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Maintaining customer lifetime value through cross selling offers with shopping vouchers gimmick in the insurance industry by using logistic regression and decision tree

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ABSTRACT

This research is conducted in the life insurance industry in order to help the company to extend and maintain customer lifetime value. A statistical model will be built using Logistic Regression (LR) and Decision Tree (DT) methods so that the company can find/use the right model of input variables (independent variables) those later determines/increases the probability/chance of the take up rate of the cross-selling offers: whether YES (accept the given offer) or NO (reject the given offer). The impact of shopping vouchers as gimmick will be seen as well. This research is using primary data in the form of data of active life insurance policyholders who currently have a term life product where the policy is approaching the maturity date (3 months before the maturity date). Policyholders, hereinafter referred to as clients, consist of custo500 clients with the following demographic profiles: Gender: Male/Female; Age: 45-60 years, Marital Status: Single, Married, Divorced; Have made a claim: Yes/No, Policy Age: 5, 10 and 15 years, Annual Premium Value: 20 - 54 Million; Communication Channels in distributing the offer: SMS, Email, Mail (specifically Mail: only given to clients over 55 years of age); The rupiah value of the vouchers offered: IDR 250k, 350k and 500k. The data was obtained from the results of cross sell activities carried out by the company from one of the cross-sell initiative batches. The statistical model will be built using the logistic regression and decision tree method with Visual Studio Code - Python software. Responds to offers in the form of Yes or No are withdrawn after 30 calendar days after the offer is made. From the results of the research, the Logistic Regression model give result with Accuracy: 0.95; Precision: 0.75; Recall: 0.66 and F1-score: 0.70. The Decision Tree model give result with Accuracy: 0.93; Precision: 0.84; Recall: 0.81 and F1-score: 0.69. The two models provide almost similar performance. Novelty of this research shows claims experience play dominant role in determining the result of the cross sell on top of the voucher gimmick offer.

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INTRODUCTION

The business life cycle in relation to customers can be divided into 4 (four) main stages, namely: 1. identification; 2. attraction; 3. retention; and 4. Development (Sabbeh, 2018). In this research, points 3 and 4 will be discussed, where cross-sell is one of the methods used to maintain (=retention) and develop (=development) deeper and wider relationships with customers. Retaining customers is important for companies, because it is 5 to 6 times more cost effective than acquiring new customers (Elyusufi, M'hamed & Kbir, n.d.) (Verbeke et al., 2012). The purpose of customer development is not only to increase the number of customer transactions but also to make it more profitable for the company (Kamakura et al., 2003)

If companies can maintain and develop relationships with customers, then Customer Lifetime Value (CLV) will certainly increase, where the total net income of a customer can increase (Sabbeh, 2018). It has been clearly proven that for companies, retaining customers is more profitable than acquiring new customers (Jain et al., 2020).

What should the company do, if the customer is always loyal to the company, does not switch to other service/product providers but the service contract provided by the company to the customer is due or mature? This condition often occurs and is a classic challenge in the insurance industry, especially life insurance, where the customer's policy contract (hereinafter referred to as the clients) has been due or has reached the maturity date. Most research focus on predicting the churn/switch probability, but such research would not answer the question: what if the clients do not churn/switch but the contract is ended?

The aim of the research is to build a statistical model using the Logistic Regression (LR) and Decision Tree (DT) methods so that companies can find/use the right model of input variables - independent variables which will later determine the probability/chance of take up cross selling offer rate: whether YES (accept the given offer, decide to continue the relationship with the company) or NO (reject the given offer, take all the benefits that are rightfully theirs and not continue the relationship with the company). The model will increase the success rate of the cross-sell initiative, this will extend the customer lifetime value at the end.

The shopping voucher is expected to attract clients' attention and clients will consider to continue their relationship with the company through a new health insurance product, the real impact will be seen. This shopping voucher is not given to all clients but it is only given to clients with certain criteria. The performance of the two models in predicting the result will be compared: which one gives the better prediction.

Theoretically, the results of the research can broaden insight into the study of factors that influence the level of success of cross sell initiatives, especially in the life insurance industry. Practically, the results of the research can be used as input for companies, where companies can take proactive action in the future so that efforts to maintain and develop relationships with customers can be more effective and efficient by paying attention to factors that have a more dominant role in decision making. customer decision when cross sell is offered.

