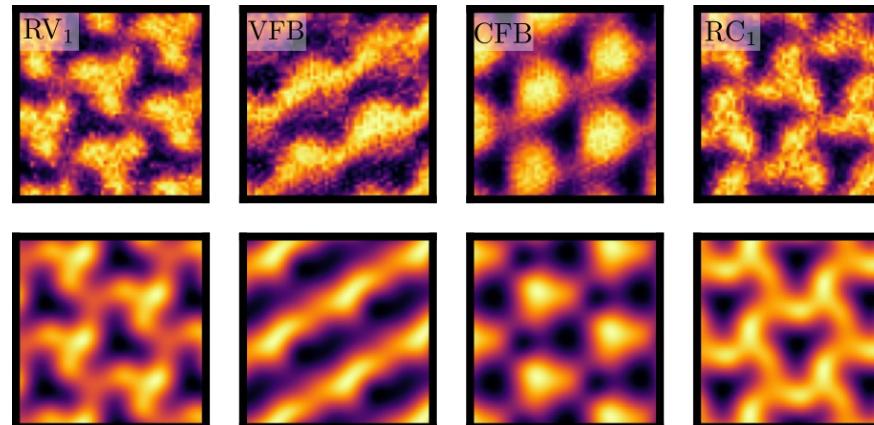


# Machine Learning the Microscopic Form of Nematic Order in twisted double-bilayer graphene

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João Augusto Sobral (University of Innsbruck -> University of Stuttgart)

Journal Club for Quantum Physics and Machine Learning (27/06/2023), ultracold.org

# Acknowledgments

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Columbia University



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Columbia University



Stefan Obernauer  
University of Innsbruck



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University of Innsbruck →  
University of Stuttgart

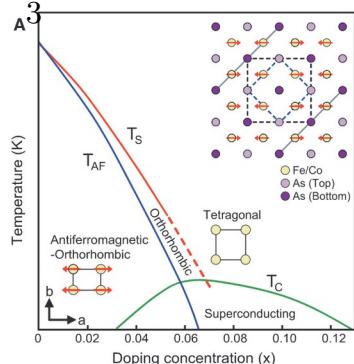
- Funding by the European Union (ERC-2021-STG, Project 101040651---SuperCorr).
- Discussions with Sayan Banerjee (UIBK), J. P. Valeriano (ICTP-SAIFR/Brazil), Igor Reis (USP/Brazil), Pedro H. P. Cintra (Unicamp/Brazil).
- More information about the slides: [joaosds.github.io](https://joaosds.github.io)



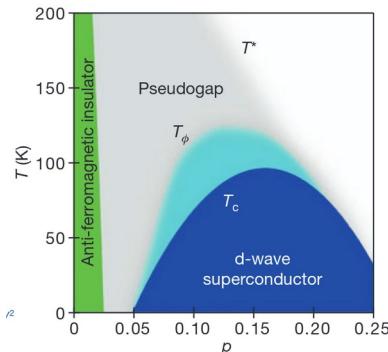
Funded by the  
European Union

# Nematicity

$\text{CaFe}_2\text{As}_2$   
Iron-based superconductor

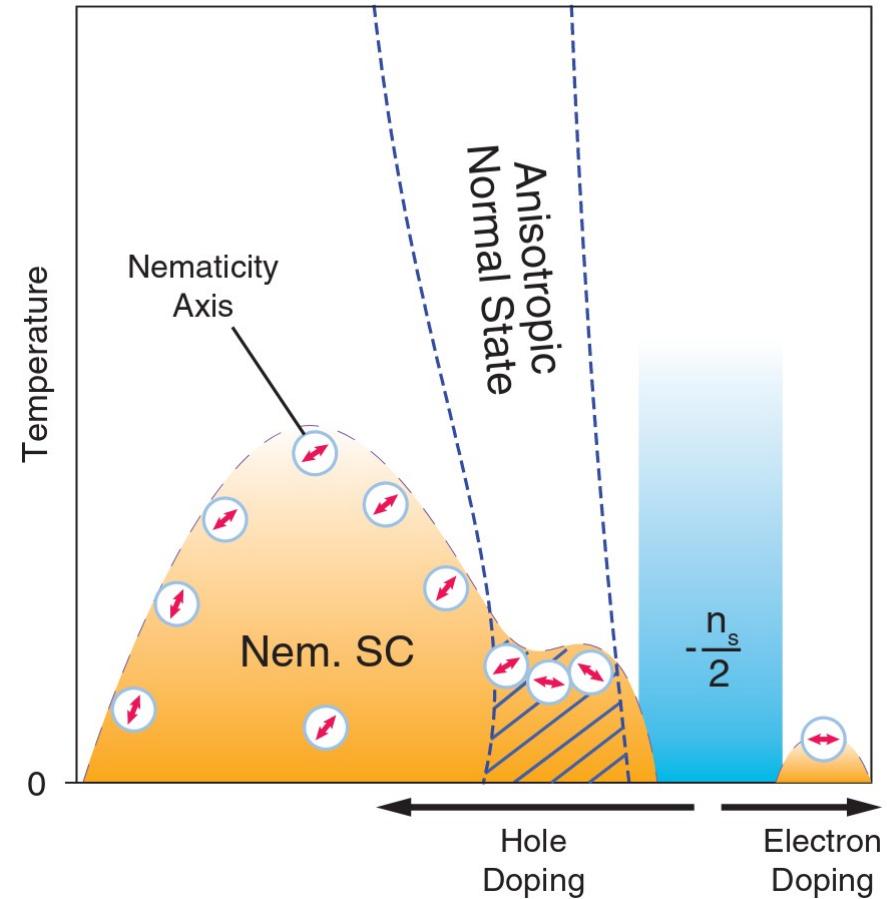


$\text{Bi}_2\text{Sr}_2\text{CaCu}_2\text{O}_{8+\delta}$   
Copper-oxide superconductors

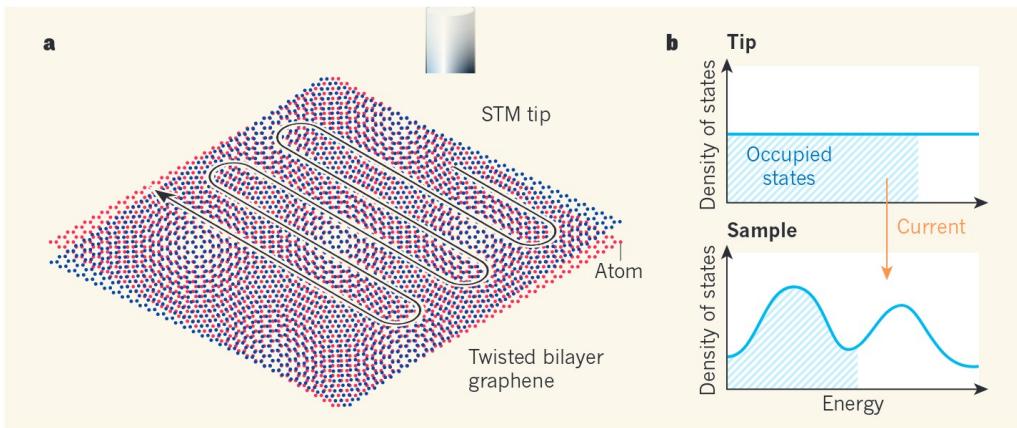


Lawler, M.J. et al, 2010. Nature, 466(7304) | Chuang, T.M, et al , 2010. Science, 327(5962), pp.181-184. | Fernandes, R.M., Chubukov, A.V. and Schmalian, J., 2014. Nature physics, 10(2), pp.97-104.

TBG: Y. Cao, D. Rodan-Legrain, J. M. Park, N. F. Q. Yuan, K. Watanabe, T. Taniguchi, R. M. Fernandes, L. Fu, and P. Jarillo-Herrero. Science 372, 264 (2021)

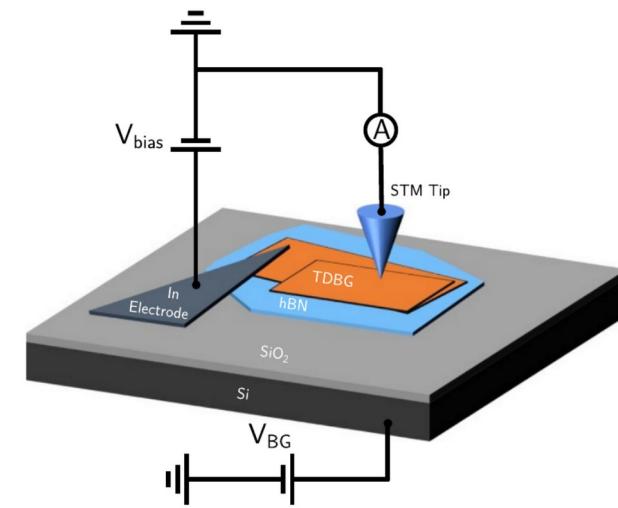
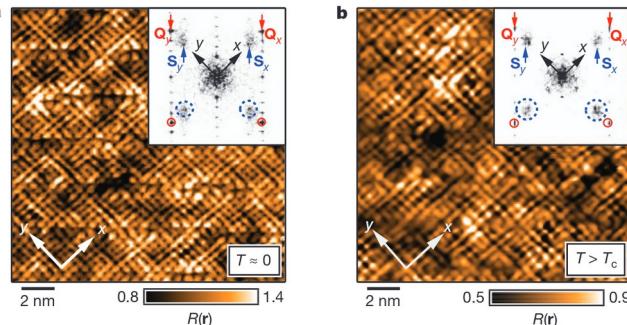


# STM

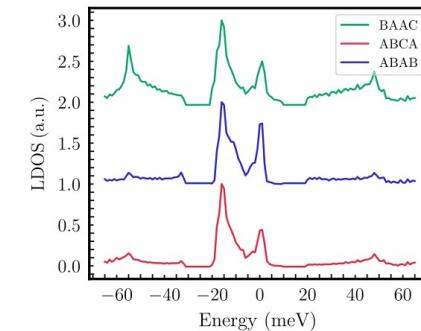
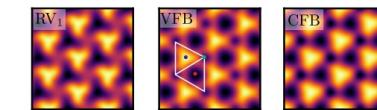


Scheurer, M.S., 2019. Spectroscopy of graphene with a magic twist. Nature, 572(7767), pp.40-41.

$$dI/dV \propto \mathcal{D}(\mathbf{r}, E)$$



R. Samajdar, M. S. Scheurer, S. Turkel, et al. 2D Materials 8, 034005 (2021).

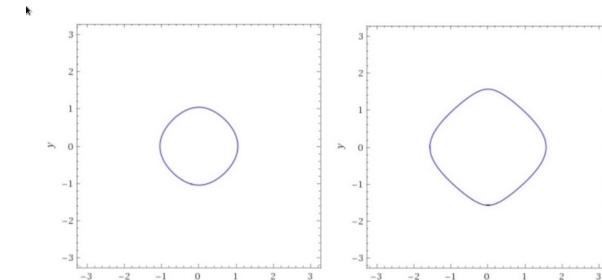
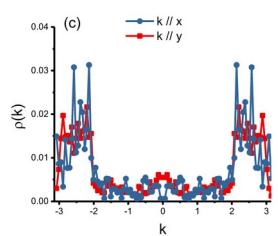
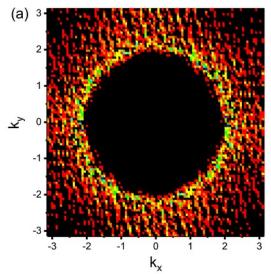


# Using AI to detect nematicity

$$H = H_0 + H_{imp}$$

$$H_0 = - \sum_{\mathbf{r}} t_x c_{\mathbf{r}+\hat{x}}^\dagger c_{\mathbf{r}} + t_y c_{\mathbf{r}+\hat{y}}^\dagger c_{\mathbf{r}} + \text{h.c.}$$

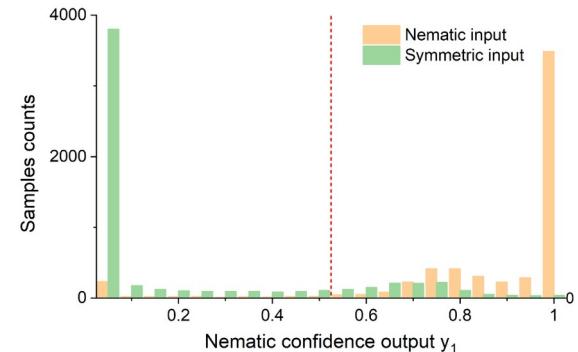
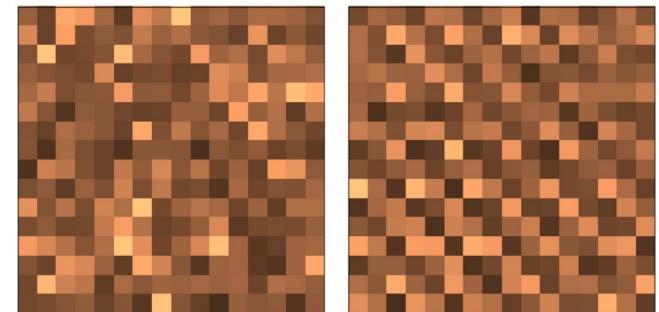
$$H_{imp} = \sum_{\mathbf{r} \in R_w} w_{\mathbf{r}} c_{\mathbf{r}}^\dagger c_{\mathbf{r}},$$



Goetz, J.B., et al 2020. SciPost Physics, 8(6), p.087.

$$O_N = \sum_{\mathbf{r}} N_{\mathbf{r}} [\underbrace{\cos(\mathbf{Q}_x \cdot \mathbf{r}) - \cos(\mathbf{Q}_y \cdot \mathbf{r})}_{\text{DOS}}]$$

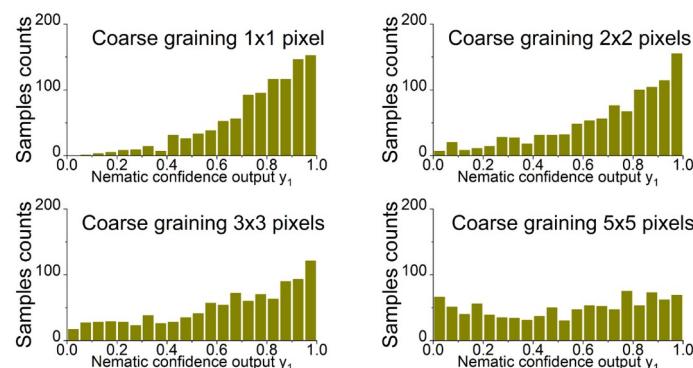
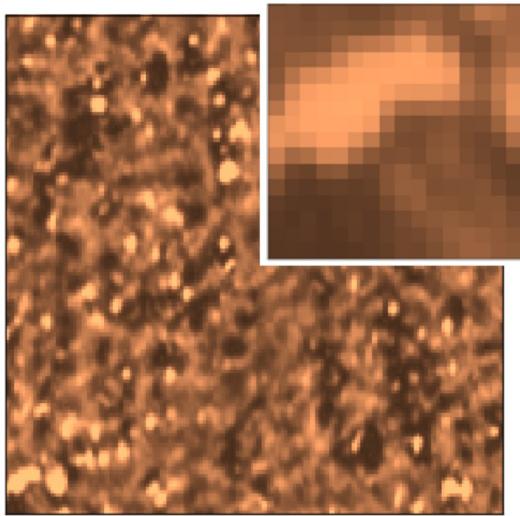
$$\mathbf{Q}_x = \left( \frac{2\pi}{a}, 0 \right) \text{ and } \mathbf{Q}_y = \left( 0, \frac{2\pi}{a} \right)$$



# Using AI to detect nematicity

CaFe<sub>2</sub>As<sub>2</sub>

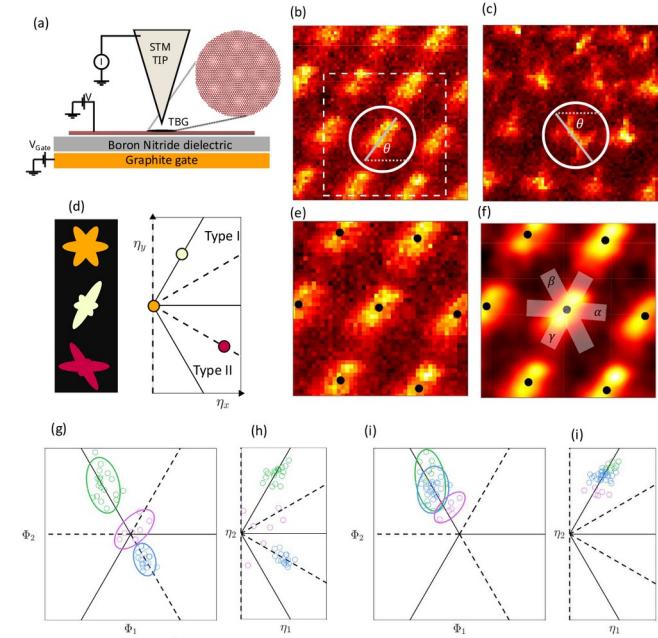
Goetz, J.B., et al 2020. SciPost Physics, 8(6), p.087.



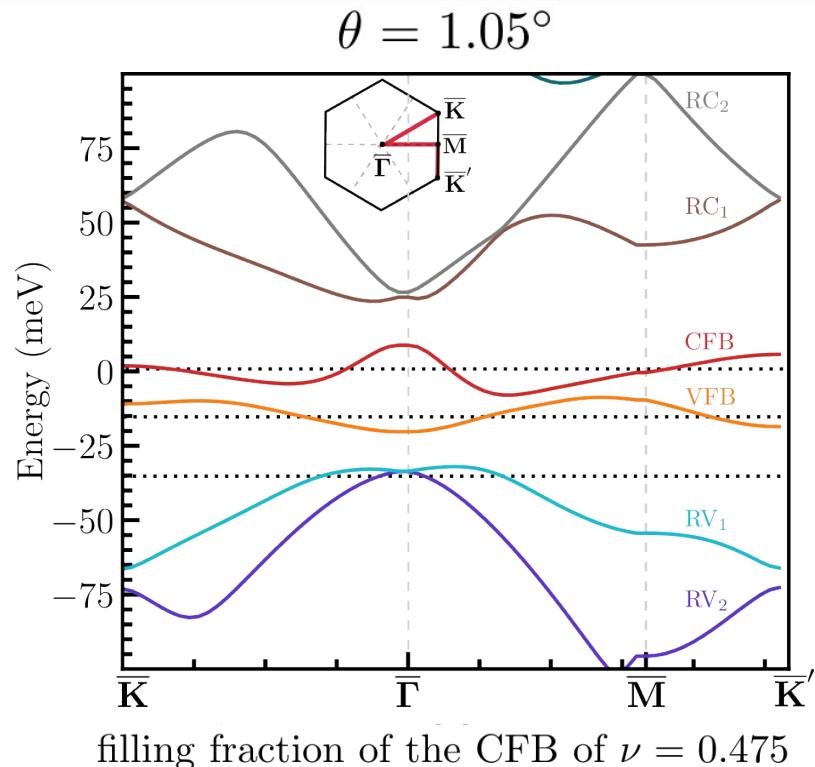
- ~90% exp dataset nematic;
- Need at least one hidden layer -  $\rightarrow$  Non linearity...;
- Disorder in TB model is needed;
- No microscopic form;

## Nematicity in TBG

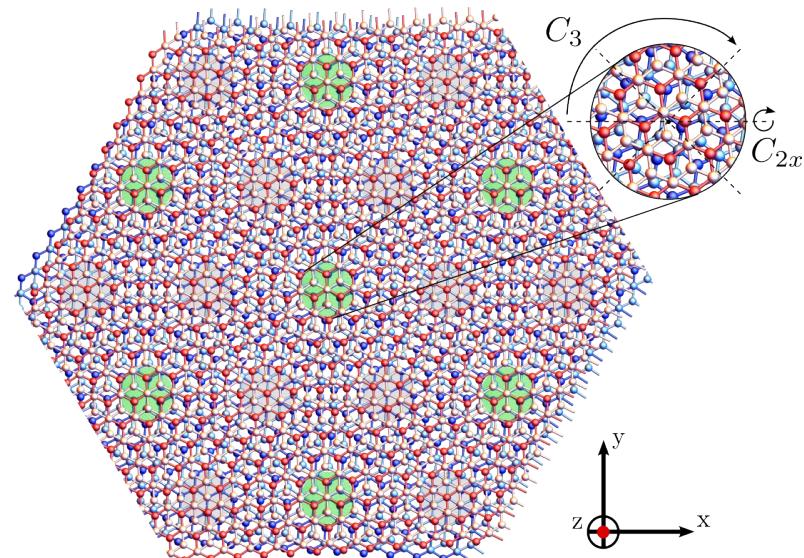
Taranto, W., et al 2022. arXiv preprint arXiv:2203.04449.



