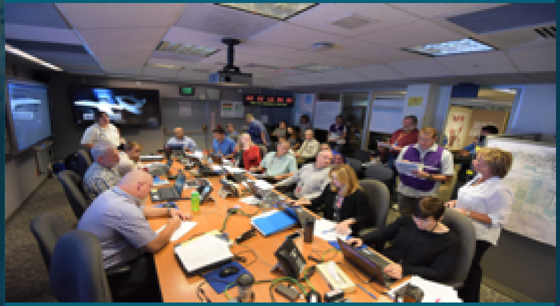
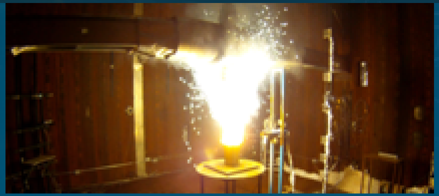
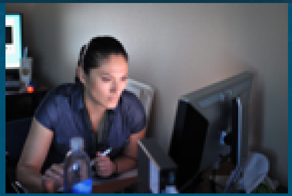
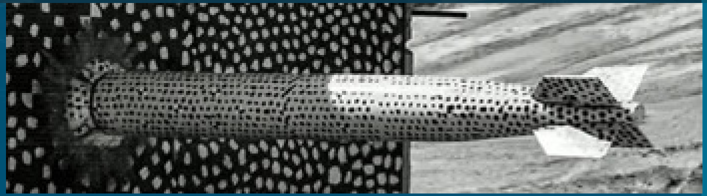
SAND2021-6288PE

Process-Structure-Property-Performance Considerations for Metal AM Lattices









Presented by

Scott Jensen

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Acknowledgments – Work From Around Sandia

Process changes

- **Scott Jensen, Benjamin White**

Measuring methods

- **Josh Elliot (CT)**, **Scott Jensen**

Machine learning prediction of performance

- **Anthony Garland**, Benjamin White, Bradley Jared, Michael Heiden, Emily Donahue, **Brad Boyce**

Size dependence

- Ashley M. Roach, Benjamin White, Anthony Garland, Bradley Jared, Jay Carroll, **Brad Boyce**

Microstructure on lattices

- **Tim Ruggles**, Benjamin White, Brad Boyce

Overview

Outline

- Process changes
- Measuring methods
- Mechanical properties
- Machine learning prediction of performance
- Size dependence

Lattice of interest:

- Properties we care about
- Geometry (As designed and as printed)
- Number of unit cells / Strut thickness

Sources of variation:

- Geometry trying to obtain (printability/angles/sizes)
- Plate location (e.g. focusing, flow, powder spreading)
- Input settings
- Feedstock
- Thermal history (Surrounded by walls?)
- Powder spreader (scraper/roller)
- Build orientation

Features affected by variation:

- Dimensions
- Missing/broken struts (pending the size of lattices, the number and location)
- Geometry deformation (e.g. sagging struts, non-cylindrical struts)
- Surface quality/undercuts (e.g. average properties or)
- Microstructure

Process Parameter Study

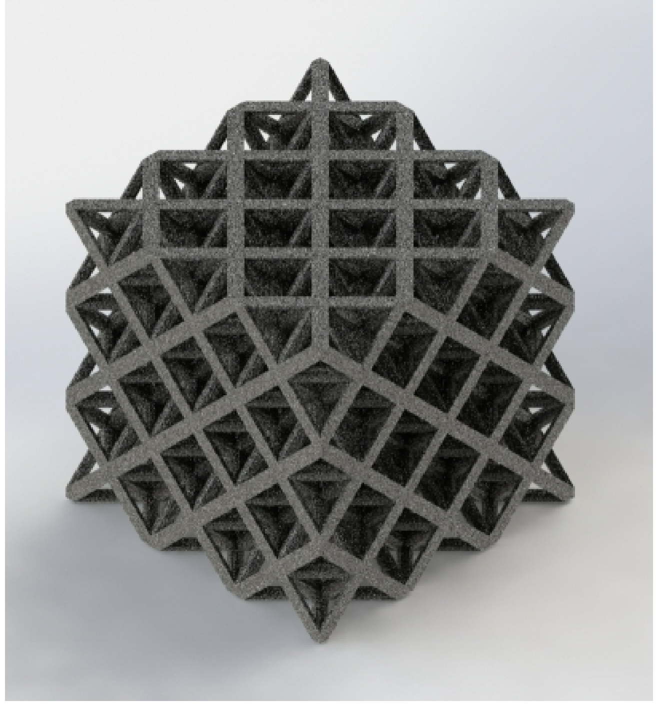
Lattices:

- 48 octets and 43 gyroids
- 3x3x3 unit cell
- 10.5 mm side (3.5 mm unit cell)
- Strut/wall thickness of 0.5 mm
- 4 plates, 2 of each type

