Article

Attrition Rate Prediction using a Frequency-Recency-Monetization-based SMOTEEN-Boosted Approach

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Abstract: Businesses today seek to generate more revenue for their products and services. However, attrition or churn for products and services over the digital market space has continued to plague businesses to proffer consumers with various alternates and choices to services and products for competitive money's worth. Today's businesses must thus, seek to yield better value while meeting consumer needs cum demands through a retention strategy. Thus, our study utilizes the recency-frequency-monetization as retention model that explores SMOTEEN-based AdaBoost ensemble to study the impact of imbalanced dataset to identify consumer churn. With chi-square feature selection, our proposed model yields F1 0.9819, Accuracy 0.9882, Recall 0.9848, Precision 0.9886, and Specificity 0.9824 respectively with 9632-correctly identified and 15-incorrectly classified cases. Conversely, other scheme yields ranges of F1 [0.6305–0.8875], Accuracy [0.6432-0.8879], Precision [0.6320–0.8805], Recall [0.6128-0.8876] and Specificity [06370-0.8894] respectively. This shows that model yields enhanced performance, and that the explored RFM-retention strategy was found to curb churn and improve monetization.

Keywords: Consumer Attrition, Consumer retention, monetization, purchase frequency, recency

1. Introduction

Today's business use digital channels as exploration frontiers, with platforms connectivity that render services to users [1] vis-a-vis meet the daily processing needs [2] of its many users. It advances a market-place for assets exchange or online shops [3]. An online shop allow consumers the capability to navigate the shop's site in quest of their choice products [4] – such that when/if satisfied with a search, they easily can purchase items at their convenience with relative ease and satisfied experience gained [5]. The core of a consumer's purchase is satisfaction, intent, and benefits [6]. To investigate such features – studies have advanced market basket analysis, a data mining model to identify products that can be purchased singly or co-occurrent as it uncovers relations between products that are purchased in combination [7], [8]. A market basket for a consumer, details relations between item evolution, cross-selling and product's concept drift [9]. As businesses grow with consumer loyalty

and frequency of purchase – the following may occur: (a) a product may get reviews update that will cause its manufacturers to update some features or components in the product – resulting in product evolution, and (b) an item is reviewed causing its makers to birth a similar but new item that is with(out) some feats – resulting in a new product as concept drift [10]. Thus, with products available in a range (of forms), and also associated with a variety of prices such that some products can have a range of substitute products; while, others do not [11], [12].

With a variety of products available, and at a variety range of price – businesses struggle with monetization especially if discounts are ceded to consumers from the competition [13]. Online shops provide simple, graceful interfaces that allow consumers to quickly search for products vis simple steps that places items purchased onto a cart for which payment sums up prices of all items therein the cart [14]. With purchase successful, sites maintain a databank of consumers for their future use [13]. Businesses use analyzed data to inform consumers of available new channels and products via previous consumer purchase-pattern [15] to improve purchase frequency and revenue generated [16], [17]. Monetization aims to increase revenue generated utilizing an existing consumer-base. Business achieves this via exploring hidden potentials in the customer-base by differentiating the consumer-levels within as champions, loyalist, hibernating, about-to-churn, promising, churned, etc [18], [19]. Successful strategies help increase monetization and improve frequency of consumer purchase [20], [21]. These help businesses mitigate attrition cum churn for products as well as shore up revenue as the requisite recipe for business success [22]. Today's businesses are disposed to such strategies that predict consumer behaviour to provide decision support aimed at the retention of consumers [23], [24].

Analysis of consumer purchase pattern provide users with [25]: (a) consumer's intent and benefit, (b) reasoned action for churn towards the provided product/service, (c) actions for impulse-buying to curb churn or attrition rates, (d) support business decisions for product evolution and concept drift – to meet the changing needs cum demands for consumers. Thus, consumer behaviour are captured data about consumer's purchase transaction cum history of products [26], [27]. Each transaction is unique, timestamped and recorded for each item or product. Thus, for this study – we explore: (a) recency of purchase, (b) monetization purchased, and (c) frequency of purchase – as retention strategies [28]. Recency is the last duration of purchase; Frequency is time in the last 30-days vis-à-vis number of times purchase is made; And monetization accounts for a revenue amount was spent by consumer [29], [30]. Machine Learning (ML) has poised a paradigm shift in how businesses resolve issues in churn rate [31], [32]. ML schemes can successfully identify churn patterns from composite datasets to make accurate predictions for target solutions that reduce consumer churn [33]–[35]. It comprehends data patterns that may go unnoticed, used to identify the possibility of customer attrition [36]–[40].

