# Tracking Fraudulent Activities In Real Estate Transactions

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## Outline

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- Classification using Predictive Discriminant Analysis
- Results & Conclusions

# Fraud



- Fraud is a significant problem in many countries around the world
- Real estate market is prone to criminal investment
  - Property market sizeable!
  - Market of high value
  - Singularity of properties (hard to assess objective value)
    - Heterogeneous – efficient market hypothesis does not apply
  - Lack of transparency
  - Tradition of speculation
- Technology
  - Advantage: Improves operational efficiency
  - Disadvantage: enabled increasingly sophisticated scams.



# Fraud in numbers



- Hundreds of millions of dollars are lost annually to mortgage fraud in Canada

  *(Criminal Intelligence Service Canada (2007)*
  - 280 properties were involved in a fraud case that amounts to approximately $30 million.

    *(Auditor General of Alberta 2010)*
- The Netherlands
  - 2.5 million Euros with a con in one day
- Many cases in Canada, Australia, UK, The Netherlands, South Africa.

## Need



- Need a method to help investigators in detecting fraud.
- Financier's (i.e. Mortgage providers) need an early warning system

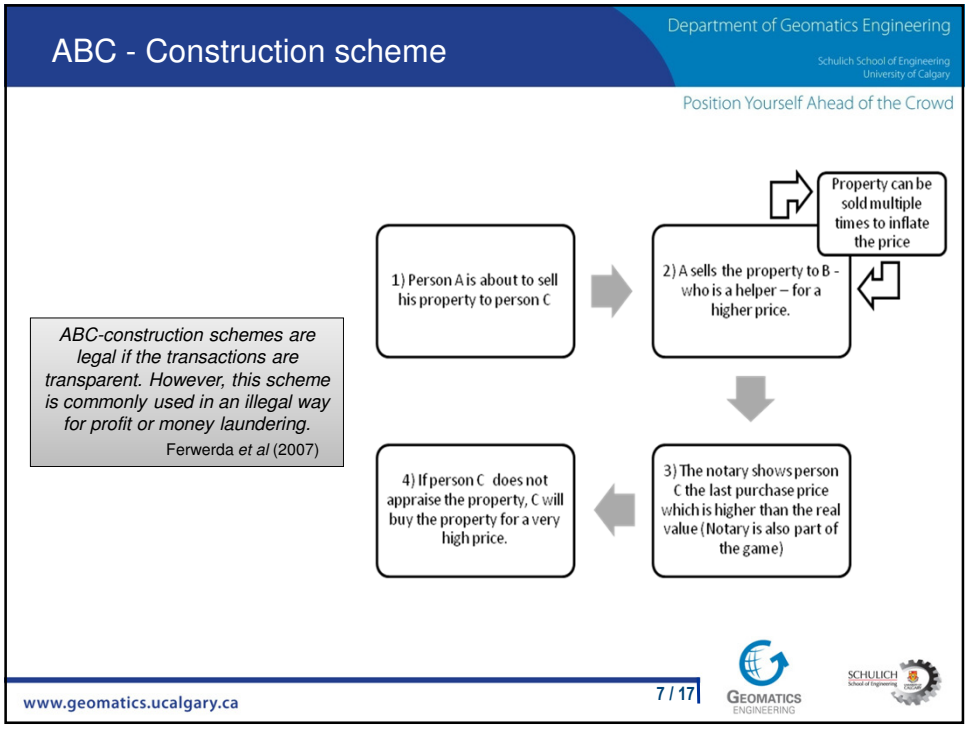


## Racketeering schemes



1. Impersonation Fraud
2. Occupancy fraud – tax evasion
3. Income Fraud and Employment Fraud
4. Air loans – loan on non-existent property
5. Appraisal fraud, Property flipping and property inflation schemes
   a. Oklahoma flip
   b. ABC-Construction

- *Experimental work in this paper focuses on detecting the ABC-Construction and Oklahoma flip*


