



Truncated regression models for the analysis of operational losses due to fraud:

A high performance computing implementation in R

About the speaker



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- Senior Risk Analyst
- Alberto has a MSc in actuarial science and has 4 years of working experience gained in the non life insurance industry



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- **Assicurazioni Generali**
 - The 3rd largest insurer in Europe
 - Over 70 thousands employees around the World
 - Operating in more than 100 countruies

Agenda

- **Truncation Issues in Insurance Fraud Modeling**
- **AGLM**
- **Computational Challenges**
- **High Performance Computing in R**
- **Q&A**
- **Back Up**

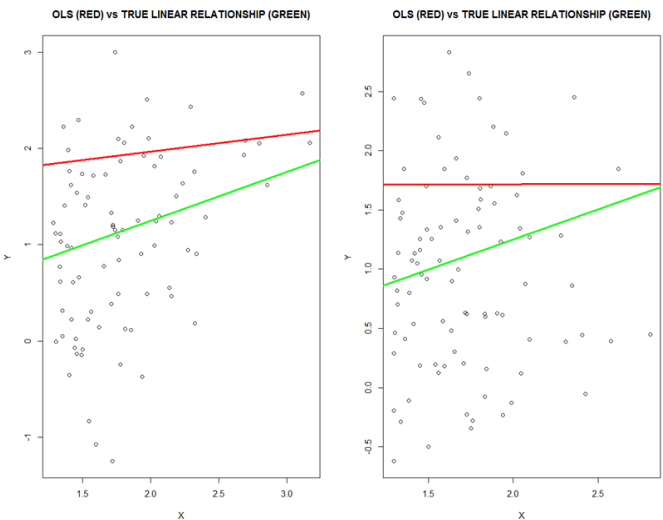


Truncation Issues in Insurance Fraud Modeling

Standard Truncation

$$Y_i^* = X_i\beta + \varepsilon_i \leq L \quad \text{included}$$

$$Y_i^* = X_i\beta + \varepsilon_i \geq L \quad \text{excluded}$$



$$L(\beta, \sigma^2 | \mathbf{y}, \mathbf{X}) = \prod_{i=1}^n \frac{\frac{1}{\sigma} \varphi\left(\frac{y_i - x_i\beta}{\sigma}\right)}{1 - \Phi\left(\frac{L - x_i\beta}{\sigma}\right)}$$



Fraud Truncation

$$Y_i^* = \sum_{j=1}^{N_i^*} Z_j^*$$

$$Y_i^* = X_i\beta + \varepsilon_i$$

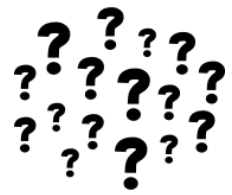
$$Z_j^* \leq L \quad \text{excluded}$$

$$Y_i^* = X_i\beta + \varepsilon_i$$

$$Z_j^* \leq L \quad \text{included}$$

The truncation has an impact on both Frequency and Severity

Standard Normal Truncated OLS may not be accurate to model these effects



AGLM (1/2)

Augmented Linear Models (AGLM) assume the following:

- $Y_i^* \left(= \sum_{j=1}^{N_i^*} Z_j^* \right)$ independent variables $\forall i$
- $Z_{i,1}^* | N_i^* = n_i, \dots, Z_{i,n_i}^* | N_i^* = n_i$ are i.i.d. random variables $\forall i$ following a lognormal distribution with parameters $Ln(\beta_0^\mu + \beta_1^\mu x_i; \sigma)$
- $\forall i N_i^* \sim Pois(e^{\beta_0^\lambda + \beta_1^\lambda x_i})$

The conditional expected value (with a logarithmic link) may be written as:

$$\log(\lambda_i) + \left(\mu_i + \frac{\sigma^2}{2} \right) = \beta_0^\mu + \beta_0^\lambda + (\beta_1^\mu + \beta_1^\lambda) x_i$$

$$\log(\lambda_i) + \left(\mu_i + \frac{\sigma^2}{2} \right) = \beta_0 + \beta_1 x_i$$

Linear Model → there are two nested linear model: one for the Frequency and one for the Severity



AGLM (2/2)

