Mining personal banking data to detect fraud

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My research group:

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Three parts:

I: Introduction

II: How big is fraud?

III: Fraud in banking

I: Introduction

What is fraud?

Criminal deception; the use of false representations to gain an unjust advantage

Concise Oxford Dictionary

Older than humanity itself.

- even animals are known to try to deceive others
- camouflage

The *economic imperative*

1) Not worth spending $200m to stop $20m fraud

e.g. Letter from London Times, August 13, 2007

"Sir, I was recently the victim of an internet fraud. The sum involved was several hundred pounds. My local police refused to investigate, stating that their policy was to investigate only for sums over £5000."

2) The Pareto principle

the first 50% of fraud is easy to stop; next 25% takes the same effort; next 12.5% takes the same effort; ...

3) Resources available for fraud detection are always limited

- in the UK around 3% of police resources go on fraud
- this will not significantly increase

II: How big is fraud?

e.g. In the USA

"Participants in our study estimate U.S. organizations lose 5% of their annual revenues to fraud.

Applied to the estimated 2006 United States Gross Domestic Product, this 5% figure would translate to approximately $652 billion in fraud losses."

Association of Certified Fraud Examiners

Cost of fraud

= immediate direct loss due to fraud

+ cost of fraud prevention and detection

+ cost of lost business (when replacing card)

+ opportunity cost of fraud prevention/detection

+ deterrent effect on spread of e-commerce

Does this matter to you?

Identity theft

Fraudsters uses your name and identifying information to

- obtain credit cards
- phone and telecoms
- bank loans
- mortgages
- rent appartments
- if stopped for speeding, or charged with crime, etc.

leaving you with the debts and problems

Identity theft in the USA:

10 million victims in 2003
Average individual loss ≈ $5,000
Total loss to individuals and businesses in 2003 ≈ $50 bn
(Federal Trade Commission survey)

+ time to sort out

⇒ Americans spent nearly 300 million hours resolving ID theft issues in 2003

Typically takes up to two years to sort out the problems, reinstate credit rating, reputation, etc, after detection

III: Fraud in banking

Banking fraud has many aspects

My main focus here is ***retail*** or ***consumer*** banking fraud

- personal banking
- credit cards
- home mortgages
- car finance
- personal loans
- current accounts
- savings accounts

Nature of plastic card fraud data

- *many transactions - billions - algorithms must be efficient*
- *mixed variable types (generally not text, image)*
- *large number of variables*
- *incomprehensible variables, irrelevant variables*
- *different misclassification costs*
- *many ways of committing fraud*
- *unbalanced class sizes (c. 0.1% transactions fraudulent)*
- *delay in labelling*
- *mislabelled classes*
- *random transaction arrival times*
- *(reactive) population drift*

Credit card data:

Transaction ID
Transaction type
Date and time of transaction (to nearest second)
Amount
Currency
Local currency amount
Merchant category
Card issuer ID
ATM ID
POS type
Cheque account prefix
Savings account prefix

Acquiring institution ID
Transaction authorisation code
Online authorisation performed
New card
Transaction exceeds floor limit
Number of times chip has been accessed
Merchant city name
Chip terminal capability
Chip card verification result
. . . . . .

A commercial example of fraud data

US Patent 5,819,226 (see USPTO website) on *Fraud detection and modeling*, (HNC Software in 1992) lists the following variables:

Customer usage pattern profiles representing time-of-day and day-of-week profiles;
Expiration date for the credit card;
Dollar amount spent in each SIC (Standard Industrial Classification) merchant group category during the current day;
Percentage of dollars spent by a customer in each SIC merchant group category during the current day;
Number of transactions in each SIC merchant group category during the current day;
Percentage of number of transactions in each SIC merchant group category during the current day;
Categorization of SIC merchant group categories by fraud rate (high, medium, or low risk);
Categorization of SIC merchant group categories by customer types (groups of customers that most frequently use certain SIC categories);
Categorization of geographic regions by fraud rate (high, medium, or low risk);
Categorization of geographic regions by customer types;
Mean number of days between transactions;
Variance of number of days between transactions;
Mean time between transactions in one day;
Variance of time between transactions in one day;
Number of multiple transaction declines at same merchant;
Number of out-of-state transactions;
Mean number of transaction declines;
Year-to-date high balance;
Transaction amount;
Transaction date and time;
Transaction type.

"Additional fraud-related variables which may also be considered are listed below"

Current Day Cardholder Fraud Related Variables bweekend current day boolean indicating current datetime considered weekend cavapvdl current day mean dollar amount for an approval cavapvdl current day mean dollar amount for an approval cavaudl current day mean dollars per auth across day ccoscdoni current day cosine of the day of month i.e. cos(day ((datepart(cst.sub.-- dt) * &TWOPI)/30)); ccoscdow current day cosine of the day of week i.e. cos(weekday ((datepart(cst.sub.-- dt) * &TWOPI)/7)); ccoscmoy current day cosine of the month of year i.e. cos(month ((datepart(cst.sub.-- dt) * &TWOPI)/12)); cdom current day day of month cdow current day day of week chdzip current cardholder zip chibal current day high balance chidcapv current day highest dollar amt on a single cash approve chidcdec current day highest dollar amt on a single cash decline chidmapv current day highest dollar amt on a single merch approve chidmdec current day highest dollar amt on a single merch decline chidsapv 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The issuer pays for a retrieval. macqrat Merchant Acquirer risk managment rate (in Europe one merchant can have multiple acquires, but they dont have records about how many or who.) mprevrsk Merchant Previous risk management at this merchant? Yes or No mtyprsk Merchant Type of previous risk management (counterfeit, multiple imprint, lost/stolen/not received) msicrat Merchant SIC risk management rate mpctaut Merchant Percent of transactions authorized

Unbalanced classes

Detector ***correctly identifies 99 in 100 legitimate transactions***

and ***correctly identifies 99 in 100 fraudulent transactions***

Pretty good?

