Tracking Fraudulent Activities in Real Estate Transactions

Thaer SHUNNAR, Palestine and Michael BARRY, Canada

Key words: ABC-Construction, Oklahoma Flip, Outlier Detection, Data Mining, Mortgage Fraud, Fraud in Real Estate, Classification, Quadratic Discriminant analysis.

SUMMARY

Land transaction fraud is a serious problem in many parts of the world, and it occurs under different land administration systems. In general, property transaction fraud falls into two categories; fraud by forgery and fraud by impersonation. Racketeers have three general motives to engage in real estate fraud: (1) to further other criminal activities, (2) for direct profit, and (3) to shelter money derived from other criminal activities.

This paper discusses fraud specific to real estate. Many attributes of the real estate sector make it prone to criminal investment. Real estate is a high value, sizeable economic sector. However, it lacks transparency; each real estate object is unique, it provides a safe investing environment, and speculation in real estate is a tradition. Fraud in real estate is widespread in developed and developing countries, and in the former many of the fraudulent schemes are enabled by technology.

The paper describes some of the schemes used to commit property frauds and the patterns that might be identified in a land registry database. Several indicators are used to identify a fraud case. These indicators may be related to the real estate object, the owner, the financier, the financing method or the purchase sum.

The testing of a classification model using Quadratic Discriminant Analysis to identify real estate objects that might have been a target of an ABC-Construction scheme is described. The model is used to classify properties into normal, suspicious and highly suspicious properties based on transaction patterns. This paper also suggests a classification system that can be used to alert users whenever a suspicious transaction occurs on a real estate object.

Tracking Fraudulent Activities in Real Estate Transactions

Thaer SHUNNAR, Palestine and Michael BARRY, Canada

1. INTRODUCTION

Land transaction fraud is a significant problem in many countries around the world, and the *Gibbs v Messer (1891)* case in Australia shows that this is nothing new. Technological advances have contributed to significant improvements in operational efficiency in land registration. However, they have also enabled increasingly sophisticated scams (CISC 2007). In this paper we briefly describe some of the methods used by fraudsters, and then examine the application of data mining to the ABC-Construction scheme.

Land transaction fraudsters have a variety of methods available to them. Favoured methods in a particular jurisdiction depend on the type of registration system and the local land administration environment. Thus, each situation tends to be unique.

There are number of reasons why real estate fraud is attractive to criminals. Drawing on Unger *et al* (2010) and Nelen (2008), it is a sizeable, high value market. Property is generally seen as a safe investment, but at the same time there is a long tradition of property speculation. At a prefatory glance, patterns in the data underlying fraudulent transactions may appear similar to those of speculative transactions. Furthermore, the real estate market lacks the transparency and homogeneity of most financial markets, and so fraudulent transactions may be more difficult to identify. As each property has unique features the market is heterogeneous. The uniqueness of property as a commodity means that the market itself is not efficient in the same way that financial market prices tend to reflect most of the information available about a particular financial instrument at a given time.

We briefly describe a number of property racketeering schemes. Following this we describe the ABC Construction scheme. We then describe experimental work using data mining based on Quadratic Discriminant Analysis to indicate possible ABC Constructions activities.

2. PROPERTY RACKETEERING SCHEMES

Fraud in real estate transactions can be bdivided into two main categories; fraud by forgery and fraud by impersonation (Pers.Comm. #1 2010). The following is a brief description of some of the common racketeering schemes:

Impersonation Fraud occurs when a fraudster impersonates the true owner (perhaps having stolen their identity documents), sells the home or takes out a mortgage, and then disappears. Our study indicates that in some cases a family member impersonates the owner in the belief that the owner will not prosecute a member of their own family.

Occupancy fraud involves misrepresentation to a financial institution. In a mortgage application, the borrower states that the purpose of buying a property is to occupy it as the primary residence or a second home, but the real intention is to purchase the property as an investment. The borrower, if undetected, will often obtain a lower interest rate than allowed for an investment property. Also, lenders may authorise larger loans on owner-occupied homes compared to loans for investment properties. In addition, the owner may also attempt to avoid capital gains tax on the property (Maggio 2008, p. 194).

Income Fraud also involves misrepresentation to a financial institution. It occurs when a borrower overstates his or her income to qualify for a larger mortgage than the bank would ordinarily issue to the applicant. These are commonly known as “stated income” mortgage loans or “liar loans”. To accomplish this, the borrower may forge or alter tax returns and bank accounts which show an inflated income (Bourn 2006).

Employment fraud is a special case of income fraud, where the borrower claims self employment in a non-existent company or claims a higher position than they actually occupy in a real company (Bourn 2006).

Air loans involve obtaining a loan on a property that does not exist. A fictitious realty listing can be used to persuade a financial institution to issue a mortgage on a non-existing property. The racketeer(s) then disappears with the cash (CISC 2007).

