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Comparing Logistic Regression and Decision Tree Classifications Performance in the Context of Personal Cloud Storage Post-Adoption Behaviour

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Abstract: Machine learning literature is replete with algorithms for classification problems. The choice of an algorithm for a particular problem is not only dependent on statistical assumptions but also its performance. The current study compares the performance of logistic regression and decision trees when used in a binary classification in the context of personal cloud storage post-adoption behaviour. The users' intention to switch from freemium to premium personal cloud storage services was the classification problem. From literature review, six features were identified as predictors of intention to adopt premium personal cloud storage service. Data comprising the six features and a single dichotomous target was collected from university students. Machine learning techniques were used to balance the sample and split the data into training and validation sets. Classification analysis was then conducted on the data using both the logistic regression and decision tree algorithms. The performance of the classification algorithms was compared using the confusion matrix and the ROC Curve. For the decision tree, precision=0.70, recall=0.52 with an overall accuracy of 0.73 while for the logistic regression, precision=0.68, recall=0.55 with an overall accuracy of 0.65. The area under ROC curve for the decision tree was 0.79 while that of the logistic regression was 0.71. The decision tree algorithm therefore performed better than the logistic regression in all the metrics used for performance comparison. Perceived Usefulness, Perceived Risk and Perceived satisfaction emerged as the most important features in predicting users' propensity to migrate from freemium to premium personal cloud storage services.

Keywords: Personal Cloud Adoption, Logistic Regression, Decision Trees, Machine Learning, IT Mindfulness

1. Introduction

Cloud computing services have greatly impacted how organizations and individual users acquire and use computing resources. Even though organizations have in the past dominated the cloud computing market, individual users have recently started making use of cloud computing services for their own needs. While there has been great research output on the adoption of cloud computing services, there is a scarcity of research on the post adoption behaviour of users. Extant literature is replete with a variety of studies focused on several post adoption behaviours of users of IT innovations. For example, such studies have investigated post-adoption behaviour such as; intention to continue use (Foroughi, Iranmanesh, & Hyun, 2019; Trenz, Huntgeburth, & Veit, 2013; Wang, Lew, Lau, & Leow, 2019), user satisfaction (Hsieh, Rai, Petter, & Zhang, 2012; Jianwen & Wakil, 2019; Vaezi, Mills, Chin, & Zafar, 2016) , effective use (Burton-Jones & Grange, 2012), amount of use (Po-An Hsieh & Wang, 2007), and enhanced use (Bagayogo, Lapointe, & Bassellier, 2014). Another stream of studies on post adoption behaviour of users that is focused on how users migrate from freemium to premium versions of IT innovations in different contexts has also emerged (Hamari, Hanner, & Koivisto, 2020; Mäntymäki, Islam, & Benbasat, 2020; Vock, Dolen, & Ruyter, 2013; Wagner, Benlian, & Hess, 2014). While the use of cloud services by individual consumers is an important feature of the cloud computing ecosystem [22], the antecedents of users' migration from the automatic freemium version to the premium version has not received adequate attention. The aim of this study is to model the predictors of users' intention to migrate from the freemium to premium versions of cloud storage service. Further, the study applied two machine learning classification techniques to model the users' intention to adopt premium cloud storage services.

2. Literature Review

2.1 Cloud Computing

The architecture of cloud computing is largely based on the service models and deployment models. The service model comprises Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS) (Ahson & Ilyas, 2011). Cloud deployment models consist of private, public, and hybrid (Buyya, Goscinski, & Broberg, 2011). There are several reasons that attract users to adopt cloud computing services namely; i) it requires minimal upfront investment, ii) no need for capital expenditure (Ristol, 2010) and iii) services are acquired on the basis of pay-per-use basis (Zhang, Cheng, & Boutaba, 2010) thus lowering operating costs. Services hosted in the cloud are generally web-based and therefore, easily accessible through a variety of devices with internet connection which in turn reduces user risks and maintenance expenses.

This study focuses on the use of personal cloud storage services offered under the IaaS and SaaS cloud service layers. The focus on cloud storage services is motivated by the trend which indicates that cloud storage complete with file syncing has experienced high amount of adoption amongst businesses and individual users (Gupta, Seetharaman, & Raj, 2013). The cloud storage platforms provide services to corporate users as well as individual users. The individual users' storage platforms not only provide storage services but also provide tools for file sharing, team collaboration and multi-device access.

