Koordinator TSDN 2022:

[Business optimization in predicting customer churn : a machine learning approach]

[ANN Team]

TURNAMEN SAINS DATA NASIONAL 2022

DISPONSORI OLEH :

data academy
CYBERTREND DATA ACADEMY

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SAFARINDO
GOOD CHOICE
LSP SAINS DATA DAN KECERDASAN BUATAN INDONESIA

PARAGONCORP
LOJIN Organic Store
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DIDUKUNG OLEH :

KOMINFO
BADAN PUSAT STATISTIK PROVINSI DKI JAKARTA
BNSP BADAN NASIONAL SERTIFIKASI PROFESI
BRIN BADAN RISET DAN INOVASI NASIONAL

JAYA RAYA
JAKARTA open data Berbagi Data untuk Transparansi
JAKARTA SATU Satu Peta, Satu Data, Satu Kebijakan
JABAR DIGITAL SERVICE
OPEN DATA JABAR

Asosiasi Data Sains dan AI Indonesia
ASOSIASI ILMUWAN DATA INDONESIA
ABDI ASOSIASI BIG DATA INDONESIA

APTIKOM
DATA SCIENCE INDONESIA
BigData

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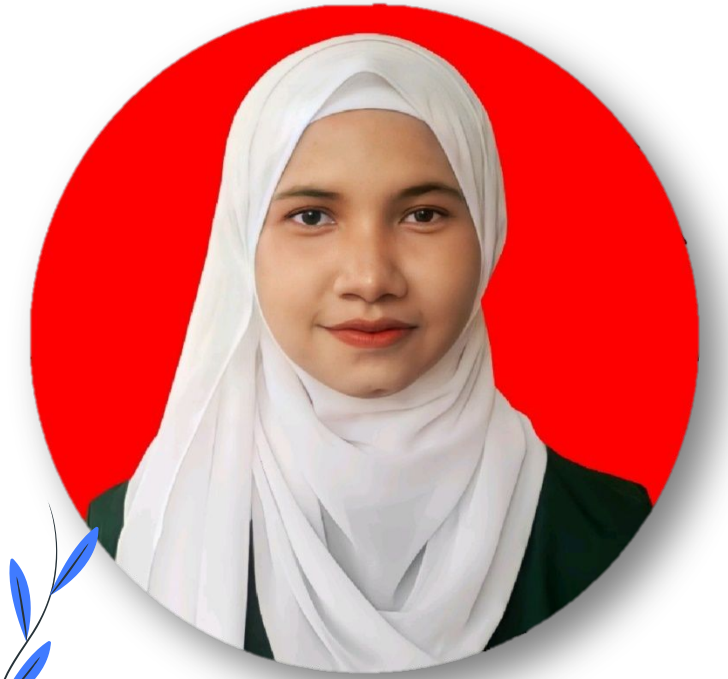

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FOREWORD

Ekonomi Digital?

(Brynjolfsson & McAfee, 2014)

Business Optimization?

(Apte, 2010)

Machine Learning?

(Al-Sahaf et al., 2019)

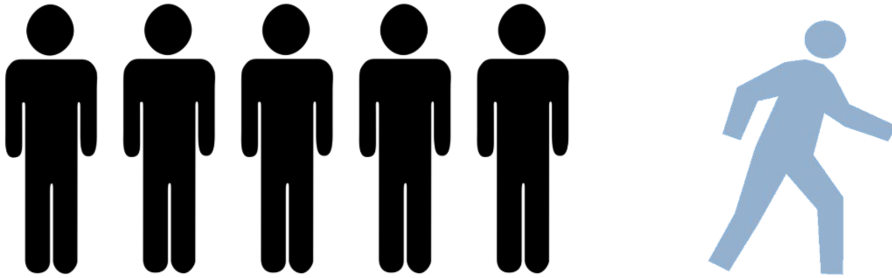
Customer Churn?

(Masarifoglu & Buyuklu, 2019)

Cashback Amount?

(Pinem et al., 2020)

PROBLEM STATEMENT



Churn

16.8%

China Internet Network Information Center (CNNIC)

E-commerce customer churn rate is up to **80%** compared with the traditional business customer management (Wu & Meng, 2016)

Objective

Membentuk sebuah model machine learning dengan false negative terkecil, mengidentifikasi prediktor/faktor yang berpengaruh terhadap churn rate dan lost opportunity customer churn, Memprediksi customer yang berpotensi churn dengan machine learning model. Serta memberikan insight & rekomendasi untuk mengidentifikasi prediktor/faktor yang berpengaruh terhadap churn rate melalui cashback amount.

Goals

Memprediksi pelanggan churn rate dan memberikan rekomendasi kepada business team agar perusahaan mampu menerapkan strategi customer retention.

Business Matrix

$$\text{Churn Rate} = \frac{\text{CUSTOMER CHURN}}{\text{TOTAL CUSTOMERS}}$$

$$\text{Lost Opportunity} = \text{Total Customers Complain \& Berpotensi Churn} \times \text{Average Monthly Spending User}$$

Exploratory Data Analysis (EDA)

Using **Correlation Matrix, Bivariate and Multivariate**

Data Overview

#	Column	Non-Null Count	Dtype
0	CustomerID	5630 non-null	int64
1	Churn	5630 non-null	int64
2	Tenure	5366 non-null	float64
3	PreferredLoginDevice	5630 non-null	object
4	CityTier	5630 non-null	int64
5	WarehouseToHome	5379 non-null	float64
6	PreferredPaymentMode	5630 non-null	object
7	Gender	5630 non-null	object
8	HourSpendOnApp	5375 non-null	float64
9	NumberOfDeviceRegistered	5630 non-null	int64
10	PreferedOrderCat	5630 non-null	object
11	SatisfactionScore	5630 non-null	int64
12	MaritalStatus	5630 non-null	object
13	NumberOfAddress	5630 non-null	int64
14	Complain	5630 non-null	int64
15	OrderAmountHikeFromlastYear	5365 non-null	float64
16	CouponUsed	5374 non-null	float64
17	OrderCount	5372 non-null	float64
18	DaySinceLastOrder	5323 non-null	float64
19	CashbackAmount	5630 non-null	float64

dtypes: float64(8), int64(7), object(5)

Source : *Kaggle*

Target Variable :

Churn (Classification Model)

Tenure (Regression Model)

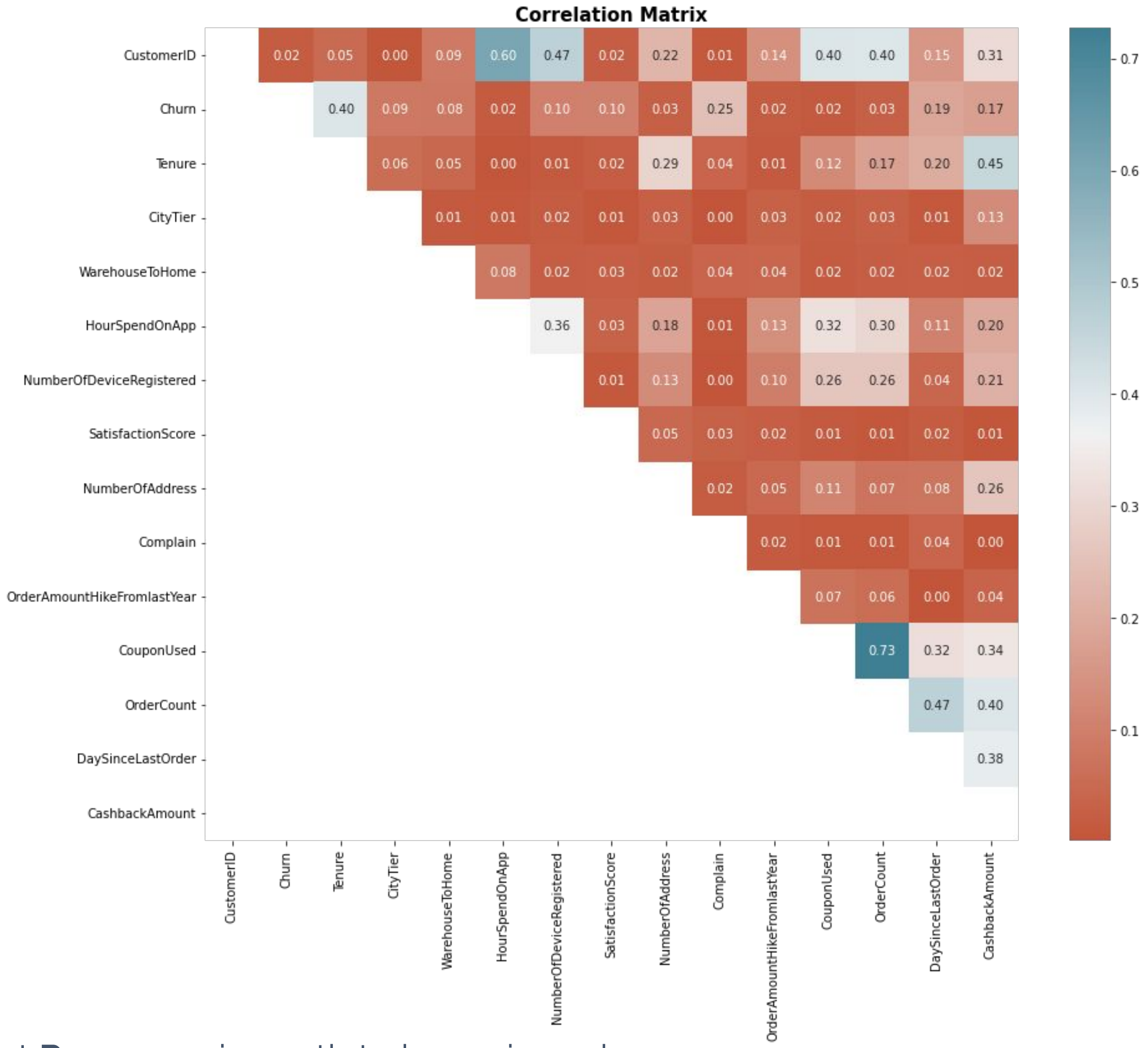
Informasi Dataset?

(20 kolom dan 5630 baris, 19 variabel input, jenis data, 1 var.target)

Dtype (Data Type)

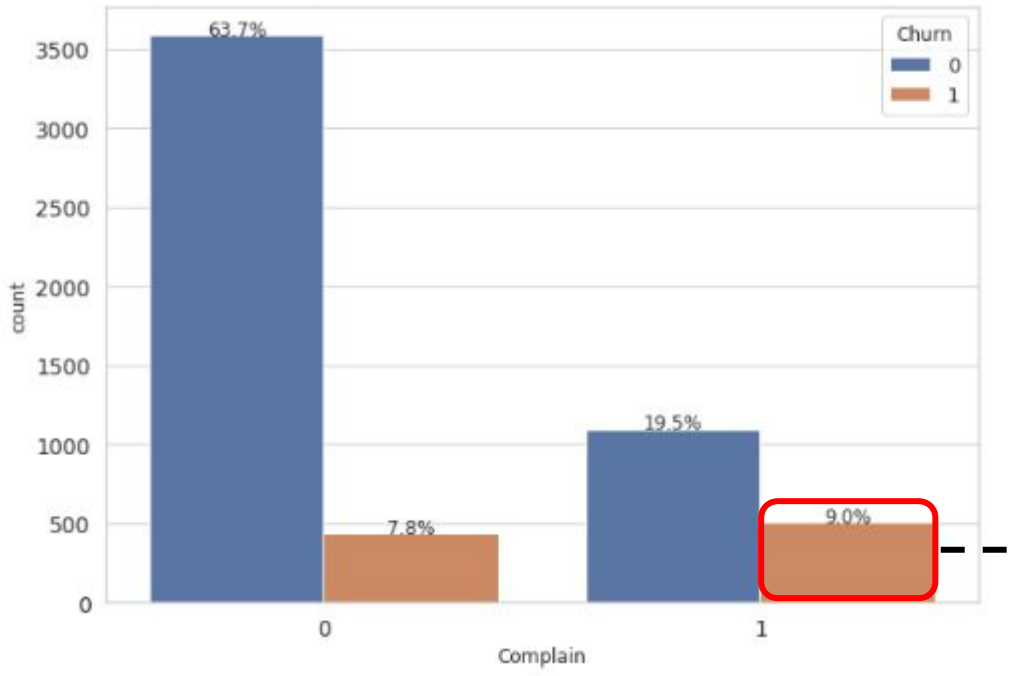
EXPLORATORY DATA ANALYSIS

Column	Correlation_ratio
Tenure	0.40
Complain	0.25
Cashbackamount	0.15
Daysincelastorder	0.15
Numberofdeviceregistered	0.11
Satisfactionscore	0.11
Citytier	0.08
Warehousetohome	0.07
Numberofaddress	0.04
Ordercount	0.03
Hourspendonapp	0.02
Couponused	0.01
Orderamounthikefromlastyear	0.01



correlation with target **Response** is worth to be reviewed.

