02417: Time Series Analysis

Week 11 – State space models, 2nd part

Christian Ankerstjerne Thilker
DTU Compute

Based on previous material from the course

April 20, 2026

Week 11: Outline of the lecture

State space models, 2nd part:

- Initialization of the Kalman filter
- ML-estimates in state space models, Sec. 10.6
- The Kalman filter when some observations are missing
- ARMA-models on state space form, Sec. 10.4
- Time-varying systems
- Examples

The linear state space model

$$\boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{G}\boldsymbol{e}_{1,t}$$
$$\boldsymbol{Y}_t = \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}$$

- $\{\boldsymbol{e}_{1,t}\}$ and $\{\boldsymbol{e}_{2,t}\}$ are mutually uncorrelated normally distributed white noise
- $V(\boldsymbol{e}_{1,t}) = \Sigma_1$ and $V(\boldsymbol{e}_{2,t}) = \Sigma_2$

Kalman Filter – Repetition

- What steps does the Kalman Filter consist of?
- How is the model used and how are the observations used?
- Model is used for prediction and combined with observations for reconstruction.
- How are the predictions/observations weighed in the reconstruction step?

Kalman filter – Initialization

- The Kalman filter has to be initialised - for both analysis and parameter estimation.

Kalman filter – Initialization

- The Kalman filter has to be initialised - for both analysis and parameter estimation.
- If you have no idea: Put $\widehat{\boldsymbol{X}}_{1|1} = \mathbf{0}$ and $\boldsymbol{\Sigma}^{xx}_{1|1} = \alpha \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix and α is a 'large' constant.

Kalman filter – Initialization

- The Kalman filter has to be initialised - for both analysis and parameter estimation.
- If you have no idea: Put $\widehat{\boldsymbol{X}}_{1|1} = \mathbf{0}$ and $\boldsymbol{\Sigma}^{xx}_{1|1} = \alpha \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix and α is a 'large' constant.
- If you know the starting state exactly: Put $\widehat{\boldsymbol{X}}_{1|1} =$ 'Known value' and $\boldsymbol{\Sigma}^{xx}_{1|1} = \mathbf{0}$, whereby the first *observation* has covariance matrix $\boldsymbol{\Sigma}^{yy}_{1|1} = \boldsymbol{\Sigma}_2$

Kalman filter – Initialization

- The Kalman filter has to be initialised - for both analysis and parameter estimation.
- If you have no idea: Put $\widehat{\boldsymbol{X}}_{1|1} = \mathbf{0}$ and $\boldsymbol{\Sigma}^{xx}_{1|1} = \alpha \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix and α is a 'large' constant.
- If you know the starting state exactly: Put $\widehat{\boldsymbol{X}}_{1|1} =$ 'Known value' and $\boldsymbol{\Sigma}^{xx}_{1|1} = \mathbf{0}$, whereby the first *observation* has covariance matrix $\boldsymbol{\Sigma}^{yy}_{1|1} = \boldsymbol{\Sigma}_2$
- If you have a good guess about the starting state: Put $\widehat{\boldsymbol{X}}_{1|1} =$ 'Guess' and $\boldsymbol{\Sigma}^{xx}_{1|1} = \boldsymbol{\Sigma}_{\text{Guess}}$.

Kalman filter – Initialization

- The Kalman filter has to be initialised - for both analysis and parameter estimation.
- If you have no idea: Put $\widehat{\boldsymbol{X}}_{1|1} = \mathbf{0}$ and $\boldsymbol{\Sigma}_{1|1}^{xx} = \alpha \boldsymbol{I}$, where $\boldsymbol{I}$ is the identity matrix and α is a 'large' constant.
- If you know the starting state exactly: Put $\widehat{\boldsymbol{X}}_{1|1} =$ 'Known value' and $\boldsymbol{\Sigma}_{1|1}^{xx} = \mathbf{0}$, whereby the first *observation* has covariance matrix $\boldsymbol{\Sigma}_{1|1}^{yy} = \boldsymbol{\Sigma}_2$
- If you have a good guess about the starting state: Put $\widehat{\boldsymbol{X}}_{1|1} =$ 'Guess' and $\boldsymbol{\Sigma}_{1|1}^{xx} = \boldsymbol{\Sigma}_{\text{Guess}}$.
- The important part is that the (un-)certainty of $\widehat{\boldsymbol{X}}_{1|1}$ is reflected in $\boldsymbol{\Sigma}_{1|1}^{xx}$.

