Business problem

Most Banks and credit card companies competing in similar segments with similar products are finding it hard to differentiate themselves. The challenge for these companies is to align the right value proposition with the right consumers. The answer lies in advanced customer segmentation based on customer financial behavior towards range of consumer finance products and markets i.e How Banks and credit card companies do segmentation for credit card customers based on customer financial behavior.

Target population

U.S. adult population of 18 years of age or older. I have selected this group since adult population of 18 years of age or older are potential customers of Banks/Credit card companies.

Data Preparation

I selected 17 variables (2 demographics and 15 behavior variables) and cleaned and prepared the variables before segmentation system. I used 2d array in SAS to find missing variables

```
array missy(16,5)

……variables

      /* make missing values zeroes */
      do i = 1 to 16;
            do j = 1 to 5;
                  if missy(i,j) = . then
                        missy(i,j) = 0;
            end;
      end;


      /* make array for 16 variable sums */
      array mysum(16);

      /* sum up the vars and make no mark or > 1 mark as missing*/
      /* now make each variable, being sure to ignore zeroes and > 1 */

      do k = 1 to 16;
         mysum(k) = missy(k,1)+ missy(k,2)+missy(k,3) + missy(k,4) +
      missy(k,5);
      end;

      /* now if the variable is not zero or > 1 create var */
      array myvar(16);

      do m = 1 to 16;
            if mysum(m) = 1 then
                        myvar(m) = (missy(m,1)*5) + (missy(m,2)*4)+
      (missy(m,3)*3) + (missy(m,4))*2 + (missy(m,5)*1);
            else myvar(m) = .;
      end;
```

The below table captures snapshot of all variables

Obs	finan_now_sig_better_off	finan_now_somewhat_better_off	finan_now_about_the_same	finan_now_somewhat_worse_off	finan_now_sig_worse_off	financially_now_better
1	0	0	0	0	1	1
2	0	0	0	0	0	.
3	0	0	1	0	0	3
4	0	0	1	0	0	3
5	0	0	1	0	0	3
6	0	0	1	0	0	3
7	0	0	0	1	0	2
8	0	1	0	0	0	4
9	0	0	0	0	1	1
10	0	0	0	1	0	2
11	1	0	0	0	0	5
12	0	0	1	0	0	3
13	0	0	0	1	0	2
14	0	0	1	0	0	3
15	0	0	1	0	0	3

Obs	finan_otlk_sig_better_off	finan_otlk_somewhat_better_off	finan_otlk_about_the_same	finan_otlk_somewhat_worse_off	finan_otlk_sig_worse_off	financial_outlook_pos
1	0	0	0	0	1	1
2	0	0	0	0	0	.
3	0	0	1	0	0	3
4	0	0	1	0	0	3
5	0	0	1	0	0	3
6	0	0	1	0	0	3
7	0	0	1	0	0	3
8	0	1	0	0	0	4
9	0	0	0	1	0	2
10	0	0	0	1	0	2
11	1	0	0	0	0	5
12	0	0	1	0	0	3
13	0	0	0	1	0	2
14	0	0	1	0	0	3
15	0	0	0	1	0	2

Obs	eco_otlk_sig_better_off	eco_otlk_somewhat_better_off	eco_otlk_about_the_same	eco_otlk_somewhat_worse_off	eco_otlk_sig_worse_off	economic_outlook_pos
1	0	0	0	1	0	2
2	0	0	0	0	0	.
3	0	0	1	0	0	3
4	0	0	0	0	1	1
5	0	1	0	0	0	4
6	0	0	1	0	0	3
7	0	0	0	1	0	2
8	0	0	1	0	0	3
9	0	0	0	0	1	1
10	0	0	0	1	0	2
11	0	0	1	0	0	3
12	0	0	0	1	0	2
13	0	0	0	1	0	2
14	0	1	0	0	0	4
15	0	0	0	1	0	2

Obs	cash_buyer_agree_a_lot	cash_buyer_agree_a_little	cash_buyer_neither	cash_buyer_disagree_a_little	cash_buyer_disagree_a_lot	cash_buyer
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	0	0	0	1	1
4	0	0	1	0	0	3
5	0	0	0	0	1	1
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	1	0	0	0	0	5
9	0	0	0	0	1	1
10	0	0	0	0	1	1
11	1	0	0	0	0	5
12	0	0	0	1	0	2
13	0	0	0	0	1	1
14	0	0	0	0	0	.
15	0	0	0	0	1	1

Obs	deal_shopper_agree_a_lot	deal_shopper_agree_a_little	deal_shopper_neither	deal_shopper_disagree_a_little	deal_shopper_disagree_a_lot	deal_shopper
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	1	0	0	0	0	5
4	0	0	1	0	0	3
5	0	0	0	0	1	1
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	1	0	0	0	0	5
9	0	0	1	0	0	3
10	0	0	0	0	1	1
11	0	0	1	0	0	3
12	0	0	1	0	0	3
13	1	0	0	0	0	5
14	0	0	0	0	0	.
15	0	0	0	1	0	2

Obs	economical_agree_a_lot	economical_agree_a_little	economical_neither	economical_disagree_a_little	economical_disagree_a_lot	economical
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	1	0	0	0	4
4	0	1	0	0	0	4
5	0	1	0	0	0	4
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	1	0	0	0	0	5
9	1	0	0	0	0	5
10	0	1	0	0	0	4
11	1	0	0	0	0	5
12	1	0	0	0	0	5
13	1	0	0	0	0	5
14	0	0	1	0	0	3
15	0	0	0	0	1	1

	bad_saver_agree_a_lot	bad_saver_agree_a_little	bad_saver_neither	bad_saver_disagree_a_little	bad_saver_disagree_a_lot	bad_saver
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	0	0	0	1	1
4	0	0	0	0	1	1
5	0	0	0	0	1	1
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	0	0	0	1	1
9	0	0	0	1	0	2
10	0	1	0	0	0	4
11	0	1	0	0	0	4
12	0	0	0	0	1	1
13	0	0	0	0	1	1
14	0	0	0	0	0	.
15	0	0	0	0	1	1

Obs	spendthrift_agree_a_lot	spendthrift_agree_a_little	spendthrift_neither	spendthrift_disagree_a_little	spendthrift_disagree_a_lot	spendthrift
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	0	0	0	1	1
4	0	0	0	0	1	1
5	0	1	0	0	0	4
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	0	0	0	1	1
9	0	0	0	0	1	1
10	0	0	0	0	1	1
11	0	1	0	0	0	4
12	0	0	0	0	1	1
13	0	0	0	0	1	1
14	0	0	0	0	0	.
15	0	0	0	0	1	1

Obs	debt_averse_agree_a_lot	debt_averse_agree_a_little	debt_averse_neither	debt_averse_disagree_a_little	debt_averse_disagree_a_lot	debt_averse
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	1	0	0	0	0	5
4	1	0	0	0	0	5

5	1	0	0	0	0	5
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	1	0	0	0	0	5
9	0	0	0	0	1	1
10	1	0	0	0	0	5
11	1	0	0	0	0	5
12	1	0	0	0	0	5
13	1	0	0	0	0	5
14	0	0	0	0	0	.
15	0	0	0	0	1	1

Obs	finan_secure_agree_a_lot	finan_secure_agree_a_little	finan_secure_neither	finan_secure_disagree_a_little	finan_secure_disagree_a_lot	financially_secure
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	1	0	0	0	4
4	0	1	0	0	0	4
5	1	0	0	0	0	5
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	1	0	0	0	4
9	0	0	0	0	1	1
10	0	0	0	0	1	1
11	0	1	0	0	0	4
12	0	0	1	0	0	3
13	0	0	0	0	1	1
14	0	0	0	0	0	.
15	0	0	0	1	0	2

Obs	risk_taker_agree_a_lot	risk_taker_agree_a_little	risk_taker_neither	risk_taker_disagree_a_little	risk_taker_disagree_a_lot	risk_taker
1	0	0	0	0	0	.
2	0	0	0	1	0	2
3	0	1	0	0	0	4
4	0	0	0	0	1	1
5	0	0	1	0	0	3
6	0	0	0	0	0	.
7	0	0	0	1	0	2
8	0	1	0	0	0	4
9	0	0	0	1	0	2
10	0	0	0	1	0	2
11	0	1	0	0	0	4