Appraisal fraud involves deliberately miss-stating the value of a property. In appraisal fraud schemes an appraiser often colludes with a racketeer to overstate or understate the property value. When the value is overstated, the lender will provide a larger loan than is warranted or persuade a buyer to pay more than the property is actually worth. In the event of a foreclosure the lender may not be able to recover the value of the loan from the sale in execution of debt. Understated values are primarily used to get a lower price on a foreclosed home (CISC 2007).

Property flipping and property inflation schemes are a special form of appraisal fraud. Property inflation includes different schemes with the sole purpose of illegally inflating property prices to deceive the lender or a prospective buyer. The widespread method to inflate the price is property flipping. Property flipping involves purchasing a property and then artificially inflating its value by moving it back and forth between a group of people. Sometimes identity theft, straw borrowers and industry insiders are used in these schemes (Financial Crimes Enforcement Network 2006, CISC 2007, Unger *et al* 2010). According to the Financial Crimes Enforcement Network (2006) after several flips, the property may be resold at a price that is 50 to 100 percent of the original cost to the syndicate.

Oklahoma Flip and ABC-Constructions schemes are the most common property flipping schemes. After the execution of these schemes the mortgagee may provide a loan larger than the real property value justifies.

ABC-Construction: This is a scheme that is widely used for money laundering or for a quick profit. It includes the inflation of property price by selling it back and forth between two (or more) persons A and B before selling it to person C. If C fails to obtain an independent appraisal they will pay an overinflated price (Unger *et al* 2010). The ABC-Construction is not illegal as long as the transactions are transparent and in line with the law (Ferwerda *et al*, 2007 cited by Unger *et al* 2010).

Oklahoma Flip: In simple terms, the Oklahoma Flip is about buying a cheap, sometimes rundown property, and flipping it several times, selling it back and forth between the con man and his/her co-conspirators or a company the con man controls. Generally no money changes hands in these "sales", but it allows the con men to inflate the value of the house. In the final transaction, the racketeers may obtain a mortgage for well over the market value of the property, and then just disappear. They may also use a straw man or an unsuspecting intermediary in the final transaction (CTV News 2005, Unger *et al* 2010)

3. THE ABC CONSTRUCTION SCHEME

ABC-Construction is widely used for money laundering. The basics of the scheme are as follows. Person A inflates the price of his/her property before a final sale takes place by selling it to a colluder B. A and B may sell the property to each other a number of times using various aliases. An unsuspecting buyer C then will buy the property for a too high price as the conveyancing attorney will show person C the last purchase price. The attorney may be a party to the scheme (Unger *et al* 2010).

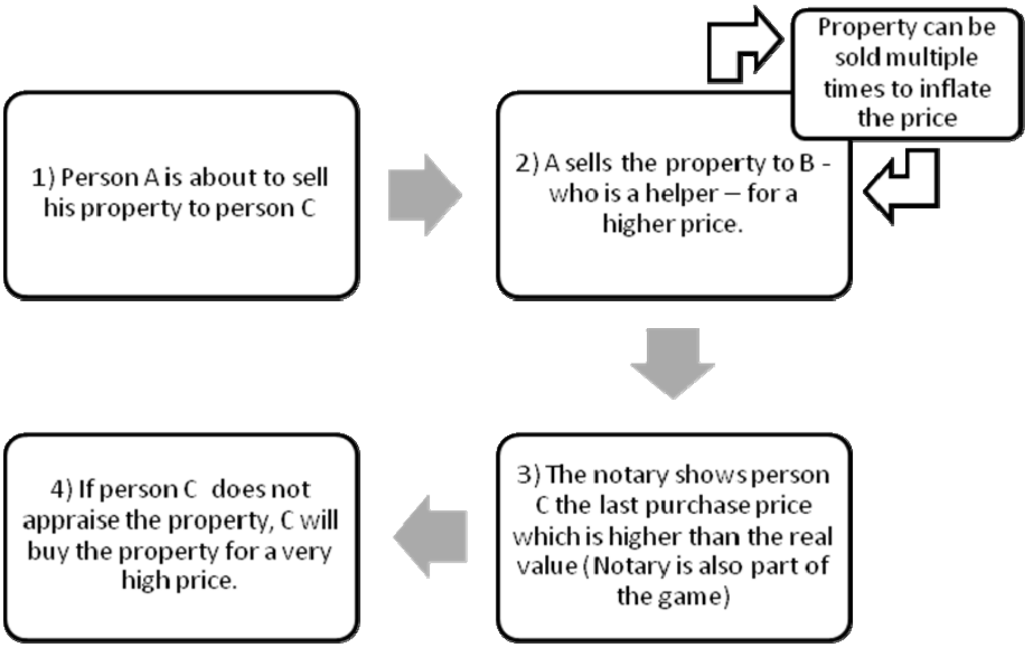


Figure 1: the steps for conducting the ABC-Construction

The scheme relies on C not doing a proper inspection of the property. Often C is an out of town buyer. The scheme works in a buoyant market when prices are rising and real estate agents don't have time to appraise every single property properly (Unger *et al* 2010).
Ferwerda *et al* (2007), cited by Unger *et al* (2010), note that ABC-construction schemes are legal if the transactions are transparent and according to the law. However, this scheme is