Customer Lifetime Value (CLV) is defined as the present value of expected benefits (e.g., gross margin) less expenses (e.g., direct service and communications costs) from customers. CLV is nothing but the net present value of the expected profit over the lifetime of the customer with the company. CLV can be used as one measure to maximize customer value; grouping customers based on their contribution to the company; determine the maximum limit of customer acquisition costs, decide on promotion policies (Kumar & Janakiraman, 2010). The results of the CLV analysis are usually in the form of valuable potential customers where this determines the marketing strategy that will later be built in targeting these customers (Tsai et al., 2013).

Most insurance policies have a specific term. The date on which the life insurance policy matures/expires, known as the policy **maturity date**. On the maturity date, the policyholder will receive all the benefits due. For example, if the policyholder has taken a savings plan for 10 years in 2020. Then after the 10th year, namely 2030, the policy will expire and the policyholder will get the maturity benefit (Poufinas & Michaelide, 2018). The longer the relationships' durations, the stickier the clients (Staudt & Wagner, 2022)

One way to build stronger relationships with customers is through **cross-selling**. Cross selling is one of the sales strategies so that customers buy more products from the company. Cross selling can increase the dependence of customers on the company, reduce the possibility of customers switching to competitors and provide opportunities for companies to continue relationships with customers. Excessive cross selling can make customers less responsive (Ansell et al., 2007) and company may lose the trust from its clients (Guenzi & Georges, 2010). Cross selling will also increase switching costs and customer loyalty, which are of course beneficial for the company (Kamakura et al., 2003).

Gimmick is a strategy used by companies to attract the attention of customers with the aim of increasing sales. Gimmick can be given in the form of financial or non-financial. Financial gimmicks can be in the form of vouchers, non-financial gimmicks can be in the form of dolls, balloons, bags, and others. Even though the gimmick is a short-term strategy, it can have a long-term positive impact on customers. Gimmick can be given as bait to new customers or used to retain old customers (Seguchi, 2022). The way consumers react to gimmick can be different one to another (Frank et al., 2014). Gimmick can be used to stimulate consumers' behaviours (Zhu et al., 2016).

Logistic Regression (LR) is a statistical model where the outcome variable or dependent variable is categorical and not numerical. The LR function "maps" or "translates" the changes in the values of the continuous or dichotomous independent variable with an equation that increases or decreases the probabilities modelled by the dependent variable (Karp, n.d.). In LR, the value of the linear model will be transformed into a probability of success between 0 and 1 (Jain et al., 2020), or in other words the model output is in the form of yes and no or 0 and 1. LR is an appropriate regression analysis to use if the variable dependent in the form of binary data (Sabbeh, 2018). LR is a technique that is often used to predict CLV parameters (Kumar & Janakiraman, 2010) (Hu, 2019) (Hosmer et al., 1997). Ilustration of this model can be seen in Figure 1.

Decision Tree (DT) is one of the non-parametric supervised machine learning methods used for classification or regression. The resulting algorithm is a model that can predict categorical data by studying the rules for determining categories based on the features possessed by the data. Based on the type of data category, decision trees are divided into two types, namely classification trees and regression trees. Classification trees have categories in the form of finite discrete data, while regression trees have categories in the form of finite discrete data or continuous data (Latifah et al., 2019). Decision tree is considered as unstable as minor changes in data can give a big change in the model prediction (Prinzie & Van den Poel, 2008) (Brankovic, 2005) (Li et al., n.d.). Ilustration of this model can be seen in Figure 1.

Both LR and DT is part of supervised learning in data mining methods. Data mining is the process of finding interesting patterns and valuable knowledge from large amounts of data, data mining is often also known as knowledge discovery from data or KDD (knowledge discovery from data) (Han et al., 2011). Supervised learning is an algorithm that is trained with labeled data. The data consists of examples of the desired answers. Example: A model that identifies the use of fake and valid credit cards, data will be trained from a data set with data labeled fake and valid (Lee, n.d.) (De Caigny et al., 2018) (Fiskin et al., 2021).

RESEARCH METHOD

This research is conducted using primary data in the form of data on active life insurance policy holders who currently have a endowment product in which the policy is approaching the maturity date (3 months before). Policyholders, consisting of 500 clients with demographic profiles which can be seen in Table 1. The data was obtained from one of the batches of cross sell activities result carried out by the company. The statistical model will be built using the logistic regression and decision tree method with Visual Studio Code - Python software. Respond to offers in the form of Yes or No are withdrawn after 30 calendar days after the offer is made. 400 data will be used as train data (80%) and 100 data will be used as test data (20%)

