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# Polynomial approximation of multivariate aggregate claim amounts distribution

Applications to reinsurance

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# Sommaire

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Introduction to multivariate aggregate claim amounts model

Study of a bivariate model with applications to reinsurance

A numerical method based on orthogonal polynomials

# Multivariate risk models: Capturing dependency

Modelization of aggregate claim amounts associated to

- ▶ individuals in a portfolio,
- ▶ **Different lines of business** that belong to **a given insurance company**,
- ▶ **A given line of business** of that belong to **several insurance companies**.

Claims are caused by an event, and the severities are correlated to the **magnitude** of it.

- ▶ **Third-party liability motor**: Bodily injured claims and property damage claims
- ▶ **Workers' Compensation**: Medical claims and income replacement claims

# Univariate risk model: How to include dependency?

A univariate total claim amount random variable is defined by,

$$X = \sum_{i=1}^N U_i,$$

- ▶  $N$  is a counting random variable,
- ▶  $\{U_i\}_{i \in \mathbb{N}}$  is a sequence of **i.i.d.** random variables.

Dependency occurs

- ▶ Between the **claim severities**
- ▶ Between the **claim frequencies**

## Model #1

Risk are modeled jointly via,

$$\begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix} = \sum_{j=1}^M \begin{pmatrix} V_{1j} \\ \vdots \\ V_{nj} \end{pmatrix},$$

- ▶  $\{\mathbf{V}_i\}_{i \in \mathbb{N}} = \{(V_{1i}, \dots, V_{ni})\}_{i \in \mathbb{N}}$  is a sequence of **i.i.d.** random vectors,
- ▶  $M$  is a counting random variable,
- ▶  $\{\mathbf{V}_i\}_{i \in \mathbb{N}}$ , and  $M$  are mutually independent.

# Multivariate collective model

## Model #2

Risk are modeled jointly via,

$$\begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{N_1} U_{1j} \\ \vdots \\ \sum_{j=1}^{N_n} U_{nj} \end{pmatrix},$$

- ▶  $\mathbf{N} = (N_1, \dots, N_n)$  is a counting random vectors,
- ▶  $\{\mathbf{U}_i\}_{i \in \mathbb{N}} = (\{U_{1i}\}_{i \in \mathbb{N}}, \dots, \{U_{ni}\}_{i \in \mathbb{N}})$  are independant sequences of **i.i.d.** random variables,
- ▶  $\mathbf{N}$ , and  $\{\mathbf{U}_i\}_{i \in \mathbb{N}}$  are mutually independent.

## Model #3

Risk are modeled jointly via,

$$\begin{pmatrix} X_1 \\ \vdots \\ X_n \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{N_1} U_{1j} \\ \vdots \\ \sum_{j=1}^{N_n} U_{nj} \end{pmatrix} + \sum_{j=1}^M \begin{pmatrix} V_{1j} \\ \vdots \\ V_{nj} \end{pmatrix},$$

- ▶  $\mathbf{N} = (N_1, \dots, N_n)$  is a counting random vectors,
- ▶  $\{\mathbf{U}_i\}_{i \in \mathbb{N}} = (\{U_{1i}\}_{i \in \mathbb{N}}, \dots, \{U_{ni}\}_{i \in \mathbb{N}})$  are independant sequences of **i.i.d.** random variables,
- ▶  $\{\mathbf{V}_i\}_{i \in \mathbb{N}} = \{(V_{1i}, \dots, V_{ni})\}_{i \in \mathbb{N}}$  is a sequence of **i.i.d.** random vectors,
- ▶  $M$  is a counting random variable,
- ▶  $\{\mathbf{V}_i\}_{i \in \mathbb{N}}$ ,  $\mathbf{N}$ ,  $M$  and  $\{\mathbf{U}_i\}_{i \in \mathbb{N}}$  are mutually independent.

# Two insurers and one reinsurer are in a pub.

Let 2 insurance portfolios associated to the same line of business that belong to two insurance companies,

- ▶ The aggregate claim amounts are given by

$$\begin{pmatrix} X_1 \\ X_2 \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{N_1} U_{1j} \\ \sum_{j=1}^{N_2} U_{2j} \end{pmatrix} + \sum_{j=1}^M \begin{pmatrix} V_{1j} \\ V_{2j} \end{pmatrix},$$

- ▶  $N_1$  and  $N_2$  are **independent**,
- ▶ Polynomial approximation of the joint **PDF** of  $(X_1, X_2)$



# A non-proportional global reinsurance treaty

Reinsurer offers insurer  $i$  a usual stop-loss reinsurance treaty with priority  $b_i$  and limit  $c_i$ ,  $i = 1, 2$ .

