

MODULE 2 LESSON 3

GOING NONLINEAR: THE EXTENDED KALMAN

The Extended Kalman Filter (EKF)

By the end of this video, you will be able to

- Describe how the EKF uses first-order linearization to turn a nonlinear problem into a linear one
- Understand the role of Jacobian matrices in the EKF and how to compute them
- Apply the EKF to a simple nonlinear tracking problem

Recap | The Linear Kalman Filter

Linear motion / process model

$$\mathbf{x}_k = \mathbf{F}_{k-1} \mathbf{x}_{k-1} + \mathbf{G}_{k-1} \mathbf{u}_{k-1} + \mathbf{w}_{k-1}$$

↑
↑
↑
↑

current
previous
inputs
process

state
state

noise

$$\mathbf{w}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}_k)$$

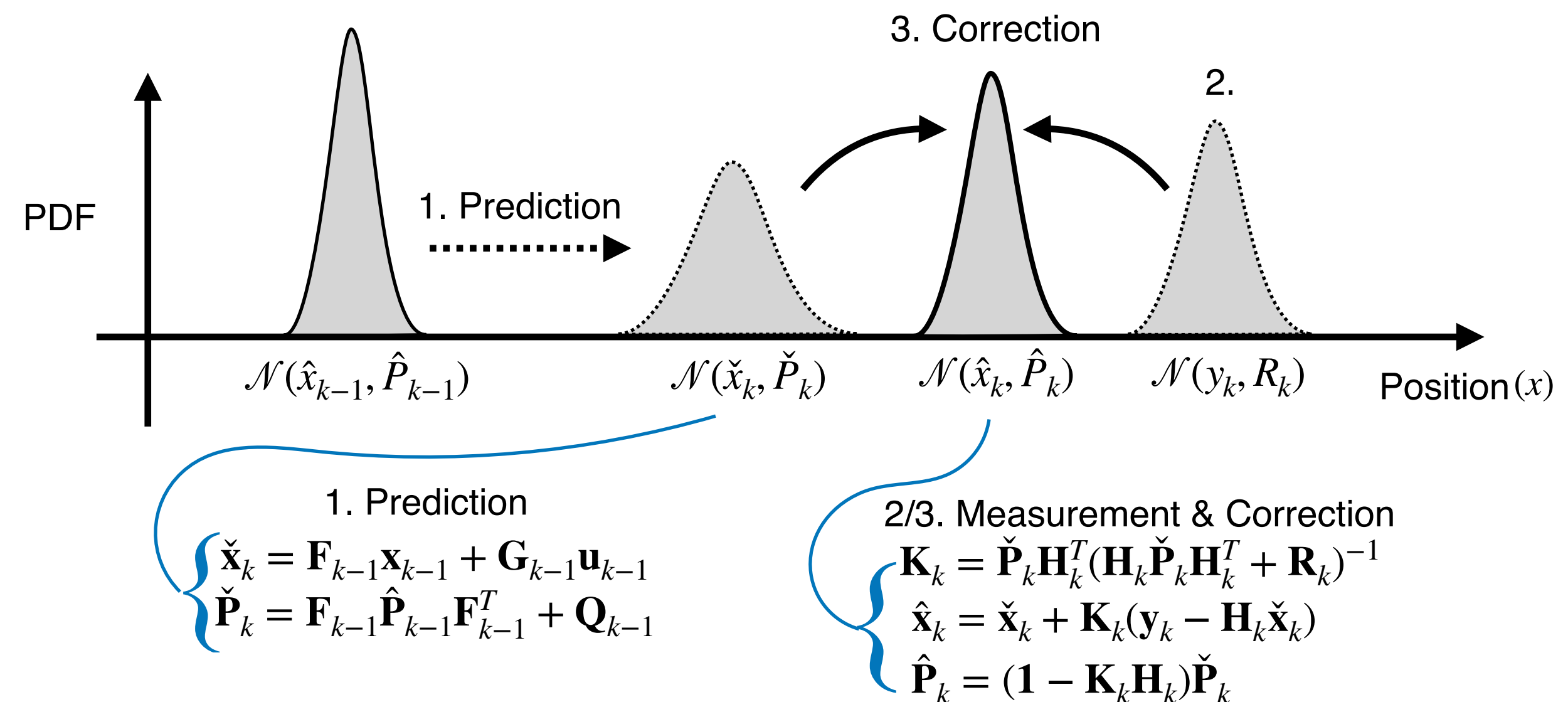
Linear measurement model

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k$$

measurement state measurement noise

$$\mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_k)$$

Linear discrete-time Kalman Filter:

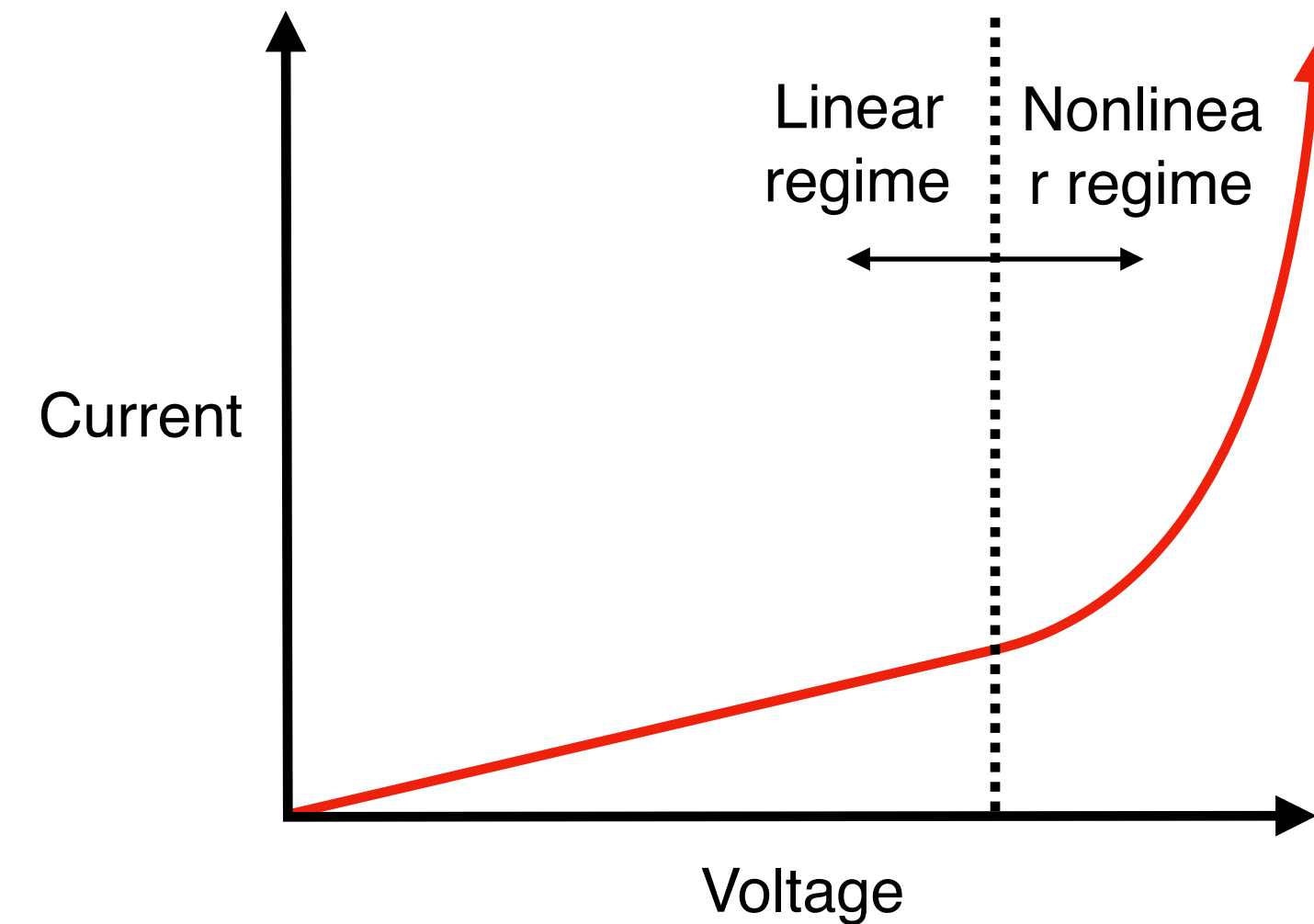


Nonlinear Kalman Filtering

Linear systems do not exist in reality!