Compression Tests

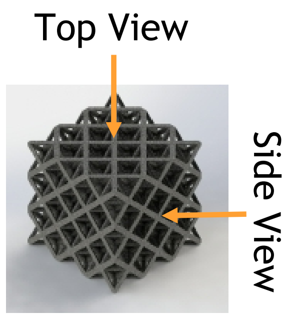
Build parameters

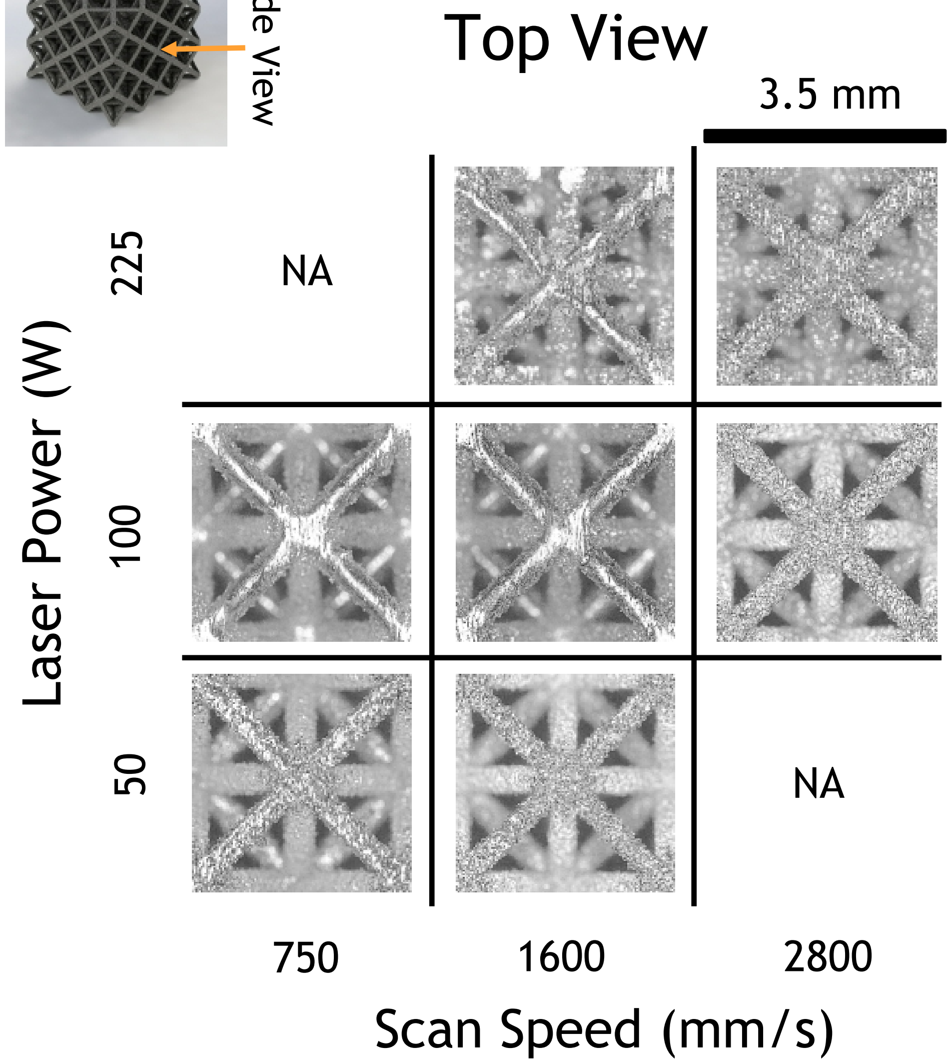
- Laser diameter: ($1/e^2$) of 50 µm
- Layer thickness: 30 µm
- Hatch Spacing 50 µm
- Varied laser power and scan speed

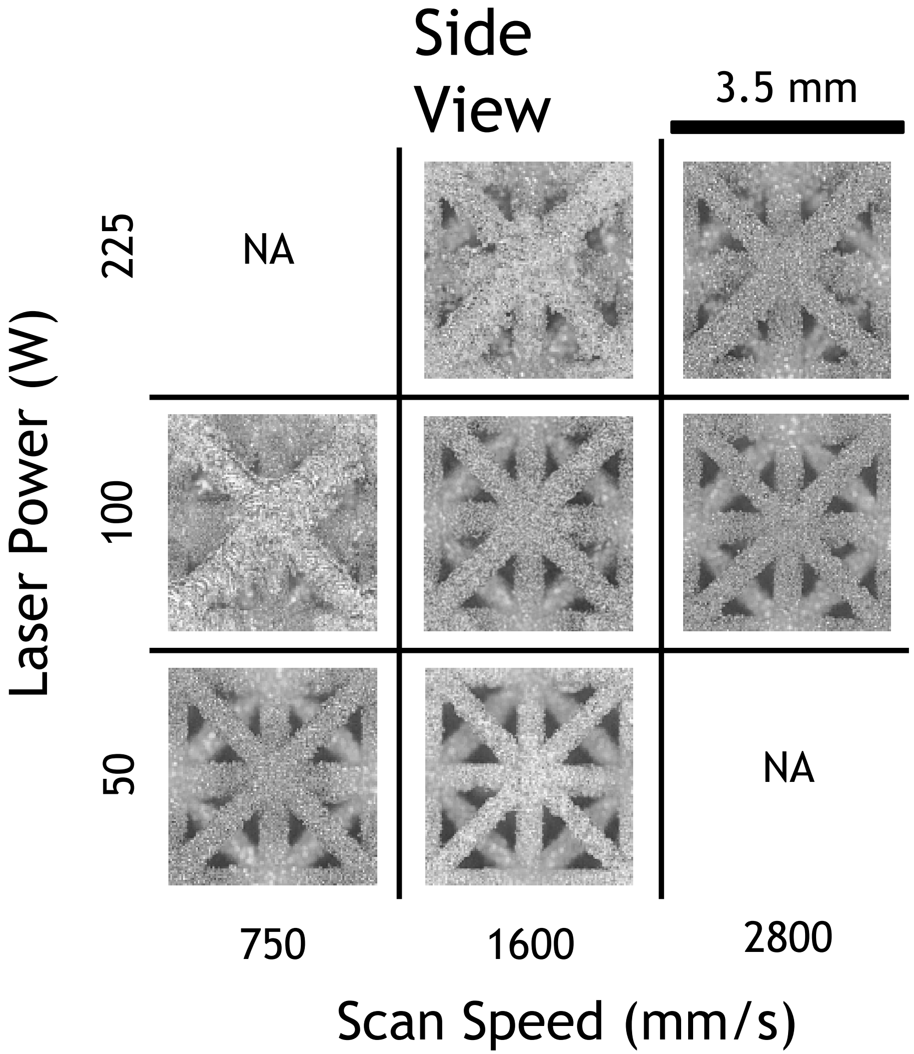


Center Unit Cell On Face (Top/Side)

(Scott Jensen)





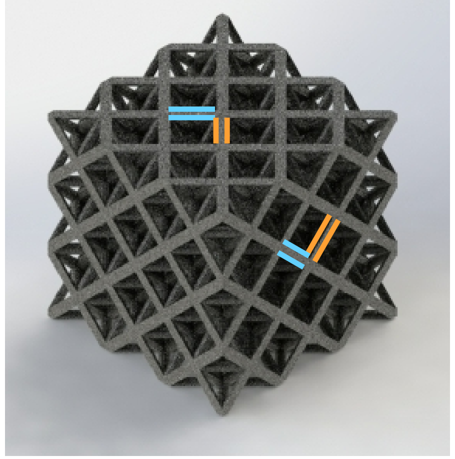


Size Measurements

(Scott Jensen)

