

# Probabilistic Models

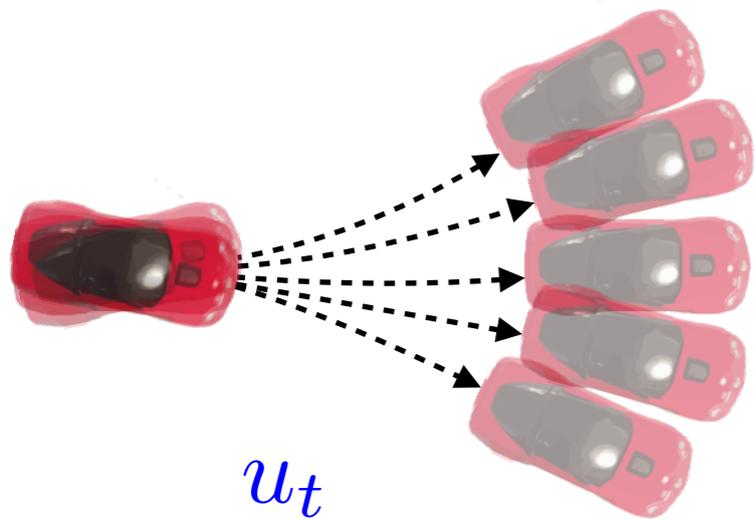
Sanjiban Choudhury

TAs: Matthew Rockett, Gilwoo Lee, Matt Schmittle

# Probabilistic models in localization

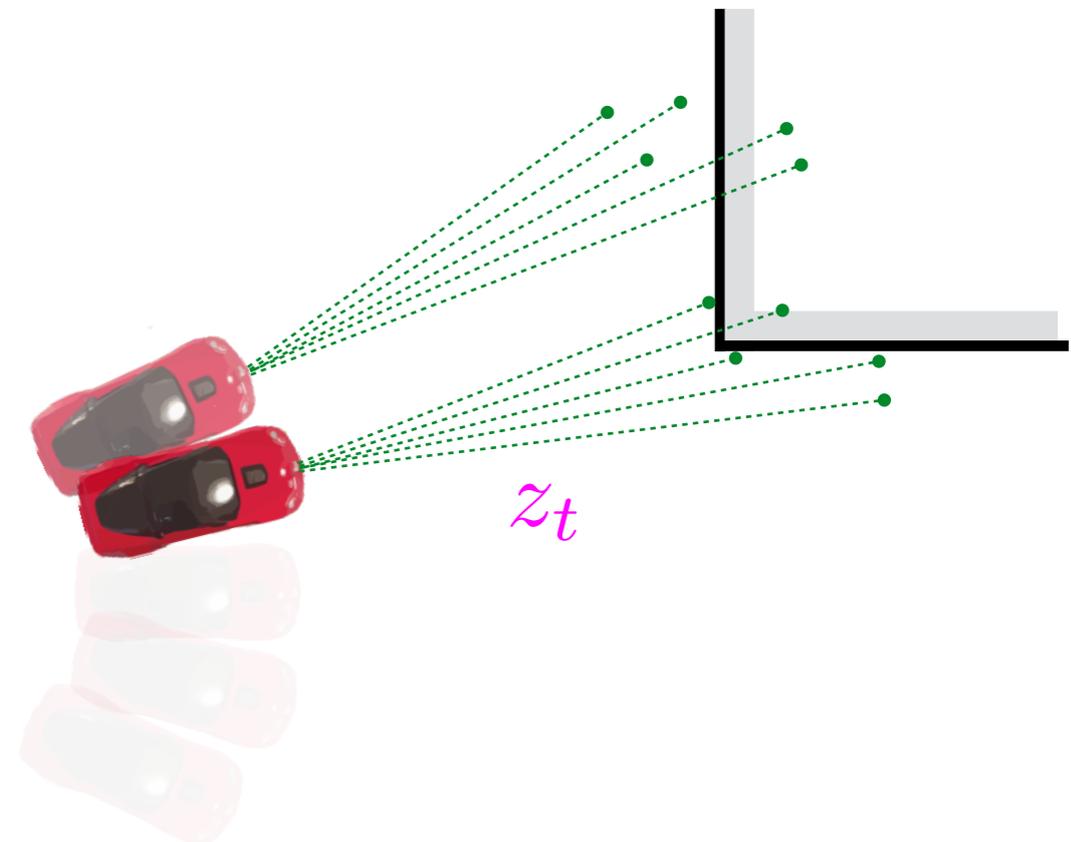
Motion model

$$P(x_t | u_t, x_{t-1})$$

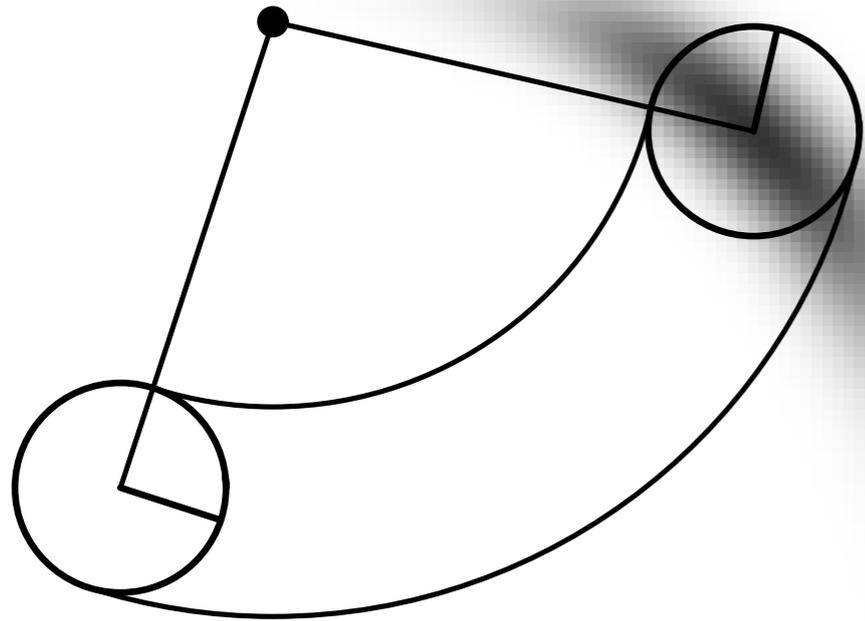


Measurement model

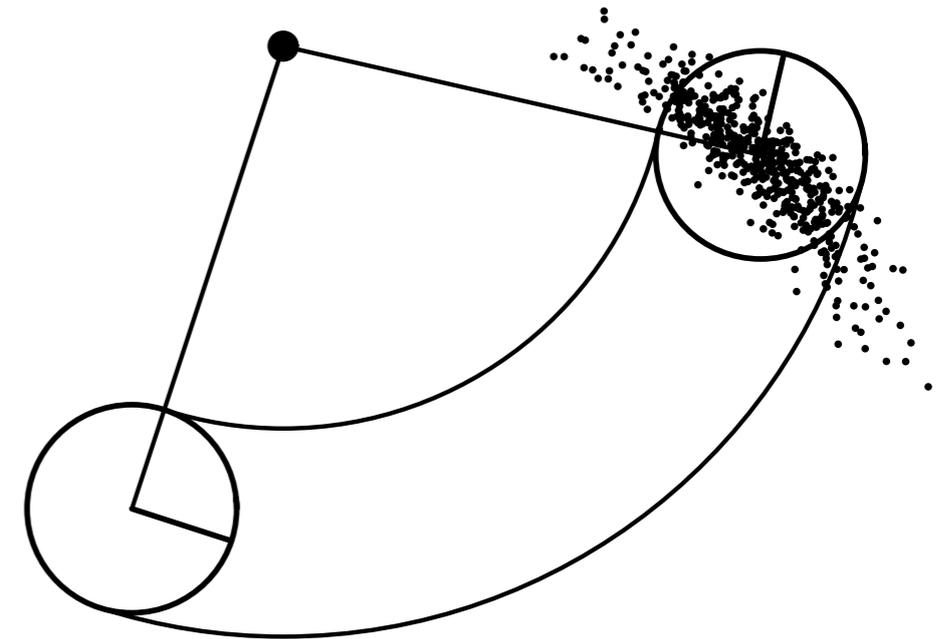
$$P(z_t | x_t)$$



# Example of a motion model



Probability density  
function



Samples from the  
pdf

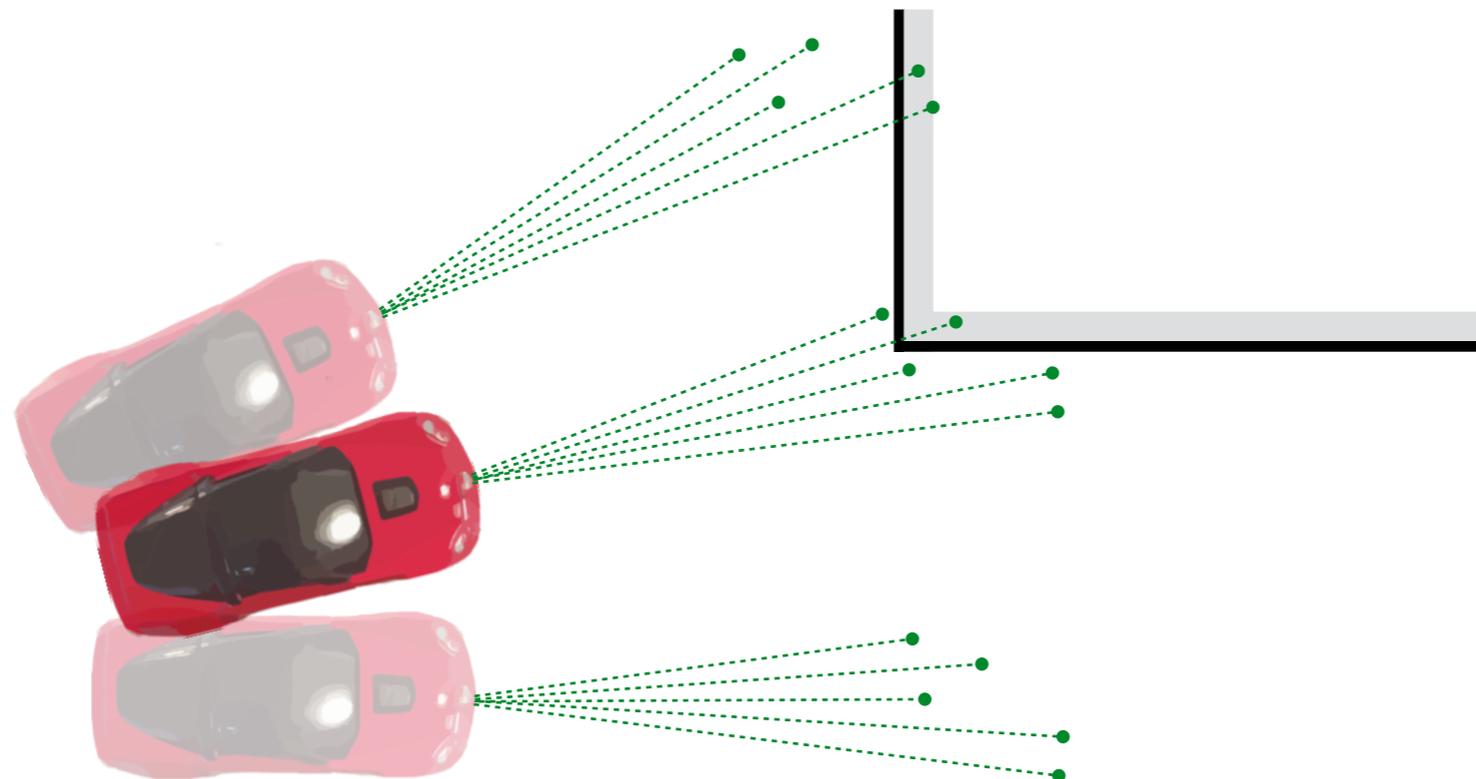
# Measurement Model

$$P(z_t | x_t, m)$$

sensor  
reading

state

map



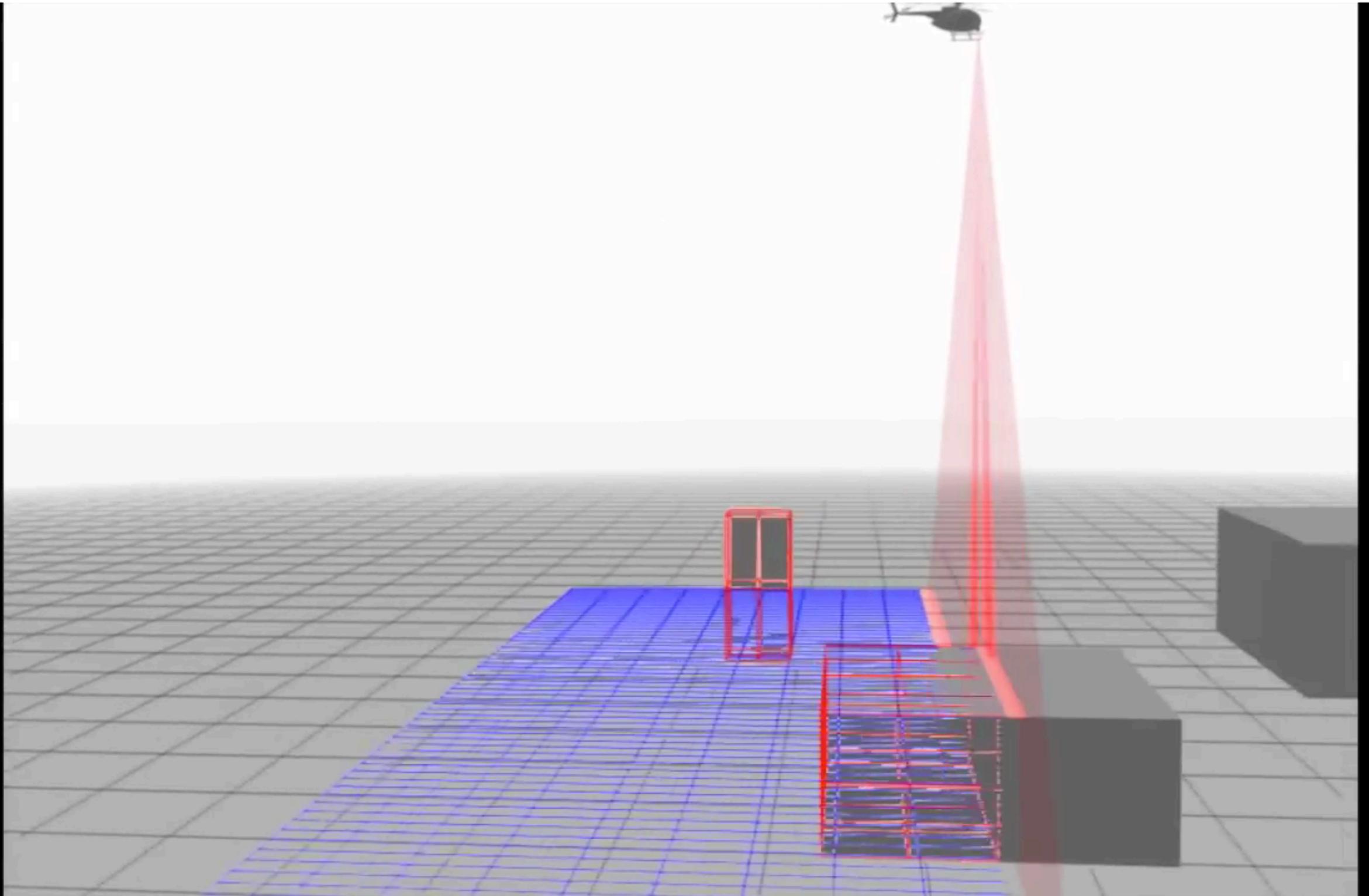
# How does a LiDAR work?



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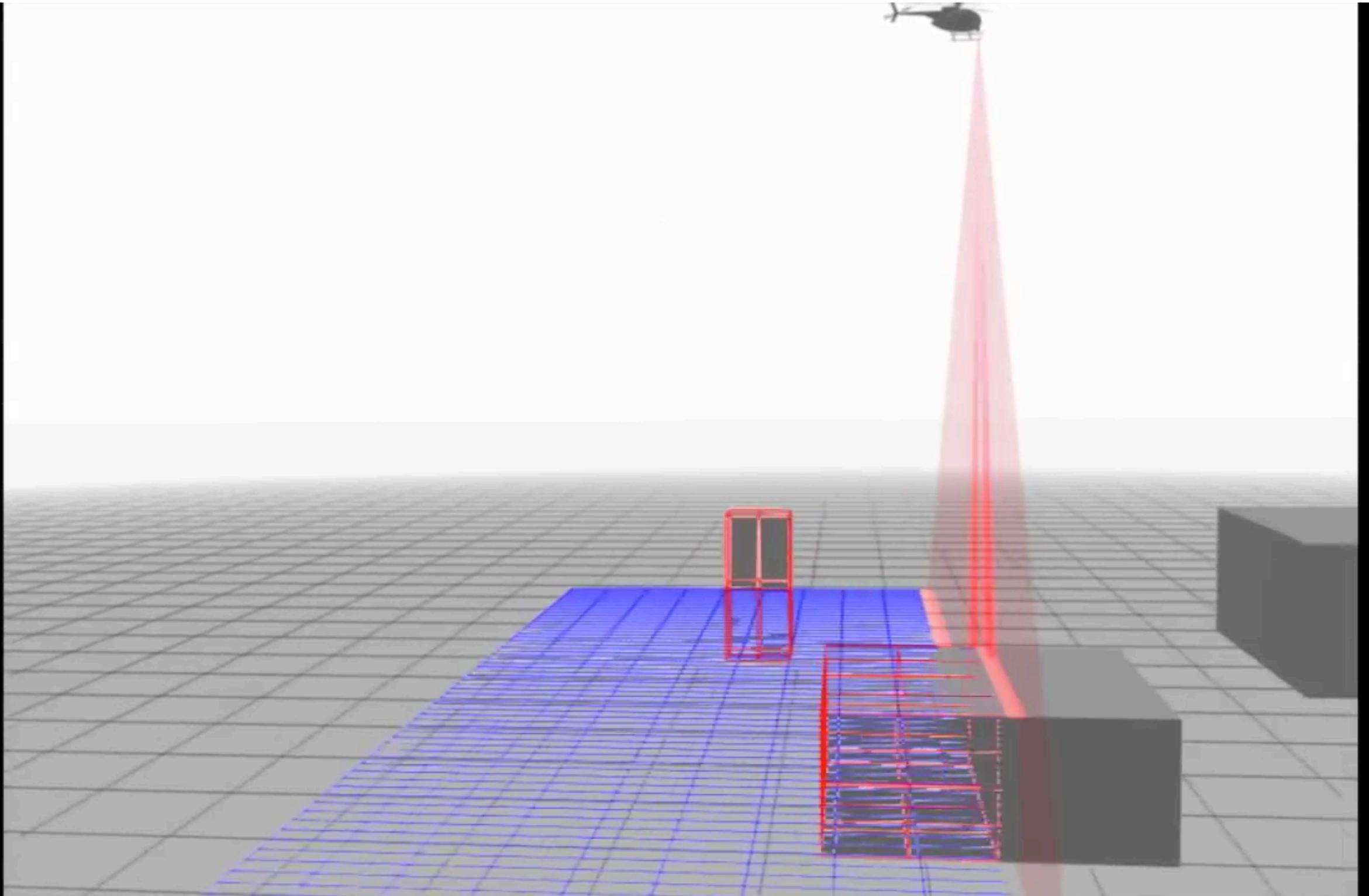


# Working with lasers in the real world



(courtesy Lyle Chamberlain)

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# Three questions you should ask

1. Why is the model probabilistic?

2. What defines a good model?

3. What model should I use for my robot?

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Several sources of stochasticity

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**Category**

**Example**

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Category	Example
Incomplete / Incorrect map	Pedestrians, objects moving around

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Unmodelled physics

Lasers goes through glass

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**Category**

**Example**

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Pedestrians, objects moving  
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Lasers goes through glass

Sensing assumptions

Multiple laser returns

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**Problem: Overconfidence** in measurement can be catastrophic

