Using Feature Selection Approaches to Identify Crucial Factors of Mobile Advertisements

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***Abstract*—In recent years, with the rapid popularization of applications (APP) and mobile devices, the market share of mobile advertisements grows dramatically. Mobile advertisements can reach potential customers ubiquitously based on individual needs. For advertisers, how to enhance the design for satisfying individual's requirements, and to increase the click through rate (CTR) and further increase customer's loyalty and repurchase rate have become one of major issues. Therefore, this study aims to identify the important mobile advertisements factors of influencing the customer's loyalty and repurchase rate, and then to provide advertisers useful information for the design of mobile advertisements. In this work, we attempt to define the potential factors of mobile advertisements, and then employ support vector machine recursive feature elimination (SVM-RFE), correlation based, and consistency based feature selection methods to identify the key attributes to directly improve the customer's loyalty and repurchase rate. Results can be used to improve the benefits of mobile advertising and to increase the market share of mobile advertising.**

***Index Terms*—Mobile advertisements, Feature selection, SVM-RFE, Consistency-based, Correlation-based.**

I. Introduction

With the growing market for mobile devices, it led to the rapid development of mobile websites and applications (APP). Thus, mobile advertising also has become one of popular marketing channels. According to 1st half-year of IAB 2014, it pointed out that internet advertising grew to 23.1 billion USD. It increases 15% compared to 2013[19]. Gartner mentioned that mobile advertising market scale will reach 18 billion USD [12] in 2014. It's also reported that Facebook occupied 49% in the whole mobile advertising market, 1.8 billion USD, in the third quarter of 2013 [21]. The Asian countries including Taiwan, Japan, South Korea paid much attentions to construct information infrastructure and build wireless environment. Thus, in 2012, Asian mobile Ads market reached to $ 7.7 billion [4]. Therefore, lots works aimed to study the value of mobile advertising.

Currently, the related studies focus on possible applications areas and its effects of APP. It's reported that APP has widely applied to education, health care, and so on [32]. In the work of Bristol, he found that there are more than 290 APP are now cancer-related, over 800 APP are associated with diabetes, or even more than 100 APP are about pain management [2]. Moreover, Swartz [31] noted that the clinical information regarding to pediatric health care have been provided in forms of online journals or e-books which can be browsed on the mobile devices. Steven et al. [32] indicated that APP has a positive influence to persuade mobile device users. It can be used to enhance the user interests in brand or brand related products [32]. From available literatures, relatively few works aimed to discover the key factors of clicking mobile advertisements (Ads) and try to increase customer's loyalty and repurchase rate.

Mobile advertising is another one of new research fields due to the popularization of mobile devices. Therefore, the related works are not as rich and diverse as Internet advertising. Chen and Hsieh [4] tried to discover the design factors for personalizing mobile Ads. Yang et al. [41] presented an integrated mobile advertising model to discover the effects of technology-based and emotion-based evaluations. This work hopes to define and identify the most important factors to influence consumers' points of reading.

Moreover, because the advertising effects might be calculated by its click amount, for advertisers, it's important to know the crucial factors that can attract customers. Most of all, the advertisers further know how to improve the customer of loyalty and repurchase rate in mobile advertising, these are able to improve brand recognized and purchase intention. Consequently, the objective of this work is to define and identify the key factors of clicking mobile Ads by using several feature selection algorithms, including support vector machine recursive feature elimination (SVM-RFE), correlation based, and consistency based feature selection methods. The selected important factors can assist advertisers to make their advertising decisions from the viewpoints of customers. Finally, an actual case study will be provided to demonstrate the effectiveness of the proposed methods.

II. Literature Review

A. Mobile Advertising

Mobile marketing is a promotional activity designed to deliver message through the use of mobile phones, smart phones and other mobile devices [36]. Ufuoma and Ayesha [37] have referred to the main function of marketing is advertising which plays a very important role between businesses and consumers in providing products and services to facilitate operations. According to Mobile Marketing

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Association (MMA), mobile advertising could be defined as a form of advertising, with mobile handset, PDA or other wireless communication device to send advertising messages [4]. As companies push for BYOD (Bring your own device) plans, they requests employees to carry mobile devices to work. It has apparently become a trend, so that mobile Ads can have their advertising effectiveness [11]. There are lots of scholars and organizations classified mobile Ads which could be summarized in Table 1.

