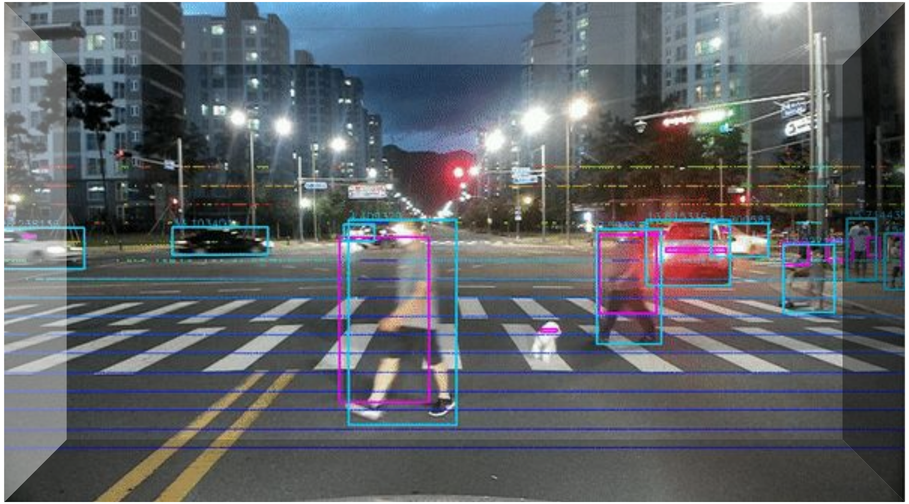
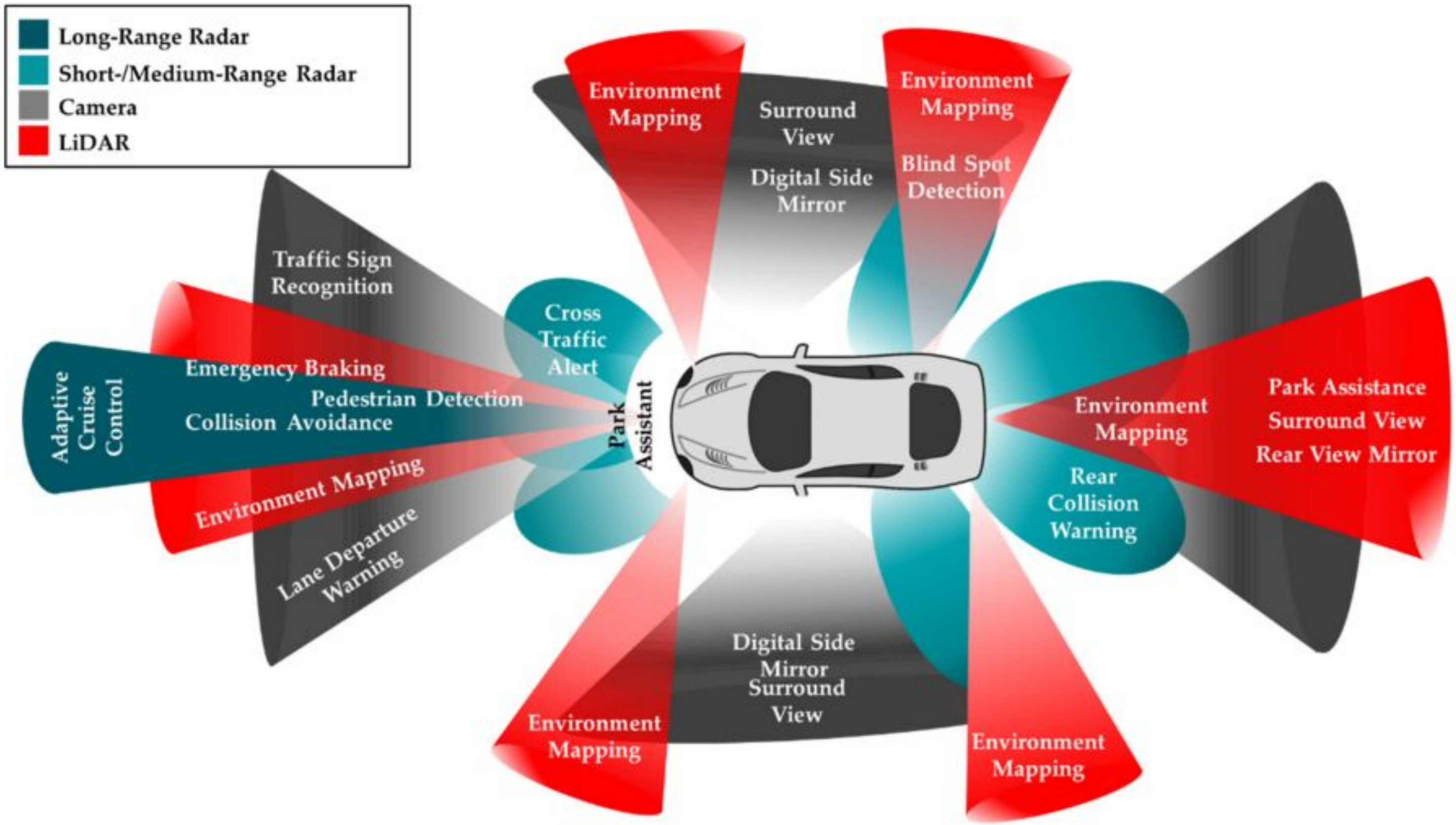