12	0	1	0	0	0	4
13	0	0	1	0	0	3
14	0	0	0	0	0	.
15	0	0	0	1	0	2

Obs	stk_mkt_averse_agree_a_lot	stk_mkt_averse_agree_a_little	stk_mkt_averse_neither	stk_mkt_averse_disagree_a_little	stk_mkt_averse_disagree_a_lot	stock_market_averse
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	0	0	1	0	2
4	0	1	0	0	0	4
5	0	0	1	0	0	3
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	0	0	0	1	1
9	0	0	0	1	0	2
10	1	0	0	0	0	5
11	0	0	0	1	0	2
12	0	0	1	0	0	3
13	1	0	0	0	0	5
14	1	0	0	0	0	5
15	0	0	0	0	1	1

Obs	conven_seeker_agree_a_lot	conven_seeker_agree_a_little	conven_seeker_neither	conven_seeker_disagree_a_little	conven_seeker_disagree_a_lot	convenience_seeker
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	1	0	0	0	0	5
4	1	0	0	0	0	5
5	1	0	0	0	0	5
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	0	0	1	0	2
9	0	1	0	0	0	4
10	0	0	0	0	1	1
11	0	0	0	0	1	1
12	0	0	0	0	1	1
13	1	0	0	0	0	5
14	0	0	1	0	0	3
15	0	0	0	0	1	1

Obs	advet_seeker_agree_a_lot	advet_seeker_agree_a_little	advet_seeker_neither	advet_seeker_disagree_a_little	advet_seeker_disagree_a_lot	advertisement_seeker
1	0	0	1	0	0	3
2	0	0	1	0	0	3
3	0	0	0	1	0	2
4	0	0	1	0	0	3
5	0	0	0	0	1	1
6	0	0	0	0	0	.
7	0	0	0	0	0	.
8	0	0	1	0	0	3
9	0	0	0	0	1	1
10	0	0	0	0	1	1
11	0	0	0	0	1	1
12	0	0	0	1	0	2
13	0	0	0	0	1	1
14	0	0	0	0	0	.
15	0	0	0	0	1	1

Obs	contended_agree_a_lot	contended_agree_a_little	contended_neither	contended_disagree_a_little	contended_disagree_a_lot	contended
1	1	0	0	0	0	5
2	0	0	0	1	0	2
3	1	0	0	0	0	5
4	1	0	0	0	0	5
5	1	0	0	0	0	5
6	0	0	0	0	0	.
7	0	0	1	0	0	3
8	0	0	1	0	0	3
9	0	0	0	1	0	2
10	0	0	0	0	1	1
11	1	0	0	0	0	5
12	1	0	0	0	0	5
13	0	1	0	0	0	4
14	0	0	0	1	0	2
15	0	0	0	1	0	2

Obs	marital_married	marital_widowed	marital_divorced	marital_seprated	marital_never_married	marital_status
1	0	1	0	0	0	4
2	0	0	0	0	1	1
3	1	0	0	0	0	5
4	1	0	0	0	0	5
5	1	0	0	0	0	5

6	1	0	0	0	0	5
7	0	0	0	0	1	1
8	0	0	0	0	1	1
9	1	0	0	0	0	5
10	1	0	0	0	0	5
11	1	0	0	0	0	5
12	1	0	0	0	0	5
13	0	1	0	0	0	4
14	0	0	0	0	1	1
15	1	0	0	0	0	5

financially_now_better

	Frequency	Percent	Cumulative	Cumulative Percent
3	367	40.73	367	40.73
2	220	24.42	587	65.15
1	149	16.54	736	81.69
4	125	13.87	861	95.56
5	40	4.44	901	100

Frequency Missing = 99

financial_outlook_pos

	Frequency	Percent	Cumulative	Cumulative Percent
3	413	45.99	413	45.99
4	216	24.05	629	70.04
2	143	15.92	772	85.97
5	67	7.46	839	93.43
1	59	6.57	898	100

Frequency Missing = 102

economic_outlook_pos

	Frequency	Percent	Cumulative	Cumulative Percent
3	355	39.53	355	39.53
2	223	24.83	578	64.37
4	180	20.04	758	84.41
1	122	13.59	880	98
5	18	2	898	100

Frequency Missing = 102

cash_buyer

	Frequency	Percent	Cumulative	Cumulative Percent
5	266	28.33	266	28.33
4	232	24.71	498	53.04
3	174	18.53	672	71.57
1	154	16.4	826	87.97
2	113	12.03	939	100

Frequency Missing = 61

deal_shopper

	Frequency	Percent	Cumulative	Cumulative Percent
3	459	49.14	459	49.14
4	165	17.67	624	66.81
5	123	13.17	747	79.98
1	117	12.53	864	92.51
2	70	7.49	934	100

Frequency Missing = 66

economical

	Frequency	Percent	Cumulative	Cumulative Percent
5	329	35.22	329	35.22
4	301	32.23	630	67.45
3	193	20.66	823	88.12
2	73	7.82	896	95.93
1	38	4.07	934	100

Frequency Missing = 66

bad saver

	Frequency	Percent	Cumulative	Cumulative Percent
1	265	28.28	265	28.28
3	228	24.33	493	52.61
2	202	21.56	695	74.17
4	161	17.18	856	91.36
5	81	8.64	937	100

Frequency Missing = 63

spendthrift

	Frequency	Percent	Cumulative	Cumulative Percent
1	343	36.84	343	36.84
3	208	22.34	551	59.18
2	197	21.16	748	80.34
4	129	13.86	877	94.2
5	54	5.8	931	100

Frequency Missing = 69

debt averse

	Frequency	Percent	Cumulative	Cumulative Percent
5	548	58.99	548	58.99
4	191	20.56	739	79.55
3	109	11.73	848	91.28
1	48	5.17	896	96.45
2	33	3.55	929	100

Frequency Missing = 71

financially secure

	Frequency	Percent	Cumulative	Cumulative Percent
3	266	28.69	266	28.69
4	213	22.98	479	51.67
2	176	18.99	655	70.66
1	159	17.15	814	87.81
5	113	12.19	927	100

Frequency Missing = 73

risk-taker

	Frequency	Percent	Cumulative	Cumulative Percent
4	258	26.93	258	26.93
3	240	25.05	498	51.98
2	201	20.98	699	72.96
1	197	20.56	896	93.53
5	62	6.47	958	100

Frequency Missing = 42

stock_market_averse

	Frequency	Percent	Cumulative	Cumulative Percent
3	315	33.51	315	33.51
4	173	18.4	488	51.91
5	162	17.23	650	69.15
2	161	17.13	811	86.28
1	129	13.72	940	100

convenience seeker

convenience seeker	Frequency	Percent	Cumulative Frequency	Cumulative Percent
5	298	31.91	298	31.91
3	192	20.56	490	52.46
1	183	19.59	673	72.06
4	166	17.77	839	89.83
2	95	10.17	934	100

Frequency Missing = 66

advertisement seeker

	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	344	36.44	344	36.44
3	330	34.96	674	71.4
2	150	15.89	824	87.29
4	80	8.47	904	95.76
5	40	4.24	944	100
Frequency Missing = 56				

content

content	Frequency	Percent	Cumulative Frequency	Cumulative Percent
5	345	36.05	345	36.05
4	316	33.02	661	69.07
3	156	16.3	817	85.37
2	108	11.29	925	96.66
1	32	3.34	957	100

Frequency Missing = 43

gender	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	565	56.50	565	56.50
1	435	43.50	1000	100.00

marital_status	Frequency	Percent	Cumulative Frequency	Cumulative Percent
5	609	60.90	609	60.90
1	186	18.60	795	79.50
3	121	12.10	916	91.60
4	67	6.70	983	98.30
2	17	1.70	1000	100.00

Q4)

a. List out the questions that you selected to do the factor analysis on

1. Ecn otlk-finan bet/worse than 12 ms ago?
2. Ecnmc outlk-next 12 mos finan bet/worse?
3. Ecnmc outlk-next 12 mos american economy
4. Often prefer to pay cash for things buy
5. Shop for best deal for financial service
6. I'm careful with my money
7. I'm no good at saving money
8. Tend to spend money without thinking
9. Don't like the idea of being in debt
10. I feel financially secure
11. I enjoy taking risks
12. Investing in stock market is risky to me
13. I prefer to let professionals do my taxes even though I can do myself
14. I find advertising for financial services to be interesting
15. I am happy with my life as it is

b. Tell me what latent unobserved construct(s) you think they measure.

