Enhancing Big Data Marketing Analytics by Learning from Rivalry

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Abstract :

We expose some deficiencies in big data marketing analytics. We warn that invalid actionable marketing insights may lead to wrong marketing decisions. Marketing managers apply available big data analytics that do not take big data V's into consideration. The big data velocity V cannot assure that the actionable insights marketing analysts produce now are still valid a minute later. In addition, because of the big data volume V, marketing analysts will only extract limited data amounts for their data analytics and the data they left out, if processed, may produce insights that are inconsistent with those produced by extracted data sets. The rest of big data V's, not studied in this article, also generate their own different problems which will also affect marketing management decisions.

We propose an evidential model that remedies for the limitations above. It produces belief structures on marketing decision parameters for the marketing manager and observes rivalry's actions from which data and belief structures are reconstructed. Marketing manager's belief structures and reconstructed rivalry's belief structures are then fused to generate aggregated actionable marketing insights upon which marketing management will act. The fused belief structure provides better decision support for marketing management since observed rivalry's actions bring added decisional evidence and better actionable insights to the marketing decision process.

We also provide an illustrative example to demonstrate the working of the proposed evidential marketing analytic model.

Keywords: Data analytics, big data, marketing management, belief structure, big data V's, evidential model, Dempster and Shafer Theory.

Introduction

The competition to attract more customer continues to intensify with new technology and new marketing tools [10] and this fight is getting even fiercer with the arrival of big data [1, 3, 4]. Big data has brought new forces that reshaped the market and impacted the race to retain customers and grab new ones [1, 3]. Other big data tools, from intelligent marketing to business intelligence, have boosted the decision power of marketing management [20]. Most often however, only a small part of big data has been exploited by those tools due to data unstructuredness. Visualizing unstructured content in big data is still an uneasy undertake and requires complex and intricate data technology to extract, transform, load, and visualize [3].

Big data has pushed rivalry in a turbulent competition environment where actionable insights are very costly in terms of both data extraction, transformation, and data analytics [15]. Despite its multiple usage interpretation, expectations are high to bring the ability to generate valuable insights from the gather of new types and volumes of data in innovative approaches that would not have been feasible technically and economically viable with conventional computational models.

The literature shows [2, 5] that big data offered new opportunities for businesses to reach new market segments and develop innovative business models. In marketing, retailers have boosted their business performance by adopting advanced big data analytical tools to collect massive data sets on product sales and applied predictive techniques to update their demand and manufacturing forecasts for the futures [17].

Even though the value of big data and big data analytics is recognized in most business areas, the literature still reports a lack of research on the benefits of big data to the marketing function in organizations [13].

This article recognizes the inadequate adoption of big data analytics in the marketing field and proposes an evidential model to salvage missed data opportunities and produce actionable business insights that is consequential to enhancing marketing management decisions.

This study will inform marketing management of missed data opportunities and some data is removed from big data or when extracted data does not represent the entire big data and the produced knowledge may ne incomplete or even invalid. In addition, the generated business insights may be invalid and all decisions made based on them may be incorrect or misleading. So big data is getting more and more popular in organizations in different application areas since its invention two decades ago [9]. It was termed originally as the gather and statistical treatment of big volumes of online data, followed by the creation of knowledge that is pertinent to the domain in study. There is no agreement when it comes to the coining of the term "Big Data," as one of the possible authors may be John Mashey, from Silicon Graphics who used the term in 1998 [9].

Because of the deficiencies observed in big data analytics, the question of reliability of the knowledge produced from big data remain a serious one. This reliability problem is also inherited by the interpretation and acting upon the actionable insights produced by big data analytics. Big data analytics has to remedy for the many V's that came with big data. The first three V's for volume, variety, and velocity were added in by Doug Laney in 2001 [11]; the fourth V for value was added by International Data Corporation [9].

