Unsupervised Learning

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Segmentacion de Clientes

En esté capitulo nos vamos a enfocar en entender y trabajar un caso de uso para segmentación de clientes, pero antes de eso aquí una pequeña lista de más aplicaciones que se pueden trabajar con los datos recopliados de mis clientes - Estadística Descriptiva - Segmentación de Clientes - Predicción de Abandono - Valor del Cliente a traves del tiempo (CTLV) La segmentación la vamos a hacer con base en una metodolgía llamada **RFM**

In [ ]:

```
# Importa Pandas, Numpy, Seaborn y Matplotlib
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt


# Importa el archivo "Online Retail.csv"
df = pd.read_csv("M30 Online Retail.csv", encoding = "ISO-8859-1")
df.head()
```

Out[ ]:

	INVOICE_NO	STOCK_CODE	DESCRIPTION	QUANTITY	INVOICE_DATE	UNIT_PRICE	CUSTOMER_ID	REGION
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01/12/2019 08:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	01/12/2019 08:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01/12/2019 08:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	01/12/2019 08:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	01/12/2019 08:26	3.39	17850.0	United Kingdom

In [ ]:

```
# Análisis Exploratorio
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   INVOICE_NO    541909 non-null  object 
 1   STOCK_CODE    541909 non-null  object 
 2   DESCRIPTION   540455 non-null  object 
 3   QUANTITY      541909 non-null  int64  
 4   INVOICE_DATE  541909 non-null  object 
 5   UNIT_PRICE    541909 non-null  float64
 6   CUSTOMER_ID   406829 non-null  float64
 7   REGION        541909 non-null  object 
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB
```

In [ ]:
```
# Convert the INVOICE_DATE column to datetime
df['INVOICE_DATE'] = pd.to_datetime(df['INVOICE_DATE'], format='%d/%m/%Y %H:%M')

# Verify the conversion
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype         
---  ------        --------------   -----         
 0   INVOICE_NO    541909 non-null  object        
 1   STOCK_CODE    541909 non-null  object        
 2   DESCRIPTION   540455 non-null  object        
 3   QUANTITY      541909 non-null  int64         
 4   INVOICE_DATE  541909 non-null  datetime64[ns]
 5   UNIT_PRICE    541909 non-null  float64       
 6   CUSTOMER_ID   406829 non-null  float64       
 7   REGION        541909 non-null  object        
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

In [ ]:
```
# Hay un porcentaje muy alto de valores nulos en la columna "CUSTOMER_ID"
print(df['CUSTOMER_ID'].isna().sum()/df.shape[0] * 100, '%')
```

```
24.926694334288598 %
```

In [ ]:
```
df['CUSTOMER_ID'].min()
```

Out[ ]: np.float64(12346.0)

In [ ]:
```
df['CUSTOMER_ID']=df['CUSTOMER_ID'].fillna(-1)
df['CUSTOMER_ID'].isna().sum()
```

Out[ ]: np.int64(0)

In [ ]:
```
df['CUSTOMER_ID'].max()
```

Out[ ]: np.float64(18287.0)

In [ ]:
```
df['CUSTOMER_ID'] = df['CUSTOMER_ID'].astype(np.int32)
df['CUSTOMER_ID'].dtype
```

Out[ ]: dtype('int32')

In [ ]:
```
categorical_cols = ['INVOICE_NO', 'STOCK_CODE', 'CUSTOMER_ID', 'REGION']

# Convert the CUSTOMER_ID column to a categorical type
df[categorical_cols] = df[categorical_cols].astype('category')

# Verify the conversion
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   INVOICE_NO    541909 non-null  category
 1   STOCK_CODE    541909 non-null  category
 2   DESCRIPTION   540455 non-null  object
 3   QUANTITY      541909 non-null  int64
 4   INVOICE_DATE  541909 non-null  datetime64[ns]
 5   UNIT_PRICE    541909 non-null  float64
 6   CUSTOMER_ID   541909 non-null  category
 7   REGION        541909 non-null  category
dtypes: category(4), datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 21.6+ MB
```

In [ ]:
```
df['DESCRIPTION'] = df['DESCRIPTION'].astype(str)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype         
---  ------        --------------   -----         
 0   INVOICE_NO    541909 non-null  category      
 1   STOCK_CODE    541909 non-null  category      
 2   DESCRIPTION   541909 non-null  object        
 3   QUANTITY      541909 non-null  int64         
 4   INVOICE_DATE  541909 non-null  datetime64[ns]
 5   UNIT_PRICE    541909 non-null  float64       
 6   CUSTOMER_ID   541909 non-null  category      
 7   REGION        541909 non-null  category      
dtypes: category(4), datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 21.6+ MB
```

In [ ]:
```
df.describe()
```

Out[ ]:

	QUANTITY	INVOICE_DATE	UNIT_PRICE
count	541909.000000	541909	541909.000000
mean	9.552250	2020-07-04 08:55:02.927097344	4.611114
min	-80995.000000	2019-12-01 08:26:00	-11062.060000
25%	1.000000	2020-03-28 11:34:00	1.250000
50%	3.000000	2020-07-19 17:17:00	2.080000
75%	10.000000	2020-10-19 11:27:00	4.130000
max	80995.000000	2020-12-09 12:50:00	38970.000000
std	218.081158	NaN	96.759853

In [ ]:
```
# Existen valores negativos en la columna QUANTITY,
# pero debido al número de registros, no se eliminarán
# Es posible que se trate de devoluciones
df[df['QUANTITY'] < 0]
```

Out[ ]:

	INVOICE_NO	STOCK_CODE	DESCRIPTION	QUANTITY	INVOICE_DATE	UNIT_PRICE	CUSTOMER_ID	REGION
141	C536379	D	Discount	-1	2019-12-01 09:41:00	27.50	14527	United Kingdom
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2019-12-01 09:49:00	4.65	15311	United Kingdom
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2019-12-01 10:24:00	1.65	17548	United Kingdom
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2019-12-01 10:24:00	0.29	17548	United Kingdom
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2019-12-01 10:24:00	0.29	17548	United Kingdom
...	...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2020-12-09 09:57:00	0.83	14397	United Kingdom
541541	C581499	M	Manual	-1	2020-12-09 10:28:00	224.69	15498	United Kingdom
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2020-12-09 11:57:00	10.95	15311	United Kingdom
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2020-12-09 11:58:00	1.25	17315	United Kingdom
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2020-12-09 11:58:00	1.25	17315	United Kingdom

10624 rows × 8 columns

In [ ]:

```
df.describe(include=['category'])
```

Out[ ]:

	INVOICE_NO	STOCK_CODE	CUSTOMER_ID	REGION
count	541909	541909	541909	541909
unique	25900	4070	4373	38
top	573585	85123A	-1	United Kingdom
freq	1114	2313	135080	495478

In [ ]:

```python
# Existen valores negativos en la columna UNIT_PRICE,
# pero es posible que se traten de ajustes contables
# por lo que no se eliminarán
df[df['UNIT_PRICE'] < 0]
```

Out[ ]:

	INVOICE_NO	STOCK_CODE	DESCRIPTION	QUANTITY	INVOICE_DATE	UNIT_PRICE	CUSTOMER_ID	REGION
299983	A563186	B	Adjust bad debt	1	2020-08-12 14:51:00	-11062.06	-1	United Kingdom
299984	A563187	B	Adjust bad debt	1	2020-08-12 14:52:00	-11062.06	-1	United Kingdom

In [ ]:

```python
# Eliminaremos los registros con CUSTOMER_ID = -1, es decir, que son nulos
# ya que no tenemos manera de agruparlos por cliente
df = df[df['CUSTOMER_ID']!=-1]
```

Recency

Indicador que nos dice que tan reciente es la compra de un cliente

In [ ]:

```python
# Obtener los clientes unicos
customer = df.groupby('CUSTOMER_ID', observed=True).agg(Count=('INVOICE_NO', 'count'))
customer
```

Out[ ]:

	Count
CUSTOMER_ID	
12346	2
12347	182
12348	31
12349	73
12350	17
...	...
18280	10
18281	7
18282	13
18283	756
18287	70

4372 rows × 1 columns

In [ ]:

```
# Obtener la última fecha de compra por cliente
max_purchase = df.groupby('CUSTOMER_ID', observed=True).agg(MaxPurchaseDate=('INVOICE_DATE', 'max'))
max_purchase.head()
```

Out[ ]:

	MaxPurchaseDate
CUSTOMER_ID	
12346	2020-01-18 10:17:00
12347	2020-12-07 15:52:00
12348	2020-09-25 13:13:00
12349	2020-11-21 09:51:00
12350	2020-02-02 16:01:00

In [ ]:

```
# Vamos a calcular nuestra metrica de Recency, esto lo haremos restando los días de la última fecha de compra a cada obser
max_purchase['RECENCY'] = (max_purchase['MaxPurchaseDate'].max() - max_purchase['MaxPurchaseDate']).dt.days
```

```
max_purchase
```

Out[ ]:

CUSTOMER_ID	MaxPurchaseDate	RECENCY
12346	2020-01-18 10:17:00	326
12347	2020-12-07 15:52:00	1
12348	2020-09-25 13:13:00	74
12349	2020-11-21 09:51:00	18
12350	2020-02-02 16:01:00	310
...	...	...
18280	2020-03-07 09:52:00	277
18281	2020-06-12 10:53:00	180
18282	2020-12-02 11:43:00	7
18283	2020-12-06 12:02:00	3
18287	2020-10-28 09:29:00	42

4372 rows × 2 columns

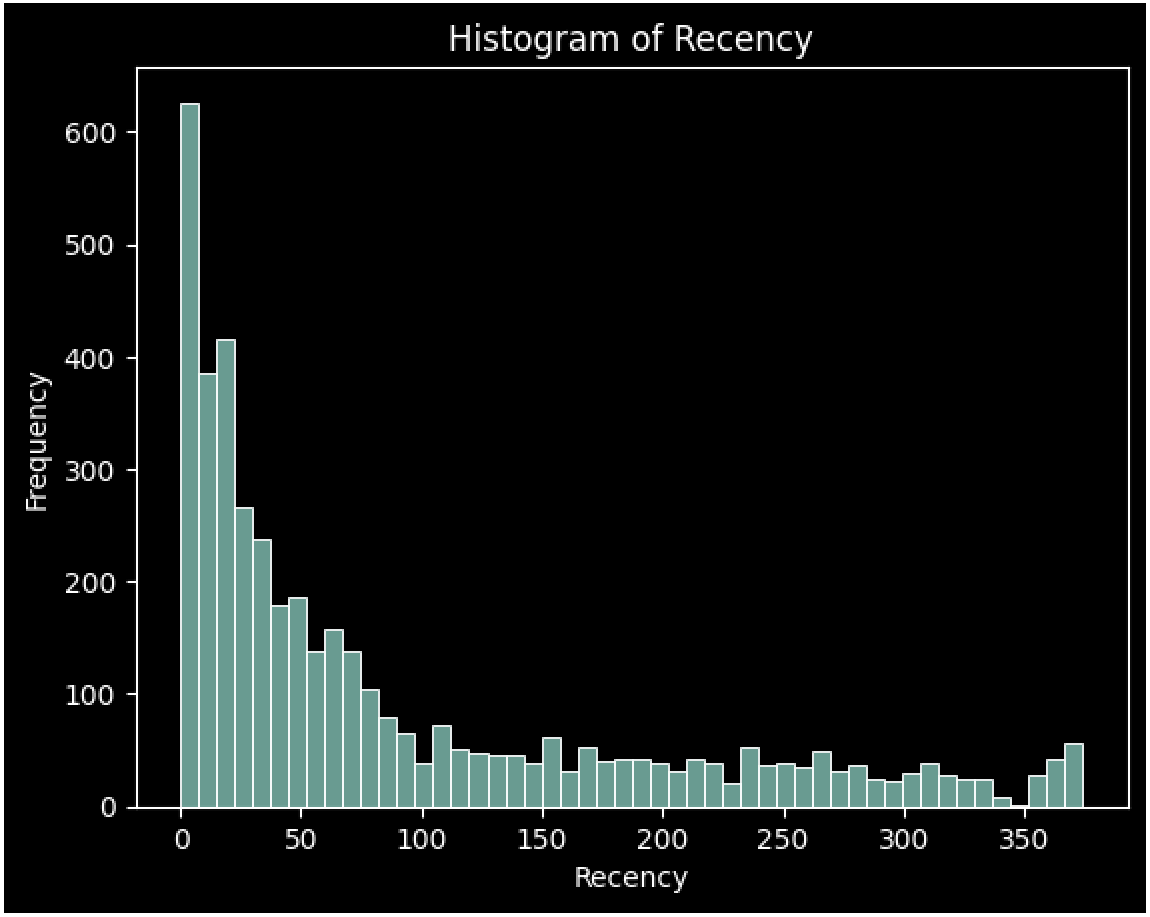
In [ ]:

```
# Unir el DataFrame de clientes únicos con el que acabamos de crear de la última fecha de compra
customer = customer.merge(max_purchase, on='CUSTOMER_ID')
customer.head()
```

Out[ ]:

CUSTOMER_ID	Count	MaxPurchaseDate	RECENCY
12346	2	2020-01-18 10:17:00	326
12347	182	2020-12-07 15:52:00	1
12348	31	2020-09-25 13:13:00	74
12349	73	2020-11-21 09:51:00	18
12350	17	2020-02-02 16:01:00	310

In [ ]:
```
# Grafica un histograma de Recency
sns.histplot(max_purchase['RECENCY'], bins = 50)
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.title('Histogram of Recency')
plt.show()
```



In [ ]:
```
# Imprime la Estadística de Resumen para Recency
max_purchase['RECENCY'].describe()
```

Out[ ]:

```
count    4372.000000
mean       91.123056
std       100.946554
min         0.000000
25%        16.000000
50%        49.000000
75%       142.000000
max       374.000000
Name: RECENCY, dtype: float64
```

Frequency

Frecuencia con la que un cliente compra uno o más productos

In [ ]:

```
# Obtener el número de compras por cliente
frequency = df.groupby('CUSTOMER_ID', observed= True).agg(FREQUENCY=('INVOICE_NO', 'nunique'))
frequency
```

Out[ ]:

	FREQUENCY
CUSTOMER_ID	
12346	2
12347	7
12348	4
12349	1
12350	1
...	...
18280	1
18281	1
18282	3
18283	16
18287	3

4372 rows × 1 columns

In [ ]:

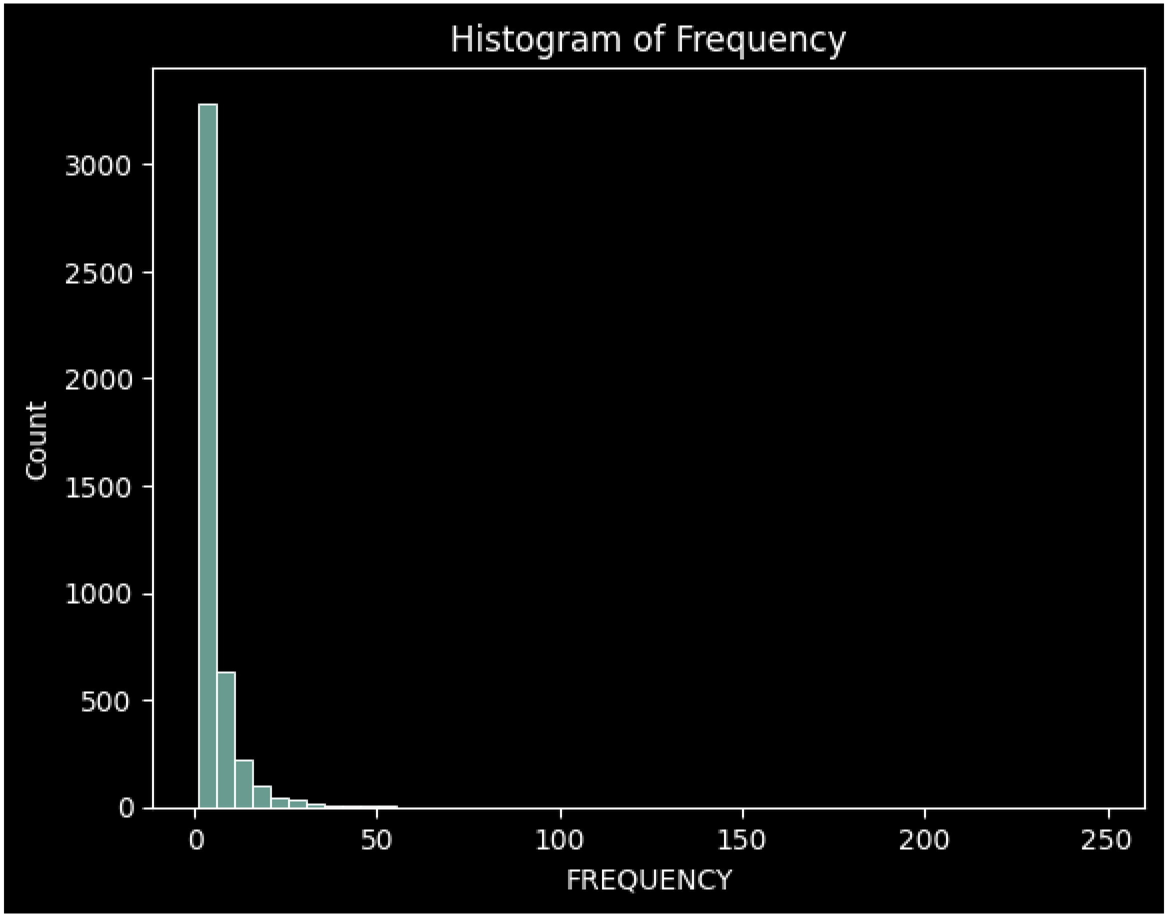
```
# Unir el DataFrame que acabamos de crear con el de los clientes unicos
customer = customer.merge(frequency, on = 'CUSTOMER_ID')
customer.head()
```

Out[ ]:

CUSTOMER_ID	Count	MaxPurchaseDate	RECENCY	FREQUENCY
12346	2	2020-01-18 10:17:00	326	2
12347	182	2020-12-07 15:52:00	1	7
12348	31	2020-09-25 13:13:00	74	4
12349	73	2020-11-21 09:51:00	18	1
12350	17	2020-02-02 16:01:00	310	1

In [ ]:

```
# Grafica un histograma de Frequency
sns.histplot(customer['FREQUENCY'], bins = 50)
plt.xlabel('FREQUENCY')
plt.title('Histogram of Frequency')
plt.show()
```



In [ ]:
```
# Imprime la Estadística de Resumen para FREQUENCY
customer['FREQUENCY'].describe()
```

Out[ ]:
```
count    4372.000000
mean        5.075480
std         9.338754
min         1.000000
25%         1.000000
50%         3.000000
75%         5.000000
max       248.000000
Name: FREQUENCY, dtype: float64
```

Monetary

Valor del monto total que ha gastado un cliente en la compra de mis productos

In [ ]:
```
# Calcular el monto total por cada compra
df['MONETARY'] = df['QUANTITY'] * df['UNIT_PRICE']
df.head()
```

Out[ ]:

	INVOICE_NO	STOCK_CODE	DESCRIPTION	QUANTITY	INVOICE_DATE	UNIT_PRICE	CUSTOMER_ID	REGION	MONETARY
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2019-12-01 08:26:00	2.55	17850	United Kingdom	15.30
1	536365	71053	WHITE METAL LANTERN	6	2019-12-01 08:26:00	3.39	17850	United Kingdom	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2019-12-01 08:26:00	2.75	17850	United Kingdom	22.00
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2019-12-01 08:26:00	3.39	17850	United Kingdom	20.34
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2019-12-01 08:26:00	3.39	17850	United Kingdom	20.34

In [ ]:
```
# Obtener el valor monetario de compra por cliente
monetary = df.groupby('CUSTOMER_ID', observed=True).agg(MONETARY=('MONETARY', 'sum'))
monetary
```

Out[ ]:

	MONETARY
CUSTOMER_ID	
12346	0.00
12347	4310.00
12348	1797.24
12349	1757.55
12350	334.40
...	...
18280	180.60
18281	80.82
18282	176.60
18283	2094.88
18287	1837.28

4372 rows × 1 columns

In [ ]:

```
# Unir el DataFrame que acabamos de crear con el de los clientes unicos
customer = customer.merge(monetary, on='CUSTOMER_ID')
customer.head()
```

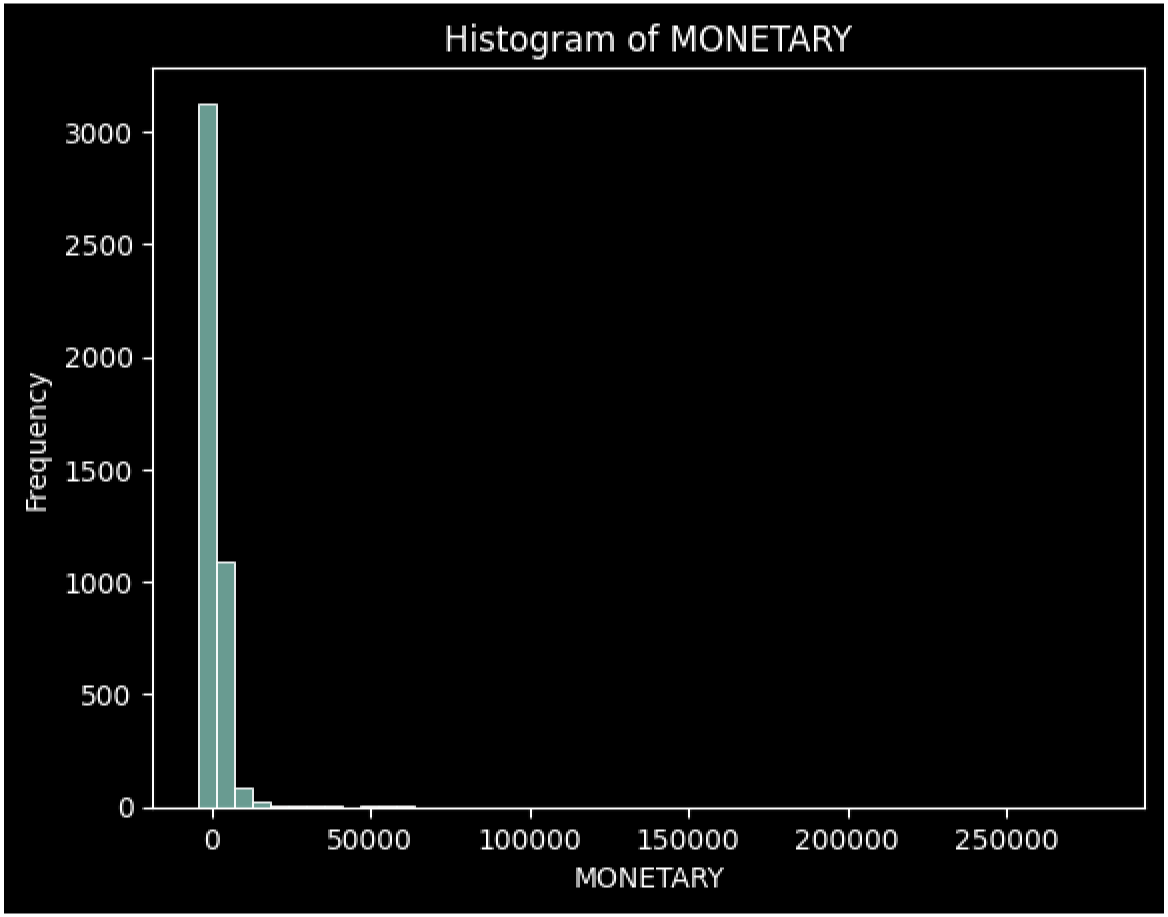
Out[ ]:

	Count	MaxPurchaseDate	RECENCY	FREQUENCY	MONETARY
CUSTOMER_ID					
12346	2	2020-01-18 10:17:00	326	2	0.00
12347	182	2020-12-07 15:52:00	1	7	4310.00
12348	31	2020-09-25 13:13:00	74	4	1797.24
12349	73	2020-11-21 09:51:00	18	1	1757.55
12350	17	2020-02-02 16:01:00	310	1	334.40

In [ ]:

```
# Grafica un histograma de Monetary
sns.histplot(customer['MONETARY'], bins = 50)
```

```python
plt.xlabel('MONETARY')
plt.ylabel('Frequency')
plt.title('Histogram of MONETARY')
plt.show()
```



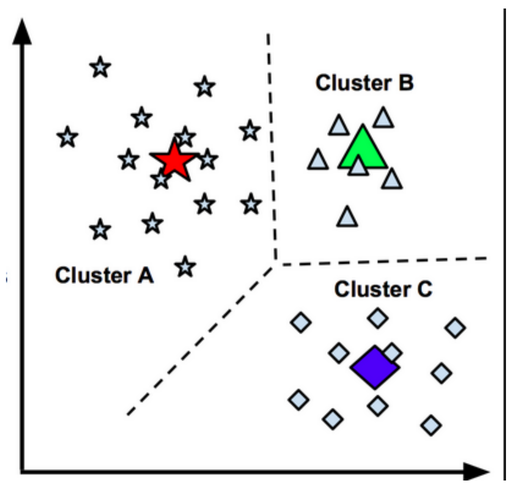
In [ ]:

```python
# Imprime la Estadística de Resumen para Monetary
customer['MONETARY'].describe()
```

Out[ ]:
```
count      4372.000000
mean       1898.459701
std        8219.345141
min       -4287.630000
25%         293.362500
50%         648.075000
75%        1611.725000
max      279489.020000
Name: MONETARY, dtype: float64
```

Algoritmo k-Means

Ya creamos nuestros indicadores principales de la metodología RFM. es hora de hacer *Machine Learning*. Para ello utilizaremos un algoritmo no supervisado llamado **k-Means**



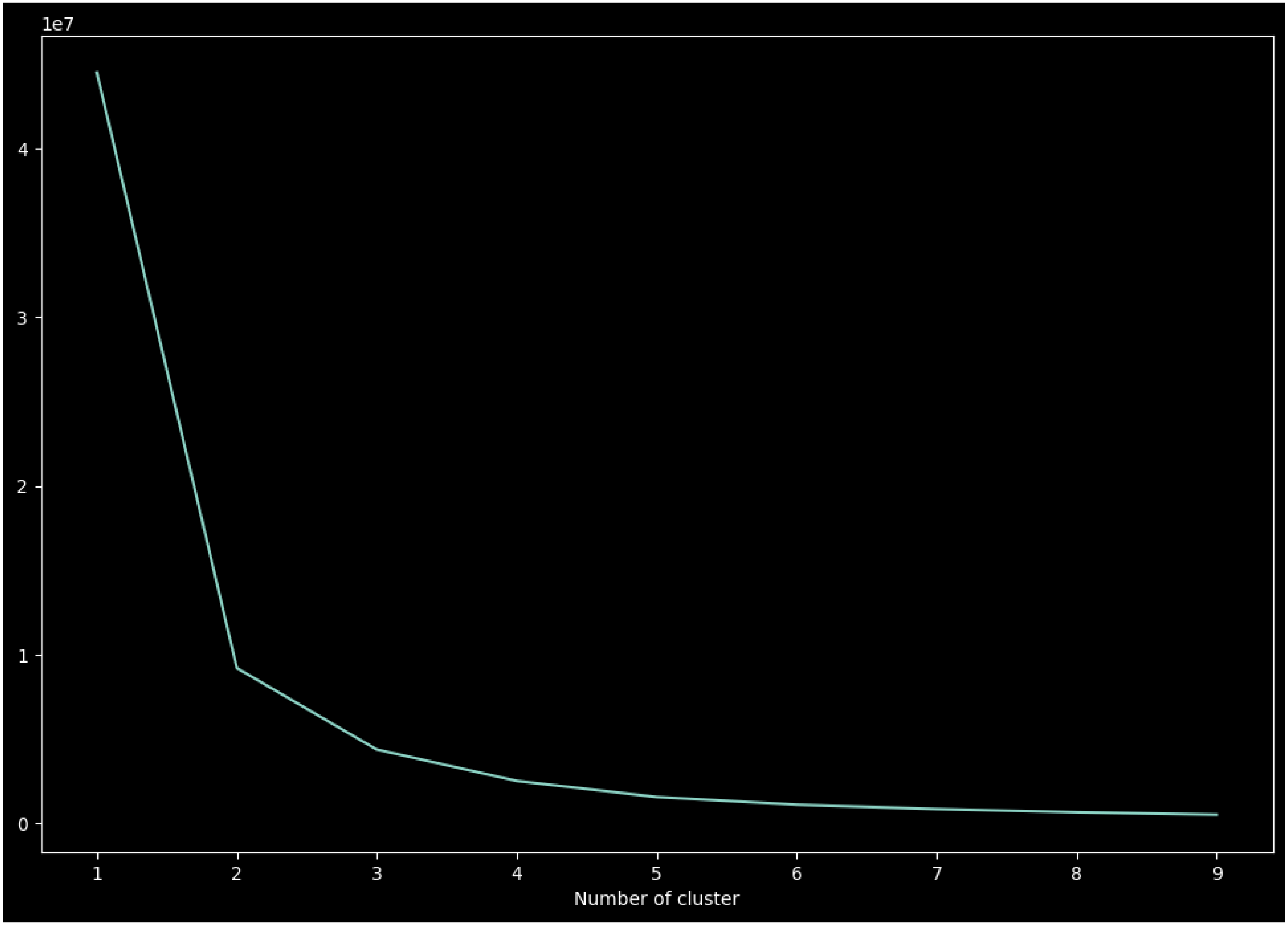
In [ ]:
```
# Funcion para ordenar los clusters
def order_cluster(cluster_field_name, target_field_name, df, ascending):
    new_cluster_field_name = 'new_' + cluster_field_name
    df_new = df.groupby(cluster_field_name)[target_field_name].mean().reset_index()
    df_new = df_new.sort_values(by=target_field_name,ascending=ascending).reset_index(drop=True)
    df_new['index'] = df_new.index
    df_final = pd.merge(df,df_new[[cluster_field_name,'index']], on=cluster_field_name)
    df_final = df_final.drop([cluster_field_name],axis=1)
    df_final = df_final.rename(columns={"index":cluster_field_name})
    return df_final
```

Elbow Method

¿Cual es mi número óptimo de clusters? Vamos a contruir una *gráfica de codo* para averiguarlo

In [ ]:
```
# Importa la librería de kMeans
from sklearn.cluster import KMeans
import warnings
```

In [ ]:
```
# Configuración inicial - Vamos a tomar como referencia el indicador de Recency
warnings.filterwarnings('ignore')
sse={}
recency = customer[['RECENCY']]

