Rule-based personalized comparison shopping including delivery cost

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A B S T R A C T

Comparison shopping allows customers to reduce time and effort when searching for product information and prices. However, traditional comparison sites mainly compare product prices without using precise information on delivery cost. To overcome this limitation, we adopted a rule-based comparison shopping framework using the eXtensible Rule Markup Language (XRML) architecture, which computes the exact personalized delivery cost at comparison sites. The prototype ConsiderD, which was developed for this purpose, computes the exact delivery costs considering the shipping rules, destination, delivery speed, and shipping rates. The XRML architecture effectively maintains the consistency of formal rules with the original Web pages. To demonstrate the performance of rule-based comparisons, we conducted an experiment on the purchase of books based on real-world data from five leading online bookstores. This experiment shows that rule-based comparison can significantly outperform data-based comparison in terms of the total cost of product and delivery. We also found that the comparison of delivery cost is very important because the variance of delivery cost can be as big as the variance of book prices itself.

1. Introduction

The number of e-stores has exploded as the hosting services of e-mails have become more popular. According to Goldman Sachs, global e-commerce sales were expected to grow at an annual rate of 19%, reaching $963 billion by 2013 (Davis 2011). Since customers are sensitive to prices, comparison sites provide the product prices of many competing e-stores in tabular form (Pablo 2011). However, the current state of data-based comparison sites cannot support personalized information such as shipping cost and the customer-specific effect of discount rates of various credit cards, coupons, and reserved e-money, because they require personalized computation and customer profile information. So current data-based systems merely show the average or typical delivery cost.

Online consumers are sensitive not only to the product prices but also to other costs such as shipping cost (Kukar-Kinney and Close 2010). According to Forrester Research (Wonham 2011), shipping and handling is one of the primary reasons for abandoning a shopping cart. So supporting the computation of shipping cost at the comparison stage is important to customers. Since the shipping cost varies depending on the price of products, destination, and speed of delivery, personalized computation is essential to provide the specific cost of a specific order.

A limitation of the data-based comparison method is that customers must additionally visit the candidate e-stores after comparison of product prices in order to find the order-specific delivery cost. To overcome this limitation of the data-based comparison approach, we propose a rule-based comparison approach to enable personalized comparisons. This research focuses on the study of delivery cost effects because the rules necessary for the computation of personalized shipping cost is available on the publicized Web pages of e-stores. However the information for the computation of credit card discounts and coupons requires access to a personal profile database which is not available at comparison sites. If a digital wallet keeps this data and shares it at the moment of comparison, it will become possible to consider this information.

The rule-based comparison approach requires extracting rules from Web pages. In order to automate the rule acquisition from Web pages, we have to extract rules from the unstructured natural language texts and tables. Moreover, consistency between extracted rules and Web pages should be maintained. To effectively support rule generation and maintenance, we adopt eXtensible Rule Markup Language (XRML) architecture and develop a prototype comparison system ConsiderD (Lim et al. 2008; Lee and Kang, 2005), which compares the personalized delivery cost in addition to the product prices. The rule acquisition method for XRML was

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proposed in the author’s previous papers (Kang and Lee 2005, Park and Lee 2007). This framework can resolve a knowledge-acquisition bottleneck to some extent by allowing the use of the vast amount of knowledge available in Web pages.

We expect that rule-based comparison will overcome the limitation of data-based comparison, and its impact will be huge because it can augment the performance of comparison shopping. To validate its performance, in this paper we experiment with the performance of rule-based comparisons in contrast with data-based comparison with real-world delivery cases. We specifically study the comparison of book purchases, and experiment with the benefits of considering delivery costs. Through this experiment with real-world data, we demonstrate that the effect of delivery cost comparison can be as significant as the comparison of product prices.

This paper proposes the architecture ConsiderD of rule-based comparison, a procedure of rule acquisition and maintenance, and demonstrates its performance with an experiment. In this procedure, we particularly propose a method of maintaining consistency between the original texts and tables in Web pages and the formal rules in the comparison site. To validate the effectiveness of rule-based comparison in the context of delivery cost considerations, we postulate four hypotheses to test with real-world data. The hypotheses are (1) effectiveness of rule-based comparison, (2) effect of the number of copies per order, (3) destination effect, and (4) delivery speed effect. An earlier version of this research was presented at the International Conference on Electronic Commerce in 2008 (Lim et al. 2008).

In Section 2, we illustrate the screen of rule-based comparison in contrast with data-based comparison. In Section 3, we review the literature on comparison shopping and its impact, knowledge acquisition, and earlier works on XRML research. Section 4 describes the rule-based comparison process using the XRML framework and the prototype system, ConsiderD. It also describes the rule acquisition and maintenance procedure to maintain consistency between the Web sites at e-stores and the rules at the comparison site. Finally, Section 5 demonstrates the performance of rule-based comparison by conducting a series of experiments. The experiments test the notion that the delivery cost comparison is as important as the product price comparison in its effectiveness. It also tests the impact of considering the features of a customized order such as the number of items per order, destination, and delivery speed.