2.2 Features Identification

Since cloud services are usually hosted by third parties, the issues of trust and risk emerge as challenges to their adoption either in freemium or premium versions. Trust comprises the willingness to be vulnerable based on positive expectations towards a technology (McKnight, Cummings, & Chervany, 1998). The importance of trust in the cloud computing context has been repeatedly highlighted due to lack of transparency surrounding cloud offerings (van der Werff et al., 2019). Studies have shown that trust beliefs have a positive effect on intention to use cloud services amongst users (Arpaci, 2016; Moqbel & Bartelt, 2015; Yu, Li, Hao, Li, & Zhao, 2017). The trust beliefs are also likely to determine if a user will migrate from freemium to premium versions of personal cloud storage services.

Feature 1: Perceived Trust (PT) predicts the intention to migrate to premium (ITMP) personal cloud storage services.

Cloud computing use is associated with several risks which include; privacy risks, integrity risks, control risks, risks of vendor lock-in and risks of performance latency (Sultan, 2010; Zissis & Lekkas, 2012). Studies in IS have identified the negative effect of risks on users' behavioral intentions. For example, a study on consumers' acceptance of e-commerce, found that perceived risks reduce consumers' intention to transact on online marketplaces. Moqbel and Bartelt (2015) found that perceived risks have negative effect on personal cloud computing adoption.

Feature 2: Perceived Risk (PR) predicts the intention to migrate to premium (ITMP) personal cloud storage services.

When seeking to perform a task, users have a choice amongst several cloud storage services. Most of the times, the users lack adequate prior knowledge about the technologies. The lack of transparency surrounding cloud service provisions also makes it difficult for consumers to make informed purchasing decisions (van der Werff et al., 2019). An important factor in overcoming the uncertainties arising from inadequate information is an individual's IT mindfulness (Dernbecher & Beck, 2017). IT mindfulness reflects an individual's propensity to actively pursue new ways of using and getting involved with IT (Carter, Clements, Thatcher, & George, 2011). Further, mindfulness in technology acceptance is the vigilant state of mind of a person that allows him/her to examine the technology being considered more comprehensively and context-specifically (Sun & Fang, 2010). Mindfulness implies that an individual is conscious of local contexts and can think more carefully about the needs for which a technology is sought. Specifically, IT mindfulness enhances a user's willingness to consider other uses and genuinely investigate the features and successes of an IT innovation (Thatcher, Wright, Sun, Zagenczyk, & Klein, 2018).

Feature 3: IT mindfulness Risk (ITM) predicts the intention to migrate to premium (ITMP) personal cloud storage services.

The technology acceptance model (TAM) (Davis, 1989) is a widely used model for predicting and explaining IT adoption and user behaviour at an individual level. Apart from being used to explain and understand IT innovations adoption in general (Koufaris, 2002), (Ndubisi & Jantan, 2003), the TAM has also been used to understand and explain cloud computing adoption in particular (Gangwar, Date, & Ramaswamy, 2015; Gottschalk & Kirn, 2013; Ratten, 2016; Stieninger, Nedbal, Wetzlinger, Wagner, & Erskine, 2014). The TAM constructs are Perceived Ease of Use (PEU), Perceived Usefulness (PU) and Intention to Adopt.

Feature 4: Perceived Usefulness (PU) predicts the intention to migrate to premium (ITMP) personal cloud storage services.

Feature 5: Perceived Ease of Use (PEU) predicts the intention to migrate to premium (ITMP) personal cloud storage services.

2.3 Machine Learning Classification Algorithms

Machine learning is the science and art of programming computers so they can learn from data (Géron, 2019). The two main areas of machine learning are supervised machine learning and unsupervised machine learning. Supervised machine learning algorithms attempt to come as close as possible to a human expert or an accepted source of truth in predicting an outcome (Iansiti & Lakhani, 2020). The supervised machine leaning algorithms rely on a series of features and a labeled outcome in a dataset. The machine learning algorithms work by searching through a set of prediction models for the model that best captures the relationship between the descriptive features and the target feature in a dataset (Kelleher, Namee, & D'Arcy, 2015). In unsupervised learning, there is no target values and what is available is only the values for the features. For unsupervised learning, the aim is to find structure within the dataset (Alpaydin, 2020).

Logistic regression is a widely used classification technique. It has been applied in classification problems in medicine, marketing, credit scoring, public health and other applications (Russell & Norvig, 2009, p. 727). A logistic regression algorithm transforms a discrete set of classes into a logistic sigmoid function whose output is a probability score. Logistic regression techniques are best suited for problems that describe and test hypotheses about relationships between a binary outcome variable (target) and categorical predictor variables (features). Decision trees are based on the recursive partitioning of the sample space. Decision trees are also referred to as classification or regression trees and have been developed over the past 20 years (Bichler & Kiss, 2004).

