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Customer satisfaction analysis: Identification of key drivers

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Abstract

A problem of identifying key drivers in customer satisfaction analysis is considered in relation to Kano theory on the relationship between product quality and customer satisfaction using tools from cooperative game theory and risk analysis. We use Shapley value and attributable risk techniques to identify priorities of key drivers of customer satisfaction, or key dissatisfiers and key enhancers. We demonstrate the theoretical and practical advantages of Shapley value and attributable risk concepts in elaborating optimal marketing strategy.

Keywords: Customer satisfaction; Kano theory; Cooperative games; Shapley value; Attributable risk

1. Introduction

The quality management theories (Kano et al., 1984; Levitt, 1986; Gale and Wood, 1994; Mittal et al., 1998; Lowenstein, 1995) indicate that many key product and service attributes have a curvilinear relationship to satisfaction. Certain attributes, termed "Must-be" attributes by Kano, have a dramatic negative impact on satisfaction when they are not delivered, but have a minimal positive impact when they are improved from an acceptable level. The non-linear nature of the relationship between "Must-be" attributes and overall satisfaction makes identification of such attributes difficult with standard linear modeling techniques. Furthermore, the relationship between these "Must-be" attributes and overall customer satisfaction is multiplicative, because failure on any one of the "Must-be" attributes causes the decline in overall satisfaction. It is not necessary to have reduction in performance on all of the "Must-be" attributes. The "Must-be" attributes define what we call the key dissatisfiers.

In this paper we present an analytical design that effectively identifies the key dissatisfiers that need attention. We evaluate combinations of attributes and the relationship of failure on any attributes in these combinations to dissatisfaction by the overall measure of satisfaction with the product. We found that a tool from cooperative game theory, namely Shapley value, can successfully serve within the environment of customer satisfaction problems for identification of the most important factors of influence. This method of arbitration in many players coalitions was introduced by Shapley (1953) and is

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described in many works on the theory of cooperative games (see Luce and Raiffa, 1958; Roth, 1988; Myerson, 1997; Straffin, 1993; Owen, 1995; Jones, 2000). Shapley value imputation produces a unique solution satisfying the general requirements of the Nash equilibrium. The Shapley partitioning is based on the axioms of symmetry (or anonymity) of players, dummy (or zero value player), and additivity. The latter two axioms are also known in the form of carriers (or effectiveness), and linearity (or aggregation). In numerous developments and generalizations it was shown that these axioms can be weakened (see Weber, 1988; Hart and Mas-Colell, 1989; Nowak and Radzik, 1995; Myerson, 1997; Bilbao, 1998; Bilbao and Edelman, 2000). For our purposes the Shapley value presents a useful and convenient instrument for solving practical problems of customer satisfaction analysis in marketing research.

In applying Shapley value to the analysis of customer satisfaction the objective of the task is to predict dissatisfaction using a subset of the attributes being studied. In our problem the attributes take the role of the players, and the value of the game is the ability to predict the satisfaction level of customers. We use Shapley value with the assumption of the transferable utility and we determine each attribute's share in explaining dissatisfaction in the overall measure. We also use the same procedure for finding the enhancers, or drivers that can lead to very high levels of customer satisfaction, that is, delight (Conklin and Lipovetsky, 2000a). Splitting categorical data into subsets related to the margins of their values allows us to explore the non-linear behavior of attributes in their influence on customer satisfaction.

Previously we successfully applied Shapley value analysis to another common problem faced by marketing managers—the choice of a set of product variants to be included in a new product introduction, or choosing a variant for a line extension (Conklin and Lipovetsky, 2000b,c). Similarly, in customer satisfaction, the Kano theory indicates that failure on *any* key attribute results in failure overall. This means that the observed incremental effect of an attribute depends on which other attributes are also in a failure mode.

