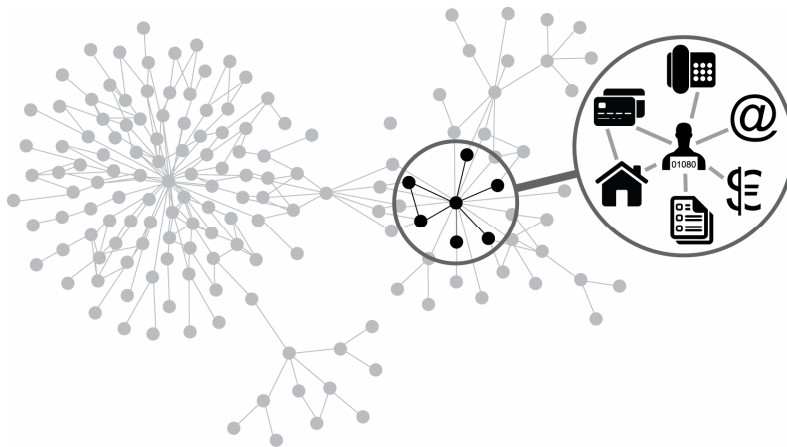


Using social network analysis techniques in the credit process



Matthew O'Kane, Detica NetReveal

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Detica NetReveal[®]

Contents



- What is Social Network Analysis?
- Why Social Network Analysis?
- Use Cases
- Results
- Questions

What is Social Network Analysis (SNA)?



- Not: Facebook, Twitter, Google+

- Not: Link Analysis

- Needs to satisfy:
 - No restrictions on usage of data to build networks
 - Every customer residing in one (or more) networks
 - A set of network-level variables available for modelling
 - Ability to model dependent observations

Why Social Network Analysis?



- IID – Independent and Identically Distributed Observations
 - But how do you identify dependent observations?

- Research demonstrates benefit
 - *Jensen, D., Neville, J., and Gallagher, B. (2004). **Why collective inference improves relational classification.** Proceedings of the Tenth International Conference on Knowledge Discovery and Data Mining (pp. 593-598). Seattle, WA: ACM.*
 - *L. McDowell, K. M. Gupta, and D. W. Aha (2007). **Cautious inference in collective classification.** In AAI*

- But what about compliance?

