

# Mutual Fund Investment Startup

## ~Python for Data Analytics~

...

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# Python Milestone 1

(Data Cleaning and EDA)



# Analytical Objective

1. There are 4 types of investing such as saham, pasar uang, pendapatan tetap and campuran so customers can choose among those 4 options
2. Because of it is investing company so we gain profit from customers who doing transactIts investing dataset (mutual fund), so we can analyze according to the dataset and macro/micro economic
3. Profit comes from transactions fee (buy and sell fee) or profit sharing if gaining capital gain

# Data Cleaning Users

## Copy

- Make a copy as `df_users_dc`

## Checking Data Types

- Melihan ukuran row x kolom dengan `.shape()`
- Melihat informasi keseluruhan dengan `.info()`
- Mencari nilai blank
- Convert kolom data (object) menjadi datetime
- Mengubah `user_id` menjadi string karena tidak diperlukan dalam proses operasi

## Treat Missing / Irrelevant Values

- Drop `user_occupation` and `user_income_source` becaus irrelevant
- In `referral_code_used` replace blank values with unknown

## Check for Values & Typo

- Check values each columns

# Data Cleaning Users

Data Manipulation

- Clustering for each income range into 3 categories to make easier to identify

Checking Duplicates

- No duplicates found

# Data Cleaning Daily Transaction

## Copy

- Make a copy as `df_DT_dc`

## Checking Data Types

- Melihat ukuran row x kolom dengan `.shape()`
- Melihat informasi keseluruhan dengan `.info()`
- Mencari nilai blank
- Convert kolom data (object) menjadi datetime
- Mengubah `user_id` menjadi string karena tidak diperlukan dalam proses operasi

## Treat Missing / Irrelevant Values

- There are many missing values in the dataset. But it doesn't mean we can just remove it. 0 or blank values means there is no transaction not there is no data. So, yes I consider it as data
- The information we can take from zero/blank data is the frequency of the transaction, so 0/blank values will be treated in data manipulation part

# Data Cleaning Daily Transaction

## Data Manipulation

- From daily transaction dataset we can take some information such number of frequencies an user balanced
- In this part I split "Daily transaction" into 2 separated dataset
- Those are frequency dataset and last balanced of user\_id

### Find the Frequencies

- Make a copy from "df\_DT\_dc" as "df\_DT\_freq"
- Find the number of frequencies by using .count() function
- add frequencies between buy and sell, also drop the columns amount because we just got the information we needed

### Find User Balance

- Make a copy from "df\_DT\_dc" as "df\_DT\_balance"
- Sort by user\_id and date to find out the last balance
- Rename column to make it compact
- Drop duplicates and keep the last one (after sorted) to get the last balance in the last date
- Merge "Frequencies Table" and "Balance Table" as "df\_daily\_tran"
- Merge "df\_users" and "df\_daily\_tran" as "df\_merged"

# Exploratory Data Analytics (EDA)

1. Make a copy from df.merged as df\_eda
2. Analyze the characteristic of the table with .info() function
3. Descriptive analysis about numeric information

```
pd.set_option('display.float_format', lambda x: '%.3f' % x)

numeric = ['user_age', 'end_of_month_invested_amount', 'total_buy_amount',
           'total_sell_amount', 'Saham_Freq', 'Pasar_Uang_Freq', 'Pend_Tetap_Freq',
           'Campuran_Freq', 'saham_bal', 'uang_bal', 'pend_tetapbal', 'campuran_bal', 'total_balance']

desc_eda = df_eda[numeric].describe()
desc_eda.loc['kurtosis'] = df_eda[numeric].kurt() #show kurtosis statistic
desc_eda.loc['skewness'] = df_eda[numeric].skew() #show Skewness statistic
desc_eda.loc['variance'] = df_eda[numeric].var() #show variance statistic
desc_eda.round(2)
```

[Colab Link](#)

# Exploratory Data Analytics (EDA)

## 4. Descriptive analysis about string variable

```
objects = ['user_id',  
           'user_gender',  
           'user_income_range',  
           'referral_code_used']  
df_eda[objects].describe()
```

|        | user_id | user_gender | user_income_range | referral_code_used |
|--------|---------|-------------|-------------------|--------------------|
| count  | 8277    | 8277        | 8277              | 8277               |
| unique | 8277    | 2           | 3                 | 2                  |
| top    | 3816789 | Male        | silver            | unknown            |
| freq   | 1       | 5176        | 6233              | 5322               |



# Exploratory Data Analytics (EDA)

## 5. Descriptive analysis about date type variable

```
df_eda['registration_import_datetime'].describe()
```

## 6. Number of Customer

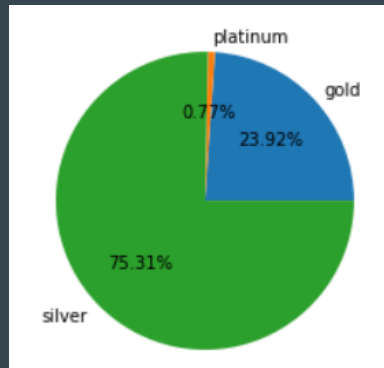
```
[90] #Number of customer  
df_eda['user_id'].count()
```