TABLE I
THE CATEGORY OF MOBILE ADVERTISEMENTS [8, 18]

1.**Message-based** -SMS Advertising -MMS Advertising
2. **Web-based** -Keyword Advertising -Banner Advertising
3.**Location-based** -Push Location-based Service -Pull Location-based Service
4. **APP-based** -In-App Advertising -Ad-watch App -Quick-Response Barcodes Ads
5.**Call-based** -Caller Ring Back Tone -Call To Action

Companies started to use mobile Ads to promote their products. For examples, Macy used interactive mobile Ads to strengthen their M-commerce strategy. In September 2013, in order to recognize daily sales by utilizing an interactive mobile Ad combining a small puzzle game [26]. From October 2013, McDonald's has also joined the groups which uses mobile Ads, and released the first Ad which combined social media and rich media technologies, and then placed it in the well-known social networking sites, Facebook and Twitter, as well as National Football League Mobile Sites [26].

Some works related to mobile Ads are described as follows. Kim [23] noted that professionally smartphones and APP can allow mobile Ads readers to enhance trust and to increase the willingness to buy products. Kim and Lee [22] discovered and theorized customer typologies based on Q theory's subjectivity in a qualitative approach and then verified and generalized sequentially these theoretical definitions and concepts through a combination of the Q and R empirical methods. Their results can be used as an antecedent of theoretical and industrial frameworks and a basic statistical data in advertising marketing and customer relationship management domains. Chen et al. [5] aimed to help mobile advertisers enhance their effectiveness in delivering mobile advertisements in the constantly evolving world of e-commerce. Their research analyzed attributes and concluded that brands, prices, promotions, preferences, and interests are key attributes for both goods and services in designing mobile advertising messages and that time is crucial only for services mobile advertising message design. Bakar and Rosmiza [1] identified the relationships between technology acceptance and purchase intentions on movie mobile advertising among youth Twitter users in Malaysia.

Chen and Hsieh [4] found six customized factors of designing mobile Ads in 2012. José et al. [20] indicated that entertainment, irritation, and perceived usefulness are three major factors for the youth accepted mobile advertising. Their study also has provided practical guideline for marketing managers to promote products/service to the youth. Yang et al. [41] collected Korean consumers' information, and build a framework to provide advertisers to predict the efficiency of mobile Ads. From literatures mentioned above, we can find that mobile Ads have attracted lots of big companies' attentions. So, to identify the crucial factors of clicking mobile Ads has become one of important issues.

B. *Feature Selection*

Feature selection can be considered as choosing a subset of features that can result in a highest classification performance [38]. Frenay et al. [10] think that feature selection can have some benefits including to reduce the dimension size, to remove irrelevant or redundant features, and to improve the performance of the classification model. Chandrashekar & Sahin [6] pointed out that feature selection allows us to get a better understanding of collected data, to help us increase learning efficiency by reducing the dimension size, and to improve the prediction accuracy. A number of soft computing approaches, such as neural networks, genetic algorithms, decision tree [7], rough sets [35], and correlation analysis [7] have been widely used to remove irrelevant, unnecessary, and redundant attributes. The conventional feature selection methods can be divided into three groups including filters, wrappers, and embedded (hybrid) methods [42].

The filter methods like preprocessor, we can choose a set of higher ranking features and used them to build predict models. Filter methods might use statistical analysis techniques to extract important features without learning methods [9]. The second group involves wrapper based methods which select factors based on the classification performance of learning methods [13]. Filter algorithm initiates the search with a given subset and searches through the feature space using a particular search strategy. It evaluates each variable independently with respect to the class in order to create a ranking. Variables are then ranked from the highest value to the smallest one. Since the filter model applies independent evaluation criteria without involving any classification algorithm, it does not inherit any bias of a classification algorithm and it is also computationally efficient. Wrapper approaches are similar to the filters except that they utilize a classification algorithm. The selected subset S is initialized with the first variable in the ranking, and then the algorithm iteratively tries to include in S the next variable xi in the ranking by evaluating the goodness of that augmented subset. The third group contains embedded (hybrid) methods which combined filter and wrapper methods to achieve better classification performance [17, 33] The features are ranked using distance criterion and then wrapper model is used to evaluate classification model [6, 28, 42]. However, when applying these feature selection to real world, we need to consider computational cost and complexity.

