Using external 'Payment Intent' data to improve discrimination in credit decisions

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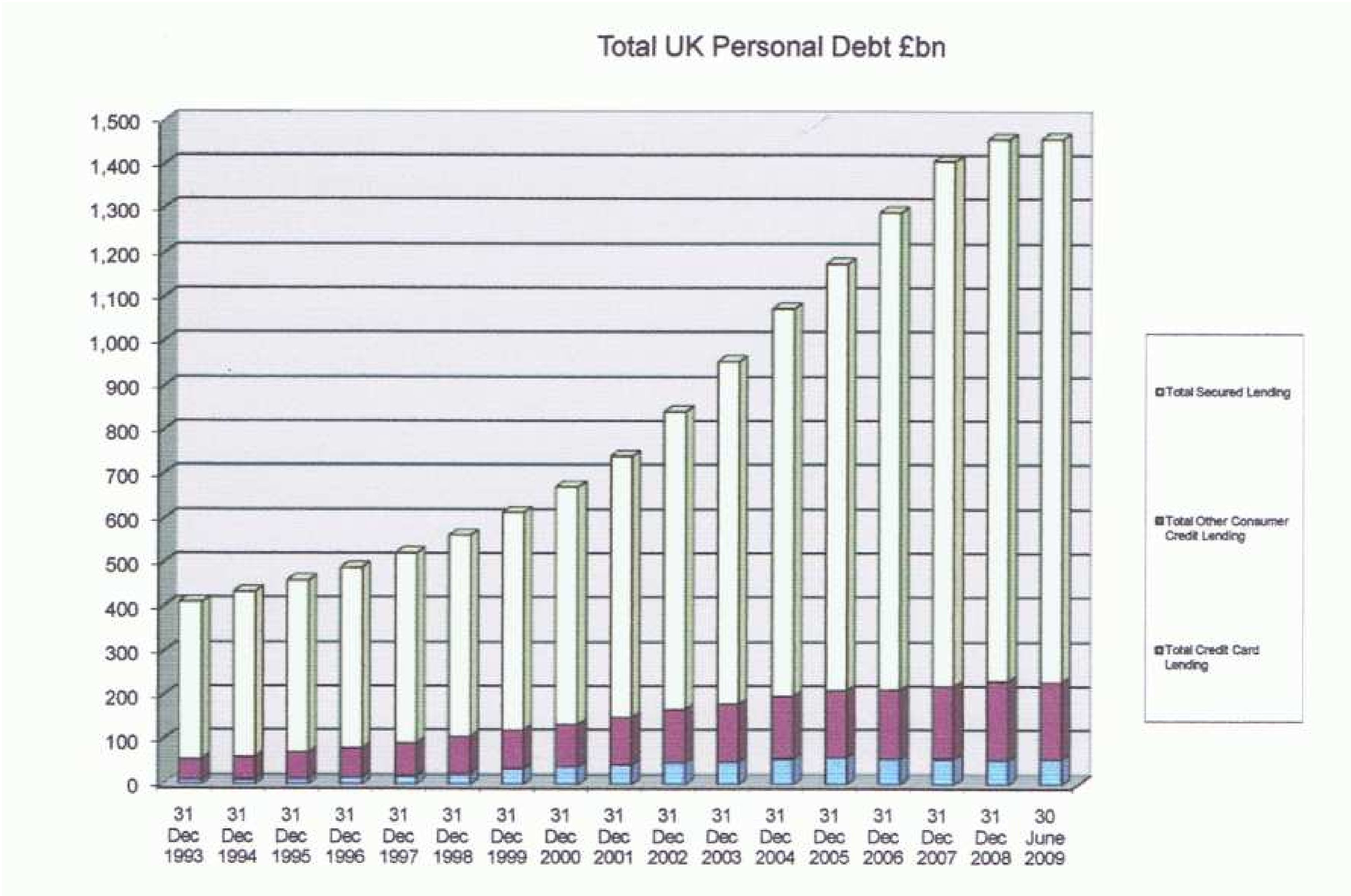
Purpose of this talk

- To show why despite 40 years of effort we still need to improve automated credit decisions
- To suggest ways in which this might be done
- To show a successful test of the new Payment Intent data coding
- To summarise the conclusions you might draw from this experiment

Agenda

- Overview
- What is Payment Intent coding?
- Test using the codes
- Business implications
- Conclusions and caveats

