

MLDL

This paper describes objective technical results and analysis. Any subjective views or opinions that might be expressed in the paper do not necessarily represent the views of the U.S. Department of Energy or the United States Government.

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MLDL

Machine Learning and Deep Learning Conference 2022

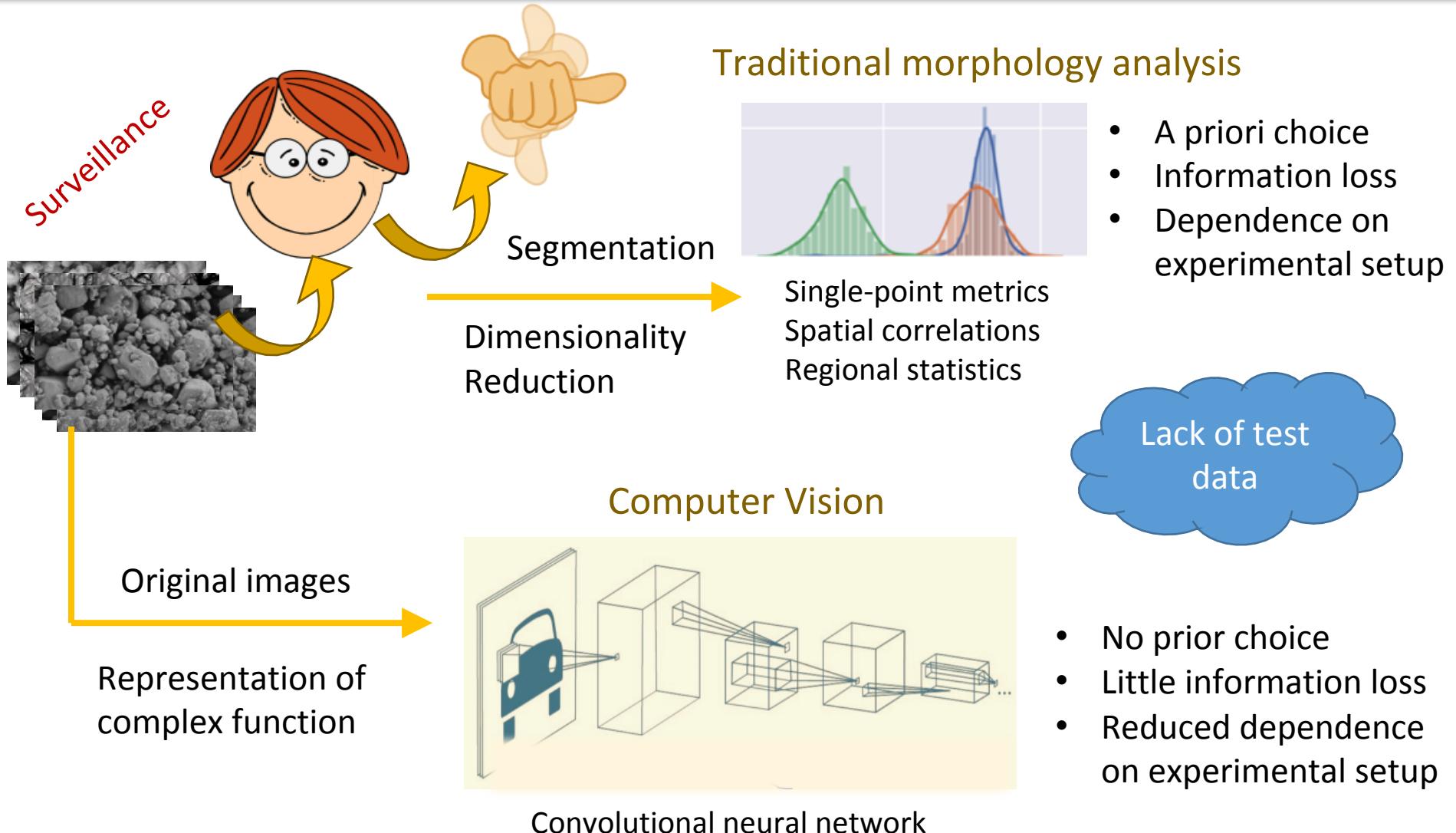
Utilization of the critic subnetwork of a generative adversarial network as detector of morphological material change in image data