2. Illustration of rule-based comparison

Let us contrast rule-based comparison with data-based comparison by showing the user screens of both approaches. The current data-based comparison sites only display rough estimates of delivery cost, as depicted in the case of BestWebBuys.com shown in Fig. 1. On the other hand, rule-based comparison using ConsiderD can compute the exact total of book price and delivery cost for a particular order, as demonstrated in Figs. 2 and 3.

Fig. 2 starts with the book price comparison first. This example compares the book price of five copies of three selected books. Note that the price of eCampus, US$183.30, offers the lowest price in this particular example. The system asks a customer to input the e-stores that the customer wishes to compare, the destination, and the shipping method. On this screen, the customer needs to select a shipping method from each e-store, because the definitions of express shipping methods are not precisely the same across all e-stores.

By clicking the button ‘Compare Total Cost including Delivery Cost’ in the lower part of Fig. 2, ConsiderD starts to calculate the total customized cost, which includes both book prices and delivery cost. The result can be seen in Fig. 3. The result displays book price, shipping cost, and total cost along with other detailed information such as shipping method, traceability, insurance, cost per shipment, and shipping cost per item. Using the system ConsiderD, the customer can easily compare the total cost of all five online bookstores at once. Otherwise, the customer has to visit each of the five e-stores and input all the information at each site until the e-store computes the total price including delivery cost.

In this particular example, Fig. 3 shows a personalized total cost of purchasing books, and the delivery cost from the United States to Korea. The lowest total cost at Amazon is $244.12, which includes $184.18 for the book and $59.94 for the shipping. Note that eCampus (which was the lowest of the book prices) is not the lowest in terms of total cost. Upon request, the customer may refer to the original Web pages of the e-stores. These will show the original document of the shipping methods from which the rules and data used to compute the total cost were extracted.

3. Literature review

This section reviews the relevant literature on comparison shopping and its impact, knowledge acquisition, and the XRML approach.

3.1. Comparison shopping

According to the Forrester Research report, online retail sales in the US are expected to reach $248.7 billion by 2014, up from $155.2 billion in 2009 (Schonfeld 2010). Therefore, the amount of information about products and services on the Internet will continuously increase. As a result, the role of comparison sites will become more important, because it reduced the time and effort of comparison (Pablo 2011).

There are many research issues in comparison shopping. Typical issues include establishing the revenue models for comparison sites, updating comparison information, supporting personalized comparison, matching customer requirements with product specifications, deciding the optimal search effort for comparison, evaluating the impact of the serial display position on the customer’s selection, understanding the influence of visiting comparison sites on customer loyalty to the e-store and e-mail, and using the domain ontology for comparison. We review the key research done on these issues.

3.1.1. Revenue models for comparison sites

Price comparison sites do not usually charge fees to users. But the comparison sites can create revenue for their advertisement services if e-stores regard the comparison site as their affiliated partner and pay referral fees (PriceSpin 2010). Retailers may pay for the advertisement by exposure, by click-throughs, or by making actual purchases (Tang et al. 1994). Comparison shopping sites can obtain large product data feeds covering many different retailers from affiliate networks such as LinkShare and Commission Junction (Wikipedia 2010). The companies specializing in data feed consolidation for price comparison charge comparison sites for accessing their data.

3.1.2. Updating policy for comparison information

Some comparison sites update comparison information using real-time software agents, although the notion of real-time is a matter of degree (Dos Santos et al. 2001). However, many sites still depend on partial manual updates, because real-time comparison requires excessive time and network traffic. In this context, we need to find the optimal updating interval. Semantic Web technology may be adopted to collect information for the purpose of comparison (Park and Kim 2007).
Fig. 1. Rough estimates of delivery cost in a data-based comparison.

Fig. 2. Choosing destination and shipping method with ConsiderD.
3.1.3. Personalized comparison

Yuan (2003) attempted to overcome the limitation of current price-sensitive shopping agents by providing customers with personalized rankings which are computed from the functions of product/merchant information, consumer behavior, user profiles, and the on-line learning capability of personalized ranking. In the area of personalized product/service rankings and comparisons, a vast amount of works are done in various communities (Agarwal and Lamparter 2005). Commercial sites such as Tripadvisor.com and Enuri.com provide personalized product rankings according to the customer’s desires. However, most of them do not support personalized computation as the rule-based comparison approach does. In this paper, we considered the personalized computation aspect of delivery costs.

3.1.4. Matching customer requirements

The manual matching effort of products across multiple shopping malls can be significantly decreased by adopting automated ontology-mapping techniques. Recently, a comparison agent called Shopbot 2.0 was proposed to provide recommendations for shoppers (Garfinkel et al. 2008). Shopbot 2.0 can integrate retail promotions with the recommendation system. In their bookstore examples, the system considered promotions such as free items and coupons in order to offer the best bet using an integer programming model.

3.1.5. Optimal comparison search effort

Comparison itself is not free. Since customers have to spend time and effort for comparison, they need to balance the comparison effort with its benefit. In this regard, if the search process requires scanning comparison sites, customers would want to minimize the scanning effort. Grosfeld-Nir et al. (2009) propose a model that measures the expected search cost based on two decision variables: the optimal display list size of the search results and the highest price that the customer is willing to accept. They developed analytic formulas that can calculate the optimal display list size and price limit.

