Motivated by the ubiquitous demand of leveraging both data and partial knowledge of physical laws for stochastic modeling and uncertainty quantification, in this dissertation, we developed a series of methods centered around generative adversarial networks (GANs) for physics-informed learning. In the defense, I will introduce three chapters in the dissertation. We will start from physics informed GANs for stochastic differential equations (SDEs). Using neural networks for parameterizing the stochastic processes, we show that physics-informed GANs can solve forward and inverse problems of SDEs with high stochastic dimensions. We then extended the application of GANs to dynamic inference with observations of particle ensembles as data, namely "generative ensemble regression". To address the oscillation and instability problem of GANs in generative ensemble regression tasks, we developed the measure-conditional discriminator for GANs. We showed that the measure-conditional discriminator is more robust than the vanilla one, and improves the stochastic dynamic inference.