TOWARDS A FRAMEWORK FOR OPERATIONAL RISK IN THE BANKING SECTOR

by

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ABSTRACT

Towards a Framework for Operational Risk

in the Banking Sector

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Shefrin (2016) notes that people would rather incur greater risks to hold on to things they already have, than the risks they would taken to get into that position in the first place, thereby risking a banks' survival, rather than expose their trading losses by consciously deceiving senior management to hide unethical operational practices. In this paper the application of machine learning techniques on the observed data demonstrates how these issues can be resolved given their flexibility to different types of empirical data.

(116 pages)

PUBLIC ABSTRACT

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Mphekeleli Hoohlo

The purpose of this research is to provide clarity; based on theory and empirical evidence, on how to tackle the specific problems in the *operational risk* (OpRisk) literature, which have earned a place in modern day recource in in risk and finance, due to how significantly its importance has increased over the last few decades. During this period, until present day, there have been and continues to be series of destructive events that have threatened the stability of financial systems due to OpRisk. In most, if not all of these cases, human error is at the center of the chain of events that lead or may lead to (OpRisk) losses. There are many attitudes that can potentially infect organisational processes, the most persistent of these attitudes stem from human failings that are exploitable Barberis & Thaler (2003), thus forming a basis for the theoretical foundation of `OpRisk`.

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DEDICATION

Dedicate it.

ACKNOWLEDGEMENTS

Acknowledge those acknowledgable individuals and things.

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CHAPTER 1
INTRODUCTION

Purpose of the study

The purpose of this research is to apply a generalised linear model (GLM) and generalized additive models for location scale and shape (GAMLSS) suitable for exposure-based operational risk (EBOR) treatments within the operational risk management framework (ORMF), effectively replacing historical loss severity curves obtained from historical loss counts, by forward-looking measures using event frequencies based on actual operational risk (OpRisk) exposures. Preliminary work on EBOR models was undertaken by (Einemann, Fritscher, & Kalkbrener, 2018). Secondly, this study provides a comprehensive computational comparison of various data-intensive techniques amongst each other, and versus *classical* statistical estimation methods for classification and regression performances.

Our understanding of existing ORMF to date is limited to the assumption that financial institutions (FI's) are risk-neutral: In lieu of the afore-mentioned this study finally seeks to invalidate the risk-neutral assumption by means of evidence-based discoveries revealed through a clustering algorithm arising naturally in the unknowns of the data by means of a prescribed model, which applies unsupervised learning techniques to determine what is going on, proposing that FI's are more risk-averse. This determination is best understood analysing subtle patterns between data features and trends in the allocated risk capital estimates. In theory, a risk manager who experiences persistent/excessive losses due to particular risk events, would over-compensate cover for these particular risk types, and this would show in reduced losses in data for these event types over time.

Fundamentals of ORMF's

Congruent to Cruz (2002), in the current study the researcher alludes to the notion that most banks' estimates for their risk's are divided into credit risk (50%), market risk (15%) and OpRisk (35%). Cruz (2002) postulates that OpRisk, which focuses on the human side of risk management is difficult to manage with the reduced ability to measure it. The process of that risk, that is the how, manifests in the conscious and/or unconscious states of mind of the risk practitioner (Hemrit & Arab, 2012), and encompasses approaches and theories that focus on how they will choose when faced with a decision, based on how comfortable they are with the situation and the variables that are present.

Definition 1.2.0.1 Operational Risk (OpRisk) is defined as: *The risk of loss resulting from inadequate or failed internal processes, people and systems, and from external events. This definition includes legal risk, but excludes strategic and reputational risk.*

(Risk, 2001).

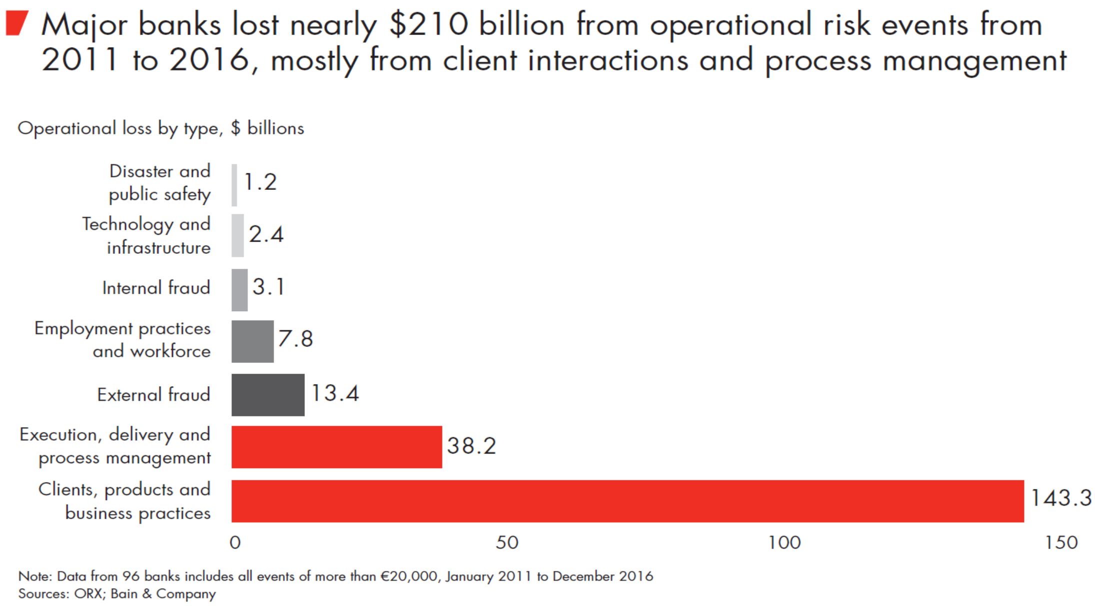
A theoretical foundation for operational risk

The major managerial concern for businesses is in the lack of universally accepted ways to identify their OpRisk, and hence the inability to successfully account for their susceptibility to this, particularly following a number of very costly and highly publicized operational events that lead to catastrophic losses for the banks in question. OpRisk became popular following a now famed fraudulent trading incident which was responsible for catastrophic losses that lead to the collapse of Barings Bank (the UK's oldest bank) in 1995. The term *OpRisk* began to be used extensively after the afore-mentioned and similar types of OpRisk events became common.

A *rogue* trader, Nick Leeson (Panjer, 2006) risked the banks' survival rather than expose his trading losses by consciously deceiving senior management to hide unethical rogue trading acts, was found responsible for unethical trading practices when he created illegal trades in his account. He then used his position in the front and back offices of the bank to hide his losses. Worse still, he went further in his fraudulent activities incurring greater risks to the bank, by lying in order to give a false impression of his profits. This supports the behavoural notion alluded to by Shefrin (2016), that in most risk-bearing decision-making situations people would rather incur greater risks to hold on to their current position and things they already have, than the risks they would have taken to get into that position in the first place.

It was later discovered that Nick was placing illegal bets in the Asian-markets, while covertly keeping these contracts out of sight from senior management to cover up his illegal trading activities. When his fraudulent behaviour was discovered (after an earthquake hit at Kobe in Japan, that collapsed the Osaka Securities Exchange) he succumbed to unrecoverable losses due to trading positions he had accumulated which resulted in a loss of around £1.3 billion to the bank, thus resulting in it's collapse (Martin, 2009). In most, if not all of case involving OpRisk hazard, human error is at the center of the chain of events that lead or may lead to OpRisk losses.

Since then, there have been a series of destructive events worldwide that have threatened the stability financial systems due to OpRisk losses. Hefty fines worthy of bankrupting entire corporate entities often have to be imposed on the guilty culprits sometimes resulting in irreparable damage to banks' overall business and reputations, such that widespread regulatory scrutiny has been heightened as a result



Source: https://www.bain.com/contentassets/f0199ad9887e402cb37cd1fd316f5ee3/bain_brief_how_banks_can_manage_operational_risk.pdf

Figure 3.1: Histogram showing a breakdown of gross losses focusing on OpRisk loss events in comparison to each other recorded from 2011 up to and including 2016

of a number of scandalous operational events. Kennett & Carrivick (2018) recognise from information offered via the operational riskdata exchange (ORX) global banking loss database that historically, gross loss sizes have been predominantly high and volatile, characterised by a period (from 2011 to 2016) driven by the occurence of large loss events. This coincides with the afore-mentioned post-crisis period, predominantly in 2012, followed by a comparatively stable period in 2017 where industry Oprisk losses saw sizes decrease significantly. Figure 3.1 illustrates comparative distribution of severity of losses per loss event type reported from 2011 to 2016 during which major banks suffered nearly $210 billion worldwide from Oprisk alone.

These OpRisk loss events were due to fraudulent trading activity consisting of rogue traders dealing in illegally placed high frequency trades for private clients where prices are hidden. For example, the January 2016 “Dark Pool” trading penalties suffered by Barclays Bank PLC amounting to about $70mn and Credit Suisse

($85mn), imposed by the United States (US) based securities exchange commision (SEC). In a case closer to home, Gous (2019) reports ongoing investigations launched in April 2015 for price fixing and “widespread” collusion between banking insiders in South Africa (SA), of the market allocation for foreign exchange (FX) currency pairs viz., USD/ZAR rates, a case which now has been referred to SA based competition tribunal for prosecution, as late as February 2017. Three local banks viz., Absa bank, Standard bank & Investec are implicated in the scandal along with 14 others; some of which have already been fined within juristictions they reside (StaffWriter, 2017), may be liable to payment of an admistrative penalty equal to 10% of their annual turnover.

This investigation led by the local based competition commission uncovered irregularities when rogue traders manipulated the price of the rand through buying and selling US dollars in exchange for the rand at fixed prices between 2007 and 2013. According to the competition commission, currency traders allegedly had been colluding or manipulating the price of the rand through these buy and sell orders to change supply of the currency in contravention of the competition act (Gous, 2019).

These acts compromise risk management’s advisory service and pedigree, and arouse huge interest as, with the SA incident, distorting the rand value has major implications on the living standards of SA’s, felt down to the man in the street. Furthermore, this kind of behaviour can lead to catastrophic operational losses resulting is a mismatch between business’ expectations and the value the risk management practice is delivering, which is prevalent across the world and remains unchanged. There are many attitudes that can potentially infect organisational processes, the most persistent of these attitudes stem from human failings that are exploitable (Barberis & Thaler, 2003); such as the human conditions’ propensity to being deceitful during periods of distress, thus forming a the basis for a (behavioural) theoretical foundation of OpRisk management.

The basel committee operational risk management framework

The Bank for International Settlements (BIS) is an organisation consisting of a group of central bank governors and heads of supervision of central banks around the world who represent an authority on good risk management in banking. More specifically, the BIS oversee the duties of the Basel Committee on Banking Supervision (BCBS)/Basel Commitee. The role of the BCBS is to set out guidelines on international financial regulation to cover risks in the banking sector. There are to date three banking accords from the BCBS under the supervision of the BIS in dealing with financial regulation viz., Basel I, Basel II & Basel III. These accords describe an overview of capital requirements for financial institutions (FI's) in order to create a level playing field, by making regulations uniform throughout the world.

The Capital Adequacy Accord (Basel I)

Basel I was established in 1988. Basel I meant that FI's were required to assign capital for credit risk to protect against credit default. In 1996, an amendment to Basel I imposed additional requirements to cover exposure due to market risk as well as credit risks. Basel I effectively minimised rules that favoured local FI's over potential foreign competitors by opening up global competition so that these banks could buffer against international solvency. In 2001, the Risk (2001) consultative package provided an overview of the proposed framework for regulatory capital (RC) charge for OpRisk upon the realisation of financial institutions' (FIs) OpRisk component, which constitutes a substantial risk component other than credit and market risk.

A construct for credit risk modelling uses in OpRisk is borne out of the structural model found in Merton (1974), whereby a theory for pricing corporate debt is presented. Merton (1974) postulates the bond's value is dependent on the volatility of the firms value at a given interest rate i.e., the risk structure of interest rates (Rosa, 2012) under possible gains or losses to investors when there is a significant (unanticipated) probability of default. This credit risk model adapted to OpRisk defines what is now called the *exposure-based* operation risk (EBOR) model. The ultimate task of defining the ideal *exposure* measure for a operational event data is specifically dealt with in this study.

The main challenge in OpRisk modeling is poor data quality and usually very few data points that are often characterised by high frequency low severity (HFLS) and low frequency high severity (LFHS) data types. OpRisk's LFHS are risks where the probability of an extreme loss is very small but costly, and HFLS risks are where frequency plays a major role in the OpRisk capital charge calculation. It is common knowledge that HFLS losses at the lower end of the loss spectrum tend to be ignored by management due to their perceived insignificance and are therefore less likely to be reported, whereas LFHS losses comprise of sensitive company information, hence more than not are well guarded and kept in secret by organisations, and therefore are not likely known to the public. Many times losses of operational nature are mistakenly attributed to credit defaults or market risk related movement.

This is founded in a seminal paper by Rosa (2012), through her illustration of modern risk exposure whereby the afore-mentioned phenomena arises: An exposure-based method is derived using a credit risk structural model to predict a series of operational losses arising from events of operational nature; which triggered off the filing of litigations involving initial public offerings (IPO's), but nevertheless related to credit or market risk losses as defined by the credit risk or market risk exposures as opposed to standard OpRisk types whose exposure was undefined. In fact, a significant gap in OpRisk literature is in the current lack of a strongly risk-sensitive *exposure* measure (cf. market and credit risk) (Aue & Kalkbrener, 2006).

In an adaptation of the Merton (1974)'s concept to OpRisk as illustrated by Rosa (2012) to OpRisk losses involving these IPO's, an EBOR model emerges out of a method which requires new types of data incorporating "predictive" factors by the use of a combination of statistical modeling and scenario analysis: Thus, allowing for the inclusion of forward-looking aspects of BEICF's in an EBOR model. An early representation of this EBOR model according to Rosa (2012) is expressed as a common credit risk model given as:

$$EL = p \cdot LGE \tag{1.1}$$

Where EL is the expected loss, p is the probability of the realised loss occurring, and LGE is the loss-given-event. Oprisk events are divided into event types ET_j $j = 1, 2, \ldots$ and business lines BL_i $i = 1, 2, \ldots$. Other necessary inputs are: the severity exposure E_{ij}, or the maximum possible loss for an event in the BL/ET combination risk cell ij, an exposure indicator capturing the scale of the bank's activities in the risk cell; and a stochastic estimate L_{ij} specified since only a fraction of the exposure is typically lost, such that $LGE = L \cdot E$. Now, suppose Y_{ij} denotes loss for business line BL_i $i = 1, 2, \ldots$ and event type ET_j $j = 1, 2, \ldots$ for BL/ET combination ij; and p_{ij} denotes the probability that the OpRisk event will occur over the next period $[T, T + \tau]$, then the total loss Y_{ij} is given by:

$$Y_{ij} = p_{ij} \cdot L_{ij} \cdot E_{ij} \qquad \text{where} \quad LGE = L \cdot E \quad \text{by} \quad 1.1 \tag{1.2}$$

Conceptually, this factor based quantification model for capital requirements can be extended to also include future events.

New Capital Adequacy Accord (Basel II)

The framework for Basel II was implemented in June 2006. The rationale for Basel II is to introduce risk sensitivity through more restrictive capital charge measures and flexibility with specific emphasis on OpRisk. The structure of the new accord is built upon a three-pillar framework: Pillar I stipulates minimum capital requirements for the calcualtion of regulatory capital for credit risk, market risk and OpRisk in order to retain capital to ward against these risks. Pillar II imposes a supervisory review process whereby additional capital requirements can be imposed; such as the bank's internal capital assessements or to act on needed adequate capital support or best practice, for mitigating their risks. Pillar III relates to market discipline i.e., transparency requirements which require banks to publicly provide risk disclosures to keep them in line by enabling investors to form an accurate view of their capital adequacy, in order to reward or punish them on the basis of their risk profile.

Basel II describes three methods of calculating capital charge for OpRisk RC viz., the standardised approach (SA), the basic indicator approach (BIA) and the internal measurement approach (IMA). The basic indicator approach (BIA) sets the OpRisk RC equal to a percentage (15%) of the annual gross income of the firm as a whole to determine the annual capital charge. The SA is similar to the BIA except the firm is split into eight business lines and assigned a different percentage of a three year average gross income per business line, the summation of which is the capital charge (Hoohlo, 2015). In the IMA, the bank uses it's own internal models to calculate OpRisk loss.

Internal measurement approach (IMA)

The internal measurement approach (IMA) allows banks to use their internally generated risk estimates, Under Basel II the IMA is a first attempt at capital charge calculation for OpRisk: "to directly capture a bank's underlying risk by using the bank's internal loss data as key inputs for capital calculation" (Mori, Harada, & others, 2001). It has similarities to the Basel II model for credit risk, where a loss event is a default in the credit risk jargon. Under the IMA, OpRisk events are divided into seven event types $j = 1, \ldots, 7$ and eight business lines $i = 1, \ldots, 8$ (Risk, 2001) forming a loss decomposition of 56 BL/ET combination sub-risks. Total capital charge is computed as:

$$
\begin{aligned}
\mathcal{C}_{OpRisk}^{IMA} &= \sum_{i=1}^{8}\sum_{j=1}^{7}\gamma_{ij}\epsilon_{ij} && (1.3)\\
where \quad \epsilon_i &: \quad \text{is the expected loss for business line } i\text{, risk type } j\\
\text{and} \quad \gamma_{ij} &: \quad \text{is an internal scaling factor}\\
\Leftrightarrow \epsilon_{ij} \equiv Y_{ij} &= p_{ij} \cdot L_{ij} \cdot E_{ij} \quad \text{from} \quad 1.2 && (1.4)
\end{aligned}
$$

The scaling factor γ_{ij} represents a regulatory parameter that is used to transform Y_{ij} into a capital charge. At its most basic level, the EBOR model is a special case of the IMA.

The BL/ET combination matrix

The 3-dimensional diagram depicts the formation of a $7 \times 8 = 56$ BL/ET combination of matrix risk-type cells: A duration parameter denoted by time $[T, T + \tau]$ representing the next period's loss (usually the next year's annual loss) over which RC is defined is shown along the depth k ordinate.

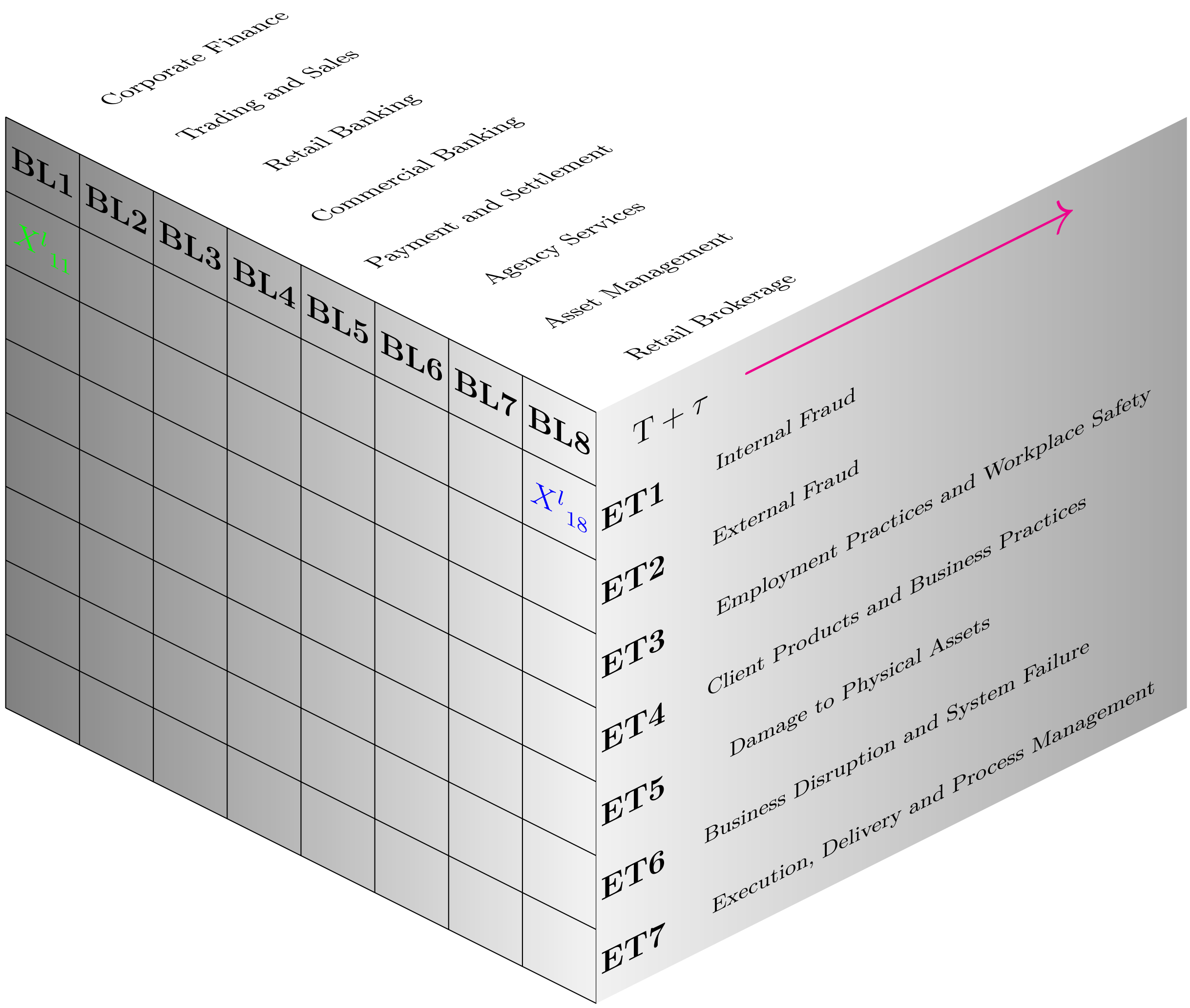


Figure 4.2: The 3-Dimensional grid of the BL/ET matrix for 7 event types and 8 business lines

Basel III

Basel III establishes tougher capital standards through more restrictive capital definitions, higher risk weighted assets[1] (RWA's), additional capital buffers, and higher requirements for minimum capital ratios (Dorval, 2013). Through Basel III, the BCBS is introducing a number of fundamental reforms grouped under three main headings (Committee & others, 2010): 1] A future of more capital through incremental trading book risk (credit items in trading book treated in the same way as if they were in banking book), 2] More liquidity through the introduction of a global liquidity risk standard: Basel III will push banks toward holding greater levels of liquid instruments, such as government bonds and more liquid corporate instruments, and 3] Lower risk under the new requirements of the capital base i.e., establish more standardized risk-adjusted capital requirements.

The future regulatory environment requires OpRisk professionals who are not only intelligent, creative and motivated but also have the courage to uphold the OpRisk advisory service standards. Businesses that want to successfuly manage OpRisk would be well advised to utilize new theoretical and empirical techniques such that large and small scale experiments play an important role in risk analysis and regulatory research.

Modern OpRisk measurement frameworks (ORMF's)

Regarding the sequence Basel I and Basel II: Regulation begins as a qualitative recommendation which requires banks to have an assets-to-capital multiple of at least 20, then focuses on ratios in which both on-balance sheet and off-balance

[1] Also reffered to as risk-weighted amount, it is a measure of the bank's total credit exposure

sheet items are used to calculate the bank's total RWA, then on tail risk. In other words, auditors' discretion is replaced by market perception of capital, meaning there is a market risk capital charge for all items in the trading business line, then exciting new static risk management approaches which involve calculating a 99.9 percentile left tail confidence interval to measure OpRisk value-at-risk (VaR) and convert it into a RC charge.

Advanced Measurement Approach (AMA)

The advanced measurement approach (AMA) is an IMA method which applies estimation techniques of OpRisk capital charge derived from a bank's internal risk measurement system (Cruz, 2002). Basel II proposed measurement of OpRisk to define capital requirements against unexpected bank losses whereas the unexpected loss (UL) is the quantile for the level α minus the mean. According to the AMA, which is thought to outperform the simpler SA approach and the BIA, RC requirements are defined according to the UL limit in one year and the loss distribution at a 99.9% confidence level ($\alpha = 0.01\%$) aggegate loss distribution[2] used as a measure of RC. The BCBS proposes to define RC as $RC = UL$. This involves simulations based on historical data to establish frequency and severity distributions for losses. In this case the RC is a VaR measure.

Loss distribution approach (LDA)

The loss distribution approach (LDA) model is based on actuarial techniques and is generally accepted as the industry (AMA) standard for OpRisk estimation. LDA models require quant level expertise in order for one to accept the statisti-

[2]The aggregate loss distribution is obtained by convoluting a loss event frequency distribution and a loss severity distribution by means of the random sums method.

cal relationships linking the actual (perceived) risk exposures. What it has done is to provide the most realistic risk profiles of a company to date (Einemann et al., 2018), based on partitioning OpRisk loss data into sufficiently homgeneous sets, typically corresponding to combinations of business lines (BL) and event types (ET), and to calibrate a frequency and severity distribution for each BL/ET combination.

LDA models cover risks that are well reflected through historical events and exposure data is used in several of the steps of the process in frequency and severity modeling. The risk-type cells can be selected at the actual loss generating process level, however most banks use the LDA for BL/ET risk-type cells. The LDA is the most comprehensive modelling approach and is the focus of this study forthwith.

What is exposure?

In the OpRisk context, the total OpRisk loss is captured by certain *exposure* measures, which are quantities that are thought to be roughly proportional to the overall risk associated with an operational event or loss (Parodi, 2014). The measure of exposure needed depends on what loss variable one is attempting at projecting which is dependent on a varied mix of factors. Specifically in relation to the LDA model for OpRisk the exposure measure is dependent on whether we are projecting the aggregate losses (severity) or the number of losses (frequency). When carrying out this decision making expercise the following were considered:

* The availability of historical exposure data over the same period for which the losses are recorded
* The exposure estimate for future periods

Exposure is residual risk, or the risk that remains after risk treatments have been applied. In the ORMF context, it is defined as: The formal definition of exposure in risk management is:

Definition of exposure

Definition 1.5.2.1 The risk remaining after risk treaments have been applied *i.e., the risk *a priori* to considering the actual experience of the corporation or FI. The* ***exposure*** *of risk type i,* d_i *is the time interval, expressed in units of time, from the initial moment when the event happened, until the occurrence of a risk correction.*

As per definition 1.5.2, the lag represents exposure; we need historical exposure for experience rating because we need to be able to compare the loss experience of different years on a like-for-like basis and to adjust it to current exposure levels (Parodi, 2014).

Definition of rate

Often the poisson count λ needs to be described as a rate; for example the OpRisk hazard rate can be specified as the rate per day. More generally, the rate is specified in terms of units of *exposure*; The **rate**, R is defined as:

Definition 1.5.2.2 *the* ***rate*** *is the mean count per unit exposure*
i.e.,

$$\begin{aligned} R &= \frac{\mu}{\tau} \qquad \text{where} \qquad R = \text{rate}, \quad \tau = \text{exposure}, d_i \quad \text{and} \\ \mu &= \text{mean count over an exposure duration of} \quad d = [T, T+\tau] \end{aligned}$$

For example, in OpRisk hazard rates, each potential OpRisk transaction event is “exposed” over the period $[T, T+\tau]$; it’s detection life cycle period, and a P&L impact determined, So the rate may be defined in terms of transcaction-days *at risk*. In this study, the intensity (rate) of occurance of loss events is the fundamental unit of of analysis for estimating the number of loss events (frequency) used for

OpRisk losses. This positions the Poisson distribution as a favourable first model; and presents the researcher with the opportunity for a intuitive intepretation of *exposure* as the rate for counting for all available observations over a time lag: The ***exposure*** measure is defined as the time interval $(T + \tau, T) =$ d i.e., the interval from the initial moment when the event happened until the moment the event is observed and adjusted for.

The Basel III capital adequacy rules permit model-based calculation methods for capital, including the AMA for OpRisk capital. Under Basel III, standardised methods for OpRisk capital have been overhauled, however for a while there was no prospect of an overhaul of the AMA. Given the relative infancy of the field of OpRisk measurement, banks are mostly free to choose among various AMA principle-based frameworks to a significant degree of flexibility (Risk, 2016). A bank that undertakes an AMA should be able to influence their capital requirements through modeling techniques resulting in lowered pressure on OpRisk capital levels, which in turn has a positive impact on the bank.

A FI's ability to determine the framework used for its regulatory OpRisk RC calculation, evolves from how advanced the FI is along the spectrum of available approaches used to determine capital charge (Risk, 2001). BCBS recognizes that a variety of potentially credible approaches to quantify OpRisk are currently being developed by the industry, and that these R&D activities should be incentivised. Increasing levels of sophistication of OpRisk measurement methodologies should generally be rewarded with a reduction in the regulatory OpRisk capital requirement.

The standardised measurement approach (SMA)

The flexibility of internal models was expected to narrow over time as more accurate OpRisk measurement was obtained and stable measures of RC were reached, ultimately leading to the emergence of best practice. Instead, internal models produced wildly differing results of OpRisk RC capital from bank to bank, contrary to the expectations of the BCBS. In March 2016, the BCBS published for consultation a standardised measurement approach (SMA) for OpRisk RC; that proposes to abandon the freedom of internal modelling (thus ending the AMA) approaches for OpRisk RC, in exchange for being able to use a simple formula to facilitate comparability across the industry.

Under the SMA, RC will be determined using a simple method comprising of two components: A stylised systemic risk model (business indicator component), and an idiosyncratic risk model (loss component), which are combined via an internal loss multiplier (ILM), whose function is to link capital to a FI's operational loss experience to determine SMA capital.

The SMA formula is thought to be consistent with regulators' intent for simplification and increased comparability across most banks. However, there is a feeling from some in the banking industry that the SMA is disadvantaged as it is not the same as measuring OpRisk. Mignola, Ugoccioni, & Cope (2016) and Peters, Shevchenko, Hassani, & Chapelle (2016) identified that the SMA does not respond appropriately to changes in the risk profile of a bank i.e., it is unstable viz., two banks of the same risk profile and size can exibit OpRisk RC differences exceeding 100%, and risk insensitive; that SMA capital results generally appear to be more variable across banks than AMA results, where banks had the option of fitting the loss data to statistical distributions.

Argument

Over the last twenty years, hard-won incremental steps to develop a measure for the size of OpRisk exposure along with the emergence of promising technologies presents a unique opportunity for bankers and treasurers - traditionally risk-averse players - to develop a novel type of way of looking at decision making under risk/uncertainty. New technologies have been introduced which make use of up to date technical solutions (such as homo heuristics developed by Gigerenzer & Brighton (2009), who mainatain their methods solve practical finance problems by simple rules of thumb, or Kahneman (2003)'s intuitive judgements and deliberate decision making), argued to more likely represent the true embedded OpRisk in financial organisations as these methods are designed to fit normal behavioral patterns in their formulation, which is consistent with how decisions are made under risk/uncertainty.

What are the important steps toward completing the post crisis reforms during the current year? Should the risk management fraternity follow the chartered[3] path followed in the Risk (2016) consultative document, scrapping away twenty years of internal measurement approaches (such as the AMA), or should the focus of financial regulators shift toward improving on what they see fit within current existing AMA frameworks. The question is should OpRisk managements' focus be on stimulating active discussions on practical approaches to quantify, model and manage OpRisk for better risk management and improved controls, or abandon the adoption of innovative measurement approaches, such as the AMA, in exchange for being able to use a simple formula across the whole industry?