Marketing management

Often, marketing managers, as any other business managers, follow Simon's decision process to approach their marketing decisions, whether these are operational, functional, or strategic decisions. A marketing management decision process then should follow all Simon's phases: intelligence, design, choice, and review. Marketing managers have their big data available to them and all available marketing data analytics for them to apply on the big data. Simon's phases require marketing managers to explore every bit of intelligence available to improve their decision process including rivalry's actions. We will later see that we can infer the values of data that lead to rivalry's actions. The reconstructed data set will be processed and it will uncover rivalry's belief structures that the marketing manager can include as additional evidence to his decision process.

Unfortunately, the big data V's are a real problem for marketing managers because of at least three reasons. First, they will not be able to include all data of the big data in the marketing data analytics. Second, they have to extract limited data sets that may not represent all the data in the big data. Third, even if they do have the power to include all the data of the big data in their process, still the actionable marketing insights they produce may be invalid a minute later due to the big data velocity V.

Another problem marketing managers encounter is the validity of available marketing data analytics available to them. Most of their marketing analytics models are standard models designed for regular data sets that have no V issues as in big data.

We assume that marketing managers employ similar decision tables that define the decision rules they apply when acting on the actionable marketing decisions that their big data-based marketing analytics produced. The decisions tables are made of hypertuples on the decision attributes $\{X_i\}_{i=1,N}$ and the management actions that apply. Table 1 depicts a generic decision table.

Table 1: Decision Table				
	X_1	…	X_N	Actions
Rule $_1$	C_{11}		C_{N1}	A_1
…				…
Rule $_M$	C_{1M}		C_{NM}	A_M

Even though each marketing manager will have his own decision table that he did not share with others, particularly with rivalry, these tables will be easily guessed by others. Even if a decision table is not easily guessable by rivals, a marketing manager can safely assume that rivalry use the same decision table when they are rational, professional, and equally familiar with the area of marketing management decisions. However, despite the rationality and professionalism of rivalry, the marketing manager has no guarantee that rivalry with behave as he expected them to, and we hence have to assume some discount factors of all evidence coming from them. Let us then denote $\{0\leq\delta_k\leq1\}_{k=1,|R|}$ to be respectively the discount factors assigned by the marketing manager to rivals $\{R_k\}_{k=1,|R|}$ where $|R|$.

Computational methodology

This paper uses evidence theory to conduct marketing analytics. Extracted data sets from the big data are processed using Dempster-Shafer Theory when belief structures are constructed [8] from the data sets and evidence is fused to produce actionable marketing insights. Before we further proceed, we thought that a brief introduction of this relatively new evidence theory would ease the reading and consultation of this paper.

The Dempster–Shafer theory (DST) is a mathematical framework for uncertainty management where all use the same frame of discernment in studying a finite set of mutually exclusive outcomes about their decision domain. This framework is capable of combining evidence from different sources and produces a degree of belief, as a belief function, that takes into account all the available evidence. The DempsterShafer (DS) theory started with Dempster in 1968 as statistical inference, but has been later formalized by
Shafer, in 1976, as a theory of evidence [6, 7]. Later after the 1980's Smets reshaped it in his Transferable Belief Model before it started to see growing development in diverse AI applications in most domains [18, 19].

In order to model a belief structure for a decision domain with a frame of discernment Ω, we let the power set 2^Ω contain every mutually exclusive subset of the frame of discernment Ω. A basic probability assignment m is used to allocate a belief value in [0, 1] for every hypothesis defined by the subset in the frame of the discernment, as follows:

$$m: 2^\Omega \rightarrow [0, 1] \quad m(\emptyset)=0$$
$$m(A)\geq0 \text{ for any A in}$$
$$2^\Omega \quad \sum_{A\subset\Omega} m(A) =1.$$

If x is an unknown quantity with possible values in our frame of discernment Ω, we can add a piece of evidence about x using a mass function m on Ω. Any subset A of Ω with a mass greater than zero is called a focal set of m. You can see that this is different from in Bayesian theory where probability distributions only have singleton focal sets. When we have no evidence on x, we use the vacuous mass function, defined by $m_\Omega(x) = 1$, which represents a completely uninformative piece of evidence.