8277

## 7. User\_income\_range

```
#Count the id as users and group it by the loan status  
#Reset the index to make it into a pandas dataframe  
  
income_category = df_eda.groupby('user_income_range')['user_id'].count()  
income_category = income_category.reset_index()  
income_category
```

|   | user_income_range | user_id |
|---|-------------------|---------|
| 0 | gold              | 1980    |
| 1 | platinum          | 64      |
| 2 | silver            | 6233    |

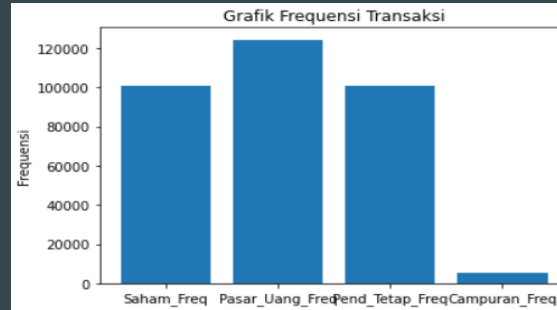


# Exploratory Data Analytics (EDA)

## 8. Transaction Frequency

```
Saham_Freq = df_eda['Saham_Freq'].sum()
Pasar_Uang_Freq = df_eda['Pasar_Uang_Freq'].sum()
Pend_Tetap_Freq = df_eda['Pend_Tetap_Freq'].sum()
Campuran_Freq = df_eda['Campuran_Freq'].sum()

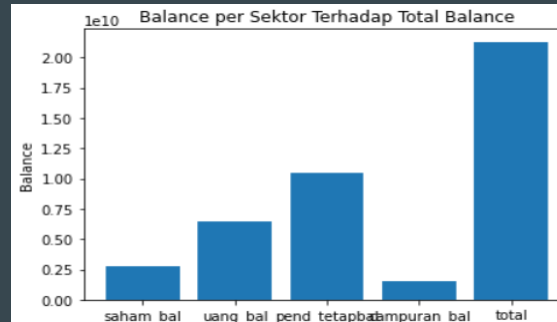
print(f"saham freq: {Saham_Freq}")
print(f"uang freq: {Pasar_Uang_Freq}")
print(f"pendapatan tetap freq: {Pend_Tetap_Freq}")
print(f"campuran freq: {Campuran_Freq}")
```



## 9. Sector Balance to Total Balance

```
saham_bal = df_eda['saham_bal'].sum()
uang_bal = df_eda['uang_bal'].sum()
pend_tetapbal = df_eda['pend_tetapbal'].sum()
campuran_bal = df_eda['campuran_bal'].sum()
total = df_eda['total_balance'].sum()

print(f"saham balance: {saham_bal}")
print(f"uang balance: {uang_bal}")
print(f"pendapatan tetap balance: {pend_tetapbal}")
print(f"campuran balance: {campuran_bal}")
print(f"total: {total}")
```



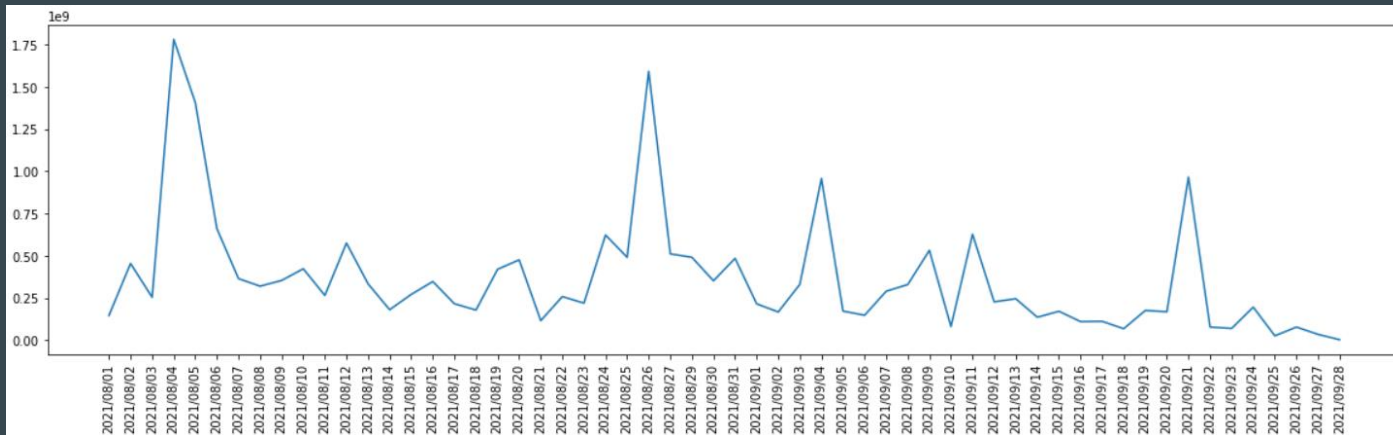
# Exploratory Data Analytics (EDA)

## 8. Trend

```
plt.figure(figsize=(20, 5))

plt.xticks(rotation=90)
plt.plot(transaction_trend['trans_date'], transaction_trend['total_balance'])

plt.show()
```