When the order of priorities of the key drivers is found by Shapley value analysis, as a complementary tool and for the purpose of comparison we employ the attributable risk theory developed in the field of medical research. A comprehensive consideration of the concepts of relative and attributable risk is given in Kahn et al. (2000) (see also Miettinen, 1974; Walter, 1976; Kleinbaum et al., 1982). We apply attributable risk evaluation for more detailed key driver analysis, and demonstrate through examples drawn from real data that its results are in a good accordance with the results obtained by Shapley value analysis, and both approaches lend themselves to identifying specific action steps that management can take to have real impact on overall satisfaction.

This paper is organized as following. Section 2 contains notations for conditional probabilities and Shapley value imputation. Section 3 describes the procedure of choosing key drivers. Section 4 considers attributable risk concepts. In Section 5 we present an example of a customer satisfaction problem. Section 6 summarizes the results.

2. Shapley value in key dissatisfier analysis

Suppose we have observations by overall satisfaction (dependent variable) and by numerous attributes of influence (independent variables). In customer satisfaction research all these variables are usually measured in ordinal scales, say, from 1 (worst) to 10 (best) values (although there could be a different scale for each variable). Without losing generality, suppose the values of several bottom levels (for example, from 1 to 5) correspond to the event that we call dissatisfaction (D) by the scale of the criterion variable, e.g. overall satisfaction. Similarly, the bottom values (for example, from 1 to 5) by any of the attributes (independent variables) corresponds to the event that we call failure (F). We denote the events of non-dissatisfaction and non-failure as D' and F', respectively. We use the following notations for probabilities: $P(D)$—probability of dissatisfaction by dependent variable; $P(F)$—probability of failure by *any* in the set of independent attributes; $P(D|F)$ and $P(D|F')$—conditional probabilities of dissatisfaction among those who failed and non-failed, respectively; $P(F|D)$—*reach* value, or conditional probability of failure among those dissatisfied; $P(F|D')$—*noise*, or conditional probability of failure among those non-dissatisfied. In empirical research we estimate these probabilities as proportions from the sample data.

Consider the difference between the conditional probabilities of failure among those who are dissatisfied and non-dissatisfied:

$$\text{success} = \text{reach} - \text{noise} = P(F|D) - P(F|D'). \quad (1)$$

We are looking for maximum values of the objective (1) subject to various subsets of attributes describing the event of failure. This criterion (1) estimates the prevalence of Failed (within a set of attributes) respondents among those who are dissatisfied in comparison with failed respondents among those non-dissatisfied by the overall measure of satisfaction. In an attribute by attribute analysis, those attributes producing a bigger value of the objective (1) can be seen as the candidates for key dissatisfiers. We call the objective (1) *success* after the originator of such kind of measure, the well-known American logician and philosopher Pierce (1884), who evaluated the success of prediction of tornado occurrences. It is also interesting to note that the measure (1) corresponds to Youden (1950) misclassification index (see also Goodman and Kruskal, 1954, 1959) usually written as $J = 1 - \alpha - \beta$ and in our notations there are relations reach $= 1 - \beta$ and noise $= \alpha$.

We know that overall dissatisfaction can have multiple causes and certain combinations of causes may interact to increase the probability of dissatisfaction. We need a way to summarize the importance of each attribute while taking into account the existence of multiple causes of dissatisfaction. This leads us to use the Shapley value method to identify these key dissatisfiers. The Shapley value approach has several advantages over traditional regression approaches. For example, highly correlated attributes will tend to have similar Shapley values. This is important because their high correlation indicates that we truly do not know which variable is the true cause. Linear statistical models tend to choose one of the highly correlated variables at the expense of the others. Since we are trying to make specific recommendations this arbitrary variable choice by linear modeling approaches is counterproductive. If we are unsure of the cause of the dissatisfaction it is better to recommend attending to both attributes instead of picking one. Linear or linearized models are generally additive by factors of influence, yet we want to find a set of dissatisfiers where failure on any single item or combination of items induces the total failure, or dissatisfaction.

The first step in the key dissatisfier procedure is to calculate an order of importance of the attributes as contributors to overall dissatisfaction, and Shapley value serves exactly for this purpose. The Shapley value, hereafter referred to as SV, was developed to provide an ordering of the worth of players in a multi-player cooperative game, or to impute the relative importance of each participant of the coalition.

