Scorecard design for fraud detection (with text mining, predictive modelling and social network theory)

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CREDIT RESEARCH CENTRE

State of the Global Insurance Industry

- Global recession
- Acquisitions and Mergers
- Stronger competition, especially from non-traditional insurance companies
- Tighter regulation

"Fraudulent claims have doubled in the first three months of 2009" - Allianz Insurance, United Kingdom

State of South African Insurance Industry

- Emerging market
- Cost of insurance more expensive in relation with people's income
- South African insurance industry has tendency to follow international trends

Insurance Fraud in South Africa

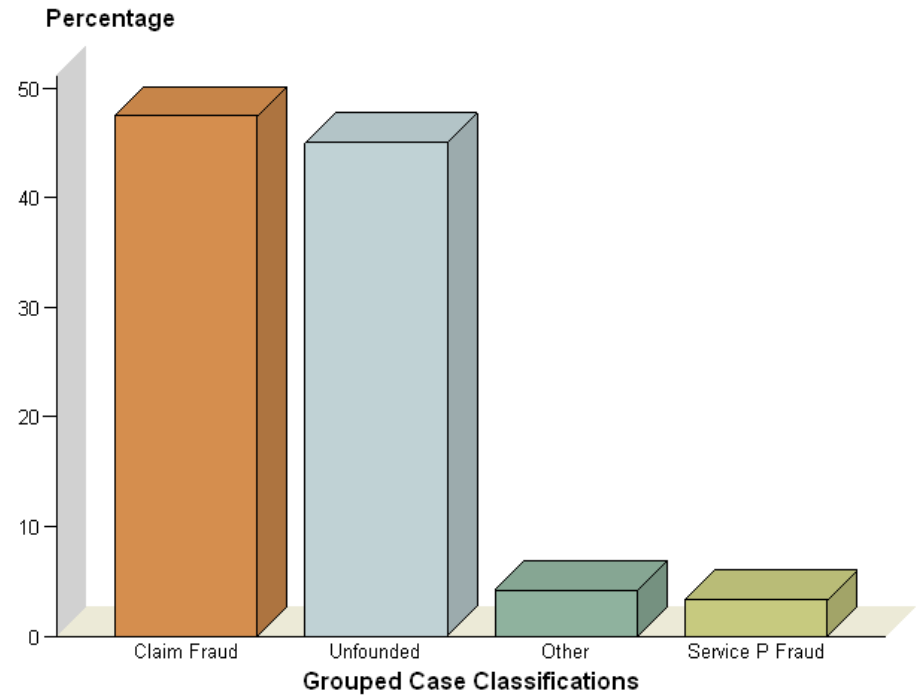
- 5%-10% of claims said to be fraudulent*
- Costing insurance industry R2 billion per year
- Set up of the South African Insurance Crime Bureau in 2008

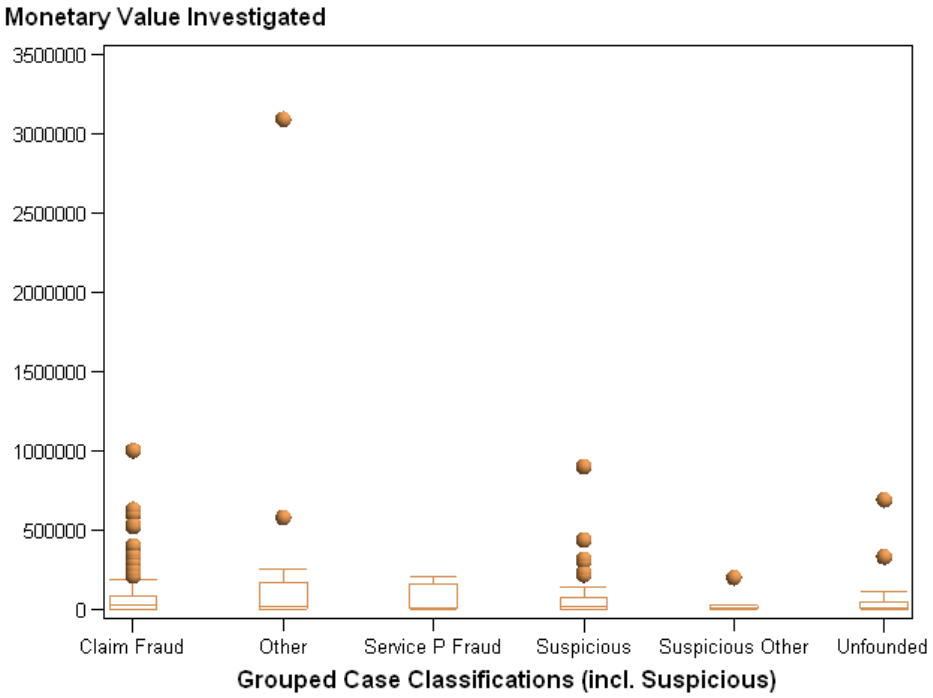
"Between 8% and 35% of short-term insurance claims paid out to policyholders annually are fraudulent." – Insurance Companies, South Africa

