



ISSN: 2723-9535

Available online at www.HighTechJournal.org

HighTech and Innovation Journal

Vol. 4, No. 3, September, 2023



Big Data Analysis using Elasticsearch and Kibana: A Rating Correlation to Sustainable Sales of Electronic Goods

Henderi Henderi ¹, Ranty Irawatia ¹, Indra Indra ², Deshinta Arrova Dewi ^{3*},
Tri Basuki Kurniawan ^{4, 5}

¹ Department of Informatics Engineering, University of Raharja, Indonesia.

² Informatics Technical Department, Universitas Budi Luhur, Indonesia.

³ Faculty of Data Science and Information Technology, INTI International University, Nilai, Malaysia.

⁴ Faculty of Science and Technology, Universitas Bina Darma, Indonesia.

⁵ Faculty of Technology and Information Science, Universiti Kebangsaan Malaysia, Malaysia.

Received 14 June 2023; Revised 13 August 2023; Accepted 19 August 2023; Published 01 September 2023

Abstract

Big data collection involves enormous amounts of raw data. To boost the sustainability of corporate value and support business intelligence and decision-making systems, in-depth data analysis is necessary. The data storage, analysis, and visualization methods, as well as the discovery of patterns and linkages, all depend on extensive data analysis. This study aims to process datasets to learn things like how ratings impact market sales transactions and how much of an impact factor connected to consumers and items have on ratings. Elasticsearch and Kibana were used for the dataset processing. This study evaluated traits related to the test parameters using a variety of test procedures. The product is scored as a representation of the product types involved in the sales transaction, and the name is assessed as a reflection of the customer. Kibana and Elasticsearch, a full-text search engine, were used in this work to do extensive data analysis on data sets. It is a visualization tool that is employed in a controlled environment to evaluate how ratings impact market exchanges for electronic goods, and it offers suggestions. The study found a substantial relationship between electronic product sales on the Amazon marketplace from 2012 to 2018. It suggested the importance of buyer constituents as users and how different product categories relate to ratings in business transactions.

Keywords: Big Data; Elasticsearch; Kibana; Rating; Decision-Making; Process Innovation; Consumers; Sustainability.

1. Introduction

Big data alters the way that data architecture and operational models are thought of. Big data has developed into a crucial component of intelligence and creativity, with the potential to improve our lives and open new possibilities for contemporary society [1]. Businesses from all industries are starting to recognize the underlying value and commercial viability of their data distribution [2]. Big data involves gathering enormous amounts of raw data. It supports corporate intelligence aids in the provision of information [3], facilitates decision-making [4], and helps create better and more manageable decisions based on information [5]. A thorough investigation of the data, including its storage, analysis, and

* Corresponding author: deshinta.ad@newinti.edu.my

<http://dx.doi.org/10.28991/HIJ-2023-04-03-09>

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support for effective visualization, is necessary in this case [6]. To boost business value, in-depth data analysis is necessary [7, 3]. The big data paradigm is firmly established as the industry's dominant force, and it offers significant advantages for both business and research when massive volumes of data are operated on [8]. However, it can be like looking in an ocean to uncover meaningful information in these data [9], and huge data does not lend itself to or respond well to standard methods of analysis and extraction [10].

Big data analytics, as used in this definition, is a methodical strategy for examining and determining the various patterns, relationships, and trends present in a significant amount of data [11]. Alternative approaches are needed to partition enormous data into manageable chunks that can be directly used as representative samples of the complete data set in big data analysis [12]. Thus, big data plays a crucial role in determining which traditional and non-traditional data can generate profits [13]. Big data is a new technology that must be used to improve the deal plan's efficiency and support the branding strategy in outbound efforts [14]. The implementation of big data analysis, on the other hand, necessitates the use of effective interactive data visualization software that offers a complete image and has quick performance, scalability, and processing time.

Utilizing big data analytics and tools to draw forth knowledge and patterns that can aid in decision-making and offer value to the company [15]. To store, analyze, and retrieve data in real-time or non-real-time, however, the present relational database is no longer able to match these demands [16]. A distributed search and analysis engine called Elasticsearch is a big data database system [17] that may be used to conduct big data analysis on the data [18].