Latent construct measure the following

Prosperous, secure and content	Spendthrift but have positive outlook	Recovering	Stressed customers	Cautious and content

c. Decide which extraction technique to use and tell me why

I used "principal "component because the first factor accounts for as much common variance as possible, then the second factor next most variance, and so on. The first component has large positive loadings for all five variables. This method finds linear functions that explain maximal variance in observed data such that components are orthogonal(uncorrelated).

d. Decide which rotation method you are going to use and why

I used varimax rotation method. A varimax rotation is an orthogonal rotation and it results in uncorrelated components. Each variable tends to be associated with one of the factors and each factor represents only a small number of variables. This rotation technique maximizes the variance of a column of the factor pattern matrix.

e. Run the factor analysis

I ran the proc factor analysis and output of factor analysis is captured in annexure 1

```
proc factor data=segmentation_data method=principal rotate=varimax
nfactors=5 plots= (scree loadings) out=cluster_data;
  var
        financially_now_better
```

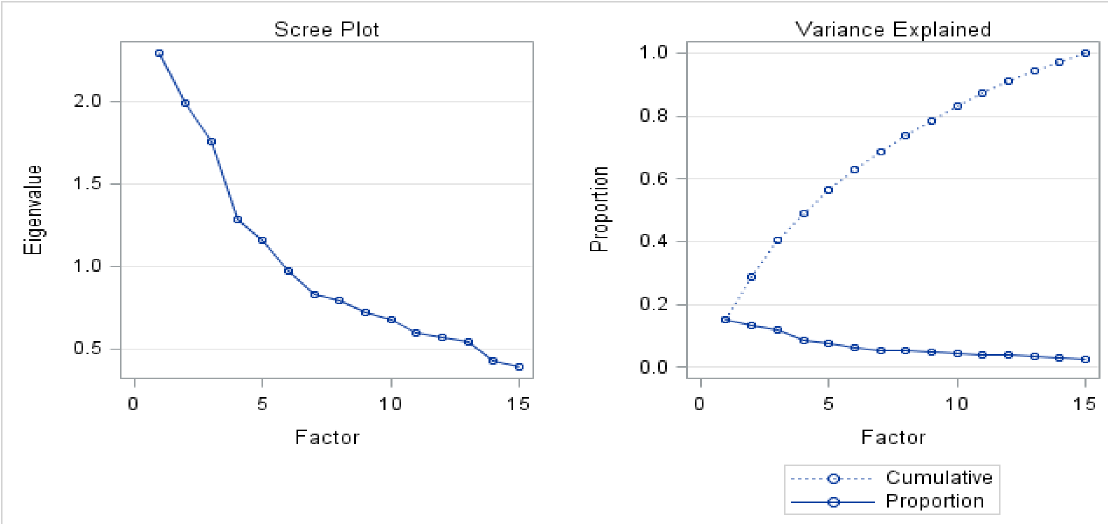
```
          financial_outlook_pos
          economic_outlook_pos
          cash_buyer
          deal_shopper
          economical
          bad_saver
          spendthrift
          debt_averse
          financially_secure
          risk_taker
          stock_market_averse
          convenience_seeker
          advertisement_seeker
          content;
run;

ods graphics off;

data cluster_data1;
  set cluster_data ;
  /* now make the var names pretty again */
  prosperous_content = Factor1;
    spendthrift_positive = Factor2;
    recovering = Factor3;
  stressed_customer=Factor4;
  cautious_content=Factor5;
run;
```

f. How many factors were extracted?

Five factors have eigen value more than 1.

g. What criteria was used to determine number of factors? How does that work?
The eigenvalue for a given factor measures the variance in all the variables which is accounted for by that factor. I looked at number of factors with eigen value more than 1.
I also used scree plots in principal components analysis and factor analysis to visually assess which components or factors explain most of the variability in the data.

Eigen values and Scree plot



Eigenvalues of the Correlation Matrix: Total = 15 Average = 1				
	Eigenvalue	**Difference**	**Proportion**	**Cumulative**
1	2.29135852	0.30214600	0.1528	0.1528
2	1.98921252	0.23529071	0.1326	0.2854
3	1.75392181	0.46962586	0.1169	0.4023
4	1.28429595	0.12366668	0.0856	0.4879
5	1.16062927	0.19185157	0.0774	0.5653
6	0.96877769	0.14353002	0.0646	0.6299
7	0.82524767	0.02875260	0.0550	0.6849
8	0.79649507	0.07144052	0.0531	0.7380
9	0.72505455	0.05153235	0.0483	0.7863
10	0.67352220	0.07260213	0.0449	0.8312
11	0.60092007	0.03051389	0.0401	0.8713
12	0.57040618	0.02798836	0.0380	0.9093
13	0.54241782	0.11334265	0.0362	0.9455
14	0.42907518	0.04040969	0.0286	0.9741
15	0.38866549		0.0259	1.0000

h. What percent of the variance is explained by the factors?

About 56% of the variance is explained by 5 factors

i. Interpret the rotated factor matrix loadings and label the factor(s)

	Factor1	Factor2	Factor3	Factor4	Factor5
	Prosperous, secure and content	Spendthrift but have positive outlook	Recovering	Stressed customers	Cautious and content
economical	0.66179	-0.34531	0.22241	0.24726	-0.10848
financially secure	0.65875	0.03726	-0.08931	-0.29077	0.33959
content	0.52792	0.14708	-0.07305	-0.24868	0.51202
financially_outlook_pos	0.2473	0.69611	-0.24747	0.35172	-0.15504
economic_outlook_pos	0.29882	0.57735	-0.19432	0.22891	-0.21612
spendthrift	-0.43473	0.50614	0.3378	-0.10938	0.26583
financially_now_better	0.34606	0.49815	-0.41035	0.16445	0.14137
bad_saver	-0.4485	0.48267	0.33117	0.03052	0.10837
cash_buyer	0.14253	0.09026	0.56798	0.15601	-0.11636
convenience_seeker	0.15703	0.17276	0.54569	-0.00349	0.18908
stock_market_averse	-0.04503	0.03096	0.49541	0.48957	0.2738
debt_averse	0.34471	-0.1839	0.18279	0.47233	-0.21019

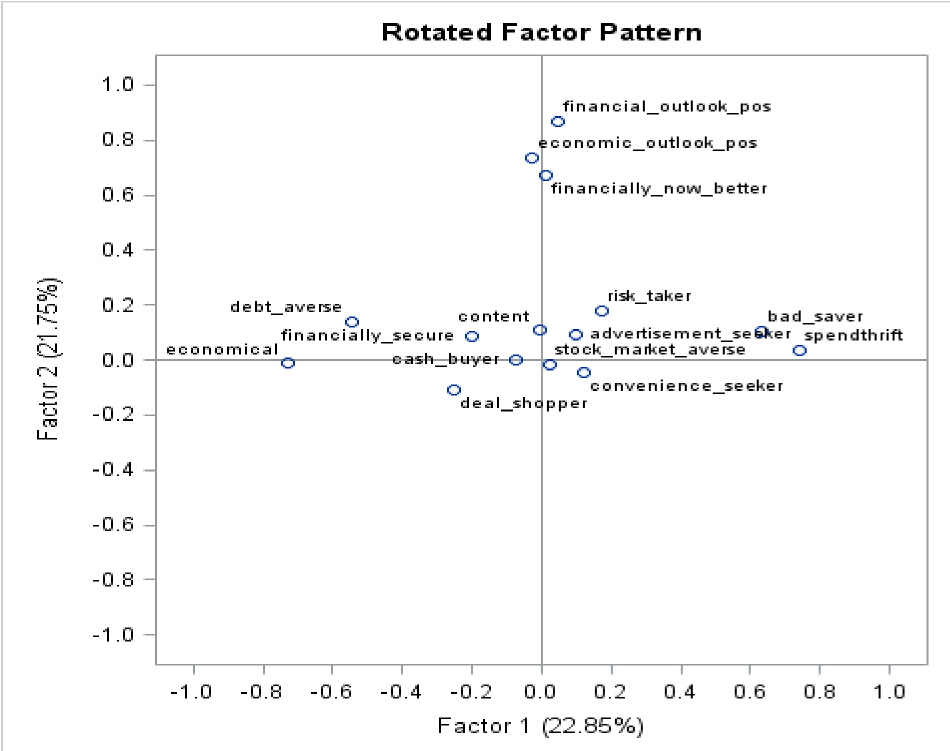
Based on the above rotated factor matrix, we observe five factors. The first factor includes three variables namely economical, financially secure and content. The second factor include five variables namely financially better now, financial outlook positive, economic outlook positive, spendthrift and bad saver. The first two factors capture more than 50% Final Communality Estimates:

Variance Explained by Each Factor				
Factor1	Factor2	Factor3	Factor4	Factor5
1.9375965	1.8446268	1.6239678	1.6063331	1.4668939

Final Communality Estimates: Total = 8.479418				
financially_now_better	financial_outlook_pos	economic_outlook_pos	cash_buyer	deal_shopper
0.58332598	0.75471818	0.55948690	0.38894107	0.54998177

economical	bad_saver	spendthrift	debt_averse	financially_secure	risk_taker
0.67957870	0.55647179	0.64190627	0.45333743	0.64318551	0.55137165

stock_market_averse	convenience_seeker	advertisement_seeker	contended
0.56306349	0.38804480	0.53633103	0.62967349



Factor scores for first 15 observations

Obs	prosperous_content	spendthrift_positive	recovering	stressed_customer	cautious_content
1	.	.	.	.	.
2	.	.	.	.	.
3	-0.88101	0.01789	-1.04780	0.93506	1.10438
4	-0.69097	-0.82478	0.64974	1.63997	-0.80098
5	0.30359	0.66889	-0.21470	1.44952	-1.35564
6	.	.	.	.	.
7	.	.	.	.	.
8	-1.67828	1.00678	-0.98270	-0.36116	1.92493
9	0.05218	-2.24746	-1.40337	-0.78456	-0.45472
10	-0.45989	-0.63134	-0.00085	-2.31419	-2.21083
11	0.17304	2.13139	-0.00943	0.36237	-0.10239
12	-1.25894	-0.04185	-1.11440	0.20003	-0.07739
13	-1.36811	-1.18356	0.49170	-0.53947	-0.14609
14	.	.	.	.	.
15	1.08652	-1.07749	-3.40666	-0.46683	-1.14497

5. Cluster analysis

a. To remove the influence of scaling, I standardize the non-factor variables (debt averse, stock_market_averse and convenience seeker) that I want to use in cluster analysis

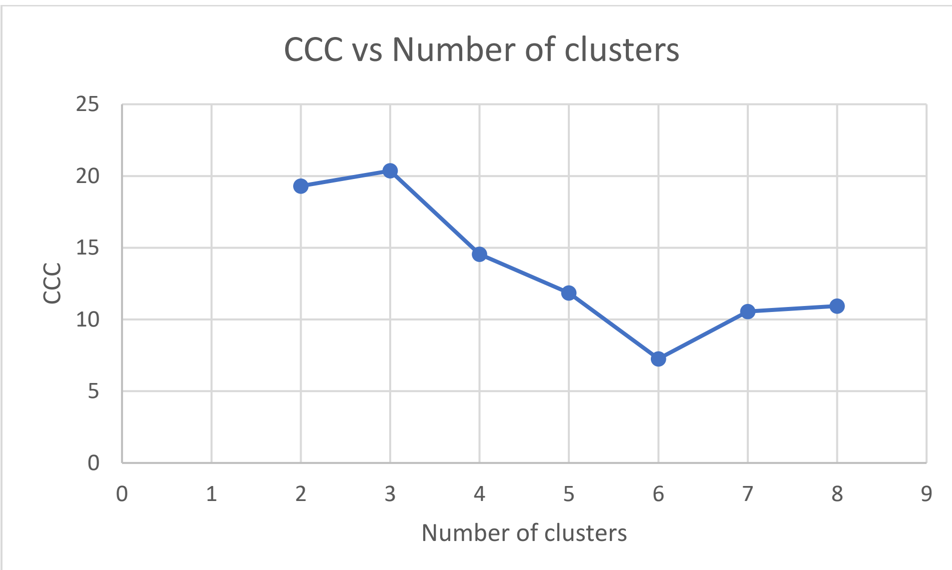
```
PROC STANDARD DATA=cluster_data1 MEAN=0 STD=1 OUT=cluster_data_std;
     VAR debt_averse
         stock_market_averse
         convenience_seeker;
RUN;
```

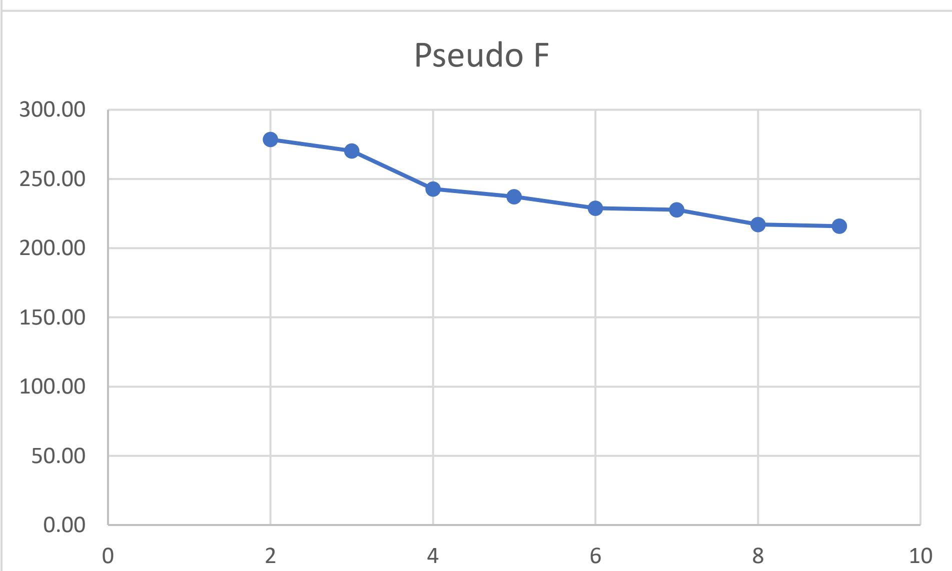
Obs	prosperous_ content	spendthrift_ positive	recovering	stressed_ customer	cautious_ content	debt_ averse	stock_ market _ averse	convenience_ seeker
	Factor1	Factor2	Factor3	Factor4	Factor5			
1.00	.	.	.	.	.	-1.11	-0.07	-0.22
2.00	.	.	.	.	.	-1.11	-0.07	-0.22
3.00	-0.88	0.02	-1.05	0.94	1.10	0.67	-0.86	1.12
4.00	-0.69	-0.82	0.65	1.64	-0.80	0.67	0.73	1.12
5.00	0.30	0.67	-0.21	1.45	-1.36	0.67	-0.07	1.12
6.00	.	.	.	.	.	.	.	.
7.00	.	.	.	.	.	.	.	.
8.00	-1.68	1.01	-0.98	-0.36	1.92	0.67	-1.65	-0.88
9.00	0.05	-2.25	-1.40	-0.78	-0.45	-2.90	-0.86	0.45
10.00	-0.46	-0.63	0.00	-2.31	-2.21	0.67	1.52	-1.55
11.00	0.17	2.13	-0.01	0.36	-0.10	0.67	-0.86	-1.55
12.00	-1.26	-0.04	-1.11	0.20	-0.08	0.67	-0.07	-1.55
13.00	-1.37	-1.18	0.49	-0.54	-0.15	0.67	1.52	1.12
14.00	.	.	.	.	.	.	1.52	-0.22
15.00	1.09	-1.08	-3.41	-0.47	-1.14	-2.90	-1.65	-1.55

b. I run Fastclus to find number of cluster

```
proc fastclus data=cluster_data_std maxc=2 maxiter=1000 out=out;
      var
            prosperous_content
            spendthrift_positive
            debt_averse
            stock_market_averse
            convenience_seeker
      ;
run;
```

c. Diagnostic statistics





Number of clusters	CCC	Pseudo F	R-square
1			
2	19.30	278.51	
3	20.36	270.38	0.26
4	14.55	242.71	0.36
5	11.86	237.32	0.44
6	7.26	228.97	0.51
7	10.56	227.74	0.54
8	10.93	217.17	0.57
9	13.40	215.89	0.59
10	10.37	196.22	0.61
15	11.00	167.14	0.67
20	13.26	153.44	0.71

