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#import libraries

import pandas as pd

import seaborn as sns

import matplotlib.pyplot as plt

import tensorflow as tf

import numpy as np

from sklearn.preprocessing import LabelEncoder

from sklearn.preprocessing import OneHotEncoder

from sklearn.preprocessing import MinMaxScaler

from sklearn.preprocessing import StandardScaler

from imblearn import under_sampling, over_sampling

df = pd.read_excel('E Commerce Dataset.xlsx', sheet_name='E Comm')

df.head()

	CustomerID	Churn	Tenure	PreferredLoginDevice	CityTier
WarehouseToHome \					
0	50001	1	4.0	Mobile Phone	3
6.0					
1	50002	1	NaN	Phone	1
8.0					
2	50003	1	NaN	Phone	1
30.0					
3	50004	1	0.0	Phone	3
15.0					
4	50005	1	0.0	Phone	1
12.0					

	PreferredPaymentMode	Gender	HourSpendOnApp
NumberOfDeviceRegistered \			
0	Debit Card	Female	3.0
3			

1		UPI	Male	3.0
4				
2		Debit Card	Male	2.0
4				
3		Debit Card	Male	2.0
4				
4		CC	Male	NaN
3				

	PreferedOrderCat	SatisfactionScore	MaritalStatus
NumberOfAddress \			
0	Laptop & Accessory	2	Single
9			
1	Mobile	3	Single
7			
2	Mobile	3	Single
6			
3	Laptop & Accessory	5	Single
8			
4	Mobile	5	Single
3			

	Complain	OrderAmountHikeFromlastYear	CouponUsed	OrderCount \
0	1	11.0	1.0	1.0
1	1	15.0	0.0	1.0
2	1	14.0	0.0	1.0
3	0	23.0	0.0	1.0
4	0	11.0	1.0	1.0

	DaySinceLastOrder	CashbackAmount
0	5.0	159.93
1	0.0	120.90
2	3.0	120.28
3	3.0	134.07
4	3.0	129.60

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 5630 entries, 0 to 5629
```

```
Data columns (total 20 columns):
```

#	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)
memory usage: 879.8+ KB

CLEANSING DATA

Handle Missing Value

#cek missing value

df.isnull().sum()

CustomerID	0
Churn	0
Tenure	264
PreferredLoginDevice	0
CityTier	0
WarehouseToHome	251
PreferredPaymentMode	0
Gender	0
HourSpendOnApp	255
NumberOfDeviceRegistered	0
PreferedOrderCat	0
SatisfactionScore	0
MaritalStatus	0
NumberOfAddress	0
Complain	0
OrderAmountHikeFromlastYear	265
CouponUsed	256
OrderCount	258
DaySinceLastOrder	307
CashbackAmount	0

dtype: int64

#semua kolom yang terdapat missing value dilakukan impute menggunakan median dari setiap kolomnya

df['Tenure'] = df['Tenure'].fillna(df['Tenure'].median())

df['WarehouseToHome'] =

```

df['WarehouseToHome'].fillna(df['WarehouseToHome'].median())
df['HourSpendOnApp'] =
df['HourSpendOnApp'].fillna(df['HourSpendOnApp'].median())
df['DaySinceLastOrder'] =
df['DaySinceLastOrder'].fillna(df['DaySinceLastOrder'].median())
df['OrderCount'] = df['OrderCount'].fillna(df['OrderCount'].median())
df['CouponUsed'] = df['CouponUsed'].fillna(df['CouponUsed'].median())
df['OrderAmountHikeFromlastYear'] =
df['OrderAmountHikeFromlastYear'].fillna(df['OrderAmountHikeFromlastYe
ar'].median())

```

```
df.isnull().sum()
```

```

CustomerID          0
Churn                0
Tenure              0
PreferredLoginDevice 0
CityTier            0
WarehouseToHome     0
PreferredPaymentMode 0
Gender              0
HourSpendOnApp      0
NumberOfDeviceRegistered 0
PreferedOrderCat    0
SatisfactionScore   0
MaritalStatus       0
NumberOfAddress     0
Complain            0
OrderAmountHikeFromlastYear 0
CouponUsed          0
OrderCount          0
DaySinceLastOrder   0
CashbackAmount      0
dtype: int64

```

Handle Duplicate Data

