International Journal of Engineering & Technology, 7 (4.31) (2018) 266-271

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Price Changes Analysis Using Association Rule Mining on Online Shopping Portals

Aini Atikah Baharudin[1], Sofianita Mutalib[2*], Nurzeatul Hamimah Abd Hamid[3], Nor Hayati Abdul Hamid[4]

Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA,
40450 Shah Alam, Selangor, Malaysia
**Corresponding author E-mail: sofi@tmsk.uitm.edu.my*

Abstract

In the recent years, the growth of online marketplace explodes and has become the new norm of shopping. Access to the internet allows consumers to visit local and global online marketplace. By using online shopping, consumers can view the latest products and comparing products' prices. Online marketplace offers flexibility and eases consumers in so many ways. On the contrary, it also has some limitations. Dynamic pricing allows sellers to enhance their marketing strategy by ensuring price competitive with other sellers. The frequent occurrence of real-time price changing limits the user to get the best deal. This paper discusses the analysis of price changes using Association Rule Mining. Price-ChARM finds a frequent pattern of price changes in corresponding to different timelines. On the online marketplace, due to multiple sellers can sell the same item with different offers such as delivery speed and dynamic pricing, the comparison can be quite tricky. We collected data from two well-known portals and we represent the dataset as set of prices for different products for the purpose of frequent itemset mining. We implement the Apriori algorithm and use a total amount of 3,960 records. We generate association rules from the frequent itemsets found in the records and visualize the confidence of 0.9 rules. The association rules represent the pattern of price changes in the portals. This study eases consumer shopping experiences by understanding the trend of price changes to provide a better decision in making a purchase.

Keywords: *Apriori Algorithm, Association Rule Mining, Dynamic Pricing, Tracking*.

1. Introduction

Online shopping shapes an advanced technology in e-commerce such as the hybrid marketplace that enables digital marketing. Online sellers create numerous alternatives to lure consumer towards the product. These alternatives also serve as a strategy to catch the consumer attention about their businesses. Recently, price comparison websites have become the new services that find the best deals online. The comparisons are ranges from hotel bookings, airline tickets, and insurances. With the increase in the e-commerce market, it is prone to compare consumer products' prices. Dynamic pricing strategy used in the most online marketplace. It allows a seller to set their price based on the demand and supply to stay competitive. As most consumers notice the price changes, they tend to use price comparison sites to find the best offer.

Hence, this paper discusses mining the change of prices of several types of handbags from different timelines using a significant amount of dataset. We use Apriori algorithm to analyze the price changes and to identify the most frequent price patterns. This method can be included in a monitoring framework for pricing information. Price-ChARM is a workflow for rule analysis of product prices that available in online shopping portals. Price-ChARM depicts the pattern of price changes according to different times. Price-ChARM applies method to produce association rules that shows the correlation between prices of products that scraped from online portals. The rules represent a meaningful pattern for the user, so that she/he can benefit the information and reduce self-monitoring time through the portals. In user perspective, if the product price is discounted, it could be best time to buy the item. The rest of the paper is organized as follows. The description of research overview is given in Section II and related studies in Section III. Section IV describes the methods; Section V elaborates the results and Section VI discusses the results. Finally, the conclusions are presented in Section VII.

2. Research Overview

The nature of shopping has gone through a big revolution. It grows from conservative brick and mortar shops to e-commerce clicks and mortar (offline to online store) and telemarketing. With a tremendous growth of the Internet, the online marketplace has taken place in consumer attention and has become a trend in a fast pace [1]. It is a place where items are sold in a variety of shapes, types, and price. Online marketplace provides benefits of online shopping, which is undeniable as it saves a lot of time to purchase item rather than practising a normal physical activity in traditional shopping [2]. It simplifies item search and shopping effort.

An item can be found online just by a simple click of a mouse. It only requires a visit to websites that sell merchandise followed by some steps done by fingertips to make a purchase and eventually, the item will arrive at your doorstep. A few procedures needed in the process of buying an item online and it may require some time to wait. The flow of purchasing an item online is just choosing the item desired, make payment, and departure for delivery of the item purchased. An example of world famous online marketplace is Alibaba that has become the largest online marketplace to sell merchandise for domestic or international products [3].