# Exploratory Data Analytics (EDA)

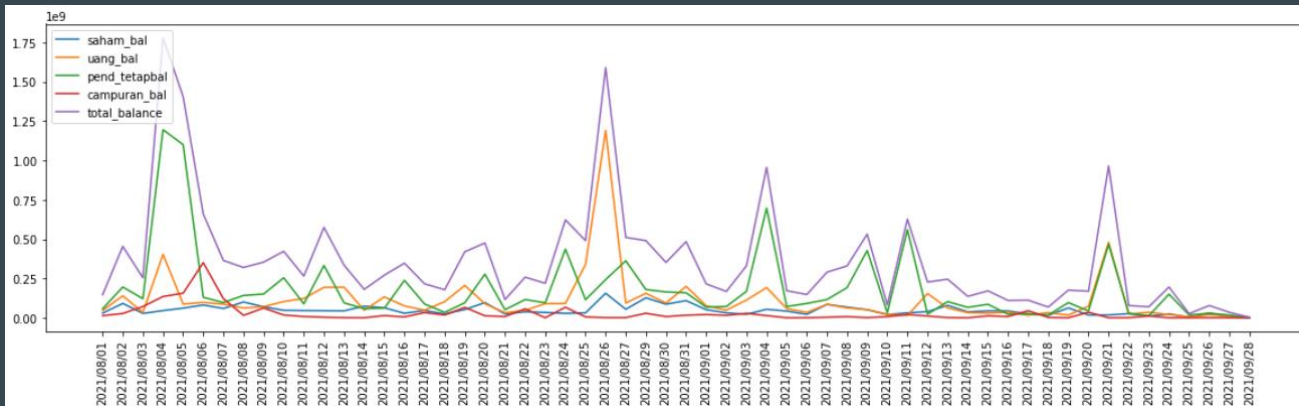
## 9. Trend Each Product

```
#Create line chart
plt.figure(figsize =(20, 5))
axis = transaction_trend2.columns.tolist()
#axis.head()

for x in axis[1:]: #
    plt.plot(transaction_trend2['trans_date'], transaction_trend2[x])

plt.xticks(rotation = 90)
plt.legend(transaction_trend2.iloc[:,1:],loc = 2)

plt.show()
```



# Python Milestone 2

(Segmentation and Clustering Analysis)



# Related Variable

In this case I want to make cluster according Total\_Freq and total\_balance

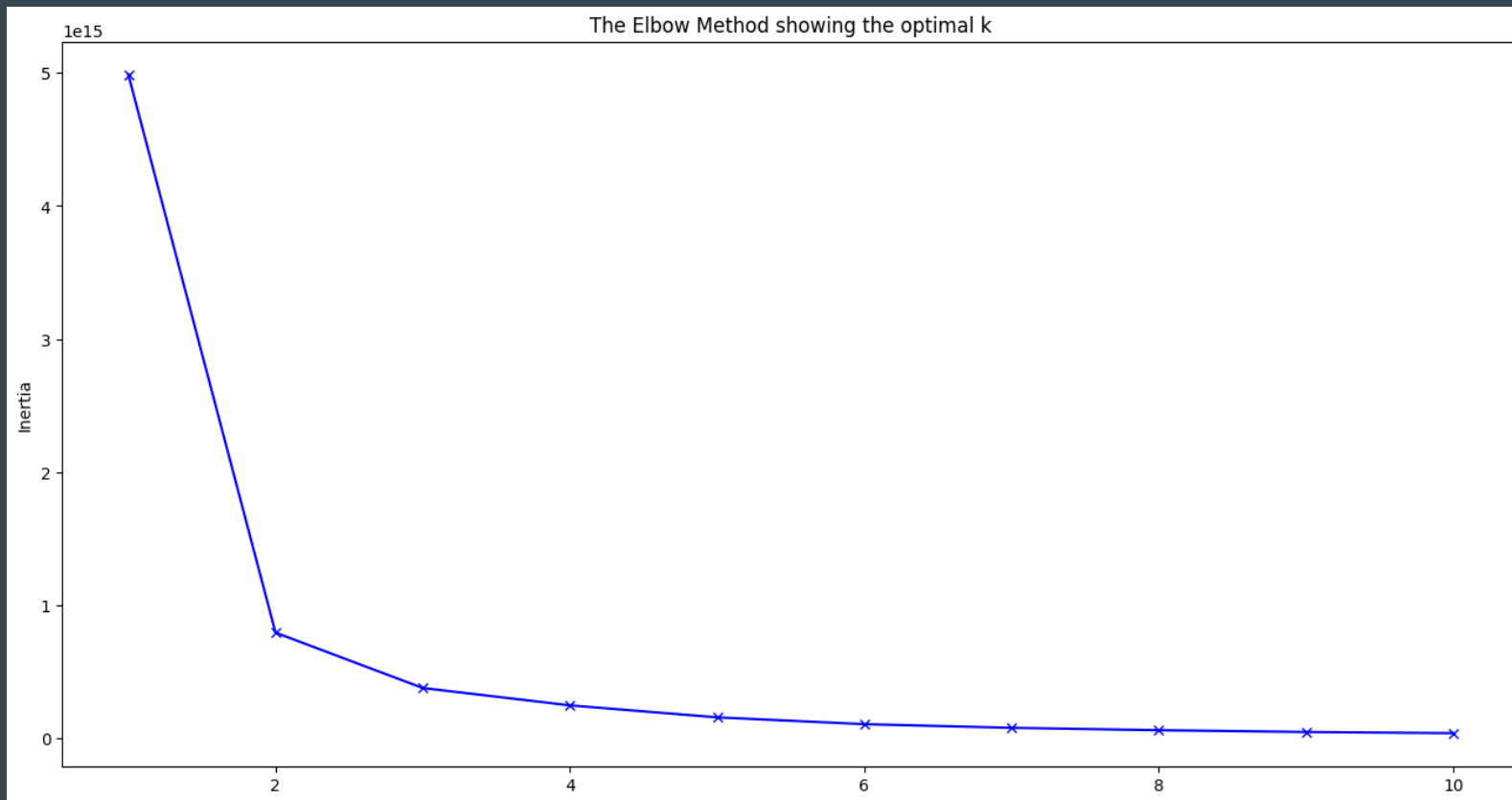
1. Total\_Freq is chosen because as fund managers, we gain profit from buy/sell transaction fee. So more often costumers doing transactions, we gain more profit
2. total\_balance reflect the buying power of each customers.

