Application of Analytics to Claim Fraud Detection

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Apex Discussion Series

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About the Presenter

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Roosevelt Mosley has 17 years of actuarial experience including 11 years of experience developing and deploying predictive models for a variety of insurance company applications. Roosevelt's predictive modeling credits include numerous industry presentations, articles and monographs.

Application of Analytics to Claim Fraud Detection

- Claim fraud is increasing, focus on fraud is magnified
- There are special investigators in the industry that are good at detecting fraud
- As good as they are, they can't review every claim and detect all fraud
- Predictive analytics can bring the expertise of the best adjusters to bear on all claims
- Predictive analytics can enhance the work of investigators by uncovering complexities the human eye may miss

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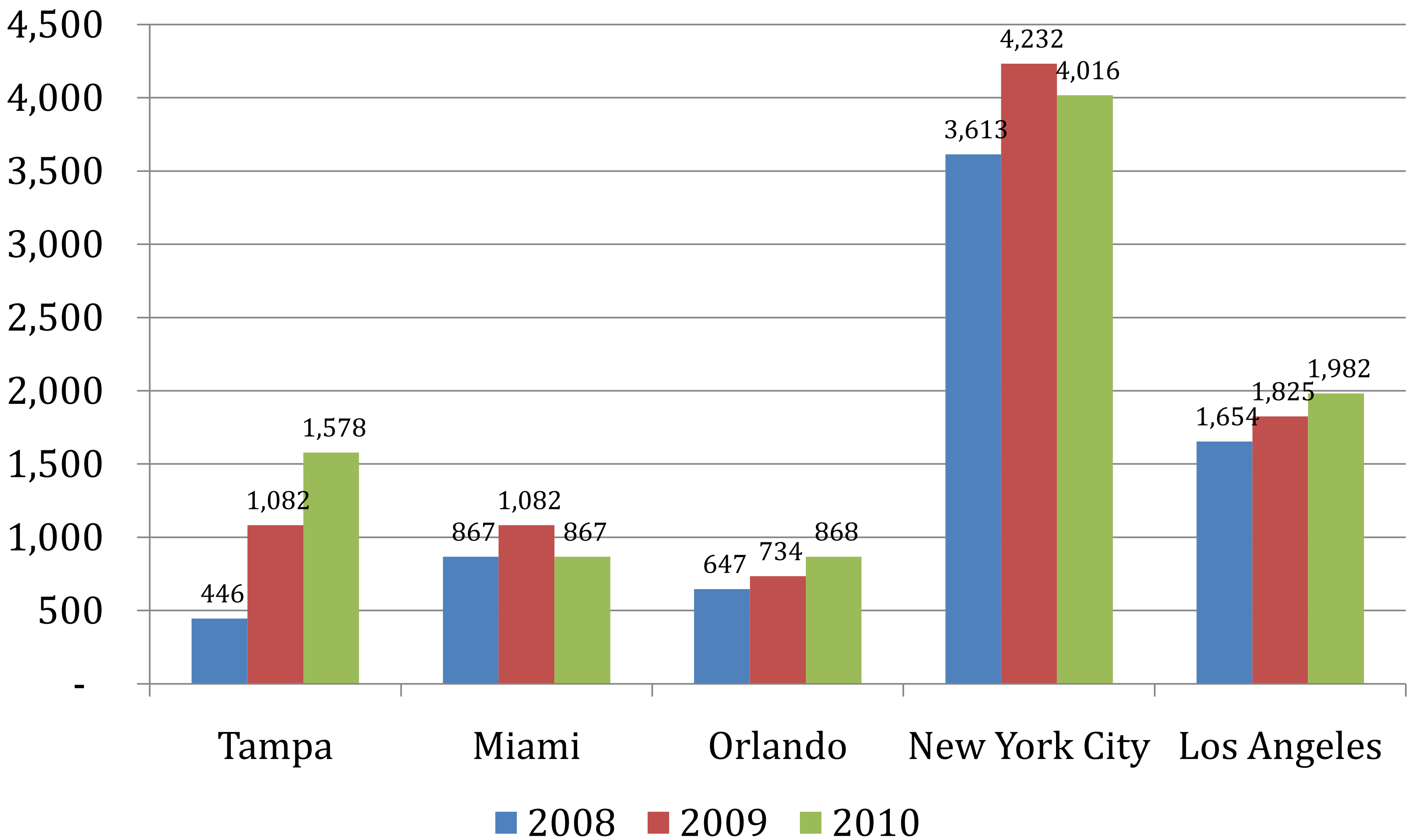
Claim Fraud is Increasing, and the Focus on Claim Fraud is Increasing as Well

Increasing Claim Fraud – 2011 Headlines

- March 30 – Suspicious claims rise 34% in Florida
- April 17 – The Battle Against Insurance Fraud in Georgia
- April 26 – Insurance Groups Stress Need for N.Y. No-Fault Reform at Hearing
- May 2 – Four Women Booked with Insurance Fraud in Louisiana
- May 5 – Council Woman Gets Jail Time for Insurance Fraud
- May 6 - Allstate Files $4 Million Insurance Fraud Case in New York
- May 8 – Questionable Claims on the Rise in Oklahoma (+15%)
- May 12 – NY State Must Stand Against No Fault Car Insurance Fraud