3.1.6. Display position effect

Xu and Kim (2008) examined the impact of a vendor’s serial position in a comparison shopping site on consumers’ vendor inspection behavior and the probability of a vendor being included in a consumer’s consideration set. They confirmed that a consumer pays more attention to vendors listed earlier in a comparison list. They also found that the time spent by the consumer inspecting a vendor influences the consumer’s acceptance of the vendor.

3.1.7. Effect of comparison on shopping cart abandonment

Behavioral studies found that there were many inhibitors on Internet shopping. Traditionally, typical inhibitors for buyers are social influences, the lack of availability, high prices, financial

Fig. 3. Comparison of book and shipping cost using ConsiderD.
status, and time pressure (Howard and Sheth 1969). To online retailers, consumer abandonment of shopping carts is a challenge to overcome. A few studies on this issue found that 88% of online consumers have abandoned their carts (Johnson et al. 2011), and the average rate of shopping cart abandonment was 59.8% (MarketingSherpa 2011). According to SeeWhy in 2009, the shopping cart abandonment rate climbed to 83% between Labor Day and November 15 (Wonham 2011). Five reasons why consumers abandoned online shopping carts were identified by Forrester Research in 2010 (Wonham 2011). The reasons were “shipping and handling costs (44%),” “not ready to purchase the product (41%),” “wanted to compare prices on other sites (27%),” “item was priced too high (25%),” and “wanted to save products in my cart for later consideration (24%).” These studies imply that the comparing delivery cost can reduce the consumer abandonment of their shopping carts.

Even though the above works on comparison shopping are interesting, these studies are limited by the capability of database comparison. To overcome this limitation, research by rule-based comparison emerges (Lim et al. 2008).

3.2 Knowledge acquisition and ontology

To build a rule-based comparison site, we need to acquire rules from Web pages of online e-stores and other sources. In this regard, the process of acquiring rules from these Web pages is similar to natural-language processing from texts and tables. However, automated knowledge acquisition has been a long-standing bottleneck in building rule-based systems. Moreover, perfect understanding of natural language is extremely difficult, because words can have more than one valid interpretation as Wetter and Nüse (1992) and Hulth et al. (2001) point out.

Machine learning techniques such as inductive learning, neural networks, and statistical models may be applied under the umbrella term of Web mining when the log data is collected from Web pages (Jicheng et al. 1999, Kim et al. 2003). If a structured data set is available, it can be used to generate rules geared towards more generalized and abstract knowledge. Several methods and tools (Agarwal and Lamparter 2005, Apte et al. 1994, Craven et al. 2000, Rau et al. 1989, Ruiz-Sanchez et al. 2003, Szpakowicz 1990) have been developed using this approach. However, since the motivation for extracting rules from natural text and tables is usually to acquire knowledge at the same level of abstraction, inductive learning (Apte et al. 1994, Rau et al. 1989, Ruiz-Sanchez et al. 2003) is not the primary issue in extracting rules from Web pages.

Recently, ontologies have become popular for specifying the knowledge of a particular domain on the Web (Guarino 1997, Maedche and Stabb 2000, van Heijst et al. 1997, Wetter and Nüse 1992). One stream of research involves using ontology to support knowledge acquisition, while another stream involves using natural language processing technology to create ontological knowledge.

Natural language processing technology may be used to automatically extract terms to add to ontology using grammar analysis (Babowal and Joerg 1999, Park and Lee 2007, Ruiz-Sanchez et al. 2003), and linguistic patterns (Schmidt and Wetter 1998, Soderland 1999) with predefined templates (Sánchez-Carreño et al. 2000, Yang et al. 2002). However, the quality of knowledge automatically extracted from natural language sources is not yet reliable enough, so the draft should be manually refined by knowledge engineers (Soderland 1999, Yang et al. 2002). While most knowledge acquisition techniques extract taxonomies from text, Valencia-Garcia et al. (2008) acquires semantic relationships among concepts for ontology. The ontology extraction process consists of tagging parts of speech, concept search, and inference. They used a predefined conceptual knowledge base in the concept search process and a relational knowledge base in the inference process. Together they produce the assumed relations between concepts.

Sanchez and Moreno (2008) attempted to learn non-taxonomic relationships from Web documents by constructing domain-related patterns for relation discovery, and used patterns to obtain additional domain knowledge in the form of non-taxonomically related concepts (Sanchez and Moreno 2008). The logic model and neural network are used to acquire knowledge from domain text (Wan et al. 2010). However, they use fixed form reports as their input text so that they could reduce the complexity of linguistic analysis.

