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# Anti Money Laundering in Financial Institutions Using Affiliation Mapping Calculation and Sequential Mining

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**Abstract:** This report discusses the importance of anti money laundering laws and the different procedures adopted by banks in the sector to curb such activities. The algorithmic approach to detect any system anomalies and suspicious characters, results in more clean systems and banking transactions. It helps ensure efficiency, faster methods and identification procedures which result in strict policies to avoid money laundering in banks and lending institutions. To direct consideration to find money laundering activities, Affiliation Mapping Calculation and Sequential Mining (AMC-SM) is proposed in this study. Affiliation Mapping Calculation (AMC) is performed on the preprocessed information sent to particular the exchanges which are happening from one-to-many and many to-one records. The AMC-SM considers time series information to identify one to many and many to one relations between electronic wires to arrive vulnerable data set.

**Key words:** Classification, data mining, anti-money laundering, suspicious transactions, AMC

## INTRODUCTION

Money laundering has been a real cause for concern for government and financial institutions, since time immemorial (Jayasree and Balan, 2013). It might have started out as a strategic plot to hide “black money” or “illegal money” from the authorities but, it has now progressed to become an art and a form of enterprise in itself (Pulakkazhy and Balan, 2013). While, technology and latest software system advancements have made life efficient and fast, individuals who wish to hide their ill gotten gains have started devising even more complex money laundering strategies. These are becoming harder to identify with every passing day.

The general definition of money laundering is the process which involves the transformation of the proceeds of an illegal business or crime into a legitimate asset or sum of money. To prevent this from occurring, government authorities and financial institutions perform thorough inspections to identify the source of the income and prevent anyone from hiding their illegal earnings as lawfully earned money (Flores *et al*., 2013).

But, it is a difficult process. With changing market and industry dynamics, new, complex and highly effective methods have been devised by experienced money laundering professionals to increase their earnings through an illegal procedure and present, it as legal income (Peng, 2011).

Certain regulatory systems, even link money laundering with other financial crimes and the improper utilization of the financial system as a whole (Helmy *et al*., 2014; Ngai *et al*., 2011). This encompasses a vast portfolio of transaction mediums like credit cards, digital currencies, securities, traditional currency and many others (Cortin *et al*., 2012; Philip and Sherly, 2012).

In general, the money acquired from crimes of extortion, drug trafficking, illegal gambling and insider trading is presented as legal money, so that financial institutions and banks will agree to handle it without any suspicion (Sabau, 2012; Suresh and Reddy, 2014). Every year, an ever increasing number of money laundering cases are brought to light and the authorities give a higher figure of the total amount of money laundered every year. In a move to curb such practices from becoming the norm in the global market, most governments have devised very strict guidelines and laws which prevent money laundering practices. In response to the government’s init iatives and the need to avoid any reputational risk, most banks, investors and lending institutions have devised effective procedures (Jayasree and Balan, 2015) which help in the identification of any form of dirty money being invested in their system.

The formation of a Financial Action Task Force (FATF) saw the introduction of strict anti money laundering guidelines, designed to ensure the prevention, detection and reporting of different money laundering activities.

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Banks and financial institutions in a country have to abide by the rules devised by the authorities as adherence to anti money laundering laws is imperative for all financial institutions. These procedures keep a check on the decreasing productivity within the economic segment of a country that is a result of money laundering activities. Furthermore, anti money laundering laws help to prevent the continuous erosion of the institution as corruption, fraudulent activities and money laundering have a strong link with each other. The continuous flow of operations of all financial institutions is ensured only with the trust of their customers. Any kind of perceived risk to the investors and depositors from any fraud, scam or corruption on an institutional level can pose the biggest hurdle to generating customer trust in the lending institutions which can have a significantly disastrous impact on the economy of a developing country.

