



What the Rules Can't See Can Hurt You

Bill Fox, Senior Director Health Care

Ken Cunningham, VP Analytics

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Myth:

Health care fraud accounts for a small amount of the money the U.S. spends on health care every year.

Fact:

The U.S. spends more on health care **FRAUD** in a year than the gross domestic product of 120 other countries .

The numbers are staggering

1,014

2,459

1,621

591

580

986

1,155

\$2.2 Billion

“The topic is interesting, although seemingly far-fetched...”

Comment received on LexisNexis Proposal to speak on Organized Crime’s involvement in health care fraud.

Accountability

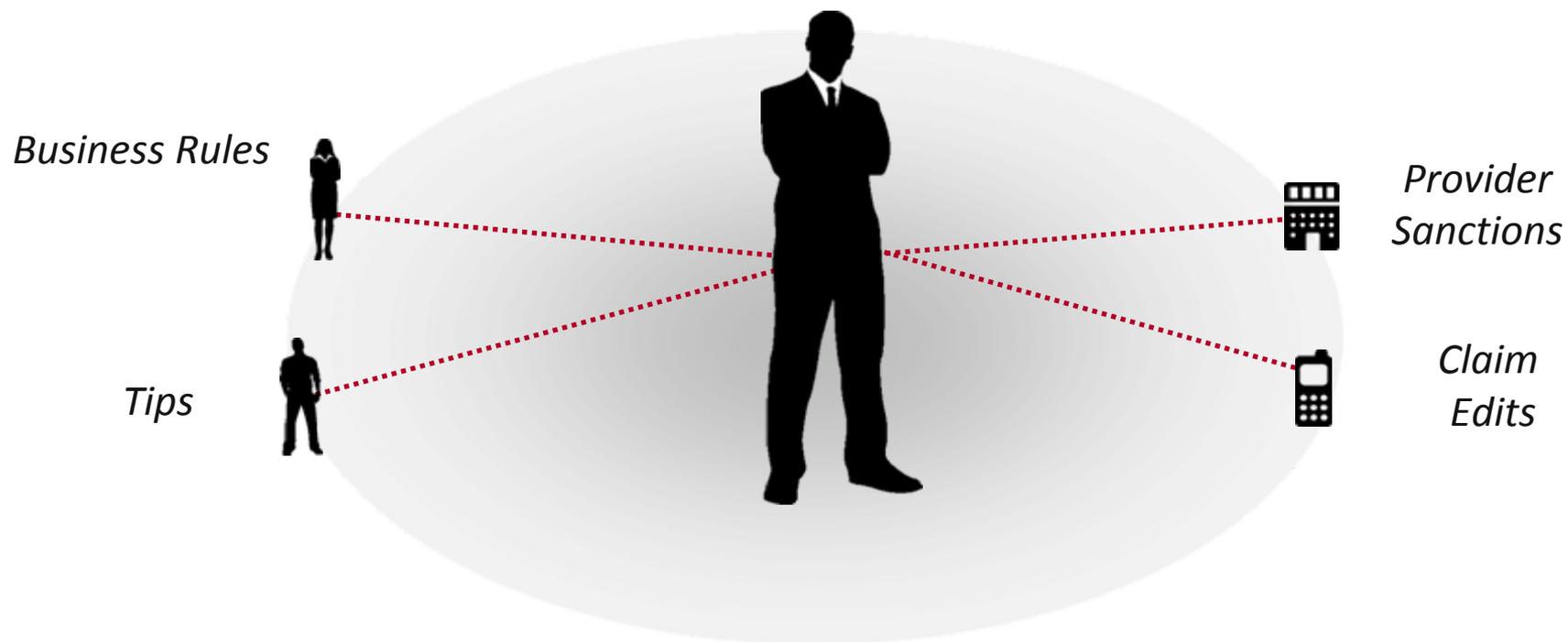
- The Patient Protection and Affordable Care Act of 2010 (PPACA) amends 18 USC § 1347:
 - A person need not have actual knowledge of or specific intent to commit a violation
 - Imposes several new civil monetary penalties and exclusions
 - Revises evidentiary standard of anti-kickback statute to eliminate the requirement of actual knowledge of, or specific intent to commit a violation of the statute
 - Limits exceptions to the Stark Law, which prohibits physician self-referral for certain health services paid for by Medicare or Medicaid

