



# Machine Learning models for Automobile Fraud Detection - A literature Review

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Session # C5 Dated : 5-Mar-19

#### Agenda

- Introduction to Auto Insurance Fraud
- Impact of Fraud on Stakeholders
- Traditional Approaches to addressing Fraud
- Machine Learning Approaches
- The way Forward



#### Fraud in Automobile Insurance

- Growing Competition in Automobile Insurance Industry
  - Frequency and Severity of claims increasing year on year
- Increasing Instances of Fraud in Auto Insurance (Moral Hazard)
- Fraudsters stage traffic accidents and issue fake insurance claims
- Fake reports of stolen vehicles
- Claims for pre-existing damages
- Soft vs. Hard Fraud
- Organized groups of fraudsters
  - Drivers, chiropractors, garage mechanics, lawyers, police officers, insurance workers etc.
- Fighting against insurance fraud is a challenging problem both technically and operationally



#### **Basic Statistics on Automobile Frauds**

- An upward trend has been noted among many types of crimes, automobile insurance fraud included
  - Federal Bureau of Investigation Financial Crimes Report to the Public (2014)
- Approximately 20-35% of automobile insurance claims are fraudulent to a certain extent
- Statistics of the U.S. Coalition against Insurance Fraud illuminate that the amount of insurance fraud accounts for 17% to 20% of total insurance company compensation
- In China, insurance regulators estimate that the proportion of insurance fraud is approximately 20%
- In 2014, the Association of British Insurers (ABI) investigates the increase in number of false claims, which is 18% more than the previous year



#### **Common Features of Fraud Accidents**

- Generally occur during the late hours and in suburban areas
- Limited scope of any witnesses
- Drivers are usually young males
- Accident cars are mostly private cars
- Police are always called to the scene (Make the subsequent claims easier and more reasonable)
- Many passengers in the vehicles, but never children or elders
- All of the participants have multiple (serious) injuries
- Almost no damage on the vehicles



#### Factors that can influence Fraud

- Accident Information
  - Occurrence time and location, Reason for Accident, Time to Start and End, Repair shop type, Site Report, Investigation, Number of damage photos
- Insured Driver Information
  - Gender of policy-holder, Historical claims, Income and profession of the claimant
- Automobile Information
  - Type of automobile, Color of the vehicle, Brand, Registered Location
- Policy Related Information
  - Insurance maturity, Underwriting Type, Insured amount
- Text Description of the accident
- Certain correlation exists between selected indicators



#### Impact of Fraud on Stakeholders

- Insurers
  - Lost Profits
  - Reputation losses
  - Increased cost of hiring highly skilled investigation team
- Policy Holders
  - Higher Premiums
  - Longer Settlement Times
  - Increased scrutiny on claims



#### Traditional Approaches to handle Fraud

- Auditing and Expert inspection
- Manual detection of fraud cases costly and inefficient
  - Number of experts is negligible compared to the increasing number of claims
  - Average time that experts spend reviewing a case is not sufficient
- Rule based Approaches
  - Detect suspicious fraud cases in a timely manner (Scoring claims)
  - Relatively effective compared to that of experts in recognizing existing fraudulent claims
- Fraudsters are very innovative and new types of fraud emerge constantly (Adaptability is required)



**Overview of Different Methods** 



Supervised Learning Unsupervised Learning Social Network Analysis

Text Mining



## Supervised Learning

- Outcome variable (Fraud Indicator) is linked to explanatory variables
- Feature selection, Feature engineering to identify best predictors
- Relationships between the variables assessed
- Stand alone Models
  - Binary Choice models (Logit model and Probit model)
  - Decision Tree (DT) using CART
  - Support Vector Machine
  - Artificial Neural Network
  - Fuzzy Logic
  - Genetic Algorithms
- Weaknesses
  - Demand a labeled (initial) data set
  - Only suitable for larger, richer data sets