Study motivation and knowledge gaps includes [41]:

1. **Explored Strategies:** Previous works have utilized single strategies without recourse to retention. This study uses a fusion of recency-frequency-money (RFM) scheme as retention models to effectively categorize item-consumers based on their purchasing behaviour and exercise minor shocks that lean on purchase theories of reasoned actions and impulse buying that influence the target consumer-behaviour [42], [43].
2. **Resolve Data Imbalance:** A crucial problem with dataset is its imbalanced nature with cases of churn-rate lagging behind as minor class, or it is observed as in the major with normal transaction lags behind. We must utilize intrinsic sampling mode in our ML such that it exploits its robust power as explicitly tailored to mitigate issues in explored imbalanced dataset [44], [45].
3. **Cross-Channel Detection:** Newer models must capture intricate changes and shocks with increased adoption in multi-channel transactions as explored by online shops today over the digital platform [46]–[48]. These, must be aimed at the overall accuracy enhancement as it has now become crucial for businesses [49]–[51].

The study contributes as thus: (a) understudy previous works for variety of methods as explored in domain task to glean insight into ML schemes that will efficiently identify churn-rate data and transaction [52]–[54]. (b) construct an adaptive boosting model with transfer learning to succinctly capture predictors that adequately and properly identifies and classifies churn or attrition rates [55],

[56], and (c) exploit the SMOTE-Edited Nearest Neighbour data balancing mode after data split – to enable for an enhanced learning of parameters in both major and minor classes and enable ML to capture the imbalanced effects in the task dataset – where models genuinely learn feats associated with major-class and ignore those of the minor-class. This leads to sub-optimal performance and high misclassification [57], [58].

2. Experiments and Methods

We explore the proposed methodology as in Figure 1 [59]:

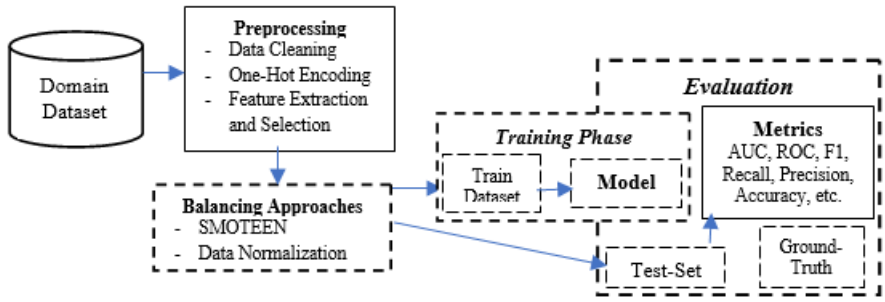


Figure 1. SMOTEEN-based Adaptive Boosting Ensemble for Churn Prediction

Step-1 – Collection: Dataset as seen in Table 1 was retrieved from [web]: datasets/gauravtopre/bank-customer-churn-dataset. It consist of churn dataset from July-August 2022 with 96,129 records [60] for 94,487 non-churners (major class) and 1,642 churner (minor class). For cross-channel – consumers were classified as in [61], [62] based on sentiment-based class grouping [63], [64].

Table 1. Dataset Description

Features	Description
consumer_id	Consumer details such as name etc
gender	Consumer gender (male or female)
age	Consumer age
consumer_address	Consumer's local bank address
consumer_country	Currency transaction is made
products_number	Transaction cart with purchase(s) made
balance_current	Check from last-to-current transaction
daily_limit	Daily amount limit consumer performs
daily_transact	Daily transactions performed
credit	Consumer bank details as account holder
transact_ave	Average transaction exchange for holder
estimated_income	Channel payment and source of income
churn	1 if transaction is True; 0 if False

Step 2 – Preprocessing actions seek to delete missing and incomplete data to improve quality of the dataset, and it also removes redundant, duplicate data to yield data integrity. With this task complete, the model then exploits the one-hot encoding technique, which converts all values from its categorical form onto its equivalent numeric form [65].

