AN ADVANTAGE OPTIMIZATION FOR PROFILING BUSINESS METRICS COMPETITIVE WITH ROBUST NONPARAMETRIC REGRESSION

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ABSTRACT

Business Intelligence can be used to support various business decisions from operational to strategic. Various new ways have been used to make progress, one of which is with electronic-based businesses, but with a large number of variations, business vulnerabilities are also increasingly difficult to anticipate. To keep up with the development of the company, it is necessary to optimize the metrics for the business. The purpose of optimization is to find the minimum or maximum value of a problem that occurs, whether the value of a company produces the desired results or vice versa. The reason for the improvement is to find a basis or estimate of the difficulty that occurs, regardless of whether the organization's estimate provides an ideal result or vice versa., where the outliers obtained are one of the parameters that can be considered in achieving profit. In this study, the Robust CMARS (Conic Multivariate Adaptive Regression Spline) was used where CMARS can manage the existing multivariate in the data and use a robust approach in handling uncertainty outliers in the data. So that the results achieved by RCMARS are in the form of a maximum value of the basis of the functions BF11, BF12, and BF13 with a maximum of 14.06% outliers.

***Keywords**: Business Intelligence, Optimization, Customer Profiles, Business Metrics, Robust Nonparametric Regression, RCMARS.*

1. INTRODUCTION

Business Intelligence provides a historical, current and predictive view of business operations. Business Intelligence functions are reporting, online analytical processing, analytics, data mining, process mining, complex event processing, business performance management, benchmarking, text mining, predictive analytics, and prescriptive analytics. [1,2,8].

BI can be used to support a variety of business decisions from operational to strategic. Basic operating decisions include determining the position or price of the product. Strategic business decisions include priorities, goals, and direction at the broadest level [2,7,8]. In all cases, BI is most effective when it combines data that comes from the market where the company operates (external data) with data from internal company sources to business such as financial and operating data (internal data) [3,5,7]. When combined, external and internal data can provide a more complete picture, in an effect format, creating "intelligence" that no single data set can impart. Among the myriad of uses for tools, BI empowers organizations to gain insight into new markets, the suitability of products and services for different market segments and measuring the impact of marketing efforts [4]. The environment in which organizations operate today is becoming increasingly complex. This complexity creates one opportunity and problems on the other. Business environmental factors can be divided into four main categories: market, consumer demand, technology, and society [5,6]. Business metrics allow the economy to grow faster, and better. In addition, scattered business metrics reflect market share and markets that change rapidly so they must adapt to changes [6]. Therefore, a strategy is needed to increase market share, sales, innovation and product improvement with optimization [7].

Optimization is used as a form of maximizing something that already exists, or designing and making something new or better. The purpose of optimization is to find the minimum or maximum value of a problem, whether a value from a company produces the desired results [8,9]. The approach is carried out by analysing customer profiles based on the level of behaviour similarity, Basic measurements of distances, attributes, times, places, and transactions between social actors are used to trace the origin of the information, or can be used to predict social behaviour [10]. Not all customer profiles are similar to one another, there is the possibility of outliers on each transaction, and the methods used have adaptations to different behaviours carried out by competitive organizations [11].

Previous research, introduced appropriate metrics to measure process similarity based on behavior profiles. The metric data used were successfully evaluated based on the estimated human similarity assessment [12].

Prior research, uncertainty arises from business administrators who can be managed by considering the relevant parts of Business Metrics. MARS is proposed for measurement with the aim of checking and displaying the connection of each multi-variable that appears [13]. Robust CMARS provides solutions to problems by optimizing the sensitivity to disturbances in problem parameters. [14,25].

CMARS is a modified version of the nonparametric regression model, multivariate adaptive regression splines (MARS), which uses conical quadratic optimization [15,16]. The model performance is compared using various criteria which include accuracy, precision, complexity, stability, robustness and computational efficiency [17]. The results imply that the method provides more precise parameter estimates even though it is computationally inefficient and that among all, random sampling yields a better model, especially for large-scale data sets [18].

Based on the research that has been done before, this research was conducted to produce an optimization model in predicting profits with e-metrics data, based on customer profiles by approaching robust nonparametric regression. Where CMARS is used to manage multivariate and robust is used to find outliers that occur in competitive organizations, based on several variables that will be used so that this modelling can be an optimization model in predicting profits based on customer profiles [26,27,28].