Ohm's Law: $I = V/R$



How can we adapt the Kalman Filter to *nonlinear* discrete-time systems?

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{w}_{k-1})$$

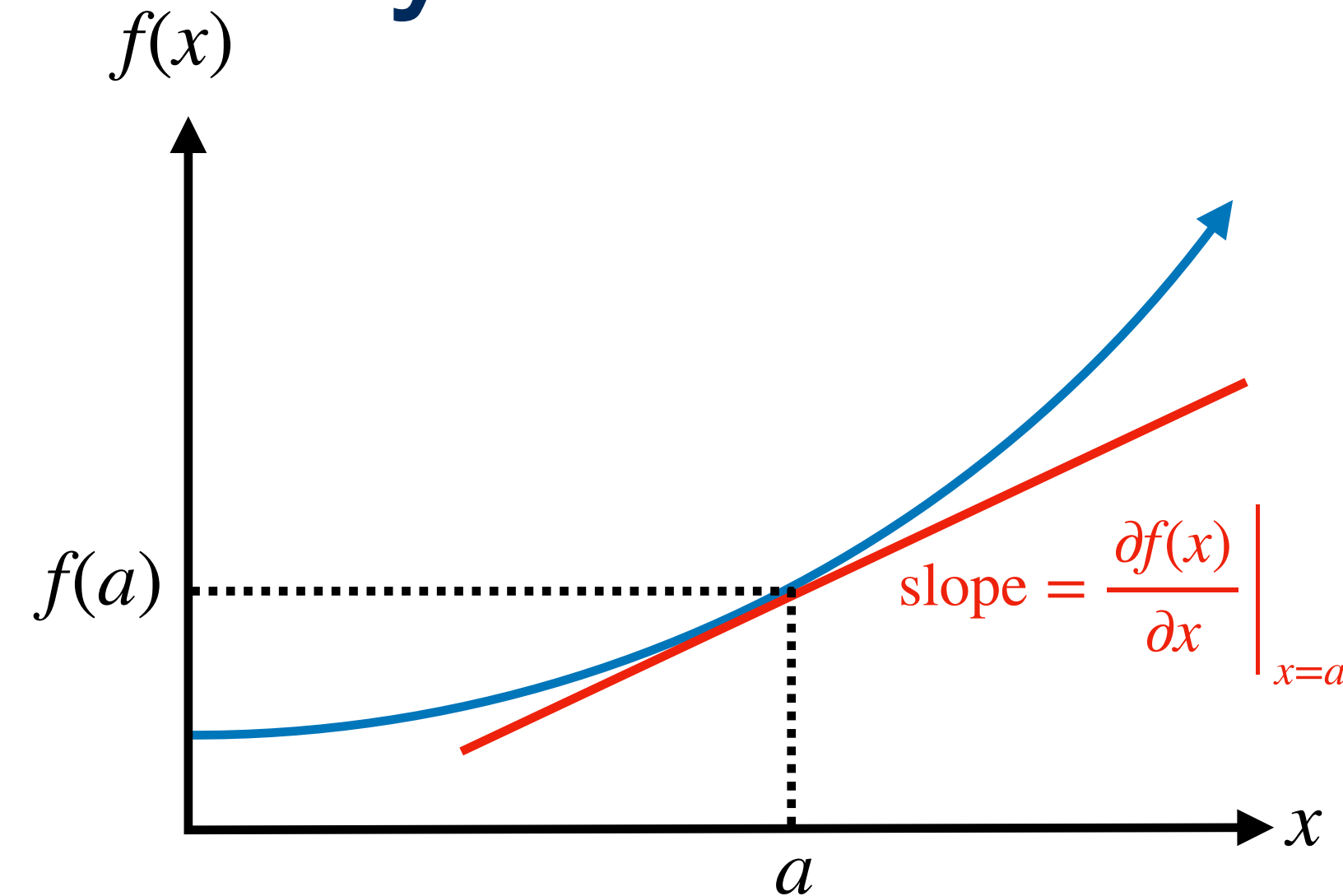
current state previous state inputs process noise

$$\mathbf{y}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{v}_k)$$

measurement state measurement noise

EKF | Linearizing a Nonlinear System

Choose an operating point a and approximate the nonlinear function by a tangent line at that point



