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Plastic Card Fraud Detection using Peer Group analysis

David Weston, Niall Adams, David Hand, Christopher Whitrow, Piotr Juszczak

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EPSRC Think Crime Initiative

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- EPSRC Think Crime Initiative
- Crime Prevention & Detection
- Funding 12 projects
- Also feasibilty studies and more

Think Crime Project

- Develop Fraud Detection Tools
- Real Data

ThinkCrime Team

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- Members of the team are
  - David Hand
  - Niall Adams
  - Christopher Whitrow
  - Piotr Juszczak
  - David Weston
  - Gordon Blunt
- Collaborating banks
  - Abbey National, Alliance and Leicester, Capital One, Lloyds TSB

Overview

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- Peer Group Analysis
  - Introduction
  - Applied to Time-Aligned Multivariate Continuous Data
  - Applied to Credit Card Transaction Data
- Performance Evaluation
- Experiments & Results
- Conclusions & Current Work

Peer Group Analysis - Introduction

Approaches to Fraud Detection

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- Broadly 2 approaches to statistical fraud detection
- Supervised or Anomaly Detection

Approaches to Fraud Detection

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- Broadly 2 approaches to statistical fraud detection
- Supervised or Anomaly Detection
  - Supervised
    - Historical Instances of Fraud
    - Less likely to falsely flag a transaction as fraudulent
    - Approach Chris is taking

Anomaly Detection

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- Does not use historical Instances of Fraud
- Build a profile of ‘usual’ behaviour
- Significant deviations considered frauds
- More likely to falsely flag a transaction as fraudulent
- Potential to adapt to changing fraud patterns
- Approach Piotr is taking

Peer Group Analysis

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- Similar to anomaly detection methods
- Do not need to build a model of usual behaviour for account holder
- Determine a peer group
- Find other accounts that you expect will behave similarly to the account holder
- Find accounts that have behaved similarly in the past
- Monitor account holder's behaviour with respect to peer group
- Anomalous behaviour, should account holder deviate strongly from peer group

Anomaly Detection to Peer Groups I

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- The weekly amount spent on a credit card for a particular account
- Week 1 to Week n

$$y_1, \ldots, y_{n-1}, y_n$$

- Target Account
- Wish to determine if the amount spent in week n is anomalous

Anomaly Detection based on account profile

Anomaly Detection to Peer Groups II

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Population Normalised Anomaly Detection

$x_{m,1}$	$x_{m,2}$	$\cdots$	$x_{m,n-1}$	$x_{m,n}$
$\vdots$				
$x_{2,1}$	$x_{2,2}$	$\cdots$	$x_{2,n-1}$	$x_{2,n}$
$x_{1,1}$	$x_{1,2}$	$\cdots$	$x_{1,n-1}$	$x_{1,n}$
y_1	y_2	$\cdots$	y_{n-1}	y_n

Anomaly Detection to Peer Groups III

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Sort accounts in order of decreasing similarity, $\pi(i)$

$x_{\pi(m),1}$	$x_{\pi(m),2}$	$\cdots$	$x_{\pi(m),n-1}$	$x_{\pi(m),n}$
$\vdots$				
$x_{\pi(k),1}$	$x_{\pi(k),2}$	$\cdots$	$x_{\pi(k),n-1}$	$x_{\pi(k),n}$
$\vdots$				$\vdots$
$x_{\pi(2),1}$	$x_{\pi(2),2}$	$\cdots$	$x_{\pi(2),n-1}$	$x_{\pi(2),n}$
$x_{\pi(1),1}$	$x_{\pi(1),2}$	$\cdots$	$x_{\pi(1),n-1}$	$x_{\pi(1),n}$
y_1	y_2	$\cdots$	y_{n-1}	y_n

- Peer Group size k

Peer Groups Example

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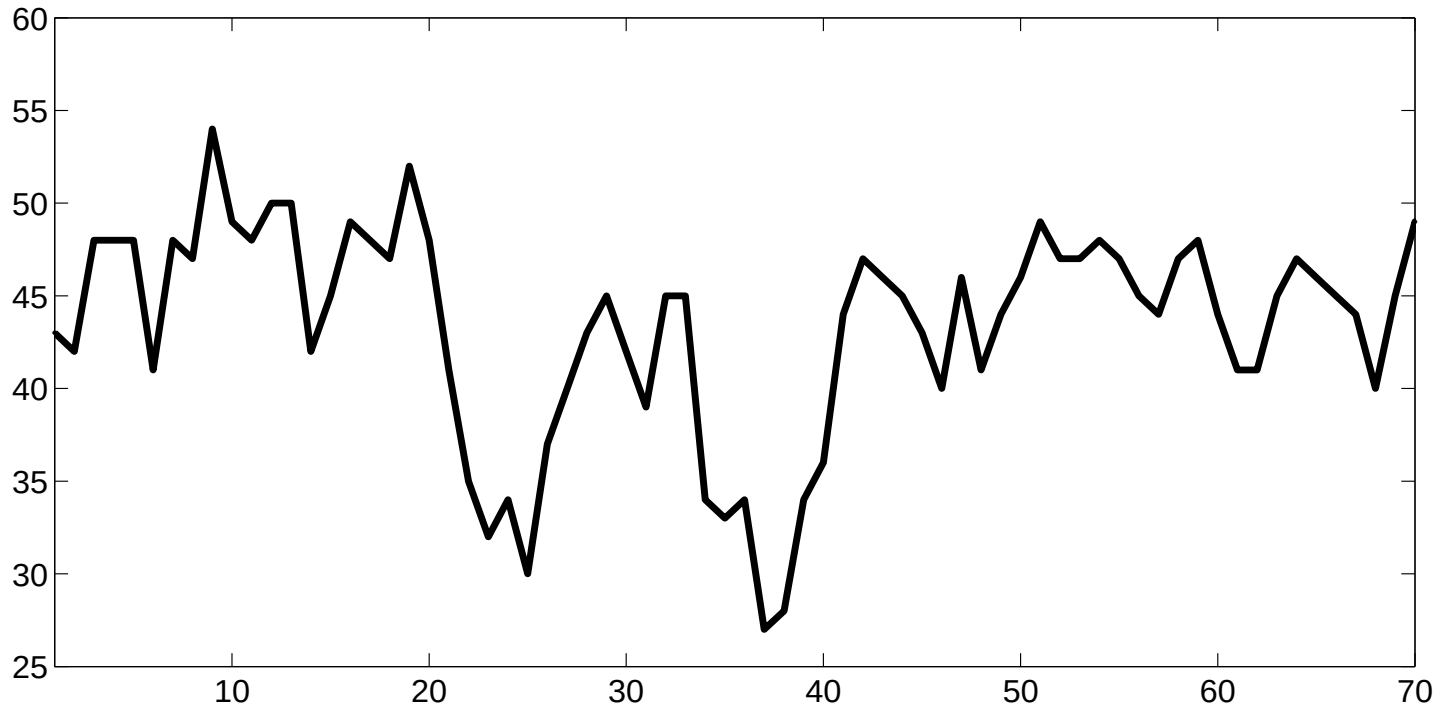

Peer Groups Example

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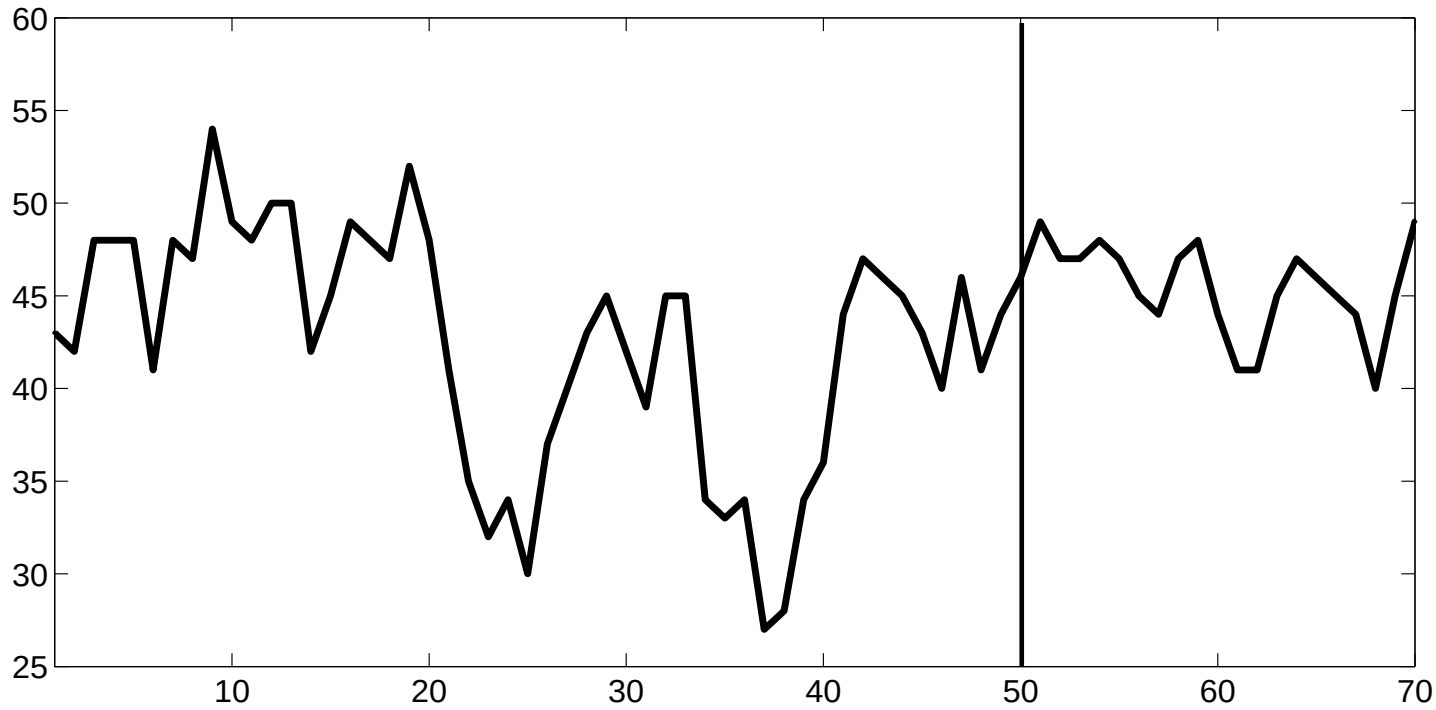

