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Add-on selling strategies in an online open market

Beomsoo Shim[1] · Hanjun Lee[2]

[1]Korea Hydro & Nuclear Power Co., Ltd., Central research institute
[2]Korea Institute for Defense Analyses

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Abstract

Add-on selling can provide new chances to increase sellers' profits and meet customers' needs. Although prior studies have advocated add-on selling for its business value, there is an argument that add-on selling can cause customer repulsion. Therefore, we need to understand customer purchasing pattern related to add-on selling in order to promote it and to mitigate the customer repulsion. To that end, we applied data mining techniques to the 24,925 transactions of data from an online open market in Korea. We then conducted feature selection to investigate the most influential factors that can explain the characteristics of add-on selling transactions using a classification model. We also identified association rules among add-on selling and promotions. Finally, based on the findings in our experiments, we proposed add-on selling strategies for the target online market.

Keywords: Add-on selling, association rule, classification model, customer repulsion, data mining.

1. Introduction

Add-on selling is often called as "suggestive selling", "sales promotion strategy" Ebster *et al*. (2006), or "companion selling". Polonsky *et al*. (2000). Add-on selling can be described as an activity associated with selling any additional products or services to current customers. Blattberg *et al*. (2001). e.g. if a customer wants to buy a new pair of leather boots, salesman can recommend the customer to buy a special polish or a leather brush to maintain its appearance. In most cases, the additional item will add value to the product being purchased, and it can be either a product or a service. These products or services can be related to each other, but they do not necessarily have to.

Add-on selling is originated from restaurant management field. Prior studies have confirmed managerial understanding that add-on selling is beneficial in full-service restaurants, and increased sales and improved tips are among the benefits (Mirman, 1982; McCarthy, 1998). Mirman (1982) found that suggesting wines and desserts in restaurants are likely to increase the sales. In general, proper suggestions also improve customer satisfaction. McCarthy (1998). Add-on selling has been applied to diverse areas from electronic product to

[1] Researcher, Korea Hydrio & Nuclear Power Co., Ltd., Central research institute, Jang dong 25-1, Yu-sung gu, Daejeon 305-343, Korea.
[2] Corresponding author: Associate research fellow, Korea Institute for Defense Analyses, 37 Heogiro, Dongdaemungu, Seoul 130-871, Korea. Email: hjlee1609@gmail.com

insurance. One of the latest sectors to implement this practice is online market where many sellers and customers to make transactions over the Internet. Add-on selling can be beneficial to both sellers and customers if it is implemented properly. That is, it brings increased revenue to sellers and added value to customers.

In spite of these advantages of add-on selling, however, there are some arguments against add-on selling that it could lead to customer repulsion which can be caused by unpreferred and/or unexpected add-on selling. For some customers, add-on selling may not be attractive at all and it can make them even annoying. Kivet *et al*. (2003) call this phenomenon as "customer repulsion" and reducing customer repulsion is critical to the successful implementation of add-on selling. In light of this, we need to deepen our knowledge about customer purchasing pattern related to add-on selling to promote the add-on selling while lessening the customer repulsion. To that end, we come up with specific research questions in the paper such as these: 1) What characteristics do add-on selling transactions show?; 2) What kinds of promotions are associated with add-on selling which will reduce customer repulsion?

To address these research questions, we analysed the actual transaction data which we collected from an online open market, in Korea. Specifically, 1) we developed classification models to investigate the influential factors leading to add-on selling by using data mining techniques such as DT (decision tree), RAE (relief attribute evaluation). Also, 2) we identified ARs (association rules) among promotions to find promotion combinations which have positive effects on mitigating customer repulsion. Based on the findings obtained from the results of classification and AR, we finally proposed add-on selling strategies from the perspective of CRM (Customer Relationship Management).

Online open markets are a place where there is an intense completion among sellers and diverse CRM tactics including add-on selling and promotions are widely applied to. To our knowledge, however, few or no research has been conducted about add-on selling in online open markets. Therefore, we chose an online open market in Korea as our research context, and collected transaction data from the market.

