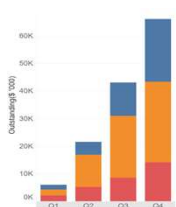


ABSTRACT

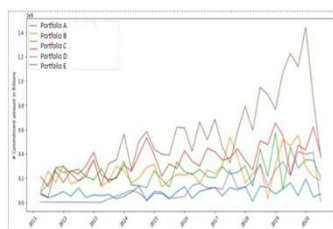
With the introduction of new regulations in banking, robust qualitative and quantitative risk models need to be deployed to make sound data driven decisions. This study enables the stakeholders to perform periodic model performance review by reporting automated regulatory reports, key model assumptions, estimating credit loss and portfolio impact under different scenarios.

INTRODUCTION

Interactive Dashboards in Risk Management enables risk managers to define certain scenarios and monitor impact on key performance indicators over time by the incorporation of business intelligence to present financial data. Various time series techniques used to calculate the Exposure At Default (EAD) for new commitments. The aim is to predict the given losses a Bank can incur by predicting one of the variables used in its calculation i.e. EAD. This will also enable the bank to comply with Current Expected Credit Loss (CECL) reporting.



Interactive dashboard covering criticized loans across certain entities



Historical performance of various portfolios

Our research questions include:

- How can we automate risk analytic dashboards that aid in internal decision making and for regulatory reporting?
- What key metrics should be considered to monitor credit risks in banks?

LITERATURE REVIEW

Our goal is to understand how multiple visualization tools can aid in creating risk analytic dashboards for better interpreting Bank's Portfolio. We also look into various models in Risk Analytics for forecasting the commitment default rate and how each model performs based on the features available in our clients data.

Study	Risk Modelling	Risk Visualization	PowerBI	Default Modelling	PCAOB Standard
Liermann, V. (2021)		✓			
Witzany (2011)	✓	✓	✓		
Eppler, M. J. (2009)				✓	
Wesley R. Bricker (2017)					✓

METHODOLOGY

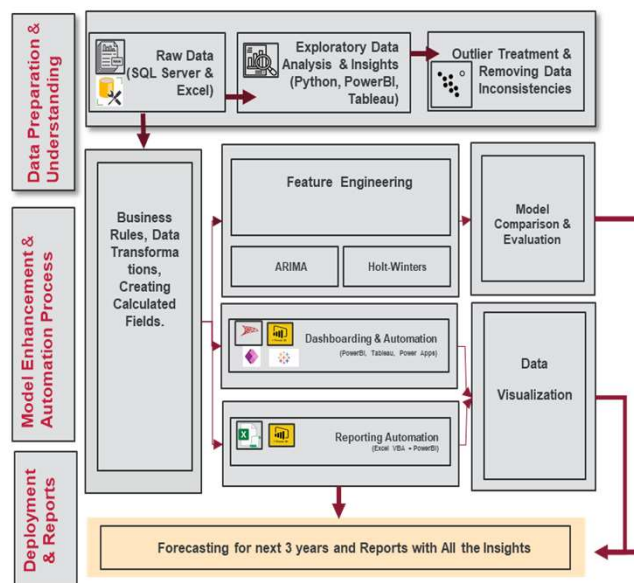
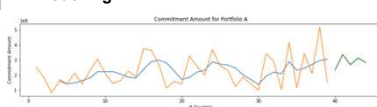


Fig 2. Study Design

RESULTS

Modelling:

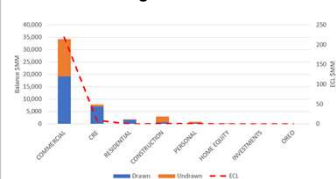


Used ARIMA Model to forecast the possible exposure for the next four quarters for given portfolios.



The ACF and PACF plots of the residuals indicate it's a random walk and hence the model is a good fit.

Dashboarding:

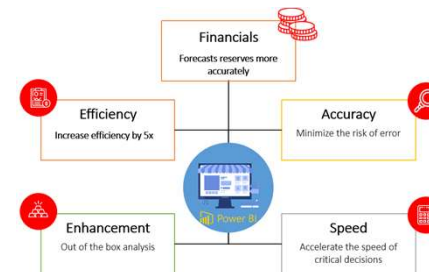


Risk Rating	Branch Account Groups	Number of Loans
Low	Commercial	10,000
Low	Residential	5,000
Low	Construction	2,000
Low	Personal	1,000
Low	Other	500
Medium	Commercial	15,000
Medium	Residential	8,000
Medium	Construction	3,000
Medium	Personal	1,500
Medium	Other	750
High	Commercial	20,000
High	Residential	12,000
High	Construction	5,000
High	Personal	2,500
High	Other	1,250

Distribution of Commitment Loans based on the Risk rating and Branch account groups. Blurred due to client confidentiality.

Expected Business Impact

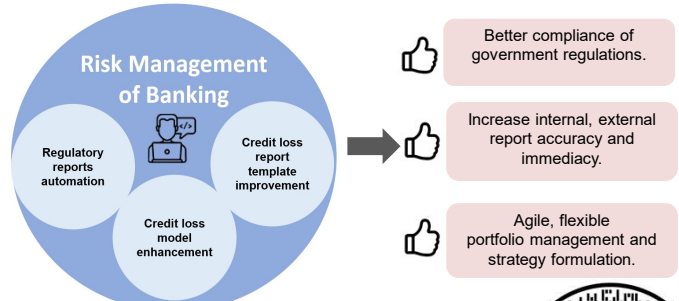
Credit Reporting Automation And New Exposure Volume Forecasting



Estimating expected losses for the bank's reporting periods using loss rates from the previous month. This helps in quick turnaround of the estimated losses, yet ensuring risk profiles of all portfolios are captured at very granular levels. All the expected losses are calculated in accordance with CECL standards and will be reported on the bank's financial statements. The project also entails creating a user-friendly template that will conduct all the calculations and summarize the results.

CONCLUSIONS

Our research mainly focuses on three applications of data analytics in the risks management of banks, and provides positive impacts on the industry through the data-driven reports and robust qualitative and quantitative analysis techniques.



ACKNOWLEDGEMENTS

We thank our industry partner for their trust, support and encouragement while we approached the business problem. We would also like to thank Professor Matthew Lanham for consistent guidance on the project.

