

Analytical Study On Prevention And Detection Of Financial Cybercrime And Frauds Using Transaction Pattern Generation Tool

Dr. Narendra Sharma¹, Krishna Annaboina²

¹Associate Professor, Dept. of Computer Science, Sri Satya Sai University of Technology and Medical Sciences Bhopal, India.

²Research Scholar, Dept. of Computer Science, Sri Satya Sai University of Technology and Medical Sciences, Bhopal, India. anneboina.krishna@gmail.com

ABSTRACT

E-commerce is a vital sales avenue for multinational businesses in today's technology environment. Due to the fast growth of e-commerce, credit card sales have increased. Unfortunately, criminals have profited from credit card theft. The discovery of safety faintness in standard credit card dispensation schemes has increased credit card theft, costing billions of dollars yearly. Modern credit card thieves are agile and use cutting-edge tactics. Global fraud complicates credit card issues for banks and other financial businesses. Many techniques, such as First Virtual, Cyber Cash, and SET, are employed to avoid financial cybercrime. Although customers and businesses rarely use these systems, they are very secure. These models protect our online transactions, but they cannot prevent fraud if a customer's credit card information is physically lost or falls into the wrong hands. The study is distinctive in that it uses data mining, statistics on one stage for modeling portion. Effort detailed in thesis necessity be beneficial to academics; in particular, a literature review of data mining approach before putting it into practice. Additionally, building additional financial applications benefits from an considerate of the role data mining plays in detecting economic misconduct.

Although the programme was developed with online transactions in mind, cardholders can also use it for offline transactions.

Keywords: Financial cybercrime, frauds, data mining.

I. INTRODUCTION

India's Internet usage is growing rapidly. It has opened doors in every field, including business. Every coin is two-sided. The internet has flaws. Cybercrime is a major negative. Internet connectivity has left us subject to security dangers connected with large networks, among other negatives.

Today, consumer-focused retail, financial, communication, and marketing enterprises employ data mining. It helps them assess sales, customer happiness, and business profitability. Finally, they may "dig down" into summary data to see transaction data. Data mining lets retailers offer tailored promotions based on a customer's point-of-sale record. Major components of data mining include a data warehouse, database, and other information repository. Servers retrieve data depending on client requests. Knowledge base evaluates pattern interestingness, while pattern evaluation module focuses search on interesting patterns.

E-commerce is a vital sales avenue for multinational businesses in today's technology environment. Due to the fast growth of e-commerce, credit card sales have increased. Unfortunately, criminals have profited from credit card theft. The discovery of safety faintness in standard credit card dispensation schemes has increased credit card theft, costing billions of dollars yearly. Modern credit card thieves are agile and use cutting-edge tactics. Global fraud complicates credit card issues for banks and other financial businesses.

The IC3 website received 275,284 complaints between January 1 and December 31, 2008, according to the 2008 Internet Crime Report [41]. From 206,884 complaints in 2007, there is a 33.1% increase. Online frauds and ethical issues dominated these publications' charges. 2008 recorded the biggest financial loss for referred complaints (\$264.59 million)

According to a Gartner survey [40] of 160 firms, online transactions have 12 times more fraud and etailors spend 66 percent more for credit card discount rates than conventional merchants. In fraud incidents, Web retailers are liable, whereas credit card companies protect conventional businesses.



1.2 OBJECTIVE OF RESEARCH:

- To talk about many types of financial cybercrimes and scams that happen nowadays, such as phishing and credit card fraud.
- Two, learn about many data mining means, and
- Term "fraud prevention" refers to strategies aimed at preventing fraud from happening. The goal of fraud detection, on the other hand, is to promptly uncover fraudulent activity after it is safeguarded. After efforts to prevent fraud have been unsuccessful, the next step is fraud detection. Since it is common to be oblivious to the fact that fraud protection has failed, ongoing usage of fraud detection is essential in practice.

1.3 RELATED WORK IN FRAUD DECTECTION:

The difficulty of detecting credit card fraud is rising in tandem with the card's rising popularity. When it comes to improving accuracy—specifically in classification—traditional data mining techniques are woefully inefficient. Credit card fraud detection relies heavily on accurate categorization. There is a proposal to use a genetic algorithm for forced it card fraud detection in order to increase its accuracy. Because it is a smart algorithm that optimizes the issue to aid with prediction and increase accuracy. Credit card fraud detection systems that came before used rules as their foundation. Banks establish these standards to identify fraudulent transactions, however these procedures compromise accuracy for many transactions.

There has been a lot of talk in the academic community about data mining as a potential solution to the problem of credit card fraud detection. To combat this, Gosh and Reilly developed a method that uses neural networks to identify fraudulent activity [1]. They used a large dataset of tagged credit card transactions to train their algorithm. Among the many forms of fraud that fall under this category include applications, counterfeit items, mail-order purchases, lost or stolen cards, non-receipt issue (NRI) fraud.

Dorronsoro et al. [3] identifies a large frequency of credit card dealings and a short decision-making window as two distinguishing features. They distinguished between real and fake actions by using Fisher's discriminating analysis.

M.Syeda et al. [4] used similar granular neural networks to haste up data mining, information detection for detecting credit card scheme. There is a comprehensive mechanism in place for this.

By using distributed data mining to break down large amounts of transactions into smaller ones, P.K. Chan et al. [5] were able to construct models of user behavior. Combining the resultant basic models creates a metaclassifier, which in turn increases the detection's accuracy.

When discussing cross-bank data exchange, Chiu and Tsai [7] consider web services. We have developed a fraud pattern mining (FPM) method to prevent assaults by mining fraud suggestion instructions, which provide material about new fraud designs.

There are a few published survey studies that classify, compare, and synthesize literature about fraud detection. In a thorough study, Phua et al. [8] surveyed fraud detection systems that rely on data mining.Kouetal. [9] compiled a list of methods for detecting credit card fraud, phone fraud, and computer intrusions. According to

V.Hanagandi et al. [11] developed a deception notch by analyzing past transactions on credit card accounts. Using density-based clustering and radial basis function networks (RBFN), they provide a method for distinguishing fraudulent from legitimate transactions. After transforming input data into cardinal constituent interplanetary, clustering, RBFN modeling make use of a small number of components.

In their analysis of credit card fraud detection problems, Ashen et al. [12] determine how successful categorization methods are. They tested the efficacy of logistic regression, neural networks, and decision trees as fraud detectors.

H. Shao et al. [13] introduced a system for identifying fraudulent activity in customs declaration data by using data mining techniques, like extensible multi-dimension criteria statistics perfect, cross fraud-detection method.

For the purpose of securing online banking, K.B. Bignell [14] outlines the design of multi-layer artificial neural networks with feed-forward.

In their demonstration of its application to the detection of fraud, Srivastava et al. [15] use a Hidden Markov mimic (HMM) to mimic the stages involved in processing credit card transactions. When first trained, an HMM takes into account the usual actions of a card holder. For a trained HMM to reject an incoming credit card payment as fraudulent, the rejection probability must be sufficiently low. Simultaneously, they also strive to avoid the denial of legitimate transactions.

In order to identify cases of electrical energy theft, J.E. Carpal et al. [17] suggests a system that uses rough groups, KDD. Our technique detects patterns of fraudulent behavior by evaluating the area between fraudulent and genuine customers in great detail using previous data sets from electricity providers. Using these patterns, they create classification criteria that electricity providers may employ to identify fraudulent clients.



II. DATA MINING METHODS

A DEFINITION OF DATAMINING:

Data mining is practice of automatically analyzing and extracting information from database data using one or more machine learning algorithms. Data mining sessions aim to find patterns and trends in data. The act of " non trivial extraction of implicit, before unidentified, possibly beneficial material from data" is known as data mining. Additionally, "the science of collecting valuable information from huge datasets or databases." To begin, let's agree data mining is a clearly clear process that, given data, generates models or patterns. Data mining approaches include searching through large datasets for meaningful patterns and trends in order to extract actionable insights. Data mining initiatives have made use of a wide variety of methods, association, classification, clustering, decision trees, prediction, neural networks, among many others. The principles and procedures of each methodology define the kind of problems they tackle. Following this, we will income a quick look at those data removal methods.

2.1 SUGGESTION:

Well-known data mining approach known as suggestion finds patterns by analyzing the connection between variables in the same transaction. This method also goes by the name "relation approach" since it finds the most common occurrences of various objects in the data set by studying their relationships. One of the many common uses of association rules is the discovery of sales correlations in medical datasets or transactional data [3].Retailers often use association because it provides valuable insights on customer purchasing habits.

By analyzing past sales data, stores may discover patterns like people constantly purchasing crisps with beers. By strategically placing beers and crisps side by side, businesses can save customers time and boost sales [4]. Market basket analysis is a common name for association rule due to its roots in retail. [1].

2.2 CLASSIFICATION:

For precise analysis and prediction of massive data sets, classification techniques sort datasets into predefined categories. Customers, objects, and other data sets may be better understood by classification, which involves specifying several qualities to establish a certain class. If you want to classify buildings according to their occupancy or construction type, for instance, you may do so simply by looking for certain criteria like structure, height, or unit. You may apply a new construction to a certain class by comparing the database's declared properties. Using these guidelines, you may categorize your consumers according to their age, gender, and socioeconomic status. In addition to determining a classification, classification may contribute into the output of other approaches like clustering, which uses shared qualities across classes to find groups, or decision trees, which decide a classification.

2.3 CLUSTERING:

Data mining often makes use of clustering as one of its primary methods. The purpose of the clustering procedure is to comprehend the similarities and differences in the dataset by analyzing one or more qualities to find data that is similar to each other. Because it divides the data into several categories to find a cluster of related outcomes, clustering is also known as segmentation. If we want to make it easier for readers to find books on a certain subject without having to search the whole library, we can use the clustering strategy for book management in libraries. This involves grouping books that have certain commonalities onto one shelf and giving it a relevant name.

2.4 DECISION TREE:

Part selection criteria might be based on decision tree approaches. Moreover, to facilitate the selection and use of certain data within the broader framework.