In view of the previously stated procedures and systems, in this research, successful better evasion recognizable proof method called as affiliation mapping calculation and sequential mining composed of German credit data set. The AMC-SM is executed to identify the patterns by minimizing the false positive rate. The commitment of AMC-SM is:

- To introduce an affiliation mapping calculation to identify one-to-many and many to-one records
- To figure the vulnerable data set by AMC uses the time series information
- To gather all the money laundering data set, Sequential Pattern model is created

## MATERIALS AND METHODS

**Methods undertaken by financial institutions to prevent money laundering:** Money laundering is linked to terrorism financing in the world and efforts to curb such activities in the financial sector include, the seizing and complete freezing of all funds and concerned bank accounts. Aside from that, carefully designed preventive measures and strategies help to avoid money laundering issues and are vital to safeguarding the reputation and credibility of an institution. These practices include, establishing the customer identity along with the details of the beneficial owner along with the controller of the actual legal title holder of the account.

Figure 1 shows the decision system on the financial institution. It is also an essential practice for financial institutions to maintain an updated customer profile at all times. Transaction monitoring is essential to ensure that all the financial activities are in accordance with the customer profile and are completely legitimate. Any inkling of a discrepancy in the finances of a customer needs prompt investigations of the financial institution, s regulatory authorities. All transactions are then evaluated for any sign of the proceeds of the crime and a thorough analysis of the actual source of funds is conducted. Any kind of suspected or identified money laundering activity or transaction is brought to the notice of the financial intelligence unit who adopts practices to finalize the actual cause of suspicion and validate its sources. Figure 2 explains the processes involved in money laundering detection.

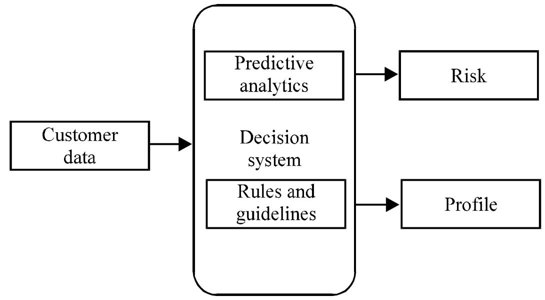


Fig. 1: Decision system

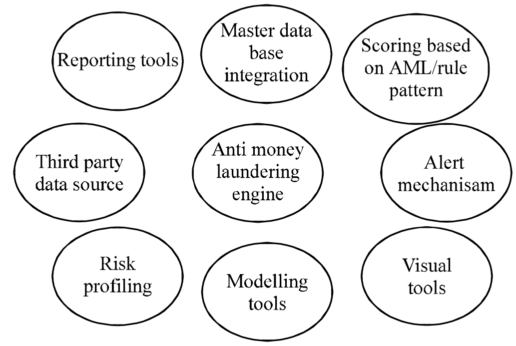


Fig. 2: Anti money laundering tools

Actions are taken to ensure that all suspicious transactions are reported and the suspected individual is identified. The procedure involves assessment of the case against the suspected individual and banks are liable to report suspicious activities to the concerned authorities and also provide a detailed description of the reasons along with the evidence as to why the transactions were viewed as dubious in the first place. It is necessary for banks and financial institutions to carry out this procedure very thoroughly, otherwise, a reported money laundering case can have a serious impact on the goodwill and position of the bank within the industry. A reputation once tainted, takes years to improve and the legal procedures along with procedural investigations conducted by the federal authorities can be major setback for any lending institution.

But, in spite of these assessment procedures, money laundering cases do crop up and banks are subjected to thorough investigations and criticism regarding their failure to identify and investigate the movement of dirty money through their system. Thus, the private sector focuses on the completion of three main procedures. The first step includes the process of excluding different terrorist elements and criminals from the financial system. This way, they aim to keep money laundering activities under control and curb monetary support to suspicious organizations before it is too late.

The second step is to provide all the information to the federal authorities about certain criminal or suspicious elements, so that proper investigation can be carried out when needed. The record of all monetary transactions proves to be the key to highlighting the activities of criminal elements and preparing a sound case against them in national or international court.

