



## A new dynamic modeling framework for credit risk assessment



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### ABSTRACT

We propose a new dynamic modeling framework for credit risk assessment that extends the prevailing credit scoring models built upon historical data static settings. The driving idea mimics the principle of films, by composing the model with a sequence of snapshots, rather than a single photograph. In doing so, the dynamic modeling consists of sequential learning from the new incoming data. A key contribution is provided by the insight that different amounts of memory can be explored concurrently. Memory refers to the amount of historic data being used for estimation. This is important in the credit risk area, which often seems to undergo shocks. During a shock, limited memory is important. Other times, a larger memory has merit. An application to a real-world financial dataset of credit cards from a financial institution in Brazil illustrates our methodology, which is able to consistently outperform the static modeling schema.

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### 1. Introduction

In banking, credit risk assessment often relies on credit scoring models, so called PD models (Probability of Default models).<sup>1</sup> These models output a score that translates the probability of a given entity, a private individual or a company, becoming a defaulter in a future period. Nowadays, PD models are at the core of the banking business, in credit decision-making, in price settlement, and to determine the cost of capital. Moreover, central banks and international regulation have dramatically evolved to a setting where the use of these models is favored, to achieve soundness standards for credit risk valuation in the banking system.

Since 2004, with the worldwide implementation of regulations issued by the Basel Committee on Banking Supervision within Basel II Accord, banks were encouraged to strengthen their internal models frameworks for reaching the A-IRB (Advanced Internal Rating Based) accreditation (BCBS, 2006; BIS, 2004). To achieve this certification, banks had to demonstrate that they were capable of accurately evaluating their risks, complying with Basel II requirements, by using their internal risk models' systems, and keep their soundness. Banks owning A-IRB accreditation gained an advantage over the others, because they were allowed to use lower coefficients to weight the exposure of

credit at risk, the risk weighted assets, and benefit from lower capital requirements. A lot of improvements have been made in the existing rating frameworks, extending the use of data mining tools and artificial intelligence. Yet, this may have been bounded by a certain unwillingness to accept less intuitive algorithms or models going beyond standard solutions being implemented in the banking industry, settled in-house or delivered through analytics providers.

Developing and implementing a credit scoring model can be time and resource consuming, easily ranging from 9 to 18 months, from data extraction until deployment. Hence, it is not rare that banks use unchanged credit scoring models for several years. Bearing in mind that models are built using a sample file frequently comprising 2 or more years of historical data, in the best case scenario, data used in the models are shifted 3 years away from the point they will be used. Should conditions remain unchanged, then this would not significantly affect the accuracy of the models, otherwise, their performance can greatly deteriorate over time. The recent financial crisis confirmed that financial environment greatly fluctuates, in an unexpected manner, posing renewed attention regarding models built upon time-frames that are by far outdated. By 2007–2008, many financial institutions were using stale credit scoring models built with historical data of the early-decade. The degradation of stationary credit scoring models is an issue with empirical evidence in the literature (Avery, Calem, & Canner, 2004; Crook, Thomas, & Hamilton, 1992; Lucas, 2004; Sousa, Gama, & Gonçalves, 2013b), however research is still lacking more realistic solutions.

Dominant approaches rely on static learning models. However, as the economic conditions evolve in the economic cycle, either deteriorating or improving, also varies the behavior of an individual, and his

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<sup>1</sup> Other names can be used to refer to PD models, namely: credit scoring, credit risk models, scorecards, credit scorecards, rating systems, or rating models, although some have different meanings.

ability to repay his debt. Furthermore, the default evolution echoes trends of the business cycle, and related with this, regulatory movements, and interest rates fluctuations. In good times, banks and borrowers tend to be overoptimistic about the future, whilst in times of recession banks are swamped with defaulted loans, high provisions, and tighten capital buffers turn highly conservative. The former leads to more liberal credit policies and lower credit standards, the later promotes sudden credit-cuts. Hence, default needs to be regarded as time changing.

Traditional systems that are one-shot, fixed memory-based, trained from fixed training sets, and static settings are not prepared to process the evolving data. And so, they are not able to continuously maintain an output model consistent with the actual state of environment, or to quickly react to changes (Gama, 2010). These are some of the features of classic approaches that evidence the constraints of the existing credit scoring systems. As the processes underlying credit risk are not strictly stationary, consumers' behavior and default can change over time in unpredictable ways. A few limitations to the existing approaches, idealized in the classical supervised classification paradigm, can be traced in published literature:

- The static models usually fail to adapt when the population changes. Static and predefined sample settings often lead to an incomplete examination of the dynamics influencing the problem (Gama, 2010; Hand, 2006).
- Certain assumptions that are implicit to the methods, often fail in real-world environments (Yang, 2007). These assumptions relate to:
  - *Representativeness* - the standard credit scoring models rely on supervised classification methods that run on 2-years-old static samples, in order to determine which individuals are likely to default in a future fixed period, 1 year for PD models (Thomas, 2010; Thomas, Edelman, & Crook, 2002). Such samples are supposed to be representative of the potential borrowers consumers of the future, the through-the-door population. They should also be sufficiently diverse to reflect different types of repayment behavior. However, a wide range of research is conducted in samples that are not representative.
  - *Stability and non-bias* - the distribution from which the design points and the new points is the same; classes are perfectly defined, and definitions will not change. Not infrequently there are selective biases over time. Simple examples of this occurrence can be observed when a bank launches a new product or promotes a brand new segment of customers. It can also occur when macroeconomics shifts abruptly from an expansion to a recession phase, or vice versa.
  - *Misclassification costs* - these methods assume that the costs of misclassification are accurately known, but in practice they are not.
- The methods that are most widely used in the banking industry, logistic regression and discriminant analysis are associated with some instability with high-dimensional data and small sample size. Other limitations regard to intensive variable selection effort and incapability of efficiently handling non-linear features (Yang, 2007).
- Static models are usually focused in assessing the specific risk of applicants and obligors. However, a complete picture can only be achieved by looking at the return alongside risk, which requires the use of dynamic rather than static models (Bellotti & Crook, 2013).

There is a new emphasis on running predictive models with the ability of sensing themselves and learn adaptively (Gama, 2010). Advances on the concepts for knowledge discovery from data streams suggest alternative perspectives to identify, understand and efficiently manage dynamics of behavior in consumer credit in changing ubiquitous environments. In a world where the events are not

preordained and little is certain, what we do in the present affects how events unfold in unexpected ways. So far, no comprehensive set of research to deal with time changing default had much impact into practice. In credit risk assessment, a great deal of sophistication is needed to introduce economic factors and market conditions into current risk-assessment systems (Thomas, 2010).

The study presented in this paper is a large extension of a previous research that delivered the winning model within the BRICS 2013 competition in data mining and finance (Sousa, Gama, Brandão et al., 2013a; Sousa et al., 2013b). This competition opened to academics and practitioners, was focused on the development of a credit risk assessment model, tilting between the robustness of a static modeling sample and the performance degradation over time, potentially caused by market gradual changes along few years of business operation. Participants were encouraged to use any modeling technique, under a temporal degradation or concept drift perspective. In the research attached to the winning model, Sousa, Gama, and Gonçalves (2013b) have proposed a two-stage model for dealing with the temporal degradation of credit scoring models, which produced motivating results in a 1-year horizon. The winners first developed a credit scoring method using a set of supervised learning methods, and then calibrated the output, based on a projection of the evolution in the default. This adjustment considered both the evolution of the default and the evolution of macroeconomic factors, echoing potential changes in the population of the model, in the economy, or in the market. In so doing, resulting adjusted scores translated a combination of the customers' specific risk with systemic risk. The winning team (Sousa, Gama, & Gonçalves) concluded that the performance of the models did not significantly differ among classification models, like logistic regression (LR), AdaBoost, and Generalized Additive Models (GAM). However, after training in several windows lengths, they observed that the model based on the longest window has produced the best performing model over the long-run, among all competitors. This finding allowed to realize that some specifics of the credit portfolios and macroeconomic environments may reveal quite stable along time. For those cases, a model built with a static learning setting may seem appropriate, if tested during stable phases. The question yet to be answered was in which conditions credit risk models degrade? And when so, if there is any alternative modeling technique to the prevailing credit scoring models? The aim of this study is to find a clearer understanding on which type of modeling framework allows a rapid adaptation to changes, and in which circumstances a static learning setting still delivers well-performing models. With this in view, we implemented a dynamical modeling framework and two types of windows for model training, which enable testing our research questions: (a) In which conditions can a dynamic modeling outperform a static model?; (b) Is the recent information more relevant to improve forecasting accuracy?; (c) Does older information always improve forecasting accuracy?

This paper introduces a new dynamic modeling framework for credit risk assessment, imported from the emerging techniques of concept drift adaptation, in streaming data mining and artificial intelligence. The proposed model is able to produce more robust predictions in stable conditions, but also in the presence of changes, while the prevailing methods cannot. This is a promissory tool both to academics and practitioners, because unlike the traditional models, it has the ability of adjusting the predictions in the presence of changes, like inversions in the economic cycles, major crisis, or intrinsic behavioral circumstances (e.g. divorce, unemployment and financial distress). Besides the goal of enhancing the prediction of default in credit, the new modeling framework also enables developing a more comprehensive understanding of the evolution of the credit rating systems over time and anticipating unexpected events. Furthermore, we study the implications to credit risk assessment of keeping a long-term memory, and forgetting older examples, which have not been done so far.

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