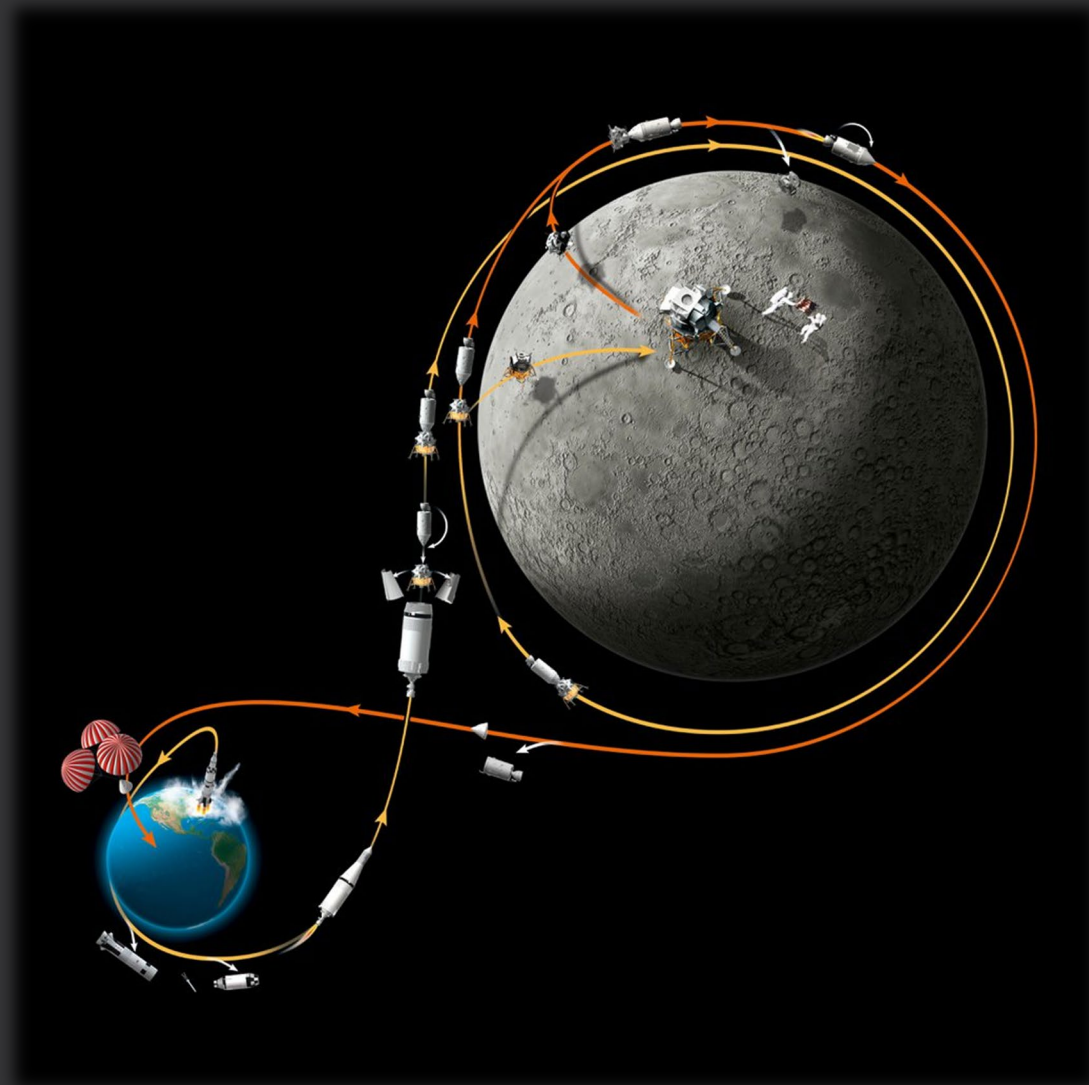
