

# Loi de Poisson bivariée Teicher

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## Résumé

Ce document contient les preuves de la fonction de densité et de l'espérance conditionnelle de la loi Poisson Teicher et celle de l'espérance tronquée de la loi exponentielle EFGM.

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# 1 Poisson Teicher

## 1.1 Définition

On a

$$M_1 = K_1 + K_0, \quad M_2 = K_2 + K_0$$

où  $M_i \sim \text{Pois}(\lambda_i)$ ,  $i = 1, 2$  et  $K_i = \text{Pois}(\alpha_i)$ ,  $i = 0, 1, 2$  avec  $K_0 \perp\!\!\!\perp K_1 \perp\!\!\!\perp K_2$ .

## 1.2 Fonction de densité

*Démonstration.*

$$\begin{aligned} f_{M_1, M_2}(m_1, m_2) &= \Pr(M_1 = m_1, M_2 = m_2) \\ &= \sum_{j=0}^{\min(m_1, m_2)} \Pr(M_1 = m_1, M_2 = m_2 | J_0 = j) \times \Pr(J_0 = j) \\ &= \sum_{j=0}^{\min(m_1, m_2)} \Pr(K_1 - j = m_1, K_2 - j = m_2) \times \Pr(J_0 = j) \\ &= \sum_{j=0}^{\min(m_1, m_2)} \Pr(K_1 = m_1 - j) \times \Pr(K_2 = m_2 - j) \times \Pr(J_0 = j) \\ &= \sum_{j=0}^{\min(m_1, m_2)} f_{K_1}(m_1 - j) f_{J_2}(m_2 - j) f_{J_0}(j) \end{aligned}$$

□

### 1.3 Espérance conditionnelle

*Démonstration.*

$$\begin{aligned} E[M_1|M_2 = m_2] &= E[K_1 + K_0 = m_1 | K_2 + K_0 = m_2] \\ &= \underbrace{E[K_1 | K_2 + K_0 = m_2]}_A + \underbrace{E[K_0 | K_2 + K_0 = m_2]}_B \end{aligned}$$

On commence part la partie A :

$$E[K_1 | K_2 + K_0 = m_2] \stackrel{||}{=} E[K_1] = \alpha_1 = \lambda_1 - \alpha_0$$

On passe à la partie B :

$$\begin{aligned} E[K_0 | K_2 + K_0 = m_2] &= \sum_{j=1}^{m_2} j \frac{\Pr(K_0 = j) \Pr(K_2 = m_2 - j)}{\Pr(K_2 + K_0 = m_2)} \\ &= \sum_{j=1}^{m_2} j \frac{\frac{\alpha_0^j e^{-\alpha_0}}{j!} \frac{\alpha_2^{m_2-j} e^{-\alpha_2}}{(m_2-j)!}}{\frac{(\alpha_0 + \alpha_2)^{m_2} e^{-(\alpha_0 + \alpha_2)}}{m_2!}} \\ &= \sum_{j=1}^{m_2} j \frac{m_2!}{j!(m_2-j)!} \left(\frac{\alpha_0}{\alpha_2}\right)^j \left(\frac{\alpha_2}{\alpha_0 + \alpha_2}\right)^{m_2} \\ &= \sum_{j=1}^{m_2} j \frac{m_2!}{j!(m_2-j)!} \left(\frac{\alpha_0}{\alpha_2}\right)^j \left(\frac{\alpha_2}{\alpha_0 + \alpha_2}\right)^{m_2} \left(\frac{\alpha_2}{\alpha_0 + \alpha_2}\right)^{-j} \left(\frac{\alpha_2}{\alpha_0 + \alpha_2}\right)^j \\ &= \sum_{j=1}^{m_2} j \frac{m_2!}{j!(m_2-j)!} \left(\frac{\alpha_0}{\alpha_0 + \alpha_2}\right)^j \left(\frac{\alpha_2}{\alpha_0 + \alpha_2}\right)^{m_2-j} \\ &= \sum_{j=1}^{m_2} j \frac{m_2!}{j!(m_2-j)!} \left(\frac{\alpha_0}{\alpha_0 + \alpha_2}\right)^j \left(1 - \frac{\alpha_0}{\alpha_0 + \alpha_2}\right)^{m_2-j} \\ &= \sum_{j=1}^{m_2} j \binom{m_2}{j} \left(\frac{\alpha_0}{\alpha_0 + \alpha_2}\right)^j \left(1 - \frac{\alpha_0}{\alpha_0 + \alpha_2}\right)^{m_2-j} \end{aligned}$$

On reconnais une loi binomial  $n = m_2$  et  $q = \frac{\alpha_0}{\alpha_0 + \alpha_2}$ . Donc,

$$E[K_0 | K_2 + K_0 = m_2] = m_2 \frac{\alpha_0}{\alpha_0 + \alpha_2} = m_2 \frac{\alpha_0}{\lambda_2}$$

En recombinaut A avec B on obtient

$$E[M_1 | M_2 = m_2] = \lambda_1 - \alpha_0 + m_2 \frac{\alpha_0}{\lambda_2}$$

□

## 2 Expo EFGM

On a

$$\begin{aligned} f_{X_2|X_1=x_1}(x_2) &= \frac{f_{X_1,X_2}(x_1, x_2)}{f_{X_1}(x_1)} \\ &= (1 + \theta)\beta_2 e^{-\beta_2 x_2} + 4\theta e^{-\beta_1 x_1} \beta_2 e^{-2\beta_2 x_2} - 2\theta e^{-\beta_1 x_1} \beta_2 e^{-\beta_2 x_2} - 2\theta \beta_2 e^{-\beta_2 x_2}. \end{aligned}$$

Alors,

$$\begin{aligned} E[X_2|X_1 = x_1] &= \int_0^\infty x_2 f_{X_2|X_1=x_1}(x_2) dx_2 \\ &= \int_0^\infty x_2 ((1 + \theta)\beta_2 e^{-\beta_2 x_2} + 4\theta e^{-\beta_1 x_1} \beta_2 e^{-2\beta_2 x_2} - 2\theta e^{-\beta_1 x_1} \beta_2 e^{-\beta_2 x_2} - 2\theta \beta_2 e^{-\beta_2 x_2}) dx_2 \\ &= (1 + \theta) \frac{1}{\beta_2} + 2\theta e^{-\beta_1 x_1} \frac{1}{2\beta_2} - \frac{2\theta e^{-\beta_1 x_1}}{\beta_2} - \frac{\theta}{2\beta_2} \\ &= \frac{1}{\beta_2} + \frac{\theta}{2\beta_2} - \frac{\theta e^{-\beta_1 x_1}}{\beta_2} \\ &= E[X_2] + \theta \frac{1}{\beta_2} \left( \frac{1}{2} - e^{-\beta_1 x_1} \right). \end{aligned}$$