The rest of this paper is organized as follows. Section 2 presents literature review about prior CRM studies related to our research. Section 3 describes research methods used in this study. Section 4 explains the experiments conducted in this study, including dataset and research framework, step-by-step explanation on the experiments and the experimental results. Add-on selling strategies for the target online open market are then provided as well based on the experimental results. Finally, Section 5 concludes the paper.

2. Literature review

The concept of CRM has become widely recognized since 1980s. Nevertheless, there is no universally accepted definition of CRM among researchers. Ling *et al*. (2001) described CRM as a combination of processes and enabling systems supporting a business strategy to build long term, profitable relationships with selective customers. Parvatiyar *et al*. (2001) defined CRM as a comprehensive strategy which implements the process of acquiring, retaining and partnering with specific customers to create value for both a company and its customers.

From the perspective of CRM, add-on selling is the mechanism to take advantage of the strong, long lasting relationships with customers. Clement *et al*. (2010). Clement *et al*. (2010) emphasized the relation between CRM and add-on selling by commenting that one of the main benefits of CRM related practice is the creation of add-on selling. This is because, add-on selling exploits the relationship with customers. Prior studies showed that add-on selling can be an effective marketing skill Mirman, (1982) and have financial impact on firms. Thomas, (2001). Although the value of add-on selling has been discussed a lot, few studies have paid attention to the development of add-on selling strategy. Therefore, this study examines the characteristics of add-on selling related customer purchase pattern aiming at developing add-on selling strategies.

We considered CRM dimensions, when developing add-on selling strategies. Swift (2001), Parvatiyar *et al.* (2001), and Kracklauer *et al.* (2004) insist that CRM consists of four dimensions such as customer identification, customer attraction, customer retention, and customer development. According to them, customer identification is a dimension associted with identifying potential customers. Customer attraction is a trial to attract the target customers by motivating customers to place orders. Customer retention means the activity of keeping the existing customers from switching to competitors. Customer development, the ultimate goal of CRM, is designed to maximize the revenue by expanding transactions through customer lifetime value analysis, up/cross selling, market basket analysis, etc. In this study, we propose add-on selling strategies from the perspective of these four dimensions.

Data mining techniques have been useful in previous CRM-related studies. These studies have applied data mining techniques to diverse cases in order to analyse and understand the customer behaviors and characteristics, and they have shown meaningful results (Bortiz *et al.*, 1995; Fletcher *et al.*, 1993; Langley *et al.*, 1995; Lau *et al.*, 2003; Salchenberger *et al.*, 1992; Su *et al.*, 2002; Tam *et al.*, 1992; Zhang *et al.*, 1999; Lee *et al.*, 2015). We review previous CRM domain literatures related to classification and association rules which we apply to analyse the add-on selling transactions in this paper.

For diverse purposes, classification has been conducted in CRM domain. Dennis *et al.* (2001) developed customer knowledge management framework using K-means. Hwang *et al.* (2004) suggested logistic regression for segmenting customers based on their customer loyalty and Yu *et al.* (2005) identified interesting visitors by analysing web log data using decision tree. Hosseini *et al.* (2010) estimated customer loyalty using K-means for cumtomer segmentation.

Association rule is also known as one of the useful data mining techniques for customer transaction data analysis. Researches based on association rules have been conducted with various purposes in CRM domain. Adomavicius *et al.* (2001), for example, examined association rules for one-to-one CRM. Aggarval *et al.* (2002) and Kubat *et al.* (2003) identified association rules from market basket analysis. Changchien *et al.* (2004) performed a research using both ANN and association rules for on-line personalized sales promotion. We elaborate our approach in section 3.