- PPACA is designed to reflect the serious harm associated with health care fraud and the need for aggressive enforcement
 - A two-level increase in offense level Medicare or Medicaid fraud resulting in losses in excess of \$7 M
 - A three –level increase in offense level for Medicare or Medicaid fraud resulting in losses of \$7 M - \$20M

It is no longer necessary for one to have knowledge of health care fraud to be held accountable for it

Predictive Modeling

How you locate fraud and abuse today



The current state of FWA detection – Limited tool set

■ Claim edits

- At the bill level
- Almost always post-pay – “pay and chase”
- Limited by “prompt-pay” fears
- Can create a highly complex web of interactions
- Processing problem for large payers

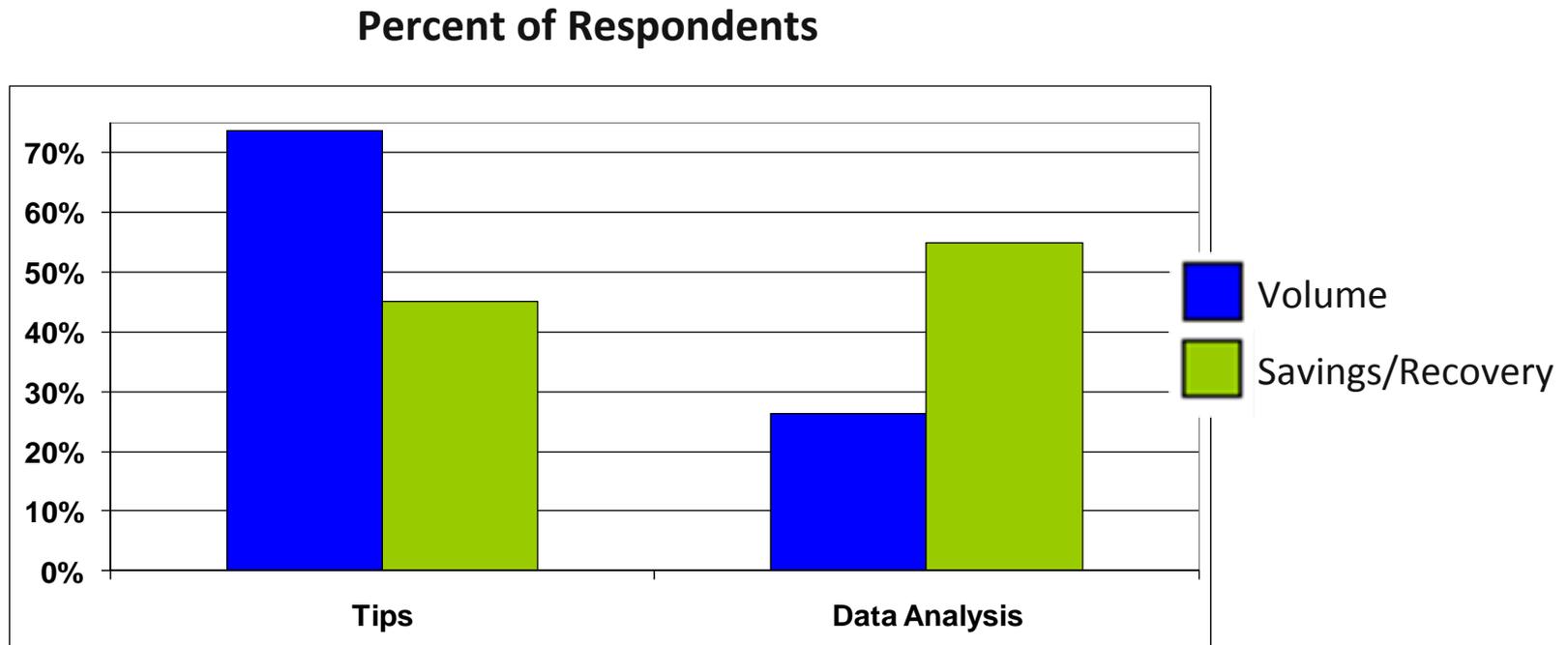
■ Rules systems

- “Expert system” – open to gaming by experts
- Also very often at the bill level
- Also very often applied post-pay
- High false positives
- Adding rules is easier than amending or removing

