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Claims leakage

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How much does fraud cost health insurers ?

“ 1% - 1.5% of benefits ”

- Dr Michael Armitage, the Age, 2007

“ 4% of benefits, of which 20% can be (currently) saved”

- Deloitte, USA 2003

“ ... as much as \$90 billion out of \$1.8 trillion”

- Blue Cross USA (www.bcbs.com/blueresources/antifraud)

Where does fraud stop and moral hazard start?

Fraud cost in context: 2000-2007

	@1% of claims	@3% of claims
>10% PHI industry profit	4 years out of 7	7 years out of 7
>25% PHI industry profit	2 years out of 7	5 years out of 7

Even 1% represents a material premium increase – and some estimates are at 5% or higher!

Standards Australia : 8001 Fraud & Corruption Control

Structural

- Sound ethical culture
- Senior management commitment
- Periodical assessment of fraud and corruption risk
- Management and staff awareness
- Fraud and corruption control planning

Operational

- Internal controls
- Fraud detection program
- Mechanisms for reporting suspicions
- Dealing with detected or suspected fraud / corruption
- Line management accountability
- Internal audit strategy
- Whistleblower protection policy
- Allocation of resources
- Insurance
- Pre-employment

Maintenance

- Review of the effectiveness of the fraud and corruption control strategies
- Ongoing monitoring of ethical culture
- Review and adjustment of the Fraud and Corruption Control Plan

High level elements of best practice fraud risk

High level elements of a best practice fraud risk management approach include:

- Education
- Policies and procedures backed by legislation
- Whistle blower hot lines
- Red flags
- Balanced metrics/scorecards
- Staffing
- Cognitive interviewing
- Case management
- Outsourcing
- Data analysis tools
 - automated rules based engines
 - data mining
 - optical character recognition and text mining
 - link analysis
 - predictive modelling
- Enterprise architecture combining data and tools across an organisation
- Behavioural analysis tools
- Telematics tools

A selection of case studies

- Insurance
 - Health Insurance
 - Financial Services
- Leading practice analytics from other industries
 - Credit Bureau
 - Retailer
- Target investigations
 - Workcover Authorities

Financial Services – Insurance Fraud Detection Technology Review

- Objectives to provide independent assessment that:
 - their view of the 'future state' technology capability is consistent with leading practice
 - the timeframe required to reach the 'future state' was practical and achievable
 - anticipated savings are quantifiable and in line with the costs of moving from 'Current' to 'Future State'
- Review of current and future state Fraud Detection technology
 - Including workflow dependencies and product sensitivities to fraud
 - Suitability of existing data structures to support improved identification (Analytic Data Set)
 - Use of external data and process based information
 - Periodicity of evaluation of rules sets in Fraud engine
 - Quantification of uplift from introducing predictive analytics
- Value from and process for referrals (from internal sources)
- Demonstrated the value of using analytical techniques to consider claims which are 'similar' to known frauds but were not investigated or identified by rules engines
- Potential to improve effectiveness by \$10m - \$16m p.a. through improved adoption and deployment of analytic techniques
 - The team in place was > 20 headcount

Review of effectiveness of Rules Engine

Rules based technologies are often used to identify claims requiring further investigation. Rules can be developed on the back of historic patterns and facts, domain expertise (e.g. the thoughts of experienced practitioners) and from the results of advanced analytical techniques. A scoring mechanism may also be included to further filter rule violations and assist in workflow routing, resource allocation and to generate key claim management activities

- Advantages
 - flexible, quick to implement and capable of being applied to large amounts of data efficiently
- Disadvantages
 - the fraud environment is dynamic i.e. rule effectiveness changes over time, if they are too 'rigid' fraud is not detected and if they are too 'loose' they identify too many false-positives
 - Rules are non learning and need to be augmented with other analysis
- Technology can minimise amount of false positives
- Periodically review the relationship between rules violation and workflow management
 - Drive intelligent workflow routing and allocation, improve consistency and control

The value of a “Data to Experience” approach

- Traditional analytical approaches are based on business acumen and experience, and are intuitive => “Experience to Data”
 - EG: *“based on experience, we need to look at root causes a, b, c and need data x, y, z”*
- Our analytical methodology blends business acumen and experience with an assumption free technique => “Data to Experience”
 - EG: *“the data suggests links between data elements d, k and p - why might this be relevant?”*
- Due to this unconstrained approach, we are not limited by hypotheses, data selected or analytical data “schema” – increased capability to identify counter-intuitive insight

Credit Bureau – Fraud Focus Group

- Objectives

- to report analysis of characteristics of credit fraud to inform detection and prevention initiatives. The users were a focus group comprised of some of the largest Australian banks and financial companies.
- pass findings to Focus Group for implementation into rules engines
- quantify the amount of 'unknown/missed' fraud