3. Experiments

This section describes the experiments we performed to answer our research questions. First, we introduce the dataset obtained from a target online open market. Then, we explain research framework in detail. We used Weka 3.7.8 for classification and SAS Enterprise Miner 9.1 for the identification of association rules among promotions and add-on selling.

3.1. Dataset

3.1.1. Research context

An online open market refers to a type of e-commerce site where products and inventory information are provided by multiple third parties, whereas transactions are processed by the market operator. Online open markets are the primary type of multichannel e-commerce. In an online open market, customer transactions are processed by the market operator and then delivered and fulfilled by the participating retailers or wholesalers. In general, since open markets aggregate products from a wide array of providers, selection is usually much wider, availability is higher, and prices are more competitive. Examples of online open market include Etsy and eBay. In this paper, we analysed transaction data from a top-ranked online open market in Korea, G-market. G-market deals with various items from cheap commodities to luxury electronic products. Its revenue is approximately more than 4 billion dollars per year. The size and revenue have grown continuously since its opening in 2000.

3.1.2. Data description

The target dataset consists of 24,925 transaction records in which 1,000 customers and 6,230 sellers (online market owners) involved. The dataset was collected from August 2009 to August 2010 and contains data of customers, sellers, products and transactions, in each separate table. Customer table has attributes such as sex, age, customer ID, region, registration date, total number of purchase, and the total amount of purchase. Seller table has attributes such as seller ID, registration date, type, level, region, the total amount of sales, and purchase satisfaction. Product table has attributes such as product ID, category, price, option price, market price, coupon, shipping fee, product satisfaction, and number of comment. Lastly, Transaction table has attributes such as transaction ID, seller ID, customer ID, purchase date, purchase options, quantity, mileage and pay method (credit card or cash). Market price in the product table represents the product's price in an off-line market. It promotes customers' purchase by providing information about how much they can save by purchasing the product in the online open market. Coupon in the table is a promotion which can be regarded as a ticket for discount in future purchase. Shipping fee in the table is a fee charged for delivery and free delivery service can be given as a promotion. All the other attributes seem to be self-explanatory.

In the target online open market, add-on selling is implemented as "option". Option leads customers to make additional purchase by providing various optional products related to the original product. For example, when purchasing a tennis racket, additional goods such as tennis ball, tennis shoes and other accessories can be suggested as options. Even essential goods such as CPU, HDD and Memory are provided as options when buying a personal computer.

3.2. Research framework

Figure 3.2 depicts our research framework. We first integrated the original data tables and pre-processed the data for data-mining. Second, we investigated the portion of the add-on selling transactions in the dataset to know whether or not the portion is sufficient enough to be discussed. Third, we proposed data-mining models to find the influential factors which explain characteristics of add-on selling transaction well. Fourth, we identified the association rules among the promotions which entice customers to add-on selling. Each step of the framework is further described below. Note that all the experimental results are discussed in Sections 4 and 5.