Peer Groups Example

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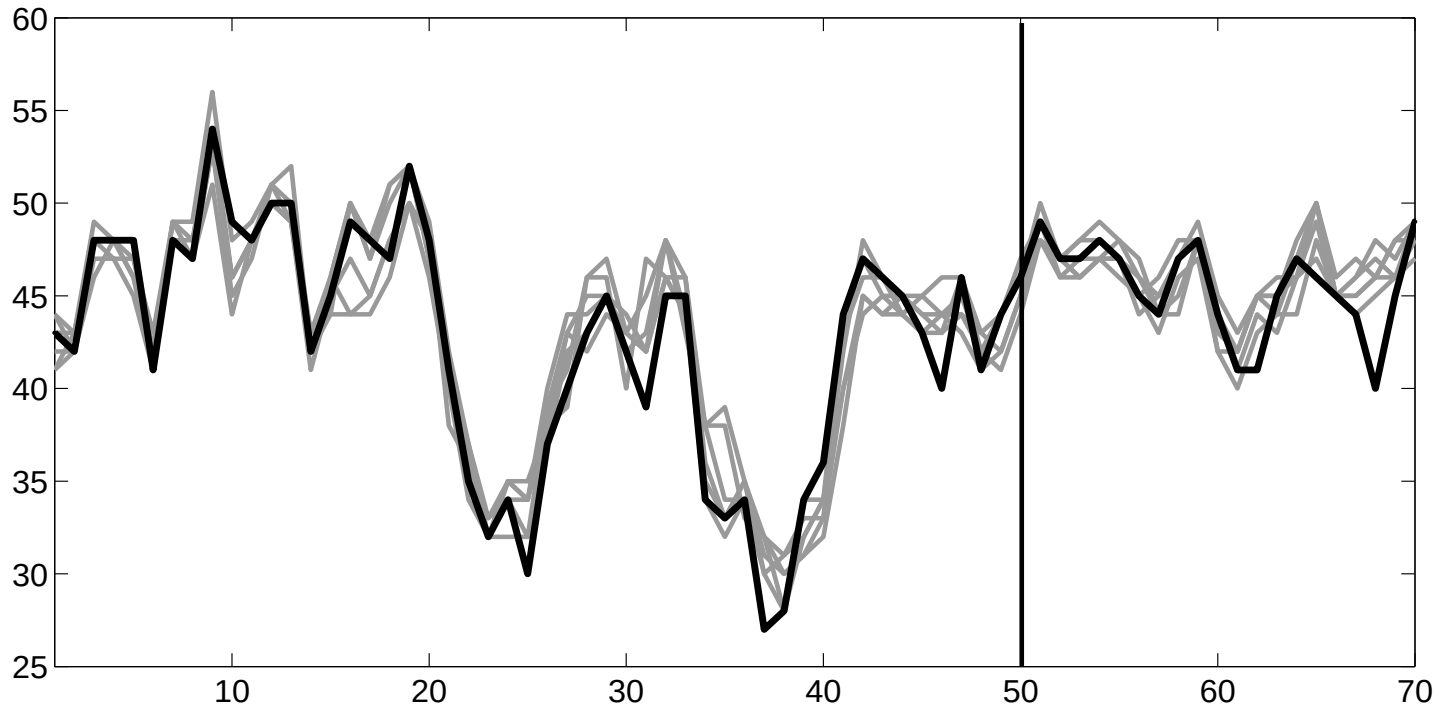

Peer Groups Example

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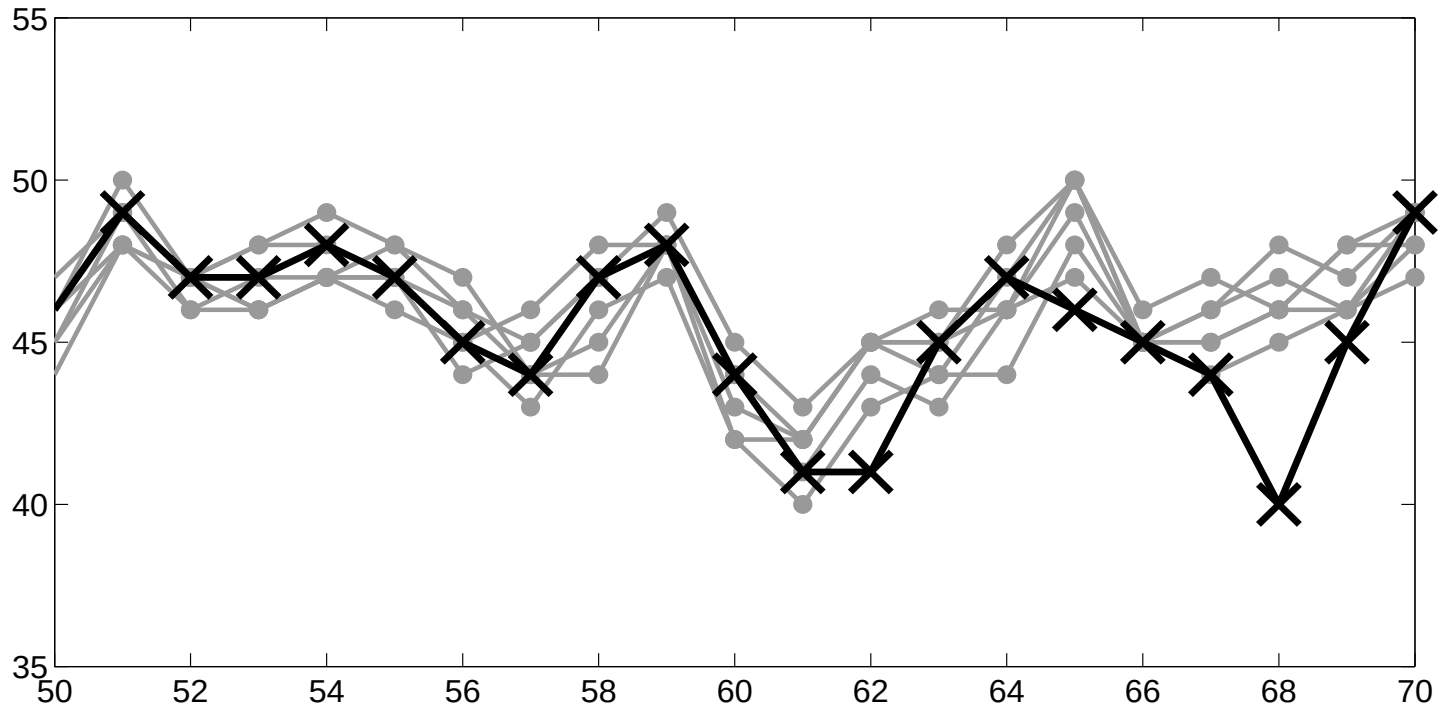

Peer Groups Example

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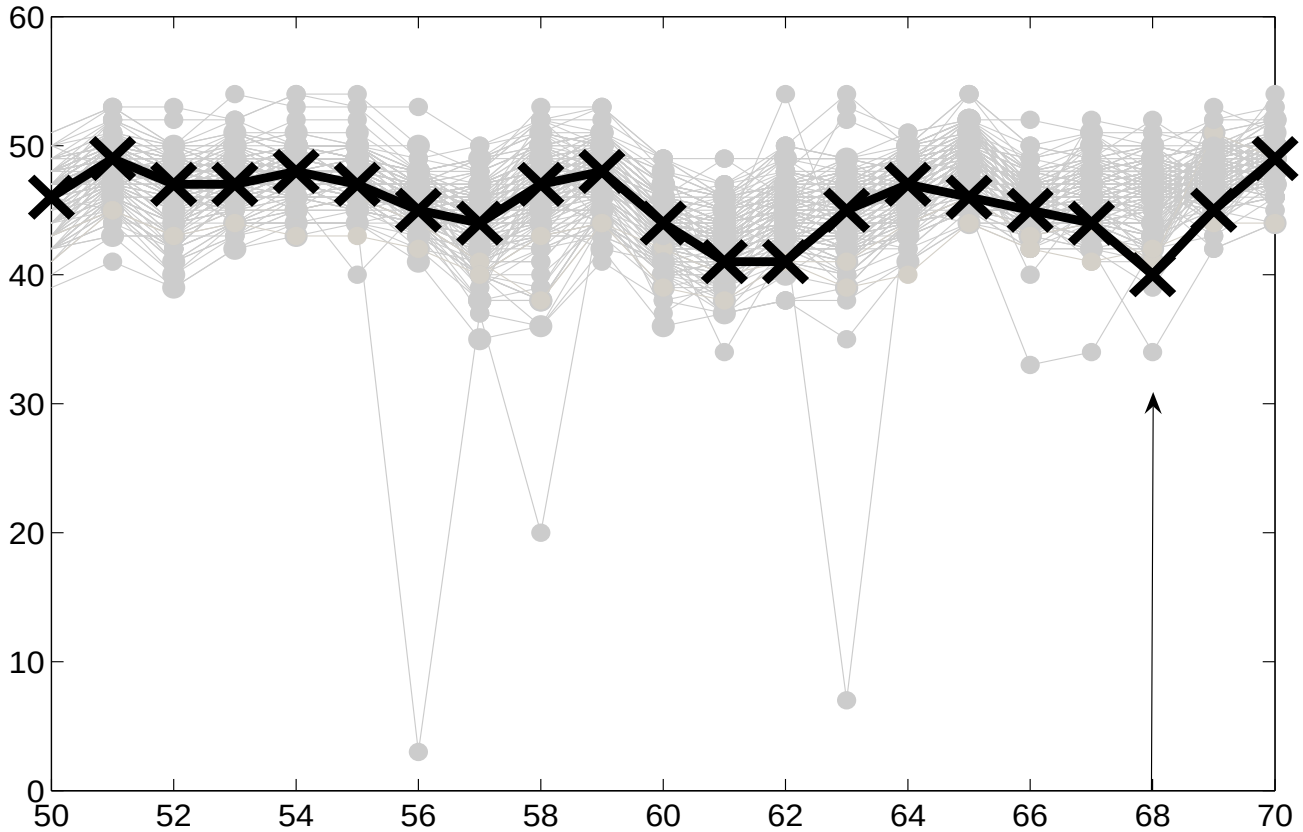

Peer Group Analysis

Detecting Anomalies

- Assuming we already have a peer group set of accounts for our target account.
- y_n is multivariate (column vector) and continuous
- Mahalanobis distance of the target from the mean of its peer group
- μ is mean of $x_{\pi(1),n}, \ldots, x_{\pi(k),n}$
- C is covariance matrix of $x_{\pi(1),n}, \ldots, x_{\pi(k),n}$
- Mahalanobis distance of a target from its peer group
  - $\sqrt{(y_n - \mu)^T C^{-1} (y_n - \mu)}$

