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Media synergy comes of age — Part 2

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Abstract

This is part II of this paper. Part I was published in Vol. 11, No.1. The research reported in this paper is a follow-on to the Schultz paper (*JDDDMP* (2006) Vol. 8, No.1. pp. 13–19) where the subject of media synergy was raised. In this study, the concepts identified in the original paper have been extended using data from the SIMM (Simultaneous Media Usage) database, which has been collected in the US since 2002. Four consumer media usage and impact variables are used in the analysis: (a) amount of time spent with each of the 31 media forms gathered in the studies, (b) what media forms were used and in what combinations (simultaneous usage) (c) the impact of the media forms in each of eight product categories and (d) consumer reported intent to purchase in a product category in coming periods. Using Chi-Square Automatic Interaction Detector analysis (CHAID), the key media forms were identified for each of three product categories: computers, automobiles and fast food restaurants. This research is an important step in the actual determination of media synergy, which can be used by media planners and buyers.

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Introduction

In the first part of this paper, Vol. 11, No.1, we discussed how this paper extended and expanded Schultz's article in Volume 8, No. 1 titled 'Media synergy: The next frontier in a multimedia marketplace'. The need for inter-media, not just intra-media measurements, was explained along with the requirement for a media consumption model. Information on the SIMM (Simultaneous Media Usage Studies), which have been conducted in the US since 2002, was explained; these form the data set for the paper. What is currently known about media synergy was discussed. Four basic measures of media consumption were identified, that is, time spent with the media form, combinations of media used simultaneously, product purchases reported by SIMM respondents and the influence of the media form on the purchase decision. The paper continues now with a discussion of the measurement approaches used in this first stage of media synergy identification.

Using Chi-Square Automatic Interaction Detector (CHAID) analysis to identify media synergy

Interaction among and between media variables are key to synergy

A number of analytical methods could be used to parse out the importance and value of the media combinations found in the SIMM data. We chose CHAID. Our belief is that any analysis of media synergy, particularly if it is to be widely adopted, should rely on a readily available statistical technique. Defining synergy as statistical interactions among the SIMM media variables, that is, two or more of them working together, seems very practical for CHAID analysis. CHAID proceeds in a stepwise progression, dividing the data according to the defined criterion-dependent measure. An example would be 'intent to purchase'. Thus, the greatest difference is identified according to the splitting of independent variables, such as one of the media influences. The parent node is split into two child nodes. Each child node becomes a parent and is split again. Once two or more splits have occurred, an interaction is identified. This is exactly the process we used with the influence of the media variable in the SIMM data. The results of our analysis using CHAID analysis follow.

Illustrations of CHAID analysis in automobiles, fast food and computers

We applied our concepts and approaches to the First Quarter, 2008 SIMM data in three widely different product categories: computers, automobiles and fast food restaurants. Each application and the output is discussed separately below.

Managing the CHAID outputs

First, some background on the creation of the CHAID models is in order. The CHAID 'trees' that follow have been 'pruned'. This was done simply because the CHAID algorithm creates such extensive data; to make the reporting of the analysis practical for this paper, we arbitrarily deleted all branches in the predictor variables with less than 5 per cent influence. On the automobile model, we eliminated the nodes with less than 11.3 per cent planning to buy or lease. This pruning does not impact the analysis or the understanding of the results. It is done simply for convenience in reporting.

'Pruning' eliminates nodes with little impact

In addition, the SIMM data contain 31 media variables. Two of these variables, Word-of-Mouth and Read an Article (generally considered public relations) cannot be planned or bought by the media person. Therefore, they were deleted from the analysis, as well. All other media forms were allowed to interact in the model.

CHAID model construction

We started first with each respondent's stated intention to purchase a computer or an automobile in the next 6 months. The fast food category was restricted to respondents who said they planned to visit a fast food location in the next month. As shown in the CHAID tree below for the computer data, 15.19 per cent of the sample planned to buy a computer in the next 6 months (see Table 1).

