# Introduction to Bayesian Statistics

Patrick Lam

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- Does not require large sample approximations
- Simulation-based approach

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- Easily set up and estimate difficult models
- ▶ Priors often help with identification

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Something to think about:

Is MLE/frequentist approach simply Bayesian statistics with an uninformative prior?