

Application of Belief Rule-Based Methodology to Map Consumer Preferences and Set Product Targets

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Background

- Funded jointly by DEFRA, Natural Science Foundation of China and industry
- Led by Professor Jian-Bo Yang (MBS)
- Feasibility study carried out from January 2006 to December 2006

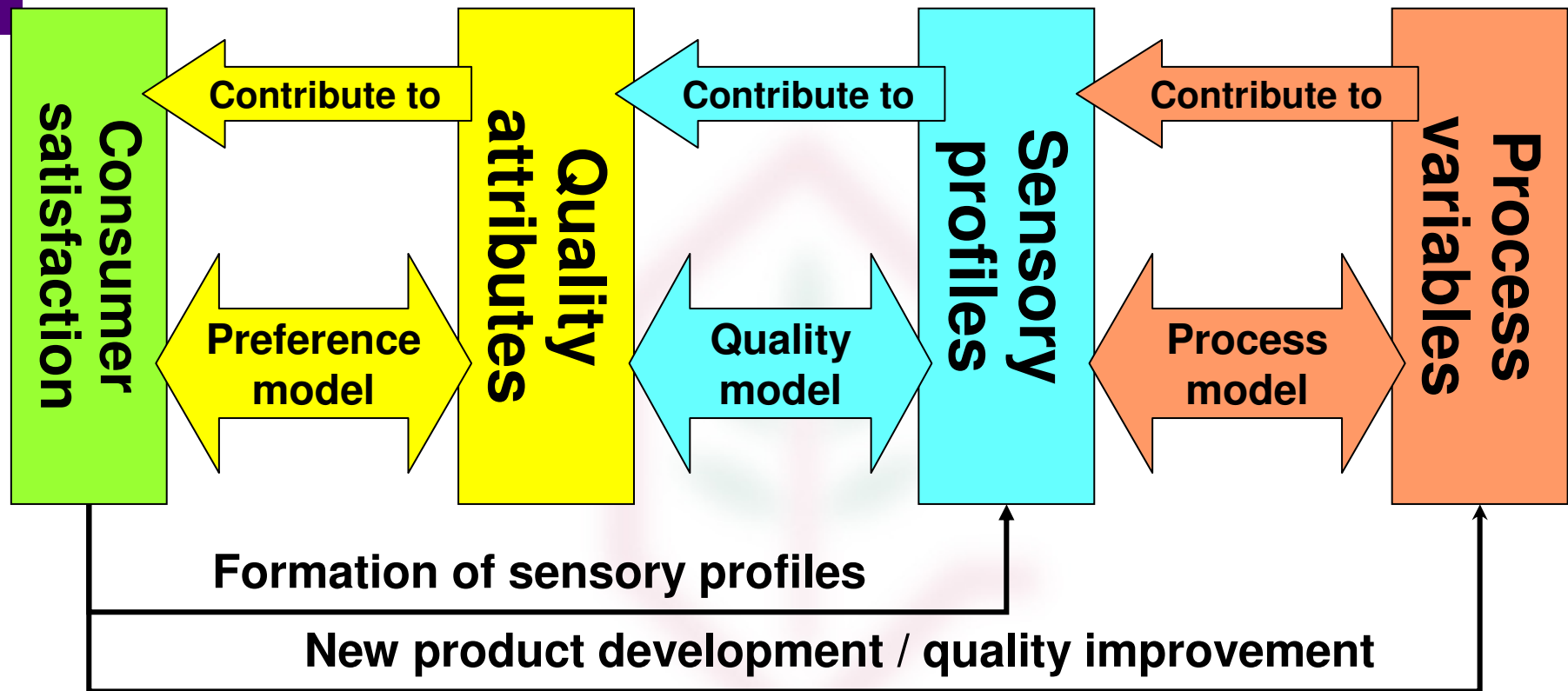


Overview of Presentation

- Quality Model
- Existing methods
- Introduction to Belief Rule-based (BRB) methodology
- Case study
- Conclusion



Quality Model for Food and Drink



Existing Methods

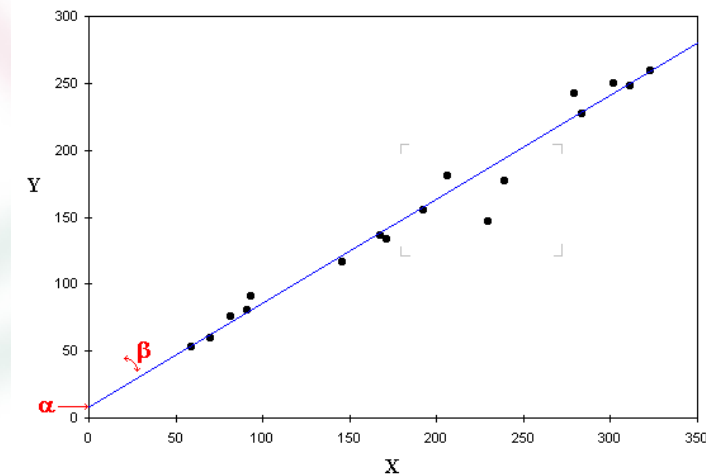
- Multiple Linear Regression (MLR)
- External Preference Mapping
- Artificial Neural Networks
- Support Vector Machines