A common difference between the above approaches and the XRML approach we adopt in this research is that the former only produces a small portion of the knowledge while the latter creates a complete rule set that can be used for Horn logic reasoning. In the context of XRML, the ontology may be used to support the extraction of rule components from Web pages (Park and Lee 2007). An interesting idea from this research is that it creates the ontology from one e-store in order to repeatedly extract similar rules from the other. Mukherjee et al. (2003) and Popov et al. (2004) used ontology for document annotation so that the machine can understand the subjects of documents and automatically classify, search, and retrieve the documents. Ontology can also be used to extract general knowledge from Web pages as a predefined template. A system may annotate knowledge on a Web page using an ontology template with an annotation tool (Vargas-Vera et al. 2001).

3.3 XRML approach

In order to overcome the difficulty of rule acquisition and maintenance from Web pages, the XRML framework was proposed (Lee and Sohn 2003). XRML does not intend to fully automate rule acquisition, but rather to assist the knowledge engineer to effectively and efficiently maintain rules if the original Web page is frequently modified. For this purpose, XRML consists of three steps: Rule Identification, Rule Structuring, and Rule Triggering. For each step, we need the Rule Identification Markup Language (RIML), Rule Structure Markup Language (RSML), and Rule Triggering Markup Language (RTML) respectively (Kang and Lee 2005). RIML identifies the rules which are implicitly expressed in Web pages, while RSML represents the formal rule structure that corresponds to the rule syntax in commercial rule-based systems. But RSML maintains tags that associate with RIML. RTML identifies the conditions that the rules will be triggered to infer.

The XRML approach uses the following procedure, as depicted in Fig. 4:

1. Identify rules: The knowledge manager identifies the rules from the browsed Web pages, which are represented in text, tables, and pictures. Then the XRML editor generates HTML/RIML files where the RIML statements are embedded in the HTML files. In the case of e-bookstores, all relevant rules can be automatically transformed to the format of commercial rule-based systems such as JRules (2010) and Blaze (2010).

2. Automatic transformation: The identified rules in HTML/RIML can be automatically transformed to the rule syntax in RSML. However, this may not always be the case. If the set of identified rules derived from Web pages is not complete, the draft rule set should be refined by adding the rules from other sources. If the generated rules are incomplete, the knowledge engineer needs to refine the rules. Even though the generated rules may not be perfect, this approach is more effective for maintenance if the original Web pages change in the future. The complete RSML statements may be further transformed to the format of commercial rule-based systems such as JRules (2010) and Blaze (2010).
(3) **Inference**: The complete RSML rule set is used for inference. In the comparison site, these rules compute the delivery cost for specific cases.

(4) **Maintenance with consistency**: When the initial rules are generated, the links between the Web pages and acquired rules are created in meta-rules (Kang and Lee 2003). If there is any change on the Web pages from which the rule base was generated, the links in RIML detect their counterpart rules in RSML, ensuring easy maintenance of consistency between them. This framework is applied to the development of ConsiderD.

4. Rule-based comparison of delivery cost

In this research, we develop the rule-based comparison shopping system ConsiderD by adopting the XRML approach. This section describes the architecture and process of rule-based comparison, and the rule generation and maintenance processes.

4.1. Rule-based comparison process

The rule-based comparison process can best be described by demonstrating the input/output screens of the ConsiderD system that are shown in Figs. 2 and 3 in Section 2. The ConsiderD prototype system provides rule-based comparison for the total cost including book price and delivery cost over multiple online bookstores. The current prototype compares five bookstores: Amazon.com, BarnsAndNoble.com, Powells.com, eCampus.com, and BooksAMillion.com.

The overall flow of rule-based comparison is diagrammatically contrasted with that of data-based comparison in Figs. 5 and 6. Note that customers in the data-based comparison system have to visit all bookstores in order to compare the precise delivery costs.

4.2. Rule generation process

The architecture of the rule-based comparison system ConsiderD is depicted in Fig. 7. There can be two scenarios for rule generation depending on who generates the rules: ConsiderD or e-stores. If some e-stores regard rule-based comparison as an effective channel of promotion, they will be motivated to create the rules themselves in a standard format such as RSML. However, this will
increase their workload, so they may be willing to leave the rule generation to ConsiderD. This is very likely because there is no dominating rule standard yet. So, we assume that the original e-stores do not generate rules for comparison sites, and thus a rule-based comparison site like ConsiderD should generate rules based on the copied public Web pages of e-stores as shown in Fig. 8a, whose corresponding HTML statements are shown in Fig. 8b. We briefly described the rule acquisition procedure of XRML approach in Section 3.3. Let us give an example to explain the feature in detail.

The rules under the title Priority Courier Shipping Rates to Europe and table in Fig. 8a show the shipping rate per shipment and per item based on the product categories. Suppose a customer wants to buy five copies and deliver them to Europe by Priority Courier. It will cost $29.99 per shipment and $5.99 will be additionally charged per copy.

In the rule identification step, the knowledge manager at ConsiderD identifies the rules, variables, and values in the Web pages in Fig. 8a with the assistance of an interactive XRML editor. In the example of Amazon.com, the rule group ‘Shipping Rates’ are identified for the HTML statement in Fig. 8b. The variable names Delivery Method and Shipping Region are identified as missing variables in the original text. The value of ‘Delivery Method’ – ‘Priority Courier’ – and the value of ‘Shipping Region’ – Europe – are identified from the heading of the table. The heads of three columns - Product Category, Per Shipment, and Per Item – are treated as the variables, while the contents of tables such as Books and VHS videotapes are treated as the values of the associated columns. The role of variables are identified as IF or THEN. The identified statements in RIML syntax are embedded in HTML statements generating the HTML/RIML statements in Fig. 8c. The RIML/HTML can be automatically transformed to rules in RSML syntax in Fig. 8d. In this case, the transformation is automatically done by the system because the original documents have all the information needed for rules.