Increase in Questionable Claims



Source: National Insurance Crime Bureau

Fraud Has a Significant Financial Impact

- Coalition Against Insurance Fraud
  - Auto - fraud and build-up added **$4.8B to $6.8B (13% - 18%)**
  - Worker's compensation – fraud cost insurers **$557M**
  - Healthcare - **$68B** lost to fraud every year
- Consumer attitudes
  - 1 in 5 adults think it is acceptable to defraud insurance companies
  - 1 in 10 people think it is OK to submit claims for items that are not lost or damaged, or for an injury that didn't occur
  - 16% of people think it is OK to inflate a claim to cover the deductible

Fraud Detection Process – The SIU is Good At It

General Fraud Identification Process

- **Identify**
  - Rely on claim adjusters to identify potentially fraudulent claims (recognition, intuition)
  - Identify triggers that alert the claim adjuster to potential fraud (fraud indicators)
- **Referral:** Potentially fraudulent claims are referred to SIU
- **Investigate:** SIU investigators handle the investigation of fraudulent claims
- **Resolution:** ???

Recognition (I’ve Seen This Before)

- Examples
  - Repeat offenders
  - Provider/patient/attorney combinations
- Approach
  - Advisory claim database
  - Experience of adjuster
- Disadvantages
  - Assumes adjuster has seen it before
  - Fraud becomes smarter (aliases, new members of same network, etc.)

Intuition (Something Smells Funny)

- Something about the claim doesn't seem right to the adjuster, and it is referred to the SIU
- Relies on ability and experience of adjuster to see suspicious cases
- Inexperienced adjusters will not have the ability to detect suspicious as well

Fraud Indicators

- Rules based system
- Identify known or potential fraud scenarios
- Advantages
  - Easy to implement and modify
  - Easy to understand
  - Effective to attack specific problems
- Disadvantages
  - Doesn’t detect new and unknown fraud
  - Creates smarter fraud

Fraud Indicators - Examples

- Distance between claimant’s home address and medical provider
- Multiple medical opinions/providers
- Certain claim types (e.g., soft tissue)
- Changing providers for the same treatment (possibly correlated with other claim activity)
- High number of treatments for type of injury
- Abnormally long treatment time off for the type of injury
- Accident severity does not correlate with severity of injury

As Good as the SIU Is…

Concerns with the Current Process

- Claim referral can be inconsistent – heavy dependence on claim adjuster
- False positives
- Claim adjuster may not be aware of all suspicious relationships
- Not all historical fraud has been identified
- Prioritization of potentially fraudulent claims

Using Predictive Analytics to Address These Concerns

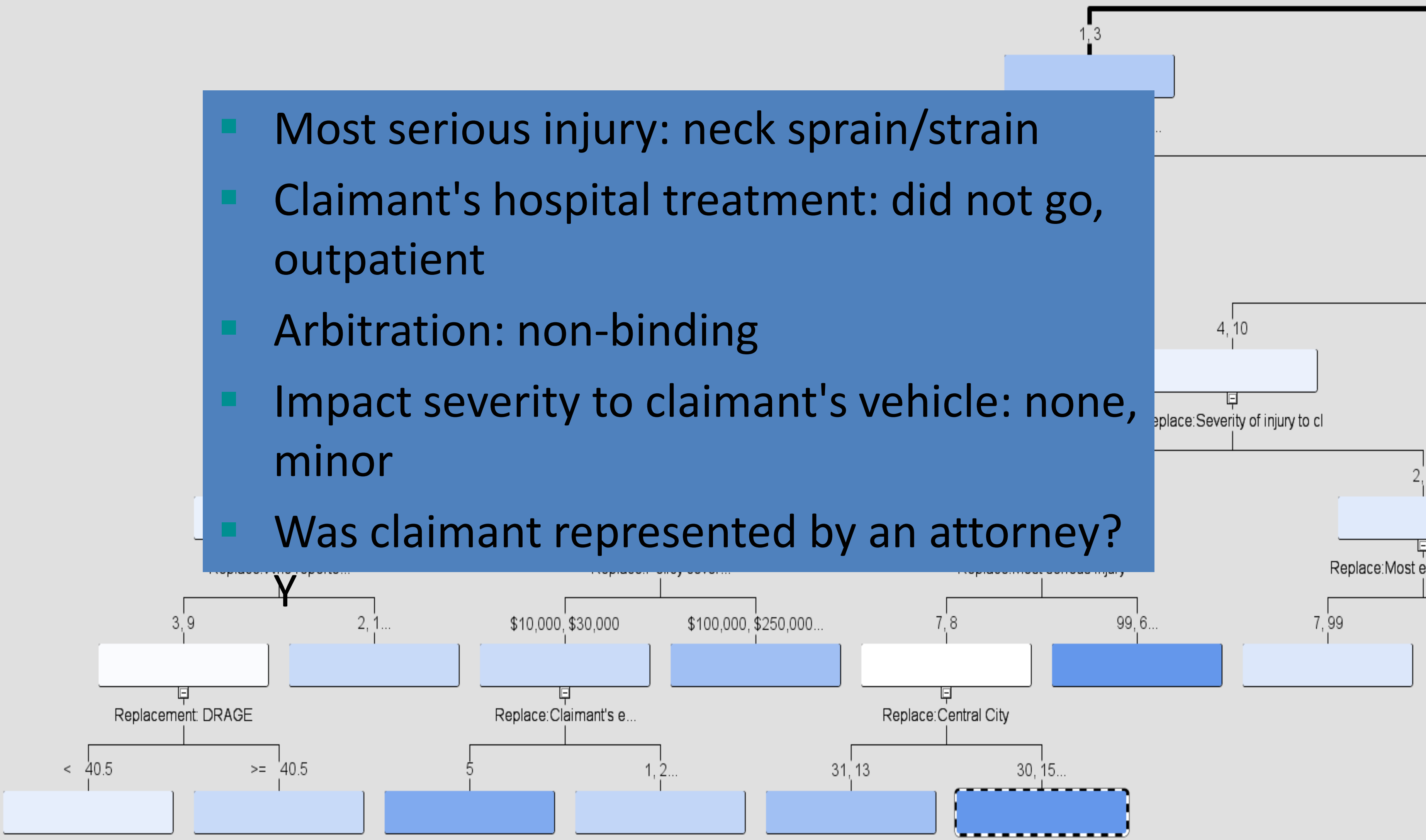
- Predictive analysis of historical referrals (consistent referrals)
- Predictive analysis of historical fraudulent claims (false positives)
- Identification of networks (recognition of claim patterns)
- Identification of suspicious claims (missed claims, prioritization)
- Combination of analytics and adjuster experience (consistent referrals, prioritization)