Detecting Anomalies

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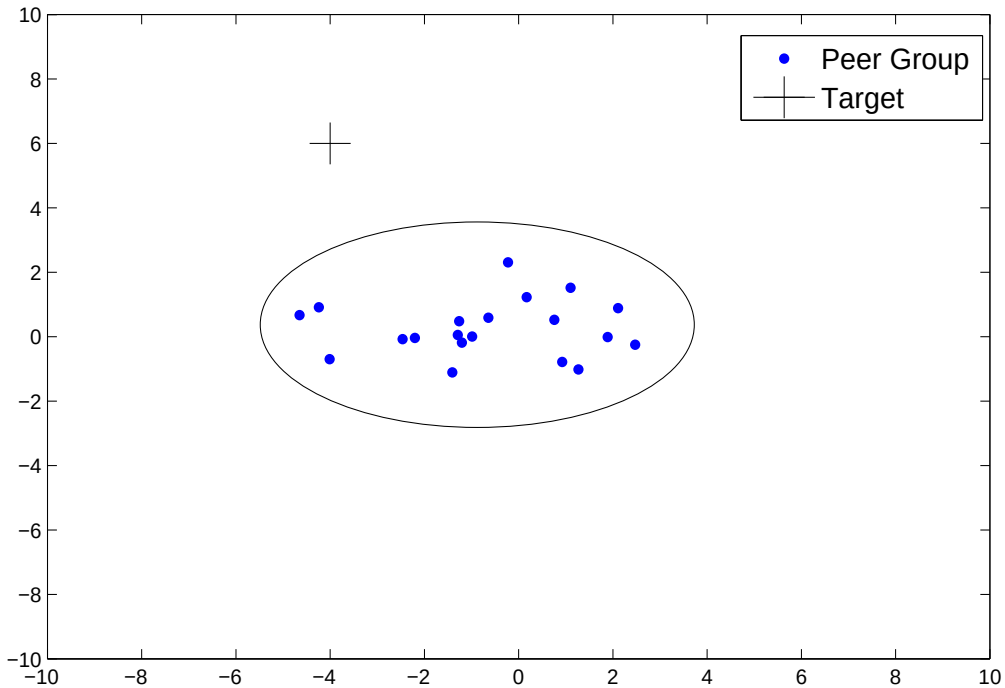
- If the distance is above an externally selected threshold, then we flag the target as fraudulent.



Robustifying Peer Groups

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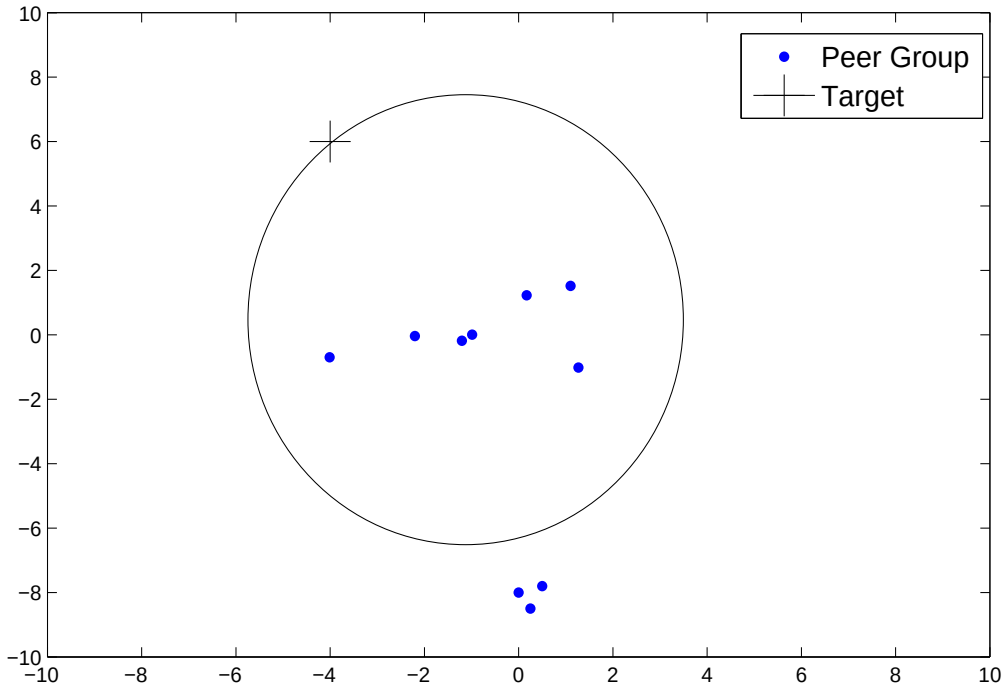
- Peer Group contaminated by fraudulent transactions
- Outlier Masking
- Outlier Swamping



Robustifying Peer Groups

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- Robustify the covariance matrix for the Mahalanobis Distance evaluation
- Use Heuristic

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Robustifying Peer Groups

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- Robustify the covariance matrix for the Mahalanobis Distance evaluation
- Use Heuristic
- An account that has deviated strongly from its peer group at time t should not contribute to any peer group at time t
- For each peer group select 75% closest to their own peer groups

Peer Group Quality

It is not necessarily the case that peer group analysis can be successfully deployed on all accounts.

$$q_t = \frac{1}{k} \sum_{i=1}^{k} (y_t - x_{\pi(i),t})^T (y_t - x_{\pi(i),t}) \quad (1)$$

where T is the transpose. This is a simple measure of how close the members of the peer group are to the target.

- A good quality peer group is one that closely follows the target over time.

$$Q_{s,e} = \frac{1}{t_e - t_s} \sum_{t=t_s}^{t_e} q_t. \quad (2)$$

Whitening the Population

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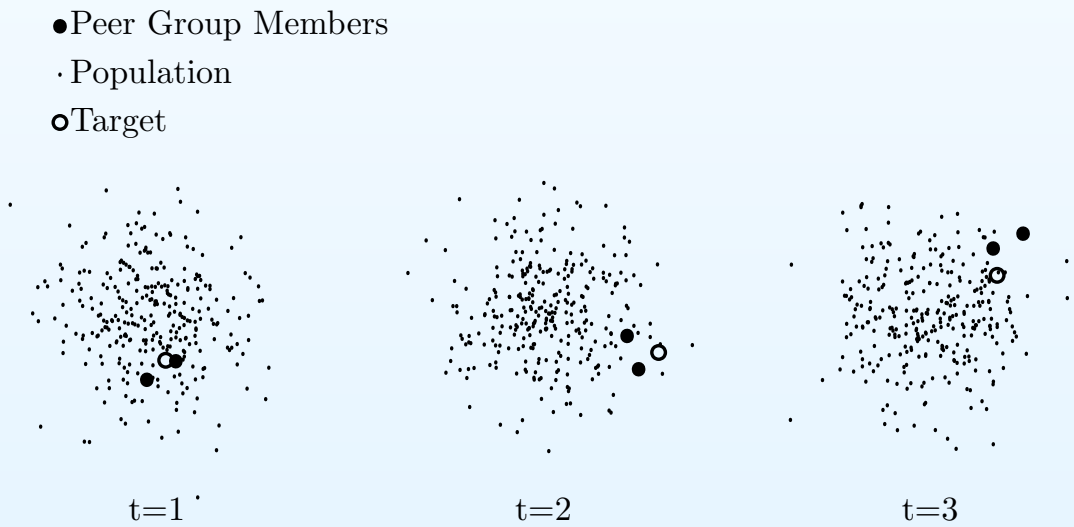
- Whitening the population to make the scatter of a peer group (of size 2) commensurate across time
- The smaller the value of $Q_{s,e}$ the better the peer group tracks the target over time.



Building Peer Groups

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- Possible to know apriori the peer group membership
- Employee fraud detection, people with the same job description can be naturally grouped together.
- IBM FAMS. Health care fraud. Geography, speciality
- Infer peer group membership from the time series itself
- Measuring similarity of time series

Applying Peer Group Analysis

Time Alignment & Feature Extraction

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- Accounts' transactions are asynchronous data streams
- Synchronise account time series by extracting features from the data streams at regular time intervals
- $M(s, e, A)$ summarise transactions of account A occurring from day s to day e inclusive
  - Mean amount spent
  - Number of transactions
  - Entropy of Merchant Category Groups
    - 16 Groups +1 for ATMs
- Returns 1 point in 3 dimensional space

Time Alignment & Feature Extraction

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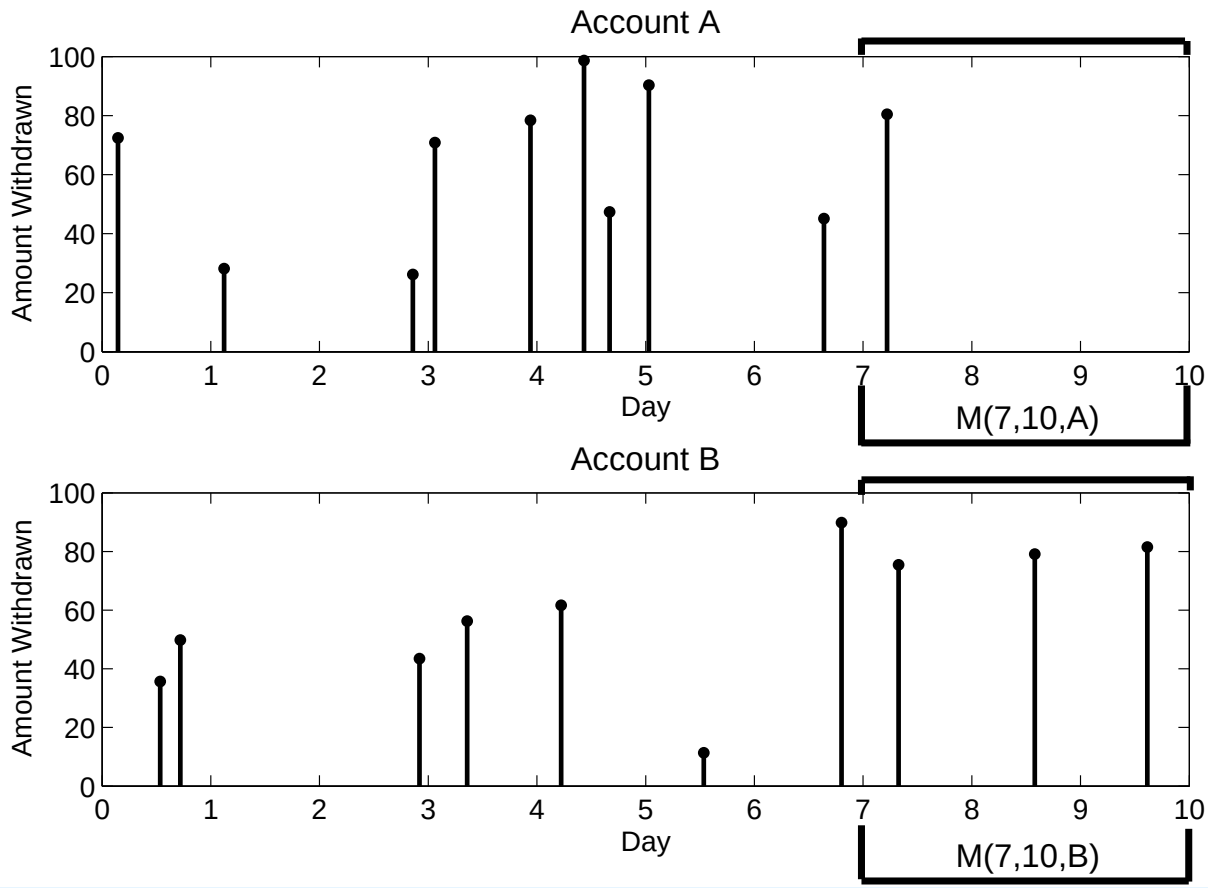

