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Asset Quality Management

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"METHOD AND SYSTEM FOR ASSET QUALITY MANAGEMENT"

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TECHNICAL FIELD

[0001] The present subject matter is, in general, related to assessing quality of assets, and particularly to a method and system for asset quality management to minimize International Financial Reporting Standards 9 (IFRS 9) provisioning impact.

BACKGROUND

[0002] IFRS provides a standardized way of describing an entity's financial performance and position so that the entity's financial statements are understandable and comparable across international boundaries. According to IFRS9, an entity needs to estimate its credit losses or exposures of a plurality of accounts associated with the entity. Further, according to IFRS9 provisions, all the credit exposures may be assigned to three stages, stage 1, stage 2, and stage 3. For financial assets in stage 1, entities are required to recognize a 12-month Expected Credit Loss (ECL). That is, stage 1 indicates all the credit exposures that have 12-months Probability of Default (PD). When a financial asset transfers to stage 2, entities are required to recognize a lifetime ECL. Stage 2 indicates the credit exposures that have a lifetime PD. A financial asset is assigned to stage 3 when the financial asset is credit impaired. For financial assets in stage 3, the entities will continue to recognize lifetime ECL. IFRS9 requires the entity to determine whether the financial asset is in one of the three stages mentioned above to determine ECL of the entity using a forward looking ECL model.

[0003] Also, the provisions of IFRS9 require the entities to estimate the ECL based on PD of each financial asset calculated based on the stage assigned to the financial asset, Loss Given Default (LGD) and Exposure at Default (EAD). Entities will be required to consider historic, current and forward-looking information (including macro-economic data). This will result in the earlier recognition of credit losses as it will no longer be appropriate for entities to wait for an incurred loss event to have occurred before credit losses are recognized. Thus, IFRS9 requires any entity, such as a bank, to determine the ECL using forward looking behavior of accounts, and transitioning of each account into future stages. Such a method is lengthy and costly due to the complexity of the ECL model. Thus, to reduce IFRS9 provision impact on the entities, the entities require a method and a system to reduce delinquency of accounts, which is one of key drivers in IFRS9 staging and risk rating. Reducing the delinquency of accounts also reduces number of accounts that roll forward from stage 1 to stage 2 and stage 2 to stage 3 of credit exposures.

BRIEF DESCRIPTION OF THE DRAWINGS

[0004] The accompanying drawings, which are incorporated in and constitute a part of this disclosure, illustrate exemplary embodiments and, together with the description, explain the disclosed principles. In the figures, the left-most digit(s) of a reference number identifies the figure in which the reference number first appears. The same numbers are used throughout the figures to reference like features and components. Some embodiments of device or system and/or methods in accordance with embodiments of the present subject matter are now described, by way of example only, and with reference to the accompanying figures, in which:

[0005] **Fig. 1** illustrates an exemplary architecture that implements embodiments consistent with the present disclosure.

[0006] **Fig. 2** illustrates a block diagram of an asset quality management system according to embodiments consistent with the present disclosure.

[0007] **Fig. 3a** illustrates a graph indicating importance of a plurality of features while validating an ML model of a pre-delinquency module of Fig. 1 and Fig. 2 according to embodiments consistent with the present disclosure.

[0008] **Fig. 3b** illustrates roll rate analysis performed using the ML model of the pre-delinquency module of Fig. 1 and Fig. 2 according to embodiments consistent with the present disclosure.

[0009] **Fig. 4a** illustrates a graph indicating importance of a plurality of features while validating an ML model of a sloppy payer detection module of Fig. 1 and Fig. 2 according to embodiments consistent with the present disclosure.

[0010] **Fig. 4b** illustrates roll rate analysis performed using the ML model of a sloppy payer detection module of Fig. 1 and Fig. 2 according to embodiments consistent with the present disclosure.

[0011] The figures depict embodiments of the disclosure for purposes of illustration only. One skilled in the art will readily recognize from the following description that alternative embodiments of the structures and methods illustrated herein may be employed without departing from the principles of the disclosure described herein.

DESCRIPTION OF THE DISCLOSURE

[0012] It is to be understood that the present disclosure may assume various alternative variations and step sequences, except where expressly specified to the contrary. It is also to be understood that the specific devices and processes illustrated in the attached drawings and described in the following specification are simply exemplary and non-limiting embodiments or aspects. Hence, specific dimensions and other physical characteristics related to the embodiments or aspects disclosed herein are not to be considered as limiting.

[0013] In the present document, the word "exemplary" is used herein to mean "serving as an example, instance, or illustration." Any embodiment or implementation of the present subject matter described herein as "exemplary" is not necessarily to be construed as preferred or advantageous over other embodiments.

[0014] While the disclosure is susceptible to various modifications and alternative forms, specific embodiment thereof has been shown by way of example in the drawings and will be described in detail below. It should be understood, however that it is not intended to limit the disclosure to the particular forms disclosed, but on the contrary, the disclosure is to cover all modifications, equivalents, and alternative falling within the spirit and the scope of the disclosure.

[0015] The terms “comprises”, “comprising”, or any other variations thereof, are intended to cover a non-exclusive inclusion, such that a setup, device or method that comprises a list of components or steps does not include only those components or steps but may include other components or steps not expressly listed or inherent to such setup or device or method. In other words, one or more elements in a device or system or apparatus proceeded by “comprises… a” does not, without more constraints, preclude the existence of other elements or additional elements in the device or system or apparatus.

[0016] The terms "an embodiment", "embodiment", "embodiments", "the embodiment", "the embodiments", "one or more embodiments", "some embodiments", and "one embodiment" mean "one or more (but not all) embodiments of the invention(s)" unless expressly specified otherwise.

[0017] The terms "including", "comprising", “having” and variations thereof mean "including but not limited to" unless expressly specified otherwise.

[0018] **Fig. 1** illustrates an exemplary architecture that implements embodiments consistent with the present disclosure.

[0019] In an embodiment, the present disclosure proposes a system that minimizes accounts moving from stage 1 to stage 2 or stage 3 of the credit exposure. According to IFRS9 provisions, if an account has shown significant increase in credit risk since its inception, the account needs to be transitioned from stage 1 to stage 2. Common measures to indicate significant increase in credit risk are Application Score, Behavior Score, Risk Grade and risk drivers such as delinquency, utilization and payment factors. The present disclosure aims to reduce delinquency of accounts since most of these measures are primarily driven and/or correlated with delinquent conduct. In IFRS9, the credit risk is deemed to have significantly increased if the account is more than 30 Days Past Due (DPD). In such a case, the account may be transitioned from stage 1 to stage 2 and hence the system enables the entity to reduce a roll forward rate to 30+DPD.