A great contribution by Dempster and many others who expanded the Dempster and Shafer theory is the combination of evidence obtained from multiple sources and the modeling of conflict [7]. Often, bodies of evidence come in small pieces obtained from different independent sources.

While these bodies of evidences are included in the decision process using belief functions, the totality of the evidence is computed by combining the belief functions using Dempster Rule and its extensions. Given two independent sources of evidence defined on the same frame of discernment Ω and with basic probability assignments m_1 and m_2, we combine evidence as follows:

$$m_\Omega(A) = \sum_{B\cap C=A} m_1(B)m_2(C)/(1\text{-}K);\ \text{for } A\neq\emptyset$$

$$\text{Where } K= \sum_{B\cap C=\emptyset} m_1(B)m_2(C) \text{ and } m_\Omega(\emptyset)=0$$

The parameter K represents the basic probability mass associated with the conflict between m_1 and m_2. It is computed as the sum of the products of the basic probability masses of all the disjoint sets from the tow sources of evidence.

Computational model

We examine the situation where big data is available to marketing management to process towards knowledge creation for a more efficient marketing unit. We look at two real world marketing management situations: In the first situation, a marketing management group, Group 1, employs available data analytics on a selective data extraction to generate actionable insights upon which marketing decisions are acted. In a second situation, a part of the big data was not available to Group 1 or a part of the big data was available to Group 1 but was not extracted, and hence not included in Group 1's data analytics. In situation 2, a second marketing management group, Group 2, adopted a part of the big data that was not available to Group 1 and applied data analytics on it to generate actionable insights.

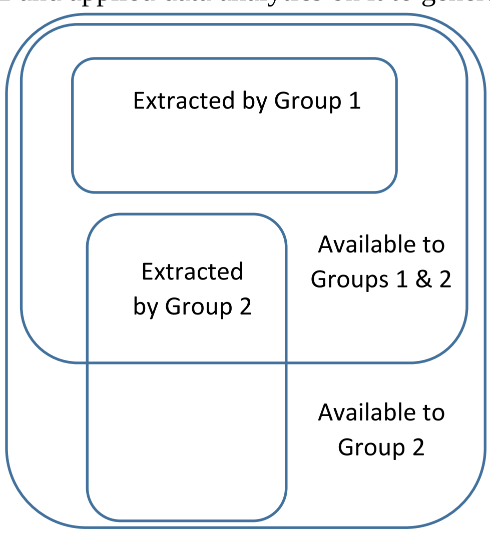

Figure 1: Real-world situation for the use of big data

The graph in Figure 1 shows a real world situation where a regular marketing manager adopts big data analytics to generate actionable insights upon which better decisions are made which will lead to a better marketing decision support system. Because of the big data V's, the marketing manager will be impacted by both cases as in Group 1 and Group 2. This simply means that the marketing manager cannot process all the data available in the big data and he has hence to often arbitrarily extract limited data sets to include in his data analytics process. Moreover, because of big data velocity and volume V's, there is no assurance that the actionable insights stay valid a minute later when more data poured in in the big data.

We propose that 1) the marketing manager continues applying available big data analytics, no matter how limited they are, to get the best possible actionable insights, 2) infer possible belief structures from rivalry's actions, and 3) fuse belief structures obtained from the marketing manager's own data analytics effort and the belief structures inferred from various rivals' actions. As in Figure 2, the newly produced belief structure from the fusion process will put the marketing manager in a better decision position compared to his initial position with a limited data analytics process.

