

1 (7.1) Calculus for a simple Gaussian random process

(a): In order to verify this directly, we have to use the definition. We first calculate $\frac{X_s - X_t}{s - t}$ which is equal to $B + C(t + s)$. Now, we have to show that the fraction $\frac{X_s - X_t}{s - t}$ converges to $B + 2Ct$ as $s \rightarrow t$ in mean square sense:

$$\begin{aligned} \lim_{s \rightarrow t} \mathbb{E} \left[\left(\frac{X_s - X_t}{s - t} - (B + 2Ct) \right)^2 \right] &= \lim_{s \rightarrow t} \mathbb{E} \left[(C(s - t))^2 \right] \\ &= \lim_{s \rightarrow t} (s - t)^2 \mathbb{E} [C^2] = \lim_{s \rightarrow t} (s - t)^2 = 0 \end{aligned}$$

Therefore, X is m.s. differentiable.

(b): Since $X_t = A + Bt + Ct^2$ is a linear combination of three independent Gaussian random variables, X_t is a Gaussian random variable itself. On the other hand, any linear combination of $X_t; t \in \mathbb{T}$ can be expressed as linear combination of Gaussian random variables A, B, C thus is a Gaussian itself. This argument shows that X_t 's are jointly Gaussian for different values of t .

Therefore, $Y_t = \int_0^t X_s ds$ which is a linear combination of jointly Gaussian random variables is a Gaussian for which we only need its mean and variance. We have:

$$\begin{aligned} \mathbb{E} \left[\int_0^t X_s ds \right] &= \int_0^t \mathbb{E} [X_s] ds = 0 \\ \text{Var} \left[\int_0^t X_s ds \right] &= \mathbb{E} \left[\left(\int_0^t X_s ds \right)^2 \right] - \mathbb{E}^2 \left[\int_0^t X_s ds \right] \\ &= \mathbb{E} \left[\left(\int_0^t X_s ds \right)^2 \right] \\ &= \iint_0^1 R_X(s, t) ds dt \\ &= \iint_0^1 \mathbb{E} [(A + Bs + Cs^2)(A + Bt + Ct^2)] \\ &= \iint_0^1 (\mathbb{E} [A^2] + st\mathbb{E}[B^2] + s^2t^2\mathbb{E}[C^2]) ds dt \\ &= \iint_0^1 (1 + st + s^2t^2) ds dt = \frac{49}{36} \end{aligned}$$

Therefore, $\int_0^t X_s ds \sim \mathcal{N}(0, \frac{49}{36})$ and we have $\mathcal{P} \left(\int_0^t X_s ds \geq 1 \right) = Q \left(\frac{1}{\sqrt{\frac{49}{36}}} \right) = Q\left(\frac{6}{7}\right)$

2 (7.3) Properties of a binary valued process

(a) Yes, This is a markov process. Consider a sequence $0 < t_1 < t_2 < \dots < t_n < t$, we have:

$$\begin{aligned}
 \mathbb{P}(Y_t = c | Y_{t_1} = c_1, Y_{t_2} = c_2, \dots, Y_{t_n} = c_n) &= \mathbb{P}((-1)^{N_t} = c | Y_{t_1} = c_1, Y_{t_2} = c_2, \dots, Y_{t_n} = c_n) \\
 &= \mathbb{P}((-1)^{N_{t_n}} (-1)^{N_t - N_{t_n}} = c | Y_{t_1} = c_1, Y_{t_2} = c_2, \dots, Y_{t_n} = c_n) \\
 &= \mathbb{P}((-1)^{N_t - N_{t_n}} = \frac{c}{c_n} | Y_{t_1} = c_1, Y_{t_2} = c_2, \dots, Y_{t_n} = c_n) \\
 &= \mathbb{P}((-1)^{N_t - N_{t_n}} = \frac{c}{c_n})
 \end{aligned}$$

where the last equation holds because of the independant increment property of poisson process. For the transition probability matrix we have:

$$\begin{aligned}
 p_{i,j}(s, t) &= \begin{cases} P \{N_t - N_s \text{ is even}\} & i = j \\ P \{N_t - N_s \text{ is odd}\} & i \neq j \end{cases} \\
 &= \begin{cases} \sum_{n=0}^{\infty} P \{N_t - N_s = 2n\} & i = j \\ \sum_{n=0}^{\infty} P \{N_t - N_s = 2n + 1\} & i \neq j \end{cases} \\
 &= \begin{cases} \sum_{n=0}^{\infty} e^{-\lambda(t-s)} \frac{(\lambda(t-s))^{2n}}{(2n)!} & i = j \\ \sum_{n=0}^{\infty} e^{-\lambda(t-s)} \frac{(\lambda(t-s))^{2n+1}}{(2n+1)!} & i \neq j \end{cases} \\
 &= \begin{cases} e^{-\lambda(t-s)} \cosh(\lambda(t-s)) & i = j \\ e^{-\lambda(t-s)} \sinh(\lambda(t-s)) & i \neq j \end{cases} \\
 &= \begin{cases} e^{-\lambda(t-s)} \frac{e^{\lambda(t-s)} + e^{-\lambda(t-s)}}{2} & i = j \\ e^{-\lambda(t-s)} \frac{e^{\lambda(t-s)} - e^{-\lambda(t-s)}}{2} & i \neq j \end{cases} \\
 &= \begin{cases} \frac{1+e^{-2\lambda(t-s)}}{2} & i = j \\ \frac{1-e^{-2\lambda(t-s)}}{2} & i \neq j \end{cases}
 \end{aligned}$$

Having transition probability, one easily has:

$$Q = \begin{pmatrix} -\lambda & \lambda \\ \lambda & -\lambda \end{pmatrix}$$

(b) Yes. Y_t is mean square continuous. The easiest way to prove is to directly use the definition of m.s. continuity:

$$\begin{aligned}
\lim_{t \rightarrow s} \mathbb{E} \left[(Y_t - Y_s)^2 \right] &= \lim_{t \rightarrow s} \mathbb{E} \left[\left((-1)^{N_t} - (-1)^{N_s} \right)^2 \right] \\
&= \lim_{t \rightarrow s} \mathbb{E} \left[\mathbb{E} \left[\left((-1)^{N_t} - (-1)^{N_s} \right)^2 \mid N_t - N_s \right] \right] \\
&= \lim_{t \rightarrow s} \mathbb{E} \left[2^2 I_{\{N_t - N_s \text{ is odd}\}} + 0 I_{\{N_t - N_s \text{ is even}\}} \right] \\
&= \lim_{t \rightarrow s} 4P\{N_t - N_s \text{ is odd}\} \\
&= \lim_{t \rightarrow s} 2 - 2e^{-2\lambda|t-s|} = 0
\end{aligned}$$

(c) No. Y_t is not differentiable in mean square sense. For this, we use the fact that a random process Y is differentiable in m.s. sense if and only if R_Y and its first-order partial derivatives exist and are continuous. Here, we have:

$$\begin{aligned}
R_Y(s, t) &= \mathbb{E} [Y_s Y_t] \\
&= \mathbb{E} \left[(-1)^{N_s} (-1)^{N_t} \right] \\
&= \mathbb{E} \left[I_{\{N_s - N_t \text{ is even}\}} - I_{\{N_s - N_t \text{ is odd}\}} \right] \\
&= P\{N_s - N_t \text{ is even}\} - P\{N_s - N_t \text{ is odd}\} \\
&= \frac{1 + e^{-2\lambda|t-s|}}{2} - \frac{1 - e^{-2\lambda|t-s|}}{2} \\
&= e^{-2\lambda|t-s|}
\end{aligned}$$

R_Y is continuous but its derivatives are discontinuous around $t = s$. Therefore Y is not m.s. differentiable.

(d) Yes. This limit exists in the m.s. sense and is equal zero.

