In many scientific fields such as particle physics, climatology or epidemiology, simulators often provide the best description of real-world phenomena. However, they also lead to challenging inverse problems because the density they implicitly define is often intractable. In this talk, we will present a suite of simulation-based inference techniques (frequentist and bayesian) that go beyond the traditional Approximate Bayesian Computation approach, which typically struggles in a high-dimensional setting. We will cover inference methods that use surrogate models based on modern neural networks, including variants of likelihood-ratio estimation algorithms, MCMC sampling techniques or probabilistic programming inference engines. We will also show that additional information, such as the joint likelihood ratio and the joint score, can often be extracted from simulators and used to augment the training data for these surrogate models. We will demonstrate that these new techniques are more sample efficient and provide higher-fidelity inference than traditional methods.

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