**Solution:** Anticipate **specific types** of failures and add stochasticity accordingly.

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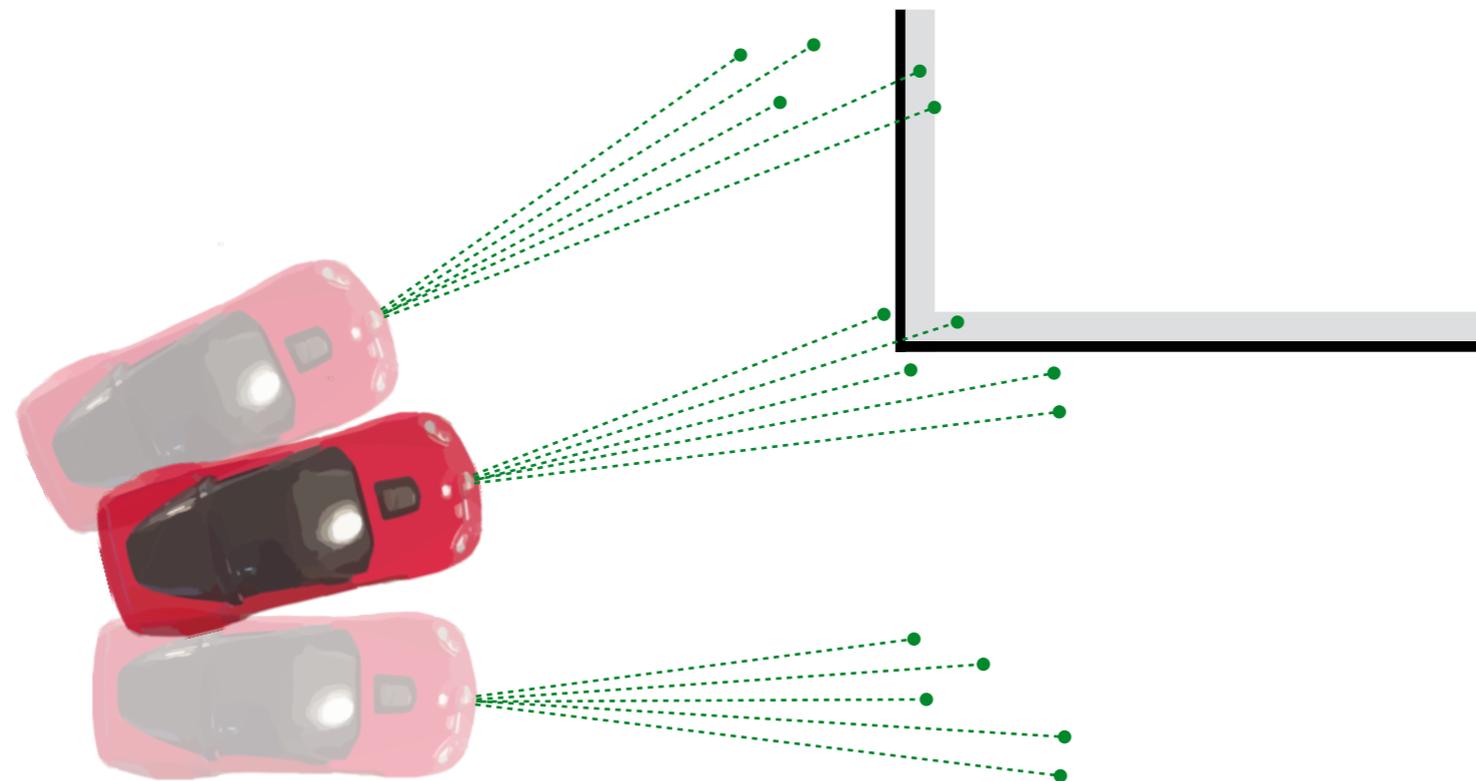
# Measurement model for LiDAR

$$P(z_t | x_t, m)$$

laser  
scan

state

map



# Measurement model for LiDAR

Assume individual beams are **conditionally independent** given map





# Measurement model for **single beam**

$$P(z_t^k | x_t, m)$$

distance    state    map  
value



# Measurement model for **single beam**

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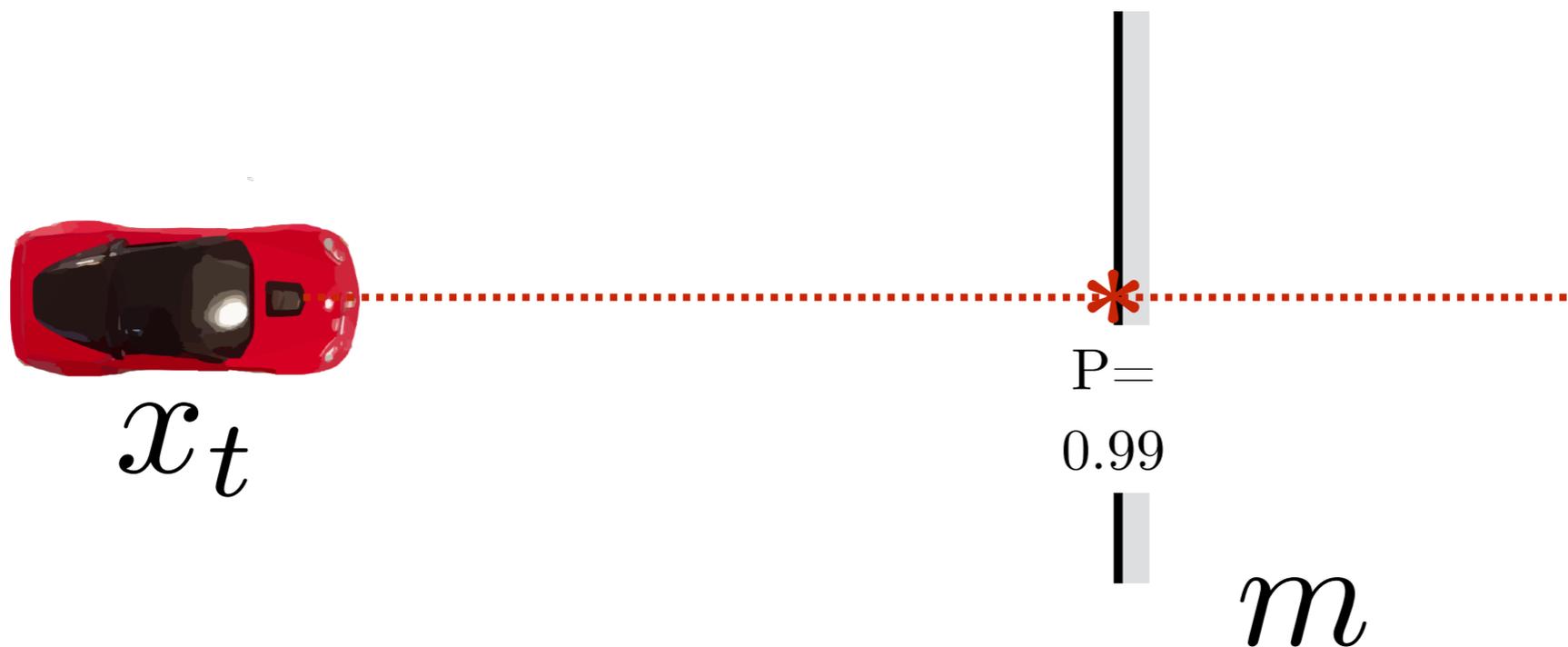
distance value    state    map



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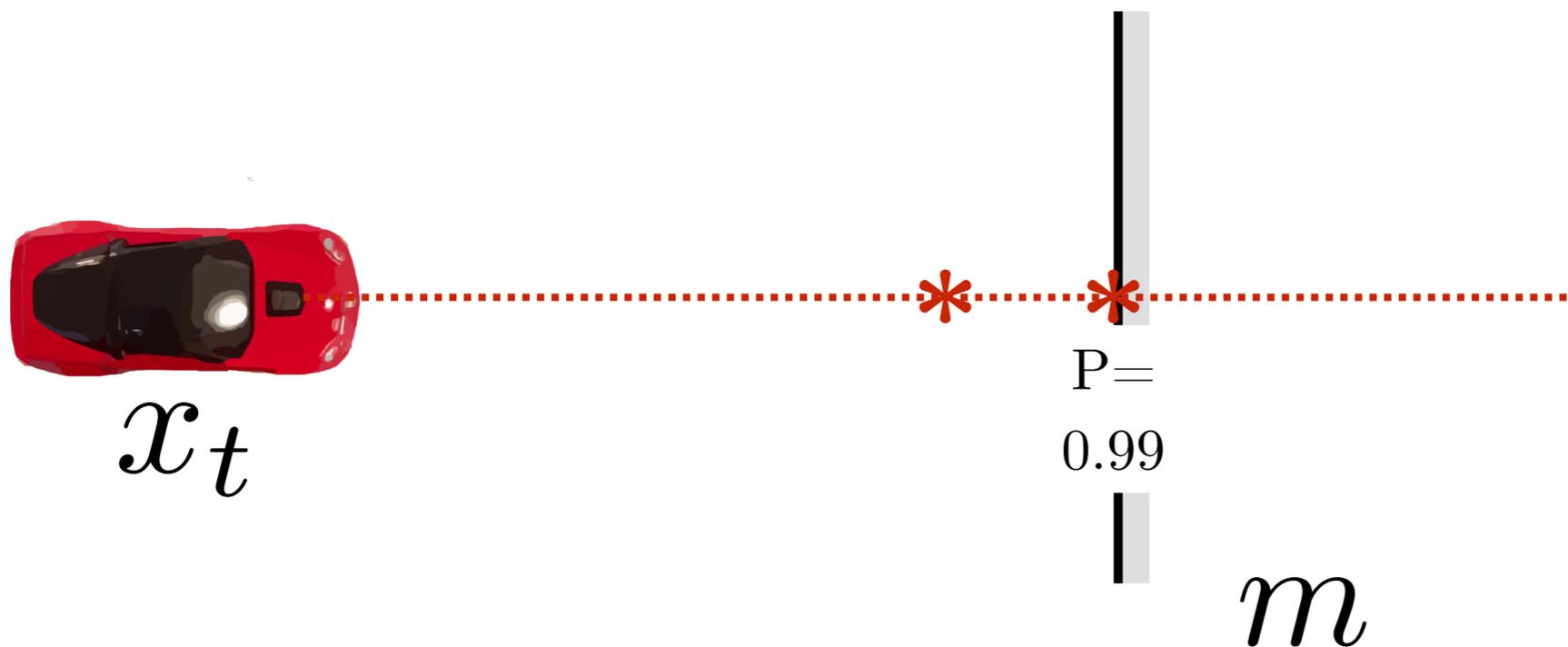
distance state map  
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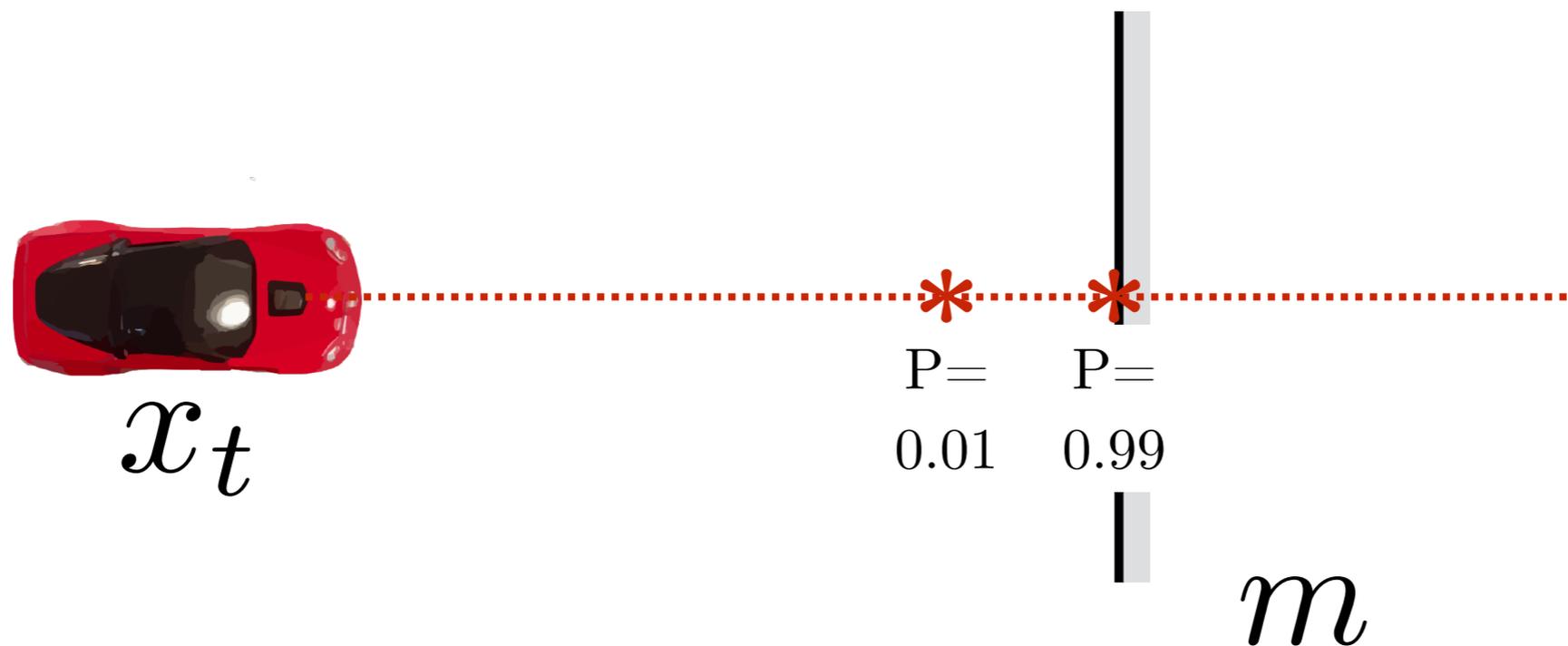
distance state map  
value