But suppose only 1 in 1000 transactions are fraudulent

		True class	
		Legit	Fraud
Predicted class	Legit	99%	1%
	Fraud	1%	99%
Numbers		999	1

		True class		
		Legit	Fraud	
Predicted class	Legit	989.01	0.01	
	Fraud	9.99	0.99	0.99 / (9.99+0.99) = 0.09
Numbers		999	1	

91% of suspected frauds are in fact legitimate

This matters because:

- operational decisions must be made (stop card?)

- good customers must not be irritated

Customers are pleased you care: up to a point

Delay in learning class labels

- if fraud alarm is raised, then true class quickly known

- if no alarm, then not detected until statement

This makes it different from the standard supervised classification paradigm

Banks cannot always say for sure when a fraud commences

Mislabelled classes

Not all fraudulent transactions are labelled as fraud
(account holder fails to check carefully)

Not all legitimate transactions are labelled as legitimate

There may be subtleties

e.g. account holder makes transactions and then claims card was stolen

Such transactions are fraudulent because the holder declares them as such

Reactive population drift

- banks implement detection/prevention strategies

- fraudsters don’t generally give up! but change strategies

Reactive population drift example 1: *Chip and PIN*

Chip and PIN intended/predicted to end card fraud

After UK rollout on 14 Feb 06, CC fraud in UK did decline
How much was a consequence of the publicity?

but

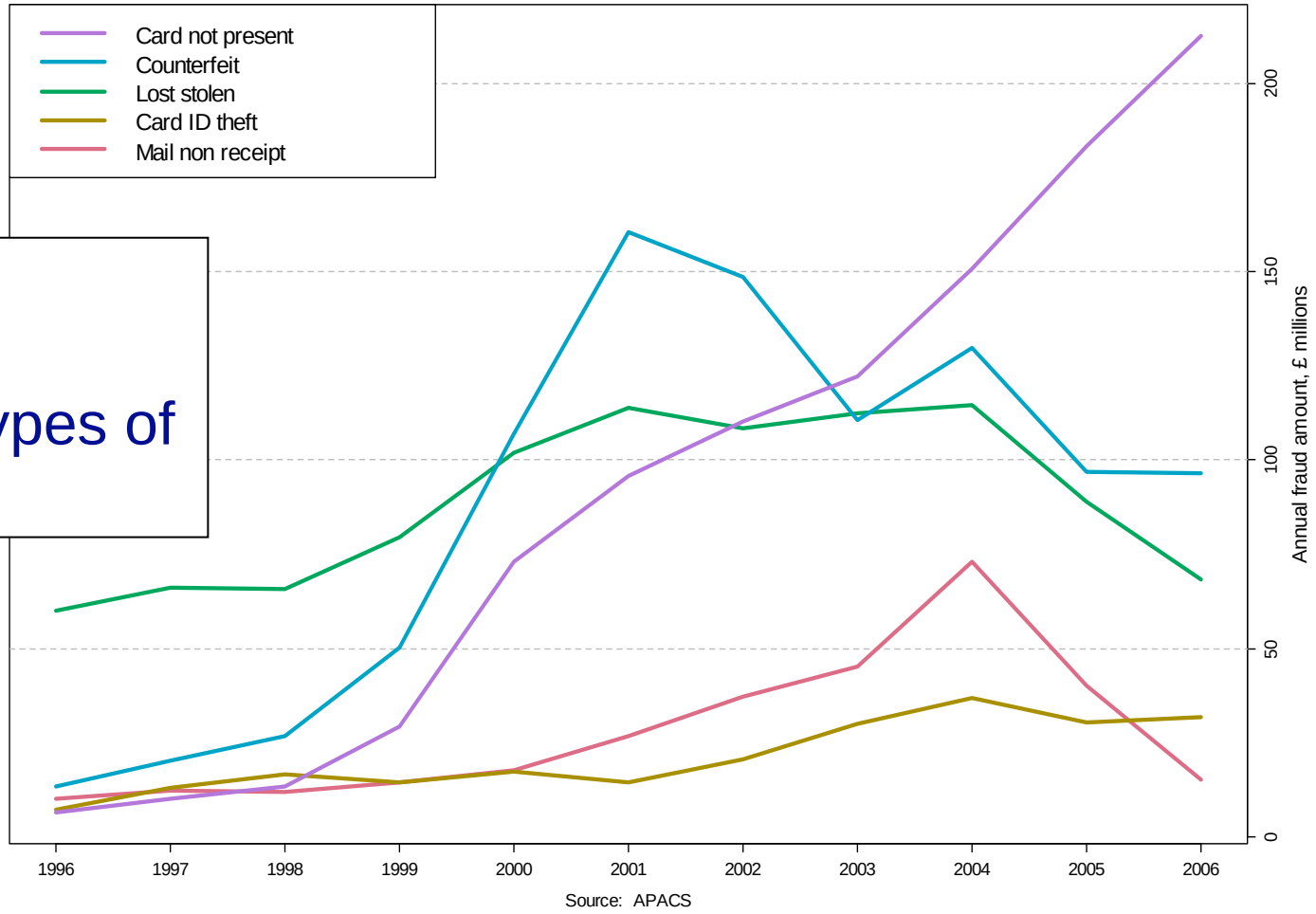
- predicted to lead to increase in identity theft

and

- Lloyds TSB observed increase in fraudulent use of UK cards in Europe (no C&P – mag stripe still counterfeited)
- observed increase in ATM and cardholder not present fraud
- in fact, crooks installed data skimmers into C&P terminals (such devices can be purchased for < £100), over £1m stolen from Shell gas stations

Plastic card fraud in the UK (Gordon Blunt)

Notice the change in different types of fraud



What is a good system?

