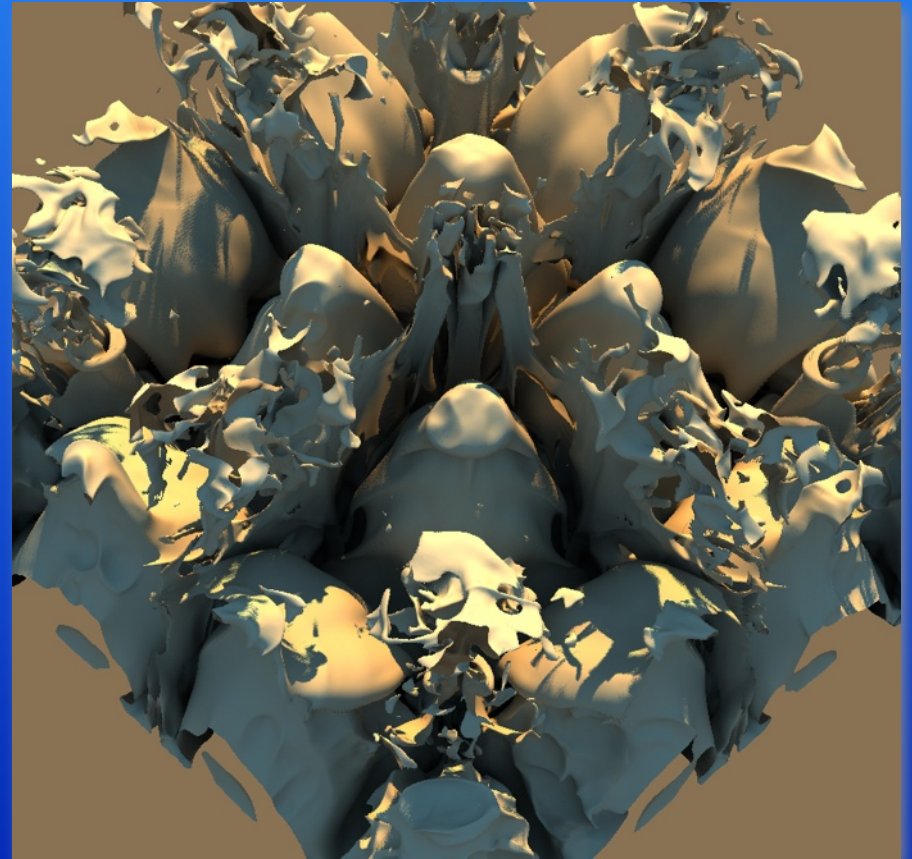
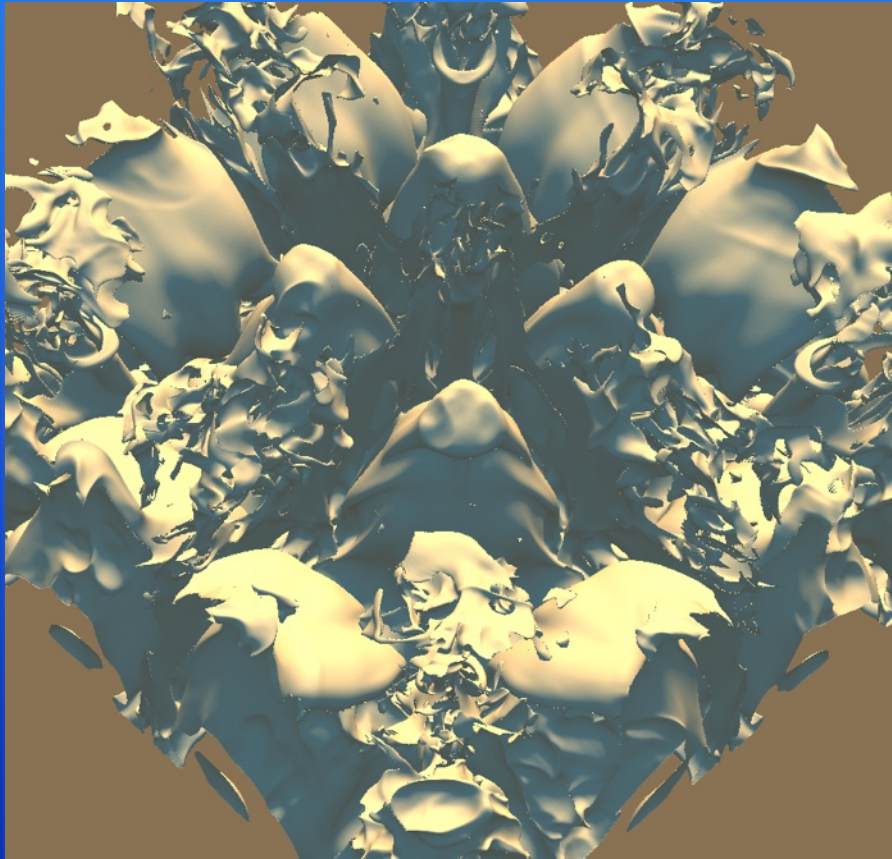
- **SIGGRAPH 98 Keynote Speech**

Scientific Computing and Imaging Institute, University of Utah

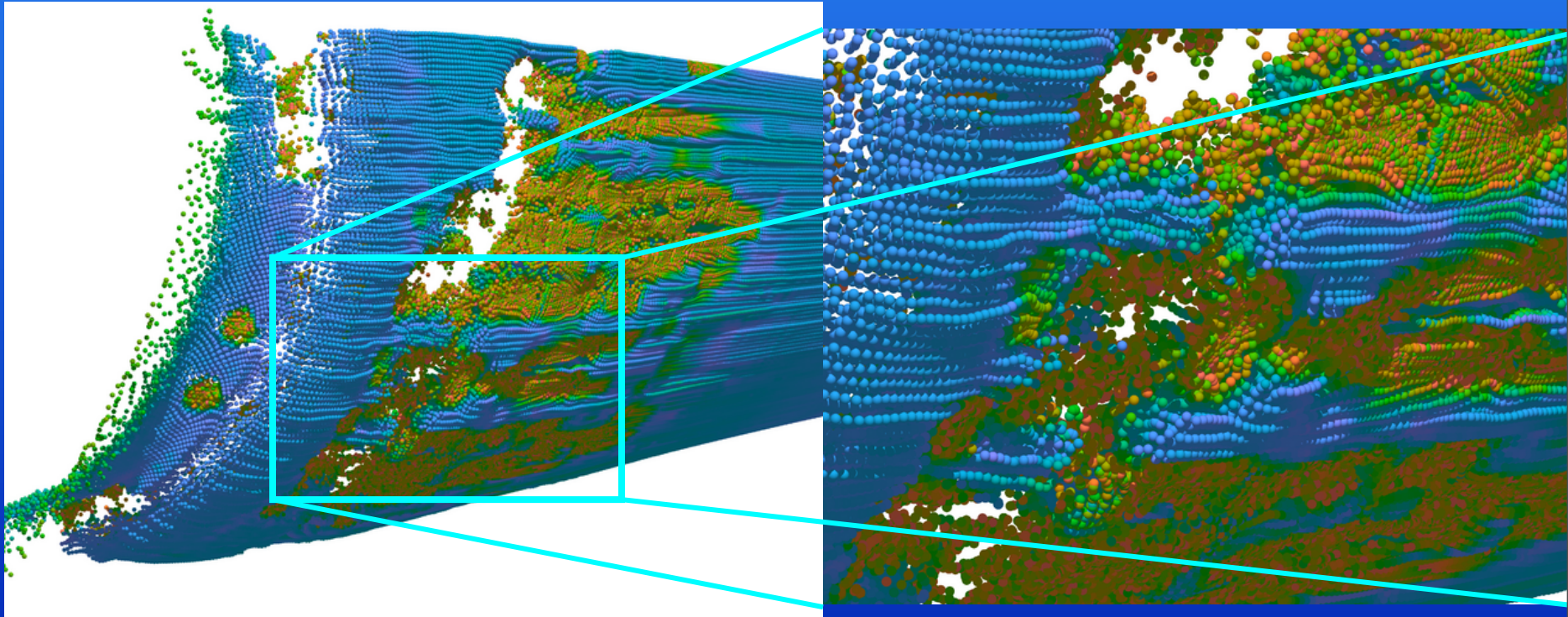
Perception - Shadows



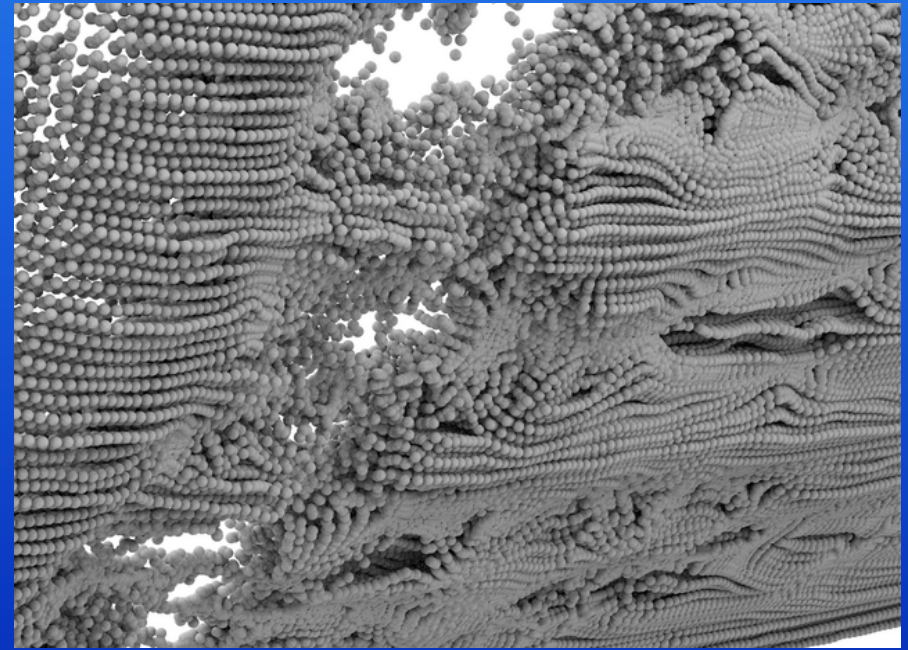
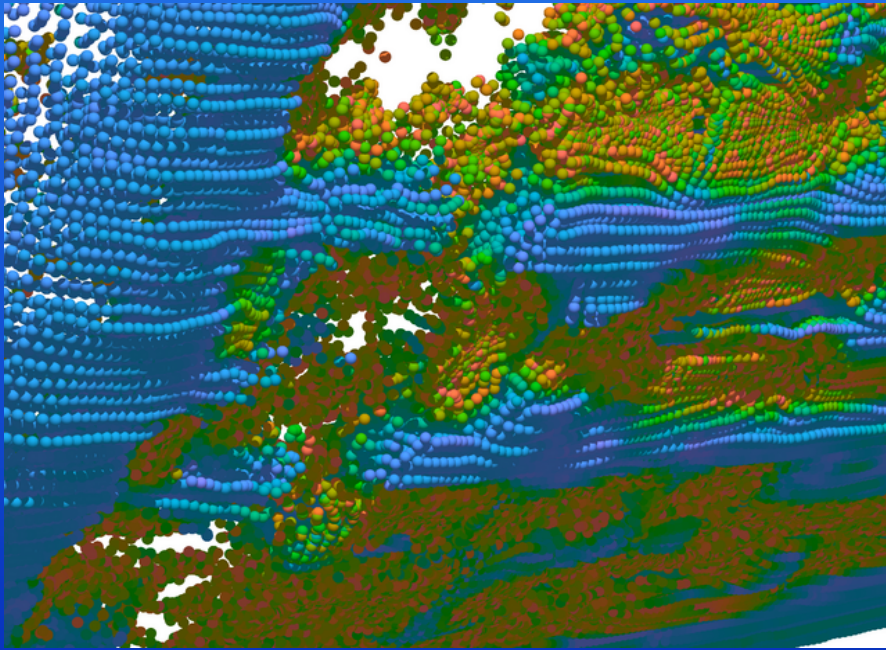
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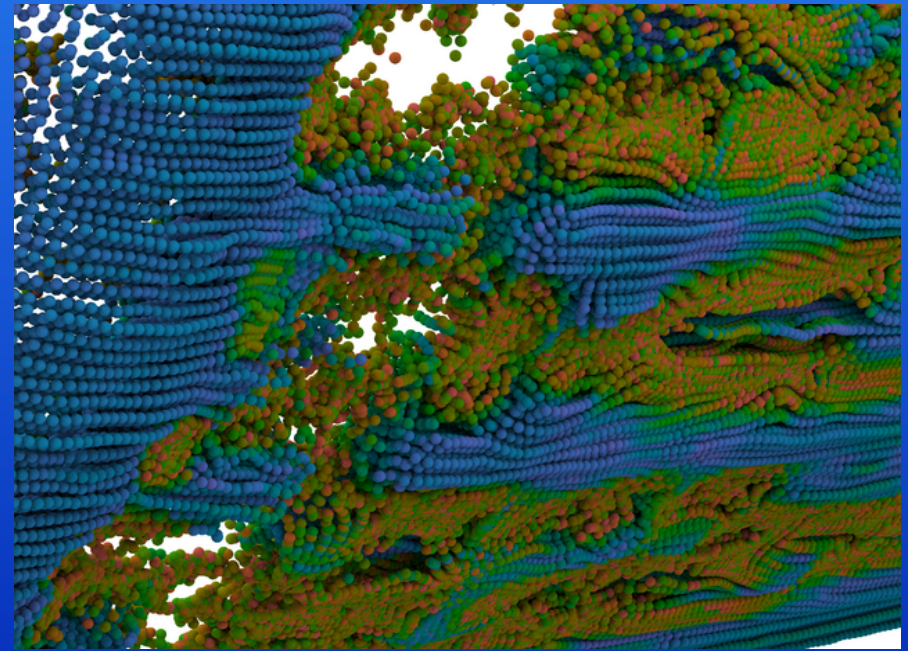
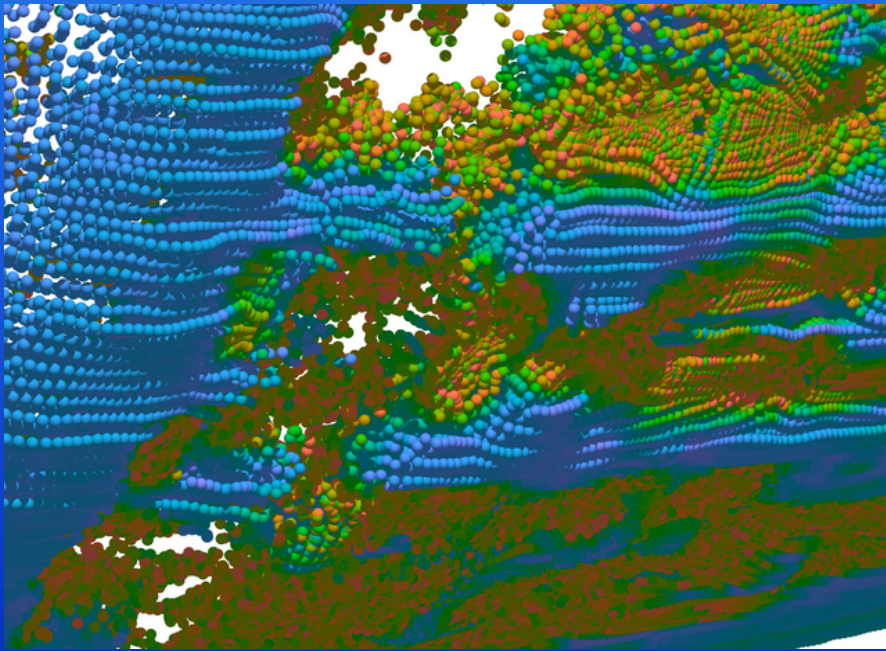
Indirect Shading of Particles



