PhD project description

“Machine learning quantum localization” – Rudolf A Roemer

Machine learning and deep learning are statistical analysis techniques that use strategies of artificial intelligence to characterize complex data and extract deep information. In recent years, these techniques have begun to be used not only in traditional computer science test cases, but also in real world applications as well as, more recently, in areas of advanced physics. In condensed matter systems, such techniques have been shown to give useful insight into Ising and spin ice models [1], low dimensional topological systems [2], strongly correlated systems [3], as well as random two- and three-dimensional topological and non-topological systems [4]. It is probably fair to say that machine and deep learning may become standard statistical analysis tools in the future.

In the PhD project, we want to use these methods to

a) Identify, characterize and classify the metal-insulator transition in the two- and three-dimensional Anderson model of localization. Previous studies have used sophisticated wavefunction based measures such as generalized participation ratios and the so-called multifractal analysis partnered with finite-size scaling techniques to identify the critical properties such as critical energies (also known as mobility edges), critical disorders and, most importantly, critical exponents [5].

b) Study the proposed many-body delocalized to localized transition in Fock space for disordered and interacting low-dimensional quantum systems such as disordered Heisenberg and Hubbard chains. In these systems, due to the exponentially growing size of the Hilbert space – and hence the size of the Hamiltonian matrices, the traditional methods used in the Anderson model are severely limited and it has been speculated that here machine+deep learning strategies might indeed be superior in identifying the existence of possible mobility edges [4].

c) Develop appropriate version of “scaling” applicable to machine+deep learning techniques. While traditional finite-size scaling approaches to phase transitions are well established, it is not clear how these approaches may be incorporated into machine+deep learning strategies. However, this is most important in order to reliably discuss the aforementioned transition as these are of course only defined in the thermodynamic limit. So the situation is somewhat similar to the case of multifractal properties [5] where we previously established there scaling properties in a supervised PhD project [6].

Upon successful completion of the projects outlined here, we will then apply the techniques to specific materials such as Si:P and Si:S or 2D TMCDs such as recently studied.