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## **Analyzing Customer Satisfaction of a Mobile Application using Data Mining Techniques**

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Received 2 November 2019; Received in revised form 19 November 2019

Accepted 22 November 2019; Available online 16 December 2019

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### **Abstract**

Traditionally, statistical methods were used to analyze customer data to gain insight. Recently, data mining techniques have evolved and have been used to analyze customer data. This paper demonstrated how Data Mining techniques can be applied to customer satisfaction analysis of MEA Smartlife, a mobile application (app) developed by Metropolitan Electricity Authority (MEA) of Thailand in order to provide some e-service features to its customers. User satisfaction rating along with demographic profile from 1,446 subjects with diverse backgrounds were collected. Machine learning techniques were then applied to the dataset following the CRISP-DM methodology. Modeling techniques for this study include decision tree, Naïve Bayes, and logistic regression as intuitiveness of the model rather than the predictive performance is more important than predicting whether the customers like the app. The resulting models achieved more than 90% accuracy while having a lower level of precision on the negative class. Feature selection techniques help improve overall accuracy and improve the negative class precision. The resulting model indicated 'ease of use' is the most important factor in determining whether customers are satisfied or dissatisfied with the app. The payment feature also plays an important role in making customers satisfied with the app.

### **Keywords**

Data mining, Customer analysis, CRISP-DM, Decision tree

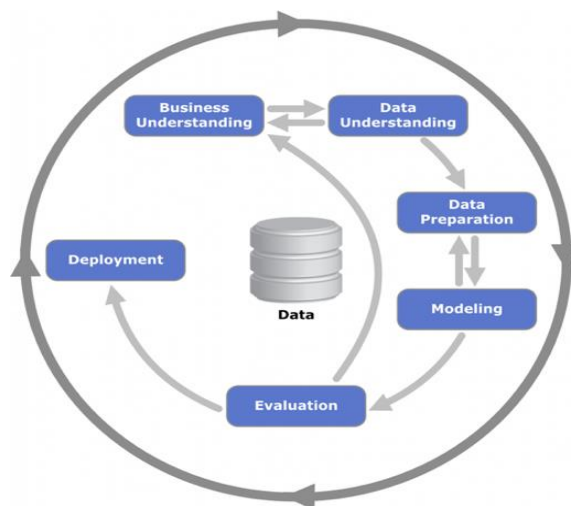
## **Introduction**

One way for firms to understand their customers is by collecting and analyzing customer feedback. Firms need to determine what makes existing customers/users happy or unhappy with a system or product of interest. A study by Gallo (2014) found that the cost of acquiring new customers is between 5 to 25 times more expensive than retaining existing customers. Reichheld and Sasser (1991) also found that a 5% improvement in a company's customer retention rate results in 15% - 50% higher in profit depending on the industry. As a result, understanding what customers want helps to retain existing customers and thus improve the overall performance of firms.

Traditionally, statistical methods were used to analyze customer data to gain insight. Recently, data mining techniques have evolved and have been used to analyze customer data. Studies have demonstrated the applicability of data mining on customer satisfaction analysis in various industries including energy, telecommunication, and healthcare [Hu, 2011; Lee, 2012; Oralhan et al., 2016; Meinzer et al., 2017]. Data mining techniques can help firms to perform various tasks of customer analysis including targeting, cross selling, and retention using different machine learning techniques e.g. segmentation, association, and churn detection. (Kadiyala & Srivastava, 2011).