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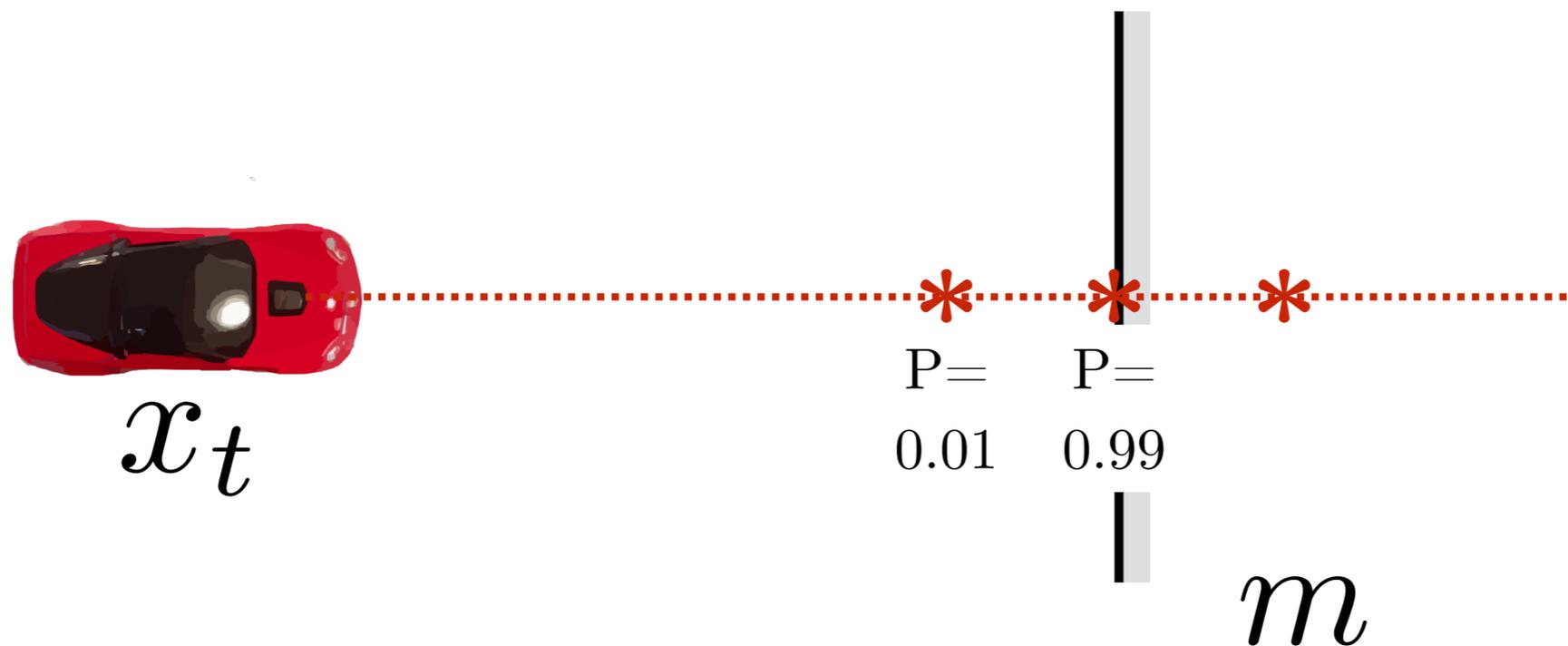
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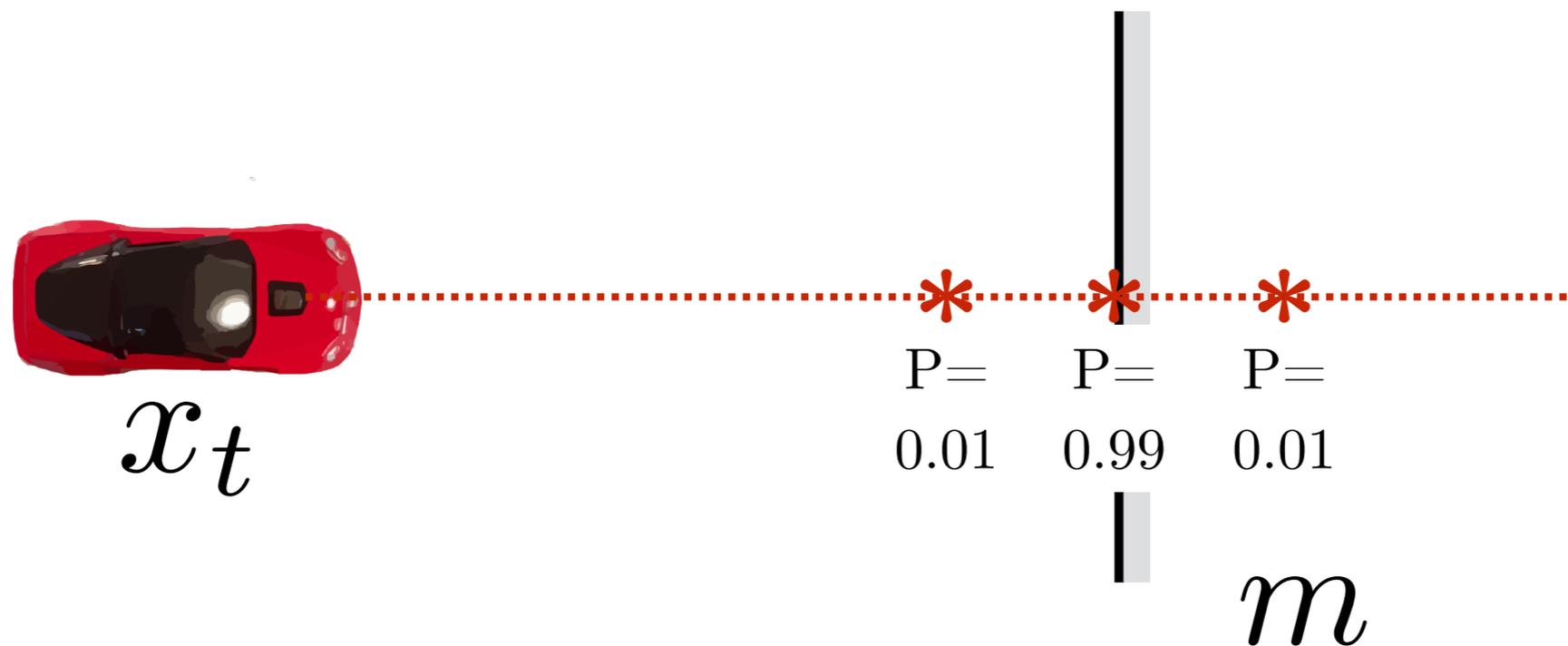
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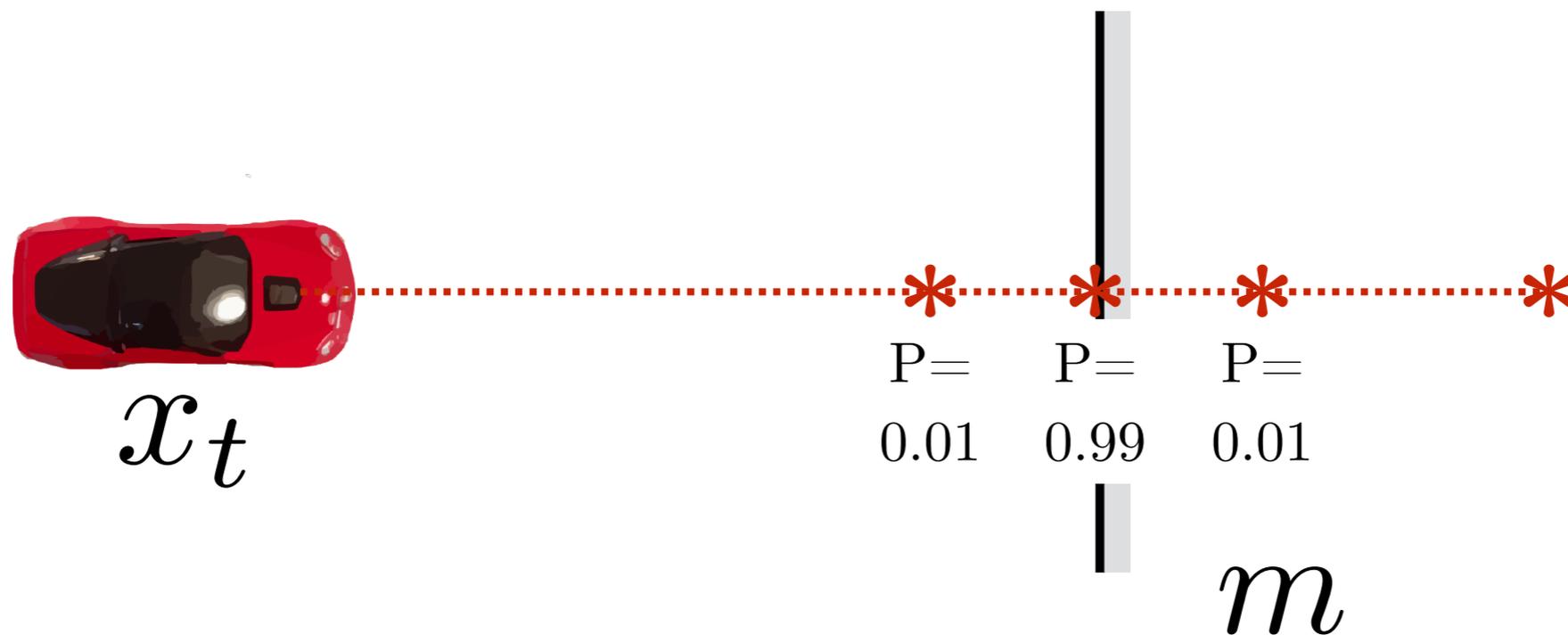
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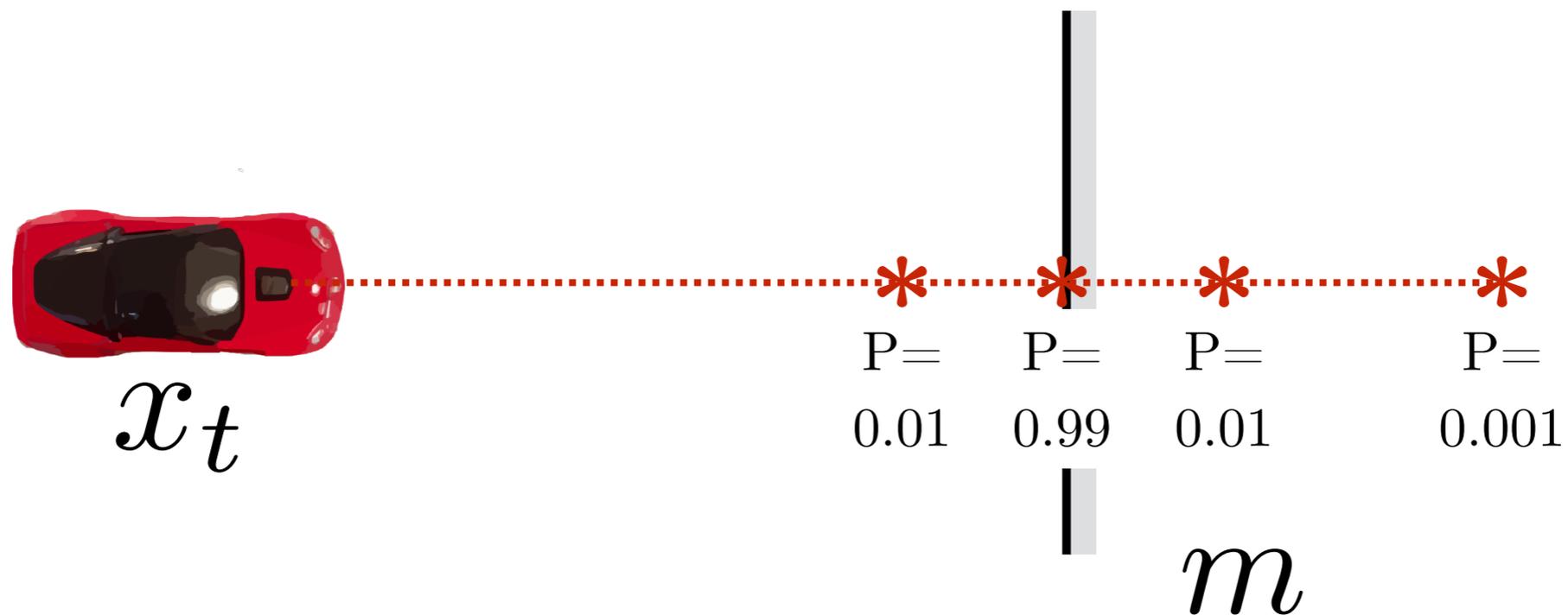
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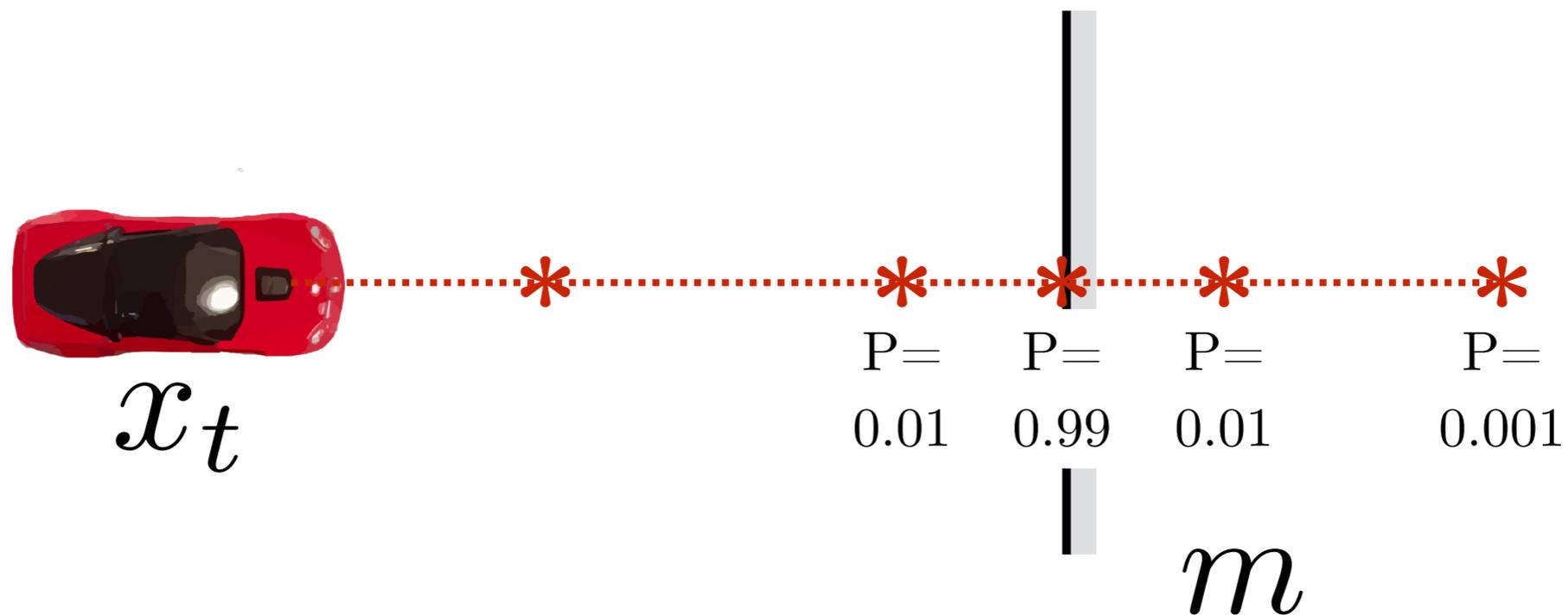
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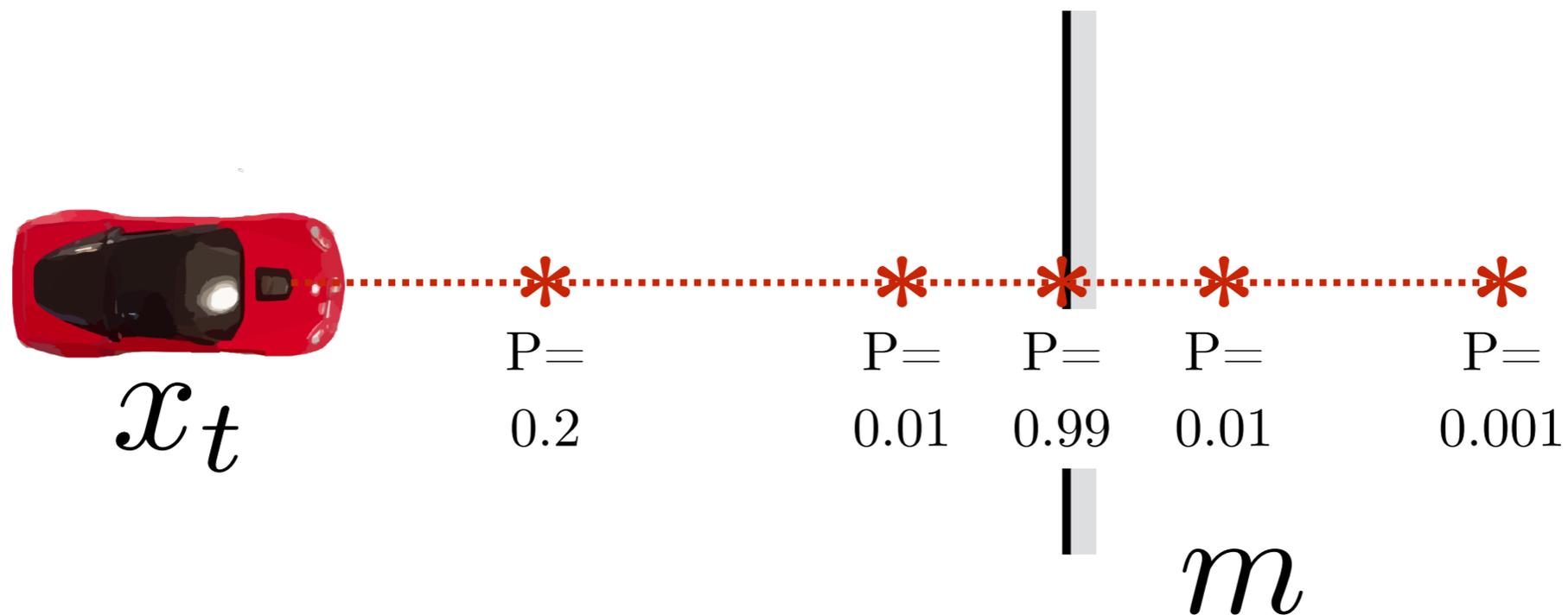
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# Pseudo-algorithm for sensor model