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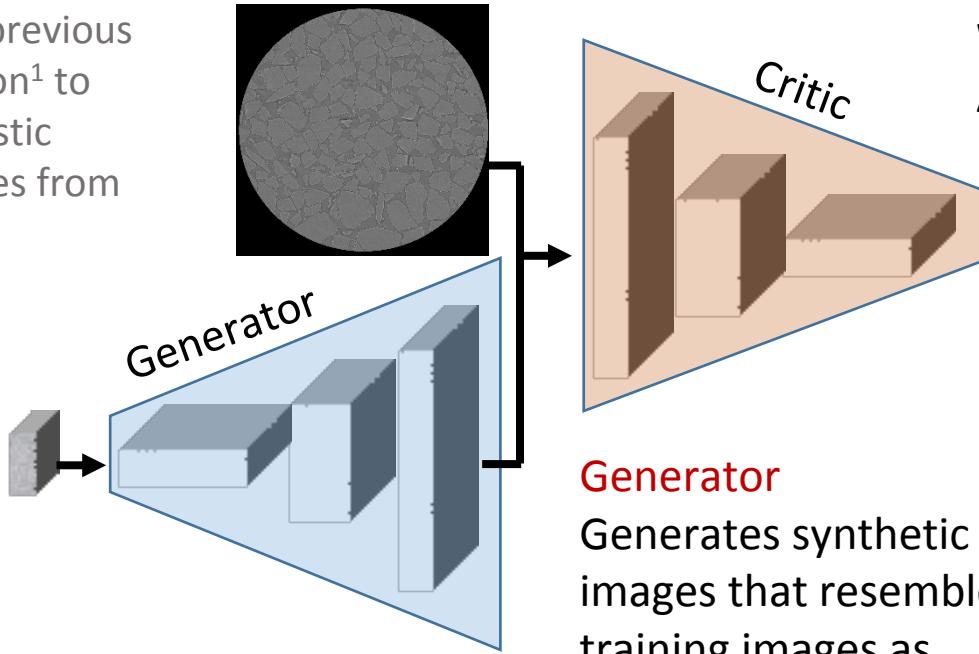
FY22 Exploratory Express LDRD, Project 226346

Problem



Algorithmic Approach

Utilization of previous implementation¹ to generate realistic microstructures from SEM images



Generator

- 3 up-sampling/convolutional (ReLU)/batch normalization layers, 1 convolutional (Tanh) layer
- Filters 256-128-64-32

Critic

- 7 convolutional layers (LeakyReLU)
- Filters 32-32-64-64-128-128-256

Wasserstein Generative Adversarial Network (WGAN)

Critic

Scores generated images according to how well they resemble the training images

Generator

Generates synthetic images that resemble training images as closely as possible

Critic and generator **trained** together with images of **pristine material**

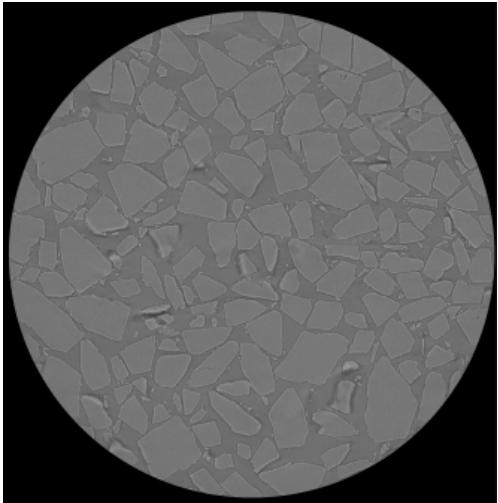
Critic **tested** with images of potentially **altered material** morphology -> Image scores

Data

Training

CT scan of pristine Pharmatose

- 1800 2d images
- Each 2d image 2,000x2,000 pixels
- Batch: 64 down-sampled (1/4)
512x512 cropped segments

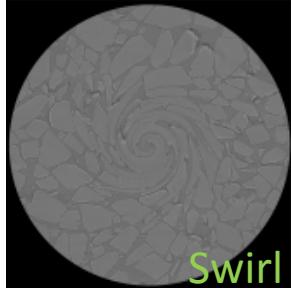


HMX microstructure generation with single 3,000x3,000 pixel SEM image ¹

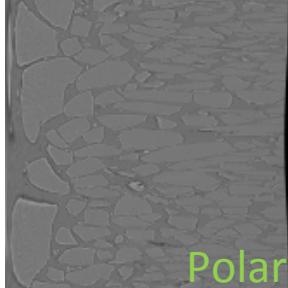
¹ Chun, S., et al., *Deep learning for synthetic microstructure generation in a materials-by-design framework for heterogeneous energetic materials*. *Scientific Reports*, 2020. **10**(1).