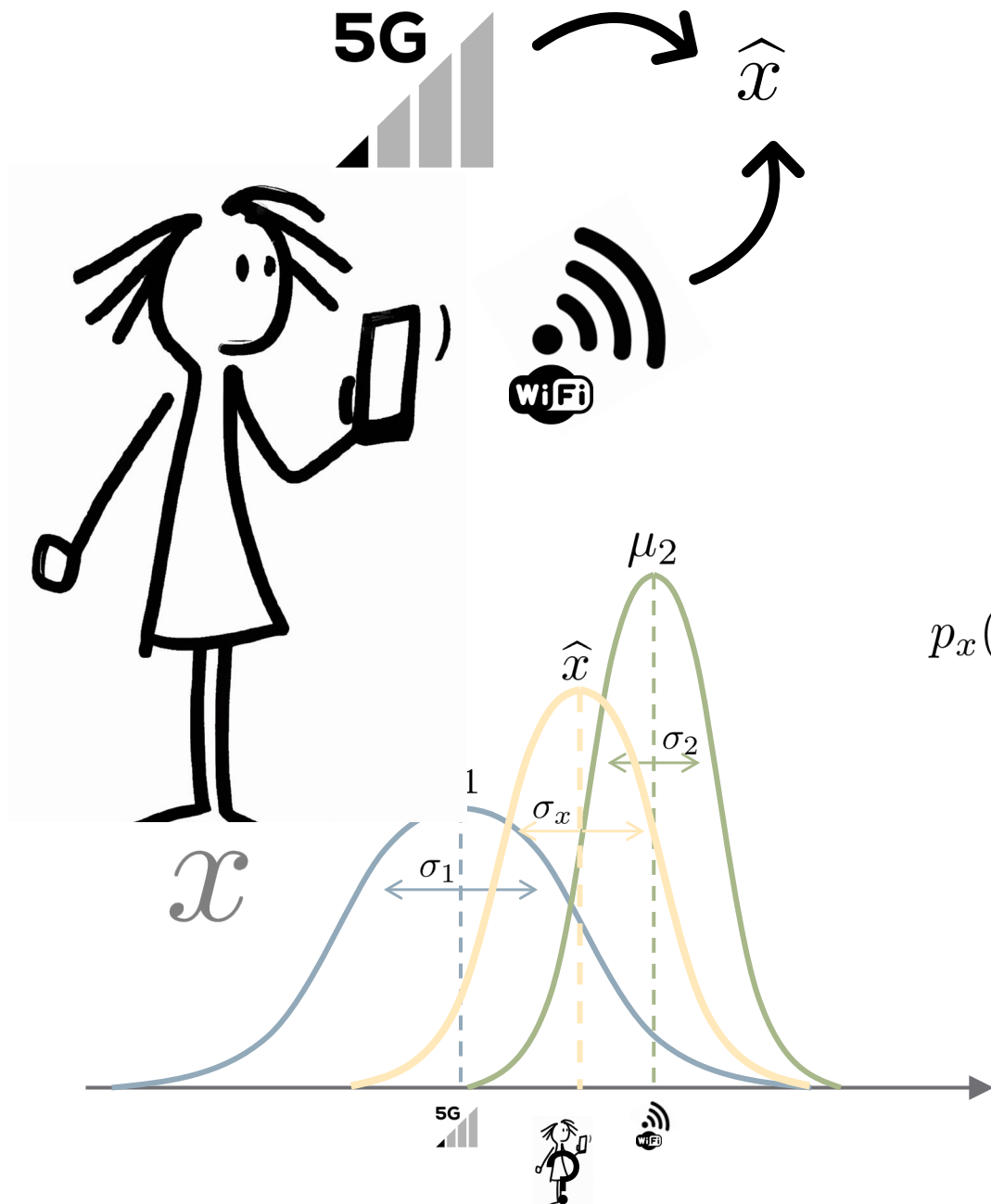




