

# MEASURING PRODUCT TYPE WITH DYNAMICS OF ONLINE PRODUCT REVIEW VARIANCE

*Completed Research Paper*

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## **Abstract**

*The concept of “product type” (experience versus search product) is increasingly important in business research and practice. However, it is not defined or measured precisely in the Internet age due to significantly lower search cost and changes in consumer information search behavior resulting from reliance on information and communications technology. We take advantage of the greatly available micro level online word-of-mouth data and infer product type based on statistical properties of online word of mouth (specifically, online product reviews). We draw on the law of large numbers (L.L.N), and the literature on informational content and online product reviews to analytically propose a mechanism to classify products. Our theoretical analyses indicate that, for a pure search product, when number of reviews (i.e. review sample size) increases as more consumers rate the product, variance of the mean rating will decrease. And for a product with more experience attributes, when number of reviews increases, the variance of the mean rating will not decrease and may instead increase depending on how dominant these experience attributes are. We collect archival data from Amazon to categorize the products and services. Implications of this analytical tool and empirical findings for research, theory and managerial practice are discussed.*

**Keywords:** *Online Product Reviews, Product Type, Law of Large Numbers, Information Content, Product Quality*

## Introduction

This decade has seen huge amount of user generated content (UGC) on World Wide Web, which experienced unprecedented growth with the support of Web 2.0 technologies. Analyzing the information role and impact of UGC on individual behavior and firm strategies has become popular among information systems (IS) and marketing scholars (Dellarocas 2003, Chevalier and Mayzlin 2006, Li and Hitt 2010, Archak et al. 2011, Sun 2012, Godes and Silva 2012). Central to the Web 2.0 is the capability of individual users participating in social activities such as word of mouth (WOM) through interactive systems like product review systems. Through these digital WOM platforms, consumers are able to share with others their consumption experience of a product, leaving public opinions online, which offers new and large amount of data for researchers and practitioners to analyze to get a better understanding of their effects. However, data alone provides limited strategic insights and implications. Indeed, although organizations today have access to enormous data sets, analytical tools are urgently needed to harness the tremendous potential of these data to improve organization's strategic decision making. To this end, much attention has been afforded to the information role of online product reviews on sales with a focus on the economic effects of review valence and volume (Chevalier and Mayzlin 2006, Dellarocas et al. 2007, Duan et al. 2008b, Zhu and Zhang 2010), text comments (Archak et al. 2011, Ghose 2010), and review variance (Clemons et al. 2006, Sun 2012). But academic work on proposing mechanisms to leverage UGC (such as online product reviews) to measure important business concepts is limited (Ghose and Ipeiotis 2007). We seek to leverage micro level online product reviews data to shed lights on an important construct of interest to both researchers and practitioners - product type.

Economists have long believed differentiation of products to be an important determinant of market behavior (Bain 1993, Chamberlin 1950), and efforts to operationalize the concept of *product type* were also well documented (Nelson 1970, 1974, 1981, Smith 1990, Laband 1991, Weathers et al. 2007). Product type has long been used in the literature to explain different consumer behaviors and marketing strategies, and has also been used as an important moderating variable by researchers to understand various market phenomenon (e.g., Zhu and Zhang 2011, Mudambi and Schuff 2011, Senecal 2004, Huang et al. 2009). Based on the Nobel Winning work of Stigler (1961) on informational cost, Philip Nelson (1970) made a pioneering effort in classifying search and experience products, arguing that for a rational consumer, experience will only be used when search becomes too expensive. With the data he obtained, Nelson proposed repair expenditure as the measure for experience products. The rationale is that repair expenditure is incurred when quality cannot be perfectly inspected prior to purchase because search is incomplete or imperfect. He expected the variance in qualities requiring experience to ascertain to increase as the level of repair expenditures increases. Without any doubt, the concept of search versus experience products that Nelson proposed had a huge appeal and impact on the economics and business professions, for both academic research (Villas-Boas 2004, Huang et al. 2009, Klein 1998, Mudambi and Schuff 2010), and business school teaching (Clarkson and Miller 1982, Greer 1984, Martin 1988). Since Nelson (1974), the search versus experience products paradigm has gradually gone through several milestone theoretical advancements. Since most products do not fall into the neat search/experience taxonomy<sup>1</sup> that exists in theory<sup>2</sup>, the dilemma of the original dichotomy was revised and reconciled by Nelson (1981), noting that rather than classifying a product as a search or an experience good, every product may be a collection of search attributes and experience attributes (Sheffet 1983). Products are conceptualized to be on a continuum of search and experience and are labeled as either one in terms of their dominant attributes (Klein 1998).

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<sup>1</sup> In this paper we do not explore the credence quality described by Darby and Karni (1973), as we assume most consumers post a review for the product within a short window of time after purchase.

<sup>2</sup> Observation made by Caves and Williamson (1985) shows sentiments among researchers about the classification of a dichotomous product type: "...Previous researchers have settled for force majeure, judgmentally sorting products into discrete classes (search vs. experience products, convenience vs. non-convenience products)..." (p. 117).

ESTIMATES OF THE RATIO OF REPAIR EXPENDITURES TO SALES BY GOOD, 1963

Goods	Nonmerchandise Receipts*	Total Repair†
Experience goods:		
Jewelry . . . . .	12.6	17.3
Typewriters . . . . .	8.8	...
Radio, television . . . . .	8.1	24.3‡
Tire, battery . . . . .	7.5	...
Aircraft, boats, motorcycles . . . . .	7.0	...
Heating and plumbing . . . . .	6.4	...
Bicycles . . . . .	6.0	...
Automobiles . . . . .	5.7	30.0§
Music instruments . . . . .	4.9	10.7
Appliances . . . . .	4.4	14.0
Search goods:		
Floor covering . . . . .	3.8	...
Garden implements . . . . .	3.5	...
Sporting goods . . . . .	2.8	...
Household trailers . . . . .	2.5	...
Cameras . . . . .	2.4	...
Furniture . . . . .	2.1	7.6
Paint and mirrors . . . . .	1.9	...
China, glassware . . . . .	1.9	...
Hardware . . . . .	1.6	...
Hobbies, games . . . . .	0.8	...

