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AMCIS 2009 Proceedings

Americas Conference on Information Systems (AMCIS)

2009

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Zhongming Ma
California State Polytechnic University - Pomona, zma@csupomona.edu

Olivia R.L. Sheng
The University of Utah, olivia.sheng@business.utah.edu

Gautam Pant
The University of Utah, gautam.pant@business.utah.edu

Alicia Iriberri
Claremont Graduate University, alicia.iriberri@cgu.edu

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Zhongming Ma
Computer Information Systems Department
California State Polytechnic University, Pomona
zma@csupomona.edu

Olivia R. L. Sheng
Department of Operations and Information Systems, The University of Utah
olivia.sheng@business.utah.edu

Gautam Pant
Department of Operations and Information Systems, The University of Utah
gautam.pant@business.utah.edu

Alicia Iriberri
School of Information Systems and Technology
Claremont Graduate University
alicia.iriberri@cgu.edu

ABSTRACT

A search engine provides two distinct types of results, organic and paid, each of which uses different mechanisms for selecting and ranking relevant Web pages for a query. For an e-commerce query, vendors represented by websites in these organic and paid results are expected to have varying reliability ratings, such as a satisfactory or unsatisfactory score from the Business Bureau (BBB) based on overall customer experiences. In this paper we empirically examine how vendors' reliability ratings in BBB are associated with cues (such as type of result, relative price, number of sites selling the product) that can be observed or derived from search results, and further we attempt to predict vendors' BBB reliability ratings using those cues.

Keywords

Reliability prediction, trust, paid results, organic results.

INTRODUCTION

Nowadays it is a common practice that a Web searcher submits a query to a search engine, compares a large number of products or services from results in search engine result pages (SERPs), and finally identifies or buys his desired product or service from a particular website. As people become increasingly dependent on search results provided by commercial search engines for their information needs, it is critical that the companies (e.g., vendors that sell products) represented by websites that appear in SERPs are reliable. According to the Better Business Bureau (BBB), an unreliable company may engage in unscrupulous methods such as high pressure sales tactics and false statements about products when dealing with customers. Identifying the reliability of vendors in search results is important and has a practical impact for Web consumers.

Major search engines, such as Google, Microsoft Live Search (Microsoft), and Yahoo!, show two types (i.e., organic and paid) of search results on the same SERP. Organic results are generated by search engine's proprietary algorithms which rank a page/site by considering many factors such as link structure and content relevance (e.g., Brin and Page, 1998; Haveliwala, 2003). Paid results appear on the top, right, and sometimes bottom of a SERP, and they are produced because content providers/advertisers place bids on one or more terms in search queries (Jansen, 2006; Jansen et al., 2007). Paid search has enormous economic impact and has become a primary business model for Web search engines (Jansen, 2006). Considering the differences in mechanisms for producing the organic and paid results, Ma et al. (2007) observe that for e-commerce queries the paid results contain more unreliable companies than do the organic results.

Given a query, a search engine displays results by SERPs and each SERP consists of organic and paid results. For relevant search results in SERPs, people can easily observe *cues* such as the types of results, (SERP) page numbers, indices (of organic and paid results), and prices. In this paper, after submitting a large number of e-commerce queries to three major search engine sites, Google (www.google.com), Microsoft (search.live.com), and Yahoo! (www.yahoo.com), we examine how a vendor's reliability (which refers to the vendor's reliability rating in BBB throughout this paper) is associated with various visible cues in search results and further we attempt to predict the vendor's reliability using those cues. This research has serious implications for the search engine companies, search advertising market providers, and even more importantly for the search engine consumers.

In this study, using the reliability reports from BBB we identify the reliability ratings for digital camera resellers, vendors who buy digital cameras from the manufacturers and resell them to consumers. To be consistent with BBB, we choose the term reliability to qualify resellers and further categorize them into one of two categories, satisfactory and unsatisfactory.

