

## Automating Electron Microscopy through Machine Learning and USETEM

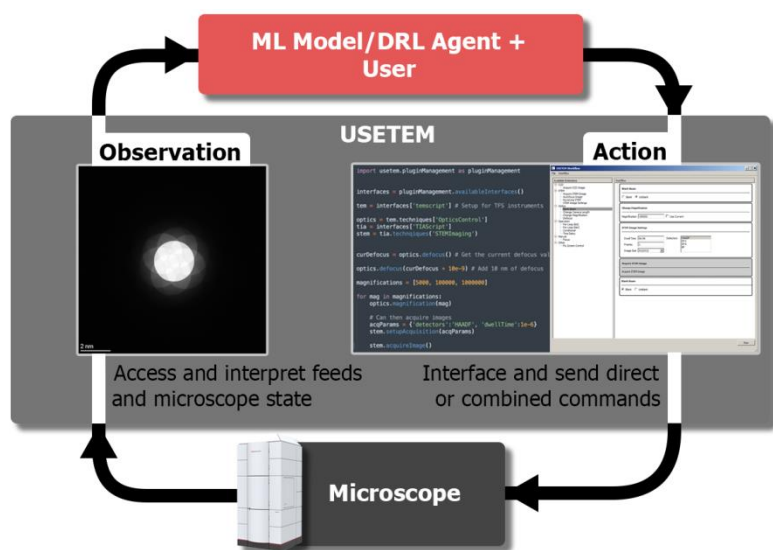
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Advances in electron microscopy have led to an increasing emphasis on multi-scale structural and chemical materials characterization. Coupled with the rise in “big data” and machine learning (ML)-based analysis, there has been a growing need for large, representative datasets for quantification or training [1]. Yet, electron microscopy has remained a manual process, with limited representative datasets providing anecdotal, rather than statistically significant results. Automation, which has been achieved in the biological and chemical sciences through CryoEM, is the natural solution, yet current progress for materials-centric characterization has been constrained to material- or task-specific data collection, which can be limiting given the sample heterogeneities of materials research [2]. These challenges demand a new level of automation and instrument control, crucial for efficient and reproducible electron microscopy.

In this presentation, we will show the use of computer vision and machine learning-assisted microscopy utilizing the Universal Scripting Engine for Transmission Electron Microscopy (USETEM) framework [3]. We will discuss the development and implementation of a Python-based Deep Reinforcement Learning (DRL) agent for control and imaging adjustments using a variety of detector feeds as feedback (Figure 1). The capability of these agents to learn patterns and operate in complex environments has already been demonstrated, with performance far exceeding human actors [4, 5]. Further, deep learning in microscopy has been shown to be promising in terms of data reconstruction and analysis [4, 6, 7]. More compelling, however, is its use in intelligent microscope control, which offers a similarly expansive parameter space with the potential for significant workflow improvement.

Ultimately, efficient characterization is necessary for accelerated materials research. By utilizing a combination of computer vision and deep reinforcement learning, we will show the potential for automated electron microscopy for materials science. Further, we will demonstrate the flexibility of USETEM as a platform for development of these open-source enhancements and workflows for microscope operation.



**Figure 1.** Figure 1. Schematic outlining interactions between ML and DRL elements, USETEM, and the microscope.

## References

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- [8] We acknowledge support of this research from the MIT RSC Fund. Additionally, this work was carried out in part through the use of MIT.nano's facilities.