The third and most important step that is followed by the lending institutions is that all their clients are subjected to strict scrutiny and a sharp check is kept on the movement of their monetary assets, in and out of the country. Banks are in the ideal position to notice any suspicious circumstances or actions and can report them to the authorities who investigate such instances further, to determine whether the case demands any serious actions to be taken against it.

The banks are thus, instructed to monitor all customer transactions very carefully and compliment the activities with their client profiles. Any transactions that raise suspicions are reported for further investigation in relation to possible terrorism financing or criminal proceeds.

The managing German credit dataset is utilized for distinguishing proof of the money laundering entities. At first in information preprocessing step, the customer record data is separated utilizing the affiliation mapping calculation. The AM calculation extricates the customer data set by recognizing the many to-one and one-to-many mapping records. The one-to-many and many to-one data exchange records are gathered as a situated to recognize the relations in AMC-SM.

In the wake of preprocessing in AMC-SM, it creates the outcome to the information mining stride to distinguish the relational logic of the framework. Sequential mining manages the defective record to recognize the relationship between the customers and the system. The Sequential mining clarifies the review patterns on the customer record to order the money launders utilizing the information mining strategy. The mining step consolidates the work with example investigation venture to review the flaw accounts and recognize the laundering evasion on every time period. The example examination is completed utilizing the pattern mining.

**Affiliation mapping procedure:** Affiliation mapping in the AMC-SM is performed on the preprocessing step. The AM isolates the customer exchange which is diverse to the unmistakable records. From the AMC-SM, the different arrangement of suspicious (i.e.,) broken records are gathered furthermore situated of records connected to the specific record is likewise distinguished. The preprocessing stride with affiliation mapping perceives the one-to-many and many-to-one connection money exchanges on the customer records. The many to-one and one-to-many money exchange in AMC-SM is clarified through the AM calculation.

**Alogrithm A; AM calculation:**

```
Begin
//Many-to-One Money Exchange
<Account name=”Customer Name”>
<generator class=”local”/>
<many-to-one name=”Address ”column=”AddressId”
not-null=”true”/>
</Account>
//One-to-Many Money Exchange
<Account name =” Customer Address”>
<generator class =” local”/>
<set name =” Customer_Name” inverse =” true” key
column =” AddressId”/>
<one-to-many class=” Customer_Name “/>
</set>
</Account>
End
```

The above AM calculation used to effectively recognize the flawed exchange completed on the many to-one and one-to-numerous many. The exchanges make the “Record” class and the generator class checks whether the exchange is done inside of the nearby record. The many to-one executes the cash to the same record from the differing source accounts. The one-to-many perform the exchange by setting the record name to the different destination accounts. The many to-one exchange conveyed and relationship between the records are mapped viably in AMC-SM.

The relational model recognizes the relationship between the quantity of exchanges and the money exchanged on the every time allotment. The money exchanged between the diverse bank customers are seen in AMC-SM mining and the relation is dissected. The affiliation mapping in the preprocessing step are utilized for the pattern mapping proof in the information mining step. The total money exchange is figured in AMC-SM and the vulnerable data set is predicted as:

$$\text{Many-to-one exchange} = \text{Exchange amount} > \text{Threshold amount} \quad (1)$$

Equation 1 portrays the many-to one exchange transform in them AMC-SM. On shifting time span, many to-one relatio nship vulnerable is distinguished if the measure of exchange surpasses the edge rate on specific record, then the record is considered as the vulnerable record in AMC-SM. The one-to-many relationship vulnerable is recognized in AMC-SM when the greatest number of exchange is completed on the specific time line:

$$\text{One-to-many exchange} = \text{Current exchange} > \text{Time frame of exchange limit} \quad (2)$$

Equation 2, depicts the one-to-many exchange prepare in the AMC-SM. SM works in recognizing the exchange laundering on the various records with shifting customers and properties. The SM catches all the probabilistic reliance of the diverse records, in this way offers the proficient frame work for money laundering.

