



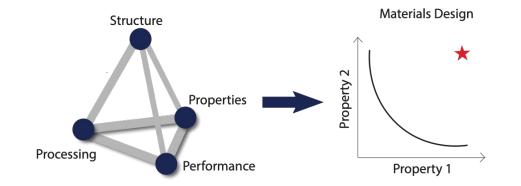
# Learning microstructure—property relationships in materials with robust features from vision transformers

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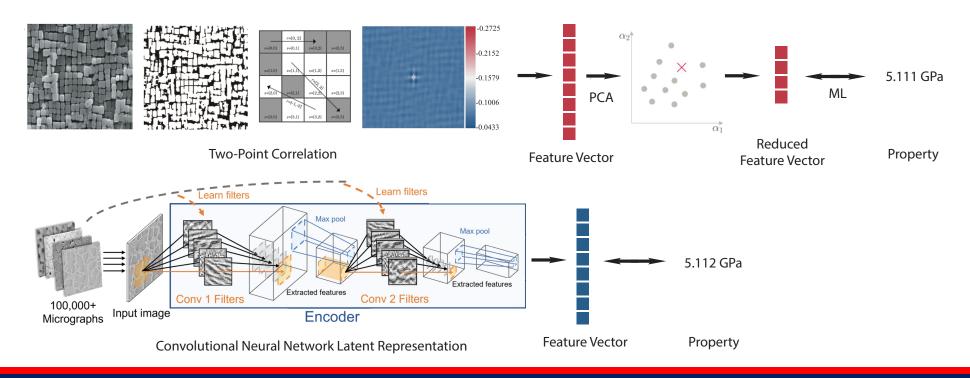
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## Microstructure-Property Relationships



Program in Applied Mathematics

- Design of structural alloys relies on quantitative understanding of microstructure–property relationships.
- Machine learning can be used to accelerate the design process.
- Quantitative descriptions of microstructures are needed to utilize machine learning.



