

# Actuarial Modeling of Cyber Risk

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# Outline

- 1 Introduction
- 2 Severity component and Generalized Pareto regression tree
- 3 A generic model for stochastic scenarios generation
- 4 Frequency component and Hawkes processes
- 5 Conclusion

# Cyber-risk

## ■ An important growing risk

- According to J. Powell (President of the U.S. Federal Reserve) cyber-attacks constitute the main threat to the global financial system.
- Huge costs : estimated to 1 % of the global GDP.

## ■ A multifaceted risk

- Various types of attacks (ransomware, phishing, classic frauds...)
- A cyber incident can be voluntary (cyber attack) or not.
- Multiple consequences of a cyber-incidents: Business interruption (sometimes months before retrieving the same level of activity), Loss of data, Indirect damages (in some cases, destruction or death).
- Strike states, companies, public administrations, individuals.

## ■ Role of Cyber-insurance

- a fundamental tool to improve the resilience of the economy.
- Cyber insurance includes various guarantees: financial reparation, immediate assistance to restart the activity, prevention and risk analysis. protection against regulation issues caused by leaks of data, crisis communication...



# Cyber-risk specificities

- 1 The risk is **new** and **constantly evolving** with a fast adaptation of the attackers (in case of malicious cyber). Very few data available
- 2 Changes through time in the reporting behavior, due to regulation and evolution in the perception of the risk.
- 3 **Extreme** events (huge losses can occur): cyber-risk has a catastrophic component. But unlike natural disaster, it is not stable since relying on human behavior. This behavior changes rapidly through time.
- 4 **Accumulation risk** : cyber-risk has a systemic component. Potential concentration of incidents which leads to loss of mutualization.

**These features may endanger risk pooling.**

Difficult quantification of the economic losses due to cyber risk



# Endangering risk pooling

- Risk pooling relies on the Law of Large Number.
- TCL : control the gap between the total losses and the premium.
- Risk pooling is endangered as soon as:
  - the risk is so volatile that **variance is infinite**.
  - the risk is "heavy tailed" and the average cost may not be defined.
  - variance is finite, but very large, because of the heterogeneity of the population.
  - policyholders are not **independent**.
  - the number of policyholders is too low.
- The event insured should be sufficiently **rare**.
- Imprecision related to statistical estimation  
(few available data + data quality issue)



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# Extremes events and heavy tailed distribution

- Cyber losses: typically the case of **heavy tail** distributions.
  - corresponds to distribution with high dispersion, i.e. with slow rate of decrease of the density function.
  - Can take high values with significantly high probability
- In statistics : corresponds to **Extreme Value Theory**.
- This theory allows to identify common behaviors in the tail of distributions.
- The **tail index**, often denoted  $\gamma$ , allows to determine the heaviness of the tail.

How to adapt classification and regression techniques to this context?



## Peaks over threshold

- Asymptotically ( $u \rightarrow \infty$ ), exceedances  $X = Y - u$  over the threshold  $u$  occur according to (univariate) generalized Pareto distribution
- **Theorem of Pickands (1975)**: If there exists  $(a_u) > 0$ ,  $(b_u)$  and a cumulative distribution function  $H$  such that

$$\lim_{u \rightarrow \infty} \mathbb{P}[Y - u \geq a_u x + b_u \mid Y > u] \rightarrow_{u \rightarrow \infty} 1 - H(x),$$

then  $H$  is a **Generalized Pareto distribution** (GPD)

$$H_{\sigma, \gamma}(x) = \begin{cases} 1 - \left(1 + \frac{\gamma}{\sigma} x\right)^{-1/\gamma} & \text{if } \gamma \neq 0 \\ 1 - \exp\left(-\frac{x}{\sigma}\right) & \text{if } \gamma = 0. \end{cases}$$

- $\sigma$  = scale parameter,  $\gamma$  = shape parameter (called the tail index)