```
df.duplicated().sum()
```

```
0
```

Tidak terdapat duplicate pada data

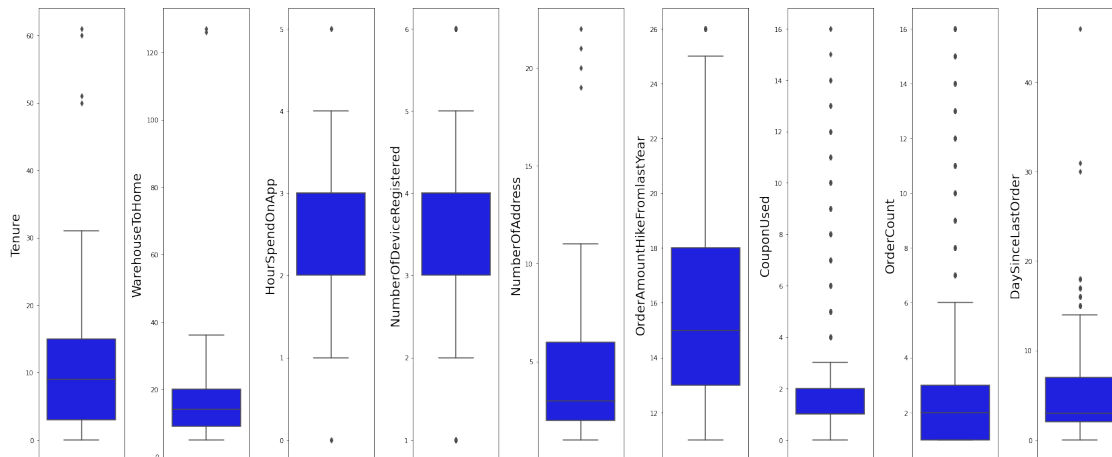
Handle Outlier

```

outlier_var = ['Tenure',
'WarehouseToHome', 'HourSpendOnApp', 'NumberOfDeviceRegistered',
'NumberOfAddress', 'OrderAmountHikeFromlastYear',
                'CouponUsed', 'OrderCount', 'DaySinceLastOrder']

```

```
plt.figure(figsize=(24, 10))
for i in range(0, len(outlier_var)):
    plt.subplot(1, len(outlier_var), i+1)
    sns.boxplot(y=df[outlier_var[i]], color='blue', orient='v')
    plt.ylabel(outlier_var[i], fontsize=20)
    plt.tight_layout()
```



#handling outlier

```
for i in outlier_var :
    q1=df[i].quantile(0.25)
    q3=df[i].quantile(0.75)
    iqr=q3-q1
    low_limit=q1-(iqr*1.5)
    high_limit=q3+(iqr*1.5)
    df = df[(df[i]>=low_limit) & (df[i]<=high_limit)]
```

df.shape

(3827, 20)

df

	CustomerID	Churn	Tenure	PreferredLoginDevice	CityTier	\
0	50001	1	4.0	Mobile Phone	3	
1	50002	1	9.0	Phone	1	
2	50003	1	9.0	Phone	1	
3	50004	1	0.0	Phone	3	
4	50005	1	0.0	Phone	1	
...	
5625	55626	0	10.0	Computer	1	
5626	55627	0	13.0	Mobile Phone	1	
5627	55628	0	1.0	Mobile Phone	1	
5628	55629	0	23.0	Computer	3	
5629	55630	0	8.0	Mobile Phone	1	

	WarehouseToHome	PreferredPaymentMode	Gender	HourSpendOnApp	\
0	6.0	Debit Card	Female	3.0	

1	8.0	UPI	Male	3.0
2	30.0	Debit Card	Male	2.0
3	15.0	Debit Card	Male	2.0
4	12.0	CC	Male	3.0
...
5625	30.0	Credit Card	Male	3.0
5626	13.0	Credit Card	Male	3.0
5627	11.0	Debit Card	Male	3.0
5628	9.0	Credit Card	Male	4.0
5629	15.0	Credit Card	Male	3.0

	NumberOfDeviceRegistered	PreferedOrderCat	SatisfactionScore
\			
0	3	Laptop & Accessory	2
1	4	Mobile	3
2	4	Mobile	3
3	4	Laptop & Accessory	5
4	3	Mobile	5
...
5625	2	Laptop & Accessory	1
5626	5	Fashion	5
5627	2	Laptop & Accessory	4
5628	5	Laptop & Accessory	4
5629	2	Laptop & Accessory	3

OrderAmountHikeFromlastYear	MaritalStatus	NumberOfAddress	Complain
\			
0	Single	9	1
11.0			
1	Single	7	1
15.0			
2	Single	6	1
14.0			
3	Single	8	0
23.0			
4	Single	3	0
11.0			
...