Mathematically, we compute this linear approximation using a first-order Taylor expansion:

$$f(x) \approx f(a) + \left. \frac{\partial f(x)}{\partial x} \right|_{x=a} (x - a) + \frac{1}{2!} \left. \frac{\partial^2 f(x)}{\partial x^2} \right|_{x=a} (x - a)^2 + \frac{1}{3!} \left. \frac{\partial^3 f(x)}{\partial x^3} \right|_{x=a} (x - a)^3 + \dots$$

First-order terms

Higher-order terms

EKF | Linearizing a Nonlinear System

For the EKF, we choose the operating point to be our most recent state estimate, our known input, and zero noise:

Linearized motion model

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{w}_{k-1}) \approx \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}) + \underbrace{\left. \frac{\partial \mathbf{f}_{k-1}}{\partial \mathbf{x}_{k-1}} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}}}_{\mathbf{F}_{k-1}} (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \underbrace{\left. \frac{\partial \mathbf{f}_{k-1}}{\partial \mathbf{w}_{k-1}} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}}}_{\mathbf{L}_{k-1}} \mathbf{w}_{k-1}$$

Linearized measurement model

$$\mathbf{y}_k = \mathbf{h}_k(\mathbf{x}_k, \mathbf{v}_k) \approx \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}) + \underbrace{\left. \frac{\partial \mathbf{h}_k}{\partial \mathbf{x}_k} \right|_{\check{\mathbf{x}}_k, \mathbf{0}}}_{\mathbf{H}_k} (\mathbf{x}_k - \check{\mathbf{x}}_k) + \underbrace{\left. \frac{\partial \mathbf{h}_k}{\partial \mathbf{v}_k} \right|_{\check{\mathbf{x}}_k, \mathbf{0}}}_{\mathbf{M}_k} \mathbf{v}_k$$

We now have a linear system in state-space! The matrices \mathbf{F}_{k-1} , \mathbf{L}_{k-1} , \mathbf{H}_k , and \mathbf{M}_k are called the *Jacobian matrices* of the system

EKF | Computing Jacobian Matrices

In vector calculus, a *Jacobian matrix* is the matrix of all first-order partial derivatives of a vector-valued function

$$\frac{\partial \mathbf{f}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial \mathbf{f}}{\partial x_1} & \cdots & \frac{\partial \mathbf{f}}{\partial x_n} \end{bmatrix} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1} & \cdots & \frac{\partial f_m}{\partial x_n} \end{bmatrix}$$

Intuitively, the Jacobian matrix tells you how fast each output of the function is changing along each input dimension

For example:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix} = \begin{bmatrix} x_1 + x_2 \\ x_1^2 \end{bmatrix} \longrightarrow \frac{\partial \mathbf{f}}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 2x_1 & 0 \end{bmatrix}$$

EKF | Putting It All Together

With our linearized models and Jacobians, we can now use the Kalman Filter equations!

Linearized motion model

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}) + \mathbf{F}_{k-1} (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \mathbf{L}_{k-1} \mathbf{w}_{k-1}$$

Linearized measurement model

$$\mathbf{y}_k = \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}) + \mathbf{H}_k (\mathbf{x}_k - \check{\mathbf{x}}_k) + \mathbf{M}_k \mathbf{v}_k$$

Prediction

$$\check{\mathbf{x}}_k = \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0})$$

$$\check{\mathbf{P}}_k = \mathbf{F}_{k-1} \hat{\mathbf{P}}_{k-1} \mathbf{F}_{k-1}^T + \mathbf{L}_{k-1} \mathbf{Q}_{k-1} \mathbf{L}_{k-1}^T$$

Optimal gain

$$\mathbf{K}_k = \check{\mathbf{P}}_k \mathbf{H}_k^T (\mathbf{H}_k \check{\mathbf{P}}_k \mathbf{H}_k^T + \mathbf{M}_k \mathbf{R}_k \mathbf{M}_k^T)^{-1}$$