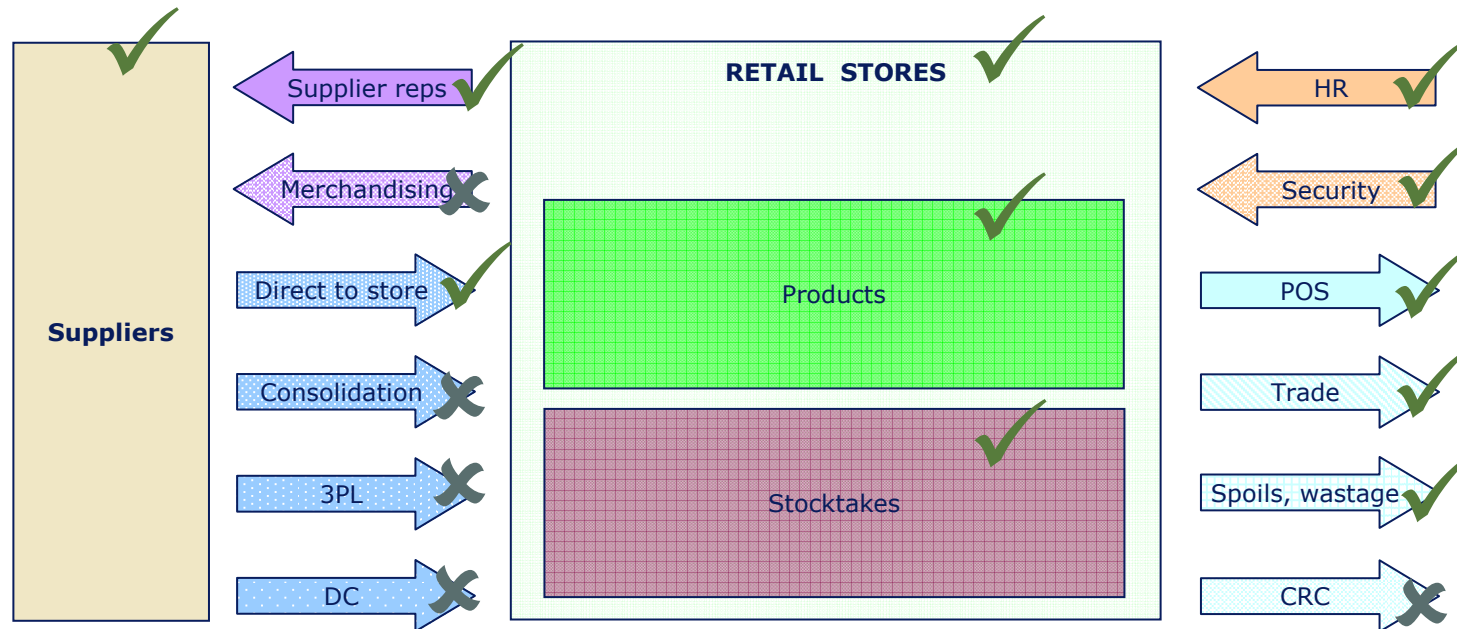
- Sample outcomes

- Predictive models validated a 30 fold improvement in identifying application fraud
- Previously thought inaccessible/invaluable data extracted and combined from mainframe logs added significant prediction power
- Lack of consistent performance metrics for fraud and credit losses across the Focus Group
- For every \$1 of known fraud and additional \$0.60 of unknown fraud is missed
 - This estimate suggests that a high proportion of fraud loss is reported as bad debt
 - Similar for PHI in terms of Claims Leakage passing through to Benefit Paid?
- Collaboration
 - Shared Fraud Database – for every 1 in 5 frauds lodged, the same record was lodged by another party
- Interesting data attribute found to be predictive – proportion of vowels in surname

Retail – Loss Prevention

- Previously a process based review had significantly improved performance using top down Forensic methodologies
- Proposed an evidence based approach from the ground up
- Again, previously ignored data combined to provide counter intuitive insights and enterprise wide data asset

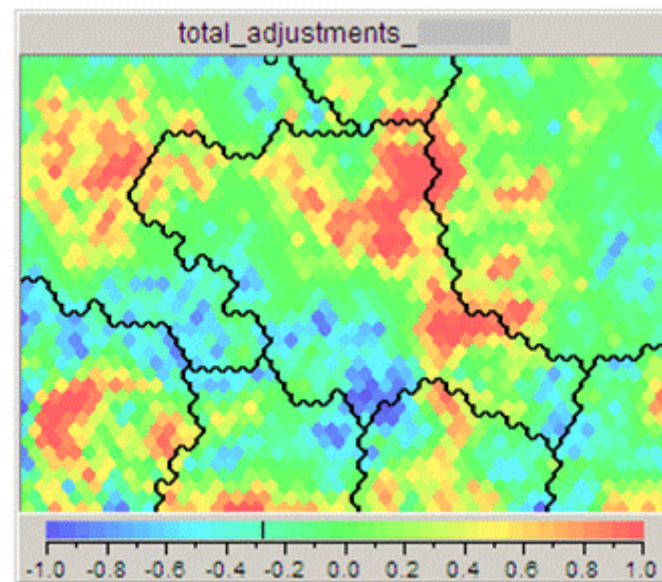
Overview of data landscape



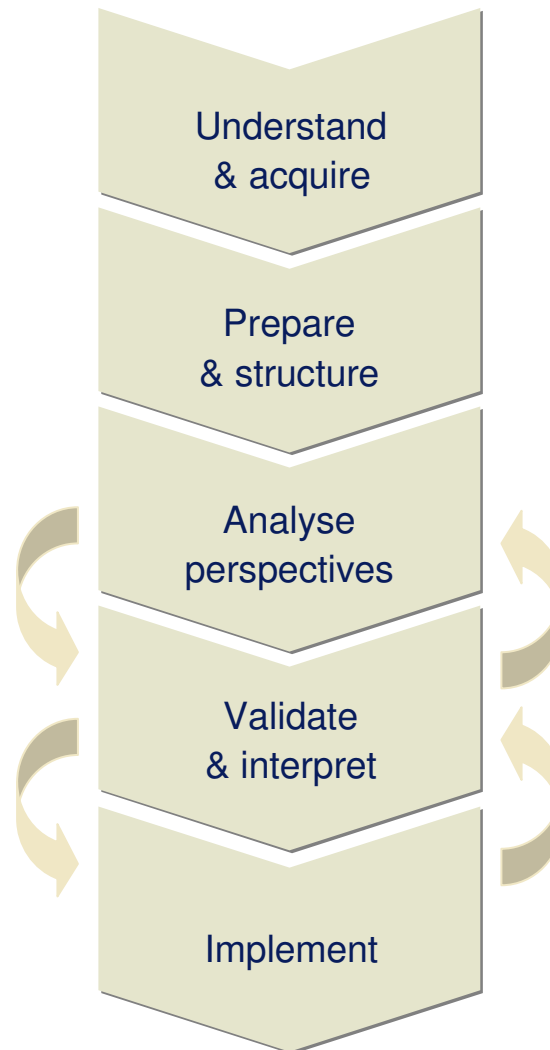
- 35.3 billion data elements
- 46 raw data sources
 - ~170Gb
 - Much greater number of raw data files
- Over 5,000 attributes considered at different perspectives for modelling
 - Whole of business, Store, Department within Store, Stocktake, Employee

