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E-COMMERCE CUSTOMERS' PREFERENCE IMPLICIT IDENTIFICATION

Tomasz Zdziebko, Ph.D.

University of Szczecin
Faculty of Economics and Management
Institute of IT in Management
Mickiewicza 64, 71-101 Szczecin, Poland
E-mail: tomasz.zdziebko@wneiz.pl

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Abstract

Knowledge of users' preferences are of high value for every e-commerce website. It can be used to improve customers' loyalty by presenting personalized products' recommendations. A user's interest in a particular product can be estimated by observing his or her behaviors. Implicit methods are less accurate than the explicit ones, but implicit observation is done without interruption of having to give ratings for viewed items. This article presents results of e-commerce customers' preference identification study. During the study the author's extension for FireFox browser was used to collect participants' behavior and preference data. Based on them over thirty implicit indicators were calculated. As a final result the decision tree model for prediction of e-customer products preference was build.

Keywords: implicit feedback, recommender systems, preference modeling, e-commerce, decision trees.

JEL classification: C88, C93.

Introduction

E-commerce plays an essential role in nowadays economy. Year by year the revenue of the Polish e-commerce sector is growing up. This is mainly due to many unquestionable advantages of this form of buying and selling goods for both customers and shops. But with thousands of products available in virtual stores customers often have to put a lot effort in finding products that meet their needs and expectations. This problem has been identified as information overload. To help users navigate and find interesting products, researchers have been developing intelligent techniques for recommender systems. The role of these systems is to provide recommendations of products likely to interest customers. Good quality recommendations can improve customers' satisfaction, increase order value and frequency of buying low popularity products. Customers who are satisfied with the quality of recommendations tend to be more loyal. Besides, the e-commerce recommendation technology is used in different domains such as music, books and article recommendations. For every recommender system it is crucial to learn users' preferences as accurately as possible. In e-commerce these preferences are usually expressed in customers' interest in products available in store.

Determining a user's interest can be performed explicitly by asking the user directly, or implicitly by observing the user's behavior. Implicit measures are generally less accurate than the explicit ones[1], but they are available in large quantities and can be acquired without any extra effort or time from the user. On the contrary, requiring users to explicitly rate items disrupts a user's normal reading and browsing behavior[2]. These can irritate users and as a consequence cause them to completely resign from giving ratings[3]. Moreover, unobtrusive monitoring of users allows them to focus on a task at hand without any interruption caused by having to give ratings for the viewed items. Another advantage of the implicit feedback over the explicit one is that it is difficult to motivate them to continuously give explicit ratings[4] even when the benefits are obvious (i.e., personalized recommendations). Both implicit and explicit methods are part of information retrieval area.

Implicit feedback in a website area can be acquired from different sources on different sides of the interaction process, such as: the server side, the proxy side, the client side. Historically, the first data source were server logs whose main purpose was a diagnostic tool. Server logs store only information about every page request to particular websites installed on a server. Proxy servers, whose main role is to facilitate access to content on WWW, also can store information about requested resources in logs. But granularity of these information is the same as information stored in server logs. In contrast to the server and proxy side, the logging user's behavior at the client side allows of a more complete grasp of the user behavior. Highly accurate logging at the client side is possible thanks to very good support for the Document Object Model and JavaScript across modern browsers. Observing users at the client side allows for high granularity monitoring of user's actions e.g. moving a mouse, scrolling contents, clicking, selecting contents, copying contents, saving pages, printing pages, key input. Wide range of monitored actions allows online shops to gain extensive amount of data about the user behavior. By using these data we can reason about the user's preferences more precisely and reliably. The most obvious indicator of user's interest is time spent on a web page. Others indicators such as number of mouse clicks or distance of page content scrolling needs to be evaluated carefully in order to reason about users' interest.