LITERATURE REVIEW

Wang et al. (2004) find that during an initial visit how observable cues in websites of small online retailers affect consumers' trust. Their findings suggest that security disclosures and awards significantly affect consumers' trust building, and seals of approval and privacy disclosures increase consumers' willingness to provide personal information. Yen (2006) reports that third-party endorsement, presence of physical store, and clarity of warranty can reduce customers' perceived risk and enhance their purchase intention towards new e-tailers. Different from their work, we examine how a vendor's overall reliability rating (identified by third-party, BBB, not perceived by customers) is associated with cues observed from search results.

After identifying digital camera resellers from top three SERPs and comparing organic with paid results, Ma et al. (2007) find that unsatisfactory companies tend to offer lower average prices than satisfactory ones, and paid results contain more unsatisfactory companies than do organic ones. Different from their work, we focus on studying how visible cues identified from search results are associated with vendors' reliability and further predicting the reliability using those cues.

While comparing organic with paid results, Jansen and his colleagues have often studied the topical relevance of search results. For example, Jansen (2007) shows that, for e-commerce queries, paid results are more relevant than organic ones. Jansen et al. (2007) find that in terms of relevance to search query, Web searchers have a bias against paid results due to the lack of trust. Unlike Jansen and his colleagues, we study the relation between the visible cues of search results and the reliability of vendors.

Cao et al. (2003-2004) separate the customers' satisfaction associated with placing an order and satisfaction with order fulfillment because placing an order online and receiving the order happen at different time. They find that price satisfaction is negatively associated with satisfaction with the fulfillment process. This situation suggests that higher price-satisfaction (reflected by a lower price) comes probably at the cost of lower level of service in shipping and customer support. This lower level of service can be expected to negatively affect satisfaction with the fulfillment process, which can lead to poor overall customer ratings, such as an unsatisfactory rating by BBB.

To issue a satisfactory or unsatisfactory reliability rating to a company, one of the factors BBB considers is the type of complaints from consumers. We suspect that several types of complaints, such as advertising issues, product issues, and refund or exchange issues, are related to trust. Consumers' trust is critical to the success of online retailers (Qu et al. 2008). For instance, on basis of two large biannual surveys, Hoffman et al. (1999) statistically report consumer perceptions (e.g. trust, privacy, and security) to Web merchants. Kim et al. (2008) find that consumers trust and perceived risk greatly affect purchasing decisions. Lee and Turban (2001) find that merchant integrity is a major positive factor for consumer trust during Internet shopping.

DATA COLLECTION

To conduct our investigation we gathered the following data: (1) queries used to search for digital cameras, (2) SERPs for each of the queries to obtain data about resellers, and (3) BBB ratings for each of the resellers identified from the SERPs.

Search Queries

Using a keyword research tool from Google Adwords, with the initial seed keyword "digital camera" we ranked the Google-suggested keywords (e.g., "canon digital camera") by search volume (the relative number of users searching for that keyword on Google) and identified eight major camera manufacturers (Canon, Nikon, Panasonic, Sony, Kodak, Olympus, Samsung, and Fujifilm). From each manufacturer's U.S. website we manually identified all the listed digital camera models. Using the combination of a maker and a model, we create a search query. For example, for the query "canon eos 5d", the model (eos 5d) specifies what specific model of camera we look for and the camera maker (canon) provides a context to help improve the relevance of the search results. With this procedure we identified a total of 243 queries, which represented all the 243 different models available from the eight major digital camera manufacturers' websites in December 2007.

SERPs and Resellers

To obtain a sample snapshot of query results, we programmatically submitted each of the 243 keywords to each of three commercial search engines and fetched the content of the top three SERPs and all of the landing pages corresponding to the URLs in the three SERPs (during a weekend in February 2008). When examining the results in these SERPs, we considered only those results that were from websites of digital camera resellers (e.g., www.newegg.com) selling brand new products, and discarded links from other sites, such as camera review websites (e.g., www.dpreview.com), price comparison websites (e.g., www.pricescan.com), auction sites (e.g. www.ebay.com), image-sharing sites (e.g., www.pbase.com), and personal websites or blogs. We also discarded results corresponding to non-US domains (e.g., amazon.com.uk). In this study, a product refers to a camera, a camera body only, or a camera kit (e.g., including lens). We considered only brand new products to make comparisons (e.g., price comparison) fair.

