USING R FOR ACTUARIAL ANALYSIS IN VALUATION AND RESERVING

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ABSTRACT: The introduction of R software into the statistical computing space has provided comprehensive language for managing and manipulating multidimensional data. Developing the capacity and skills of students and actuarial analysts is essential for actuarial practices. In this study, the use of R is proposed as a decision support tool for in the field of actuarial teaching and practice, as a complement to the existing excel and other existing platform. Count data was fitted using six regression models, out of which zero-inflated Poisson model is considered to be most suitable model for the count data based on model selection criteria; also procedure for reserving is demonstrated. It is expected that this would promote the use of R among academia and practitioners.

KEYWORDS: R, Decision support tool, Actuarial Analysis, Valuation, Reserving.

1. INTRODUCTION

R is a well-documented language and environment with a core group of developers across many countries. The Software is being regularly updated as new packages are introduced, making the software extensible. R is an open source implementation of S and S-PLUS. The 'S systems' developed by John Chambers is considered as commercial implementation of R. This article presents R to analyst, actuaries and practitioner who require a choice of a good computing and readily available platform, and R is considered adequate the following reasons:

First, R has an effective and well-defined programming language with a simple syntax similar to C programming language. Second, R can be extended, and unified extensions are carried out using packages. R codes are made up C and FORTRAN codes which are supposed to be easily understood by users in order to make computationally intensive tasks easier. Third, R is well-known and embraced for its ability to produce high quality graphics without cumbersome codes. Lastly, there are quite a number of packages in R which has in-built datasets; these datasets can be used for research purposes or test performance of a newly proposed model, datasets relating to stock, life financial data, insurance data and many others. R has been found to offer so much in terms of data manipulation and statistical modelling. Features of R relative to excel are as follows:

R is not labour intensive, it has a well-structured computer programs which helps in easily checking computational errors. Excel has visual Basic for Application (VBA) versioning problems, which could make it inadequate for data analysis and most useful purposes. VBA for Excel is often used to create and maintain complex financial spread-sheet models. R has been designed as a big calculator, a rapid prototype tool and a free alternative to SAS.

Useful features in R includes, open source object based, and functioning language built on S^+ which is designed for manipulating data/objects for implementing statistical analysis. It can easily be connected to external databases for examples, RODBC package in R provides access to databases, including dynamic Structured Query Language (SQL) queries. Graphical User Interface (GUIs) can be easily produced in a straightforward manner. Also, R has easy and beautiful output for data, pictures and charts.

This study is aimed at exposing general analyst and actuarial analyst to the use of an efficient, yet accessible software. Many authors have adopted R software package to implement some actuarial analysis; particularly the use in Extreme value analysis to determine extreme risk in insurance companies [AA17, AAO17, OAA18].

The remaining part of this paper is sectionalized as follows: Section 2 is the materials and methods; which include steps in applying R to insurance data; variable selection criteria for valuation, and reserving models. In section 3, results are discussed. And finally, in section 4, the conclusion was drawn from the study.

2. MATERIALS AND METHODS

The most commonly used packages in R for actuarial analysis include 'actuar' by [DGP08], 'ChainLadder' by [G+17], 'lifecontingencies' by Spedicato ([Spe13]), 'LifeTables' by [SS15], and for

count data we have 'COUNT' by [Hil16], and 'InsuranData' package by [DM14]. Insurance analyses are widely based on generalized linear model (GLM) in the case of valuation and reserving.

2.1 GLM Models in Insurance Analysis

The generalized linear modelling is used to assess and measure the relationship between a response variable and explanatory variables. [JP08] states that GLM differs from ordinary regression modelling in two important respects (i) The distribution of the response is chosen from the exponential family which implies that (the response can be, and usually is, heteroscedastic). Therefore the distribution of the response need not be normal or close to normal and may be explicitly non-normal. A transformation of the mean of the response is linearly related to the explanatory variables.

With GLM, the response variable needs not to be normally distributed, therefore, there is need a link function as a component of GLM. The link function links the mean of the dependent variable Y_i, that is, $E(Y_i) = \mu_i$ to the linear term $g(\mu_i) = x'\beta$. There are two basic link function in GLM, the log link and the logit link.

