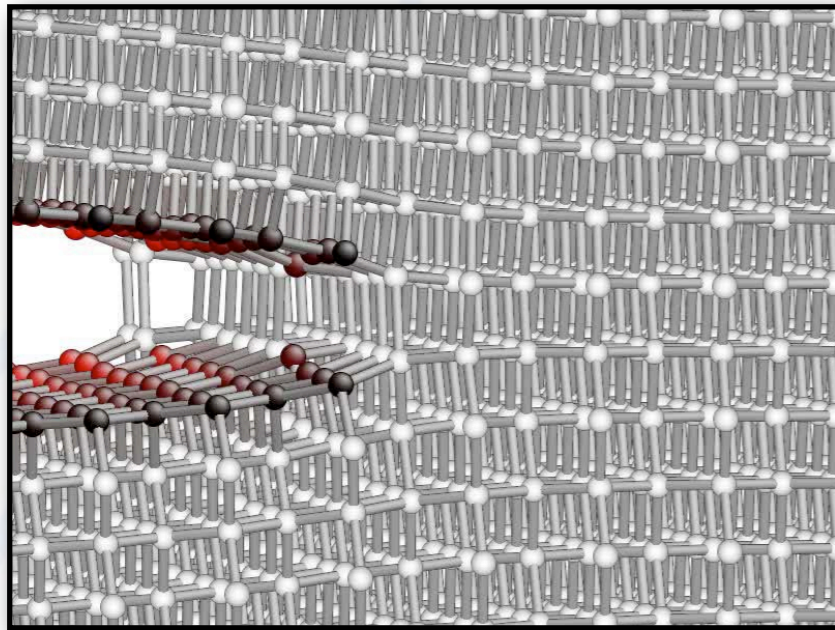
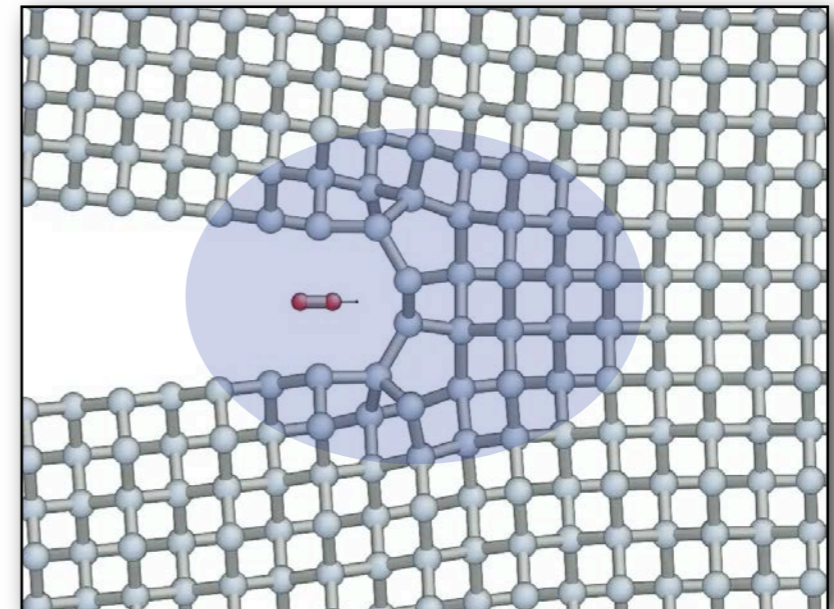