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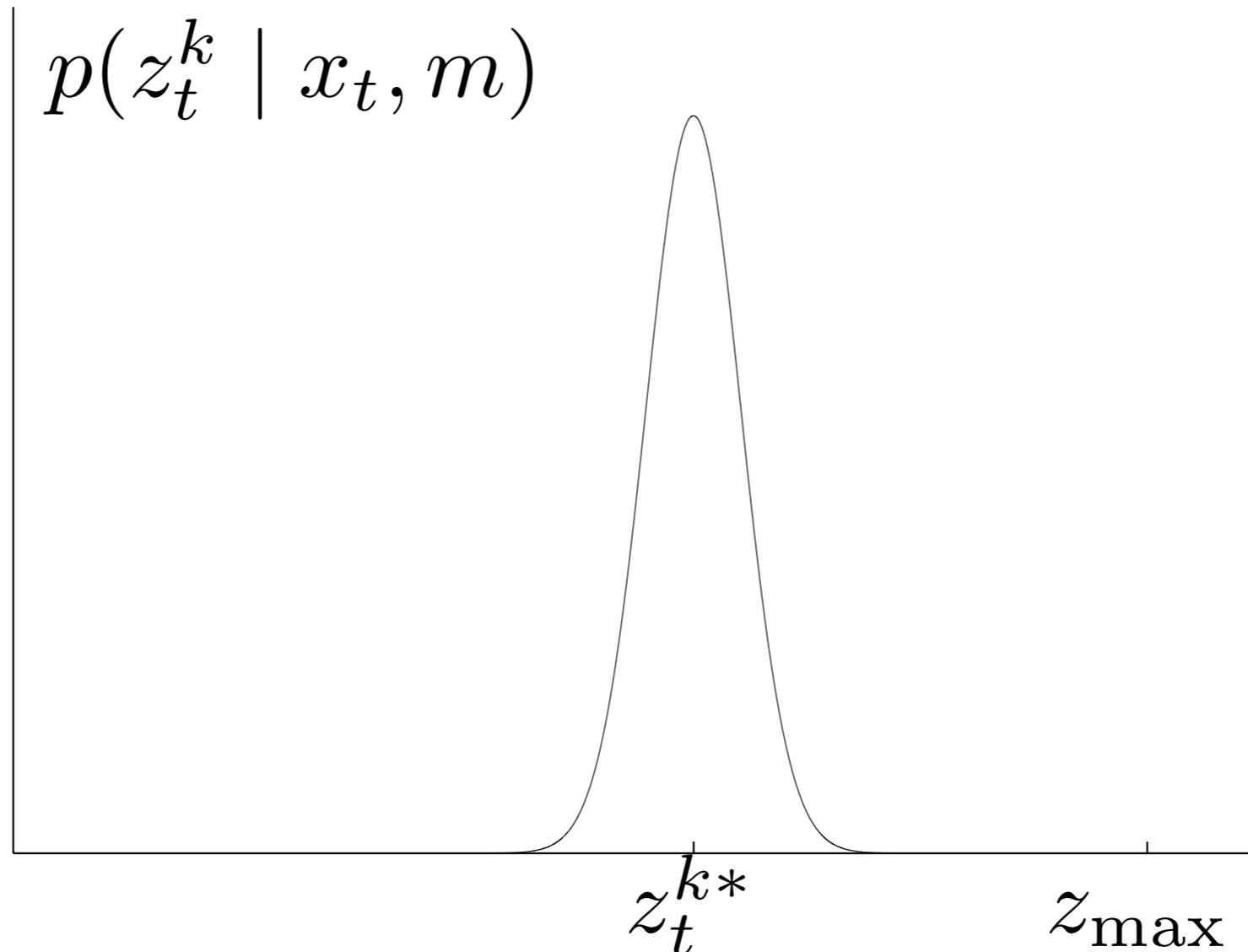
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5. Multiply all probabilities to get  $p$