Multiple Linear Regression

$$y = a + b_1x_1 + b_2x_2 + \dots + b_kx_k$$

- Probably simplest...
- ... but not adequate
- Relationships complex and non-linear
- Attribute set > product set



External Preference Mapping

- Vector:

$$y = a + b_1x_1 + b_2x_2 + \varepsilon$$

- Circular:

$$y = a + b_1x_1 + b_2x_2 + c(x_1^2 + x_2^2) + \varepsilon$$

- Elliptical:

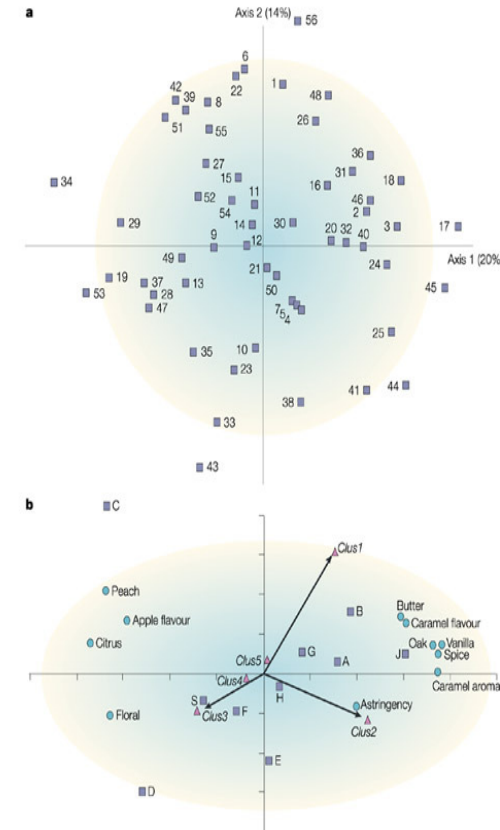
$$y = a + b_1x_1 + b_2x_2 + c_1x_1^2 + c_2x_2^2 + \varepsilon$$

- Quadratic:

$$y = a + b_1x_1 + b_2x_2 + c_1x_1^2 + c_2x_2^2 + dx_1x_2 + \varepsilon$$

Most extensively used...?

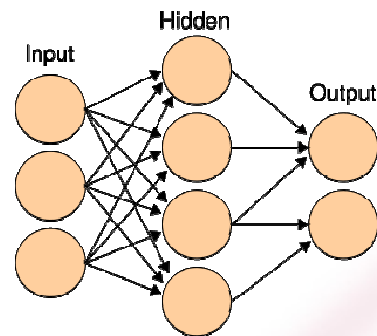
Models preferences as function of PCs



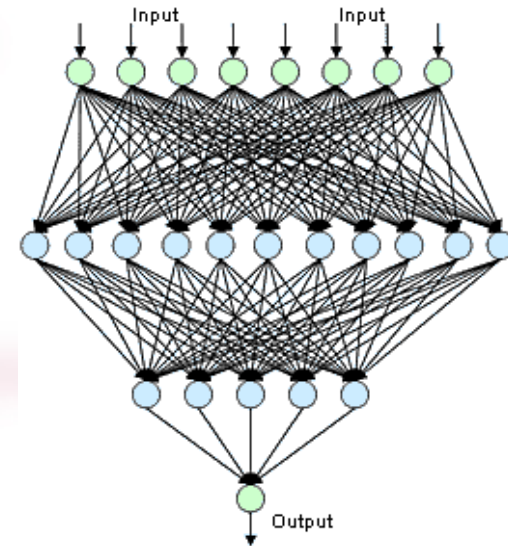
Nature Reviews | Neuroscience



Artificial Neural Networks



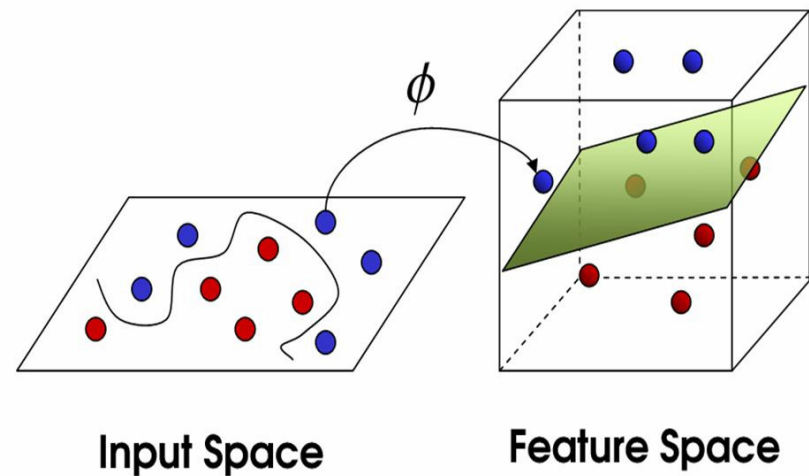
- Models preferences as functions of attributes
- Multilayer network
- Attributes as inputs; preferences as output
- 3-layer networks most commonly used
- Black box simulator!!!



