DEVELOPMENT OF INTELLIGENT PRIORITIZATION OF ACCOUNT FRAMEWORK FOR AUDIT PROCESSING OF FOREIGN EXCHANGE RECORDS

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Abstract

Finding irregularities or detecting “not-normal” instances in a small amount of time is the main objective of an audit. This can be cumbersome if it involves a voluminous amount of data. It takes three (3) days on the average for auditors to manually produce an audit report. thus, anomalous cases take time to determine and full investigation of these cases were delayed. Also, auditors are having difficulty in prioritizing which item should come first thus it is important to have a formal framework that auditors can use to conduct the audit more efficiently. This capstone project proposed an alternative framework for intelligent prioritization of account. Statistical and machine learning techniques were used in identifying the priority level of audit of foreign exchange records. These techniques involve data decomposition using Seasonal and Trend decomposition using Loess (STL), Cubic Spline Smoothing, Automatic autoregressive integrated moving average (ARIMA), Generalized Extreme Studentized Deviate (GESD) test, unsupervised outlier detection model using Isolation Forest and Density-based spatial clustering of applications with noise (DBSCAN) and Clustering Large Applications based on RANdomized Search (CLARANS) with Recency, Frequency and Monetary (RFM) Analysis for its customer segmentation. The proposed methodology seeks to augment the existing audit process and reduce processing time in auditing monthly foreign exchange records and not necessarily replace the current audit process. Since each component investigated different aspect that influences a record, scoring of a record was done equally. While results of each component was produced independently, results were designed to be read as one output, each complementing the other. The proposed framework performed well, at 93%, with no Information Rate. Furthermore, adopting the framework supported the objective of an audit, which is to have a more holistic view of records compared to the traditional method.

Keywords Anomaly detection, foreign exchange transactions, machine learning techniques, audit report

1. INTRODUCTION

One of the recommendations during the Bank for International Settlements (BIS) All Governors meeting held last 2015 (BIS, 2018) was for central banks to focus on projects that assess how data analysis can improve the effectiveness of supervision of banks. This was stressed further in the Irving Fisher Committee (IFC) Report (2020), where it recognized that though financial innovation and digitalization transforms the financial sector, it also opened data gaps in central bank statistics. One of its recommendations for central banks is to ensure that statistical methodologies used to measure financial activities adhere to sound professional and scientific standards. Also, recognizing these data gaps, the Chief Data Officer of the United States Federal Reserve Board, in his presentation during the seventh European Central Bank (ECB) statistics conference, highlighted its increased business risk and pointed out that increased data complexities require new approaches and solutions (Casey, 2014). In response to the challenge, the Philippines, represented by the Bangko Sentral ng Pilipinas (BSP) proactively seeks to innovate its capabilities to adapt in today's rapidly changing environment.

In National Risk Assessment last 2017, the Philippines identified its overall money laundering and terrorist financing threats as high (AMLC, 2017). Monitoring subject threats are being done by the Anti-Money Laundering Council (AMLC) with the support from different agencies such as Bangko Sentral ng Pilipinas (BSP). BSP, being the central bank of the Philippines, is tasked: (i) to provide policy directions in the areas of money, banking, and credit, (ii) to supervise the operations of banks and (iii) to exercise such regulatory and examination powers over banking operations of non-bank financial institutions, money service businesses, credit granting businesses, and payment system operators.

To fulfill its mandate as a regulating body, BSP uses several systems to monitor all banking records not only within the Philippines but also all foreign records coming from and to the Philippines. One of these systems being used by BSP is the International Transaction Reporting System (ITRS). ITRS is a system that collects data from banks at the level of individual records. The ITRS measures: (i) individual cash records that pass through domestic banks and enterprise accounts that pass through foreign banks, (ii) non-cash records, and (iii) stock positions. Statistics are compiled from forms submitted by domestic banks.

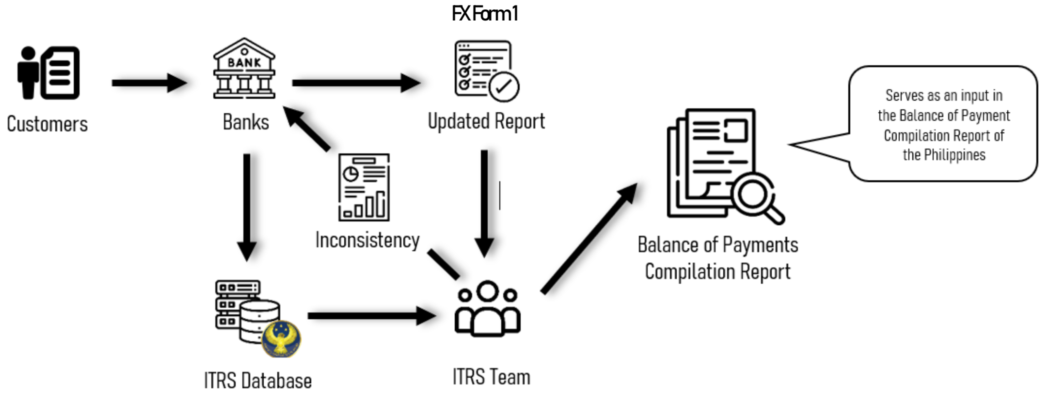

FX Form1
Customers
BANK
Banks
Updated Report
Inconsistency
Balance of Payments Compilation Report
Serves as an input in the Balance of Payment Compilation Report of the Philippines
ITRS Database
ITRS Team

Figure 1. *BSP ITRS Subgroup Process Overview*

In Figure 1, banks submit a report to central banks through an online system. Countries using ITRS among others, are Indonesia, China, Malawi, South Africa, Ghana, Ukraine, Poland, and Hungary. In the Philippines, the report being submitted by banks is called the consolidated report on Foreign Exchange Assets and Liabilities (FX Form 1). It is a report consisting of twelve (12) Schedules, with a different number of items, which varies depending on the nature of the record. For one (1) schedule for example, there are approximately sixty (60) items, which vary in number of records, that need to be monitored. Not all banks are required to submit the said report but only the Authorized Agent Banks (AABs) that has a license to service foreign exchange records. Selling and Receiving of Foreign Exchange (FX) shall be duly reported by the FX selling/remitting/receiving AABs under the appropriate schedules of FX Form 1 based on the instructions of, and declared purpose by, the FX purchaser. All rules and regulations of reporting bank are indicated in the Manual of Foreign Exchange Records (December 2020- an enhanced and complete version of BSP Circular No. 1389, as amended, as it incorporates all amendments made since 1993 and consolidates all regulations on foreign exchange and related records), available in the BSP website.

The data collected by ITRS is significant in the compilation of Balance of Payments Position (BOP) of a country in making comprehensive analysis to support policy formulation and implementation. BOP is a statistical overview that systematically summarizes the economic records of an economy with other countries of the world during a certain period. With the available data in ITRS, management wants to gain insights from it in a timely manner to be able to make informed policy decisions. Manually checking of huge amount of records causes delays in the production of ITRS report. It wastes valuable time that could have been used for other projects. In effect, the department's development is inhibited.

Currently, the auditors use a common or the classical rule-based method for monitoring each item code. Auditors check if the record exceeds a threshold value, which is currently the average amount of all records for the subject item. This works well, but the presence of extreme values can affect the calculation. Furthermore, this approach requires auditors to sift through hundreds of thousands of records every month. Thus, it takes time to determine anomalous cases.

The rule-based monitoring method is an important part of any recording system. The method can be improved with the help of data science. Through proper implementation of other techniques, audit processing can be done in a small amount of time. As a matter of fact, there are numerous studies that were conducted on the application of machine learning and data science that improved the efficiency of audit processing of some practical examples like banking records, structural defects in goods, medical diagnostics, error detection in texts or the cleaning of data and many others (Chakraborty & Joseph, 2017).

Finding irregularities or detecting "not-normal" instances or sometimes called anomaly detection or outlier detection is the main process of audit processing (Liu, 2019). In this project, a potential anomalous record is defined as a record that deviates from the "normal" behavior of all the records of a bank; a data point that is inconsistent with either the item or customer historical behavior. These records could be a possible indication of errors in the report. This project proposes a framework that will serve as a guide in identifying which audit items are potentially anomalous and need to be prioritized. The proposed methodology seeks to augment the existing audit process and reduce processing time in auditing monthly foreign exchange records and not necessarily replace the current audit process.

2. Objective of the Study

The main goal of this project is to propose an alternative methodology in prioritizing accounts of different records by developing a framework using a combination of statistical and machine learning techniques that will identify potential anomalous records in the monthly report submitted by different banks. The said framework will aid auditors in making the audit process more effective and efficient. Not all items had an available labeled dataset, thus this study will utilize unsupervised machine learning techniques in model development, but the entire framework will be tested using the available labeled data of selected items.

Specifically, this project employed three methodologies that will flag the presence of anomalous records and the outcome was consolidated to categorize a record for audit whether low priority, medium priority, or high priority:

Component A: Identify anomalies per account through time series decomposition

Component B: Identify anomalous records using an Unsupervised Outlier Detection Approach on a Bank Type -Level

Component C: Identify anomalous records based on Customer Behavioral segments using clustering and classification techniques

3. Review of Related Literature

Importance of Financial Regulatory

The Financial Stability Board (FSB) highlights how artificial intelligence (AI) can be useful to financial institutions and regulators alike. More specifically, FSB Section 3.4 outlines various use cases, with an elaboration on regulatory reporting and data quality in FSB Section 3.4.2: “Macroprudential surveillance and data quality assurance". The volume of data received, and other data quality issues are seen as key challenges in this regard. Thus, the FSB states that “Machine learning can help improve data quality, for example, by automatically identifying anomalies (potential errors) to flag them to the statistician and/or the data-providing source. This may allow for both lower-cost and higher-quality reporting and more efficient and effective data processing and macroprudential surveillance of data by authorities" (FSB, 2020).

Regtech – or regulatory technology – is emerging as a means to deploy current and emerging technology solutions to reduce the increasing costs of compliance for companies and to improve internal reporting and supervisory capacity for regulators. Many of the regtech solutions are derived and adapted from existing financial technology (fintech) solutions, but emerging solutions are being developed de novo with new technologies to cater for specific regulatory or compliance-related needs (Gurung & Perlman, 2018). In 2018, the BSP identified two projects for regtech adoption. One of which uses an API, back office reporting and visualization software that can automate BSP’s tedious and insecure manual reporting and analysis system, which requires banks to submit reports via email. Using the API, regulators can plug into FI's IT systems to obtain raw data which they can validate and use to derive their own observations and conclusions. The new system may reduce compliance costs on FIs, increase quality and volume of data available for regulators, reduce late penalties by enforcing consistent and timely automatic submission and drive data driven supervisory and policy measures by providing near real time customizable reports to staff using charts, graphs and dashboards (Espenilla, 2018). From here it can be observed that the BSP indeed takes regulatory and innovation seriously.

In 2017, the AMLC secretariat conducted a risk assessment on the exposure of the Philippines to external threats based on Suspicious Transactions Reports (STR). The study revealed that the Philippines has high exposure to threats originating within and outside the Philippine jurisdiction (AMLC, 2017). The AMLC highlighted the importance of quick identification of suspicious transaction, further recommending that there is indeed a need for immediate referral and investigation of STRs to the appropriate Law Enforcement Agencies (LEAs), Supervisory Authorities (SAs), AMLC Public-Private Program Partners and other jurisdictions through their respective Financial Intelligence Units (FIUs).

The high threat of the Philippines in money laundering activities encouraged the Asian Development Bank to provide technical assistance to the BSP and the AMLC to issue the country's anti money laundering implementing rules and regulations and to comply with the Financial Action Task Force (FATF) standards. FATF is an inter-governmental policy making body that sets standards for AML/CFT and other related threats (ADB, 2019).