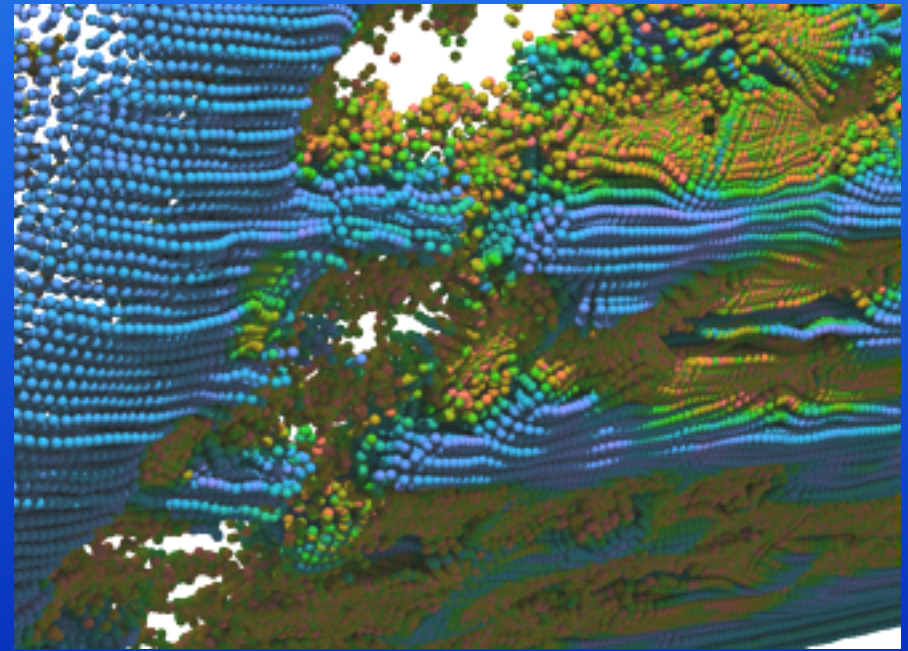
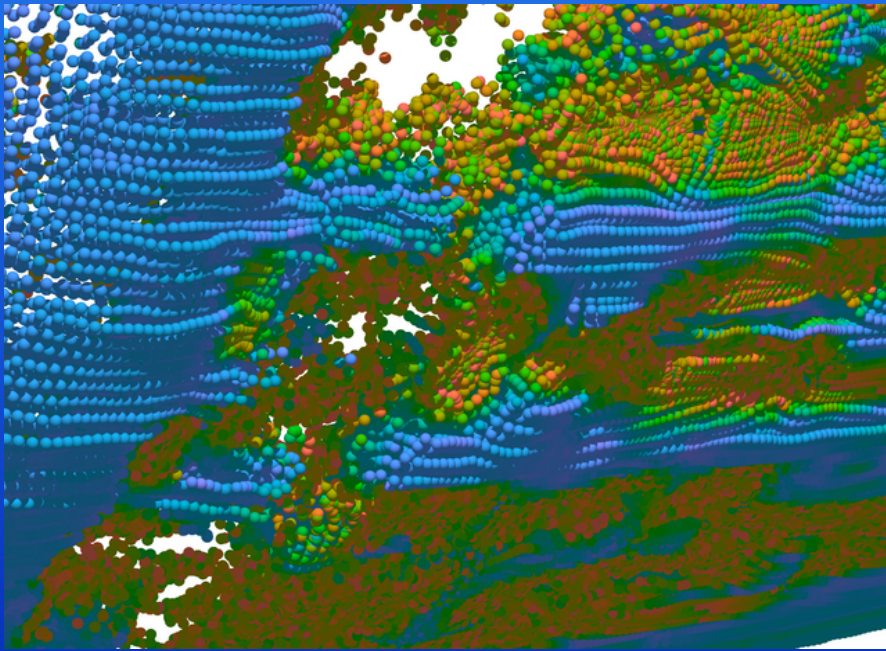
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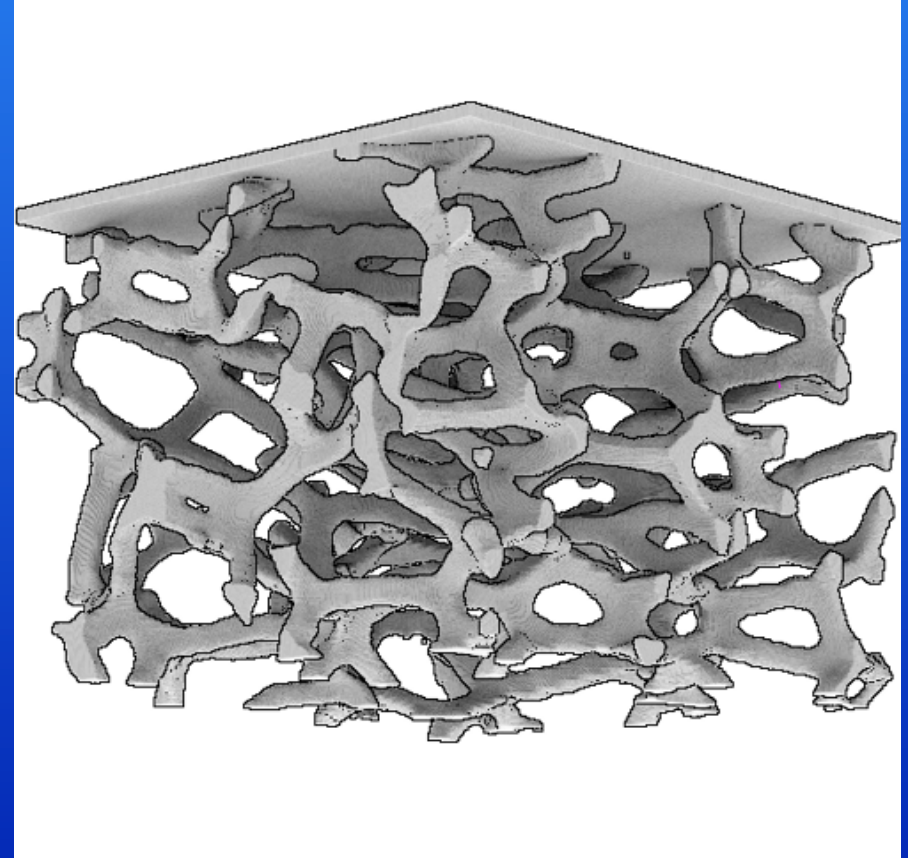
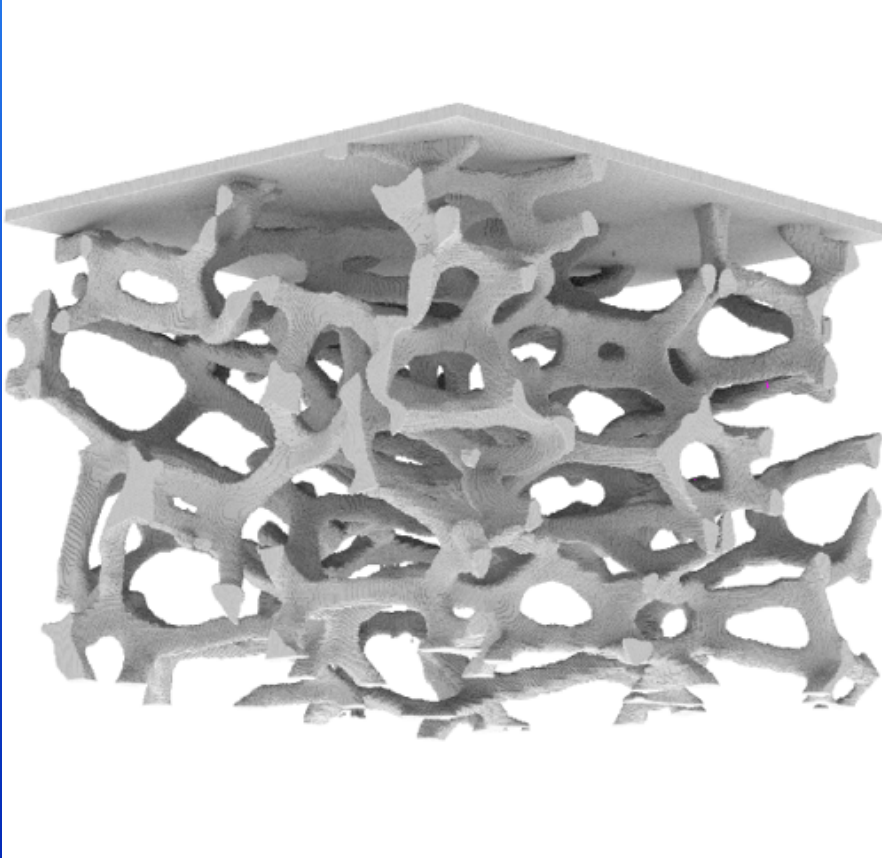
Indirect Shading of Particles

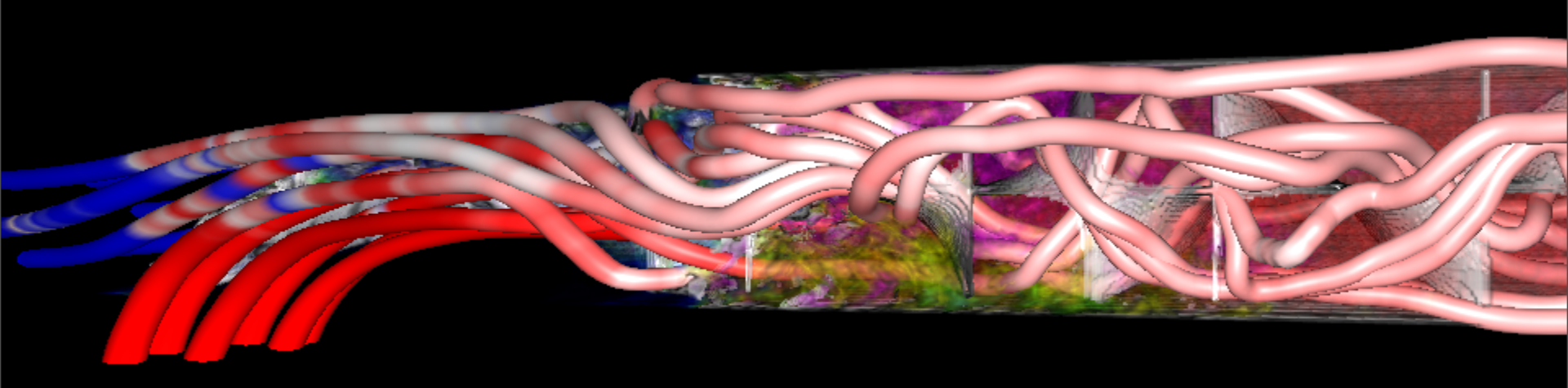
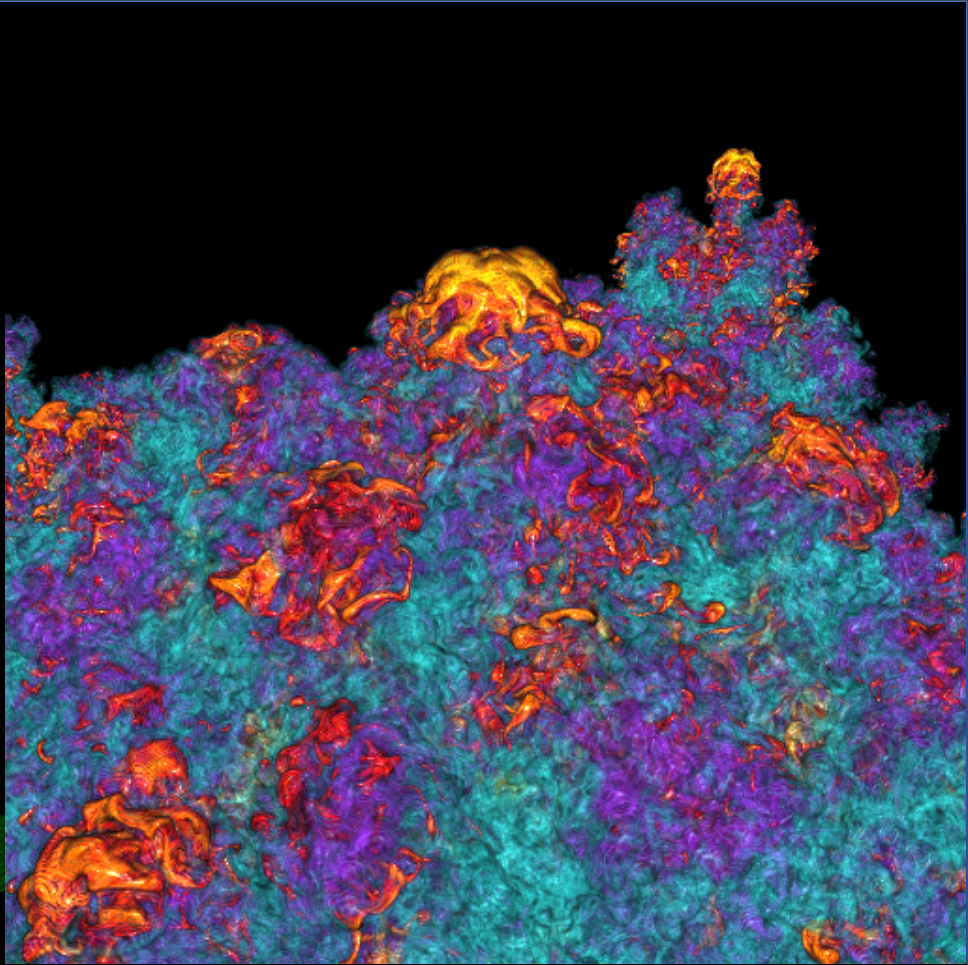
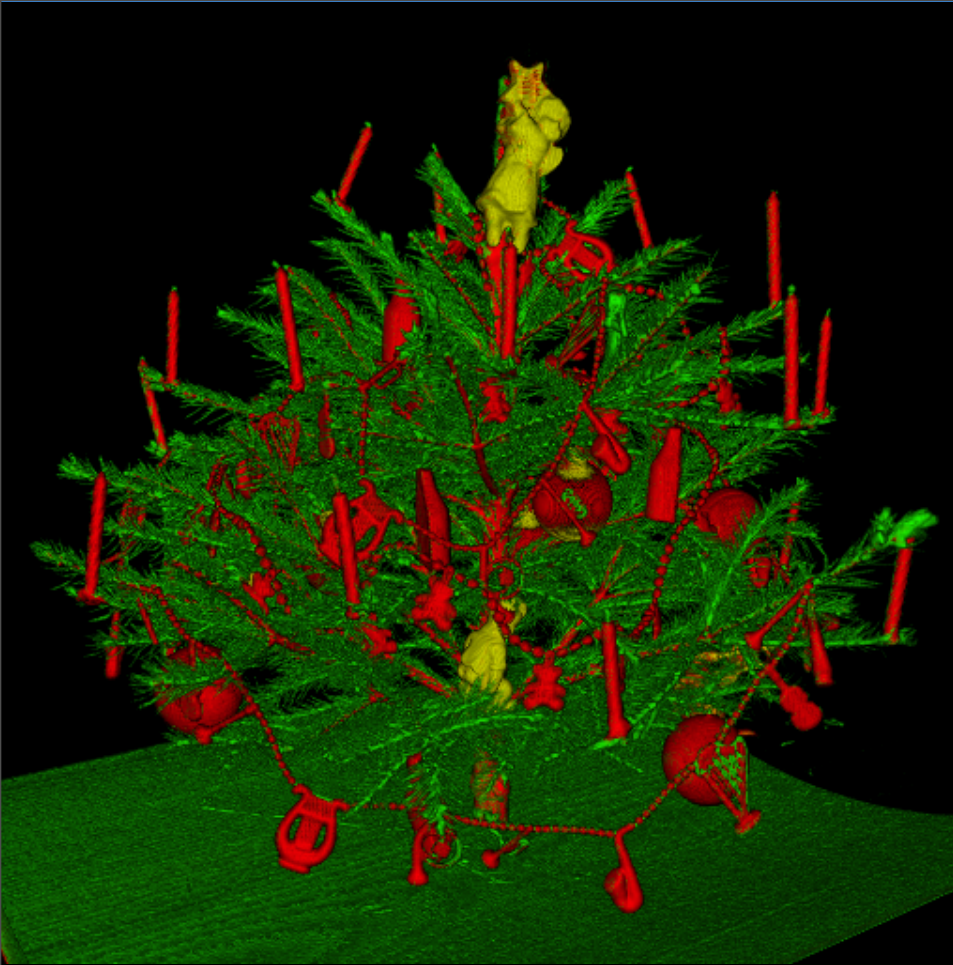


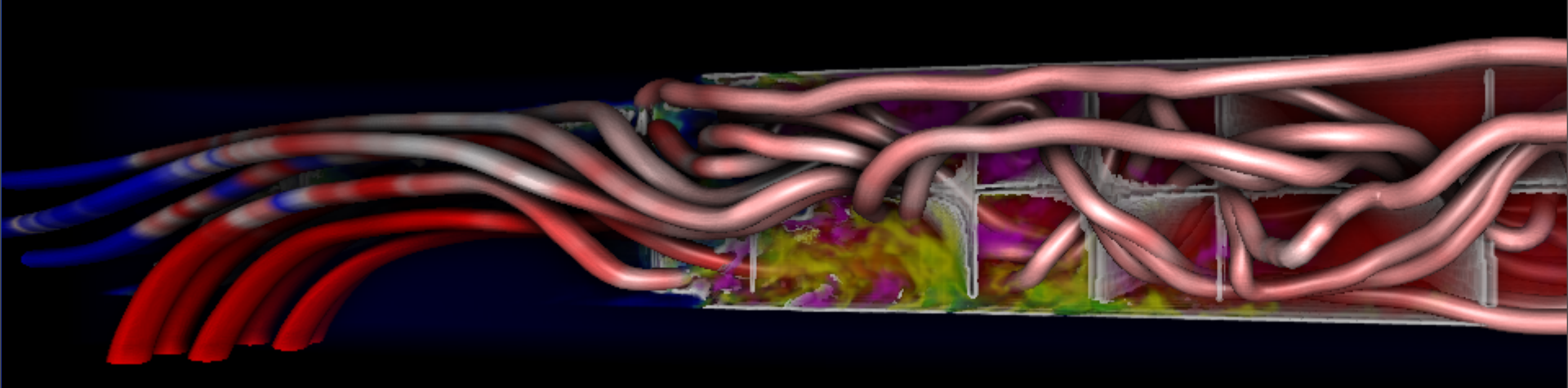
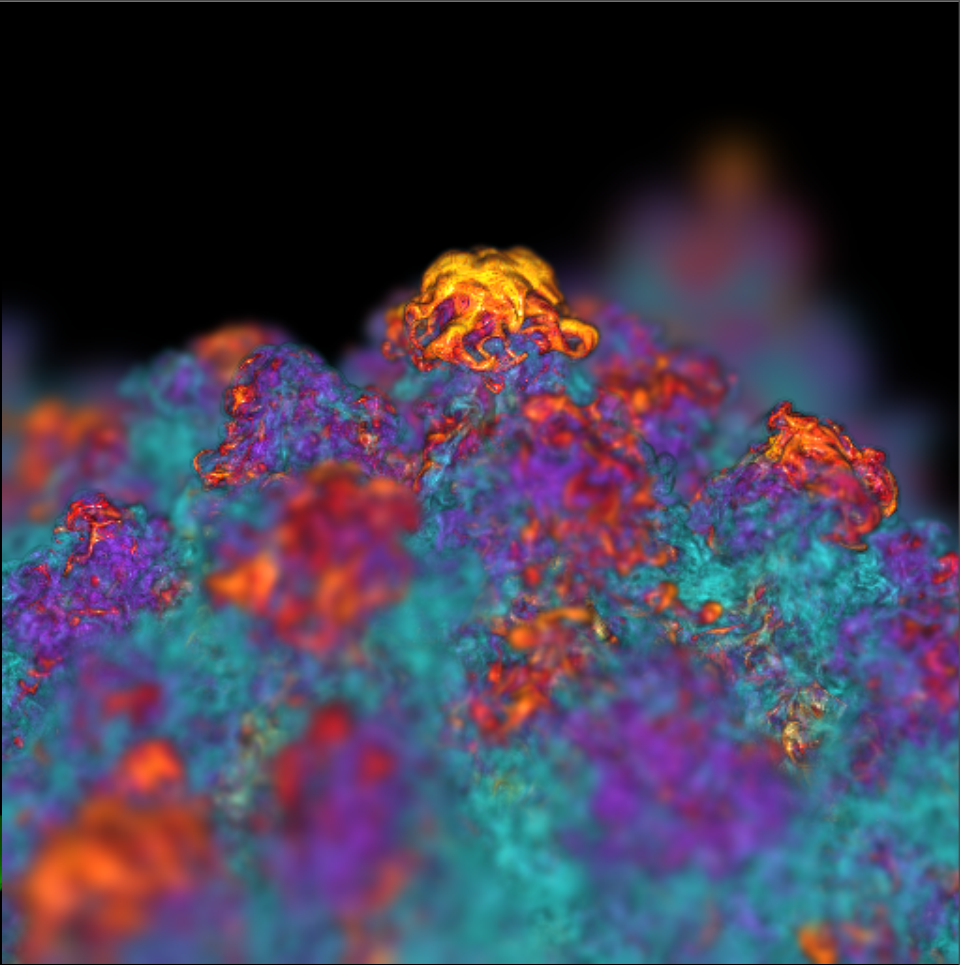
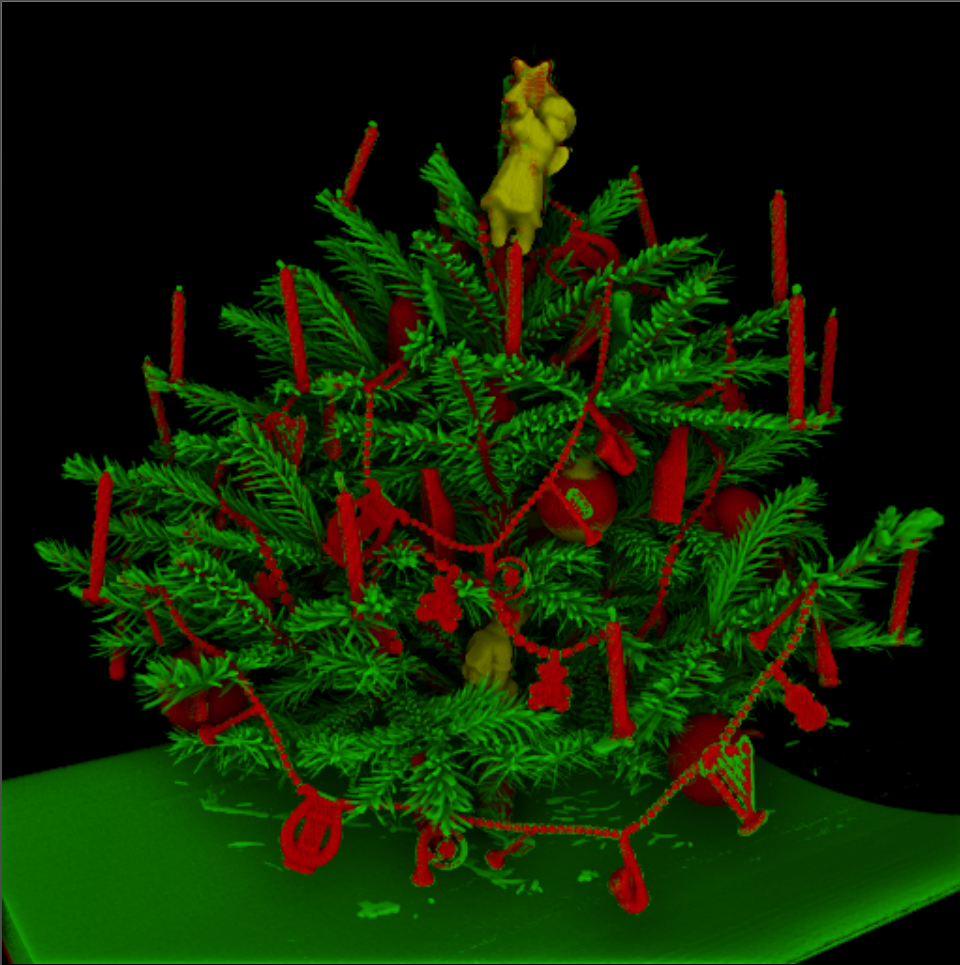
Indirect Shading of Particles