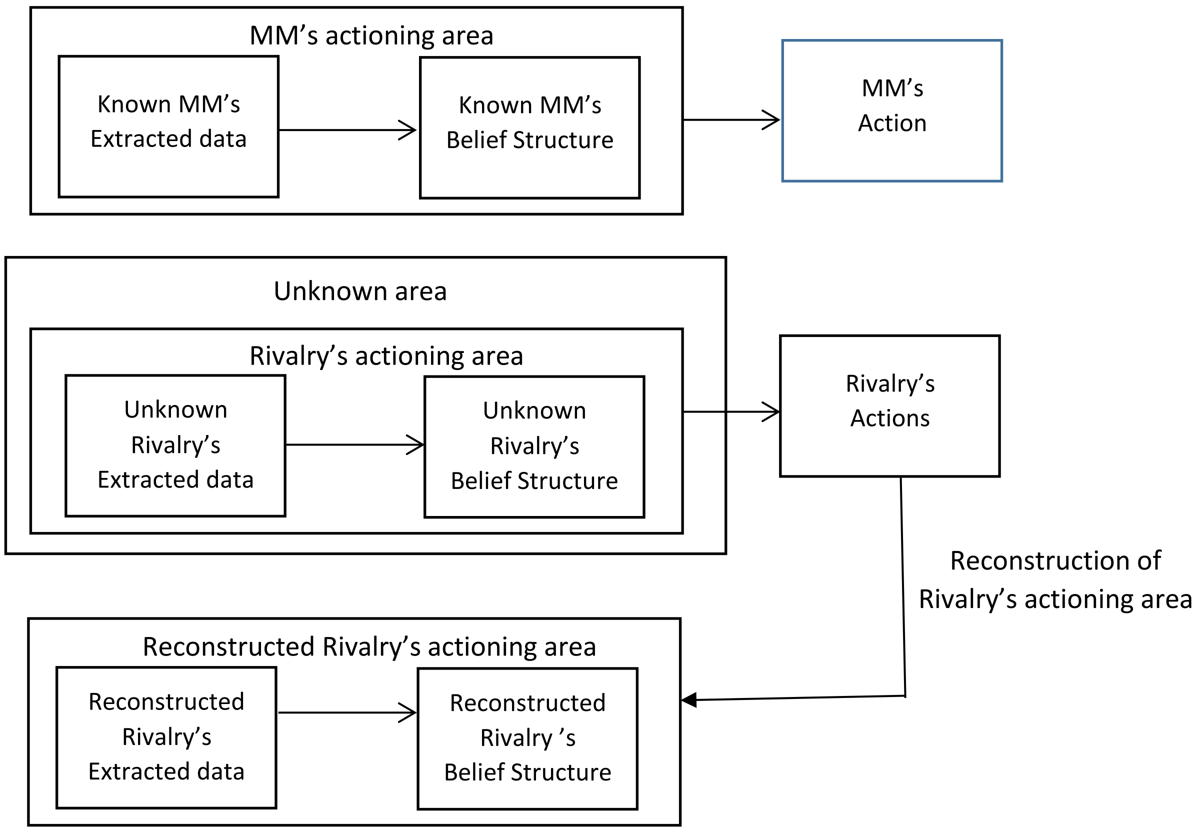

Figure 2: Reconstruction from rivalry's actions

The big data B is available to all, including the marketing manager and his rivalry $\{R_k\}_{k=1,|R|}$ where |R| is the size of known rivalry. Let $\{D_k\}_{k=1,|R|}$ be the data sets extracted by rivalry from the parts of the big data available or not available to G. And let $\{A_k\}_{k=1,|R|}$ be the actions undertaken by rivalry upon acting on actionable insights generated by the data analytics applied on $\{D_k\}_{k=1,|R|}$.

Also let D be the data extracted by our marketing manager G on which he applied available data analytics to produce the actionable insights and let A be action undertaken upon them. Without loss of generalities, we assume that rivals do not extract the same data sets to input in their data analytics. This is assumptions is very valid when big data velocity is high and when big data volumes are large.

PS. It is important to note that the data extracted by rivalry may overlap with the marketing manager's extracted data.

We assume that the marketing manager decisions and rivalry decisions follow a common decision table where decision rules are defined deterministically on the decision attributes $\{X_k\}_{i=1,N}$.