Outlier Detection from Peer Groups

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- Once a day at midnight
- Summary statistic for day t, behaviour of the past d days $M(t-d+1, t, A)$
- Smaller d, the more sensitive to new transactions
- Mahalanobis distance in 3 dimensional space

Active and Inactive Accounts

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- Account inactive on day t if it has not performed any transactions on that day
- Do not test for outlierness for inactive accounts
- Unusually long periods of inactivity will not be considered fraudulent

Active and Inactive Accounts

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- Account inactive on day t if it has not performed any transactions on that day
- Do not test for outlierness for inactive accounts
- Unusually long periods of inactivity will not be considered fraudulent
- Account not active over entire summary statistic window
- Active peer group members. Closest k accounts that are active on at least one day of the summary statistic window

Building Peer Groups

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- Subdivide training data into n non-overlapping windows
  - $M(1, \frac{L}{n}, A), \ldots, M((n-1)\frac{L}{n} + 1, L, A)$
- Point in $3n$ dimensional space
- Complication, potential for bias
- Standardise each window by whitening

Building Peer Groups

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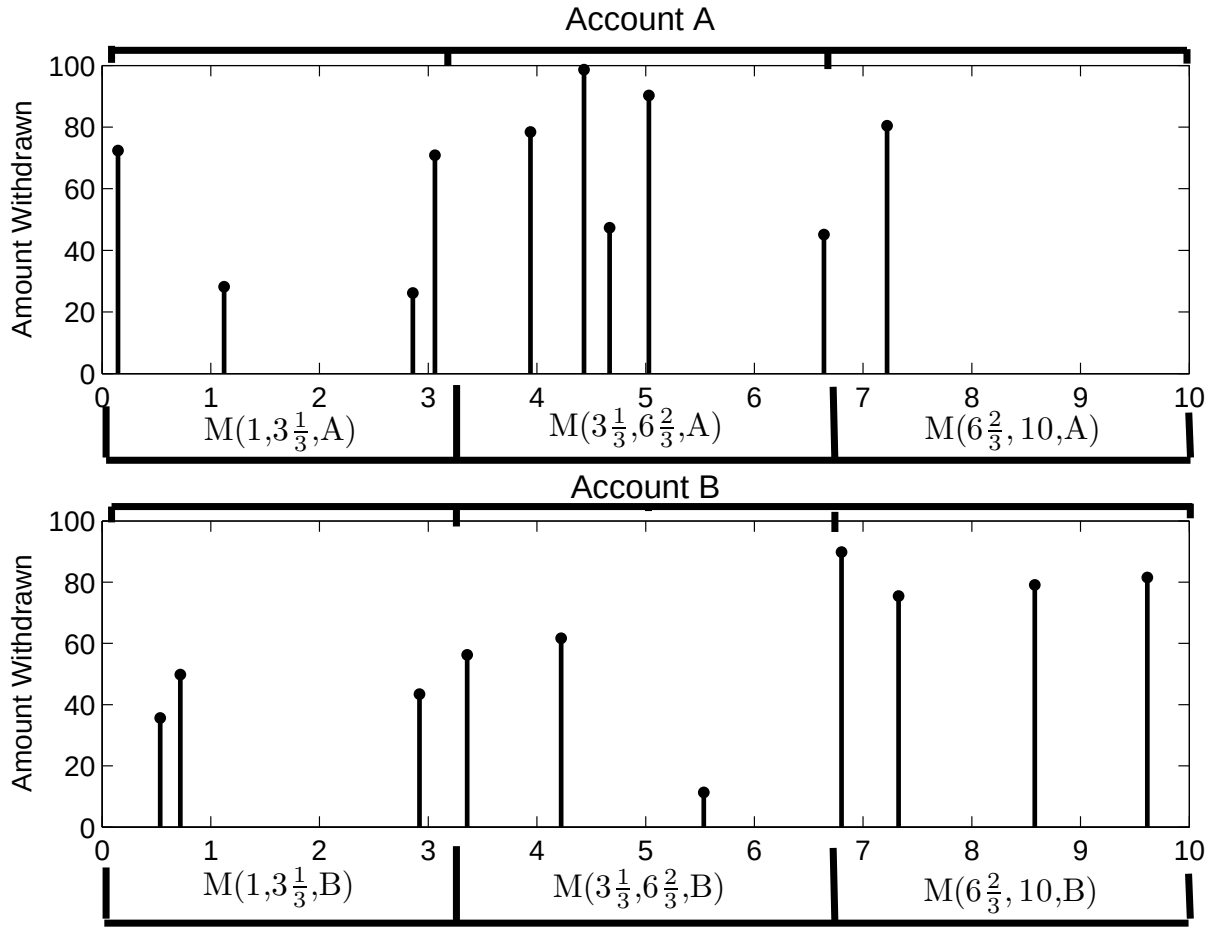

Building Peer Groups

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- Find k nearest neighbours
- Large number of accounts
- Accounts that have high volume of transactions unlikely to be tracked by accounts with low volume
- First sort by number of transactions in training data

Performance Evaluation

Performance Criteria

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- Reduce total amount lost to fraud
- Reduce number of fraudulent transactions
- Reduce the time between fraud starting and fraud detection
- Reduce the number of account holders affected by flagging legitimate transactions as fraud
- Number of possible performance metrics

Performance Metric

- If an account has been flagged as containing fraudulent transactions. The card issuer would need to investigate this account.
- minimise the amount of fraud given the number of investigations the card company can make

Performance Curve

- x-axis number of fraudulent accounts missed as a proportion of the number of fraudulent accounts
- y-axis number of fraud flags raised as a proportion of the number of accounts
- Different to ROC curve. The smaller the area under the curve the better the performance.
- Random classification is represented by a diagonal line from the top left to the bottom right.

Performance Curve

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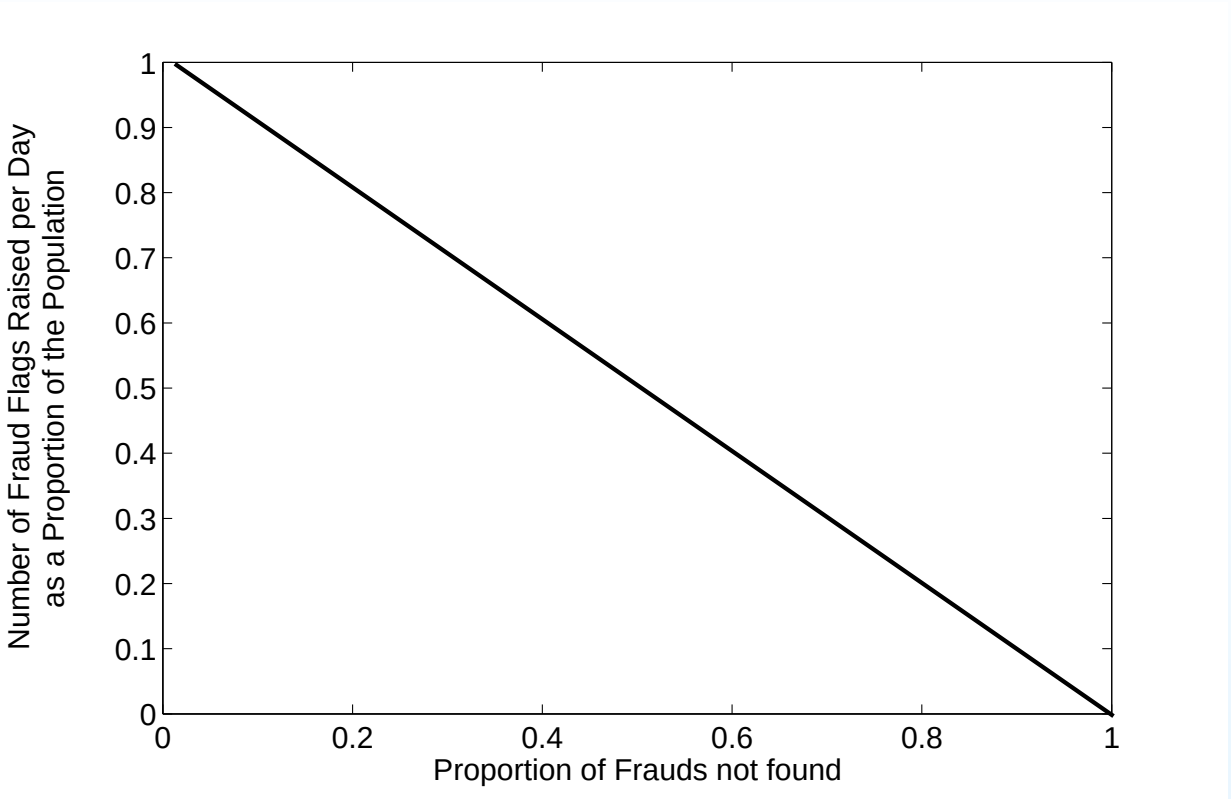

- The lower the curve the better the performance.
- Twice Area under Curve [0,1], smaller the area the better the performance