commonly used in an illegal way for profit or money laundering. One striking case occurred in the Netherlands. The “Bureau Financieel Toezicht” (Bereau of Financial Supervision) – which monitors the work of notaries in The Netherlands – discovered that the building in which it resides was part of an illegal ABC scheme. It turned out that the former director of “Bouwfonds” who was the prime suspect in the case made 2.5 million Euros with the deal in one day (Kreling & Meeus 2008).

4. FRAUD INDICATORS

We now describe aspects of identifying ABC-Construction schemes. The first step is to develop a list of indicators which incorporate the most important characteristics of an ABC-Construction scheme.

An indicator in this paper refers to an action that causes an attribute crossing a certain threshold or having a certain value that could raise suspicions about the object the attribute describes. A scheme is a series of steps or actions used by fraudsters. A pattern refers to the effects of executing a certain scheme inside the data sets. A pattern may be reflected by the effect of a scheme on the values of transaction attributes or by certain correlations between some of the attributes.

Before addressing the indicators of the ABC-Construction scheme, some of these indicators are part of a common set of indicators that can be found in the literature that indicate fraudulent activities or criminal behaviour in real estate transactions. Some common attributes used in identifying unusual behaviour are:

1. An unusual number of property transactions by one seller, especially in relatively short periods of time.
2. Unusual changes in ownership, especially changes at short intervals.
3. Properties that change hands quickly between owners
4. Unusual fluctuations in a particular property’s price. This could be an unusual rise or unusual drop in the price which is exceptional relative to the current market and to neighbouring property prices.
5. Foreign ownership may be an indication of money laundering. On its own, this is not an indicator. However, foreign ownership adds weight to a suggestion of racketeering if other indicators are present.
6. Properties registered without a mortgage

(Unger *et al* 2010, Nelen 2008)

Unger *et al* (2010) use objective data related to real estate objects such as unusual movements in housing prices and unusual changes in ownership to identify objects that might be involved in criminal activities. The purpose of this prediction model is to identify conspicuous real estate objects to assist the tax and fraud investigation authorities in the Netherlands. Their study combines methods from economics and criminology to investigate the problem. Econometric methods identify unusual movements in the prices without the ability to decide if the movements are the outcome of criminal activities. On the other hand, criminologists can point out maleficent behaviour constructions but cannot quantify the frequency of these transactions in the records (Unger *et al* 2010).

In most cases, exceptional behaviours are represented by suspicious data points inside the datasets. These data points can be distinguished from normal data points by abnormalities in the transactions which translate into abnormalities in a certain attribute or in a combination of attributes to create patterns. For example, quick changes in property ownership will create more transactions in the database for that property. So, if you group all transactions, for example in the past year, based on the properties, you will find that that property has an exceptionally high number of transactions. This indicates that suspicious activities have occurred.

Three main indicators in an ABC construction scheme are:

1. An unusual numbers of transactions taking place on the same property as fraudsters flip the property back and forth between themselves. All of the sales except the last one are fictitious and take place between the fraudsters.
2. Unusual number of transactions with the same name on the same property. This happens as one person sells a property and then buys it again and sells it a second time. This may be repeated a number of times before the last sale to the actual buyer takes place. Thus there will be fewer buyers than transactions in the scheme.
3. Unusual increases in the price of the property. This may happen at two levels; the first is the unusual overall increase of the price in a relatively short period of time. This could be pointed out by comparing the increase of the targeted property with the increase in other neighboring property price increases over the same period of time. The second level is the high increment in the price for each transaction which does not correspond to the appraised value. This can occur because these are not arms length transactions and no money change hands between fraudsters. Unger *et al* (2010) mention that this is one of the most visible indicators. One case mentioned by Unger *et al* (2010) is a case of building in Ukraine which was purchased for a price that was 10 times higher than the purchase price of three days earlier.

5. REAL ESTATE TRANSACTIONS SIMULATOR

Pollakowski and Ray (1997) state that the lack of a uniform data source is considered one of the biggest problems that researchers in the housing market have to deal with. Three reasons for this are: (1) heterogeneity of housing assets, (2) transactions infrequency for individual property, and (3) different sources may have different data set structures.

Because access to real data is difficult, if not impossible in some cases, the solution was to develop a simulator to generate real estate transaction datasets. The simulator enables the simulation of “normal” property transactions. Patterns that occur in the ABC-Construction scheme and the Oklahoma Flip can then be introduced into the data.