INSIGHTS
(Comparison Complain to Churn and Not Churn)

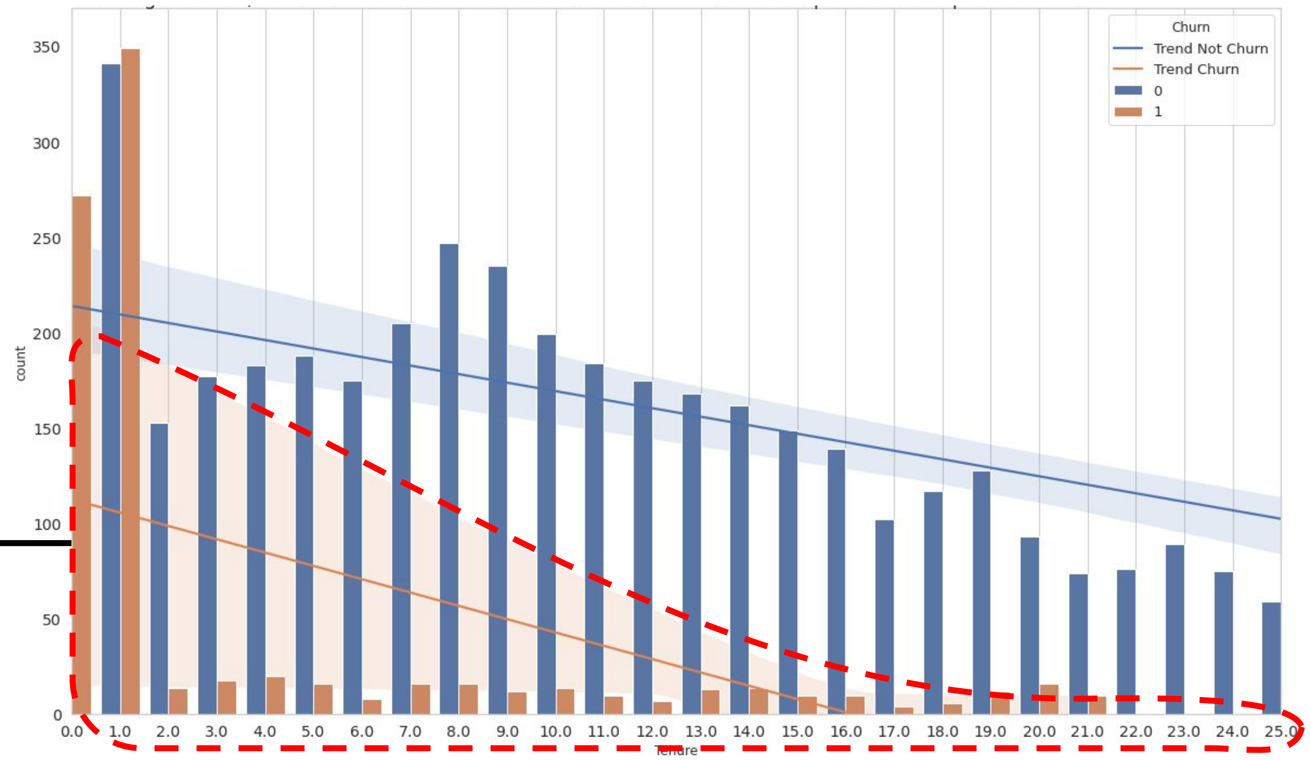


1. Customer dengan **churn tertinggi** sebesar **9.0%** berada pada **customer complain**.

2. Customer dengan **churn terendah** sebesar **7.8%** berada pada **customer tiidak complain**.

Semakin meningkatnya complain customer maka semakin tinggi tingkat churn rate.

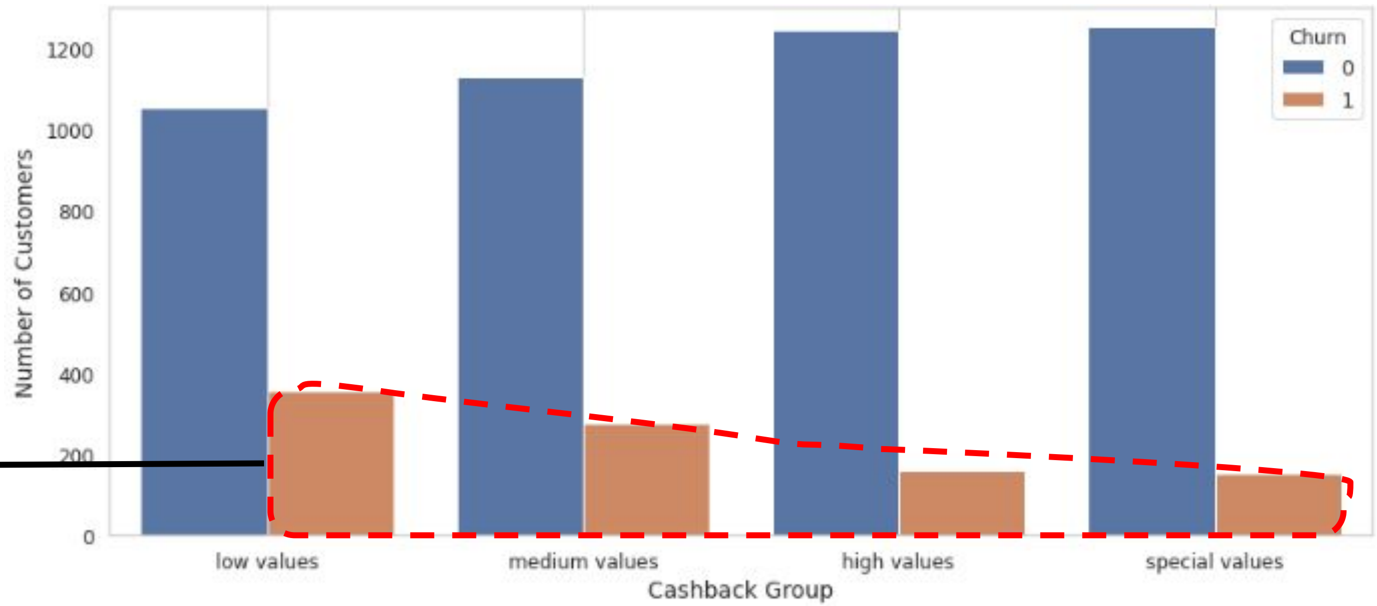
INSIGHTS
(Churn and Not Churn)



The longer tenure, the lower number of churns. And not churn has a steeper trend compared to Churn.

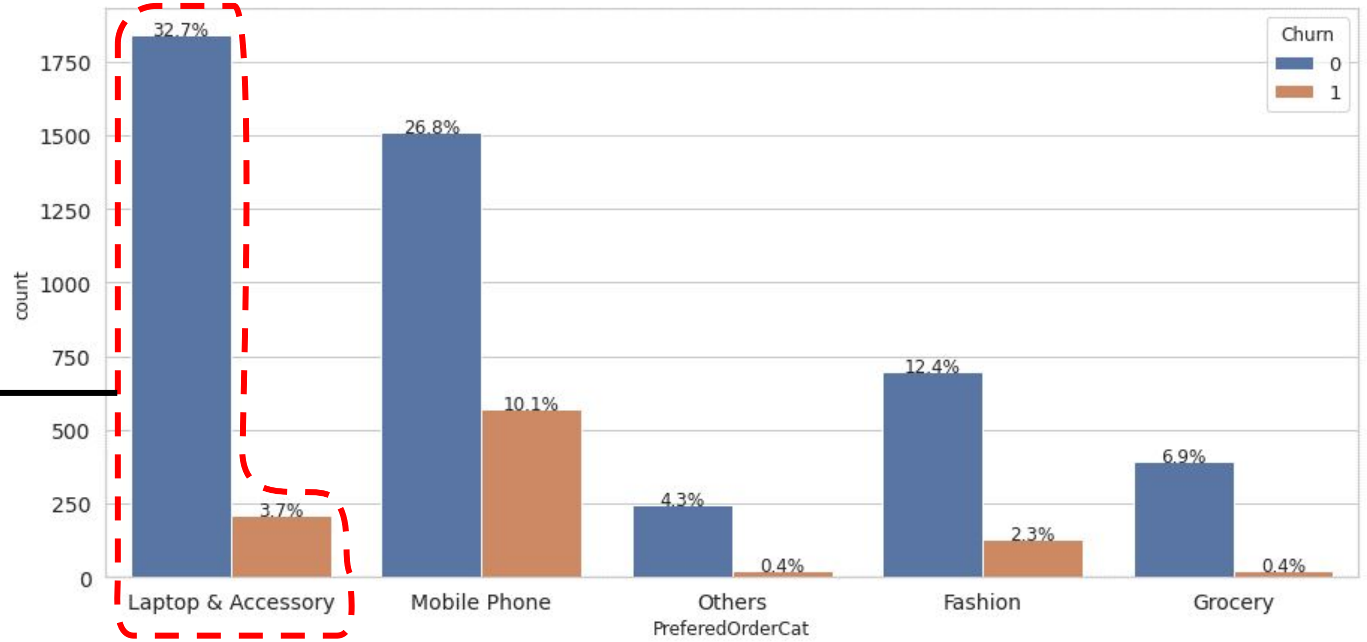
INSIGHTS
(Distribution of Cashback Customers)

Increase Cashback Amount has trend Positive in Not Churn On the contrary Increase Cashback Amount has trend Negative in Churn

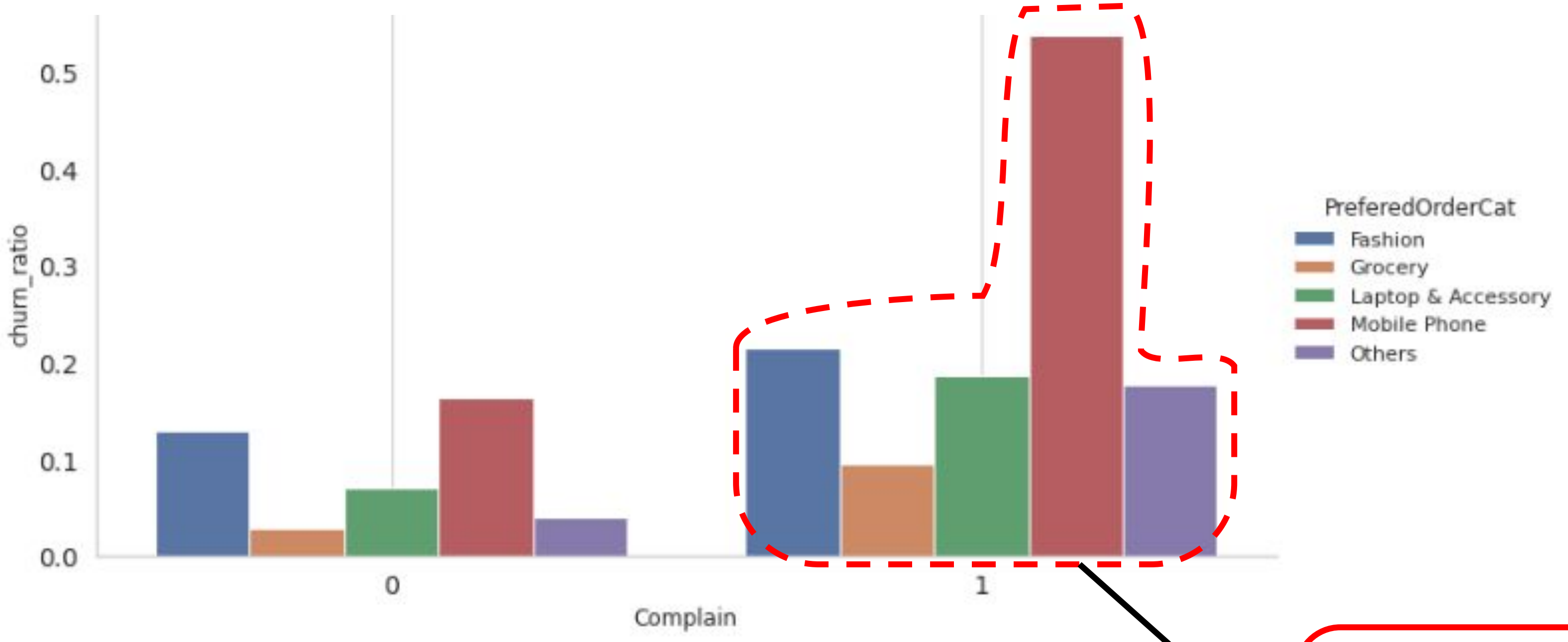


INSIGHTS
(Prefered Order Categories Customer)

Customer who ordered Laptop and Accessory has a significant number of Not Churn compared same order category with Churn.