Testing

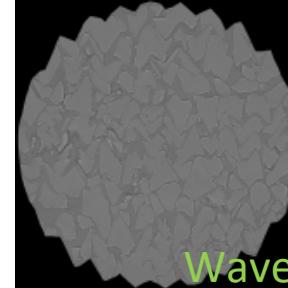
Image Transformations



Swirl

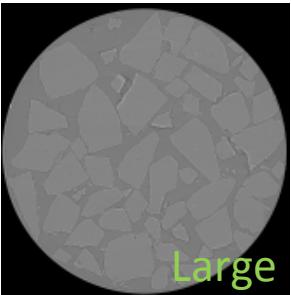


Polar

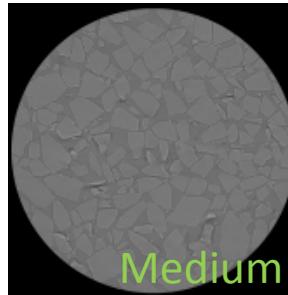


Wave

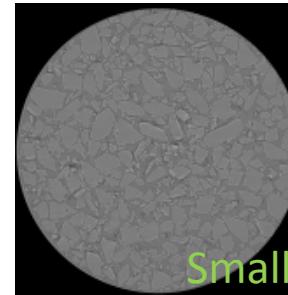
Varying Particle Sizes



Large

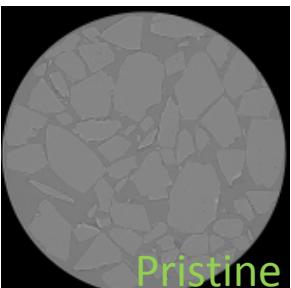


Medium

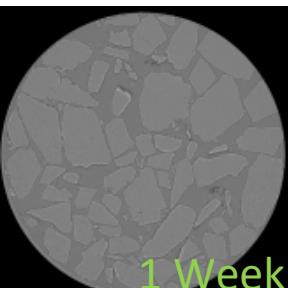


Small

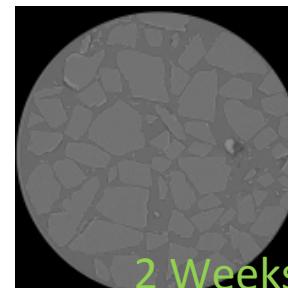
Aged Material (120°C)