The real estate transaction simulation module consists mainly of one class "*PropertyTransactionSimulator*" that creates properties and transactions involving them. The class uses the initial parcels array simulated from the main LRS system (see (Shunnar & Barry 2010)).The final output of the simulator is a transactions dataset comprising one table. Each record in that table represents one transaction on one property. The dataset scheme generated by the simulator can be seen in figure 2

RealEstateTransactions	
PK	**TitleNumber**
	PropertyID RegDate Value BuyerFName BuyerLName BuyerID Mortgage MortgageRegDate MortgageValue LTV_ratio

Figure 2: Attributes of the generated Table from the Real Estate Transactions Simulator.

5.1. Dataset Simulation

To test the fraud detection technique on ABC-Construction schemes, a dataset containing 37380 records representing transactions over a two year period was simulated. The parameters used in the simulation were determined based on statistics obtained from the real estate market in the city of Calgary, Alberta. Following is a description of the main parameters used for the simulation:

Number of transactions per day: to determine the number of transactions, Calgary Real Estate Board (CREB) monthly statistics for property sales for the months from October 2009 to October 2010 were used (CREB 2010). The statistics include total sales for each month for the different kinds of properties (single family, condominium, Towns, Country Residential and Rural land). Sales for each day of the year were interpolated according to the monthly sales. Figure 3 shows the interpolated sales for a full year. The generated numbers are then fed into the simulator.

Property prices: An Initial price is set for every property using sales statistics from CREB (2010) and Teranet (2006). The statistics from CREB do not have prices for all properties; however, MATLAB was used to generate prices for 308315 dwellings based on statistical values obtained from Teranet (2006) for property values in Calgary, Alberta for the year of 2006. The histogram figure 4.a shows the distribution of the generated property prices. The generated prices were used to set the initial property prices in the simulation process.

Loan-To-Value ratio (LTV): LTV ratio is the value of a mortgage loan as a percentage of the total value of real property. No precise statistics were found to use as a base for the simulation of LTV ratio. However, Montia (2010) mentions that the average LTV ratio for 2009 in England was 0.7. Also, real estate agents and listing services mention that low LTV ratios are below 80% and ratios of 90% or more are considered high and rare. Based on those numbers, an array of 400 LTV ratio values was generated. The histogram shown in figure 4b shows the distribution of the generated LTV ratios.

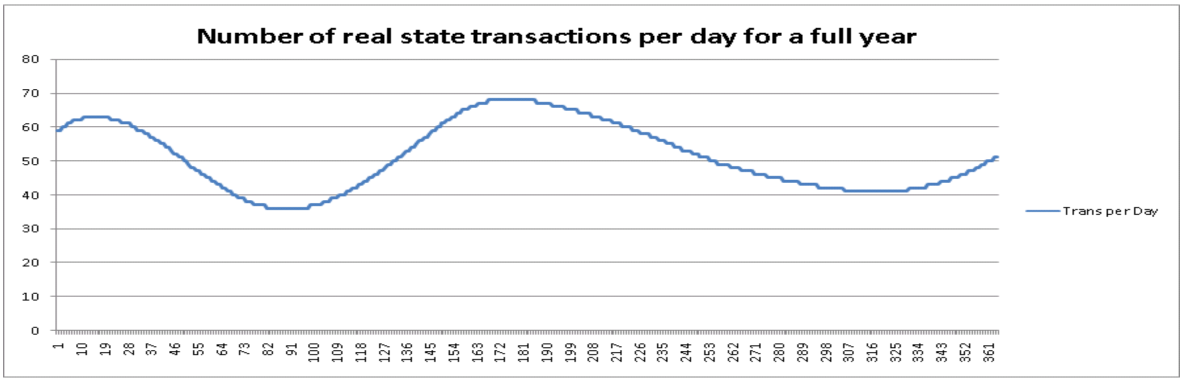


Figure 3: Interpolated real estate sales per day for a full year.

All the attributes were fed to the simulator in order to generate the dataset comprising 37380 transactions. After that, 774 transactions were generated on 245 properties. These separately generated transactions represent patterns of fraudulent activities, primarily the ABC-Construction and the Oklahoma Flip. The normal simulation process does not generate fraud patterns. Finally, the 774 transactions were added to the original dataset.