# Twisted double-bilayer graphene (TDBG)



- Stiffness of bilayer graphene  $\rightarrow$  uniform samples, low strain.



$$H_{AB-AB} = \begin{pmatrix} H_0(\mathbf{k}_1) & S^\dagger(\mathbf{k}_1) & H'_0(\mathbf{k}_1) & U^\dagger & H_0(\mathbf{k}_2) & S^\dagger(\mathbf{k}_2) \\ S(\mathbf{k}_1) & H_0'(\mathbf{k}_1) & U & H_0(\mathbf{k}_2) & S(\mathbf{k}_2) & H_0'(\mathbf{k}_2') \end{pmatrix} + V$$

interactions within graphene monolayers

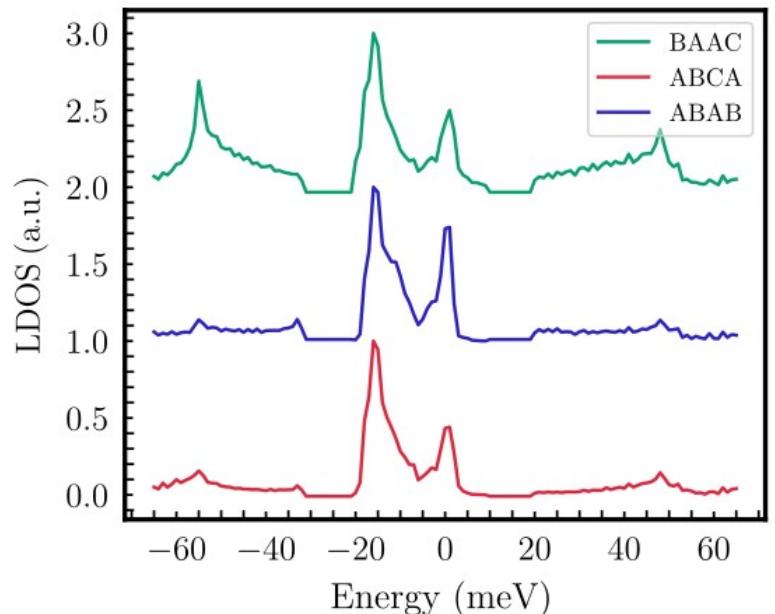
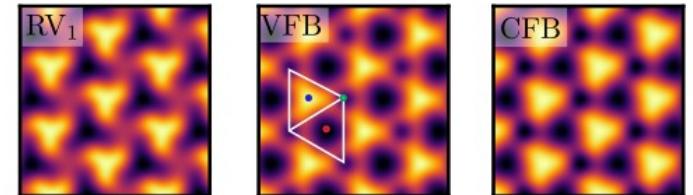
interlayer asymmetric potential

Moiré interlayer coupling between twisted layers

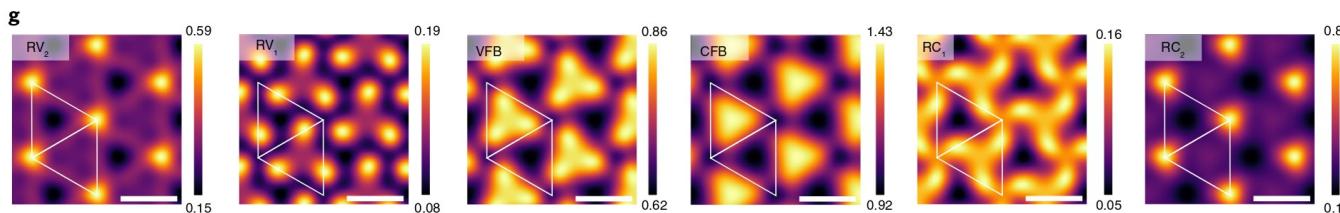
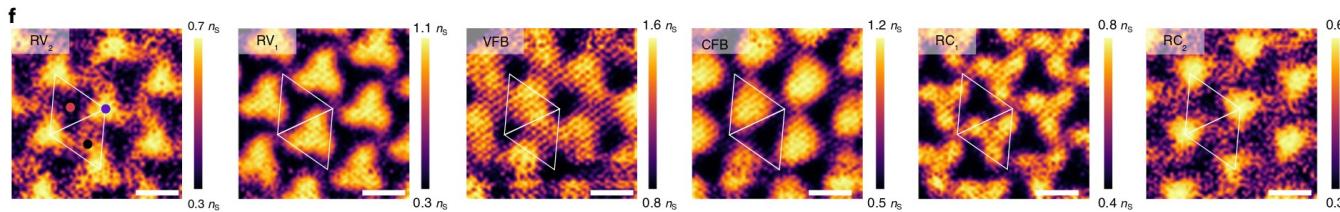
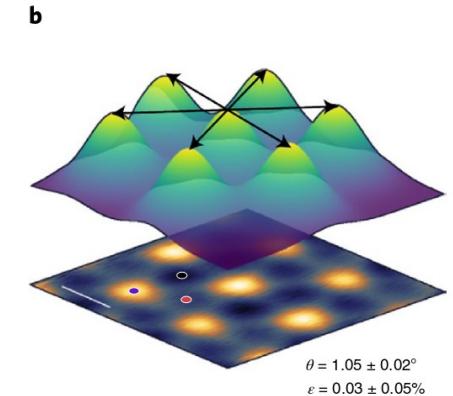
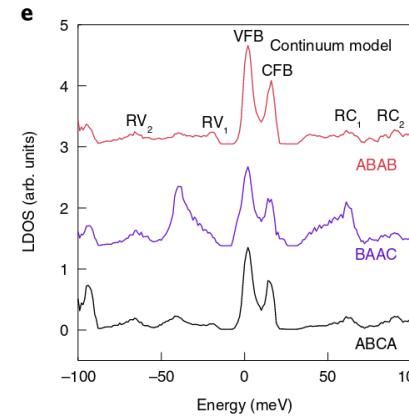
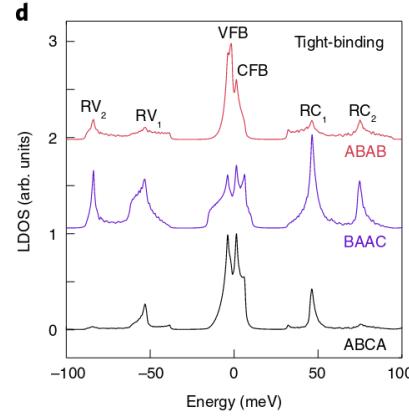
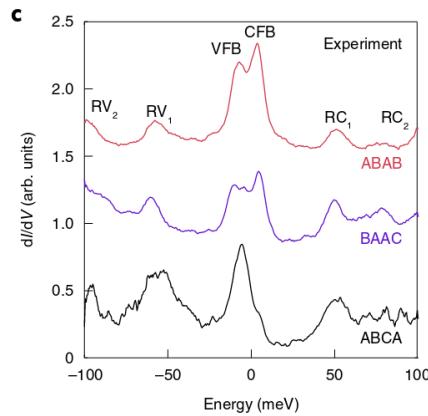
interlayer coupling of AB stacked BG

# Local Density of States (LDOS)

$$\begin{aligned}\mathcal{D}(\mathbf{r}, E) &= \\ &= \sum_{n,\mathbf{k}} \sum_{\mathbf{G}, \mathbf{G}'} e^{-i(\mathbf{G}-\mathbf{G}') \cdot \mathbf{r}} \delta(E - E_{n,\mathbf{k}}) \\ &\quad \times \left( \left[ U_{n,\mathbf{k}}^{A_4}(\mathbf{G}') \right]^* U_{n,\mathbf{k}}^{A_4}(\mathbf{G}) \right. \\ &\quad \left. + \left[ U_{n,\mathbf{k}}^{B_4}(\mathbf{G}') \right]^* U_{n,\mathbf{k}}^{B_4}(\mathbf{G}) \right) \\ &\quad \text{(LDOS) projected onto} \\ &\quad \text{4th graphene layer}\end{aligned}$$



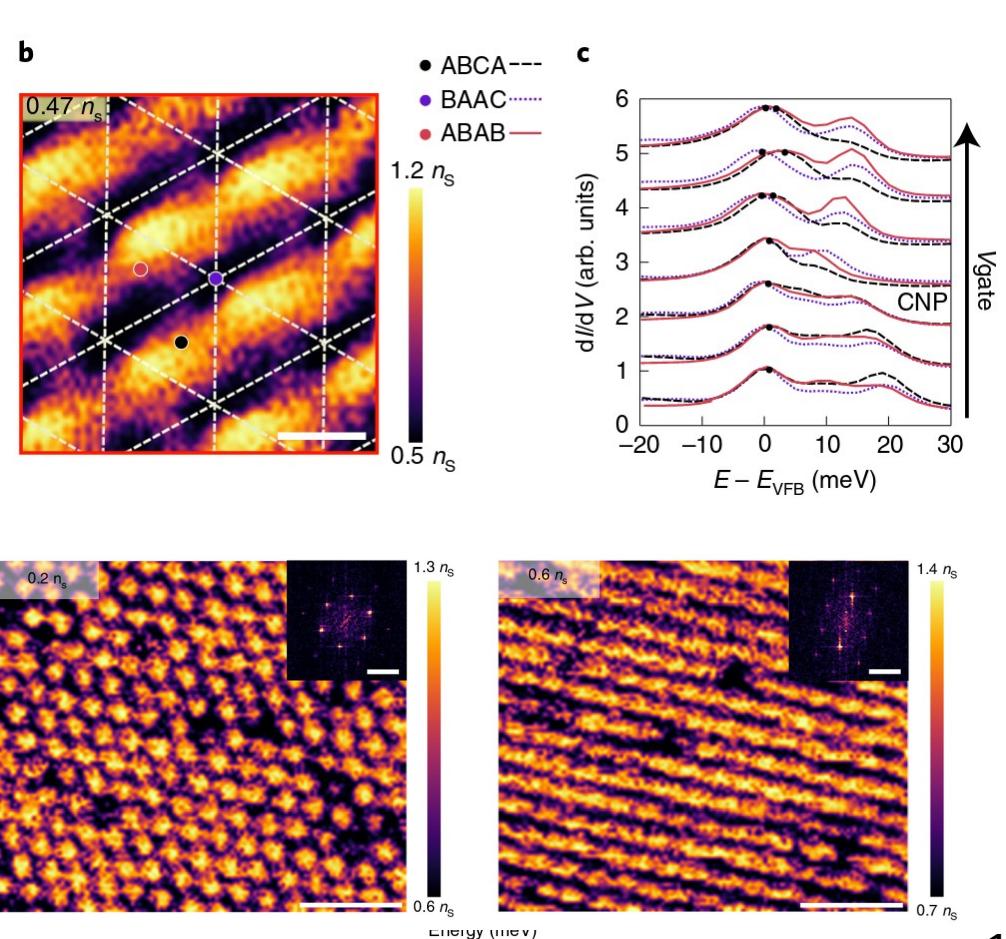
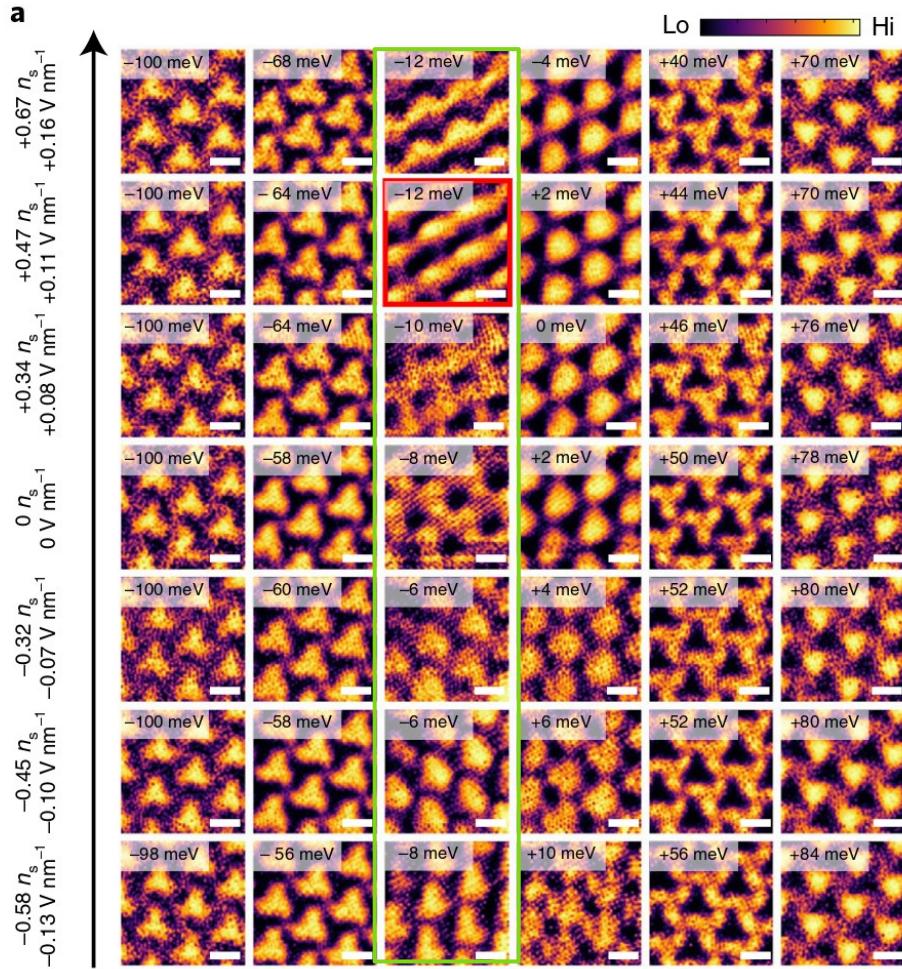
# Nematicity in TDBG



● ABAB   ● BAAC   ● ABCA

Rubio-Verdú, C., et al, 2022. Nature Physics, 18(2), pp.196-202. | R. Samajdar, M. S. Scheurer, S. Turkel, et al. 2D Materials 8, 034005 (2021).

# Nematicity in TDBG



# Nematicity in TDBG

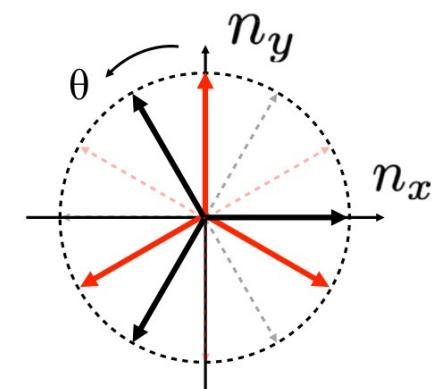
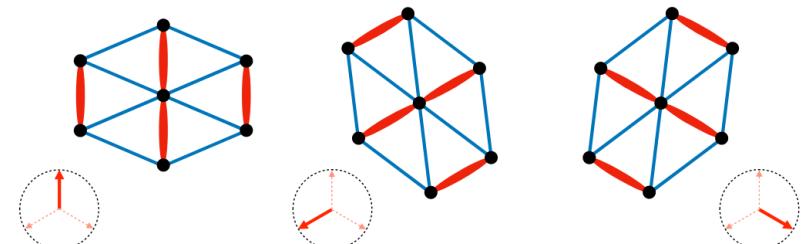
spin, layer, sublattice and valley degrees of freedom

$$\mathcal{H}_\Phi = \int_{\mathbf{r}} \int_{\Delta \mathbf{r}} \Phi \cdot \phi_{\ell,s,\eta;\ell',s',\eta'}(\mathbf{r}, \Delta \mathbf{r}) c_{\sigma,\ell,s,\eta}^\dagger(\mathbf{r} + \Delta \mathbf{r}) c_{\sigma,\ell',s',\eta'}(\mathbf{r}) + \text{H.c.}$$

$$\Phi = \Phi (\cos 2\varphi, \sin 2\varphi)$$

intensity

nematic director angle



- Graphene nematicity (GN);
- Moiré Nematicity (MN);

R. Samajdar, M. S. Scheurer, S. Turkel, et al. 2D Materials 8, 034005 (2021).

# Moiré Nematicity (MN)

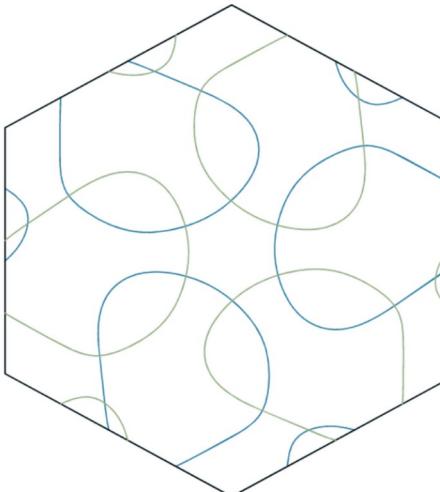
$$\mathcal{H}_{\Phi}^{MN} = \Phi \cdot \mathbf{f}(\mathbf{k}) c_{\alpha}^{\dagger}(\mathbf{k}) c_{\alpha}(\mathbf{k})$$

$$E_{n,\mathbf{k}} \rightarrow E_{n,\mathbf{k}} + \Phi \cdot \mathbf{f}(\mathbf{k}),$$

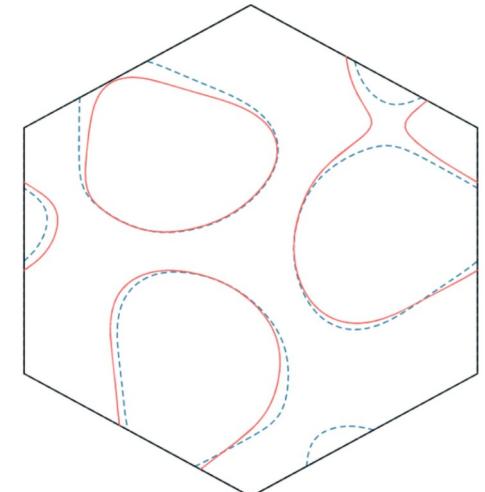
$$\mathbf{f}(\mathbf{k}) = \sum_{m_1, m_2 \in \mathbb{Z}} \phi_{m_1, m_2} \cos(\mathbf{k} \cdot \mathbf{R}_{m_1, m_2})$$

Transforms as E irred. of  $D_3$

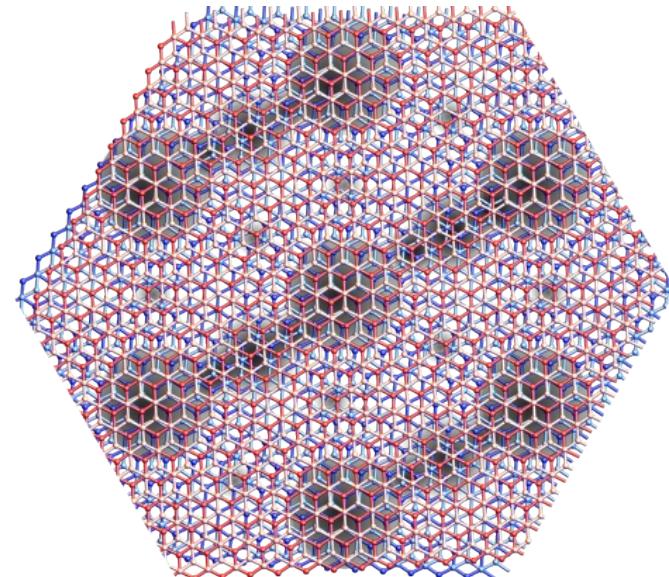
$C_3$  symmetric



Moiré Nematicity



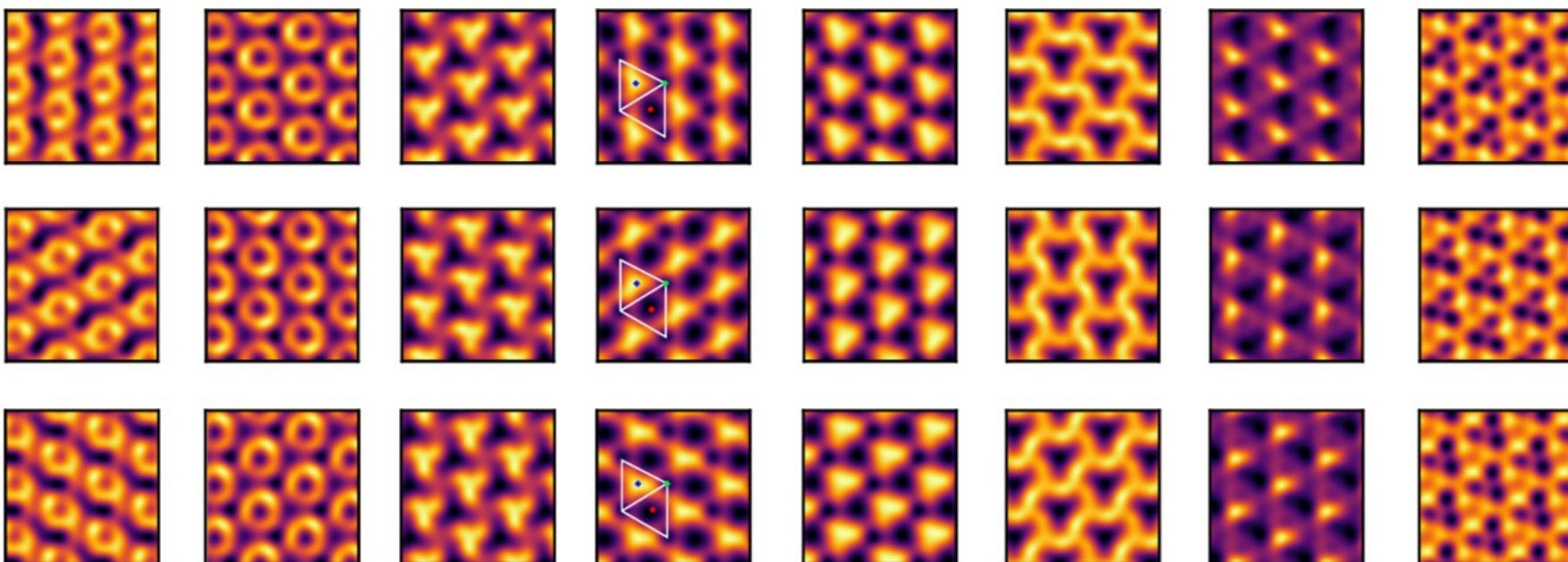
- Stronger effects close to van-Hove singularities
- Breaks  $C_3$  symmetry at moiré scale.
- Learnable parameters:  $\varphi_{MN}$  and  $\Phi_{MN}$ .