Most of researches in the field of implicit feedback indicators focused mainly on evaluating the user behavior at an unlimited scope of websites. Participants of the studies usually visited websites from many different categories (e.g. information portal, blogs, company websites, searchers). One of the drawbacks of this approach is the fact that the user behavior may depend on the type of a site as well as it can be different on particular websites. These may be caused by differing users' goals on websites from various categories. Another factor influencing the user behavior may be caused be layout and functionality which is different for every website. When studying the literature the author encountered very few studies on the evaluation of implicit feedback in the e-commerce environment[5].

Due to the lack of studies in this field author has conducted his own research. This article presents the main results of the study, which was conducted on selected Polish e-commerce websites. For the purpose of the FireFox extension was built by the author.

1. Related works

Implicit feedback techniques have been used for retrieving, filtering and recommending a variety of items: web sites, articles (both academic and journal), email messages, music, movies and products from e-commerce stores. Researchers have used different source data and different construction of their research environment. As for a client-side technique researchers used tools for monitoring user behavior such as a browser specially created for necessity of study, a modified browser which (e.g. modified Internet Explorer), a script in Javascript language attached to a browser. Besides monitoring the user behavior, in most studies participants were asked to explicitly indicate their interest in visited resources.

Monitored behavior can be classified into six categories such as: Examination, Retain, Reference, Annotate, Create[6]. For instance, reading is considered as an action that allows one to Examine an object. It is worth noting that confidence in the behaviors that is available for inference varies according to a category of the observed behavior. For instance behaviors from the Examination category are a weaker evidence of user interests than behaviors from the Annotate or Create category. However, most often observed actions belong to the Examine category which expresses the weakest evidence of users' interests. On the other end of scale there are behaviors such as creating, printing, saving which occur less frequently.

According to two dimensional classifications provided by Kim and Orad every action can also be classified into a minimum possible scope of item being acted upon. For instance Bookmarking can be performed on Object, while Reading can be observed on Segment of Object. This classification highlights that behaviors observed at a larger scale are less precise. For instance, obtaining implicit feedback about a class of objects will presumably provide less precise information about the users' interests than obtaining implicit feedback about an object or a segment of objects.

Most widely explored behaviors for implicit feedback are a document (web page) selection and the time spent on a web pages. The finding that users spend more time on documents that they find relevant has been replicated in large number of studies[7]. However some researchers indicate that time may not be a reliable interest indicator[8]. It can be caused by the absence of user or by performing another task while a website is open (i.e. checking e-mail, watching movie, using a communicator, exploring another website). Therefore in the proposed framework the time spent by the user on a web page is divided into three types depending on the total time the page is loaded (Complete Duration), if the browser tab is active (Active Tab Duration), and if the user is actively interacting with the webpage (User Activity Duration). Another mostly explored implicit feedback indicators consist of a mouse-move distance, a scroll distance, a key input.

Claypool et. al[9] created a *CuriousBrowser* which was a web browser that could record implicit actions and explicit ratings by users. The browser was used to record mouse clicks, mouse movement, scrolling and elapsed time. The results of these studies indicate that the time spent on a page, the amount of scrolling on a page, and the combination of time and scrolling has a strong correlation with an explicit interest.

Kim and Chan[10] who also used authors browser added camera to the experiment. The main purpose of the camera was to record users' face orientation while performing the study. Eleven volunteers participated in the study. Each of them was asked to spend at the computer a total of 2 hours divided into sessions. Moreover, the participants were asked to bookmark more than 10 pages, save more than 5 pages and use memo on more than 5 pages. The result of the study shows that the indicators such as: *Complete*, *Active*, *LookAtIt* and *MouseMove* were good predictors of interest of 8 participants.

Velayathan and Yamada[11] developed a logging tool called the Ginis site logging tool to monitor and log the user browsing behavior. They performed a user experiment using ten participants to observe the browsing behavior, and evaluated the behaviors by performing classification learning by means of C4.5 algorithm. This tool is capable of monitoring a large number of user behaviors. They successfully confirmed that all the rules generated by the C4.5 classification learning algorithm had 60% or higher fitness, where the error for all the tests was lower than 40%.