The joint distribution of  $(X_1, X_2)$  is useful

- ▶ **Pricing purposes:** Determination of the stop loss premium.
- ▶ **Risk Management purposes:** The risk exposure of the reinsurer is modeled through,

$$Z = \min [(X_1 - b_1)_+, c_1] + \min [(X_2 - b_2)_+, c_2].$$

↪ *Value-at-Risk* computation and solvency capital determination.

# A 2-dimensional Polynomial approximation

Let  $(X_1, X_2)$  be a random vector with probability measure  $\mathbb{P}_{X_1, X_2}$ , and PDF  $f_{X_1, X_2}$ .

- ▶  $\nu$  is a reference probability measure, constructed via the product of two univariate probability measure,

$$\nu(x_1, x_2) = \nu_1(x_1) \times \nu_2(x_2)$$

$$f_\nu(x_1, x_2) = f_{\nu_1}(x_1) \times f_{\nu_2}(x_2)$$

- ▶  $\{Q_k^{\nu_i}\}_{k \in \mathbb{N}}$  is an orthonormal polynomial system  $\nu_i$ ,  $i = 1, 2$ .
- ▶  $\{Q_{k,l}\}_{k,l \in \mathbb{N}}$  is an orthonormal polynomial system  $\nu$ , where

$$Q_{k,l}(x_1, x_2) = Q_k^{\nu_1}(x_1) Q_l^{\nu_2}(x_2), \quad k, l \in \mathbb{N}.$$

# A 2-dimensional Polynomial approximation

If  $\frac{d\mathbb{P}_{X_1, X_2}}{d\nu} \in L^2(\nu)$ , then

$$\frac{d\mathbb{P}_{X_1, X_2}}{d\nu}(x_1, x_2) = \sum_{k, l=0}^{+\infty} a_{k, l} Q_{k, l}(x_1, x_2),$$

where

$$a_{k, l} = \mathbb{E} [Q_{k, l}(X_1, X_2)] = \mathbb{E} [Q_k^{\nu_1}(X_1) Q_l^{\nu_2}(X_2)]$$

The Parseval identity

$$\left\| \frac{d\mathbb{P}_{X_1, X_2}}{d\nu} \right\|^2 = \sum_{k, l=0}^{+\infty} a_{k, l}^2 < +\infty$$

is checked

# Méthode d'approximation polynomiale en dimension 2

The PDF of  $(X_1, X_2)$  admits a polynomial representation

$$f_{X_1, X_2}(x_1, x_2) = \sum_{k, l=0}^{+\infty} a_{k, l} Q_{k, l}(x_1, x_2) f_{\nu}(x_1, x_2).$$

**PDF** Approximations follow from truncations,

$$f_{X_1, X_2}^{K, L}(x_1, x_2) = \sum_{k=0}^K \sum_{l=0}^L a_{k, l} Q_{k, l}(x_1, x_2) f_{\nu}(x_1, x_2),$$

where  $K$ , and  $L$  denote the orders of truncation. Survival function approximations follow from integration

$$\bar{F}_{X_1, X_2}^{K, L}(u_1, u_2) = \int_{u_1}^{+\infty} \int_{u_2}^{+\infty} \sum_{k=0}^K \sum_{l=0}^L a_{k, l} Q_{k, l}(x_1, x_2) f_{\nu}(x_1, x_2) dx_1 dx_2.$$

# Polynomial approximation for a bivariate aggregate claim model

The probability measure associated to

$$\begin{aligned} \begin{pmatrix} X_1 \\ X_2 \end{pmatrix} &= \begin{pmatrix} \sum_{j=1}^{N_1} U_{1j} \\ \sum_{j=1}^{N_2} U_{2j} \end{pmatrix} + \sum_{j=1}^M \begin{pmatrix} V_{1j} \\ V_{2j} \end{pmatrix} \\ &= \begin{pmatrix} W_1 \\ W_2 \end{pmatrix} + \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix}, \end{aligned}$$

has a lot of singularities.