[0020] In an embodiment, the exemplary architecture 100 shown in Fig. 1 includes one or more components to implement a method of predicting delinquency of a customer’s bank account 105 to apply one or more 0 DPD and 1-29 DPD bank accounts, which may have been transitioned to stage 2 at a point of observation for early collection management and to improve the status of such bank accounts. In an embodiment, a financial entity 102 may be associated with at least one customer 104 having a financial asset such as an account 106 of the financial entity 102. As an example, the account 106 may be associated with a credit card, a debit card, one or more loans, insurance, or any other financial service provided by the financial entity 102. The financial entity 102 may implement the IFRS 9 provisions to assess the account 105 of the customer 104 based on customer data 108 associated with the account 106 stored in a bank server 110. The financial entity 102 may predict a probability of delinquency of the account 105 using an asset quality management system 112 that is communicably coupled with the bank server 110 through a communication network 114. In some embodiments, the asset quality management system 112, herein alternatively referred to as a system 112, may also be configured within the bank server 110. The system 112 may at least include a pre-delinquency module 116 and a sloppy payer detection module 118 to evaluate a rate of delinquency and a rolling forward rate for the account 105 of the customer 104.

[0021] The financial entity 102 may be a bank that provides financial services such as credit card and/or debit card facilities, loans, insurance and other services. The customer 104 may be an account holder with the financial entity 102 and avails one or more financial services with the financial entity 102.

[0022] In an embodiment, the bank server 110 may be a computing system associated with the financial entity 102 and configured to perform a plurality of predefined functionalities. Additionally, the bank server 110 may be configured to store customer data 108 associated with a plurality of customers associated with the financial entity 102. As an example, the customer data 108 may include, without limiting to, data related to customers, one or more financial services associated with the customers, current status of the financial services such as loan lent, loan repaid, loan pending for repaying, one or more transactions associated with cards of the customers and the like.

[0023] The communication network 114 may be a wired network such as a LAN, WAN or MAN or a wireless network such as Wi-Fi, mobile communication network or any other type of network that is configured to facilitate communication between the asset quality management system 112 and the bank server 110.

[0024] In an embodiment, the system 112, may provide services to the bank server 110 to determine if a customer, such as a customer 104, is likely to fall under the provisions of IFRS 9 and to enable early collection management from the customer 104. The pre-delinquency module 116 of the system 112 detects one or more accounts of the financial entity 102 that are likely to fall under 0 “Days Past Due” (DPD) at the point of observation and predict one or more accounts that are likely to roll forward to 30+ DPD in next 3 months. The DPD indicates a number of days that have passed since the expected payment is overdue. The sloppy payer detection module 118 of the system 112 predicts one or more 1-29 DPD accounts of the financial entity 102 that are likely to be cured and roll back to 0 DPD in the next 3 months of a performance window. Any account 105 may roll back to 0DPD if the customer 104 is able to pay back the overdue amount plus charges incurred. The operation of the pre-delinquency module 116 and sloppy payer detection module 118 are explained in detail with the help of Figs. 2 and 3.

[0025] **Fig. 2** illustrates a block diagram of the system 112 of Figure 1 according to embodiments consistent with the present disclosure.

[0026] In an embodiment, the system 112 comprises at least a processor 202, a memory 204 and one or more modules 206. The modules 206 may include the pre-delinquency module 116 and the sloppy payer detection module 118. The memory 204 may at least include one or more data required for training, testing and validating one or more machine learning (ML) models implemented by pre-delinquency module 116 and the sloppy payer detection module 118. The system 112 may store the data such as development dataset 208 and Out-Of-Time (OOT) sample dataset 210 in the memory 204. The memory 204 may also include input data 212 as input for the pre-delinquency module 116 and the sloppy payer detection module 118 and output data 214 generated by the pre-delinquency module 116 and the sloppy payer detection module 118.

[0027] In an embodiment, the pre-delinquency module 116 detects one or more accounts that may be categorized as 0 DPD accounts at the point of observation and predict one or more such accounts that may likely to roll forward to more than 30 DPD, referred hereinafter as, 30+ DPD in the performance window. The pre-delinquency module 116 may implement a trained ML model 216, such as an eXtreme Gradient Boost (XGBoost) algorithm, to detect 0 DPD accounts and 30+DPD accounts. For the sake of brevity, the operation of the pre-delinquency module 116 may be explained with the help of the account 105 of the customer 104. However, the operation of the pre-delinquency module 116 may be applicable to a plurality of accounts associated with any financial entity in the manner disclosed herein.

[0028] The pre-delinquency module 116 may create a development dataset for training and testing the ML model 216. The pre-delinquency module 116 may store the created development dataset in the memory 204 as development dataset 208. In an embodiment, the development dataset 208 includes account data of a plurality of accounts associated with a plurality of customers for at least one full year to account for any seasonality effect. For example, development snapshot months to create the development dataset 208 may be December 2020, March 2021, June 2021, and September 2021. In an embodiment, the pre-delinquency module 116 may derive various parameters or features from the account data of the plurality of accounts. The parameters or features define customer's behavior on attributes such as delinquency, past due, utilization, cash balance, transaction, payment profile, cash advance, balance, payment, overlimit and the like.

[0029] In an embodiment, each of the attributes mentioned above may define various aspects of the customer's spending or repaying behavior. Delinquency features indicate customer's delinquency behavior based on delinquency bucket, such as worst delinquency hit in last 12 months. Past due features indicate customer's behavior in terms of past due amount to measure past due severity, e.g., proportion of months with past due amount greater than $ 500 or any other predefined threshold. Utilization features indicate outstanding balance to limit ratio, such as highest ratio in last 12 months. Cash balance features are derived from balance of cash advance, such as number of increases in cash balance over last 12 months. Transaction features indicate transaction data, such as spend volume in terms of number of increases in total spend volume in last 3 months.

[0030] In an embodiment, the payment profile indicates the account's transaction category, such as transactor or revolver. Cash advance features indicate cash advance activity, e.g., number of months since last cash advance transaction. Balance features enable tracking trend of outstanding balance over time, such as number of times the balance increased in last 3 months. Payment features indicate customers' payment ratio, such as minimum payment to balance ratio in last 3 months. Overlimit features indicate overlimit events, such as proportion of months with overlimit in last 6 months.