Alibaba.com is an international online marketplace that mainly focuses on importers and exporters globally [4]. It represents the most successful online marketplace that currently existed.

2.1. Online shopping in Malaysia

Online shopping consumers have a variety of choices and consumers are prone to a wider scope of information for the product through a better access [5]. There are three main reasons for a consumer to shop online. Firstly, in terms of time, location and the purchasing process seems to be easier as compared to traditional shopping. Secondly, the competitive prices offered by online retailers could attract consumer attention instantly. New online retailer tends to set for a lower price to attract the consumer. And lastly, the selection of product is diverse as there is no physical space limit for online retailers to store their products [5]. Consumers are motivated to use online shopping as a platform to compare prices which promotes the use of online shopping activity. Based on the findings, the higher frequency of purchase to an online retailer will offer more chance to get repeated visits by the same consumer. In Malaysia, online shopping via television or telephone is also considered as online shopping. In 2017, Malaysian e-commerce sectors have recorded a total trade of RM1.77 trillion. The trade is expected to reach RM2 Trillion in 2018 [20].

2.2. E-Commerce

The usage of internet is growing day by day and consequentially the usage of e-commerce starts to bloom [6]. Despite the trust issues on the websites, lack of physical touch and visual aid trigger the negative effects towards consumer when using the e-commerce [7]. The figure below shows the flow of online marketplace in Malaysia.

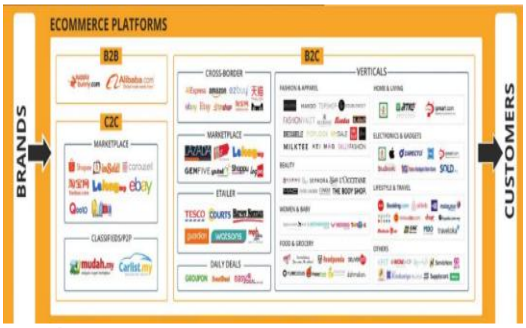

Fig 1: Malaysia E-commerce overview (E-Commerce IQ, 2016).

From the figure, there are three types of business lies underneath e-commerce platforms which are business-to-business (B2B), customer-to-customer (C2C), and business to customer (B2C). From the brands to the customers' hand, the flow of e-commerce can be illustrated in a single process with an existing of market research, consulting, e-commerce software, marketing and goes into the type of business before proceeding to payments and logistics and reach customers' hand. This encouraged suppliers to produce creative ideas about planning marketing strategies to attract shoppers [8]. Unlike traditional shopping, more information is provided on the Internet for online shopping since there is no physical contact or surroundings with the product or staff. Information is updated from time to time to ease user choose the item and provide options for the consumer to support decision making by the consumer for using e-commerce (e.g., price comparison) [9].

2.3. Customer Behaviour

Four main reasons for the choices consumer make before purchasing products are motivation, perception, earning and belief [9]. Kooti et al. [10] stated that based demographic factor which is age, the tendency of online shopping increases as the consumers get older, it gets to the highest peak in between age 30 to 50 and slowly dropping down afterwards. They added, in terms of social factors, social networks have been identified to be one of the reasons in developing consumer towards online shopping because it is the platform of sharing thoughts and stories and consumers who are socially connected are likely to share their experience of online shopping on social media compared to the ones who are not socially connected. Consumers behavior are shaped by the motivations they get such as finding the best deal, the convenience of online shopping, product promotions, information displayed and the quality of the service but different motivations hold different categories of consumer [11].

2.4. Pricing Strategy

To gain profit, the seller needs to put the price low to increase sale probability but the starting price usually high to maximize revenue. Hence, the seller has to balance out the sale probability and revenue maximization [12]. One of the pricing strategies is dynamic pricing which allows changing of prices for similar products. In addition, it has become so popular on e-commerce but produced negative impacts such consumers' dissatisfaction and affects the sellers' reputation from the negative information spread by the consumer [13].

