Actividad Módulo 23: Numpy y Problemas Estadísticos

1. Importar el archivo "supermarket_sales.csv"
2. Importar librería Numpy. Generar estadística descriptiva de las columnas unit_price y quantity. Calcular moda, media y mediana.
3. Obtener:
   - Ticket promedio por ciudad
   - Ticket promedio por product line y ciudad
   - Ticket promedio por género
   - Ticket promedio por género y product line
4. Usar método rank para generar top 5 (en número y % al grand total):
   - Ventas por ciudad
   - Ventas por memeber
   - Ventas por customer type
5. Cálculo de matriz de correlación:
   - Entre la hora (sin minutos) y el total
   - Entre el precio unitario con el rating de la transacción para validar si los productos más caros son los que dejan mayor margen de ganancia

In [ ]:
```
# 1. Importar archivo y cargarlo en un pd.dataframe
import pandas as pd
df = pd.read_csv('supermarket_sales.csv')
df.sample(10)
```

Out[ ]:

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	co
660	322-02-2271	B	Mandalay	Normal	Female	Sports and travel	42.97	3	6.4455	135.3555	2/3/2019	11:46	Cash	128.
303	439-54-7422	A	Yangon	Normal	Female	Electronic accessories	51.19	4	10.2380	214.9980	3/18/2019	17:15	Credit card	204.
6	355-53-5943	A	Yangon	Member	Female	Electronic accessories	68.84	6	20.6520	433.6920	2/25/2019	14:36	Ewallet	413.
350	860-79-0874	C	Naypyitaw	Member	Female	Fashion accessories	99.30	10	49.6500	1042.6500	2/15/2019	14:53	Credit card	993.
728	210-74-9613	C	Naypyitaw	Normal	Male	Fashion accessories	97.26	4	19.4520	408.4920	3/16/2019	15:33	Ewallet	389.
302	735-06-4124	C	Naypyitaw	Normal	Male	Food and beverages	48.61	1	2.4305	51.0405	2/25/2019	15:31	Cash	48.
472	405-31-3305	A	Yangon	Member	Male	Fashion accessories	43.13	10	21.5650	452.8650	2/2/2019	18:31	Credit card	431.
442	138-17-5109	A	Yangon	Member	Female	Home and lifestyle	89.21	9	40.1445	843.0345	1/15/2019	15:42	Credit card	802.
390	541-89-9860	C	Naypyitaw	Member	Female	Fashion accessories	80.48	3	12.0720	253.5120	2/15/2019	12:31	Cash	241.
994	652-49-6720	C	Naypyitaw	Member	Female	Electronic accessories	60.95	1	3.0475	63.9975	2/18/2019	11:40	Ewallet	60.

In [ ]:

```
# Analisis primario del dataframe
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Invoice ID               1000 non-null   object
 1   Branch                   1000 non-null   object
 2   City                     1000 non-null   object
 3   Customer type            1000 non-null   object
 4   Gender                   1000 non-null   object
 5   Product line             1000 non-null   object
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64
 8   Tax 5%                   1000 non-null   float64
 9   Total                    1000 non-null   float64
 10  Date                     1000 non-null   object
 11  Time                     1000 non-null   object
 12  Payment                  1000 non-null   object
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB
```

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

Out[ ]:

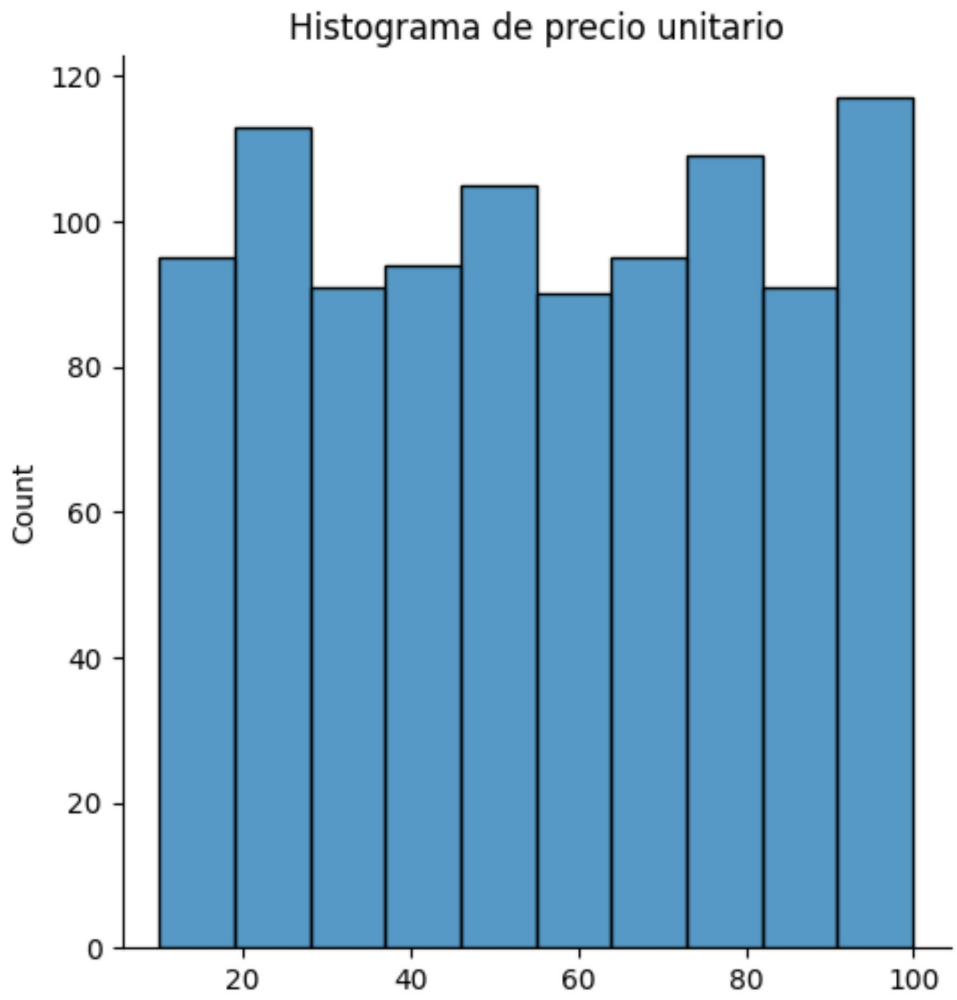
	Unit price	Quantity	Tax 5%	Total	cogs	gross margin percentage	gross income	Rating
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1000.000000	1000.000000	1000.00000
mean	55.672130	5.510000	15.379369	322.966749	307.58738	4.761905	15.379369	6.97270
std	26.494628	2.923431	11.708825	245.885335	234.17651	0.000000	11.708825	1.71858
min	10.080000	1.000000	0.508500	10.678500	10.17000	4.761905	0.508500	4.00000
25%	32.875000	3.000000	5.924875	124.422375	118.49750	4.761905	5.924875	5.50000
50%	55.230000	5.000000	12.088000	253.848000	241.76000	4.761905	12.088000	7.00000
75%	77.935000	8.000000	22.445250	471.350250	448.90500	4.761905	22.445250	8.50000
max	99.960000	10.000000	49.650000	1042.650000	993.00000	4.761905	49.650000	10.00000