Elasticsearch is a Java-based, server-based full-text search engine that was derived from Apache Lucene [19, 20], [21], with a document-based data storage approach and a distributed search engine design [22]. Elasticsearch's real-time statistical queries and great scalability enable speedy data processing and discovery [21]. The use of big data analysis in sales models through the marketplace, where the development and growth of information technology are accelerating quickly and have changed activities and purchasing habits, also plays a significant role. With the speed and expansion of internet use, consumer behavior in terms of shopping has changed. It can discriminate between in-person purchases and product marketing [23], and consumer preferences for e-commerce and retail services have an immediate impact on both channels for buying and selling [24].

Extraction and analysis of transaction data can be done to achieve marketing and sales strategy optimization [25]. To assess business performance in a way that benefits both customers and the products of manufacturers, it is necessary to have an awareness of the features of consumption and the relationship between the sale of various items by various consumers [25, 26]. Data-driven analysis replaced the conventional paradigm based on experience or experience-driven analysis [27]. According to studies on big data and online product prediction, further study is needed to fully understand how ratings affect sales volume. In contrast, the other study claimed that ratings are more important to prospective customers' decisions than product costs [28, 29]. Elasticsearch and Kibana were used in this study to gather data on the relationships between ratings and related elements in the transaction pattern for the sale of electronic products. Additionally, this research intends to support strategic decision-making.

2. Materials and Method

This study uses datasets of the Kaggle repository in CSV format obtained from Amazon's online marketplace from 1999-2018. It contains 1,292,954 transactions, 9,436 product items, and 1,162,405 users. The research infrastructure uses a containerization model with docker 20.10.7 build 20.10.7 ubuntu5~18.04.2, Portainer version 2.9.0 as container orchestration, and Docker images Elasticsearch 7.17.0 and Kibana 7.17.0 in the Ubuntu Linux Desktop 18.04 LTS operating system and for hardware. It involves 2 CPU cores of 3.0 GHz, 8 GB of RAM, and 512 GB of SSD storage media.

The Elasticsearch solution was chosen because it has great scalability [21], can handle massive volumes of data with hundreds of millions of levels with optimal performance, and can manage both structured and unstructured data. It can also process and find data quickly through real-time statistical queries. This study uses Elasticsearch, which is used for searching and indexing, in accordance with research on Twitter sentiment analysis [30], and Kibana, which is used for monitoring and visualizing technological developments [3, 31]. The Elasticsearch technique used in this study was created and put into use to address market-related data-related concerns, although with different data [32].

Five phases were used to conduct the test. Mapping the overall transaction pattern comes first, followed by establishing the rating pattern and the relevant attributes, and last, confirming the function and involvement of each feature in the rating. Each test model is put to the test while taking several variables into account, including accessibility, dependability, correlation, and attribute validity. As illustrated in Figure 1, technical testing was performed for each test model utilizing a visualization model according to the type of attribute investigated. The proposed big data analytics with laboratory exercise [33] was selected as the basis for the technical testing in this study.

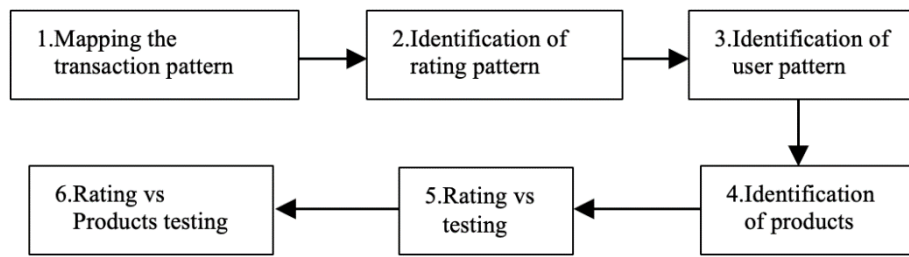


Figure 1. Testing stage

2.1. Data Import and Creating Index Pattern

In the first stage, datasets in the form of CSV are imported into Elasticsearch, and an index pattern is created with the name `elk_amazon_2021`. Proof of the imported data is done using the terminal console with the command:

```
{curl curl elasticsearch_IP_address:9200/_cat/indices?v/}
```

2.2. Determining Time Interval using Discover

In this stage, modeling is carried out with the Discover feature on Kibana by plotting the data with the index pattern `elk_amazon_2021`. Visualization using Discover, in Figure 2, shows the transaction pattern has increased from 2012 to 2015 and appears to have decreased from 2016 to 2018. This stage is in line with the previous research [34] because pre-processing the data into an intelligent format facilitates the practical analysis of the volume of data transactions.