Mirzaei and Iyer (2014) performed a comprehensive review on the application of data mining to customer relationship management. According to Swift (2001) and Parvatiyar and Sheth (2001), the five domains of customer relationship management are customer acquisition, customer attraction, customer retention, customer development and customer equity growth. Customer acquisition involves finding customers who could become profitable customers to the organization. D'Haen et al. (2013) employed a combination of data sources and data mining to predict customer profitability during acquisition. Customer attraction is the process that involves allocating appropriate resources to the targeted customers. Chun (2012) created a decision model of predicting customer response patterns in direct marketing using the Monte Carlo simulation. Customer retention is the process of retaining current customers and it is the most prevalent concern in customer relation management. Churn analysis is one the most popular analysis in performing customer churn analysis and data mining have been used widely. Migueis et al. (2012) predicted customer churn using the Hidden Markov Model (HMM) which is one of the data mining technique widely used today. Customer development encompasses consistent expansion of transaction value and relationships of the existing customers e.g... up/cross selling. Chen and Fan (2012) used Multiple Kernel (MK) Learning and Support Vector Machine (SVM) to predict customer behavior. Finally, customer equity growth optimizes customers' value in terms of their future revenues and long-term profitability. The customer profitability task can be performed using techniques like decision tree or markov chain (Mirzaei & Iyer 2014).

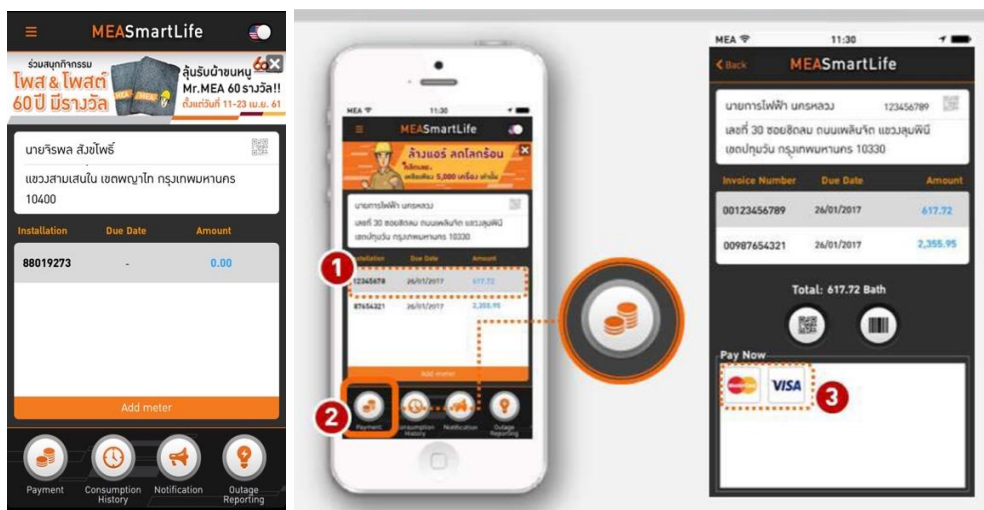
Various frameworks for applying data mining to customer analysis have been proposed. Most frameworks for applying data mining were modeled according to different stages of Customer Relationship Management (CRM) in which different types of data mining algorithms such as association, classification, clustering, forecasting, regression, sequence discovery and visualization can be applied (Kadiyala & Srivastava 2011; El-Zehery et al. , 2014). In this paper, we applied the Cross-Industry Standard Process for Data Mining or CRISP-DM for short, in analyzing customer satisfaction. Similar framework were also available for life cycles assisting data mining projects including KDD (Fayyad, 1996), SEMMA (Santos & Azevedo 2005), and CRISP-DM. The CRISP-DM approach, however, is the most popular data mining life cycle (KDNugget, 2007). Developed in 2000 by SPSS, NCR and Daimler Chrysler, CRISP-DM is comprised of 6 processes: 1) business understanding; 2) data understanding; 3) data preparation; 4) modeling; 5) evaluation; and 6) deployment (Chapman et al. , 2000) as illustrated in Figure 1. Business Understanding involves the process of understanding the business problem, i.e., what business problem are we trying to solve? The Data Understanding phase involves examining the data to determine its quality as well as discovering patterns from within the dataset. The Data Preparation phase involves constructing the data into a format that is ready to be used by data mining algorithms. It also involves identifying appropriate attributes that should be used during the modeling phase. Modeling involves the process of applying data mining learners such as neural network or decision tree onto the dataset so that the model can be used to find answers to business problems. The Evaluation phase involves testing the accuracy of the model created to see whether the model can be generalized against unseen data. Finally, the Deployment phase involves deploying the model into a working system.