'Classifies fraudulent transactions as fraudulent, and legitimate transactions as legitimate' ?

But: no method is perfect
Need: criteria for assessing effectiveness

Timeliness: time scale: count of fraud transactions misclassified

Standard two class classification criteria inadequate:

- misclassification rate: treats two types of misclassification equally
- Gini coefficient (AUC): averages over all misclassification cost ratios
- Kolmogorov-Smirnov statistic: data driven cost ratio

Unbalanced classes

		True class	
		Fraud	Legitimate
Predicted class	Fraud	A	B
	Legitimate	C	D

A very well known consumer credit organisation evaluates fraud using the two ratios

$$R_1 = A/(A+C) \quad (= \text{ Sensitivity})$$

$$R_2 = B/(A+B) \quad (= 1\text{- Precision})$$

In itself, this would appear to be fine

But in fact, the units of assessment they use are *accounts*

An account is flagged as potentially fraudulent if ***at least one transaction is so flagged***

Problem 1: This means that one can make the probability of flagging an account as fraudulent as near to 1 as one wishes by examining enough transactions

Problem 2: Fails to include *timeliness* in the measure

A superior measure

Consider each series of transactions ending with either

(i) a *fraud flag* on a true fraud

Or

(ii) or end of observed sequence

n n n n f n n f n n **n** n n f n n n n n **n** n n n n n n **f**

		True class	
		Fraud	Legitimate
Predicted class	Fraud	$m_{f/f}$	$m_{n/f}$
	Legitimate	$m_{f/n}$	$m_{n/n}$

n n n n f n n f n n **n** n n f n n n n n **n** n n n n n n **f**

		True class	
		Fraud	Legitimate
Predicted class	Fraud	1	2
	Legitimate	3	21

		True class	
		Fraud	Legitimate
Predicted class	Fraud	$m_{f/f}$	$m_{n/f}$
	Legitimate	$m_{f/n}$	$m_{n/n}$

Overall performance measure for given threshold:

$$T_1 = \left(m_{f/f} + m_{n/f} + k m_{f/n} \right) \Big/ \left(k m_f + m_n \right)$$

where *k* is the estimated relative cost of misclassifying a fraud as legitimate compared to misclassifying a legitimate as fraud

Or, if the bank can afford to investigate *C* cases

T_2: minimise $m_{f/n}$ subject to $\left(m_{f/f} + m_{n/f} \right) = C$

Constructing suspicion scores

- Rules: detect known suspicious behaviour

  e.g. most office workers do not shop in working hours

- Supervised classification: learn to distinguish fraud from legit
- Anomaly detection: detect anomalous behaviour
- Precursors: identify behaviour which precedes fraud
- Change points: change of state in account
- Multilevel: transaction/account/merchant
- Link analysis: networks

Example 1: Supervised classification (Chris Whitrow)

Basic principle:

> Given a set of known fraudulent and legitimate transactions/accounts, along with descriptive variables for each, condense these to a rule enabling correct classification of new transactions/accounts from only the descriptive variables

Classification methods compared:

- logistic regression
- quadratic discrimination
- naive Bayes classifier
- decision tree
- k-nearest neighbour
- SVMs with radial basis kernels
- random forests

Bank A:

- 175 million transactions: 1st August 05 to 30th Nov 05
- 16.8 million accounts
- 5,946 accounts experienced fraud at POS terminals in obs'n period
- 76 variables per transaction; mostly categorical