Support Vector Machines

- Machine learning algorithm
- Classification and regression
- Requires specifying relationships in advance

Principle of Support Vector Machines
(SVM)



Belief Rule-Based System



Belief Rule-Based System (BRB)

- Causality characterised by BRB...
- ... generalisation of IF-THEN rules
- Example Belief Rule:

IF (Taste is HIGH) and
(Aroma is HIGH)
THEN Quality is
(Good, 50%)
(Average, 40%) and
(Poor, 10%)

Attributes

Outcomes

Belief Degrees



General Belief Rule

$R_k : \text{If } A_1^k \text{ and } A_2^k \text{ and...and } A_T^k$
 $\text{THEN } (D_1, \beta_{1k}), (D_2, \beta_{2k}), \dots, (D_N, \beta_{Nk})$
 $k \in \{1, \dots, L\}$

$$\sum_{i=1}^N \beta_{i,k} \leq 1.$$

With a rule weight θ_k and attribute weights $\delta_{1k}, \delta_{2k}, \dots, \delta_{Nk}$,

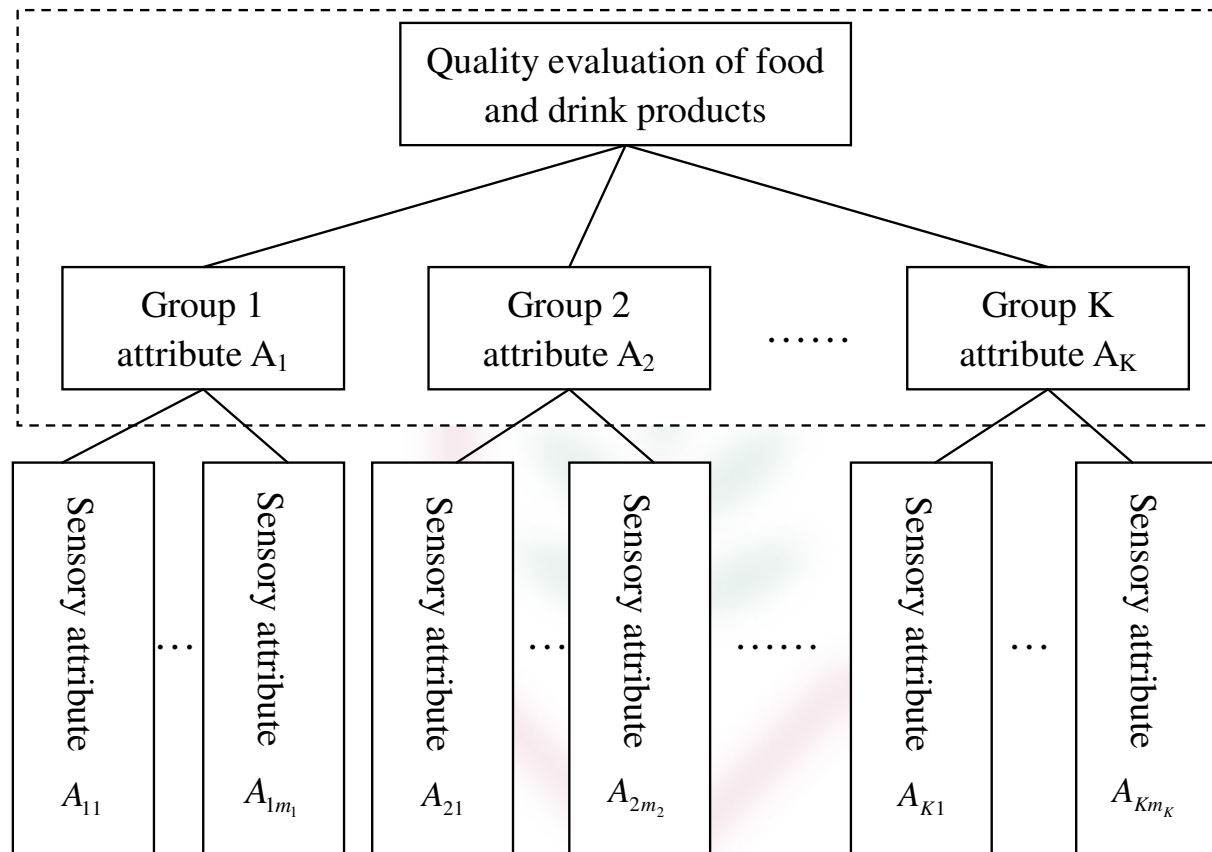


Matrix Expression of Belief Rules

Belief Output	Input					
	$A^1(w_1)$	$A^2(w_2)$	...	$A^k(w_k)$	...	$A^L(w_L)$
D_1	$\beta_{1,1}$	$\beta_{1,2}$	...	$\beta_{1,k}$	...	$\beta_{1,L}$
D_2	$\beta_{2,1}$	$\beta_{2,2}$		$\beta_{2,k}$		$\beta_{2,L}$
			...		...	
D_i	$\beta_{i,1}$	$\beta_{i,2}$	...	$\beta_{i,k}$	...	$\beta_{i,L}$
			...		...	
D_N	$\beta_{N,1}$	$\beta_{N,2}$	...	$\beta_{N,k}$	...	$\beta_{N,L}$