In [ ]:
```python
# 2. Importar Numpy y generar estadística descriptiva de unit_price y quantity
import numpy as np

# Cargar pd.series a np.arrays
unit_price_np = df['Unit price'].to_numpy()
quantity_np = df['Quantity'].to_numpy()

# Estadísticas descriptivas de unit_price y quantity

mean_unitprice = unit_price_np.mean()
median_unitprice = np.percentile(unit_price_np, 50)
vals, count = np.unique(unit_price_np, return_counts=True)
mode_unitprice = vals[np.argmax(count)]

print(f'La moda de unit_price es de ${mode_unitprice:.2f}')
print(f'La mediana de unit_price es de ${median_unitprice:.2f}')
print(f'La media de unit_price es de ${mean_unitprice:.2f}')


mean_quantity  = quantity_np.mean()
median_quantity = np.percentile(quantity_np, 50)
vals, count = np.unique(quantity_np, return_counts=True)
mode_quantity = vals[np.argmax(count)]

print(f'\nLa moda de quantity es de {mode_quantity:.0f} unidades')
print(f'La mediana de quantity es de {median_quantity:.0f} unidades')
print(f'La media de quantity es de {mean_quantity:.2f} unidades')
```

```
La moda de unit_price es de $83.77
La mediana de unit_price es de $55.23
La media de unit_price es de $55.67

La moda de quantity es de 10 unidades
La mediana de quantity es de 5 unidades
La media de quantity es de 5.51 unidades
```

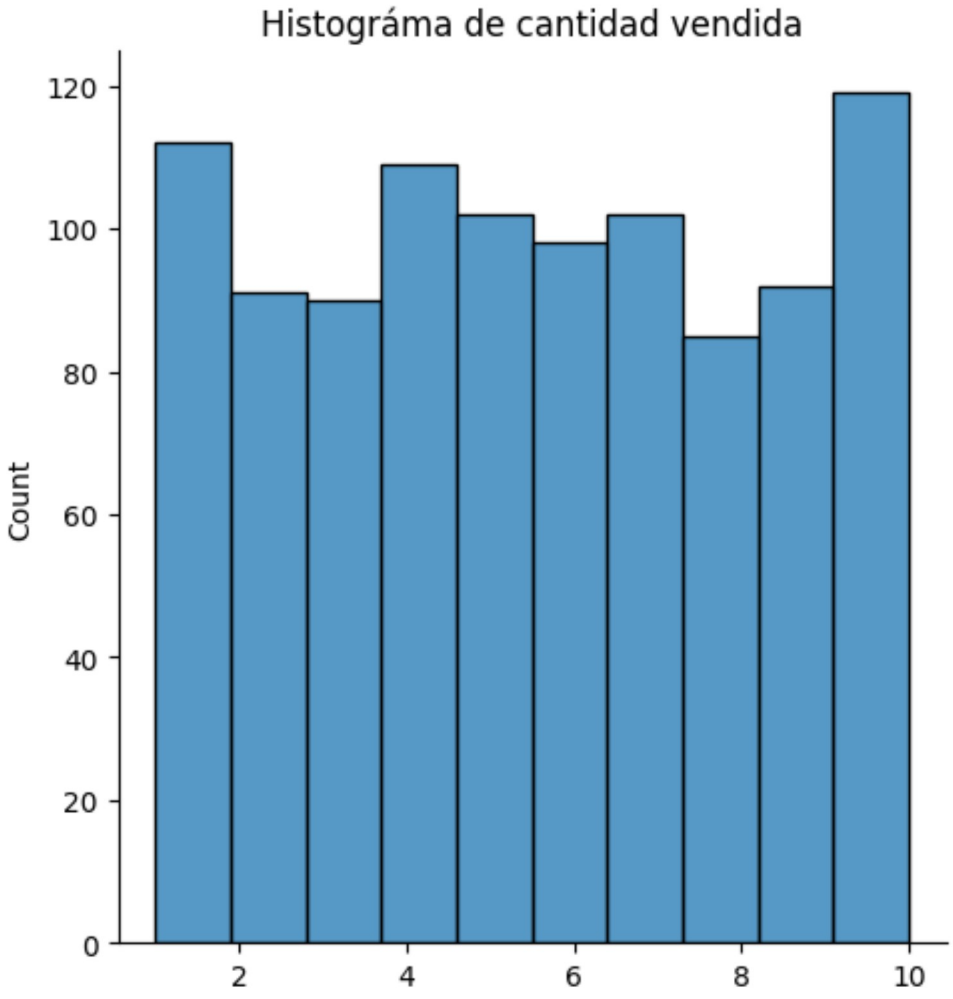
In [ ]:
```
# Gráficos para exploración de las series mencionadas
import matplotlib.pyplot as plt
import seaborn as sns

sns.displot(unit_price_np, bins=10)
plt.title('Histograma de precio unitario')
```

