



Exceptional service in the national interest

Application of 3D Characterization for Mechanical Modelling of Additively Manufactured AlSiMg

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SAND2022-2545 C

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Outline

- Motivation
- 3D Characterization
 - Statistical analysis of porosity
 - Particle tracking
- Predictive Modelling
 - Formulation
 - Sensitivities
- Conclusion

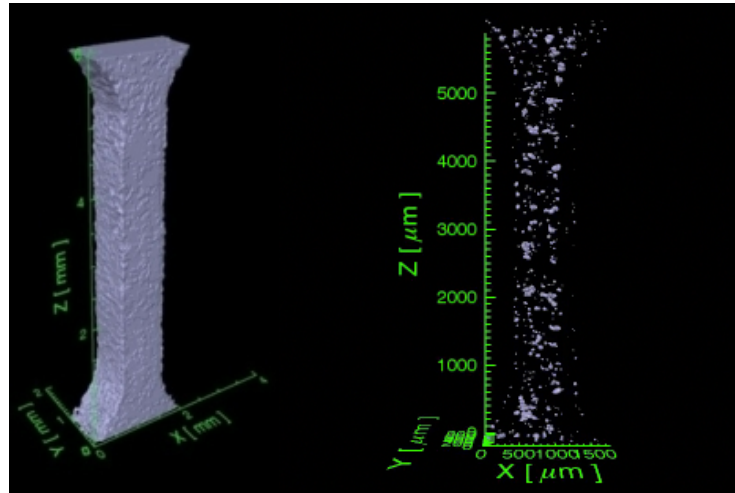


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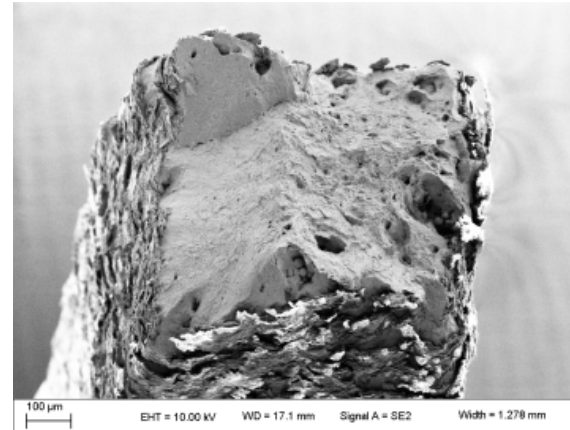
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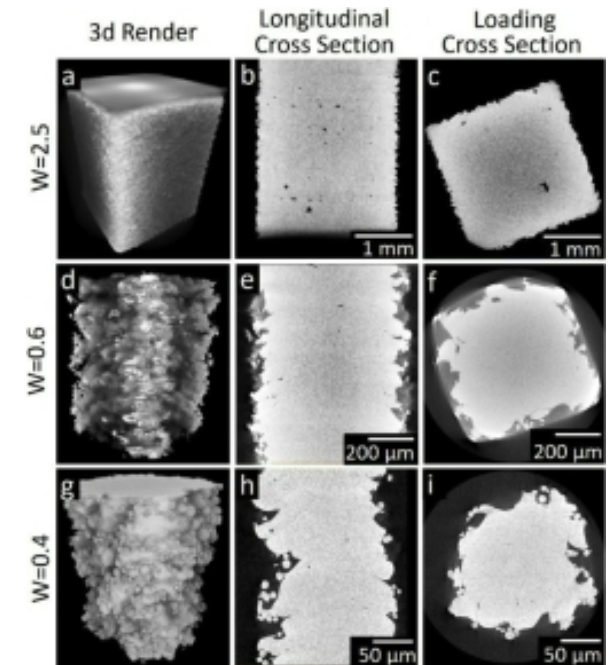
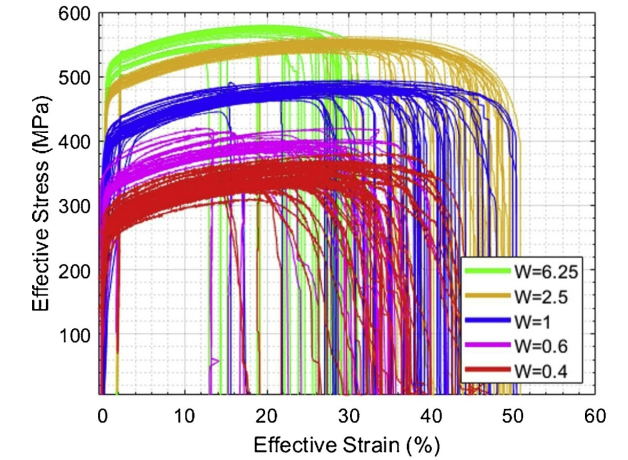
LPBF can produce significant mechanical variability



(J. Madison, T. Ivanoff, O. Underwood, SNL)

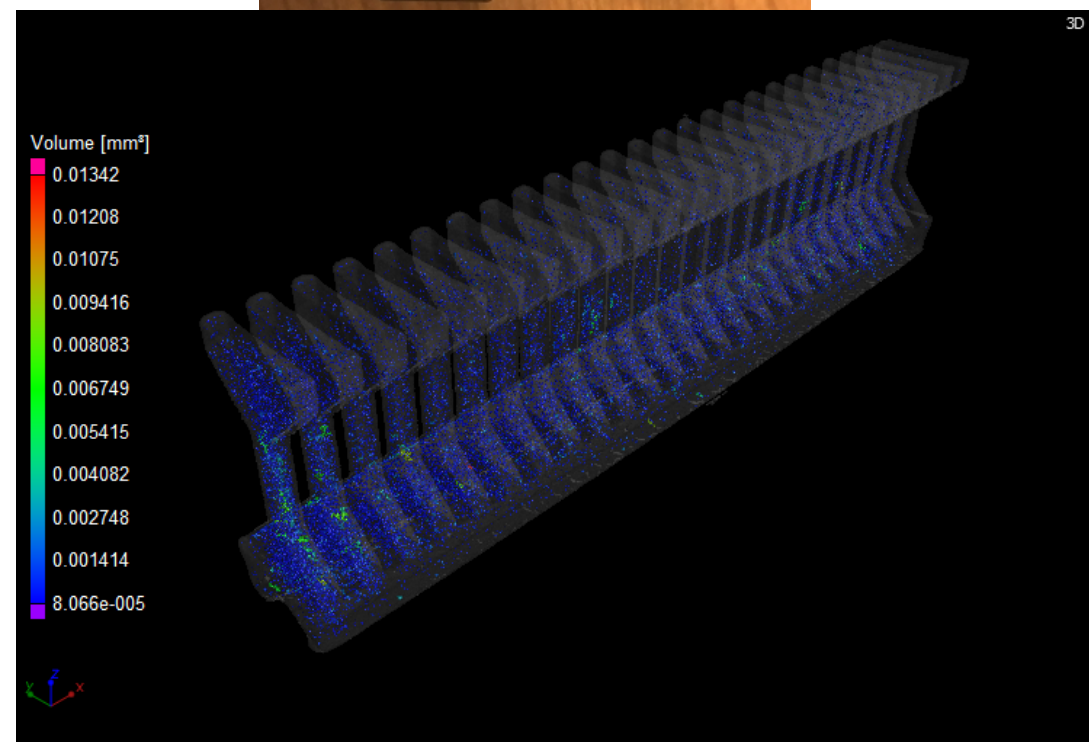
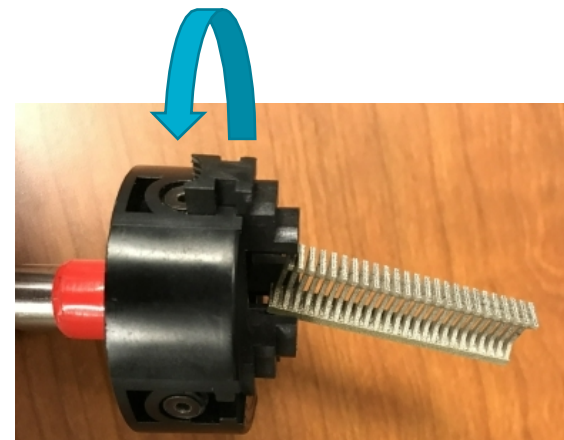
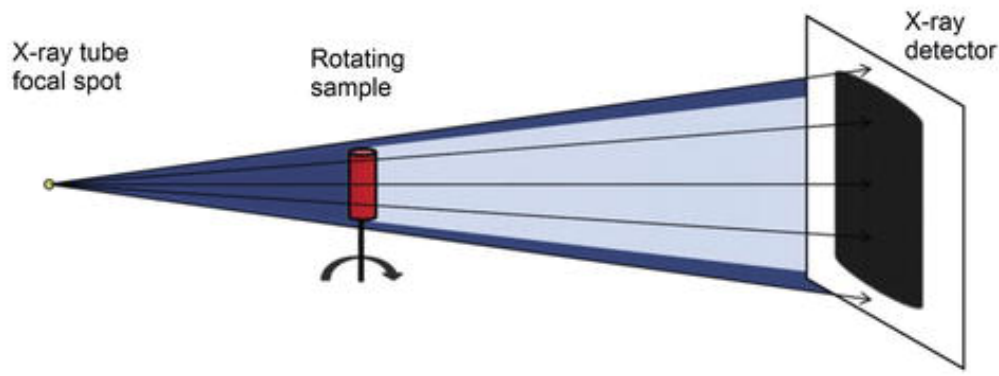


Kramer et al., *IJF* 2019



Roach, A.M. et al. *Additive Manufacturing* 2020

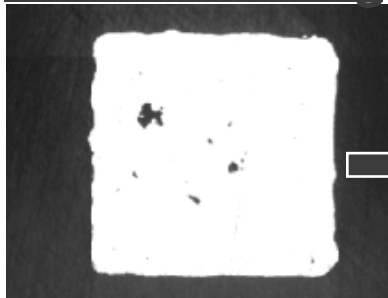
Computed Tomography (CT) offers a way to quantify defect structure





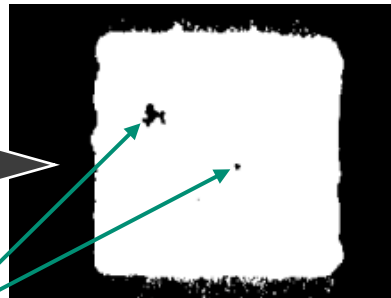
Challenges remain in use of CT data

Serial sectioning



Voids

Low threshold (80)



Lose image detail
Create image artifacts

Middle threshold (155)



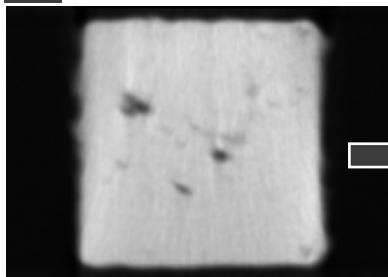
Most accurate
representation

High threshold (230)



Loses object edges
False voids possible

CT



Low threshold (100)



Retain object edges
Lose all void detail

Middle threshold (160)



Retain object edges
Capture some detail

High threshold (210)



Lose object edges
Capture voids (slightly
enlarged)



Challenges remain in use of CT data

Serial sectioning



Low threshold (80)



Middle threshold (155)



High threshold (230)



edges
possible

CT



Retain object edges
Lose all void detail



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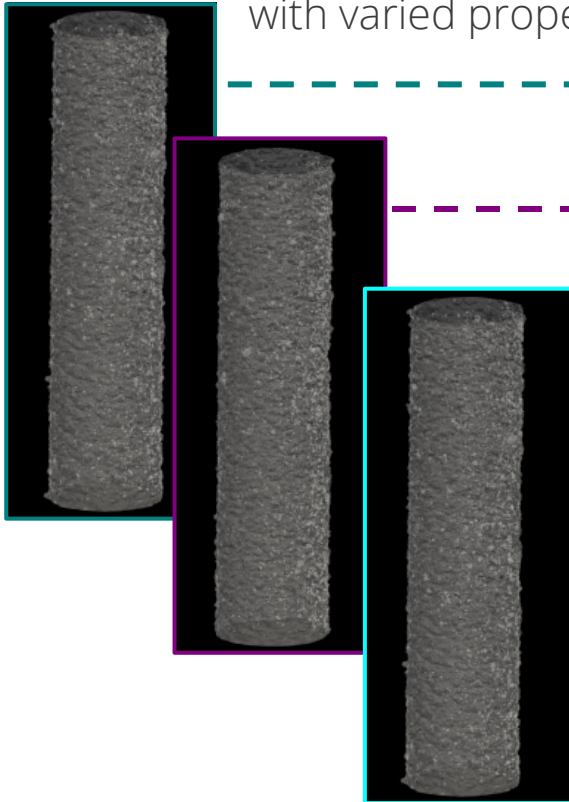
threshold (210)

Can we make meaningful
performance predictions with
knowledge of defect structure?

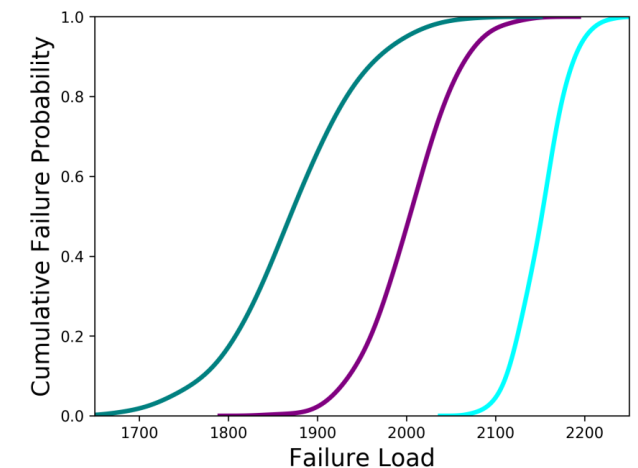


Vision: Rapid failure prediction based on microstructure enabled by Machine Learning

Synthetic
Microstructures
with varied properties



Simulation Code



Requirements: Training data with accurate microstructure and mechanical behavior



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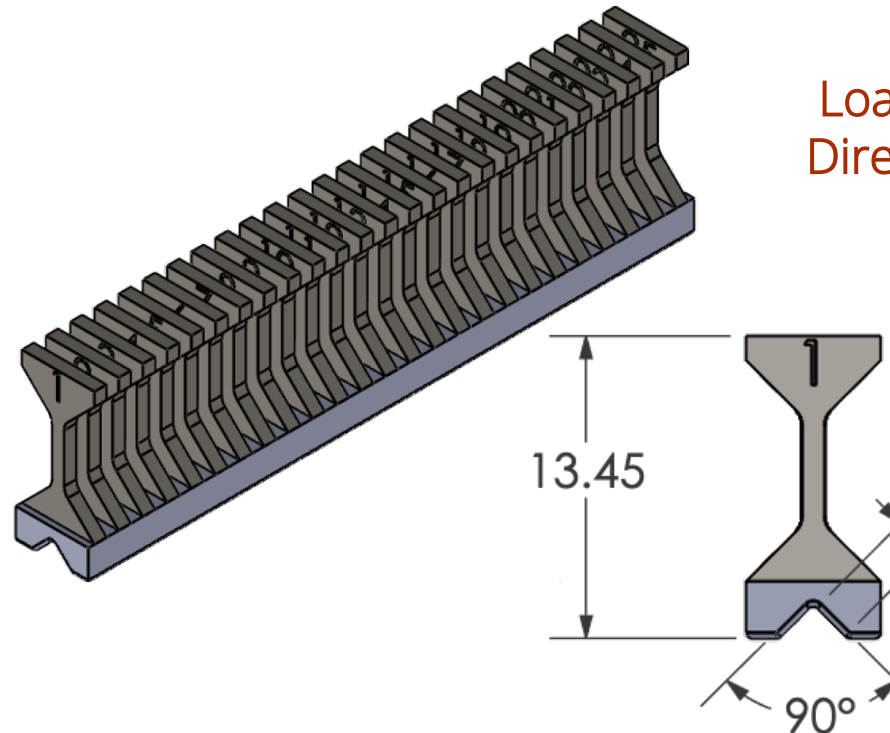
In situ tensile experiment with μ CT

Zeiss Xradia 620 μ CT

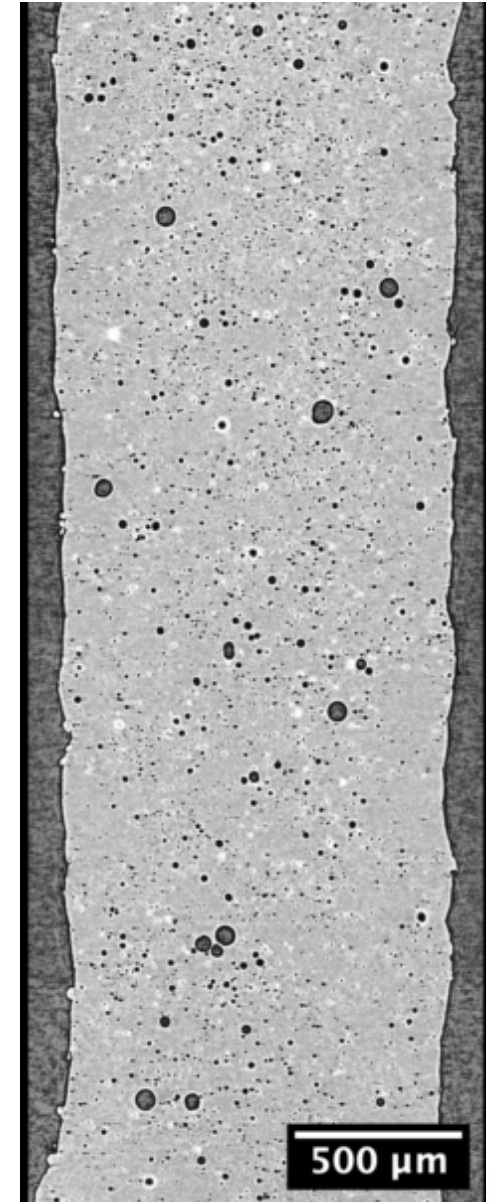
- Effective voxel size of 2.1 μm
- Intermittent scans at fixed displacements
- ~3hr per scan

Tensile specimen

- 1 x 0.45 mm x 4.17 mm gauge section
- Al-10Si-Mg powder <44 μm diameter
- Printed on EOS M400-1
- Stress-relief annealed after build (550 $^{\circ}\text{C}$)



