Estimating market shares in each market segment using the information entropy concept

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Abstract

Sales data of a certain product for the various competitors are usually available at the aggregate level. However, these data give no clue to the heterogeneities in the sales pattern across different market segments. Heterogeneities are caused by different purchasing behavior in each market segment; as a purchaser in a segment will be attracted to the attributes of the product most important to that segment. This concept can be formalized via a simple attraction model that utilizes an elasticity measure for each quality or price attribute [G.S. Carpenter, L.G. Cooper, D.M. Hanssens, D.F. Midgley, Modeling asymmetric competition, Marketing Science 7 (4) (1998) 393–412]. Assessment of these elasticities is not difficult since customer response – in each market segment – to perception of quality and price is tracked by most firms [J. Ross, D. Georgoff, A survey of productive and quality issues in manufacturing. The state of the industry, Industrial Management 3 (5) (1991) 22–25]. This paper attempts to formulate a generic framework based on the information entropy concept that utilizes such an attraction model to estimate competitors' sales in each market segment.

Keywords: Marketing; Attraction model; Information entropy; Probabilistic allocation

1. Introduction

Formal marketing plans incorporate information resources, in more than 95% of the firms [2]. However, many data are at the aggregate level (e.g. total sales of a product, in all segments), and formulating a market strategy that target a special market segment needs data at the level of the various market segments (e.g. sales in each market segment).

In marketing science, market segmentation is the process of grouping customers in distinct homogenous segments that have the same purchasing behavior [1]. Customers in each segment are likely to have similar responses towards a marketing mix; i.e. they place more or less the same relative importance on the various – quality and price – attributes of the product.

Moreover, in marketing science, positioning is the process by which a manager of a certain product tries to create a favorable perception for his/her product in the minds of the customers in the target market segment.

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Positioning is always expressed relative to the position of competitors; i.e., it is the ‘relative competitive comparison’ as perceived by the target market segment.

The aim of this paper is to assist managers in formulating a successful marketing strategy by providing them with detailed sales information – based on unbiased estimations. A successful marketing strategy gives an organization an edge in the marketplace, through proper positioning, in the most promising segment. We argue that providing a manager with unbiased estimations of competitors’ sales (including his/her own business) in each market segment, would serve as an important clue for formulating a successful marketing strategy. Such a marketing strategy will allow the organization to concentrate its limited resources on the segments in which it has clear competitive advantages.

In this paper, the unbiased estimations of competitors’ sales, in a specific market segment, represent a plausible allocation of the segment between the various competitors. In general, there are many plausible allocations. So the idea of this paper is to identify the least biased allocation, given the available knowledge about the customers’ behavior in that specific segment. This knowledge is formalized by the attraction model used in the paper. As explained, in the next sections, the least biased allocation is the allocation that possesses the maximum information entropy.

The rest of the paper is organized as follows: In Section 2, we give a brief overview of the information entropy concept. In Section 3, we formulate a generic framework based on the information entropy concept that utilizes an attraction model to estimate market shares in each market segment (i.e., competitors’ sales in each market segment). This framework is generic because it is applicable to any product or service. Finally, Section 4, concludes the paper with a summary, and some useful directions for future research.

2. The information entropy concept

Shannon – the father of information theory – used entropy as a proxy measure for the information content associated with a probabilistic model for a data source [4]. In general, the information content is proportional to the associated uncertainty. To comprehend this fact, we are going to apply it to our market example below.

In our example, if all competitors have equal probability to sell a product in a certain market segment, and no competitor predominates, then our uncertainty about the actual market shares in this segment is maximal. In this case, telling managers the actual market shares provides them with significant amount of information. However, if a certain competitor predominates (i.e., a certain competitor has higher probability than the rest) then there is less uncertainty, and consequently the information content is less. In fact, if there were no uncertainty, the information content would be zero.

Shannon devised an entropy function to estimate the average information content associated with a random variable. This function has the following properties:

- The function is continuous – i.e., changing the value of one of the probabilities (associated with a possible state of the random variable) by a very small amount only changes the entropy by a small amount.
- The maximum of this function occurs when all probabilities are equal (i.e., all states are equally likely).
- If the outcome of the random variable is certain, then the entropy is equal to zero.

Shannon defined the entropy function associated with a discrete random variable, with possible ‘n’ states (outcomes) as

\[ \sum_{i=1}^{n} X_i \log_2 \left( \frac{1}{X_i} \right) \]

where \( X_i \) is the probability of the \( i \)th outcome of the random variable.

Basically, the entropy is the sum – over all possible outcomes – of the product of the probability of outcome \( i \) times its “surprisal”. Where the surprisal of the \( i \)th outcome is defined as the log of the inverse of the probability.

The interpretation of the above formula is as follows: The entropy of a random variable is the expected value of its outcome’s surprisal.
In some cases, initial probabilities – say $X^0_i$ – can be given for the outcomes. These initial probabilities can be considered as educated guesses that are based on some prior information. In this case, $X^0_i$ will be the benchmark to determine the surprisal associated with the $i$th outcome. Based on this benchmark, the surprisal will be equal to: $\log_2(X^0_i/X_i)$.

That is if $X_i = X^0_i$, then the surprisal is equal to zero.

If $X_i < X^0_i$, then the surprisal is positive (more uncertainty vis-à-vis the outcome).