RIML documents are semi-automatically generated in the rule identification step. Park and Lee (2007) designed an ontology-based method of acquiring rules from multiple online shopping malls under the assumption that the sites have similar rules. The basic idea is that we can reuse the information of already-acquired rules from one site when we need to acquire rules from another similar site. So, we define the ontology of rules and store the generalized ontology about rule components such as rules, variables, and values. Using the ontology, rule components can be automatically identified from a new site if the site uses similar terms. For example, when we have acquired rules from Amazon.com as in Fig. 8, we can create an ontology from the rules and use them to automatically identify rule components of similar sites such as BarnesandNoble.com. The recall rate for variable identification by this approach was 83.33%, and 94.16% for value identification (Park and Lee 2007).

4.3. Maintenance of knowledge consistency

The strong advantage of the XRML framework is its capability of assisting the maintenance of knowledge consistency when the original Web pages are changed. This is made possible by the tags that the HTML/RIML maintains to link with the rules in RSML. In order to maintain knowledge consistency, ConsiderD should periodically monitor whether or not the Web pages are updated. For this purpose, ConsiderD needs the periodical matching function of new and old versions of Web pages. If any change is detected, ConsiderD needs to proceed with the following steps to detect which rules are changed.

1. Detect the rules and rule components automatically that are changed in the HTML/RIML file.
2. Update the detected HTML/RIML either by the knowledge manager or the system. It will be safer for the knowledge manager to confirm the updated result even though the system may automatically update.
3. Transform the updated HTML/RIML automatically to RSML.

In the domain of shipping cost computation, most changes will happen in the product category and shipping rates without drastic changes to rule structures. So, updating can be automatically implemented without serious difficulty.

5. Performance of rule-based comparison of delivery cost

There are five evaluation methods to validate design science research such as this study. They are observational, analytical, experimental, testing, and descriptive evaluation methods (Hevner et al. 2004). We adopt the experimental evaluation method and simulate the performance of rule-based comparison.

5.1. Conceptual model

As mentioned in Section 1, data-based comparison sites such as BestWebBuy.com can only provide book prices with a rough estimate of delivery costs per order. However, ConsiderD provides a comparison of exact total costs. Our concern is how significant
the effect of the exact comparison of delivery costs is. Under what circumstances does the effect of considering delivery cost escalate? From this perspective, we explore the following questions:

(1) **Does the consideration of exact delivery cost significantly reduce the total cost of books and delivery?** The answer may somewhat depend upon the price of products and its bulkiness. Nevertheless, the study with books will give insight about the importance of considering delivery costs in comparison.

(2) **Will the effect of considering the exact delivery cost escalate when the number of items per order is smaller?** This is intuitively true because the relative portion of delivery cost may be larger as the number per order is smaller. The result can guide the consumers if they have to depend upon the rule-based comparison more seriously when they buy a single copy.

(3) **Will the effect of considering the exact delivery cost escalate when the delivery destination is distant?** This is intuitively true because the distant delivery implies a relatively higher portion of delivery cost. The result can guide the consumers to see whether they have to depend upon the rule base comparison more seriously when they buy things from abroad.

(4) **Will the effect of considering the exact delivery cost escalate when the speed of delivery is faster?** This is intuitively true because the express delivery implies a relatively higher portion of delivery costs. The result can guide the consumers whether they have to depend upon the rule base comparison more seriously when they use express delivery.

Even though customers prefer lower costs, we need to understand whether or not customers are really sensitive to the effect of the comparison, because price is not the only factor that will...
influence the customer’s choice of e-shops. Even though this behavioral issue is important, we limit the scope of our research in this paper to the above four questions when purchasing books from one of five online bookstores.

Four hypotheses are established to test the above inquires, as depicted in Fig. 9.

**Hypothesis 1.** Rule-based comparison significantly reduces the total cost of books and delivery.

**Hypothesis 2.** The effect of rule-based comparisons is significantly greater when a single copy is purchased rather than multiple copies of a book.

**Hypothesis 3.** The effect of rule-based comparison is significantly greater when the delivery destination is international rather than domestic.

**Hypothesis 4.** The effect of rule-based comparison is significantly greater when the delivery speed is express rather than regular.

### 5.2. Experimental settings

To test the hypotheses, we created an artificial data set based on real business rules in the online bookstores’ Web sites. Let us define the terms and notations.