Some points we have to notice are it is normal when customers dont have either balance or frequencies in their account. Because investors divided into some classes

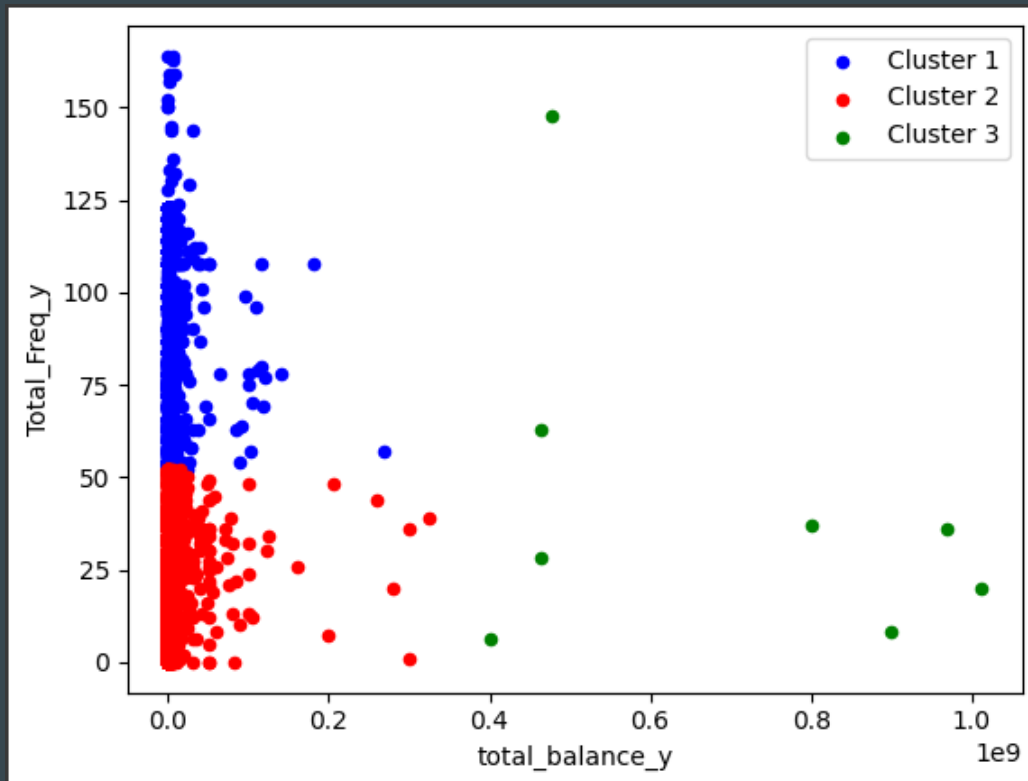
1. Short term investors = Usually high frequencies, prefer cash in the end of month/quarter (0 balance at the end of the month)
2. Long term investors = Low frequencies, making deep analysis of the market before enter positions. As soon as they enter the market, they keep their positions for years at least 1 year

# Elbow Method

[Colab Link](#)



# Clustering



[Colab Link](#)

# Segmentation

| x                        | 0            | 1            | 2              |
|--------------------------|--------------|--------------|----------------|
| Gender                   | Male         | Male         | Female         |
| Age                      | 26           | 27           | 39             |
| Income Range             | Silver       | Silver       | Gold           |
| Total Frequency          | 20           | 83           | 43             |
| Total Balance            | 1.716.676,29 | 2.349.707,50 | 685.778.338,25 |
| Total Transaction        | 916.760,04   | 2.348.775,22 | 455.228.150,50 |
| Saham Balance            | 444.725,37   | 587.351,74   | 6.500.000      |
| Pasar Uang Balance       | 726.924,01   | 643.763,58   | 435.568.988,75 |
| Pendapatan Tetap Balance | 1.377.780,66 | 1.069.620,35 | 527.564.393    |
| Campuran Balance         | 9.171.888,25 | 2.890.038,29 | 12.666.666,60  |



**Learner investors,**  
Contribute 0,1% of  
total transaction

**Experience investors,**  
high frequency of  
transaction.  
Contribute 0,5% of  
total transaction

**Big money, long  
term investors, give  
99% contribution of  
total transaction**

# Cluster 0 (Learner Investors)

| x                        | 0            |
|--------------------------|--------------|
| Gender                   | Male         |
| Age                      | 26           |
| Income Range             | Silver       |
| Total Frequency          | 20           |
| Total Balance            | 1.716.676,29 |
| Total Transaction        | 916.760,04   |
| Saham Balance            | 444.725,37   |
| Pasar Uang Balance       | 726.924,01   |
| Pendapatan Tetap Balance | 1.377.780,66 |
| Campuran Balance         | 9.171.888,25 |

