Interactive Tool to Find Focal Spots in Human Computer Interfaces in eCommerce

eCommerce Consumer Analytics Tool (eCCAT)

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Abstract. eCommerce is one of the popular electronic services available in the vast Internet world. eCommerce endpoints, also called eCommerce websites, in general, are a composition of several web pages. Within eCommerce endpoints, there exist specific web page types that are abnormal in their consumption of information and user behavior called focal spots. Finding a focal spot is key for understanding and improving the human interaction interface on eCommerce endpoints. In order to make business decisions concerning these focal spots, decision analytics teams are employed to identify focal spots with abnormal consumer perception and to address areas in which to expand business. We propose a methodology for transforming user activity data into useful business analytics to find focal spots if any. In this work, we developed a prototype of a one-stop solution for non-technical users to understand customer response analysis on a given eCommerce endpoint. The proposed system, 'eCommerce Consumer Analytics Tool (eCCAT)', consists of a data extraction and automated analysis component and a visualization component. The interactive tool further provides a way to find a page in the eCommerce endpoint with an extreme key performance indicator.

1 Introduction

eCommerce is one of the most important and predominant channels in the retail world today. Like traditional physical retail, eCommerce is faced with several of the same crucial components concerning delivery: supply chain, shopping experience, assortment, point of sale, etc. However, unlike its physical counterpart, eCommerce is exposed as the nexus of multiple customer touch points, simultaneously servicing search, evaluation, and purchase use cases [1]. As a result, the eCommerce experience must accommodate and solve for not only an array of usage situations but also of cognitive styles at a large scale.

This paper attacks the problem of identifying areas within the eCommerce experience that are crucial to financial outcomes and therefore the success of the platform

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through a visual analytics system called eCommerce Consumer Analytics Tool (eC-CAT). The effectiveness of analytical reports is highly dependent on human computer interaction widgets and effective data visualization [2]. In particular to demonstrate the system capabilities, we employ reports in which a key performance indicator, such as revenue participation, conversion rate and traffic of each page type in an eCommerce endpoint, is visualized in a user interface that can easily be consumed without in-depth context of the eCommerce website map or any formal training of the system [3].

2 Focal Spots

A website or endpoint on the Internet is a collection of webpages. eCommerce end-points, when generalized, follow a pattern of webpage types: 1. Home Page, 2. Product Listing Pages, 3. Product Description Pages, 4. Cart Page, and 5. Checkout Page. We are interested in page types that are abnormal in their user behavior and information consumption called focal spots that pose a direct impact on business results. Among these page types, Product Listing Pages (PLPs) are notably profuse in their informational content and sensitivity to user cognitive styles [4]. Because PLPs are a class of display methods for information retrieval and recommendations, they are instrumental in serving the multitude of information needs. We focus on understanding the user experience of these focal spots, covering a holistic set of factors including user interface, content served, timing performance, etc. Furthermore, focal spots themselves are comprised of multiple web pages. These focal spot pages can be analyzed in a similar methodology where pages that are abnormal in their user behavior or performance called focal points are identified and serve as specific, actionable areas for improvement. The impact of user experience at these focal points can be either positive or negative.

3 Data Collection and Processing

Customer feedback and data is collected from eCommerce end points using web beacons which have been used for many analytics purposes including understanding the behavior of customers. Web beacons are API calls that carry log data made in the client browser with the beacon server as the other end point of the call. Each web beacon turns into a log record in the log server where the beacon server stores the received data over the call. A log record represents an activity performed by a client or an activity record. Some of the key attributes in activity records that are crucial in analysis are timestamp, session identifier activity type, and activity parameters to name a few. Sessionization is one of the foremost steps in analysis of activity records. Sessionization segments all the activity records into groups, each group representing a session. ‘Session’ is a broad term used to represent a time slot constrained by specific parameters. Widely used sessionization algorithms split activities by 30 min of inactivity with a session identifier [5]. Further analysis into a session leads to an understanding of the dynamics of each activity in the session. For example, both a page view and a click are activities that determine the performance of a page. Connecting activities within a session based on navigational patterns turns each session into a set of activity networks. There is a path from each node in an activity network to a network node that represents conversion. A page in a given website is said to be converted if and only if there is a path from the network node representing the page to the conversion page.