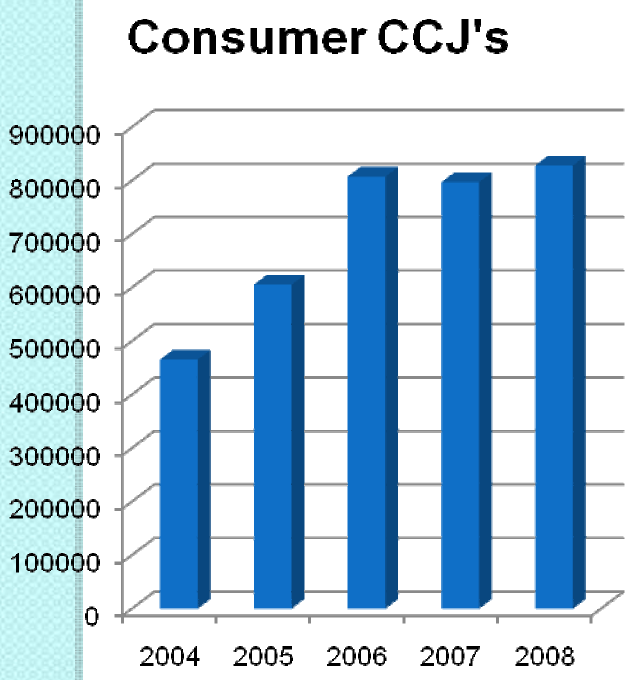
Total UK Personal Debt



Source: Credit Action Debt Statistics: August 2009.

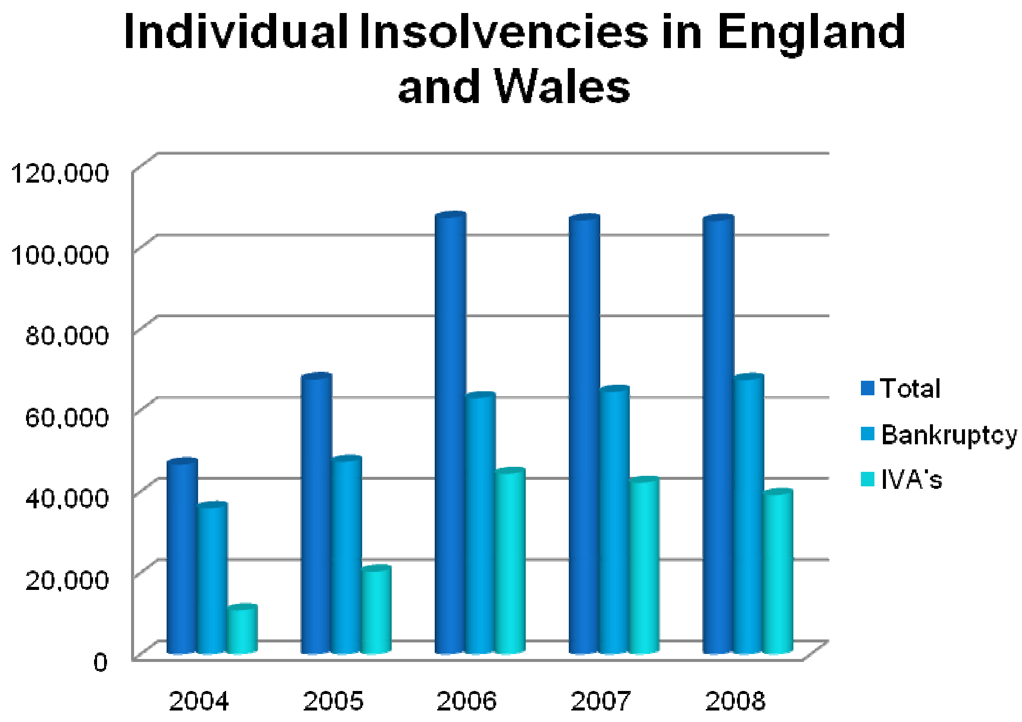
Debt Recovery

- CCJ's



Source: The Registry Trust

- Insolvency



Source: The Insolvency Service

Debt in the UK at June 2009

- Unsecured consumer credit lending £231billion
  - growing at 1.9% a year
- Average unsecured household debt was £21,480
  - for those with an unsecured loan of some kind
- Average debt owed by every UK adult was £30,460
  - Including mortgages
  - This is 133% of average earnings
- 1.93m new problem debt enquiries in 2008 / 2009
  - Citizen's Advice Bureau (CAB) only – an annual increase of 11%
- CAB clients owe an average of £16,971
  - It would take the average client 93 years to pay off this amount