- **DB:** Case of using *Data-Based Comparison* approach
- **RB:** Case of using *Rule-Based Comparison* approach
- **TC(X):** Total Cost by approach X = (DB or RB)
- **BP(X):** Book Price by approach X
- **DC(X):** Delivery Cost by approach X

In this experiment, to estimate the number of book copies per order, we adopted the statistic of a leading bookstore as summarized in Table 1. Note that about 30% of orders involve purchasing a single copy, and 80% of orders involve purchasing less than or equal to three copies. The statistic may vary from store to store, and from time to time, but we adopted the same distribution for this test purpose. Therefore, we classified the number of copies into five categories from one to five.

#### 5.2.1. Simulation scenario

In order to simulate the book-buying behavior of customers, we assumed that a buyer would find the site with the lowest total price and order all books from the same site. This is realistic because in many cases people buy only a few copies at once, and they order all of them from one e-store because splitting orders usually makes the order and payment procedures more complicated, and a bundled order usually reduces the delivery cost. Therefore, the experimental data was created assuming that customer behavior depended on the following scenario.

1. Comparison capability and cost factors to consider
   1. In the case of *data-based comparison*, buyers minimize the total book price without considering the delivery cost, because information about the precise delivery cost is not given.
   2. In the case of *rule-based comparison*, buyers minimize the total cost including both book price and delivery cost.

2. The buyer orders all books per purchase from the same bookstore.

#### 5.2.2. Book data

We chose five well-known online bookstores for this study: Amazon.com, BarnesandNoble.com, Powells.com, BooksAMillion.com, and eCampus.com. Real-world data was collected from their Web sites during August in 2010. Referring to the best sellers list, 100 titles were selected, providing the same opportunity of price competitiveness among the bookstores. So each of the five bookstores recommended twenty titles with the cheapest prices from the categories of business and investment, computers and Internet, fiction, mystery and thrillers, non-fiction, professional and technical, science fiction and fantasy.

The average price of the selected books is $17.26 and the standard deviation is $14.44, with a minimum of $4.50 and a maximum of $81.98. The price distribution is depicted in Fig. 10.

#### 5.2.3. Delivery cost data

The key factors that determine the delivery cost are speed and destination. The speed is usually classified into three levels: standard, expedited, and priority delivery (2nd day or next day air delivery). The delivery cost also varies by distance to destination. In this study, we selected four destinations: United States (domestic), Canada (as an example of an adjacent foreign country), United Kingdom (as an example of Europe), and Korea (as an example of Asia). We assume the other service quality among the bookstores equal for the purpose of this experiment. Thus the rules that compute the delivery cost consider the per-shipment cost, number of copies, destination and speed, as summarized in Table 2.

#### 5.2.4. Valid data set

The experimental cases are generated for from one to five copies. For each number of copies, titles are randomly selected 100 times, creating 100 cases. Since there are 13 types of destination and speed combinations, the total size of the dataset is 6500 (5 × 13 × 100). However, 869 cases are non-applicable (denoted NA) because some delivery methods are not provided by some bookstores, so the number of valid data points is 5631. The delivery cost per order is calculated by (Per Shipment Cost) + (Per Copy Cost) × (Number of Copies). Table 3 summarizes four independent

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**Table 1**

<table>
<thead>
<tr>
<th>Number of copies</th>
<th>Percentage of purchase (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>29.5</td>
</tr>
<tr>
<td>2</td>
<td>28.4</td>
</tr>
<tr>
<td>3</td>
<td>20.2</td>
</tr>
<tr>
<td>4</td>
<td>7.6</td>
</tr>
<tr>
<td>5 and above</td>
<td>14.3</td>
</tr>
<tr>
<td>Total</td>
<td>100.0</td>
</tr>
</tbody>
</table>

**Fig. 9.** Models to test.
variables (comparison method, number of items per order, delivery destination, and delivery speed) and the dependent variable (total cost difference between data-based and rule-based approaches) of the experiment.

5.3. Experiment results

5.3.1. Effectiveness of rule-based comparison

The efficacy of the proposed architecture is measured by the effectiveness of cost reduction. Table 4 shows the results of the experiment. It shows the book price (BP), delivery cost (DC), and total cost (TC) per order and per copy. These values are contrasted for the data-based (DB) approach, the rule-based (RB) approach, and the difference between them. It shows that the weighted average of TC(DB) per order by market share in Table 1 is $70.14 and that of TC(RB) is $67.42, so the total cost reduction \( \frac{TC(DB)}{TC(RB)} \) is $2.72 per order and $1.26 per copy. This means that the rule-based comparison approach can reduce the 4.18% (=1.26/30.17) of purchase cost per copy. If we apply this reduction rate to the book purchase from Amazon.com whose annual media sales was about $12.77 billion in 2009, the savings could have been as big as $533.7 million.

The paired t-test supported the hypothesis that this difference was statistically significant with 99% confidence \( (t = 50.33) \). So Hypothesis 1 is accepted. It is interesting to note that data-based comparison could only find 48.59% of the true minimal total cost while rule-based comparison can find 100%.