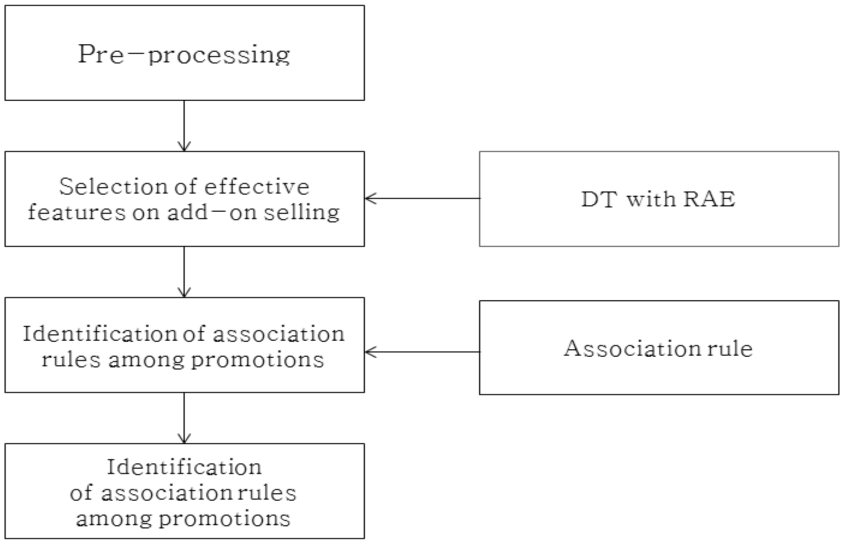

Figure 3.1 Framework for experiments

3.2.1. Investigation of the portion of the add-on selling transactions

In this section, transaction data was statistically analysed to investigate the total number of add-on selling transactions and how much amount of the revenue they brought. Table 3.1 shows the result. The portion of add-on selling transactions accounts for over 30% among the whole transactions and the portion of the added prices to option accounts for over 12% in the total revenue. Although there is no specific standard, our data is big enough to conduct a research about add-on selling based on the analysis.

Table 3.1 The results of statistical analysis from the transaction data

The number of add-on selling transactions	The number of non add-on selling transactions	The total number of transactions
6,712 (30.23%)	15,491 (69.76%)	22,203 (100%)
average of added prices to option	average of prices without option	The total revenue in the data
16,342,260 (12%)	119,843,240 (88%)	136,185,500 (100%)

3.2.2. Pre-processing

We first joined the four data tables (e.g., customer, seller, product, and transaction tables), using MS SQL Server 2008. The united table consists of 34 attributes with transaction ID as a primary key. We deleted 1,262 transaction records which have missing values in many columns. Finally, 20,891 transaction records were selected to build a model to classify transactions. However, since it is usual to balance between the number of positive instances and that of negative instances, we select only 5,981 non add-on selling transaction instances randomly, out of 14,910 to balance with the transaction data.

For our experiment, having discussed with domain experts, we finally selected 13 attributes which are expected to be influential on add-on selling. They contain customer's purchase information such as quantity, seller satisfaction, product satisfaction, number of comments, shipping fee, discount price, coupon used, coupon given, mileage given, number of comments, seller level as well as demographic information such as age and sex.

Then, we grouped the selected transaction data by transaction ID. Most of attributes are used without any calculations explained in Table 3.2. Sample records are shown in Table 3.3.

Table 3.2 Attributes for classification of add-on selling

Attribute	Meaning	Datatype
Mileage_given	The amount of mileage given	Integer
Age	Customer's age	Integer
Discount price	The discounted price for purchase in the shop	Integer
Coupon_given	Number of coupons given	Integer
Coupon_used	The number of coupons used	Integer
Product_satisfaction	Customer's evaluation on the product	Integer (0 to 5)
Quantity_of_transaction	The number of items purchased in a transaction	Integer
Shipping_fee	Shipping fee paid	Integer
Number_of_comments	The number of posted comments on the product	Integer
Seller_satisfaction	Customer's evaluations on the seller	Integer (0 to 5)
Seller_level	Seller's grade	Integer (0 to 5)
Product_classification	Product classification between experience good and search good	Boolean (E or S)
Sex	Customer's sex	Boolean (M or F)

Table 3.3 Examples of records of the dataset integrated for experiments

T_ID	Mileage_given	Age	Discount price	Coupon_given	Coupon_used	Product_ satisfaction
Quantity_ of_ transaction	Shipping_ fee	Number_ of_comments	Seller_ satisfaction	Seller_ level	Product_ classification	Sex
c13244	2	41	3,600	1	0	4
1	0	254	4	3	S	M
c13245	0	32	0	0	2	3
2	2,000	15	3	2	E	F

3.2.3. Feature selection for add-on selling

To investigate the influential factors leading to add-on selling transaction, we adopted classification model. If a classification model shows the best performance with the selected factors, those factors are the most influential to the dependant variable, which represents whether add-on selling happened or not.