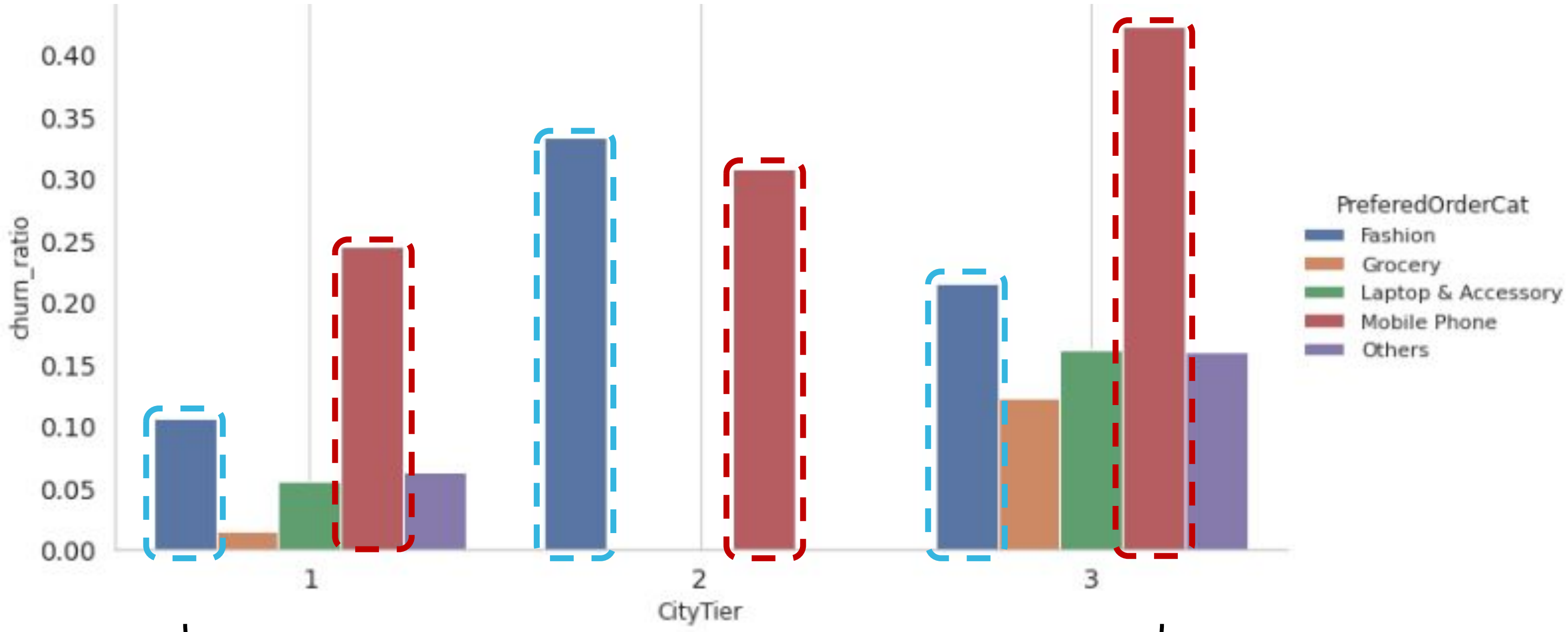


INSIGHTS
(Distribution of Complain & Order Categories vs Ratio Churn)



Customers with complaints have a ratio churn increase in all order categories.

INSIGHTS
(Distribution of Complain & Order Categories vs Ratio Churn)

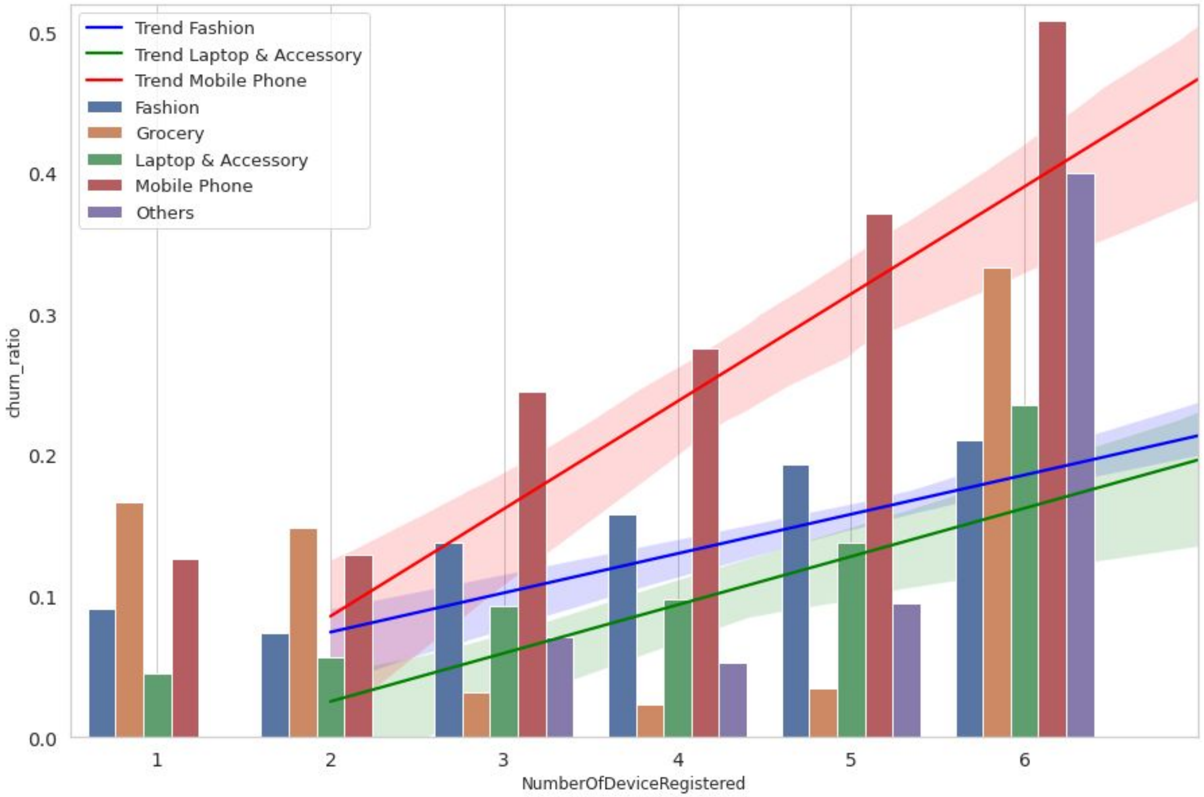


More City Tier increase, more ratio churn increase in Fashion and Mobile Phones

INSIGHTS
(Distribution of Complain & Order Categories vs Ratio Churn)

"

More Number Of Device Registered increased and more ratio churn increased in Fashion, laptops & accessories, and Mobile Phones.



Data Pre-Processing

Data Cleaning

Check Irrelevant Data

Check Missing Data

Check Duplicate

Check Outlier

Feature Encoding

One Hot Encoder

Simple Imputer

Iterative Imputer

Transforming

Pipeline

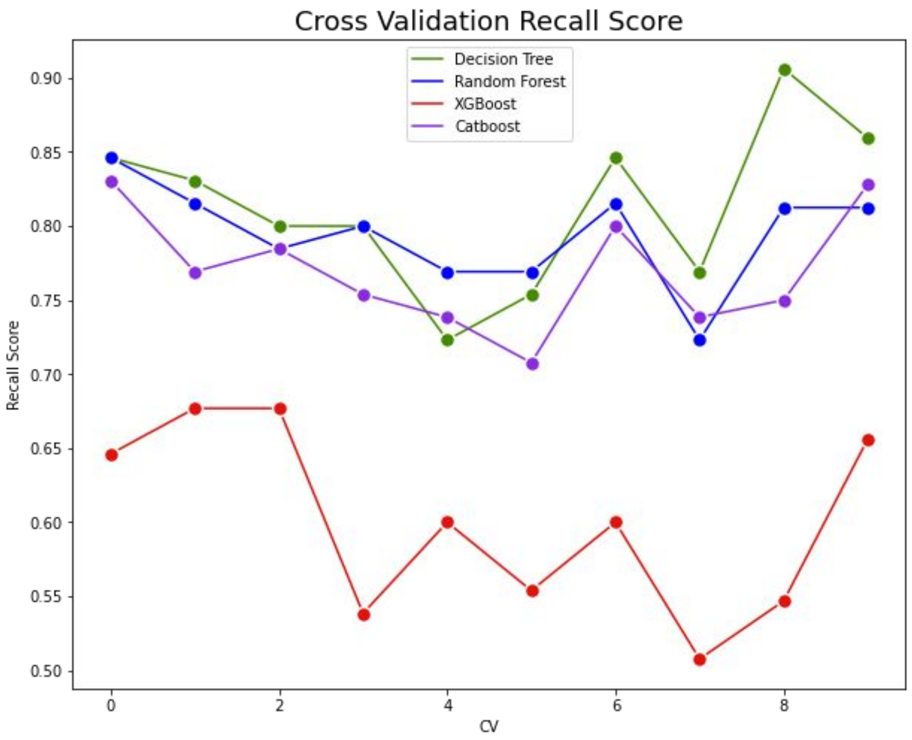
Robust Scaler

Standard Scaler

Predict Churn

Selection Models & Cross Validation, Handling Imbalance, Hyperparameter Tuning, Feature Importance with SHAP

Model Selection and Cross-Validation



Models	Mean	Standar Deviasi	Recall
Decision Tree	0.803951	0.038707	0.863095
Catboost	0.780246	0.047106	0.809524
Random Forest	0.760799	0.048173	0.797619
Xgboost	0.609570	0.066454	0.553571
Logistic Regression	0.530575	0.051384	0.476190

NB : Due to an imbalance dataset

Handling Imbalance

NB : Due to imbalance dataset

CatBoost

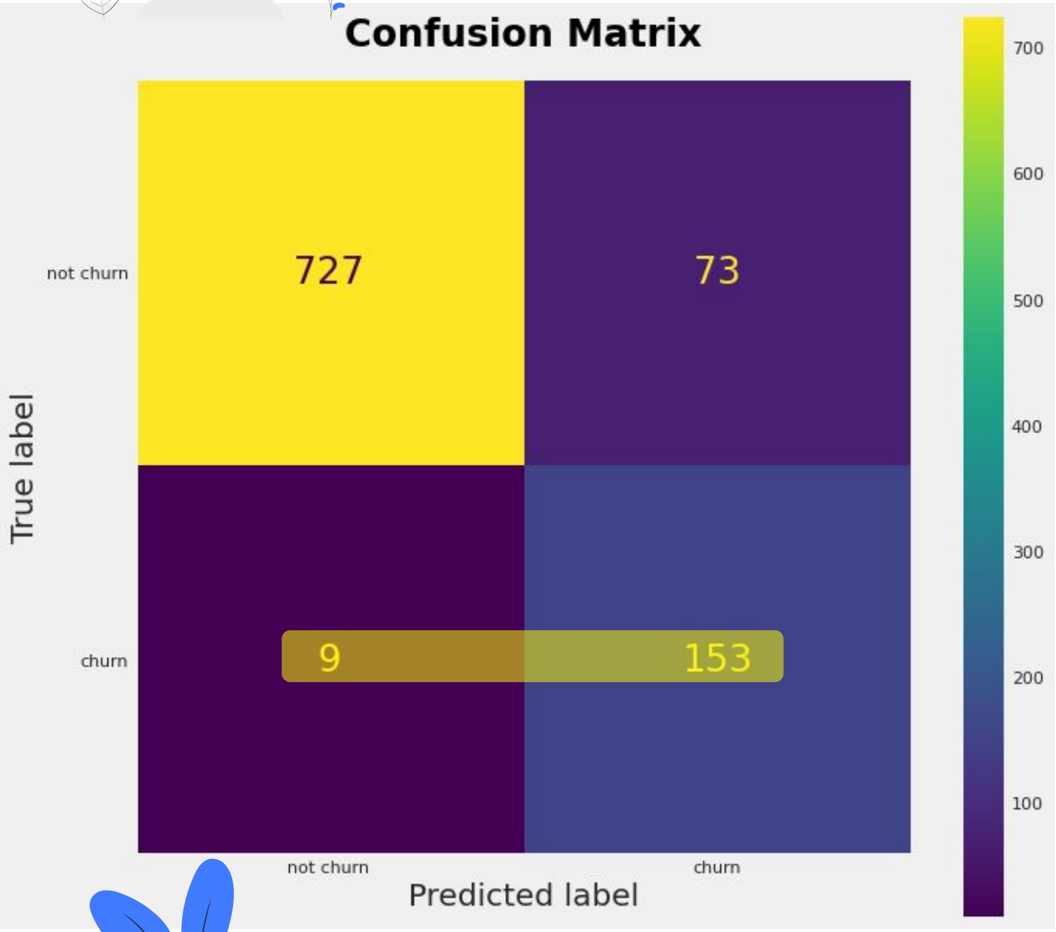
	Without	Undersampling	Oversampling
Train Recall	0.953360	0.996913	0.999826
Test Recall	0.784038	0.928990	0.915144

DECISION TREE

	Without	Undersampling	Oversampling
Train Recall	1.000000	1.000000	1.000000
Test Recall	0.836538	0.881202	0.819519

Catboost have best fit in undersampling and oversampling. But we choose undersampling because it has gap (train-test) smaller than other.

