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Knowledge Acceleration Estimator (KAE) Model of Customer Behavior using Business Metrics

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Abstract: Business metrics in Financial Technology 1500 users spread across North Sumatera Province. The impact of commercial digital business (commercial enterpreneurship and social entrepreneurship) is very large on users who are currently increasing in number. To produce Knowledge Acceleration (KAE) Model using Business Metrics on the impact of Commercial Entrepreneurship and Social Entrepreneurship in their utilization. Uncertainty arising from sustainable business operators by considering aspects of Business Metrics related. MARS an linear regression analysis method non-parametrics intended for statistics with the aim of facilitating research and modeling the relationships of each of the multi variables that arise.

INTRODUCTION

The development of the 4.0 revolution and we will encounter the 5.0 revolution, the development of digital payment technology continues to grow along with the acceleration of knowledge[1]. In this development, of course, it brings changes that greatly impact digital businesses with the aim of attracting customer's interest in obtaining easy transactions[2]. However, the parties from the Banking regulated in Indonesia in the formulation of the regulation that we call PBI (Bank Indonesia Regulation) regarding financial technology (FinTech) were set in 2017[3]. Regulations on the management of financial technology that includes payment systems, market support, management investment and risk management, loans, financing and capital providers and other financial service[2, 4]. Merchants are groups of small entrepreneurs in the form of goods/services that have a digital business form that collaborates with the Bank in providing payment receipt services via. E-payment[5, 6]. The role of the entrepreneur must be able to see opportunities and challenges as well as the impact of revenue growth in making decisions and the emergence of competition consisting of variant merchant superior products offered and customer convenience[7, 8]. In this case, of course there are efforts to use business metrics such as profits, income and the stock market, to maintain business order to change the pattern of competition in developing countries[9]. Our research focuses on data modeling by using a non-parametrics method approach to user behavior in financial technology. Multi Adaptive Regression Linear Spline (MARS) is one of the approaches that we do by looking at the relationships and models between targets and predictions to be achieved[1, 10]. This method is multi-duplicative to see the pattern and balance of the many variables and types of possibilities in the big data source that, we use[3, 10]. The emergence of variant types and the number of similar business actors must be able to anticipate, so as not to be distracted by the payment technology mining[8]. Therefore, we provide a model of knowledge acceleration approach in predicting small business actors by looking at the balance and diversity of competition.

MATERIALS AND METHODS

KAE by business metrics payment model: Merchant is a place that accommodates customer transaction details. The data includes static and dynamic elements that identify each transaction (Fig. 1).

Customers receive transaction data from the Merchant and match each information they have in which the standard payment format has been prepared to be able to process payments. The payment process is via. trusted partners such as a bank or telecommunications operator. When the payment request is ready to be transferred, the consumer checks and identifies with the PIN sent by the account manager.

The account manager will accept payment requests, identify customers and process payment requests. The identification process includes checking available funds and the amount requested. When the process is complete, the payment notice is forwarded to the data center as a payment service. The data set then identifies the address of the bank/telco operator at the payment notice and then sends a message to the merchant to notify that the payment process has taken place[11]. The processor on the merchant side accepts the payment notice and provides real-time notification on whether the transaction is accepted or rejected.

Personal Financial Management (PFM):

- Assessment of personal financial analysis
- Assessment of Personal financial health
- Financial product recommendation service consisting of Investment and Insurance products. Tools to monitor and control the level of expenditure to meet the customer's financial planning goals

Model knowledge acceleration manage service mobile Apps: Figure 2, we do the 6 stages, from our application approach we get the behavior of user habits that tend to be often done towards the use of financial technology[8]. We accelerate the Knowledge base in the average transaction and efficiency comparison between existing merchant competitive[1]. By determining the probabilities that arise and the various variants, we use MARS to determine the target variable (Y) and predictor (x) (Table 1).