[3]Meaning as of the publication [@risk2016supporting] the methods brought forth in the consultative document have not been approved for the public, the ideas within an experimental (leased) phase for the exclusive use of BCBS and certain FI's

Context of the study

Regulatory reforms are designed and fines imposed to protect against operational errors and other conduct costs connected with wrongdoing and employee misconduct. Despite the introduction and use of these seemingly robust strategies, regulations, processes and practices relating to managing risk in FI's, bank losses continue to occur at a rather distressing frequency. A cyclical pattern of OpRisk loss events still persists; as evidenced in the recent price fixing and collusion cases, defeating the explicit objectives of risk management frameworks. This demonstrates a scourge of reflexivity prevailing in financial markets emphasising that, there are theories that seem to work for a time only to outlive their use and become insufficient for the complexities that arise in reality.

Why OpRisk?

A forceful narrative in management theory is that an organisation running effective maintenance procedures combined with optimal team and individual performers i.e., the right balance of skills in the labour force and adequate technological advancements, means systems and services can be used to more efficiently produce material gains, enhance organisational effectiveness, meet business objectives and increase investment activity. Conversely, the risk of the loss of business certainty associated with lowered organisational competitiveness and inadequate systems technology that underpins operations and services is a key source leading to a potential breakdown in investment services activity (Hoohlo, 2015).

In fact, OpRisk controls could set banks apart in competition. Consider the case of a risk practitioner in a financial system who assumes that he/she is consiously and accurately executing tasks and analysing an observed subject trusting the validity and relying on visual information that their sense of sight reveals alone. In the absence of visual confirmation they are hindered from extracting and/or analysing information about the system and their efforts to regulate could potentialy fail. In this scenario, the organisational methods and functioning of information systems would usually pose shortcomings, which obscure the full extent of OpRisk challenges from the eyes of the risk practitioner allowing for operational errors.

When an attack such as an operational error occurs at a speed that the OpRisk agent (an individual legal entity or a group) is unable to react quickly enough, due to limitations of their processing speed, and they are not able to process all the information in the given time span, they could lose control/fail of fail in compliance, disincentivising support for regulation, particularly Basel III recovery and resolution processes. In latter days more often than not, OpRisk loss cases reflect lack of sufficient controls being the driver of current OpRisk management catastrophies. The agent on this end of the spectrum of the risk management strategy, which mitigates risk and enforces regulation dependent on visual and information controls is better off than an agent on the other extreme, who does not react at all to changes in the system environment.

A new class of EBOR models approach

In this study, an important new algorithm for ORMFs and is laid out coupled with data intensive estimation techniques; viz. Generalised Additive Models for locatin Scale & Shape (GAMLSS), Generalized Linear Models (GLMs), Artificial Neural Networks (ANNs), Random Forest (RF) & Decision Trees (DTs), which have capabilities to tease out the deep hierarchies in the features of covariates irrespective of the challenges associated with the non-linear or multi-dimensional nature of the underlying problem, at the same time supporting the call from industry for a new class of EBOR models that capture forward-looking aspects.

Problem statement

Main problem

Conventional OpRisk frameworks in banking commonly exhibit control and system deficiencies whereby information processing is slow and have the tendency to rely on manual, uncertain, unpredictable and unrealistic management and measurement methods, obscuring reporting and resulting in undesirable pre-market conditions. The OpRisk management's function should be able to assist in the ability to mitigate risks through acquiring and/or refining risk management solutions which deliver reliable and consistent benefits of improved operational controls and enhanced risk management frameworks.

In our prevailing banking phenomena of increasing OpRisks, the problem consists of questioning whether a firm's susceptibility to OpRisk hazard's growth, results in the degree of OpRisk losses slowing due to tightning OpRisk controls and enhancements to OpRisk frameworks. It would be prudent not to declare things are improving if the evidence is not quite firm that this is true. This is essentially a check for situations, from these data, whether there is evidence of the unchecked spread of negligent behaviour leading to operational loss events or not; or on the contrary, those situations other than the unrestricted spread of these "rogue" events conscequently driving OpRisk losses i.e., which may requiring a re-thinking our approach to improving OpRisk controls and enhancing OpRisk management frameworks.

Sub-problem 1

The existing models in OpRisk measurement for which historical loss distributions are the best predictors of future losses, assume that we do not learn from past losses. This is problematic for “predictable” risk types due to model’s practice of undercapitalising known risks before occur, and overcapitalising for risks after the losses materialise, creating innappropriate capital estimates (Group & others, 2013). These concerns motivate the development of an EBOR modelling framework which not only captures past losses but also how exposures to forward-looking affect risk attitudes.

Sub-problem 2

Furthermore, we challenge the weakness in current OpRisk theory which assumes banks are risk neutral, asserting they are more risk averse. Consequently, “predictive” future losses can be determined who’s estimated RC adapts to changes in the risk profile of the bank i.e., with the introduction of new products or in changes to the business mix of the portfolio (e.g. mergers and aquisitions, trade terminatons, allocations or disinvestments), providing sufficient incentives for OpRisk management to mitigate risk.

Objectives of the study

The research objectives are three-fold:

Exposure-based OpRisk (EBOR) models

To quantify OpRisk losses by introducing generalised additive models for location, scale and shape (GAMLSS) in the framework for OpRisk management, that captures exposures to forward-looking aspects of the OpRisk loss prediction problem. EBOR treatments effectively replace historical loss severity curves obtained from historical loss counts, by looking into deep hierarchies in the features of covariates in investment banking (IB), and by forward-looking measures using event frequencies based on actual operational risk (OpRisk) exposures in the business environment and internal control risk factors (BEICF) thereof.

Modeling OpRisk depending on covariates

To investigate the performance of several supervised learning classes of data-intensive methodologies for the improved assessment of OpRisk against current *traditional* statistical estimation techniques. Three different machine learning techniques viz., DTs, RFs, and ANNs, are employed to approximate weights of input features (the risk factors) of the model. A comprehensive list of user defined input variables with associated root causes contribute to the *frequency* of OpRisk events of the underlying value-adding processes. Moreover, the *severity* of OpRisk is also borne out through loss impacts in the dataset . As a consequence of theses new mwthodologies, capital estimates should be able to adapt to changes in the risk profile of the bank, i.e. upon the addition of new products or varying the business mix of the bank providing sufficient incentives for ORMF to mitigate risk (Einemann et al., 2018).

Interpretation Issues using cluster analysis

To identify potential flaws in the mathematical framework for the loss distribution approach (LDA) model of ORM, which is based the derivation of OpRisk losses based on a risk-neutral measure $\mathbb{Q}$, by employing Cluster Analysis (CA). The study addresses weaknesses in the current *traditional* LDA model framework, by assuming managerial risk-taking attitudes are more risk averse. More precisely, CA learns the deep hierarchies of input features[4] that constitute OpRisk event *frequencies* & *severities* of losses during banking operations.

In theory, a risk manager who experiences persistent/excessive losses due to particular risk events, would over-compensate cover for these particular risk types. This would show in reduced losses in those loss event types over time, subsequently determining whether risk adverse techniques over-compensate for persistent losses. The wish is to bring the prescribed model to equilibrium by applying a method that tries to establish what accurately ascribes to decision rules that people wish to obey in making predictions about what operational loss events might result in the future, then use empirical data to test this idea in a way that is falsifyable.

Significance of the study

This study fills a gap in that advancing OpRisk VaR measurement methods beyond simplistic and traditional techniques, new data-intensive techniques offer an important tool for ORMFs and at the same time supporting the call from industry for a new class of EBOR models that capture forward-looking aspects of ORM

[4] A typical approach taken in the literature is to use an unsupervised learning algorithm to train a model of the unlabeled data and then use the results to extract interesting features from the data [@coates2012learning]

(Embrechts, Mizgier, & Chen, 2018). The current *traditional* approach consists of a loss data collection exercise (LDCE) which suffers from inadequate technologies at times relying on spreadsheets and manual controls to pull numbers together, and therefore do not support the use of data intensive techniques for the management of financial risks. In this study, a new dataset with unique feature characteristics is developed using an automated LDCE, as defined by Committee & others (2011) for internal data. The dataset in question is at the level of individual loss events, it is fundamental as part of the study to know when they happened, and be able to identify the root causes of losses arising from which OpRisk loss events.

This study will provide guidance on combining various supervised learning techniques with extreme value theory (EVT) fitting, which is very much based on the Dynamic EVT-POT model developed by Chavez-Demoulin, Embrechts, & Hofert (2016). This can only happen due to an abundance of larger and better quality datasets and which also benefits the loss distribution approach (LDA) and other areas of OpRisk modeling. In Chavez-Demoulin et al. (2016), they consider dynamic models based on covariates and in particular concentrate on the influence of internal root causes that prove to be useful from the proposed methodology. Moreover, EBOR models are important due to wide applicability beyond capital calculation and the potential to evolve into an important tool for auditing process and early detection of potential losses, culminating in structural and operational changes in the FI, hence releasing human capital to focus on dilemmas that require human judgement.

Organisation of the study

This study consists of seven chapters. Chapter 1 outlines the purpose, followed by an overview of the relevance and importance in the existing work. Then the general concept behind EBOR models is introduced and an argument is presented of the relevance of a new class of EBOR models to remediate some of the shortcomings in OpRisk LDA modeling, followed by statement of the research problems and objectives. This chapter is concluded by an account of significance.

The introductory chapter is succeded by a general literature review Chapter 2, succeeded by three stand alone chapters, the purpose of each is to provide clarity, based on theory and empirical evidence, focusing on three specific research objectives each contributing to resolve specific problems in the OpRisk literature, given how its importance has become more pronounced in time. In these chapters the application of machine learning techniques on the observed data take centre-stage demonstrating how issues in OpRisk capital requirement estimation are more effectively resolved.

Chapter 2 gives an overview of theoretical foundations of OpRisk, followed by a review of the LDA model used to calculate an estimate of the OpVaR measure. A breakdown analysing the EBOR models approach follows promising to remediate some of the LDA shortcomings and on how EBOR components presented in the study offer a novel approach in contrast to the current literature demonstrating its value and exposing the gap in finer detail. Chapter 2 concludes with a lead up to Chapter 4 by proposing a research methodology in which a combination of ML techniques and statistical theory underlying ORMF's would benefit measurement of capital requirements for OpVaR.

Chapter 4 deals with the application of EBOR techniques using the GLM and GAMLSS models in more detail, and the empirical determinants due to the different components of OpRisk measurement under the new class of EBOR models. The chapter deals with the analysis of EBOR techniques to the portfolio of a wide range OpRisk losses found in the dataset and their integration into an LDA framework.

CHAPTER 2
LITERATURE REVIEW

Introduction

A look into literary sources for OpRisk indicates (Acharyya, 2012) that there is insufficient academic literature that looks to characterize its theoretical roots, as it is a relatively new discipline, choosing instead to focus on proposing a solution to the quantification of OpRisk. This chapter seeks to provide an overview of some of the antecedents of OpRisk measurement and management in the banking industry. As such, this chapter provides a discussion on why OpRisk is not trivial to quantify and attempts to understand its properties in the context of risk aversion with the thinking of practitioners and academics in this field.

According to Cruz (2002), FI's wish to measure the impact of operational events upon profit and loss (PnL), these events depict the idea of explaining the *volatility of earnings* due to OpRisk data points which are directly observed and recorded. By seeking to incorporate new data intensive machine learning (ML) approaches to help understand the data, the framework analyses response variables that are decidedly non-normal, including categorical outcomes and discrete counts.

Due to commonly held beliefs (Aue & Kalkbrener, 2006), one of the main challenges toward the next generation of LDA models is in their incapability of dealing with the handling of statistical validation of qualitative adjustments, citing ill-conceived justification for its direct application to RC: However, in the advent of recent developments .viz ML techniquess, it is believed the advantages of conducting our investigations outweigh this disadvantage, shedding further light on our understanding of how forward-looking aspects of BEICF's affect firm-level OpRisk RC. Lastly, this resolves the problem associated with the context dependent nature of OpRisk as an apparent gap in the literature.

The theoretical foundation of OpRisk

Hemrit & Arab (2012) argue that common and systematic operational errors in hypothetical situations poses presumtive evidence that OpRisk events, assuming that the subjects have no reason to disguise their preferences, are created subconsciously. This study purports, supported by experimental evidence behavioural finance theories should take some of this behaviour into account when trying to explain in the context of a model, how investors maximise a specific utility/value function.

In a theoretical paper, Wiseman & Catanach Jr (1997) discussed several organizational and behavioural theories, such as prospect theory (PT), which influence managerial risk-taking attitudes. Their findings demonstrate that behavioural views, such as PT and the behavioural theory of the firm explain risk seeking and risk averse behaviour in the context of OpRisk even after agency based influences are controlled for. Furthermore, they challenge arguments that behavioral influences are masking underlying root causes due to agency effects. Instead they argue for mixing behavioral models with agency based views obtaining more complete explanations of risk preferences and risk taking behavior (Wiseman & Catanach Jr, 1997).

Wiseman & Catanach Jr (1997) suggest that managerial risk-taking attitudes are influenced by the decision (performance) context in which they are taken. In essence, managerial risk-taking attitude is considered as a proxy for measuring OpRisk (Acharyya, 2012). In so doing, Wiseman & Catanach Jr (1997) investigate more comprehensive economic theories viz. PT and the behavioural theory of the firm, that prove relevant to complex organizations who present a more fitting measure for OpRisk. Upon further investigation, Barberis & Thaler (2003) reveal that in finance, behavioral theory explains whether certain financial phenomena can be viewed as the result of less than fully rational thinking. Their argument goes, that through integrating OpRisk management into behavioral theory it may be possible to improve our understanding of firm level RC by refining the resulting OpRisk models to account for these behavioral traits. Thus implying that people's economic preferences described in the model have an economic incentive to improve the OpRisk RC measure.

Despite the reality that OpRisk does not lend itself to scientific analysis in the way that market risk and credit risk do, someone must do the analysis, value the RC measurement and hope the market reflects this. Besides, financial markets are not objectively scientific, a large percentage of successful people have been lucky in their forecasts, it is not an area which lends itself to scientific analysis.

Overview of operational risk management

It is important to note how OpRisk manifests itself: The causes and sources of operational loss events as observed phenomena associated with operational errors and are wide ranging (King, 2001). By definition, the occurence of a loss event is due to PnL volatitlity from a payment, settlement or a negative court ruling within the capital horizon over a time period (of usually one year) (Einemann et al., 2018). As such, PnL volatitlity is not only related to the way firms finance their business, but also in the way they *operate*.

In operating practice, one assumes that on observing or on following instructions we are consciously analysing and accurately executing our tasks based on the information available. However, the occurence of operational loss events indicates that there are sub-concious faults in information processing, which we are not consciously aware of but ultimately lead to PnL losses. These operational loss events are almost always initiated at the dealing phase of the investment banking process; which more often than not implicates front office (FO) personnel who bear the brunt of responsibility for the loss e.g., during the trading process in cases where OpRisk events occur as a result of a mismatch between the trade booked (booking in trade feed) and the details agreed by the trader.

The middle office (MO) and back offices (BO) conduct OpRisk managements' task of building mathematical models to be used to predict OpRisk losses and ultimately determine capital adequacy required to absorb these losses. The implications from modelling can be used to better understand the broad view of the overall company's OpRisk exposure, through PnL attribution carried out from deal origination to settlement. For instance, the results of the model can be used to better understand the interrelationships between risk factors and potential dependencies on various mitigation and management strategies (Acharyya, 2012) e.g., human error is a potential risk factor resulting PnL losses, whose negative impacts can be mitigated by an efficient trade amendment policy offsetting the outflow of PnL with an equal and opposite inflow or cash injection.

Furthermore (Acharyya, 2012), organizations may hold OpRisk due to external causes such as failure of third parties or vendors (either intentionally or unintentionally) in maintaining promises or contracts. The criticism in the literature is that no amount of capital is realistically reliable for the determination of RC as a buffer to OpRisk, particularly the effectiveness of the approach of capital adequacy from external events as there is effectively no control over them.

The loss collection data exercise (LCDE)

In this study, a new dataset with unique feature characteristics is developed using the official loss data collection exercise (LDCE), as defined by Committee & others (2011) for internal data. The dataset in question is at the level of individual loss events which can therefore be modelled in a granular way, which facilitates the reflection of loss-generating mechanisms (Einemann et al., 2018): It is therefore also fundamental as part of this study to know when they happened, and be able to identify the root causes of losses arising from which OpRisk loss events. Similarly to the afore-mentioned, this study intodeuces an analogous mathematical framework for EBOR modeling, however the proposed OR framework is better suited with a higher probability to determine the amount of capital necessary to absorb operational losses as it is applicable to a larger number of OpRisk types.

The LCDE is carried out drawing statistics directly from the trade generation and settlement system, which consists of a tractable set of documented trade detail extracted at the most granular level, i.e. on a trade-by-trade basis (as per number of events (frequencies) and associated losses (severities)) and then aggregated daily. The development, calibration and validation of EBOR models is challenginf since new types of data and ahigher degree of expert involvement acroos the institution is required, providing a transparent quantitative framework for combining forward-looking point-in-time data and historical loss experience (Einemann et al., 2018). The afore-mentioned LDCE is an improved reflection of the risk factors by singling out the value-adding processes associated with individual losses on a trade-by-trade level. The dataset is then split into proportions and trained, validated and tested.

Loss Distribution Approach (LDA)

The Loss Distribution Approach (LDA) is an AMA method whose main objective is to provide realistic estimates to calculate VaR for OpRisk RC in the banking sector and it's business units based on loss distributions that accurately reflect the frequency and severity loss distributions of the underlying data. Having calculated separately the frequency and severity distributions, we need to combine them into one aggregate loss distribution that allows us to produce a value for the OpRisk VaR.

A general class of LDA model characteristics

We begin by defining some concepts:

- Consider a matrix consisting of business lines BL and OpRisk event types ET. In line with Basel II, the bank estimates for each business line/event type (BL/ET) combination, the probability function (p.f.) of a single event severity[1] (PnL impact) and the event frequency[2] over a period, say for the next three months according to @hoohlo2015new. More precisely, according to @frachot2001loss, in each cell of the BL/ET matrix combinations separate distributions for loss frequency and loss severity are modeled and following an actuarial approach aggregated to produce a loss distribution at the group level.
- More precisley, let $N_1, \ldots, N_m$ represent random variables for the loss frequencies i.e., the values $N_k \in \mathbb{N}_{>\not{k}}$ for each $k \in \{1, \ldots, m\}$. Let the individual op-

[1]refers to the PnL impact resulting from the frequency of events

[2]refers to the number of events that occur within the specified time period (daily buckets) T and $T + \tau$

erational losses $(S_{k1}, \ldots, S_{kN_k})$ denote independent and identically distributed (i.i.d) rv's of the severity distribution S_k, which are independent of N_k, be samples obtained from BL/ET combination types k. The aggregate loss variable X_k in this cell is given as

$$X_k = \sum_{l=1}^{N_k} S_{kl} \tag{2.1}$$

The aggregate OpRisk loss can be seen as a sum $\mathbf{X} = X_1 + X_2 + \cdots + X_m$; the aggregate loss distribution at group level defined by

$$\begin{aligned} \mathbf{X} &= \sum_{k=1}^{m} X_k & (2.2) \\ &= \sum_{k=1}^{m} \sum_{l=1}^{N_k} S_{kl} \quad \text{by equation2.1} & (2.3) \end{aligned}$$

- Three month daily statistics are taken of the time series of internal processing errors (frequency data) and their associated severities and used in each cell of the BL/ET matrix. Daily buckets are chosen in order to ensure data points are sufficient for ML/statistical analysis.

Computing the frequency distribution

- $\mathbf{N}_{ij}$ represents the number of times of OpRisk event failures between times T & $T + \tau$ in BL/ET combination ij, where subscripts i refers to the BL and j to ET. More generally the rv N_k[3] has distribution function (d.f)[4] $\mathbf{P}_k(n/\theta_0)$, where θ_0 is an unknown parameter to be estimated in some way, the two best known methods used are the maximum likelihood estimators (m.l.e) or the

[3] $N_1 = N_{ij}$, where subscript $i = 1$ & $j = 1$ i.e., N_{11} corresponds to dealing with ET_1 e.g., internal Fraud and BL_1 e.g., Corporate Finance

[4] The term distribution function (d.f) is monotonic increasing function of n which tends to 0 as $n \Longrightarrow -\infty$, and to 1 as $n \Longrightarrow \infty$

method of moments.

- The d.f. $\mathbf{P}_k(n/\theta_0)$ for the loss frequency, is defined as the probability that N_k takes a value less than or equal to n, where n is a small sample from the entire population of observed frequencies, i.e.

$$\mathbf{P}_k(n) = Pr\left(N_k \leq n\right) \quad \text{k} = 1, 2, \ldots, \tag{2.4}$$

  And a corresponding probability density function (p.d.f)[5]: A d.f term associated with the rv defined by ordinary summations of the N_k's in the discrete case anagolous to the Stieltjes Integrals (of functions relating to the rv N_k and quantile n thereof) defined in the continuous case. The term for p.d.f (called probability function) is the also called the probability mass function (p.m.f) given by the probability that the variable takes the value n, i.e.

$$p_k(n) = Pr\left(N_k = n\right), \quad \text{k} = 1, 2, \ldots, \tag{2.5}$$

- The r.h.s of equation (2.4) is the summation of the r.h.s of equation (6.2), we derive a relation for the d.f associated with given rv's N_k:

$$\mathbf{P}_k(n) = \sum_{l=1}^{N_k} p_k(l) \tag{2.6}$$

  Where $N_k \in \mathbb{N}_{>\nvdash}$ for each $k \in \{1, \ldots, m\}$ between T and some terminal time $T + \tau$.

[5] A non–negative function $p(n)$ integral, extended over the entire x axis, is equal to 1 for a given continuous random variable X. i.e. it is the area under the probability density curve, of the discrete random variable N_k takes discrete values of n with finite probabilities.

Computing the severity distribution

- Suppose S_{kl} is a random variable representing the amount of one loss event in a cell of the BL/ET combination matrix. Define next period's loss in each cell $k = 1, \ldots, m$, where k is the number of BL/ET combinations, S_{kl}^{T+1}. According to equation 2.1, next period's aggregate loss severity X_k^{T+1}

$$X_k^{T+1} = \sum_{l=1}^{N_k^{T+1}} S_{kl}^{T+1} \quad \text{k} = 1, \ldots, m \tag{2.7}$$

Therefore, it follows by equation 2.2, the LDA model for the amount of the total operational loss in BL_i, $i = 1, \ldots, 8$, loss type ET_j, $j = 1, \ldots, 7$ over a given time T & $T + \tau$, over the future:

$$\begin{aligned} \mathbf{X}^{T+\tau} &= \sum_{k=1}^{m} X_k^{T+1} \\ \mathbf{X}^{T+\tau} &= \sum_{i=1}^{8} \sum_{j=1}^{7} \sum_{l=1}^{N_k^{T+1}} S_{kl}^{T+1} \end{aligned} \tag{2.8}$$

- The rv's S_{ij}^l are i.i.d and independent of N_{ij}. A fixed number in a chosen business line (e.g. Corporate Finance) for a particular loss type (e.g. Internal Fraud) would be denoted by S_{11}^l, representing random samples of the PnL impacts in the $k = 1$ cell in the BL/ET matrix. The loss severity distribution is denoted by $\mathbf{F}_k(x)$ where x is a small sample from the entire population of loss severity S_{kl}. Since loss severity variate S is continuous (i.e. can take on any real value), we define a level of precision h such that the probability of S being within $\pm h$ of a given number x tends to zero. The loss severity, S_k has a (d.f.) $\mathbf{F}_k(x/\theta_1)$, where θ_1 is an unknown parameter to be estimated in some way, the two best known ways being the m.l.e and/or the method of moments. Now

$$\mathbf{F}_{S_k}(x) = \int_0^{x_\alpha} f_{S_k}(x)dx \qquad \text{by definition} \tag{2.9}$$

where $f_{s_k}(x)$ is the probability density function (p.d.f.).

- Therefore by numerical approximation; i.e., the Stieltjes integral definition [@evans2001statistical], whereby:

$$\int_0^{x_\alpha} \phi(x) f_{S_k}(x)dx \qquad \text{corresponds to} \qquad \sum_0^{x_\alpha} \phi(x) f_{S_k}(x) \tag{2.10}$$

Implying that the severity p.d.f

$$\begin{aligned} \mathbf{F}_{S_k}(x) &= \mathbb{P}[X_k \leq x] \\ \implies &= \mathbb{P}\left(\sum_{l=1}^{N_k} S_{kl} \leq x\right) \quad \text{by equation 2.1} \end{aligned} \tag{2.11}$$

Once again, the subscript S_{kl} identifies the random variable for severity (PnL impact) of one loss event while the argument x is an arbitrary sample of the loss severities.

Computing the combined loss distribution

- With the frequency choice of $\mathbf{P}_k$ and severity $\mathbf{F}_{S_k}$ loss distributions derived, we define a compound loss distribution $\mathbf{G}_k(x)$: The distribution of the rv X_k, where the sample is drawn by combining frequency and severity loss distributions following an actuarial approach i.e., from a distribution which is a product a sample from the frequency d.f. (expression 2.6, which is deterministic) the p.d.f (expression 2.11), therefore it is probabilistic. We see a fundamental relation corroborated by @frachot2001loss, @cruz2002modeling, @embrechts2013modelling, & others:

$$\mathbf{G}_k(x) = \begin{cases} \sum_{n=1}^{\infty} p_k(n)\mathbf{F}_k^{n\star}(x) & \text{x} > 0 \\ p_k(0) & \text{x} = 0 \end{cases} \tag{2.12}$$

where $\star$ is the *convolution* operator on d.f.'s, $\mathbf{F}^{n\star}$, the n-fold convolution of $\mathbf{F}$ with itself. [6] The elements of the convolution function (when $x > 0$) survive; since p kills off the elements of X_n which do not satisfy the condition $X_n < x$, otherwise $G_k(x)$ is 0.

- The compound loss distribution 2.12, $\mathbf{G}_k(x)$ cannot be represented in analytical form; approximations, expansions, and recursions of numerical algorithms used to obtain solutions have been proposed, viz., Monte Carlo simulations, Panjer's recursive approaches, and/or taking the inverse of the characteristic function [@frachot2001loss; @aue2006lda; @panjer2006operational; & others]. In the LDA separate distributions of frequency and severity are derived from loss data then combined by Monte Carlo simulation.

- The method consisting of taking a set $\langle \mathbf{X}_1, \ldots, \mathbf{X}_l \rangle$, otherwise known as the ideal generated by elements $\mathbf{X}_1, \ldots, \mathbf{X}_l$ which are l simulated values of the random variable X_k for $s = 1, \ldots, S$ [@fraleigh2003first].It as named in the 1940's after a popular gambling location and owes its popularity to this place and their similarities to games of chance. The way it works in layman's terms is; in place of simulating scenario's based on a base case, any possible scenario

[6]The convolution of two functions $f(x)$ and $g(x)$ is the function

$$\int_0^x f(t)g(x-t)dt \tag{2.13}$$

, i.e. $\mathbf{F}_k^{n\star}(x) = Pr(X_1 + \ldots + X_n \leq x)$, the d.f. of the sum of n independent random variables with the same distribution as X.

through the use of a probability distribution (not just a fixed value) is used to simulate a model many times.

Computing the total economic capital

The loss data collection exercise (LDCE) doesn't make it possible to always have a collection of all past event losses (Frachot, Georges, & Roncalli, 2001), instead, ometimes when OpRisk losses are generated only summmed up losses are made available i.e., most times the LCDE contains individual OpRisk losses otherwise contains aggregates of losses. In the LDA estimation for the capital-at-risk (CaR) measure for aggregated losses, specifically when dealing with the severity distribution, it's estimation is not a straightforward parametization estimation process which makes use of tha popular method of moments, or maximum likelihood estimation (m.l.e). The data structure would require analytical expressions for $\mathbf{X}_k$ to be available in order to permit it.

In the current manner of which the LDCE is condicted, data is generated through an automated data feed which consists of granular data at an event-wise individual trade-by-trade basis, whereby losses xs are obtained per loss event. Each loss event is also identified by a unique trade identifier. This makes it possible to have a collection of all possible past individual events and the losses accompanying them, therefore circumventing considerations for the need to use other replacement estimation methods rather than the better suited m.l.e.

In what follows, the problem of computing the total capital charge of the the bank as a whole is addressed. Define the *Capital-at-Risk* (CaR) to be the capital charge for OpRisk which corresponds to the quantile of the level α minus the mean of the combined loss distribution $\mathbf{G}$. Loosely, this definition defines OpRisk as a VaR measure: VaR_α, where x is a quantile for the confidence level α minus the mean ($\alpha \in (0,1)$ fixed). Other risk measures exist but have the restritive constraint requiring finite mean, contrary to combined loss distribution which is generally very heavy tailed. The Basle Committee on Banking supervision defines CaR as the unexpected loss

$$\begin{aligned} \text{UL} &= \inf x | G_k(x) \geq \alpha \\ \longrightarrow \text{CaR} &= \sum_{k=1}^{m} \text{VaR}_\alpha(X_k) \\ &= G_k^{-1}(x) \end{aligned} \tag{2.14}$$

Let $\mathbf{X}$ be the total loss of the bank. By equation 2.2 and considering that the losses X_k are independent; the distribution $\mathbf{G}$ is the convolution of the distributions $\mathbf{G}_k$:

$$\mathbf{G}(x) = \bigstar_{k=1}^{m} \mathbf{G}_k(x) \tag{2.15}$$

As previously defined, the CaR of the bank is:

$$\text{CaR}(\alpha) = \mathbf{G}^{-1}(\alpha) \tag{2.16}$$

Dependence Effects (Copulae)

Economic capital allocation which considers dependence between cells is benefitted in a way that recognises the risk-reducing impact of correlation effects between the risks of the BL/ET combinations. The choice of VaR comes with a superadditive property, and OpRisk VaR models are known to exhibit dynamic dependence between loss processes. Due to special dependence effects copulas are normally used and can always be found for the joint model. Dependence matters due to the effect of the addition of risk measures over different risk classes (cells in the

BL/ET matrix). Copulas are a statistical tool which conveniently incorporate correlation into a function that combines each of the frequency (marginal) distributions to produce a single bivariate cumulative distribution function. Our model is used to determine the aggregate (bivariate) distribution of a number of correlated random variables through the use a chosen copula.

More precisely, the frequency distributions of the individual cells of the BL/ET matrix are correlated through a choice of a copula in order to replicate observed correlations in the observed data. Let m be the number of cells, $\mathbf{G_1}, \mathbf{G_2}, ..., \mathbf{G_m}$ the distribution functions of the frequency distributions in the individual cells and $\mathbf{C}$ the so–called copula. Abe Sklar proved in 1959 through his theorem (Sklar's Theorem) that for any joint distribution $\mathbf{G}$ the copula $\mathbf{C}$ is unique. $\mathbf{C}$ is a distribution function on $[0,1]^m$ with uniform marginals. We refer to a recent article by Chavez-Demoulin, Embrechts, & Nešlehová (2006) for further information: It is sufficient to note that $\mathbf{C}$ is unique if the marginal distributions are continuous.

$$\mathbf{G}(x_1,\ldots,x_m) = \mathbf{C}\left(\mathbf{G_1}(x_1),\ldots,\mathbf{G_m}(x_m)\right) \tag{2.17}$$

Conversely, for any copula $\mathbf{C}$ and any distribution functions $\mathbf{G_1}, \mathbf{G_2}, ..., \mathbf{G_m}$, the functions $\mathbf{C}\left(\mathbf{G_1}(x_1),\ldots,\mathbf{G_m}(x_m)\right)$ is a joint distribution function with marginals $\mathbf{G_1}(x_1),\ldots,\mathbf{G_m}(x_m)$. Moreover, combining given marginals with a chosen copula through Equation 2.17 always yields a multivariate distribution with those marginals. The copula function has then a great influence on the aggregation of risk.

