

# Lecture 04

# **From post-acquisition to real-time analysis: ensemble networks and automated experiment**

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# Motivation

Robust post-experiment **analytics**

Hyperspectral measurements of **sensitive materials**

Measurements of **specific atoms**

Selective **atom removal**

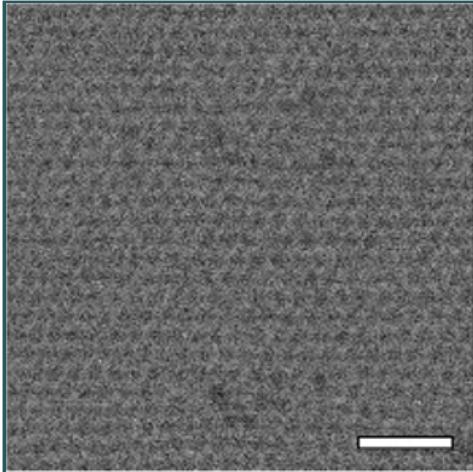
Extract **beam-matter interactions**

**Creation** of various **defects**

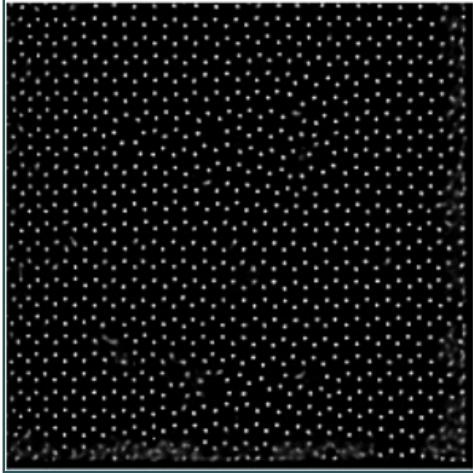
**Measurements** of created **defects**

# Variation of STEM images

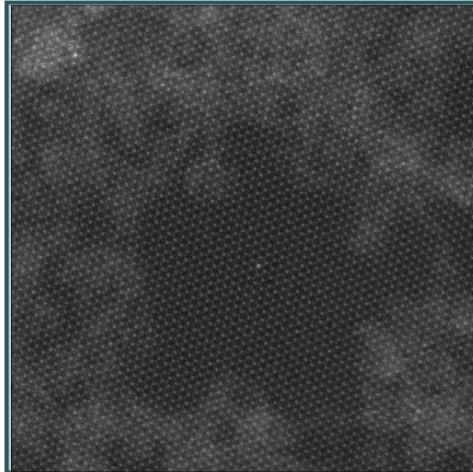
Graphene (MAADF)



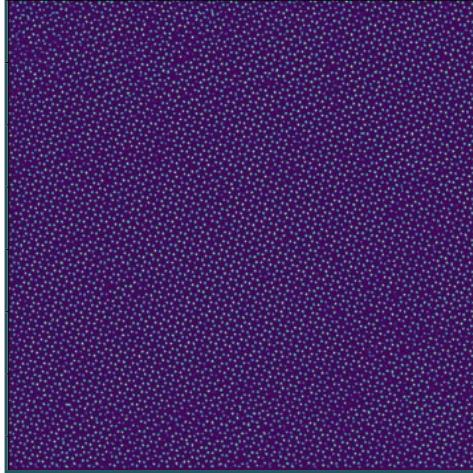
Model prediction



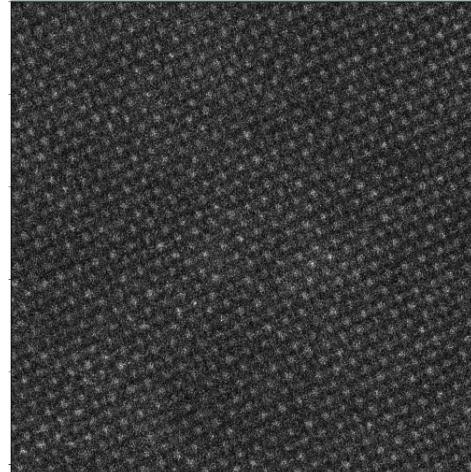
MoS<sub>2</sub> (HAADF)



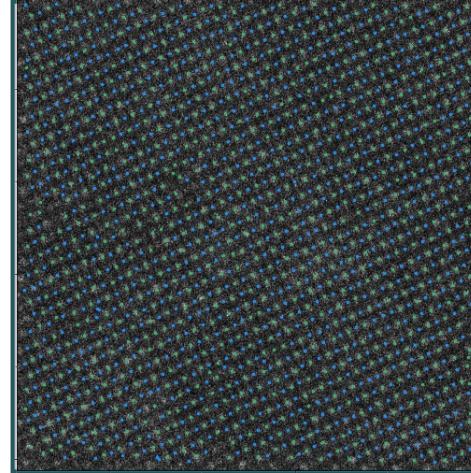
Model prediction



CrSBr (multilayered) (HAADF)



Model prediction



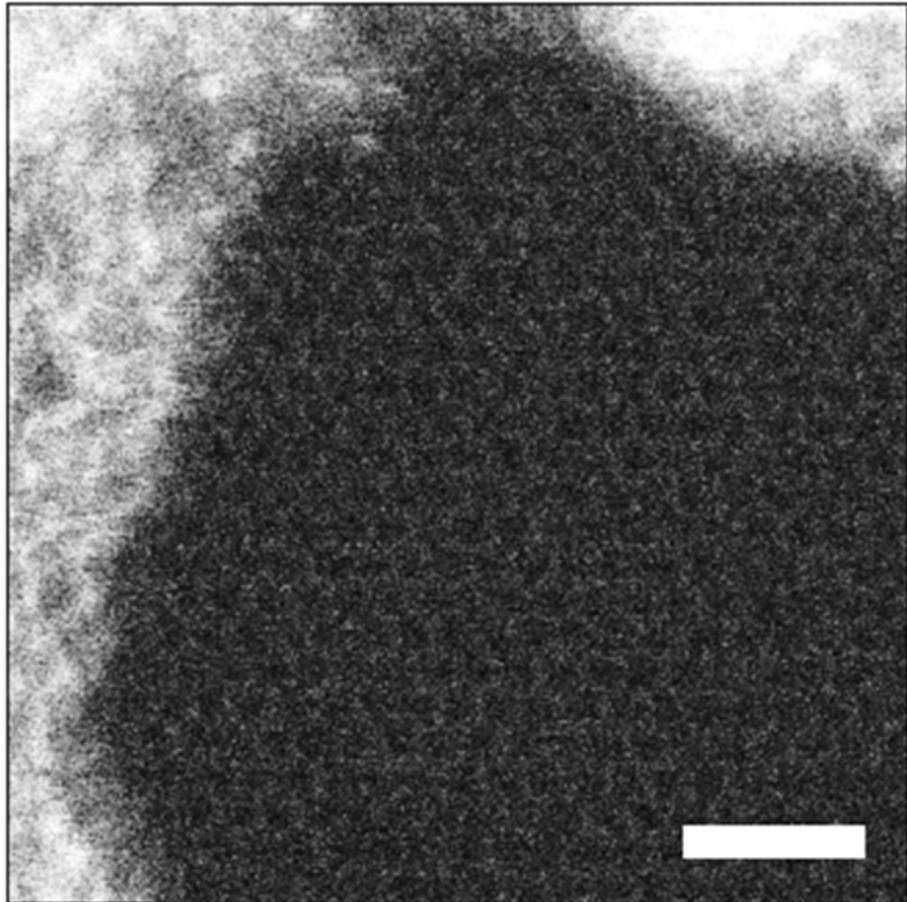
## Handling different...

- Materials
- Microscope settings
- Environmental behaviors (uncontrollable):
  - Contamination
  - Electrical noises
  - Other items that cause changes to the image signal
- Material evolution of material under stimuli (e.g., beam itself!)

# Ensemble learning

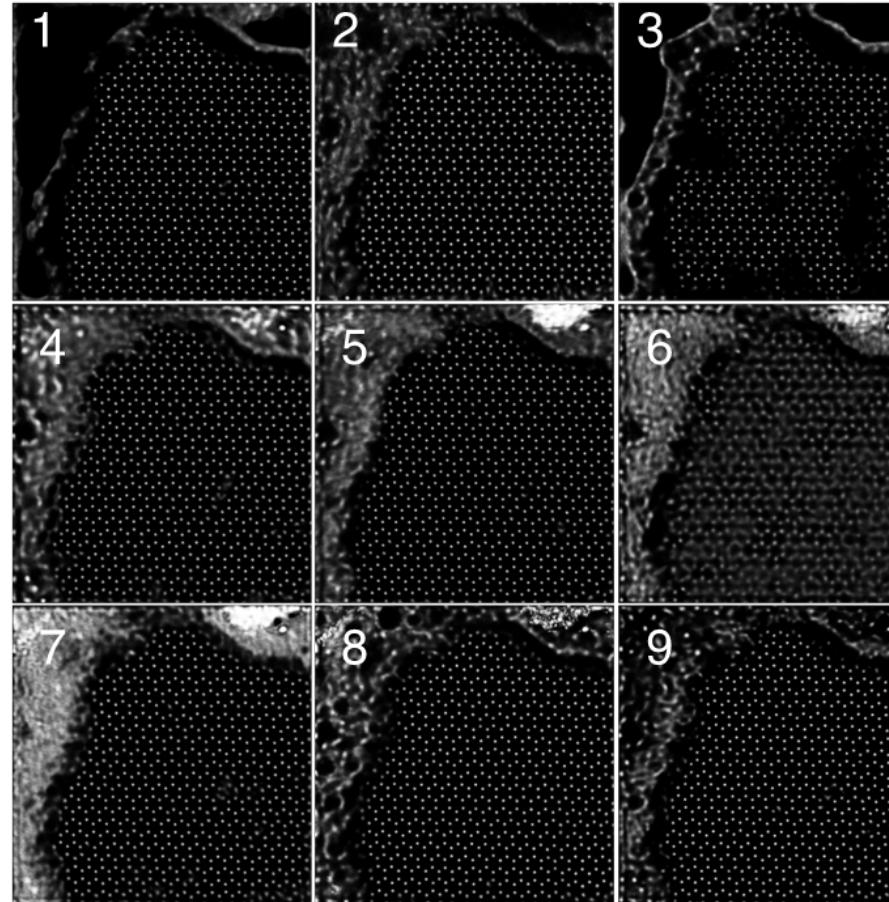
Key for robustness and enables on-the-fly predictions

