Quantifying and Predicting Prepayments in the Microfinance Environment

Nandan Sudarsanam
Dibu John Philip

Published online: 11 August 2016

This research was supported by the NSE–IFMR Finance Foundation Financial Deepening and Household Finance Research Initiative.

Suggested citation: Nandan Sudarsanam & Dibu John Philip (2016) Quantifying and Predicting Prepayments in the Microfinance Environment, NSE-IFMR Finance Foundation Financial Deepening and Household Finance Research Initiative

Link: http://foundation.ifmr.co.in/quantifying-predicting-prepayments-in-the-microfinance-environment/

Quantifying and Predicting Prepayments in the Microfinance Environment

Nandan Sudarsanam and Dibu John Philip

Department of Management Studies

Indian Institute of Technology Madras

Chennai, Tamil Nadu, India.

Abstract

Financial institutions that lend to customers are interested in understanding and predicting repayment patterns. Two critical subjects of interest in this context are the advances and delays in payment with respect to the stipulated repayment schedule. In this study, we focus on the advances in payment, also referred to as prepayment, of loans on a time-quantum scale. While this translates to interest relief for the customer, it could potentially result in a loss for the institution, albeit small. More importantly, from the institution's perspective, it could indicate a form of preterm attrition, a sign of the unsuitability of the product, or the customer's preference for a competitor. This could in turn lead to pre-closures, and even an overall attrition of customers. The contributions of this research are two-fold. First, we present a framework for quantifying prepayments on a fixed scale over the duration of the loan. Second, we recommend and demonstrate the use of a machine learning technique called Temporal Difference (TD) learners to improve the performance of predicting the customer's prepayment state in the future. TD Learners work with traditional predictive modeling techniques to improve their performance in environments of sparse data. The recommended approach shows an overall improvement in predictive capacity compared to the conventional approach of using only the predictive model. Specifically, with the sample data set, we find that at best the proposed method is 57% better than the traditional approach, and at worst, is indistinguishable in performance. We discuss the specific suitability of such an approach in the microfinance context, where institutions could be looking at unexplored products, demographics or locations and thereby operate in environments that are not data rich.

1 Introduction

Loan repayment patterns could serve as valuable indicators of various customer-centric behavioral phenomena in the microfinance environment. A financial institution could potentially gain business insights, at both individual as well as systemic levels, and ultimately improve profitability by understanding these patterns. Prepayment is one such repayment pattern that is of particular interest to practitioners. Prepayment is the practice of paying off a debt ahead of the stipulated repayment schedule, partly or wholly. Typically, in the microfinance context, this leads to interest relief for the customer. However, practitioners and academics have viewed prepayment behaviour as being more than just the rational response of seeking interest relief (Kang and Zenios, 1992; Yamamoto and Zenios, 1993). They have examined and discussed various other business insights that can be drawn from understanding states and patterns of prepayment. These studies generally consider prepayment as a form of customer attrition (Hall and Lundstedt, 2005). This can be a result of a customer refinancing her loan, either because of a lower rate from a competitor or because the new source of debt is seen as being more customer-friendly (the reasons for being customer friendly can range from convenience of branch locations, to more flexibility in repayment, etc.). Another line of enquiry into prepayment patterns focuses more on suitability of the product and less on seeing it as explicit attrition. For instance, we found that some customers who were on a weekly repayment cycle would pay for the whole month in advance, and return the subsequent month to pay off the amount due for the next four weeks. Such behaviour was flagged as a recurring prepayment pattern, which could lead to business insight on the suitability of the specific product for that customer segment.