ABC - Construction scheme
Department of Geomatics Engineering
Schulich School of Engineering
University of Calgary
Position Yourself Ahead of the Crowd
ABC-construction schemes are legal if the transactions are transparent. However, this scheme is commonly used in an illegal way for profit or money laundering.
Ferwerda et al (2007)
1) Person A is about to sell his property to person C
2) A sells the property to B - who is a helper – for a higher price.
Property can be sold multiple times to inflate the price
3) The notary shows person C the last purchase price which is higher than the real value (Notary is also part of the game)
4) If person C does not appraise the property, C will buy the property for a very high price.
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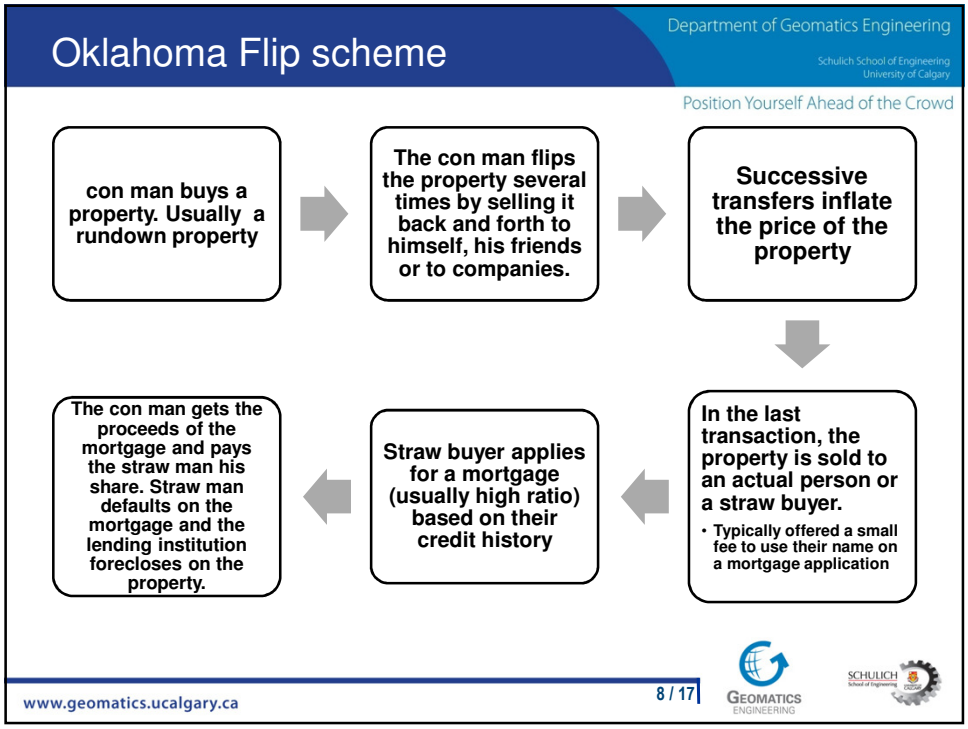
Oklahoma Flip scheme
Department of Geomatics Engineering
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University of Calgary
Position Yourself Ahead of the Crowd
con man buys a property. Usually a rundown property
The con man flips the property several times by selling it back and forth to himself, his friends or to companies.
Successive transfers inflate the price of the property
In the last transaction, the property is sold to an actual person or a straw buyer.
• Typically offered a small fee to use their name on a mortgage application
Straw buyer applies for a mortgage (usually high ratio) based on their credit history
The con man gets the proceeds of the mortgage and pays the straw man his share. Straw man defaults on the mortgage and the lending institution forecloses on the property.
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## Mischief Indicators



Indicators: Suspicious or Highly Suspicious Properties – a function of :

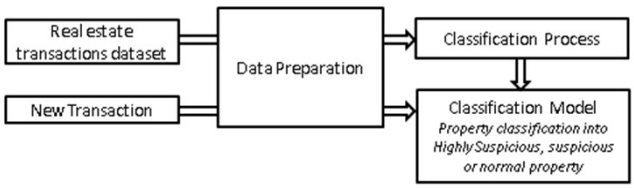
| | | |
|---|---|---|
| Person / property involved unusual number of transactions | Unusual fluctuations in house price | Movement of property between the same persons |
| High ratio of mortgage to purchase price | Properties that quickly change hands between owners | Unusual purchase price |
| Financing methods | Properties financed without a mortgage | Foreign ownership |



## Classification of properties



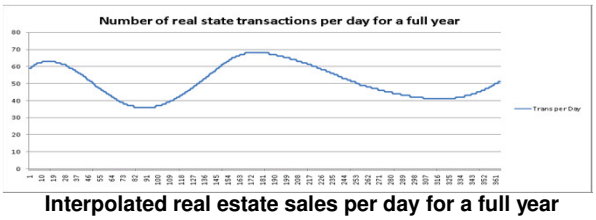
- Goal
  - Develop a warning system for detecting illegal / mischievious activities



