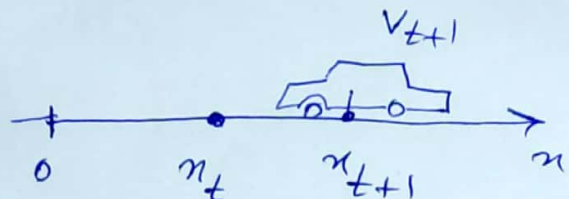
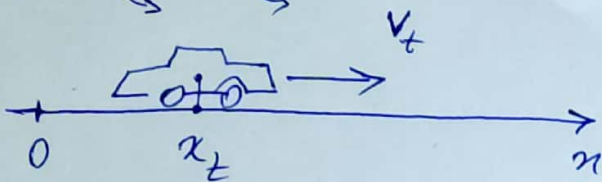


$P(C | \text{Parents})$



sub \Rightarrow

$v_{t+1} = v_t$

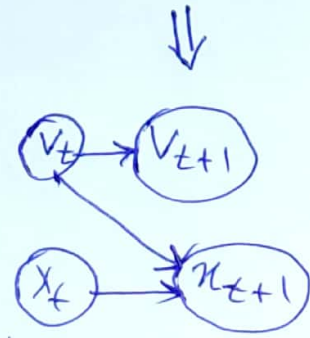
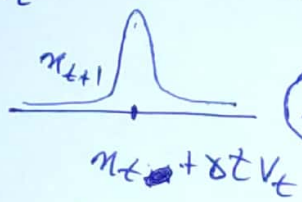
$x_{t+1} = x_t + \Delta t v_t$

$v_{t+1} \approx v_t$

$x_{t+1} \approx x_t + \Delta t v_t$



$x_{t+1} \approx x_t + \Delta t v_t$



$P(x_{t+1} | x_t, v_t)$

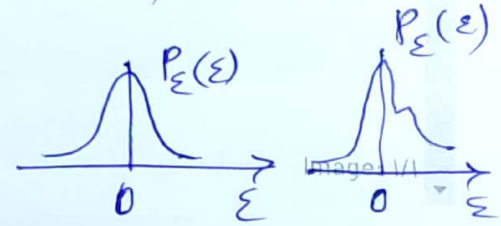
noise model

~~$x_{t+1} = x_t + v_t + \epsilon$~~

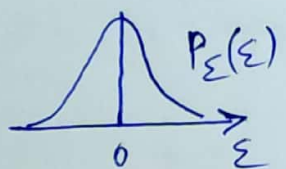


$Y = f(X) + \epsilon$
 (deterministic) (stochastic) noise

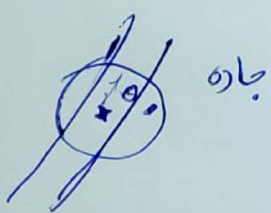
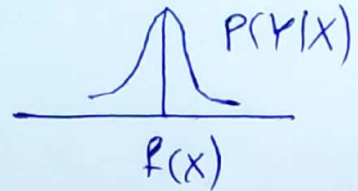
noise: Random variable $\epsilon \propto P_\epsilon$



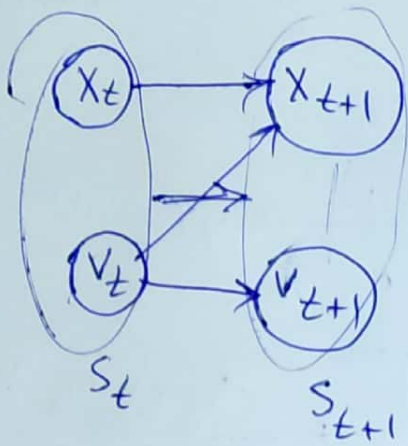
$Y = f(X) + \epsilon \Rightarrow \epsilon = Y - f(X)$



$P(Y|X) = P_\epsilon(Y - f(X))$



$$S_t = \begin{bmatrix} X_t \\ V_t \end{bmatrix}$$



We are interested in

$$P(S_{t+1} | S_t) \rightarrow \text{transition model} \\ = P(X_{t+1}, V_{t+1} | X_t, V_t)$$

$$\begin{aligned} & \left. \begin{aligned} V_{t+1} &= V_t + \varepsilon_v \\ X_{t+1} &= X_t + \Delta t V_t + \varepsilon_x \end{aligned} \right\} = \Pr(X_{t+1} = X_t + \Delta t V_t + \varepsilon_x, V_{t+1} = V_t + \varepsilon_v) \\ & \Rightarrow \Pr(\varepsilon_x = X_{t+1} - X_t - \Delta t V_t, \varepsilon_v = V_{t+1} - V_t) \end{aligned}$$