LDA model shortcomings

After most complex banks adopted the LDA for accounting for RC, significant biases and delimitations in loss data remain when trying to attribute capital requirements to OpRisk losses (Frachot et al., 2001). OpRisk is related to the internal processes of the FI, hence the quality and quantity of internal data are of greater concern as the available data could be rare and/or of poor quality. Such expositions are unsatisfactory if OpRisk, as Cruz (2002) professes, represents the next frontier in reducing the riskiness associated with earnings. Jongh, De Wet, Raubenheimer, & Venter (2015) and Galloppo & Previati (2014) sought to address the shortcomings of Frachot et al. (2001) by finding possible ways to improve the problems of biases, such as "ommitted varaible bias" (OVB) and data delimitation in operational risk management. Furthermore, Opdyke (2014) advanced on this problem through a study intending on eliminating biases due to heavy tailed distributions i.e., overestimation of capital adequacy estimates in a time lag after realised losses due to extrapolation to the 99.9th percentile and an overstretched distribution.

Jongh et al. (2015), Galloppo & Previati (2014), Opdyke (2014) & others follow along lines in the literature of recent attempts aimed at finding a statistical-based model for OpRisk capital calculation, which suggest integrating internal and external data as well as scenario assessments to endeavour on improving on accuracy for the estimates. In recent work, Badescu, Lan, Lin, & Tang (2015) reported that LDA modelling is found wanting due to the very complex characteristics of data sets required to establish OpVaR. Furthermore, insightful are continually emerging new found techniques are being built to deal with these issues that arise in LDA modeling; opening new and contentious areas of work, keeping practitioners and academics guessing at what revolutionary phase may follow w.r.t the latest research methods.

Opdyke (2014), Agostini, Talamo, & Vecchione (2010), Jongh et al. (2015), Galloppo & Previati (2014), and others seem to explicate how greater accuracy, precision and robustness uphold a valid and reliable estimate for OpRisk capital as defined by Basel II/III. Transforming this basic knowledge into a "risk culture" or firm-wide knowledge for the effective management of OpRisk serves as a starting point forming a control function that provides attribution and accounting support within a framework, methodology and theory for understanding OpRisk. FI's are beginning to implement sophisticated risk management systems similar to those for market and credit risk, linking theories which govern how these risk types are controlled to theories that govern financial losses resulting from OpRisk events.

Agostini et al. (2010) also argued that banks should adopt an integrated model by combining a forward-looking component (scenario analysis) to the historical OpVaR, reinforcing foremost discussions in today's literature by involving subject matter expert analysis of the case, through an integration model which is based on the idea of estimating the parameters of the historical and subjective distributions and then combining them using advanced credibility theory (ACT). The basis for the use of ACT is the idea that a better estimation of the OpRisk measure can be obtained by combining the two sources of information advocating for the combined use of both experiences.

Agostini et al. (2010) seek to explain through a weight called the credibility, the amount of credence given to two components (historical and subjective) determined by statistical uncertainty of information sources, as opposed to the conventional weighted average approach chosen on the basis of qualitative judgements. Agostini et al. (2010) proposed the integration method be deemed as self-contained and independent of any arbitrary choice in the weights of the historical or subjective components of the model, which serves as a more compelling representation of facts.

Benefits and Limitations

The basic idea of integration methodologies discussed in the afore-mentioned section is to estimate the parameters of the frequency and severity distributions based on the historical losses and correct them; via a statistical theory, to include information coming from the scenario analysis. These approaches are deemed to have significant advantages over conventional LDA methods proposing that an optimal mix of the two modeling components i.e., historical and subjective parts, could better predict OpVaR over traditional methods. Particularly in the work by Agostini et al. (2010), whose integration model represents a benchmark in OpRisk measurement by including a component in the AMA model that is not obtained by a direct average of historical and subjective VaR.

These methods has the advantage of being completely self contained and independent of any arbitrary choice or weighting of the historical or subjective components in the model made by the analyst. These components weights are derived objectively, through robust means based on statistical uncertainties of information sources rather than through risk managers choices based on qualitative motivations. However, they suffer from not explaining the prerequisite need for coherence between the historical and subjective distribution functions, required for the model to work; particularly when in a number of papers (Chau, 2014) it's proposed that using mixtures of (heavy tailed) distributions commonly used in the setting of OpRisk capital estimation cannot be avoided (Opdyke, 2014).

Looking beyond current Oprisk modeling frameworks

Historical severity curves obtained from historical loss counts that are usually presented in conventional quantification techniques, such as in LDA modelling, have been widely considered to be the most reliable models when used in OpRisk loss estimation. However, they are not useful and have not been very successfull when used to predict future losses, particularly in the measurement of “predictive” OpRisk loss types capturing forward-looking aspects of the BEICFs thereof. As stated in the industry position paper, see Group & others (2013), these are OpRisk loss types with defined risk exposure and identifiable risk drivers, which are then incorporated as explanatory variables in “alternative” models whose aim is to replace the afore-mentioned LDA modelling techniques by measures using event frequencies based on actual exposures and available risk factors, instead of hisorical loss counts in the capital adequacy prediction problem (Einemann et al., 2018).

EBOR methodology for capturing forward-looking aspects of ORM

In a theoretical paper, Einemann et al. (2018) construct a mathematical framework for an EBOR model to quantify OpRisk for a portfolio of pending litigations. Their work unearths an invaluable contribution to the literature, discussing a strategy on how to integrate EBOR and LDA models by building hybrid frameworks which facilitate the migration of OpRisk types from a *classical* to an exposure-based treatment through a quantitative framework, capturing forward looking aspects of BEICF’s (Einemann et al., 2018), a key source of the OpRisk data.

As mentioned in their paper (Einemann et al., 2018), they were the first to lay the groundwork for future development of their technique across industry, and to establish a common language through a strategy for integrating EBOR models and LDA models. In the former EBOR model they incorporate “predictable” loss types e.g., they test their hypothesis on a portfolio of pending litigations, litigations being “predictable” as far as when given the event triggering the filing of the litigation case had already happened, and only the final outcome in court has to be modelled. In the latter LDA modelling case, they consider LDA components which cover risks that are well reflected through historical events.

The general exposure-based operational risk (EBOR) concept

The general theory for measuring and allocating risk capital is independent of specific risk types: It is the basis from which standard risk measures are founded. Risk capital calculated at the aggregate level forms the basis from which the allocation of risk capital to individual events is derived; in fact Aue & Kalkbrener (2006) shows why a consistent framework for measuring risk and firm performance hindges, in fact, on a uniform application of risk theory to capital adequacy calculation for market, credit and Oprisk. In particular, standard risk measures like value-at-risk (VaR) or expected shortfall (ESF) are based on the Monte Carlo simulation of the loss distribution which is a numerical representation of a simple closed form of the total event distribution function. More precisely,

$$\mathrm{VaR}(\alpha) = \inf\{z \in \mathbb{R} \| \mathbb{P}(Z \leq z) \geq \alpha\}, \tag{2.18}$$

$$\mathrm{ESF}(\alpha) = \mathbb{E}(Z \| \mathrm{VaR}(\alpha)) \tag{2.19}$$

The allocation of risk capital to BL/ET combination risk cells is based on ESF contributions, which is numerically evaluated in the tail of the aggregate loss distribution if a sample list of Z has been calculated. The tail focused allocation technique is particularly well suited to model risk capital allocations to individual exposures, due to the fact that that each sample z of Z can be reduced down in granularity of the n loss events .i.e., $\sum_{j=1}^{n} z_j$, defined as its contribution to the tail of the aggregate loss distribution (Aue & Kalkbrener, 2006):

$$\text{ESF}_i(\alpha) = \mathbb{Z}(Z_i\| > (VaR)(\alpha)). \tag{2.20}$$

If the underlying portfolio is limited in granularity, risk capital is allocated to a small number of portfolio constituents whose risk management strategy precludes tail focused allocation techniques like ESF which are based on a high quantile features designed to highlight risk concentrations (Einemann et al., 2018). Decidedly desiring alternative techniques which give more weight to the body of the underlying distributions.

EBOR modeling techniques are specifically designed to quantify specific aspects of OpRisk consisting of determining the aggregate event loss variable $\mathbf{Y}$ which may have rather concentrated risk profiles, obtained by linking OpRisk events to event types with defined exposures, in addition to "predictive" factors, through the introduction of a given set of *risk factors* who also sufficiently capture risk exposure to forward-looking aspects. As a conscequence, capital estimates adapt to real-time changes in the risk profile of a bank e.g., point-in-time changes in the portfolio mix, or the introduction of a new product. The aggregate event loss variable of the EBOR model derived from 1.1, with indivudual losses yields

$$\mathbf{Y} = \sum_{j}^{n} I_r \cdot L_r \cdot EI_r, \quad \text{where} \quad r \in i, \ldots, n \tag{2.21}$$

The EBOR model concept defines n potential loss events, where n is considered as the *frequency exposure* and no longer denotes $n = 56$ different components of the LDA model cells corresponding to BL/ET matrix combinations, but to individual loss events. At this stage, EBOR is not conidered as an option in the Basel II accord for OpRisk. Indeed, the regulatory framework proposes four approaches i.e., SA, BIA, IMA ans the SMA.

The EBOR model is a special case of the IMA conditional on the IMA being allowed to depend only on aggregate number of events, and on the total loss amounts by BL/ET risk type cells but not on individual losses (Frachot et al., 2001). Frachot et al. (2001) demonstrates this when we find out the conditions under which both methods coincide i.e., $\mathcal{C}^{IMA}_{OpRisk} = \mathcal{C}^{LDA}_{OpRisk}$ and $\mathrm{EL}^{IMA}_k = \mathrm{EL}^{LDA}_l$ i.e., $Y_{ij} = S^{T+\tau}_{ij}$. It comes that the internal scaling factor γ_k:

$$\begin{aligned}
\gamma_k &= \frac{\mathcal{C}^{IMA}_{OpRisk}}{\sum_r^n I_r \cdot L_r \cdot EI_r} = \frac{\mathcal{C}^{LDA}_{OpRisk}}{\sum_{l=1}^{N_k} X_{kl}} \\
&= \frac{G^{-1}(\alpha)}{\sum_{l=1}^{N_k} X_{kl}} \qquad (2.22) \\
&\Longrightarrow \sum_r^n I_r \cdot L_r \cdot EI_r = \sum_{l=1}^{N_k} X_{kl}
\end{aligned}$$

$$(2.23)$$

Where n is fixed to the number of observations in the internal database and $\mathbf{G}^{-1}(\alpha)$ is the quantile of ϑ for the level α. For illustrative purposes lets assume the poisson/log-normal compound distribution where the frequency parameter ($N \sim \mathcal{P}(\theta)$), and the severity parameters ($\zeta \sim \mathcal{LN}(\mu, \sigma)$): The IMA model can justifiably be developed as a proxy for the LDA model supposedly to capture the LDA model in a simplified way provided γ_k has the following functional form:

$$\gamma = \gamma(\theta, \mu, \sigma; \alpha) \qquad (2.24)$$

In turn, see Section 1.4.2 & 1.3, and provided expression 2.24 holds, than it is justified that the EBOR model is also a special case of the LDA model (Einemann et al., 2018).

The aggregate event loss $\mathbf{Y}$'s relates to the sum of $(I_1, \ldots, I_n)$ denoting the event indicator; a vector of independent (bernoulli) rv's, whose joint event probabilities are specified through a bernoulli mixture model defined by: $\ni \mathbb{P}(I_j = 1|\Psi = \psi) = p_j(\psi)$ and $\psi = \mathbb{R}^m$, such that they have to attain values $y = (y_1, \ldots, y_n) \in \{0, 1\}^n$; whose sum is called the event **frequency variable**, taking the states 1 or 0 depending on whether there is a realised loss, or a pending loss/near miss. EI_j is the deterministic *severity exposure* of the j_{th} event and L_j is the (stochastic) severity ratio which specifies the loss ratio or loss-given-event (LGE) as a percentage of exposure.

Integration of EBOR and LDA models

The only missing piece for a sound Oprisk capital calculation exercise is left in merging the LDA and EBOR models in a fully integrated and diversified way (Einemann et al., 2018). This setup is achieved by specifying the dependence of the LDA frequency and EBOR frequency through an additional dimension of the copula, such that the EBOR model is considered as and additional cell, anagolously to the BL/ET matrix combinations in classical LDA model. Einemann et al. (2018) deduced a simple recursion formula which is used for a joint LDA and EBOR simulation algorithm smoothening the EBOR modelling integration into an LDA model. The output is a total number of EBOR events, $n_{r+1}(l)$ translated into a joint state of realisations $I_1(l), \ldots, I_n(l)$ for a specific scenario, such that

$$n_{r+1}(l) = \sum_{j=1}^{n} I_j(l) \tag{2.25}$$

The integration concept would also trigger changes of the LDA models input data to avoid double counting of loss potential, therefore it is assumed that the LDA and EBOR events are separated beforehand leaving the task of specifying the model.

Limitations of the EBOR model

In measuring and allocating OpRisk capital (Einemann et al., 2018)'s model is particularly well-suited to the specific risk type dealt with in their paper i.e., the portfolio of litigation events, due to better usage of existing information and more plausible model behavior over the litigation life cycle. However, it is bound to under-perform for many other OpRisk event types since these EBOR models are typically designed to quantify specific aspects of OpRisk i.e., litigation risk have rather concentrated risk profiles. However, it cannot be stresses enough that EBOR models are important due to their wide applicability beyond capital calculation and its potential to evolve into an important tool for auditing process and early detection of potential losses.

A new class of EBOR models capturing forward-looking aspects

I am using GLM and GAMLSS methods to build a predictive OpRisk model in the sense that by including all the relevant risk factors that are responsible for PnL loss mechanisms, the model has a "comprehensive" effect, an all encompassing effect on the number and sizes of operational losses, and it's more expansive in it's uses to model a wider range of Oprisk loss types. The model incorporates an inbulit offset feature, which is an intuitively significant addition an differentes this modelling technique to the non-ideal actuarial model specified in Einemann et al. (2018). The *offset* is an additional model variable which is particularly useful in the modelling of growth rate phenomena in the data.

The afore-mentioned non-ideal nature in the actuarial technique for integrating EBOR models and LDA models is compounded by the real-world fact that OpRisk data is often difficult to parse into EBOR data and LDA data types as required by the integrated model, furthermore OpRisk data is often incomplete and many relevant variables are inconsistently coded and massively categorical. For these reasons (Yan, Guszcza, Flynn, & Wu, 2009), in most actuarial modeling situations modelers are forced to exclude variables that are relevant to predicting frequency and severity of losses exacerbating the problem of OVB. In contrast, the offset option from GLM's offers it's classical uses of avoiding OVB amongst others, and is useful in predictive modelling.

GLM model specification for count data

In this paper, we develop a data intensive GLM analysis of the *frequency* response variable viz. the loss ratio term anagolous to Einemann et al. (2018)'s frequency variable, called the LossIndicator; using an explanatory vector of p random variables (rv's) $\Psi = (\psi_1, \ldots, \psi_p)$, the risk factors, which are those casual factors that create losses with random uncertainty and decidedly non-normal, and who introduce dependencies between variables including categorical outcomes and discrete counts; and an *offset* variable d_i which is discussed as a measure of exposure in the context of a poisson regression. In the loss ratio modeling, the goal is to build a model targeting the response $f(y;\theta)$:= the LossIndicator, which is to be layered on to the existing plan.

The *offset* is selected as a measure of trading risk exposure: i.e., the required correction for the period in days, d exposed to risk, and risk factors are the business environment and internal control factors (BEICF's) thereof e.g., information such as the trading times, trader identification, loss event capture personnel, trade status and instrument types, loss event description and reasons for the losses, loss event type categorisation, individual loss amounts, market variables which have an economic interpretation, trading desk and business line, beginning and ending date and time of the event, and settlement times, etc.

Frequency model specification

As specified in the LDA model (Subsection 2.5.2), let $\mathbf{N}_{ij}$ be the number of times of OpRisk loss event failures over time $[T, T + \tau]$. The stochastic process $N_{ij} \leq n$ is called the frequency process. N_{ij} is equivalent to the r.h.s of Equation 2.25, corresponding to Einemann et al. (2018)'s EBOR model *frequency exposure*, where n is the maximun number of events. The unit of exposure n now takes on the value of the upper bound of the rv $\mathbf{N}_{ij}$, the frequency variable in the current LDA model.

$$\mathbf{N}_k = \sum_{k=1}^{m} I_k \tag{2.26}$$

Where n is some terminal time $T + \tau$. Nelder & Wedderburn (1972), Ohlsson & Johansson (2010) and Covrig et al. (2015) show that this process is a poisson process which follows a poisson distribution with parameter $\theta = \lambda$, or otherwise the rate. Here we describe the *exponential dispersion model* (EDM) of the GLM, which generates the poisson distribution by the model..

$$f(y, \lambda) = \frac{\lambda^y e^{-\lambda}}{y!} \tag{2.27}$$

Modeling counts as realised operartional hazard in an OpRisk group requires correction for the period d exposed to risk. The exposure measue is readily incorporated into the estimation procedure and is a quantity that is roughly proportional to the risk. As this statement suggests, the offset/exposure measure must be on the same scale as the linear predictor in the basic GLM framework. So the mean frequency will be estimated by the multiplicative model (Covrig et al., 2015 & @ohlsson2010non) corresponding to a logarithmic link function, a *log link*, where a new variable d_i appears

$$\begin{aligned} \lambda_i &= d_i \cdot e^{\beta_0} \cdot e^{\beta_1 x_{i1}} \cdot e^{\beta_2 x_{i2}} \ldots e^{\beta_p x_{ip}} \quad \text{Taking logs on both sides} \\ \ln\lambda_i &= \ln d_i + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} \end{aligned} \tag{2.28}$$

$\ln d_i$ is the natural log of risk exposure, called the *offset variable* which affects the algorithm only directly before and after regression estimation, effectively replacing the rate λ with an adjusted rate (counts divided by exposures: $R = \frac{\lambda}{d}$) as the target variable; using exposure as weight; dispensing with the offset (Yan et al., 2009).

In the definition for exposure, the offset is most commonly discussed as a measure of exposure in the context of poisson regression. For example when modeling rates in some observations from an OpRisk dataset, for set entries corresponding to a $d_i = 6$ month time lag between the moment the Oprisk event was conceived, T until the Oprisk event is realised at $T + \tau$; while another set of events correspond to a $d_j = 1$ year lag, then it is appropriate to use (log of) months of exposure as and offset. If not, model variables correlated with months of exposure might possibly pick up some of the varaition that should be explained by months of exposure, resulting in biased parameter estimates.

Frequency model illustration

In their paper, the EBOR model pioneered by Einemann et al. (2018), a non-inflated successful claimed amount providea a plausible estimate for the capital charge for litigation risk, but mainly because it is particularly well-suited to the specific risk type dealt with i.e., due to better usage of extensive existing information (Boettrich & Starykh, 2017) and the more plausible model behavior over the litigation life cycle. This is important, it fits in with the required data availability prerequisite, such as the requirement for case specific information for each litigation needed for accounting, as well as in the required identification of dependencies across the porfolio which makes it easier for outflow estimates in the provisioning process (Einemann et al., 2018).

Nevertheless, their EBOR model is bound to under-perform for many other OpRisk event types whose data types fall outside of the contraints, since these EBOR models designed for litigation risk are typically designed to quantify specific aspects of OpRisk. Litigation risk have rather concentrated risk profiles i.e., litigations can be grouped into clusters whereby a court ruling for one litigation impacts the likelihood of a payment for other litigations in the same cluster and, on the other hand does not influence the the outcome of litigations outside the cluster (Einemann et al., 2018). For example, in a chart of litigation settlement as a percentage of IPO issuing amounts, see Rosa (2012) which demonstrates the highest concentrations of payments toward the end of Q2 2012 on toward early Q3, tapering off in the early and latter parts of year.

GAMLSS model specification for PnL impact data

As a way of addressing the OpRisk growth enigma and on how to go about thinking of VaR and the problems associated with the possibilities in 2.8.2 e.g., of extreme events, we re-examine HFLS/LFHS data severity modelling by introducing the GAMLSS framework. GAMLSS employs the power of modern statistical techniques and methods for performing a univariate regression analysis; more precisely the loss *severity variable*, where not only the location of the severity distribution but also the scale and shape of the distribution can be modelled by explanatory variables (Stasinopoulos, Rigby, & Bastiani, 2018). Much like how the linear model (LM) is a submodel of the GLM, the GLM and Generalized Additive Models (GAM) are submodels of the GAMLSS, therefore extends the features of these model types viz., assumed EDM for the response in GLM and GAM, moreover for the GAMLSS the assumed response distribution can belong to any parametric distribution.

Furthermore, GAMLSS are semi-parametric regression type models in the sense that all the parameters of the response variable distribution can be modelled using parametric and/or non-parametric smooth functions of explanatory variables, thus allowing for a very general and flexible system for modelling OpRisk loss severity variable. Due to this, they are often viewed as “beyond mean regression” (Kneib, 2013) models or distributional regression model (Fahrmeir, Kneib, Lang, & Marx, 2013) approaches. What this means is that the location, scale and shape of the response variable is allowed to change according to explanatory variables, which are expecially useful for OpRisk loss severity data modelling, whose attributes are continuous and positively skew, and/or leptokurtic.

Severity model specification

The idea behind the semi-parametric characteristic of GAMLSS modelling is to let the data determine the relationship between the predictor $\eta = g(\mu)^7$, and the explanatory variables s_k, rather than enforcing a linear (or polynomial) relationship. As mentioned earlier, there are instances where the assumption of a constant scale parameter (σ), and shape parameters (ν, τ) is not appropriate such as for some highly skew and kurtotic distributions. On these occations modelling $\sigma, \nu, \&\tau$ as a function of explanatory variables solves the problem.

A whole new industry of modelling emerges from initially modelling the dispersion parameter beginning with Harvey & others (1976), followed on by Aitkin (1987), then furthered within the GLM by Nelder & Pregibon (1987), Smyth (1989) & Verbyla (1993) in which the response may follow an expontial family distribution: Stasinopoulos et al. (2018)'s advanced mean and dispersion additive (MADAM) models is permitting of response variable following any simply known mean variance relationship whose formulation uses either GOV or marginal likelihood (approach to select the degree of penalisation) methods of fitting for the estimation of smooth function of predictor variables.

GAMLSS models allow the predictor to now predicts some $g_k(\cdot)$ for $k = 1, 2, 3, 4$, a smooth monotonic link function relating the distribution parameter θ_k to a linear or non-linear parametric functions e.g., the expected value of the response which may follow a EDM family, or in addition nonparametric smoothing functions h_{jk} of the explanatory variables x_{jk}, to the predictor η_k. Assuming $i = 1, \ldots, n$ independent observations $Y_1, Y_2, \ldots, Y_n$ with p.d.f $f_Y(y_i|\mu, \sigma, \nu, \tau)$ and

$$Y_i = D(\mu_i, \sigma_i, \nu_i, \tau_i) \tag{2.29}$$

[7] η now referred to as the predictor and not linear predictor, since the smoothing terms introduce non-linearities in the model

Where D is any distribution with (up to) four distribution parameters. In general the model has a structure something like

$$g_k(\theta_k) = \eta_k = \mathbf{X}_k \beta_k + \sum_{j=1}^{J_k} h_{kj}(\mathbf{x}_{kj}) \tag{2.30}$$

Where $\mathbf{X}_k$ is a known design matrix, and $(\beta)_k = (\beta_{k1}, \ldots, \beta_{kJ'_k})^{\mathsf{T}}$ is a parameter vector of length J'_k to be estimated and h_{jk} are non-parametric smooth functions of explanatory variables X_{kj} and $\mathbf{x}_{kj}$ are vectors of length n, for $k = 1, 2, 3, 4$ and $j = 1, \ldots, J_k$. The explanatory variables can be similar or different for each of the distributional parameters, which can be modelled as linear i.e., $\mathbf{X}_k \beta_k$ or smooth term functions $h_{kj}(x_{kj})$ for $k = 1, 2, 3, 4$ (Stasinopoulos et al., 2018).

Severity model illustration

More often than not, the commonly rare and low quality OpRisk data types exhibit lesser to lower concentrated risk profiles, which compounds the OpRisk data dilemnna when it comes to measuring OpRisk, as the less data available the less accurate VaR the estimation is likely to find. This means for less concentrated risk type profiles the more data available the more sensitive the deviance becomes which impacts on the variation of exposure in the model output. It’s important to note that deviances may be intepreted as weighted sums of distances of estimated means from observations Y_i; Ohlsson & Johansson (2010) indicates that minimising the unscaled deviance plays a pivotal role in severity distribution modelling, as it is trivially equivalent to maximizing the likelihood in the normal linear model (LM) and/or minimising of the the sum of squares in methods used during frequency distribution model estimation.

Moreover, most OpRisk loss profiles are not necessarily concentrated and therefore the EBOR model is limited in it's current form. EBOR models are important nevertheless, due to their wide applicability beyond capital calculation and also due to the potential to evolve into an important tool for auditing process and early detection of potential losses, albiet the basis of moving toward a new EBOR model as more data becomes available. In this new framework the offset variable which eliminates OVB also introduces a sensitivity to the deviance and therefore caters for this variation of exposure. This paper advances toward a framework stringing along these challenges and benefits in mind.

Gap in the Literature

The existing (Einemann et al., 2018's) EBOR model is specific to certain risk types, such as litigation risk due to it's concentrated risk profiles, and only if the data comes in a specific kind of packaging in order to apply as a predictive and/or explanatory model designed to capture forward-looking aspects of the OpRisk measurement problem. This EBOR model in it's current form is not suitable for the treatment of most OpRisk types as their risk profiles are not necessarily concentrated and the data forms don't strictly adhere to the requirements for the model to work.

The new EBOR model is compelling since it is based in established statistical techniques, so called GLM's and GAMLSS methods (Nelder & Wedderburn, 1972) which are more comprehensive as their parametric and/or semi-parametric nature is specifically dealt with and they offer an offset viz. *exposure* variable, which features by eliminating the constraints regarding needed concentrated risk profiles in the afore-mentioned EBOR model. Furthermore, data points are extracted using digital information directly from the internal loss generating mechanisms created and collected at an individual event-wise level, free from potentially erroneous assumptions and manipulations and processed through the loss collection data exercise (LCDE).

The GLM's offset function for one eliminates OVB, and secondly due to the GLM's well established machine learning technique, whose efficiency is a function of the number of data points, it introduces a sensitivity minimising the unscaled deviance (which is trivially equivalent to maximizing the likelihood or minimising the cost function since that deviances are intepreted as weighted sums of distances estimated means from observations) and hence estimating standard errors. The offset variable d, see Equation 2.28 serves as function used to measure performance in the multiplicative poisson model over time.

Knowledge affirms that no amount of capital is realistically reliable in the quantification of OpRisk particularly through the modelling approach of capital adequacy (i.e., the determination of risk adjusted capital as a buffer to risk), due to weaknesses in current VaR methods which don't have learning and don't factor in loss aversion. Introducing GLM's and GAMLSS techniques advances the recent literature that a better estimation model which focuses the theoretical lens through weighting of probabilities to determine whether the rate of OpRisk's hazards' is slowing gains us a better understanding of how past losses affect risk attitudes. That is, through machine learning the modelled future should overprovide for the loss events that have already occured which fits normal behavioural patterns around individuals psycological makeup which is consistent with risk aversion.

Learning from the actual data could potentially change the shape and/or scale of the d.f; GAMLSS is specifically adapted to changing location, shape or scale parameters and therefore unrestricted to a "single best" model moving away from a "normal" statisical theory which assumes risk neutrality to open up another line of research, which suggests a better modelling method for more efficient human behaviour.

Conclusion

Finance models depicting OpRisk theory describe human behavior, and therefore models of uncertainty measured in the past are the best estimates for future risk and are at best subjective approximations. They are not as accurate as those modelling market risk and credit risk as their theory closely lend to scientific analysis further compounded by the fact that in OpRisk accurate and reliable quantitative data is rarely available and often of low quality. This weakens OpRisk management as models based on historical losses have an inherently backward looking character and are not well linked to the loss generating mechanisms, and hence do not fully capture exposures to forward looking aspects. The underlying problem in OpRisk modeling are capital estimates do not react quickly enough to changes in the risk profile.

In this study we are moving away from statistical models constrained theories assuming that means are a linear functions of covariates and normally distributed random errors, such as (general) linear regression models, to adopt very flexible and unifying frameworks viz. GLM's and GAMLSS and superimpose these on the OpRisk model, incorporating theories from behavioural finance to the learning of high dimensional, non-linear OpRisk loss generating processes and control systems. For example, GLM's capabilities are of a general exponential distribution class unconstrained by the normal assumption and a choice of a monotonic transformation of the mean .viz, an offset variable (Ohlsson & Johansson, 2010), while the GAMLSS model allows any distribution for the response variable and all the parameters of the distribution can be modelled as functions of expalanatory variables, to name a few.

These new GLM and GAMLSS based EBOR models is unique in that it lays the foundation for an intepretrable mathematical representation for OpRisk, using an iterative process through training and validating, i.e., given a series of inputs the data is trained and validated and eventually produces a prediction that is as close to the actual output. As opposed to other machine learning techniques e.g., artificial neural networks which are criticised due to their lack of intepretabil;ity of hte weights obtained during the model building process. The basis of the power of this process, so called “learning”, is that the models do not necessarily assume any functional form between target variable and covariates, instead the functional relationship is determined by the data in the process of finding the weights.

CHAPTER 3
DATA EXPLORATION AND EXPOSURE VARIABLE ANALYSIS

Introduction

Many of the ideas and concepts (Dobson & Barnett, 2008) of linear regression modelling carry over to generalized regression modelling, however the "generalized" term is used to refer to all linear models other than simple straight lines found in the linear case. That is, the generalized linear regression (GLR) model reduces (multiple) linear regression (MLR) if and only if the error term (random component of the response variable y) has a normal distribution i.e., $\mu = 0$, & σ^2:

$$E(\mathbf{Y_i}) = \mu_\mathbf{i} = \mathbf{x_i}^T\beta + \epsilon_i \qquad \epsilon_i \sim \mathbf{N}(\mathbf{0}, \sigma^\mathbf{2}), \tag{3.1}$$

In the case of the OpRisk dataset, the relationship between outcomes and drivers of risk are frequently not normal, therefore models of the form 3.1 where random variables $\mathbf{Y_i}$ are independent, are not applicable. The transposed vector $\mathbf{x_i}^T$ represents the ith row of the dataset $\mathbf{X}$. In such cases, due to recent advances in statistical theory and computational techniques, generalised linear models (GLM); which are analogous to linear models, are used to assess and quantify the relationships between a target variable and explanatory variables (Dobson & Barnett, 2008).