Out[ ]:
```
Text(0.5, 1.0, 'Histograma de precio unitario')
```



In [ ]:
```
sns.displot(quantity_np, bins=10)
plt.title('Histográma de cantidad vendida')
```

Out[ ]:
```
Text(0.5, 1.0, 'Histográma de cantidad vendida')
```



Insights 1:

- Como se puede inferir de las medidas de tendencia central. Al ser las medianas muy cercanas a la moda, no existe un sesgo de los datos de precio unitario ni de cantidad.
- Al hacer los histogramas de ambas series de datos nos podemos dar cuenta que tampoco siguen una distribución normal puesto quye no existe nada parecido a una campana de Gauss. La distribución de ambas series de datos asemejan más a distribuciones uniformes.

In [ ]:
```
# 3.1 Obtener ticket promedio por ciudad
# Pandas
df.pivot_table(values='Total', index='City', aggfunc='mean').round(2)
```

Out[ ]:

City	Total
Mandalay	319.87
Naypyitaw	337.10
Yangon	312.35

In [ ]:
```
# Numpy
city_np = df['City'].to_numpy()
total_np = df['Total'].to_numpy()

# Ticket promedio para la ciudad de Mandalay
city_avg_ticket = total_np[city_np == 'Mandalay'].mean()
print(f'The average ticket for the city of Mandalay is of ${city_avg_ticket:.2f}')

# Ticket promedio para la ciudad de Naypyitaw
city_avg_ticket = total_np[city_np == 'Naypyitaw'].mean()
print(f'The average ticket for the city of Naypyitaw is of ${city_avg_ticket:.2f}')

# Ticket promedio para la ciudad de Yangon
city_avg_ticket = total_np[city_np == 'Yangon'].mean()
print(f'The average ticket for the city of Yangon is of ${city_avg_ticket:.2f}')
```

```
The average ticket for the city of Mandalay is of $319.87
The average ticket for the city of Naypyitaw is of $337.10
The average ticket for the city of Yangon is of $312.35
```

In [ ]:

```python
# 3.2 Ticket promedio por product line y ciudad
# Pandas
df.pivot_table(index=['Product line', 'City'], values='Total', aggfunc='mean').round(2)
```

Out[ ]:

		Total
Product line	**City**	
Electronic accessories	**Mandalay**	310.03
	Naypyitaw	344.89
	Yangon	305.29
Fashion accessories	**Mandalay**	264.73
	Naypyitaw	331.69
	Yangon	320.25
Food and beverages	**Mandalay**	304.30
	Naypyitaw	360.10
	Yangon	295.92
Health and beauty	**Mandalay**	376.99
	Naypyitaw	319.53
	Yangon	268.04
Home and lifestyle	**Mandalay**	350.98
	Naypyitaw	308.79
	Yangon	344.88
Sports and travel	**Mandalay**	322.39
	Naypyitaw	350.27
	Yangon	328.35