Predictive Analysis of Historical Referrals

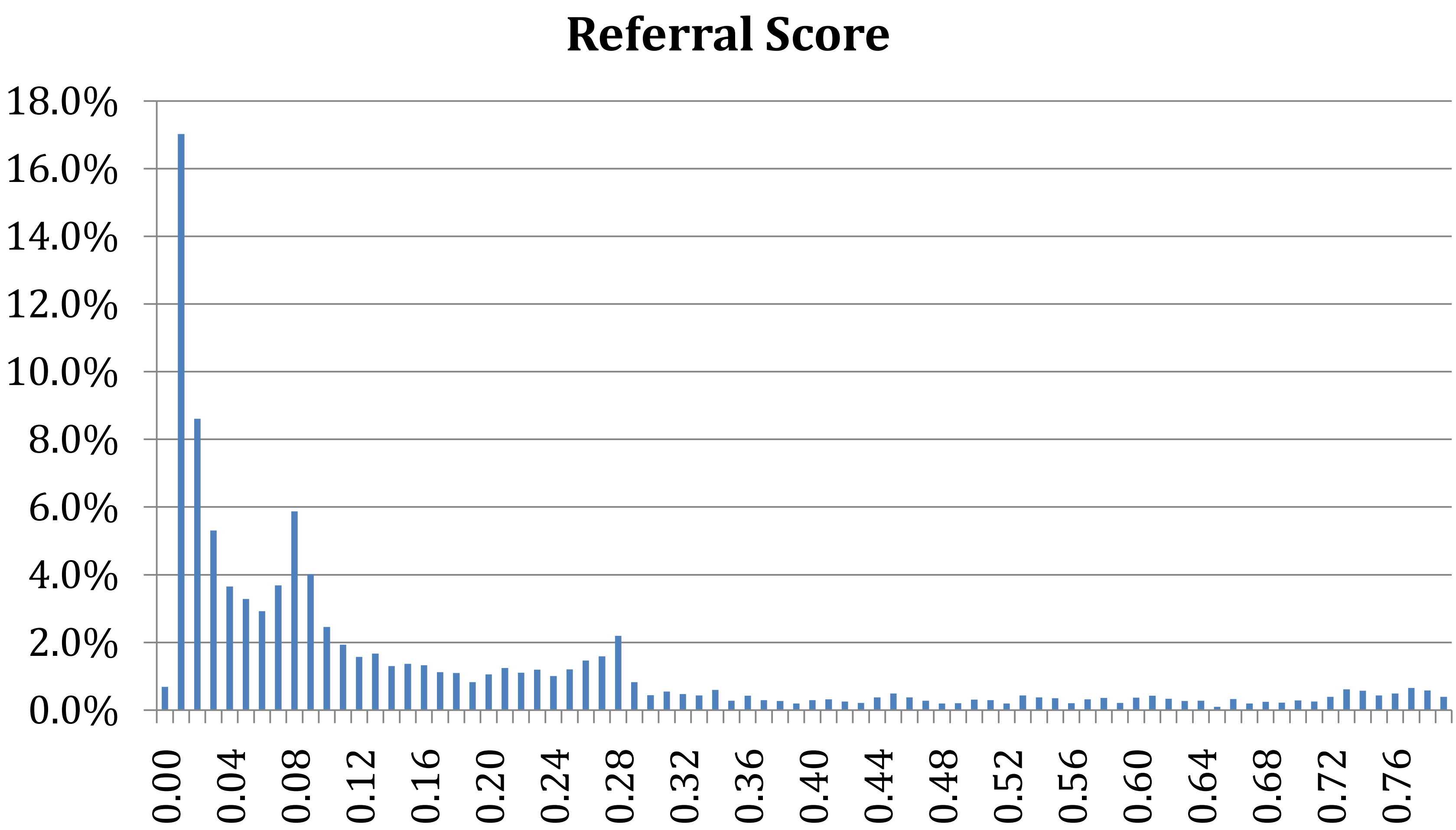
- Target: history of claim referrals to SIU
- Independent Factors: details of claim
- Models Tested
  - Decision tree
  - Neural network
  - Linear regression
  - Ensemble
- Result: given the history of claim referrals, the likelihood that a new claim should be referred to SIU based on the claim characteristics

Decision Tree

- Most serious injury: neck sprain/strain
- Claimant's hospital treatment: did not go, outpatient
- Arbitration: non-binding
- Impact severity to claimant's vehicle: none, minor
- Was claimant represented by an attorney?