Not just consumer credit

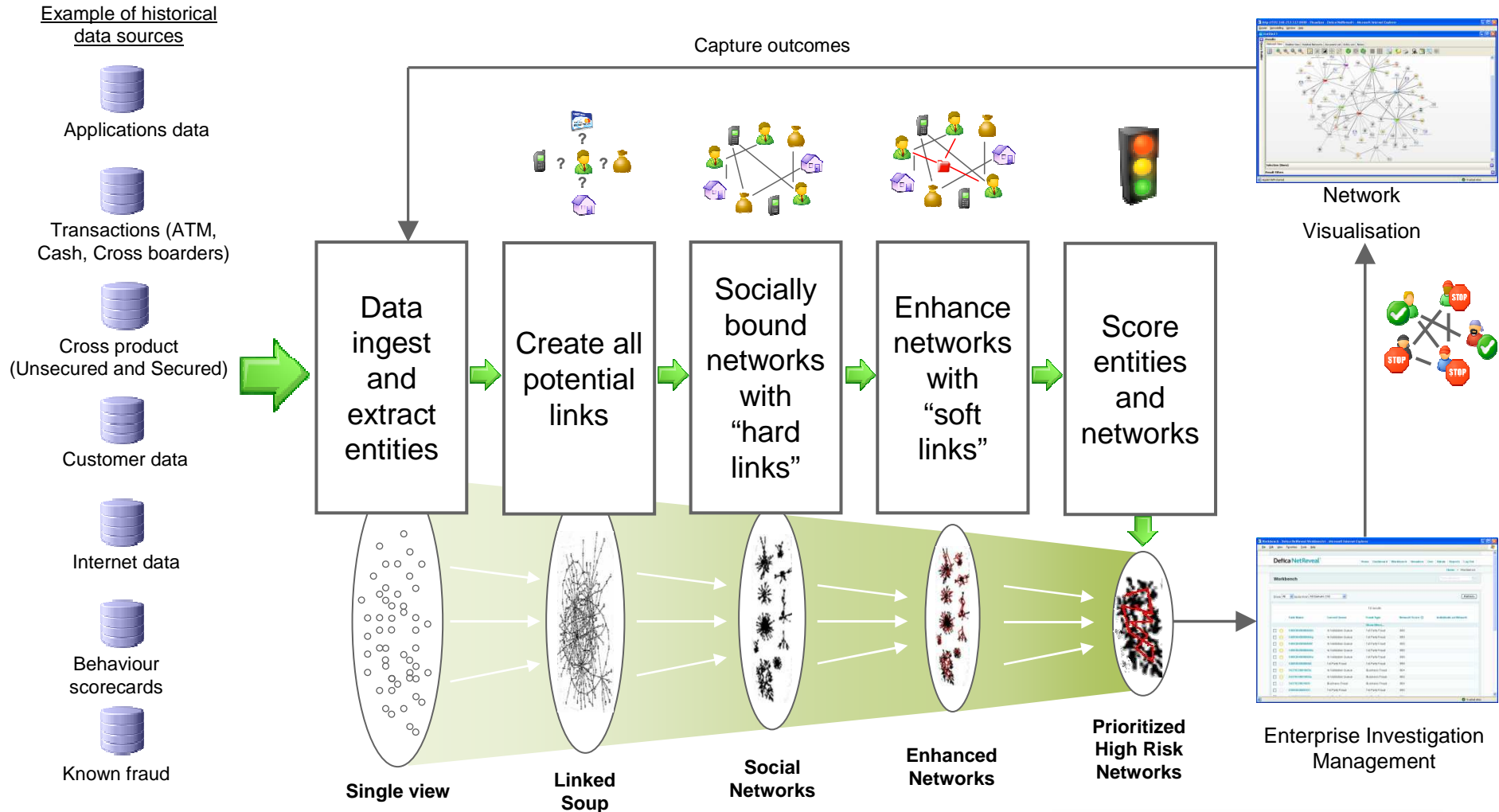


“Britain's economic downturn claimed another prominent retailer Wednesday as music, games and DVD retail chain Zavvi filed for a form of bankruptcy protection, blaming the collapse of the Woolworth Group's distribution arm”

Associated Press 12/24/08

Was Zavvi’s risk independent of other companies it did business with?

Approach: Social Network Analysis

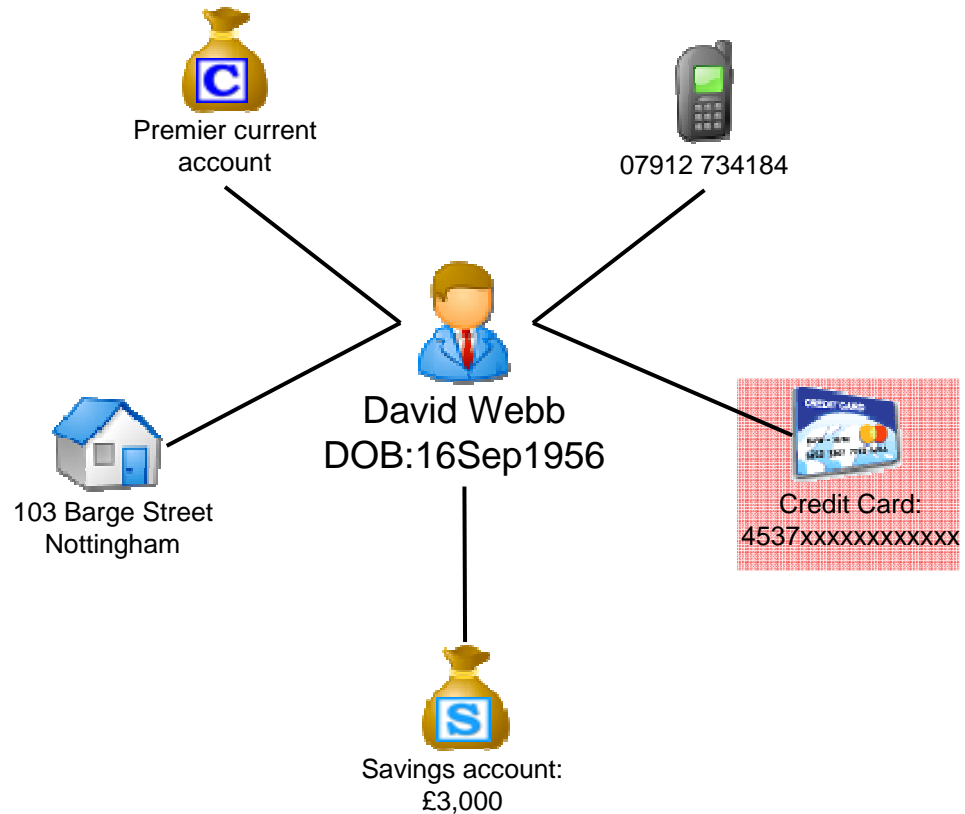


Scenario: Well-behaved customer on bad networks

David Webb has missed a payment on his credit card

From a traditional viewpoint he looks to be an ideal customer since:

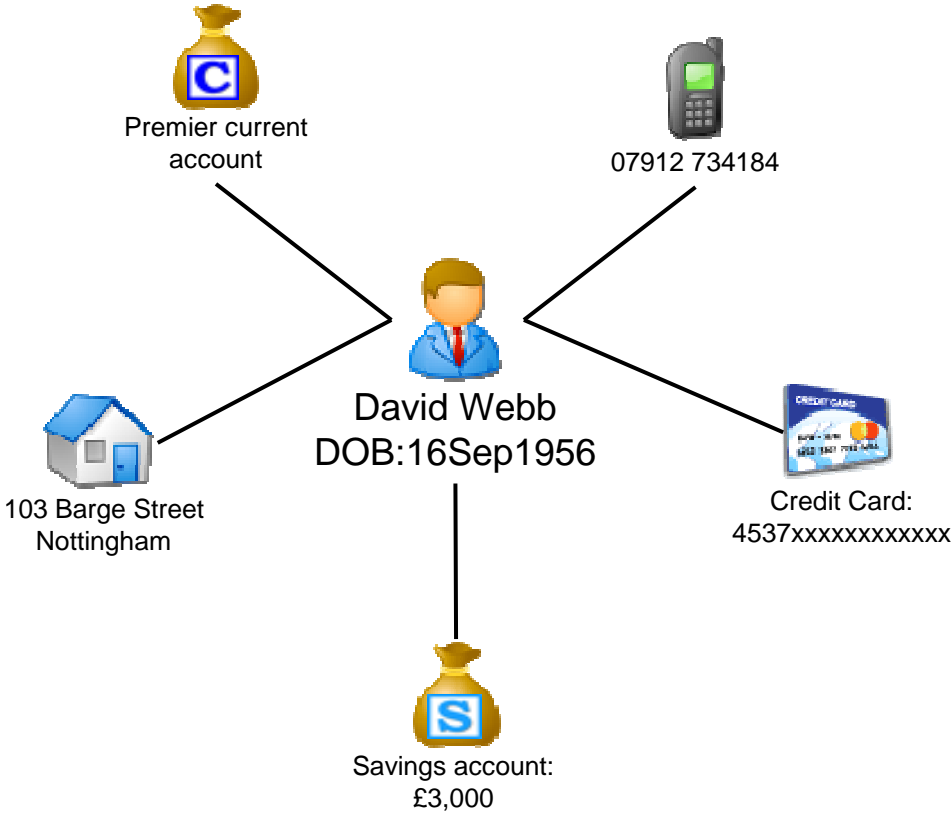
- He is a premier current account holder
- He has a savings account containing a modest amount
- Has a credit card that:
 - is regularly paid off
 - has a low utilisation
 - is not used to obtain cash
 - never exceeds limit