A complete review of research into implicit feedback techniques is provided by Diane Kelly[12].

2. Research description

In order to evaluate the application of implicit feedback to learn the user preferences on e-commerce websites the author conducted open research. The aim of the research was to collect data about participants' behavior and interest and to look for patterns between them.

The research was conducted between February and September 2011. The research was open for everyone. Information about it was propagated through: a specially created website, e-mails and social portals. Participants were asked to install Firefox extension (named BPE) on their computers. Their task was to browse the offer of selected Polish e-commerce stores in order to look for interesting products. They were instructed to behave ordinarily, take breaks during their study and perform other tasks. They could perform the study tasks at any time from any place they wanted. Their activity was monitored by BPE Extension on only five Polish e-shops such as: merlin.pl, agito.pl, electro.pl, empik.com, morele.net selected for the study. These stores are one of the biggest e-shops in Poland.

The technology of the extension for FireFox browser was selected for building a research tool for a few important reasons. Firstly, the participants could use a well known browser instead of authorial browsers build only for the purpose of the study. Secondly, via the extension any real e-commerce site could be monitored. This technology also allowed the author to collect the interest ratings explicitly provided by user.

An important aim of the study was to collect only these behavior data which could be collected by means of techniques which did not require users to install any extra software. This limitation was introduced in order to apply the results of the study to real e-commerce websites without commanding their customers to install additional software.

FireFox is a very popular browser which allows for installation of extensions called Addons to enhance its functionality. FF extensions are build with two languages: JavaScript for logic programming and XUL for interface description. BPE Extension allows monitoring of various users behaviors by means of Events DOM model.

BPE Extension contains preference window where users can deactivate the extension, provide personal data, open a study description, open a poll window and finish the study by sending results to the server.

The extension actively monitors visited products pages on five e-commerce websites. It registers information about visited pages and user behaviors only on product pages where detailed information about particular product is presented. Other pages are left out from analysis because the aim of the study was to find patterns between user behaviors on product pages and the level of interest towards them. On every product page BPE registers parameters describing physical attributes of the page (Table 1).

Table 1. Page parameters registered by BPE extension

Parameter	Description
Document_length	Number of characters contained within all texts on the page
Desc_length	Number of characters contained within product' description
Review_length	Number of characters contained within reviews' of the product
Recommend_length	Number of characters contained within other recommended products on the page
Image_number	Number of product's images
Page_height	Page height expressed in pixels

Source: the author's own study.

During page browsing BPE is monitoring users behavior via DOM events generated by their activity. These events are used to calculate 24 implicit indicators listed in Table 2. These indicators can also be calculated without the extension only just by attaching regular JavaScript code to a monitored page. These indicators reflect a different kind of activities performed by users. The time spent on a web page is one of the most intuitive candidates for user interest indicators. Beside page_time and tab_activ_time other indicators expressing time are the author's proposal. User_activ_time is calculated as a sum of periods of two seconds when a user was actively interacting with website. Very often users open many pages in different tabs or leave a computer while a website is still open. User_activ_time is supposed to express time when a user is actively interacting with a webpage.