Prior to the add-on selling classification, we conducted feature selection by employing the wrapper approach with backward elimination using Weka 3.7.8. Relief attribute evaluator was used to evaluate 13 input variables to select most influential K variables when classifying transactions into add-on selling or non-purchase. The descending order of importance of the 13 input variables is: *Discounted price, Age, Number_of_comments, Shipping_fee, Product_satisfaction, Seller_level, Seller_satisfaction, Coupon_given, Mileage_given, Coupon_used, Sex, Quantity of transaction, Product_classification.* Among these, the most influential 9 variables are desribed in Section 4.1.

Then, we tried to develop DT classifying transaction data into add-on selling and non-add-on selling to examine which factors show the best performance. Among many different decision tree algorithms, C4.5 algorithm was used to develop decision tree model with 0.25 confidence factor for pruning in this study. Comparisons of the classification results of models using 10-fold cross-validation are made in Section 4.1.

3.2.4. Identification of association rules among promotion

To know what kinds of promotions are associated with add-on selling, we first, identified 4 types of promotions which are used in the target online open market. They are *Market price, Coupon, Free delivery, Mileage* , and *Additional discount* as Table 3.4. To estimate exact effects of promotions on add-on selling, we gathered the data only from add-on selling transactions.

Table 3.4 The meaning of promotion attributes

Attribute	Meaning	Data type
Market_price	market price exists or not	Boolean
Coupon	Coupon is given or not	Boolean
Free_delivery	Delivery is free or not	Boolean
Mileage	Mileage is given or not	Boolean

Using SAS Enterprise Miner 9.15, we conducted an experiment to identify association rules among the four promotions. We used only option based transaction records, because we aim to find the effective promotion mix over option based purchase. Each record consists of 6 attributes such as *Option, Market_price, Coupon, Free_delivery,* and *Mileage* including transaction ID. Table 3.5 shows a few examples of the records.

After several trials with different parameter values, we finally set minimum support to 10% and minimum confidence to 20% for AR experiments.

Table 3.5 Examples of promotion instances for AR experiments

Transaction ID	Option	Market_price	Coupon	Free_delivery	Mileage
04906	T	T	F	T	T
04909	T	F	F	T	T
04910	T	F	F	F	T

4. Discussion

4.1. Results from building a classification model

Based on the data mining technique, DT, we find the best model and the best set of attributes in terms of accuracy.

Table 4.1 shows the accuracy of each case as the number of input variables decreases. We can figure out that the highest accuracy was acquired with when 9 attributes such as Discounted price, Age, Number_of_comments, Shipping_fee, Product_satisfaction, Seller_level, Seller_satisfaction, Coupon_given, Mileage_given were used. Therefore, we finally conclude that those 9 attributes are the most influential factors and they represent the characteristics of add-on selling transaction well.

Table 4.1 Accuracy comparisons

The number of features	Accuracy (%)
13	81.95
12	81.97
11	82.01
10	81.97
9	82.18
8	80.10
7	80.42
6	79.98
5	74.90
4	74.58
3	73.88
2	73.42
1	71.91

4.2. Results of identification of association rules among promotions

As shown in Table 4.2, association rules were found from add-on selling transaction data. The table shows that '*OPTION*' and '*COUPON*' are frequently associated with other promotion attributes. For instance, people who are likely to accept to make add-on selling high tend to take promotions such as '*COUPON*', '*COUPON* & *MILEAGE*', or '*COUPON* & *MARKET_PRICE*'. Also, we can find out that (*MARKET_PRICE* and *FREE_DELIVERY*) are associated with each other in add-on selling transaction data. Based on the results above, those pairs of promotion mixes, i.e., COUPON, COUPON & MILEAGE, COUPON & MARKET_PRICE and MARKET_PRICE & FREE_DELIVERY are significantly influential on leading to make add-on selling.