**Figure 1** CRISP-DM Process

**Source:** Wikipedia, 2019

For this study, we apply the CRISP-DM model for analyzing Metropolitan Electricity Authority (MEA) data. The MEA is a state enterprise in Thailand and provides electricity to Bangkok residents. It is required by the government that every state enterprise needs to report to the government on how well it services its customers (SEPO, 2019). One of the Key Performance Indicators (KPI) reported was how its customers like their e-service. MEA uses the result of its customer satisfaction survey on their mobile application called MEA Smartlife to report to the government (MEA, 2017). MEA Smartlife, as illustrated in Figure 2, is a mobile application (app) that allows MEA customers to pay their electrical bills, view historical electrical usage, receive news and alerts, and report an electrical outage. MEA distributes a customer satisfaction survey annually and the survey results are reported to the government to help the MEA to understand its customer better and thus providing better service.



**Figure 2** MEA Smartlife App

Source: MEA, 2017

The paper is organized into 6 parts. First, business understanding for this particular problem is discussed. Then, data understanding was performed by Tableau to visualize and identify some quick patterns and insights. The data preparation part then discussed the issue of data quality and how the dataset has been preprocessed for the analysis and mining. The modeling part discussed in detail how data mining algorithms were applied and how they were used to identify which factors influence the decision to like or dislike the app. Finally, evaluation and deployment were used to discuss how the model was utilized to improve customer satisfaction.

## **Business Understanding**

As previously mentioned, business understanding involves the process of understanding the business problem. Therefore, as a state enterprise in Thailand, MEA needs to report its performance to the government annually. One of the Key Performance Indicators (KPI) is its e-service capability. MEA uses its user satisfaction rating from the MEA Smartlife survey as its KPI. The commitment between MEA and the government is that MEA will try to achieve the overall user satisfaction level of 80% (score of 4 or higher on a Likert scale). As a result, the business goal is to understand what makes a user like or dislike the app.

The objective of data mining is to build a classifier that can predict whether a customer is satisfied with the MEA Smartlife app. However, this classifier must provide an intuitive model rather than a black box model so that insights such as factors that most influence users' satisfaction rating can be gained, whether they depend on demographic factors, such as sex or education level, or other criteria. Once the business understanding phase has been done, the next phase is to try to understand the collected data.

## **Data Understanding**

During the data understanding phase, data was explored in order to get some initial understanding about the collected dataset. In this study, data was explored using Rapidminer and Tableau, a data mining and visualization tool to see its quality and if there is any significant pattern or if some insight can be gained by using visualization. The dataset was then examined to see the general data description as well as any visible pattern. Correlation and Principle Component Analysis were also performed on the dataset to determine the relationship among the attributes.

### **General Description of Data**

For the general description of the data, each attribute of the dataset was examined to see the description of the data e.g., max, min, and average. For this particular dataset, there were user satisfaction ratings along with demographic profiles from 1,446 subjects. This data is collected annually and used in MEA's internal report. The dataset includes 21 attributes in which six attributes contain demographic information, e.g., sex, age, and education, while another 14 attributes contain subjective ratings on data quality, application features, and user experiences of the app. The subjective rating is the Likert scale data ranging from 1 representing 'very dissatisfied' to 5 'very satisfied'. The last attribute is the 'overall satisfaction' of the app and it is treated as the target attribute for data mining algorithms. An eighty percent overall satisfaction score (average rating of 4 or more) is

the goal to achieve. Figure 3 below illustrate the data and some descriptive statistics for each attribute.