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L\left(\boldsymbol{\theta}; \mathcal{Y}_{N^*}\right) = f\left(\mathcal{Y}_{N^*} | \boldsymbol{\theta}\right)$$

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent, and so:

$$\begin{aligned} L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) &= f(\mathcal{Y}_{N^*} | \boldsymbol{\theta}) = f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\mathcal{Y}_{N^*-1} | \boldsymbol{\theta}) \\ &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\boldsymbol{Y}_{N^*-1} | \mathcal{Y}_{N^*-2}, \boldsymbol{\theta}) \cdots f(\boldsymbol{Y}_1 | \boldsymbol{\theta}) \end{aligned}$$

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent, and so:

$$\begin{aligned} L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta}) &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\mathcal{Y}_{N^*-1} | \boldsymbol{\theta}) \\ &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\boldsymbol{Y}_{N^*-1} | \mathcal{Y}_{N^*-2}, \boldsymbol{\theta}) \cdots f(\boldsymbol{Y}_1 | \boldsymbol{\theta}) \end{aligned}$$

- So to evaluate the likelihood function, we need one step predictions of the *conditional density functions*.

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent, and so:

$$\begin{aligned} L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) &= f(\mathcal{Y}_{N^*} | \boldsymbol{\theta}) = f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\mathcal{Y}_{N^*-1} | \boldsymbol{\theta}) \\ &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\boldsymbol{Y}_{N^*-1} | \mathcal{Y}_{N^*-2}, \boldsymbol{\theta}) \cdots f(\boldsymbol{Y}_1 | \boldsymbol{\theta}) \end{aligned}$$

- So to evaluate the likelihood function, we need one step predictions of the *conditional density functions*. Do we know how to do this?

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta})$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent, and so:

$$\begin{aligned} L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = f(\mathcal{Y}_{N^*} | \boldsymbol{\theta}) &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\mathcal{Y}_{N^*-1} | \boldsymbol{\theta}) \\ &= f(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}) f(\boldsymbol{Y}_{N^*-1} | \mathcal{Y}_{N^*-2}, \boldsymbol{\theta}) \cdots f(\boldsymbol{Y}_1 | \boldsymbol{\theta}) \end{aligned}$$

- So to evaluate the likelihood function, we need one step predictions of the *conditional density functions*. Do we know how to do this?
- The Kalman filter supplies these!

Maximum Likelihood Estimates

- Let $\mathcal{Y}_{N^*}$ contain the available observations and let $\boldsymbol{\theta}$ contain the parameters of the model
- The likelihood function is the density of the random vector corresponding to the observations evaluated in the observations as a function of the set of parameters (not a density!):

$$L\left(\boldsymbol{\theta}; \mathcal{Y}_{N^*}\right) = f\left(\mathcal{Y}_{N^*} | \boldsymbol{\theta}\right)$$

- The ML-estimates are (as always) found by selecting $\boldsymbol{\theta}$ so that the density function is as large as possible at the actual observations
- The random variables $\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}$ and $\mathcal{Y}_{N^*-1}$ are independent, and so:

$$\begin{aligned} L\left(\boldsymbol{\theta}; \mathcal{Y}_{N^*}\right) &= f\left(\mathcal{Y}_{N^*} | \boldsymbol{\theta}\right) = f\left(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}\right) f\left(\mathcal{Y}_{N^*-1} | \boldsymbol{\theta}\right) \\ &= f\left(\boldsymbol{Y}_{N^*} | \mathcal{Y}_{N^*-1}, \boldsymbol{\theta}\right) f\left(\boldsymbol{Y}_{N^*-1} | \mathcal{Y}_{N^*-2}, \boldsymbol{\theta}\right) \cdots f\left(\boldsymbol{Y}_1 | \boldsymbol{\theta}\right) \end{aligned}$$

- So to evaluate the likelihood function, we need one step predictions of the *conditional density functions*. Do we know how to do this?
- The Kalman filter supplies these!
- Think of the Kalman filter as a method that produces Gaussian conditional densities for your model. From now on and for the rest of the lecture, we assume linear, Gaussian models.

