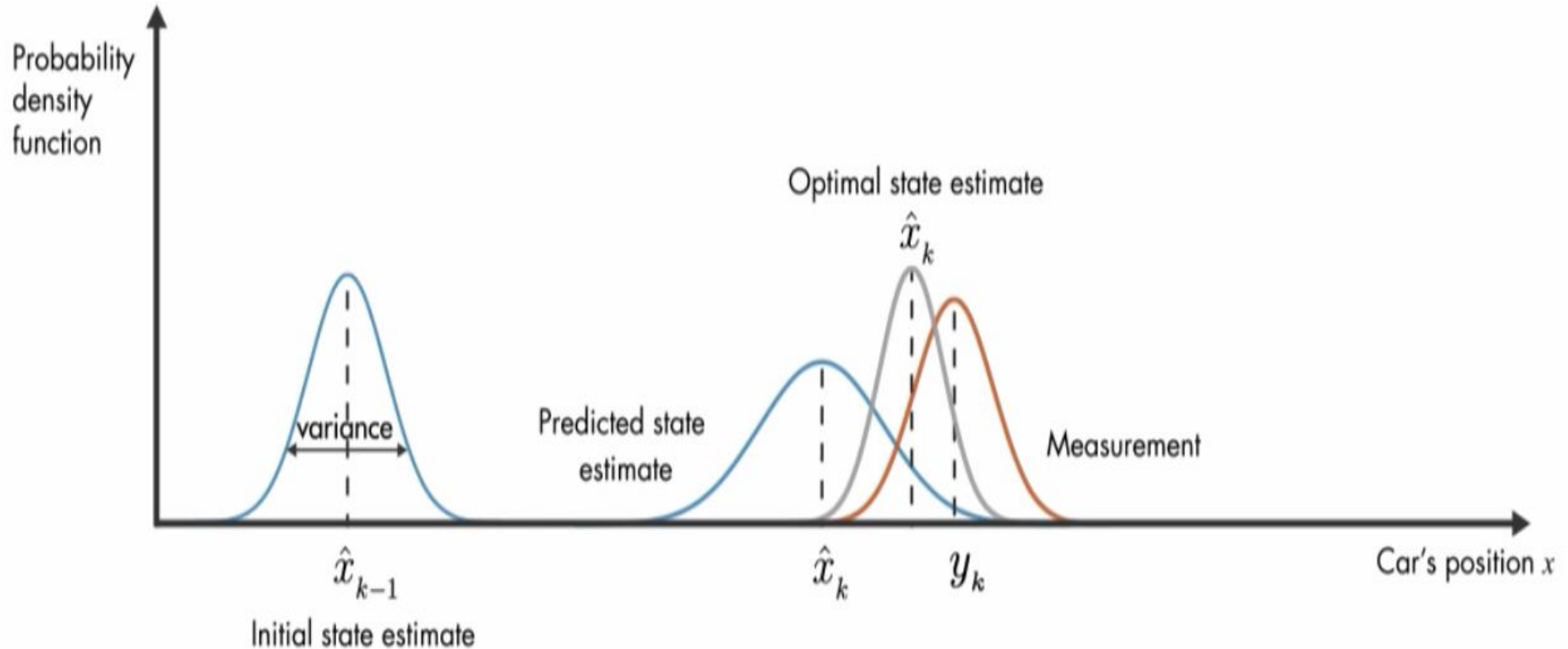


Kalman Filter and Particle Filter

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Kalman Filter



Kalman Filter

Prediction

Project the state ahead

$$x_{k+1} = Ax_k + Bu_k$$

Project the error covariance ahead

$$P_{k+1} = AP_kA^T + Q$$

Correction

Compute the Kalman Gain

$$K_k = P_kH^T(HP_kH^T + R)^{-1}$$

Update the estimate via measurement

$$x_k = x_k + K_k(z_k - Hx_k)$$

Update the error covariance

$$P_k = (I - K_kH)P_k$$

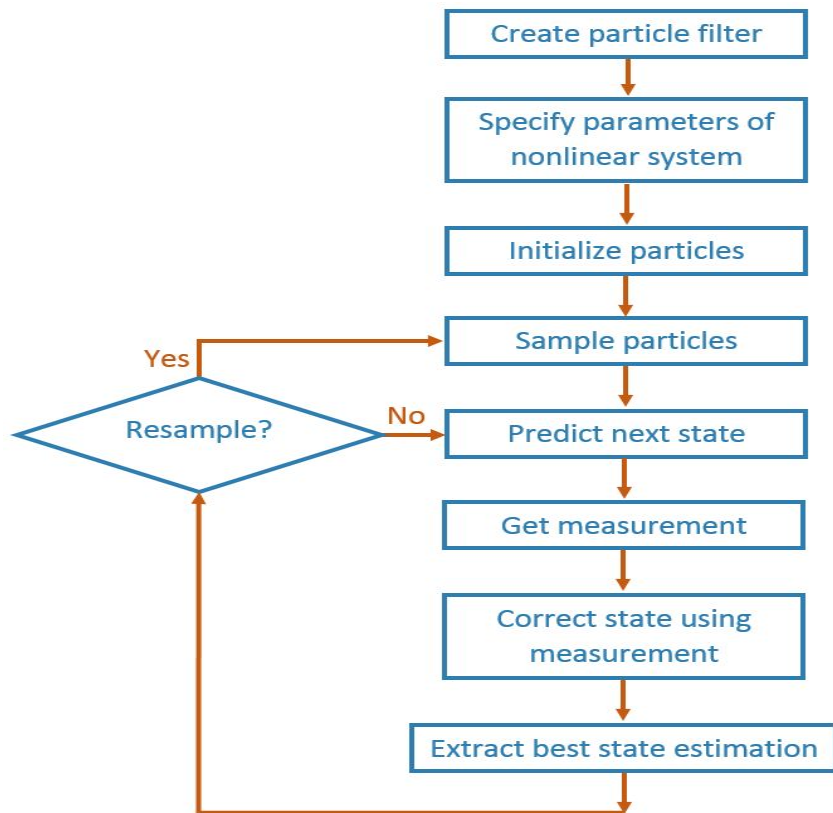
Initialize R, P, Q once

Bayesian Filter Vs Kalman Filter

Extended Kalman Filter

	Kalman filter	EKF
state prediction	$A_t \mu_{t-1} + B_t u_t$	$g(u_t, \mu_{t-1})$
measurement prediction	$C_t \bar{\mu}_t$	$h(\bar{\mu}_t)$

Particle Filter



Source: <https://mathwork.com>

```
1:  Algorithm Particle_filter( $\mathcal{X}_{t-1}, u_t, z_t$ ):  