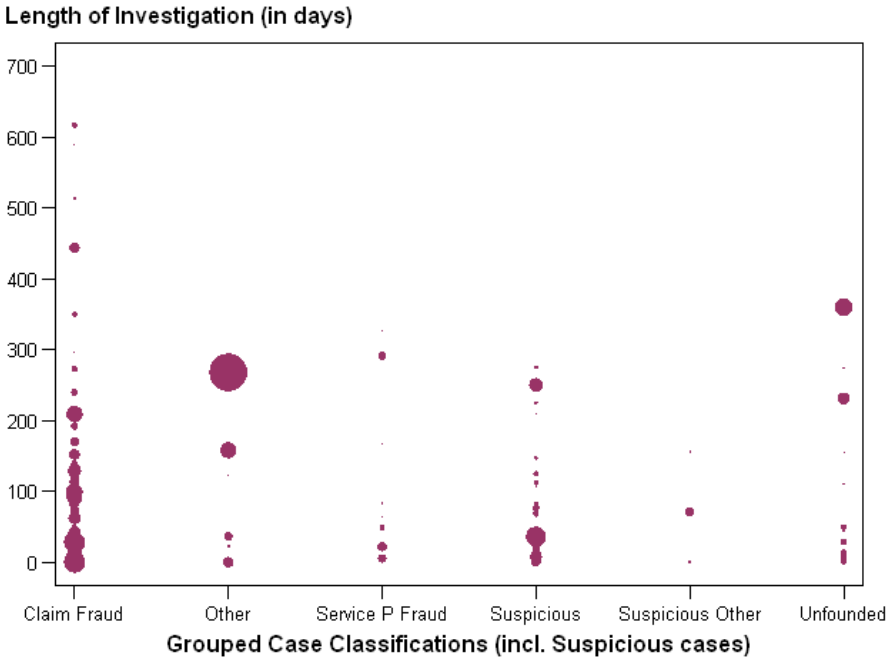
*South African Insurance Association, 2008

Investigated Cases

- Large proportion unfounded
- Mean(investigation period) = 80 days
- Other = internal fraud etc.







Challenges in Fraud Management

- Fraud detection reactive, rather than pro-active
- Diagnostic indicators commonly used – but not tested
- Special Investigations Unit – limited resources, fraud management spreadsheets
- “Feedback loop” not complete
- Infrequent event data, “tip of the iceberg”
- Detection techniques used with varying degrees of success
  - Redundant complexity (out-dated rules)
  - Disparate systems and utilization
  - Deteriorating performance over time

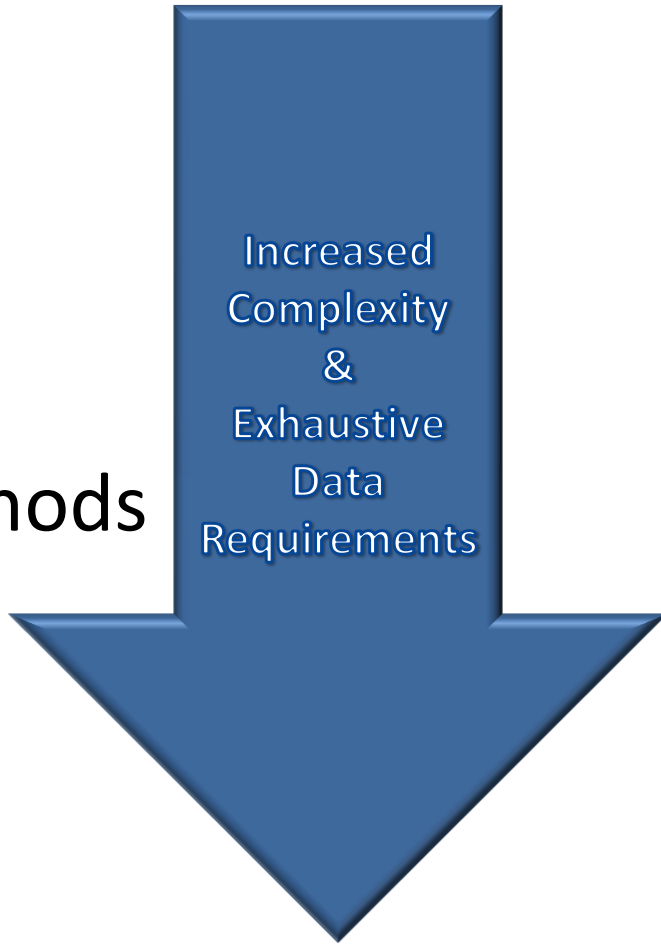
Key Properties* of a Suspicious Activity Assessment System