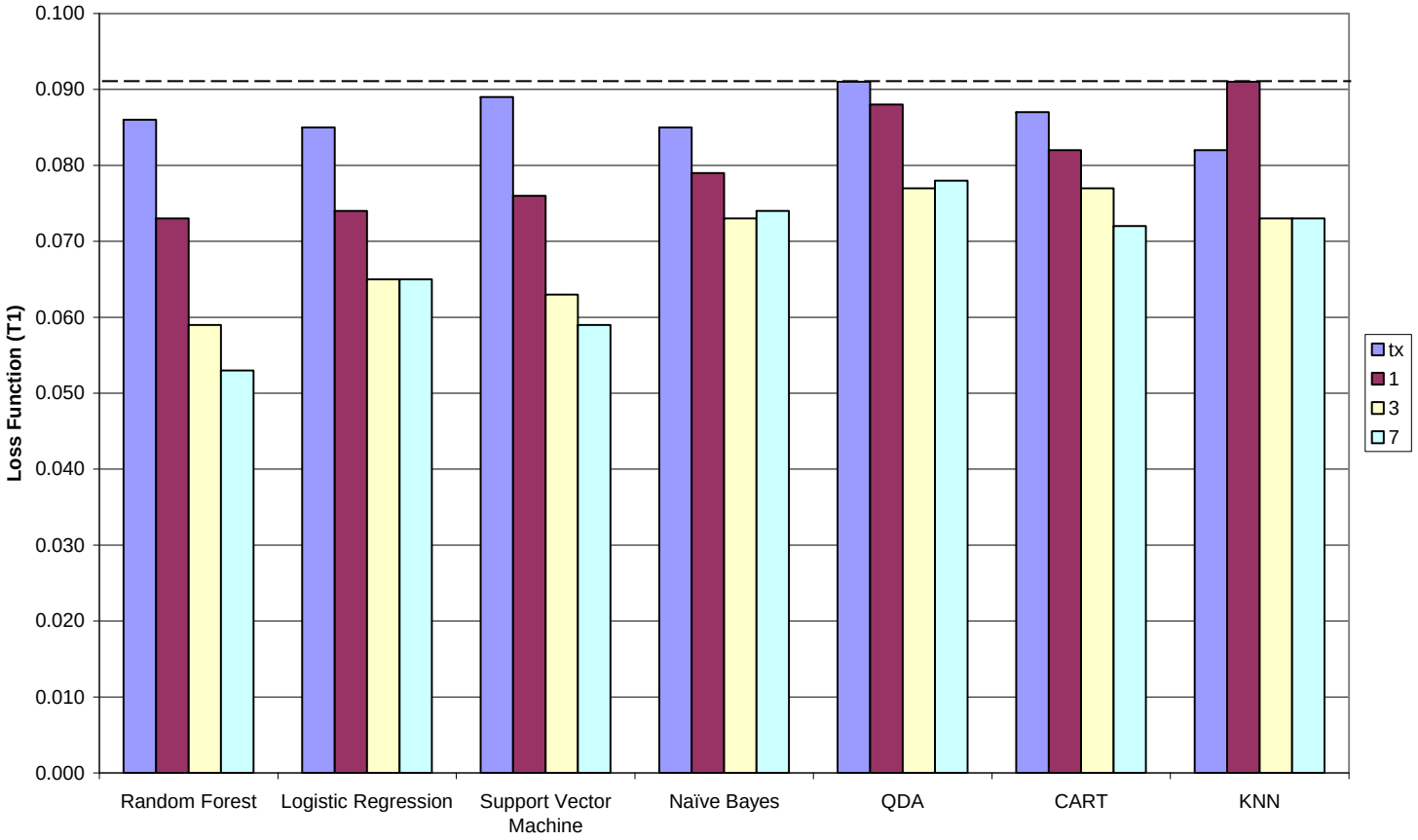
- rolling window activity records - 0, 1, 3, 7 days
- activity records sacrifice immediacy of individual transactions
- but potential for more accuracy

Two explorations:

1: ***Random***: Train on random 70%, test on remainder

2. ***Prediction***: Train up to 30th Oct 05, test after

Random performance



Example 2: One class modelling: outliers (Piotr Juszczak)

Basic principle: *build a model for the 'norm' for this customer and detect when it deviates*

'Norm' can be based on

- this customer compared with other customers
- this customer compared with self at previous times
- a combination of these

Basic advantage of one-class approach

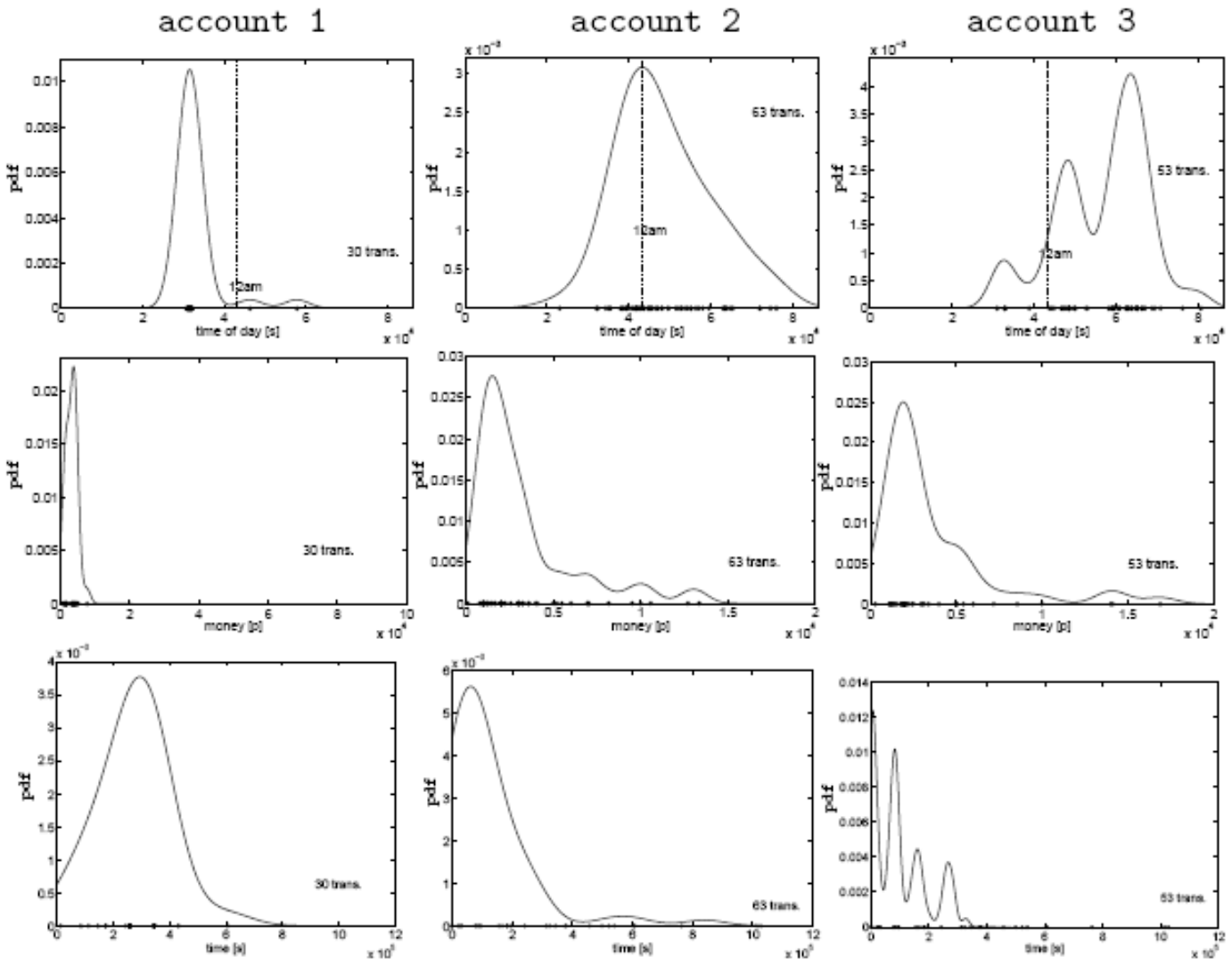
- can detect new kinds of anomalies, not seen before
- more power in dynamic fraud environment?