Metody i narzędzia *Big Data*

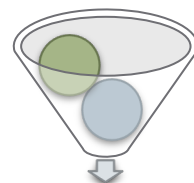
Filtr Kalmana





$$p_1(x; \mu_1, \sigma_1)$$

$$p_2(x; \mu_2, \sigma_2)$$



$$p_x(x; \underbrace{\mu_1, \mu_2}_{\hat{x}}, \underbrace{\sigma_1, \sigma_2}_{\sigma_x})$$

$$p_x(x; \mu_1, \mu_2, \sigma_1, \sigma_2) = p_1(x; \mu_1, \sigma_1) \cdot p_2(x; \mu_2, \sigma_2)$$

$$p(x|\mu) \propto p(\mu|x) \cdot p(x)$$

$$\hat{x} = \frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2}{\sigma_1^2 + \sigma_2^2} \quad \sigma_x^2 = \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$$

jakość pomiarów

jakość pomiarów

$$\hat{x} = \frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2}{\sigma_1^2 + \sigma_2^2} = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2} \mu_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} \mu_2$$

$$\hat{x} = \mu_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} (\mu_2 - \mu_1)$$

nowe = stare + α przyrost

$$\sigma_x^2 = \frac{(\sigma_1 \sigma_2)^2}{\sigma_1^2 + \sigma_2^2} \Rightarrow \frac{1}{\sigma_x^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

$$\sigma_x^2 = \sigma_1^2 - \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2} \sigma_1^2$$

nowe = (1 - α) stare

Skale pomiarowe

$$\mu_1 \leftarrow C \mu_1 \Rightarrow \sigma_1 \leftarrow C \sigma_1$$

$$\mu_x \leftarrow C \mu_x \Rightarrow \sigma_x \leftarrow C \sigma_x$$

$$\hat{x} = \mu_1 + K (\mu_2 - C \mu_1)$$

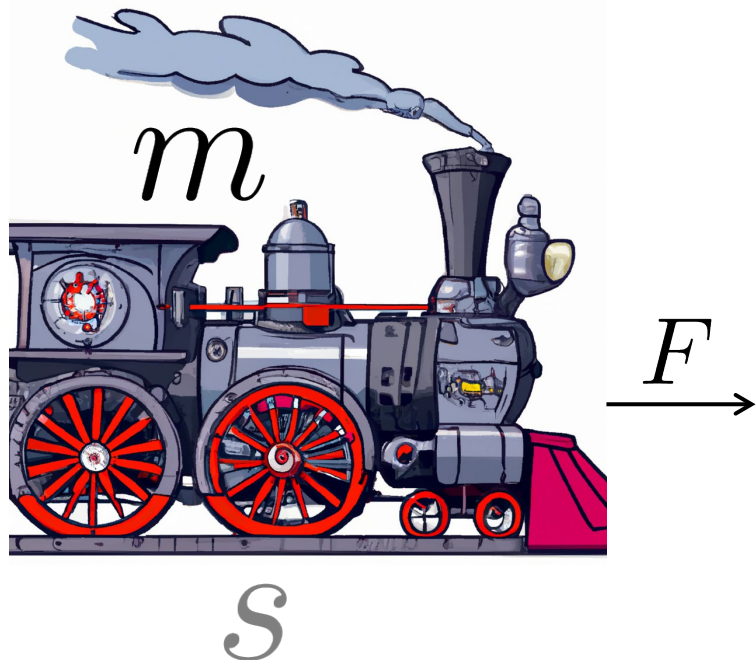
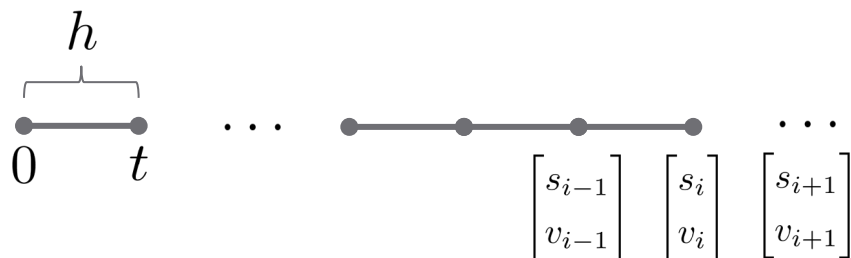
$$K = \frac{C \sigma_1^2}{(C \sigma_1)^2 + \sigma_2^2}$$

$$\sigma_x^2 = \sigma_1^2 - K C \sigma_1^2$$

$$a(t) = \frac{F}{m}$$

$$\begin{bmatrix} s_i \\ v_i \end{bmatrix} = \begin{bmatrix} 1 & h \\ 0 & 1 \end{bmatrix} \begin{bmatrix} s_{i-1} \\ v_{i-1} \end{bmatrix} + \begin{bmatrix} h^2/2 \\ h \end{bmatrix} \frac{F_i}{m}$$

$$y_i = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} s_i \\ v_i \end{bmatrix}$$



Proces

$$\mathbf{x}_i = \mathbf{A}\mathbf{x}_{i-1} + \mathbf{B}u_i + \mathbf{w}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$$

$$y_i = \mathbf{C}\mathbf{x}_i + \mathbf{z}_i \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$$