Audit of Foreign Exchange records in The Bangko Sentral ng Pilipinas

Foreign exchange records form part of the balance of payments of a country, thus the need to have quality data is a must. Any item (goods, services or asset) that is exported from the country – its value should be reported. In the same way, any item imported in the country should be reported accordingly (BSP, 2020). Currently, banks submit subject records through a consolidated report weekly to the BSP through email and system checking is limited only in the report structure of the file. The system consolidates it into a monthly report and auditors manually conducts an initial audit based on different perspectives (i.e., average record, knowledge of the item, counterparties background, etc.). Each item is distributed to different auditors. Initial audit refers to initial checks (i.e., any missing field, names are correct, amount is within threshold, etc.). All questionable records based on the said criteria will be returned to the reporting company for confirmation and correction of report if necessary.

Techniques available for Anomaly Detection

Fraud is an uncommon, well considered, imperceptibly concealed, time evolving and often carefully organized crime which appears in many types of forms (Baesens et al., 2015). There are three main categories of algorithms for fraud or anomaly detection, namely supervised, unsupervised, and semi-supervised methods. Supervised methods use a labeled dataset, and the lack of it has led researchers to pay more attention to unsupervised learning methods in recent years (Kasuni et al., 2011). Unsupervised learning is the most flexible setup which does not require any labels. Furthermore, there is also no distinction between a training and a test dataset. The idea is that an unsupervised anomaly detection algorithm scores the data based on intrinsic properties of the dataset. Based on systematic literature research unsupervised outlier or anomaly detection techniques are categorized in: proximity-based techniques, subspace techniques and statistical / probabilistic models. Typically, distances or densities are used to give an estimation of what is normal and what is an outlier (Goldstein & Uchida, 2016). There are numerous applications of anomaly detection techniques for different types of data available. One application is an Autoregressive Integrated Moving Average (ARIMA) model that is fitted on the regular spending behavior of the customer and is used to detect frauds if some deviations or discrepancies appear (Moschini et al., 2020). The model was compared to four anomaly detection approaches such as K-means, Box-plot, Local Outlier Factor and Isolation Forest. The result of the study showed that the ARIMA model presents a better detecting power than the benchmarking model. It noted, however, that the study used a labeled dataset, and is limited for customers with complete daily count of records.

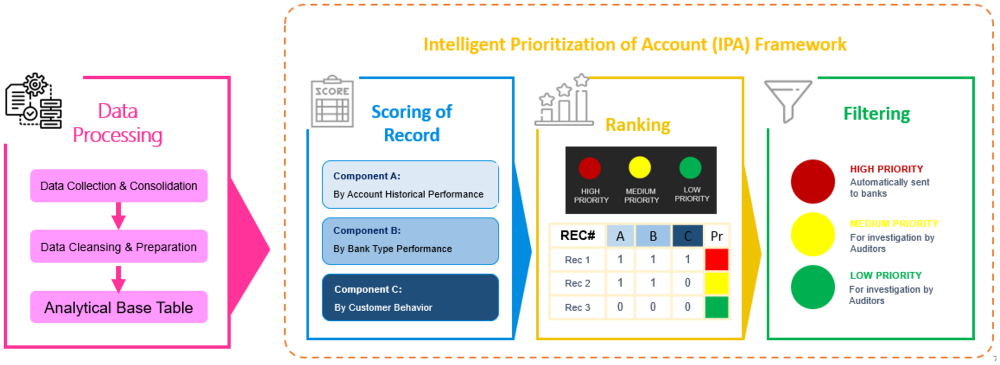
Meanwhile, in 2019, an experiment was conducted in the application of unsupervised outlier detection in financial statement audits (Lenderink, 2019). Isolation Forests (IF), K-Nearest Neighbors (KNN), Histogram-based Outlier Score (HBOS) and Autoencoder Neural Networks were selected in order to conduct experiments with. The selected techniques are evaluated based on their detection rate of the synthetic outliers. All outlier detection techniques have an outlier score as output, providing each journal entry with an outlier score. Performance is measured based on the proportion of top journal entries that must be selected based on outlier score to obtain a recall of 100% for the synthetic outliers. In other words, sorting journal entries based on their outlier score, how many of these top scoring journal entries are to be included to contain all synthetic outliers. In the case of Isolation Forests, on the average, only the top 2:12% of journal entries include all synthetic outlying journal entries. This makes Isolation Forest the best performing outlier detection technique during these experiments. K-Nearest Neighbors scored a percentage of 19:31%, Histogram-based Outlier Score 3:54% and Autoencoder Neural Networks 56:78%. The experiment concluded that unsupervised outlier detection techniques and more specific, Isolation Forests, are suitable to detect outliers that are of interest during financial statement audits. Isolation Forests has been able to provide auditors with abnormal journal entries that haven’t been detected following regular audit procedures. Applying these techniques therefore reduces the risk of missing anomalous journal entries that could be of interest and so improves the quality of financial statement audits.

In 2011, a group of researchers demonstrated the effectiveness of various statistical techniques for discovering quantitative data anomalies (Kasunic et al., 2011). The following tests were found to be effective when used for Earned value management variables that represent cumulative values: Grubbs’ test, Rosner test, box plot, autoregressive integrated moving average (ARIMA), and the control chart for individuals. For variables related to contract values, the moving range control chart, moving range technique, ARIMA, and Tukey box plot were equally effective for identifying anomalies in the data. Among anomaly detection methodology, control charts have been considered important technique

As there are many anomaly detection techniques available, there are studies that suggest combining a set of methodologies for anomaly detection. The idea of developing a framework in identifying records for audit priority was inspired by a study presented in the 2017 Staff Working Paper from the Bank of England (Chakraborty and Joseph, 2017) where machine learning was used in predicting regulatory alerts on the balance sheet of financial institutions in an environment of incomplete information. The study created a stylized framework of identifying 3-level alerts and trained machine learning models on a set of supervisory alerts which indicate the need for closer scrutiny of a firm. The target variable was a binary classification if the account has 3-level alerts. The study employed Naïve Bayes classifier, k-nearest neighbor, decision trees and random forest machine learning techniques and found out that advanced machine learning approaches are seen to generally outperform conventional approaches. It concluded that the logic model does not perform considerably better in terms of accuracy than the trivial benchmark of never raising an alert. On the other hand, most models' test performance plateaus at around 92% accuracy, which is an example of the at-maximum effect. It states that there is no substantially best model in many situations, but many different models may show similar performance. A small deviation from the at-maximum effect is the slightly better performance of the random forest classifier. This is an example of an appropriate model choice as the intrinsic working of random forests matches well the data generation process. Namely, by a combination of thresholding, a non-trivial rule of combining three or more thresholds and noise inductions through the removal of variables. Furthermore, the paper pointed out that since balance sheet items are not independent from each other, Naive Bayes classifier showed a relatively poor performance compared to the other models as the data invalidated the "naïve" base model assumption.

The studies presented above served as a guide in identifying the machine learning model techniques that will be applied to address the objectives of the current project. Specifically, the related studies guided the current project in the development of framework in determining anomalous records, and in the application of the selected machine learning techniques.

4. METHODOLOGY



REC#	A	B	C	Pr
Rec 1	1	1	1	🟥
Rec 2	1	1	0	🟨
Rec 3	0	0	0	🟩

Figure 2: *Overview of the proposed intelligent prioritization of account framework*

Data preparation and processing

The data available provides a systematic record of foreign exchanges under the following mode:

- Actual receipts and disbursements of foreign exchange between residents and non-residents;
- Actual purchases and sales of foreign exchange that is eligible to form part of the country's international reserve;
- Transfer of foreign assets to and from residents; and
- Records between residents and non-residents with the banks acting as intermediaries that will give rise to actual receipts and future disbursements

It is a report composed of twelve (12) item groups which differ depending on the purpose of records being measured.

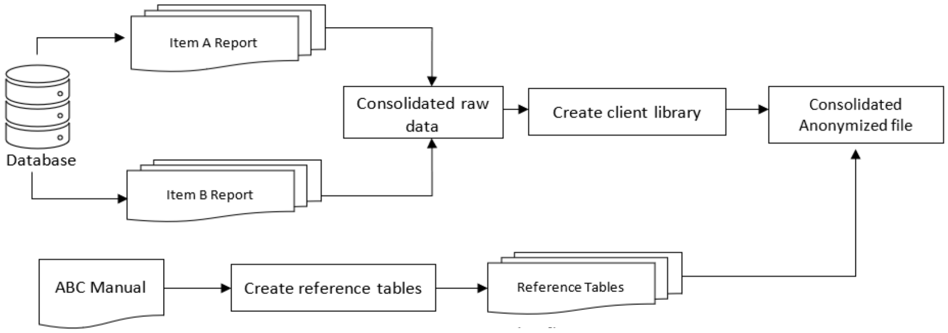


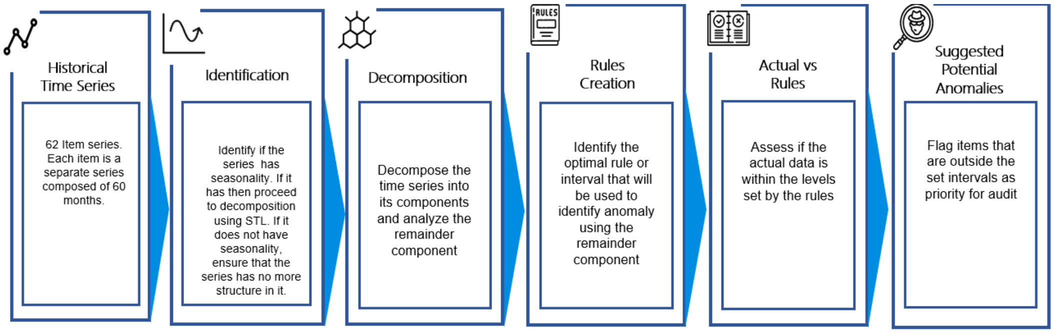
Figure 3: *Data extraction and pre-processing flow*

For this study, the BSP has approved to use selected records from 2015 to 2019 given that data will be anonymized prior to its use outside BSP network and premises. Anonymization was necessary due to the confidentiality nature of the data. Note that data given was unlabeled and all identified anomalies were confirmed by a BSP subject matter expert.

Model Development and Simulation

From the original dataset, three subsets were created and used in the three components of the framework. The development of the framework being proposed is guided by three perspectives: first, an account is seen to have intrinsic behavior on its own, leading to Component A. Second, using behavior of a bank based on its type guided Component B. Finally, movement of the level of records of a person based on its historical records led to Component C. Each record will be tagged as anomalous based on the priority definition threshold from these three components.

Component A: Identify anomalies per account based on historical behavior using time series decomposition



Historical Time Series

62 Item series. Each item is a separate series composed of 60 months.

Identification

Identify if the series has seasonality. If it has then proceed to decomposition using STL. If it does not have seasonality, ensure that the series has no more structure in it.

Decomposition

Decompose the time series into its components and analyze the remainder component

Rules Creation

Identify the optimal rule or interval that will be used to identify anomaly using the remainder component

Actual vs Rules

Assess if the actual data is within the levels set by the rules

Suggested Potential Anomalies

Flag items that are outside the set intervals as priority for audit

Figure 4: *Component A Process Overview*

Records vary on a day to day basis. Currently, banks submit their report weekly with daily information which then is consolidated to a monthly report. Auditors tag an item for priority if the value of the record is above the mean value of all the records for the month for that account. Anomaly detection problem for time series is usually formulated as finding outlier data points relative to some standard or usual signal. While there are plenty of anomaly types, this project focused only on the most important ones from a business perspective, such as unexpected spikes, drops, trend changes and level shifts. Specifically, Component A used time series decomposition for the detection of anomalous behavior of an account. Currently, an account is considered for priority of audit if the level of its total amount is more than the average amount for the year. In this project, we focused on removing “normal” patterns from the series and analyzed the irregular series to determine and establish the level of what is acceptable and what is not per account.

The objective of this component was to use the available data points to identify the presence of pattern (i.e., seasonality and trend) in each series, remove those patterns, then propose rules in identifying anomalies on the residuals for each account that may be used by the auditors for future audit. Rules would be account-specific thus, accounts that deviates from the rule provided should be considered as priority for audit. This process should be done to all selected accounts (62accounts).