Name	Type	Missing	Statistics	Filter (21 / 21 attributes):	Search for Attribute:
Overall Satisfaction	Binominal	0	Least unsatisfied (268)	Most satisfied (1178)	Values satisfied (1178), unsa
Sex	Polynominal	21	Least M (648)	Most F (777)	Values F (777), M (648)
Age	Integer	26	Min 16	Max 70	Average 35.996
Education	Polynominal	26	Least PS (5)	Most BS (838)	Values BS (838), MS (372), ...
Payment	Integer	0	Min 0	Max 5	Average 3.797
Usage History	Integer	0	Min 0	Max 5	Average 4.010
Reliability	Integer	0	Min 0	Max 5	Average 4.203
Usage During Emergency	Integer	0	Min 0	Max 5	Average 1.816

**Figure 3** Descriptive statistics of attributes

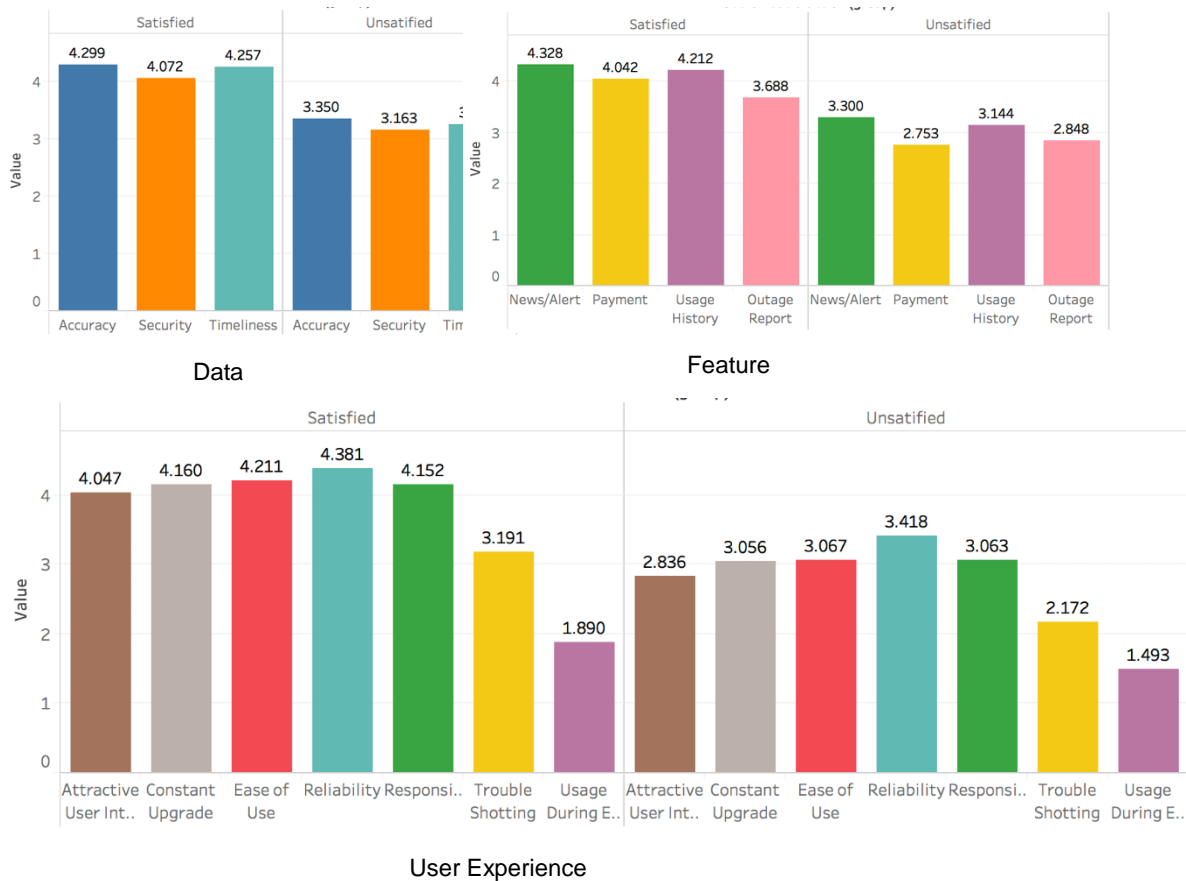
The distribution of the overall satisfaction rating was first explored. As shown in Figure 4, the majority of users (around 81%) rated the app ‘4’ or ‘5’ (‘satisfied and ‘very satisfied’) according to the Likert scale. Only 19% of the users were less satisfied with the app and gave a rating of 3 or lower.