Pristine



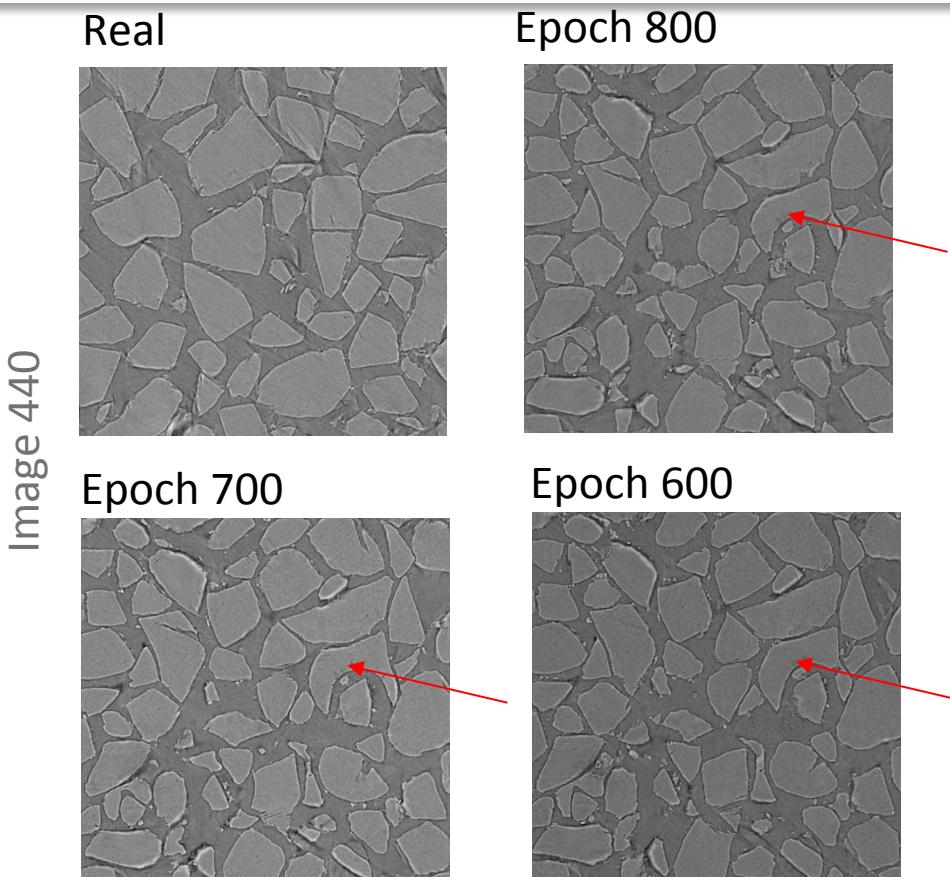
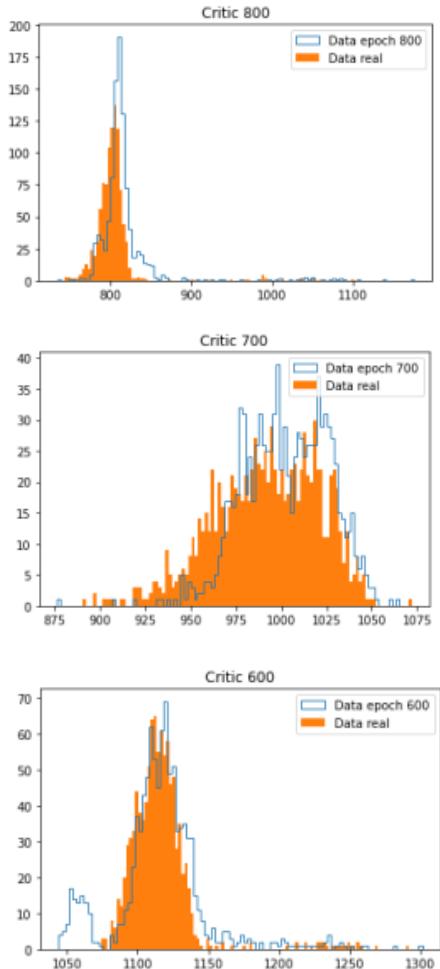
1 Week



2 Weeks

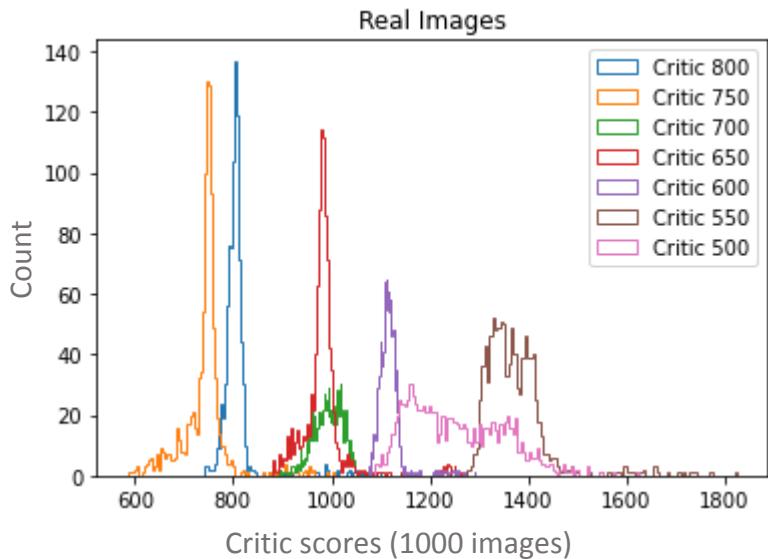
Results – Image Generation

Critic scores (1000 images)