Model

$$\bar{\mathbf{x}}_i = \mathbf{A}\hat{\mathbf{x}}_{i-1} + \mathbf{B}u_i$$

$$\bar{y}_i = \mathbf{C}\bar{\mathbf{x}}_i$$

Dane: $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{Q}, \mathbf{R}$

Szukane są kolejne wartości $\hat{\mathbf{x}}_i, \mathbf{P}_i^+$

$$\mathbf{Q} = \mathbb{E}[\mathbf{w}_i \mathbf{w}_i^T]$$

$$\mathbf{R} = \mathbb{E}[\mathbf{z}_i \mathbf{z}_i^T]$$

$$\mathbf{w} \perp \mathbf{z}$$

$$\mathbf{e}_i = \mathbf{x}_i - \bar{\mathbf{x}}_i$$

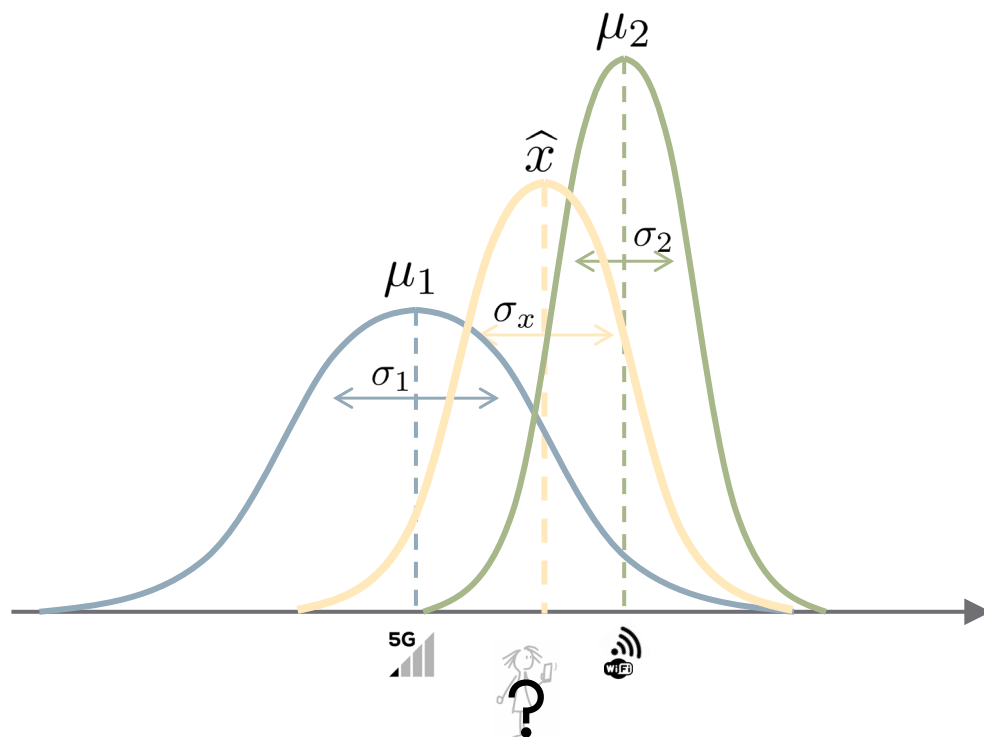
$$\hat{\mathbf{e}}_i = \mathbf{x}_i - \hat{\mathbf{x}}_i$$