GLM's differ in that

- The distribution of the target variable is chosen from the exponential family
- A transformation of the mean of the response is linearly related to the explanatory variables, however their association need not be of the simple linear form in equation 3.1

Generalized linear (regression) models (GLM) for count data

As with the linear model, consider independent rv's $\mathbf{Y_i}$ not i.i.d, whose probability depends on a parameter θ_i. The choice of parameter θ_i determines the response distribution which is assumed to have the same form as the exponential family, in turn characterising the statistical unit i. Thus, the exponential family representation depends on varying parameters θ_i, and a constant scale parameter ϕ. the pdf of $\mathbf{Y_i}$ is

$$f(y_i;\theta_i;\phi) = \exp\left[\frac{a(y_i)b(\theta_i) - c(\theta_i)}{\phi} - d(y_i,\phi)\right], \quad y_i \in Y \tag{3.2}$$

where a, b, c, & d are regarded as known functions. Expanding the expression in equation 3.2 yields

$$\begin{aligned} f(y_i;\theta_i;\phi) &= \exp\left[\frac{a(y_i)b(\theta_i) - c(\theta_i)}{\phi} - d(y_i,\phi)\right] \\ &= \frac{1}{e^{d(y,\phi)}} \exp\left[\frac{a(y_i)b(\theta_i) - c(\theta_i)}{\phi}\right] \\ &= r(y,\phi)\frac{1}{e^{\frac{c(\theta_i)}{\phi}}} \exp\left[\frac{a(y_i)b(\theta_i)}{\phi}\right] \\ &= r(y,\phi)s(\theta,\phi) \exp\left[\frac{a(y_i)b(\theta_i)}{\phi}\right] \qquad (3.3) \\ \text{where} \quad r(y,\phi) &= \frac{1}{e^{d(y,\phi)}} \quad \text{and where} \quad s(\theta,\phi) = \frac{1}{e^{\frac{c(\theta_i)}{\phi}}} \end{aligned}$$

since the scale parameter ϕ is constant, the distribution belongs to the exponential family if it can be written in the form

$$f(y;\theta) = r(y)s(\theta)\mathbf{e}^{a(y)b(\theta)} \tag{3.4}$$

If $a(y) = y$, the distribution is in canonical form and $b(\theta)$ is called the natural parameter of the response distribution (De Jong & Heller, 2008). The specific elements of a GLM are (Covrig et al., 2015; Dobson & Barnett, 2008):

1. The random component given by the independent random variables $Y_1, Y_2, \ldots, Y_n$ not identically distributed. Note that the rv's $\mathbf{Y_i}$ for the Oprisk data, indexed by the subscript i, have different expected values μ_i. Sometimes there may be only one observation y_i for each Y_i, but there may be several observations $y_{ij}, (j = 1, \ldots, n_i)$ for each $\mathbf{Y_i}$. The pdf or probability mass function of $\mathbf{Y_i}$ is given in equation 3.4 for $f(y)$, which specifies that the distribution of the response is in the exponential family. The support set X of the rv Y_i is subset of $\mathbf{N}$ of $\mathbf{R}$.

2. The second advance is the extension of computational methods to estimate the models systematic component, so called the "linear predictor" described in equation 3.1 built with $p + 1$ parameters $\beta = (\beta_0, \beta_1, \ldots, \beta_p)$ and with p explanatory variables:

$$\eta_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij}, \qquad i = 1, 2, \ldots, n \tag{3.5}$$

3. The equation for η_i specifies to the situation that there is some non-linear function, a transformation of the mean, $g(\mu)$, that is linearly related to the explanatory variables contained on the r.h.s of equation 3.5, $\mathbf{X_i}^T\beta$, i.e.,

$$g(\mu_i) = \mathbf{X_i}^T\beta \tag{3.6}$$

   The function $g(\mu_i)$ is called the link function.

Table 3.1: The generalized linear model link functions with their associated units of interpretation. Note: This list is not exhaustive and there are likely more GLMs that are used within prevention research.

Link Function	$g(\mu)$	Target variable Effect	Canonical link for
Identity	μ	Original Continuous Unit	normal
Log	$\ln\mu$	count	poisson
Logit	$\ln\frac{\mu}{1-\mu}$	Risk	binomial
Probit	$\phi^{-1}(\theta)$	Risk	binomial
Power	μ^p	Count	$\Gamma(p=-1)$
		Count	inverse Gaussian(p=-2)

Interpretation

Given a response variable y, for the initial formulation of glm's by Nelder & Wedderburn (1972), $b(\theta)$ determines the nature of the response distribution and the choice of link is suggested by the functional form of the relationship between the response and explanatory variables. In choosing these components extra steps are taken compared to ordinary regression modeling. Commonly used links functions are given in Table 3.1 which also presents the units produced for the various GLM links.

Offsets

Modeling counts as realised operational hazard in an OpRisk group requires correction for the period in days d exposed to risk. If μ is the mean of the count y then the occurence rate of interest $R = \frac{\mu}{d}$ and

$$g\left(\frac{\mu}{d}\right) = \mathbf{x}^T\beta \tag{3.7}$$

When g is the log function, this becomes

$$\ln\left(\frac{\mu}{d}\right) = \mathbf{x}^T\beta \quad \Rightarrow \quad \ln\mu = \ln d + \mathbf{x}^T\beta \tag{3.8}$$

Where the variable d appears representing the risk *exposure* and $\ln d$ is called an "offset". Equation 3.8 differs from the usual specification of the linear predictor due to the inclusion of the term $\ln d$. An offset is effectively another explanatory variable in the regression, with a β coefficient = 1. With the offset, y has expected value directly proportional to exposure:

$$E(Y) = \mu = de^{x^T\beta} \tag{3.9}$$

Offsets are used to correct for differing periods of observation (De Jong & Heller, 2008) i.e., in the opRisk dataset these are the times to detection (exposure) of the realised losses. The exposure measure is a known constant which is readily incorporated into the estimation procedure and is a quantity that is roughly proportional to the risk (Parodi, 2014) i.e., when the exposure (time to detection) doubles whilst everthing else (e.g. interest on an interest rate swap) remains the same, the risk also doubles.

Exploratory data analysis

The main source of the analysis dataset is primary data, a collection of internal OpRisk losses for the period between 1 January 2013 and 31st March 2013 at an investment bank in SA. The method of data generation and collection is at the level of the individual trade deal, wherein deal information is drawn directly from the trade generation and and settlement system (TGSS) and edit detail from attribution reports generated in middle office profit & loss (MOPL). The raw source consists of two separate datasets on a trade-by-trade basis of daily frequencies (number of events) and associated loss severities.

The raw frequency data consists of 58,953 observations of 15 variables, within the dataset there are 50,437 unique trades. The raw severity data consists of 6,766 observations of 20 variables; within the severity dataset there are 2,537 unique trades. The intersection between the frequency and severity datasets consists of 2,330 individual transactions which represent realised losses, pending and/or near misses. This dataset is comprised of 3-month risk correction detail, in the interval between 01 January 2013 and 31 March 2013.

Table 3.2: The contents of the traded transactions of the associated risk correction events.

Covariate	Levels	Storage Type
Trade		numeric
UpdateTime		numeric
UpdatedDay		numeric
UpdatedTime		numeric
TradeTime		numeric
TradedDay		numeric
TradedTime		numeric
Desk	10	categorical
CapturedBy	5	categorical
TradeStatus	4	categorical
TraderId	7	categorical
Instrument	23	categorical
Reason	19	categorical
Loss		numeric
EventTypeCategoryLevel	5	categorical
BusinessLineLevel	8	categorical
LossIndicator	2	binary
exposure		numeric

Two new variables are derived from the data; a target variable (LossIndicator) is a binary variable whereupon, a 1 signifies a realised loss, and 0 for those pending losses, or near misses. The *exposure* variable is computed by deducting the time between the trade amendment (UpdateTime) and the time when the trade was booked (TradeTime). It is a measure that is meant to be rougly proportional to the risk of the transaction or a group of transactions. The idea is that if the exposure (e.g. the duration of a trade, the number of allocation(trade splits), etc.) doubles whilst everything else (e.g. the rate, nominal of the splits, and others) remains the same, then the risk also doubles.

In R, the GLM function works with two types of covariates/explanatory variables: numeric (continuous) and categorical (factor) variables as depicted in table 3.2. Multi-level categorical variables are recoded by building dummy variables corresponding to each level. This is achieved through an implemented algorithm in R, through a transformation as recommended for the estimation of the GLM, particularly in the estimation of the poisson regression model for count data.

The model revolves around the fact that for each categorical variable (covariate), previously transformed into a dummy variable, one must specify a reference category from which the corresponding observations under the same covariate are estimated and assigned a weight against in the model (Covrig et al., 2015). By default in the GLM, the first level of the categorical variable is taken as the reference level. As best practice, De Jong & Heller (2008), Frees & Sun (2010), Denuit, Maréchal, Pitrebois, & Walhin (2007), Cameron & Trivedi (2013) and others recommend that for each categorical variable one should specify the modal class as the reference level; as this variable corresponds to the level with the highes order of predictability, excluding the dummy variable corrresponding to (weight coefficient = $e^0 = 1$) the biggest absolute frequency.

Description of the dataset

In this section, section 3.4, the dataset called *OpRiskDataSet_exposure*, provides data on the increase in the numbers of operational events over a three month period, beginning 01 January 2013 to end of 20 March 2013. For each transaction, there is information about: trading risk exposure, trading characteristics, causal factor characteristics and their cost.

Characteristics of exposure

The exposure of risk of type i, d_i shows the daily duration, from when the trade was booked to the moment the operational risk event was observed and ended. This measure is defined this way when specifically applied to projecting the number of loss events (frequencies) and can be plotted as follows depicted in graphs depicted in Figure 4.2.

The variable follows a logistic trend on $[0, 1]$, implying an FIs operational risk portfolio rises like a sigmoid function throughout the period of observation, typically starting from 0, which then observes a plateau in growth. The average exposure is 389.99 or about 1 year.

Grid plots 4.2 portray the logistic function, together with a simple comparison of first-digit frequency distribution analysis, according to Benford's Law, with exposure data distribution. The close fitting nature implies the data are uniformly distributed across several orders of magnitude, especially within the 1 year period.

Overall Loss Severity

Loss Severity as per Trading Role

(a) Intra-day trend analysis of loss severities: overall and as per trading role

OpRisk events during month

Trading frequency

(b) Intra-month trends of OpRisk trading incidents compared to frequency of trading activity

Figure 4.1: (a) Scatterplots of intra-day trend analysis for logs of severities of operational events and for those identifying the trading role responsible/originating the loss incidents. (b) As for (a) but intra-month, and in the form of histograms depicting the frequency distrbution of the number daily operational indicents and the frequency of trades.

Distribution **Density** **Digital Analysis**

Figure 4.2: A simple comparison of the Sigmoidal like features of the fat-tailed, right skewed distribution for exposure, and first-digit frequency distribution from the exposure data with the expected distribution according to Benford's Law

Characteristics of the covariates

The characteristics of the operational risk portfolio are given by the following covariates: *UpdatedDay*, *UpdatedTime* - the day of the month and time of day the OpRisk incident occurs respectively; *TradedDay*, *TradedTime* - the day in the month and time of day the deal was originated respectively; The *LossIndicator* as indicated before is a binary variable consisting of two values: A 0, which indicates pending or near misses, and 1, if the incident results in a realised loss, meaning that there is significant p&L impact due to the OpRisk incident.

the *Desk* is the location in the portfolio tree the incident originated, it is a factor variable conisting of 10 categories; *CapturedBy*, the designated analyst who actions the incident, a factor variable consisting of 5 categories; *TraderId*, the trader who originates the deal, a factor variable with 7 categories; *TradeStatus*, the live status of the deal, a factor variable with 4 categories; *Instrument*, the type of deal, a factor variable with 23 categories; *Reason*, a description of the cause of the OpRisk incident, a factor variable with 19 levels; *EventTypeCategoryLevel*, 7 OpRisk event types as per Risk (2001), a factor variable with 5 categories; *BusinessLineLevel*, 8 OpRisk business lines as per Risk (2001), a factor variable with 8 categories.

The continuous numerical variable *Loss*, shows the financial impact (severity) of the OpRisk incident in Rands. For the most part (i.e. 96.1% of the time) OpRisk incidents result in pending losses and/or near misses, most realised losses (2.3%) lie within the [$\mathbf{R}200,00$, $\mathbf{R}300,000$] range. In the current portfolio there are also five p&L impacts higher than **R**2.5 **million**.

Characteristics of daily operational activity

The distribution of daily losses and/or pending/near misses by operational activities are represented in 4.3. Figure 4.3a shows that most operational events occur in times leading up to midday (i.e. 10:50AM to 11:50AM), the observed median is 11:39AM, and of these potential loss events, most realised losses occur closest to mid-day. The frequencies of the loss incidents in the analysed portfolio sharply decreases during the following period, i.e. from 12:10PM to 13:10PM, during which the least realised losses occur.

Figure 4.3b shows that operational activity increases in intensity in the days leading up to the middle of the month, i.e. 10^{th} - 15^{th}; the observed mean is 14.49 days, and of these potential loss events, realised losses especially impact on the portfolio during these days.

Similarly, the influence of trading desk's on the frequency of operational events can be analysed on the basis of the portfolio's bidimensional distribution by variables *Desk* and *LossIndicator*, which shows the proportions realised losses vs pending and/or near misses for each particular desk. The bidimensional distribution of *Desk* and *LossIndicator* is presented in a contingency table, Table 3.3, in which it's considered useful to calculate proportions for each desk category.

Thus, as illustratred in figure 4.5, from 23,5%; the highest proportion of re-

(a) Frequency distributions of operational incidents by the time in the day

(b) Frequency distributions of operational incidents by the day in the month

Figure 4.3: The frequency distributions of All the losses, the realised losses, and pending/near misses of operational incidents by the day in the month when the indidents' occurred

Figure 4.4: Density plots showing a comparison of realised vs pending losses and/near misses over a month for the day in the month the OpRisk incident was updated to the day in the month trades were traded/booked

Table 3.3: Occurence of realised losses: proportions on desk categories

Desk	No. of transactions no Loss	Loss	Total
Africa	49	10	59
Bonds/Repos	113	31	144
Commodities	282	45	327
Derivatives	205	24	229
Equity	269	66	335
Management/Other	41	2	43
Money Market	169	52	221
Prime Services	220	62	282
Rates	336	53	389
Structured Notes	275	26	301

alised losses per desk is the Money Market (MM) desk, the figures are decreasing, followed by Prime Services (22%); Bonds/Repos (21,5%); Equity (19,7%); Africa (16,9%); Commodities (13,8%); Rates (13,6%); Derivatives (10,5%); Structured Notes (SND) (8.6%), to the least proportion in the Management/Other, a category where only 4,7% of operations activities were realised as losses.

This behaviour can be extended beyond the trading desk, as represented in Figure 4.6, a mosaic plot grid presenting the structure of the OpRisk portfolio by Instrument, TraderId, CapturedBy [1] and the operational losses.

[1] i.e. the type of financial instrument, the trader who originated the incident on the deal, and

Figure 4.5: Histograms showing the proportions of realised losses vs all losses including pending and/or near misses by desk category

One can notice that the width of the bars corresponding to the different categories, i.e. Instrument, TraderId, CapturedBy, is given by their proportion in the sample. In particular, for the category 'at least one realised loss', in the top right mosaic of Figure 4.6 portrays a increase in "riskiness" trending up from Associate to AMBA, Analyst, Vice Principal, Managing Director, Director, up to the risky ATS category, which are automated trading system generated trades.

Figure 4.6 bottom right mosaic plot for technical support personnel for the category 'at least one realised loss', portrays a downward trend, slowing in riskiness from Unauthorised User downward to Tech Support, Mid Office, Prod Controller down to the least risky Prod Accountant. This intepretation makes sense given unauthorised users are more likely to make impactful operational errors, technical support personnel would also be accountable for large impacts albiet for contrasting reasons, they are mandated to perform these deal adjustments which have unavoidable impacts associated with them, whereas the former group are unauthorised to perform adjustments therefore may lack the skill, or be criminally minded insiders acting on their own or in unison to enable their underhanded practices and intentions without raising any suspicion.

In another mosaic plot, Figure 4.7, the bidimensional distribution of transac-

the role of the technical support personnel who is involved in the query resolution.

Type of instrument traded **Role identification**

Figure 4.6: Mosaic grid plots for the bidimensional distribution by traded instrument, the trader originating the operational event, and by the technical support personnel involved in query resolution, against the dummy variable showing if a realised loss was reported.

Table 3.4: Summary statistics for all losses as per Instrument type

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Mean	23	34,603	46,007	306	7,697	44,157	192,513

Mosasic plot for trader identification and loss indicator, by trade status

Figure 4.7: A mosaic plot representing the structure of the operational risk portfolio by trader identification (TraderId), the status ofthe trade (TradeStatus) and the number of realised losses vs pending or near misses

tions by trader and realised vs pending losses, conditional on the trade status is presented and analysed. Here, and in the contingency table, Table 3.6, we can clearly see the following trends: In BO-BO confirmed status - an increase in realised losses from the leftmost TraderID (i.e. AMBA) to right, and the opposite for transactions performed in BO Confirmed status (both with two exceptions). In particular, the biggest number of realised losses in both BO and BO-BO Confirmed statuses occur due to automated trading systems (ATS) who also give rise to the exceptions mentioned.

Table 3.5 presents the most frequent category in the operational risk dataset for each possible covariate.

Crosstab of trader identification and loss indicator, by trade status

		Trader Identification						
TradeStatus	Loss Indicator	Amba	Analyst	Associate	ATS	Director	Mng Director	Vice Principal
BO-BO Confirmed	0	24	136	320	0	282	52	49
	1	2	15	43	0	50	18	16
BO Confirmed	0	17	299	153	13	257	102	153
	1	3	71	12	8	62	23	30
Terminated	0	83	9	1	0	0	2	1
	1	17	1	0	0	0	0	0
Terminated/Void	0	2	0	0	0	2	1	1
	1	0	0	0	0	0	0	0

Table 3.5: A contingency table showing the bidimensional distribution of transactions by trader identification vs realised and/or pending losses, conditional on the trade status

Modal classes for the categorical variables

Variable	Modal class or category	Name of modal class
Desk	Rates	DeskRates
CapturedBy	TECHSUPPORT	CapturedBy_TECHSUPPORT
TradeStatus	BO confirmed	TradeStatus_BO confirmed
TraderId	DIRECTOR	TraderId_DIRECTOR
Instrument	Swap	Instrument_Swap
Reason	Trade enrichment for system flow	Reason_Trade enrichment for system flow
EventTypeCategoryLevel	EL7	EventTypeCategoryLevel_EL7
BusinessLineLevel	BL2	BusinessLineLevel_BL2

Table 3.6: A contingency table showing the bidimensional distribution of transactions by trader identification vs realised and/or pending losses, conditional on the trade status

CHAPTER 4
EXPOSURE-BASED OPERATIONAL RISK ANALYSIS

Introduction

The fundamental premise of the nature behind ORMF's is to provide an exposure-based treatment of OpRisk losses which caters to modeling capital estimates for forward-looking aspects of ORM. This proves tricky due to the need for specific knowledge about potential loss events viz. the required knowledge of the likelihood and magnitude of a loss from the time the loss event occurs until the actual realised loss materialises, given a case specific underlying loss-generating mechanism. By this very nature OpRisk is being characterised by the significant lag that results between the moment the event is conceived to the point the loss materializes.

For example, in the case of rogue trading, there is a frequency exposure associated with traders *going rogue*, due to a probability of rogue events happening between a specific group of traders over time, which is then modeled for each rogue trading event and the impact (severity based on the size of the position) of the loss when it is realised (at time of detection). This timing paradox often results in questionable capital estimates, especially for those near misses, pending and realised losses that need to be captured in the model.

Applicability of EBOR methodology for capturing forward-looking aspects of ORM

OpRisk is characterised by a time delay τ, wherein the p&l impact lags behind the moment the OpRisk event is conceived up until the event is observed and accounted for. In this paper the author advances knowledge of the current ORMF's toward a new EBOR framework which aims to provide an exposure-based treatment of OpRisk losses catering for modeling capital estimates of forward-looking aspects of OpRisk.

Einemann et al. (2018) unearth the current EBOR model anagolous to the BL/ET matrix combinations in the LDA model, wherein an additional cell is considered in the classical LDA model whose contributions build a hybrid ORMF which integrates EBOR models with the LDA model, facilitating the migration of OpRisk types from a classical to EBOR treatment through a quantitative framework (Einemann et al., 2018). Conceptually, the EBOR model component can be extended to include potential future events e.g., future litigations, based on some underlying property, capturing forward looking aspects of business environment and internal control factors (BEICF's) thereof.

The fundamental premise behind the LDA is that each firm's OpRisk losses are a reflection of it's underlying OpRisk exposure (Einemann et al., 2018). Dobson & Barnett (2008) relates OpRisk events to a varying or a constant degree of exposure, which needs to be taken into account when modeling counts or frequencies of occurance. In particular, the assumption behind the use of the Poisson distribution in the model to estimate the frequency of losses for all available observations, is that both the the intensity (or rate) of occurrence and the opportunity (or exposure) for counting can assume either of these two afore-mentioned forms (Dobson & Barnett, 2008). In the former case the varying degrees of exposure impact on the rate of events, whereas in the latter case the exposure is constant hence not relevant to the model.

When observed counts all have the same exposure, modeling the mean count μ as a function of explanatory variables $x_1, \ldots, x_p$ is the same as modeling the rate R. The actual measure of exposure we need to use depends specifically on projecting the count of OpRisk events (frequency of realised losses) as the target variable in the model as opposed to the measure if the target variable were the severity of the losses, e.g. in modeling rogue trading severity exposure of events is based on size of loss position at time to detection or CapturedBy as severity risk factors.

Sub-problem 1

In our prevailing banking phenomena of increasing OpRisks, the problem consists of questioning whether a firm's susceptibility to OpRisk hazard's growth, results in the degree of OpRisk losses slowing due to tightning OpRisk controls and enhancements to OpRisk frameworks. It would be prudent not to declare things are improving if the evidence is not quite firm that this is true. This is essentially a check for situations, from these data, whether there is evidence of the unchecked spread of negligent behaviour leading to operational loss events or not; or on the contrary, those situations other than the unrestricted spread of these "rogue" events conscequently driving OpRisk losses i.e., which may requiring a re-thinking our approach to improving OpRisk controls and enhancing OpRisk management frameworks.

Exposure-based OpRisk (EBOR) models

The existing models in OpRisk measurement for which historical loss distributions are the best predictors of future losses, assume that we do not learn from past losses. This is problematic for "predictable" risk types due to model's practice of undercapitalising known risks before occur, and overcapitalising for risks after the losses materialise, creating innappropriate capital estimates (Group & others, 2013). These concerns motivate the development of an EBOR modelling framework which not only captures past losses but also how exposures to forward-looking affect risk attitudes using event frequencies based on actual exposures in the business environment and internal control risk factors (BEICF) thereof.

Hypothesis 1

To quantify OpRisk losses by introducing GLM's, GAMLSS models towards a new framework for OpRisk management, who are "predictive" due to learning capabilities, capturing exposures to forward-looking aspects in addition to how past losses affect may risk attitudes. EBOR treatments effectively replace historical loss severity curves obtained from historical loss counts, replacing how missed losses are undercapitalized for, and/or overcapitalizing realised losses after they occur, by looking for evidence in deep hierarchies of the features from these data to affirm that this is true.

Derivation of the poisson model from the exponential family of distributions

Operational riskiness in FIs grows as trading transactions grow in complexity i.e., the more complex and numerous trading activity builds the higher the rate at which new cases of OpRisk events occur. Therefore, it is likely that the rate of operational hazard may be increasing exponentially over time. The scientifically interesting question is whether the data provides any evidence that the increase in the underlying operational hazard generation is slowing. The afore-mentioned postulate provides a plausible model to start investigating this question.

In the obove discussions, the question of increasing OpRisk hazard rates due to increasing transaction complexity arises, wherein μ_i, the expected number of new cases on day t_i is modeled. As a starting point, and with reference to LDA model steps, one begins by using Poisson modeling for counts to estimate the rate of loss events frequencies. The Poisson model's flexibility permits the modelling of numerous operational loss counts and when the data are mostly zeroes and ones (when Poisson means are low). The model assumes that the number of expected new OpRisk hazards often increase exponentially over time. Hence, if μ_i is the expected number of new cases over time $[T, T+\tau] = t_i$, then an appropriate model takes the form:

$$E(\mathbf{Y}_i) = \mu_i = d_i \exp\left(\beta t_i\right) \tag{4.1}$$

where the random variables $\mathbf{Y_i}$ are independent, $d_i = \text{exposure}_i$, and β's are a set of unknown parameters in β. For a list of N different Oprisk events, note that the random variables Y_i are the basis for the OpRisk hazard defined by a binary response variable *LossIndicator* which denotes the presence or absence loss. Define random variabels $Y_1, \ldots, Y_N$ as follows

Definition 4.4.0.1

$$\mathbf{Y}_i = \begin{cases} 1 & \textit{for realised OpRisk losses} \\ 0 & \textit{for pending losses and near misses} \end{cases} \tag{4.2}$$

indexed by the subscript i, who may have different expected values μ_i. It is important to note that sometimes there may be one observation y_i for each Y_i, but on other occasions there may be several observations $y_{ij} \quad (j = 1, \ldots, n_i)$ for each Y_i. Equation 4.1 can be turned into GLM form by using a log link so that

$$\ln\mu_i = \ln d_i + \beta t_i \tag{4.3}$$

Parameter μ will depend on risk factors, which are the causal factors that are associated with OpRisk hazards and therefore the basic unit that create losses with random uncertainty e.g., the transaction population size, the period of observation, and various characteristics of the population (i.e., UpdatedTime, Instrument, TraderId, etc.). The transposed vector $\mathbf{x}_i^T$ represents the ith row of the design matrix $\mathbf{X}$, it takes the form; $t_i = x_{ij}^T, (j = 1, \ldots, p_i)$ for p explanatory variables (covariates or dummy variables).

The response variable is a series of OpRisk events $\mathbf{Y}$ where the probability of the event occuring in a very small time (or space) is low and the events occur independently. Since this is a count, the Poisson distribution is probably a reasonable distribution to try. The Poisson distribution is denoted by $\mathbf{Y_i} \sim \mathbf{Poi}(\theta_i)$. Rewriting Equation 3.4 as

$$f(y;\theta) = \exp[a(y)b(\theta) + c(\theta) + d(y)], \tag{4.4}$$

Substituting $a(y) = y$, $b(\theta) = \ln\theta$, $c(\theta) = -\theta$, and $d(y) = -\ln y!$; given ln is some monotone differentiable (link) function, so the GLM for this situaton uses a poisson response distribution, log link: Equation 4.4 can be expressed as:

$$f(y_i;\theta) = \exp\left[y\ln\theta - \theta - \ln y!\right] \tag{4.5}$$

Equation 4.5 is the probability function for the discrete random variable $\mathbf{Y}$, it can be rewritten as

$$f(y,\theta) = \frac{\theta^y e^{-\theta}}{y!} \tag{4.6}$$

Where y takes the values $0, 1, 2, ...$ If a random variable has a poisson distribution, its expected value $E(Y)$ and variance $Var(Y)$ are equal i.e., $\theta = \lambda$.

The choice of the poisson distribution for use on real world data is questionable, mainly because earnings volatility is high in the real world, therefore real world data is often **overdispersed** i.e., has a larger variance than the expected value. A quadratic term ($\beta_2 t_i^2$) could be added to the model, which usefully approximates other situations which may influence the counts adapted to the poisson case other than only those due to the unchecked prevalence of Oprisk hazards. The RHS of Equation 4.3 with the quadratic term so other situations other than the unrestricted spread of OpRisk hazards becomes

$$\mu = d_i \exp\left(\beta_0 + \beta_1 x_{ij} + \beta_2 x_{ij}^2\right) \tag{4.7}$$

A poisson regression operational hazard model

The random component is given by the independent random variables $Y_1, Y_2, \ldots, Y_n$, not i.i.d (Covrig et al., 2015; Wood, 2017). $\mathbf{Y}$ takes a (exponential) family argument, depending on parameters lnλ, where λ represents the average frequency of the OpRisk transactions. The response data y_i is an observation of Y. The target variable *LossIndicator* defined as per definition 4.4.0.1 is the basis for the poisson distribution as a reasonable model of choice. As per equation 4.6, it's probability mass function (pdf) is:

$$\begin{aligned} Y \quad \sim \quad \text{Poi}(\lambda), \quad f(y;\lambda) = \frac{\lambda^y e^{-\lambda}}{y!} \\ \text{where} \quad y \in \mathbb{N}, \text{and} \quad \lambda > 0. \end{aligned} \tag{4.8}$$

Again, the expectation and variance $E[Y] = \mathrm{VaR}[Y] = \lambda$[1], are both equal to parameter λ simultaneously. The model's systematic component, equation 3.5

[1] If you were to guess an independent Y_i from a random sample, the best guess is given by this expression

specifies the linear predictor and is built with $p+1$ parameters $\beta = (\beta_0 \ldots, \beta_p)^t$, with p explanatory variables:

$$\eta_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_{ij}, \qquad \text{where} \quad j = 1, \ldots, p_i \tag{4.9}$$

If sample variables $Y_i \sim \text{Poi}(\lambda_i)$, then $\mu_i = E[Y_i] = \lambda_i$; the link function between the random and systematic components, viz. a tranformation by the model by some function $g()$, which does not change features essential to to fitting, but rather a scaling in magnitude: i.e., the link between naturakl canonical parameter θ in equation 3.2 and parameter λ, the mean frequency of poisson distribution $\theta = \ln\lambda$, or otherwise the rate, will be predicted by the model...

$$\begin{aligned} \lambda_i &= d_i \exp(\beta_0 + \sum_{j=1}^{p} \beta_j x_{ij}) \quad \text{or} \\ \lambda_i &= d_i \cdot e^{\beta_0} \cdot e^{\beta_1 x_{i1}} \cdot e^{\beta_2 x_{i2}} \ldots e^{\beta_p x_{ip}} \end{aligned} \tag{4.10}$$

Where d_i represents the risk exposure for transaction i. Taking logs on both sides of equation 4.10, the regression model for the estimation of loss frequency is:

$$\ln\lambda_i = \ln d_i + \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip} \tag{4.11}$$

where $\ln d_i$ is the natural log of risk exposure, called the “offset variable”.

The poisson distribution is restrictive when applied to approximate counts, due to the assumption made about it that the mean and variance of the number of events are equal. However, in models for count data where means are low so that the number of zeros and ones in the data is exessive are well adapted to the poisson case (Wood, 2017).

These cases are characteristic of scenarios in OpRisk other than those modeling situations when the unchecked spreading of negligent behaviour may result in an operational hazard. For example, the negative binomial and/or quasipoisson regression models ascribe to data that exhibits *overdispersion*, wherein the variance is much larger than the mean for basic count data, therefore they have been eliminated in this paper.

Logistic regression and GLM's: Loss frequency, Indicator variables

As per section 3.2 in chapter 3 a GLM is introduced starting by estimating the expected number of OpRisk events (the mean OpRisk frequency) by a poisson model given by equation 4.8, followed by the binomial model using the glm function. In calling the GLM we specify the target variable *LossIndicator*; the explanatory variables are composed of numeric, continuous and categorical variables. Where the variable in the argument of a GLM is categorical, we choose to specify the modal class as the reference level. A user defined function "getmode" accomplishes the following; it selects the modal observation in each factor, and the dataset is reordered using the *relevel* function in RStudio.

Estimation of some poisson regression model

Let us consider a model where the *LossIndicator* is the target variable: We shall estimate the mean quarterly rate in the OpRisk hazard portfolio through poisson regression models i.e., the target variable is *LossIndicator*, the mean daily loss frequency in the risk correction statistics is estimated through the poisson regression model.