# What kind of **stochasticity** should we consider?

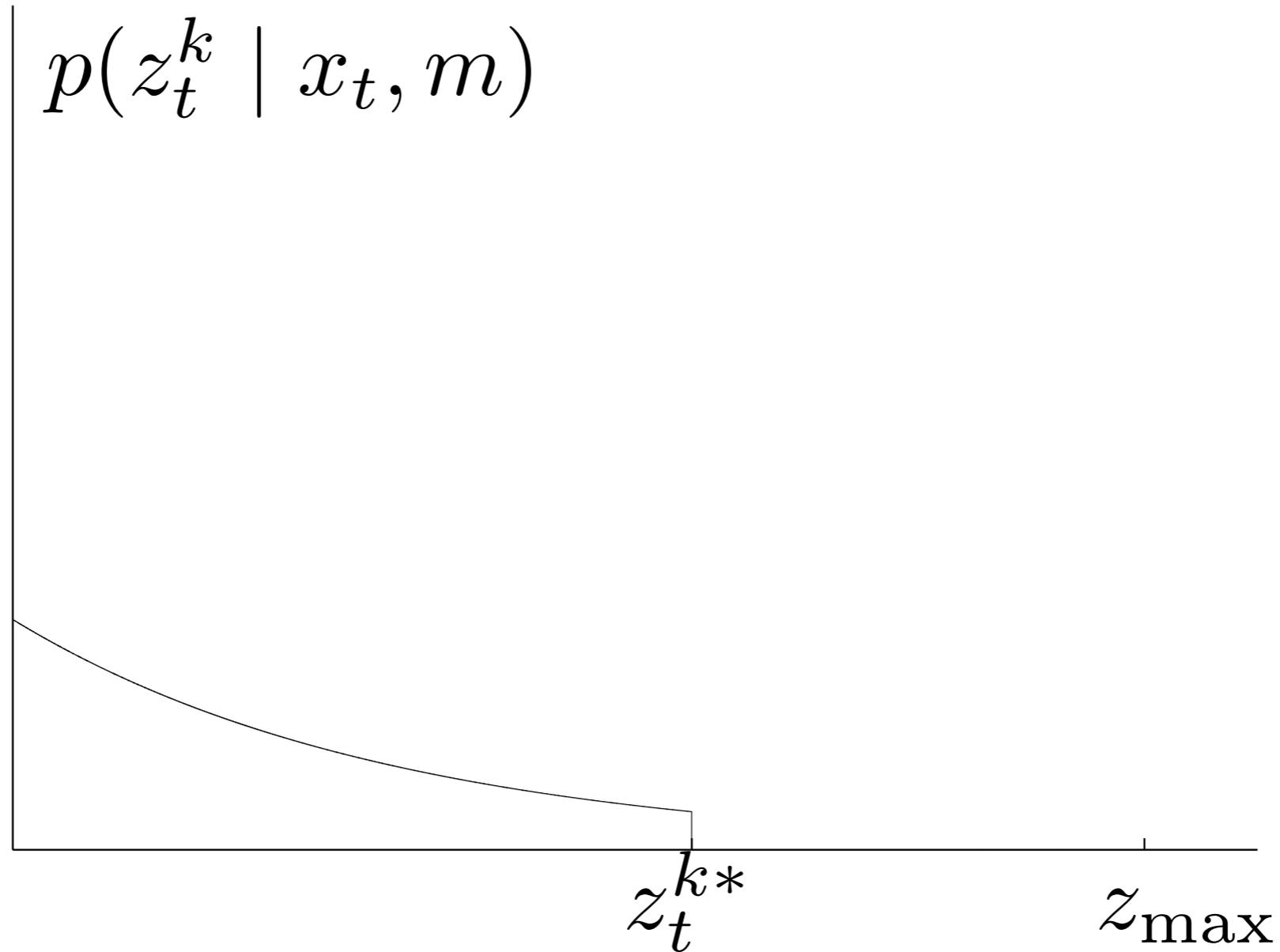
1. Simple measurement noise in distance value
2. Presence of unexpected objects
3. Laser returns max range when no objects
4. Failures in sensing

# Factor 1: Simple measurement noise



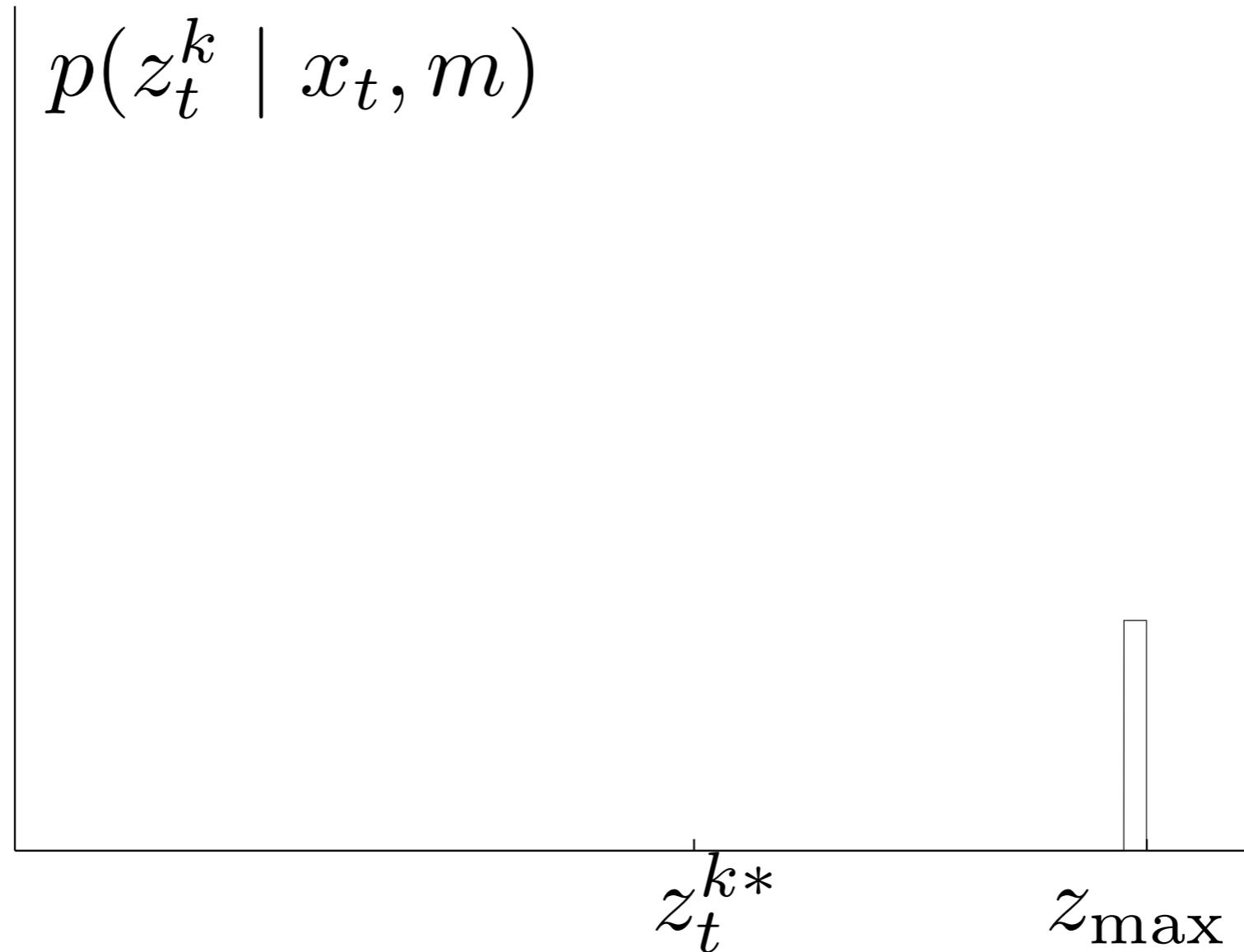
$$p_{\text{hit}}(z_t^k | x_t, m) = \begin{cases} \eta \mathcal{N}(z_t^k; z_t^{k*}, \sigma_{\text{hit}}^2) & \text{if } 0 \leq z_t^k \leq z_{\max} \\ 0 & \text{otherwise} \end{cases}$$