Bank B:

- 44,637 accounts
- 2,374,311 transactions
- 3,742 fraudulent accounts
- 53,844 fraudulent transactions
- 3 months data

77 variables, we used

- size of transaction
- difference between current and previous transaction size
- sum of current and previous transaction sizes
- product of current and previous transaction sizes
- time of transaction
- time between current and previous transaction
- merchant category
- ATM ID code


account 1
account 2
account 3
pdf
time of day [s]
money [p]
time [s]
30 trans.
63 trans.
53 trans.
12am

Preprocessing the categorical variables (MCC and ATM)

$A(j,i)$ = no. times ATM *j* is accessed from account *i*

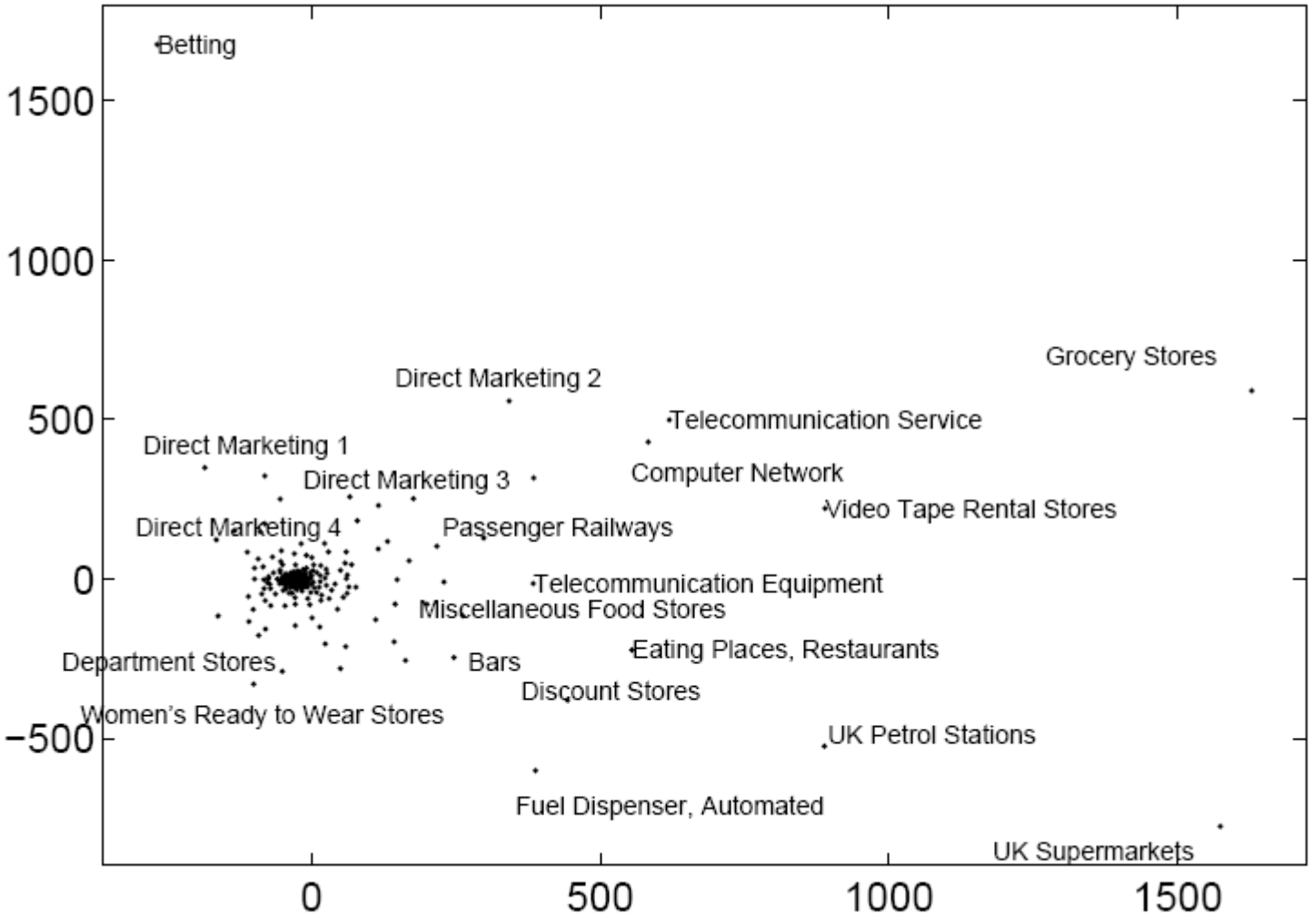
$$ATM(j) = \left(A(j,1), A(j,2), ..., A(j,K)\right)^T$$

