Calculation of Risk Weighted Assets (RWA) via Machine Learning Technique

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Abstract

RWAs have limited literature and confidence in reported RWAs is ebbing. Market participants question the reliability and comparability of capital ratios, and contend that banks may not be as strong as they are portrayed by risk-based capital ratios. With this paper, an altogether new idea was proposed to calculate RWA across banking industries. Machine learning approach will strengthen its calculation engine and make it more robust over time. It will predict the required RWAs on the basis of historical data and expectation feeds. As we know, machine learning is the vital concept of 21st century and can be harnessed in finance domain for evaluation of various risk attributes dynamically and can be tested in normal as well as stressed conditions.

Keywords: A-IRB, Deep Learning, F-IRB (IRB – Internal Rating Based methodology), ML (Machine Learning), Risk Weighted Assets (RWA)

I. INTRODUCTION

CREDIT Risk Charge (CRC) is calculated as the sum of individual credit charges. It gets its value from a fraction of total RWAs. For instance, CRC = 8% of RWA. The methodologies of RWA calculation as Foundation IRB (F-IRB) and Advanced IRB (A-IRB) are extended forms of quite basic methodology called standardized method and they refer to a set of credit risk measurement techniques proposed under Basel II and Basel III capital adequacy rules for banking institutions. Under these rules, banks can use foundation IRB and advanced IRB approach only subject to approval from their local regulators and subject to their banking valuation and nature.

Under artificial intelligence chapter, it is illustrated that machine learning algorithms can be used to train deep learning networks as per standardized approach of calculation of RWA. It is also confirmed that RWA results calculated on F-IRB or A-IRB formula for any sector by keeping one or the other factors variable, Machine Learning (Deep Learning of Artificial Neural Network) can compete with the result and can fit the formula based curve. The Proof of Concept (POC) using A-IRB was more than enough to suggest that standardized method is the best predictor of RWAs. It is calculated by machine learning algorithms like deep learning networks.

II. COMPARISON AND BENEFITS OF ML APPROACHES ON RWA CALCULATION

Data set for financial instruments (thousands of records for a financial institutions) can be prepared for the training of regression algorithm which would be equivalent to Standardized Method. Risk weights can be calculated for different types of exposures and thereby RWAs can be derived. Deep learning via Artificial Neural Network (ANN) architecture can be accomplished which in turn would be regression function for smooth RWA calculation. ANN and deep learning are some of the most eminent suggestions for Machine Learning based framework for RWA calculation

A. Background on formula for A-IRB Methodology

Advanced IRB (A-IRB) formula is designed to evaluate RWA requirements of the following:

1. Corporate Exposure
2. Residential Mortgage Exposure
3. Revolving Retail Exposure (Credit Card)

In this study, I compared Revolving Retail Exposure (Credit Card produIct) with ML techniques.The comparison is given in Table I.

Following notions are used in the formula used in this paper:

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TABLE I.
ML APPROACH TO CONCERNS

1. Reliability of Capital Ratio	
Key Concerns on RWA calculation	**ML Approach to these concerns**
Inaccurate measurement of financial risk, both on and off-balance sheet	Optimized measurement of risk every time as it can be a combination of historical simulation as well as parametric definition on various limits.
Understatement of financial risk	Parametric definitions can help us overcome understatement of risk.
Tail risk not captured properly, thus low probability/high impact events mispriced	Prolonged training with sufficient data set would make sure that tail risks are captured properly
2. Pro-cyclicality	
Key Concerns on RWA calculation	**ML Approach to these concerns**
RWAs which rely on ratings and are mostly based on historical parameters, may be too low in good times and rise too late in bad times.	We can have an estimate for parameters based on stressed financial condition and different geographic location. RWA can be predicted more accurately with robust system and sufficient training.
Probability of default: "point in time" versus "through the cycle" affects cyclicality of capital.	Probably, derivation of probability of default will remain unchanged and elasticity in the estimate of risk parameters will take care of cyclicality of capital.
3. Bank's Concern	
Key Concerns on RWA calculation	**ML Approach to these concerns**
Uneven regulations and supervision of banks' RWA practices across jurisdictions.	Uneven regulations and supervision of banks' RWA practices across jurisdictions can be minimized by using same factor for same region in various ML based calculations.
Model approvals are neither uniformly robust nor uniformly reviewed.	We can have just one model at macroscopic level and deep learning neural network can prove to be the most efficient learning program.
4. Complexity of Internal Models	
Key Concerns on RWA calculation	**ML Approach to these concerns**
The formula for calculating RWAs is very complex in itself and leaves large potential for different interpretations.	The formula for calculating RWAs is very complex in itself and we can demonstrate the curve fitting for AIRB formula by equivalent neural network learning
Use of some static factors in evaluation of RWAs like correlation factors for different type of exposure.	Use of some static factors in evaluation of RWAs like correlation factors can be determined on the spot from exposure data for efficient calculation of RWAs or it can be taken as input also.

