Customer buying behaviour analysis in mass customization

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Motivation

- Correlation among product attributes/features can help to depict customer buying behaviour
- However, Product evolution (upgrades) usually render information gathered from past buying behaviour at least partially unusable.

The Problem

Which of the customers buying behaviour to be use when product has gone through engineering changes? e.g. Upgraded product, new product, facelift etc.

An Example: Example 1

Let us assume a car is configured using 6 attributes
$X = \{1, 2, ..., 6\}$, and Rule $F = \{f_1\}$ where:

$f_1 = \{2 \rightarrow 1\}$: Cruise control requires Automatic Gearbox.

Order #	Automatic GearBox (AG)	Cruise Control (CC)	Reverse Camera (RC)	Sunroof (SR)	KeyLess Go (KG)	Parktronic (PA)
O001	1	1	1	1	1	0
O002	1	1	0	1	1	0
O003	1	0	1	0	1	0
O004	1	0	0	0	0	1
O005	1	1	1	1	0	1
O006	1	0	0	0	0	1
O007	1	0	1	1	1	1
O008	1	0	0	0	1	1
O009	0	0	1	0	1	1
O010	0	0	1	1	0	0

Attributes association Example

- *Support*($p \Rightarrow q$): This is the proportion of configurations that contain both attribute sets p and q.
- *Confidence* ($p \Rightarrow q$): Given set of configuration which contains attributes set p, this is the proportion of configurations where attribute set q is also selected

sr.	lhs		rhs	support	confidence
1	{CC}	$\Rightarrow$	{SR}	0.3	1
2	{CC}	$\Rightarrow$	{AG}	0.3	1
3	{PA}	$\Rightarrow$	{AG}	0.5	0.83
4	{KG}	$\Rightarrow$	{AG}	0.5	0.83
5	{SR}	$\Rightarrow$	{RC}	0.4	0.8
6	{SR}	$\Rightarrow$	{AG}	0.4	0.8
7	{CC}	$\Rightarrow$	{RC}	0.2	0.66

Customer driven associations

$Sr\#$	Relation	p	q	Description
1	$\neg p \wedge \neg q$	0	0	Configuration without attribute p and q
2	$\neg p \wedge q$	0	1	Configuration with attribute q but not p
3	$p \wedge \neg q$	1	0	Configuration with attribute p but not q
4	$p \wedge q$	1	1	Configuration with both attribute p and q

Table 1 : Possible relationships among two attributes in a configuration

Predicting future configurations as per customer buying behaviour

Input

Product configured in the past

Attributes		
1	**2**	**3**
1	0	1
1	1	0
1	1	1

Section 2

Attribute association rules

(1)	100%
(1,2)	67%
(1,3)	67%
(2,3)	33%

Section 2

Pruning association rules

(+) Config rule $(2 \rightarrow \neg 3)$

(1)	100%
(1,2)	67%
(1,3)	67%

Section 3

Validate attribute associations

(1)	100%
(1,2)	67%
(1,3)	33%

Output

Predict future configurations

Attributes		
1	**2**	**3**
1	0	1
1	1	0
1	1	0

Association Rule verification: Example

- Let Reverse Camera (RC), Keyless Go (KG), Parktronic (PA)) are individually selected 60% of the time in prior demand.
- Now, new configuration restrictions (e.g. Upgraded product) specify that at least two of the attributes (out of three) have to be present in every feasible configuration.

Problem

Now, is it feasible to assume that the attributes will be selected at the same rate as before?

Association rules verification: Example

$$OPT_{Example2} : \textbf{Minimize} \sum_{i=1}^{3} Z_i^+ + Z_i^- \tag{1}$$

$$\underbrace{\begin{pmatrix} 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 \end{pmatrix}}_{A} \underbrace{\begin{pmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \end{pmatrix}}_{X} + \underbrace{\begin{pmatrix} Z_1^+ \\ Z_2^+ \\ Z_3^+ \end{pmatrix}}_{Z^+} - \underbrace{\begin{pmatrix} Z_1^- \\ Z_2^- \\ Z_3^- \end{pmatrix}}_{Z^-} = \underbrace{\begin{pmatrix} 0.6 \\ 0.6 \\ 0.6 \end{pmatrix}}_{\pi} \tag{2}$$

$$X_1 + X_2 + X_3 + X_4 = 1 \tag{3}$$

$$0 \leq X_j, Z_i^+, Z_i^- \leq 1 \tag{4}$$

Association Rule verification

1. How to consider all possible solutions? Very large number of decision variables.
2. How to build $A_{i,j}$ matrix?
   - Do we have to explicitly write all the columns of A?
   - Can we work with a small set of configurations and add more when needed?