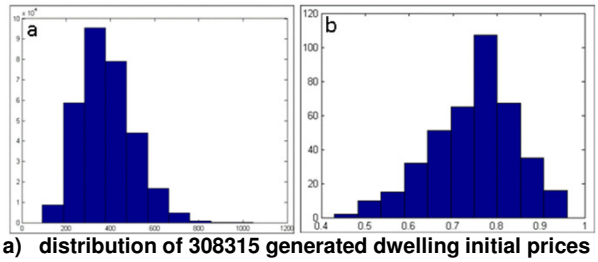
## Dataset simulation



- Land Records Simulator was used.
- We used statistics from the real estate market for the city of Calgary (Calgary Real Estate Board) in addition to other sources to configure the simulator




**Interpolated real estate sales per day for a full year**




**a) distribution of 308315 generated dwelling initial prices**
**b) Distribution of the 400 generated LTV ratios**



## Dataset preparation



- Transformation, labeling, attributes selection over selected time frame (2yrs).

Original dataset

| Transaction # | Property ID | Date | Value | Name | Mortgaged | Mortgage Date | Mortgage Value |
|---|---|---|---|---|---|---|---|

Grouping by property

| Property ID | # Trans | # people | Initial value | Last value | Average Change | Total period | Average Flip period | LTV Ratio |
|---|---|---|---|---|---|---|---|---|

Final Data set

| Property ID | **# Trans** | **# people** | **Average Change** | **Average Flip period** | **LTV Ratio** | Class |
|---|---|---|---|---|---|---|

## Sample selection



- Used dataset
  - 38154 transactions originally generated
  - All transactions are grouped by property
  - **Resulting dataset filtered by removing all properties with only one transaction**
  - A random sample was selected and labelled as follow

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

  - This sample is used to build the model

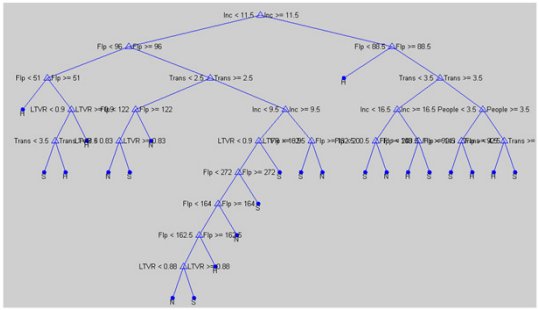


## Classification with Decision Trees



- We used a well tested Top Down Induction of Decision Tree (TDIDT) algorithm
  - Used full dataset to build the tree
  - Used Leave One Out (L-O-O) method to validate the results
  - Results of L-O-O:

| | |
|---|---|
| **hit rate** | **78.7%** |
| **cross-validation error** | **21.3%** |



## Classification using QPDA



- QPDA (Quadratic Predictive Discriminant Analysis)
  - PDA Addresses the extent to which are two or more groups of individual variables (e.g. properties) can be separated (e.g. highly suspicious, suspicious, normal) based on measurements of these individuals on several variables (e.g. Number of transactions, number of people involved in transactions, etc ...).
  - PDA creates *j* discriminant functions where *j* is the number of distinct groups. Quadratic refers to the degree of the discriminant functions created for the model.
  - Goal is to create a classification model to classify properties into j = 3 distinct groups based on transaction history
    - Groups are (Normal, Suspicious, and Highly Suspicious) – categorical / discrete



## PDA Classification results



| | | | | | |
|---|---|---|---|---|---|
| Method | Quadratic Predictive Discriminant Analysis | | | | |
| Full Dataset | 286 | | | | |
| Training set | 286 | | | | |
| Testing set | 286 | | | | |
| | | **Predicted group** | | | Total |
| | | N | S | H | |
| | N | 93 | 30 | 0 | 123 |
| **Actual group** | S | 5 | 52 | 8 | 65 |
| | H | 3 | 10 | 85 | 98 |
| Total | | 101 | 92 | 93 | 286 *N* |

| | |
|---|---|
| Hit rate | 80.42% |
| Error rate | 19.58% |

# Conclusions



- Two different methods yielded similar results
- Hoped for better classification precision
  - Seen better results elsewhere 12% in detecting tumours
- Exploratory study indicates these techniques could be useful in practice.
  - Need to test the results on real data
- Should complement a range of techniques that can apply.