## Recommendations :

1. Give more promotions to gain more transactions or top up on their accounts
2. Give education about investing through short videos or articles
3. Give promotions with referral because this cluster is huge in numbers

# Cluster 1 (Experience Investors)

| x                        | 1            |
|--------------------------|--------------|
| Gender                   | Male         |
| Age                      | 27           |
| Income Range             | Silver       |
| Total Frequency          | 83           |
| Total Balance            | 2.349.707,50 |
| Total Transaction        | 2.348.775,22 |
| Saham Balance            | 587.351,74   |
| Pasar Uang Balance       | 643.763,58   |
| Pendapatan Tetap Balance | 1.069.620,35 |
| Campuran Balance         | 2.890.038,29 |

## Recommendations :

1. Give advance education about retirement income from investing
2. Give promotion or coupon from referral because this cluster is huge in numbers

# Cluster 2 (Big Money)

| x                        | 2              |
|--------------------------|----------------|
| Gender                   | Female         |
| Age                      | 39             |
| Income Range             | Gold           |
| Total Frequency          | 43             |
| Total Balance            | 685.778.338,25 |
| Total Transaction        | 455.228.150,50 |
| Saham Balance            | 6.500.000      |
| Pasar Uang Balance       | 435.568.988,75 |
| Pendapatan Tetap Balance | 527.564.393    |
| Campuran Balance         | 12.666.666,60  |

## Recommendations :

1. Give transaction fee discount
2. Low profit sharing to fund managers

# Python Milestone 3

(Python Logistic Regression Model)

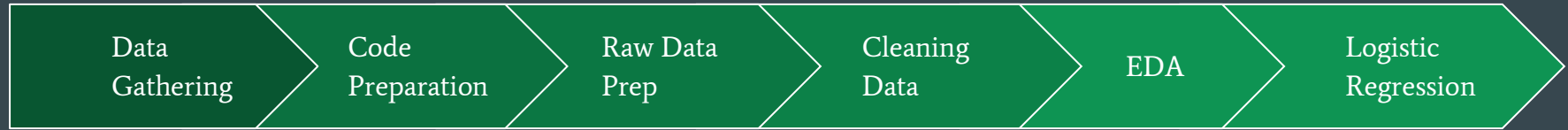


# Understanding Business Problem

1. Mutual Investment Company has some investment products : stocks, bond, money market, and mixed investment mutual funds
2. Company has some issues such as churn rate, and limitation of campaign budget (30%) and it give impact to the company profit
3. According to previous data, cost per campaign is Rp1.000 and the transaction fee (buy and sell) is 0,15%



# Steps



# Code Preparation

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import cluster
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
```

[Colab Link](#)

# Raw Data Preparation

| user_id | registration_import_datetime | user_gender | user_age | user_income_range | referral_code_used | Total_Transaction | Saham_Freq | Pasar_Uang_Freq | Pend_Tetap_Freq |
|---------|------------------------------|-------------|----------|-------------------|--------------------|-------------------|------------|-----------------|-----------------|
| 3651808 | 2021-09-12 13:05:04          | Male        | 52       | silver            | no referral        | 0                 | 11         | 11              | 11              |
| 3934978 | 2021-08-30 14:26:12          | Male        | 21       | silver            | no referral        | 238604            | 20         | 20              | 20              |
| 3944498 | 2021-08-31 20:37:09          | Male        | 17       | silver            | no referral        | 160000            | 19         | 19              | 19              |
| 3980156 | 2021-09-05 07:08:38          | Male        | 24       | silver            | used referral      | 10000             | 16         | 16              | 16              |

| Campuran_Freq | Total_Freq | date       | saham_bal | uang_bal  | pend_tetapbal | campuran_bal | total_balance | churn |
|---------------|------------|------------|-----------|-----------|---------------|--------------|---------------|-------|
| 0             | 33         | 2021-09-30 | 30000.000 | 10000.000 | 60000.000     | 0.000        | 100000        | 1     |
| 0             | 60         | 2021-09-30 | 800.000   | 87804.000 | 110000.000    | 0.000        | 198604        | 1     |
| 0             | 57         | 2021-09-30 | 0.000     | 0.000     | 40000.000     | 0.000        | 40000         | 0     |
| 0             | 48         | 2021-09-30 | 0.000     | 0.000     | 0.000         | 0.000        | 0             | 0     |

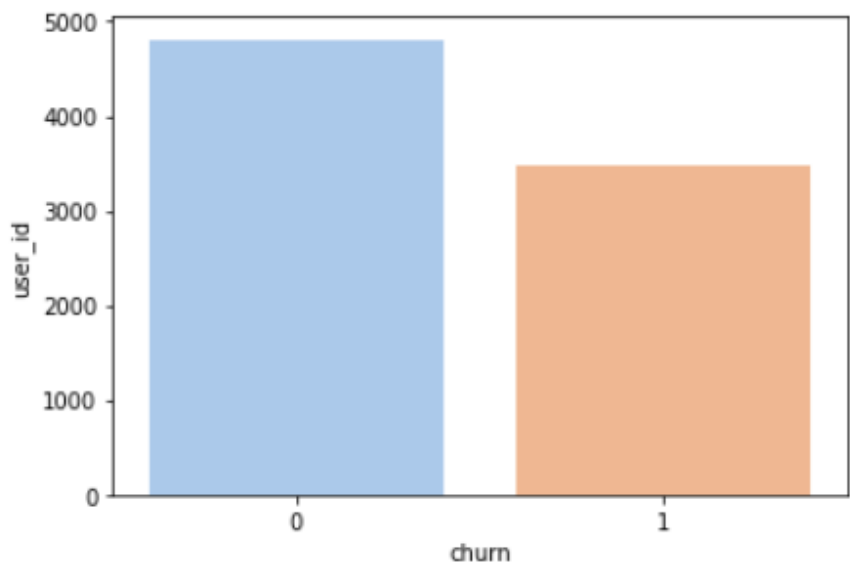
# Category of each variable