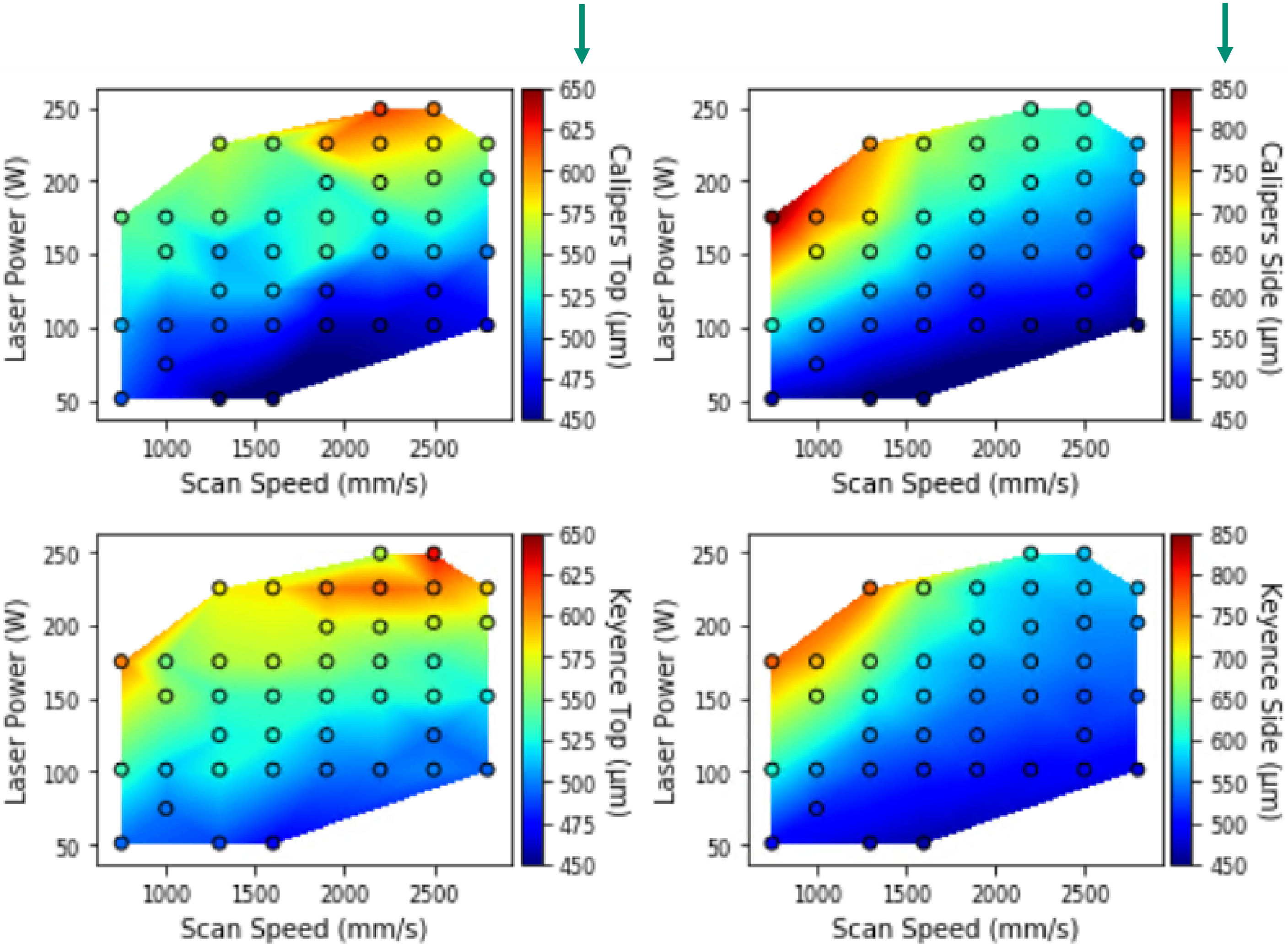
Calipers Top

Measuring in horizontal plane - ignores downskin



Calipers Side

45 degrees from horizontal - partially captures downskin



Caliper Measurements

- 2 Perpendicular struts were measured with calipers on every side
- 4 Sides were averaged

Scale difference in figures

- Top versus side

Keyence used a ratio of area

Strut Type Definitions

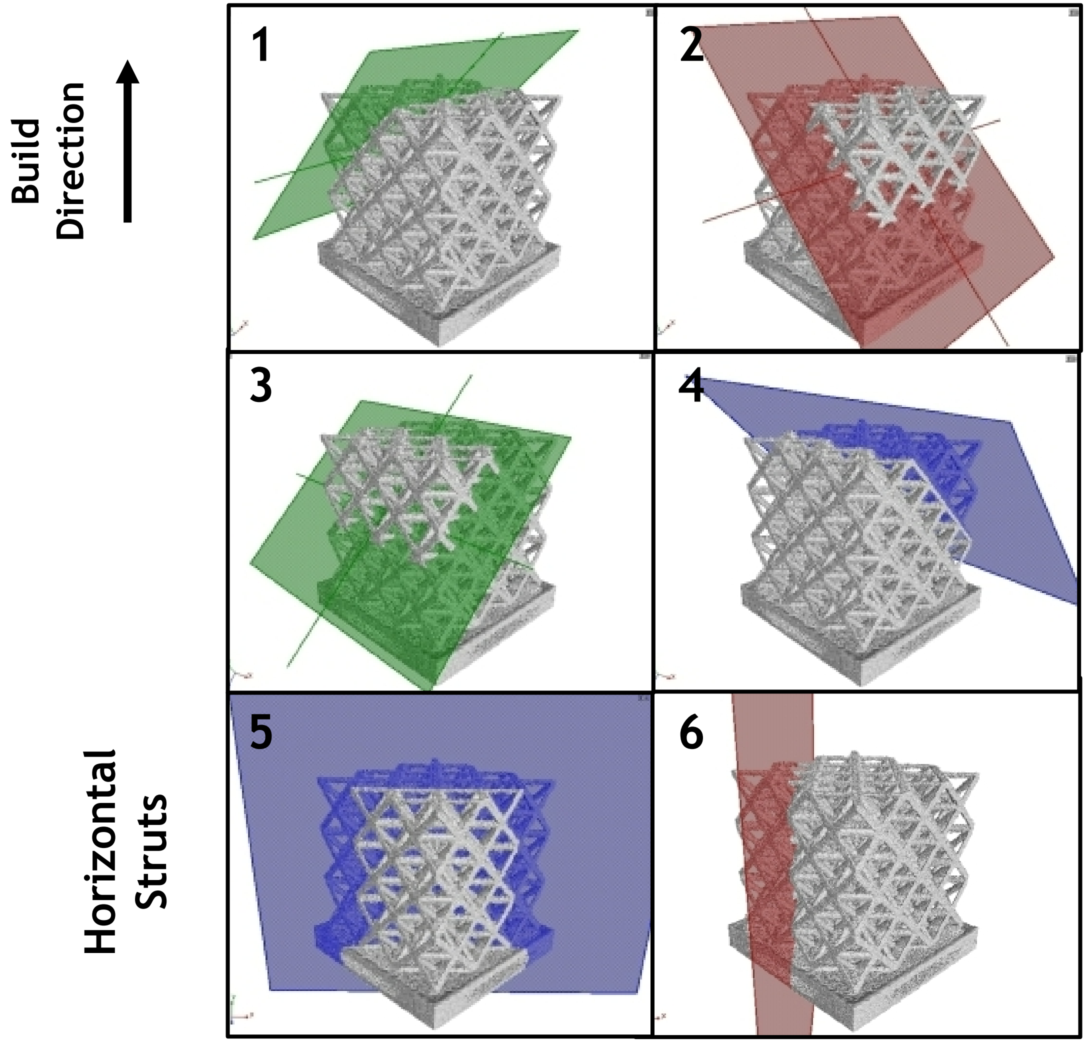
(Josh Elliott)

Each strut type includes all struts parallel to a particular direction

Printing direction: [0,1,0]

Note: Rotation about Y-axis could not be determined, as no features were available to register. This means that strut types 1 and 2 may be mixed up with 3 and 4 for some lattices.