MLE / KF – Prediction

- Assume that at time t we have:

$$\widehat{\boldsymbol{X}}_{t|t} = E\left[\boldsymbol{X}_t|\mathcal{Y}_t\right] \quad \text{and} \quad \boldsymbol{\Sigma}^{xx}_{t|t} = V\left[\boldsymbol{X}_t|\mathcal{Y}_t\right]$$

  That is, $\boldsymbol{X}_{\boldsymbol{t}} \sim N(\widehat{\boldsymbol{X}}_{t|t}, \boldsymbol{\Sigma}^{xx}_{t|t})$

MLE / KF – Prediction

- Assume that at time t we have:

$$\widehat{\boldsymbol{X}}_{t|t} = E\left[\boldsymbol{X}_t|\mathcal{Y}_t\right] \quad \text{and} \quad \boldsymbol{\Sigma}^{xx}_{t|t} = V\left[\boldsymbol{X}_t|\mathcal{Y}_t\right]$$

  That is, $\boldsymbol{X}_t \sim N(\widehat{\boldsymbol{X}}_{t|t}, \boldsymbol{\Sigma}^{xx}_{t|t})$

- Using the model we obtain predictions for time $t+1$:

$$\begin{aligned}
\widehat{\boldsymbol{X}}_{t+1|t} &= \boldsymbol{A}\widehat{\boldsymbol{X}}_{t|t} \\
\boldsymbol{\Sigma}^{xx}_{t+1|t} &= \boldsymbol{A}\boldsymbol{\Sigma}^{xx}_{t|t}\boldsymbol{A}^T + \boldsymbol{G}\boldsymbol{\Sigma}_1\boldsymbol{G}^T \\
\widehat{\boldsymbol{Y}}_{t+1|t} &= \boldsymbol{C}\widehat{\boldsymbol{X}}_{t+1|t} \\
\boldsymbol{\Sigma}^{yy}_{t+1|t} &= \boldsymbol{C}\boldsymbol{\Sigma}^{xx}_{t+1|t}\boldsymbol{C}^T + \boldsymbol{\Sigma}_2
\end{aligned}$$

MLE / KF – Prediction

- Assume that at time t we have:

$$\widehat{\boldsymbol{X}}_{t|t} = E\left[\boldsymbol{X}_t | \mathcal{Y}_t\right] \quad \text{and} \quad \boldsymbol{\Sigma}^{xx}_{t|t} = V\left[\boldsymbol{X}_t | \mathcal{Y}_t\right]$$

  That is, $\boldsymbol{X_t} \sim N(\widehat{\boldsymbol{X}}_{t|t}, \boldsymbol{\Sigma}^{xx}_{t|t})$

- Using the model we obtain predictions for time $t+1$:

$$\begin{aligned}
\widehat{\boldsymbol{X}}_{t+1|t} &= \boldsymbol{A}\widehat{\boldsymbol{X}}_{t|t} \\
\boldsymbol{\Sigma}^{xx}_{t+1|t} &= \boldsymbol{A}\boldsymbol{\Sigma}^{xx}_{t|t}\boldsymbol{A}^T + \boldsymbol{G}\boldsymbol{\Sigma}_1\boldsymbol{G}^T \\
\widehat{\boldsymbol{Y}}_{t+1|t} &= \boldsymbol{C}\widehat{\boldsymbol{X}}_{t+1|t} \\
\boldsymbol{\Sigma}^{yy}_{t+1|t} &= \boldsymbol{C}\boldsymbol{\Sigma}^{xx}_{t+1|t}\boldsymbol{C}^T + \boldsymbol{\Sigma}_2
\end{aligned}$$

- Due to the gaussian white noise process, $f(\boldsymbol{Y}_{t+1} | \mathcal{Y}_t, \boldsymbol{\theta})$ is the (multivariate) normal density (see Chapter 2) with mean $\widehat{\boldsymbol{Y}}_{t+1|t}$ and variance-covariance $\boldsymbol{\Sigma}^{yy}_{t+1|t}$

MLE / KF – The likelihood function

- Using the prediction (innovation) errors and variances

$$\widetilde{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = C\boldsymbol{\Sigma}^{xx}_{t+1|t}C^T + \boldsymbol{\Sigma}_2$$

that is, $\boldsymbol{Y}_t \sim N(\widehat{\boldsymbol{Y}}_{t+1|t}, \boldsymbol{\Sigma}^{yy}_{t+1|t})$

MLE / KF – The likelihood function

- Using the prediction (innovation) errors and variances

$$\widetilde{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = C\boldsymbol{\Sigma}^{xx}_{t+1|t}C^T + \boldsymbol{\Sigma}_2$$

  that is, $\boldsymbol{Y}_t \sim N(\widehat{\boldsymbol{Y}}_{t+1|t}, \boldsymbol{\Sigma}^{yy}_{t+1|t})$

- the likelihood function can be expressed as

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = \prod_{i=1}^{N^*} \left[(2\pi)^m \det \boldsymbol{\Sigma}^{yy}_{t|t-1}\right]^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\widetilde{\boldsymbol{Y}}_i^T (\boldsymbol{\Sigma}^{yy}_{t+1|t})^{-1}\widetilde{\boldsymbol{Y}}_i\right]$$