In [ ]:
```
# Numpy
product_line_np = df['Product line'].to_numpy()

for product in df['Product line'].unique():
    filter_arr = product_line_np == product
    dummy_city_arr = city_np[filter_arr]
    dummy_total_arr = total_np[filter_arr]
    for city in df['City'].unique():
        product_city_avg_ticket = dummy_total_arr[dummy_city_arr == city].mean()
        print(f'The average ticket in {city} for {product} products is ${product_city_avg_ticket:.2f}')
```

```
The average ticket in Yangon for Health and beauty products is $268.04
The average ticket in Naypyitaw for Health and beauty products is $319.53
The average ticket in Mandalay for Health and beauty products is $376.99
The average ticket in Yangon for Electronic accessories products is $305.29
The average ticket in Naypyitaw for Electronic accessories products is $344.89
The average ticket in Mandalay for Electronic accessories products is $310.03
The average ticket in Yangon for Home and lifestyle products is $344.88
The average ticket in Naypyitaw for Home and lifestyle products is $308.79
The average ticket in Mandalay for Home and lifestyle products is $350.98
The average ticket in Yangon for Sports and travel products is $328.35
The average ticket in Naypyitaw for Sports and travel products is $350.27
The average ticket in Mandalay for Sports and travel products is $322.39
The average ticket in Yangon for Food and beverages products is $295.92
The average ticket in Naypyitaw for Food and beverages products is $360.10
The average ticket in Mandalay for Food and beverages products is $304.30
The average ticket in Yangon for Fashion accessories products is $320.25
The average ticket in Naypyitaw for Fashion accessories products is $331.69
The average ticket in Mandalay for Fashion accessories products is $264.73
```

In [ ]:
```
# 3.3 - Ticket promedio por género
# Pandas
df.pivot_table(index='Gender', values='Total', aggfunc='mean').round(2)
```

Out[ ]:

	Total
Gender	
Female	335.10
Male	310.79

In [ ]:
```
# Numpy
gender_np = df['Gender'].to_numpy()

for gender in df.Gender.unique():
    avg_ticket_gender = total_np[gender_np == gender].mean()
    print(f'The average ticket from {gender} customers is ${avg_ticket_gender:.2f}')
```

```
The average ticket from Female customers is $335.10
The average ticket from Male customers is $310.79
```

In [ ]:
```
# 3.4 - Ticket promedio por género y linea de productos
# Pandas
df.pivot_table(index=['Product line', 'Gender'], values='Total', aggfunc='mean').round(2)
```

Out[ ]:

		Total
Product line	**Gender**	
Electronic accessories	**Female**	322.64
	Male	316.69
Fashion accessories	**Female**	317.06
	Male	291.08
Food and beverages	**Female**	368.57
	Male	273.50
Health and beauty	**Female**	290.02
	Male	348.10
Home and lifestyle	**Female**	380.21
	Male	294.14
Sports and travel	**Female**	324.71
	Male	340.36

In [ ]:
```
# Numpy
for product in np.unique(product_line_np):
    filter_arr = product_line_np == product
    dummy_gender_arr = gender_np[filter_arr]
    dummy_total_arr = total_np[filter_arr]
    for gender in np.unique(gender_np):
        gender_product_avg_ticket = dummy_total_arr[dummy_gender_arr == gender].mean()
        print(f'The average ticket from {gender} customers for {product} products is of ${gender_product_avg_ticket:.
```

```
The average ticket from Female customers for Electronic accessories products is of $322.64
The average ticket from Male customers for Electronic accessories products is of $316.69
The average ticket from Female customers for Fashion accessories products is of $317.06
The average ticket from Male customers for Fashion accessories products is of $291.08
The average ticket from Female customers for Food and beverages products is of $368.57
The average ticket from Male customers for Food and beverages products is of $273.50
The average ticket from Female customers for Health and beauty products is of $290.02
The average ticket from Male customers for Health and beauty products is of $348.10
The average ticket from Female customers for Home and lifestyle products is of $380.21
The average ticket from Male customers for Home and lifestyle products is of $294.14
The average ticket from Female customers for Sports and travel products is of $324.71
The average ticket from Male customers for Sports and travel products is of $340.36
```