This study seeks to provide the practitioner with business intelligence by quantifying and predicting patterns in the advance repayments of debt. While the construct and findings in this research should be applicable to delays in payment as well, the motivation to initially look at prepayments stems from the idea that it can indicate a broader array of business phenomena, such as convenience of repayment and customer attrition. In contrast, the primary indicator in delayed payments tends to be the customer's inability to pay. The predictions are constructed as a function of certain state variables such as the customer's financial status, demographic, and interactions with other financial products. The predictions also take into account the path created by continually evolving transactions between the customer and the microfinance institution (MFI). Specifically, the study attempts to create a realistic scenario about data availability for the prediction process. For instance, when an MFI seeks to gain insights about a relatively new product or branch, the institution trains an intelligent system by utilizing the data of complete loans from pilot projects that are currently being disbursed. It then seeks to learn about the probable repayment profile of a new applicant, of which prepayment serves as an important input. The decision support system then uses this minimal data to recommend various business decisions, which in turn could increase the chances of the institution becoming more sustainable, and thus making it capable of serving more people, all based on the system recommendation. This approach, though apparently very simple and straightforward, poses several challenges. For example, data at hand might be limited in some ways: regional changes might lead to drastic changes in the demographic and/or behavioural profiles of customers leaving only the pilot projects as a source of data; the percentage of customers for which we might have complete data (most of the customers would be mid-way in their loan tenure) might be very less. This *asymmetry in data* as illustrated in Table 1 is the problem we try to tackle. We propose the method of Temporal Differences (TD) (Sutton, 1988), in which we measure prepayments over the duration of a product, and use intermediate repayment patterns to predict the customer's cumulative prepayment towards the end of the stipulated tenure of the product. This method has the potential to start exploiting the limited data in hand, without waiting for a majority of customers to finish their loan tenures. This is in contrast to traditional approaches that are static in the sense that they try to match two points in the customer's tenure, while completely ignoring the dynamics of the customer behaviour through the course of the loan (Thomas et al., 2001). As shown in Fig. 1, TD learners themselves are not predictors. They work with predictors, which could be econometric models or any supervised learner, to exploit the data in a more effective way thereby improving the overall predictive capabilities. Section 2 provides the context of microfinance in India and motivates this research. Section 3 explains the quantification of prepayments. The concept of learning from TDs is borrowed in this work as it is best suited for problems of this nature. This is explained in detail in Section 4. Finally, Section 5 discusses the case study and experimental results.

2 Background

Financial inclusion has become an essential part of the efforts that many developing nations have taken to fight poverty and to achieve all-inclusive economic growth (Banerjee et al., 2013). Despite this, a significant portion of the population in these countries remains without access to financial

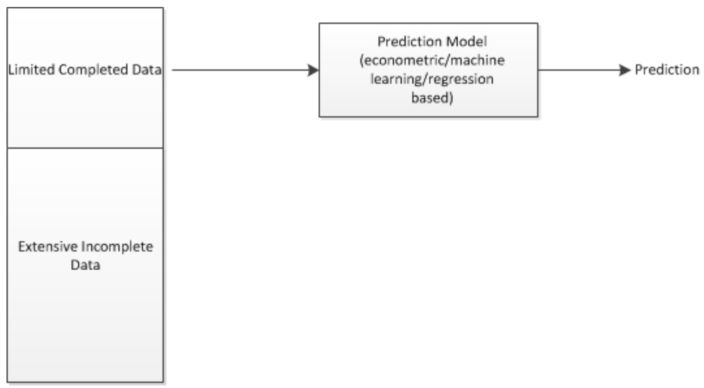
URN	m0	m1	m2	m3	...	m11	m12
1	on-time	on-time	on-time	on-time	...	prepaid	prepaid
2	on-time	prepaid	prepaid	on-time	...	prepaid	on-time
3	prepaid	prepaid	prepaid	prepaid	...	NA	NA
4	on-time	on-time	on-time	NA	...	NA	NA
5	on-time	prepaid	NA	NA	...	NA	NA

Table 1: Each row in this table corresponds to the monthly (m0, m1, ...) repayment profile of a customer. While the initial rows have data for all the 12 months, data becomes sparse as we move down the table (NA denotes missing values). This is because majority of the customers might be in the middle of a loan product, with very few of them having complete data. A TD learner can quickly start exploiting this data without waiting for a majority of the customers to complete their loan tenure, by looking into intermediate repayment patterns.