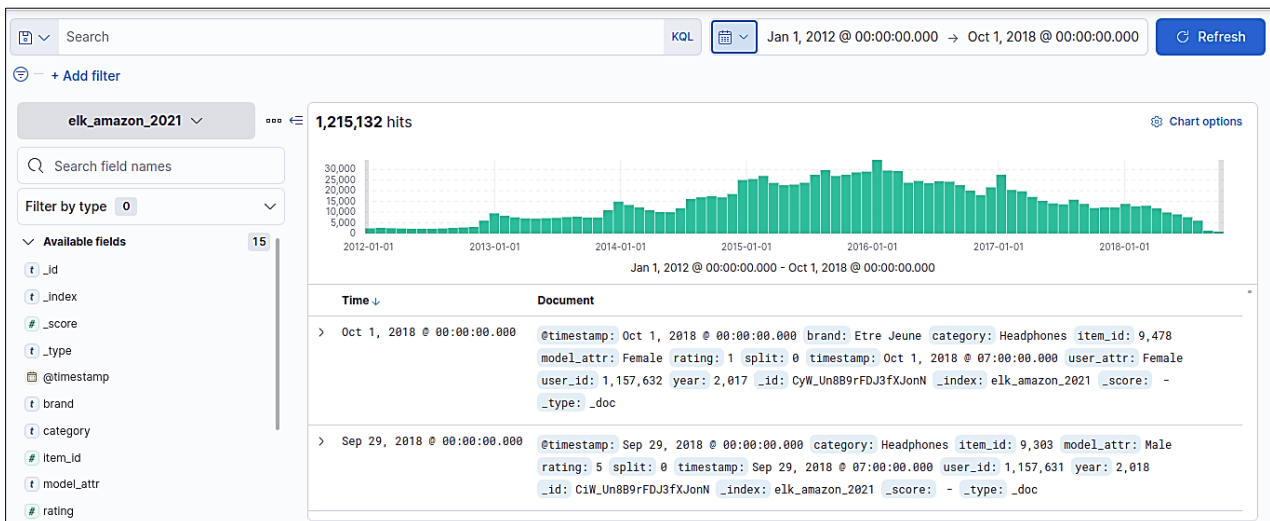


Figure 2. Transaction Pattern using Discover on Kibana

2.3. Attribute Testing and Rating Attribute Testing

The evaluated attribute affects the transaction. The study's focus property is the rating attribute, with the timestamp attribute serving as the transaction period, the user ID serving as the transaction actor, and the item ID serving as the transaction object. Each test's time interval argument will be the timestamp attribute. The rating attribute testing is then designed to determine whether rating characteristics are correlated with transaction patterns over time as determined by the findings of the Discover index `elk_amazon_2021`. Model testing is carried out utilizing Kibana's TSVB and Lens for visualization. To find the link between the volume of customers and the pattern of sales transactions, testing is done on the user ID attribute to gather information about attribute reliability. To determine the association between a product and sales transaction patterns, testing on the item ID attribute is carried out to gather attribute reliability information. Kibana's Lens visualization is used for testing. Five testing stages are shown in Fig. 1 and testing is carried out utilizing Kibana's Lens visualization.

3. Results and Discussion

As seen in Figure 3, the rating function on sales transactions is revealed by mapping the rating property with the bar vertical stacked mode. As can be observed, from the start of 2016 to 2017, the pattern of transactions from 2012 to 2015 had a very sharp growth. In terms of transaction patterns for 2015 and 2016, there are interesting developments. Transactions started to fall gradually and then quickly till October 1, 2018. The results clearly show that Elasticsearch and Kabana can manage massive data volumes with hundreds of millions of levels while still performing at their best.