Table 4.2 The results of association rules among promotions in add-on selling transactions

Lift	Support (%)	Confidence (%)	Rule
1.03	21.94	93.02	COUPON → OPTION
1.03	21.94	24.28	OPTION → COUPON
1.08	19.28	49.04	OPTION & MARKET_PRICE → FREE_DELIVERY
1.08	19.28	42.28	FREE_DELIVERY → OPTION & MARKET_PRICE
1.16	11.90	50.45	COUPON → OPTION & MILEAGE
1.16	11.90	27.37	OPTION & MILEAGE → COUPON
1.18	10.94	46.39	COUPON → OPTION & MARKET_PRICE
1.18	10.94	27.84	OPTION & MARKET_PRICE → COUPON
1.13	10.94	49.87	OPTION & COUPON → MARKET_PRICE
1.13	10.94	67.15	MARKET_PRICE → OPTION & COUPON

4.3. Strategies for promoting add-on selling

Based on the results extracted from this study, we developed add-on selling strategies for every dimension of CRM which will help the open market lead its customers to add-on selling with less customer repulsion as follows:

- As can be seen in Table 6, the most influential factors leading to add-on selling are 9 attributes such as Discounted price, Age, Number_of_comments, Shipping_fee, Product_satisfaction, Seller_level, Seller_satisfaction, Coupon_given, Mileage_given. Therefore, the following strategies for CRM are recommended. (sellers should develop add-on selling strategies by utilizing these results). Provide evidence for each CRM strategy below.

- Sellers had better reward customers in light of reducing customer repulsion by giving more tangible compensations such as additional mileages, coupons and free delivery when customers make add-on selling. (*customer retention*)
- Customer repulsion is caused most by the thought that add-on selling ends up with more expensive price than other market price. It would be desirable to clearly provide customers with the other market price. (*customer development*)
- As it was proven that add-on selling could result in satisfaction of both product and seller, we suggest that sellers should try to obtain positive reputation through making their customers well satisfied with superb products and high quality of services. (*customer retention*)
- Our findings show that high number of comments with positive opinion on products can lead to make add-on selling look quite convincing because high number of comments can make potential customers get enough product information in advance. Therefore, it could be helpful to show the best comment in the front of the list.

• Also, the data used in this paper is already refined to know which customers tend to make add-on selling more than others. So, practicing CRM activities directly targeted on those customers would be more cost-effective and also helpful in making add-on selling with less customer repulsion than targeting all the customers. Surely, it is necessary to regularly refine new data as more transaction data is going to be accumulated. (*customer identification, customer attraction*)

• Based on the results of identification of association rules among promotions, we can also develop the following add-on selling strategies.

- Since (*COUPON* and *OPTION*), (*OPTION* & *MARKET_PRICE* and *FREE_DELIVERY*), (*COUPON* and *OPTION* & *MILEAGE*), (*COUPON* and *OPTION* & *MARKET_PRICE*), (*OPTION* & *COUPON* and *MARKET_PRICE*) are mutually associated with each other as shown in Table7, it is suggested for sellers to develop add-on selling strategies using those association rules. For example, if there are customer swho have little interest or some repulsion on making add-on selling, the seller can motivate such customers to make add-on selling with promotions which lead customers to make add-on selling such as free delivery, coupon, or additional mileage on condition of add-on selling beforehand. It is going to be effective to make add-on selling with less customer repulsion. *(customer retention)*

5. Conclusions

In this paper, we developed add-on selling strategies with consideration of mitigating customer repulsion. For this purpose, applying data mining techniques to the transaction data, we could deepen our knowledge on the purchasing pattern related to add-on selling. The proposed strategies can be utilized for better CRM strategies in the target online open market.

This study has a few things to be desired. The facts that data set is relatively small and contains transaction data for a short term are limitations of our study. Also, it would be better if this study is proved to investigate whether the strategies we proposed are actually effective or not. Nevertheless, we believe that the experiments as conducted in this study are deserved to be paid attention of researches related to add-on selling where a huge amount of invaluable data still remains unused.

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