Sources: Credit Action

How to improve automated credit decisions

- Use more data
- Use better data
  - Focus
  - Relevance
- Predict more outcomes
- Improve predictive modelling
- Design better decision control systems
- Define success and timescale in advance

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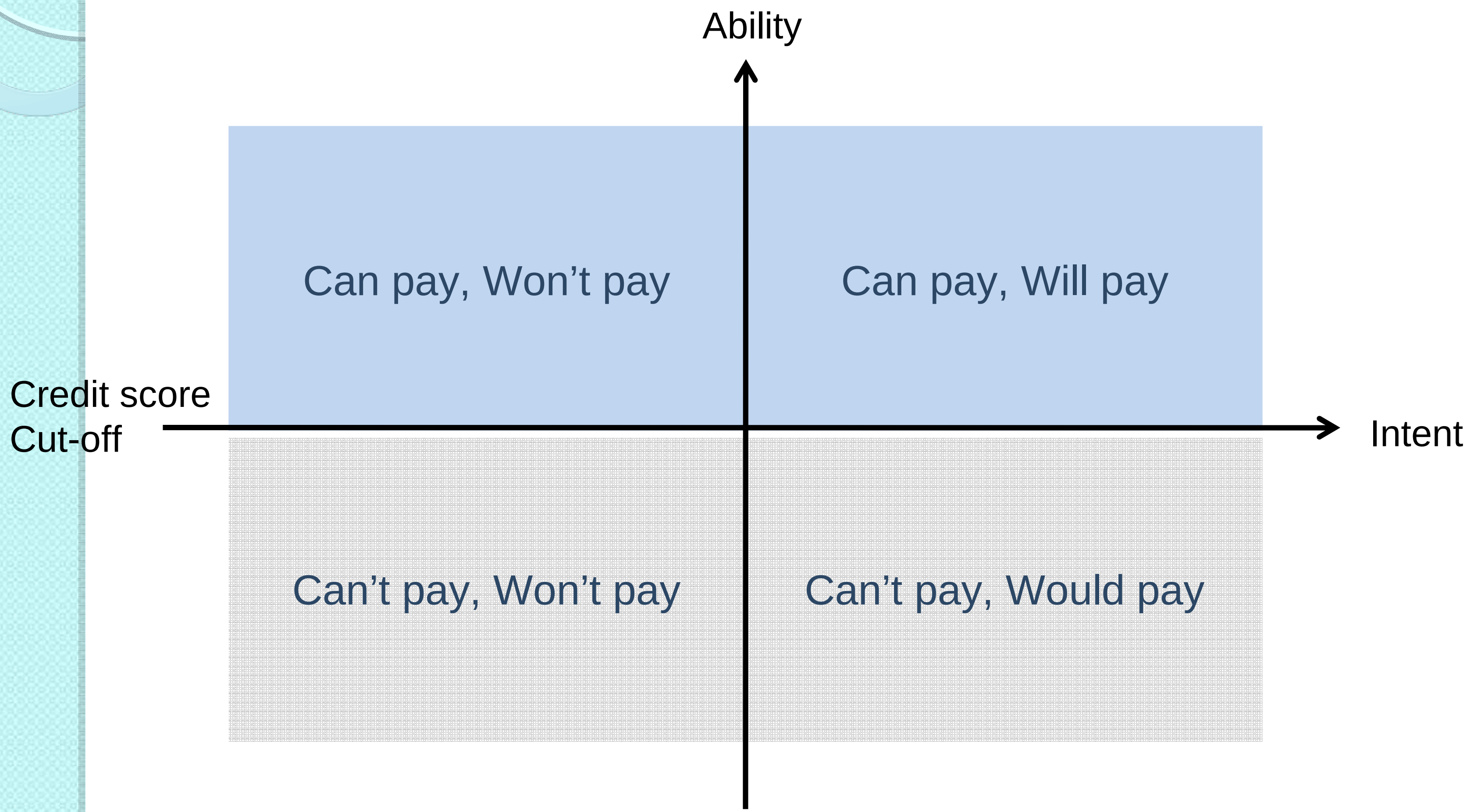
Fraudscreen coding - a predictor of payment intent, not ability