❖ N(x) denotes the normal cumulative distribution function
❖ G(z) denotes the inverse cumulative distribution function
❖ PD is the probability of default
❖ LGD is the loss given default
❖ EAD is the exposure at default
❖ M is the effective maturity (not required for Credit Card exposure)

Correlation

$$R = 0.04$$

Capital Requirement

$$K = LGD * \left[N\left(\sqrt{\frac{1}{1-R}} * G(PD) + \sqrt{\frac{R}{1-R}} * G(0.999) \right) - PD \right]$$

Risk Weighted Assets

$$RWA = K * 12.5 * EAD$$

B. Machine learning approach for retail exposure (Credit card products)

Data set for Financial Instruments (thousands of records for a financial institution) can be prepared for the training of regression algorithm which would be equivalent to Standardized Method.

The sample that we can use in training and testing set is displayed in Fig. 1.

In the diagram above following measures can be observed in Fig. 2:

❖ Financial instruments data needs to be pre-processed and split before it can be used to train model. We can split the data in 6:4, where 60% is for training and remaining is for testing the model.
❖ We need to have a layered Neutral Network Regression model in parallel with our data sets. This will require a lot more investigation and research.
❖ Once the training is complete, we save the weights for

Fig. 1. Sample Training Data Set For Retail Exposure or Credit Card Exposure

CPTY	BEG	CLT	PD	LGD	MATURITY (yrs)	CORRELATION	GROSS EXP	NET EXP	Risk Weights		Formula used to calculate Expected	
Training Set										Expected RWA		
ABC123	234	120	0.15	0.1	0.1	0.04	90000	70000	1	125000		
PQR123	434	220	0.1	0.1	0.1	0.04	120000	50000	1	145000		
XYZ123	634	120	0.12	0.1	0.1	0.04	120000	100000	1	170000		
ABC456	239	120	0.25	0.1	0.1	0.04	200000	160000	1	280000		
ABC789	284	325	0.05	0.1	0.1	0.04	80000	70000	1	115000		
ABC123	634	120	0.11	0.1	0.1	0.04	70000	50000	1	95000		
Testing Set										ML Prediction of RWA	Expected RWA	Error (Optimisati
XYZ123	224	120	0.25	0.1	0.1	0.04	200000	170000	1	190000	185000	-5000
ABC123	554	120	0.12	0.1	0.1	0.04	80000	70000	1	90000	75000	-15000
PQR123	134	220	0.05	0.1	0.1	0.04	120000	110000	1	100000	115000	15000
ABC123	934	120	0.1	0.1	0.1	0.04	100000	100000	1	90000	100000	10000