Table 1: data variable type

No	Variable Name	Variable Type	Variable Category	Variable Value
1	Y = Respond	Dependent	Categorical	Yes / No
2	X [0] = Gender	Independent	Categorical	Male / Female
3	X [1] = Age	Independent	Numerical	45-60 Years Old
4	X [2] = Marital Status	Independent	Categorical	Single, Married, Divorced
5	X [3] = Previous Claims	Independent	Categorical	Yes / No
6	X [4] = Policy Age	Independent	Numerical	5, 10, 15 Years
7	X [5] = Yearly Premium Value	Independent	Numerical	20-54 Million
8	X [6] = Vouchers Value	Independent	Numerical	IDR 250k (for 20-30 Mio premium), 350k (for 31-40 Mio premium) and 500k (for premium > 40 Mio)
9	X [7] = Promotion Medium (Communication Channels)	Independent	Categorical	SMS, Email, Mail. Mail only for clients > 55 years old

Table 1 above describe in detail the 8(eight) independent variables (*Xi*) as input variables in which may influence/impacting dependent variable (*Y*) as ouput label.

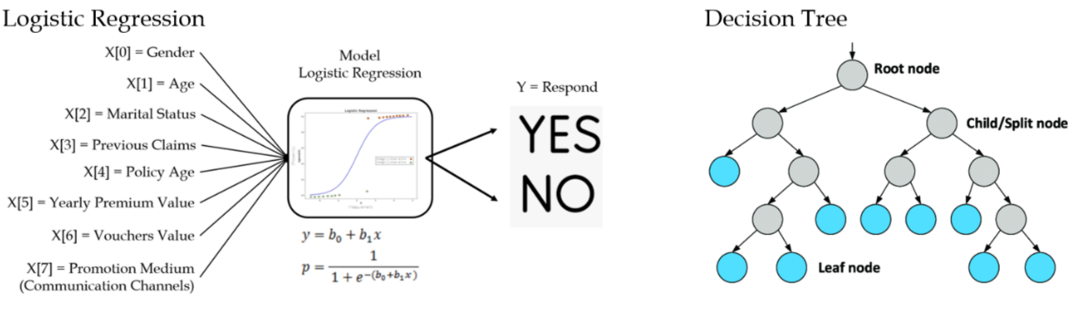

Figure 1: illustration of the research model

Figure 1 above ilustrate how the models are built. In Logistic Regression, the independent variables become input of the model and the output label is described by a log regression formula. In Decision Tree model, the determinant variables will build the tree, consist of the branch and leaf node, each branch and leaf describe the decision split of each determinant variables.

RESULTS AND DISCUSSIONS

The result of the Logistic Regression model can be seen in Figure 2, Table 2, and Table 3.

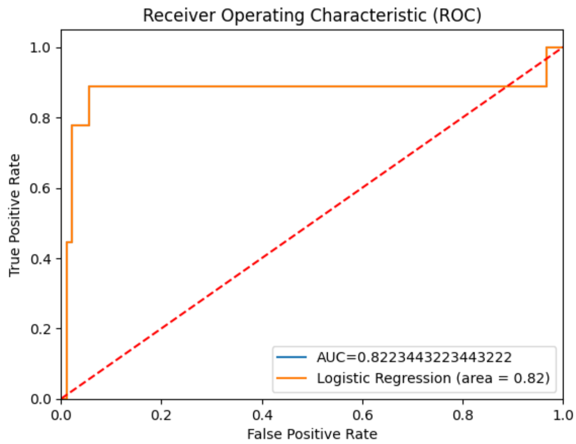

Figure 2. Roc and auc value for logistic regression model

Figure 2 show indicate a good performance of the Logistic Regression model as the AUC and ROC value are both above 0.8.

Table 2: logit regression results

Dep. Variable:	y	No. Observations:	500
Model:	Logit	Df Residuals:	491
Method:	MLE	Df Model:	8
Date:	Tue, 05 Sep 2023		0.2999
Time:	9:59:46	Pseudo R-squ.:	-110.69
		Log-Likelihood:	
		LL-Null:	
converged:	TRUE		-158.1
Covariance Type:	nonrobust	LLR p-value:	4.88E-17

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	5.4898	2.659	2.065	0.039	0.279	10.701
X[0]	0.171	0.358	0.478	0.633	-0.53	0.872
X[1]	-0.2598	0.053	-4.945	0	-0.363	-0.157
X[2]	0.1207	0.225	0.537	0.591	-0.32	0.561
X[3]	1.8112	0.423	4.286	0	0.983	2.639
X[4]	-0.0606	0.044	-1.382	0.167	-0.146	0.025
X[5]	0.1058	0.063	1.688	0.091	-0.017	0.229
X[6]	1.523	4.955	0.307	0.759	-8.188	11.234
X[7]	0.0656	0.31	0.211	0.833	-0.543	0.674

Table 2 give us the coefficient correlation value which will be used in formulating the log regression of the Logistic Regression. In term of the *p-value*, we can see that only variables X [1] and X [3], statistically significant influence as the *p-value* < 0.05.