# Moiré Nematicity (MN)

Moiré Nematicity (MN)  $\boxed{\Phi = 5 \text{ meV}}$

-85 meV (RV<sub>2</sub>) -66 meV (RV<sub>2</sub>) -37 meV (RV<sub>1</sub>) -15 meV (VFB) +1 meV (CFB) +24 meV (RC<sub>1</sub>) +66 meV (RC<sub>2</sub>) +77 meV (RC<sub>2</sub>)



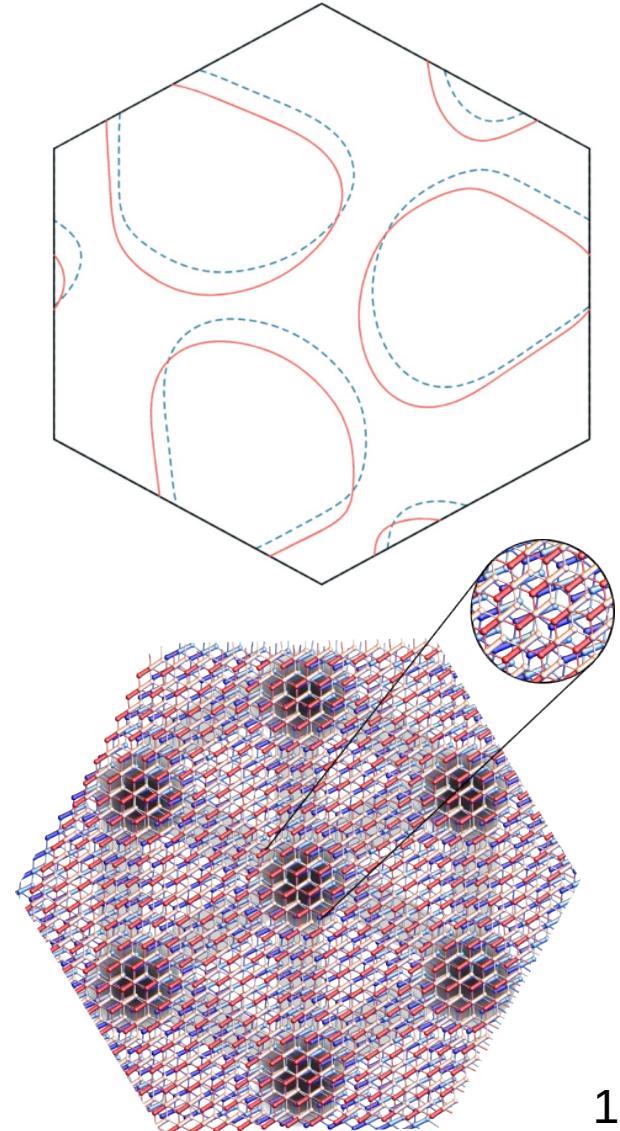
# Graphene nematicity (GN)

$$\phi_{l,s; l', s'} (\eta) = \delta_{l,l'} \psi_l \left( \frac{(e^{i\alpha_l \eta \rho_z} \rho_x)_{ss'}}{\eta (e^{i\alpha_l \eta \rho_z} \rho_y)_{ss'}} \right), \quad \psi_l, \alpha_l \in \mathbb{R}.$$

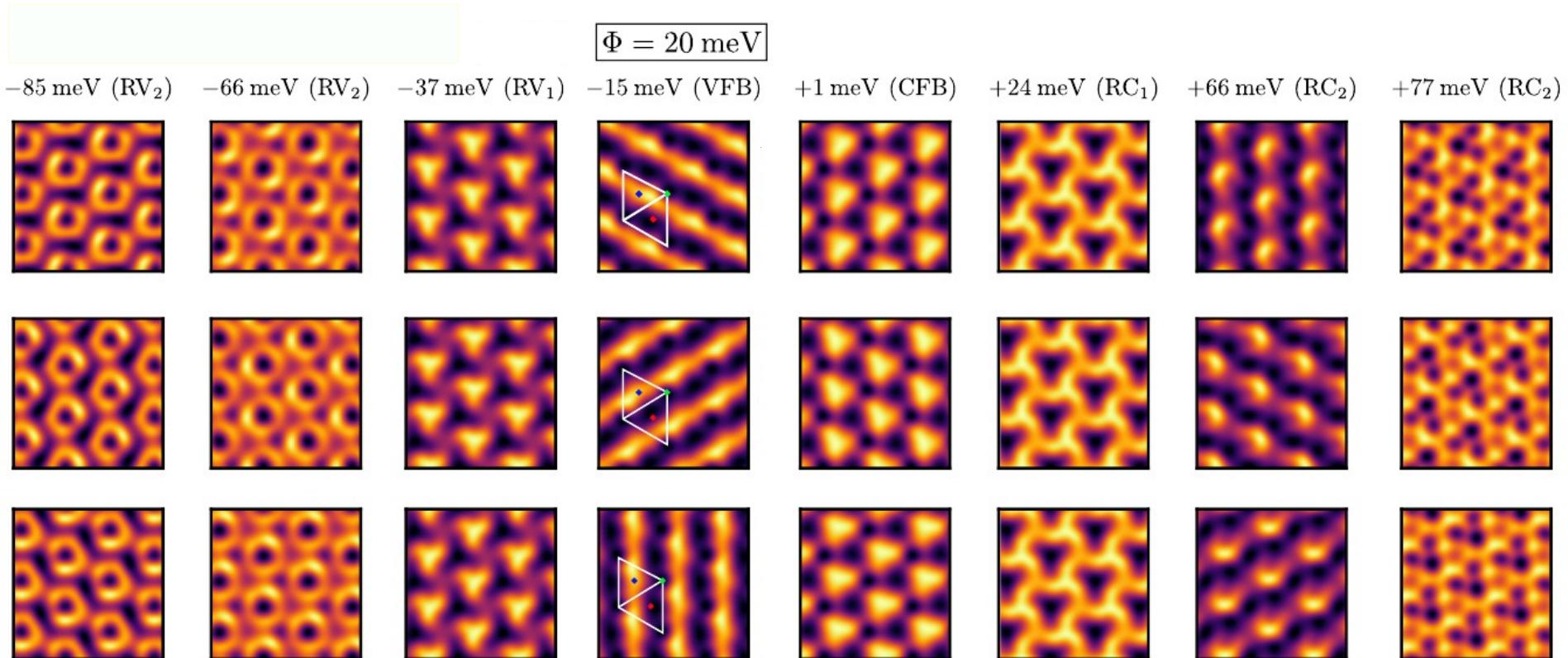
$$H_0(\mathbf{k}) \rightarrow H_0(\mathbf{k}) + \Phi \cdot \phi_{s,s'} = \\ = \begin{pmatrix} 0 & -\hbar\nu k_- + \Phi \cdot M_\alpha \\ -\hbar\nu k_+ + \Phi \cdot M_\alpha^\dagger & d \end{pmatrix} \quad M_{\alpha_l} = (1, -i\eta) e^{i\alpha_l \eta}.$$

$$\mathcal{H}_l = -\hbar\nu \left[ R(\pm\theta/2) \left( \mathbf{k} - \mathbf{K}_\eta^l \right) \right] \cdot (\eta \rho_x, \rho_y) + \boxed{\Phi \cdot (\rho_x, \eta \rho_y)}$$

- Shifts Dirac cones.
- Breaks C3 symmetry at atomic scale;
- Learnable parameters:  $\varphi_{GN}, \Phi_{GN}, \alpha, \dots$



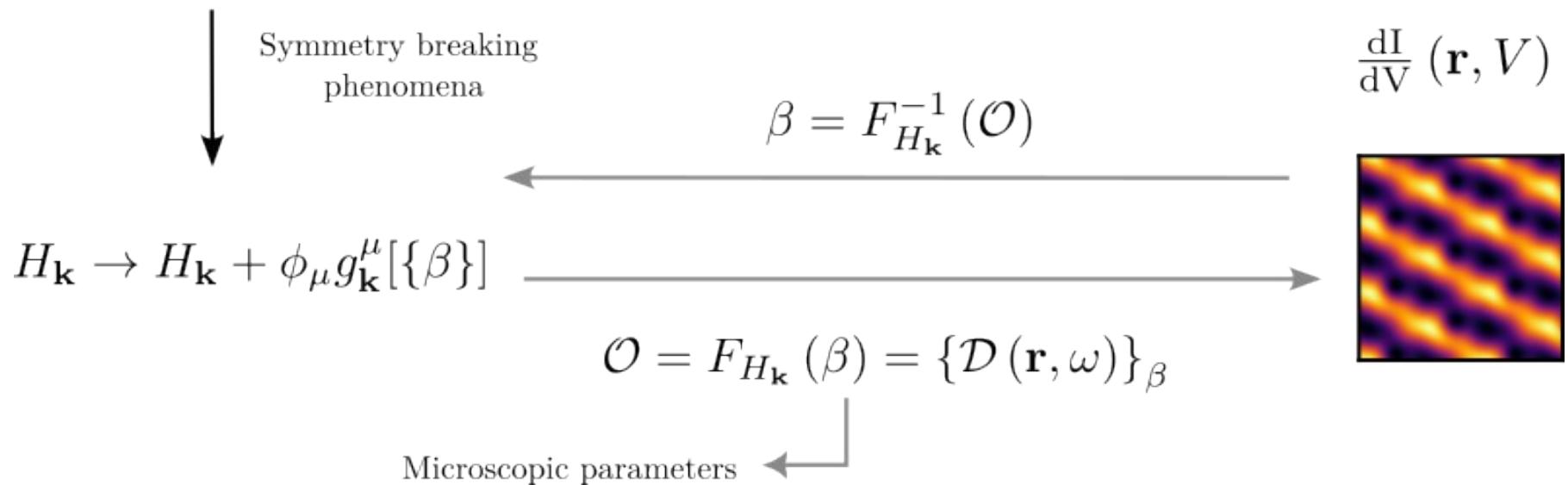
# Graphene nematicity (GN)



# Solving the Inverse Problem

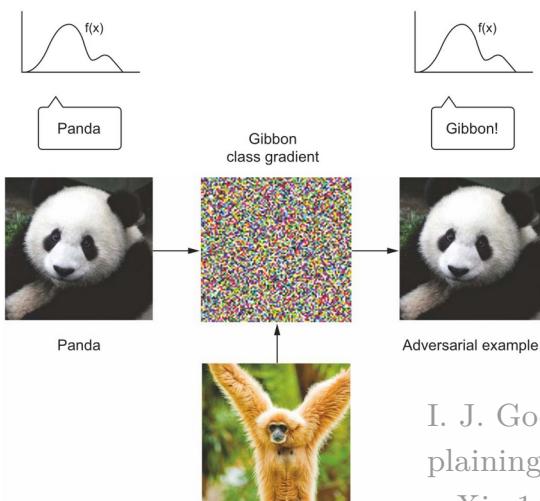
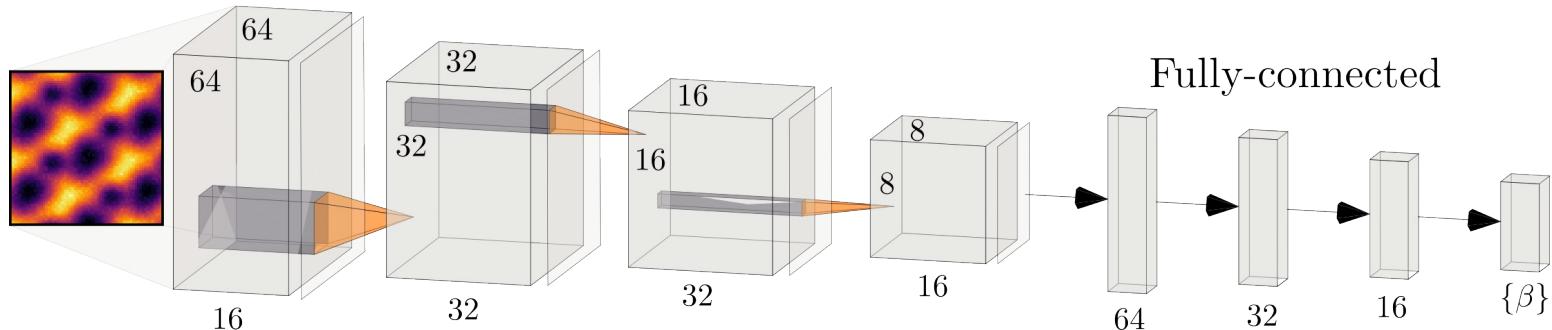
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$$H_{\mathbf{k}} = H_{\mathbf{k}} [t_j]$$

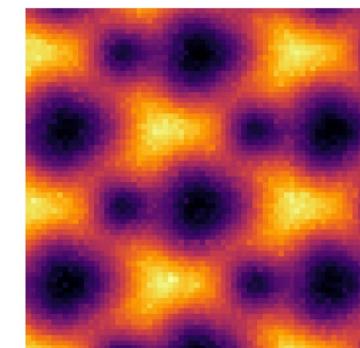


# DL Architecture

Convolution and max pooling

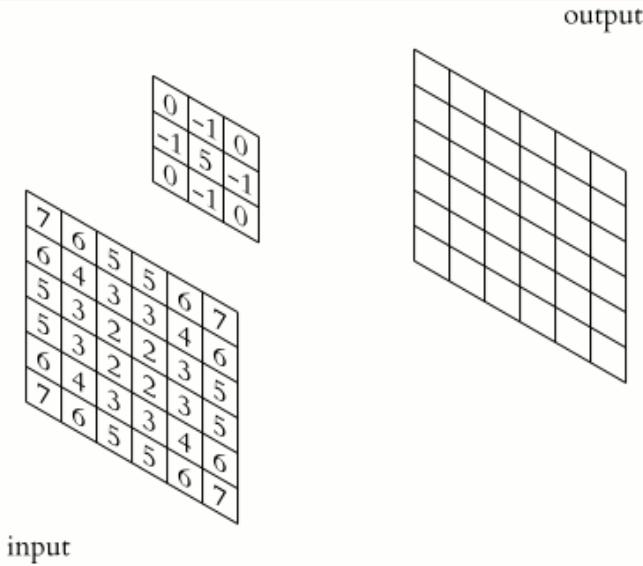


$$p_g(z) = \frac{\exp(-(z-\mu)^2/2\sigma^2)}{\sqrt{2\pi}\sigma}$$
$$\sigma \approx 0.31, \mu = 0$$



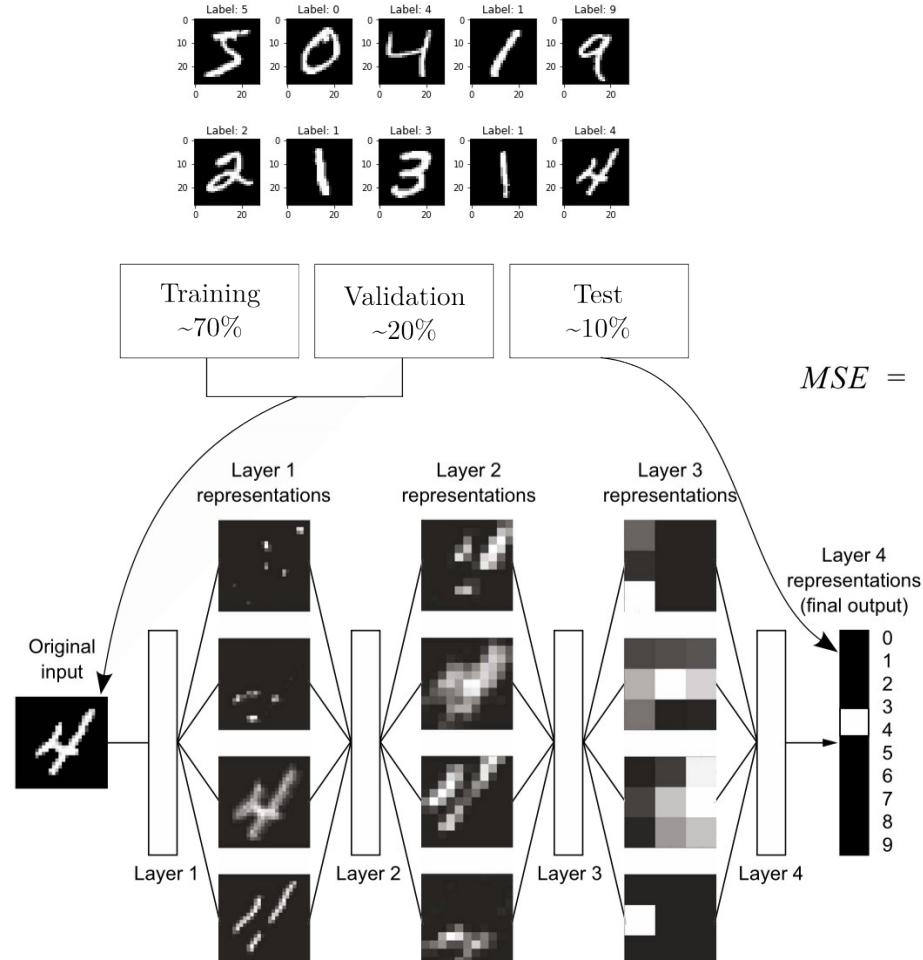
I. J. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and Harnessing Adversarial Examples,” (2015), arXiv:1412.6572 [cs, stat].