Strut Type	STL Coord. System. Plane Normal Vector
1	[-1, 1, 0]
2	[1, 1, 0]
3	[0, 1, 1]
4	[0, 1, -1]
5	[1, 0, 1]
6	[1, 0, -1]

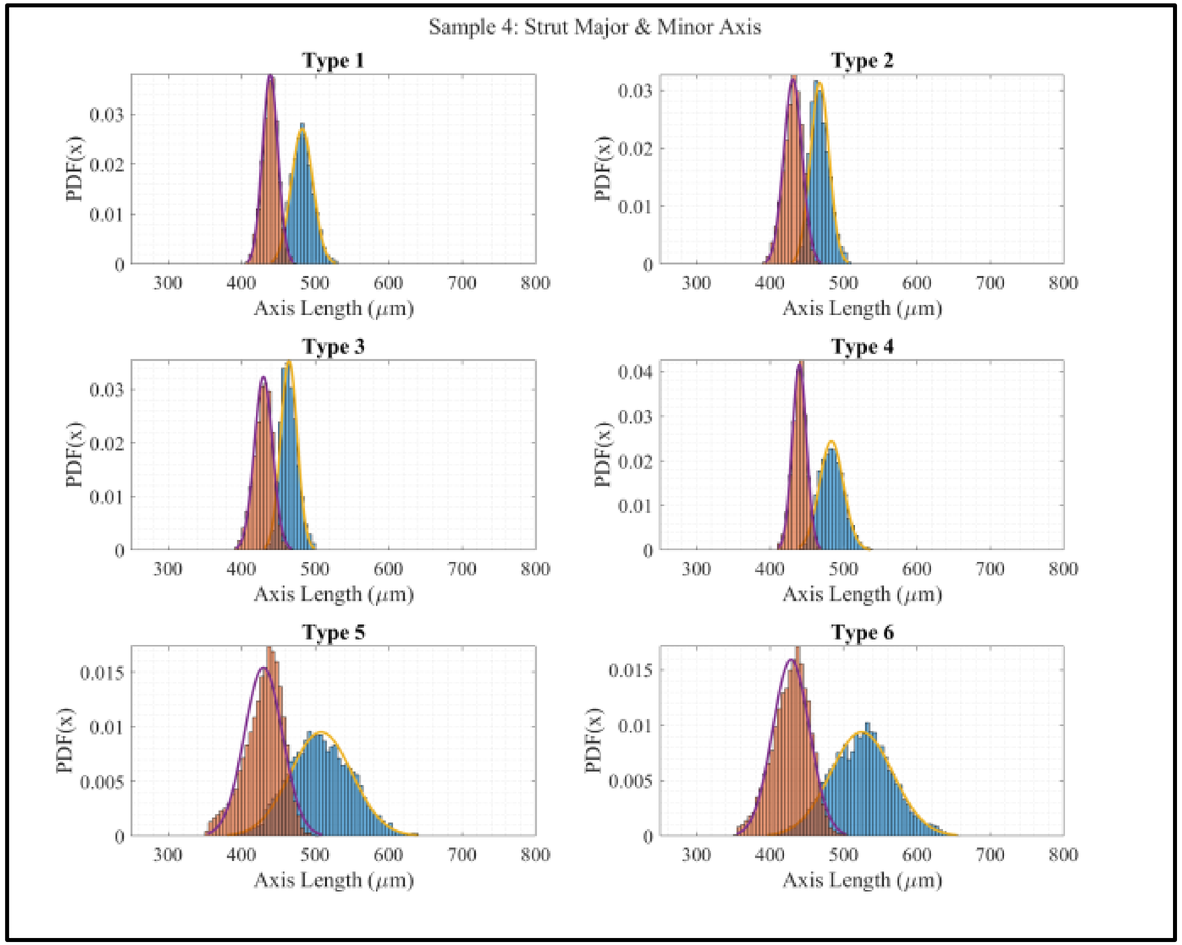


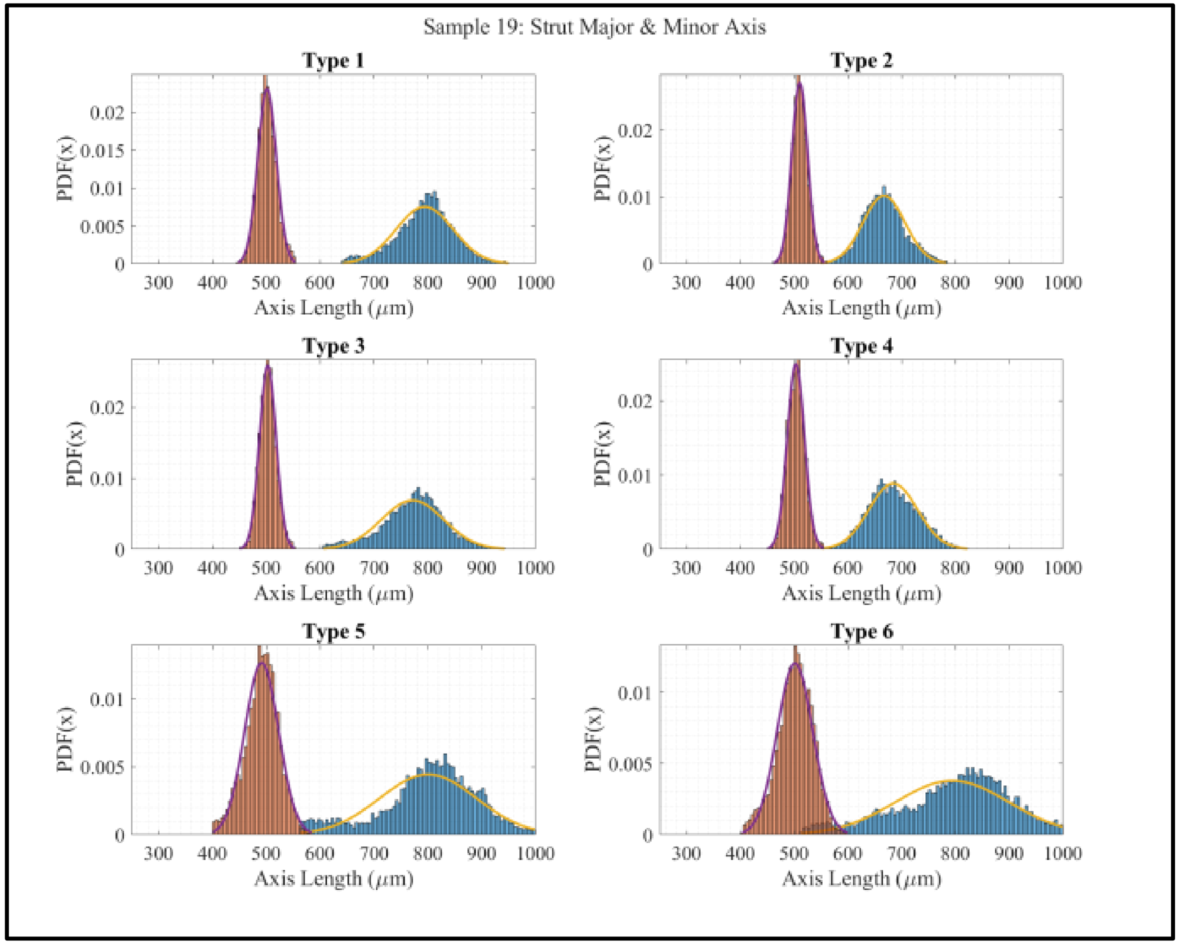