Average Performance Curve

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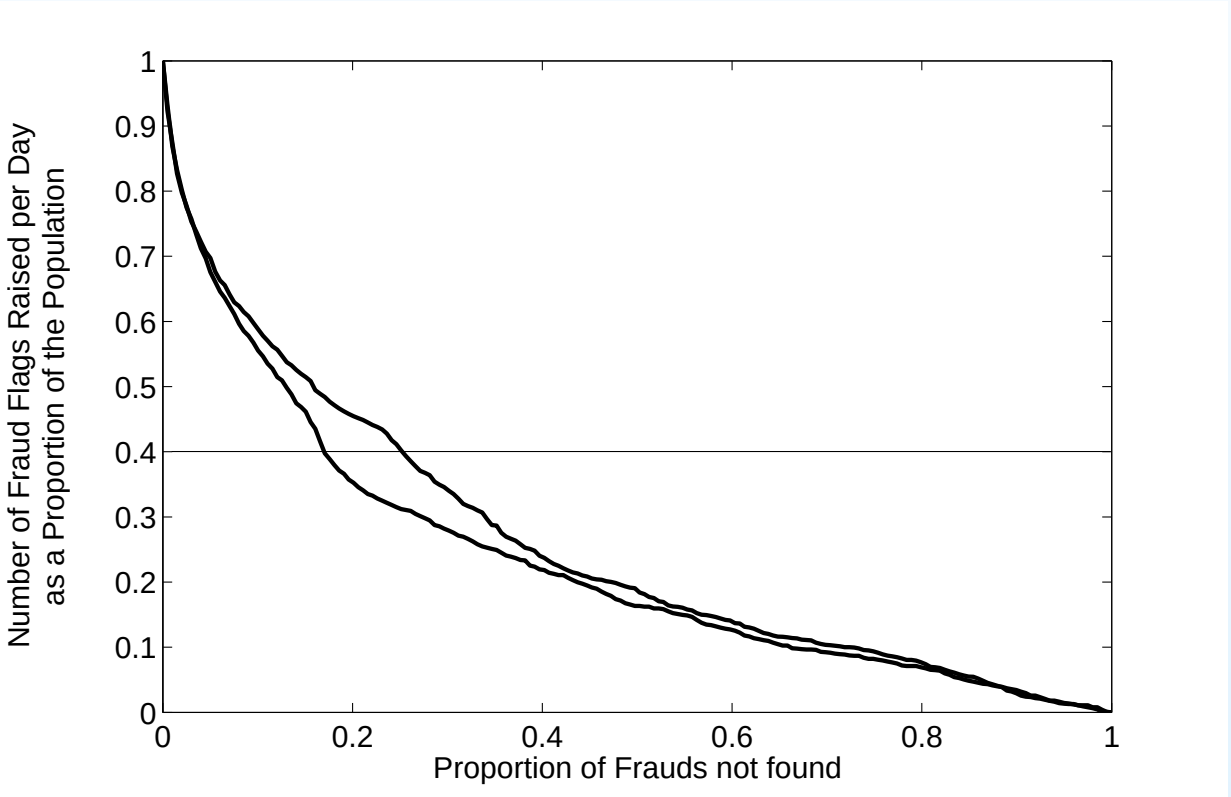
- Produce one curve for each day
- Take the average of the curves.
- For a given proportion of fraud flags raised



Experiments & Results

Experiments

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Data

- 4 months of data
- Accounts with > 80 transactions and fraud free for first 3 months.
- About 4000 accounts 6% defrauded in final month
- Performed Peer Group Analysis once a day for the remaining month

Parameters

- Peer Group building 8 segments
- Summary Statistic window size 7 days
- Active Peer Group Size 100
- Robustifying Peer Groups not used

Varying Length of Summary Statistic Window

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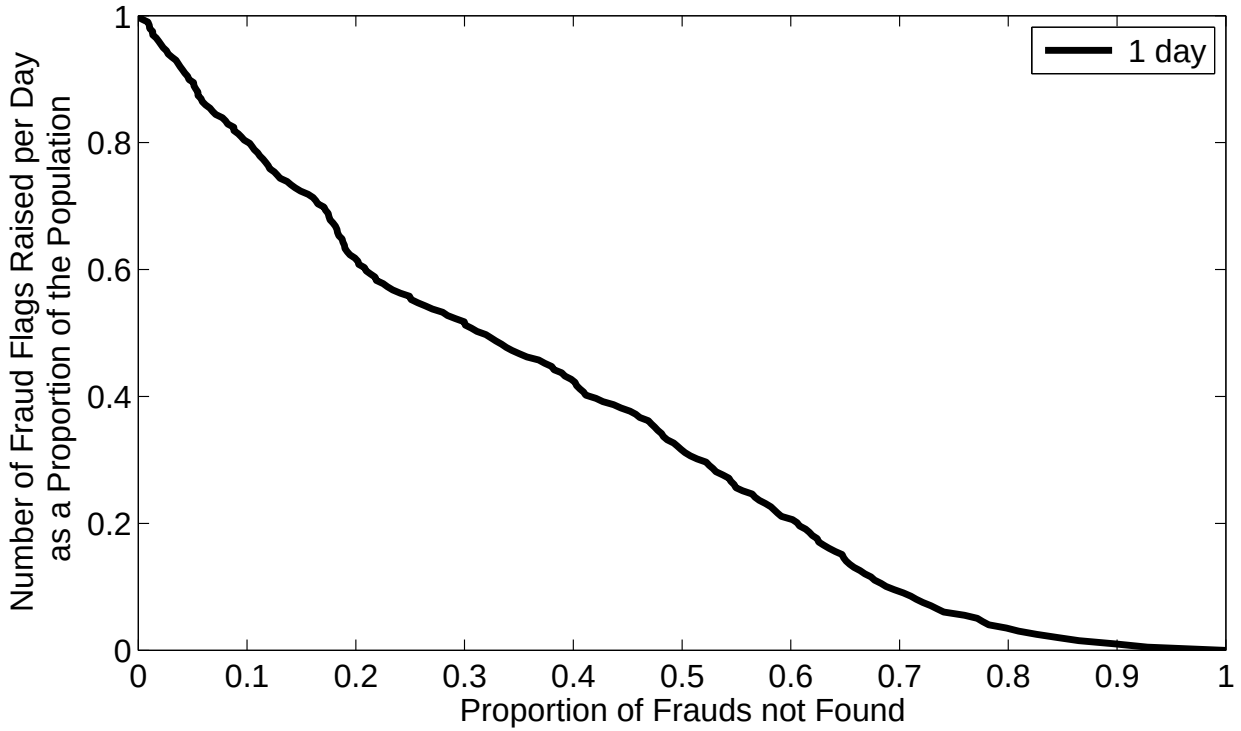

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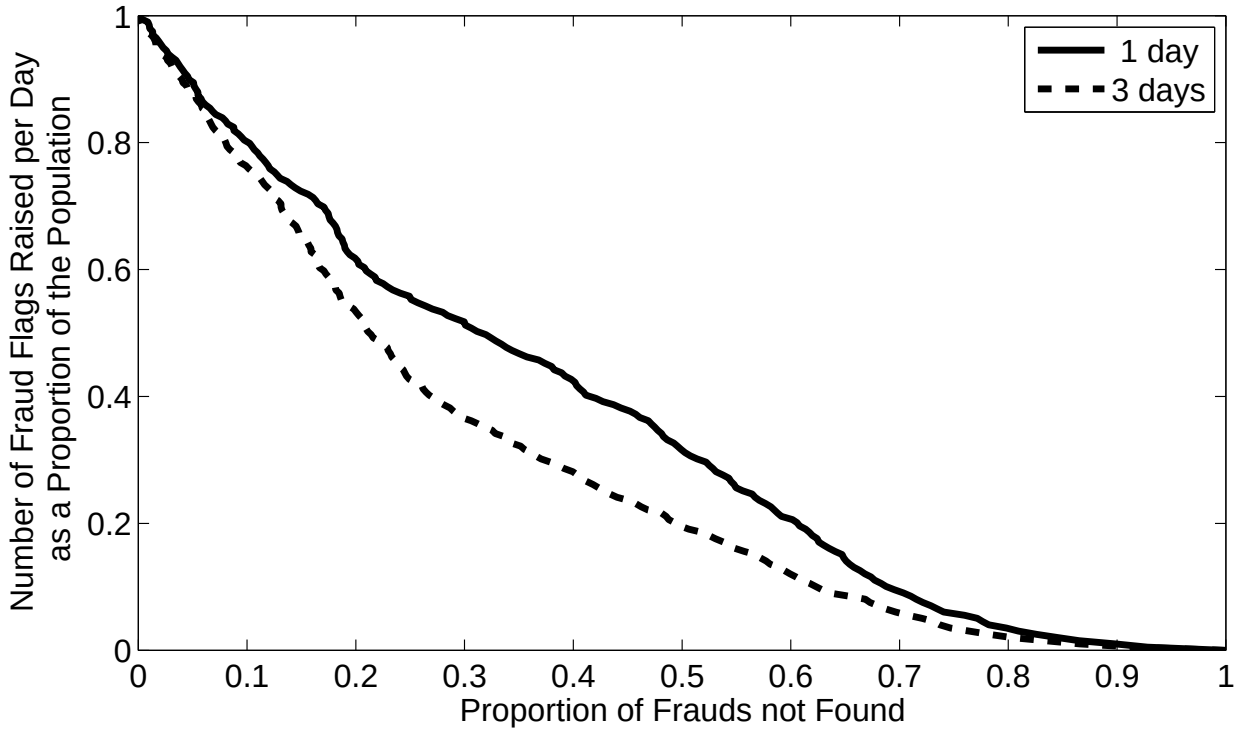

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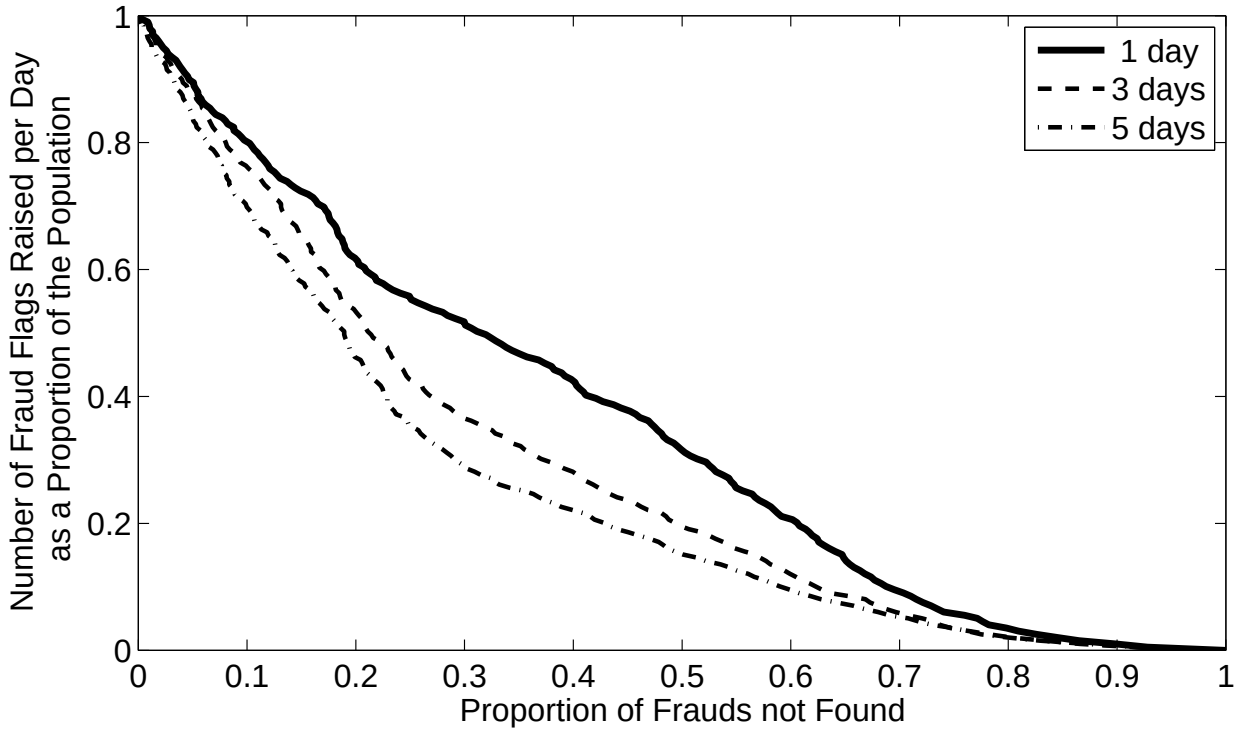