# Complex chemistry & realistic systems...

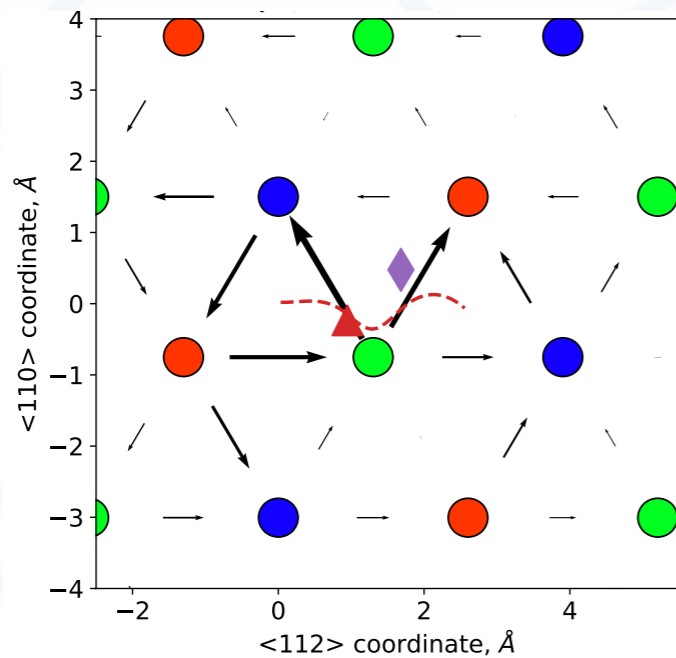
... require large systems, long timescales and quantification of uncertainty



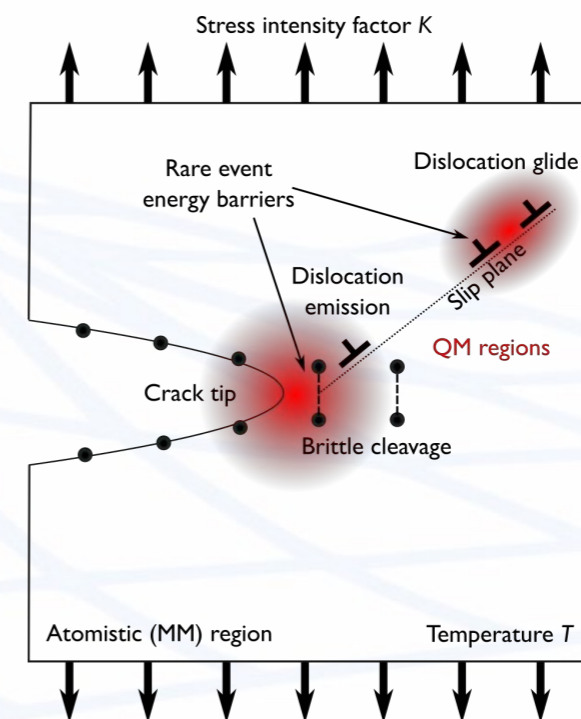
## Three Dimensional Systems



## Stress Corrosion Cracking



## Dislocation/impurity interaction



## Cleavage vs. Emission



# General-purpose machine learning potential for silicon

Gaussian Approximation Potential (GAP) framework – data-driven Gaussian Process model, trained from DFT data via SOAP representation of atomic environments

(~2.5k configs, ~170k atomic environments, sparsified to 9k)

$$E = \sum_{i<j} V^{(2)}(r_{ij}) + \sum_i \sum_s^M \alpha_s K(\mathcal{R}_i, \mathcal{R}_s),$$