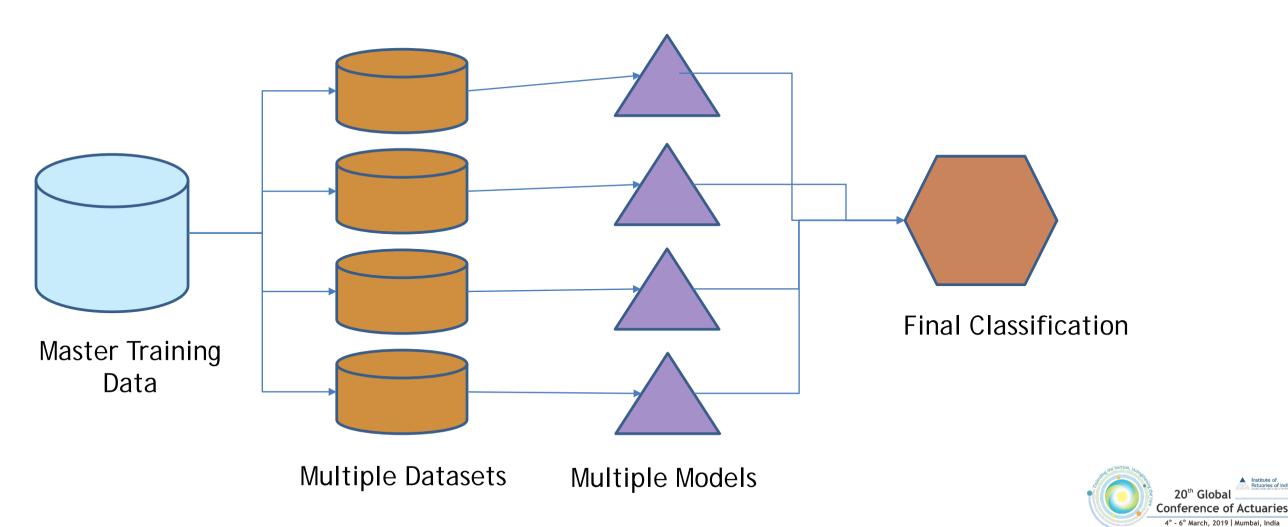


Supervised Learning – Ensemble Learning

- New machine-learning framework Treats multiple learners as different modules to solve the same problem
- Improves the generalization ability of learning systems significantly
  - Boosting
  - Bagging
  - Random Decision Forests  $\rightarrow$  Combines Bagging and Random subspace methods
    - Automatically selects features Not sensitive to irrelevant features
    - Reduces possibility of overfitting
    - Considers the interaction between features
    - Applicable to binary class and multiple class problems
    - Does not require complex parameter selection process
    - Performance of RF depends on the classification ability of each tree and the diversity and correlation among them



#### Supervised Learning - Ensemble Learning



Supervised Learning - Advanced Approaches

- PCA RF PNN (Li et al., 2018)
  - PCA and retaining all components (Independent components but no loss of detail)
  - Potential Nearest Neighbours → Selects the samples that are nearest to the sample to be tested in the training set based on the principle of PNN
  - Mean Decrease Accuracy (MDA) and Mean Decrease Gini (MDG) to evaluate the importance of variables



Supervised Learning - Advanced Approaches

- Fuzzy C-Means Clustering and Supervised Classifiers (Subudhi & Panigrahi, 2017)
  - Cluster Centers generated through Fuzzy C-Means clustering (FCM)
  - Genetic Algorithm (GA) for optimizing the cluster centers
  - A new insurance claim is classified as genuine, malicious or suspicious based on its distance computed from the optimized cluster centers
  - Suspicious claims are identified among the insurance records and their behavior is further verified by supervised classifiers
    - SVM, Multilayer Perceptron (MLP), GMDH (Group method for data handling) and Decision Tree



### **Unsupervised Learning**

- Obtaining labels is costly and time consuming
- Clustering
  - Frauds and Non-frauds can be separated based on distance between the attributes
  - Traditional clusters as well as Neural Network based clusters exist
- Distance based identification of outliers and thus frauds
  - KNN Based, Density based methods
- Spectral Ranking for Anomaly Detection (Nian et al., 2016)
  - Ranking represents the degree of relative abnormality



Social Network Analysis (Subelj et al., 2011)

- Helps in Detecting Organized collusion activities
  - Detection of groups of collaborating fraudsters, and their connecting accidents
- Combine intrinsic attributes of entities with their relational attributes (based on graphs)
- Iterative Assessment Algorithm
  - Allows detection of new types of fraud as soon as they are encountered (No learning from labelled data)
- Uses networks of collisions to assign suspicion score to each entity



### Social Network Analysis - Steps

- Different types of networks are constructed from the data set
  - Driver Networks, Participants Networks, Connect Passengers Through Accidents networks, Vehicle Networks
- Components are investigated based on their structural properties(diameter, cycles etc.) - Suspicious ones are identified
  - Fraudulent components share several structural characteristics (much larger and Denser)
  - There are vertices with extremely high degree and centrality
- Suspicious Components are further analyzed in order to detect key entities inside them (assigns a suspicion score to each entity)
- Obtained results should always be investigated by the domain expert or investigator



### **Text Mining**

- Mining of different documents collected during investigation
  - Topic Modelling/Sentiment Analysis
  - Clustering & Other Pattern identification
  - Combining Classification and Topic Models
- Latent Dirichlet Analysis (LDA) based Text Analytics (Wang & Xu, 2018)
  - Combines the precision of data mining methods and the experience of human experts
  - Generative model that can be used to identify hidden topic information in large-scale document collections
  - Obtain the distribution of the keywords for each topic and the distribution of the topics in each description
  - Deep learning is employed to seek high-quality attributes
  - 10-fold cross-validation is used to ensure the validity



**Technical Difficulties in Fraud Detection** 

- Skewed Class Distribution → only a small portion of accidents or participants is fraudulent
  - Collaborated effort of all insurers to develop a master fraud database
- Lack of labeled data sets  $\rightarrow$  labeling is expensive and time consuming
  - Joint Knowledge sharing based on experience of new frauds
- Lack of unlabeled data sets
- Garbage In Garbage Out
  - Data capturing mechanisms need to be improved (Integrated and verified with various sources of information)



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# 20<sup>th</sup> Global \_\_\_\_\_ Conference of Actuaries

4<sup>th</sup> - 6<sup>th</sup> March, 2019 | Mumbai, India

#### THANK YOU

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