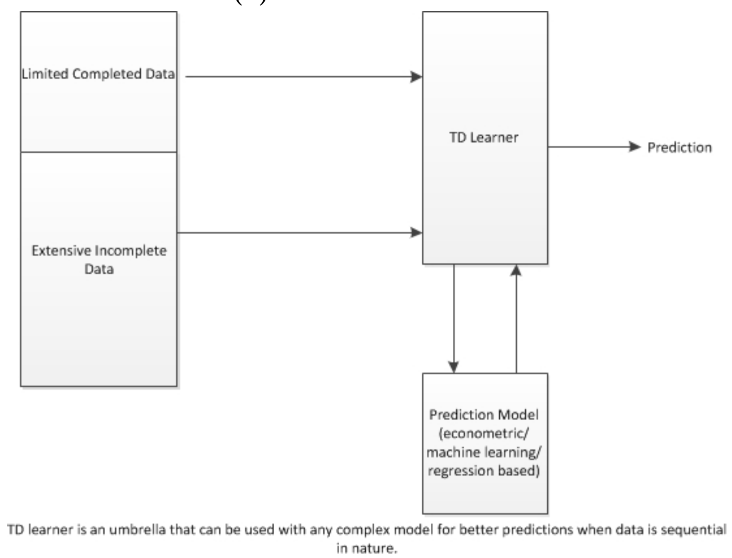
services, and appraisals of past inclusion initiatives show a checkered history of improving the condition of the targeted beneficiaries (Littlefield et al., 2003; Morduch, 2000). One of the possible reasons for this could be the slow pace, or even the complete inability to achieve a win-win situation (Robinson, 2001), societal benefits and profitability, or sometimes even the financial sustainability of the MFIs. To make positive strides in financial inclusion, the multifarious challenges that go with such complex objectives need to be addressed successfully.

The microfinance scenario in India started off as one in which financing the poor was seen as a liability by the major banks, and it was thought to be not sustainable sans external support or subsidies from the government. Further, only public sector banks were involved in this area. However, things started changing gradually by early the 1970s. The poor were considered bankable, and more private sector agencies and NGOs ventured into the microfinance market, as lending to the poor was no more considered a loss-making process (Thorat, 2006). However, many MFIs have been, and continue to be, subsidised by the government or through private donations. Sustainability or long-term profitability was of rising concern (Hermes and Lensink, 2007; Hulme and Mosley, 1996). In order to meet the grand long-term goal of successfully addressing the problems of the have-nots, MFIs should be made capable of standing on their own feet, i.e,. self-sustainable. Hefty competition and economic crises in many microfinance markets require MFIs to now pursue their social and financial objectives in much tighter environments (Caudill et al., 2009).

The most widely encountered challenges in the context of the sustainability and self-sufficiency of MFIs as discussed in the extant literature



(a) Traditional learner.



(b) TD learner.

Figure 1: Traditional and TD learner.

(Hermes and Lensink, 2007; Brau and Woller, 2004) revolve around, a) reach and b) suitability. Reach, which is a supply-side problem, primarily involves getting financial service providers, both traditional and niche banks, and MFIs to set up branches in geographical locations where there is a lack of formal institutions (Goldberg, 2005). Reach problems can be addressed through the use of Information and Communications Technologies (ICTs). If cell phone based transactions (Asongu, 2013) and more user-friendly ATMs could eliminate the need for traditional brick and mortar branches, then the economics of wider reach can be radically redefined.

The problem of the suitability of products and services, the demand centric side of the challenges, speaks about the appropriateness, or lack thereof, of traditional financial products and practices for the low-income, remotely accessible customer (Nourse, 2001; Musona and Coetzee, 2001; Rahman, 2000). The Basel Committee on Banking Supervision (BCBS) defines suitability as *"the degree to which the product or service offered by the intermediary matches the retail client's financial situation, investment objectives, level of risk tolerance, financial need, knowledge and experience."* Indian regulatory bodies such as the Reserve Bank of India (RBI) and the Insurance Regulatory and Development Authority (IRDA) have come up with guidelines and matrices for institutions to ensure product suitability. The 2007 Comprehensive Guidelines on Derivatives were revised by the RBI in 2011 to address issues of suitability (RBI, 2011). Further, the 2015 Report of the Committee on Medium-term Path on Financial Inclusion (RBI, 2015) emphasizes the importance of product suitability to avoid the dangers of mis-selling. IRDA in its Exposure Draft on Guidelines on Prospect Product Matrix for Life Insurance came up with a suitability index, viz. the Prospect Product Matrix, that scores product appropriateness for a client based on her life stage, generic needs, income segment and other factors. While these requirements focus on client protection, they have a direct impact on the long-term profitability of the institution in many ways. When a product matches the client's requirements or capabilities, it protects her from over-indebtedness and simultaneously safeguards the institution from a possible default and loss situation.