2. BACKGROUND

In the regression model it is possible that there are outliers which cause some regression assumptions not to be fulfilled so that the prediction value becomes less accurate and the CMARS Model depends on parameters [25]. Minor disturbances in the data can result in different model parameters. This can lead to an unstable solution [26]. In RCMARS, the goal is to reduce estimation errors while maintaining the highest possible efficiency [27,28]. To achieve this goal, the authors apply several approaches such as scenario optimization, strong partners and the use of stronger estimators. so that this modelling is expected to be a model in predicting profits, which will later be used as a decision making for a competitive organization.

3. RESEARCH AND METHODOLOGY

In the research methodology, the steps that will be taken analyze the customer relationship management between merchants and customers and merchants and merchants. After that, the data are classified and grouped based on similar merchants, merchants of different types. Then it is mapped to find outliers that occur between transactions.

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3.1. Customers Relationship Management Business Metric

Customer relationship management (CRM) is one of many different approaches that allow a company to manage and analyse its own interactions with past, current and potential customers [19].The main purpose of a customer relationship management system is to integrate and automate sales, marketing, and customer support [20].The role of the CRM system is to analyse customer data collected through various sources and present it so that business managers can make more informed decisions [21,31]. In this case, CRM is seen based on data that has been captured from the use of mobile wallets by users who transact against a merchant, show Fig.1.

A mobile wallet is an application that can be installed on a smartphone that can be used as a medium for transactions [22]. For example, making payments for food, drinks, shopping etc. The data is taken based on a network that is done using a mobile wallet, where the data is customer data that has been registered with various merchants and customers throughout North Sumatra [14]. CRM can be generated based on data networking that has been done on a mobile wallet which can be seen in Fig 2:

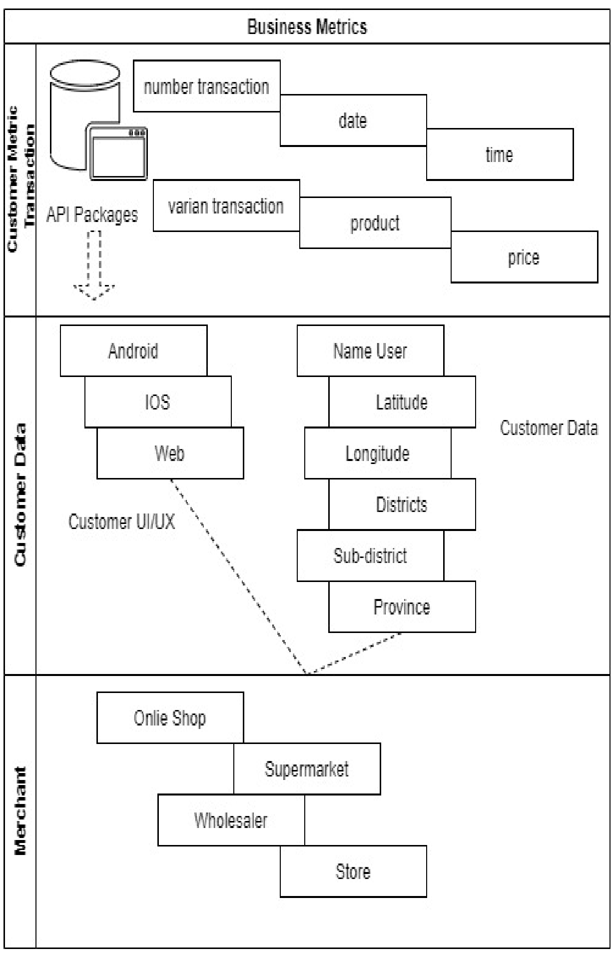

Figure 1. Business Metrics Source Data

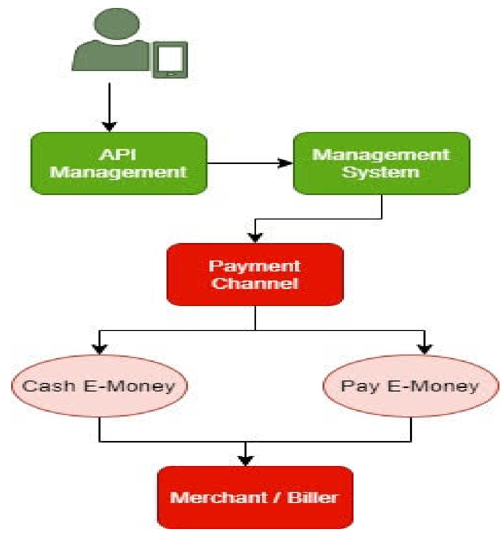

Figure 2. Multi Payment Channel

3.2. Profiling Data

Customer data is taken based on latitude, longitude, urban village, sub-district, regency and province [1,14]. From the data that has been captured, the data is grouped, classified and then based on customer profiles between merchants and users, merchants of the same type and merchants of different types. The following customers can be seen in table 1 [There is an attached table 1].

3.3. E-Metrics data

Electronic-Metrics or so-called e-metrics are electronic-based customer behavior (e-customer behavior) [23]. The technological era has brought big changes to society, this can be seen in presenting everything electronically which provides convenience about how a customer behaves electronically and provides information that can be applied [24].

[There is an attached table 1]. Table 2. explains that transactions made by users against merchants. There are several similarities made by users, namely transacting at the same merchant. The frequency of merchants and total merchants whose variants vary depending on the type of business actor, especially the digital business. In e-metric, where every merchant who is caught in user behavior activities using Financial Technology.

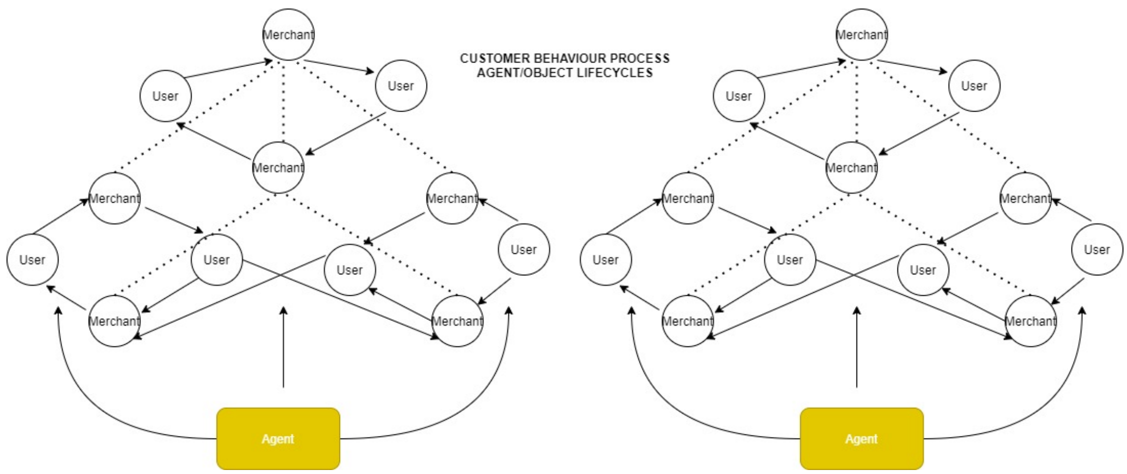

Figure 3. Customer Behaviour Process Lifecycle's

Every object or entity contained in the universe of speech has characteristics on its features and weights. When there is an object whose habit is known, then efficiently the behaviour of other habits can be determined based on the measurement of the similarity or closeness between these objects [1,13,14]. In topology, U a and b are a vector that has both magnitude and direction, and X is a vector space, and z is the distance function for $a\ b\ c \in X$ applies $z\ (a, b) = z\ (a, b) - z\ (b, c)$ and $a = b$. So, (X, z) denotes the distance space for the vector space X with distance function d. The relationship between similarity and inequality reveals that they are complementary, that is $s\ (a, b)\ c = 1 - s\ (a, b)$.

At this stage the merchant variants are grouped and classified so that later there will be outliers or differences that can be used as an advantage at the merchant. Customer purchases will represent each preferred behaviour and a formula can be used to calculate a score for each customer using the following table.3. variables:

Table 3. Variable Independent

INPUT VARIABLES	
X1	Transaction No
X2	Date
X3	Hour
X4	Reference No
X5	Customer's name
X6	Transaction
X7	Merchant name
X8	Sub-Districts
X9	Districts
X10	Region

On $a, b \in X$, there is a form that is defined as $a \cap b \in X$, means that there is a relationship between a and b, as $a \cap b$ also is a vector inside a vector space X, which has the weight and direction of the goal. Differenceaand b is the distance owned by each express merchant and customer $d\ (a, b)$ as shows the existence of each a and b on vector space X, is that $a = b$ or $a \cap b > 0$.

