Transforming Program Integrity with Identity and Fraud Analytics

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Market Challenges & Trends

Unprecedented risks with EMR adoption, HIEs, ACOs and patient centered medical homes

Administrative burdens

Sharing of Medical Information Electronically

Budgetary pressures

Tougher Rules (CMS 6028-FC) on new provider enrollment and screening standards

HIPAA 5010, ICD-10

PPACA-mandated exchanges

IRS and Patient Protection and Affordable Care Act (ACA) requirements

HIPAA Privacy, Security, Enforcement, and Breach Notification Rules

Interest in Big Data & Analytics opportunities

Increasing Government Regulations

Medicaid Expansion

$2.6 trillion in health care costs

Stricter Medical Loss Ratio (MLR) requirements

Questionable claims

Health Care Fraud Statute (18 U.S.C. §1347)

1.5 million medical identity theft victims

Limited manpower for investigations

Improper payments

# of Consumers Entering Health Care System

Higher insurance premiums

Labor-intensive costly recovery

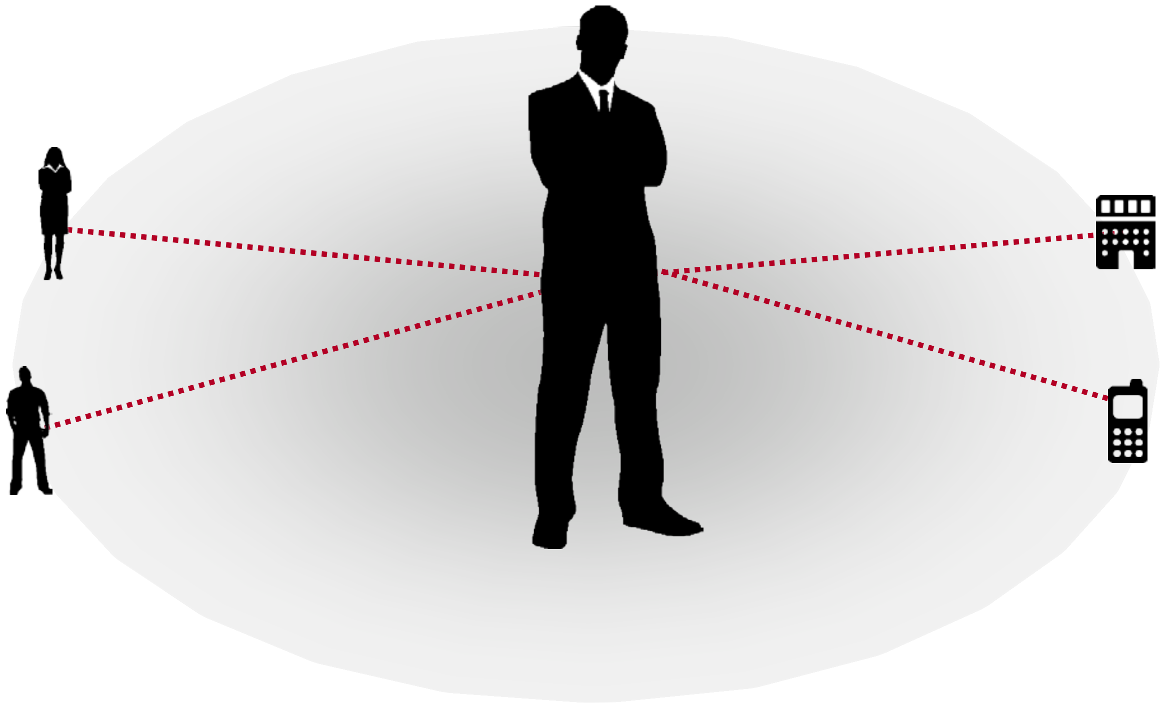
Pursuit to reduce costs

Outdated data and incorrect information

Data security and breaches

HIPAA Privacy, Security, Enforcement, and Breach Notification Rules

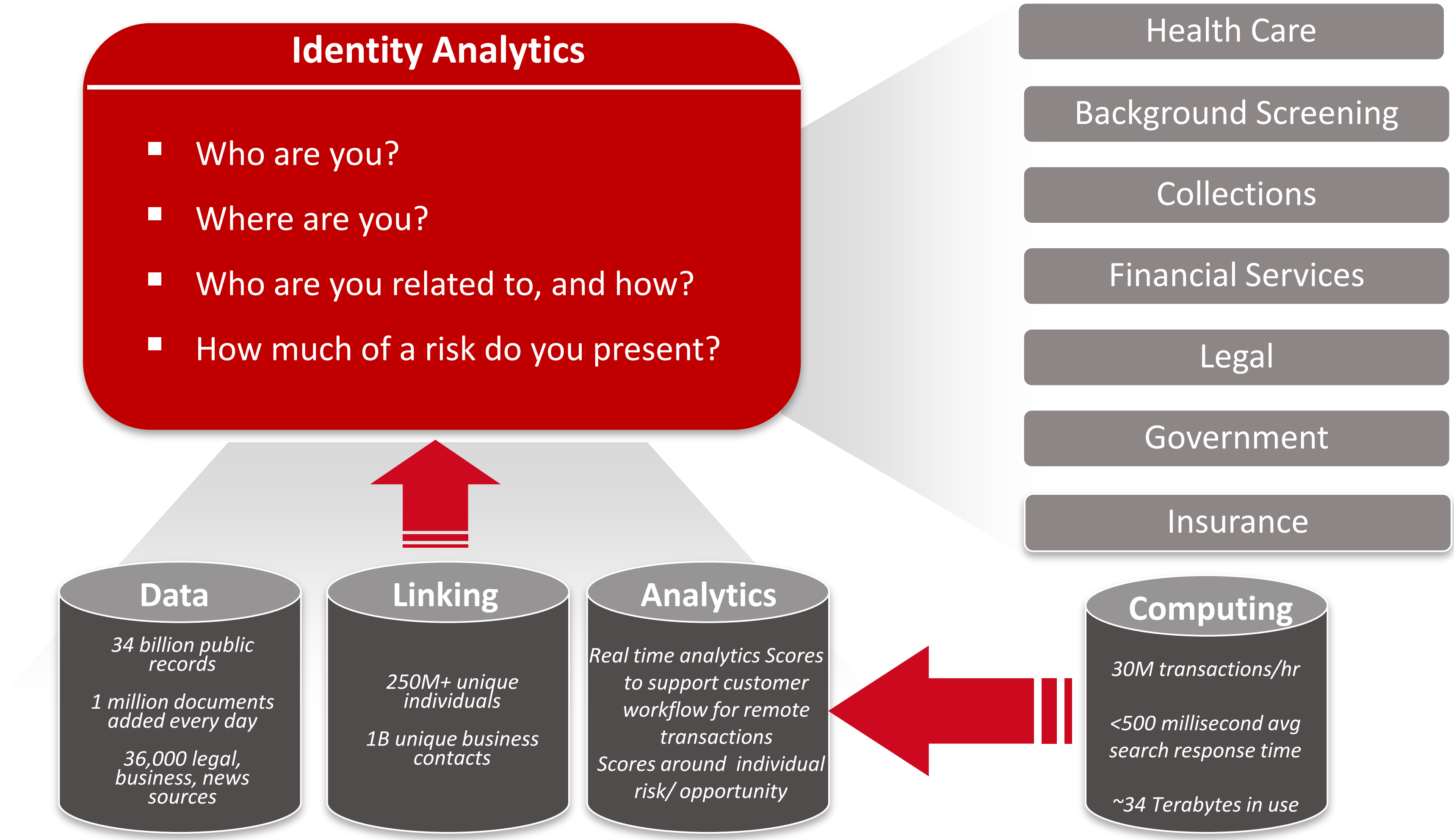
How You Locate Fraud And Abuse Today



Bringing it All Together: A Comprehensive Model to Detect and Prevent FWA

Overview of an Identity Risk Solutions Provider

Assesses the risks and opportunities associated with people, businesses and assets.