According to the work of Novakovic [28], he evaluated several feature selection methods including Gain (IG), Gain Ratio (GR), Symmetrical Uncertainty (SU), Recursive Elimination of Features (Relief-F), One-R (OR), Chi-Squared

(CS). Based on classification performances of Naive Bayes, the experimental results show that OR is the best followed by CS, t GR, SU, IG, and RF. Veronica et al. [39] used five kinds of feature selection methods including Correlation-based Feature Selection (CFS), Consistency-based, INTERACT, IG, Relief-F, Recursive Feature Elimination for Support Vector Machines (SVM-RFE), Feature Selection-Perceptron (FS-P), they found Relief-F has the best performance and IG can have a stable performance. Among them, SVM-RFE can be one of optimal solution for feature selection. Therefore, we use SVM-RFE in this study.

C. SVM-RFE

Support vector machine recursive feature elimination (SVM-RFE) was first proposed by Guyon et al. [14] to aid in gene selection for cancer classification. SVM-RFE is a wrapper approach used in two-class circumstances [30]. It was demonstrated that the features selected by SVM-RFE yielded better classification performance than the other methods mentioned in the study of Guyon et al. [14]. According to the work of Chandrashekar and Sahin [6], SVM-RFE uses the weights of SVM to rank the feature for their removal. Let w_j be defined as equation (1).

$$w_j = \frac{\mu_j(+) - \mu_j(-)}{\sigma_j(+) + \sigma_j(-)} \tag{1}$$

where $\mu_j(+)$ and $\mu_j(-)$ are the mean of the samples in class (+) and $(-)$ and σ_j is the variance of the respective classes and j =1 to D. This equation (1) can be employed to be ranking criteria to sort the features. The rank vector *w* can be used to classify since features rank proportionally contributes to the correlation. A voting scheme could be defined in equation (2).

$$D(x) = w(x - \mu) \tag{2}$$

where *w* is the rank of the features or weight, $D(x)$ is the decision and μ is the mean of the data. Hence the rank of the features can be used as classifier weights. The change in the weight w_j can be viewed as removing a feature *j*. It is suggested to use the change in the objective function, a linear discriminant function *J* which is a function of w_j. This concept of using the weights as the ranking and the search is done using the change in the objective function is applied to the SVM classifier to perform SVM-RFE method.

There are lots of successful of SVM-RFE to real applications. For examples, Shieh and Yang [34] presented a multiclass SVM-RFE to streamline the selection of optimum product form features. Bolón-Canedo et al. [3] tried to find the most up-to-date feature selections methods for microarray databases. For microarray data, the optimal combination of feature selection methods is SVM-RFE and mRMR (minimum Redundancy Maximum Relevance) [3]. Korkmaz et al. [24] utilized SVM for drug discovery with three feature selection methods including SVM-RFE, wrapper method and subset selection. Maldonado [27] pointed out one advantage of SVM-RFE is the possibility to perform non-linear feature selection. Therefore, SVM-RFE has been employed to a feature selection method is this study [27].

III. Implemental Procedure

The implemental procedure involves 8 major steps. They are to define factors of mobile advertising, design questionnaire, pre-test questionnaire, collect data, prepare data, implement feature selection methods, build SVM classifier, and evaluate results and make conclusions.

The details of the procedure have been provided as follows.

Step 1: Define factors of mobile advertising

In this step, we try to define potential factors of mobile advertisements depending upon available literatures. We survey published works and attempt to define possible factors from related studies. Next, according to these defined factors, we can go to next step to design questionnaire for collecting data.

Step 2: Design questionnaire

In this step, an importance level of the defined factors is measured in this questionnaire. In this questionnaire, customers express the feeling about the level of importance for a certain factor regarding the probability of increasing loyalty, and repurchase rate, respectively. Every single one factor will be expanded into a pair of question items.