Major and Minor Axis Information

(Josh Elliott)

100 W 2800 mm/s

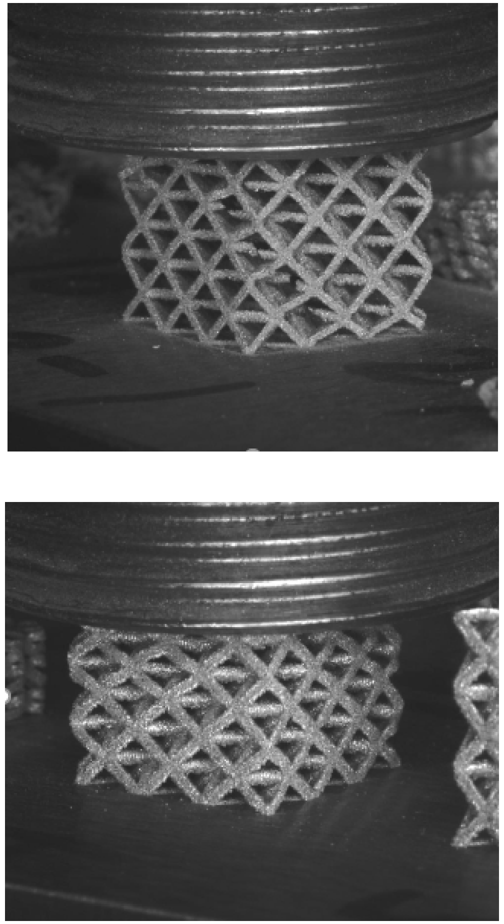
175 W 1300 mm/s

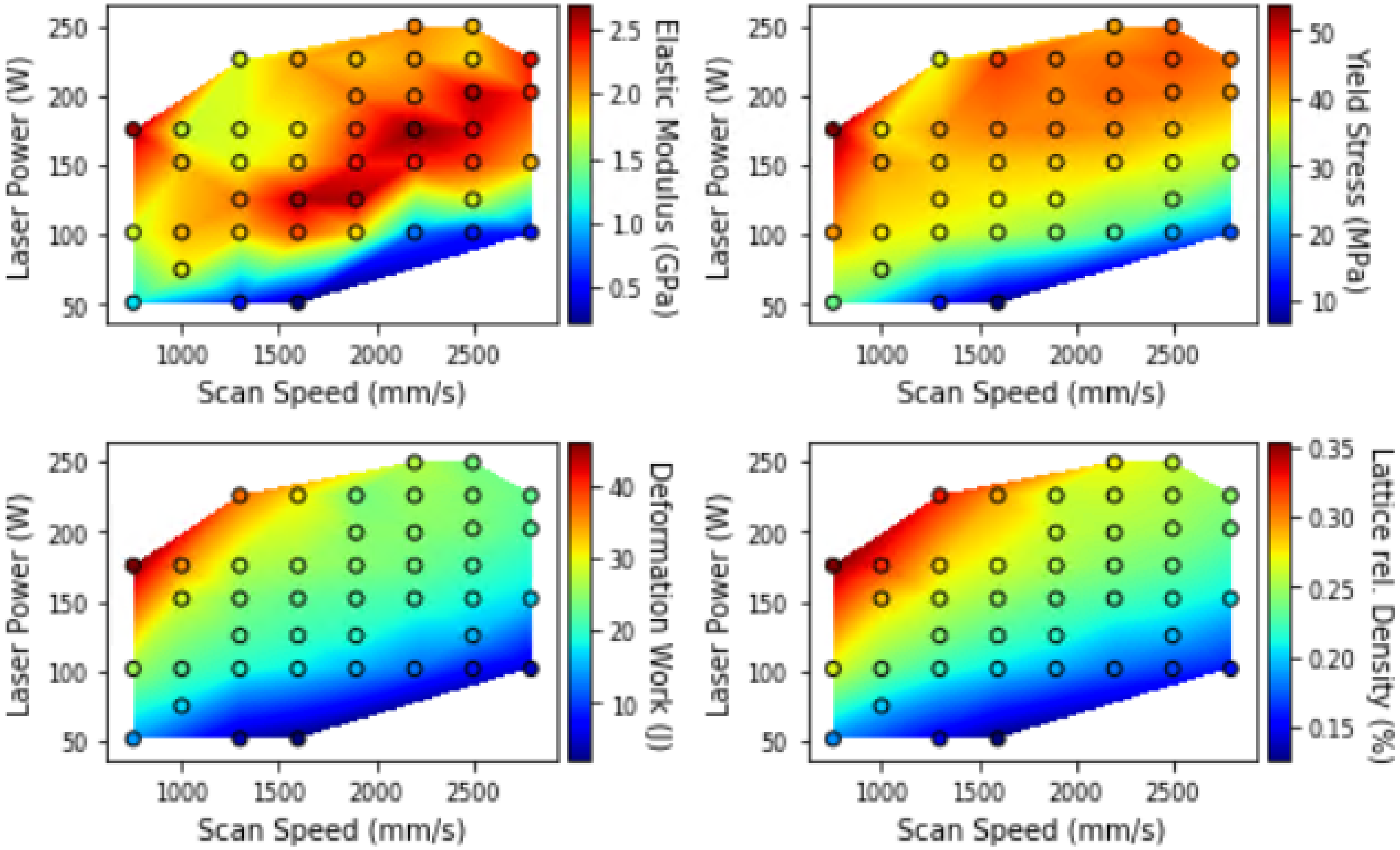




Compression Tests

(Scott Jensen)