2.1.1 Exponential Family

According to [NW72], random variable y has a distribution in the exponential family, if the probability mass function of y has the form

$$f(y, \theta, \phi) = \exp\{(y\theta - b(\theta))/\phi + c(y, \phi)\} \quad (1)$$

GLM have two components; the systematic component which consist of the linear predictor as follows

$$\eta_i = \sum_{j=1}^{p} x_j \beta_j = x_i'\beta \quad (2)$$

And the link function

$$\eta_i = g(\mu_i); \mu_i = E(Y_i),$$
$$\mu_i = g^{-1}(\eta_i) = E(Y_i) \quad (3)$$

Where $\mu_i = E(Y_i)$ is the random component and Y: belong to the exponential family.

For some functions $b(.)$, $c(.,.)$, and where we usually require $\phi > 0$. This is the canonical form with canonical parameter θ, and is sometimes referred to as canonical dispersion family, usually $\phi \in \Re$. The GLM includes many important distributions such as the Gaussian, Poisson, gamma and inverse Gaussian distributions [Dob02].

2.2 Poisson Regression

Popular choices for $g(\mu_i)$ are the identity link $\mu_i = x'\beta$ and log link $\log(\mu_i) = x'\beta$. With the log link $\hat{\mu}_i = \exp(x'\hat{\beta})$ being positive, but with the identity link, positivity is not guaranteed.

The mean and variance and variance of Poisson regression is given as

$$E(Y_i) = \exp(x'\beta)$$
$$V(Y_i) = \exp(x'\beta) \quad (4)$$

The likelihood function of Poisson regression is expressed as:

$$InL(\beta) = \sum_{i=1}^{n} y_i x_i'\beta - \exp(x_i'\beta) - Iny_i) \quad (5)$$

2.3 Negative Binomial Regression

The link function for Negative binomial regression is $\log(\mu_i) = x'\beta$, where the parameters μ_i and α represent the mean and the dispersion of the negative binomial. The mean and variance for this model are:

$$E(Y_i) = \exp(x'\beta)$$
$$V(Y_i) = \exp(x'\beta) + \alpha \exp(x'\beta)^2 \quad (6)$$

[Hil07] discuss the negative binomial regression model extensively. Likelihood Function of Negative Binomial is given as:

$$\begin{aligned}
l_i &= \frac{\Gamma(y_i + k)}{\Gamma(k)\Gamma(y_i)}\left(\frac{k}{k + \mu_i}\right)^k \left(\frac{\mu_i}{k + \mu_i}\right)^{y_i} \\
&= \frac{(y_i + k - 1)L(k)\Gamma(k)}{\Gamma(k)\Gamma(y_i)}\left(\frac{k}{k + \mu_i}\right)^k \left(\frac{\mu_i}{k + \mu_i}\right)^{y_i} \\
&= \frac{(y_i + k - 1)L(k)}{(y_i - 1)!}\left(\frac{k}{k + \mu_i}\right)^k \left(\frac{\mu_i}{k + \mu_i}\right)^{y_i} \\
&= \frac{(y_i + e^{k^*} - 1)Le^{k^*}}{(y_i - 1)!}\left(\frac{e^{k^*}}{e^{k^*} + \mu_i}\right)^{e^{k^*}} \left(\frac{\mu_i}{e^{k^*} + \mu_i}\right)^{y_i}
\end{aligned} \quad (7)$$

While the Log-Likelihood Function is

$$L_i = \sum_{j=0}^{y_i-1} \ln(e^{k^*} + j) - \ln\left[(y_i - 1)!\right] + e^{k^*} \ln(e^{k^*}) \quad (8)$$

$$+ y_i \ln(\mu_i) - (e^{k^*} + y_i)\ln(\mu_i + e^{k^*})$$

2.4 Zero-Inflated distributions

If Y follows zero-inflated Poisson (ZIP) distributions, it is given by

$$P(Y = y) \begin{cases} \omega + (1-\omega)\exp(-\lambda) & y = 0 \\ \\ (1-\omega)\exp(-\lambda)\lambda^y / y! & y > 0 \end{cases} \quad (9)$$

where $0 \leq \omega < 1$.

