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 [4]:
```
# Importa Pandas, Numpy, Seaborn y Matplotlib
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

# Importa el archivo "Online Retail.csv"
import warnings
warnings.filterwarnings('ignore')
import os
os.chdir('/Users/Lenovo/Desktop/EBAC')
```

In [8]:
```
# Análisis Exploratorio
data = pd.read_csv('M30 Online Retail.csv', encoding='latin-1')
print(data.head())

# Resumen estadístico
print(data.describe())

# Valores nulos
print(data.isnull().sum())
```

```
  INVOICE_NO STOCK_CODE                          DESCRIPTION  QUANTITY  \
0     536365     85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1     536365      71053                  WHITE METAL LANTERN         6
2     536365     84406B       CREAM CUPID HEARTS COAT HANGER         8
3     536365     84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4     536365     84029E       RED WOOLLY HOTTIE WHITE HEART.         6

       INVOICE_DATE  UNIT_PRICE  CUSTOMER_ID          REGION
0  01/12/2019 08:26        2.55      17850.0  United Kingdom
1  01/12/2019 08:26        3.39      17850.0  United Kingdom
2  01/12/2019 08:26        2.75      17850.0  United Kingdom
3  01/12/2019 08:26        3.39      17850.0  United Kingdom
4  01/12/2019 08:26        3.39      17850.0  United Kingdom
            QUANTITY     UNIT_PRICE    CUSTOMER_ID
count  541909.000000  541909.000000  406829.000000
mean        9.552250       4.611114   15287.690570
std       218.081158      96.759853    1713.600303
min    -80995.000000  -11062.060000   12346.000000
25%         1.000000       1.250000   13953.000000
50%         3.000000       2.080000   15152.000000
75%        10.000000       4.130000   16791.000000
max     80995.000000   38970.000000   18287.000000
INVOICE_NO           0
STOCK_CODE           0
DESCRIPTION       1454
QUANTITY             0
INVOICE_DATE         0
UNIT_PRICE           0
CUSTOMER_ID     135080
REGION               0
dtype: int64
```

In [12]:

```
# Eliminar todos los valores nulos
data = data.dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 406829 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   INVOICE_NO    406829 non-null  object
 1   STOCK_CODE    406829 non-null  object
 2   DESCRIPTION   406829 non-null  object
 3   QUANTITY      406829 non-null  int64
 4   INVOICE_DATE  406829 non-null  object
 5   UNIT_PRICE    406829 non-null  float64
 6   CUSTOMER_ID   406829 non-null  float64
 7   REGION        406829 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 27.9+ MB
```

In [16]:

```
# Delimitacion de valores positivos de 'Quantity' (deseams analizar lo realmente comprado)
datos_reales = data[data['QUANTITY'] > 0]
datos_reales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 397924 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   INVOICE_NO    397924 non-null  object
 1   STOCK_CODE    397924 non-null  object
 2   DESCRIPTION   397924 non-null  object
 3   QUANTITY      397924 non-null  int64
 4   INVOICE_DATE  397924 non-null  object
 5   UNIT_PRICE    397924 non-null  float64
 6   CUSTOMER_ID   397924 non-null  float64
 7   REGION        397924 non-null  object
dtypes: float64(2), int64(1), object(5)
memory usage: 27.3+ MB
```

Recency

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

In [78]:

```
# Obtener los clientes unicos
customer = pd.DataFrame(datos_reales[['CUSTOMER_ID']].drop_duplicates())
print(customer)
```

```
        CUSTOMER_ID
0           17850.0
9           13047.0
26          12583.0
46          13748.0
65          15100.0
...             ...
536969      13436.0
537255      15520.0
538064      13298.0
538812      14569.0
541768      12713.0

[4339 rows x 1 columns]
```

In [50]:

```python
# Obtener la última fecha de compra por cliente
max_purchase = datos_reales[['INVOICE_DATE', 'CUSTOMER_ID']]
max_purchase['INVOICE_DATE'] = pd.to_datetime(max_purchase['INVOICE_DATE'], format='mixed', dayfirst=True)
max_purchase = max_purchase.sort_values(['CUSTOMER_ID', 'INVOICE_DATE'], ascending=[True, False])
max_purchase = max_purchase.drop_duplicates(subset='CUSTOMER_ID', keep='first')
max_purchase
```

Out[50]:

	INVOICE_DATE	CUSTOMER_ID
61619	2020-01-18 10:01:00	12346.0
535004	2020-12-07 15:52:00	12347.0
359058	2020-09-25 13:13:00	12348.0
485502	2020-11-21 09:51:00	12349.0
80323	2020-02-02 16:01:00	12350.0
...	...	...
111045	2020-03-07 09:52:00	18280.0
222954	2020-06-12 10:53:00	18281.0
519825	2020-12-02 11:43:00	18282.0
530454	2020-12-06 12:02:00	18283.0
423939	2020-10-28 09:29:00	18287.0

4339 rows × 2 columns

In [56]:

```python
# Vamos a calcular nuestra metrica de Recency, esto lo haremos restando los días de la última fecha de compra a
df = datos_reales.merge(max_purchase, on = 'CUSTOMER_ID', how = 'left')
df['INVOICE_DATE_x'] = pd.to_datetime(df['INVOICE_DATE_x'], format='mixed', dayfirst=True)
#df['INVOICE_DATE_y'] = pd.to_datetime(df['INVOICE_DATE_y'], format='mixed', dayfirst=True)
df['RECENCY'] = (df['INVOICE_DATE_y'] - df['INVOICE_DATE_x']).dt.days
df
```

Out[56]:

	INVOICE_NO	STOCK_CODE	DESCRIPTION	QUANTITY	INVOICE_DATE_x	UNIT_PRICE	CUSTOMER_ID	REGION	INVOICE
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2019-12-01 08:26:00	2.55	17850.0	United Kingdom	2
1	536365	71053	WHITE METAL LANTERN	6	2019-12-01 08:26:00	3.39	17850.0	United Kingdom	2
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2019-12-01 08:26:00	2.75	17850.0	United Kingdom	2
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2019-12-01 08:26:00	3.39	17850.0	United Kingdom	2
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2019-12-01 08:26:00	3.39	17850.0	United Kingdom	2
...	...	...	...	...	...	...	...	...	
397919	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2020-12-09 12:50:00	0.85	12680.0	France	2
397920	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2020-12-09 12:50:00	2.10	12680.0	France	2
397921	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2020-12-09 12:50:00	4.15	12680.0	France	2
397922	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2020-12-09 12:50:00	4.15	12680.0	France	2
397923	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2020-12-09 12:50:00	4.95	12680.0	France	2

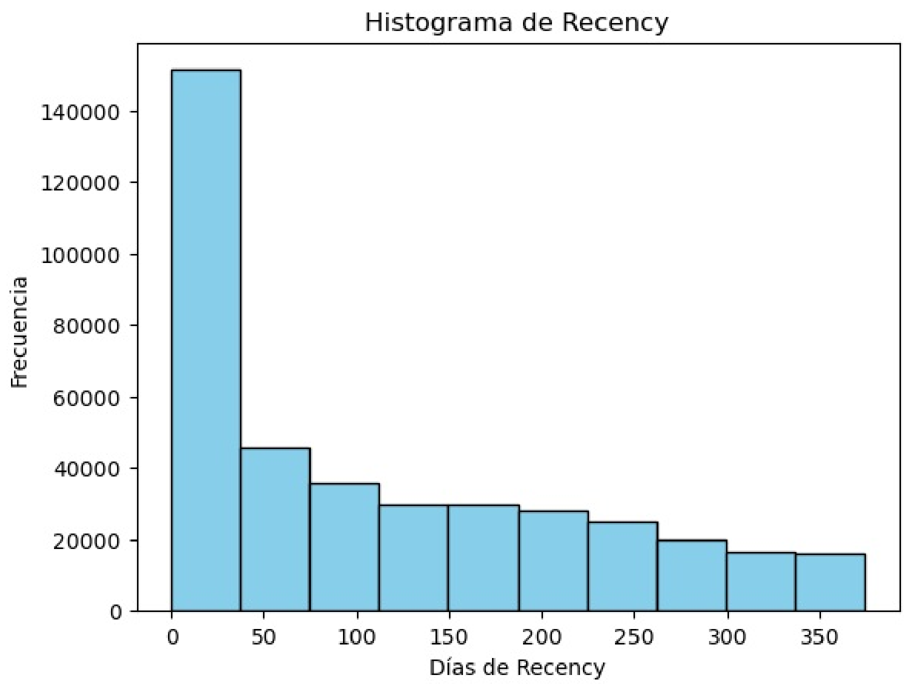
397924 rows × 10 columns

In [120…

```
# Unir el DataFrame de clientes únicos con el que acabamos de crear de la última fecha de compra
recency = df[['CUSTOMER_ID', 'RECENCY']]
customer = max_purchase.merge(recency, on = 'CUSTOMER_ID', how = 'left')
```

