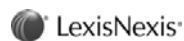


Social Network Analytics: Its Role in the Identification and Prevention of Health Care Fraud

Presenters: Bill Fox, Senior Director of Healthcare
Nov 16 , 2011

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Risk Solutions


Fighting Fraud with Social Network Analytics: Overview/Agenda

- I. Introduction to LexisNexis Risk Solutions
- II. Challenges Facing Health Care Entities
- III. Trends in Social Network Analytics
- IV. Social Network Analytics in Action - Three Examples
- V. Q & A

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Presentation Title 2

Challenges Facing Health Care Entities	
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Challenges Facing Health Care Enterprises: Big data getting bigger

Big Data: Datasets whose size is beyond the ability of typical database software tools to capture, store, manage and analyze



- Disparate data is spread across separate physical locations
- Scale of data is huge...and growing every day
- Adding relationships exponentially expands the size of the BIG Data analytics challenge.
- The amount of data available is more than the human mind can organize and use, but too valuable to ignore ...\$300B??

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Big Data– Turning a challenge into a strength

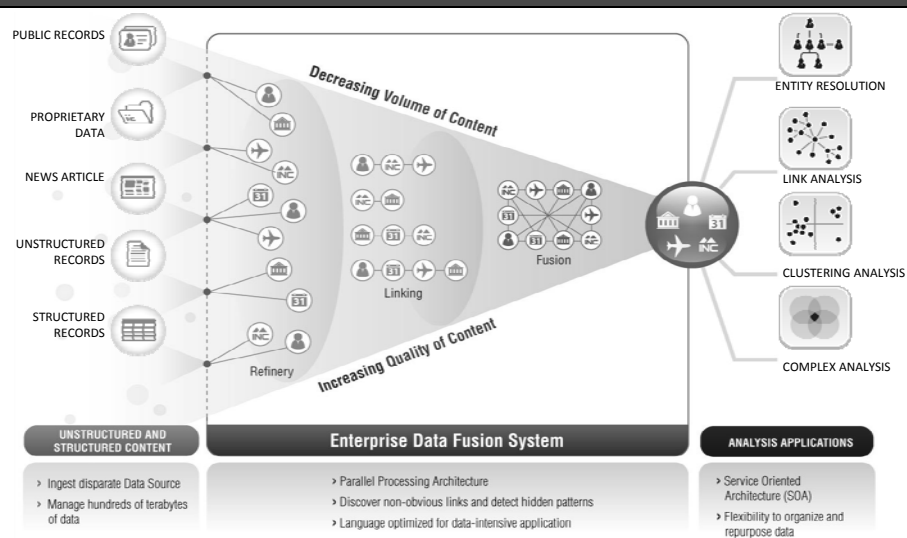


- Big data represents untapped potential for the health care sector
 - Opportunities to reduce health care costs through ...
- LexisNexis has leveraged parallel-processing computing platforms and large scale graph analytics for over a decade

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Big Data Analytics and Computing Platform Requirements



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Technology Advances are Enabling a More Proactive Response



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The emergence of open-source massive parallel-processing computing platforms opens new opportunities for enterprises to increase the agility and scale of solutions focused on addressing fraud and abuse.

- Effectively ingest and integrate massive volumes of disparate data.
- Process and Analyze exponentially faster than traditional databases.

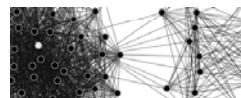
Large Scale Graph analytics, generally thought to be the domain of companies like Google, offer new variables that provide relationship context between events, exposing patterns and outliers that otherwise would be hidden.

- Can be applied to many other many areas beyond network analysis and social graph analysis, such as epidemiology and mathematics.
- Suited to revealing well organized fraud networks hidden within BIG Data and generating actionable results.

Graphic Analysis and Social Network Analysis

- Graph Analysis
 - Twitter uses Graph Analysis to help the site determine who's connected to whom in the Twittersphere.
 - Google uses Graph Analysis to power its PageRank feature.
 - LexisNexis uses Graph Analysis to resolve Identities and combat fraud.
- Social Network Analysis
 - Graph Analysis that specifically focuses on graphs built on social relationships.

twitter

Google
PageRankWhat do we REALLY
know about PageRank?