Table 2. Implicit indicators calculated by BPE extension

Implicit indicator	Indicator description
Search_referral	Boolean value indicating whether search result page was source of visit on this product page
Page_time	Time between page load and page unload
Tab_activ_time	Amount of time (ms) while tab containing particular page is being active
User_activ_time	Amount of time (ms) while user is actively interacting with page thus generates keyboard and mouse events
Prod_desc_time	Amount of time (ms) while mouse pointer is positioned over description of the product
Prod_image_time	Amount of time (ms) while mouse pointer is positioned over pictures of the product
Prod_review_time	Amount of time (ms) while mouse pointer is positioned over users' review of the product
Prod_recommend_time	Amount of time (ms) while mouse pointer is positioned over other recommended products
Mouse_distance	Total distance (in pixels) of mouse pointer's movement
Horizontall_scroll	Total distance (in pixels) of horizontal scroll of page content
Vertical_scroll	Total distance (in pixels) of vertical scroll of page content
Mouse_clicks	Total number of mouse clicks regardless which mouse key has been pressed
Lb_mouse_clicks	Total number of left mouse button clicks
Rb_mouse_clicks	Total number of right mouse button clicks
Mb_mouse_clicks	Total number of middle mouse button clicks
Copycut_action	Total number of copy/cut action performed via keyboard shortcut
Save_action	Total number of save action performed via keyboard shortcut
Print_action	Total number of print action performed via keyboard shortcut
Bookmark_action	Total number of bookmarking action performed via keyboard shortcut
Resize_action	Total number of page resinzing action performed via keyboard shortcut
Find_action	Total number of find action performed via keyboard shortcut
Select_action	Total number of page content selection action
Select_text_size	Total number of selected chars
Keydown_action	Total number of key pressing event

Source: the author's own study.

Nowadays almost every product page contains such sections as: description, images, review and users' opinions and recommendations of other related products. The author hypothesized that moving a mouse pointer into these sections may indicate a user's interest. In order to express users' engagement four indicators were proposed. They define time while mouse pointer is within these areas. Because of a different HTML structure of every website, there were hard coded patterns for calculation of these indicators.

Beside non-relative indicators which were calculated directly from the user behaviors, indicators relative to page characteristic were also constructed. In order to calculate these indicators the following measures were calculated for every website: total page characters length, total recommendation area characters length, page height, number of product pictures, visible page height. By using the behavior data and the page measure data the relative indicators were calculated (Table 3).

Table 3. Relative indicators calculated by BPE extension

Relative indiciator	Description
Rel_page_time	page_time / document_length
Rel_user_activ_time	user_activ_time / document_length
Rel_tab_active_time	tab_activ_time / document_length
Rel_prod_desc_time	prod_desc_time / description_length
Rel_prod_recommend_time	prod_recommend_time / recommendation_length
Rel_prod_review_time	prod_review_time / review_length
Rel_prod_image_time	prod_image_time / image_number
Rel_mouse_distance	mouse_distance / page_height
Rel_vertical_scroll	vertical_scroll / page_height
Rel_horizontal_scroll	horizontal_scroll / page_width

Source: the author's own study.

When a user is leaving the product page, the Interest evaluation window is displayed (Figure 1). This window contains two questions concerning the product and the page being left. Originally this study is designed for the Polish speaking participants. The first question "How much has this product interested you?" allowed the user to express his/her explicit interest in this product. This interest could be rated on a five point scale from 1–5 (5 – very much and 1 – not at all). Another question "Have you known this product before?" checked if the user was familiar with the viewed product. After the form had been filled in, the answers were stored. When the user happened to return to that product page again during the survey, all the previously marked answers were be displayed.