If a results was from a reseller's website and the page advertised/sold the corresponding model of camera, we recorded the type of result (i.e., organic or paid), page number (i.e. 1, 2, or 3), (paid or organic) result's index in the SERP, URL of the result, and price of the product. In addition, we recorded whether a dollar sign ($) appeared in the title of a search result. The price was identified from the reseller's website and did not include shipping cost or tax. The top half portion of Table 1 summarizes the number of all distinct websites for resellers and the number of price observations (i.e. search results pointing to reseller's websites selling the corresponding camera models) for the 243 queries. For instance, from the Google search results we identified 86 distinct reseller websites and 1545 price observations.

		Google	Microsoft	Yahoo!
Websites of all resellers	Distinct websites	86	72	43
	Price observations	1545	976	933
Websites of all resellers with only satisfactory or unsatisfactory ratings	Distinct websites	62	54	35
	Price observations	1358	947	925

Table 1. Number of distinct websites of resellers and price observations

BBB Ratings

The Better Business Bureau (BBB) deals with consumers and businesses and provides a reliability report for a company on the basis of the company's size, volume of business, number of transactions, number and type of complaints, and how the company handled complaints. Most of the time, the BBB provides a company with an overall rating, either satisfactory or unsatisfactory, in its reliability report. Occasionally it issues a reliability score according to a fine-grained scheme, ranging from A+ to F. We convert these finer ratings such that those equal to or above C- (i.e., BBB acceptable rating) are labeled satisfactory and those under C- are labeled unsatisfactory. We manually identified the reliability record for each reseller's website in our data set. The bottom half of Table 1 shows the number of distinct websites and number of price observations after discarding the corresponding search results which did not have a BBB reliability rating (i.e., no rating) or were not listed by BBB (i.e., not found). In the next section for our regression and classification analyses we used only those observations reported in the bottom half of Table 1.

BizRate (http://www.bizrate.com/) is also commonly known for providing ratings for e-commerce vendors. Different from BBB, BizRate collects ratings online from individual consumers after they complete their transactions and reports the aggregated results. A potential problem is that such comments can be misleading and incorrect as the comments may not be verified. Another reason for not using BizRate ratings is the mechanism for showing BizRate surveys to users. Only after a vendor contracts with BizRate for using its services, will some randomly selected consumers see the BizRate survey after they finish their transactions in that company's website. It is reasonable to think that compared to a satisfactory company, an unsatisfactory company is less likely to allow customers to provide feedback which eventually would be available to the public. In fact among all websites/vendors we identified from our data set, BizRate gave outstanding or good ratings for 15 companies and rated none as poor or unsatisfactory (BizRate provides four different ratings: outstanding, good, satisfactory, and poor). In other words, if we had used BizRate in our study the number of negative (unsatisfactory) instances will be zero, which would not allow the analyses on the significant independent variables or classification in the next section.

RESEARCH METHODS, RESULTS, AND ANALYSES

Attributes

The selection and ranking of organic search results are based on search engine algorithms that consider various factors related to websites, such as in-links and reputation of in-linked pages. While the selection of paid results depends on the bidding on keywords and the ranking is generally determined by the bid price and click-through-rate (Sullivan, 2007). Ma et al. (2007) find that organic results contain fewer unsatisfactory companies than do paid ones. Thus, we choose the obvious visible cue, *resultType* (i.e., organic or paid), as an attribute for distinguishing satisfactory and unsatisfactory companies. Further we derive a Boolean attribute, *inBothTypes*, to represent whether the same vendor appears in both organic and paid results of the top three SERPs (for the same query from the same search engine).

The search result index is another simple visible cue, and it represents the ranking of the result and is critical for both vendors and consumers. We denote this attribute as *index*. When identifying the index for a (paid or organic) result on a SERP, we consider the results in the previous SERP. The index of organic results is straight forward: it always starts from 1 for the first result in the first SERP and the index of the first organic result on the second SERP is the number of organic result in the first SERP + 1. For paid results on the same SERP, we consider results listed on top to be ranked higher than those appearing on the right, and right to be ranked higher than bottom. For example, for the second top paid result on the second SERP, its index is the number of all paid results on the first SERP + 2.