3. Methodology

The survey to collect the data was conducted amongst students in two universities in Kenya. A snowball sampling strategy was used to identify the respondents. A few students who were already known to the researcher received the questionnaire which they then shared within their circle of friends. University students were used for the study since they are believed to be already using and familiar with personal cloud storage services like Google Drive and Dropbox. While as students they mainly use freemium versions, they are potential customers for the premium versions in a near future. The students therefore provide a suitable data for predicting migration from freemium to premium versions of personal cloud storage services. A total of 122 responses were received. The dataset features, IT Mindfulness (ITM), Perceived Risk (PR), Perceived Trust (PT), and perceived satisfaction (PS) were measured through a five-point Likert type scale. The target, Intention to migrate to premium (ITMP) personal cloud storage services was measured as a dichotomous variable indicating whether the respondent intend to migrate (1) or no intention (0) to migrate to premium personal cloud storage services. The measures for all the study constructs were either adopted or adapted from extant literature. The measures for PR, PT and ITA were adapted from prior studies (Li & Chang, 2012; Moqbel & Bartelt, 2015; Pavlou, 2003). The measures of ITM were adapted from Thatcher et al. (Thatcher et al., 2018). Exploratory data analysis (EDA) was done before using the data to generate the models.

4. Exploratory Data Analysis

Exploratory data analysis was performed to understand the nature of the dataset. The dataset was explored through descriptive analysis, correlation analysis, frequency distributions and sample balancing.

4.1 Descriptive Analysis

A descriptive analysis was done to summarize the sample characteristics. The target variable ITMP=0 had 41 observations while ITMP=1 had 80 observations. The main descriptive statistics are summarized in Table 1 and Table 2.

Table 1: Descriptive statistics for the Minority Class

	PEU	PU	PR	PT	ITM	PF	ITMP
count	41.000000	41.000000	41.000000	41.000000	41.000000	41.000000	41.0
mean	3.878049	4.048780	2.975610	3.902439	3.707317	3.829268	0.0
std	0.899864	0.739974	1.012122	0.538743	0.642024	0.738324	0.0
min	1.000000	2.000000	1.000000	3.000000	2.000000	2.000000	0.0
25%	4.000000	4.000000	2.000000	4.000000	3.000000	4.000000	0.0
50%	4.000000	4.000000	3.000000	4.000000	4.000000	4.000000	0.0
75%	4.000000	5.000000	4.000000	4.000000	4.000000	4.000000	0.0
max	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	0.0

Table 2: Decsriptive Statistics for the Majority Class

	PEU	PU	PR	PT	ITM	PF	ITMP
count	80.000000	80.000000	80.000000	80.000000	80.000000	80.000000	80.0
mean	4.000000	4.325000	2.675000	3.912500	3.975000	4.100000	1.0
std	0.779484	0.611597	1.003475	0.697078	0.527113	0.518029	0.0
min	1.000000	2.000000	1.000000	2.000000	3.000000	3.000000	1.0
25%	4.000000	4.000000	2.000000	4.000000	4.000000	4.000000	1.0
50%	4.000000	4.000000	2.000000	4.000000	4.000000	4.000000	1.0
75%	4.000000	5.000000	3.000000	4.000000	4.000000	4.000000	1.0
max	5.000000	5.000000	5.000000	5.000000	5.000000	5.000000	1.0

4.2 Correlation Analysis

The correlational analysis was conducted to understand the collinearity amongst the feature variables and the target variable. The feature variables PF, ITM, PR and PU had a stronger correlation with the target variable ITMP compared to PEU and PT.

Figure 1:Correlation Coefficients of the Feature and Target Variables

4.3 Frequency Distributions

The frequency distributions of the predictor variables, also known as features in machine learning, is represented in Figure 2. The variables PR, PT, ITM and PF had normal frequency distribution while PEU and PU were slightly negatively skewed.