Table 1: Plan to purchase a computer in the next 6 months

	Per cent
No	84.81
Yes	15.19
Total	100.00

Table 2: Lease or purchase a car or truck in the next 6 months

	Per cent
No	88.57
Yes	11.43
Total	100.00

Table 3: *In an average month, how many times do you plan to eat at a fast food restaurant?*

	Per cent
0	23.3
1	10.2
2	12.6
3	9.1
4	11.7
5	7.3
6	5.0
7	2.5
8	4.2
9	1.1
10 or more	13.0
Total	100.0
Mean	4.54

Table 2 shows the intent to purchase or lease a new automobile in the next 6 months.

As shown in the table, 11.43 per cent of respondents said they planned to buy or lease a car or truck in the next 6 months.

In the fast food category, a slightly different dependent variable was used, that is, planned visits to a fast food restaurant. Table 3 shows the raw data.

For this analysis, we used the mean number of expected visits, 4.54, rounded up to 5. This was used as the dependent variable in the CHAID analysis that follows.

With these purchase intentions, we then reviewed the media forms that respondents said most influenced them in each category analysed. As can be seen below, these media forms vary widely by product category, again reinforcing our premise that media optimization models do not provide the information needed to make informed media planning or purchase decisions.

Table 4 shows the media forms that respondents said most influenced their purchases in the computer category. Note that in

Table 4: Do you plan to make a computer purchase within the next 6 months by media influence?

Media influence	No	Yes	Total
Coupons	26.8	31.0	27.4
Inserts	20.6	25.0	21.3
Newspapers	19.8	24.7	20.5
TV	19.2	26.8	20.3
In-Store	18.3	23.3	19.1
Direct	18.2	23.1	18.9
Magazines	15.6	22.7	16.7
Cable	12.3	19.3	13.3
Radio	11.7	18.5	12.7
Internet	10.6	19.3	11.9
Email	10.4	16.8	11.4
Yellow pages	6.5	10.5	7.1
Outdoor	6.3	11.0	7.0

Table 5: Lease or purchase a car or truck in the next 6 months by media influence (June 2008)

Media influence	No	Yes	Total
Coupons	27.0	30.7	27.4
Inserts	21.0	23.4	21.3
Newspapers	20.1	24.1	20.5
TV	19.5	26.8	20.3
In-Store	18.5	23.9	19.1
Direct	18.4	22.8	18.9
Magazines	16.0	22.4	16.7
Cable	12.6	18.8	13.3
Radio	12.1	17.9	12.7
Internet	11.2	18.0	11.9
Email	10.7	16.3	11.4
Yellow pages	6.7	10.0	7.1
Outdoor	6.4	11.6	7.0

Tables 4 and 5, we show three columns: No Influence, Yes Influence and Total Influence. In our discussion below, we focus on the Yes Influence column, since these are the media forms that respondents say influence them in that product category.

'Plan to purchase' influences media usage

As can be seen from the table above, promotional activities, that is, Coupons and Inserts have substantial promotional impact in this category, with Newspapers and Television being the primary media influencers. Interestingly, In-Store trails the promotional and media influences in terms of impact. This would seem to indicate that decisions on computer purchases are made prior to entering the retail arena. Note that, as stated earlier, we have truncated the tables above simply for the sake of space.

Table 5 shows the media influence in the Lease or Purchase a Car or Truck category.

As shown above, Coupons are the most influential media form in this category, followed by Television. Newspapers, Inserts and In-Store

Table 6: Eating at a fast food restaurant correlated with media influence

Media influence	Correlation
TV	0.154
In-Store	0.149
Cable	0.136
Radio	0.134
Coupons	0.130
Outdoor	0.120
Internet	0.117
Direct	0.115
Magazines	0.111
Email	0.111
Inserts	0.107
Newspapers	0.078
Yellow pages	0.065

(dealers) these make up the top five media influencers in the Car and Truck category.

In the Fast Food category, a slightly different analysis was used. As shown in Table 6, we have identified the Media Influence correlation with the media form.

Broadcast media are by far the most influential media form in the Fast Food category, that is, Television, Cable and Radio. Promotional elements, that is, In-Store and Coupons, have a major influence as well.

With this understanding of which media forms are most influential in each category, we can now begin to apply our CHAID analysis to identify which combinations of media are likely the most critical in developing an effective media plan.

