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Extended abstract

Data proliferation in the retail industry enables data-driven segmentation systems that support retailers to embrace more customer-centric strategies. This research is motivated by the abundance of data reflecting the buying behavior of retail shopper and utilizes them for identifying shopping patterns. These patterns correspond to different shopper segments with specific preferences that may guide tailor-made services. In this context we propose a shopper segmentation approach that highlights the shopping intentions of consumers that motivate them to visit the stores. Our approach proposes a holistic view of the consumer shopping attitude that sees beyond the consumer's entire sales history or associations of the purchased products. We move the attention from the purchased products to the shopping needs that motivate the shopper's shopping trips and, in particular, we translate shopping basket per visit to shopping intention per visit. We adopt a broader perspective of shopping trips and we delve into the product categories in shopping baskets to reveal the shopping intention behind each basket. While other researchers view shoppers just as associations of product items i.e. cereals→ milk (e.g. Cil, 2012; Srikant & Agrawal, 1995;) or as a bulk of visits(e.g. high spending shoppers) (e.g. Aeron et al., 2012; Boone & Roehm, 2002; Han et al., 2014; Liao et al., 2011, Park e t al., 2014), we want to give a description of the consumers' behavior during their visits.

We applied to and validated our approach through two heterogeneous retail cases to demonstrate its generalizability. The first one concerns sales data from different channels and stores of a major fast-moving consumer goods (FMCG) retailer. The second one concerns sales data obtained by the physical stores of a Fortune 500 specialty retailer of home improvement and construction products – also known as do-it-yourself (DIY) retailer. Applying our system's segmentation approach to two heterogeneous retailers, we identified and assessed how different retailer (e.g. shopping channel/ place, product brand), shopper (e.g. basket variety, volume) and data (e.g. data variety, volume) features affect the design and application of shopper segmentation systems. We highlight those features/elements that prospective practitioners and academics should consider if they want to conduct successful shopper segmentation analysis. We detected various data characteristics (e.g. data variety, basket variety, and shopping channel) that affect both the data mining results, as well as the translation of the shopper visit segments to shopping intentions.

Delving deeper into the literature, we identified studies mainly in the marketing domain (e.g. Bradlow et al., 2017) that discuss several features that affect big data analytics systems in general. However, they do not present evidence of how these features affected relevant segmentation cases. Also, in the IS literature, there is a great majority of papers (e.g. Aeron et al., 2012; Boone & Roehm, 2002; Boztuğ & Reutterer, 2008; Miguéis et al., 2012; Rust & Huang, 2014) that perform shopper segmentation. Though, to the best of our knowledge, authors describe their own case and not "the bigger" picture, i.e. how system inputs and features (e.g. data) affect and alter the segmentation process, system and results/outputs; it is only implied, and they do not discuss how different features affected segmentation results. In our interdisciplinary study, we

identify all these features that the marketing literature has highlighted for studying consumer behavior and shopping habits. Thus, this research also aspires to bridge marketing researchers and managers with data scientists. The consumer segmentation analysis and its results should be both handled considering the "marketing" characteristics of the shoppers and the retailers. Especially the accumulated experience of the marketing managers and their intuition is necessary for a reliable, meaningful interpretation of the shopper segment results.

Figure 1 summarizes the features affecting each phase of shopper segmentation. As shown, the translation layer is the one that is affected by most of the features. At this phase to extract wisdom from the results, we need experts' opinion that know the market. Experts not only consider the tangible, quantitative features (e.g. value, volume etc.) to identify shoppers missions and motives, but also intangible elements such as their domain knowledge and accumulate experience. Likewise, we could claim that variety is the most important feature that affects all the phases of our approach, from the outliers' elimination, and the product taxonomy calibration, to the identification of the unit of analysis and the translation of the results into insights. Closing, we should mention that price feature didn't affect our segmentation. First, it wasn't available in all our cases, secondly even in the FMCG case, that was available it didn't influence our results. Hence, we partially confirm existing literature that admits that price feature plays an important role in more particular products e.g. cars.