The following fits the model (the log link is canonical for the poisson distribution, and hence the R default) and checks it. Other GLM arguments are: The aforementioned link function poisson(link="log"); a data frame containing the OpRisk dataset, data=crs$training; and the r offset=log(exposure), i.e. the variable representing a component known apriori, coefficient= 1, introduced in the linear predictor (Covrig et al., 2015). Firstly, consider a GLM introducing two explanatory variables, one numerical variable, *UpdatedTime*, and another categorical variable *Desk*. This will be our global model. We will use *LossesIndicator* as the target variable while these two unique variables will be explanatory variables.

```
Call:
glm(formula = LossesIndicator ~ TradedDay + Desk, family = poisson(link="log"),
    data = crs$training, offset = log(Exposure))

    Null deviance: 1898.7  on 1630  degrees of freedom
Residual deviance: 1661.4  on 1620  degrees of freedom
AIC: 2187.4

Number of Fisher Scoring iterations: 15
```

The output result of the estimation is in figure 8.4 presented subsection 6.8.1 of the Appendix 6.7, where variables who were found to be significant predictors are indicated. The coefficients of the categorical variable *Desk* are reordered and weighted against the modal class: *DeskRates*. Interestingly the modal class does not show up in the results section since the coefficient of the modal class $ e^0 = 1 $, the remaining classes are weighted against it.

Using this bivariate model, the estimated quarterly OpRisk (LossIndicators) frequency of realised losses for each *Desk* category (excluding the insignificant ones) are:

* $0,0013 = e^{-8.053221} \cdot e^{-0.014087} \cdot e^{1.457695}$, for the combination of the **TradedDay** and **DeskAfrica** category, which implies that frequency of realised losses for this combination of preditor variables is 4.3 $\quad (= \cdot e^{1.457695})$ fold (times) higher

than the realised loss frequency of OpRisk causes in the reference desk category, viz. the **Rates** desk.

* $0,0018 = e^{-8.053221} \cdot e^{-0.014087} \cdot e^{1.764230}$, for the combination of the **TradedDay** and **DeskBonds/Repos** category, which implies that frequency of realised losses for this combination of preditor variables is 5.83 $\quad(= \cdot e^{1.764230})$ times higher than causes in the reference desk category.
* $0,0008 = e^{-8.053221} \cdot e^{-0.014087} \cdot e^{0.924033}$, for the combination for the combination of the **TradedDay** and **DeskCommodities**, which implies that frequency of realised losses for this combination of preditor variables is $2,52 \quad (= \cdot e^{0.0.924033})$ fold higher than the causes in the reference desk category.
* $0,0012 = e^{-8.053221} \cdot e^{-0.014087} \cdot e^{1.365152}$, for the combination of the **TradedDay** and **DeskEquity**, which implies that frequency of realised losses for this combination of preditor variables is $3,92 \quad (= \cdot e^{1.365152})$ fold higher than the causes in the reference desk category.
* $0,0026 = e^{-8.053221} \cdot e^{-0.014087} \cdot cdote^{2.129594}$, for the combination of the **TradedDay** and **DeskPrime Services**,an increase of $8,4 \quad (= \cdot e^{2.129594})$ fold times higher w.r.t the baseline (the **Rates** desk)
* about $0.00015 = e^{-8.053221} \cdot e^{-0.014087} \cdot e^{-0.716361}$ of the last desk category **DeskSND**, which means a decrease of about 51

The predicted mean frequency (λ) of OpRisk losses for operational losses i, for the bivariate model **freqfit1**, is given by:

$$\begin{aligned} \mu_i &= \text{exposure}_i \cdot e^{-8.053221 \cdot \text{Intercept}_i} \cdot e^{-0.014087 \cdot \text{TradedDay}_i} \cdot e^{1.457695 \cdot \text{DeskAfrica}_i} \\ &\cdot \; e^{1.764230 \cdot \text{DeskBonds/Repos}_i} \cdot e^{0.924033 \cdot \text{DeskCommodities}_i} \cdot e^{1.365152 \cdot \text{DeskEquity}_i} \\ &\cdot \; e^{2.129594 \cdot \text{DeskPrime Services}_i} \cdot e^{-0.716361 \cdot \text{DeskSND}_i} \end{aligned} \tag{4.12}$$

We now fit a more comprehensive model wherein all 13 explanatory variables are introduced into the global model; this shows realised losses for quarterly OpRisk incidents in the all varibles inclusive case. Again, we use *LossIndicator* as the target variable, while the other 13 variables are predictor (explanatory) variables. Fitting the glm global model yields output seen in subsection 6.8.2 of the Appendix 6.7 on page 145.

The selection of the best-fit model from the list of possible combinations of predictor variables traditionally follows of a process removing/adding each variable progressively after each estimation, and propagating backward/forward, comparing goodnes of fit tests at each stage. For example, if we compare the values of the Aikaike information criteria (AIC) for the bivariate model **freqfit1** and the multivariate model **freqfit**, by AICs; we see that for the first (bivariate) model the AIC value is 2253.4 and 1907.6 for the second (multivariate) model, which suggests that the second model, **freqfit**, the model in which we considered an all inclusive list of 13 predictor variables is a better fit since there is a marked reduction/improvement in AIC magnitudes compared to the first value, hence **freqfit** is prefered over the bivariate (first) model.

Estimation of some binomial regression model

Another approach to the estimation of the mean frequency is to assume that the variable that shows the mean frequency follows a binomial distribution. Consider the predictors of such a regression model are given by the global model and presented by calling the glm model yielding output results seen subsection 6.8.2, section 6.8 in Appendix 6.7.

```
Call:
glm(formula = LossesIndicator ~ UpdatedDay + UpdatedTime + TradedDay +
    TradedTime + Desk + CapturedBy + TradeStatus + TraderId +
    Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1,
    family = binomial(link = "logit"), data = crs$training,
```

```
    offset = log(Exposure))

    Null deviance: 2380.8  on 1630  degrees of freedom
Residual deviance: 1270.6  on 1553  degrees of freedom

AIC: 1426.6

Number of Fisher Scoring iterations: 18
```

The AIC value for the binomial model of 1426.6 is less than that of the poisson model 1907.6, therefore by the same token to that fashioned in section 4.6.1, an estimation of the models by a comparison of information criteria (AIC's) which enables the choice the most appropriate or "best" fit model is carried out: First through establishing significance viz., if the residual deviance and the corresponding number of degrees of freedom don't have value significantly bigger than 1 i.e., the multivariate model freqfit $\frac{1270.6}{1553} = 0.8$, and therefore retaining the binomial model i.e., the model with the smaller AIC value.

Model selection and multimodel inference

Burnham & Anderson (2002)'s introduction of the information-theoretic approach permits a data-based selection for the "best-fit" model in the analysis of the OpRisk dataset *OpRiskDataSet_exposure.csv*, and a ranking and weighting of what remains. This approach allows traditional (formal) statistical inference to be based on the selected "best-fit" model, which is now based on more than one model (multimodel inference). As a requirment the r package to load is the *MuMIn* Rstudio package.

Data dredging

We then use the *dredge* function to generate models using combinations of the terms in the global model. This function also calculates AICc values and rank models according to it. Note that AICc is AIC corrected for finite sample sizes. The process of analyzing data where the experimentalist has few or no a priori information, thus “all possible models” are considered by subjectively ad iteratively searching the data for patterns and “significance”, is often called “data mining”, “data snooping” or the term “data dredging”.

The function “MuMLn::dredge” returns a list of 4097 models, which is every combination of predictor variable in the global model freqfit. Model number 894 is the best-fit: All predictor variables included in this model have a positive effect on the target variable except for the preditor TrddD (**TradedDay**) which has a negative effect on the likelihood of a realised loss (target variable *LossIndicator*) i.e., the later in the month of the transaction, the less likely a loss is realised. Additionally, from the delta (=delta AIC) one cannot distinguish between models 894, 382, 1918 and 1406 since (using the common rule of thumb) they have AIC < 2.

Of the top seven models (listed below); 1918 & 2942 each hold nine; 894, 1406 & 1854 hold eight; 382 & 830 hold seven; and lastly 318 hold six predictor variables respectively. Where a variable doesn’t have a value associated with it does not mean no effect, but rather that it was not included in the model. For example, model 894 returns a combination of the eight variables 1/2/3/4/5/6/7/8, corresponding to top most model in the following output predictor variables (abbreviated in the header row), see figure 9.5, subsection 6.9.1, section 6.9 in the Appendix 6.7.

Information from the AICc’s values suggest, that of the top eight models have similar support, and their Akaike weights are not high relative to the $[0, 1]$ weight range: This is characteristic of the endemic nature of data dredging, as the literature suggests (Burnham & Anderson, 2002), and should generally be avoided to curb attendant inferential problems if a single model is chosen, e.g the risk of finding spurious effects, overfitting, etc. Burnham & Anderson (2002) advises that model averaging is useful in finding a confirmatory result as estimates of precision should include model selection uncertainty. Even so, one can rule out many models on a priori grounds.

We now use “get.models” function to generate a list in which its objects are the fitted models. We will also use the “model.avg” function to do a model averaging based on AICc. Note that “subset=TRUE” will make the function calculate the average model (or mean model) using all models. However, if we want to get only the models that have delta AICc < 2; we therefore use “subset=TRUE”

Now we have AICc values for our models and we have the average (mean) model, we denote this **Amodel** sumamrized below. For full comprehensive results, see figures 9.6, 9.6 & 9.6 in Appendix 6.9.2.

```
Call:
model.avg(object = get.models(freqfits, subset = TRUE))

Component model call:
glm(formula = LossesIndicator ~ <4096 unique rhs>, family =
poisson(link = "log"), data = crs$training, offset = log(Exposure))

Component models:
                           df   logLik    AICc  delta weight
1/3/4/5/6/9/10/12          71  -901.58 1951.72   0.00   0.08
1/2/3/4/5/6/9/10           74  -898.47 1952.07   0.36   0.07
1/3/4/5/6/9/10             70  -902.97 1952.32   0.60   0.06
1/2/3/4/5/6/9/10/12        75  -897.57 1952.47   0.75   0.06
1/3/4/5/6/8/9/10           71  -902.12 1952.80   1.08   0.05
1/2/3/4/5/6/8/9/10         75  -897.89 1953.12   1.40   0.04
1/3/4/5/6/9/10/11/12       72  -901.23 1953.20   1.48   0.04
```

```
 [ reached getOption("max.print") -- omitted 4888 rows ]
```

Discussion on single "best model" vs ensemble

No single "best model" rather an ensemble wins when going about the thinking of the OpRisk problem as opposed to the traditional way, as better subsidies are designed as protection against the possibilities of extreme events. Traditionally the question of how often and extreme event will happen or how much of a buffer to put up to subsidise against OpRisk, was answered by using distributions and looking at pecentiles of extreme events of one "best model". This may shift going about the historical thinking of OpRisk VaR to the more accurate predictive analytical measure resulting in less subsidy between risks within the pool of independent risks, guarding against over/under compensated buffers which in turn results from the reduction of variance that arises due to aggregating/pooling independent risks.

Model performance evaluation

We have gained initial insights through data exploration in Section 3.3 and then built models. The next critical step is to evaluate our model using data mining techniques. For this we need to split our data sample into three subsets. We use a 70/15/15 sampling strategy; the 70% subset sample for the *training dataset*, 15% for the *validation dataset* and another 15% for the *testing dataset* whose function is to provide error estimates of the final result,for this we use the validation dataset i.e., it's used to test different parameter setings or different choices of variables whilst we are data mining, the testing dataset is not used in building or even fine tuning the models that we build, for the sake of model building we defined and used the training dataset (Williams, 2011).

The resulting error estimates come out in the process of testing the performance of the models we build, by first using the validation dataset in preliminary and intermediate stages, putting in adjustments where required and re-evaluating the error rate, until the final modelling phase where the refined model is evaluated using the testing dataset to provide an unbiased error of the final results.

Confusion Matrix and Statistics

To measure the level of accuracy of the decisions made by the model compared with the actual decisions, a *confusion matrix* is used. The confusion matrix, otherwise known as an *error matrix* is a mechanism used to provide an understanding of how well the model will perform on new previously unseen data i.e., used to evaluate the model.

The confusion matrices for the Training, Validation and Testing datasets for the poisson **Amodel** that we have previously seen are displayed obove. Two tables per dataset are displayed, the first list the actual counts of observations and the second the percentages. We can observe using the Testing dataset, that for 69% of the predictions the model correctly predicts pending or near misses i.e., no pnl loss impact (called the true negatives). That is, 243 out of the 350 loss events are correctly predicted as pending or near misses. similarly we see that the model correctly predicts OpRisk losses (called the true positives) on 6% of the events.

In terms of how correct the model is, we observe that it correctly predicts OpRisk losses 22 out of the 66 events on which losses actually materialise. This is 33% accuracy in predicting Oprisk events. This is called the true positive rate, also know as the recall of a model. It is a measure of how mant of the actual positives the model can identify, or how much the model can *recall*. This recall is also known

Figure 8.1: Basic comparison of prediction and actuals as confusion matrices using both counts and calculated as a percentage. Summary statistics are computed and displayed

as the *specificity*. Similarly, the true negative rate is another measure which also arises and is known as the *sensitivity* is 85%.

We also see 41 potential events when we expect pnl loss impacts and none occur (called the false positives). If we were using this mode to help us decide whether or not to be wary and closely monitor future daily trading activity, then there aren't probably serious conscequences in this instance, we heightened our risk threshold without need. More serious though is that there are 44 actual loss events when our model tells us there will be no pnl impact yet losses occur (called the false negatives). We are inconveniently incurring OpRisk losses without moderating for the risk. Notice that the overall accuracy of the training dataset is 78% which is not surprising as the estimated accuracy of the resulting learned model leads to overoptimistic estimates due to overspecialisation of the learning algorithm to the data.

ROC Curve

An ROC chart plots the true positives against the false positive rate, essentially to compare the performance of the model against known outcomes and is used to identify a suitable trade-off between effor and outcomes. Generally the larger area-under-curve (auc) also the probability that the classifier scores a randomly drawn positive sample higher than a randomly drawn negative sample. For a more comprehensive comparison, see figure 9.10 in Appendix 6.9.3.

Discussion on MuMIn model performance

Conceptually the "best model" **Amodel** represents the phenomena hypothesised from the information in the observed data, which then forms the basis for making inferences about the OpRisk frequency processes or system that generated

(a)

(b)

Figure 8.2: (a) ROC Curve for a binomial GLM on the validation dataset (b) As for (a) but on the testing dataset. The area under the curve `auc` is a measure of the performance of the model. A perfect model would have 100% of the area under the curve

the data. Multimodel inference leads to even more robust inferences, especially in the point of view that the selection of the model used to estimate the mean frequency must, at the same time, serve the ultimate root cause analysis objective of OpRisk control, that is to decide when calculating the capital requirement using a robust OpVaR measurement technique, to take into account as many characteristics of the trading OpRisk dataset as possible, as well to consider how the variables interact with each other.

The performance measures here can ether tell us that we are going to experience realised losses from OpRisk events more often than we would like, or overcompensate for losses that do not materialise. This is an important issue i.e., the fact that the different types of errors have different conscequences for us. Higher risks (extremal events) are normally compensated more than necessary and often than not cause social division within management structures when sectors cannot reconcile or afford the protection.

Data augmentation

After monitoring profiling and integration, the known HFLS & LFHS data management dilemna needs to be overcome at the last stage, which requires some innovation. Furthermore, ML algorithms are data driven therefore the more data the better the model. In the OpRisk context, problems due to data sensitivity concerns and cost constraints have limited the study to only three months of available data, which by implication means increasing the number of data points in some way. One way of adding to the base data is deriving from the internal sources of an institution using an extrapolation technique i.e., based on heuristics the relevant fields are updated or provided with values.

We have a population of $K = 2330$ OpRisk events over the first quarter

Q12013, and of these events we have a number $N = 371$ of realised losses. N is a discrete random variable modelled as a Poisson variable with rate λ. Each loss X_i is another random variable with an underlying sverity distribution. How does the size K of the population enter the risk model?. It doesn't appear explicitly in the model (Parodi, 2014), however, it is taken into account during the creation of the model. Intuitively, the poisson rate λ is likely to be proportional to the current OpRisk sample size, or more specifically, it is the rate of some expected operational event over per specified time interval.

Predicting test set results and evaluating the parameter λ Yields a daily rate of $\lambda = 0.20739163$ per day quarter, which computes to a cut-off probability of 0.18009498. By a simple growth formula, one years of data (4 quarters) i.e., 3 months * 4 = 1 year:

$$\begin{aligned}
\text{1yr Population} &= \text{Initial Population} + \text{Initial Population} * (1+\lambda)^n \\
&= 2330 + 2330 * (1 + 0.18009498) + 2330 * (1 + 0.18009498)^2 \\
&+ 2330 * (1 + 0.18009498)^3 \\
&= 11,791 \text{observations} \qquad (4.13)
\end{aligned}$$

This corresponds to a 1yr population of $11,791$ observations. The next step is to use an extrapolation script to generate the $11,791$ observations for the augmented dataset. The extrapolation algorithm which augments the existing data to increase the size of the population by the heuristics approach, effectively increasing the number of rows, which is best done in the Matlab code (due to it's matrix based foundations), see section 6.10 on page 163in the Appendix 6.7.

Deploying the R model

Often for one to obtain the benefit of a model, it's "scored" through applying it to a new dataset using a form of a predict() function. This is the simplest approach to deployment and is practiced regularly as new data entries become available, particularly using the R concept, whereby model outcomes are saved for later use then at a later time a new dataset scored using the saved model and applying it to some new data enhancing the data mining capabilities within an organisation.

After building the augmented dataset we simulate the application of the model to it. We can then schedule the model to be applied regularly as new data points come in, spurring off secondary and tertiary processes such as the flagging of potentially hazardous future events, high risk individuals or perhaps identifying clients who need to be audited or to communicate to the trader the predicted critical risk indicators for tomorrow.

The estimation of some generalised additive models for location scale and shape (GAMLSS) for severity loss estimation

Figure 10.3a and 10.3b shows plots of the pnl impact, `Loss`, against three selected explanatory variables chosen for the purpose of demonstrating the complexity of their relationship, hence the need for a statisical model for the analysis of the OpRisk data viz., GAMLSS. In the first two plots labelled figure 10.3a (a) for the two explanatory variables in the bivariate plots, `Loss` vs `UpdatedTime` and `Loss` vs `UpdatedDay`, there is obvious nonlinear dependence between the mean of the response variable Loss and the `UpdatedTime` and `UpdatedDay`, here nonparametric smoothing functions may be needed. There is also a clear indication of the non-homogeniety of the variance of Loss, therefore modelling the variance of `Loss` requires a statistical model which caters for the dependency of the variance of its's mean and/or explanatory variables.

The first boxplot displays how the day in the month `UpdatedDay` varies according to the OpRisk event, and the second how the `Loss` varies according according to same. There is clear indication of positive skewness in the distribution of `Loss` depending on the explanatory variable `EventTypeCategoryLevel`, and asymmetrical boxes about the median a nd long upper and lower whiskers, especially in the first boxplot, emphasizing the need to explicitly modelfor this.

Model strategy in GAMLSS framework

The OpRiskDataSet_exposure data contains intra-day pnl impacts (Losses) of amendment activity of during trading across primary and secondary markets of an investment banking platform. We use model selection to discover the effect of pnl losses i.e., fitting different distributions to the response variable in order to select a plausible distribution for the GAMLSS. Let $\mathcal{M} = \{\mathcal{D}, \mathcal{G}, \mathcal{T}, \Lambda\}$ represent Stasinopoulos et al. (2018)'s expansion of equation 2.30. Teh components of $\mathcal{M}$ are defined as follows (Voudouris, Gilchrist, Rigby, Sedgwick, & Stasinopoulos, 2012):

1. $\mathcal{D}$ specifies the distribution of the response variable,
2. $\mathcal{G}$ specifies the link functions,
3. $\mathcal{T}$ specifies the terms appearing in all the predictors for μ, σ, ν and τ,
4. Λ specifies the smoothing hyper-parameters which determine the amount of smoothing in the $h_{kj}()$ functions of equation 2.30.

(a) Plots of `Loss` against explanatory variables

(b) Boxplots of `UpdatedDay` and `Loss` against explanatory variable `EventtypeCategoryLevel1`

Figure 10.3: (a) Plot of the Loss (pnl impact) against explanatory variables UpdatedTime and UpdatedDate. (b) As for (a) against EventTypeCategory.

Component $\mathcal{D}$: Selection of the distribution

We begin model selection using only three distribution parameter distribution otherwise known as the Lambda, Nu and Sigma (LMS) method (Stasinopoulos et al., 2018) selected from the family of zero adjusted distributions; on zero and the positive real line $[0, \infty)$, and then move to its extensions (four distribution parameters). Of the zero adjusted distributions, only the Zero adjusted gamma ZAGA(μ, σ, ν) and the zero adjusted inverse gamma ZAIG(μ, σ, ν) can be fitted explicitly in GAMLSS, therefore we begin with this in mind. The parameters μ, σ and ν in this case, are the approximate mean, approximate coefficient of variation and skewness parameters.

The introduction of a fourth parameter τ for modelling the kurtosis of the distribution leads to the creation of the generalized beta type 2 distribution, denoted by GB2(μ, σ, ν, τ), which is the only four parameter distribution for fitting a GAMLSS to estimate the (non-linear nature) mean OpRisk loss severity explicity.

Generalized Beta type 2 distribution (GB2)

Given $X = x$, Y (the `Loss` severity is the target variable) is modelled here by a generalized beta type 2 GB2(μ, σ, ν, τ)[2] distribution is defined by:

$$f(y|\mu, \sigma, \nu, \tau) = |\sigma| y^{\sigma\nu - 1} \{\mu^{\sigma\nu} \mathrm{B}(\nu, \tau)[1 + (y/\mu)^{\sigma}]^{\nu+\tau}\}^{-1} \tag{4.14}$$

The choice of distribution for the OpRisk severity `Loss` variable is based on

[2]The GB2 adjusts the obove density $f(y|\mu, \sigma, \nu, \tau)$, resulting from the condition $y > 0$, where $\mu > 0$, $-\infty < \sigma < \infty$, $\nu > 0$ and $\tau > 0$. The mean and the variance of Y are given by $E(Y) = \mu \mathrm{B}(\nu + \frac{1}{\sigma}, \tau - \frac{1}{\sigma})/\mathrm{B}(\nu, \tau)$ for $-\nu < \frac{1}{\sigma} < \tau$ and $E(Y^2) = \mu^2 \mathrm{B}(\nu + \frac{2}{\sigma})/\mathrm{B}(\nu, \tau)$ for $-\nu < \frac{2}{\sigma} < \tau$, See @stasinopoulos2008instructions.

it being the only simple explicit for the mean and median of the response variable. Additionally:-

* The variate takes values within to the appropriate range viz., $[0, \infty)$;
* The distribution is relevant because in has an explicit p.d.f, c.d.f and inverse c.d.f, explicit moment based measures of location, scale, skewness and kurtosis (i.e. population mean, standard deviation, γ_1, γ_2 [@rigby2017distributions]);
* Explicit centiles and centile based measures viz., median, semi-interquartile range, skewness and kurtosis ($\gamma, \mathrm{st}_{0.49}$ resp.);
* Continuity of $f(y|\mu, \sigma, \nu, \tau)$ w.r.t y and it's derivatives w.r.t μ, σ, ν, τ;
* Allows for flexibility in specifying the distribution of severity and also allowing for the modelling of distribution parameters as function of explanatory variables

GAMLSS model for the four parameters of the GB2 distribution

The parameters μ, σ, ν, and τ of the GB2 distribution are modelled as functions of explanatory variables using semi-parametric additive models, extended to incorporate non-linear parametric and/or non-parametric smooth functions x. Specifically, the model assumes that conditional on $(\mu_i, \sigma_i, \nu_i, \tau_i)$, for $i = 1, 2, \ldots, n$, observations where $Y \sim$ GB2(μ, σ, ν, τ) i.e., Y_i are independent GB2$(\mu_i, \sigma_i, \nu_i, \tau_i)$ variables with p.d.f $\{_{Y_i}(\dagger_i)$ obtained from equation 4.14.

Component $\mathcal{G}$: selection of the link functions

Also for $k = 1, \ldots, 4$ let $g_k(\cdot)$ be known momotonic link functions relating the parameters to expalnatory variables through extended semi-parametric additive models given by:

$$
\begin{aligned}
g_1(\mu) &= \eta_1 = \mathbf{X}_1\beta_1 + \sum_{j=1}^{J_1} h_{1j}(\mathbf{x}_{1j}) \\
g_2(\sigma) &= \eta_2 = \mathbf{X}_2\beta_2 + \sum_{j=1}^{J_2} h_{2j}(\mathbf{x}_{2j}) \\
g_3(\nu) &= \eta_3 = \mathbf{X}_3\beta_3 + \sum_{j=1}^{J_3} h_{3j}(\mathbf{x}_{3j}) \\
g_4(\theta) &= \eta_4 = \mathbf{X}_4\beta_4 + \sum_{j=1}^{J_4} h_{4j}(\mathbf{x}_{4j}) \qquad (4.15)
\end{aligned}
$$

where for $i = 1, 2, \ldots, n$ $j = 1, 2, \ldots, J_k$ and $\beta_k^T = (\beta_1 k, \beta_2 k, \ldots, \beta_{J'_k} k)$ is a parametric vestor of length J'_k, $\mathbf{x}_{ik}$ a fixed known design vector of length J''_k and h_k a non-linear function []. The explanatory values x_{jk} are assumed to be fixed and known and the univariate function h_{jk} is an additive smooth parametric function assumed to have continuous first and second order derivatives. If for $k = 1, 2, 3, 4$, $J_k = 0$, then the GAMLSS model 4.15 reduces to a non-linear parametric model. If in addition, $h_k(x_{ik}, \beta_k) = \mathbf{x}_{ik}^T \beta_k$ for $i = 1, 2, \ldots, n$ and $k = 1, 2, 3, 4$, then equation 4.15 reduces to a linear parametric model (Rigby, Stasinopoulos, Heller, & De Bastiani, 2017).

Model estimation and selection

There are several different strategies that could be applied for model selection of the terms used to model the four parameters, however the procedure in the analysis as outlined in Stasinopoulos et al. (2018) and Voudouris et al. (2012), comprised of the function `stepGAIC.A`, is by selcting all terms for all the parameters by a forward, backward or stepwise procedure, assuming the particular response distribution function (also found in Stasinopoulos, Rigby, Heller, Voudouris, & De Bastiani, 2017 & @rigby2017distributions). The final model may contain different combinations for μ, σ, ν, and τ.

Component $\mathcal{T}$ and Λ: selection of the terms and smoothing parameters in the model

Given that a set of plausible distributions have been identified, let χ be the selection of all terms available for consideration. Their parameters are modelled as regression models. In particular the non-linear parameter vectors β_k and the non-parametric functions h_{jk} for $j = 1, 2, \ldots, J_k$ and $k = 1, 2, 3, 4$ in equation 4.15 are estimatied by maximizing the penalised log-likelihood as a way of understanding how the location, scale, skewness and kurtosis parameters of the loss severity distribution are affected by the explanatory variables.

This is essentially shown conducted, in R, dropping unneccessary terms, selecting and adding additive terms and smoothing terms. In order to do this a formula is created containing all the linear main effects and second-order interactions plus smooth function of expalnatory variables. In R this is achieved through a "scope" statement whereby the function `FORM` is used as the upper argument, as demonstrated in see Appendix 6.11.4.

Checking the model

Figure 13.4 displays the (normalized quantile) residuals, from model GB2(). Panel (a) and (b) plot the residuals against the fitted values of μ and against the explanatory variables respectively. While panel (c) and (d) provide a kernel density estimate and normal QQ plot for them respectively. the residuals appear slightly skewed to the right and the QQ plot shows extreme outliers in the upper tails of the distribution of y. Also note that not all plots in figure 13.4 are useful, nevertheless the GB2() distribution model provides a reasonable fit to the data, substan-

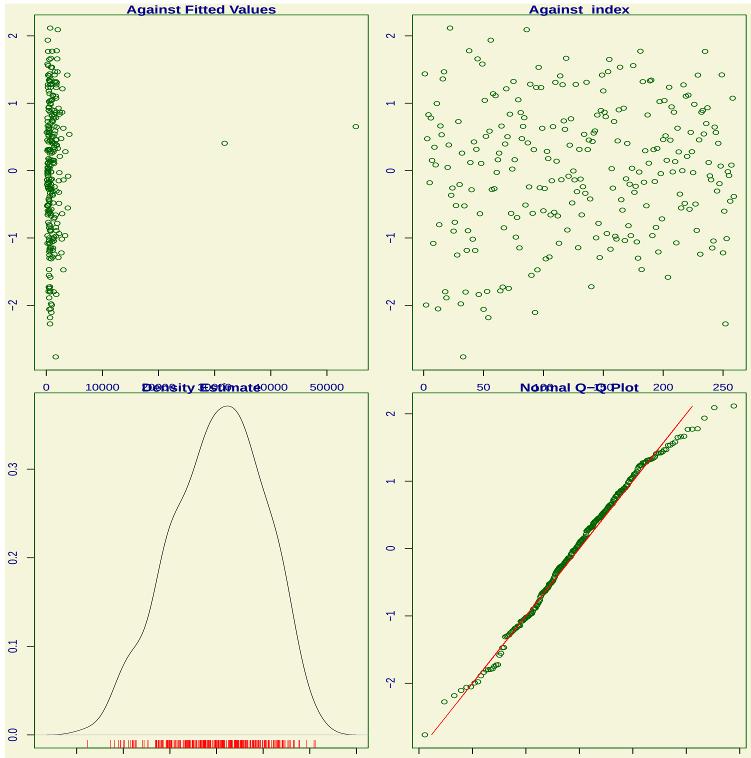


Figure 13.4: The result of the plot displays (normalized quantile) residuals from model GB2(μ, σ, ν, τ), the top-left panel plots the residuals against the fitted values of μ, the bottom-left panel provides a kernel density estimate and the normal QQ plot for the residuals in bottom-right panel. The last panel results are meaningless

.

tially better than to the and preferable to the models.

Figure 13.5 shows summary statistics of the GB2 distribution model. The GB2 distribution is the best fit for the data based on the model selection strategy discussed in section 4.12, the empirical GAMLSS-based model $Y \sim$ GB2(μ, σ, ν, τ) where Y = log(Losses due to OpRisk events) and

Figure 13.5: Summary statistics of fitted distribution GB2(μ, σ, ν, τ), the "Generalized beta type 2 (i.e. of the second kind)" using fitting method: RS()

Figure 13.6: Summary of the fitted models for the OpRisk 2013Q1 data, showing the effective degrees of freedom (df) used in the model and the AIC(k =length of loss variable).

$$
\begin{aligned}
\log(\mu) &= \texttt{UpdatedDay} + \texttt{Desk} + \texttt{CapturedBy} + \texttt{TradeStatus} + \texttt{TraderId} + \texttt{Instrument} \\
+ &\quad \texttt{Reason} + \texttt{EventTypeCategoryLevel1} + \texttt{Exposure} + \mathrm{pb}(\texttt{CapturedBy}) + \mathrm{pb}(\texttt{TraderId}) \\
+ &\quad \mathrm{pb}(\texttt{TradeStatus}) + \texttt{TraderId:Reason} + \texttt{UpdatedDay:Desk} + \texttt{Desk:Exposure} \\
+ &\quad \texttt{Reason:EventTypeCategoryLevel1} + \texttt{TradeStatus:EventTypeCategoryLevel1}, \\
\sigma &= \texttt{BusinessLineLevel1}, \\
\log(\nu) &= 1, \\
\log(\tau) &= \texttt{Instrument} \qquad (4.16)
\end{aligned}
$$

Testing hypothesis from the fitted model

Using the `stepGAIC.A()` function in GAMLSS, we compare the models tat best fit the 2013Q1 dataset of OpRisk losses, pending and near misses, conditional on the available explanatory variables such as the `UpdatedDay`, `UpdatedTime`, `CapturedBy`, `TraderId`, `Reason`, `Desk`, `Instrument`, etc. The conclusion from Table 13.6 is that the GB2 model provides the best fit to expalnatory variables according to criterion `GAIC()` i.e., loss severity (pnl impact) requires modelling of both skewness and kurtosis and is not adequately modelled by either skewness or kurtosis alone. The fitted models for μ, σ, ν and τ, given by equation 4.15 for the chosen model is displayed.