The coding structure is built at geo & individua[l level]

6 geo level codes

1. Low mail order activity
2. Only good trading
3. Somewhat good trading
4. Mainly poor trading
5. Very poor trading
6. Evidence of name & Address manipulation

Geo areas based on full postcode less 1 digit c.240 homes

Fraudscreen code:

Geography	Individual	Code	Colour
Low Trading	GeoMatch	1a	blue
	Dubious	1b	amber
	Good	1c	green
Good	GeoMatch	2a	blue
	Dubious	2b	amber
	Returner	2c	green
	Good	2d	green
Moderate Good	GeoMatch	3a	blue
	Dubious	3b	amber
	Returner	3c	green
	Good	3d	green
Moderate Bad	GeoMatch	4a	blue
	Bad	4b	red
	Dubious	4c	amber
	Doubtful	4d	amber
	Probably OK	4e	amber
	Returner	4f	green
	Good	4g	green
Bad	GeoMatch	5a	blue
	Bad	5b	red
	Dubious	5c	amber
	Doubtful	5d	amber
	Probably OK	5e	amber
	Returner	5f	green
	Good	5g	green
Very Bad	GeoMatch	6a	blue
	Bad	6b	red
	Dubious	6c	amber
	Doubtful	6d	amber
	Probably OK	6e	amber
	Returner	6f	green
	Good	6g	green

32 individual level codes

GeoMatch
Not on the Fraudscreen database

Bad
Have traded fraudulently or uneconomically in all instances

Dubious
Have traded uneconomically/fraudulently on some occasions

Doubtful
Have a mix of trading well and uneconomically

Probably ok
Traded well on one occasion, no bad trading indicated

Returner
At least two orders returned to different members

Good
Traded well on all occasions with different members

Each client has a bespoke 'coding signature'

Fraudscreen code:

Geography	Individual	Code	Colour
Low Trading	GeoMatch	1a	
	Dubious	1b	
	Good	1c	
Good	GeoMatch	2a	
	Dubious	2b	
	Returner	2c	
	Good	2d	
Moderate Good	GeoMatch	3a	
	Dubious	3b	
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Very Bad	GeoMatch	6a	
	Bad	6b	
	Dubious	6c	
	Doubtful	6d	
	Probably OK	6e	
	Returner	6f	
	Good	6g	

Translation table/signature

Codes	Colour	Treatment
1c, 2d, 3d, 4g, 5g, 6g		Offer 1
1a, 2a, 3a, 4a, 5a		Offer 2
1b, 2b, 2c, 3b, 3c, 4d, 4e, 4f, 5d, 5e, 5f, 6a, 6e, 6f		Offer 3
4b, 4c, 5b, 5c, 6b, 6c, 6d		Offer 4/decline

- The signature is built from analysis of an historic dataset, including back end payment performance information.
- Code allocation and treatment is driven by the clients own acceptance criteria.

Payment Intent codes add value to many sectors

Mail order

Retail

Credit

Insurance

Mortgages

Collections

Utilites

- Payment intent is a behaviour
- It endures over time
- It crosses many sectors, regardless of product type and value

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Aims of the Test

- Assess the value added by Fraudscreen Payment Intent coding
- Quantify as far as possible the financial impact of the coding in a typical credit situation
- Simplify the test, so that extraneous factors did not confuse the issue!

The Test file

- Applications for mail order accounts – a well understood scoring application
- Substantial volume
- Simple ‘accept reject’ strategy
- Good quality, recently developed credit scorecard which already performed well