Let us apply a simple belief structure construction mechanism, as in Raggad [14], that produces belief structures on $\Omega = \prod_{i=1,N} 2^{dom(Xi)}$ denoted simply $\Omega = \prod_{i=1,N} 2^{Xi}$ based on the data extracted by both our marketing manager and his rivalry. Let m and $\{m_k\}_{k=1,|R|}$ be the basic belief assignments on Ω of the marketing manager and his rivalry, respectively. Of course, our marketing manager will not be able to see $\{m_k\}_{k=1,|R|}$ that lead to rivalry actions but he can employ the common decision table above and reconstruct the rivalry unknown data sets. In general, the reconstructed data sets will only be as good as the decision table used to infer them.

Belief Construction

As in Raggad [14], we start by constructing a belief structure on D extracted by the marketing manager. D is made of M tuples containing the N feature-based attributes $\{X_i\}$, i=1,N. We then construct the power sets 2^{X_i}, i=1,N and construct the frame of discernment $\Omega=2^{X}{}_1 x \ldots x\ 2^{X}{}_N$. If $e=\{e^1, \ldots, e^N\}$ is a hypertuple where e^k is a subset of X_k, then let Δ_α be a partial order relation on all the data sets on hand. If x and y are elements of a set E, we say that $x\Delta_\alpha y$ if and only if $|x\cap y|/|x| \geq \alpha$. The intersection defines the amount of support x provides to y, or alternatively, the amount of α-compatibility between x and y (i.e., a compatibility with level α).

We define the evidence support s_D^α (e) of x in D as the set of y in D such that $y\Delta_\alpha e$. That is, $s_D(e) = \{y\varepsilon D$, such that $y\Delta_\alpha e\}$. The subset D is a poset with respect to the partial order relation Δ_α and it may hence have elements that are related to e (α-compatible with) and others that are not related to e (not α-compatible). Only the compatible elements y in D such that $y\ \Delta_\alpha\ e$ are accepted to support e.

Let **Ω**, defined above, be our frame of discernment. The belief structure for D in **Ω** is defined as follows:

$$m_D^\alpha: \Omega \rightarrow [0\ 1]$$
$$m_D^\alpha (e) = |s_D^\alpha (e)|/ |s_D^\alpha (\Omega)| \qquad \text{where}$$
$$s_D^\alpha (\Omega) = \{\{y\varepsilon D \text{ such that } y\Delta_\alpha e\}, e\varepsilon\ \Omega\ \}$$

It is sometimes useful, for simplicity, to denote as follows:

$$|s_D^\alpha (e)| = |e\Delta_\alpha D| = \text{Cardinal of } \{y\varepsilon D, \text{ such that } y\Delta_\alpha e\}.$$

We then have the following:

$$m_D^\alpha (e) = |e\Delta_\alpha\ D|/|\Omega\ \Delta_\alpha D|,$$
$$m_D^\alpha (\Omega) = |\ \Omega\ \Delta_\alpha\ D|/|\ \Omega\ \Delta_\alpha D|=1.$$

That is, if we consider the decision attributes $\{X_i$, i=1,N$\}$, we can produce knowledge in terms of probability distributions of $\{X_i$, i=1,N$\}$ in order to be able to make a decision. The probability distributions are a good Bayesian model to manage uncertainty in this decision process. We are however not sure that these probabilities even exist given the types of data sources populating the big data and given the ambiguities associated with them. Smets [18, 19] showed that we can use pignistic probabilities to approximate these Bayesian probabilities and adopt a Transferred Belief Model instead of Bayesian. In order to do so, we need to construct belief structures on extracted subsets that contain $\{X_i$, i=1,N$\}$, as shown above, and induce basic probability assignments [14, 18, 19]. This is however only possible after envisaging the product of all the power sets on domains of single feature attributes X_i, i=1,N. That is, we obtain a table of hypertuples made of the respective attributes' domains in 2^{X1} x … x 2^{XN}. As in Raggad [14], we denote $\Omega = 2^{X1}$ x … x 2^{XN} that we earlier called frame of discernment of the belief structure that we intend to construct.