CHAPTER 5
METHODS FOR MODELING OPRISK DEPENDING ON COVARIATES

Introduction

This section of the paper concentrates on combining various supervised learning techniques with extreme value theory (EVT) fitting, which is very much based on the Dynamic EVT-POT model developed by Chavez-Demoulin et al. (2016). This can only happen due to an abundance of larger and better quality datasets and which also benefits the loss distribution approach (LDA) and other areas of OpRisk modeling. In Chavez-Demoulin et al. (2016), they consider dynamic models based on covariates and in particular concentrate on the influence of internal root causes that prove to be useful from the proposed methodology.

Motivated by the abundance of data and better data quality, these new data-intensive techniques offer an important tool for ORM and at the same time supporting the call from industry for a new class of EBOR models that capture forward-looking aspects of ORM (Embrechts et al., 2018). Three different machine learning techniques viz., decision trees, random forest, and neural networks, will be employed using R. A comprehensive list of user defined variables associated with root causes that contribute to the accumulation of OpRisk events (frequency) has been provided, moreover, a lot can be gained from this dataset as it also bears the impacts of these covariates on the severity of OpRisk.

Modeling Oprisk: The loss distribution approach (LDA)

Machine Learning (ML) is used as a substitute tool for the traditional model based Autoregressive Moving Average (ARMA) used for analysing and representing stochastic processes. As opposed to the statistical tool, ML does not impose a functional relationship between variables, the functional relationship is determined by extracting the pattern of the training set and by learning from the data observed.

Using computationally intensive (using ML techniques on historical data) OpRisk measurement techniques and mixing with a theory is not a new approach for modeling, particularly in calculating OpRisk RC; as evidenced through Agostini et al. (2010) in a study whereby the LDA model for forecasting OpRisk RC, via VaR, was implemented in conjunction with the use of advanced credibility theory (CT). The idea at the basis of their use of CT, is to advance the very recent literature that a better estimation of the OpRisk RC measurement can be obtained by integrating historical data and scenario analysis i.e., combining the historical simulations with scenario assessments through formulas that are weighted averages of the historical data entries and scenario assessments, advocating for the combined use of both experiences.

However, applying ML is an original way of looking at the approximation issue as opposed to advanced CT. The essential feature of PT are assumptions which are more compatible with basic principles of perception and judgement for decisions taken under uncertainty, whereas ML will reveal additional chance probabilities determined through the natural clusters of unknown data feature findings from which new discoveries are made.

Twenty-one key risk indicators (kri's) with eight feature groups including person identification, trade origination, root causes and market value sensitivities are in the chosen covariates. For each risk event there is information about: trading risk exposure, trading characteristics, causal factor characteristics and the losses created by these factors. The development, training and validation of the machine learning (ML) models lends itself to this new type of data and requires a higher degree of involvement across operations. Moreover, at this level of granularity the different types of data is particularly suited to exposure-based treatment, and other forward-looking aspects within the OpRisk framework, for improved forecasts of OpRisk losses.

The aggregated operational losses can be seen as a sum S of a random number N individual operational losses

$$(X_1, \dots, X_N)$$

. The total required capital is the sum of VaR of each BL/ET combination calibrated through the underlying mathematical model whose analytic expression is given by:

$$\mathbf{G}_{\vartheta(t)}(x) = Pr[\vartheta(t) \leq x] = Pr\left(\sum_{n=1}^{N(t)} X_n \leq x\right), \qquad \text{where} \quad \vartheta(t) = \sum_{n=1}^{N(t)} X_n. \tag{5.1}$$

$\mathbf{G}(t)$ can only be obtained numerically using the Monte Carlo method, Panjer's recursive approach, and the inverse of the characteristic function (Frachot et al. (2001); Aue & Kalkbrener (2006); Panjer (2006); & others).

Research Objective II

To test the accuracy of several classes of data-intensive techniques in approximating the weights of the risk factors; i.e., the input features of the model viz., TraderID, UpdatedDay, Desk, etc. of the underlying value-adding processes, against traditional statistical techniques, in order to separately estimate the frequency and severity distribution of the OpRisk losses from historical data. As a consequence, capital estimates should be able to adapt to changes in the risk profile e.g., upon the addition of new products or varying the business mix of the bank (e.g., terminations, voids, allocations, etc.) to provide sufficient incentives for ORM to mitigate risk (Einemann et al., 2018).

Analysis and interpretation issues with behavioral finance theory

Behavioral management theory is very much concerned with social factors such as motivation, support and employee relations. A critical component of behavioral finance is building models which better reflect actual behavior. Studies have revealed that these social factors are not easy to incorporate into finance models or to understand in the traditional framework.

The traditional finance paradigm seeks to understand financial markets using models in which agents are “rational”. According to Barberis & Thaler (2003), this means that agents update their beliefs on the onset of new information, and that given their beliefs, they make choices that are normatively acceptable, and that most people do this most of the time. Neoclassical theory has grown to become the primary take on modern-day economics formed to solve problems for decision making under uncertainty/risk. Expected Utility Theory (EUT) has dominated the analysis and has been generally accepted as the normative model of rational choice, and widely applied as a descriptive model of economic choice (Kahneman & Tversky, 2013).

Expected utility theory

Expected utility theory[1] (EUT): We see a fundamental relation for expected utility (Expectation) of a contract X, that yields outcome x_i with probability p_i, where $X = (x_1, p_1; ...; x_n, p_n)$ and $p_1 + p_2 + \ldots + p_n = 1$ given by:

$$U(x_1, p_1; \ldots; x_n, p_n) = p_1 u(x_1) + \ldots + p_n u(x_n) \tag{5.2}$$

corroborated by Morgenstern & Von Neumann (1953); Friedman & Savage (1948); Kahneman & Tversky (2013) & others.

A common thread running through the rational viz., the neoclassical take of modern-day economics vs the non-neoclassical schools of thought are findings of behavioral economics which tend to refute the notion that individuals behave rationally. Many argue that individuals are fundamentally irrational because they do not behave rationally giving rise to a literature and debates as to which heuristics and sociological and institutional priors are rational (Altman, 2008).

In the real world there is a point of transition between the traditional (neoclassical) approach to decision making, based on data and data anaysis (logic and rational), by adding new parameters and arguments that are outside rational conventional thinking but are also valid. For example, that neoclassical theory makes use of the assumption that all parties will behave rationally overlooks the fact that human nature is vulnerable to other forces, which causes people to make irrational choices.

An essential ingredient of any model trying to understand trading behavior is an assumption about investor preferences (Barberis & Thaler, 2003), or how investors evaluate risky gambles. Investors systematically deviate from rational-

[1] Expected utility theory provides a model of rationality based on choice.

ity when making financial decisions, yet as acknowledged by Kuhnen & Knutson (2005), the mechanisms responsible for these deviations have not been fully identified. Some errors in judgement suggest distinct mental operations promote different types of financial choices that may lead to investing mistakes. Deviations from the optimal investment strategy of a rational risk neutral agent are viewed as risk-seeking mistakes and risk-aversion mistakes (Kuhnen & Knutson, 2005).

Theoretical investigations for the quantification of moderm ORMF

Kuhnen & Knutson (2005) explain that these risk-seeking choices (such as gambling at a casino) and risk-averse choices (such as buying insurance) may be driven by distinct neural[2] phenomena, which when activated can lead to a shift in risk preferences. Kuhnen & Knutson (2005) found that certain areas of the brain precede risk-seeking mistakes or risky choices and other areas precede risk-aversion mistakes or riskless choices. A risk-aversion mistake is one where a gamble on a prospect of a gain is taken by a risk-averse agent in the face of the chance of a prospective loss. The fear of losing prohibits one's urge to gamble, but people engage in gambling activity anyway. Barberis & Thaler (2003) show that people regularly deviate from the traditional finance paradigm evidenced by the extensive experimental results compiled by cognitive psycologists on how people make decisions given their beliefs.

Kahneman & Tversky (2013) maintains, preferences between prospects which violate rational behaviour demonstrate that outcomes which are obtained with certainty are overweighted relative to uncertain outcomes. This will contribute to a risk-averse preference for a sure gain over a larger gain that is merely probable or a

[2]As recent evidence from human brain imaging has shown [@kuhnen2005neural] linking neural states to risk-related behaviours [@paulus2003increased].

risk-seeking preference for a loss that is merely probable over a smaller loss that it certain. As a psycological principle, overweighting of certainty favours risk-aversion in the domain of gains and risk-seeking in the domain of losses.

The present discussion replicates the common behavioral pattern of risk aversion, where people weigh losses more than equivalent gains. Furthermore, neuroeconomic research shows that this pattern of behavior is directly tied to the brain's greater sensitivity to potential losses than gains (Tom, Fox, Trepel, & Poldrack, 2007). This provides a target for investigating a more comprehensive theory of individual decision-making rather than the rational actor model and thus yield new insights relevant to economic theory[3] (Kuhnen & Knutson, 2005).

If people are reasonably accurate in predicting their choices, the presence of systematic violations of risk neutral behavior provides presumptive evidence against this i.e., people systematically violate EUT when choosing among risky gambles. This seeks to improve and adapt to reality and advance different interpretations of economic behaviour; viz., to propose a more adequately descriptive model, that can represent the basis for an alternative to the way the traditional model is built for decisions taken under uncertainty. This has led some influential commentators to call for an entirely new economic paradigm to displace conventional neoclassical theory with a psycologically more realistic preference specification (List, 2004). People exhibit a specific four-fold behaviour pattern when facing risk (Shefrin, 2016). There are four combinations of gain/loss and moderate/extreme probabilities, with two choices of risk attitude per combination. OpRisk measurement focuses on only those casual factors that create losses with random uncertainty, for the value adding processes of the business unit.

[3]Representing ability of FI's financial market models to characterise the repeated decision-making process that applies to loss aversion

CHAPTER 6
THEORETICAL INVESTIGATIONS INTO THE QUANTIFICATION OF MODERN ORMF'S

Introduction

A substantial body of evidence suggests that loss aversion, the tendency to be more sensitive to losses than to gains plays an important role in determining how people evaluate risky gambles. In this paper we evidence that human choice behavoir can substantially deviate from neoclassical norms.

PT takes into account the loss avoidance agents and common attitudes toward risk or chance that cannot be captured by EUT; which is not testing for that inherent bias, so as to expect the probability of making the same operational error in future to be overcompensated for i.e., If an institution suffers from an OpRisk event and survives, it's highly unlikely to suffer the same loss in the future because they will over-provide for particular operational loss due to their natural risk aversion. This is a testable proposition which fits normal behavioral patterns and is consistent with risk averse behaviour.

A new class of ORMF models approach

A substantial body of evidence shows that decision makers systematically violate EUT when choosing between risky prospects. Indeed, people would rather satisfy their needs than maximise their utility, contravening the normative model of rational choice (i.e., EUT) which has dominated the analysis of decision making under risk. In recent work (Barberis & Thaler, 2003) in behavioral finance, it has been argued that some of the lessons learnt from violations of EUT are central to understanding a number of financial phenomena. In response to this, there has been several theories put forward advocating for the basis of a slightly different intepretation which describes how individuals actually make decisions under uncertainty/risk. Of all the non-EUT's, we focus on Prospect Theory (PT) as this framework has had most success matching most empirical facts[1].

Kahneman & Tversky (2013) list the key elements of PT, which are 1] a value function, and 2] a non-linear transformation of the probability scale, that factors in risk aversion of the participants. According to Kahneman & Tversky (2013), the probability scale overweights small probabilities and underweights high probabilities. This feature is known as loss/risk aversion: This means that people have a greater sensitivity to losses (around 2.5 times more times) than gains, and are especially sensitive to small losses unless accompanied by small gains[2]. Loss aversion is a strong differentiator when it comes to explaining exceptions to the general risk patterns that characterize prospect theory.

Prospect theory

According to Kahneman & Tversky (2013), the decision maker, who is a risk agent within the FI, constructs a representation of the losses and outcomes that are relevant to the decision, then assesses the value of each prospect and chooses according to the losses (changes in wealth), not the overall financial state of the FI. Therefore, by relaxation of the expectation principle in equation 5.3.1, the overall value $\bigvee$ of the regular prospect $(x, p; y, q)$: In such a prospect, one receives x

[1] OpRisk loss events in FI's are largely due to human failings that are exploitable e.g., fraudulent trading activity, and PT is based on the same behavioural element of how people make financial decisions about prospects

[2] Diminishing marginal utility for gains but opposite for losses.

with probability p, y with probability q, and nothing with probability $1 - p - q$, is expressed in terms of two scales, $\pi(\cdot)$, and $\nu(\cdot)$, where $\pi(\cdot)$ is a decision weight and $\nu(\cdot)$ a number reflecting the subjective value of the outcome. Then $\bigvee$ is assigned the value:

$$\bigvee = \pi(p)\nu(x) + \pi(q)\nu(y) \qquad \text{iff} \qquad p + q \leq 1 \tag{6.1}$$

The scale, π, associates with each probability p a decision weight which reflects the impact of p on the over-all value of the prospect. The second scale, ν, assigns to each outcome x a number $\nu(x)$, which measures the value of deviations from a reference point i.e., gains or losses. π is not a probability measure and $\pi(p) + \pi(1 - p) < 1$. Through PT we add new parameters and arguments to improve the mathematical modelling method for decisions taken under risk/uncertainty, such that the value of each outcome is multiplied by a decision weight, not by an additive probability.

PT looks for common attitudes in people (in FI's) with regard to their behaviour toward taking financial risks or gambles that cannot be captured by EUT. In light of this view, people are not fully invested in either of the percieved outcomes x and y, Which tells us that $p + q \leq 1$. In lieu of this, an FI using (internal) historical OpRisk loss data to model future events; say a historical case of fraud at the FI occurs and is incorporated in the model, the probability of making the same error in future is provided for in the model versus risk events that haven't happened. The modelled future should over-provide for the loss events that have already occured, which fits normal patterns around individuals psycological make up and is consistent with risk-averse behavior. The idea at the basis of PT is that a better modeling method can be obtained which leads to a closer approximation of the over-all-value of OpRisk losses.

Theoretical investigations for the quantification of modern ORM

Within the variety of relations among risk preferences, people have difficulty in grasping the concept of risk-neutrality. In a market where securities are traded, risk-neutral probabilities are the cornerstone of trade, due to their importance in the law of no arbitrage for securities pricing. Mathematical finance is concerned with pricing of securities, and makes use of this idea.

That is, assuming that arbitrage activities do not exist, two positions with the same pay-off must also have an identical market value (Gisiger, 2010). A position (normally a primary security) can be replicated through a construction consisting of a linear combination of long, as well as short positions of traded securities. It is a relative pricing concept which removes risk-free profits due to the no-arbitrage condition.

This idea seems quite intuitive from an OpRisk management perspective. The fact that one can take internal historical loss data and use this to make a statement on the `OpRisk` VaR measure for the population, is based on the underlying assumption of risk neutrality. Consider a series of disjoint risky events occurring at times τ to $\tau + 1$. We can explore the concept of a two state economy in which value is assigned to gains and losses, rather than to final assets, such that an incremental gain or loss can be realised at state $\tau + 1$, contingent on the probability which positively impacts on the event happening.

Risk-neutral measure $\mathbb{Q}$

Risk-neutral probabilities simply enforce a linear consistency for views on equivalent losses/gains, with regard to the shape of the value function. The shape the graph depicts a linear relationship based on responses to gains/losses and value. The risk neutral probability is not the real probability of an event happening, but should be interpreted as (a functional mapping) of the number of loss events (frequency).

Suppose we have: Θ = Gain/Loss; $\nu(x)$ = risk event happening; and X = Individual gain/loss (or both), then

$$\Theta = \sum_{i=1}^{n} \Pr[\nu(x_i)] * X_i \tag{6.2}$$

where

$$\sum_{i=1}^{n} \Pr[\nu(x_i)] = 1 \qquad \text{and} \qquad \Pr[\nu(x_i)] \geq 0 \quad \forall i$$

Note that the random variable Θ is the sum of the products of frequency and severity for losses (in `OpRisk` there are no gains).

This formula is used extensively in actuarial practices, for decisions relating to quantifying different types of risk, in particular in the quantification of value-at-risk (VaR) (a risk measure used to determine capital adequacy requirements, commonly adopted in the banking industry).

A quantile of the distribution of the aggregate losses is the level of exposure to risk, expressed as VaR. People exhibit a specific four-fold behaviour pattern when facing risk (Shefrin, 2016). There are four combinations of gain/loss and moderate/extreme probabilities, with two choices of risk attitude per combination. OpRisk measurement focuses on only those casual factors that create losses with random uncertainty, for the value adding processes of the business unit.

Cluster analysis

Cluster analysis (CA) is an unsupervised machine learning technique, which sets out to group combinations of covariates according to levels of similarity into clusters. The CA algorithm attempts to optimise homogeneity within data groups, and heterogeneity between groups of observations. Thus, in the context of ORM, CA regroups these combinations of covariates into clusters (so that features within each group are similar to one another, and different from features in other groups), ordering and prioritising the root causes of losses.

A new and challenging argument can be demonstrated through clustering correlated data objects in the OpRisk dataset, by asserting that clustering should show more than one distinct group. In addition, the more groups of distinct clusters, losses are expected to drop, and losses in distinct clusters should also show a decreasing trend over time, with intensifying exposure. Ultimately, subtle patterns of frequencies and associated severities of losses in the OpRisk data can be revealed.

The OpRisk dataset is subdivided for training patterns, validated and tested with the k-means clustering algorithm. To achieve this the k-means algorithm randomly subdivides the data in k groups. Firstly, each groups mean is found by clustering the centers in the input variable-space of the training patterns. In each cluster within each group, the significant variables' coefficients which determine cluster have set centers closest to the cluster centers generated by the k-means clustering algorithm applied to the input vectors of the training data (Flake, 1998). These clusters have centers closest:- as defined by a differential metric i.e., the Euclidean distance, to a relationship (e.g. a linear combination of coefficients and variables) which most accurately predicts the target variable.

Research Objective 3

To identify potential flaws in the loss distribution approach (LDA) model of ORM by employing CA. The *classical* LDA model, through a mathematical framework derives a negative pay-off function (loss) based on a risk-neutral measure $\mathbb{Q}$. The study addresses weaknesses in the current LDA model framework, by assuming managerial risk-taking attitudes are more risk averse.

More precisely, the goal is to use CA to learn deep hierarchies of features[3] found during operations, to then determine whether risk adverse techniques over-compensate for persistent loss event types over time.

Description of the dataset

The characteristics of the traded transactions or of the associated risk correction event are given by the following variables: Trade, UpdateTime, UpdatedDay, TradedTime, TradedDay, Desk, CapturedBy, TradeStatus, TraderId, Instrument, Reason behind the risk correction event, Nominal, FloatRef floating rate reference for fixed income products, ResetDate and ResetRate, Theta, Loss severity, four EventTypeCategoryLevel viz., EL1 - IF, EL4 - CPBP, EL6 - BDSF, and EL7 - EDPM & all seven associated BusinessLineLevel, and the LossIndicator. The exposure variable shows the length of the time interval from the initial moment when the risk event happened, until the occurrence of a risk correction.

The data is limited to the training dataset over the interval 01 January - 31 March 2013, in Figure 5.1, portrays detail of the trend of OpRisk losses against ex-

[3] A typical approach taken in the literature is to use an unsupervised learning algorithm to train a model of the unlabeled data and then use the results to extract interesting features from the data [@coates2012learning]

posures for each of the 1631 observations and 16 variables. In the first plot, transactions with small exposures are concentrated in the first quadrant where HFLS losses persist. This is in line with the sentiment in risk management circles, that small exposures are not actively managed and hence risk mitigation is not a priority. As a result many of the unforeseeable LFHS losses occur here, as they are not anticipated and therefore slip through OpRisk defences, who more often than not, do not mitigate against these events.

Loss severities decrease with increasing exposures, as seen by the lowering variabilities (and colour concentration of the exposure) between loses and exposures. This support the view that more impactful past losses invoke active risk management and mitigation, as risk managers overcompensate for these severities in their management practices i.e., they are more risk averse. In addition there are graphically displayed correlations (which work for numerical explanatory variables only), which are ordered by their strengths. There is a weak positive relationship between exposure and UpdatedDay, TradedTime & TradedDay; a weak negative relationship with UpdatedTime.

Exploratory data analysis

The estimation of k-*means clustering algorithm*

A cluster analysis will identify groups within a dataset. The target variable is LossIndicator, a binary variable indicating a 1 if a realised loss occurs and 0 for those pending or near misses. The K-means clustering algorithm will search for K clusters (specified by the user). The resulting k clusters are represented by the mean or average values of each of the variables. Let us consider a model where

OpRisk loss severities vs exposure **Ordered correlations by strength**

Figure 5.1: Graphically displayed correlations by strength and a plot of OpRisk loss severities vs exposure

the LossIndicator is the target variable: The user whose task it is to specify k, may guess right or in practice they may obtain a priori, the knowledge of how to select the appropriate k in advance.

Rather than the trial and error method which involves guessing k values and successively computing minimum separation between centers, there are several data mining techniques found in the literature, that can be used to determine the optimal k (Rousseeuw, 1987). The output plot for the estimation of the optimal k is presented in Figure **??** below. We have iterated over cluster sizes from 2 to 10 clusters. The program KMeans resets the random number seed to obtain the same results each time. where the optimal k found to be significant close to $k = 10$.

The plot displays the 'sum(withinss)' for each clustering and the change in this value from the previous clustering. The Sum(WithinSS) (blue line) as a performance metric indicates that beyond $k = 4$ clusters the model overfits: Its computes the absolute error which is initially large, then monotonicaly decreases to the point $k = 4$, it then begins to increase subsequent to the point where the Diffprevious

Figure 5.2: Finding the optimal number of k groups by the Silhouette Statistic SS: Sum is a measure to approximate the optimal number of k groups by the Silhouette Statistic SS

Sum(WithinSS) (red line) intersects viz., at $k = 4$ clusters, which means $k = 4$ is the local optimal number of clusters i.e., beyond which the iterative relative errors converges faster than the absolute errors and successively reduces as k increases from 4 to 10.

Rattle program code

Results

```
Cluster sizes:

[1] "478 404 570 179"

Data means:

      Trade  UpdatedDay UpdatedTime   TradedDay  TradedTime
0.762016409 0.448559166 0.486589314 0.487369712 0.601539912
```

```
       Loss    exposure
0.003232348 0.121083376


Cluster centers:


      Trade UpdatedDay UpdatedTime TradedDay TradedTime        Loss
1 0.8106844  0.3943515   0.4123358 0.2912134  0.8556825 0.004692829
2 0.8716248  0.4900990   0.5409218 0.7948845  0.8270263 0.002132631
3 0.8378683  0.4493567   0.5264944 0.4160234  0.2165842 0.002308103
4 0.1431301  0.4970205   0.4351758 0.5443203  0.6397973 0.004757466
    exposure
1 0.08060460
2 0.06359981
3 0.07134609
4 0.51729829


Within cluster sum of squares:


[1]  84.88017  89.27845 148.89661  59.37208


Time taken: 1.86 secs


Rattle timestamp: 2018-12-13 07:22:48 User
```

Figure 5.3: A scatterplot matrix for the k-means clustering of size 4, and the covariates of frequency loss events consisting of 369 loss event frequencies amounting to R 61 534 745 P&L severity of loss impact.

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APPENDICES

Appendix A: R Code and Data Preparation for Chapter 3

Required: R Packages from CRAN

```
if (!require(caTools)){
  install.packages("caTools")
  library(caTools)
}
if (!require(caret)){
  install.packages("caret")
  library(caret)
}
if (!require(R2HTML)){
  install.packages("R2HTML")
  library(R2HTML)
}
if (!require(rattle)){
  install.packages("rattle")
  library(rattle)
}
if (!require(magrittr)){
  install.packages("magrittr")
  library(magrittr)
}
if (!require(dplyr)){
  install.packages("dplyr")
  library(dplyr)
}
if (!require(Hmisc)){
  install.packages("Hmisc")
  library(Hmisc)
}
if (!require(chron)){
  install.packages("chron")
  library(chron)
}
  if (!require(ggplot2)){
  install.packages("ggplot2")
  library(ggplot2)
  }
```

Data preparation for understanding the raw frequency and raw severity data mentioned in section 3.3 on page 65 of collected internally over the period between 1 January 2013 and 31 March 2013 i.e., Q12013 at an investment bank in SA

```
file_loc <- "C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub
/OpRisk_PHD_Thesis/Data"
setwd(file_loc)
list.files(file_loc)
frequency <- openxlsx::read.xlsx("Raw_Formatted_Data.xlsx",
                      check.names = TRUE, sheet = "Frequency")
severity <- openxlsx::read.xlsx("Raw_Formatted_Data.xlsx",
                      check.names = TRUE, sheet = "Severity")
projdata <- openxlsx::read.xlsx("OPriskDataSet_exposure.xlsx",
                      check.names = TRUE, sheet = "CleanedData")
```

Data preparation providing the numbers of OpRisk events collected through pre-processing by following the LCDE as described in section 3.4 on 68 over Q12013, limited to the co-variates selected to fit into the models

```
# Load data
fname <- "file:///C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub
/OpRisk_PHD_Thesis/Data/OPriskDataSet_exposure.csv"
crs$dataset <- read.csv(fname,
              sep=";",
              dec=",",
              na.strings=c(".", "NA", "", "?"),
              strip.white=TRUE, encoding="UTF-8")

# Select variables for loss incident model
crs$input     <- c("UpdatedDay", "UpdatedTime", "TradedDay", "TradedTime",
                  "Desk", "CapturedBy", "TradeStatus", "TraderId",
                  "Instrument", "Reason", "Nominal", "Theta", "Unexplained",
                  "EventTypeCategoryLevel1", "BusinessLineLevel1")
crs$numeric   <- c("UpdatedDay", "UpdatedTime", "TradedDay", "TradedTime",
                  "Nominal", "Theta", "Unexplained")
crs$categoric <- c("Desk", "CapturedBy", "TradeStatus", "TraderId",
                  "Instrument", "Reason", "EventTypeCategoryLevel1",
                  "BusinessLineLevel1")
crs$target    <- "LossIndicator"
crs$risk      <- NULL
crs$ident     <- NULL
crs$ignore    <- c("FloatRef", "LastResetDate", "LastResetRate", "Loss")
crs$weights   <- NULL
```

The algorithm only accepts numerical data and so categorical data is transformed into numeric. This is done using an approach where each value of a categoric variable is turned into a variable itself. Multi-level categoric variables are recoded by building dummy variables corresponding to each level by the following commands:

Numerical and categoric variables (to be transformed by below conversion code) depicted in table 3.2 on page 66:

```
# Remap factor variables and transform into numeric variables.
crs$dataset[["TNM_Desk"]] <- as.numeric(crs$dataset[["Desk"]])
crs$dataset[["TNM_CapturedBy"]] <- as.numeric(crs$dataset
                                            [["CapturedBy"]])
crs$dataset[["TNM_TraderId"]] <- as.numeric(crs$dataset[["TraderId"]])
crs$dataset[["TNM_Instrument"]] <- as.numeric(crs$dataset
                                            [["Instrument"]])
crs$dataset[["TNM_Reason"]] <- as.numeric(crs$dataset[["Reason"]])
crs$dataset[["TNM_EventTypeCategoryLevel1"]] <- as.numeric(crs$dataset
                                      [["EventTypeCategoryLevel1"]])
crs$dataset[["TNM_BusinessLineLevel1"]] <- as.numeric(crs$dataset
                                           [["BusinessLineLevel1"]])
```

Scatterplots and Histograms plots of loss severities and frequency counts against selected explanatory variables showing basic summary statistics of intra-day trading activity

Figures 4.1a and 4.1b on page 69:

```
# Scatterplots for loss severities
plot(projdata$UpdatedTime, log(projdata$Loss+0.000000001), ylim = c(6, 18),
     col = "navy", xlab = "Updated Time", ylab = "Log. Loss")
xyplot(Loss ~ as.factor(TraderId) , data = projdata)

# Histograms for loss severities
hist(projdata$UpdatedDay, col = "#9999CC", main = "All losses", xlab = "Updated Day"
     , ylab = "Frequency")
hist(projdata$TradedDay)
```

Characteristics of exposure: Exposure data is used for several of the steps of the process in frequency and severity modelling

Figure 4.2 on page 70:

```
# #==============================================================
# # Use ggplot2 to generate density plot for exposure

 p04 <- crs %>%
```

```
   with(dataset[sample,]) %>%
   dplyr::select(exposure, LossIndicator) %>%
   ggplot2::ggplot(ggplot2::aes(x=exposure)) +
   ggplot2::geom_density(lty=1, lwd=1) +
   ggplot2::geom_density(ggplot2::aes(fill=LossIndicator, colour=LossIndicator)
            , alpha=0.55) +
   ggplot2::xlab("exposure") +
   ggplot2::ggtitle("Distribution of exposure (sample) by LossIndicator")
   ggplot2::labs(y="Density") +
   theme_bw(base_size = 15)

# # Display the plots.
 gridExtra::grid.arrange(p04)

# #============================================================
# # Generate just the data for an Ecdf plot of the variable 'exposure'.
 ds <- rbind(data.frame(dat=crs$dataset[crs$sample,][,"exposure"], grp="All"))

 # The 'Hmisc' package provides the 'Ecdf' function.
 library(Hmisc, quietly=TRUE)

 # Plot the data.
 Ecdf(ds[ds$grp=="All",1], col="red", xlab="exposure", lwd=2,
      ylab=expression(Proportion <= x), subtitles=FALSE)

 # Add a title to the plot.
 title(main="Logistic",
       sub=paste("Rattle", format(Sys.time(), "%Y-%b-%d %H:%M:%S"), Sys.info()["user"]))
 p05 <- Ecdf(ds[ds$grp=="All",1], col="#E495A5", xlab="exposure", lwd=2,
             ylab=expression(Proportion <= x), subtitles=FALSE)

 ## BaseR codes for plot
 p05b <- plot(p05$x,p05$y,type='l',col='red')

# #============================================================
 # Benford's Law
 # The 'ggplot2' package provides the 'ggplot' function.
 library(ggplot2, quietly=TRUE)

 # The 'reshape' package provides the 'melt' function.
 library(reshape, quietly=TRUE)

 # Initialize the parameters.
 target <- "LossIndicator"
 var    <- "exposure"
 digit  <- 1
 len    <- 1
```

```
 # Build the dataset
 ds <- merge(benfordDistr(digit, len),
             digitDistr(crs$dataset[crs$sample,][var], digit, len, "All"))
 for (i in unique(crs$dataset[crs$sample,][[target]]))
   ds <- merge(ds, digitDistr(crs$dataset[crs$sample,][crs$dataset[crs$sample,]
                                        [target]==i, var], digit, len, i))

 # Plot the digital distribution
 p <- plotDigitFreq(ds)
 p <- p + ggtitle("Digital Analysis") +
          geom_line(lwd = 1) +
          scale_color_discrete(name = "", labels = c("Benford",
                                                    "Estimated")) +
          scale_linetype(name = "", labels = c("Benford",
                                              "Estimated")) +
         scale_color_manual(values = c("red", "green"), labels = c("Benford",
                                             "Estimated")) +
          xlab("# of Digits") + ylab("Frequency") +
          theme_bw(base_size = 15)
print(p)
```