Q: How would you feel the importance of the title of mobile advertisement?
(A) Very important (B) Important (C) Neutral
(D) Unimportant (E) Very unimportant

Step3:Pre-test

The original questionnaire will be issued for pretesting. In this step, according to the feedbacks of respondents, we can modify the questionnaire items.

Step4: Collect data

After pretesting, the modified questionnaire will be issued to target customers, including those who have experiences of watching mobile ads.

Step5: Prepare data

Before implementing feature selection methods, we will code the collected data. After preprocessing, we can analyze the collected examples.

Step 6: Implement feature selection methods

Step 6.1 SVM-RFE

In this work, we use SVM-RFE [14]. The algorithm of SVM-RFE can be found as follows.

Inputs:

Training examples

$$X_0 = [X_1, X_2, ..., X_k, ..., X_l]^T \tag{3}$$

Class labels

$$y = [y_1, y_2, ..., y_k, ..., y_l]^T \tag{4}$$

Initialize:

Subset of surviving features

$$s = [1, 2, ..., n] \tag{5}$$

Feature ranked list

$$r = [] \tag{6}$$

Repeat until

$$s = [] \tag{7}$$

Restrict training examples to good feature indices

$$X = X_0(:, s) \tag{8}$$

Train the classifier

$$\alpha = SVM - train(X, y) \tag{9}$$

Compute the weight vector of dimension length(s)

$$W = \sum_k \alpha_k y_k x_k \tag{10}$$

Compute the ranking criteria

$$c_i = (w_i)^2, \ for all i \tag{11}$$

Find the feature with smallest ranking criterion

$$f = \arg\min(c) \tag{12}$$

Update feature ranked list

$$r = [s(f), r] \tag{13}$$

Eliminate the feature with smallest ranking criterion

$$s = s(1: f-1, f+1; length(s)) \tag{14}$$

Output:

Feature ranked list

$$r \tag{15}$$

Step 6.2 Consistency based feature selection method [25]

This method evaluates the worth of a subset of attributes by the level of consistency in the class values when the training instances are projected onto the subset of attributes. Consistency of any subset can never be lower than that of the full set of attributes; hence the usual practice is to use this subset evaluator in conjunction with a Random or Exhaustive search which looks for the smallest subset with consistency equal to that of the full set of attributes.

Step 6.3 Correlation based feature selection method:

This approach evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low inter-correlation are preferred [16].

By the way, we use four search methods in correlation and consistency based method. These search techniques can be described as follows.

-Best First Method:

This technique searches the space of attribute subsets by greedy hill climbing augmented with a backtracking facility. Setting the number of consecutive non-improving nodes allowed controls the level of backtracking done. Best first may start with the empty set of attributes and search forward, or start with the full set of attributes and search backward, or start at any point and search in both directions (by considering all possible single attribute additions and deletions at a given point).

-Genetic Search Method:

This technique performs a search using the simple genetic algorithm described in Goldberg (1989)[15].

-Greedy Stepwise Method:

This technique performs a greedy forward or backward search through the space of attribute subsets. It may start with no/all attributes or from an arbitrary point in the space. Stops when the addition/deletion of any remaining attributes results in a decrease in evaluation. It can also produce a ranked list of attributes by traversing the space from one side to the other and recording the order that attributes are selected.

-Linear Forward Selection Method:

This technique is an extension of Best First method. It takes a restricted number of k attributes into account. Fixed-set selects a fixed number k of attributes, whereas k is increased in each step when fixed-width is selected. The search uses either the initial ordering to select the top k attributes, or performs a ranking (with the same evaluator the search uses later on). The search direction can be forward or floating forward selection (with optional backward search steps).

Step 7: Build SVM classifier by SMO

In this step, we implements Platt's sequential minimal optimization algorithm for training a support vector classifier [29].

Step 8: Evaluate results and make conclusions

Finally, from the results of from step 6 to step 7, we find the important factors of mobile advertising, understand the internet users' thinks, and then we can draw conclusions based on them.

IV. Results

A. Define the potential factors of mobile advertisements

Table 2 defines the whole potential factors of mobile Ads. The factors will be our candidate set for feature selection.