[0031] In an embodiment, the pre-delinquency module 116 may derive the one or more features indicating the attributes for a number of accounts labeled as "good" and another number of accounts labeled as "bad". Good accounts indicate that the accounts did not roll forward to 30+ DPD. Bad accounts indicate that the accounts rolled forward to 30+DPD and with a balance of more than a threshold amount, such as $ 100.

[0032] In an embodiment, the pre-delinquency module 116 may apply random under-sampling to one or more accounts labeled as "Good" in development dataset 208 to balance ratio between "Good" accounts and "Bad" accounts as original population of "Good" accounts is significantly higher than that of "Bad" accounts, which will lead to insufficient model learning on the "Bad" accounts. Another reason to under-sample the "Good" accounts is to enhance model efficiency by reducing data volume from the "Good" accounts samples. The pre-delinquency module 116 may further split the development dataset 208 into train and test samples with a ratio of 70:30 using stratified random sampling for modelling. The pre-delinquency module 116 may apply weight adjustment factor of 10 to “Good” accounts dataset for analysis.

[0033] The pre-delinquency module 116 may create a first Out-Of-Time (OOT) sample dataset using more recent snapshot months to validate model performance. For example, first OOT snapshot months are November 2021, December 2021 and January 2022, while the development snapshot months are December 2020, March 2021, June 2021, and September 2021. The pre-delinquency module 116 may also create a second OOT sample dataset using the most recent snapshot months, which do not have performance data available to generate the Good/Bad labels to validate model performance. Hence, the pre-delinquency module 116 designs the second OOT sample dataset for stability tests only. For example, snapshot months of the second OOT sample dataset are February 2022, March 2022 and April 2022.

[0034] The pre-delinquency module 116 trains the ML model 216 by providing values of the one or more feature derived from the account data of a plurality of accounts, categorized as the training dataset, as input to the ML model 216. Further, the pre-delinquency module 116 trains the ML model 216 by providing learning to the ML model 216 in terms of labeled outputs, which include “Good” or “Bad” labels for each account. The ML model 216, upon execution of each sample of the training dataset, adapts and enhances to efficiently categorize the accounts as good or bad.

[0035] In an embodiment, the pre-delinquency module 116 may validate the ML model 216 using one or more metrics such as variable importance, Kolmogorov-Smirnov (KS) statistic, a Gini coefficient, risk rank ordering, Population Stability Index (PSI) and characteristics stability index (CSI). The pre-delinquency module 116 may validate the ML model 216 based on the development sample, the first and the second OOT samples and determine important metrics. Gain is a metric used in evaluating the features importance in the ML model 216. The relative contribution of a feature to the ML model 216 is calculated by taking the model’s gain value as a ratio of the total gain across all the features in the ML model 216. A higher value of this metric, when compared to another feature implies that it is more important for generating a prediction. For example, as shown in Fig. 3a, delinquency related features have the most contribution in determining if an account is good or bad. Further, the pre-delinquency module

116 may evaluate a variable trend analysis for each variable representing the attributes and an effect of each variable on detecting “Bad” accounts.

[0036] KS statistic is a non-parametric measure to determine whether two underlying distributions differ by comparing their cumulative distributions. A KS value of 30% or more is preferred as a standalone threshold. The pre-delinquency module 116 may validate the ML model 216 by calculating KS statistic for the ML model 216. In an embodiment, the pre-delinquency module 116 may validate the ML model 216 by evaluating the Gini coefficient. The Gini coefficient is a trade-off curve that plots the proportion of “Bads” (y-axis) that is cumulatively increased by the proportion of “Goods” (x-axis). This curve shows how many “Bads” are captured by the ML model 216 at the low score end of the distribution for a given number of “Goods”. Gini is the ratio of area between trade-off curve and a diagonal line to the area above the diagonal line. Gini of 40% or more is preferred as a standalone threshold.

[0037] In an embodiment, the pre-delinquency module 116 may validate the ML model 216 using the PSI. The PSI measures changes in proportion of accounts in each score range in current population compared to those in baseline sample. It detects a degree of shift in the overall population distribution over time. PSI of <10% indicates stable distribution while PSI between 10% and 25% indicates some degrees of shift in distribution. Significant shift in distribution is concluded when PSI>25% that requires next course of action in the use of the ML model 216. In an embodiment, the pre-delinquency module 116 may validate the ML model 216 by evaluating the PSI with training, testing, and OOT sample datasets. In one example, the ML model 216 is stable with a PSI less than 10% across test and OOT sample datasets.

[0038] In an embodiment, the pre-delinquency module 116 may validate the ML model 216 using the CSI. The CSI measures the stability at individual feature level by comparing the feature distribution between the current period and baseline sample. The same benchmarking threshold considered for PSI applies to CSI as well. In another embodiment, the pre-delinquency module 116 may validate the ML model 216 by evaluating a CSI for each variable with training, testing, and OOT sample datasets. In one example, the features of the ML model 216 are stable with CSI less than 10% across test and OOT sample datasets. Thus, the pre-delinquency module 116 may train and validate the ML model 216 to evaluate a performance of an account in real time.

[0039] In an embodiment, the pre-delinquency module 116 receives observation data of the account 105 as input from the bank server 110 and may categorize the account 105 as good, indeterminate or bad using the trained ML model 216. The pre-delinquency module 116 may receive the observation data of the account 105 from the bank server 110 and may store in the memory 204 as input data 212. The observation data may include, but not limited to, one or more data of the account 105 associated with past 12 months of time, also known as the observation window. Further, observation data associated with the most recent month of the observation window is known as a point of observation as referred in hereafter. The one or more data may include, but not limited to, month-end billing details, liability accounts data, transactions data, cross product performance, credit card details. The pre-delinquency module 116 may further evaluate a performance or a roll-rate analysis of each account in the next 3 months, also known as the performance window. Roll-rate analysis indicates a probability of an account rolling forward in terms of DPD.

[0040] In one embodiment, the trained ML model 216 may derive a list of features for the account 105 based on the one or more data received. The features are categorized into attributes as described earlier during validation of the ML model 216. For example, the attributes may include, but not limited to, ratios over time, crossed features characteristics, event count, normalization, trends, recency/lagging of the account. In one example, the features include a ratio between balance in the last one month and an average balance in the past 6 months, payment made in the last 3 months as percentage balance in the last 2-4 months, number of times delinquency for more than 20 days in the last 3 months, percentage of cash credit from total credit products (active), number of consecutive increases in balance and time since last credit product open or close. Further, in an embodiment, the trained ML model 216 prioritizes a number of features among the list of features based on experience in collection modelling, considering equipment constraints during the development.