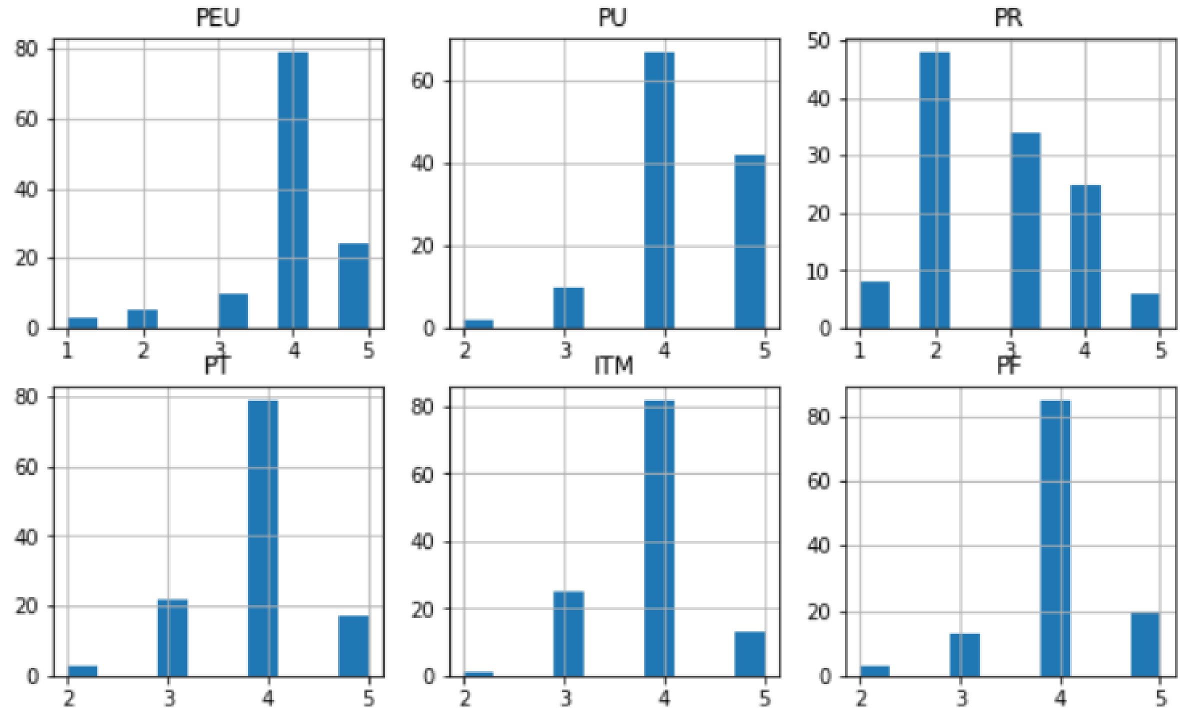

Figure 2: Frequency Distribution of the Feature Variables

4.4 Sample Balancing

Machine learning classification techniques are known to perform better when the dataset is balance across the outcome variable. In the study's sample, there were 80 observations for ITAP=1 and 41 observations for ITAP=0. Unbalanced datasets though normal in real world applications, usually affect the quality and reliability of results in machine learning tasks [63]. A technique to address the data imbalance is oversampling (Gosain & Sardana, 2017). Oversampling, which is a data leveling approach to the dataset imbalance problem involves adding new instances to the minority class label (ITMP=0). The minority class was then oversampled to 80 instances to match the majority class (ITAP=1). Following oversampling, the dataset now comprised of 160 instances (samples).

5. Model Building

The dataset was first divided into the training set (60 percent) and the validation set (40 percent) of the total observations in the dataset. The total observations were 160 after up-sampling of the minority class leading to a training dataset of 96 observations and a validation dataset of 64 observations. The training set was used to generate both the logistic regression model and the decision tree model. The models generated were then applied on the validation dataset for both the models.

5.1 Logistic Regression

The logit analysis was done using the Python's Statsmodels library. The model fitted the effects of PEU, PU, PR, PT, ITM and PF on the ITMP. The estimated coefficients indicate that PEU had the lowest effect (β=-0.11) on ITMP while PU had the largest effect (β=0.99) on ITMP. The effect of PR was negative (β=-0.86) and that of PU, PT, ITM and PF were positive. In this study, all the feature variables were retained as they are known to have relationships with pre-adoption and post-adoption decisions as discussed in Section 2.

The logit analysis results for the training set are summarized in Table 2.

Table 3: The Logit Algorithm Output

```
                         Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: 0.185
Dependent Variable: ITAP             AIC:              122.4038
Date:               2020-10-01 05:32 BIC:              140.3542
No. Observations:   96               Log-Likelihood:   -54.202
Df Model:           6                LL-Null:          -66.521
Df Residuals:       89               LLR p-value:      0.00039823
Converged:          1.0000           Scale:            1.0000
No. Iterations:     6.0000
-------------------------------------------------------------------
         Coef.    Std.Err.      z      P>|z|     [0.025     0.975]
-------------------------------------------------------------------
const   -5.9043     2.5245   -2.3388   0.0193   -10.8522   -0.9563
PEU     -0.1148     0.2827   -0.4061   0.6847    -0.6688    0.4393
PU       0.9888     0.4413    2.2408   0.0250     0.1239    1.8537
PR      -0.7570     0.2784   -2.7193   0.0065    -1.3026   -0.2114
PT      -0.3347     0.4422   -0.7569   0.4491    -1.2015    0.5320
ITM      0.6841     0.5774    1.1848   0.2361    -0.4475    1.8157
PF       0.7734     0.4162    1.8583   0.0631    -0.0423    1.5892
=================================================================
```

The resulting logit model is summarized by Equation

$$P(ITMP = 1) = \frac{1}{1 + e^{-(-5.9 - 0.11PEU + 0{,}99PU - 0.76PR - 0.33PT + 0.68ITM + 0.77PF)}}$$

5.2 Decision Tree

The decision tree was generated using the Python’s sklearn library. In a decision tree, each internal node denotes a test on a feature while each branch represents an outcome of the test and the class outcome is denoted by a leaf. The decision tree and the decisions are summarized by Figure 3.