To achieve this match, a comprehensive understanding of the customer's financial status and behaviour, and her interaction with various financial products is required (Dunn, 2002). The use of business intelligence is hence not a luxury but a necessity for survival in this sector. Equipped with this intelligence, an MFI can make a range of informed business decisions that have the potential to address all the three challenges of reach, suitability, and sustainability.

3 Quantifying Prepayments

When a customer pays back a loan more aggressively than she is supposed to in its normal tenure, she gains relief on interest; the MFI, on the other hand, incurs a loss. These prepayments might lead to what we call "preterm attrition".

Suppose a customer takes out a loan of amount P at an interest rate of r % per month. The actual tenure of the loan is N months, and it is a monthly repayment loan. Then, the equated monthly installment (EMI) is calculated as,

$$\text{EMI} = \frac{P \times \frac{r}{100} \times (1 + \frac{r}{100})^N}{(1 + \frac{r}{100})^N - 1}. \tag{1}$$

As long as the customer pays back an amount equal to her calculated EMI for a particular month (as well as for all the preceding months where EMI were due), everything works fine. We call this state as the *normal* state. Another state into which the customer can fall is the *aggressive* state, which is defined as a state in which the customer pays back more than what is due for a particular month. This might happen because of a variety of reasons, one being availability of another loan at a more attractive rate of interest from elsewhere. If a customer remains in the *aggressive* state for a couple of months consecutively, this might indicate a chance of her closing the loan early, which might lead to a loss for the MFI.

Now, let repay_actual(n) be the actual amount she pays back in month n. We define ahead_by(n) as

$$\text{ahead\_by}(n) = \text{repay\_actual}(n) - \text{repay\_expected}(n), \tag{2}$$

where repay_expected(n) is defined as

$$\text{repay\_expected}(n) = \text{EMI} - \text{ahead\_by}(n-1) \times \left(1 + \frac{r}{100 \times N}\right). \tag{3}$$

From these, prepayment percentage for month n can be calculated as,

$$\text{prepayment\%}(n) = \frac{\text{ahead\_by}(n) \times \frac{r}{100 \times N}}{(\text{EMI} \times N) - P} \tag{4}$$

The cumulative prepayment percentage (CPP), $\sum_{n=1}^{N} \text{prepayment\%}(n)$, presents the repayment pattern of a customer, indicating whether she is on-schedule in her payments, or whether there is a behaviour of paying more than required and/or earlier. An MFI will be interested in predicting this CPP, given the repayment pattern up to some specific month. We look into this prediction problem in the next section.

4 Methodology

In this study we suggest a Temporal Difference (TD) learning approach to solve the problem of predicting the CPP at the end of a loan term and improve upon the performance of current practices. Prediction using the method of temporal differences is well explained in prior studies (Sutton, 1988). Consider a monthly repayment loan, and without loss of generality, consider the prepayment problem. Traditional approaches would observe the prepayment pattern leading up to any given intermediate month, and then pair this with the final state that is realized at the term end. This paired data would be used as a training set for any supervised learning algorithm. This approach requires data that links each intermediate state to the final state. However, in many situations, such data might be limited. When an MFI opens a new branch or introduces a new loan product, and decides to analyze data to improve their business, it might have few customers who have completed the full tenure for the selected product. Thus, the MFIs lack the actual value of the CPP at term-end, making the data impractical for training. Using data from other branches might not be appropriate for social, political, or geographical reasons. These constraints, which are present in the traditional approaches, limits the size of the training set to only the fully completed loans in the branch under question, and a major part of the data from loans that are mid-stream will not be used for training. TD learners partly overcome this difficulty by solving the same prediction problem, by utilizing the inter-relationship between the monthly payments that can be extracted from partial data. This method exploits the fact that the confidence about the predictions of final CPP is related to not just one month, but evolves as the months pass by. Thus, TD methods make more efficient use of the training data in such multi-step prediction problems, and could be a powerful tool in the analysis of loan repayment, especially when there is a significant number of open loans that have covered only a partial term of repayment. This should lead to more accurate predictions under conditions of limited experience, which is crucial in many financial applications.

