

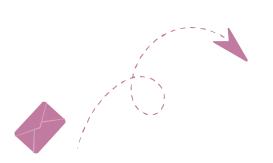




the world in your hand

DATA SCIENCE

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Case Study

Prediksi pelanggan yang akan membayar tagihan Indihome tepat waktu. Sesuai kebijakan perusahaan, disebut tepat waktu apabila pelanggan membayar sebelum tanggal 21 untuk tagihan bulan berjalan. Jika pelanggan membayar di antara tanggal 21 sampai akhir bulan, maka pelanggan akan berstatus isolir dengan konsekuensi layanan Indihome akan diputus sementara hingga pelanggan melakukan pembayaran. Adapun jika pelanggan tidak membayar hingga akhir bulan, maka pada tagihan berikutnya pelanggan akan berstatus PraCTO/PraNPC.

Prediksi pelanggan yang akan membayar tagihan Indihome tepat waktu akan bermanfaat untuk memetakan pelanggan yang low-risk dan high-risk, sehingga dapat dilakukan program loyalty yang tepat sasaran untuk meningkatkan *cash collection monthly ratio* (C3MR).



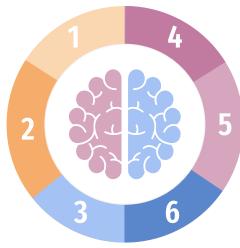


Flowchart

Data Preprocessing

Exploratory Data Analysis and Feature Selection

3



Training Machine Model Learning

> Mercury is the closest planet to the Sun

Evaluation

6 **Deployment**





Importing Data to Python

Load Data from Sql

Rename Column per month

Join table





монтн	INET_PAY			S_PAY	INET_REV	POTS_REV	
M1	Pay_status_inet_M1	Payment_inet_M 1	Pay_sta tus_pot s_M1	Paymen t_pots_ M1	Revenue_billing_inet_M 1	Revenue_billing_pots_M 1	
M2	Pay_status_inet_M2	Payment_inet_M 2	Pay_sta tus_pot s_M2	Paymen t_pots_ M2	Revenue_billing_inet_M 2	Revenue_billing_pots_M 2	
M3	Pay_status_inet_M3	Payment_inet_M 3	Pay_sta tus_pot s_M3	Paymen t_pots_ M3	Revenue_billing_inet_M 3	Revenue_billing_pots_M 3	
M4	Pay_status_inet_M4	Payment_inet_M 4	tus_pot	Paymen t_pots_ M4	Revenue_billing_inet_M 4	Revenue_billing_pots_M 4	
M5	Pay_status_inet_M5	Payment_inet_M 5	Pay_sta tus_pot s_M5	Paymen t_pots_ M5	Revenue_billing_inet_M 5	Revenue_billing_pots_M 5	
M6	Pay_status_inet_M6	Payment_inet_M 6	tus_pot	Paymen t_pots_ M6	Revenue_billing_inet_M 6	Revenue_billing_pots_M 6	





MONTH	INET	_TICKET		POTS_TICKET			
M1	Tipe_gangguan_inet_M 1	N_ticket_ticke t_M1	Mttr_inet_ M1	Tipe_ganggu an_pots_M1	N_ticket_ticket_M1	Mttr_pots_M1	
	Tipe_gangguan_inet_M 2						
M3	Tipe_gangguan_inet_M 3	N_ticket_ticke t_M3	Mttr_inet_ M3	Tipe_ganggu an_pots_M3	N_ticket_ticket_M3	Mttr_pots_M3	
M4	Tipe_gangguan_inet_M 4	N_ticket_ticke t_M4	Mttr_inet_ M4	Tipe_ganggu an_pots_M4	N_ticket_ticket_M4	Mttr_pots_M4	
M5	Tipe_gangguan_inet_M 5	N_ticket_ticke t_M5	Mttr_inet_ M5	Tipe_ganggu an_pots_M5	N_ticket_ticket_M5	Mttr_pots_M5	
M6	Tipe_gangguan_inet_M 6	N_ticket_ticke t_M6	Mttr_inet_ M6	Tipe_ganggu an_pots_M6	N_ticket_ticket_M6	Mttr_pots_M6	