Referral Score



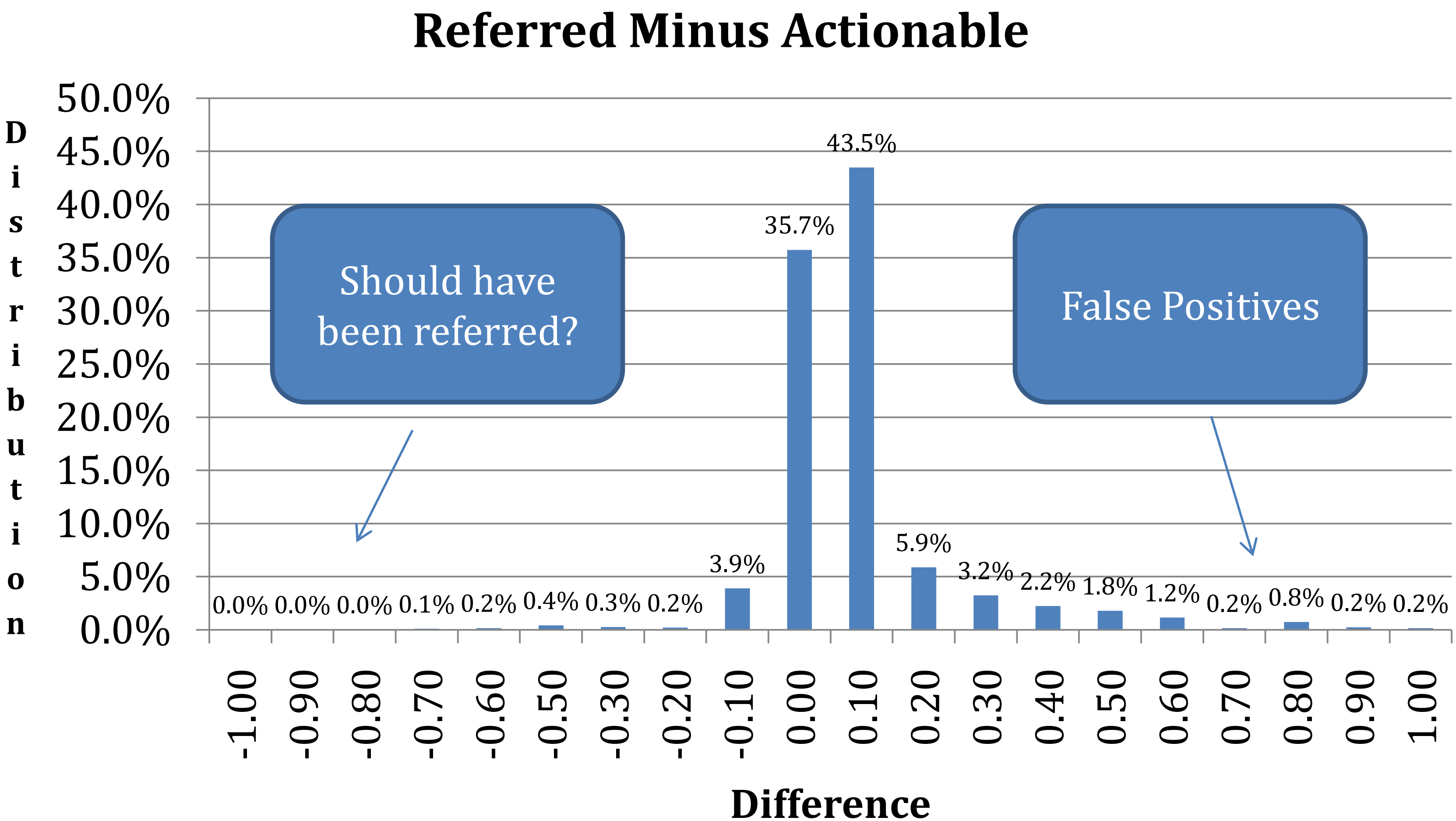
Analysis of Historical Fraudulent Claims

- <u>Target</u>: history of actionable claim referrals to SIU
- <u>Independent Factors</u>: details of claim
- <u>Models Tested</u>
  - Decision tree
  - Neural network
  - Linear regression
  - Ensemble
- <u>Result</u>:
  - given the history of claim referrals, the likelihood that action will be taken on a new claim based on the claim characteristics
  - Comparison to referral claims

Decision Tree Comparison – Variable Importance

Variable	Actionable Importance	SIU Referral Importance	Ratio
Central City	1.000	0.464	46.4%
Replace:Claimant's state of residence	0.967	1.000	103.5%
Impact severity to claimant's vehicle	0.962	0.828	86.2%
Was claimant represented by an attorney?	0.850	0.905	106.4%
Policy coverage limits per person	0.750	0.411	54.9%
Arbitration	0.547	0.368	67.2%
Most serious injury	0.530	0.375	70.9%
Settlement_lag	0.456	0.000	0.0%
Who reported injury to insurer	0.439	0.374	85.3%
Most expensive injury	0.423	0.239	56.5%
DRAGE	0.312	0.306	98.0%
Lawsuit status	0.295	0.000	0.0%
Driver, other violation	0.285	0.000	0.0%
Amount Spent on Medical Professionals	0.255	0.412	161.6%