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After each variable has the appropriate category according to table 3, a segment is created from the intersection of the values *a = b or a ∩ b > 0*. In table 4, you can see the groupings of merchants who have similarities and habits carried out by customers against competitive merchants. and it can be seen in table 4 [There is an attached table 4].

4. RESULT AND DISCUSSION

4.1 CMARS (Conic Multivariate Adaptive Regression Splines)

In CMARS, the goal is to reduce the estimation error over various variances. CMARS has a maximum number of base functions (BFs) [17,18,25]. Where BF works to minimize large data and the process stops when the model reaches the maximum value [26].

$$Y = f(X) + \varepsilon \qquad (1)$$

Where *Y* is the response variable, *X* is a ve the predictor variable, and εis an additive stochastic component which is assumed to have zero mean and finite variant. Here, the following general models are considered for each input *X* [27].

PRSS with M_{max} BFS that has been accumulated in the forward stepwise algorithm from the MARS approach has the following form:

$$PRSS := \sum_{i=1}^{N} (y_i - f(\tilde{x}_i))^2 + \sum_{m=1}^{M_{max}} \lambda_m \sum_{\substack{|\alpha|=1 \\ \alpha=(\alpha_1,\alpha_2)^T}}^{2} \sum_{\substack{r<s \\ r,s\in V_m}} \int \theta_m^2 [D_{r,s}^{\alpha} \psi_m(t^m) \qquad (2)$$

$$PRSS = \sum_{i=1}^{N} \left(y_i - \theta_0 - \sum_{m=1}^{M} \theta_m \psi_m(\tilde{x}_i^m) - \sum_{m=M+1}^{M_{max}} \theta_m \psi_m(\tilde{x}_i^m) \right)^2 + \sum_{m=1}^{M_{max}} \lambda_m \sum_{\substack{|\alpha|=1 \\ \alpha=(\alpha_1,\alpha_2)^T}}^{2} \sum_{\substack{r<s \\ r,s\in V_m}} \int \theta_m^2 [D_{r,s}^{\alpha} \psi_m(t^m)]^2 \, dt^m, \qquad (3)$$

$$PRSS = \sum_{i=1}^{N} (y_i - \theta^T \psi(\tilde{d}_i))^2 + \sum_{m=1}^{M_{max}} \lambda_m \sum_{\substack{|\alpha|=1 \\ \alpha=(\alpha_1,\alpha_2)^T}}^{2} \sum_{\substack{r<s \\ r,s\in V_m}} \int \theta_m^2 [D_{r,s}^{\alpha} \psi_m(t^m)]^2 dt^m \qquad (4)$$

$$PRSS \approx \| y - \psi(\tilde{d})\theta \|_2^2 + \sum_{m=1}^{M_{max}} \lambda_m \sum_{i=1}^{(N+1)^{K_m}} L_{im}^2 \theta_m^2. \qquad (5)$$

This is a set of variables associated with the m-BF, ψ_m , ψ_m , $t^m = (t_m, t_{m2}, ..., t_{m\,KM})$ is the vector of the variable contributing to the m-BF, $\psi_{m.}$ [There is an attached table 5].

BF11 = max (0, X4 - 9.028e + 011) * BF2;
BF12 = max (0, 9.028e + 011 - X4) * BF2;
BF13 = max (0, X2 - 43568) * BF2;

The MARS optimization model with BF we provide it in a form like:
Y = 22826.9 + 71265.7 * BF1 - 82086.2 * BF3 - 70628 * BF5 + 107875 * BF7 - 42769.8 * BF9 - 3.48783e-007 * BF11 - 7.48442e-006 * BF12 + 224,909 * BF13.
[There is an attached table 5]. Based on table 5, determine the maximum basis function, which is two to four times the number of predictor variables used. In this study, 10 predictor variables were used so that the maximum number of BFs was 11, 12 and 13. Because if there are more than 3 interactions, it will cause a very complex model interpretation. Whereas for the minimum observation, 0, 1, 3, 5, 7 and 9 were selected. From the results of the model interpretation, the sensitivity and specificity values were obtained which can be seen in table 6. [There is an attached table 6].