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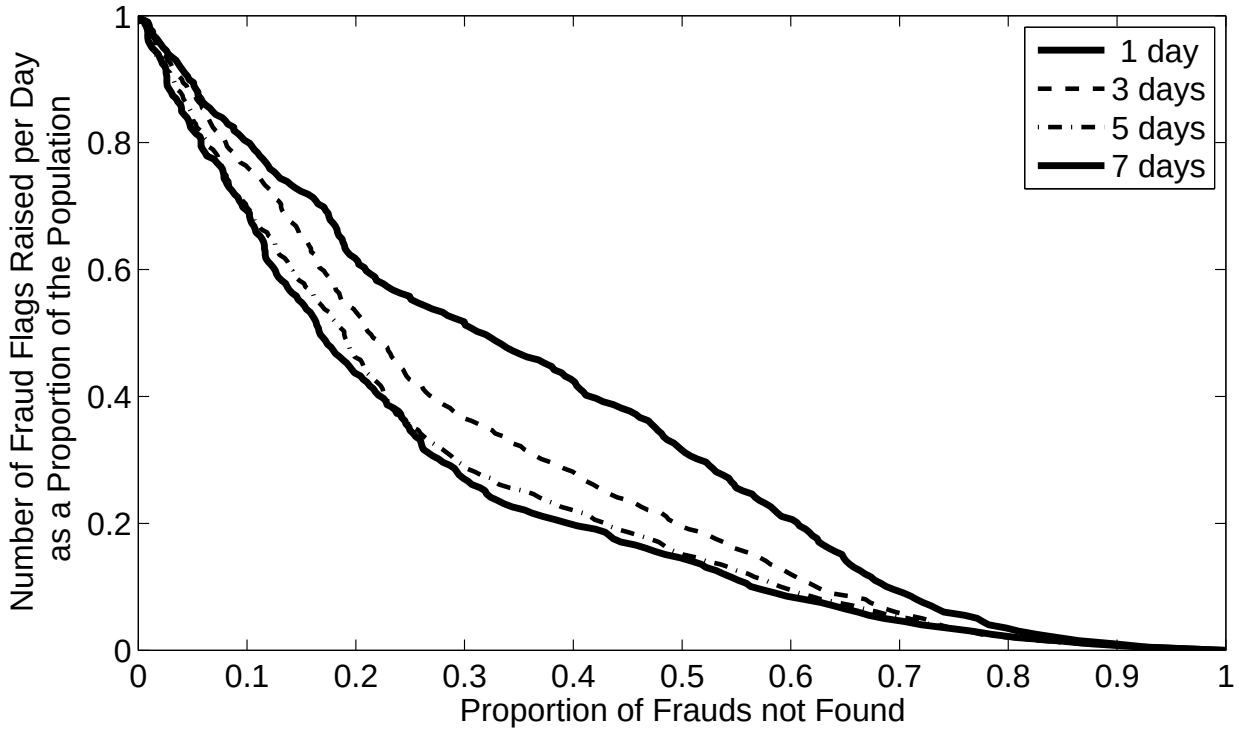

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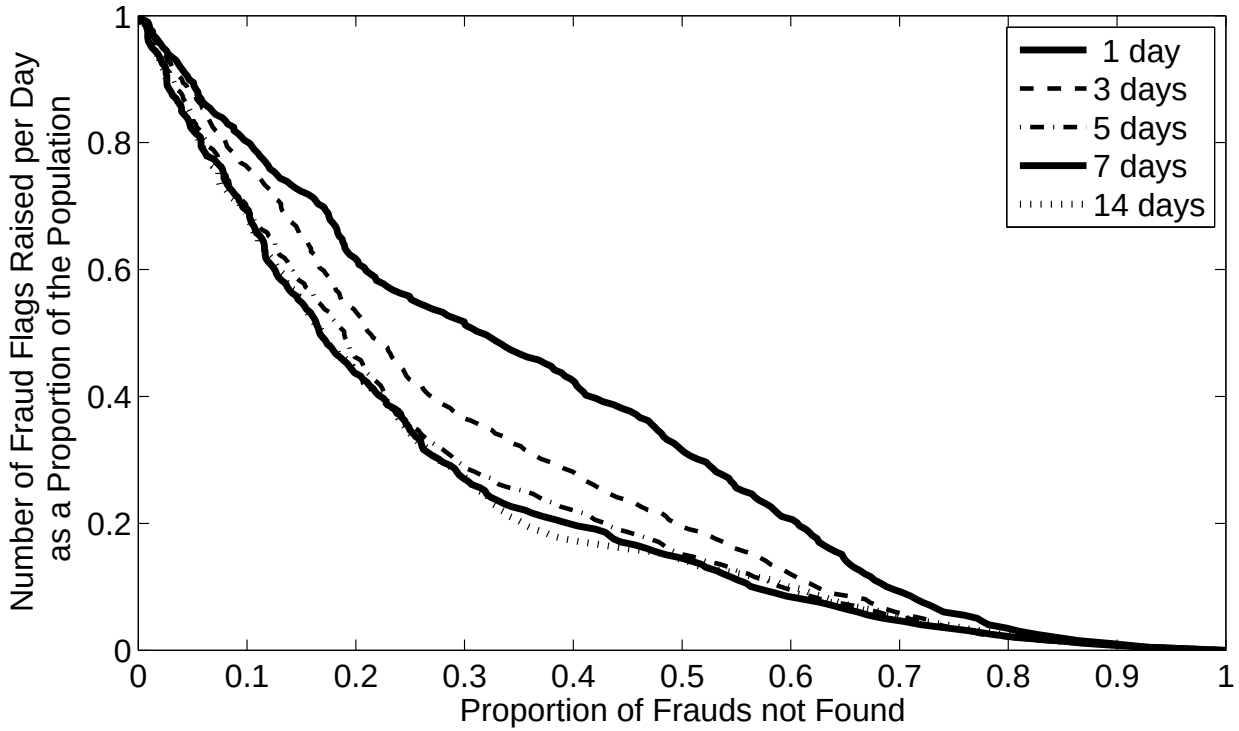

Global Outlier Detector

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- Is peer group analysis doing nothing more than finding outliers to the population?
- Special case, use largest possible peer group
- All accounts apart from target account
- Subtract Performance Curve for Peer Group from Global.
- Values less than zero imply Peer Group method is performing better.

Peer Groups Performance

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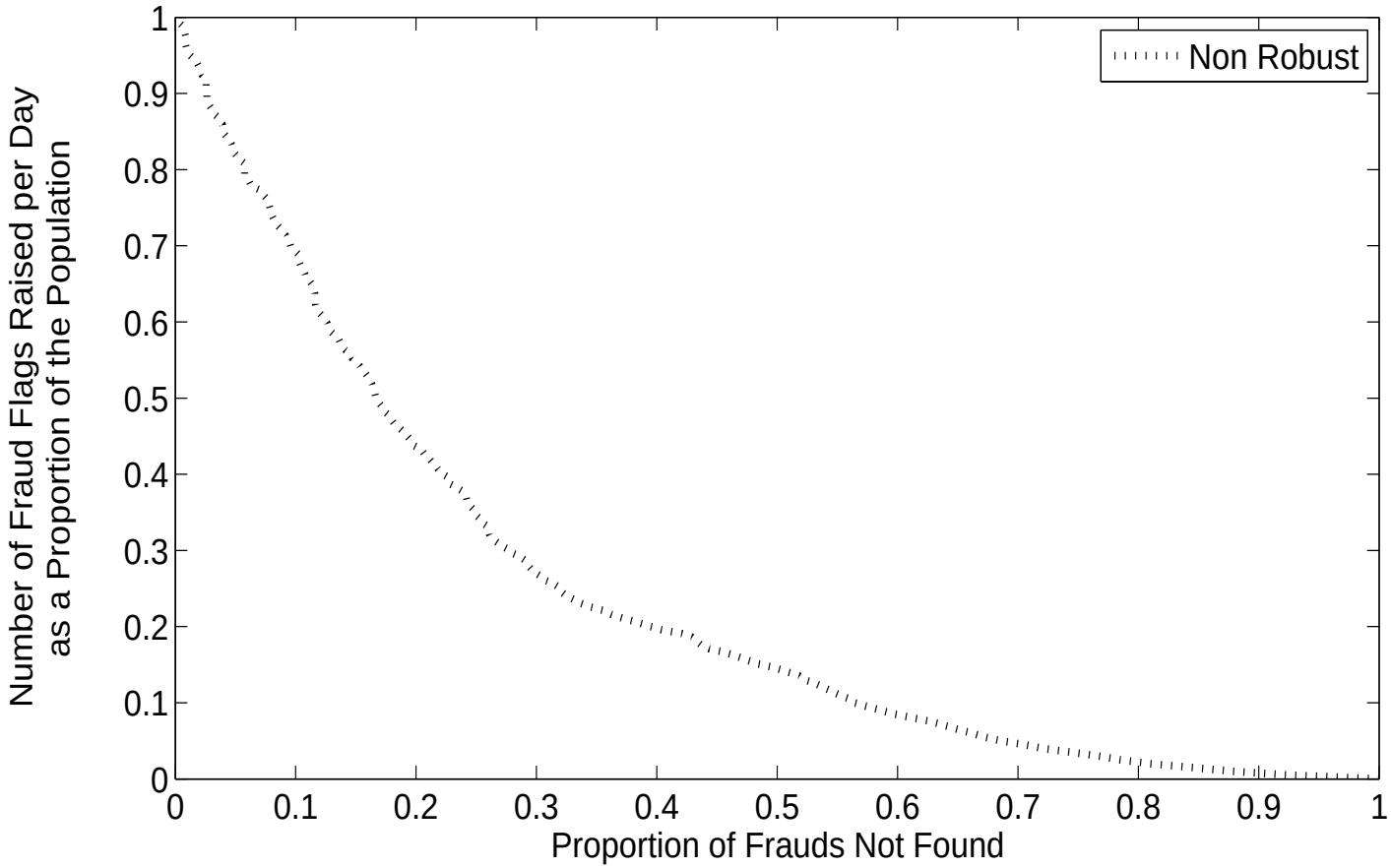