The decision tree begins with an easy question with two (or more) possible solutions. With each response comes a new set of questions designed to bolster the data's categorization or identification, allowing for either prediction or classification. Classification systems often utilize decision trees to connect type information, and predictive systems use them to accelerate the structure of the tree and the output depending on different predictions based on past data. [5].

2.5 PREDICTION:

The process of making a forecast by studying previous occurrences or examples. For example, when using the



credit card authorization, you may determine whether a purchase is fraudulent by combining decision tree analysis of previous transactions with categorization pattern matches. It is very likely that the transaction is legitimate based on the Match between the bought flights to the UK and transactions in the UK. [5].

2.6 NEURAL NETWORKS:

These days, many individuals rely on Neural Networks. Method often used when data mining technology was in its infancy. The AI community came together to build the artificial neural network. Users are not need to possess extensive expertise in the field or the database in order to operate neural networks, since they are highly automated (as stated in [4]). To get the most out of the neural network, you must be familiar with the following..

- Connections between the nodes.
- Get the most out of your computing power.
- Cutoff point for training completion. There are two primary components of a neural network: the node and the connection.
- Node—matching the node to a neuron in the human brain is completely free.
- The structure of the network is defined by this arrangement of neurons and the connections between them. One powerful method of predictive modeling is neural networks. Even for specialists, it's a challenging concept to grasp. It generates very complicated things that are difficult to grasp in their entirety. The neural network has many different types of uses. Using this, the company was able to uncover instances of fraud [4].

To improve the compression ratio, data compression techniques have made use of a variety of tools, including discrete cosine transforms, discrete wavelet transforms, neural networks, and deep learning algorithms [5, 6]. When it comes to data compression, unsupervised learning models, including self-organization feature maps, are the most popular neural networks. SOFM (6.3) the author laid up the foundation for SOFM, vector quantization, and entropy coding.

III. DATAWARE HOUSE IMPLEMENTATION

Once transaction data has served its operational purpose, it is removed from the database. If a company doesn't have a decision support facility, they collect data and then throw it away. A data warehouse, a kind of interactive media, receives the data, nevertheless, in the presence of a decision support environment. Think of the data warehouse as a repository for all relevant business records assembled to aid in decision-making. For a more comprehensive analysis, see W.H. Inmon's work from 1996. This definition states that a data warehouse is a collection of nonvolatile, subject-oriented, integrated, time-variant data that helps with management's decision-making.

3.1 DATA WAREHOUSE ARCHITECTURE

Providing business users with read-only access to summarized data from the past is a big challenge for data warehouse design.

The relational model lends itself well to the following data warehouse architectures:

- Star schema
- Snow flake schema
- Constellation schema

Star schema architecture:

•

Among data warehouse designs, star schema is the most basic. The two main parts of a star schema are fact table, dimension tables. These tables let you to browse through certain categories, summarize, dig down, and set criteria.

Today, data warehouse implementations still mostly employ the star schema, despite it being the most basic data warehouse design. This is because it accounts for 90–95 percent of all instances.

Snow flake schema architecture:

As a modification to the star schema concept, the snowflake schema normalizes some of the dimension tables and further separates the data into other tables. The schema graph that comes out of it looks like a snowflake.

Unlike star schema models, snowflake models provide for the possibility of maintaining dimension tables in normalized form to reduce repetition. With the dimensional structure incorporated as columns, a large dimension table may easily become massive. This reduction in area is negligible, however, when contrasted with the regular



size of the fact table.

3.2 IMPLEMENTATION ENVIRONMENT

The FCDS implementation was carried out in Oracle 9i. As explained in Chapter 6, data warehouse is created, applied in Oracle 9i and comprises of a number of tables. Same chapter also contains images of each table. Lookup tables are made to keep track of a customer's recent spending patterns. Current online transactions are provided to the FCDS as input. For this transaction, a risk score is generated using a linear equation and the TRSGM's criteria.

To make the setup easier to use, stored procedures, functions, packages, and triggers were created. These were used to determine how each transaction differed from the typical profile of the consumer.

3.3 SAMPLE RESULTS

Genuine Transaction



Figure 1 Example output of Data Mining Submission for Genuine Transaction-I

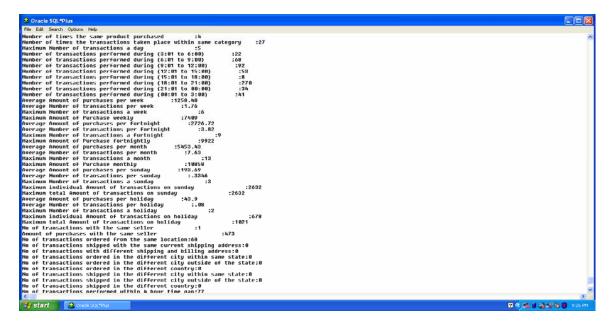


Figure 2 Illustration output of Data Mining Application for Genuine Transaction-II

PAGES: 9-31



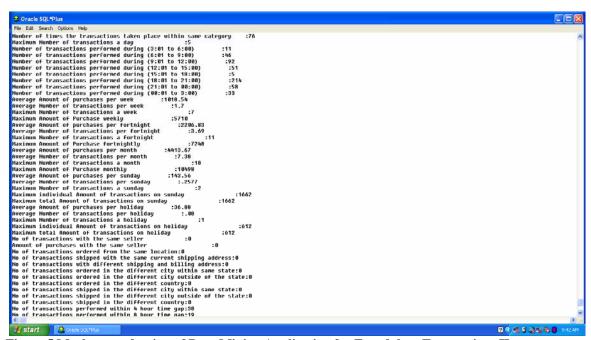
ᡱ Oracle SQL#Plus	
File Edit Search Options Help	
Haximun Humber of transactions a week :6	~
laximum Amount of Purchase weekly :7409	
average Amount of purchases per fortnight :2726.72	
average Number of transactions per fortnight :3.82	
Maximum Humber of transactions a fortnight :9	
laximun Anount of Purchase fortnightly :9992 Norrane Mount of Durchases or nontb :5453.43	
Iverage Anount of purchases per nonth :5458.43 Iverage Number of transactions per nonth :7.63	
Avainum Nunder of transactions a month :13	
taxinun Anount of Purchase monthy :1058	
Average Anount of purchases per sunday :193.69	
werage Nunber of transactions per sunday :.3346	
Naximun Number of transactions a sunday :3	
Naximum individual Anount of transactions on sundau :2632	
Maximum total Amount of transactions on sunday :2632	
Average Amount of purchases per holiday :43.9	
Average Number of transactions per holiday :.08	
Maximum Number of transactions a holiday :2	
Maximum individual Amount of transactions on holiday :678	
Maximum total Amount of transactions on holiday :1021	
No of transactions with the same seller :1	
Anount of purchases with the same seller :473	
No of transactions ordered from the same location:68	
No of transactions shipped with the same current shipping address:0	
No of transactions with different shipping and billing address:0	
No of transactions ordered in the different city within same state:0	
Ho of transactions ordered in the different city outside of the state:0 Ho of transactions ordered in the different country:0	
no or transactions ordered in the different country:0 No of transactions shipped in the different city within same state:0	
NO OF TRANSACTIONS SHIPPED IN THE DIFFERENCE ITY WITHIN SAME STATE:0	
No of transactions shipped in the different country 0	
to of transactions performed within 4 hour time gap:77	
No of transactions performed within 8 hour time gap:34	
No of transactions performed within 16 hour time gap:68	
No of transactions performed within 24 hour time gap:32	
No of transactions performed within 7 day time gap:317	
No of transactions performed within 15 day time gap:55	
io of transactions performed after 15 days:4	
Generated Risk Score: 40080184	
Senuine Transaction	
2L/SQL procedure successfully completed.	
SQL>	
	~
	<u>)</u>
start 🔹 Orade SQLTPlus	😰 🔦 👧 🔮 🖓 関 🗴 229 PM
Figure 2. Illustration and and the Mining Scheringing for Course	The second se

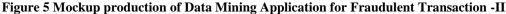
Figure 3 Illustration output of Data Mining Submission for Genuine Transaction-III Fraudulent Transaction

🕹 Oracle SQL*Plus	
File Edit Search Options Help	
SOL> @tpg:	
1969 /	
Enter value for card_id: 200	
old 987: v_cardid:=&card_id;	
new 987: v_cardid:=200;	
Enter value For category_id: 4	
old 988: v_catid:=&category_id; new 988: v_catid:=4:	
neu 988: v_catid:=4; Enter value For product id: 40060	
enter value var product_int. woodu	
new 989: U proid400602	
Enter value for amount: 11000	
old 990: v amount:=&amount	
nev 990; v amount:-11009;	
Enter value for seller id: 35	
old 991: v_seller_id:=&seller_id;	
new 991: v_seller_id:=35;	
Enter value for shipping_id: 10	
old 992: v_shipping_id:=&shipping_id:	
new 992: v_shipping_id:=10:	
Enter value for location_id: 43	
old 993: v_location_id:=Blocation_id;	
nev 993: v_location_id:=43; Enter value for holiday: 0	
encer value tor nolloay: ⊎ old 994: v holiday:=&holiday	
new 994: v holiday:-animay, new 994: v holiday:animay,	
Number of transactions:510	
Average Anount of purchases per day :145.36	
Average number of transactions per day 2.2795	
Amount spend in the current category :38826	
Time passed since the same category purchased	
:169.538576388888888888888888888888888888888	
Time passed since the same category purchased Days: 169 Hours:12 minutes:55	
seconds : 33	
Time passed since the same product purchased :	
Time passed since the same product purchased Days: Hours: minutes: seconds:	
Time passed since the last transaction :109.871574074074074074074074074074074074074	
:109,87157407407407407407407407407407407407407407	
Nakinun Anount of Transaction 22130	
Axinun Anount of Purchase dailu :3228	
Number of transactions during day :466	
Number of transactions during late night :44	
Number of times the same product purchased :0	
Number of times the transactions taken place within same category	
	<u>></u>
Start + Orade SQL*Plus	😨 🔦 👧 🕎 🖏 🌒 9:41 AM

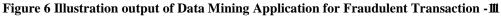
Figure 4 Illustration output of Data Mining Application for Fraudulent Transaction - 1.