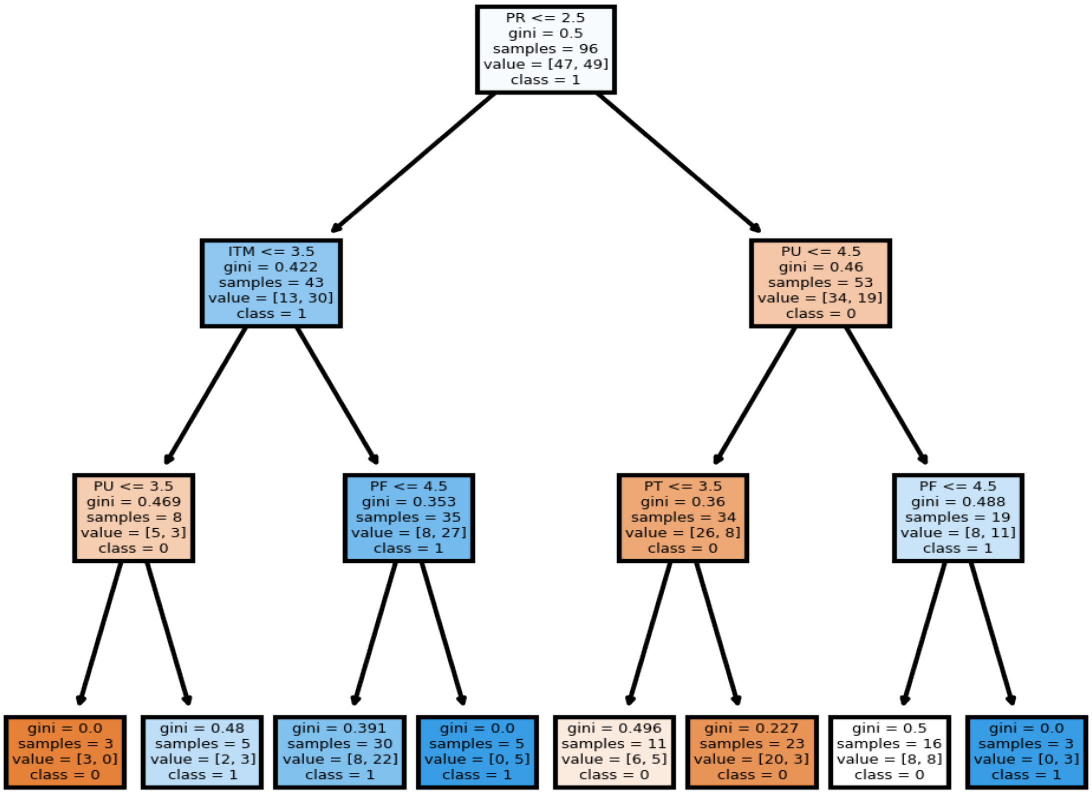

Figure 3: Decision Tree and Decision Rules

The decision rules can be expressed as follows:

```
|--- PR <= 2
|   |--- ITM <= 4
|   |   |--- PU <= 4
|   |   |   |--- class: 0
|   |   |--- PU >  4
|   |   |   |--- class: 1
```

```
|   |--- ITM >  4
|   |   |--- PF <= 4
|   |   |   |--- class: 1
|   |   |--- PF >  4
|   |   |   |--- class: 1
|--- PR >  2
|   |--- PU <= 4
|   |   |--- PT <= 4
|   |   |   |--- class: 0
|   |   |--- PT >  4
|   |   |   |--- class: 0
|   |--- PU >  4
|   |   |--- PF <= 4
|   |   |   |--- class: 0
|   |   |--- PF >  4
|   |   |   |--- class: 1
```

5.3 Performance Comparison of the Models

The fitted models ware evaluated using the confusion matrix and the area under the character operator characteristic (ROC) curve. The performance metrics were based on how well the fitted model performed on unseen data or the validation dataset which comprised 40 percent of the entire dataset (64 samples). This step involves predicting the classes in the validation data set and generating a confusion matrix and a ROC curve.