```

...
5625      Married      6      0
18.0
5626      Married      6      0
16.0
5627      Married      3      1
21.0
5628      Married      4      0
15.0
5629      Married      4      0
13.0

```

```

      CouponUsed  OrderCount  DaySinceLastOrder  CashbackAmount
0           1.0         1.0           5.0         159.93
1           0.0         1.0           0.0         120.90
2           0.0         1.0           3.0         120.28
3           0.0         1.0           3.0         134.07
4           1.0         1.0           3.0         129.60
...
5625      1.0         2.0           4.0         150.71
5626      1.0         2.0           3.0         224.91
5627      1.0         2.0           4.0         186.42
5628      2.0         2.0           9.0         178.90
5629      2.0         2.0           3.0         169.04

```

[3827 rows x 20 columns]

Setelah dilakukan handling outlier, jumlah row data dari 5630 berkurang menjadi 3827

#handling redundan value

```
df['PreferredPaymentMode'] = df['PreferredPaymentMode'].replace(['Cash
on Delivery', 'Credit Card'], ['COD', 'CC'])
```

```
df.head()
```

```

      CustomerID  Churn  Tenure PreferredLoginDevice  CityTier
WarehouseToHome \
0      50001      1      4.0      Mobile Phone      3
6.0
1      50002      1      9.0      Phone      1
8.0
2      50003      1      9.0      Phone      1
30.0
3      50004      1      0.0      Phone      3
15.0
4      50005      1      0.0      Phone      1
12.0

```

```

      PreferredPaymentMode  Gender  HourSpendOnApp
NumberOfDeviceRegistered \
0      Debit Card  Female      3.0

```

3			
1	UPI	Male	3.0
4			
2	Debit Card	Male	2.0
4			
3	Debit Card	Male	2.0
4			
4	CC	Male	3.0
3			

	PreferedOrderCat	SatisfactionScore	MaritalStatus
NumberOfAddress \			
0	Laptop & Accessory	2	Single
9			
1	Mobile	3	Single
7			
2	Mobile	3	Single
6			
3	Laptop & Accessory	5	Single
8			
4	Mobile	5	Single
3			

	Complain	OrderAmountHikeFromlastYear	CouponUsed	OrderCount	\
0	1	11.0	1.0	1.0	
1	1	15.0	0.0	1.0	
2	1	14.0	0.0	1.0	
3	0	23.0	0.0	1.0	
4	0	11.0	1.0	1.0	

	DaySinceLastOrder	CashbackAmount
0	5.0	159.93
1	0.0	120.90
2	3.0	120.28
3	3.0	134.07
4	3.0	129.60

Feature Transformation

#One Hot Encoding

```
one_hot_var = ['PreferredPaymentMode', 'PreferredLoginDevice',
               'PreferedOrderCat', 'MaritalStatus']
```

```
for i in one_hot_var :
    onehots = pd.get_dummies(df[i], prefix=i)
    df = df.join(onehots)
```