Doubtful business

Now a example of doubtful deal is shown along by chance of transaction being honest or fraudulent. Photo of table suspect is also revealed where filed suspect_count is incremented



🗟 Oracle SQL*Plus	
File Edit Search Options Help	
SQL> @ tpg;	
1969 /	
Enter value for card id: 107	
old 987: v cardid:-&card id:	
new 987: v cardid:=107:	
Enter value for category id: 4	
old 988: v catid:-Bcategory id:	
new 988: v catid:=4;	
Enter value for product id: 40053	
old 989: v proid:=&product id;	
new 995 U proid-#4063:	
Enter value for amount: 32000	
chi de la contra da la contra da contra Contra da contra da contr	
her 990: v anount = 32009;	
Enter value for seller id: 50	
and opt: u seller id:=&seller id:	
uld 991: v_seller_ld=58:ler_ld; new 991: v_seller_id=58:	
Enter value for shipping_id: 34 old 992: v shipping id:=&shipping id:	
new 992: v_shipping_id:=34:	
Enter value for location_id: 56	
old 993: v_location_id:=&location_id;	
new 993: v_location_id:=56;	
Enter value for holiday: 0	
ald 994: v_holiday:=&holiday	
new 994: v_holiday:=8;	
Number of transactions:682	
Average Amount of purchases per day :1631.46	
Average number of transactions per day :.3299	
Amount spend in the current category :537810	
Time passed since the same category purchased	
:135.166747685185185185185185185185185185185	
Time passed since the same category purchased Days: 135 Hours:4 minutes:0	
seconds:7	
Time passed since the same product purchased :	
Time passed since the same product purchased Days. Hours minutes seconds:	
Time passed since the last transaction	
108.654699074074074074074074074074074074074	
Time passed since the last transaction Days: 108 Hours:15 minutes:42 seconds:46	
Maximum Amount of Transaction :19841	
Maximum Anount of Purchase daily :28717	
Number of transactions during day :543	
Number of transactions during late night :59	
Number of times the same product purchased :0	
Number of times the transactions taken nlace within same category :122	
	3
f start + Orade SQL*Phs	2 🔦 🔍 🖓 📕 11:07 Ab
👬 start 🔰 🕹 Orade SQL*Plus	

Figure 7 Example output of Data Mining Application for Doubtful Transaction-I

🖄 Oracle SQL®Plus	
File Edit Search Options Help	
Number of times the transactions taken place within same category :122	~
Maximum Humber of transactions a day :4	-
Number of transactions performed during (3:01 to 6:00) :22	
Number of transactions performed during (6:01 to 9:00) :66	
Number of transactions performed during (9:01 to 12:00) :109	
Number of transactions performed during (12:01 to 15:00) :52	
Humber of transactions performed during (15:01 to 18:00) :5	
Number of transactions performed during (18:01 to 21:00) :270	
Humber of transactions performed during (21:01 to 00:00) :36	
Humber of transactions performed during (00:01 to 3:00) :42	
Average Anount of purchases per week :11433.17	
Average Number of transactions per week :1.77	
Maximun Hunber of transactions a week :6	
Maximum Anount of Purchase weekly :56061	
Average Anount of purchases per fortnight :24771.86	
Average Humber of transactions per fortnight :3.83	
Haximun Humber of transactions a fortnight :9	
Haximun Anount of Purchase fortnightly :7/300	
Average Amount of purchases per month :49549.72 Average Munber of transactions per month :7.65	
Maximum Number of transactions a month :12 Naximum Anount of Purchase monthu :78135	
maximum mount or rurchase monthy : 78155 Average Anount of purchases per sunday : 11635.42	
Average Muduk of purchases per Sunday :1032.42 Average Mudber of Eransactions per Sunday :.3115	
Navinum Number of transactions a sunday :4	
Naximum homore or transactions a sounday .** Naximum individual Anount of transactions on sunday :19841	
Naximum indicidual mutof transactions on sunday :22554	
Average Anount of purchases per holiday :601.14	
Average Mucher of transactions per holiday :.14	
Maximum Number of transactions a holiday :2	
Maximum individual Anount of transactions on holidau :5518	
Maximum total Amount of transactions on holiday :9193	
No of transactions with the same seller :3	
Amount of purchases with the same seller :13711	
No of transactions ordered from the same location:0	
No of transactions shipped with the same current shipping address:0	
No of transactions with different shipping and billing address:0	
No of transactions ordered in the different citu within same state:0	
No of transactions ordered in the different city outside of the state:0	
No of transactions ordered in the different country:0	
No of transactions shipped in the different city within same state:0	
No of transactions shipped in the different city outside of the state:0	
No of transactions shipped in the different country:0	
No of transactions performed within 4 hour time gap:91	
No of transactions merformed within & hour time dam:32	×
	> .::
1 start 2 onde Southlas	🛛 🔦 🕵 🕲 🕲 🔒 11:00 AM

Figure 8 Illustration output of Data Mining Submission for Doubtful Transaction-II



2 Oracle SQLMPlus	
File Edit Search Options Help	
Maximum Humber of transactions a month :12	
Maximum Amount of Purchase monthly :70135	
iverage Anount of purchases per sunday :1635.42	
verage Number of transactions per sunday :.3115	
laxinun Number of transactions a sunday :4	
laximun individual Amount of transactions on sunday :19841	
laximum total Amount of pransactions on sunday : 28554 Norage Amount of purchases per holiday :601.14	
overage mount or purchases per notical contract per contr	
versige number of transactions a holiday :14	
Haximum number of cransactions a notical 2	
Maximum Initial Amount of transactions on holiday :9193	
to of transactions with the same seller :3	
Amount of purchases with the same seller :13711	
No of transactions ordered from the same location:0	
No of transactions shipped with the same current shipping address:0	
to of transactions with different shipping and billing address:0	
to of transactions ordered in the different city within same state:0	
No of transactions ordered in the different city outside of the state:0	
No of transactions ordered in the different country:0	
No of transactions shipped in the different city within same state:0	
No of transactions shipped in the different city outside of the state:0	
No of transactions shipped in the different country:0	
No of transactions performed within 4 hour time gap:91	
No of transactions performed within 8 hour time gap:32	
No of transactions performed within 16 hour time gap:56	
Ho of transactions performed within 24 hour time gap:21 Ho of transactions performed within 7 day time gap:322	
no or transactions performed within 1 day time gap:322 No of transactions performed within 15 day time gap:60	
no of transactions performed after 15 day time gaptoo No of transactions performed after 15 day:11	
robability of the transaction being genuine7466705	
robability of the transaction being fraudient: 25332958	
Nuscicious Transaction	
corrated Risk Score: 52263376	
L/SQL procedure successfully completed.	
SQL> select * from suspect where cardid=107;	
CARDID TRANSACTI DAYS HOURS MINUTES SECONDS SUSPECT_COUNT	
107 16-APR-10 108 15 42 46 1	
QL>	
	🛛 🔦 🕵 🖓 👘 11:10 A
start 🕴 😫 Orade SqL*Plus	

Figure 9 Illustration out put of Data Mining Application for Doubtful Transaction-III Multiple product instruction provision

😫 Oracle SQL "Plus	
File Edit Search Options Help	an and a second
SQL> @ tpg2;	
2075 /	
Enter value for card id: 10	
old1016: v_cardid:=&card_id;	
new1816: v_cardid:=18;	
Enter value for shipping_id: 79	
ald1817: v_shipping_id:=Rshipping_id;	
new1017: v_shipping_id:=79;	
Enter value for location_id: 80	
old1018: v_location_id:=&location_id;	
neu1018: v_location_id:=80;	
Enter value for holiday: 0	
old1019: v_holiday:=Choliday;	
new1019: v_holiday:=0;	
Enter value for no_of_products: 2 ald1020:no_of_products:=&ao_of_products:	
ald1020: no_of_products:=&no_of_products; new1020: no_of_products:=2;	
neuruzu: no_or_products:=2; Enter value for category id: 5	
enter value for Category_10: 5 Old1022: v cati(1):=&category id:	
0101022: 0_cati(1):=0catgory_10; new1022: v_cati(1):=5;	
Enter value for product 1d: 50012	
Later value for product_id: Suborz	
Terrer value for amount: 1250	
old 162 +: v pro-amount (1) := famount ;	
neu1824: v proamount(1):=1258;	
Enter value for seller id: 56	
old1025: v seller id(1):=&seller id;	
nev1025: v seller id(1):=56;	
Enter value for category id: 7	
old1026: v_catid(2):=&category_id;	
new1026: v_catid(2):=7;	
Enter value for product id: 70053	
old1827: v proid(2):=&product id;	
new1827: v proid(2):=78853;	
Enter value for amount: 3245	
old1028: v_proamount(2):=&amount	
neu1028: v_proanount(2):=3245;	
Enter value for seller_id: 15	
old1029: v_seller_id(2):=Gseller_id;	
new1029: v_seller_id(2):=15;	
Number of transactions:596	
Average Amount of purchases per day :914.31	
Average number of transactions per day :.3266	
Time bassed since the same category 1 nurchased	8
Start Crade SOL*Plus	🛛 🖉 🖓 💐 🖏 🚺 6:10 РМ

Figure 10 Example output of Data Mining Application for Multiple Order Creation Support - I