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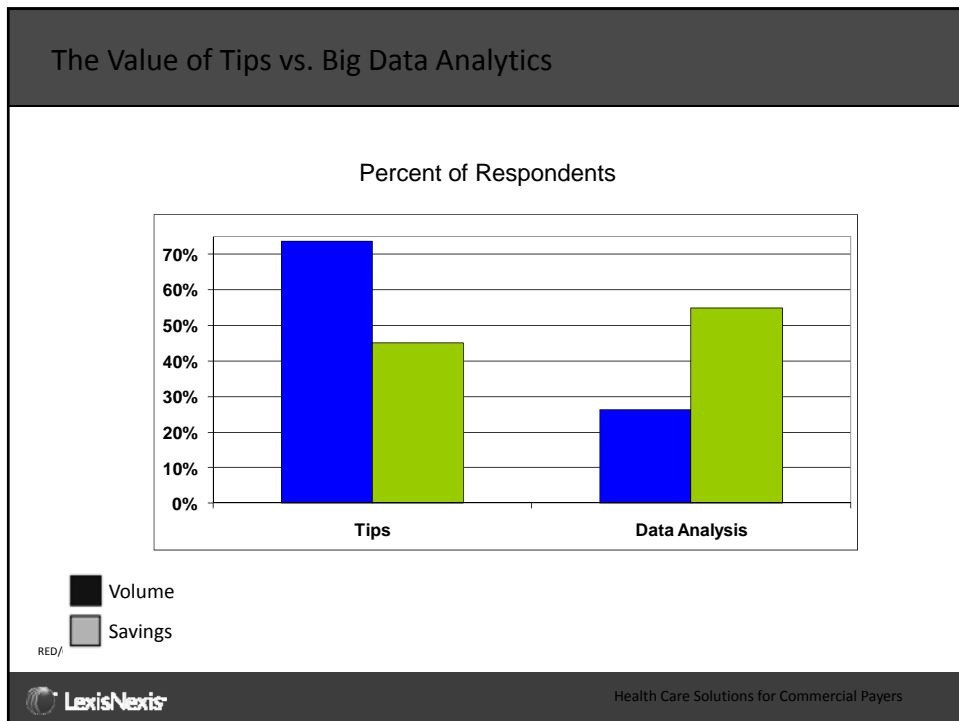


Enterprise Fraud Control
- A starting point

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Traditional Way Carriers Identify Collusion

1. Link the Claim Parties through Carrier records - phone numbers and address data (threads)
2. Add additional Public Records data to find more links or strengthen links
3. Use a Visualization tool to weed out links that seem weak or unimportant
4. Use business rules or queries to filter visualization “starting points”

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Issues with the Traditional Process

False Positives

- Relationships based on entity characteristics that frequently change (phone, address, etc..) results in many false positives

Missed links due to limited data

- The scope of data examined is typically limited – which leads to missed links, ***missed opportunities for cost savings and recoveries***

Labor intensive process requiring expertise

- Manually finding links using just a visualization tool is time consuming and effectiveness is often driven by the level of expertise the analyst has with the data and tools

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Reinvention of Value

"It is clear that Internet technology represents the moment of a change equivalent to the change brought on by the printing press and the steam machine," says Kosta Peric of SWIFT.

As the head of innovation for the Society for Worldwide Interbank Financial Telecommunication, Peric says, "It's about the connectedness of people," Peric says. "What we are talking about is the reinvention of value and ways of expressing that value."

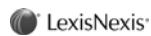
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Trends in Social Network Analytics

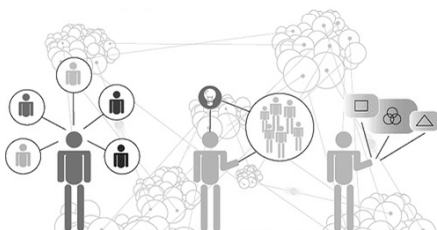
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Trends in Social Network Analysis

Addition of External Data



- Mixes first-party data with public and third-party data sources
- Adds fidelity to existing entities
- Adds new linkages into the analysis
- Adds new entities into the analysis
- Exposes ring leaders and brokers that don't directly participate