■ Tips and leads

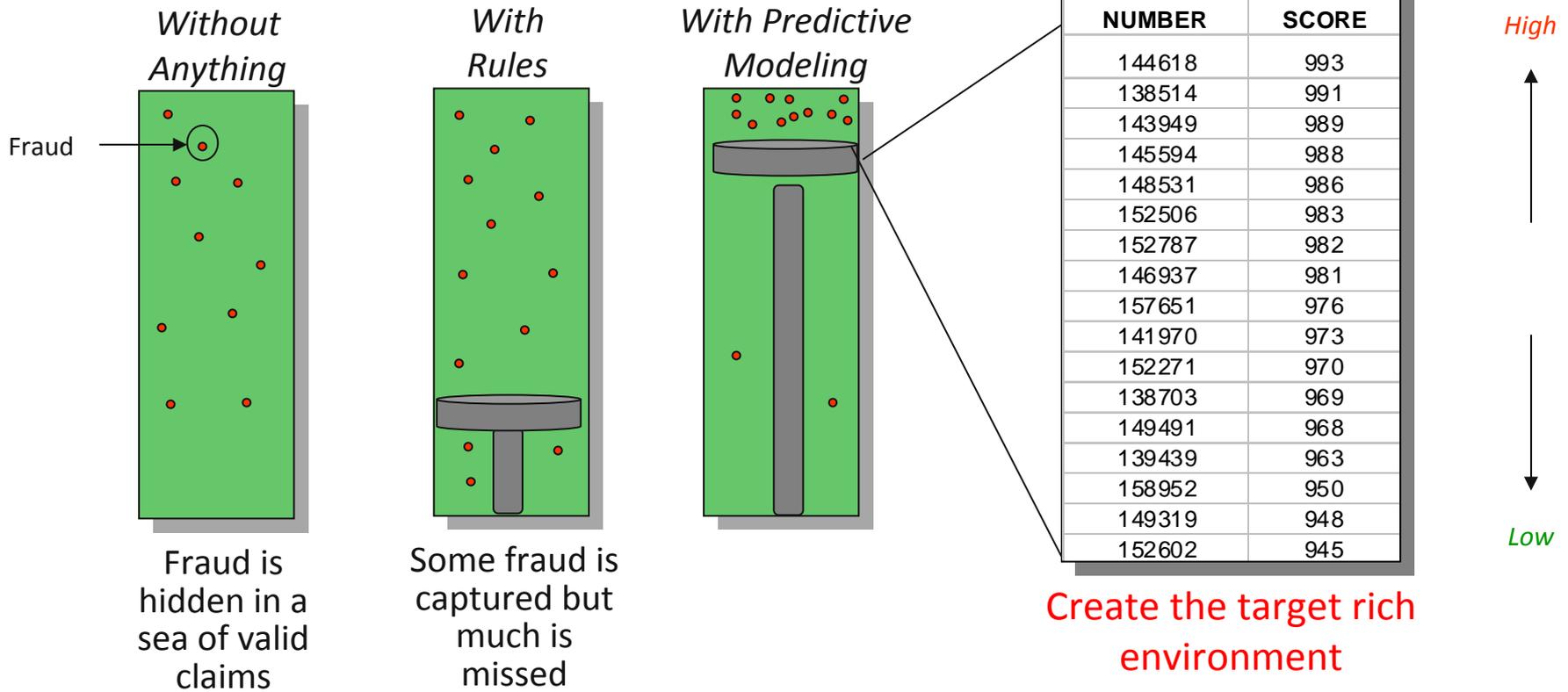
The value of predictive modeling

- Is more accurate than other fraud detection methods
- Data collected and assembled from a variety of resources
- Schemes do not depend on up-front assumptions
- Statistically determines data patterns that are associated with claims that have a high fraud-propensity score



Claim Scoring Using Predictive Models

Predictive analytics provides a score for each claim, policy, etc., allowing activity to be concentrated on areas that have the highest probability of financial return



Healthcare – The Special Case

- Medicaid, Medicare, Blues and Commercial Plans - different business rules/different priorities –all strapped for resources
- Prompt Pay Rules vary by state but always require virtually immediate decision making
- MLR and reform mean uncertainty for many years to come
- Fraud risk control requires an enterprise approach that includes delivery, quality and compliance
- Most FWA is provider driven so the focus is on “providers of interest”
- The claim workflow will be modified over time to allow for more effective fraud and abuse control