# The Brain of Autonomous Machines: From Sensor Fusion to Intelligent Estimation

Adrian Guel-Cortez

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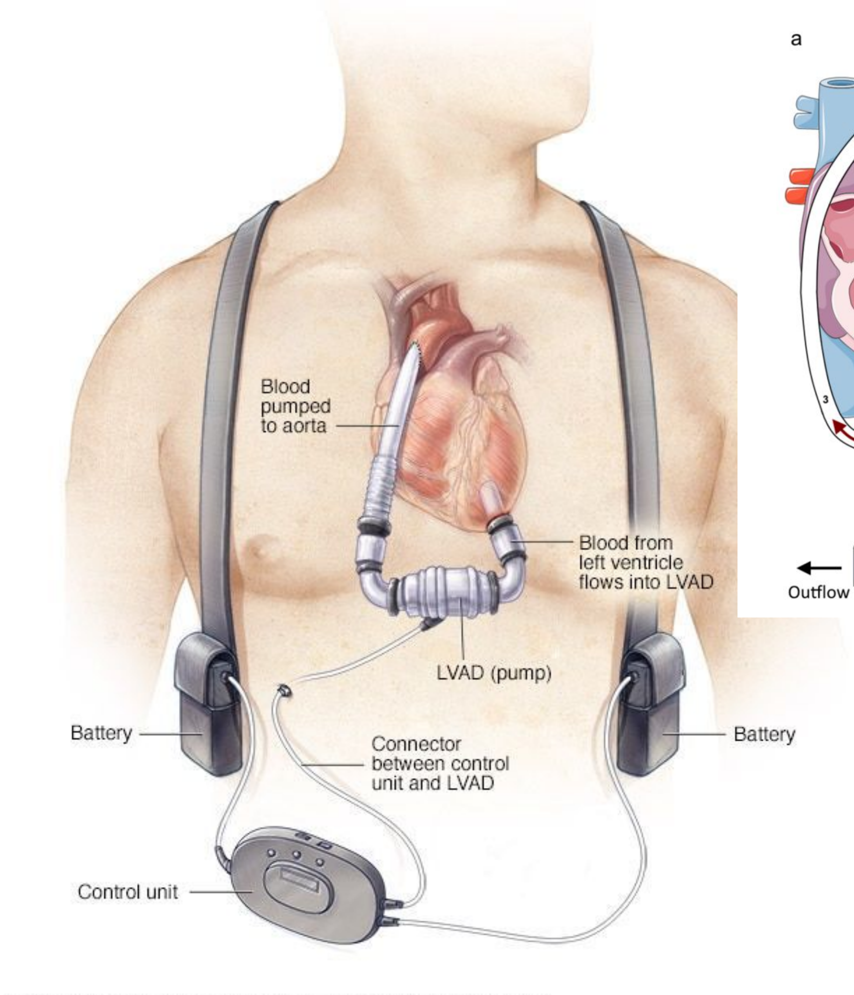