The Log-Likelihood function is:

$$\pi_i = \left(1 - F_Y^{\text{LogNorm}} \left(c, \beta_0^\mu - \frac{\sigma^2}{2} + \beta_1^\mu x_i; \sigma \right) \right)$$

$$l(\underline{y}, \underline{x}; \underline{\beta}, \sigma^2, c) = \sum_{i=1}^n \left[n(\beta_0^\lambda + \beta_1^\lambda x_i) + n \log(\pi_i) - (e^{\beta_0^\lambda + \beta_1^\lambda x_i}) \pi_i - \log(n_i!) + \sum_{j=1}^{n_i} \log \left(f_Y^{\text{Lognorm}} \left(z_j; \beta_0^\mu - \frac{\sigma^2}{2} + \beta_1^\mu x_i; \sigma \right) \right) - \log(\pi_i) \right]$$

This is possible thanks to a property of the Poisson distribution and, in general, of the Panjer Class:

$$N_D = \sum_{i=1}^N I_{\{Z_i > c\}} \quad Pr(Z > c) = \pi \quad N \sim \text{Pois}(\lambda) \quad \Rightarrow \quad N_D \sim \text{Pois}(\pi\lambda)$$

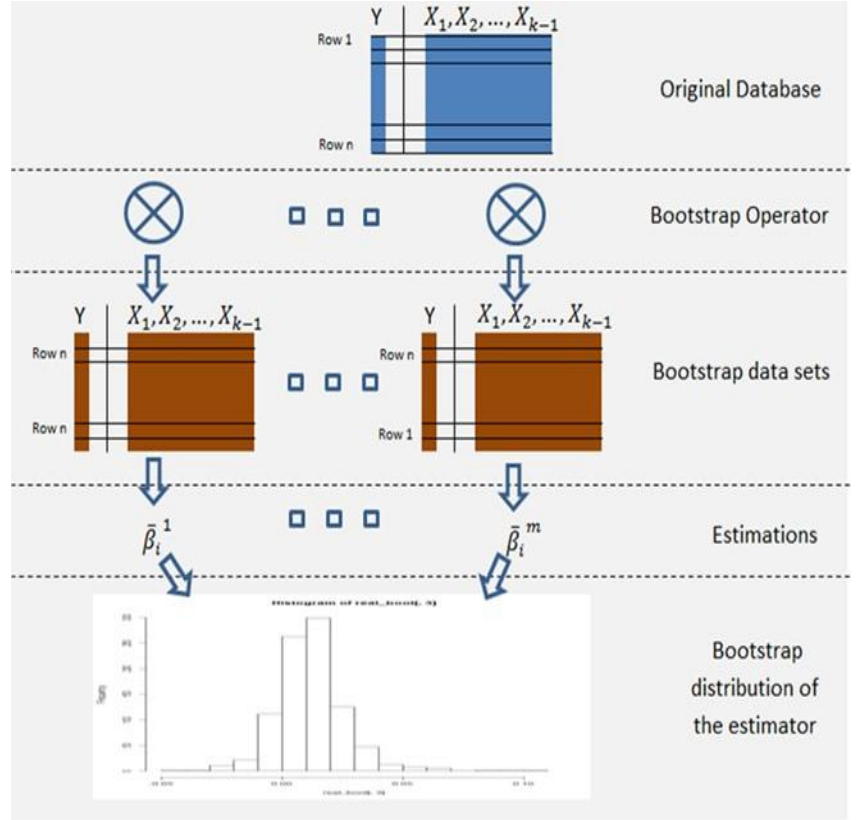


Computational Challenges

The numerical calculation of both confidence intervals and p -values are very time-consuming exercises given the complexity associated with the numerical optimization of the Log-Likelihood function

Luckily, bootstrap simulations, being independent calculations, are often eligible for parallelization

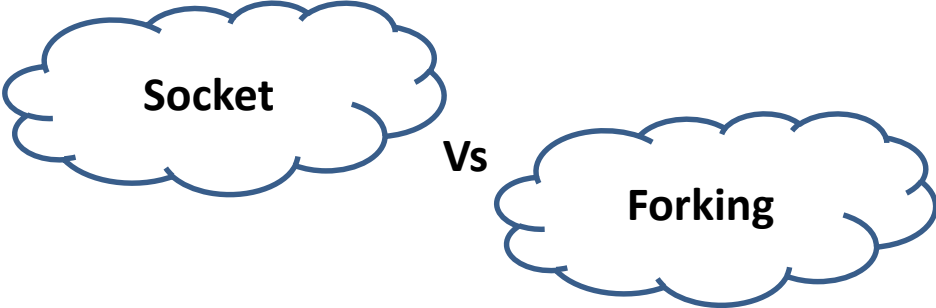
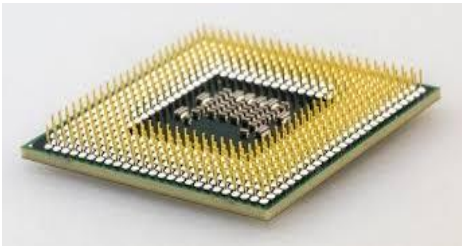
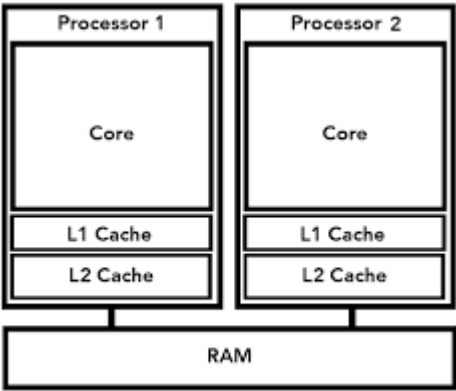
The package *parallel* allowed for a practical implementation of the AGLMs overcoming one of their main limitations