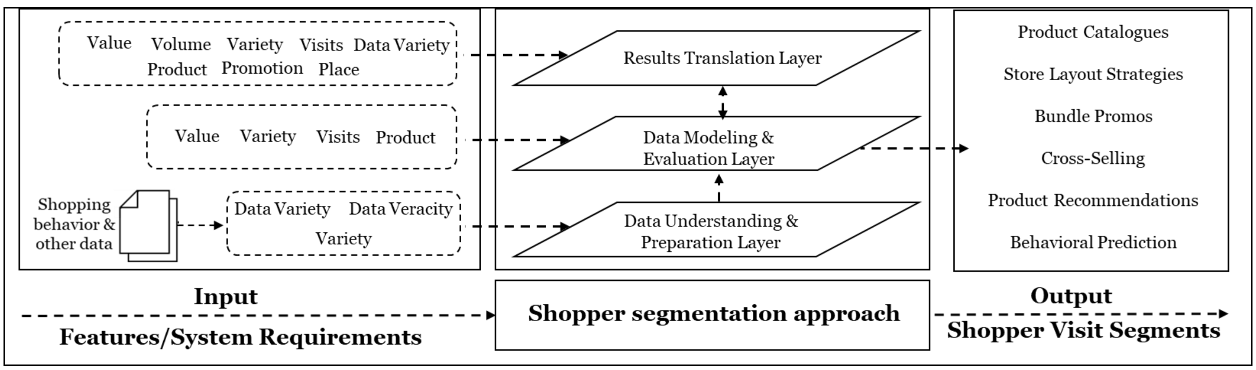

Figure 1. Shopper Segmentation system

Moreover, the two cases revealed that the units of analysis used in the literature, i.e. product items in a single visit, or all shopper visits, are not sufficient and applicable in every retail context, but there are cases where we should examine groups of "x" sequential visits. The value of "x" differs according to the domain the data derived from. As we proved and as other researches support (Wolf and McQuitty 2011), a shopper usually visits a retail store that sells products for home improvement many times and purchases few materials each time. We devise and test a new unit of analysis where we examine groups of x continuous visits. This intermediate unit of analysis is dictated by the particularity of some retail domains that demand many store visits during small time windows.

Regarding the value of such a system, it is stressed when considering the consumer-oriented business decisions it can support. Our approach/system could be evolved into to a tool for designing innovative marketing campaigns and bundled promotions and cross-coupon programs for product categories that belong to the same shopping visit segment. Likewise, we can create offline and online product catalogues. For instance, we have detected women that a professional visit a DIY store for to purchase woodwork products. Thus, to promote the new collection, it could be more effective to send them product catalogues that meet their specific preferences, instead of including all the products. Additionally, the extracted knowledge could be valuable for advertising purposes; e.g. breakfast products advertisements. On the other hand, it might be used to dictate a new redesigned store layout where product categories in the same visit segment are positioned in nearby store aisles and shelves. This way shoppers will locate products more easily and buy more in less time. Further, the store manager could reengineer store operations management and replenishment strategies by ordering groups of products based on the identified visit segments (Griva et al., 2018). Last, predicting future behaviors and missions based on historical data can support several operations e.g. product replenishment, out of stock situations.

Future research may address some limitations of this study e.g. cases where the purpose of the visit is to return items, or buying as a gif etc. Also, we can use data derived from alternative technologies (e.g. Radio Frequency Identification-RFID, Global Positioning System-GPS) to evaluate the proposed approach. For instance, data that indicate the shoppers in-store movements and the product categories they interact with during a visit. Then comparing the resulting visit segments from POS and the IoT (Internet of Things) data we can identify the selling gaps. From a technical perspective, we can apply more data mining techniques and compare the resulting visit segments. Also, other techniques e.g. graph mining could also be examined to further analyze each resulting segment and cope with the difficulty to identify more detailed segments in the DIY.

Keywords

Shopper Segmentation, Retail Analytics, Shopper Behavior, Cluster Analysis, Data Mining

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