```
numerical_column = ['user_age', 'Total_Transaction', 'Saham_Freq', 'Pasar_Uang_Freq', 'Pend_Tetap_Freq', 'Campuran_Freq',  
                    'Total_Freq', 'saham_bal', 'uang_bal', 'pend_tetapbal', 'campuran_bal', 'total_balance']  
binary_categorical_column = ['user_gender', 'referral_code_used']  
polytomous_categorical_column = ['user_income_range']  
all_categorical_column = binary_categorical_column + polytomous_categorical_column
```



# EDA

```
user_id
churn
0      4809
1      3468
<AxesSubplot:xlabel='churn', ylabel='user_id'>
```

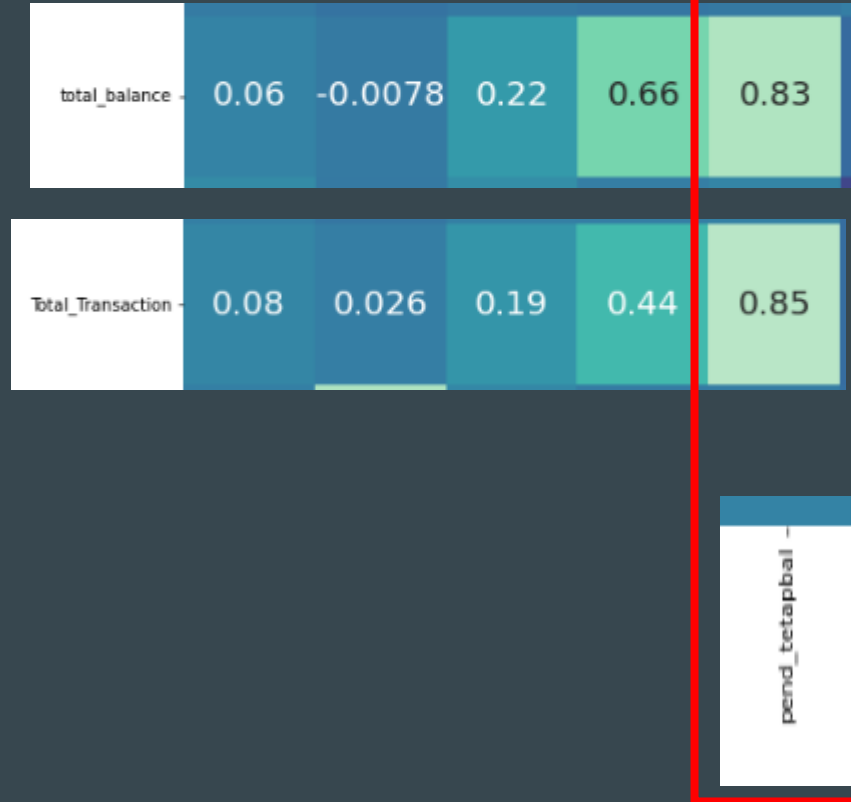
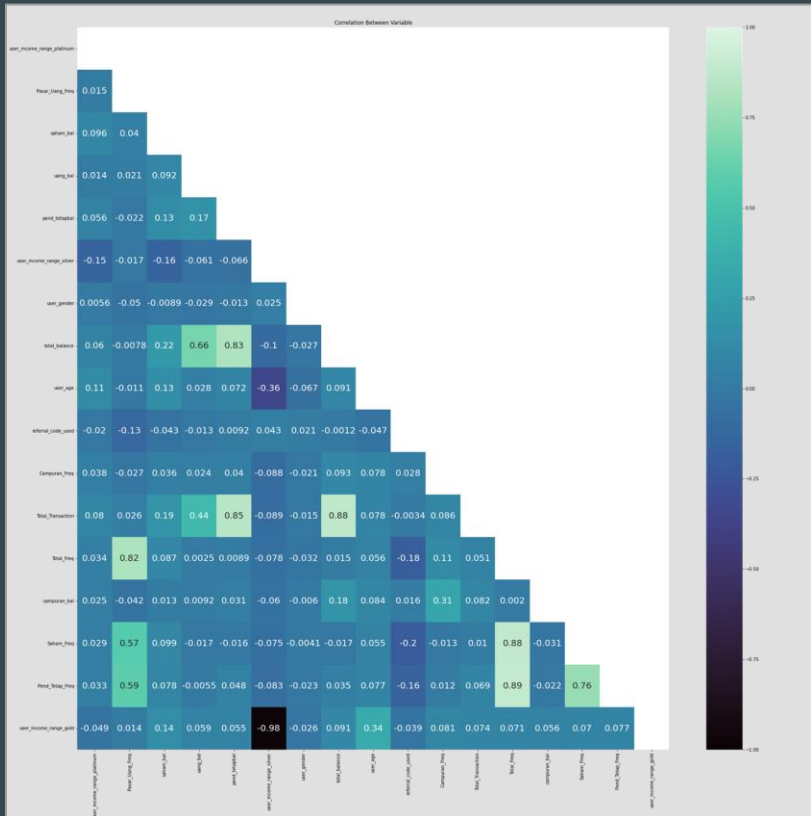


churn rate

$$3468 / (4809 + 3468) = 0,418$$



# Uji Korelasi dan Contoh



# Drop High Correlation Var