Correlation

$R = 0.04$

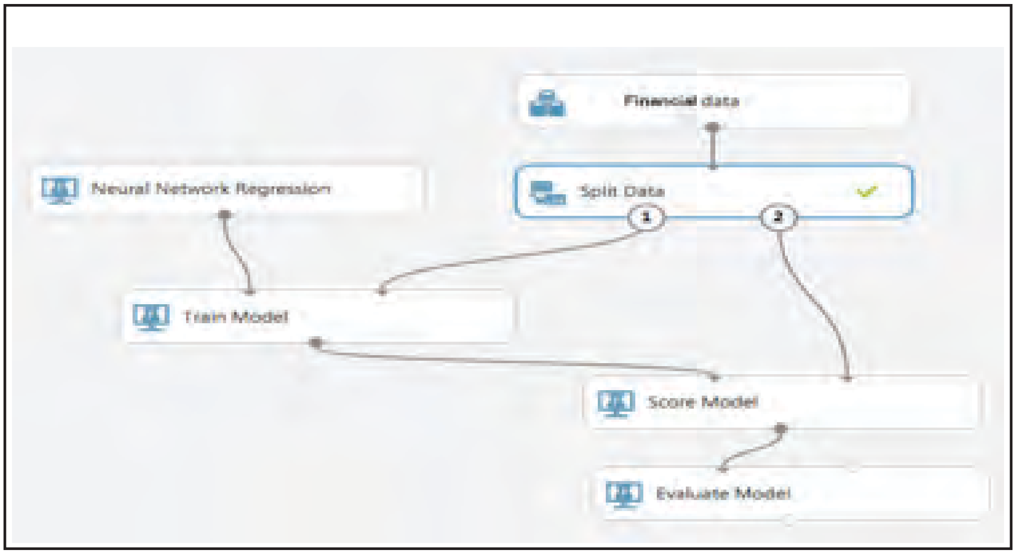
Capital Requirement

$K = LGD * \left[N\left(\sqrt{\frac{1}{1-R}} * G(PD) + \sqrt{\frac{R}{1-R}} * G(0.999)\right)\right.$

Risk-weighted assets

$RWA = K * 12.5 * EAD$

Fig. 2. Artificial Neural Network based predictor map



our predictor. We can load the weights on various neurons and test the data set for the remaining 40% cases.

❖ We keep evaluating our model until we get minimum errors in prediction and we can continue to upgrade and use the same model indefinitely.

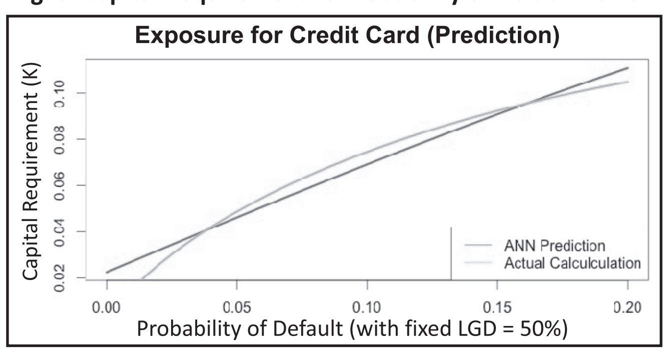
❖ As we see in above chart, we are predicting risk weights corresponding to BA level transaction, we can equate this model to standardized methods.

C. Training and results on A-IRB

R Program: Tracing curve for the AIRB formula and the trained Artificial Neural Network

Here, I am proposing deep learning methods to calculate RWA based on existing standardized methods as illustrated in fig. 2. However, POC was derived from the A-IRB methodology which is an internal method, quite advanced, and mathematically quite compact. A deep learning network will eventually fit the A-IRB formula in the set of weights of its network after sufficient training. A back propagation and gradient descent training will minimize the errors and stabilize weights. Deep learning will be required if set of data is too large and calculation of RWA for individual row of data and their further aggregation will require set of calculations. The whole task can be completed only under highly advanced technology like Big Data frameworks, Cloud Computing, Learning Algorithms etc.

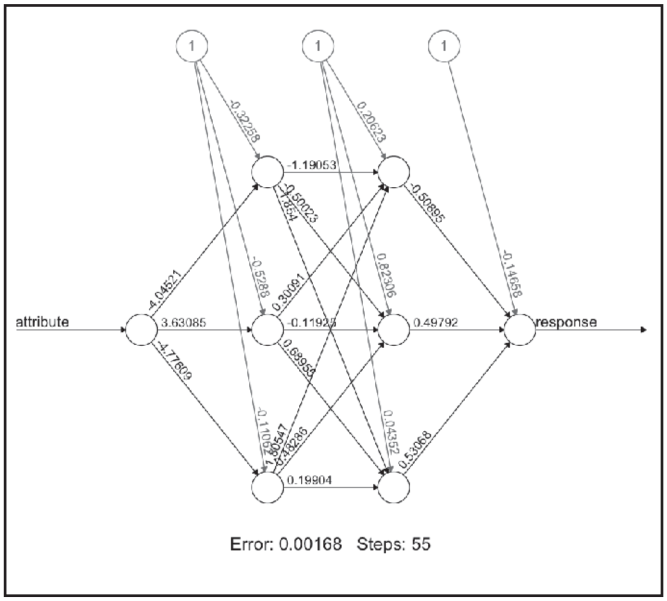
Fig. 3. Capital Requirement vs Probability of Default Vs LGD



As shown in fig. 3, Artificial Neural Network (or Deep Learning) curve fitting on A-IRB formula can be demonstrated in R/Python.