Creating predictive media allocation models

A. Computer purchasers' media combinations

Figure 1 shows the pruned CHAID tree of media consumption for those respondents who planned to buy a computer in the next 6 months.

The first branch is for Internet Usage. Those consumers with No Internet Usage did consume Some Radio and Some Email. Therefore, even though the branch was based on Internet usage, we have gained some valuable information about consumers who do not use the Internet but do use other forms of media. Consumers who had low Internet media consumption also had Some Email and Some Cable, again a useful fact in media planning. The largest percentage of consumers who planned to purchase a computer in the next 6 months were High Internet Users, and they were also High on Magazines and Email. Thus, from this CHAID tree, we can suggest to media planners, if they wanted to reach people who have stated they would likely purchase a computer in the next 6 months, the best media forms to reach them would be some combination of Internet, Magazines and Email. Thus, what we have created is a predictive media approach, not one based on historical data, which is common in the industry.

Table 7 shows the CHAID analysis for the Computer category.

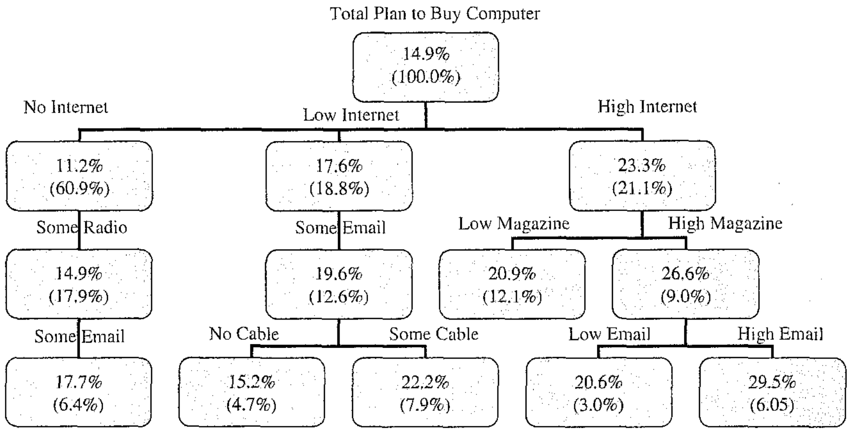

Figure 1: Pruned CHAID tree for computers

Table 7: CHAID analysis for the computer category

Node	Mean	Pct	Parent	Vars	Split	F	Prob.
0	14.9	100.0					
1	11.2	60.9	0	Internet	<=0	197.2	0.000
2	17.6	18.0	0	Internet	(0, 0.125]	197.2	0.000
3	23.3	21.1	0	Internet	>0.125	197.2	0.000
4	9.7	43.0	1	Radio	<=0	68.5	0.000
5	14.9	17.9	1	Radio	>0	68.5	0.000
6	12.9	5.3	2	Email	<=0	23.2	0.000
7	19.6	12.6	2	Email	>0	23.2	0.000
8	20.9	12.1	3	Magazines	<=0.25	19.2	0.000
9	26.6	9.0	3	Magazines	>0.25	19.2	0.000
10	8.5	29.8	4	Magazines	<=0	31.2	0.000
11	12.4	13.2	4	Magazines	>0	31.2	0.000
12	13.4	11.5	5	Email	<=0	12.0	0.001
13	17.7	6.4	5	Email	>0	12.0	0.001
14	15.2	4.7	7	Cable	<=0	18.2	0.000
15	22.2	7.9	7	Cable	>0	18.2	0.000
16	20.8	3.0	9	Email	<=0.125	16.2	0.000
17	29.5	6.0	9	Email	>0.125	16.2	0.000
Node	**Per cent**	**Cum Pct**	**Mean**				
17	6.0	6.0	29.5				
15	7.9	13.9	22.2				
8	12.1	26.0	20.9				
16	3.0	29.1	20.8				
13	6.4	35.4	17.7				
14	4.7	40.2	15.2				
12	11.5	51.7	13.4				
6	5.3	57.0	12.9				
11	13.2	70.2	12.4				
10	29.8	100.0	8.5				

B. Plan to buy a car

If we now turn to those consumers who have said they plan to purchase or lease an automobile in the next 6 months, we get a somewhat different picture. Figure 2 shows the pruned CHAID tree by categories of media influence.