```
# Create correlation matrix
corr_matrix = df_churn_new.corr().abs()

# Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))

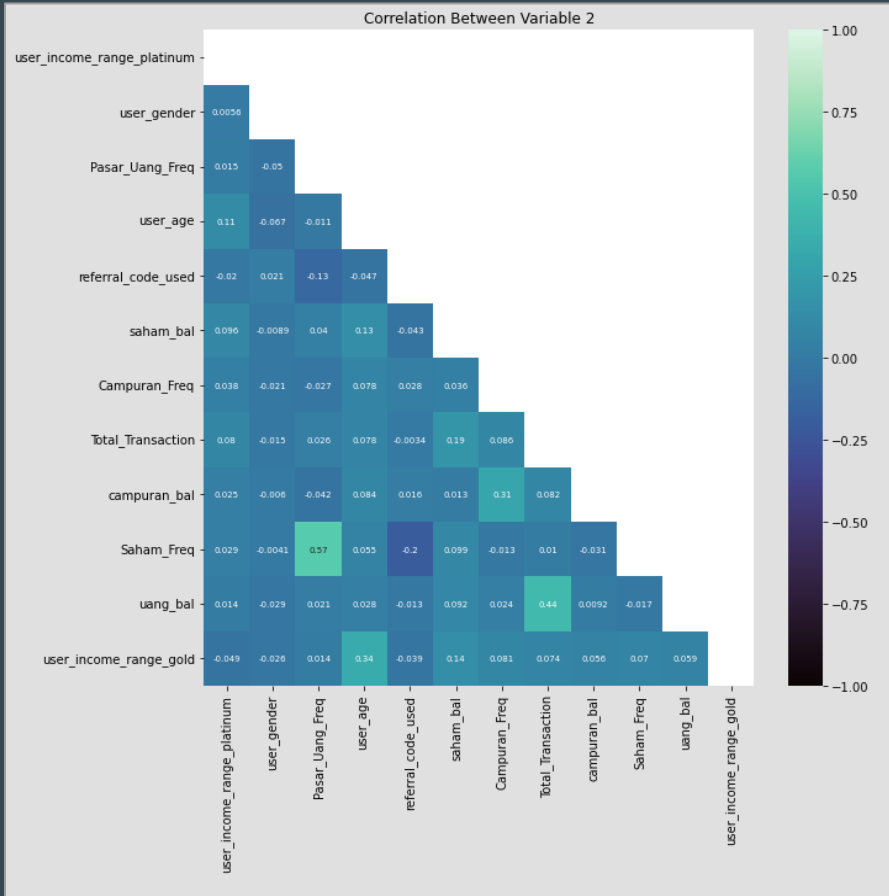
# Find features with correlation greater than 0.7, and add into to_drop list
to_drop = [column for column in upper.columns if any(upper[column] > 0.7)]
to_drop
```

```
['Pend_Tetap_Freq',
 'Total_Freq',
 'pend_tetapbal',
 'total_balance',
 'user_income_range_silver']
```



Dropped columns

# New Correlation After Drop Column



# Fit Logistic Regression - Accuracy Rate

```
model = LogisticRegression(class_weight='balanced',max_iter=500)
model.fit(x_training, y_training)
```

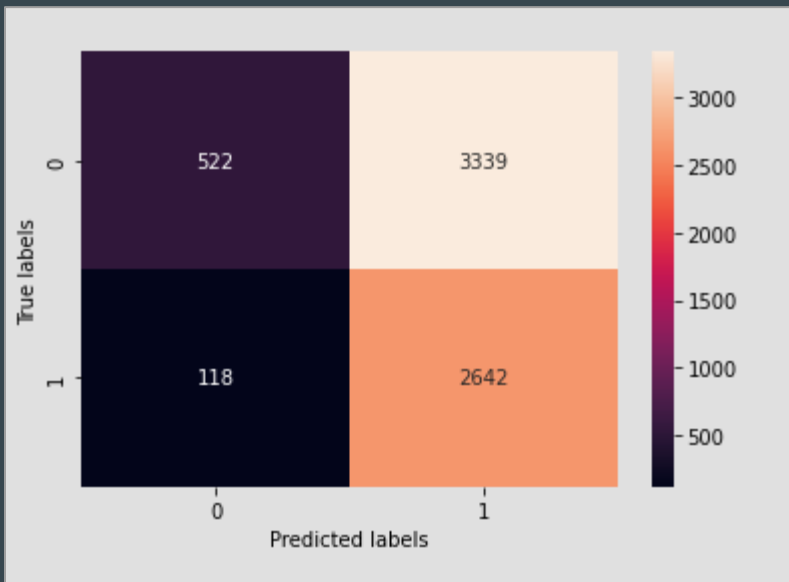
```
LogisticRegression
LogisticRegression(class_weight='balanced', max_iter=500)
```