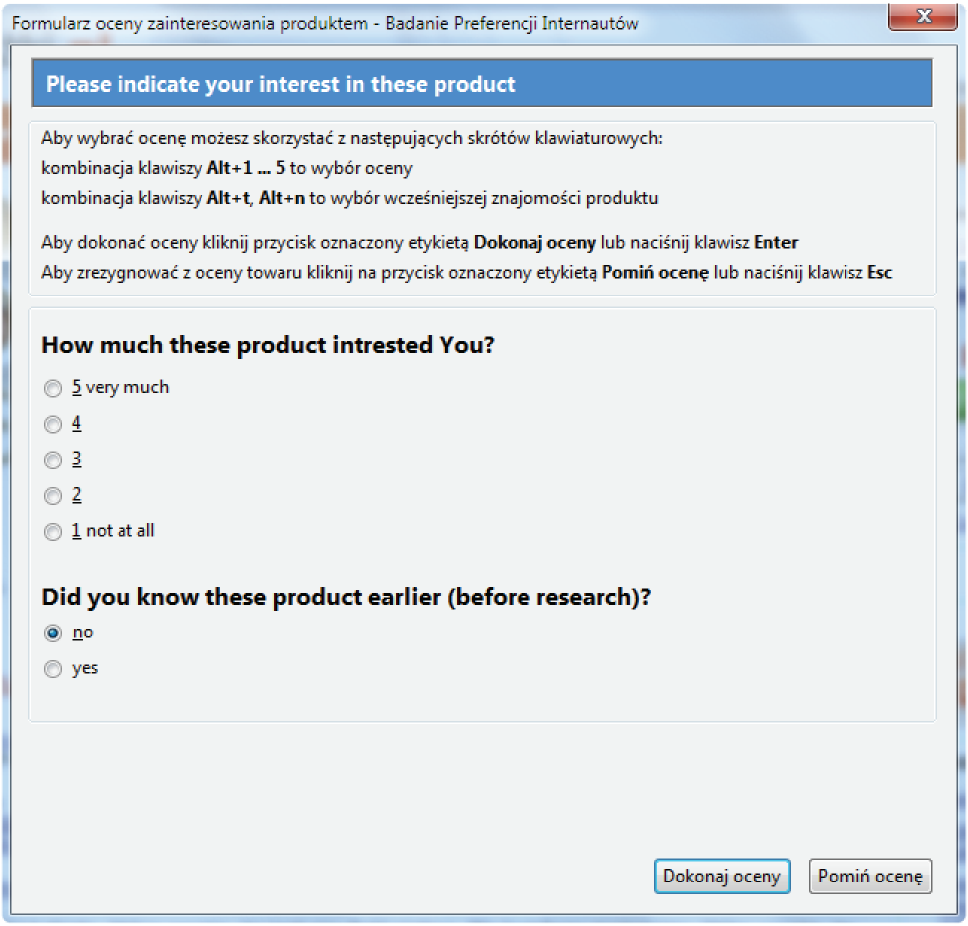

Fig. 1. Explicit Interest evaluation form

Source: the author's own study.

3. Results

During the research time between February and September 2011 eighty five volunteers took part in the study. They rated 1396 products in total. The mean number of products rated by one user was 16.42. Half of the participants rated less than 14 products. This shows that engagement in the study of the majority of users was very low. Users mostly gave high ratings (Table 4).

Table 4. Products ratings distribution

Rating	Number of ratings
1	130
2	180
3	325
4	346
5	415

Source: the author's own study.

The users rated the highest number of products, i.e. 454, in Merlin.pl store. In Komputronik.pl, Morele.net, Agito.pl and Electro.pl the users rated 267, 238, 218 and 205 products, respectively. The users tended to give higher ratings to products known before the study (Figure 2).

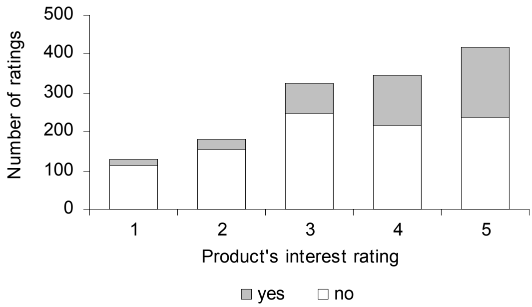

Fig. 2. Ratings distribution vs. product familiarity

Source: the author's own study.

After applying Kruskal-Wallis test eighteen variables were selected for which null hypothesis was rejected: desc_length, page_height, mouse_distance, mouse_clicks, lb_mouse_clicks, vertical_scroll, prod_desc_time, prod_review_time, prod_recommend_time, prod_other_time, page_time, tab_activ_time, user_activ_time, rel_page_time, rel_user_activ_time, rel_prod_desc_time, rel_prod_review_time, rel_vertical_scroll.