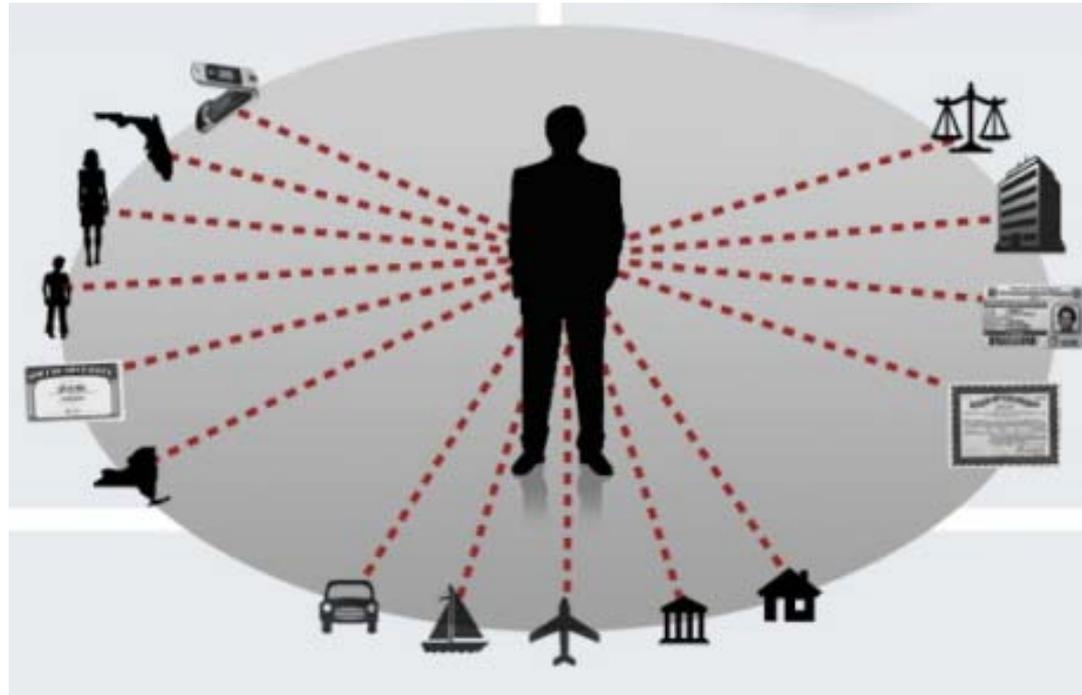
Models can identify providers of interest

- FWA is mainly provider driven, so find problem providers
 - Problems are revealed in diagnosis, treatment, and billing patterns
 - Identifies “nearby” patterns rule may miss
- Models supplement current tools and experience
 - Prior identified FWA can “seed” a model
 - Model targeting can take account of policies
 - Even without prior identified problems, models can be built
- Model scoring is fast, scalable, and targeted