High Performance Computing in R (1/2)

Evaluate $F(x)$ n times

$n/2$ on core A $n/2$ on core B



```

cl = makeCluster(4)

clusterExport(cl, ls(), envir = environment())
system.time(parLapply(cl, 1:100, function(x)
  Parametric_bootstrap_sample(a,b,c,d,sigma,Regressor,
truncation))
)

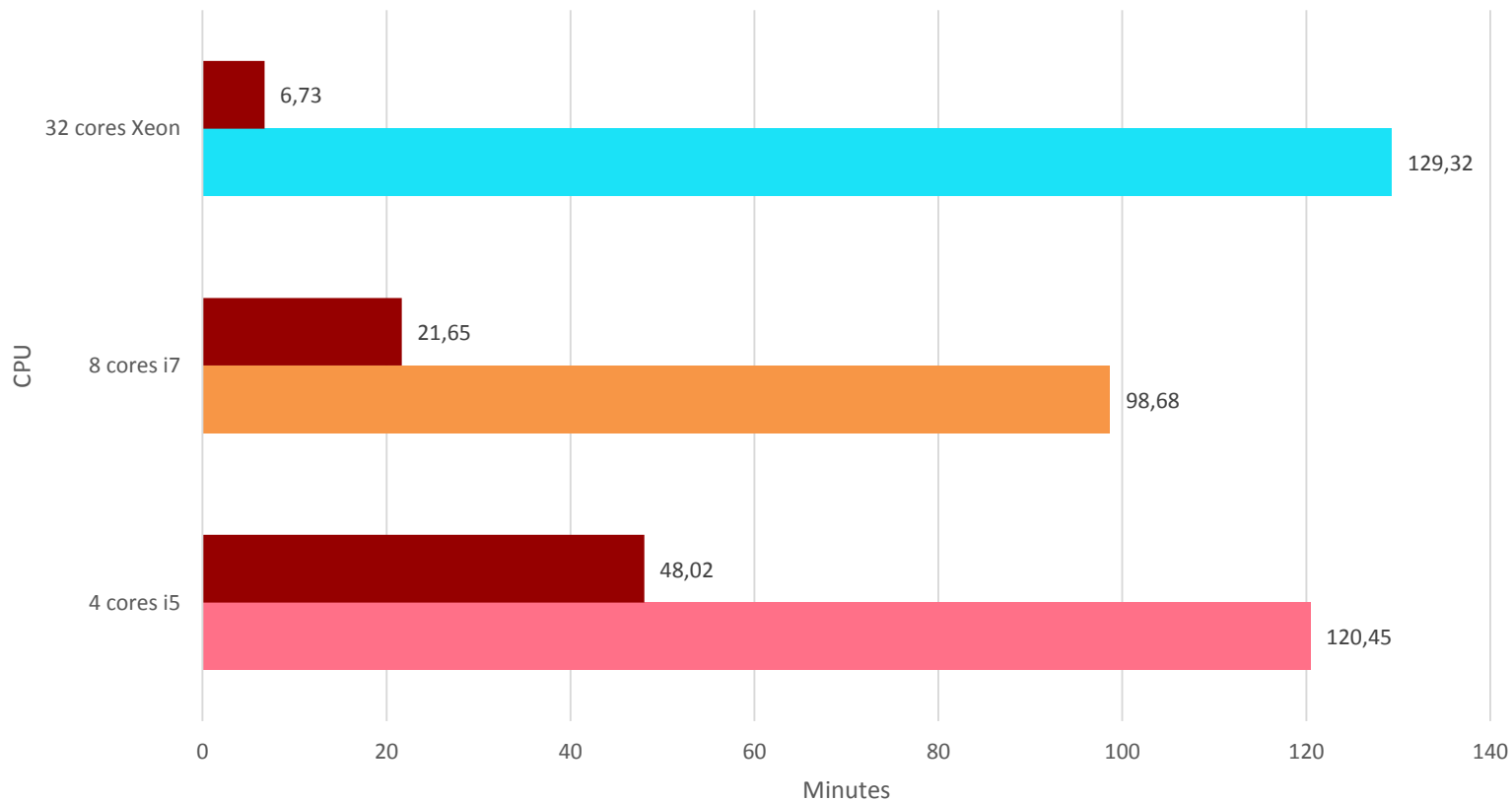
stopCluster(cl)