```
df.head()
```


	CustomerID	Churn	Tenure	PreferredLoginDevice	CityTier
WarehouseToHome \					
0	50001	1	4.0	Mobile Phone	3
6.0					
1	50002	1	9.0	Phone	1
8.0					
2	50003	1	9.0	Phone	1
30.0					
3	50004	1	0.0	Phone	3
15.0					
4	50005	1	0.0	Phone	1
12.0					

	PreferredPaymentMode	Gender	HourSpendOnApp
NumberOfDeviceRegistered ... \			
0	Debit Card	Female	3.0
3 ...			
1	UPI	Male	3.0
4 ...			
2	Debit Card	Male	2.0
4 ...			
3	Debit Card	Male	2.0
4 ...			
4	CC	Male	3.0
3 ...			

	PreferredLoginDevice_Phone	PreferedOrderCat_Fashion
0	0	0
1	1	0
2	1	0
3	1	0
4	1	0

	PreferedOrderCat_Grocery	PreferedOrderCat_Laptop & Accessory
0	0	1
1	0	0
2	0	0
3	0	1
4	0	0

	PreferedOrderCat_Mobile	PreferedOrderCat_Mobile Phone
0	0	0
1	1	0
2	1	0
3	0	0
4	1	0

	PreferedOrderCat_Others	MaritalStatus_Divorced
MaritalStatus_Married \		
0	0	0

0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		

MaritalStatus_Single	
0	1
1	1
2	1
3	1
4	1

[5 rows x 37 columns]

```
df = df.drop(columns=['PreferredPaymentMode', 'PreferredLoginDevice',
'PreferedOrderCat', 'MaritalStatus'])
```

```
df.head()
```

	CustomerID	Churn	Tenure	CityTier	WarehouseToHome	Gender	\
0	50001	1	4.0	3	6.0	Female	
1	50002	1	9.0	1	8.0	Male	
2	50003	1	9.0	1	30.0	Male	
3	50004	1	0.0	3	15.0	Male	
4	50005	1	0.0	1	12.0	Male	

	HourSpendOnApp	NumberOfDeviceRegistered	SatisfactionScore	\
0	3.0	3	2	
1	3.0	4	3	
2	2.0	4	3	
3	2.0	4	5	
4	3.0	3	5	

	NumberOfAddress	...	PreferredLoginDevice_Phone
PreferedOrderCat_Fashion		\	
0	9	...	0
0			
1	7	...	1
0			
2	6	...	1
0			
3	8	...	1
0			
4	3	...	1
0			

	PreferedOrderCat_Grocery	PreferedOrderCat_Laptop & Accessory	\
0	0	1	
1	0	0	
2	0	0	
3	0	1	
4	0	0	

	PreferedOrderCat_Mobile	PreferedOrderCat_Mobile Phone	\
0	0	0	
1	1	0	
2	1	0	
3	0	0	
4	1	0	

	PreferedOrderCat_Others	MaritalStatus_Divorced
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		

	MaritalStatus_Single
0	1
1	1
2	1
3	1
4	1

[5 rows x 33 columns]

#Label encoding

```
mapping_gender = {
    'Female' : 0,
    'Male' : 1
}
```

```
df['Gender'] = df['Gender'].map(mapping_gender)
```

```
df.head()
```

	CustomerID	Churn	Tenure	CityTier	WarehouseToHome	Gender	\
0	50001	1	4.0	3	6.0	0	
1	50002	1	9.0	1	8.0	1	

2	50003	1	9.0	1	30.0	1
3	50004	1	0.0	3	15.0	1
4	50005	1	0.0	1	12.0	1

	HourSpendOnApp	NumberOfDeviceRegistered	SatisfactionScore	\
0	3.0	3	2	
1	3.0	4	3	
2	2.0	4	3	
3	2.0	4	5	
4	3.0	3	5	

	NumberOfAddress	...	PreferredLoginDevice_Phone
PreferredOrderCat_Fashion	\		
0	9	...	0
0			
1	7	...	1
0			
2	6	...	1
0			
3	8	...	1
0			
4	3	...	1
0			

	PreferredOrderCat_Grocery	PreferredOrderCat_Laptop & Accessory	\
0	0	1	
1	0	0	
2	0	0	
3	0	1	
4	0	0	

	PreferredOrderCat_Mobile	PreferredOrderCat_Mobile Phone	\
0	0	0	
1	1	0	
2	1	0	
3	0	0	
4	1	0	

	PreferredOrderCat_Others	MaritalStatus_Divorced
MaritalStatus_Married	\	
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		