Table 3: classification report and confusion matrix of logistic regression model

		precision	recall	f1-score	support	Confusion Matrix:	
	0	0.97	0.98	0.97	91	[89	2]
	1	0.75	0.67	0.71	9	[3	6]
accuracy				0.95	100		
macro	avg	0.86	0.82	0.84	100		
weighted	avg	0.95	0.95	0.95	100		

Table 3 show the confusion matrix result and inform us the performance of the Logistic Regression model in term of precision, recall, accuracy, and f1-score.

Logistic Regression Model obtained:

z = 5.4898 + 0.1710 X [0] - 0.2598 X [1] + 0.1207 X [2] **+ 1.8112 X [3]** - 0.0606 X [4] + 0.1058 X [5] + **1.5230 X [6]** + 0.0656 X [7]

$$y = \frac{1}{1+e^{-z}}$$

Whereas:

Y = Clients Respind
X [0] = Gender
X [1] = Age
X [2] = Marital Status
X [3] = Previously Claims
X [4] = Policy Age/Vintage
eValue = 2.71828
X [5] = Premium Value
X [6] = Vouchers Value
X [7] = Promotion Media/Communications Channels

Analysis – Logistic Regression:

This logistic regression model has a high accuracy of 0.95, which means that the model can correctly predict the RESPOND variable in 95% of cases, the model can correctly classify most observed clients. The precision of the model with a value of 0.75 indicates that the model's prediction of positive values is not very reliable – of the positive values predicted by the model, only 75% are truly positive and this is due to the high false positives rate (the model is too aggressive in predicting positive values). positive so that 25% are wrong in predicting their positive value]. Recall has a value of 0.66 which means that the model is also not very good at identifying all positive cases, only 66% are identified correctly by the model, this is due to the possibility that there are several false negatives value (client is positive, but classified as negative by the model). F1-scores of 0.70 indicate the harmonic mean of precision and recall, which indicates a measure of the overall model performance.

The result of the Decision Tree model can be seen in Figure 3, Figure 4, Table 4, and Table 5.

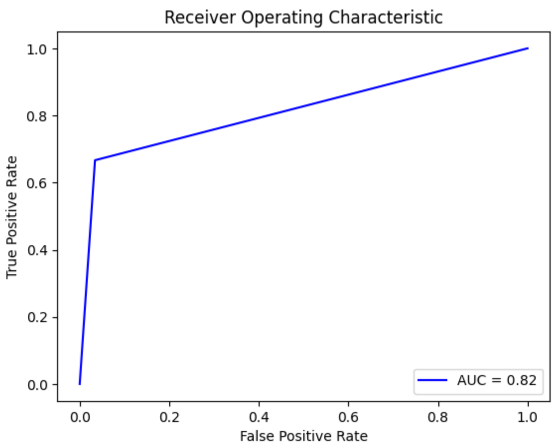

Figure 3. ROC and AUC Value for Decision Tree Model

Figure 3 indicate a good performance of the Decision Tree model as the AUC and ROC value are both above 0.8.

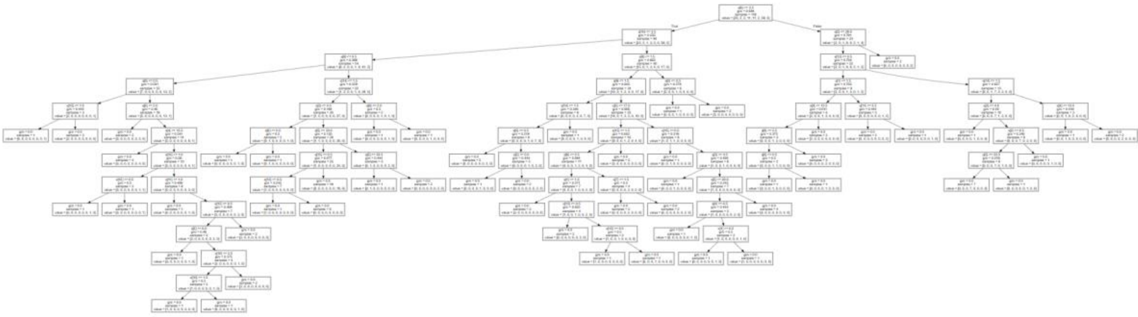

Figure 4: decision tree model result

Figure 4 illustrate Decision Tree branches, leafs, and nodes and how each of determinant variables split the decisions.