As in Raggad [8, 9], given our frame of discernment **Ω** defined above, the belief structure for D in **Ω** is defined as follows:

$$m_D^\alpha: \Omega \rightarrow [0\ 1]$$
$$m_D^\alpha (e) = |s_D^\alpha (e)|/ |s_D^\alpha (\Omega)| \qquad \text{where}$$
$$s_D^\alpha (\Omega) = \{\{y\varepsilon D \text{ such that } y\Delta_\alpha e\}, e\varepsilon\ \Omega\ \}$$
$$m_D^\alpha (e) = |e\Delta_\alpha\ D|/|\ \Omega\ \Delta_\alpha D|,$$
$$m_D^\alpha (\Omega) = |F\Delta_\alpha\ D|/|\ \Omega\ \Delta_\alpha D|=1.$$

Given the common decision table, available to both our marketing manager and his rivalry, we can proceed back to the decision table rules and infer the values of $\{X_i$, i=1,N$\}$ that led to the actions taken by rivalry. Let E be the reconstructed data set that included all tuples inferred from rivalry decisions. At this point, we have a data set E ready for data analytics and we propose applying the same belief structure construction mechanism applied on the marketing manager's extracted data set D. Let u be the basic belief assignment produced by our belief structure construction algorithm.

At this point, we have succeeded in having two different belief structured one from the marketing manager m and one reconstructed from rivalry decisions u, built on $\Omega=\prod_{i=1,N} 2^{dom(Xi)}$:

$m: 2^{\Omega} \rightarrow [0, 1]$

$m(\emptyset)=0$

$m(A)\geq 0$ for any A in 2^{Ω} $\sum_{A\subset\Omega} m(A)$ =1.

$u: 2^{\Omega} \rightarrow [0, 1]$ $m(\emptyset)=0$

$m(A)\geq 0$ for any A in 2^{Ω}

$\sum_{A\subset\Omega} m(A)$ =1.

Given the $\{\delta_k\}_{k=1,|R|}$ respectively for the rivals $\{R_k\}_{k=1,|R|}$ where |R|, we can apply the discount factor as follows:

Let $\delta=[\sum_{k=1,|R|} \delta_k]/|R|$

$u': 2^{\Omega} \rightarrow [0, 1]$

$u'(\emptyset)=0$ $u'(A) =$

$\delta u(A)$ $u'(\Omega) = \delta u(\Omega)$

$+ 1\text{-}\delta$ $\sum_{A\subset\Omega} u'(A) =1.$

If f denotes the fused belief structure on $\Omega=\prod_{i=1,N} 2^{Xi}$: then

$f: 2^{\Omega} \rightarrow [0, 1]$ $f(\emptyset)=0$
$f(A)\geq 0$ for any A in 2^{Ω}

$f_{\Omega}(A) = \sum_{B\cap C=A} m(B)u'(C)/(1-K)$; for $A\neq\emptyset$
Where $K= \sum_{B\cap C=\emptyset} m(B)u'(C)$ and $f_{\Omega}(_{\emptyset})=0$
$\sum_{A\subset\Omega} f(A) =1$

Once, we obtained the fused belief structure, we need to compute its belief structure as follows:

$BetP(X) = \sum_{Y\varepsilon 2^{\Omega}, Y\neq\emptyset} |X\cap Y|f(Y)]/ [|Y|(1-f(\emptyset)]$
Where $X=(x_1, \ldots, x_N)$ and x_i ε $dom(X_i)$, i=1,N.