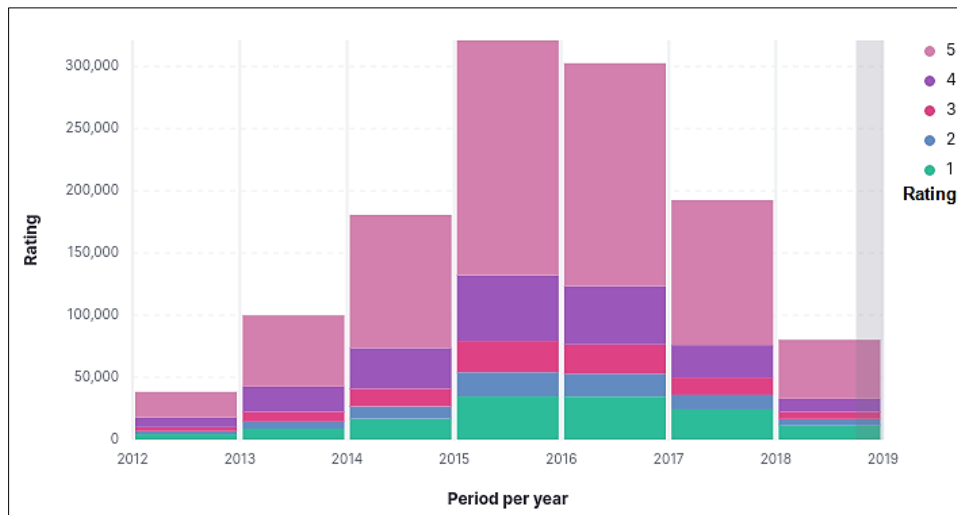


Figure 3. Rating pattern on sales transactions from January 1, 2012 – October 1, 2018

According to earlier studies by Mu et al. [25], the data about marketing and sales success from extracting and analyzing transaction data in this study can be utilized to influence judgments about strategy optimization. The number of sales transactions dropped significantly in the 2016-time frame. Till 2018, it was in effect and figure 3 depicts the drop, which appeared abrupt and was accompanied by a reduction in the rating of five. The difference between ratings one through four does not differ significantly from the difference between ratings five cumulatively.

As illustrated in Figure 4, the test results on the user-ID attribute, which represents the number of purchasers participating in the transaction, create a visualization with a pattern resembling the outcomes of the rating visualization. It demonstrates how the rating affects the total density of purchasers. Additionally, there was an increase in the total ratings in Table 1, which describes the transactional pattern over the course of three years (from 2012 to 2015).