To see why, first note that since R_Y is continuous, the integral itself exists in the m.s. sense. Then, the limit of time average exists in the m.s. sense if $\mathbb{E} \left[\left(\frac{1}{T} \int_0^T y_t dt - 0 \right)^2 \right]$ can be made arbitrarily small as $T \rightarrow \infty$.

$$\begin{aligned}
\mathbb{E} \left[\left(\frac{1}{T} \int_0^T y_t dt - 0 \right)^2 \right] &= \frac{1}{T^2} \mathbb{E} \left[\left(\int_0^T y_t dt \right)^2 \right] \\
&= \frac{1}{T^2} \int_0^T \int_0^T R_Y(s, t) ds dt \\
&= \frac{1}{T^2} \int_0^T \int_0^T e^{-2\lambda|t-s|} ds dt \\
&= \frac{1}{T^2} \int_0^T \int_0^t e^{-2\lambda(t-s)} ds dt + \frac{1}{T^2} \int_0^T \int_0^s e^{-2\lambda(s-t)} dt ds \\
&= \frac{2}{T^2} \int_0^T \int_0^t e^{-2\lambda(t-s)} ds dt \\
&= \frac{2}{T^2} \int_0^T \left[\frac{e^{-2\lambda(t-s)}}{2\lambda} \right]_0^t dt \\
&= \frac{2}{T^2} \int_0^T \frac{1 - e^{-2\lambda t}}{2\lambda} dt \\
&= \frac{2}{T^2} \left[\frac{t}{2\lambda} - \frac{e^{-2\lambda t}}{-4\lambda^2} \right]_0^T \\
&= \frac{2}{T^2} \left[\frac{T}{2\lambda} + \frac{e^{-2\lambda T} - 1}{4\lambda^2} \right] \\
&= \frac{1}{\lambda T} + \frac{e^{-2\lambda T} - 1}{2\lambda^2 T^2}
\end{aligned}$$

As we can see, $\lim_{T \rightarrow \infty} \frac{1}{\lambda T} + \frac{e^{-2\lambda T} - 1}{2\lambda^2 T^2} = 0$ and our claim is justified.

3 (7.15) Integral of a Brownian bridge

(a) To see if B_t defined as $B_t = W_t - tW_1$ is integrable, we have to see whether its autocorrelation function is integrable and if it is finite.

$$\begin{aligned}
\int_0^1 \int_0^1 R_B(s, t) ds dt &= \int_0^1 \int_0^t s(1-t) ds dt + \int_0^1 \int_0^s t(1-s) dt ds \\
&= 2 \int_0^1 \int_0^t s(1-t) ds dt \\
&= 2 \int_0^1 \frac{t^2}{2} (1-t) dt \\
&= 2 \left[\frac{t^3}{6} - \frac{t^4}{8} \right]_0^1 = \frac{1}{12}
\end{aligned}$$

Since R_B is integrable on $[0, 1]$, B_t is also integrable on $[0, 1]$, so $X = \int_0^1 B_t dt$ is well defined in the m.s. sense.

(b) For the joint distribution of a jointly Gaussian random variable, we need to specify means and correlations. We have:

$$\begin{aligned}\mathbb{E}[X] &= \mathbb{E} \left[\int_0^1 W_t dt \right] - \mathbb{E} \left[W_1 \int_0^1 t dt \right] \\ &= \mathbb{E} \left[\int_0^1 W_t dt \right] - \frac{1}{2} \mathbb{E}[W_1] = 0\end{aligned}$$

$$\begin{aligned}\text{Var}(X) &= \mathbb{E} \left[\left(\int_0^1 B_t dt \right)^2 \right] \\ &= \int_0^1 \int_0^1 R_B(s, t) ds dt = \frac{1}{12}\end{aligned}$$

X and W_1 have covariance

$$\begin{aligned}\text{Cov}(X, W_1) &= \mathbb{E}[XW_1] \\ &= \mathbb{E} \left[W_1 \int_0^1 (W_t - tW_1) dt \right] \\ &= \mathbb{E} \left[\int_0^1 W_1 W_t dt - W_1 W_1 \int_0^1 t dt \right] \\ &= \int_0^1 \mathbb{E}[W_1 W_t] dt - \mathbb{E}[W_1 W_1] \int_0^1 t dt \\ &= \int_0^1 R_W(1, t) dt - \frac{1}{2} R_W(1, 1) \\ &= \int_0^1 t dt - \frac{1}{2} \\ &= \frac{1}{2} - \frac{1}{2} = 0\end{aligned}$$

X and W_1 are uncorrelated and therefore independent. They have a joint Gaussian distribution:

$$\begin{pmatrix} X \\ W_1 \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \frac{1}{12} & 0 \\ 0 & 1 \end{pmatrix} \right)$$