Abstract:

This talk will address the following question: In what cases does learning a good hypothesis require more resources than verifying a hypothesis proposed by someone else? If verification is significantly cheaper than learning, that could have important practical implications for delegation of machine learning tasks in commercial settings, and might also have consequences for verification of scientific publications, and for AI safety. Two results will be discussed: (1) There exists a learning problem where verification requires quadratically less random samples than are required for learning. (2) The broad class of Fourier-sparse functions (which includes decision trees, for example) can be efficiently verified using random samples only, even though it is widely believed to be impossible to efficiently learn this class from random samples alone.

This is joint work with Shafi Goldwasser (UC Berkeley), Guy Rothblum (WIS), and Amir Yehudayoff (Technion).

** "Learning" -- as defined in Valiant's Probably Approximately Correct (PAC) framework