😤 Oracle SQL*Plus	
File Edit Search Options Help	and the second
ime passed since the same category 1 purchased 156.9394/22222222222222222222222222222222222	
ne passed since the same category 1 purchased bays: 150 nours:22 minutes:24 ne passed since the same category 2 purchased	
130.9977083333333333333333333333333333333333	
ine passed since the same category 2 purchased Days: 130 Hours:22 minutes:56 econds:42	
ime passed since the same product 1 purchased :157.005	
ime passed since the same product 1 purchased Days: 157 Hours:0 minutes:7 econds:12	
ine passed since the same product 2 purchased :1654.559861	
ine passed since the same product 2 purchased Days: 1654 Hours:13 minutes:26 econds:12	
(ine passed since the last transaction 130.9977083333333333333333333333333333333333	
'ine passed since the last transaction Days: 130 Hours:22 ninutes:56 seconds:42	
aximum Amount of Transaction :13469	
aximum Amount of Purchase daily :20684	
unber of transactions during day :537	
unber of transactions during late night :59	
unber of times the same product 1 purchased :7	
unber of times the same product 2 purchased :1	
unber of times the transactions taken place within same category 1 :53 unber of times the transactions taken place within same category 2 :91	
under of times the transactions taken place within same category 2 :34 aximum Number of transactions a day :4	
aximum number of transattions a day in unber of transattions performed during (3:01 to 6:00) :15	
under of transactions performed during (6:01 to 9:00) :77	
under of transactions performed during (9:01 to 9:00)	
under of transactions performed during (12:01 to 15:00) :2	
under of transactions performed during (15:01 to 18:00) :6	
unber of transactions performed during (18:01 to 15:00) .263	
under of transactions performed during (1:01 to 80:08) :73	
under of transactions performed during (08:01 to 3:00) :48	
verage Anount of purchases per week :6489.87	
verage Number of transactions per week :1.63	
aximun Number of transactions a week :7	
aximun Anount of Purchase weekly :32633	
verage Anount of purchases per fortnight :13888.06	
verage Number of transactions per fortnight :3.53	
aximum Number of transactions a fortnight :10	
aximum Amount of Purchase fortnightly :39475	
verage Amount of purchases per month :27776.12	
verage Number of transactions per month :7.07	
laximum Number of transactions a month :13	
start 🕹 Orade SOL*Plus 🔛 CHAPTER 7 - Microsol	🖬 🔦 💑 🕄 🍇 関 6:121

Figure 11 Example output of Data Mining Application for Multiple OrderProductSupport - II

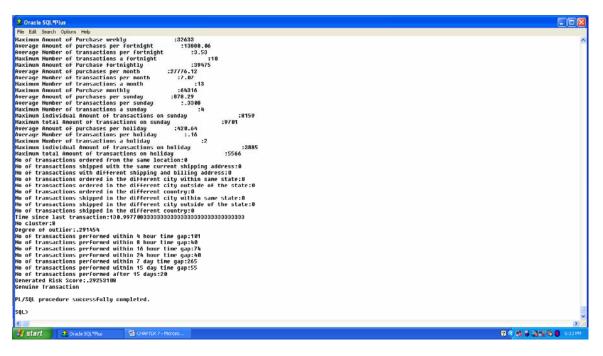


Figure 12 Example output of Data Mining Application for Several Order Product Support - III

3.4 RESULT ANALYSIS & DISCUSSIONS

The TRSGM's ability to produce a very dynamic risk score is by far its most intriguing finding. For example, if a consumer makes a purchase and the transaction value changes slightly while all other inputs remain constant, the risk score that is created will likewise be altered. The risk score would also take into account this small modification. We have repeatedly used the application for various transaction amounts with a small fluctuation while keeping all other inputs constant. Additionally, we reset all the lookup tables



prior to taking the result a second time and moving forward. Here is an example.

For input Card Id	125
Category Id: 6ProductId	60050
Seller Id	750
Shipping Id: 410LocationId:980	

Registered under MSME Government of India

Table 1 Example output of application for dissimilar transaction quantities

Amoun t	5000	50001	5002	5003
RiskSc	0.2927	0.2927		0.2928
ore	7495	7506		7596

😫 Oracle SQL+Plus	
File Edit Search Options Help	
SQL) Gtpg: 1960 / 1960 / Enter value for card_id: 125 cld 987: v_cardid:=t25; Enter value for category_id: 6 ald 988: v_catid:=t6; Enter value for product_id: 00050 cld 909: v_prold:=t60050; Enter value for anount: 5000 ald 909: v_anount:=t6000; Enter value for anount: 5000; Enter value for anount: 5000; Enter value for anount: 5000; Enter value for sinping_id:=t600; Enter value for sinping_id:=t800; Enter value for isfipping_id:=t800; Enter value for isfipping_id:=t800; Enterv	
PL/SQL procedure successfully completed.	
SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>	
	2
🛃 start 🔹 Oracle SQL*Plus	😰 🔜 🕄 🖏 🖏 🐻 🔂 11:56 A

Figure 13 Sample output of Data Mining Application for dissimilar deal amounts-I



😫 Oracle SQL*Plus	
File Edit Search Options Help	
SQL> Atpg:	
1969 /	
Enter value for card_id: 125	
old 987: v_cardid:=&card_id; new 987: v_cardid:=125:	
new Y8/: v_card1d:=125; Enter value for category id: 6	
ald 988: v catid=*category id;	
nev 988: v catid:=6;	
Enter value for product_id: 60050	
old 989: v_proid:=&product_id: new 989: v_proid:=60050:	
new 999: 0_prolo:=0005-0; Enter value for amount: 5001	
old 991; v amount:-Kanount;	
nev 990: v_amount:-5001;	
Enter value for seller_id: 750	
old 991: v_seller_id:=8seller_id; new 991: v_seller_id:=758:	
neu 991: v_seller_id:=758; Enter value for shipping id: 410	
old 992: v shipping id:-*eshipping id:	
new 992: v_shipping_id:=410;	
Enter value for location_id: 980	
old 993: v_location_id:=&location_id; new 993: v_location_id:=980;	
new 993: 0_location_lo:-980; Enter value for holidau: 0	
old 994: v holiday:=&holiday	
new 994: v_holiday:=0;	
Generated Risk Score: 29277506	
Genuine Transaction	
PL/SQL procedure successfully completed.	
SQL>	
sdr>	
sqL> sqL> sqL>	
SQL>	
36L)	
S0L>	
SOL>	
SQL>	
SQL> SQL> SQL>	
S01>	
	😰 🛛 💀 🖉 🔂 👔 🖂 11:50 AM
🛃 start 🔰 🤮 Orade SQL*Plus	🖸 🔁 😳 11:50 AM

Figure 14 Example output of Data Mining Request for dissimilar transaction amounts - II

Sql > Brups: 1969 / Enter value for card d1:45 add 907: v_ardd1:46ard_14; http://alue for Cardgory_1d1; http://alue for		
Sql > flog: 1969 / Enter value for card_id: 125 ald 097: v_acrdid:-Kard_id; batter value for Catgoyy_id: 6 and vms: v_catdid-6; Enter value for Catgoyy_id: 6 and vms: v_catdid-6; Enter value for amount: 5002 Cater value for seller_id: 750 Cater value for seller_id: 750 Cater value for seller_id: 750 Enter value for seller_id: 750 Enter value for seller_id: 750 Enter value for ischipping_id: 410 01 0992: v_shipping_id:-shipping_id; new 998: v_catdid-6; Enter value for ischipping_id: 410 01 0992: v_shipping_id:-shipping_id; new 991: v_sclir_id: 760 Enter value for ischipping_id:-shipping_id; new 992: v_shipping_id:-shipping_id: Enter value for ischipping_id:-shipping_id; new 992: v_shipping_id:-shipping_id: Enter value for ischipping_id:-shipping_id: New YVS: v_location_id: 986 Enter value for ischipping_id:-shipping_id; New YVS: v_location_id: 986 New YVS: v_location_id: 986	😫 Oracle SQL*Plus	
<pre>1960 / Chetr value for card_id: 125 cald 097: v_cardid:-Ecard_di; hatr value for Category_li; how value tor product_id: 40050 cald 098: v_catid:-fc; feter value for product_id: 40050 cald 098: v_uroid:-fore-concert tor value for seller_id: 750 v_anout:-5002; how v990: v_anout:-5002; how v990: v_anout:-5002; how v990: v_uroid:-fc; how how v990: v_uroid:-fc; how v990: v_uroid:-fc; how v990: v_uroid:-fc; how v990: v_uroid:-fc; how v9</pre>	File Edit Search Options Help	
Genuine Transaction PL/SQL procedure successFully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL	S01.> Bitps; 1969.7 Enter value for card_id: 125 Cold 907: v_cardid:-Ecard_id; new 907: v_cardid:-Ecard_id; new 908: v_cardid:-Ecard_org.id; new 908: v_cardid:-Ecard_org.id; new 908: v_cardid:-Ecardgory_id; new 908: v_cardid:-Ecardgory_id; new 908: v_cardid:-Ecardgory_id; new 908: v_anount: 014 909: v_anount:-5002 014 9091: v_anount:-5002 014 9091: v_scller_id:-750; Enter value for soll=1d:-750; Enter value for location_1d: 1d: 100 014 991: v_scller_id:-750; Enter value for location_1d: 1d: 100 014 992: v_shipping_id:=4hl0; Enter value for location_id: 1d: 900; Peter value for location_id: 900; Peter value for location_id: 900; Peter value for holiday:=0; Peter value for holiday:=0; <th>*</th>	*
SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL>	Genuine Transaction	
SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL>	PL/SQL procedure successfully completed.	
	SUL> SUL> SUL> SUL> SUL> SUL> SUL> SUL>	
🛃 Start 🔄 Could SQLPAu		
	Start & Oracle SQL*Plus	🖸 🖓 👷 🗞 🛢 🖂 1150 PM

Figure 15 Example output of Data Mining Application for dissimilar transaction amounts - III



A Oracle SQL*Plus	
File Edit Search Options Help	
SQL> Atpg:	
Enter value for card id: 125	
old 987: v_cardid:=&card_id;	
new 987: v_cardid:=125;	
nter value for category_id: 6	
1d 988: v_catid:=&category_id;	
rew 988: v_catid:=6;	
Inter value For product_id: 60050 old 909: v proid:=&product_id:	
inter value for anount: 5003	
old 998: v amount:-Ganount:	
new 990: v amount:=5003;	
nter value for seller_id: 750	
nld 991: v_seller_id:=&seller_id;	
iew 991: v_seller_id:=758;	
Inter value for shipping_id: 410	
old 992: v_shipping_id:=&shipping_id: new 992: v_shipping_id:=&410;	
nter value for location id: 980	
old 993: v location id:=&Location id;	
new 993: v location id: 988;	
Enter value for holiday: 0	
old 994: v_holiday:=&holiday	
new 994: v_holiday:=0;	
Generated Risk Score: 29287596	
Senuine Transaction	
PL/SQL procedure successfully completed.	
501.5	
qL>	
QL>	
QL> QL>	
QL>	
μτ> μτ> μτ>	
nger -	
	(
start 🔹 🕹 Oracle SQL*Plus	😰 🗘 🏟 🕒 11.59 A