for k in range(1, 10):
    # Instancia el algoritmo de k-means iterando sobre k
    kmeans = KMeans(n_clusters=k, max_iter=1000)

    # Entrena el algoritmo
    kmeans.fit(recency)

    # Adjunta las etiquetas
    recency["clusters"] = kmeans.labels_

    # Adunta la inercia o variación al arreglo sse
    sse[k] = kmeans.inertia_

# Grafico de codo (Elbow)
plt.figure(figsize=(12,8))
plt.plot(list(sse.keys()), list(sse.values()))
plt.xlabel("Number of cluster")
plt.show()
```



In [ ]:
```
# Instanciar el algoritmo con 4 clusters para Recency
kmeans = KMeans(n_clusters=4)

# Entrenar el algoritmo
kmeans.fit(customer[['RECENCY']])
```

```python
# Obtener las predicciones
customer['RECENCY_CLUSTER'] = kmeans.predict(customer[['RECENCY']])

# Ordenar los clusters
customer = order_cluster('RECENCY_CLUSTER', 'RECENCY', customer, False)

# Estadística Descriptiva del cluster creado
customer.groupby('RECENCY_CLUSTER')['RECENCY'].describe()
```

Out[ ]:

RECENCY_CLUSTER	count	mean	std	min	25%	50%	75%	max
0	494.0	310.912955	38.940253	253.0	276.0	308.0	353.00	374.0
1	615.0	192.720325	32.608673	140.0	165.0	190.0	218.00	252.0
2	964.0	84.669087	23.930399	53.0	64.0	78.0	104.25	139.0
3	2299.0	19.423662	15.022921	0.0	7.0	17.0	30.00	52.0

In [ ]:

```python
# Instanciar el algoritmo con 4 clusters para FREQUENCY
kmeans = KMeans(n_clusters=4)

# Entrenar el algoritmo
kmeans.fit(customer[['FREQUENCY']])

# Obtener las predicciones
customer['FREQUENCY_CLUSTER'] = kmeans.predict(customer[['FREQUENCY']])

# Ordenar los clusters
customer = order_cluster('FREQUENCY_CLUSTER', 'FREQUENCY', customer, True)

# Estadística Descriptiva de los clusters
customer.groupby('FREQUENCY_CLUSTER')['FREQUENCY'].describe()
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
FREQUENCY_CLUSTER								
0	3913.0	3.086123	2.342807	1.0	1.0	2.0	4.0	10.0
1	417.0	17.213429	6.260377	11.0	12.0	15.0	20.0	38.0
2	39.0	58.846154	22.904307	39.0	43.0	52.0	64.5	128.0
3	3.0	213.666667	40.501029	169.0	196.5	224.0	236.0	248.0

In [ ]:

```
# Instanciar el algoritmo con 4 clusters para MONETARY
kmeans = KMeans(n_clusters=4)

# Entrenar el algoritmo
kmeans.fit(customer[['MONETARY']])

# Obtener las predicciones
customer['MONETARY_CLUSTER'] = kmeans.predict(customer[['MONETARY']])

# Ordenar los clusters ¿Como tienes que ordenar el cluster?
customer = order_cluster('MONETARY_CLUSTER', 'MONETARY', customer, True)

# Estadística Descriptiva de los clusters
customer.groupby('MONETARY_CLUSTER')['MONETARY'].describe()
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
MONETARY_CLUSTER								
0	4332.0	1359.641714	2045.005429	-4287.63	291.0375	640.795	1553.8650	18793.41
1	33.0	37238.807273	14403.896372	19786.44	26763.3400	33350.760	50992.6100	65892.08
2	5.0	129057.952000	36658.292209	88125.38	113384.1400	123725.450	132572.6200	187482.17
3	2.0	267963.755000	16299.186073	256438.49	262201.1225	267963.755	273726.3875	279489.02

Score de Segmentación

El algoritmo de k-means nos da una segmentación generalizada, pero podemos personalizarla aún más creando una métrica que asigne una calificación al valor del cluster. Esto es lo que vamos a hacer!!