Step 3 – Feature Selection extracts first, the data points that form its input, and also determines the points that the model will identify as corresponding output. Also, its selection capability allows it to discard irrelevant predictor with no importance to the target class. This, acts as dimension reduction acts for docile feats in dataset, causing a fastened construction of the model for improved generalization [66]. For the task, we show the predictor importance as in Figure 2, leading to a selection of a total of 11-features explored. With our computed threshold yield a value of 11.506. Thus, features in color 'blue' were not chosen; Whereas, our feature importance chose feats of other colors

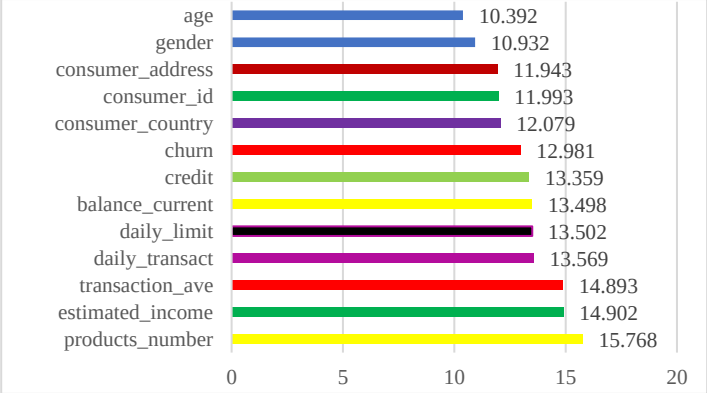


Figure 2. Feature selection plot by importance

Step-4 Dataset Split/ Balancing: The explored dataset is first split into train (75%) and test-set (25%). Afterwards, balancing redistributes data to yield an equal distribution of major-and-minor classes so the model efficiently learns captured intricate feats in dataset [67]. We use SMOTE-ENN with SMOTE (oversample) of minor-class, and Edited Nearest Neighbour (undersample) of major-class, yielding overlapped data points in both classes [68]. Figure 4 shows the SMOTE-ENN approach as applied to churn dataset [69], [70].

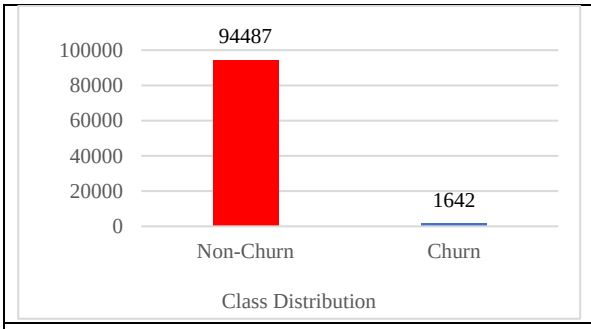


Figure 3. Original Dataset plot

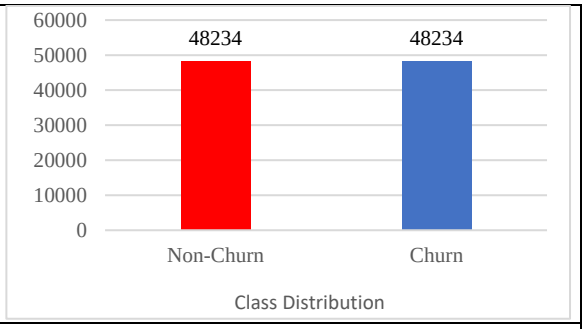


Figure 4. SMOTEEN balanced dataset

Step-5: AdaBoost Construct and Train: For this study, we use adaptive boost ensemble for ground truth. Its benefits includes: (a) is commonly explored [71], (b) it greatly reduces over-parameterization and overtraining [72], (c) results in improve generalization, and (d) assists These, assist the model to optimize the aggregated outputs and significantly minimize train-errors via out-of-fold. These, improves flexibility [73]. Our model for churn is configured as in Table 2 [74] classifies data [75] via AdaBoost – a decision tree that leans on gradient boost to fuse weak classifier to yield an optimal fit. It uses the expansion term and loss functions to control its tree complexity so that each weak learner is corrected with each move – to make Adaboost a strong learner [76]–[78] as in Equation 1. Table 2 shows hyper-parameters configurations for AdaBoost [79] with max_depth of 5, learn_rate 0.251, and n_estimators 250, respectively.