Live Raw data (ADF)

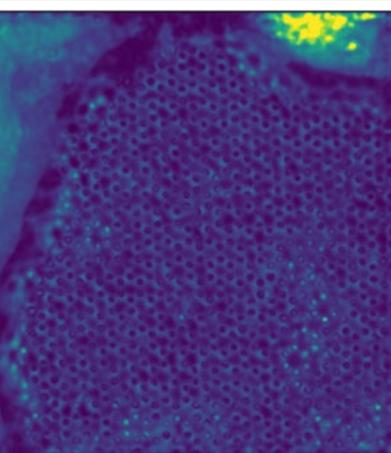
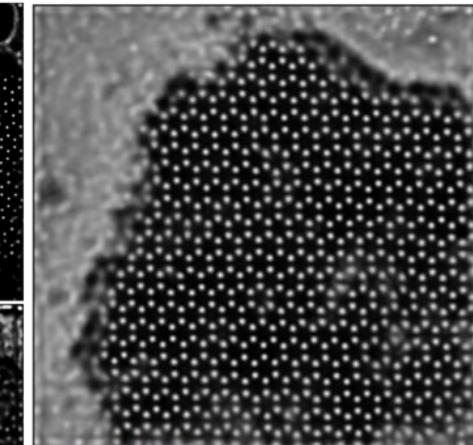


Graphene

Individual model predictions



Ensemble prediction

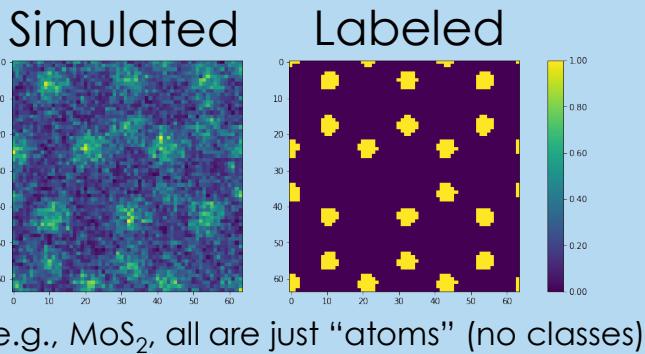


Ensemble uncertainty

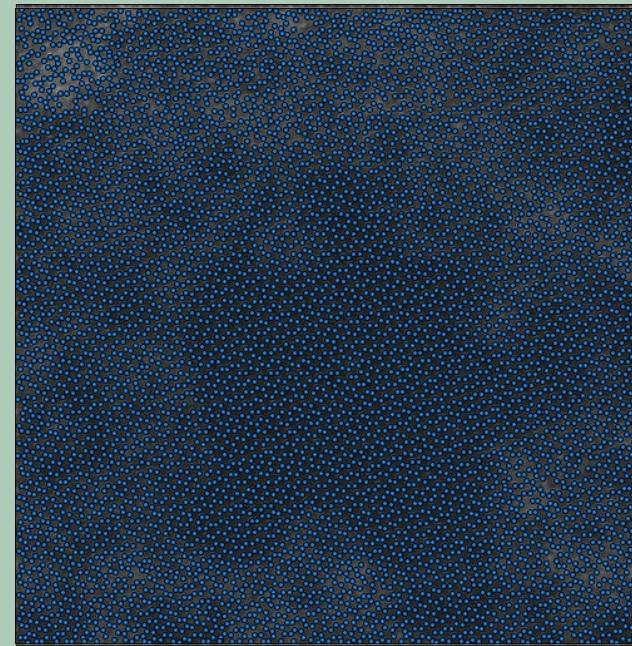
(Note: may have single or multiple classes)

# Atomic classification

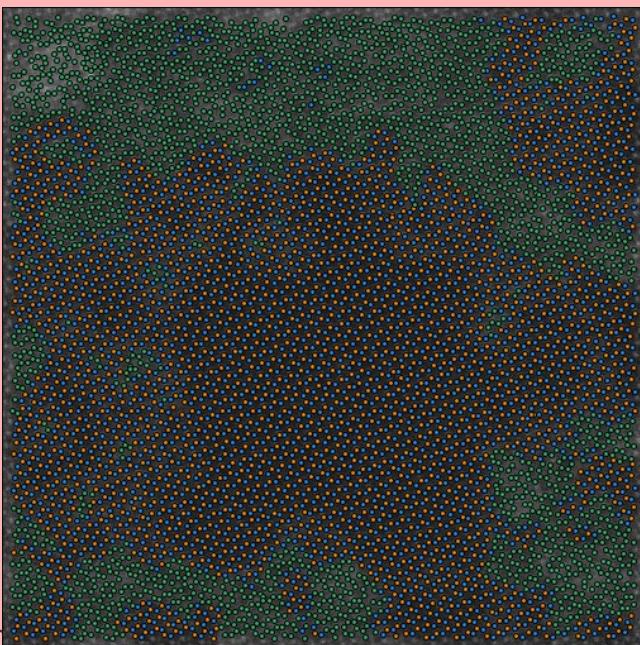
## 1. Train with **simulated** data



## 2. **Experimental** image prediction with initial model

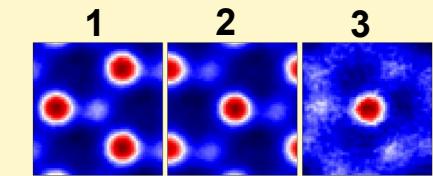
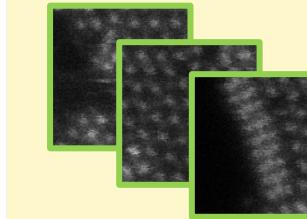


## 4. Redeploy new model



## 3. Augmentation retrain using experimental image

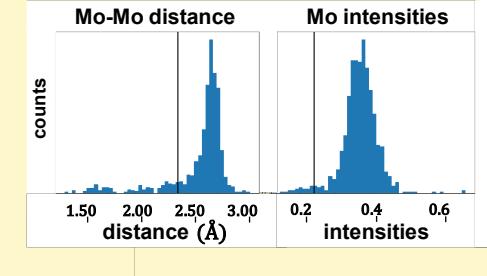
### Image patch local analysis



### Graph analysis



### Intensity & distance comparison



“I might have more atom types appear during my experiment”

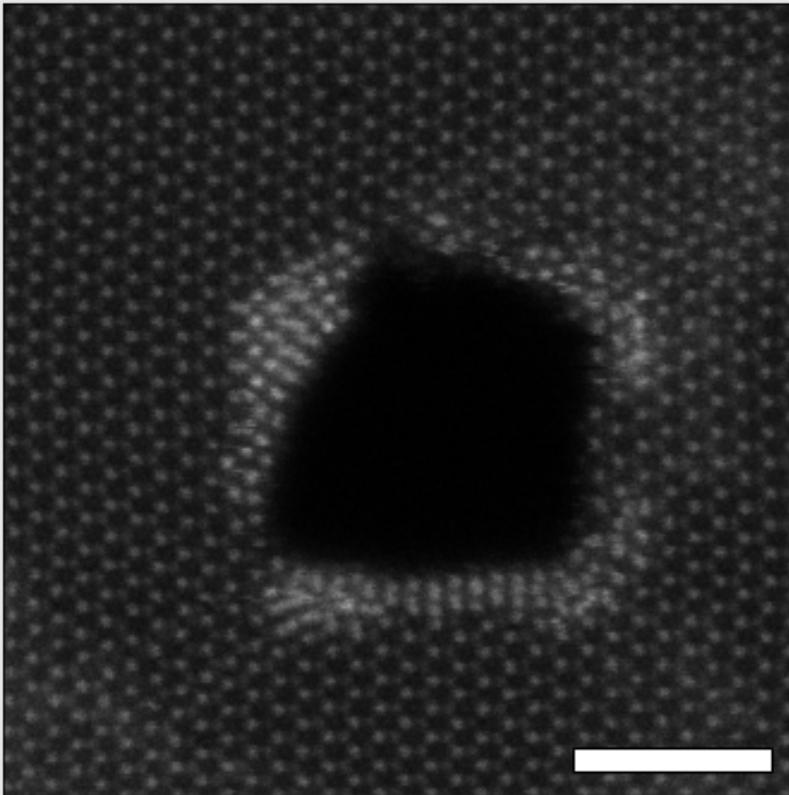
or

“Microscope conditions might change day to day for reason XYZ...”

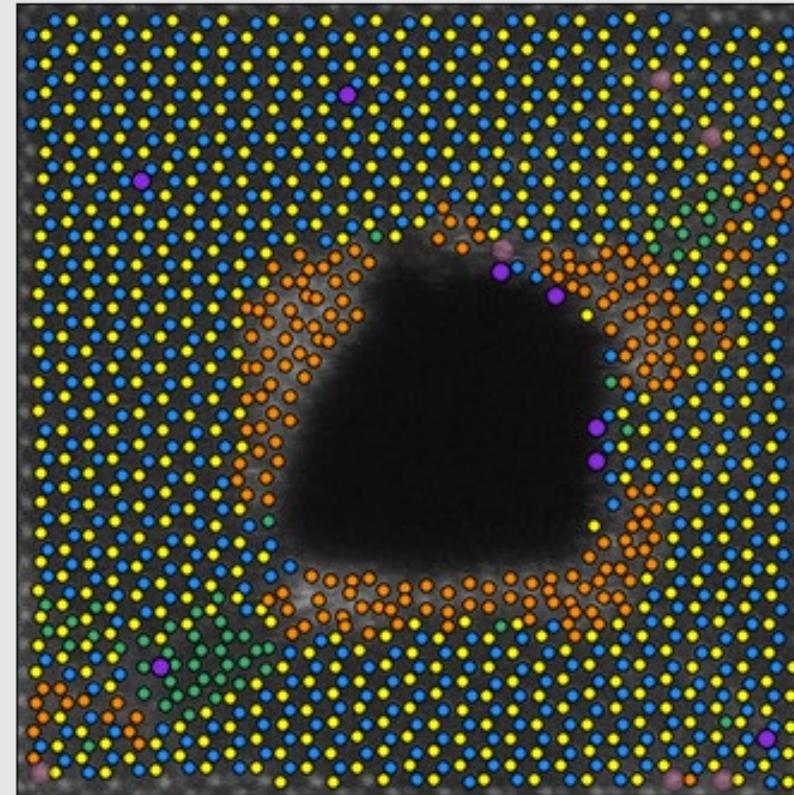
# Atomic classification

- Many atom and defect types can evolve
- Defect configuration space is large!
- We do not need to train new models for each new type (impractical)