```
# Accuracy dr prediksi model dengan data training
model.score(x_training, y_training)
```

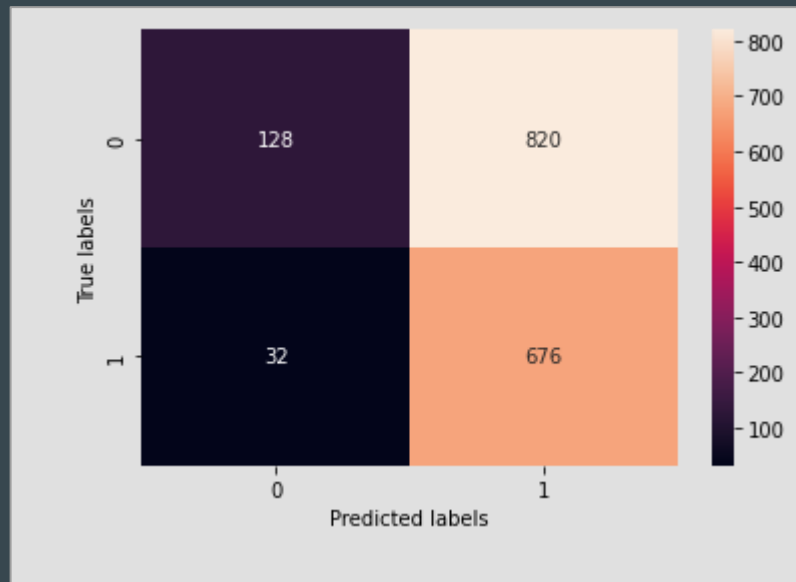
```
0.4778734330161607
```



# Confusion Matrix & Performance Test



|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Not Churn    | 0.82      | 0.14   | 0.23     | 3861    |
| Churn        | 0.44      | 0.96   | 0.60     | 2760    |
| accuracy     |           |        | 0.48     | 6621    |
| macro avg    | 0.63      | 0.55   | 0.42     | 6621    |
| weighted avg | 0.66      | 0.48   | 0.39     | 6621    |



|              | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| Not Churn    | 0.80      | 0.14   | 0.23     | 948     |
| Churn        | 0.45      | 0.95   | 0.61     | 708     |
| accuracy     |           |        | 0.49     | 1656    |
| macro avg    | 0.63      | 0.54   | 0.42     | 1656    |
| weighted avg | 0.65      | 0.49   | 0.39     | 1656    |

# Benefit Cost Analysis (Transaction Fee)

|   | user_id | Total_Transaction | fee_trans |
|---|---------|-------------------|-----------|
| 0 | 3816789 | 100000            | 150.000   |
| 1 | 3802293 | 8500000           | 12750.000 |
| 2 | 3049927 | 149000            | 223.500   |
| 3 | 3836491 | 0                 | 0.000     |
| 4 | 3783302 | 2889569           | 4334.354  |

$\text{fee\_trans} = 0,15\% \times \text{Total\_Transaction}$

= Rp 22.001.245,962

```
user_id      3802293378330237226103787202383709937402903768...
Total_Transaction  14667407309
fee_trans      22001245.962
Churn          1207
dtype: object
```

```
# Get 70% threshold of profit
prft70_threshold = df_tot_trans['fee_trans'].quantile(0.7)

# Get top 70% customers
prft70_customer = df_tot_trans[df_tot_trans['fee_trans'] > prft70_threshold]

# Merge with actual churn outcome
prft70_customer = prft70_customer.merge(y, left_index = True, right_index = True)
prft70_customer.sum()
```

fee\_trans  
Quantile 70%

# Benefit Cost Analysis (Churn Customers)

|    | predicted_score | churn | Flag         |
|----|-----------------|-------|--------------|
| 0  | 0.532           | 0     | Medium Churn |
| 1  | 0.983           | 0     | Mostly Churn |
| 5  | 0.527           | 1     | Medium Churn |
| 8  | 0.519           | 1     | Medium Churn |
| 10 | 0.670           | 1     | Mostly Churn |

```
pct70_customer['churn'].value_counts()
```

```
1    1603
```

```
0     880
```

```
Name: churn, dtype: int64
```

```
def threshold_category(pct70_customer):  
  
    if (pct70_customer['predicted_score'] <= 0.3 ):  
        return 0  
    elif (pct70_customer['predicted_score'] > 0.3) and (pct70_customer['predicted_score'] <= 0.6):  
        return 'Medium Churn'  
    else:  
        return 'Mostly Churn'  
  
pct70_customer['Flag'] = pct70_customer.apply(threshold_category, axis = 1)  
pct70_customer
```

# Potential Benefit per Campaign

If case transaction fee = 0,15%

Cost campaign = Rp 1000

Churn users = 1603

Potential Benefit = 22.001.245,962 - (Rp1000 x  
1603)

= Rp 20.398.245,962

**THANKS FOR YOUR ATTENTION**