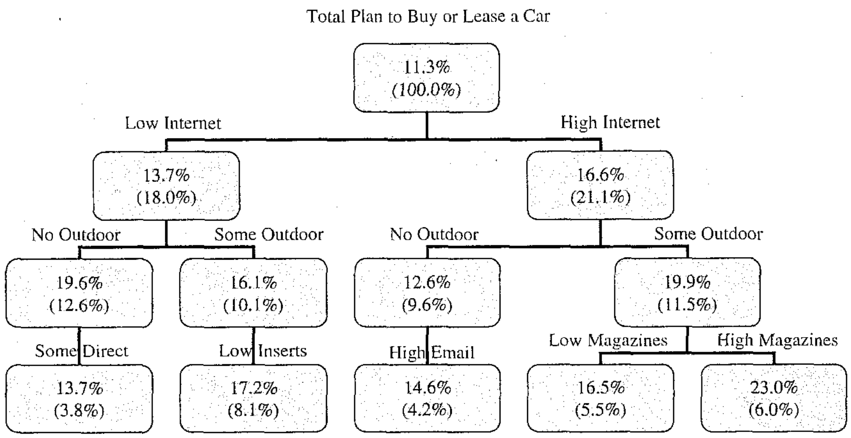

Figure 2: Pruned CHAID tree total plan to buy or lease a car

As shown, the first branch is between High and Low Internet. Those who say the Internet influences them the most in terms of potential Auto purchases also report Some Outdoor exposure along with High Magazine influence. Those with Low Internet influence report No Outdoor and Some Direct. Thus, an automobile marketer clearly must be represented on the Internet. The planner would then likely change the media allocation for Outdoor based on the level of Internet usage. This insight on the impact and influence of the various media is clearly quite different based on this CHAID tree.

CHAID trees vary by product category

Table 8 shows the node values to support the pruned CHAID tree for automobile purchasers.

C. Visits to fast food restaurants

The pruned CHAID tree for respondents planning to visit fast food restaurants in the next month is quite different. Recall that the mean average number of planned visits to fast food restaurants in the next month is 4.54; this is shown in the first node of the pruned CHAID tree in Figure 3.

As shown in the figure, High Television is the most dominant node in the pruned CHAID tree. Television and Some Outdoor and High Coupons represent the most viable set of media alternatives to reach Heavy Users of Fast Food Restaurants. Alternatively, for those respondents who reported that Television had little influence on their visits to Fast Food Restaurants, Coupons appear to be the best Media influence. For those reporting Low Television influence, High In-store and both High and Low Newspaper media would appear to be the most effective forms of media for these groups.

Table 9 shows the node values that support the pruned CHAID tree analysis for the respondents to the questions on Fast Food Restaurants.

As we have demonstrated with the pruned CHAID trees and the illustrations above, the SIMM data can provide substantial insights into how media can and should be planned in all categories forwarding the future.

Table 8: Node values to support the pruned CHAID tree for automobile purchasers

Node	Mean	Pct	Parent	Vars	Split	F	Prob.
1	8.7	60.9	0	Internet	<=0	111.7	0.000
2	13.7	18.0	0	Internet	(0, 0.125]	111.7	0.000
3	16.6	21.1	0	Internet	>0.125	111.7	0.000
4	7.7	37.3	1	Magazines	<=0	15.7	0.000
5	9.6	16.0	1	Magazines	(0, 0.25]	15.7	0.000
6	11.8	7.6	1	Magazines	>0.25	15.7	0.000
7	10.7	7.8	2	Outdoor	<=0	21.8	0.000
8	16.1	10.1	2	Outdoor	>0	21.8	0.000
9	12.6	9.6	3	Outdoor	<=0	41.2	0.000
10	19.9	11.5	3	Outdoor	>0	41.2	0.000
11	7.1	29.8	4	Radio	<=0	13.2	0.001
12	9.9	7.5	4	Radio	>0	13.2	0.001
13	10.6	11.7	5	Inserts	<=0.25	9.6	0.004
14	7.0	4.3	5	Inserts	>0.25	9.6	0.004
15	7.9	2.6	7	Direct	<=0	6.3	0.002
16	13.7	3.6	7	Direct	(0, 0.25]	6.3	0.002
17	8.7	1.7	7	Direct	>0.25	6.3	0.002
18	17.2	8.1	8	Inserts	<=0.25	8.1	0.009
19	11.5	2.0	8	Inserts	>0.25	8.1	0.009
20	10.9	5.4	9	Email	<=0.125	6.7	0.019
21	14.8	4.2	9	Email	>0.125	6.7	0.019
22	16.5	5.5	10	Magazines	<=0.25	15.4	0.000
23	23.0	6.0	10	Magazines	>0.25	15.4	0.000