Predictive Modeling Provides A Score *Plus More*

Sample Model Score: 985 For this Provider

Significant Edits



Criminal Record

Two Sanctions

Bankruptcy

Social Network/Relationship Analytics

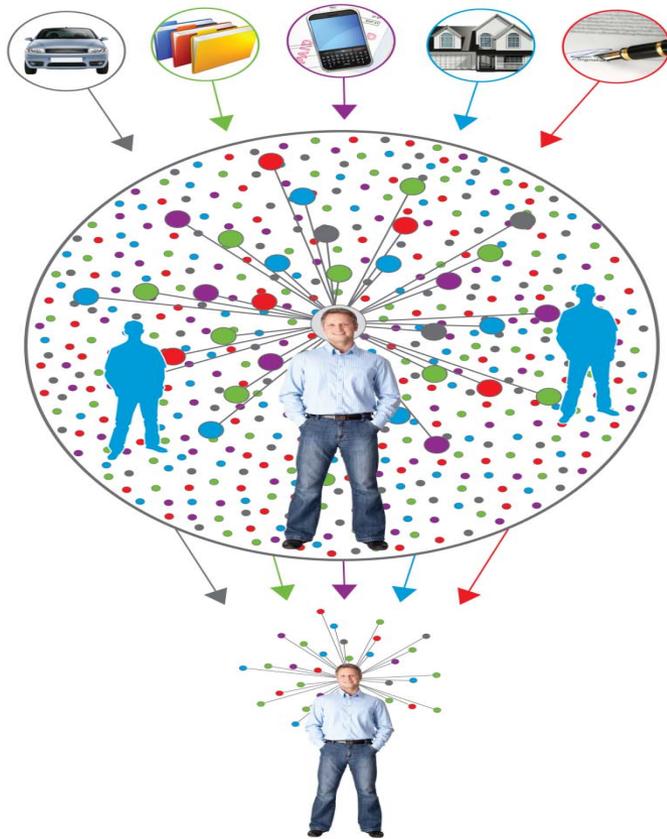
Social Network Analysis

- Much of the fraud, waste, and abuse that plagues healthcare payers is the result of organized, sometimes collusive, activities among providers and patients
- The identification of large scale rings is important and creates headlines to raise awareness of the problem
- More localized collusion can be harder to find and is much more prevalent
- Using public records databases and advanced data analytics, these collusive relationships can be identified and addressed
- Along with Provider of Interest identification, this approach allows payers to address fraud, waste, and abuse much more broadly than the traditional bill level approach

What is Social Network Analysis?

1. Connects claims, parties, and vehicles to create groups of claims (clusters).
2. Groups of claims are augmented with public records information, associate data, medical data, and contributory data.
3. Analytics is used to find interesting investigation points and highlight the most important relationships.

Create a Unique ID



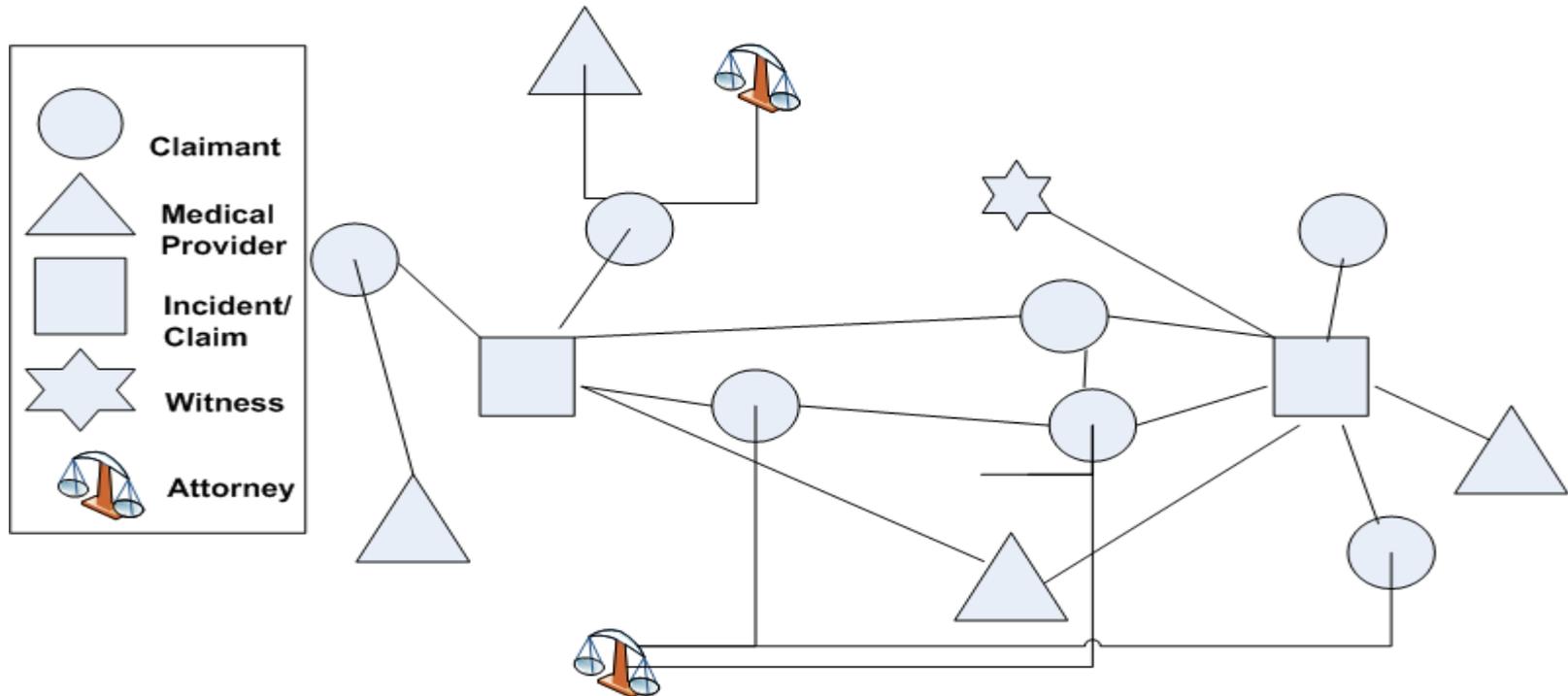
LexisNexis Advanced Linking Technology assigns a unique and persistent identifier to a person