$\Rightarrow$ dissimilarity matrix between ATMs

$\Rightarrow$ reduce dimensionality of ATMs using MDS

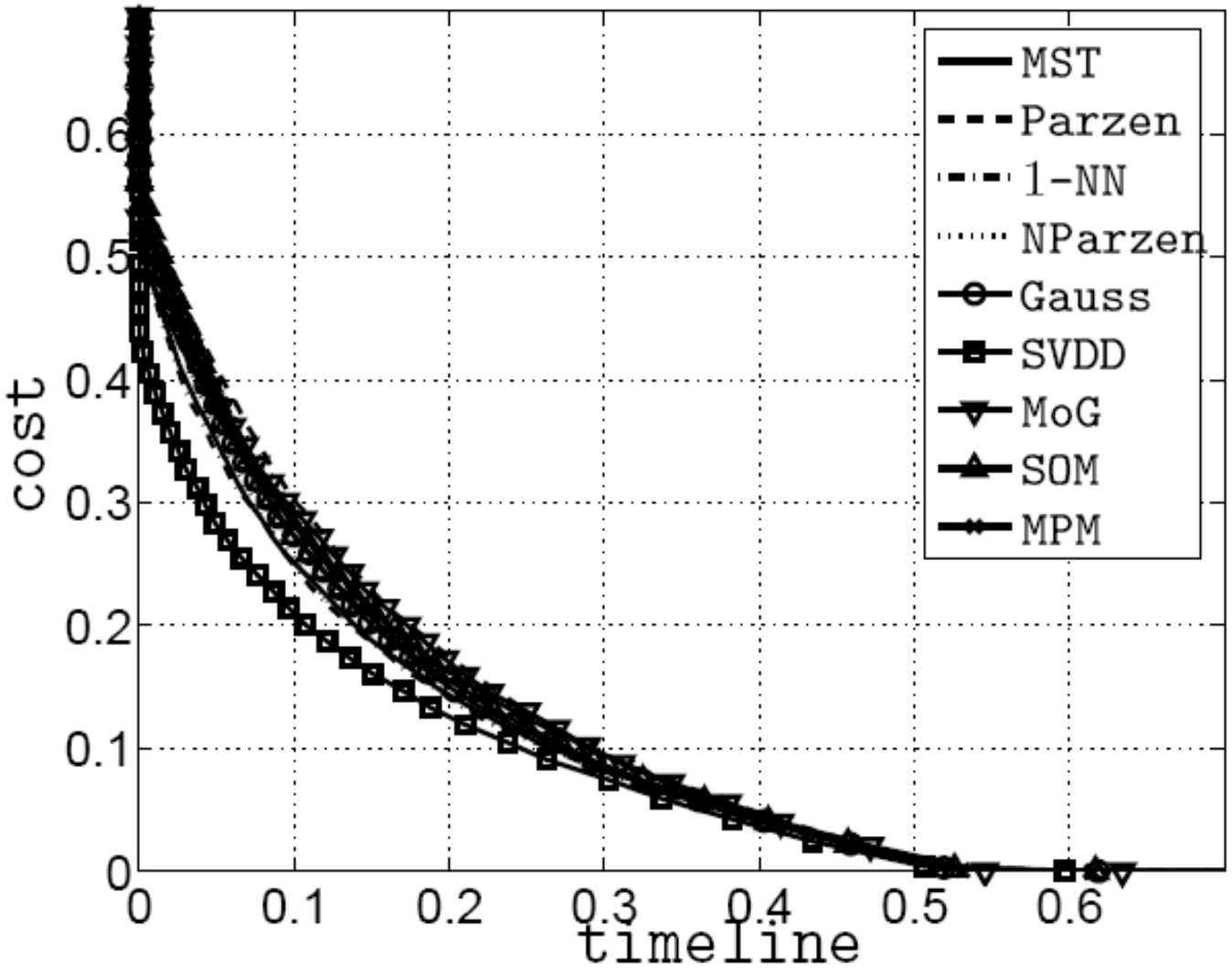
$\Rightarrow$ combine with continuous variables