B. Results for increasing customer loyalty

Table 3 summarized the results of correlation based, and consistency based feature selection methods. We first use 4 searching techniques and then a vote mechanism has been utilized to selected important features. In consistency based feature selection method, we found four factors, "Language", "Perceived ease of use", "Credibility", and "Game-based". And in correlation based feature selection method, we discovered five factors "Language", "Perceived ease of use", "Credibility", "Price", "Game-based".

TABLE II
THE DEFINED POTENTIAL FACTORS

No.	Factors	Definitions	Supports
1	Involvement	The degree that customers involve in mobile Ads.	[40]
2	Language	Language used in mobile Ads.	[40]
3	Type of Website	The advertising products of mobile Ads is suitable the website which Ads is located.	[40]
4	Irritation	Mobile ads make consumers disgust, hate and other negative effects.	[40] [20] [21]
5	Perceived Usefulness	Customers think the information in mobile Ads is helpful.	[41] [20]
6	Perceived ease of use	Mobile ads are very simple and approachable, without any effort in.	[41]
7	Credibility	Mobile Ads let customers feel reliable and trusted.	[41] [21]
8	Price	Mobile Ads can provide detailed price information of products/services.	[4]
9	Preference	Mobile Ads can provide information to customers according to their preferences.	[4]
10	Interest	Mobile Ads provide related content depending on users' personal interests.	[4]
11	Brand Name	Mobile Ads provide information of specific brand.	[4]
12	Informativeness	Mobile ads deliver consumers rich/enough information content.	[21]
13	Game-based	Mobile Ads are integrated into games to marketing.	[26]

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TABLE III
RESULT OF CORRELATION BASED AND CONSISTENCY BASED FEATURE SELECTION METHODS (CUSTOMER LOYALTY)

Attribute Evaluator / Search Method	Consistency (Number of folds, %)	Correlation (Number of folds, %)
Best First	**18**(80%)	**18**, **39**(80%)
	16(60%)	**16**, **3**(60%)
	3, **39**(40%)	**20**(40%)
Genetic Search	**39**, 36, **3**, **18**(80%)	**18**, **39**(80%)
	25, **16**, 9, 4(60%)	**3**, **16**(60%)
	5, 14, 27(40%)	8, 9, **20**, 35(40%)
Greedy Stepwise	**18**(80%)	**18**, **39**(80%)
	16(60%)	**3**, **16**(60%)
	3, **39**(40%)	**20**(40%)
Linear Forward Selection	**18**(80%)	**18**, **39**(80%)
	16(60%)	**3**, **16**(60%)
	3, **39**(40%)	**20**(40%)
Vote Mechanism	3 Language	3 Language
	16 Perceived ease of use	16 Perceived ease of use
	18 Credibility	18 Credibility
	39 Game-based	20 Price
		39 Game-based

TABLE IV
RESULTS OF SVM-RFE (CUSTOMER LOYALTY)

Attribute Evaluator / Search Method	SVM-RFE (By order from Important)
Ranker	1 Involvement
	11 Irritation
	13 Perceived Usefulness
	16 Perceived ease of use
	18 Credibility

Table 4 lists the results of SVM-RFE. SVM-RFE ranks all factors. We merely pick some top factors. Top 5 factors include “Involvement”, “Irritation”, “Perceived Usefulness”, “Perceived ease of use” and “Credibility”. Compare results of three feature selection methods. They all indicated that “Perceived ease of use”, “Credibility” are important for increasing customer loyalty.

C. Results for increasing repurchase rate

In this subsection, we aim to find the crucial factors for increasing repurchase rate. Table 5 summarized the results of correlation based, and consistency based feature selection methods. In consistency based feature selection method, we found two factors, “Credibility”, and “Informativeness”. And in correlation based feature selection method, we discovered four factors “Credibility”, “Interest”, “Brand Name”, and “Informativeness”.

Table 6 shows the results of SVM-RFE. We merely pick some top factors. Top 5 factors include “Type of Website”, “Perceived Usefulness”, “Credibility”, “Preference” and “Brand Name”. Compare results of three feature selection methods. They all indicated that “Credibility” is important for increasing re-purchase rate.