Initial Seeds					
Cluster	prosperous_content	spendthrift_positive	debt_averse	stock_market_averse	convenience_seeker
1	-1.297473199	2.744811679	0.672631239	-1.652730243	-0.883885461
2	-1.483528869	-2.570090328	0.672631239	1.521052042	1.121496775
3	3.087275126	-0.356918458	-2.005401995	-1.652730243	1.121496775

Minimum Distance Between Initial Seeds =	6.32773

Iteration History				
		Relative Change in Cluster Seeds		
Iteration	Criterion	1	2	3
1	1.4039	0.4120	0.4088	0.4235
2	0.8090	0.0245	0.0265	0.0178
3	0.8038	0.0192	0.0211	0.0108
4	0.8009	0.0194	0.0213	0.00202
5	0.7986	0.0126	0.0129	0.00302

Convergence criterion is satisfied.

Criterion Based on Final Seeds =	0.7976

Cluster Summary						
Cluster	Frequency	RMS Std Deviation	Maximum Distance from Seed to Observation	Radius Exceeded	Nearest Cluster	Distance Between Cluster Centroids
1	352	0.7948	3.2886		2	1.8800
2	364	0.7845	3.6014		1	1.8800
3	234	0.8470	3.5260		2	2.5931

Statistics for Variables				
Variable	Total STD	Within STD	R-Square	RSQ/(1-RSQ)
prosperous_content	1.00000	0.75618	0.429647	0.753299
spendthrift_positive	1.00000	0.97760	0.046732	0.049023
debt_averse	1.00000	0.56556	0.680835	2.133174
stock_market_averse	1.00000	0.76775	0.411812	0.700137
convenience_seeker	1.00000	0.89009	0.209430	0.264910
OVER-ALL	1.00000	0.79874	0.363470	0.571017

Pseudo F Statistic =	270.38

Approximate Expected Over-All R-Squared =	0.26955

Cubic Clustering Criterion =	20.363

Cluster Means					
Cluster	prosperous_content	spendthrift_positive	debt_averse	stock_market_averse	convenience_ seeker
1	-0.567	0.268	0.496	-0.621	-0.507
2	-0.103	-0.160	0.445	0.806	0.541
3	1.141	-0.196	-1.446	-0.296	-0.081

Cluster Standard Deviations					
Cluster	prosperous_content	spendthrift_positive	debt_averse	stock_market_averse	convenience_ seeker
1	0.735	0.895	0.363	0.825	1.002
2	0.869	1.023	0.395	0.686	0.805
3	0.569	1.034	0.928	0.796	0.836

d.

Cluster	N Obs	Variable	N	Mean	Std Dev	Minimum	Maximum
1	352	prosperous_content	308	-0.5671558	0.7354088	-1.8259751	2.1395400
		spendthrift_positive	308	0.2680387	0.8949582	-2.3149697	2.7448117
2	364	prosperous_content	296	-0.1034562	0.8686943	-1.9675266	2.8363205
		spendthrift_positive	296	-0.1598440	1.0234453	-2.6162318	2.2814908
3	234	prosperous_content	180	1.1405946	0.5689222	-0.4713011	3.0872751
		spendthrift_positive	180	-0.1957894	1.0343874	-2.6854466	2.1403039

e.

Cluster	N Obs	Variable	N	Mean	Std Dev	Minimum	Maximum
1	352	debt_averse	348	0.4956348	0.3628099	-1.1127243	0.6726312
		stock_market_averse	350	-0.6212510	0.8252070	-1.6527302	1.5210520
		convenience_seeker	346	-0.5071518	1.0019489	-1.5523462	1.1214968
		gender	352	0.4545455	0.4986384	0	1.0000000
		marital_status	352	3.9857955	1.5311848	1.0000000	5.0000000
2	364	debt_averse	353	0.4450363	0.3953823	-1.1127243	0.6726312
		stock_market_averse	356	0.8056138	0.6862518	-0.8592847	1.5210520
		convenience_seeker	359	0.5405504	0.8047370	-1.5523462	1.1214968
		gender	364	0.4065934	0.4918738	0	1.0000000
		marital_status	364	4.0384615	1.4728596	1.0000000	5.0000000
3	234	debt_averse	228	-1.4455208	0.9279843	-2.8980797	0.6726312
		stock_market_averse	234	-0.2964130	0.7955529	-1.6527302	1.5210520
		convenience_seeker	229	-0.0811488	0.8361736	-1.5523462	1.1214968
		gender	234	0.4444444	0.4979692	0	1.0000000
		marital_status	234	3.6111111	1.6927149	1.0000000	5.0000000

f.

We observe that cluster 1 include customers that have high score in Factor2 (spendthrift and positive) i.e, these customers perceive that they are relatively financially better, have positive financial and economic outlook, and are spendthrift. Simultaneously these customers have negative mean score in Factor 1 (prosperous and content) i.e customers in this cluster are not financially secure, neither economical nor content. We also observe that customers in this segment are neither stock market averse and nor convenience seeker.

We observe that cluster 3 include customers that have high score in Factor1 (prosperous and content) i.e, these customers perceive that they are financially secure, economical and content. Simultaneously customers in this segment have negative mean score in Factor 2 (financial and economic outlook positive), i.e customers in this cluster don't perceive that they are financially better, have non-positive financial and economic outlook positive, and are non-spendthrift. Also, customer in this segment are not debt averse.

We observe that cluster 2 include customers that have marginally negative score in both Factor1 (prosperous and content) and Factor2 (financial and economic outlook positive), i.e, these customers. Simultaneously customers in this segment are stock market averse. Based on the mean, we also observe that cluster 2 has less males as compared to cluster 1 and 3.

Cluster comparison

Variable	Cluster 1	Cluster 2	Cluster 3
Factor 1 (prosperous_content)	Low	Medium	High
Factor 2 (spendthrift_positive)	High	Medium to low	Low
debt_averse	High	High	Low
stock_market_averse	lowest	High	Low
convenience_seeker	lowest	High	Low
Gender (Male % of sample is 43.5%)	Slightly higher than sample average percentage of male	Less than sample male average percentage	Slightly higher than sample male average percentage

h. Executive summary of the segmentation system

Most Banks and credit card companies face challenge of assigning the right value proposition to the right consumer's segment. In fact, often, Banks and credit card companies compete in similar segments with similar products are finding it hard to differentiate themselves. Banks can solve this challenge with new non-traditional ways of market segmentation. I tried to answer this with advanced customer segmentation based on customer financial behavior towards range of consumer finance products and markets. I selected 17 variables (2 demographics and 15 behavior variables) and cleaned and prepared the variables before segmentation system. I selected U.S. adult population of 18 years of age or older as my Target population.

First, I did Factor analysis using PROC Factor to select key factors. Based on Eigen value and scree plot, I selected five factors out from 15 behavior variables. Post Factor analysis I did cluster analysis using FASTCLUS. Clustering is the task of dividing the population or data points into several groups such that data points in the same groups are more like other data points in the same group than those in other groups. Since FASTCLUS uses K-means clustering and in K-means feature variance impact feature influence and hence I standardize the variable before cluster analysis. In this approach, the number of clusters required at the end should be mentioned beforehand, which makes it important to have prior knowledge of the dataset. I observed that ccc indicates that three clusters would be optimum. I used principal component method, and performs iterative clustering in which the notion of similarity is derived by the closeness of a data point to the centroid of the clusters. I observe the parameters such as cubic clustering criterion, pseudo F statistic, and R square and figure out the three clusters are optimum. I observe that cluster 1 include customers that have high score in Factor2 (spendthrift and positive) whereas cluster 3 include customers that have high score in Factor1 (prosperous and content).