Preference Mapping by BRB



BRBs for Preferences & Group Attributes

Rule	Rule weight	Antecedent attributes (weight)				Consequence			
		$A_1 (\delta_1)$	$A_2 (\delta_2)$	...	$A_K (\delta_K)$	C_1	C_2	...	C_N
1	θ_1	A_1^1	A_2^1	...	A_K^1	β_{11}	β_{12}	...	β_{1N}
2	θ_2	A_1^2	A_2^2	...	A_K^2	β_{21}	β_{22}	...	β_{2N}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
M	θ_M	A_1^M	A_2^M	...	A_K^M	β_{M1}	β_{M2}	...	β_{MN}

Rule	Rule weight	Antecedent attributes (weight)				Consequence (A_h)			
		$A_{h1} (\delta_{h1})$	$A_{h2} (\delta_{h2})$	...	$A_{hm_h} (\delta_{hm_h})$	C_{h1}	C_{h2}	...	C_{hT_h}
1	θ_{h1}	A_{h1}^1	A_{h2}^1	...	$A_{hm_h}^1$	$\beta_{11}^{(h)}$	$\beta_{12}^{(h)}$	...	$\beta_{1T_h}^{(h)}$
2	θ_{h2}	A_{h1}^2	A_{h2}^2	...	$A_{hm_h}^2$	$\beta_{21}^{(h)}$	$\beta_{22}^{(h)}$	...	$\beta_{2T_h}^{(h)}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
M_h	θ_{hM_h}	$A_{h1}^{M_h}$	$A_{h2}^{M_h}$	...	$A_{hm_h}^{M_h}$	$\beta_{M_h1}^{(h)}$	$\beta_{M_h2}^{(h)}$	...	$\beta_{M_hT_h}^{(h)}$



Training

Product	Consumer preference					Output of BRB model				
	C_1	C_2	...	C_N	Average score	C_1	C_2	...	C_N	Expected value
1	b_{11}	b_{12}	...	b_{1N}	y_1	α_1^1	α_2^1	...	α_N^1	O_1
2	b_{21}	b_{22}	...	b_{2N}	y_2	α_1^2	α_2^2	...	α_N^2	O_2
$\vdots$	$\vdots$	$\vdots$	...	$\vdots$	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$	$\vdots$
n	b_{n1}	b_{n2}	...	b_{nN}	y_n	α_1^n	α_2^n	...	α_N^n	O_n

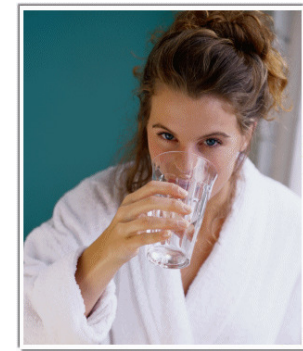


In summary

- Each rule has a set of attributes (input) and a set of outcomes (output)
- Each attribute has an importance (weight)
- Each outcome has a probability (belief)
- Belief-rules are formed from training data (inputs and outputs)
- Rules aggregated into groups



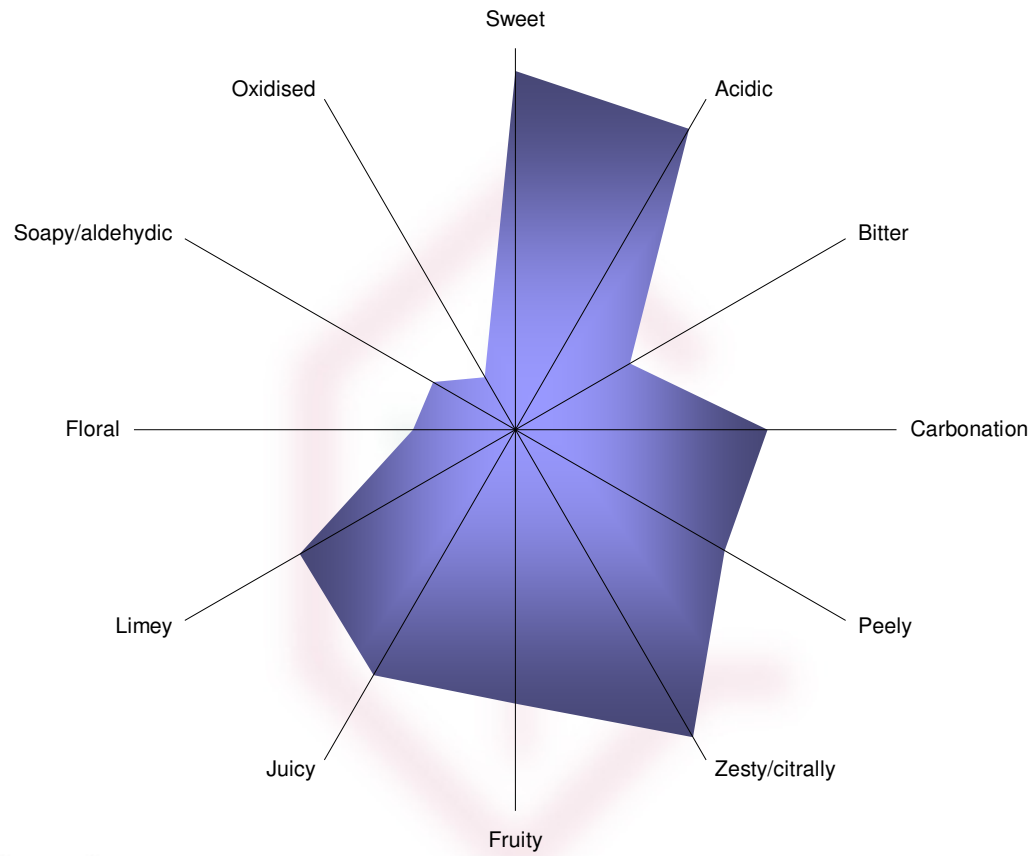
Case Study - Lemonade



- 28 products profiled and rated
- 12 attributes assessed
- 1 hedonic rating (9-point)