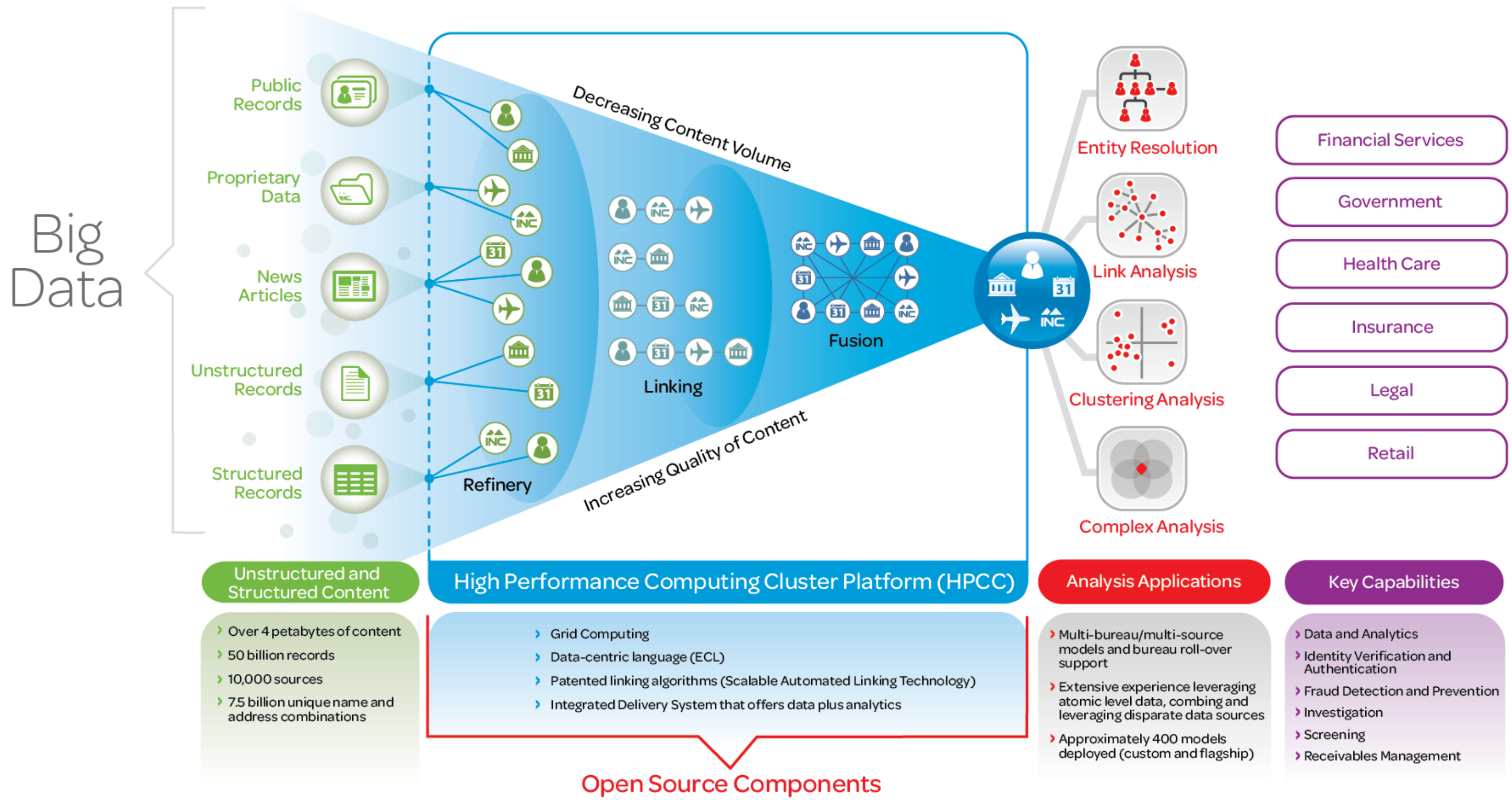


Data of Many Types is Aggregated from Thousands of Sources Over Decades…

Through proprietary inking technology, profiles have been built on over 500 million identities. These databases have in excess of 45,000 data sources providing these updates as frequently as each data provider allows including daily, bi-weekly, weekly and monthly that include, but is not limited to:

- Tri-bureau Credit Header data
- Traditional landline and wireless Phone data
- Utility Files
- Concealed Weapons Permits
- Firearms & Explosive Licenses
- **Corporation Filings**
- **Criminal and Court Records**
- **Department of Corrections data**
- Real Property Deed & Mortgages
- Property
- Professional Licenses
- **Tax Liens & Judgments**
- Planes & Pilots
- Hunting & Fishing Licenses
- UCC Filings
- Assessment
- **DEA Controlled Substance Licenses**
- **Medical Licenses, Certification**
- **Sanction and Exclusion**
- **NPI**
- Vehicle Registrations
- SEC Filings
- Foreclosures
- Deaths
- Marriages and Divorce Records
- Education Records
- Various Contributory Data Sources
- Watercraft

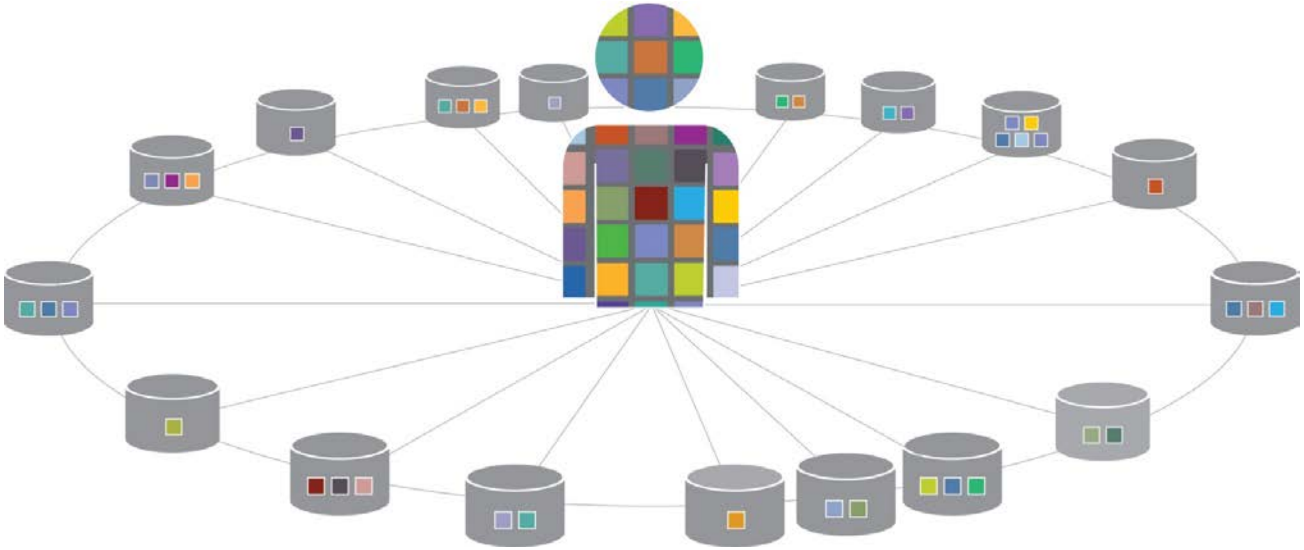
Big Data Technology is Utilized to Establish Identity



- **High Performance Computing Cluster Platform (HPCC)** enables data integration on a scale not previously available and real-time answers to millions of users. Built for big data and proven for 10 years with enterprise customers.
- **Offers a single architecture**, two data platforms (query and refinery) and a consistent data-intensive programming language (ECL)
- **ECL Parallel Programming Language** optimized for business differentiating data intensive applications

Identity Analytics Provide Accurate, Reliable Identity Resolution

In real-time, data from tens of thousands of disparate sources can be brought together to form a multifaceted view that can enable health care payers to resolve, verify, and authenticate identity with 99.9% confidence



Turning Data Into Identities

Big Data technology fuses the messy, disparate, incorrect input data into single identities

SSN	DOB	NAME	ADDRESS	CITY	STATE	ZIP
***801594		Shannan Weschek	25 Franklin PL	Miami	FL	33101
***801591	8/77	Shannan Smith	114 W. 19th	Boca Raton	FL	33429

LexID #	SSN	DOB	NAME	ADDRESS	CITY	STATE	ZIP
1275602253	***801591		Shannan Yeschek	25 Franklin PL	Miami	FL	33101
1275602253	***801591	19770800	Shannan Smith	114 W. 19th	Boca Raton	FL	33429
1275602253	***801594	00000811	Shannan Yeschek	15 E. Broad Street	Boston	MA	02134
1275602253	***801591	19770811	Shannan R Yeschek	114 W. 19th	Boca Raton	FL	33429
1275602253	***801591	19770800	Shannan Smith	25 Franklin PL	Miami	FL	33101
1275602253	***801591	00770811	Shannan R Smith	15 E. Broad Street	Boston	MA	02134
1275602253	***801591	197708	Shannan Yeschek	25 Franklin PL	Miami	FL	33101

Examples From Real Data Sets

Typical Data from a Government Agency – Is There Fraud in This File?