Zero-inflated negative binomial for counts is formed from ZIP which can be defined similarly.

Mean and variance given as:

$$E(Y) = (1-\omega)\lambda = \mu, \quad (10)$$

The use of regression models based on ZIP was established by [Mul86, Hei89, Hei94, Lam92]. Following [Lam92], we have:

$$\log(\lambda) = X\beta \text{ and}$$
$$\log(\omega/1-\omega) = Z\Upsilon \quad (11)$$

where X and Z are matrices of covariates, β and Υ are vector of parameters. Assuming two linear predictors are related in some ways, [Lam92] gives a simplest form of (11) which is refers to the $ZIP(\tau)$ model as follows:

$$\log(\lambda) = X\beta, \ \log(\omega/1-\omega) = \tau X\beta \quad (12)$$

Where τ is a scalar parameter, which implies that $\omega = (1 + \lambda^{-r})^{-1}$.

2.5 Hurdle Models

If the distribution of Y follows zero-truncated Poisson distribution it follows that:

$$P(Y = y) = \begin{cases} \pi_0 & y > 0 \\ \\ \dfrac{(1-\pi_0)e^{-\lambda}\lambda^y}{(1-e^{-\lambda})y!} & y = 0 \end{cases} \quad (13)$$

The hurdle models (Poisson) is reparametization of the zero-inflated Poisson distribution given in equation (9) with $\pi_0 = \omega + (1-\omega)e^{-\lambda}$. In regression frameworks different parameters (π_0 or ω) are modelled making the hurdle and zero-inflated models no longer equivalent.

According to [RDH98], analogously to Lambert's ZIP(τ) model, a Poisson hurdle model follows that:

$$\log(\lambda) = X\beta ,$$
$$\log[-\log(1-\pi_+) = \tau X\beta \quad (14)$$

Where $\pi_+ = 1 - \pi_0$ is the probability of clearing the "hurdle" and generating a non-zero count.

2.6 Model Selection Criteria

Criteria such as, the Akaike Information Criteria (AIC), Bayesian Information Criteria (BIC) are used to select a most suitable model. [AAO17] considered some other information criteria for count data, based on Bayesian analysis, most of which algorithm are provided in the BDWreg package by [Has16]. These criteria help in variable selection process, the lowest AIC or BIC indicate a better model. In actuarial analysis, the Chi-square/ F-test help in identifying the significance of a given model/variable. Other measures include consistency measure.

2.7 Count Data

Poisson is the first and popular model used in fitting count data, but the assumption of Poisson is that the mean and the variance should be equal (equidispersion), if the assumption is violated, Poisson is not found to be a good model to be used. Models such as negative Binomial (for over-dispersion), Zero Inflated Poisson (ZIP) model, Zero Inflated Binomial (ZINB) model, COM-Poisson [CM62], Discrete Weibull, and many others are considered better alternative to Poison model to fitting frequency. The Gamma model is used to model severity, while the Tweedie combines frequency and severity; all these models have commands in R. Package COUNT by [Hil16] is required to fit the regression models to count data.

2.8 Data Description

2.8.1 Health Insurance Data

For the purpose of illustration, data of health insurance encounter is collected at State Hospital, Ota Ogun State, Nigeria. The data consist of one hundred and fifteen (115) registered users of

National Health Insurance Scheme (NHIS) between September 2016 and July, 2017. The response variable is found to be over-dispersed with mean of 0.70689 and variance of 1.79160. Therefore, the response variable is over-dispersed with excess zeros, having counts of 63.8% zeros. The response variable is Encounter, while predictors are Age, type (secondary=0 or Primary=1) secondary NHIS users refer to patients being referred to the State hospital health facility, sex(female=0, male=1), number of drug(s) administered (DrugAdm), number of drug(s) out of Stock (DrugsOS).