A classification model of product interest was built with SAS Enterprise Miner Software. Equal number of cases for each predicted class (rating) was selected for tree learning procedures. Predictive capabilities of extracted models were validated with the 10-fold cross validation method. The parameter influencing the depth of a result tree – maximum number of branches – was set to three. Minimal leaf size was set experimentally to five and ten leafs. After performing the tree building procedure several times with different parameters a tree with misclassification rate of 0.592 was built (Figure 4). The tree had better predictive accuracy than a random model (0.8 misclassification rate because of 5 classes), which can be observed on a cumulative lift (Figure 3).

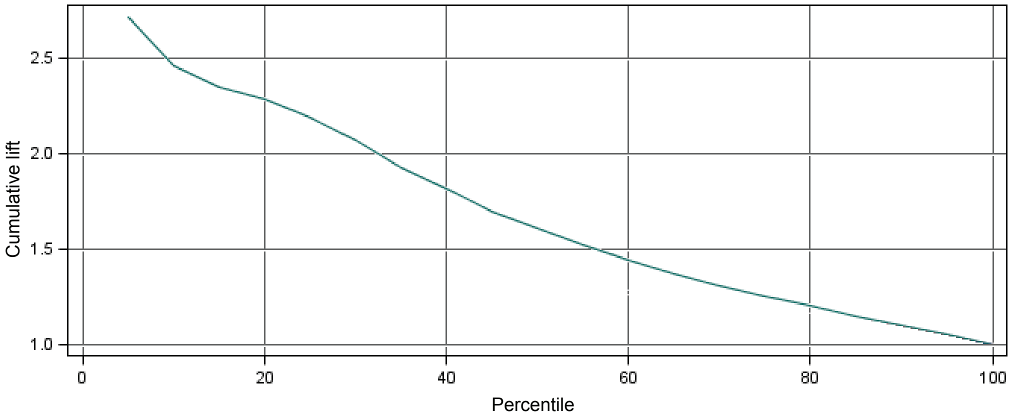

Fig. 3. Cumulative lift of the product interest decision tree model

Source: the author's own study.

The confusion matrix (Table 5) shows that the best predictive accuracy was achieved for the interest ratings of 5 and 2.

Table 5. Confusion matrix for interest decision tree

		Predicted interest					Classification Accuracy (%)
		1	2	3	4	5	
Real interest	1	54	30	11	11	24	41.5
	2	21	69	15	14	11	53.1
	3	16	40	34	14	26	26.2
	4	18	31	15	38	28	29.2
	5	7	29	15	9	70	53.8
Sum		116	199	90	86	159	

Source: the author's own study.