Scenario: Well-behaved customer on bad networks



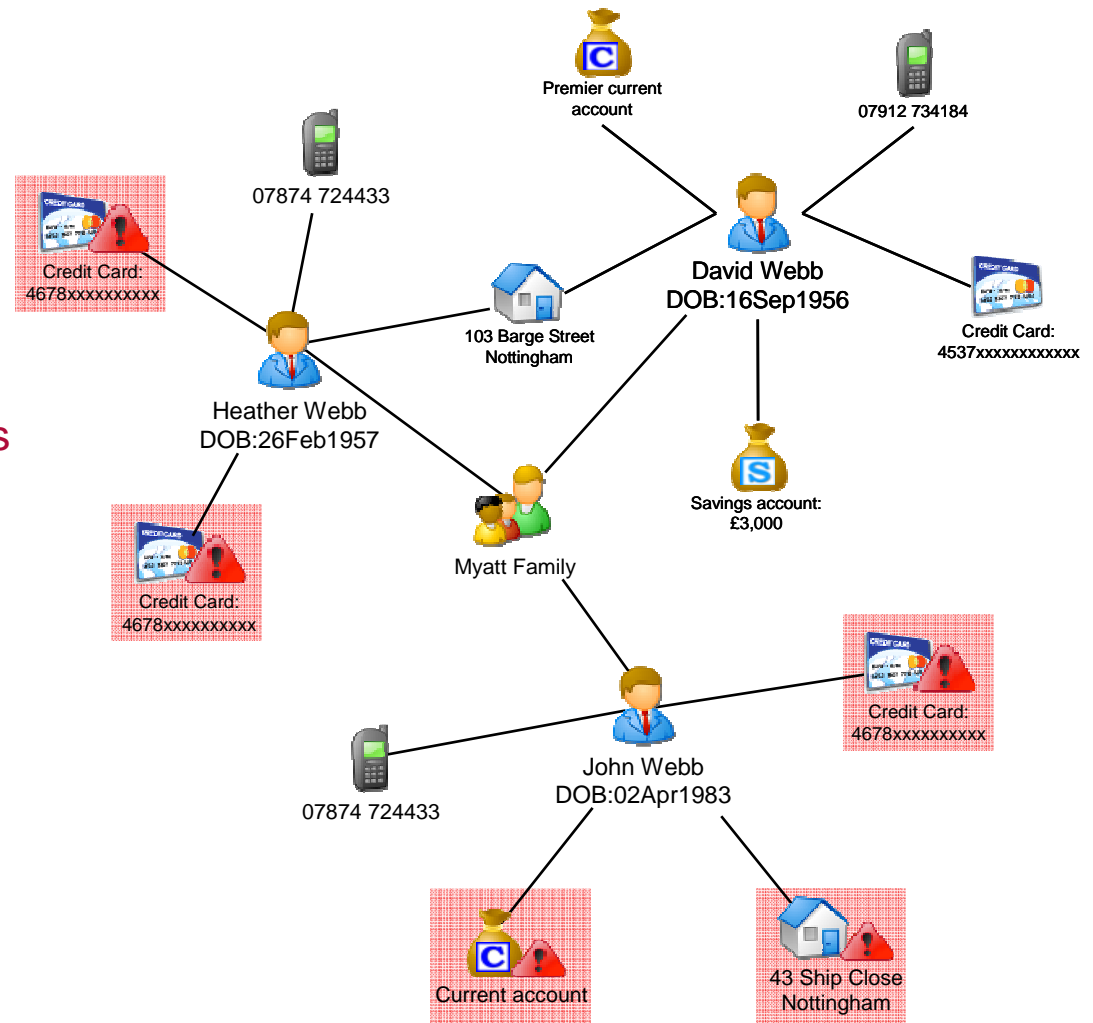
However, when we look at the behaviour of others on his network....



Scenario: Well-behaved customer on bad networks

However, when we look at the behaviour of others on his network....

- David's wife Heather:
 - has two credit cards
 - has recently missed payments