Workcover Authority

- Value proposition – maximise effectiveness of compliance resource through targeted analytics
- View below highlights the complexity of compliance amongst employers (proximity of employers with different compliance outcomes):
 - Red represents non-compliant employers who owe the Authority
 - Green represents compliant employers
 - Blue represents non-compliant employers where they are owed a refund



Framework for presentation – the Deloitte Analytic Insights® methodology



Understand and acquire : Health insurance perspectives

- Membership
 - Families
 - Individuals
 - Corporate
- Providers
 - Modality
 - Chains
 - Invoices
- Claims
 - Products
 - Items
- Employees

Understand and acquire : Insurance data sources

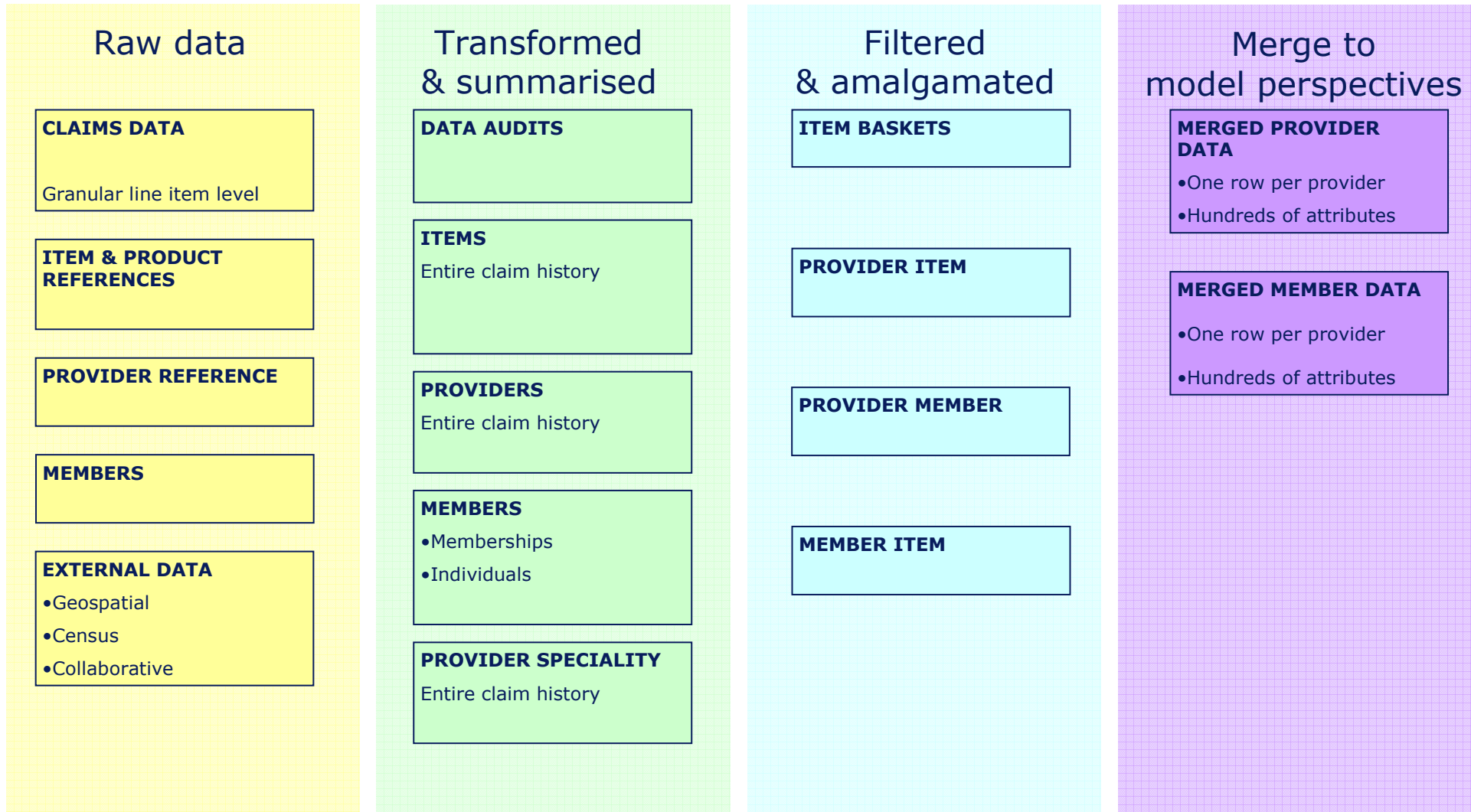
- Typically disparate systems which are not connected
- Often imperfect and incomplete data
- Data sources
 - Proprietary mainframe
 - HiCaps
 - SAS
 - Teradata
 - Oracle
 - Microsoft
 - SQL
 - Access
 - Excel
- Design of Analytical Data Sets
- Understand implementation constraints
 - E.g. Employee workload at time of referral
- Understand geographic / product variance
 - Pricing by modality by region
 - Product availability by region
 - Legacy product implications

Prepare and structure insurance example

- Data audit
- Cleanse
- Aggregate
- Derive and transform

- Item baskets
- Peer to peer profiling
- “Level the playing field”
- Catchment area served