CatBoost Classifier + Undersampling



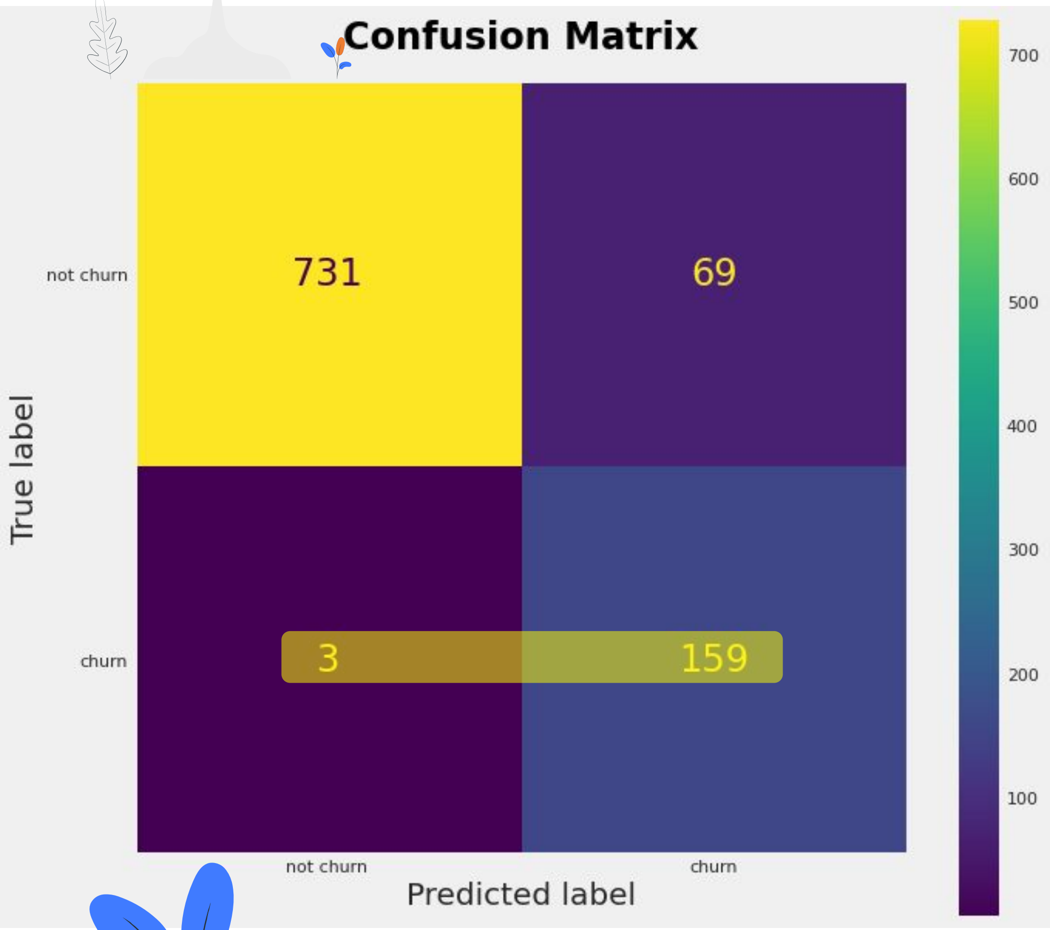
classification_report before tuning:

	precision	recall	f1-score	support
0	0.99	0.91	0.95	800
1	0.68	0.94	0.79	162
accuracy			0.91	962
macro avg	0.83	0.93	0.87	962
weighted avg	0.94	0.91	0.92	962

Recall 0.9444444444444444

Recall ; How many customers did we correctly predict to take an interest with our product compared to all customers which are truly churn? **94%**

CatBoost Classifier + Undersampling + Tuning



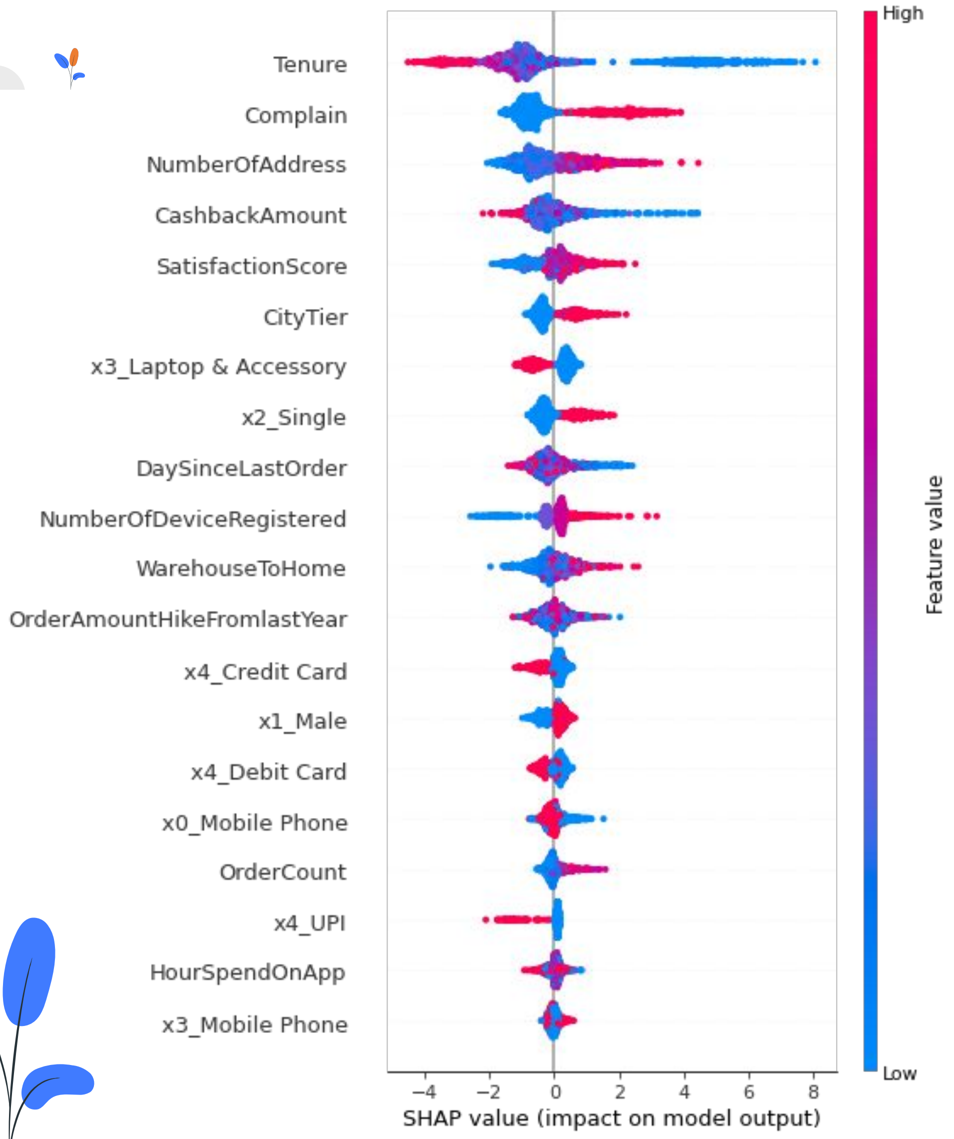
classification_report after tuning:

	precision	recall	f1-score	support
0	1.00	0.91	0.95	800
1	0.70	0.98	0.82	162
accuracy			0.93	962
macro avg	0.85	0.95	0.88	962
weighted avg	0.95	0.93	0.93	962

Recall 0.9814814814814815

Recall ; How many customers did we correctly predict to take an interest with our product compared to all customers which are truly churn? **98%**

CatBoost Classifier + Tuning + Undersampling



Feature yang menghasilkan churn sebagai berikut

- Tenure dengan nilai rendah
- Complain = 1
- Number of Address dengan nilai tinggi
- Cashback dengan nilai rendah

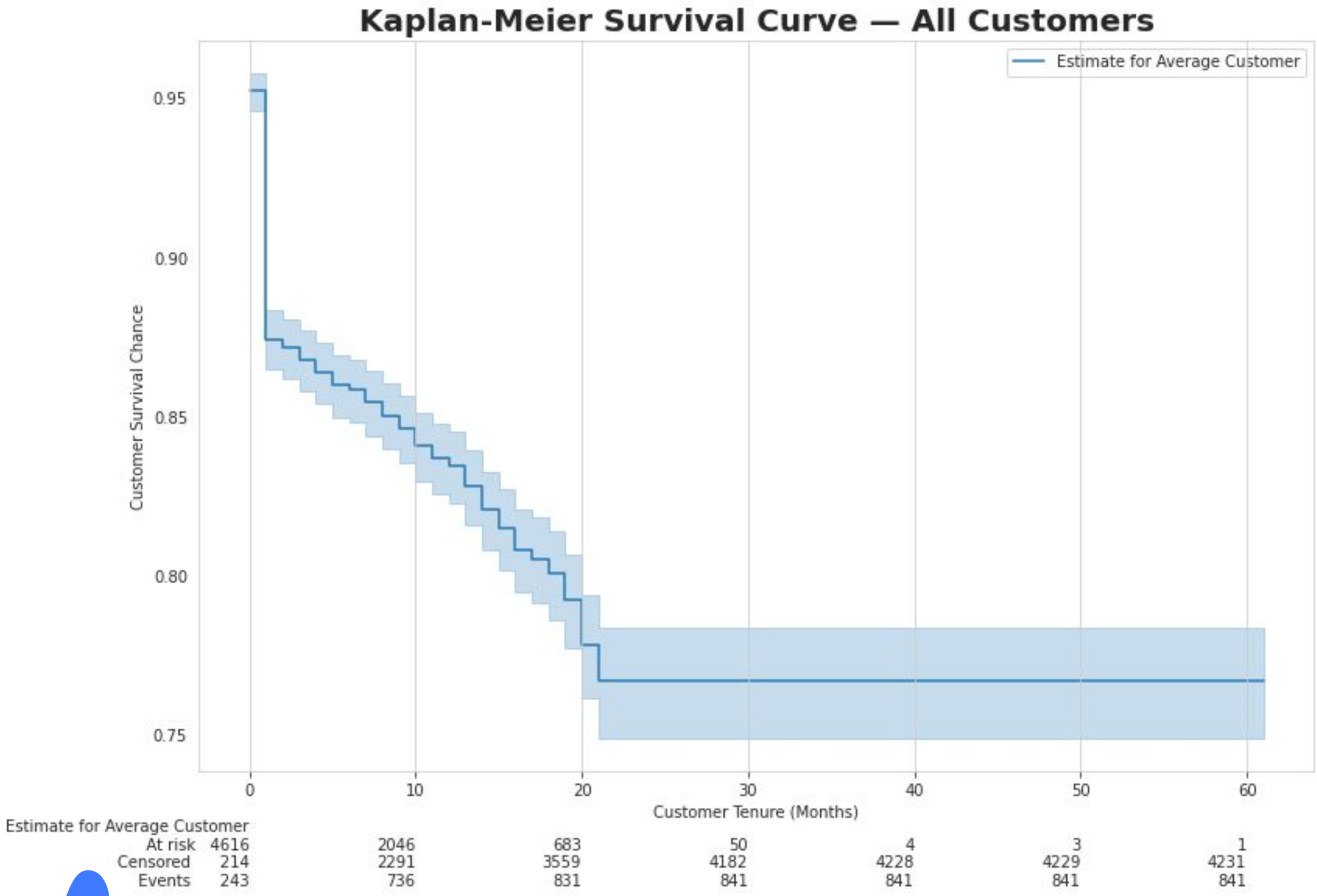
Feature yang menghasilkan retention

- Tenure dengan nilai tinggi
- Complain = 0
- Number of Address dengan nilai rendah
- Cashback dengan nilai tinggi

Survival Analyst

Using Kaplan-Meier (KM) and COx Proportional Hazard (CPH) Model

Kaplan-Meier(KM) Survival Curve

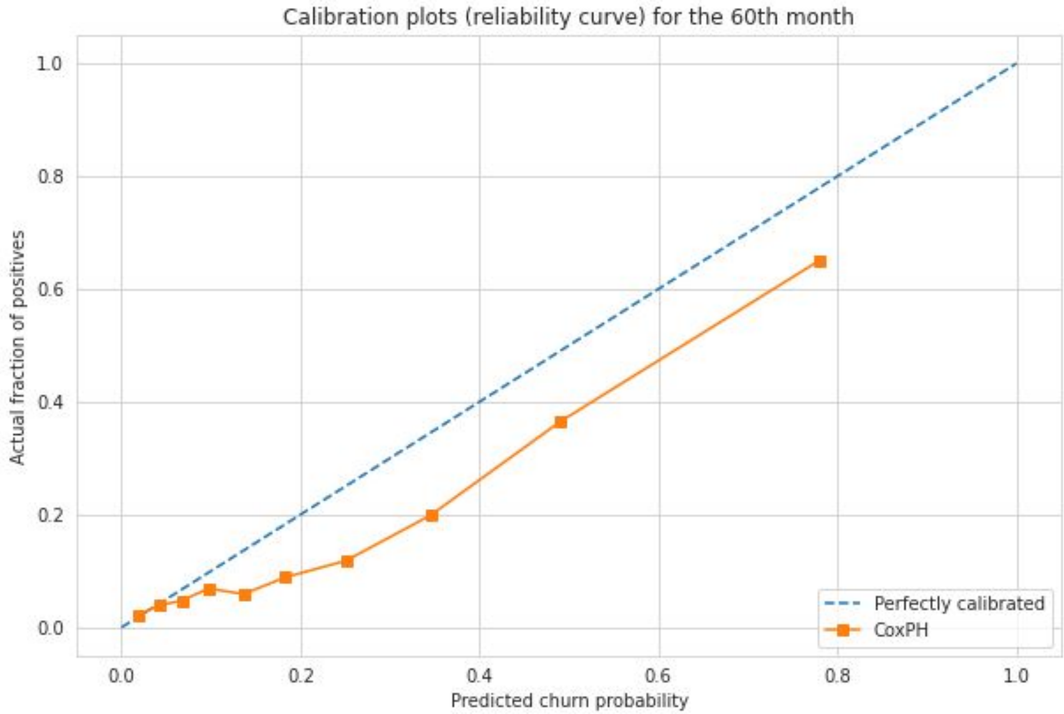


- Pada **21** bulan pertama terjadi churn sebesar **841** customer **(16.6%)** & **tidak** terjadi **churn sampai 60 bulan**
- Pada **20 bulan pertama** terdapat **683** customer **at risk** yang artinya customer tersebut tidak terindikasi churn
- Pada 20 bulan pertama juga terdapat 3559 customer censored artinya customer tersebut terindikasi akan churn namun belum melakukannya

COx Proportional Hazard (CPH) Model

model	lifelines.CoxPHFitter
duration col	'Tenure'
event col	'Churn'
baseline estimation	breslow
number of observations	5073
number of events observed	841
partial log-likelihood	-6296.226
time fit was run	2022-11-19 08:47:34 UTC
model	base model