Multi Adaptive Regression Linear Spline (MARS): The special advantage of MARS lies in its ability to estimate the contribution of BF, so that, additional and interactive effects of predictors are allowed to predict response variables[1, 10]. MARS is a non-parametric regression procedure that does not make specific assumptions about the underlying functional relationships between dependent and independent variables to estimate the general function of high-dimensional arguments, given the sparse data:

$$[+(x-T)]_+ , [-(x-T)]_+ \quad (1)$$

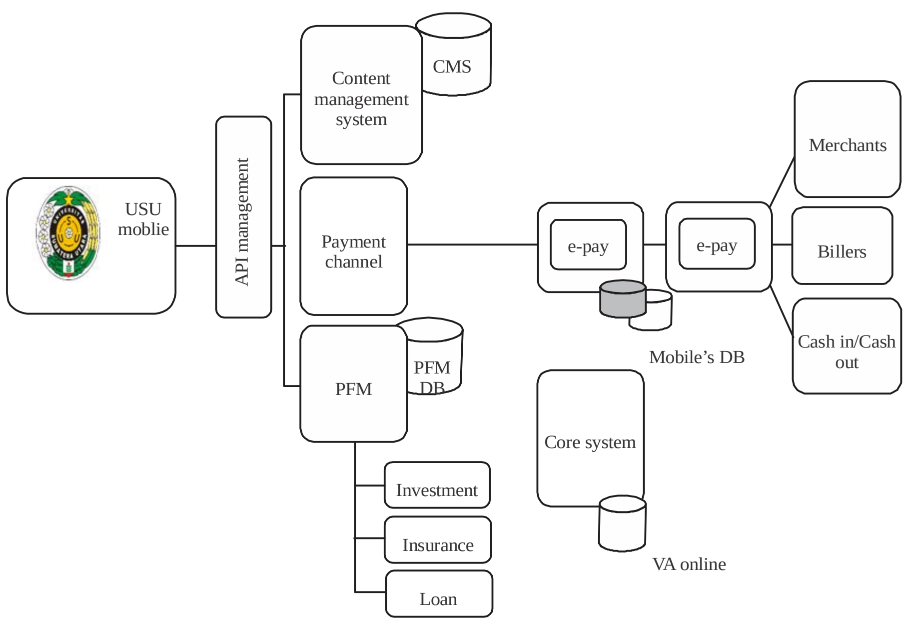

Fig. 1: KAE by business metrics Arsitektur payment model

Table 1: Business metrics variant of value transaction

Business metrics	Value transaction
Variant transaction	1500; 3000; 3001; 4200; 5500; 6500; 7000; 8000; 9000; 9500;10000; 12000; 13000; 14500; 15000; 16000; 18500; 19000;20000; 24000; 25000; 27500; 29500; 30000; 31000; 36000;40000; 42500; 45000; 48000; 50000; 60000; 70000; 72000;75000; 85000; 90000; 100000; 140000; 185000
Name merchant	Abu Bakar NL; Aneka Gorengan NL; Apotek Maju LK; Bennynatanael Sinaga; Bubur Ayam BPK Suparman; Burger Bunenglk; Frans Pebrian Lubis; Fristi Cell NL; Galon Rendi LK; Ibrahim Yusuf; Indomaret; IR.ONE S; Kede Jon NL; KFC Adam Malik Medan; KFC Asia Mega Mas Medan; KFC BTC Mareland; KFC Cemara Asri Medan; KFC Center Point Medan; KFC Setiabudi Home Centra; KFC Simpang Mataram Medan; Mariana BR Sinaga;mieaceh Andre; Mie Ayam Palangkaraya; Milala Bengkel; Percetakan EKA; Pop ICE Wanti; RM Reni; Rujak Jelani; Rujakjelani-Sales Medan 3 Zulvan-; Sales Medan 3zulvan Suhada; Sambelan Bu Sri; Sate Bang Jon LK; Siti Aminah; Sosis Goreng Alkudus NL; Soto Friska LK; Toko Bayu LK; Toko Dedi LK; Toko Elya LK; Toko Ginting LK; Warkop Radoel LK; Warung Abas LK; Warung Bibi LK; Warung Eyanglk; Warung Firdaus; Warung Joko LK; Warung Juss Pakyadilk; Warung Simpang Tiga; Warung Tiara LK