TABLE V
RESULT OF CORRELATION BASED AND CONSISTENCY BASED FEATURE SELECTION METHODS (RE-PURCHASE RATE)

Attribute Evaluator / Search Method	Consistency (Number of folds, %)	Correlation (Number of folds, %)
Best First	**18**(100%)	**18**(100%)
	31(60%)	**31**(60%)
	3, **32**(40%)	**32**, **28**, **26**, 3(40%)
Genetic Search	**18**(100%)	**18**(100%)
	31(80%)	**32**(60%)
	32, 26, 20, 14(60%)	**31**, **28**, 27, **26**(40%)
Greedy Stepwise	**18**(100%)	**18**(100%)
	31(60%)	**31**(60%)
	32, 3(40%)	**32**, **28**, **26**, 3(40%)
Linear Forward Selection	**18**(100%)	**18**(100%)
	31, **32**(60%)	**31**(60%)
	20, 3(40%)	3, **26**, **28**, **32**(40%)
Vote Mechanism	18 Credibility	18 Credibility
	31 Informativeness	26 Interest
	32 Informativeness	28 Brand Name
		31 Informativeness
		32 Informativeness

TABLE VI
RESULTS OF SVM-RFE (RE-PURCHASE RATE)

Attribute Evaluator / Search Method	SVM-RFE (By order from Important)
Ranker	6 Type of Website
	13 Perceived Usefulness
	18 Credibility
	21 Preference
	27 Brand Name

D. Results of SVM

In order to evaluate the performances of three feature selection methods. We use the selected important features by three methods to build SVM. Tables 8 and 9 summarize the results of SVM for loyalty and re-purchase rate, respectively. From these tables, we can find SVM-RFE outperforms correlation based and consistency based methods.

TABLE VII
SELECTED FACTORS BY SVM-RFE

Dependent Variables / SVM-RFE (Selected Factors)	Loyalty (Accuracy)	Re-purchase Rate (Accuracy)
1	63%	68%
2	70%	73%
3	**73%**	**79%**
4	68%	79%
5	71%	79%

TABLE VIII
RESULTS OF SVM (LOYALTY)

Feature Selection / Evaluation	Consistency (+SVM)	Correlation (+SVM)	SVM-RFE (+SVM)	SVM (only)
Accuracy	70%	65%	**73%**	62%
Precision	70%	65%	**74%**	62%
Recall	70%	65%	**73%**	62%
F1-score	69%	64%	**72%**	62%
Time	0.02s	0.02s	0.02s	0.03s

For loyalty data, SVM-RFE can have the best performance when using three important features, “Involvement”, “Irritation”, and “Perceived Usefulness”. For repurchase rate data, SVM-RFE also can have the best performance when using three important features, “Type of Website”, “Perceived Usefulness”, and “Credibility”.

TABLE IX
RESULTS OF SVM (RE-PURCHASE RATE)

Feature Selection / Evaluation	Consistency (+SVM)	Correlation (+SVM)	SVM-RFE (+SVM)	SVM (only)
Accuracy	76%	76%	**84%**	63%
Precision	77%	77%	**84%**	63%
Recall	76%	76%	**84%**	64%
F1-score	76%	76%	**84%**	63%
Time	0.02s	0.01s	**0.01s**	0.01s

V. CONCLUSIONS

This work tries to define potential factors of mobile advertisements. Then, we employ support vector machine recursive feature elimination (SVM-RFE), correlation based, and consistency based feature selection methods to identify the key attributes to directly improve the customer’s loyalty and repurchase rate. Results indicated that SVM-RFE outperforms correlation based and consistency based feature selection methods.

Moreover, for increasing customer loyalty, we identify

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three important factors. They are “Involvement”, “Irritation”, and “Perceived Usefulness”. Therefore, mobile advertisers need to improve the degree that customers involve in mobile Ads, and avoid to make consumers disgust, hate and other negative effects. Finally, the information contained in mobile Ads should be helpful to customers.

For increasing repurchase rate, we also recognize three important factors. They are “Type of Website”, “Perceived Usefulness”, and “Credibility”. Consequently, advertisers should put their mobile Ads on a suitable website which match the position of marketing products. By the way, the provided mobile Ads should let customers feel reliable and trusted. Moreover, the information in mobile Ads should helpful. For the direction of future works, readers can use another different feature selection method to identify important factors mobile ads. By the way, more examples should be collected for precise analysis.