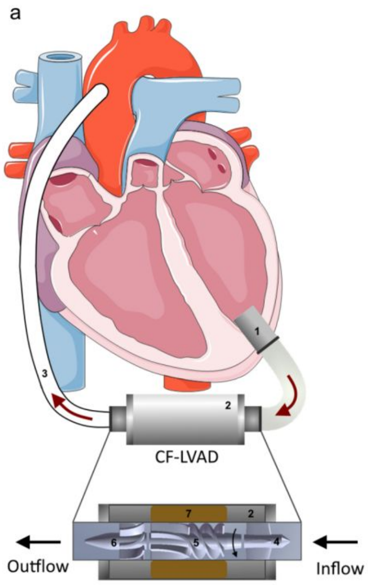


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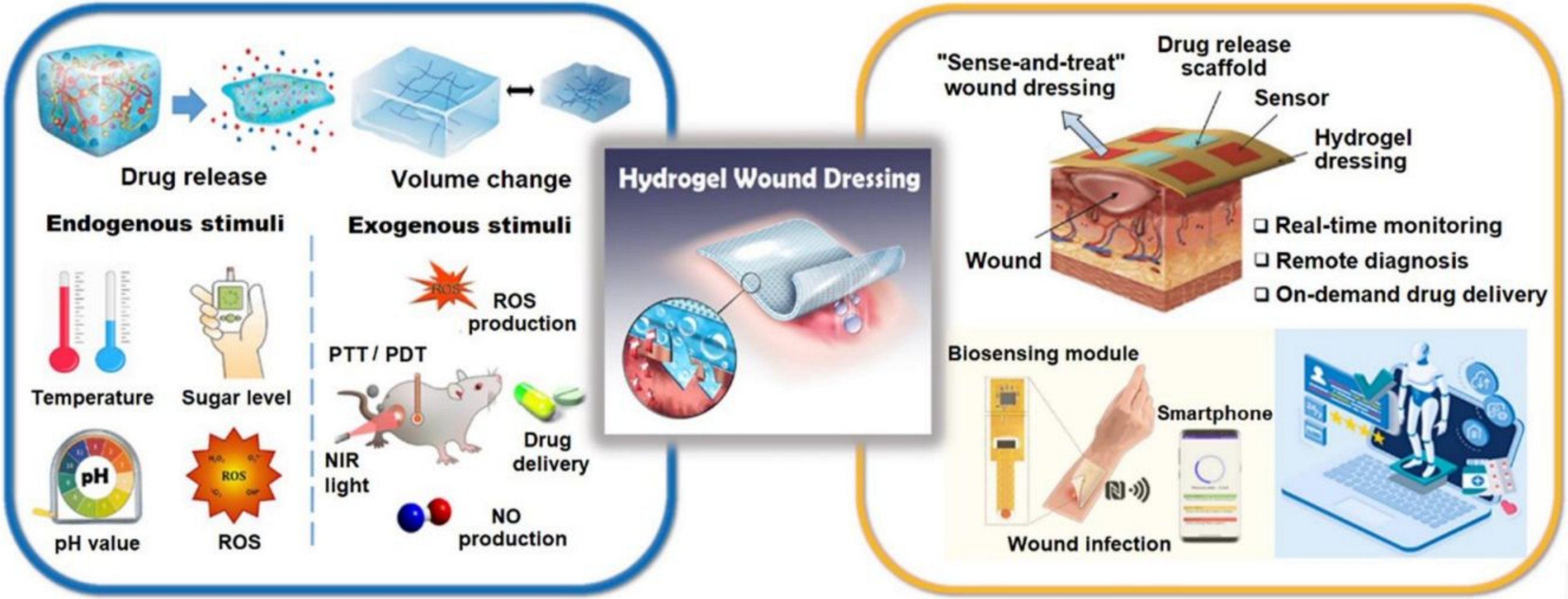


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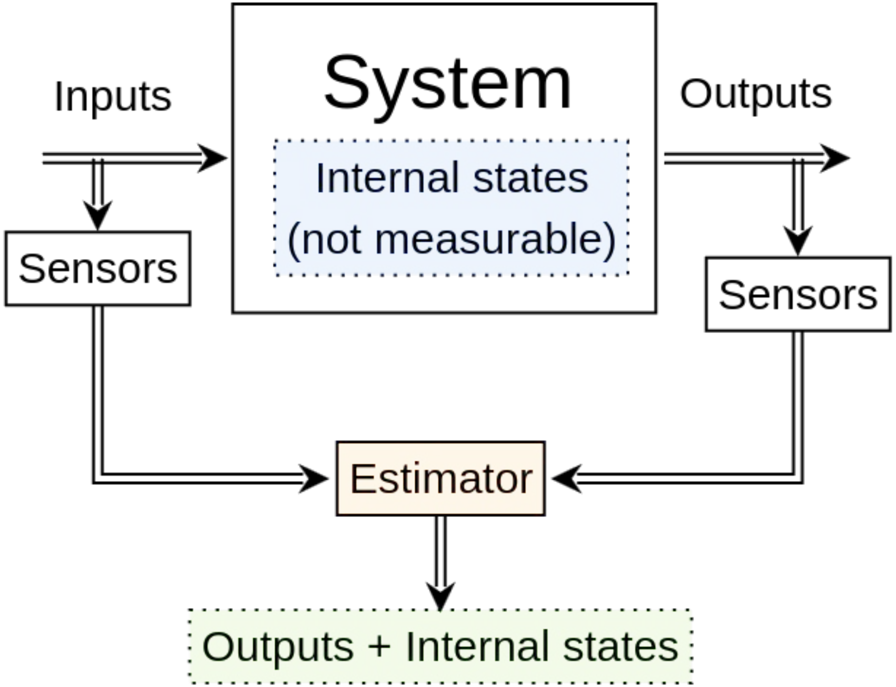