2.8.2 UK Motor Data

In R, "Chainladder" package is used for the estimation of outstanding claims reserves in general insurance, including the claims development results as required under Solvency II. Details can be found in [G+17]. The Chainladder package has seventeen dataset in form of loss triangle. The models give an unbiased estimator for IBNR (Incurred but Not Reported) claims. UKMotor data built in, "Chainladder" package is used for illustration. The data contains triangle of cumulative claims payments for seven origin (accident) years over time (development years). It is paid and incurred triangle data from the United Services Automobile Association Company for the private passenger auto liability/medical line of business
The datasets include the origin (year) and development year (horizontal) respectively. As

stated by [G+17], historical insurance data is usually presented in form of a triangle structure, showing the development of claims over time for each exposure (origin) period. An origin period could be the year the policy was written or earned, or the loss occurrence period. The origin period can be yearly, quarterly or monthly. The development period of an origin period is also referred to as age or lag.

3.0 RESULTS

From table 1 below, it is observed that zero-inflated Poisson Model is suitable to fit the count data. Coefficient of the count part of the model is given in table 2. The coefficient is generated exponentially with the command:

exp(cbind(CO=coef(fm_hp1),confint(fm_hp1)))

Since exponential of zero is 1, any coefficient less than 1 means it has negative impact on the counts (Encounter).
Therefore, all of the above is significant since confidence level at 2.5% increases in 97.5% in each case. It follows that as Age increases encounter increases by a factor of 1.002, every unit increase in male gender increases encounter by a factor of 1.398 since it coded as (0,1), also every unit increase in primary NHIS users reduces encounter by a factor of 0.665.

Table 1: Five Fitted Models with Model Selection Criteria for Health Insurance data

Model	Poisson	Negbim	Zero_Pois	Zero_NB	Hurdle_Pois	Hurdle_NB
AIC	243.1879	238.5256	221.7028	223.6954	238.049	239.616
BIC	259.6575	259.6575	207.700	207.700	224.049	213.616
Loglik	-115.594	-112.25	-98.850	-98.850	-107.024	-106.808
df	6	6	12	13	12	13

Table 2: Coefficient of count part of Zero-Inflated Model

	CO	2.5 %	97.5 %
count_(Intercept)	1.056893e+00	5.135165e-01	2.175244e+00
count_Age	1.002052e+00	9.891622e-01	1.015109e+00
count_type	6.654294e-01	3.848110e-01	1.150685e+00
count_Sex	1.398254e+00	8.588787e-01	2.276357e+00
count_DrugsAdm	1.019925e+00	9.874722e-01	1.053445e+00
count_DrugsOS	1.251913e+00	1.033409e+00	1.516617e+00

Table 3: Development year and origin year of UKMotors

origin	1	2	3	4	5	6	7
2007	3511	6726	8992	10704	11763	12350	12690
2008	4001	7703	9981	11161	12117	12746	
2009	4355	8287	10233	11755	12993		
2010	4295	7750	9773	11093			
2011	4150	7897	10217				
2012	5102	9650					
2013	6283						

Table 4: Estimation of Reserves

	Latest	Dev.To.Date	Ultimate	IBNR	S.E	C.V
2008	12746	0.9732000	13097	351	125.8106	0.35843464
2009	12993	0.9260210	14031	1038	205.0826	0.19757473
2010	11093	0.8443446	13138	2045	278.8519	0.13635790
2011	10217	0.7360951	13880	3663	386.7919	0.10559429
2012	9650	0.5739948	16812	7162	605.2741	0.08451188
2013	6283	0.3038201	20680	14397	1158.1250	0.08044210
Total	62982	0.6872913	91638	28656	1708.1963	0.05961042

3.1 Mack's Loss Triangle

Thomas Mack published in 1993 a method which estimates the standard errors of the chain-ladder forecast without assuming a distribution under three conditions. According to the notation given by Mack 1999, let C_{ik} denote the cumulative loss amounts of origin period (e.g. accident year) $i = 1, \ldots \ldots m$, with losses known for development period (e.g. development year) $k \leq n+1-i$.

The aim is to forecast the amounts C_{ik} for $k \leq n+1-i$ the Mack chain-ladder-model.