REFERENCES

[1] Bakar, M. S. A., Rosmiza, B., “Technology Acceptance and Purchase Intention towards Movie Mobile Advertising among Youth in Malaysia,” *Procedia - Social and Behavioral Sciences*, Vol. 130, pp. 558-567, 2014.

[2] Bristol, T. J., "Nursing school? There's an app for that!," *Teaching and Learning in Nursing*, Vol. 9, pp. 203–206, 2014.

[3] Bolón-Canedo, V., Sánchez-Maroño, N., Alonso-Betanzos, A, Benítez, J.M., Herrera, F., “A review of microarray datasets and applied feature selection methods,” *Information Sciences*, 282, 111–135, 2014.

[4] Chen, P. T., Hsieh, H, P., “Personalized mobile advertising: Its key attributes, trends, and social impact,” *Technological Forecasting & Social Change*, Vol. 79, pp. 543-557, 2012.

[5] Chen, P. T., Cheng, J. Z., Yu, Y. W., Ju, P. H.,“ Mobile advertising setting analysis and its strategic implications,” *Technology in Society*, Vol. 39, pp. 129-141, 2014.

[6] Chandrashekar , G., Sahin, F., “A survey on feature selection methods,” *Computers and Electrical Engineering*,” 40, 16–28, 2014.

[7] Chen, K.-Y., Chen, L.-S., Chen, M.-C., Lee, C.-L., “Using SVM based method for equipment fault detection in a thermal power plant,” *Computers in Industry*, 62(1), 42-50, 2011.

[8] Diane, R., “Get Your Business Moving: 9 types of Mobile Marketing,” 2010, Available:http://harpsocial.com/2010/03/get-your-business-moving-9-types-of-mobile-marketing/.

[9] Dash, M. and Liu, H., “Feature selection for classification,” *Intelligent Data Analysis*, 1(3), 131-156, 1997.

[10] Frenay, B., Doquire, G., Verleysen, M., “Estimating mutual information for feature selection in the presence of label noise,” *Computational Statistics & Data Analysis*, 71, 832-848, 2014.

[11] Gartner, “Gartner Predicts by 2017, Half of Employers will Require Employees to Supply Their Own Device for Work Purposes,” 2013, Available:http://www.gartner.com/newsroom/id/2466615.

[12] Gartner, “Gartner Says Mobile Advertising Spending Will Reach $18 Billion in 2014,” 2014, Available:http://www.gartner.com/newsroom/id/2653121.

[13] Guyon, I. and Elisseeff, A., “An introduction to variable and feature selection,” *Journal of Machine Learning Research*, 3(7-8), 1157-1182, 2003.

[14] Guyon, I., Weston, J., Barnhill, S., Vapnik, V., “Gene Selection for Cancer Classification using Support Vector Machines,” *Machine Learning*, 46, 389–422, 2002.

[15] Goldberg, D. E., “Genetic algorithms in search,” *optimization and machine learning*. Addison-Wesley, 1989.

[16] Hall, M. A., “Correlation-based Feature Subset Selection for Machine Learning. Hamilton,” New Zealand, 1998.

[17] Huang, J., Cai, Y. and Xu, X., “A hybrid genetic algorithm for feature selection wrapper based on mutual information,” *Pattern Recognition Letters*, 28(13), 1825-1844, 2007.

[18] Institute for Information Industry-Foreseeing Innovative New Digiservices, III-FIND, “LBS type of advertising by consumers as an important model for future development of mobile ads,” 2011, Available:http://www.find.org.tw/find/home.aspx?page=many&id=321.

[19] Interactive Advertising Bureau, IAB, “2014 Internet Advertising Revenue Half-Year Report,” 2014, Available:http://www.iab.net/media/file/IAB_Internet_Advertising_Revenue_Report_HY_2014_PDF.pdf.

[20] José, M. P., Silvia, S. B., Carla, R. M. and Joaquin, A. M.,“Key factors of teenagers’ mobile advertising acceptance,” *Industrial Management & Data Systems*, Vol. 113, No. 5, pp. 732-749, 2013.

[21] Kim, Y. J., Han, J., “Why smartphone advertising attracts customers: A model of Web advertising, flow, and personalization,” *Computers in Human Behavior*, Vol. 33, pp. 256-269, 2014.