#### Program in Applied Mathematics A

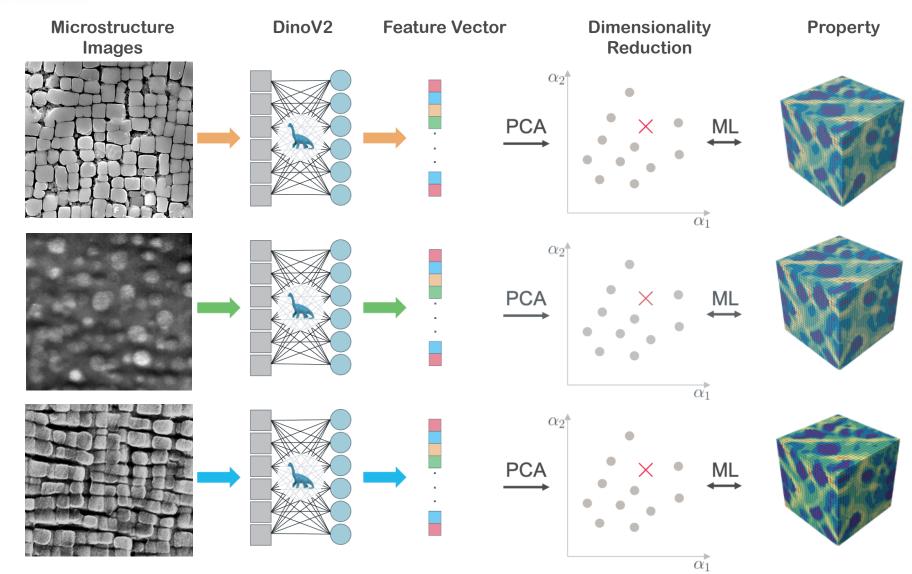




|              | NYU<br>(0.33 |        |        |       |        | KITTI<br>(2.10) |                      |         | $\begin{array}{c} \text{NYUd} \rightarrow \text{SUN RGB-D} \\ (0.421) \end{array}$ |          |  |
|--------------|--------------|--------|--------|-------|--------|-----------------|----------------------|---------|------------------------------------------------------------------------------------|----------|--|
| Method       | Arch.        | lin. 1 | lin. 4 | DPT   | lin. 1 | lin. 4          | DPT                  | lin. 1  | lin. 4                                                                             | DPT      |  |
| OpenCLIP     | ViT-G/14     | 0.541  | 0.510  | 0.414 | 3.57   | 3.21            | 2.56                 | 0.537   | 0.476                                                                              | 0.408    |  |
| MAE          | ViT-H/14     | 0.517  | 0.483  | 0.415 | 3.66   | 3.26            | 2.59                 | 0.545   | 0.523                                                                              | 0.506    |  |
| DINO         | ViT-B/8      | 0.555  | 0.539  | 0.492 | 3.81   | 3.56            | 2.74                 | 0.553   | 0.541                                                                              | 0.520    |  |
| iBOT         | ViT-L/16     | 0.417  | 0.387  | 0.358 | 3.31   | 3.07            | 2.55                 | 0.447   | 0.435                                                                              | 0.426    |  |
| DINOv2       | ViT-S/14     | 0.449  | 0.417  | 0.356 | 3.10   | 2.86            | 2.34                 | 0.477   | 0.431                                                                              | 0.409    |  |
|              | ViT-B/14     | 0.399  | 0.362  | 0.317 | 2.90   | 2.59            | 2.23                 | 0.448   | 0.400                                                                              | 0.377    |  |
|              | ViT-L/14     | 0.384  | 0.333  | 0.293 | 2.78   | 2.50            | 2.14                 | 0.429   | 0.396                                                                              | 0.360    |  |
|              | ViT-g/14     | 0.344  | 0.298  | 0.279 | 2.62   | 2.35            | 2.11                 | 0.402   | 0.362                                                                              | 0.338    |  |
| PNAN         |              |        |        | 2     |        |                 |                      |         | - may                                                                              | - Maria  |  |
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| SUN-RGBd     | BR           |        |        | 7     |        |                 | 12<br>10<br>10<br>10 | Le      |                                                                                    | Ł        |  |
| KITTI SUN-RG |              |        |        |       |        |                 |                      |         |                                                                                    |          |  |



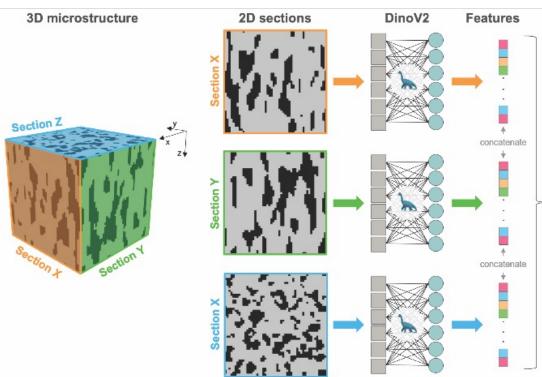
## Methodology



## Case Study 1 – Young's modulus from simulations

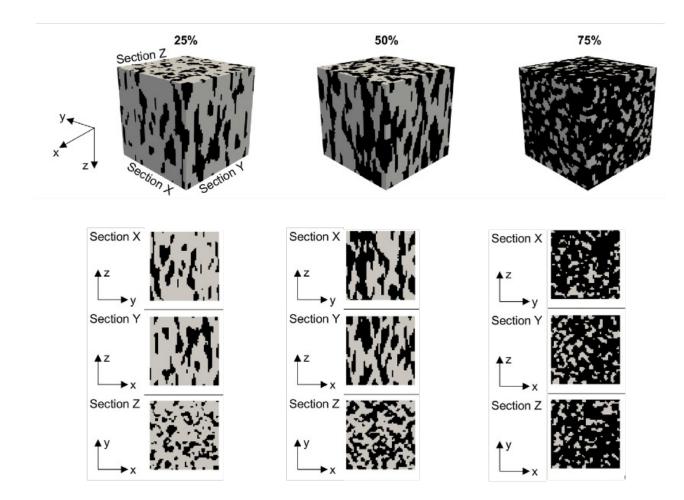
5900 x 3 slices of simulated microstructures\* and their corresponding Young's moduli