TD learning, like traditional supervised learning algorithms, uses past experience of an incompletely known system to predict its future behavior. However, the major difference is in how the algorithm assigns credit to a prediction that is made. While traditional methods assign credit by means of the difference between predicted and actual outcomes, the TD method assigns credit by means of the difference between temporally successive predictions. TD methods make more efficient use of the training data in multi-step prediction problems. Specifically, in this research, we consider all loans with a tenure of one year and having an EMI repayment schedule. We calculate the monthly prepayment percentage of each customer using Eqns. 1 - 4. We format the data to appear as is shown in Table 2. We are interested in predicting the CPP at the end of the loan term from any given month

URN	m0	m1	m2	m3	m4	m5	m6	m7	...	m11	m12
1	0	0	0	0	0	7	6	1	...	2	1
2	0	4	1	0	0	5	2	0	...	2	0
3	10	7	3	2	2	0	5	NA	...	NA	NA
4	0	0	0	0	0	2	NA	NA	...	NA	NA
5	0	3	1	NA	NA	NA	NA	NA	...	NA	NA

Table 2: Prepayment profile (in percentage) of customers.

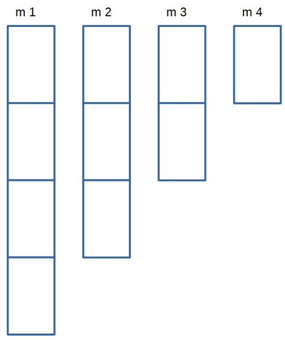
in the loan period, using the TD approach in conjunction with a suitable supervised learner.

4.1 Predicting cumulative prepayment scores

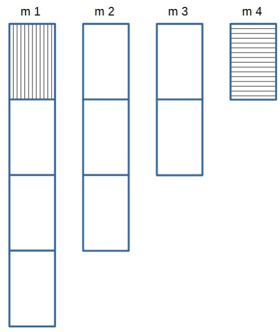
We now run TD learners on a real-world data set that is obtained from a financial institution (details of the data set and the practitioner are presented in section 5). For ease of implementation, we convert the final table into its cumulative version (as is shown in Table 2); that is, what now comes under month n is the CPP up to and including the n-th month's prepayment percentage. Since we are currently looking only into 1-year loans, month 12's value is the CPP at the end of the loan tenure. Only a small percentage of the total data set will have prepayment percentages up to month 12. Hence, the data table will have a structure similar to a left upper triangle matrix as shown in Fig. 2a. We now run TD learners on this data. For ease of illustration, let us assume that we want to predict the cumulative attrition for month 4 from month 1. The TD learning system works as follows:

1. A model (such as linear regression or neural networks) is created for predicting month 4's CPP from month 3; that is, month 3's data will be the predictor, and month 4's data will be the response or target values for training. The size of this training data will be limited by the size of the cases for which data is complete. Let us call this model model_{3_4}. This is a single model built from all customers who have repayment data for month 3 as well as month 4.

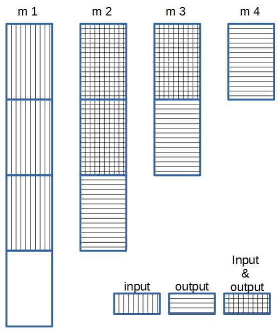
2. Similarly, another model is created to predict month 4's CPP from month 2. The TD learner uses the predictions of model_{3_4} (month 3's data goes as input to model_{3_4}) as the target variable and month 2's data as the predictor for training the model, as shown in Fig. 2c. That is, model_{2_4} predicts the output of model_{3_4} from month 2.