Table 4. Feature importance of decision tree model

Feature Importance Ranking:	
1	PreviouslyClaims: 0.45973736673838816
2	NilaiPremiTahunan: 0.32388727706563236
3	Age: 0.1651730711902227
4	UmurPolis: 0.023617630561213954
5	NilaiVouchers: 0.014465798718743542
6	Gender: 0.008856611460455242
7	MaritalStatus: 0.004262244265344087
8	PromotionMedia: 0.0

Table 4 show which features are more important in descending order. PreviouslyClaims feature is more important than NilaiPremiTahunan and so on.

Table 5. Classification Report and Confusion Matrix of Decision Tree Model

		precision	recall	f1-score	support	Confusion Matrix:	
	No	0.96	0.97	0.96	88	[85	3]
	Yes	0.73	0.67	0.7	12	[4	8]
accuracy				0.93	100		
macro	avg	0.84	0.82	0.83	100		
weighted	avg	0.93	0.93	0.93	100		

Table 5 show the confusion matrix result and inform us the performance of the Decision Tree model in term of precision, recall, accuracy, and f1-score.

Analysis – Decision Tree:

This logistic regression model has a high accuracy of 0.93, which means that the model can correctly predict the RESPOND variable in 93% of cases, the model can correctly classify most observed clients. The precision of the model with a value of 0.84 indicates that the model's prediction of positive values is not very reliable, from the positive values predicted by the model, only 84% are truly positive and this is due to the high false positives rate (the model is still aggressive in predicting positive values). Recall has a value of 0.81, which means that the model is also not very good at identifying all positive cases, only 81% are identified correctly by the model, this is due to the possibility that there are several false negatives value (client is positive, but classified as negative by the model). F1-scores of 0.69 indicate the harmonic mean of precision and recall, which indicates a measure of the overall model performance.

The prediction performance comparison of the two models can be seen in Table 6. The two models provide almost similar performance. Logistic Regression has better accuracy and F1-Score values, Decision Tree has better Precision and Recall values.

Table 6. Result comparison: logistic regression vs decision tree

	Logistic Regression	Decision Tree
Accuracy	**0.95**	0.93
Precision	0.75	**0.84**
Recall	0.66	**0.81**
F1-Score	**0.7**	0.69

Table 6 summarize the performance comparison of the both model in term of precision, recall, accuracy, and f1-score.

CONCLUSION

If we look at the Logistic Regression model, we can conclude that the Previously Claims [X3] and Vouchers Value [X6] variables are positive variables those have a dominant influence in increasing the probability of a client in accepting existing cross sell offer. This shows that the experience of a client when the claim process is carried out is a determining factor when selecting an insurance service provider, apart from the gimmick factor in the form of vouchers. This is a very logical finding because an insured client certainly does not want a complicated claim process.

If we look at the features importance of the existing Decision Tree model, again, we see that the Previously Claims variable is a very decisive variable for a client when deciding whether to continue a relationship with an insurance company or not. The findings of these 2 (two) models are importance feedback for company in running their business, where companies must really pay attention to the claim process and experience, because claim experience is a dominant factor and more influential than gimmicks in the form of vouchers.

The Logistic Regression model predicts 95% of the RESPOND variable values correctly, and 93% if using the Decision Tree model. With this level of accuracy, the model can really help the cross-sell initiatives carried out by companies, in which, to increase the take up rate of cross sell initiatives being carried out, companies simply send offers to clients with a higher YES probability. By doing this smart move, of course, companies can save their resources, whether it is manpower and time. Investment vouchers issued can also be given more precisely on target. This research gives a broader and wider perspective to the company, on top of the shopping vouchers gimmich, the company should also investigate other variables (in this case claims experience) which will give huge influence to the success rate of the cross-sell initiatives.

The existing model is obtained from data on 500 clients in one of the batches of cross-sell initiatives which provide a relatively high take-up rate of around 9%. The existing model should be re-tested with client's data in batches those have a lower take-up rate, and tested on client's data for all batches of cross-sell initiatives so that a more representative model can be obtained

The model is obtained with the input of only 8 (eight) X variables to get a Y value. In order to get a better representation of the actual conditions, the model can be developed further by including additional X as input variables such as: number of clients' children, income, the location of the domicile, whether clients have a history of certain diseases, whether the clients smoke or not, the clients' type of work (occupation) and etc.

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