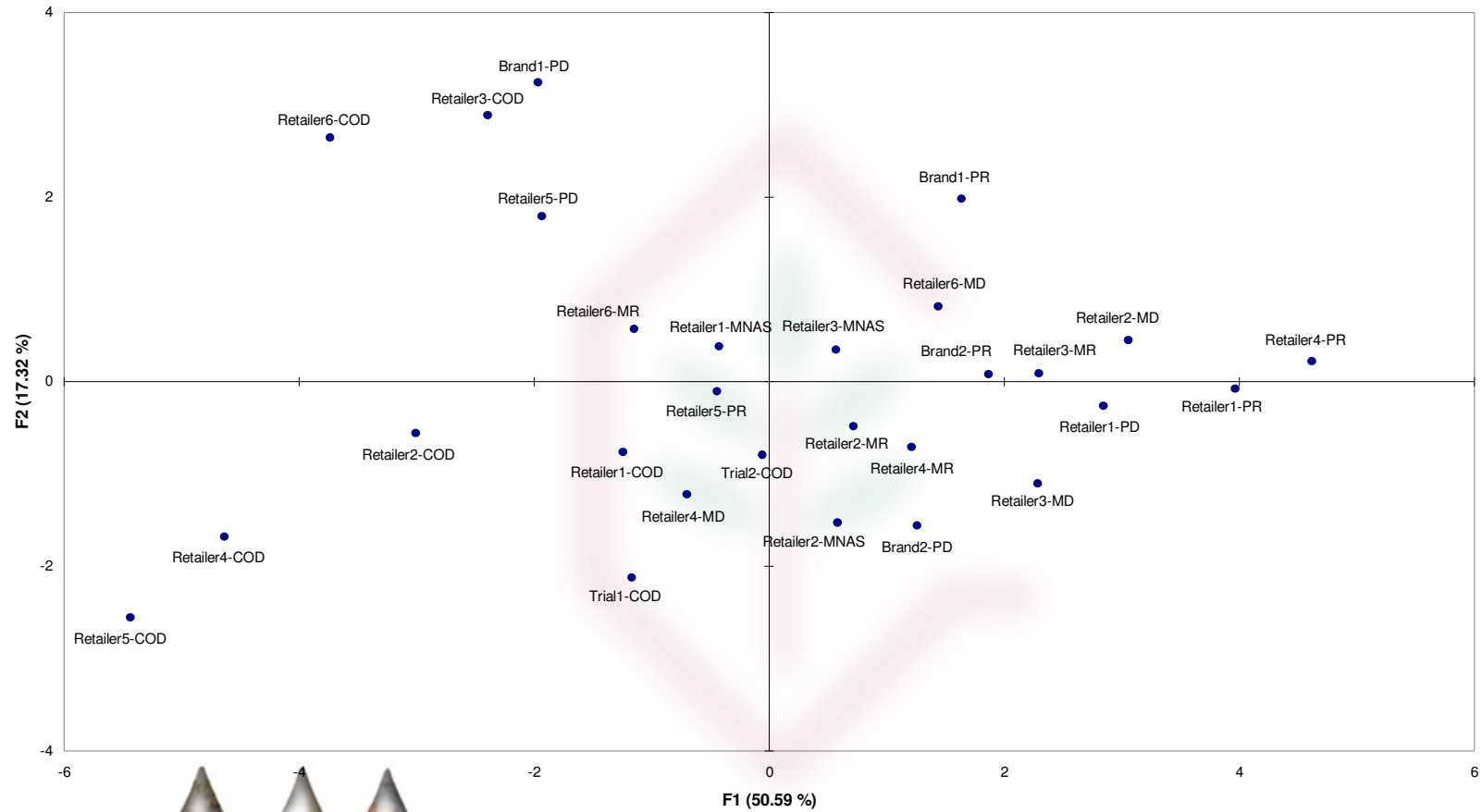


Profiles

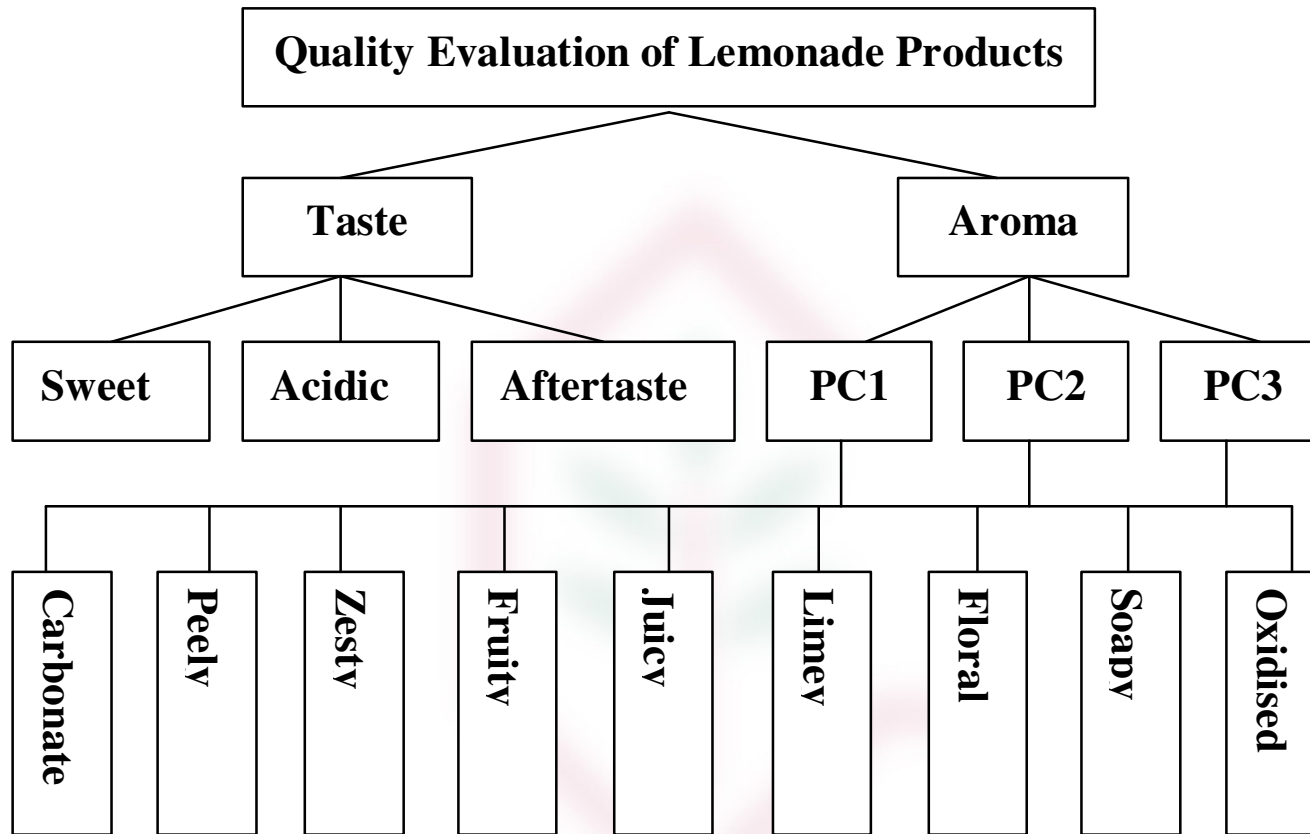


PCA

Lemonade Products



BRB Model



PCs for 9 Attributes

Item	Principal components		
	PC1	PC2	PC3
Eigenvalue	4.725	1.994	0.740
% variance	52.502	22.161	8.226
Cumulative %	52.502	74.663	82.889
Eigenvector			
Carbonation	0.349	-0.017	0.202
Peely	0.338	0.297	0.463
Zesty/citrally	0.411	0.164	0.083
Fruity	0.421	0.044	-0.010
Juicy	0.435	0.059	-0.115
Limey	0.301	0.360	-0.474
Floral	-0.161	0.520	-0.543
Soapy/aldehydic	-0.232	0.519	0.309
Oxidised	-0.241	0.459	0.332



Assessment Grades

Grade	Sweet	Acidic	Aftertaste	PC1	PC2	PC3
High	74.70	65.33	37.95	4.99	5.059	4.752
Medium	46.46	47.46	21.96	0	0	0
Low	18.21	29.59	6.02	-6.25	-4.428	-5.199

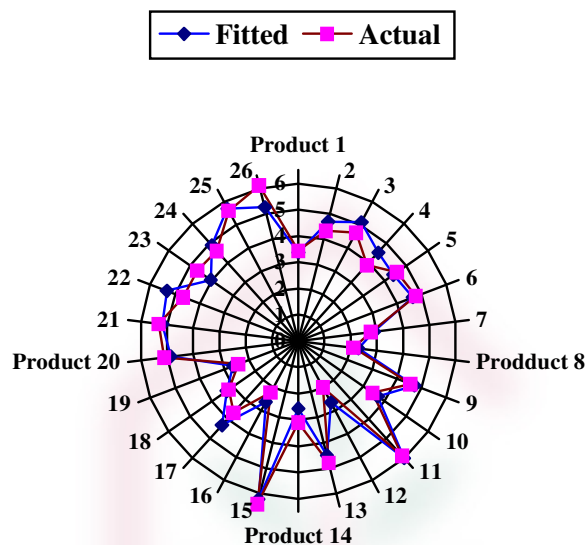


BRB for Overall Quality