New HAADF-STEM image



With augmented ensemble network

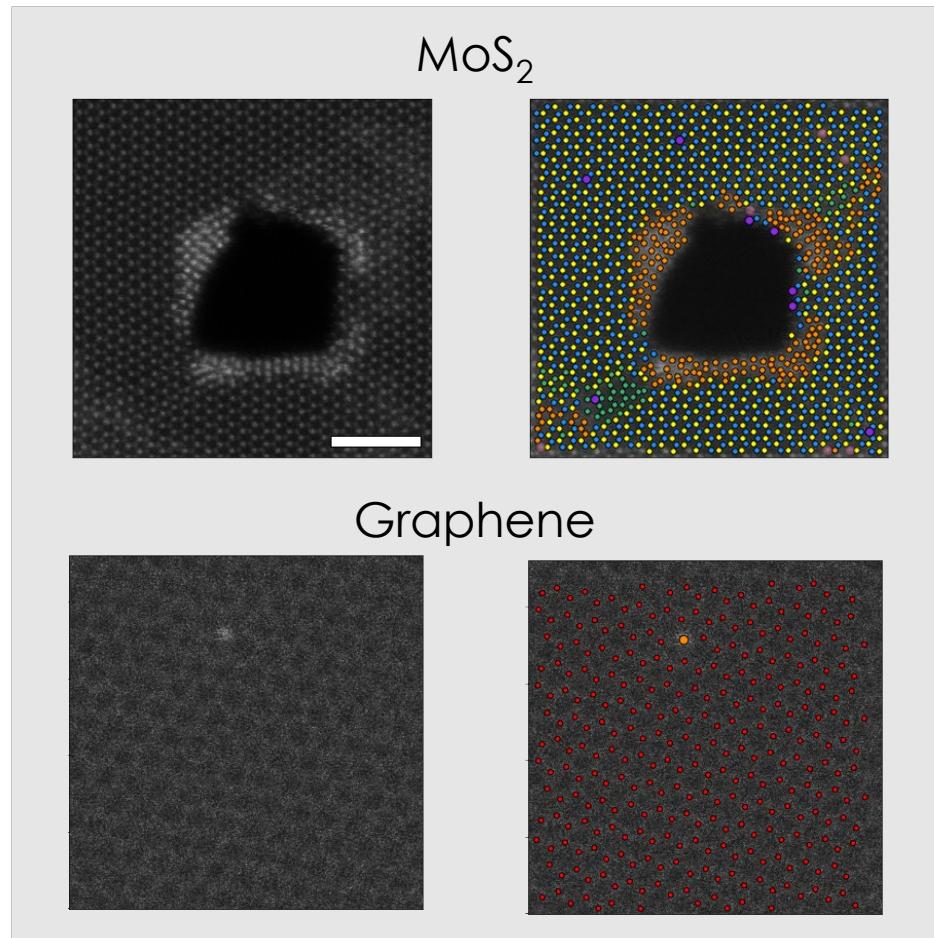


●	Mo
●	Mo_svl
●	S2
●	S1
●	nanowire
●	contamination
●	A site sub

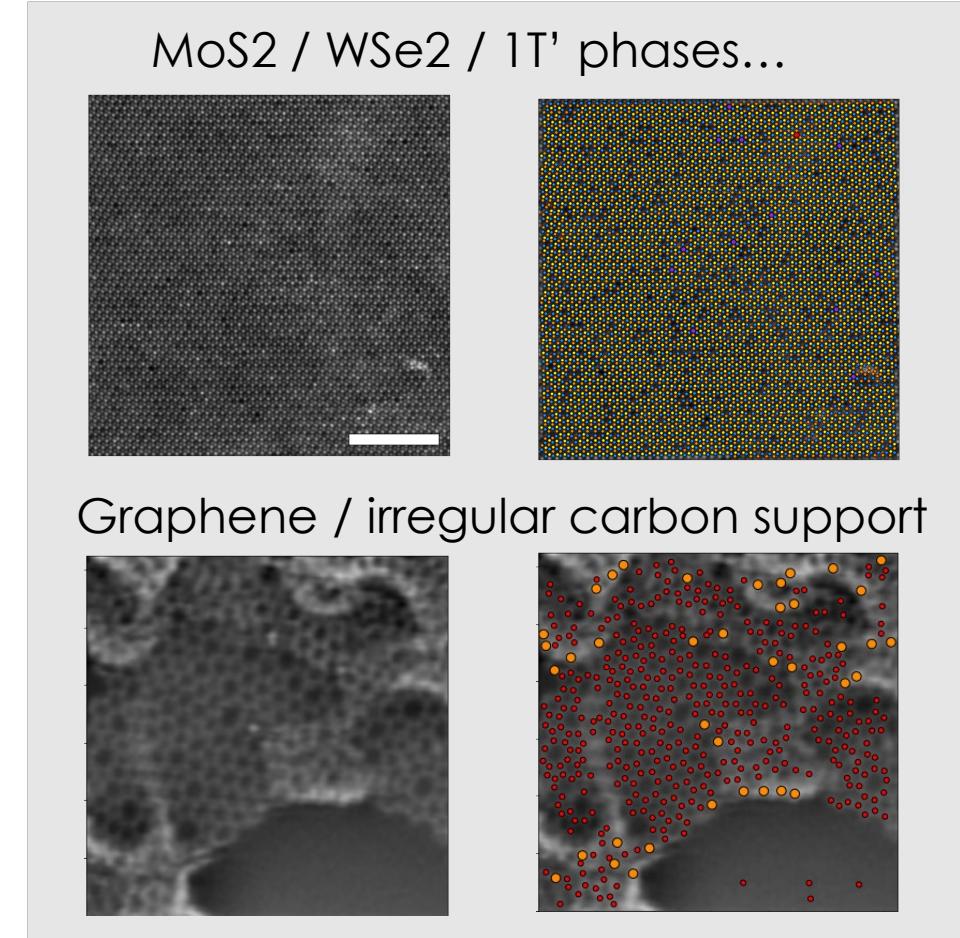
# Model transfer

A quick note...

- Similar symmetry? **Maybe you do not need to train a new model from scratch**
  - at least, maybe not the image simulation part!
- Imaging modalities and conditions: HAADF, MAADF, ABF, a-ADF, CoM, etc.