- Speciality
- Tenure
- Known fraud by typology



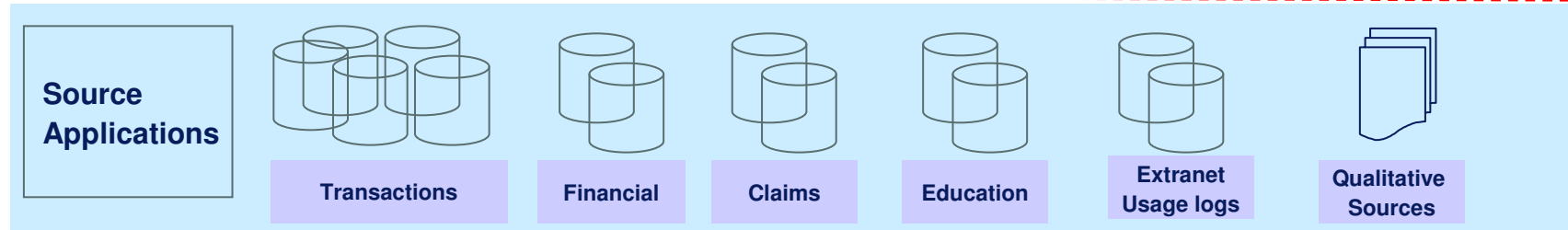
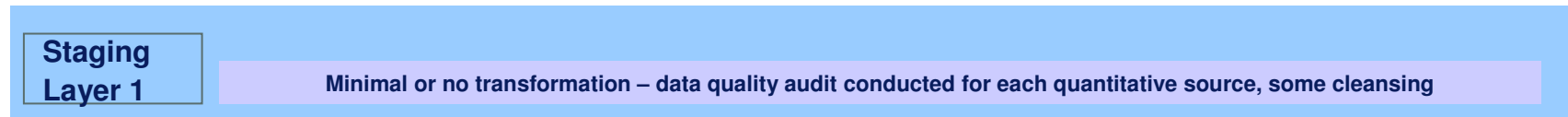
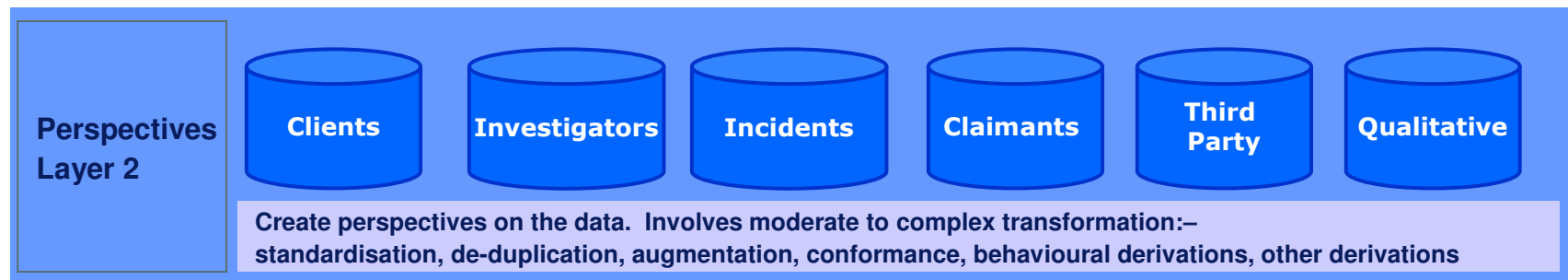
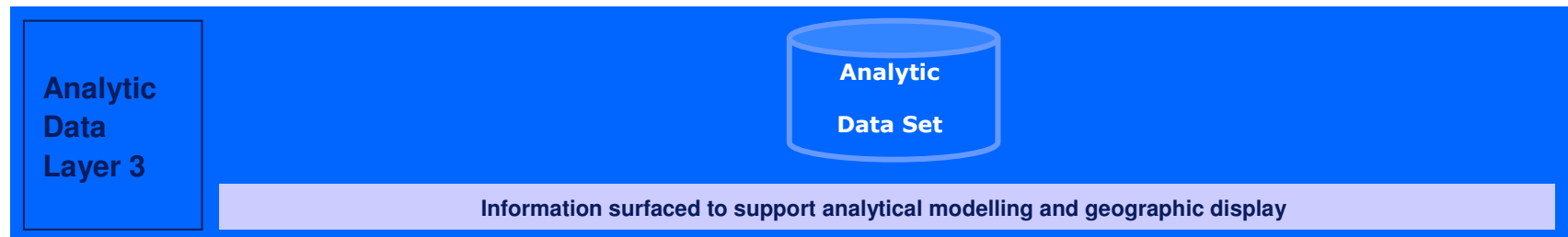
Prepare & structure : samples of attributes

- Provider attributes

- What proportion of items claimed relate to popular padding items?
- On a dollar weighed basis, do I charge more per item than all other providers of the same item?
 - “Average Dollar Weighted Log Ratio Provider Item charge”
 - Similar metrics for:
 - Number of items per policy
 - Number of services per visit
 - Range of price per item
 - Amounts of refunds
 - Reversals and rejected payments
- How does the amount I charge for items compare with the scheduled amount for items
 - How is this gap spread relative to other providers?

- Member attributes

- Do I claim items across my families policy in an unusual way compared to other members claiming similar items?
- Is my amount refunded per subsequent visit to a provider within a year higher than usual?
- Do I try and claim benefits which are atypical considering my age group and/or gender?
- How unusual is the total portfolio of items I have claimed, between and within modalities?
- Is the profile of the different providers I have used unexpected?
- Where am I ranked in terms of:
 - Number of different providers
 - Frequency of visits, revisits