SSN	Last_Name	First_Name	Street Address	Apt	City	St
392-80-XXXX	SMEJXXX	DONALD	13XX SPRINGXXXX DR	101	Anywhere	XX
218-32-XXXX	HALEXXXXX	Richard	13XX SPRINGXXXX DR	102	Anywhere	XX
560-40-XXXX	HALXXXXXX	K	13XX SPRINGXXXX DR		Anywhere	XX
022-56-XXXX	WOJXXXXX	DUSTIN	13XX SPRINGXXXX DR	3E	Anywhere	XX
436-14-XXXX	BRYXXXX	BERTHA	13XX SPRINGXXXX DR	202	Anywhere	XX
532-49-XXXX	HALLXXXXX	KAY	13XX SPRINGXXXX DR	basement	Anywhere	XX
532-59-XXXX	HALLXXXXX	K	13XX SPRINGXXXX DR		Anywhere	XX
544-09-XXXX	CARXXX	TOM	13XX SPRINGXXXX DR	101	Anywhere	XX
544-08-XXXX	CARXXX	TOM	13XX SPRINGXXXX DR	103	Anywhere	XX
545-05-XXXX	POLXXX	MARK	13XX SPRINGXXXX DR	117	Anywhere	XX
545-50-XXXX	POLXXX	MARK	13XX SPRINGXXXX DR		Anywhere	XX
566-34-XXXX	CROWXXX	REBEL	13XX SPRINGXXXX DR		Anywhere	XX
566-45-XXXX	VINXXX	MATTXXX	13XX SPRINGXXXX DR	3G	Anywhere	XX
602-59-XXXX	DEOXXXXX	ILICIA	13XX SPRINGXXXX DR		Anywhere	XX

Typical Data from a Government Agency – Is There Fraud In This File?

K's dead mother

SSN	Last_Name	First_Name	Street Address	Apt	City	St	Best_SSN	Possible Age	Seen at Address	SSN	Date of Death
392-80-XXXX	SMEJXXX	DONALD	13XX SPRINGXXXX DR	101	Anywhere	XX			Not at Address		20081225
218-32-XXXX	HALEXXXXX	Richard	13XX SPRINGXXXX DR	102	Anywhere	XX		60	Not at Address		19841100
560-40-XXXX	HALXXXXXX	K	13XX SPRINGXXXX DR		Anywhere	XX		75	Not at Address		19851200
022-56-XXXX	WOJXXXXXX	DUSTIN	13XX SPRINGXXXX DR	3E	Anywhere	XX			Not at Address		
436-14-XXXX	BRYXXXX	BERTHA	13XX SPRINGXXXX DR	202	Anywhere	XX	555-96-XXXX	75	Not at Address	SSN not found in the public record	
532-49-XXXX	HALLXXXXX	KAY	13XX SPRINGXXXX DR	basement	Anywhere	XX	562-42-XXXX	10	Not at Address		
532-59-XXXX	HALLXXXXX	K	13XX SPRINGXXXX DR		Anywhere	XX	562-42-XXXX	5	Not at Address	SSN not found in the public record	
544-09-XXXX	CARXXX	TOM	13XX SPRINGXXXX DR	101	Anywhere	XX		75	Not at Address		
544-08-XXXX	CARXXX	TOM	13XX SPRINGXXXX DR	103	Anywhere	XX			Not at Address		
545-05-XXXX	POLXXX	MARK	13XX SPRINGXXXX DR	117	Anywhere	XX	429-02-XXXX	75	Not at Address	SSN not found in the public record	
545-50-XXXX	POLXXX	MARK	13XX SPRINGXXXX DR		Anywhere	XX	429-02-XXXX	58	Not at Address		
566-34-XXXX	CROWXXX	REBEL	13XX SPRINGXXXX DR		Anywhere	XX	560-82-XXXX	75	Not at Address		
566-45-XXXX	VINXXX	MATTXXX	13XX SPRINGXXXX DR	3G	Anywhere	XX			Not at Address		
602-59-XXXX	DEOXXXXX	ILICIA	13XX SPRINGXXXX DR		Anywhere	XX	602-59-XXXX		Not at Address		

K's two children

None of these identities are seen as living at this address

It was a trick – they were all fraud.

A single family home has been turned into an apartment building.

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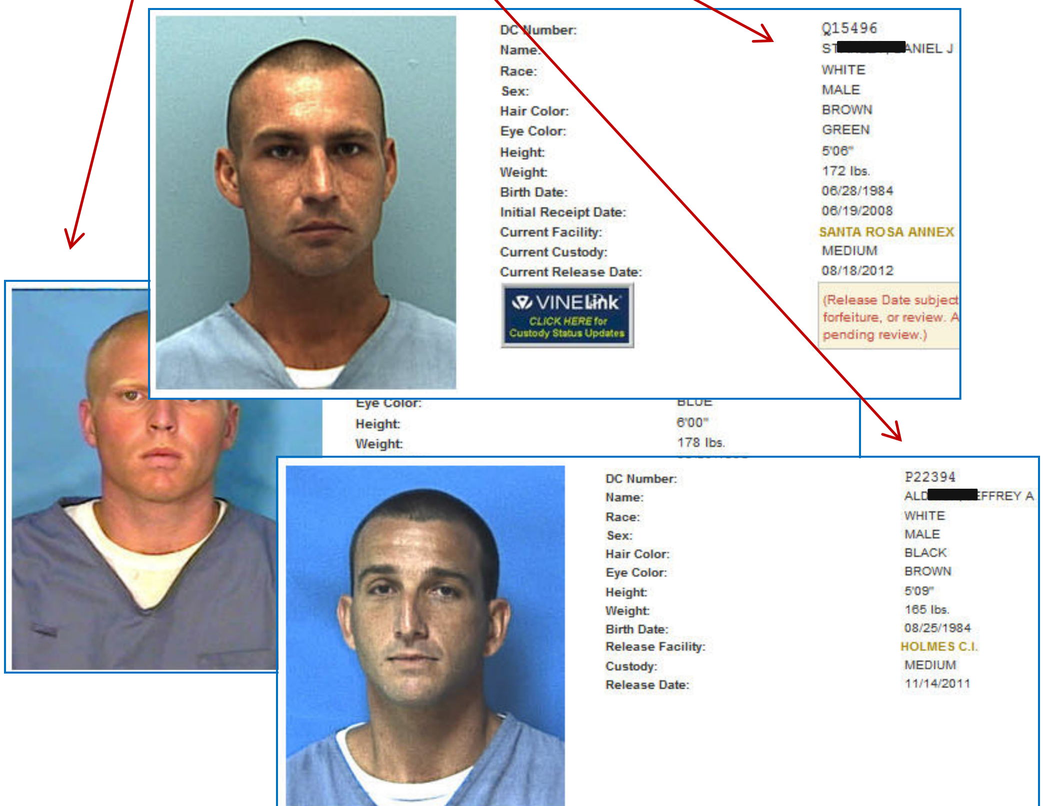
Prisoners Doing What Prisoners Do

