

Sequential Models in Data Science

Recursive Bayesian Filtering and Markov Models

Yirmeyahu Kaminski

INTRODUCTION

The exercise is to be done by pairs of students. Each pair must present a Jupyter notebook containing all theoretical answers as well as all Python functions. The notebook will be tested as this. No modification should be necessary for making it work.

All over the questions, x_k and y_k denotes respectively the state vector and the measurements.

1 KALMAN FILTER WITH BIASED NOISE

Derive the Kalman filter equations for the following linear-Gaussian filtering model with non-zero mean noises:

$$\begin{aligned}x_k &= Ax_{k-1} + q_{k-1}, \\y_k &= Hx_k + r_k,\end{aligned}$$

where $q_{k-1} \sim \mathcal{N}(m_q, Q)$ and $r_k \sim \mathcal{N}(m_r, R)$.

It is recommended to use the two lemmas that were defined in task 2, section 3.

2 EXTENDED KALMAN FILTER

Consider the following non-linear space model:

$$\begin{aligned}x_k &= x_{k-1} - 0.01 \sin(x_{k-1}) + q_{k-1}, \\y_k &= 0.5 \sin(2x_k) + r_k,\end{aligned}$$

where $q_{k-1} \sim \mathcal{N}(0, 0.01^2)$ and $r_k \sim \mathcal{N}(0, 0.02)$.

1. Write the extended Kalman filter obtained by the **Taylor** linearization.
2. Write the extended Kalman filter obtained by the **statistical** linearization.
3. Implement in python these versions of the EKF. Draw on the same graph in three different colors (with a clear caption) the trajectory of the system and the estimated states by the two different methods of EKF.

3 GRID BASED FILTER

Consider a situation where the state space is discrete and finite: $\forall n, x_n \in S$ and $|S| = N < \infty$. Let $S = \{x^1, \dots, x^N\}$.

Define the coefficients $w_{k-1|k-1}^i$ by the following relation:

$$p(x_{k-1}|y_{1:k-1}) = \sum_{i=1}^N w_{k-1|k-1}^i \delta(x_{k-1} - x^i).$$

The prediction step leads to the following expression:

$$p(x_k|y_{1:k-1}) = \sum_{i=1}^N w_{k|k-1}^i \delta(x_k - x^i).$$

Then the update step leads to:

$$p(x_k|y_{1:k}) = \sum_{i=1}^N w_{k|k}^i \delta(x_k - x^i).$$

Prove the following relations:

1. $\forall i, w_{k|k-1}^i = \sum_{j=1}^N w_{k-1|k-1}^j p(x^i|x^j)$, where $p(x^i|x^j)$ is the transition probability from state x^j to state x^i ,
2. $\forall i, w_{k|k}^i = \frac{w_{k|k-1}^i p(y_k|x^i)}{\sum_{j=1}^N w_{k|k-1}^j p(y_k|x^j)}$, where $p(y_k|x^l)$ is the probability distribution of the measurement y_k given the system is in state x^l .
3. Consider the following situation. Let x_k be a sequence of real numbers that satisfies:

$$\begin{aligned} x_k &= x_{k-1} + L v_{k-1} \\ y_k &= \left(\frac{1}{2} + r_k\right) x_k, \end{aligned}$$

where L is a positive real number, v_{k-1} is a Rademacher random variable the distribution of which is given by:

$$\mathbb{P}(v_{k-1} = i) = \begin{cases} \frac{1}{2} & \text{if } i \in \{-1, 1\} \\ 0 & \text{otherwise} \end{cases}$$

and r_k is a uniform random variable in $[0, 1/2]$. Let x_0 be a Gaussian random variable, such that $x_0 \sim \mathcal{N}(0, 1)$. Implement a grid based filter to track the state vector x_k over 100 time steps, within the state space $S = \{x_0, x_0 \pm L, \dots, x_0 \pm NL\}$, where $N = 100$. Take $L = 2$. Draw a plot with the actual state and the estimated one with two different colors and an implicit legend, over the tracking interval.

4 REJECTION SAMPLING AND MONTE CARLO INTEGRATION

Consider a probability density distribution $f : \mathbb{R} \rightarrow \mathbb{R}_+$. Let g be another density distribution such that there exists $c > 0$ such that $f(x) \leq cg(x)$ for all $x \in \mathbb{R}$. The purpose of rejection sampling is to make use of g , which is supposed to be simple to sample in order to produce samplings from f . The algorithm works as follows:

1. Draw a random variable x following the distribution given by g ,
2. Draw a random variable u from the uniform distribution over $(0, 1)$,
3. If $u \leq \frac{f(x)}{cg(x)}$, accept x as a sample from the distribution given by f . Otherwise return to 1.

To prove that this algorithm indeed generates a sample from f , we shall prove that the cumulative distribution function of x given by:

$$F_x(t) = \mathbb{P}\left(x \leq t \mid u \leq \frac{f(x)}{cg(x)}\right),$$

satisfies $F_x(t) = F(t)$, where F is the cumulative distribution function of f . Answer the following questions, that will guide you.

1. Prove that $\mathbb{P}\left(x \leq t \mid u \leq \frac{f(x)}{cg(x)}\right) = \frac{\mathbb{P}\left(x \leq t, u \leq \frac{f(x)}{cg(x)}\right)}{\mathbb{P}\left(u \leq \frac{f(x)}{cg(x)}\right)}$,
2. Prove that $\mathbb{P}\left(u \leq \frac{f(x)}{cg(x)}\right) = \frac{1}{c}$,
3. Deduce that $F_x(t) = F(t)$.

Let $f(x) = 0.2 \frac{1}{\sqrt{2\pi}0.1} \exp\left(-\frac{(x-1)^2}{2 \cdot 0.01}\right) + 0.8 \frac{1}{\sqrt{2\pi}0.8} \exp\left(-\frac{(x-2)^2}{2 \cdot 0.64}\right)$ and $g(x) = \frac{1}{\sqrt{2\pi}10} \exp\left(-\frac{x^2}{2 \cdot 100}\right)$. Find the smallest c such that $f \leq cg$. Apply the rejection algorithm to compute $n = 1000$ samples of f . Draw the graph of f and the histogram of these samples on the same drawing. Use this algorithm to compute the following integral with the Monte-Carlo method:

$$\int_{-\infty}^{+\infty} (x^2 - 3x + 5) \cos(x) f(x) dx.$$

May the force be with you!