R Code used in the above implementation is also

Fig. 4. Weights updated on Artificial Neural Network after model is trained



illustrated in the Appendix.

III. CONCLUSION

This paper suggests that a superior technique of artificial intelligence (machine learning) can replace all existing methodology over next 10 years as far as RWA calculation is concerned. There is a lot to differentiate between this ML based approach and the existing rule based approach and this paper is just a guide to outline benefits and feasibility of AI/ML techniques to measure RWA and gradually get out of existing rule based methodologies like Standardized Method, Foundation IRB or Advanced IRB.

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Appendix

R Code to illustrate curve fitting of A-IRB over Artificial Neural Network Architecture

Training Data from rule based methodology

```
Library("neuralnet")
set.seed(10000)

EAD = 200000
LGD = 0.5
R = 0.04

#i = 0:100
#PD = 0.000 to 0.200

M = 2

eq0 <- function(x) {x/500}
eq3 <- function(PD) {(LGD*pnorm(((1/(1-R))^0.5)*qnorm(PD)+((R/(1-R))^0.5)*qnorm(0.999))-LGD*PD)}
eq4 <- function(K) {K*12.5*EAD}

response = matrix(data=NA, nrow=100,ncol=1)
attribute <- as.data.frame(seq(0,0.2,length=100),ncol=1)
for (i in 1:100){response[i,1] = eq3(attribute[i,1])
#RWA[i] = eq4(K[i])}

data <- cbind(attribute, response)
fit<-neuralnet(response~attribute,
data = data,
hidden = c(3,3),
threshold = 0.01)
```

Predicting RWA via trained model

```
resp = matrix(data=NA, nrow=40,ncol=1)
testdata <- as.matrix(seq(0.000,0.200,length=40),ncol=1)
for (i in 1:40){
resp[i,1] = eq3(testdata[i,1])
#RWA[i] = eq4(K[i])}
pred <- compute(fit,testdata)
result <- cbind(testdata,pred$net.result,resp)
colnames(result) <- c("Attribute", "Predicted_K", "Actual_K")
round(result,4)
```

Plotting Graph for visualization

```
plot(testdata,pred$net.result, type="l", col="red", main="Exposure for Credit Card
(Prediction)", cex.main = 2.0, cex.lab = 1.5, cex = 1.5, lwd = 3,
xlab = "Probability of Default (with fixed LGD = 50%)", ylab = "Capital Requirement (K)")
lines(testdata,resp, type="l", col="green", main="Exposure for Credit Card (Actual)",
cex.main = 2.0, cex.lab = 1.5, cex = 1.5, lwd = 3,
xlab = "Probability of Default (with fixed LGD = 50%)", ylab = "Capital Requirement (K)")
legend('bottomright', c("ANN Prediction","Actual Calculculation"), lty=c(1,1), lwd=c(1,1),col=c("red","green"))
```

About the Author

Prabhat Kumar is Senior Business Analyst with Risk and Compliance Department of Foray Software Private Limited. He was Assistant Consultant at Tata Consultancy Services from September 2016 to August 2017 and worked with its Risk and Compliance practice. Prior to this, he worked for Wipro Technologies in the same domain. He completed B. Tech (Bioinformatics) in 2007 and learnt the concept of machine learning algorithms including Hidden Morkov Model (HMM), Genetic Algorithm, Artificial Neural Network, and other clustering and classification algorithms in his engineering course. He has presented more than 10 papers in national level symposiums and has fetched several awards for the VIT University, Vellore.

After B.Tech, he completed CFA from ICFAI university and Executive Program in Applied Finance from IIM Calcutta and continued his profession as a Business Analyst in Risk practice. This is his first paper that focuses on the major problem of risk finance at an international level.