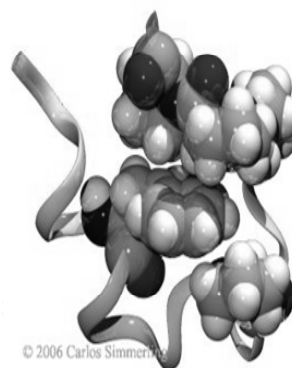
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Trends in Social Network Analysis

Use of Data Supercomputing

- Rapidly becoming accessible to typical organizations
- Enables analysis that is simultaneously broad and deep
 - Allows locally successful analysis to be expanded to national scope
 - Highlights entities "working" across geographies
- Enables rapid recomputation of derived data
 - Ensures timely identification of emerging and bust-out activity
- Enables previously unthinkable operations on BIG data



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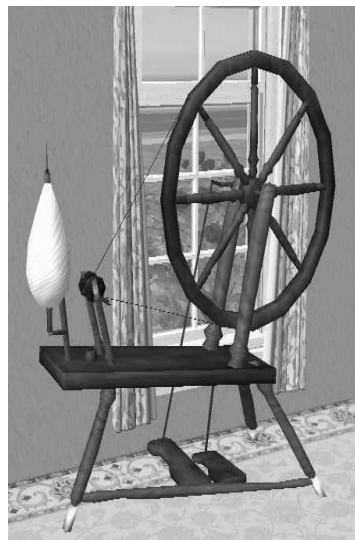
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Trends in Social Network Analysis

Reliance on “Created” Data

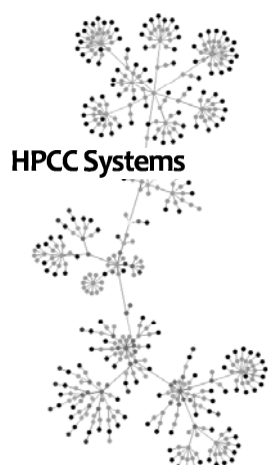
- Transform “straw” into “gold”
 - Process numerous discrete data points into high-value data
- LexisNexis® Advanced Linking Technology (example)
 - Resolve numerous names, addresses, phones, and other info into a “Person ID”
 - Better accuracy than other resolution techniques
 - Resilient to name, address, and other info changes (i.e. stable over time)
- Improves detection, simplifies processing, makes results easier to understand



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LexisNexis Targets Fraud Using Large Scale Graph Analytics



- Powered by HPCC Systems™, the LexisNexis massive parallel-processing open-source computing platform.
- Graph \ Network 3 Billion derived public data relationships between people merged with risk indicators.
- Graph Analytics examine up to 20 billion data points to create variables that allows for predictive analysis incorporating relationship context and associated risk.
- Targets fraud across all sectors including health care, financial services and government.

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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.

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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.

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Social Network Analytics in Action – Three Examples

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Social Network Analytics

On June 6, 2008, the Department of Justice announced the arrest of Felcoranenda Estudillo on charges of defrauding Medicare of approximately \$12 million in an elaborate scheme involving home health care services and kickbacks for referrals of patients who were not eligible for services.

Estudillo was a registered nurse and operated Wescove Home Health Services from her home in West Covino, CA. Her husband, Oscar Estudillo, owned the business, as well as several others that used the same home address as their base. Mrs. Estudillo is the only person named in the indictment, but records show her husband was the legal owner of the business.

