Compressive sensing (CS) is a general paradigm that enables us to measure objects (such as images, signals, or functions) by using a number of linear measurements proportional to their sparsity, i.e. to the minimal amount of information needed to represent them with respect to a suitable system. The vast popularity of CS is due to its impact in many practical applications of data science and signal processing, such as magnetic resonance imaging, X-ray computed tomography, or seismic imaging.

In this talk, after presenting the main theoretical ingredients that made the success of CS possible and discussing recovery guarantees in the noise-blind scenario, we will show the impact of CS in computational mathematics. In particular, we will consider the problem of computing sparse polynomial approximations of functions defined over high-dimensional domains from pointwise samples, highly relevant for the uncertainty quantification of PDEs with random inputs. In this context, CS-based approaches are able to substantially lessen the curse of dimensionality, thus enabling the effective approximation of high-dimensional functions from small datasets. We will illustrate a rigorous noise-blind recovery error analysis for these methods and show their effectiveness through numerical experiments. Finally, we will present some challenging open problems for CS-based techniques in computational mathematics.