In [58]:

```
# Grafica un histograma de Recency
plt.hist(df['RECENCY'], bins=10, color='skyblue', edgecolor='black')
plt.title('Histograma de Recency')
plt.xlabel('Días de Recency')
plt.ylabel('Frecuencia')
plt.show()
```



In [60]:
```
# Imprime la Estadística de Resumen para Recency
# Resumen estadístico
print(df.describe())
```

```
           QUANTITY                 INVOICE_DATE_x     UNIT_PRICE  \
count  397924.000000                        397924  397924.000000
mean       13.021823  2020-07-10 19:39:59.930338560       3.116174
min         1.000000            2019-12-01 08:26:00       0.000000
25%         2.000000            2020-04-07 11:12:00       1.250000
50%         6.000000            2020-07-31 14:39:00       1.950000
75%        12.000000            2020-10-20 14:33:00       3.750000
max     80995.000000            2020-12-09 12:50:00    8142.750000
std       180.420210                           NaN      22.096788

         CUSTOMER_ID                 INVOICE_DATE_y        RECENCY
count  397924.000000                        397924  397924.000000
mean    15294.315171  2020-10-29 21:27:49.261718784     110.689076
min     12346.000000            2019-12-01 09:53:00       0.000000
25%     13969.000000            2020-10-27 14:20:00       0.000000
50%     15159.000000            2020-11-23 12:58:00      76.000000
75%     16795.000000            2020-12-05 14:35:00     195.000000
max     18287.000000            2020-12-09 12:50:00     374.000000
std      1713.169877                           NaN     110.607396
```

Frequency

Frecuencia con la que un cliente compra uno o más productos

In [62]:
```
# Obtener el número de compras por cliente
frequency = datos_reales.groupby('CUSTOMER_ID').size().reset_index(name='FREQUENCY')
frequency
```

Out[62]:

	CUSTOMER_ID	FREQUENCY
0	12346.0	1
1	12347.0	182
2	12348.0	31
3	12349.0	73
4	12350.0	17
...	...	...
4334	18280.0	10
4335	18281.0	7
4336	18282.0	12
4337	18283.0	756
4338	18287.0	70

4339 rows × 2 columns

In [122…

```
# Unir el DataFrame que acabamos de crear con el de los clientes unicos
customer2 = customer.merge(frequency, on = 'CUSTOMER_ID', how = 'left')
customer2 = customer2.sort_values(['FREQUENCY'], ascending=[True])
customer2
```