The Shapley value is usually defined as a kth participant's input to a coalition:

$$S_k = \sum_{\text{all } M} \gamma_n(M)[\upsilon(M \cup \{k\}) - \upsilon(M)], \quad (2)$$

with weights of probability to enter into a coalition M defined as following:

$$\gamma_n(M) = \frac{m!(n-m-1)!}{n!}. \quad (3)$$

In (2) and (3), n is the total number of all the participants, m is the number of participants in the Mth coalition, and $\upsilon(\cdot)$ is the characteristic (or value) function used for estimation of utility for each coalition. By $M \cup \{k\}$ a set of participants which includes the kth participant is denoted, when M means a coalition without the kth participant. In our case, the participants of the coalition are attributes. As was shown in Conklin and Lipovetsky (1998), regrouping items in sum (2) we can represent the Shapley value imputation in the form more convenient for calculations:

$$S_k = \frac{1}{n}\upsilon(M_{\text{all}}) + \sum_{j=1}^{n-1} \frac{1}{n-j}(\bar{\upsilon}(M_{kj}) - \bar{\upsilon}(M_j)), \quad (4)$$

where $\bar{\upsilon}(M_{kj})$ is the average of the value function by attribute combinations of size j containing attribute k, and $\bar{\upsilon}(M_j)$ is the average of the value function by all attribute combinations of size j.

Value functions υ in (2) and (4) are defined by our objective function (1). Let us rewrite (1) in a more explicit form:

$$\upsilon(M) = P\Big(\sum M > 0|D = 1\Big) - P\Big(\sum M > 0|D = 0\Big). \quad (5)$$

By $D = 1$ and $D = 0$ we denote dissatisfied and non-dissatisfied respondents by the overall measure, respectively. M is a subset of attributes being considered and the summation is across attributes for each respondent. $\sum M > 0$ corresponds to failure on any attribute in the subset. The first and the second probabilities in (5) are estimated as proportions of the failed within those who are dissatisfied and non-dissatisfied, respectively (or reach and noise values in (1)). This characteristic function satisfies the axioms required by Shapley value imputation. First, symmetry of players: all attributes are initially considered to be equal by their possible influence on the output. Second, zero value player: characteristic function for a dummy player is $\upsilon(0) = 0$ due to the definition of reach and noise functions in (1). Third, additivity: considering just dissatisfaction area within Kano theory we work in the domain of the linear behavior of the total Kano curve, and similarly for the Delight area.

Although the equations are fairly straightforward, the computational difficulties soon become apparent. If we use all of the combinations of n attributes taken j at a time to calculate the mean of the value function in (4) then we quickly run out of time to do the computations. However, the formula (4) provides a clear sense of the SV as marginal inputs from various subsets of attributes averaged by all possible coalitions. This suggests a promising approach for reducing the computational burden. Since each term in (4) is constructed by calculating the mean value of combinations with and without the attribute, then we can estimate those means by sampling combinations. Random sampling could be easily done and we incorporate this approach in our code whenever the number of attributes being evaluated is more than 10 (Conklin and Lipovetsky, 1998).

The Shapley value imputation provides a value for each attribute and therefore an ordering of priorities for improvement. However, organizations are limited in the number of areas that can be the subject of improvement initiatives. Therefore, we want to find the set of dissatisfiers that are the most important and account for a large proportion of the overall dissatisfaction among customers.

3. Choosing key drivers

Suppose we ordered all the attributes by their SV (4). The highest value in (4) identifies the attribute with a large amount of overlap between failure on this attribute and dissatisfied values overall. This is the reach part of the objective function. If we add the second ranked attribute the overlap (or reach) increases between dissatisfied overall and failures on either of the two attributes in our list of potential key dissatisfiers (for a visual guidance see the tables with numerical results that we discuss further). However, we might also increase overlap with customers who are not dissatisfied, i.e. an increase in the noise part of the objective. This pattern will continue as we add attributes to the set of potential dissatisfiers. Thus, we have two different goals in the analysis: to get the overlap with the maximum number of customers who give an overall dissatisfaction rating (reach) while minimizing the overlap with customers who are not dissatisfied (noise). Therefore we need to evaluate both objectives simultaneously.