Example:

Let us give an example to demonstrate the framework where a marketing manager has a big data available to him and a data analytics model to apply a belief structure and its pignistic probabilities on the some marketing decision parameters. These are actionable marketing insights because the marketing manager has now a decision-theoretic model that he can adopt to maximize his marketing objectives and select the best actions. In this example, the marketing manager's objective is to collect and approve as many bank loan applications while respecting the approval decision rules written in terms of the client's income (X_1), his age (X_2), his properties (X_3), his credit score (X_4), his family size (X_5), and his spending habits (X_6). We are using ordinal categorical format, for all the decision parameters, interpreted differently as needed, as follows: 1: VL: Very low; 2: L: Low; 3: M: Moderate; 4: H: High; 5: VH: Very. The decision table for acting upon actionable marketing insights is defined in Table 2.

Table 2: Decision Rules								
	Income	**Age**	**Education**	**Properties**	**Credit score**	**Size of family**	**Spending habits**	**Decision**
Rule 1	{2 , 3}	{3}	{1 , 2}	{2, 3}	{2 , 3}	{2 , 3}	{2 , 3}	A1
Rule 2	{2}	{2, 3}	{3}	{1, 2}	{2}	{2}	{2}	A2
Rule 3	{1, 2}	{4, 5}	{2, 3}	{3}	{1, 2}	{1, 2}	{2, 3}	R
Rule 4	{3, 4}	{5}	{5}	{4, 5}	{3, 4}	{1, 4}	{3, 4}	A3
Rule 5	{5}	{1, 2}	{4}	{3, 4}	{5}	{5}	{5}	R
Rule 6	{2, 3}	{3}	{4}	{5}	{2, 3}	{2, 3}	{1, 3}	A3

Legend: VL: Very low; L: Low; M: Moderate; H: High; VH: Very High.

Rule conditions:
Income: VL: 1, L:2, M:3, H:4, VH:5
Age: VL: 1, L:2, M:3, H:4, VH:5
Education: VL: 1, L:2, M:3, H:4, VH:5
Properties: VL: 1, L:2, M:3, H:4, VH:5
Income: VL: 1, L:2, M:3, H:4, VH:5
Credit score: VL: 1, L:2, M:3, H:4, VH:5
Family size: VL: 1, L:2, M:3, H:4, VH:5
Spending habits: VL: 1, L:2, M:3, H:4, VH:5

Rivalry actions:
R1: R; R2: A3; R3: A2; R4: A3; R5: R; R6: A3; R7: A2; R8: R; R9: R; R10: A1.

Assume we observed 10 rivalry actions as R1:R, R2:A3, R3:A2, R6:A3, R7:R, R8:A3, R9:A2, and R10:R.

Table 2: Reconstructed rivalry's hypertable data set							
{5}	{1, 2}	{4}	{3, 4}	{5}	{5}	{5}	R
{2, 3}	{3}	{4}	{5}	{2, 3}	{2, 3}	{1, 3}	A3
{2}	{3}	{3}	{1}	{2}	{2}	{2}	A2
{3}	{3}	{4}	{5}	{3}	{2}	{3}	A3
{1}	{1}	{4}	{4}	{5}	{5}	{5}	R
{3}	{3}	{4}	{5}	{2}	{3}	{3}	A3
{2}	{2}	{3}	{2}	{3}	{2}	{2}	A2
{3}	{2}	{4}	{4}	{5}	{5}	{5}	R

Because the belief structure construction mechanism we used only accepts tuple data sets and not hypertuple data sets, we have to transform Table 2 into a regular atomic tuple data table. We easily obtain an atomic tuple data set as in Table 3.

Table 3: Transforming hypertable into a regular atomic table

5	1	4	3	5	5	5	R
5	1	4	4	5	5	5	R
5	2	4	3	5	5	5	R
5	2	4	4	5	5	5	R
2	3	4	5	2	2	1	A3
2	3	4	5	2	2	3	A3
2	3	4	5	2	3	1	A3
2	3	4	5	2	3	3	A3
2	3	4	5	3	2	1	A3
2	3	4	5	3	2	3	A3
2	3	4	5	3	3	1	A3
2	3	4	5	3	3	3	A3
3	3	4	5	2	2	1	A3
3	3	4	5	2	2	3	A3
3	3	4	5	2	3	1	A3
3	3	4	5	2	3	3	A3
3	3	4	5	3	2	1	A3
3	3	4	5	3	2	3	A3
3	3	4	5	3	3	1	A3
3	3	4	5	3	3	3	A3
2	3	3	1	2	2	2	A2
3	3	4	5	3	2	3	A3
1	1	4	4	5	5	5	R
3	3	4	5	2	3	3	A3
2	2	3	2	3	2	2	A2
3	2	4	4	5	5	5	R