# CNN's learning procedure



@[https://en.wikipedia.org/wiki/Kernel\\_\(image\\_processing\)](https://en.wikipedia.org/wiki/Kernel_(image_processing))

| Operation       | Kernel $\omega$   | Image result $g(x,y)$ |
|-----------------|---|-----------------------|
| Identity        | $\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$         |                       |
| Ridge detection | $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 4 & -1 \\ -1 & -1 & -1 \end{bmatrix}$ |                       |
|                 | $\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$ |                       |

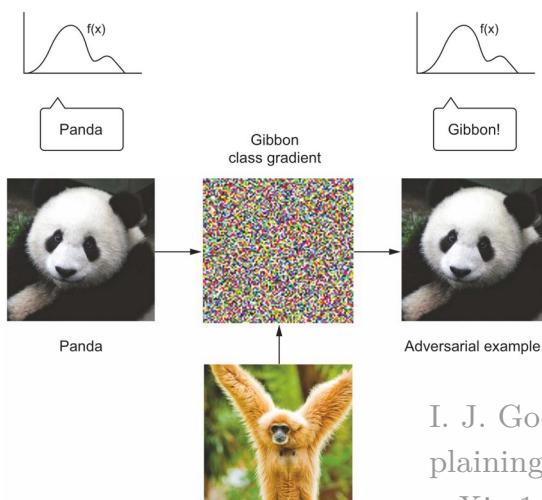
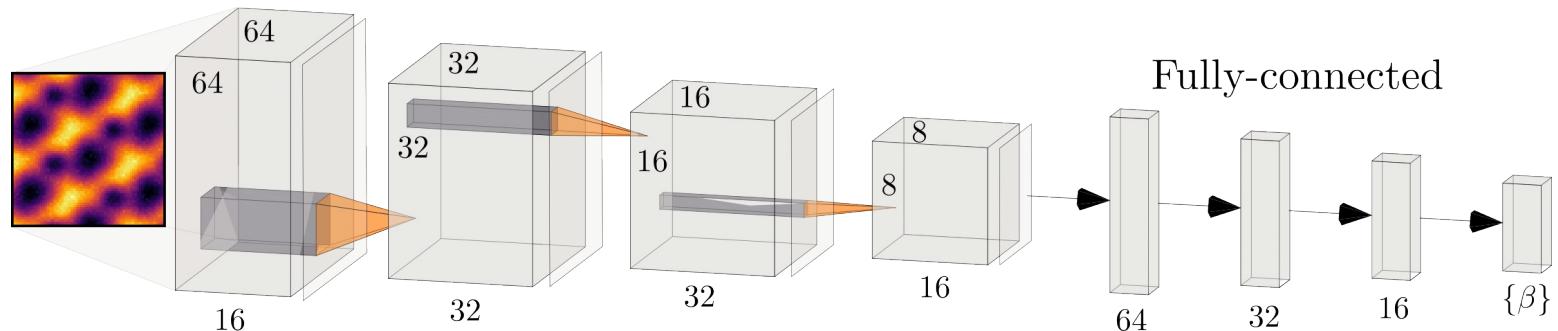


$$MSE = \frac{1}{n} \sum \left( y - \hat{y} \right)^2$$

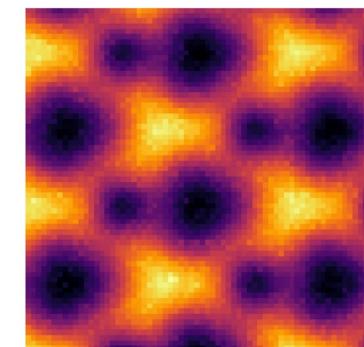
The square of the difference between actual and predicted

# DL Architecture

## Convolution and max pooling



$$p_g(z) = \frac{\exp(-(z-\mu)^2/2\sigma^2)}{\sqrt{2\pi}\sigma^2}$$
$$\sigma \approx 0.31, \mu = 0$$



I. J. Goodfellow, J. Shlens, and C. Szegedy, “Explaining and Harnessing Adversarial Examples,” (2015), arXiv:1412.6572 [cs, stat].

# Orientation of Nematic Director

intensity

$$\Phi = \Phi (\cos 2\varphi, \sin 2\varphi)$$

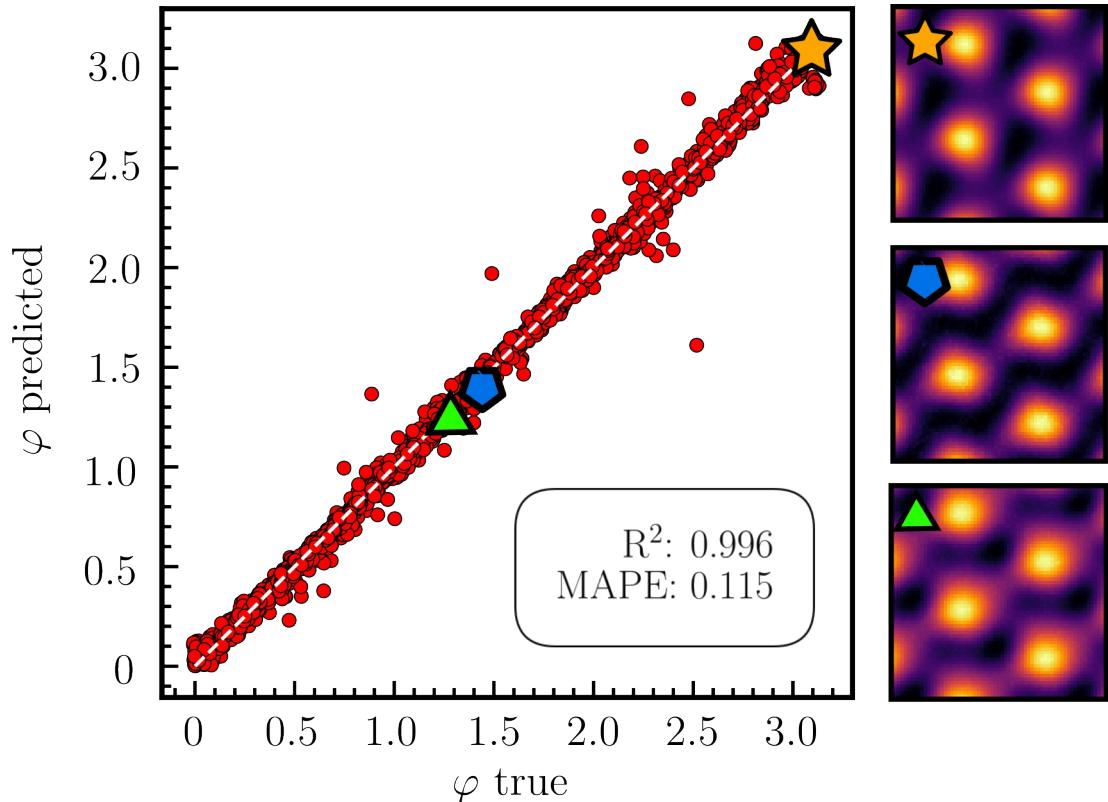
nematic director

angle

$$\varphi_i = \frac{1}{2} \arctan 2(\sin 2\varphi, \cos 2\varphi) \Rightarrow$$

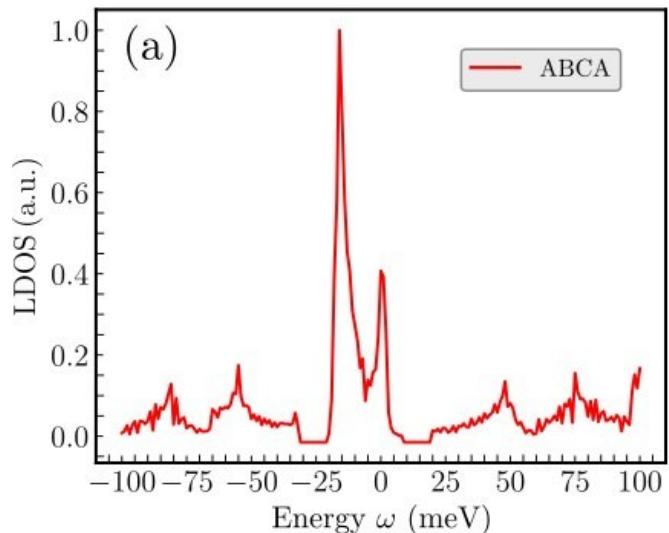
$$\Rightarrow \varphi = \begin{cases} \varphi_i, & \text{sgn}\varphi_i = 1 \\ \varphi_i + \pi, & \text{sgn}\varphi_i = -1 \end{cases}$$

→



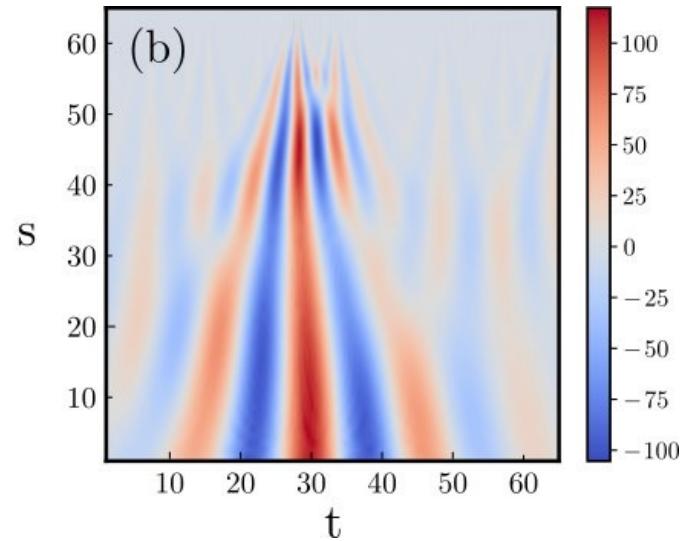
$$\mathcal{D}_{\text{th}} \rightarrow \phi_{\text{MN}}, \phi_{\text{GN}} \in [0.001, 0.1] \text{ eV}, \varphi = \varphi_{\text{MN}} = \varphi_{\text{GN}} \in [0, \pi]$$

# More data: Adding $\mathcal{D}_{\mathbf{r}_0}(\omega)$ channels



CWT  
→

with Morlet  
wavelets

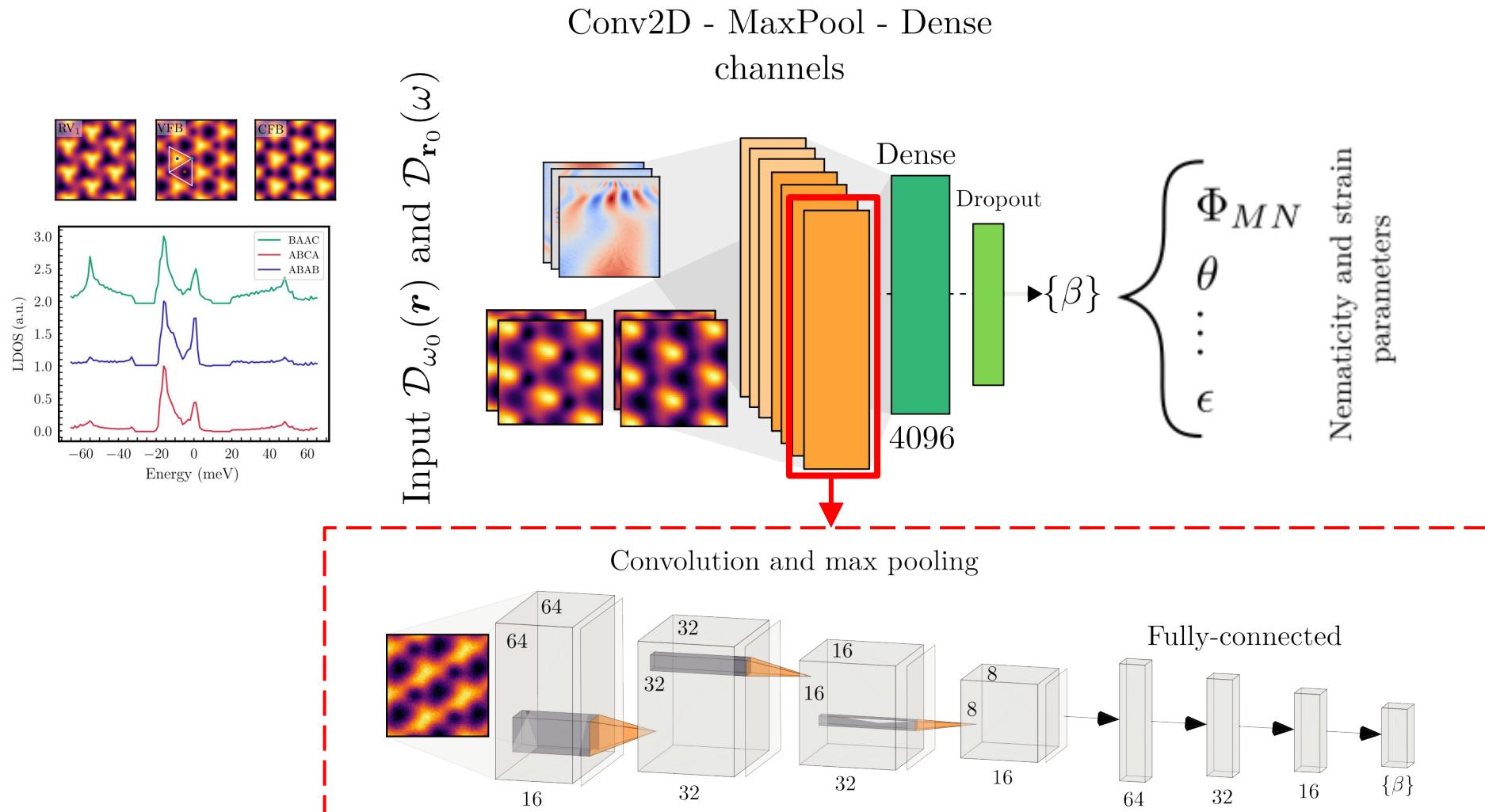


with gaussian noise

$$p_G(z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}}$$

$$\sigma = 0.31, \mu = \mathcal{D}(\omega)$$

# New architecture



# Back to the nematic microscopic form

---

$$E_{n,\mathbf{k}} \rightarrow E_{n,\mathbf{k}} + \Phi \cdot \mathbf{f}(\mathbf{k}),$$

$$\mathbf{f}(\mathbf{k}) = \sum_{m_1, m_2 \in \mathbb{Z}} \phi_{m_1, m_2} \cos(\mathbf{k} \cdot \mathbf{R}_{m_1, m_2})$$

---

$$H_0(\mathbf{k}) \rightarrow H_0(\mathbf{k}) + \Phi \cdot \phi_{s,s'} = \begin{pmatrix} 0 & -\hbar\nu k_- + \Phi \cdot M_\alpha \\ -\hbar\nu k_+ + \Phi \cdot M_\alpha^\dagger & d \end{pmatrix}$$

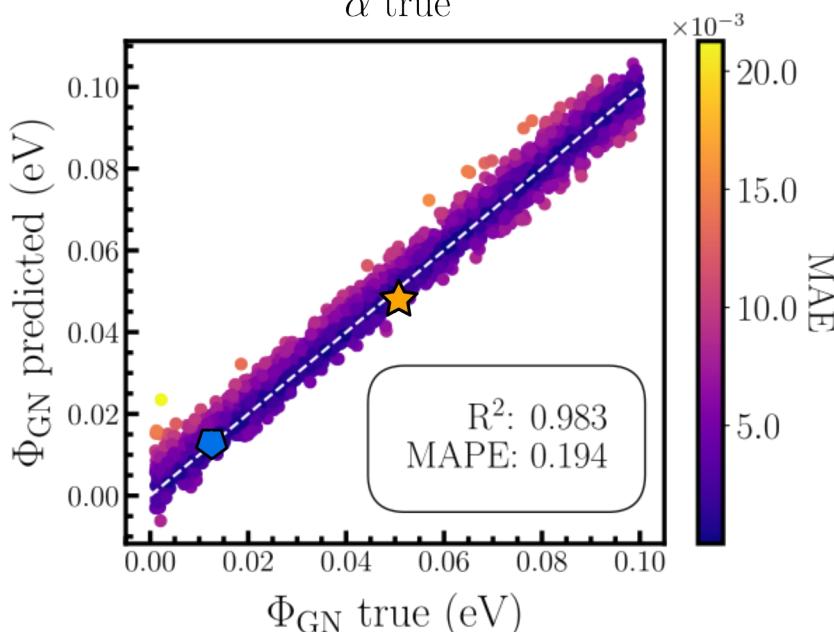
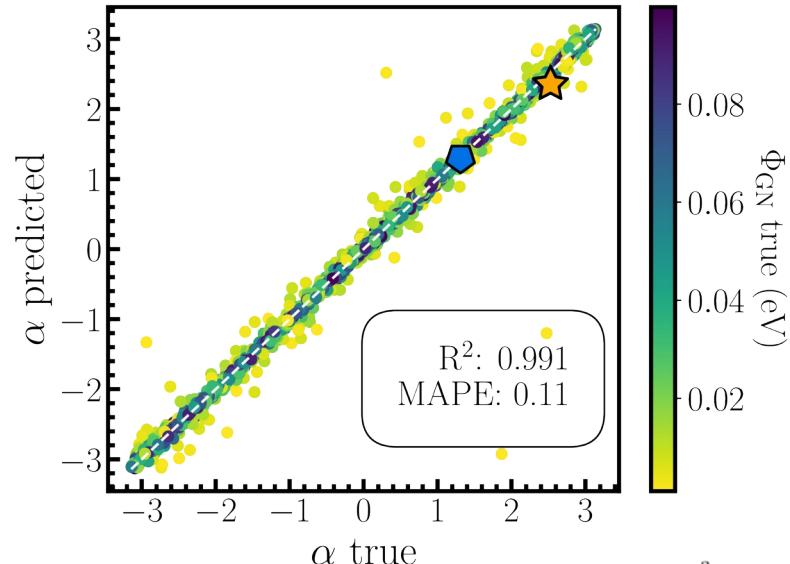
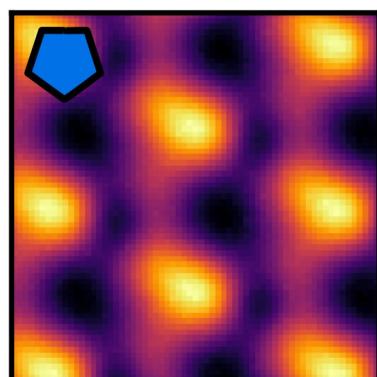
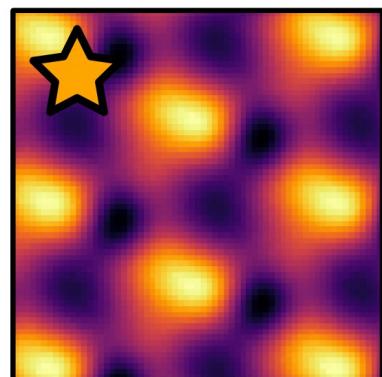
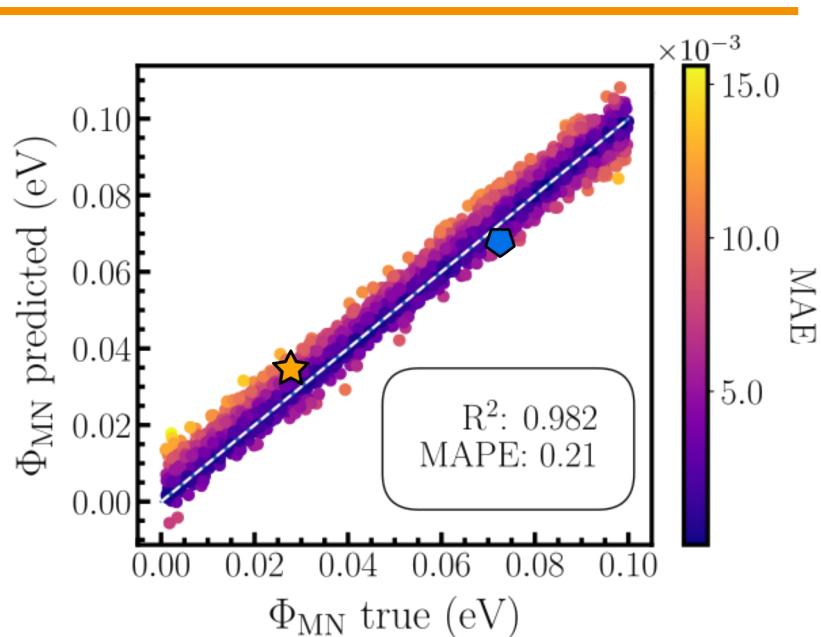
$$M_{\alpha_l} = (1, -i\eta) e^{i\alpha_l \eta}.$$

---

Learn

$$\beta = \{\Phi_{MN}, \Phi_{GN}, \alpha\}$$

# Form of nematicity



# Including strain

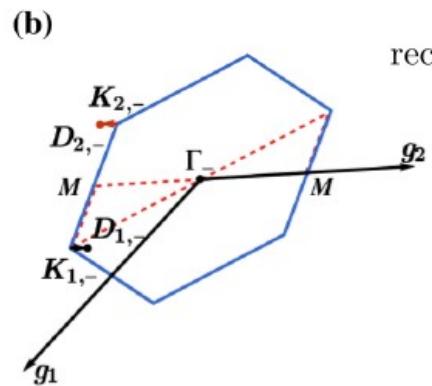
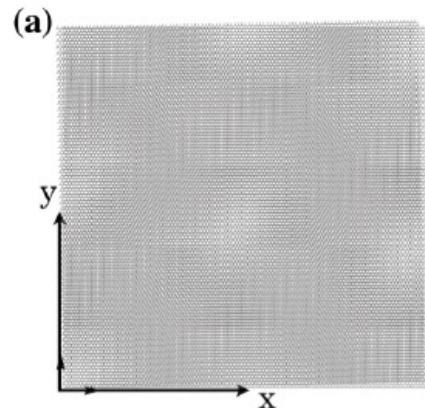