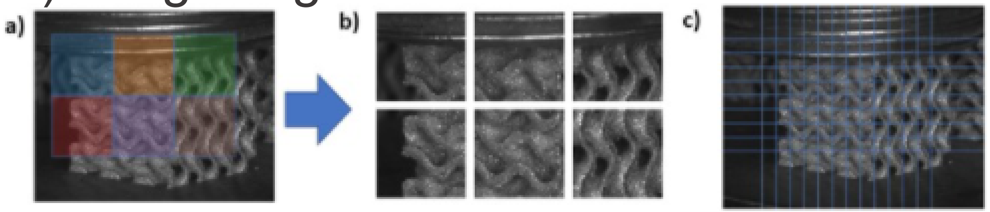


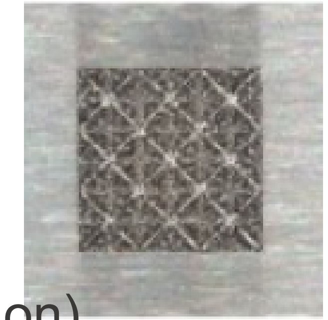
Machine Learning

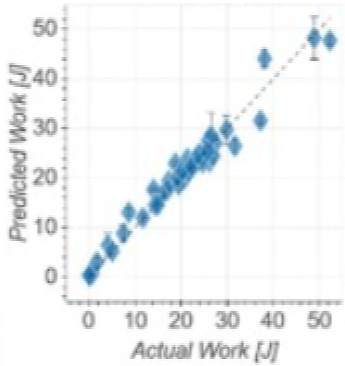
(Anthony Garland)

48 octets and 43 gyroids

1) Image segmentation







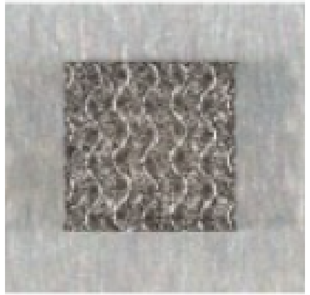
2) Normalize distribution to gaussian (quantile normalization)

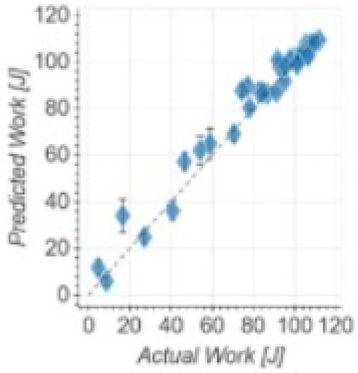
3)Trained the ML - Resnet16 (Fastai)