Node	Mean	Pct	Cum Pct
23	23.0	6.0	6.0
18	17.2	8.1	14.1
22	16.5	5.5	19.6
21	14.8	4.2	23.8
16	13.7	3.6	27.4
6	11.8	7.6	35.0
19	11.5	2.0	37.0
20	10.9	5.4	42.4
13	10.6	11.7	54.2
12	9.9	7.5	61.7
17	8.7	1.7	63.3
15	7.9	2.6	65.9
11	7.1	29.8	95.7
14	7.0	4.3	100.0

Discussion of results, limitations and next steps

Marketers increasingly have access to the kinds of purchase intentions and media usage data that we have used to gain insights into how to improve the media planning process. There are, however, problems and opportunities going forward.

Using CHAID analysis

Given large samples and an abundance of variables (we had 31 media variables in our data), techniques such as CHAID provide a powerful way of quickly and reliably uncovering potential interactions between the variables. However, no statistical technique is impervious to weaknesses, and it is important to be aware of the constraints that circumscribe our methodologies. First, as a general caveat that applies to *all* classification techniques, it is important to understand that the

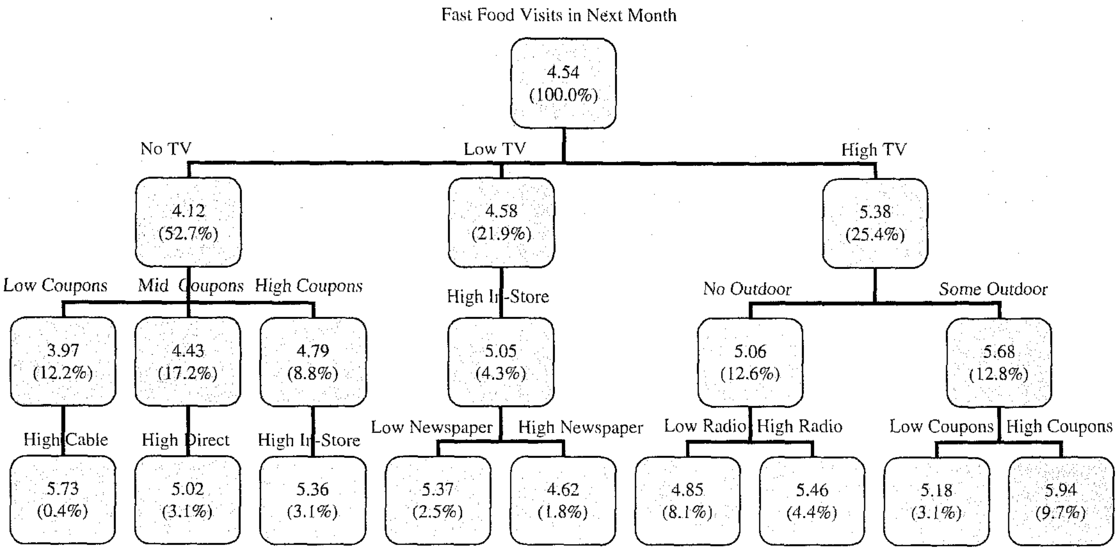

Figure 3: Pruned CHAID fast food visits

CHAID algorithm may capitalize on chance because each variable is considered a potential basis for splitting at each stage in the analysis.[1] In other words, CHAID determines, for every available predictor, the optimal split such that the within-group variance of the response is minimized.[2] This potential source of bias is larger when there are more predictors, or when the sample size is small. In our study, we did have a large number of predictors but, on the other hand, our sample size was large: consequently, one potential source of bias was partially offset by the sample size, thereby increasing our confidence in our results. The user should keep in mind that large probability samples reduce the likelihood of chance relationships, and large samples are particularly recommended when using the CHAID algorithm.