# On the choice of the reference probability measure

- ▶ The probability measure of  $\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \sum_{j=1}^M \begin{pmatrix} V_{1j} \\ V_{2j} \end{pmatrix}$ , is

$$d\mathbb{P}_{Y_1, Y_2}(y_1, y_2) = f_M(0)\delta_{0,0}(y_1, y_2) + d\mathbb{G}_{Y_1, Y_2}(y_1, y_2).$$

$d\mathbb{G}_{Y_1, Y_2}$  is a defective probability measure having support on  $\mathbb{R}_+^2$ .

- ▶  $\nu$  is defined as the product of gamma measures.

↪  $\nu_i$  is a gamma measure  $\Gamma(m_i, r_i)$ ,  $i = 1, 2$ .

$$f_{\nu_i}(x) = \frac{e^{-x/m_i} x^{r_i}}{\Gamma(r_i) m_i^{r_i}}, \quad x \geq 0.$$

↪  $\{Q_k^{\nu_i}\}_{k \in \mathbb{N}}$  is sequence of generalized Laguerre polynomials,  
 $i = 1, 2$ .

# On the choice of the reference probability measure

- ▶ The probability measure of  $\begin{pmatrix} W_1 \\ W_2 \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{N_1} U_{1j} \\ \sum_{j=1}^{N_2} U_{2j} \end{pmatrix}$ , is

$$\begin{aligned} d\mathbb{P}_{W_1, W_2}(w_1, w_2) &= f_{N_1}(0)f_{N_2}(0)\delta_{0,0}(w_1, w_2) \\ &+ d\mathbb{G}_{W_1}(w_1) \times d\mathbb{G}_{W_2}(w_2) \\ &+ f_{N_1}(0)d\mathbb{G}_{W_2}(w_2) \times \delta_0(w_1) \\ &+ f_{N_2}(0)d\mathbb{G}_{W_1}(w_1) \times \delta_0(w_2). \end{aligned}$$

- ▶ Univariate polynomial approximation for  $\mathbb{G}_{W_i}$ ,  $i = 1, 2$ .
  - ↪ Gamma probability measure and generalized Laguerre polynomials.

# On the integrability condition

## Theorem

Let  $\mathbf{Y} = (Y_1, Y_2)$  be a random vector. If

**H1** The set

$$\Gamma_{\mathbf{Y}} = \inf\{(\mathbf{s}_1, \mathbf{s}_2) \in \mathbb{R}_{+*}^2, \mathcal{L}_{\mathbf{Y}}(\mathbf{s}_1, \mathbf{s}_2) = +\infty\},$$

is not empty.

**H2** There exists  $\mathbf{a} = (a_1, a_2) \in \mathbb{R}_+^2$  such that  $y_i \mapsto f_{\mathbf{Y}}(y_1, y_2)$  are strictly decreasing for  $y_i \geq a_i$ , and  $i = 1, 2$ .

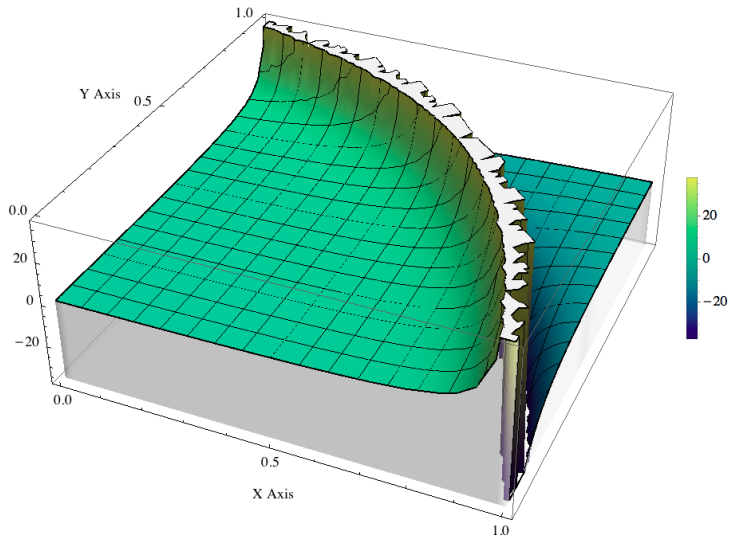
Then for  $\mathbf{y} \geq \mathbf{a}$ ,

$$f_{\mathbf{Y}}(y_1, y_2) \leq A_{\mathbf{Y}}(\mathbf{s}_1, \mathbf{s}_2) e^{-(s_1 y_1 + s_2 y_2)}, \quad \mathbf{s} \leq \gamma_{\mathbf{Y}},$$

where  $\gamma_{\mathbf{Y}} \in \Gamma_{\mathbf{Y}}$ .