Concordance	0.829
Partial AIC	12640.452
log-likelihood ratio test	1223.310 on 24 df
-log2(p) of ll-ratio test	805.834

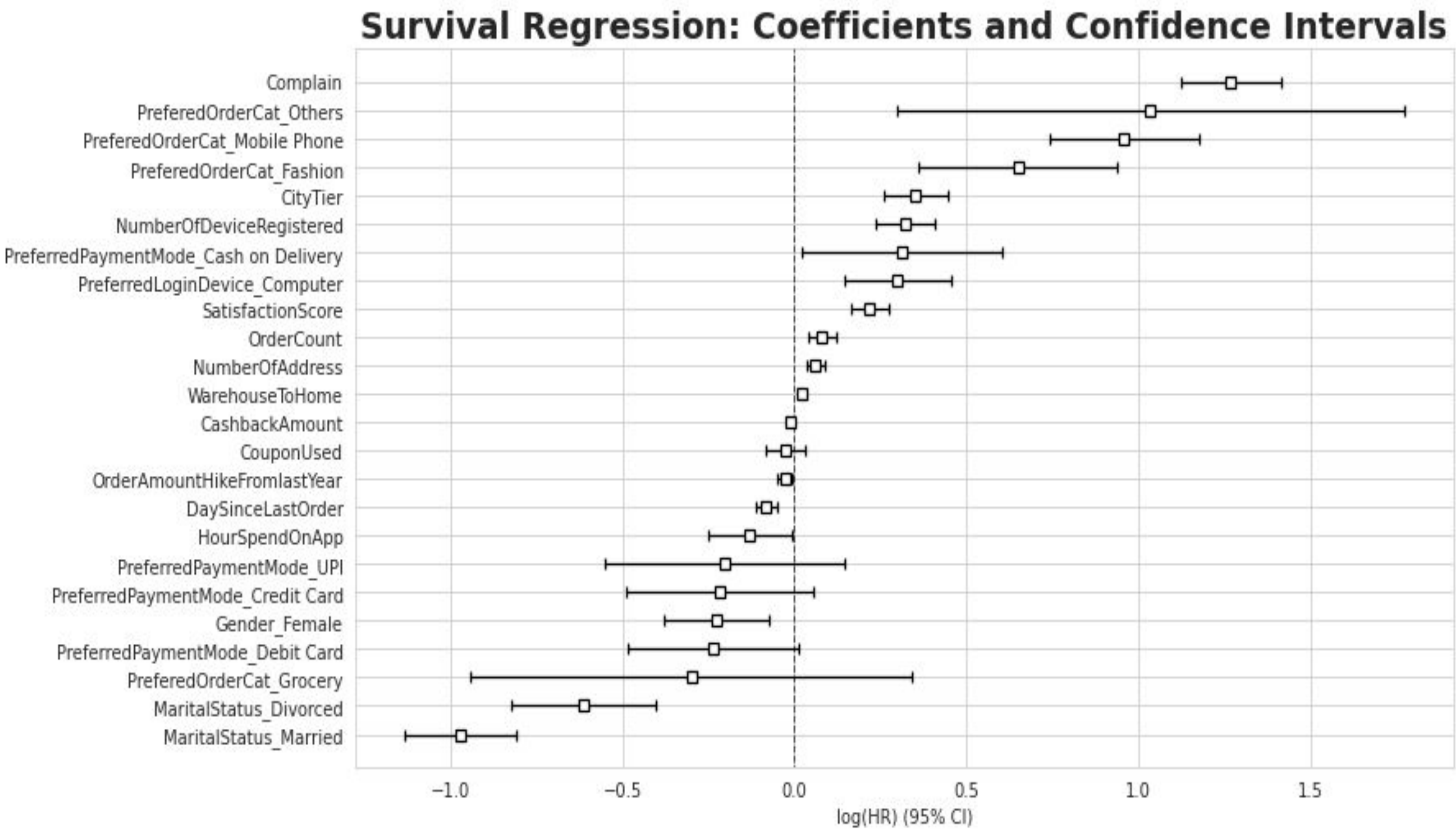


The Brier Score of our CPH Model is 0.11 at the end of 60 months

- Concordance 0,829 ditafsirkan serupa dengan AUC-ROC regresi logistik
- Brier Score 0.11 at the end of 60 month menandakan bahwa prediksi dari model sampai 60 bulan masih mendekati nilai sebenarnya.

Insights

CPH Model Visualization



Feature yang menghasilkan churn sebagai berikut

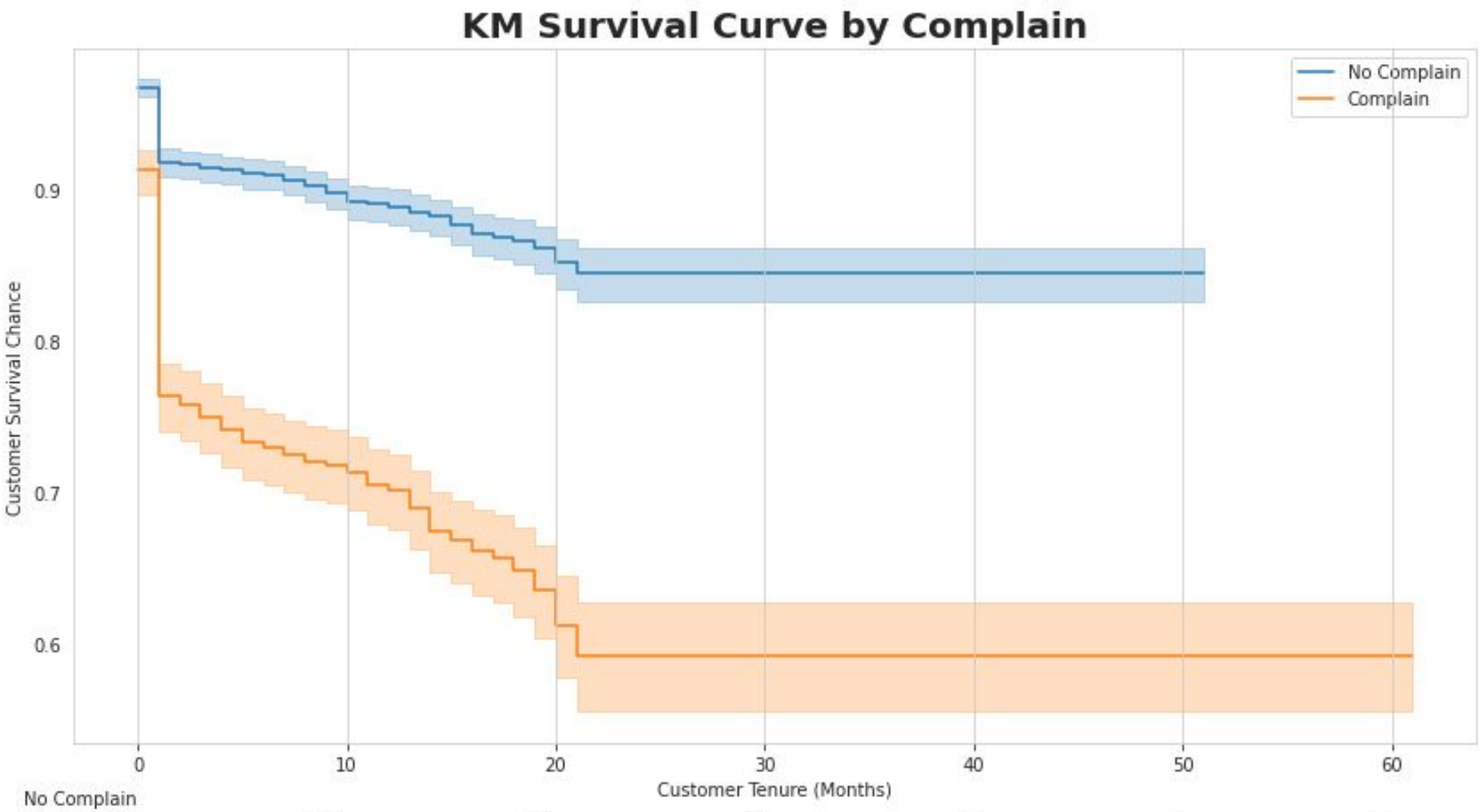
- Complain
- Order Category Other
- Order Category Fashion
- Order Category Mobile_Phone

Feature yang menghasilkan retention

- Marital Status Married
- Marital Status Divorced
- Order Category Grocery
- Payment Mode Debit Card

Insights

KM Survival Curve by Complain

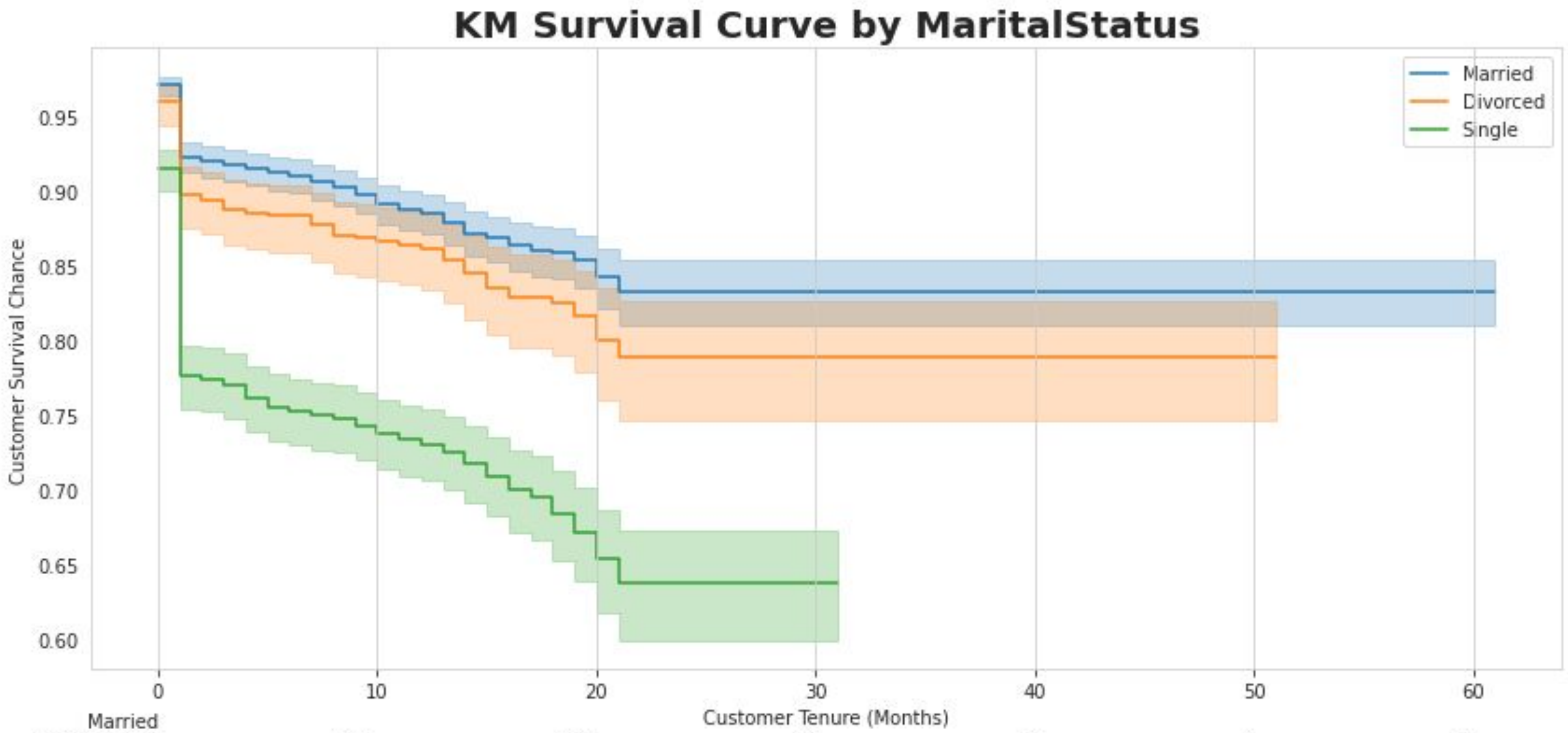


	0	10	20	30	40	50	60
No Complain							
At risk	3356	1460	497	31	2	1	0
Censored	165	1831	2754	3216	3245	3246	3247
Events	118	348	388	392	392	392	392
Complain							
At risk	1260	586	186	19	2	2	1
Censored	49	460	805	966	983	983	984
Events	125	388	443	449	449	449	449

- Customer Survival chance with no complain memiliki 89% dan with complain memiliki 68%
- pada 20 bulan pertama customer yang no complain :
  - event (sudah churn) sebesar 388 orang (10%)
  - censored (terindikasi churn tp belum churn) sebesar 2754 orang (75%)
  - at risk(not churn) sebesar 497 orang (15%)