Similar for MCCs

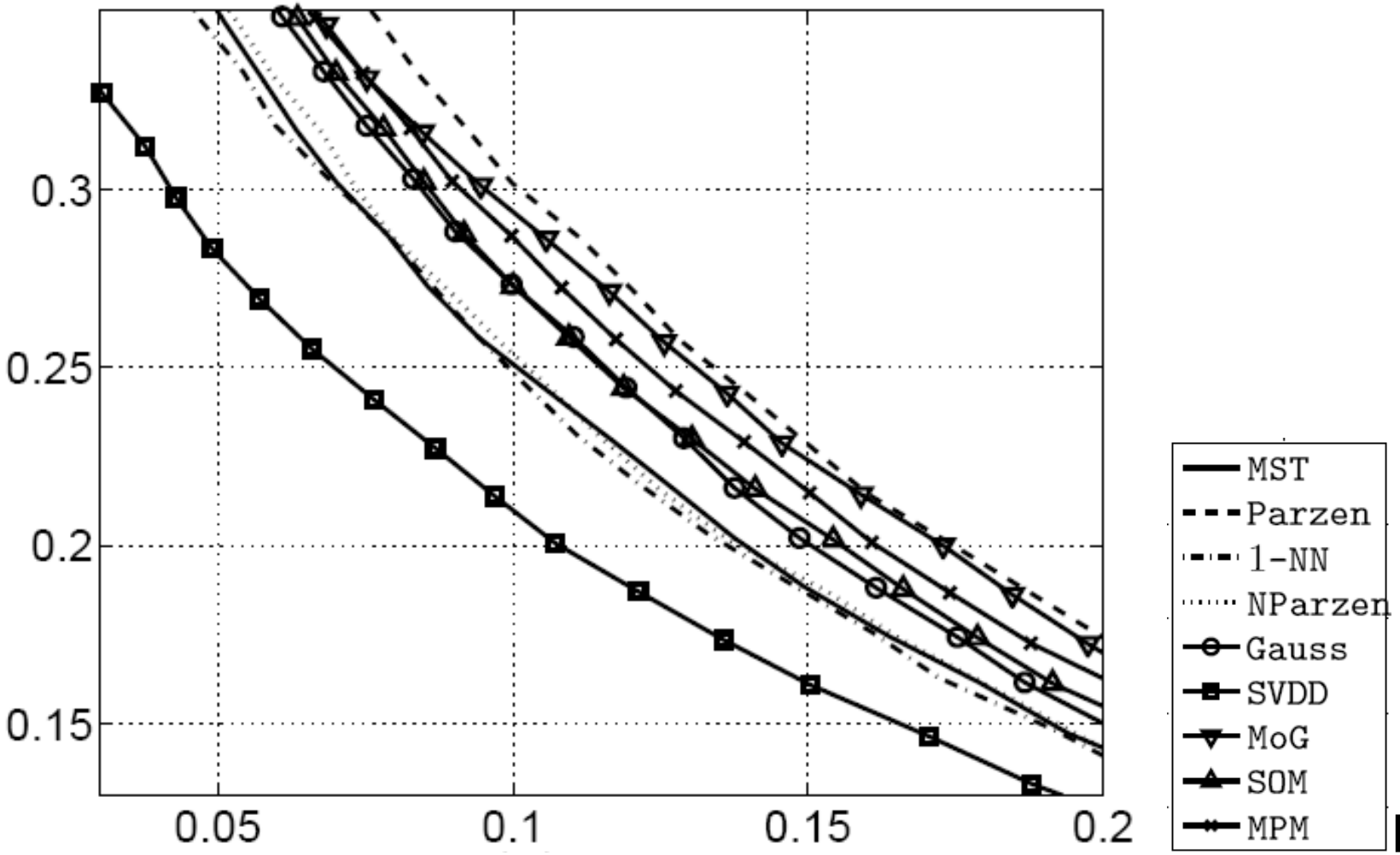


Used several methods for building the pdfs:

- Parzen kernel
- Naive Bayes with Parzen kernel for each variable
- Single multivariate Gaussian
- Mixture of multivariate Gaussian
- 1-nearest neighbour
- Support Vector Data Description
- Self-Organising map
- Minimum spanning tree data description
- Minimax probability machine


MST
Parzen
1-NN
NParzen
Gauss
SVDD
MoG
SOM
MPM
cost
timeline
0
0.1
0.2
0.3
0.4
0.5
0.6

Data set 1


0.3
0.25
0.2
0.15
0.05
0.1
0.15
0.2
MST
Parzen
1-NN
NParzen
Gauss
SVDD
MoG
SOM
MPM

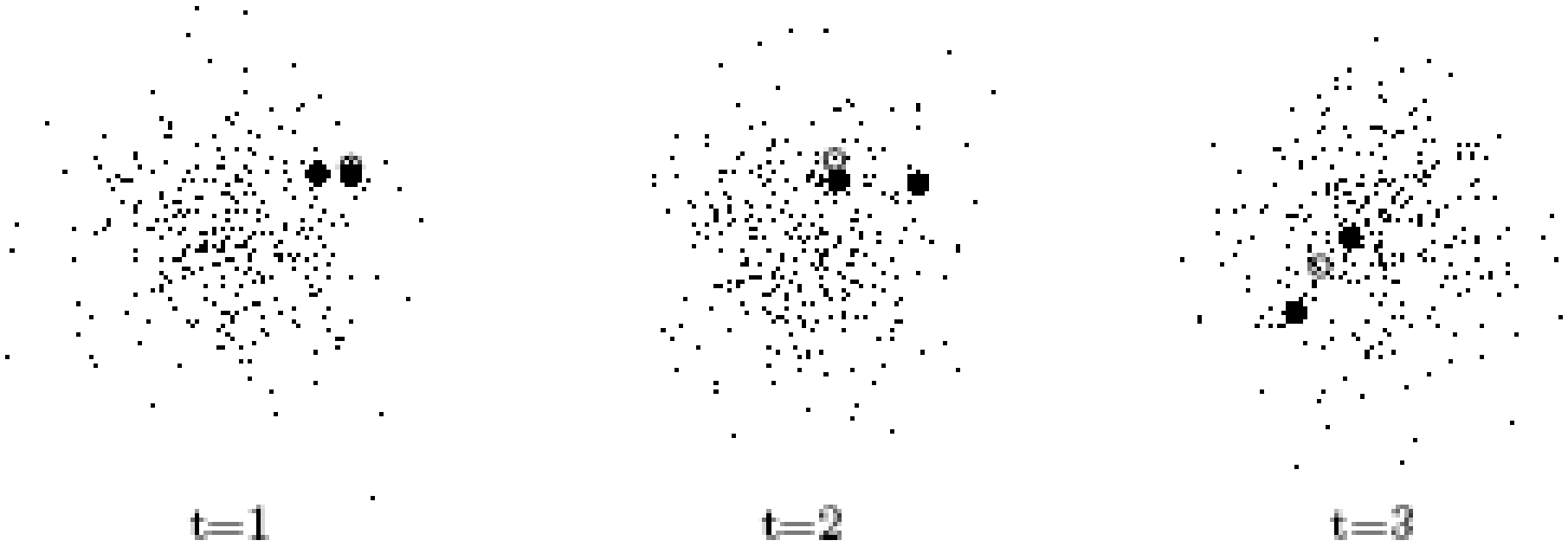
Data 1

Example 3: One class modelling: Peer group analysis **(Dave Weston)**

Individual account profiles:
Model behaviour and compare new transaction with past