Loading
Direction

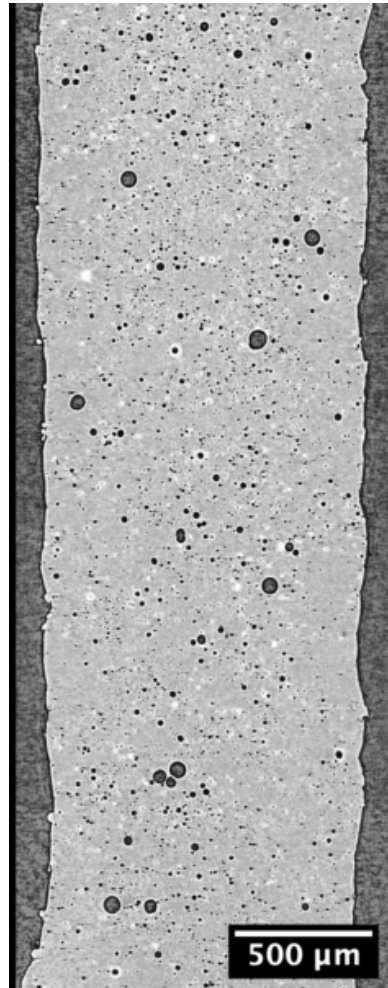




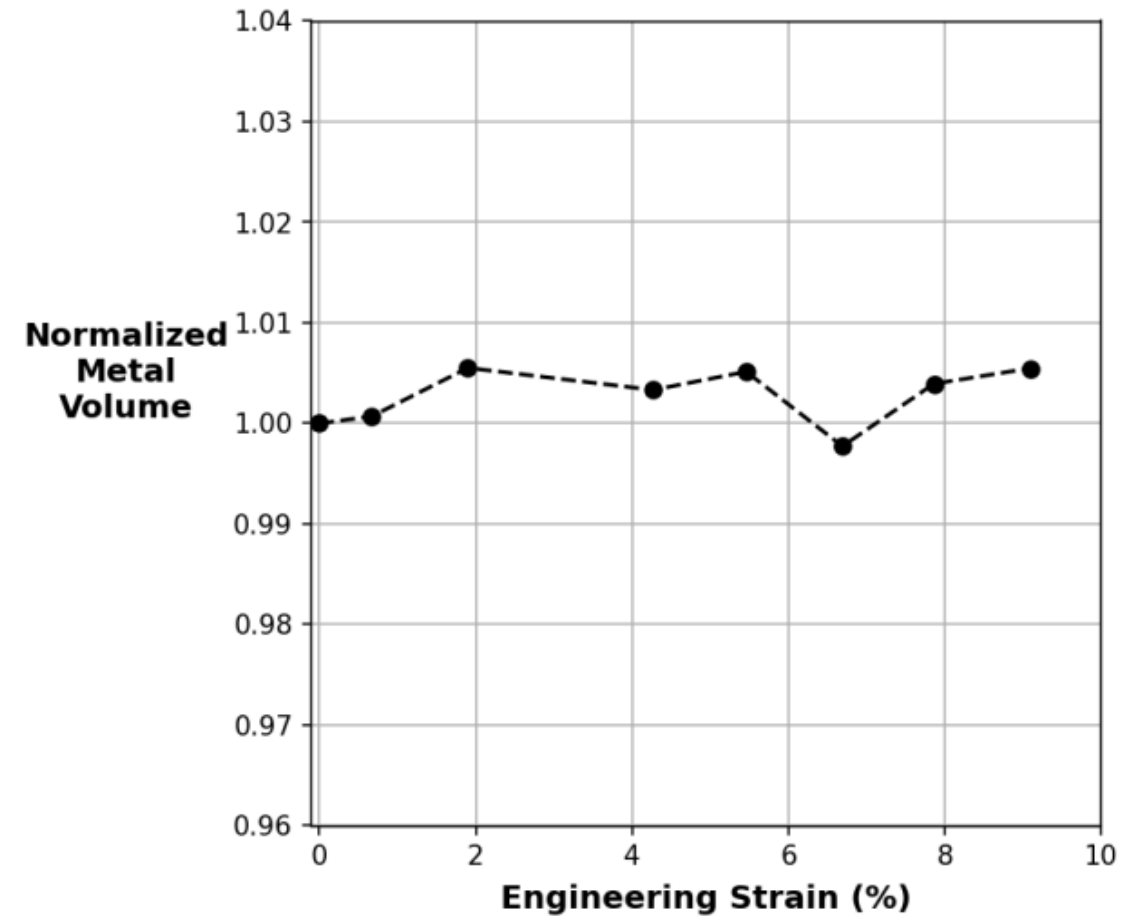
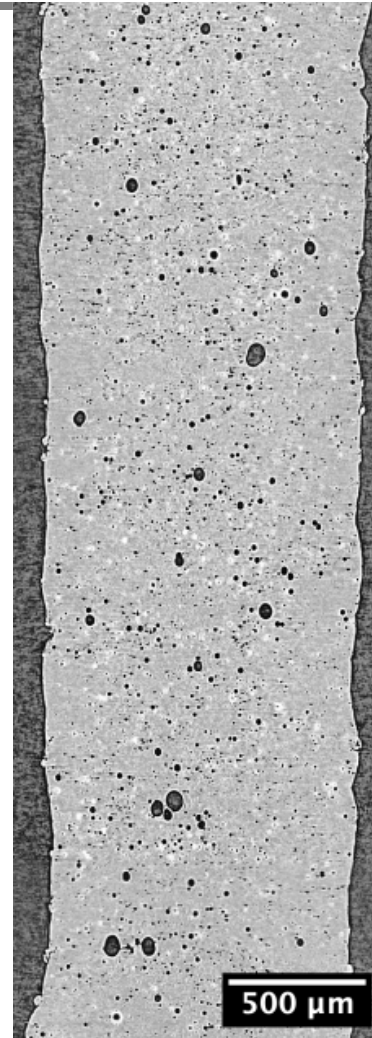
Statistical assessment of scan requires a constant sample volume

Initial Scan

Last Intact Scan



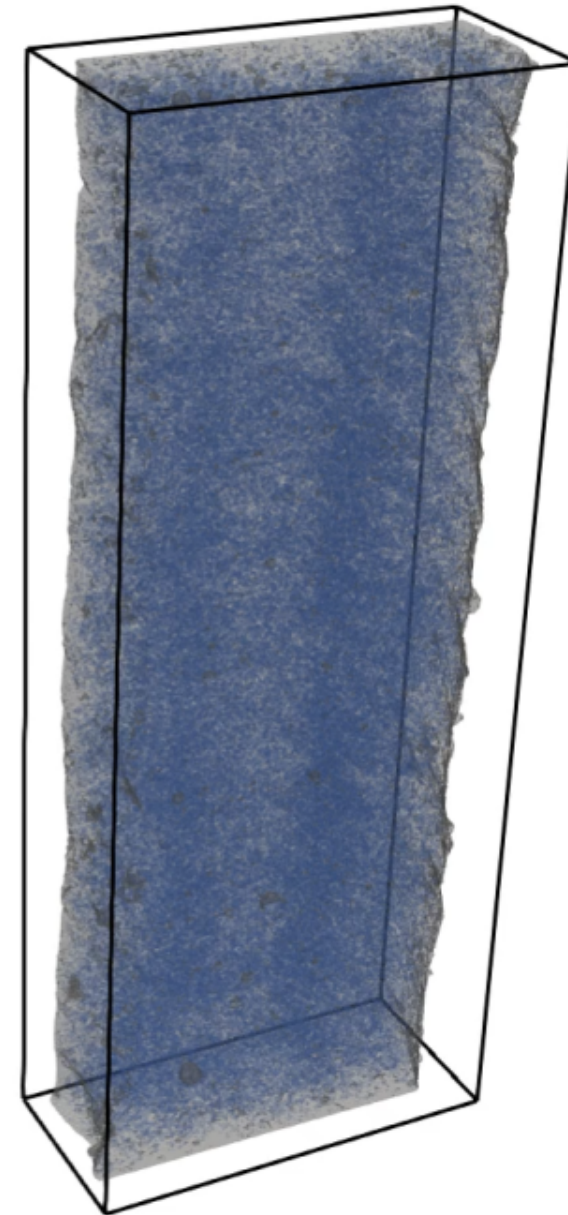
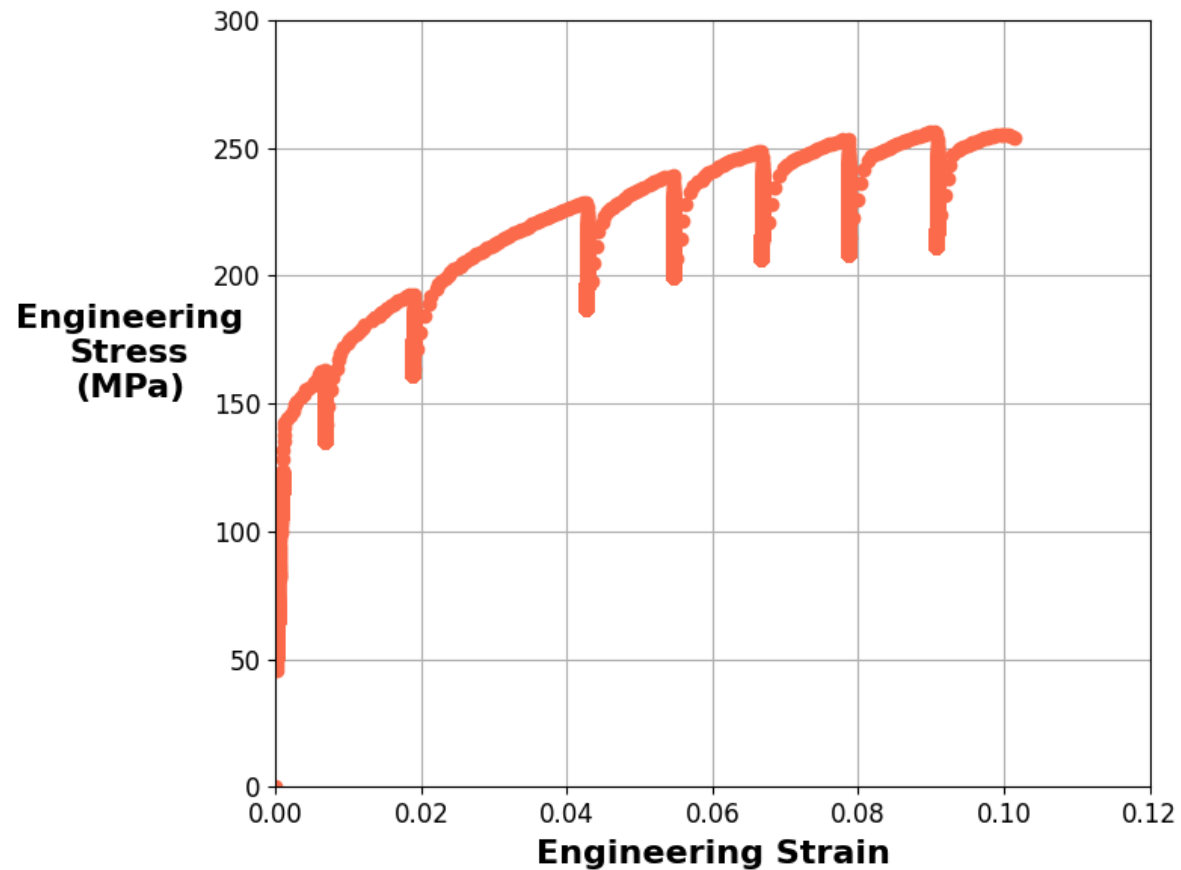
Loading
Direction





Tensile results

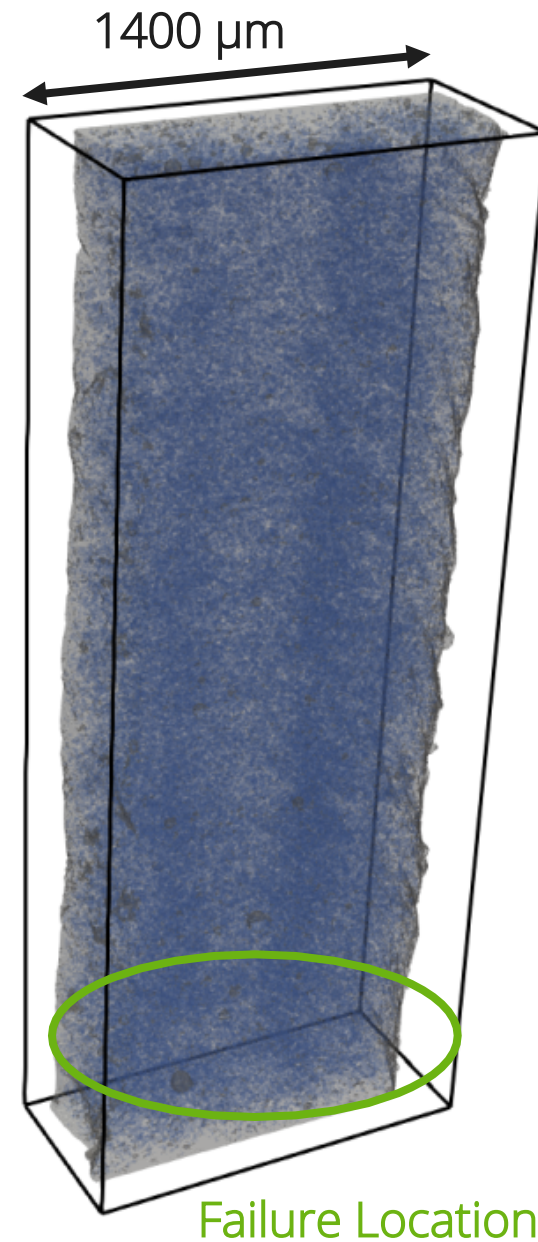
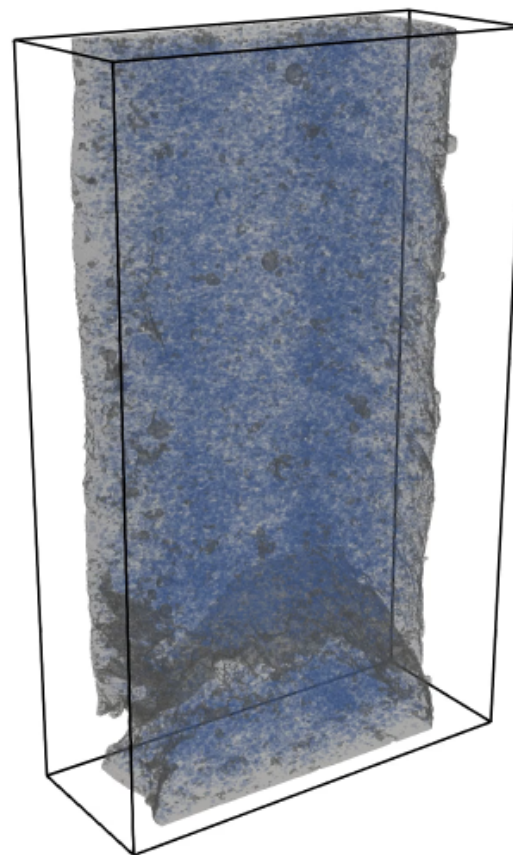
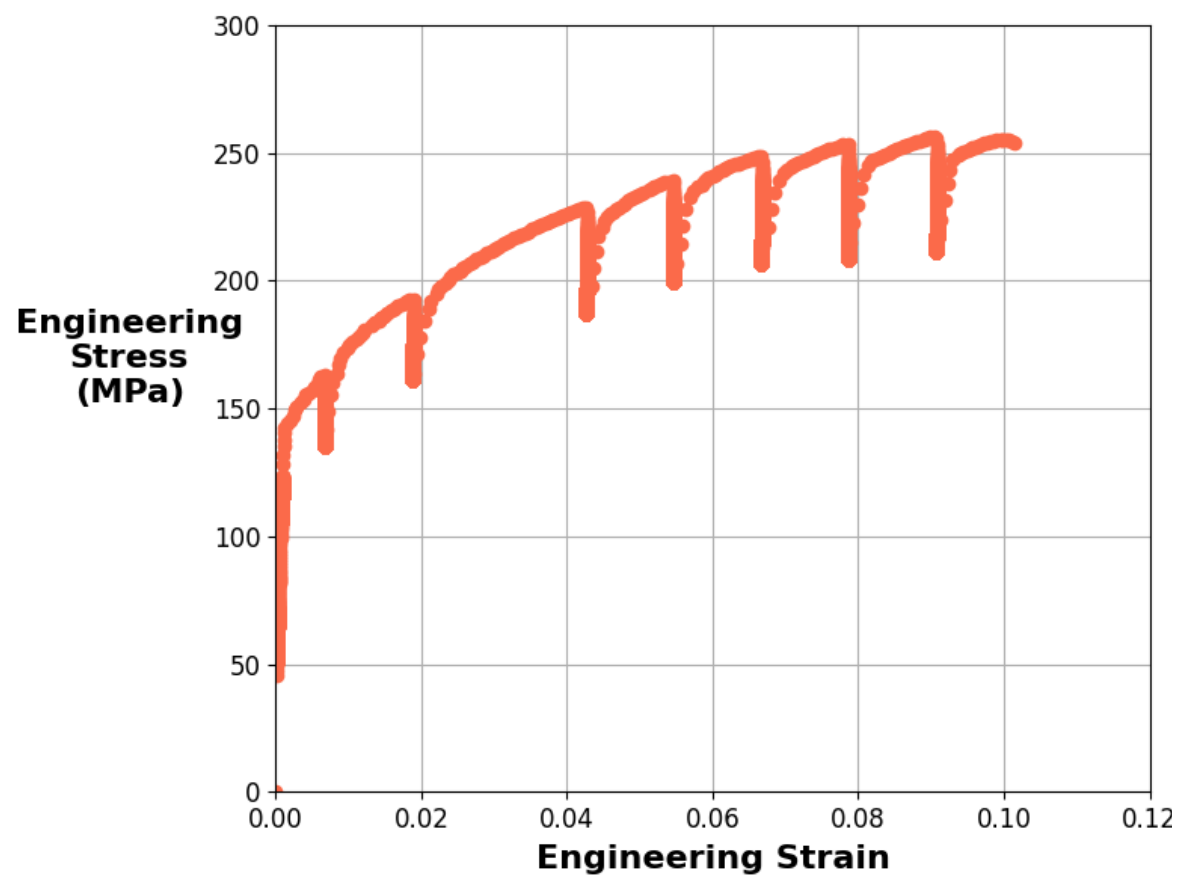
Stress determined using minimum cross-sectional area from initial scan





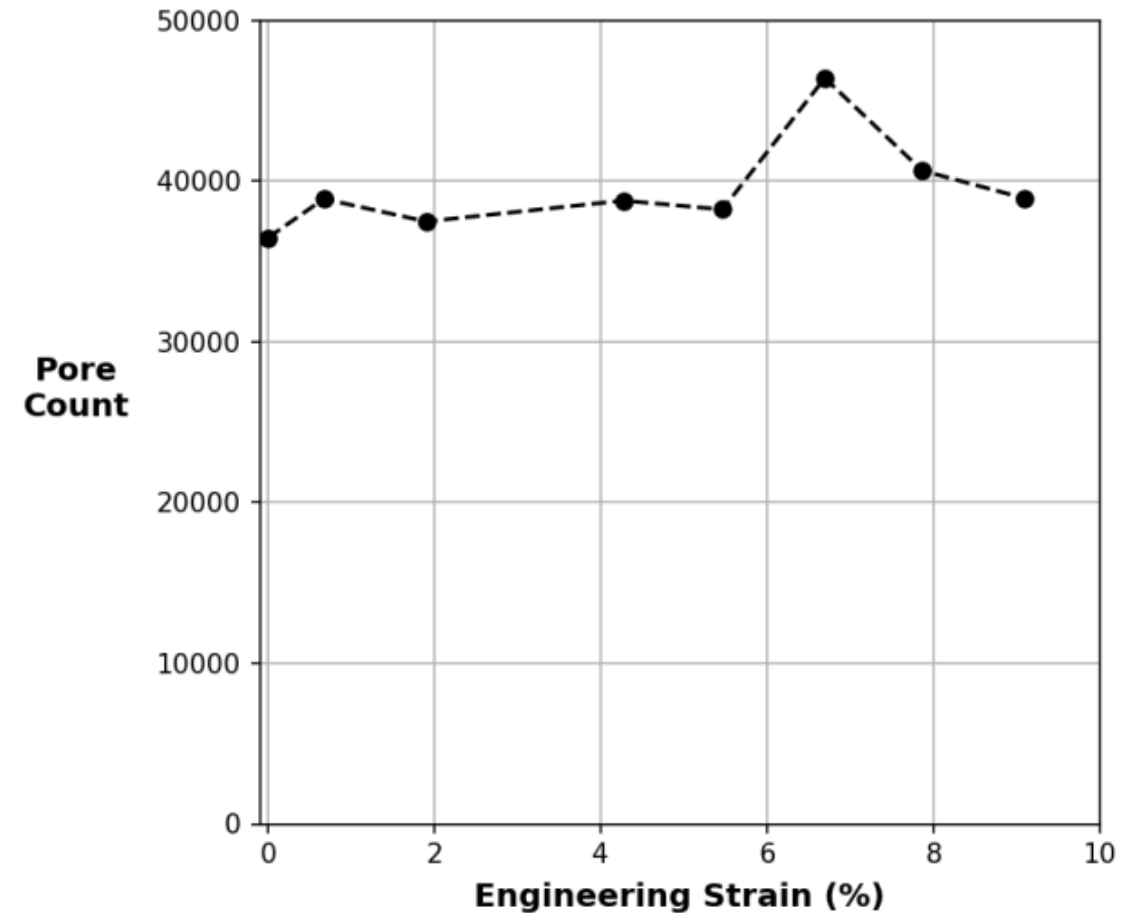
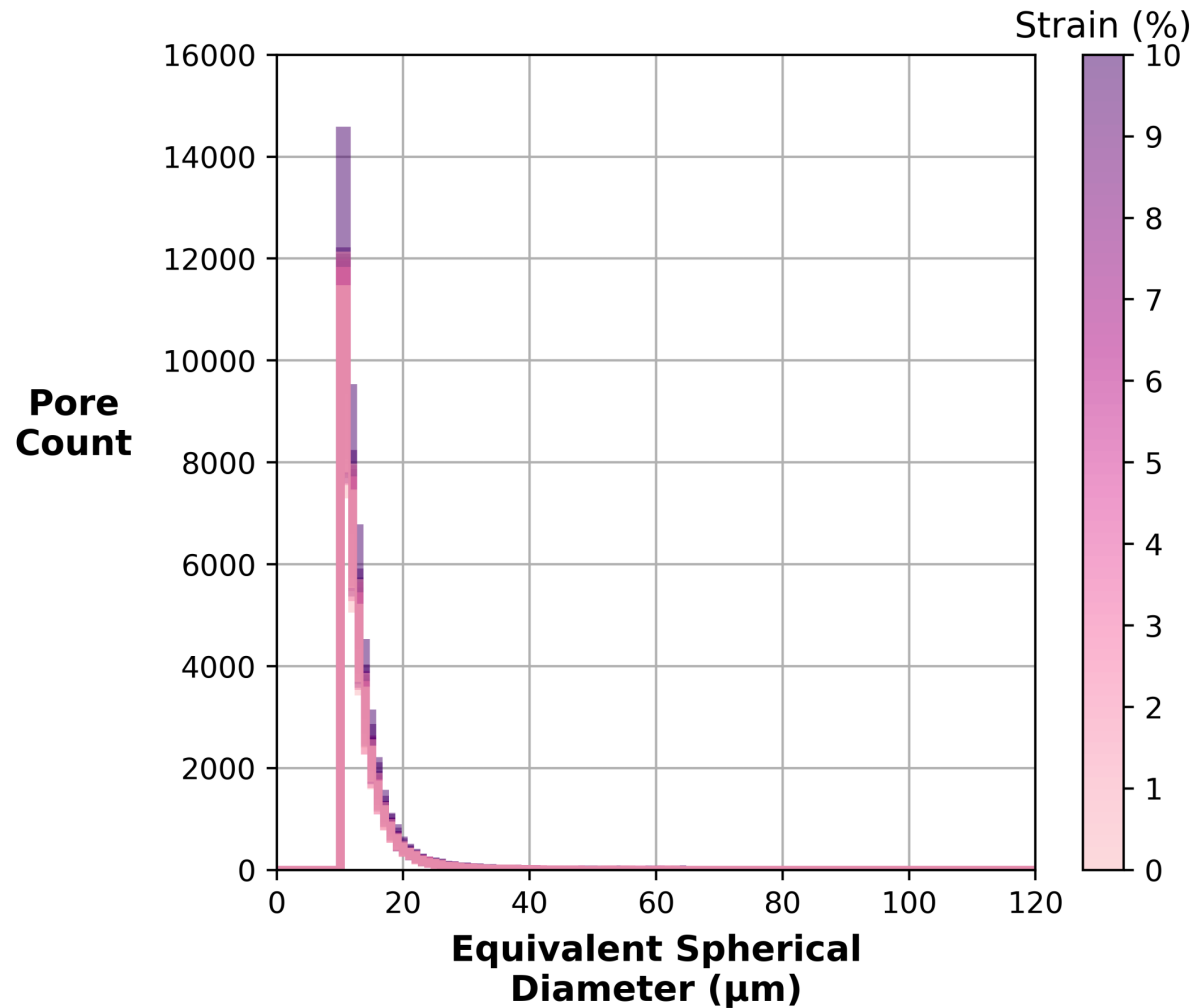
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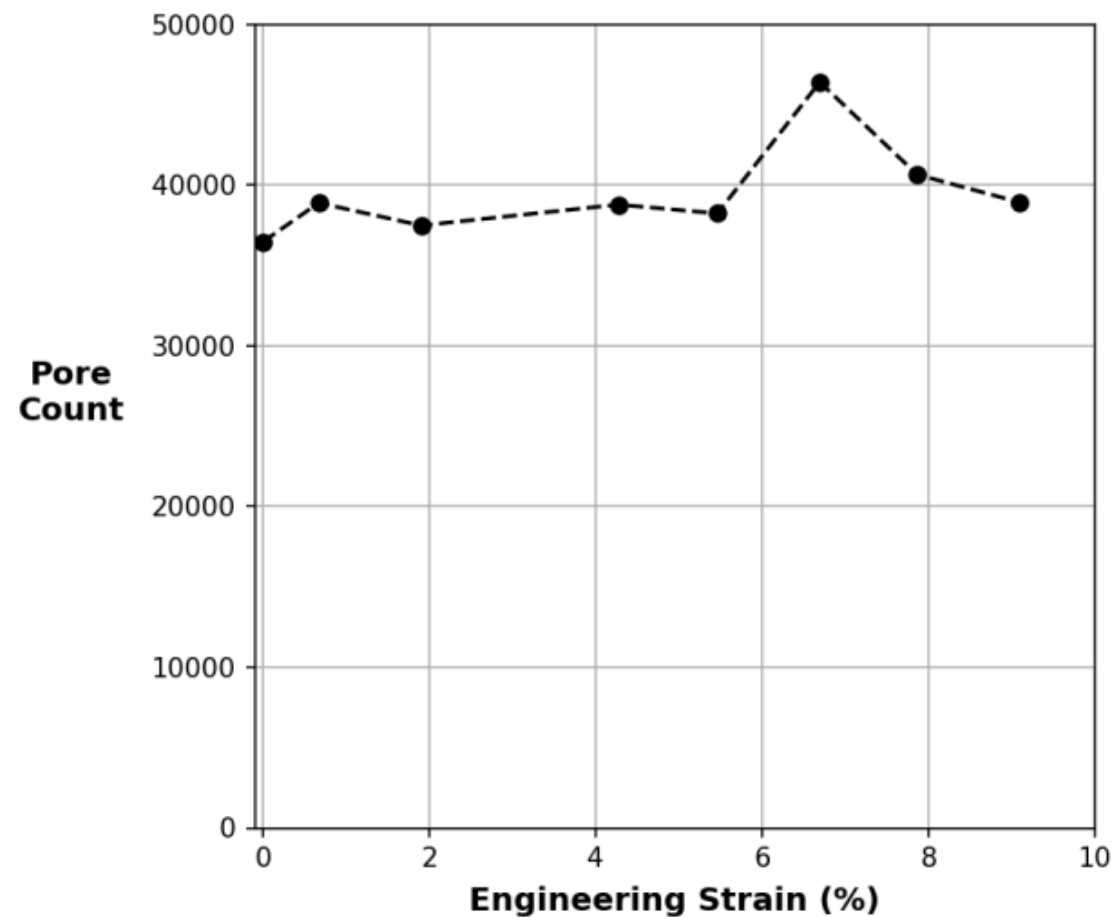
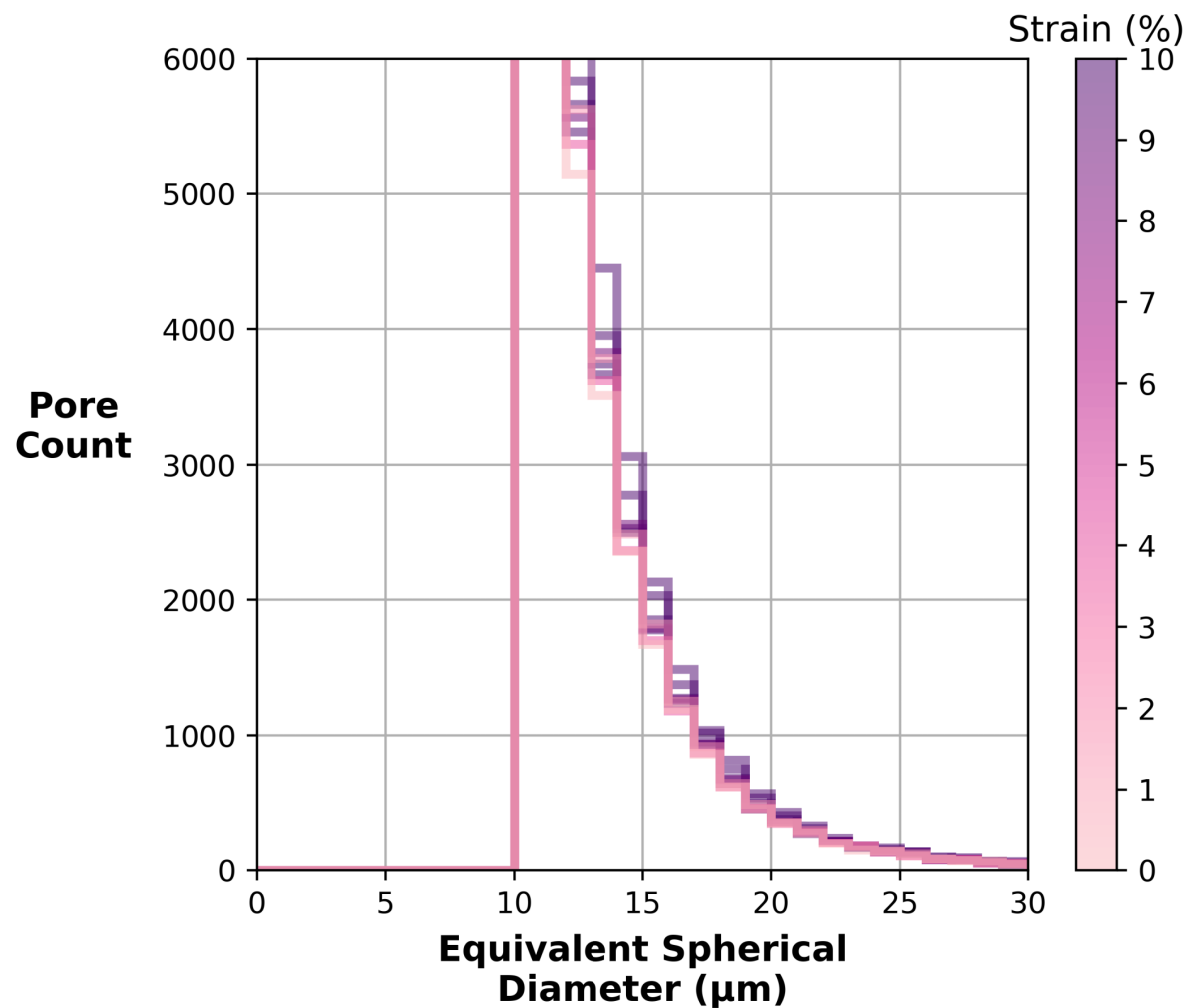


Pore size distribution increases slightly, with minimal evidence of nucleation during loading

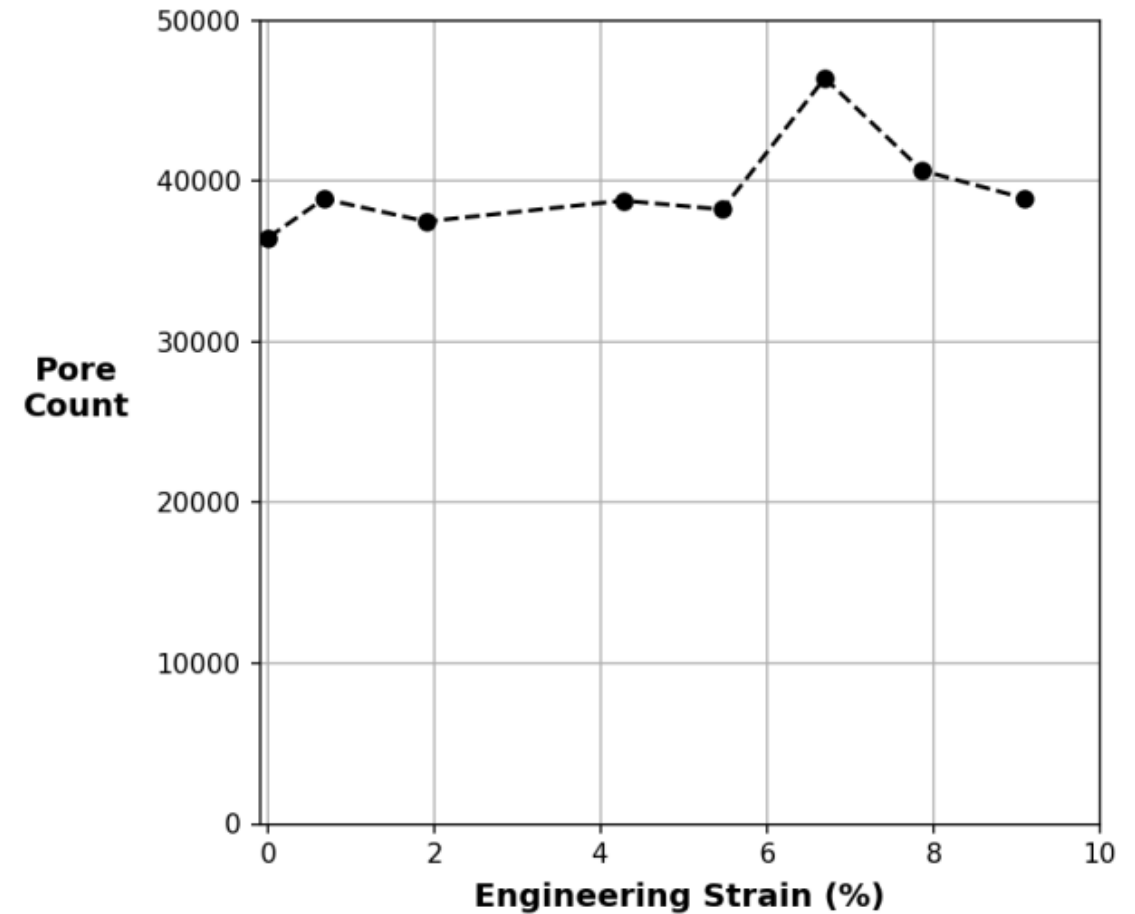
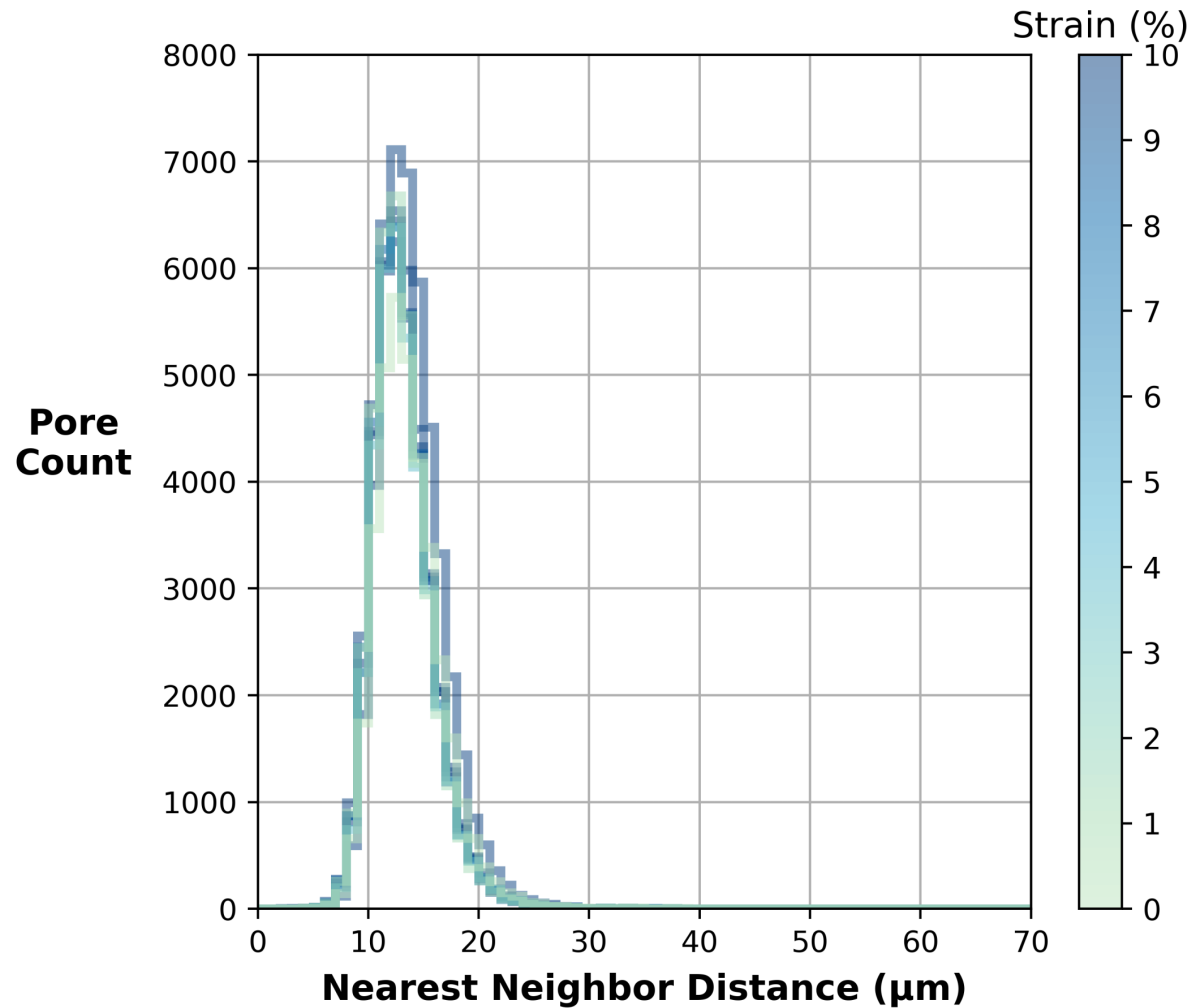




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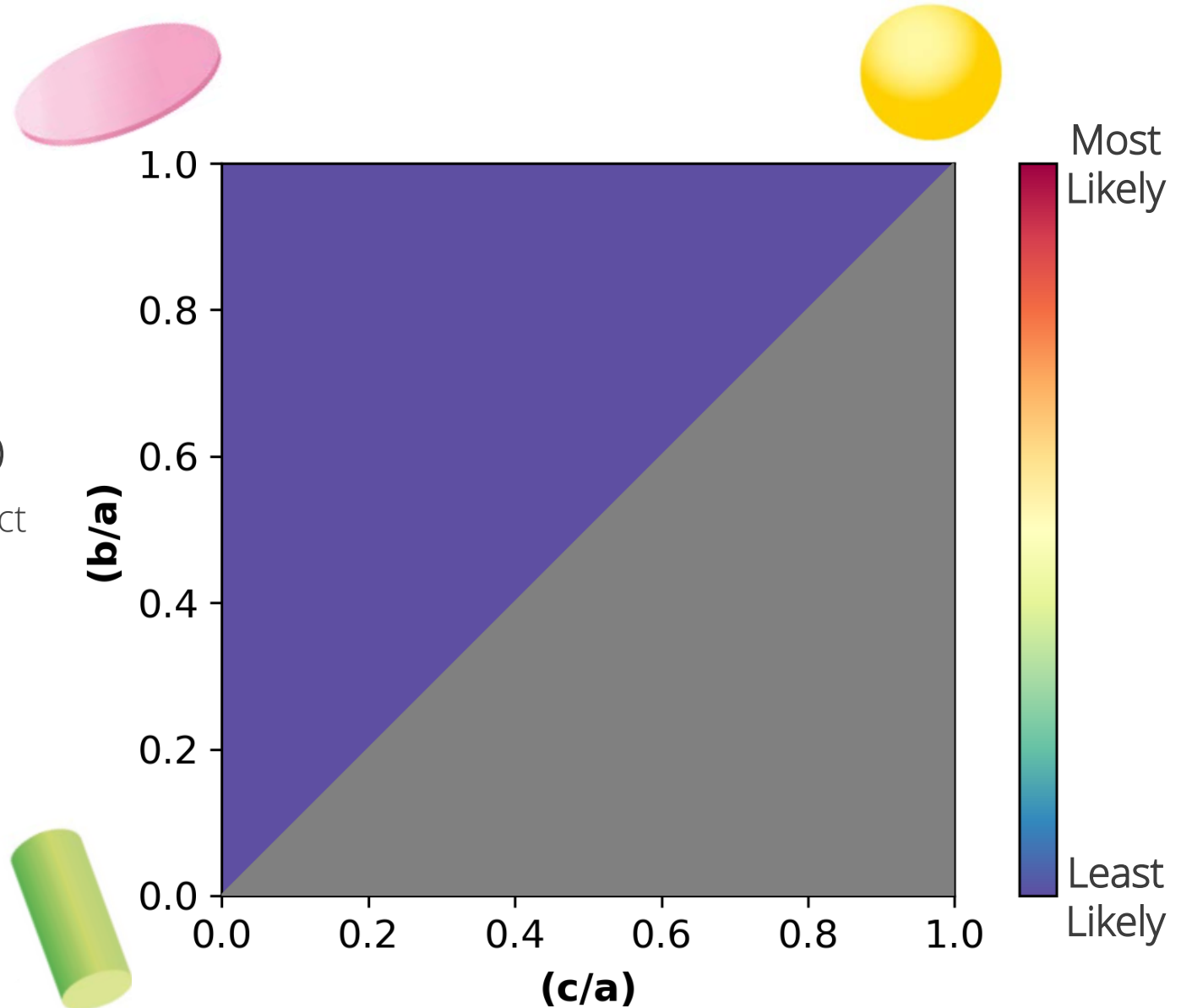
Nearest neighbor distances support lack of pore nucleation



Pores are highly spherical in unloaded state

Shape distributions from best-fit ellipsoid of each pore

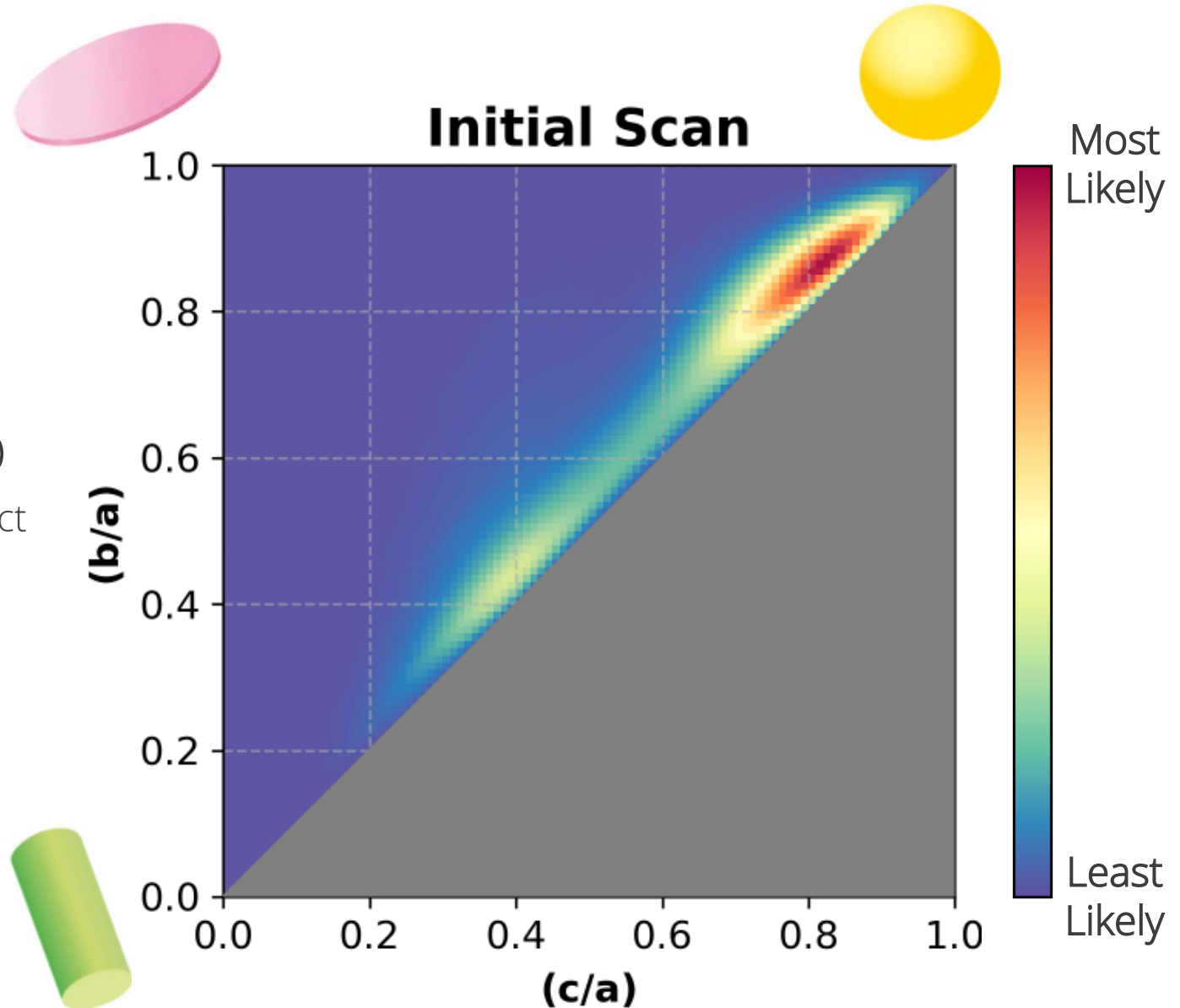
- Three axes in the ellipsoid: one major (a) and two minor (b , c)
- Aspect ratios are defined as (b/a) and (c/a)
- Can create 2D histogram of ellipsoid aspect ratios, given:
 - $a > b > c$ (gray region is non-physical)
- Rod-like features (2 low aspect ratios)
- Plate-like features (1 high aspect ratio)
- Spherical features (2 high aspect ratios)



Pores are highly spherical in unloaded state

Shape distributions from best-fit ellipsoid of each pore

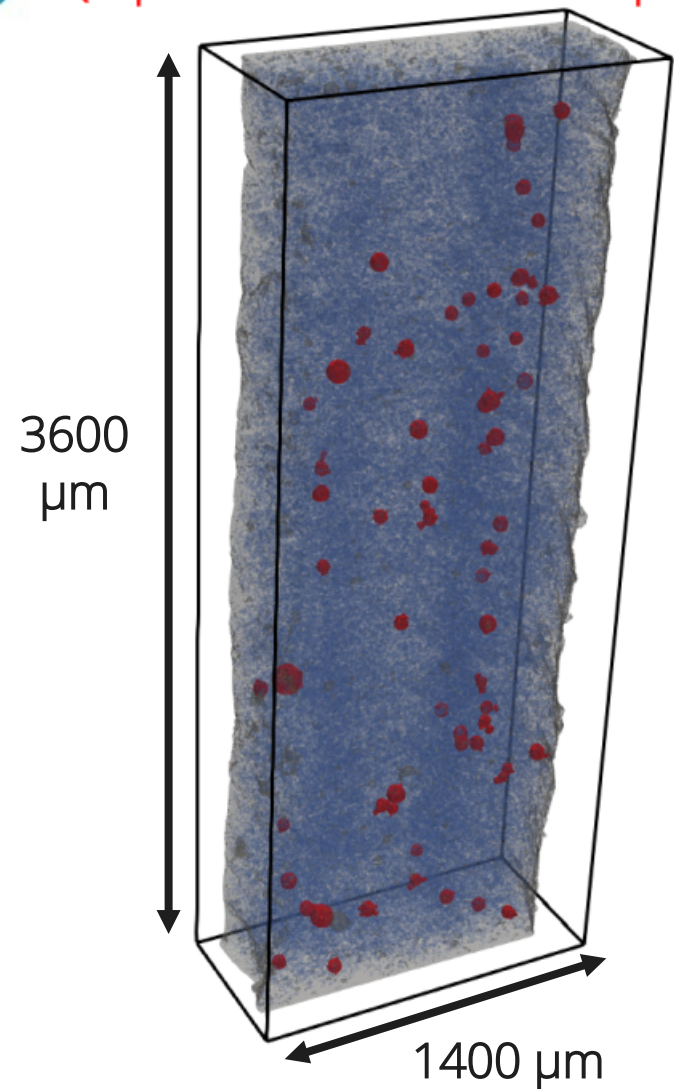
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Can analyze pore growth by tracking the largest pores in the volume

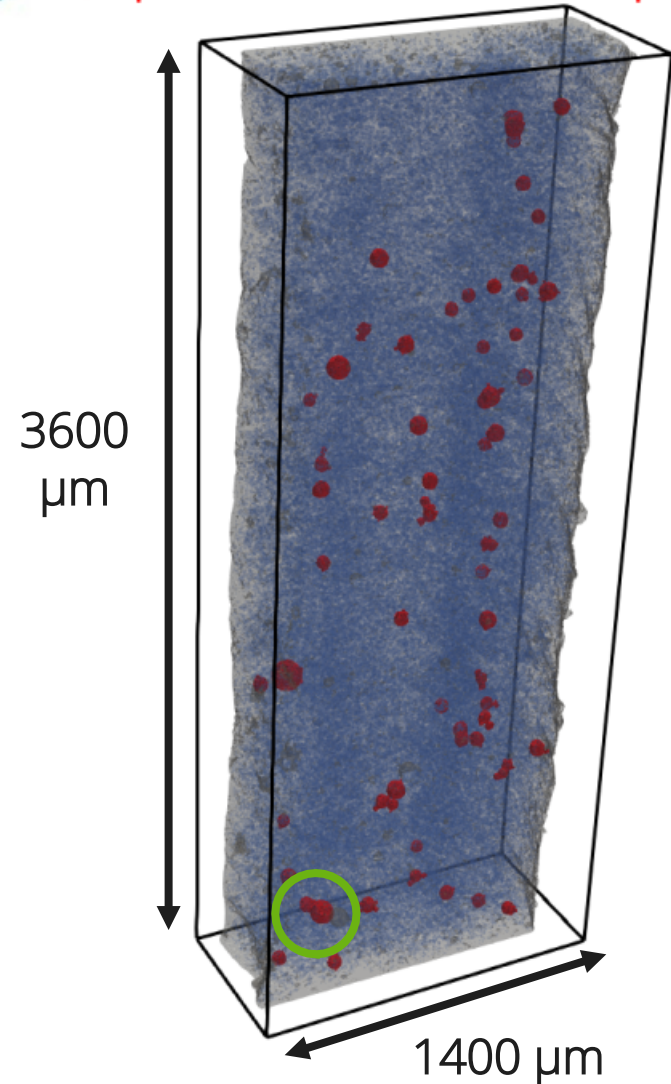
59 Largest pores
(equivalent diameter $\geq 45 \mu\text{m}$)





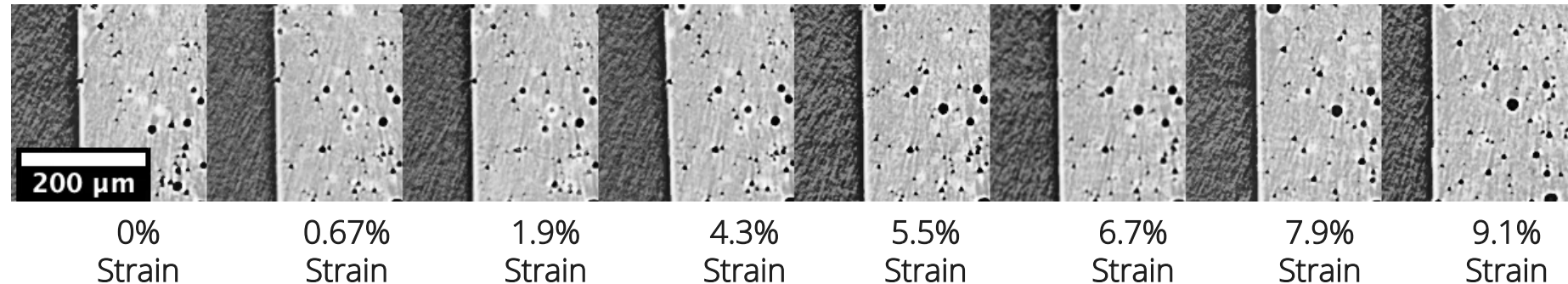
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Normalized cross-correlation in Fourier space can track small regions of the volume

Failure Location

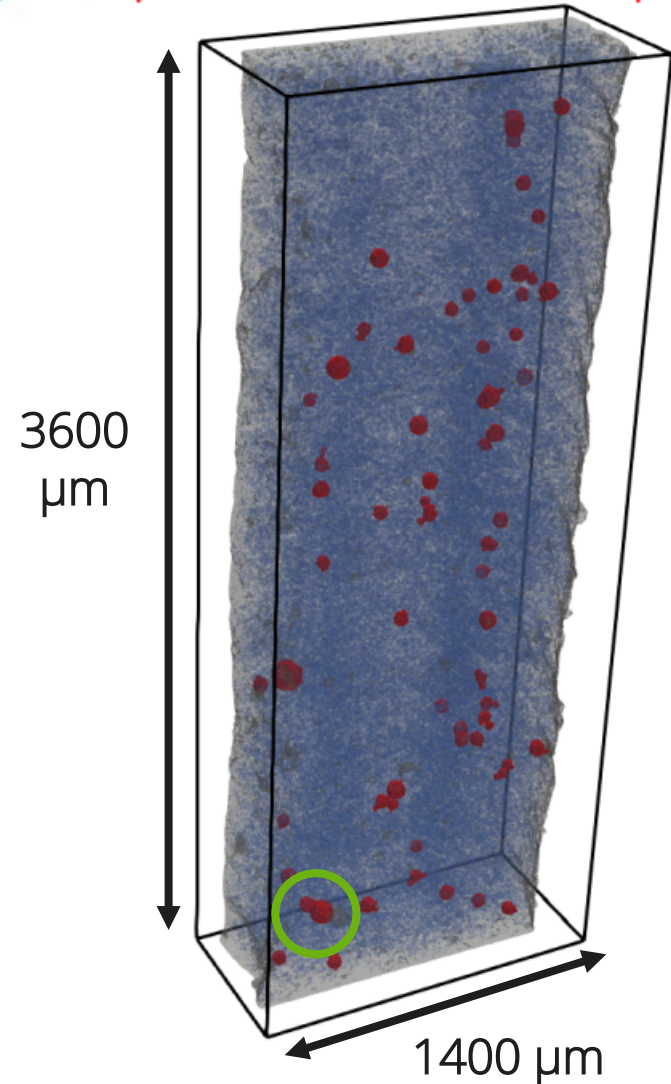


⊗ Loading Direction



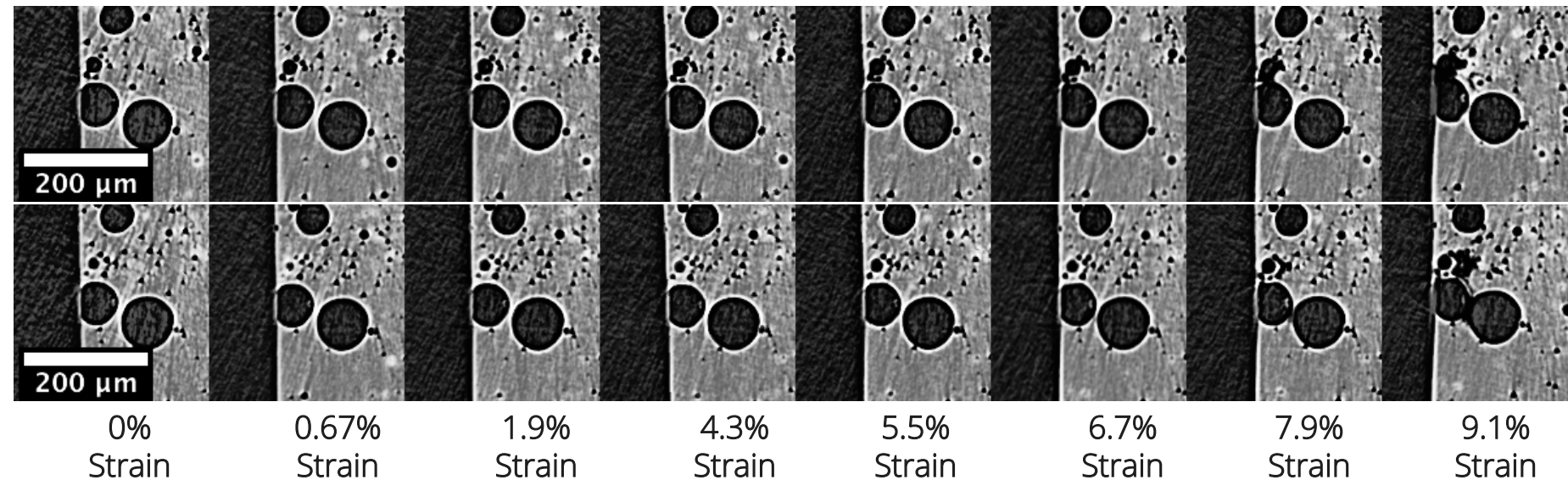
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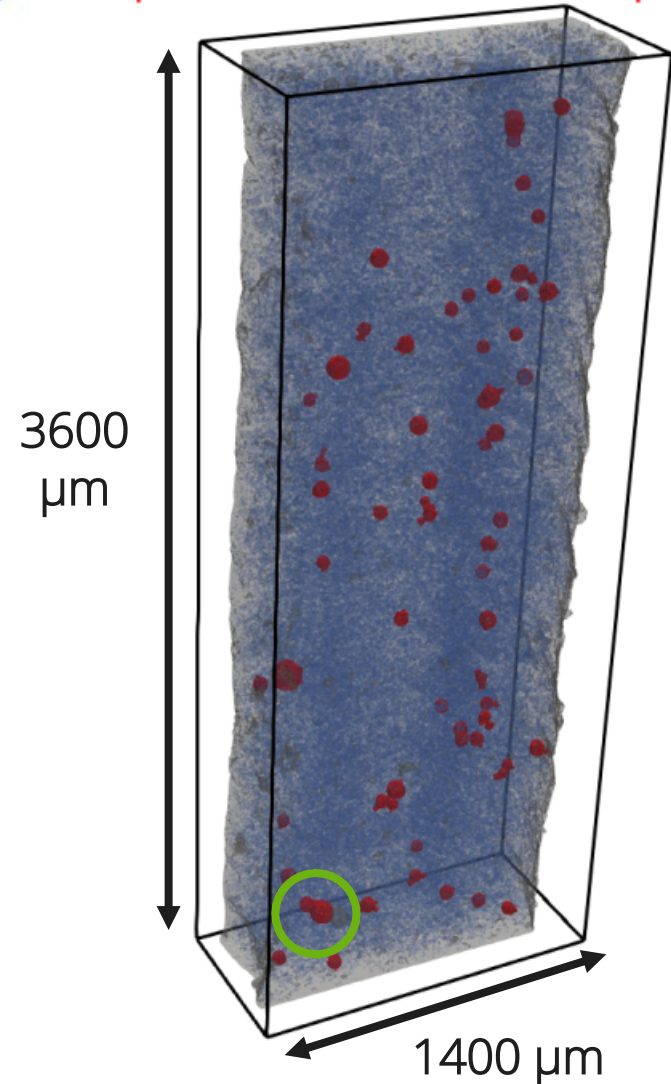


⊗ Loading
Direction



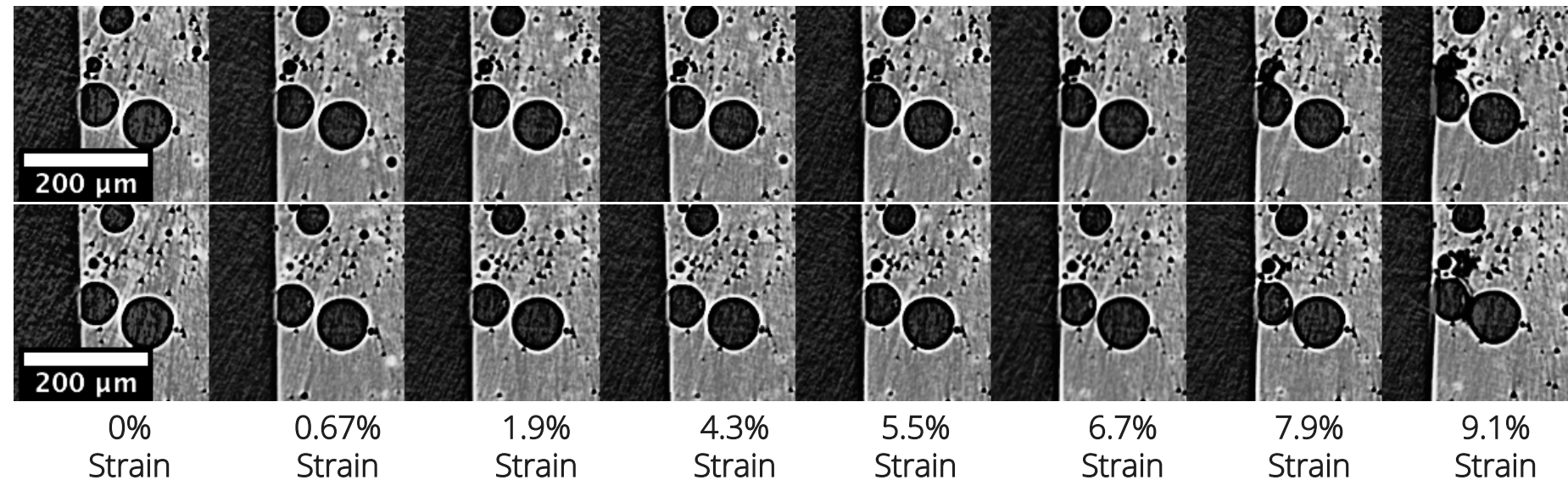
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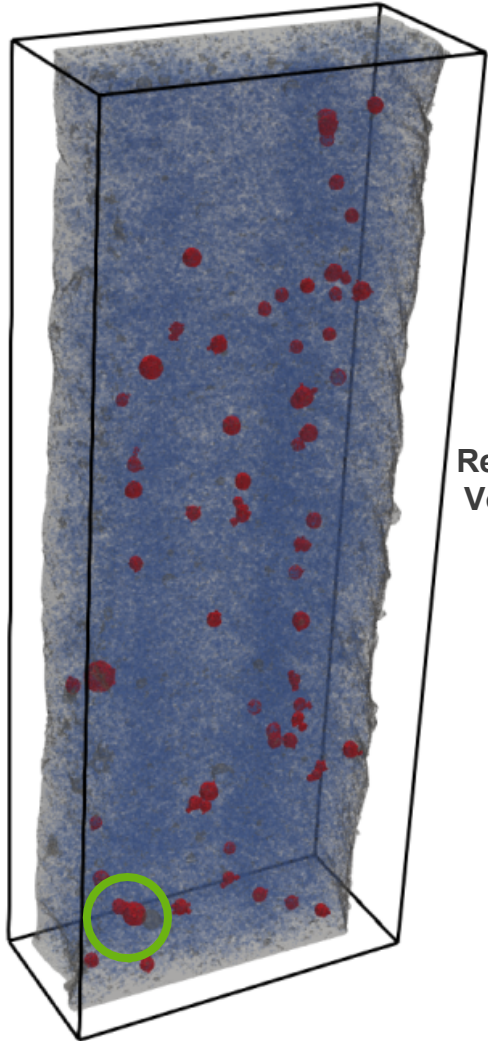
Failure Location



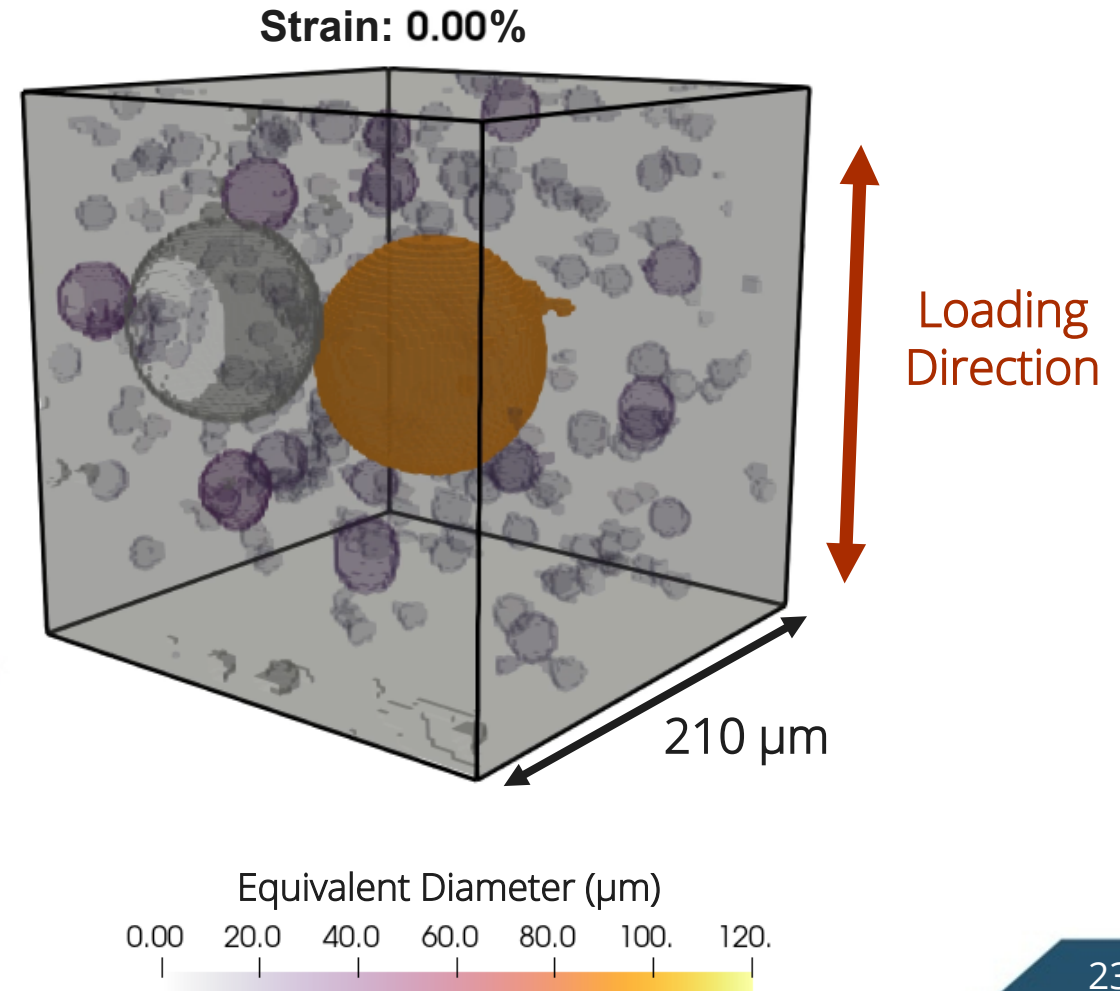
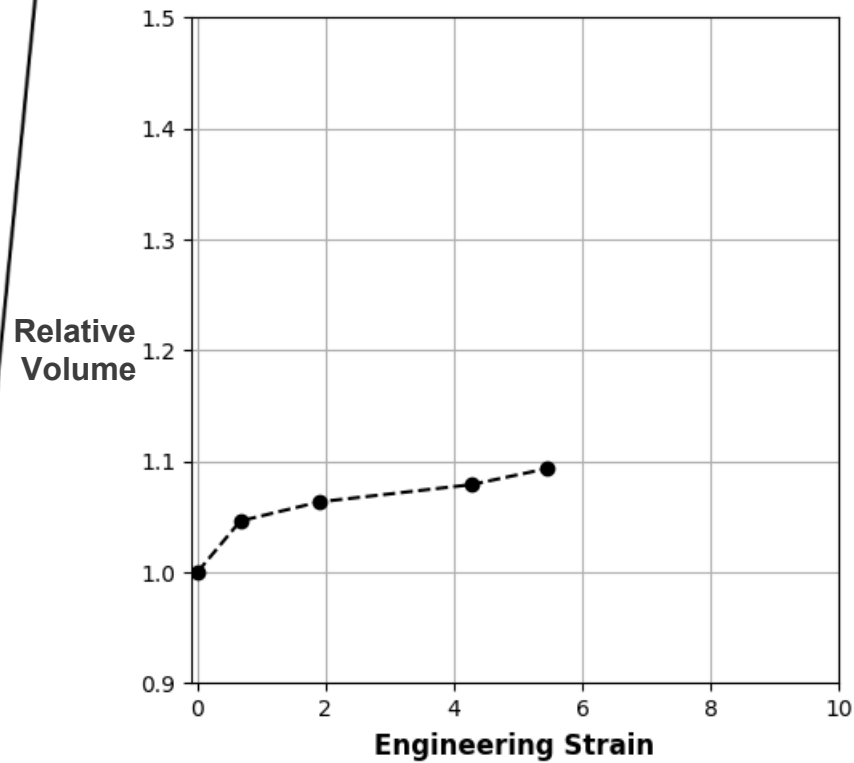
⊗ Loading
Direction



Can analyze pore growth by tracking the largest pores in the volume

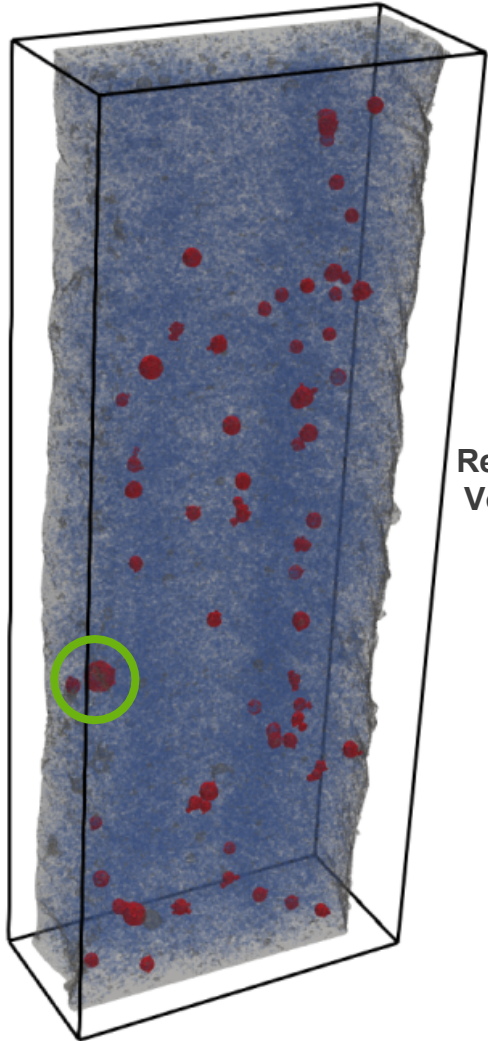


Failure Location

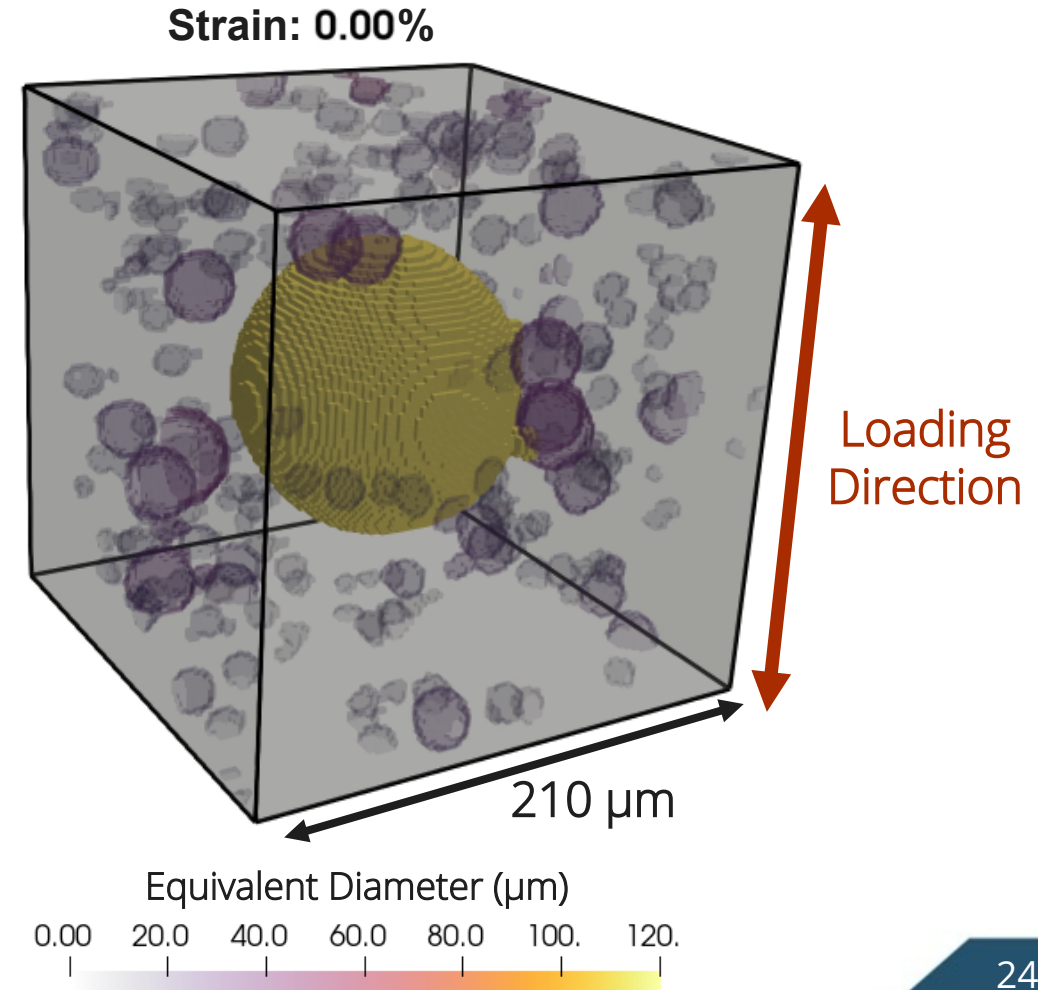
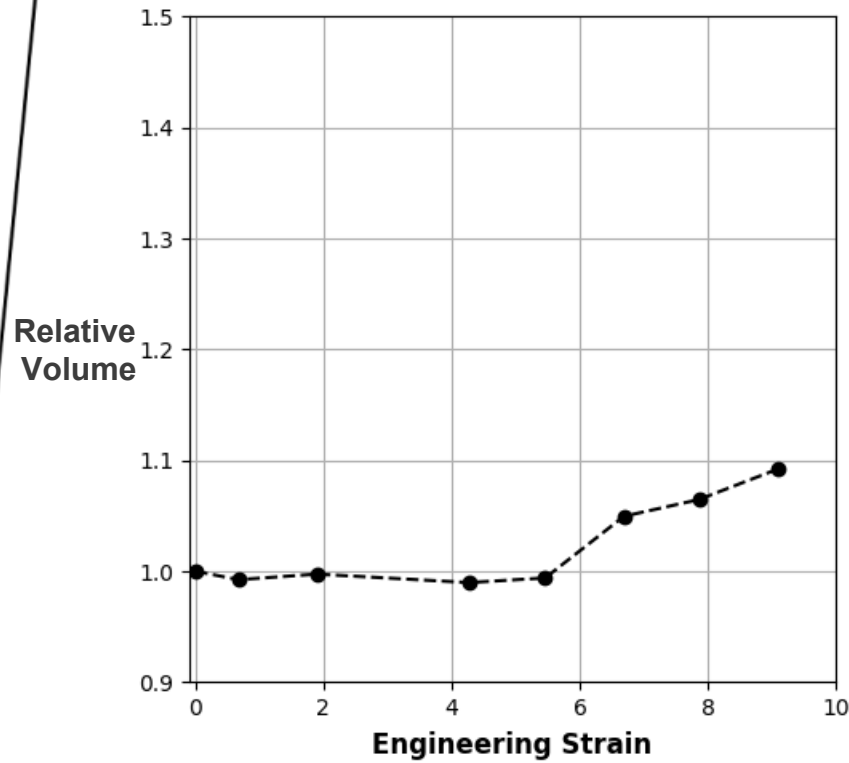




Can analyze pore growth by tracking the largest pores in the volume

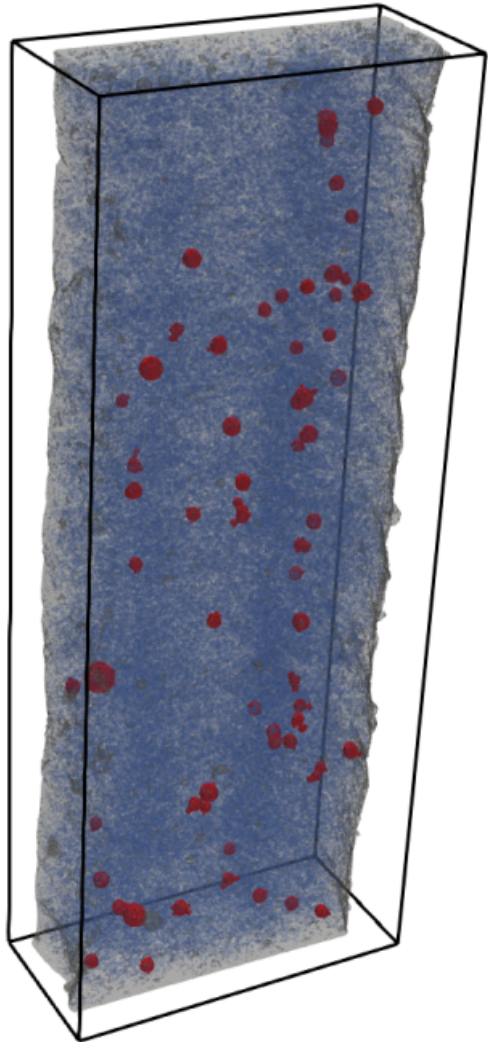


Largest Pore in Volume

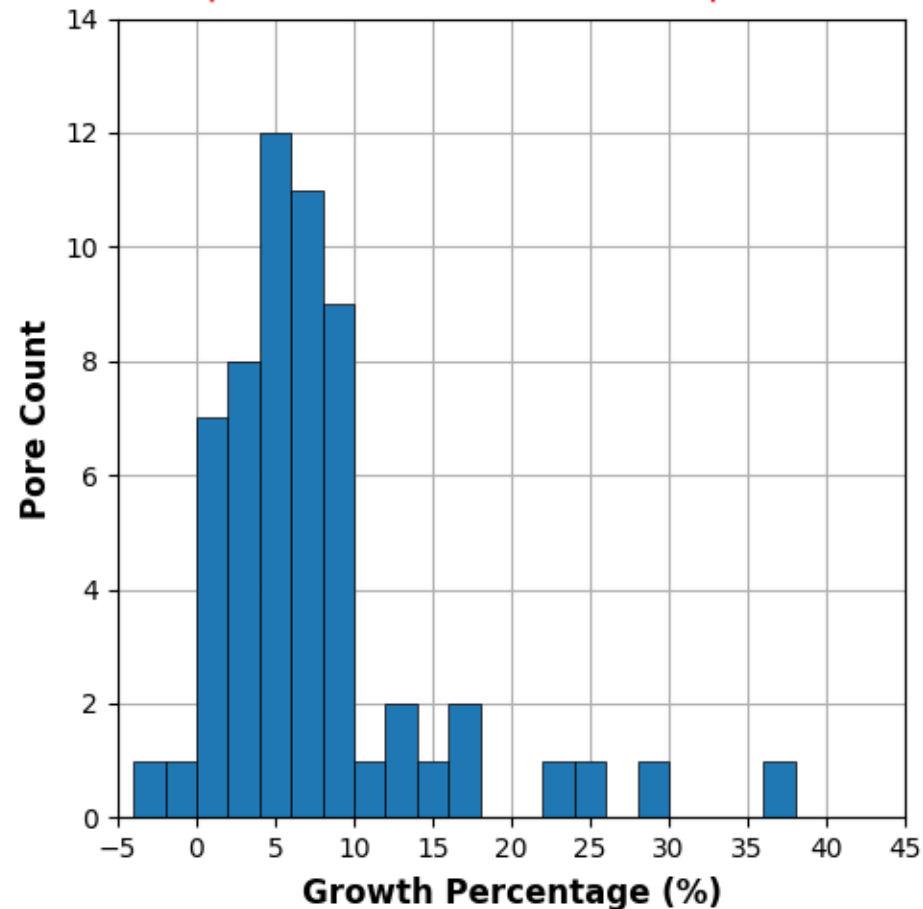




Can analyze pore growth by tracking the largest pores in the volume



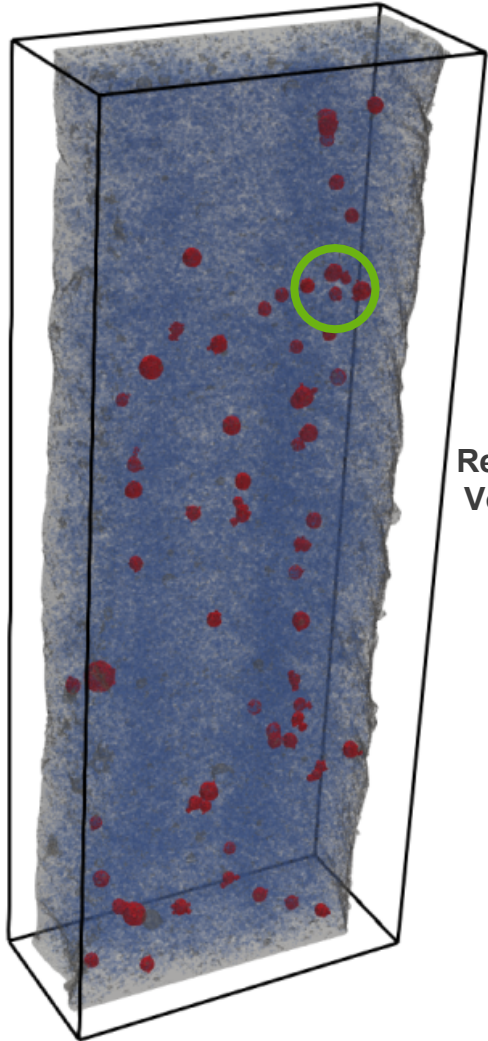
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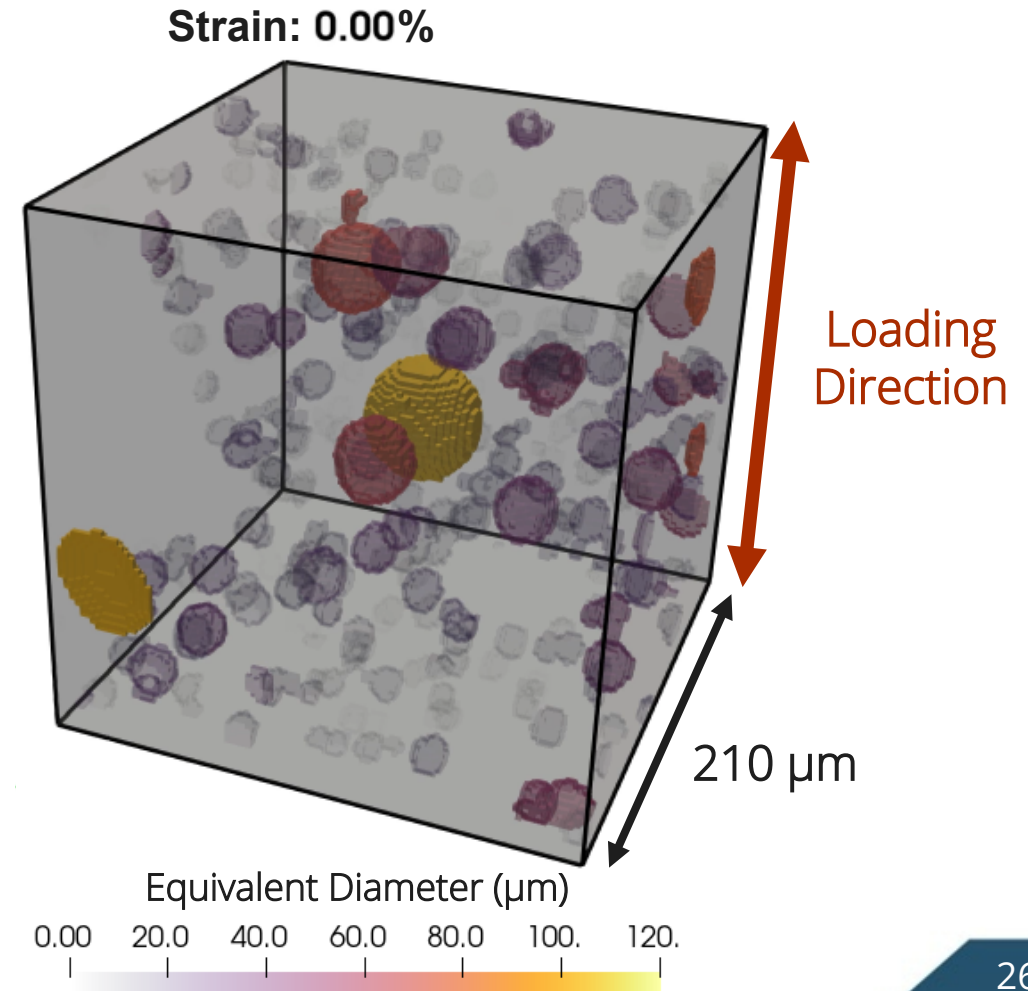
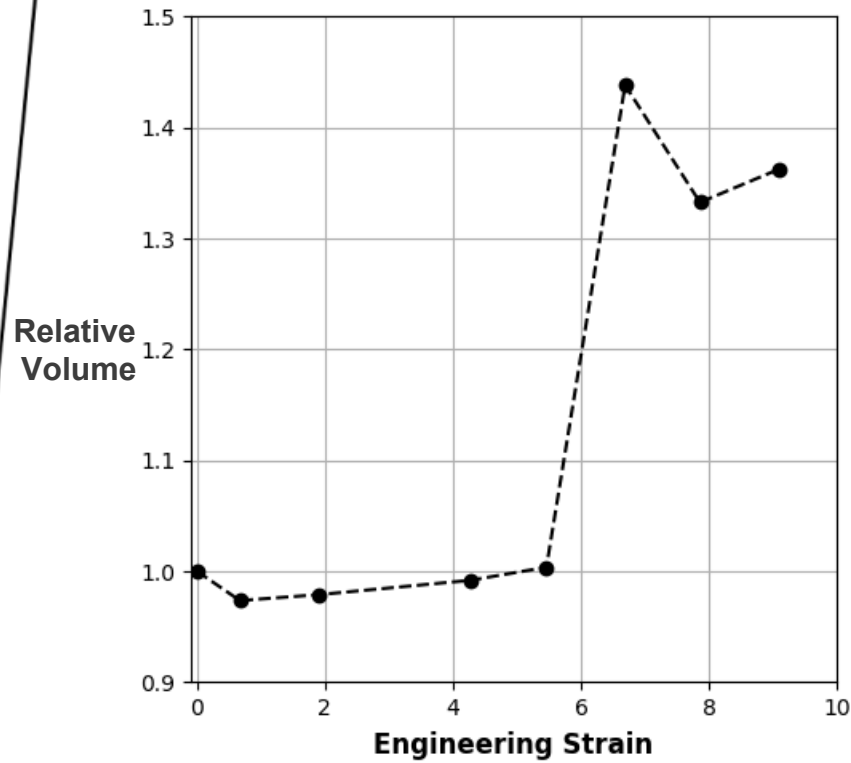
- Most large pores grow in volume between 2-10%
- Only two pores found to shrink
- Some pores appear to get much larger, due to pore merging



Can analyze pore growth by tracking the largest pores in the volume

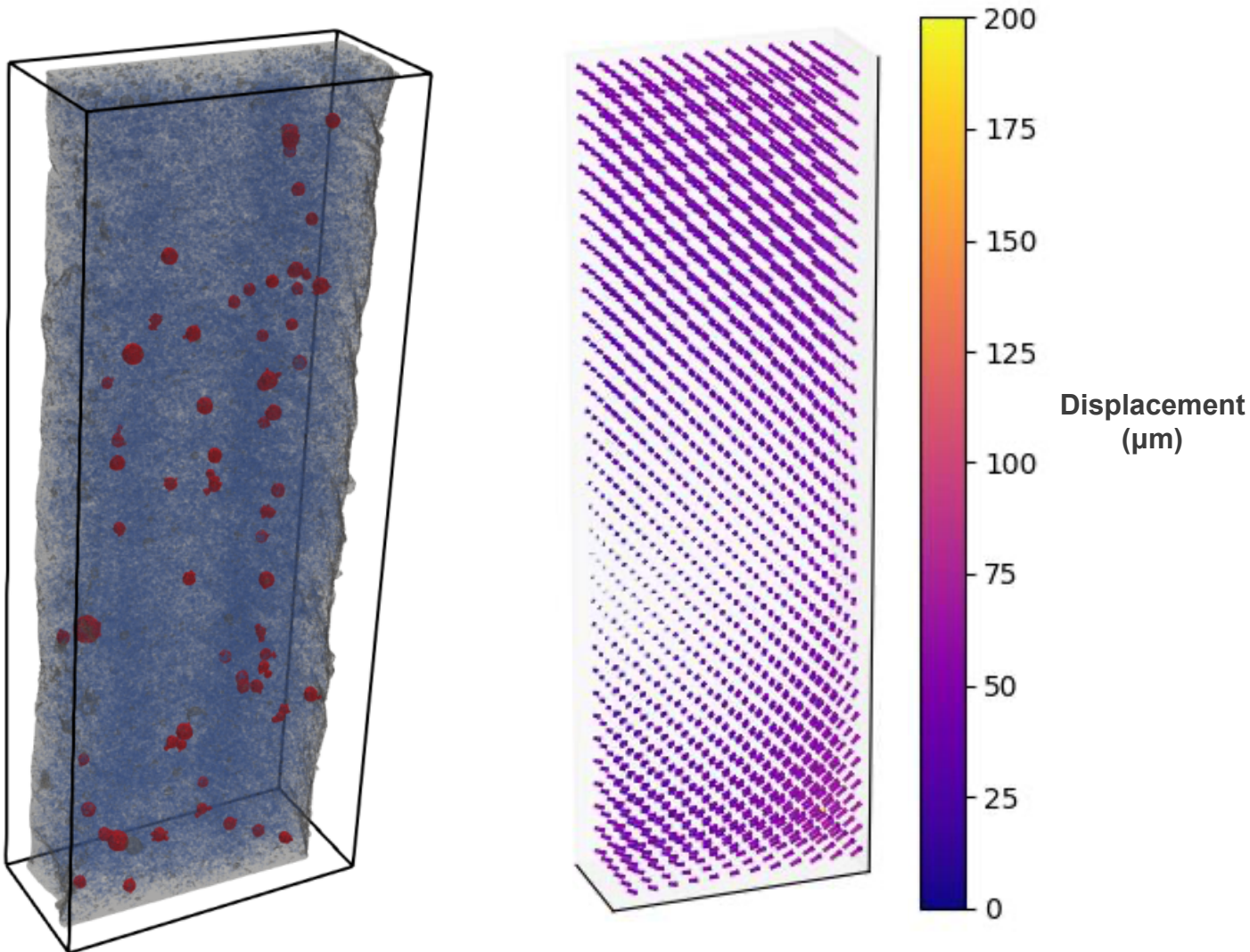


Pore Merging





Particle tracking can be extended to generate displacement fields for the entire volume



- Uses thin plate spline algorithm with tracked particles as control points
- Plan to convert this to local strain measurements to compare to FEA modelling



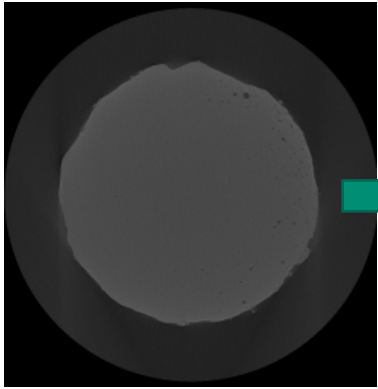
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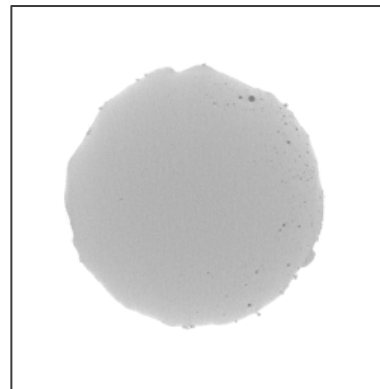
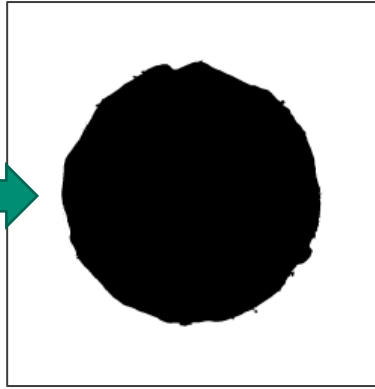
Modeling Workflow

CT Processing

Import Image



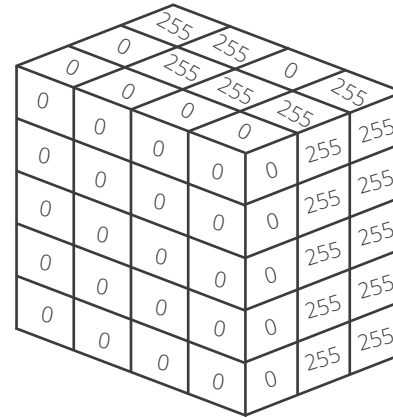
Threshold



"High Res" Tiff Stack

Meshing

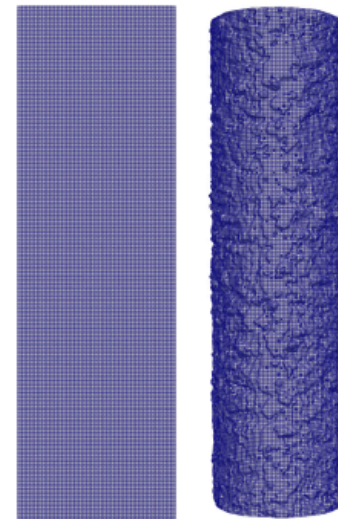
Numpy Array



SPN File

0
0
0
1
1

Cubit/Sculpt
Mesh



Simulation

Calibrate plasticity
parameters



With plasticity
parameters fixed,
calibrate damage
parameters porous
mesh



Predict failure in
porous samples using
varying resolution



Model Setup

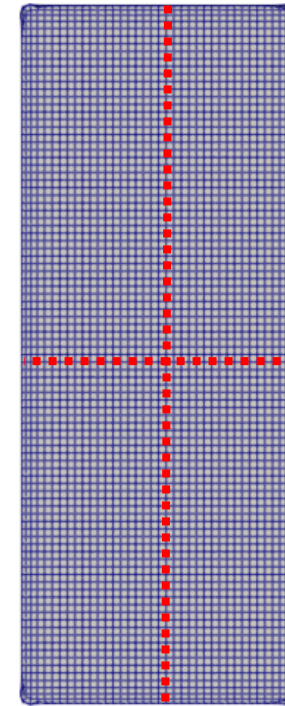
- Implicit tension models run in Sierra FEA code
- “Pads” added on top and bottom of part to provide force buffer for boundary conditions. *Unnecessary if portion of grips are included in scan
- Cubit/Sculpt creates mesh by converting cartesian grid voxels to hexahedral elements and smoothing edges
- Constitutive response captured with plasticity and local damage models

Voce¹ Hardening

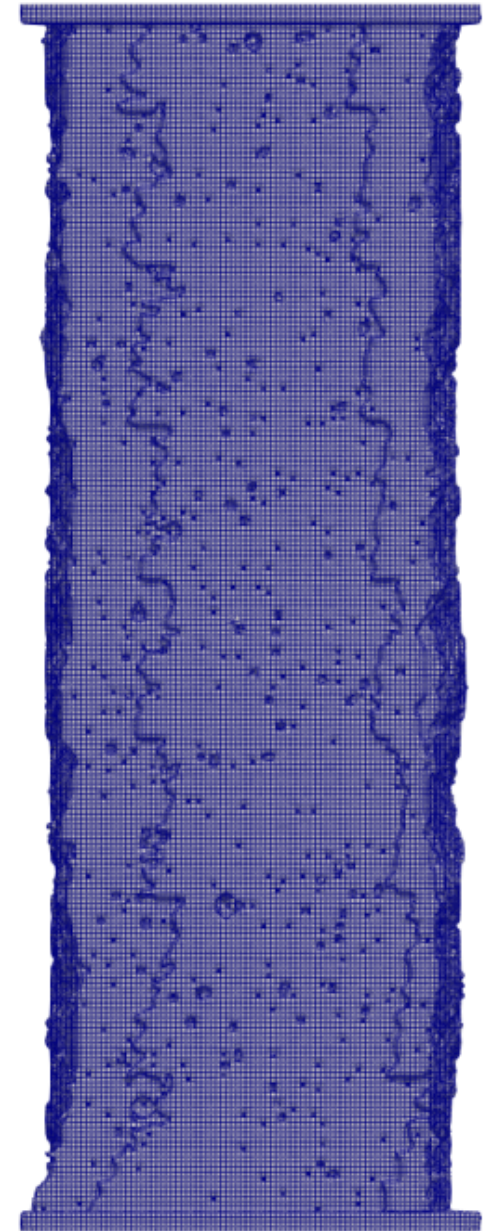
$$\bar{\sigma} = \sigma_y + A(1 - \exp(-n\bar{\epsilon}^p))$$

Cocks-Ashby² Void Growth

$$\dot{\phi} = \sqrt{\frac{2}{3}} \dot{\epsilon}_p \frac{1 - (1 - \phi)^{m+1}}{(1 - \phi)^m} \sinh \left[\frac{2(2m - 1)}{2m + 1} \frac{\langle p \rangle}{\sigma_e} \right]$$



Nodal lateral constraints applied on red lines for Poisson contraction

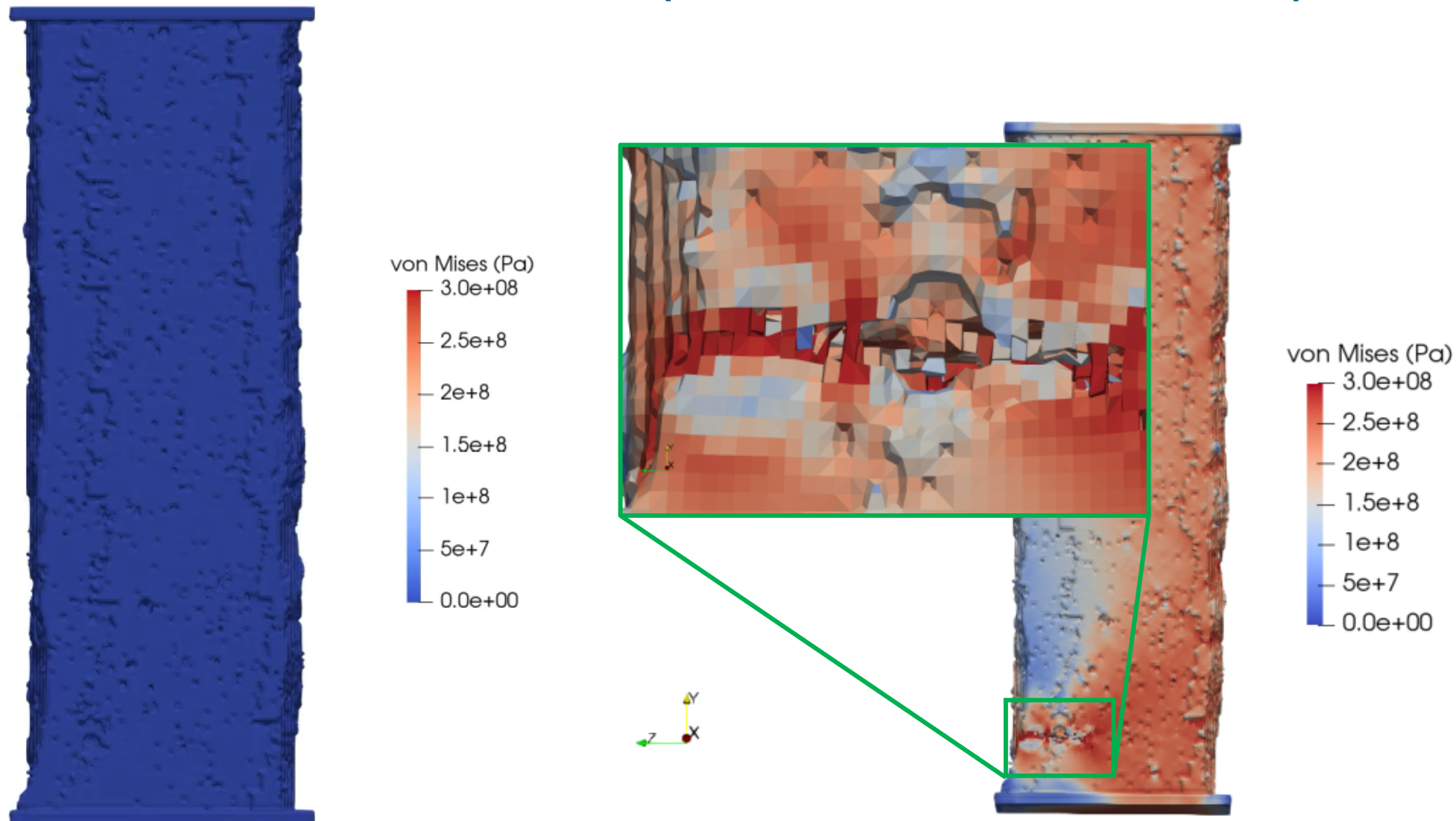


¹Voce, E., J. Inst. Metals 1948

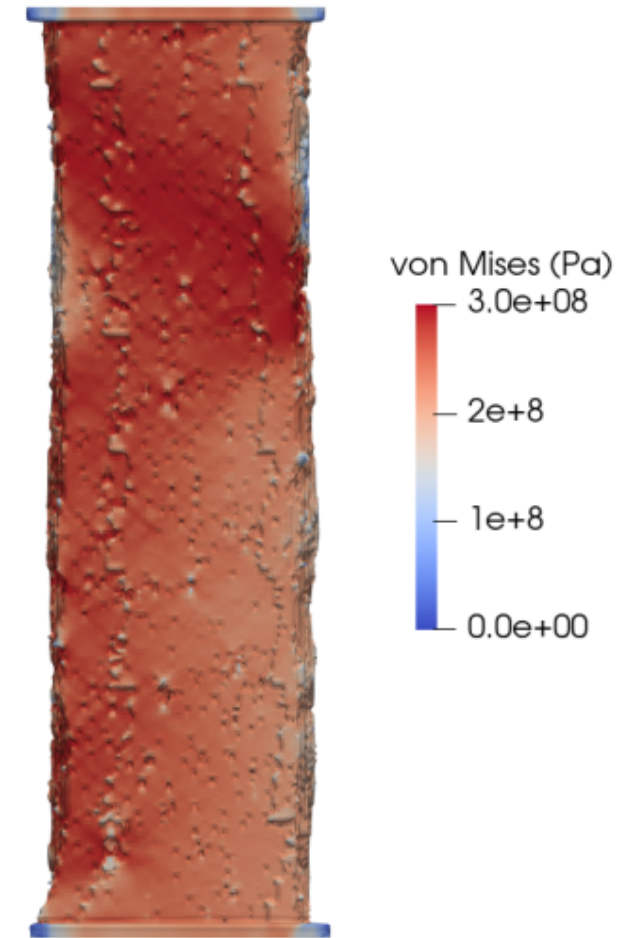
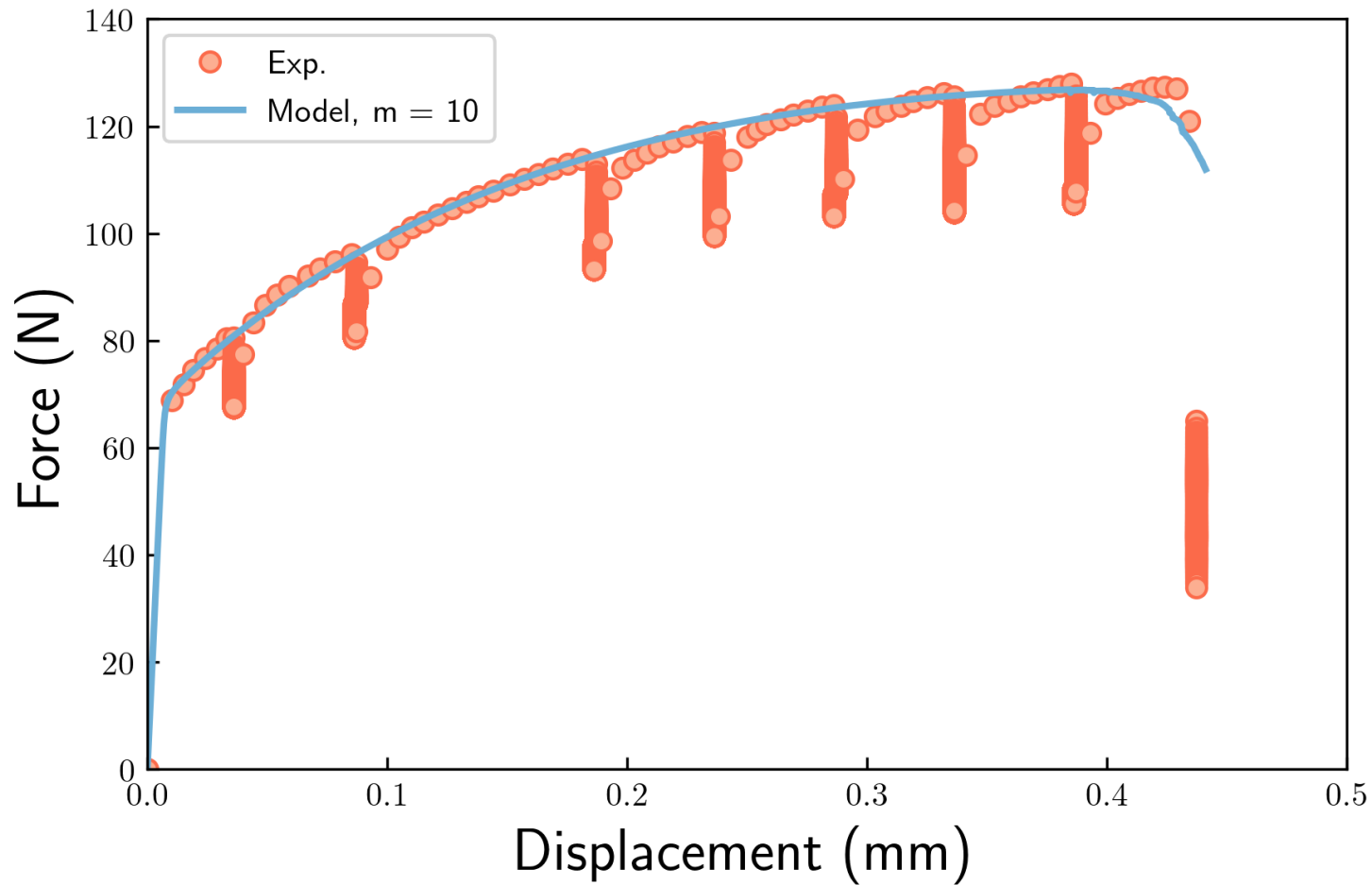
²Cocks, A.C.F. and Ashby, M.F., Metal Science 1980



Failure location can be accurately predicted with sufficient mesh resolution and calibration (15 micron mesh size, $m=20$)

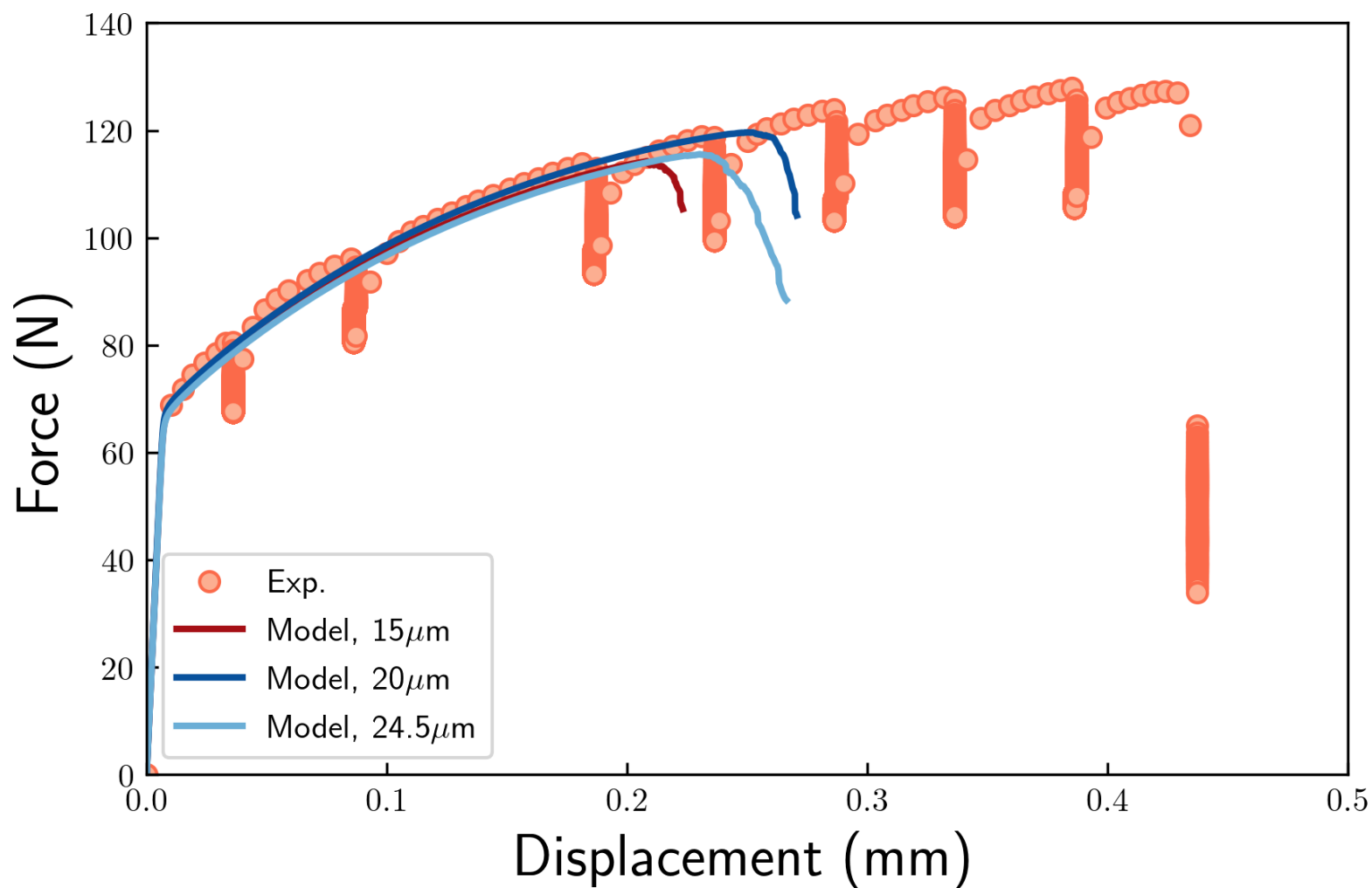


Calibration to force-displacement data alone can be insufficient



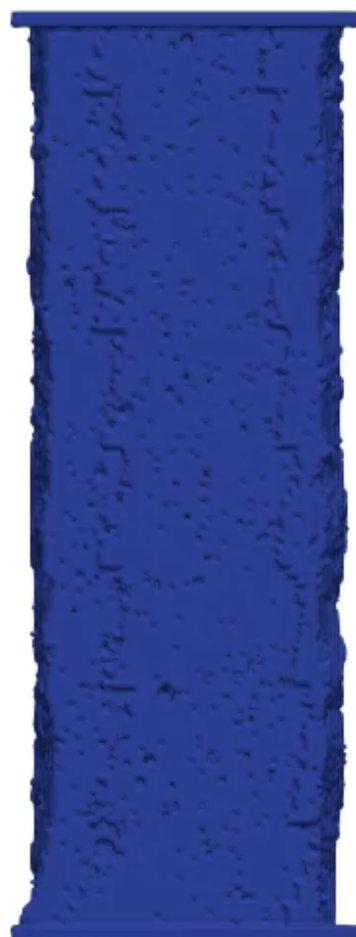


Force-displacement response- fixed damage parameters, different voxel sizes

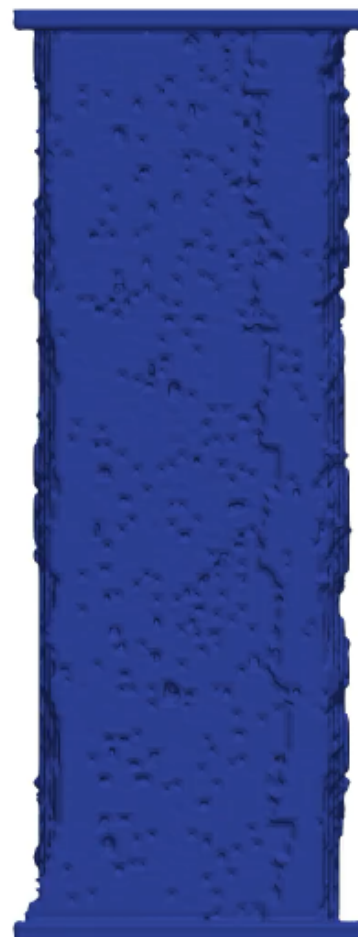




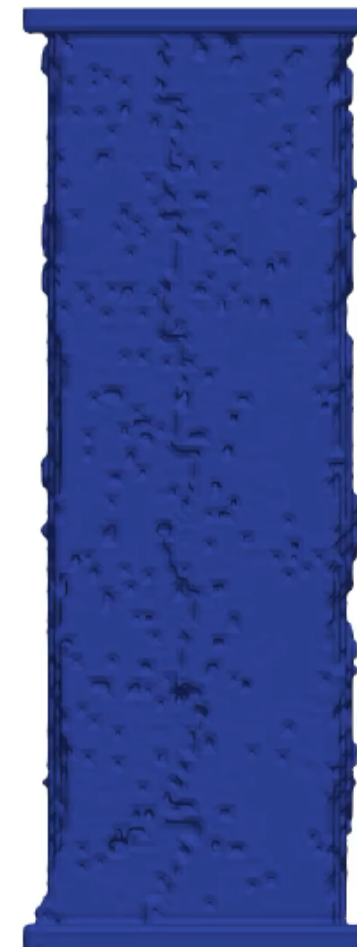
Mesh size results



767k elements
155 cpus
3.7 hr wall time



340k elements
70 cpus
4.2 hr wall time

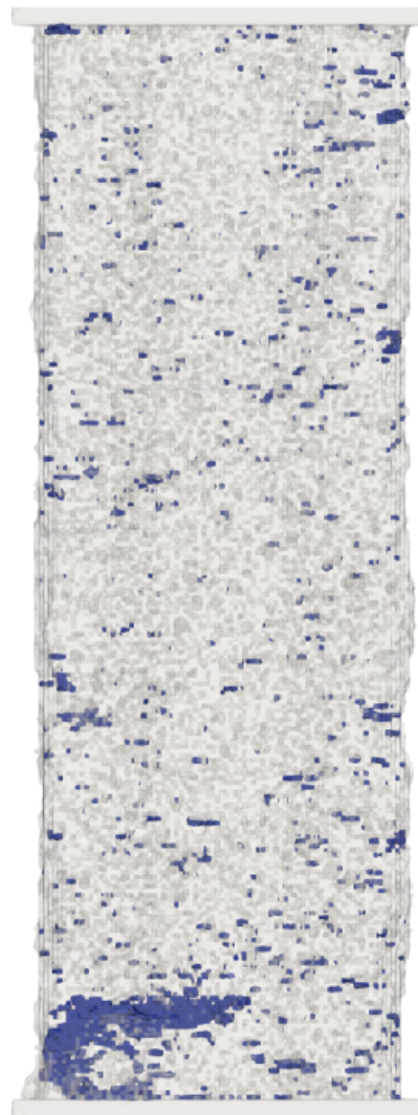
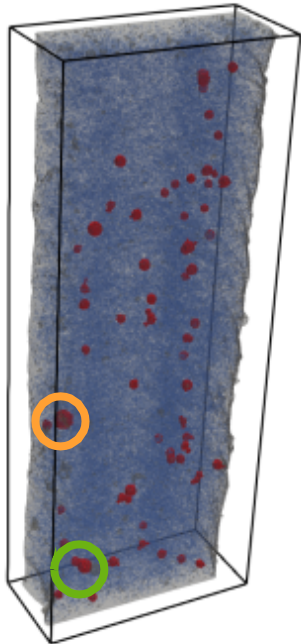


189k elements
40 cpus
3.7 hr wall time

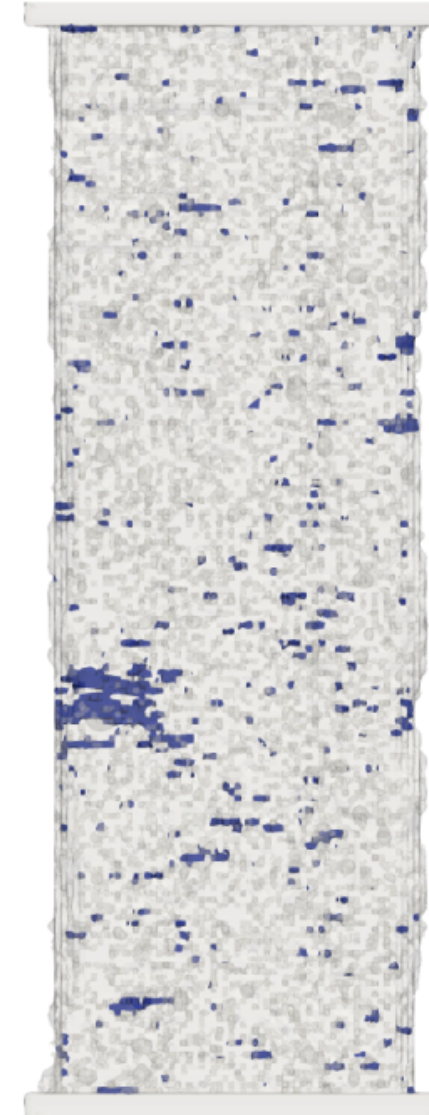


Fracture locations – fixed damage parameters, different voxel sizes

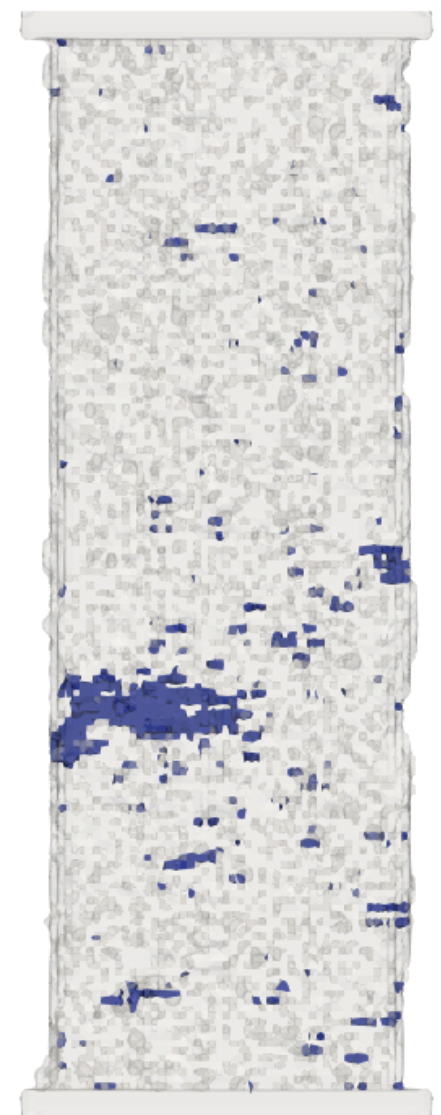
- Deleted elements shown in blue
- Fracture location changes lower resolution meshes
- Local damage parameters are inherently mesh-size dependent



15μm voxel size

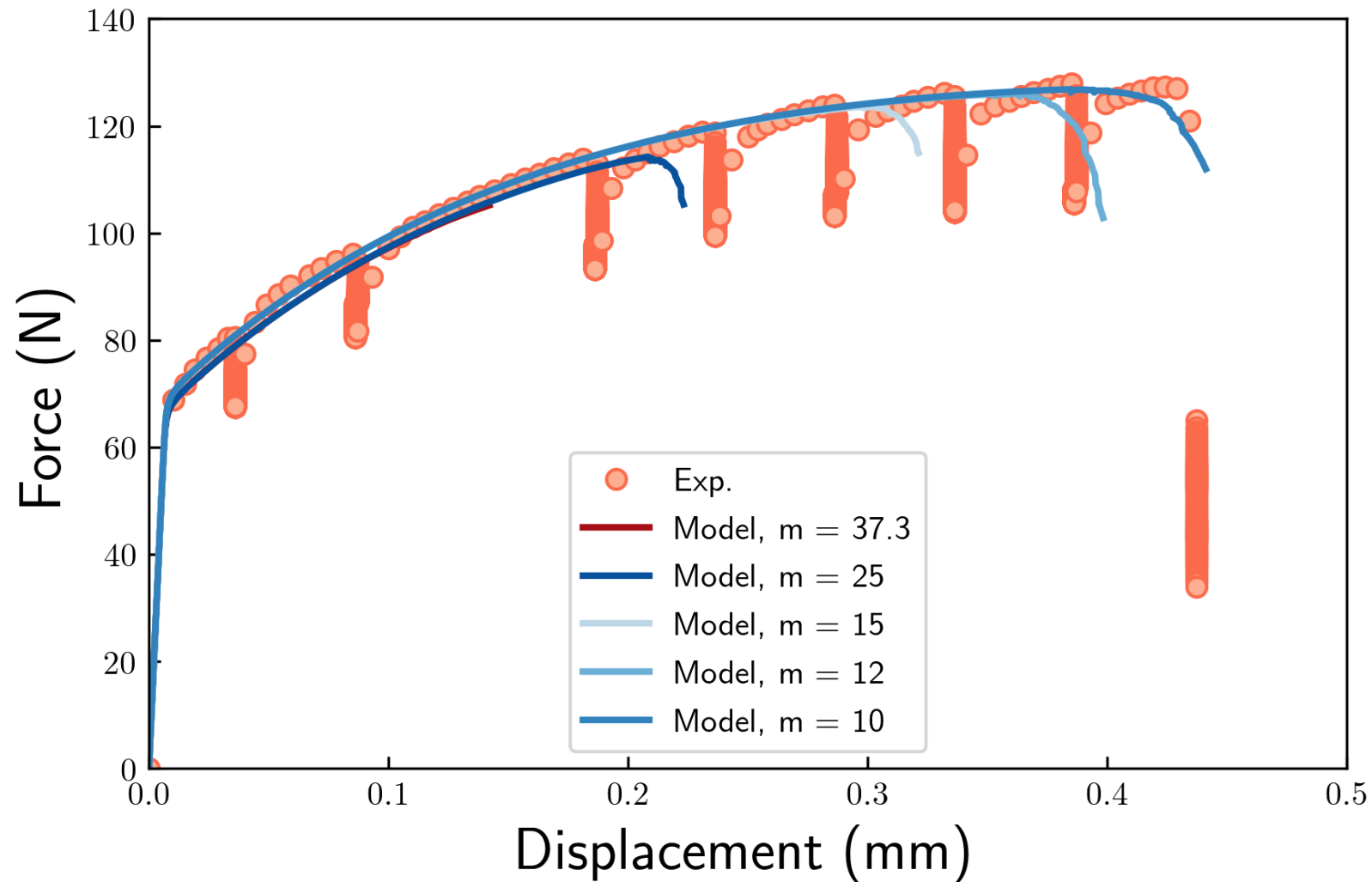


20μm voxel size



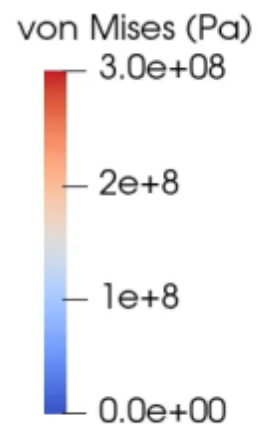
24.5μm voxel size

Force-displacement response- fixed 15 μ m voxel size, different damage parameter m

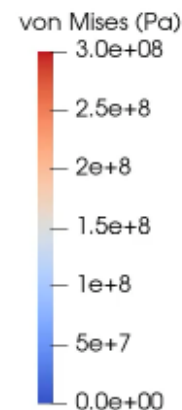
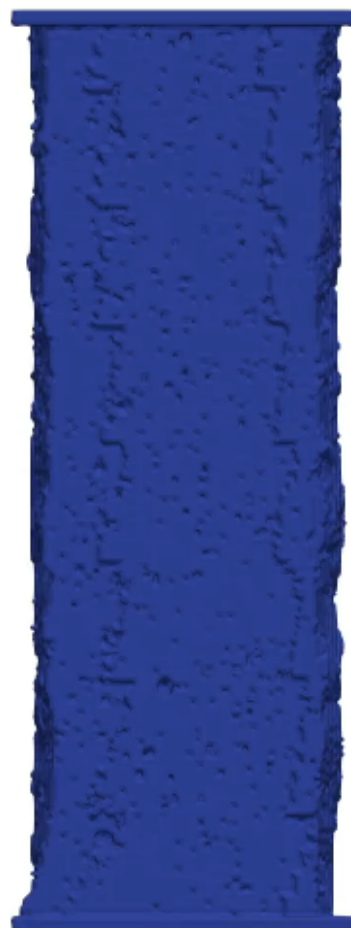




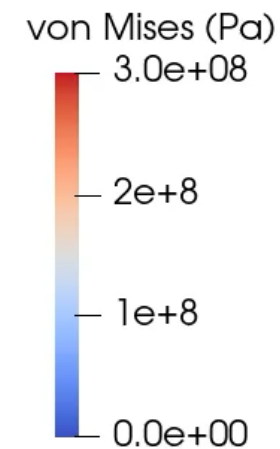
Von Mises response– fixed 15 μm voxel size, different damage parameter m



$m=20$



$m=15$

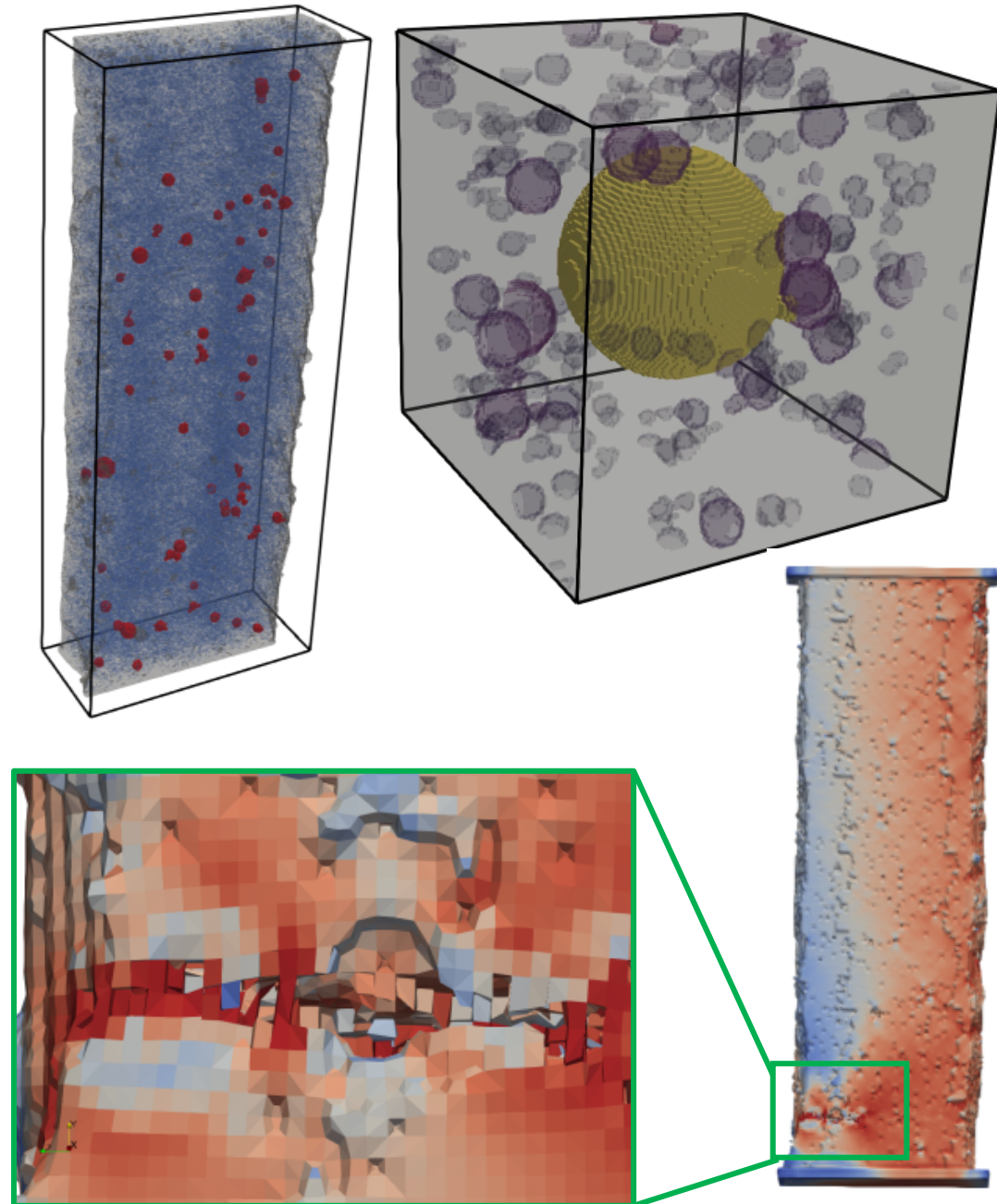


$m=10$



Conclusions

- In situ 3D characterization enables comprehensive analysis of pore statistics and porosity evolution under loading
- Microstructure response was dominated by pore growth, with largest pores growing ~5% in volume under similar % strains
- Failure location in AM parts can be predicted via FE modeling
- Calibration to global metrics (force-displacement) may be insufficient to predict failure sites
- Model parameters and predictive capabilities are sensitive to mesh size and computational limitations
- 3D characterization without grips in tensile experiments poses numerous challenges to FE modelling





Backup