Insights

Churn Prediction and Prevention

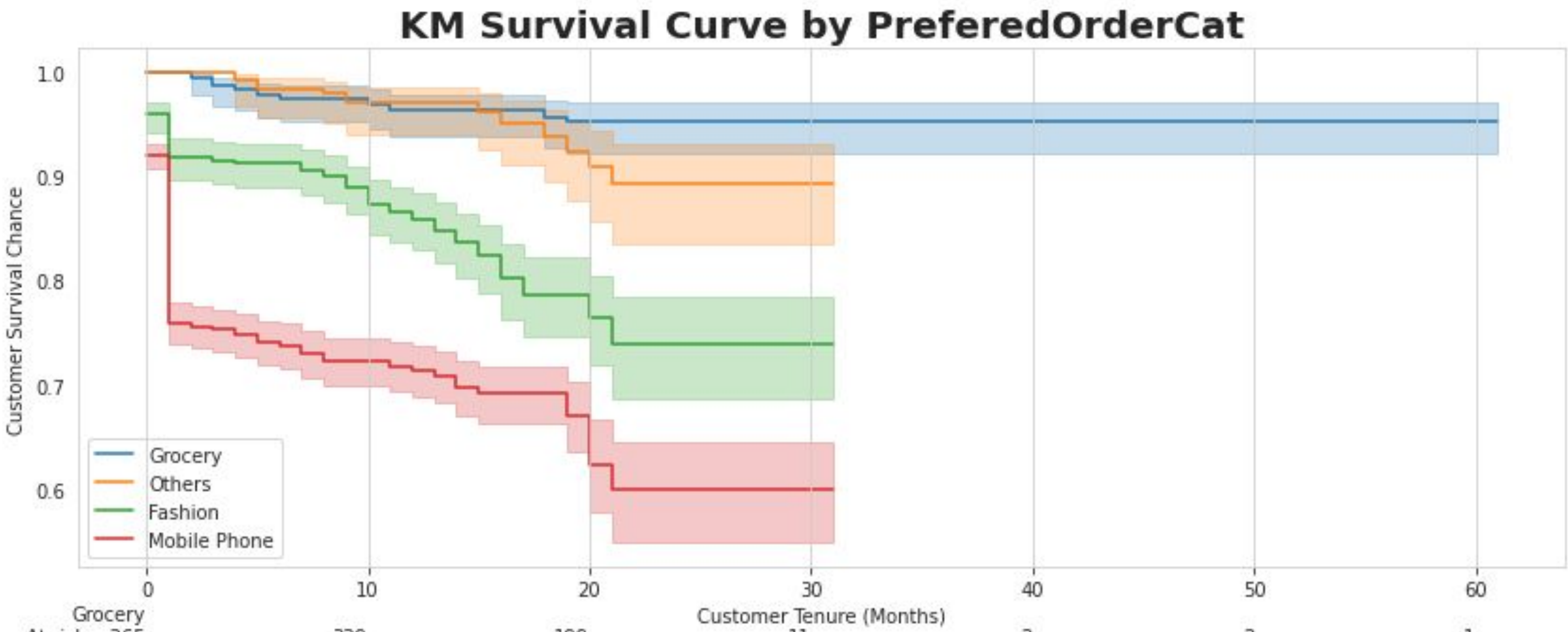


	0	10	20	30	40	50	60
Married							
At risk	2494	1161	377	29	2	2	1
Censored	101	1254	1997	2341	2368	2368	2369
Events	77	257	298	302	302	302	302
Divorced							
At risk	778	368	141	10	2	1	0
Censored	36	377	585	714	722	723	724
Events	34	103	122	124	124	124	124
Single							
At risk	1344	517	165	11	0	0	0
Censored	77	660	977	1127	1138	1138	1138
Events	132	376	411	415	415	415	415

- Customer Survival chance yang Marital Status
  - Married memiliki 88%
  - Divorced memiliki 85%
  - Single memiliki 73%
- pada 20 bulan pertama customer yang Marital Status Married :
  - event (sudah churn) sebesar 377 orang (14%)
  - censored (terindikasi churn tp belum churn) sebesar 1997 orang (75%)
  - at risk(not churn) sebesar 298 orang (15%)

Insights

Churn Prediction and Prevention

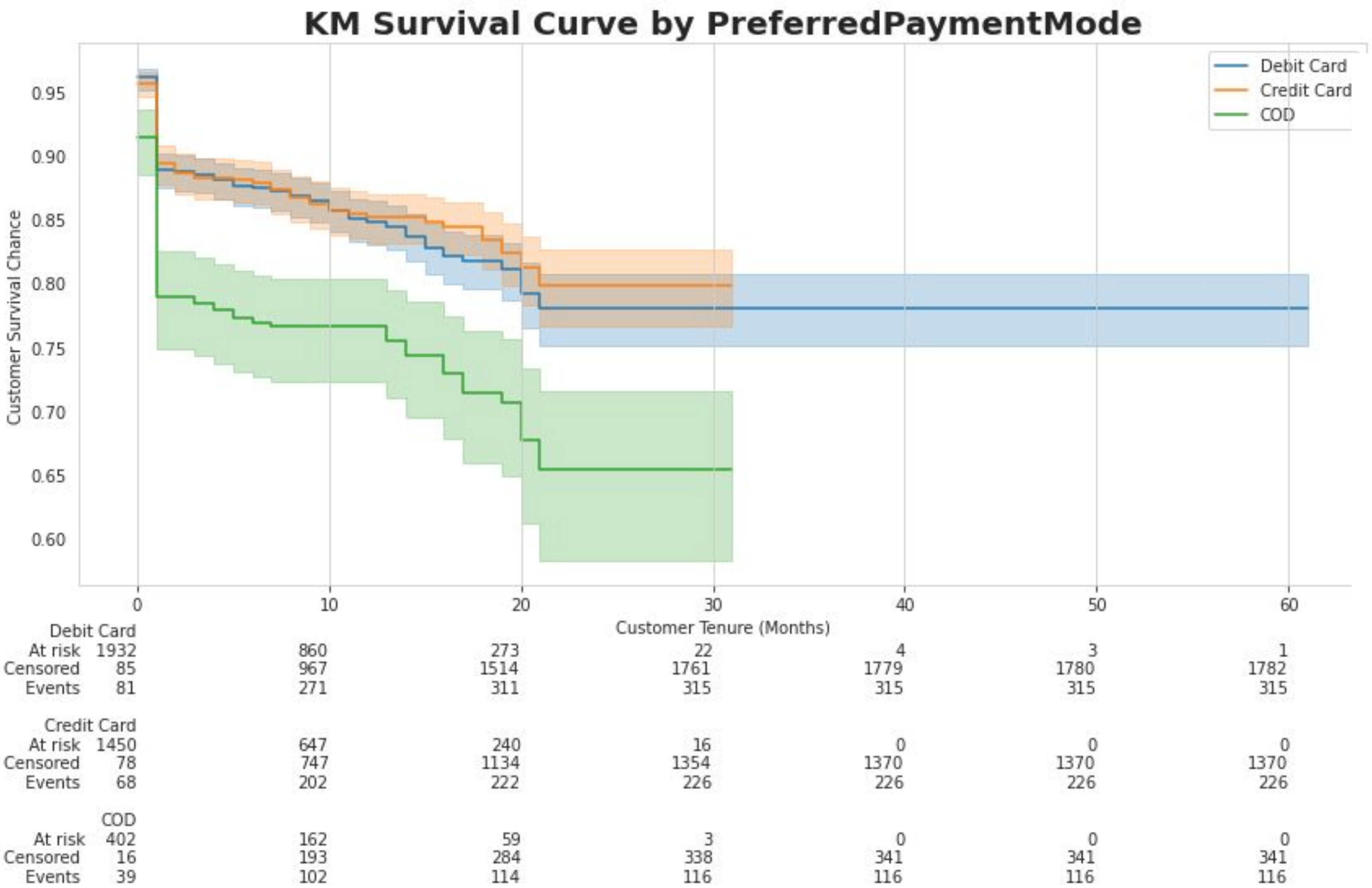


	0	10	20	30	40	50	60
Grocery							
At risk	365	339	199	11	2	2	1
Censored	1	16	151	339	348	348	349
Events	0	11	16	16	16	16	16
Others							
At risk	241	233	111	5	0	0	0
Censored	1	2	114	218	223	223	223
Events	0	7	17	19	19	19	19
Fashion							
At risk	724	397	120	12	0	0	0
Censored	8	278	523	627	639	639	639
Events	31	88	120	124	124	124	124
Mobile Phone							
At risk	1582	375	101	9	0	0	0
Censored	125	1020	1270	1358	1367	1367	1367
Events	148	460	484	488	488	488	488

- Customer Survival chance yang Prefered Order Category
  - Grocery memiliki 95%
  - Others memiliki 92%
  - Fashion memiliki 83%
  - Mobile Phone memiliki 73%
- pada 20 bulan pertama customer yang Prefered Order Category Grocery :
  - event (sudah churn) sebesar 16 orang (5%)
  - censored (terindikasi churn tp belum churn) sebesar 151 orang (41%)
  - at risk(not churn) sebesar 199 orang (54%)

Insights

Churn Prediction and Prevention



- Customer Survival chance yang Prefered Payment Mode
    - Debit Card memiliki 84%
    - Credit Card memiliki 86%
    - COD memiliki 74%
- pada 20 bulan pertama customer yang Prefered Prefered Payment Mode Credit card :
    - event (sudah churn) sebesar 222 orang (14%)
    - censored (terindikasi churn tp belum churn) sebesar 1134 orang (71%)
    - at risk(not churn) sebesar 240 orang (15%)

Calculate Expected Loss & Estimated Revenue Uplift

Let's now drill down a bit more and focus on censored subjects, i.e. those who have not churned yet. We will predict the future survival function of our censored (not churned) customers - the new timeline is the remaining duration of the customer, i.e. normalized back to starting at 0.

CustomerID	Cashback Amount	Exp_Churn_Month	Exp_Loss	baseline	OrderCat_Grocery_Uplift	PaymentMode_Credit Card_Uplift	PaymentMode_Debit Card_Uplift
50046	130.58	11.00	1,436.38	11.00	16.00	14.00	15.00
50048	120.88	19.00	2,296.72	19.00	20.00	19.00	20.00
50177	112.00	15.00	1,680.00	15.00	20.00	15.00	20.00
50194	124.78	14.00	1,746.92	14.00	19.00	17.00	14.00
50230	147.36	14.00	2,063.04	14.00	17.00	16.00	17.00

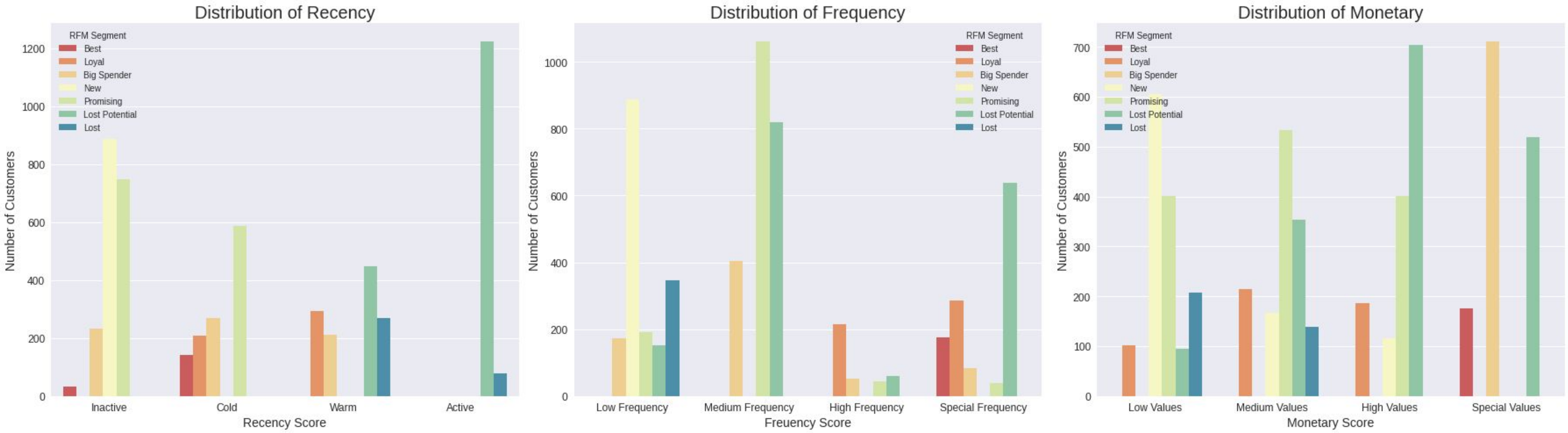
CustomerID 50046 diprediksi akan

- Churn pada bulan ke 11
- Expected Loss sebesar $14,363
- Estimated Revenue Uplift Jika bisa dialirkan ke order category grocery $160 dan payment cc $ 140 atau payment Debit Card $ 150 sehingga akan tidak churn