0	268 Unsatisfied	5
1		7
2		20
3		236
4	1178 Satisfied	781
5		397

**Figure 4** Overall Satisfaction Rating

### Data Exploration

Tableau was used to perform data exploration to see if there was a significant pattern in the dataset. Figure 5 illustrates the distribution of this subjective evaluation based on three categories: data, app features, and user experience. In terms of data, users who were 'satisfied' with the app seemed to give a higher rating on this criterion. Among data criteria, security had the lowest rating. For app features, the pattern was similar to the data criteria. However, for those dissatisfied users, they gave a lower rating on the payment feature of the app. One of the reasons for this low rating was because credit card payments were charged a credit card processing fee. Finally, for User Experience (UX), again, satisfied users rate the app on these criteria proportionately higher than those who are not satisfied. Both the 'Trouble Shooting' and 'Usage During Emergency' ratings are relatively low because a lot of users gave a '0' (Not Applicable) for these criteria. This will need to be replaced with '3' (neutral) during the data modeling phase.



**Figure 5** Distribution of Subjective evaluation on data, feature, and user experience

### Data quality verification

The data quality was also examined. Just like any real-world dataset, there are some missing values, for this particular case, there are 26 rows with missing demographic values. For the subjective evaluation, there is no missing values for these attributes. However, for some attributes such as ‘usage during emergency’, quite a number of users gave this rating ‘0’ which represents ‘not applicable’ rather than ‘not satisfied’. Thus, the average value of such attribute is relatively low. A data preparation technique to replace the value of ‘0’ (not applicable) to ‘3’ (neutral) will need to be applied which will be explained later. Another concern for this dataset is that the ratio of positive (satisfied) and negative (dissatisfied) seems relatively high (about 4: 1). This might impact the overall accuracy especially for the negative class.

### Correlation Analysis

Once the quality and the pattern of the data was examined, correlation analysis was performed. Correlation is the degree to which changes in one variable are mirrored by changes in another. In Rapidminer, the correlation matrix can be calculated using a “Correlation Matrix Operator.” For this dataset, the correlation matrix is a 14x14 matrix since there are 14 numeric attributes in this dataset. Table 1 below only shows the first seven elements of the correlation matrix. Note that the diagonal of this covariance matrix is equal to 1 because the data was normalized using z-transformation before calculating the correlation matrix. Other elements of the correlation matrix explain the relationship between two attributes that the element represents. A positive covariance,  $c^{jk}$ , means that the  $j^{\text{th}}$  and  $k^{\text{th}}$  attributes have a positive relationship, in other words, they increase or decrease together.

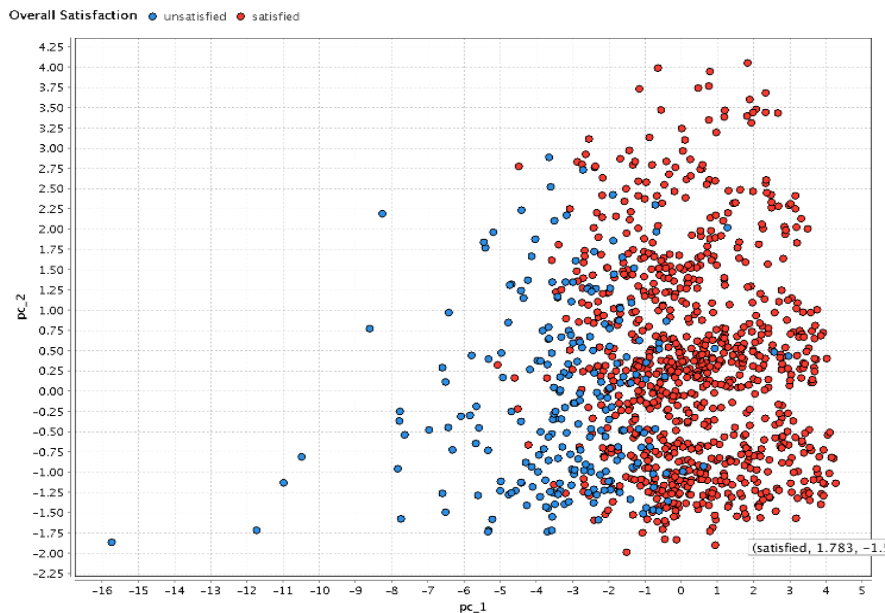
**Table 1** Correlation Matrix of the Normalized Data