Correction

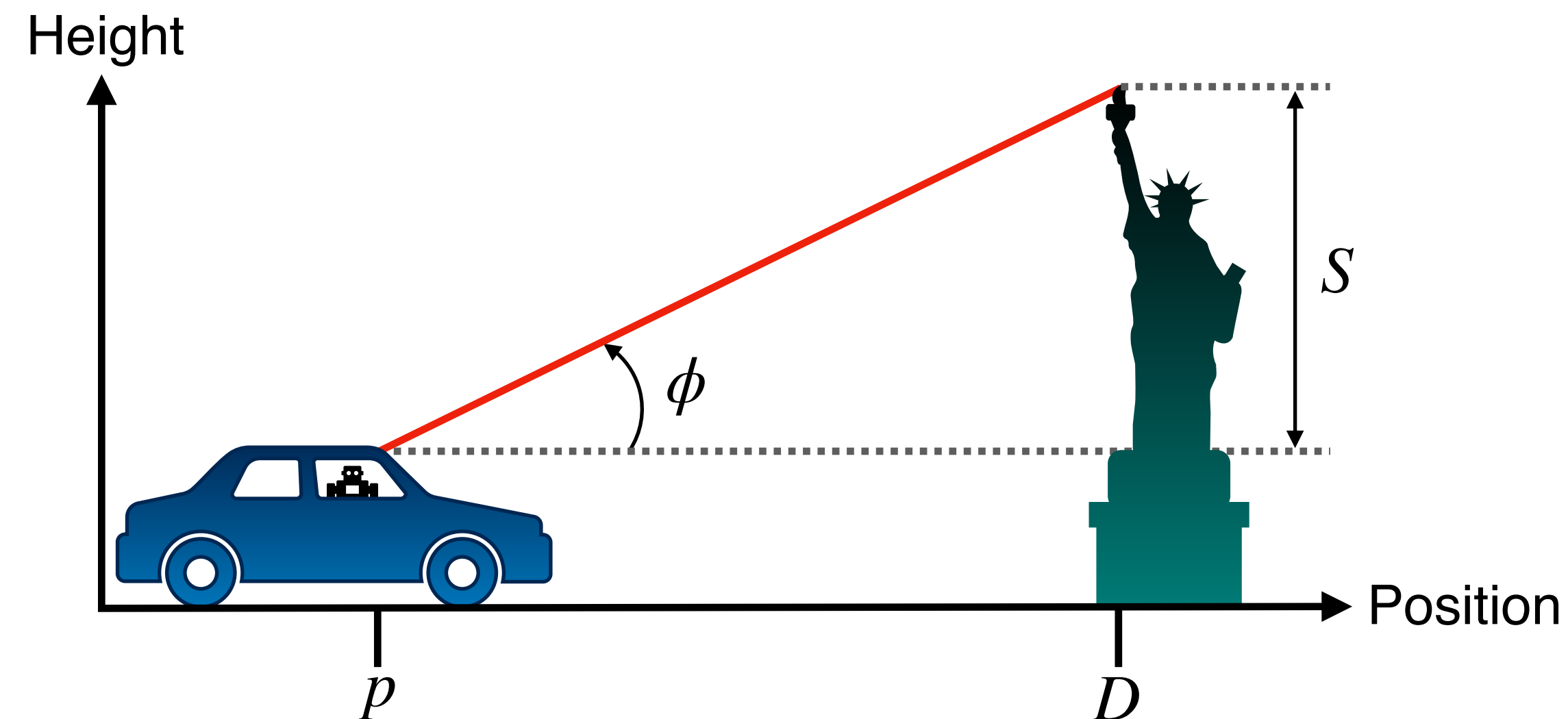
$$\hat{\mathbf{x}}_k = \check{\mathbf{x}}_k + \mathbf{K}_k (\mathbf{y}_k - \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}))$$

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \check{\mathbf{P}}_k$$

$\check{\mathbf{x}}_k$ Prediction
 (given motion model)
 at time k

$\hat{\mathbf{x}}_k$ Corrected prediction
 (given measurement)
 at time k

EKF | Short Example



$$\mathbf{x} = \begin{bmatrix} p \\ \dot{p} \end{bmatrix} \quad \mathbf{u} = \ddot{p}$$

S and D are known in advance

Motion/Process model

$$\begin{aligned} \mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{w}_{k-1}) \\ &= \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} + \begin{bmatrix} 0 \\ \Delta t \end{bmatrix} \mathbf{u}_{k-1} + \mathbf{w}_{k-1} \end{aligned}$$