```



High Performance Computing in R (2/2)

Benchmarks with different CPUs



Thanks for your attention

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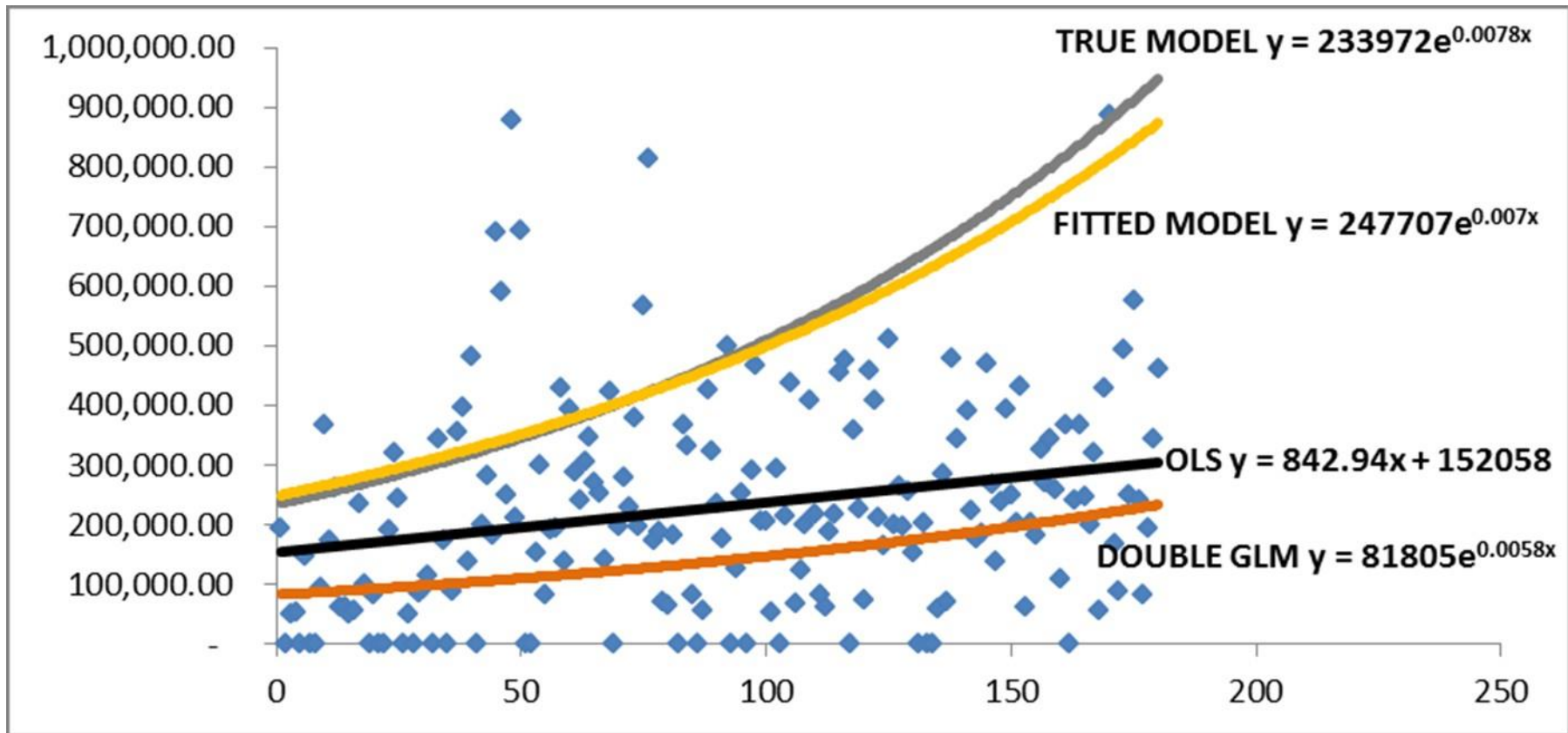
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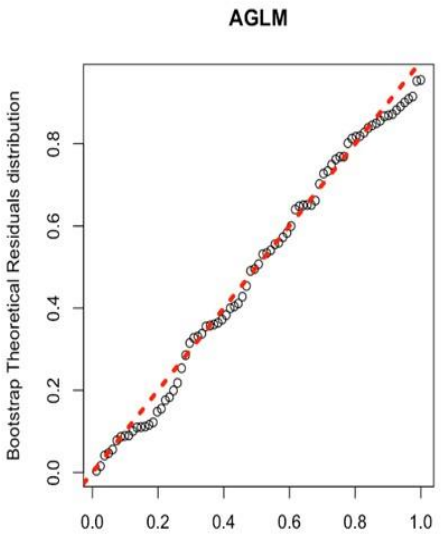