- Dynamic – updates as new public records are available.
- Extremely Accurate - based on multiple public record and insurance sources

Connects to information maintained in other LexisNexis data sources: Public Records, Carrier Discovery, and Claims Discovery

Create Clusters

After assigning a LexisNexis Unique ID to person data, the engine will create clusters of claims. A cluster equals a group of claims and persons that are connected.



Rules Based Fraud Detection Falls Short

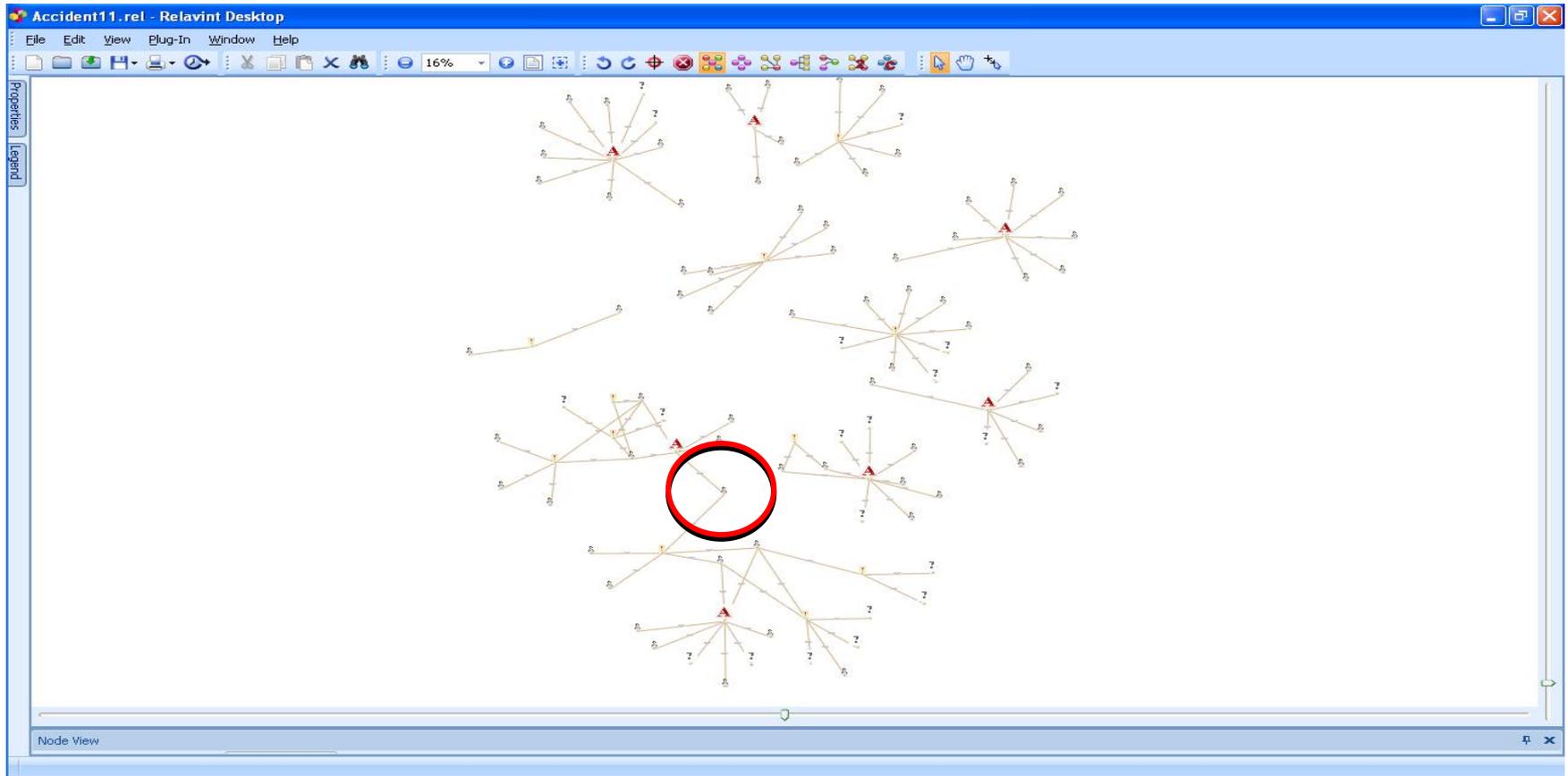


Fraudsters know all the thresholds and game the system.