2:     $\bar{\mathcal{X}}_t = \mathcal{X}_t = \emptyset$   
3:    for  $m = 1$  to  $M$  do  
4:      sample  $x_t^{[m]} \sim p(x_t \mid u_t, x_{t-1}^{[m]})$   
5:       $w_t^{[m]} = p(z_t \mid x_t^{[m]})$   
6:       $\bar{\mathcal{X}}_t = \bar{\mathcal{X}}_t + \langle x_t^{[m]}, w_t^{[m]} \rangle$   
7:    endfor  
8:    for  $m = 1$  to  $M$  do  
9:      draw  $i$  with probability  $\propto w_t^{[i]}$   
10:     add  $x_t^{[i]}$  to  $\mathcal{X}_t$   
11:   endfor  
12:   return  $\mathcal{X}_t$ 
```

Source: Probabilistic Robotics (Chapter 4) by Dieter Fox, Sebastian Thrun, and Wolfram Burgard

Particle Filter Vs Kalman Filter

References

- Probabilistic Robotics (Chapter 3 and 4) by Dieter Fox, Sebastian Thrun, and Wolfram Burgard
- MathWorks.com
- <https://medium.com/intro-to-artificial-intelligence/extended-kalman-filter-simplified-udacitys-self-driving-car-nanodegree-46d952fce7a3>

Thank You!