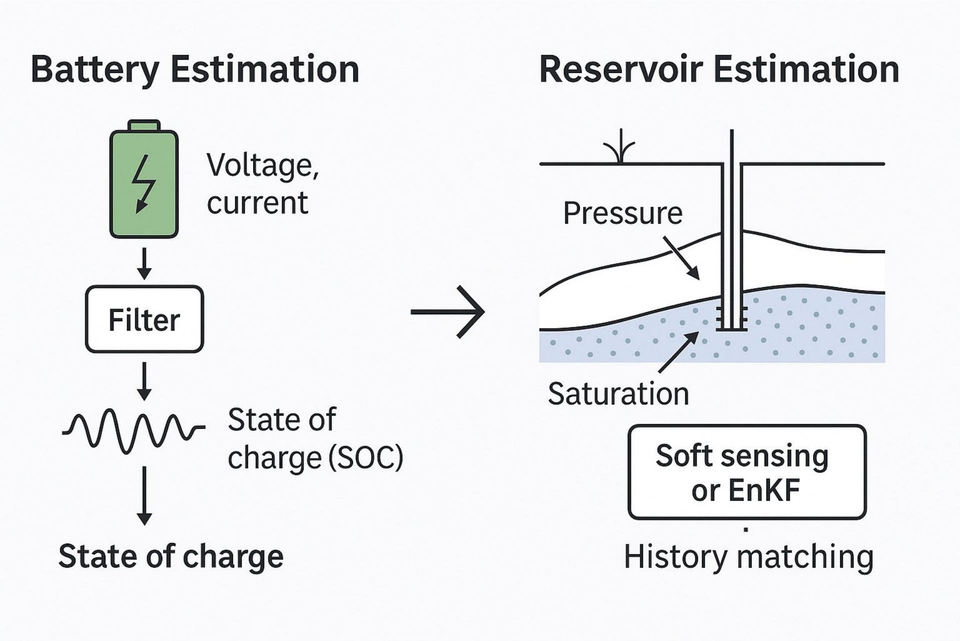


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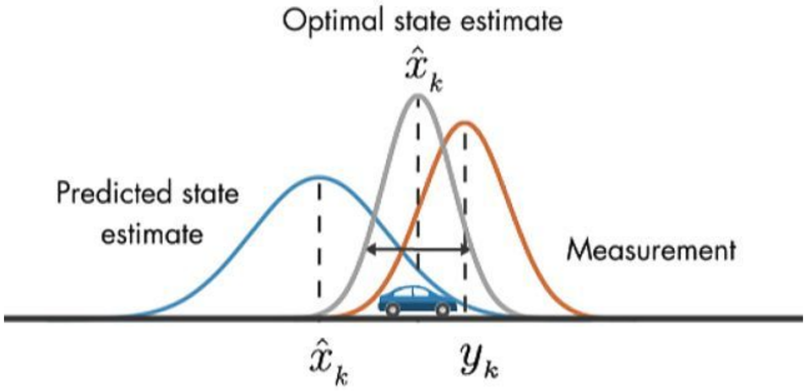
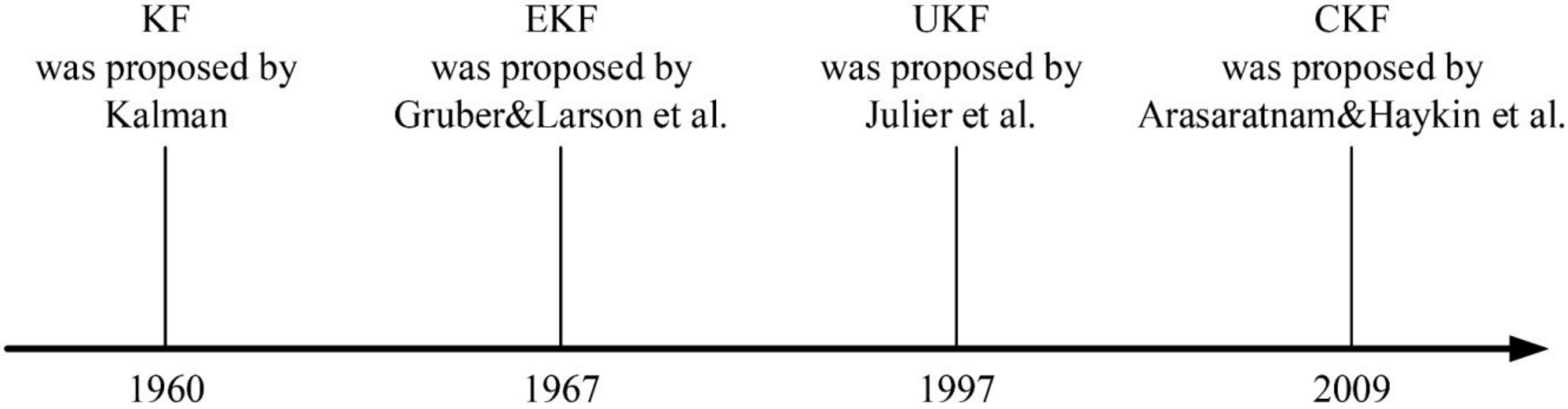



extended Kalman filter (EKF),
unscented Kalman filter (UKF),
cubature Kalman filter (CKF)