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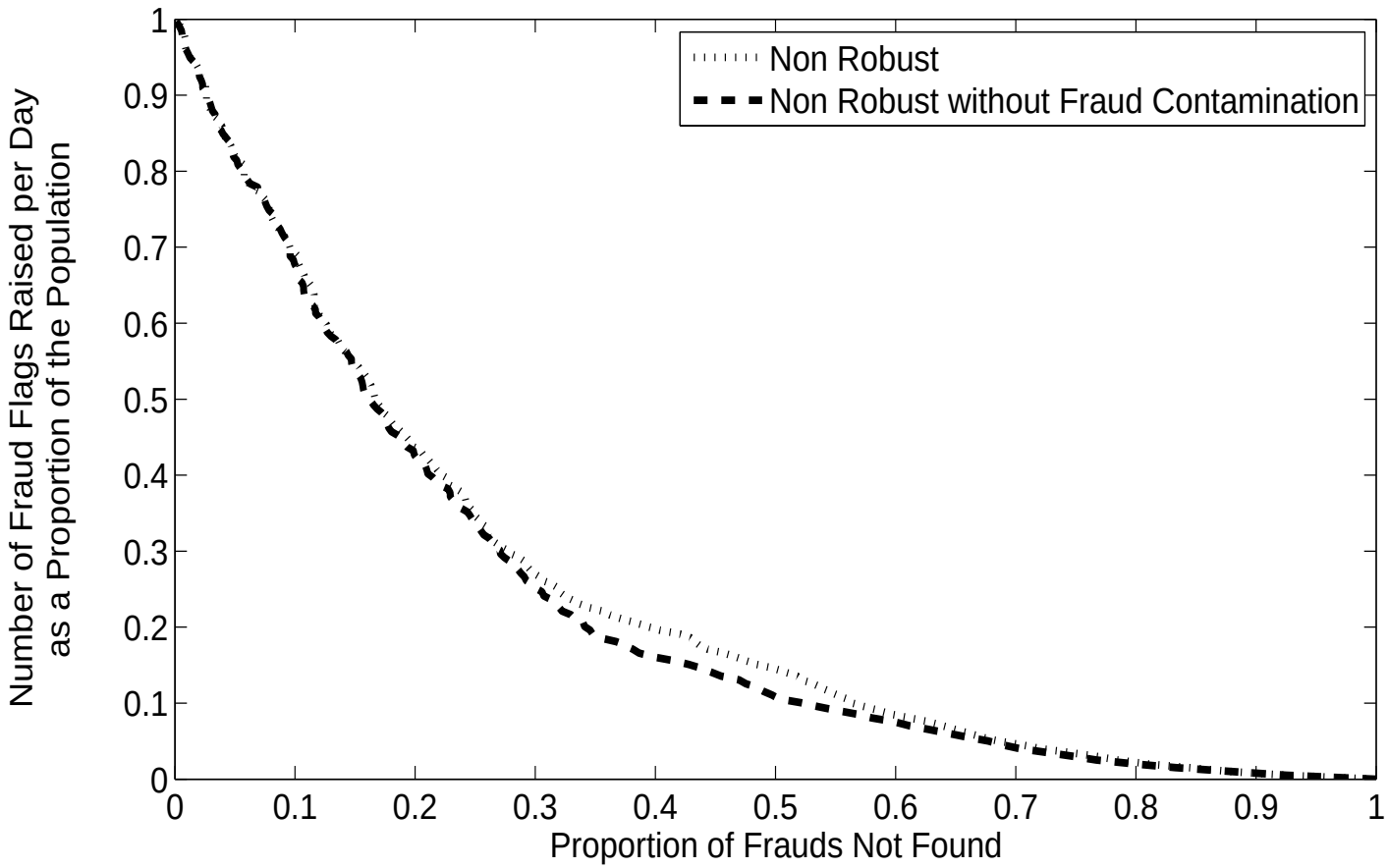

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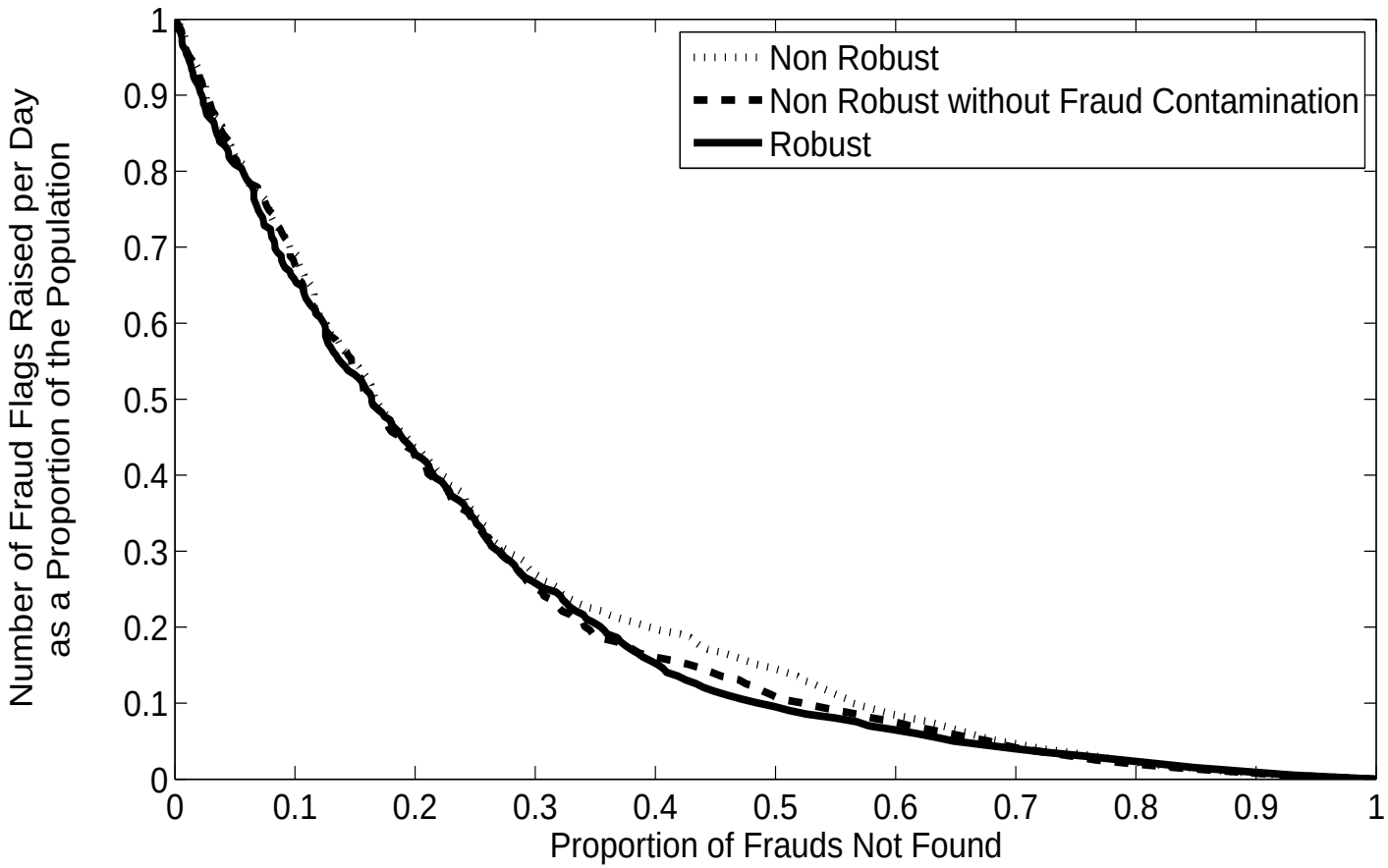

Peer Groups Performance

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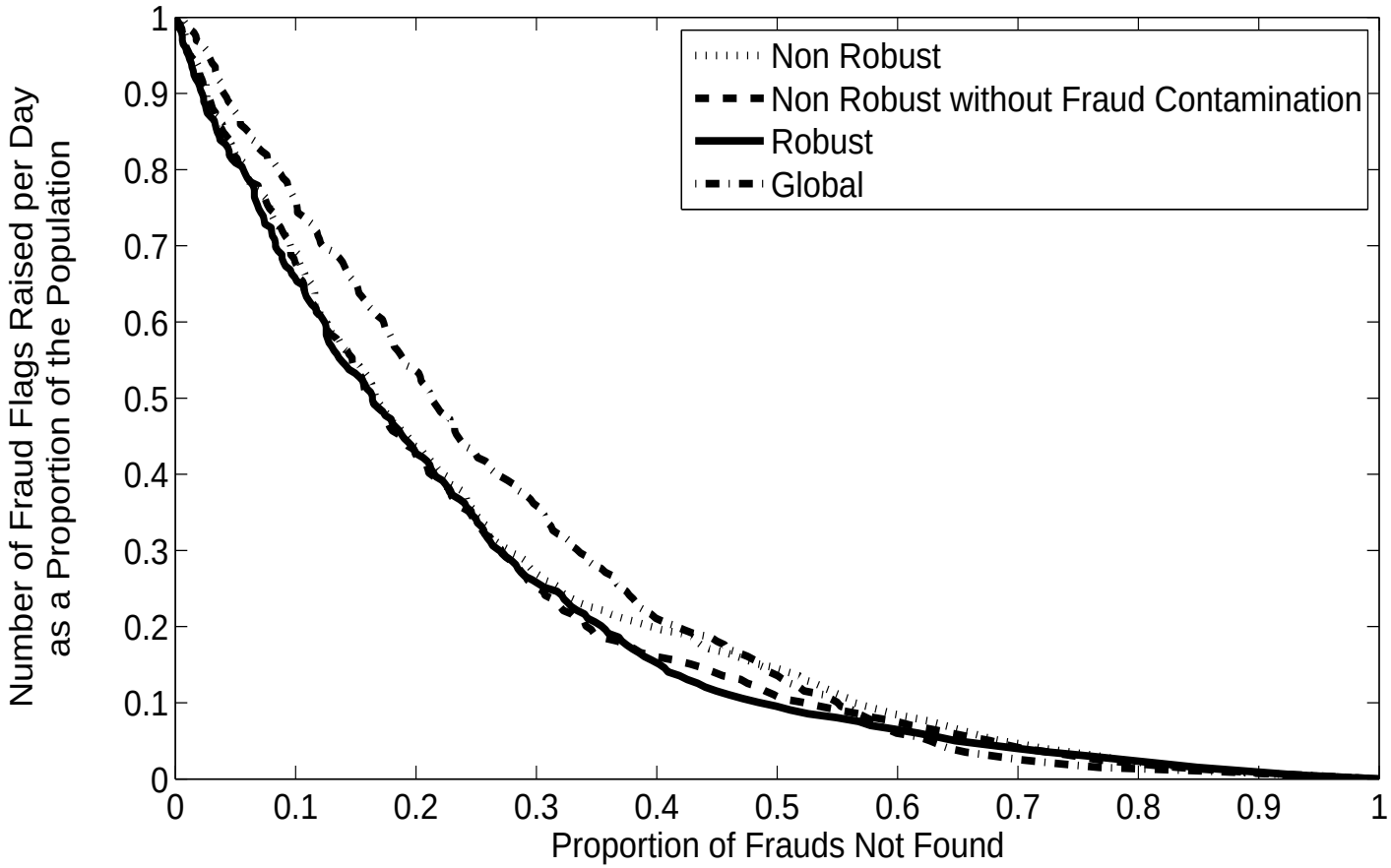

