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Research Article

Segmenting Suppliers of e-commerce Transaction Brokers Case Study: Hotel Rooms Provider

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Abstract: The aim of this study is to develop model for segmenting suppliers suitable for transaction broker e-commerce systems, specifically hotel room providers. Transaction brokers act as market intermediaries that have two types of clients, which are customers and suppliers. Hence, they must employ both electronic Customer Relationship Management (e-CRM) and electronic Supplier Relationship Management (e-SRM) such that the firms can build strong and beneficial relationships with both parties. One of the most important e-SRM functions is segmenting suppliers, where the results are used to design unique services for each segment to strengthen relationships. Our research findings are: (1) Variables suitable for segmenting suppliers; (2) data warehouse design needed for the segmentation; (3) techniques for segmenting suppliers based on their value and churn tendency. We have conducted experiments using the case study data obtained from Klikhotel.com and the results indicate that our proposed techniques have successfully segmented suppliers.

Keywords: Churn prediction, clustering suppliers, electronic supplier relationship management, supplier segmentation

INTRODUCTION

Transaction broker business model has been widely adopted in financial services, travel services and job placement services of e-commerce systems (Laudon and Traver, 2010). As market intermediaries, transaction brokers have two groups of clients, which are customers and suppliers. To gain revenue and profits, transaction brokers should be able to successfully market supplier's products to customers. In our previous research (Ibrahim *et al*., 2015), we found that this can be achieved by developing strong relationship with suppliers. Hence, transaction brokers must employ electronic Supplier Relationship Management (e-SRM) besides the electronic Customer Relationship Management (e-CRM) that is generally needed by any e-commerce system.

Among other components, the e-SRM system should include Customer and Supplier Centric Intelligent (CSCI) component that provides functions for customer and supplier data analysis, where the results can be used to manage customers and suppliers. This CSCI can also be part of the firm Business Intelligent (BI) system. Segmenting suppliers, which can be done by analyzing transaction broker's data, is important part of the CSCI as the results can be used for handling different segments of suppliers.

Unlike customer segmentation techniques as part of e-CRM that have been widely discussed in literature, we found that discussion of supplier segmentation techniques for e-commerce systems is very limited. The existing techniques that we found, such as discussed in Rezaei and Ortt (2012), are intended for segmenting "traditional" suppliers who supply goods to firm buyers, and involve purchasing goods transactions (between buyer and suppliers). These techniques become part of firms' supply chain management systems (Chenoweth *et al*., 2012; Decideware, 2014). On the other hand, transaction brokers do not actually buy products from their suppliers. They just sell the suppliers' products (services) online and, in some business model, get fees from successful transactions. Given this business model, segmenting transaction broker suppliers require some different approach. Hence, we intend to contribute in designing e-commerce supplier segmentation techniques suitable for e-commerce transaction brokers.

This study presents some related literature review, the proposed variables suitable for segmenting suppliers in the context of transaction brokers with the case study

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of hotel rooms' provider, three proposed techniques for segmenting suppliers, segmenting suppliers with a case study data, and research conclusion.

LITERATURE REVIEW

Transaction broker e-commerce business model: In general, intermediaries can be categorized into four groups, which are consultant, broker, mediator and resource provider. The brokers possess the following characteristics (Department of Industry, Tourism and Resources, Howard Partners, April, 2007):

- They act as creators and/or acquirers of sought after knowledge and/or technology. Brokers can also perform an integration role bringing multiple parties together into a collaboration 'deal'. Roles may involve assistance in negotiating contracts, purchases, or sales.
- They perform as agencies, parties acting for either buyers or sellers of knowledge (rarely both) on the basis of their capacity to meet needs through their networks and ability to initiate and negotiate deals. An example would be a technology broker, acting on behalf of a client, who identifies/seeks out a technology and works towards creating a deal. Brokers are typically paid a commission on the value of a transaction or a success fee.

The B2B2C (business to business to consumers) e-commerce business model that acts as market intermediary is known as transaction broker. Industries that widely using this model include financial services, travel services and job placement services (Laudon and Traver, 2010).

Supplier Relationship Management (SRM) in transaction broker system: As intermediary firms, transaction brokers conduct business with suppliers and buyers. In order to build products' brand that will be marketed successfully, transaction brokers should build strong relationships with suppliers through electronic Supplier Relationship Management (e-SRM) to help suppliers in developing brands and also develop relationship with customers through e-CRM.

SRM is a relatively new concept that is enhanced from Customer Relationship Management (CRM) concept (Lang *et al*., 2002). SRM objectives are: Attract and acquire suppliers, develop suppliers and their loyalties. SRM should focus on helping key suppliers improve quality, cost, and performance as well as integrating key suppliers into the organization (Chenoweth *et al*., 2012).

In the e-commerce transaction broker systems, suppliers are website users that should conduct online activity for updating product information, prices, stocks, creating campaigns and so on. However, suppliers should still be helped by the firms' staff if needed. To develop stronger relationship and boost their sales, the system should also provide "intelligence" knowledge dig from data that can be used by staff as well as generate automatic personal services. To facilitate these, in our previous research (Ibrahim *et al*., 2015), we have proposed integrated e-SRM and e-CRM suitable transaction broker firms, which include components of:

- **Supplier Facing Applications (SFA):** provide features to support the staff in managing and developing relationships with suppliers through "traditional" techniques (by phone, fax, in person).
- **Supplier Touching Applications (STA):** provide features to help suppliers in performing self-service online activities in managing products, campaigns, personalized reports, etc.
- **Customer and Supplier Centric Intelligent (CSCI):** provide functions for data analysis where the results can be used to provide personal services in SFA and STA.

The CSCI can employ Business Intelligent (BI) system, which includes data warehouse, data mart, OLAP functions, data mining techniques and dashboards. In order to build strong relationship with suppliers, (Decideware, 2014) suggests as follows: (a) Segment the entire suppliers into several strata based on needed criteria; (b) Develop and implement programs that are appropriate to each of those segments. Hence, segmenting suppliers is important data mining technique that should be included in the CSCI.

Segmenting suppliers based on capability and willingness: As stated in the Introduction section, (Rezaei and Ortt, 2012) proposed new approach in segmenting suppliers, which is based on 'supplier capabilities' and 'supplier willingness'. In Rezaei and Ortt (2012), the variables extracted from many research findings are classified into variables of capabilities and willingness. Some example of these is as follows:

Capability variables: Price/cost, cost control, profit impact of supplier, delivery, quality, production, manufacturing/transformation facilities and capacity, management and organization, supplier process capability, market sensing, customer linking, desire for business, and innovation.

Willingness variables: Commitment to quality, frequent communications, attitude, impression, commitment to continuous improvement in product and process, willingness to co-design and participate in new product development, willingness to integrate supply chain management relationship, ethical standards, and consistency and follow-through.

Recency, Frequency and Monetary (RFM): Recency, Frequency, Monetary (RFM) analysis is a traditional approach to analyzing customer behavior in the retailing and has been widely adopted. This analysis divides customers into groups, based on how recently they have made a purchase, how frequently they make purchases, and how much money they have spent (Tsiptsis and Chorianopoulos, 2009). The RFM analysis uses:

- **Recency:** The time (in units such as days/months/years) since the most recent purchase transaction or shopping visit.
- **Frequency:** The total number of purchase transactions or shopping visits in the period examined.
- **Monetary:** The total value of the purchases within the period examined or the average value (e.g., monthly average value) per time unit. This analysis divides each of the three dimensions of RFM into equal sized chunks and places customers in the corresponding chunk along each dimension.

Web usage mining: Clickstream can be used to measure pages and campaigns and analyze all kinds of behavior, such as visits, visitors, time on site, page view, bounce rate, and so on Kaushik (2010). Clickstream and associated data, which are generated from user interactions with websites, can also be analyzed to discover patterns (Liu, 2007). In general, the process consists of two steps:

- **Data preparation:** Data of web application logs database are selected as needed, cleaned, identified, parsed, integrated, transformed and then stored in another database. The data analyzed can be categorized into four primary groups, which are usage, content, structure and user data.
- **Pattern discovery phase:** The transformed data are fed into pattern discovery algorithms, the output are analyzed for selecting the useful ones. There are several techniques for analyzing the data including clustering. The useful patterns discovered can then be used to personalize services (for examples of such services, see (Kousalya and Saravanan, 2014; Tsiptsis and Chorianopoulos, 2009).

Clustering is a data mining technique that groups together a set of items having similar characteristics. In the web usage domain, there are two kinds of interesting clusters that can be discovered, which are user clusters and page clusters. Clustering of user transactions records is one of the most commonly used tasks in Web usage mining (Liu, 2007). In the context of SRM discussed previously, clustering suppliers are identical to segmenting suppliers.

PROPOSED METHODS

In our previous works (Moertini *et al*., 2014), we proposed an evolutionary development method of BI system supporting customer relationship management system for small-medium enterprises. The stages include developing (incremental) data warehouse and data mining techniques for analyzing data stored in the data warehouse. Here, we present some results of the data warehouse design and data analysis techniques suitable for transaction brokers.

As has been stated in the Introduction, CSCI component should provide functions for customer and supplier data analysis. One of the data analysis methods that should be adopted is clustering or segmenting. In the case of segmenting suppliers, clustering suppliers based on their strategic value is important. The result can be used to design specific services for certain value segment of suppliers. On the other hand, preventing suppliers from churning is also important. Data analysis method that results in churn prediction models is also significant. Hence, we propose both techniques. As the case study, our techniques are mainly designed for transaction broker e-commerce selling hotel rooms, where the suppliers are hotels. Segmenting hotels of transaction broker e-commerce require specific variables and techniques. The following are the discussion of variable identifications, data warehouse design that support the data collection and pre-processing, and the proposed algorithms, which are improved version of the concept presented in Moertini *et al*. (2015a).

Variables identifications: Effective supplier segmentation should go beyond the mere purchasing function and should include other activities and functional areas, such as production, finance, logistics, marketing and sales, and R&D. Hence, as discussed in Rezaei and Ortt (2012), formulating the important variables for segmenting suppliers is significant. In the case of segmenting suppliers of transaction broker e-commerce selling hotel rooms, we cannot just adopt the variables listed in Section 2.C as those are mostly suitable for segmenting suppliers supplying products for buyer organizations. We need to formulate or customize them such that the variables are suitable for transaction brokers. Another finding, while the variables used in customers segmentations found in literatures are ones related to customer purchases and behavior, in our research we find that in segmenting transaction broker suppliers, the variables needed are not only the ones corresponding with the suppliers but also the ones coming from customers and external factors.
The following are the variables that we identified:

Sales and customers behavior:
Recency, frequency and amount of sales: The more recent, frequent and amount of purchase made by

Table 1: The relation between capability-willingness and variables defined

Capability and willingness variables	Measureable TB e-commerce variables
Profit impact of suppliers	Total room night, total revenue
Price/cost	Average daily rate
Delivery	Room allocated
Quality	Customer view, room sales
Performance history	Percentage changed of periodical performance, average of sales
Management and organization, supplier process capability, desire for business	producing campaigns, updating room/hotel information
Market sensing, innovation	Room rates, updating room rates and producing campaigns, room sales
Customer linking	Number and score of customer view
Commitment to quality, frequent communications, commitment to continuous improvement in product and process, consistency and follow-through	Customer review, recent update of room/hotel information, room availability
Impression	Customer review
Reciprocal arrangements	Commission agreement
Willingness to co-design and participate in new product development	Frequency of creating or involvement in promotion campaign

TB: Transaction Brokers

customers (via the website), the more likely that the suppliers will be loyal.

Customer view counts: The number of clicks on supplier products indicates the popularity of the corresponding products, which in turn may generate more sales. Less products clicks may lead suppliers to churn.

Supplier actions and behavior:
Product price: Most customers seek "good price". Also, certain segment customers may want to pay specific range of room price. Therefore, price set by suppliers will affect sales.

Product stock: The more suppliers trust the e-commerce firm, the more likely that they will allocate more products to be sold online by the firm.

Website access frequency: How frequent the suppliers manage their products, hotel and room information as well as producing campaigns online indicate their willingness in selling their products via the website.

External factor of season: Product sales may fluctuate along with seasons. For instance, in the case of selling hotel rooms, the high season is around holidays or summer, the low is around January-February, and the medium is the rest times of the year.

To justify the relevancy of those formulations, we present the relation between the above variables and the capability-willingness variables defined in Rezaei and Ortt (2012) are shown in Table 1.

Data warehouse design: Data warehouse is a subject-oriented, integrated, time-variant (historical) and non-volatile collection of data supporting fast and systematic data analysis needed in decision making process. It is populated from the enterprise databases as well as other sources by ETCL (*extract, transform, clean* and *load*) functions (Golfarelli and Rizzi, 2009).

Table 2: Dimension tables identification

Dimension Table	Attributes
DProduct	Name, other descriptive information
DTime	Day, week, quarter, semester, year
DSupplier	Name, other descriptive information
DLocation	Street, city, subregion, region, country, zipcode
DCustomer	Name, other demographic information
DSeason	Name, other descriptive information

Table 3: Fact tables identification

Fact Table	Measures
FactOrder	Count, amount, paidstatus
FactSales	Count, amount
FacttCustView	Viewcount
FactStock	Stock, price
FactSupAccess	Accesscount, accessStatus

The basic schema employed in data warehouse and data mart is star schema. It consists of fact and dimension tables. The fact table, which is usually the center of a star schema, contains facts that are linked through their dimensions. Hence, it has primary keys of its linked dimensions and measure attribute(s) that represent specific business aspect or activity. The dimensions provide descriptive characteristics about the facts through their attributes.

The data needed for segmenting suppliers, which based on the variables identified, will be better provided by a data warehouse. Some part of the data warehouse schema designed is provided here. Table 2 and 3 show the dimensions and fact tables identification. Figure 1 depicts the data warehouse design where for figure simplicity, not all of the relationships are drawn. Attributes in dimension and fact tables can be added as needed.

The data warehouse design is shown in Fig. 1. For simplicity, not all of the relationships are drawn. Attributes in dimension and fact tables can be added as needed

Supplier segmentation techniques: As segmenting suppliers based on their value and churn tendency is as important step in designing personal services for suppliers, we proposed 3 techniques as follows:

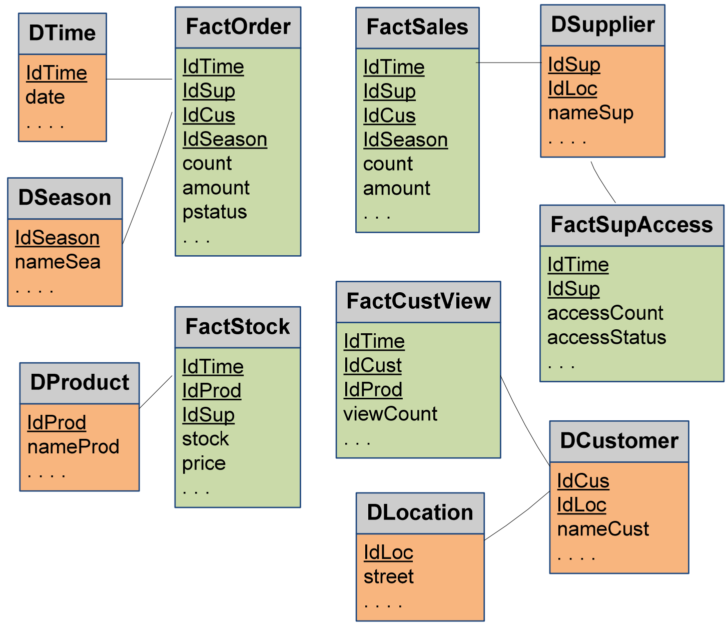

Fig. 1: Data warehouse schema supporting supplier segmentation

Table 4: The rules of segmenting suppliers

No	RFM Patterns	Supplier Segment	Churn Trend
1	R↑F↑M↑	Best supplier	Unlikely
2	R↑F↑M↓	Seller	Maybe
3	R↑F↓M↑	Valuable supplier	Unlikely
4	R↑ F↓ M↓	First Time Supplier	Likely
5	R↓ F↑ M↑	Long Time Supplier	Maybe
6	R↓ F↑ M↓	Frequent Supplier	Likely
7	R↓ F↓ M↑	Expensive Supplier	Maybe
8	R↓ F↓ M↓	Uncertain Supplier	Likely

- Segmenting suppliers based on their value: Suppliers are segmented using well known RFM (*Recency, Frequency, Monetary*) methods. With simple computations, clusters of supplier, where each has specific patterns, can be computed.
- Segmenting suppliers based on their churn tendency using variables affecting sales: Using some variables and the results of their regression, suppliers are determined their level of churn behavior.
- Segmenting suppliers based on their churn tendency using solely website access frequency: Based on their most recent (such as in the last 6 months) frequency of accessing the website, suppliers is segmented into few level of churn tendency.

Technique-1: Segmenting Suppliers Based on Their Value: We adopt the RFM discussed in Recency, Frequency and Monetary (RFM) where the variables of R, F, and M are defined as follows:

- **R (*Recency*):** Count of days since the last date of sale transaction until now (the date of data extraction).
- **F (*Frequency*):** Count of sale transactions.
- **M (*Monetary*):** While in CRM the M is sum of purchasing, in e-SRM we select sum of sale transactions (in monetary currency unit).

In determining the value of R, F and M, the data is obtained during a specific observation time (such as 6 months).

Based on the value of RFM, we define supplier RFM statuses as follows:

- R↑: Sell products recently; R↓: Lately being dormant;
- F↑: High frequency of sale transactions; F↓: Low frequency of sale transactions;
- M↑: High value of sale transactions; M↓: Low value of sale transactions;

The formula in determining the status of ↑ (high) and ↓ (low) of RFM is the following:

- If R ≥ average of R then R status = ↑ (high), otherwise R status = ↓ (low)
- If F ≥ average of F then F status = ↑ (high), otherwise F status = ↓ (low)
- If M ≥ average of M then M status = ↑ (high), otherwise M status = ↓ (low)

The average of R, F, and M is computed from R, F, and M value of all suppliers during observation time.

Using the statuses of RFM and by adopting the technique for CRM in Birant (2011), suppliers are segmented using the patterns as depicted in Table 4 "(Irene, 2014)".

Technique-2: Segmenting suppliers based on churn tendency using variables affecting sales: As depicted in Section 3.A, hotel rooms sale are affected highly by seasons. During high season, where sales are expected to increase, the decreasing of sales indicates bad situation that could lead hotels to churn. However, during low or medium season, the decreasing of sales may not lead hotels to churn. Another fact found is that the more hotels trust the transaction broker firm, the more they would allocate rooms to be sold in the website. Customer's view/clicks on the hotels web pages also indicate the popularity of the hotel that could lead to book transactions. The more clicks the more unlikely those hotels will churn. Hence, seasons, sales, number of rooms allocated and customer clicks are important variables in segmenting suppliers based on their churn tendency.

We define the main principles that are used in predicting the churn level tendency as follows "(Amelinda, 2014)":

- Regardless of the season and other factors, if room sale is ascending during the observation time, it is unlikely the supplier will churn.
- Otherwise (if the room sale is descending), other variables will be evaluated to determine the predicted supplier churn level.

In measuring the trend (ascending or descending) we use regression coefficient of Laudon and Traver (2010):

$$a = \frac{\sum_{n}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{n}(x_i - \bar{x})^2}$$

where: y_i can be sales, view/click or room rates at the time unit of x_i, n is the number of instance/record of x and y. The detailed patterns used in determining the churn level is depicted in Table 5 "(Amelinda, 2014)".

Technique-3: Segmenting suppliers of based on churn tendency using website access frequency: As depicted in Section 3.A, the suppliers capability (process capability, desire for business, etc.) and willingness (frequent communications, willingness to participate, etc.), among other things, can be measured by how frequent they access the transaction broker e-commerce to conduct online activity on managing things.

Table 5: Measures and churn level

Season	a_{Sales}	a_{tV}	a_{tR}	Churn level
High	<0	<0	a.v.	5
		≥0	<0	4
			≥0	3
	≥0	a.v.	a.v.	1
LowMed	<0	<0	<0	4
			≥0	3
		≥0	<0	4
			≥0	2
	≥0	a.v.	a.v.	1

tV = trend of web page view (by customers); tR = trend of room number offered; a.v. = any value; 1 = lowest, 5 = highest

Table 6: Some example of time series with 24-bit bitmap

IdSupplier	Statuses (24 bits)
IdS1	101011111010 011111111110
IdS7	1101010111010 011101110101
IdS23	0111001111010 010001110111
. . . .	

In our previous research we have developed an efficient technique for predicting suppliers churn behavior based on their web access frequency (Moertini *et al.*, 2015b). As web usage mining, the technique consist of two major steps, which are data preprocessing and analysis.

In the data preprocessing, the supplier statuses in accessing the website during a certain period (e.g., weekly), which can be obtained from the web logs, is stored as a bit in a data warehouse/mart table. If during the period of observation, a supplier access the web, the status is represented with 1, otherwise is 0 (for example, Table 6). Hence, the statuses of accessing the website are represented as a bitmap for each supplier.

For analyzing the bitmaps, with the assumption that the patterns of suppliers' frequency in conducting activities who tend to churn are known in advance, we design two algorithms. Some example of the patterns:

- If in the last period of observation of 24 weeks (6 months), a supplier is less active, i.e., dormant during k% x 24 weeks (for instance, k = 25) or more, then this supplier may churn in the future.
- If in the last 6 months, a supplier's frequency in conducting activities decline from time to time, then then this supplier is very likely to churn. If the frequency is declining sometime in the middle of the time only (then up again sometime later), then then this supplier may be churn.

The excerpts of the two algorithms are as follow.

Algorithm: PredictChurn-1

Input: (a) File containing records of IdSupplier and its bitmap of statuses fInput; (b) File containing count of 1, fCountOne; (c) Value of *threshold1, threshold2, threshold3*

1011	0111	1011	1110
window1	*window2*	*window3*	*window4*

mask1 = 1111000000000000;
mask2 = 0000111100000000;
mask3 = 0000000011110000;
mask4 = 0000000000001111;

Fig. 2: Some example of the bitmap windows and the corresponding masks

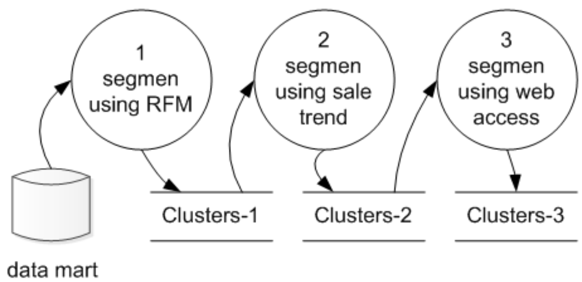

Fig. 3: The use of 3 techniques

Output: Array of IdSupplier who predicted to churn, IdSupChurn[], and its churn level, ChurnLevel[] where the level is 1 = low or 2 = medium or 3 = high

Descriptions: Predicting supplier's churn behavior level based on count (frequency) of bit 1: If the count< *threshold1* then cLevel = 3, else if *threshold1*> = count <*threshold2* then cLevel = 2, else if *threshold2*> = count<*threshold3* then cLevel = 1.

Steps:
For each bitmap representing a supplier web access status
obtain count of 1 in the bitmap by look up to f Count One
using *threshold1, threshold2, threshold3,* determine supplier *cLevel*, store *IdSupplier* and *cLevel* in arrays
end

Algorithm: PredictChurn-2 //In this algorithm, number of windows used are 4 (four)

Input: (a) File containing records of IdSupplier and its bitmap of statuses, fInput; (b) File containing count of 1, fCountOne; (c) Masking bitmaps, mask1, mask2, mask3, mask4 (Fig. 2 for window and mask examples).

Output: array of IdSupplier who predicted to churn, IdSupChurn[], and its churn level, 1, 2, or 3

Descriptions: The predicted churn level of every supplier is determined by the frequency changes from "window time" to "window time". Here, the overall bitmap will divided into windows by masking it with the defined masks. Predicting supplier's churn behavior is based on the change of count (frequency) of bit 1 in the windows. The churn level is predicted based on known patterns of the frequency changes from window to window.

Steps:
for each bitmap representing a supplier web access status
obtain count of 1 in the bitmap-window by look up to fCount One
by using the count changes (down, steady or up) from window to window,
determine supplier *cLevel*, store *IdSupplier* and *cLevel* in arrays
end

The complexity of both algorithms is *O(n)* as the operation for obtaining the count of bit 1 in a bitmap can be done by look up table with with *O(1)* operation (Moertini *et al*., 2015b) for detailed discussion).

Combining the techniques for churn prediction: If transaction brokers need to pay special attention to the suppliers who tend to churn, the previous 3 techniques can be combined and used together for segmenting suppliers in 3 consecutive processes as follows (Fig. 3) (Moertini *et al*., 2015a):

Process 1: Suppliers are segmented based on their value. Cluster members of maybe and likely churn tendency can further be passed to Process 2.

Process 2: Using some additional variables and regression function, suppliers passed from Process 1 are further processed by the second technique, segmenting suppliers using variables affecting sales. Suppliers found to have medium to high of churn tendency are further passed to Process 3.

Process 3: Based on their most recent (such as in the last 6 months) frequency of accessing the website, suppliers are further analyzed to find final level of churn behavior.

The segment results of Process 1, 2 and 3 can then be used to design personal services to manage relationships with suppliers.

RESULTS AND DISCUSSION

We have implemented the data warehouse design and algorithms, then analyzed case study data obtained from an Indonesian transaction broker selling hotel rooms, Klikhotel.com. The dataset were collected from August 2013 to September 2013 with total of 450 records. The experiment results are as follows (Moertini *et al*., 2015a):

Output of process-1: The following is the list of supplier segment, churn tendency, total of suppliers in the segment: Best Supplier/Unlikely: 99, Expensive/Maybe: 22, First Time Supplier/Likely: 57, Frequent Supplier/Likely: 18, Longtime Supplier/Maybe: 49, Seller/Maybe: 14, Uncertain Supplier/ Likely: 181, Valuable Supplier/Unlikely: 10. Thus, there are 341 suppliers (hotels) found to have Maybe and Likely tendency of churning. These 341 suppliers are further fed into Process-2.

Output of process-2: By processing the 341 hotels, we find that only 17.9% or 61 hotels have the tendency to churn. The following is the result list: 2 hotels are very high (5), 26 are high (4), 22 are medium high (3) and 11 are low medium (2).

Output of process-3: By feeding the 61 hotels into algorithms of PredictChurn-1 and PredictChurn-2, we obtain the following results: (a) Output of PredictChurn-1: cL = 1: 8 hotels, cL = 2: 13 hotels, cL = 3: 26 hotels, thus total: 47 hotels; (b) Output of PredictChurn-2: cL = 1: 1 hotels, cL = 2 : 2 hotels, cL = 3 : 26 hotels, thus total : 29 hotels.

Thus, this experiment produces results that there are 47 or 29 hotels that need special care to prevent them from churning.

CONCLUSION

By employing the right segmentation techniques, suppliers can be clustered such that certain clusters can be targeted for special care to boost their sales and loyalty, or to prevent them from churning. These techniques can be implemented as the functions of the CSCI or firm BI system, which will be beneficial to firms (Teoh *et al*., 2014).

In segmenting suppliers, it is important to determine the relevant variables, which may correspond to sales, customer behavior, and external factors. Our proposed techniques, which are applicable for transaction broker e-commerce systems selling hotel rooms, show how to process the variables values using defined patterns and algorithms. In experimenting with the case study data, it is shown that the techniques proposed have successfully segment suppliers such that a small number of suppliers can be targeted for specific churn treatment.

As our techniques are developed for specific transaction broker only, further research are needed to enhance them such that they are applicable to general transaction brokers and e-commerce system that involve suppliers as the website users. More intelligent techniques can be developed based data mining techniques that generate models from data.

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