SSN	Last_Nam	First_Nam	Midc	Street Address	Apt	City	St	Zip Code	Refund A	Best_SSN	best_address	best_city	best_	curr_incar
59528[redacted]	ST[redacted]	DANIEL		9421 RO[redacted]	205	BELLFLO[redacted]	[redacted]	[redacted]706	1296					Y
59168[redacted]	AL[redacted]	JEFFREY		9421 RO[redacted]		BELLFLO[redacted]	[redacted]	[redacted]706	798		160 1[redacted]	SANTA RC	FL	Y
59484[redacted]	CH[redacted]	JESSE		9421 RO[redacted]		BELLFLO[redacted]	[redacted]	[redacted]706	1112	265710390	101 CH[redacted]ST	PANACEA	FL	
58911[redacted]	TA[redacted]	DANIEL	A	9421 RO[redacted]05		BELLFLO[redacted]	[redacted]	[redacted]706	1238		646 TAY[redacted]	CARYVILLE	FL	Y
55272[redacted]	FO[redacted]	EARL		9421 RO[redacted]05		BELLFLO[redacted]	[redacted]	[redacted]706	752		[redacted]X 1254	SALEM	MO	

LN Incarcerated Flag



DC Number: Q15496
Name: ST[redacted]ANIEL J
Race: WHITE
Sex: MALE
Hair Color: BROWN
Eye Color: GREEN
Height: 5'06"
Weight: 172 lbs.
Birth Date: 06/28/1984
Initial Receipt Date: 06/19/2008
Current Facility: SANTA ROSA ANNEX
Current Custody: MEDIUM
Current Release Date: 08/18/2012
(Release Date subject forfeiture, or review. A pending review.)
VINELink CLICK HERE for Custody Status Updates

Eye Color: BLUE
Height: 6'00"
Weight: 178 lbs.

DC Number: P22394
Name: ALD[redacted]EFFREY A
Race: WHITE
Sex: MALE
Hair Color: BLACK
Eye Color: BROWN
Height: 5'09"
Weight: 165 lbs.
Birth Date: 08/25/1984
Release Facility: HOLMES C.I.
Custody: MEDIUM
Release Date: 11/14/2011

LN has seen very large fraud rings around prisoners and recently released prisoners

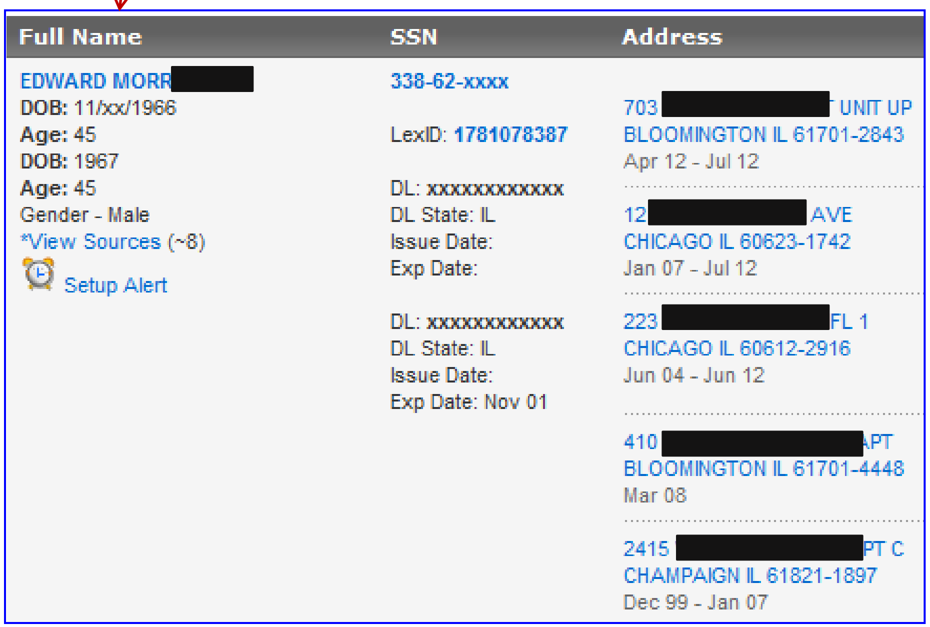
This is a micro fraud ring that incorporates prisoners and others who are helping from the outside or are victims of identity theft

Stolen Identity with Address Issues

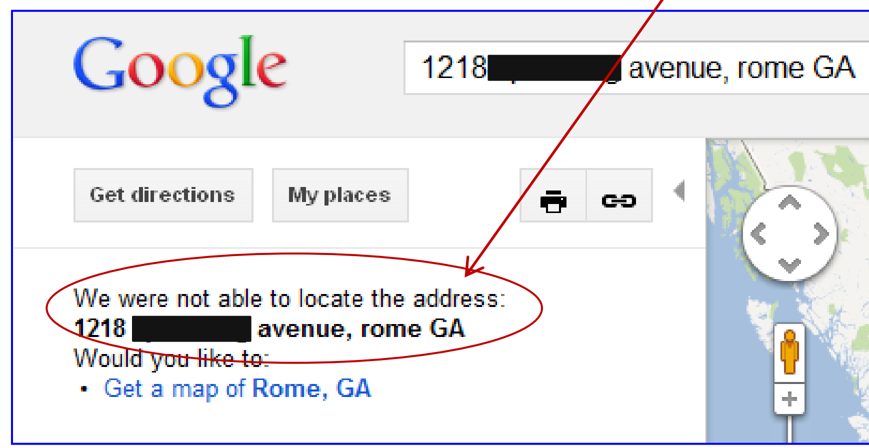
First	Mid	Last	Address	City	ST	Refund	SSN	Address Match	Best Address	Issues
Edward		MorrXXX	1218 XXX Ave	Rome	GA	368	33862XXXX	Not seen at address	Chicago, IL	Input address invalid
Edward		MorrXXX	1218 XXX Ave	Rome	GA	368	33862XXXX	Not seen at address	Chicago, IL	Input address invalid

Self Reported data to Georgia DoR

Identity filter thinks that this person does not live at given address and that the address is also invalid