```

MaritalStatus_Single
0      1
1      1
2      1
3      1
4      1

```

[5 rows x 33 columns]

Feature Transformation

#Normalization

```

minmax = df[['HourSpendOnApp', 'SatisfactionScore']]
minmax_features = MinMaxScaler().fit_transform(minmax.values)
minmax_features_df = pd.DataFrame(minmax_features, index=minmax.index,
columns=minmax.columns)

```

```

for i in minmax_features_df.columns:
    df[i]=minmax_features_df[i]

```

#Standardization

```

ssv=df[['Tenure', 'WarehouseToHome', 'NumberOfDeviceRegistered', 'NumberO
fAddress', 'OrderAmountHikeFromLastYear', 'CouponUsed', 'OrderCount', 'Day
SinceLastOrder', 'CashbackAmount']]
scaled_features = StandardScaler().fit_transform(ssv.values)
scaled_features_df = pd.DataFrame(scaled_features, index=ssv.index,
columns=ssv.columns)

```

```

for i in scaled_features_df.columns:
    df[i]=scaled_features_df[i]

```

df.head()

	CustomerID	Churn	Tenure	CityTier	WarehouseToHome	Gender	\
0	50001	1	-0.647125	3	-1.189416	0	
1	50002	1	-0.033419	1	-0.936189	1	
2	50003	1	-0.033419	1	1.849317	1	
3	50004	1	-1.138089	3	-0.049891	1	
4	50005	1	-1.138089	1	-0.429733	1	

	HourSpendOnApp	NumberOfDeviceRegistered	SatisfactionScore	\
0	0.666667	-0.903938	0.25	
1	0.666667	0.346286	0.50	
2	0.333333	0.346286	0.50	
3	0.333333	0.346286	1.00	
4	0.666667	-0.903938	1.00	

NumberOfAddress ... PreferredLoginDevice_Phone

	PreferedOrderCat_Fashion \
0	1.816800 ...
0	
1	1.040287 ...
0	
2	0.652031 ...
0	
3	1.428543 ...
0	
4	-0.512738 ...
0	

0
1
1
1
1

	PreferedOrderCat_Grocery	PreferedOrderCat_Laptop & Accessory \
0	0	1
1	0	0
2	0	0
3	0	1
4	0	0

	PreferedOrderCat_Mobile	PreferedOrderCat_Mobile Phone \
0	0	0
1	1	0
2	1	0
3	0	0
4	1	0

	PreferedOrderCat_Others	MaritalStatus_Divorced
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		

	MaritalStatus_Single
0	1
1	1
2	1
3	1
4	1

[5 rows x 33 columns]

pemisahan features dan target

X = df[[col for col in df.columns if (str(df[col].dtype) != 'object')]]

```

and col not in ['Churn', 'CustomerID']]
X = df.drop('Churn',1)
y = df['Churn'].values
print(X.shape)
print(y.shape)

```

```

(3827, 32)
(3827,)

```

```

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
FutureWarning: In a future version of pandas all arguments of
DataFrame.drop except for the argument 'labels' will be keyword-only
This is separate from the ipykernel package so we can avoid doing
imports until

```

#Handle Data Imbalance

```

# checking jumlah tiap label pada kolom target
df['Churn'].value_counts()

```

```

0    3133
1     694
Name: Churn, dtype: int64

```

```

X_under, y_under =
under_sampling.RandomUnderSampler(0.5).fit_resample(X, y)
X_over, y_over = over_sampling.RandomOverSampler(0.5).fit_resample(X,
y)
X_over_SMOTE, y_over_SMOTE = over_sampling.SMOTE().fit_resample(X, y)

```