Segmentation of Customer

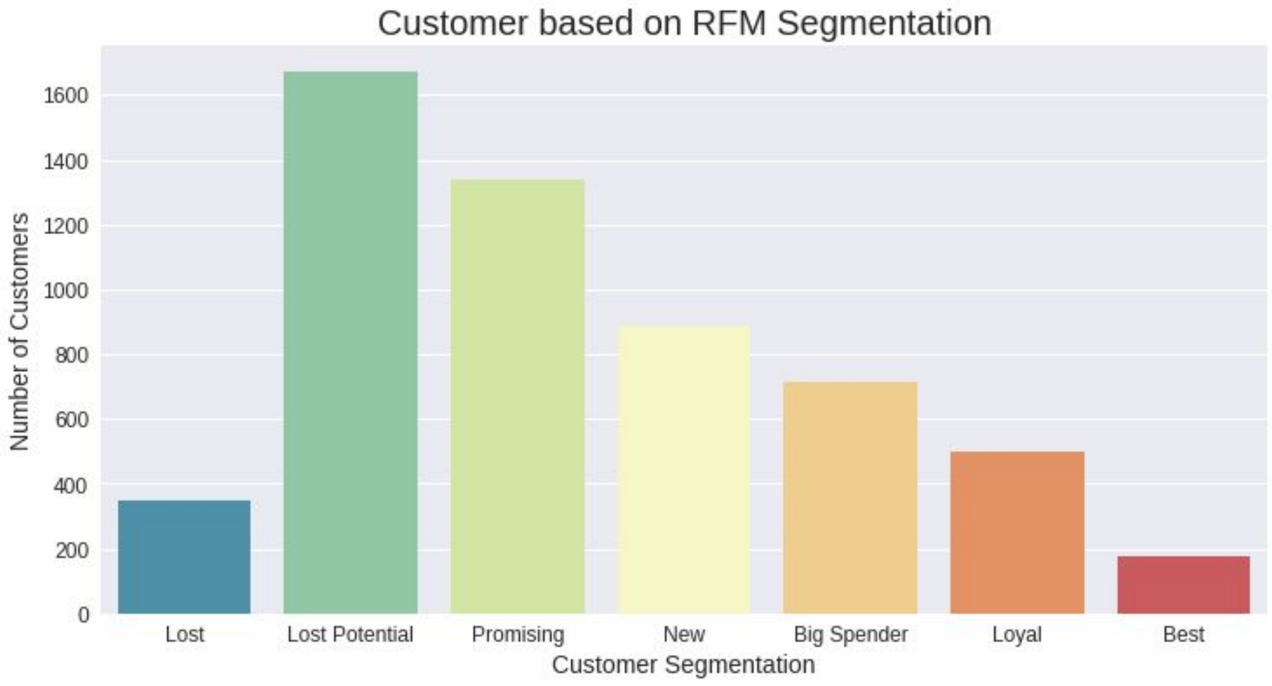
Using **RFM Segmentation**, **K-Means**, and **Gaussian**

RFM Segmentation



- Kolom yang digunakan
  - Kolom "DaySinceLastOrder" sebagai "recency"
  - Kolom "OrderCount" sebagai "frequency"
  - Kolom 'CashbackAmount' sebagai 'monetary'
- Kolom "recency" dibagi menjadi 4 segment
  - 'active','warm','cold','innactive'
- Kolom "frequency" dibagi menjadi 4 segment
  - 'special','high','medium','low'
- Kolom 'monetary' dibagi menjadi 4 segment
  - 'low values','medium values','high values','special values'

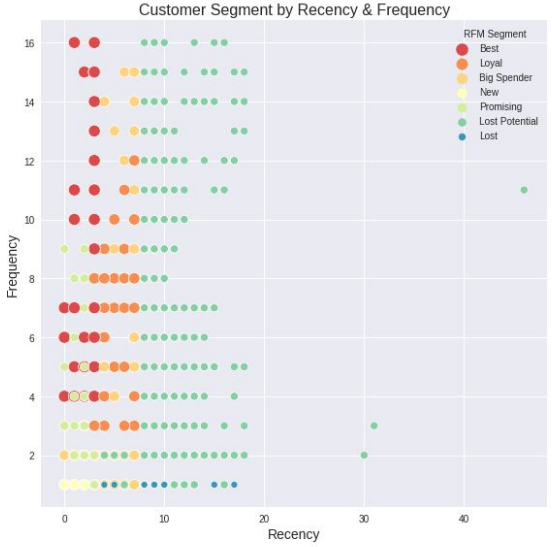
RFM Segmentation

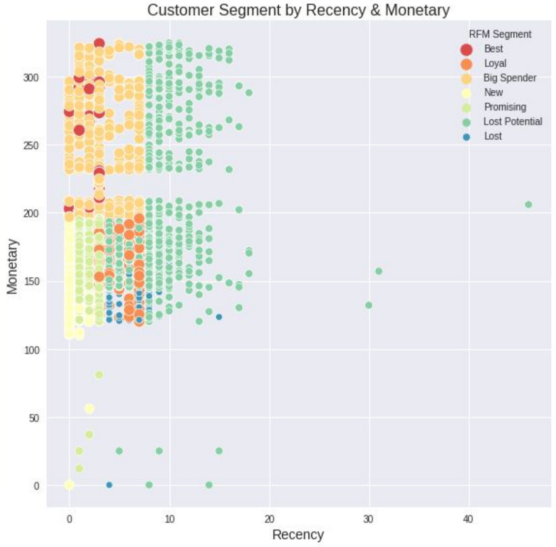


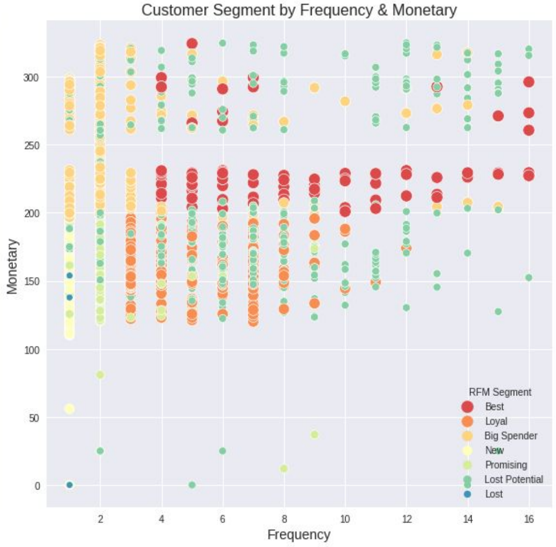
- RFM segment berdasarkan score dari distribusi Recency, Frequency, Monetary
- RFM membagi 7 customer segment
  - ['Best', 'Loyal', 'Big Spender', 'New', 'Promising', 'Lost Potential', 'Lost']

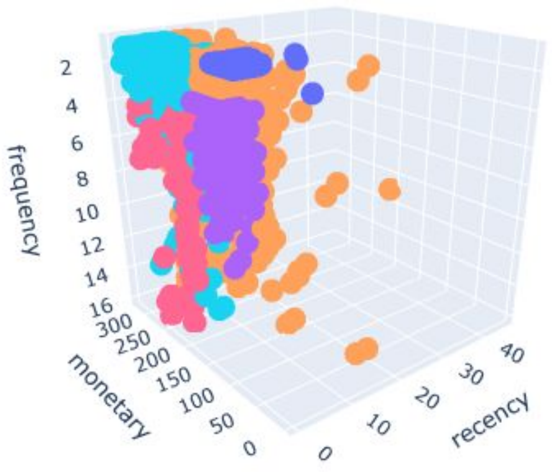
Insights

RFM Segmentation



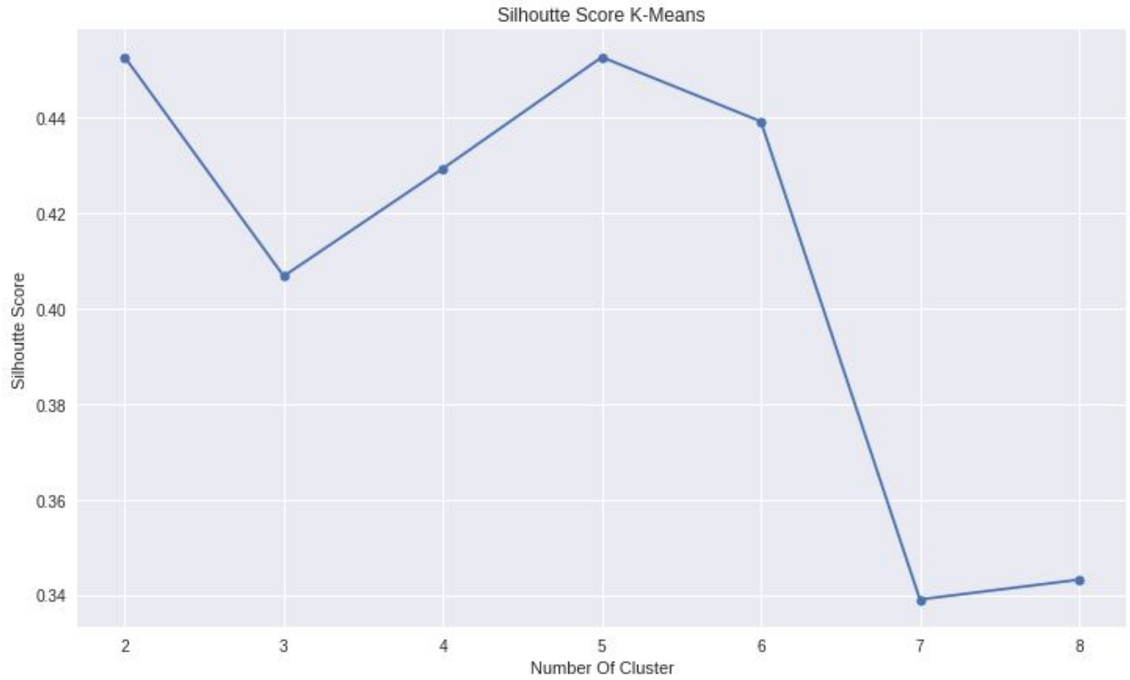


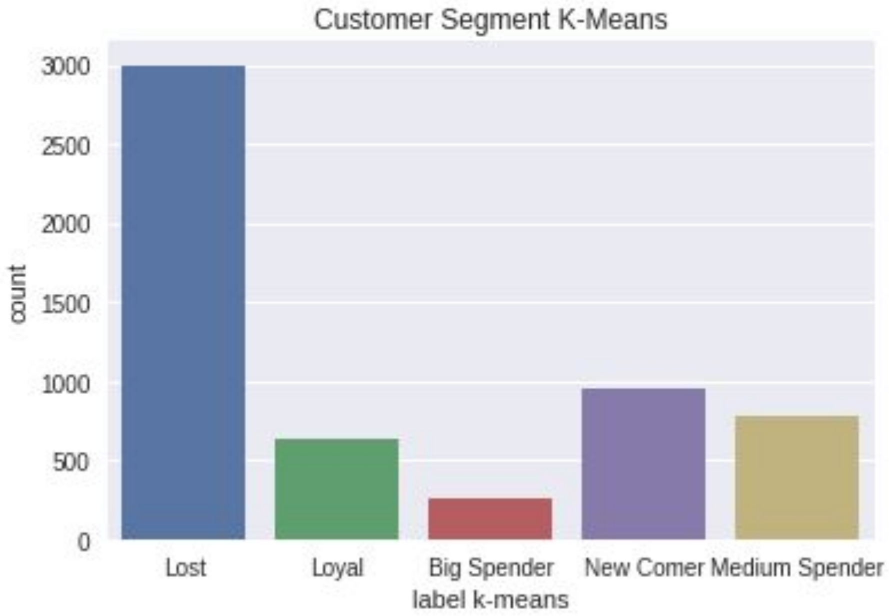




- Best : Customer yang melakukan transaksi baru-baru ini, sering melakukan transaksi, dan mempunyai total transaksi yang paling tinggi.
- Loyal : Customer yang sudah melakukan transaksi lebih dari 4 kali.
- Big Spender : Customer yang melakukan transaksi dengan total transaksi paling tinggi.
- New : Customer yang melakukan transaksi baru-baru ini dan baru bertransaksi sebanyak 1 kali.
- Promising : Customers yang baru-baru ini melakukan transaksi, serta frekuensi dan total transaksinya diatas rata-rata customers lain.
- Lost Potential : Customers yang sudah lama tidak melakukan transaksi, tetapi frekuensi dan total transaksinya diatas rata-rata customers lain.
- Lost : Customers yang sudah lama tidak melakukan transaksi, hanya melakukan satu kali transaksi, dan total transaksi sedikit.

