Probabilistic Uncertainties and State Estimation

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Recap: uncertainties in control systems

Sources of uncertainties: initial conditions, parameters, process and measurement noise

Types of uncertainties: epistemic versus aleatoric, deterministic versus probabilistic

Deterministic uncertainties \equiv set valued uncertainties

Exercise: deterministic uncertainties in control systems

A robot moving in 2D is experiencing process noise $(w_x(t), w_y(t))$ such that for all time t:

$$w_x^2 + 3w_y^2 \le 10$$
 OR $5w_x^2 + w_y^2 \le 20$

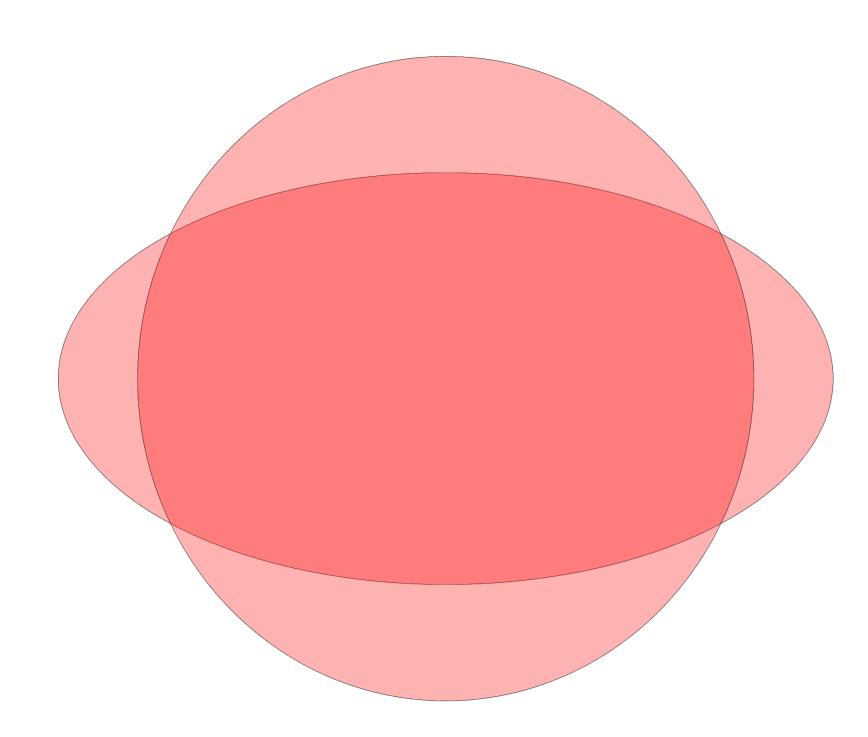
So the disturbance set is

Exercise: deterministic uncertainties in control systems

A robot moving in 2D is experiencing process noise $(w_x(t), w_y(t))$ such that for all time t:

$$w_x^2 + 3w_y^2 \le 10$$
 OR $5w_x^2 + w_y^2 \le 20$

So the disturbance set is union of elliptical discs



Probabilistic/stochastic uncertainties

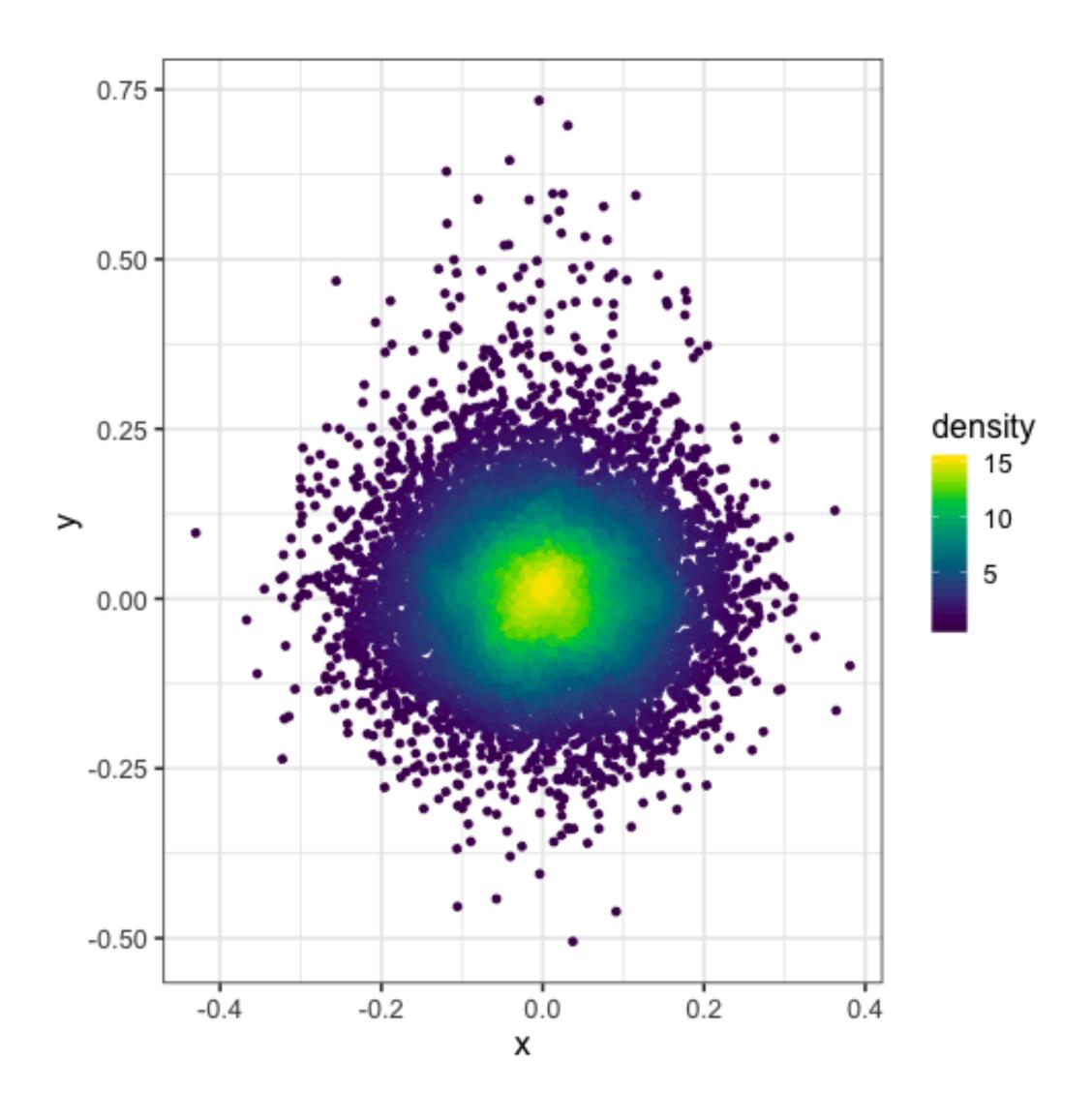
Initial conditions: $x_1(0), \ldots, x_n(0)$ may not be exactly known [but we may know that some values are "more likely" than the other]

Parameters: p_1, \ldots, p_s may not be exactly known [ditto]

Noises: w_1, \ldots, w_q and v_1, \ldots, v_r if present, are unknown and unmeasured [ditto]