Histograms for frequency characteristics of daily and monthly operations for daily losses and/or pending/near misses

Figures 4.3a and 4.3b on page 72:

```
### Histograms
# LossIndicator
par(mfrow=c(1,3))
### ALL Losses
hist(projdata$UpdatedTime, col = "blue", main = "All losses", xlab = "Update Time",
     ylab = "Frequency")
### Near Misses/Pending Losses
hist(projdata$UpdatedTime[projdata$LossIndicator == 0], col = "red",
     main = "Near Misses", xlab = "Update Time", ylab = "Frequency")
### Realised losses
hist(projdata$UpdatedTime[projdata$LossIndicator == 1], col = "green",
     main = "Realised losses", xlab = "Update Time", ylab = "Frequency")
par(mfrow=c(1,1))
#_____________________________________________________________________________________
# # Update Day
 summary(projdata$UpdatedDay)

### Histograms
# LossIndicator
par(mfrow=c(1,3))
```

```
### ALL Losses
hist(projdata$UpdatedDay, col = "#9999CC", main = "All losses", xlab = "Updated Day",
     ylab = "Frequency")
### Near Misses/Pending Losses
hist(projdata$UpdatedDay[projdata$LossIndicator == 0], col = "#CC6666",
     main = "Near Misses", xlab = "Updated Day", ylab = "Frequency")
### Realised losses
hist(projdata$UpdatedDay[projdata$LossIndicator == 1], col = "#66CC99",
     main = "Realised losses", xlab = "Updated Day", ylab = "Frequency")
par(mfrow=c(1,1))
```

Density plots of overlaid trade proportions of realised losses vs pending losses/near misses

Figures 4.4 on page 73:

```
# Density Plot for Updated Day
p01 <- crs %>%
  with(dataset[sample,]) %>%
  dplyr::mutate(LossIndicator=as.factor(LossIndicator)) %>%
  dplyr::select(UpdatedDay, LossIndicator) %>%
  ggplot2::ggplot(ggplot2::aes(x=UpdatedDay)) +
  ggplot2::geom_density(lty=3) +
  ggplot2::geom_density(ggplot2::aes(fill=LossIndicator, colour=LossIndicator),
           alpha=0.55) +
  ggplot2::ggtitle("Distr. of Updated DaY") +
  ggplot2::labs(fill="LossIndicator", y="Density") +
  ggplot2::xlab("Day of Month that Trade Was Updated")

# Density Plot for Traded day
p02 <- crs %>%
  with(dataset[sample,]) %>%
  dplyr::mutate(LossIndicator=as.factor(LossIndicator)) %>%
  dplyr::select(TradedDay, LossIndicator) %>%
  ggplot2::ggplot(ggplot2::aes(x=TradedDay)) +
  ggplot2::geom_density(lty=3) +
  ggplot2::geom_density(ggplot2::aes(fill=LossIndicator, colour=LossIndicator),
           alpha=0.55) +
  ggplot2::ggtitle("Distr. of TradedDay") +
  ggplot2::labs(fill="LossIndicator", y="Density") +
  ggplot2::xlab("Day of Month for Trade")

# Display the plots.
gridExtra::grid.arrange(p01, p02, nrow = 1)
```

Table 3.3 on 73

```
# addmargins(table(projdata$Desk, projdata$LossIndicator), 2)
```

Histograms of overlaid trade proportions of realised losses vs pending loss/near misses

Figures 4.5 on page 74:

```
# Plot Desk category distribution
p03 <- crs %>%
  with(dataset[sample,]) %>%
  dplyr::mutate(LossIndicator=as.factor(LossIndicator)) %>%
  dplyr::select(Desk, LossIndicator) %>%
  dplyr::group_by(Desk, LossIndicator) %>%
  dplyr::summarise(n = n()) %>%
  ggplot2::ggplot(ggplot2::aes(x=Desk, y=n, fill=LossIndicator)) +
  ggplot2::geom_bar(stat="identity") +
  ggplot2::ggtitle("Desk category distribution") +
  ggplot2::theme_minimal() +
  ggplot2::theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggplot2::ylab("Frequency")

# Create new variable to proportion no. of realised losses
T01 <- crs %>%
  with(dataset[sample,]) %>%
  dplyr::mutate(LossIndicator=as.factor(LossIndicator)) %>%
  dplyr::select(Desk, LossIndicator) %>%
  dplyr::group_by(Desk, LossIndicator) %>%
  dplyr::summarise(n = n())

T02 <- T01 %>%
  group_by(Desk) %>%
  summarise(N=sum(n))

T03 <- inner_join(T01, T02)

# Plot Desk category by proportion
T04 <- T03 %>%
  mutate(Prob=n/N) %>%
  filter(LossIndicator==1) %>%
  select(Desk, Prob) %>%
  arrange(desc(Prob)) %>%
  ggplot2::ggplot(ggplot2::aes(x=Desk, y=Prob, fill=Desk), alpha=0.55) +
  ggplot2::geom_bar(stat="identity", fill="grey", colour="black", show.legend = FALSE)+
  ggplot2::ggtitle("Proportion of losses per Desk") +
  ggplot2::theme_minimal()+
  ggplot2::theme(axis.text.x = element_text(angle = 90, hjust = 1))+
  ggplot2::ylab("Loss Ratio (n/N)")+
  ggplot2::xlab("Desk")

#Display both plots in one row
```

```
gridExtra::grid.arrange(p03, T04, nrow = 1)
####============================================================
```

Mosaic grid plots for the bidimensional distributions by traded ***Instrument****,* ***TraderId*** *and number*

Figures 4.6 on page 75:

```
par(mfrow=c(1,2))
plot(table(projdata$LossIndicator, projdata$Instrument), main="By Instrument",
     col=rainbow(20), las=1)
plot(table(projdata$LossIndicator, projdata$TraderId), main="By Trader",
     col=rainbow(20), las=1)
plot(table(projdata$LossIndicator, projdata$CapturedBy), main="By Tech Support",
     col=rainbow(20), las=1)
par(mfrow = c(1, 1))
####============================================================
```

Mosaic grid plots for the structure of OpRisk portfolio by traded ***TradeStatus****,* ***TraderId*** *by the number of realised losses vs pending loss/near misses*

Figures 4.6 on page 75:

```
# # Contingency Table
 library(vcd)
 STD <- structable(~TradeStatus + TraderId + LossIndicator
                                         , data = projdata)
 # Mosaic plot
 MS01 <- mosaic(STD, condvars = 'TradeStatus', col=rainbow(20),
                  split_horizontal = c(TRUE, FALSE, TRUE))
 MS01
```

Appendix B: R Code for Chapter 4

Required: R Packages from CRAN (in addition to packages already found in Chapter 3)

```
if (!require(MuMIn)){
  install.packages("MuMIn")
  library(MuMIn)
}
if (!require(parallel)){
  install.packages("parallel")
  library(parallel)
}
if (!require(R2HTML)){
  install.packages("R2HTML")
  library(R2HTML)
}
if (!require(e1071)){
  install.packages("e1071")
  library(e1071)
}
if (!require(ROCR)){
  install.packages("ROCR")
  library(ROCR)
}
```

Data partitioning of the pre-processed OpRisk dataset into Training/Validation/Testing proportions, in preparation for machine learning model building treatments. The original dataset is partitioned into three random subsets initiated by a random number sequence with a randomly selected seed.

The function `getmode` specifies the modal class as the reference level in the GLM from which the corresponding observations are estmated and weighted against, see chapter 3 section 3.3 on page 65

```
building <- TRUE
scoring <- ! building

# Load data
fname <- "file:///C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub
/OpRisk_PHD_Thesis/Data/OPriskDataSet_exposure.csv"
crs$dataset <- read.csv(fname,
              sep=";",
              dec=",",
              na.strings=c(".", "NA", "", "?"),
```

```
              strip.white=TRUE, encoding="UTF-8")
exposure <- crs$dataset[,ncol(crs$dataset)]

# Select variables for loss incident model
crs$dataset <- as.data.frame(crs$dataset)

# The following varaible selections have been noted

crs$input <- crs$dataset %>%
  group_by(UpdatedDay,
           UpdatedTime,
           TradedDay,
           TradedTime,
           Desk,
           CapturedBy,
           TradeStatus,
           TraderId,
           Instrument,
           Reason,
           EventTypeCategoryLevel1,
           BusinessLineLevel1) %>%
  transmute(LossesIndicator = LossIndicator,
            Losses = Loss,
            Exposure = exposure)

getmode <- function(x){
  u <- unique(x)
  as.integer(u[which.max(tabulate(match(x,u)))])
}

for (i in 5:(ncol(crs$input) - 3)){
     crs$input[[i]] <- relevel(crs$input[[i]], getmode(crs$input[[i]]))
}

#==========================================================================================
# A predefined value is used to reset the random seed so that results are repeatable
crv$seed <- 42

# Build the training/validation/testing datasets. Set parameter values


set.seed(crv$seed)    # set random seed to make your partition reproducible

crs$nobs <- nrow(crs$input)                 # nobs=2331

crs$train <- sample(crs$nobs, 0.7*crs$nobs) # proportion of training data = 1632
```

```
crs$nobs %>%
  seq_len() %>%
  setdiff(crs$train) %>%
  sample(0.15*crs$nobs) ->                  # proportion of validation data = 350
  crs$validate

crs$nobs %>%
  seq_len() %>%
  setdiff(crs$train) %>%
  setdiff(crs$validate) ->                  # proportion of testing data = 349
  crs$test


crs$training <- as.data.frame(crs$input[crs$train,])
crs$validation <- as.data.frame(crs$input[crs$validate,])
crs$testing <- as.data.frame(crs$input[crs$test,])
```

Models

Estimation of some poisson regression models for OpRisk loss frequency distribution: To build the model we pass on to the model building function `glm` *i.e., the formula that describes the model to build.*

We will use "LossesIndicator" as the dependent variable, while the `TradedDay` and `Desk` variables will be predictor variables. This will be our global model

```
freqfit1 <- glm(LossesIndicator ~ TradedDay + Desk, data=crs$training,
               family=poisson(link = 'log'), offset = log(Exposure))

summary(freqfit1)
```

Basic model build summary

```
Call:
glm(formula = LossesIndicator ~ TradedDay + Desk, family = poisson(link="log"),
    data = crs$training, offset = log(Exposure))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.1207  -0.5339  -0.2400  -0.0518   4.0933

Coefficients:
                       Estimate Std. Error z value            Pr(>|z|)
```

Figure 8.4: Estimation of some Poisson distribution for target variable `LossesIndicator` and the two explanatory variables `TradedDay` and `Desk`

```
(Intercept)            -7.954918   0.190551 -41.747 < 0.0000000000000002 ***
TradedDay              -0.018916   0.006404  -2.954              0.00314 **
DeskAfrica              1.167006   0.388993   3.000              0.00270 **
DeskBonds/Repos         1.515074   0.271912   5.572       0.000000025193 ***
DeskCommodities         0.724682   0.246709   2.937              0.00331 **
DeskDerivatives        -0.283438   0.305313  -0.928              0.35323
DeskEquity              1.420351   0.220317   6.447       0.000000000114 ***
DeskManagement/Other -14.765953 398.825678  -0.037              0.97047
DeskMM                  0.291186   0.235977   1.234              0.21722
DeskPrime Services      2.227346   0.220554  10.099 < 0.0000000000000002 ***
DeskSND                -0.980626   0.298308  -3.287              0.00101 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 1898.7  on 1630  degrees of freedom
Residual deviance: 1661.4  on 1620  degrees of freedom
AIC: 2187.4

Number of Fisher Scoring iterations: 15
```

Let us now fit a broader GLM to be our global model, still `LossesIndicator` *as the dependent variable, while the rest of the predictive variables will be predictor variables.*

```
freqfit <- glm(formula = LossesIndicator ~ UpdatedDay + UpdatedTime + TradedDay +
    TradedTime + Desk + CapturedBy + TradeStatus + TraderId +
    Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1,
    family = poisson(link = "log"), data = crs$training,
    offset = log(Exposure)))
```

Global model build summary

```
Call:
glm(formula = LossesIndicator ~ UpdatedDay + UpdatedTime + TradedDay +
    TradedTime + Desk + CapturedBy + TradeStatus + TraderId +
    Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1,
    family = poisson(link = "log"), data = crs$training,
    offset = log(Exposure))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-4.7605  -0.3575  -0.1105  -0.0315   3.9754

Coefficients:
```

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	-7.8113982	0.6701090	-11.657	< 0.0000000000000002	***
UpdatedDay	0.0043298	0.0097374	0.445	0.656565	
UpdatedTime	0.5850748	0.7146037	0.819	0.412935	
TradedDay	-0.0001216	0.0082899	-0.015	0.988297	
TradedTime	-0.8201083	0.7856849	-1.044	0.296572	
DeskAfrica	1.5831846	0.5281939	2.997	0.002723	**
DeskBonds/Repos	2.3432611	0.3958404	5.920	0.00000000322505	***
DeskCommodities	0.6910019	0.4627163	1.493	0.135343	
DeskDerivatives	0.3832286	0.5020354	0.763	0.445255	
DeskEquity	1.1778919	0.3969116	2.968	0.003001	**
DeskManagement/Other	-14.7535497	367.5957685	-0.040	0.967985	
DeskMM	1.2027479	0.5903580	2.037	0.041618	*
DeskPrime Services	-0.1311216	1.3579826	-0.097	0.923079	
DeskSND	0.0518179	0.7105464	0.073	0.941864	
CapturedByMIDOFFICE	0.2618294	0.3319433	0.789	0.430242	
CapturedByPROD ACCOUNTANT	0.0934629	0.5393415	0.173	0.862423	
CapturedByPROD CONTROLLER	-0.4702595	0.3321428	-1.416	0.156824	
CapturedByUNAUTHORISED	-0.9738648	0.5370115	-1.813	0.069756	.
TradeStatusBO-BO Confirmed	-0.3379764	0.2363953	-1.430	0.152801	
TradeStatusTerminated	2.1847205	1.3465905	1.622	0.104716	
TradeStatusTerminated /Void	11.3395140	1443.2959040	-0.008	0.993731	
TraderIdAMBA	0.4943858	0.5830511	0.848	0.396478	
TraderIdANALYST	-0.2062667	0.2944408	-0.701	0.483592	
TraderIdASSOCIATE	-0.7844915	0.3507247	-2.237	0.025301	*
TraderIdATS	2.7382867	0.6662928	4.110	0.00003961139187	***
TraderIdMNGDIRECTOR	0.6153055	0.3144102	1.957	0.050346	.
TraderIdVICE PRINCIPAL	0.2229076	0.3662304	0.609	0.542754	
InstrumentBill	0.7859508	0.6781491	1.159	0.246471	
InstrumentBond	-0.3433677	0.4080143	-0.842	0.400035	
InstrumentBuySellback	0.1566566	0.6720075	0.233	0.815670	
InstrumentCall Deposit	-1.2603996	0.3973057	-3.172	0.001512	**
InstrumentCombination	0.6328848	1.2513624	0.506	0.613028	
InstrumentCredit DefaultSwap	-1.9878550	0.6529647	-3.044	0.002332	**
InstrumentCurr	-1.0355350	0.5045561	-2.052	0.040134	*
InstrumentCurrSwap	-0.6964712	0.5165406	-1.348	0.177550	
InstrumentDeposit	0.0584655	0.3945317	0.148	0.882193	
InstrumentEquityIndex	-0.8243925	1.0794767	-0.764	0.445048	
InstrumentETF	1.0751791	1.1397155	0.943	0.345489	
InstrumentFRA	-1.6745203	0.9177750	-1.825	0.068070	.

```
InstrumentFRN          0.2792480    0.5903548   0.473              0.636201
InstrumentFuture/
Forward               -0.7303512    0.3917942  -1.864              0.062305 .
InstrumentIndexLinked
Bond                  -0.6022619    0.7595690  -0.793              0.427836
InstrumentIndexLinked
Swap                  -0.0154039    0.6024804  -0.026              0.979602
InstrumentOption       0.0277106    0.5621959   0.049              0.960688
InstrumentOther       -0.1830206    0.2891929  -0.633              0.526821
InstrumentRepo/Reverse-2.0252367    0.7133321  -2.839              0.004524 **
InstrumentSecurityLoan-1.0447821    0.3461497  -3.018              0.002542 **
InstrumentStock       -0.6782734    1.4169911  -0.479              0.632172
InstrumentTotalReturn
Swap                  -1.0219974    0.3990992  -2.561              0.010444 *
ReasonAcquirer         4.2877314    1.2671128   3.384              0.000715 ***
ReasonBrokerage
Related                1.7788236    1.0318752   1.724              0.084730 .
ReasonCalendar Related 1.2768935    0.3888510   3.284              0.001024 **
ReasonCapture Errors
Direct/Amount/Rate/CP  0.2418004    0.4150033   0.583              0.560131
ReasonClient Request
to Amend Economics of
Deal              -0.9290734    1.0584940  -0.878              0.380089
ReasonCommodities
Early Delivery        -0.4631230    1.2048262  -0.384              0.700689
ReasonCorrected
NDEUSSA Reset Level   -2.8475291    0.8317484  -3.424              0.000618 ***
ReasonCPI Fixings     -4.2562507    0.9924649  -4.289     0.00001798306834 ***
ReasonEarly Terminati
on/Delivery/ Close out-2.6225044    0.7518160  -3.488              0.000486 ***
ReasonFees/Commissions
Related               -1.4712607    0.9402884  -1.565              0.117655
ReasonOperations
request to change
Economics of Trade    -0.1702668    0.8638805  -0.197              0.843753
ReasonPayments Related-0.5039834    0.7179092  -0.702              0.482669
ReasonPortfolio Move
 / Restructure        -1.8408735    1.1353256  -1.621              0.104921
ReasonSales Credits    2.1487308    1.1446783   1.877              0.060498 .
ReasonSystem Update
Call Accounts         -4.2209045    0.9534873  -4.427     0.00000956382022 ***
ReasonTrade
Restructure           -0.6497247    2.2083716  -0.294              0.768598
ReasonTri-Optima      -3.2769186    1.4560359  -2.251              0.024412 *
ReasonValuation Group
```

```
Request                  0.7265138    0.6359340   1.142             0.253273
EventTypeCategoryLevel
1EL1                     2.4984605    0.6443312   3.878             0.000105 ***
EventTypeCategoryLevel
1EL4                     1.3739551    0.6054219   2.269             0.023243 *
EventTypeCategoryLevel
1EL6                     5.6915077    0.8154721   6.979     0.00000000000296 ***
EventTypeCategoryLevel
1EL8                    -4.0471414    1.1004892  -3.678             0.000235 ***
BusinessLineLevel
1BL1                     2.0456821    0.7730115   2.646             0.008136 **
BusinessLineLevel
1BL3                     0.1576673    0.6308477   0.250             0.802642
BusinessLineLevel
1BL4                    -1.2651162    0.4937915  -2.562             0.010406 *
BusinessLineLevel
1BL5                    -1.1905846    0.5243289  -2.271             0.023166 *
BusinessLineLevel
1BL6                     1.7544025    1.4007670   1.252             0.210403
BusinessLineLevel
1BL7                     2.2553305    2.2524125   1.001             0.316684
BusinessLineLevel
1BL9                     0.2496745 1613.4575790   0.000             0.999877
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 1898.7  on 1630  degrees of freedom
Residual deviance: 1228.1  on 1553  degrees of freedom
AIC: 1888.1

Number of Fisher Scoring iterations: 15
```

Estimation of some binomial regression modelS: The formula that describes the model to build.

The target variable is “remapped” or transformed into a factor variable from a numerical variable by use of the code below:

```
crs$dataset[["TFC_LossIndicator"]] <-
  as.factor(crs$dataset[["LossIndicator"]])

ol <- levels(crs$dataset[["TFC_LossIndicator"]])
```

```
lol <- length(ol)
nl <- c(sprintf("[%s,%s]", ol[1], ol[1]),
        sprintf("(%s,%s]", ol[-lol], ol[-1]))
levels(crs$dataset[["TFC_LossIndicator"]]) <- nl
```

We will use "LossesIndicator" as the dependent variable.

```
freqfit <- glm(LossesIndicator ~ UpdatedDay + UpdatedTime + TradedDay
       + TradedTime + Desk + CapturedBy + TradeStatus + TraderId +
  Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1,
  data=crs$training, family=binomial(link="logit"), offset=log(Exposure))

summary(freqfit)
```

Basic model build summary

```
Call:
glm(formula = LossesIndicator ~ UpdatedDay + UpdatedTime + TradedDay +
    TradedTime + Desk + CapturedBy + TradeStatus + TraderId +
    Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1,
    family = binomial(link = "logit"), data = crs$training, offset = log(Exposure)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.2957  -0.4346  -0.0987  -0.0001   4.0153

Coefficients:
                       Estimate      Std. Error z value           Pr(>|z|)
(Intercept)          -7.9749408      1.0332350  -7.718 0.0000000000000118 ***
UpdatedDay            0.0158775      0.0144454   1.099           0.271707
UpdatedTime          -0.5014732      0.9397316  -0.534           0.593594
TradedDay            -0.0007336      0.0120301  -0.061           0.951373
TradedTime            0.9590326      1.0673571   0.899           0.368913
DeskAfrica            4.3345648      0.9075486   4.776 0.0000017870595853 ***
DeskBonds/Repos       5.0241306      0.6499654   7.730 0.0000000000000108 ***
DeskCommodities       2.0972543      0.6780211   3.093           0.001980 **
DeskDerivatives      -0.1864882      0.7413218  -0.252           0.801380
DeskEquity            1.8915605      0.5960148   3.174           0.001505 **
DeskManagement/Other -18.2048936  1520.1898190  -0.012           0.990445
DeskMM                1.9981588      0.7940263   2.516           0.011853 *
DeskPrime Services    0.5307160      1.3075756   0.406           0.684832
DeskSND               2.3274858      1.0644292   2.187           0.028771 *
CapturedByMIDOFFICE   0.8804690      0.4547261   1.936           0.052836 .
CapturedByPROD ACCOUN
TANT                  0.4517261      0.6963223   0.649           0.516512
CapturedByPROD
CONTROLLER           -1.2989586      0.4743150  -2.739           0.006170 **
```

```
CapturedByUNAUTHORISED 0.3986375      0.8119582   0.491             0.623456
TradeStatusBO-BO
Confirmed             -1.5378456      0.3303144  -4.656 0.0000032287903266 ***
TradeStatusTerminated  1.5155682      1.3644806   1.111             0.266685
TradeStatusTerminated
/Void                -15.5553055   4600.1942577  -0.003             0.997302
TraderIdAMBA          -0.0025153      0.7912919  -0.003             0.997464
TraderIdANALYST       -0.6145646      0.4385093  -1.401             0.161069
TraderIdASSOCIATE     -0.9420685      0.5319834  -1.771             0.076584 .
TraderIdATS            2.6800452      0.9148818   2.929             0.003396 **
TraderIdMNGDIRECTOR    1.3616232      0.5228248   2.604             0.009205 **
TraderIdVICE PRINCIPAL-0.7050650      0.5070382  -1.391             0.164360
InstrumentBill        -0.8718713      0.9354385  -0.932             0.351313
InstrumentBond         0.2366580      0.6067829   0.390             0.696521
InstrumentBuySellback  1.3218806      1.0448559   1.265             0.205824
InstrumentCall Deposit-2.1675836      0.5991862  -3.618             0.000297 ***
InstrumentCombination-16.7614537    746.7004950  -0.022             0.982091
InstrumentCredit
DefaultSwap           -1.5055382      0.9616767  -1.566             0.117458
InstrumentCurr        -2.8712232      0.7263157  -3.953 0.0000771343104836 ***
InstrumentCurrSwap    -2.0228703      0.7723046  -2.619             0.008812 **
InstrumentDeposit      0.2775796      0.5010409   0.554             0.579575
InstrumentEquityIndex-20.9093522   4247.6245656  -0.005             0.996072
InstrumentETF          0.6949521      2.5050338   0.277             0.781456
InstrumentFRA        -18.4966479   2217.1713497  -0.008             0.993344
InstrumentFRN          1.0640690      0.6934803   1.534             0.124934
InstrumentFuture
/Forward              -1.3009786      0.5043702  -2.579             0.009897 **
InstrumentIndexLinked
Bond                 -18.5083821   1980.8539595  -0.009             0.992545
InstrumentIndexLinked
Swap                  -1.3276177      0.8399563  -1.581             0.113974
InstrumentOption      -0.3366249      0.7407203  -0.454             0.649501
InstrumentOther       -0.7233858      0.4259873  -1.698             0.089481 .
InstrumentRepo/Reverse-1.6068842      0.8756603  -1.835             0.066498 .
InstrumentSecurityLoan-1.6209368      0.5052288  -3.208             0.001335 **
InstrumentStock      -15.5171850    917.6844311  -0.017             0.986509
InstrumentTotalReturn
Swap                  -2.1376528      0.5110535  -4.183 0.0000287895194553 ***
ReasonAcquirer       -15.7038902  10686.9945316  -0.001             0.998828
ReasonBrokerage Related4.1338623      2.1977014   1.881             0.059973 .
ReasonCalendar Related 2.8178751      0.5313717   5.303 0.0000001139021850 ***
ReasonCapture Errors
 - Direction / Amount
 / Rate / CP           1.4848841      0.5279634   2.812             0.004916 **
```

```
ReasonClient Request to
 Amend Economics
of Deal              -0.3720879     1.2198215  -0.305           0.760340
ReasonCommodities
Early Delivery        2.4241223     1.2227799   1.982           0.047427 *
ReasonCorrected
NDEUSSA Reset Level   0.4751118     0.9464671   0.502           0.615678
ReasonCPI Fixings    -16.6208128  1172.4035169  -0.014           0.988689
ReasonEarly
Termination / Delivery
 / Close out         -43.1745557  1552.0277206  -0.028           0.977807
ReasonFees/Commissions
Related               -0.8431985     1.0953186  -0.770           0.441407
ReasonOperations request
 to change Economics
 of Trade            -40.9898225  1552.0278612  -0.026           0.978930
ReasonPayments Related  0.6979688     0.7737247   0.902           0.367009
ReasonPortfolio Move
 / Restructure       -14.7140963   850.1374455  -0.017           0.986191
ReasonSales Credits    2.9232638     1.3710077   2.132           0.032990 *
ReasonSystem Update Call
 Accounts            -79.5591356  1906.0449509  -0.042           0.966706
ReasonTrade
Restructure          -55.6249278  2864.4577747  -0.019           0.984507
ReasonTri-Optima      -1.9567842     1.4525216  -1.347           0.177928
ReasonValuation Group
 Request               2.2511805     0.9782985   2.301           0.021385 *
EventTypeCategoryLevel1
EL1                   44.5975989  1552.0274644   0.029           0.977076
EventTypeCategoryLevel1
EL4                    1.2665117     0.6101433   2.076           0.037916 *
EventTypeCategoryLevel1
EL6                   81.6802380  1906.0447914   0.043           0.965819
EventTypeCategoryLevel1
EL8                   -5.4027759     1.3335661  -4.051 0.0000509176014626 ***
BusinessLineLevel1
BL1                    2.7388864     1.0366354   2.642           0.008240 **
BusinessLineLevel1
BL3                     -1.6356998     0.8999922  -1.817           0.069147 .
BusinessLineLevel1
BL4                     -4.1488349     0.7241412  -5.729 0.0000000100835606 ***
BusinessLineLevel1
BL5                     -2.2516395     0.7017310  -3.209           0.001333 **
BusinessLineLevel1
BL6                      0.8510447     1.4106248   0.603           0.546302
```

```
BusinessLineLevel1
BL7                    -16.5197686  2691.6096464  -0.006          0.995103
BusinessLineLevel1
BL9                     24.2348398  1520.1905636   0.016          0.987281
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2380.8  on 1630  degrees of freedom
Residual deviance: 1270.6  on 1553  degrees of freedom
AIC: 1426.6

Number of Fisher Scoring iterations: 18
```

Model selection and multimodel inference: MuMIn

"All possible models" are considered by subjectively ad iteratively searching the data for patterns and "significance".

we use "dredge" function to generate models using combinations of the terms in the global model. The function will also calculate AICc values and rank models according to it.

```
cl <- makeCluster(2) # Assign R cores to the job
options(na.action=na.fail)
freqfits <- dredge(freqfit)
stopCluster(cl)
freqfits
```

"MuMLn::dredge" returns a list of 4097 models, below is the build summary

We use `get.models` function to generate a list in which its objects are the fitted models. We will also use the "model.avg" function to do a model averaging based on AICc.

```
cl <- makeCluster(2) # Assign R cores to the job
Amodel <- model.avg(get.models(freqfits, subset = TRUE))
summary(Amodel)
stopCluster(cl)
```

Now we have AICc values for our models and we have the average model (or mean model).