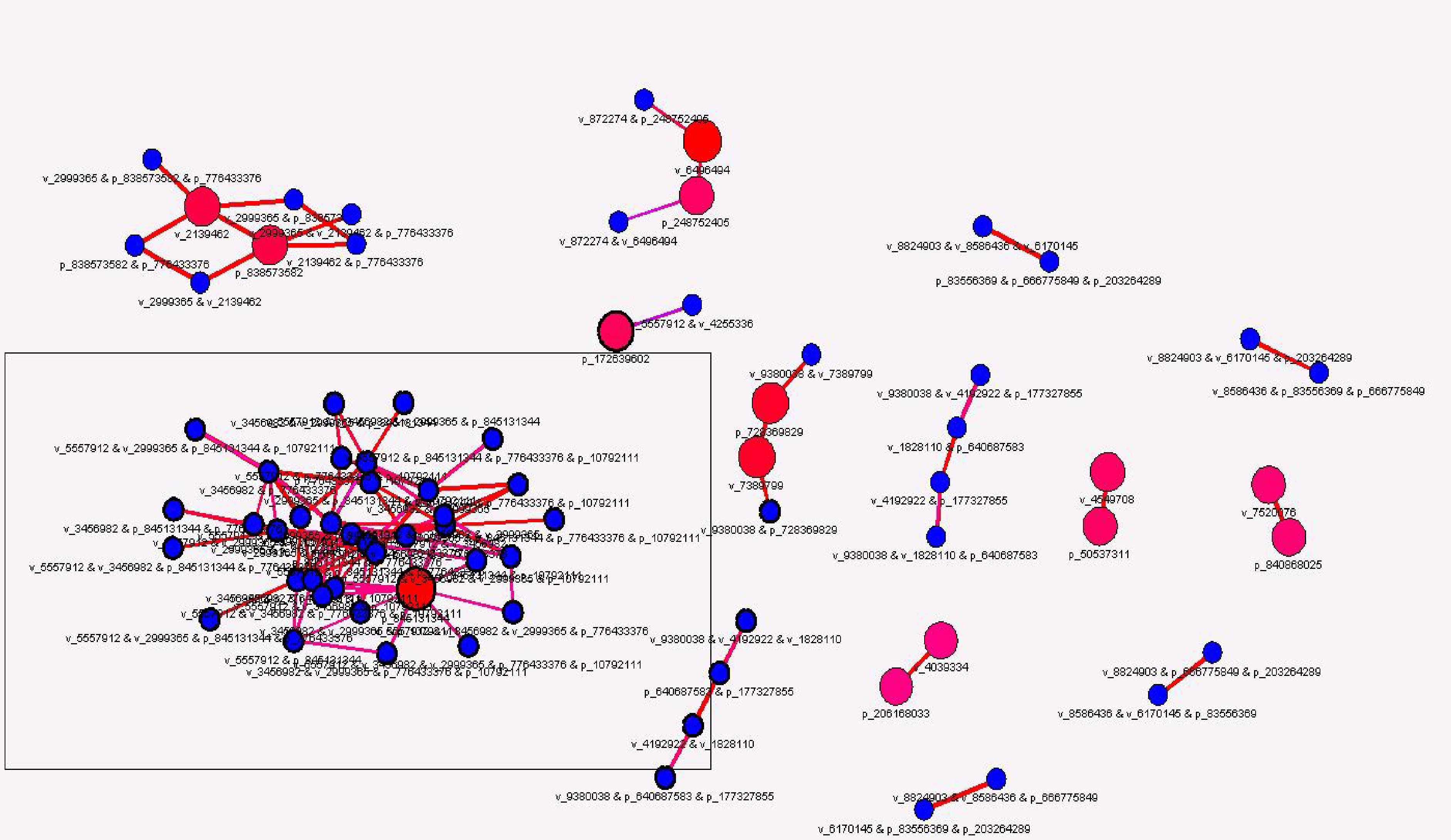
Difference in Referred vs. Actionable Claims



Identification of Networks

- Association Analysis
  - Technique used in market basket analysis
  - Identification of items that occur together in the same record
  - Produces event occurrence as well as confidence interval around the occurrence likelihood
  - Can lead to sequence analysis as well, which considers timing and ordering of events