[0041] In another embodiment, the trained ML model 216 may receive a number of features grouped into the plurality of attributes. In one embodiment, the plurality of attributes also include, but not limited to, vintage, as input. Each metric is further quantified in terms of the various attributes. In an embodiment, vintage may be quantified in terms of count of months/years since open date, such as quantifying a length of relationship for each and all cards associated with a plurality of accounts. In an embodiment, delinquency profile may be quantified in terms of severity, such as maximum delinquency in last 3/6/12 months, frequency of occurrence such as number of months hitting 1/30/60+ in last 3/6/12 months, recency such as months since last 30/60/90+ delinquent and normalization such as proportion of months delinquent in last 3/6/12 months.

[0042] In an embodiment, utilization may be quantified in terms of severity such as maximum utilization in last 3/6/12 months, velocity such as number of increases in utilization in last 3/6/12 months, and normalization such as proportion of months overlimit in last 3/6/12 months. In an embodiment, payment profile may be quantified in terms of crossed variable such as average payment to previous cycle's balance in last 3/6/12 months, normalization such as proportion of months with payment when previous cycle's balance >0 in last 3/6/12 months, account details such as transactor or revolver at month end and whether the account has changed from transactor to revolver in last 3/6/12. In an embodiment, balance may be quantified in terms of recency. such as months since last balance >0, ratio, such as average balance in recent x months as percentage of average balance in recent y months (e.g. last 3 months vs last 12 months), velocity, such as number of increases in balance over the last 3/6/12 months and normalization, such as percentage of months balance>0 in the last 3/6/12 months.

[0043] In an embodiment, cash balance may be quantified in terms of recency such as number of months since cash balance>0, trend such as number of increases in cash balance over the last 3 months, normalization such as percentage of months cash balance>0 in the last 3/6/12 months, crossed cash balance such as max ratio of cash balance to credit limit in the last 1/3/6/12 months. In an embodiment, the cash advance may be quantified in terms of normalization such as percentage of months cash advance>0 in the last 3/6/12 months and past due in terms of normalization such as percentage of months past due amount>0 /500 in the last 3/6/12 months.

[0044] The trained ML model 216 processes the features for the account 105 to determine a DPD of the account 105 based on learning from the training datasets. In an embodiment, the trained ML model 216 may categorize the account 105 as "good" if the DPD is more than 0 and less than 29. The ML model 216 may categorize the account 105 as "bad" if DPD is more than 30 and a balance in the account 105 is greater than a threshold amount. In one example, the threshold amount is $100. The trained ML model 216 may categorize the account 105 as "indeterminate" if the DPD is more than 30 and the balance in the account 105 is less than or same as the threshold amount. The trained ML model 216 may categorize each of the plurality of accounts associated with the financial entity 102 as “good”, “bad” or “indeterminate”. In one embodiment, the pre-delinquency module 116 may exclude the accounts that are classified as “indeterminate” from modelling to minimize Good/Bad misclassification. Further, in an embodiment, an immaterial balance analysis is performed to analyze and evaluate the “indeterminate” accounts to categorize as “good” or “bad”. The trained ML model 216 may further determine an “at risk bad rate” that is defined by a ratio of a number of bad accounts to a number of sum of “bad” and “good” accounts.

[0045] The pre-delinquency module 116 may determine one or more accounts that are 0 DPD at observation and thus, reduces number of accounts that roll forward to 30+ DPD. Thereby, the pre-delinquency module 116 also reduces “at risk bad rate” in the coming three months. Further, the pre-delinquency module 116 also performs a roll rate analysis for each account.

[0046] Fig. 3b illustrates an example of roll rate analysis performed using the trained ML model 216. In this example, the pre-delinquency module 116 performs the roll rate analysis at T=0 DPD for performance window of T=1 month to 3 months DPD. Further, at most, 95.2%, of the accounts in T=1 to 3 window are 0 DPD accounts. Of these, 96.3 % stayed in 0 DPD and 3.3% moved to 1-29 DPD in T=4 to 6 window. Further, a majority 61.1% of 1-29 DPD accounts have self-cured in T=4 to 6 window and moved to 0 DPD, while 32% of accounts stayed in 1-29 DPD in T=4 to 6 window. However, approximately 6.6 % of accounts rolled forward from 1-29 DPD to 30-59 DPD or 60-89 DPD in T=4 to 6 window. Further, a significant share of 30-59 DPD and 60-59 DPD accounts in T=1 to 3 window have still stayed or rolled forward to 30-59 DPD and 60-59 DPD in T=4 to 6 window, as highlighted in bright red in Fig. 3b. Thus, the pre-delinquency module 116 enables a financial entity to estimate how many accounts may roll forward to 30+DPD and facilitates in early collection management for such accounts.

[0047] In an embodiment, the sloppy payer detection module 118 detects one or more accounts that may be categorized as 1-29 DPD accounts at the point of observation and predict one or more such accounts that may likely be self-cured back to 0 DPD. The sloppy payer detection module 118 may implement a trained machine learning (ML) model 218, such as eXtreme Gradient Boost (XGBoost) algorithm to detect 1-29 DPD accounts at the point of observation that may be self cured to 0 DPD accounts in the performance window. For the sake of brevity, the operation of the sloppy payer detection module 118 may be explained with the help of the account 105 of the customer 104. However, the operation of the sloppy payer detection module 118 may be applicable to a plurality of accounts associated with any financial entity in the manner disclosed herein.

[0048] The sloppy payer detection module 118 may create a development dataset for training and testing the ML model 218. The sloppy payer detection module 118 may store the created development dataset in the memory 204 as development dataset 208. In an embodiment, the development dataset 208 includes account data of a plurality of accounts associated with a plurality of customers for at least one full year to account for any seasonality effect. For example, development snapshot months to create the development dataset 208 may be December 2020, March 2021, June 2021, and September 2021. In an embodiment, the sloppy payer detection module 118 may derive various features from the account data of the plurality of accounts. The parameters or features define customer's behavior on attributes such as delinquency, past due, utilization, cash balance, transaction, payment profile, cash advance, balance, payment, overlimit and the like. The features corresponding to the attributes are same as those described earlier for the pre-delinquency module 116 and stored as features data 212.

[0049] In an embodiment, the sloppy payer detection module 118 may derive the one or more features indicating the attributes for a number of accounts labeled as “good” and another number of accounts labeled as “bad”. Good accounts indicate that the accounts with 0 DPD. Bad accounts indicate that the accounts rolled forward to 1+DPD and with a balance of more than a threshold amount such as $ 100.