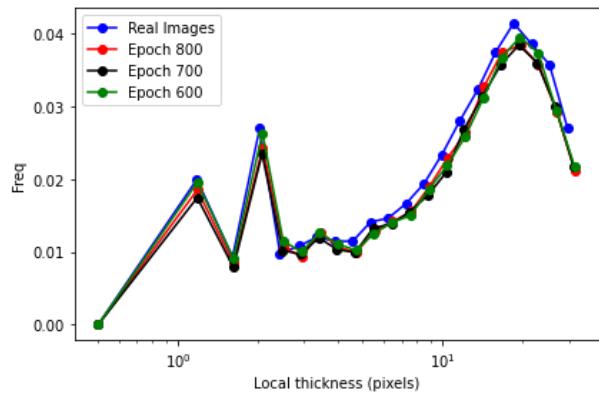


- For a given epoch, the critic scores real and fake images similarly
- Scores vary significantly between epochs
- “Blobs” in fake images don’t seem to improve
- Training restriction 512x512 pixels image size

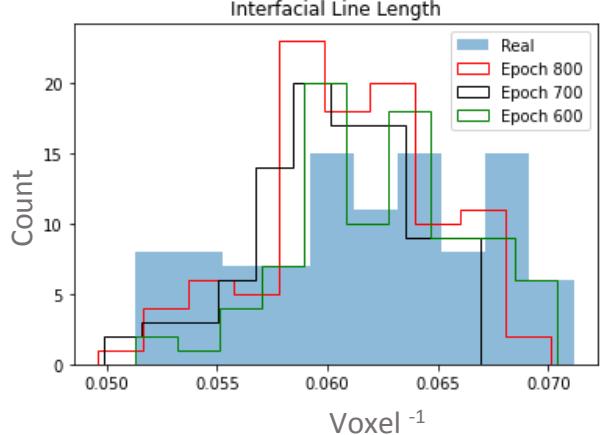
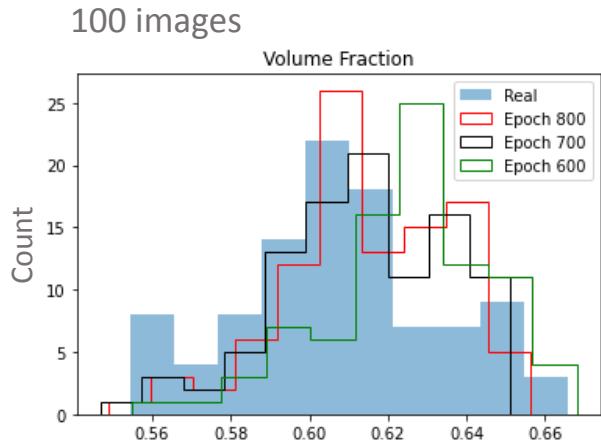
Results – Image Generation



Converging?

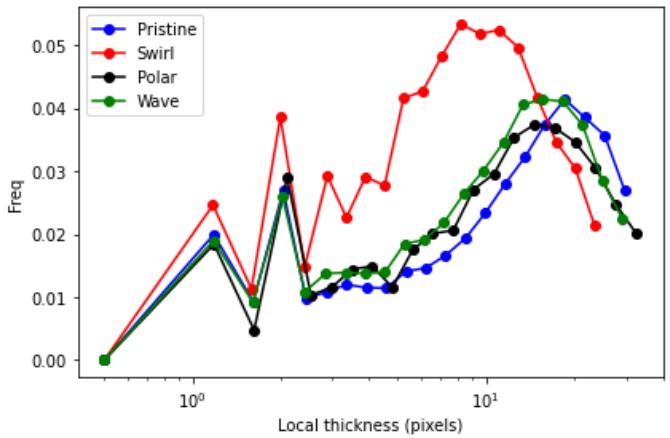
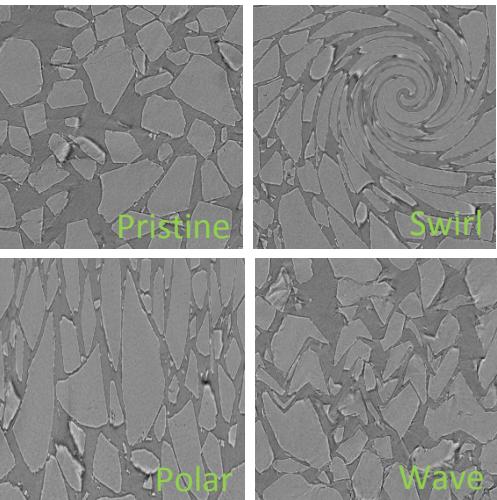
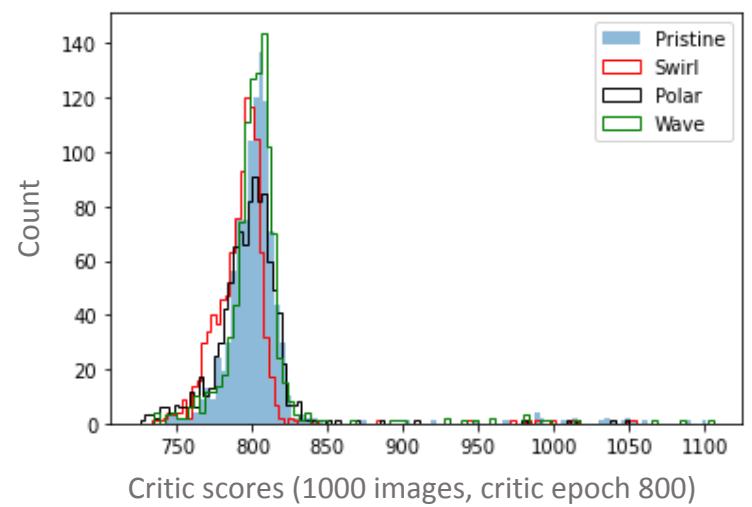