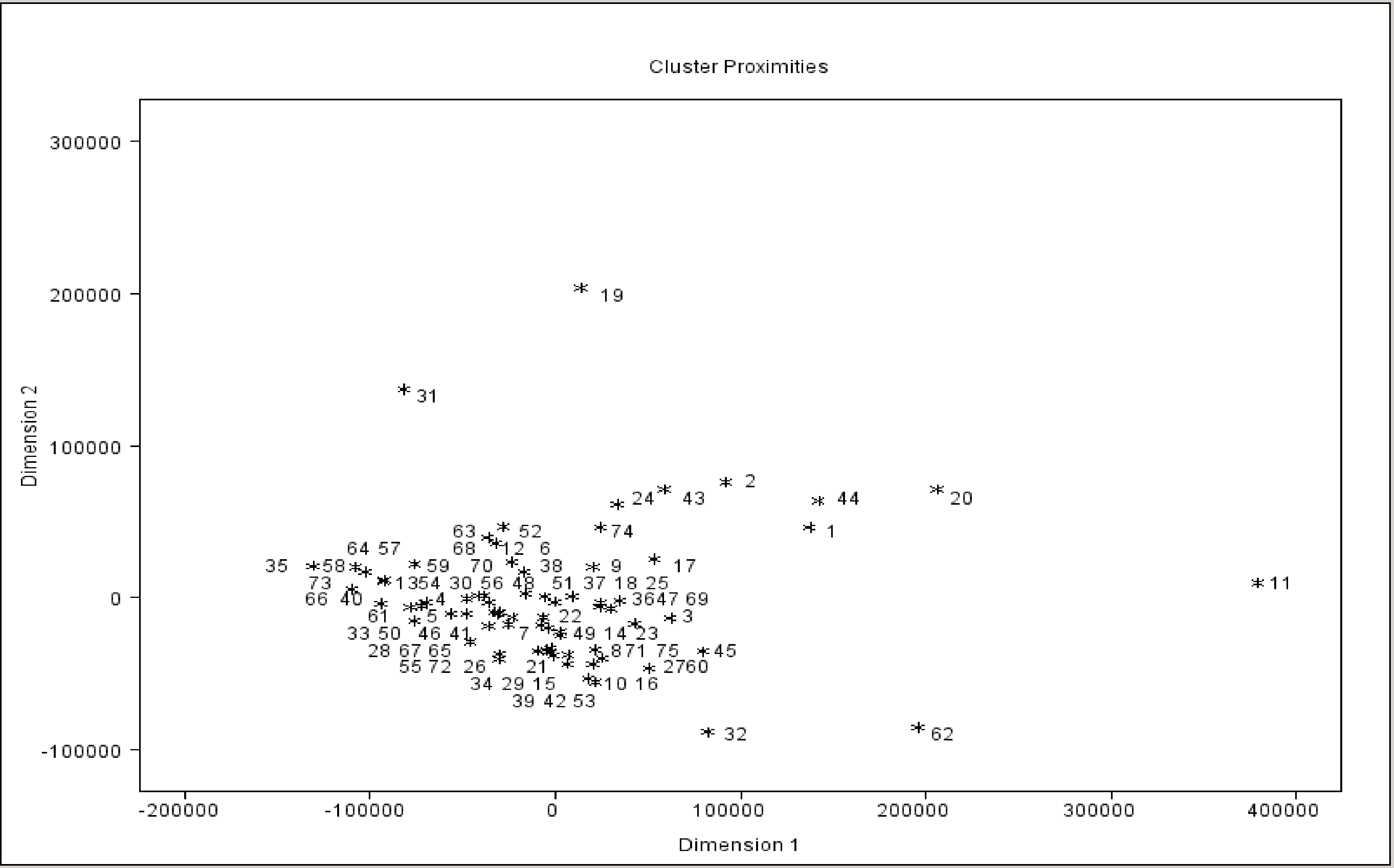
Network Example



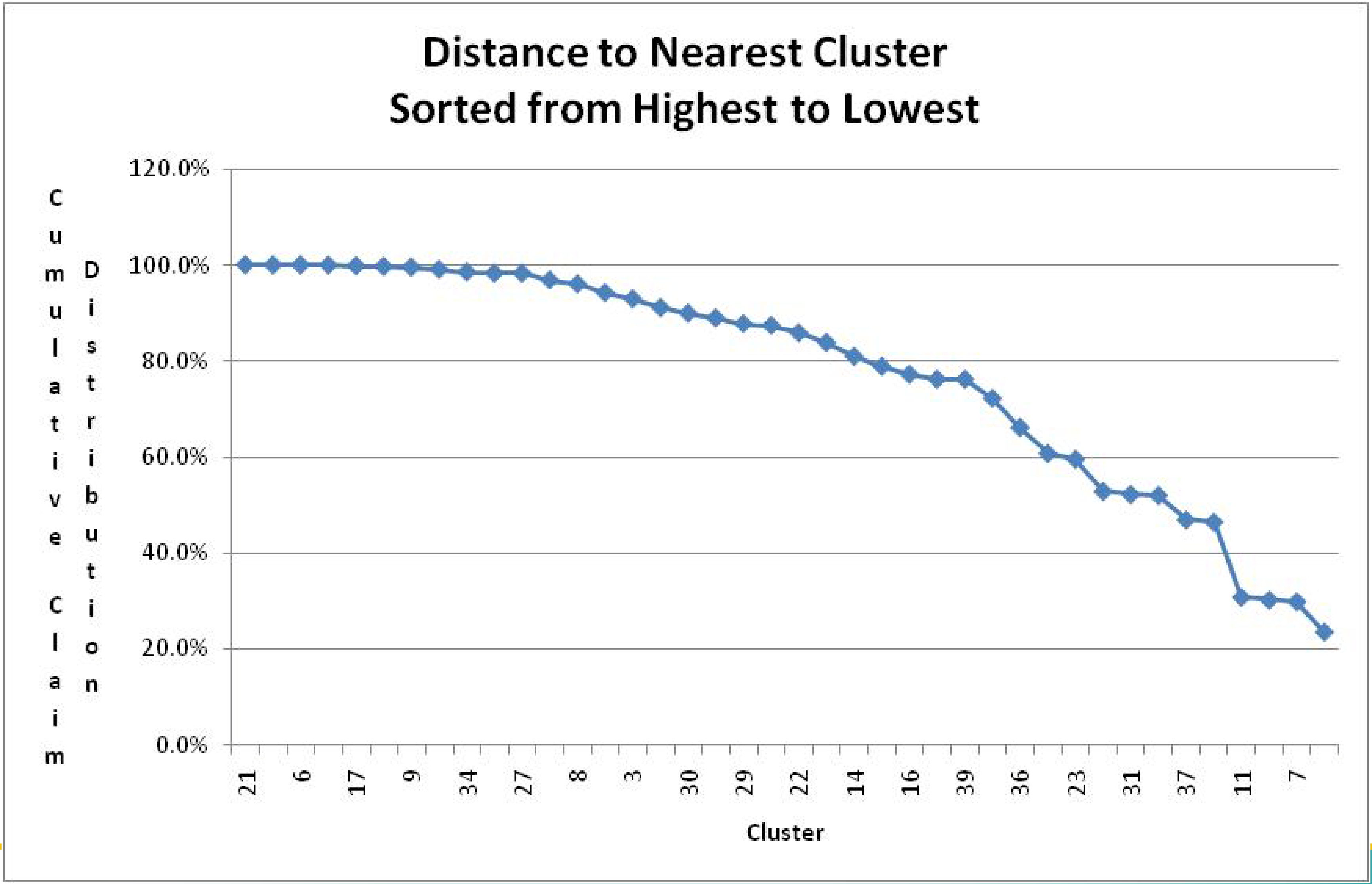
Identification of Suspicious Claims

- Unsupervised classification technique
- Groups data into set of discrete clusters or contiguous groups of cases