[0050] In an embodiment, the sloppy payer detection module 118 may consider accounts data including 50% of accounts labeled as “Good” and 50% of accounts labeled as “Bad”. The sloppy payer detection module 118 may further split the development dataset 208 into train and test samples with a ratio of 70:30 using stratified random sampling for modelling. The sloppy payer detection module 118 may apply weight adjustment factor of 10 to “Good” accounts dataset for analysis.

[0051] The sloppy payer detection module 118 may create a first Out-Of-Time (OOT) sample dataset using more recent snapshot months to validate model performance. For example, first OOT snapshot months are November 2021, December 2021 and January 2022, while the development snapshot months are December 2020, March 2021, June 2021, and September 2021. The sloppy payer detection module 118 may also create a second OOT sample dataset using the most recent snapshot months which do not have performance data available to generate the Good/Bad labels to validate model performance. Hence, the sloppy payer detection module 118 designs the second OOT sample dataset for stability tests only. For example, snapshot months of the second OOT sample dataset are February 2022, March 2022 and April 2022.

[0052] The sloppy payer detection module 118 trains the ML model 218 by providing the one or more feature values derived from account data of a plurality of accounts, categorized as the training dataset, as input to the ML model 218. Further, the sloppy payer detection module 118 trains the ML model 218 by providing learning to the ML model 218 in terms of labeled outputs, here, Good or bad accounts for each account. The ML model 218 upon execution of each sample of the training dataset adapts and enhances to efficiently categorize the accounts as “good” or “bad”.

[0053] In an embodiment, the sloppy payer detection module 118 may validate the trained ML model 218 using one or more metrics such as variable importance, Kolmogorov-Smirnov (KS) statistic, a Gini coefficient, risk rank ordering, Population Stability Index (PSI) and characteristics stability index (CSI). For example, as shown in Fig. 4a, delinquency related features have the most contribution in determining if an account is good or bad. Further, the sloppy payer detection module 118 may evaluate a variable trend analysis for each variable representing the attributes and an effect of each variable on detecting “Bad” accounts.

[0054] In an embodiment, the sloppy payer detection module 118 receives observation data of the account 105 as input from the bank server 110 and may categorize the account 105 as "good, indeterminate or bad using the validated ML model 218. The sloppy payer detection module 118 may determine if an account has a 1-29 DPD and never 60+ DPD in the last 6 months. The sloppy payer detection module 118 may receive the observation data of the account 105 from the bank server 110 and may store in the memory 204 as input data 212. The observation data may include, but not limited to, one or more data of the account 105 associated with the observation window particularly at the point of observation. The one or more data may include, but not limited to, month-end billing details, liability accounts data, transactions data, cross product performance, credit card details. The sloppy payer detection module 118 may further evaluate a performance or a roll-rate analysis of each account in the performance window.

[0055] In one embodiment, the validated ML model 218 may derive a list of features for the account 105 based on the one or more data received. The features are categorized into attributes as described earlier during validation of the validated ML model 218. For example, the attributes include, but not limited to, ratios over time, crossed features characteristics, event count, normalization, trends, recency/lagging of the account. In another embodiment, the validated ML model 218 may receive a number of features grouped into the plurality of attributes as described earlier in the description of the pre-delinquency module 116.

[0056] The validated ML model 218 processes the features for the account 105 may determine a DPD of the account 105 based on learning from the training datasets. In an embodiment, the validated ML model 218 may categorize the account 105 as “good” if the DPD is 0. The Trained ML model 218 may categorize the account 105 as “bad” if DPD is more than 1 and a balance in the account 105 is greater than a threshold amount. In one example, the threshold amount is $100. The validated ML model 218 may categorize the account 105 as “indeterminate” if the DPD is more than 1 and the balance in the account 105 is less than or same as the threshold, for example, $100. The validated ML model 218 may categorize each of the plurality of accounts associated with the financial entity 102 as “good”, “bad” or “indeterminate”. In one embodiment, the sloppy payer detection module 118 may exclude the accounts that are classified as “indeterminate” from modelling to minimize Good/Bad misclassification. Further, in an embodiment, an immaterial balance analysis is performed to analyze and evaluate the “indeterminate” accounts to categorize as “good” or “bad”. In other embodiment, the validated ML model 218 may categorize the account 105 is “good” if the DPD is 0 in 3 months performance window and “bad” if the DPD is 1+ in 3 months performance window. The validated ML model 218 may further determine a “delinquency rate” that is defined by a ratio of a number of “bad” accounts to a total number of “bad” and “good” accounts.

[0057] Thus, the sloppy payer detection module 118 may determine one or more accounts that are 1-29 DPD at observation to predict which account is likely to cure in the performance window and thus, differentiates the potential self-cure accounts versus the remaining accounts. Further, the sloppy payer detection module 118 also performs a roll rate analysis for each account. Fig. 4b illustrates an example of roll rate analysis performed using the validated ML model 218. In this example, the sloppy payer detection module 118 performs the roll rate analysis at T=0, for the accounts that are 1-29 DPD and never 60+ DPD in the past 6 months for performance window of T=1 month to 3-month DPD. As illustrated in Fig. 4b, a significant share of 49.6% in T=1 to 3 window are 0 DPD accounts. Of these, 74.1% stayed in 0 DPD, while 23.9% moved to 1-29 DPD and 1.3 % moved to 30-59 DPD in T=4 to 6 window. Further, only 37.4% of 1-29 DPD accounts have self-cured in T=4 to 6 window and moved to 0 DPD, while majority, 56% stayed in 1-29 DPD in T=4 to 6 window. However, approximately 6.6% of accounts rolled forward from 1-29 DPD to 30-59 DPD or 60-89 DPD in T=4 to 6 window. Further, significant share of 30-59 DPD and 60-59 DPD accounts in T=1 to 3 window have still stayed or rolled forward to 30-59 DPD and 60-59 DPD in T=4 to 6 window, as highlighted in bright red in Fig. 4b. Thus, the sloppy payer detection module 118 enables a financial entity to estimate how many accounts may roll forward or stay at 1+ DPD and facilitates in early collection management for such accounts.

[0058] Thus, the system 112 provides an augmented framework that includes the pre-delinquency module 116 and the sloppy payer detection module 118, which provide additional and advance opinion to the financial entities to reduce accounts being transitioned to lifetime probability of default or completely defaulting and early detection of such accounts. The pre-delinquency module 116 allows early identification of potential delinquent accounts to commence preventive measures against delinquency in advance. The sloppy payer module 118 helps in differentiating accounts that are likely to be self-cured to prioritize collection practices on high-risk accounts. The system 112 further identifies small pockets of accounts with significantly higher or lower than expected risk of existing risk segmentation. Thus, the system 112 predicts risk more accurately so that the financial entity can apply more accurate / effective collection action to reduce transition of accounts from stage 1 to stage 2 of IFRS9 standards, which indirectly lowers the IFRS9 provision impact.