Figure 16 Example output of Data Mining Submission for different deal amounts - IV

For input Card Id	:210
Category Id: 5ProductId:50010Amount	: 4500Shipping Id : 590LocationId:110

Table 2 Example output of application for dissimilar sellers

SellerI d	801	587	986	30
RiskSc	0.2881	0.2878	0.2881	0.2880
ore	1595	0605	1623	2632



The Ed. Sendi Options Help SQL Strp: 1990 / Distry: Up: 1990 / Enter value for card_di: 210 100 wit W97: v_cardid:-carging: Enter value for category_di: 5 101 0981: v_caldid:-category_di: 101 0981: v_caldid:-category_di: 101 0981: v_caldid:-category_di: 101 0981: v_uproid:-forgeout_lo: 101 0981: v_uproid:-forgeou	2 Oracle SQL*Plus	
Sub Steps: 1969 / Inter value for card_id: 218 Cher value for card_id: 218 Cher value for card_id: 218 Cher value for product_li: 5008 Cher value for product_li: 5008 Cher value for anount: 4508 Cher value for anount: 4508 Cher value for anount: 4508 Cher value for anount: 4508 Cher value for information of the control of t		
<pre>1969 / ` inter value for card_id: 210 inter value for card_id: 210 inter value for card_id: 210 inter value for product_id: 50010 inter value for product_id: 50010 inter value for product_id: 50010 inter value for shown::->000; inter value for shown::->000; inter value for shown::->000; inter value for intervalue for inte</pre>	He bak search opuors hep	
<pre>1969 / ` inter value for card_id: 210 inter value for card_id: 210 inter value for card_id: 210 inter value for product_id: 50010 inter value for product_id: 50010 inter value for product_id: 50010 inter value for shown::->000; inter value for shown::->000; inter value for shown::->000; inter value for intervalue for inte</pre>	SOL> Otpg:	·
<pre>bid 997: v_cardid:-teard_id; networks: v_cardid:-tairupup.id; inter value for Category.id: 5 inter value for product_id: 50010 old 909: v_proid:-50013; inter value for anount : 5000 old 909: v_proid:-50013; inter value for should: 5000 old 901: v_soller_id:-50010r_id: netw 901: v_soller_id:-50010r_id: old 901: v_soller_id:-50010r_id: id:-5000 old 902: v_soller_id:-50010r_id: id:-5000 old 902: v_soller_id:-50010r_id: id:-5000 old 902: v_soller_id:-5000 old 903: v_soller_id:-5000 old 903: v_sollidsy:-5000 old 904: v_solved old 905: v_sollidsy:-5000 old 905: v_sollidsy:-5000 old 905: v_sollidsy:-5000 old 905: v_solved old 905: v_solved old</pre>	1969 /	
<pre>new yyr: v_cardid-210; Enter value for categony_id: 5 ald 988: v_catid:=tcategony_id; mev 988: v_catid:=tcategony_id; mev 989: v_prodic-id: 5900 ald 990: v_prodic-id: 5900 ald 990: v_anount:-4500; Enter value for soller_id: 801 ald 991: v_soller_id:=testup: mev 992: v_shiping_id:=testup: ald 991: v_slipting_id:=testup: ald 991: v_cation_id:=110; ald 991: v_location_id: 110 ald 991: v_location_id:-110; Enter value for holday: Builds; enter value for holday: Builds; Enter value for holday: Builds; Enter value for location_id: 110 ald 991: v_location_id:-110; Enter value for holday: Builds; Enter value for location_id: 110; ald 991: v_location_id:-110; Enter value for holday: Builds; Enter va</pre>	Enter value for card_id: 210	
<pre>inter value for contensus (i: 5 inter value for contensus (i: 5) inter value for product.id: 50000 ald 908: u_proid:*50000; i_proid:*50000; i_proid:*5000; i_proid:*50</pre>		
<pre>nld 08%: v_citid:-tcategory_id; new 08%: v_citid:-tcategory_id; new 08%: v_prodct-S0010 old 090: v_prodct-S0010; new 090: v_prodct-S0010; new 090: v_anount:-tanount; new 090: v_soller_id:-tanount; new 090: v_soll</pre>		
<pre>mew 088: 0 catid:-5; Cater value for product.id: 50010 old 009: 0 prodict-Sof010; Enter value for anount: 4500 old 090: 0 sof010:-50010; Enter value for anount: 4500 old 090: 0 sof010:-50010; Enter value for shipping.id:-50010; Enter value for shipping.id:-50010; Enter value for shipping.id:-50010; Enter value for location.id:; Enter value for location.id: Enter value for location.id:; Enter value for location.id: Enter value for locatio</pre>		
<pre>Enter value for product id: 50010 old 900: v_prodi-S0010; imew 900: v_prodi-S0010; imew 900: v_anount:-Sanount; new 900: v_anount:-Solu; imew 900: v_sloping id: Solu; imew 900: v_sl</pre>		
<pre>old 900: u_proid:-&product_d: new 900: u_proid:-Soft0: Enter value for anount: 4500 old 900: u_anount:-&Soun Enter value for seller_id: &&d1: ald 901: u_scltr_id:=&k01 Enter value for shipping_id:Soft0: u_scltr_id:=&k01 Enter value for init=k0: u_scltr_id:=&k01 Enter value for init=k0; Enter value for init=k0; Ente</pre>		
<pre>new 090; v_proid:-50018; Enter value for anount: 45000 0ld 0901; v_anount:-45000; Enter value for sciller_id: 801 0ld 091; v_sciler_id: 4501 0ld 091; v_sciler_id: 4501 0ld 092; v_shipping_id:-500; Enter value for location_id: 110 0ld 092: v_shipping_id:-500; Enter value for location_id: 110 0ld 092: v_location_id: 110 0ld 093: v_location_id: 110; enter value for location_id: 110 0ld 093: v_location_id: 110; Enter value for location_id: 110 0ld 093: v_location_id: 110 0ld 093: v_location_id: 110; Enter value for location_id: 110 0ld 093: v_location_id: 110; Enter value for location_id: 110 0ld 093: v_location_id: 110 0ld 094: v_locati</pre>		
<pre>old 990: v_anout:-tanount; new 990: v_anoutta500; Enter value for sciller_id:-801; Enter value for shipping_id:-5500 old 992: v_shipping_id:-8500; Enter value for location_id: 110 old 992: v_location_id:-110; Enter value for location_id:-110; Enter value for location_id:-110; Enter value for holiday: 0 old 991: v_location_id:-110; Enter value for holiday: 0 enu 993: v_location_id:-110; Enter value for holiday: 0 enu 994: v_location_idi:-110; Enter value for holiday:</pre>	new 989: v proid:=50010;	
new 990: v_anount:-K500; Enter value for sciler_ii:s801 ald 991: v_sciler_ii:s801; Enter value for shipping_id:S00 ald 992: v_shipping_id:S00; Enter value for location_id:100; Enter value for location_id:100; Enter value for location_id:0:100; Enter value for blocation_id:0:100; Enter value for bl	Enter value for amount: 4500	
<pre>Enter value for sciler_ii:801 ald 901: v_sciler_ii:801; Enter value for shipping_ii:4-5501 ald 902: v_shipping_ii:530 ald 902: v_shipping_ii:530; Enter value for location_ii:110 ald 903: v_location_ii:110; Enter value for location_ii:10; enter value</pre>		
<pre>nld 091: u_sciler_ii:=Rsciler_ii; new 091: u_sciler_ii:=Rsciler_ii: Enter value for shipping_ii:=Ss0: Enter value for location_ii:10: new 092: u_shipping_ii:=Ss0: Enter value for location_ii:10: Inter value for location_ii:=10: Inter value for holiday: Enter value f</pre>		
<pre>meu 091:</pre>	Enter value for seller 1d: 801	
Enter value for shipping_id:590 Old 992: v_shipping_id:4590; Enter value for location_id:110 old 993: v_location_id:10; enter value for location_id:10; Enter value for holiday: Enter value for h		
<pre>old 992: v_shipping_id:=kshipping_id; new 992: v_shipping_id:=kshipping_id; new 993: v_location_id:=flucation_id; new 993: v_location_id:=flucation_id; new 993: v_locidiou; ald 994: v_holiday:=0; Benerated Risk Score:_2001595 Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL></pre>		
new 992: v_shipping'id:=590; Enter value for location_id:=110 shi 993: v_location_id:=10; Fater value for lociton_id:=10; new 993: v_shiiday: 0 shi 994: v_shiiday:=0; Benuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>	old 992: v shipping id:-&shipping id:	
<pre>old UV9: v_location_id:=tlocation_id; new V93: v_location_id:=tlocation_id: fater value for holiday: 0 ald 90%; v_holiday:=tholiday; new V93: v_holiday:=tlocation_id: femulae transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL></pre>	new 992: v shipping id:=590:	
new 998: Ulacation id:-110; Enter value for holiday: 0 old 994: v_holiday:=0; Generated Risk Score:2.8011595 Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
Fater value for holiday: 0 and 994: v_holiday: shortiday; new 994: v_holiday:-60; Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
old 09%; v_holiday;-tholiday; new 99%; v_holiday:-0; Generated Risk Score:28811595 Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
new 994: v_lolidøj-06; Generated Hisk Score:.28011595 Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
Generated Hisk Score:288011595 Genulne Transaction SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
Genuine Transaction PL/SQL procedure successfully completed. SQL> SQL> SQL> SQL> SQL> SQL> SQL> SQL>		
SU-> SU-> SU-> SU-> SU-> SU-> SU-> SU->	Genuine Transaction	
SU-> SU-> SU-> SU-> SU-> SU-> SU-> SU->		
\$QL2 SQL2 SQL2 SQL2 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3	PL/SQL procedure successfully completed.	
\$QL2 SQL2 SQL2 SQL2 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3 SQL3		
SQL2 SQL2 SQL2 SQL2 SQL2 SQL2 SQL2 SQL2	SQL>	
(J2 SU2 SU2 SU2 SU2 SU2 SU2 SU2 SU	SUL2	
50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2 50.2	50L7	
SQL2 SQL2 SQL2 SQL2 SQL2 SQL2 SQL2	SQL>	
SQL> SQL> SQL> SQL> SQL>	SOL>	
xqL> SqL> SqL> SqL>	SQL>	
\$QL> \$QL> <	SQL>	
\$\$\. \$\. \$\.	SQL>	
sor>	SUL2 Page Page Page Page Page Page Page Page	
	50L7	
		×
1 Start + Costs S0 1984		
	🛃 start 🔹 🕹 Orade SQL*Plus	😰 🔮 🤹 🖓 🔮 🗒 📴 221 PM