If $X_i > X^0_i$, then the surprisal is negative (less uncertainty vis-à-vis the outcome).

And the entropy function will be defined as

$$\sum_{i=1}^{n} X_i \log_2 \frac{X^0_i}{X_i}.$$

In the next section, we will utilize the above function to rank various plausible probabilistic allocations of sales in the market segments. The least biased allocation would possess the highest expected surprisal value. That is, the least biased allocation would maximize the above function, without violating any given constraint. Note that if there are no constraints imposed on $X_i$, then the maximum entropy would be equal 0; and the optimal values of $X_i$ would be equal to the corresponding values of $X^0_i$.

3. The proposed generic framework

3.1. Notations and definitions

Before proceeding with the framework development, we first describe the notations and definitions of the variables as follows:

**Subscripts**
- $i = 1, \ldots, n$ competitors
- $s = 1, \ldots, m$ segments
- $q = 1, \ldots, v$ quality attributes (e.g. reliability, ease of use, features, after sales services, etc.)
- $p = 1, \ldots, w$ price attributes (e.g. standard purchase price, rebates, promotional discounts, channel discounts, etc.)

**Input variables**
- $Q_{qi}$ perceived quality attribute $q$ of the competitor $i$
- $P_{pi}$ perceived price attribute $p$ of the competitor $i$
- $e_{qs}$ elasticity of the quality attribute $q$ for segment $s$
- $e_{ps}$ elasticity of the price attribute $p$ for segment $s$
- $R_{is}$ market reach of competitor $i$ in segment $s$
- $M_s$ market size of segment $s$
- $TS_i$ total sales of competitor $i$ in all segments

**Auxiliary variables**
- $QB_q$ baseline perception of quality attribute $q$ for all competitors
- $PB_p$ baseline perception of price attribute $p$ for all competitors
- $VI_{is}$ overall index of the relative value associated with the product of competitor $i$ in segment $s$

**Output variables**
- $X^0_{is}$ the indicated market share of competitor $i$ in segment $s$
- $X_{is}$ the best estimation of the market share of competitor $i$ in segment $s$
3.2. Attraction model

Below we will explain the attraction model used, which is based on the work of Marquez and Blanchar [3]. In this paper, the purpose of the attraction model is to indicate the values of \(X^0_{is}\). Each \(X^0_{is}\) has a dual interpretation. \(X^0_{is}\) can be interpreted either as the indicated market share of competitor \(i\) in segment \(s\), or as the initial probability that segment \(s\) is allocated to competitor \(i\).

Marquez and Blanchar define the baseline perceptions as follows:

\[
QB_q = \min_{i=1}^{n}(Q_{qi}), \quad i = 1, \ldots, n,
\]

\[
PB_p = \min_{i=1}^{n}(P_{si}), \quad i = 1, \ldots, n.
\]

Marquez and Blanchar formulate VI\(_{is}\) as follows:

\[
VI_{is} = \prod_{q=1}^{v} \left(\frac{Q_{qi}}{QB_q}\right)^{c_{iq}} \prod_{p=1}^{w} \left(\frac{P_{si}}{PB_p}\right)^{c_{ip}}.
\]

Finally, Marquez and Blanchar formulate \(X^0_{is}\) as follows:

\[
X^0_{is} = \frac{R_{is} \times VI_{is}}{\sum_{i=1}^{n} R_{is} \times VI_{is}}.
\]

Note that the market reach, \(R_{is}\), can vary from very monopolistic (i.e. 1) to non-existent reach (i.e. 0).

3.3. Optimization model

The purpose of the optimization model is to identify the values of \(X_{is}\). Each \(X_{is}\) has a dual interpretation. \(X_{is}\) can be interpreted either as the best estimation of the market share of competitor \(i\) in segment \(s\), or as the best estimation of the probability that segment \(s\) is allocated to competitor \(i\). Basically, \(X_{is}\) is the optimal value derived from the maximization of the entropy function, under constraints.

We will start by stating the three basic constraints imposed on \(X_{is}\):

\[
X_{is} \geq \delta \quad \text{(extremely small fraction; e.g. } \delta = 2^{-52}) \quad \forall i = 1, \ldots, n \quad \text{and} \quad \forall s = 1, \ldots, m,
\]

\[
\sum_{i=1}^{n} X_{is} = 1 \quad \forall s = 1, \ldots, m,
\]

\[
\sum_{s=1}^{m} X_{is} \times M_s = TS_i \quad \forall i = 1, \ldots, n.
\]

As explained in Section 2, our objective is to maximize the entropy function, which can be expressed as follows:

\[
\text{maximize} \quad \sum_{s=1}^{m} \sum_{i=1}^{n} X_{is} \log_2 \frac{X^0_{is}}{X_{is}}.
\]

This maximization problem has a unique solution, because the objective function is strictly concave, and all constraints are linear.

4. Conclusion

In this paper, we proposed a generic framework to estimate the market shares in each market segment. The idea is to maximize an entropy function taken into consideration the imposed constraints. Initial estimations are indicated from an attraction model. This framework is generic because it can be used for any product or service.
In future work, we intend to incorporate this framework into a decision support system, which analyze decisions in light of their impacts on shares and profits. Also as an extension of this work, a more complex attraction model can be considered.

References