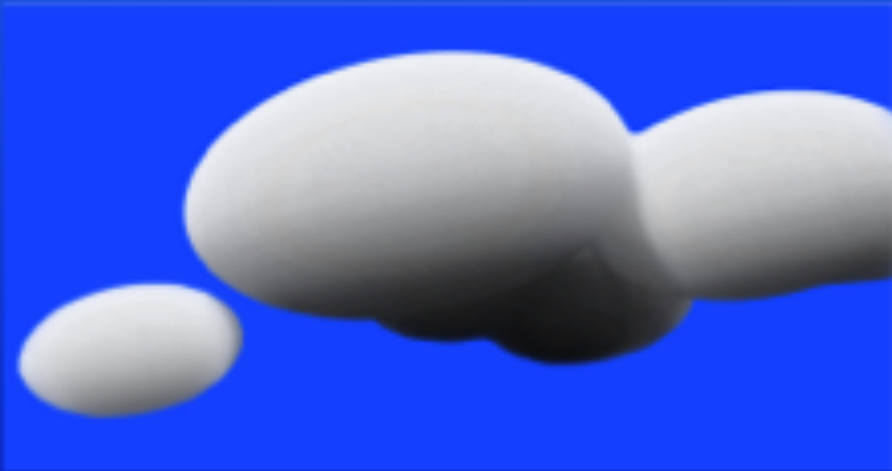
Silhouettes







Volumetric Modeling

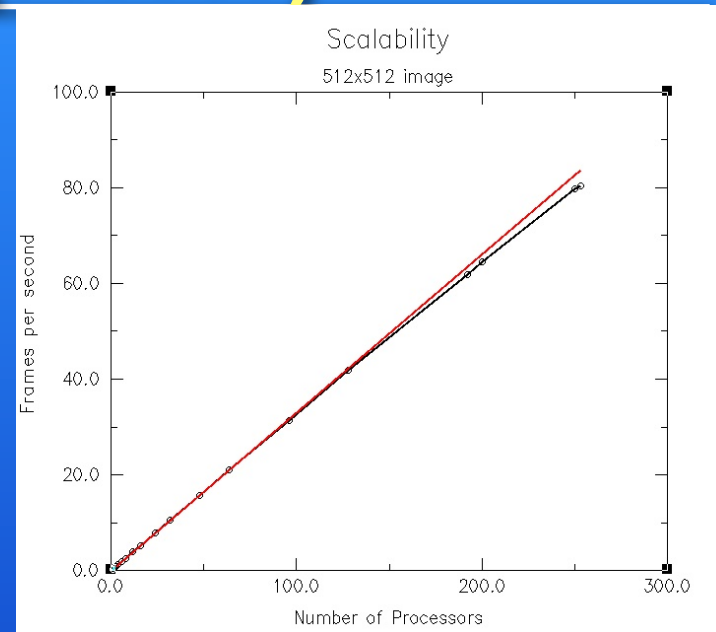


Scientific Computing and Imaging Institute, University of Utah

Real-Time Ray Tracer (RTRT)

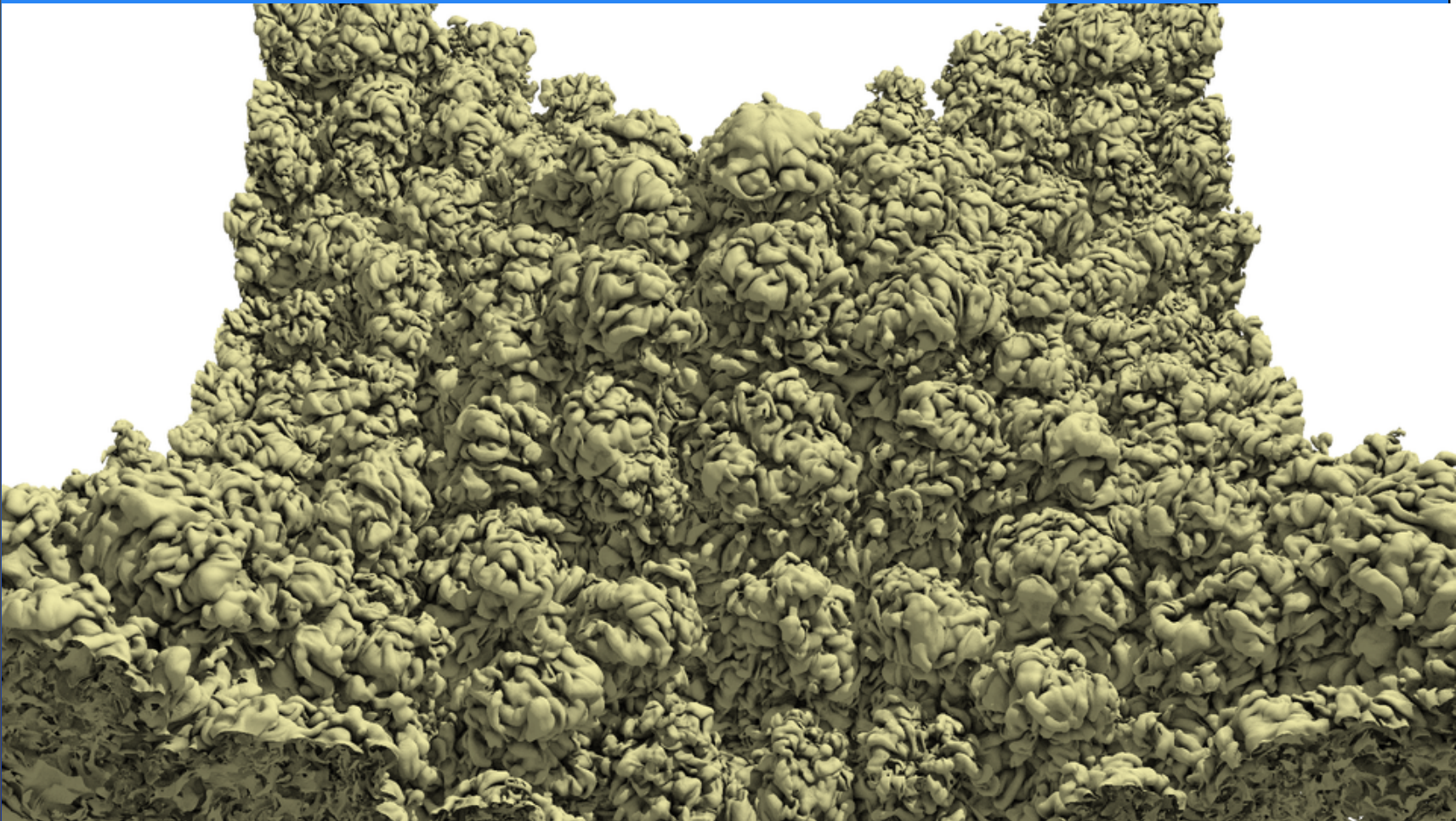
Implemented first on an SGI architecture - up to 1024 processors, then a distributed memory version for clusters, now on other SMD machines

Approximately linear speedup
Load balancing and memory coherence are key to performance



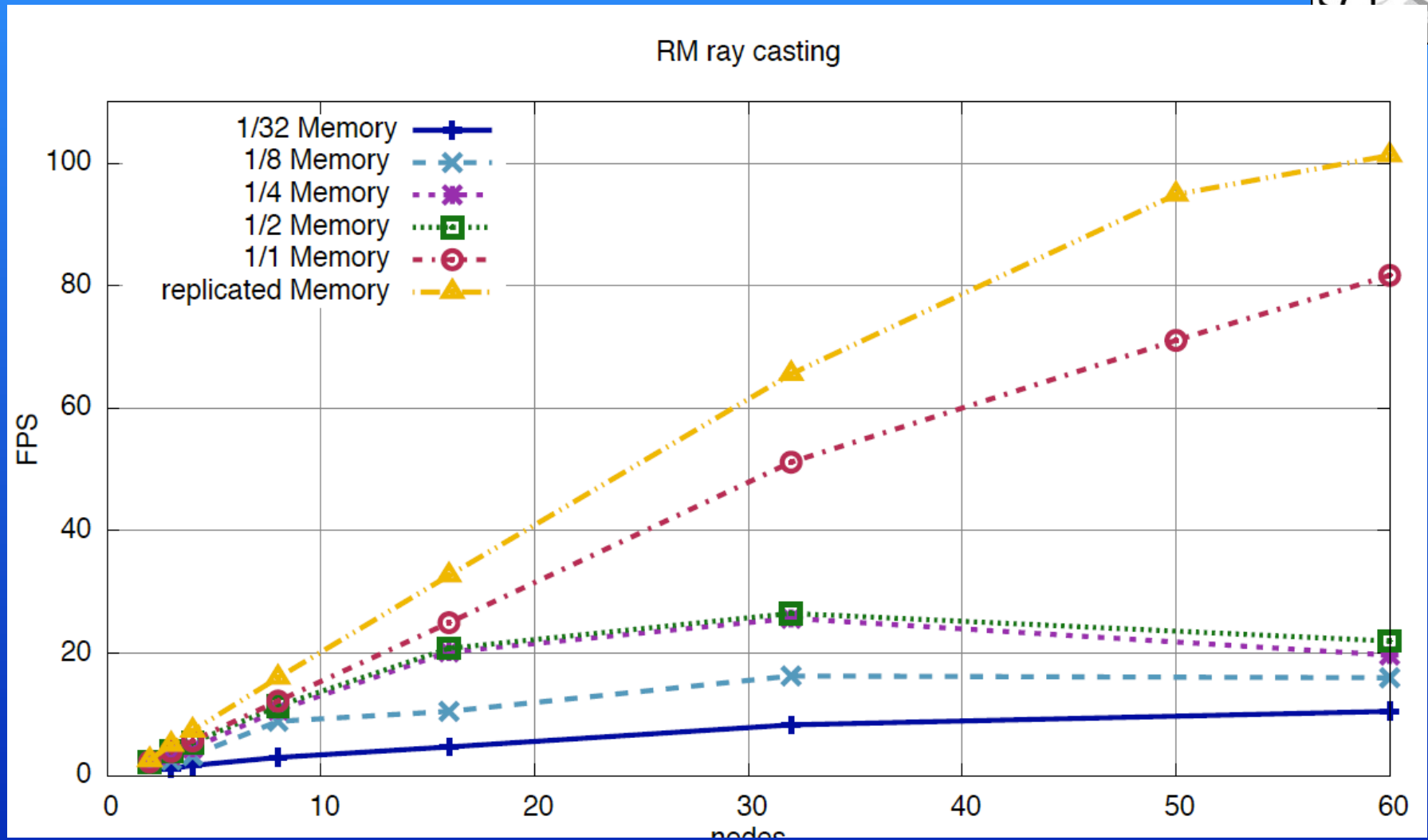
Scientific Computing and Imaging Institute, University of Utah

Current Cluster RT Visualization



Scientific Computing and Imaging Institute, University of Utah

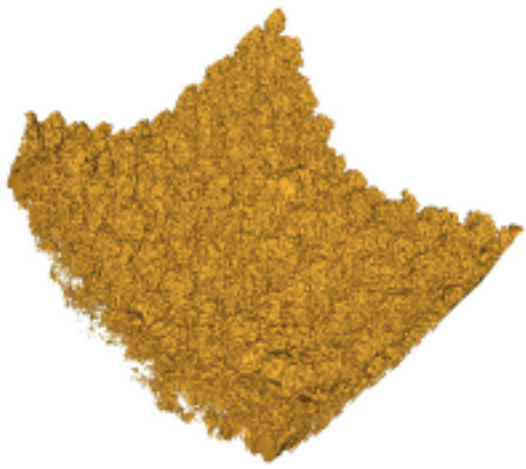
Current Cluster RT Visualization



VTK integration

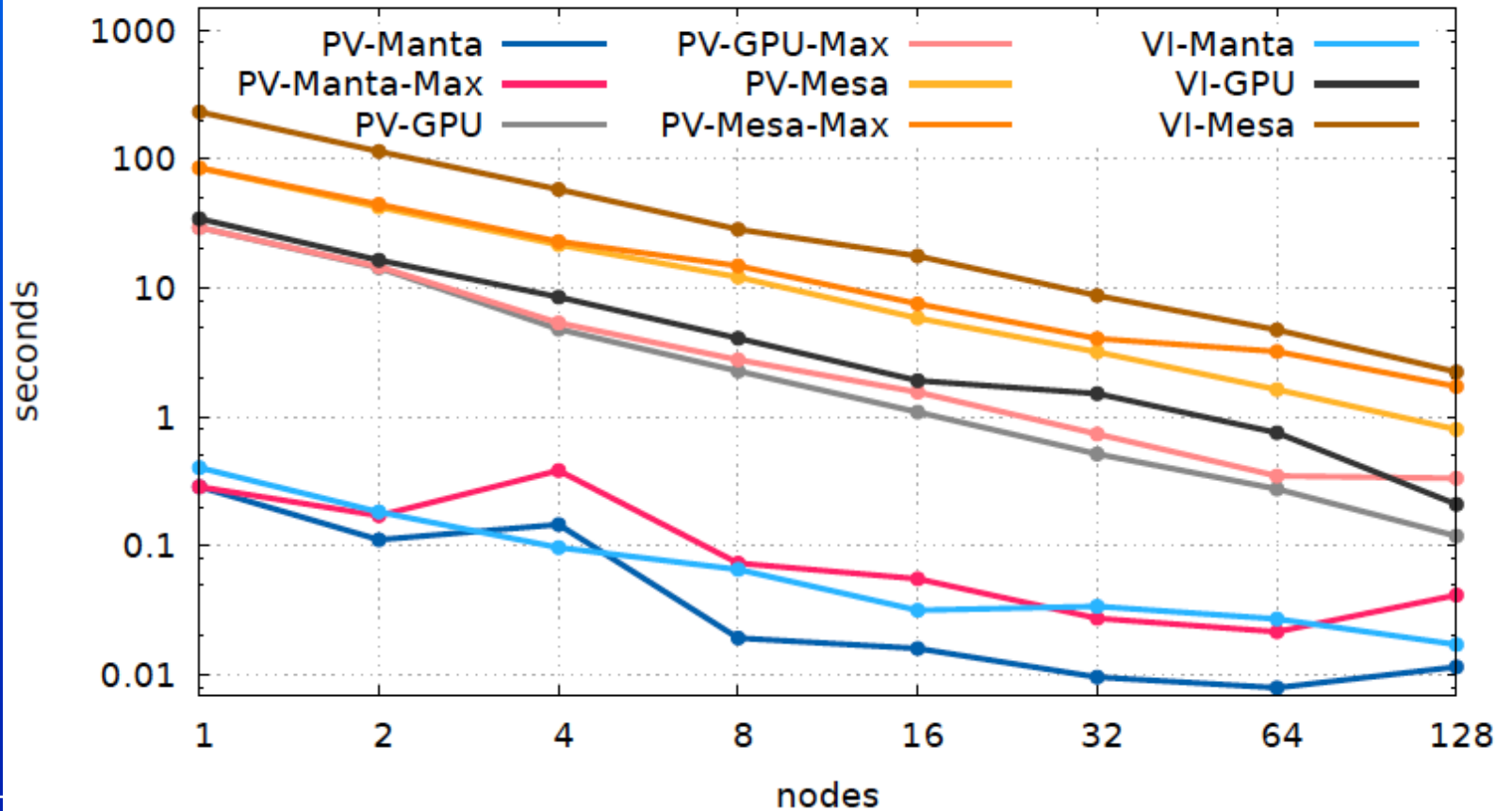
VTK integration gives a common framework for running through two common visualization packages