Fig. 1: Modification of Moiré Structure and Brillouin Zone with  $\epsilon = 0.7\%$ ,  $\varphi = 0^\circ$  and  $\theta = 1.05^\circ$  [5].

moiré superlattice  
reciprocal and primitive  
latticevectors

small angle  
rotation

$$\begin{cases} \mathbf{g}_i \cong \mathcal{E}^T \mathbf{G}_i \\ \mathbf{a}_i \cong \mathcal{E}^{-1} \mathbf{A}_i \end{cases}$$

monolayer graphene  
reciprocal and primitive  
latticevectors

learnable parameters

$$\mathcal{E} = \mathcal{T}(\theta) + S_{ua}(\overbrace{\epsilon, \dot{\theta}_\epsilon})$$

$$\mathcal{E} = \frac{1}{2} R(\theta_\epsilon)^{-1} \begin{pmatrix} -\epsilon & 0 \\ 0 & \nu\epsilon \end{pmatrix} R(\theta_\epsilon)$$

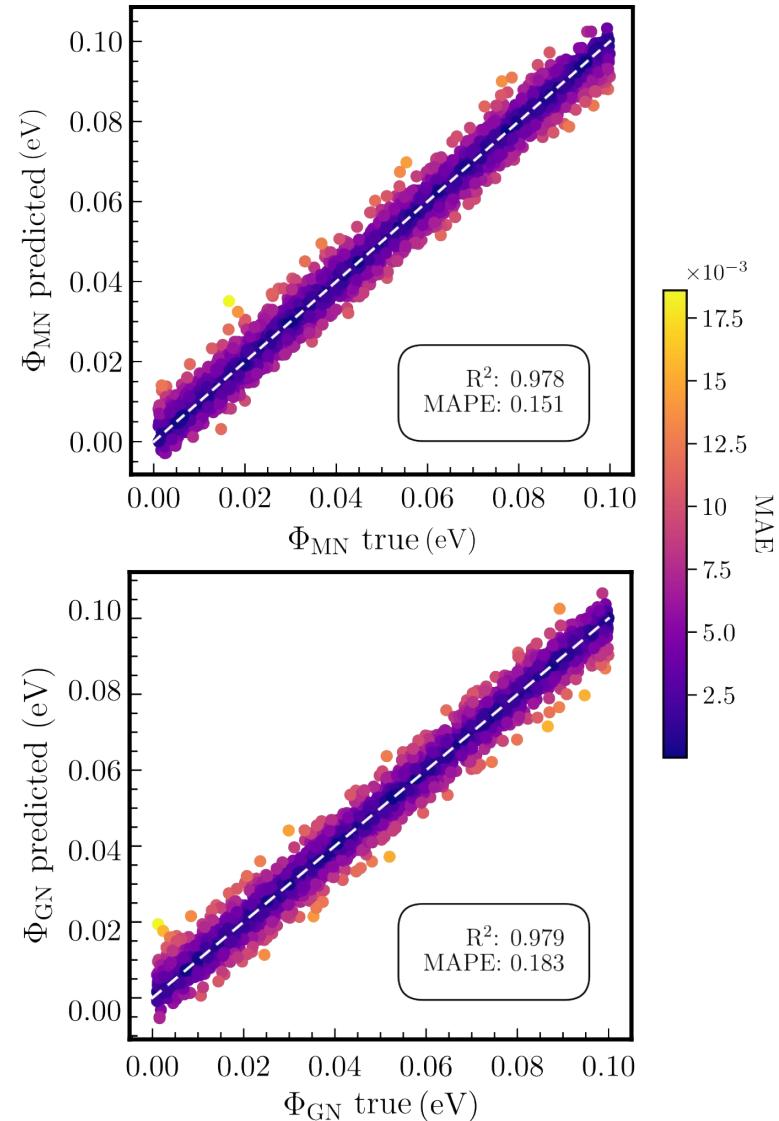
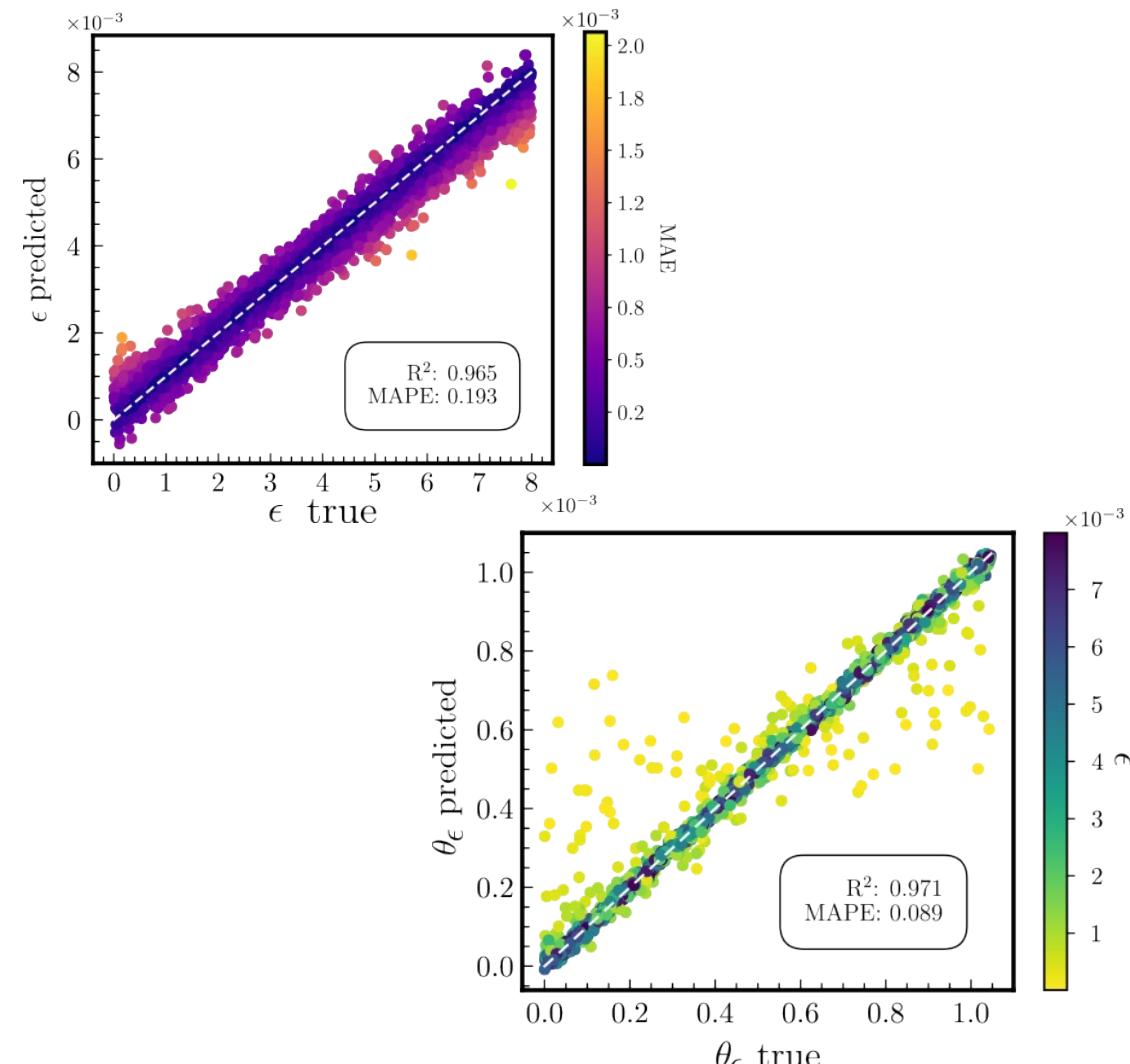
uniaxial strain

Bi, Z., Yuan, N.F. and Fu, L., 2019. Physical Review B, 100(3), p.035448.

Learn

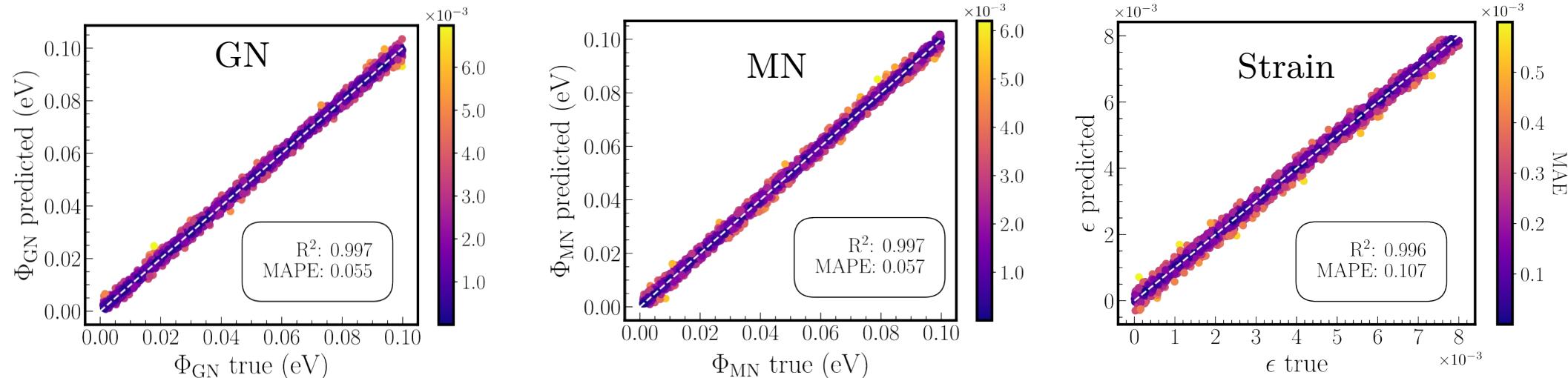
$\Phi_{MN}, \Phi_{GN}, \theta_\epsilon, \epsilon$

# Including strain



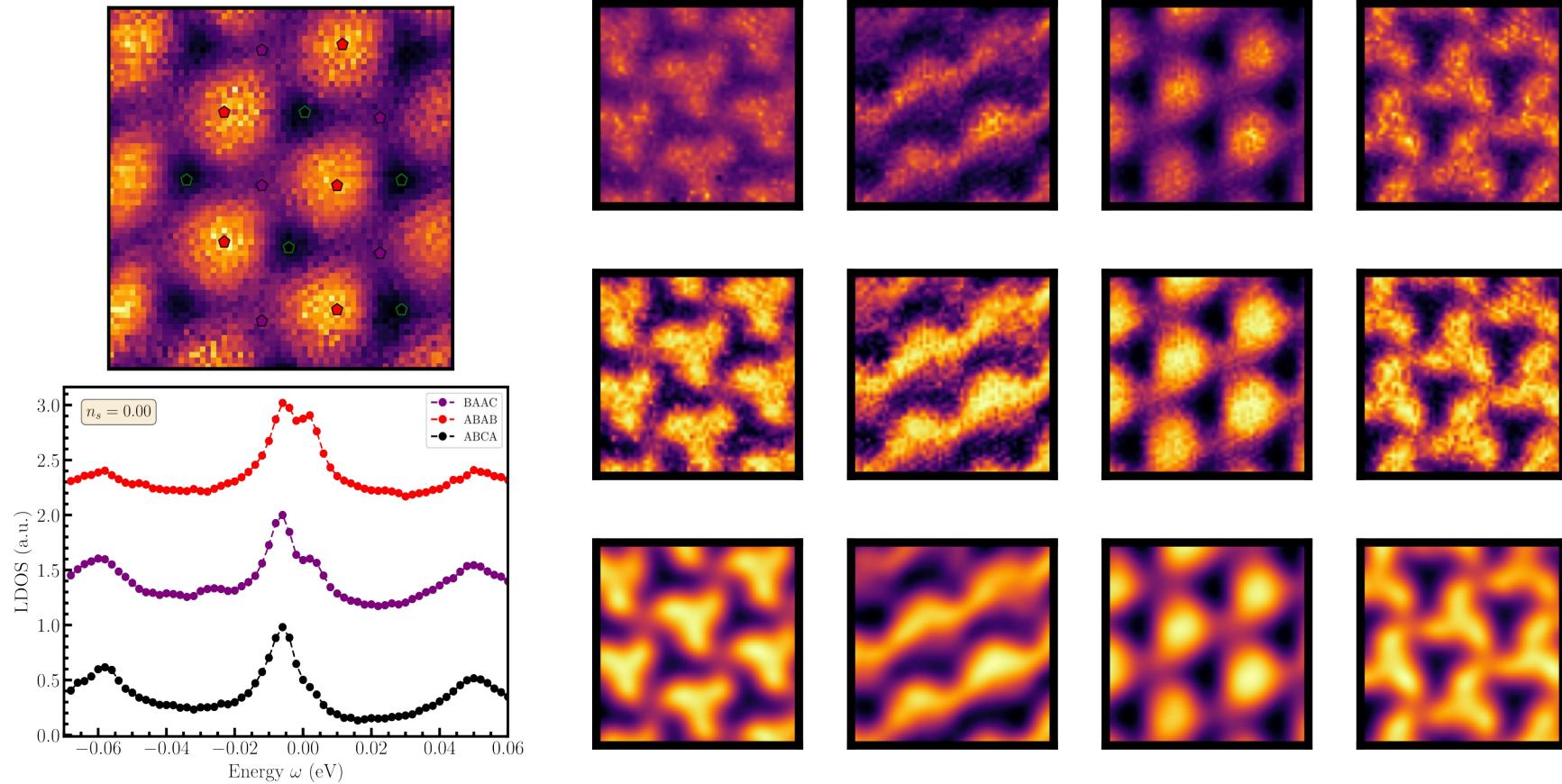
# Including strain, fixed $\theta_\varepsilon$

---

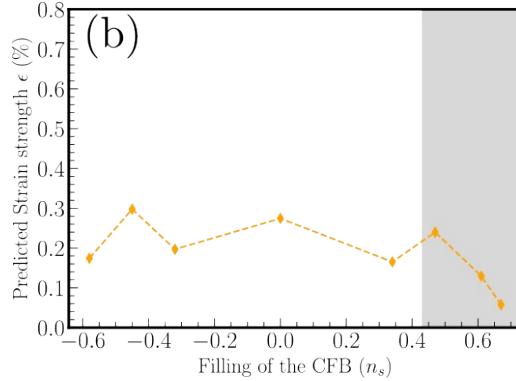
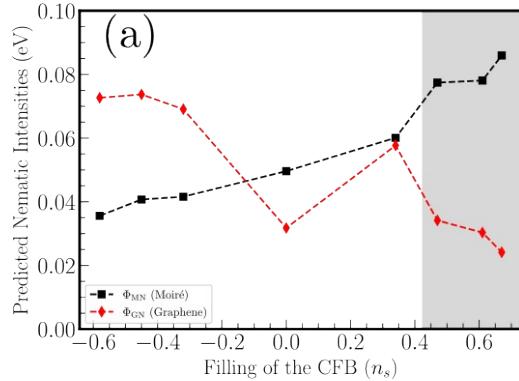


- Can we apply the trained CNN directly to experimental data?