MLE / KF – The likelihood function

- Using the prediction (innovation) errors and variances

$$\widetilde{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = C\boldsymbol{\Sigma}^{xx}_{t+1|t}C^T + \boldsymbol{\Sigma}_2$$

  that is, $\boldsymbol{Y}_t \sim N(\widehat{\boldsymbol{Y}}_{t+1|t}, \boldsymbol{\Sigma}^{yy}_{t+1|t})$

- the likelihood function can be expressed as

$$L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = \prod_{i=1}^{N^*} \left[(2\pi)^m \det \boldsymbol{\Sigma}^{yy}_{t|t-1}\right]^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\widetilde{\boldsymbol{Y}}_i^T (\boldsymbol{\Sigma}^{yy}_{t+1|t})^{-1}\widetilde{\boldsymbol{Y}}_i\right]$$

- Yielding the log-likelihood function:

$$\log L(\boldsymbol{\theta}; \mathcal{Y}_{N^*}) = -\frac{1}{2}\sum_{i=1}^{N}\left(\log\det \boldsymbol{\Sigma}^{yy}_{t|t-1} + \widetilde{\boldsymbol{Y}}_i^T (\boldsymbol{\Sigma}^{yy}_{t+1|t})_i^{-1}\widetilde{\boldsymbol{Y}}_i\right) + c$$

- The variance of the parameter estimates $\boldsymbol{\theta}^*$ can be approximated by the 2nd order derivatives of the log-likelihood.

MLE / KF – Reconstruction – Missing data

At time $t+1$ there are two possibilities for the reconstruction part:

The observation $\boldsymbol{Y}_{t+1}$ is available:

We update the state estimate using the reconstruction step of the Kalman Filter:

$$\begin{aligned}
\boldsymbol{K}_{t+1} &= \boldsymbol{\Sigma}^{xx}_{t+1|t} \boldsymbol{C}^T \left(\boldsymbol{\Sigma}^{yy}_{t+1|t} \right)^{-1} \\
\widehat{\boldsymbol{X}}_{t+1|t+1} &= \widehat{\boldsymbol{X}}_{t+1|t} + \boldsymbol{K}_{t+1} \left(\boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t} \right) \\
\boldsymbol{\Sigma}^{xx}_{t+1|t+1} &= \boldsymbol{\Sigma}^{xx}_{t+1|t} - \boldsymbol{K}_{t+1} \boldsymbol{\Sigma}^{yy}_{t+1|t} \boldsymbol{K}^T_{t+1}
\end{aligned}$$

MLE / KF – Reconstruction – Missing data

At time $t+1$ there are two possibilities for the reconstruction part:

The observation $\boldsymbol{Y}_{t+1}$ is available:

We update the state estimate using the reconstruction step of the Kalman Filter:

$$\begin{aligned}
\boldsymbol{K}_{t+1} &= \boldsymbol{\Sigma}^{xx}_{t+1|t} \boldsymbol{C}^T \left(\boldsymbol{\Sigma}^{yy}_{t+1|t} \right)^{-1} \\
\widehat{\boldsymbol{X}}_{t+1|t+1} &= \widehat{\boldsymbol{X}}_{t+1|t} + \boldsymbol{K}_{t+1} \left(\boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t} \right) \\
\boldsymbol{\Sigma}^{xx}_{t+1|t+1} &= \boldsymbol{\Sigma}^{xx}_{t+1|t} - \boldsymbol{K}_{t+1} \boldsymbol{\Sigma}^{yy}_{t+1|t} \boldsymbol{K}^T_{t+1}
\end{aligned}$$

The observation $\boldsymbol{Y}_{t+1}$ is missing:

We get no new information and we use:

$$\begin{aligned}
\widehat{\boldsymbol{X}}_{t+1|t+1} &= \widehat{\boldsymbol{X}}_{t+1|t} \\
\boldsymbol{\Sigma}^{xx}_{t+1|t+1} &= \boldsymbol{\Sigma}^{xx}_{t+1|t}
\end{aligned}$$

MLE / KF – Reconstruction – Missing data

At time $t+1$ there are two possibilities for the reconstruction part:

The observation $\boldsymbol{Y}_{t+1}$ is available:

We update the state estimate using the reconstruction step of the Kalman Filter:

$$\boldsymbol{K}_{t+1} = \boldsymbol{\Sigma}^{xx}_{t+1|t} \boldsymbol{C}^T \left(\boldsymbol{\Sigma}^{yy}_{t+1|t} \right)^{-1}$$

$$\widehat{\boldsymbol{X}}_{t+1|t+1} = \widehat{\boldsymbol{X}}_{t+1|t} + \boldsymbol{K}_{t+1} \left(\boldsymbol{Y}_{t+1} - \widehat{\boldsymbol{Y}}_{t+1|t} \right)$$

$$\boldsymbol{\Sigma}^{xx}_{t+1|t+1} = \boldsymbol{\Sigma}^{xx}_{t+1|t} - \boldsymbol{K}_{t+1} \boldsymbol{\Sigma}^{yy}_{t+1|t} \boldsymbol{K}^T_{t+1}$$