- ParaView
- VisIt



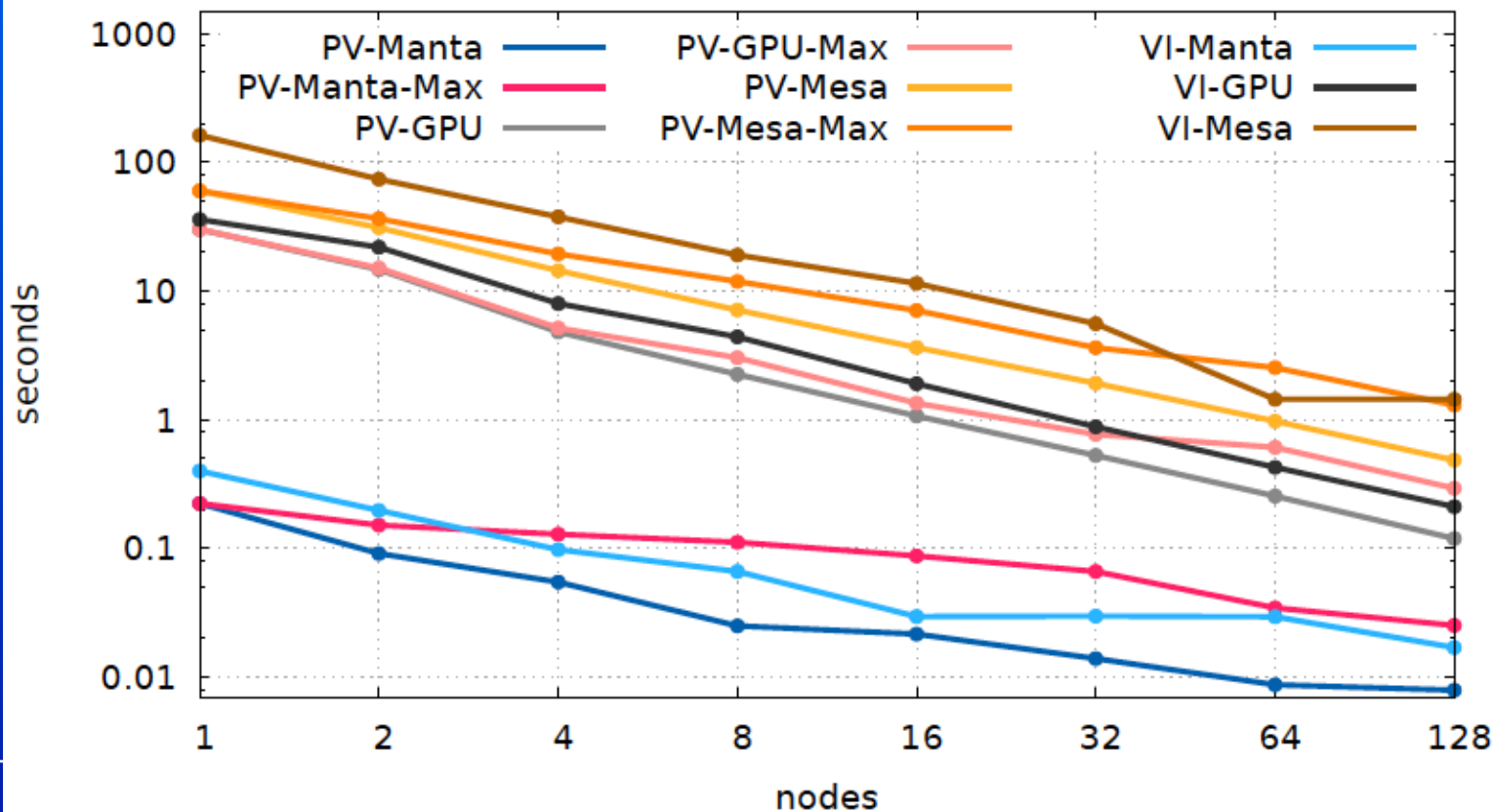
Ray-tracing over-riding VTK renderer

Render Time Strong Scaling for RMO

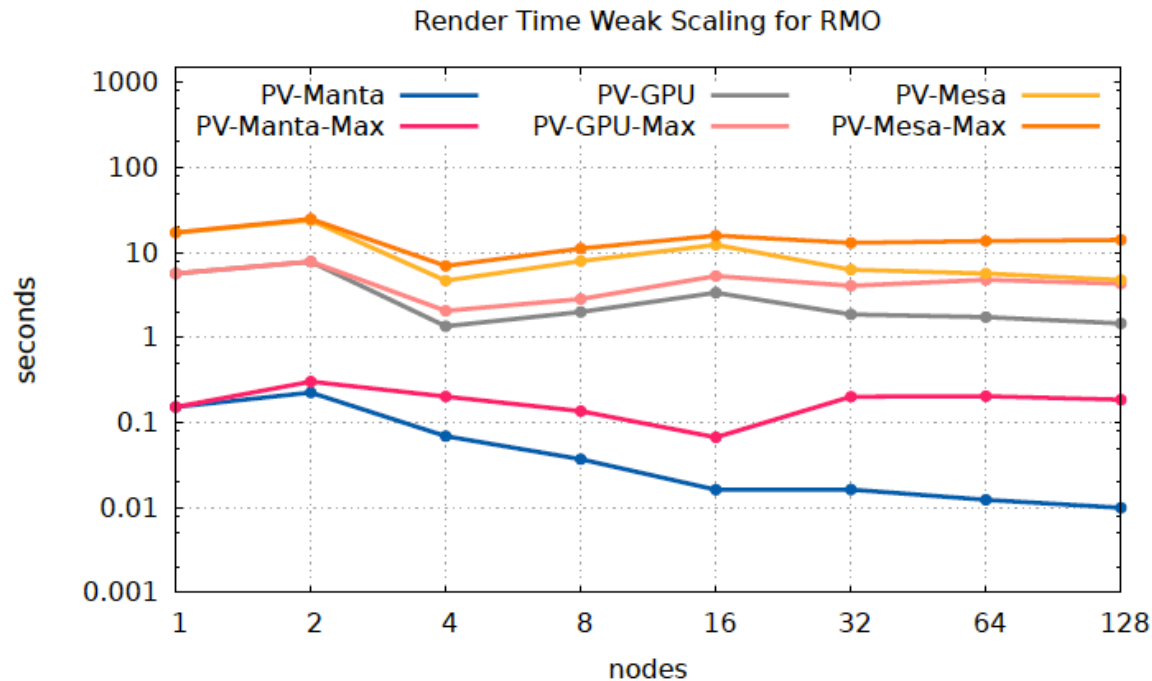


Ray-tracing over-riding VTK renderer

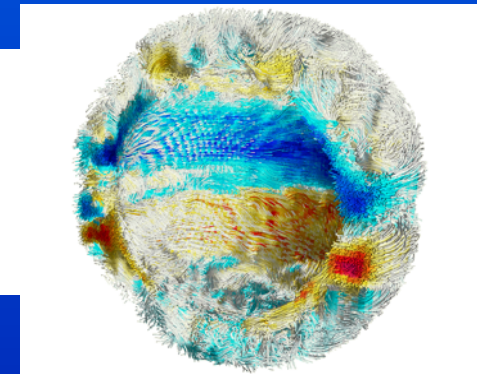
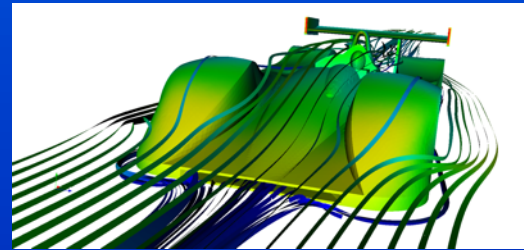
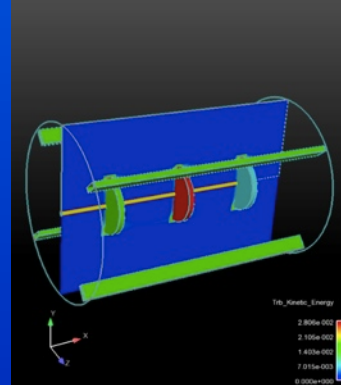
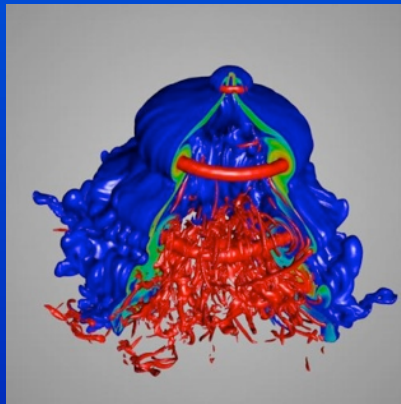
Render Time Strong Scaling for rm_zoomed_in