CHAID chance terms in results mirrored by sample size

Secondly, the statistical design and mathematical structure of CHAID may leave certain types of interactions undetected. The CHAID approach builds tree diagrams that describe the effects of 'nested' interactions, where the term 'nested' refers to effects that exist only for some subgroups of the population. But in marketing communications, we may sometimes find non-nested interactions such as symmetric or offsetting interactions. For example, an advertisement might have a positive effect on the low-income group, but a negative effect on those with high incomes. The potential pitfall here is that, although the advertising does have a measurable and statistically significant effect within each income subgroup, the interaction may be difficult to detect because the overall effect is zero. Such offsetting or symmetric interactions are likely to escape detection by CHAID.[3] This limitation can be handled by carefully thinking through the theoretical basis for suspecting different types of interactions and explicitly examining them. For example, if theory suggests that we would expect higher-income groups to differ from lower-income groups, then we should conduct an analysis by subgroup.

Table 9: Node values that support the pruned CHAID tree analysis for fast food restaurants

Node	Mean	Pct	Parent	Vars	Split	F	Prob.
0	4.54	100.0					
1	4.11	52.7	0	TV	<=0	229.5	0.00
2	4.58	21.9	0	TV	(0, 0.25)	229.5	0.00
3	5.38	25.4	0	TV	>0.25	229.5	0.00
4	3.46	14.5	1	Coupons	<=0	69.2	0.00
5	3.97	12.2	1	Coupons	(0, 0.125)	69.2	0.00
6	4.43	17.2	1	Coupons	(0.125, 0.375)	69.2	0.00
7	4.79	8.8	1	Coupons	>0.375	69.2	0.00
8	4.21	5.5	2	In-store	<=0	15.3	0.00
9	4.59	12.1	2	In-store	(0, 0.25)	15.3	0.00
10	5.05	4.3	2	In-store	>0.25	15.3	0.00
11	5.06	12.6	3	Outdoor	<=0	40.1	0.00
12	5.68	12.8	3	Outdoor	>0	40.1	0.00
13	3.28	12.5	4	Radio	<=0	52.4	0.00
14	4.58	2.1	4	Radio	>0	52.4	0.00
15	3.91	11.8	5	Cable	<=0.125	22.2	0.00
16	5.73	0.4	5	Cable	>0.125	22.2	0.00
17	4.00	6.8	6	Direct	<=0	21.6	0.00
18	4.57	7.3	6	Direct	(0, 0.25)	21.6	0.00
19	5.02	3.1	6	Direct	>0.25	21.6	0.00
20	4.50	5.7	7	In-store	<=0.25	22.6	0.00
21	5.34	3.1	7	In-store	>0.25	22.6	0.00
22	4.50	2.4	8	Newspapers	<=0	6.6	0.02
23	3.98	3.1	8	Newspapers	>0	6.6	0.02
24	4.94	4.9	9	Yellow pages	<=0	17.7	0.00
25	4.35	7.1	9	Yellow pages	>0	17.7	0.00
26	5.37	2.5	10	Newspapers	<=0.25	10.7	0.00
27	4.62	1.8	10	Newspapers	>0.25	10.7	0.00
28	4.85	8.1	11	Radio	<=0.125	18.0	0.00
29	5.46	4.4	11	Radio	>0.125	18.0	0.00
30	5.18	3.1	12	Coupons	<=0.125	16.8	0.00
31	5.84	9.7	12	Coupons	>0.125	16.8	0.00