The overall process of component A is presented in Figure 4. The first task was to determine if the series is deconstruct-able – meaning if there are patterns present. If there is an identified pattern, then the given time series was deconstructed by removing the identified patterns, such as seasonality and trend, until a residual is achieved. The residual was then analyzed to determine the levels that will define what is suspected anomaly and what is not for each specific account. Identification characteristics (or patterns) of each time series was done through time plots and were further verified by statistical tests.

Seasonality of a series refers to its predictable changes affected by seasonal factors such as time of the year or day of the week. For this project, seasonality and trend were considered as part of the “normal” behavior of each series, thus the need to be taken out from the original series. Specifically, seasonality was checked using the WO overall seasonality test which was developed by Webel and Ollech (2018). By default, the WO-test combines the results of the QS-test and the Kruskal Wallis test, both calculated on the residuals of an automatic non-seasonal ARIMA model. If the p-value of the QS-test is below 0.01 or the p-value of the Kruskal Wallis test is below 0.002, the WO-test will classify the corresponding time series as seasonal.

For series that are found to be seasonal, removing the season and trend of the subject series was done to get its irregular component. Meanwhile, for series that are not seasonal, detrending the series was done to get its irregular component.

Non-seasonal time series consists of trend components and irregular components. Decomposing the subject time series involves trying to separate its trend and irregular component. In this project, it is imposed that a trend structure is present thus spline technique was explored in approximating the trend. Spline, in its simplest sense, is a tool that is used to draw smooth curves between points in a metal. In statistics, splines are used in order to mathematically reproduce flexible shapes. Several weights (or knots) are placed on various positions within the data range, to identify the points where adjacent functional pieces join each other. Smooth functional pieces (usually low-order polynomials) are chosen to fit the data between knots. The type of polynomial and the number and placement of knots is what then defines the type of spline (Perperoglou et al., 2019)

Meanwhile, the seasonal time series assumed to consist of a trend component, a seasonal component and irregular component. To identify the seasonal and trend component of subject series, decomposition of seasonal series was done using the Seasonal and Trend decomposition using Loess (STL) decomposition technique. Unlike high performance machine learning techniques which perform poorly for anomaly detection because of overfitting, seasonal decomposition does very well for this task, removing the right features (i.e., seasonal and trend components) while preserving the characteristics of anomalies in the residuals. In STL, it is assumed that a time series can be decomposed as the sum of trend, seasonality, and remainder components: $y_t = \tau_t + s_t + r_t$, t = 1, 2, · · ·, N where

y_t denotes the original observation at time t,
$\tau_t$denotes the trend,
$s_t$denotes the seasonality if the time series is periodic and
r_t is the irregular component.

The irregular component will be the de-seasonalized detrended series

The irregular component (the residuals), or what is left over in a time series after decomposition, was checked to ensure that the decomposition removed the seasonality and trend, meaning there is no more (or close to none) pattern left. A good decomposition will produce an irregular component that are uncorrelated and has zero mean. Aside from time plot, these two properties were checked using AutoCorrelation Function (ACF) plot, histogram of the residuals (with an overlaid normal distribution for comparison), and Ljung-Box test with the correct degrees of freedom. ACF is an (complete) auto-correlation function which gives us values of auto-correlation of any series with its lagged values. In simple terms, it describes how well the present value of the series is related with its past values. There are several autocorrelation coefficients, corresponding to each panel in the lag plot. For example, r_1 measures the relationship between y_t and y_{t-1} , r_2 measures the relationship between y_t and y_{t-2} , and so on. The value of r_k can be written as

$$r_k = \frac{\sum\limits_{t=k+1}^{T} (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum\limits_{t=1}^{T} (y_t - \bar{y})^2}$$

where T is the length of the time series.

Meanwhile, Ljung Box-test is a more formal test for autocorrelation by considering a whole set of r_k values as a group, rather than treating each one separately. Specifically, Ljung Box-test is based on

$$Q^* = T(T+2)\sum_{k=1}^{h}(T-k)^{-1}r_k^2.$$

where h is the maximum lag being considered and T is the number of observations.

The remainder of all the decomposed series, both the seasonal and not seasonal series, will be identified if white noise or not. If found to be not white noise, the series will be tested for stationarity using the ndiffs and nsdiffs function in r. Said functions uses a unit root test (i.e., kpss test) to estimate the number of differences (non-seasonal and seasonal respectively) required to make the given series stationary. Once the series is stationary and the remainder component is still not white noise then the original series will be modeled through the auto.arima() function in R Software.

After decomposition, the remainder or residual was used in establishing the rules for identifying suspected anomalies in the series. Establishing the rules based on the remainder component was done using two methods: the first one is the InterQuartile Range (IQR), which is a measure of variability based on dividing a dataset into quartiles (Dodge, 2008). It takes a distribution and uses the 25% and 75% interquartile range to establish the distribution of the irregular. Detecting anomalies using IQR methods requires setting a decision range, where any data point lying outside this range is considered as anomaly. In this project, the decision range was set to a factor of three (3) times above the 75th inter quartile and there (3) times below the 25th inter quartile range, and any points beyond the limits were considered anomalies. The next method is the Generalized extreme studentized deviate test (GESD). It is an iterative hypothesis test proposed by Rosner in 1983. In this test, the upper bound or the total number of outlier values is given in the null hypothesis. After that, a separate test is performed by using the Grubbs statistics as given in (Cohn et al., 2013)

$$T_k = \frac{\max\left|\mathbf{z}_i - M\right|}{\sigma},$$

where M and σ denote the mean and standard deviations in the data. The observation corresponding to

$$\max |\mathbf{z}_i - M|$$

is removed using Grubbs statistics, and T2 is computed from the remaining sample. A sample mean and standard deviation are computed for the remaining n-1 data values. This process is repeated until Tk is determined for a prespecified k. Here, k represents the number of outliers in the data set known as the upper bound specified in the null hypothesis (Hyndman & Athanasopoulos, 2018).

Since the objective of the project is prioritization of accounts by detecting anomalies, the results of two methods were compared per month based on how stringent it was in determining the decision range for each account.

A detailed flowchart of the decomposition process was created to ensure proper case handling of each available series. In case the residual is still not acting as white noise after decomposing, either seasonal series through STL or a non seasonal series through cubic spline smoothing, or after differencing, the model for the series will be selected through auto.arima() function available in R. Said function uses a variation of the Hyndman-Khandakar algorithm (Hyndman & Khandakar, 2008), which combines unit root tests, minimization of the AIC and MLE to obtain the best possible ARIMA model.

Component B: Identify anomalous records using an Unsupervised Outlier Detection Approach on a Bank-Level

Meanwhile, Component B, considered the behavior of the records per bank type – and in assessing anomalies, an unsupervised machine learning model called the Isolation Forest was adopted.

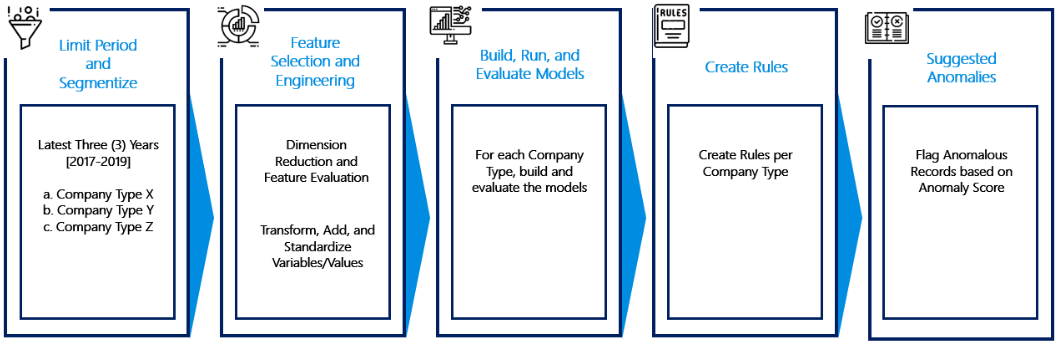

Limit Period and Segmentize
Latest Three (3) Years [2017-2019]
a. Company Type X
b. Company Type Y
c. Company Type Z
Feature Selection and Engineering
Dimension Reduction and Feature Evaluation
Transform, Add, and Standardize Variables/Values
Build, Run, and Evaluate Models
For each Company Type, build and evaluate the models
RULES
Create Rules
Create Rules per Company Type
Suggested Anomalies
Flag Anomalous Records based on Anomaly Score

Figure 5: Process Overview of Component B

In this component, the data set was limited to the most recent period, that is from 2017-2019 or 3 years, and segmented it according to bank type: X Y or Z. Second, features were selected and engineered from the filtered data set. Third, Isolation Forest Models were built, run, and evaluated for each of the Company Types. Fourth, rules were created based on these models, and lastly, the rules were implemented to flag anomalous transactions.

Records are attributable to the bank type's layering and structure particularly in their assets and capacity, that is, for each bank type, there are different levels of products and services that the banks under it can offer. For instance, Banks categorized to be in bank type X are banks with relatively lower capacity and offer a limited number of products and services, while bank type Z are banks with full capacity to offer an extensive set of products and services. Essentially, at the minimum three models were created for Component B for each of these Bank Types.

Data Preparation

Before the implementation of the models, the variation in magnitude was addressed. Numeric variable was standardized from 0 to 1, so that the data is internally consistent and comparable with other data points. The aim of this step was to standardize the range of amounts so that each item contributes equally to the analysis.

Additionally, since the data is a mixed data set (numeric and categorical), categorical data was converted to ensure that it would be understood by the machine. One-hot coding used for the preprocessing of categorical data. With one-hot, each categorical value is converted into a new categorical column and assign a binary value of 1 or 0 to those columns. Each integer value is represented as a binary vector. One hot encoding makes the data more useful, easily rescalable and better for prediction.

Feature Selection and Engineering, Dimension Reduction

Feature selection and engineering were also explored. Additional variables were engineered. Since one-hot encoding produces additional feature for every value in the categorical variable, this expanded the dimensionality of the dataset. The dimensionality of the data set and the predictive importance of both original and engineered features were handled using a dimension reduction technique called Principal Component Analysis (PCA).

PCA is an unsupervised dimensionality reduction technique that can be used to create a compact representation of the dataset while minimizing information loss. For instance, if a data set is represented as vectors in a high-dimensional space, it might be observed that numerous variables are correlated, and that the data closely fits a lower dimensional linear manifold. PCA can be used to find the lower dimensional representation in terms of uncorrelated variables called principal components (Hastie, et al., 2014). PCA constructs relevant features by transforming correlated features linearly into fewer uncorrelated variables, called principal components, by projecting the original data into the reduced PCA space using the eigenvectors of the covariance/correlation matrix. The resulting projected data are essentially linear combinations of the original data capturing most of the variance in the data (Jolliffe 2002). The goals of PCA can be summarized below (Hastie, et al., 2014).

1. extract the most important information from the data table;
2. compress the size of the data set by keeping only this important information;
3. simplify the description of the data set; and,
4. analyze the structure of the observations and the variables.

In order to evaluate the predictive importance of the variables and engineered features, a PCA score called Loadings was utilized in this project. Loadings is the correlation between a principal component and a variable and estimates the information they share (Hastie, et al., 2014).

The importance of each feature is reflected by the magnitude of the corresponding values in the eigenvectors (higher magnitude — higher importance). As an example, from the loadings score, information on how important features 1, 2 and 3 are for the first component can be acquired. Similarly, determining which features are most important for the second component, and so on, can be revealed.

In short, the absolute values of the eigenvectors' components corresponding to the m largest eigenvalues can be checked to determine the more important feature. The larger the absolute values, the more important the feature is in contributing to a particular principal component. This information was used in assessing whether to keep or drop the features before running it to the model. The result of the feature selection was evaluated through trials by variation, and by comparing its effects to the recall rate of the framework using the available labeled dataset.