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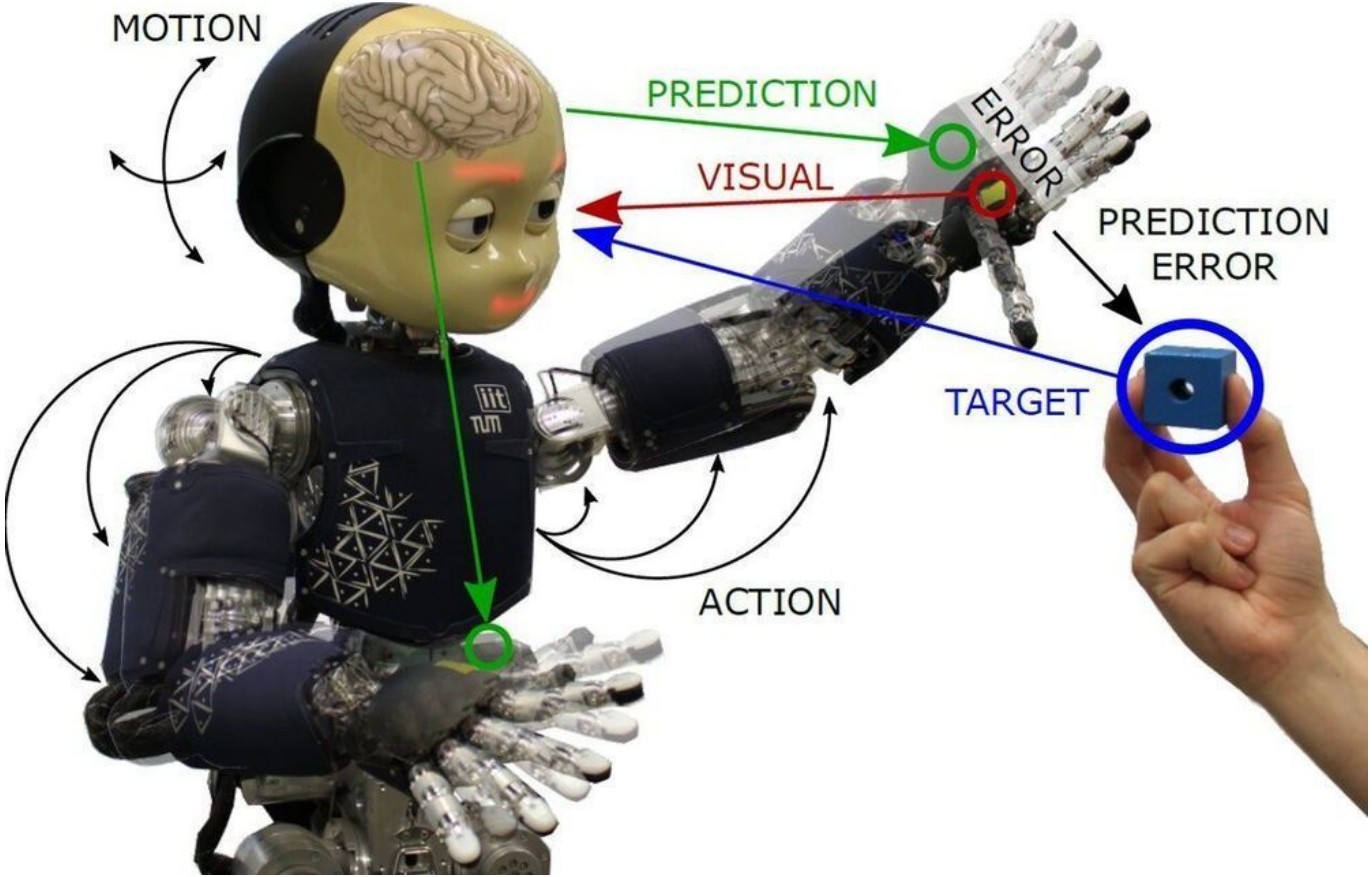