 - has exceeded her limit on a number of occasions
- David's son John:
 - has a high utilisation on his credit card
 - has a large overdraft on his current account
 - has missed payments on his mortgage



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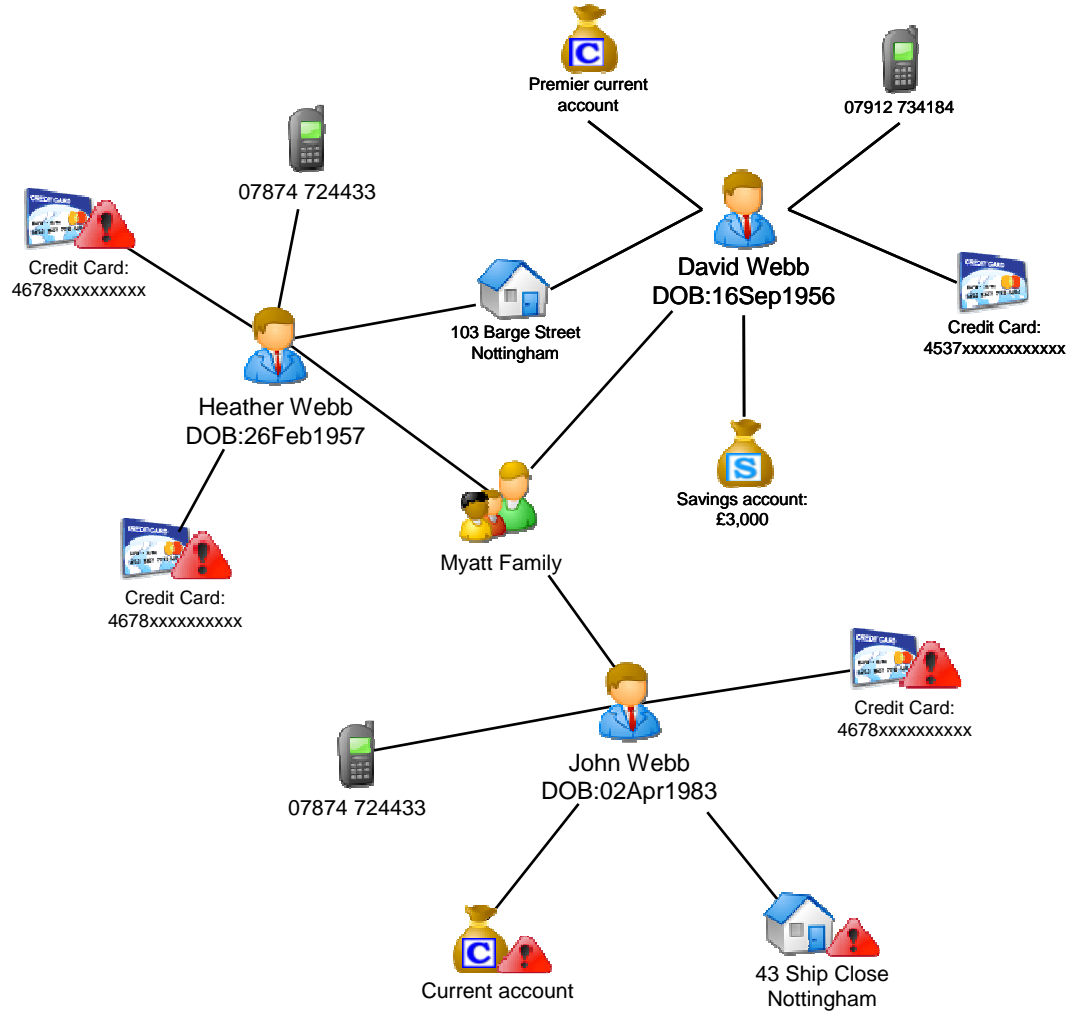
Scenario: Well-behaved customer on bad networks