# Tail index

- Typically three types of behaviors depending on  $\gamma$ 
  - $\gamma < 0$ : « Weibull domain », light tail distributions
  - $\gamma = 0$ : « Gumbel domain », also light tail, like normal distribution or log-normal.
  - $\gamma > 0$ : « Fréchet domain »: heavy tail, Pareto-like distributions.
- A way to classify a distribution with respect to its tail behavior.
- If  $\gamma > 0.5$ , variance is infinite: mutualisation is less efficient (a much larger value of policyholders is required).
- If  $\gamma > 1$ , the average loss is not properly defined (one sometimes says it is "non insurable").



# Generalized Pareto CART

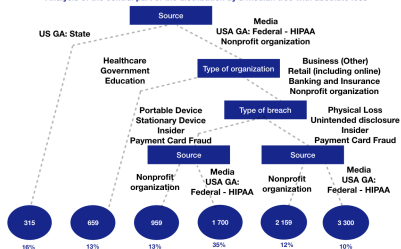
- **Building risk classes**, focusing on the tail characteristic of the distribution (Farkas, Lopez, Thomas (2021))
- Using modified **CART** (Clustering And Regression Tree) introduced by Breiman et al. (1984): **Generalized Pareto regression trees**
- **Applications:**
  - classification of vulnerabilities/risk factors,
  - help to separate types of incidents or circumstances according to whether they can be covered without endangering risk pooling.
  - design of parametric insurance products.



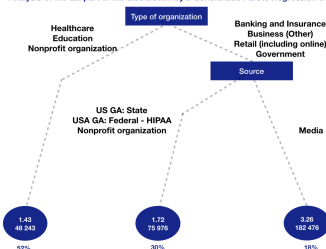
## Illustration on the PRC database

- Privacy Rights Clearing House data-base (PRC). 8800 events over the period 2005-2019.
- Left: **standard CART**, with splitting rule using an absolute loss (median regression) → risk factors for classification for the central part of the distribution,
- Right: **Generalized Pareto regression tree**, with splitting rule using a GDP-log-likelihood loss → risk factors for classification for the tail

Analysis of the central part of the distribution by a median tree with absolute loss



Analysis of the tail part of the distribution by a Generalized Pareto Regression tree



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## Loss of risk pooling : when there is no independence

- Example in insurance : natural catastrophes and portfolios with spatial correlations:



- But for cyber risk: how to define proximity?
- Tool to test diversification of a cyber portfolio: accumulation scenarios based on epidemiological models with network effects.

## Contagion models with networks effects

- Multi-group SIR (Susceptible-Infected-Removed) models with different sub-populations.

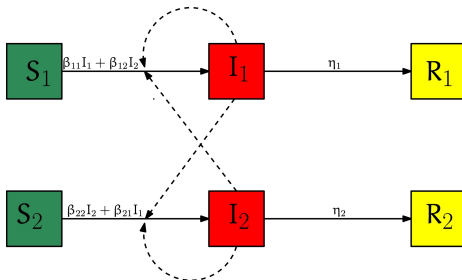


Figure from Magal et al. (2018)

- $\mathcal{B} = (\beta_{i,j})_{1 \leq i,j \leq K}$  matrix of infection rates :  $\beta_{i,j}$  materializes how  $j$  contaminates  $i$ .
- We also introduce a flexible framework to model the initial attacks that trigger the contagion.

# Multigroup compartmental epidemiological model

- Multi-group SIR: consider  $K$  **subpopulations**:  $1 \leq i \leq K$

$$\frac{dS_i(t)}{dt} = - \left( \alpha_i(t) + \sum_{j=1}^K \beta_{i,j} I_j(t) \right) S_i(t)$$

$$\frac{dI_i(t)}{dt} = \left( \alpha_i(t) + \sum_{j=1}^K \beta_{i,j} I_j(t) \right) S_i(t) - \gamma_i I_i(t)$$

$$\frac{dR_i(t)}{dt} = \sum_{i=1}^K \gamma_i I_i(t).$$

- $\mathcal{B}$  matrix of infection rate :  $\beta_{i,j}$  materializes how  $j$  contaminates  $i$ .  
→ **network effects**.