In [ ]:
```
# 4.1 - Top 5 ventas por ciudad (y % del total de ventas)
for city in np.unique(city_np):
    dummy_total_arr = total_np[city_np == city]
    total_top = np.concatenate([dummy_total_arr])
    total_top = np.sort(total_top)
    total_top = total_top[::-1]
    total_top_percent = (total_top / total_top.sum())*100

    print(f'The top 5 transactions in {city} had a total of:')
    for i in range(5):
        print(f'\t{i+1}. ${total_top[i]:.2f} - {total_top_percent[i]:.2f}% of the total sales in the city')
```

```
The top 5 transactions in Mandalay had a total of:
        1. $1022.49 - 0.96% of the total sales in the city
        2. $1022.38 - 0.96% of the total sales in the city
        3. $944.62 - 0.89% of the total sales in the city
        4. $942.45 - 0.89% of the total sales in the city
        5. $922.63 - 0.87% of the total sales in the city
The top 5 transactions in Naypyitaw had a total of:
        1. $1042.65 - 0.94% of the total sales in the city
        2. $1034.46 - 0.94% of the total sales in the city
        3. $1023.75 - 0.93% of the total sales in the city
        4. $1020.71 - 0.92% of the total sales in the city
        5. $1003.59 - 0.91% of the total sales in the city
The top 5 transactions in Yangon had a total of:
        1. $1039.29 - 0.98% of the total sales in the city
        2. $951.83 - 0.90% of the total sales in the city
        3. $932.34 - 0.88% of the total sales in the city
        4. $931.03 - 0.88% of the total sales in the city
        5. $926.95 - 0.87% of the total sales in the city
```

In [ ]:

```
# 4.2 - Top 5 de ventas por tipo de cliente
customer_np = df['Customer type'].to_numpy()

for customer in np.unique(customer_np):
    dummy_total_arr = total_np[customer_np == customer]
    total_top = np.concatenate([dummy_total_arr])
    total_top = np.sort(total_top)
    total_top = total_top[::-1]
    total_top_percent = (total_top / total_top.sum())*100

    print(f'The top 5 transactions for {customer} customers had a total of:')
    for i in range(5):
        print(f'\t{i+1}. ${total_top[i]:.2f} - {total_top_percent[i]:.2f}% of the total sales for that type of custom
```

```
The top 5 transactions for Member customers had a total of:
        1. $1042.65 - 0.63% of the total sales for that type of customers
        2. $1034.46 - 0.63% of the total sales for that type of customers
        3. $1020.71 - 0.62% of the total sales for that type of customers
        4. $951.83 - 0.58% of the total sales for that type of customers
        5. $950.25 - 0.58% of the total sales for that type of customers
The top 5 transactions for Normal customers had a total of:
        1. $1039.29 - 0.65% of the total sales for that type of customers
        2. $1023.75 - 0.64% of the total sales for that type of customers
        3. $1022.49 - 0.64% of the total sales for that type of customers
        4. $1022.38 - 0.64% of the total sales for that type of customers
        5. $1003.59 - 0.63% of the total sales for that type of customers
```

In [ ]:

```python
# 4.3 - Top 5 de ventas por método de pago
payment_np = df['Payment'].to_numpy()

for payment in np.unique(payment_np):
    dummy_total_arr = total_np[payment_np == payment]
    total_top = np.concatenate([dummy_total_arr])
    total_top = np.sort(total_top)
    total_top = total_top[::-1]
    total_top_percent = (total_top / total_top.sum())*100

    print(f'The top 5 transactions for {payment} payments had a total of:')
    for i in range(5):
        print(f'\t{i+1}. ${total_top[i]:.2f} - {total_top_percent[i]:.2f}% of the total of payments done with this me
```