Using this segmentation approach, a limited array of features can be assembled in different combinations to create a unique value proposition for each segment. By building a richer, deeper view of customer segments, Banks and financial institution can sharpen their value proposition and clarify positioning and promotions.

Annexure 1 -SAS code

```
filename rawdata
'\\client\C$\Users\Amit\Desktop\MSDA\Practicum\first1k.txt' LRECL=65576;

data work.simmonsdata;
     infile rawdata;
     input my_id 1-7

          male 2281
          female 2282

          marital_married 2344
          marital_widowed 2345
          marital_divorced 2346
          marital_seprated 2347
          marital_never_married 2348

          finan_now_sig_better_off 4049
          finan_now_somewhat_better_off 4048
          finan_now_about_the_same 4047
          finan_now_somewhat_worse_off 4046
          finan_now_sig_worse_off 4045

          finan_otlk_sig_better_off 4054
          finan_otlk_somewhat_better_off 4053
          finan_otlk_about_the_same 4052
          finan_otlk_somewhat_worse_off 4051
          finan_otlk_sig_worse_off 4050

          eco_otlk_sig_better_off 4059
          eco_otlk_somewhat_better_off 4058
          eco_otlk_about_the_same 4057
          eco_otlk_somewhat_worse_off 4056
          eco_otlk_sig_worse_off 4055

          cash_buyer_agree_a_lot 5973
          cash_buyer_agree_a_little 5995
          cash_buyer_neither 6039
          cash_buyer_disagree_a_little 6061
          cash_buyer_disagree_a_lot 6083

          deal_shopper_agree_a_lot 5977
          deal_shopper_agree_a_little 5999
          deal_shopper_neither 6043
          deal_shopper_disagree_a_little 6065
          deal_shopper_disagree_a_lot 6087

          economical_agree_a_lot 5984
          economical_agree_a_little 6006
          economical_neither 6050
          economical_disagree_a_little 6072
          economical_disagree_a_lot 6094
```

```
bad_saver_agree_a_lot 5985
bad_saver_agree_a_little 6007
bad_saver_neither 6051
bad_saver_disagree_a_little 6073
bad_saver_disagree_a_lot 6095

spendthrift_agree_a_lot 5987
spendthrift_agree_a_little 6009
spendthrift_neither 6053
spendthrift_disagree_a_little 6075
spendthrift_disagree_a_lot 6097

debt_averse_agree_a_lot 5988
debt_averse_agree_a_little 6010
debt_averse_neither 6054
debt_averse_disagree_a_little 6076
debt_averse_disagree_a_lot 6098

finan_secure_agree_a_lot 5979
finan_secure_agree_a_little 6001
finan_secure_neither 6045
finan_secure_disagree_a_little 6067
finan_secure_disagree_a_lot 6089

risk_taker_agree_a_lot 4453
risk_taker_agree_a_little 4534
risk_taker_neither 4696
risk_taker_disagree_a_little 4777
risk_taker_disagree_a_lot 4858

stk_mkt_averse_agree_a_lot 5982
stk_mkt_averse_agree_a_little 6004
stk_mkt_averse_neither 6048
stk_mkt_averse_disagree_a_little 6070
stk_mkt_averse_disagree_a_lot 6092

conven_seeker_agree_a_lot 5991
conven_seeker_agree_a_little 6013
conven_seeker_neither 6057
conven_seeker_disagree_a_little 6079
conven_seeker_disagree_a_lot 6101

advet_seeker_agree_a_lot 5971
advet_seeker_agree_a_little 5993
advet_seeker_neither 6037
advet_seeker_disagree_a_little 6059
advet_seeker_disagree_a_lot 6081

content_agree_a_lot 4454
content_agree_a_little 4535
content_neither 4697
content_disagree_a_little 4778
content_disagree_a_lot 4859;
```

```
run;

data mycalcs;
      set work.simmonsdata;
 if male =.  and female =1 then gender =0 ;
 else if female =. and male =1 then gender = 1;
 else gender = 2;


      array missy(16,5)

            finan_now_sig_better_off
            finan_now_somewhat_better_off
            finan_now_about_the_same
            finan_now_somewhat_worse_off
            finan_now_sig_worse_off

            finan_otlk_sig_better_off
            finan_otlk_somewhat_better_off
            finan_otlk_about_the_same
            finan_otlk_somewhat_worse_off
            finan_otlk_sig_worse_off

            eco_otlk_sig_better_off
            eco_otlk_somewhat_better_off
            eco_otlk_about_the_same
            eco_otlk_somewhat_worse_off
            eco_otlk_sig_worse_off

            cash_buyer_agree_a_lot
            cash_buyer_agree_a_little
            cash_buyer_neither
            cash_buyer_disagree_a_little
            cash_buyer_disagree_a_lot

            deal_shopper_agree_a_lot
            deal_shopper_agree_a_little
            deal_shopper_neither
            deal_shopper_disagree_a_little
            deal_shopper_disagree_a_lot

            economical_agree_a_lot
            economical_agree_a_little
            economical_neither
            economical_disagree_a_little
            economical_disagree_a_lot

            bad_saver_agree_a_lot
            bad_saver_agree_a_little
            bad_saver_neither
            bad_saver_disagree_a_little
            bad_saver_disagree_a_lot

            spendthrift_agree_a_lot
```

```
    spendthrift_agree_a_little
    spendthrift_neither
    spendthrift_disagree_a_little
    spendthrift_disagree_a_lot

    debt_averse_agree_a_lot
    debt_averse_agree_a_little
    debt_averse_neither
    debt_averse_disagree_a_little
    debt_averse_disagree_a_lot

    finan_secure_agree_a_lot
    finan_secure_agree_a_little
    finan_secure_neither
    finan_secure_disagree_a_little
    finan_secure_disagree_a_lot

    risk_taker_agree_a_lot
    risk_taker_agree_a_little
    risk_taker_neither
    risk_taker_disagree_a_little
    risk_taker_disagree_a_lot

    stk_mkt_averse_agree_a_lot
    stk_mkt_averse_agree_a_little
    stk_mkt_averse_neither
    stk_mkt_averse_disagree_a_little
    stk_mkt_averse_disagree_a_lot

    conven_seeker_agree_a_lot
    conven_seeker_agree_a_little
    conven_seeker_neither
    conven_seeker_disagree_a_little
    conven_seeker_disagree_a_lot

    advet_seeker_agree_a_lot
    advet_seeker_agree_a_little
    advet_seeker_neither
    advet_seeker_disagree_a_little
    advet_seeker_disagree_a_lot

    content_agree_a_lot
    content_agree_a_little
    content_neither
    content_disagree_a_little
    content_disagree_a_lot

   marital_married
    marital_widowed
  marital_divorced
    marital_seprated
    marital_never_married ;

/* now make missing values zeroes */
```

```
      do i = 1 to 16;
           do j = 1 to 5;
                if missy(i,j) = . then
                     missy(i,j) = 0;
           end;
      end;

      /* make array for 16 variable sums */
      array mysum(16);

      /* sum up the vars and make no mark or > 1 mark missing*/
      /* now make each variable, being sure to ignore zeroes and > 1 */

      do k = 1 to 16;
           mysum(k) = missy(k,1)+ missy(k,2)+missy(k,3) + missy(k,4) +
missy(k,5);
      end;

      /* now if the variable is not zero or > 1 create var */
      array myvar(16);

      do m = 1 to 16;
           if mysum(m) = 1 then
                myvar(m) = (missy(m,1)*5) + (missy(m,2)*4)+
(missy(m,3)*3) + (missy(m,4))*2 + (missy(m,5)*1);
           else myvar(m) = .;
      end;

      /* now make the var names pretty again */
      financially_now_better = myvar(1);
      financial_outlook_pos = myvar(2);
      economic_outlook_pos = myvar(3);
      cash_buyer = myvar(4);
      deal_shopper = myvar(5);
      economical = myvar(6);
      bad_saver = myvar(7);
      spendthrift = myvar(8);
      debt_averse = myvar(9);
      financially_secure = myvar(10);
      risk_taker = myvar(11);
      stock_market_averse = myvar(12);
      convenience_seeker = myvar(13);
      advertisement_seeker = myvar(14);
      content = myvar(15);
      marital_status=myvar(16);
run;

/* now check one out - first grab just a few observations */
Data small;
      Set mycalcs (obs=15);
run;

Proc print data=small;
      Var
```

```
          finan_now_sig_better_off
          finan_now_somewhat_better_off
          finan_now_about_the_same
          finan_now_somewhat_worse_off
          finan_now_sig_worse_off