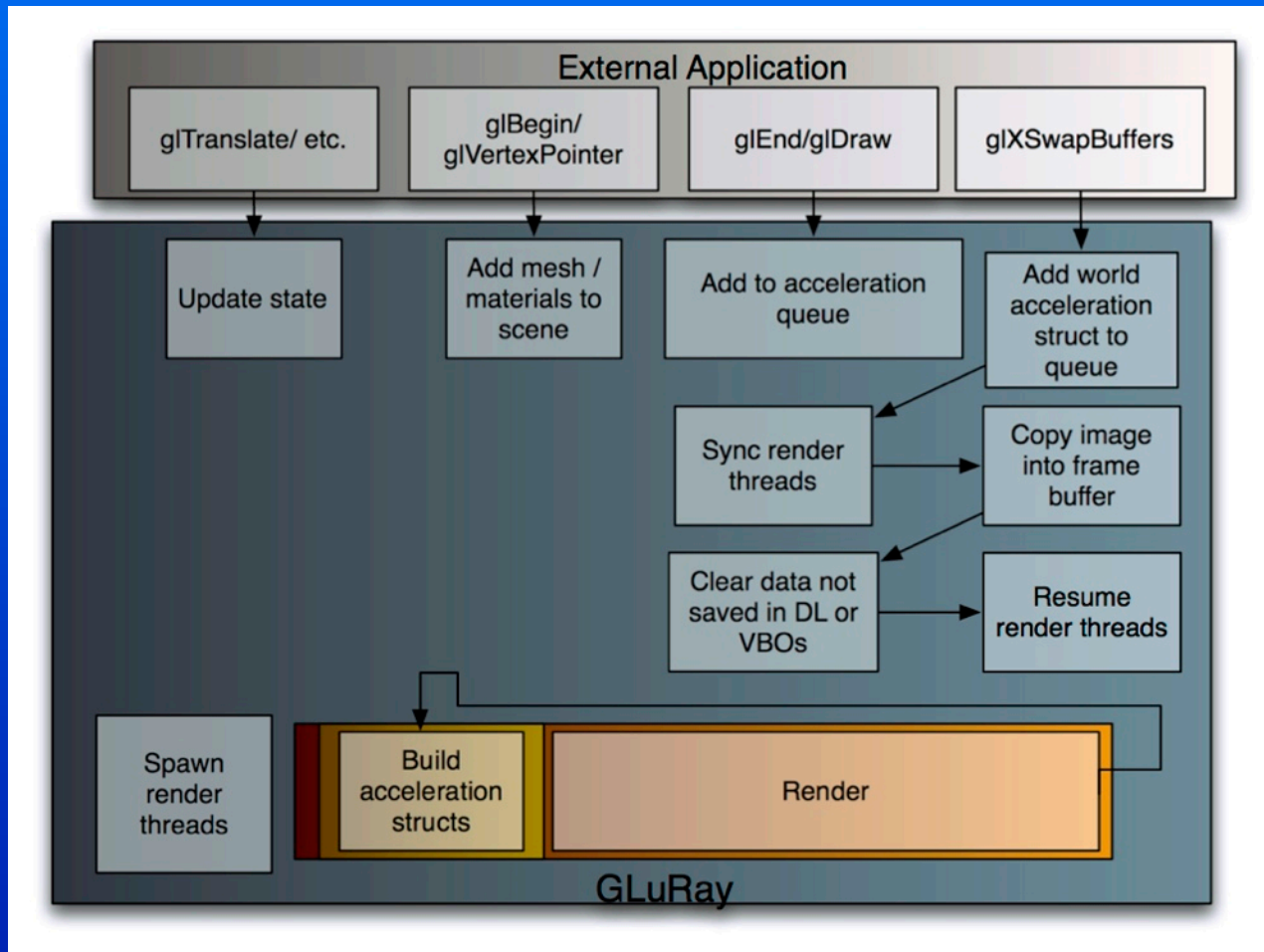
Weak Scaling



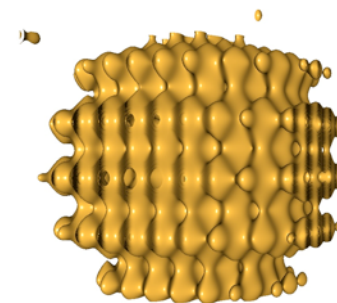
Vis Software



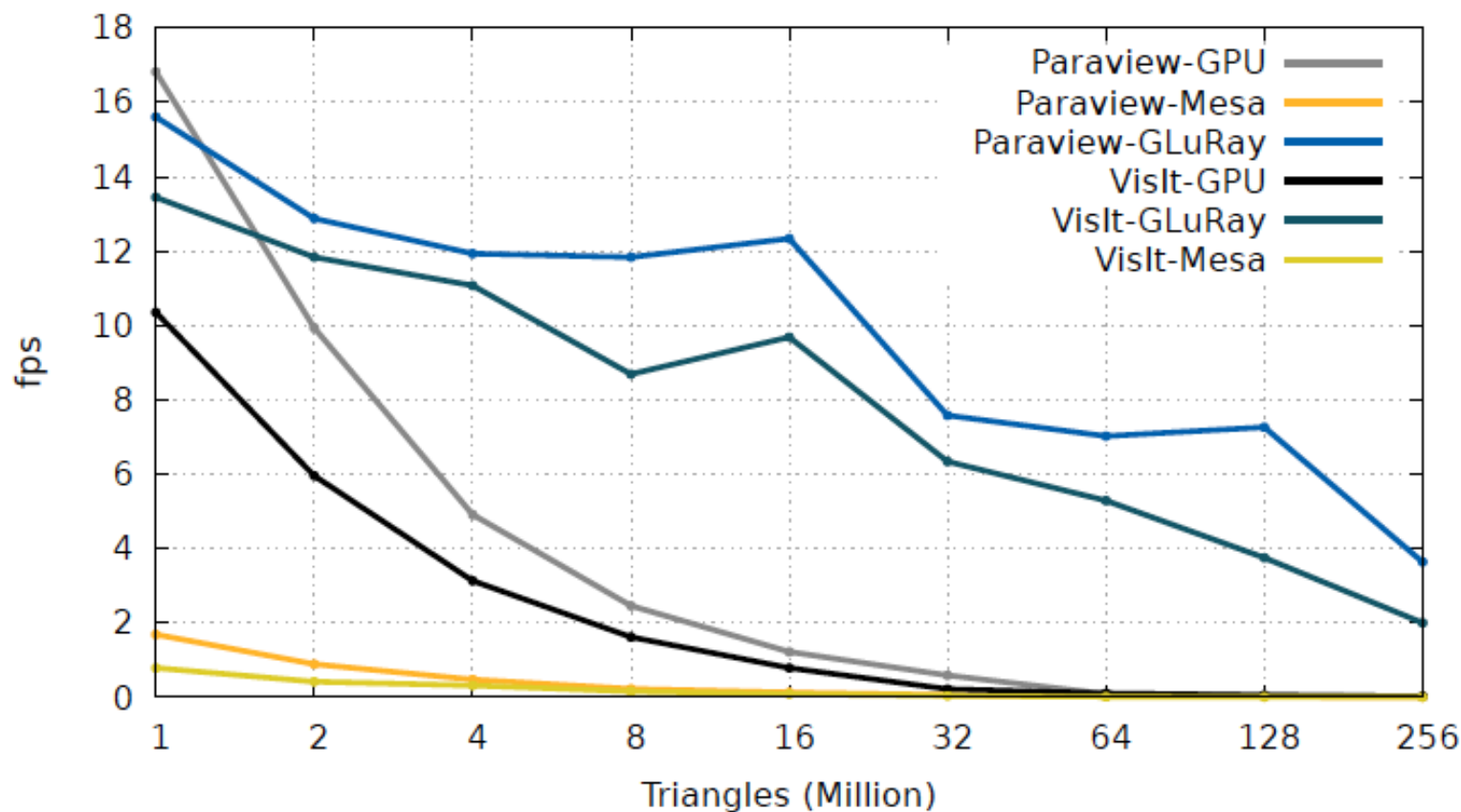
Parallel Architecture



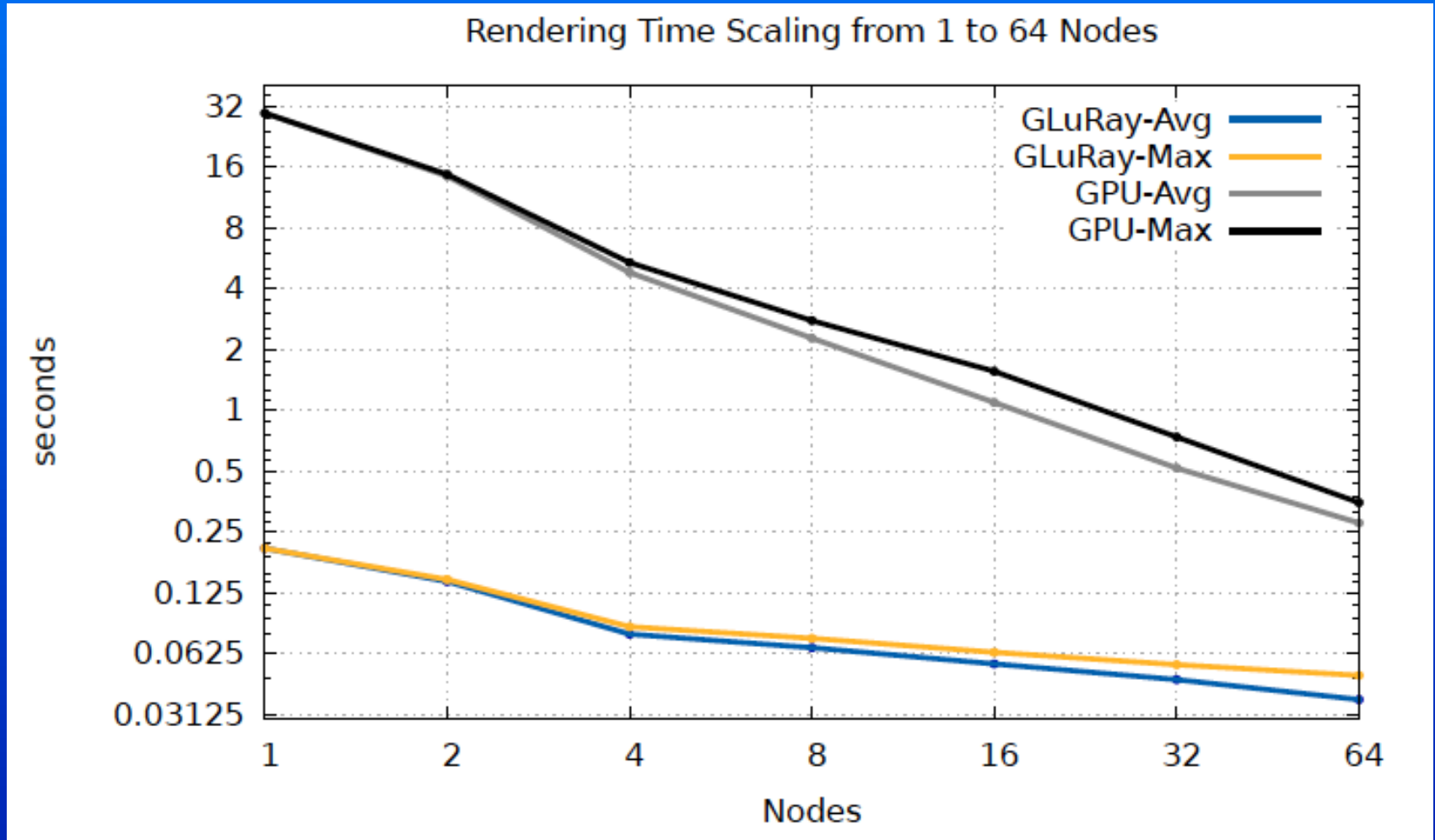
Polygon Scaling



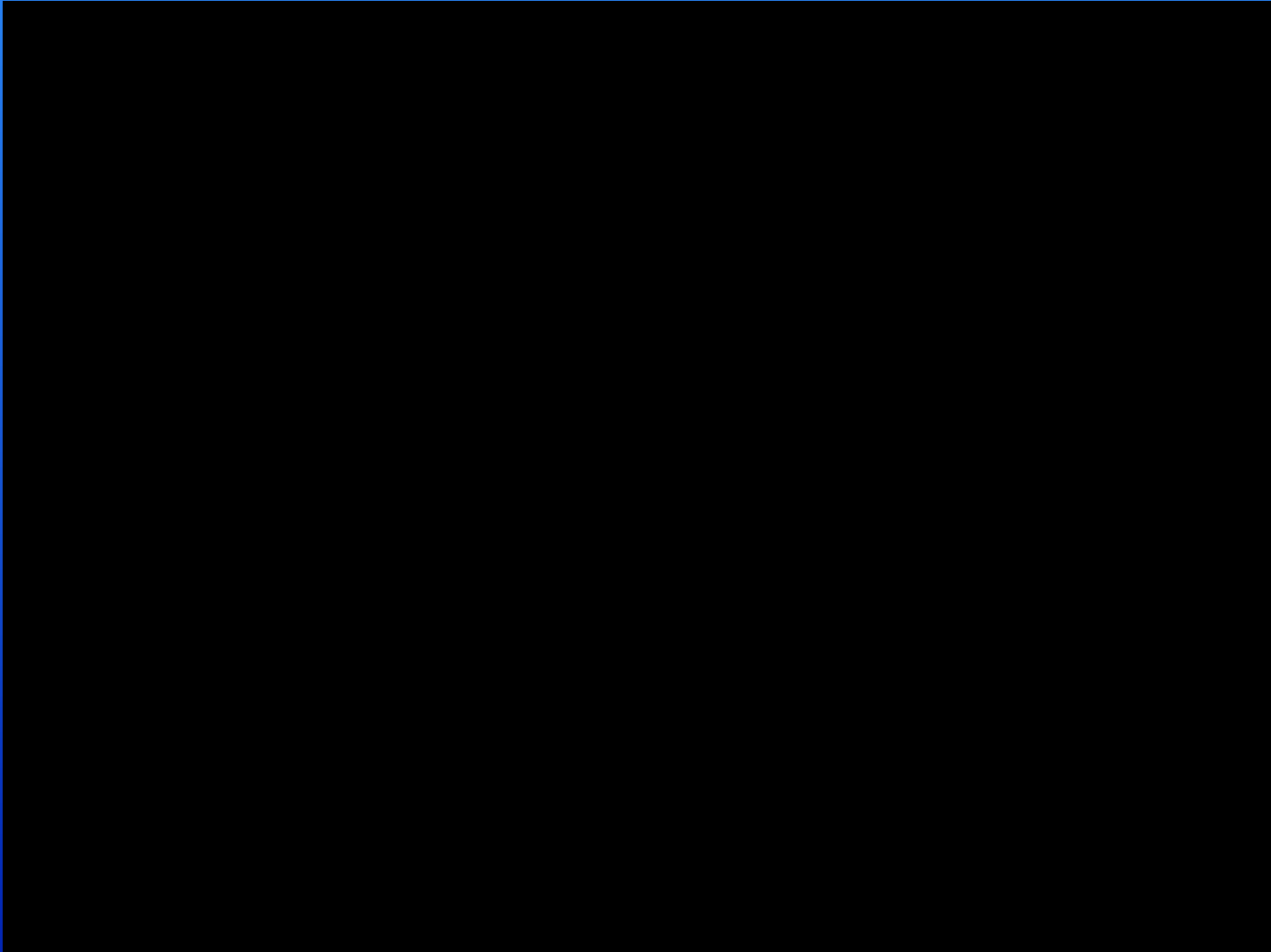
Polygon_Count_Scaling_with_Wavelet



Strong Scaling



Michelangelos David



Scientific Computing and Imaging Institute, University of Utah

Michelangelo David - Part 2



**One billion polygons
to billions of pixels**

Welcome to the first
gigapixel, multi-view
rendering of

The Digital Michelangelo
Project's David



Scientific Computing and Imaging Institute, University of Utah

Big Data & Computational Research



Parallel computing power grows x1000 / decade

Challenges:

- Scalable multi-physics multiscale problems with possibly many millions of cores.
- Estimate the error and/or uncertainty in the solution
- Energy consumption
- Heterogeneous architectures

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Exascale Challenge for Future Algorithms and Software?



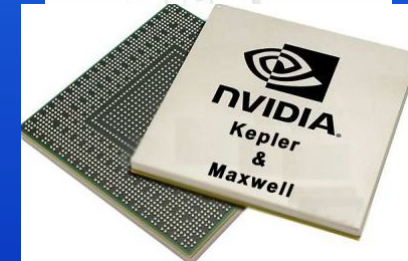
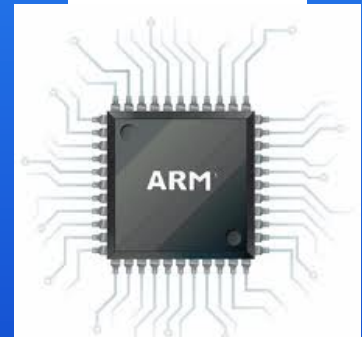
2013 Titan: 288K cpu cores 5M gpu cores

Blue Gene Q 2 Petaflops* per MegaWatt

202X Exascale “goal” requires 50 Petaflops per Megawatt, 1B cores - not possible with existing hardware/software approaches

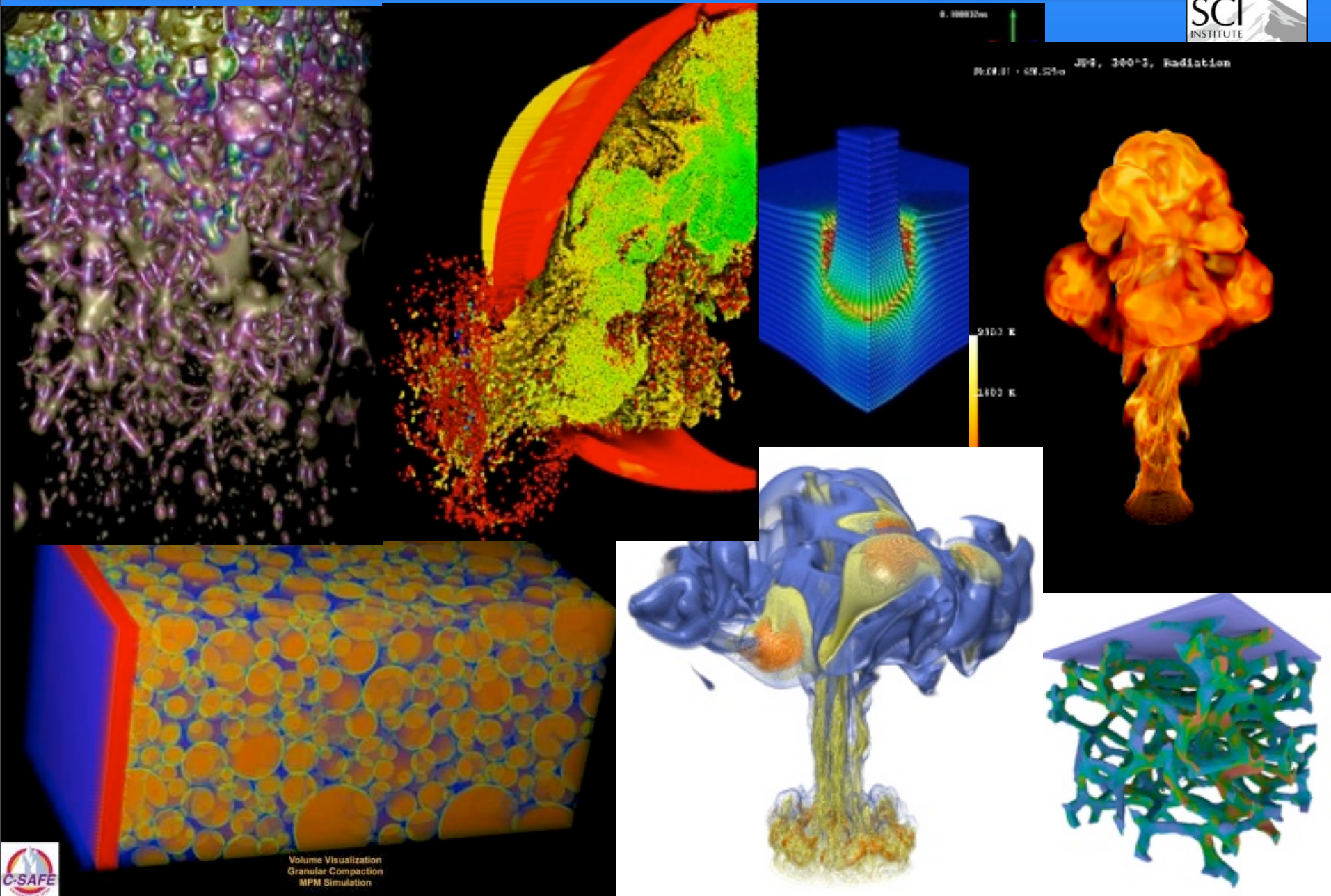
Harrod SC12: “today’s bulk synchronous (BSP), distributed memory, communicating sequential processes (CSP) based execution model is approaching an efficiency, scalability, and power wall.”

HPC software now has to take into account considerable uncertainty in architectures

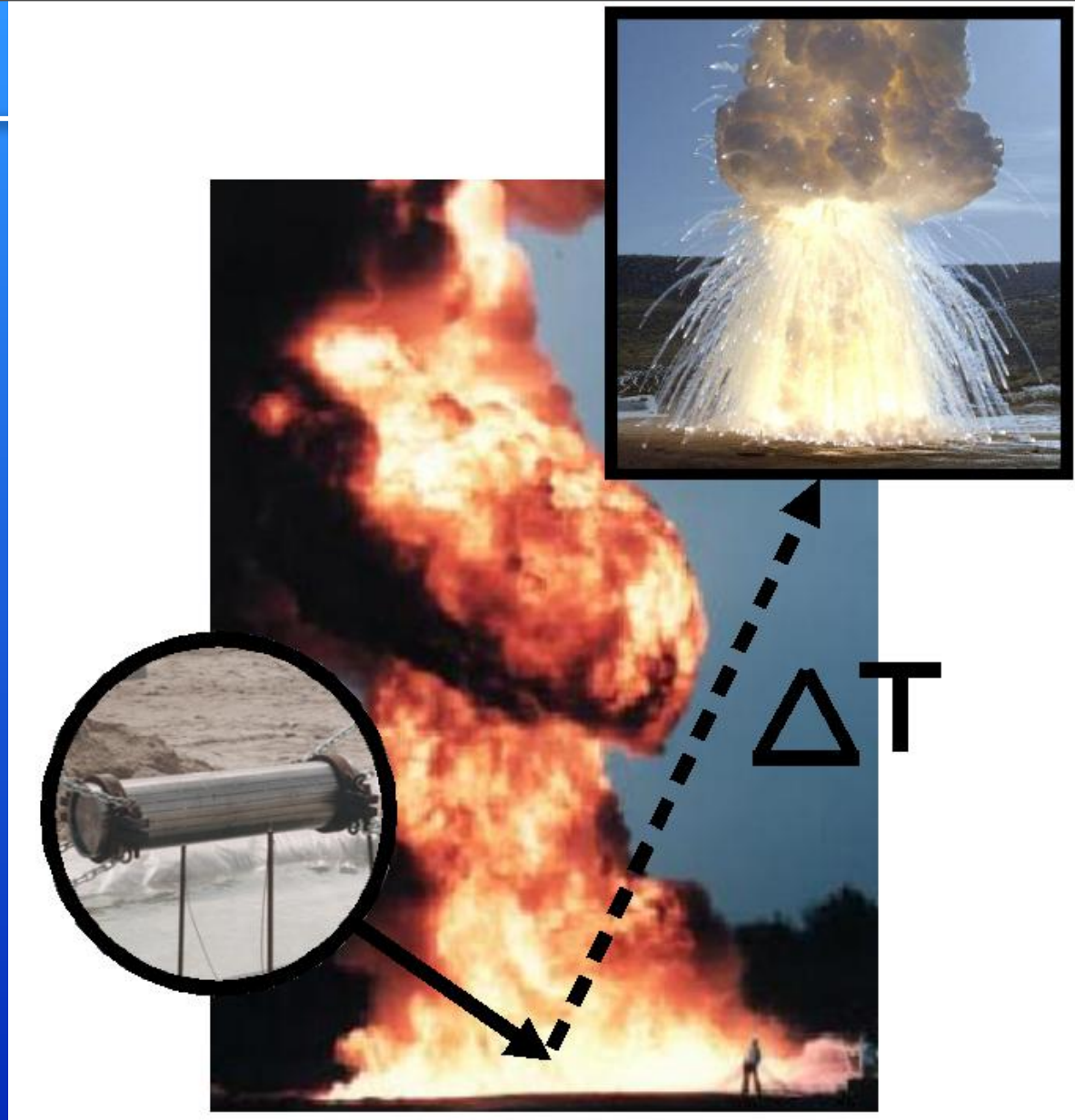


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DOE ASCI Center: C-SAFE

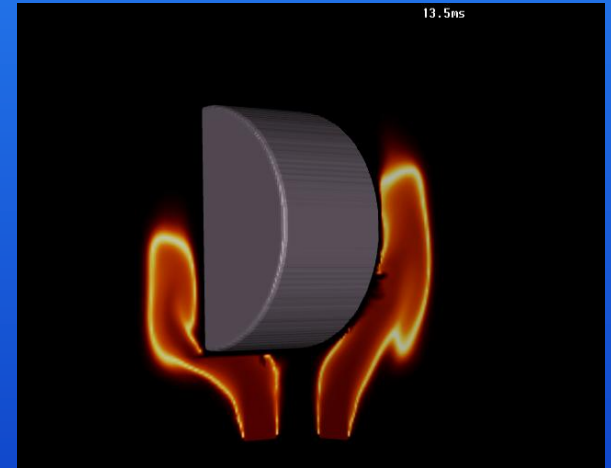
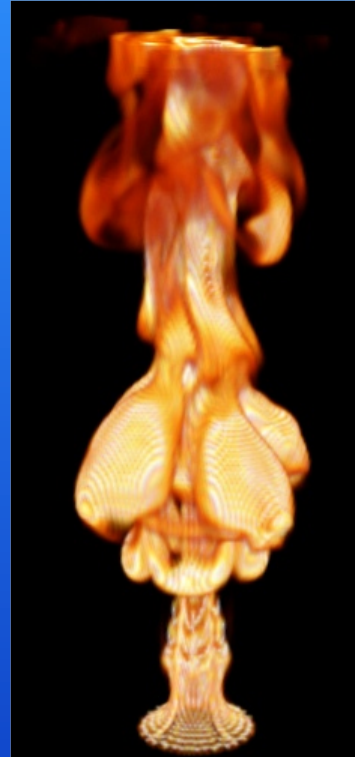
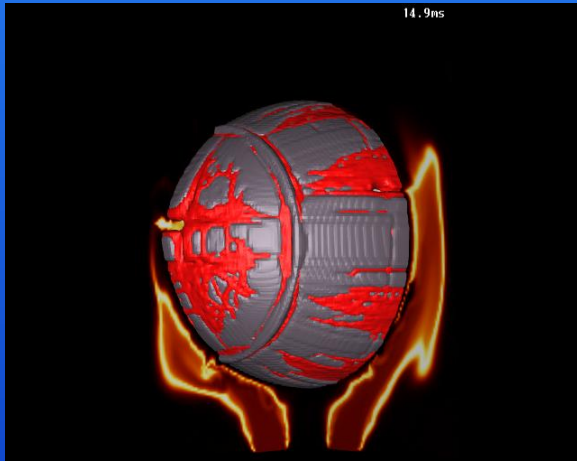