Attributes	Data A...	Data Timel...	Data S...	Outage...	News/...	Payment	Usage ...
Data Accuracy	1.000	0.777	0.635	0.357	0.556	0.381	0.603
Data Timeliness	0.777	1.000	0.635	0.358	0.564	0.386	0.597
Data Security	0.635	0.635	1.000	0.461	0.447	0.343	0.523
Outage Report	0.357	0.358	0.461	1.000	0.393	0.435	0.443
News/Alert	0.556	0.564	0.447	0.393	1.000	0.415	0.725
Payment	0.381	0.386	0.343	0.435	0.415	1.000	0.455
Usage History	0.603	0.597	0.523	0.443	0.725	0.455	1.000



It can be seen from Table 1 that the three most highly correlated attributes indicate those are in the same group of attributes i.e. Data Accuracy and Data Timeliness represent attributes in Data group, Attractiveness User Interface and Ease of Use are in User Experience group, and News/Alert and Usage History are in app features group.

Principle Component Analysis (PCA) was also performed in order to reduce the dimension of the dataset making it easier to understand and visualize. For this particular dataset, the first principal component, PC1, has the largest eigenvalue of 0.494 while other principal components have lesser eigenvalues. The value of PC1 and PC2 were then plotted on to a 2D scatter graph as illustrated in Figure 6 with colored labels representing the overall user rating. It is clearly seen that the higher value of PC 1 ( $PC1 > '-3'$ ) represents a 'satisfied' rating while the lower value of PC 1 ( $PC1 < '-3'$ ) represents an 'unsatisfied' user rating. From this PCA, it can be clearly seen that, with proper technique, it is possible to classify the examples into a satisfied and unsatisfied group. Also, from the loading factors, attributes such as 'ease of use' and 'data accuracy' carry most of the information that can be used to differentiate between a satisfied and unsatisfied group.



**Figure 6** Principle Component Analysis (PCA)

## Data Preparation

During the data preparation phase, three issues were addressed in order to have a good set of data for the next step. The three issues include: missing demographic information; '0' or 'not applicable' on some attributes; mapping overall satisfaction rating into binary class, and feature selection.

For the first issue of missing demographic information, the missing attribute was replaced using the ‘Impute Missing Value’ technique in RapidMiner. ‘Impute Missing Value’ filled the missing information with the demographic information of the similar record on the dataset. The value of ‘0’ in some attributes were replaced with ‘3’ since the overall rating of ‘0’ meaning ‘not applicable’, thus, should be treated as ‘neutral’ or ‘3’.

The dataset was also performed binary class mapping of the overall satisfaction rating (target attribute) into 2 classes: ‘satisfied’ and ‘unsatisfied’. The overall satisfaction rating of ‘4’ and ‘5’ were converted to ‘satisfied’ class while the rating of ‘1’, ‘2’, and ‘3’ were converted to ‘unsatisfied’ class. This was done because the business objective is to understand what make users satisfied (give ‘4’ or ‘5’ rating), not to predict what the user will rate the app.

The final issue was to reduce the number of attributes that will be used by data mining algorithms. Feature selection techniques were performed to improve the overall accuracy by removing irrelevant attributes. Datasets with too many attributes can suffer from the ‘curse of dimensionality.’ This term was first coined by Bellman (1957) and it explains a situation in which as the number of attributes increase, the volume of the data space also increases rapidly so that the sample data become sparse making it more difficult to perform machine learning tasks, e.g., such as classification or clustering (Bellman 1957). For this study, three feature selection techniques: Genetic Algorithm (GA); Forward; and Backward selection were applied. Figure 7 illustrates the comparative performance of each technique and how many attributes it can reduce. After feature selection has been performed, 10 attributes were kept from the original dataset. These attributes include sex; age; data accuracy, news/ alert feature, payment feature, reliability, constantly upgrade, trouble shooting, the attractiveness of UX/UI, and ease of use. The data prepared in this section was then used in the modelling as explained in the following section.