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Feature aggregation from 2D sections:

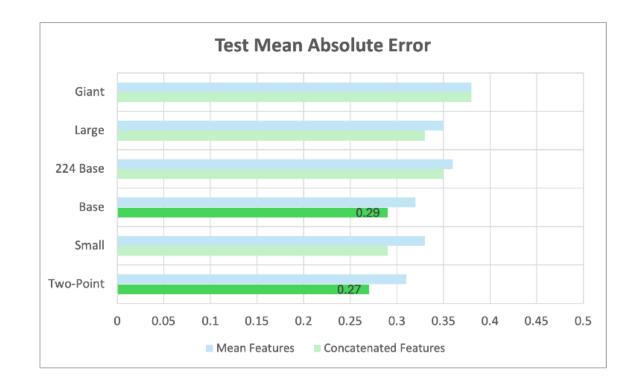
- concatentation
- mean pooling

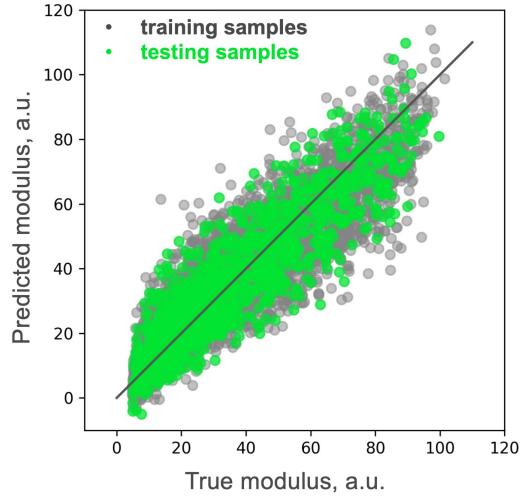




#### Case Study 1: Results

• The best DinoV2 model is the base model with 17 principal components of concatenated (3 · 768) features.





Parity plot showing the prediction results of the base DinoV2 model.

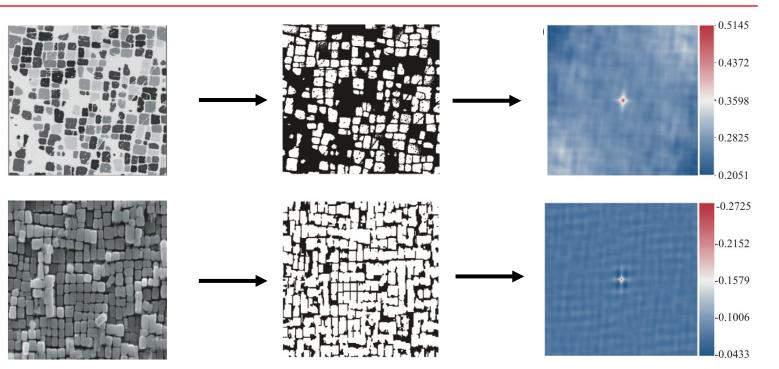


## Digital Data vs. Experimental Data

The digital microstructures are already binary images.