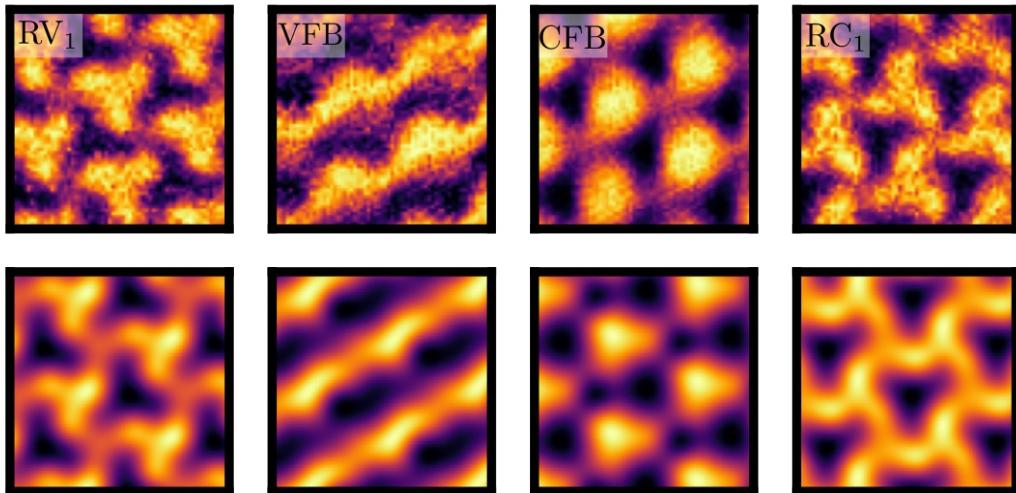
# Preprocessing of $D_{\text{exp}}$



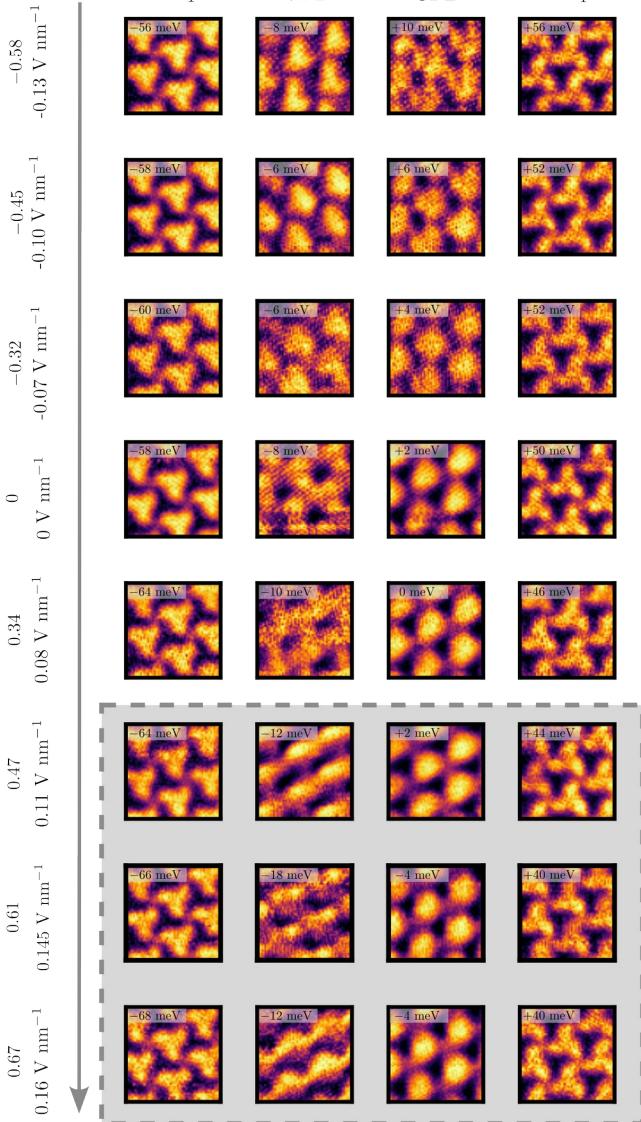
# Predictions on $D_{\text{exp}}$



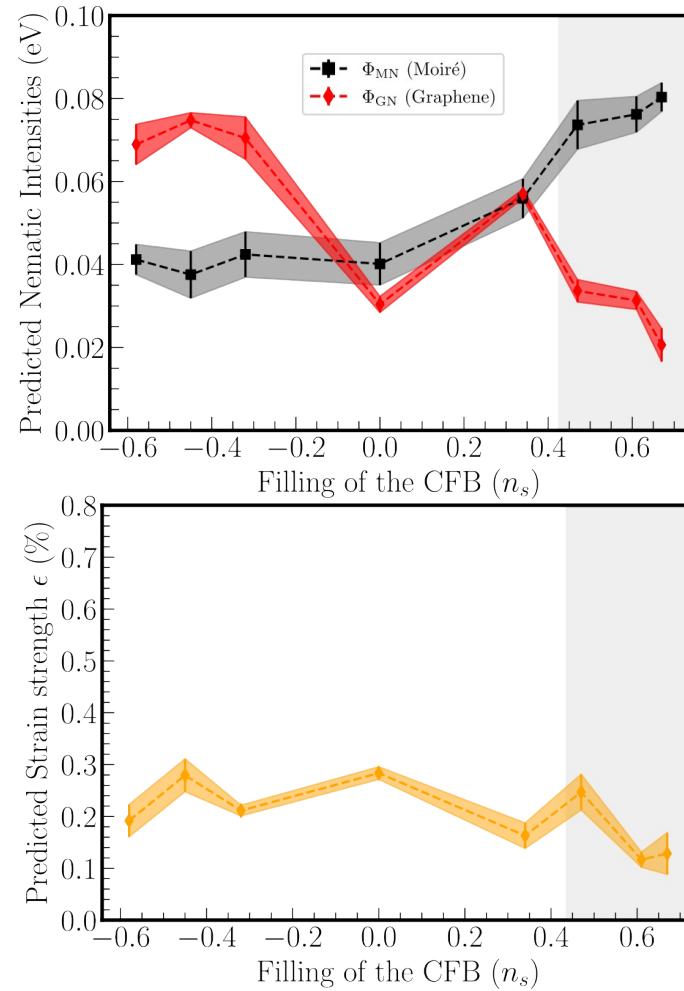
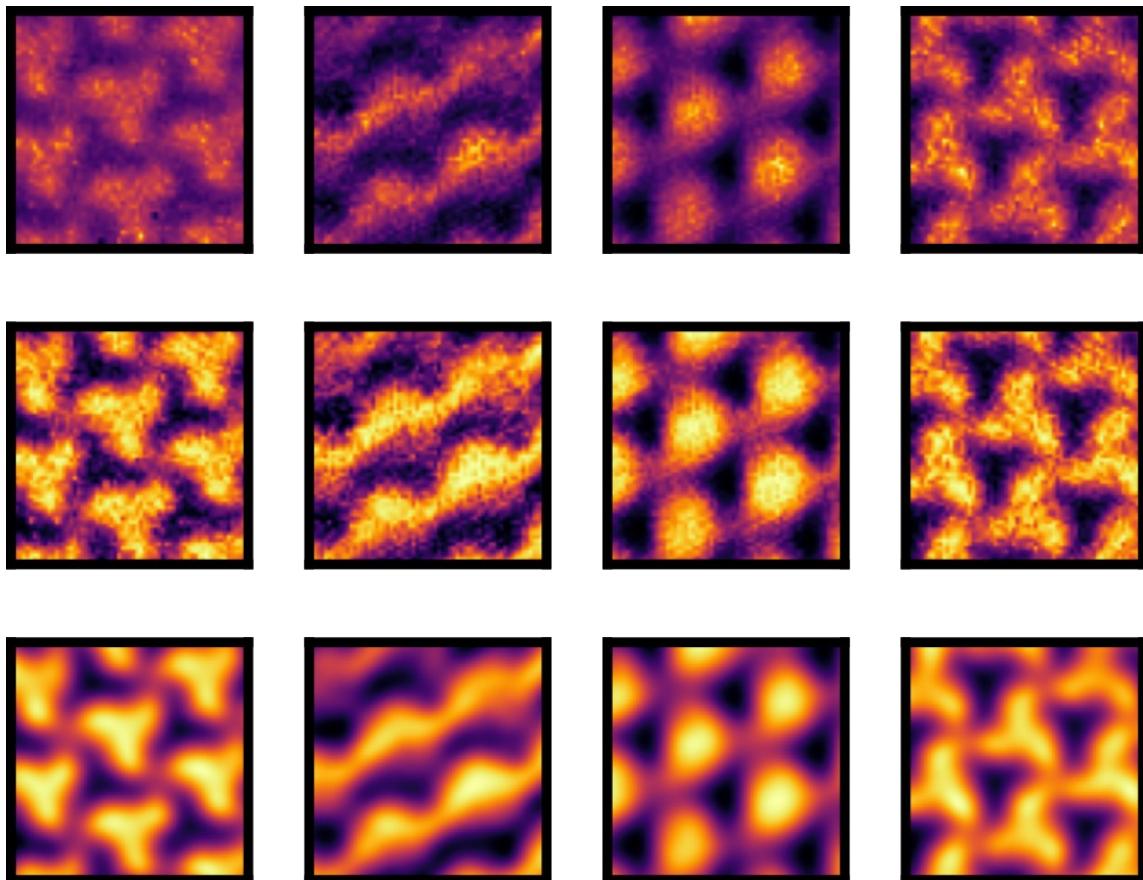
(c)



Filling of the CFB ( $n_s$ )  
Displacement Field



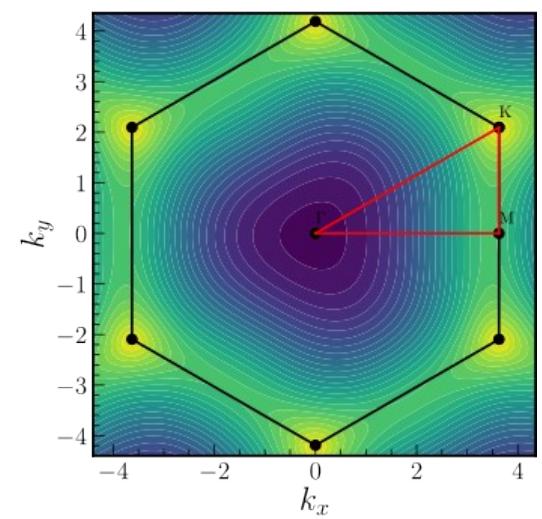
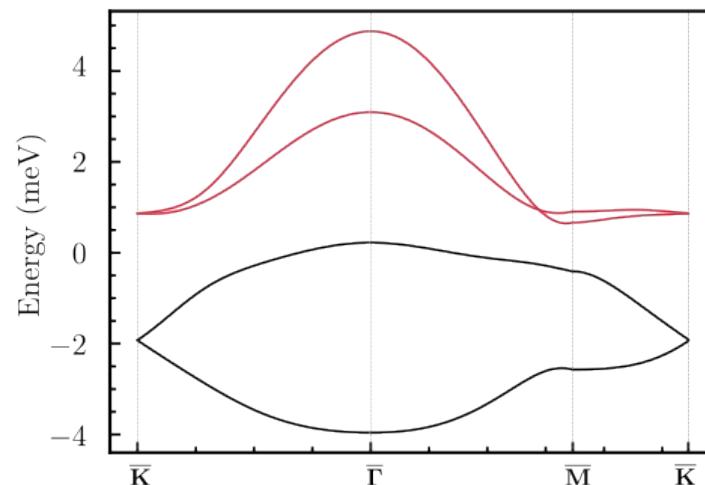
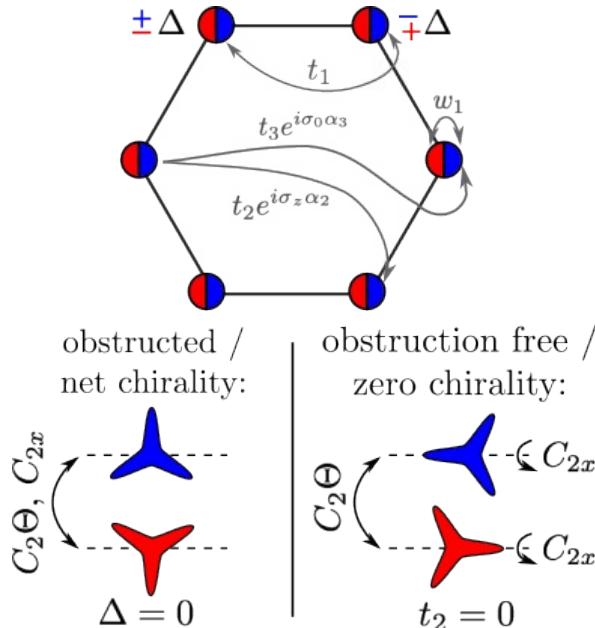
# Prediction on $D_{\text{exp}}$ (Preprocessing stage)



# Beyond TDBG and the continuum model

## Minimal tight-binding model (four bands per spin & valley)

$$H = \sum_{\vec{k}} \sum_{l=1,2} c_{\vec{k},l}^\dagger \vec{g}_{\vec{k}}^l \cdot \vec{\rho} c_{\vec{k},l} + w_1 \sum_{\vec{k}} \left( e^{-i\theta_w} c_{\vec{k},1}^\dagger c_{\vec{k},2} + \text{H.c.} \right),$$



# Beyond TDBG and the continuum model

## Nematic order

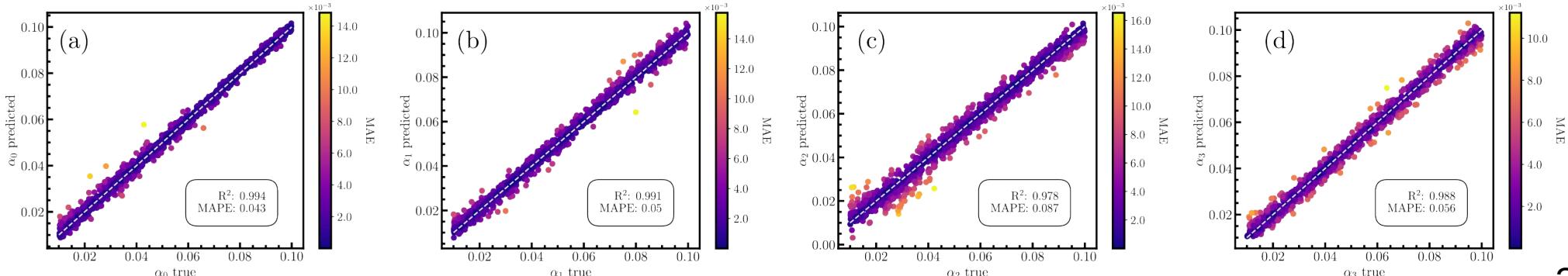
$$\Delta h_{\mathbf{k}} = \phi \cdot \mathbf{g}_{\mathbf{k}} = \phi_1 g_{1,\mathbf{k}} + \phi_2 g_{2,\mathbf{k}}$$

$$\begin{aligned} \mathbf{g}_{\mathbf{k}} \equiv \begin{pmatrix} g_{1,\mathbf{k}} \\ g_{2,\mathbf{k}} \end{pmatrix} &= \alpha_0 \rho_0 \sigma_0 \begin{pmatrix} f_{1,\mathbf{k}} \\ f_{2,\mathbf{k}} \end{pmatrix} + \alpha_1 \rho_0 \sigma_x \begin{pmatrix} f_{1,\mathbf{k}} \\ f_{2,\mathbf{k}} \end{pmatrix} \\ &+ \alpha_2 \rho_0 \sigma_y \begin{pmatrix} -f_{2,\mathbf{k}} \\ f_{1,\mathbf{k}} \end{pmatrix} + \alpha_3 \rho_z \sigma_z \begin{pmatrix} -f_{2,\mathbf{k}} \\ f_{1,\mathbf{k}} \end{pmatrix} \end{aligned}$$

Learn  $\alpha_0, \alpha_1, \alpha_2, \alpha_3$

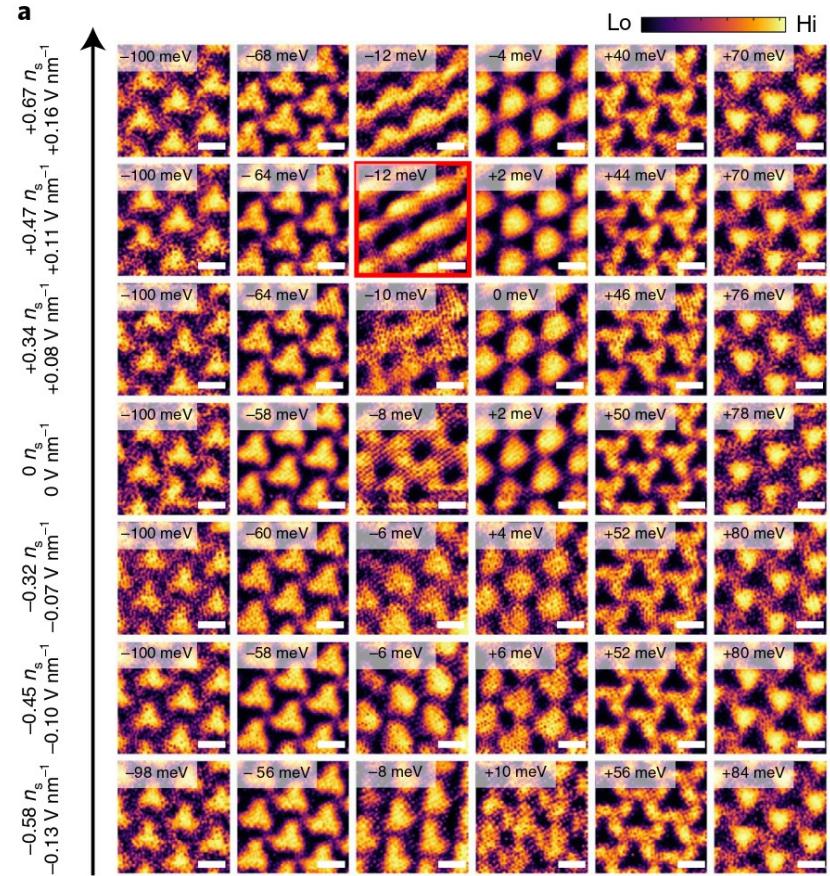
if we focus on leading lattice harmonic

$$\mathbf{f}_{\mathbf{k}} = \frac{8}{3} \left( \cos k_y - \cos \frac{\sqrt{3}k_x}{2} \cos \frac{k_y}{2}, \sqrt{3} \sin \frac{\sqrt{3}k_x}{2} \sin \frac{k_y}{2} \right)^T$$



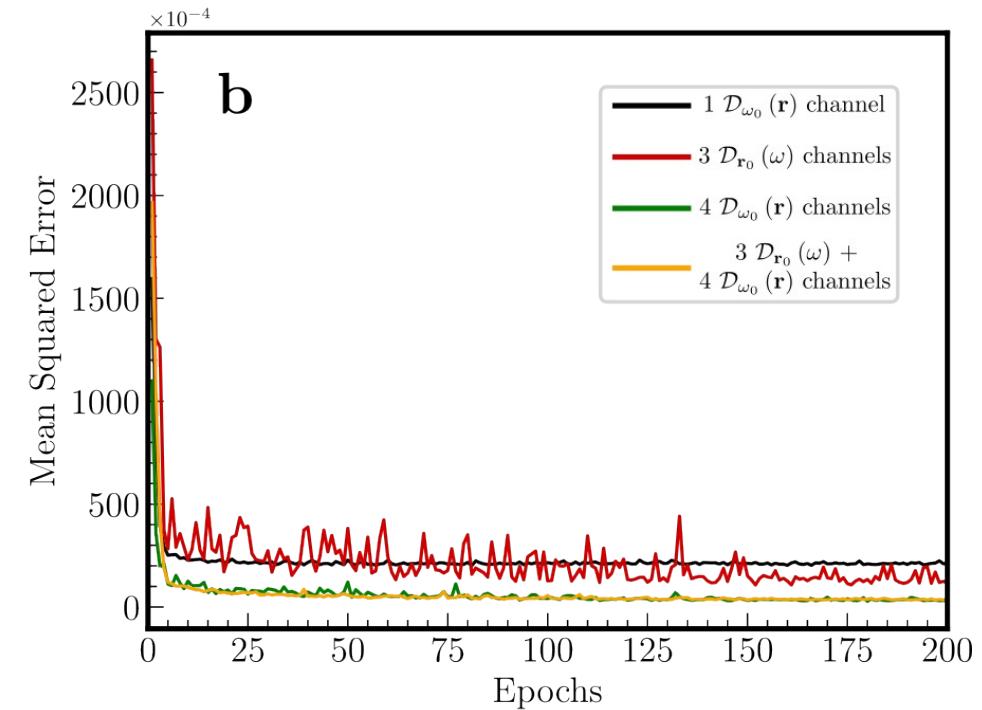
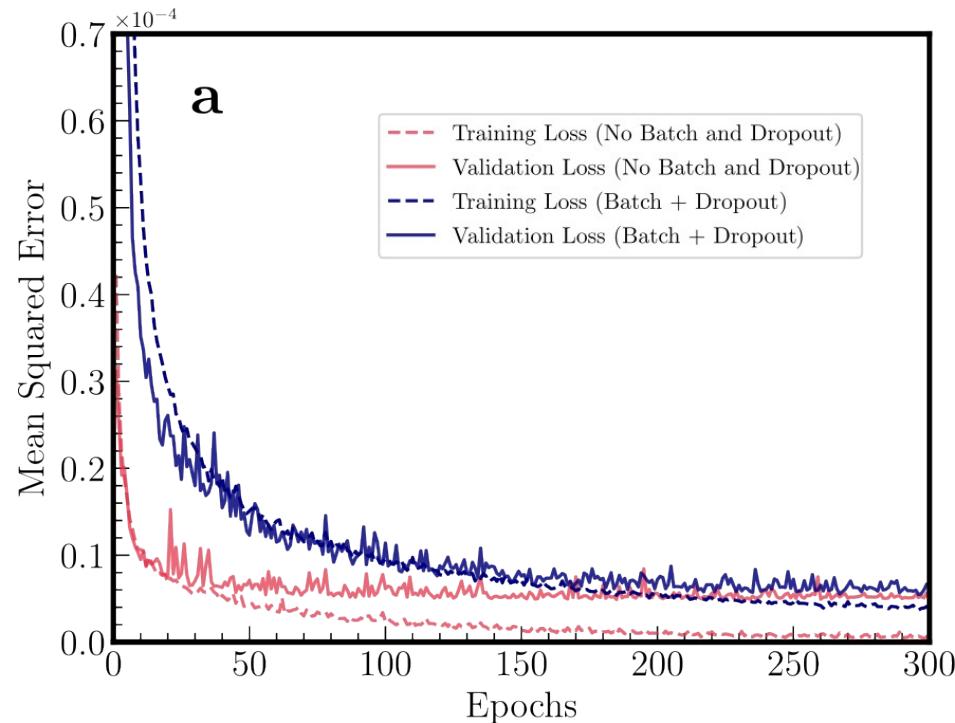
# Overview and Outlook

- CNN's can distinguish nematicity and strain influence.
- Possible crossover between GN and MN for TDBG;
- Applicability beyond the continuum model and TDBG;
- Microscopic parameter learning from data (kind of Hamiltonian Learning);
  - Automated analysis of larger datasets;
  - Extensible to a variety of experimental setups? Comparison between different theoretical models?