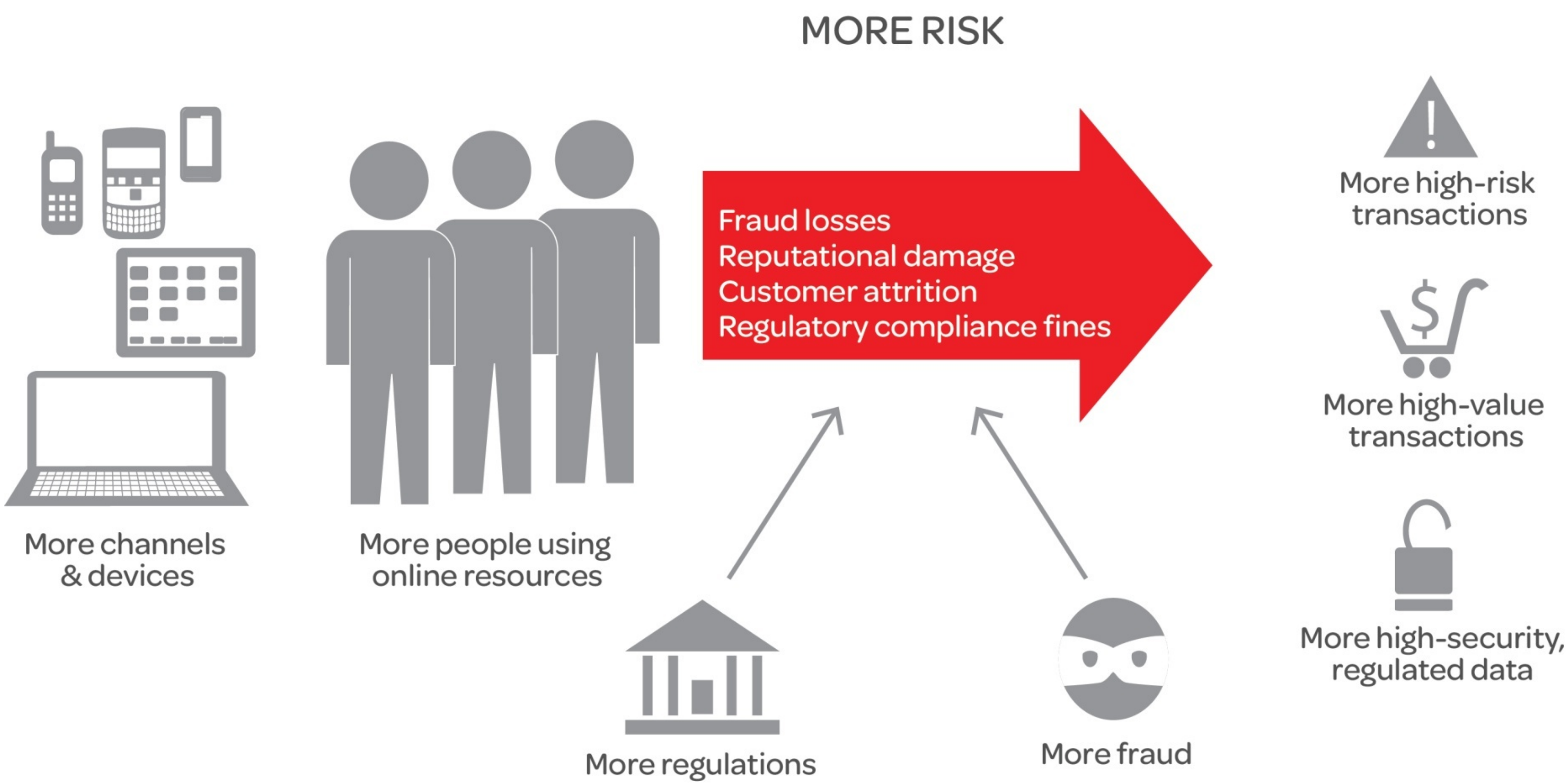
Accurint



Public Records search reports that Edward lives in Chicago and the address is not valid

The Role of Identity Analytics

Key Challenge: Commercial, government and non-profit organizations are seeking to provide controlled, secure access to their products, services and information



Knowing Who's Participating

ENROLLMENT	DISCOVER	**Discover the identity** Undertake data capture, identity resolution and identity enrichment. *"Tell us who you are."*
	VERIFY	**Verify the identity** Establish that the identity exists. "*Does Bob Jones exist?*"
	AUTHENTICATE	**Authenticate the identity** Determine whether an individual or business owns the identity. "*Are you Bob Jones?*"
ASSESSMENT	EVALUATE	**Evaluate the identity** Assess against legislation, regulations and rules to determine if an individual or business meets regulatory requirements.
	ALERT	**Alert to identity changes** Receive notification when an individual or business is exhibiting high-risk behavior (continuous evaluation).

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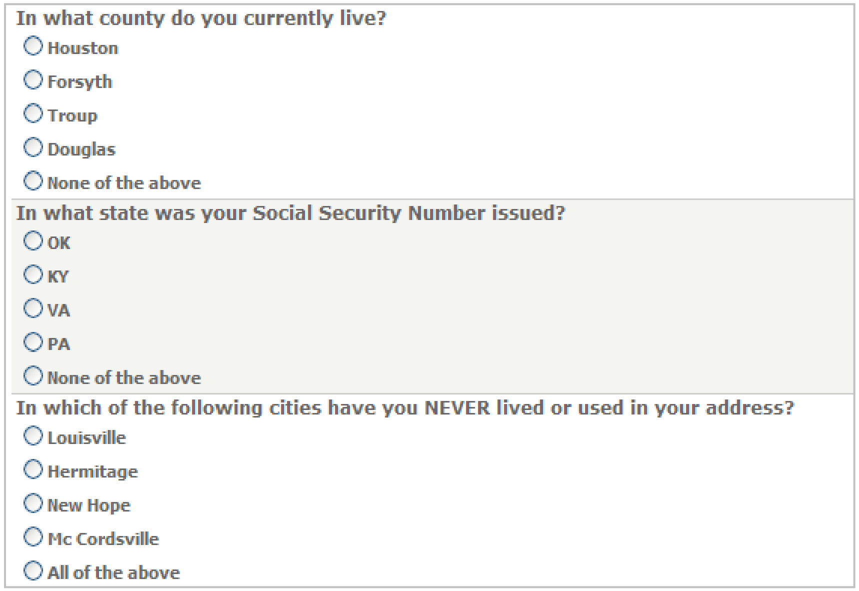
Authentication Questions – Know Who You Are Dealing With


In what county do you currently live?
- Houston
- Forsyth
- Troup
- Douglas
- None of the above

In what state was your Social Security Number issued?
- OK
- KY
- VA
- PA
- None of the above

In which of the following cities have you NEVER lived or used in your address?
- Louisville
- Hermitage
- New Hope
- Mc Cordsville
- All of the above

Feature Highlights

- Dynamic knowledge-based authentication (KBA)
- Public records driven question/answer solution
- Does not use credit file information – non FCRA
- Multiple configuration options and language offerings
- Numerous question type options
- Can integrate with customer supplied data

Key Benefits

- Increases identity assurance during account setup and other high risk activities
- Allows authentication efforts to be uniform across customer contact channels
- Reduce fraud during high risk transactions

The Florida Department of Children and Families is the first state in the country to implement automated identity verification and authentication within its online ACCESS eligibility portal. The state estimates a 3X ROI and potential savings of $60 million.

Members: Data Hygiene

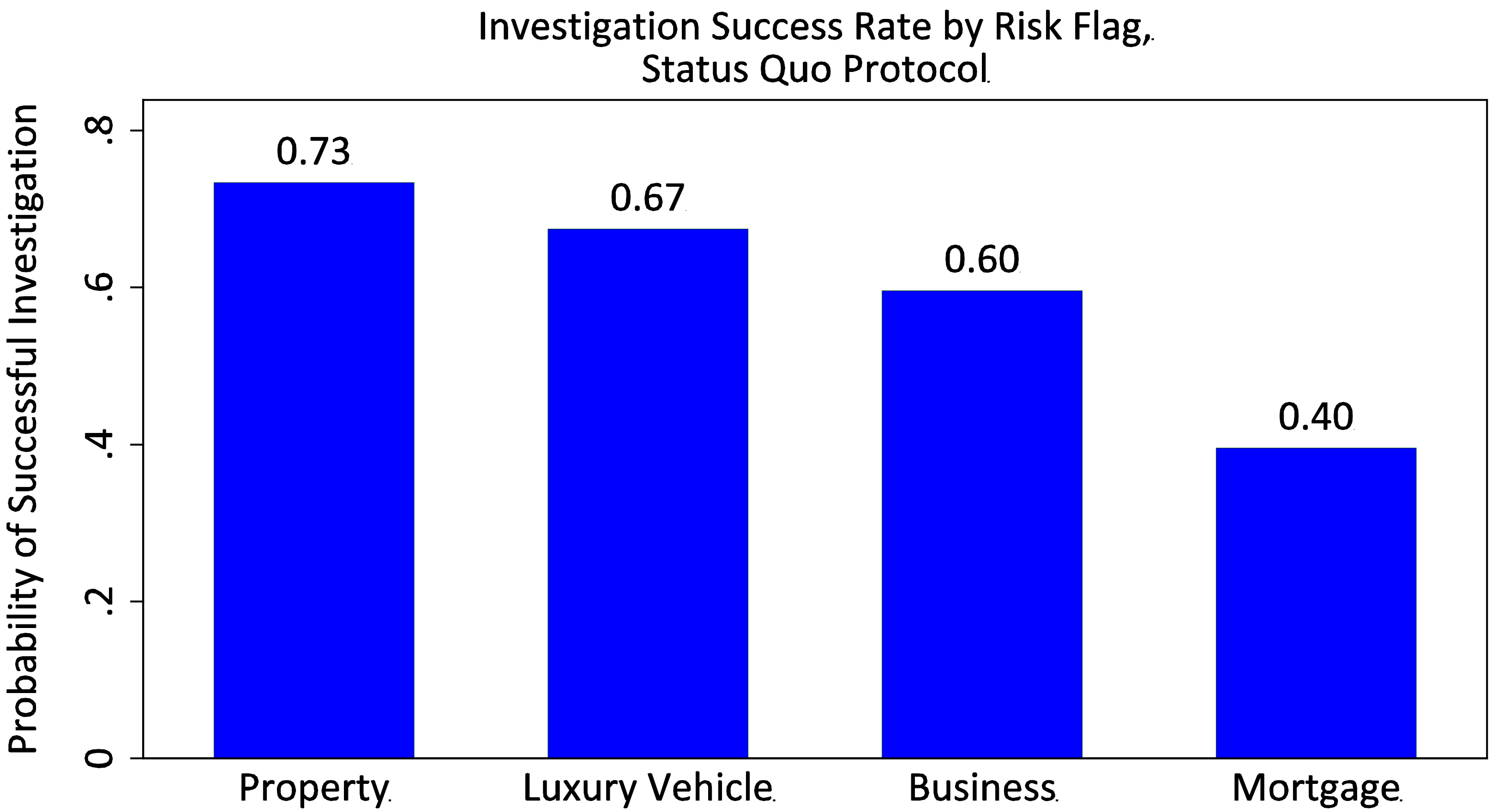
- Initial Verification of Member Contact Information
  - Can provide monthly data feed with new Medicaid member contact information to ensure they have the most current information *before* they do initial outreach, improving member experience and contact success from the very beginning
  - Can provide monthly data feed with existing member information on monthly basis to capture changes in contact information as quickly as possible with as little inconvenience to the member as possible
- Member Surveys
  - Distributing member surveys to targeted populations to identify services that may have been received in locations other than a primary care provider's office
- Maximizing Personnel Resources
  - Corrected phone information reduces the amount of time required to conduct phone blast campaigns, making this a more effective outreach program than it had been in the past
- HEDIS/Medicare Five Star Rating Program for MCO's