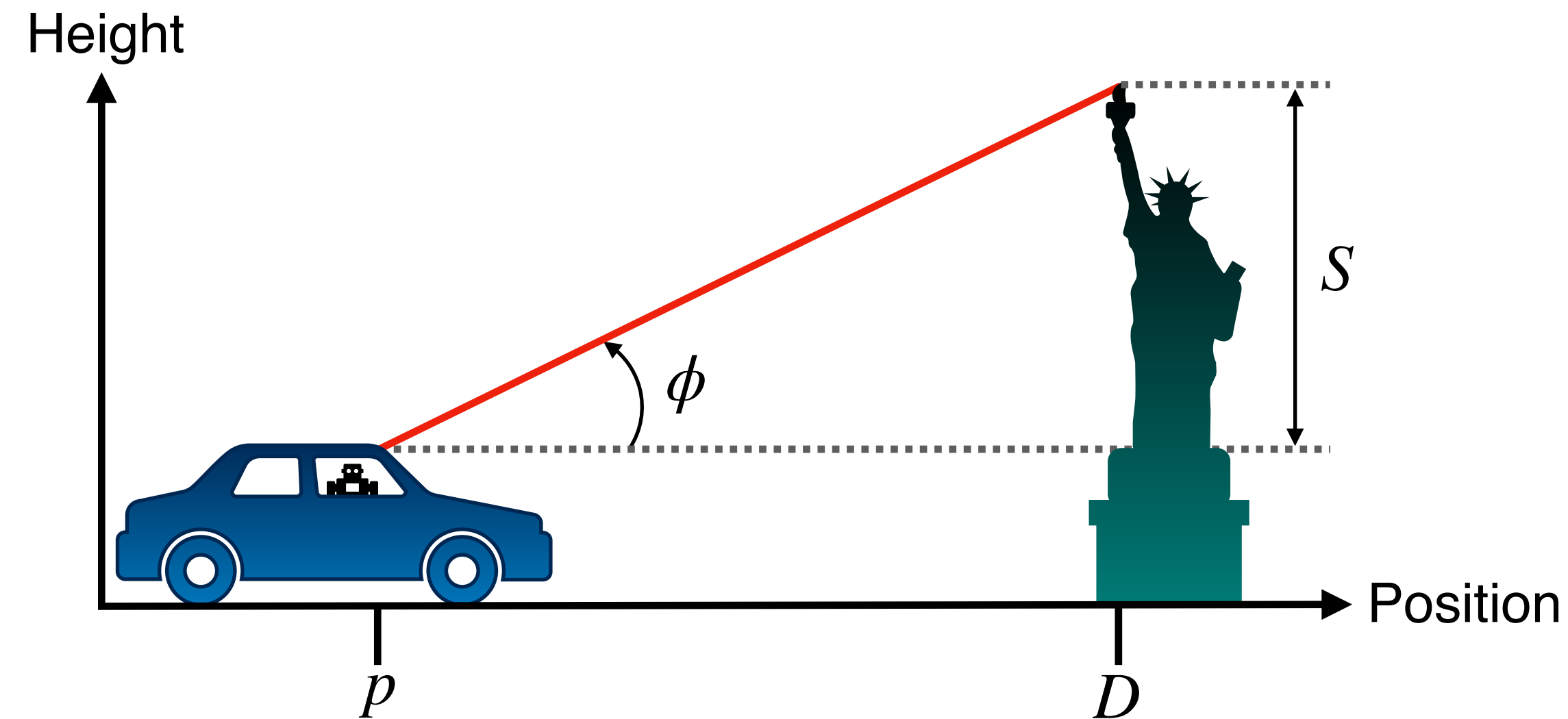
Landmark measurement model

$$\begin{aligned} y_k &= \phi_k = h(p_k, v_k) \\ &= \tan^{-1} \left(\frac{S}{D - p_k} \right) + v_k \end{aligned}$$

Noise densities

$$v_k \sim \mathcal{N}(0, 0.01) \quad \mathbf{w}_k \sim \mathcal{N}(\mathbf{0}, (0.1)\mathbf{1}_{2 \times 2})$$