\* The percentage of nonmerchandise receipts to sales of stores specializing in the sale of the specified good.  
 † To the percentage of nonmerchandise receipts, we add the ratio of the receipts of service specialists to the sales of the good for those goods whose service specialists are specified in the U.S. Bureau of the Census (1966b).  
 ‡ The U.S. Commerce Department estimates this percentage as roughly 29% (U.S. Department of Commerce 1964).  
 § Commerce estimates for this percentage is roughly 23%.  
 || Furniture stores have a percentage of nonmerchandise receipts of 2.7. But they also sell television and appliances. The tabulated figure adjusts for the proportion of sales in the three categories.

**Figure 1. Original Classification by Nelson (1970, page 319)**

The nature of product type depends on information search cost. The role of information technology (IT) on market and hierarchies has been observed by IS scholars two decades ago (Malone et al. 1987), that more products or services are becoming searchable and the information on electronic market helps reduce hierarchies. Nowadays, information disseminates much faster and less costly than ever before, and there are now more channels through which opinions from others can be transmitted in a mediated way. Online markets become ubiquitous and have reduced consumer search costs for information on product price and attributes to a large extent (Bakos 1997). The changed landscape of commodity and service markets may change people's information search behavior, therefore may change the category that some products should belong to, and also challenge some of the arguments made by Nelson (1970), e.g., “by search I mean the direct inspection of a good, for example, a woman trying on a dress (Nelson 1981, p. 42)”, which appears counter-intuitive for product sold online since direct inspection is not possible. However, for research that focuses on the online context, the aforementioned type of information acquisition behavior is usually categorized as “experience”. Unless the product has many credence quality attributes of which the utility can only be known after some time of usage, sampling can offer a relatively accurate estimate of the product’s utility to the consumer.

While the empirical applications of the concept “product type” is burgeoning over the last decade, especially in IS and marketing disciplines (e.g., Huang et al. 2009, Mudambi and Schuff 2010, Senecal 2004, Smith and Menon 2005), the substantive measurement of product type remains taken for granted. The latest research still conveniently categorizes products based on Nelson’s original scheme of search versus experience goods, and operationalizes the construct with products from the original list (Huang et al. 2009, Mudambi and Schuff 2010). However, as Lucas (1976) noted, when rules of the game change, economic agents will change their behavior and using data from the old “game” or taking as given historical relationships between variables will provide little insight into how agents will behave under new rules of the game. We believe it is important to theoretically advance the measurement of product type in the Internet age for products, in order to draw credible implications for research and practice.

We focus on online markets, however, we should note that whether products are actually purchased online or not does not matter, the key is that consumers refer to online markets for information and share their experience with the product with digital WOM (online product review ratings). Based on utility theory, we show that consumers’ ratings of products provide a mechanism to distinguish between search and experience products. We argue that, for some products, even without actually experience a product, a

consumer may still form reasonable expectation about their utility from the product. Based on whether information is transferrable from one person to another, we categorize an attribute as search attribute when the information about the attribute is transferrable, i.e., a consumer can form reasonable expectation about her utility derived from the attribute prior to consumption by checking the information about the attribute. When the information about the attribute is non-transferrable, then it is considered an experience attribute. Our study connects the seemingly unrelated literature of product type, online product reviews, and information content to theorize the role of online product reviews for research and practice.

In this paper, we dissect the information contained in online product reviews into two integral segments - objective product quality and consumer-specific product quality (preference). Recall that a search attribute is defined as one which information and utility is transferrable from one person to another, we approach objective product quality with the view of search-attributes-based quality that offers common utility towards all consumers, and approach preference with the concept of experience-attributes-based quality that offers idiosyncratic utility that differs based on consumer segment. Based on this distinction and powered by the large amount of micro-level consumer review data, we seek to address the following research question:

*How do we categorize products based on the sequential dynamics of product review variance and what are the implications for research and practice?*

We focus on a setting in which reviews are truthful, in the sense that consumers truthfully report and rate the products based on their consumption experiences of the products. However, reviews may be misleading due to differences in consumer preferences. Although manipulation of reviews is likely, we note that it may be a tiny share when number of reviews is large enough and/or when the review platform has better control of consumer identities. We study the research questions based on the statistical properties of review distributions. In what follows, based on prior literature on online product review and information content, we first argue that online product reviews' variance could contain two types of information about the product: the crowd's consensus (or lack thereof) about its quality, and the crowd's preferences in terms of product attributes. Second, based on the law of large numbers, we propose a mechanism to evaluate a product's type based on its attributes. The analytical analyses show that if the variance of the mean rating decreases as number of reviews increases, a product is a pure search product; while a product has more experience attributes if as number of reviews increases, the variance of mean rating will not decrease and can also increase as experience attributes become more important in consumers' decision making. We then use archival data from several sources to implement our empirical study to re-categorize products. Finally, we discuss implications of this study for measuring product type and firm strategies.

## **Literature Review**

### ***Product Type***

The concept of product type (search versus experience product) has been studied extensively in the literature. For any product, the consumer has a choice between searching or experimenting to obtain information about the product's attributes (Nelson 1970, p. 317). Rationally, "experience", or sampling, will be used when the expectation of costs associated with information search becomes too high. And for experience products, product attributes can only be ascertained until upon consumption. Most of the studies that involve the construct of "product type" base their rationale on Nelson's original studies (Nelson 1970, Nelson 1974). In studying consumer behavior for search and experience products, Huang et al. (2009) used Nelson's original classification even though they acknowledged that the Internet is likely to change the traditional relationship between search and experience products. Similarly, Mudambi and Schuff (2010) used Nelson's original classifications and noted that "for products outside of Nelsons original list of products, researchers have disagreed on their categorizations" (p. 191). These two studies are among a huge body of business and economics literature that specifically hypothesized about the role of product type as an antecedent or moderating variable. Prior studies have also approached the issue by sampling at the extremes, to avoid being arbitrary. For example, in an experimental study to understand the effect of recommendation of different type of products, Senecal (2004) used calculator versus wine for the product type treatment. In a recent study to examine product performance uncertainty, Weathers et al. (2007) took a perceptual approach with a contingent view, and proposed a concept similar to

“perceived product type”. In their conceptualization, specifically, the classification is based on the extent to which consumers feel the need to directly use products to make an informed decision. We concur with their argument that the greater the need to use one’s senses to evaluate a product, the more experience attributes the product possesses. The more one feels that second-hand information will allow for adequate evaluation of the product, the more search qualities the product possesses. Weathers et al. (2007) posted an important aspect of search (versus experience) product: information on product characteristics can be transferred more easily. The literature also evolves to favor “search attributes” and “experience attributes” (Klein 1998, Nelson 1981) over search products and experience products. Other attempts to measure product type include Smith (1990) and Laband (1991). To sum up, if we assume that utility can be inferred based on product characteristics, for search attributes, utility can be estimated prior to consumption since information on search attributes can be obtained easily from the seller or previous buyers. However, for experience products, utility is known only until, or after consumption.