Overall Recommendation

This extra information provided by SNA reveals financial stress not seen by the bank.

David should be contacted as a priority

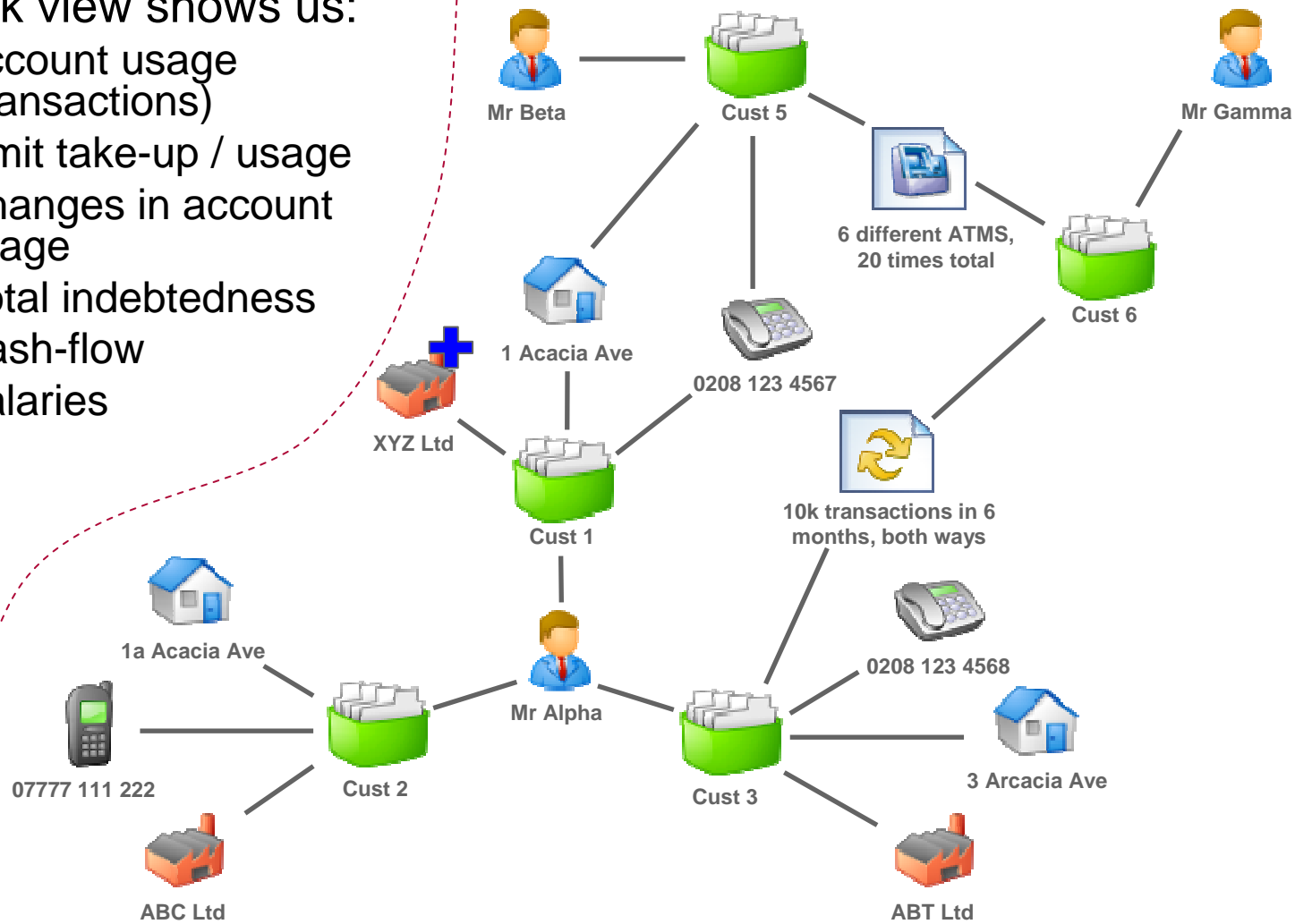


Network variables



■ Network view shows us:

- Account usage (transactions)
- Limit take-up / usage
- Changes in account usage
- Total indebtedness
- Cash-flow
- Salaries



Social network data



CustNc	Name	Balance	Badflag	Network_Balance	Network_Arrears	Network_Transactions
21324	Mr Smith	-£123 02	1		£10 234 01	5	£129 01
24524	Mr Alpha	£2 134 02	0		£24 09	0	£346 56
90833	Mr Small	£923 02	0		£99 234 23	0	£9 45
23897	Mrs Law	-£1 02	1		-£10 234 32	2	£29 87
34958	Ms Apple	£321 02	0		-£4 34	0	£1 45
93287	Mr Bray	£3 457 02	0		£323 54	0	£76 83
48573	Mrs Jones	£8 956 02	1		-£7 564 76	2	£345 84
92387	Mr Fry	£1 234 02	0		£56 345 34	0	£3 129 36

- **Social Network Analysis output creates an additional *networked analytical view*:**
 - **New network variables can be accessed by a decision science team or made available within web reporting system**
 - **Provides ‘quick wins’ around views of a network’s indebtedness, arrears state and account usage**

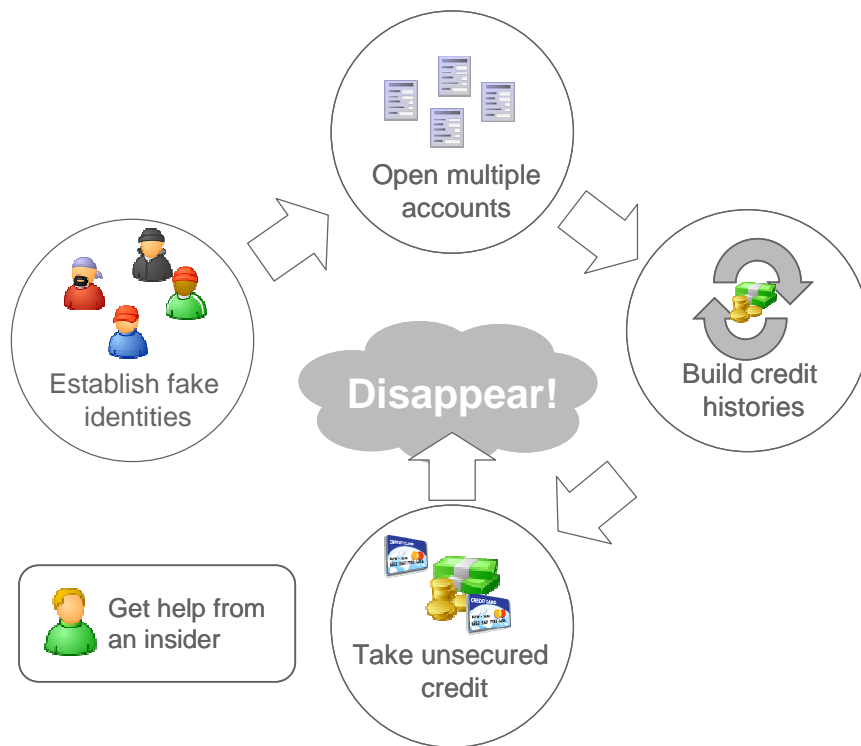


Use Cases / Results

Bust-out fraud, a growing first-party fraud trend



First party fraudsters have become more sophisticated and capable of extracting significant money through well organised operations that prey on weak defences

