Optimizing credit limit policies to maximize customer lifetime value

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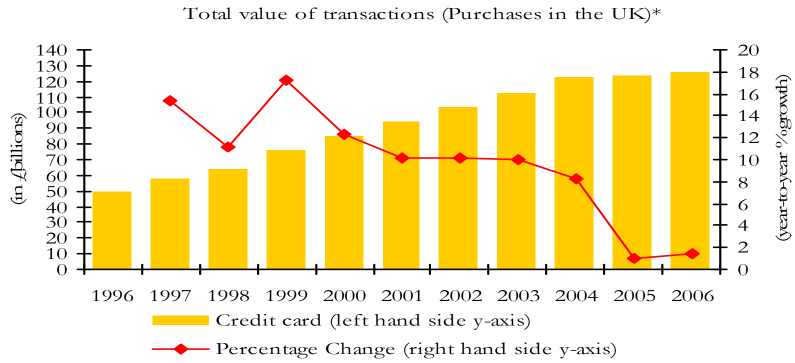
Outline

- Motivation
- Markov decision process (MDP)
- The use of the behavioral score
- Low default account
- A case study
- Future research

Credit card market : key figures



- **In 2005…**
  - number of credit card holders reached 31.6million
  - the average number of cards per person was 2.4 credit cards

* Source: APACS, the UK payments association

Credit Card

- Prominent payment tool
- High penetration
- Key payment method in e-shopping
- Widely used by retailers

Challenges

- Usage rate slowdown
- 59% of customers are transactors
- Intense competition among credit card issuers

Question

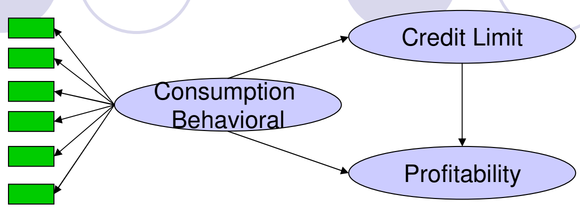
How can banks raise the credit card portfolio by encouraging customers to increase spending?

Possible policies

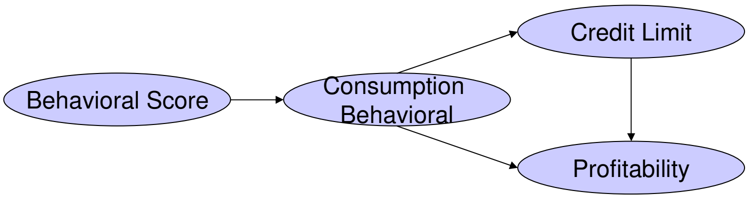
- *Offer additional credit products*
- *Offer 0% interest rate on balance transfer*
- *Extend 0% interest rate on new purchases*
- *Reduce pricing (adjust APR, Annual Percentage Rate)*
- ***Increase credit limit***

Manage the credit limit by Markov decision process [Bank One Card Services, 2003]

Bank One Services' Approach



Our Approach



The choice of behavioural score

- Default indicator
- Popular
- Properly capture repayment behavioral
- Reduce computational time
- Link credit limit and behavioural score dynamically

Markov Decision Process

- The formulation of MDP requires:
  - *A set of states (classification of customers)*
  - *Transition probabilities (from one state to another)*
  - *Revenue corresponding to different states*
  - *Possible actions*
- The deliverables would be
  - *a set of optimal actions for each state*

Choice of MDP

<u>Advantage</u>

- A lot of time-series credit card records
- Possible to estimate the expected profit
- Possible to apply different actions

<u>Hurdle</u>

- Markovian assumption
  - *assume a state depends mainly on information concerning the current position of the account and its recent history, which means that the probability of moving from state x to state y depends only on x, conditionally independent of which states and actions preceded the move to state x*

State Variables

- Time t : in month
- State variables:
  - Credit limits, l
  - Behavioural score, i

Model

- Transition probability:
  - $P(\, i' \mid l,\, i\,)$ = *the probability that the system moves from credit limit l and behaviour score i to a behaviour score of i' at one time period*
- Optimality equation:

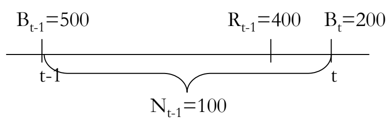
$$V_t(l,i) = \underset{l' \geq l}{Max}\left\{ \sum_{i'} p(i' \mid l,i)[r(i' \mid l,i) + \lambda V_{t-1}(l',i')] \right\}$$

- *the discounted profit (with discount factor λ) over the next t month given the customer with credit limit l and behavioural score i*

Profit Function

f = rate of interchange fee (in %)
r = APR / 12
B_t = credit account balance at the beginning of t
N_t = new purchase during t
P_t = repayment by the end of t