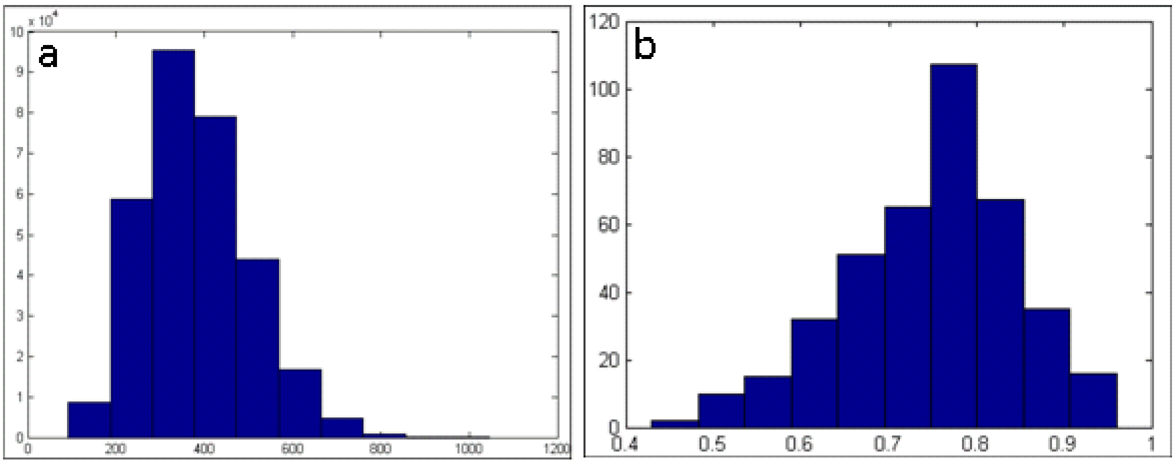


Figure 4: a) distribution of 308315 generated dwelling initial prices. b) Distribution of the 400 generated LTV ratios.

6. DATA ANALYSIS

In order to detect fraudulent ABC-Constructions from the transaction dataset, we classify real estate objects into 3 different classes or bands: 1) Highly suspicious 2) Suspicious and 3)

Normal properties. The classification of a property depends on the nature of the transactions that occurred over a chose time period, which in our simulated case is 2 years.

As mentioned in section 4 above, there are three main indicators of an ABC-Construction scheme which are; (1)an unusual number of transactions on the property, (2) repetition of the same name in different transactions on the same property, and (3) an unusual increase in the property's price between the transactions. Attributes corresponding to these indicators were used to build the classification model.

Figure 5 illustrates how a suggested real time classification system for real estate properties would work using the classification model proposed in this paper.

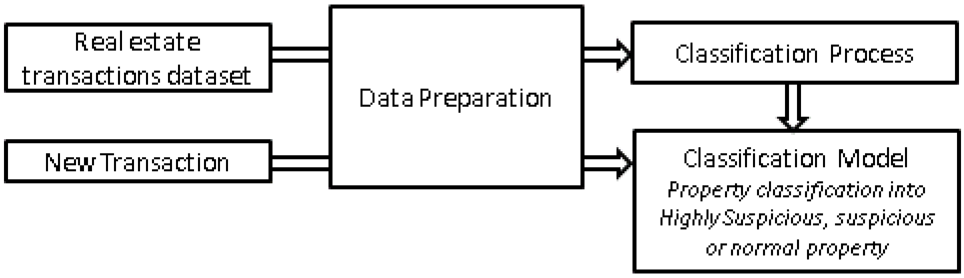


Figure 5: Real time classification system for real estate objects.

In the following sections, a comprehensive discussion is given about the data preparation process followed by general background of the classification technique we use and application of this technique on our dataset. Finally, classification results are discussed.

6.1. Data Preparation

The original simulated transaction dataset (TDS1) contains transactions that occurred over two years. Our goal is to build a classification model that can classify real estate objects into the aforementioned three classes based on their corresponding transactions and not to classify the transactions themselves.

The first step in data preparation is to generate a new dataset (PDS1) from TDS1 by grouping the records based on the property. Figure 5 depicts the scheme of PDS1 and following is a brief description of each attribute in this dataset as it is the one we use in the classification process.

1- *PropertyID*: the ID of the property the record represents.
2- *NumberOfPersonsInvolved*: represents the total number of different persons that are involved in the transactions on the property.
3- *InitialValue*: represents the value of the property in the first transaction in the selected epoch.
4- *LastValue*: represents the value of the property in the last transaction during the selected epoch.
5- *AverageChange*: represents the average increase or decrease in the value of the property between each two consecutive transactions took place over it.

6- *PeriodOfTransactions*: Represents the period in days between registration dates of the first and the last transactions on the property.
7- *AverageFlipPeriod*: represents the average flipping period of the property. We define flipping period as the number of days between any two consecutive transactions on a certain property.
8- *MortgageValue*: Represents the value of the mortgage attached to the last transactions on the property in the selected epoch.
9- *LTVR*: Represents the LTV ratio for the loan attached with the last transaction on the property.

PDS1	
PK	**PropertyID**
	NumberOfTransactions NumberOfPersonsInvolved InitialValue LastValue AverageChange PeriodOfTransactions AverageFlipPeriod MortgageValue LTVR

Figure 6: Attributes of the dataset generated from TDS1 to be used in the classification.