K-Means

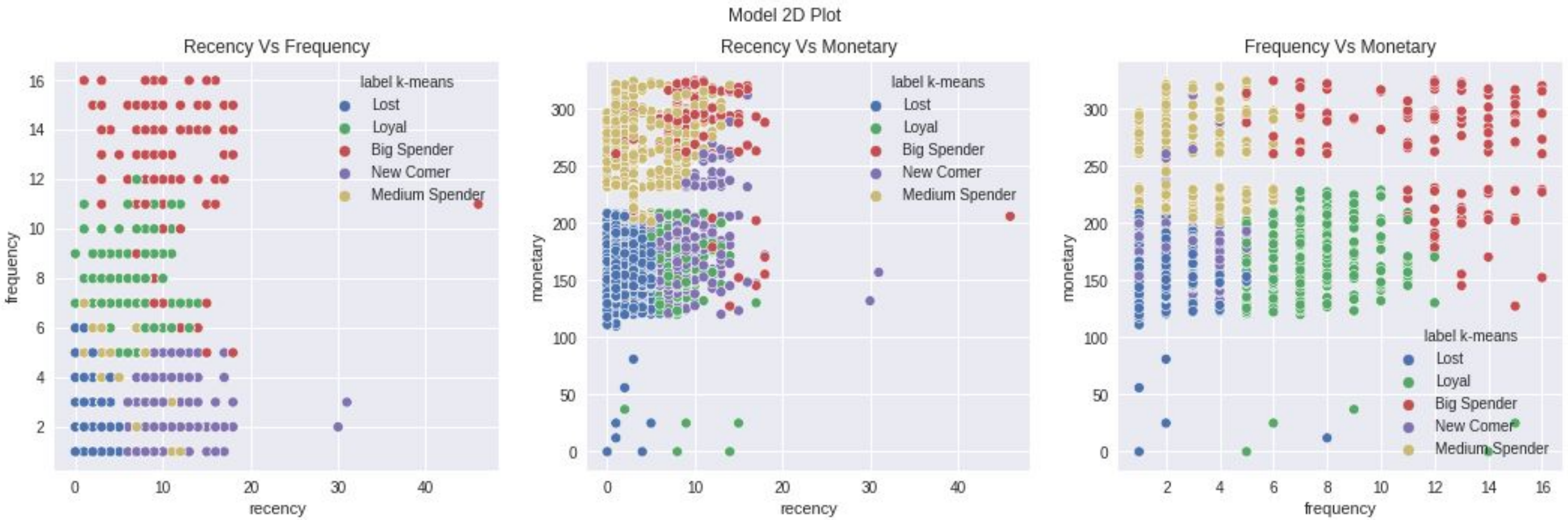


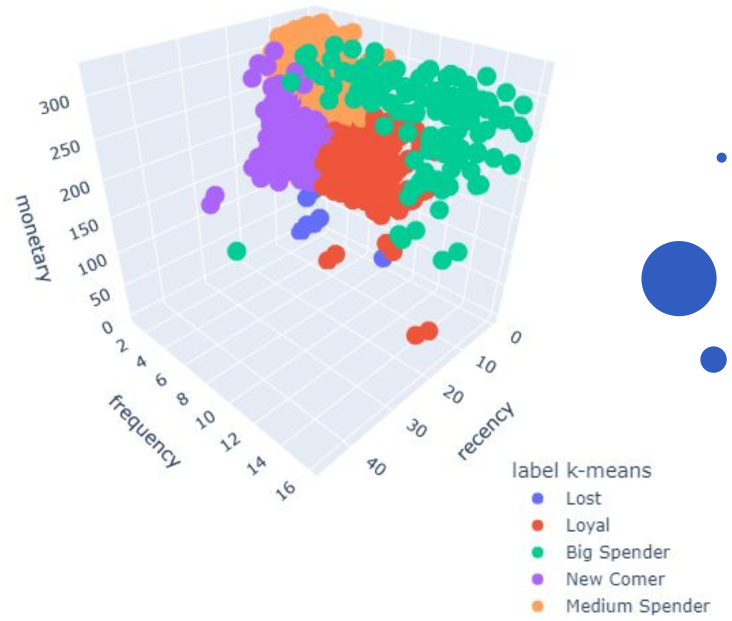


- *Silhoutte Score* terbaik didapatkan pada cluster 2
- Kami memutuskan untuk tidak menggunakan 2 *cluster* karena *cluster* yang terbentuk kemungkinan besar hanya *customer* dengan *frequency* 1 kali dengan *monetary* yang rendah dan *customer* diluar *cluster* tersebut
- Kami akan menggunakan 5 *cluster* karena 5 *cluster* memiliki nilai *silhoutte score* tertinggi setelah 2

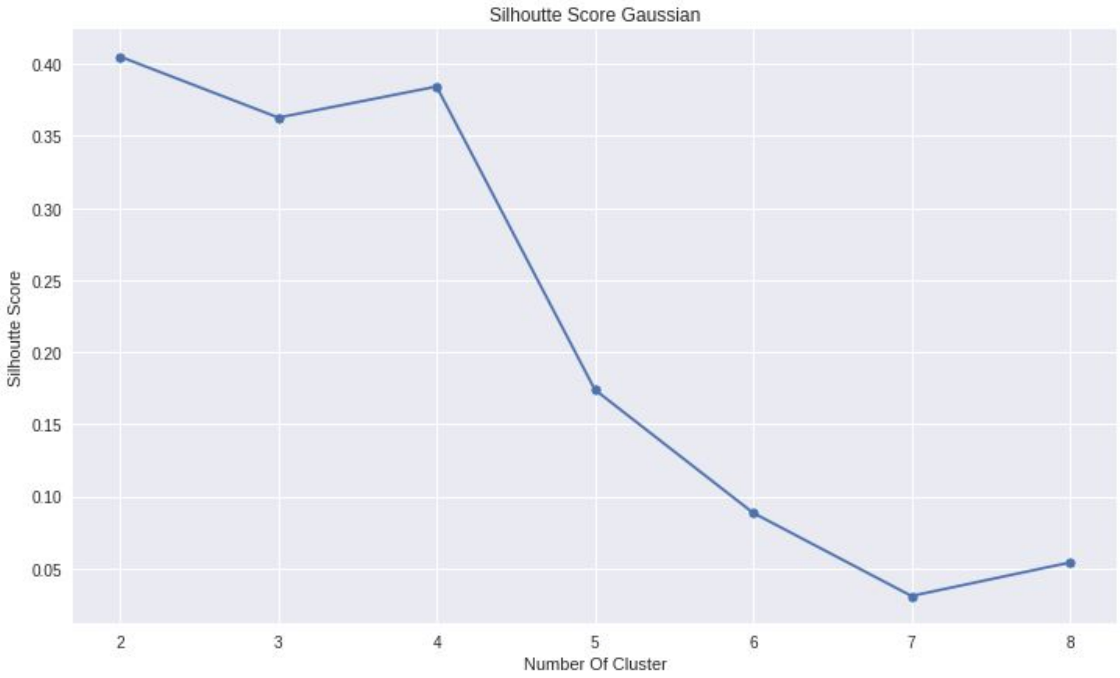
Insights

K-Means





Gaussian

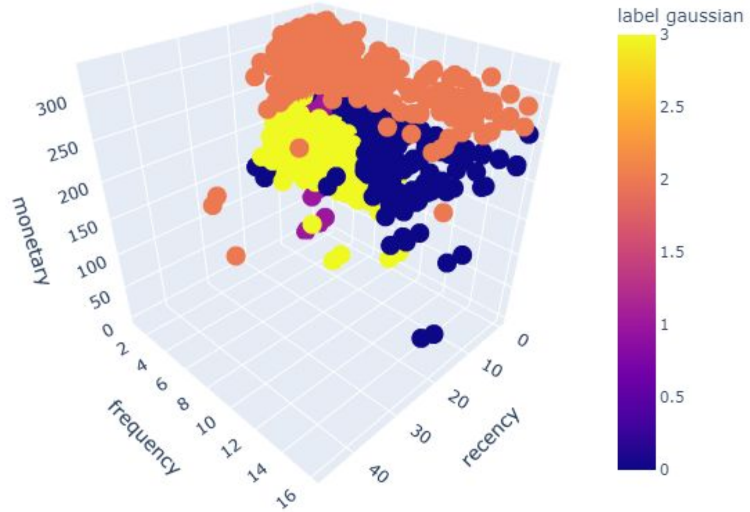


- *Silhoutte Score* terbaik didapatkan pada cluster 2
- Kami memutuskan untuk tidak menggunakan 2 *cluster* karena *cluster* yang terbentuk kemungkinan besar hanya *customer* dengan *frequency* 1 kali dengan *monetary* yang rendah dan *customer* diluar *cluster* tersebut
- Kami akan menggunakan 4 *cluster* karena 4 *cluster* memiliki nilai *silhoutte score* tertinggi setelah 2

Insights

Gaussian

Model 2D Plot



Insights

Summary RFM Segmentation

Model RFM Segmentation merupakan model yang memiliki interpretasi paling tinggi dibandingkan model lain & model ini dibuat dengan **domain knowledge** yang kami punya

RFM Segment	RFM Segment Score	n customer	mean recency	min recency	max rencency	mean freq	min freq	max freq	mean monetary	min monetary	max monetary	most payment type	avg review score	most product buy
Best	7	176	2.625000	0.0	3.0	8.357955	4.0	16.0	230.968920	200.96	324.43	Debit Card	3.051136	Fashion
Loyal	6	501	4.846307	3.0	7.0	4.842315	3.0	12.0	158.280918	120.11	196.19	Debit Card	2.972056	Laptop & Acc
Big Spender	5	712	3.200843	0.0	7.0	2.567416	1.0	15.0	244.787219	196.67	324.26	Debit Card	3.005618	Fashion
New	4	888	1.010135	0.0	2.0	1.000000	1.0	1.0	138.116137	0.00	196.10	Debit Card	3.087838	Mobile Phone
Promising	3	1336	2.079341	0.0	3.0	2.006737	1.0	9.0	153.928451	12.00	196.37	Debit Card	3.058383	Mobile Phone
Lost Potential	2	1671	8.461999	4.0	46.0	4.210054	1.0	16.0	195.301556	0.00	324.99	Debit Card	3.115500	Laptop & Acc
Lost	1	346	6.132948	4.0	17.0	1.000000	1.0	1.0	141.281647	0.00	163.22	Credit Card	3.080925	Laptop & Acc

Priority Customer Treatment

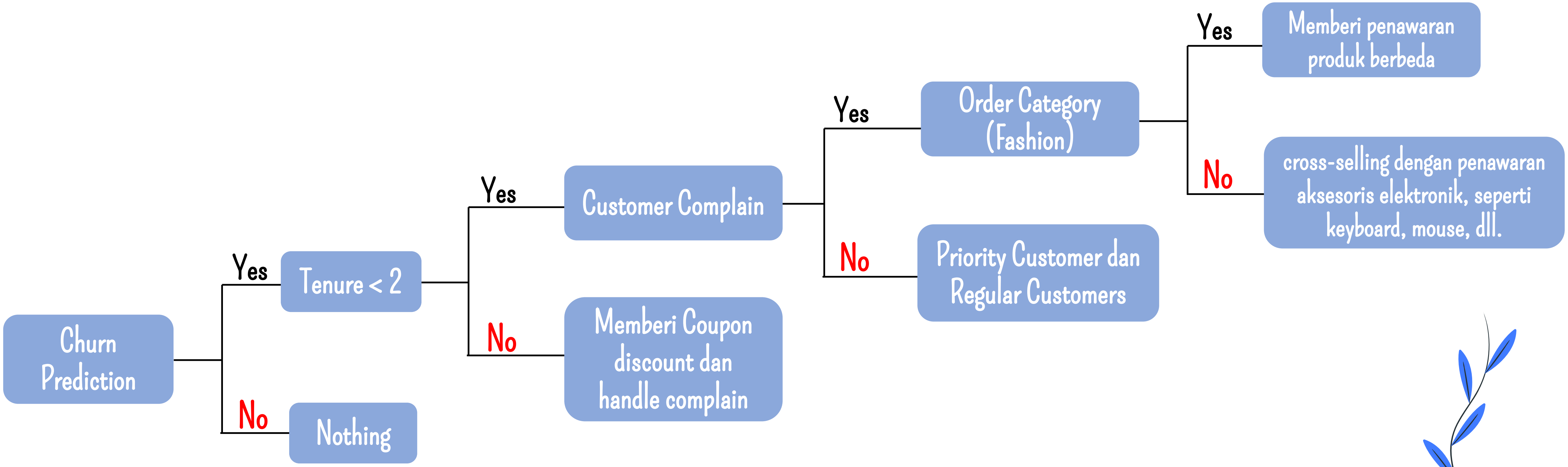
RFM Segment	RFM Segment Score	n cus	mean recency	min recency	max rencency	mean freq	min freq	max freq	mean monetary	min monetary	max monetary	most payment type	avg review score	most product buy	sum Exp Loss	sum Grocer Uplift	sum Credit Card Uplift	sum Debit Card Uplift
Loyal	**6**	5	3.00000	3.0	3.0	3.000	3.0	3.0	153.3800	145.7	172.36	Cash on Delivery	3.80000	Mobile Phone	9740.67	600.41	1221.61	463.76
New	**4**	19	1.10526	0.0	2.0	1.000	1.0	1.0	125.2715	112.0	134.47	Credit Card	3.89473	Mobile Phone	32903.0	1372.46	3987.19	3389.94
Promising	**3**	23	2.30434	1.0	3.0	2.347	1.0	7.0	141.9330	120.7	159.47	Cash on Delivery	3.69565	Mobile Phone	48200.0	2271.93	3944.68	3975.56
Lost Potential	**2**	2	8.50000	8.0	9.0	5.500	5.0	6.0	12.50000	0.0	25.00	E wallet	2.00000	Mobile Phone	225.00	0.00	25.00	25.00

RFM Segment	Strategi
Loyal	Loyalty program/reward point dan penawaran barang eksklusif (Cross / Up Selling Strategy)
New	Welcome e-mail untuk membangun reletionship, penawaran loyalty program/reward point, dan voucher diskon (Cross / Up Selling Strategy)
Promising	Penawaran terbatas secara rutin, voucher diskon dan cashback via e-mail (Retention Strategy)
Lost Potential	Penawaran terbatas secara rutin, voucher diskon dan cashback via e-mail (Retention & Reactivate Stretegies)

Kesimpulan

- Total Expected Loss sebesar $ 910,687
- Estimated Revenue Uplift
    - Order category grocery $42,448
    - Payment Credit Card $ 91,785
    - Payment Debit Card $ 78,543

CUSTOMER CHURN TREATMENT



Summary & Recommendations

Dari data visualisasi diperoleh churn ratio memiliki korelasi tenure, complain, cashback Amount, & preferedordercat

Hasil predict churn sangat dipengaruhi oleh tinggi rendahnya Tenure, Complain, Number of Address dan cashback Amount

Hasil Survival Analysis, customer memiliki survival chance terbesar pada No Complain, Marital Status Married, Payment Mode Credit Card, Order Category Grocery

Hasil RFM Segmentation menunjukkan priority customer treatment pada segment Loyal, New, Promising, dan Lost Potential

- Total Expected Loss sebesar $ 910,687
- Estimated Revenue Uplift
    - Order category grocery $42,448
    - Payment Credit Card $ 91,785
    - Payment Debit Card $ 78,543

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