```python
# Vamos a crear nuestro score sumando el valor de cada uno de los clusters
customer['SCORE'] = customer['RECENCY_CLUSTER'] + customer['FREQUENCY_CLUSTER'] + customer['MONETARY_CLUSTER']

# Obtener el promedio para cada una de las métricas de las calificaciones creadas (Score)
customer.groupby('SCORE')[['RECENCY', 'FREQUENCY', 'MONETARY']].mean()
```

SCORE	RECENCY	FREQUENCY	MONETARY
0	311.120163	1.425662	331.770407
1	193.304419	2.191489	532.758267
2	85.576236	2.868559	945.175796
3	21.903123	4.082583	1261.840085
4	12.045576	17.243968	5193.833217
5	4.687500	40.343750	21760.863438
6	5.882353	61.235294	45213.001176
7	3.800000	112.000000	91680.914000
8	0.333333	129.000000	222833.376667

```python
# Crea una funcion que asigne lo siguiente:
# Si score <= 1 entonces 'Low-Value', si score >1 y <=4 entonces 'Average', si score >4 y <=6 entonces 'Potential', por úl
def segment(score):
    if score <= 1:
        return 'Low-Value'
    elif score > 1 and score <= 4:
        return 'Average'
    elif score > 4 and score <= 6:
        return 'Potential'
    else:
        return 'High-Value'


# Crear una columna aplicando esta función al campo 'SCORE'
customer['SEGMENT'] = customer['SCORE'].apply(segment)
```

```python
# Vamos a dar un vistazo a la tabla final
customer.head()
```

Out[ ]:

	Count	MaxPurchaseDate	RECENCY	FREQUENCY	MONETARY	RECENCY_CLUSTER	FREQUENCY_CLUSTER	MONETARY_CLUSTER	SCORE	SEGM
0	2	2020-01-18 10:17:00	326	2	0.00	0	0	0	0	Low-'
1	182	2020-12-07 15:52:00	1	7	4310.00	3	0	0	3	Ave
2	31	2020-09-25 13:13:00	74	4	1797.24	2	0	0	2	Ave
3	73	2020-11-21 09:51:00	18	1	1757.55	3	0	0	3	Ave
4	17	2020-02-02 16:01:00	310	1	334.40	0	0	0	0	Low-'

In [ ]:

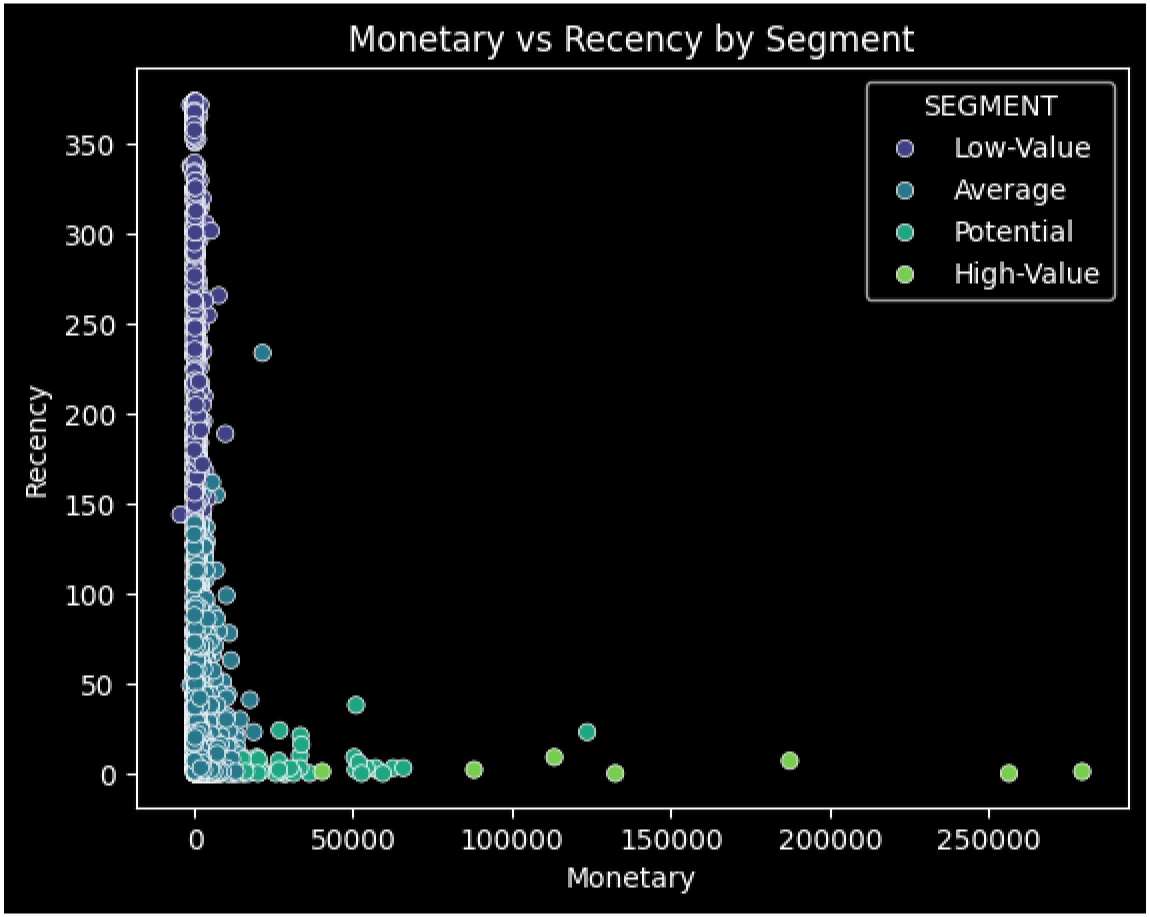
```
# Imprime la proporción o el total de clientes por segmento
customer['SEGMENT'].value_counts(normalize=True)
```

Out[ ]:

```
SEGMENT
Average       0.734904
Low-Value     0.252059
Potential     0.011208
High-Value    0.001830
Name: proportion, dtype: float64
```

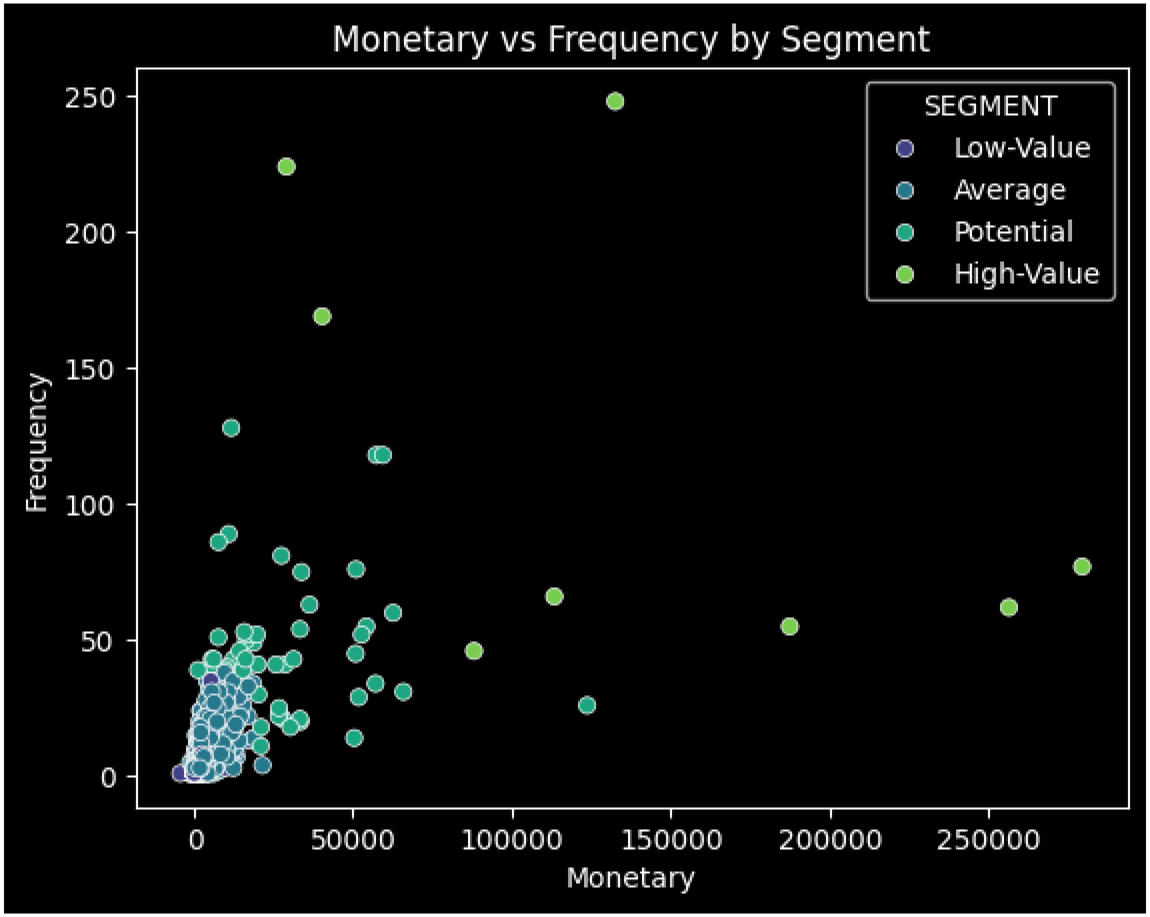
In [ ]:

```
# Define un estilo 'bmh'
# plt.style.use('bmh')
# Debido a la forma que mi IDE renderiza los gráficos, al utilizar el estilo 'bmh'
# las etiquetas no se visualizan correctamente, por lo que se utilizará el estilo por defecto

# Filtra los valores para RECENCY < 4000
customer = customer[customer['RECENCY'] < 4000]

# Crea un grafico de dispersion de 'MONETARY' VS 'RECENCY' por Segmento
sns.scatterplot(data=customer, x='MONETARY', y='RECENCY', hue='SEGMENT', palette='viridis')
plt.xlabel('Monetary')
plt.ylabel('Recency')
plt.title('Monetary vs Recency by Segment')
plt.show()
```



Para los segmentos Low-Value y Average, el valor de las compras por cliente parece ser muy bajo, y el tiempo que ha paso desde la última compra es indiferente. En cambio, para los segmentos más altos, es claro que tienen a comprar más seguido.

In [ ]:
```
# Crea un grafico de dispersion de 'MONETARY' vs 'FREQUENCY' vs  por Segmento
sns.scatterplot(data=customer, x='MONETARY', y='FREQUENCY', hue='SEGMENT', palette='viridis')
plt.xlabel('Monetary')
plt.ylabel('Frequency')
plt.title('Monetary vs Frequency by Segment')
plt.show()
```



Para los dos segmentos más bajos, parece que el valor de las comprar y la frecuencia no esta muy correlacionado, pero para los segmentos más altos, hay una correlación inversa entre el valor de las compras y la frecuencia, es decir, los clientes que compran más seguido, gastan menos en cada compra.