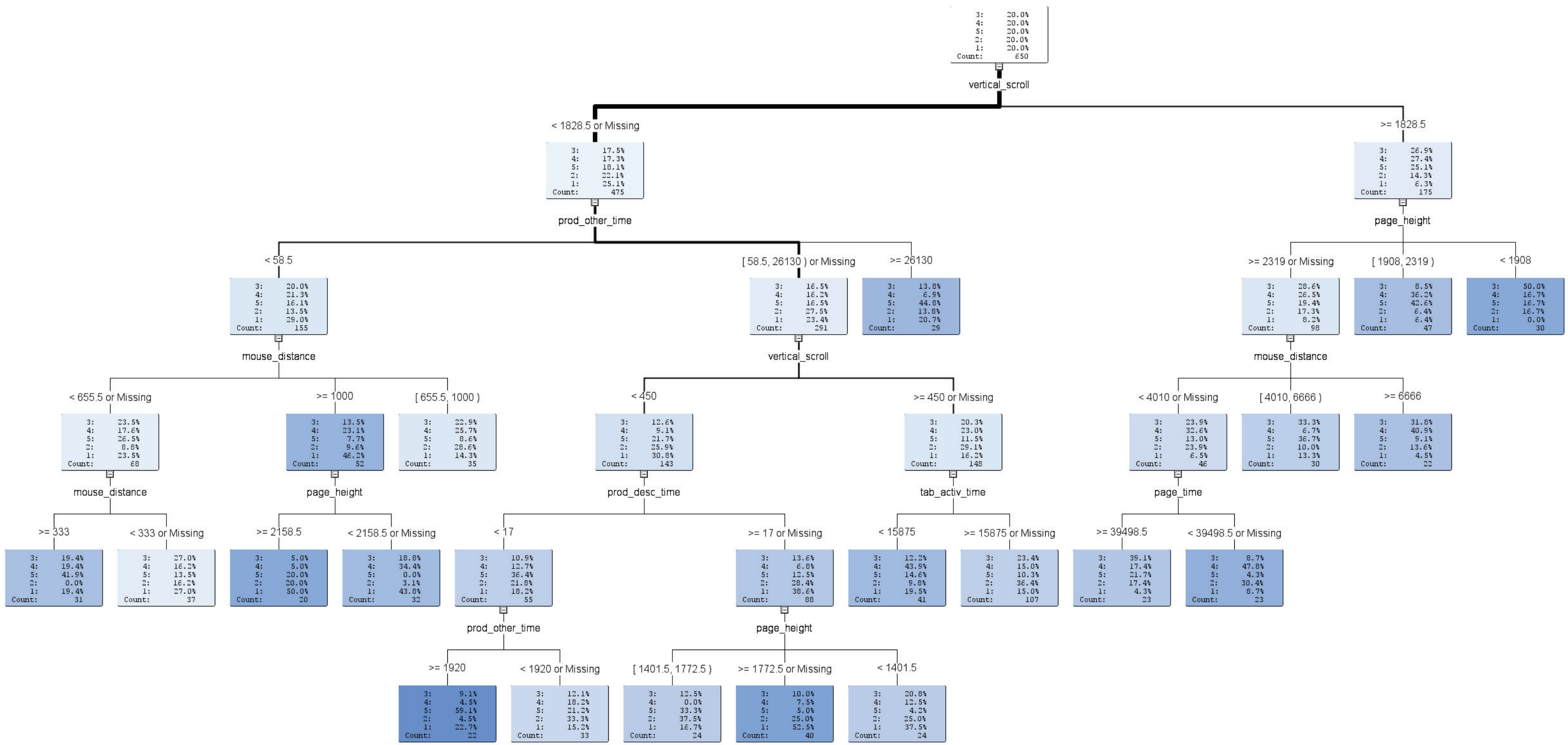

Fig. 4. Decision tree model of product interest

Source: Author's study.

Conclusions

The presented above study revealed the existence of patterns between the users' behaviors on product pages in e-commerce stores and their interest towards the viewed products. The decision tree built for the purpose of this problem shows relative good quality of its predictive abilities. Even though it is far from perfect, this tree classifier has a better predictive accuracy than a random model. The problem of identifying the users' interest via observing their behavior is probably far more complex. There are many more factors influencing the users' attitudes towards products which cannot be measured implicitly.

Notes

[1] Nichols (1997), pp. 31–36).
[2] Middleton, Shadbolt, Roure (2003).
[3] Avery, Zeckhauser (1997), pp. 40–88.
[4] Morita, Shinoda (1994); Kim, Carroll, Rosson (2002).
[5] Kim, Yum, Song, Kim (2005).
[6] Oard, Kim (2001).
[7] Cooper, Chen (2001); Miller, Riedl, Konstan (2003); Seo, Zhang (2000).
[8] Jung (2001); Kelly, Belkin (2001).
[9] Claypool, Le, Wased, Brown (2001).
[10] Kim, Chan (2008).
[11] Velayathan, Yamada (2005).
[12] Kelly (2005).

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