According to Cao et al. (2003-2004), a lower price may result in a lower level of service, also by Ma et al. (2007), the average price from unsatisfactory companies tends to be lower than that by satisfactory companies. Thus for the same product, we estimate that a (relatively) lower price could indicate a poor reliability. We derive the following normalized metric to measure the relative price. We do not use absolute price in dollar amount because there is no low or high for a price by itself (without comparison) and because for different camera models the prices vary dramatically.

$$p_{rel} = \frac{P - P_{\min}}{P_{\max} - P_{\min}}$$

In the above metric, P_{min} and P_{max} represent the lowest and highest price for the same model from all resellers in the top three SERPs from a search engine, and P is the price by the reseller of the current search result. P_{rel} is between 0 and 1. The larger the P_{rel}, the relatively higher the reseller's price is. If $P_{min} = P_{max}$ we set P_{rel} at 0.5.

Intuitively, a company gains more profit by selling a more expensive product. When we divide all camera models into low, medium, and high ends according to their average prices, it is possible that a company tends to make more money by selling high and medium ends of cameras, so we consider such a price range could be an indicator for distinguishing satisfactory and unsatisfactory reseller. Therefore for each of the camera models and results from each search engine, we computed an average price by averaging all prices from different resellers in the top three SERPs, sorted the average prices for all models, and evenly divided them into three categories, low, medium, and high. We denote this price range attribute as P_{ran}.

Moreover, when a product is popular (i.e., more people buy it), often there are more companies selling it, and thus we assume that an unsatisfactory company by offering a lower price has a chance to lure more customers. Therefore, whether a product is popular may be an indicator for distinguishing satisfactory resellers from unsatisfactory ones. We use number of reseller's distinct websites (in the top three SERPs) to catch this popularity, and denote this metric as *numDistinctSite*.

In order to identify a site/reseller from search results we extracted the second-level domain name from the URL. For example, jr is the second-level domain name for www.jr.com. We denote *siteCount* as the number of times a site/reseller appears in URLs of (paid and organic) search results in the top three SERPs. For example, a value of two for siteCount for a site means that this reseller/site appeared in two different search results (either one in paid one in organic, or both in paid, or both in organic results) in the top three SERPs.

Last, for a search result from SERPs we can easily identify whether or not a dollar sign, $, appears in the title of the search result. Vendors may use this sign to attract customers' attention since we observed that sometimes they were shown next to a relatively lower price. We denote this attribute as *dollarSign*.

The dependent variable, DV (discussed in the following section), or class label (discussed in the section of Predicting Reliability) is the vendor's reliability rating which has a binary value: 0 for unsatisfactory and 1 for satisfactory.

Significant Variables

We examine which of the following independent variables (IVs) are significant for the DV, reliability of a company. First we convert categorical IVs into dummy variables. In particular,

- resultType: 0 for organic result and 1 for paid result
- inBothTypes: 0 for the vendor not appearing in both organic and paid results and 1 for appearing in both
- dollarSign: 0 for no dollar sign appearing in the result title and 1 otherwise
- P_{ran}: Because of its three categorical levels, by choosing the high end as the reference category, we produced the following two dummy variables from P_{ran}
  - d_{low}: 1 for low, 0 for medium and high end products
  - d_{med} : 1 for medium, and 0 for low and high end products

Table 2 shows the nine IVs, coefficients (B), and significance values for each search engine by logistic regression in SPSS 15.0. The table displays significant significance values and their corresponding search engines in bold for clarity. Cox & Snell R square values are 0.367, 0.426, and 0.477 for Google, Microsoft, and Yahoo! data sets, respectively. Four of the nine IVs, resultType, inBothType, P_{rel}, and numDistinctSite, are significant across all three search engine data sets. dollarSign is significant for the Google data set, and siteCount is significant for the Yahoo! data set only. Index is insignificant in distinguishing the DV for every data set. The fact of insignificance for index makes sense because the position of a search result (in top three SERPs) can hardly tell a vendor's reliability.