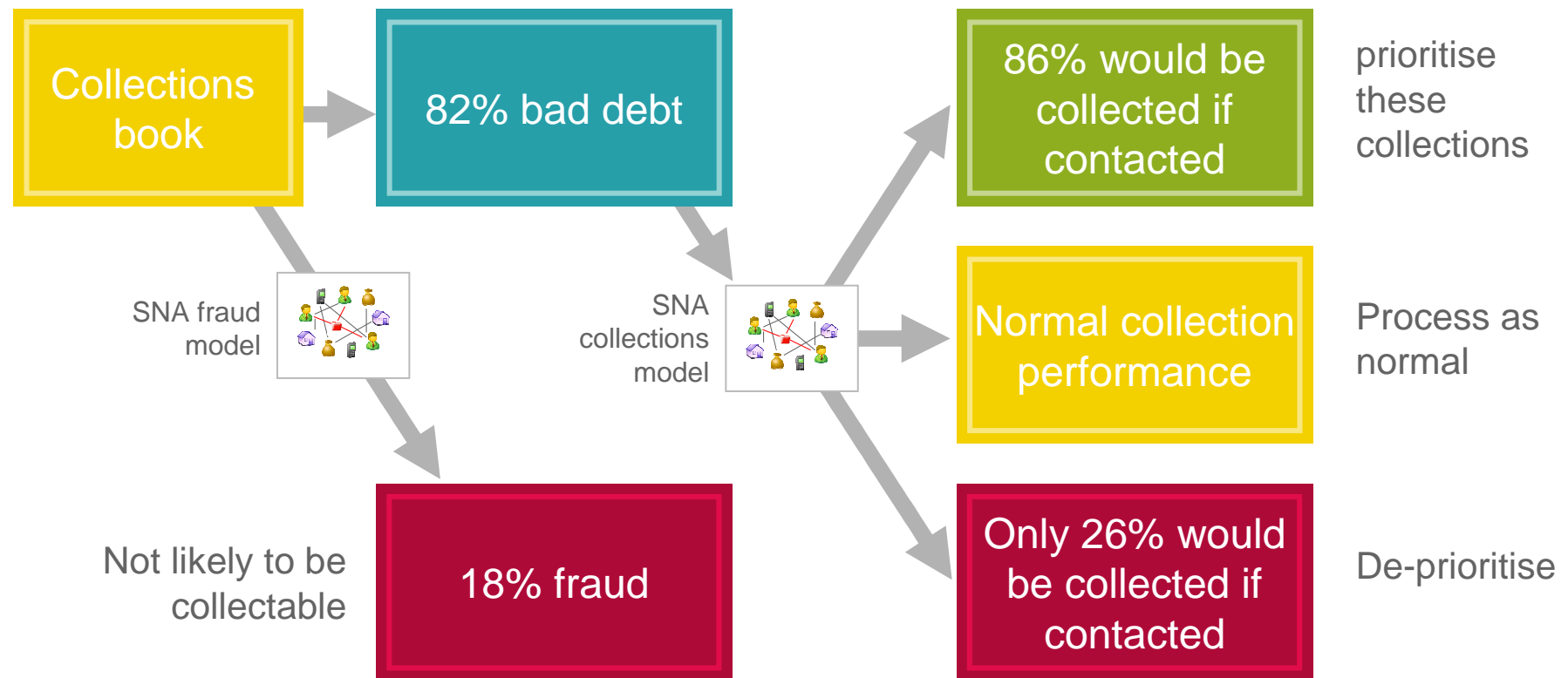


Customer level analytics is struggling:

- Rules encode what you know you are looking for
 - BUT, they cannot discover new *modus operandi* or multiple people operating “below the radar”
- Regular data mining helps to tune rules and discover what you don’t know
 - BUT, it only acts on one customer at a time
- Data matching techniques help provide “single views”
 - BUT, they assume you have honest individuals providing reasonably consistent names, dates of birth, SSNs and addresses – fraudsters don’t
- Hand assembled link analysis diagrams are invaluable in complex cases
 - BUT, they are time consuming and only applied to a minute fraction of situations
- Reducing thresholds on systems only results in too many false positives

Tier 1 bank example

- Using network variables, better categorises and prioritise the collections book



Tier 1 Bank case study: Collections prioritisation



Scenario 1

probability of 'being collectable' $\rightarrow 0$

- One individual has two late payments
- Analysis shows that if:
 $\text{£1,000} \leq \text{Total network debt} \leq \text{£5,000}$
only 33% of late payments will be made good
- If in addition we add:
Network credit availability < £400
then only 26% of late payments will be made good