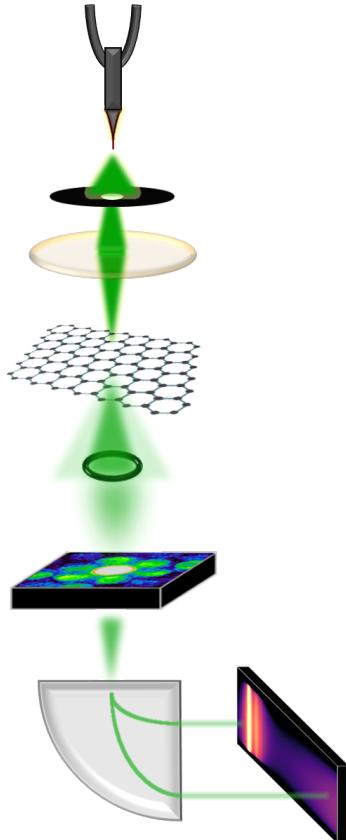


Versatile /  
multiple uses

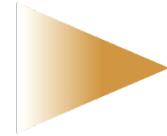


# **Automated Experiments**

# What is smart control and what does it do for us in the scanning transmission electron microscope



- 1. Deciphering image data**
- 2. Precise beam placement**



*must occur **during** experiments  
(fast, reliable)*

## SOFTWARE SOLUTIONS

**Image recognition,**  
dose control,  
structure-property extraction...

## HARDWARE SOLUTIONS

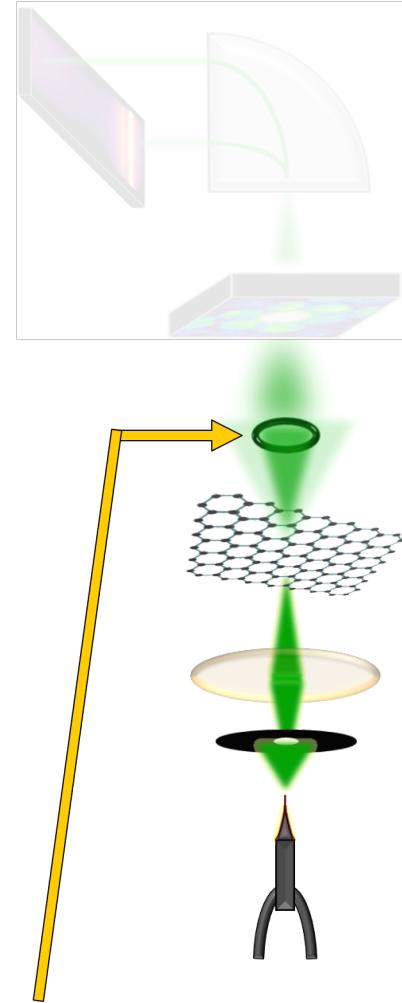
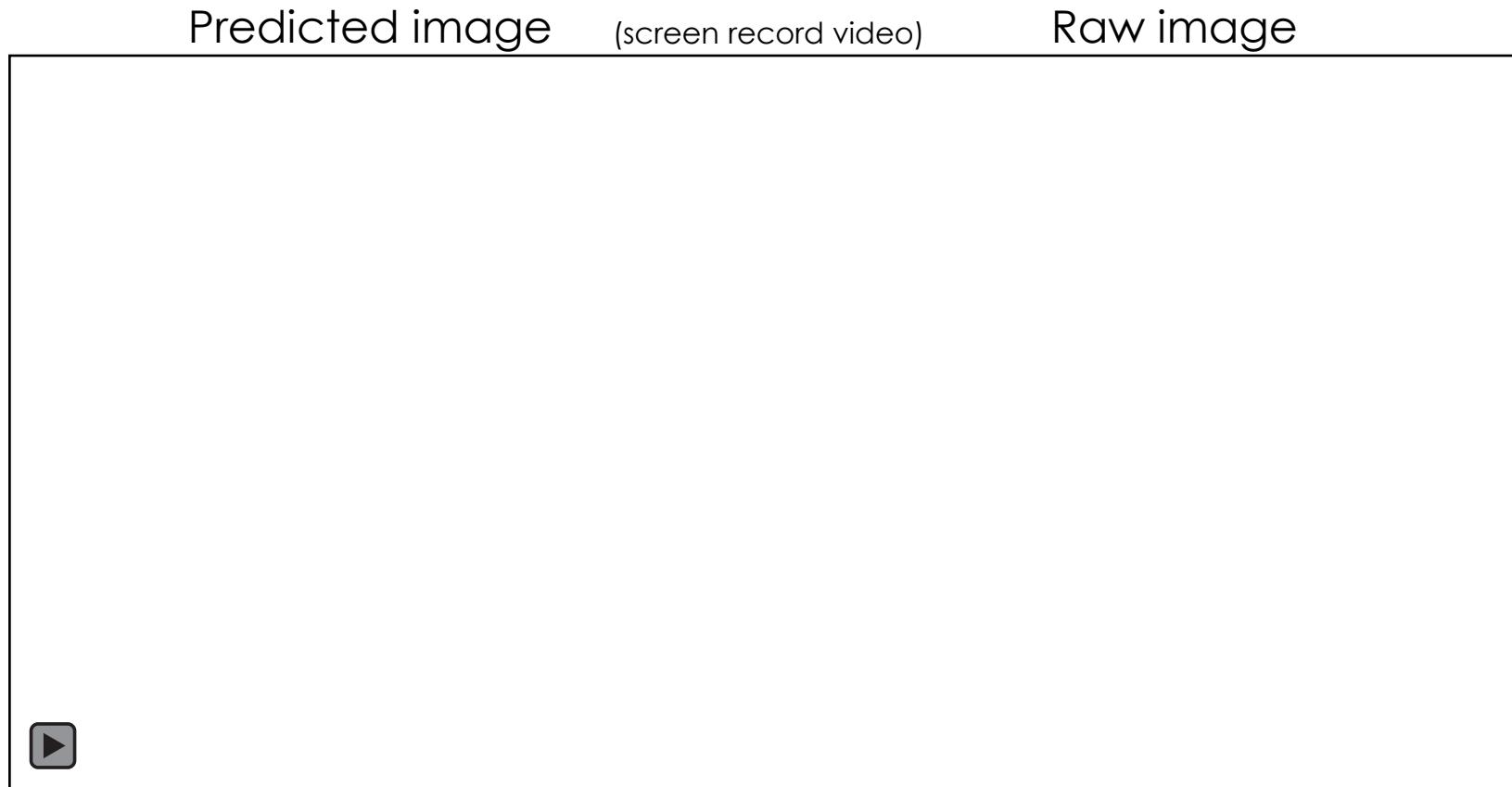
**Scan control,**  
beam blanking...

### **Enable new class of experiments**

- Drive and study reactions, atom by atom
- Measurements of dynamic processes in sensitive materials
- Single atom-beam time dynamics
- “Self-driving” experiments?
- ...?

# Atomic coordinates

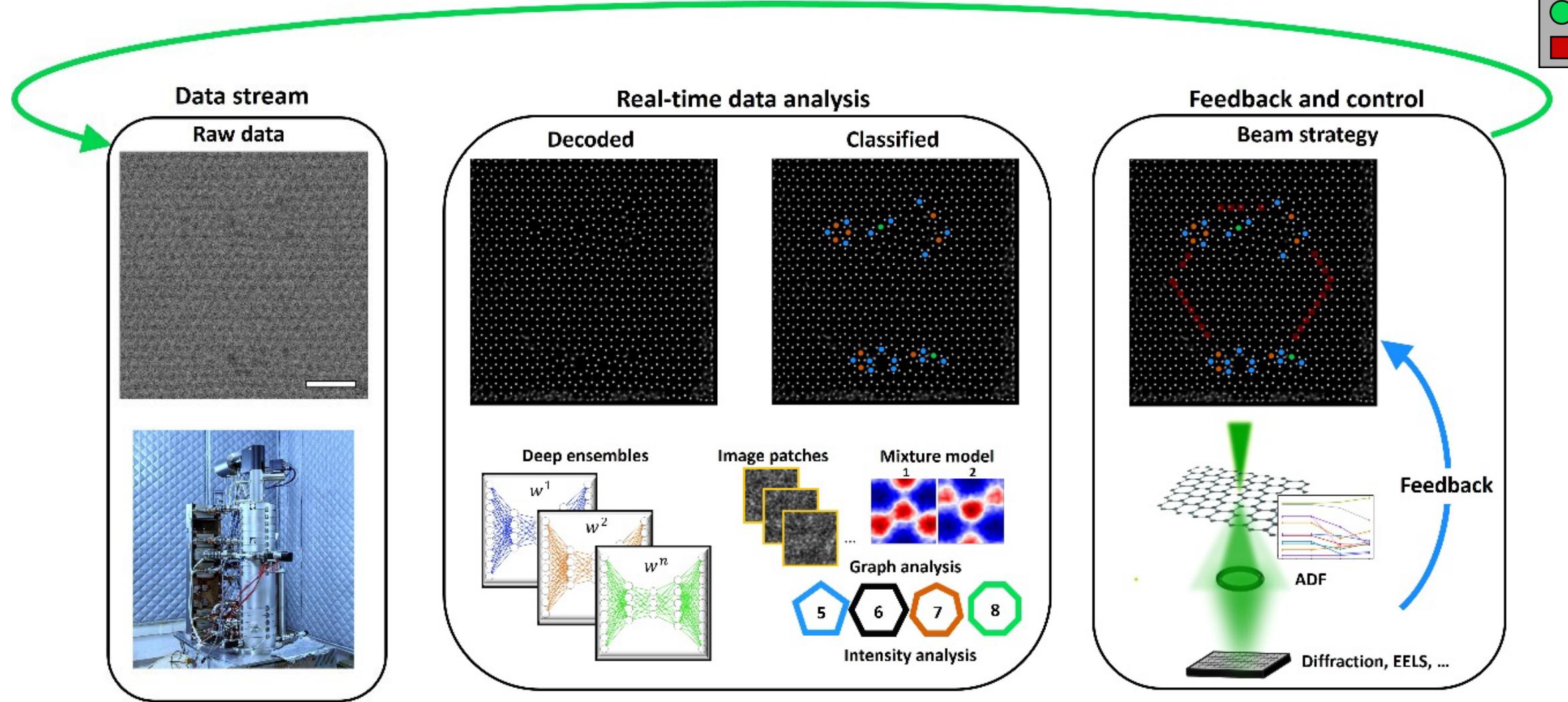
- \*Robust\* technique to locate (and classify) atomic species from a noisy detector image
- Single layer graphene, 60kV
- Key: ensemble learning with deep convolutional neural networks



Usually: STEM images from annular dark field (ADF)

# Experimental workflow

○ atom  
● 5-ring  
● 7-ring  
● 8-ring  
■ beam



Ensemble learning intro: **Ghosh A. et. al., npj Comput. Mater. 2021, 7 (1), 1–8**

Use in real-time on microscope: **Roccapriore K.M, et. al., ACS Nano 2022, 16, 10, 17116–17127**

Open slide master to edit

# Avoidance patterning

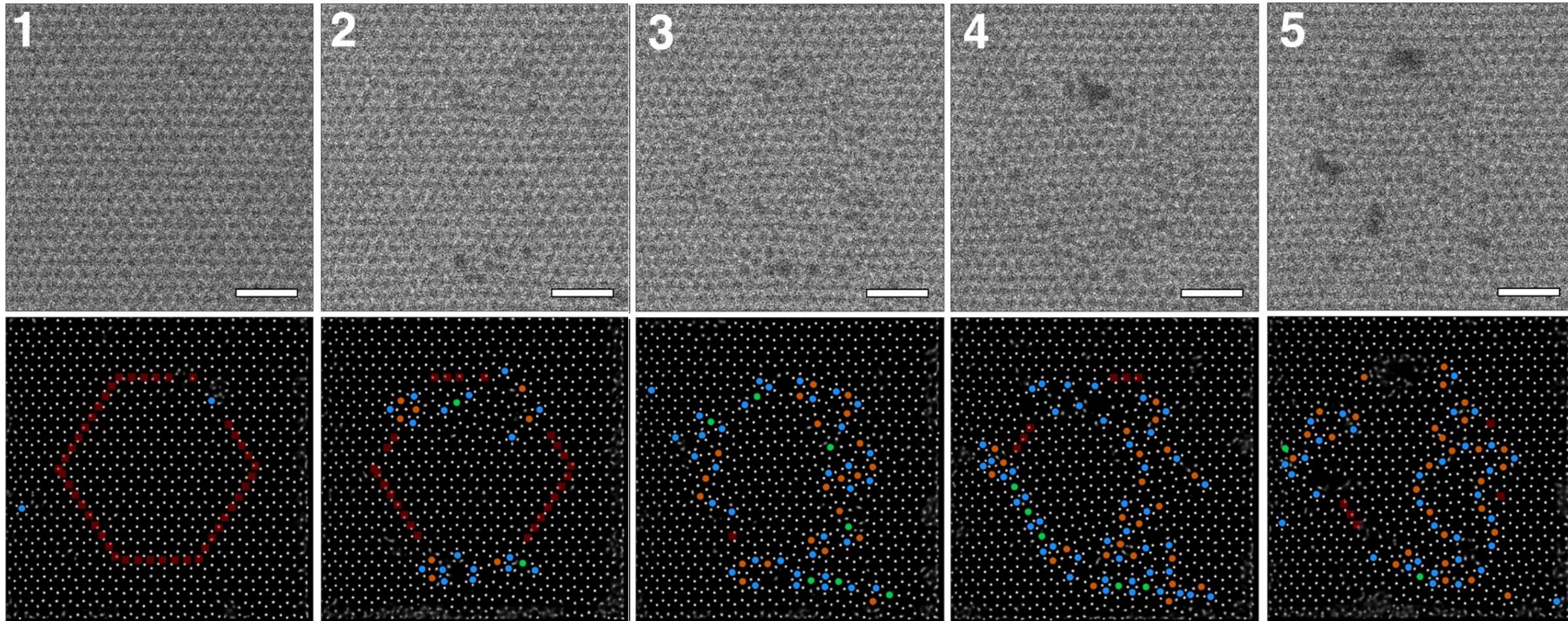
Topological defects

Graphene

Specify desired end-state

Image → Action → Image → Action...