Balance at time t: $B_t = B_{t-1} + N_{t-1} - P_{t-1}$
Profit in period t $= N_{t-1} f + (B_{t-1} - P_{t-1})r$
$= N_{t-1} f + (B_{t-1} - B_{t-1} + B_t - N_{t-1})$
$= N_{t-1}(f-r) + B_t r$



Actual Profit: 100f + (500-100)r
Estimate Profit: 200r
If we assume r = f = 2%,
Actual Profit = Estimate Profit = 4

If we assume r = f and LGD equals to 1 (where D represents default accounts)

Estimate profit at t ≡ EP_t $= \begin{cases} rB_t, \forall i' \neq D \\ -B_t, otherwise \end{cases}$

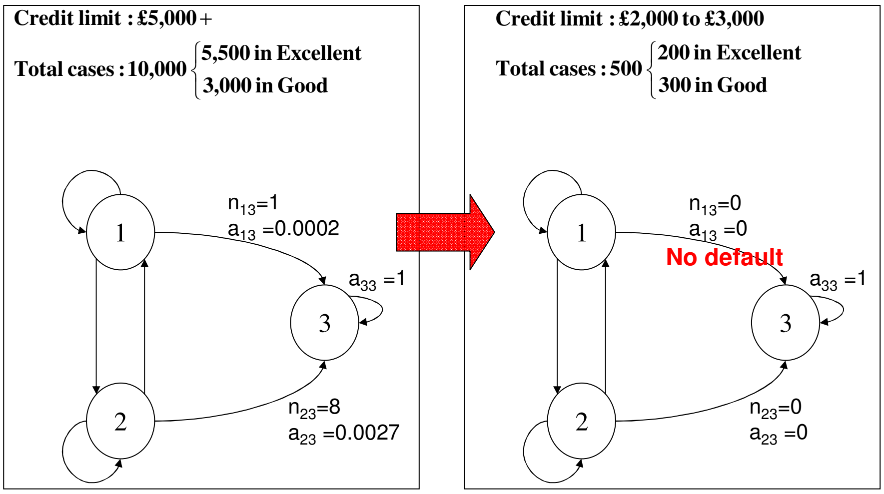
Validation:.
i.e. assume **AP_t= the actual profit, Diff= AP_t - EP_t**
Test:
Diff follows normal distribution with mean equals to zero

Low default portfolios

- High behavioral score accounts
- Seldom or "No" default case in the sampling period
- Build a "structural zeros" model
- Underestimate the lost
- Generate unusual and not practical policy

Example (LDP)

Definition:
1 – Excellent
2 – Good
3 – Bad
n_{ij} – number of accounts transit from state i to j
a_{ij} – transition probability from state i to j



Low default portfolios (LDP)

- Define:
  1. PD for the accounts with best behavioral score: p(D|l,I)
  2. Accounts with states (l,i),(l,i+1),….(l,I) are the low default portfolios
  3. N(l,i) = the total number of accounts in (l,i),(l,i+1),….,(l,I)
  4. N_D(l,i) = the total number of accounts in (l,i),(l,i+1),….,(l,I) transit to default
- Apparently:

  p(D|l,i) ≥ p(D|l,i+1) ≥… ≥p(D|l,I)
- If we assume:
  1. **p(D|l,i) = p(D|l,i+1) =… = p(D|l,I)**
  2. Default incidence follows the **binomial distribution**

Then with a confidence level 1-γ, there are N_D(l,i) default in the low default portfolio :

$$1-\gamma \le \sum_{j=0}^{N_D(l,i)} \binom{N(l,i)}{j} p(D|l,I)^j (1-p(D|l,I))^{N(l,i)-j}$$

Case Study

- Credit card dataset from a UK bank
- From 2001 to 2004 inclusive
- Monthly records
- Attributes: credit limit, behaviour score, special account status, account balance
- 50,000+ cases for analysis
- APR: 24%
- Discount value: 0.995

Classification of states

#	Behaviour Score/Account Description
0	Closed
1	Inactive
2	Bad (Bankruptcy or charge-off)
3	In risk account
4	Score 1
5	Score 2
6	Score 3
7	Score 4 (highest score group)

#	Credit limit (in £)
0	missing/closed
1	≤500
2	501-1000
3	1001-1500
4	1501-2500
5	2501-3500
6	3501-4500
7	4501-5500
8	≥ 5501

Transition matrix

Credit Limit: ≤ £500 (# of transition 148,207)