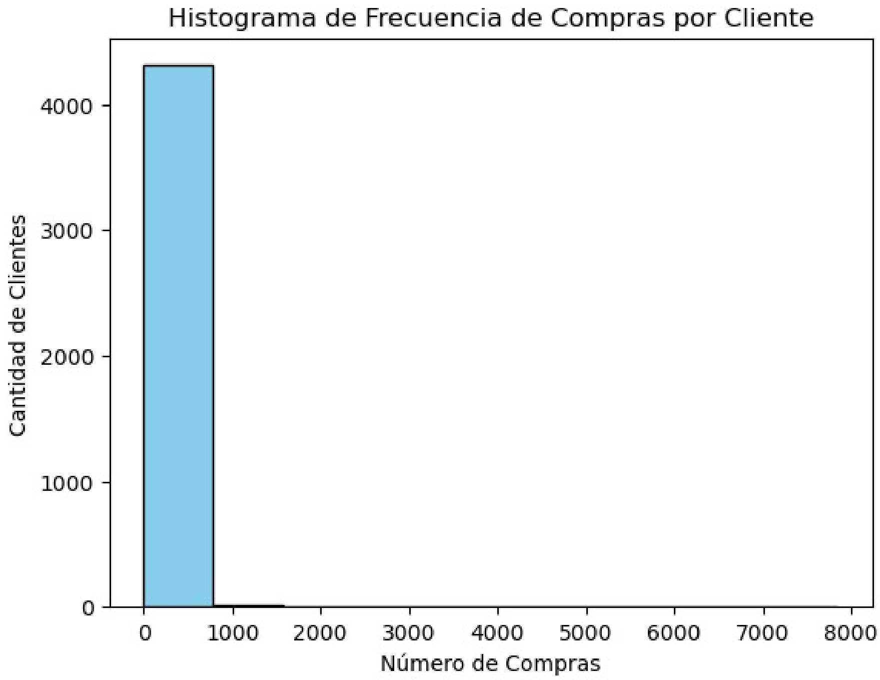
Out[122…

	INVOICE_DATE	CUSTOMER_ID	RECENCY	FREQUENCY
0	2020-01-18 10:01:00	12346.0	0	1
293182	2020-10-24 12:02:00	16742.0	0	1
163101	2020-05-25 12:39:00	14705.0	0	1
65735	2019-12-08 14:53:00	13270.0	0	1
386460	2020-11-23 13:57:00	18084.0	0	1
...	...	...	...	...
369211	2020-12-08 12:07:00	17841.0	163	7847
369210	2020-12-08 12:07:00	17841.0	163	7847
369209	2020-12-08 12:07:00	17841.0	163	7847
369207	2020-12-08 12:07:00	17841.0	163	7847
367472	2020-12-08 12:07:00	17841.0	268	7847

397924 rows × 4 columns

In [94]:

```
# Grafica un histograma de Frequency
plt.hist(frequency['FREQUENCY'], bins=10, color='skyblue', edgecolor='black')
plt.title('Histograma de Frecuencia de Compras por Cliente')
plt.xlabel('Número de Compras')
plt.ylabel('Cantidad de Clientes')
plt.show()
```



In [98]:

```
# Imprime la Estadística de Resumen para Frequency
print(customer2['FREQUENCY'].describe())
```

```
count    4339.000000
mean       91.708689
std       228.792852
min         1.000000
25%        17.000000
50%        41.000000
75%       100.000000
max      7847.000000
Name: FREQUENCY, dtype: float64
```

Monetary

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

In [114…

```
# Calcular el monto total por cada compra
df['MONETARY'] = df['QUANTITY'] * df['UNIT_PRICE']
```

```python
# Obtener el valor monetario de compra por cliente
monetary = df.groupby('CUSTOMER_ID')['MONETARY'].sum().reset_index(name='MONETARY_TOTAL')
monetary = monetary.sort_values(['MONETARY_TOTAL'], ascending=[True])
monetary
```

Out[114…

	CUSTOMER_ID	MONETARY_TOTAL
685	13256.0	0.00
3218	16738.0	3.75
1794	14792.0	6.20
3015	16454.0	6.90
4099	17956.0	12.75
...	...	...
1880	14911.0	143825.06
3009	16446.0	168472.50
3729	17450.0	194550.79
4202	18102.0	259657.30
1690	14646.0	280206.02

4339 rows × 2 columns

In [124…

```python
# Unir el DataFrame que acabamos de crear con el de los clientes unicos
customer3 = customer2.merge(monetary, on = 'CUSTOMER_ID', how = 'left')
customer3
```