Despite “blobs”
image properties
appear to be
well reproduced



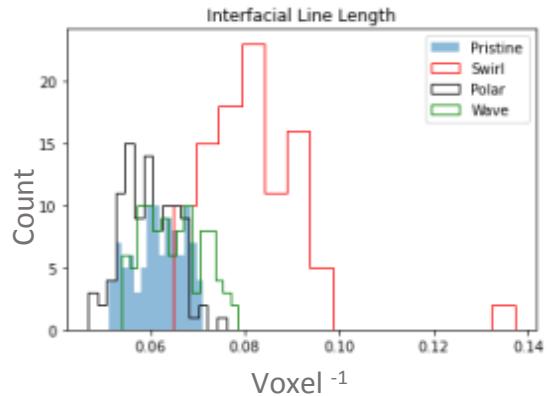
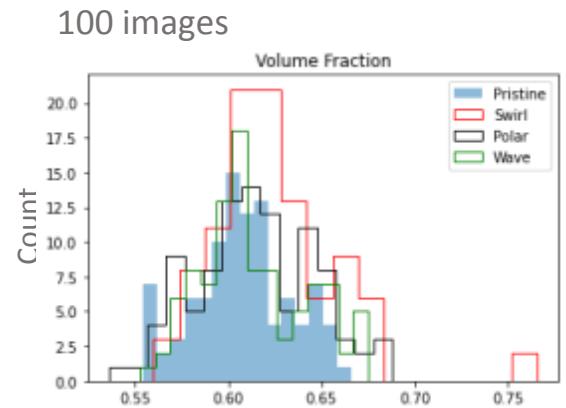
- Volume fraction: epoch 800 closest to real images
- Interfacial line length: different epochs similar distribution

