

**PROBABILITY OF DEFAULT FOR LIFETIME CREDIT LOSS FOR IFRS 9 USING
MACHINE LEARNING COMPETING RISKS SURVIVAL ANALYSIS MODELS**

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Introdução

This study introduces a machine learning competing risks survival analysis model aiming at exploring the Probability of Default component of credit risk. Due to modelling of a cumulative probability of default over time, the model is applicable to assess Lifetime Expected Credit Loss under the International Financial Reporting Standard (IFRS) 9 regulation for financial institutions. Whilst most credit models focus on the default event itself, in many loan transactions, there is a competing event affecting risk: the possibility of the borrower prepay their debt before maturity.

Problema de Pesquisa e Objetivo

The lifetime expected credit loss (Lifetime ECL), introduced by the International Financial Reporting Standard 9 (IFRS 9), implied the development of new credit models. More particularly, the models should measure the present value of potential losses that could arise from the default on an obligation throughout the life of the loan. In our study, we focus on the Probability of Default (PD) and derive a statistical model that supports handling competing risks (credit risk and prepayment risk) in a machine learning survival analysis setup.

Fundamentação Teórica

The IFRS 9 indicates mechanisms to calculate provisions, by assessing ECL considering the entire time horizon of the financial instrument (Gornjak, 2020). According to Dirick et al. (2017) early studies explored survival analysis techniques in credit risk investigating parametric accelerated failure time (AFT) survival methods or non-parametric baseline approach based on Cox proportional hazards model. More recently, machine learning algorithms begin to be incorporated in survival analysis, for instance, Binder, Allignol, Schumacher, and Beyersmann (2009).

Metodologia

We derive a statistical model that supports handling competing risks (credit risk and prepayment risk) in a machine learning survival analysis setup. As there is no available implemented computer package or library, we build the computational algorithm with subdistribution hazards using boosting as an ensemble method. The dataset consists of 118,967 credit card refinancing operations of a US financial institution, with a time-maturity of 36 months.

Análise dos Resultados

We observe, comparing different survival analysis techniques, that ComponentWise Gradient Boosting (CWGB) models showed better performance on both scenarios (subdistribution hazards and cause-specific models), closely followed by cause specific Cox Proportional Hazards, and that Gradient Boosting Survival was outperformed in all comparisons.

Conclusão

We introduced a method to assess competing risks in credit portfolios, embedding machine learning techniques within a survival analysis framework. We focus on the probability of default component of lifetime credit exposure. The adequate assessment of credit risk, within the context of other competing risk is paramount to better define provisions and economic capital. We find that our model can give new perspectives and lead to new insights about the behavior or credit risk over the entire lifetime of the loan.

Referências Bibliográficas

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