The observation $\boldsymbol{Y}_{t+1}$ is missing:

We get no new information and we use:

$$\widehat{\boldsymbol{X}}_{t+1|t+1} = \widehat{\boldsymbol{X}}_{t+1|t}$$

$$\boldsymbol{\Sigma}^{xx}_{t+1|t+1} = \boldsymbol{\Sigma}^{xx}_{t+1|t}$$

Note: The same technique is used for multi-step predictions.

The ARMA(p, q) model as a state space model

$$Y_t + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

State space form:

$$\boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{G}\boldsymbol{\varepsilon}_{1,t}$$
$$\boldsymbol{Y}_t = \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{\varepsilon}_{2,t}$$

The ARMA(p, q) model as a state space model

$$Y_t + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

State space form:

$$\begin{aligned} \boldsymbol{X}_t &= \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{G}\boldsymbol{\varepsilon}_{1,t} \\ \boldsymbol{Y}_t &= \boldsymbol{C}\boldsymbol{X}_t \end{aligned}$$

Consider the following state space model, where row i is given by how Y_t influences Y_{t+i}:

$$\begin{aligned} \boldsymbol{X}_t &= \begin{bmatrix} -\phi_1 & 1 & 0 & \cdots & 0 \\ -\phi_2 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -\phi_{d-1} & 0 & 0 & 0 & 1 \\ -\phi_d & 0 & 0 & \cdots & 0 \end{bmatrix} \boldsymbol{X}_{t-1} + \begin{pmatrix} 1 \\ \theta_1 \\ \vdots \\ \theta_{d-1} \end{pmatrix} \boldsymbol{\varepsilon}_t \\ \boldsymbol{Y}_t &= \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix} \boldsymbol{X}_t \end{aligned}$$

where $d = max(p, q+1)$ and any extra parameter is fixed to zero.

The ARMA(p, q) model as a state space model

$$Y_t + \phi_1 Y_{t-1} + \cdots + \phi_p Y_{t-p} = \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

State space form:

$$\begin{aligned} \boldsymbol{X}_t &= \boldsymbol{A} \boldsymbol{X}_{t-1} + \boldsymbol{G} \boldsymbol{\varepsilon}_{1,t} \\ \boldsymbol{Y}_t &= \boldsymbol{C} \boldsymbol{X}_t \end{aligned}$$

Consider the following state space model, where row i is given by how Y_t influences Y_{t+i}:

$$\boldsymbol{X}_t = \begin{bmatrix} -\phi_1 & 1 & 0 & \cdots & 0 \\ -\phi_2 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -\phi_{d-1} & 0 & 0 & 0 & 1 \\ -\phi_d & 0 & 0 & \cdots & 0 \end{bmatrix} \boldsymbol{X}_{t-1} + \begin{pmatrix} 1 \\ \theta_1 \\ \vdots \\ \theta_{d-1} \end{pmatrix} \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{Y}_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix} \boldsymbol{X}_t$$

where $d = max(p, q+1)$ and any extra parameter is fixed to zero.
Advantage of writing ARMA-processes on state-space form? *Plug-and-play into Kalman filter framework!*

Estimation in ARMA(p, q)-models using the KF

- Using the Kalman filter we can get the mean and variance of the one-step predictions of the observations:

$$\widehat{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{C}\widehat{\boldsymbol{X}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = \boldsymbol{C}\boldsymbol{\Sigma}^{xx}_{t+1|t}\boldsymbol{C}^T + \boldsymbol{\Sigma}_2$$

- The Kalman filter can handle missing observations

Estimation in ARMA(p, q)-models using the KF

- Using the Kalman filter we can get the mean and variance of the one-step predictions of the observations:

$$\widehat{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{C}\widehat{\boldsymbol{X}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = \boldsymbol{C}\boldsymbol{\Sigma}^{xx}_{t+1|t}\boldsymbol{C}^T + \boldsymbol{\Sigma}_2$$

- The Kalman filter can handle missing observations
- An ARMA(p, q)-model can be written as a state space model

Estimation in ARMA(p, q)-models using the KF

- Using the Kalman filter we can get the mean and variance of the one-step predictions of the observations:

$$\widehat{\boldsymbol{Y}}_{t+1|t} = \boldsymbol{C}\widehat{\boldsymbol{X}}_{t+1|t}$$
$$\boldsymbol{\Sigma}^{yy}_{t+1|t} = \boldsymbol{C}\boldsymbol{\Sigma}^{xx}_{t+1|t}\boldsymbol{C}^T + \boldsymbol{\Sigma}_2$$

- The Kalman filter can handle missing observations
- An ARMA(p, q)-model can be written as a state space model
- This gives us a way of calculating ML-estimates in the ARMA(p, q)-model even when some observations are missing.