### ***Information Roles and Information Content of Online Product Reviews***

While consumers are more concerned about the objectivity of the product reviews, businesses also want to understand the information role of online product reviews. Effect of online product reviews on sales has received tremendous attention for many products in different markets, e.g., books, movies, etc. Chevalier and Mayzlin (2006) found a significant effect of review valence on book sales. Liu (2006) find that the explanatory power of review on sales comes from volume of reviews instead of valence of reviews. Duan et al. (2008a) accounted for the fact that reviews may be influenced by movie sales (endogeneity) and found no significant effect of review valence on consumer purchase decisions. Sun (2012) found that besides the valence of rating, the variance of mean ratings could affect sales volume of books. In sum, online product reviews do pose a challenge in interpretation for businesses. Research has also focused on whether a product review is helpful. Forman et al. (2008) studied reviewer disclosure of identity-descriptive information and found it to shape community members' judgment of products and reviews. Using data from Amazon.com, Mudambi and Schuff (2010) found for experience products, reviews with extreme ratings are less helpful than reviews with moderate ratings.

Recent studies also identified that the online product review may not reflect true product quality for several reasons. Dellarocas (2006) argues that one reason consumer generated reviews may not represent actual product quality is because firms hire professional reviewers to inflate the ratings of their products. Nevertheless, the results suggest that even in the presence of manipulation, reviews are still informative because producers of the highest-quality products also receive the greatest benefit from such manipulation. Li and Hitt (2008) identified the self-selection bias of online product reviews by arguing that early buyers and late buyers may have different preferences about a product. Ghose and Ipeirotis (2007) talked about objective and subjective reviews, and proposed review subjectivity's effect on review helpfulness. The view the literature has taken about the mean rating not representing true product quality focuses on self-selection biases. We focus on the variance of online product review ratings to argue that if online product review reflects consumer preferences, rating cannot be aggregated or averaged in numeric terms to indicate quality (Theil 1971). Therefore, to understand the informational role of product reviews, we need to get a better understanding of the informational content contained in product reviews.

In terms of information content, online product reviews are essentially UGC that contains second hand information. Holbrook (1978) made an important distinction between two types of content: factual content and evaluative content. Factual content is defined as “logical, objectively verifiable descriptions of tangible product features”. In contrast, evaluative content is defined as “emotional, subjective, impressions of intangible aspects of the product” (p. 547). Such a distinction has been manifested in many occasions in the literature, such as understanding consumer response to advertising content (Olney et al. 1991), product search and experience attributes (Nelson 1970, 1974, 1981), and objective and subjective reviews (Ghose and Ipeirotis 2007). Similar to the conceptualization of search versus experience products, for most online product reviews, factual and evaluative contents are always “compresent”, only their relative balance varies (Ullmann 1957). Though an online product review rating is a number instead of text, it is based on a mix of objective assessments of tangible product features and subjective assessments of intangible aspects of the product. For search attributes, as we defined, utility is known prior to consumption, would be associated with objective product quality. While experience products for which the attributes cannot be evaluated before purchase are more likely to be evaluated based on their unobservable attributes, such as fitness.

## **Views on Product Quality**

Product quality is a heavily debated concept, for which different scholars have viewed it from different vintage points. Tuchman (1980) holds a transcendent view and observed that “a condition of excellence implying fine quality from poor quality...Quality is achieving or reaching for the highest standard as against being satisfied with the sloppy or fraudulent” (p.38). On the other hand, scholars like Kuehn and Day (1962) argue that “the quality of a product depends on how well it fits patterns of consumer preferences. (p. 101)”. More explicitly, Juran et al. (1999) simply ascribe quality to be “fitness for use” (p. 242). It is obvious that these two schools of thoughts are in conflict and may cause breakdowns in communication among researchers from different fields (Garvin 1984). Based on the comprehensive review and discussions of product quality by Garvin (1984), we separate the product-based approach and user-based approach of quality, and label them as two dimensions of a product: (objective) product quality and preference, respectively. The concept of objective product quality is mainly employed by economists, and it is argued that the observable attributes of a product determines its quality. This distinction lends a vertical or hierarchical dimension to quality. For example, a memory card with less failure times and reads faster is considered to be of higher quality than one that has more failures and reads slower. In this case, quality is objective, and utility experienced by one user is transferrable to another user, or using economist’s term, this objective quality is “common knowledge” to buyers. On the other hand, preference sees quality to be “in the eyes of the beholder”. When different buyers have different needs, the product that best fit their needs are regarded as having the highest quality. The literature has also discussed aggregation for product quality. Since objective product quality is based on evaluation of objective indices such as product performance, reliability, conformance, durability, serviceability (Garvin 1984), it is plausible to aggregate the objective quality metric. Naturally, the mean of the quality measure reported by different consumers would be an unbiased estimator of product quality. However, aggregating or averaging consumer preference can be problematic. Product-consumer fit is based on subjective quality indices such as experience attributes, features, aesthetics and perceived quality, and these are consumer-specific. In this respect, Theil (1971) talked about the difficulty of devising an unbiased statistical procedure for aggregating wildly varying preferences of consumers.