```

print('Original')
print(pd.Series(y).value_counts())
print('\n')
print('UNDERSAMPLING')
print(pd.Series(y_under).value_counts())
print('\n')
print('OVERSAMPLING')
print(pd.Series(y_over).value_counts())
print('\n')
print('SMOTE')
print(pd.Series(y_over_SMOTE).value_counts())

```

```

/usr/local/lib/python3.7/dist-packages/imblearn/utils/_validation.py:591: FutureWarning: Pass sampling_strategy=0.5 as
keyword args. From version 0.9 passing these as positional arguments
will result in an error

```

```

FutureWarning,
/usr/local/lib/python3.7/dist-packages/imblearn/utils/_validation.py:5
91: FutureWarning: Pass sampling_strategy=0.5 as keyword args. From
version 0.9 passing these as positional arguments will result in an
error
FutureWarning,

```

Original
0 3133
1 694
dtype: int64

UNDERSAMPLING
0 1388
1 694
dtype: int64

OVERSAMPLING
0 3133
1 1566
dtype: int64

SMOTE
1 3133
0 3133
dtype: int64

newX=X_over_SMOTE
newX

	CustomerID	Tenure	CityTier	WarehouseToHome	Gender
HourSpendOnApp \					
0	50001	-0.647125	3	-1.189416	0
0.666667					
1	50002	-0.033419	1	-0.936189	1
0.666667					
2	50003	-0.033419	1	1.849317	1
0.333333					
3	50004	-1.138089	3	-0.049891	1
0.333333					
4	50005	-1.138089	1	-0.429733	1
0.666667					
...
...					
6261	55450	-1.015348	1	0.187361	0
0.687695					
6262	54585	-1.015348	1	-0.781836	1
0.703181					
6263	50233	-0.060094	3	-1.088522	0
0.345407					
6264	53374	-1.015348	2	1.243140	1
0.666667					
6265	53705	-1.015348	1	0.380744	0
0.723353					

	NumberOfDeviceRegistered	SatisfactionScore	NumberOfAddress
Complain \			
0	-0.903938	0.250000	1.816800
1			
1	0.346286	0.500000	1.040287
1			
2	0.346286	0.500000	0.652031
1			
3	0.346286	1.000000	1.428543
0			
4	-0.903938	1.000000	-0.512738
0			
...
...			
6261	0.346286	1.000000	-0.512738
0			
6262	1.596510	0.054771	-0.342616
0			
6263	0.346286	0.740945	-0.886931
1			
6264	1.530865	0.763127	-0.512738
0			
6265	1.596510	0.792515	-0.380685
0			

	PreferredLoginDevice_Phone	PreferedOrderCat_Fashion
0	0	0
1	1	0
2	1	0
3	1	0
4	1	0
...
6261	0	0
6262	0	0
6263	0	0
6264	0	0
6265	0	0

	PreferedOrderCat_Grocery	PreferedOrderCat_Laptop & Accessory
0	0	1
1	0	0
2	0	0
3	0	1
4	0	0
...
6261	0	0
6262	0	0
6263	0	0
6264	0	0

6265	0	0
------	---	---

	PreferedOrderCat_Mobile	PreferedOrderCat_Mobile Phone \
0	0	0
1	1	0
2	1	0
3	0	0
4	1	0
...
6261	0	0
6262	0	1
6263	0	0
6264	0	1
6265	0	0

	PreferedOrderCat_Others	MaritalStatus_Divorced
MaritalStatus_Married \		
0	0	0
0		
1	0	0
0		
2	0	0
0		
3	0	0
0		
4	0	0
0		
...
...		
6261	0	0
0		
6262	0	0
0		
6263	0	0
0		
6264	0	0
0		
6265	0	0
0		

	MaritalStatus_Single
0	1
1	1
2	1
3	1
4	1
...	...
6261	0
6262	1
6263	0