(a) Dataset



(b) Traditional learner

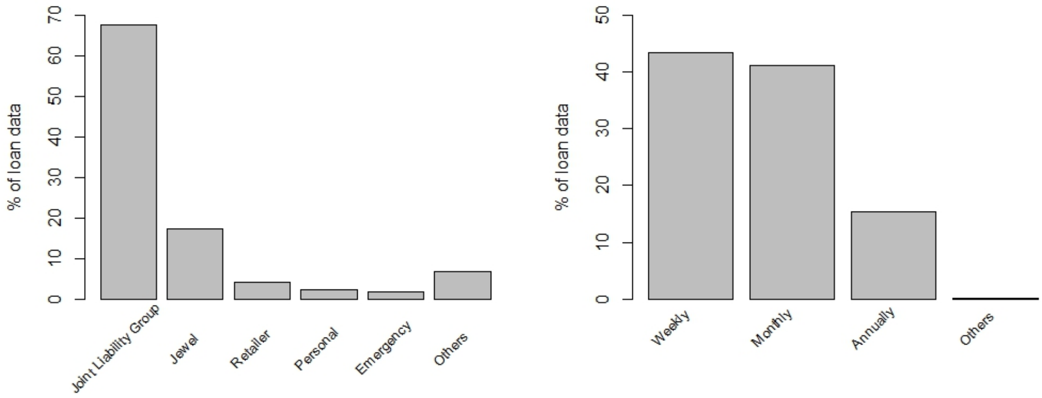


(c) TD learner

Figure 2: Comparison of data utilization by a traditional supervised learning approach with a TD Learner: Predicting month 4's cumulative attrition from month 1.

3. We further create model$_{1_4}$ with model$_{2_4}$'s predictions. In general, model$_{i_4}$ uses model$_{i+1_4}$'s predictions as the response variable.

Figs. 1 and 2 clearly illustrate the advantages of a TD learner over the traditional method. A traditional learner would be content with the creation of a single model, model$_{1-4}$, which is trained using the limited cases that have complete data available up to month 4, as shown in Fig. 2b. On the other hand, a TD learner (see Fig. 2c) progressively gets more data points to train the models. Additionally, a TD learner better exploits intermediate transaction patterns to create more robust predictors. This is helpful when the customer transaction patterns are affected by seasonal variations, as evident from the data that we have.



(a) Summary of loan products.

(b) Summary loan repayment frequencies.

Figure 3: Summary of the data set.

5 Case Study and Implications

In this study, we worked with IFMR Rural Finance (IRF), a provider of technology and process solutions to financial institutions that are involved low-income environments. We analyzed data sets collected from IRF's clients with the objective of modeling the financial behaviour of their current and prospective customers. These data sets contained transaction and demographic information of close to half a million end-customers across 250 rural branches in India for a time span that stretches from August 2008 to November 2014. Fig. 3 shows a broad summary of the available data set pertaining to debt products.

This data set can be viewed as containing two sets of information: self-reported customer characteristics and transactional details. The practitioner gathers various self-reported data from potential customers (awareness drives or walk-ins) and existing customers on a quasi-periodic basis. These range from purely demographic indicators such as age, gender, educational status, and family size, to purely financial details such as family income, family expense, and assets. For existing customers, additional information on their product-level transactions is also available. This includes the other products they own, open and close dates, their loan repayment transactions, etc. Merging and sorting the tables give us a final data set to work on. From this table, for the analysis we describe in the next subsection, we extract information relating to a particular type of loan, which has a tenure of a year and comes with a monthly repayment pattern.

The data is consumed in its raw form without any scaling or normalization. This is because the purpose of this exercise is to improve the prediction and not superior interpretation of which factors affect the output. Since the econometric model used for prediction is a simple linear regression model, the statistical inference will be the same whether we chose to normalize or not. This is the training data for our analysis.

5.1 Results

We compare the performance of a traditional supervised learner to the proposed TD learner in predicting the CPP in the end of the loan tenure, given the CPP for a particular month. For this, we look into the predictions of the CPP at the end of a loan tenure made by the traditional and TD model from different stages of the loan tenure.

Fig. 4 shows the prediction error when predicting the final CPP from different stages of the loan period, comparing a traditional supervised learning method to a TD learner (see Sec. 4.1) that uses a linear regression model as its back-engine. These results are obtained from running the algorithms on a test data set. It can be seen that the TD method outperforms the traditional method by a very high margin, especially at the early stages of a loan.