4.2 Robust CMARS

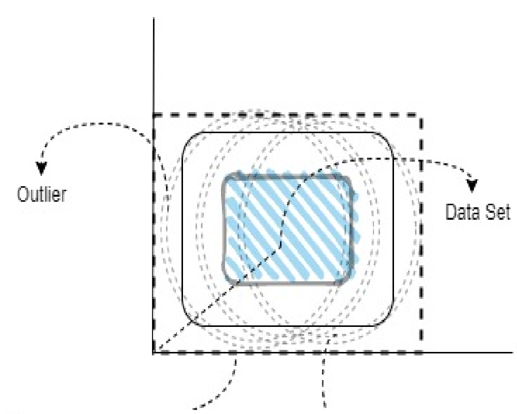

Figure 4. Robust Optimization Business Metrics

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Uncertainty is usually based on statistical estimates and probabilistic assurance [28]. If the uncertainty set has a special shape such as ellipsoidal or polyhedral, then a robust optimization problem can be solved efficiently [29]. In order not to increase the complexity of the optimization problem, it sets uncertainty U_1 and U_2 are polyhedral for input and output in robust data model [30]. Based on the set, U_1 and U_2. robust counterpart can be defined as follows Eq [6].

$$\min_{\alpha} \max_{\substack{W\epsilon U1 \\ z\epsilon U2}} ||z - w\varepsilon||_2^2 + \emptyset||L\alpha||_2^2 \qquad (6)$$

U_1 represents a poly type with $2_{N\text{-}Mmax}$ with an angle $W_1, W_2, \ldots W_{2N\text{-}Mmax.}$ [There is an attached table.7].

Based on Figure 4, RCMARS can solve outliers' problems that occur with competitive merchants. Where CMARS manages multi variations of habits that occur between customers and merchants as well as merchants and merchants. Meanwhile, Robust overcomes the outlier problem by producing a maximum value of 14.06%.

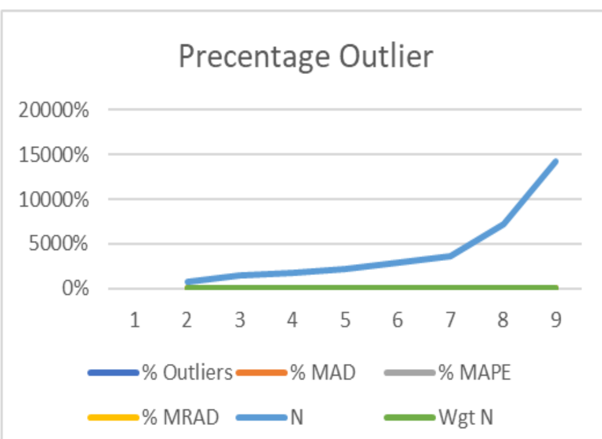

Figure 5. Percentage Outlier

5. CONCLUSION

In the research, the authors solved the optimal problem of data containing uncertainty on competitive merchants and then evaluated the results by paying attention to accuracy and stability (based on variance). In this case CMARS can manage the existing multivariate in the data and use a robust approach in dealing with uncertainty outliers in the data. So that the results achieved are in the form of a maximum value of the basis of the functions BF11, BF12, and BF13 with a maximum of 14.06% outliers.

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Table 1. User Data

Name	Latitude	Longitude	Sub-Districts	Districts	City	Province
Darryl Felix Picauly	3,58485	98,664227	Petisah Tengah	Medan Petisah	Kota Medan	SU
Putri Riennika Aprillia	3,56633447	98.65160557	Padang Bulan Selayang I	Medan Selayang	Kota Medan	SU
Sumiati	3,5854296	98.6949601	Sei Rengas Ii	Medan Area	Kota Medan	SU
Hendra Sinaga	3,56345527	98.69279136	Teladan Barat	Medan Kota	Kota Medan	SU
Eli Nur Cahaya Purba	3,597597125	98.644 75406	Dwi Kora	Medan Helvetia	Kota Medan	SU
Armansyah Saragih	3,61312634	98,69972507	Sidorejo Hilir	Medan Tembung	Kota Medan	SU
Alham Kinanda	3,56879307	98,70037799	Pasar Merah Timur	Medan Area	Kota Medan	SU
Setiawan	3,5389627	98.71110756	Harjosari I	Medan Amplas	Kota Medan	SU
Suzana	3,540446162	98.70916486	Harjosari I	Medan Amplas	Kota Medan	SU
Elfira Suci Dayanti	3,5403623	98,6959919	Harjosari Ii	Medan Amplas	Kota Medan	SU
Ratna Sari	3,602601667	98.70901	Kenangan Baru	Percut Sei Tuan	Deli Serdang	SU
Chairatun Aulia	3,559745	98.69143333	Siti Rejo I	Medan Kota	Kota Medan	SU