Node	Per cent	Cum Pct	Mean
31	9.7	9.7	5.84
16	0.4	10.1	5.73
29	4.4	14.6	5.46
26	2.5	17.1	5.37
21	3.1	20.2	5.34
30	3.1	23.2	5.18
19	3.1	26.4	5.02
24	4.9	31.3	4.94
28	8.1	39.4	4.85
27	1.8	41.2	4.62
14	2.1	43.3	4.58
18	7.3	50.6	4.57
22	2.4	53.0	4.50
20	5.7	58.7	4.50
25	7.1	65.8	4.35
17	6.8	72.6	4.00
23	3.1	75.7	3.98
15	11.8	87.5	3.91
13	12.5	100.0	

Third, CHAID is a powerful tool for identifying interactions, but according to Banslaben[4] it does not produce the results of regression analysis. The way to handle this limitation is to use the output of CHAID as input into a regression analysis in order to build a model with more predictive power.[5]

The advantages of CHAID analysis

Keeping the above limitations and their suggested remedies in mind, CHAID does offer some attractive features for the media planner, especially when large samples are available. At a much lower level of technical complexity than neural networks, CHAID offers one of the most compelling advantages of a neural network — it is a model-free approach.[1] A model-free approach is attractive because it is *robust* in a statistical sense — classical statistical techniques that rest upon distributional assumptions such as normality may not produce meaningful results if the underlying distribution is non-normal. The model-free structure of the CHAID algorithm, and its minimal scaling requirements (categorical data suffice), make it broadly applicable to a plethora of media planning situations. With minimal fuss and data requirements, CHAID produces recommendations on the best combination of media forms to reach a desired population in the target market for the product.

CHAID is 'model-free'

In order to take advantage of media synergies, we must organize a systematic way to look for them. The CHAID algorithm is an important first step in identifying the most promising parts of the media mix in which to look for synergies. The results of the CHAID analysis provide guidance for the next step in developing a more sophisticated model-based approach to media planning that quantitatively incorporates the synergies between the media identified in a qualitative way through CHAID.

Recent examples of model-based approaches for media planning are provided in studies by Naik and Raman,[6] Raman and Naik,[7] Naik *et al.*[8] and Raman and Naik.[9] The techniques and algorithms developed by these authors are a logical follow-up to the initial policy recommendations developed on the basis of the CHAID algorithm, which identifies the most effective combination of media in a qualitative and model-free way.

Regression can support/extend CHAID

For example, the results of our CHAID analysis on the computer data suggested that if we want to reach people who have stated that they would likely purchase a computer in the next 6 months, the best media forms by which to reach them would be Internet, Magazines and Email. Thus, the next step would be to estimate a regression model containing Internet, Magazines and Email as explanatory variables, with all possible interactions included in the model: TV/Magazine, Magazine/Email, Email/Internet and a three-way interaction among all three media forms. Any number of media forms and any number and order of interactions among media, as identified by the CHAID algorithm, may be included. The interactions among media may be of any order — in other words, we may have third-degree interactions, fourth-degree interactions, etc. Higher-order interactions correspond to higher-order synergies — thus, a third-degree interaction describes how the synergy obtained through the joint usage of all three media forms affects consumer response.

The beauty of the CHAID algorithm is that it is not restricted in the order of interactions that it can identify. Using Kalman Filters and optimal control theory, Naik and Raman[6] have shown how to estimate such a general model with an arbitrary number of main media effects, and an arbitrary number and order of media synergies. Moreover, the authors have explicitly derived closed-form expressions to determine the optimal budget and its optimal allocation among the different media, taking any number and order of interactions into account.

Next steps

Extending media analysis

We envision increasing adoption of mathematical techniques for media planning in the future. Up until now, mathematical algorithms for media planning have mainly been driven by 'classical' methodologies that depend on explicitly structured models, classical statistics and classical deductive logic. But the powerful methods of neural networks, neuro-fuzzy control and intelligent systems provide a complementary route to media planning — this alternative route is useful when classical techniques fail due to intractable mathematical or computational requirements. We expect that media planning experts in the future will increasingly embrace both classical and machine intelligence technologies.

With these approaches, we believe true media synergy can be determined and current media planning and buying capabilities enhanced enormously.

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