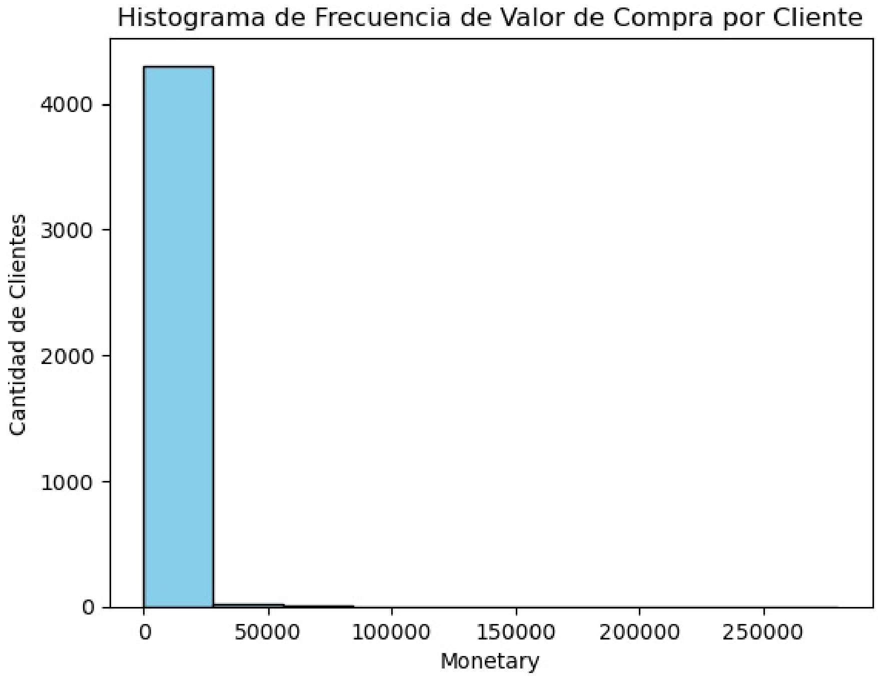
Out[124…

	INVOICE_DATE	CUSTOMER_ID	RECENCY	FREQUENCY	MONETARY_TOTAL
0	2020-01-18 10:01:00	12346.0	0	1	77183.60
1	2020-10-24 12:02:00	16742.0	0	1	464.90
2	2020-05-25 12:39:00	14705.0	0	1	179.00
3	2019-12-08 14:53:00	13270.0	0	1	590.00
4	2020-11-23 13:57:00	18084.0	0	1	90.48
...	...	...	...	...	...
397919	2020-12-08 12:07:00	17841.0	163	7847	40991.57
397920	2020-12-08 12:07:00	17841.0	163	7847	40991.57
397921	2020-12-08 12:07:00	17841.0	163	7847	40991.57
397922	2020-12-08 12:07:00	17841.0	163	7847	40991.57
397923	2020-12-08 12:07:00	17841.0	268	7847	40991.57

397924 rows × 5 columns

In [106…

```python
# Grafica un histograma de Monetary
plt.hist(monetary['MONETARY_TOTAL'], bins=10, color='skyblue', edgecolor='black')
plt.title('Histograma de Frecuencia de Valor de Compra por Cliente')
plt.xlabel('Monetary')
plt.ylabel('Cantidad de Clientes')
plt.show()
```

