Disentangling Spatial Correlations from Inhomogeneous Materials with Shift-Invariant Artificial Neural Networks: A Novel Approach to Study Superconductivity

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With the advent of atomic resolution imaging techniques comes the challenge of disentangling the intrinsic electronic properties of materials from their stochastic atomic-scale disorder. In the past decade, machine learning image analysis techniques, based in artificial intelligence, have rapidly evolved, while their applications in physics are just emerging. Here, I demonstrate the use of machine learning to test correlation hypotheses between spatially resolved measurements of disordered materials to overcome the limitations of standard Fourier analysis techniques. Shift-invariant artificial neural networks (SIANNs) are applied to uncover the doping-dependence of the charge density wave (CDW) structure in the cuprate superconductor (Pb,Bi)_2 (Sr,La)_2 CuO_6_+_delta(Bi-2201) imaged via scanning tunneling microscopy. In Bi-based cuprates, the electronic inhomogeneity, caused by local variations in doping, limits the precision with which the CDW wavevector can be measured. This machine learning algorithm overcomes these limitations and allows clear differentiation between commensurate and incommensurate CDW instabilities with physically distinct mechanisms. I show how the cuprate phase diagram and other enigmatic properties of superconductors, a class of materials that has important uses in electrical transmission and particle accelerators, can be studied with this new technique. More broadly, this work lays the foundation for a machine learning approach to quantify intrinsic periodic order and correlations from datasets where these trends are masked by disorder.

Awards Won:

Intel ISEF Best of Category Award of $5,000

First Award of $3,000

European Union Contest for Young Scientists Award