- Performs disjoint cluster analysis on the basis of Euclidean distances computed from one or more quantitative input variables and cluster seeds
- **Objects in each cluster tend to be similar, objects in different clusters tend to be dissimilar**

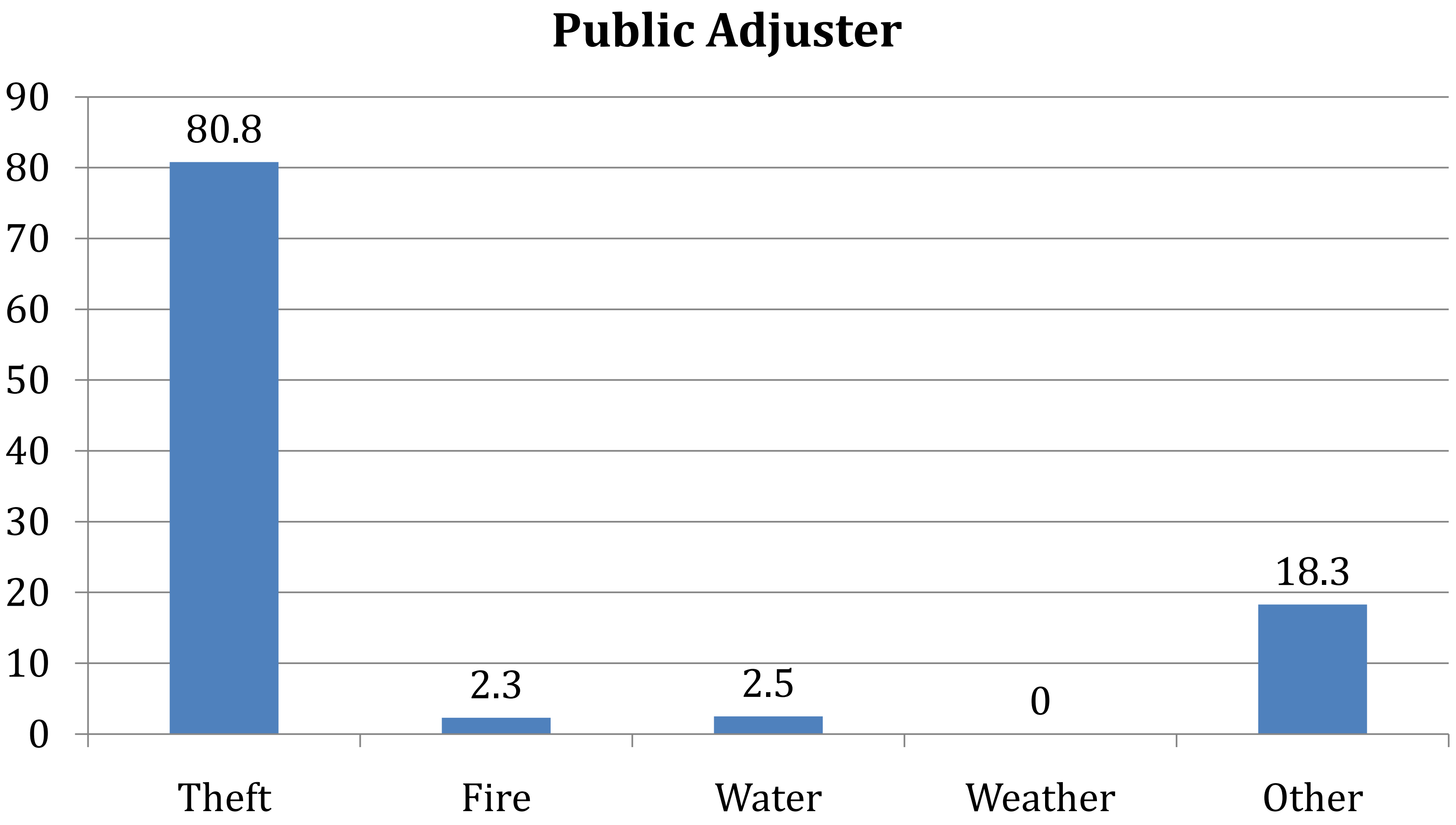
Cluster Proximities – All Causes of Loss



