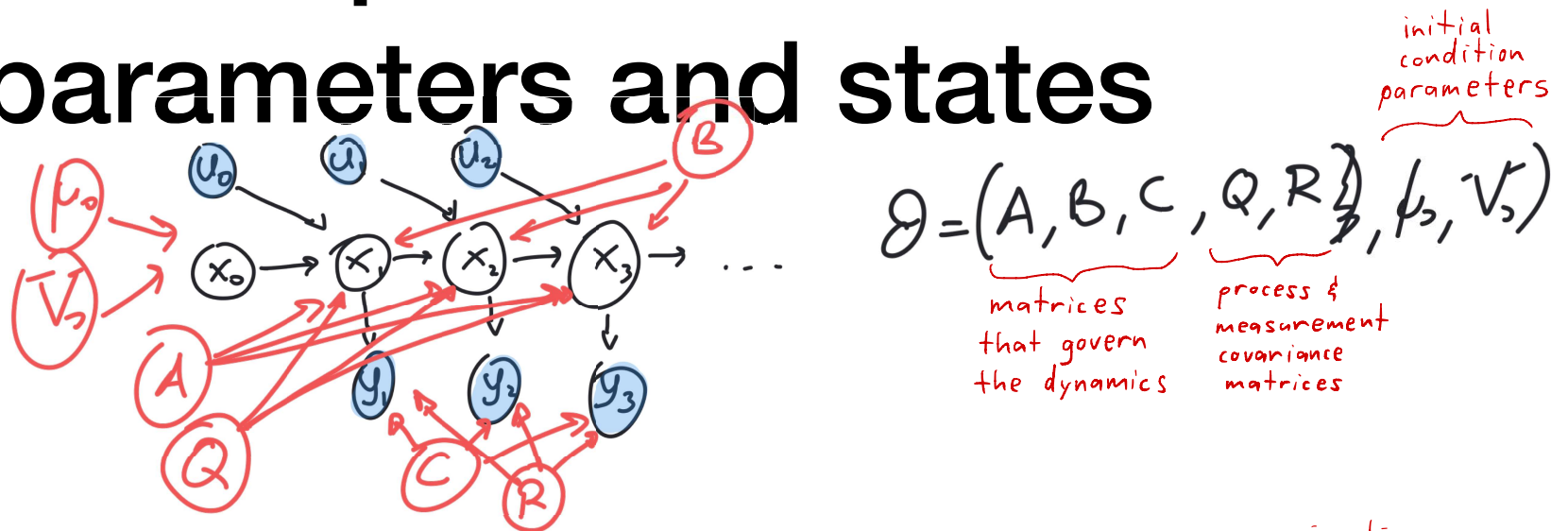


Lecture 20: State-space models - Kalman filters

Professor Ilias Bilonis

How do we estimate the parameters of the model?

Joint posterior over parameters and states



prior: $\theta \sim p(\theta)$

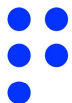
parameter posterior:

$$p(\theta | y_{1:n}, u_{0:n-1}) \stackrel{\text{sum rule}}{=} \int \underbrace{p(\theta, x_{0:n} | y_{1:n}, u_{0:n-1})}_{\text{joint posterior}} d x_{0:n} \quad \text{marginalize}$$

$$p(\theta, x_{0:n} | y_{1:n}, u_{0:n-1}) \propto \underbrace{p(x_{0:n} | y_{1:n}, u_{0:n-1}, \theta)}_{\text{state posterior}} \underbrace{p(\theta)}_{\text{parameter prior}}$$

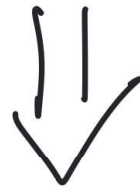
$$\propto \underbrace{p(y_{1:n} | x_{0:n}, u_{0:n-1}, \theta)}_{\text{likelihood}} \underbrace{p(x_{0:n} | u_{0:n-1})}_{\text{states prior}} \underbrace{p(\theta)}_{\text{parameter prior}}$$

$$= p(\theta) p(x_0 | \theta) \prod_{t=1}^n p(x_t | x_{t-1}, u_{t-1}, \theta) p(y_t | x_t, \theta)$$



Maximum likelihood estimate of the parameters

$$p(\theta | y_{1:n}, u_{0:n-1}) = \int p(\theta, x_{0:n} | y_{1:n}, u_{0:n}) dx_{0:n}$$



Expectation Maximization
(for linear case w/ Gaussian)
Bishop 9.3