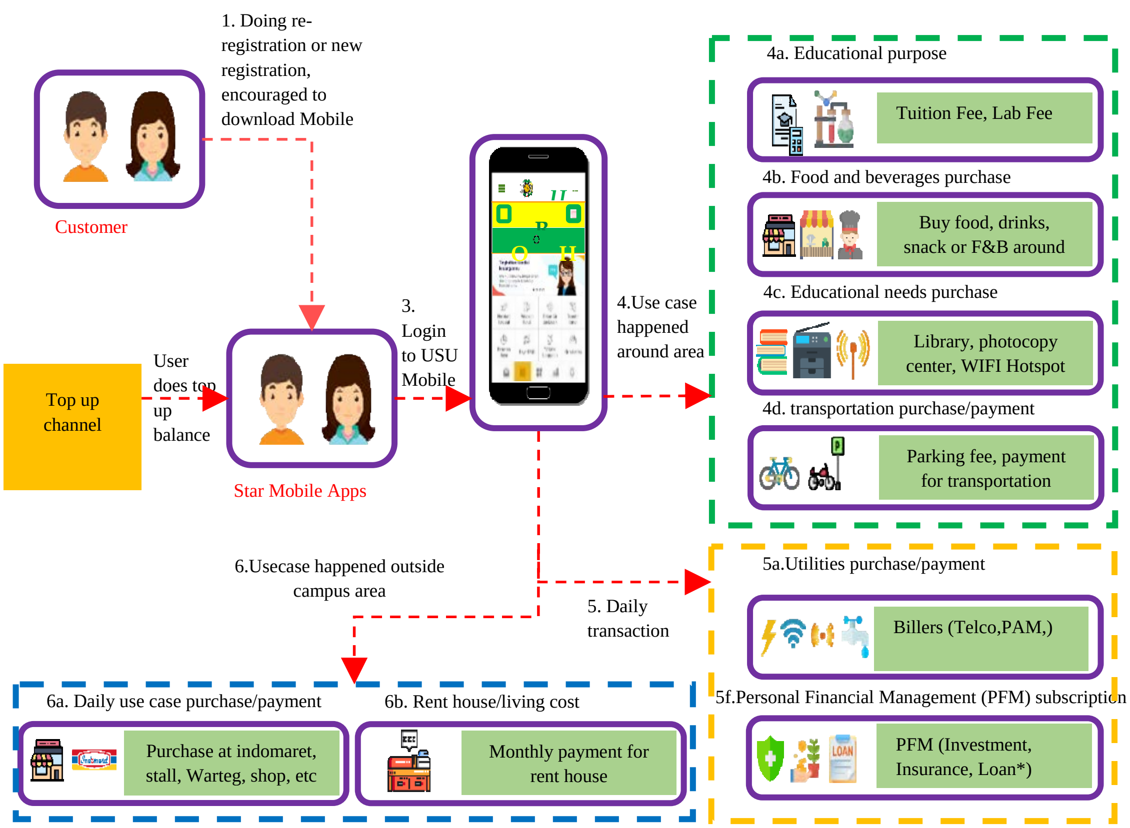

Fig. 2: Knowledge acceleration manage service mobile Apps

where [q] +: = max {0, g} and τ are univariate vertices. Each function is linear with a node at the value of r and the corresponding pair of functions is called the reflected pair. Let us consider a general model of the relationship between predictor variables and responses. The goal is to build the pair that is reflected for each predictor x_j ($j = 1, 2,..., p$) with the p-dimensi knot $\tau_i = (\tau_{i,1}, \tau_{i,2}, ... \tau_{i,p})^T$ at $x_i = (x_{i,1}, x_{i,2},.... x_{i,p})^T$ or just adjacent to each data vector $\dot{x}_i = (\dot{x}_{i,1}, \dot{x}_{i,2}, ..., \dot{x}_{i,p})^T$ ($i = 1, 2, ..., N$) of the predictor. We do not lose the generality, the assumption that $\tau_{i,j} \neq \dot{x}_{i,j}$ for all i and j, to prevent the difference in the matter of optimizing this research later[10]. Actually, we can choose node $\tau_{i,j}$ further than the predictor value $\dot{x}_{i,j}$ if there is a position that promises better data mounting[10]. After this preparation, the BF collection of research is:

$$\wp:\left\{\left(x_j - T\right)+, \left(T - x_j\right)+T \in \left\{x_{1,j}, x_{2,j}, \ldots, x_{N,j}\right\}, J \in \left\{1,2,\ldots,p\right\}\right\} \quad (2)$$

So, we can represent f(x) with linear combinations which are respectively built by the set p and with the intercept θ_o, so that, (Eq. 2) takes the form:

$$y = \theta_0 + \sum_{m=1}^{M} \theta_m \psi_m(x) + \in \tag{3}$$

Here, ψ_m (m = 1, 2, ..., M) is the BF of p or the product of two or more of these functions, ψ is taken from a set of linear independent basis elements M and θ_m is an unknown coefficient for m-basis functions (m = 1, 2, ..., M) or for constants 1 (m = 0). One set of vertices that satisfies i, j is assigned separately for each dimension of the predictor variable and is chosen, so that, it coincides with the level of predictor represented in the data. BF interactions are made by multiplying existing BF with truncated linear functions involving new variables. In this case, the existing BF and the newly created BF interaction are used in the MARS approach[10]. Provided that observations are represented by data x_i, y_i (i = 1, 2, ..., N), the BF to m form can be written as follows:

$$\psi_m(x) := \prod_{j=1}^{K_m} \left[S_{k_j^m} \cdot \left(x_{k_j^m} - T_{k_j^m} \right) \right] + \tag{4}$$

where k_m is the number of truncated linear functions multiplied in the BF to -m, xk^m_j is the predictor variable corresponding to the -j intersecting the linear function in the BF to -m, Tk^m_j is the node value corresponding to the variable, xk^m_j and Sk^m_j is the chosen sign +1 or:

$$\text{GCV:} = \frac{1}{N} \frac{\sum_{i=1}^{N} \left(y_i - \hat{f}_\alpha(x_i) \right)^2}{\left(1 - c(\alpha)/N \right)^2} \tag{5}$$

The MARS algorithm for estimating the function model f(x) consists of two sub-algorithms: The stepwise forward algorithm looks for BF and at each step, a split that minimizes the ‘less suitable’ criteria of all possible separations for each BF is selected[1]. The process stops when the user-specified M_{max} value is reached. Then, the stepwise backward algorithm begins to prevent excess conformity by reducing the complexity of the model without reducing conformity to the data and to eliminate from the BF Model that contributes to the smallest increase in residual error squares at each stage, producing optimally estimated models with respect to each the number of terms, called fα. This study notes that reveals some estimation complexity[1]. To estimate the optimal α value gener Generalized Cross-Validation (GCV) can be used indicating a lack of conformity for the MARS Model.

RESULTS AND DISCUSSION

In this study, data used to solve real life problems is discrete. Data modeling, also called a discrete or knowledge acceleration model approach is widely used to establish relationships between several predictors and response variables[1]. There are various forms of regression models, each of which is used for different purposes such as data description, summarization, parameter estimation for learning and control in almost every field of engineering and science (Table 2).

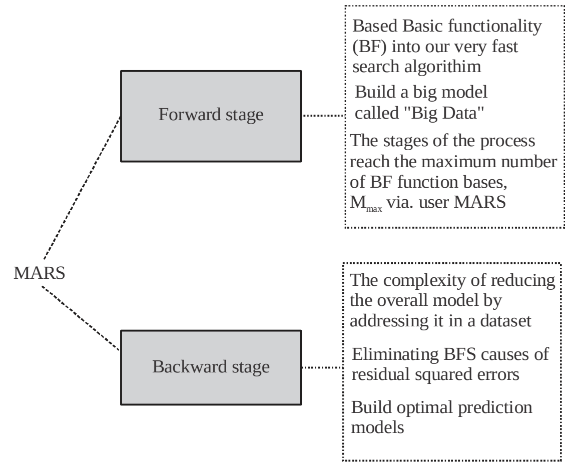

Fig. 3: The two-stage process in MARS

Table 2: Learning calculation results

Name	Learning statistics
RMSE	0.114
MSE	0.131
GCV	0.139
MAD	0.363
GCV R^2	0.362

In Fig. 3, we adopt the denotation of the linear 1-dimensional piecewise BFS expressed in the equation. MARS Model, the optimal estimated model with the amount reduced by BF and max M is the Forward and Backward Phase of the MARS by its software, with the help of General-Cross Validation (GCV) which is given the best predictive optimal and selected optimal model[1, 10]. However, Forward Stage of MARS, the highest level of interaction (max. M) and BF of the relationship are assigned, BFs on the backward stage are represented in Algorithm 1.

Algorithm 1; Algorithm for basis function MARS Method:

BF1 = max	{0,x_2-0.251038}	(merchant$ = .)
BF3 = max	{0,007, x_6-186917} BF_1	(name_merchant$ is in SubSet1)
BF5 = max	{0,x_9 -0,1272981}.BF_2	(name_merchant $ is in SubSet2)
BF7 = max	{0,x_2-0.8,68922}.BF_6	(name_merchant $ is in SubSet3)
BF9 = max	{0,x_2+ 0.631769} BF_8	(name_merchant $ is in SubSet4)
BF11= max BF_{12}	{0,008x_2-0.370786E-008}	(name_merchant $ is in SubSet5)
BF13 = max	{0,x_2+0.404497} BF_{14}	(name_merchant $ is in SubSet6)
BF15 = max	{0,x_{2-1500}}	max(0, value_ transaction-15000)