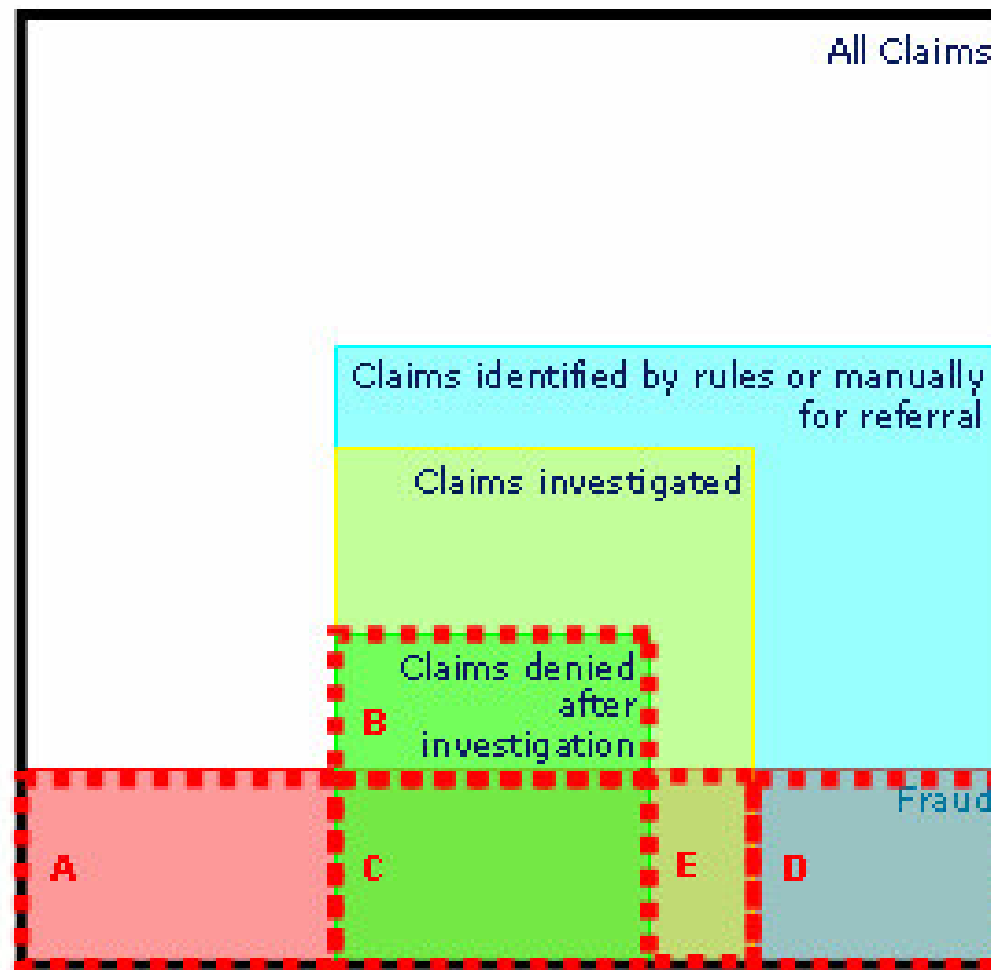


Analyse perspectives

- Rules-based
- Geospatial
- Artificial intelligence and machine learning
 - Supervised
 - Limit surfing
 - Claim padding
 - Known fraud
 - Model of Models
 - Unsupervised
 - New pattern identification
 - Social Network Analysis
 - A Superset of Link Analysis
 - Google use this method for page rank algorithm
 - Providers with scarce behaviour rise to the top if linked with other providers exhibiting similar behaviour through members and over defined time periods between member visits

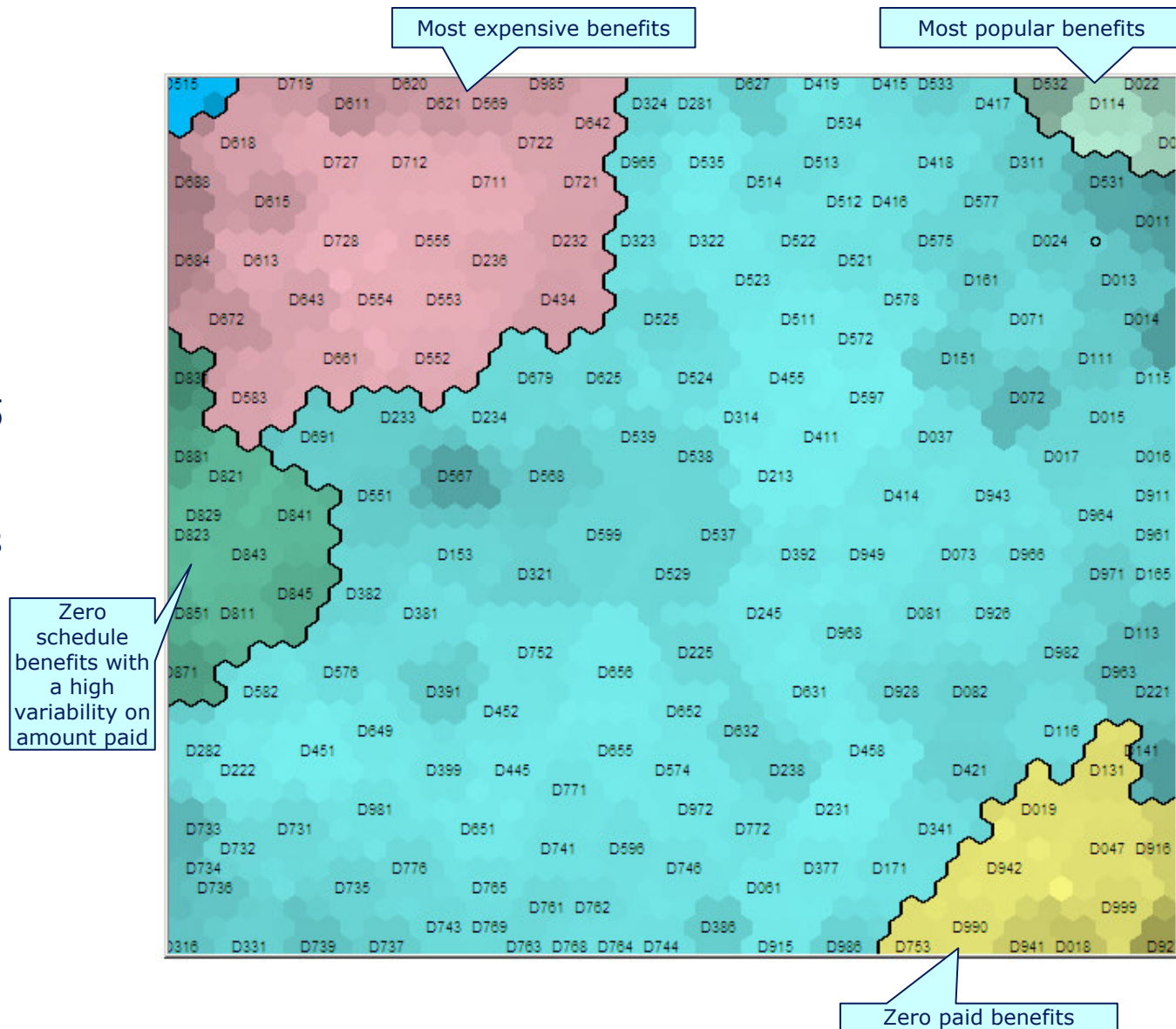
The case for unsupervised analytic techniques