Build, Run and Evaluate Model using Isolation Forest

In nature, anomalies are difficult to identify due to the following:

1. Severe Class Imbalance: Anomalies or outliers in general are much fewer than our normal records
2. Severe Class Overlap: The reason why we audit is difficult is because there is a small gap between legal and fraudulent activities
3. Concept Drift: Anomalies can be done in different ways and evolves and changes in time
4. Complexity and volume of our data

From the above characteristics, there are two distinct properties of an anomaly (Liu, Ting, & Zhou, 2008):

a. They are the minority consisting of fewer instances
b. They have attribute-values that are very different from what we consider normal

In other words, anomalies are "few and different". One logical way to identify it is to isolate it from the rest and this is where the idea of "Isolation" comes in. Isolation means separating an instance from the rest of the instances. After which, data-induced random tree will be produced to partition instances that are few and different from the rest. In doing so, it can be noted that the random partitioning will produce noticeable shorter paths, or in laymen, isolates sooner, for anomalous instances.

It was Lui, Ting & Zhou who first proposed a tree-based unsupervised outlier detection technique. Lui describes the term 'isolation' as 'separating an instance from the rest of the instances'. The researchers note that iForest shares intuitive similarity to random forest, another tree-based algorithm but is mainly used for classification problems.

iForest functions under the assumption that it is more likely to be able to isolate outliers. Hence, when a forest of random trees collectively produces shorter path lengths for some points, those points are likely to be anomalous :

i. In a single isolation tree, the data is recursively partitioned with axis-parallel cuts at randomly chosen partition points in randomly selected attributes (features).
ii. This is done for n data points to isolate the points into nodes with fewer and fewer points until they are isolated in singleton nodes containing one instance.
iii. The intuition behind the technique is that tree branches containing outliers are noticeably less deep, because these data points are located in sparse locations.
iv. The distance of the leaf to the root is used as the outlier score.
v. Since iForest creates multiple trees (n estimators) the average path length for each data point is calculated over the different trees in the isolation forest.
Using this average path length, an "Anomaly Score" will be computed.

Create Rules: Model Algorithm and Parameter Tuning

Isolation Forest is black-box methodology. Its algorithm is illustrated in a simplified pseudocode below:

1. Randomly select two features or set of features
2. Split the data points by randomly selecting a value between the maximum and the minimum
3. Repeat step 2 iteratively until fewer and different data points are isolated
4.Termination point is until everything is split, or the data points are completely duplicate
5. Calculate the "anomaly score" for each tree and average across. Outliers with lower path length will have higher anomaly scores, and thus, tagged as anomalous.

In implementing the model, scikit-learn in Python was used for the black-box algorithm and model parameters such as n_estimators, max_sample, Contamination, and max_features, were tuned.

Key Parameters	Description
n_estimators int, default=100	The number of base estimators in the ensemble.
max_samples "auto", int or float, default="auto"	The number of samples to draw from X to train each base estimator.
Contamination 'auto' or float, default='auto'	The amount of contamination of the data set, i.e. the proportion of outliers in the data set.
max_features int or float, default=1.0	The number of features to draw from X to train each base estimator.

Table 1: *Isolation Forest Key Parameters*

Based on research, iForest model is quite sensitive to the parameter Contamination relative to its other parameters. Contamination is the proportion of outliers or anomalies in the dataset which in this project, based on business domain understanding, to be around 10%. For this project, contamination was set and tested from seven and a half percent to twelve percent (7.5% to 12.5%).

Suggested Anomalies: Flag Anomalous Records using Anomaly Score

In creating iTrees, a data point x in a sample size n was used to predict an output called anomaly score using the formula (Liu, Ting, & Zhou, 2008):

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}}$$

E(h(x)) is the expected value of the average path length or search height of x, meaning how soon can the data point x be separated, c(n), the denominator, answers what is the average path length that it would take to find any general node, not just the data point x, across all of the trees

The score shows how long it takes to isolate the particular point x relative to isolating every other data point. If E(h(x) is much lower than c(n), then the anomaly scores(x,n) will be nearer to 1. For example, if E(h(x)) is 2 and the sample average c(n) is 5, then the anomaly score is 2 raised to negative 2 divided 5, which is 0.76 and is nearer to 1

And if E(h(x)) is about the same as c(n), then the anomaly score s(x,n) will be lower, or if both are exactly the same, it will be exactly 0.5. For example, if E(h(x)) is 5 and our c(n) is 5, then the anomaly score is 2 raised to negative 5 divided 5, which is 0.5.

Notice that the score will become higher, if E(h(x)) is much lower than the average path length, meaning, if x isolates much sooner compared to the isolation of other data points, then that point is considered as anomalous.

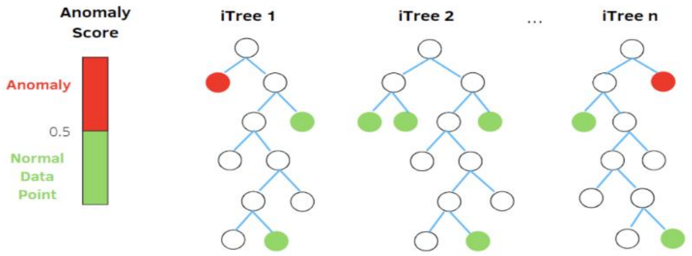


Figure 6: *Anomaly Detection using Isolation Forest**

*Illustrated by E. Anello (betterprogramming.pub)

Component C: Determine the behavior of a transactor using customer segmentation

Component C is a new perspective in terms of the current audit process. The objective of this method is to determine the customer behavioral segments that transacts on different bank types and detect any anomalies on their transactions. In order to achieve it, Data Pre-processing and Clustering Technique were applied.

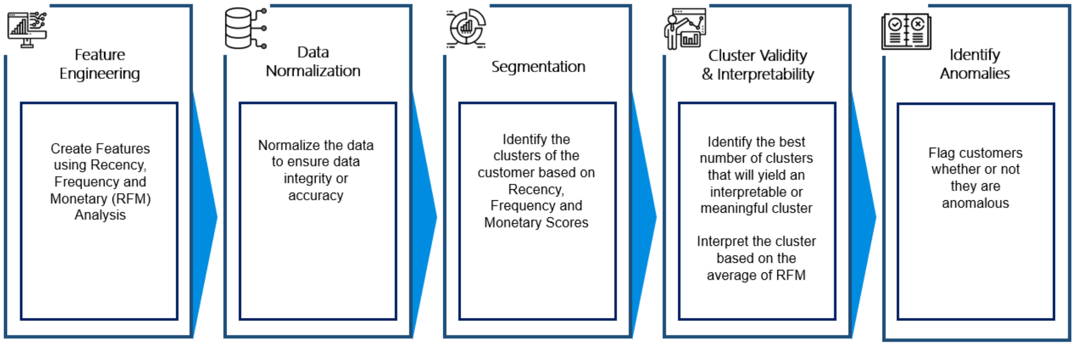

Feature Engineering
Create Features using Recency, Frequency and Monetary (RFM) Analysis
Data Normalization
Normalize the data to ensure data integrity or accuracy
Segmentation
Identify the clusters of the customer based on Recency, Frequency and Monetary Scores
Cluster Validity & Interpretability
Identify the best number of clusters that will yield an interpretable or meaningful cluster
Interpret the cluster based on the average of RFM
Identify Anomalies
Flag customers whether or not they are anomalous

Figure 7. Component C Process Overview

Feature Engineering. To identify the most effective subset of the original features to use in clustering, Feature Engineering was done. For Feature Engineering, Recency, Frequency and Monetary (RFM) (Cullinan, 1977) were used as attributes of concern. In order to compute the Recency, Frequency and Monetary, the following formula were used:

Recency

Recency is the number of days between the first date of the period examined (1/1/2017) and the date of the customer's last record. It answers the question, how recent was the customer's last record? For example, a customer who has conducted his last record on 03/15/2019 is characterized by R=803

Frequency (F)

Frequency is defined as the count of financial records the customer did within the period of interest (1/1/2017 to 12/31/2019). It answers the question, how often did this customer make a record in a given period?

Monetary (M)

Monetary is the total value of financial records the customer made within the examined period. It answers the question, how much money did the customer spend in a given period?

RFM Score (RFM Factor)

It is calculated using the formula

$$RFM_{Score} = R + F + M$$

Data Normalization. Normalization of data or Feature Scaling is an important step prior to the actual clustering because it enables the reduction of the scale of the variables which affects the statistical distribution of the data. Based on the unit of measurement of the RFM data in this project, monetary has a larger scale compared to Recency and Frequency. To do the Feature Scaling, Min-Max Normalization was applied. The data values were scaled between a range of 0 to 1 only. Consequently, the effect of outliers on the data suppresses. Also, it generates a smaller value of the standard deviation of the data scale. The formula for Min-Max Scaling is as follows:

M = (X -Xmin) / (Xmax -Xmin)
Where:
M is our new value
X is the original cell value
Xmin is the minimum value of the column
Xmax is the maximum value of the column

Segmentation. Clustering identifies which observations are alike, and potentially categorize them therein. For this project, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) was used. The DBSCAN algorithm uses two parameters:

minPts: The minimum number of points grouped together for a region to be considered dense. This will be the threshold.
eps (ε): A dissimilarity measure that will be used to locate data points in the neighborhood of any datapoint.

It can be more explained using the terms Density Reachability and Density Connectivity.

Reachability in terms of density establishes a point to be reachable from another if it lies within a distance (eps) from it.
Connectivity, on the other hand, involves a transitivity-based chaining-approach to determine whether points are in a cluster.

For comparison, a centroid-based clustering, specifically k-medoids, was also utilized. With the objective of minimizing the dissimilarity of all the observations to the nearest medoid, the Clustering Large Applications based upon Randomized search (CLARANS) was employed in this project. CLARANS is a partitioning method of clustering that searches a graph where every node, k medoids, is a potential solution.

Cluster Validity and Interpretability. To identify the most optimal number of clusters we will use Dunn Index (DI) (Yang et al., 2014). Dunn Index (DI) is calculated based on the following equation:

$$D_{nc} = \frac{min}{i = 1, \ldots, nc}\left[min\ j = i + 1, \ldots, nc\ \left(\frac{d(c_i, c_j)}{max_{k=1,\ldots,nc} diam(c_k)}\right)\right]$$

Where $d(c_i, c_j)$ is different function between cluster $c_i and\ c_j$ defined as:

$$d(c_i, c_j) = \frac{min}{x \in c_i, y \in c_j} d(x, y)$$

and $diam(c)$ is cluster diameter probably considered as cluster dispersion size. Cluster diameter of C can be defined as flows:

$$diam(C) = \frac{max}{x, y \in C} d(x, y)$$

Identify Anomalies. In this project there are two assumptions that can be considered as anomalies in using clustering.
Noise is considered as anomalous (Ester et al., 1996). Example in below figure, Cluster 1 and Cluster 2 are clusters containing normal instances A1 and A2 are considered anomalous. This can be detected using DBSCAN Clustering.

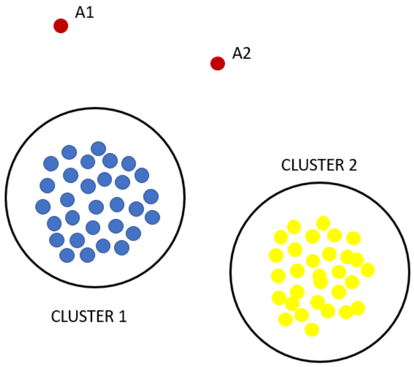


Figure 8(a). Noise is considered as anomalous

Anomalies are far away from the centroid. Under this assumption, anomalous events are detected using a distance score. This can be detected using CLARANS Clustering. See below Figure.