VARIABLE 1

VARIABLE 2

Scenario 2

probability of 'being collectable' $\rightarrow 1$

- One individual has two late payments
- Analysis shows that if:
The network is not in debt
70% of late payments will be made good
- If in addition we add:
Network credit availability > £1,750
then 86% of late payments will be made good

VARIABLE 1

VARIABLE 2

The Power of Network Analysis in Credit Risk: Credit Cards



Analysis of customer behaviour using Detica NetReveal®

LATE PAYMENTS

- Well-behaved customers don't make any late payments

NETWORK UPLIFT

- However, amongst this group, those that are on networks with others that DO make late payments are **65%** more likely to default



CREDIT UTILISATION

- Well-behaved customers have low credit utilisations

NETWORK UPLIFT

- However, amongst this group, those that are on networks with others that have a HIGH utilisation are **70%** more likely to default



EXCEEDING CREDIT LIMIT

- Well-behaved customers rarely exceed their credit limits

NETWORK UPLIFT

- However, amongst this group, those that are on networks with others that DO exceed their limits regularly are **55%** more likely to default



CASH TRANSACTIONS

- Well-behaved customers rarely take out cash on their cards

NETWORK UPLIFT

- However, amongst this group, those that are on networks with others that regularly take out cash are **60%** more likely to default



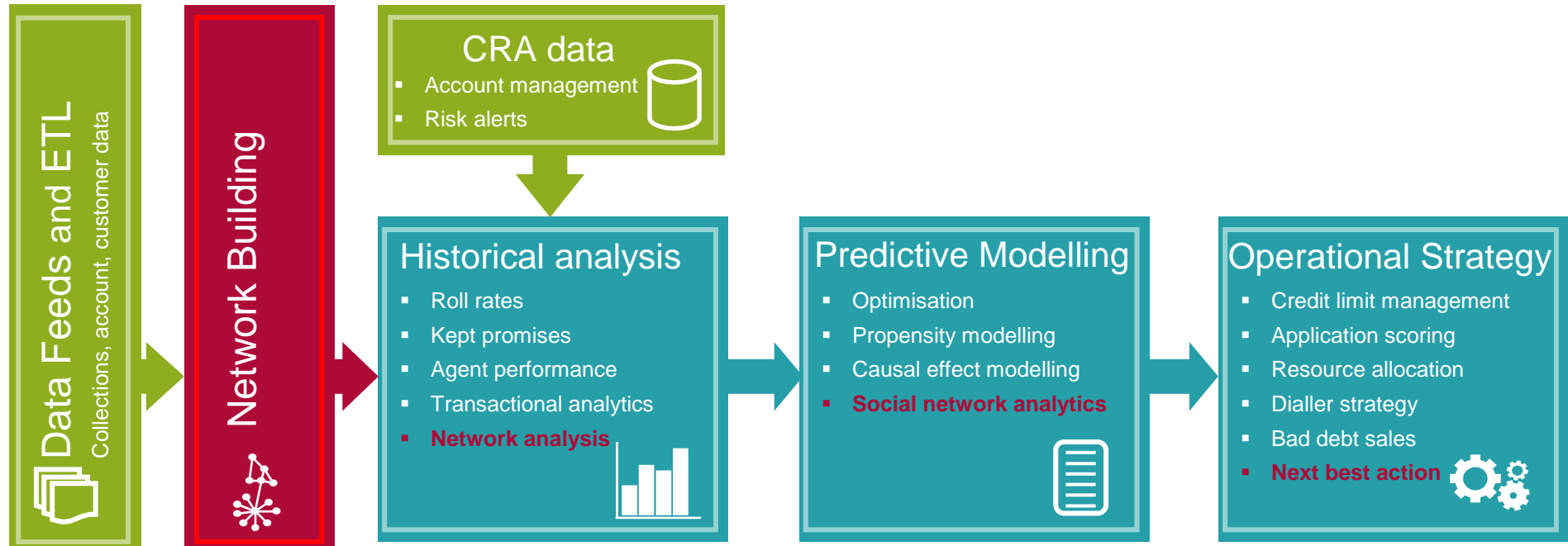
PURE NETWORK PREDICTORS

- Customers on networks with a high number of other customers in collections are **5 times** more likely to default

- Customers on networks with a high delinquency count are **4.5 times** more likely to default



'Best in Class' Social Network Analytics



- **Social network analysis provide:**

- **Single view of customer across all products and brands**
- **The ability to include dependent characteristics**
- **Improved insights into 'thin-file' and new to bank customers**

Thank you



■ Questions?

Contact details

If you have any questions regarding this document or would like to find out more about Detica NetReveal[®], please contact:

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