This main result is obtained because the standard deviation (2.75) of delivery cost between bookstores is slightly higher than that of book prices (2.71) even though the average book prices are twice as high as the average delivery cost. According to the ANOVA test, the book price and delivery cost differences among five bookstores are both significant with 99% confidence \( (F = 28.10 \text{ and } F = 101.38 \text{ respectively}) \). After the rule-based comparison, the most price-competitive bookstore is selected at the frequency of 46.57%, while the least competitive one is selected at the frequency of 1.28%. This is a significant deviation from an equal distribution in terms of book prices. Therefore, it is clear that the comparison of delivery cost with the help of a rule-based system is crucial.

Table 3
Independent variables and dependent variable of the experiment.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Independent variables</td>
<td>Comparison method</td>
<td>Rule based (RB) or data based (DB)</td>
</tr>
<tr>
<td></td>
<td>Number of items per order</td>
<td>One to five copies</td>
</tr>
<tr>
<td></td>
<td>Delivery destination</td>
<td>United States (domestic), Canada (adjacent), United Kingdom (EU), or Korea (Asia)</td>
</tr>
<tr>
<td></td>
<td>Delivery speed</td>
<td>Standard, expedited, or priority delivery</td>
</tr>
<tr>
<td>Dependent variable</td>
<td>Total cost difference</td>
<td>TC(DB) – TC(RB)</td>
</tr>
</tbody>
</table>

$2.72 per order and $1.26 per copy. This means that the rule-based comparison approach can reduce the 4.18% (=1.26/30.17) of purchase cost per copy. If we apply this reduction rate to the book purchase from Amazon.com whose annual media sales was about $12.77 billion in 2009, the savings could have been as big as $533.7 million.

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Table 2
Rules for delivery cost computation (Unit: US$).

<table>
<thead>
<tr>
<th>Type</th>
<th>Destination</th>
<th>Speed</th>
<th>Amazon</th>
<th>BarnesandNoble</th>
<th>Powells</th>
<th>BooksAMillion</th>
<th>eCampus</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Per shipment</td>
<td>Per copy</td>
<td>Per shipment</td>
<td>Per copy</td>
<td>Per shipment</td>
</tr>
<tr>
<td>1</td>
<td>US</td>
<td>Standard</td>
<td>3</td>
<td>0.99</td>
<td>3</td>
<td>0.99</td>
<td>2.99</td>
</tr>
<tr>
<td>2</td>
<td>US</td>
<td>Expedited</td>
<td>NA</td>
<td>3.99</td>
<td>0.99</td>
<td>4.99</td>
<td>1.99</td>
</tr>
<tr>
<td>5</td>
<td>Canada</td>
<td>International standard</td>
<td>4.99</td>
<td>3.99</td>
<td>3.99</td>
<td>2.49</td>
<td>2.5</td>
</tr>
<tr>
<td>8</td>
<td>Korea</td>
<td>International standard</td>
<td>4.99</td>
<td>4.99</td>
<td>7.49</td>
<td>5.49</td>
<td>7</td>
</tr>
<tr>
<td>10</td>
<td>Korea</td>
<td>International priority</td>
<td>29.99</td>
<td>5.99</td>
<td>29.99</td>
<td>5.99</td>
<td>37</td>
</tr>
</tbody>
</table>

Fig. 10. Price distribution of the generated data.
5.3.2. Effect of number of copies per order

Fig. 11 shows the cost reduction effect with respect to the number of copies purchased. From the graph, it is clear that the difference of total cost per copy is as big as $1.85 for a single copy, and converges to about $1 as the number of copies increases. We tested the hypothesis that the difference between the single copy and multiple copies is statistically significant with 99% confidence ($t = 14.02$). So Hypothesis 2 is accepted. This result arises because the portion of per-shipment cost effect increases as the number of copies decreases.

5.3.3. Destination effect

In order to compare the effect of destination, we compare domestic (US) delivery with international (Canada, Korea, England) delivery. The average difference in the total cost $TC(DB) - TC(RB)$ for domestic cases is $1.81$, while that of the international cases is $3.72$, as shown in Fig. 12. According to the paired t-test about the difference between domestic and international cases, the difference is significant with 99% confidence ($t = 17.46$). So Hypothesis 3 is accepted.

This result implies that the rule-based comparison approach distinctively outperforms the data-based comparison approach in the case of international delivery, because the international case had a higher delivery cost than the domestic case. Delivery to Canada shows a difference of $4.14$ which is higher than the others. This result arises because there is a higher delivery cost difference to Canada among bookstores.

5.3.4. Delivery speed effect

Fig. 13 shows that the rule-based comparison approach has a greater effect on cost reduction when the priority delivery method is selected rather than the standard one. This result arises because the fluctuation in delivery cost for the priority cases is higher than for the standard cases. The significance is confirmed by the paired t-test with 99% confidence ($t = 13.61$). So Hypothesis 4 is accepted.

6. Conclusion and discussion

The current comparison sites depend on the data-based comparison approach displaying product information and prices retrievable from a database. Even though the delivery cost is an
important cost factor from the customer perspective of total cost, the current comparison sites cannot support the exact computation of delivery cost. In order to overcome this limitation, we developed the architecture of the rule-based comparison approach, which can support the exact computation of delivery cost tailored to each specific order. This architecture is applied to the development of the prototype system ConsiderD, which compares the total of book prices and delivery cost. In order to ensure effective rule generation and maintenance of consistent rules with the original Web pages, the XRML approach was adopted.