IVs	Search Engine	Coefficients (B)	Sig.
resultType	**Google**	-2.217	**.000**
	Microsoft	-2.834	**.000**
	Yahoo!	-3.222	**.000**
inBothTypes	**Google**	2.732	**.000**
	Microsoft	3.332	**.000**
	Yahoo!	4.711	**.000**
index	Google	0.008	.380
	Microsoft	-0.010	.439
	Yahoo	0.007	.550
dollarSign	**Google**	-1.203	**.000**
	Microsoft	-20.515	.997
	Yahoo!	0.010	.981
P_{rel}	**Google**	2.452	**.000**
	Microsoft	1.610	**.000**
	Yahoo!	2.580	**.000**
numDistinctSite	**Google**	0.077	**.001**
	Microsoft	0.129	**.002**
	Yahoo!	0.154	**.000**
siteCount	Google	-0.017	.874
	Microsoft	0.241	.131
	Yahoo!	-0.355	**.020**
d_{low}	Google	0.032	.865
	Microsoft	0.043	.859
	Yahoo!	-0.724	**.004**
d_{med}	**Google**	-0.355	**.048**
	Microsoft	-0.399	.146
	Yahoo!	-0.435	.083
(constant)	Google	0.708	.053
	Microsoft	0.776	.081
	Yahoo!	1.606	**.000**

Table 2. Logistic regression results for three search engines

Next we discuss how coefficients in Table 2 are associated with the DV.

- All the coefficient values (B) for resultType are negative (between -2.217 and -3.322), which indicates that a higher resultType value lowers reliability score. Given the notation that organic result is denoted as 0 and paid result as 1, and a reliability score of 0 represents unsatisfactory and and a score of 1 represents satisfactory, the negative coefficients support the finding in Ma et al. (2007) that paid results contain more unsatisfactory companies than do organic ones.
- The fact that coefficients for inBothTypes are positive suggests that it is a good sign in terms of a vendor's reliability if the same vendor is present in both organic and paid search results.

- Among the eight IVs, index has the least impact on the DV because its coefficients are very close to 0, i.e., -0.010 and 0.008, and thus the exponentiated coefficient, Exp(B), is very close to 1.0 which means that by this IV the probabilities of being satisfactory and unsatisfactory are nearly the same.
- The negative coefficients of dollarSign for Google and Microsoft data sets reveal that having a dollar sign on the result title in SERPs to highlight a (often lower) price is a bad sign in terms of reliability for these two search engines. The coefficient is only 0.010 (close to 0) for the Yahoo! data set, which shows that the dollar sign has almost no effect in indicating the satisfactory or unsatisfactory rating for a company in Yahoo! search results.
- Knowing that a P_{rel} value is between 0 and 1, the lower the P_{rel}, the relatively lower the sale price is. All coefficients for P_{rel} are positive which means that a company offering a lower price has a lower reliability score. This result can be explained by a conclusion by Cao et al. (2003-2004) that price satisfaction is negatively associated with satisfaction with fulfillment process, and is consistent with another finding in Ma et al. (2007) that compared to satisfactory companies, unsatisfactory companies tend to offer lower average prices.
- The coefficients for numDistinctSite are positive but close to 0 (between 0.077 and 0.154). The positive coefficients indicate that the more popular a camera is (i.e., greater number of distinct sites or more competition among vendors), the more reliable a company is likely to be. This conclusion is different from what we had assumed, but this is a positive finding for Web consumers because unsatisfactory companies do not seem to increase its proportion in search results as the number of resellers increases.
- siteCount is significant only for the Yahoo! data set and its coefficient value is negative, which suggests that in Yahoo SERPs the multiple occurrence of a vendor is negatively associated with the vendor's reliability rating.
- Knowing that the high end is the reference category when coding the dummy variables for price ranges, the negative coefficients for d_{med} suggest that the medium end of cameras has lower coefficients than does the high end, which indicates that the medium end cameras are associated with unsatisfactory vendors to a greater extent than are the high end cameras. The same is true for the low end of cameras in Yahoo! because of its negative coefficient (-0.724). The positive coefficient values of d_{low} (0.032 and 0.043) for Google and Microsoft suggest that the low end of cameras has slightly higher coefficients than does the high end, indicating that in Google and Microsoft results the low end cameras are associated with satisfactory vendors to a greater extent than are the high end cameras.