Column generation procedure

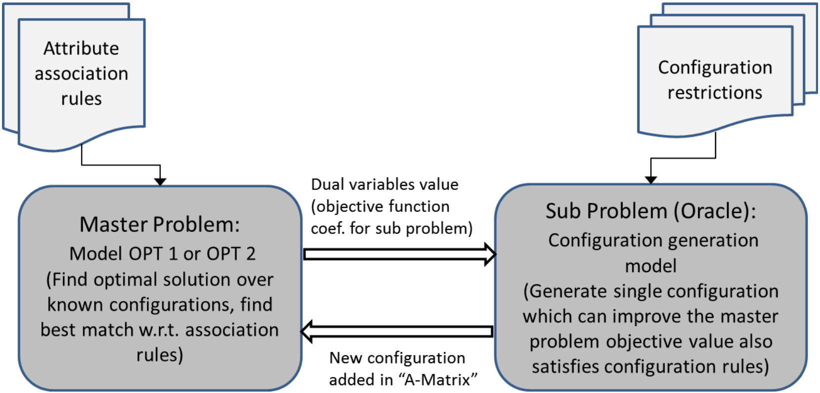
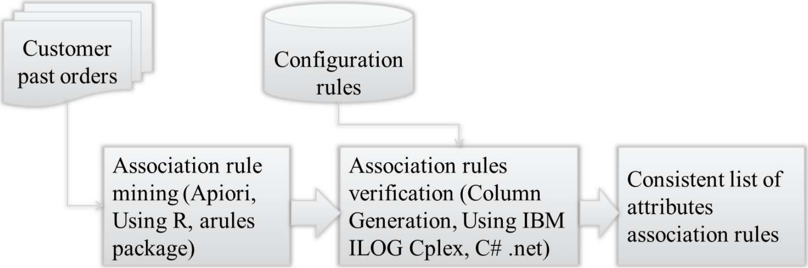


Figure 1 : Column generation procedure to find right order set

Implementation flow of customer drive attributes association rule mining



Predicting future configurations as per customer buying behaviour

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Output

Predict future configurations

Attributes		
1	**2**	**3**
1	0	1
1	1	0
1	1	0

First Computations

Experiment #	# of attributes	# of orders	# association rules	# Pruned association rules (after applying configuration rules)
$Segment_1$	200	30,000	2,000	1,200
$Segment_2$	120	25,000	1,800	1,300
$Segment_3$	100	10,000	1,500	1,100

Table 2 : Computational experiments with three different vehicle segments

First Computations

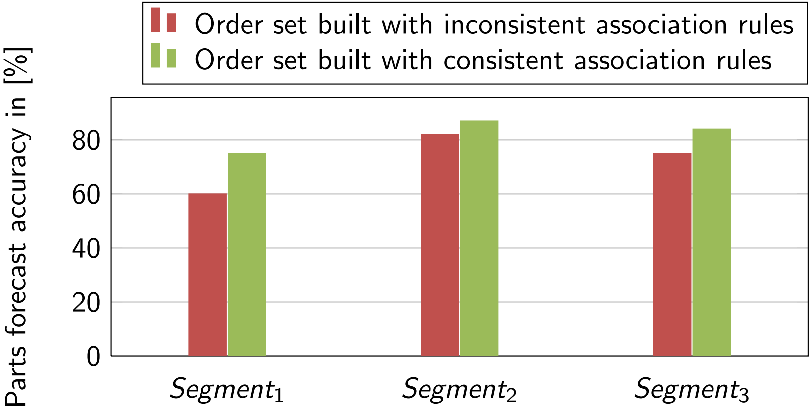

Figure 2 : Comparing part demand forecast accuracy between configuration sets built with consistent and inconsistent attribute association rules

Conclusions and Future work

- In mass customization, due to frequent changes in products, we are required to validate product attribute associations learnt from customer prior demand.
- The association rule mining technique when combined with the configuration problem gives the required framework for calculating consistent and feasible attribute associations.
- Currently, we only consider attribute associations which are frequent (e.g. above minimum support or confidence)
- Current implementation we simply remove/ignores attribute association which are having conflicts