MON TH		POTS_USAGE								
M1	Call_lokal_M1	Call_sljj_M 1	call mobile ivi i	1 1	Call_other_ M1	Duree_lokal_M1		Duree_mob ile_M1		Duree_oth er_M1
M2	Call_lokal_M2	Call_sljj_M 2	Call mobile MZ		Call_other_ M2	Duree_lokal_M2		j Duree_mob ile_M2	l.	Duree_oth er_M2
М3	Call_lokal_M3	Call_sljj_M 3	Call mobile M3		Call_other_ M3	Duree_lokal_M3		j Duree_mob ile_M3		Duree_oth er_M3
M4	Call_lokal_M4	Call_sljj_M 4	Call MODILE 1914		Call_other_ M4	Duree_lokal_M4		j Duree_mob ile_M4	1.	Duree_oth er_M4
M5	Call_lokal_M5	Call_sljj_M 5	Call mobile M5		Call_other_ M5	Duree_lokal_M5		j Duree_mob ile_M5		Duree_oth er_M5
M6	Call_lokal_M6	Call_sljj_M 6	Call mobile Mb		Call_other_ M6	Duree_lokal_M6		j Duree_mob ile_M6		Duree_oth er_M6





TARGET		POP						
ld_customer	Υ	Length_of_stay	Divre_id	Technology	Kw	Indihome_type	Total_Minipack	Speed





Data Preprocessing

Drop Duplicate

Check Missing Value

Remove ID

Separating X and Y

Test and Train Split

Select Numerical & Categorical variables

Outlier Handling for Numerical Data

Numerical Imputation

Categorical Imputation

Categorical Dummy Variables Join Numerical & Categorical Data





Exploratory Data Analysis & Feature Selection

Check Statistical
Summary

Check Distribution

Check Relation between
Independent Variables and
Dependent Variables

Check Correlation

Select K Best





Training Machine Model Learning

Scaling

Regresion Logistic Model





Evaluation

Performance Training without Hyperparameter Tuning

Accuracy: 0.808500 Sensitivity: 0.542331 Spesificity: 0.921574 Precision: 0.746045 ROC AUC Score: 0.840675

Performance Training with Hyperparameter Tuning

Accuracy: 0.808500 Sensitivity: 0.541565 Spesificity: 0.921899 Precision: 0.746565 ROC AUC Score: 0.840657

Performance Testing without Hyperparameter Tuning

Accuracy: 0.809500 Sensitivity: 0.543981 Spesificity: 0.925638 Precision: 0.761890 ROC AUC Score: 0.843997

Performance Testing with Hyperparameter Tuning

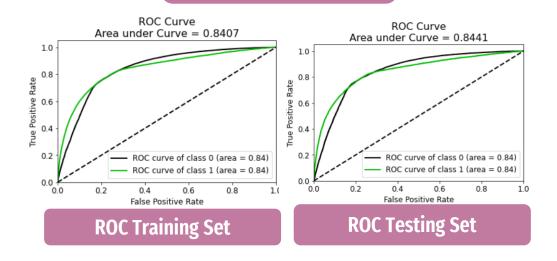
Accuracy: 0.809700
Sensitivity: 0.543543
Spesificity: 0.926118
Precision: 0.762915
ROC AUC Score: 0.844134





Evaluation

ROC Curve







Evaluation

Feature Importance

Pay_status_inet_M2_NOT_LATE	-0.255484426896891
Pay_status_inet_M4_NOT_LATE	-0.2385198772575212
Pay_status_inet_M1_LATE_SAME_MONTH	0.2322490724125231
Pay_status_inet_M3_NOT_LATE	-0.21614527291683056
Pay_status_inet_M1_NOT_LATE	-0.1858010402451609
Pay_status_inet_M6_NOT_LATE	-0.1643566394711911
Pay_status_inet_M6_LATE_SAME_MONTH	0.15776140383629983
Pay_status_inet_M5_NOT_LATE	-0.1426051132368522
Length_of_stay	-0.13771730965892082
Pay_status_inet_M3_LATE_SAME_MONTH	0.09766587437124673





Deployment

Importing Data
Submission to Python

Get ID

Select Numerical & Categorical variables

Outlier Handling for Numerical Data

Numerical Imputation

Categorical Imputation

Get Selected Features

Scaling

Make Prediction

Make a DataFrame

Save Prediction





Thank You