Results – Scores for transformed images

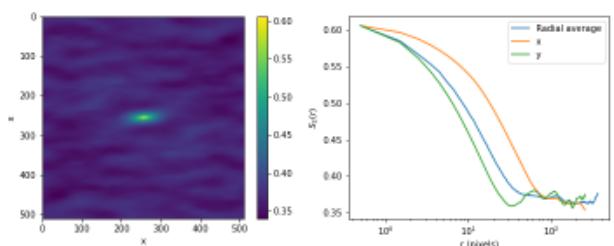


7/7/2022 4:01 PM

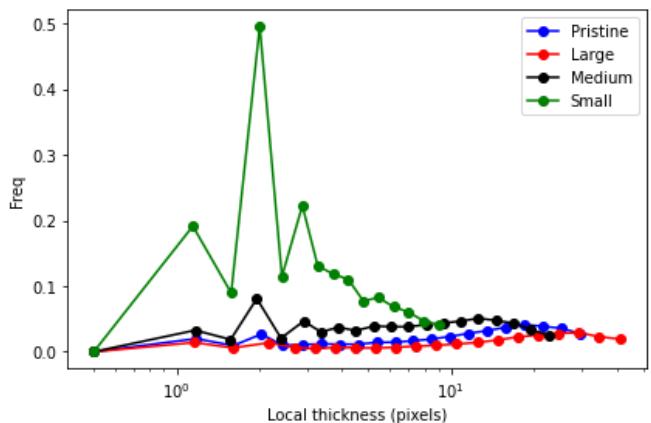
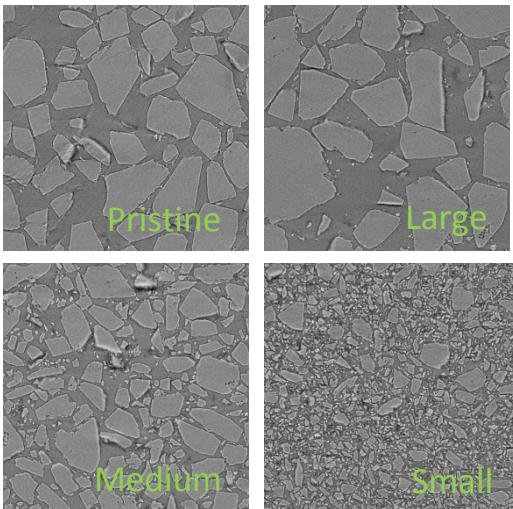
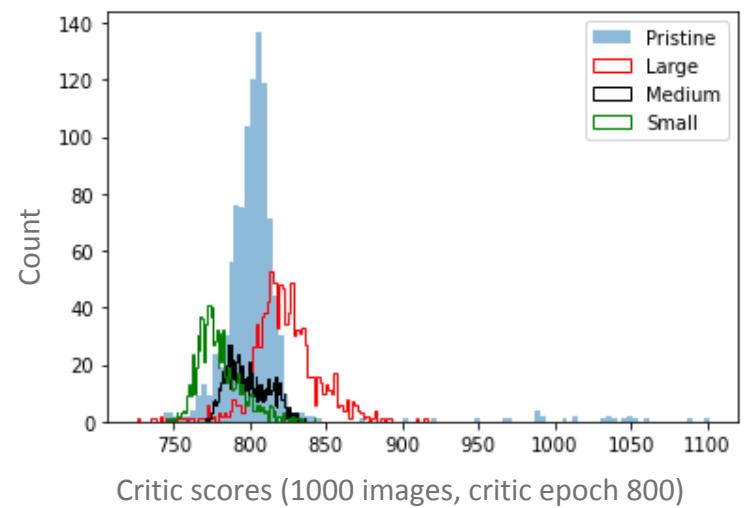
Although there is some response, critic is not sensitive enough to pick up differences in particle shape



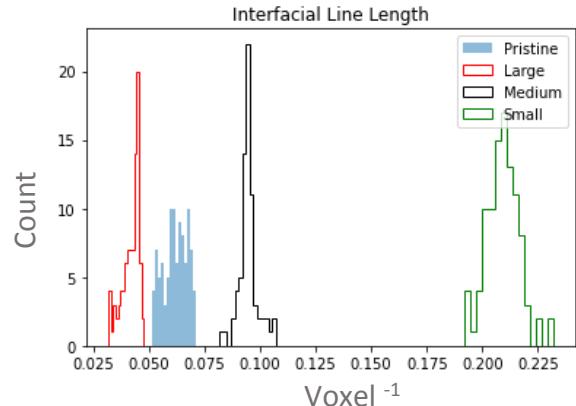
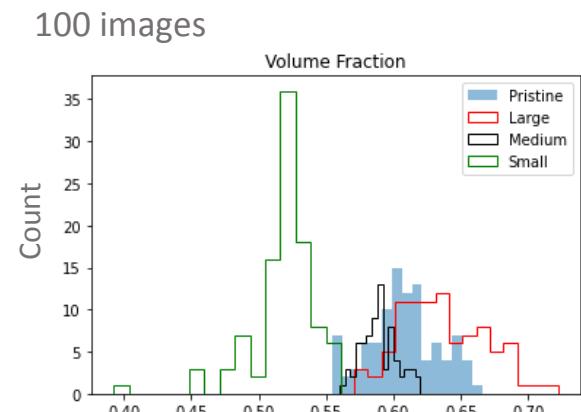
Two-point correlation function
Example image, polar transformation