Figure 17 Example output of Data Mining Application for dissimilar sellers-I

🔹 Oracle SOL Plus	
The Edit Search Options Help	
	~
SQL> Gtpg:	-
Sul / utpg /	
Enter value for card id: 210	
old 987: v_cardid:=&card_id;	
new 987: v_cardid:=210;	
Enter value for sitegory (d. 5 nid 988: v stid:=Kategory (d.	
nu 986. U catil-science en	
Enter value for product id: 50010	
old 989: v_proid:=&product_id:	
neu 989: v_proid:=50010;	
Enter value for anount: 4500 01d 990: v anount:-Banount:	
ulu 990. v_anuunt:-sanuunt, new 900. v_anuunt:-ston;	
Enter value for seller id: 587	
old 991: v_seller_id:=&seller_id;	
new 991: v_seller_id:=507:	
Enter value for shipping_id: 590 01d 992:	
ald 972. v_shipping_10.*6801pping_10;	
Enter value for location id: 110	
old 993: v_location_id:=&location_id;	
new 993: v_location_id:=110;	
Fater value far hiliday: 0 01d 994: v boliday-scholiday;	
eve 994. v holiday: en la se	
Generated Risk Score: 28780605	
Genuine Transaction	
PL/SQL procedure successfully completed.	
SQL>	
SQL> SQL>	
SQL>	
súr>	
SQL>	
Stil > Stil >	
SQL>	
	×
	2 9 🕵 🖓 🗐 🕲 🖉 2:24 PM
a start Strate Strate	

Figure 18 Illustration output of Data Mining Application for dissimilar sellers-II



🕏 Oracle SQL*Plus	
Se oracie sour-your	
The Euler stream spectra map	
SQL> @tpg:	
1969 /	
Enter value for card_id: 210	
old 987: v_cardid:=@card_id;	
new 987: v_cardid:=210;	
Enter value For cätegory id: 5 Did 988: v catid:secategoru id:	
nld 988: v catiút-startogovjid; nev 988: v catiút-startogovjid;	
neu yas:	
ald 989 Uproduct_10. Swood 1d;	
new 989: U proid:=Sello:	
Enter value for anoint: 4500	
old 990: v amount:-Ganount;	
nev 990: v amount:-4500;	
Enter value for seller id: 986	
ald 991: v seller id:=8seller id;	
new 991: v_seller_id:=986;	
Enter value for shipping_id: 590	
old 992: v_shipping_id:=&shipping_id:	
neu 992: u_shipping_id:=590;	
Enter value for location_id: 110	
old 993: v_location_id:=&location_id;	
neu 998:	
enter value for nollaay: o holiday:-&holiday	
Generated Risk Score: 28811623	
Genuine Transaction	
PL/SQL procedure successfully completed.	
zdr>	
SQL>	
SQL>	
SQL) SQL)	
Sul>	
S01>	
SU>	
SQL>	
SQL >	
sit>	
	×
🖅 Start 🔰 🕹 Orada SQL*Plus	👔 😟 🖏 🎭 🖞 🖏 🛢 🚨 2:29 PM



😫 Oracle SQL*Plus	
File Edit Search Options Help	
SQL> @tpg:	1
1969 /	
Inter value for card_id: 210 D1d 987: v_cardid:=Gcard_id;	
10 907. V_Cardid.=210;	
nter value for category 1d: 5	
1d 988: v_catid:=&category_id;	
ev 988: v_catid:=5;	
nter value For product_id: 50010 1d 909: v proid:=&product_id;	
ev 989: v proid:=50010:	
nter value for anount: 4500	
1d 990: v_amount:-Gamount;	
ev 990: v_amount:=4500;	
nter value for seller id: 30	
ld 991: v_seller_id:=&seller_id; ev 991: v_seller_id:=38;	
nter value for shipping id: 590	
1d 992: v shipping id:=&shipping id:	
eu 992: v_shipping_id:=590;	
nter value for location_id: 110	
ld Y93: v_location_id:=&location_id; ev 993: v_location_id:=110;	
ter value for holidau: A	
ld 994: v holiday:=&holiday	
ew 994: v_holiday:=0;	
enerated Risk Score: 20802632	
enuine Transaction	
L/SQL procedure successfully completed.	
qL>	
qL>	
QL>	
1.5	
jL>	
μ.> μ.> μ.>	
qu> qu>	
Start Start Crade SQL*Plus	🛛 🔮 🤨 🥸 🖉 🖉 🖉 🖉 🖉 🖉 🖉

Figure 20 Example output of Data Mining Application for dissimilar sellers-IV

We have also checked if customer purchases the same product, category, amount, seller, shipping
address on dissimilar location, then its alteration is reflected in risk score.For input Card Id1600Category Id: 7ProductId70150Amount5300Shipping Id: 1596SellerId110



Locatio	351	352	353	354	
nId					
RiskSc	0.2545	0.2460	0.2288	0.2497	
ore	3484	8244	1003	576	



Figure 21 Example output of Data Mining Application for dissimilar locations-I

2 Oracle SQL TPlus	
File Edit Search Options Help	
SQL> Otpg;	
30.2 McDg / /	
Enter value for card id: 1600	
old 987: v_cardid:=&card_id:	
new 987: u_cardid:=1600:	
Enter value for category_id: 7 pld 988: v_catid:=&category_id;	
na vss: 0_catla:-cctegory_la; new vss: v_catla:-r;	
Enter value for product 1d: 70150	
1d 989: v_proid:=&product_id;	
1ew 989: v_proid:=70150;	
Enter value for amount: 5300	
old 990: v_anount:=&anount new 990: v_anount:=5300;	
new 990: 0_anount:=5300; Enter value for seller_id: 771	
ld 991: v_seller_id:=&seller_id;	
new 991: v seller id:=771;	
nter value for shipping id: 1596	
old 992: v_shipping_id:=&shipping_id;	
new 992: v shipping id:=1596; Inter value for location id: 352	
nter value for location_id: 552	
lew 993: v location_idi=352;	
nter value for holiday: 0	
old 994: v_holiday:-Gholiday;	
new 994: v_holiday:=0;	
Senerated Risk Score:.24608244 Senuine Transaction	
aenuine Transaction	
PL/SQL procedure successfully completed.	
SQL>	
iQL>	
iqu> iqu>	
OL >	
SQL>	
SQL>	
S0L>	
SQL> SQL>	
2017 2019	
	3
🛃 start 🕹 Orade Southkus	🖬 🔦 🔥 🍓 🖓 😌 🕴 4:16 PM

Figure 22 Example output of Data Mining Submission for dissimilar locations-II



Oracle SQL®Plus	
e Edit Search Options Help	
L> @tpq;	
9 /	
er value for card_id: 1600	
987: v_cardid:=&card_id:	
987: v_cardid:=1600:	
er value for category_id: 7	
988: v_catid:=&category_id;	
988: v_catid:=7;	
er value for product_id: 70150	
989: v_proid:=&product_id;	
989: v_proid:=70150;	
er value for amount: 5300	
990: v_anount:=&anount: 990: v_anount:=5300:	
er value for seller_id: 771	
991: v_seller_id:=&seller_id; 991: v_seller_id:=771:	
991: v_seller_id:=771; er value for shipping id: 1596	
992: v shipping id:=8shipping id;	
992: v shipping_id:=1596;	
er value for location id: 353	
1990: Ulocation_1d:=Alocation_1d;	
993: U location_id:=353:	
er value for holiday: 0	
994: v holiday:-Gholiday;	
904: U holiday: - B;	
erated Risk Score: 22881083	
uine Transaction	
SQL procedure successfully completed.	
•	
•	
•	
)
start 🕘 Oracle SQL*Plus	🛛 🔦 💐 🖏 🔮 4:20 PM

Figure 23 Example output of Data Mining Application for dissimilar locations-III

Oracle SQLTPlas Fee Control C	
	•
QL> Otpg;	
969 / Riter value for card id: 1600	
1d 987: v cardid:=&card id;	
w 987: v cardid:=1600;	
inter value for category_id: 7	
ld 988: v_catid:-Kcategory_id; we 988: v_catid:-Kcategory_id;	
refer value for product 1d: 70150	
1d 989: v proid:=&product_id;	
1989: v_proid:=70150;	
inter value for amount: 5000 10 990:	
te 990. v anount:-Sang	
inter value for seller id: 771	
old 991: v_seller_id:=&seller_id;	
ew 991: V_seller_id:-771; Ther walke for shipping id: 1596	
Id 992: U shipping id: 15-6 shipping id;	
new 992: v shipping id:=1596;	
nter value for location_id: 354	
ld 993: U location id:-*location id; ew 993: U location id:-*location id:	
nter value for holiday: 0	
old 994: v holidau:=Gholidau:	
new 994: v_holidaý:-0;	
ienerated Risk Score: 2007576 jennine Transaction	
L/SQL procedure successfully completed.	
iQL>	
off >	
iQL >	
ių ->	
045	
sár>	
sqL>	
J Start ≥ Orada SQL™As	🛛 🔇 🚓 🖓 💘 🗞 🕴 4:22 PM
A relief S visue sign rate	10 C 12 C 12 C 12 C 10 C 12 C 10

