

## 1 Sum of independent random variables

**Lemma 1.** *If  $X$  and  $Y$  are independent random variables, then*

$$\mathbb{P}(X + Y \leq z) = \mathbb{E}[F_X(z - Y)] = \mathbb{E}[F_Y(z - X)].$$

*Proof.* We have

$$\begin{aligned} \mathbb{P}(X + Y \leq z) &= \mathbb{E}[1_{\{X+Y \leq z\}}] \\ &= \int_{\mathbb{R}^2} 1_{\{x+y \leq z\}} d(\mathbb{P}_X \times \mathbb{P}_Y)(x, y) \\ &= \int_{\mathbb{R}} \left( \int_{\mathbb{R}} 1_{\{x+y \leq z\}} d\mathbb{P}_X(x) \right) d\mathbb{P}_Y(y) \\ &= \int_{\mathbb{R}} F_X(z - y) d\mathbb{P}_Y(y) \\ &= \mathbb{E}[F_X(z - Y)], \end{aligned}$$

where in the third inequality we used Fubini's Theorem. □

If  $X$  and  $Y$  are continuous,  $X + Y$  is also continuous, and its density can be derived by differentiating the above expression, and using Exercise 7 of HW 5 to bring the differentiation inside the integral.

## 2 Gaussian, Gamma, and Exponential distributions

**Theorem 1.**

- (a) *If  $N_1 \sim N(\mu_1, \sigma_1^2)$  and  $N_2 \sim N(\mu_2, \sigma_2^2)$ , then  $N_1 + N_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$ .*
- (b) *If  $G_1 \sim \text{Gamma}(k_1, \theta)$  and  $G_2 \sim \text{Gamma}(k_2, \theta)$ , then  $G_1 + G_2 \sim \text{Gamma}(k_1 + k_2, \theta)$ .*
- (c) *If  $N \sim N(0, 1)$ , then  $N^2 \sim \text{Gamma}(1/2, 2)$*
- (d) *If  $X, Y \sim N(0, 1)$ , then  $X^2 + Y^2 \sim \text{Exp}(2)$ .*
- (e) *If  $X, Y \sim N(0, 1)$ , then  $\sqrt{X^2 + Y^2}$  and  $\arcsin(Y/\sqrt{X^2 + Y^2})$  are independent. Furthermore,  $\arcsin(Y/\sqrt{X^2 + Y^2})$  is uniform over  $(-\pi/2, \pi/2)$ .*

*Proof.* (a) It follows from applying the convolution formula for continuous random variables, and doing lots of algebra. The whole thing is even in Wikipedia:

[https://en.wikipedia.org/wiki/Sum\\_of\\_normally\\_distributed\\_random\\_variables](https://en.wikipedia.org/wiki/Sum_of_normally_distributed_random_variables)

- (b) It also follows from applying the convolution formula, and doing some algebra. For the sake of simplicity, we prove it for the case  $\theta = 1$ .

$$\begin{aligned}
f_{G_1+G_2}(z) &= \int_0^z f_{G_1}(x)f_{G_2}(z-x) dx \\
&= \int_0^z \frac{x^{k_1-1}e^{-x}}{\Gamma(k_1)} \frac{(z-x)^{k_2-1}e^{-(z-x)}}{\Gamma(k_2)} dx \\
&= e^{-z} \int_0^z \frac{x^{k_1-1}(z-x)^{k_2-1}}{\Gamma(k_1)\Gamma(k_2)} dx && \text{variable change: } x=zt \\
&= e^{-z} z^{k_1+k_2-1} \int_0^1 \frac{t^{k_1-1}(1-t)^{k_2-1}}{\Gamma(k_1)\Gamma(k_2)} dt && \text{almost the density of a Beta}(k_1, k_2) \text{ r.v.} \\
&= \frac{e^{-z} z^{k_1+k_2-1}}{\Gamma(k_1+k_2)}
\end{aligned}$$

- (c) We have

$$\mathbb{P}(N^2 \leq z) = \mathbb{P}(|N| \leq \sqrt{z}) = 2 \int_0^{\sqrt{z}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx.$$

Then, differentiating with respect to  $z$ , we obtain

$$f_{N^2}(z) = \frac{z^{\frac{1}{2}-1} e^{-\frac{z}{2}}}{\sqrt{2\pi}},$$

which is the density of a *Gamma*(1/2, 2).

- (d) From (c), we know that  $X^2$  and  $Y^2$  are *Gamma*(1/2, 2). Then, applying (b) we get that  $X^2 + Y^2$  is *Gamma*(1, 2), which is the same as *Exp*(2).
- (e) Note that  $R = \sqrt{X^2 + Y^2}$  and  $\Theta = \arcsin(Y/\sqrt{X^2 + Y^2})$  correspond to the radius and angle in polar coordinates. As a result, the probability of the event  $\{0 \leq \Theta \leq \theta_0\} \cap \{R \leq r_0\}$  can be computed using polar coordinates as follows:

$$\begin{aligned}
\mathbb{P}(\{0 \leq \Theta \leq \theta_0\} \cap \{R \leq r_0\}) &= \int_{\{0 \leq \Theta \leq \theta_0\} \cap \{R \leq r_0\}} \frac{1}{2\pi} e^{-\frac{x^2+y^2}{2}} dx dy \\
&= \int_0^{\theta_0} \int_0^{r_0} \frac{1}{2\pi} e^{-\frac{r^2}{2}} r dr d\theta \\
&= \theta_0 \int_0^{r_0} \frac{1}{2\pi} e^{-\frac{r^2}{2}} r dr \\
&= \mathbb{P}(0 \leq \Theta \leq \theta_0) \mathbb{P}(R \leq r_0).
\end{aligned}$$

Thus, they are independent, and  $\Theta$  is uniform. □

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