```
6264          0
6265          1
```

```
[6266 rows x 32 columns]
```

FEATURE ENGINEERING

Feature Selection

Pada tahap ini, kami tidak menghapus suatu feature sebagai pertimbangan penggunaan semua feature pada tahap modelling

Feature Extraction

Pada feature extraction ini kami menambahkan kolom avg_totalbelanja, aov dan gmv, dengan penjelasan sebagai berikut:

avg_totalbelanja = rata-rata total uang belanja yang harus dibayarkan sebelum coupon/voucher digunakan

aov (average order value)= rata-rata jumlah uang yang dibelanjakan setiap customer tiap bulan

gmv (gross merchandise value)= total pembelian yg terjadi tiap bulan

Pada case ini kamu mengamsumsikan voucher/coupon yang diberikan ecommerce sebesar 10%

```
newX['avg_totalbelanja']=newX['CashbackAmount']*10
newX['aov']=newX['avg_totalbelanja']*0.9
newX['gmv']=newX['aov']*newX['OrderCount']
newX
```

	CustomerID	Tenure	CityTier	WarehouseToHome	Gender
HourSpendOnApp \					
0	50001	-0.647125	3	-1.189416	0
0.666667					
1	50002	-0.033419	1	-0.936189	1
0.666667					
2	50003	-0.033419	1	1.849317	1
0.333333					
3	50004	-1.138089	3	-0.049891	1
0.333333					
4	50005	-1.138089	1	-0.429733	1
0.666667					
...
...					

6261	55450	-1.015348	1	0.187361	0
0.687695					
6262	54585	-1.015348	1	-0.781836	1
0.703181					
6263	50233	-0.060094	3	-1.088522	0
0.345407					
6264	53374	-1.015348	2	1.243140	1
0.666667					
6265	53705	-1.015348	1	0.380744	0
0.723353					

	NumberOfDeviceRegistered	SatisfactionScore	NumberOfAddress
Complain \			
0	-0.903938	0.250000	1.816800
1			
1	0.346286	0.500000	1.040287
1			
2	0.346286	0.500000	0.652031
1			
3	0.346286	1.000000	1.428543
0			
4	-0.903938	1.000000	-0.512738
0			
...
...			
6261	0.346286	1.000000	-0.512738
0			
6262	1.596510	0.054771	-0.342616
0			
6263	0.346286	0.740945	-0.886931
1			
6264	1.530865	0.763127	-0.512738
0			
6265	1.596510	0.792515	-0.380685
0			

... PreferredOrderCat_Laptop & Accessory	
PreferredOrderCat_Mobile \	
0	...
0	1
1	...
1	0
2	...
2	0
1	...
3	1
0	...
4	0
1	...
...	...
.	..

6261	...	0
0		
6262	...	0
0		
6263	...	0
0		
6264	...	0
0		
6265	...	0
0		

	PreferedOrderCat_Mobile Phone	PreferedOrderCat_Others \
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
...
6261	0	0
6262	1	0
6263	0	0
6264	1	0
6265	0	0

	MaritalStatus_Divorced	MaritalStatus_Married
MaritalStatus_Single \		
0	0	0
1		
1	0	0
1		
2	0	0
1		
3	0	0
1		
4	0	0
1		
...
...		
6261	0	0
0		
6262	0	0
1		
6263	0	0
0		
6264	0	0
0		
6265	0	0
1		

avg_totalbelanja

aov

gmv

0	-1.848515	-1.663664	1.797703
1	-11.044724	-9.940251	10.741126
2	-11.190807	-10.071727	10.883194
3	-7.941622	-7.147460	7.723322
4	-8.994839	-8.095355	8.747588
...
6261	-0.421845	-0.379661	-0.201607
6262	-3.694140	-3.324726	-1.765496
6263	-10.487847	-9.439062	10.199557
6264	-4.323919	-3.891527	-2.066479
6265	-5.896246	-5.306621	-2.817922

[6266 rows x 35 columns]