$$\hat{Y}_i^t = \sum_{k=1}^{t} f_k(x_i) = \hat{Y}_i^t + f_k(x_i) \qquad (1)$$

Table 2. AdaBoost settings with Hyper-parameter configuration

Features	Values
n_estimators	250
learning_rate	0.25
max_depth	5
random_state	25
eval_metric	[“error’, ‘logloss’]
eval_set	(x,val, y_val)
verbose	True

For enhanced performance, AdaBoost reduces its loss function $l(Y_i^t, \hat{Y}_i^t)$ as contained in the goal function using its regularization term $\Omega(f_t)$. The loss function helps reduce overtrain of the model and ensures all training data fit; while, its regularization term ensures that tree complexity is appropriately tuned to yield higher performance that is devoid of poor generalization as in Equation 2 [80], [81].

$$L^t = \sum_{i=1}^{n} l\left(Y_i^t, \hat{Y}_i^{t-1} + f_k(x_i)\right) + \Omega(f_t) \quad (2)$$

The collective knowledge of decision tree is enhanced via this iterative mode to classify intrinsic patterns captured in each transaction that results in churn (or not). Our train-data via SMOTEENN yields a blend (synthetic and original) samples that guarantees comprehensive learning for the AdaBoost with enhanced flexibility to a variety of train/test setting on dataset and partitions explored [82].

3. Results

3.1. Performance Evaluation

Table 3 shows performance evaluation metrics for the proposed model alongside benchmark models that have been successfully explored on churn.

Table 3. SMOTEEN-based AdaBoost Performance with Benchmark Models

Model	F1	Accuracy	Precision	Recall	Specificity	Confusion Matrix
Logistic Regression	0.6305	0.6423	0.6320	0.6128	0.6370	TP (36) FN (17) FP (16) TN (98)
Memetic Algorithm	0.7025	0.7181	0.7241	0.7381	0.7026	TP (77) FN (09) FP (07) TN(184)
Random Forest Model	0.8781	0.8783	0.8765	0.8790	0.8792	TP (197) FN (09) FP (21) TN(9420)
XGBoost Ensemble	0.8875	0.8879	0.8805	0.8876	0.8894	TP (198) FN (03) FP (15) TN(9430)
Our Proposed Model	0.9819	0.9882	0.9886	0.9848	0.9824	TP (201) FN (03) FP (12) TN(9431)

For the heterogeneity of dataset used, we employed chi-square feature selection so that a total of 11-predictors were used from a total of 13 features. Results shows that our proposed SMOTEEN-AdaBoost ensemble yielded best result with F1 of 0.9819, Accuracy 0.9882, Recall 0.9848, Precision 0.9886, and Specificity 0.9824 respectively as with [83], [84] to correctly identify 9632-cases with 15-incorrectly classified cases. Other schemes as in Table 3 yields the ranges of F1 [0.6305–0.8875], Accuracy [0.6432-0.8879], Precision [0.6320–0.8805], Recall [0.6128-0.8876] and Specificity [06370-0.8894] respectively. This implies that our proposed AdaBoost ensemble can effectively identify ground-truth with improved overall performance [85], [86].

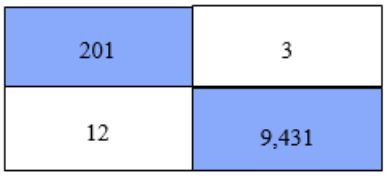


Figure 4. Confusion Matrix

4. Conclusion

Finding the balance between recall and specificity is also a crucial feat as too much emphasis on one, can ripple across the dataset – to yield a significant tradeoff for the other. In addition, Accuracy can yield the idea of a model's reliability, which may also be less insightful for imbalanced datasets

that in some cases, render distorted perceived model performance. In truth – F1 helps to assess a model's performance on criteria such as data imbalance – as it has been found to provide an altruist insight into a technique's effectiveness in classifying positive cases without the overprediction of false positives. The chaotic nature of breaches vis-à-vis noisy datasets with their many features, will continue to yield studies into the use of deep ensemble learning heuristics as the suitable mode for addressing many cyber-attacks.

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