- 5-ring
- 7-ring
- 8-ring



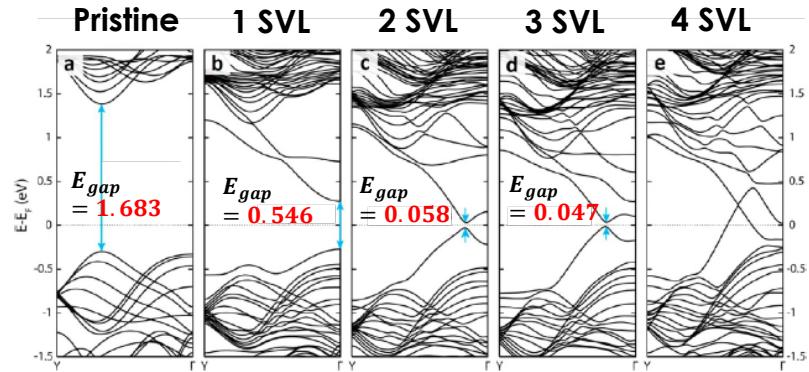
# Selective atom removal

**MoS<sub>2</sub>: single vacancy lines (SVL) → functional properties**

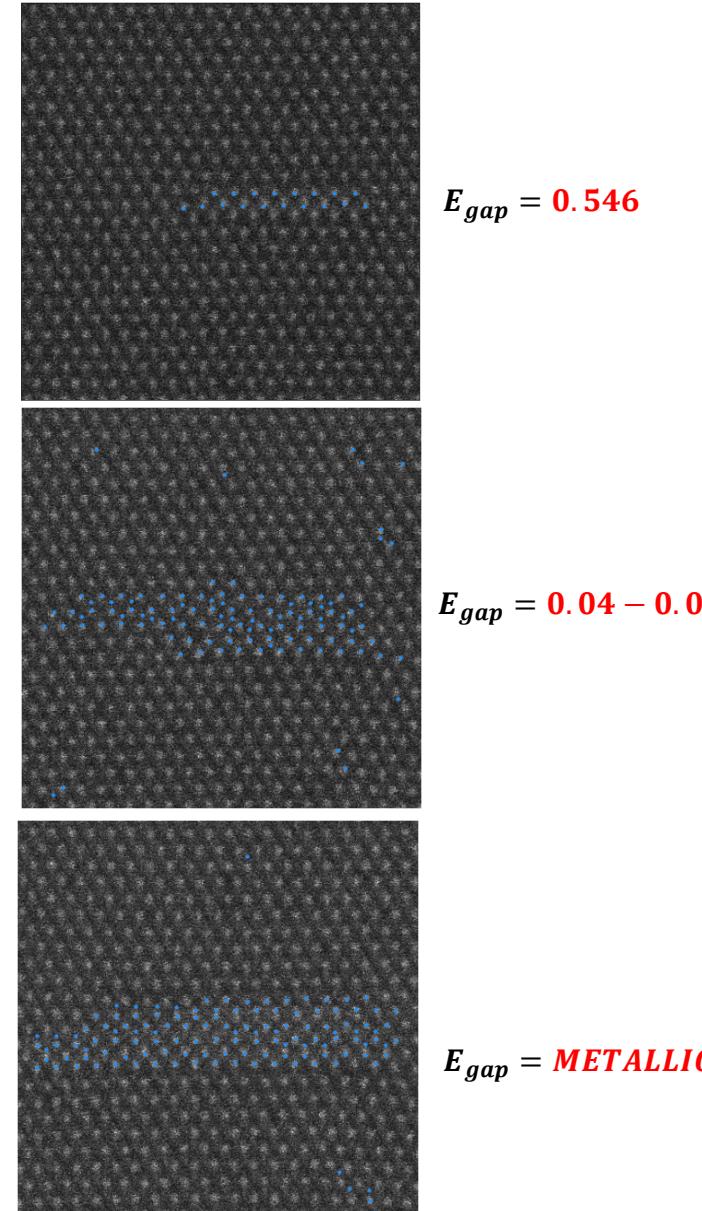
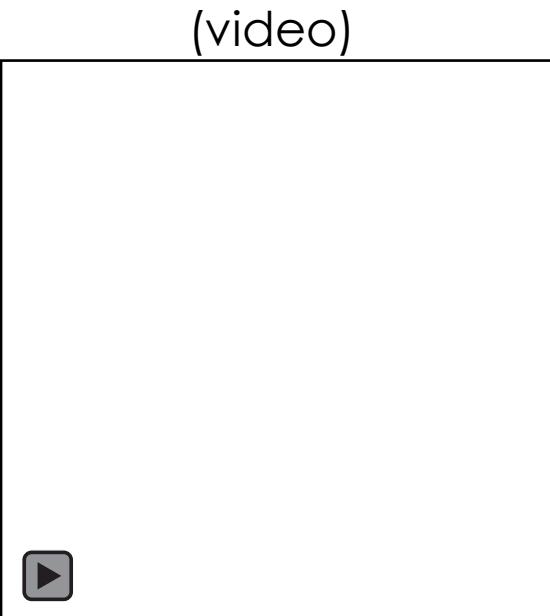
- Atomic band structure engineering?
- Atomic circuitry?

Requirements:

- ✓ Location of these columns (classified atomic coordinates)
- ✓ Feedback & sensitivity: one (not two!) sulfur ejection



Shanshan Wang, Gun-Do Lee, Sungwoo Lee, Euijoon Yoon, and Jamie H. Warner  
ACS Nano 2016 10 (5), 5419-5430  
DOI: 10.1021/acsnano.6b01673



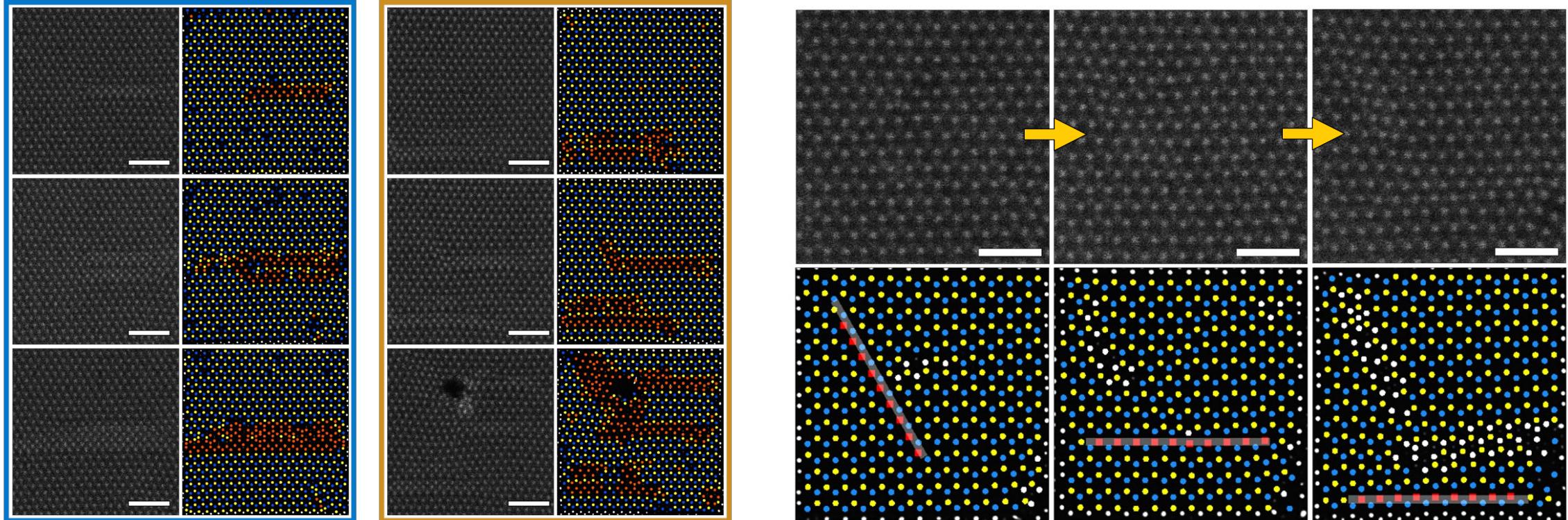
Open slide master to edit

# Selective atom removal

## Towards complex geometries (SVLs)



- Precise sulfur targeting
- Feedback assisted (ADF) to **ensure only single sulfur removal**