- Misclassified Fraud – A, E and D and will have different typologies to those successfully identified in C
- Supervised models will learn from B and C, therefore continuing to miss the unknown fraud typologies



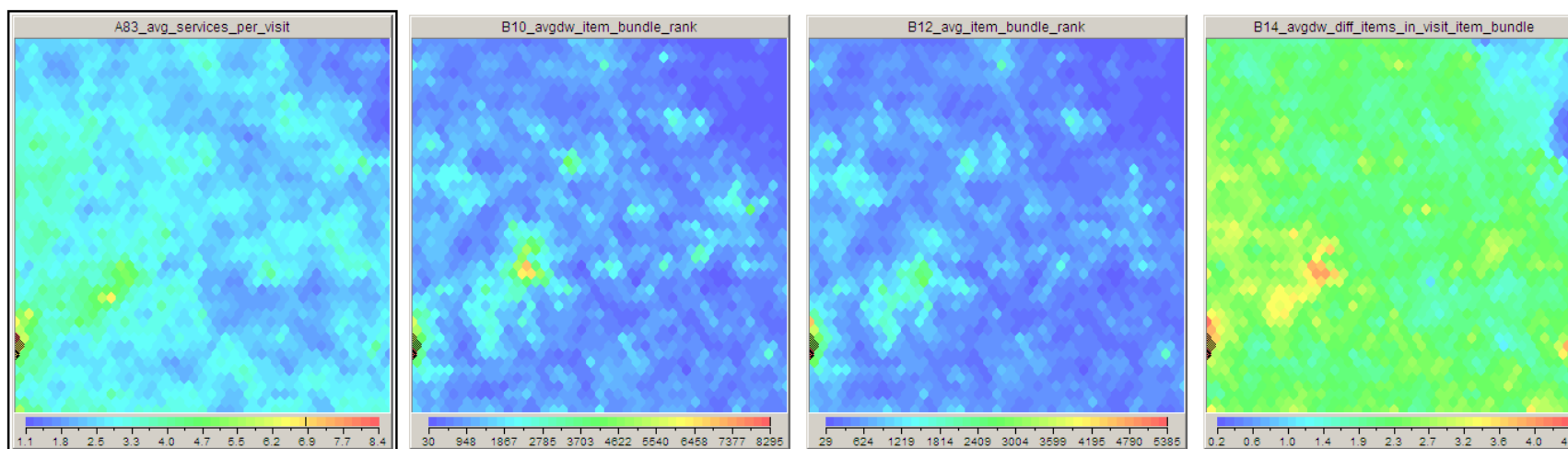
Clustering and labels on popular dental items model

- Value from this labelling can be substantial
 - allows comparison of items based on simultaneous consideration of 55 variables summarising their usage by members and providers
 - *What items are most like other items?*
- Input into item bundle analysis



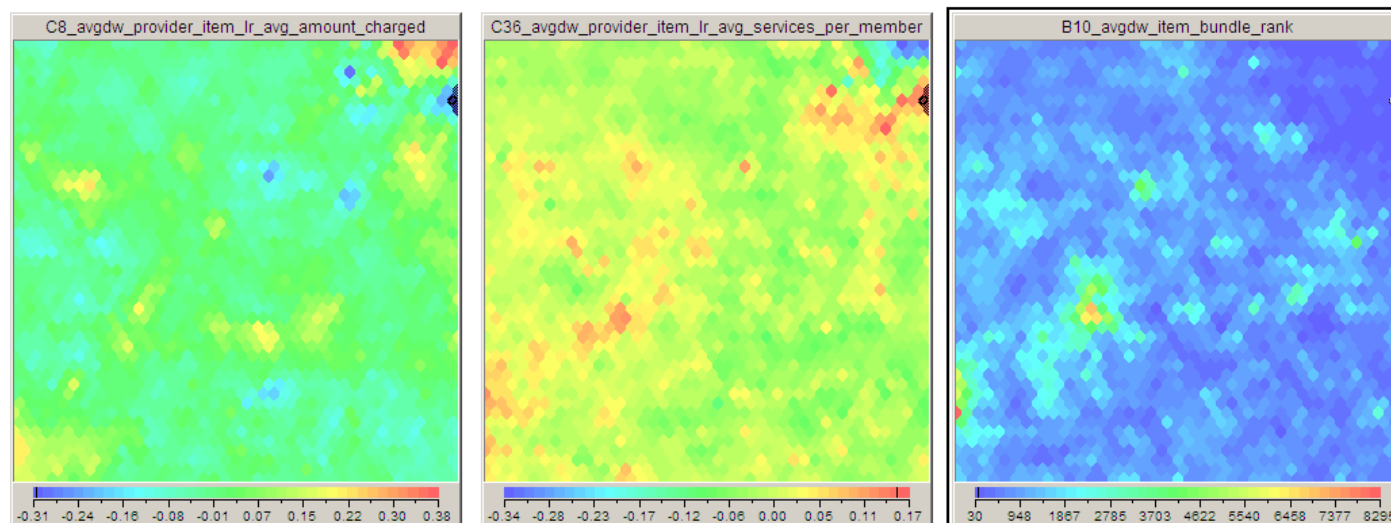
Provider Perspective - rare and costly bundles of items

- Population of > 3000 Dentists
- A group of providers (< 15) are observed with high services per visit and a combination of relatively unusual item bundles
- Interactively consider:
 - A83 avg services per visit
 - B10 rare bundle of items with higher benefit paid comparatively (with all other providers who provided the bundle) for that bundle
 - B12 rare bundle based upon number of visits
 - B14 higher price paid for each item within each bundle