C-SAFE



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Time scales



Explosion

Fire

Heatup



10^{-6} - 10^{-4}

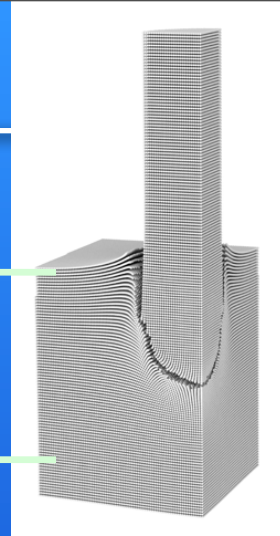
10^{-3} - 10^1

10^3 - 10^4

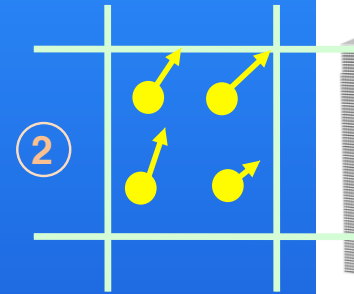
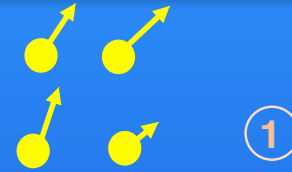
Seconds

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The Material Point Method (MPM)



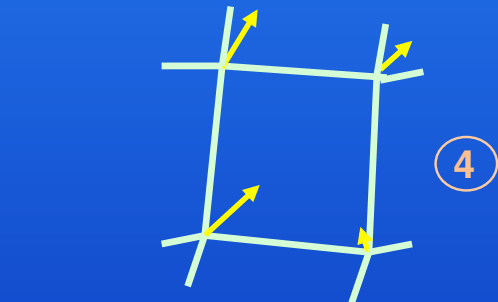
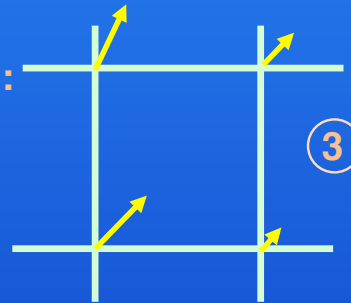
1. Lagrangian material points carry all state data (position, velocity, stress, etc.)
2. Overlying mesh defined



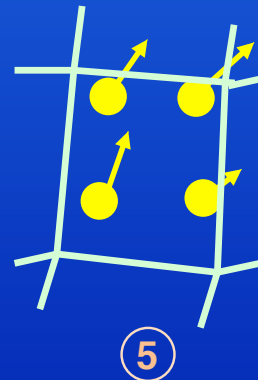
3. Particle state projected to mesh, e.g.:

$$v_g = \sum_p S_{gp} m_p v_p / \sum_p S_{gp} m_p$$

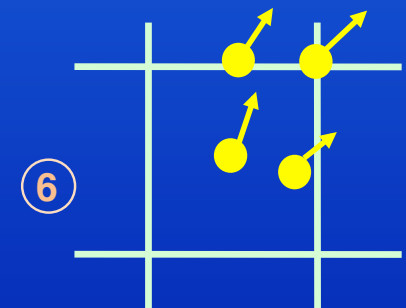
4. Conservation of momentum solved on mesh giving updated mesh velocity and (in principal) position. Stress at particles computed based on gradient of the mesh velocity.



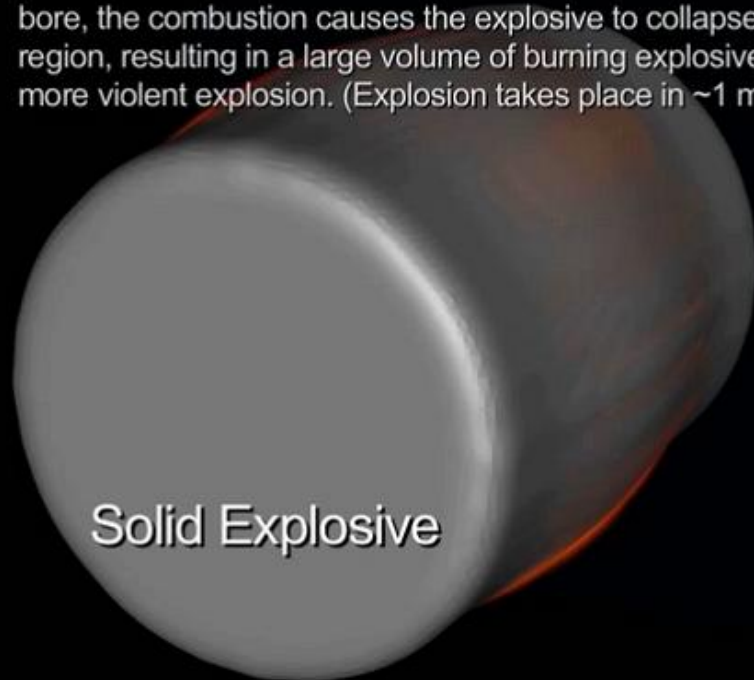
5. Particle positions/velocities updated from mesh solution.



6. Discard deformed mesh. Define new mesh and repeat



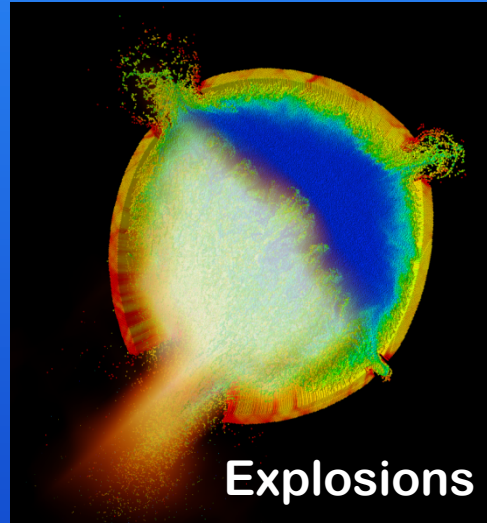
These simulations demonstrate the difference between containers enclosing a completely solid explosive versus an explosive with a hollow bore. In each case, ignition occurs at the interface between the hot steel and the solid PBX9501. In the case with the hollow bore, the combustion causes the explosive to collapse into the bore region, resulting in a large volume of burning explosive, and a much more violent explosion. (Explosion takes place in ~1 millisecond.)



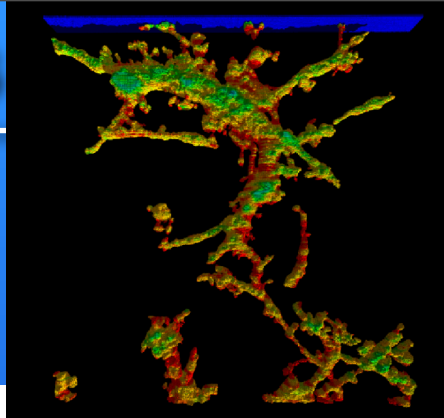
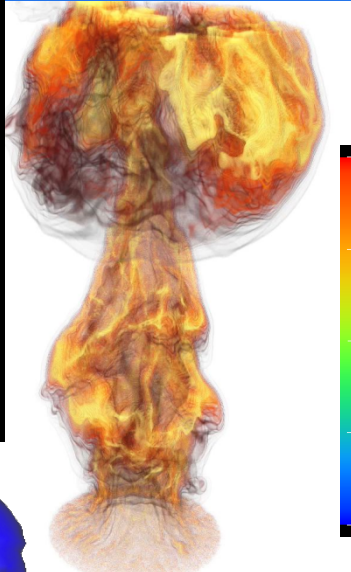
Solid Explosive



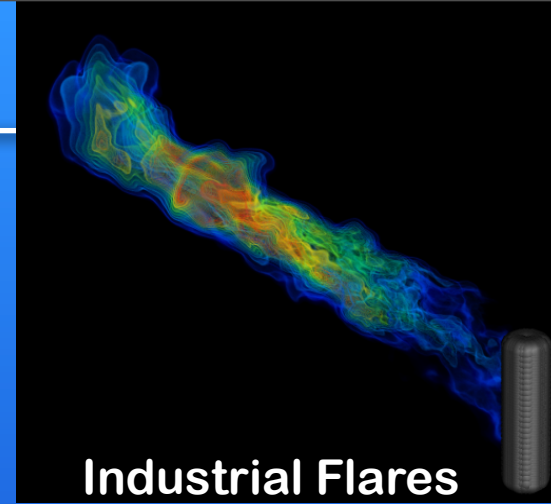
Uintah Applications



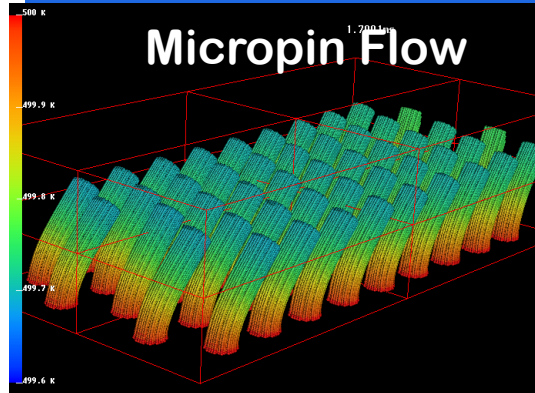
Plume Fires



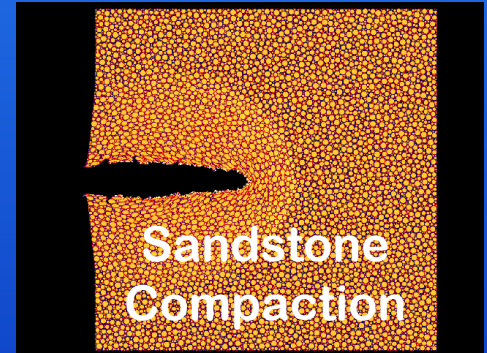
Angiogenesis



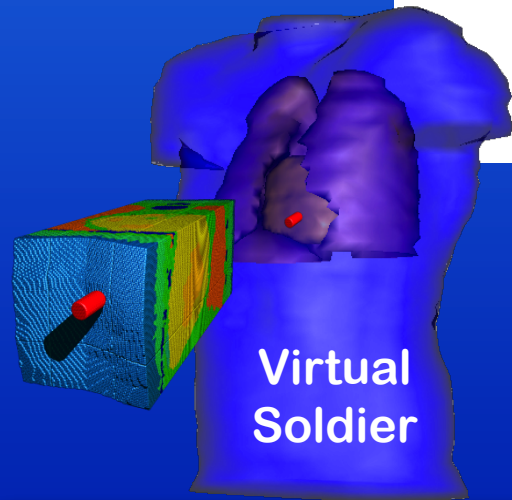
Industrial Flares



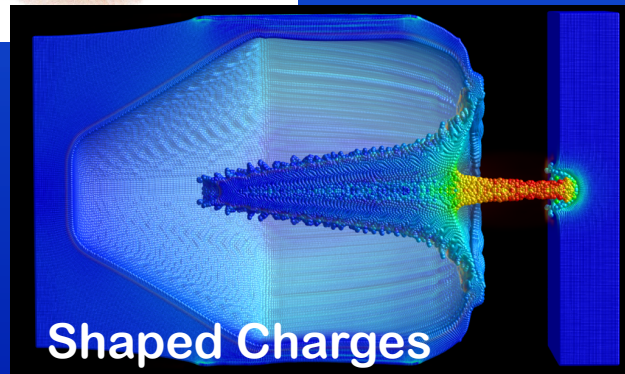
Micropin Flow



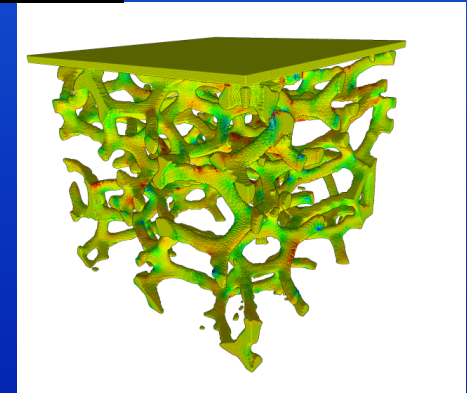
Sandstone Compaction



Virtual Soldier



Shaped Charges

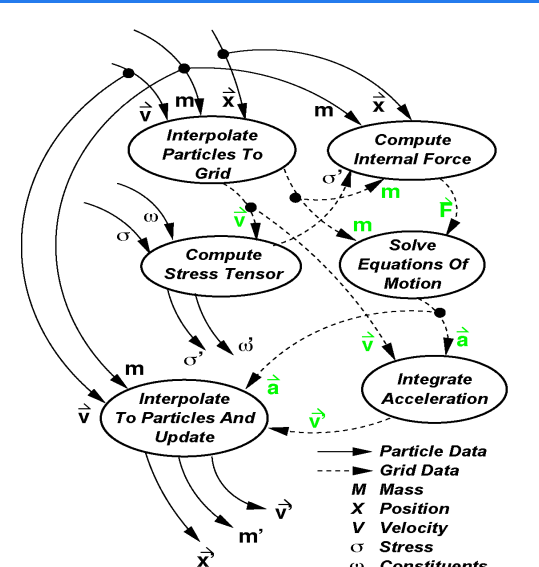


Foam Compaction

Utah Uintah Software Parallelism



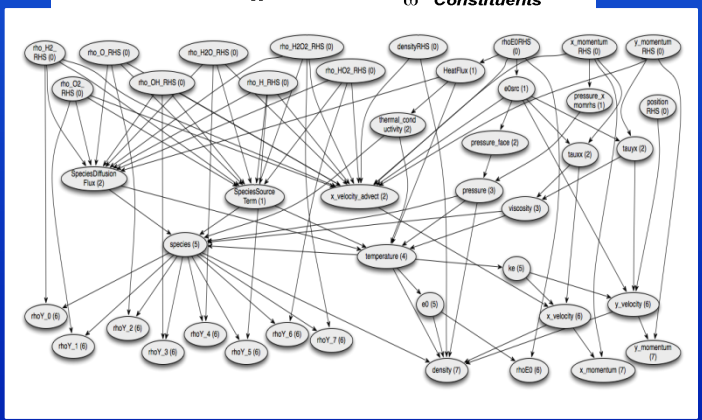
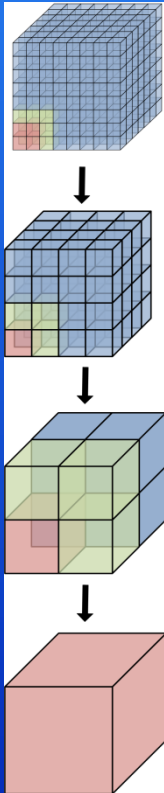
Uintah uses both data parallelism and task parallelism



- Structured Grid + Unstructured Points
- Patch-based Domain Decomposition
- Adaptive Mesh Refinement

- Dynamic Load Balancing
- Profiling + Forecasting Model
- Parallel Space Filling Curves
- Works on MPI and/or thread level

- Uses asynchronous task directed graph approach to scale to 200K cores even for adaptive mesh refinement and fluid-structure interaction



Spanish Fork Accident



Images from KUTV and Deseret News

Highway 6 Explosion

Use Utah Uintah Software

**To explain why this
happened**

**And ensure it never
happens again**

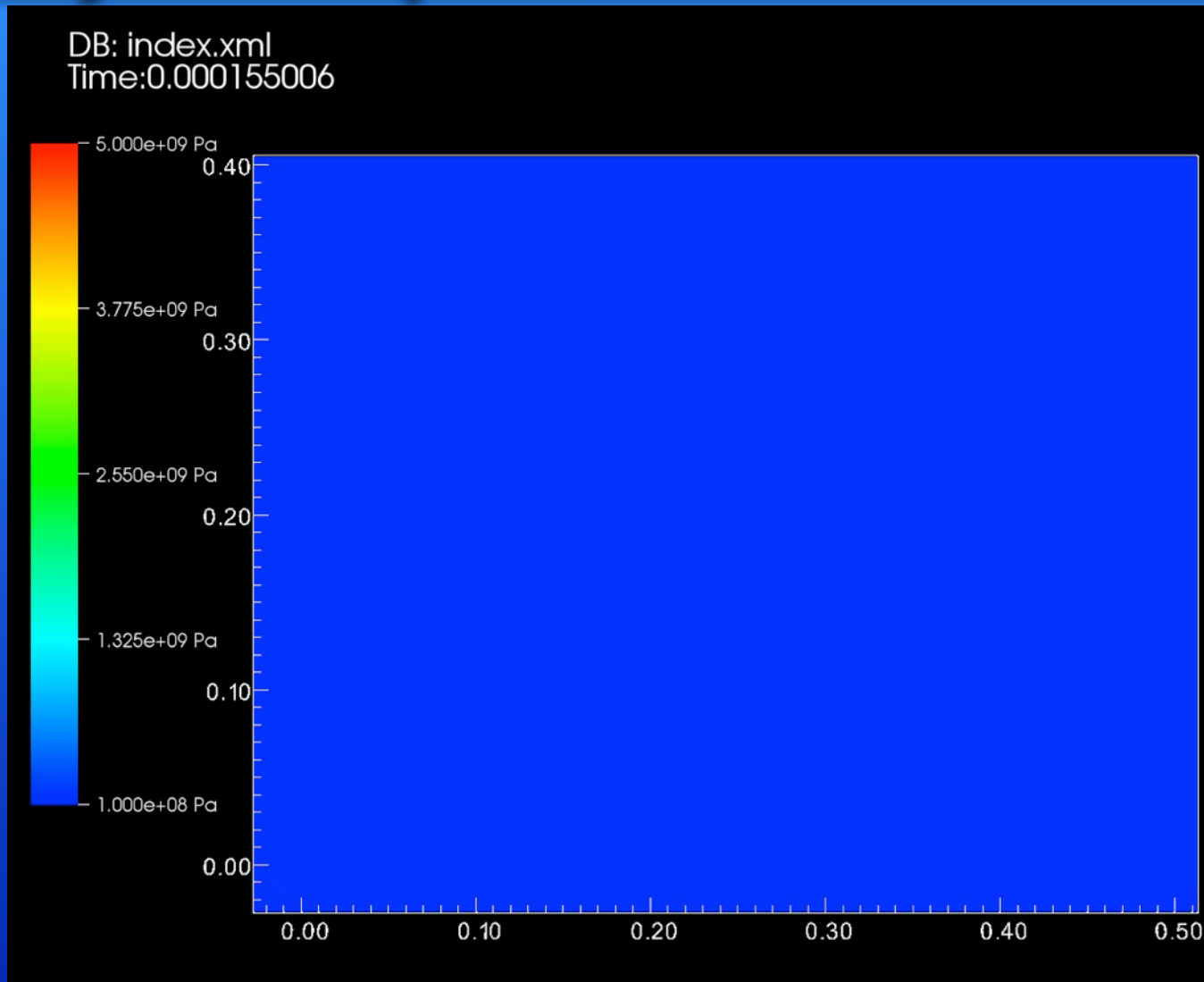
**Results by Jacqueline
Beckvermit**

DOE Titan (5M cores)