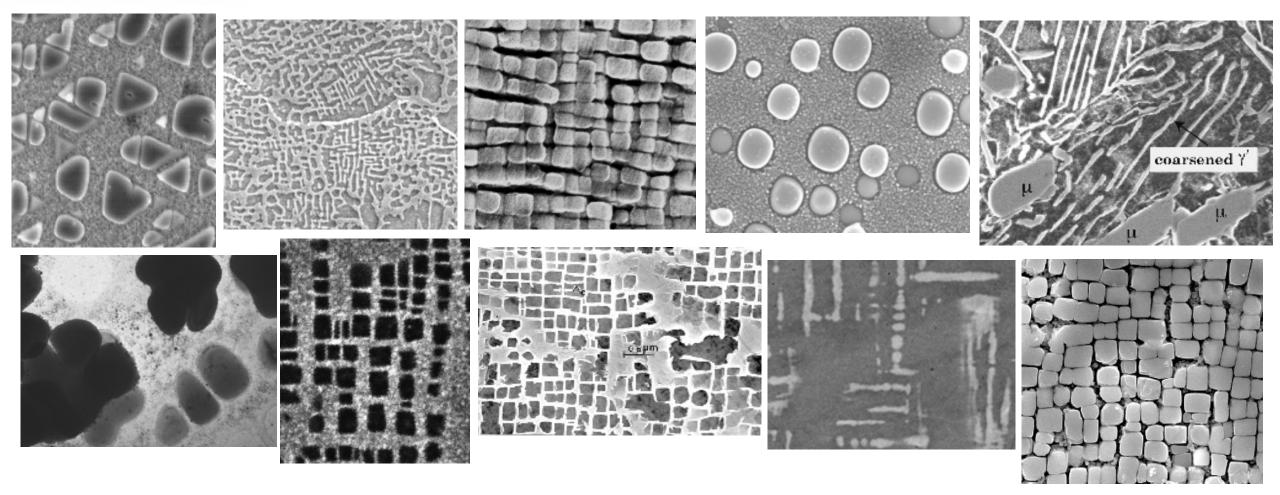


The experimental microstructures are greyscale images, which require additional steps for calculating two-point correlations.





#### Case Study 2 – Hardness from experiments



103 experimental microstructures and their corresponding Vickers Hardness values

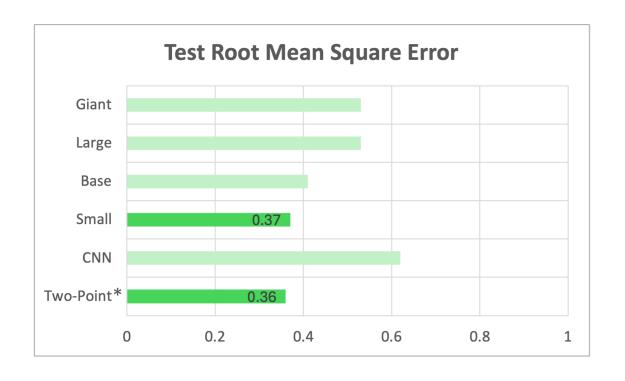
Zhang et al. 2018. Bocchini et al. 2017. Yan et al. 2014. Mitchell et al. 2008. Zhong et al. 2013. Hongyu et al. 2010. Mignanelli et al. 2014. Huda 2009. Peng et al. 2018. Barbosa et al. 2005. Murr et al. 2013.

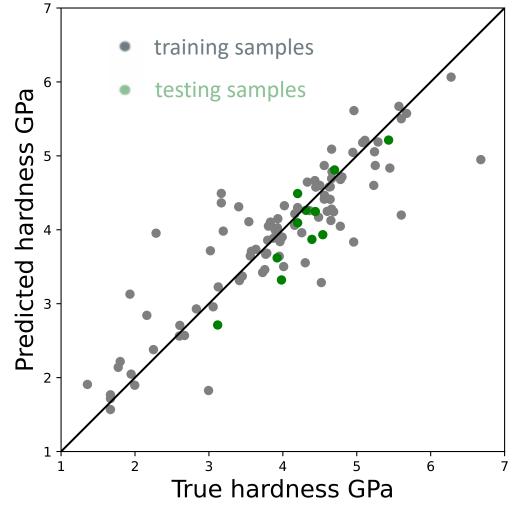
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### Case Study 2: Results

- The best DinoV2 model is the small model with 28 principal components.
- The two-point correlation function outperformed the best DinoV2 small model by 1%.