Figure 9.5: Model selection data mining exercise

Figure 9.6: component models for computing the average (mean) model `AModel`

Figure 9.7: Continued from 9.6

Figure 9.8: Continued from 9.7

Evaluate model performance on the test dataset

Obtain the response from the Linear model.

```
 Av.PredTT <- predict(Amodel, crs$testing, type = "response")

 # Export into excel

HTMLStart(); HTML(data.frame(Av.PredTT)); w <- HTMLStop()
browseURL(w)

shell(paste("start excel", w))
Est <- "file:///C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub/
OpRisk_PHD_Thesis/Data/OPriskDataSet_GoF_Amodel_InCode.csv"
pred <- read.csv(Est,
                   sep=",",
                   dec=".",
                   na.strings=c(".", "NA", "", "?"),
                   strip.white=TRUE, encoding="UTF-8")
```

Generate the confusion matrix showing counts and generate an ROC curve for the GLM model on the appropriate dataset partition

```
confusionMatrix(table(pred$response, crs[["testing"]][["LossesIndicator"]]))

crs$pr <- Av.PredTT

# Remove observations with missing target.

no.miss   <- na.omit(crs[["testing"]][["LossesIndicator"]])
miss.list <- attr(no.miss, "na.action")
attributes(no.miss) <- NULL

if (length(miss.list))
{
  predic <- prediction(crs$pr[-miss.list], no.miss)
} else
{
  predic <- prediction(crs$pr, no.miss)
}

pe <- performance(predic, "tpr", "fpr")
au <- performance(predic, "auc")@y.values[[1]]
pd <- data.frame(fpr=unlist(pe@x.values), tpr=unlist(pe@y.values))
p <- ggplot(pd, aes(x=fpr, y=tpr))
p <- p + geom_line(colour="red")
```

```
p <- p + xlab("False Positive Rate") + ylab("True Positive Rate")
p <- p + ggtitle("ROC Curve Linear OPriskDataSet_exposure.csv [validate] LossesInd
p <- p + theme(plot.title=element_text(size=10))
p <- p + geom_line(data=data.frame(), aes(x=c(0,1), y=c(0,1)), colour="grey")
p <- p + annotate("text", x=0.50, y=0.00, hjust=0, vjust=0, size=5,
                  label=paste("AUC =", round(au, 2)))
print(p)

# Calculate the area under the curve for the plot.


# Remove observations with missing target.

no.miss   <- na.omit(crs[["testing"]][["LossesIndicator"]])
miss.list <- attr(no.miss, "na.action")
attributes(no.miss) <- NULL

if (length(miss.list))
{
  predic <- prediction(crs$pr[-miss.list], no.miss)
} else
{
  predic <- prediction(crs$pr, no.miss)
}
performance(predic, "auc")
```

Figure 9.9: Comparison of Poisson, Binomial GLM's confusion matrices for Training, Validation & Testing datasets

Figure 9.10: Comparison of Poisson, Binomial GLM's ROC Curves for Training, Validation & Testing datasets

Data augmentation code: Extrapolation simulation in Matlab

Notably, the code for the predict condition was run via the Matlab Terminal:

```
% Updated Time
% generate the vector DD

DDD = 1:31;

% generate the vector VVV

VVV = 1:12;

% generate the vector UUU

UUU = 2013 : -1 : 2006;

% making the full thrity five days vector
% Years
Thirty_five_days = [UUU';UUU';UUU';UUU(1:end-1)'];
%Months
Thirty_five_days2 = [VVV';VVV';VVV(1:7)'];
% Days
Thirty_five_days3 = DDD';

% The updated time algorithm

% initializing the time matrix
for i = 1 : length(UUU)

    UUU_trans{i} = num2cell(zeros(1,12));

end

for i = 1 : length(UUU)
    for j = 1 : length(UUU_trans{1,1})

        UUU_TRANS{1,i}{1,j} = num2cell(zeros(31,4));
    end

end

% The number of random numbers
H = 1000;
UPD =.789155092592539;
format long
% filling in the time matrix
```

```
for i = 1 : length(UUU)
    for j = 1 : length(UUU_trans{1,1})

        UUU_TRANS{1,i}{1,j}(:,end) = num2cell((1:31)');
        UUU_TRANS{1,i}{1,j}(:,end-1) = num2cell(VVV(j));



    end

end

UUU = num2cell(UUU);
%         UUU = sortrows(UUU,2);


for i = 1 : length(UUU)
    for j = 1 : length(UUU_trans{1,1})
        for k = 1 : length(UUU_TRANS{1,5}{1,1})
            % PART 1
            UUU{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUU{i,j} = UUU{i,j}';
            UUU{i,j}(:,2) = num2cell(Thirty_five_days(:,1));
            UUU{i,j} = sortrows(UUU{i,j},1);

            %PART 2
            UUU2{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUU2{i,j} = UUU2{i,j}';
            UUU2{i,j}(:,2) = num2cell(Thirty_five_days2(:,1));
            UUU2{i,j} = sortrows(UUU2{i,j},1);
            % PART 3
            UUU3{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUU3{i,j} = UUU3{i,j}';
            UUU3{i,j}(:,2) = num2cell(Thirty_five_days3(:,1));
            UUU3{i,j} = sortrows(UUU3{i,j},1);
            % PART 1
            UUU_TRANS{1,i}{1,j}(k,end-3) = UUU{i,j}(k,2);

            % PART 2
            UUU_TRANS{1,i}{1,j}(k,end-2) = UUU2{i,j}(k,2);
            %PART3
            UUU_TRANS{1,i}{1,j}(k,end-1) = UUU3{i,j}(k,2);
            rH{i,j} = num2cell(((i)^(0).*(j)^(0)).*rand(H,1));
            yH{i,j} = rH{i,j}(cell2mat( rH{i,j}) <= UPD);
            gH{i,j} = num2cell(cell2mat( yH{i,j}(1:31)));
            UUU_TRANS{1,i}{1,j}(k,end) = gH{i,j}(k,1);
        end
```

```
    end

end

UPDATED_TIME = UUU_TRANS;


%% Traded time

% generate the vector DD

DDDT = 1:31;

% generate the vector VVV

VVVT = 1:12;

% generate the vector UUU

UUUT = 2013 : -1 : 2006;

% making the full thrity five days vector
% Years
Thirty_five_daysT = [UUUT';UUUT';UUUT';UUUT(1:end-1)'];
%Months
Thirty_five_days2T = [VVVT';VVVT';VVVT(1:7)'];
% Days
Thirty_five_days3T = DDDT';

% The updated time algorithm

% initializing the time matrix
for i = 1 : length(UUUT)

    UUU_transT{i} = num2cell(zeros(1,12));

end

for i = 1 : length(UUUT)
    for j = 1 : length(UUU_transT{1,1})

        UUU_TRANST{1,i}{1,j} = num2cell(zeros(31,4));
    end

end

% The number of random numbers
```

```
HT = 1000;
UPDT =.789155092592539;
format long
% filling in the time matrix
for i = 1 : length(UUUT)
    for j = 1 : length(UUU_transT{1,1})

        UUU_TRANST{1,i}{1,j}(:,end) = num2cell((1:31)');
        UUU_TRANST{1,i}{1,j}(:,end-1) = num2cell(VVVT(j));



    end

end

UUUT = num2cell(UUUT);
%         UUU = sortrows(UUU,2);


for i = 1 : length(UUUT)
    for j = 1 : length(UUU_transT{1,1})
        for k = 1 : length(UUU_TRANST{1,5}{1,1})
            % PART 1
            UUUT{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUUT{i,j} = UUUT{i,j}';
            UUUT{i,j}(:,2) = num2cell(Thirty_five_daysT(:,1));
            UUUT{i,j} = sortrows(UUUT{i,j},1);

            %PART 2
            UUU2T{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUU2T{i,j} = UUU2T{i,j}';
            UUU2T{i,j}(:,2) = num2cell(Thirty_five_days2T(:,1));
            UUU2T{i,j} = sortrows(UUU2T{i,j},1);
            % PART 3
            UUU3T{i,j} =num2cell((((i)^(0)).*((j)^(0)).*rand(1,31)));
            UUU3T{i,j} = UUU3T{i,j}';
            UUU3T{i,j}(:,2) = num2cell(Thirty_five_days3T(:,1));
            UUU3T{i,j} = sortrows(UUU3T{i,j},1);
            % PART 1
            UUU_TRANST{1,i}{1,j}(k,end-3) = UUUT{i,j}(k,2);

            % PART 2
            UUU_TRANST{1,i}{1,j}(k,end-2) = UUU2T{i,j}(k,2);
            %PART3
            UUU_TRANST{1,i}{1,j}(k,end-1) = UUU3T{i,j}(k,2);
            rHT{i,j} = num2cell(((i)^(0).*(j)^(0)).*rand(HT,1));
```

```
            yHT{i,j} = rHT{i,j}(cell2mat( rHT{i,j}) <= UPDT);
            gHT{i,j} = num2cell(cell2mat( yHT{i,j}(1:31)));
            UUU_TRANST{1,i}{1,j}(k,end) = gHT{i,j}(k,1);
        end
    end

end

TRADED_TIME = UUU_TRANST;

%% RULE for correcting the traded time
SIZZZE = size(UUU_TRANS{1,3}{1,2});
for i = 1 : 8
    for j = 1 : length(UUU_transT{1,1})
        for k = 1 : length(UUU_TRANST{1,5}{1,1})


            if  TRADED_TIME{1,i}{1,j}{k,1} >= UPDATED_TIME{1,i}{1,j}{k,1}

                TRADED_TIME{1,i}{1,j}{k,1} = UPDATED_TIME{1,i}{1,j}{k,1};
            end

            if TRADED_TIME{1,i}{1,j}{k,1} >= UPDATED_TIME{1,i}{1,j}{k,1}...
                    && TRADED_TIME{1,i}{1,j}{k,2} >= UPDATED_TIME{1,i}{1,j}{k,2}


                TRADED_TIME{1,i}{1,j}{k,1} = UPDATED_TIME{1,i}{1,j}{k,1};
                TRADED_TIME{1,i}{1,j}{k,2} = UPDATED_TIME{1,i}{1,j}{k,2};
            end



            if TRADED_TIME{1,i}{1,j}{k,1} >= UPDATED_TIME{1,i}{1,j}{k,1}...
                    && TRADED_TIME{1,i}{1,j}{k,2} >= UPDATED_TIME{1,i}{1,j}{k,2}...
                    && TRADED_TIME{1,i}{1,j}{k,3} >= UPDATED_TIME{1,i}{1,j}{k,3}


                TRADED_TIME{1,i}{1,j}{k,1} = UPDATED_TIME{1,i}{1,j}{k,1};
                TRADED_TIME{1,i}{1,j}{k,2} = UPDATED_TIME{1,i}{1,j}{k,2};
                TRADED_TIME{1,i}{1,j}{k,3} = UPDATED_TIME{1,i}{1,j}{k,3};
            end


            if TRADED_TIME{1,i}{1,j}{k,1} >= UPDATED_TIME{1,i}{1,j}{k,1}...
                    && TRADED_TIME{1,i}{1,j}{k,2} >= UPDATED_TIME{1,i}{1,j}{k,2}...
                    && TRADED_TIME{1,i}{1,j}{k,3} >= UPDATED_TIME{1,i}{1,j}{k,3}...
                    && TRADED_TIME{1,i}{1,j}{k,4} >= UPDATED_TIME{1,i}{1,j}{k,4}
```

```
                TRADED_TIME{1,i}{1,j}{k,1} = UPDATED_TIME{1,i}{1,j}{k,1};
                TRADED_TIME{1,i}{1,j}{k,2} = UPDATED_TIME{1,i}{1,j}{k,2};
                TRADED_TIME{1,i}{1,j}{k,3} = UPDATED_TIME{1,i}{1,j}{k,3};
                TRADED_TIME{1,i}{1,j}{k,4} = UPDATED_TIME{1,i}{1,j}{k,4};

            end
        end
    end

end

%% The traded time table
% Fill the updated time
for i = 1 : 8

   TABLE_TRADED_TIME{1,i} = vertcat(TRADED_TIME{1,i}{1,1},...
       TRADED_TIME{1,i}{1,2}, TRADED_TIME{1,i}{1,3},...
       TRADED_TIME{1,i}{1,4}, TRADED_TIME{1,i}{1,5},...
       TRADED_TIME{1,i}{1,6}, TRADED_TIME{1,i}{1,7},...
       TRADED_TIME{1,i}{1,8}, TRADED_TIME{1,i}{1,9},...
       TRADED_TIME{1,i}{1,10}, TRADED_TIME{1,i}{1,11},...
       TRADED_TIME{1,i}{1,12});

end

% The final concatenation
FINAL_TABLE_TRADED_TIME = vertcat(TABLE_TRADED_TIME{1,1},...
    TABLE_TRADED_TIME{1,2},TABLE_TRADED_TIME{1,3},...
    TABLE_TRADED_TIME{1,4},TABLE_TRADED_TIME{1,5},...
    TABLE_TRADED_TIME{1,6},TABLE_TRADED_TIME{1,7},...
    TABLE_TRADED_TIME{1,8});


%% The updated time table
% Fill the updated time
for i = 1 : 8

   TABLE_UPDATED_TIME{1,i} = vertcat(UPDATED_TIME{1,i}{1,1},...
       UPDATED_TIME{1,i}{1,2}, UPDATED_TIME{1,i}{1,3},...
       UPDATED_TIME{1,i}{1,4}, UPDATED_TIME{1,i}{1,5},...
       UPDATED_TIME{1,i}{1,6}, UPDATED_TIME{1,i}{1,7},...
       UPDATED_TIME{1,i}{1,8}, UPDATED_TIME{1,i}{1,9},...
       UPDATED_TIME{1,i}{1,10}, UPDATED_TIME{1,i}{1,11},...
       UPDATED_TIME{1,i}{1,12});
```

```
end

% The final concatenation
FINAL_TABLE_UPDATED_TIME = vertcat(TABLE_UPDATED_TIME{1,1},...
    TABLE_UPDATED_TIME{1,2},TABLE_UPDATED_TIME{1,3},...
    TABLE_UPDATED_TIME{1,4},TABLE_UPDATED_TIME{1,5},...
    TABLE_UPDATED_TIME{1,6},TABLE_UPDATED_TIME{1,7},...
    TABLE_UPDATED_TIME{1,8});

% Find the unique traded times, Sort the traded times and assign
% unique trade number to each in ascending order
UNIQ = sortrows(unique(cell2mat(FINAL_TABLE_TRADED_TIME),'rows'),[1 2 3 4]);
UNIQO = sortrows(unique(cell2mat(FINAL_TABLE_TRADED_TIME),'rows'),[1 2 3 4]);

% generate a random number
raNDgen1 = (324434 : 26835144)';
raNDgen2 = rand(length(raNDgen1),1);

% merge the two vectors
raNDgen = [raNDgen1, raNDgen2];
% sort according to the second column
Sort_raNDgen = sortrows(raNDgen,2);

% Cut at 2976 and sort according to the first column
Sort_raNDgen1 = Sort_raNDgen(1: length(FINAL_TABLE_TRADED_TIME), :);
Sort_raNDgen2 = sortrows(Sort_raNDgen1,1);

% assign the computed trade numbers to the corresponding trade times
UNIQO(:,5) = Sort_raNDgen2(:,1);
% size of UNIQO
SASS = size(UNIQO);
% finding the position of the sorted traded times in the original times
for i = 1 : length(FINAL_TABLE_TRADED_TIME)
POS{i,1} = num2cell(find(ismember(cell2mat(FINAL_TABLE_TRADED_TIME(:,1:end)),UNIQO(i,1:4
end


%% THE_FINAL_TRADED_TIME
THE_FINAL_TRADED_TIME = zeros(length(FINAL_TABLE_TRADED_TIME), SASS(2));

for i = 1 : length(FINAL_TABLE_TRADED_TIME)

THE_FINAL_TRADED_TIME(cell2mat(POS{i,1}),:) = UNIQO(i,:);

end
```

```
 Headers = OPriskDataSetexposure(1,:);

MATRIX = zeros(length(FINAL_TABLE_TRADED_TIME),length(Headers));

%% The traded time

% converting time into usal time formats
% there are 24 hours in the a day , to fins the hour
rt = 24.*THE_FINAL_TRADED_TIME(:,end-1);
hh = round(rt);

% the minutes
rr = 60.*abs(rt - hh);

mm = round(rr);

% the seconds
rg = 60.*abs(rr - mm);

ss = round(rg);

% Updated time as a vectors
Vec_tedTime = [THE_FINAL_TRADED_TIME(:,1:end-2), hh, mm, ss];

% converting the date back to string
formatOut = 'yyyy-mm-dd HH:MM:SS PM';
Vec_tradedTimeSTRING = datestr(Vec_tedTime(:, 1:end),formatOut);

%% The updated time
% converting time into usal time formats
% there are 24 hours in the a day , to fins the hour
rt = 24.*cell2mat(FINAL_TABLE_UPDATED_TIME(:,end));
hh = round(rt);

% the minutes
rr = 60.*abs(rt - hh);

mm = round(rr);

% the seconds
rg = 60.*abs(rr - mm);

ss = round(rg);

% Updated time as a vectors
Vec_updatedTime = [cell2mat(FINAL_TABLE_UPDATED_TIME(:,1:end-1)), hh, mm, ss];
```

```
% converting the date back to string
formatOut = 'yyyy-mm-dd HH:MM:SS PM';
Vec_updatedTimeSTRING = datestr(Vec_updatedTime(:, 1:end),formatOut);

%% generate the compatible columns
% capturedBy
UNI_STRINGS = unique(OPriskDataSetexposure(2:end,9));
% TraderID
UNI_STRINGS1 = unique(OPriskDataSetexposure(2:end,11));

for j = 1 : length(UNI_STRINGS)

    CapturedBy{j} = OPriskDataSetexposure(strcmp(OPriskDataSetexposure(:,9),...
        UNI_STRINGS(j))==1,9);
    % percentage proportion
    LEngC(j) = length(CapturedBy{j})./length(OPriskDataSetexposure);
    format long
   N_STR(j) = ceil(LEngC(j).* length(THE_FINAL_TRADED_TIME));

   N_STRRR{j} = num2cell(zeros(N_STR(j),1));

end


for j = 1 : length(UNI_STRINGS)
   N_STRRR{j}(:,1) = (UNI_STRINGS(j,1));
end
%
CAPTUREDBY_TOTAL = vertcat(N_STRRR{1,1},N_STRRR{1,2},...
    N_STRRR{1,3},N_STRRR{1,4},N_STRRR{1,5});

CAPTUREDBY_TOTAL = CAPTUREDBY_TOTAL(1:length(THE_FINAL_TRADED_TIME));
CAPTUREDBY_TOTAL = [CAPTUREDBY_TOTAL, num2cell(rand(length(CAPTUREDBY_TOTAL),1))];
CAPTUREDBY_TOTAL = sortrows(CAPTUREDBY_TOTAL,2);
%%


%% generate the compatible columns
% TraderID
Tra_UNI_STRINGS = unique(OPriskDataSetexposure(2:end,11));
% TraderID
Tra_UNI_STRINGS1 = unique(OPriskDataSetexposure(2:end,11));

for j = 1 : length(Tra_UNI_STRINGS)

    TraderID{j} = OPriskDataSetexposure(strcmp(OPriskDataSetexposure(:,11),...
        Tra_UNI_STRINGS(j))==1,11);
```

```
    % percentage proportion
    LEngC(j) = length(TraderID{j})./length(OPriskDataSetexposure);
    format long
   TRAN_STR(j) = ceil(LEngC(j).* length(THE_FINAL_TRADED_TIME));

   TRAN_STRRR{j} = num2cell(zeros(TRAN_STR(j),1));

end


for j = 1 : length(Tra_UNI_STRINGS)
   TRAN_STRRR{j}(:,1) = (Tra_UNI_STRINGS(j,1));
end

TRADERID_TOTAL = vertcat(TRAN_STRRR{1,1},TRAN_STRRR{1,2},...
    TRAN_STRRR{1,3},TRAN_STRRR{1,4},TRAN_STRRR{1,5},...
    TRAN_STRRR{1,6},TRAN_STRRR{1,7});

 TRADERID_TOTAL = TRADERID_TOTAL(1:length(THE_FINAL_TRADED_TIME));
TRADERID_TOTAL = [TRADERID_TOTAL, num2cell(rand(length(TRADERID_TOTAL),1))];
TRADERID_TOTAL = sortrows(TRADERID_TOTAL,2);
%% Business lines

BL1 = [cellstr('BL1') cellstr('BL1') ;...
    cellstr('Credit Derivatives') cellstr('Investment Banking')]';

BL2 = [cellstr('BL2') cellstr('BL2') cellstr('BL2') cellstr('BL2')...
    cellstr('BL2') cellstr('BL2') cellstr('BL2') cellstr('BL2')...
    cellstr('BL2') cellstr('BL2') cellstr('BL2') cellstr('BL2')...
    cellstr('BL2');...
    cellstr('Rates') cellstr('MM') cellstr('Equity')...
    cellstr('Commodities') cellstr('Africa')...
    cellstr('Options') cellstr('Bonds/Repos')...
    cellstr('Forex') cellstr('Prime Services')...
    cellstr('Credit Derivatives') cellstr('Management')...
    cellstr('Group Treasury') cellstr('SND')]';

BL3 = [cellstr('BL3') cellstr('BL3') cellstr('BL3') ;...
    cellstr('Africa') cellstr('MM') cellstr('SND')]';

BL4 = [cellstr('BL4') cellstr('BL4') cellstr('BL4')...
     cellstr('BL4') cellstr('BL4') cellstr('BL4');...
    cellstr('ACBB') cellstr('Credit Derivatives') cellstr('Funding')...
     cellstr('MM') cellstr('Portfolio Management') cellstr('SND')]';

 BL5 = [cellstr('BL5') cellstr('BL5') ;...
    cellstr('Credit Derivatives') cellstr('MM')]';
```

```
BL6 = [cellstr('BL6') cellstr('BL6') ;...
    cellstr('Management') cellstr('Prime Services')]';

BL7 = [cellstr('BL7') cellstr('BL7') ;...
    cellstr('Portfolio Management') cellstr('SND')]';

BL9 = [cellstr('BL9') cellstr('Portfolio Management')];

%% generate the compatible columns
% Business line
BUB_UNI_STRINGS = unique(OPriskDataSetexposure(2:end,22));
%
for j = 1 : length(BUB_UNI_STRINGS)

    Bus{j} = OPriskDataSetexposure(strcmp(OPriskDataSetexposure(:,22),...
        BUB_UNI_STRINGS(j))==1,22);
    % percentage proportion
    LEngB(j) = length(Bus{j})./length(OPriskDataSetexposure);
    format long
    Bu_STR(j) = ceil(LEngB(j).* length(THE_FINAL_TRADED_TIME));

    BUs_STRRR{j} = num2cell(zeros(Bu_STR(j),1));

end


for j = 1 : length(BUB_UNI_STRINGS)
    BUs_STRRR{j}(:,1) = (BUB_UNI_STRINGS(j,1));
end
%
BUS_TOTAL = vertcat(BUs_STRRR{1,1},BUs_STRRR{1,2},...
    BUs_STRRR{1,3},BUs_STRRR{1,4},BUs_STRRR{1,5},...
    BUs_STRRR{1,6}, BUs_STRRR{1,7}, BUs_STRRR{1,8});

BUS_TOTAL = BUS_TOTAL(1:length(THE_FINAL_TRADED_TIME));
BUS_TOTAL = [BUS_TOTAL, num2cell(rand(length(BUS_TOTAL),1))];
BUS_TOTAL = sortrows(BUS_TOTAL,2);

%% BUSINESS LINES

BUSINESS_LINESL = [BL1;BL2;BL3;BL4;BL5;BL6;BL7;BL9];

for j = 1 : length(THE_FINAL_TRADED_TIME)

    BUSINESS_LINES{j} = num2cell((j.^0).*zeros(length(BUSINESS_LINESL),3));
    BUSINESS_LINES{j}(:,3) = num2cell((j.^0).*rand(length(BUSINESS_LINESL),1));
```

```
    BUSINESS_LINES{j}(:,1:2) = BUSINESS_LINESL(:,1:2);

    POSITION{j} = find(strcmp(BUSINESS_LINES{j}(:,1),...
        BUS_TOTAL(j,1))==1, 1, 'last' );
    % the desk
    DESK(j,1) = BUSINESS_LINESL(POSITION{j},2);
end
%%
% fill in the matrix
MATRIX(:,1) = (THE_FINAL_TRADED_TIME(:,end));
MATRIX(:,7) = (THE_FINAL_TRADED_TIME(:,end-1));
MATRIX(:,6) = (THE_FINAL_TRADED_TIME(:,end-2));
MATRIX(:,4) = cell2mat(FINAL_TABLE_UPDATED_TIME(:,end));
MATRIX(:,3) = cell2mat(FINAL_TABLE_UPDATED_TIME(:,end-1));


MATRIX = num2cell(MATRIX);

MATRIX(:,8) = DESK(:,1);
MATRIX(:,22) = BUS_TOTAL(:,1);
MATRIX(:,9) = CAPTUREDBY_TOTAL(:,1);
MATRIX(:,11) = TRADERID_TOTAL(:,1);
% fill in the updated time and the traded time
MATRIX(:,2) = cellstr(Vec_updatedTimeSTRING);
MATRIX(:,5) = cellstr(Vec_tradedTimeSTRING);


% % Exporting the results to Excel
% filename = 'Hoohlo.xlsx';
% writetable(cell2table(MATRIX ,...
%     'VariableNames',Headers),...
%     filename,'Sheet',1,'Range','A1')
```

Deploying the R Model.

Import extrapolated data (1 year data), use the estimated model `Amodel` to predict forecasted estimates

```
 newfname <- "file:///C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub
/OpRisk_PHD_Thesis/Data/Extrap_Data_Model.csv"

 crs$newdataset <- read.csv(newfname,
                sep=",",
                dec=".",
                na.strings=c(".", "NA", "", "?"),
                strip.white=TRUE, encoding="UTF-8",header=T)
```

```
head(crs$newdataset)

Forecast <- predict(Amodel, crs$newdataset, type = "link")
Forecast
```

Appendix C: R Code for GAMLSS

Required: R Packages from CRAN (in addition to packages already found in Chapter 3)

```
if (!require(gamlss)){
  install.packages("gamlss")
  library(gamlss)
}
```

Data exploration of OpRisk loss severity dataset in preparation for GAMLSS machine learning treatment. The raw data and the pre-processed datasets are initiated and analysed.

Plots exploring loss severity characteristics, see chapter 4 section 4.10 on page 100

```
options(scipen = 999)
file_loc <- "C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub/
OpRisk_PHD_Thesis/Data"
setwd(file_loc)
list.files(file_loc)

frequency <- openxlsx::read.xlsx("Raw_Formatted_Data.xlsx",
                                  check.names = TRUE, sheet = "Frequency")
severity <- openxlsx::read.xlsx("Raw_Formatted_Data.xlsx",
                                 check.names = TRUE, sheet = "Severity")
projdata <- openxlsx::read.xlsx("OPriskDataSet_GAMLSS.xlsx",
                                 check.names = TRUE, sheet = "CleanedData")

names(projdata) <- sub("\\.", "", names(projdata))
dput(names(projdata))

par(mar=c(1,1,1,1))
PPP <- par(mfrow=c(2,2))
plot(Loss ~ UpdateTime, data = projdata, col=gray(0.7), pch=15, cex=0.5)
plot(Loss ~ UpdatedDay, data = projdata, col=gray(0.7), pch=15, cex=0.5)
par(PPP)
```

Data partitioning of the pre-processed OpRisk dataset into Training/Validation/Testing proportions, in preparation for machine learning model building treatments. The original dataset is partitioned into three random subsets initiated by a random number sequence with a randomly selected seed.

```
# Load packages
```

```
library(rattle, quietly = TRUE)
library(magrittr, quietly = TRUE) # Utilize the %>% and %>% pipeline operators
library(Hmisc, quietly = TRUE)
library(chron, quietly = TRUE)
library(dplyr, quietly = TRUE)
library(ggplot2)
library(caTools)
library(caret)
library(gamlss)

building <- TRUE
scoring <- ! building

# A predefined value is used to reset the random seed so that results are repeatable

crv$seed <- 42 # set random seed to make your partition reproducible
# Load the dataset OPriskDataSet_exposure
#==============================================================================
fname <- "file:///C:/Users/Mphekeleli/Documents/R PROJECT/OpRiskPHDGitHub/
OpRisk_PHD_Thesis/Data/OPriskDataSet_exposure_severity.csv"
crs$dataset <- read.csv(fname,
                        sep=",",
                        dec=".",
                        na.strings=c(".", "NA", "", "?"),
                        strip.white=TRUE, encoding="UTF-8")

exposure <- crs$dataset[,ncol(crs$dataset)]
crs$dataset <- as.data.frame(crs$dataset)

# The following varaible selections have been noted
crs$input <- crs$dataset %>%
  group_by(UpdatedDay,
           UpdatedTime,
           TradedDay,
           TradedTime,
           Desk,
           CapturedBy,
           TradeStatus,
           TraderId,
           Instrument,
           Reason,
           EventTypeCategoryLevel1,
           BusinessLineLevel1) %>%
  transmute(LossesIndicator = LossIndicator,
            Losses = Loss,
            Exposure = exposure)
```

```
# Create function "getmode" which finds the modal class in the categorical variables
getmode <- function(x){
  u <- unique(x)
  as.integer(u[which.max(tabulate(match(x,u)))])
}
# Reorder the categorical variables so that the modal class
# is specified as the reference level
for (i in 5:(ncol(crs$input) - 3)){
  crs$input[[i]] <- relevel(crs$input[[i]], getmode(crs$input[[i]]))
}

# Build the training/validation/testing datasets
# nobs=2331 training=1632 validation=350 testing=349

set.seed(crv$seed)

crs$nobs <- nrow(crs$input)

crs$train <- sample(crs$nobs, 0.7*crs$nobs)

crs$nobs %>%
  seq_len() %>%
  setdiff(crs$train) %>%
  sample(0.15*crs$nobs) ->
  crs$validate

crs$nobs %>%
  seq_len() %>%
  setdiff(crs$train) %>%
  setdiff(crs$validate) ->
  crs$test


crs$training <- as.data.frame(crs$input[crs$train,])
crs$validation <- as.data.frame(crs$input[crs$validate,])
crs$testing <- as.data.frame(crs$input[crs$test,])
```

Selection of the distribution.

Begin to model the response Losses (y) using the three parameter Zero adjusted gamma (ZAGA) distribution, followed by the Zero adjusted inverse gamma (ZAIG) distribution, and lastly using the four parameter Generalized beta type 2 (GB2) distribution. Start by fitting the full linear model μ including all explanatory variables.

```
mod1 <- gamlss(Losses ~ UpdatedDay + Desk + CapturedBy + TradeStatus + TraderId
```

```
     + Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1 + Exposure,
     mu.start = NULL,  sigma.start = NULL, nu.start = NULL, tau.start = NULL,
     sigma.fo = ~1, nu.fo = ~1, data=crs$training,  family = ZAGA, n.cyc=80)
mod1

mod2 <- gamlss(Losses ~ UpdatedDay + Desk + CapturedBy + TradeStatus + TraderId
     + Instrument + Reason + EventTypeCategoryLevel1+ BusinessLineLevel1 + Exposure,
     mu.start = NULL,  sigma.start = NULL, nu.start = NULL, tau.start = NULL,
     sigma.fo = ~1, nu.fo = ~1, data=crs$training,  family = ZAIG, n.cyc=80)
mod2

mod3 <- gamlss(Losses ~ UpdatedDay + Desk + CapturedBy + TradeStatus + TraderId
     + Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1 + Exposure,
     mu.start = NULL,  sigma.start = NULL, nu.start = NULL, tau.start = NULL,
     sigma.fo = ~1, nu.fo = ~1, tau.fo = ~1, data=crs$training,  family = GB2, n.cyc=170
mod3

GAIC(mod1, mod2, mod3)
```

Selection of terms.

Now we use ***drop1()*** to check whether any linear terms can be dropped and then using ***add1()***, we consider adding a two-way interaction term into the linear model mod1

```
drop1(mod3)
add1(mod3, scope=~(UpdatedDay + Desk + CapturedBy + TradeStatus + TraderId +
Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1 + Exposure)^2)
```

We use ***FORM*** as an upper bound for ***scope***, starting from all explanatory terms sos that all interactions are considered

```
FORM <- as.formula("~(UpdatedDay + Desk + CapturedBy + TradeStatus + TraderId
+ Instrument + Reason + EventTypeCategoryLevel1 + BusinessLineLevel1 + Exposure)^2
+pb(UpdatedDay) + pb(Desk) + pb(CapturedBy) + pb(TradeStatus)+ pb(TradeStatus)
+ pb(TraderId) + pb(Instrument) + pb(Reason)+ pb(EventTypeCategoryLevel1)
+ pb(BusinessLineLevel1) + pb(Exposure)")
```

The estimation of some GAMLSS for OpRisk loss severity distribution: To build the model we pass on to the model building function ***gamlss*** *i.e., the formula that describes the model to build.*

```
mod14 <- stepGAICAll.A(mod1, scope=list(lower=~1, upper=FORM), k=log(371))

GAIC(mod14,mod24,mod34)
mod14
```

```
plot(mod14)
mod14$anova
```

(a)

(b)

Figure 11.11: (a)Summary statistics of quantile residuals from models GB2, ZAIG & ZAGA (b)Displays (normalized quantile) residuals from model GB2(μ, σ, ν, τ).

(a)

(b)

Figure 11.12: (a) Display of (normalized quantile) residuals from model ZAIG(μ, σ, ν) (b) As for (a) but on the model ZAGA(μ, σ, ν)