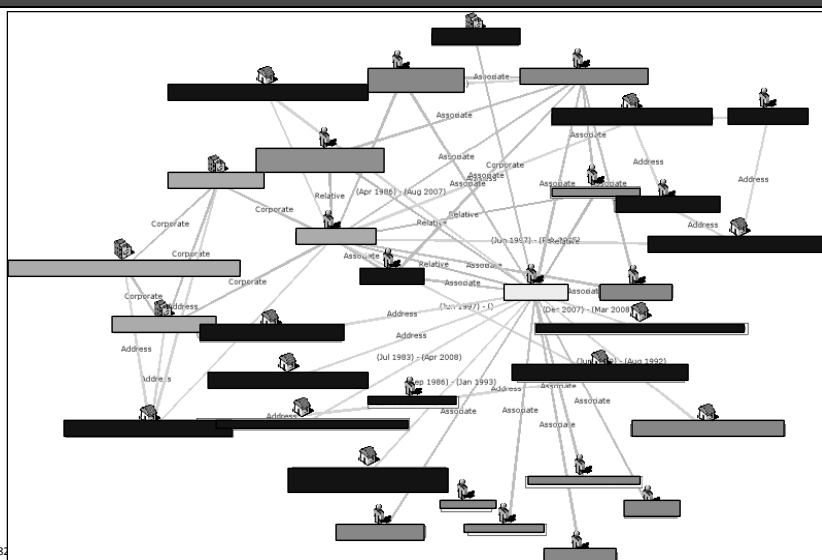
The link analysis chart on the following slide was constructed to show the complex array of relationships among Estudillo, her husband, and the varied business they own and operate. Businesses were linked to the Estudillos that were not reflected in the indictment.

The identities linked to the Estudillos in the following slide have been masked but are an accurate representation of the relationships revealed by the link analysis.

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Social Network Analytics

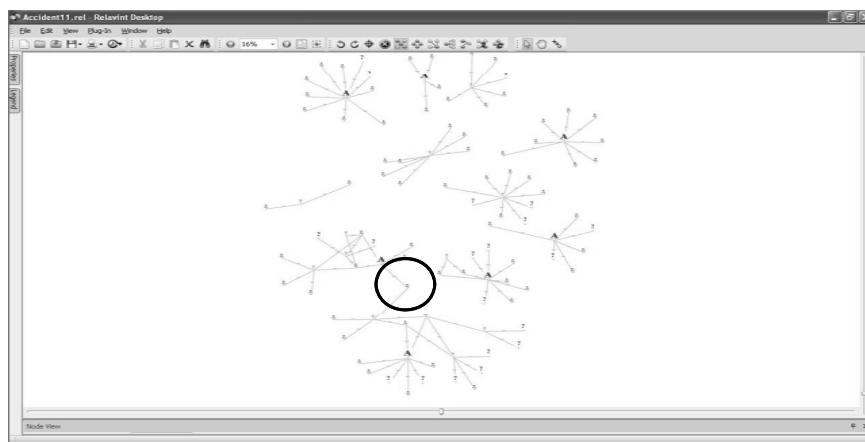


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Fraud Detection: Social Network Analytics

A top insurer flagged 7 claims as "collusion claims"



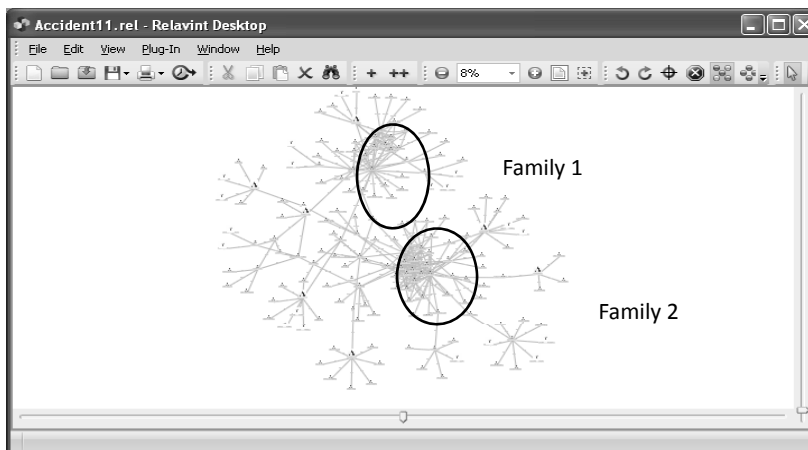
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Using carrier data alone, they found one connection between 2 of the 7 claims.



Fraud Prevention: *Social Network Analytics*

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



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



Purpose of Proof-of-Concept

Applied social network analytics to information provided by the state of New York and public data supplied by LexisNexis to identify relationships between a group of New York Medicaid recipients living in high-end condominiums located within the same complex and any links those individuals might have to medical facilities or others providing care to New York Medicaid recipients.