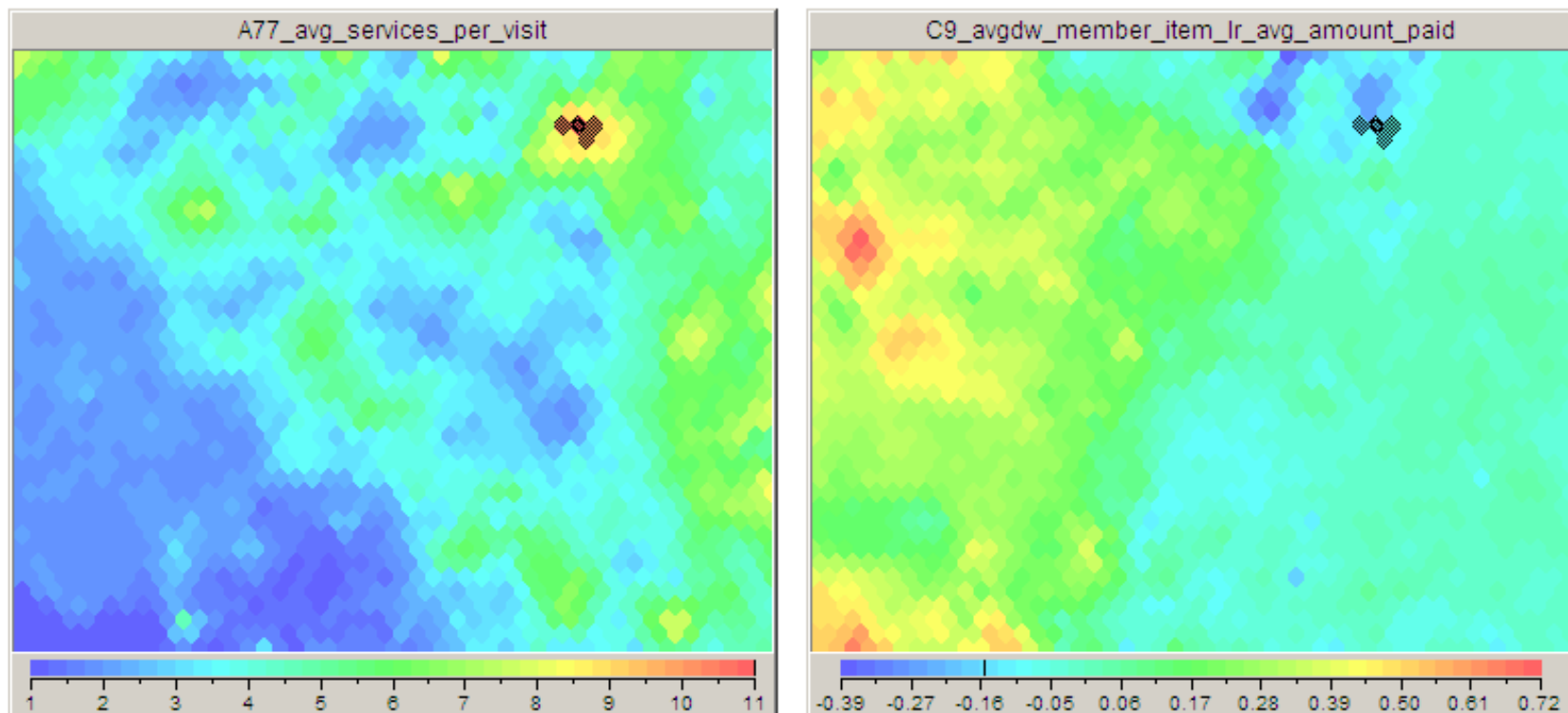
Provider perspective - manipulating the gap

- Population of approx. 3000 Dentists
- A group of providers (< 20) are potentially manipulating the gap
- Interactively consider:
 - C8 – comparatively lower \$ charged per item compared to \$ charged for the same items by all providers
 - C36 – average no. of services per member per item compared to all providers
 - B10 – popularity of items provided in a single visit



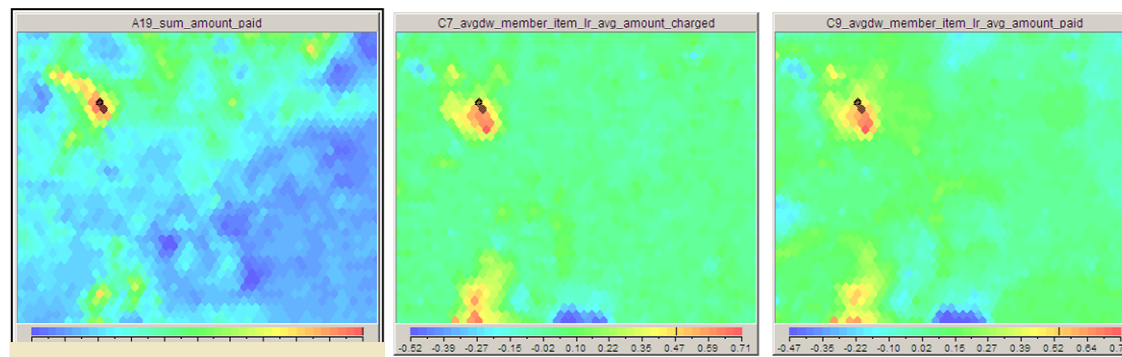
Member Perspective – Item Surfing

- Population of approx. 20,000 Optical Members
- A group of members (< 30) are observed with high services per visit and a comparatively lower paid amount than other members claiming this item

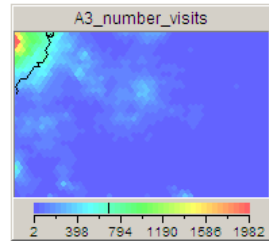


Member perspective – high value payments

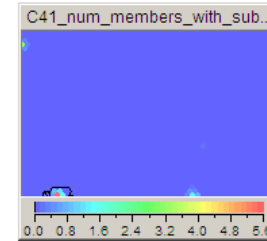
- Population of approx. 20,000 Members
- A group of providers (< 30) are observed with higher payments than their peers
- Interactively consider:
 - A19 – these members are paid the most within the modality
 - C7 – these members are charged more than other members for the same items
 - C9 – these members are paid more than other members for the same items



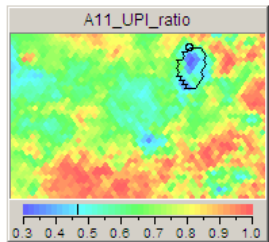
Interactive consideration of filtered dental provider SOM