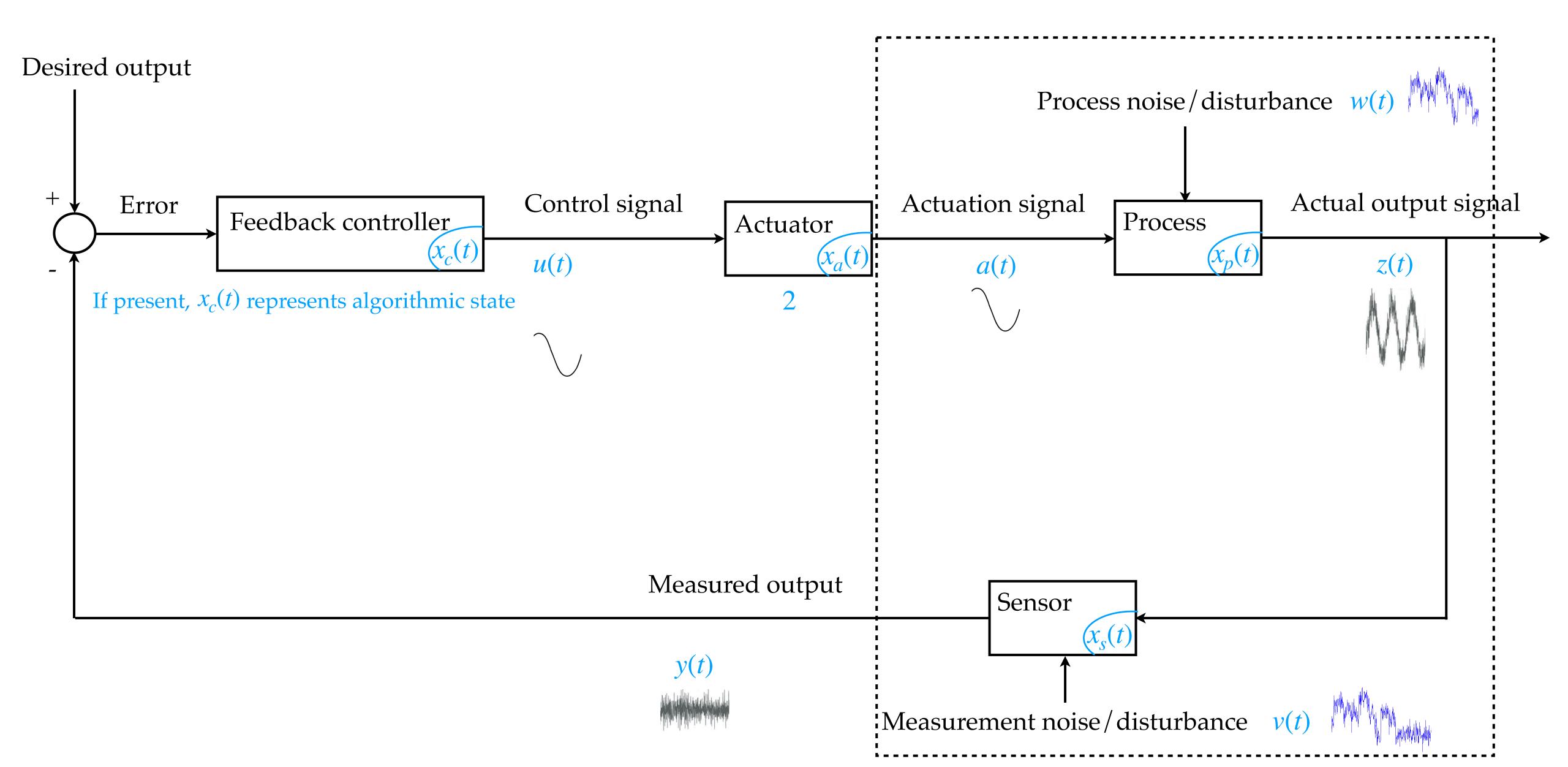
This is more information than simply specifying the set where the values must belong to

Example: probabilistic/stochastic uncertainties by density



With high probability (x, y) = (0,0)