3. Related Studies

The purpose of Association Rules Mining is to find all the rules in a market basket data which is known as transaction data and to determine how frequent items are purchased by the customer in one transaction per customer [14 – 15]. Aggarwal and Yu [14] also stated that the idea of an association rule is to make user interpret the presence of some sets of items, with another presence of an item in a transaction. He added, this information is going to be useful in customer targeting, sales promotions and shelving. Let say if a person wants to buy item X, he tends to buy item Y, it produced a relationship between the items. The association is accepted as a rule, when the association rule is over user-specified minimum support and minimum confidence [14, 16]. Association rule mining includes two main processes [17]:

- Finding all frequent itemsets with certain support value in the transactional data.
- Generating strong association rules from the frequent itemsets that meet confidence threshold.

A rule is defined as an implication of the form $X \rightarrow Y$, where $X, Y \subseteq I$ and $X \cap Y = \varnothing$. The left-hand side of the rule is named antecedent and the right-hand side is named consequent. When a specific association satisfies the minimum support threshold, then *i* is identified as a frequent itemset. The support of an itemset *i* in *T*, denoted by $s(i)$, is the proportion of transactions that contain *i*. The confidence of an association rule, $i2 \rightarrow i4$, denoted by $conf\,(i2 \rightarrow i4)$, refers to the strength of the association.

The support shows the benefits of the discovered rule and the confidence shows the certainty of the captured association rule [18]. A normal calculation of support-confidence conventional method is [19]:

- Confidence($X \rightarrow Y$) > support(Y), means X has positive effect on Y.
- Confidence($X \rightarrow Y$) = support(Y), means X has no effect on Y.
- Confidence($X \rightarrow Y$) < support(Y), means X has negative effect on Y.

This method has been used widely in recommendation systems such as in hypermarket. Recommendation systems could be functioned in finding what users are looking for on various kind things, such as books, movies, music and so on. Recommendation systems can reduce times for the user to scroll it down, searching for what they want. In recent years, there are many recommendation

systems have been implemented such as in YouTube and Amazon [18].
A portal can capture in detail how a user accesses its pages and functions on a per session basis. The detail may include pages viewed, links selected, products viewed, time spent, etc. Useful measures such as page/ad/product ratings, clickthroughs, etc. can be automatically and efficiently calculated. The information would be useful to provide quality online services and improve the portals [21-22]. For example, data mining supports the automatic classification of visitors of a website based on data in the web server log which show how and what they access. Data mining application would analyze data from many different dimensions or angles [9, 23]. It can perform categorization and summarization of the relationship identified. Other data mining applications for electronic commerce include personalisation of product recommendation [10] and analysis of the competitors for better prices and offers. More than just analyzing your competitors' prices, these platforms can pull assortment, reviews, and more. This helps the organization to gain a competitive advantage.

4. Methods

The method of this study involves several phases which contain a few sub-phases. Initially, the dataset was collected from 11Street and Lazada websites.

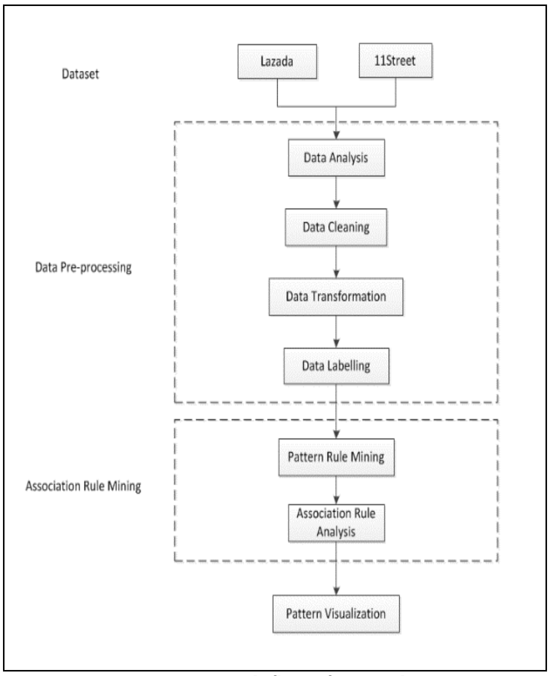

Fig 2: Research flow of price-ChARM.