# On the integrability condition



# On the integrability condition

1. Find  $(\gamma_{Y_1}, \gamma_{Y_2})$  such that

$$\mathcal{L}_{Y_1, Y_2}(\gamma_{Y_1}, \gamma_{Y_2}) < +\infty$$

and

$$\gamma_{Y_1}, \gamma_{Y_2} > 0$$

2. Choose  $r_1, r_2, m_1,$  and  $m_2$  such that

$$0 < r_1, r_2 \leq 1$$

and

$$0 < \frac{1}{m_1} < 2\gamma_{Y_1}, \quad 0 < \frac{1}{m_2} < 2\gamma_{Y_2}.$$

## Generating function study

The defective **PDF** of  $(Y_1, Y_2)$  admits the polynomial representation

$$g_{Y_1, Y_2}(y_1, y_2) = \sum_{k, l=0}^{+\infty} a_{k, l} Q_{k, l}(y_1, y_2) f_\nu(y_1, y_2).$$

Taking the Laplace transform leads to

$$C(z_1, z_2) = (1 + z_1)^{-r_1} (1 + z_2)^{-r_2} L_{g_{Y_1, Y_2}} \left[ \frac{z_1}{m_1(1 + z_1)}, \frac{z_2}{m_2(1 + z_2)} \right],$$

where  $C(z_1, z_2) = \sum_{k, l=0}^{+\infty} a_{k, l} c_k^{\nu_1} c_l^{\nu_2} z_1^k z_2^l$ , and

$$c_k^{\nu_i} = \sqrt{\binom{k + r_i - 1}{k}}, \quad i = 1, 2.$$

## Survival function of $(Y_1, Y_2)$

- ▶  $M$  is governed by a geometric distribution  $\mathcal{NB}(1, 3/4)$
- ▶  $(V_1, V_2)$  is governed by a bivariate exponential distribution  $DBVE(\rho, \mu_1, \mu_2)$ 
  - ↪  $\rho = \frac{1}{4}$
  - ↪  $\mu_1 = \mu_2 = 1$
- ▶ Polynomial approximations are compared to Monte-Carlo based approximations.

The parametrization

$$m_1 = \frac{1}{(1-p)\mu_1}, \quad m_2 = \frac{1}{(1-p)\mu_2}, \quad r_1 = r_2 = 1.$$

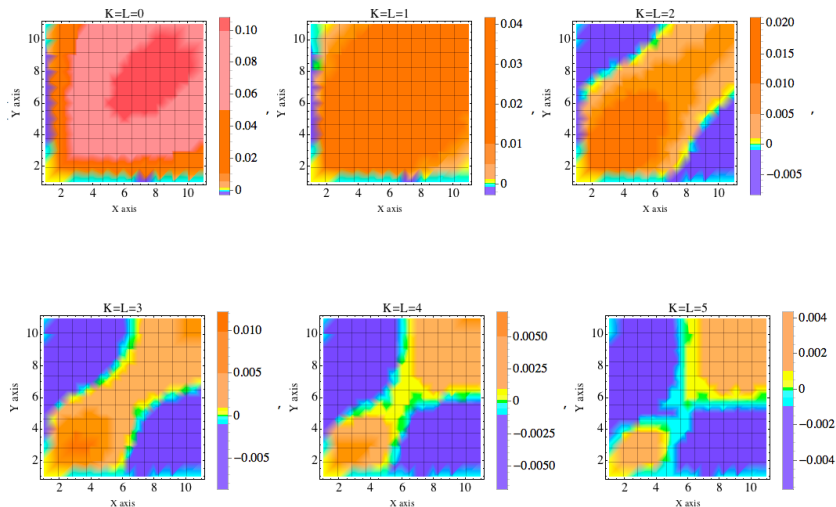
leads to a generating function of the form