- Rules based detection plays a key role in the “Giant Mortgage Fraud Magic Act”.
- Advanced Persistent Threat (APT) is not just Cyber.
- Key differentiator is in how to leverage BIG DATA to measure proximity of seemingly low risk events to each other.

Fraud Detection: Social Network Analytics

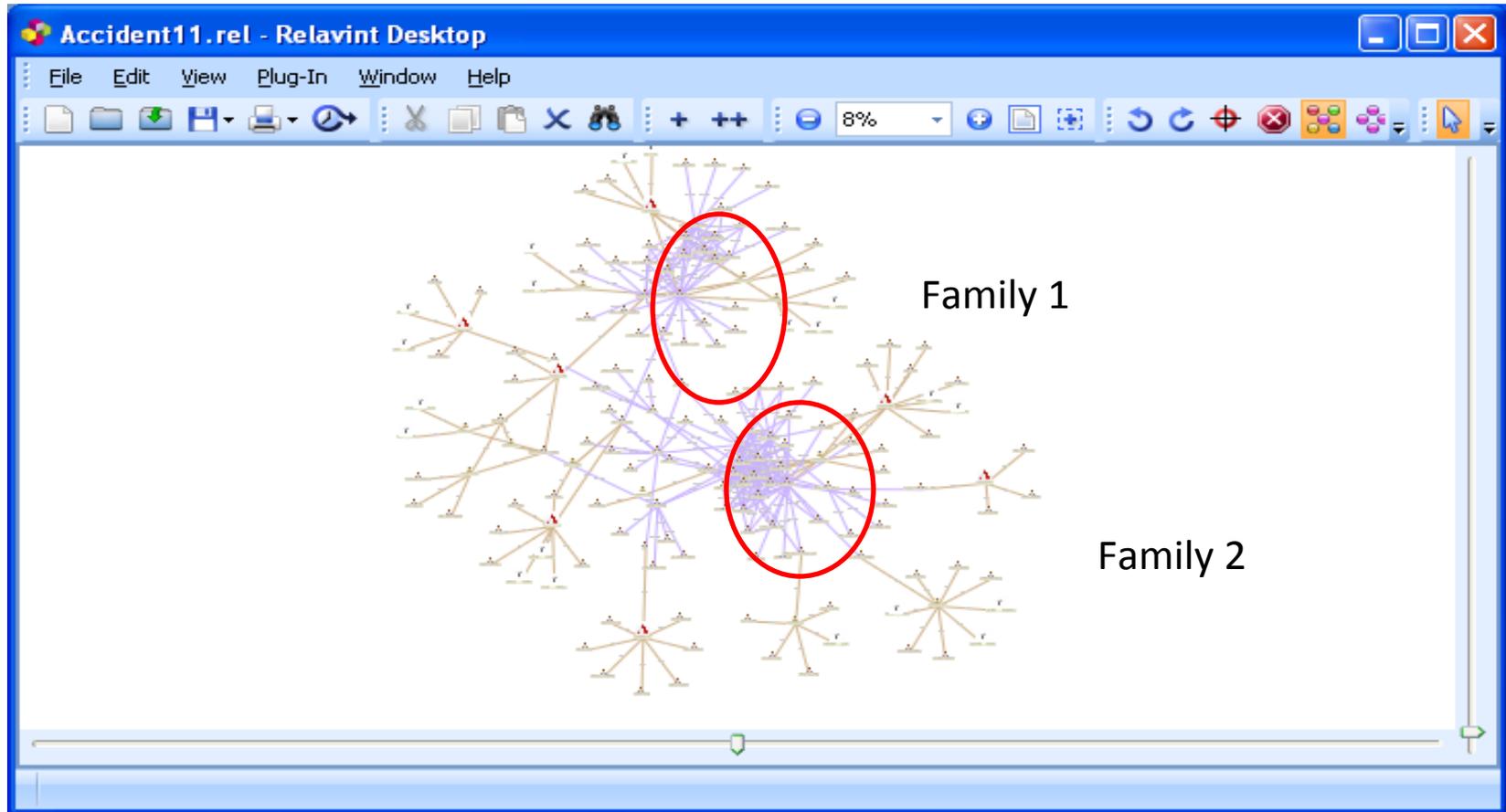
A top insurer flagged 7 claims as “collusion claims”