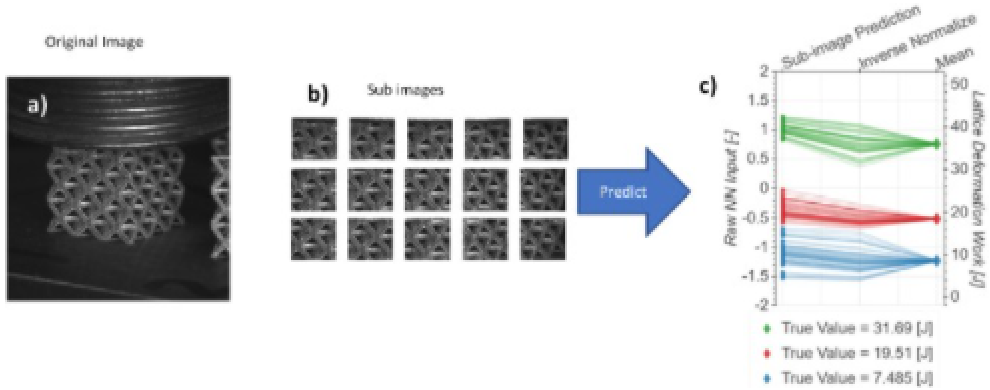
- Changed kernel convolution weights

4) Reverse Normalization and Average output

- 45 windowed images



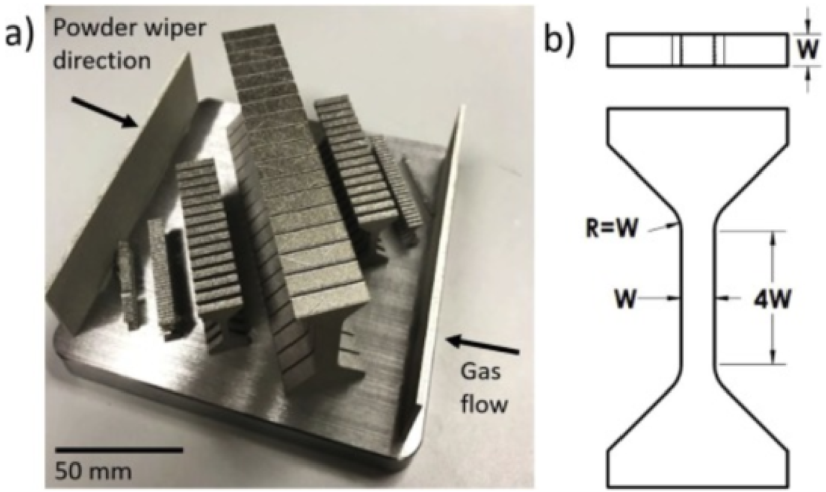


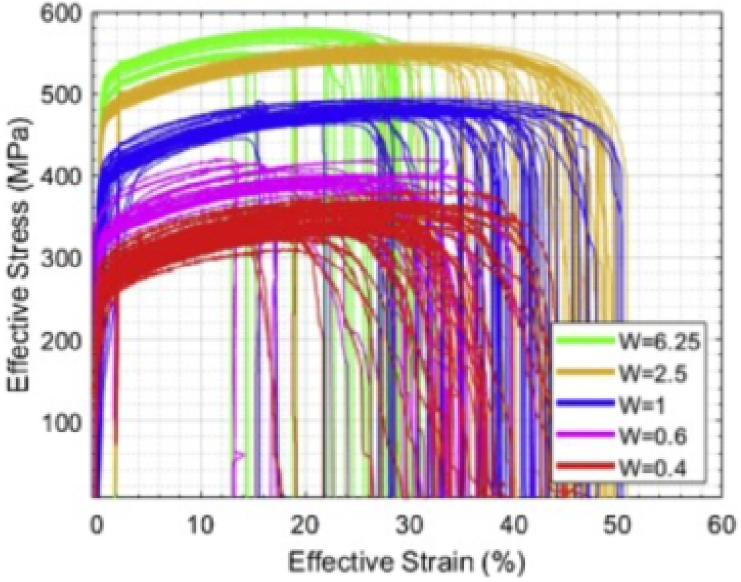


https://doi.org/10.1016/j.addma.2020.101217

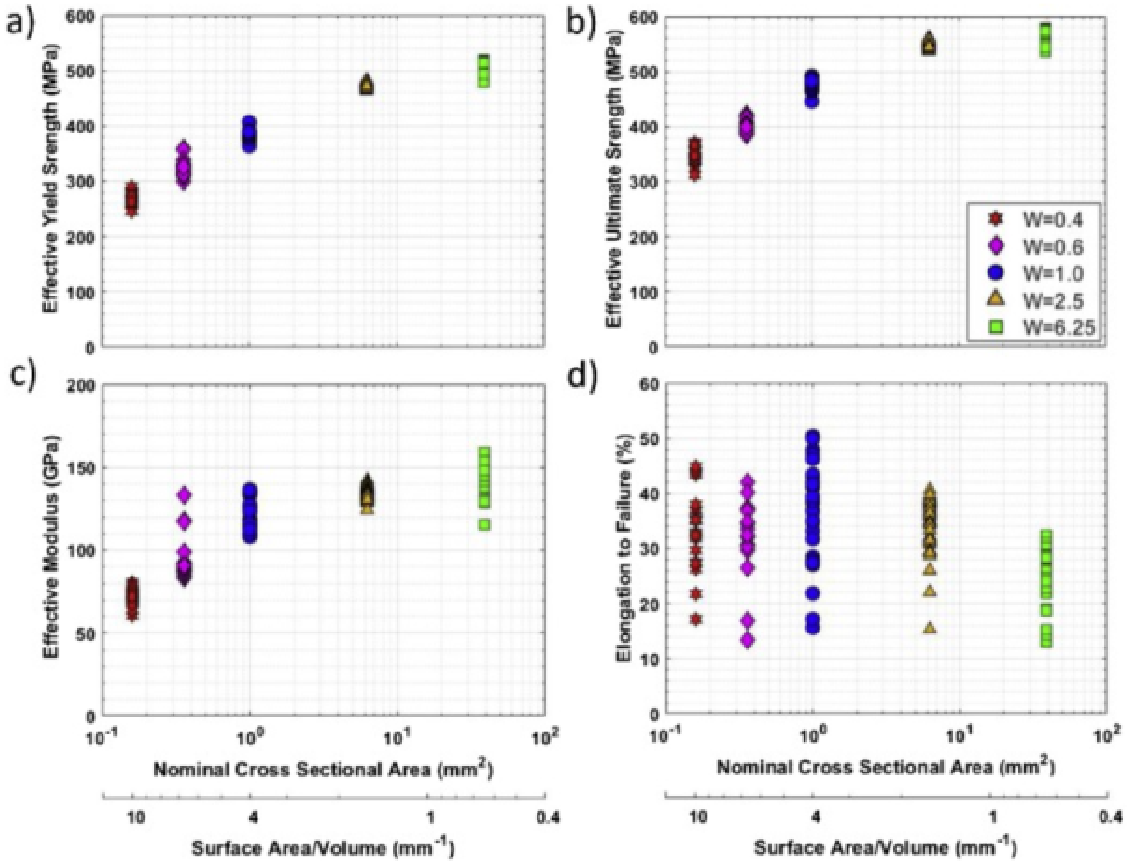
Size Dependence

(Brad Boyce)





Surface/voids are responsible for the drop in properties



https://doi.org/10.1016/j.addma.2020.101090

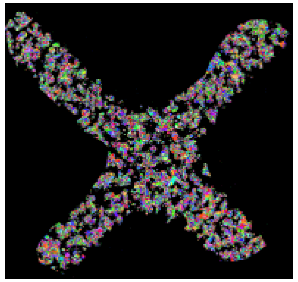
Microstructure

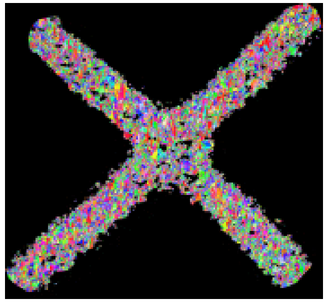
(Tim Ruggles)

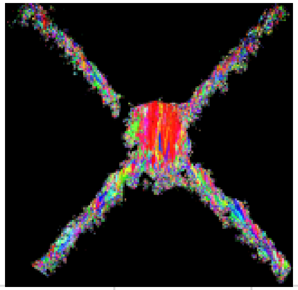
Investigate the microstructure of several samples created with a range of processing parameters (laser speed and power).

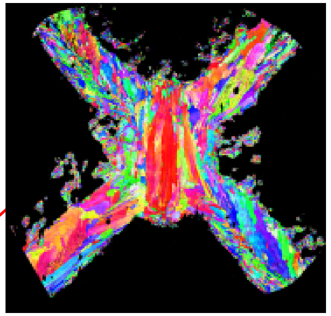
Characterize the microstructure with EBSD.

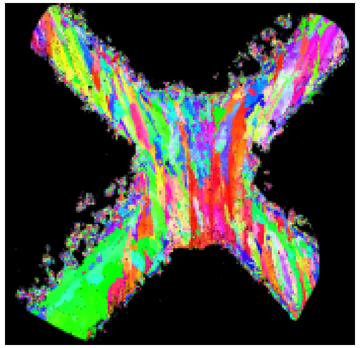
Use machine learning to relate this microstructure to processing parameters and/or material properties

