Credit Default Risk Management

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Abstract

Credit risk is most simply defined as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms. The goal of credit risk management is to maximise a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Integrating credit risk in an investment portfolio is a subject that many financial institutions have been working on.

1 Introduction

Portfolio of credit risky corporate assets generate payoffs that linked to a credit related event such as a default, credit downgrade or bankruptcy. The return of the portfolio depends on credit risk, in other words, the probability of losses due to a borrower's failure to make payments on debt. For this reason, an appropriate credit default risk management is mandatory.

The aim of this paper is to represent how we manage a modelling portfolio of corporate loans as well as its credit risk. This paper describes, in the first place, the modelling of a fictive portfolio in JAVA with cholesky/eigenvalue decomposition method. In addition, risk management of this portfolio will be focused on by showing its risk metrics of portfolio: Expected Loss (EL), volatility, expected shortfall (ES), value at risk(VaR) and risk contribution of each obligor (RC). Finally, we will analyse the Monte Carlo error and implement the importance sampling method in order to improve the accuracy of our credit risk analysis.

2 Implementation JAVA: Our approach

The portfolio contains 3 types of total 140 exposures. Our workflow can be represented by graph below:

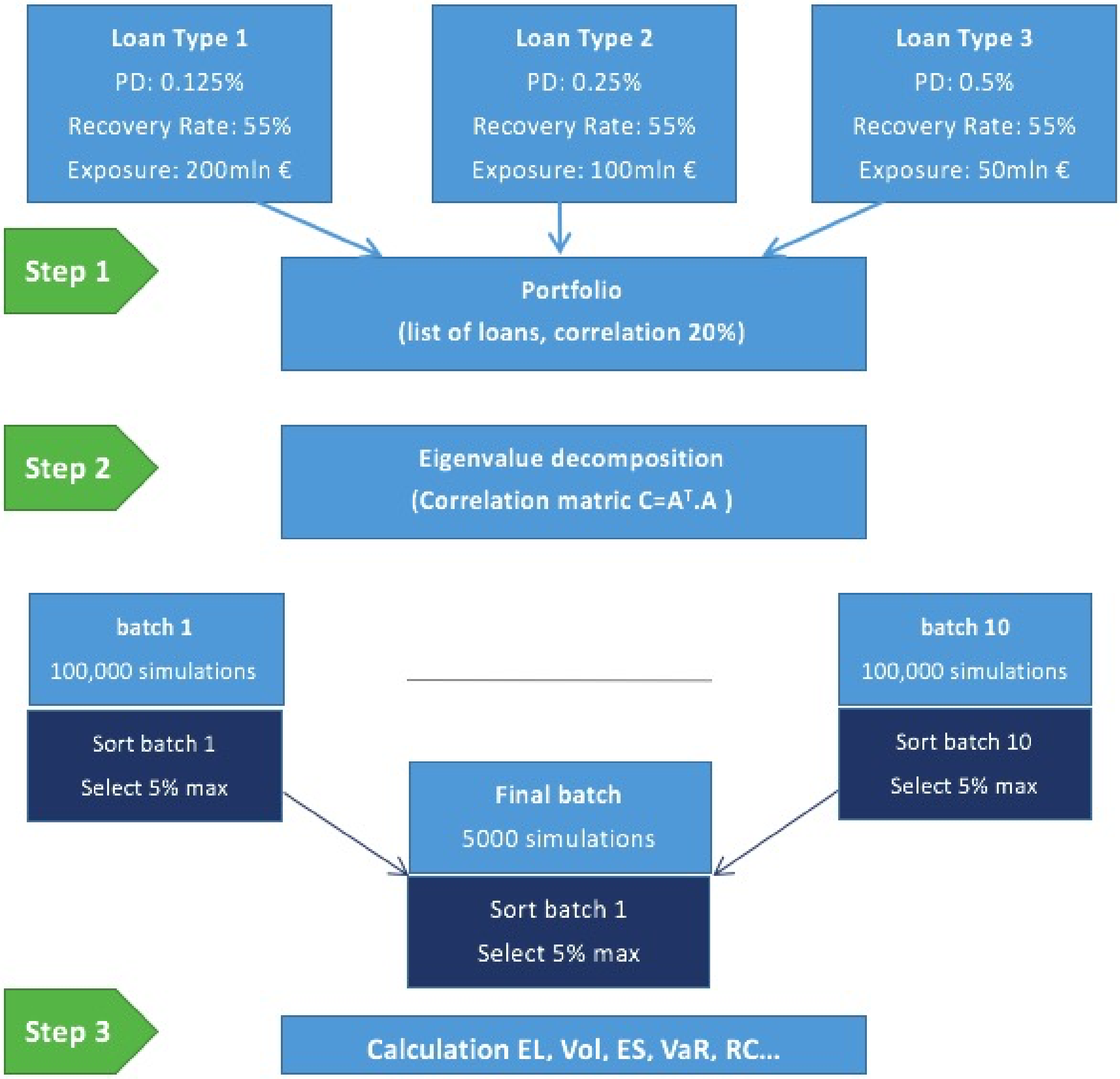

Figure 1: Workflow of portfolio implementation in JAVA

3 Risk metric and Monte Carlo Error Analysis

Risk Metric

The table 1 shows the results based on a 100,000 sample points

Table 1: Risk Metric & Risk contribution of obligor

	Cholesky/Eigenvalue	Importance Sampling				
		$\sigma = 1$	$\sigma = 0.5$	$\sigma = 1.5$	$\sigma = 2$	$\sigma = 3$
EL	1.56E7	1.56E7	1.56E7	1.56E7	1.56E7	1.56E7
Volatility	3.87E7	3.87E7	6.78E8	2.78E7	2.92E7	3.51E7
VAR (95%)	9.00E7	9.00E7	9.00E7	9.00E7	9.00E7	9.00E7
Expected Shortfall	1.47E8	1.47E8	1.47E8	1.47E8	1.47E8	1.47E8
Dispersion ES	7.60E7	7.60E7	5.36E9	3.61E7	4.18E7	4.63E7
Number points in tail 5%	5000	5000	1787	11828	18070	26902
RC each obligor type 1	1.392%	1.392%	1.395%	1.383%	1.431%	1.412%
RC each obligor type 2	0.742%	0.742%	0.760%	0.741%	0.737%	0,744%
RC each obligor type 3	0.590%	0.590%	0.582%	0.586%	0.580%	0,585%

Analysis

- Firstly, we note that with Cholesky or Eigenvalue decomposition, we have exactly the same result of risk metric as we do with importance sampling when $\sigma = 1$. This can be explained by the fact that when $\sigma = 1$, the weight which is calculated in importance sampling method become 1, which is exactly the case while dealing with Cholesky or Eigenvalue decomposition.

- With our portfolio, we have an expected loss of 15.6mil compared to a total exposure of 12bn (0.13%). In addition, there is considered to be only a 5% chance that losses will exceed 90mil over the next day. But by looking at expected shortfall, we conclude that we have only 147mil on average of losses on the portfolio in the worst 5% of cases which seems acceptable.