All the attributes in PDS1 are numerical values, which is important for the classification to work. Also all values are rounded to the closest integer value and percentages are represented in integers from 0 to 100.

According to our findings, a property has to be turned over at least twice to be considered for scrutiny. This means that all the properties with only one transaction are considered normal properties and excluded from the data mining process upfront. In the resulting dataset – PDS1 – 98% of the records represent properties with only one transaction during the two year period. These records were all removed. Consequently, the final reduced datasets RPDS1 contains 598 records.

6.2. Classification

We used Quadratic Discriminant Analysis (QDA) to generate a classification model for the real estate objects.

Discriminant Analysis (DA) “is a multivariate statistical technique whose aim is to assign an object to one of predefined groups, in an optimal way” (Nogueira *et al* 2005). DA techniques in general seek discriminant functions that separate the different groups (classes) of the observations. In particular, we are using a QDA classifier which seeks the best quadratic functions to separate the three classes (Highly Suspicious, Suspicious and Normal).

To use QDA, a random sample of 287 records was selected from the original dataset. Each record in the sample was then manually assigned to one of the three classes. To label the records, we use rules inferred from a telephone and email survey conducted of land and property experts from around the world in tracing illegal activities in real estate transactions in addition to the indicators we found in the literature.

The rules followed for the labeling task indicate not only ABC-Construction schemes but also may indicate Oklahoma Flip schemes (see the Appendix for some examples of the rules we established). Table 1 shows the number of records in the three different classes in the sample dataset.

Table 1: number of records assigned for each group in the sample dataset

Complete set	Class H	Class S	Class N
286	98	65	123

H = Highly suspicious   S = Suspicious   N = Normal

The following section shows the results of applying QDA classification on our dataset.

6.3. Results

The full sample dataset is used to estimate the discriminant functions and generate the classification model. Then, the classifier is used to determine the class label of each record in the same set to validate the classification model.

In the first test, five attributes of the sample set are used in the classification. Namely; *NumberOfTransactions, NumberOfPersonsInvolved, AverageChange, AverageFlipPeriod,* and *LTVR.*

Figure 7 shows a sample of results of the classification. It depicts the miss-classification instances generated from the quadratic discriminant functions. The results obtained from the validation process shows 56 misclassified instances out of the 286 records in the set. These numbers produce a resubstitution error of around 19.58 %. This error is relatively high. Based on Nogueira (2005) on calssifying internet users, we would expect an error rate of 7.98%. However, this does not rule out the technique.

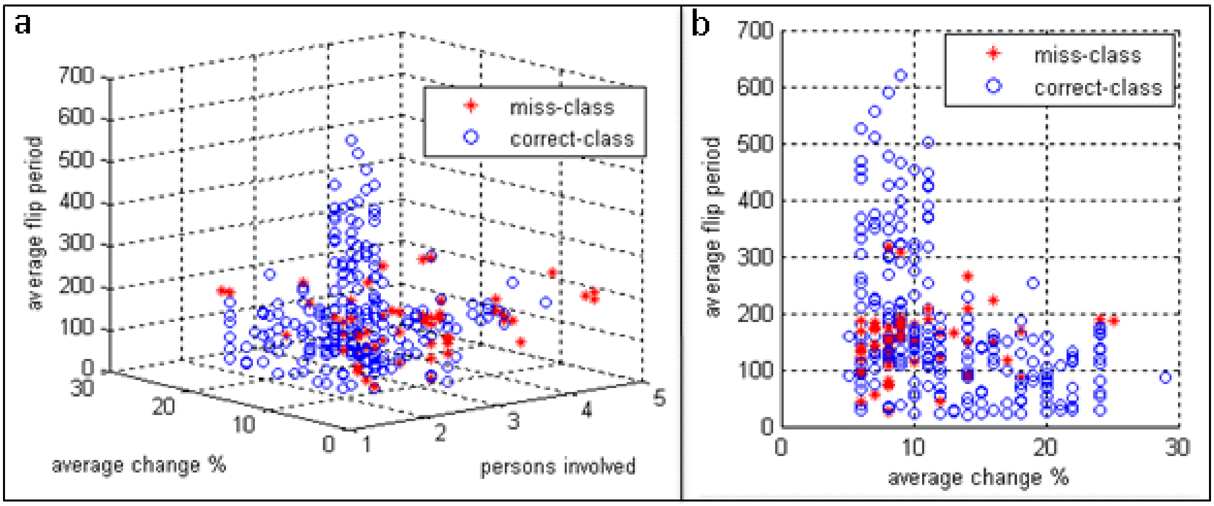


Figure 7: classification results of the QDA classifier. a) 3D plot for classification results. b) 2D plot of the classification results.