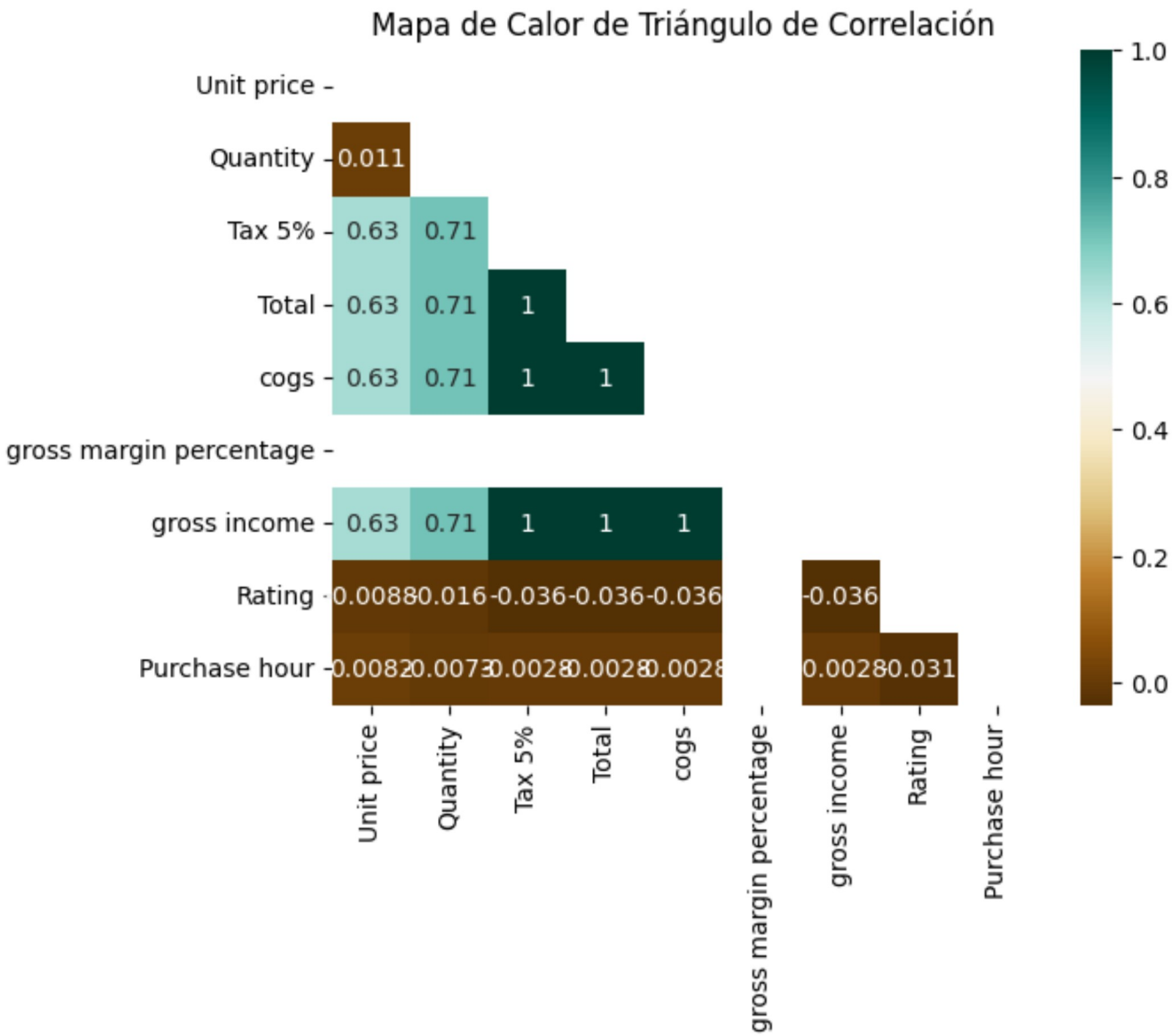
```
The top 5 transactions for Cash payments had a total of:
        1. $1003.59 - 0.89% of the total of payments done with this method
        2. $1002.12 - 0.89% of the total of payments done with this method
        3. $950.25 - 0.85% of the total of payments done with this method
        4. $943.30 - 0.84% of the total of payments done with this method
        5. $935.27 - 0.83% of the total of payments done with this method
The top 5 transactions for Credit card payments had a total of:
        1. $1042.65 - 1.03% of the total of payments done with this method
        2. $1039.29 - 1.03% of the total of payments done with this method
        3. $1022.38 - 1.01% of the total of payments done with this method
        4. $1020.71 - 1.01% of the total of payments done with this method
        5. $944.62 - 0.94% of the total of payments done with this method
The top 5 transactions for Ewallet payments had a total of:
        1. $1034.46 - 0.94% of the total of payments done with this method
        2. $1023.75 - 0.93% of the total of payments done with this method
        3. $1022.49 - 0.93% of the total of payments done with this method
        4. $951.83 - 0.87% of the total of payments done with this method
        5. $937.82 - 0.85% of the total of payments done with this method
```