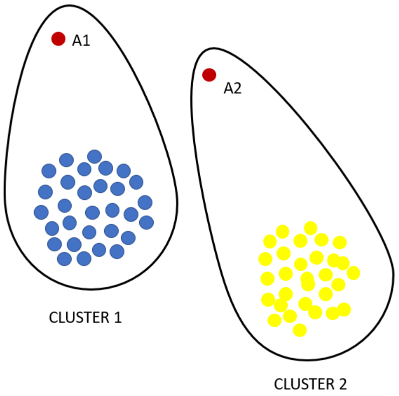
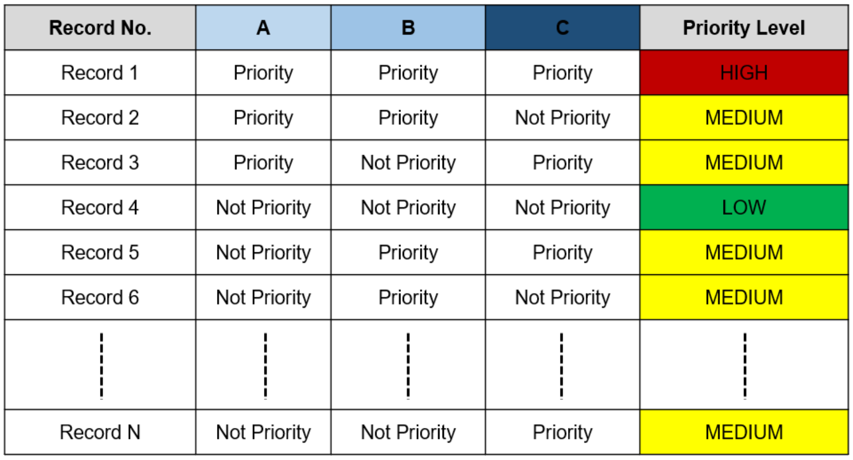


Figure 8 (b). Anomalies are far away from the centroid

The data points or records identified as anomalous will be considered as a Priority for Component C and will be added in other priorities done in Component A and B for Priority Ranking and Filtering which will be discussed in the next section.

Priority Ranking and Filtering

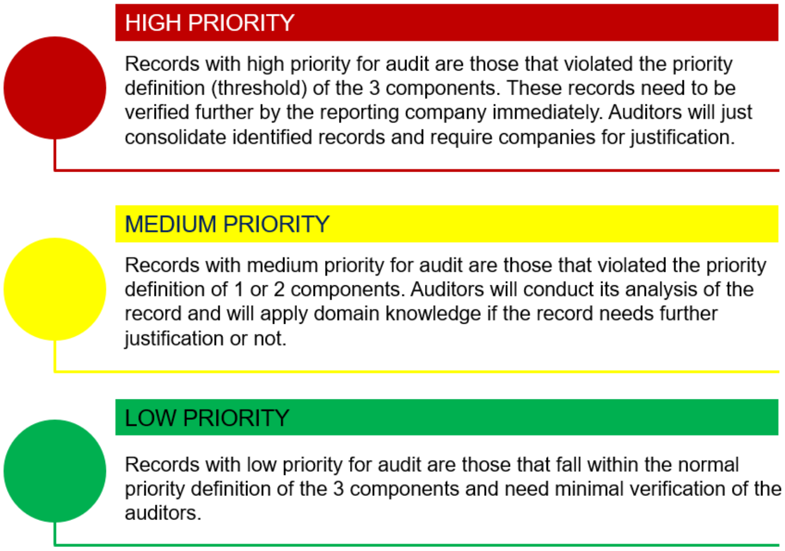
The combined results from the three components was used to identify the priority level of a record. A sample priority matrix result can be seen in below table:



Record No.	A	B	C	Priority Level
Record 1	Priority	Priority	Priority	HIGH
Record 2	Priority	Priority	Not Priority	MEDIUM
Record 3	Priority	Not Priority	Priority	MEDIUM
Record 4	Not Priority	Not Priority	Not Priority	LOW
Record 5	Not Priority	Priority	Priority	MEDIUM
Record 6	Not Priority	Priority	Not Priority	MEDIUM
⋮	⋮	⋮	⋮	⋮
Record N	Not Priority	Not Priority	Priority	MEDIUM

Table 2: ***Sample Priority Matrix Result***

Records were ranked according to its level of priority for audit and were filtered accordingly. Table 3 presents the Priority rating definition that was set for this project and can be used by the auditors.



HIGH PRIORITY

Records with high priority for audit are those that violated the priority definition (threshold) of the 3 components. These records need to be verified further by the reporting company immediately. Auditors will just consolidate identified records and require companies for justification.

MEDIUM PRIORITY

Records with medium priority for audit are those that violated the priority definition of 1 or 2 components. Auditors will conduct its analysis of the record and will apply domain knowledge if the record needs further justification or not.

LOW PRIORITY

Records with low priority for audit are those that fall within the normal priority definition of the 3 components and need minimal verification of the auditors.

Table 3: ***Priority Rating Definition***

5. RESULTS AND DISCUSSIONS

Component A: Identify anomalies per item based on historical behavior using time series decomposition

Component A uses time series decomposition to analyze each item series and establish the rules that can be used by the auditors in identifying anomalies. This approach mimics the current steps being done by the auditors to assess the consistency of the behavior of an item series by looking into its historical performance. In this project, out of 162 items available in the dataset, Component A was limited to item group A - item type 1 record, 62 in total, from January 2015 to December 2019 (60 available data points per item), as most of the volume of records fall in this item group.

Each item follows different behaviors in terms of complete reporting and can be classified into following categories:

No.	Category based on completeness	Account
1	With records every month	56%
2	With less than 10 months of no records	23%
3	With more than 10 months but less than 30 months without records	8%
4	With 30 or more months without records	13%

Table 4: *Categories of items based on months with transactions*

It is also worth to note that some series has zero values for consecutive months, while for other series, zero values can be found intermittently. Based on this, it can be observed that item series that falls under the same category almost follow the same behavior and has the same nature of fluctuations over time. This observation of intermittent behavior of zero values in the records may be reflective of a change in economic condition or business status which may serve as a springboard for further investigation of the auditors. As such, this observation led to the organization of items into two (2) major categories:

Items with consecutive zero values – Static Item Series

In business perspective, each item is expected to have a record for at least three consecutive months. In this project, it has been found that it is not the case. Some items do not have a reporting for the entire year (value and volume is zero), and then will have a record for just 1 month in the next year, such that this record is either static (no value) during the first period then has a record in between or has record at first then static (no value) onwards. This behavior signals a need for investigation as it may indicate either a new business for close monitoring or an intentional error. As such, items having that kind of behavior were considered static and will be flagged as anomaly for that particular month, if that item deviates or is different from its value (zero value and volume) for the last three months.

All other items – Non Static Items

Some items has an intermittent behavior which may be reflective of error in the report. Thus, the categorization is important for the auditors to determine which item should be focused on.

Static Items	12 items series
Non Static Items	50 item series

Table 5: *Category of items based on behavior*

Identification of seasonality

Time series exhibit a variety of patterns and decomposing its components will be helpful as each pattern represents and underlying pattern category (Heinze, 2018). In this project, patterns being considered as “normal” components of each series were seasonality and trend. The first pattern that was identified was the seasonality of each item. It was commonly believed that foreign exchange transactions were affected by seasonality. Seasonality is a component of time series which data is affected by regular and predictable seasonal factors such as time of the year or day of the week. Presence of seasonality in each 62 series were tested prior to decomposition of the series using the WO overall seasonality test, which combines the result of the QS-test and Kruskal Wallis test. In the said test, if the p-value of the QS-test is below 0.01 or the p-value of the Kruskal Wallis test is below 0.002, the WO-test will classify the corresponding time series as seasonal – this is the default setting of the test.

Contrary to the belief that foreign exchange transactions, regardless of purpose, are seasonal in general, based on the test out of the 62 items series only one item series (S1ReG055) was found to have a seasonal component, meaning only one item is influenced by changes in time factors. Said item series is related to earnings of residents working in supranational companies. During 2015 to 2017, the value of the subject item series has its peak during the last quarter of the year. This changed in 2018 to 2019, which moved the peak to the first quarter of the year, which maybe reflective of a change in policy in giving earnings of workers amongst supranational companies (i.e., United Nation, International Monetary Fund, etc.).

It was noted that the WO-test for seasonality has a very stringent test, with p-value at .01 of the QS-test while the p-value of the Kruskal Wallis test at 0.002. Thus, the default p-value was changed to 0.05, and all item series was retested for seasonality. This increased the number of item series that were to be seasonal from one item series to seven item series.

For the remaining series which were found not to have a seasonal component, trend was identified. Trend is a general direction in which the series is moving. It is characterized to be whether increasing or decreasing (Gurung & Perlman, 2018). In this project, items that were not seasonal and non-static were considered to be non-seasonal items with trend. Trend was determine using cubic spline smoothing which provides a smooth historical trend as well as linear forecast function (Hyndman et al., 2005).

Decomposition of components

Decomposition was done for 62 item series, except for items that were considered as static. For item series found to have a seasonal component, decomposition was done using the STL technique. There are other traditional methods available in decomposing time series but for this project, STL technique was used in decomposing seasonal series to make the process more efficient and less time consuming. Meanwhile for non-seasonal items, splinef() function in R software was used to determine the trend and subtract it from the original series to get the remainder component. Consequently, the auto-correlation function (ACF) of the residuals of each item was checked. This is done to verify that there is no more (or close to none) pattern left in the series. ACF generates values of auto-correlation of any series with its lagged values. In simple terms, it describes how well the present value of the series is related from its past values. Furthermore, each series was tested using the Ljung-Box test which is a more formal test for autocorrelation. Ljung- Box test is one of the statistical tests that checks if autocorrelation exists in a given series. For the remainder of series which still does not behave like a white noise after the proposed decomposition, either seasonal or not seasonal, subject series were transformed to be stationary. Subsequently, it was tested again for white noise and series which are still found to be "not white noise" was modeled through auto.arima() function in R Software.

For clarity, below are the sample cases that may be present in the data with corresponding recommended model:

CASE	SERIES TYPE	MODEL
1	Seasonal Series – Decomposed using STL – Remainder White Noise	STL MODEL
2	Seasonal Series – Decomposed using STL – Remainder not white noise – Stationary Series – Remainder White Noise	SEASONAL DIFFERENCED MODEL
3	Seasonal Series – Decomposed using STL - Seasonal Series– Remainder not white noise – Stationary Series – Remainder not	ARIMA MODEL
4	detrending methods (i.e., Moving average, Spline) – Remainder White Noise	DETRENDED MODEL
5	Non seasonal Series – Decomposed using detrending methods (i.e., Moving average, Spline) – Remainder not white noise – Stationary Series – Remainder White Noise	NON-SEASONAL DIFFERENCED MODEL
6	Non seasonal Series – Decomposed using detrending methods (i.e., Moving average, Spline) — Remainder not white noise – Stationary Series – Remainder not White Noise	ARMA MODEL

Figure 25 : *Sample result of decomposition using STL*

Table 6: *Case Handling Scenarios*

Flagging potential anomalies

Since the objective of this component is the prioritization of items by detecting anomalies, rules or the established normal value level of an item using GESD is more stringent than the IQR which has a wider range of limits. That is, it is easier for a value to be tagged as potential anomaly under the rules of GESD than the IQR. As GESD tends to be the better performing method in outlier removal (Rosner, 1983), potential anomalies tagged through the GESD method were selected.

Sample Results

Each item series was decomposed depending on the result of its seasonality test. After decomposition, residuals were checked as it is useful in determining if the decomposition has adequately captured the information in each item series. After which, each series was modelled according to its case, then tagged the potential anomalies, accordingly.