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Methodology

- Derived public data relationships are built from our +/- 50 terabyte data base for the entire U.S. population. We use this to build a large scale network map of the Medicaid Recipients and everyone associated within 2 degrees.
- We use patented LexisNexis algorithms to cluster the network map and generate statistics to measure every cluster.
- We query the graph for the clusters with the most significant statistics.
- For each cluster, if all these recipients are connected..
 - How many of them are living in expensive residences, owned expensive property or drive expensive cars?
 - How many recipients are contacts of medical businesses?
 - How many medical businesses are associated with any of the people in the cluster?
 - How many are currently receiving benefits?

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City Walk Sample: Vehicle Statistics

What is the list of preferred expensive vehicles?

Make Description	# Owned	Make Description	# Owned
Mercedes-Benz	46	Chevrolet	2
Lexus	41	Hummer	2
BMW	27	Jeep	2
Infiniti	13	Nissan	2
Acura	9	Toyota	2
Lincoln	8	Aston Martin	1
Audi	7	Bentley	1
Land Rover	7	Cadillac	1
Porsche	6	GMC	1
Jaguar	5	Honda	1
Mercedes Benz	3	Volkswagen	1
Saab	3	Volvo	1



Property Deed Reference Counts for City Walk

Dominant buyers and sellers at City Walk

Name	Deeds Held	Name	Deeds Held
Hudson Eight	78	Mike Greem	21
Hudson Five	74	Scott Hill	21
Hudson First	73	Betty Donaway	21
Hudson Nine	65	Al Clark	19
Harry Anderson	45	Dave Miller	17
Hudson Ten	41	Mark Walker	16
Hudson Seven	39	Mike Smith	16
Home Nationwide	33	Val Edwards	15
Hudson Three	33	Eric Garcia	14
Brian Smith	28	Dane Young	14
Alan Stevens	25	Bill Moore	14
Chris Doe	24	Karen Carter	14
Sophie Davis	23	Casey Baker	14
Washington Mutual	23	Art Nelson	14
Fleet Mortgage Co.	21	Cathy Parker	13

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What this Pilot *Doesn't* Tell Us – Could be *Better*

- Clusters are limited to showing only Medicaid recipients that reside within City Walk apartments. Therefore, this pilot doesn't tell us anything about Metrocity's broader Medicaid population.
- Clusters are limited to showing only Medicaid recipients from Metrocity. It's possible that the relationships identified among residents of the City Walk extend beyond Metrocity's geographic boundaries.
- Cluster statistics are limited to only public data variables and don't include any benefit details, dollar amounts, treatment history or provider information. Access to this information could further enhance our understanding of the relationships identified with the limited amount of information used to conduct this proof of concept.



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Example Cluster Statistics

Example: MARK WHITE inactive recipient, is connected to:

Recipients	2
Recipients Active	0
Recipients with end date of 9999	0
Recipients living at expensive residence	2
Recipients have owned expensive property	0
Recipients have owned expensive vehicles	1
Recipients business contact or people at work for Med Entity	2
Total Medical Entities connected to people within cluster	8

Vehicles Owned by Recipients in cluster

(2005) Silver Audi A8 Quattro (\$ 66590)

(2006) Porsche S Cayenne (\$ 56300),

(2004) Porsche S Cayenne (\$ 55900),

(2002) Silver Lexus SC 430 (\$ 58455),

(2002) Lexus 430 SC (\$ 58455),

(2006) Porsche S Cayenne (\$ 56300)