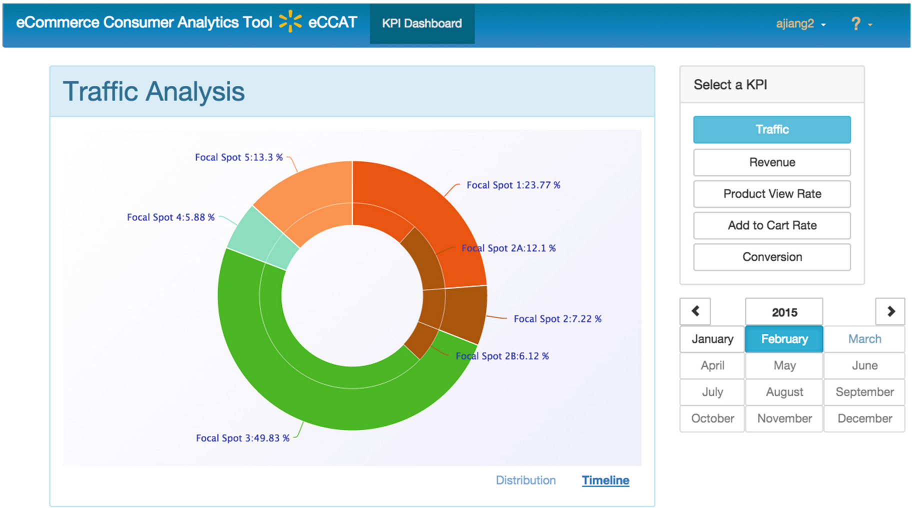
Once sessionization of activity records is complete, multiple types of analyses can be carried out to discover important business insights. A report can be generated by counting the number of times a page is viewed, the number of times the page is converted, the number of times the page is driving traffic to other pages in the endpoint and other metrics and aggregated to analyze the performance of a given focal spot. The set of metrics upon which focal spots and their respective constituent pages are evaluated are considered key performance indicators (KPIs) which are directly associated with business impact. Each page within the focal spots can then be sorted in order of a certain metric, for example conversion, to identify the pages with the worst performance. We define these distinct pages as focal points, and they represent specific opportunities for improvement.

4 eCommerce Consumer Analytics Tool (eCCAT)

Data visualization is crucial to understanding any domain's performance over time and the key components that contribute to the advancement of that domain [6]. The eCommerce Consumer Analytics Tool (eCCAT) pairs this domain data visualization with display interaction to allow decision makers, regardless of formal training or in-depth knowledge of the domain map, to understand the performance of the endpoint, its focal spots, and take direct actions on focal points. We choose to elevate focal spots out of all pages within the eCommerce endpoint to create maximally informative visual analytics to eliminate information overload without compromising utility. Business problems are frequently evaluated on a comparative basis, which can be either broad or specific, encompass confirmatory or exploratory analysis, and serve several use cases from reporting to specific problem solving. The complexity and variety of these problems makes visual analytics fundamental in fine-tuning the decision-making process [7]. To accommodate for these possibilities, we created an interactive visual interface with automated data analysis that is agnostic to cognitive styles while retaining a level of intuitiveness from problem-solving heuristics that is consistent with making business decisions.

As shown in Figs. 1 and 2, the eCCAT incorporates three main styles of data visualization: 1. Relative contribution, 2. Time series, and 3. Tabular data. Each visualization provides information that is key to making a decision and is augmented with interactive devices that allow the decision maker to segment information by various dimensions such as time aggregated on, KPI metric, and focal spot on the fly.

