

#### Session 089: Unleashing the Power of Claims Data Through Machine Learning

SOA Antitrust Compliance Guidelines SOA Presentation Disclaimer

## Unleashing the power of claims data through Machine Learning

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## Enormous opportunity

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# Opportunities



## Data Capture

- Apply structure & meaning to claims data (or supporting documents)
- Common challenge across Markets
  - Claims forms
  - Receipts
  - Health Records
  - Attending Physician Statements
  - Other documents
- Approaches Computer Vision, Natural Language Processing
- Classification and standardization

# Workflow

- Claims processing, triage and adjudication
  - Integrate machine learning based predictions with robotic processing automation
  - Claims classification/segmentation
    - Preliminary processing
    - triage for complexity
    - Map to appropriate action
  - Recommendation engine (Next best action)



# Pattern Detection & Prediction

- Predict claims (incidence/severity/drivers)
  - Understand
    - Pricing, experience studies
    - Product/service development
    - Plan Design modifications
  - Act:
    - Case Management
    - Interventions/Drug Adherence



# Model Interpretability is a game

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# New Methodologies Present opportunities











## **Claims analytics**



Use cases:

- Foreign death fraud models
- Claims risk assessment
  - Critical illness approval/denial and misrepresentation models

## FOREIGN DEATH FRAUD



### Foreign death fraud - overview



## "Warning: increasingly common and sophisticated scams

...In many countries, con artists operate without consequences because local authorities often do not have the physical or financial resources needed to combat Internet crimes...Organized fraud networks are developing more and more innovative and sophisticated approaches to deceive...The criminals conduct extensive searches to create credible documents: complete profiles of fictitious businesses, medical reports, falsified export certificates, etc. The names and logos of reputable organizations, governments and government agencies are often used fraudulently. Websites that appear very authentic are also falsified..."

Government of Canada Advisory, 30 May 2013 http:// Travel.gc.ca/travelling/health -safety/overseas-fraud

- Misrepresentation of death occurred abroad can be as high as 2% of all individual life claims
- High fraud rates are observed in Middle East, Africa and China with misadventure being the common cause..
- Machine learning methods can leverage multiple data sources to provide insight on main drivers of fraud and identify high risk foreign death claims

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### Data to consider

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Demographics	Claim Data	Underwriting and policy data	Third Party/ External	Geospatial
+	+	÷	*	+
Age / Date of birth	Country	Foreign travel, aviation, avocations	Corruption Perception Index	Population density
+	+	•		
Gender	Cause	Tobacco, drug and alcohol usage	Credit/public records	Unemployment rate
Ŧ		+		
Income	Claim amount	Agent, face amount	Lifestyle	Tobacco tax
ŧ	+	•	*	
Occupation	Claim Age	Beneficiary	MIB	Home value
ŧ		÷	*	
Income	Policy duration	Personal and family health history	MVR	Household size
ŧ		+	+	
Pre-existing diagnosis	Body found	Disability, bankruptcy, felony	Rx	Household composition
	Ŧ	+		
	Claim proofs	Product, simplified UW vs Full		Education



## **Corruption Perception Index (CPI)**

#### Important continuous indicator that allows to smooth out underrepresentation of fraud cases in individual countries



### CORRUPTION PERCEPTIONS INDEX 2012

The perceived levels of public sector corruption in 176 countries/territories around the world.



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## Third-party data

Examples of third-party data include..









## Machine learning to detect key fraud drivers

#### Country Face amount Claim age Claim amount Cause Policy duration CPI Gender Occupation UW type Body found Smoker

#### Variable importance

- Data:
  - Demographics
    Policy data
    Claims
    Corruption Perception Index
- Average fraud rate: 1.5%
- Machine learning methods allow to estimate marginal impacts of all variables on fraud likelihood and thus detect key fraud drivers



## Machine learning to explore fraud cases



Machine learning methods
 can be applied to segment
 claims from least risky to
 most risky classes

 The decision tree identifies claims with face amounts higher than \$700K and policy duration under 4 years as high risk with fraud likelihood of 46%



## Machine learning to produce fraud risk score



Distribution of claims by fraud risk score

- Given sufficient data, more sophisticated machine learning methods can be applied to produce a continuous risk score
- The score can then be used to determine optimal strategy for claim investigations
- Machine learning methods produce 0-10 fraud score for each claim. Claims can then be segmented into low, medium and high risk categories for targeted investigations



## Partnership is the key to fraud detection Data is essential

## CLAIMS RISK ASSESSMENT





## Claims approval/denial and misrepresentation

#### Motivation

- Claims adjudication is a complex process that requires significant amount of human intervention
- Average claim processing time can exceed several weeks

#### Objective

- Use machine learning to identify critical illness insurance (CI) claims that have a high risk of being denied
- Triage claims based on adjudication difficulty and likely outcome

#### Our approach

Two model approach is proposed to classify CI claims based on:

- Risk of claim denial
- Risk of claim involving misrepresentation, non-disclosure or fraud

## How does it work?



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## Approval/denial vs misrepresentation



#### **Claims denials**

Denied (any reason) , rescinded, death, litigation

#### **Claims misrepresentations**

 Medical misrepresentation, fraud, non-med nondisclosure, rescission identity fraud, rescission family history, denial family history, etc

#### **Key drivers**

- Cause of claim, duration and reporting lag are the key drivers of claim denial and misrepresentation predictions
- Cause of claim is the most important feature predicting claim denial whereas policy duration is the most important feature for predicting likelihood of claim misrepresentation

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## Implementation



## Dashboard



Enter Claim age	Case has a high risk of denial, with a low risk of misrepresentation.		
20			
Enter gender		Reason for recommendation	
Female			
Enter policy duration (years)		Denia	
10	200%	Misre	
Enter Claim amount	150% 9		
5000	100% 5		
Enter reporting lag (days)	3 JU 76		
0100	5%		
Enter cause of claim	-30%		
Gastro-Intestinal Acute Pancreatitis		ause of Clain	
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## Key findings



- Approval/denial and misrepresentation models provide an efficient risk segmentation of all CI claims allowing for claims to be triaged based on quantitative risk assessment
- □ The most impactful drivers of denials and misrepresentation are identified during risk assessment
- **Easy to use through a user friendly interface**



## Thank you for your attention!

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