- $\alpha_i(t)$  represents an intensity of attacks in class  $i$ .

Example: single initial burst  $\alpha_i(t) = \alpha 1_{0 \leq t < 1}$  for some  $i$ .

# Impact of protection measures

- Multi-group SIR: consider  $K$  subpopulations:

$$\frac{dS_i(t)}{dt} = -\eta_i(t) \left( \alpha_i(t) + \sum_{j=1}^K \beta_{i,j} I_j(t) \right) S_i(t)$$

$$\frac{dI_i(t)}{dt} = \eta_i(t) \left( \alpha_i(t) + \sum_{j=1}^K \beta_{i,j} I_j(t) \right) S_i(t) - \gamma_i I_i(t)$$

$$\frac{dR_i(t)}{dt} = \sum_{i=1}^K \gamma_i I_i(t).$$

- $\eta_i(t)$  represents how group  $i$  is protected against the threat.

- Example:  $\eta_i(t) = 1 - \lambda 1_{I_i(t) \geq s}$ , or  $\eta_i(t) = 1 - \lambda 1_{\sum_k I_k(t) \geq s}$



## How can we use these models?

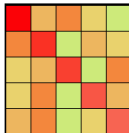
- **"Ranking" of sectors** : one can identify which group is more "systemic" than others in the sense that, if attacked, it will lead to a higher number of infected.
- **Quantifying the "peak"**: helps to identify how many "tech" assistance will be required at the peak of the crisis.  
**Saturation risk** which can cause an increase of the costs.
- **Diversification**
- **Identify the benefits of protection:**
  - of a given group: protecting some key groups may help to prevent the infection from spreading.
  - from different reaction.



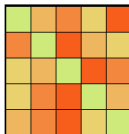
## Topology of the network

Some examples of comparisons that show the impact of the topology of the network

- Two classes of matrices  $\mathcal{B}$  :
  - "Clustered" : the transmission is essentially intern to a class.



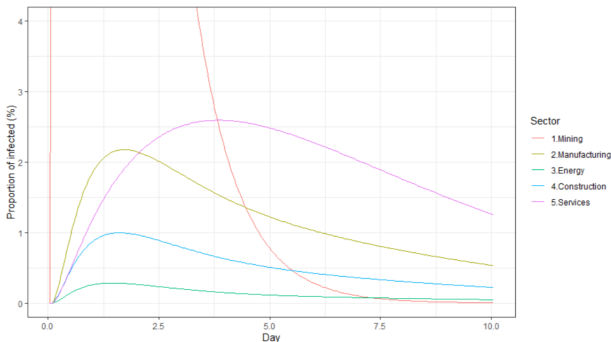
- "Non-clustered" : the transmission is stronger from one class to another than within a given class.



→ the "Non-clustered" situation is worse, since the outbreak rapidly spreads from one class to any others.

## Example of epidemic dynamics of Wannacry type

- Calibration of a Wannacry-type scenario  $\mathcal{B} = \beta \mathcal{B}_0$
- Contagion matrix  $\mathcal{B}_0$  based on macroeconomic data: OECD data to identify the connectivity between some sectors of activity.



Evolution of the proportion of infected - Attack on Mining.