Sample statistics

TOTAL STARTERS

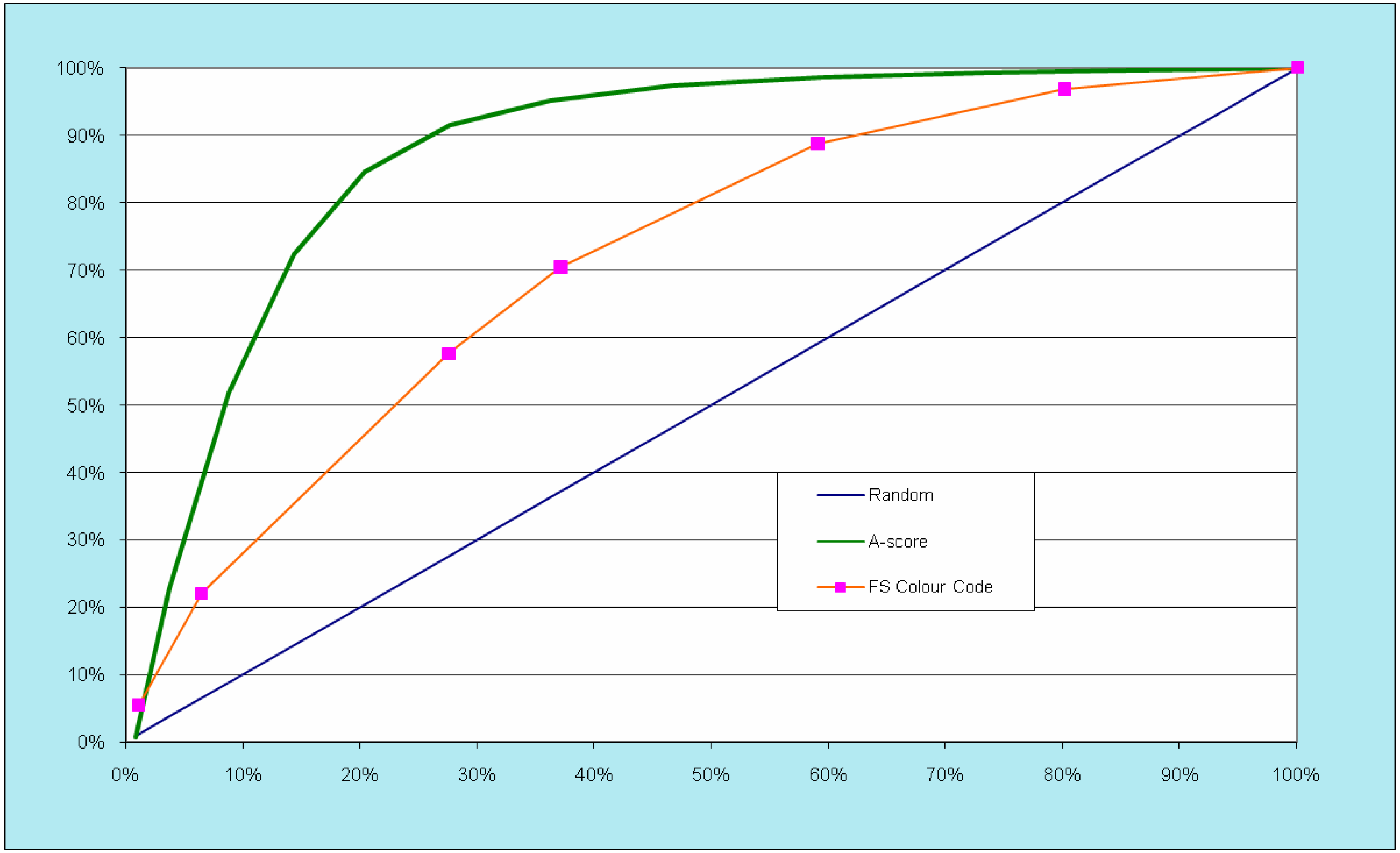
Score	FS Colour Code							
	Deep Red	Red	Lower blue	Amber	Mid Blue	Green	Top Green	Grand Total
<430	129	510	1,178	444	920	719	651	4,550
431-490	1,439	4,748	7,173	3,071	3,209	1,668	584	21,890
491-550	1,740	5,438	12,162	4,503	6,729	3,000	1,164	34,736
551-610	1,157	4,224	11,360	4,235	7,185	4,157	1,827	34,143
611-670	827	3,348	10,302	4,202	7,731	5,303	2,717	34,428
671-730	537	2,705	10,454	4,424	8,787	7,010	4,362	38,277
731-790	407	2,370	10,952	4,143	10,587	8,945	6,272	43,674
791-850	291	2,148	11,826	4,572	12,902	11,792	8,841	52,371
851-910	266	2,001	12,855	5,165	15,360	15,251	12,824	63,720
911-970	191	1,817	12,119	5,451	16,251	16,841	16,901	69,569
971-1030	164	1,443	8,582	4,923	12,912	14,936	17,297	60,255
1031-1090	65	761	4,680	3,290	7,496	9,875	13,125	39,290
1091-1150	41	381	1,968	1,932	3,467	5,079	7,742	20,609
1151-1210	14	120	705	905	1,211	2,096	3,672	8,721
>1211	5	51	318	393	522	923	1,731	3,942
TOTAL	7,268	32,063	116,631	51,650	115,266	107,589	99,707	530,172