- Accurate
- Fast
- Cost-effective
- Flexible
- Consistent
- Reliable
- Easy to interpret
- Adaptive

*Abrahams, 2008

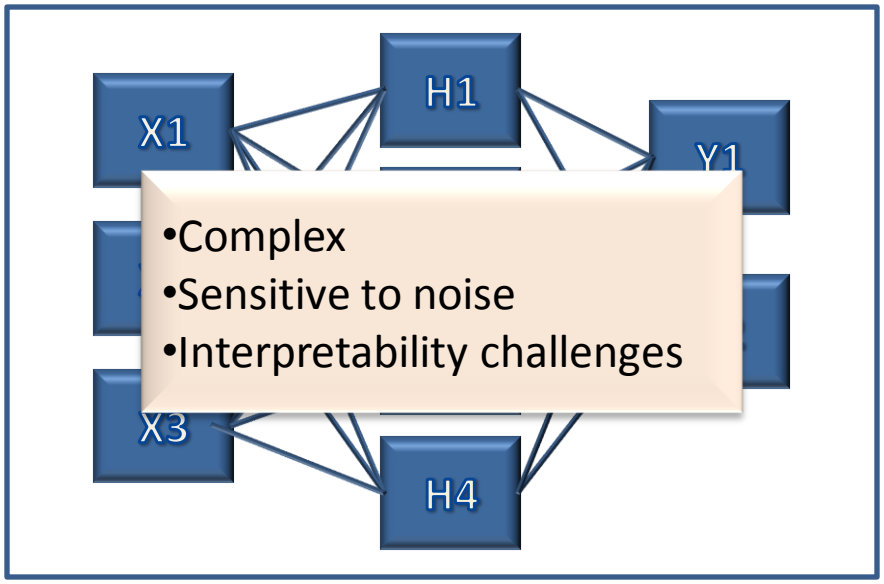
Fraud Detection Techniques

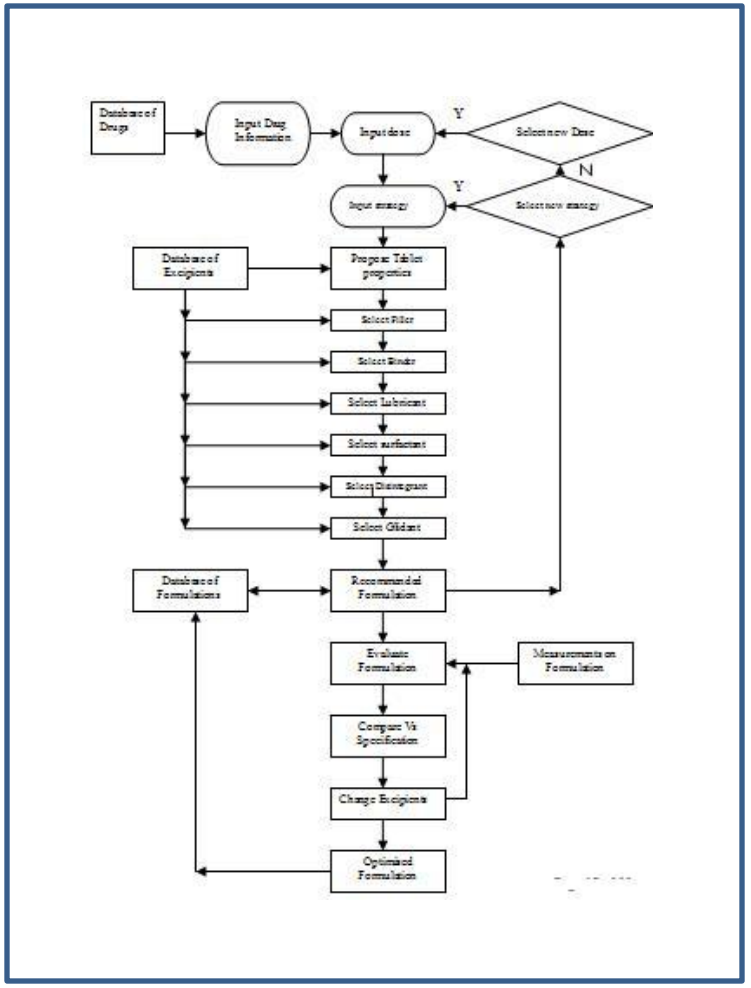
- Diagnostic Fraud Indicators
- 3rd party data searching
- Anomaly Detection
- Profiling
- Supervised/Unsupervised Methods
- Artificial Intelligence
- Text Mining
- Social Network Theory