Feature Selection Techniq	Naïve Bayes			Decision Tree			Logistic Regression		
	GA	Forward	Backward	GA	Forward	Backward	GA	Forward	Backward
Accuracy	91.15	91.56	91.28	91.7	91.63	91.56	92.53	92.53	92.53
Precision Unsatisfied	72.44	73.7	77.73	77.82	76.92	76.84	83.33	83.61	85.4
Precision Satisfied	96.3	96.4	94.2	94.83	95	94.97	94.36	94.29	93.85
Recall Unsatisfied	84.33	84.7	74.25	77.24	78.36	77.99	74.63	74.25	72.01
Recall Satisfied	92.7	93.12	95.16	94.99	94.65	94.65	96.6	96.69	97.2
No. of Attribute selected	11	11	4	12	10	18	10	11	14

Figure 7 Application of Feature Selection Techniques on the Dataset

## Modelling

The modeling phase involves the initial modeling using the original dataset and then iteratively adjusting the model and the dataset in order to increase the accuracy of the model.

During this phase, the model selection, generating test case, and the model creation are explained.

### **Select Modelling Technique**

As understanding of what makes users rate '4' or '5' (satisfied) is more important than predicting if customers will be satisfied/ dissatisfied with the app, the modelling techniques to be used here must be a 'white box' model so that further improvement of the app can be understood and better done. As a result, three classification models: Naïve Bayes; decision tree; and logistic regression were used as these models can provide insight and understanding of what the users think about the app.

### **Generate Test Design**

From previous section, when applying feature selection to the dataset, the accuracy seems to improve. For this reason, datasets with 10 selected features were used as an input for 3 classification models: Naïve Bayes, Decision Tree, and Logistic Regression. The dataset used for modelling were pre-processed using techniques discussed earlier to fill missing data and map overall satisfaction ratings to binary classes. The dataset was then divided into 2 groups at 80% and 20% of the sample. The first group of the data was used as a training dataset and the latter was used as a test dataset. During the training process, the parameters for each classification model were also optimized to improve the accuracy of the model. Once the model was optimized, the test dataset was used to validate the accuracy of the model again.

### **Model Creation**

The initial classification model trained by the original dataset gave the accuracy of about 90% but had relatively low precision (75%) for negative (unsatisfied) class. After performing the feature selection, the overall accuracy improved slightly to 92.76% , 91.03% and 92.41% for Naïve Bayes, Logistic Regression, and Decision Tree respectively as illustrated in Table 2. However, the negative class precision is significantly better averaging at 81% for all techniques.

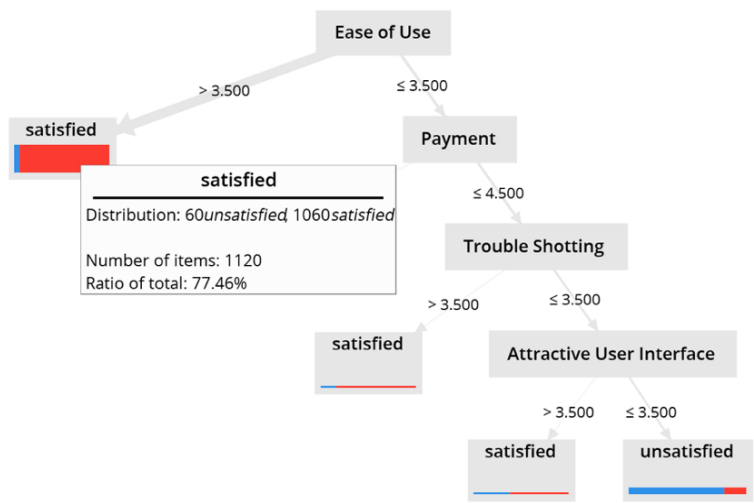
**Table 2** Classification performance of Decision Tree, Logistic Regression, and Naïve Bayes