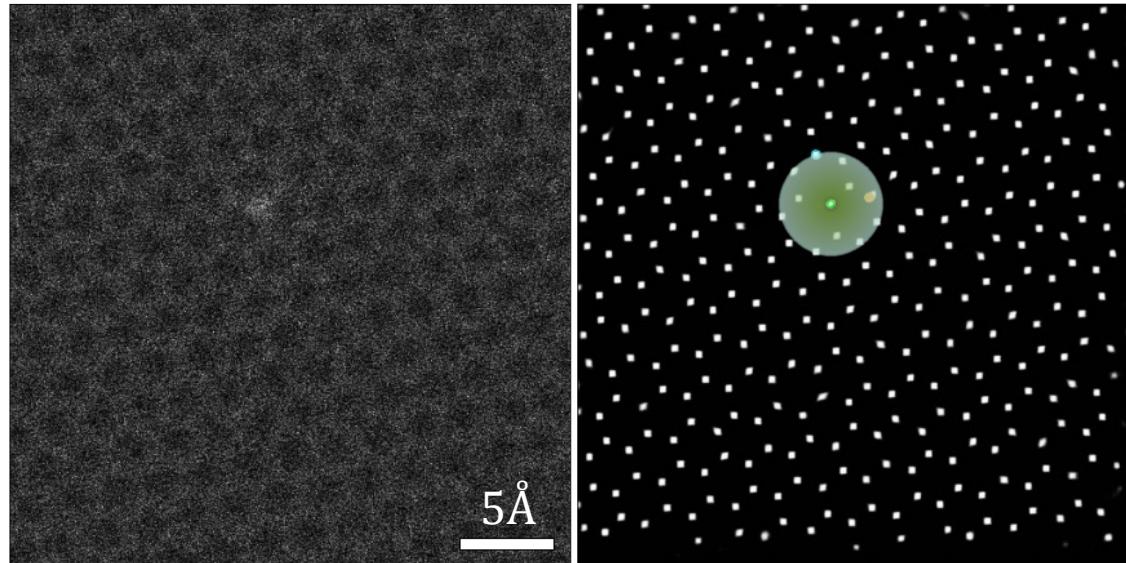
# **Where should we place beam?**

**Causal relationships may not be obvious**

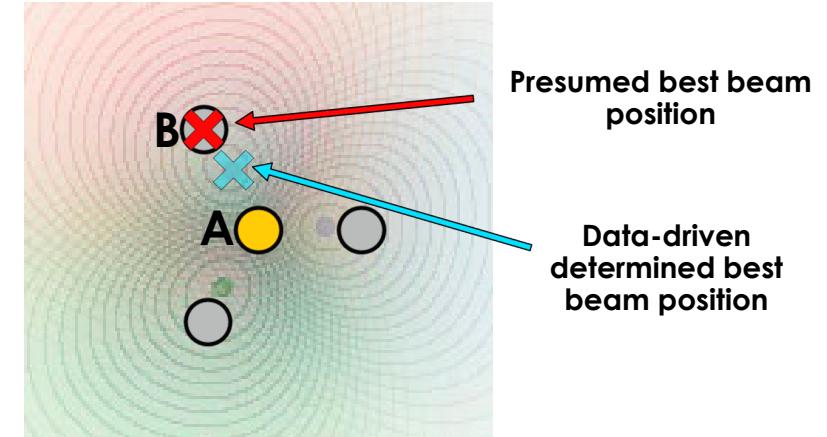
# Atomic manipulation rules

Where to place the beam **to achieve desired state?**

Data driven approach to 'learn' the rules



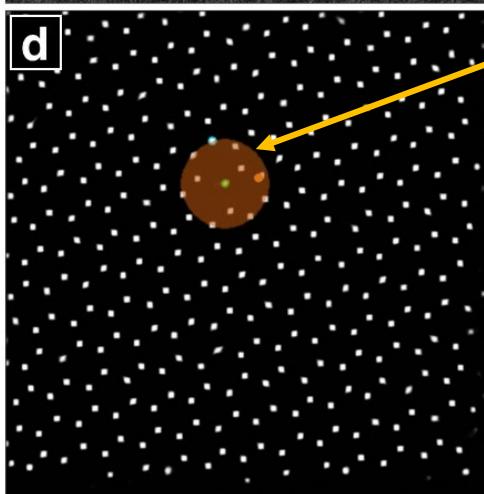
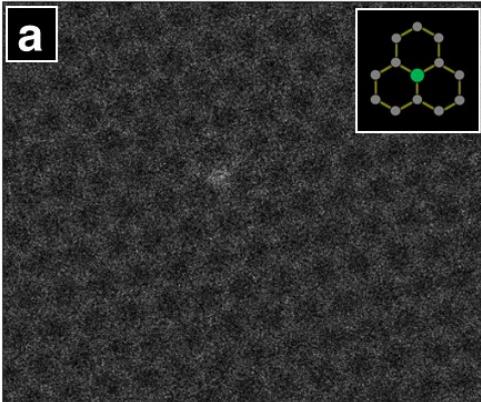
Goal:  
Move Si from **A** to **B** most efficiently



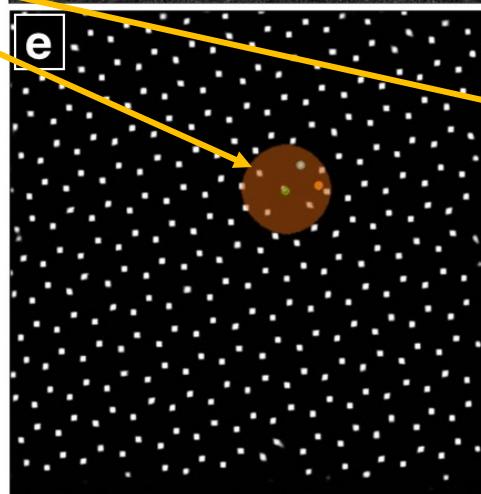
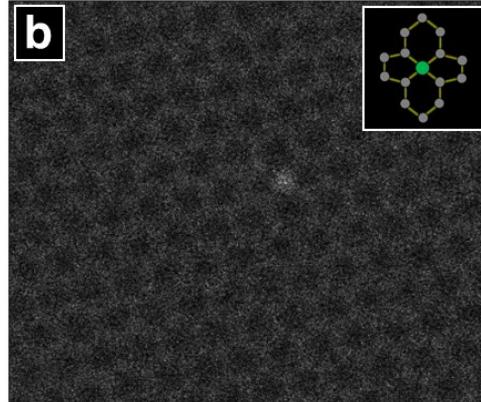
- We cannot do this reliably manually, **requires automated experiment!**
- **Robust, fast, and LIVE** atomic coordinate extraction is needed (out of distribution drift!)
- Drift, stability, concerns.

# Learning atomic manipulation rules: Si in graphene

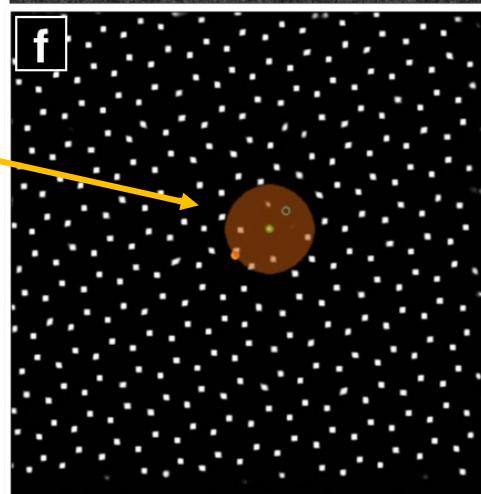
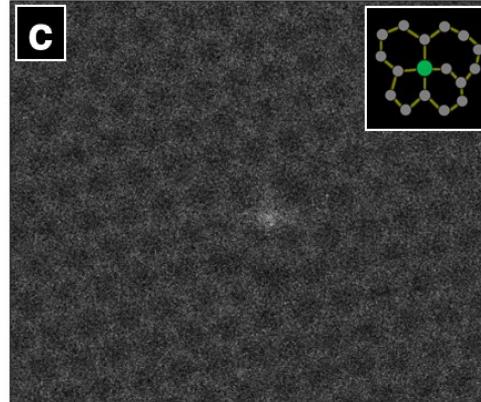
Pristine (3-fold)



Defected (4-fold)



Multiple defects

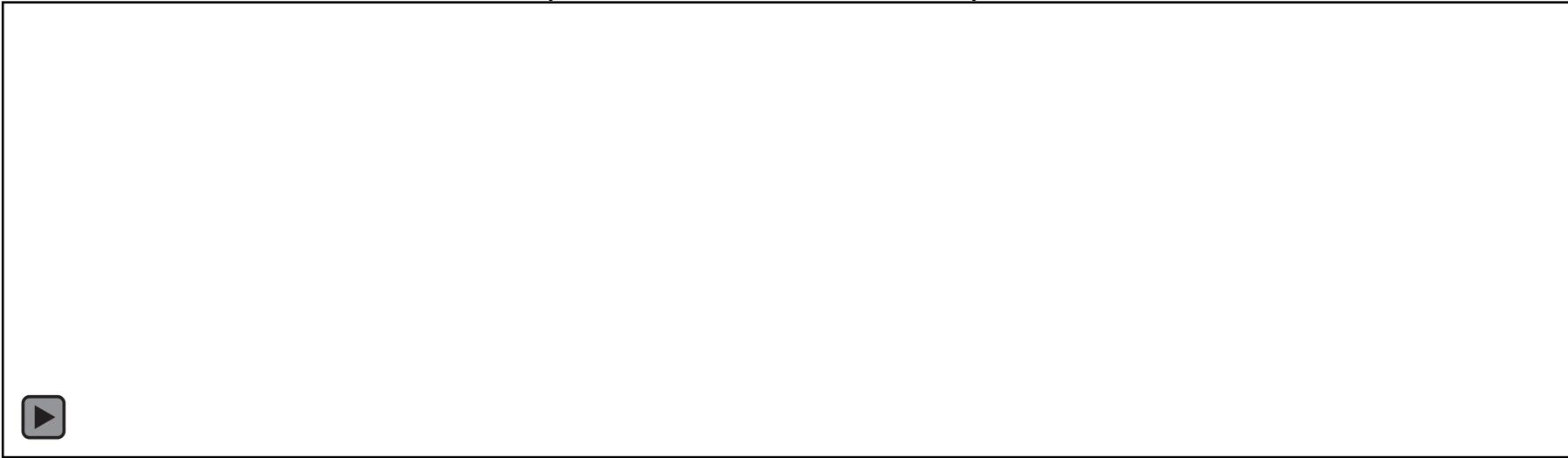


Distribution of  
possible  
beam  
locations

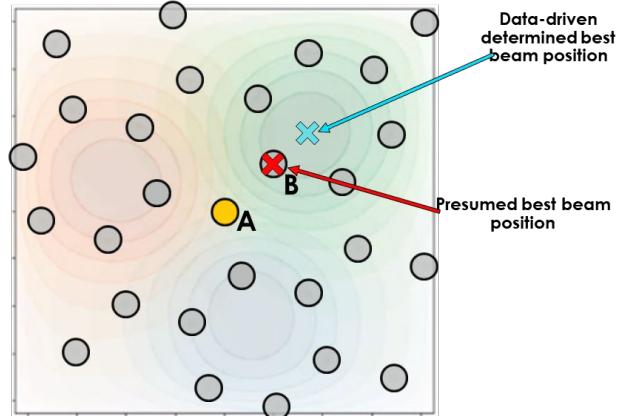
Generally, a real “goal” is not one jump, it might be many jumps