Back Up

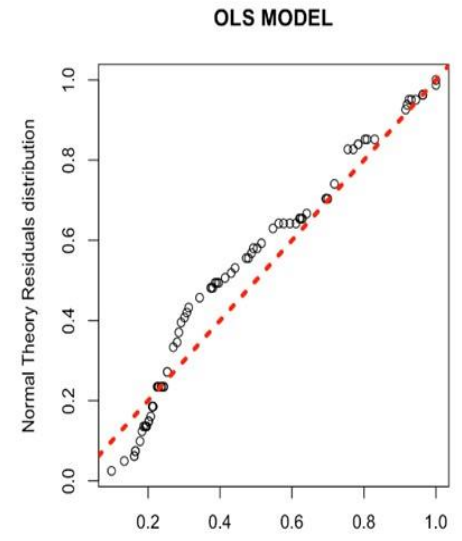


Back Up

	Estimate	Boot Std.errors	5% Boot P	95% Boot Upper Percentile	P value
sigma	3.5227	0.0396	3.4526	3.5829	0%
freq_intercept	6.2982	0.0642	6.1894	6.4008	0%
freq_GDP.g	0.0001	0.0000	0.0000	0.0001	17%
freq_EU.28.core.cpi	1.2749	0.1372	1.0932	1.5446	28%
freq_X10Y.bund..price.	-0.5243	0.0362	-0.5859	-0.4670	1%
freq_Ftse.Europe	0.0002	0.0007	-0.0008	0.0014	47%
freq_usd.eur	-62.4089	0.8765	-63.5263	-60.6429	0%
freq_Non.Performing.Loans	2.1563	0.0834	2.0303	2.3048	21%
freq_Default_Probabilities	-0.0035	0.0001	-0.0037	-0.0033	7%
sev_intercept	2.2461	0.0581	2.1720	2.3631	0%
sev_GDP.g	-0.0001	0.0000	-0.0001	0.0000	2%
sev_EU.28.core.cpi	-1.6322	0.3023	-2.0253	-1.0307	23%
sev_X10Y.bund..price.	0.5807	0.0384	0.5276	0.6539	1%
sev_Ftse.Europe	0.0001	0.0011	-0.0018	0.0018	50%
sev_usd.eur	73.2776	1.9904	71.2863	77.8341	0%
sev_Non.Performing.Loans	-1.5149	0.1037	-1.6406	-1.2995	10%
sev_Default_Probabilities	0.0023	0.0013	-0.0005	0.0039	0%

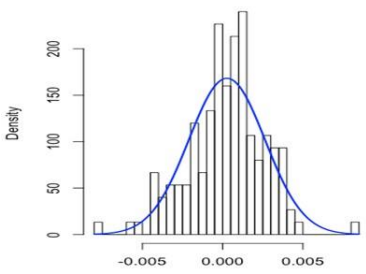


Empirical Residuals Distribution, AD test of coherence = 0.76

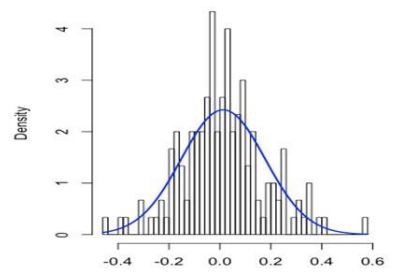


Empirical Residuals Distribution, AD test of coherence = 0.76

Bootstrap simulations : Default Probs



Bootstrap simulations : Interest Rate



Frequenza Media mensile	5,494	Frequenza Media Annua	65,929
Importo medio per evento	€ 23,119.32	Totale medio annuo	€ 1,524,244,758.27
Totale medio mensile	€ 127,020,396.52		