**Pattern analysis:** Distinguished money laundering dataset using affiliation mapping calculation, now arrange the way of exchange and cash exchanged utilizing Sequential Pattern Analysis. Review the dataset, process the pattern n (t) number of transmission way utilizing in relation model. The "n" speaks to the aggregate number of accessible way in the relational framework and "t" speaks to the quantity of record included in money laundering set. The inspecting did in the AMC-SM to gather the whole sum exchanged ways and accessible ways of gathering used to process the likelihood of money laundering. The algorithmic B stride of the pattern analysis is depicted as:

**Alogrithm B:**

Begin: Step 1: Read dataset of customers, $T_m$ -Money Exchanged Step 2: Distinguish different account source set S For each account data
Step 3: Calculate Total Money Exchanged S=$T_m$ n(t)
Step 3.1: Many-to-One Exchange = Exchange Amount > Threshold Amount
Step 3.2: One-to-many Exchange = Current Exchange > Time Frame of Exchange Limit
Step 4: Distinguish transmission paths using pattern analysis S
Step 4.1: Add S to transaction set $T_m$
End For
End

**Framework defined for anti money laundering and associated data mining procedures:** A technical based approach is seen as the better option while seeking to implement anti money laundering methods in banks and other lending institutions. Data mining is hence, the key to proper money laundering free system transactions and a classification based algorithm is an option explored by many banks for this purpose. In order to better identify any discrepancies in the system, algorithm based systems are used to ensure efficient data mining procedures.

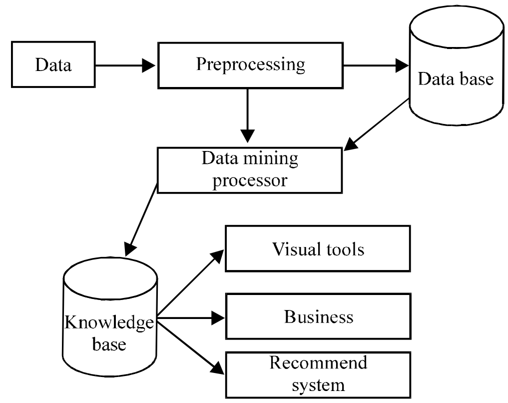


Fig. 3: AML detection DM framework

The working of the proposed algorithm begins when all of the data is stored into the data warehouse where the preprocessing work is done to ensure proper data cleaning, along with transformation. Only selected data is chosen for the data mining engine which is the major place where the data mining algorithm is actually applied.

Figure 3 explains the workflow of the framework. The knowledge that is gleaned is then passed onto the knowledge base and it is further utilized for visualization efforts, business applications and other recommended systems. Then, the procedural work is done with a firm focus on the dynamic detection mechanism of all the identified suspicious transactions. The suspicious transactions are identified by any reported abnormal relationships that are seen between the different transactional accounts. From within a stream of different financial transactional data, it is thus, possible to discern various patterns that depict an abnormality in the database of transaction patterns.

## RESULTS

The financial transactions are seen as stream data and a dynamic mining method is employed in order to identify all suspicious patterns which occur on different stream transactions. A classification algorithm is used which is based on different multiple class rules of association as ascertained by the data streams. A FP tree is used to improve the dimensions of space and time efficiency.

The data mining algorithms ensure a solution to the issue of anti money laundering. The algorithm itself is a classification based program which ensures accurate detection of any suspicious transactions.

Table 1: Accuracy level

| No. of accounts | Accuracy level (%) | | |
|---|---|---|---|
| | FFD framework | JTA model | AMC-SM mining |
| 100 | 21.4 | 23.19 | 26.70 |
| 200 | 27.2 | 31.40 | 35.32 |
| 300 | 26.1 | 30.00 | 36.00 |
| 400 | 40.1 | 43.40 | 47.00 |
| 500 | 51.2 | 52.11 | 59.00 |
| 600 | 55.4 | 54.68 | 62.00 |
| 700 | 56.7 | 58.70 | 69.00 |

