Start coding or generate with AI.

Calculate the Customer Life Time Value (CLTV)

RFM METHOD

```
import numpy as np
import pandas as pd
import time
import datetime as dt
```

```
df = pd.read_csv("/content/customer_purchases.csv")
```

```
df.head()
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	12/1/2010 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	12/1/2010 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	12/1/2010 8:26	2.75	17850.0	United Kingdom
	[illegible]	[illegible]	KNITTED UNION FLAG HOT WATER	[illegible]	12/1/2010	[illegible]	[illegible]	United

```
df['date'] = pd.DatetimeIndex(df['InvoiceDate']).date
```

```
recency_df = df.groupby(by='CustomerID', as_index=False)['date'].max()
recency_df.columns = ['CustomerID','LastPurshaceDate']
```

```
recent_date=recency_df.LastPurshaceDate.max()
print(recent_date)
```

```
2011-12-09
```

```
recency_df['Recency'] = recency_df['LastPurshaceDate'].apply(lambda x: (recent_date - x).days)
recency_df.head()
```

	CustomerID	LastPurshaceDate	Recency
0	12346.0	2011-01-18	325
1	12347.0	2011-12-07	2
2	12348.0	2011-09-25	75
3	12349.0	2011-11-21	18
4	12350.0	2011-02-02	310

```
# ## Frequency
```

```
# Dropping duplicates
df1= df
df1.drop_duplicates(subset=['InvoiceNo', 'CustomerID'], keep="first", inplace=True)
```

```
# Calculating the frequency of purchases
frequency_df = df1.groupby(by=['CustomerID'], as_index=False)['InvoiceNo'].count()
frequency_df.columns = ['CustomerID','Frequency']
frequency_df.head()
```

	CustomerID	Frequency

```
## Monetary
df['TotalCost'] = df['Quantity'] * df['UnitPrice']
monetary_df = df.groupby(by='CustomerID',as_index=False).agg({'TotalCost': 'sum'})
monetary_df.columns = ['CustomerID','Monetary']
monetary_df.head()
```

	CustomerID	Monetary
0	12346.0	0.00
1	12347.0	163.16
2	12348.0	331.36
3	12349.0	15.00
4	12350.0	25.20

```
## Creating RFM Table
temp_df = recency_df.merge(frequency_df,on='CustomerID')
temp_df.head()
```

	CustomerID	LastPurshaceDate	Recency	Frequency
0	12346.0	2011-01-18	325	2
1	12347.0	2011-12-07	2	7
2	12348.0	2011-09-25	75	4
3	12349.0	2011-11-21	18	1
4	12350.0	2011-02-02	310	1

```
rfm_df = temp_df.merge(monetary_df,on='CustomerID')
```

```
# Using CustomerID as index
rfm_df.set_index('CustomerID',inplace=True)
rfm_df.head()
```

	LastPurshaceDate	Recency	Frequency	Monetary
CustomerID				
12346.0	2011-01-18	325	2	0.00
12347.0	2011-12-07	2	7	163.16
12348.0	2011-09-25	75	4	331.36
12349.0	2011-11-21	18	1	15.00
12350.0	2011-02-02	310	1	25.20

```
# Ranking the each metric R , F & M
rfm_df['R_rank'] = rfm_df['Recency'].rank( ascending=False)
rfm_df['F_rank'] = rfm_df['Frequency'].rank(ascending=True)
rfm_df['M_rank'] = rfm_df['Monetary'].rank(ascending=True)
rfm_df.head()
# normalizing each rank with Max rank
rfm_df['R_rank_norm']=(rfm_df['R_rank']/rfm_df['R_rank'].max())*100
rfm_df['F_rank_norm']=(rfm_df['F_rank']/rfm_df['F_rank'].max())*100
rfm_df['M_rank_norm']=(rfm_df['F_rank']/rfm_df['M_rank'].max())*100
rfm_df.head()

rfm_df['RFM_Score']=0.15*rfm_df['R_rank_norm']+0.28*rfm_df['F_rank_norm']+0.57*rfm_df['M_rank_norm']
rfm_df=rfm_df.round(0)
rfm_df.head()
```

LastPurshaceDate Recency Frequency Monetary R_rank F_rank M_rank F

Segmenting customers based on RFM score

0 - 50 - Low valued customer

50 - 75 - Medium valued customer

76 - 100 - High valued customer