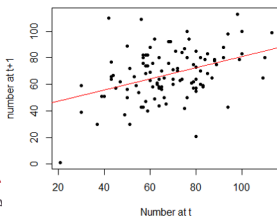
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# Auto-excitation and clustering of cyber-events

- Privacy Rights Clearing House data-base (PRC).
- Regression of the number of event during the following month  $t + 1$  as a function of the number of event during the current month  $t$  (should be independent for a Poisson process model to be valid)
- Auto-correlation dramatically increases when focusing on attacks of the same type

Regression

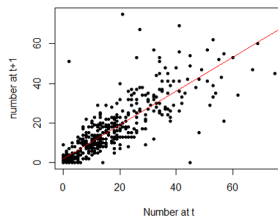


ENSA



$$R^2 = 0.154 [0.030, 0.278]$$

Regression per type of attack



$$R^2 = 0.726 [0.687, 0.766]$$

# Hawkes model

- **Hawkes processes** to model contagion of cyber events, cascading phenomenon in the supply chain : Self-exciting model with stochastic intensity, fully specified by the point process itself (equivalently its jump times  $(\tau_n)_n$ )
- $H$  Hawkes process with (deterministic) **excitation kernel  $\Phi$**  and base intensity  $\lambda_0$  is the counting process ( $H_0 = 0$ ) with intensity process

$$\lambda(t) := \lambda_0(t) + \int_{(0,t)} \Phi(t-s) dH_s = \lambda_0(t) + \sum_{\tau_n < t} \Phi(t-\tau_n) \quad t \in [0, T],$$

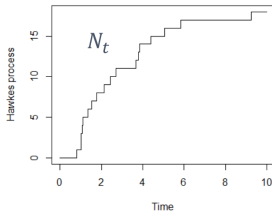
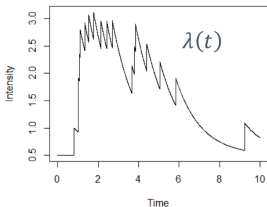
- Hawkes models used in finance, such as credit risk (Errais, Giesecke and Goldberg (2010)...), high-frequency finance (Bacry et al. (2015)...), in cyber-security (Baldwin et al. (2017)) and many others fields.



# Toy example of Hawkes process with exponential kernel

- $(H_t)_{t \geq 0}$  counting process with jump times  $(\tau_n)_{n \geq 1}$
- Intensity process of the counting process with exponential kernel

$$\lambda(t) = \mu + \sum_{\tau_n < t} \alpha \exp(-\beta(t - \tau_n))$$



- Each jump represents an attack/claim
- Intensity decreases exponentially between jumps

## Pricing Expansion formula

- Evaluation of quantities/insurance contracts (such as Stop Loss contracts) with underlying cumulative loss processes indexed by a Hawkes process (compound Hawkes process)

$$L_t = \sum_{i=1}^{H_t} X_i.$$

- 2 key ingredients : Thinning algorithm (Poisson Imbedding) + Malliavin calculus (Mecke Formula)
- **Expansion formula** : compromise between simplicity/tractability of approximate formulas and accuracy.
- Control of the error if standard valuation formulas are used (Poisson model with independence): correcting term due to the self-exciting property.





# Evaluation of insurance contracts

of the form (such as Stop Loss contracts)

$$\mathbb{E}[K_T h(L_T)] = \mathbb{E} \left[ \int_{(0,T]} Z_t dH_t F \right]$$

- $K_T$ : effective loss covered by the (re)insurance company,

$$K_T := \sum_{i=1}^{H_T} g(\eta_i, \vartheta_i) e^{-\kappa(s-\tau_i)} = \int_{(0,T]} Z_t dH_t$$

$Z$  a  $\mathbb{F}$ -predictable process,  $(\eta_i, \vartheta_i)_{i \geq 1}$  iid r.v. independent of  $H$ ,

$$Z_s := \sum_{i=1}^{+\infty} g(\eta_i, \vartheta_i) e^{-\kappa(T-s)} \mathbf{1}_{(\tau_{i-1}, \tau_i]}(s), \quad s \in [0, T]$$



■  $L_T := \sum_{i=1}^{H_T} f(\eta_i) e^{-\kappa(s-\tau_i)}$ : loss that activates the contract.

$F := h(L_T)(= \mathbf{1}_{\{m \leq L_T \leq M\}})$  is a functional of the Hawkes process.