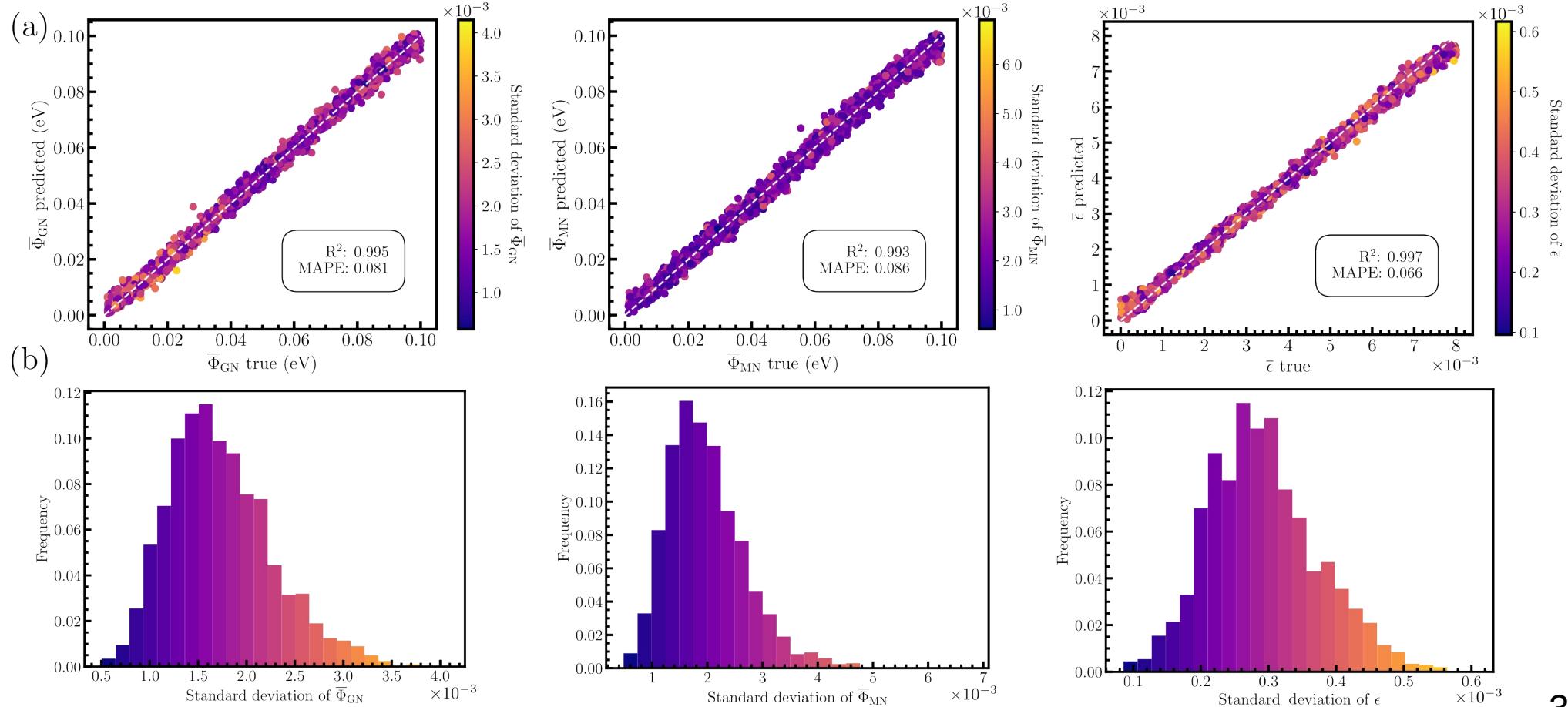


# Backup slides

# Number of channels and overfitting

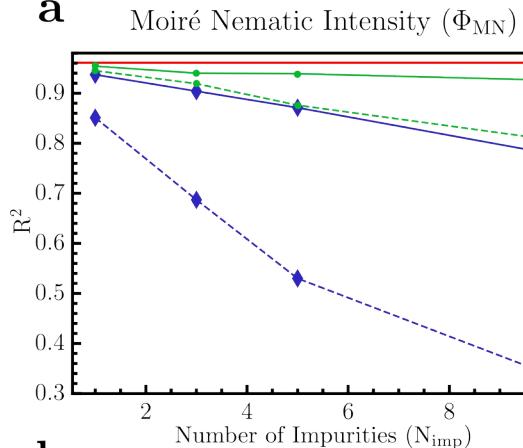


# Average over different runs

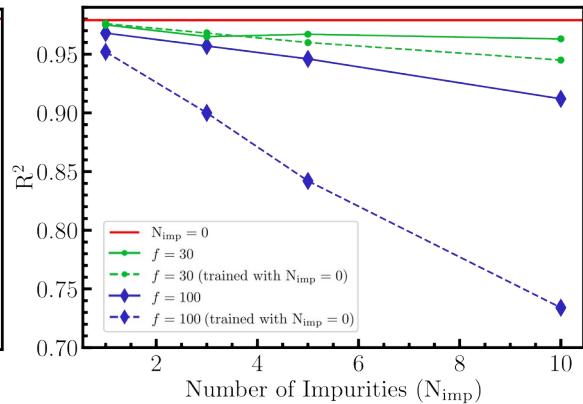


# Robustness regarding impurities

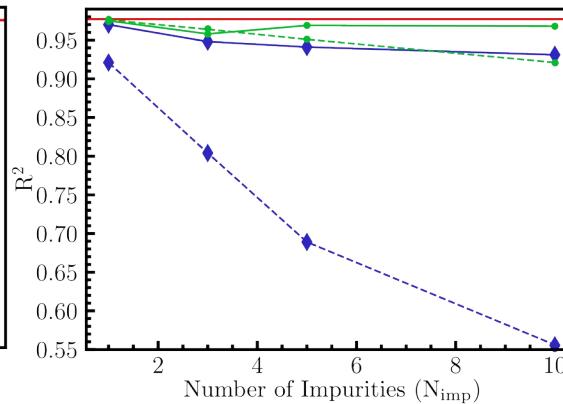
a



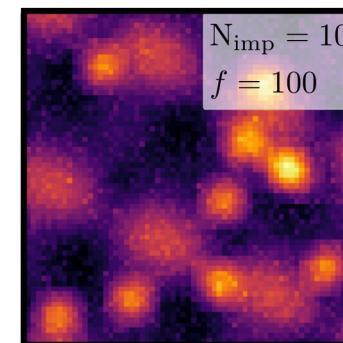
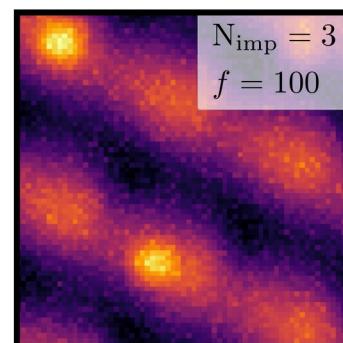
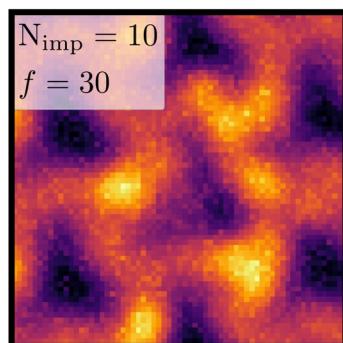
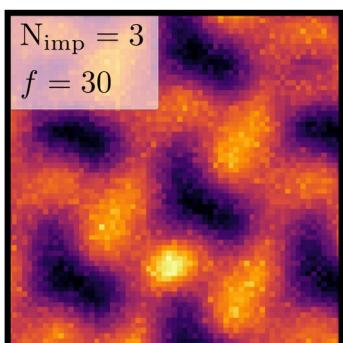
Graphene Nematic Intensity ( $\Phi_{GN}$ )



Strain Intensity ( $\epsilon$ )

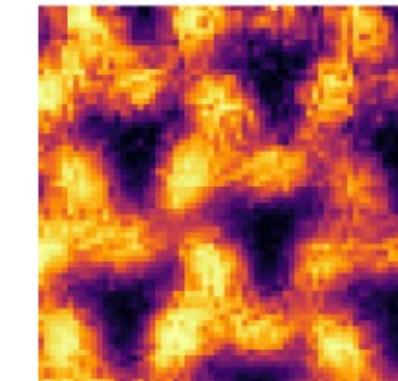
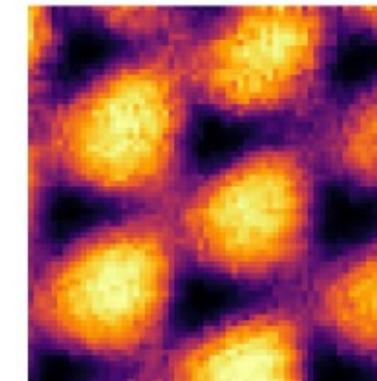
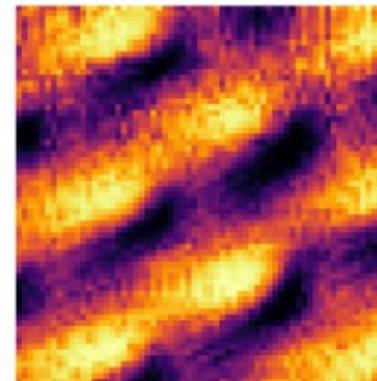
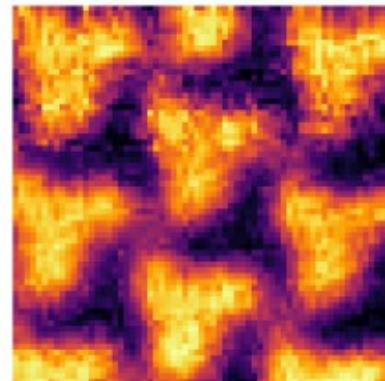
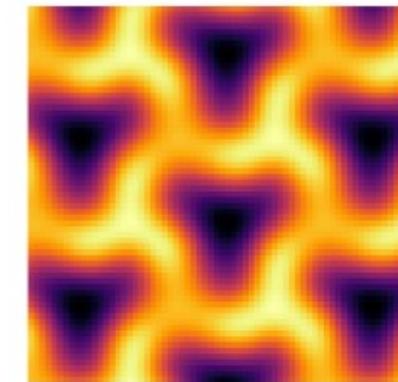
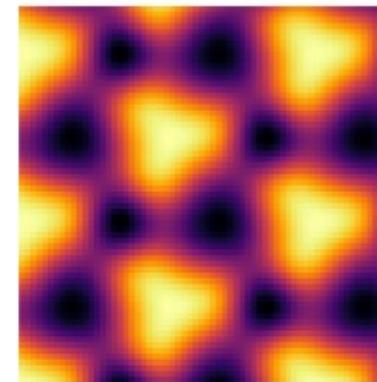
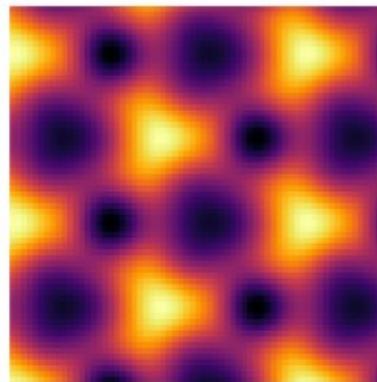
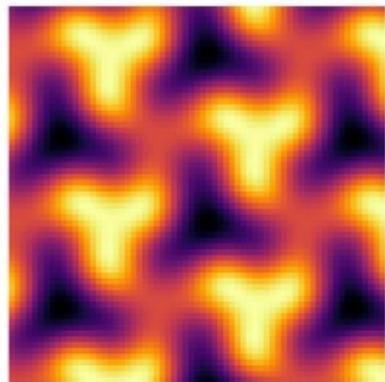


b

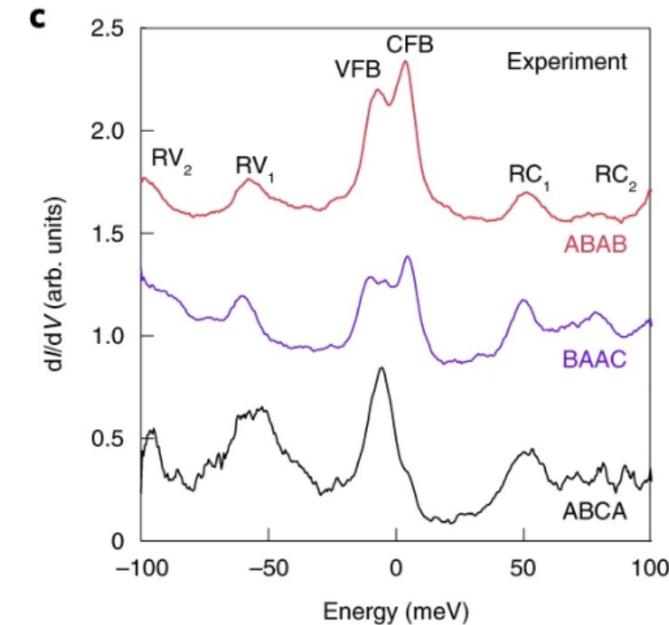
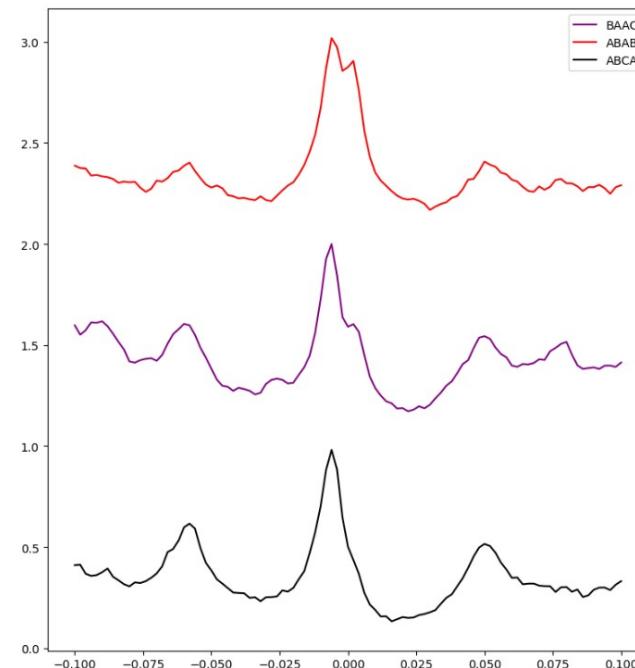
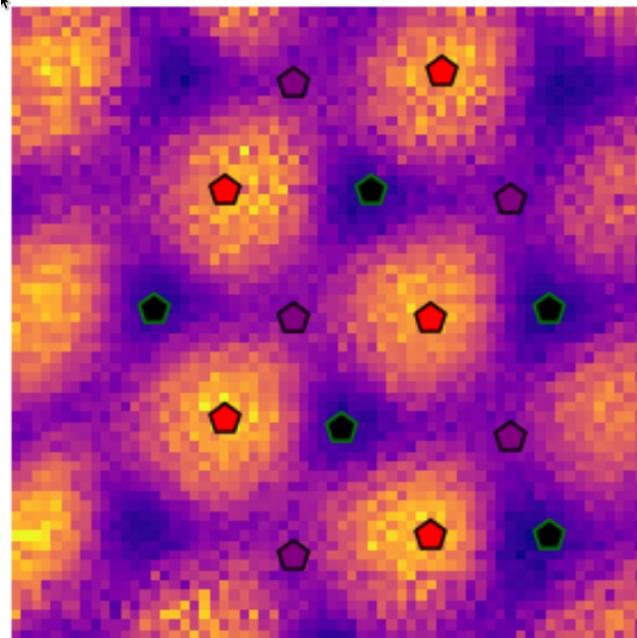


# Preprocessing of the experimental data

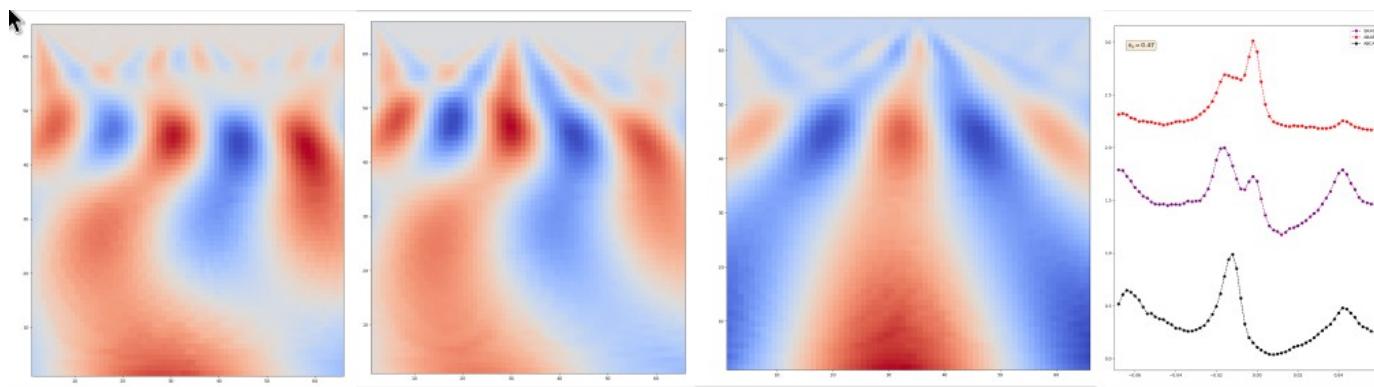
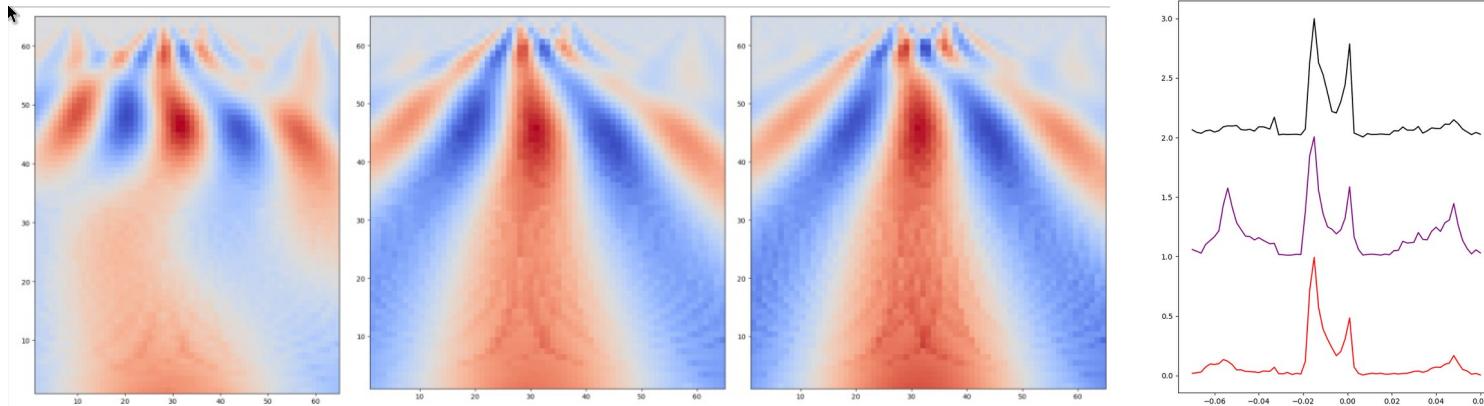
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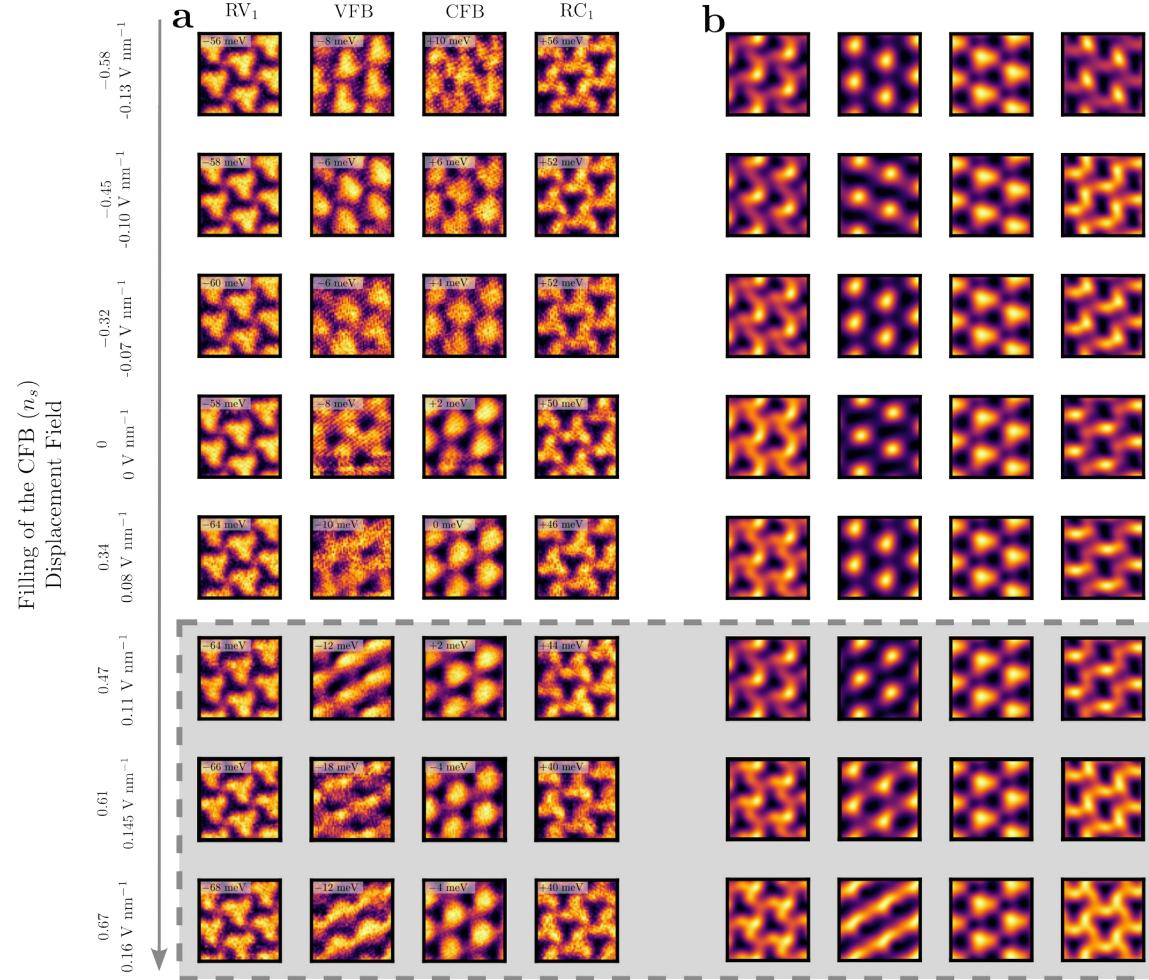
# Preprocessing of the experimental data