Predicting Reliability

With the eight attributes discussed in the section of Attributes, how well can we predict the reliability of a website/reseller? Using a publicly available data analysis tool, Weka (Witten and Frank, 2005), we chose decision tree (i.e., J48 classifier in Weka) because this classifier is highly accurate for binary classification problems, does not impose assumptions about the distribution of data, and its results are well suited for human interpretation (Ranganathan et al., 2006). In the following Table 3 we show the classification performance that is based on ten-fold cross validation with default parameters in Weka.

Search engine	Class label (prior distribution)	Precision	Recall	Accuracy
Google	Satisfactory (63.8%)	88.0%	89.5%	85.5%
	Unsatisfactory (36.2%)	81.1%	78.6%	
Microsoft	Satisfactory (64.5%)	90.6%	90.2%	87.6%
	Unsatisfactory (35.5%)	82.3%	83.0%	
Yahoo	Satisfactory (61.1%)	92.6%	88.7%	88.8%
	Unsatisfactory (38.9%)	83.3%	88.9%	

Table 3. Classification performance for three sets of results from three search engines

The second column displays the prior distributions of satisfactory and unsatisfactory companies in the observations. Unsatisfactory companies exist in over a third (i.e., 35.5-38.9%) of the identified search results from the three search engines. The decision tree classifier achieves accuracy between 85% and 89%. Among the three data sets from three search engines, the performance from Microsoft and Yahoo! data sets is slightly higher than that from the Google data set. We also ran the decision tree classifier using only the four significant attributes identified in the regression analysis and the classification performance is slightly lower than that in Table 3. Specifically, the accuracy values using the four significant variables are 81.3%, 84.5%, and 85.0% for Google, Microsoft, and Yahoo! data sets, respectively. Six of the eight attributes, except the two price related attributes, can be easily identified using an automatic program without involving complex text analysis for identifying prices from Web pages. With just the six easily identified attributes for classification, the accuracy values are 71.2%, 82.3%, and 81.4% for Google, Microsoft, and Yahoo! data sets, respectively.

CONCLUSIONS AND FUTURE DIRECTIONS

Search engines have become a necessary and convenient tool for people to find information and shop online. However, search results do not disclose information about a company's reliability to Web searchers. This information is critical because vendor's reliability is one major concern for Web consumers, especially considering the facts that unsatisfactory companies widely exist in search results in general and in paid results in particular and they tend to offer lower prices. In this study we empirically examine thousands of price observations generated by 243 e-commerce (i.e., digital camera) search queries from three major commercial search engines (Google, Microsoft, and Yahoo!). We find that several variables, identified or derived from search engine results and therefore can be considered as cues visible to a Web surfer or automated crawler, are significant in inferring a company's reliability. Those variables include search result type, relative price, total number of resellers, and whether the same reseller appears in both organic and paid results. Further we employ decision tree classifier to predict the reliability and achieve accuracy between 85% and 89% for the three data sets from the three search engines. Using our approach, an interesting practical application, embedded in a Web browser but independent of a search engine, can be developed to predict a site/reseller's reliability for Web searchers.

We realize that to search for an interested camera, Web consumers use many different queries besides combining the manufacturer name and model as we did in this study. Expanding the empirical analysis and prediction evaluation to a larger variety of relevant keywords would be an interesting future direction. However, we feel that the way we created our queries is reasonable to produce relevant results. When identifying relevant search results (i.e., a reseller site that sells the right camera), our software program fetched the top three SERPs and the landing pages for the results in these SERPs, and thus later we could (manually) examine only those pages. Our approach can be considered strict in terms of identifying relevant results. For example if the landing page corresponding to a search result does not mention the relevant product, then we assume that the site does not sell the product. In this study we focus on just one type of product, digital camera, at one "time point" (i.e., snapshot). We recognize that it is desirable to include different categories of products and across multiple time points. Hence our future directions include studying a different type of product, spanning multiple time points, and using site ratings from different sources to further test this approach. Investigating, comparing, and classifying different company-rating websites and price comparison sites can also be an interesting future direction.

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