According to the experimental test with the cases of online book purchase from five leading online bookstores, we found that the effect of comparing the delivery cost was even higher than that of comparing book prices. The effect of rule-based comparison was particularly acute when international customers purchased a small number of items per order selecting the express delivery method. This phenomenon was validated by testing four hypotheses. In the case of purchasing a copy, rule-based comparison could save $2.72 per order and $1.26 more per copy than data-based comparison. We also discovered that only 48.59% of the true minimum cost sites could be found by data-based comparison while 100% of the true minimum cost sites were found by rule-based comparison.

We demonstrated the performance of the rule-based approach for the comparison of delivery cost in this paper. Although the result of this exploratory study cannot be generalized to the purchase of all kinds of items, this study certainly foreshadows the importance of considering delivery cost in the comparison sites. This is particularly true when the variation in delivery cost is higher across the e-stores.

If the personal profile information in the smart phone or PC can be integrated at the moment of comparison, the capability of personalized comparison will become augmented because personalized discount rates of credit cards, coupons, and saved e-money of each e-store can be taken into consideration. Every e-store can provide various kinds of coupons that have different discount rates with respect to product types. Rule-based comparison can provide exact comparison over such complicated features. The personalized comparison service can be combined with loyalty programs and customer relationship management services. Location-based comparison on smart phones and mobile pads will also be possible.

The effectiveness of rule-based comparison will also be expanded for the personalized comparison of items with various features such as complex customized products and insurance products. In this case, the effect is not the delivery cost reduction, but the product price reduction per se.

It is interesting to note that the effectiveness of the comparison varies depending on which e-stores customers usually visit. According to the experimental result, the possibility of hits received by the bookstore with the most competitive price is 46.57%, while with the least competitive store is only 1.28%. This implies that the customers who used to purchase at an e-store with poor competitiveness will gain the most benefit from rule-based comparison.

We also need to look at the study from a different perspective by possibly investigating the actual behavior of customers during and after the comparison. Future inquiries for a further investigation could include the following questions: How sensitive are customers to the price difference? A certain class of customers and products (for instance, the low-income customers for bulky products) may be more sensitive to the delivery cost comparison. It would be interesting to expand the types of items beyond books with an emphasis on the dimensions of high/low price items and small/large-size items. How dependent are customers on comparison sites? Customers loyal to a particular e-store may less dependent on the comparison site. The advancement of personalized, rule-based comparisons may influence the customer’s behavior. What determines the customers’ ultimate selection? What is the appropriate taxonomy of customers in the context of the comparison shopping behavior study? There are abundant research opportunities in this field. We may use software agents to monitor the frequency of updated information on the merchant Web sites. In addition, we need to detect knowledge changes and create consistent rules as automatically as possible.

Acknowledgment

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References


Table 4

Average cost of experimental results.

<table>
<thead>
<tr>
<th>No. of copies</th>
<th>Data-based comparison (DB)</th>
<th>Rule-based comparison (RB)</th>
<th>Cost difference (DB – RB)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Book price (BP)</td>
<td>Delivery cost (DC)</td>
<td>Total cost (TC)</td>
</tr>
<tr>
<td></td>
<td>Per copy</td>
<td>Per copy</td>
<td>Per copy</td>
</tr>
<tr>
<td>1</td>
<td>19.02</td>
<td>18.25</td>
<td>37.27</td>
</tr>
<tr>
<td>2</td>
<td>33.5</td>
<td>22.44</td>
<td>55.94</td>
</tr>
<tr>
<td>3</td>
<td>53.67</td>
<td>27.21</td>
<td>80.88</td>
</tr>
<tr>
<td>4</td>
<td>74.62</td>
<td>32.25</td>
<td>106.87</td>
</tr>
<tr>
<td>5</td>
<td>94.35</td>
<td>37.09</td>
<td>131.44</td>
</tr>
<tr>
<td>Weighted average</td>
<td>45.12</td>
<td>25</td>
<td>70.14</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Per copy</th>
<th>DC(D)</th>
<th>TC(DB)</th>
<th>BP(DB)</th>
<th>Per copy</th>
<th>DC(RB)</th>
<th>TC(RB)</th>
<th>BP(RB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.06</td>
<td>1.38</td>
<td>1.24</td>
<td>0.77</td>
<td>1.65</td>
<td>2.24</td>
<td>1.12</td>
<td>0.93</td>
</tr>
<tr>
<td>0.46</td>
<td>4.18</td>
<td>0.93</td>
<td>0.41</td>
<td>4.71</td>
<td>0.94</td>
<td>0.56</td>
<td>0.94</td>
</tr>
<tr>
<td>0.56</td>
<td>3.95</td>
<td>1.26</td>
<td>0.77</td>
<td>1.82</td>
<td>2.12</td>
<td>1.26</td>
<td>0.94</td>
</tr>
</tbody>
</table>


PriceSpin. Price comparison websites. Available at wwwpricespin.net/solutions.html.