```
rfm_df["Customer_segment"]=np.where(rfm_df['RFM_Score'] > 75 ,"High Value Customer",(np.where(rfm_df['RFM_Score'] < 50 , "Low value Cus
rfm_df.head()
```

	LastPurshaceDate	Recency	Frequency	Monetary	R_rank	F_rank	M_rank	F
CustomerID								
12346.0	2011-01-18	325	2	0.0	169.0	1722.0	178.0	
12347.0	2011-12-07	2	7	163.0	4171.0	3560.0	3579.0	
12348.0	2011-09-25	75	4	331.0	1642.0	2809.0	3976.0	

```
#PREDECTIVE MODELLING
```

Q.2 Predective Modeling , Probabilistic Model

```
pip install lifetimes
```

```
Requirement already satisfied: lifetimes in /usr/local/lib/python3.10/dist-packages (0.11.3)
Requirement already satisfied: numpy>=1.10.0 in /usr/local/lib/python3.10/dist-packages (from lifetimes) (1.23.5)
Requirement already satisfied: scipy>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from lifetimes) (1.11.4)
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.10/dist-packages (from lifetimes) (1.5.3)
Requirement already satisfied: autograd>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from lifetimes) (1.6.2)
Requirement already satisfied: dill>=0.2.6 in /usr/local/lib/python3.10/dist-packages (from lifetimes) (0.3.7)
Requirement already satisfied: future>=0.15.2 in /usr/local/lib/python3.10/dist-packages (from autograd>=1.2.0->lifetimes) (0.18.3)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.0->lifetimes) (
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=0.24.0->lifetimes) (2023.3.pos
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1->pandas>=0.24.0->li
```

```
import lifetimes
import matplotlib.pyplot as plt
```

```
import matplotlib.pyplot as plt
features = ['CustomerID', 'InvoiceNo', 'InvoiceDate', 'Quantity', 'UnitPrice']
data_clv = df[features]
data_clv['TotalSales'] = data_clv['Quantity'].multiply(data_clv['UnitPrice'])
data_clv['InvoiceDate'] = pd.to_datetime(data_clv['InvoiceDate'])
print(data_clv.shape)
data_clv.head()
```

(25900, 6)

	CustomerID	InvoiceNo	InvoiceDate	Quantity	UnitPrice	TotalSales
0	17850.0	536365	2010-12-01 08:26:00	6	2.55	15.30
7	17850.0	536366	2010-12-01 08:28:00	6	1.85	11.10
9	13047.0	536367	2010-12-01 08:34:00	32	1.69	54.08
21	13047.0	536368	2010-12-01 08:34:00	6	4.25	25.50
25	13047.0	536369	2010-12-01 08:35:00	3	5.95	17.85

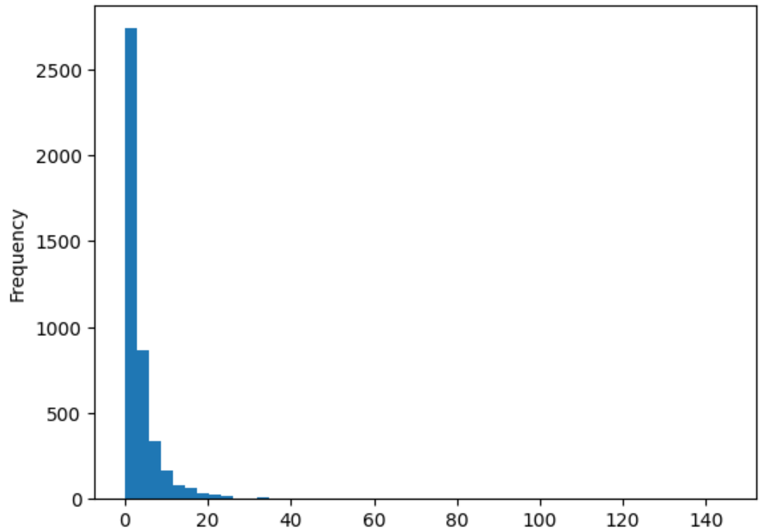
```
summary = lifetimes.utils.summary_data_from_transaction_data(data_clv, 'CustomerID','InvoiceDate','TotalSales')
summary = summary.reset_index()
summary.head()
```

	CustomerID	frequency	recency	T	monetary_value
0	12346.0	0.0	0.0	325.0	0.000000
1	12347.0	6.0	365.0	367.0	22.993333
2	12348.0	3.0	283.0	358.0	97.253333
3	12349.0	0.0	0.0	18.0	0.000000
4	12350.0	0.0	0.0	310.0	0.000000

```
summary['frequency'].plot(kind='hist', bins=50)
plt.show()

# Display summary statistics
print(summary['frequency'].describe())
print("---")

# Calculate percentage of one-time buyers
one_time_buyers = round((sum(summary['frequency'] == 1) / len(summary)) * 100, 2)
print(f"Percentage of customers purchasing the item only once: {one_time_buyers}%")
```