[22] Kim, K. Y., Lee, B. G., “Marketing insights for mobile advertising and consumer segmentation in the cloud era: A Q–R hybrid methodology and practices,” *Technological Forecasting and Social Change*, In Press, Corrected Proof, 2014.

[23] Kim, K. J., “Can smartphones be specialists? Effects of specialization in mobile advertising,” *Telematics and Informatics*, Vol. 31, pp. 640-647, 2014.

[24] Korkmaz, S., Zararsiz, G., Dincer Goksuluk, D., “Drug/nondrug classification using Support Vector Machines with various feature selection strategies,” *Computer Methods and Programs in Biomedice*, 117, 51-60, 2014.

[25] Liu, H., Setiono, R., “A probabilistic approach to feature selection - A filter solution,” *presented 13th International Conference on Machine Learning*, 319-327, 1996.

[26] Lauren, J., Mobile Marketer, “Mobile Marketer reported: Top 10 mobile advertising campaigns of 2013,” 2013, Available:http://www.mobilemarketer.com/cms/news/advertising/16847.html.

[27] Maldonado, S., Montoya, R., Weber, R., “Advanced conjoint analysis using feature selection via support vector machines,” *European Journal of Operational Research*, 241, 564–574, 2015.

[28] Novakovic, J., “The impact of feature selection on the accuracy of naïve bayes classifier,” *presented 18th Telecommunications forum TELFOR 2010*, Serbia, Belgrade, 1113-1116, 2010.

[29] Platt, J., “Fast Training of Support Vector Machines using Sequential Minimal Optimization,” In B. Schoelkopf and C. Burges and A. Smola, editors, *Advances in Kernel Methods - Support Vector Learning*, 1998.

[30] Rakotomamonjy, A., “Variable selection using SVM-based criteria,” *Journal of Machine Learning Research*, 3, 1357–1370, 2003.

[31] Swartz , M. K., “Coming Soon To an App Near You,” *Journal of Pediatric Health Care*, Vol. 28, pp. 285, 2014.

[32] Steven, B., Potter, R. F., Shiree, T., Jennifer A. R., Duane V., “The Effectiveness of Branded Mobile Phone Apps,” *Journal of Interactive Marketing*, Vol. 25, pp. 191-200, 2011.

[33] Shi, J., Yin, W., Osher, S., and Sajda, P., “A fast hybrid algorithm for large-scale L1-regularized logistic regression,” *Journal of Machine Learning Research*, 11, 713-741, 2010.

[34] Shieh, M.-D., Yang, C.-C., “Multiclass SVM-RFE for product form feature selection,” *Expert Systems with Applications*, 35, 531–541, 2008.

[35] Swiniarski, R.-W. and Hargis, L., “Rough sets as a front end of neural-networks texture classifiers,” *Neurocomputing*, 36, 85-102, 2001.

[36] TechTarget, “What is mobile marketing?,” 2009, Available:http://searchmobilecomputing.techtarget.com/definition/mobile-marketing.

[37] Ufuoma, A., Ayesha, B. D.,“Mobile advertisements and information privacy perception amongst South African Generation Y students,” *Telematics and Informatics*, 2014.

[38] Uysal, A. K. and Gunal, S., “A novel probabilistic feature selection method for text classification,” *Knowledge-Based Systems*, 36, 226-235, 2012.

[39] Veronica, B. C., Noelia S. M., Amparo, A. B., “An ensemble of filters and classifiers for microarray data classification,” *Pattern Recognition*, 45(1), 531-539, 2012.

[40] William, F., Chen, J. C. and William, H. R., “The effect of variations in banner ad, type of product, website context, and language of advertising on internet users’ attitudes,” *Computers in Human Behavior*, Vol. 31,pp. 37-47, 2014.

[41] Yang, B., Kim, Y., Yoo, C., “The integrated mobile advertising model: The effects of Technology- and emotion-based evaluations,” *Journal of Business Research*, Vol. 66,pp. 1345-1352, 2013.

[42] You, W., Yang, Z., Ji, G., “Feature selection for high-dimensional multi-category data using PLS-based local recursive feature elimination,” *Expert Systems with Applications*, 41(4), 1463-1475, 2014.

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