- The importance sampling method developed here relies on introducing a scalar parameter into the asset correlation model that may be adjusted to increase correlations, thereby inducing a greater number of correlated defaults and thus producing samples further out in the loss tail. Concretely, it allows us to generate more same points in the tail of last 5% of distribution compared to Monte Carlo standard. Indeed, for instance, with $\sigma = 2$, we have 18070 sample points in the tail of distribution instead of having 5000 points (5% of total simulations) as usual. The bigger sigma is, the more number of points generated in this area. This kind of technique helps to reduce estimator variance as well as accelerate the calculation by achieving faster convergence.

To illustrate the effectiveness of the importance sampling method, we consider 4 cases with different scale factor sigma (0,5; 1,5; 2 or 3). As we see, if we scale the largest eigenvalue down by a factor 0.5^2 ($\sigma = 0.5$), the volatility (standard deviation of the importance sampling integrand) will increase. By contrast, if we scale up the largest eigenvalue by a factor $\sigma = 1,5$ or 2, the volatility tends to decrease. Moreover, we observe a decrease of Monte Carlo error (dispersion ES) in the tail of distribution when we use scale-up factor (> 1). This is coherent with the aim of variance reduction technique of importance sampling, which also means a lower Monte Carlo error. In term of run-time savings, the computational speed up is given approximately by the ratio of the squared standard errors. In this case we see that, with $\sigma = 1.5$, the expected loss could run $\left(\frac{3.87E7}{2.78E7}\right)^2 = 1.93$ times faster, while for $\sigma = 2$, the speed up is about a factor of 1.75.

- In the matter of risk contribution, the obligors type 1 play the most important part on risk calculation (1.40% on average). This can be explained by its highest exposure loan (200M) despite of its least probability default (0.125%) and its small number of exposures (20) . On the other hand, the obligors type 3 which have the smallest exposure (50M) and the biggest probability default (0.5%) contribute the least on risk (0.59% on average). Furthermore, the risk contribution of each obligor remains the same as we adjust the value of σ, which means that it doesn't depend on whether we apply the importance sampling method or not.

4 Conclusion

Our work focuses on the implementation of a portfolio whose credit risk management plays the most important role and on how we manage to improve the accuracy as well as the run-time savings. However, in order to simplify the problems, we have been using some underlying assumptions such as a flat correlation matrix, normal distribution for random losses. Still, there are many rooms for improvement in the future project, for instance, finding the optimal choice for the scale parameter used in the importance sampling method which is mentioned in the paper of William J. Morokoff [1].

References

[1] William J. Morokoff. An importance sampling method for porfolio of credit risky assets.

[2] https://en.wikipedia.org/wiki/Importance_sampling