5.3.1 Confusion Matrix

The following classifications were used for the confusion matrix

- true positives (TP): These are cases in which the model predicted yes (ITAP=1) and the actual observation was also yes (ITAP=1).
- true negatives (TN): The model predicted no (ITAP=0) and actual observation was no (ITAP=0).
- false positives (FP): The model predicted yes (ITAP=1) but actual observation was no (ITAP=0). This results in a Type I error.
- false negatives (FN): The model predicted no (ITAP=0) but actual observation was yes (ITAP=1). This results in a Type II error.

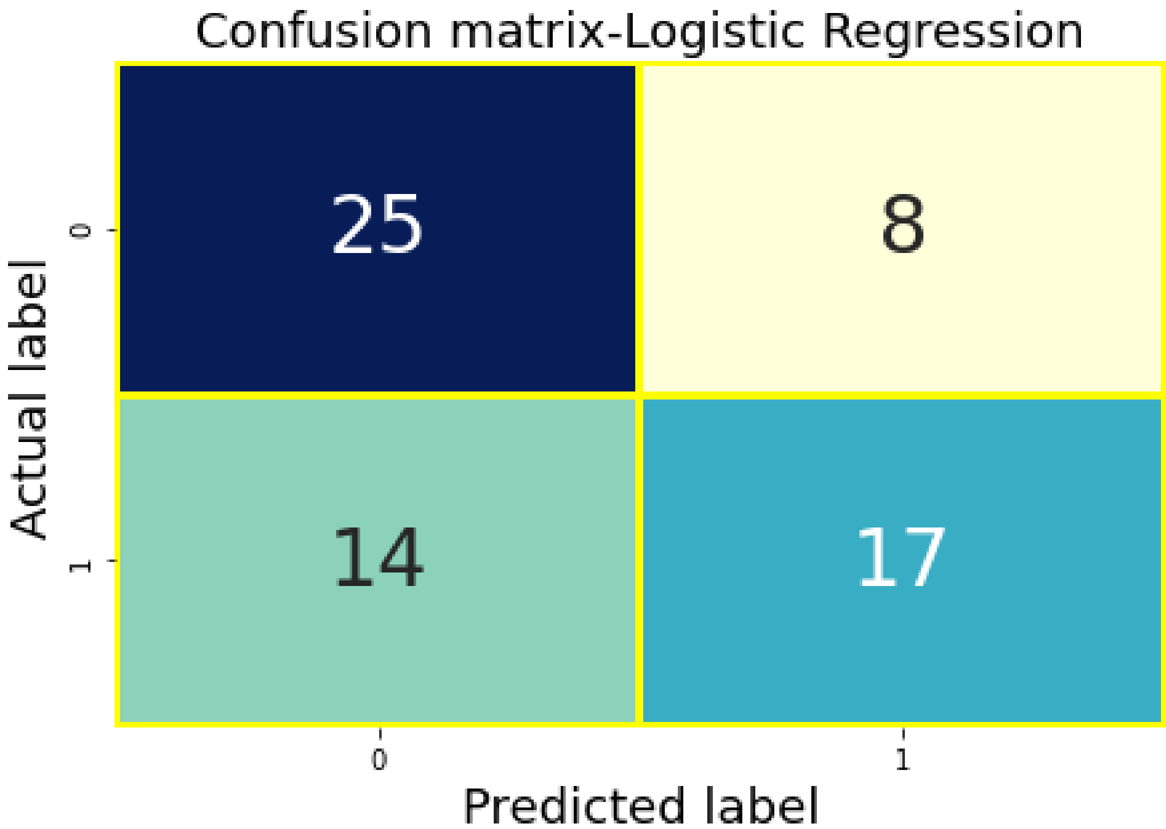

Figure 4: Confusion Matrix for Logistic Regression

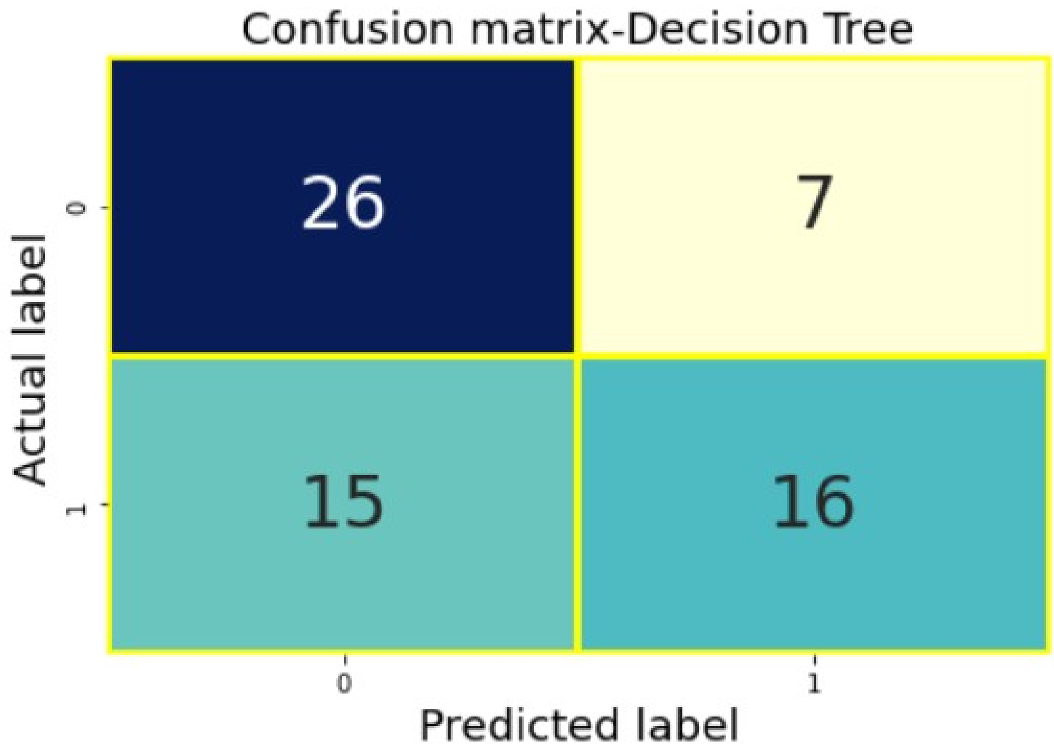

Figure 5: Confusion Matrix for Decision Tree

From the Confusion Matrix, other model evaluation metrics such as Accuracy, Precision and Recall were computed and presented in Table 3.

Table 4: Comparison of Logistic Regression and Decision Tree Based on Confusion Matrix

Metric	Formula		Value	Comments
Accuracy	(TP+TN)/(TP+FP+TN+FN)	Logistic Regression	(41/64) = 0.64	The model correctly predicted that a user intended to migrate (ITMP=1) or did not intend to migrate (ITMP=0) 64 percent of the times.
