

EECS 16B CSM

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1 PCA

2 Linearization

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Linearization

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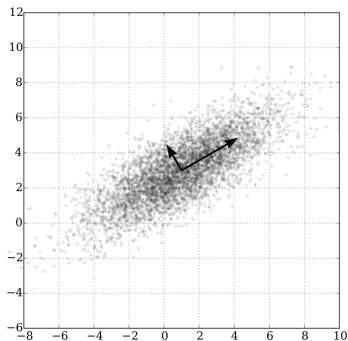
Linearization

- allows us to reduce dimensionality
- preserve only most important singular components

PCA

Steps

- 1 do SVD
- 2 pick the first σ_i that you want
- 3 first v_i from V^T are the singular components



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State Space Form

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Linearization

$$\frac{d}{dt}\mathbf{x}(t) = f(\mathbf{x}(t), \mathbf{u}(t)) \quad (1)$$

But what if $f(\mathbf{x}(t), \mathbf{u}(t))$ isn't linear?

Linearity

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Linearization

Given a system $y(t) = f(x(t))$,

$$ax(t) \iff ay(t) \tag{2}$$

$$x_1(t) + x_2(t) \iff y_1(t) + y_2(t) \tag{3}$$

$$ax_1(t) + bx_2(t) \iff ay_1(t) + by_2(t) \tag{4}$$

Taylor Approximations

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Linearization

Calculus review!

$$f(x) = \sum_{n \geq 0} \frac{f^{(n)}(x_0)}{n!} (x - x_0)^n = \frac{f(x_0)}{0!} + \frac{f'(x_0)}{1!} (x - x_0) + \frac{f''(x_0)}{2!} (x - x_0)^2 + \dots \quad (5)$$

$$\approx f(x_0) + f'(x_0)(x - x_0) \quad (6)$$

Linearization

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Linearization

$$\mathbf{J}_x = \begin{bmatrix} \partial_{x_1} f_1 & \partial_{x_2} f_1 & \cdots & \partial_{x_n} f_1 \\ \partial_{x_1} f_2 & \partial_{x_2} f_2 & \cdots & \partial_{x_n} f_2 \\ \vdots & \vdots & \ddots & \vdots \\ \partial_{x_1} f_n & \partial_{x_2} f_n & \cdots & \partial_{x_n} f_n \end{bmatrix} \quad (7)$$

$$\mathbf{J}_u = \begin{bmatrix} \partial_{u_1} f_1 & \partial_{u_2} f_1 & \cdots & \partial_{u_n} f_1 \\ \partial_{u_1} f_2 & \partial_{u_2} f_2 & \cdots & \partial_{u_n} f_2 \\ \vdots & \vdots & \ddots & \vdots \\ \partial_{u_1} f_n & \partial_{u_2} f_n & \cdots & \partial_{u_n} f_n \end{bmatrix} \quad (8)$$

$$\frac{d}{dt} \mathbf{x}(t) \approx \mathbf{J}_x(\mathbf{x}(t) - \mathbf{x}^*) + \mathbf{J}_u(\mathbf{u}(t) - \mathbf{u}^*) \quad (9)$$