[0059] Further, the ML model 216 of the pre-delinquency module 116 and the ML model 218 of the sloppy payer detection module 118 provide significant lift in discrimination along with stability in validation samples. These models are formed by a wide variety of data sources including credit card transaction data, which can complement the existing Behavior Score and Risk Grades. These models were trained using XGBoost modelling technique to optimize model accuracy and uncover the predictability potential of the internal performance data using deep learning algorithm. These models were designed to work on top of the existing Behavior Scorecards and Collection Strategies.

[0060] In an embodiment, one or more computer-readable storage media may be utilized in implementing embodiments consistent with the present disclosure. A computer-readable storage medium refers to any type of physical memory on which information or data readable by a processor may be stored. Thus, a computer-readable storage medium may store instructions for execution by one or more processors, including instructions for causing the processor(s) to perform steps or stages consistent with the embodiments described herein. A non-transitory computer readable medium may include media such as magnetic storage medium, optical storage, volatile and non-volatile memory devices etc. Further, non-transitory computer-readable media may include all computer-readable media except for a transitory. The code implementing the described operations may further be implemented in hardware logic (e.g., an integrated circuit chip, Programmable Gate Array (PGA), Application Specific Integrated Circuit (ASIC), etc.).

[0061] The described operations may be implemented as a method, system or article of manufacture using standard programming and/or engineering techniques to produce software, firmware, hardware, or any combination thereof. The described operations may be implemented as code maintained in a “non-transitory computer readable medium”, where a processor may read and execute the code from the computer readable medium. The processor is at least one of a microprocessor and a processor capable of processing and executing the queries.

[0062] The illustrated steps are set out to explain the exemplary embodiments shown, and it should be anticipated that ongoing technological development will change the manner in which particular functions are performed. These examples are presented herein for purposes of illustration, and not limitation. Further, the boundaries of the functional building steps have been arbitrarily defined herein for the convenience of the description. Alternative boundaries can be defined so long as the specified functions and relationships thereof are appropriately performed. Alternatives (including equivalents, extensions, variations, deviations, etc., of those described herein) will be apparent to persons skilled in the relevant art(s) based on the teachings contained herein. Such alternatives fall within the scope and spirit of the disclosed embodiments. Also, the words "comprising," "having," "containing," and "including," and other similar forms are intended to be equivalent in meaning and be open ended in that an item or items following any one of these words is not meant to be an exhaustive listing of such item or items or meant to be limited to only the listed item or items. It must also be noted that as used herein, the singular forms “a,” “an,” and “the” include plural references unless the context clearly dictates otherwise.

[0063] Finally, the language used in the specification has been principally selected for readability and instructional purposes, and it may not have been selected to delineate or circumscribe the inventive subject matter. Accordingly, the disclosure of the embodiments of the disclosure is intended to be illustrative, but not limiting, of the scope of the disclosure.

[0064] With respect to the use of substantially any plural and/or singular terms herein, those having skill in the art can translate from the plural to the singular and/or from the singular to the plural as is appropriate to the context and/or application. The various singular/plural permutations may be expressly set forth herein for sake of clarity.

"METHOD AND SYSTEM FOR ASSET QUALITY MANAGEMENT"

ABSTRACT

The present disclosure relates to a method and system for asset quality management by a financial entity. The system includes a pre-delinquency module and a sloppy payer detection module for efficient management of assets. The pre-delinquency module detects a number of 0 DPD accounts at a point of observation that may roll forward to 30+ DPD accounts in performance window using a validated ML model. The sloppy payer detection module detects a number of 1-29 DPD accounts at the point of observation that may be cured to 0 DPD accounts in performance window. Further, the pre-delinquency module evaluates an "At risk" bad rate while the sloppy payer detection module evaluates a delinquency rate that is further used to prioritize early collection process for the most risky accounts accordingly.