Table 2: False positive rate

| Accounts | False positive rate (%) | | |
|---|---|---|---|
| | FFD framework | JTA model | AMC-SM |
| 50 | 0.09 | 0.08 | 0.06 |
| 100 | 0.07 | 0.06 | 0.04 |
| 150 | 0.10 | 0.10 | 0.07 |
| 200 | 0.14 | 0.12 | 0.10 |
| 250 | 0.15 | 0.13 | 0.09 |
| 300 | 0.22 | 0.20 | 0.13 |
| 350 | 0.23 | 0.17 | 0.12 |

Table 3: The processing time in view of the everyclient account

| Size of each account (KB) | Processing time (sec) | | |
|---|---|---|---|
| | FFD | JTA model | AMC-SM |
| 50 | 440 | 477 | 425 |
| 100 | 515 | 510 | 470 |
| 150 | 698 | 692 | 585 |
| 200 | 787 | 776 | 732 |
| 250 | 867 | 860 | 752 |
| 300 | 931 | 970 | 885 |
| 350 | 987 | 942 | 840 |

To successful distinguish the money laundering accounts, Sequential Mining model utilizing the AMC-SM trialresults. AMC-SM is thought about against the current Financial Fraud Detection (FFD) system (Ngai *et al*., 2011) and Joint Threshold Administration (JTA) (Kamra and Bertino, 2011) model key. Java is utilized to explore the components and investigate themeasures of the outcome rate with tables. Results are exhibited for diverse number of exchange records. The exploratory work utilizes the Statlog (German credit data) data set to gauge the rate of increase result. Table 1 tabulates the accuracy level of fraud identification in FFD framework, JTA mode and AMC-SM.

Table 2 introduced the false positive rate taking into account the customer accounts. As outlined, the normal false positive rate is measured on the diverse client checks. The false positive rate is lessening in light of the fact that the relational model is presented in the AMC-SM. The proposed model decreases the false positive rate by 25-48% when contrasted with the FFD (Ngai *et al*., 2011) structure. The affiliation mapping in the preprocessing step are utilized for the relation recognizable proof in this manner decreasing the false positive rate by 11-40% when contrasted with the current JTA model (Kamra and Bertino, 2011). The money exchanged between the distinctive bank customers are seen in AMC-SM and the relationship dissected on the 350 client accounts in Table 2.

Table 3 shows the processing time in view of the every client account. The span of client tally is utilized to gauge the handling time of the framework. The focusing on aftereffects of the AMC-SM preparing time is contrasted and two present condition of proposed technique. The condition of propsed techniques taken for the test work is FFD structure and JTA model. Evaluating successive example is sufficiently natural to effectively mine the customer data, in this manner diminishing the preparing time by 6-14% in AMC-SM when contrasted and existing FFD (Ngai *et al*., 2011) system. The example data is compress with the relationship model adequately transform and perceive the customer accounts, consequently diminishing the handling time by 6-13% when contrasted and JTA model (Kamra and Bertino, 2011).

## DISCUSSION

The algorithm based study is focused on improving the detection of suspicious transactions within the system and thus, eliminate the possibility of illegal transactions via banks and lending institutions. The accuracy of the system ensures timely identification of all suspicious and possible money laundering transactions which assists the lending institutions in preventing any illegal actions through their systems.

## CONCLUSION

In this research, affiliation mapping calculation utilizing the pattern analysis is created a model to recognize money laundering accounts successfully with no false positive rate. At first, the Affiliation Mapping (AM) technique is utilized on the German credit data from UCI store to particular the exchanges. The exchanges of one-to-many and many to-one records are distinguished viably through the mapping strategy. At that point, the isolated exchange set uses the Relational model to distinguish the laundering records. At long last to arrange, the way of money exchange, review successive example is reached out in AMC-SM procedure. The AMC-SM also gives the legitimate framework in the greater part of this present reality spaces. Exploratory results show that the proposed AMC-SM distinguishes the moneylaundering account as well as recognizes the defense less record with the negligible preparing time. The AMC-SM gives 26.312% lesser false positive rate and 17.144% enhanced general framework proficiency.

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