Peer Groups Versus Global Outlier Detector

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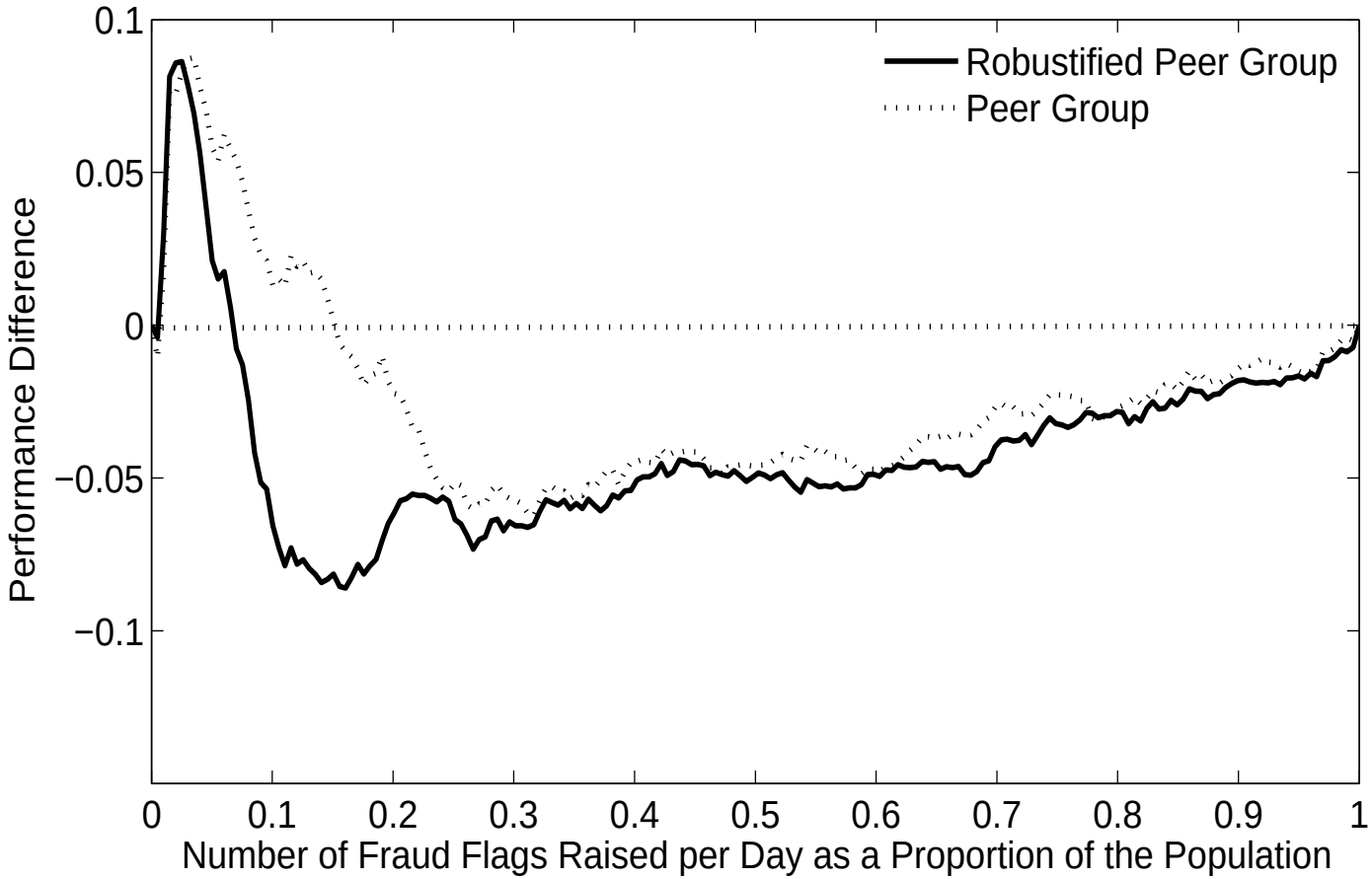
Performance of the peer group analysis compared with global population outlier detector.



Peer Groups Versus Global Outlier Detector

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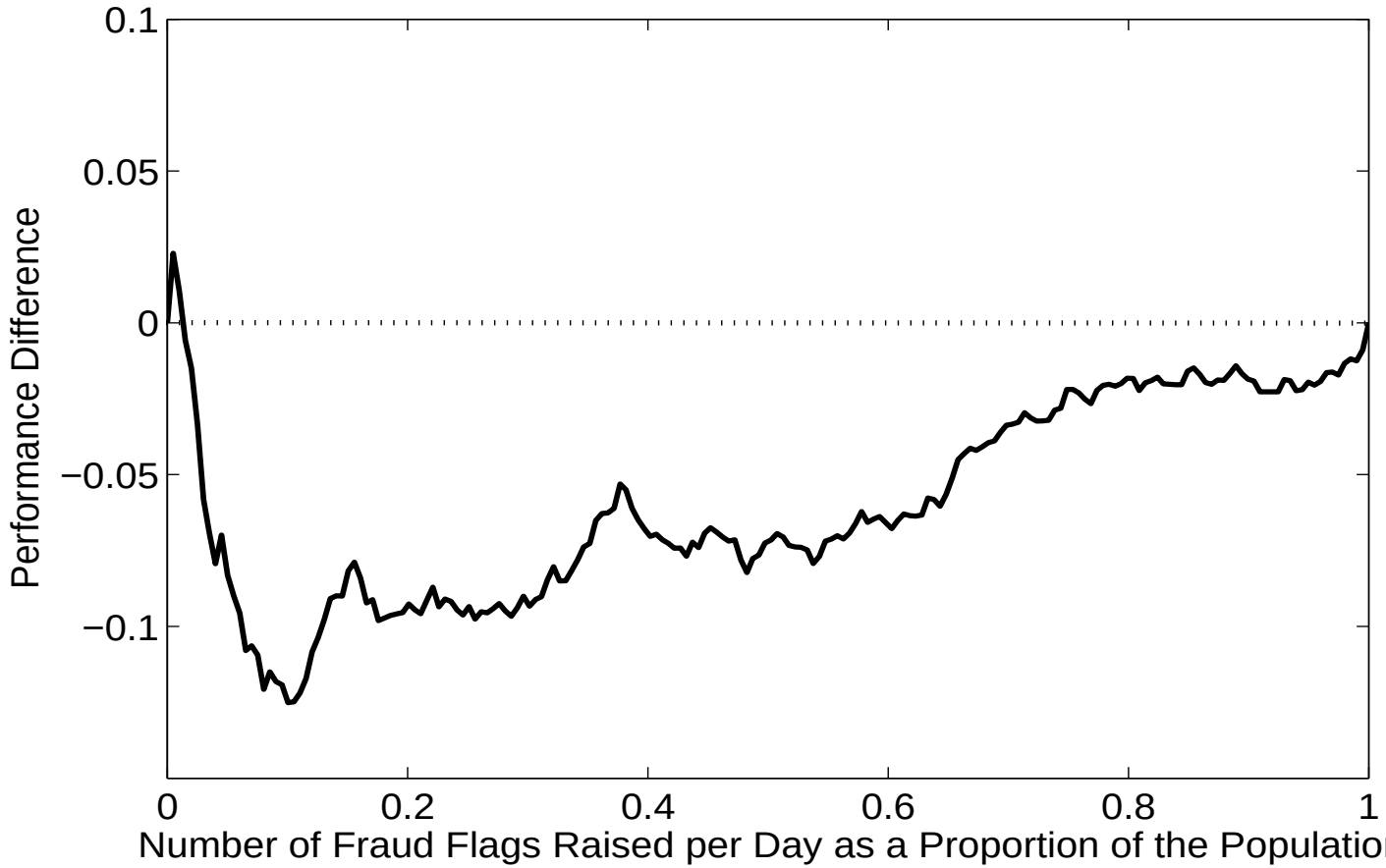
Performance of the robustified peer group analysis compared with global population outlier detector on screened data.



Conclusions & Current Work

Conclusions

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- We have demonstrated there exist credit card transaction accounts that evolve sufficiently closely to enable fraudulent behaviour to be detected.
- Finding frauds that are not global outliers to the population.

Current work

- Combining Methods

1 Day Symposium, 23rd November 2007

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Statistical and machine learning approaches to detecting fraud and predicting consumer behaviour

- Competing Risks in Retail Finance, *Crowder MJ*
- Event History Analysis for Debt Collection Portfolios, *Zhou F, Hand DJ, Heard NA*
- A dynamic scorecard for monitoring baseline performance with application to tracking a mortgage portfolio, *Whittaker J, Whitehead C, Somers M*
- Estimating the iceberg: how much fraud is there in the UK? *Blunt G, Hand DJ*
- Evaluating Fraud Detection Systems, *Hand DJ*
- Transaction Aggregation: A Winning Strategy vs. Fraud? *Whitrow C, Weston D, Juszczak P, Hand DJ, Adams N*
- Detecting Plastic Card Fraud using Peer Group Analysis, *Weston D, Whitrow C, Juszczak P, Hand DJ, Adams N*
- Behavioural finance as a multi-instance learning problem,*Juszczak P, Hand DJ*