But
- Spending behaviour just before Christmas is anomalous
- Individual profile models may flag such transactions

So
- Identify others with similar past behaviour (peer group)
- Compare new transaction with their new transactions
- Target account tracks peer group



Peer group quality: dispersion about past target behaviour

A clustering time series problem

Bank C:

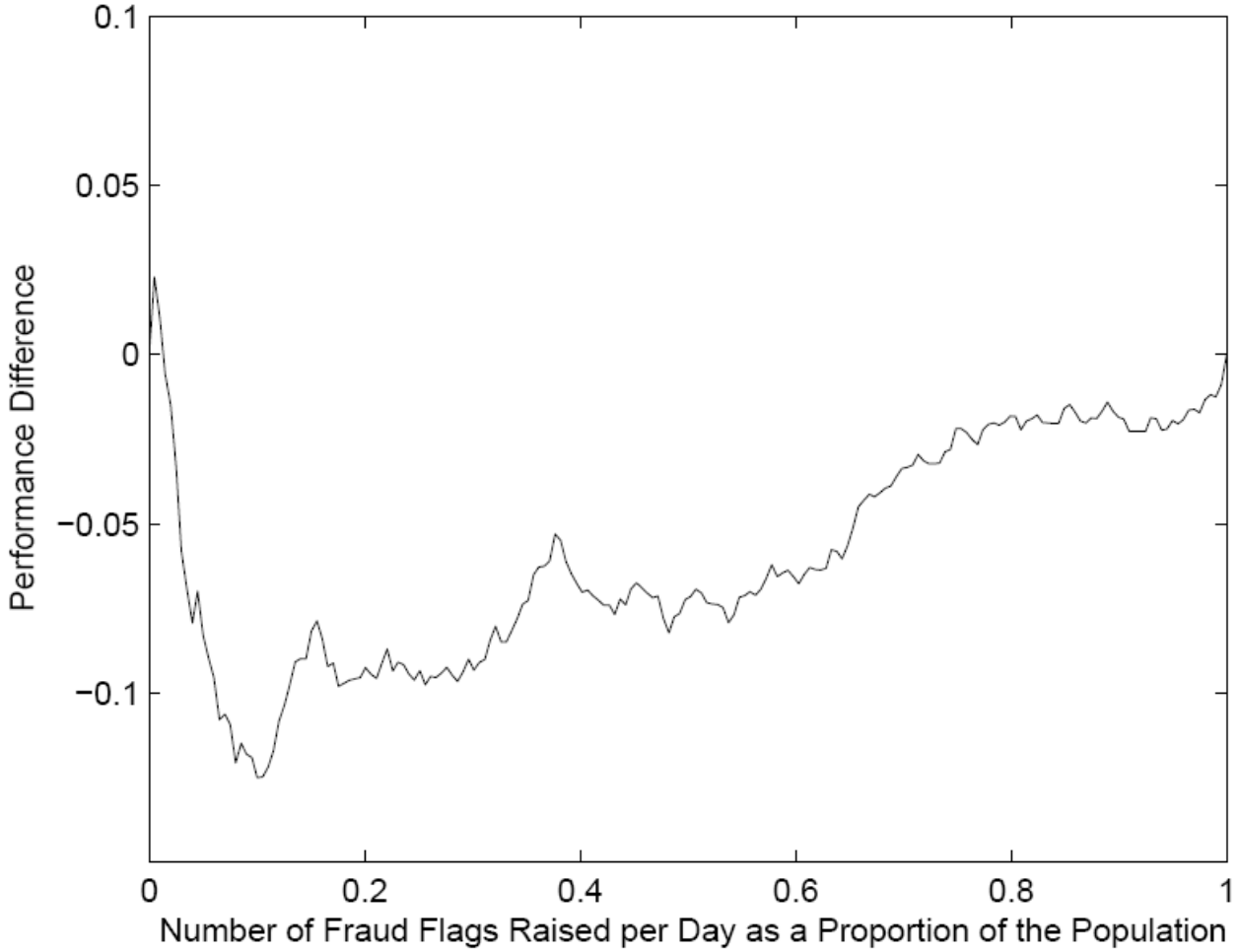
4,159 accounts, with at least 80 transactions over a 4 month period with no fraud in first 3 months: 241 had fraud in last month

Build 4,159 peer groups using first 3 months data

Split 3 months into *n* windows and summarise each window by
- total amount withdrawn
- total number of transactions
- entropy of MCCs

$\Rightarrow$ combine windows to give up to 3*n* dmensional space for finding peer groups

Population outlier detection - robustified peer group



Conclusions

Fraud detection problems

- may involve high dimensions, messy data, large *n*
- typically have unbalanced classes
- often have mislabelled classes, delay in labelling
- may involve dynamic, reactive data distributions

There are

- many approaches / different aspects
- issues of how to measure performance

Other, deeper questions

The economic imperative

About methodology

How much do we learn from ad hoc comparisons of methods on particular data sets?

About society

Is society changing?

Accepting some degree of fraud?

Fraud management requires a holistic approach, blending tactical and strategic solutions with the state-of-the-art technology solutions and best practice in fraud strategy and operations

James Gilmour, Editor *Credit Risk International*, 2003

END

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http://stats.ma.ic.ac.uk/djhand/public_html/