Further analysis shows that the misclassification is concentrated in misclassifying properties that should be classified as H or N, based on our prior knowledge of the simulated data, to class S. As shown in table 2, the error rate of misclassifying highly suspicious properties into normal properties is 1.04% which is a very low error rate. However, a 13.98% error rate (out of the total of 19.59%) is generated from misclassifying properties from highly suspicious or normal into suspicious properties. As discussed in section 6.2 above, from a practical perspective this is acceptable because properties classified as suspicious by the model should still be investigated. It is an area which warrants further investigation.

Table 2: Details of the misclassified instances and classification error rates.

Type of miss	H to S	H to N	N to S	N to H	S to H	S to N	Total
Number of misses	10	3	30	0	8	5	56
Error rate	3.49%	1.04%	10.49%	0%	2.79%	1.74%	19.58%

7. CONCLUSIONS

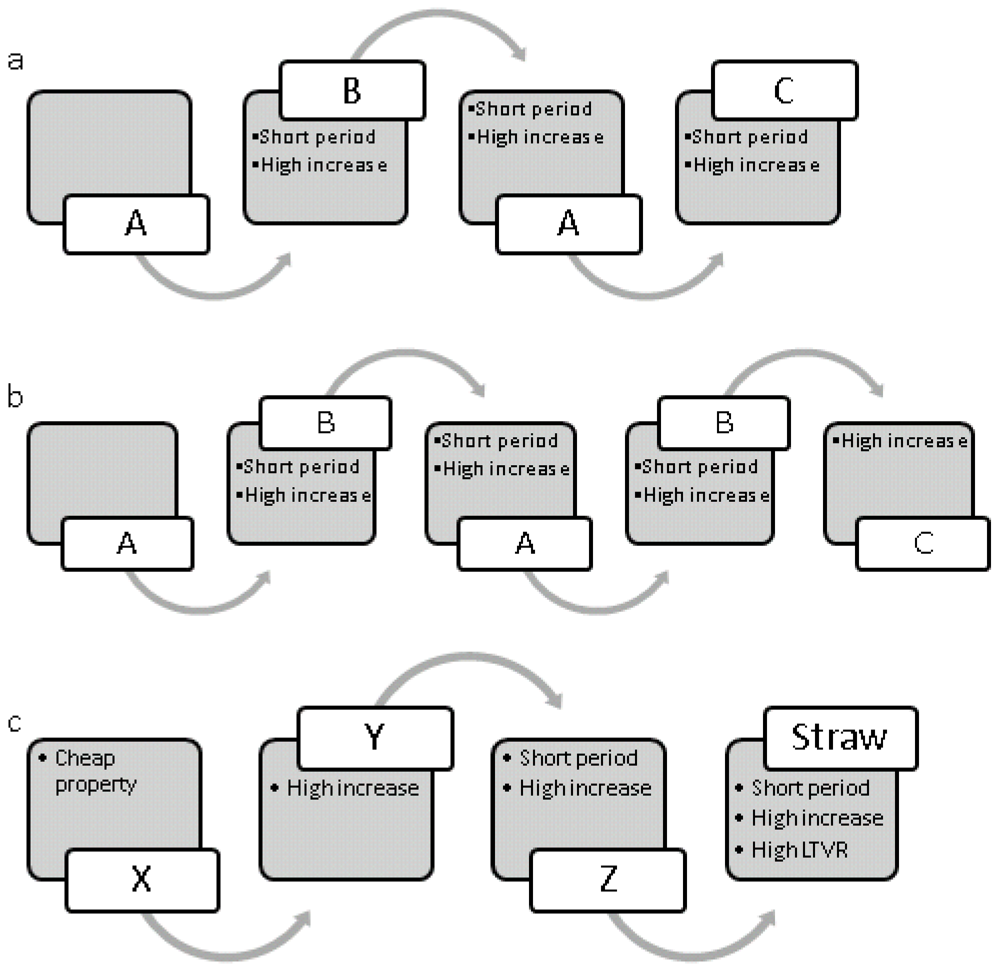
Classification of real estate objects according to market activities could be applied to increase the security of ownership and help in preventing fraud attempts. In today's fast growing real estate market, different racketeering schemes are used and ABC-Constructions are among the most common methods.

This paper described the use of Quadratic Discriminant Analysis (QDA) to classify real estate objects based on a fraud pointer which may indicate the execution of ABC-Construction schemes. The use of three classes (highly suspicious, suspicious and normal objects) to classify properties reduces the error rate of misclassifying suspicious objects as normal ones. In this preliminary study, the results were encouraging, and it appears that QDA is one of a number of methods that may be suitable for flagging properties that are subject to ABC Construction and Oklahoma Flip schemes.

APPENDIX

Some examples of the rules used to label the sample dataset are shown below. Each of the figures a, b, and c represents a series of transactions taking place on one property. The white boxes represent the entity which sells or buys the property. The arrows represent the direction of a transaction on the property and finally the shaded boxes list the noticeable attributes that describe each transaction.