As a result, the eCCAT is used as a problem-solving partner, answering questions (explicit or implicit) posed by the decision maker who supplements the information with his or her domain specific knowledge. The supplement of visual analytics to the business domain, regardless of specificity of function, can lead to advances in the domain itself through effective decision making and improved understanding [8].



Top Opportunities for Focal Spot 2A

Show Metric Definitions

Focal Points	Count	Conversion	Product View	Add To Cart	Score
Focal Point 1	99	22.22%	57.58%	40.40%	42,205
Focal Point 2	105	20.95%	50.48%	31.43%	5,022
Focal Point 3	117	24.79%	58.97%	41.03%	43,085
Focal Point 4	121	19.01%	57.58%	40.40%	42,205
Focal Point 5	165	20.61%	59.33%	36.89%	126,456
Focal Point 6	98	6.12%	82.65%	14.29%	134,841

Fig. 1. Relative contribution of focal spots and tabular display of key focal points and its KPIs

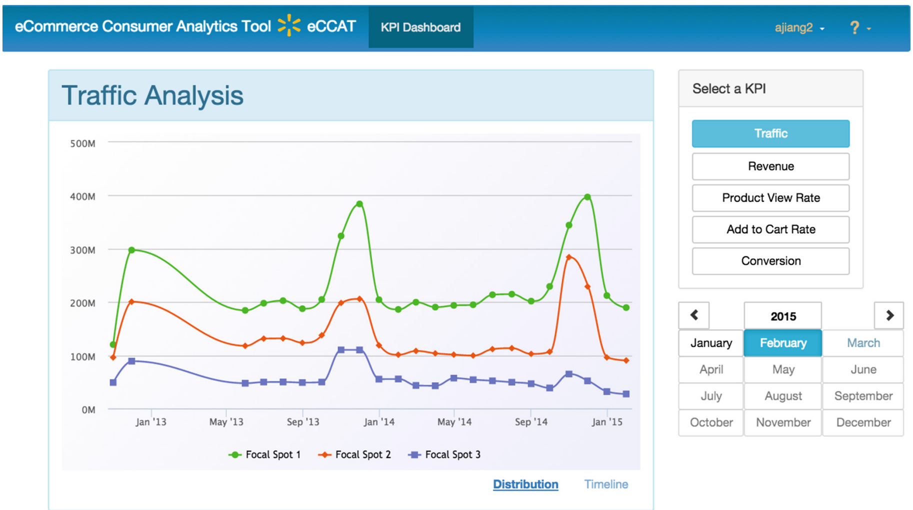


Fig. 2. Time series visualization of focal spots and interactive devices

5 Conclusion

eCommerce plays a vital role in the retail industry. This paper proposed a mechanism to identify focal spots in an eCommerce platform called eCCAT. The eCCAT system incorporated analysis of data derived from sessionization of user activity records obtained from web beacons. Aggregation and time series of key performance indicators allowed us to generate analysis of focal spots. A visual analytics interface replete with interactive devices and data visualization, agnostic to cognitive problem solving styles, was created to surface information about focal spots directly to decision makers.

For future work, a statistical time series model could be built to monitor the change in a KPI metric to discover focal points automatically. Particularly, the metric within a specified time window can be used in fitting a time series model (e.g. autoregressive integrated moving average model). When a model that fits data well is found, a one-step prediction interval is constructed. The new observation will be compared with the predicted interval to determine whether the value is significantly different (in the statistical sense) from the underlying structure of historical data. If such difference is found, a focal point is discovered and attention should be paid to dive deeper into the time point of change to determine the cause of change (especially for negative ones), e.g. data logging errors, site issues, external factors, etc. Finally, as new observation becomes available, the model is fitted again with the time window slid forward to cover new data. This 'fit-predict-slide' cycle repeats as new data arrive since site performance itself will change as a result of new features deployed.

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