```
count    4372.000000
mean        3.413541
std         6.674343
min         0.000000
25%         0.000000
50%         1.000000
75%         4.000000
max       145.000000
Name: frequency, dtype: float64
---
Percentage of customers purchasing the item only once: 19.62%
```

```
#Fitting the BG/NBD model
bgf = lifetimes. BetaGeoFitter (penalizer_coef=0.0)
bgf.fit(summary['frequency'], summary['recency'], summary['T'])
```

```
<lifetimes.BetaGeoFitter: fitted with 4372 subjects, a: 0.02, alpha: 55.62, b: 0.49, r: 0.84>
```

```
bgf.summary
```

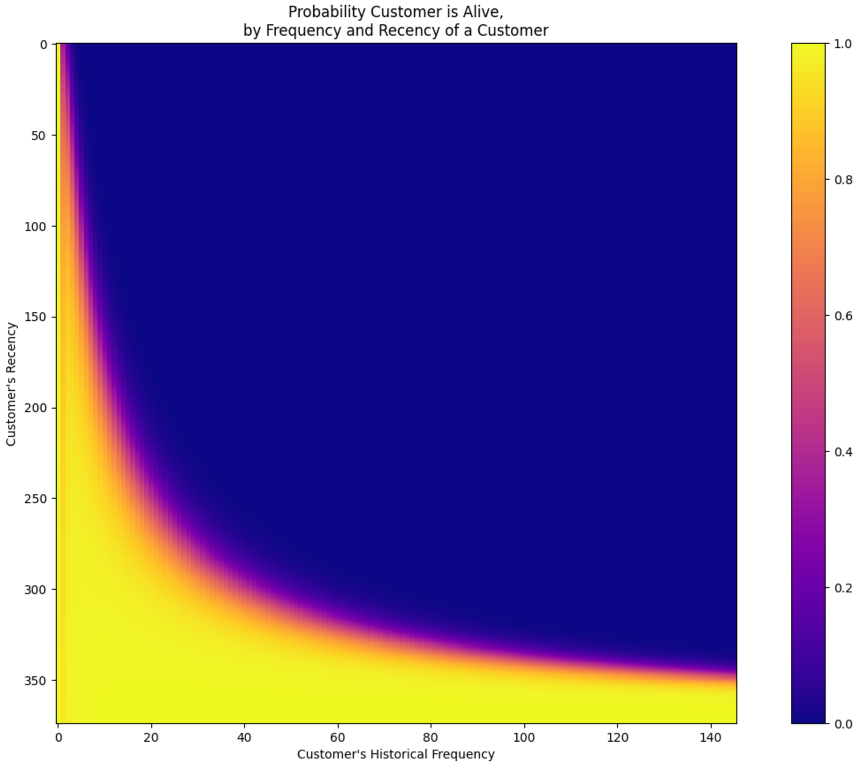
	coef	se(coef)	lower 95% bound	upper 95% bound
r	0.843025	0.026206	0.791661	0.894389
alpha	55.619383	2.088118	51.526671	59.712095
a	0.021519	0.006381	0.009012	0.034026
b	0.488673	0.176970	0.141812	0.835534

```
summary['probability_alive'] = bgf.conditional_probability_alive (summary['frequency'], summary['recency'], summary['T'])
summary.head()
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive
0	12346.0	0.0	0.0	325.0	0.000000	1.000000
1	12347.0	6.0	365.0	367.0	22.993333	0.995966
2	12348.0	3.0	283.0	358.0	97.253333	0.981687
3	12349.0	0.0	0.0	18.0	0.000000	1.000000
4	12350.0	0.0	0.0	310.0	0.000000	1.000000

```
from lifetimes.plotting import plot_probability_alive_matrix

fig = plt.figure(figsize=(16, 10))
plot_probability_alive_matrix(bgf, cmap='plasma')
plt.show()
```




```
t = 30
summary['pred_num_txn'] = round(bgf.conditional_expected_number_of_purchases_up_to_time(t, summary['frequency'], summary['recency'], su
top_10_customers = summary.sort_values(by='pred_num_txn', ascending=False).head(10)
top_10_customers.reset_index(inplace=True)
top_10_customers
```