Figure 2 above shows the research flow of the study. As mentioned before, the datasets were obtained from 11Street and Lazada websites content with information of handbags. By using a web scraping tool of WebHarvy, the scraped data is automatically saved into csv file. During data pre-processing, all the process of data cleaning, data analysis followed by data transformation and data labelling were done manually using Excel. With the correct format and transformation of data, the implementation of Apriori algorithm became feasible to produce association rules with meaningful information. By implementing Apriori algorithm using a particular tool, it only accepts data that is purely nominal. In the end, the useful information or pattern of association rules obtained can be visualized. As for the dataset, only the product and timeline of each product is selected for the implementation of Apriori as shown in the table below.
The total amount of records in the dataset contains 33 different timelines with 120 products from Lazada and 11street.

Table 1: Sample of data for a handbag from 11street and Lazada.

tID	Handbag_name	price	reviews
11street:1	Kipling Sling Bag Multi Pocket Nylon Travel Bag	RM42.90	star5(117)
11street:2	Kipling Sling Bag Waterproof Nylon Travel Shoulder Bag	RM39.90	star5(165)
11street:3	Kipling Bag Backpack Laptop Bag	RM13.50	star5(132)
11street:4	Sokano Trendz Women Elegant Faux Crocodile	RM26.99	star5(3)
11street:5	Kipling Shoulder Backpack	RM79.00	star5(11)
11street:6	Anello 3 Ways Handbag	RM25.90	
11street:7	Wedding Bridal Gown Garment Dustproof Cover Storage Bag	RM23.10	star5(1)
11street:8	MCM Patricia Mini	RM399.00	
11street:9	Hush Puppies Perf Bucket (Black)	RM159.50	
11street:10	Kipling Women'S Nuria Cross-Body & Clas Seoul	RM99.00	star5(7)
Lazada:1	Women Sweet Lady Handbag Crossbody	RM 81.40	(1 review)
Lazada:2	Women Sweet Lady Handbag Crossbody	RM 160.7	(1 review)
Lazada:3	Handbag For Women Fashion Sweet Lady Leather Shoulder Bag Hand Bag Top Handle Bags Pink	RM 79.00	(1 review)
Lazada:4	Handbag For Women Fashion Sweet Lady Leather Shoulder Bag Hand Bag Top Handle Bags Rose	RM 87.50	(1 review)
Lazada:5	Multi-Functional Female Package (Red)	RM 66.61	(8 reviews)
Lazada:6	Multi-Functional Female Package (Black)	RM 51.70	(1 review)
Lazada:7	Evening Hand Bag Ladies Party Elegant Shoulder Handbag	RM34.70	(1 review)
Lazada:8	Korean Style Canvas Women Ladies Shoulder Bag (Brown)	RM 86.00	(1 review)
Lazada:9	Casual Shoulder Oblique Cross Handbag Four Packs Of Mother Packs (Blue)	RM 66.61	(1 review)
Lazada:10	PU Leather Handbags Women Messenger Bags Crossbody	RM 56.20	(1 review)

Table 2: Time of Web Scrapping.

Date	Batch 1	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7
26-09-17	11am (t001)	10pm (t015)	11pm (t002)	None	None	None	None
07-10-17	7pm (t026)	None	None	None	None	None	None
08-10-17	3pm (t027)	None	None	None	None	None	None
09-10-17	2pm (t003)	2pm (t016)	2pm (t028)	10pm (t004)	10pm (t017)	10pm (t029)	11pm (t008)
11-10-17	3pm (t005)	8pm (t009)	8pm (t009)	8pm (t018)	8pm (t030)	None	None
15-10-17	5pm (t031)	None	None	None	None	None	None
16-10-17	3pm (t019)	6pm (t011)	9pm (t020)	10pm (t012)	10pm (t013)	None	None
17-10-17	6pm (t032)	8pm (t006)	9pm (t014)	9pm (t021)	9pm (t022)	9pm (t023)	None
18-10-17	8pm (t007)	8pm (t033)	9pm (t024)	9pm (t025)	None	None	None

Table 3 shows information of the prices in different times from 2017-09-26 till 2017-10-17 and sample of products which are p001, p002 and p003.

Table 3: Sample of preprocessed data for a handbag from Lazada.

tID	Time Scrape	p001	p002	p003
t015	2017-09-26 22:10:08	RM 81.40	RM 160.7	RM 79.00
t016	2017-10-09 14:17:43	RM 79.00	RM 160.7	RM 75.00
t017	2017-10-09 22:31:27	RM 75.00	RM 79.00	RM 160.7
t018	2017-10-11 20:39:51	RM 75.00	RM 160.7	RM 79.00
t019	2017-10-16 15:43:57	RM 75.00	RM 79.00	RM 75.00
t020	2017-10-16 21:43:41	RM 75.00	RM 75.00	RM 79.00
t021	2017-10-17 21:56:35	RM 79.00	RM 160.7	RM 75.00

The first column in Table 3 represents the timeline id for each record. The total amount of records in the dataset contains 33 different timelines with 120 numbers of products. For each online marketplace, the records are integrated as shown in Table 4 that has presented by a dataset with the columns (attributes) represents products and the rows (instances) represent timeline. Each record that has price changes or reduction is labelled as yes and no for the opposite. The dataset is then saved into arff format to be implemented with Apriori algorithm using WEKA.

Table 4: Sample of transformed data for a handbag from Lazada.

tID	Time Scrape	p001	p002	p003
t015	2017-09-26 22:10:08	no	no	no
t016	2017-10-09 14:17:43	yes	no	yes
t017	2017-10-09 22:31:27	yes	yes	yes
t018	2017-10-11 20:39:51	yes	no	no
t019	2017-10-16 15:43:57	yes	yes	yes
t020	2017-10-16 21:43:41	yes	yes	no
t021	2017-10-17 21:56:35	yes	no	yes

4.1. Apply Apriori Algorithm

The implementation of Apriori algorithm in WEKA was simply done using several parameter settings. The parameters used are min_conf which represents the value of minimum confidence threshold and min_sup is the value of minimum support threshold and these values were tested in finding significant rules from the dataset. Figure 4 shows the Apriori algorithm for generating the itemsets.

Apriori (T, ε)
    $L_1 \leftarrow$ {large 1-itemsets that appear in more than ε transaction}
    $k \leftarrow 2$
        while $L_{k-1} \neq \emptyset$
            $C_k \leftarrow$ Generate (L_{k-1})
            For transaction $t \in T$
                $C_t \leftarrow$ Subset (C_k, t)
                For candidate $c \in C_t$
                    $count[c] \leftarrow count[c] + 1$
            $L_k \leftarrow \{c \in C_k \mid count[c] \geq \varepsilon\}$
            $k \leftarrow k + 1$
    Return $\bigcup_k L_k$

Fig 3: Apriori Algorithm [14].

It has two main processes which are combining and pruning itemset. Firstly, each item in the dataset is combined to produce itemset until no combination can be created. Secondly, the pruning of itemset is done by counting the occurrence of the itemsets in the dataset and pruning the itemsets if the count is less than minimum support that has been set by the user. The higher the minimum support value, the higher the frequency of occurrence of each itemset.

4.2. Visualization

Some meaningful information can be obtained from the associated rules generated from Apriori algorithm and the association rules were visualized using scatter plot.

5. Results

The results for both datasets of 11Street and Lazada with min_sup of 0.1 and min_conf of 0.9 were recorded. As shown in Table 5, the association rules gained confidence up to 1 and with the setting. Apriori produces 24 rules only from 11Street dataset, and Table 5 shows the best 10 rules.

Table 5: Sample of Association Rules from 11Street with min conf 0.9 and min sup 0.1.

No.	Association Rule	Confidence
1	t010=t t012=t 19 ==> t011=t 19	1
2	t004=t t008=t t011=t 18 ==> t012=t 18	1
3	t004=t t010=t t012=t 16 ==> t011=t 16	1
4	t010=t t012=t t024=t 15 ==> t011=t 15	1
5	t023=t 14 ==> t024=t 14	1
6	t004=t t008=t t011=t t024=t 13 ==> t012=t 13	1
7	t008=t t010=t t012=t 12 ==> t011=t 12	1
8	t008=t t010=t t011=t 12 ==> t012=t 12	1
9	t004=t t010=t t012=t t024=t 12 ==> t011=t 12	1
10	t004=t t011=t 28 ==> t012=t 27	0.96

As referring to the results of 11Street records above, rule 1 represents that the occurrence of changes in timeline 10 and timeline 12, is more likely to affect changes in price in timeline 11 and the details of the timeline can be referred in Table 2. This applies the same to the next rules until the 5th rules that represent changes in timeline 23 are more likely to change timeline 24. Similarly, with the same values of parameters used for Lazada records, it produces 51 rules. The sample of association rules is generated as shown in Table 6 below. Rule 1 represents that the changes in timeline 17 and 29 are more likely to affect price change in timeline 28. Same goes to changes in timeline 29 and 31 is most likely to affect changes of price in timeline 30 as well. Based on the number of rules generated, Lazada had given more discounts to the sold items.

Table 6: Sample of Association Rules from Lazada with min conf 0.9 and min sup 0.1.

No.	Association Rule	Confidence
1	t017=t t029=t 52 ==> t028=t 52	1
2	t030=t 40 ==> t031=t 40	1
3	t016=t t029=t 32 ==> t028=t 32	1
4	t028=t t030=t 32 ==> t031=t 32	1
5	t029=t t031=t 31 ==> t030=t 31	1
6	t029=t t030=t 31 ==> t031=t 31	1
7	t016=t t017=t t029=t 30 ==> t028=t 30	1
8	t028=t t029=t t031=t 29 ==> t030=t 29	1
9	t028=t t029=t t030=t 29 ==> t031=t 29	1
10	t017=t t031=t 26 ==> t030=t 26	1

Next, the rules were visualized in scatter plot for a better view. The next figures are the graphs for data visualization of both 11Street and Lazada association rules for 3-itemsets. The x and y-axis represent the antecedent of the rules whereby the coloured points represents the consequent of the rule. The legend on the side shows the confidence value for each rule generated.

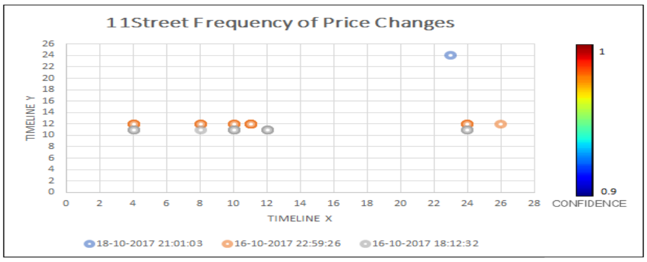

Fig. 4: 11Street Frequency of Price Changes.

Based on the graph in Figure 5, an example of a rule can be seen is t010=t t012=t 19 ==> t011=t 19. It represents when timeline 10 and timeline 12 have price changes, then timeline 11 also has price changes which dated on the 16th of October 2017 at 10.59pm as shown on the orange point in the graph with a confidence value above 0.9. Same goes to Lazada website, the analysis is shown in the graph below.

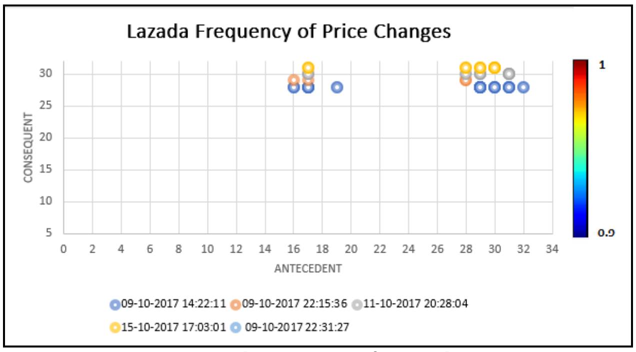

Fig 5: Lazada Frequency of Price Changes.

Figure 5 shows the scatter plot for the frequency of price changes using Lazada records. The value of min_conf and min_sup is similar to 11Street records which were 0.9 and 0.1 respectively. An example of rule for Lazada website is t017=t t029=t 52 ==> t028=t 52. When timeline 17 and timeline 29 has price changes, then timeline 28 also has price change which is on the 9th of October 2017 at 10.15pm as shown on the orange point of the graph with a confidence value above 0.9.

6. Discussion on Apriori Algorithm Results

Useful information can be drawn out of rules generated with different values of parameters. Based on the results shown in the scatter plot graphs, in Lazada records, there are many price fluctuations with high confidence values as compared to 11Street records based on different timelines. One timeline denotes which product involves with price fluctuation. In this case, the indication of price fluctuation is seen in one dimension whereby the information is acquired from single time occurrence of price fluctuation as shown in Table 7.

In another dimension, the information of rule generated is gained by retrieving product identity from the rule sets. For example, let's take one sample of rule from each record. The first rule generated from 11Street is t010=t t012=t 19 ==> t011=t 19. The products that match with this rule set are p020 and p106 which belong to product Faux Leather Cross Body Shoulder Bag and Clutch Change Coin Bag Purse Mini respectively. The reason is that the value is true for all candidates in the rule and no other product can be matched with the rule.

Whereas, the first rule generated from Lazada is t017=t t029=t 52 ==> t028=t 5. The products that match which this rule set is p012 for C&K Woman's Top Handle Handbag (Beige), p043 for Sokano Trendz Premium Pu Leather With Cutie Bear Keychain (Wine Red), p051 for Carlo Rino Top Handle Bag, and p112 for Louis Vuitton One Handle Flap Bag. By looking at this dimension, price fluctuation is affected by numerous timelines that affects what kind of product.

Table 7: Number of changes in the timeline.

No.	11Street	Lazada
1	16/10/2017 6:12:32 PM	9/10/2017 2:22:11 PM
2	16/10/2017 10:59:26 PM	9/10/2017 10:15:36 PM
3	18/10/2017 8:21:43 PM	9/10/2017 10:31:27 PM
4	None	11/10/2017 8:28:04 PM
5	None	15/10/2017 5:03:01 PM

Table 7 shows the comparison of the number of price changes occurred at both websites. According to the timelines, 11Street has three occurrences of price changes as stated in the table above whereas Lazada has five occurrences of price changes as stated. Hence, Lazada has more of price fluctuations of handbags as compared to 11Street.

7. Conclusion

In conclusion, the implementation of Apriori would be useful for analyzing information from online shopping portals. In this study, Lazada has a higher amount of price changes as compared to 11Street. This can be obtained from the association rules generated by Apriori algorithm which produced the rules for timelines of both datasets. In the future, the analysis can be improved by using cross-validation as to test whether there is overlapped rules or result among small dataset so that the accuracy of the result can be determined. The analysis can be done more efficiently by using other techniques from Association Rule Mining such as partition, FP-growth and more. It is recommended to improve the data visualization of the result obtained from the data mining algorithm used. For instance, the real-time update of what item on which timeline has price changes. Other than that, the analysis of price changes can retrieve the original and specific information of each item from each rule generated. Lastly, the analysis can be improved by making into a system of real-time price changes analysis associated with a price tracker for tracking the best deal of an item.

Acknowledgement

The authors would like to thank Research Management Centre for the REI 19/2015 grant and faculty for the research support.

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