# Factor 2: Unexpected objects



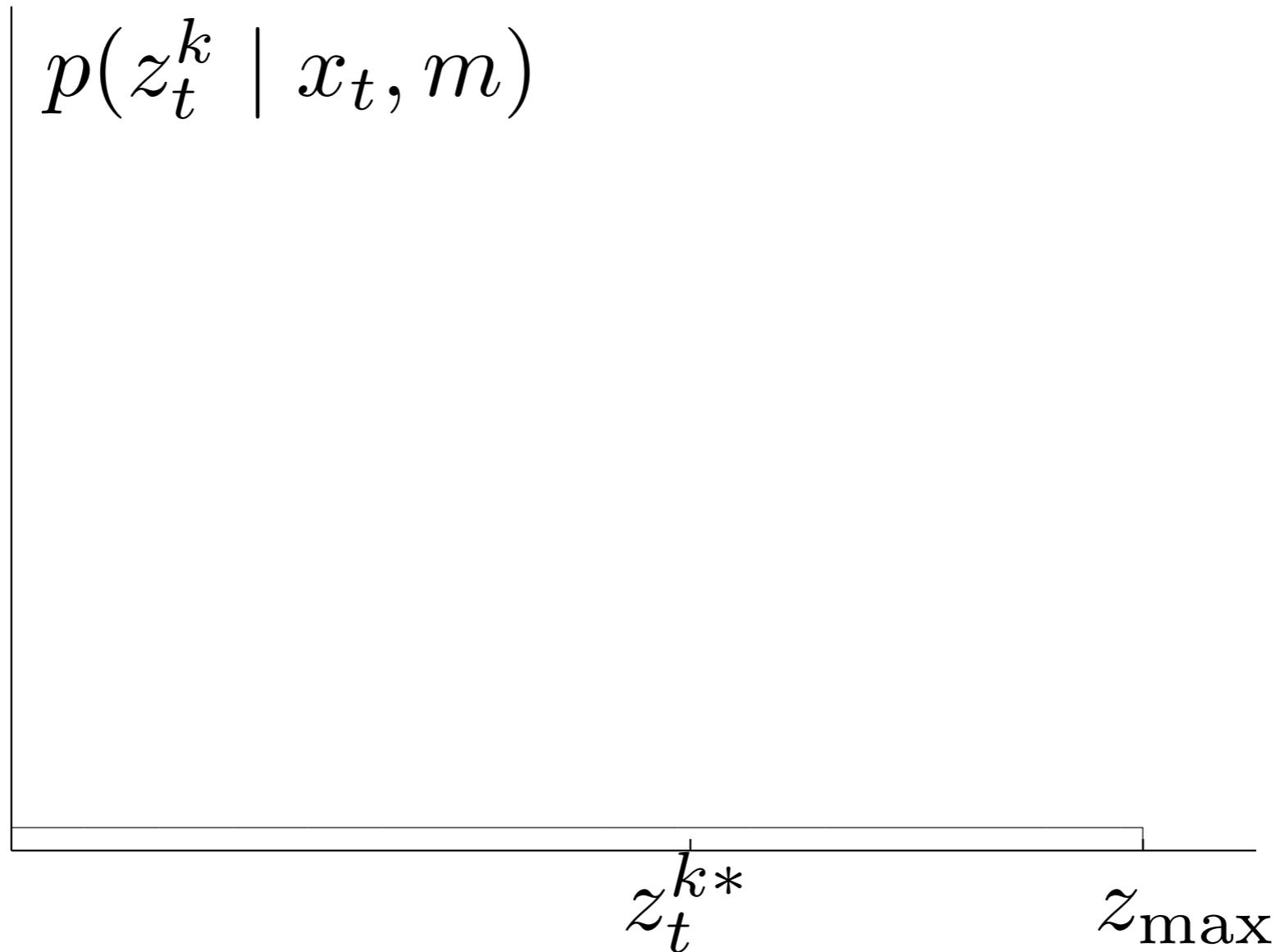
$$p_{\text{short}}(z_t^k | x_t, m) = \begin{cases} \eta \lambda_{\text{short}} e^{-\lambda_{\text{short}} z_t^k} & \text{if } 0 \leq z_t^k \leq z_t^{k*} \\ 0 & \text{otherwise} \end{cases}$$

# Factor 3: Maximum range



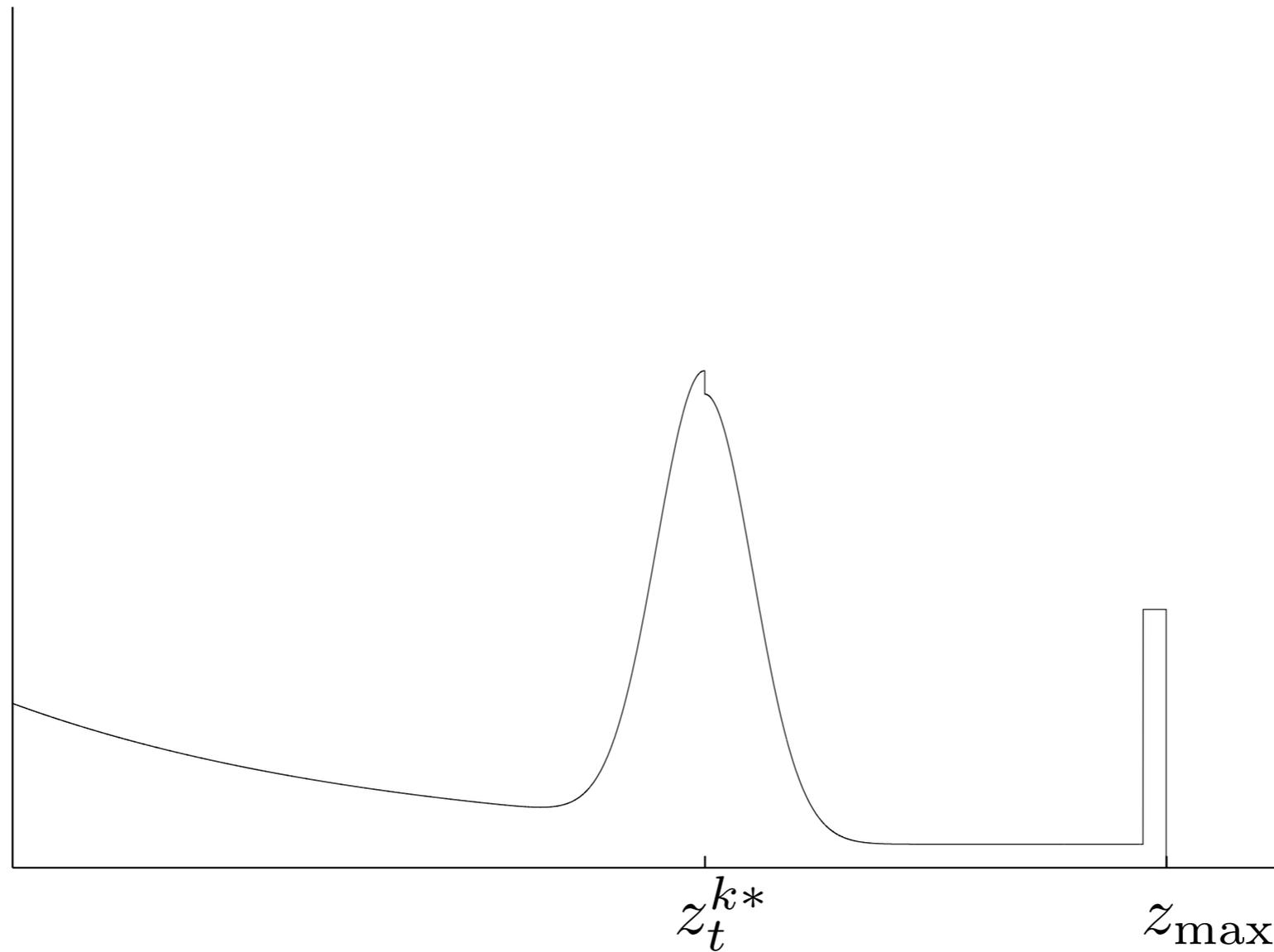
$$p_{\max}(z_t^k | x_t, m) = I(z = z_{\max}) = \begin{cases} 1 & \text{if } z = z_{\max} \\ 0 & \text{otherwise} \end{cases}$$

# Factor 4: Failures in sensing



$$p_{\text{rand}}(z_t^k | x_t, m) = \begin{cases} \frac{1}{z_{\max}} & \text{if } 0 \leq z_t^k < z_{\max} \\ 0 & \text{otherwise} \end{cases}$$