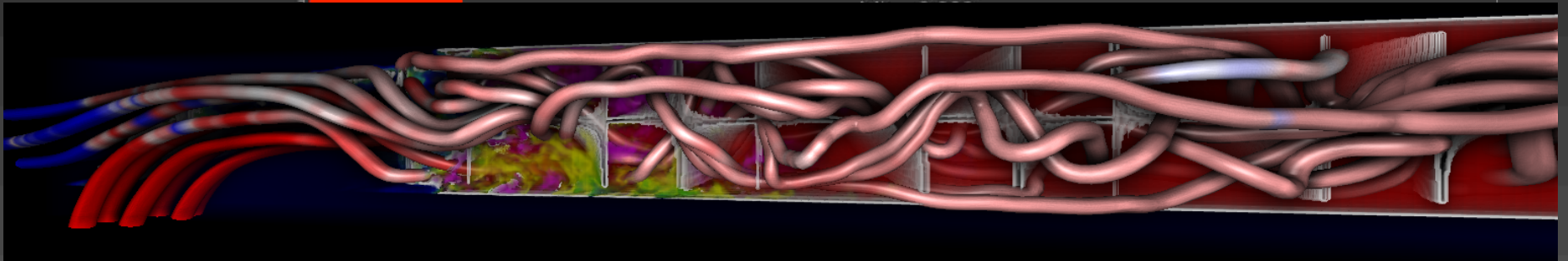
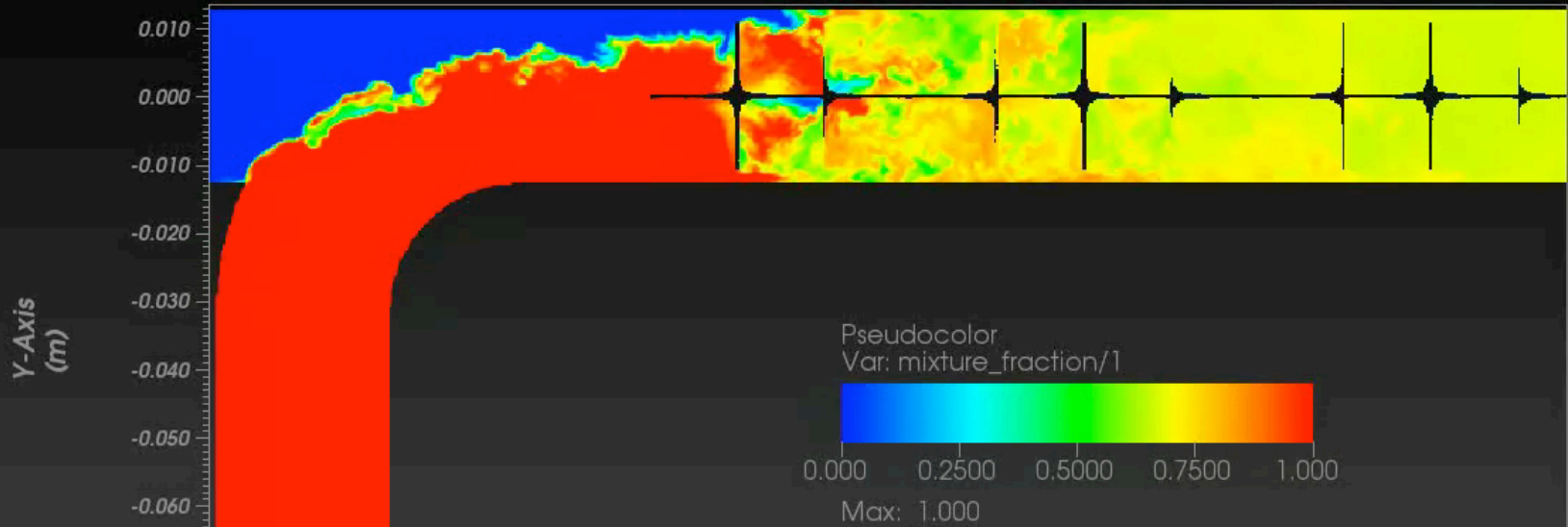
Scientific Computing and Imaging Institute, University of Utah

Highway 6 Explosion



Scientific Computing and Imaging Institute, University of Utah

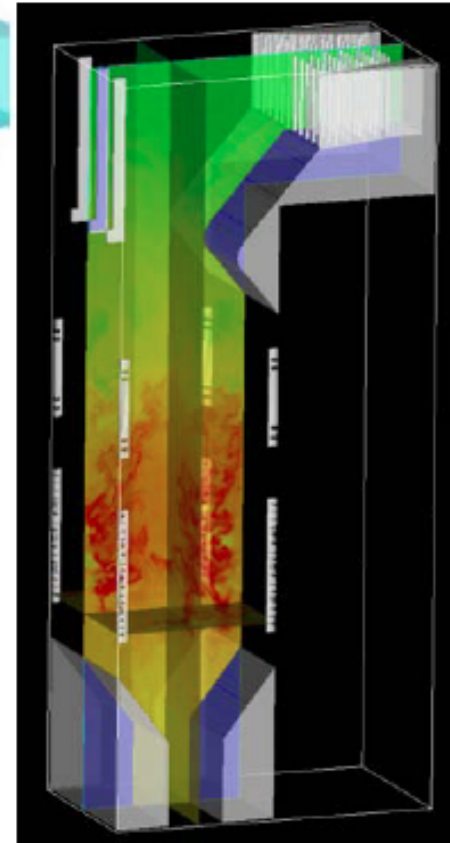
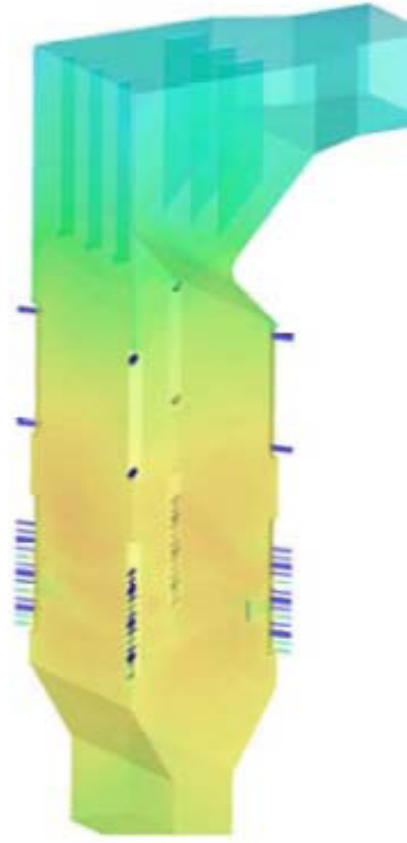
ICSE Carbon Dioxide Cleanup – Red is CO₂



Turbulent flow problem - need to quantify the uncertainty in the Simulation to estimate how much CO₂ is removed.

Need at least 100K cores to resolve the problem scales.

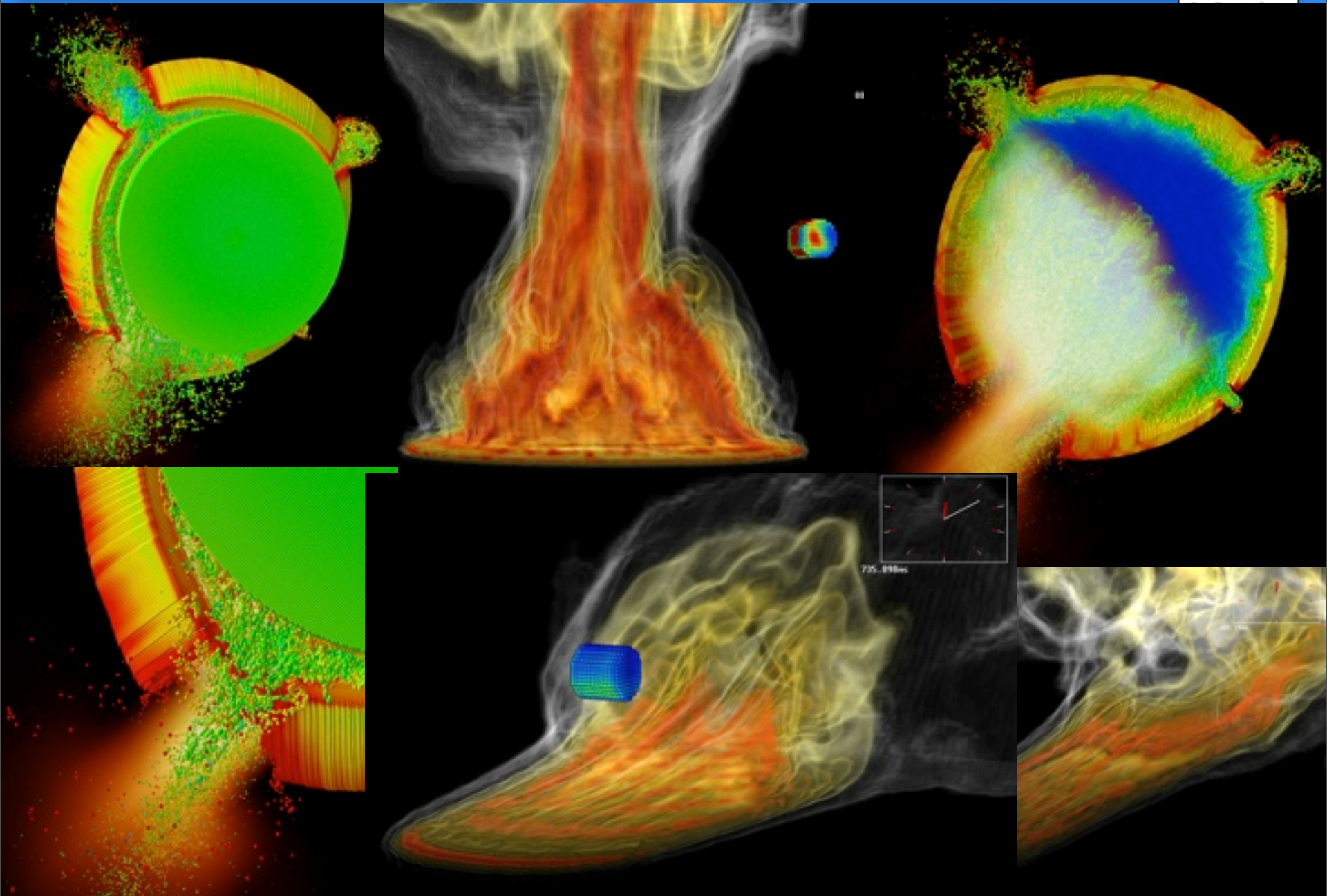
Scientific Computing and Imaging Institute, University of Utah



(a) BSF test bed (b) RANS Simulation domain (c) LES Simulation domain

Figure 45. LES Simulation domain and grid of BSF

Manta - Real Time Ray Tracer

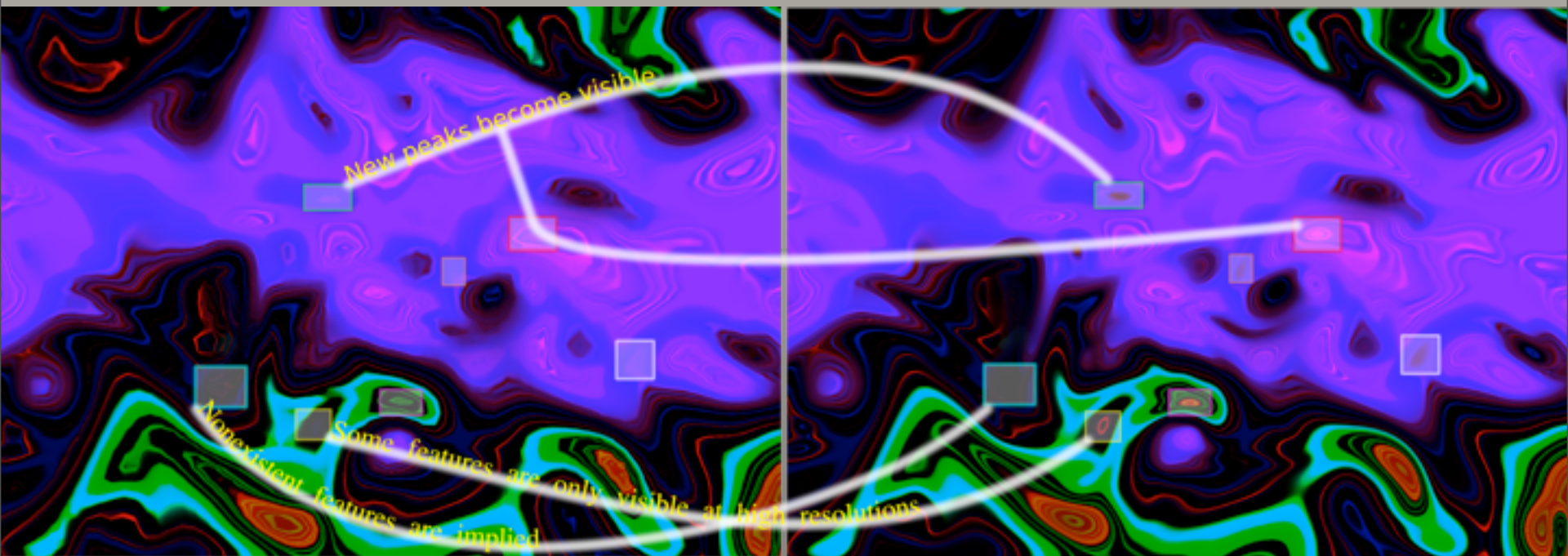


Wednesday, September 11, 13

The Need for High Resolution Visualization

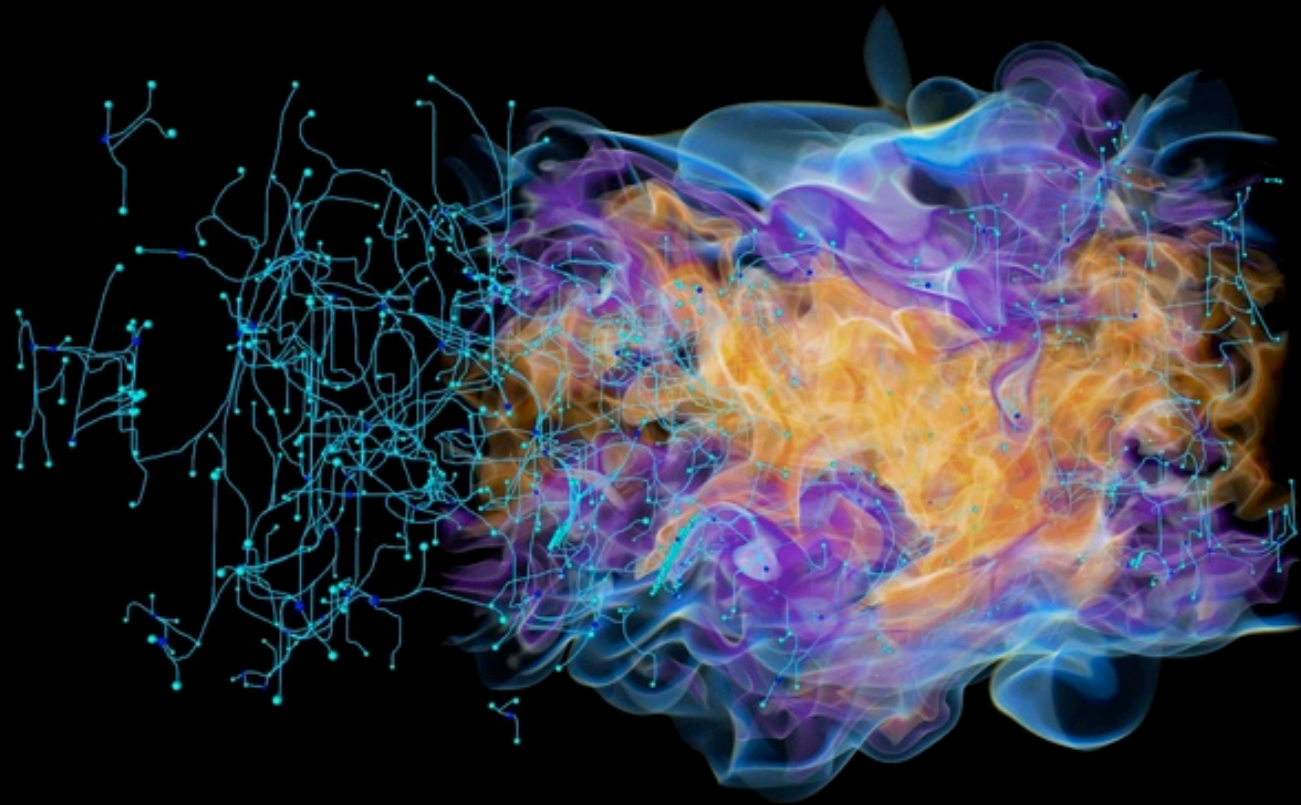
“...the data show for the first time how detailed transport and chemistry effects can influence the mixing of reactive scalars. It may be advantageous to incorporate these effects within molecular mixing models. It is worth noting that at present it is impossible to obtain this type of information any other way than by using the type of highly resolved simulation performed here.”