Results – Scores for varying particle sizes



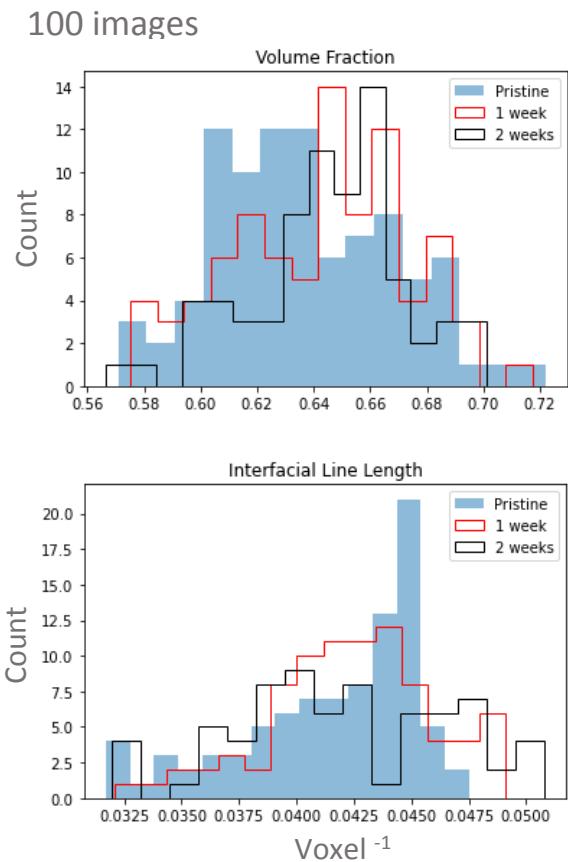
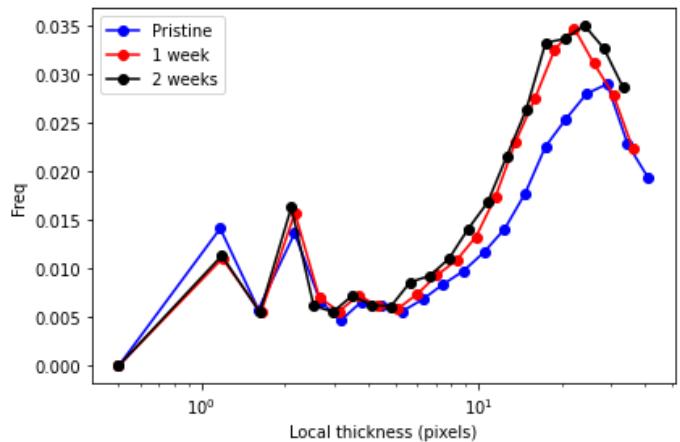
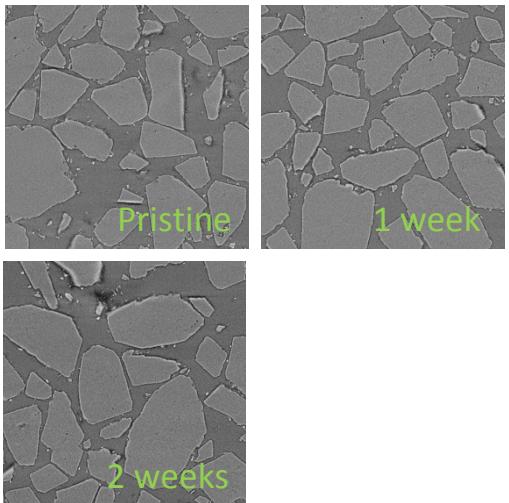
Critic scores images of different particle sizes differently and in consistent order



Results – Scores for aged data

- Network training in progress
- Scores will be available soon

Unlikely, that critic scores can differentiate between materials ...



Only subtle differences between pristine and aged material using traditional metrics.

Conclusions

Concept works, the critic of a GAN can be used as a detector of morphological change but significant improvements needed before the critic can be used in practice:

- Image generation without “blobs”
- Increase critic sensitivity
- Increase of training image size

Help (ideas, collaborations) from ML/DL community very much appreciated

Potentially interested customers: NA-193, Aging & Lifetimes