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size....

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?
- State-space models are often used to model physical systems, hence we can often derive a model from physical equations (ODEs, e.g. the falling body).

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?
- State-space models are often used to model physical systems, hence we can often derive a model from physical equations (ODEs, e.g. the falling body).
- For temperature models, a so-called resistor-capacitor based model can be adopted

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?
- State-space models are often used to model physical systems, hence we can often derive a model from physical equations (ODEs, e.g. the falling body).
- For temperature models, a so-called resistor-capacitor based model can be adopted

$$\dot{X}(t) = \frac{1}{C_x}\left(\frac{1}{R_{xz}}\left(Z(t) - X(t)\right) + a\, u_1(t)\right)$$
$$\dot{Z}(t) = \frac{1}{C_z}\left(\frac{1}{R_{xz}}\left(X(t) - Z(t)\right) + \frac{1}{R_{za}}\left(u_2(t) - Z(t)\right) + b\, u_3(t)\right)$$

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?
- State-space models are often used to model physical systems, hence we can often derive a model from physical equations (ODEs, e.g. the falling body).
- For temperature models, a so-called resistor-capacitor based model can be adopted

$$\dot{X}(t) = \frac{1}{C_x}\Big(\frac{1}{R_{xz}}(Z(t) - X(t)) + a\, u_1(t)\Big)$$
$$\dot{Z}(t) = \frac{1}{C_z}\Big(\frac{1}{R_{xz}}(X(t) - Z(t)) + \frac{1}{R_{za}}(u_2(t) - Z(t)) + b\, u_3(t)\Big)$$

  Number of parameters (C_x, C_z, R_{zu}, R_{xz}, a, b) is 6. For an equivalent system with free parameters (with $\dim(X_t) = 2$, $\dim(U_t) = 3$) it would be 10!

Formulating state-space models

- When formulating state-space models, we can let all parameters in the model be free and estimate all of them:

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

- This scales quadratically with the system size.... Can we do better?
- State-space models are often used to model physical systems, hence we can often derive a model from physical equations (ODEs, e.g. the falling body).
- For temperature models, a so-called resistor-capacitor based model can be adopted

$$\dot{X}(t) = \frac{1}{C_x}\Big(\frac{1}{R_{xz}}(Z(t) - X(t)) + a\, u_1(t)\Big)$$
$$\dot{Z}(t) = \frac{1}{C_z}\Big(\frac{1}{R_{xz}}(X(t) - Z(t)) + \frac{1}{R_{za}}(u_2(t) - Z(t)) + b\, u_3(t)\Big)$$

  Number of parameters ($C_x, C_z, R_{zu}, R_{xz}, a, b$) is 6. For an equivalent system with free parameters (with $\dim(X_t) = 2$, $\dim(U_t) = 3$) it would be 10!

- But how do we go from this continuous-time system to a discrete-time system where we know how to apply the Kalman filter, ML etc.?

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$.

Formulating state-space models

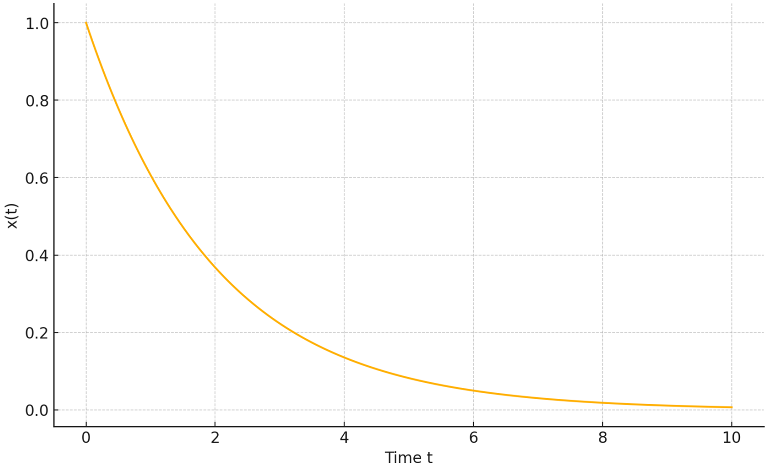
- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