The objective of total overlap of a subset of attributes (where respondents failed) with the overall satisfaction (where respondents are dissatisfied) corresponds to the conditional probability $P(F|D)$ that we also call reach value. This characteristic can be evaluated using the other given probabilities by Bayes' theorem:

$$\text{reach} \equiv P(F|D) = \frac{P(D|F)P(F)}{P(D)} = \frac{P(D|F)P(F)}{P(D|F)P(F) + P(D|F')P(F')}. \quad (6)$$

The reach level shows the prevalence of the event of failure by any attributes in the subset F among those who are dissatisfied by the overall measure, and we are interested in the maximum value for the criterion (6) because this indicates that we are accounting for a large part of the total number of dissatisfied customers. On the other hand, we also want to minimize the noise because its high value would mean we are wasting resources by focusing on problems that are not actual causes of dissatisfaction. This logic implies the use of the same objective (1) applied to order the attributes in the Shapley value procedure. Using the expression (6) and a similar expression (up to the change of D to D') for noise, we can represent the success objective (1) as follows:

$$\begin{aligned}\text{success} &= \text{reach}\left(1 - \frac{\text{noise}}{\text{reach}}\right) \\ &= P(F|D)\left(1 - \frac{P(D'|F)}{P(D|F)}\frac{P(D)}{P(D')}\right). \qquad (7)\end{aligned}$$

We see that the success measure is higher for the bigger values of three characteristics: those are reach $= P(F|D)$, index $P(D')/P(D)$ defined as the odds of probabilities of non-dissatisfied and dissatisfied customers, and the index $P(D|F)/P(D'|F)$ defined by the odds of conditional probabilities of dissatisfied and non-dissatisfied subject to the failed customers.

By definition, as we add attributes to the list of key dissatisfiers in SV order, we always increase the reach part of the objective. We also increase the noise portion of the objective. Since the attributes are added in order of their SV we reach a point where the added noise overwhelms the added reach and the objective (1) begins to decrease. This is the point we choose for defining our final set of key dissatisfiers. Given this objective, one could argue for an exhaustive search for the "best" objective result. Such an approach would generally find a slightly different solution than the SV ordered solution. However, the SV result will be more stable because it is an averaging over all combinations. This means that small differences in the effects of the attributes across the sample (respondent heterogeneity) will have less impact on the final solution compared to an exhaustive search for the "best" solution.

Once a set of potential key dissatisfiers is identified, analysis of the data becomes straightforward. We divide the respondents or customers into two groups. The first being those who gave a failure rating on any of the attributes in the set of potential key dissatisfiers, and the second being those who gave no failure rating on any of those. All the data in the study is compared across these two groups. In general, differences are extremely dramatic on all key satisfaction and loyalty measures such as likelihood to recommend or future purchase intent. In addition, differences on demographic or behavioral variables identify the characteristics that are related to these customers. This leads to specific recommendations and action plans for improvement.

Similar to key dissatisfier analysis we also perform key enhancer analysis. At first we omit from the data all the respondents who failed by the key dissatisfiers, then we choose the parts of the ordinal scales of overall satisfaction and the attributes that we define as indicating "delight" on the part of customers. For the key enhancer analysis, we usually take the top one or two ordinal scale points by all the variables. Then we apply all the steps of the procedure for choosing the best key dissatisfiers, except that we are taking data from the top levels of all scales for defining enhancers. Thus, as the result of key driver analysis we identify three groups of respondents—dissatisfied from the first procedure, delighted, from the second application of the procedure and neutral (those that remain). It is interesting to mention that in contrast to regression analysis the missing values in the data can be easily accomodated in key dissatisfiers (and enhancers) analysis—we simply consider them as not corresponding to our definition of dissatisfied/failed (and satisfied/succeeded) responses.