Cases	No. of Series
STATIC	12
S-STL-WHITE NOISE	7
NSDET-SPLINE-WHITE NOISE	29
NS-DIFFERENCING-WHITE NOISE	6
NS-ARIMA(0,0,0)	1
NS-ARIMA(0,0,1)	2
NS-ARIMA (0,1,0)	1
NS-ARIMA(0,1,1)	2
NS-ARIMA(0,2,0)	1
NS-ARIMA(0,3,1)	1

Table 7: *Component A: Overall model category of each item*

The table above shows the model used for each item series to cull out the remainder from the original series which was used in tagging potential anomalies. Note that the for the 12 item series found to be static, once its value is above/below its value = 0, for the past consecutive month, automatically, this series and all its records, will be tagged as potential anomaly. Meanwhile, for the item series included in the dataset with available priority tagging, below table shows the chosen model according to its case:

IDENTIFIED MODEL	INCLUDED
STATIC	S1ChB006
	S1ClA004
	S1PrA003
S-STL-WHITE NOISE	S1TrB009
NSDET-SPLINE-WHITE NOISE	S1FrA002
	S1FrA001
	S1PaB005
	S1PoB007
	S1OtB010
	S1OpB008

Table 8: *Component A: Model identified for the selected item series*

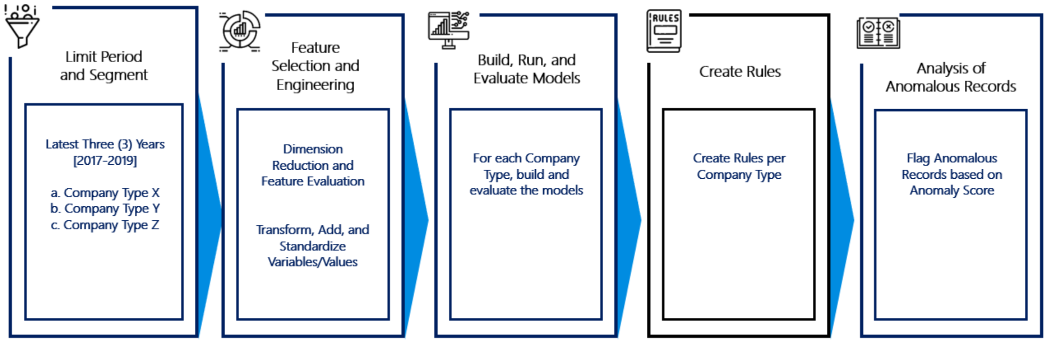
Static item series (S1ChB006, S1CIA004,S1PrA003) are records related to merchandise shipments, item series with NSDET-SPLINE type of model are related to freight payment, and operational related payments(port payment, lease, etc). S1TrB009 item series is related to transportation commission and fees. This is an interesting insight in business perspective as this may be used in further analyzing and determining its effect in the movement of trade statistics.

The remainder of all seasonal series decomposed using STL were found to be white noise. For the sample seasonal series above, months that were tagged as potential anomaly are as follows: 201610, 201708, 201712, 201803, 201811, 201903, 201905, 201909. Periods that have the most number of tags from the seasonal item series are 201505 and 201512 (both periods were tagged as anomaly for 3 item series). Transactions that fell on subject flagged items and months should be verified by the auditors.

For non-seasonal items, four (4) different case handlings were done to extract the remainder as white noise. Periods with the most number of potentially anomalous tags from the nonseasonal item series are the following: 201506 – with 13 items tagged as anomaly, 201505 – with 11 items tagged as anomaly, 201712 – with 10 items tagged as anomaly. As the objective of Component A is really to suggest a priority item for auditors, the results showed that instead of checking 62 items, for example in period 201712, auditors will check only ten (10) items that are tagged as priority giving them more time to analyze subject records and provide more in-depth insights on each record.

Component B: Identify anomalies per item based on company type

After framework rules are created on the accounts level in Component A, the behavior of the records per bank type was considered. In assessing anomalies, an unsupervised machine learning model called Isolation Forest was used.



Limit Period and Segment
Latest Three (3) Years [2017-2019]
a. Company Type X
b. Company Type Y
c. Company Type Z
Feature Selection and Engineering
Dimension Reduction and Feature Evaluation
Transform, Add, and Standardize Variables/Values
Build, Run, and Evaluate Models
For each Company Type, build and evaluate the models
RULES
Create Rules
Create Rules per Company Type
Analysis of Anomalous Records
Flag Anomalous Records based on Anomaly Score

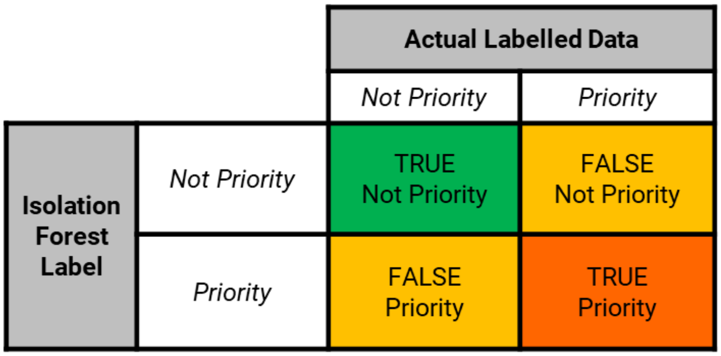
Figure 9: *Process Overview of Component B series*

Build, Run and Evaluate Model

Using iterations from the engineered features and varying model parameters on Contamination Rate and Number of Trees, the best model per Bank Type was evaluated. To have a baseline model, dataset with original features and default parameters were used in identifying potential anomalous records per bank type. After which, effect of using different model parameters in the original dataset was inspected. The said process was repeated using the dataset with engineered features.

Model Metrics

In order to evaluate each model iterations, a confusion matrix was utilized.



		Actual Labelled Data	
		Not Priority	*Priority*
Isolation Forest Label	*Not Priority*	TRUE Not Priority	FALSE Not Priority
	Priority	FALSE Priority	TRUE Priority

In the confusion matrix, there are four (4) cases where records can fall into:
TRUE Priority (TP): The model labeled the record as Priority, and it is actually a Priority
TRUE Not Priority (TNP): The model labeled the record as Not Priority, and is actually Not Priority
FALSE Priority (FP): The model labeled the record as Priority, but it is actually Not Priority
FALSE Not Priority (FNP): The model labeled the record as Not Priority, but it is actually Priority

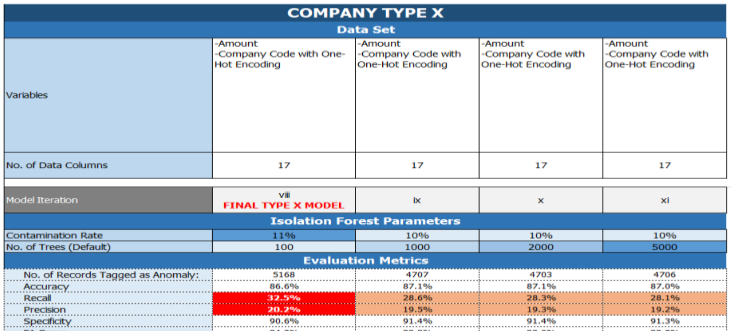
Although accuracy is a good measure and the most intuitive one, it is only best for symmetric datasets wherein our FNP and FP are almost close. Based on the results, this is not the case for the available dataset in this project. Thus, additional metrics will be used.

Precision signifies how certain the model provides a True Priority result while recall indicates how much “Priority” records were not missed. Recall is used if having False Priority is more acceptable than having False Not Priority, while Precision is used if a True Priority is more of the concern. Meanwhile, a high F1 Score indicates that the model provided a good mix of recall and precision. Lastly, Specificity is chosen if the intention is to cover all True Not Priority.

For this project, Recall and Precision is emphasized, which will give the auditors a good level of certainty that (1) the model is tagging actual anomalous records correctly, and (2) the model is not missing actual anomalous records. These are two of the intended results for having the framework, which will contribute in making the auditing process more efficient.

Model Building

In discussing how the models were developed, this section will begin with the baseline model for Bank Type X. Only the AMOUNT and COMPCODE were used for the initial modelling, and the results are shown below:



COMPANY TYPE X				
Data Set				
Variables	-Amount -Company Code with One-Hot Encoding	-Amount -Company Code with One-Hot Encoding	-Amount -Company Code with One-Hot Encoding	-Amount -Company Code with One-Hot Encoding
No. of Data Columns	17	17	17	17
Model Iteration	viii FINAL TYPE X MODEL	ix	x	xi
Isolation Forest Parameters				
Contamination Rate	11%	10%	10%	10%
No. of Trees (Default)	100	1000	2000	5000
Evaluation Metrics				
No. of Records Tagged as Anomaly:	5168	4707	4703	4706
Accuracy	86.6%	87.1%	87.1%	87.0%
Recall	32.5%	28.6%	28.3%	28.1%
Precision	20.2%	19.5%	19.3%	19.2%
Specificity	90.6%	91.4%	91.4%	91.3%

Table 9: *Company Type X Final Model*

Looking at the results of the iteration for the Bank Type X data for different variable combinations and contamination rates, the Isolation Forest produced varying results. It can be observed that (1) the Amount and COMPOCODE variables are enough to provide relatively good Accuracy vis-a-vis other models, and (2) as the contamination rate increases, the recall rate also increase, however, the increase negatively impacts the accuracy and precision of the model. Using the results of iteration from Bank Type X, it was observed that out of the eight iterations, the optimal contamination rate is 11%, as highlighted in iteration viii above. This rate is near to actual rate of anomalous records that is being experienced in the business domain by the auditors (at 10%).

Now, although the accuracy of the model is relatively good at 86.6%, the Recall and Precision are low at 32.5% and 20.2%, respectively. This result suggests that additional parameter tuning might be necessary.

Provided these low results, adding more in the number of trees parameter was explored. In the below results, it can be observed that there were no improvements in the metrics when the number of trees increased, thus the use of the default number of trees of 100 was retained.

Given the results of our metrics from the different iterations, it was concluded that the model with the baseline features (AMOUNT and COMPCODE) at 11% contamination and at 100 trees is the most optimal as well as ideal for Bank Type X model. Same process was repeated for Bank Type Y and Bank Type Z. For Bank Type Y it was concluded that the model with the baseline features (AMOUNT and COMPCODE) at 15% contamination and at 100 trees is the most optimal as well as ideal model for this bank type while for Bank Type Z, the model with the baseline features (AMOUNT and COMPCODE) at 12.5% contamination and at 100 trees is the most optimal as well as ideal model for this type

Since the objective of our framework is to improve the auditing process, we emphasize the importance of having a good Recall and Precision. Though the baseline models for all bank types have high Accuracy rate, the researcher highly recommends further improvements on the models by resolving the following limitations:

- Acquire more original and numeric variables from the ITRS Record and external figures for better feature selection for model building
- To increase Recall, introduce more features and validate potentially increasing the contamination rate by acquiring more labelled data and align it with the current experienced anomaly rates by the auditors
- To increase Precision and F1 score, explore other possible iterations in the variables and model parameters using a super computer

Furthermore, the researchers still propose to utilize the Component B Bank Type X model for the initial operationalization of our framework. This will be accounted by the overall nature of our consolidated models and the final priority ranking with Component A and Component C scores.

Component B Rules

Given these findings, below is the summary of the proposed rules for Component B:

Bank Type	Variables	Dimension Reduction	Contamination Rate	Number of Trees
If record under Type X	Baseline Features	No	11%	100
Y	Baseline Features		15%	
Z	Baseline Features		12.5%	

Table 10: *Proposed Rules for Component B*

Component C: Identify anomalies per item based on customer behavior
In parallel of the analysis of company type level in Component B, the behavior of the customers was analyzed. To identify anomalies, Clustering techniques such as Density-based spatial clustering of applications with noise (DBSCAN) and Clustering Large Applications based on RANdomized Search (CLARANS) will be used.

To discuss the results for Component C, recall the following Process Overview.