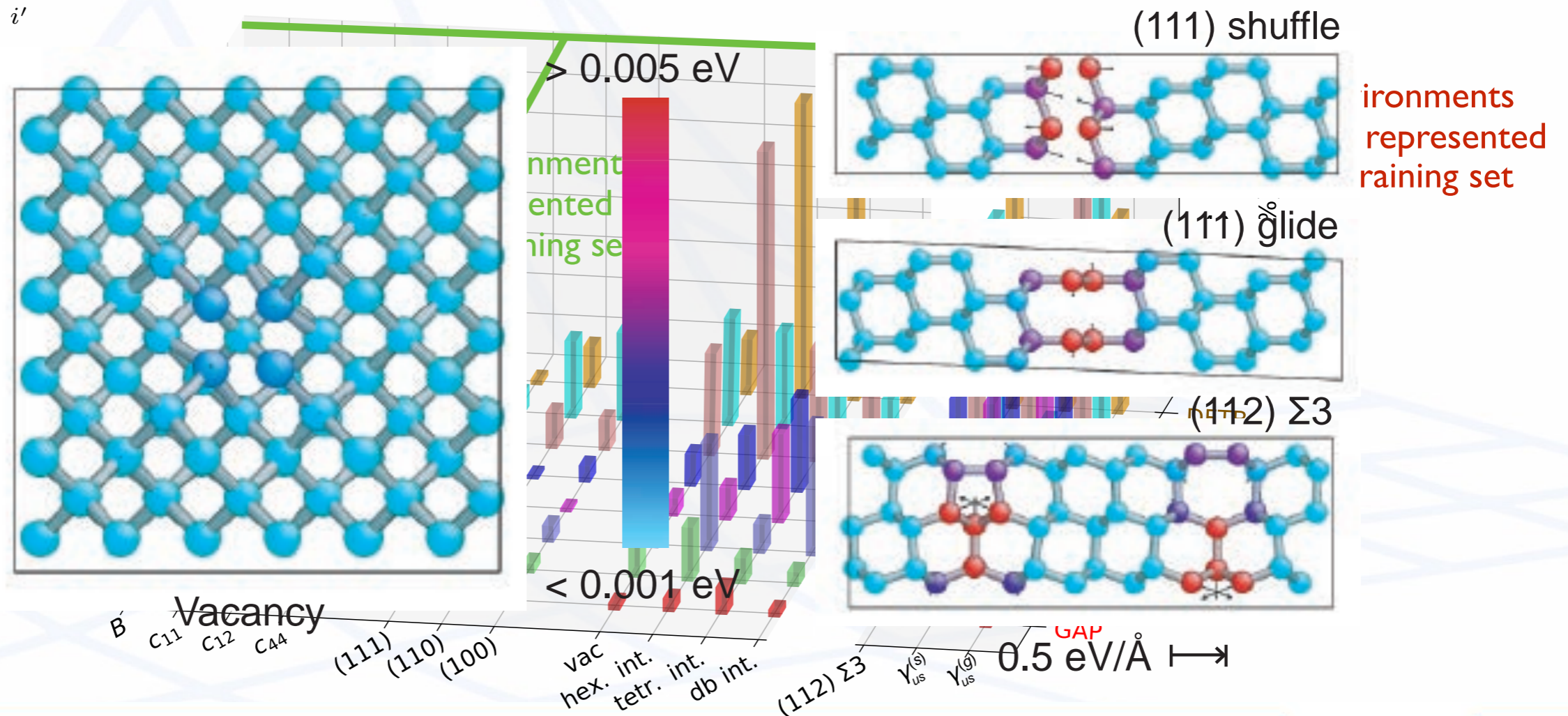
$$\tilde{K}(\mathcal{R}_i, \mathcal{R}_j) = \int_{\hat{R} \in SO_3} d\hat{R} \left| \int d\mathbf{r} \rho_i(\mathbf{r}) \rho_j(\hat{R}\mathbf{r}) \right|^2$$

$$\rho_i(\mathbf{r}) = \sum_{i'} f_{\text{cut}}(r_{ii'}) e^{-(\mathbf{r}-\mathbf{r}_{ii'})/2\sigma_{\text{atom}}^2}$$

$$\alpha = [\mathbf{K}_{MM} + \mathbf{K}_{MN}\mathbf{L}\mathbf{\Lambda}^{-1}\mathbf{L}^T\mathbf{K}_{NM}]^{-1}\mathbf{K}_{MN}\mathbf{L}\mathbf{\Lambda}^{-1}\mathbf{y},$$

Posterior variance (over an effective ensemble of potentials trained on same data) is analytic:

$$K(\mathcal{R}_i, \mathcal{R}_i) - \mathbf{k}^T (\mathbf{K}_{MM} + \sigma_e \mathbf{I})^{-1} \mathbf{k}$$