A recent analysis of a Medicaid Managed Care plan member file produced a 35% improvement in current address information

LN-HRA-SUNY Study: Flag Performance

- Property, luxury vehicles strongly predict successful investigations
    - ➢Luxury vehicle cases take 25% less time to investigate
- Business activity less successful predictor
- Mortgage activity very poor predictor
- 4.6% of new enrollees have one of these flags
    - ➢Extrapolation: 2.3% to 3.4% of NYC new Medicaid enrollees could be successfully investigated with these flags

New York City HRA Beneficiary Risk Score Project



LN-HRA-SUNY Study: Streamlined Investigation

- Reduces investigation time by 21%
- Reduces costly interviews by 56%
- Reduces success rate by 30%
- **Next step**: predict when simpler method can be used

LN-HRA-SUNY Study: LN Scoring System

- At the Study's onset, LN proposed a scoring system
- LN assigned a score of 300 to 999, with a score of 620 or lower indicating "Medium Risk" or "High Risk."
- The score was based on 10 flags of potential fraudulent activity and 4 flags of mitigating circumstances (such as declaring bankruptcy).
- Of 125,000 new Medicaid enrollees, 3% were classified as "high risk" and 18% were classified as "medium risk."

LexisNexis-HRA- SUNY Study: LN Scores

Value of Risk Score	Predicted Probability of Investigations Success
520 (High Risk)	66.4%
600 (Medium Risk)	52.7%
680 (Low Risk)	38.8%

•Moving from the Low Risk to the High Risk group predicts an 28 point increase in the probability of investigative success, an improvement of 71%

•**Conclusion**: the proposed scoring rule offers substantial improvements over random selection of cases with key risk flags.

Providers: A Comprehensive Approach

Program Integrity begins with knowing your providers

Screen all current in-network providers

Implement robust provider validation and evaluation in addition to credentialing

Assign dynamic risk scores and track provider files between credentialing periods for pertinent activity; alerts generated for changes

Extend screening standards to include providers within managed care


90% of your Big Data Problem, isn't Big Data.
It's the ability to handle Big Data for better insight.

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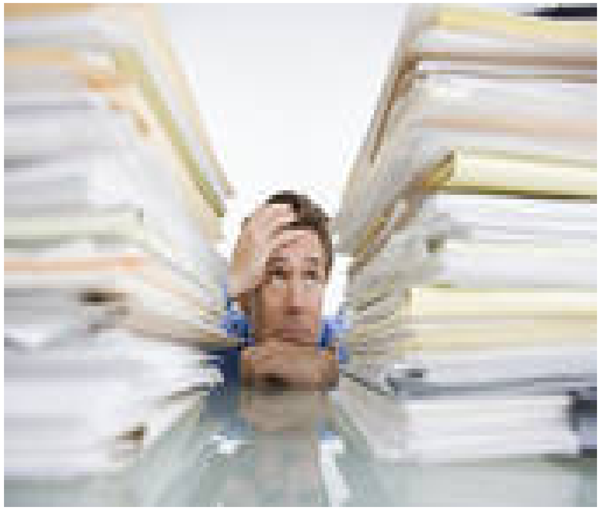
Challenges Facing Health Care Enterprises: Big data getting bigger

***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??

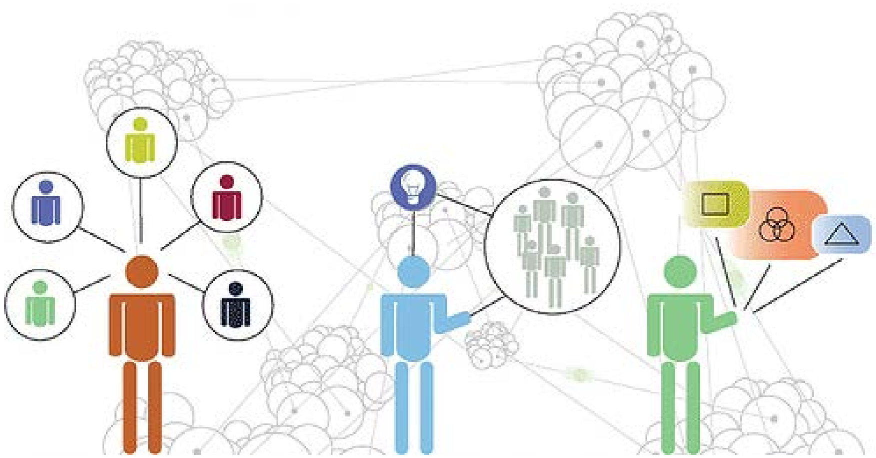
Social Network Analytics Helps Make Sense of Big Data

- Social Network Analysis identifies relationship clusters leveraging “big data” and advanced linking to reveal the relationships that criminal networks try so hard to keep hidden, enabling the effective investigation and termination of insidious and costly fraud rings

- Social Network Analytics can reveal
  - Patient relationships with known perpetrators of health care fraud
  - Links between recipients, businesses, and assets, as well as relatives and associates
  - Links between licensed and non-licensed providers
  - Suspect relationships of employees, suppliers, and partners with patients and providers

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
- Ads new entities into the analysis
- Exposes ring leaders and brokers that don't directly participate

Social Network Analysis: Example 1, New York State

Applied relationship analytics to information provided by a large state and public data supplied by LexisNexis to identify relationships between a group of the State's 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 for other Medicaid recipients in the State.

Social Network Analysis: Example 1

"Condo X" Sample: Vehicle Statistics

What is the list of preferred expensive vehicles owned by members?