Rule	weight	Group attributes		Consumer preferences									
		Taste (0.5)	Aroma (0.5)	0	1	2	3	4	5	6	7	8	9
1	0.101	Low	Low	0.103	0.005	0.007	0.002	0.107	0.043	0.005	0.254	0.365	0.107
2	0.731	Low	Medium	0.111	0.005	0.005	0.060	0.007	0.782	0.026	0.001	0.003	0.000
3	0.023	Low	High	0.000	0.095	0.132	0.240	0.458	0.013	0.050	0.003	0.004	0.005
4	0.635	Medium	Low	0.171	0.008	0.007	0.033	0.039	0.003	0.614	0.124	0.001	0.002
5	0.318	Medium	Medium	0.009	0.423	0.007	0.529	0.000	0.007	0.009	0.005	0.005	0.005
6	0.546	Medium	High	0.008	0.018	0.000	0.013	0.891	0.000	0.042	0.010	0.007	0.011
7	0.079	High	Low	0.000	0.006	0.027	0.045	0.002	0.913	0.000	0.003	0.001	0.003
8	0.142	High	Medium	0.752	0.153	0.041	0.047	0.002	0.002	0.004	0.000	0.000	0.000
9	1.000	High	High	0.164	0.166	0.600	0.000	0.000	0.000	0.015	0.055	0.000	0.000