Beh.Score	Closed	Inactive	Bad	In risk	Score 1	Score 2	Score 3	Score 4
Closed	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Inactive	0.014406	0.979429	0.000000	0.000000	0.003170	0.002662	0.000317	0.000016
Bad	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
In risk	0.064220	0.000000	0.247706	0.293578	0.394495	0.000000	0.000000	0.000000
Score 1	0.013959	0.001917	0.002381	0.001433	0.895166	0.078660	0.006215	0.000271
Score 2	0.010931	0.008313	0.000046	0.000000	0.183952	0.705401	0.084328	0.007027
Score 3	0.008428	0.014558	0.000000	0.000000	0.048525	0.273784	0.582301	0.072405
Score 4	0.009086	0.001136	0.000000	0.000000	0.011357	0.089722	0.374219	0.514480

Credit Limit: ≥ £5501 (# of transition 430,082)

Beh.Score	Closed	Inactive	Bad	In risk	Score 1	Score 2	Score 3	Score 4
Closed	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Inactive	0.020130	0.960591	0.000053	0.000000	0.002815	0.016040	0.000266	0.000106
Bad	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
In risk	0.045455	0.000000	0.424242	0.378788	0.151515	0.000000	0.000000	0.000000
Score 1	0.011714	0.000237	0.001279	0.000663	0.784971	0.177504	0.020933	0.002700
Score 2	0.012572	0.001401	0.000038	0.000000	0.114888	0.673701	0.173707	0.023693
Score 3	0.012628	0.010615	0.000010	0.000000	0.023731	0.112820	0.632805	0.207390
Score 4	0.012284	0.001030	0.000006	0.000000	0.006557	0.013001	0.123014	0.844108

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Inactive	0.014406	0.979429	0.000000	0.000000	0.003170	0.002662	0.000317	0.000016
Bad	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
In risk	0.064220	0.000000	0.247706	0.293578	0.394495	0.000000	0.000000	0.000000
Score 1	0.013959	0.001917	0.002381	0.001433	0.895166	0.078660	0.006215	0.000271
Score 2	0.010930	0.008312	0.000218	0.000000	0.183920	0.705280	0.084314	0.007026
Score 3	0.008427	0.014555	0.000160	0.000000	0.048517	0.273740	0.582208	0.072393
Score 4	0.009084	0.001136	0.000151	0.000000	0.011355	0.089708	0.374163	0.514403

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Score 2	0.012571	0.001401	0.000132	0.000000	0.114877	0.673638	0.173691	0.023691
Score 3	0.012628	0.010615	0.000059	0.000000	0.023730	0.112815	0.632774	0.207380
Score 4	0.012284	0.001030	0.000031	0.000000	0.006557	0.013000	0.123011	0.844087

Profit

		Behaviour Score							
Monthly reward in £		**Closed**	**Inactive**	**Bad**	**In risk**	**Score 1**	**Score 2**	**Score 3**	**Score 4**
Credit Limit	**Closed**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	≤£500	0.00	0.00	-375.2	7.3	6.5	2.2	1.5	1.0
	£501-1000	0.00	0.00	-740.2	14.6	11.4	5.0	1.8	1.3
	£1001-1500	0.00	0.00	-1065.5	21.5	14.7	5.2	2.1	1.6
	£1501-2500	0.00	0.00	-1495.1	31.2	18.8	7.4	3.2	2.7
	£2501-3500	0.00	0.00	-2127.9	43.5	27.2	13.4	5.3	3.7
	£3501-4500	0.00	0.00	-3056.4	54.8	33.3	18.4	7.8	5.4
	£4501-5500	0.00	0.00	-3931.4	76.9	39.2	23.4	10.1	6.9
	≥ £5501	0.00	0.00	-5727.3	114.4	60.3	42.4	19.6	14.6

- With the same credit limit, consumers with lower behaviour score generates higher reward

Results

Optimal Policy		Behaviour Score							
		Closed	Inactive	Bad	In risk	Score 1	Score 2	Score 3	Score 4
Credit Limit	C	C	C	C	C	C	C	C	C
	1	C	3	C	1	8	8	1	1
	2	C	3	C	2	8	8	8	8
	3	C	3	C	3	8	8	8	8
	4	C	4	C	4	8	8	8	8
	5	C	5	C	5	8	8	8	8
	6	C	6	C	6	8	8	8	8
	7	C	8	C	7	8	8	8	8
	8	C	8	C	8	8	8	8	8

Index: C : Closed

1 : ≤£500

2 : £501-1000

3 : £1001-1500

4 : £1501-2500

5 : £2501-3500

6 : £3501-4500

7 : £4501-5500

8 : ≥ £5501

Conclusion

- To link the credit limit policy to customers' behavioural score
- A set of optimal policy with expected profit estimation
- Fast generation time

Future research

- Classification – decision tree model
- Segmentation – mover-stayer model
- Economic variables – logistics regression model

Q&A

Thank you for your attention!