



AXIS/ORMIR Student Challenge Utility for Fitting Loss Distributions

Haoen CUI and Peng JIN

Department of Mathematics
University of Illinois at Urbana-Champaign

May 01, 2018

Agenda

AXIS's Demand

- Distribution Fitting
 - Coverage Modification
 - Changing Volume
 - Binned Data
- Documentation
 - Usable
 - Maintainable
 - Scalable



Agenda

- Statistical Models
 - Coverage Modifications of Severity Random Variables
 - Coverage Modifications of Frequency Random Variables
 - CDF Interpolation
 - Modeling Loss Ratio via GLM
- Demonstration
- Documentation
- Conclusion

Coverage Modifications of Severity Random Variables

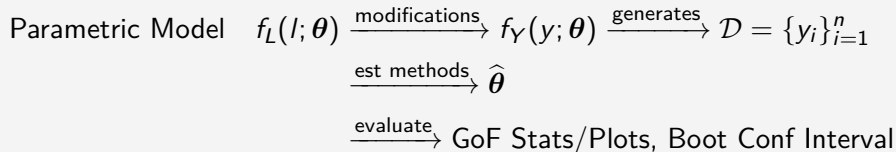
• Definition

- L , raw loss size random variable
 - Likelihood: $f_L(l; \theta)$
- Y , coverage modified loss size random variable
 - Likelihood: $f_Y(y; \theta)$
 - Dataset: \mathcal{D}

• Coverage Modifications

- Deductible
(ordinary/franchise)
- Limit
- Per loss / per payment
- Coinsurance factor α
- Interest rate r

Data Fitting Procedure for Coverage Modified Severity Random Variables



Coverage Modifications of Frequency Random Variables

- Definition

- N^L , raw loss count random variable
- N^P , **deductible** modified **payment** count random variable

Theorem: N^L and N^P are from the same parametric family under conditions

Assume compound frequency model, $N^P = \sum_{i=1}^{N^L} \mathbb{1}\{L > d\}$ where N^L is parametrized by (α, β) and $\nu := \mathbb{P}(L > d)$. Let $G(\cdot)$ denote the probability generating function of a random variable. Then, *under some conditions*,

$$G_{N^P}(z) = G_{N^L}(z; \alpha^*, \beta^*)$$

where change of parameter is given by

$$\alpha = \mathbb{P}(N^L = 0) \quad \alpha^* = \mathbb{P}(N^P = 0) \quad \beta^* = \nu\beta$$

Coverage Modifications of Frequency Random Variables

Table 1: Examples for Change of Parameters Under Coverage Modifications

N^L with parameters $\theta = (\alpha, \beta)$	N^P with parameters $\theta^* = (\alpha^*, \beta^*)$
Poisson(λ)	$\lambda^* = \nu \lambda$
Zero-Modified Poisson(p_0^M, λ)	$p_0^{M*} = \frac{1-e^{-\lambda^*}}{1-e^{-\lambda}} p_0^M + \frac{e^{-\lambda^*}-e^{-\lambda}}{1-e^{-\lambda}}$ and $\lambda^* = \nu \lambda$

Data Fitting Procedure for Coverage Modified Frequency Random Variables

Parametric Model $(a, b, 0)$ or $(a, b, 1)$ $p_{N^L}(n; \theta)$ and $\nu = \mathbb{P}(L > d)$

$\xrightarrow{\text{modifications}} p_{N^P}(n; \theta^*) \xrightarrow{\text{generates}} \mathcal{D} = \{n_i\}_{i=1}^n$

$\xrightarrow{\text{est methods}} \hat{\theta}^* \xrightarrow{\text{transform}} \hat{\theta} \xrightarrow{\text{evaluate}} \text{GoF Stats/Plots, Boot Conf Interval}$

Binned Data and CDF Interpolation

- Definition

- L , raw loss size random variable
- Dataset $\mathcal{D} = \{F_n(l_b)\}_{b=1}^B$ where $(l_b)_{b=1}^B$ is the set of pre-determined break points

- Goal

- Find $\hat{F} \in \mathcal{F}$ based on data \mathcal{D}
- where \mathcal{F} is constrained such that its members are all valid distributions

Data Fitting Procedure for Global Parametric Family \mathcal{F}_θ

Suppose \mathcal{F}_θ is a *global (not piecewise)* parametric family, then

$$\hat{F}_\theta = \underset{F_\theta \in \mathcal{F}_\theta}{\operatorname{argmind}}(F_\theta, F_n)$$

where $d(\cdot, \cdot)$ is a distance measure between distributions (e.g., Kullback–Leibler divergence) and F_n is empirical distribution based on the observed dataset \mathcal{D} .

Binned Data and CDF Interpolation

In general, we may consider to interpolate the dataset \mathcal{D} to get our estimate \hat{F} . However, we will need to ensure the constraint for arbitrary \mathcal{F} . There is no equivalent conditions for a general class of functions.