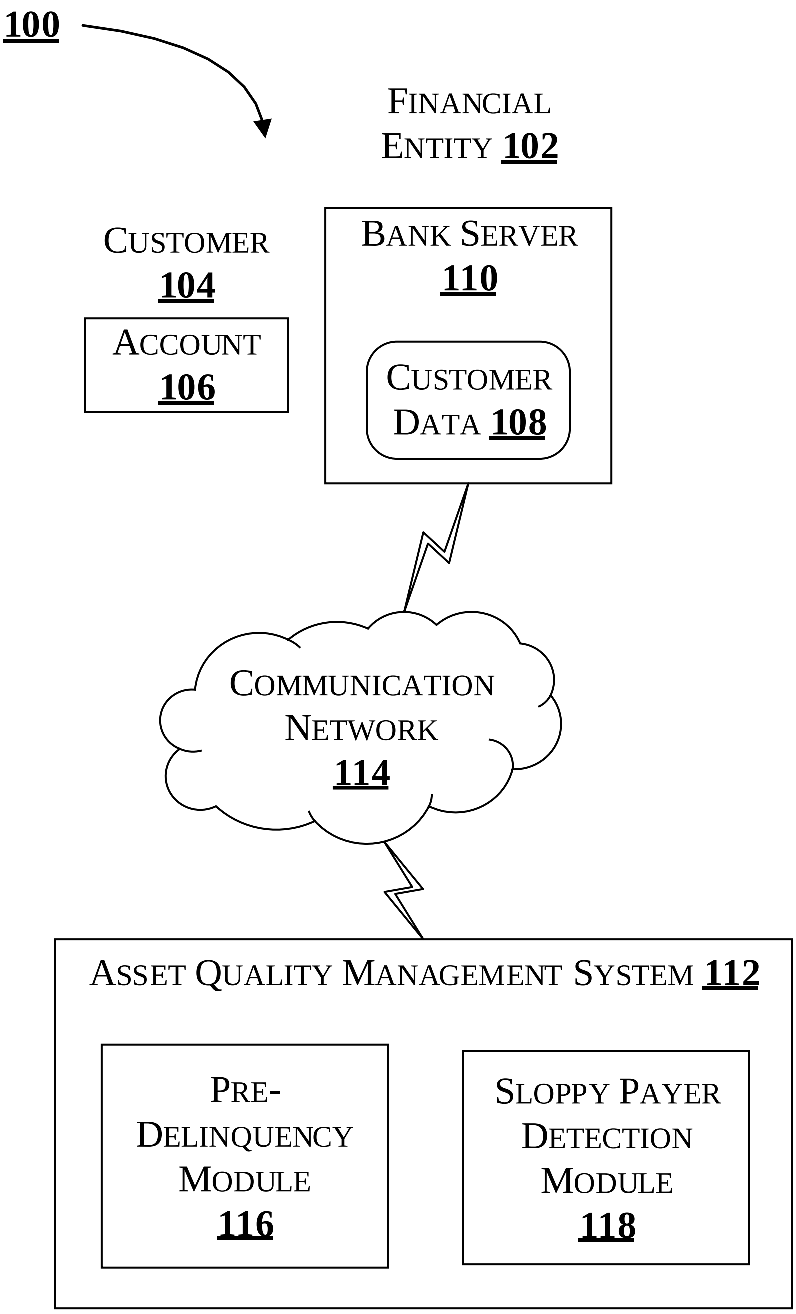

100
FINANCIAL ENTITY 102
CUSTOMER 104
ACCOUNT 106
BANK SERVER 110
CUSTOMER DATA 108
COMMUNICATION NETWORK 114
ASSET QUALITY MANAGEMENT SYSTEM 112
PRE-DELINQUENCY MODULE 116
SLOPPY PAYER DETECTION MODULE 118

Fig. 1

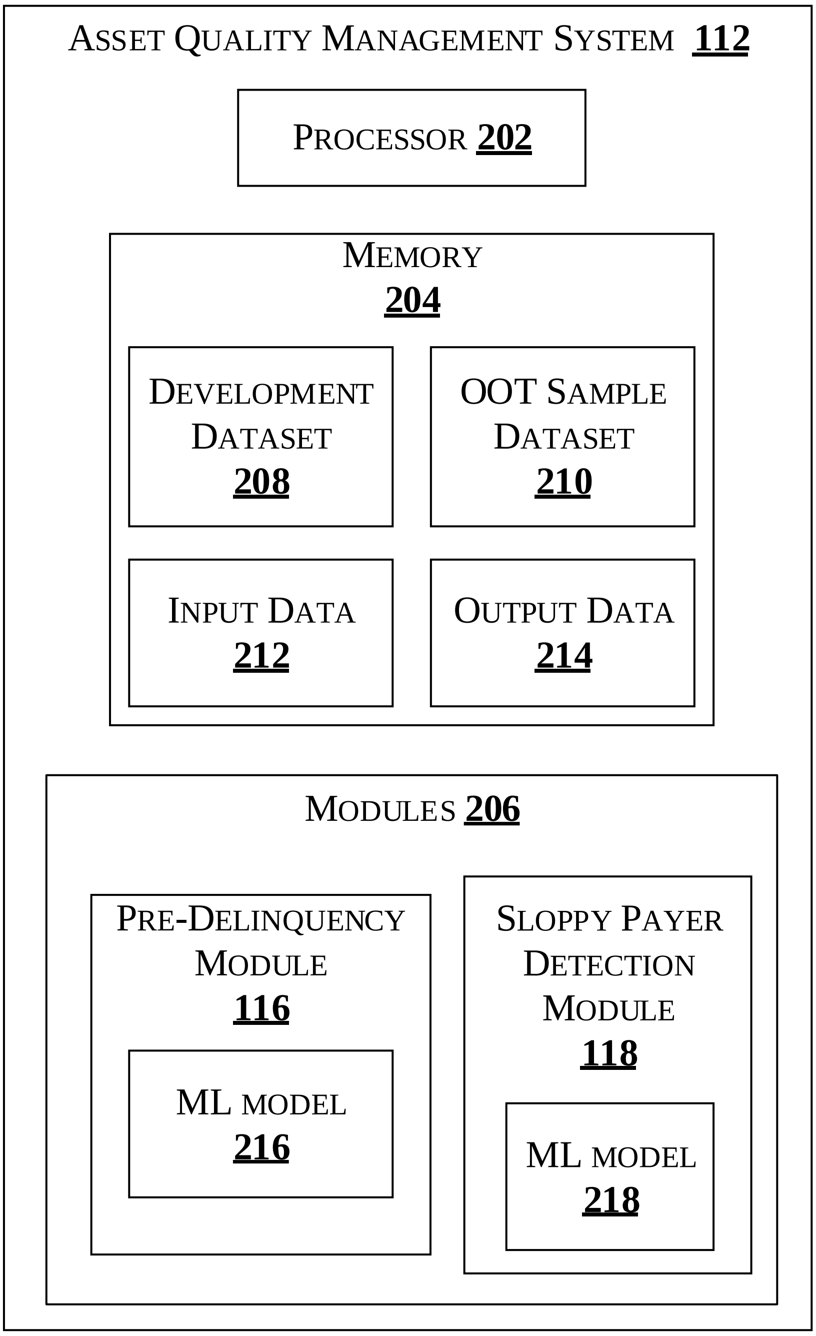

ASSET QUALITY MANAGEMENT SYSTEM 112
PROCESSOR 202
MEMORY 204
DEVELOPMENT DATASET 208
OOT SAMPLE DATASET 210
INPUT DATA 212
OUTPUT DATA 214
MODULES 206
PRE-DELINQUENCY MODULE 116
ML MODEL 216
SLOPPY PAYER DETECTION MODULE 118
ML MODEL 218