The Mack-chain-ladder model gives an unbiased estimator for IBNR (Incurred But Not Reported) claims.

Package such as 'lifecontingencies' is used to calculate annuity, financial and actuarial mathematics on life contingencies insurance. It also contains life table which is used to estimate 'Expected curtated lifetime' at birth and last attainable age under Society of Actuaries (SOA). Some of the functions are found in the appendix.

4. CONCLUSION

R is widely used in implementing various analysis, this study only narrow the use down to Actuarial analysis. The use of R in implementing core actuarial analysis has been demonstrated in this article with the aim of making actuarial Science students and practitioners find an equitable but efficient method in carrying out both non-life and life actuarial analysis. The excel spread-sheet widely used is found to be limited in implementing some core analysis which has been highlighted in section one of this article. By this article, R have been introduced to new users, also provides guide to both old users of R on how to implement basic and core actuarial analysis leaving readers to further explore use of the software as much as required.

Statistician, financial analysts, and people in related discipline would find this study useful as it deals with analysis in these fields, providing updated functions for teaching and learning process. On a final note, by adopting the concepts in this article, students and practitioners would be independent in carrying out basic and core analysis; bringing about improving students and practitioners' skills and enhance performance; thereby impacting positively on research, business, and economy.

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APPENDIX A

R Code for Count Regression Model

```
>require(pscl)
>require(MASS)
>require(AER)
>require(COUNT)

pois<-
glm(Encounter~Age+Sex+type+DrugsAdm+Drugs
OS,family=poisson)
summary(pois)
exp(cbind(CO=coef(pois),confint(pois)))
negbim <-
glm.nb(Encounter~Age+type+Sex+DrugsAdm+Dru
gsOS)
summary(negbim)
exp(cbind(CO=coef(negbim),confint(negbim)))
zeropoisson <-
zeroinfl(Encounter~Age+type+Sex+DrugsAdm+Dru
gsOS,dist = "poisson")
summary(zeropoisson)
exp(cbind(CO=coef(zeropoisson),confint(zeropoisso
n)))
zeronegbin <-
zeroinfl(Encounter~Age+type+Sex+DrugsAdm+Dru
gsOS,dist = "negbin")
 summary(zeronegbin)
exp(cbind(CO=coef(zeronegbin),confint(zeronegbin
)))
```

#HURDLE
```
## logit-poisson
fm_hp1 <- hurdle(Encounter~Age+type
+Sex+DrugsAdm+DrugsOS, data=NHIS)
exp(cbind(CO=coef(fm_hp1),confint(fm_hp1)))
## logit-negbin
fm_hnb1 <-
hurdle(Encounter~Age+type+Sex+DrugsAdm+Drug
sOS,NHIS, dist = "negbin")
exp(cbind(CO=coef(fm_hnb1),confint(fm_hbn1)))
```

Code for reserving
```
R>require(ChainLadder)
R>data(UKMotor)
R>list(UKMotor)
R> list(UKMotor)
```

```
(fit1 <- glmReserve(UKMotor))
(fit1 <- glmReserve(UKMotor))
summary(fit1, type = "model") # extract the
underlying glm
plot(fit1, which = 1, xlab = "dev year", ylab = "cum
loss")
R> (fit2 <- glmReserve(UKMotor, var.power = 2))
```

Importing triangle Mack's Loss from excel
Importing triangle from excel CSV or SPSS sav to
show the 'Origin' and 'development'. Copy the path
from where the data is saved, e.g Desktop,
Documents, with forward slides.

```
R>myCSVfile<-
"C:/Users/Name/location/fileName.csv"
R>mysavfile
<-"C:/Users/Name/location/fileName.sav".

## Use the R command:

#choose file

myCSVfile <- file.choose()
## to select the file interactively
R>triangle <- read.csv(file=myCSVfile, header =
FALSE)

R>library(ChainLadder)

#Convert to triangle

R>tri <- as.triangle(as.matrix(triangle))
tri
mackloss <- MackChainLadder(tri,
est.sigma="Mack")
mackloss
```

```
#LOSS DEVELOPMENT
mackloss$f
#full triangle
R>mackloss$FullTriangle
```