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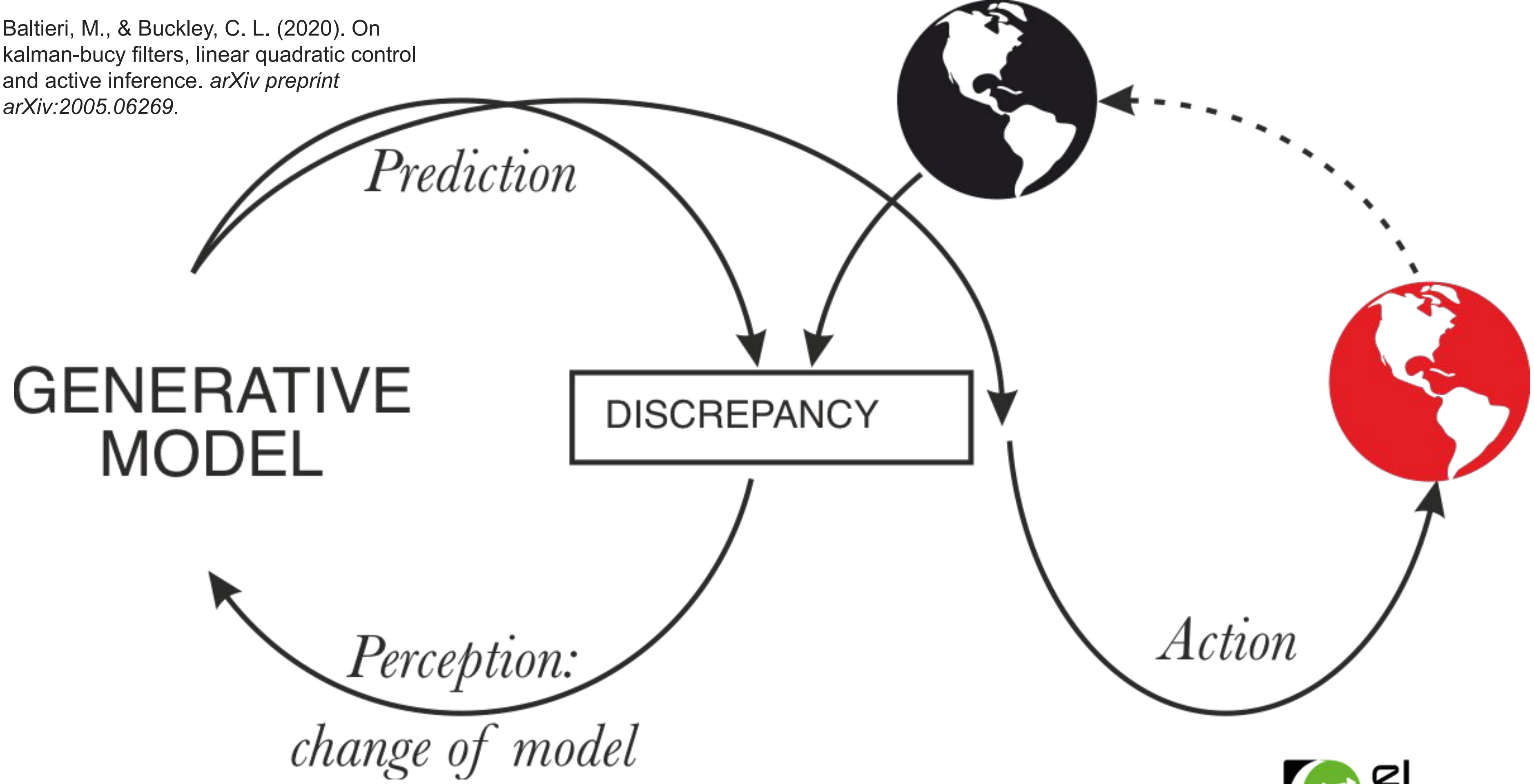


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# Dummy example for sensor fusion

$$\mathbf{x} = \begin{bmatrix} \text{position} \\ \text{velocity} \\ \text{acceleration} \end{bmatrix} \quad \mathbf{F} = \begin{bmatrix} 1 & dt & 0.5dt^2 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix}$$


- **Accelerometer** directly observes acceleration:

$$\mathbf{z}_{\text{accel}} = [0, 0, 1] \cdot \mathbf{x} + v$$

- **GPS** directly observes position:

$$\mathbf{z}_{\text{gps}} = [1, 0, 0] \cdot \mathbf{x} + w$$

# A dummy SLAM algorithm

The system's state at time $k$ is:

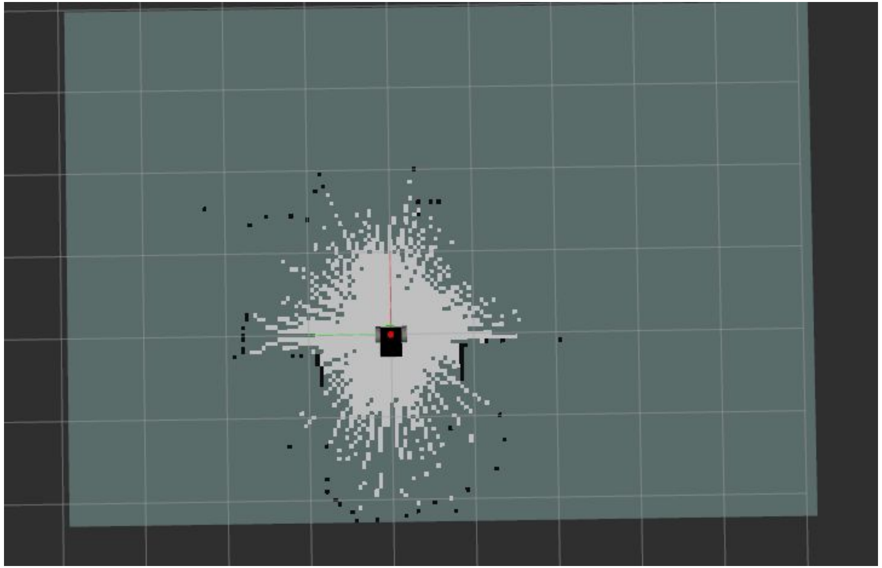
$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix}$$

where:

- $x_k, y_k$: robot position in 2D.
- $\theta_k$: robot orientation (heading angle).

$$\mathbf{u}_k = \begin{bmatrix} v_k \\ \omega_k \end{bmatrix}$$

- $v_k$: linear velocity.
- $\omega_k$: angular velocity.