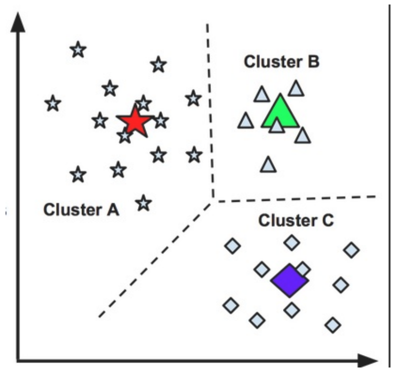


In [110…
```
# Imprime la Estadística de Resumen para Monetary
print(customer3['MONETARY_TOTAL'].describe())
```

```
count      4339.000000
mean       2053.793018
std        8988.248381
min           0.000000
25%         307.245000
50%         674.450000
75%        1661.640000
max      280206.020000
Name: MONETARY_TOTAL, 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 [130…
```
# 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
```

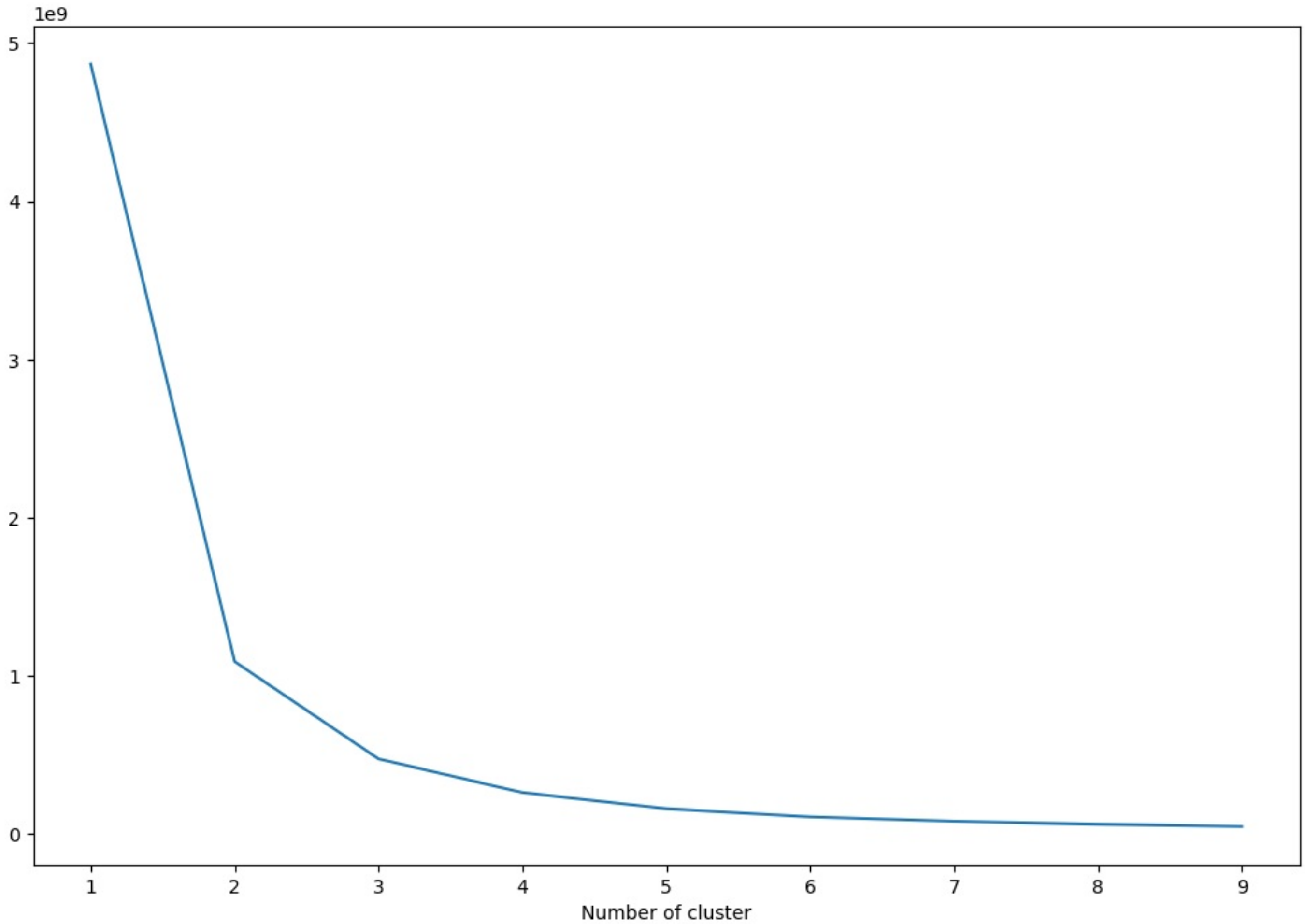
Elbow Method

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

In [118…
```
# Importa la librería de kMeans
from sklearn.cluster import KMeans
```

In [142…
```
# Configuración inicial - Vamos a tomar como referencia el indicador de Recency
```

```python
sse={}
recency = customer3[['RECENCY']].copy()

for k in range(1, 10):
    # Instancia el algoritmo de k-means iterando sobre k
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)

    # 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 [144…
```python
# Instanciar el algoritmo con 4 clusters para Recency
kmeans = KMeans(n_clusters = 4, random_state = 42, n_init = 10)

# Entrenar el algoritmo
kmeans.fit(customer3[['RECENCY']])

# Obtener las predicciones
customer3['RECENCY_CLUSTER'] = kmeans.predict(customer3[['RECENCY']])

# Ordenar los clusters
customer3 = order_cluster('RECENCY_CLUSTER', 'RECENCY', customer3, False)

# Estadística Descriptiva del cluster creado
customer3.groupby('RECENCY_CLUSTER')['RECENCY'].mean()
```

Out[144…
```
RECENCY_CLUSTER
0    311.187300
1    200.704129
2     98.258574
3     11.829231
Name: RECENCY, dtype: float64
```

In [148…
```python
# Instanciar el algoritmo con 4 clusters para Frequency
```

```
kmeans = KMeans(n_clusters = 4, random_state = 42, n_init = 10)

# Entrenar el algoritmo
kmeans.fit(customer3[['FREQUENCY']])

# Obtener las predicciones
customer3['FREQUENCY_CLUSTER'] = kmeans.predict(customer3[['FREQUENCY']])

# Ordenar los clusters
customer3 = order_cluster('FREQUENCY_CLUSTER', 'FREQUENCY', customer3, True)

# Estadística Descriptiva de los clusters
customer3.groupby('FREQUENCY_CLUSTER')['FREQUENCY'].mean()
```

Out[148…

```
FREQUENCY_CLUSTER
0     219.80549
1    1518.82922
2    5166.00793
3    7847.00000
Name: FREQUENCY, dtype: float64
```