	index	CustomerID	frequency	recency	T	monetary_value	probability_alive	p
0	1895	14911.0	145.0	372.0	373.0	45.236483	0.999791	
1	4042	17841.0	112.0	372.0	373.0	9.544821	0.999749	
2	330	12748.0	114.0	373.0	373.0	5.457982	0.999810	
3	2192	15311.0	90.0	373.0	373.0	43.113222	0.999760	
4	568	13089.0	82.0	367.0	369.0	44.713902	0.999610	

```
#checking the relationship between frequency and monetary_value
return_customers_summary = summary[summary['frequency']>0]
print(return_customers_summary.shape)
return_customers_summary.head()
```

```
(2991, 7)
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive	pred_nu
1	12347.0	6.0	365.0	367.0	22.993333	0.995966	
2	12348.0	3.0	283.0	358.0	97.253333	0.981687	
5	12352.0	6.0	260.0	296.0	-26.291667	0.991857	
9	12356.0	2.0	303.0	325.0	25.950000	0.983167	
11	12358.0	1.0	149.0	150.0	142.800000	0.957457	

```
#checking the relationship between frequency and monetary_value
return_customers_summary[['frequency','monetary_value']].corr()
```

	frequency	monetary_value
frequency	1.000000	0.072713
monetary_value	0.072713	1.000000

```
return_customers_summary = return_customers_summary[return_customers_summary['monetary_value'] > 0]
```

```
ggf = lifetimes.GammaGammaFitter(penalizer_coef=0.001)
ggf.fit(return_customers_summary['frequency'], return_customers_summary['monetary_value'])
```

```
<lifetimes.GammaGammaFitter: fitted with 2681 subjects, p: 2.23, q: 1.06, v: 5.24>
```

```
ggf.summary
```

	coef	se(coef)	lower 95% bound	upper 95% bound
p	2.232904	0.095091	2.046526	2.419282
q	1.061704	0.028088	1.006651	1.116757
v	5.237124	0.274339	4.699419	5.774829

```
summary = summary[summary['monetary_value']>0]
summary['exp_avg_sales'] = ggf.conditional_expected_average_profit(summary['frequency'],summary['monetary_value'])
```

```
summary.head()
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive	pred_nu
1	12347.0	6.0	365.0	367.0	22.993333	0.995966	
2	12348.0	3.0	283.0	358.0	97.253333	0.981687	
9	12356.0	2.0	303.0	325.0	25.950000	0.983167	
11	12358.0	1.0	149.0	150.0	142.800000	0.957457	
12	12359.0	5.0	324.0	331.0	1.380000	0.994694	

```
print(f"Expected Average Sales: {summary['exp_avg_sales'].mean()}")
print(f"Actual Average Sales: {summary['monetary_value'].mean()}")
```

```
Expected Average Sales: 40.26715887993627
Actual Average Sales: 38.419385969390525
```

```
summary["predicted_clv"] = ggf.customer_lifetime_value(bgf,
                                                       summary['frequency'],
                                                       summary['recency'],
                                                       summary['T'],
                                                       summary['monetary_value'],
                                                       time=1,
                                                       freq='D',
                                                       discount_rate=0.01)
summary.sort_values(by='pred_num_txn', ascending=False).head()
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive	pred_
1895	14911.0	145.0	372.0	373.0	45.236483	0.999791	
330	12748.0	114.0	373.0	373.0	5.457982	0.999810	
4042	17841.0	112.0	372.0	373.0	9.544821	0.999749	
1674	14606.0	88.0	372.0	373.0	10.123523	0.999697	
568	13089.0	82.0	367.0	369.0	44.713902	0.999610	

```
summary['manual_predicted_clv'] = summary['pred_num_txn'] * summary['exp_avg_sales']
summary.head()
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive	pred_nu
1	12347.0	6.0	365.0	367.0	22.993333	0.995966	
2	12348.0	3.0	283.0	358.0	97.253333	0.981687	
9	12356.0	2.0	303.0	325.0	25.950000	0.983167	
11	12358.0	1.0	149.0	150.0	142.800000	0.957457	
12	12359.0	5.0	324.0	331.0	1.380000	0.994694	

```
profit_margin = 0.05
summary['CLV'] = summary['predicted_clv'] * profit_margin
summary.head()
```

	CustomerID	frequency	recency	T	monetary_value	probability_alive	pred_nu
1	12347.0	6.0	365.0	367.0	22.993333	0.995966	
2	12348.0	3.0	283.0	358.0	97.253333	0.981687	
9	12356.0	2.0	303.0	325.0	25.950000	0.983167	
11	12358.0	1.0	149.0	150.0	142.800000	0.957457	
12	12359.0	5.0	324.0	331.0	1.380000	0.994694	

the CLV for each customer for the next 30 **days**

```
summary['CLV'].describe()
```

```
count    2681.000000
mean        1.263387
std         4.978443
min         0.005741
25%         0.182682
50%         0.376245
75%         0.854357
max       131.826949
Name: CLV, dtype: float64
```