~~P(X_{t+1})~~

$$P(S_{t+1} | S_t) = P(X_{t+1}, V_{t+1} | X_t, V_t)$$

$$= \Pr(\varepsilon_x = X_{t+1} - X_t - \Delta t V_t, \varepsilon_v = V_{t+1} - V_t)$$

prob. density

$$P_\varepsilon(\varepsilon_x, \varepsilon_v) \quad \text{joint distribution of } \varepsilon_x, \varepsilon_v$$

if $\varepsilon_x, \varepsilon_v$ are independent $P_\varepsilon(\varepsilon_x, \varepsilon_v) = P_{\varepsilon_x}(\varepsilon_x) P_{\varepsilon_v}(\varepsilon_v)$

$$\Rightarrow P(S_{t+1} | S_t) = P_\varepsilon(\varepsilon_x = X_{t+1} - X_t - \Delta t V_t) P_v(V_{t+1} - V_t)$$

$$= P(X_{t+1}, V_{t+1} | X_t, V_t) = P(X_{t+1} | X_t, V_t) P(V_{t+1} | V_t)$$

$$= \frac{1}{\sigma_x \sqrt{2\pi}} \exp\left(-\frac{1}{2} \left(\frac{X_{t+1} - X_t - \Delta t V_t}{\sigma_\varepsilon}\right)^2\right) \frac{1}{\sigma_v \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{V_{t+1} - V_t}{\sigma_v}\right)^2}$$

$$P(X_{t+1}, V_{t+1} | X_t, V_t)$$

$$= \frac{1}{\sqrt{2\pi} \sigma_x} \exp\left(-\frac{1}{2\sigma_x^2} (X_{t+1} - \overbrace{(X_t + \Delta_t V_t)}^{M_x})^2\right) \frac{1}{\sqrt{2\pi} \sigma_v} \exp\left(-\frac{1}{2\sigma_v^2} (V_{t+1} - \overbrace{V_t}^{M_v})^2\right)$$

$$= \frac{1}{(\sqrt{2\pi})^2 \sigma_x \sigma_v} \exp\left(-\frac{1}{2} \left[\frac{(X_{t+1} - \mu_x)^2}{\sigma_x^2} + \frac{(V_{t+1} - \mu_v)^2}{\sigma_v^2} \right]\right)$$

$$= \frac{1}{(\sqrt{2\pi})^2 \sigma_x \sigma_v} \exp\left(-\frac{1}{2} [X_{t+1} - \mu_x, V_{t+1} - \mu_v] \begin{bmatrix} \sigma_x^{-2} & 0 \\ 0 & \sigma_v^{-2} \end{bmatrix} \begin{bmatrix} X_{t+1} - \mu_x \\ V_{t+1} - \mu_v \end{bmatrix}\right)$$

$$\Sigma = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_v^2 \end{bmatrix}$$

$$\mu = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

$$S_{t+1} = \begin{bmatrix} X_{t+1} \\ V_{t+1} \end{bmatrix}$$

$$= \frac{1}{(\sqrt{2\pi})^d \det(\Sigma)^{1/2}} \exp\left(-\frac{1}{2} (S_{t+1} - \mu)^T \Sigma^{-1} (S_{t+1} - \mu)\right)$$

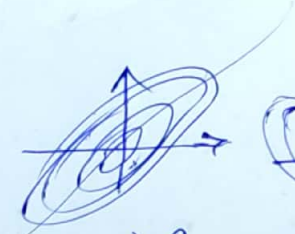
$d=2$
دو متغیر

→ general case for when ϵ_x, ϵ_v are ~~not~~ dependent

$$\Sigma = \begin{bmatrix} \sigma_x^2 & \sigma_{xv} \\ \sigma_{xv} & \sigma_v^2 \end{bmatrix}$$



$\sigma_{xv} = 0$



$\sigma_{xv} > 0$



$\sigma_{xv} < 0$