		Decision Tree	(42/64) = 0.66	The model correctly predicted that a user intended to migrate (ITMP=1) or did not intend to migrate (ITMP=0) 66 percent of the times.
Precision	TP/(TP+FP)	Logistic Regression	(17/25) = 0.68	The model is 68 percent times accurate in predicting those who intent to migrate to premium cloud storage services (i.e. ITMP=1)

		Decision Tree	(16/23) = 0.70	The model is 70 percent times accurate in predicting those who intent to migrate to premium cloud storage services (i.e. ITMP=1)
Recall (Sensitivity)	TP/(TP+FN)	Logistic Regression	(17/31) = 0.55	The model can identify those who intend to migrate to premium cloud storage services (ITMP=1) 55 percent of the times.
		Decision Tree	(16/31) = 0.52	The model can identify those who intend to migrate to premium cloud storage services (ITMP=1) 52 percent of the times.
Specificity	TN/TN+FP	Logistic Regression	(25/33) = 0.76	The model can identify those who do not intend to migrate to premium cloud storage services (ITMP=0) 76 percent of the times.
		Decision Tree	(26/33) = 0.79	The model can identify those who do not intend to migrate to premium cloud storage services (ITMP=0) 79 percent of the times.

5.3.2 Area under Receiver Operating Characteristic Curve

The area under the curve of ROC for logistic regression was 0.71 (Figure 6)