# Malliavin IPP formula (Mecke formula)

**Aim:** transformation of  $\int \dots dH_t$  into  $\int \dots dt$ .

- If  $H = N$  is an homogeneous Poisson process with intensity  $\mu > 0$

$$\mathbb{E} \left[ \int_{(0,T]} Z_t dN_t F \right] = \mu \int_0^T \mathbb{E} [Z_v F \circ \varepsilon_v^+] dv$$

- $F \circ \varepsilon_v^+ =: F^v$  denotes the functional on the Poisson space where a deterministic jump is added to the paths of  $N$  at time  $v$
- **adding a jump at some time  $v$  = adding "artificially" a cyber event at time  $v$  (stress test).**
- In case of a Poisson process  $N$ : the additional jump at some time  $v$  only impacts the payoff of the contract by adding a new event in the cumulative loss
- **In case of a Hawkes process  $H$ : it also impacts the dynamic (after time  $v$ ) of the counting process  $H$ .**



# Thinning Algorithm

Representation of a Hawkes process in terms of a Poisson measure  $N$  on  $[0, T] \times_+$  (known as "**Poisson imbedding**" or "Thinning Algorithm")

$$\begin{cases} H_t = \int_{(0,t]} \int_+ \mathbf{1}_{\{\theta \leq \lambda_s\}} N(ds, d\theta), \\ \lambda_t = \mu + \int_{(0,t)} \Phi(t-u) dH_u. \end{cases} \quad (1)$$

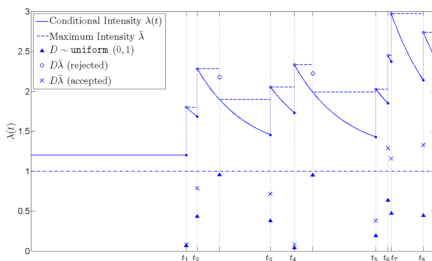


Illustration from Ogata (1981)

## Expansion formula for the Hawkes process

Assume  $Z$  bounded  $\mathbb{F}^H$ -predictable process,  $F$  bounded  $\mathcal{F}_T^N$ -measurable r.v. and  $\|\Phi\|_1 < 1$ .

$$\begin{aligned} \mathbb{E} \left[ F \int_{[0, T]} Z_t dH_t \right] &= \mu \int_0^T \mathbb{E} [Z_v F^v] dv \\ &+ \mu \sum_{n=2}^{+\infty} \int_0^T \int_0^{v_1} \cdots \int_0^{v_{n-1}} \prod_{i=2}^n \Phi(v_{i-1} - v_i) \mathbb{E} [Z_{v_1}^{v_n, \dots, v_2} F^{v_n, \dots, v_1}] dv_n \cdots dv_1. \end{aligned}$$

- the first term corresponds to the formula for a Poisson process (setting  $\Phi$  at zero)
- the sum in the second term can be interpreted as a **correcting term due to the self-exciting property** of the counting process.
- Extensions to intensity process depending of the claims' sizes.

## Concluding remarks and Extensions

- We proposed models and developed methodologies for a better assessment of cyber-risk and to contribute to the viability of the cyber-insurance economic model.
  - Taking into account the specificities of cyber-risk (high volatility in claims, accumulation risk...)
  - with a concern to their practical implementation/calibration
  - But the relevance of such modeling is currently constrained by the limited data available: a need to nourish them with consistent and reliable data (on policyholders, on claims), for a better risk analysis.
- Future works
  - Study of the behavioral aspects of the different actors (insurers, but also policyholders and hackers).
  - Transfer of risk, e.g. parametric insurance.
  - Similarities and connections with other risks : disruption of the supply chain; conjunctions between different risks (shortage of raw materials, geopolitics, health...)

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Joint Research Initiative **Cyber-risk: actuarial modeling** :

<https://sites.google.com/view/cyber-actuarial/home>



Thank you for your attention !