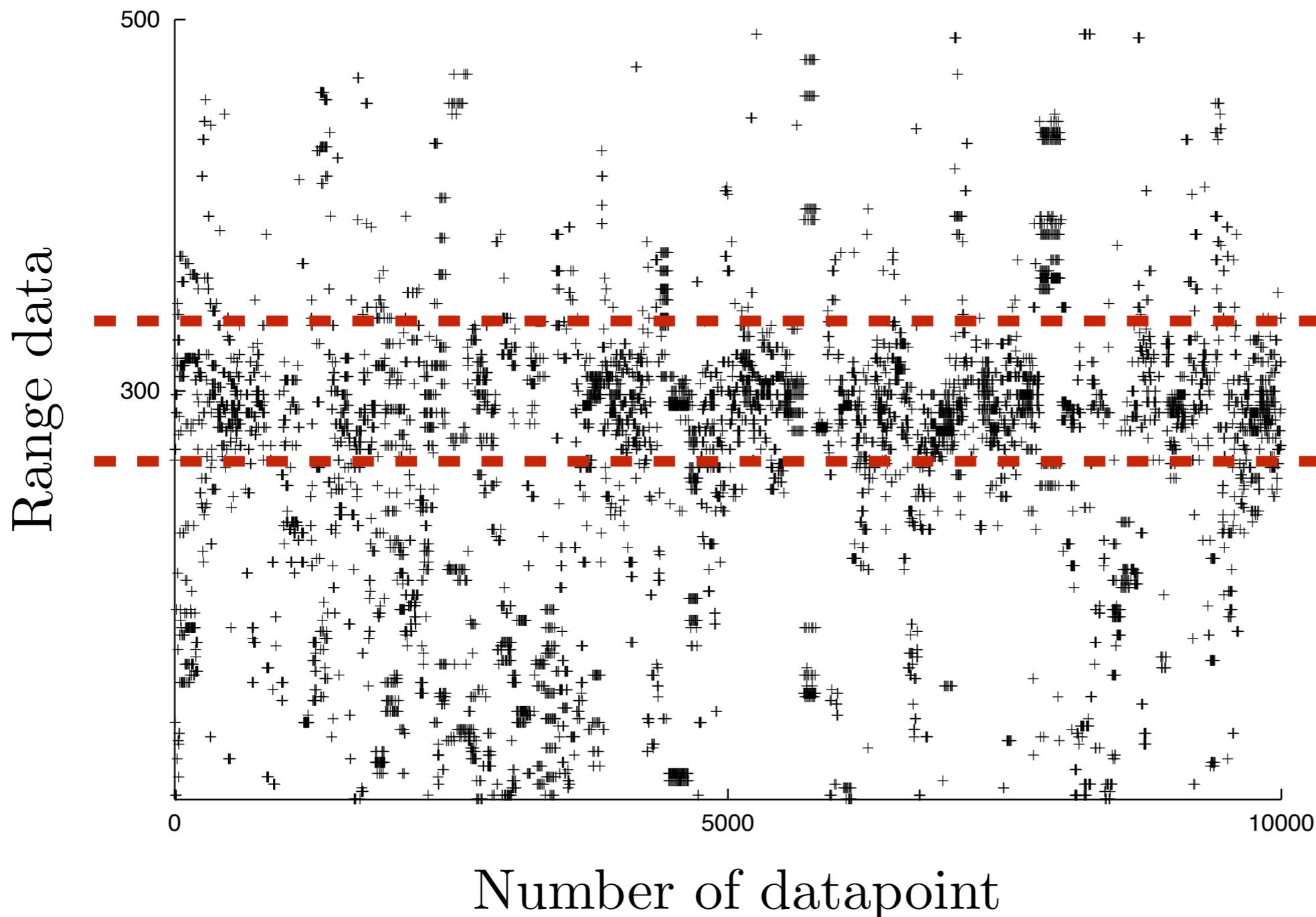
# Combined probabilistic model



$$p(z_t^k | x_t, m) = \begin{pmatrix} z_{\text{hit}} \\ z_{\text{short}} \\ z_{\text{max}} \\ z_{\text{rand}} \end{pmatrix}^T \cdot \begin{pmatrix} p_{\text{hit}}(z_t^k | x_t, m) \\ p_{\text{short}}(z_t^k | x_t, m) \\ p_{\text{max}}(z_t^k | x_t, m) \\ p_{\text{rand}}(z_t^k | x_t, m) \end{pmatrix}$$

# Question: How do we tune parameters?

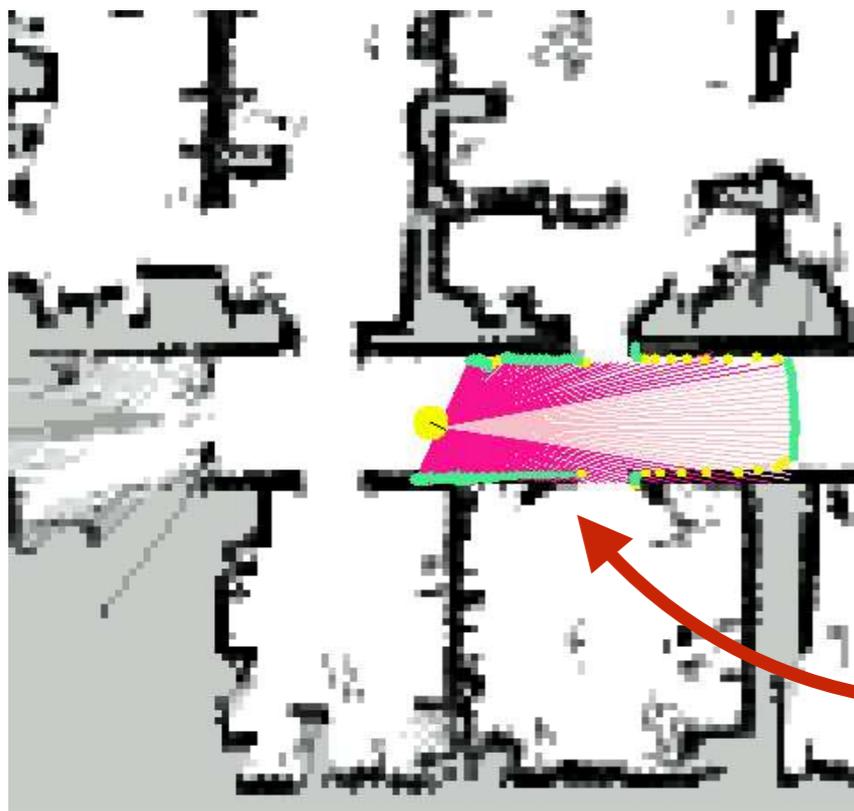
*In theory:* Collect lots of data and optimize parameters to maximize data likelihood



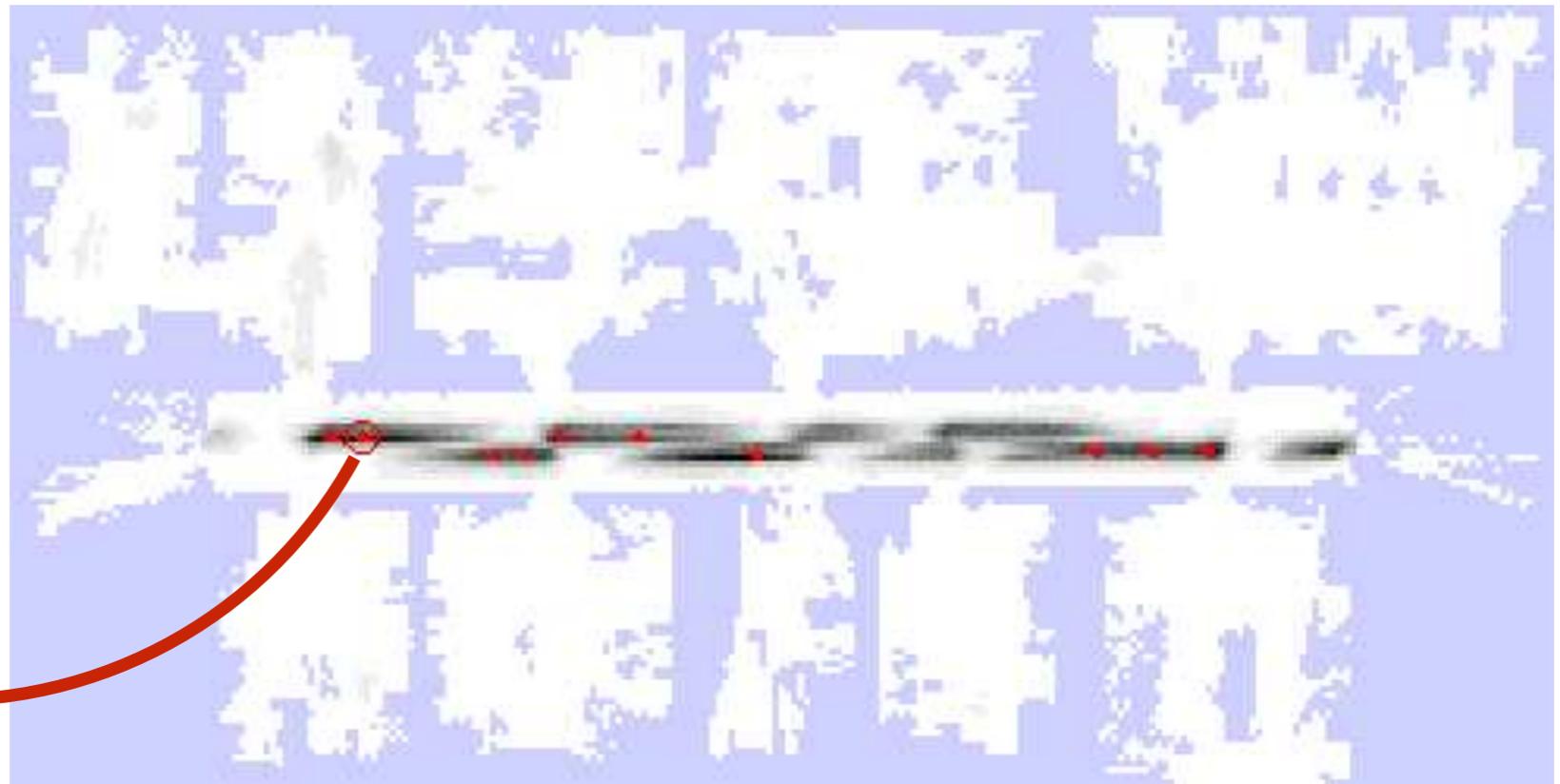
Example:  
Place a robot  
300 cm from  
a wall and  
collect lots of  
data

# Question: How do we tune parameters?

**In practice:** Simulate a scan and plot the likelihood from different positions



Actual scan



Likelihood at various locations

# Problem: Overconfidence

$$P(z_t | x_t, m) = \prod_{i=1}^K P(z_t^k | x_t, m)$$

Independence assumption may result in repetition of mistakes

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## Solution

1. Subsample laser scans: Convert 180 beams to 18 beams
2. “Smooth” out the probability model

$$P(z_t^k | x_t, m) \longrightarrow P(z_t^k | x_t, m)^{\frac{1}{N}}$$