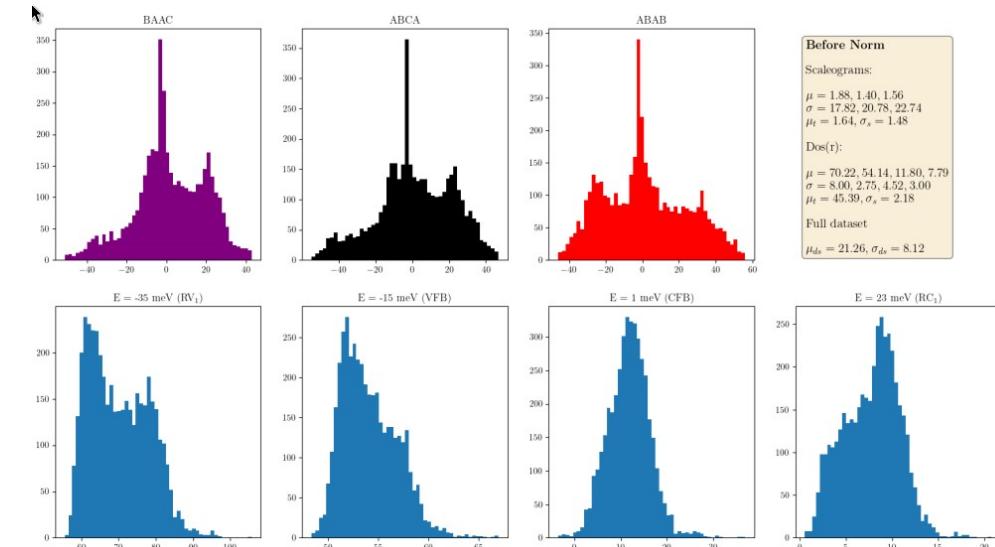
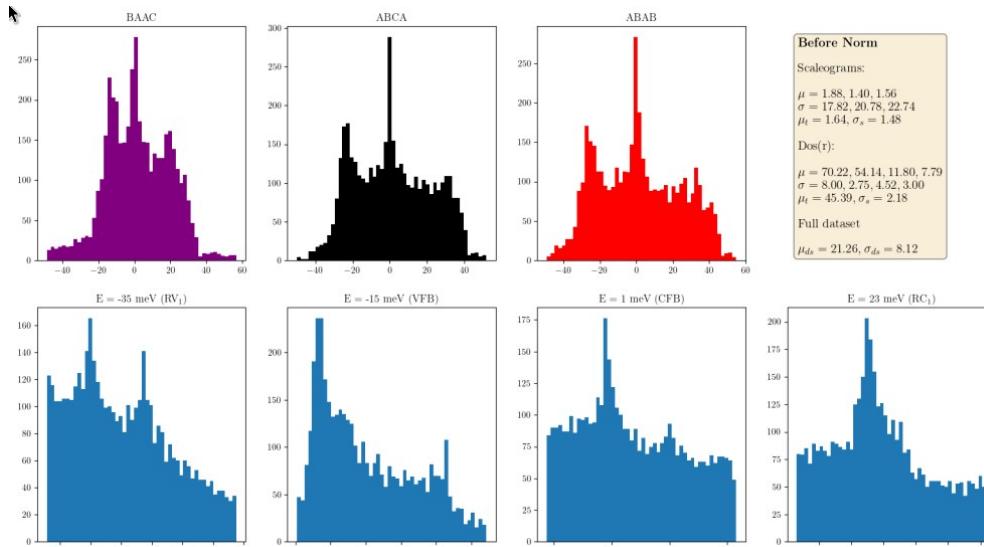
# Preprocessing of the experimental data



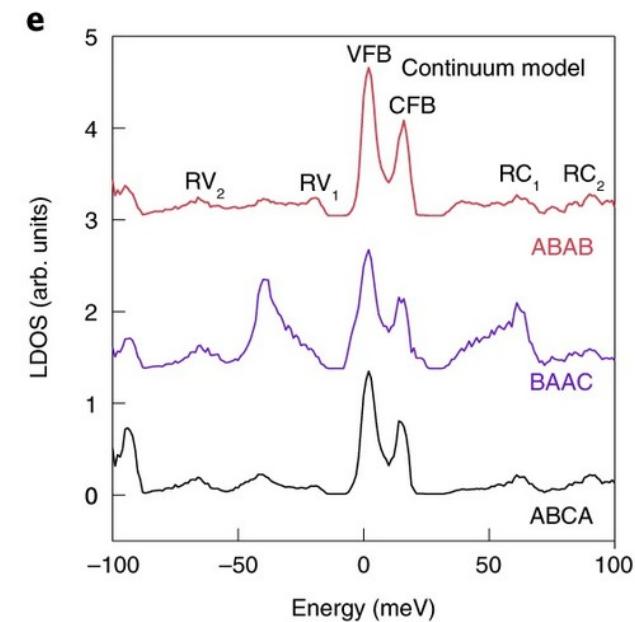
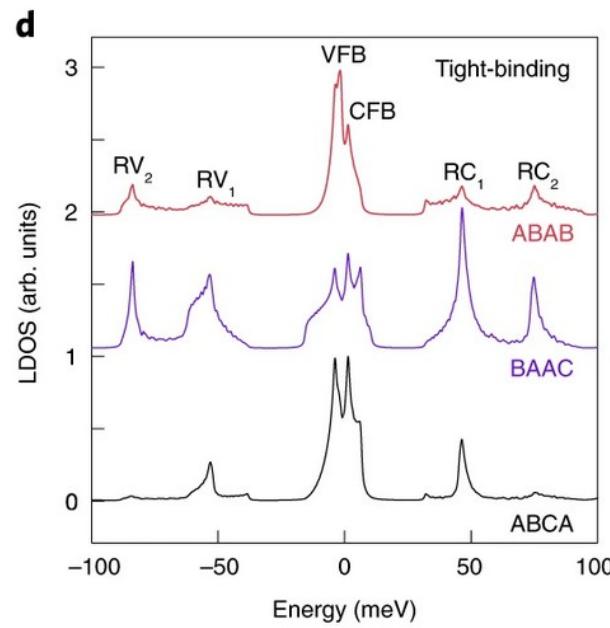
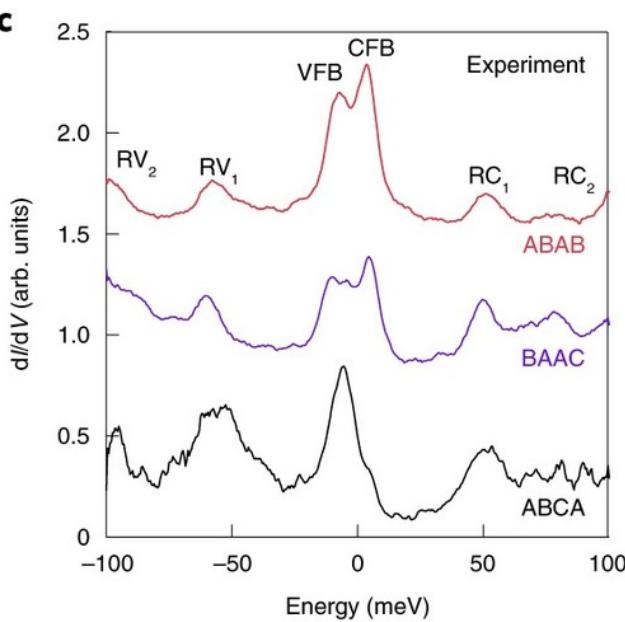
# Predictions on $D_{\text{exp}}$



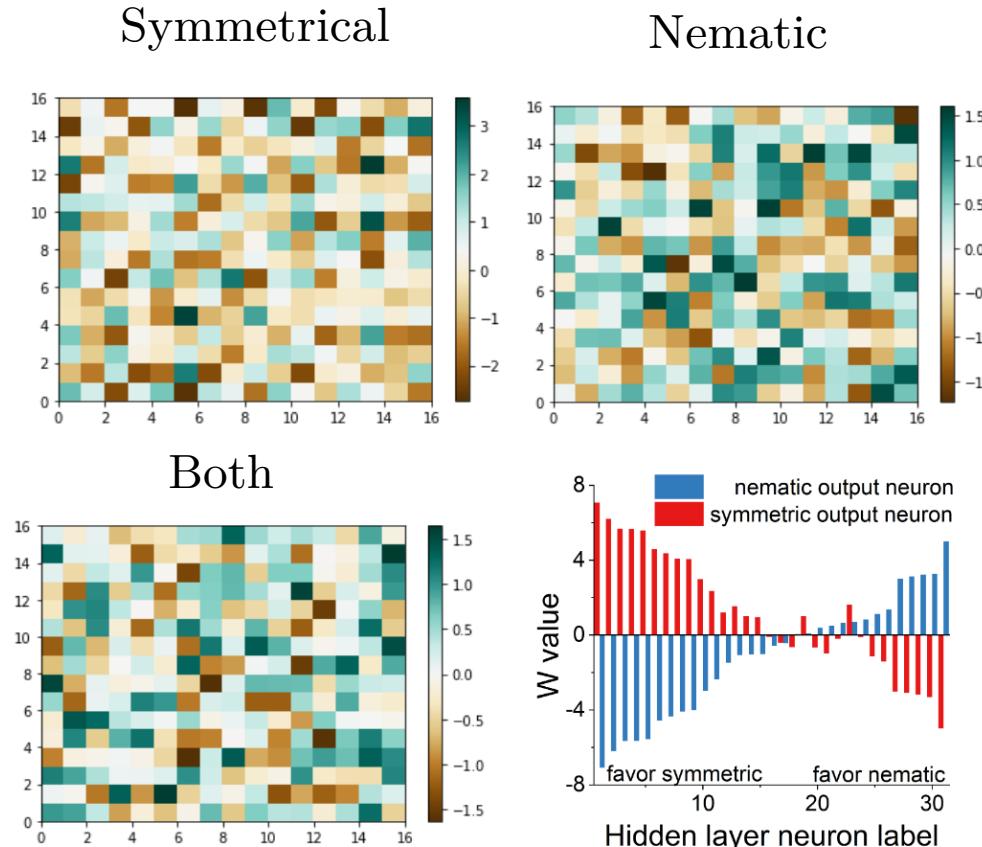
# Preprocessing of the experimental data



# Limitations of theoretical model/data resolution

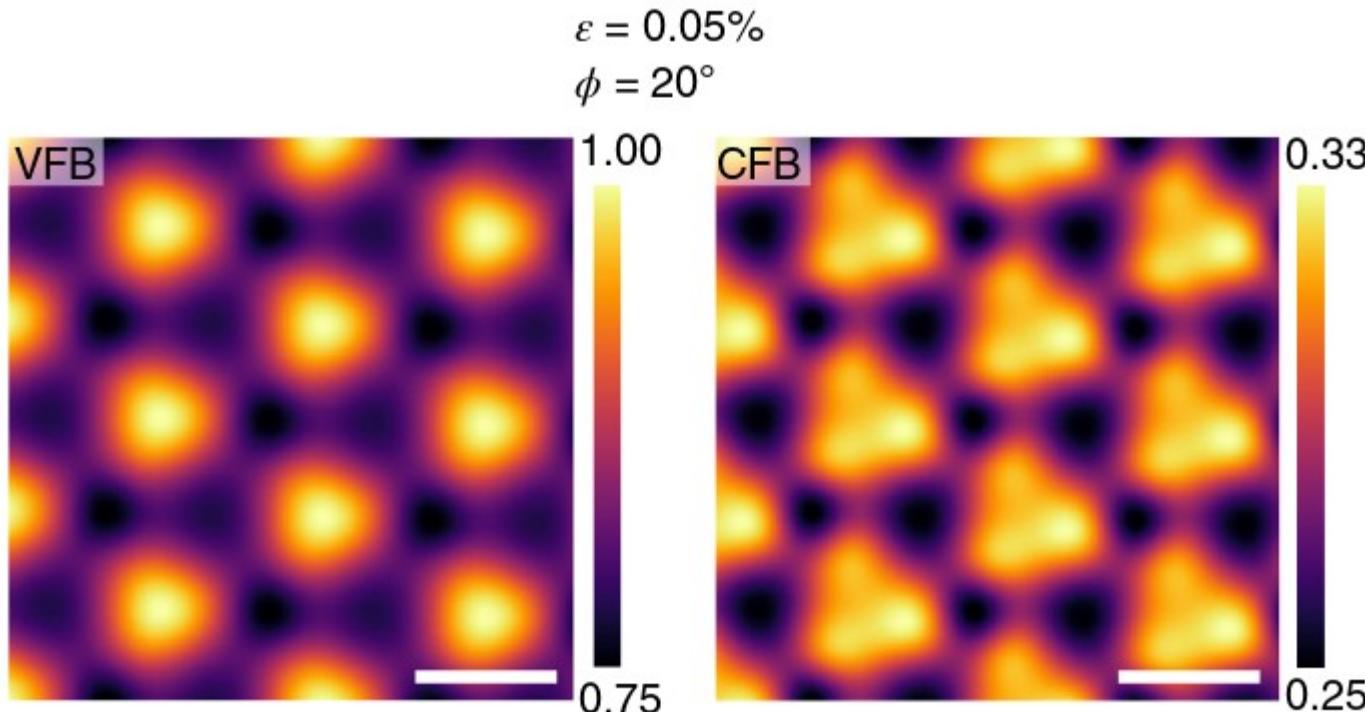


# Interpretability? Correlations in AI nematic study

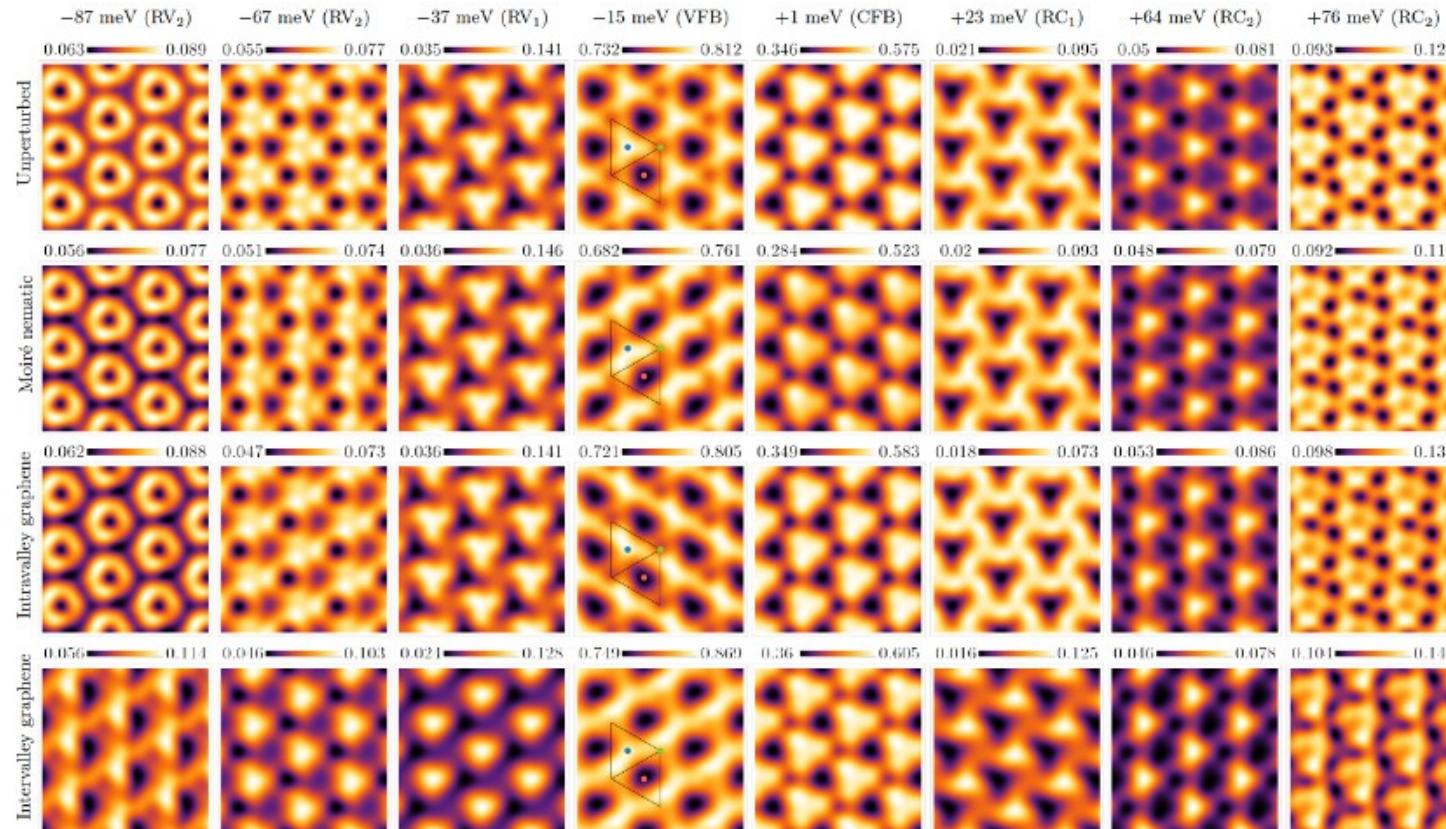


# Tight Binding in TDBG

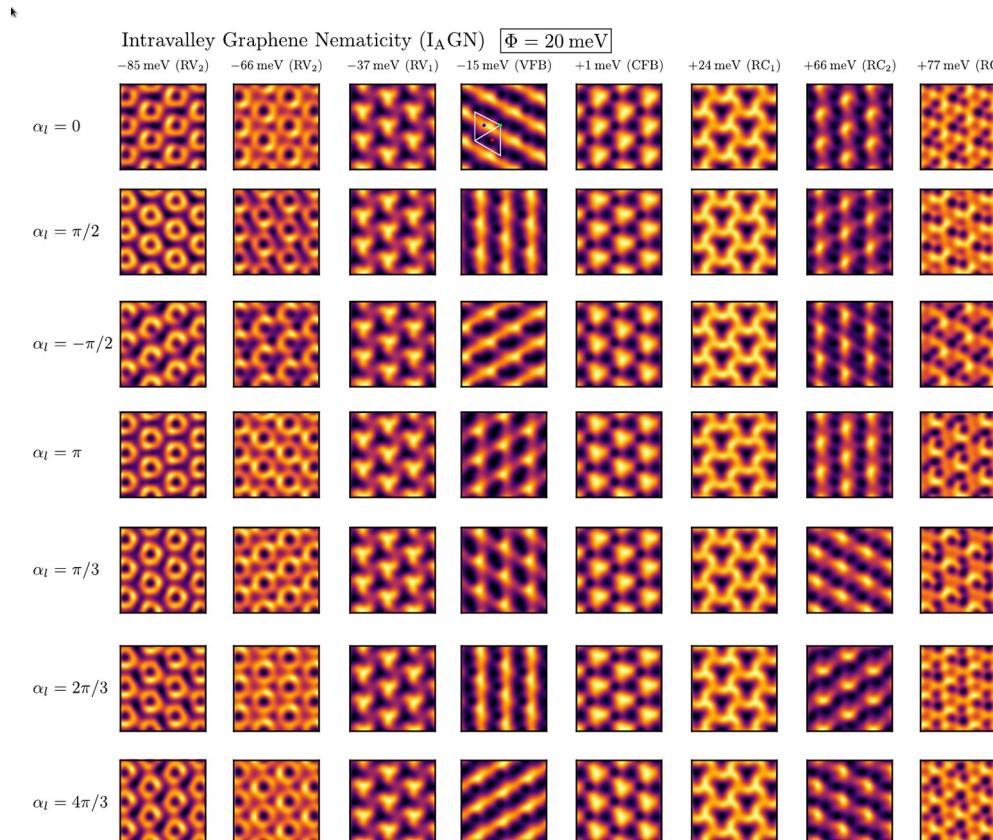
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# More nematic couplings: Intervalley GN



# More nematic couplings: Intervalley GN



R. Samajdar, M. S. Scheurer, S. Turkel, et al. 2D Materials 8, 034005 (2021).