GINI coefficients of score and code

Score				
	SCORE		Cumul	Cumul
Low	High	Median	% Goods	% Bads
400	430	415	0.9%	0.8%
431	490	460.5	3.8%	22.9%
491	550	520.5	8.8%	51.9%
551	610	580.5	14.3%	72.3%
611	670	640.5	20.4%	84.7%
671	730	700.5	27.7%	91.6%
731	790	760.5	36.2%	95.2%
791	850	820.5	46.6%	97.4%
851	910	880.5	59.4%	98.5%
911	970	940.5	73.3%	99.3%
971	1030	1000.5	85.4%	99.7%
1031	1090	1060.5	93.3%	99.9%
1091	1150	1120.5	97.5%	100.0%
1151	1210	1180.5	99.2%	100.0%
1211	1300	1255.5	100.0%	100.0%
	Total			
			K-S	**64.26%**
			Gini	**75.42%**

FS Colour				
FS Colour			Cumul	Cumul
			% Goods	% Bads
Deep Red			1.1%	5.6%
Red			6.4%	22.1%
Lower blue			16.0%	34.9%
Amber			37.1%	70.5%
Mid Blue			59.0%	88.7%
Green			80.1%	96.9%
Top Green			100.0%	100.0%
	Total			
			K-S	**33.42%**
			Gini	**42.45%**

GINI Graph – Score and Code



Two Test models

- Delta Score

MODEL 2 - SCORE + DELTA ON COLOUR CODE	Marginal IV	Info Value	Gini	KS
A-score	-0.150	2.843	75.4%	64.3%
FS Colour Code	0.026	0.723	42.4%	33.4%
Cross-Char	-0.119	2.937	77.6%	65.6%
Model			77.6%	65.5%

- Logistic Regression

MODEL 3 - LOGISTIC REGRESSION	Marginal IV	Info Value	Gini	KS
A-score	0.000	2.843	75.4%	64.3%
FS Colour Code	0.002	0.723	42.4%	33.4%
Cross-Char	0.013	2.937	77.6%	65.6%
Model			78.0%	65.6%

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Seeing the swap-sets

BAD RATE								
	FS Colour Code							
Score	Deep Red	Red	Lower blue	Amber	Mid Blue	Green	Top Green	Grand Total
<430	12.8%	10.6%	9.3%	7.8%	2.9%	1.5%	0.2%	5.6%
431-490	38.8%	36.7%	35.2%	32.5%	30.1%	25.7%	23.9%	33.6%
491-550	35.1%	30.3%	29.5%	27.7%	26.1%	20.5%	16.5%	27.8%
551-610	32.8%	24.5%	22.2%	19.1%	18.5%	12.7%	9.6%	19.9%
611-670	21.4%	16.0%	14.3%	13.0%	11.0%	7.6%	5.2%	12.0%
671-730	12.3%	9.5%	7.3%	7.2%	5.5%	3.8%	2.9%	6.0%
731-790	5.5%	4.7%	3.7%	3.3%	2.6%	2.1%	1.2%	2.8%

Cut-off Strategy	
Single	Variable

A gross contribution of 2.3% net of bad debt

Account Category	Single cut-off		Variable Cut-off		Contribution from Variable Cut-off £'000s	Contribution %
	Number	Amount £'000s	Number	Amount £'000s		
Good a/c at £500	453,014	226,507	467,901	233,950.5	7,443.5	3.68%
Bad a/c at £1,000	(24,039)	(24,039)	(26,895)	(26,895)	(2,856)	(1.41%)
Net Total	428,975	202,468	441,006	207,055.5	4,587.5	2.27%

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Conclusions

- Using Fraudscreen Payment Intent coding can significantly improve the performance of some credit application processes
- The codes measure willingness to pay – a customer behaviour
- So results can be replicated for other processes
  - Pre-collections
  - Collections
  - Recoveries

Caveats

- Credit portfolios vary, and so does the impact of using these codes
- Effectiveness depends on the colour signature, and this can vary from one portfolio to another
- Implementation may require a scorecard amendment for fully effective monitoring

Acknowledgements

- Our anonymous client for allowing their data to be used
- fraudscreen predicting payment intent www.fraudscreen.co.uk Fraudscreen Ltd for allowing the use of their payment intent coding
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For further information...

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