$$X(t) = x_0\,e^{at}$$

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

$$X(t) = x_0\,e^{at}$$



Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

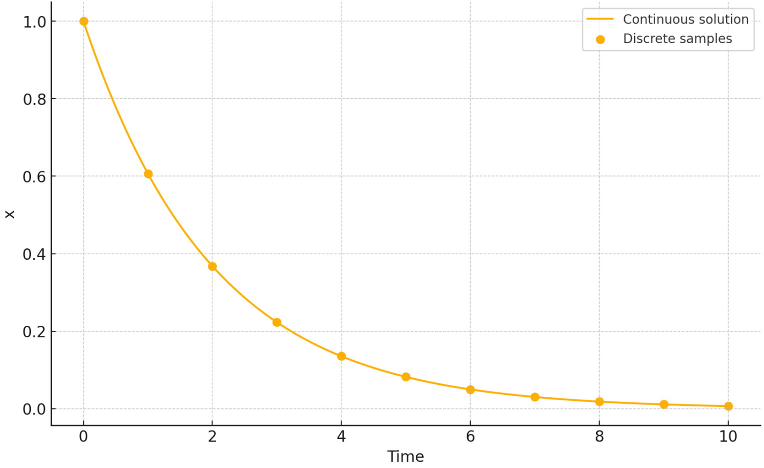
$$X(t) = x_0\,e^{at}$$

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

$$X(t) = x_0\,e^{at}$$

- We can evaluate this at any discrete point in time with $X(k) = x_0\,e^{ak}$, $k \in \mathbb{N}$.

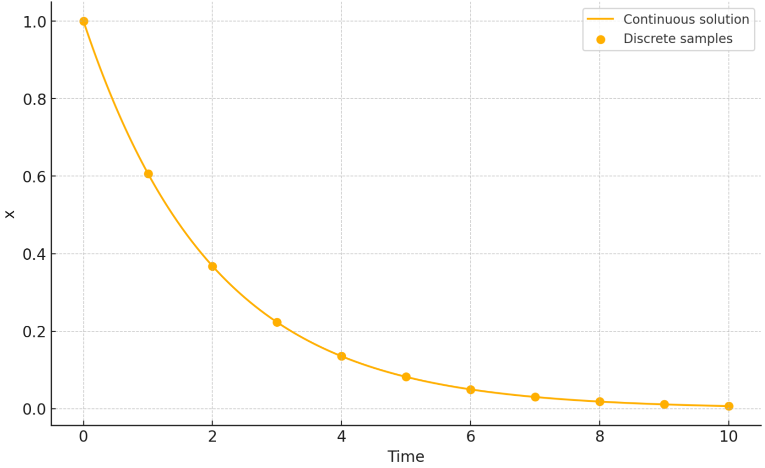


Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\, X(t)$. This has the solution

$$X(t) = x_0\, e^{at}$$

- We can evaluate this at any discrete point in time with $X(k) = x_0\, e^{ak}$, $k \in \mathbb{N}$.



Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

$$X(t) = x_0\,e^{at}$$

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution
$$X(t) = x_0\,e^{at}$$

- This gives us a framework for using a continuous-time model in the discrete-time state-space model framework

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution

$$X(t) = x_0\,e^{at}$$

- This gives us a framework for using a continuous-time model in the discrete-time state-space model framework
- We can now write $X_{t+1} = e^{a\Delta t} X_t = A_d X_t$, where the discrete-time state-space system matrix is $A_d = e^{A\Delta t}$.

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution
$$X(t) = x_0\,e^{at}$$
- This gives us a framework for using a continuous-time model in the discrete-time state-space model framework
- We can now write $X_{t+1} = e^{a\Delta t} X_t = A_d X_t$, where the discrete-time state-space system matrix is $A_d = e^{A\Delta t}$.
- We can do similar things with B:
$$\exp\left(\begin{bmatrix} A_c & B_c \\ 0 & 0 \end{bmatrix}\right) = \begin{bmatrix} \Phi & B_d \\ 0 & I \end{bmatrix}$$
where subscript d is for discrete time and c is continuous time.