Medical Entities Associated

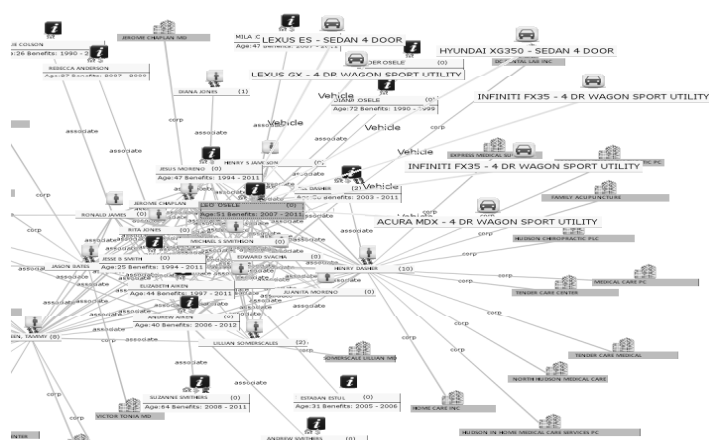
STEWART HALL, MD, LLC
SMITH DENTAL P C
WHITE DENTAL, P.C.
THOMAS AMBULETTE SERVICE, INC.
V WILSON PHYSICIANS
SG NELSON DENTAL P.C.
ESTER DENTAL CONSULTANT
U S A MEDICAL SERVICE CORP
HAPPY MANOR HEALTHCARE INC
RIVERSIDE HEALTHCARE INC
GLEN MILLER HEALTHCARE, INC.
SOUTHERN HEALTHCARE SYSTEMS, INC.
SOUTHERN HEALTHCARE OF STONE COUNTY, INC.
CALVIN ROBINSON MD
RUBIN KING MD
PLEASANT HEALTHCARE INC
RIVERSIDE HEALTHCARE INC
GLEN MILLER HEALTHCARE, INC.
METRO CITY HEALTHCARE SYSTEMS, INC.
SOUTHERN COUNTY, INC.



Cluster Visualization

Properties	
Label	LEO OSELE
First Name	LEO
Last Name	OSELE
SSN	
DOB	
Date First Se	199001
MedicaidReci	1
MedicaidClus	13
MedicaidBusin	0
recip_id	
HighEndResi	Yes
automated_v	720000
occupant_ow	true
purchase_dat	20030819
purchase_am	580402
mortgage_am	0
mortgage_dat	0
highend_prop	Yes
sales_price	580402
total_deed_a	2
vehicle_count	5
medical_bld	0
dt_clean_beg	20070201
dt_clean_end	20111130
highend_veh	Yes
base_price	31505
make_desc	Lexus
summary_ve	(2002) Lexus 300 ES (\$31505) (2009) Infiniti FX35 (\$39450) (2008) Infiniti FX35 (\$39450) (2006) Lexus 470 GX (\$47185) (2008) Acura SPORT MDX (\$47995)

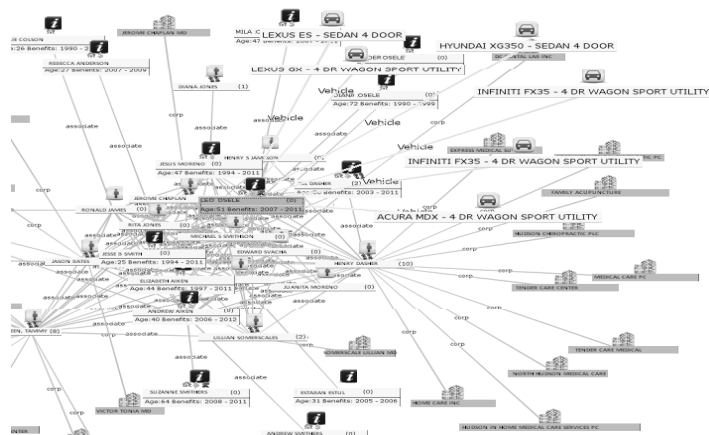
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Cluster Visualization

Properties	
Label	LEO OSELE
First Name	LEO
Last Name	OSELE
SSN	
DOB	
Date First Se	199001
MedicaidFaci	1
MedicaidClus	13
MedicaidBusin	0
med_id	
HighEndResi	Yes
automated_v	720000
occupant_ow	true
purchase_dat	20030819
purchase_am	580402
mortgage_am	0
mortgage_dat	0
highend_prop	Yes
sales_price	580402
total_debt_a	2
total_highend	1
vehicle_count	5
medical_bdd	0
cl_clean_beg	20070201
cl_clean_end	20111130
highend_veh	Yes
base_price	31505
make_desc	Lexus
summary_ve	(2002) Lexus 300 ES (531595) (2009) Infiniti FX35 (539450) (2008) Infiniti FX35 (539450) (2008) Lexus 470 GX (547185) (2008) Acura SPORT MDX (547995)

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Swimming with the Sharks: Leveraging Big Data and Analytics to Reveal Hidden Collusion

Questions?

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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.

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