## Currently in Texture analysis:

 We have great tools for describing orientation likelihoods

But new techniques can measure intragranular strain

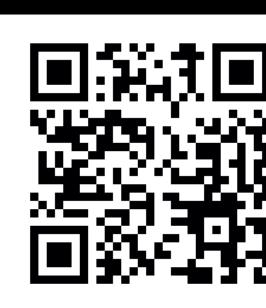
Past research has extracted strain **Expectation** from HEDM

 But now we want the orientation dependent strain likelihood

 This is much harder, but also much more directly useful!

### Pythonic ODFs and SODFs for EBSD and far field HEDM

Scan here to read more!



**Austin Gerlt, The Ohio State University** 

**Orientations** (w/ Bunge angles):  $g = g(\phi_1, \Phi, \phi_2)$ 

Strain tensor:  $\epsilon = \epsilon(\epsilon_{xx}, \epsilon_{yy}, \epsilon_{zz}, \epsilon_{xy}, \epsilon_{yz}, \epsilon_{xz})$ 

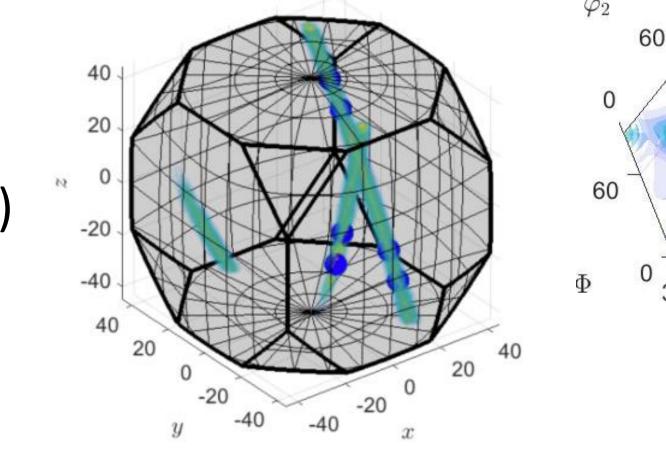
Note: Orientations exist in the Lie Space SO3, and thus use non-Euclidean probability functions

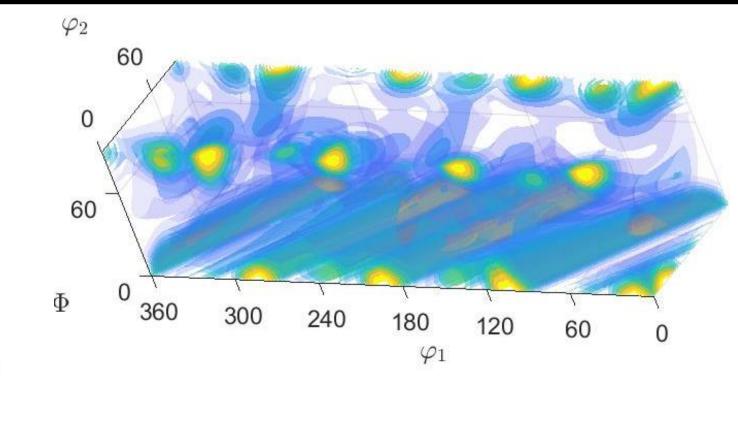
### Orientation Distribution Function (ODF):

Gives scalar **Likelihood** of a given orientation.

Usually a truncated series of Wigner D matrices (eg: TSL/MTEX)

$$ODF(g) = \sum_{\ell=0}^{\infty} \sum_{m=-l}^{\ell} \sum_{n=-l}^{\ell} c_{mn}^{\ell} D_{mn}^{\ell}(g) = \mathcal{P}(g)$$





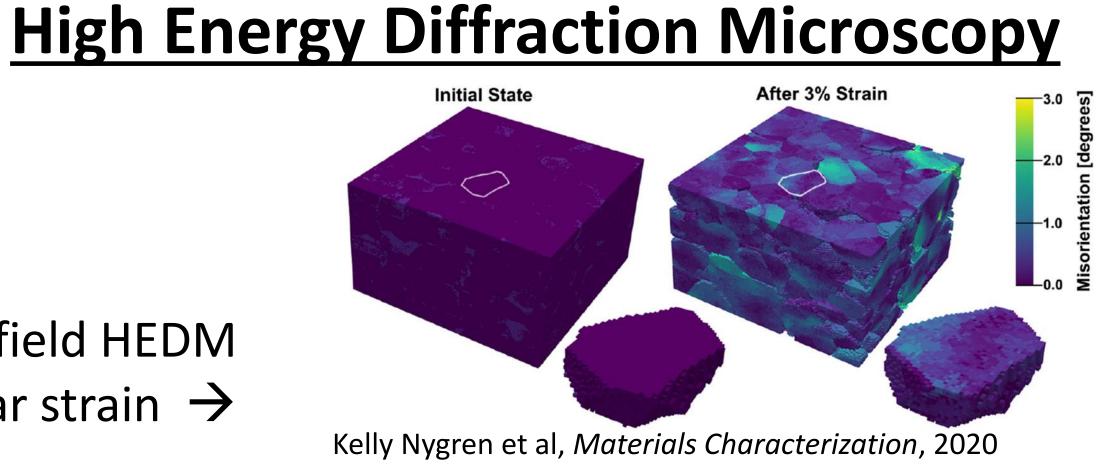
For the original Bunge version, the corrected C.S. Mann representation, and details on ODFs, Scan this QR  $\rightarrow$ 

### **High Resolution EBSD**

# Gregory Sparks, G. et al, 2021 *Ultramicroscopy*, 2021

 $\leftarrow$  HR-EBSD with  $0.02^o$  angular resolution showing slip in Ti-7Al

> Combined near and far field HEDM showing intragranular strain  $\rightarrow$



### Strain Expectation Function (SEF):

Gives the Expected strain, but NOT the probability.

$$SEF(g) = E(\epsilon) \text{ or } E(\epsilon|g)$$

- Several papers (Wang, Bernier, and Barton), yet no public code.
- Incorrectly call it an SODF, also ignore conditional probabilities.
- Still, incredible works that laid the groundwork for this study.