Since quality is a multi-dimensional concept (Gavin 1984), and as Archak and his colleagues observed, “by compressing a complex review to a single number, we implicitly assume that the product quality is one-dimensional”(Archak et al. 2011), the one-dimensional view of online product reviews may be problematic when consumer tastes vary (Rosen 1974) and attributes offer idiosyncratic utility (as opposed to common utility) to consumers (Nelson 1981). Since aggregating or averaging preference is usually not meaningful (Theil 1971), this may partly explain the mixed findings of relationship between review valence and sales (Duan et al. 2008a). Indeed, “review” literally means evaluation of a publication, product or service, which is not intended to only indicate the objective quality of a product, but more broadly about “opinion of the product” which may have a subjective element that is individual consumer-specific. This implicit multi-dimensional nature of online product reviews, serve as our basis for devising the analytical tool to categorize products.

## **Theoretical Model**

### **Connect Product Rating to Product Type**

Based on the above discussions, in this paper, we take the product differentiation and “goods-attributes” perspectives (Tirole 1988) to set up the model. Products are defined as bundles of attributes; each attribute is either a search attribute or an experience attribute. A search attribute is defined as one for which information can be transferred (from the seller or other prior consumers to the buyer) without ambiguity and for which a consumer can form rational expectation about the utility prior to consumption based on the information given to her. In other words, search attributes offer common utility. An experience attribute is defined as one for which a consumer's utility depends on the degree of match between himself and the attribute, and experience attributes offer idiosyncratic utility (Nelson 1981). A product is usually on the continuum between pure search good and pure experience good. Figure 1 shows a real example of distributions of reviews drawn from Amazon.com<sup>3</sup>.

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<sup>3</sup> The online product review distributions are generated based on the real review data from a product on amazon.com. ASIN: B00005LENO.

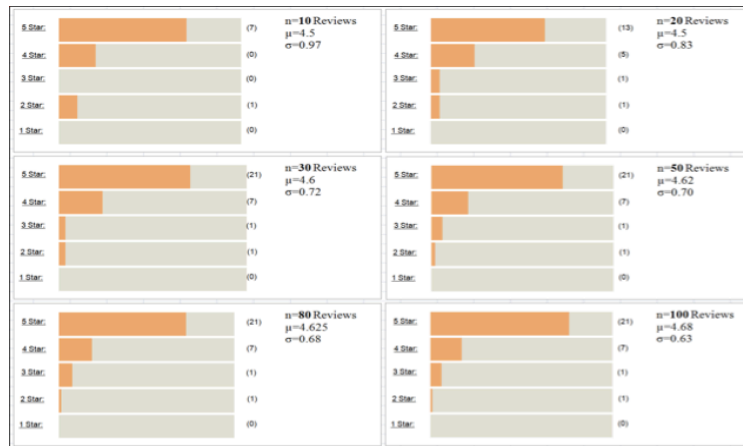


Figure 2. An Example from Amazon.com.

With these two types of product quality in mind, we discuss the distributions of consumer experience of objective product quality and preference. Since we assume that objective product quality information is transferable, such as product defects, functions or imperfections, which are not ambiguous and consumers can form rational expectation of their utility based on objective product quality information. One simple example will be the specifications of a computer - speed of the hard drive, screen resolution, dead pixels, etc. Consistent with the literature, we label these search attributes. Assuming that consumers rate a product truthfully according to the utility they receive from the product, the distribution of the ratings of a pure search product (with only objective product quality) will reflect the distributions of the actual qualities of the same product in the factory or warehouse. Put it another way, for a given product, a reviewer's rating on objective quality is a random draw from a pool of same products from a warehouse. Based on this, as more people purchase and review the product on its objective quality, ratings would be clustered near the average quality or true quality of the product ("central tendency"). Therefore law of large numbers applies for objective quality distribution of consumer's review of a search attribute. On the other hand, for experience attributes, there are several forces that drive the assumptions for L.L.N. invalid, or drive the distribution away from central tendency. First, experience attributes are associated with consumer preferences. Therefore, consumers with same taste (in the same market segment) will likely rate similarly, thereby rendering the observations less likely to be independently distributed. Therefore the L.L.N. would not apply for preference distribution. Below we formalize this logic.

### The Theoretical Model

#### Product Differentiation Model

We borrow model of product differentiation (vertical vs. horizontal) from the literature. We consider the following setting for a product, which may have a search or an experience attribute, or both. In general, vertically differentiated attributes are search attributes, while horizontally differentiated attributes, which depends on consumer tastes, may be either search or experience attributes. Those horizontally differentiated attributes, such as color, which information can be easily transferred, will fall into search attributes, while those rely on "experience" to know true utility, such as flavor, will be experience goods. Consider a simple setting where a product has only one search attribute and one experience attribute. Suppose buyer  $i$  purchased product  $j$  and submitted a rating  $r_{ij}$ . The rating would be determined by two sources of utility buyer  $i$  receives from the product: common utility  $q_j$  and idiosyncratic utility  $t_{ij}$  (Nelson 1981). Relating to the product quality literature (Garvin 1984), since objective quality is common knowledge, while consumer-specific quality is related to consumer preference and product-consumer fit, we relate search attributes to product objective quality, and experience attributes to consumer-specific product quality. Similar to Li and Hitt (2008), utility derived from the two dimensions of quality of product  $j$  is written as:

$$U(q_j, t_{ij}) = q_j + t_{ij} + \varepsilon_{ij}, \quad (1)$$

where  $\varepsilon_{ij}$  is a random error that follows  $N(0, \sigma_\varepsilon^2)$ .

The buyer would post a rating based on the utility received from the product, assuming a linear equation:

$$r(U) = a(q_j + t_{ij} + \varepsilon_{ij}) + b, \quad (2)$$

where  $a$  and  $b$  are both constants.