Figure 24 Example output of Data Mining Application for dissimilar locations-IV

• The program calculates cluster coverage of each new incoming transaction amount, if it is larger than 10%, the perfect shoulders, transaction is legitimate given the customer's history of regular payments. As a result, the application assigns the transaction a risk score of 0. Here's an illustration



😫 Oracle SQL*Plus	
File Edit, Search Options Help	
SQL*Plus: Release 9.2.0.1.0 - Production on Wed Apr 21 13:10:08 2010	
Copyright (c) 1982, 2002. Oracle Corporation. All rights reserved.	
Connected to: Uracle9i Enterprise Edition Release 9.2.0.1.0 - Production	
Walley: Enterprise collion Release 9.2.0.1.0 - Production With the Partitioning, OLAP and Derate Data Hining options JServer Release 9.2.0.1.0 - Production	
SQL> set serveroutput on: SQL> @ tpg:	
1969 /	
Enter value for card_id: 270 old 987: v_cardid:=&card_id;	
new 987: v_cardid:=270; Enter value for category id: 3	
old 988: v_catid:=&category_id; new 988: v_catid:=3:	
Enter value for product_id: 30050	
old 989: v_proid:=&product_id;	
new 989: v_proid:=30050; Enter value for anount: 8000	
Id 990: U amount:-Canount;	
new 990: v_amount:=8000;	
Enter value for seller_id: 5	
old 991: v_seller_id:=&seller_id;	
new 991: v_seller_id:=5; Enter value for shipping id: 5	
inter value for snapping_10: 5 Did 992: v_shipping_id:=&shipping_id;	
new 992: v shipping id:-5;	
Enter value for location id: 34	
old 993: v location id:=&location id;	
new 993: v_location_id:=34;	
Enter value for holiday: O	
old 994: v_holiday:≈&holiday:	
new 994: v_holiday:=0;	
Cluster Coverage of this amount:33.33%	
Generated Risk Score:0	
Genuine Transaction	
PL/SQL procedure successfully completed.	
SQL>	
	<u>x</u>
🛃 start 🔹 🕹 Orade SOL*Plus	M CLI 🖉 🛢 🖉 🖉 🖓 🖉 🖓 🖉

Figure 25 Example output of Data Mining Application for Cluster Attention

Author has thoroughly tested applications, verified that transactions that closely match customer buying patterns (such as the highest purchase in a given category, the most transactions in a given period of time, the most transactions ordered from the same location, etc.) generate the lowest scores. The transaction generates a higher risk score since it deviates more from the typical profile and the customer's purchasing patterns. Here's an illustration. As this particular group of transactions increased, the risk score declined.

The customer having cardid 1570 has the maximum purchasing habit in the given field as below.

Category	2
Timeframe	:18:01to21:00
Location Id	205
Seller Id	257

2 Oracle SQL*Plus	
File Edit Search Options Help	
SQL> Atpg:	^
1969 /	
Enter value for card_id: 1570	
old 987: v_cardid:=&card_id;	
new 987: v_cardid:-1570;	
Enter value For category_id: 2	
old 988: v_catid:=&category_id; new 988: v_catid:=2;	
new yok:	
nter value for product_10; 20000	
Enter value for amount: 6000	
old 990: v_amount:-Gamount;	
new 990: v_anount:=6000;	
Enter value for seller_id: 257	
ald 991: v_seller_id:=&seller_id;	
new 991: v_seller_id=257;	
Enter value for shipping_id: 56 old 992: v shipping_id:=&shipping_id;	
pig 992: v_shipping_1g:=asnipping_1g: new 992: v_shipping_id:=asnipping_1g:	
new 92: 0_snipping_id: 305	
old 993: v location id:-Glocation id;	
new 998: v location_id:=205;	
Enter value for holiday: O	
old 994: v_holiday:=&holiday	
new 994: v_holiday:=0;	
Average Amount of purchases per day :411.68	
Average number of transactions per day :.2729 Amount spend in the current category :282517	
HNOUNT Spend in the current category :282517 Time passed since the same category purchased	
The passed since the same category purchased to the passed to the same category purchased to the same category purchased to the passed to the same category purchased to the passed to t	
The passed since the same category purchased Days: 164 Hours:13 minutes:31	
seconds 143	
Time passed since the same product purchased :	
Time passed since the same product purchased Days: Hours: minutes: seconds:	
Time passed since the last transaction	
161.314155092592592592592592592592592592593	
line passed since the last transaction Days: 161 Hours:7 minutes:32 seconds:23 Maximum Amount of Transaction :6260	
Maximum Amount of Transaction :0200 Maximum Amount of Purchase daily :8410	
Maximum Amount of Futures during a save	
Number of transactions during late night :69	
Number of times the same product purchased :0	
Number of times the transactions taken place within same category 189	×
	<u>)</u>
🗾 start 🔰 🙏 orade SQL*Plus	😰 🖓 🖓 🚯 🛢 🜉 7.45 PM
	3 4 4 4 4 7

Figure 26 Example output of Data Mining Application for supreme buying practice input-I



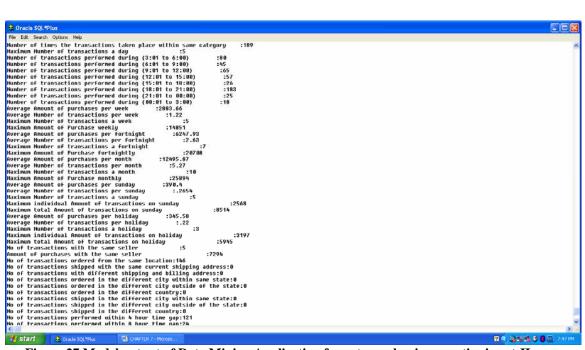


Figure 27 Model output of Data Mining Application for extreme buying practice input-II

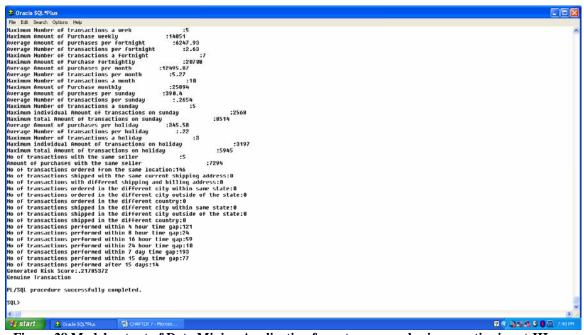


Figure 28 Model output of Data Mining Application for extreme purchasing practice input-III

Fraudulent transactions shouldn't go unnoticed in the same way. In light of these two considerations, the model is flexible. Although 0.8 is the top threshold value used here, it can be altered with further knowledge. The weighting of each characteristic is also determined in accordance with the advice of the credit card company.

Bayesian learning produced one intriguing finding. When a customer uses their card with ID number 8 for their first transaction, it seems suspicious. After a brief interval, he executes a second transaction that is worth \$13,500 and is flagged as fraudulent by Bayesian learning.



😫 Oracle SQL*Plus	
File Edit Search Options Help	
IQL> ed tpg;	
SQL> G tpg:	
1969 /	
nter value for card_id: 8	
1d 987: v_cardid:=&card_id;	
eu 987: v_cardid:=8;	
nter value for category_id: 4 1d 988: v_catid:=&category_id;	
nu 985: U_catit:=caregory_in; ew 988: U_catit:=4:	
nter value for product id: 40033	
1d 989: u proid:=&product id:	
new 989: v proid:=40033;	
Enter value for amount: 17000	
old 990: v amount:-Gamount;	
new 998: v_amount:=17808;	
Enter value for seller_id: 35	
old 991: v_seller_id:=&seller_id;	
ew 991: v_seller_id:=35:	
nter value for shipping_id: 56	
old 992: v_shipping_id:=&shipping_id; new 992: v_shipping_id:=56;	
new yyz:	
lild 993: U location_id:=Rlocation_id;	
w 993: v location id:=10:	
nter value for holiday: 0	
old 994: v_holiday:=&holiday	
new 994: v_holiday:=0;	
probability of the transaction being genuine:.8269506	
robability of the transaction being Fraudulent: 17304963	
Suspicious Transaction	
lenerated Risk Score: 53207992	
L/SQL procedure successfully completed.	
QL> select * from suspect where cardid=8;	
CARDID TRANSACTI DAYS HOURS MINUTES SECONDS SUSPECT_COUNT	
8 19-APR-10 132 19 5 47 1	
:QL> @tpg;	
969 /	
nter value for card_id: 8	
1d 987: u cardid:=&card id:	N.
🖅 start 🔰 单 Orade SQL*Plus	🕎 🖓 🖓 🖏 🖞 🛢 🔂 1240 PP

Figure 29 Example output of Data Mining Application for Bayesian Learning - I

😫 Oracle 50L Plus	B
The Edit Search Options Help	
CARDID TRANSACTI DAYS HOURS HINUTES SECONDS SUSPECT_COUNT	
8 19-APR-10 132 19 5 47 1	
QL> @tpq;	
469 / V	
nter value for card id: 8	
1d 987: v cardid:=&card id;	
eu 987: v cardid:=8;	
nter value for category id: 2	
1d 988: v catid:=&category id;	
eu 988: v catid:=2:	
nter value for product id: 20067	
1d 989: v_proid:=tproduct_id;	
new 989: v proid:-20067;	
inter value for amount: 13500	
1d 998: v_amount:=&anount	
new 998: v_amount:=13508;	
nter value for seller_id: 80	
old 991: v_seller_id:=&seller_id;	
new 991: v_seller_id:=80;	
nter value for shipping_id: 56	
old 992: v_shipping_id:=&shipping_id;	
new 992: v_shipping_id:=56;	
nter value for location_id: 18	
old 993: v_location_id:=&location_id;	
nev 993: v_location_id:=10; Inter value for holidau: 0	
inter value for nollogy: 0 1d 994:	
la 994: 0_nollag:=st	
raddulent Transaction	
raduulent fransaction robability of the transaction being genuine:.36032903	
robability of the transaction being genuineaboazeda	
reported of the classical state of the state	
L/SQL procedure successfully completed.	
QL> select * from suspect where cardid=8;	
CARDID TRANSACTI DAYS HOURS MINUTES SECONDS SUSPECT_COUNT	
8 19-APR-18 0 0 1 20 0	
	~
Start Onde SOLTHUE	2 2 2 3 3 4 5 5 5 1 8 1 8 1 8 1 1 1 1 1 1 1 1 1 1 1
f start 🕹 Orade Southus	10 12:00 10 10 10 10 10 10 10 10 10 10 10 10 1

Figure 30 Example output of Data Mining Application for Bayesian Learning-II



IV. CONCLUSION

As we covered in Chapter 1, many techniques, such as First Virtual, Cyber Cash, and SET, are employed to avoid financial cybercrime. Although customers and businesses rarely use these systems, they are very secure. These models protect our online transactions, but they cannot prevent fraud if a customer's credit card information is physically lost or falls into the wrong hands.