Formulating state-space models

- Consider the simple system $\dot{X}(t) = a\,X(t)$. This has the solution
$$X(t) = x_0\,e^{at}$$
- This gives us a framework for using a continuous-time model in the discrete-time state-space model framework
- We can now write $X_{t+1} = e^{a\Delta t} X_t = A_d X_t$, where the discrete-time state-space system matrix is $A_d = e^{A\Delta t}$.
- We can do similar things with B:
$$\exp\left(\begin{bmatrix} A_c & B_c \\ 0 & 0 \end{bmatrix}\right) = \begin{bmatrix} \Phi & B_d \\ 0 & I \end{bmatrix}$$
where subscript d is for discrete time and c is continuous time.
- This way, we can formulate a discrete-time system:
$$X_{t+1} = A_d X_t + B_d\,U_t$$
where $A_d = A_d(\theta)$ and $B_d = B_d(\theta)$ are functions of the continous-time parameters. And we can now apply all the state-space frameworks we have been taught in this course!

Falling body - Revisited

Remember the discretised state-space model of a falling body

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} - \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} g + \epsilon_t$$

$$Y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Falling body - Revisited

Remember the discretised state-space model of a falling body

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} - \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} g + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Imagine that we believe g to be changing over time, but we don't know how or why. How can we incorporate this?

Falling body - Revisited

Remember the discretised state-space model of a falling body

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} - \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} g + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Imagine that we believe g to be changing over time, but we don't know how or why. How can we incorporate this? We can rewrite the model with g as a state!

Falling body - Revisited

Remember the discretised state-space model of a falling body

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} - \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} g + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Imagine that we believe g to be changing over time, but we don't know how or why. How can we incorporate this? We can rewrite the model with g as a state!

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 & -0.5 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Falling body - Revisited

Remember the discretised state-space model of a falling body

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} - \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} g + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Imagine that we believe g to be changing over time, but we don't know how or why. How can we incorporate this? We can rewrite the model with g as a state!

$$\boldsymbol{X}_t = \begin{bmatrix} 1 & 1 & -0.5 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix} \boldsymbol{X}_{t-1} + \epsilon_t$$
$$Y_t = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \boldsymbol{X}_t + e_t$$

Under what conditions should the process noise for g be non-zero?

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \end{aligned}$$

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad & \boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad & \boldsymbol{Y}_t = \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or} \end{aligned}$$

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or } \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t} \end{aligned}$$

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad & \boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad & \boldsymbol{Y}_t = \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or } \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t} \end{aligned}$$

When would you do this?

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or } \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t} \end{aligned}$$

When would you do this? Unknown or uncertain inputs.

Parameter estimation as state-estimation

For the linear state-space model

$$\text{System equation:} \quad \boldsymbol{X}_t = \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t}$$
$$\text{Observation equation:} \quad \boldsymbol{Y}_t = \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t},$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\text{System equation:} \quad \boldsymbol{X}_t = \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t}$$
$$\text{Observation equation:} \quad \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or } \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}$$

When would you do this? Unknown or uncertain inputs. Update parameter estimate as more information becomes available.

Parameter estimation as state-estimation

For the linear state-space model

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \boldsymbol{A}\boldsymbol{X}_{t-1} + \boldsymbol{B}\boldsymbol{u}_{t-1} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \boldsymbol{C}\boldsymbol{X}_t + \boldsymbol{e}_{2,t}, \end{aligned}$$

when $\boldsymbol{u}_t$ unknown, (with observations or not), it can be estimated as a state by

$$\begin{aligned} \text{System equation:} \quad \boldsymbol{X}_t &= \begin{bmatrix} \boldsymbol{A} & \boldsymbol{B} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_{t-1} \\ \boldsymbol{u}_{t-1} \end{bmatrix} + \boldsymbol{e}_{1,t} \\ \text{Observation equation:} \quad \boldsymbol{Y}_t &= \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t}, \text{ or } \boldsymbol{Y}_t = \begin{bmatrix} \boldsymbol{C} & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{X}_t \\ \boldsymbol{u}_t \end{bmatrix} + \boldsymbol{e}_{2,t} \end{aligned}$$

When would you do this? Unknown or uncertain inputs. Update parameter estimate as more information becomes available. Assumption of varying parameters.

Summary of state-space models

- Two kinds of noise.

Summary of state-space models

- Two kinds of noise. Why is this useful?

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea?

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of?

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.
- Handling missing values.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.
- Handling missing values. Why is this so easy?

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.
- Handling missing values. Why is this so easy? Just don't update during reconstruction step.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.
- Handling missing values. Why is this so easy? Just don't update during reconstruction step.
- Adaptive parameter estimates.

Summary of state-space models

- Two kinds of noise. Why is this useful? Instant versus sustained effect.
- Model identification. What is the general idea? Formulate physical equations or at least sensible equations.
- Kalman filter. What are the two steps that it consists of? Reconstruction and prediction.
- Handling missing values. Why is this so easy? Just don't update during reconstruction step.
- Adaptive parameter estimates. Include parameters as states.