Therefore, with a sample of reviews we obtain a distribution, of which the variance of sample mean is:

$$\text{Var}(r) = a^2 \times (\sigma_q^2 + \sigma_t^2 + \sigma_\varepsilon^2) + 2a \times \text{Cov}(q, t) \quad (3)$$

Therefore, we propose that a product's review rating variance to come from two sources of product uncertainty (Dimoka et al. 2012), first,  $\sigma_q^2$  represents product quality uncertainty (due to variations in objective product quality of the search attribute), which results from imperfect production/distribution process.  $\sigma_t^2$  represents product-consumer fit uncertainty (due to consumer preference variations for the experience attribute). We assume that search and experience attributes are independent dimensions of a product (Nelson 1981), therefore  $\text{Cov}(q_j, t_j) \equiv 0$ . Since experience attribute, per its definition, is one in which one cannot form rational expectation of the utility from available information, it should be independent from or at least have weak correlation with search attribute. If experience attribute is related to search attribute, then it would suggest that one can derive utility related to the experience attribute from the search attribute, violating the assumption of experience attribute. In fact, when an experience attribute, say A, is highly related to a search attribute B (either positive or negative correlated), then this experience attribute should be classified as another search attribute or absorbed in search attribute B. Under the assumption that the search attribute and experience attribute are independent. Equation [3] can be simplified as:

$$\text{Var}(r) = a^2 \times (\sigma_q^2 + \sigma_t^2 + \sigma_\varepsilon^2) \quad (4)$$

When consumers have similar or the same preference,  $\sigma_t^2 = 0$ , and the source of variance of online product review  $\text{Var}(r)$  comes primarily from objective quality, which is drawn from a distribution of objective product quality (usually in a normal distribution), resulting from a production process. Given this, the product quality a consumer gets would be a random draw from the distribution, as sampling or the number of reviews increase, the law of large numbers assures that the distribution for the quality assessment would have an increasing fraction of buyers get and rate near the mean of the true quality, implying lower variance of the mean rating.

Three assumptions made to draw the inference are that: (a) objective product quality information is transferrable or equivalently, common knowledge, meaning that by consuming the objective product quality information, one can reasonably determine ex ante what her utility would be after consumption (b) each reviewer rates the product independently according to the consumption utility she derives, and (c) the mean and variance of the sample of quality rating are finite. Our conceptualization of the two dimensions of product attributes is compatible with the discussions on product differentiations. In the product differentiation literature, quality usually refers to a situation where consumers agree on which product is of better quality (common knowledge). Typical examples include automobiles and computers. In automobiles, faster acceleration, better braking and higher gas mileage are all objective quality attributes. In computers, faster processing capability, lower heat release, more megabytes of RAM, and faster speed of hard drive are all objective quality attributes. In contrast, preference concerns the elements about which there is no common agreement. Colors and shapes are usually preference-related than quality differentiators. However, since information about color and shapes can be easily transferred, they are search attributes in our framework. On the other hand, food flavors are also preference-related, but which information cannot be easily transferred and a customer may not know whether she would like it or not until after she consumes the food. Therefore while the quality of ingredients is a quality



differentiator, the taste of food is usually a preference differentiator. Same arguments apply to books and music. In this paper, we categorize an attribute as search attribute when the information about the attribute is transferrable, i.e., a consumer can form reasonable expectation about her utility derived from the attribute prior to consumption by checking the information about the attribute. When the information about the attribute is non-transferrable, then it is considered an experience attribute. If such an assumption holds, by simply observing the dynamics of distributions of the consumer ratings, one can derive valuable insights regarding product type. Specifically, consider online product review as a discrete random variable whose value  $r_1, r_2, \dots, r_n$  are drawn from an independent rating process, with expected value  $\mu$ , and finite variance. Let  $S_n = r_1 + r_2 + \dots + r_n$ , then for any  $\varepsilon$ , based on the law of large numbers (L.L.N), we have  $P(|S_n/n - \mu| < \varepsilon) \rightarrow 1$ , as  $n \rightarrow +\infty$ . Similarly, we can think of the quality testing process of a product, generally when the tested sample size increases, the mean of the sample is likely to converge to the true quality.

*Proposition 1. If a product has pure search attributes, as number of reviews increases, the variance (or standard deviation) of the mean rating would decrease.*

Since if a statement is true, its contrapositive is always true, we can re-write the first proposition:

*Proposition 2. (The Contrapositive of Proposition 1) If, as number of reviews increases, the variance (or standard deviation) of the mean rating does not decrease, a product has at least one experience attribute.*

### Product-Attributes Model (Modeling Multiple Attributes Case)

Then we extend the model to scenario when a product has multiple search and experience attributes.

For a buyer  $i$  who bought product  $j$  with  $m$  search attributes and  $n$  experience attributes ( $m/n = \tau$ ). Let  $s$  index a search attribute and  $k$  index an experience attribute. Therefore, a consumer's utility derived from product  $j$ 's  $m$  search attributes is  $\sum_{s=1}^m q_s$ , where  $s=1, 2, \dots, m$ . When uncertainty comes from preference, the distribution of ratings will be related to the distance the consumers taste is from products experience attribute. Therefore, using the same set up as Sun (2012) and a variant of Hotelling's transportation model (1929), we think of consumers taste space as a straight line of length 2 on which the experience attribute of a product is located at the midpoint. Consumers are uniformly distributed on the line: A consumer's location represents her ideal type of attribute for this product in the taste space. If consumer  $i$  with distance  $x_i$  from the product purchases the product, her utility derived from that experience attribute  $k$  would be  $(1 - x_{ik}) \times t_k$ ,  $x_{ik} \in [0, 1]$ . Suppose a product has  $n$  experience attributes, her utility derived from product  $j$ 's experience attributes is written as:  $\sum_{k=1}^n [(1 - x_{ik}) \times t_k]$ ,  $k = 1, 2, \dots, n$

Therefore, with a random error  $\varepsilon_i$ , a consumer  $i$ 's utility from a product  $j$  with  $m$  search attributes and  $n$  experience attributes can be written as:  $U_{ij} = \sum_{s=1}^m q_s + \sum_{k=1}^n [(1 - x_{ik}) \times t_k] + \varepsilon_i$

Assuming there are a total of  $N$  raters in the sample, the variance of the sample mean can be written as:

$$\begin{aligned} \text{Var}(r) &= \text{Var}\left(\sum_{s=1}^m q_s\right) + \text{Var}\left(\sum_{k=1}^n [(1 - x_{ik}) \times t_k]\right) + \text{Var}(\varepsilon_i) \\ &= \sum_{s=1}^m \text{Var}(q_s) + \sum_{k=1}^n \text{Var}(t_k) + \sum_{k=1}^n \text{Var}(x_{ik} \times t_k) + \text{Var}(\varepsilon_i) \end{aligned} \tag{5}$$

As number of rating increases, the variance for the sample mean rating may not be reduced because when people have different tastes, it is similar to the situation that ratings are drawn from different market segments (buyers with different tastes). Different people could have different tastes towards the same product. For example, by examining the motion pictures, Holbrook (1999) suggest that ordinary consumers and professional critics do emphasize different criteria in the formation of their tastes. Therefore increase in number of reviews may not reduce variance for the mean, instead, it may increase it.