$$C(z_1, z_2) = \frac{1}{1 + z_1 z_2 (p^2 - \rho(1-p)^2 - p)}.$$

and

$$a_{k,l} = [p^2 - \rho(1-p)^2 - p]^k \delta_{kl}, \quad k, l \in \mathbb{N}$$

# Numerical illustrations: Survival function of $(Y_1, Y_2)$



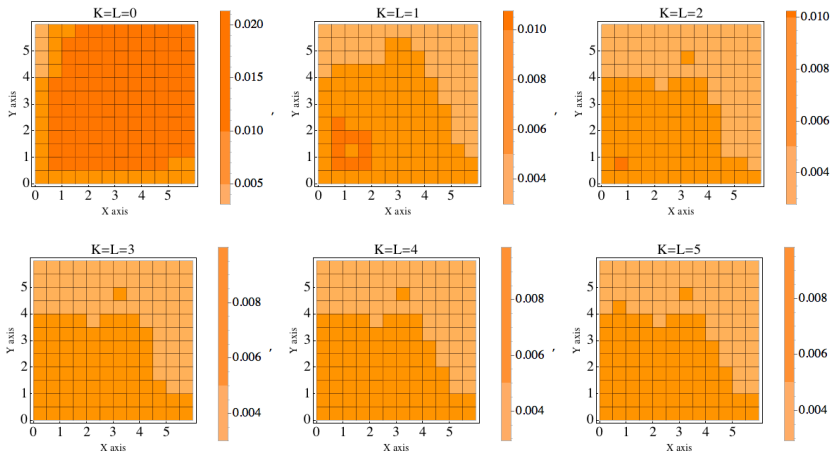
# Numerical illustrations: Distribution of $(X_1, X_2)$

- ▶  $N_1$  and  $N_2$  are geometrically distributed  $\mathcal{NB}(1, 3/4)$ ,
- ▶  $\{U_{1j}\}_{j \in \mathbb{N}}$  are  $\{U_{2j}\}_{j \in \mathbb{N}}$  are sequences of **i.i.d.**  $\Gamma(1, 1)$ -distributed,  
    ↪ The **PDF** is available in a closed form.
- ▶ Polynomial approximation of the survival function of  $(X_1, X_2)$  with increasing truncation order.
- ▶ Priorities:  $c_1 = c_2 = 1$ .
- ▶ Limits:  $b_1 = b_2 = 4$ .
- ▶ Polynomial approximations with orders of truncation equal to 10 of the survival function of

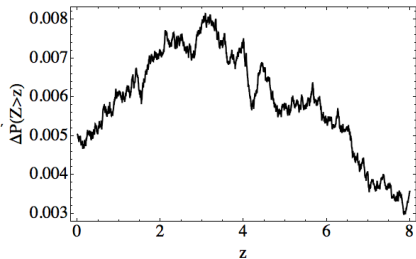
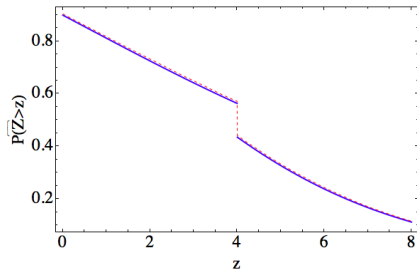
$$Z = \min [(X_1 - b_1)_+, c_1] + \min [(X_2 - b_2)_+, c_2].$$

- ▶ The polynomial approximations are compared to Monte Carlo approximations.

# Numerical illustrations: Survival function of $(X_1, X_2)$



# Numerical illustrations: Reinsurance cost



$z$	Monte Carlo approximation	Polynomial approximation
0	0.90385	0.898808
2	0.73193	0.724774
4	0.44237	0.435013
6	0.24296	0.237576



# Conclusion and Perspectives

- ▶ The polynomial approximation is an efficient numerical method:
  - ↪ A good approximation of a bivariate aggregate claim amounts going along with motivation in reinsurance.

## Perspectives

- ▶ Applications of the method to the approximation of other function in actuarial science and other fields of applied probabilities.
- ▶ Statistical extensions when data are available,
- ↪ The approximation can turn into a semi-parametric estimator of the **PDF**.