Table 2. E-Metric Data

Transaction No	Date	Hour	Reference No	Customer's name	Transaction	Merchant name
J190100028785	04/01/2019	18:10:49	900400148349	"Darryl Felix Picauly	Rp 15.000	SOSIS GORENG ALBAIK NL
J190100063799	11/01/2019	22:18:21	901100217341	"Darryl Felix Picauly	Rp 30.000	MILALA BENGKEL
J190100063816	11/01/2019	22:24:07	901100218155	"Darryl Felix Picauly	Rp 15.000	SWEET BOBA
J190100063824	11/01/2019	22:27:36	901100218518	"Darryl Felix Picauly	Rp 10.000	WARUNG ANDINI LK
J190100080855	15/01/2019	10:03:07	901500038426	"Darryl Felix Picauly	Rp 15.000	TOKO BAYU LK
J190100081017	15/01/2019	10:27:41	901500045168	"Darryl Felix Picauly	Rp 10.000	SWEET BOBA
J190100092427	16/01/2019	14:18:21	901600115773	"Darryl Felix Picauly	Rp 10.000	SWEET BOBA
J190100092448	16/01/2019	14:20:00	901600116257	"Darryl Felix Picauly	Rp 15.000	SATE JO ANDAH LK
J190300191290	19/03/2019	21:46:00	921900369521	"Ratna Sari	Rp 15.000	SATE JO ANDAH LK
J190100040006	07/01/2019	15:21:34	900700103494	"Putri Riennika Aprillia	Rp 10.000	TOKO IWAN LK
J190100056472	10/01/2019	18:29:55	901000160879	"Putri Riennika Aprillia	Rp 15.000	TOKO IWAN LK
J190100072976	14/01/2019	15:19:08	901400108316	"Sumiati	Rp 10.000	MILALA BENGKEL
J190100072976	14/01/2019	15:19:08	901400108316	"Sumiati	Rp 15.000	BURGER KING LK
J190100045712	08/01/2019	20:27:00	900800159641	"Hendra Sinaga	Rp 15.000	IR.ONE S
J190100056460	10/01/2019	18:28:35	901000160649	"Eli Nur Cahaya Purba	Rp 10.000	SOSIS GORENG ALBAIK NL
J190200056756	06/02/2019	22:34:49	910600375534	"Armansyah Saragih	Rp 10.000	NGEJUS
J190200088182	11/02/2019	07:34:39	911100030125	"Armansyah Saragih	Rp 15.000	SWEET BOBA
J190200103267	12/02/2019	10:54:18	911200106098	"Armansyah Saragih	Rp 10.000	WARUNG ANDINI LK
J190200110868	12/02/2019	21:21:43	911200407167	"Armansyah Saragih	Rp 15.000	TOKO BAYU LK
J190200062211	07/02/2019	15:04:46	910700209730	"Alham Kinanda	Rp 18.500	WARUNG ANDINI LK
J190200073364	08/02/2019	16:12:53	910800213607	"Alham Kinanda	Rp 10.000	WARUNG JUSS PAK YADI LK
J190200077048	08/02/2019	21:03:50	910800324374	"Setiawan	Rp 10.000	SOSIS GORENG ALBAIK NL
J190200115407	13/02/2019	11:43:45	911300143342	"Setiawan	Rp 45.000	MILALA BENGKEL
J190200091150	11/02/2019	11:47:00	911100120416	"Suzana	Rp 30.000	MILALA BENGKEL
J190200116210	13/02/2019	13:07:37	911300181560	"Suzana	Rp 10.000	SWEET BOBA
J190200097370	11/02/2019	18:23:09	911100309671	"Elfira Suci Dayanti	Rp 15.000	SWEET BOBA
J190200102079	12/02/2019	09:22:21	911200063726	"Elfira Suci Dayanti	Rp 10.000	WARUNG ANDINI LK
J190200059781	07/02/2019	11:05:48	910700100207	"Elfira Suci Dayanti	Rp 60.000	MILALA BENGKEL
J190100111769	18/01/2019	18:15:00	901800169735	"Chairatun Aulia	Rp 15.000	BURGER KING LK