          financially_now_better;
run;

PROC PRINT DATA=SMALL;
     Var
          finan_otlk_sig_better_off
          finan_otlk_somewhat_better_off
          finan_otlk_about_the_same
          finan_otlk_somewhat_worse_off
          finan_otlk_sig_worse_off
          financial_outlook_pos;
run;

PROC PRINT DATA=SMALL;
     Var
          eco_otlk_sig_better_off
          eco_otlk_somewhat_better_off
          eco_otlk_about_the_same
          eco_otlk_somewhat_worse_off
          eco_otlk_sig_worse_off
          economic_outlook_pos;
run;

PROC PRINT DATA=SMALL;
     Var
          cash_buyer_agree_a_lot
          cash_buyer_agree_a_little
          cash_buyer_neither
          cash_buyer_disagree_a_little
          cash_buyer_disagree_a_lot
          cash_buyer;
run;

PROC PRINT DATA=SMALL;
     Var
          deal_shopper_agree_a_lot
          deal_shopper_agree_a_little
          deal_shopper_neither
          deal_shopper_disagree_a_little
          deal_shopper_disagree_a_lot
          deal_shopper;
run;

PROC PRINT DATA=SMALL;
     Var
          economical_agree_a_lot
          economical_agree_a_little
          economical_neither
          economical_disagree_a_little
```

```
          economical_disagree_a_lot
          economical;
run;

PROC PRINT DATA=SMALL;
     Var
          bad_saver_agree_a_lot
          bad_saver_agree_a_little
          bad_saver_neither
          bad_saver_disagree_a_little
          bad_saver_disagree_a_lot
          bad_saver;
run;

PROC PRINT DATA=SMALL;
     Var
          spendthrift_agree_a_lot
          spendthrift_agree_a_little
          spendthrift_neither
          spendthrift_disagree_a_little
          spendthrift_disagree_a_lot
          spendthrift;
run;

PROC PRINT DATA=SMALL;
     Var
          debt_averse_agree_a_lot
          debt_averse_agree_a_little
          debt_averse_neither
          debt_averse_disagree_a_little
          debt_averse_disagree_a_lot
          debt_averse;
run;

PROC PRINT DATA=SMALL;
     Var
          finan_secure_agree_a_lot
          finan_secure_agree_a_little
          finan_secure_neither
          finan_secure_disagree_a_little
          finan_secure_disagree_a_lot
          financially_secure;
run;

PROC PRINT DATA=SMALL;
     Var
          risk_taker_agree_a_lot
          risk_taker_agree_a_little
          risk_taker_neither
          risk_taker_disagree_a_little
          risk_taker_disagree_a_lot
          risk_taker;
run;
```

```
PROC PRINT DATA=SMALL;
     Var
          stk_mkt_averse_agree_a_lot
          stk_mkt_averse_agree_a_little
          stk_mkt_averse_neither
          stk_mkt_averse_disagree_a_little
          stk_mkt_averse_disagree_a_lot
          stock_market_averse;
run;

PROC PRINT DATA=SMALL;
     Var
          conven_seeker_agree_a_lot
          conven_seeker_agree_a_little
          conven_seeker_neither
          conven_seeker_disagree_a_little
          conven_seeker_disagree_a_lot
          convenience_seeker;
run;

PROC PRINT DATA=SMALL;
     Var
          advet_seeker_agree_a_lot
          advet_seeker_agree_a_little
          advet_seeker_neither
          advet_seeker_disagree_a_little
          advet_seeker_disagree_a_lot
          advertisement_seeker;
run;

PROC PRINT DATA=SMALL;
     Var
          content_agree_a_lot
          content_agree_a_little
          content_neither
          content_disagree_a_little
          content_disagree_a_lot
          content;
run;
PROC PRINT DATA=SMALL;
     Var marital_married
          marital_widowed
        marital_divorced
         marital_seprated
          marital_never_married
        marital_status ;
run;
data segmentation_data;
     set mycalcs(keep= financially_now_better financial_outlook_pos
economic_outlook_pos  cash_buyer  deal_shopper
          economical  bad_saver  spendthrift debt_averse
financially_secure  risk_taker  stock_market_averse convenience_seeker
          advertisement_seeker content gender marital_status);
run;
```

```
proc freq
      data= segmentation_data order=freq;
      tables financially_now_better financial_outlook_pos
economic_outlook_pos  cash_buyer  deal_shopper
           economical  bad_saver  spendthrift debt_averse
financially_secure  risk_taker  stock_market_averse convenience_seeker
           advertisement_seeker content gender marital_status/
plots=freqplot;
run;

ods graphics off;

PROC GCHART DATA= segmentation_data;
      PIE financially_now_better financial_outlook_pos
economic_outlook_pos  cash_buyer  deal_shopper
           economical  bad_saver  spendthrift debt_averse
financially_secure  risk_taker  stock_market_averse convenience_seeker
           advertisement_seeker content gender marital_status/ DISCRETE
VALUE=INSIDE
           PERCENT=INSIDE SLICE=OUTSIDE;
run;

ods graphics on;

proc factor data=segmentation_data method=principal rotate=varimax
nfactors=5 plots= (scree loadings) out=cluster_data;
      var
           financially_now_better
           financial_outlook_pos
           economic_outlook_pos
           cash_buyer
           deal_shopper
           economical
           bad_saver
           spendthrift
           debt_averse
           financially_secure
           risk_taker
           stock_market_averse
           convenience_seeker
           advertisement_seeker
           content;
run;

ods graphics off;
data cluster_data1;
      set cluster_data ;
      /* now make the var names pretty again */
      prosperous_content = Factor1;
     spendthrift_positive = Factor2;
     recovering = Factor3;
      stressed_customer=Factor4;
      cautious_content=Factor5;
```

```
run;
proc print data=cluster_data1 (obs =15);
      var prosperous_content
    spendthrift_positive
    recovering
      stressed_customer
      cautious_content;
run;

PROC STANDARD DATA=cluster_data1 MEAN=0 STD=1 OUT=cluster_data_std;
      VAR debt_averse
            stock_market_averse
            convenience_seeker;
run;
ods graphics off;

proc print data=cluster_data_std (obs =15);
      var prosperous_content
    spendthrift_positive
    recovering
      stressed_customer
      cautious_content
      debt_averse
      stock_market_averse
      convenience_seeker;
      run;
      ods graphics on;
      proc fastclus data=cluster_data_std maxc=7 maxiter=1000 out=out;
            var
                  prosperous_content
                  spendthrift_positive
                  debt_averse
                  stock_market_averse
                  convenience_seeker
            ;
      run;
proc candisc data=out out=can;
var prosperous_content
      spendthrift_positive
            debt_averse
            stock_market_averse
            convenience_seeker ;
class cluster;
run;
proc plot;
plot can2*can1=cluster;
run;
proc means data=out;
      var
            prosperous_content
            spendthrift_positive
      ;
      class cluster;
run;
```

```
proc print data=out;
run;
/* do means for non-driver variables by cluster */
proc means data=out;
      var
            debt_averse
            stock_market_averse
            convenience_seeker
            gender
            marital_status
      ;
      class cluster;
run;
proc print data=out;
      run;
```

Appendix B

Output of Candisc

Number of Observations Read	1000
Number of Observations Used	784

Class Level Information				
CLUSTER	Variable Name	Frequency	Weight	Proportion
1	1	103	103.0000	0.131378
2	2	118	118.0000	0.150510
3	3	140	140.0000	0.178571
4	4	123	123.0000	0.156888
5	5	69	69.0000	0.088010
6	6	152	152.0000	0.193878
7	7	79	79.0000	0.100765

Multivariate Statistics and F Approximations					
S=5 M=0 N=385.5					
Statistic	Value	F Value	Num DF	Den DF	Pr > F
Wilks' Lambda	0.01802114	178.35	30	3094	<.0001
Pillai's Trace	2.52268562	131.87	30	3885	<.0001
Hotelling-Lawley Trace	7.39782029	190.31	30	2050.2	<.0001
Roy's Greatest Root	3.43428872	444.74	6	777	<.0001
NOTE: F Statistic for Roy's Greatest Root is an upper bound.					