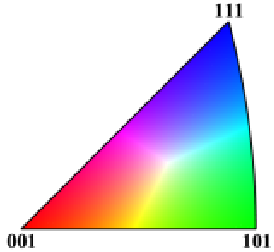


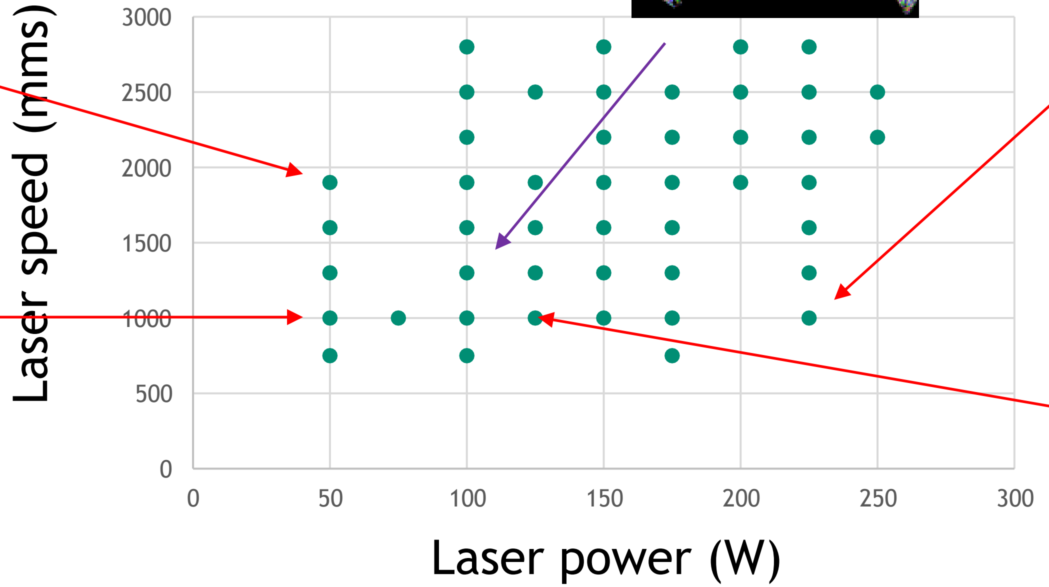










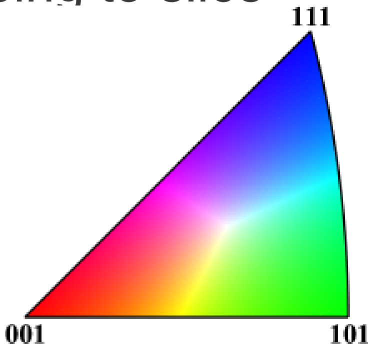


(Tim Ruggles)

Microstructure at nominal parameters (113 W, 1400 mms)

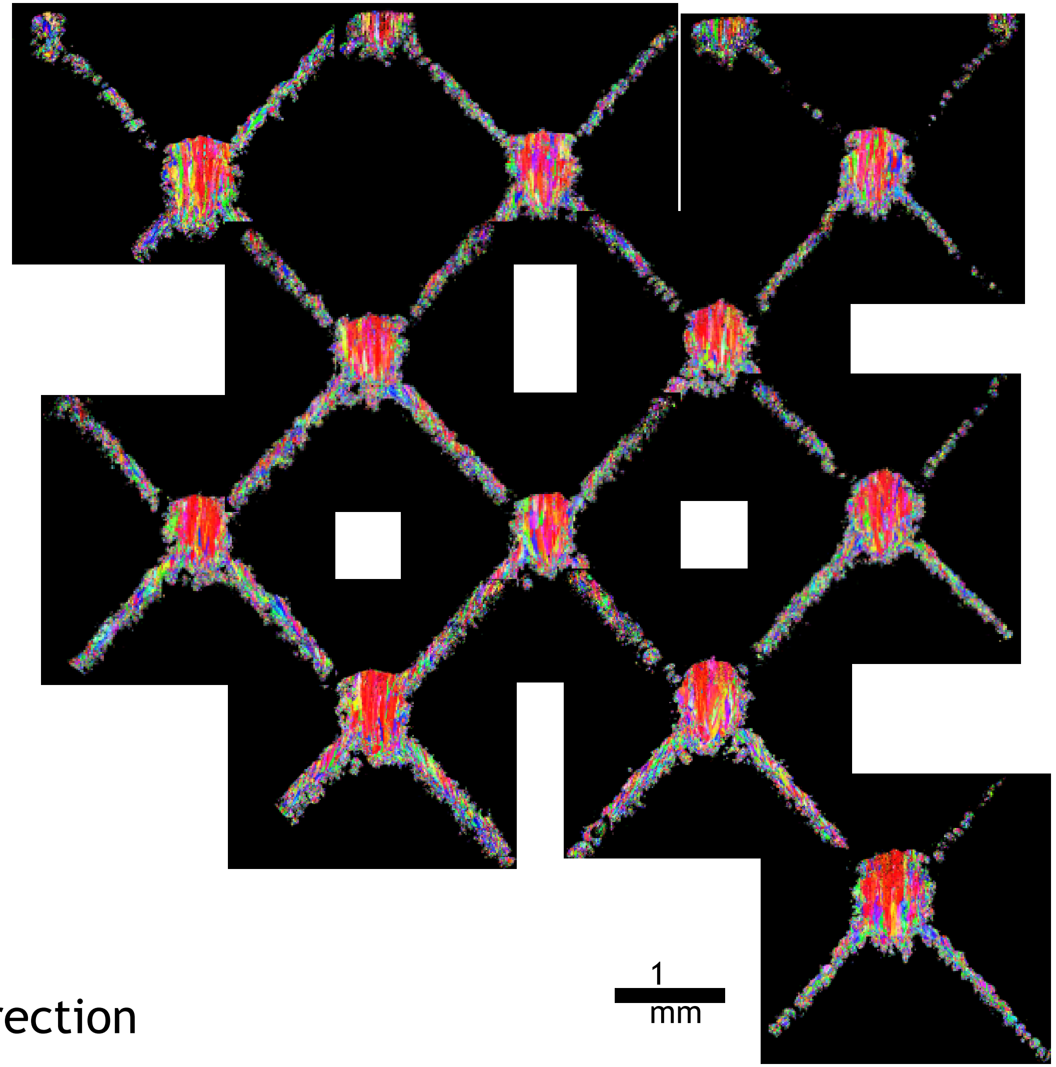
Microstructure was found to be relatively consistent between nodes.

Material preparation is not trivial (the goal being to slice through the mi



IPFX

Growth Direction



Conclusions

Surface/geometry metrics are not well defined and are convoluted in off-nominal cases

Measuring metrics
- Calipers capture same trends/changes in strut size as high magnification optical images across process space
- Hard to capture defects without CT
- High asymmetry exist in all struts especially at larger power density

Machine learning has been demonstrated to capture lattice performance (compression energy) from 2d images and may be applied to obtain other properties as well
- Some features may not correlate with outside surface images (internal features)
- Need to consider if there are bad struts and if they are in the images

Defects are going to be driving tensile properties unless struts are much larger
- For lattices with more unit cells the variability of single struts likely averages out
- It's unclear what is better, more or thicker struts given a specific density

Microstructure is highly variable across the process space
- Process dependent grain size
- Nodes have large grain growth vs struts whose thinner members limit seeding/growth
- Outer surface appears to have smaller grains

Questions?

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