# Gather those statistics!

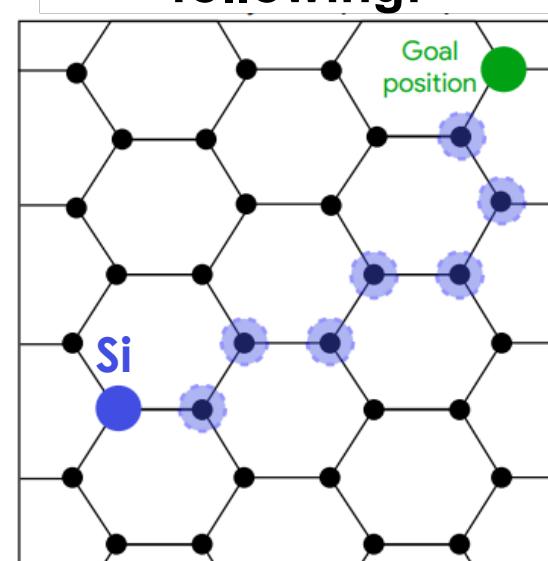
(screen record video)



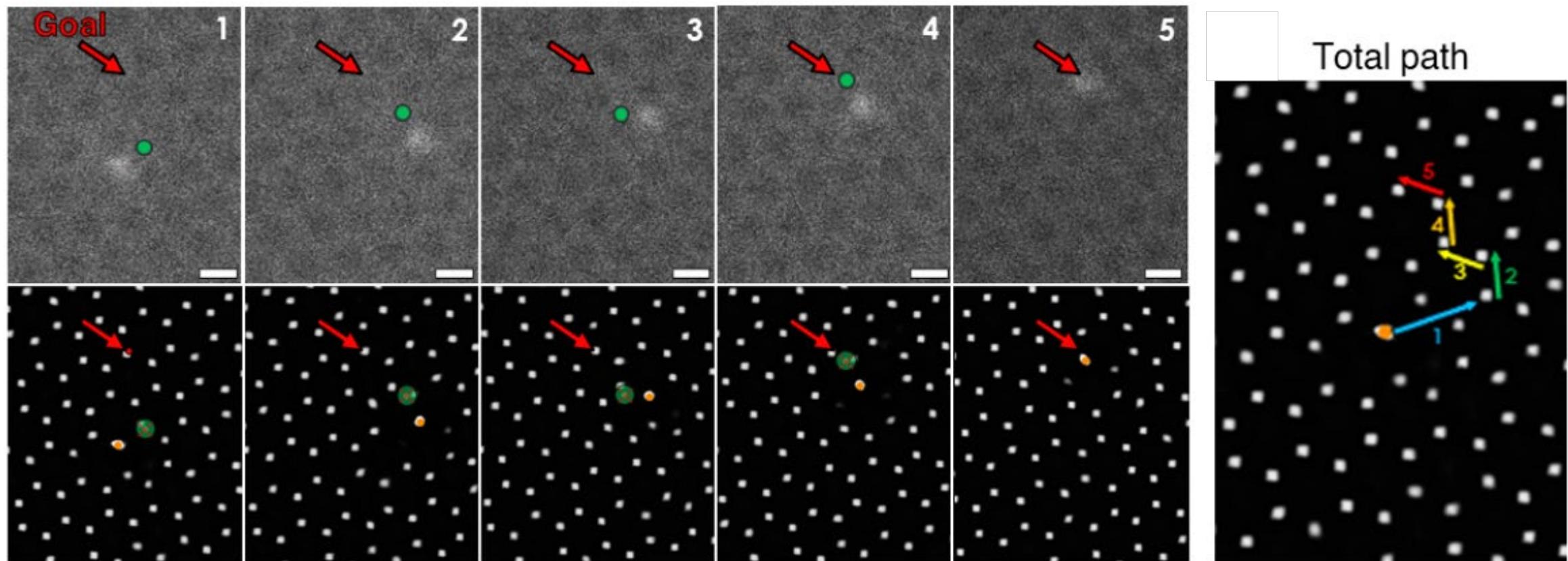
## Learned rates for 3-fold Si



Now, let's do the  
following:



# Autonomous manipulation of Si in graphene

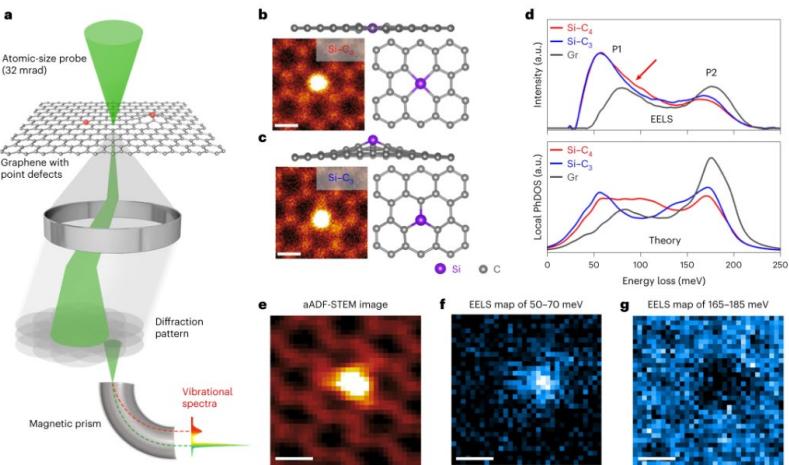


- Deployment of learned agent allows to “drag” single silicon throughout graphene lattice – *completely automated*

# **Sensitive & dynamic measurements**

**Measure native state, not defected state.**  
**Or...**  
**Systematically measure transient states**

# STEM-EELS: use cases



[nature](#) > [nature materials](#) > [articles](#) > [article](#)

Article | Published: 16 March 2023

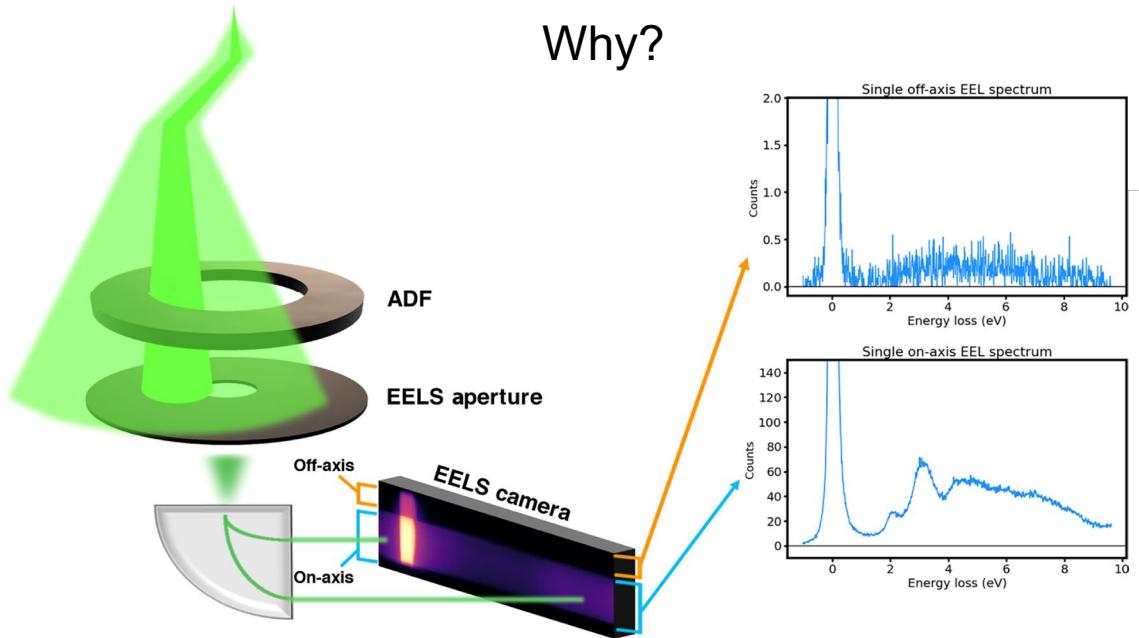
## Single-atom vibrational spectroscopy with chemical-bonding sensitivity

Mingquan Xu, De-Liang Bao, Aowen Li, Meng Gao, Dongqian Meng, Ang Li, Shixuan

Du, Gang Su, Stephen J. Pennycook, Sokrates T. Pantelides & Wu Zhou

~20-minute exposure!