An Internet Virtual Credit Card Model has been provided by Anshul Jain et al. [1]. In this scenario, the bank will provide a login name and password. Then A virtual credit card number and expiration date would be provided by bank after classification into the bank's website. In order to complete an online transaction, the customer must provide and remember four pieces of information: their login ID, password, virtual credit card number, virtual card's expiration date. In my perspective, it will cost the customer more and make it harder for them to recall these extra facts.

The Reserve Bank of India recently mandated that all banks in India offer unique passwords to their credit card holders for use during online transactions. This strategy is already being applied in other nations. Although the first transaction is quite safe, in my opinion, this strategy is insufficient to stop fraud since, while the consumer is completing the first transaction, a fraudster might potentially get the password by hacking the computer or using another method.

4.1 PROPOSED FINANCIAL CYBER CRIME PREVENTION MODEL

In this arrangement, the credit card holder receives a unique password for online transactions as well as the ability to choose the length of time the password will remain active. The client must sign onto the bank's website. He can then set his password for the online transaction as well as its expiration date. If it has expired, he cannot finish the transaction. If he is the legitimate cardholder, he must connect onto the bank website, set a password, and specify an expiration date for the password.

As a result, in this paradigm, the password is only active until its expiration date has passed. When the password expires, the customer must request a new password from the bank along with confirmation of its validity. The customer's chosen expiration date needs to fall between the current day and the card's real expiration date.

While in our concept, the user will provide the password, making it a user-defined word that is simple for him to remember. Customers that deal frequently may choose to make their password expiration date very brief in order to prevent falsification. Additionally, he has the option of setting the password expiration date to the following day. As a result, the customer may ensure the security of each of his online transactions. Customers might choose a long expiration date if they don't transact frequently or see of it as overhead. When financial cybercrime spikes significantly in a given month, users can choose a shorter expiration date to prevent fraud.

4.2 SIGNIFICANCE OF THE RESEARCH

The study is distinctive in that it uses data mining, statistics, artificial intelligence on one platform for modeling portion. Work detailed in thesis must be beneficial to researchers; in particular, a literature review of data mining techniques is an effort to offer a roadmap for the researchers to explore, choose the best data mining approach beforehand putting it into practice. Additionally, building additional financial applications benefits from an sympathetic of the role data mining plays in detecting monetary corruption.

Although the programme was developed with online transactions in mind, cardholders can also use it for disconnected dealings.

Although we have created a specific application, we believe, current approach can be successfully applied to prevent infiltration in other database applications with just small application-specific modifications.

We contacted practically all of Gujarat's banks, but none of them are currently utilizing any form of software for detecting financial cybercrime. Consequently, our data mining program has been quite helpful to them.

4.3 LIMITATION OF THE STUDY:

Customers who frequently use their credit cards are the only ones who use the data mining programme that has been built. It is not for people who only deal occasionally throughout the year. The customer's whole purchasing history must be learned by the model in order for it to accurately forecast future transactions. As the customer completes more transactions, perfect gets stronger, studies customer's behaviour, more accurately anticipates the transaction.

Parameter holiday is different for each country, despite the fact that the application is global and was created with consideration for all nations. Therefore, to apply this update, the application needs just modest changes.

PAGES: 9-31 2/24/24



4.4 FUTURE SCOPE OF THE RESEARCH:

Present work takes into account the customer's site when they conduct an online transaction. It is not taken into account which machine is used for the online transaction, in future effort IP address may also be taken into account, designs may be developed for this IP address. Only issue is that IP addresses are changeable rather than static. Therefore, it is important to take this element into consideration.

The research has been prepared and carried out with the utmost care to fulfill the research objectives. It is impossible to halt in this sector since it constantly has to be updated to take into account the dynamic changes that have occurred as the genuine issues.

Although the DBSCAN data mining procedure is only used for transaction amounts, it can also be used for additional attributes.

REFERENCES

- "Securing Big Data Environment from Attacks" by Udhaya Tupakula and Vijay Varadharajan, Advanced Cyber Security Research Centre, Faculty of Science and Engineering, Macquarie Australia in 2016 at IEEE publication[978-1-5090- 2403-2/16] DOI. 10.1109/Bigdatasecurity-HPSC-IDS-2016.
- "Cyber Crime Investigation in the Era of Big Data", by Andrii Shalaginov, Jon William Johnsen, Katrin Franke, NTNU Digital forensics group, Faculty of information technology and electrical engineering, Norwegian University. 2017 IEEE International Conference on Big Data.978-1-5386- 2715-0/17.
- Crime Analysis and Predictin Using Big Data" by aarthi srinivasnadathur, gayathri narayannan, Indraja ravichandran, srividhya.S,kavalvizhi form department of information technology, SRM Institute of Science and Technology, Kattankulathur,Kancheepuram, Tamilnadu, India. Published in "International Journal of Pure and Applied Mathematics" Volume 119 No. 12, 2018. ISSN: 1314- 3395.
- 4. Technologies of safety in the bank sphere from cyber attacks"by Nyrkov Anatoliy .P, Abramova Kritstina.V, Koroleva, Gaskarov from Admiral Kakarov State University of Maritime and Inland Shipping, Russia. 978-1-5386-4340-2/18 @IEEE in year 2018.
- 5. "Crime analysis using K-Means Clustering" by Jyothi Agarwal, Renuka Nagpal, Rajini sehgol form Amity University, Nodia, in the International Journal of Computer Application [0975-8887] volume 83, No 4 December 2013.
- 6. Priyanka Kulkarni, & Dr. Swaroopa Shastri. (2024). Rice Leaf Diseases Detection Using Machine Learning. Journal of Scientific Research and Technology, 2(1), 17–22. https://doi.org/10.61808/jsrt81
- 7. A Data Mining Framework To Analyze Road Accident Data Journal Of Big Data, Sachin Kumar and Durga Toshniwal 2015.
- "Cyber Crime Analysis in Social Media using Data Mining Technique", by M. Ganesan, P. Mayilvahanan, Department of Computer Science, Vels University. In International Journal of Pure and Applied Mathematics(IJPAM) volume 116 No. 22 [1311-8080] 2017.
- 9. "Survey of Analysis of crime detection techniques using data mining and Machine Learning", by S. Prabhakaran, and silpa mitra, in National Conference on Mathematical Techniques and its applications [1742-6596].
- "Predictive Modelling of Crime Dataset using Data mining", by prajakta yerpude and Vaishnavi Gudur, Department of Compute science, in International Journal of Data Mining and Knowledge Process. vol-4 -2017.
- 11. Shilpa Patil. (2023). Security for Electronic Health Record Based on Attribute using Block-Chain Technology. Journal of Scientific Research and Technology, 1(6), 145–155. https://doi.org/10.5281/zenodo.8330325
- Mohammed Maaz, Md Akif Ahmed, Md Maqsood, & Dr Shridevi Soma. (2023). Development Of Service Deployment Models In Private Cloud. Journal of Scientific Research and Technology, 1(9), 1–12. https://doi.org/10.61808/jsrt74
- 13. Antariksh Sharma, Prof. Vibhakar Mansotra, & Kuljeet Singh. (2023). Detection of Mirai Botnet Attacks on IoT devices Using Deep Learning. Journal of Scientific Research and Technology, 1(6), 174–187.
- 14. Dr. Megha Rani Raigonda, & Shweta. (2024). Signature Verification System Using SSIM In Image Processing. Journal of Scientific Research and Technology, 2(1), 5–11. https://doi.org/10.61808/jsrt79
- 15. Shri Udayshankar B, Veeraj R Singh, Sampras P, & Aryan Dhage. (2023). Fake Job Post Prediction Using Data Mining. Journal of Scientific Research and Technology, 1(2), 39–47.
- 16. Gaurav Prajapati, Avinash, Lav Kumar, & Smt. Rekha S Patil. (2023). Road Accident Prediction Using Machine Learning. Journal of Scientific Research and Technology, 1(2), 48–59.



- 17. Dr. Rekha Patil, Vidya Kumar Katrabad, Mahantappa, & Sunil Kumar. (2023). Image Classification Using CNN Model Based on Deep Learning. Journal of Scientific Research and Technology, 1(2), 60–71.
- 18. Ambresh Bhadrashetty, & Surekha Patil. (2024). Movie Success and Rating Prediction Using Data Mining. Journal of Scientific Research and Technology, 2(1), 1–4. https://doi.org/10.61808/jsrt78
- 19. Dr. Megha Rani Raigonda, & Shweta. (2024). Signature Verification System Using SSIM In Image Processing. Journal of Scientific Research and Technology, 2(1), 5–11. https://doi.org/10.61808/jsrt79
- 20. Priyanka Kulkarni, & Dr. Swaroopa Shastri. (2024). Rice Leaf Diseases Detection Using Machine Learning. Journal of Scientific Research and Technology, 2(1), 17–22. https://doi.org/10.61808/jsrt81