In [150…

```
# Instanciar el algoritmo con 4 clusters para Monetary
kmeans = KMeans(n_clusters = 4, random_state = 42, n_init = 10)

# Entrenar el algoritmo
kmeans.fit(customer3[['MONETARY_TOTAL']])

# Obtener las predicciones
customer3['MONETARY_CLUSTER'] = kmeans.predict(customer3[['MONETARY_TOTAL']])

# Ordenar los clusters ¿Como tienes que ordenar el cluster?
customer3 = order_cluster('MONETARY_CLUSTER', 'MONETARY_TOTAL', customer3, True)

# Estadística Descriptiva de los clusters
customer3.groupby('MONETARY_CLUSTER')['MONETARY_TOTAL'].mean()
```

Out[150…

```
MONETARY_CLUSTER
0      3529.948620
1     48839.130439
2    139718.945633
3    276678.939825
Name: MONETARY_TOTAL, dtype: float64
```

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!!

In [172…

```
# Vamos a crear nuestro score sumando el valor de cada uno de los clusters
customer3['SCORE'] = customer3['RECENCY_CLUSTER'] + customer3['FREQUENCY_CLUSTER'] + customer3['MONETARY_CLUSTEI

# Obtener el promedio para cada una de las métricas de las calificaciones creadas (Score)
customer3.groupby('SCORE')[['RECENCY', 'FREQUENCY', 'MONETARY_TOTAL']].mean()

#customer3['SCORE'] = pd.to_numeric(customer3['SCORE'], errors='coerce')
```

Out[172…

SCORE	RECENCY	FREQUENCY	MONETARY_TOTAL
0	310.733165	285.051394	4640.516711
1	209.427671	333.970393	5115.920180
2	113.918029	362.750493	6809.823931
3	19.653690	258.431636	4239.812395
4	111.703892	2363.658688	54567.132969
5	123.012898	4547.024349	90587.027819
6	56.316749	5472.763896	81386.468819
7	24.560918	6432.498377	104365.363391

In [174…

```
# 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 'Potenti
def segment(score):
    if score <= 1:
        return 'Low-Value'
    elif score > 1 and score <= 4:
        return 'Average'
    elif score > 4 and score <= 6:
```

```python
        return 'Potential'
    else:
        return 'High-Value'

# Crear una columna aplicando esta función al campo 'SCORE'
customer3['SEGMENT'] = customer3['SCORE'].apply(segment)
```

In [176…

```python
# Vamos a dar un vistazo a la tabla final
customer3.head()
```

Out[176…

	INVOICE_DATE	CUSTOMER_ID	RECENCY	FREQUENCY	MONETARY_TOTAL	RECENCY_CLUSTER	FREQUENCY_CLUSTER	MO
0	2020-01-18 10:01:00	12346.0	0	1	77183.60	3	0	
1	2020-10-24 12:02:00	16742.0	0	1	464.90	3	0	
2	2020-05-25 12:39:00	14705.0	0	1	179.00	3	0	
3	2019-12-08 14:53:00	13270.0	0	1	590.00	3	0	
4	2020-11-23 13:57:00	18084.0	0	1	90.48	3	0	

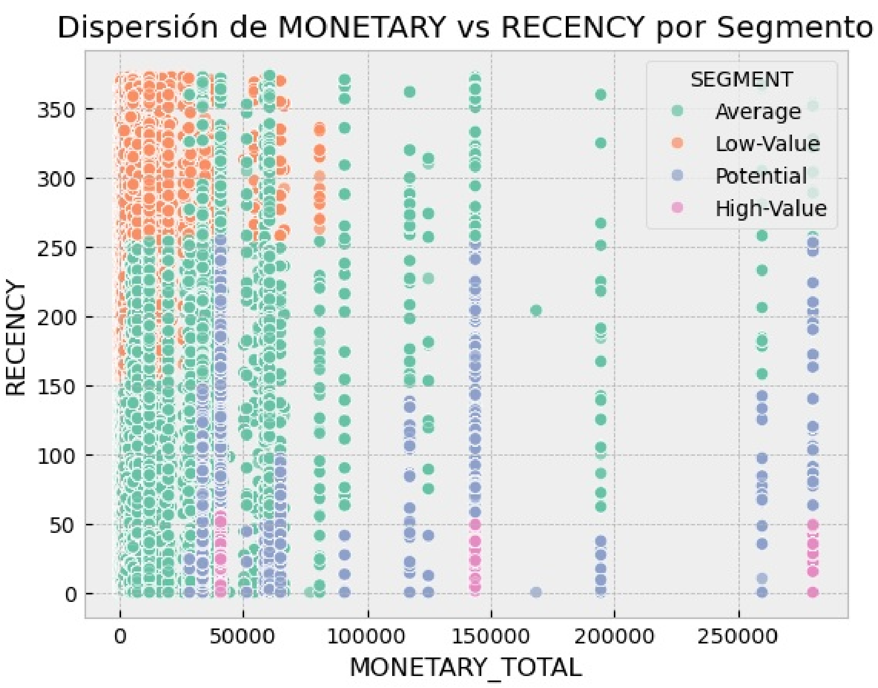
In [178…

```python
# Imprime la proporción o el total de clientes por segmento
print(customer3['SEGMENT'].value_counts())
```

```
SEGMENT
Average       259038
Low-Value     114995
Potential      19270
High-Value      4621
Name: count, dtype: int64
```