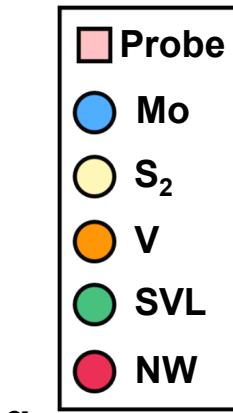
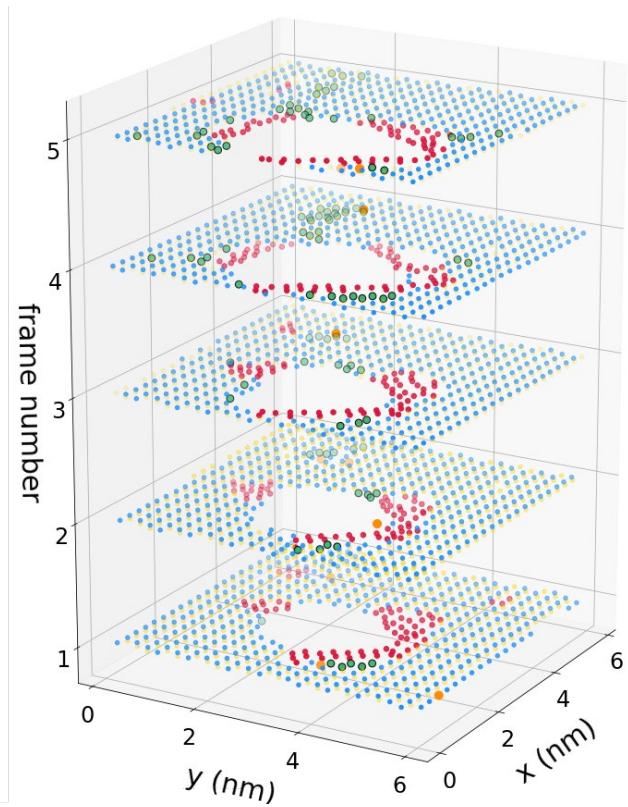
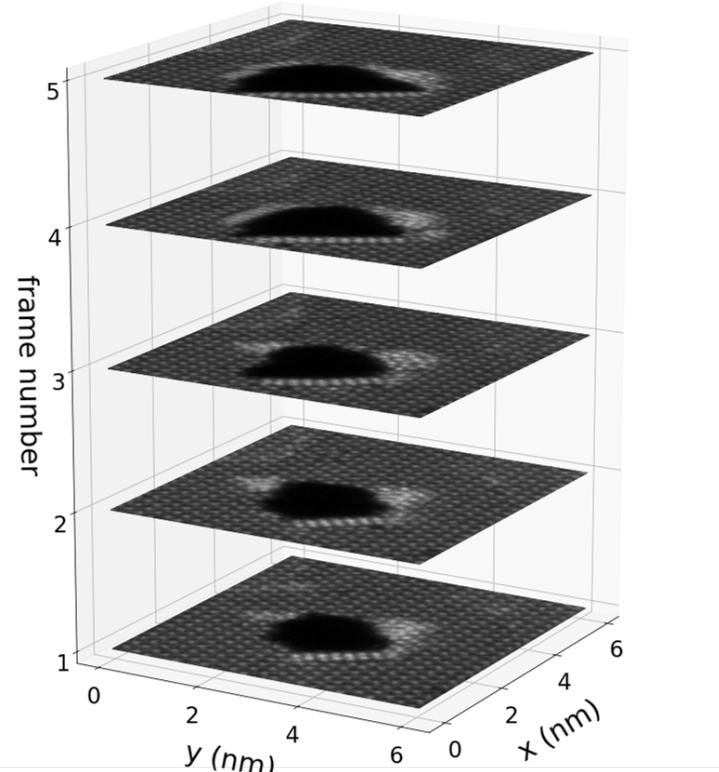
Why?



- Monochromation // off-axis → more phenomena to explore but...
- Only viable for **extremely** stable specimens and systems! (these are usually the well-understood ones too!)
- ...Unless we probe intelligently

# Sensitive & dynamic measurements

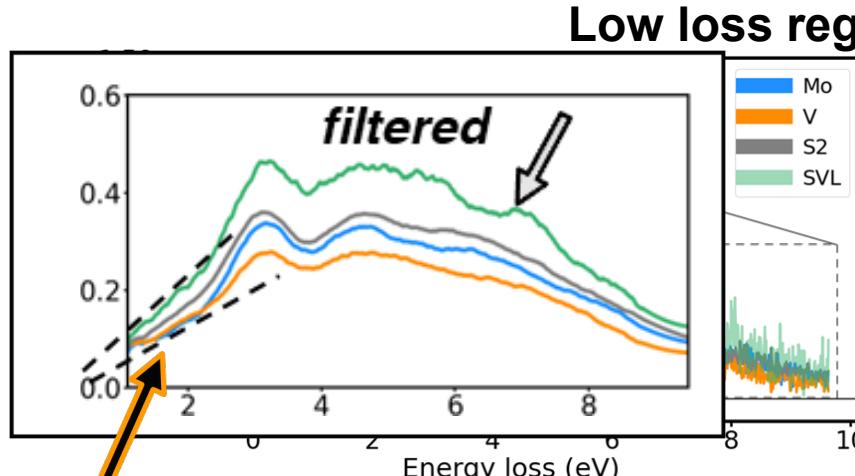
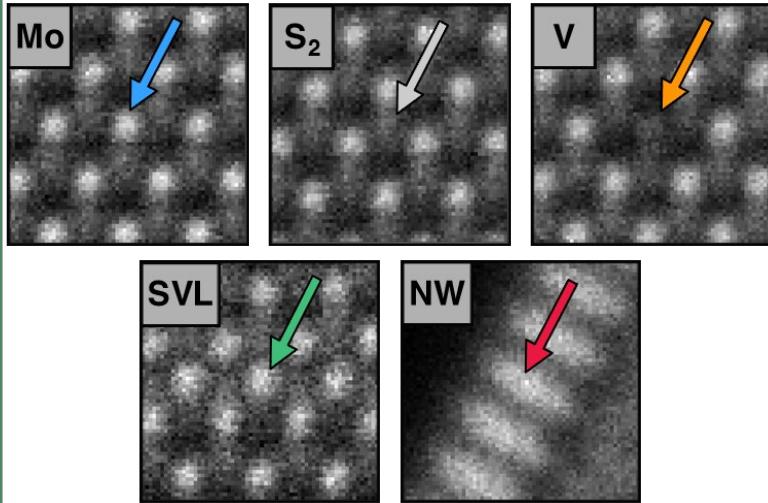
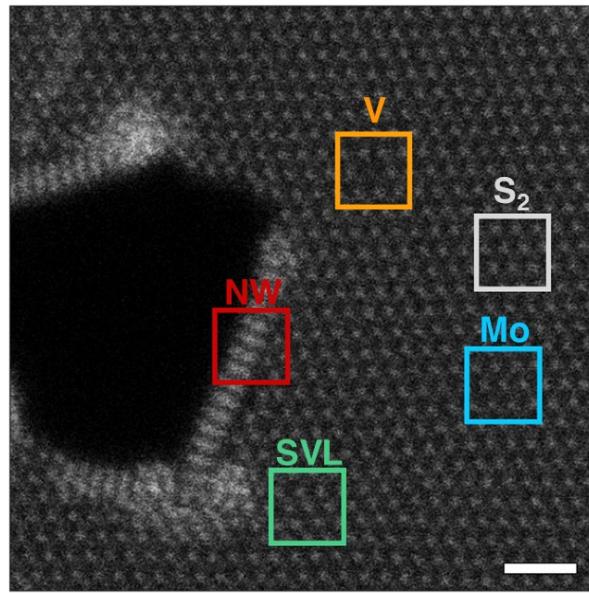
Energy loss spectroscopy in single-layer, V-substituted MoS<sub>2</sub>



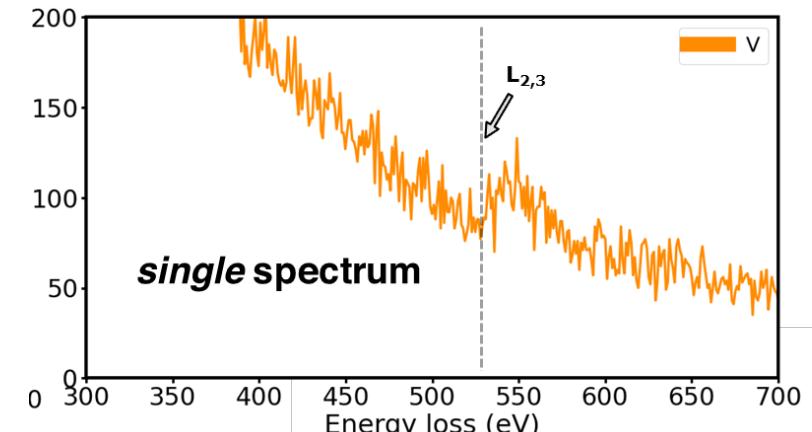
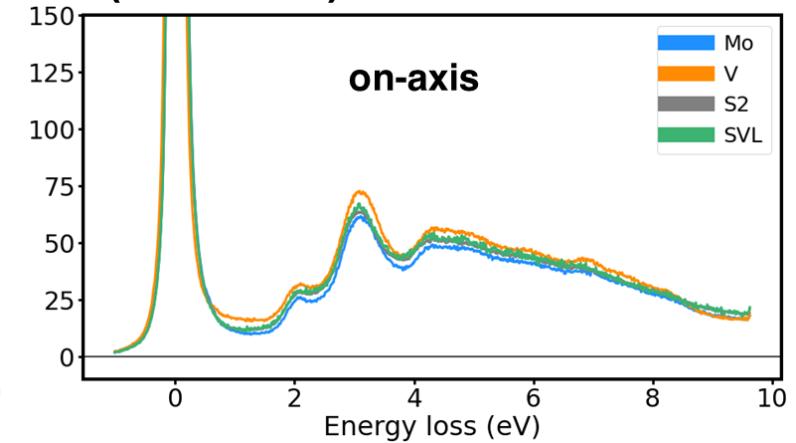
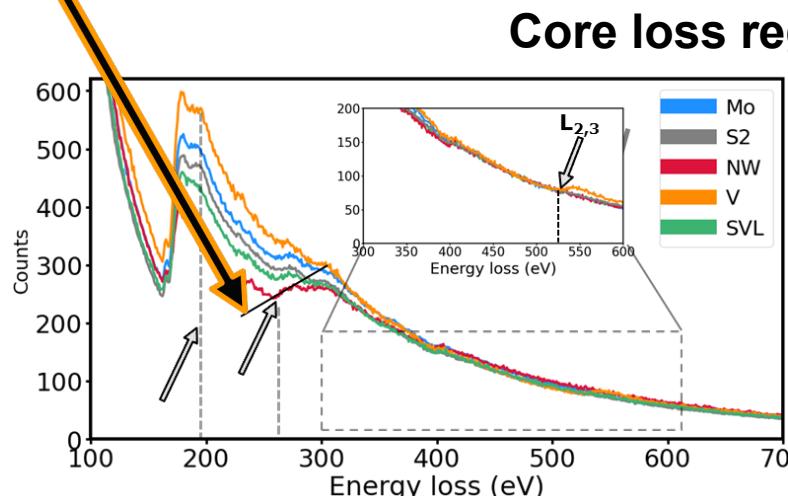
*increasing  
structural  
changes*

# Sensitive & dynamic measurements

Energy loss spectroscopy in single-layer, V-substituted MoS<sub>2</sub>



The slopes!



# **Hands-on notebook!**