	Decision Tree	Logistic Regression	Naïve Bayes
Pos. Class Recall	97.03	96.61	93.64
Neg. Class Recall	64.81	74.07	88.89
Pos. Class Precision	92.34	94.21	97.36
Neg. Class Precision	83.33	83.33	76.19
Overall Accuracy	<b>91.03</b>	<b>92.41</b>	<b>92.76</b>

**Evaluation**

From Table 3, the performance from three classification models on this dataset indicates naïve bayes performing slightly better than decision tree and logistic regression. However, both logistic regression and decision tree did better on negative class precision than naïve bayes. Also, decision tree provides a more intuitive classification model.

Figure 8 illustrates the model created by the decision tree algorithm. The most important factor in determining whether the customer is satisfied or dissatisfied with the app is how easy an application is (ease of use). Another important factor is how the users like the payment feature of the app. This is very useful insight for the MEA because they can focus more resources on making the app even more user friendly and making the payment feature more efficient for the users.



**Figure 8** Decision Tree Model

Another factor that is very important for user satisfaction is the 'payment' feature of the app. When applying the feature selection techniques, this attribute was kept 8 out of 9 times indicating that it carries more information than other attributes when deciding whether a customer will like the app. In decision tree model in Fig. 8, it is the second level node indicating the importance of the attribute as most users use this app to pay their electric bill. As a result, it is very important for the MEA to focus on payment features of the app by making them easy and convenient to use. Finally, user satisfaction does not depend on the demographic profile of the user. In other words, a demographic profile cannot help determine if a user will be satisfied with the app.

## **Deployment**

Once the model has been evaluated, the insight gain from the model was distributed and explained to stakeholders. All the classification models employed in this project provide important and useful insight. Users of the MEA Smartlife app care more about 'ease of use' than any other application feature. In decision tree model, when people perceive that the app is easy to use, they give a positive (satisfied) rating to the app. This also reflects on the Logistic Regression model and Naïve Bayes model as well, where the 'ease of use' feature has the highest coefficient and highest probability density.

The IT team responsible for the MEA Smartlife app then uses this insight to improve the app. Some features were adjusted in order to improve its easiness. The payment feature was also enhanced by adding more payment channels with a less expensive transaction fee. It is expected that the user satisfaction rating will be higher in the following years.

## **Summary and Conclusion**

This paper discussed the process of applying data mining algorithms for Customer Satisfaction Analysis of a mobile app called MEA Smartlife. The goal of this analysis is to understand what make MEA Smartlife users 'satisfied' (give a '4' or '5' Likert Scale rating) with the app. Although applying data mining to customer analysis is not new, previous research has not provided guidance on how data should be explored and prepared before performing data mining tasks. This paper, however, utilized the CRISP-DM framework for customer analysis which is the standard framework for applying data mining in various industries. The CRISP-DM methodology provides step by step procedure to perform data mining tasks including business understanding, data understanding, data preparation, modeling, evaluation, and deployment.

Applying selected data mining algorithms on an original dataset resulted in a impressive accuracy at about 90%. The problem with these models is that the negative class precision is relatively low (averaging 75%). This is due to the fact there are too many attributes in the dataset relative to the number of negative class examples (20 attributes but

only 236 negative examples). The model is therefore suffered from the ‘curse of dimensionality.’ To alleviate this problem, the number of attributes was reduced using the feature selection technique during data preparation. Thus, the model accuracy increased. This is especially true for the negative (dissatisfied) class which increased to about 81%.

This study demonstrates the applicability of data mining techniques to customer analysis in order to gain insight what makes a customer satisfied or dissatisfied. Customer insight helps retain existing customers. For future research, it might be interesting to see how clustering algorithm performs on this dataset i.e. cluster the dataset into groups and use rule association techniques to reveal significant patterns within each cluster.

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