Jacqueline Chen, Sandia National Laboratories



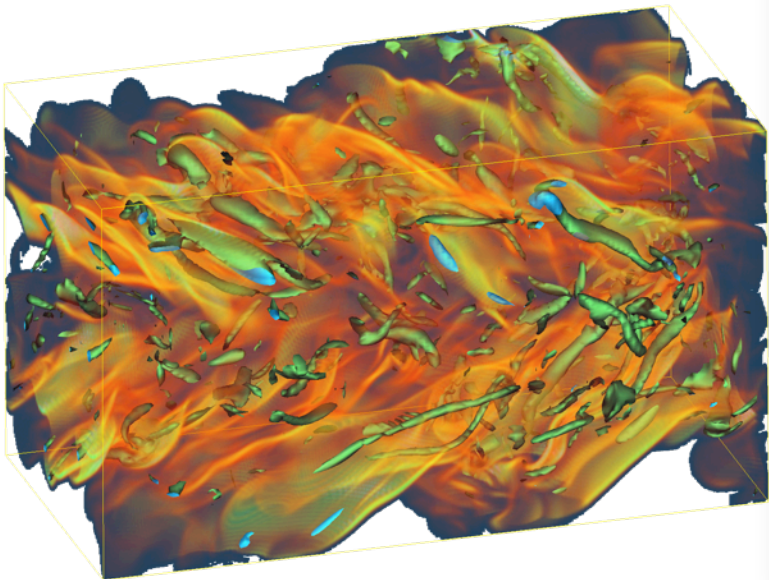
Lower Resolution

High Resolution



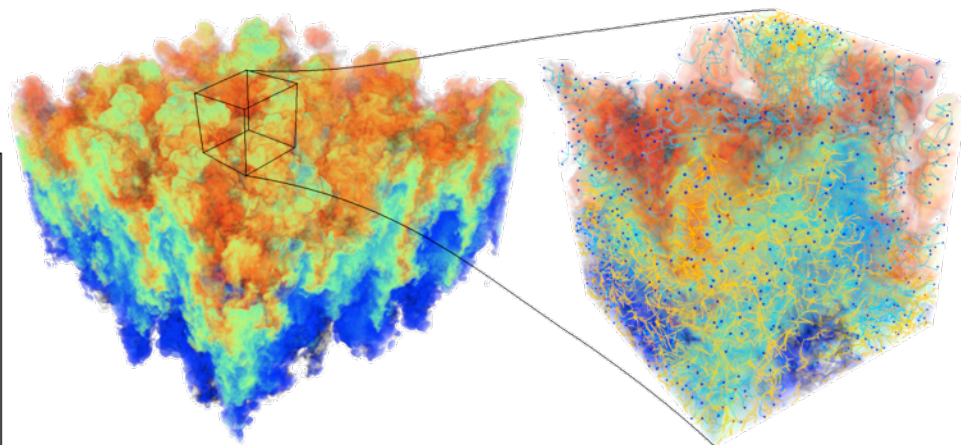
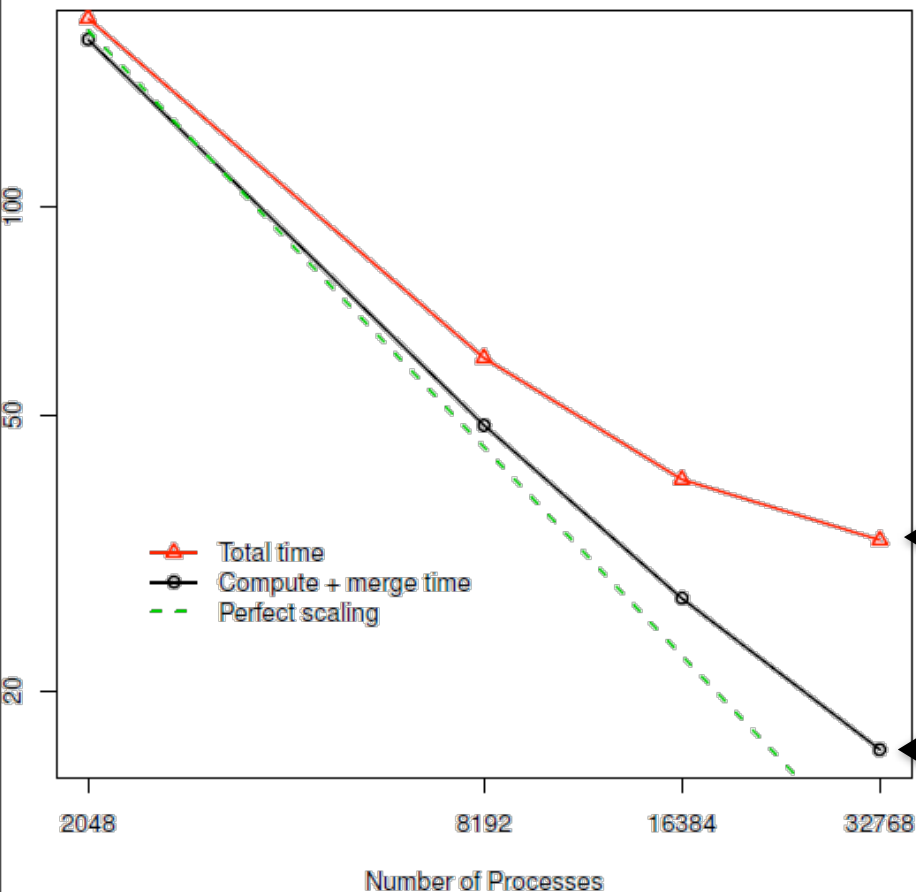
Topological Analysis of Massive Combustion Simulations

- Non-premixed DNS combustion (J. Chen, SNL): Analysis of the time evolution of extinction and reignition regions for the design of better fuels



New Parallel Topological Computations Achieve High Performance at Scale

Total & Compute+Merge Time For Rayleigh-Taylor Mixing

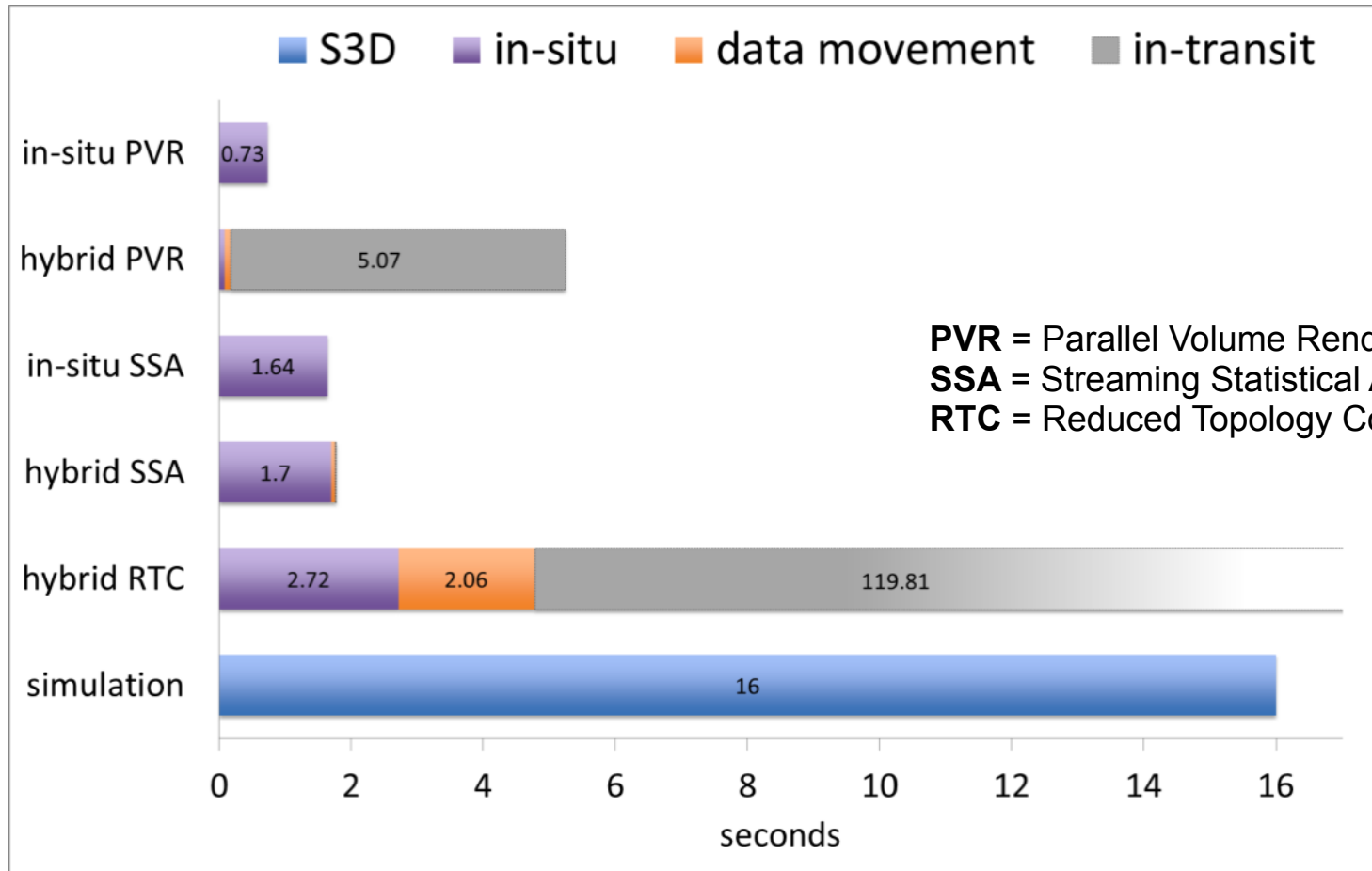


Computation + I/O

Pure Computation

Exploring algorithm design and task allocation

in-situ+in-transit workflows enable matching algorithms with architectures



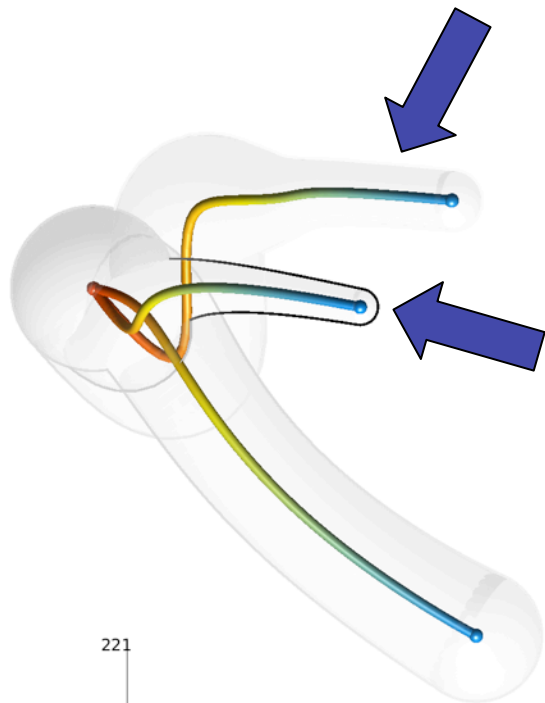
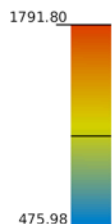
- 4896 cores total (4480 simulation/in situ; 256 in transit; 160 task scheduling/data movement)
- Simulation size: 1600x1372x430 ; All measurements are per simulation time step

[SC12a] **Combining In-Situ and In-Transit Processing to Enable Extreme-Scale Scientific Analysis**

Visualization of 10D Combustion Simulation of Jet CO/H₂-Air Flames

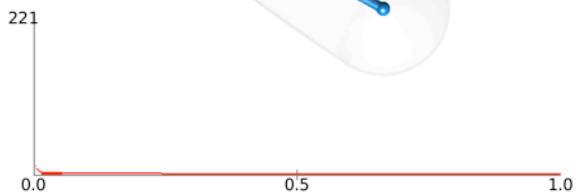
Value: 1066.76
Input std: 0.61
Density: 0.0004

Local Extinction

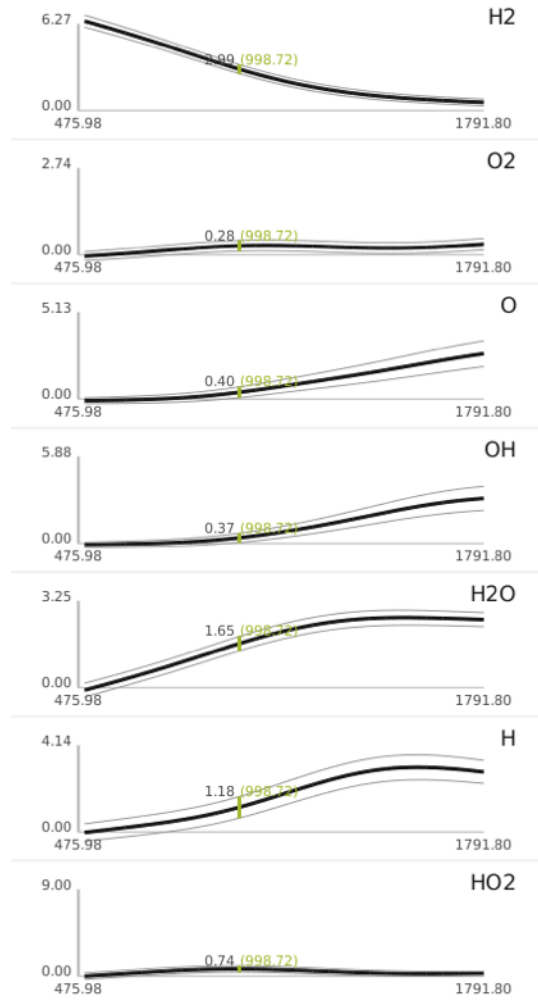


Pure Oxidizer

Pure Fuel

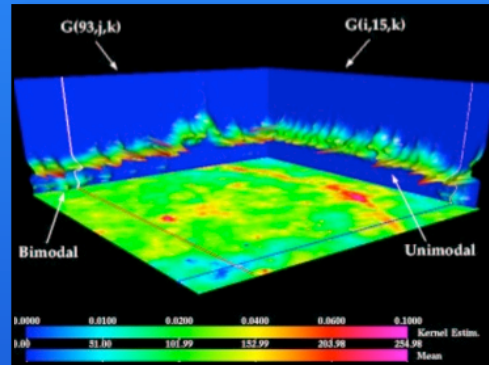


10 dimensional data set describing the heat release wrt. to various chemical species in a combustion simulation

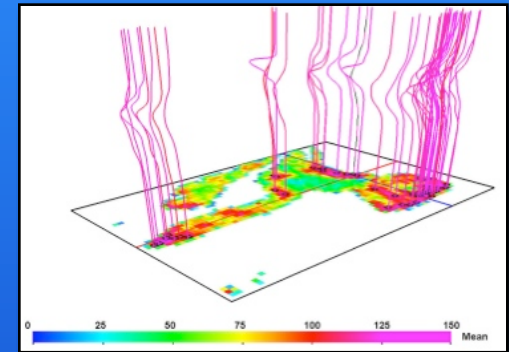


Ensembles

- Multi-run/model simulations
- Distribution of data at every point
- Mean/std dev may not be appropriate

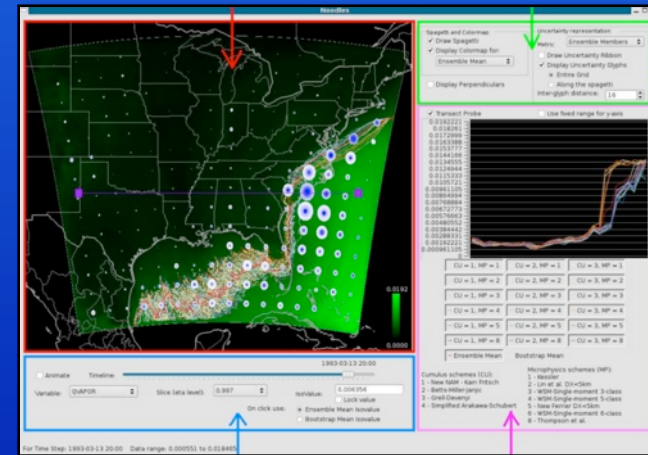
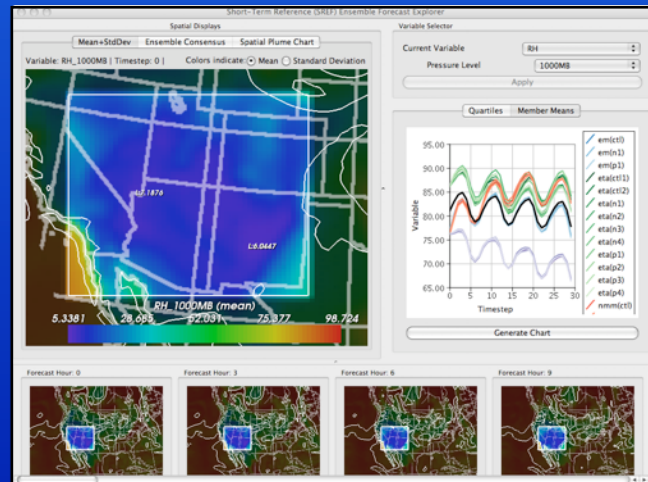


D. Kao, A. Luo, J. Dungan, A. Pang.
Visualizing Spatially Varying Distribution Data.
In *Proc Information Visualization*, 2002.



D. Kao, M. Kramer, A. Luo, J. Dungan, A. Pang.
Visualizing Distributions from Multi-Return Lidar Data to Understand Forest Structure.

K. Potter, et al.
Ensemble-Vis: A Framework for the Statistical Visualization of Ensemble Data.
In *IEEE ICDM Workshop on Knowledge Discovery from Climate Data: Prediction*, 2009.



J. Sanyal, S. Zhang, J. Dyer, A. Mercer, P. Amburn.
Noodles: A Tool for Visualization of Numerical Weather Model Ensemble Uncertainty
In *Proc IEEE Vis*, 2010.

Big Data Challenges in Sci. Vis.



Scalable methods

In-situ / in-transit methods

Feature extraction / tracking

Power aware algorithms

Reliability / resiliency

Uncertainty quantification

Visual comparisons

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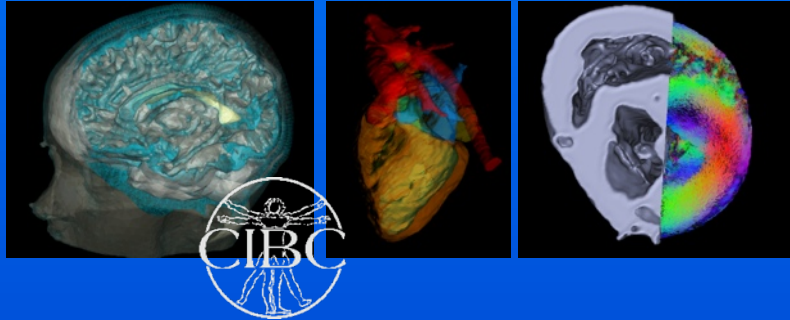
The SCI Institute



Acknowledgments



NIH/NIGMS Center for Integrative Biomedical Computing

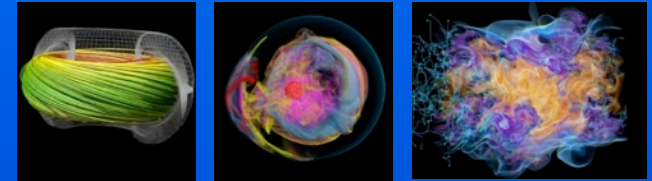


Center for Extreme Data Management, Analysis, and Visualization



SDAV

Scalable Data Management, Analysis and Visualization



UTAH Center for Computational Earth Sciences

NIH NIMIC



IAMCS
Institute for Applied Mathematics and Computational Science



National Science Foundation
Directorate for Computer & Information Science & Engineering (CISE)



More Information



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