This is already powerful, but we can go further!

# $E(\epsilon_{yy})$ $E(\epsilon_{zz})$

### Strain Orientation Distribution Function (SODF):

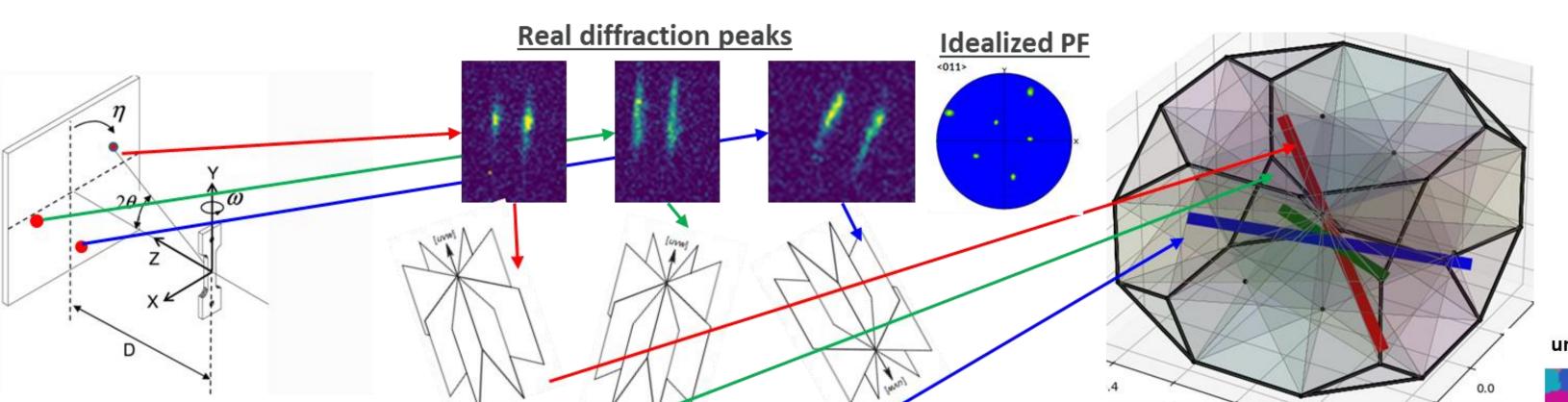
Gives the scalar Likelihood of finding any given combination of Orientation AND Strain.

$$SODF(g,\epsilon) = \sum_{\ell=0}^{\infty} \sum_{m=-l}^{l} \sum_{n=-l}^{l} \begin{bmatrix} c_{mn}^{\ell} D_{mnxx}^{\ell}(g) & c_{mn}^{\ell} D_{mnxy}^{\ell}(g) & c_{mn}^{\ell} D_{mnxz}^{\ell}(g) \\ & c_{mn}^{\ell} D_{mnyy}^{\ell}(g) & c_{mn}^{\ell} D_{mnyz}^{\ell}(g) \\ & & c_{mn}^{\ell} D_{mnzz}^{\ell}(g) \end{bmatrix} = \mathcal{P}(g,\epsilon)$$

- Could also be reframed as the conditional probability,  $\mathcal{P}(g|\epsilon)$
- This hasn't been done before, and the best method for doing so is still unclear
  - Currently trying a 4D FEM, as well as a variant on Generalized Spherical Harmonics.

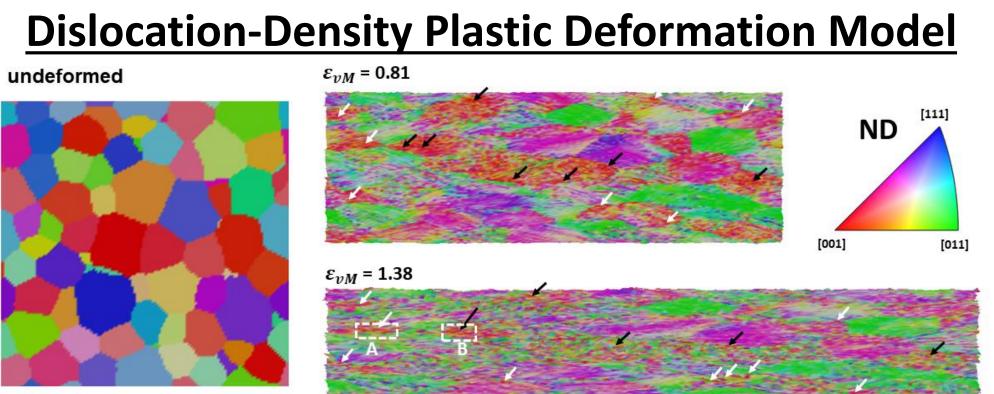
### Challenge 1: create open source pythonic ODFs

Need a user-friendly MTEX-like solution, but for HEDM (thus must also solve Pole figure inversion)



### Challenge 2: Extrapolate to create the SODF

Crucial to building better Plasticity models. An SEF tell how far a solution differs from the mean, but an SODF states how likely a solution is.



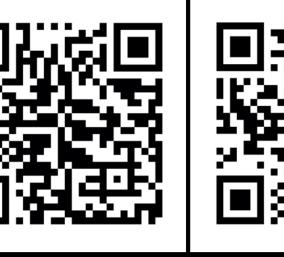
Chakraborty et al, Met Trans A, 2022

Background Information



#### **Citations**





Repos and Results

