

Ex 10.1: Let  $s \leq t$ , then we have that:

$$\begin{aligned} B(s) + B(t) &= B(t) - B(s) + B(s) + B(s) \xrightarrow{\stackrel{s=0}{\sim}} B(0) \xrightarrow{\stackrel{t=0}{\sim}} B(0) \\ &= B(t) - B(s) + 2(B(s) - B(0)) \end{aligned}$$

By the independence of increments property, we have:  $[B(t) - B(s)] \perp\!\!\!\perp [B(s) - B(0)]$

Moreover, we know:  $\begin{cases} B(t) - B(s) \sim N(0, t-s), \\ B(s) - B(0) \sim N(0, s) \end{cases}$

Thus by the "linear combination" property of Gaussian random variables, we get:

$$B(s) + B(t) \sim N(0, \underbrace{t-s+2s}_{=t+3s})$$

Ex 10.2: Let  $s \leq t$ , then we know that  $\begin{cases} X(s) \sim N(\mu_s, \sigma^2_s) \\ X(t) \sim N(\mu_t, \sigma^2_t) \end{cases}$

Hence  $\begin{bmatrix} X(s) \\ X(t) \end{bmatrix} \sim N_2(\Lambda, \Sigma)$  where:

$$\Lambda = \begin{bmatrix} \mu_s \\ \mu_t \end{bmatrix} \quad \text{and} \quad \Sigma = \begin{bmatrix} \sigma^2_s & \text{cov}(X(s), X(t)) \\ \text{cov}(X(s), X(t)) & \sigma^2_t \end{bmatrix}$$

Now

$$\begin{aligned} \text{cov}(X(s), X(t)) &= E[(X(s) - \mu_s)(X(t) - \mu_t)] \\ &= E[X(s)X(t)] - E[X(s)].E[X(t)] \\ &= E[X(s).((X(t) - X(s) + X(s))] - \mu_s \cdot \mu_t \\ &= E[X(s).((X(t) - X(s)))] + E[X(s)^2] - \mu_s^2 \end{aligned}$$

$$\begin{aligned} (\text{indep. of increments}) &= \underbrace{E[X(s)]}_{\mu_s} \cdot \underbrace{E[(X(t) - X(s))]}_{\sigma^2_s} + \underbrace{\sigma^2_s \cdot s + (\mu_s)^2}_{\downarrow} - \mu_s^2 \cdot t \\ &= \mu_s \times (t-s) \cdot p + \sigma^2_s + \mu_s^2 - \mu_s^2 \cdot t \\ &= \cancel{\mu_s \cdot t} - s^2 \cancel{\mu^2} + \sigma^2_s + \mu_s^2 \cancel{- \mu_s^2 \cdot t} = \sigma^2_s \end{aligned}$$

Hence

$$\Sigma = \begin{bmatrix} \sigma^2_s & \sigma^2_s \\ \sigma^2_s & \sigma^2_t \end{bmatrix} \quad \square$$

Problem 4 in Exam 2007:

a) See previous exercise 10.3.

b) Let  $Z(t) := \frac{W(t)}{\sqrt{t}}$  then  $\text{Var}(Z(t)) = \left(\frac{1}{\sqrt{t}}\right)^2 \cdot \text{Var}(W(t)) = \frac{1}{t} \sigma^2 = \frac{\sigma^2}{t}$

$$\begin{aligned}\text{Cov}(Z(s), Z(t)) &= \text{Cov}\left(\frac{W(s)}{\sqrt{s}}, \frac{W(t)}{\sqrt{t}}\right) = \frac{1}{\sqrt{s}\sqrt{t}} \text{Cov}(W(s), W(t)) \\ &= \frac{1}{\sqrt{s}\sqrt{t}} \cdot \sigma^2 s = \sigma^2 \cdot \frac{\sqrt{s}}{\sqrt{t}}\end{aligned}$$

Thus  $\text{Cov}(Z(s), Z(t)) = \frac{\sigma^2 \frac{\sqrt{s}}{\sqrt{t}}}{\sqrt{s}\sqrt{t}} = \sqrt{\frac{s}{t}}$   $\square$

$\Sigma$  7.2: We know that  $S_0 = 0$ ,  $S_n = \sum_{i=1}^n X_i$   $X_i \sim \text{Poisson}(\mu)$

a) Since the interarrival times  $X_i$ 's are independent, we have:  $S_n \sim \text{Poisson}(\mu n)$

b) We know that (see slide 5/19 in the slides for chapters 7-10):

$$P(N(t) = n) = F_n(t) - F_{n+1}(t) \quad \text{, where } F_n \text{ is CDF of } S_n.$$

$$P(N(t) = n) = \sum_{k=0}^{n-1} \frac{e^{-\lambda t} (\lambda t)^k}{k!} - \sum_{k=0}^{n-1} \frac{e^{-\lambda t} (\lambda t)^k}{k!} ((\lambda t)^{n+1})$$

Extra exercise (Ex 7.3 [ROSS 2014]):

a)  $P(N(t) = n | S_n = y)$ ? This is the probability ~~to~~, given that at time  $y$  the  $n$ -th event has happened, that by time  $t$  there is still only  $n$  events that have happened. This probability is zero if  $y > t$  and is equal to  $P(X_{n+1} > t-y)$  i.e. the  $(n+1)$ -th event takes longer than  $(t-y)$  amount of time to happen. Thus:

$$P(N(t) = n | S_n = y) = P(X_{n+1} > t-y) \cdot \mathbb{1}_{\{y < t\}} = (1 - F(t-y)) \cdot \mathbb{1}_{\{y < t\}}$$

$$\begin{aligned}b) P(N(t) = n) &= \int_0^\infty P(N(t) = n | S_n = y) f_{S_n}(y) dy = \int_0^\infty (1 - F(t-y)) \cdot \mathbb{1}_{\{y < t\}} f_{S_n}(y) dy \\ &= \int_0^t (1 - (1 - e^{-\lambda(t-y)})) \cdot \frac{\lambda e^{-\lambda y} (\lambda y)^{n-1}}{(n-1)!} dy = \dots = \frac{\lambda^n e^{-\lambda t}}{(n-1)!} \int_0^t y^{n-1} dy = \frac{(\lambda t)^n}{n!} e^{-\lambda t}\end{aligned}$$

Thus  $N(t) \sim \text{Poisson}(\mu t)$   $\square$