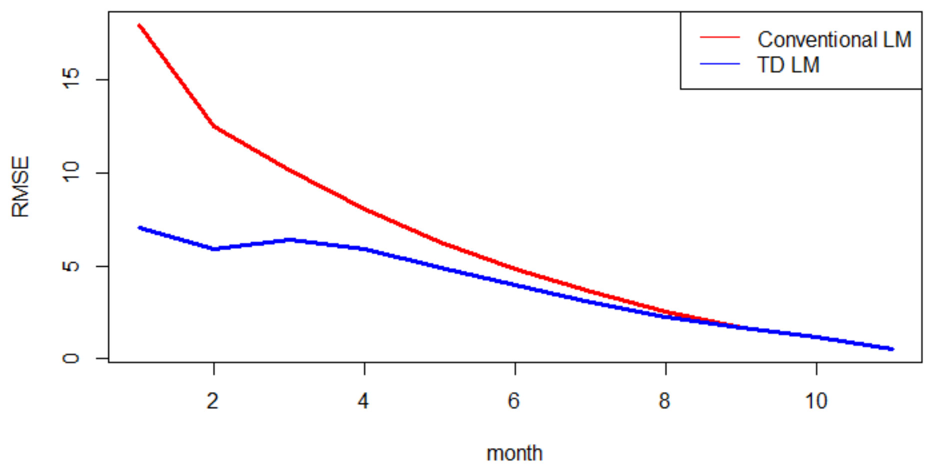


Figure 4: RMSE [1] vs. predicting month for conventional and TD methods.

[1] Root-Mean-Square Error

5.2 Implications

There are various business insights and actionable items that this improvement in prediction can bring about. At the systemic level, certain recurrent patterns might indicate phenomena related to branches, products, personnel, or policy. For instance, when customers in a certain branch recurrently prepaid four of their weekly repayments and mimicked a monthly payment, this pattern led to divergent questions of whether the customers understood the repayment schedule or found it difficult to physically access that branch. This might have implications for better explaining the product or opening up more branches. At the individual level, it could indicate that the product is not suitable, that the repayment schedule needs to be different, or even the increased likelihood of the customer leaving the MFI for a competitor.

The major implications of these results are twofold. 1) A relatively new loan user can be judged more accurately right from her initial months into the loan period. This enables the institution to take corrective measures from its side if necessary, before much loss is incurred. A person who is predicted to have a very aggressive repayment pattern can be encouraged to take up other products, or given other incentives if she is deemed profitable if she stays back. This also helps in understanding the suitability of the products that are on offer in a particular region. 2) The majority of the customers in the data set provided are in the middle of their loan tenures. Only a very small percentage have data for all 12 months of the tenure. This makes the data set very sparse. While the traditional method is limited by this fact as explained earlier, the TD learners are able to start building more robust predictors right away, without waiting for more customers to complete their loans so as to increase the density of the training data.

6 Future Work

This study aimed to predict prepayment states in sparse and assymetric data environments using Temporal Difference learners. While this study focuses its efforts on a mathematical conception of prepayment, there is nothing that constrains the use of these techniques to prepayments. In fact, any behaviour associated with repayment, which is likely to have similar asymmetric data availability, could be a good candidate for modelling through temporal differences. One obvious area of interest could be delinquency. While there are some fundamental differences between attrition and delinquency — such as the fact that attrition has a guaranteed terminal state that coincides with the loan tenure, whereas delinquency does not have any such guarantees — it still fits our broader framework for using this approach. This idea could also be extended to go beyond single loans to looking at cycles of loans and other products.

There is scope for future work in the refinement of the suggested model. Given the mathematical model adopted by the CPP, it should facilitate the explicit construction of bounds that subsequent prepayment values can take (rather than allow the supervised learner to implicitly learn this). For instance, a single payment that covers the next three repayments poses different lower bound constraints for the CPP of the next three months. Also, much of this work does not explicitly model patterns or paths in the repayment. It is likely that unsupervised grouping of prepayment patterns is likely to provide us with business insights as well as stronger features for better predictions.

Finally, the greater value of prepayment prediction is in its use as an input for decision-making. In that regard, it would be important to understand the effects that prepayment patterns have on actual attrition (which refers to the likelihood that a customer chooses to not renew the product, or opt for another product upon expiry of the current product). Also, it is worth exploring and understanding the exact role that prepayment predictions could play in a broader credit or profit score, which in turn would result in holistic business intelligence leading to greater long-term profits and sustainability for financial institutions in the low-income space.