- Polynomials: *The Bernstein Form of a Polynomial* by Cargo and Shisha (1966) provides a sufficient condition for an increasing quantile function modeling by a polynomial of degree n
- Piecewise Pareto: Linear relationship between $\log(\text{rank})$ and $\log(\text{loss})$

$$\forall l \geq l_0 \quad \ln \left(\mathbb{P}(L > l) \right) = -\alpha \ln(l) + \alpha \ln(l_0)$$

- Hunter and Drown (2017) implemented some methods to interpolate CDFs
 - R package: `binsmooth`
 - Publication: *Better Estimates from Binned Income Data: Interpolated CDFs and Mean-Matching*, available on arXiv

Modeling Loss Ratio via GLM

- Tweedie distribution (μ, ϕ, p)
 - Poisson(λ) distributed sum of Gamma(shape= α , scale= θ) random losses
 - Tweedie mean, $\mu = \lambda\alpha\theta$
 - Tweedie poewr, $p = \frac{1}{\alpha+1} + 1$
 - Tweedie dispersion, $\phi = \frac{\lambda^{1-p}(\alpha\theta)^{2-p}}{2-p}$
- CAS Monograph *Generalized Linear Models for Insurance Rating* suggests to model loss ratio (aka pure premium) using GLM with Tweedie distribution
 - Note that Tweedie GLM implicitly assumes frequency and severity moves in the same direction

Coverage Modifications of Severity Random Variables

Policy Setup

☒ Deductible

Please enter deductible amount:

100000

Ordinary or Franchise

Ordinary

Per Loss or Per Payment

Per Payment

☒ Policy Limit

Please enter policy limit:

5000000

Please enter inflation rate:

0

Please enter coinsurance factor:

1

Model Plot

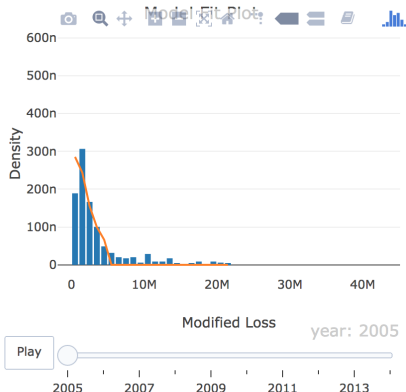


Figure 2: Model Plot with Estimated Parameters

Figure 1: Policy Configuration

Adding User-Defined Distributions

- Run User-Defined Distribution in *R* Code

```
# R default: Define Distribution
```

```
source(helper_file.R)
```

```
dbeta
```

```
pbeta
```

```
rbeta
```

```
# helper.R: Coverage Modification
```

```
actuar::coverage(pdf = ddist, cdf = pdist,  
                  deductible = deductible, limit = limit,  
                  franchise = franchise, inflation = inflation,  
                  coinsurance = coinsurance,  
                  per.loss = per.loss)
```

```
# helper.R: Fit Distribution
```

```
fitdistrplus::fitdist(data = temp_data_raw, distr = dist.name,  
                      method = method)
```

Adding User-Defined Distributions

- Run User-Defined Distribution in *R Shiny*

```
# helper.R: Add to the list of distributions
Distribution.list <- list(
  "select.beta"=c(ddist = dbeta, pdist = pbeta,
                  rdist = rbeta, qdist = qbeta,
                  dist.name = "beta", dist.nparams = 2),
  ...)

# App new.R: Add to User Interface
box(title = "Fitting Specification",
     selectInput(inputId = "loss.dist",
                  "Select distribution of raw loss random variable",
                  c("Beta"="select.beta", ...)))
```

Summary of Documentations

- *User Manual*: Step-by-step procedure to run the utility
- *Statistics Manual*: Details of statistical assumptions, results, and procedures
- *Maintainability*
 - Users can add new loss distributions
 - Code formatted and commented under Google R style
 - Reproducibility ensured by R project and packrat
- *Scalability*
 - Modular and functional programming
 - Ability to add user-defined loss distributions

Model Constrains and Directions of Future Works

- Credibility framework (e.g., Bayesian)
- From parametric to non-parametric
- Cross Validation

Conclusion

AXIS's Demand

- Distribution Fitting
 - Coverage Modification
 - Changing Volume
 - Binned Data
- Documentation
 - Usable
 - Maintainable
 - Scalable



Project Deliverables

- Statistical Models
 - Coverage Modifications
 - Severity Random Variables
 - Frequency Random Variables
 - CDF Interpolation
 - Modeling Loss Ratio via GLM
- Platform
 - Interface: R Shiny
 - Development: R project and packrat
- Documentation
 - User Manual
 - Statistics Manual

References

- G. E. Willmot, H. H. Panjer, S. A. Klugman. (2012). *Loss Models: From Data to Decisions, 4th Edition*.
- M. B. Finan. (2017). *An Introductory Guide in the Construction of Actuarial Models: A Preparation for the Actuarial Exam C/4*. Retrieved From Link.
- D. Bahnemann. (2015). *Distributions for Actuaries*. Retrieved From Link
- M. Goldburd, A. Khare, and D. Tevet. (2016). *Generalized Linear Models for Insurance Rating*. Retrieved From Link