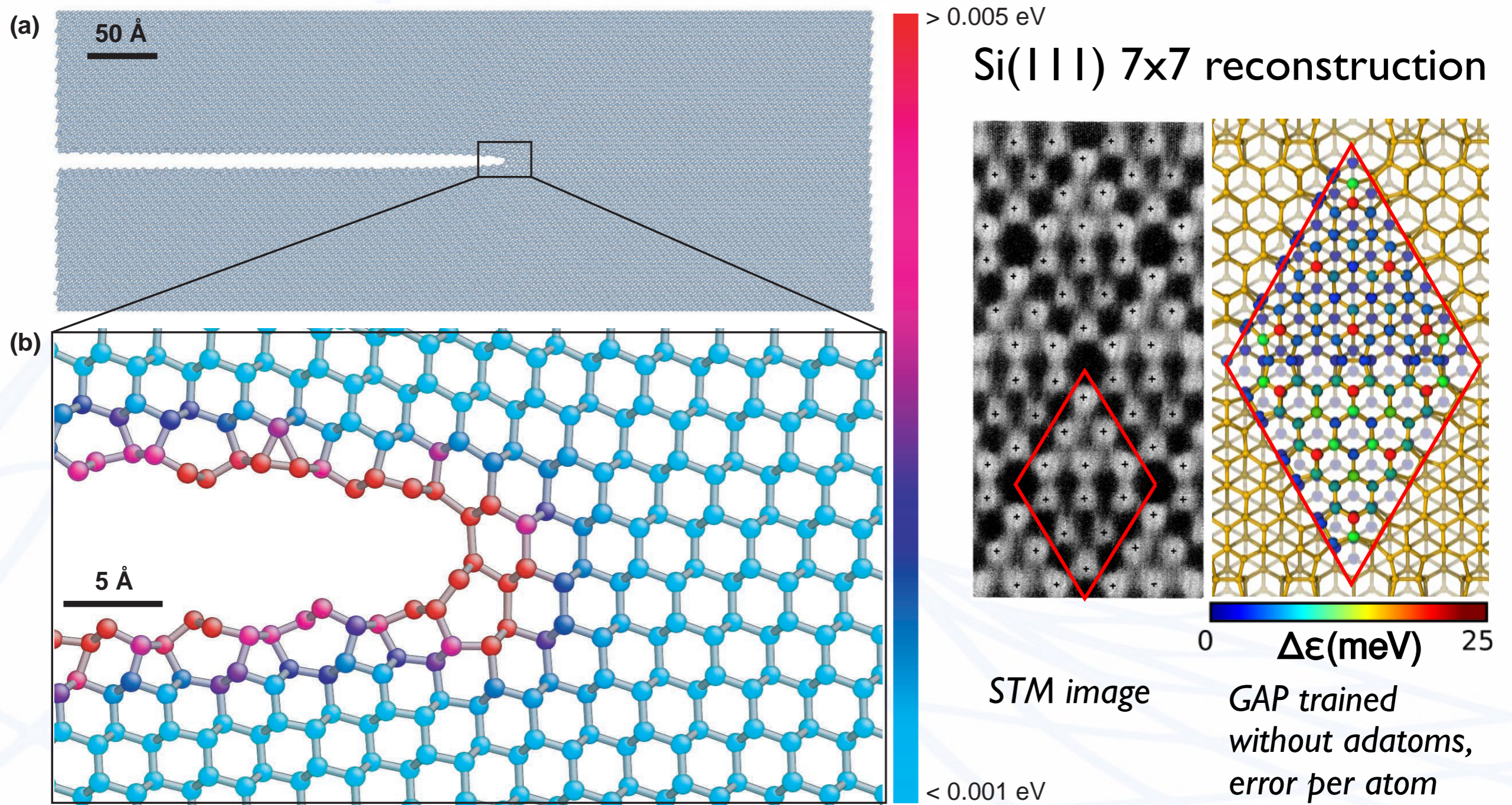


A. P. Bartok et al. *Science Advances* **3**, e1701816 (2017)

A. P. Bartok, JRK, N. Bernstein and G. Csanyi, *PRX* **8**, 041048 (2018)



# Uncertainty Quantification for the Silicon GAP model



Gaussian Approximation Potential (GAP) for silicon – data-driven model, with per-atom predicted errors from variance of posterior probability distribution

A. P. Bartok et al. *Science Advances* **3**, e1701816 (2017)

A. P. Bartok, JRK, N. Bernstein and G. Csanyi, *PRX* **8**, 041048 (2018)