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

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Social Network Analysis: Example 1

Property Deed Reference Counts for Residence

Dominant buyers and sellers at “Condo X”

Name	Deeds Held	Name	Deeds Held
Person A8	78	Person H	21
Person A5	74	Person I	21
Person A1	73	Person J	21
Person A9	65	Person K	19
Person B	45	Person L	17
Person A10	41	Person M	16
Person A7	39	Person N	16
Business One	33	Person O	15
Person A3	33	Person P	14
Person C	28	Person Q	14
Person D	25	Person R	14
Person E	24	Person S	14
Person F	23	Person T	14
Person G	23	Person U	14
Business Two	21	Person V	13

LexisNexis

Cluster Visualization Introduction

Medicaid Recipient

Expensive Residence

Owns expensive property

Business Contact of Medical Business Entity

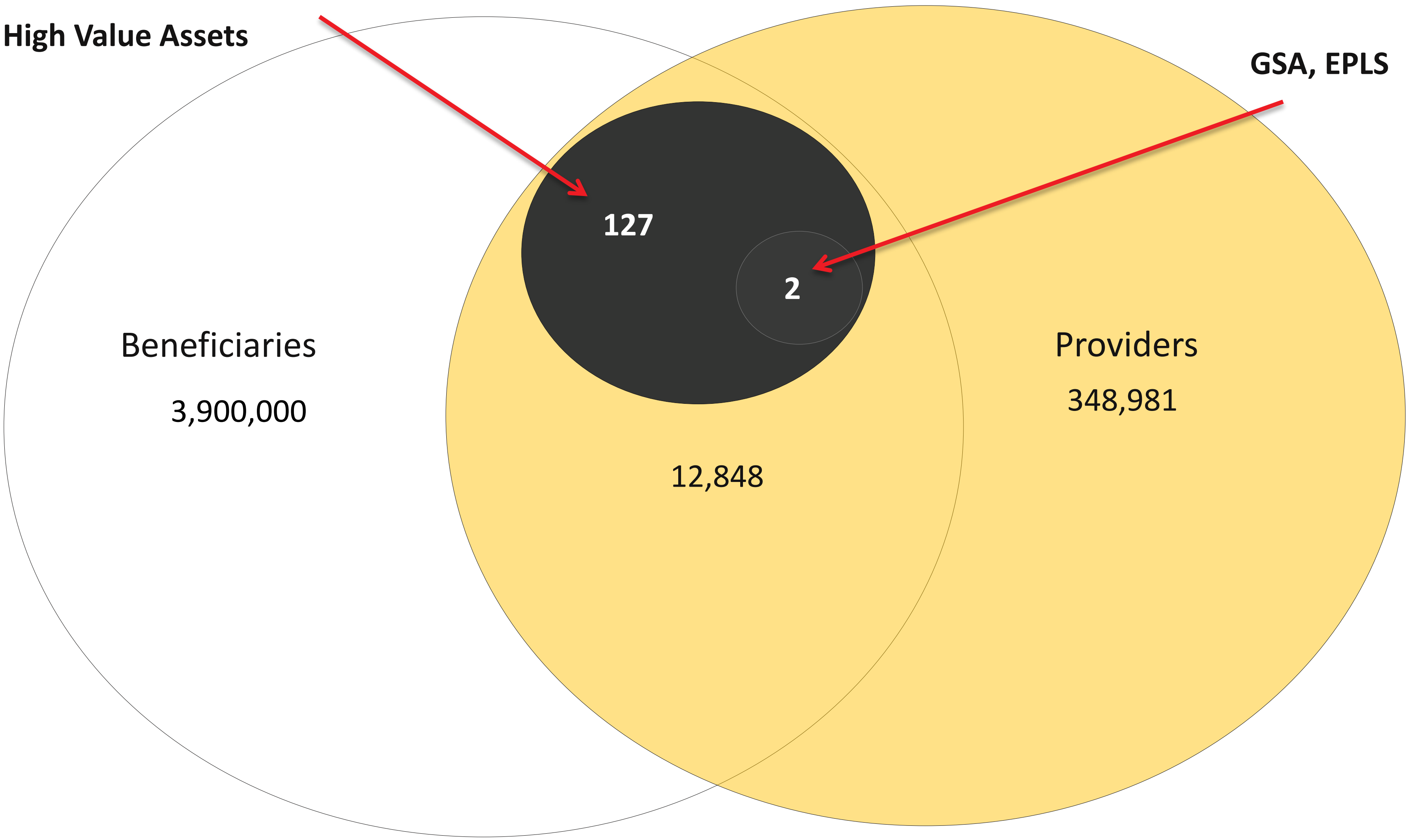
Owns Expensive Vehicles

1. Detection and Visualization of a large cluster containing associated active Medicaid recipients who have unusual lifestyle data points. Note: Slick Willy and his icons for vehicle, residence and property.

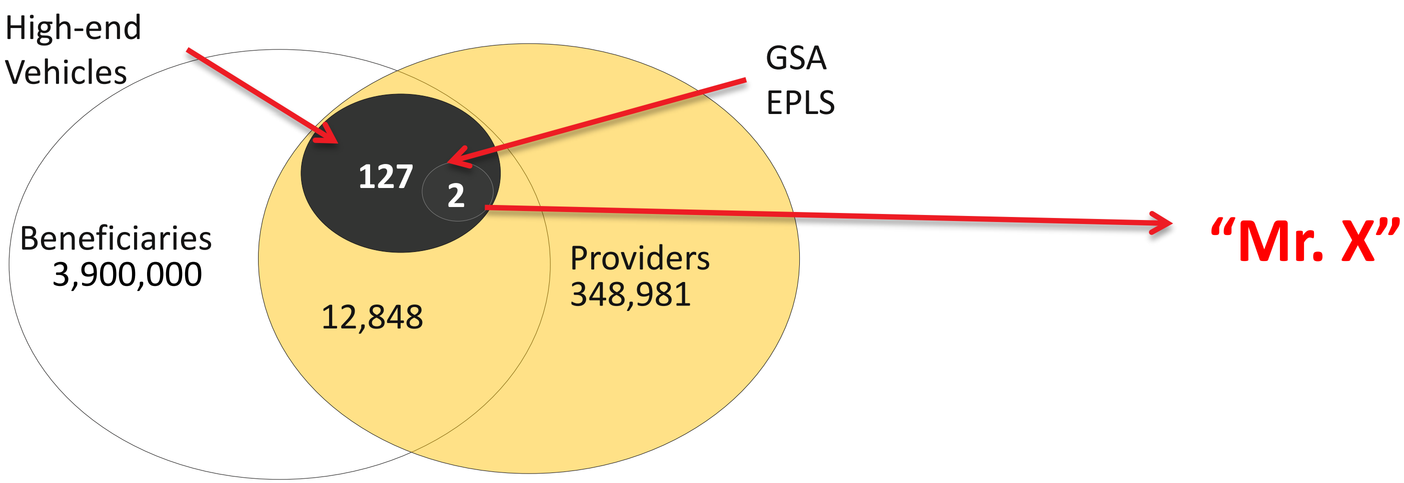
2. Zoomed in view of Slick Willy to see his vehicles and his relationship to business contacts of Medical Business Entities and other Medicaid Recipients.

3. Prima Donna, lives at expensive residence, owns expensive property, owns expensive vehicles and is a business contact of a medical business entity. Her cluster is connected adjacently to the Slick Willy cluster.

Social Network Analysis: Example 2, Florida



Social Network Analysis: Example 2, Florida



Interesting Indicators	Exclusions & Sanctions
2009 Acura RL White (base price $50K)	02/20/2006 DHS: Debarred / Excluded
Medicaid Beneficiary	09/14/2006 OPM: Debarred / Suspended
Registered Provider	
Numerous Medical Business Ownerships (discussed below)	

Social Network Analysis: Example 2, Florida

Clusters of interesting asset variables in tight social networks are often associated with coordinated activities.