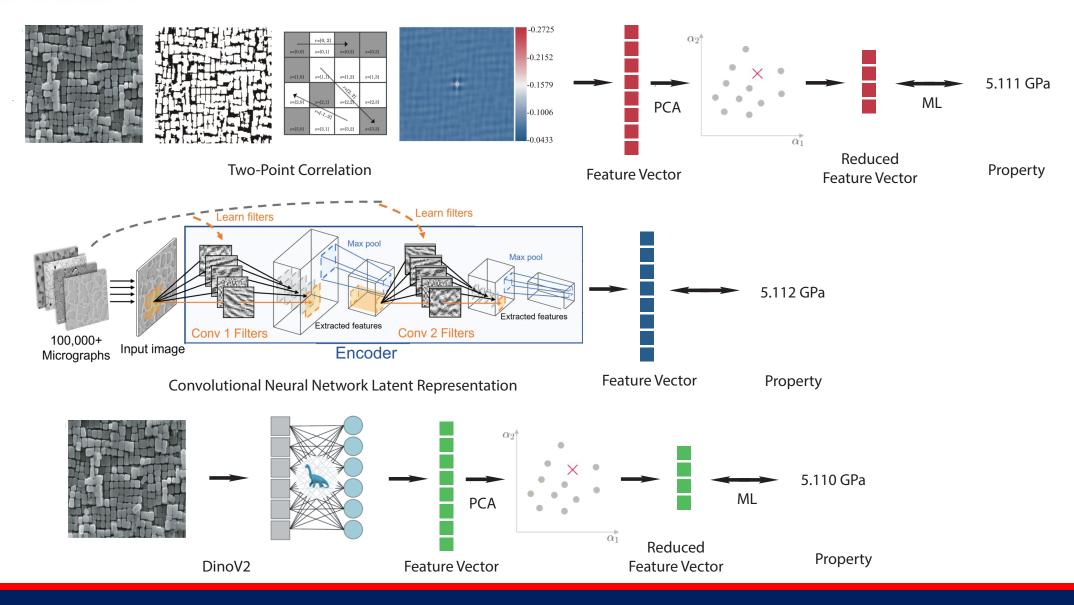




Parity plot showing the prediction results of the small DinoV2 model.



#### Summary





## Questions?



Contact Information:

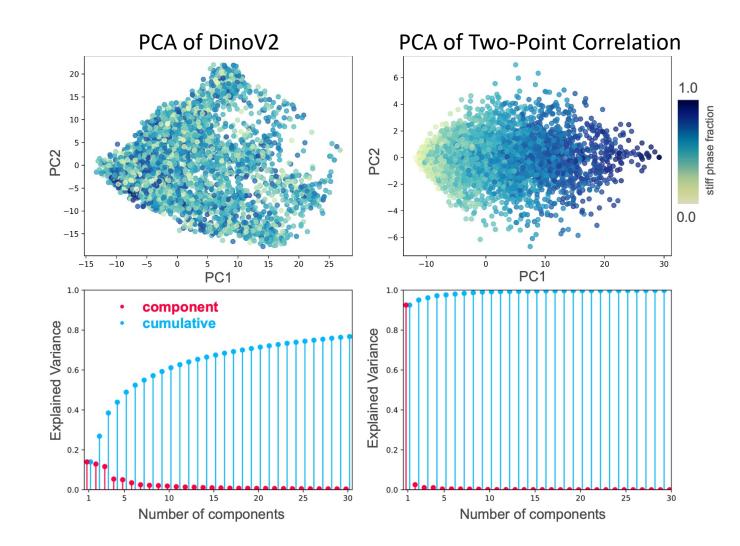
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- Sheila Whitman: sheilaw@arizona.edu

Come say hi at the poster session #156!

# A Program in Applied Mathematics

### Simulated Dataset – Feature Exploration

- The two-point correlation function prioritize the phase volume fraction
- The principal components of DinoV2 features are more balance in terms of explained variance.





#### **Experimental Dataset - Feature Exploration**

Analyzing the first two principal components provides insight into what DinoV2 features represent.