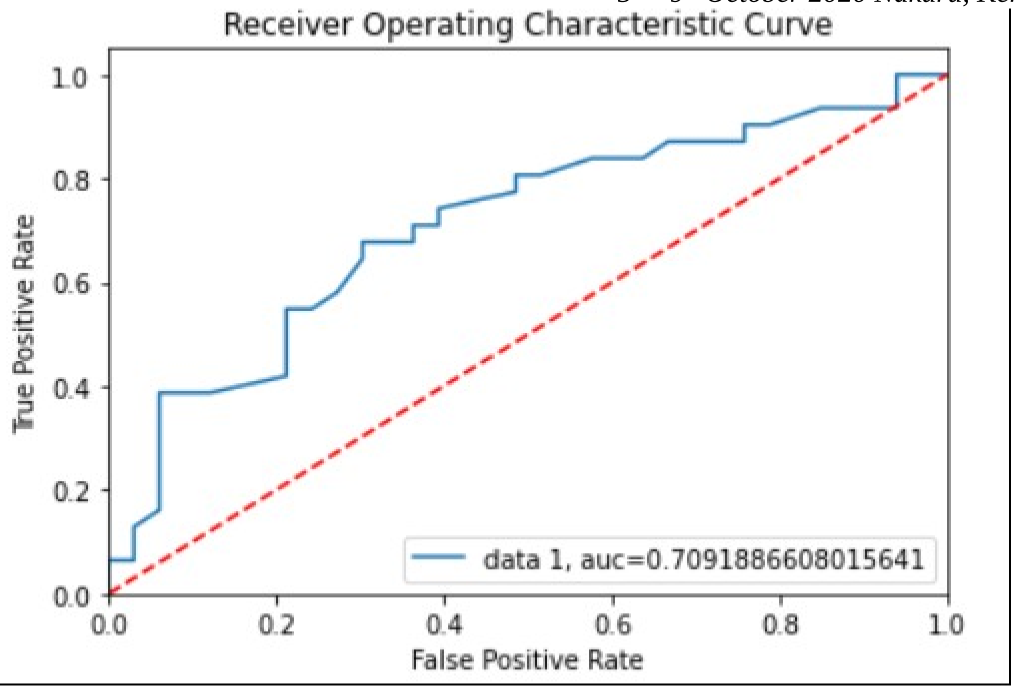

Figure 6: Area Under ROC Curve for Logistic Regression

The area under the curve of ROC for decision tree was 0.79 (Figure 7)

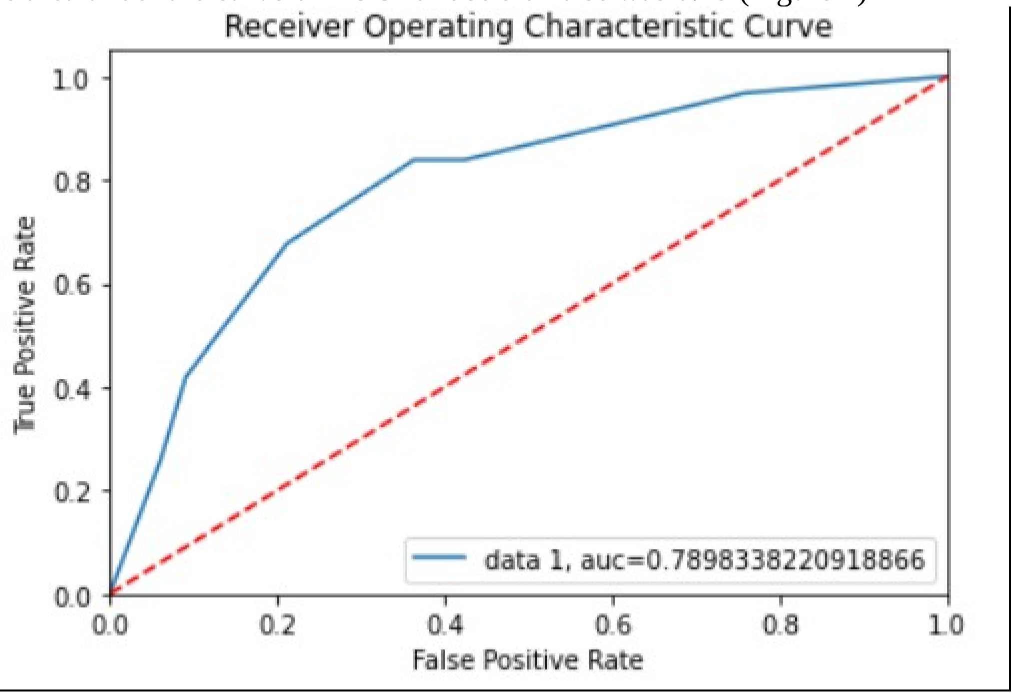

Figure 7:Area Under ROC Curve for Decision Tree

6. Conclusion

This paper compared the performance of logistic regression and decision tree techniques in machine learning classification problems. The comparison was done within the context of predicting users' intention to migrate from freemium to premium personal cloud storage services. The performance of the classification algorithms was compared using the confusion matrix and the ROC Curve. For the decision tree, precision=0.70, recall=0.52 with an overall accuracy of 0.73 while for the logistic regression, precision=0.68, recall=0.55 with an overall accuracy of 0.65. The area under ROC curve for the decision tree was 0.79 while that of the logistic regression was 0.71. The decision tree algorithm therefore performed better than the logistic regression in all the metrics used for performance comparison except recall. Perceived Usefulness, Perceived Risk and Perceived satisfaction emerged as the most important features in predicting users' propensity to migrate from freemium to premium personal cloud storage services.

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