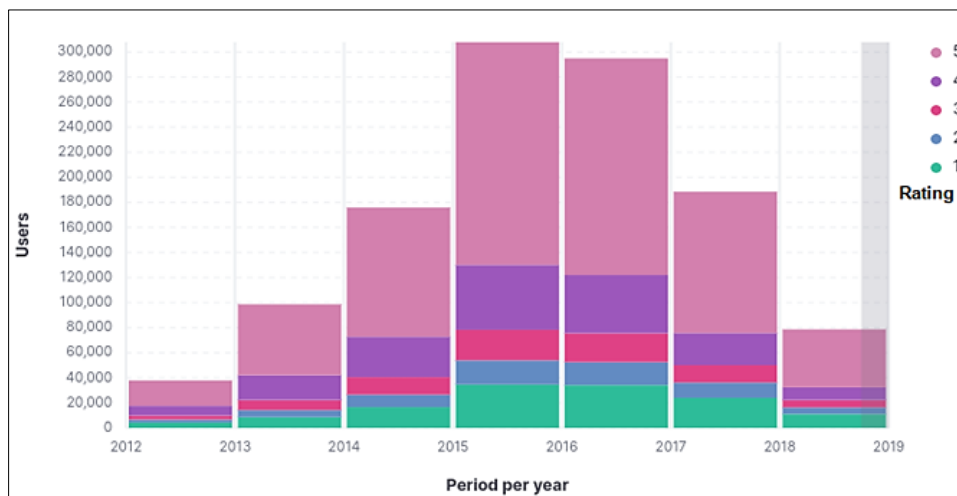


Figure 4. Consumers are affected by rating

Table 1. Sum of rating period January 1, 2012 – October 1, 2018

<i>Periodic Rating Table: 1 Jan 2012-1 Oct 2018</i>					
Periode per year	1-Rating	2-Rating	3-Rating	4-Rating	5-Rating
2012	4,297	2,468	3,196	7,733	20,695
2013	8,688	5,630	8,158	20,106	57,273
2014	16,664	10,007	14,184	32,670	107,151
2015	34,750	19,413	25,163	52,737	188,824
2016	34,604	18,433	23,333	47,077	179,172
2017	23,979	11,964	13,968	26,050	116,498
2018	11,172	5,234	5,928	10,339	47,466
Sum:	134,154	73,239	93,948	196,712	717,079

Additionally, Figure 3 demonstrates how Elasticsearch and Kibana were combined to fully understand and visualize the data in accordance with Bhatnagar's findings [3]. This conclusion is also consistent with another study [28] that claimed that ratings, rather than product costs, play a more significant impact in prospective purchasers' decision-making. Customers frequently find it impossible to read every review before choosing a product [35].

The transaction fell gradually from the beginning of 2016 to 2017 and then decreased again till October 1, 2018. The finding suggests a strong relationship between the rating on the Amazon marketplace and patterns of buy transactions. This finding backs up the other study's [36] assertion that most consumers start out with firm buy intentions. Elasticsearch has the best speed for handling enormous amounts of data with hundreds of millions of levels.

The data in Table 1 shows that the researchers discovered a correlation between ratings and relevant components in the market's pattern of electronic product sales transactions. When used in decision-making processes, this information can assist and enhance business intelligence [3, 4]. This knowledge is useful and may be used to advise possible business decisions [9].

In this study, key-value structures are used to help in querying and analysis so that relationships between data can be better described [20]. Figure 5 illustrates the item-ID property as a key-value structure. According to these findings, Elasticsearch might be utilized to create a system for extracting data from descriptive columns, similar to previous research [37].

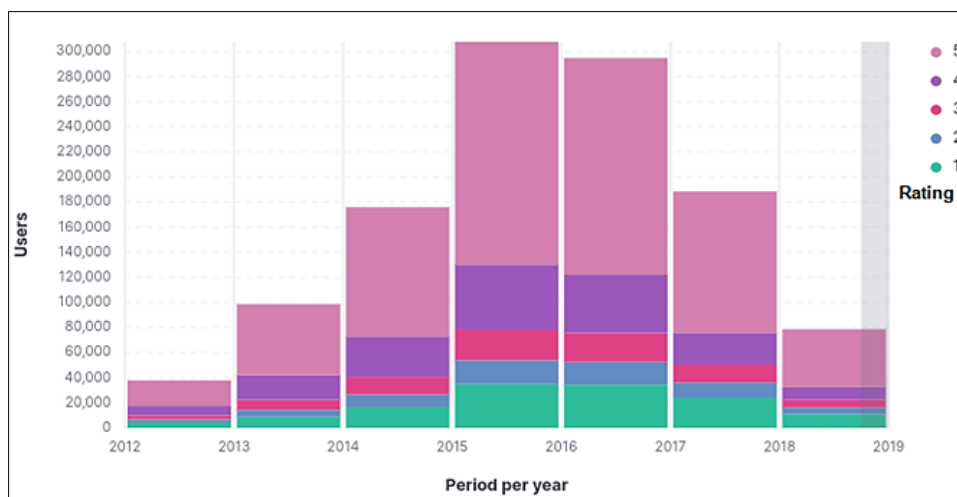


Figure 5. Rating affected by product

It is interesting to observe that the cumulative density of product types does not affect the rating significantly. It indicates that the product type does not significantly influence the pattern of sales levels. Also, that reflects the cumulative types of products involved in the transaction and provides a pattern that is not much different from the rating pattern. This information can help an individual make slow operational decisions, not in line with real-time visualization, which can be helpful for quick operational decisions.