4. Attributable risk analysis

For comparison with more common techniques we incorporate some ideas from attributable risk analysis—the approach known in statistics for medical research (Kleinbaum et al., 1982; Kahn et al., 2000). Attributable risk (AR) is defined as the expected number of diseased members of a population reduced by those without the risk factor, relative to diseased members. In our notations of D for dissatisfied and $F(F')$ for failed (non-failed), and in terms of customer satisfaction, AR is the prevalence of the dissatisfied total over the dissatisfied among non-failed, relative to dissatisfied total,

$$\mathrm{AR} = \frac{NP(D) - NP(D|F')}{NP(D)} = 1 - \frac{P(D|F')}{P(D)}, \qquad (8)$$

where N is total sample. The reach value (6) can be represented as following:

$$\mathrm{reach} = \frac{P(D|F)P(F)}{P(D)} = 1 - \frac{P(D|F')}{P(D)}P(F'). \qquad (9)$$

Comparison of (8) and (9) shows that we can write the relation between reach and *attributable risk* as

$$1 - \mathrm{reach} = (1 - \mathrm{AR})(1 - P(F)). \qquad (10)$$

This relation can be represented as follows:

$$\mathrm{reach} = \mathrm{AR} + P(F) - \mathrm{AR} * P(F). \qquad (11)$$

Both reach value and attributable risk make sense of probabilities of the corresponding events, so (11) shows that reach value can be interpreted as the sum of two independent events with probabilities of attributable risk and of *risk factor* (or failure). Another characteristic of attributable risk theory is so called *relative risk* (RR) defined as

$$\mathrm{RR} = P(D|F)/P(D|F'), \qquad (12)$$

which can be interpreted as a ratio of probability of dissatisfaction within those who failed and those who not failed. Attributable risk can be expressed via this characteristic and reach value (6) as

$$\mathrm{AR} = \mathrm{reach}(1 - 1/\mathrm{RR}). \qquad (13)$$

So attributable risk yields a more conservative value than the Reach value. Both AR and RR characteristics can be used as additional measures of key driver analysis in customer satisfaction research.

5. Numerical example of customer satisfaction analysis

Consider an example using real data on a service that is sold through a retail outlet. The overall satisfaction and several attributes are measured on a 10 point scale. The results of the key dissatisfier analysis are presented in Table 1. Total sample size here is 407 respondents, with 65 of them dissatisfied, so the overall dissatisfaction rate equals 16%. In Table 1 the attributes are arranged by Shapley value in the descending priority order. In this case we are using the Shapley value to understand the value of each attribute in making a successful prediction of the state of a customer's satisfaction.

Due to the product nature it comes with no surprise that satisfaction with retail service is the most important attribute in predicting overall

Table 1
Key dissatisfiers

# In set	Attribute	At risk: dissatisfied on any in set		Not at risk: satisfied on all in set		Set statistics			Risk measures	
		Cumul. N	Overall dissat. rate (%)	Cumul. N	Overall dissat. rate (%)	Reach (%)	Noise (%)	Success (%)	Relative risk (%)	Attributable risk (%)
1	Retail experience	70	57.1	337	7.4	61.5	8.8	52.8	7.7	53.5
2	Service performance	96	51.0	311	5.1	75.4	13.7	61.6	9.9	67.8
3	Transaction fees	140	37.9	267	4.5	81.5	25.4	56.1	8.4	71.9
4	Problem resolution	155	35.5	252	4.0	84.6	29.2	55.4	8.9	75.2
5	Other transactions	166	34.3	241	3.3	87.7	31.9	55.8	10.3	79.2
6	Encountered problems	181	32.0	226	3.1	89.2	36.0	53.3	10.3	80.6
7	Initialization of service	183	31.7	224	3.1	89.2	36.5	52.7	10.1	80.4
8	Other services	187	32.1	220	2.3	92.3	37.1	55.2	14.1	85.8

satisfaction. This item had 70 respondents who were dissatisfied, and 57.1% of those were dissatisfied on the overall satisfaction measure. At the same time, there were 337 respondents who were satisfied with the retail service they received and only 7.4% of them were dissatisfied overall. The reach value for this attribute is 61.5% and the noise is only 8.8% yielding a success value of 52.8%. The corresponding relative risk is 7.7% and the attributable risk is 53.5%.