*Proposition 3. If, as number of reviews increases, the variance (or standard deviation) of the mean rating increases, a product has at least one experience attribute.*

*Proposition 4. As number of reviews increases, the more the variance (or standard deviation) of rating increases, the more experience attributes a product has.*

## Empirical Applications

Our empirical task is to classify product type based on the propositions. The key challenge here is to translate the propositions to the empirical data and construct appropriate *test* statistics to rank product type based on the dominant attributes (experience vs. search) of a product. In this study we shall attempt to resolve this statistical challenge. We collect data from Yelp.com and amazon.com. Data was collected for the period of Feb 3, 2006 to Feb 5, 2012. Each review, we collect the time stamp (date), sequence (sorted by the website), and the star rating (an integer between 1 and 5). We describe our data set as follows.

### Method 1. T-tests on Yelp Restaurants Data

We collect online product reviews data from yelp.com. Yelp.com features its consumer reviews for local services, such as restaurants, entertainment, etc. We sample the local services reviews of all the restaurants in the 50 largest cities<sup>4</sup> in the U.S.. We sample the 50 largest cities because they usually have more services and ratings, allowing us to amass more data and perform robust analyses.

**Table 1. Descriptive Statistics for Restaurants Sample**

restaurants	total reviews	average volume	>50 reviews	>100	>250	>500	>1,000 reviews
5,557	2,081,089	3,952 (6,086)	4,329	2,994	1,501	805	403

It is easy to compare the value of the variance (e.g., variance of the first 10 reviews versus the first 25 reviews), we acknowledge that it is too far-reaching to draw conclusions based on review data of a single restaurant, because it is possible that some restaurant may have very few experience attributes, and the positive effect of rater preference heterogeneity may be offset by the negative L.L.N. effect of some search attributes. Therefore, we feel the need to construct a panel of restaurants, and statistically test whether restaurants review variance decrease as number of reviews increase, on average.

To test the hypotheses to show that as sample size increases, variance will either increase or decrease with confidence, we construct a *t*-statistic. To illustrate how variance of the samples changes as more consumers rate the restaurants, we choose the 805 restaurants from the 5,557 most popular restaurants in the largest 50 cities in US, which have more than 500 product reviews. Therefore, the first 500 product reviews of the 805 restaurants were used for analysis. If null is rejected and the test statistic  $t > 0$ , we classify this product as a search product. If null is not rejected, or the null is rejected and  $t < 0$ , we classify this product as an experience product. Level of experience attributes depends on the *t* statistic value.

First, from Figure 4, we observe that, temporally, as number of reviews increases, the variance of the sample mean of reviews increase on average, and the standard deviation of the mean variance decrease. We then report the paired *t*-test statistics.

We can clearly see that for restaurants, the variance of ratings increase as sample size increases, therefore, restaurants are dominated by experience attributes.

<sup>4</sup> The choices of cities are based on the size using population as the criteria. We referred to the US census bureau for the population estimates. Source: U.S. Census Bureau. Web: [www.census.gov](http://www.census.gov).

**Table 2 Statistical Tests for the Restaurant Sample (N=805, # of reviews>500)**

$x_i$	var	mean	median	st.d	st. error	t-statistic	p value
1	var10	0.812	0.789	0.298	0.010	$H_0 : x_i = x_{i-1}$	
2	var15	0.857	0.834	0.259	0.009	6.910	<0.001
3	var20	0.877	0.883	0.231	0.008	4.550	<0.001
4	var25	0.898	0.907	0.217	0.008	6.180	<0.001
5	var50	0.917	0.910	0.187	0.007	5.030	<0.001
6	var100	0.925	0.924	0.177	0.006	4.200	<0.001
7	var150	0.930	0.926	0.171	0.006	3.650	<0.001
8	var200	0.937	0.937	0.167	0.006	6.140	<0.001
9	var250	0.942	0.937	0.164	0.006	5.060	<0.001
10	var300	0.944	0.944	0.161	0.006	3.340	<0.001
11	var350	0.947	0.948	0.160	0.006	5.350	<0.001
12	var400	0.951	0.950	0.157	0.006	6.490	<0.001
13	var450	0.953	0.951	0.156	0.005	4.380	<0.001
14	var500	0.956	0.956	0.155	0.005	5.040	<0.001

**Method 2. Estimating the Effect of Sample SIZE Variance with Amazon.com Data**

Second, we collect online product reviews data from Amazon.com. Amazon.com is a large online market for products in U.S., it features a myriad category of products and reviews, which allows us to obtain different products, thus validating and generalizing our results. Besides, Amazon.com is also among the first to host an online product review system, accumulating millions of consumer reviews, which allows us to do statistical tests with confidence. We obtained all the reviews for 4 product categories pre-defined by Amazon and often sampled by researchers, including *video games, digital cameras, hard drive, and GPS*. The summary statistics for the 4 samples are as follows.

**Table 3. Summary Statistics for Amazon Product Samples**

Category	Groups	Total Observations	Average Number of Reviews
Videogame	648	37,789	58.32
Digital Camera	473	27,142	57.38
Hard Drive	130	8,955	68.88
GPS	138	11,458	83.03

To obtain the data we need, for the first step, our approach is to collect the entire review history for all the products of the same type, such as memory card, and order them by time stamps.  $N=25$  is usually considered a large number, therefore we retain products that have more than 25 reviews. For each review for each product, we obtain review valence, sequence (order) of review, time stamp of a review, number of words and review text. To assess the impact of sample size of ratings on the variance of the sample mean, we form the variable *SIZE*, which captures the position of a review in the sequence of reviews for a given product/service/product-attribute (Godes and Silva 2012), which also indicates the sample size of the first  $n$  ratings. We followed the marketplace or portal’s sequential ordering of reviews based on time stamp<sup>5</sup>. We then calculate the rolling variance and standard deviation of the mean rating for each product for the first 2, 3, ... $n$  reviews with an *R* program.