For example, rule (a) below represents a typical ABC-Construction scheme. The property moves from A to B to A and Finally to C. In this case, A and B are the racketeers who flipped the property two times between themselves before selling it to person C. Along with each of the transactions, we can notice a short flipping period and a high increase in the value.



ACKNOWLEDGMENTS

This study has been conducted with the support of the John Holmlund Chair in Land Tenure and Cadastral Systems and the Canadian National Science and Engineering Research Council Talking Titler project

REFERENCES

Bourn, J 2006, 'International benchmark of fraud and error in social security systems', *Report by the comptroller auditor general*, National Audit Office, London.

CISC 2007, 'Mortgage fraud and organized crime in Canada', *Criminal Intelligence Service Canada – Central Bureau, Intelligence Analysis and Knowledge Development Branch*, November 2007.

CREB 2010, *Housing statistics archives*, Calgary Real Estate Board, viewed 10 November 2010, < http://www.creb.com/public/seller-resources/housing-statistics-archives.php>.

CTV News 2005, *Stealing Home*, Viewed 20 March 2010 <http://www.ctv.ca/CTVNews/WFive/20050321/wfive_stealinghome_050318/>

Ferwerda, H, Staring, R, de Vries Robbe´, E, and van de Bunt, J 2007. 'Malafide Activiteiten in de Vastgoedsector', *Een Exploratief Onderzoek naar Aard, Actoren en Aanpak*, SWP, Amsterdam.

Financial Crimes Enforcement Network 2006, 'Mortgage loan fraud - An industry assessment based upon suspicious activity report analysis', *Office of regulatory analysis, regulatory policy and programs division, Financial Crimes Enforcement Network*, United States Of America, November 2006.

Kreling, T & Meeus, J 2008, '*Waakhond zit zelf in 'fout' pand'*, NRC Handelsblad newspaper, 7 June, viewed 12 January, 2011, <http://www.nrc.nl/binnenland/article1908494.ece/Waakhond_zit_zelf_in_fout_pand>.

Maggio J E 2008, 'Private security in the 21st century: concepts and applications', *Jones and Bartlett Publishers*, United States of America.

Montia, G 2010, *Average loan-to-value ratio eases to 70%*, Finance Markets, 25 January, viewed 23 December 2010, < http://www.financemarkets.co.uk/2010/01/25/average-loan-to-value-ratio-eases-to-70/>.

Nelen, H., 2008. 'Real estate and serious forms of crime'. *International Journal of Social Economics*, Vol. 35 No. 10 pp 751-761.

Nogueira, A, de Oliveira, M R, Salvador, P, Valadas, R & Pacheco, A 2005, 'Classification of Internet users using discriminant analysis and neural networks', *next generation internet networks*, 2005, pp. 341- 348, 18-20 April 2005.

Pollakowski, H O & Ray, T S 1997, 'Housing price diffusion patterns at different aggregation levels: an examination of housing market efficiency', *Journal of Housing Research*, vol. 8, no. 1, pp 107-124

Shunnar, T & Barry, M 2010. 'Knowledge discovery from land record systems'. *The XXIV FIG International Congress*, Sydney, Australia. 11 – 16 April.

Teranet, 2006, 'The Teranet National Bank house price index', *Developed by Teranet in alliance with National Bank of Canada*, viewed 12 December 2010, <http://www.housepriceindex.ca/documents/MethodologyEN.pdf>.

Unger, B, Ferwerda, J, Trouw, J, Nelen, H, & Ritzen, L 2010, 'Detecting criminal investments in the Dutch real estate sector'. *Study prepared by the Dutch Ministry of Finance, Justice and Interior Affairs*, 19 January.

BIOGRAPHICAL NOTES

Thaer Shunnar is an MSc student in the Department of Geomatics Engineering at the University of Calgary. He has a B.Sc. in Computer Engineering from An-Najah National University (Palestine). Subsequently he worked as a software developer and software engineer. His research interests are in data mining and knowledge discovery from land registration systems.

Michael Barry holds the John Holmlund Chair in Land Tenure and Cadastral Systems in the Geomatics Engineering Department at the University of Calgary, where he has been working since 2002. Prior to that he was at the University of Cape Town, South Africa. His research interests are analysing and developing systems to support land tenure security and land administration in general.

CONTACTS

Thaer Shunnar
Department of Geomatics Engineering
University of Calgary
2500 University Drive N.W., Calgary, Alberta
Canada T2N 1N4
Tel. +1 403 220 8038
Fax. +1 403 284 1980
taishunn@ucalgary.ca

Dr. M. Barry
Department of Geomatics Engineering
University of Calgary
2500 University Drive N.W., Calgary, Alberta
Canada T2N 1N4
Tel. +1 403 220 5826
Fax. +1 403 284 1980
mbarry@ucalgary.ca