EKF | Short Example



Motion model Jacobians

$$\mathbf{F}_{k-1} = \left. \frac{\partial \mathbf{f}}{\partial \mathbf{x}_{k-1}} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}$$

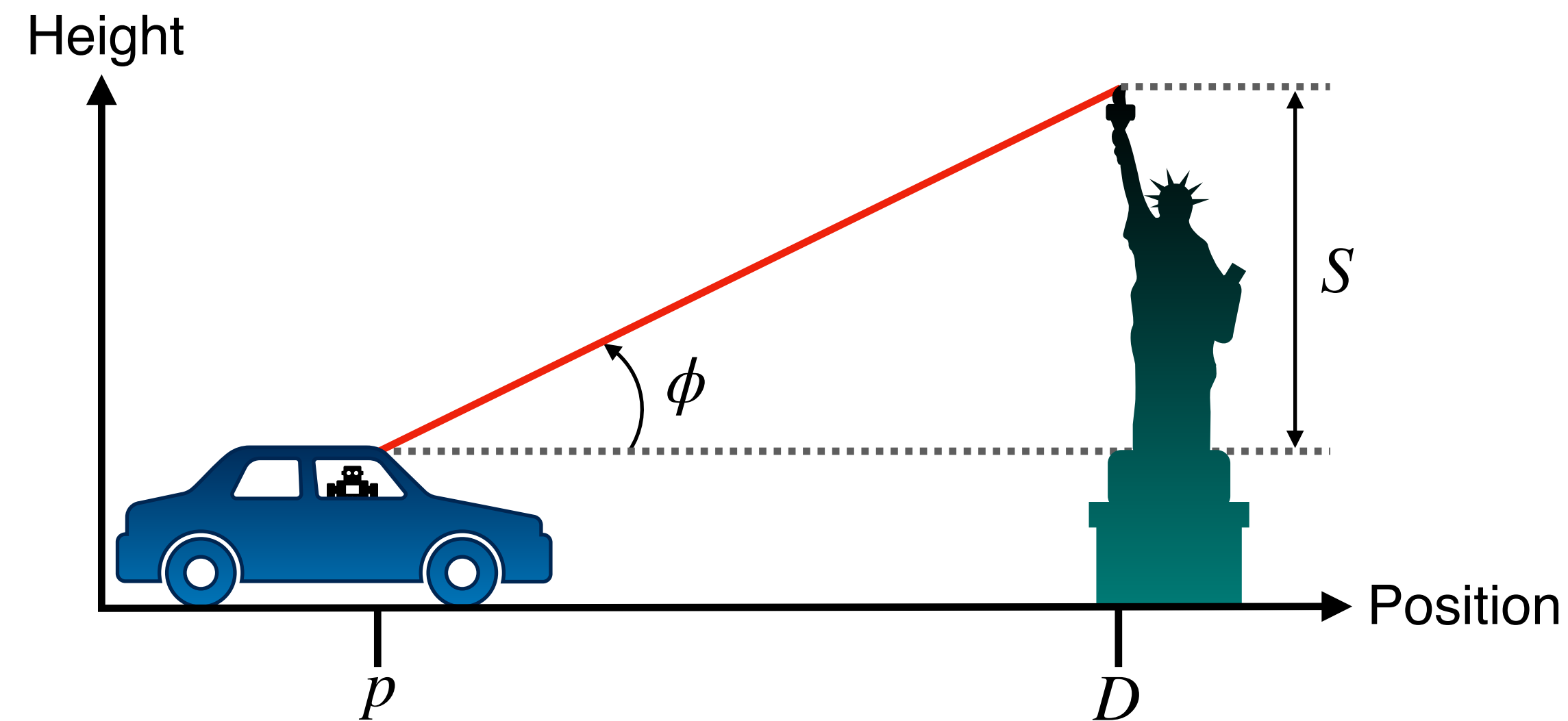
$$\mathbf{L}_{k-1} = \left. \frac{\partial \mathbf{f}}{\partial \mathbf{w}_{k-1}} \right|_{\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}} = \mathbf{1}_{2 \times 2}$$