Fitted Predictions



Method	Actual mean score	Predicted mean score	Accuracy
BRB methodology	3.11	3.23	96.32%
ANN (12-10-1)	3.11	3.19	97.46%
Multiple linear regression	3.11	2.62	84.09%



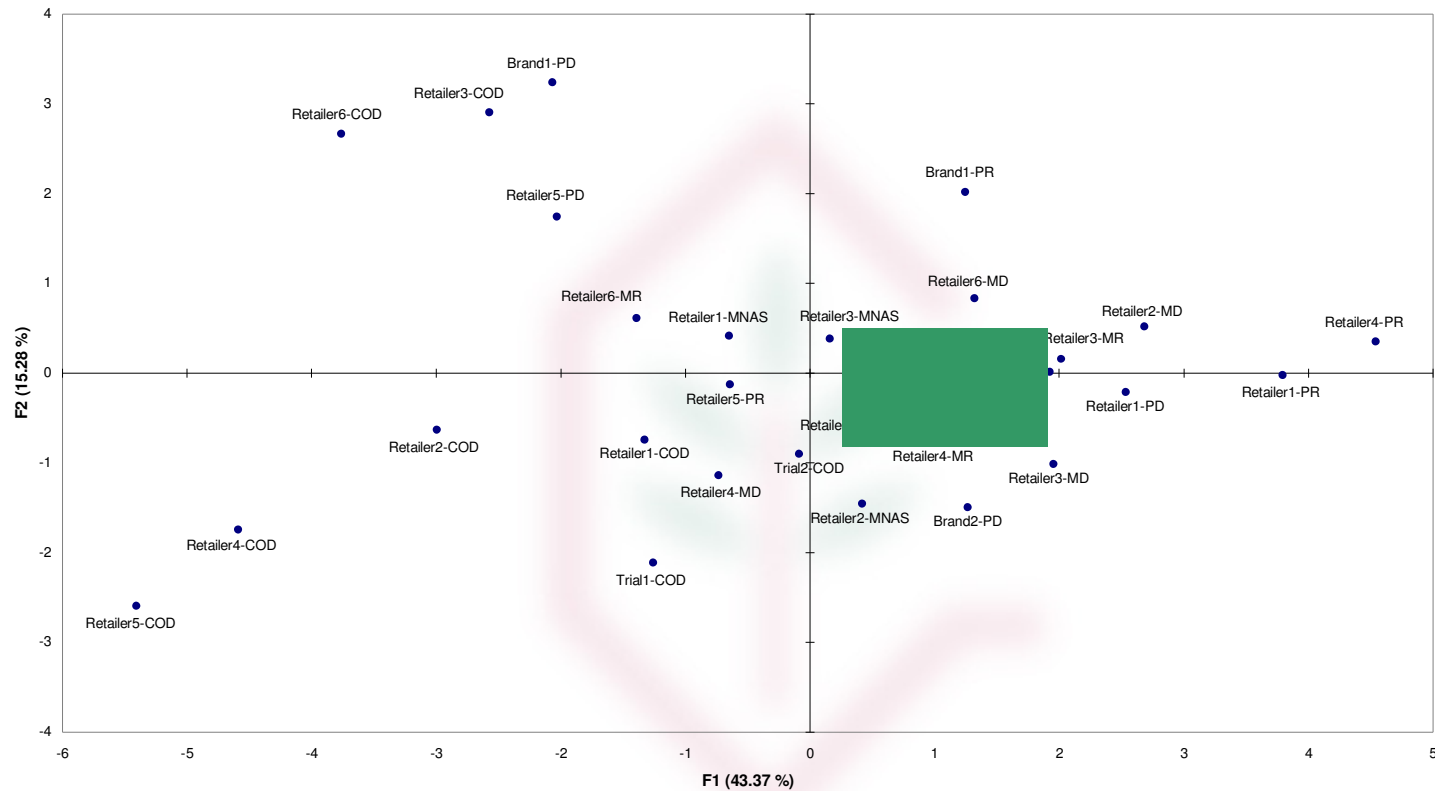
Target Values

Sensory attribute	Minimum	Maximum	Target values			
			Solution 1	Solution 2	Solution 3	Solution 4
Sweet	18.21	74.7	21.11	21.90	29.85	18.21
Acidic	29.59	65.33	46.44	46.45	46.45	45.40
Aftertaste	6.02	37.95	6.02	6.02	6.02	6.02
Carbonation	24.90	50.87	43.03	50.49	50.22	50.14
Peely	13.52	44.31	41.33	44.22	31.97	27.88
Zesty/citrally	11.30	65.19	47.52	49.44	50.33	55.56
Fruity	10.69	50.74	20.07	14.53	47.86	27.89
Juicy	4.99	51.94	45.97	22.37	14.75	21.94
Limey	7.23	45.63	24.31	45.51	18.23	40.39
Floral	3.27	43.57	24.76	16.33	31.19	11.72
Soapy/aldehydic	9.29	49.8	24.92	15.07	24.15	37.02
Oxidised	10.67	47.29	10.87	15.17	18.44	13.54



PCA with Target Values

Lemonade with Hypothetical Targets



Conclusions

- Transparent
- Accommodate expert knowledge
- Outputs as distributions
- Retro-fitting
- Handle uncertainty



Further Work...