Given the state $\mathbf{x}_{k-1}$, control input $\mathbf{u}_{k-1}$, and time step $\Delta t$, the predicted state is:

$$\mathbf{x}_k^- = f(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}) = \begin{bmatrix} x_{k-1} + v_{k-1}\cos(\theta_{k-1})\Delta t \\ y_{k-1} + v_{k-1}\sin(\theta_{k-1})\Delta t \\ \theta_{k-1} + \omega_{k-1}\Delta t \end{bmatrix}$$

- This is a **nonlinear kinematic model** of a unicycle-type robot.

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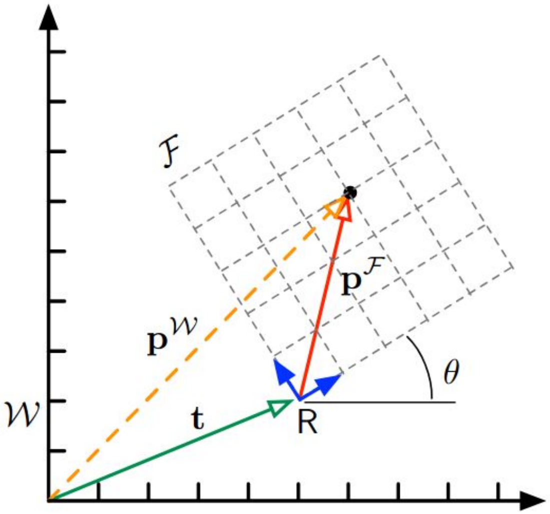
Each **landmark** $i$ at known position $(l_{x,i}, l_{y,i})$ provides a noisy measurement:

$$\mathbf{z}_{k,i} = \begin{bmatrix} r_{k,i} \\ \phi_{k,i} \end{bmatrix} = h(\mathbf{x}_k, \mathbf{l}_i) = \begin{bmatrix} \sqrt{(l_{x,i} - x_k)^2 + (l_{y,i} - y_k)^2} \\ \arctan 2(l_{y,i} - y_k, l_{x,i} - x_k) - \theta_k \end{bmatrix} + \mathbf{v}_k$$

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




**1. Relative position vector (from robot to landmark):**

$$\Delta x = l_x - x$$
$$\Delta y = l_y - y$$

**2. Range (Euclidean distance):**

$$r = \sqrt{(l_x - x)^2 + (l_y - y)^2}$$

This is the **hypotenuse** of the right triangle formed by $\Delta x, \Delta y$.

**3. Global bearing (angle from x-axis to the landmark):**

$$\psi = \arctan 2(\Delta y, \Delta x)$$

**4. Relative bearing (to the robot's heading):**

$$\phi = \psi - \theta = \arctan 2(l_y - y, l_x - x) - \theta$$

This is the **angle between the robot's heading** and the line-of-sight to the landmark.

https://www.iri.upc.edu/people/jsola/JoanSola/objectes/curs_SLAM/SLAM2D/SLAM%20course.pdf

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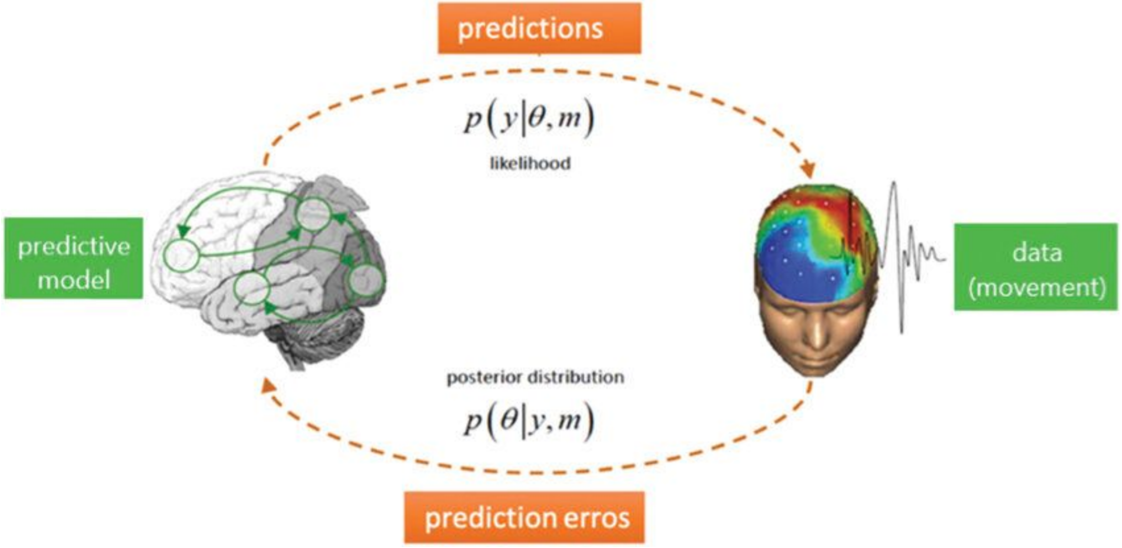
# Future learning:
# A Bayes Brain.