Table 3: MARS data training data model results

Percentile (%)	N	R^2	MSE	MAD	RMSE	MRAD
99.86	710	0,47430	0.948785	0.40921	0.64099	0.24077
99.30	706	0,60465	0.963248	0.95256	0.13885	0.23758
98.59	701	0,68651	0.247041	0.61566	0.76602	0.23419
96.48	686	0,79909	0.331950	0.10234	0.16316	0.20633
92.97	661	0,86207	0.927621	0.70673	0.45363	0.14726
85.94	611	0,94398	0.146530	0.05022	0.26859	0.08226

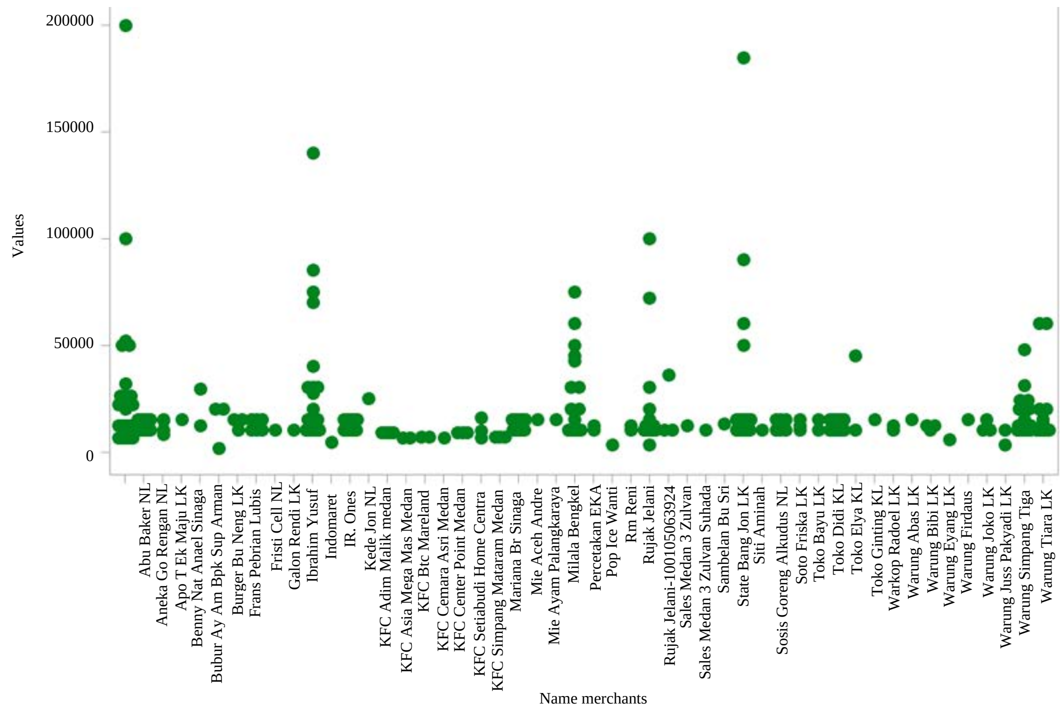

Fig. 4: Customer behavior growth on merchants ecosystem

The optimization MARS Model with the BFs above is presented in the subsequent form: $Y = \theta_o+\Sigma^M_{m=1}\theta_m\psi_m(x)+\varepsilon$, = 0.309448 -007+1+BF1-0.251038-007+BF3-0.186917-007+BF5+0.127298-007 +BF7-0.868922-008+BF9+0.631769-008+BF11-0.370786-008+BF13+0.404497-013+BF15; Description of the variables that are built based on the implementation of the MARS Method, our estimates are randomly starting from the determination of the dependent and independent variables. From the results of this trial as follows:

Assessment of statistical calculations or agreed upon statistics, announced in Table 2, to approve the results of the proposed model. This research, Mean Square Error (MSE), Root Mean Square Error (RMSE), General Cross Validation (GCV), accuracy to measure the predictive ability of each model. Therefore, the accuracy criteria indicate which model has higher predictive ability than the others accuracy to measure the ability of each model. Therefore, the criteria prove which model has the ability more than others and which one is the best (Fig. 4 and Table 3).

CONCLUSION

The results of this study, that in general intense competition in the diverse merchant ecosystem, it is necessary to anticipate challenges and opportunities through the MARS method approach and knowledge acceleration with the aim of maximizin sustainable business decisions. With this optimization method, businesses must take steps, so as not to be distracted by opening new business opportunities.

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