Cumulative Distribution – Distance to Nearest Cluster (Theft)



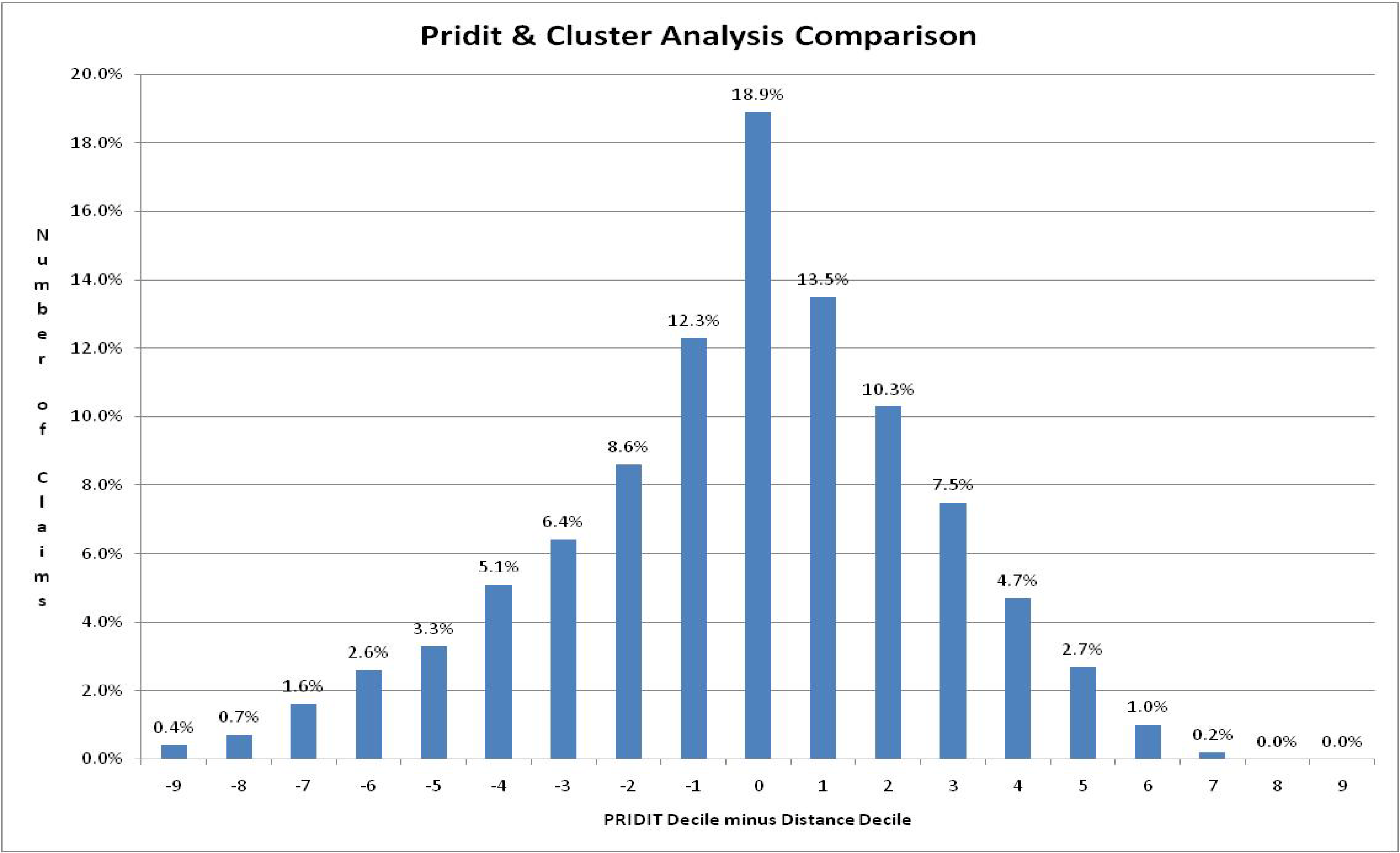
Distance from Cluster Mean



Combination of Analytics and Adjuster Experience

- PRIDIT
  - Variables are ordered so that lowest value is associated with highest or lowest probability of the latent variable, for example "fraud"
  - Use Cumulative distribution of claims at each value, i, to create RIDIT statistic for claim t, value I
  - Principal Component Analysis is applied to the RIDIT scores

PRIDIT Comparison



Fraud Classification Using Principal Component Analysis of RIDITs

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Application of Results – Claim Fraud Report

Claim Details

Arbitration	3	**Accident Date**	10/18/1999
Report Lag	3 days	**Report Date**	10/21/1999
Days Open	932	**Coverage**	Bodily Injury
Lawsuit	Suit Filed		
State	46		
Accident Location	Small Town		
Injury Severity	No Information Available		
Claimant Aage	46		

Fraud Model Scores

	Score	Indicator
SIU Referral	53	
Past Identified Fruad	36	
Claim Anomaly	13	
Composite	34	

Fraud Model Reason Codes

1	Delayed Reporting
2	Accident in Small Town
3	
4	

Wrap Up - Predictive Analysis for Fraud

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Questions

Thank You!

- For additional information, visit www.pinnacleactuaries.com
- Specific follow up questions: rmosley@pinnacleactuaries.com
- Complete the **survey**
- Join us in August for "Impact of Healthcare Reform on Liability Insurance"