The purpose of the procedure is to find a set of key dissatisfiers for management to focus on for improvement. Instead of evaluating all possible subsets of attributes we focus on adding variables to the set of dissatisfiers sequentially in the order of their Shapley value. The second most important variable is satisfaction with the service performance. The statistics shown in Table 1 are the cumulative statistics for the set that includes both satisfaction with retail service *and* satisfaction with service performance. Looking at this set of two attributes as key dissatisfiers we find that we now have a total of 96 respondents who are dissatisfied on at least one of these attributes and the overall dissatisfaction rate among these respondents is 51.0%. There are now 311 respondents who are satisfied with *both* attributes and their overall dissatisfaction rate is 5.1%. The corresponding reach rises to 75.4% and the noise rises to 13.7%. Since the reach increased more than the noise the overall success value increases by considering both variables.

Now, observe what happens when we add the third most important variable, satisfaction with the transactional fees. Here, more noise is added than reach so the success value decreases. Therefore, it is logical to focus efforts on the first two attributes because going beyond those is counter productive. The first two attributes have a total combined attributable risk of 67.8%.

The results of the Key enhancer analysis are presented in Table 2. Here we reduce the analysis by removing those who failed on the two attributes identified as key dissatisfiers. This is because we want to determine which attributes would be enhancers after the dissatisfiers are fixed. The sample size is 311 respondents not failed by two key dissatisfiers, and 70 among these consumers are delighted overall, so the delight rate equals 22.5%. We again present the attributes in Shapley value order, now based on their success at predicting delight. Here, the first attribute, satisfaction with service performance has the highest value on the success criteria and also provides a good amount of attributable risk (69.4%). Adding other attributes to the set of key enhancers does not increase our success in predicting delight so we limit our definition of enhancers to this single attribute.

Overall, we have used the technique to identify two attributes that need critical attention because they drive dissatisfaction and one attribute that also drives delight. In general, we find it more difficult to identify good enhancers than dissatisfiers because customer satisfaction research tends

Table 2
Key enhancers

# In set	Attribute	Potential advocates: delight on any in set		Neutral: not delight on any in set		Set statistics			Risk measures	
		Cumul. N	Overall delight rate (%)	Cumul. N	Overall delight rate (%)	Reach (%)	Noise (%)	Success (%)	Relative risk (%)	Attributable risk (%)
1	Service performance	108	51.9	203	6.9	80.0	21.6	58.4	7.5	69.4
2	Retail experience	136	44.9	175	5.1	87.1	31.1	56.0	8.7	77.2
3	Transactions fees	142	43.0	169	5.3	87.1	33.6	53.5	8.1	76.3
4	Other transactions	145	42.1	166	5.4	87.1	34.9	52.3	7.8	75.9
5	Initialization of service	149	41.6	162	4.9	88.6	36.1	52.5	8.4	78.1
6	Other services	153	41.2	158	4.4	90.0	37.3	52.7	9.3	80.3
7	Problem resolution	167	37.7	144	4.9	90.0	43.2	46.8	7.8	78.4
8	Encountered problems	296	23.6	15	0	100.0	93.8	6.2	–	100.0

to focus on processes that are key components of the service. Therefore, we are less likely to have measured processes that truly enhance the consumer experience.

6. Concluding remarks

A basis of key driver analysis is the calculation of the Shapley value of the attributes. The Shapley value, as applied here, is a measure of the importance of including each attribute in the set of key dissatisfiers, i.e. the attributes that need managerial attention. The Shapley value works by assessing the relative effect on the dependent variable by different combinations of predictor variables. We have demonstrated the practical advantages of the Shapley value as a useful decision tool that can be applied for numerous problems of categorical data modeling arising in various managerial fields. Following the strategy suggested by the Shapley value for key drivers, the managers can choose the best direction toward improving customer acquisition and retention.

Since the recommendations generated from key driver analysis are specific and tied to attributes it is easier to generate action plans for improvement. We have found that the key to successful customer relationship management is the ability of a firm to follow through and actually improve performance in areas that need it. Clear detailed action recommendations increase the probability of follow through.

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