At this point, we obtained the reconstructed rivalry table and the same belief reconstruction process we applied to produce the marketing manager's belief structure is applied a second time on the reconstructed rivalry's table to produce the reconstructed rivalry's belief structure.

We then obtain the following:

$m: 2^\Omega \rightarrow [0, 1]$
$m(\emptyset)=0$
$m(A)\geq 0$ for any A in 2^Ω

$\sum_{A\subset\Omega} m(A) =1.$

$u: 2^\Omega \rightarrow [0, 1]$ $u(\emptyset)=0$
$u(A)\geq 0$ for any A in 2^Ω $\sum A\subset\Omega\ u(A) =1.$

After discounting:
$u'(A) = \delta u(A)$ $u'(\Omega) = \delta u(\Omega) + 1-\delta$ $\sum A\subset\Omega\ u'(A) =1.$

If f denotes the fused belief structure on $\Omega=\prod_{i=1,N} 2^{dom(Xi)}$: then

$f: 2^\Omega \rightarrow [0, 1]$ $f(\emptyset)=0$ $f(A)\geq 0$ for any A in
2^Ω $f_\Omega(A) = \sum_{B\cap C=A} m(B)u'(C)/(1-K)$; for
$A\neq\emptyset$
Where $K= \sum_{B\cap C=\emptyset} m(B)u'(C)$ and $f_\Omega(\emptyset)=0$
$\sum_{A\subset\Omega} f(A) =1$

The rest of the process is straight forward. The marketing analyst needs to compute the pignistic probabilities and apply his traditional decision theoretical model where the action that maximizes the marketing manager's utility function is recommended.

Future research directions:

This article looked into deficiencies in big data analytics due to 1) limited data extraction as important data may stay behind with important insights that are lost with the unprocessed data and 2) the application of data analytics that were not made for data that change in an unknown pace and that come at high speeds in different formats and unknown veracity.

The article proposed the correction of these deficiencies by improving the marketing manager's actionable insights by learning from rivalry actions, guessing their belief structures, and combine them with his belief structures and produce a better decision position with what was learned from rivalry's actions.

A possible extension of this work is to study the interactive learning case between a rival and another to produce a game theoretic model where rivals start a sequential interactive learning process where a possible 'Dempster-Shafer' equilibrium may be reached. A proof of the existence of such equilibrium is very important for the rivals to ease and stabilize the race in investing in the big data technology that is useful but still lacking valid engines capable of producing valid marketing insights that do not change because of the V's characterizing the big data technology.

Conclusion

We uncovered some deficiencies in big data marketing analytics. We cautioned that invalid actionable marketing insights may lead to wrong marketing decisions. Marketing managers apply available big data analytics which do not take big data V's into consideration. The big data velocity V cannot assure that the actionable insights marketing analysts produce now are still valid a minute later. Also because of the big data volume V, marketing analysts will only extract limited data amounts for their data analytics and the data they left out, if added, may not produce insights that are consistent with those produced by extracted data sets. The rest of big data V's, not studied in this article, also generate their own different problems that will affect marketing management decisions.

We proposed an evidential model that remedies for the limitations above, that produces belief structures on marketing decision parameters and observe rivalry's actions from which data and belief structures are reconstructed and then fused on marketing management's own belief structures. The fused belief structure provides better decision support for marketing management since observed rivalry's actions bring added decisional evidence and better actionable insights to the marketing decision process.

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