- Integration of formulations
- Investigate preference factors
 - Cultural
 - Context
 - Etc



Credits

- Professor Jian-Bo Yang (Project Leader)
 - jian-bo.yang@mbs.ac.uk
- Department for Environment, Food & Rural Affairs (DEFRA)
 - <http://www.defra.gov.uk/>



Thank you!



References

- S. Arditti, "Preference mapping: A case study, Food Quality and Preference", Vol.8, pp.323-327, 1997.
- A. Bahamonde, J. Díez, J.R. Quevedo, O. Luaces and J.J. del Coz, "How to learn consumer preferences from the analysis of sensory data by means of support vector machines (SVM)", Trends in Food Science & Technology, Vol.18, pp.20-28, 2007.
- R.K. Boccoth and A. Paterson, "An artificial neural network model for predicting flavour intensity in blackcurrant concentrates", Food Quality and Preference, Vol.13, pp.117-128, 2002.
- M. Bomio, "[Neural networks and the future of sensory evaluation](#)", Food Technology, Vol.52, No.8, pp.62-63, 1998.
- N.M. Faber, J. Mojet and A. A. M. Poelman, "Simple improvement of consumer fit in external preference mapping", Food Quality and Preference, Vol.14, pp.455-461, 2003.
- L. Geel, M. Kinear, H.L. de Kock, "Relating consumer preference to sensory attributes of instant coffee", Food Quality and Preference, Vol.16, pp.237-244, 2005.
- J.X. Guinard, B. Uotani and P. Schlich, "Internal and external mapping of preferences for commercial lager beers: comparison of hedonic ratings by consumers blind versus with knowledge of brand and price", Food Quality and Preference, Vol.12, pp.243-255, 2001.
- S. Haykin, Neural Networks — A Comprehensive Foundation, McMillan College Publishing Company, New York, 1994.
- B. Heyd and M. Danzart, "Modelling Consumers' Preferences of Coffees: Evaluation of Different Methods", Lebensmittel-Wissenschaft und-Technologie, Vol.31, pp.607-611, 1998.
- R. Krishnamurthy, A.K. Srivastava, J.E. Paton, G.A. Bell and D.C. Levy, "Prediction of consumer liking from trained sensory panel information: Evaluation of neural networks", Food Quality and Preference, Vol.18, pp.275-285, 2007.
- J. Liu, J. B. Yang, D. Ruan, L. Martinez, and J. Wang, "[Self-tuning of fuzzy belief rule bases for engineering system safety analysis](#)", Annals of Operations Research, 2007 (in press).
- C. Martínez, M.J.S. Cruz, G. Hough and M.J. Vega, "Preference mapping of cracker type biscuits", Food Quality and Preference, Vol.13, pp.535-544, 2002.
- E. van Kleef, H.C.M. van Trijp and P. Luning, "Internal versus external preference analysis: An exploratory study on end-user evaluation", Food Quality and Preference, Vol.17, pp.387-399, 2006.
- J. Tan, X. Gao, D.E. Gerrard, "[Application of fuzzy sets and neural networks in sensory analysis](#)", Journal of Sensory Studies, Vol.14, No.2, pp.119-138, 1999.
- V.N. Vapnik, The Nature of Statistical Learning Theory, Springer, 1995.
- Y. M. Wang, J. B. Yang and D. L. Xu, "Environmental impact assessment using the evidential reasoning approach", European Journal of Operational Research, Vol.174, pp.1885-1913, 2006.
- D. L. Xu, J. Liu, J. B. Yang, G. P. Liu, J. Wang, I. Jenkinson, J. Ren, "Inference and learning methodology of belief-rule-based expert system for pipeline leak detection", Expert Systems with Applications, Vol.32, pp.103-113, 2007.
- J. B. Yang, "Rule and utility based evidential reasoning approach for multi-attribute decision analysis under uncertainties", European Journal of Operational Research, Vol.131, pp.31-61, 2001.
- J. B. Yang, J. Liu, D. L. Xu, J. Wang, H. W. Wang, "Optimization models for training belief rule based systems", IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, Vol.37, No.4, pp.569-585, 2007.
- J. B. Yang, J. Liu, J. Wang, H. S. Sii, H. W. Wang, "A generic rule-base inference methodology using the evidential reasoning approach – RIMER", IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, Vol.36, pp.266-285, 2006.
- J. Zhang and Y. Chen, "Food sensory evaluation employing artificial neural networks", Sensory Review, Vol.17, No.2, pp.150-158, 1997.