Second we define product category. Ideally the same group of products should have similar number of experience and search attributes, however, it may not realize because even different types of laptops can have different colors, different platforms or video performance. It is also possible that one product has

<sup>5</sup> We were not able to identify the order of reviews that arrived on the same day, but the marketplace/portal allows sequential ordering (sort by date function), and we follow the marketplace/portal’s ordering. An alternative approach to deal with potential “ties” in the sequence for reviews that arrive on the same date is provided by Godes and Silva (2012), where authors defined the variable *ORDER* as:  $ORDER(d^i) = \sum_{d \leq d^i} N(\Delta_{d^i}) + 1$ , where  $N(S)$  is the cardinality of set  $S$ . The shortcoming of this method is that, econometrically speaking, it is not a true dynamic panel. We employed same approach as an robustness check, and there is no change in coefficient estimates, in terms of magnitude and significance.

more experience attributes than another product in the same category. For example, an exotic restaurant may be more experience-dominant while chain restaurant, such as, Subway, may be more search-attribute-based. Our model can be used at the product level too. However, given the goal of this paper is to understand product type at the category level, our main analyses are at the category level. As a result, we may observe some noise due to the coarse definition of product categories. For simplicity of this study, we follow the product categories that are classified by Amazon.com.

### Model Specifications and Estimations

Formally, we model the sequential dynamics of ratings' standard deviation ( $STD(r, SIZE)$ ) at the product or attribute level as a function of (a) sample size ( $SIZE$ ), and (b) quadratic term of sample size ( $SIZE^2$ ).

We use standard deviation to measure variation because it is in the same unit as the sample mean. In our model, we control for unobserved product, or product-attribute level heterogeneity via product, or product-attribute fixed effects. Variance of the sample ratings with the first  $n$  reviews is defined and measured as follows:

$$STD(r, SIZE) = E[r_{SIZE}^2] - (E[r_{SIZE}])^2 \quad (6)$$

Where  $r$  is the value of the rating,  $SIZE$  denotes the sample size ( $SIZE=2, 3, 4, \dots$ ),  $E[\cdot]$  is the expectation of  $\cdot$ .

For each category of products (e.g., computers, restaurants), or attribute, we estimate the following model:

$$STD(r, SIZE)_{it} = \alpha_i + \beta_1 * SIZE_{it} + \beta_2 * SIZE_{it}^2 + \varepsilon_{it} \quad (7)$$

where  $SIZE_{it}$  is the sequence of the  $t^{th}$  review of the  $i^{th}$  product ordered by the time stamp (therefore it captures the sample size of the first  $t$  reviews),  $\alpha_i$  captures product or attribute-specific time invariant component of the variance,  $\beta_1$  captures the estimated effect of sample size of ratings on variance,  $\beta_2$  captures quadratic effect of sample size on variance,  $\varepsilon_{it}$  captures individual random errors. This empirical specification applies to both products (services) category level analysis and also product attribute level analysis.

In Table 4 we show the method we employ to estimate Equation (7). We observe that sample size could have an effect on the coefficient estimates; however, it only has a marginal impact on the significance level ( $t$ -statistic). The  $t$ -statistic takes sample size and standard error into account, therefore is favorable for comparison between products. Therefore, we use  $t$  statistic as a comparative statistic to order experience vs. search product in the following analysis. Since quadratic term is included, we performed additional joint  $F$  test of  $SIZE$  and  $SIZE^2$ , and the ordering does not change.

Within this set of 4 products, we found that GPS and external hard drive tend to be search goods, and video game and digital camera to be experience goods. And in this set of products, video game has most experience attributes. Due to the exploratory nature of the empirical analysis, we do not suggest cut off points.

**Table 4. Fixed Effect Estimation Results in Amazon Data (DV= $STD_t$ )**

Category	$SIZE$	$t$ statistic	$SIZE^2$	Constant
Video Game	0.00039***	5.47	-2.6e-6***	0.151***
Digital Camera	0.00019**	2.42	-1.08E-6	0.192***
Hard Drive	-0.0004*	-1.67	5.28e-6***	0.197***
GPS	-0.0002*	-1.90	2.45e-6***	0.209***

Cluster robust standard errors in parentheses, standard errors adjusted for all clusters (Groups)

Coefficients significant at \*\*\*  $p < 0.001$ , \*\*  $p < 0.01$ , \*  $p < 0.05$

## Discussions and Implications

### ***Key Findings and Contributions***

This study tries to classify products based on the sequential dynamics (sample size) of review variances and draw implications for research and practice. This is made possible by the large amount of micro-level review data. This research provides several unique contributions: first, we proposed a model to categorize products based on the statistical properties of the online product reviews. Our theoretical model indicates that, for a pure search product, as number of reviews (i.e. sample size) increases as more consumers rate the product, variance of the mean rating will decrease. And for a product with dominant experience attributes, when number of reviews increases, the variance of the mean rating will increase. Second, using the data from archival sources, we illustrated how our method can be used to re-categorize products. Most importantly, this paper provides an empirical framework grounded with theory support that can be directly employed by researchers and practitioners to understand their product type, not only at the category level, but also at the product level and attribute level. That is, one can employ our test to know where a particular product/service or attribute stands, relatively to other products/services and attributes.

### ***Implications for Research on Product Type***

First, the results of this study serve as a new mechanism to classify products. The mechanism derived in this paper can be applied for any other online product review data that do not severely violate the assumptions. Second, the empirical method proposed in this paper translates the analytical propositions into several intuitive sets of results for both commodity goods and services. Third, our study is among a few efforts to measure product type, since the impacts of the reduced search cost (Bakos 1997) on different products are not the same, using the categorization more than 40 years ago (Nelson 1970) may limit the applications of the measure to draw accurate theoretical implications and actionable findings. For example, to avoid ambiguity, many studies sample products based on extreme examples of search or experience goods (Senecal 2004), while some others acknowledged the measure for product type could potentially be problematic, especially for products outside of Nelson (1970)'s original list (Mudambi and Schuff 2010). What is more, some scholars used Nelson's original classification even though they acknowledged that "Internet is likely to change the traditional relationship between search and experience goods" (Huang et al. 2009, p. 56). In this respect, our study tries to answer the call by leveraging free and large amount of data generated by users to inform scholarly research. Future research can use either the analytical tool or the results from our study and design experiments and archival analysis involving the construct of "product type" with more confidence. Also, since we are proposing a mechanism for measuring product type, as time go by, consumers' information search behavior and information search costs may change and product type might also change. However, our analytical method can still be applied for future data for new evidence.