Table 2 demonstrates that a rise in rating is accompanied by an increase in the accumulation of product items and vice versa. As a result, there is a strong association between rating and the increase of product item kinds throughout the course of five years of transactions. Making the best choice for the sales product item type and maximizing decision-making inside the business unit can both be accomplished using this information [38].

Additionally, Table 2 demonstrates a strong association between the rating and the categories of product items involved in the transaction. Furthermore, modifications to the rating pattern have a big impact on the accumulation of the different kinds of goods that are purchased. The strength of Elasticsearch, which preserves important business insight and offers tools for data analysis, delivers this information, enabling the executive or management to make a probable business decision.

Elasticsearch and Kibana are used in this study as a part of the big data analysis approach to account for features like volume, visualization, vagueness, and complexity as well as to foresee the usual statistical computations, which are less useful in the big data context. The findings, meantime, can address the involvement, influence, and rating correlation on the volume of sales of electronic goods that big data has suggested. On the other hand, this study expands on a perspective on the connection between product types and ratings on sales that are based on earlier research and cites the rating perspective on product pricing [28].

Table 2. Periodic rating versus item ID

<i>Periodic Rating vs. item_id</i>					
@timestamp per year	1-items	2- items	3- items	4- items	5- items
2012	877	698	828	1,177	1,629
2013	1,403	1,222	1,462	1,959	2,675
2014	2,504	2,048	2,427	3,193	4,496
2015	4,243	3,528	3,988	5,073	6,919
2016	4,190	3,310	3,784	4,612	6,446
2017	3,167	2,277	2,558	3,061	4,893
2018	1,946	1,385	1,506	1,812	3,175
	Sum: 18,330	Sum: 14,468	Sum: 16,553	Sum: 20,887	Sum: 30,233

The findings of this study are consistent with other studies [27] that claim that the analytical mechanism moved from the conventional idea based on experience, namely experience-driven to data-driven. The findings of the data visualization research are consistent with studies on monitoring and visualization using Kibana [3] and big data [39], which suggested a software solution for visual analytics utilizing Elasticsearch and Kibana.

The organization also benefited from this study's increased efficiency and decision-making [40], particularly in sales and marketing, and it also looked at how well-prepared the field of communication is to deal with the effects of big data. This study established how big data can be used to analyze both conventional and unconventional data to generate revenue [41]. This study showed that big data is a new technology that must be implemented to relieve the marketing strategy in outbound campaigns, reconfigure the deal plan to make it more effective [14], and has a significant impact on management and technology as well as give a wider impact on the industry's preparedness [13].

4. Conclusion

Particularly given the amount, pace, and variety of data in numerous sectors, big data will play a more and more important role in the future. To make the best conclusions possible, big data analysis must be handled quickly, utilizing cutting-edge analytical methods. Additionally, choosing an infrastructure that meets its requirements is essential for big data analysis. In anticipation of conventional statistical computations in the setting of big data, this study suggests employing a combination of Elasticsearch and Kibana as integrated tools in data processing. This study produced several conclusions, including a suggested remedy for the function and correlation of ratings on sales transactions. Another result is that there is a definite correlation between sales and the total number of purchasers and ratings. On the plus side, the rating has less of an impact on the product type overall. The total density of product types has little impact on the ranking. This fact puts into context the study's findings that sales volume and rating are correlated.

5. Declarations

5.1. Author Contributions

Conceptualization, H.H.; methodology, H.H.; software, T.B.K.; validation, H.H., D.A.D., and T.B.K.; formal analysis, H.H.; investigation, D.A.D. and T.B.K.; resources, R.I.; data curation, I.I.; writing—original draft preparation, H.H.; writing—review and editing, D.A.D.; visualization, D.A.D. and T.B.K.; supervision, T.B.K.; project administration, R.I.; funding acquisition, H.H. and D.A.D. All authors have read and agreed to the published version of the manuscript

5.2. Data Availability Statement

The data presented in this study are available in the article.

5.3. Funding

The present research is funded by the University of Raharja, Indonesia, and the INTI International University, Malaysia.

5.4. Institutional Review Board Statement

Not applicable.

5.5. Informed Consent Statement

Not applicable.

5.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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