

# State space models

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## State space models

We introduce the state space representation

$$\begin{aligned}\mathbf{x}_{t+1} &= \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t + \mathbf{e}_t \\ \mathbf{y}_t &= \mathbf{C}_t \mathbf{x}_t + \mathbf{w}_t\end{aligned}$$

where  $\mathbf{y}_t$  is the  $m$ -dimensional measurement vector at time  $t$ , being the observed signal, whereas  $\mathbf{x}_t$  is the internal  $n$ -dimensional state vector.

The matrices  $\mathbf{A}_t$ ,  $\mathbf{B}_t$ , and  $\mathbf{C}_t$  are known, potentially time-varying, matrices of appropriate dimensions.

The noise processes  $\mathbf{e}_t$  and  $\mathbf{w}_t$  detail model uncertainty and measurement noise, respectively, which are here assumed to be uncorrelated, satisfying

$$\begin{aligned}E\{\mathbf{e}_s \mathbf{e}_t^T\} &= \begin{cases} \mathbf{R}_e & \text{if } s = t \\ \mathbf{0} & \text{otherwise} \end{cases} \\ E\{\mathbf{w}_s \mathbf{w}_t^T\} &= \begin{cases} \mathbf{R}_w & \text{if } s = t \\ \mathbf{0} & \text{otherwise} \end{cases} \\ E\{\mathbf{e}_s \mathbf{w}_t^T\} &= \mathbf{0} \quad \forall s, t\end{aligned}$$

Furthermore, we assume the system to be stable, such that  $\det(\lambda \mathbf{I} - \mathbf{A}) = 0$  have all its solution inside the unit circle.

## State space models

*Example:*

One may express an ARMA( $p, q$ ) process, on state space form using a controllable canonical form by introducing

$$d = \max(p, q + 1)$$

and letting  $a_\ell = 0$ , for  $\ell > p$ , and  $c_\ell = 0$ , for  $\ell > q$ . Then,

$$\begin{aligned}\mathbf{x}_t &= \begin{bmatrix} -a_1 & -a_2 & \dots & -a_{d-1} & -a_d \\ 1 & 0 & \dots & 0 & 0 \\ 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 1 & 0 \end{bmatrix} \mathbf{x}_{t-1} + \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} e_t \\ y_t &= \begin{bmatrix} 1 & c_1 & \dots & c_{d-1} \end{bmatrix} \mathbf{x}_t\end{aligned}$$

Alternatively, one may use the observable canonical form with

$$\begin{aligned}\mathbf{x}_t &= \begin{bmatrix} -a_1 & 1 & 0 & \dots & 0 \\ -a_2 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -a_{d-1} & 0 & 0 & \dots & 1 \\ -a_d & 0 & 0 & \dots & 0 \end{bmatrix} \mathbf{x}_{t-1} + \begin{bmatrix} 1 \\ c_1 \\ c_2 \\ \vdots \\ c_{d-1} \end{bmatrix} e_t \\ y_t &= \begin{bmatrix} 1 & 0 & \dots & 0 \end{bmatrix} \mathbf{x}_t\end{aligned}$$

Note that this form assumes the ARMA parameters to be known.

These are only examples of space representations; one can easily form new ones.

## State space models

*Example:*

Consider an AR(1) with an unknown parameter  $a_1$

$$y_t + a_1 y_{t-1} = v_t$$

We can create the state  $x_t = a_1$ , then

$$\begin{aligned}x_{t+1} &= 1 x_t \\ y_t &= \begin{bmatrix} -y_{t-1} \end{bmatrix} x_t + v_t\end{aligned}$$

Thus,  $\mathbf{A}_t = 1$ ,  $\mathbf{B}_t = 0$ , and  $\mathbf{C}_t = \begin{bmatrix} -y_{t-1} \end{bmatrix}$ .

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Thus,  $\mathbf{A}_t = 1$ ,  $\mathbf{B}_t = 0$ , and  $\mathbf{C}_t = [-y_{t-1}]$ .

Estimating the internal state,  $\hat{x}_t$ , would thus yield an estimate of  $a_1$ .

In case one wish to allow the estimate of  $a_1$  to vary over time, one can then add a modelling noise, letting

$$\begin{aligned} x_{t+1} &= 1 x_t + e_t \\ y_t &= [-y_{t-1}] x_t + v_t \end{aligned}$$

where the variance of the noise dictates how fast the parameter can change.



## State space models

*Example:*

The Swedish fighter jet, Gripen, uses a state space representation with the internal states

$$\mathbf{x}_t = [v_y \ p \ r \ \phi \ \psi \ \delta_a \ \delta_r]^T$$

denoting the velocity in the  $y$  direction, the roll angle rate, turning angle rate, roll angle, course angle, aileron deflection and rudder deflection, respectively.

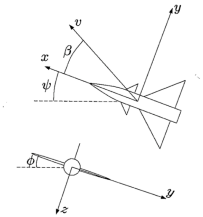
As inputs, one use the aileron deflection and rudder deflection,

$$\mathbf{u}_t = [\delta_a^c \ \delta_r^c]^T$$

This yields the state space representation

$$\frac{\partial}{\partial t} \mathbf{x} = \begin{bmatrix} -0.292 & 8.13 & -201 & 9.77 & 0 & 12.5 & 17.1 \\ -0.152 & -2.54 & 0.561 & -0.004 & 0 & 107 & 7.68 \\ 0.364 & -0.0678 & -0.481 & 0.0012 & 0 & 4.67 & -7.98 \\ 0 & 1 & 0.0401 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -20 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -20 \end{bmatrix} \mathbf{x} + \begin{bmatrix} 0 & -2.15 \\ -31.7 & 0.0274 \\ 0 & 1.48 \\ 0 & 0 \\ 0 & 0 \\ 20 & 0 \\ 0 & 20 \end{bmatrix} \mathbf{u} + \mathbf{N} \mathbf{w}$$

The output are the 4th and 5th states (roll angle, course angle).



## State space models

It is not difficult to express a state space representation on the usual transfer function form.

Using the  $z$  notation yields

$$z\mathbf{x}_t = \mathbf{A}_t \mathbf{x}_t + \mathbf{B}_t \mathbf{u}_t + \mathbf{e}_t$$

implying that

$$(z\mathbf{I} - \mathbf{A}_t) \mathbf{x}_t = \mathbf{B}_t \mathbf{u}_t + \mathbf{e}_t$$

and thus

$$\mathbf{y}_t = \mathbf{C}_t (z\mathbf{I} - \mathbf{A}_t)^{-1} \mathbf{B}_t \mathbf{u}_t + \mathbf{C}_t (z\mathbf{I} - \mathbf{A}_t)^{-1} \mathbf{e}_t + \mathbf{w}_t$$

which is called the input-output or transfer function form, since the matrices

$$\begin{aligned} &\mathbf{C}_t (z\mathbf{I} - \mathbf{A}_t)^{-1} \mathbf{B}_t \\ &\mathbf{C}_t (z\mathbf{I} - \mathbf{A}_t)^{-1} \end{aligned}$$

will form the transfer functions from  $\mathbf{u}_t$  and  $\mathbf{e}_t$  to  $\mathbf{y}_t$ , respectively.