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Table 3. Merchant Groupings

MERCHANT	P	GROUPING															
SOSIS GORENG ALBAIK LK	16	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
MILALA BENGKEL	10	1	2	3	4	5	6	7	8	9		11		10			
TOKO IWAN LK	6	1	2	3	4	5	6										
WARUNG ANDINI LK	13	1	2	3	4	5	6	7	8	9	10	11		13			
TOKO BAYU LK	3		2		4	5											
SATE JO ANDAH	13	1	2	3	4	5	6	7	8	9	10	11		13	14		
BURGER KING	10	1	2	3	4	5	6	7	8	9		11					
IR. ONE LK	2	1	2														
NGEJUS	11	1	2	3			4	7	8	9	10		12	13	14		
SWEET BOBA	11	1	2	3	4	5	6	7	8		10	11			14		

Table 4. Data Training

Parameter	*Estimate*	*SE*	*T-Ratio*	*P-Value*
Constant	22826.86284	1431,69411	15.94395	0.00000
Basis Function 1	71266.32101	4482.43558	15.89902	0.00000
Basis Function 3	-82086.83243	4268.98503	-19.22865	0.00000
Basis Function 5	-70628.58793	4663.11530	-15.14622	0.00000
Basis Function 7	.107876E + 06	7851.51622	13,73948	0.00000
Basis Function 9	-42770.20427	5951.23844	-7.18677	0.00000
Basis Function 11	-0.00000	0.00000	-3.93087	0.00009
Basis Function 12	-0.00000	0.00000	-4.38946	0.00001
Basis Function 13	224,90833	74,36817	3.02426	0.00258
F-Statistic = 57.71525		SE of Regression = 11535.53361		
P-Value =. 0.00000		Residual Sum of Squares = .934141E + 11		
[MDF, NDF] = [8, 702]		Regression Sum of Squares = .614407E + 11		

Table 5. Transaction Sensitivity

Score Range		*If Score*	*Sensitivity*	*Specificity*
1.0000000		> 1.0000000	0.0000000	1.0000000
0.9999999	1.0000000	> 0.9999999	0.2509506	1.0000000
0.0000000	0.9999999	> 0.0000000	1.0000000	1.0000000
0.0000000	0.0000000	> 0.0000000	1.0000000	0.8125000
0.0000000	0.0000000	> 0.0000000	1.0000000	0.6294643
0.0000000	0.0000000	> 0.0000000	1.0000000	0.3169643
0.0000000	0.0000000	> 0.0000000	1.0000000	0.1651786
0.0000000	0.0000000	> 0.0000000	1.0000000	0.1093750
-0.0000000	0.0000000	> -0.0000000	1.0000000	0.0691964
-0.0000000	-0.0000000	> -0.0000000	1.0000000	0.0357143

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Table 7. Percentage of Error Statistics Due to Outliers

% Outlier	% MAD	(MAD)	% MAPE	(MAPE)	% MRAD	N	Wgt N
Lrn 1%	25.58	25.58	70.60	70.60	21.37	8	8.00
2%	36.27	18.13	82.48	41.24	27.57	15	15.00
2.5%	39.39	15.76	84.83	33.93	29.81	18	18.00
3%	42.38	14.13	86.46	28.82	32.74	22	22.00
4%	46.58	11.65	88.26	22.07	37.12	29	29.00
5%	50.15	10.03	89.56	17.91	41.25	36	36.00
10%	64.92	6.49	93.93	9.39	61.36	72	72.00
20%	86.15	4.31	98.67	4.93	85.61	143	143.00
0.14%	6.40	45.53	29.35	208.70	5.78	1	1.00
0.70%	19.40	27.58	61.48	87.43	17.25	5	5.00
1.41%	29.10	20.69	75.05	53.36	53.36	10	10.00
3.52%	44.23	12.58	87.27	24.82	34.69	25	25.00
7.03%	56.38	8.02	91.56	13.02	49.29	50	50.00
14.06%	75.19	5.35	96.63	6.87	72.98	100	100.00