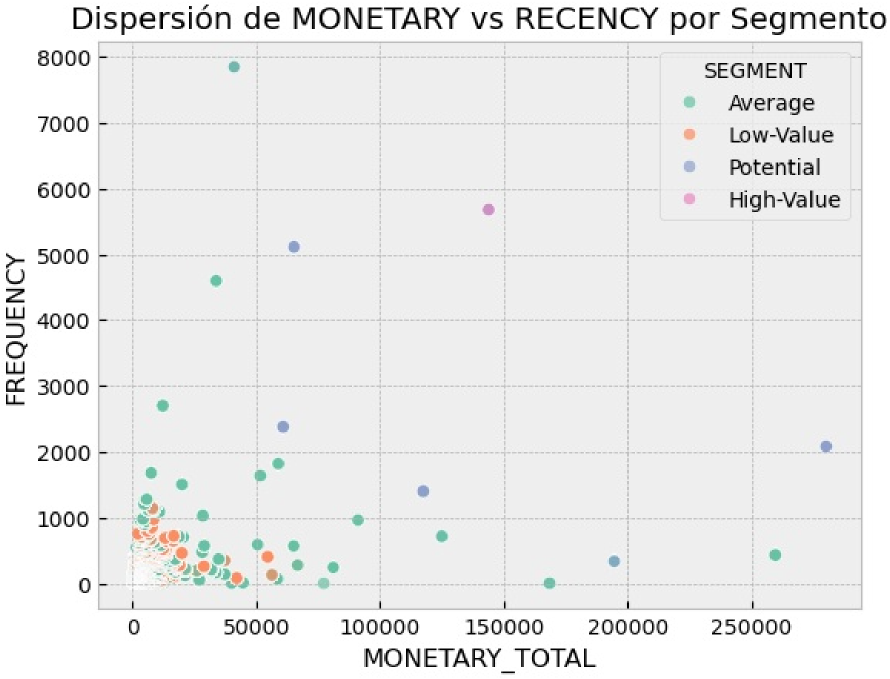
In [188…

```python
# Define un estilo 'bmh'
plt.style.use('bmh')

# Filtra los valores para RECENCY < 4000
custom_filter = customer3[customer3['RECENCY'] < 4000]

# Crea un grafico de dispersion de 'MONETARY' VS 'RECENCY' por Segmento
sb.scatterplot(
    data = custom_filter,
    x = 'MONETARY_TOTAL',
    y = 'RECENCY',
    hue = 'SEGMENT',
    palette = 'Set2',
    alpha = 0.7
)

plt.title('Dispersión de MONETARY vs RECENCY por Segmento')
plt.show()
```



In [186…

```python
# Crea un grafico de dispersion de 'MONETARY' vs 'FREQUENCY' vs  por Segmento
sb.scatterplot(
    data = custom_filter,
    x = 'MONETARY_TOTAL',
    y = 'FREQUENCY',
    hue = 'SEGMENT',
    palette = 'Set2',
    alpha = 0.7
)

plt.title('Dispersión de MONETARY vs FREQUENCY por Segmento')
plt.show()
```



CONCLUSION FINAL

A partir de este analisis podemos entender mejor al consumidor, catalogandolo de tal forma que nos ayude a identificar potenciales o de alto valor. Con las ultimas dispersiones podemos hacer generar una conclusion de como se relaciona la frecuncia con el gasto total o gasto total con cuanto tiempo ha pasado desde la ultima compra.

Este tipo de analisis nos pueden ayudar a la toma de decisiones a la hora de segmentar a nuestros clientes, y para ver en cuales podemos por ejemplo, generar un poco mas de gasto para su retencion.

In [ ]: