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

Andrew Polonsky, Thomas Ivanoff, Nathan Heckman,  
and Kyle Johnson

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SAND2022-2545 C

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# Outline

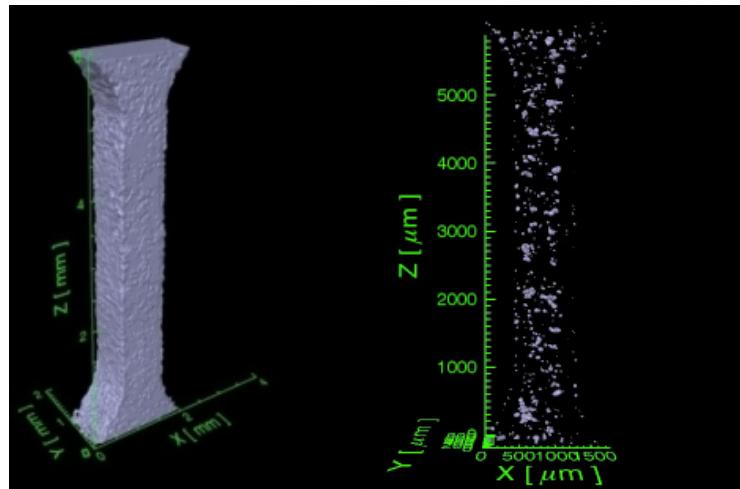
- Motivation
- 3D Characterization
  - Statistical analysis of porosity
  - Particle tracking
- Predictive Modelling
  - Formulation
  - Sensitivities
- Conclusion



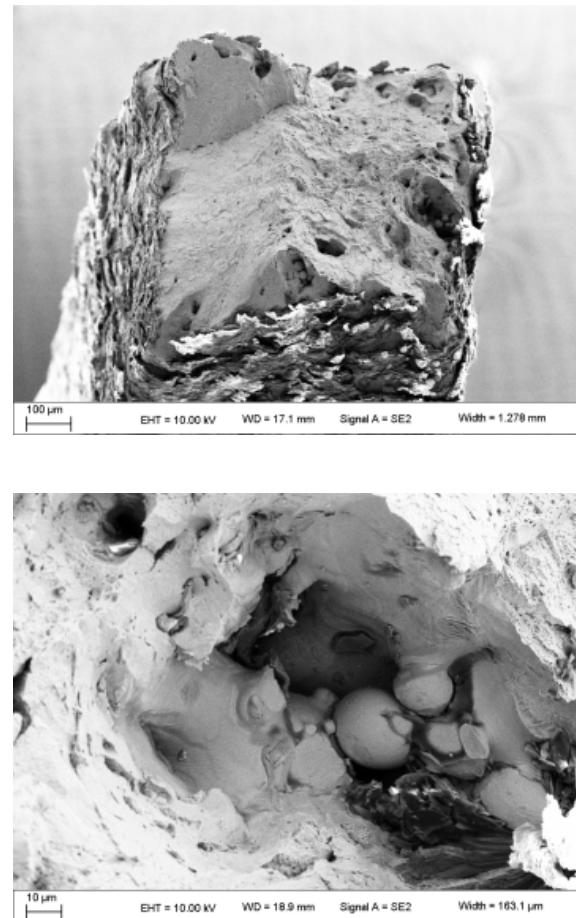
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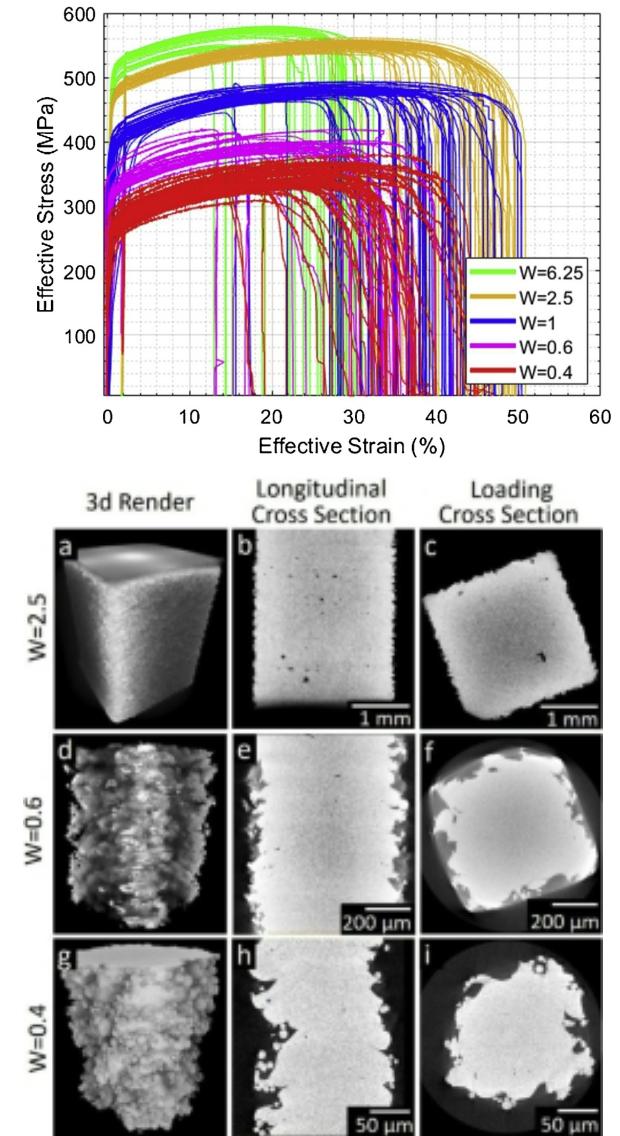
# LPBF can produce significant mechanical variability



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

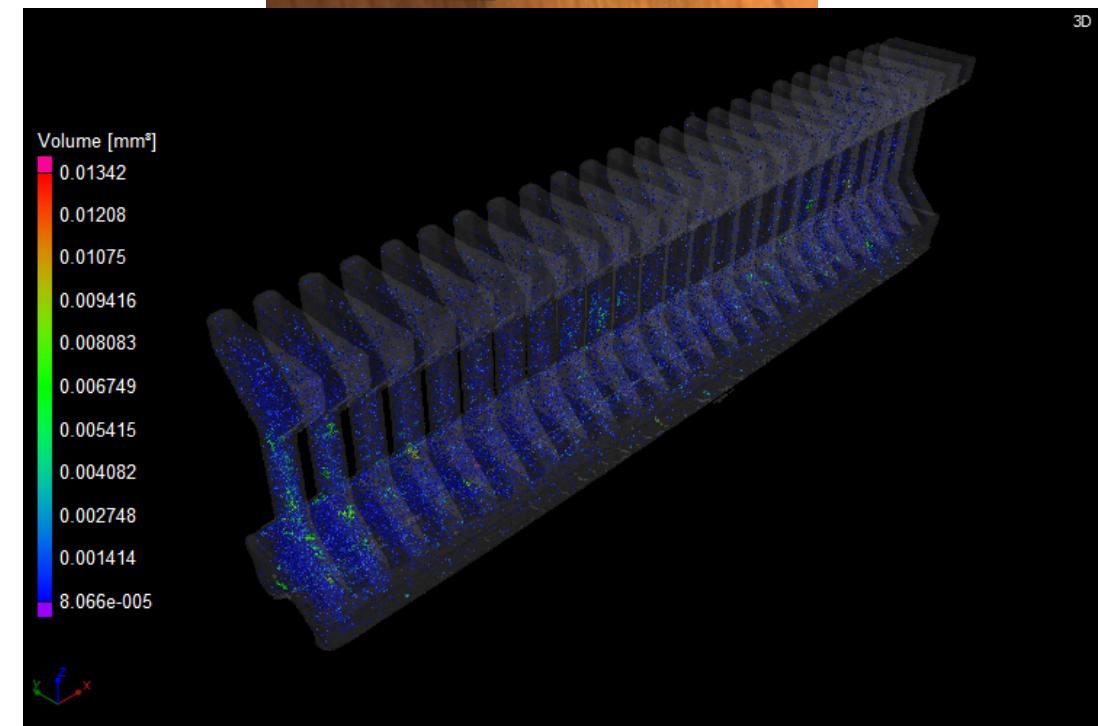
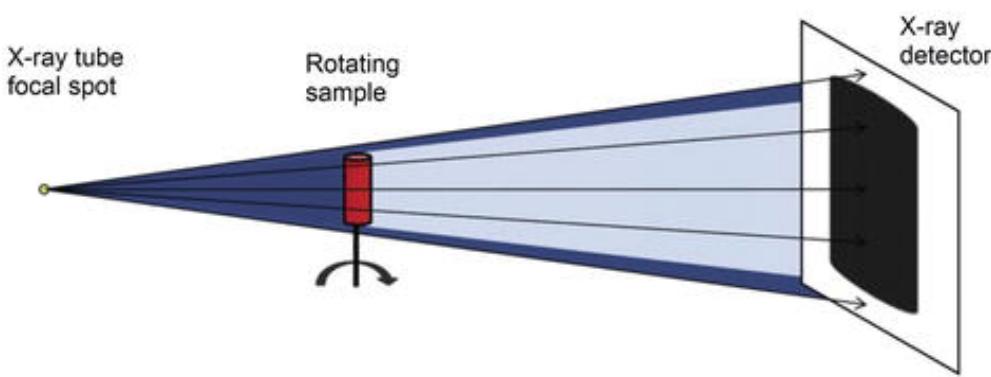


Kramer et al., *IJF* 2019



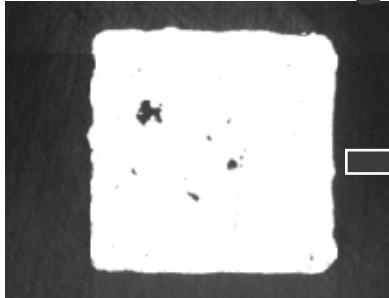
Roach, A.M. et al. *Additive Manufacturing* 2020

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



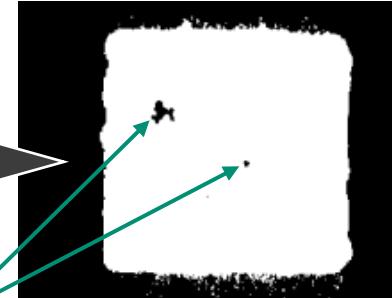
# Challenges remain in use of CT data

## Serial sectioning



**Voids**

Low threshold (80)



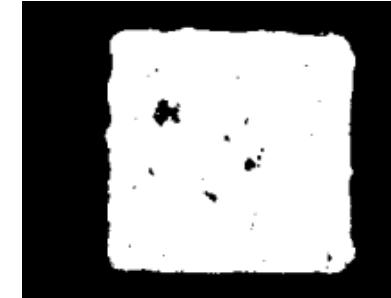
Lose image detail  
Create image artifacts

Middle threshold (155)



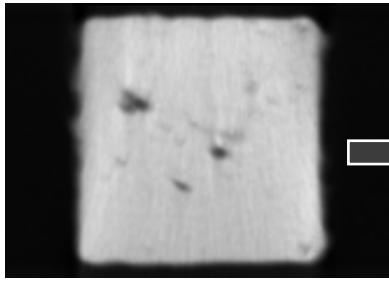
Most accurate  
representation

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)



## CT



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

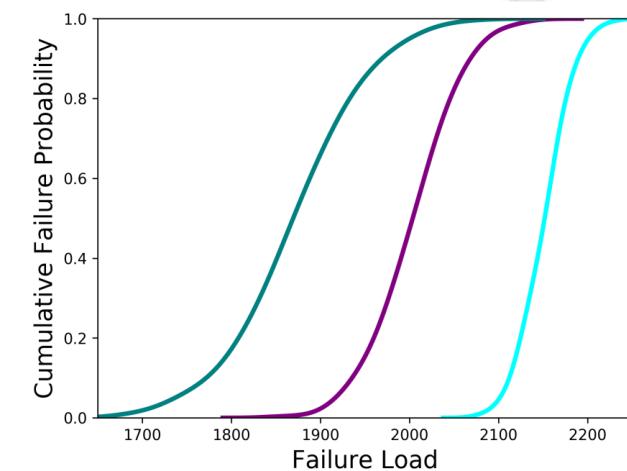
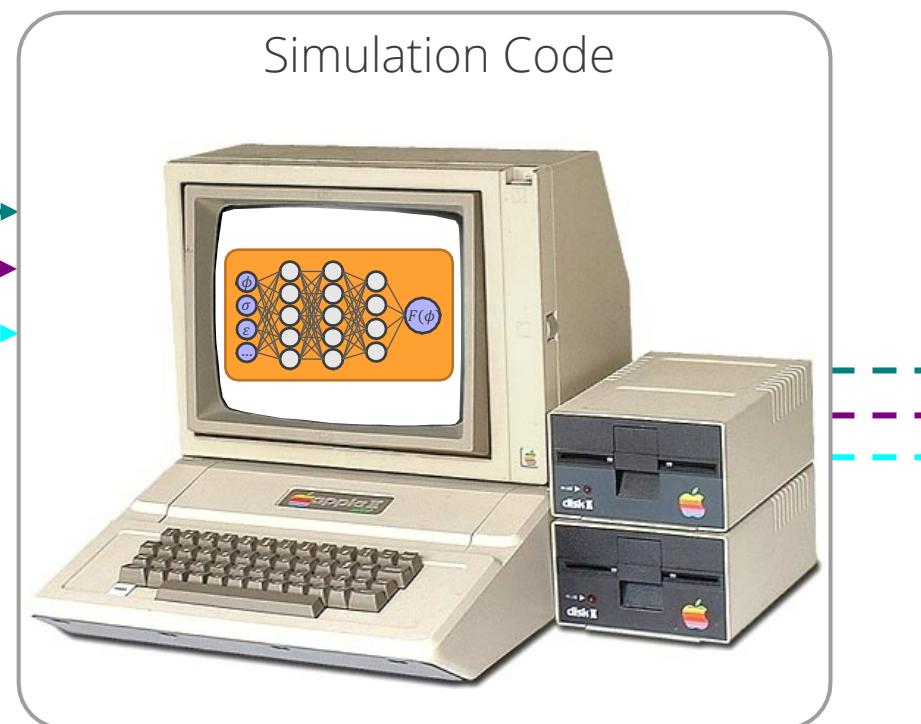
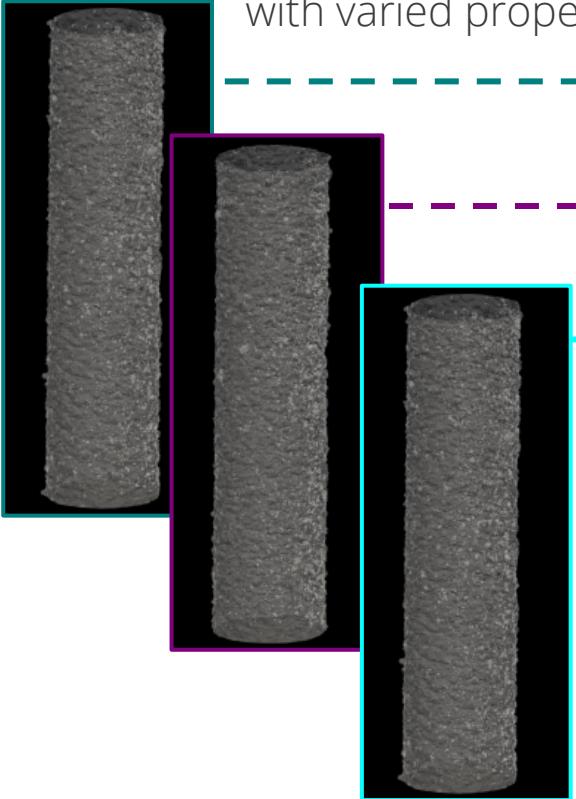
Retain object edges  
Lose all void detail

Retain object edges  
Capture some detail

Lose object edges  
Capture voids (slightly enlarged)

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

Synthetic  
Microstructures  
with varied properties



Requirements: Training data with accurate  
microstructure and mechanical behavior



# Outline

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# In situ tensile experiment with $\mu$ CT

## Zeiss Xradia 620 $\mu$ CT

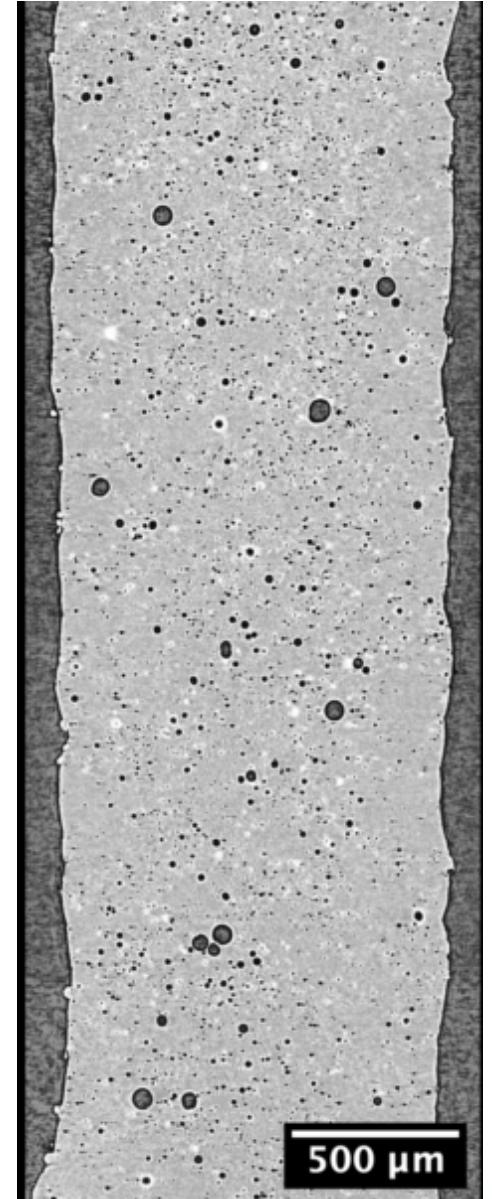
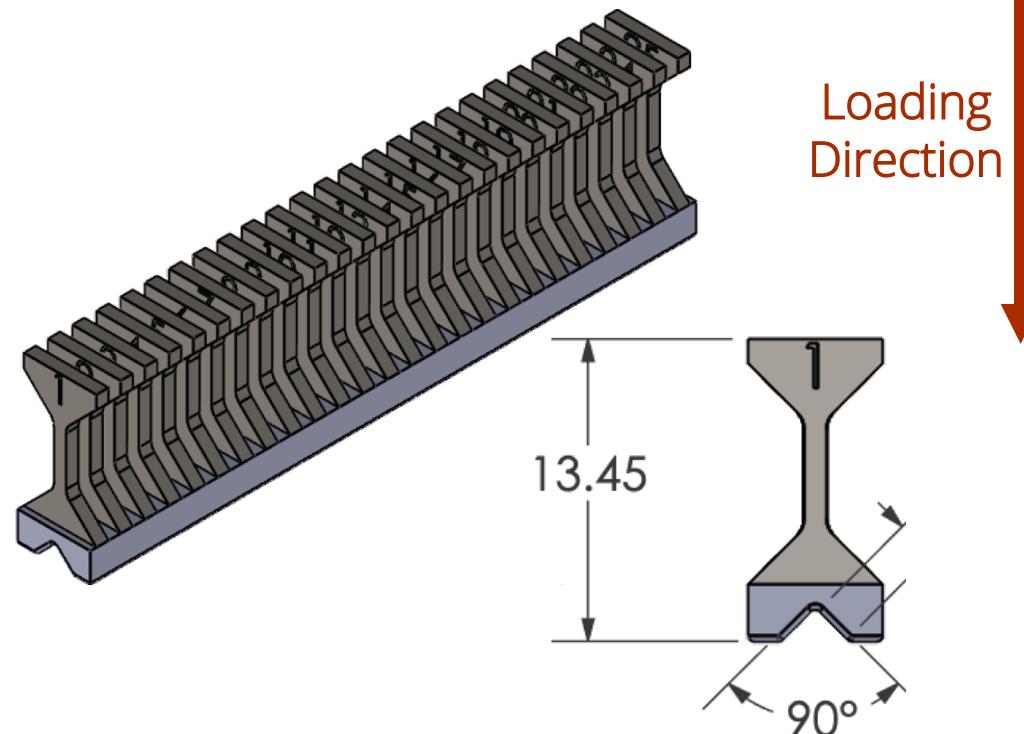
- Effective voxel size of 2.1  $\mu$ m
- Intermittent scans at fixed displacements
- ~3hr per scan



## Tensile specimen

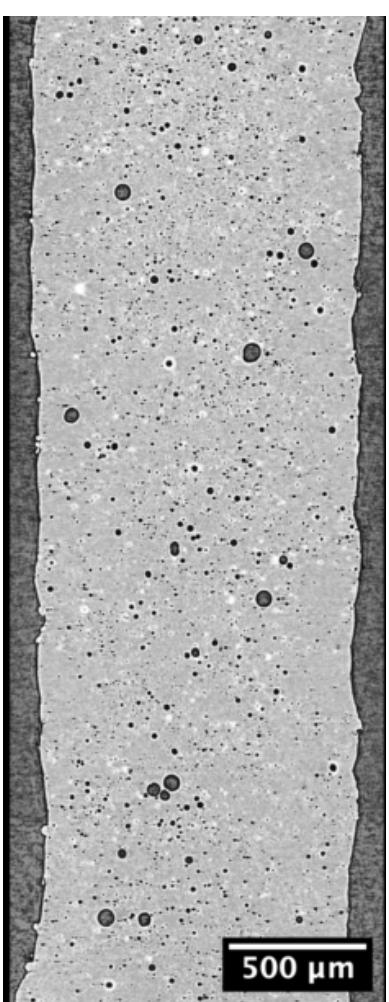
1 x 0.45 mm x 4.17 mm gauge section

- Al-10Si-Mg powder <44  $\mu$ m diameter
- Printed on EOS M400-1
- Stress-relief annealed after build (550 °C)

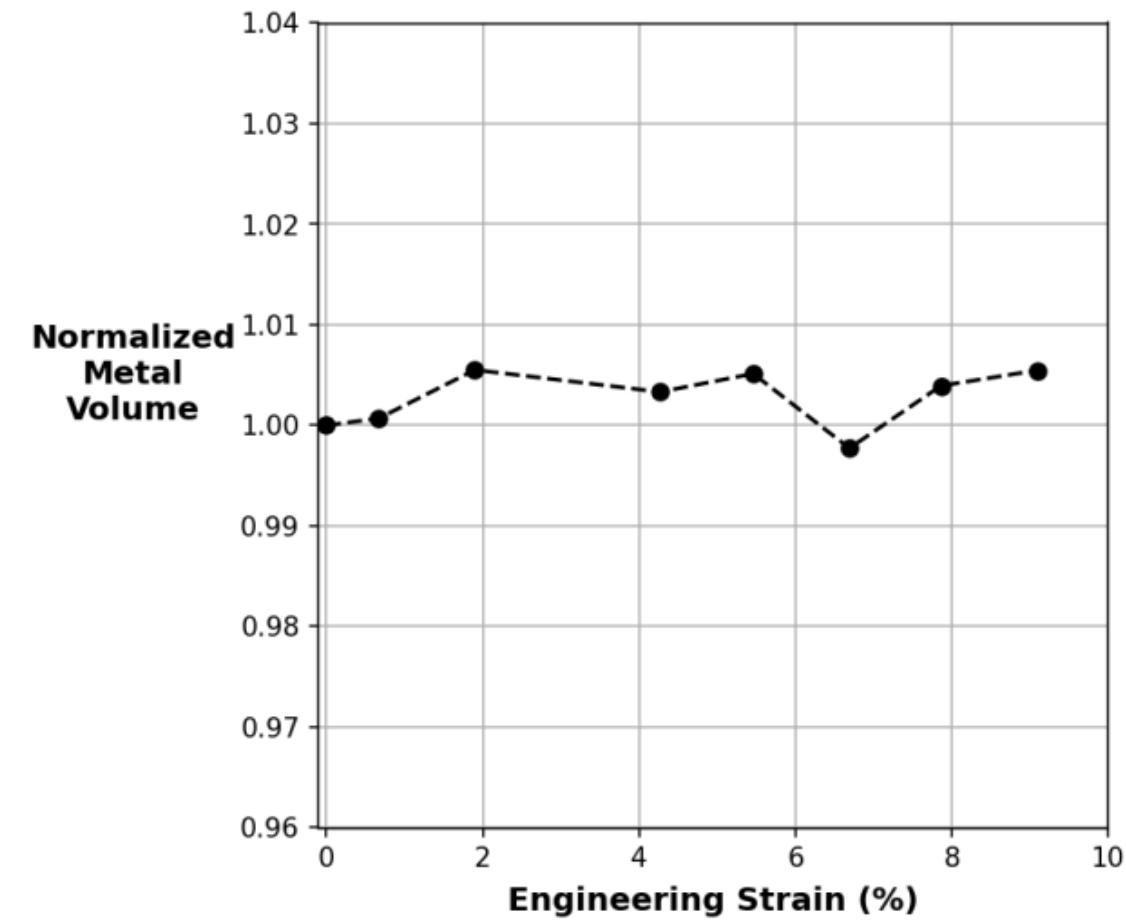
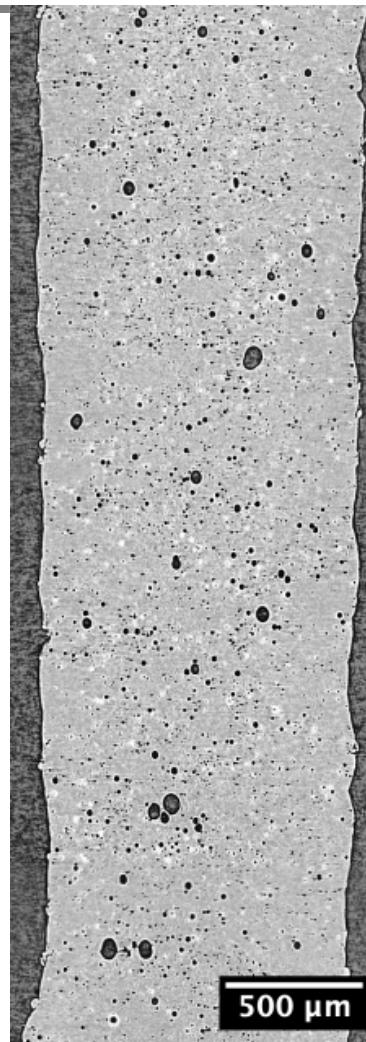


# Statistical assessment of scan requires a constant sample volume

Initial Scan

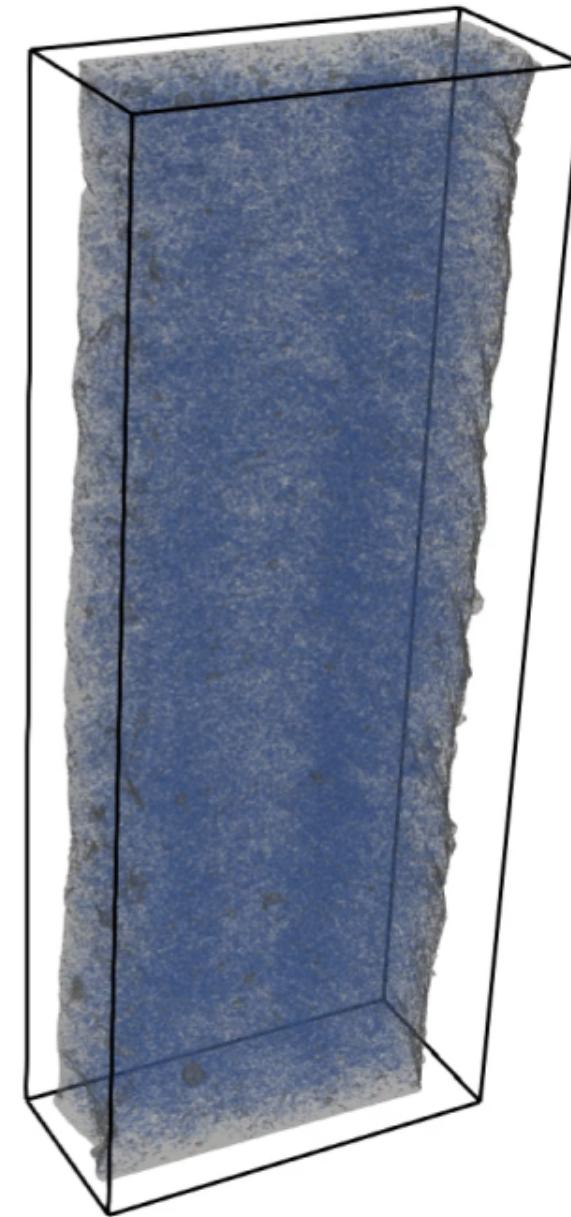
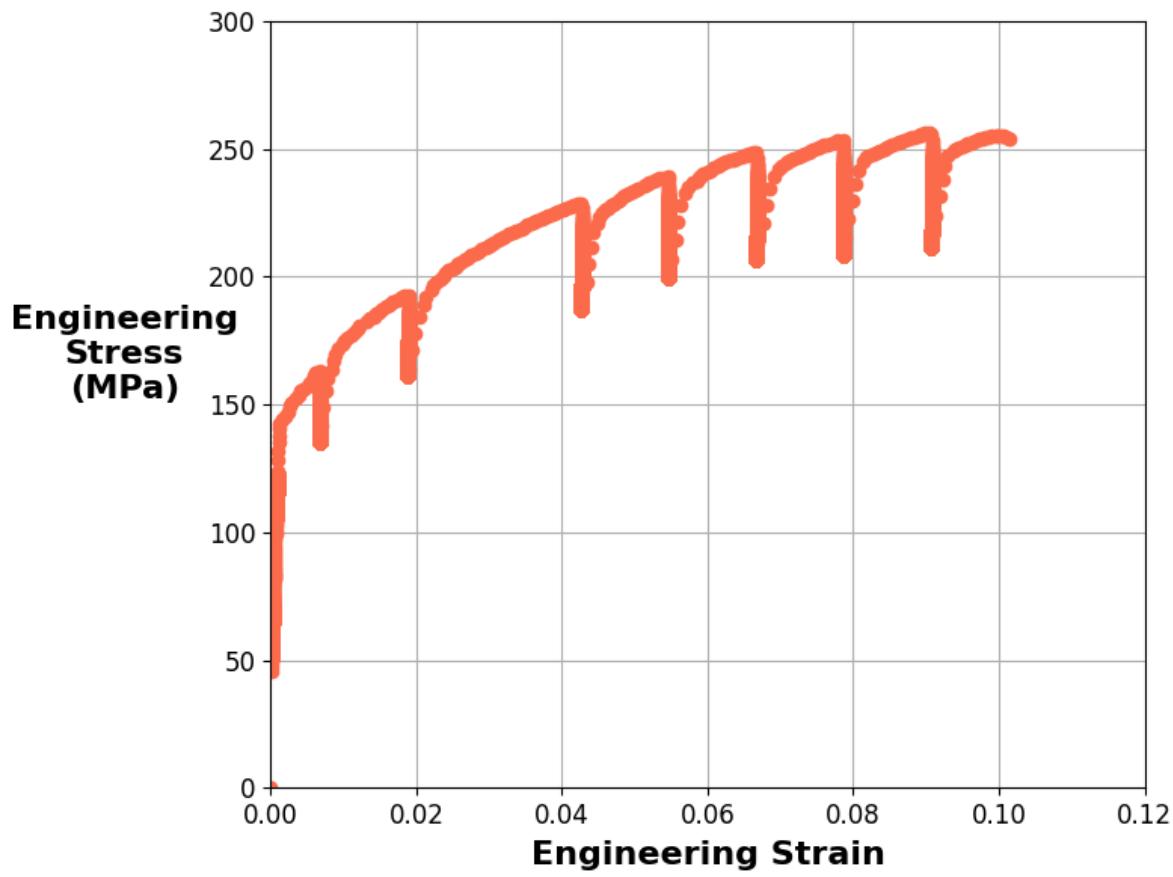


Last Intact Scan



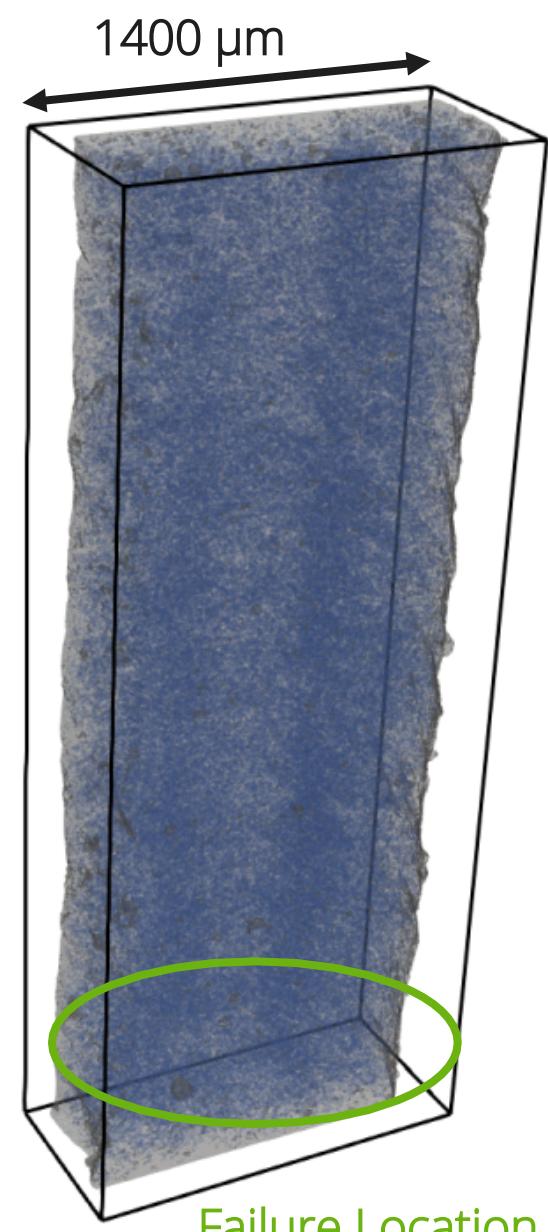
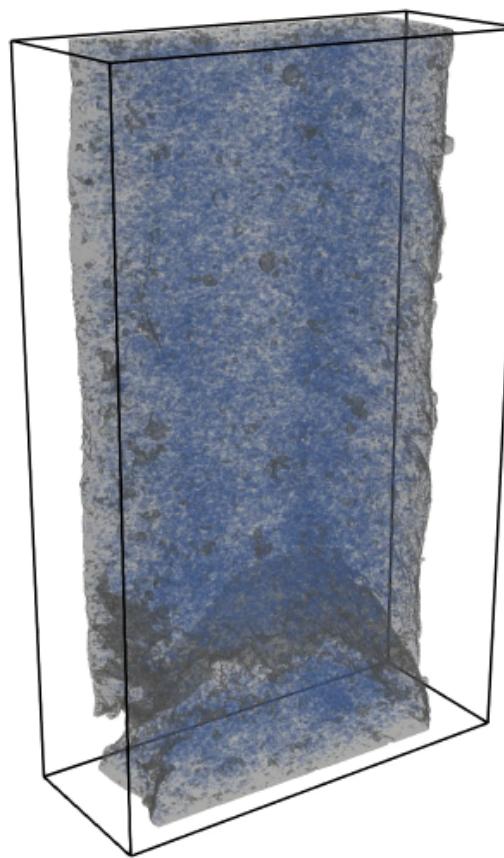
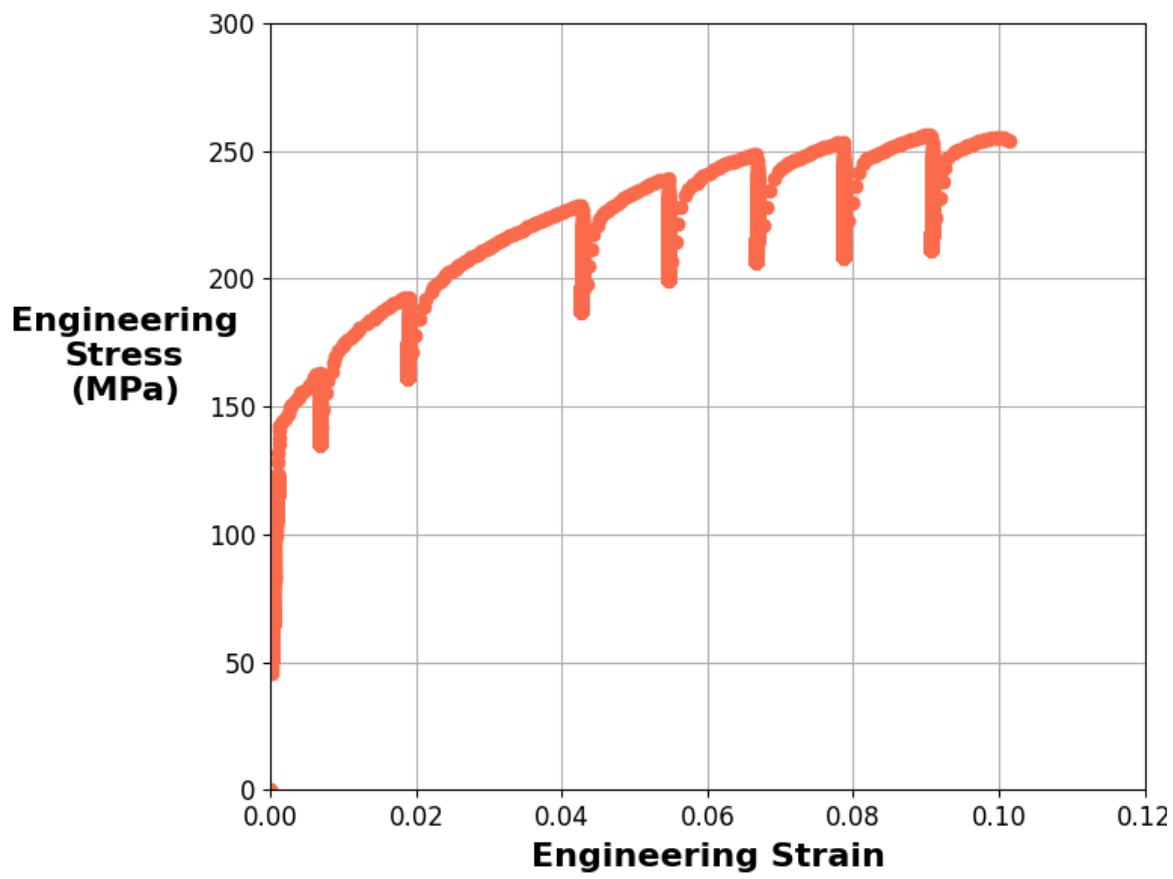
## Tensile results

Stress determined using minimum cross-sectional area from initial scan



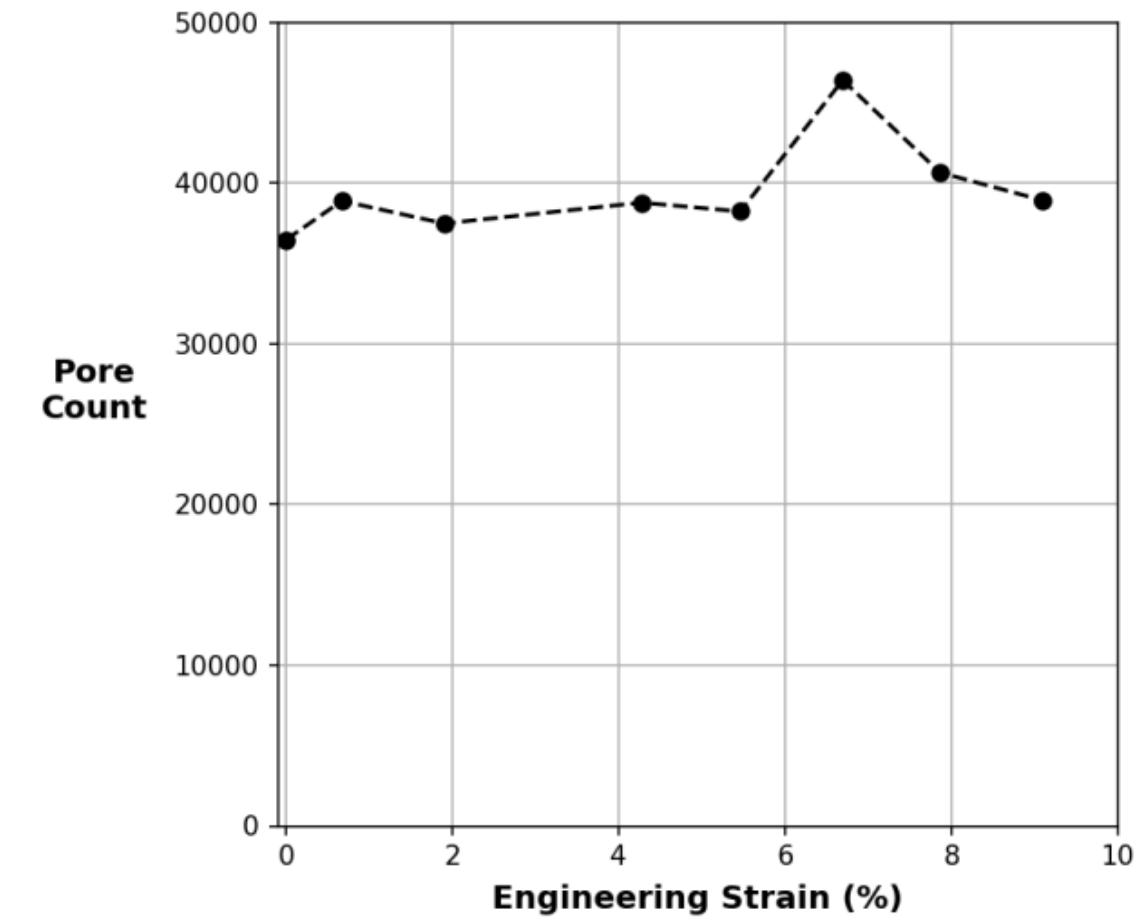
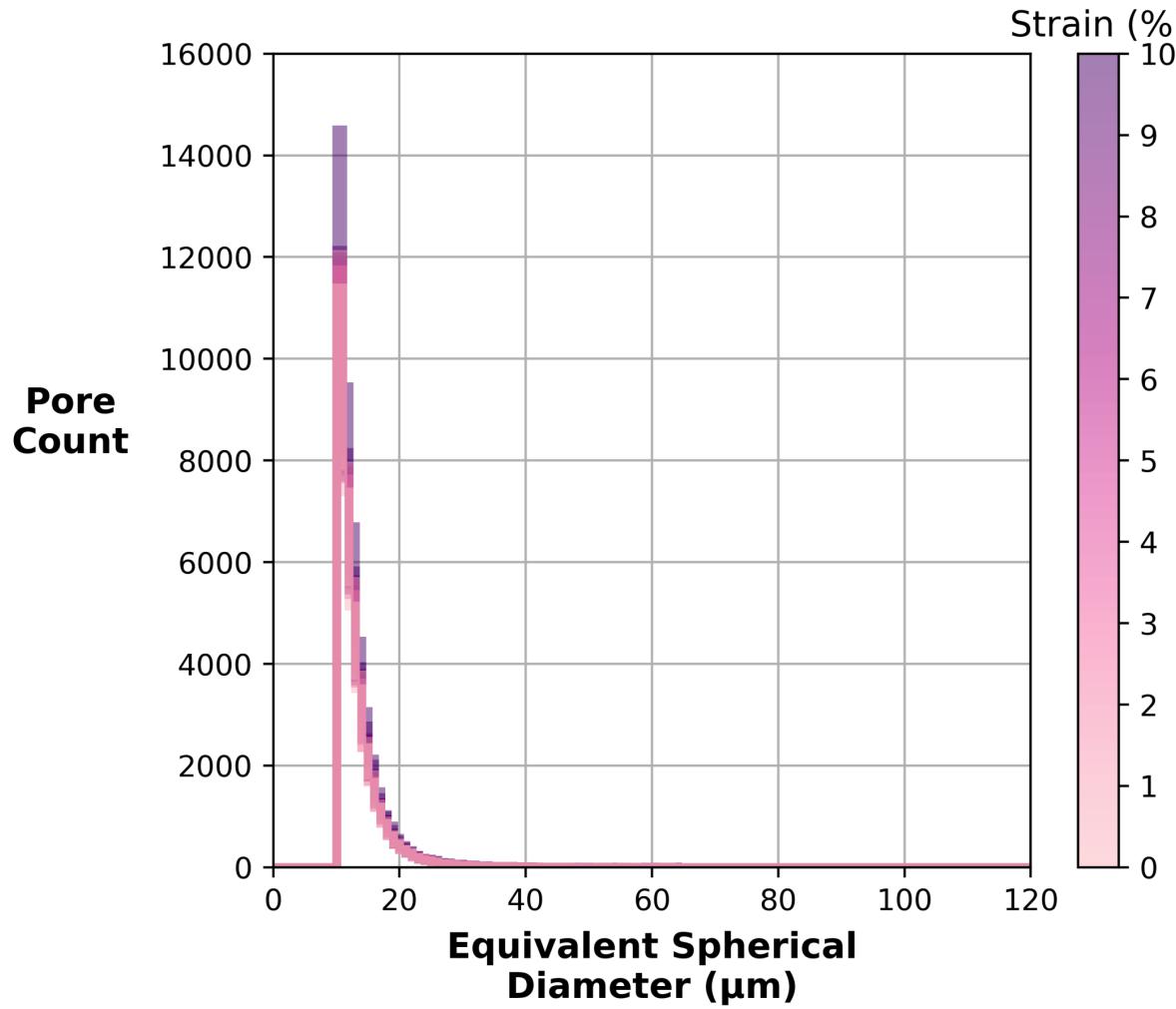
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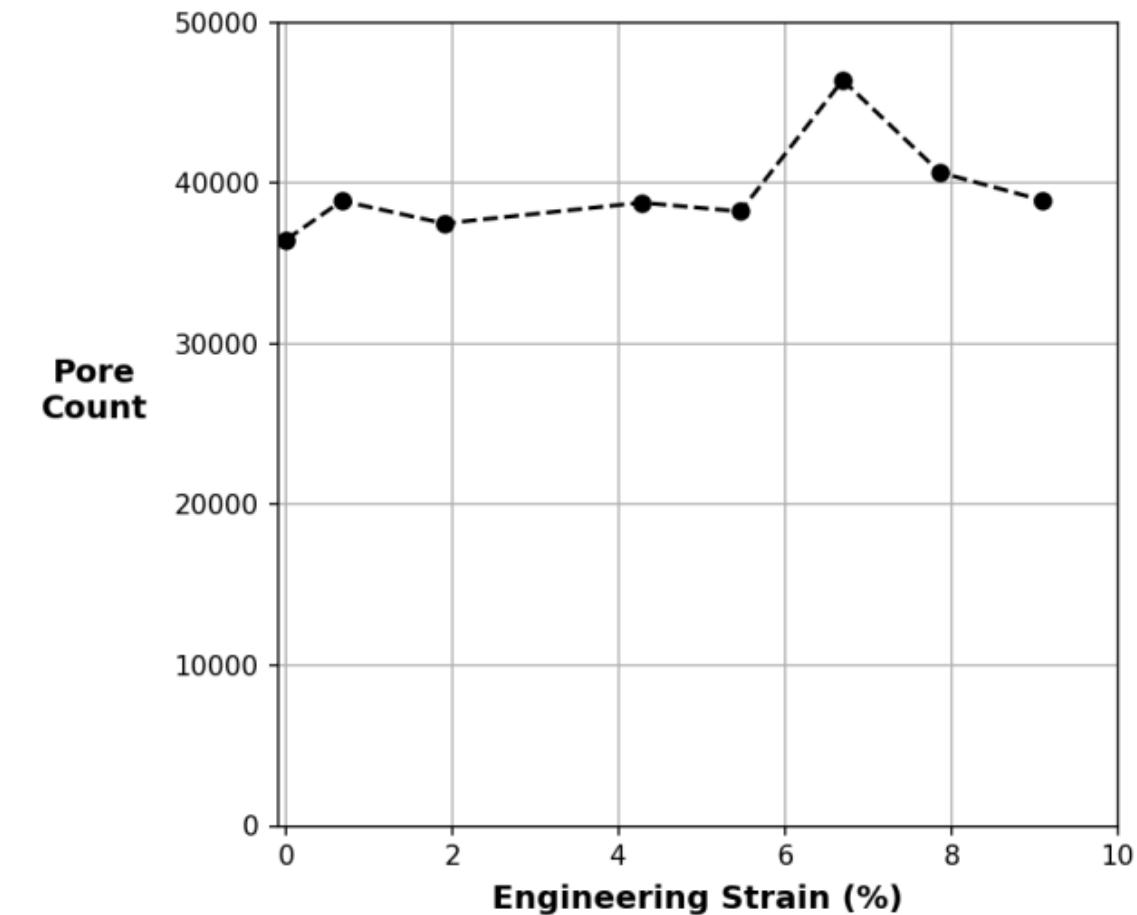
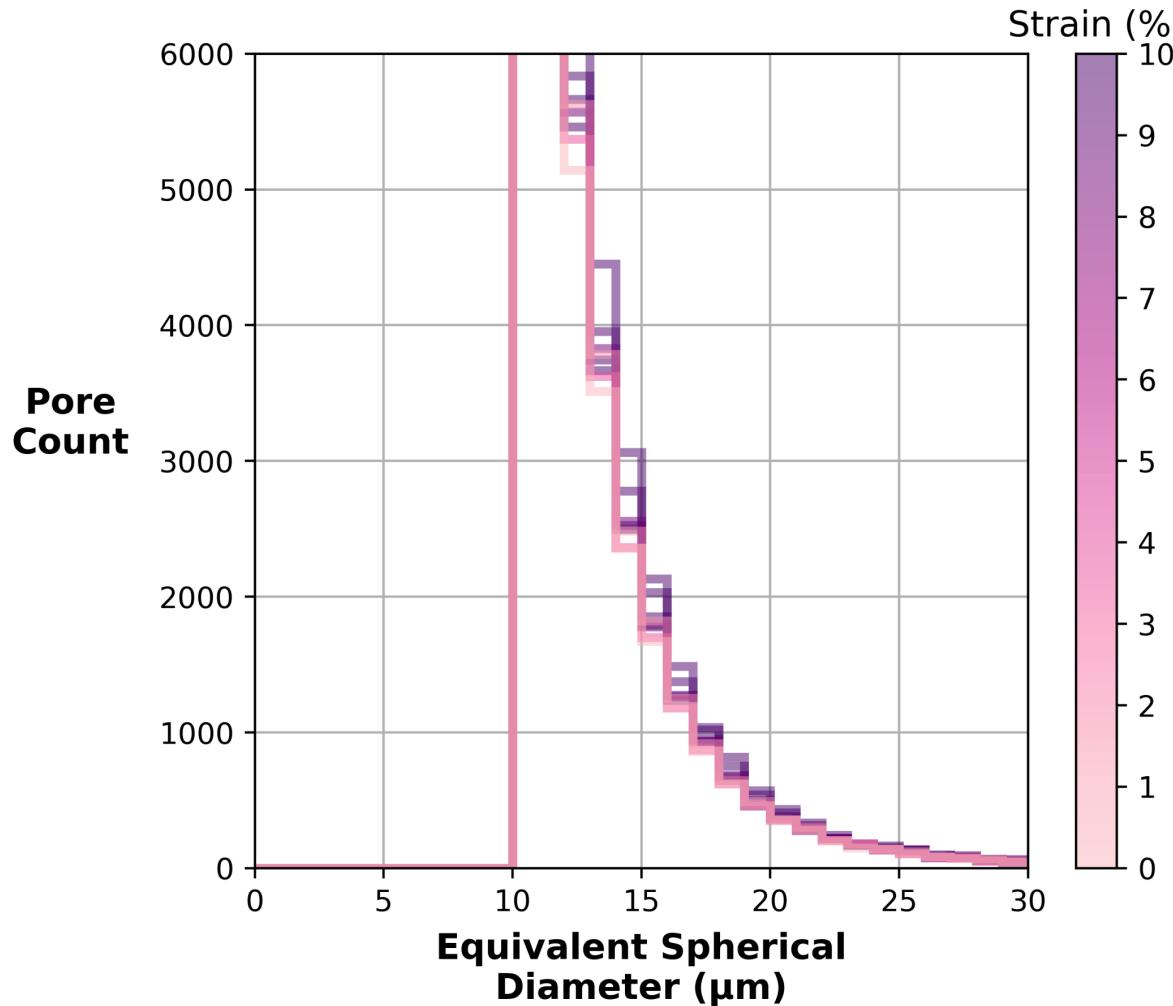


Failure Location

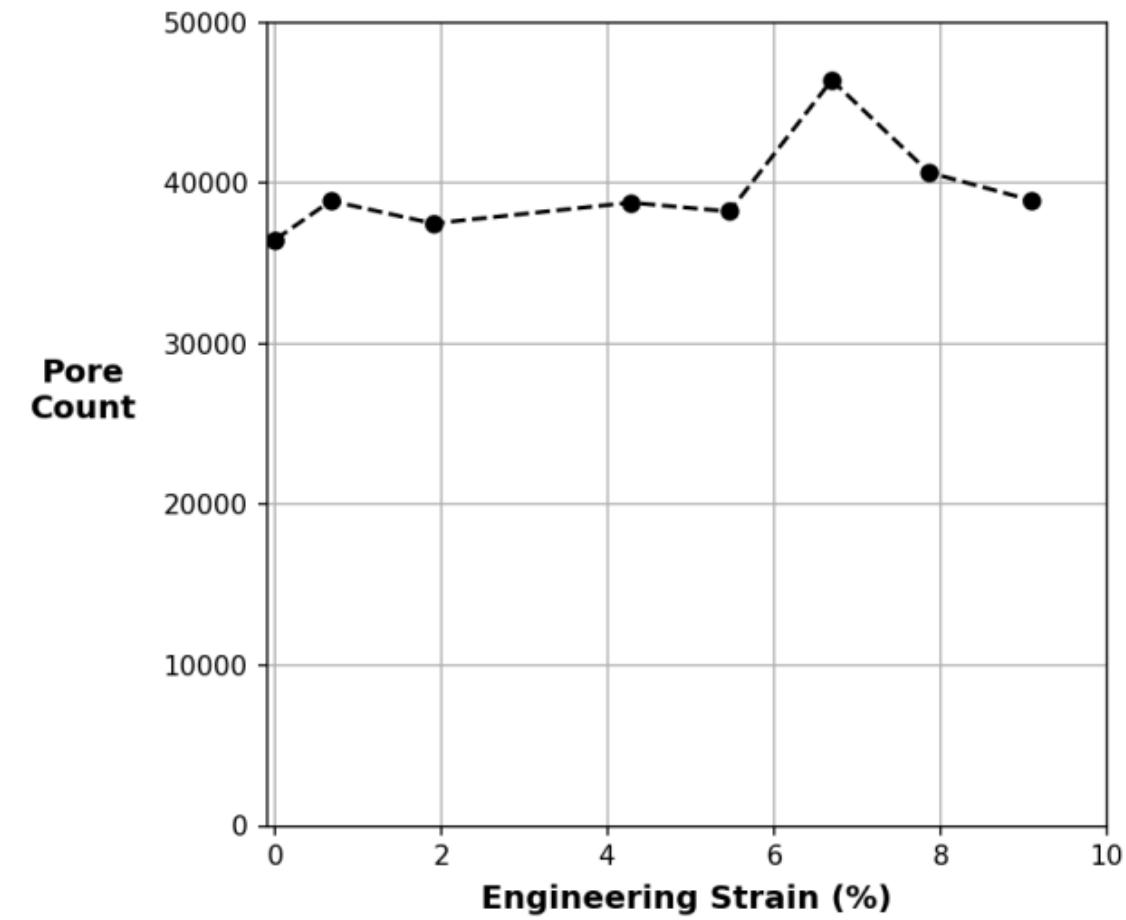
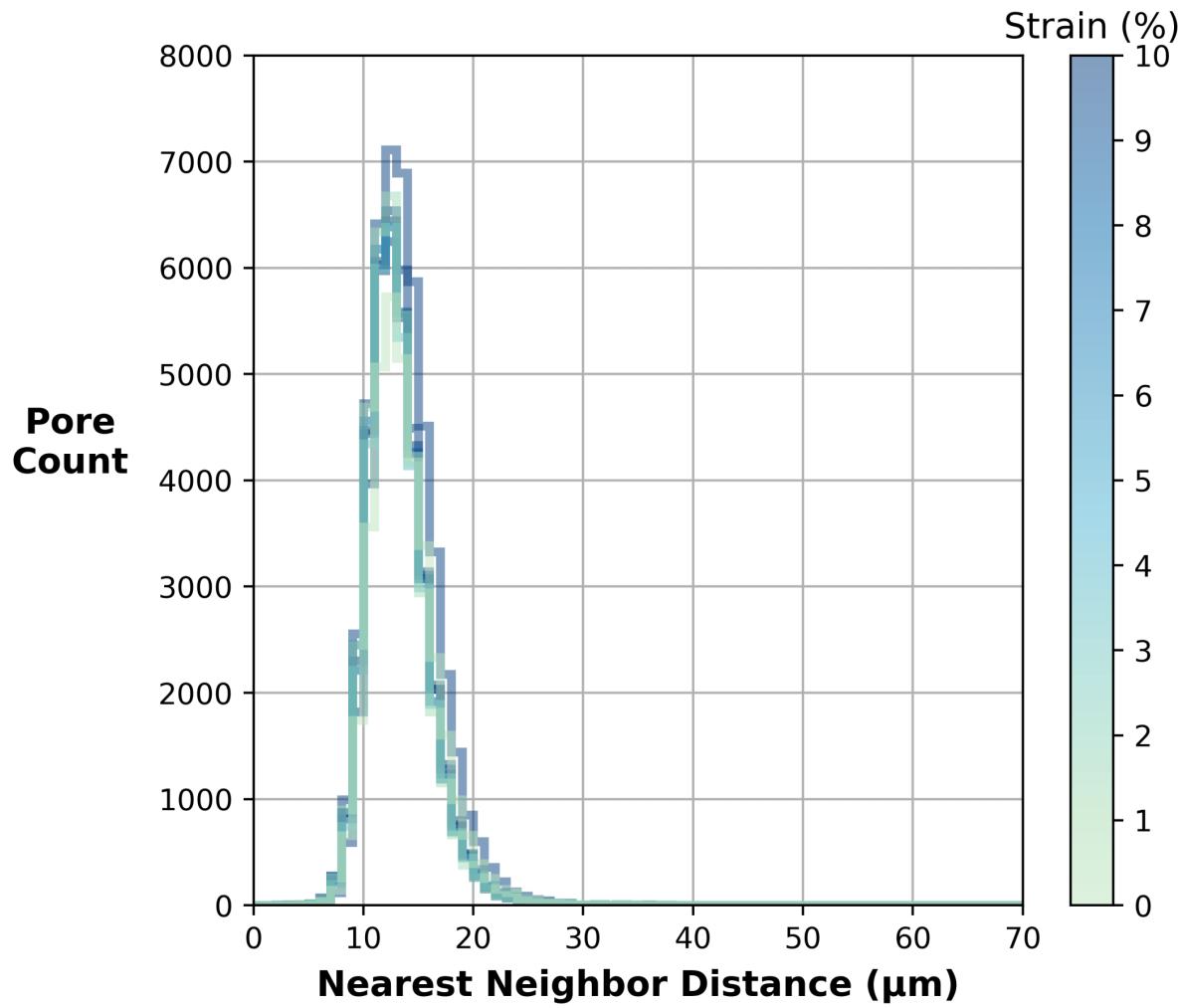
# Pore size distribution increases slightly, with minimal evidence of nucleation during loading



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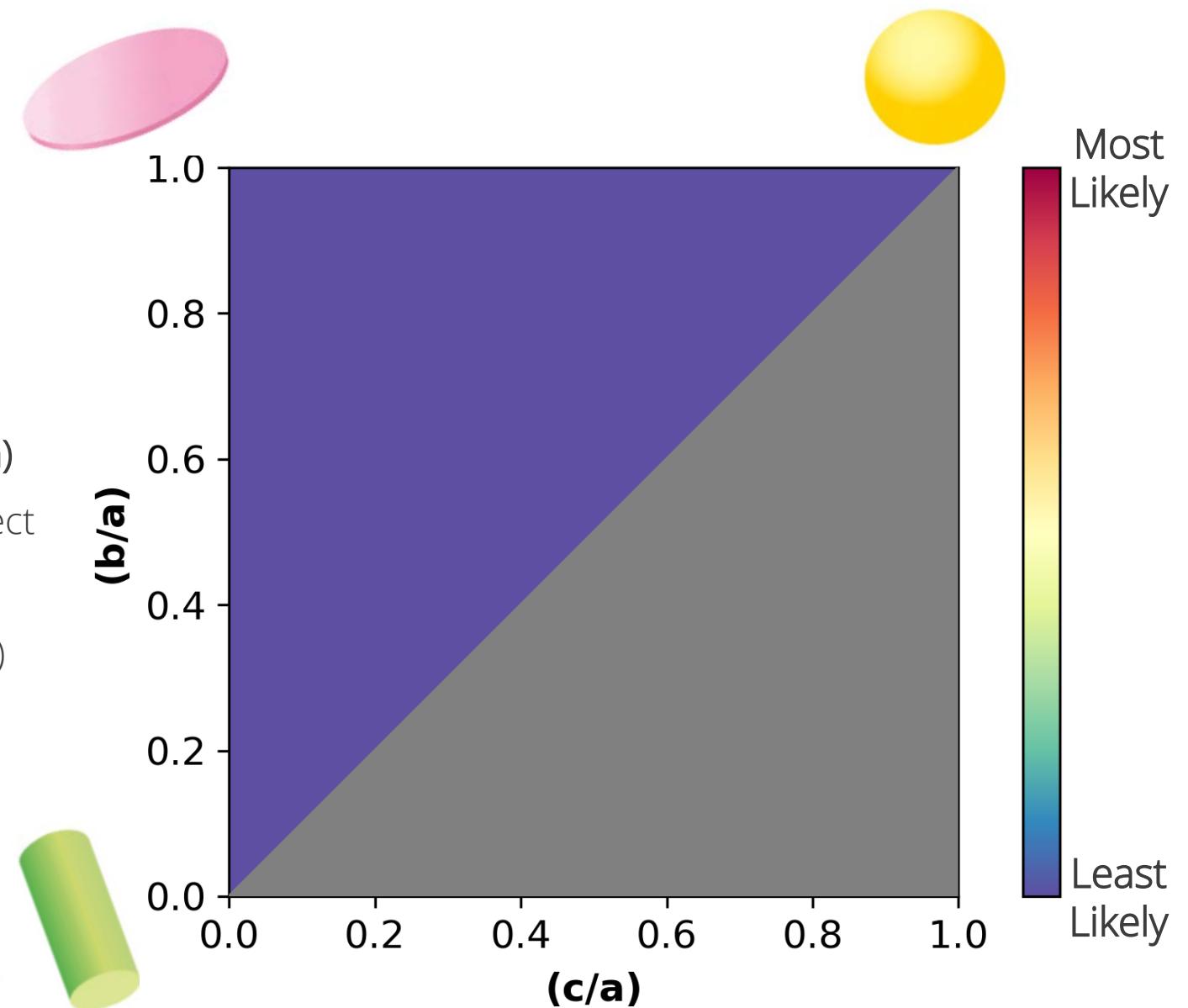
# Nearest neighbor distances support lack of pore nucleation



# Pores are highly spherical in unloaded state

Shape distributions from best-fit ellipsoid of each pore

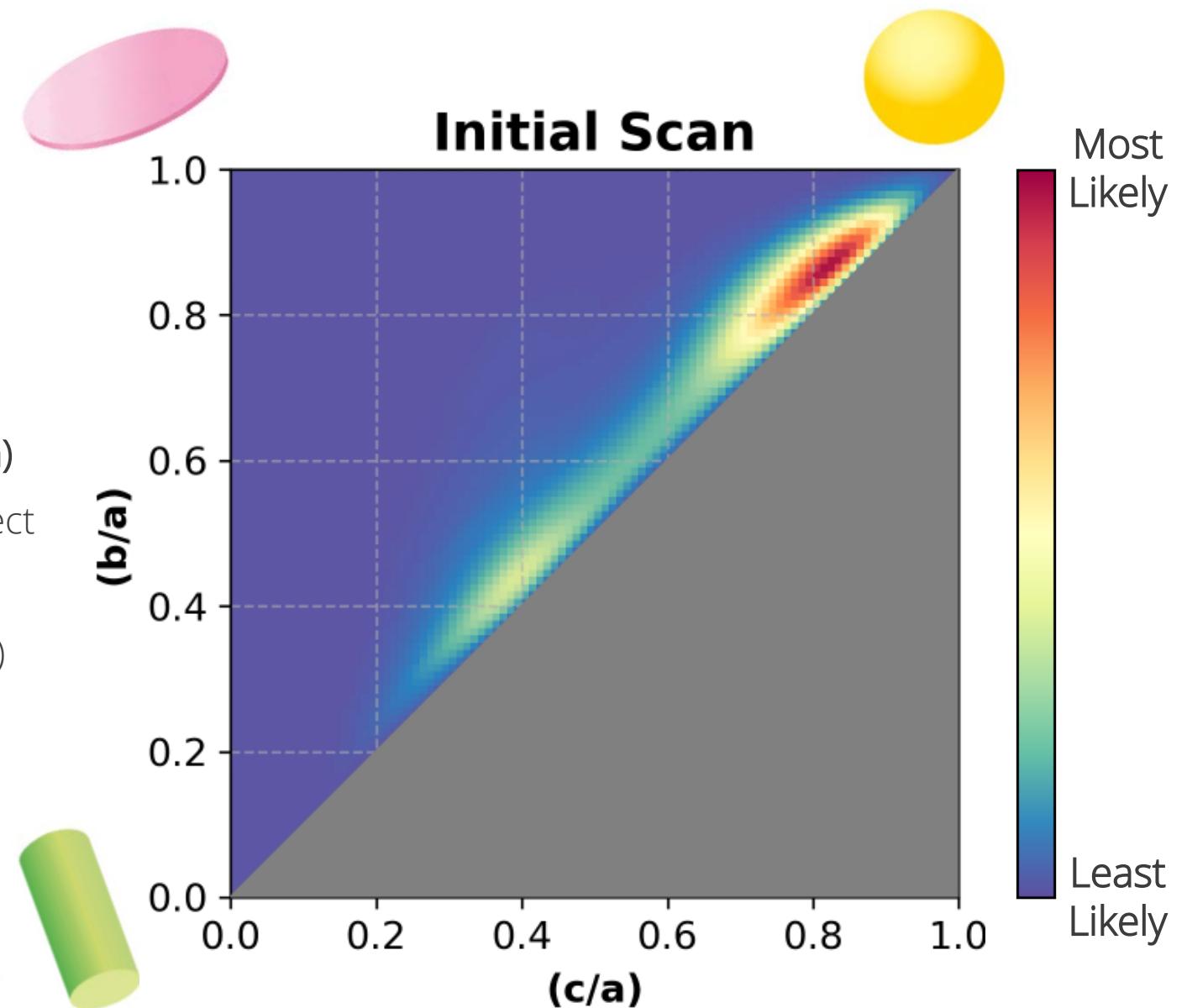
- Three axes in the ellipsoid: one major (a) and two minor (b, c)
- Aspect ratios are defined as  $(b/a)$  and  $(c/a)$
- Can create 2D histogram of ellipsoid aspect ratios, given:
  - $a > b > c$  (gray region is non-physical)
- **Rod-like features** (2 low aspect ratios)
- **Plate-like features** (1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



# Pores are highly spherical in unloaded state

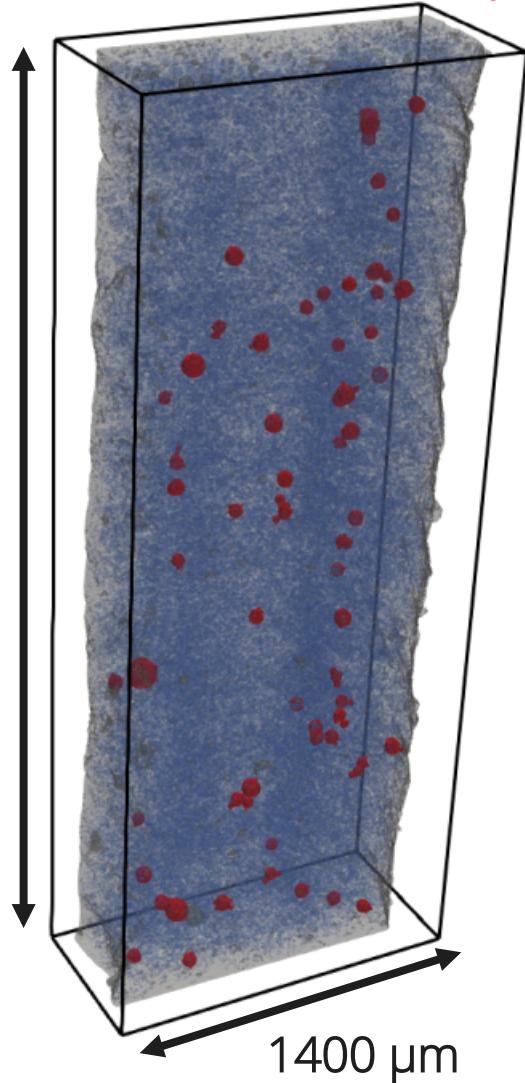
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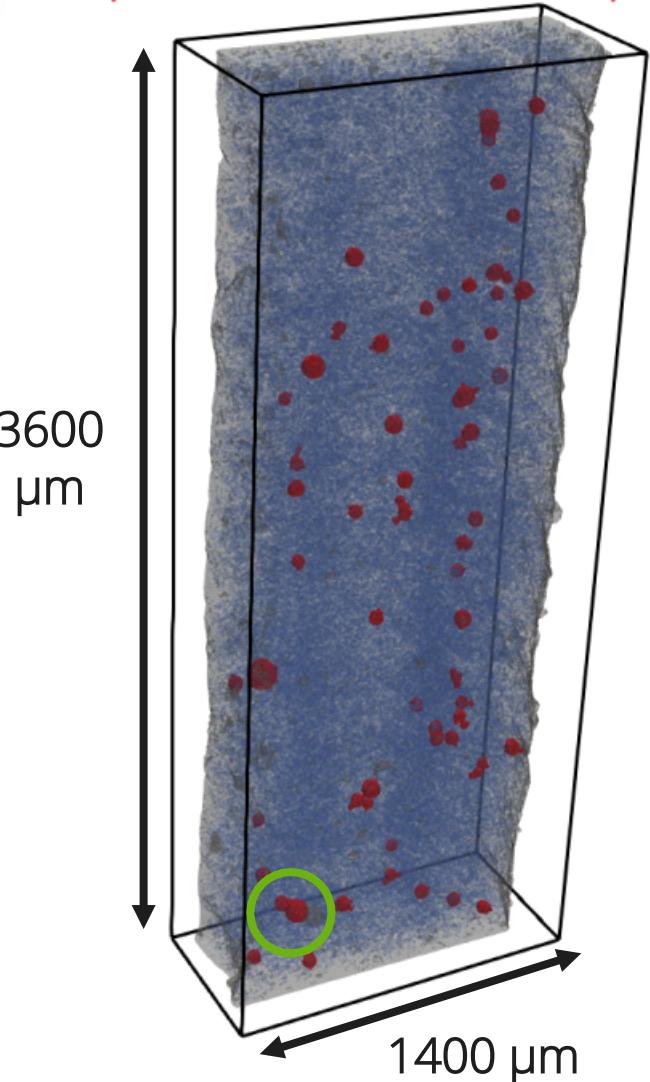
## Can analyze pore growth by tracking the largest pores in the volume

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

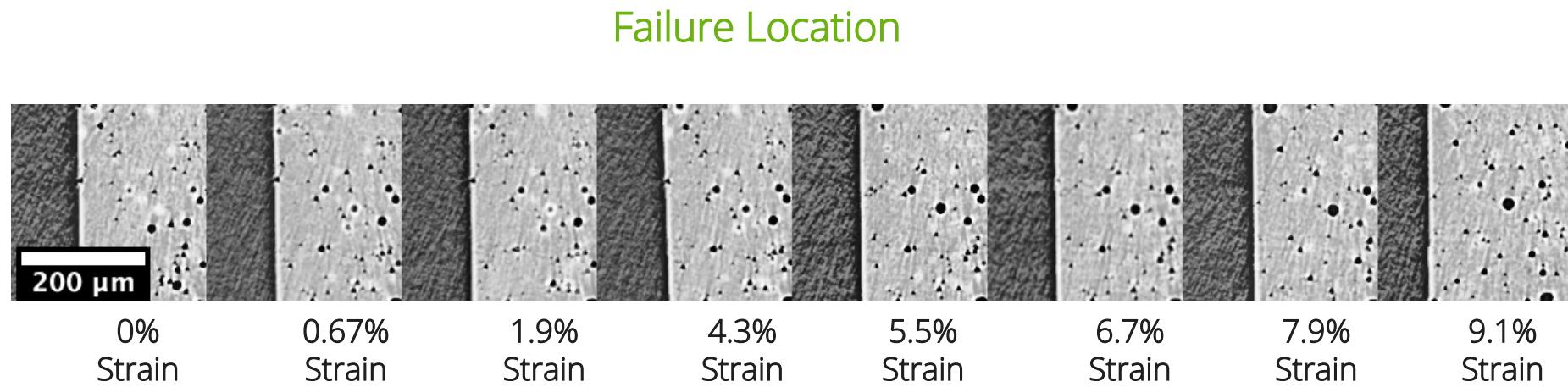


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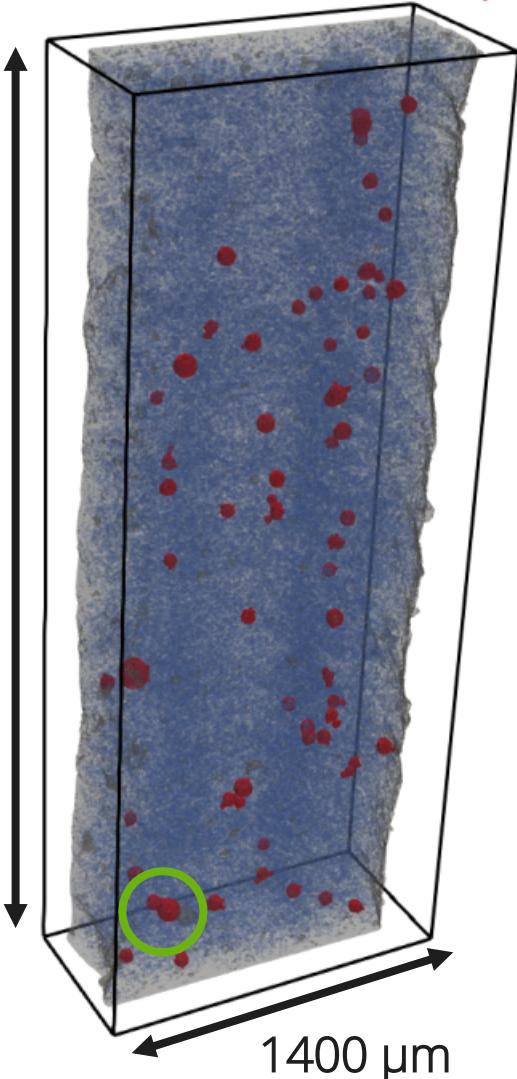
Normalized cross-correlation in Fourier space can track small regions of the volume



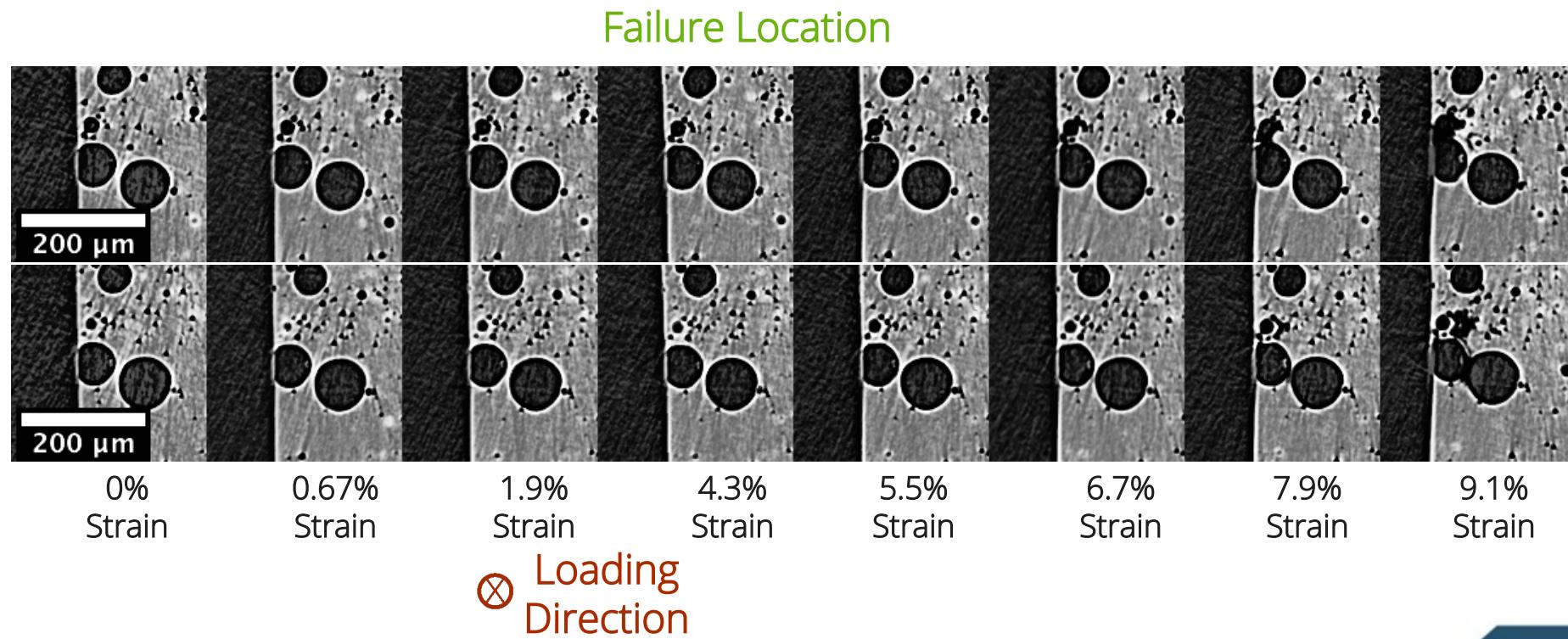
⊗ Loading  
Direction

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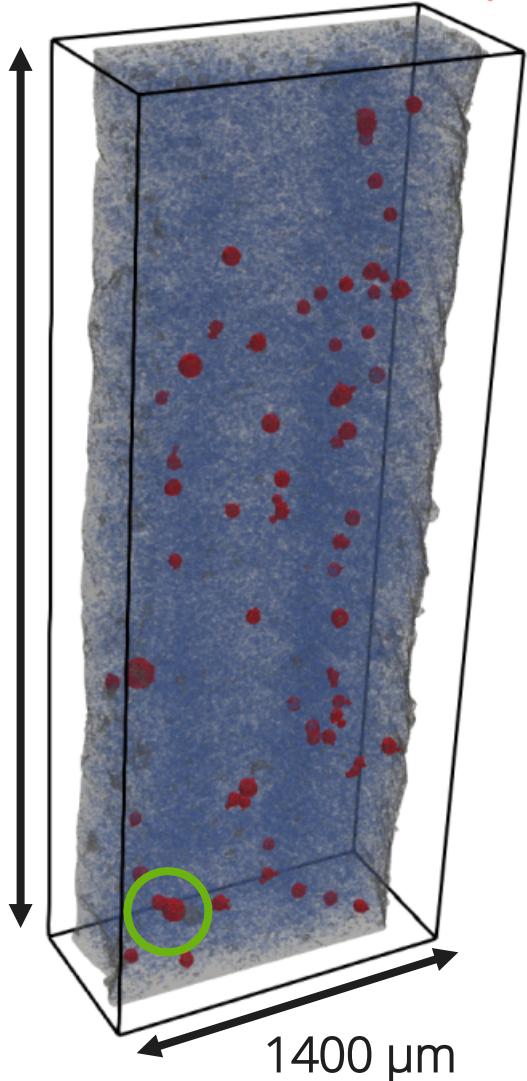


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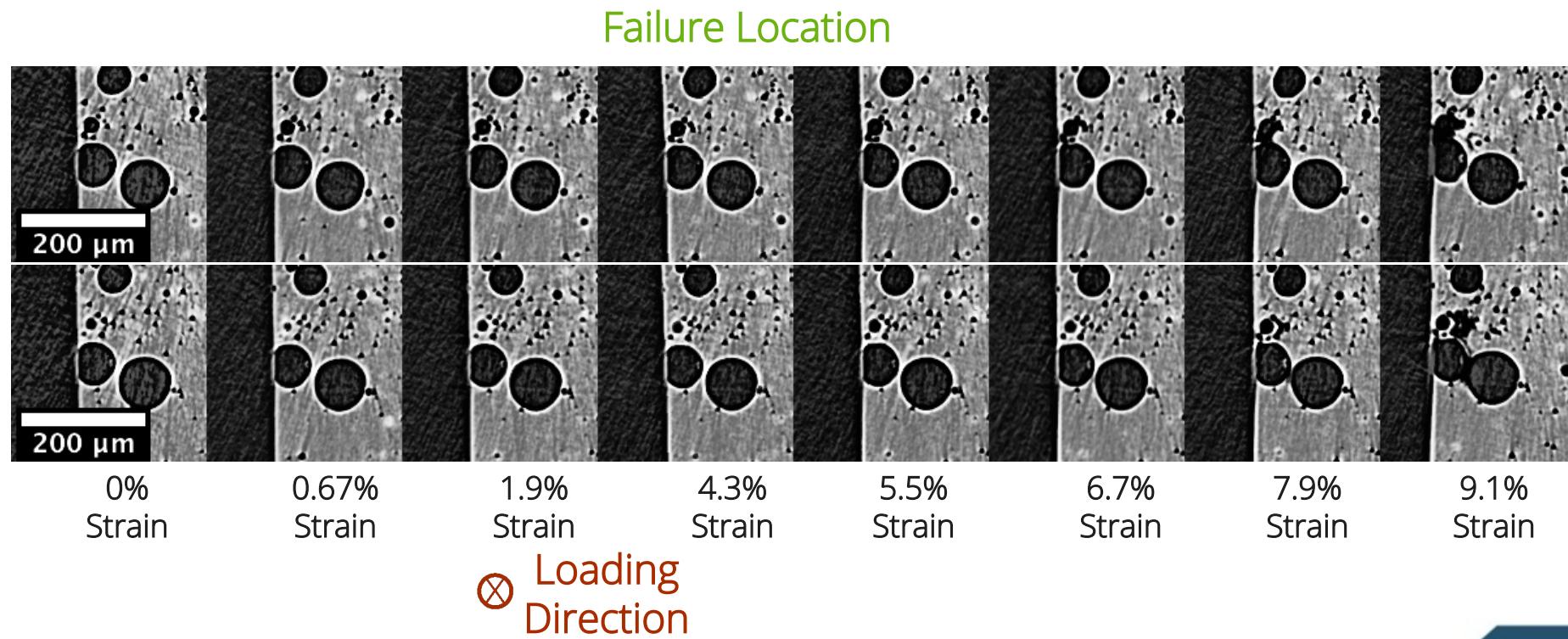


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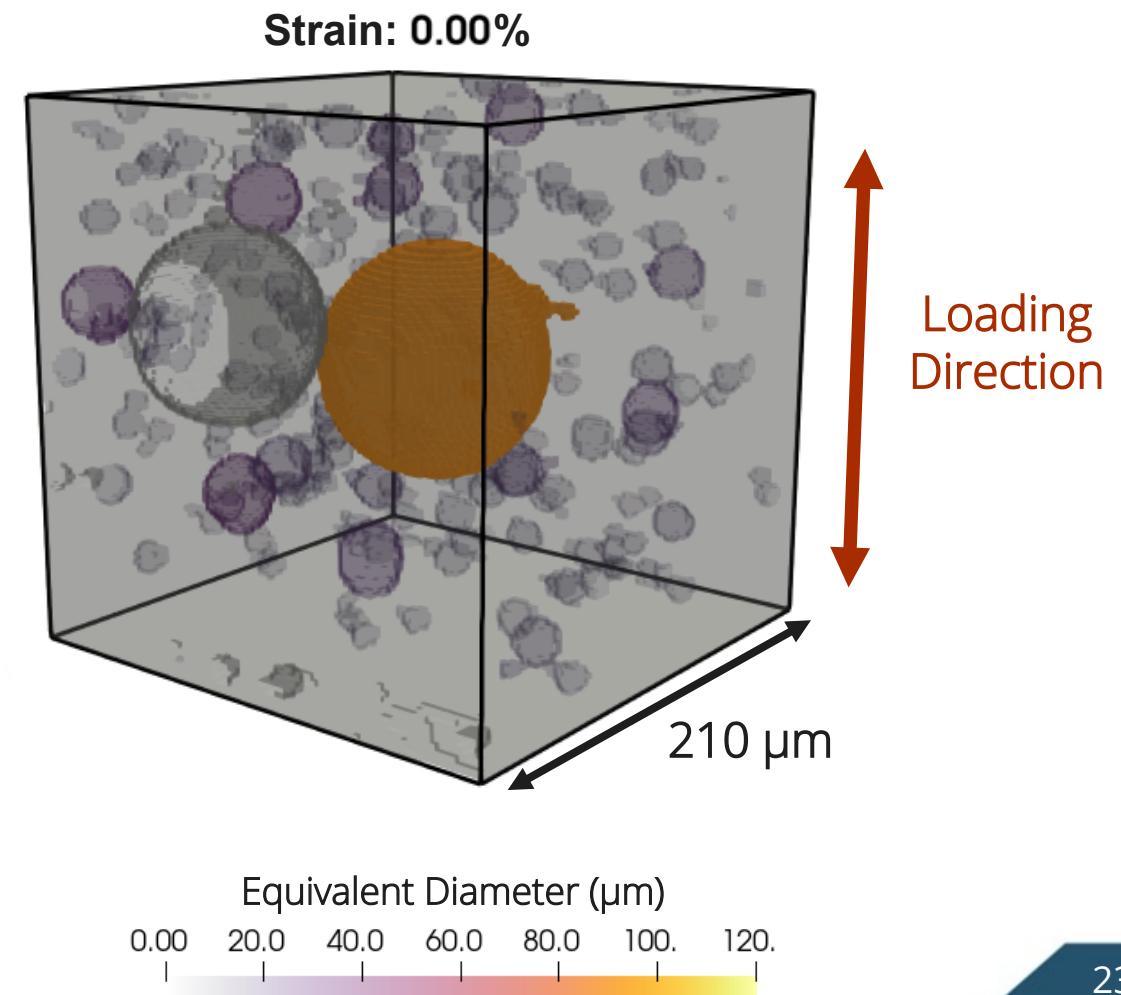
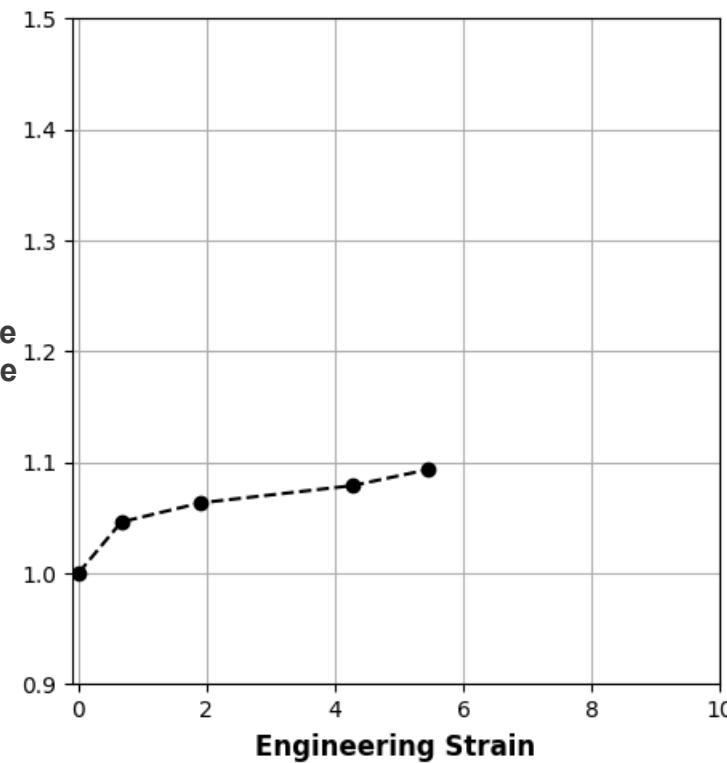
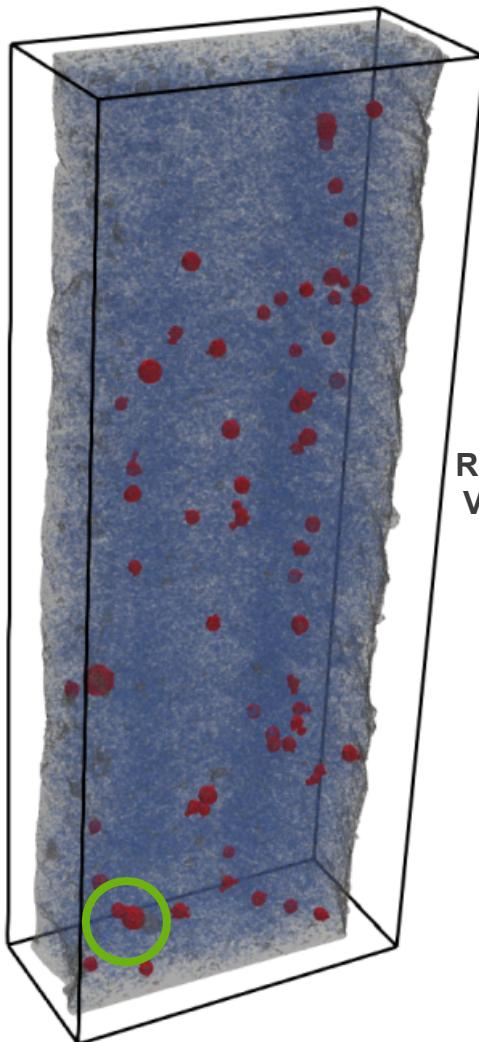
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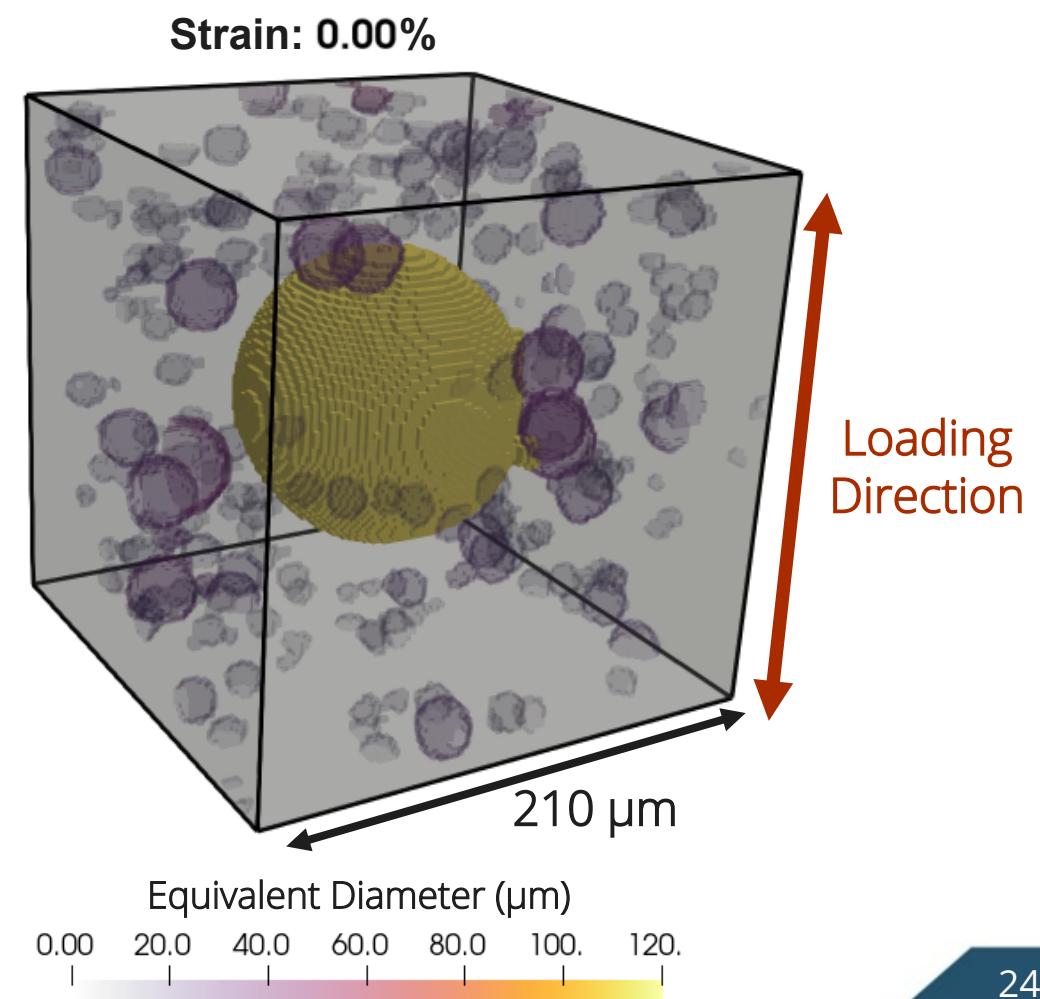
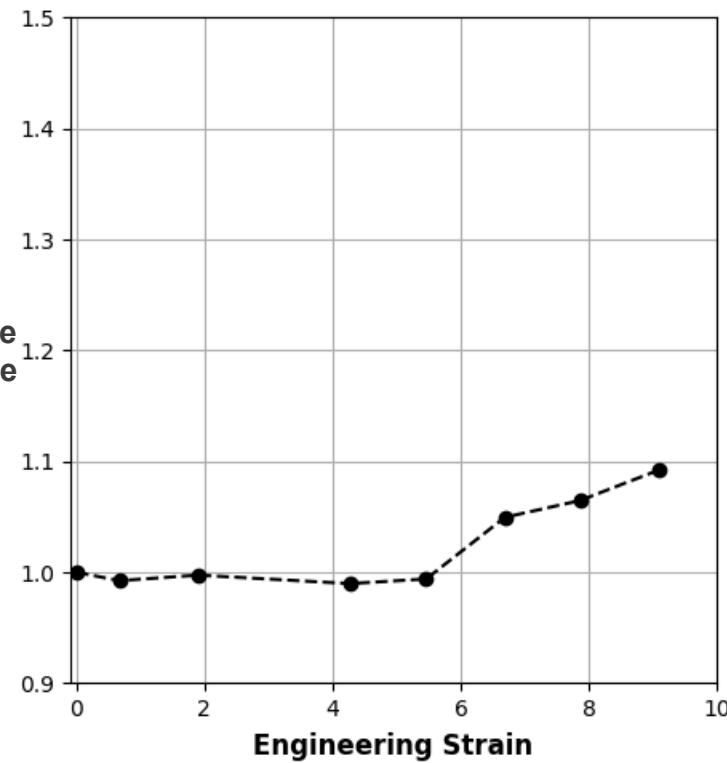
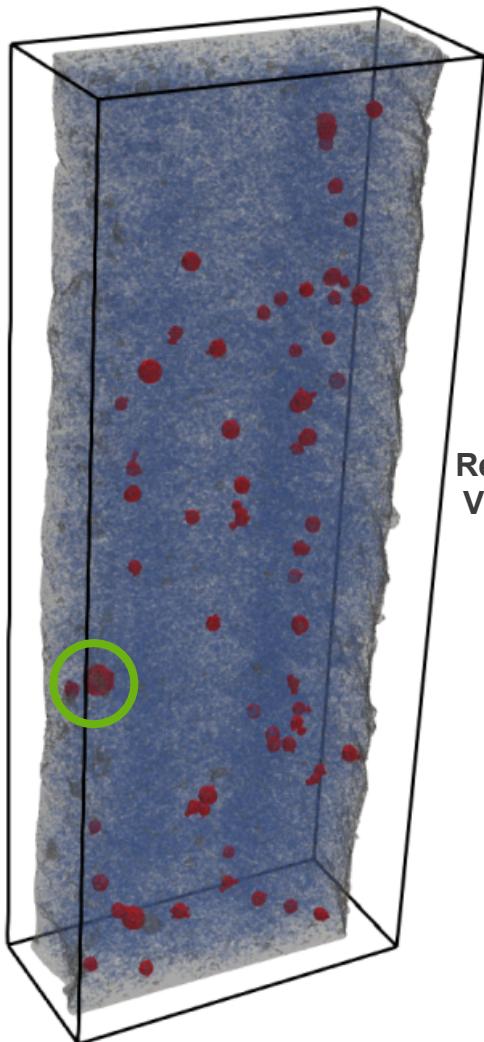
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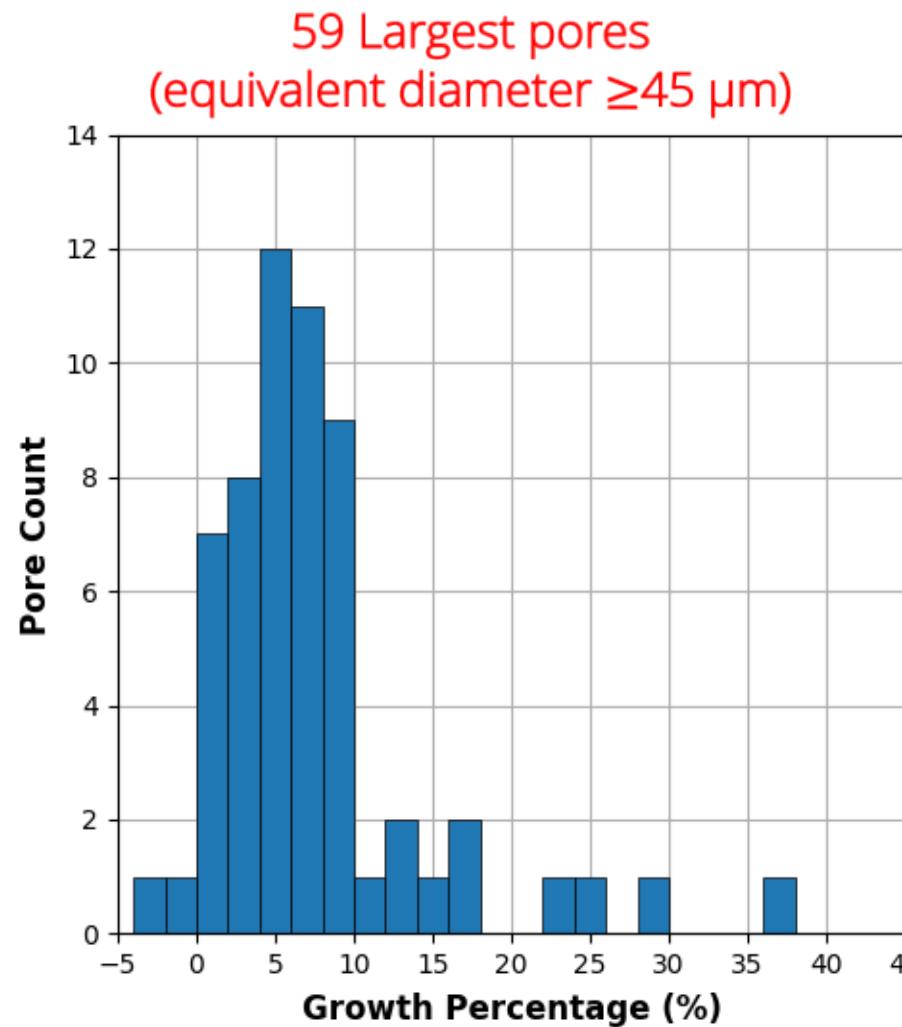
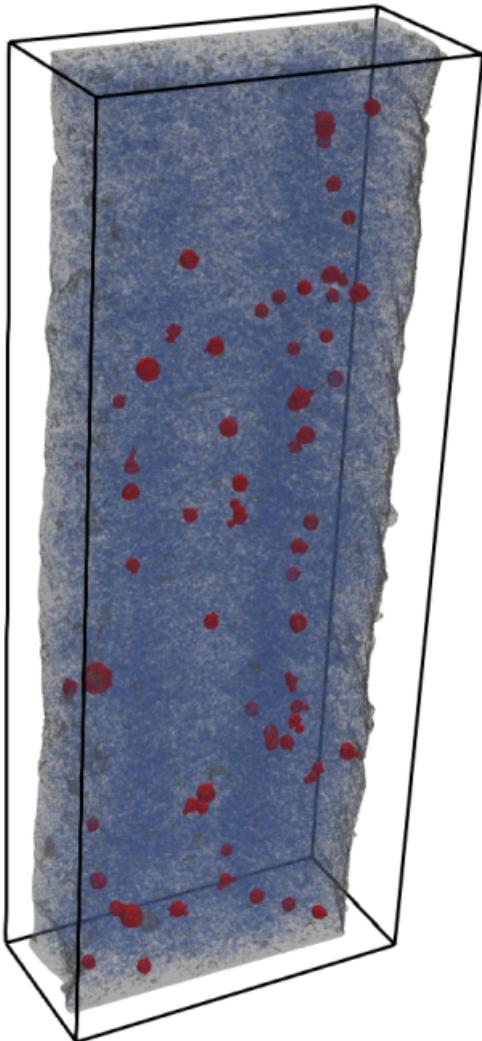
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Can analyze pore growth by tracking the largest pores in the volume

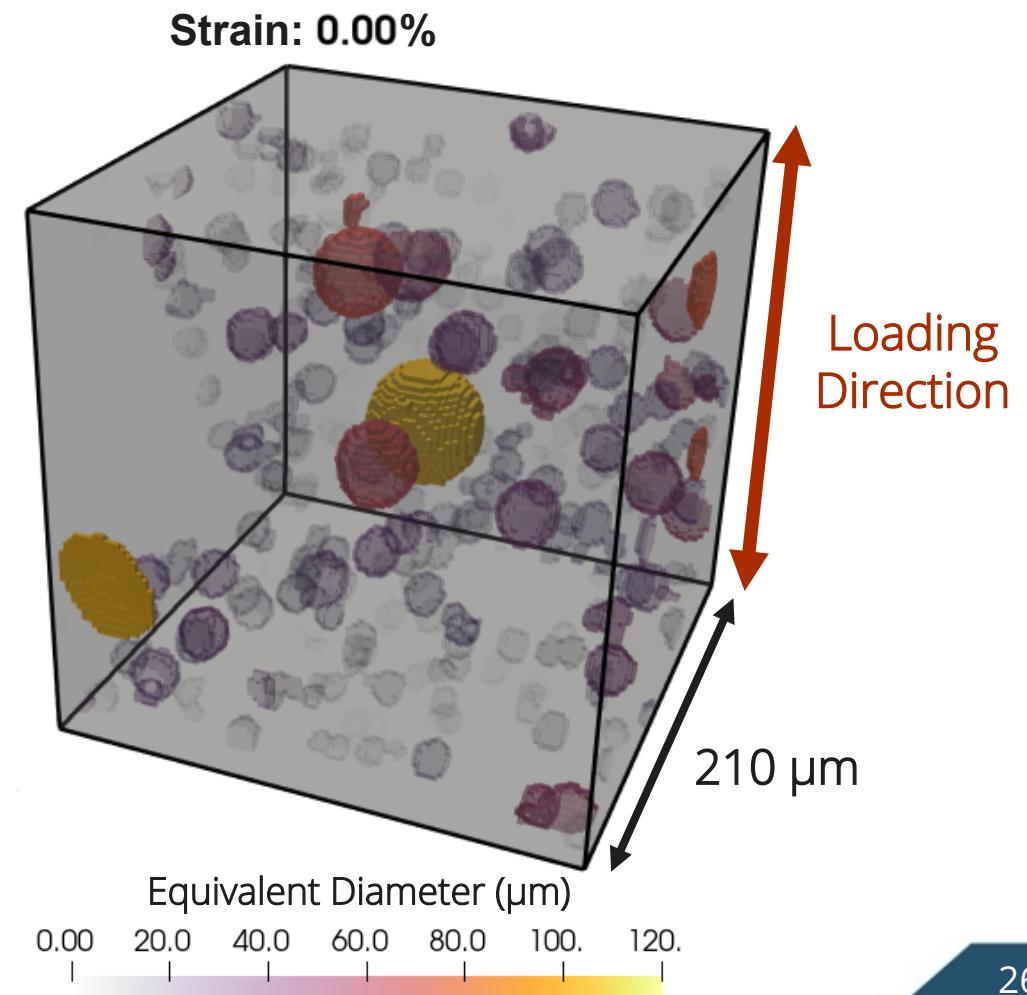
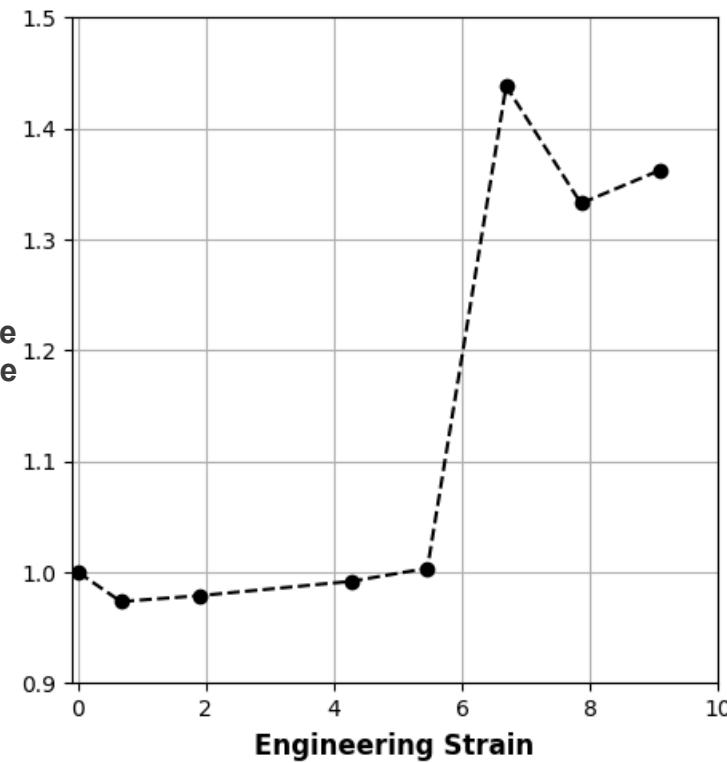
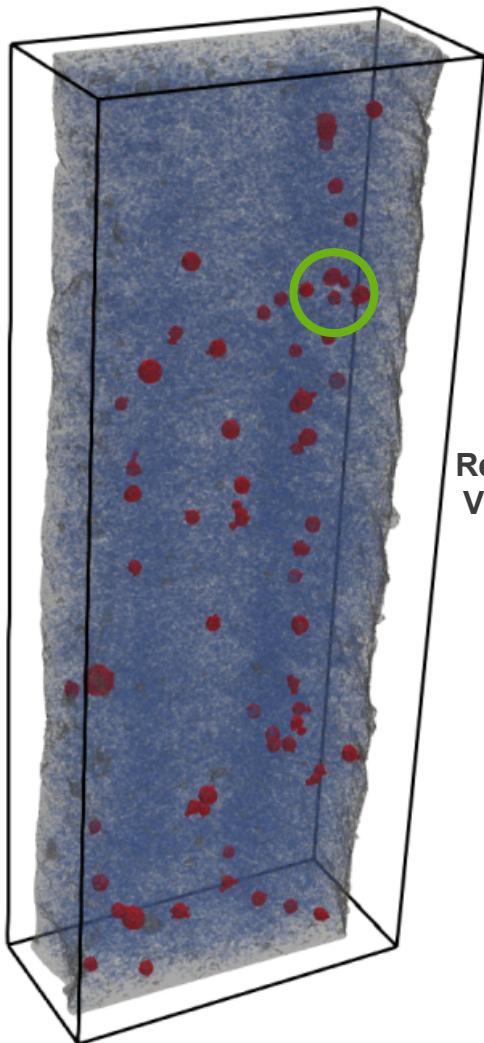


# Can analyze pore growth by tracking the largest pores in the volume

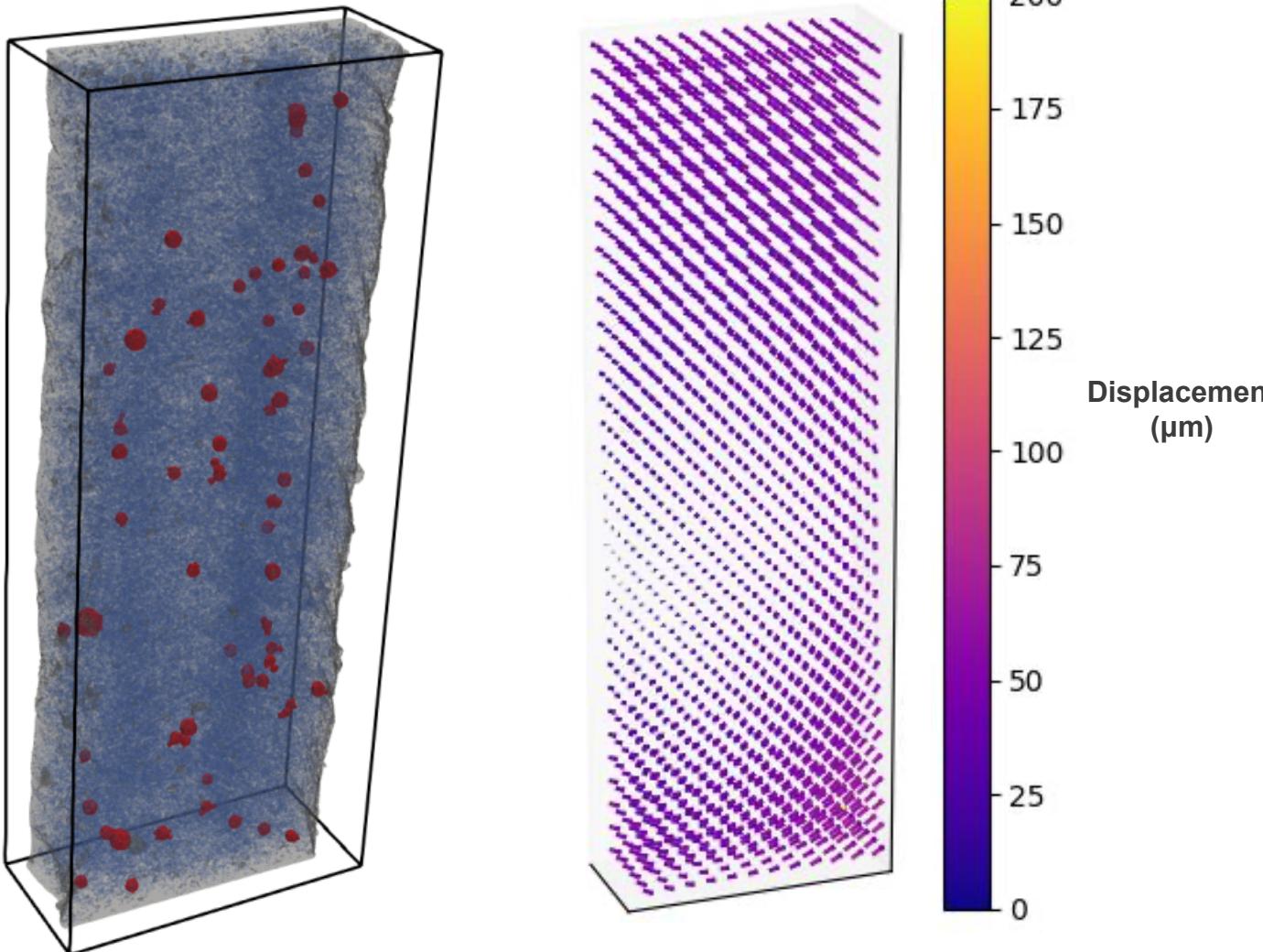


- Most large pores grow in volume between 2-10%
- Only two pores found to shrink
- Some pores appear to get much larger, due to pore merging

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



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



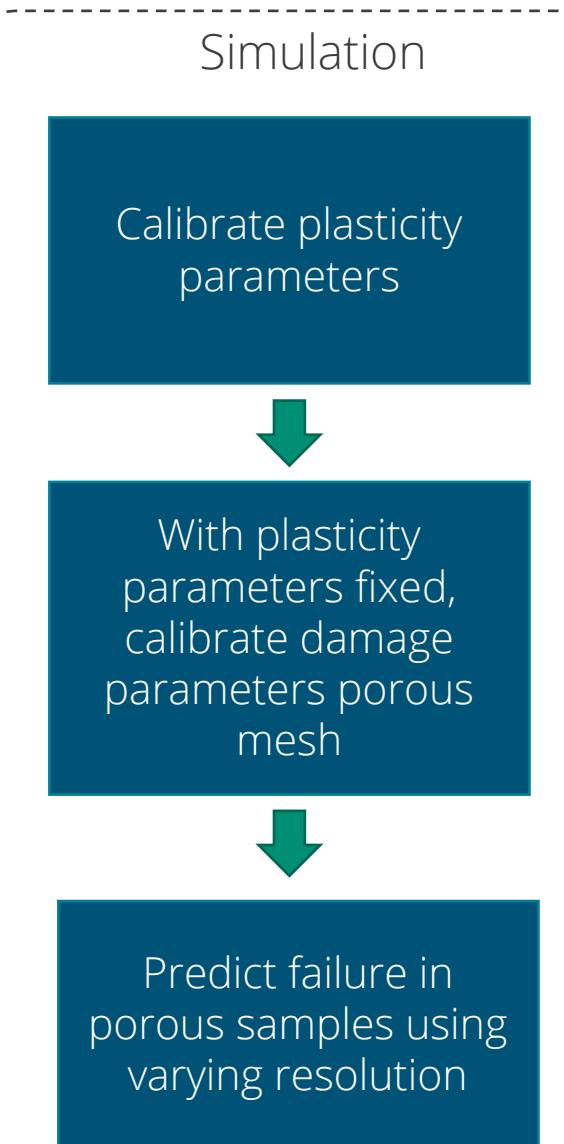
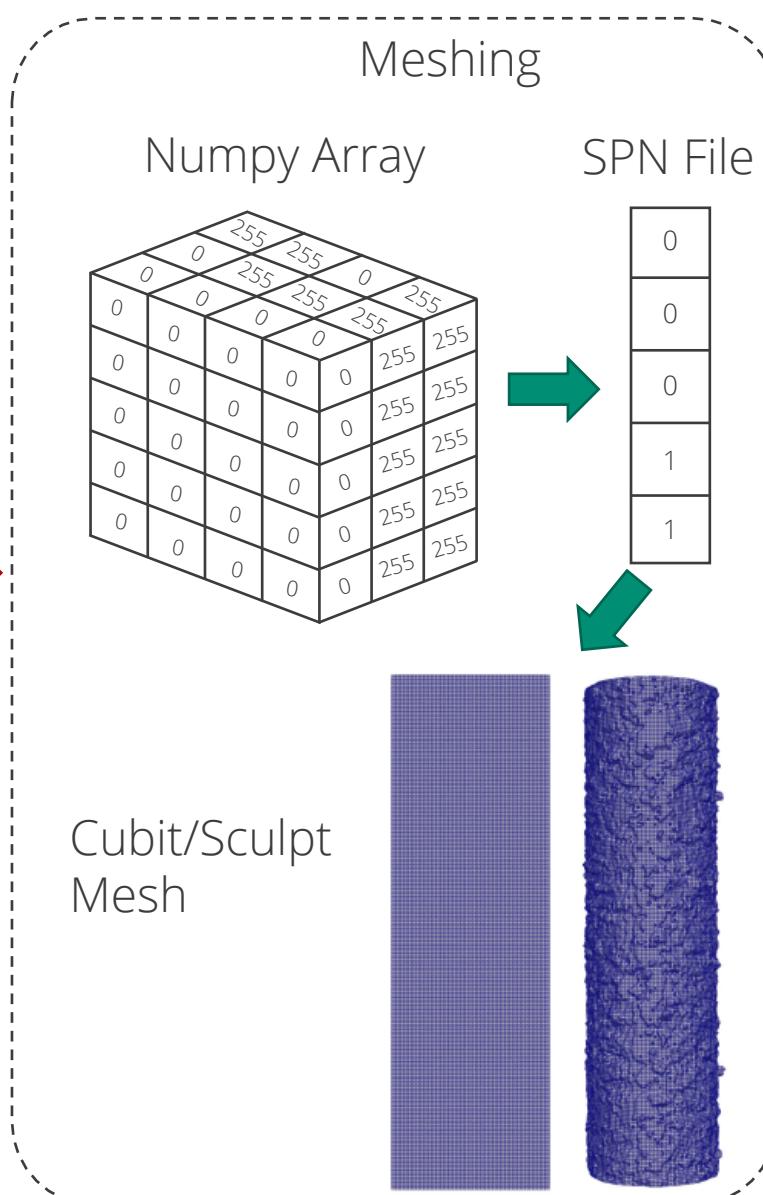
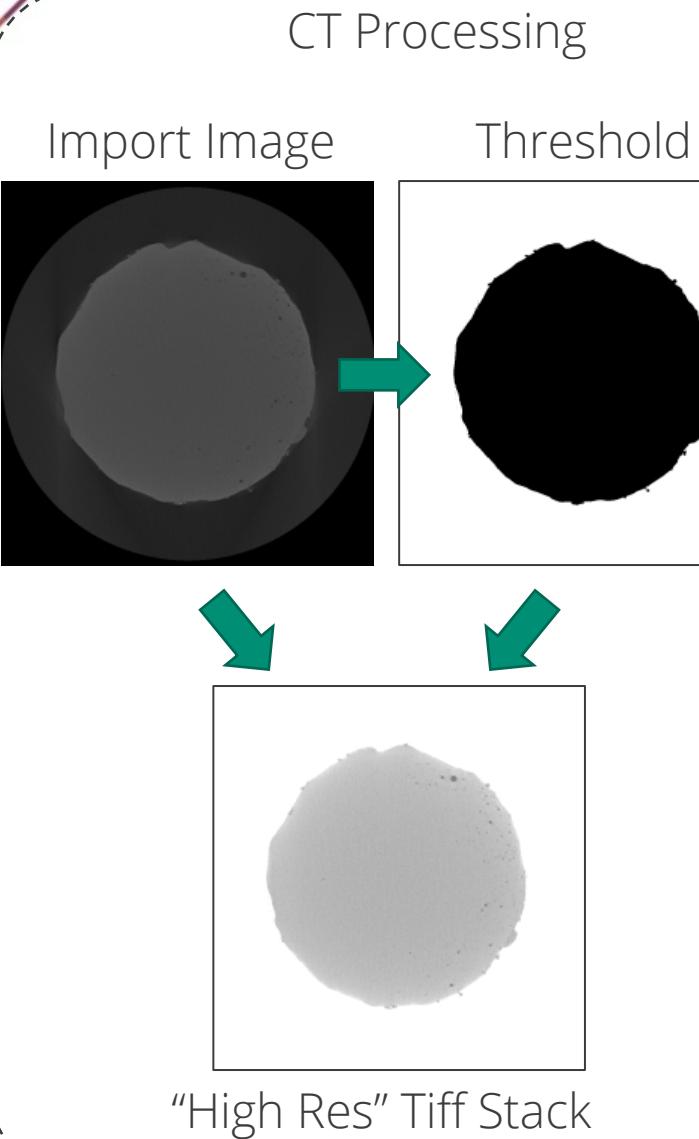
- Uses thin plate spline algorithm with tracked particles as control points
- Plan to convert this to local strain measurements to compare to FEA modelling



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# Modeling Workflow



# Model Setup

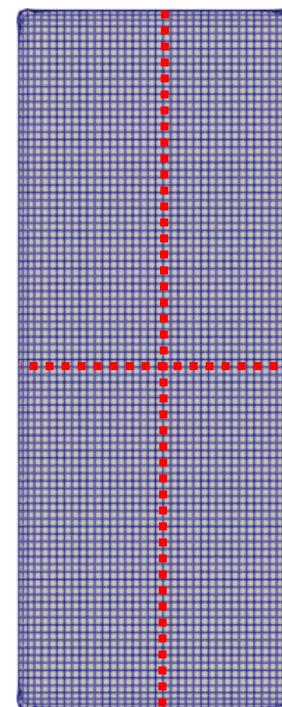
- Implicit tension models run in Sierra FEA code
- “Pads” added on top and bottom of part to provide force buffer for boundary conditions. \*Unnecessary if portion of grips are included in scan
- Cubit/Sculpt creates mesh by converting cartesian grid voxels to hexahedral elements and smoothing edges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

Voce<sup>1</sup> Hardening

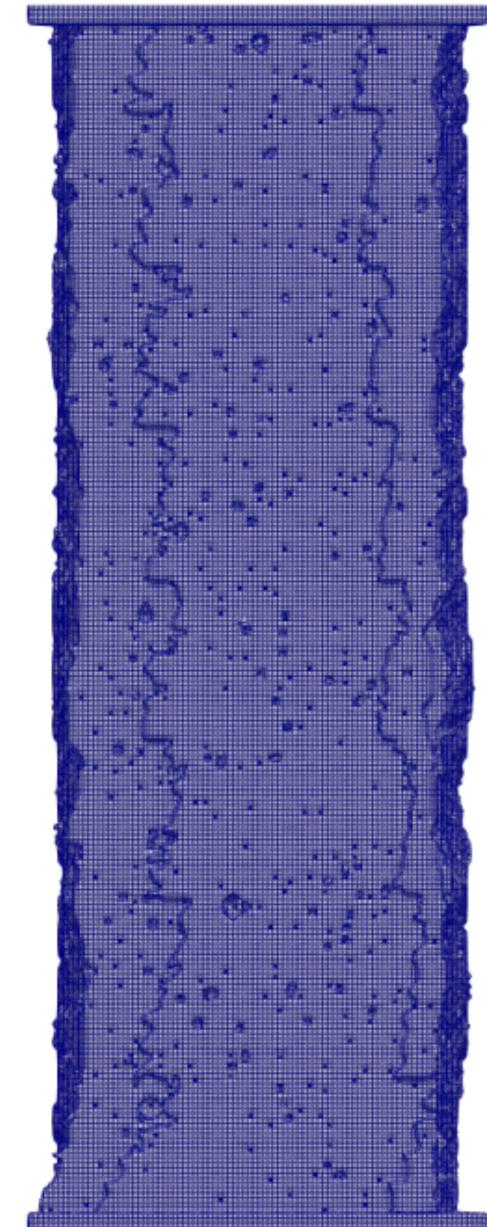
$$\bar{\sigma} = \sigma_y + A(1 - \exp(-n\bar{\varepsilon}^p))$$

Cocks-Ashby<sup>2</sup> Void Growth

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



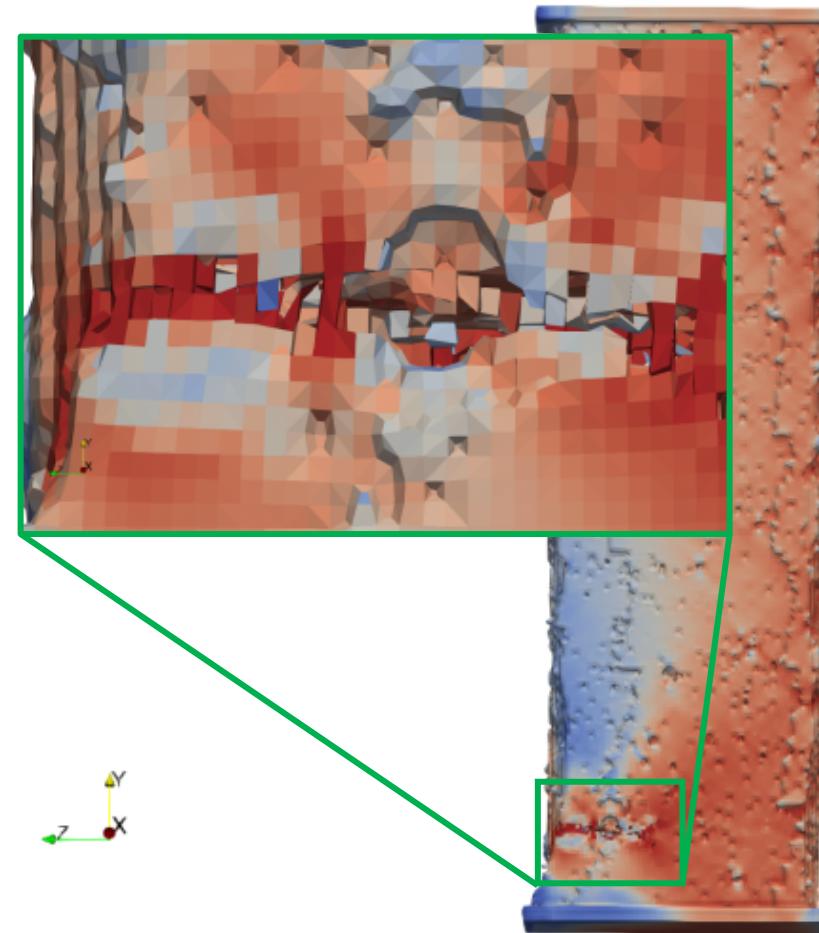
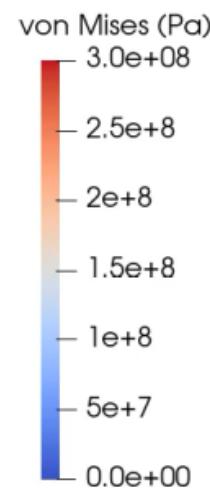
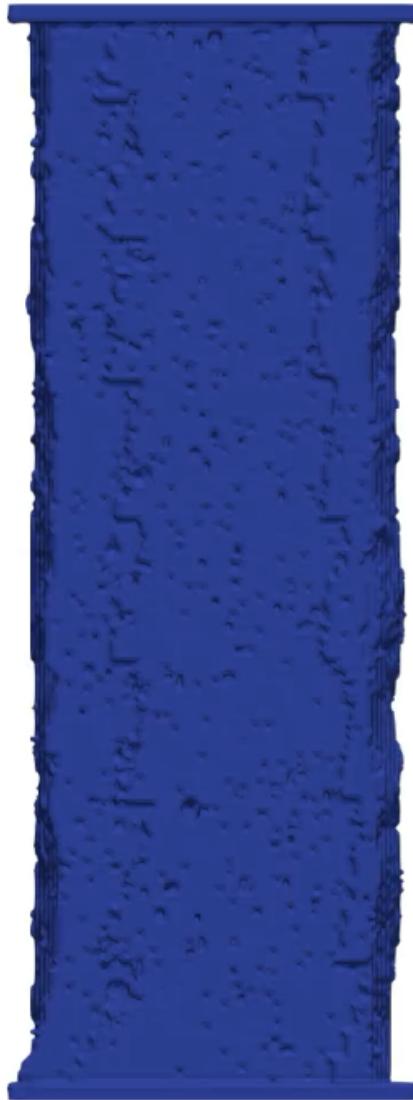
Nodal lateral  
constraints applied  
on red lines for  
Poisson contraction



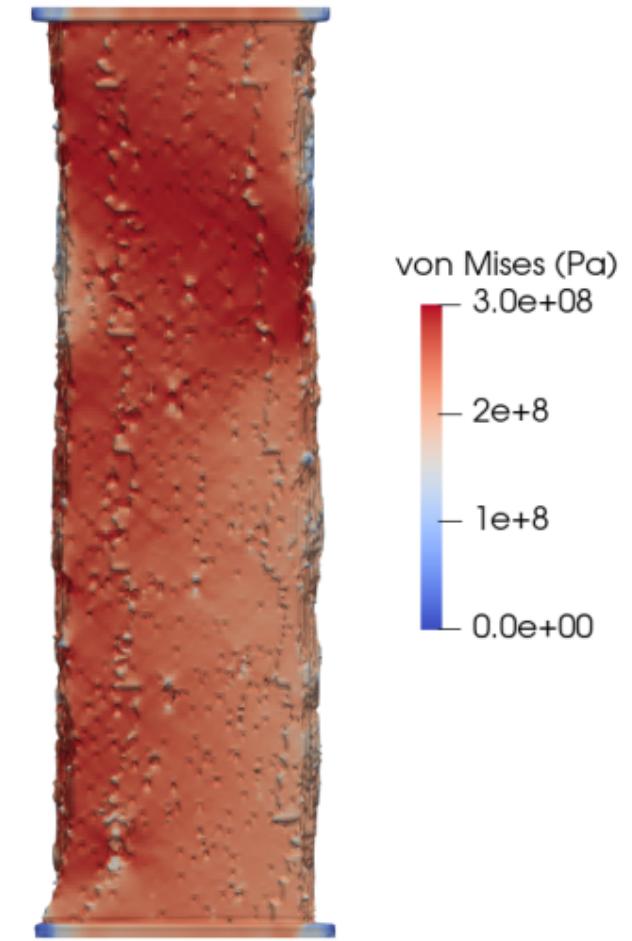
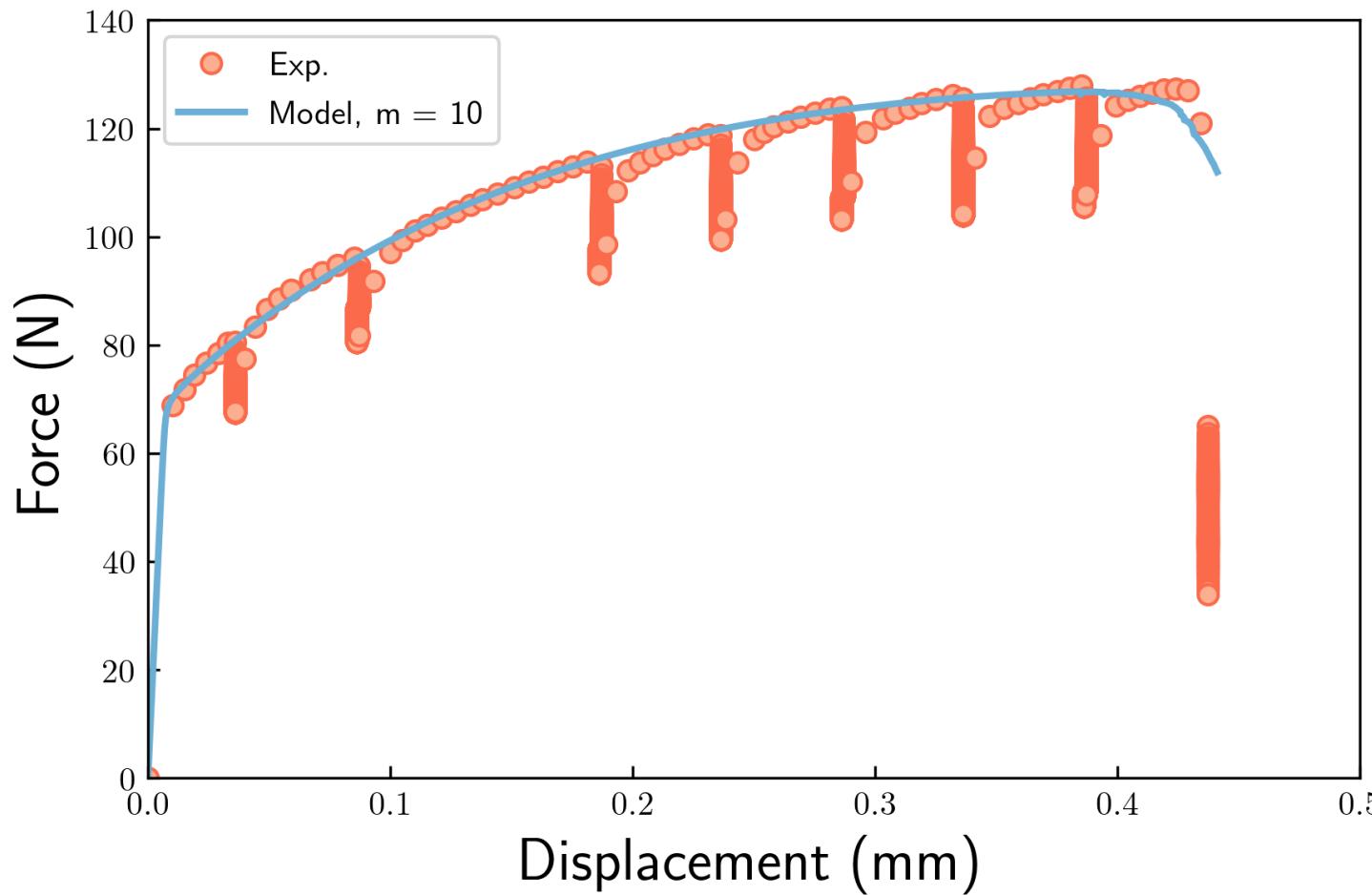
<sup>1</sup>Voce, E., J. Inst. Metals 1948

<sup>2</sup>Cocks, A.C.F. and Ashby, M.F., Metal Science 1980

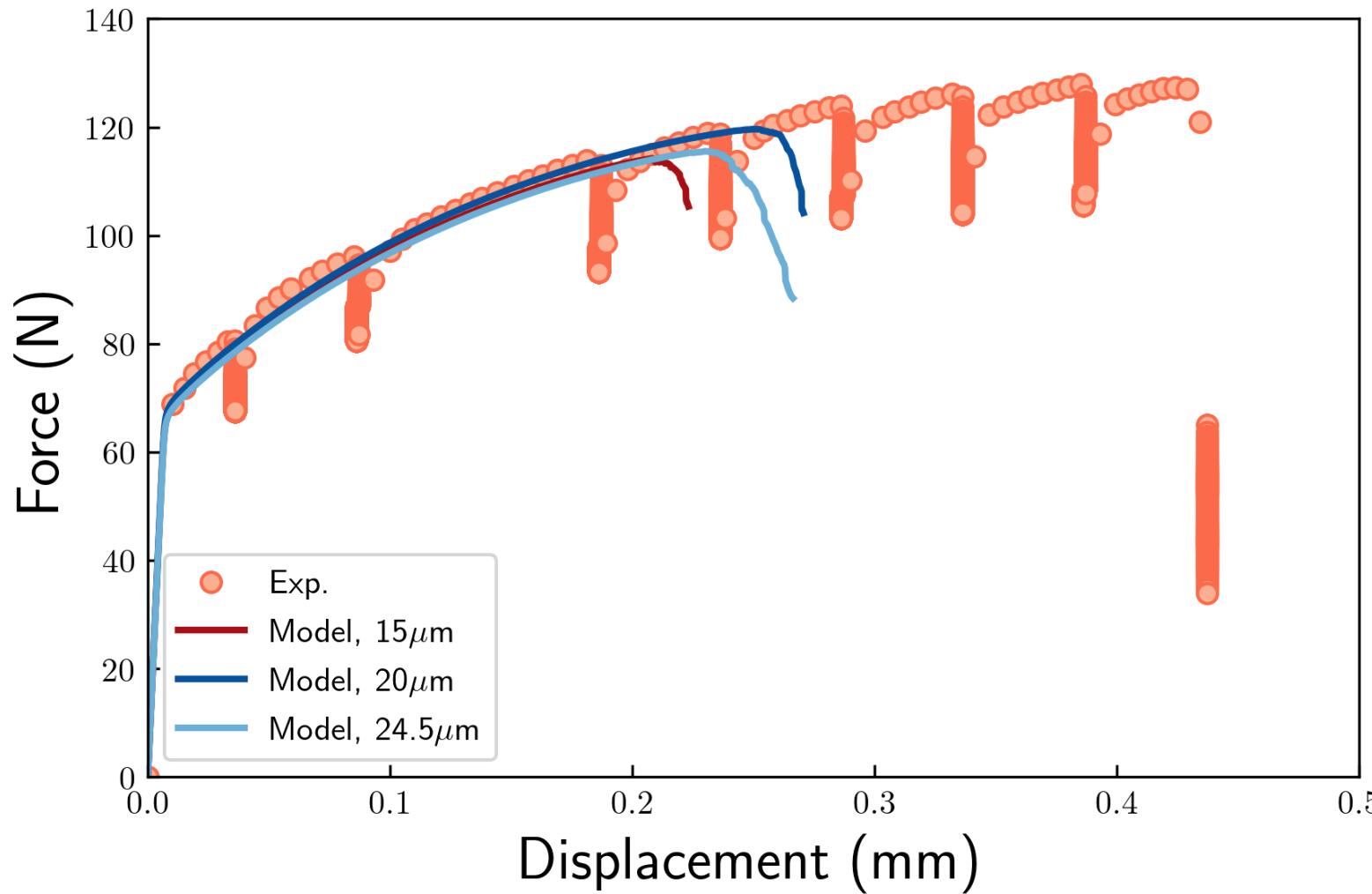
Failure location can be accurately predicted with sufficient mesh resolution and calibration (15 micron mesh size,  $m=20$ )



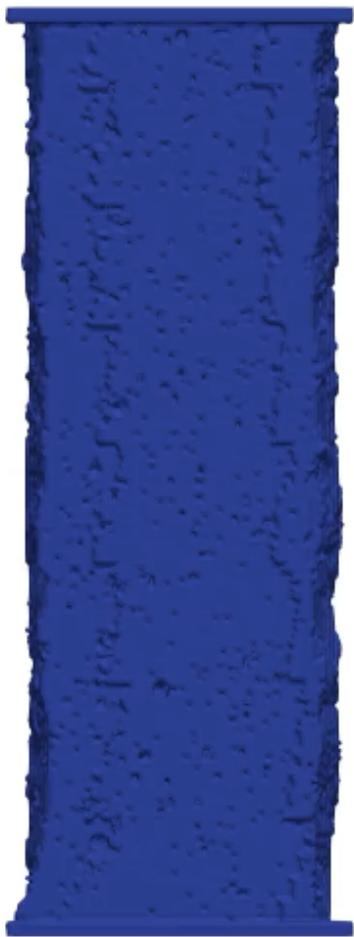
# Calibration to force-displacement data alone can be insufficient



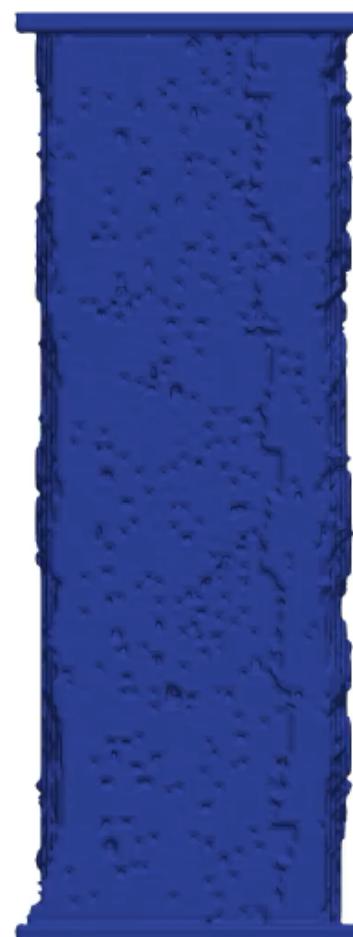
# Force-displacement response- fixed damage parameters, different voxel sizes



# Mesh size results



767k elements  
155 cpus  
3.7 hr wall time



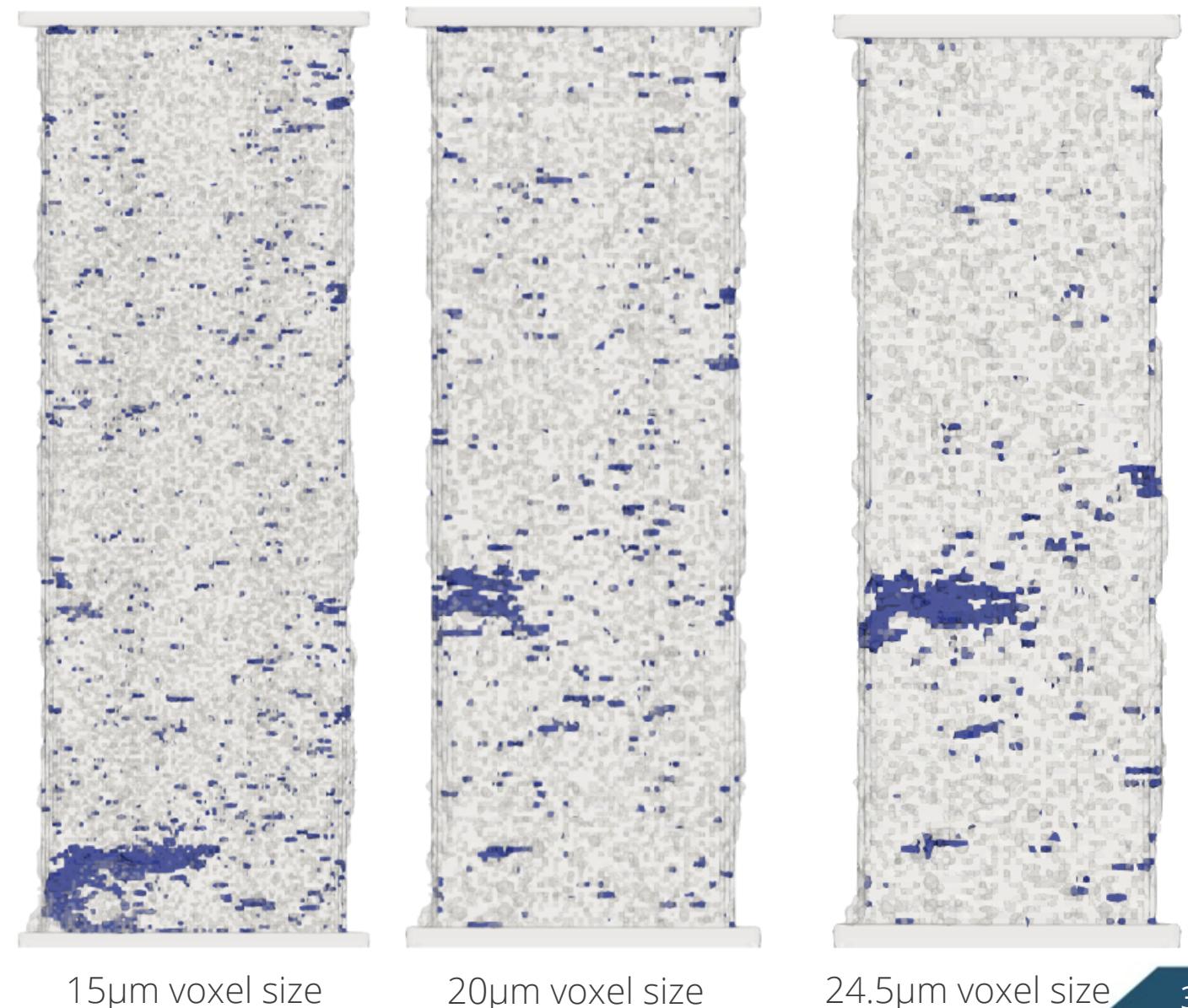
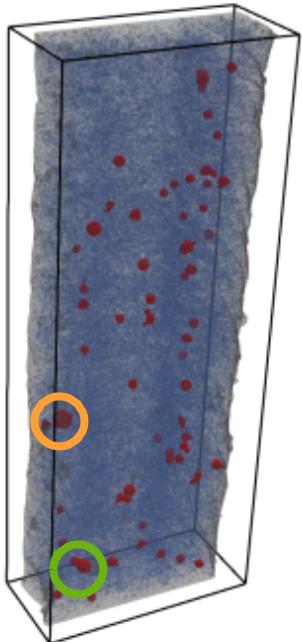
340k elements  
70 cpus  
4.2 hr wall time



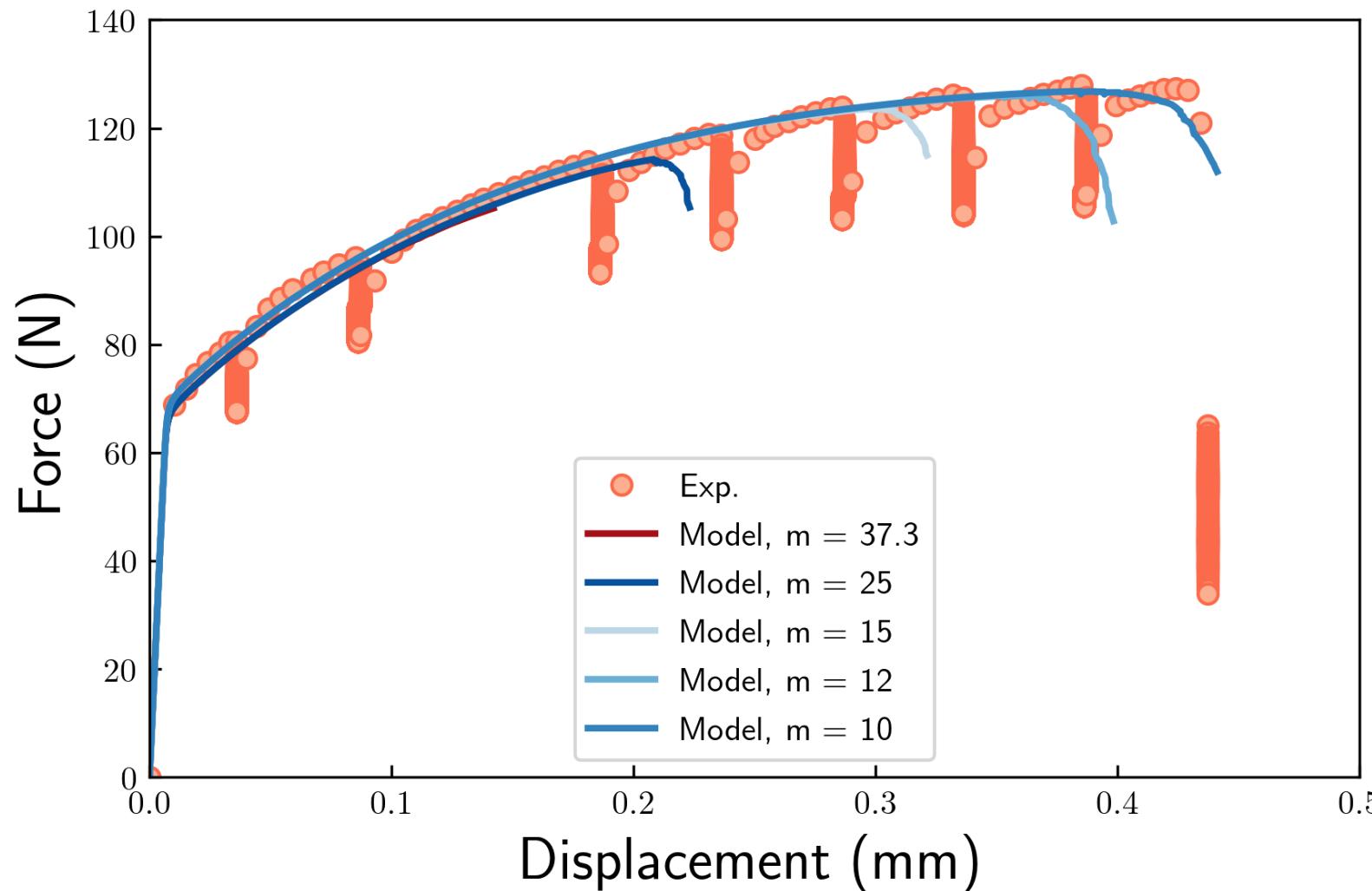
189k elements  
40 cpus  
3.7 hr wall time

# Fracture locations – fixed damage parameters, different voxel sizes

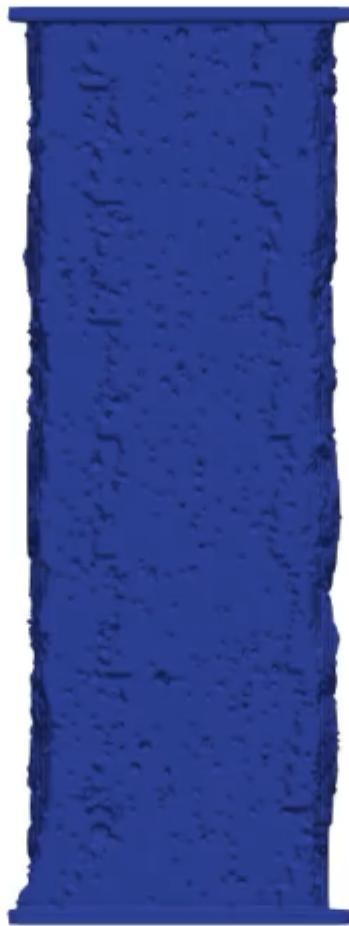
- Deleted elements shown in blue
- Fracture location changes lower resolution meshes
- Local damage parameters are inherently mesh-size dependent

15 $\mu\text{m}$  voxel size20 $\mu\text{m}$  voxel size24.5 $\mu\text{m}$  voxel size

# Force-displacement response- fixed 15 $\mu\text{m}$ voxel size, different damage parameter $m$



# Von Mises response- fixed 15 $\mu$ m voxel size, different damage parameter m



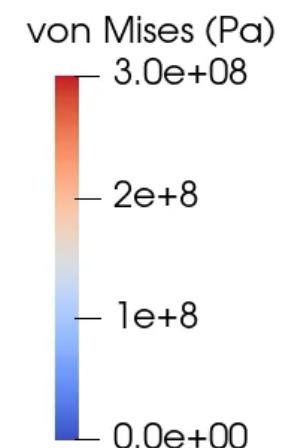
m=20



m=15

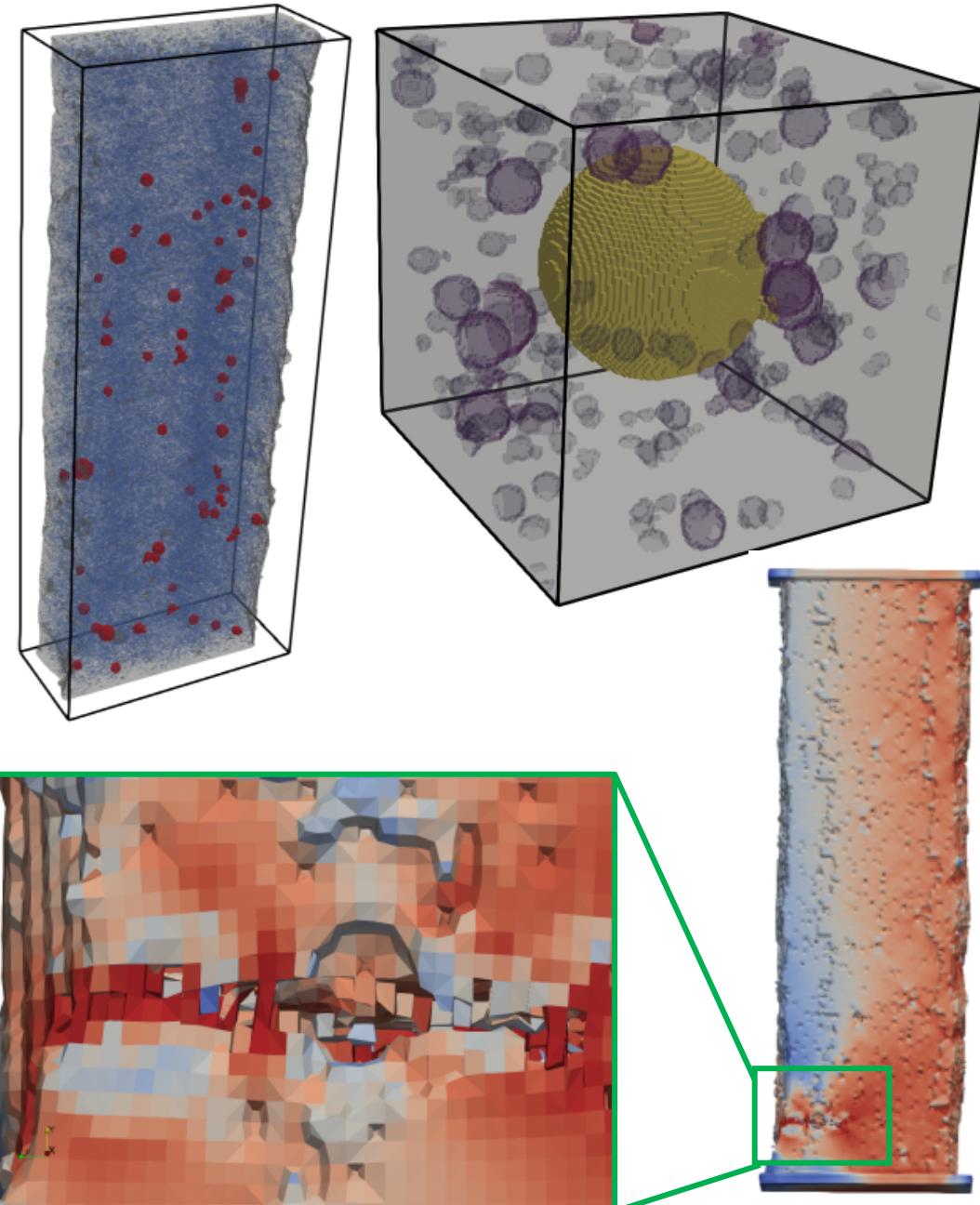


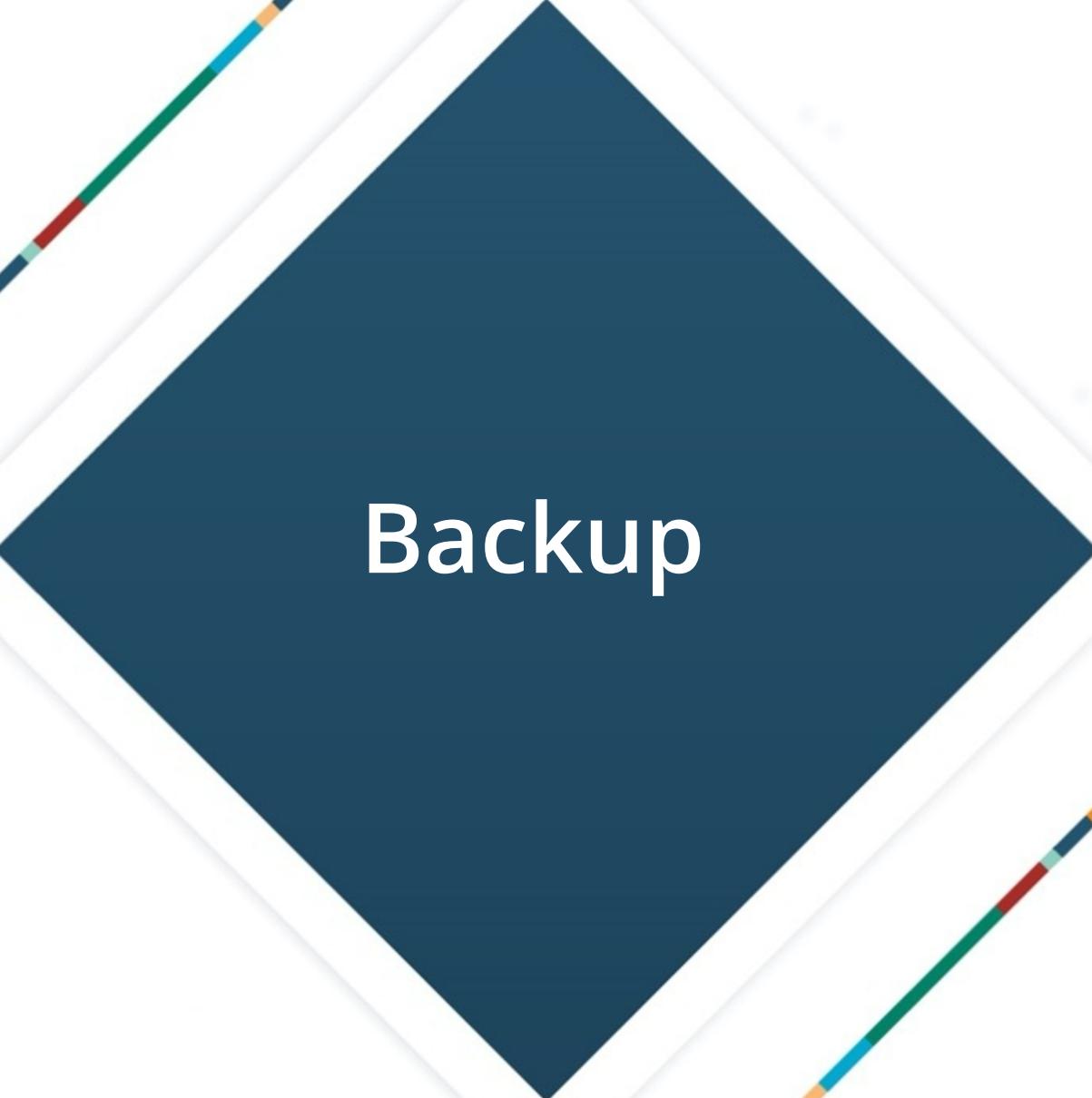
m=10



# 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