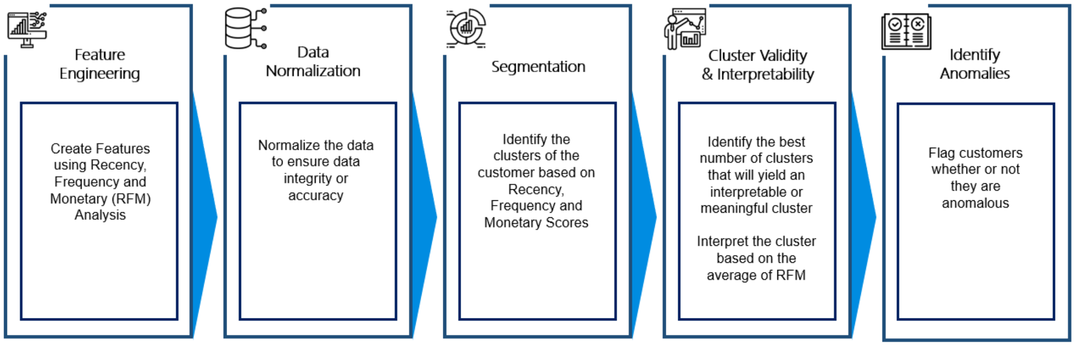

Feature Engineering
Create Features using Recency, Frequency and Monetary (RFM) Analysis
Data Normalization
Normalize the data to ensure data integrity or accuracy
Segmentation
Identify the clusters of the customer based on Recency, Frequency and Monetary Scores
Cluster Validity & Interpretability
Identify the best number of clusters that will yield an interpretable or meaningful cluster
Interpret the cluster based on the average of RFM
Identify Anomalies
Flag customers whether or not they are anomalous

Figure 10: *Process Overview of Component C*

Feature Engineering Using Recency, Frequency and Monetary (RFM) Analysis

Calculate Recency, Frequency and Monetary values for every customer

Based from the definition of Recency (R), Frequency (F) and Monetary (M), the data was processed accordingly

Recency (R) : difference between the analysis date and the most recent date, that the customer has transacted. The analysis date here has been taken as the maximum date available for the variable REFDTE.

Frequency (F) : Number of transactions performed by every customer (PARTY1).

Monetary (M) : Total money spent by every customer (PARTY1)

To determine the RFM value of the customer (PARTY1) using the RFM value, the symbol the following symbols was coined

Symbol	Description
_Up	is a value higher than the average value
_Down’	is a value lower than the average value

Table 11: *Symbols for RFM Score*

This means that the higher the value it will be better for the company and the lower of the average it will get worse for the company. But for Recency (R), the symbol _Down means the lower of the average then the better for the company and the symbol _Up means higher than average then the value is not good for the company.

Data Normalization

Normalization of data aims to manage data between one attribute to another attribute does not have a great distance. This study needs to be normalized because the data, Recency (R), Frequency (F) are very different from Monetary (M). M is the amount of money issued by customers. Data that has been identified as RFM will be normalized by using min-max method using R Software. Min-Max Normalization was chosen as the method of data normalization because it preserves the relationships among the original data values thus it guarantees that all the features will have the exact same scale (guaranteed to reshape the features to be between 0 and 1) compared to Z-score Normalization which is also helpful in the normalization of the data but not with the exact same scale (normalized values can have different ranges). It is also easier to compute compare to Z-Score Normalization. It can be useful in algorithms that do not assume any distribution of the data like K-Nearest Neighbors which is vital in determining the best number of clusters.

Segmentation

To understand the behavior of the customers, there is a need to segment it using the RFM Scores that were derived and define it using the symbols _Up and _Down per quantities – Recency, Frequency and Monetary

Segments	Description	Behavior
R_Down F_Up M_Up or R_Down F_Up M_Down	Frequent Customer	This customer group is customers who has recently made a transaction with a high number of transactions and the amount of money spent is either high or low
R_Up F_Up M_Up or R_Up F_Up M_Down or R_Up F_Down M_Down or R_Up F_Down M_Up	Inactive or Lost Customer	Group of customers who have not made a purchase with the number of transactions and the total money spent is either higher or lower than the average in the past.
R_Down F_Down M_Down or R_Down F_Down M_Up	New Customer	This customer group is the customer has just made a transaction with a low number of transactions and the money is either low or high

Table 12: *Customer Segmentation using RFM Scores*

Cluster Validity & Interpretability

Density-based spatial clustering of applications with noise (DBSCAN)

For DBSCAN, the parameters ε and minPts are required and must be specified and determined. Ideally, the value of ε is given by the problem to solve (e.g. a physical distance), and minPts is then the desired minimum cluster size.

As a rule of thumb, a minimum minPts can be derived from the number of dimensions D in the data set, as minPts ≥ D + 1. The low value of minPts = 1 does not make sense, as then every point on its own will already be a cluster. With minPts ≤ 2, the result will be the same as of hierarchical clustering with the single link metric, with the dendrogram cut at height ε. Therefore, minPts must be chosen at least three (3). However, larger values are usually better for data sets with noise and will yield more significant clusters. Also, minPts = 2·dim can be used, but it may be necessary to choose larger values for very large data, for noisy data or for data that contains many duplicates. In this project, minPts = 2*dim = 2*3 dimensions = 6 was used since there are three (3) dimensions namely Recency, Frequency and Monetary.

On the other hand, the value for ε can then be chosen by using a k-distance graph, plotting the distance to the k = minPts-1 nearest neighbor ordered from the largest to the smallest value. Good values of ε are where this plot shows an "elbow". if ε is chosen much too small, a large part of the data was not be clustered; whereas for a too high value of ε, clusters will merge, and the majority of objects will be in the same cluster. In general, small values of ε are preferable, and as a rule of thumb only a small fraction of points should be within this distance of each other.

The function kNNdistplot() using R Software was used to draw the k-distance plot. The aim is to determine the "knee", which corresponds to the optimal eps parameter. This knee corresponds to a threshold where a sharp change occurs along the k-distance curve.

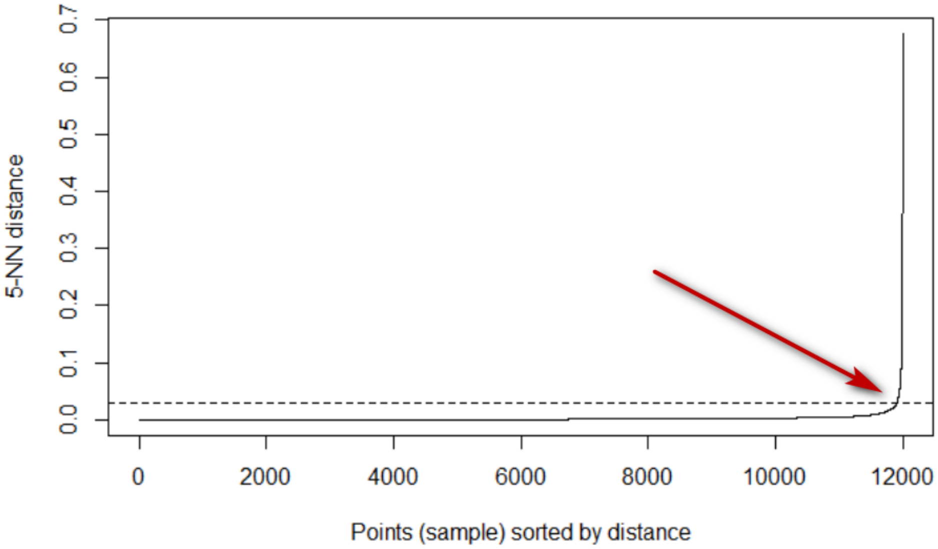
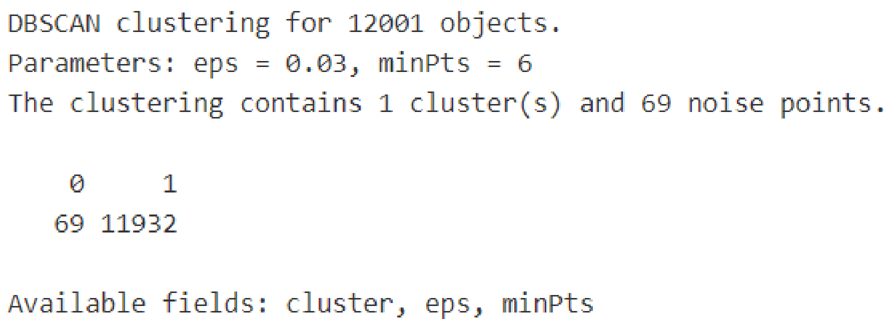


Figure 11: *K-NN distance plot*

It can be seen that the optimal eps value is around a distance of 0.03.

Once MinPts and optimal eps value were determined, DBSCAN was performed using dbscan() function in R software.



```
DBSCAN clustering for 12001 objects.
Parameters: eps = 0.03, minPts = 6
The clustering contains 1 cluster(s) and 69 noise points.

    0     1
   69 11932

Available fields: cluster, eps, minPts
```

Figure 12: *DBSCAN Results*

Identify Anomalies

From the DBSCAN Results, it already explicitly shows that there are 69 noise points, these noise points were considered as potentially anomalous. To further verify, cluster plot is needed to have a visualization how far these points. fviz_cluster() function was used

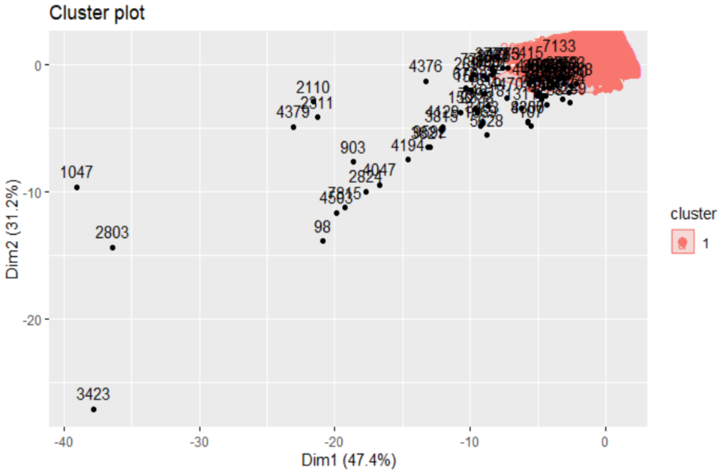


Figure 13: *Cluster Plot of DBSCAN*

The black points on the cluster plot corresponds to the noise points. These noise points were extracted from the dataset to tag it as potentially anomalous customers.

```
Frequent Customers Inactive or Lost Customers           New Customers
                53                         12                       4
```

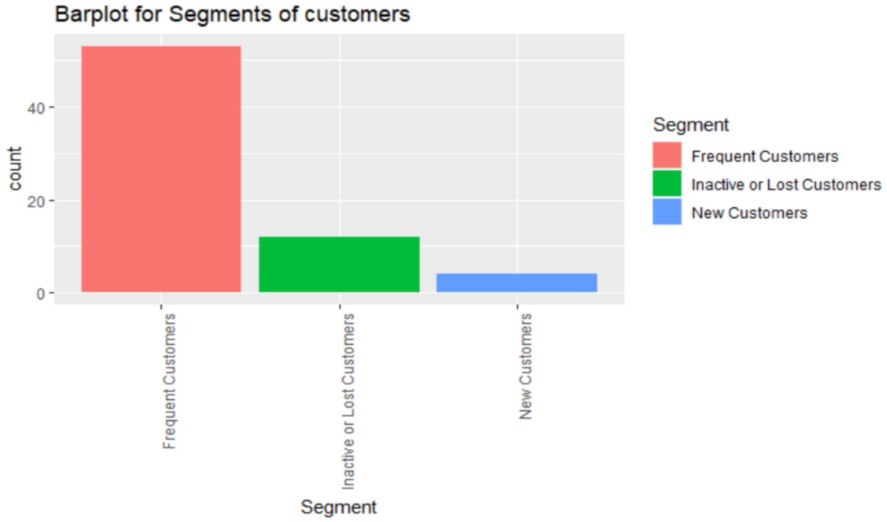


Figure 14: *Frequency Plot of Noise Points per Customer Segment*

To further analyze the behavior of these noise points, the difference of cluster means from overall means was computed

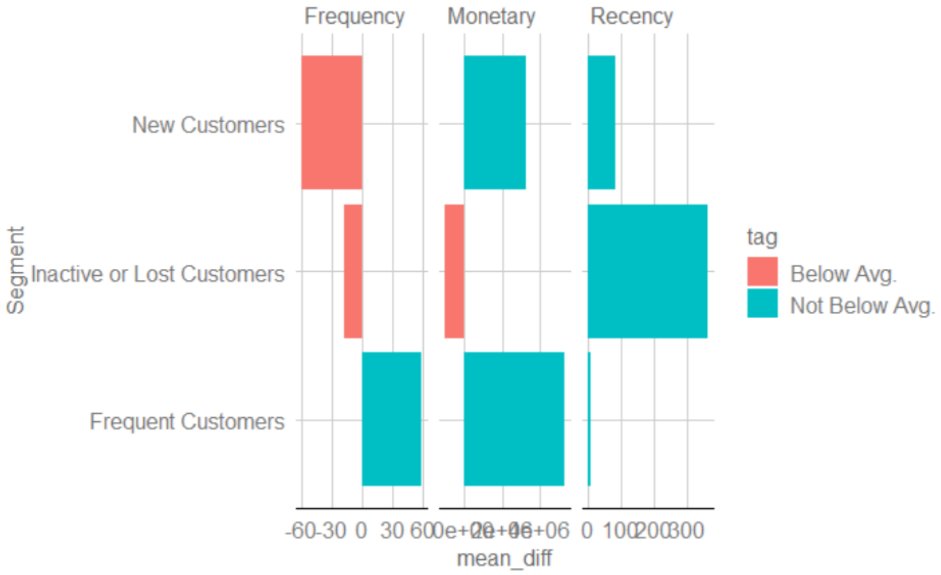


Figure 15: *Mean Difference Plot of Noise Points*

Based from the Mean Difference Plot, it can be concluded that for New Customers has low frequency of records and above average on the amount they spent on their records. For Inactive or Lost Customers, their frequency of records and the amount they spent is low. Lastly, For Frequent Customers, they have a high frequency and amount in their records.