- 3 Billion Public Data Relationships
- Leverage SNA Intelligence
- Identifying the key actors and activities

Example Interesting Vehicles

(2010) Red Ferrari California ($192,000), (2009) Black GMC SLT Yukon ($ 44,750), (2010) Black GMC K1500 SLT Sierra ($ 41,775), (2011) Mercedes-Benz E350 ($ 494,00), (2009) Black Mercedes-Benz AMG SL63 ($135000)
(2011) White Audi 5.2 QUATTRO R8 ($161000), (2011) White BMW M3 ($ 55400)
(2010) Black Mercedes-Benz S600 ($149700), (2010) Mercedes-Benz 4 MATIC GL550 ($ 82850)
(2010) White Mercedes-Benz AMG CL63 ($145200)

Example Interesting Residences

D[redacted]	15	[CITY]	$167,000.00
F, [redacted] M	60	[CITY]	$499,000.00
G[redacted]	23	[CITY]	$670,000.00
G[redacted]N	76	[CITY]	$550,000.00
G[redacted]RO	22	[CITY]	$489,000.00

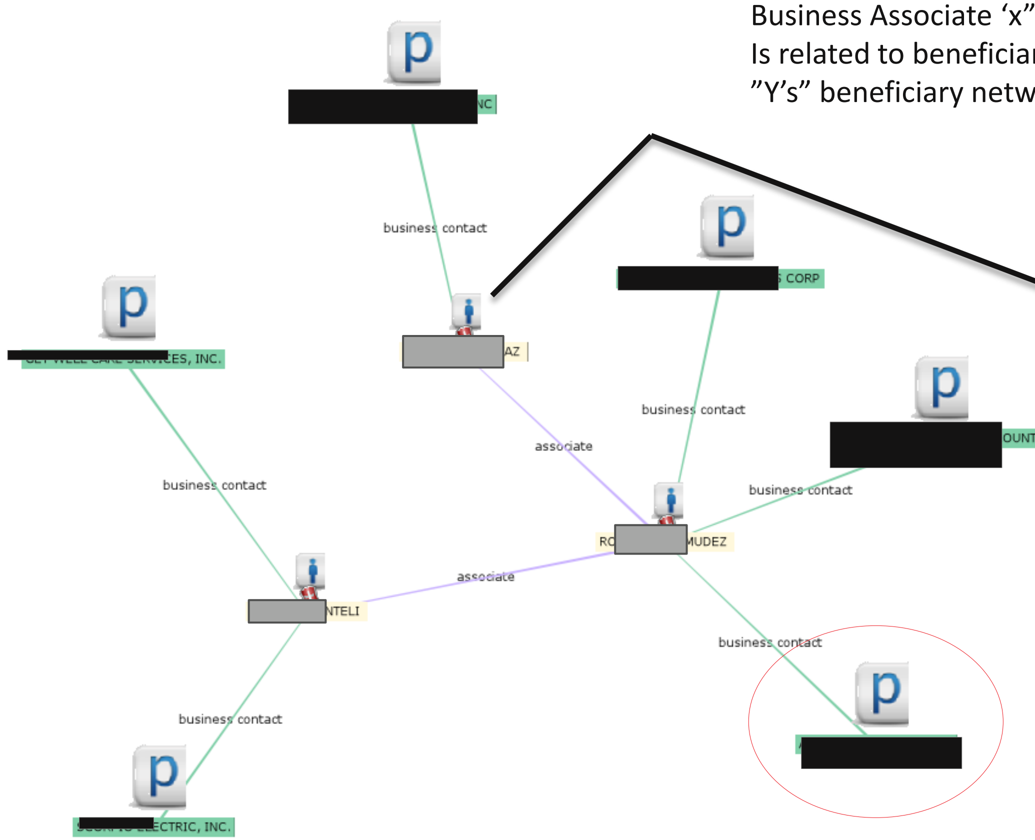
G, [redacted]A	43	[CITY]	$800,000.00	(2009) Red Audi 4.2 QUATTRO R8 ($112500)

Case Study: Linkages and Associations

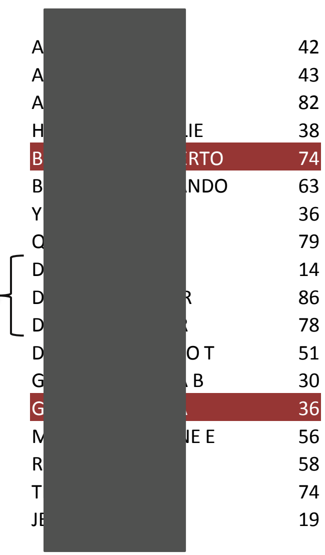
Numerous close associates also operating medical businesses

Provider Cluster

Beneficiary Cluster



Business Associate ‘x”
Is related to beneficiaries in
”Y’s” beneficiary network



Focus on “Company x” next slide

Case Study: Turning Big Data into Actionable Intelligence

Name: A[redacted]CS
Address: ...

Name: A[redacted]ES INC.
Address: ...

Name: A[redacted]NC.
Address: ...

Name: AP[redacted]CY
Address: ...

Name: E[redacted]
Address: ...

Name: INTE[redacted]GE
Address: ...

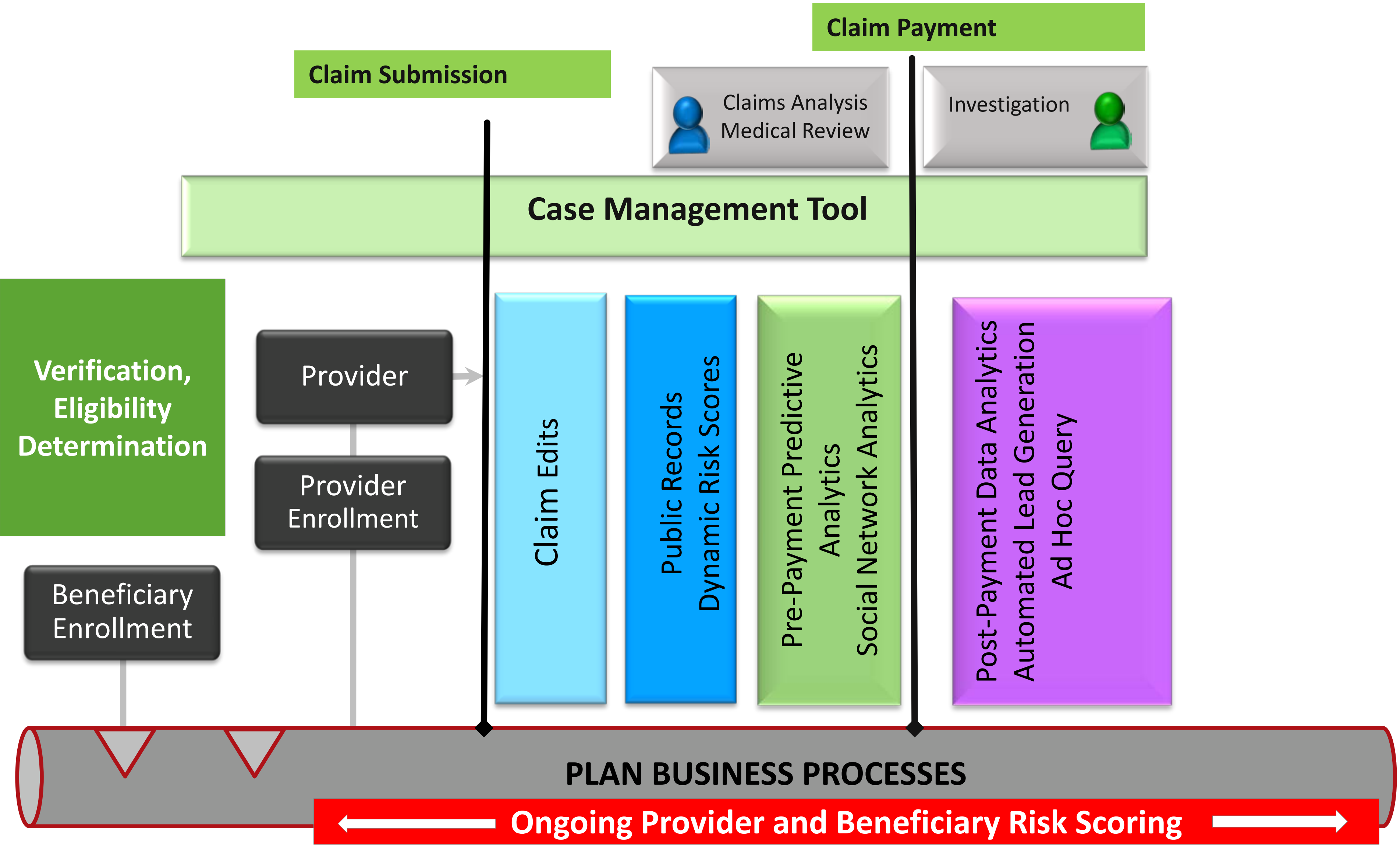
Name: JO[redacted]UNT
Address: ...

Name: M[redacted]ACY
Address: ...

Name: P[redacted]NC
Address: ...

Name: S[redacted]RP.
Address: ...

Identity Analytics and Predictive Modeling Workflow



Bringing it All Together: A Comprehensive Model to Detect and Prevent FWA

Thank you!

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