$$\mathbf{w} \perp \mathbf{e}$$

$$\mathbf{P} = \mathbb{E}[\mathbf{e}_i \mathbf{e}_i^T]$$

$$\mathbf{P}^+ = \mathbb{E}[\hat{\mathbf{e}}_i \hat{\mathbf{e}}_i^T]$$

Fuzja pomiarów z różnych urządzeń

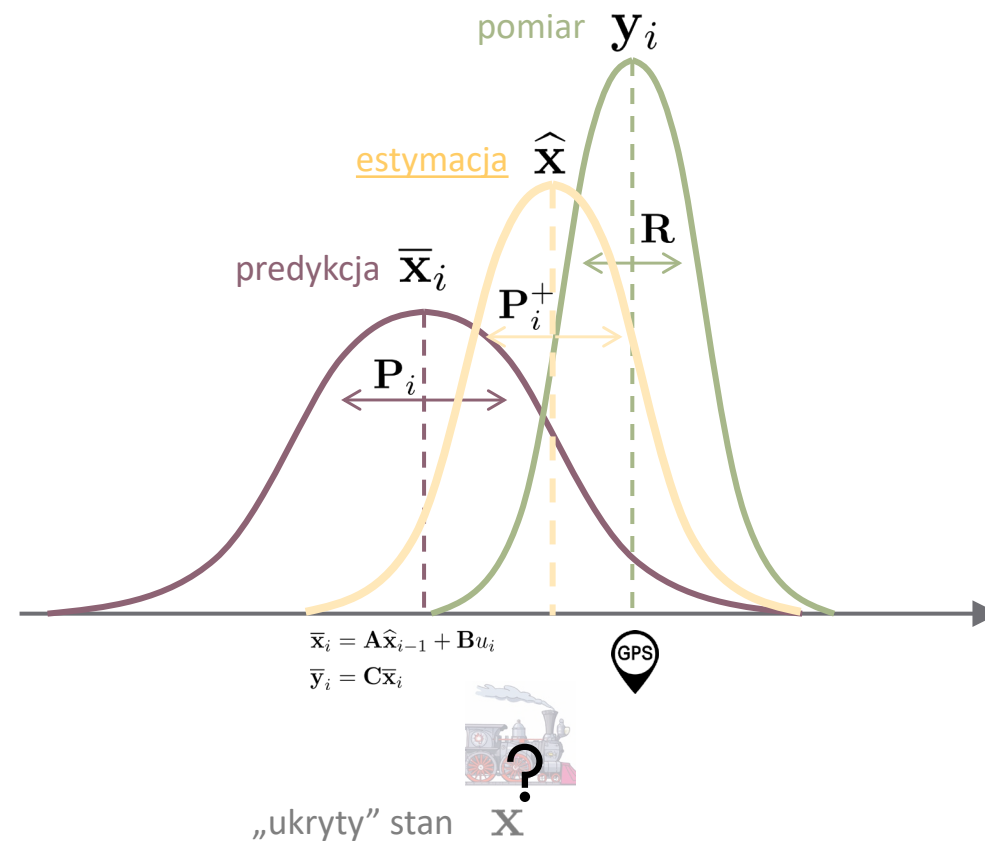


Okazuje się, że brakuje nam P_i

$$\mathbf{P} = \mathbb{E}[\mathbf{e}_i \mathbf{e}_i^T] = \mathbb{E}[(\mathbf{x}_i - \bar{\mathbf{x}}_i)(\mathbf{x}_i - \bar{\mathbf{x}}_i)^T]$$

$$\mathbf{P}_i = \mathbf{A} \mathbf{P}_{i-1}^+ \mathbf{A}^T + \mathbf{Q}$$

Fuzja pomiaru i predykcji z modelu



Dane: $\mathbf{A}, \mathbf{B}, \mathbf{C}, \mathbf{Q}, \mathbf{R}$

Szukane są kolejne wartości $\hat{\mathbf{x}}_i, \mathbf{P}_i^+$

Wersja wielowymiarowa

$$\hat{x} = \mu_1 + K(\mu_2 - C\mu_1)$$

$$K = \frac{C\sigma_1^2}{(C\sigma_1)^2 + \sigma_2^2}$$

$$\sigma_x^2 = \sigma_1^2 - KC\sigma_1^2$$

$$\mathbf{K} = \mathbf{P}\mathbf{C}^T (\mathbf{C}\mathbf{P}\mathbf{C}^T + \mathbf{Q})^{-1}$$

Założenie: dysponujemy dokładną wartością \mathbf{K}

$$\hat{\mathbf{x}} = \bar{\mathbf{x}} + \mathbf{K}(\mathbf{y} - \mathbf{C}\bar{\mathbf{x}}_i)$$

$$\mathbf{P}^+ = \mathbf{P} - \mathbf{K}\mathbf{C}\mathbf{P}$$

Algorytm filtru Kalmana



<https://filterpy.readthedocs.io/en/latest/>

[https://nbviewer.org/github/rlabbe/Kalman-and-Bayesian-Filters-in-Python/blob/master/table of contents.ipynb](https://nbviewer.org/github/rlabbe/Kalman-and-Bayesian-Filters-in-Python/blob/master/table%20of%20contents.ipynb)



THE END