Using carrier data alone, we found a connection between 2 of the 7 claims.

Fraud Prevention: *Social Network Analytics*

Collusion AFTER Advanced Linking Technology is Applied
Assigned unique IDs to all parties and added 2 additional degrees of relative data



Showed 2 family groups interconnected on the 7 original claims ***plus linked to 11 more.***

Isolated risk?

Lone Individuals vs. Organized Group.

Variables that describe the proximity and connectedness of risk through relationships.

- Non-visual rank ordering, prioritizing for investigation and mitigating of risk.
 - Suspicious insurance claims by proximity to other suspicious insurance claims, providers and body shop contacts.
 - New unsecured accounts by proximity to secured accounts and other newly unsecured accounts.
 - Suspicious property transactions proximity to associated suspicious property transactions.
- Predictive analytics based on variables that contain awareness of proximity through relationships
 - Predict risk through associations to keep step with emerging fraud schemes.
 - Measure the predictive nature within networks of, personal injury claims, suspicious mortgage transactions, potential bust out activities.

Case Study

A case study

- Brief overview of project scope and data
 - This project's focus is to target providers of interest -- those who have behavior outside the norm
 - We utilize billing data with particular emphasis on ICD9 (diagnosis) CPT (treatment) codes and payment amounts as well as the interactions of those characteristics
- How is this project different from our usual
 - The project did not have a "target" (or "bad") list from client
 - The project focused on providers with unusual behavior which have characteristics our experience indicated could be of interest

Identifying Providers of Interest

- How did we do it
 - We created more than 3,000 modeling attributes from the data provided our analytic models to consider.
 - We filtered out providers that would seem not to be of interest based on basic characteristics such as low activity levels
 - Our first effort found “outliers” in behavior for the providers utilizing those more than 3,000 attributes
 - We then utilized in-house domain expertise to determine which providers which had “outlier” characteristics also had characteristics which made their behavior “of interest

Modeling

- Brief overview of project scope and data
 - The first step was to limit the provider list to those that may be interesting on a basic characteristics level
 - Only used claims that were “submitted” for editing
 - Rolled up providers into unique NPI numbers
 - Determined bill, patient, and billing amount minimums to be “of interest”
- Utilized multiple analytic techniques against the selected providers to find unusual behavior characteristics
- Made use of sanctions and other public records sources to supplement model alerts

Results

- The client reviews providers that “scored” at the top of the score-ranked “provider of interest” list
- Detailed profiles of provider behaviors help identify the problems
- Characteristics of the targets (and the models themselves) are tailored to client policies, workflow, and problems
- Incorporation into the workflow – “pre-pay” and “post-pay” – is key

Results – Sample Provider descriptions

- Slightly more claims than patients per day; interesting edits; charging more than double for a certain x-ray procedure. Edits are interesting because they seem avoidable
- Claims to spend an average of 13 hours per day on E&M procedures alone (highest day was > 24 hours)
- 91% of claims have 98942 (chiro manipulation 5+ regions), charging more than twice as much per patient, charging 3 times what his peers are charging for certain procedures, more than 50% claims edited, about 60% of lines are uncommon Dx/Treatment combination
- 83% of claims are 99215 (complex), yet 77% of claims have just one diagnosis (not complex); high on 80 minute office consults

In Summary: Key message

LexisNexis® solutions for health care payers deliver information-rich analytic tools that address key challenges including identity management, fraud, waste and abuse prevention, and data enrichment.

Bill Fox, JD, MA
Senior Director Health Care
LexisNexis Risk Solutions
Bill.fox@lexisnexis.com
856-325-9627

Linked In Group: [LexisNexis Health Care Solutions](#)
Twitter: LexisHealthCare
Blog: <http://blogs.lexisnexis.com/healthcare/>