	Canonical Correlation	Adjusted Canonical Correlation	Approximate Standard Error	Squared Canonical Correlation	Eigenvalues of Inv(E)*H = CanRsq/(1-CanRsq)			
					Eigenvalue	Difference	Proportion	Cumulative
1	0.880048	0.878019	0.008059	0.774485	3.4343	1.5848	0.4642	0.4642
2	0.805645	0.802563	0.012541	0.649065	1.8495	0.4594	0.2500	0.7142
3	0.762634	.	0.014952	0.581611	1.3901	0.8959	0.1879	0.9021
4	0.575110	0.573448	0.023917	0.330752	0.4942	0.2645	0.0668	0.9690
5	0.432173	.	0.029062	0.186773	0.2297		0.0310	1.0000

	Test of H0: The canonical correlations in the current row and all that follow are zero				
	Likelihood Ratio	Approximate F Value	Num DF	Den DF	Pr > F
1	0.01802114	178.35	30	3094	<.0001
2	0.07991092	146.67	20	2568	<.0001
3	0.22770835	128.07	12	2050.7	<.0001
4	0.54425036	91.96	6	1552	<.0001
5	0.81322667	89.23	2	777	<.0001

Total Canonical Structure					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.775407	0.052308	0.184363	0.162032	0.579451
spendthrift_positive	-0.252002	-0.060638	-0.032169	0.961624	0.084033
debt_averse	-0.908518	0.260428	-0.056404	-0.109348	0.302711
stock_market_averse	-0.107331	0.438511	0.880514	0.025333	-0.142271
convenience_seeker	0.233917	0.921486	-0.277382	0.070822	-0.119121

Between Canonical Structure					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.913028	0.056385	0.188122	0.124681	0.335060
spendthrift_positive	-0.369960	-0.081496	-0.040925	0.922574	0.060583
debt_averse	-0.951425	0.249669	-0.051187	-0.074833	0.155676
stock_market_averse	-0.123112	0.460464	0.875233	0.018989	-0.080139
convenience_seeker	0.256806	0.926123	-0.263895	0.050811	-0.064222

Pooled Within Canonical Structure					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.554247	0.046641	0.179494	0.199517	0.786517
spendthrift_positive	-0.149513	-0.044880	-0.025996	0.982849	0.094677
debt_averse	-0.795975	0.284628	-0.067310	-0.165037	0.503630
stock_market_averse	-0.079471	0.405032	0.888017	0.032313	-0.200040
convenience_seeker	0.185807	0.913089	-0.300110	0.096911	-0.179683

Total-Sample Standardized Canonical Coefficients					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.822308578	0.167539329	0.277711861	0.019814176	1.248561536
spendthrift_positive	-0.322863591	-0.091645281	-0.046171396	1.218071236	-0.065500293
debt_averse	-1.397643460	0.489922642	-0.100515038	-0.294379128	1.053460683
stock_market_averse	-0.148242991	0.451610632	1.466031331	0.063135372	-0.272900608
convenience_seeker	0.397618331	1.455939545	-0.688042068	0.132182429	-0.243044385

Pooled Within-Class Standardized Canonical Coefficients					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.5484277413	0.1117381216	0.1852162225	0.0132148005	0.8327114678
spendthrift_positive	-.2594189688	-.0736364365	-.0370984412	0.9787129699	-.0526290945
debt_averse	-.7604823171	0.2665755014	-.0546919950	-.1601768460	0.5732064323
stock_market_averse	-.0954442743	0.2907634873	0.9438847364	0.0406488680	-.1757034198
convenience_seeker	0.2386303456	0.8737810357	-.4129279358	0.0793291867	-.1458629067

Raw Canonical Coefficients					
Variable	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
prosperous_content	0.822308578	0.167539329	0.277711861	0.019814176	1.248561536
spendthrift_positive	-0.322863591	-0.091645281	-0.046171396	1.218071236	-0.065500293
debt_averse	-1.473156872	0.516392719	-0.105945775	-0.310284166	1.110378211
stock_market_averse	-0.150255964	0.457742995	1.485938382	0.063992679	-0.276606290
convenience_seeker	0.393630038	1.441335810	-0.681140694	0.130856579	-0.240606539

Class Means on Canonical Variables					
CLUSTER	**Can1**	**Can2**	**Can3**	**Can4**	**Can5**
1	-1.753718641	-1.091847586	1.928221564	-0.034609874	-0.114421710
2	-0.834521794	2.020260630	0.941636129	0.336939802	-0.474927726
3	-0.708055978	1.022750037	-1.827780607	0.171198401	-0.088775719
4	-1.760684259	-2.034523901	-0.929701669	-0.161240044	-0.063557472
5	4.521000931	-1.062052070	-0.062905752	-0.389352217	-0.877897506
6	1.595944575	-0.205506319	0.272943482	0.831569484	0.654676209
7	0.509695607	1.084171329	0.295896122	-1.770412517	0.621990147

```
                         Plot of Can2*Can1.  Symbol is value of CLUSTER.

   3 +                          7277 7        7
     |                       2222 2
     |                    27222222 2    7  7        7
     |                  2 22222 2     27 7      7
     |               2  2     222222 22 2     272       6
     |                   222 2222    7  66 66     77            7
   2 +                  2 22    3333376      26  7
     |               2       3332332     3222
     |                  3 3332 2 2    73 6      76 66              5
     |                      3333337 7 2   33 6 26        6      7 5 6
     |                2   3 373 2    33  2372    7  67       66
     |                 222 2 222 33 33 3222 6   3   77      66                55
   1 +                2     333 33 3 6  6  3667666                      5        5
     |                   3333 372 12 2  2 22 276   3  76
     |                 313 111    3 33 3    63 7               5 5                     5
Can2 |                    1   333 31 176 6   3 63 6     6 6        5     5          5
     |                  3 3 1 1     33   77  77  6 6     6 65      6       6    5
     |                1          67666  3 3 33  7    6 6               5
   0 +                    3 3 3 3336    3 7666   3 6 6     5           5
     |                4 34 3      776          76     7  6        5 5    5
     |              4 1 1 1              6 6 66      7  6        5  5   5  5   5
     |          1      4 4447117       6 66      6  6    6 5555 6 6           5
     |                 111 11 1    7 7   7 3 6     66666656           5
     |             1 11     4 1  7    3 3 6 76     66666   5         5
  -1 +                  4  4 1111     1 11  16               56     5      5
     |               1 1111 1        1       66 6     6
     |             111111   44444 441   443166           6                    5  5
     |         1 11 4  44 411  1  44  16  7                          5
     |              1111 11      1 7  66  4           6            6
     |        11  1 1    4 44 41  1    4  1  7                6    5
  -2 +               4  4444 11       1  7           6
     |            44444     11  1        6          6
     |                 44 4 444      44   66                         5
     |             44 44  4    4 4          4     6           5      5 5
     |          4      44 4  44            6      6          5
     |              4444444      44  4          56      6
  -3 +          4 44 4       4        4         5 6
     |                       4
     |                    4                              5
     |                                     4
     |                                        6
     |
  -4 +                                                           5 5
     |                                                       5555
     |                                                    5  5
     |
     |
     |
  -5 +
    ---+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+---------+--
      -4    -3    -2    -1     0     1     2     3     4     5     6     7     8

                                          Can1
```

NOTE: 216 obs had missing values. 233 obs hidden.