7 Conclusions

The proposed algorithm attempts to solve the problem of having sparse and asymmetric data to make predictions of prepayment over the remaining tenure of a loan. As a result, this partially solves the problem of *cold-start* that a financial institution may face owing to the introduction of a new product, entering into a new demographic, or starting in a new location. The mathematical framework of prepayment, referred to as CPP, uses a percentage- based prepayment conception that can be validated using customer behaviour and can also be easily translated to a scoring system. The predictive engine using Temporal Difference learners shows a significant improvement over the traditional supervised learner, especially in the early cycles of a loan repayment. The improved scores are expected to have a positive impact on a wide range of aspects of the money lending business.

The most significant of these is a better understanding of the customer. This could lead to better screening of customers and proactive strategies for customer engagement to prevent attrition. At an organizational level, it could also lead to better financial planning. Finally, this idea could be extended to modeling other aspects of repayment such as delinquency and default.

References

Asongu, S. A. (2013). How has mobile phone penetration stimulated financial development in africa? *Journal of African Business*, 14(1):7–18.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., and Jackson, M. O. (2013). The diffusion of microfinance. *Science*, 341(6144):1236498.

Brau, J. C. and Woller, G. M. (2004). Microfinance: A comprehensive review of the existing literature. *Journal of Entrepreneurial Finance, JEF*, 9(1):1–27.

Caudill, S. B., Gropper, D. M., and Hartarska, V. (2009). Which microfinance institutions are becoming more cost effective with time? Evidence from a mixture model. *Journal of Money, Credit and Banking*, 41(4):651–672.

Dunn, E. (2002). It pays to know the customer: addressing the information needs of client-centered MFIs. *Journal of International Development*, 14(3):325–334.

Goldberg, N. (2005). Measuring the impact of microfinance: taking stock of what we know. *Grameen Foundation USA publication series*.

Hall, A. and Lundstedt, K. G. (2005). The competing risks framework for mortgages: modeling the interaction of prepayment and default. *RMA JOURNAL*, 88(1):54.

Hermes, N. and Lensink, R. (2007). The empirics of microfinance: what do we know? *The Economic Journal*, 117(517):F1–F10.

Hulme, D. and Mosley, P. (1996). *Finance against poverty*, volume 2. Psychology Press.

Kang, P. and Zenios, S. A. (1992). Complete prepayment models for mortgage-backed securities. *Management Science*, 38(11):1665–1685.

Littlefield, E., Morduch, J., and Hashemi, S. (2003). Is microfinance an effective strategy to reach the Millennium Development Goals? *Focus Note*, 24(2003):1–11.

Morduch, J. (2000). The microfinance schism. *World development*, 28(4):617–629.

Musona, D. and Coetzee, G. (2001). Dropouts among selected Zambian microfinance institutions: causes and potential impact on product design. *MicroSave-Africa working paper*.

Nourse, T. H. (2001). The missing parts of microfinance: Services for consumption and insurance. *SAIS Review*, 21(1):61–69.

Rahman, S. (2000). Commercialization of microfinance in Bangladesh perspective. *Global Development Research Center, Osaka, Japan.[http://www. gdrc. org/icm/country/bangla-001. html].*

RBI (2011). Comprehensive guidelines on derivatives: Modifications. https://rbidocs.rbi.org.in/rdocs/notification/PDFs/CGD021111FL.pdf.

RBI (2015). Report of the committee on medium-term path on financial inclusion. https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/FFIRA27F4530706A41A0BC394D01CB4892CC.PDF.

Robinson, M. S. (2001). *The microfinance revolution: sustainable finance for the poor*. World Bank Publications.

Sutton, R. S. (1988). Learning to predict by the methods of temporal differences. *Machine learning*, 3(1):9–44.

Thomas, L. C., Ho, J., and Scherer, W. T. (2001). Time will tell: behavioural scoring and the dynamics of consumer credit assessment. *IMA Journal of Management Mathematics*, 12(1):89–103.

Thorat, Y. (2006). Microfinance in India: Sectoral issues and challenges. *Towards a sustainable microfinance outreach in India*, pages 27–42.

Yamamoto, Y. and Zenios, S. A. (1993). Predicting prepayment rates for mortgages using the cascade-correlation learning algorithm. *The Journal of Fixed Income*, 2(4):86–96.