Now that the behavior of the potentially anomalous customers was determined, tagging them as Priority in the dataset was done. Based from the results of DBSCAN and CLARANS, DBSCAN is an easier cluster technique to identify potential anomalies given that it is more sensitive to outliers. Potential anomalies can also be easily tagged which answers the objective of this study.

Priority Ranking and Filtering

In this study, identifying the priority level of a record for audit was based on three (3) components as proposed in the outlined framework. Component A investigated the items' historical behavior, Component B evaluated the company type, while Company C explored the specific customer behavior. Each component has delved into a record using different methodologies having the same objective of the framework, that is to evaluate a record in more than one aspect. Different rules of what is normal were established, and records which deviate from this were tagged as priority Table 13 presents a summary of the components.

	Component A	Component B	Component C
Perspective	Item's own historical behavior	Company Type behavior	Customer Behavior
Feature Selection	n/a	PCA	RFM Analysis
Algorithms	STL, Moving Average, Cubic Spline Smoothing, ARMA/ARIMA	Isolation forest	DBSCAN, CLARANS
Priority rule	GESD: Outside of 95% of the critical value	At 10 percent contamination	Noise Points

Table 13: *Summary of each component*

Since each component investigated different aspect that influences a record, scoring of a record was done equally. While results of each component was produced independently, results were designed to be read as one output, each complementing the other.

		Actual Tag		
		Priority (P)	Not Priority (NP)	Total
IPA Tag	High	91	128	219
	Medium	544	4064	4608
	Low	2965	45537	48502

Table 14: *Results of Priority Rating using the IPA Framework*

The second dataset provided has a priority tag for each record. Note that the Not Priority (NP) tag for this dataset does not necessarily mean that a record is not a priority. There are cases that the record was not audited due to the volume of records being handled by the auditor and was eventually tagged as NP. Furthermore, records tagged as Priority (P) does not necessarily mean that the record is erroneous. Subject dataset was used to evaluate the result of the entire framework. For the purpose of evaluation, once a record is tagged as a priority in one component, its final tag will be Priority.

		Predicted Tag		
		Priority (P)	Not Priority (NP)	Total
Actual Tag	Priority (P)	1734	1866	3600
	Not Priority (NP)	21190	28539	49729
	Total	22924	30405	53329

▨	True Positive	▨	False Negative
■	False Positive	■	True Negative

Table 15: *Confusion Matrix of the results*

The confusion matrix above shows the actual tag versus the resulted tag of a record when the framework was used in evaluating the priority level of a record. For the auditors, this table shows that there are more records tagged as priority by the framework than the ones manually tagged by the auditors, that is 22,924 records tagged as Priority compared to just 3,600 originally tagged. Though type 1 errors (or any type of error) is best to be avoided, in this case, this implies that the framework broadens the scope of records being audited which aids the job of an auditor in the initial screening of records.

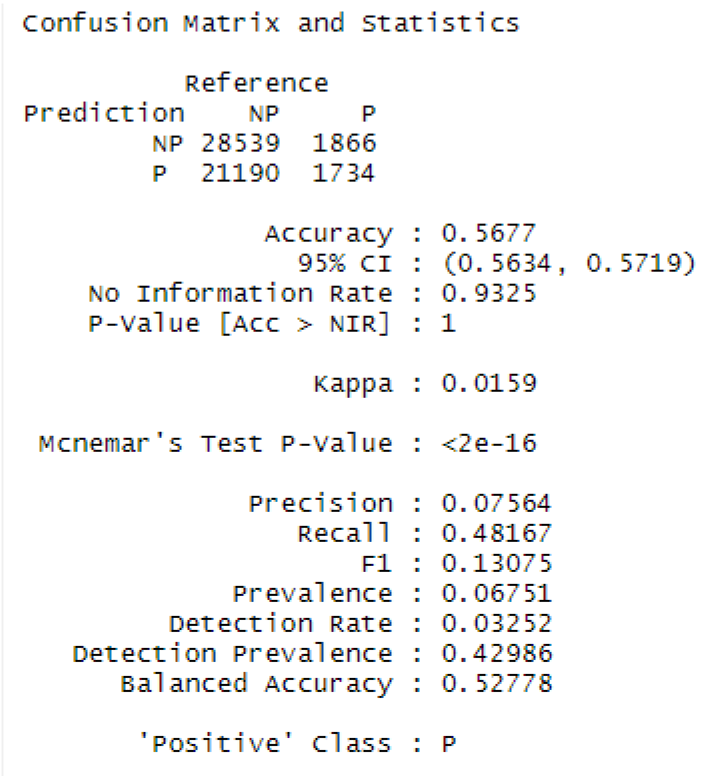
Model and Framework Evaluation

Computing the metrics to evaluate the framework, the following are the results:

Metric	Percentage
Sensitivity or Recall or True Positive Rate	48.2%
Specificity, Selectivity or True Negative Rate	57.4%
Precision or Positive Predictive Value	8%
Accuracy	57%
F-score	13%

Table 16: *Metrics used to evaluate the results*

Sensitivity or recall refers to the true positive rate produced by the framework. In other words, a highly sensitive test is one that correctly confirms the true nature of the subject. Meanwhile, Specificity or Selectivity refers to True Negative Rate. Precision refers to the positive predictive values which signifies the probability that the test will produce true positive.



```
Confusion Matrix and Statistics

          Reference
Prediction    NP     P
        NP 28539  1866
        P  21190  1734

               Accuracy : 0.5677
                 95% CI : (0.5634, 0.5719)
    No Information Rate : 0.9325
    P-Value [Acc > NIR] : 1

                  Kappa : 0.0159

 Mcnemar's Test P-Value : <2e-16

              Precision : 0.07564
                 Recall : 0.48167
                     F1 : 0.13075
             Prevalence : 0.06751
         Detection Rate : 0.03252
   Detection Prevalence : 0.42986
      Balanced Accuracy : 0.52778

       'Positive' Class : P
```

Figure 17: *Confusion Matrix for Evaluation of Framework*

In evaluating the framework, it is important to note that the available labeled dataset has a limitation to what was manually covered by the audit. In table 16, recall, which is at 48 percent, and precision which is at 7 percent alone, seems low, but since specificity is already above 50 percent and given the limitation of the available dataset that we have, the performance of the framework is a good benchmark compared to the manual process. This is supported by the Confusion Matrix above, which shows that at No information Rate, the performance of the framework is at 93 percent already. In addition to this, to evaluate if the Framework really brought improvement, McNemar's test was used. McNemar's test is being used to determine if there was a statistically significant difference in the proportion of items with priority rating before and after the implementation of the framework.

Conclusion: At α = 0.05 level of significance, there is a sufficient statistical evidence to conclude that that the proportion of records tagged as priority under the proposed framework is significantly different from that of a "no information framework". Specifically, it is observed that a total of 22,924 records were tagged as priority under the proposed framework while 3,600 records were tagged as priority under a "no information framework". This implies that the proposed framework is better than the no information framework.

6. CONCLUSION

The proposed Intelligent Prioritization of Account (IPA) framework offers a solution that can augment the current manual audit process. The IPA framework ensured that all records will be part of the scope of audit and will be checked accordingly. Adopting the IPA framework supported the objective of the auditors to have a more holistic view of the record through its evaluation in different perspectives that support each other. Deeper analysis and more informed action recommendations can be focused on based from data discovery.

In summary, the implementation of the framework is seen to provide the following benefits for the BSP:

• will increase process efficiency through the immediate prioritization of records, earlier launch of investigation (as needed);

• will strengthen data quality through the addition of procedures that validates against other aspects not currently routinely considered;

• will enhance audit process through a more statistically based validation process;

• will empower decision making through the insights presented in the different sections of this study and the proof-of-concept offered by the study in the application of artificial intelligence in central banking.

7. RECOMMENDATIONS

Based on the experience of this study on handling BSP data, the following recommendations are presented:

- Maintain a central archive of ITRS records pre- and post- audit.

The availability of labeled data set was found to be a limitation of the study. It is recommended that all records under ITRS be labeled and collected in a central archive. Having a labeled dataset allowed for supervised algorithms to learn from these data.

- Standardize entries in report (i.e., customer names)

In addition to labeled dataset, during the exploration and cleanup of data, it was noted that data quality, specifically customer names, are not standard. Ensuring quality of each data entry increases the accuracy of any algorithm to learn the data.

- Explore using different parameter levels used in this study

In component A for example, all parameters adopted were based on the default setting in R Software. Exploring different level parameters may provide different results

- Periodic retraining of the algorithms used in the study

Periodic retraining might be needed to redefine historical behavior, capture changes in regulations and incorporate pattern evolution

- Framework Expansion or Model Improvement

The proposed framework is currently limited to the available fields in the ITRS report. External factors can be explored depending to the item being investigated, for example foreign exchange rates, inflation rate, Gross Domestic Product, oil prices, etc. Identification of external factors should be done with subject matter expert to ensure appropriate factors will be included in model development. Furthermore, models are currently based on nominal amount of a record. Future work to complement the current framework may be done using models build on a different measure. Also, models in component A are based on month on month changes. An exploration in the day to day fluctuations may also complement the current framework.

- Model expansion to cover all items in the ITRS Report

Due to data availability, current models are limited to a number of items preselected in the study. Expanding the models to incorporate all items in the ITRS report might provide different insight and might open for new opportunities.

Furthermore, below are the list of recommendations specific per component.

Component	Recommendation
Component A: Identify anomalies per item based on historical behavior using time series decomposition	Explore using different seasonal decomposition technique Use different detrending method in decomposing non-seasonal series Conduct parameter tuning in GESD and IQR
Component B: Identify anomalies per item based on company type	Higher processor specifications (e.g. super computer) to run larger data with more avenue for parameter tuning (e.g. increasing number of trees) and feature engineering exploration Further deep dive on the tagged anomalous records, to qualify accuracy and effectiveness of Component B anomaly detection using the built Isolation Forest models Acquire more labeled and updated data to train the iForest models Explore other feature importance methods and variable transformation techniques to properly select variables and improve model
Component C: Identify anomalies per item based on customer behavior	Use DBSCAN for clustering instead of CLARANS given that it is the more viable technique and is more sensitive to outliers Conduct further RFM runs to derive new segments for analysis and model improvements

Table 17: *Recommendations per Component*

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