Artificial Intelligence

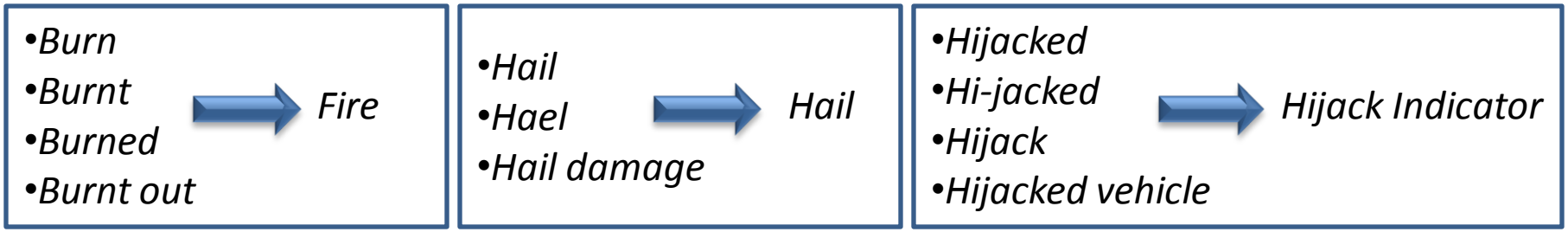
- Machine Learning
- Neural Networks
- Expert Systems





Text Mining

- Natural Language Processing
- Semantics – meaning of words
- Syntax – structural relationship between words
- Text Parsing
- Dimension Reduction Techniques



Social Network Theory

Policy Holder 1

Policy Holder 2

Policy Holder 3

Policy Holder 4

Links Data Set → Community Detection → Network metrics → Scores

*Fast unfolding of communities in large networks, 2008

(Hypothetical) Fraud Risk Scorecards

Probability of Fraud

Claim level - Quantitative factors
Claim amount out of normal bounds for loss class
Vehicle burnt / total theft with coverage recently increased
Dubious location of loss
Recent similar claim
No towing charges, although extensive damage
Claim level - Qualitative factors
Lack of witnesses
Attitude: Aggressive/Evasive/Vague
Threaten to obtain attorneys
Policy Information
Claim within 3 months of inception
Recent cover increase
Customer Information
New customer
Insured moved to lower income risk address
Mobile phone contact only
Occupation
Fraud bureau scores
Credit Bureau scores
Social Networks
Claimant's attorney syndicate
Suspicious home address

Potential Loss

Claim level - Quantitative Factors
Hijack / Burnt out vehicle
Insured verified coverage just prior to loss date
Claim level - Qualitative Factors
Information inconsistencies
Policy information
High premium payments compared to verifiable legitimate income
Repeated and unexplained change of beneficiary
Unusually high commission paid to broker/ intermediary
Total sum insured
Customer information
Geographic region of home address
Temporary post office box
Insured recently divorced
Fraud Bureau Score
Credit Bureau Score
Social Networks
Suspicious home address

Likelihood	Consequences				
	Insignificant	Minor	Moderate	Major	Severe
Almost certain	M	H	H	E	E
Likely	M	M	H	H	E
Possible	L	M	M	H	E
Unlikely	L	M	M	M	H
Rare	L	L	M	M	H

Conclusion

- Fraud remains a big challenge
- A pro-active and accurate suspicious activity assessment system should enable insurance companies to
  - Prioritise and improve quality and quantity of investigations
  - Reduce fraud expenditure
  - Uncover organised crime
- By utilising volumes of internal, external, structured and unstructured data
- Whilst maintaining an easy to implement and easy to interpret design

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Thank you