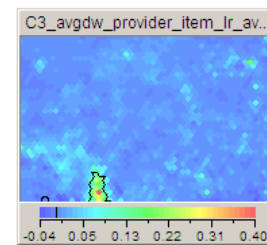
- High activity



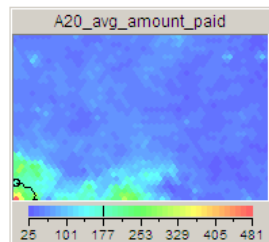
- Padding



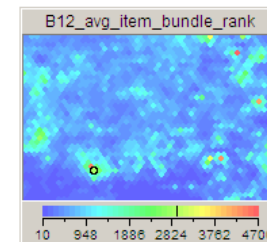
- Low UPI ratio



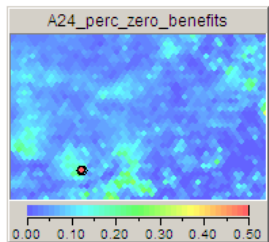
- High services



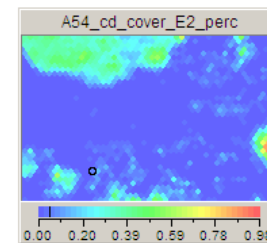
- Expensive



- Unusual bundles



- High proportion zero benefits

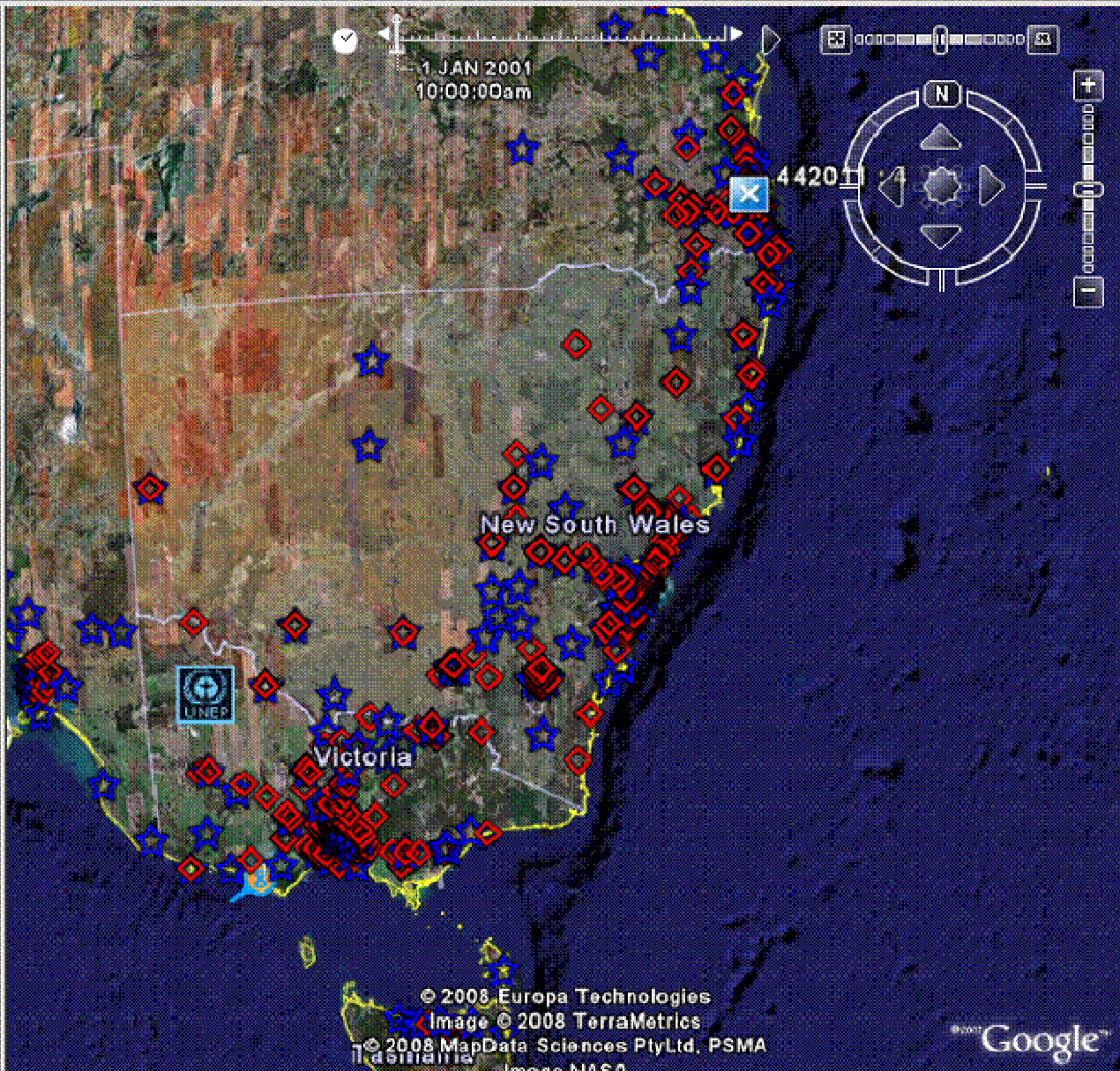


- Product related groups

Search

Places Add Content

- My Places
- Temporary Places
- OFTS Pre**
 - 080806 C
 - ARMY
 - High
 - Medi
 - Low
 - NAVY
 - RAAF
 - Locatio



Layers

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Layers

Validate and interpret

- Value requires collaboration with specialists
- Facilitated workshops
- Strategic findings
- Tactical deliverables
 - Lists of suspicious transactions, providers, members and/or employees

Implement

- Design and automate regular delivery of Analytical Data Sets
- Knowledge transfer to fraud teams and front office
- Operationalise insights to reject at point of claim
- Reactive retrospective analysis

Conclusion

- In-house / outsource / co-source consideration
- Collaboration
- Maximise your data asset across business units
 - Analytic Data Set – how rich is yours?
 - Segmentation
 - Product management
 - Pricing
 - Acquisition / retention / cross-sell

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