Measurement model Jacobians

$$\mathbf{H}_k = \left. \frac{\partial h}{\partial \mathbf{x}_k} \right|_{\check{\mathbf{x}}_k, \mathbf{0}} = \begin{bmatrix} \frac{S}{(D - \check{p}_k)^2 + S^2} & 0 \end{bmatrix}$$

$$M_k = \left. \frac{\partial h}{\partial v_k} \right|_{\check{\mathbf{x}}_k, \mathbf{0}} = 1$$

EKF | Short example



Data

$$\hat{\mathbf{x}}_0 \sim \mathcal{N} \left(\begin{bmatrix} 0 \\ 5 \end{bmatrix}, \begin{bmatrix} 0.01 & 0 \\ 0 & 1 \end{bmatrix} \right)$$

$$\Delta t = 0.5\text{s}$$

$$u_0 = -2 \text{ [m/s}^2\text{]} \quad y_1 = 30 \text{ [deg]}$$

$$S = 20 \text{ [m]} \quad D = 40 \text{ [m]}$$

Using the Extended Kalman Filter equations, what is our updated position?

$$\hat{p}_1$$

EKF | Short Example Solution

Prediction

$$\check{\mathbf{x}}_1 = \mathbf{f}_0(\hat{\mathbf{x}}_0, \mathbf{u}_0, \mathbf{0})$$

$$\begin{bmatrix} \check{p}_1 \\ \check{\dot{p}}_1 \end{bmatrix} = \begin{bmatrix} 1 & 0.5 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0.5 \end{bmatrix} (-2) = \begin{bmatrix} 2.5 \\ 4 \end{bmatrix}$$

This is the same
result as in the
linear Kalman Filter
example because
the motion model is
already linear!

$$\check{\mathbf{P}}_1 = \mathbf{F}_0 \hat{\mathbf{P}}_0 \mathbf{F}_0^T + \mathbf{L}_0 \mathbf{Q}_0 \mathbf{L}_0^T$$

$$\check{\mathbf{P}}_1 = \begin{bmatrix} 1 & 0.5 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0.01 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0.5 & 1 \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 0.36 & 0.5 \\ 0.5 & 1.1 \end{bmatrix}$$

EKF | Short example solution

Correction

$$\begin{aligned}\mathbf{K}_1 &= \check{\mathbf{P}}_1 \mathbf{H}_1^T (\mathbf{H}_1 \check{\mathbf{P}}_1 \mathbf{H}_1^T + \mathbf{M}_1 \mathbf{R}_1 \mathbf{M}_1^T)^{-1} \\ &= \begin{bmatrix} 0.36 & 0.5 \\ 0.5 & 1.1 \end{bmatrix} \begin{bmatrix} 0.011 \\ 0 \end{bmatrix} \left([0.011 \quad 0] \begin{bmatrix} 0.36 & 0.5 \\ 0.5 & 1.1 \end{bmatrix} \begin{bmatrix} 0.011 \\ 0 \end{bmatrix} + 1(0.01)(1) \right)^{-1} \\ &= \begin{bmatrix} 0.39 \\ 0.55 \end{bmatrix}\end{aligned}$$

$$\hat{\mathbf{x}}_1 = \check{\mathbf{x}}_1 + \mathbf{K}_1(\mathbf{y}_1 - \mathbf{h}_1(\check{\mathbf{x}}_1, \mathbf{0}))$$

$$\begin{bmatrix} \hat{p}_1 \\ \hat{\dot{p}}_1 \end{bmatrix} = \begin{bmatrix} 2.5 \\ 4 \end{bmatrix} + \begin{bmatrix} 0.39 \\ 0.55 \end{bmatrix} (30 - 28.1) = \begin{bmatrix} 3.24 \\ 5.05 \end{bmatrix}$$

Bonus!

$$\begin{aligned}\hat{\mathbf{P}}_1 &= (\mathbf{I} - \mathbf{K}_1 \mathbf{H}_1) \check{\mathbf{P}}_1 \\ &= \begin{bmatrix} 0.36 & 0.50 \\ 0.50 & 1.1 \end{bmatrix}\end{aligned}$$

Summary | Extended Kalman Filter (EKF)

- The EKF uses *linearization* to adapt the Kalman filter to nonlinear systems
- Linearization works by computing a local linear approximation to a nonlinear function about a chosen operating point
- Linearization relies on computing *Jacobian matrices*, which contain all the first-order partial derivatives of a function