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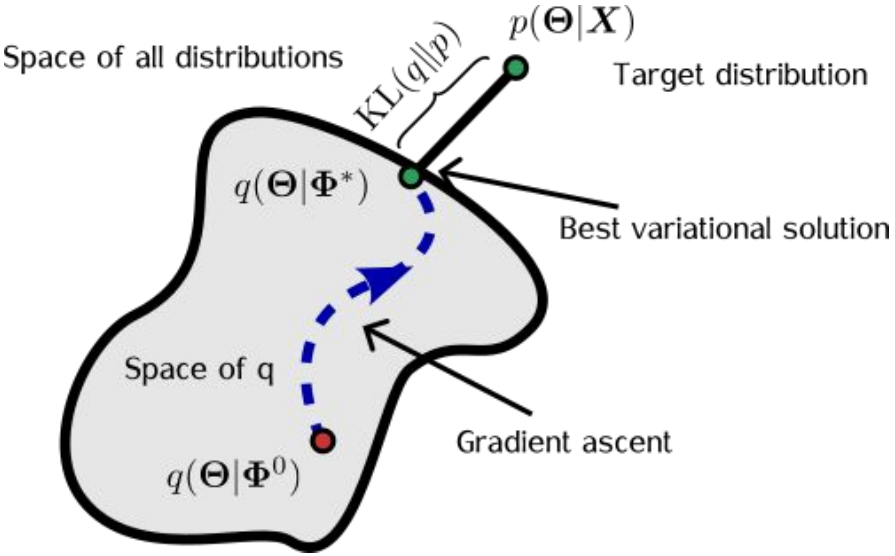
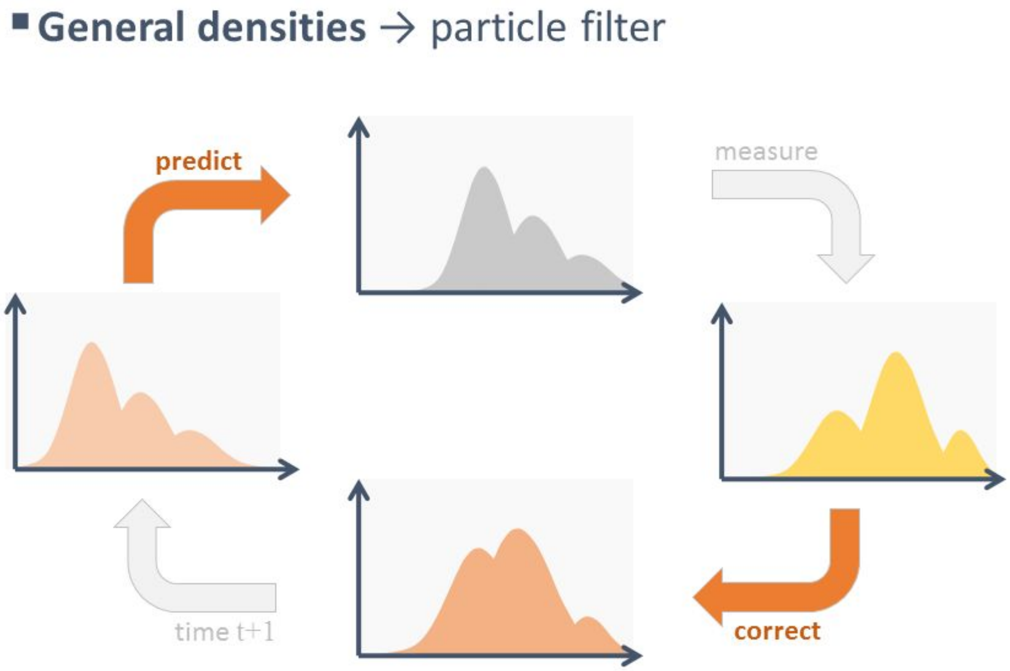
# Variational Inference




https://towardsdatascience.com/variational-inference-the-basics-f70ac511bcea/

# Particle filters

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**THANKS!**

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