Fig. 2

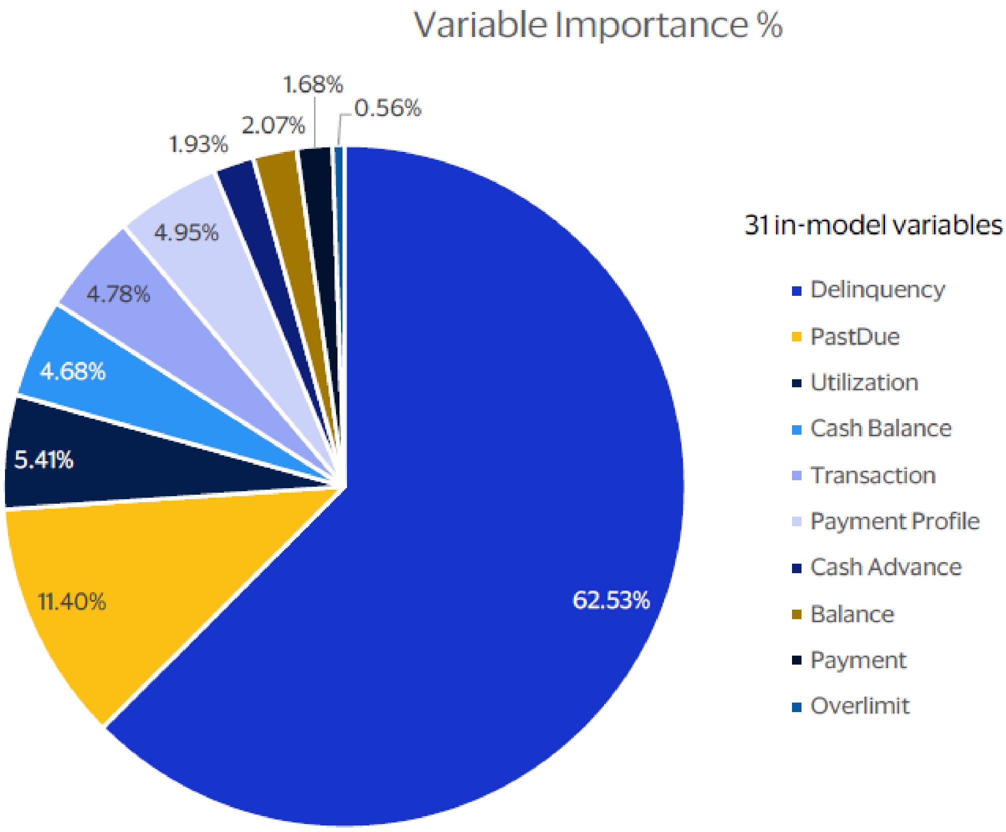
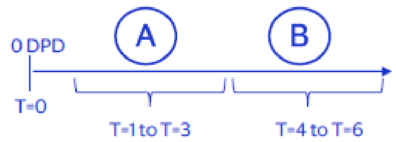


Fig. 3a



Roll Rate of Accounts in 0 DPD at reporting month (T=0)

Worst Status @ T=1 to 3	%Total	Worst Status @ T=4 to 6						
		Closed Good	0 DPD	1-29 DPD	30-59 DPD	60-89 DPD	90-119 DPD	Severe[3]
0 DPD	95.2%	0.2%	96.3%	3.3%	0.2%	0.0%	0.0%	0.0%
1-29 DPD	4.5%	0.3%	61.1%	32.0%	4.8%	1.8%	0.0%	0.0%
30-59 DPD	0.3%	2.1%	37.3%	22.3%	11.6%	26.6%	0.0%	0.0%
60-89 DPD	0.0%	21.5%	43.6%	19.2%	9.9%	5.7%	0.0%	0.0%

Low improvement rate after bucket 0 accounts rolled forward to 30+DPD

Some continued to roll forward after accounts rolled from 0 DPD to 1-29 DPD

Majority self-cured or stayed as 1-29 DPD after accounts rolled from 0 DPD to 1-29 DPD

Fig. 3b

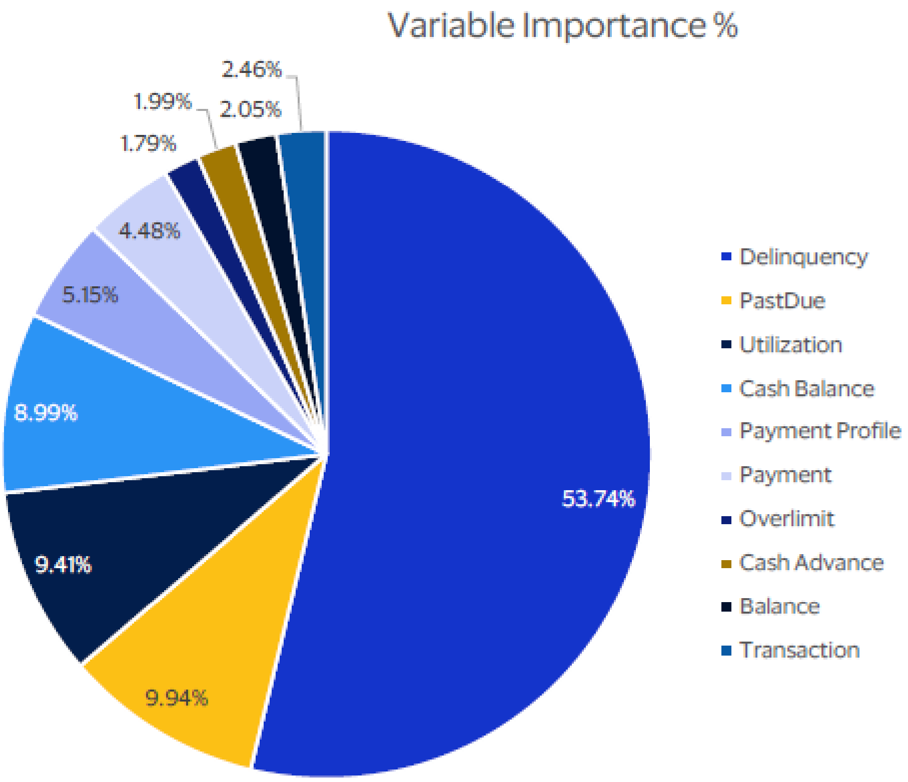
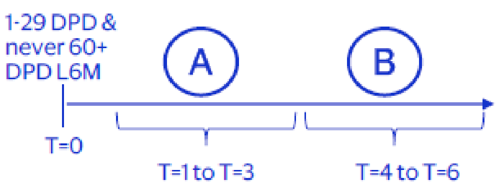


Fig. 4a



Roll Rate of Accounts in 1-29 DPD at reporting month (T=0) but never hit 60+ DPD in last 6 months

Worst Status @ T=1 to 3	%Total	Worst Status @ T=4 to 6					
		Closed Good	0 DPD	1-29 DPD	30-59 DPD	60-89 DPD	Severe[3]
0 DPD	49.6%	0.5%	74.1%	23.9%	1.3%	0.2%	0.0%
1-29 DPD	41.5%	0.1%	37.4%	56.0%	5.3%	1.2%	0.0%
30-59 DPD	7.2%	2.0%	42.2%	30.2%	13.8%	11.8%	0.0%
60-89 DPD	1.7%	20.4%	44.1%	17.1%	9.4%	8.9%	0.1%

A B

1-29 DPD accounts rolled forward to 30+ DPD have high roll forward rate and they are not sloppy payer

Only 37.4% self-cured to 0 DPD and majority remained as 1-29 DPD

Majority self-cured with some still stayed as 1-29 DPD

Fig. 4b