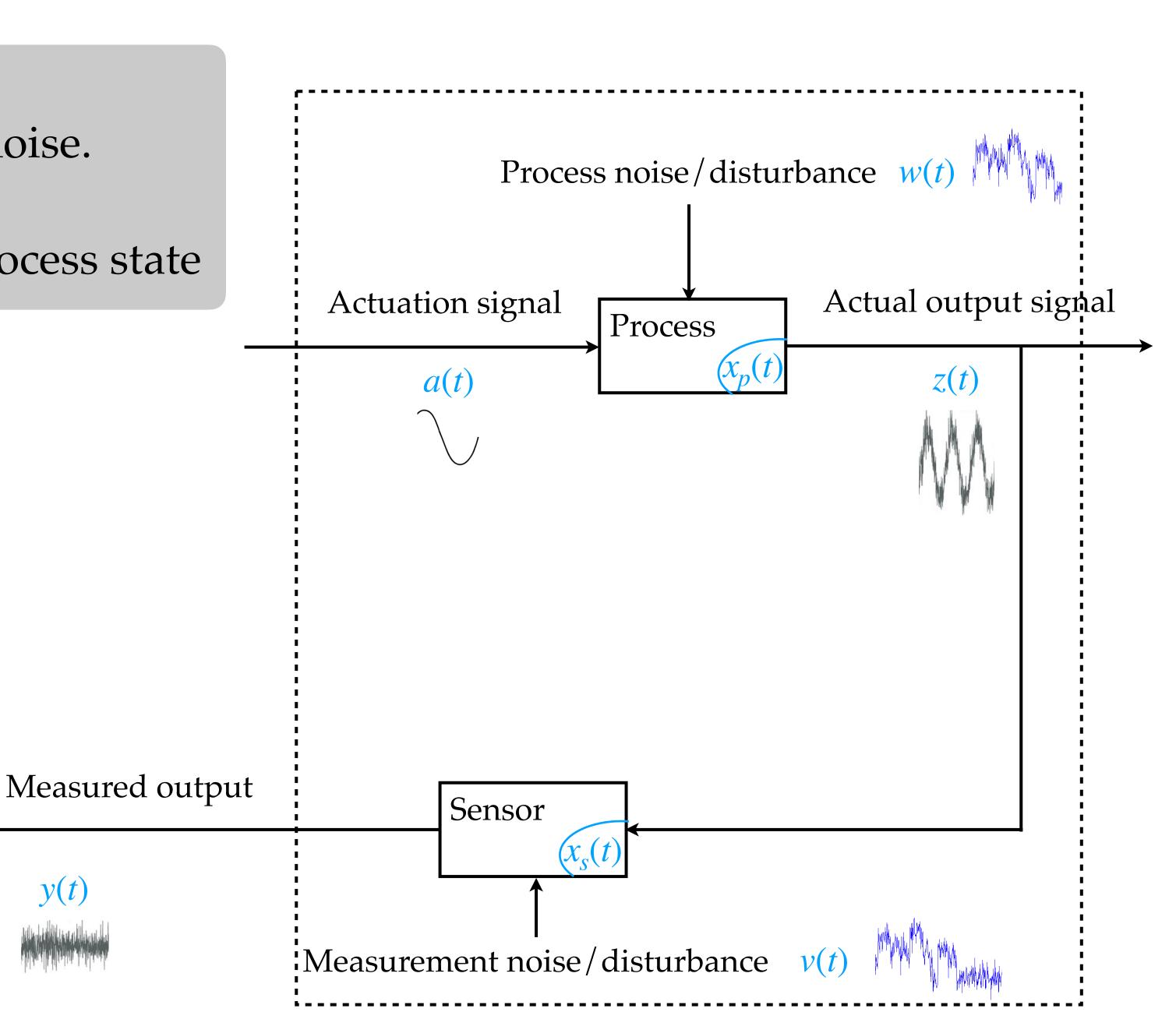
State estimation problem in control



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Given process model + process noise, measurement model + measurement noise.

Compute the "best" estimate of the process state



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Filter = an algorithm to solve this problem

Measured output Sensor $\frac{1}{1}$ Measurement noise/disturbance v(t)

Actuation signal

a(t)

Process noise/disturbance w(t)

Process

Actual output signal

From Lec. 14, slide 6:

Process model:

$$x_{1}(t+1) = f_{1}\left(x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), w_{1}(t), \dots, w_{q}(t)\right)$$

$$x_{2}(t+1) = f_{2}\left(x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), w_{1}(t), \dots, w_{q}(t)\right)$$

$$\vdots = \vdots$$

$$x_{n}(t+1) = f_{n}\left(x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), w_{1}(t), \dots, w_{q}(t)\right)$$

Measurement model:

$$y_{1}(t) = g_{1} (x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), v_{1}(t), \dots, v_{r}(t))$$

$$y_{2}(t) = g_{2} (x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), v_{1}(t), \dots, v_{r}(t))$$

$$\vdots = \vdots$$

$$y_{p}(t) = g_{p} (x_{1}(t), \dots, x_{n}(t), u_{1}(t), \dots, u_{m}(t), v_{1}(t), \dots, v_{r}(t))$$

Given
$$f_1, \ldots, f_n, g_1, \ldots, g_p$$
,
and feedback u_1, \ldots, u_m ,
as well as probabilistic descriptions
of $w_1, \ldots, w_q, v_1, \ldots, v_r$,

estimate x_1, \ldots, x_n

We also have the history of noisy measurements (raw data) up until the time *t*

What do we mean by "best estimate"

True process states $x_1(t), \ldots, x_n(t)$ are probabilistic

Example (nonlinear control system): three process states (x_1, x_2, θ) and two controls (V, ω)

$$x_1(t+1) = x_1(t) + V(t)\Delta t \times \cos \theta(t)$$

$$x_2(t+1) = x_2(t) + V(t)\Delta t \times \sin \theta(t)$$

$$\theta(t+1) = \theta(t) + \Delta t \times \omega(t) + w(t)$$

We know what the statistics of the process noise w(t) is

So our estimates $\hat{x}_1(t), \hat{x}_2(t), \hat{\theta}(t)$ will be **probabilistic**

What do we mean by "best estimate"

Common way to measure "best": minimum mean squared error (MMSE)

Find $\hat{x}(t)$ that minimizes

Expected value of $[(x(t) - \hat{x}(t))^2 |$ history of measurements up until time t

It turns out that the minimizer is what is called "conditional expectation of the process state"

Many algorithms: Kalman filter, particle filters