### ***Theoretical Implications for Information Content of Online Product Reviews***

In order to make reviews helpful for consumer decision-making, we argue that for different types of products, different online product review systems should be created. The information role of the product review distribution also indicates that, for pure search goods, consumer text comments are redundant information which may make the product review less informative due to information overload. Since people generally have the capacity to interpret statistical properties of everyday events (such as political polls) based on heuristics (Darke et al. 1998, Nisbett et al. 1983), especially when they are in a scenario that motivates them to require high accuracy<sup>6</sup>, consumers no longer need to read the text comments because the distributional characteristics already conveys what they want to know (average rating for expectation of product quality and variance of rating for product quality uncertainty).

This study also points out the need for a multi-dimensional design of online product review systems. The current review systems (e.g., amazon.com and yelp.com) allows consumers to post a rating (An integer between 1 and 5) and a text comment to complement the rating, therefore it is useful to expand the uni-dimensional review system into multiple dimensions to separate main search attributes and experience

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<sup>6</sup> We argue that online shopping indeed is a task that motivates consumers to achieve high decision accuracy because they are driven to maximize utility in this task.

attributes to help match buyer preference with the products attributes. For example, for a laptop computer, there can be dimensions such as build quality, processing efficiency, aesthetics, etc. Also, since consumers are bounded in rationality (Simon 1997), too much unstructured information may be detrimental to consumer decision making (Jones et al. 2004), thereby undermining the information role of online product reviews. By correctly identifying a product's type, online product review systems could be designed towards higher efficiency accordingly. For example, a pure search product would benefit from a uni-dimensional numeric rating, while products with dominant experience attributes would benefit from more structured text comments, which allows other buyers to identify "consumer-product fit".

### ***Managerial Implications***

As Villas-Boas observes, for experience goods consumers can gain further information regarding how well a product fits their preferences only by experiencing it after purchase. Therefore, for manufacturers and retailers, educating consumers about product attributes could lower consumer's pre-purchase uncertainty and enhance performance. For example, online retailers can adopt the state-of-the-art technologies such as "3D virtual experience" (Jiang and Benbasat 2007) to provide more experience attributes-related information. Presumably adopting such technologies is costly. We argue that for experience attributes that cannot be easily transferred, it will be beneficial to educate consumers to find what kind of attributes they need from the products. Another related issue is product returns for online retailers (WSJ 2008). The value of product returns (products returned for any reason within 90 days of sale) exceeded \$100 billion annually in the US (Guide et al. 2006). And returns are costly for both retailers and consumers (Hong and Pavlou 2010). Therefore, it is important to design review systems that can better inform consumers for different types of products.

Another implication for managers of online or offline shops is that by looking at the variance trend of their products with product review data, they can get to know whether the consumers view their products with the same standard (searchable attributes), or different standards (preferences). For example, in the restaurant sample, even though 68% of all restaurants are found to have experience attributes (and therefore any restaurant is more likely to have experience attributes), there are still 32% out of all restaurants that only have search attributes. Let's consider two restaurants, one only serves fast food such as KFC (search) and the other is an exotic French restaurant (experience). In the former case, to boost sales, taking a vertical differentiation strategy is optimal (e.g., the restaurant can increase volume per meal, or lower price). In the latter case, for the French restaurant that features a lot of experience attributes, only people who like the taste matter since later adopters can figure out the taste. Thus there is no need for the French restaurant to cater to the general taste of the public.

### ***5.4 Limitations and Future Research***

This study has several limitations. First, with limited resources and space, we only analyze and present results based on a limited number of product categories, future research could generalize our results as reviews for more product categories becomes available.

Another viable explanation for increasing variance as review sample size increases is the effect of another selection bias that sets in as reviews increase - selection bias of late reviews. One question that has risen from prior research is about the motivation of later reviewers to post a review when there already exists many reviews in the system. From reviewer motivation standpoint, to gain some attention from later adopters or to make his review more prominent, later reviewers may try to express some views that are different from the average. Combining reviewer motivation with a self-selection view, assuming the average review rating is 4, why would a consumer who feels that the restaurant deserves a "4-star" want to report such a review? First of, such a review would not contribute any information to the system or later adopters; second, such a review cannot stand out from the existing 1000 reviews. Therefore, consumers who hold different views from the average are more likely to report a review, as reviews increase. We leave this for future research.

Third, fraudulent reviews may bias the estimates. Dellarocas (2006) shows that firms may strategically manipulate online reviews by hiring professional reviewers. Although fraudulent reviews have been assumed not to have an effect when review sample is large, identifying fraudulent review can improve the precision of the estimates. For Amazon date, one way of alleviating the problem will be using data only from consumers who have purchased from Amazon ("Amazon verified purchase"), future research could test whether there is any difference between reviews from Amazon verified purchases and other reviews.

Since other marketplaces, such as eBay and buy.com, also host product reviews, future research could look at the results for the same products from different review sources.

## **Concluding Remarks**

There is a great hype today about the new phenomenon of social media, business analytics, and micro level data. The digital revolution and digital innovation (Brynjolfsson and McAfee 2011) have brought about the data that researchers have dreamed about a decade ago. One challenge that hangs over the air is how to make sense of the available data to inform research and practice. Resolving this challenge is bound to put forth both theoretical and empirical challenges, which has already caught attention of many scholars in the management science field<sup>7</sup>. As a type of consumer generated content, online product reviews are prime examples of the micro level data, which are free and readily available in the online space. Making sense of such data for our own research, as we continue to revise and advance our understandings of new IT phenomenon, can be beneficial. Our paper provides an initiative to make sense of online product review data for the purpose of informing both scholarly research and business practice.

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<sup>7</sup>As a matter of fact, the workshop on statistical challenges in e-commerce research (SCECR) was organized as an effort to take advantage of the newly available data.

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