In [ ]:

```python
# 5.1 - Matriz de correlación entre la hora y el total
df['Purchase hour'] = pd.to_datetime(df['Time']).dt.hour
df['Purchase hour'] = pd.to_numeric(df['Purchase hour'])

mask = np.triu(np.ones_like(df.corr(numeric_only=True), dtype=bool))
heatmap = sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='BrBG', mask=mask)
heatmap.set_title('Mapa de Calor de Triángulo de Correlación')
```

Out[ ]:

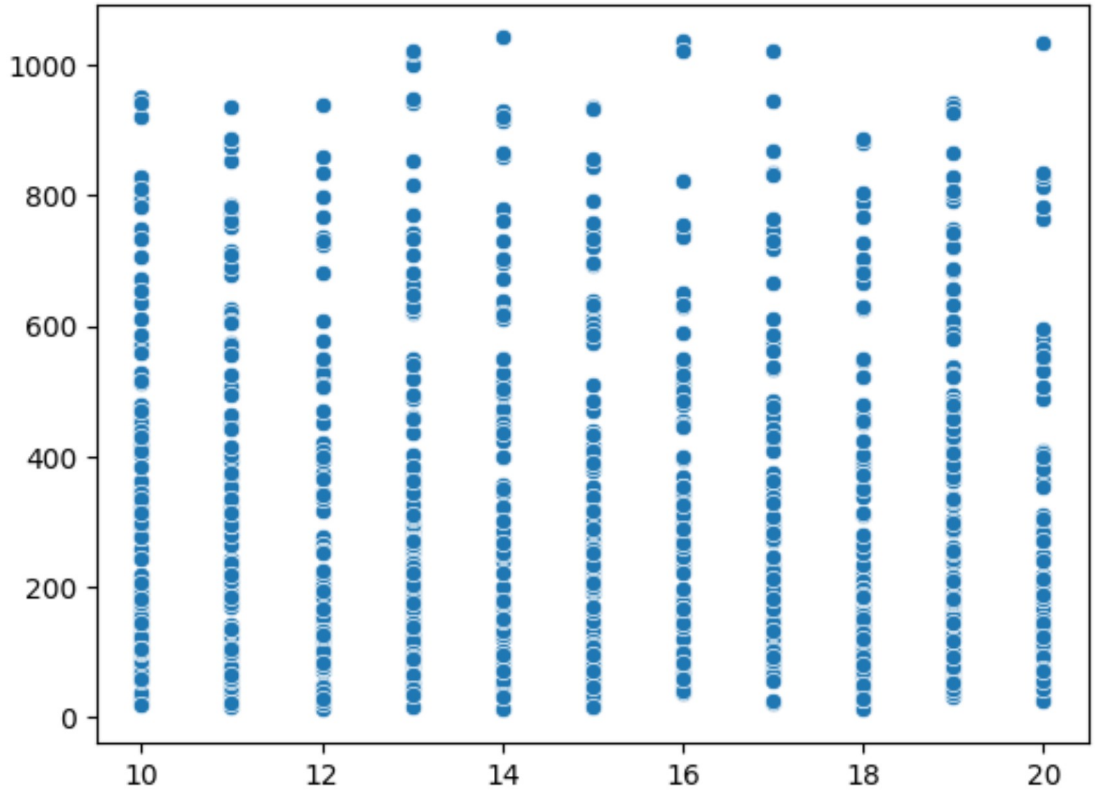
```
Text(0.5, 1.0, 'Mapa de Calor de Triángulo de Correlación')
```



In [ ]:
```
hour_np = df['Purchase hour'].to_numpy()
corr = np.corrcoef(hour_np, total_np)
print(f'El factor de correlación entre la hora de compra y el total de la compra es de {corr[1,0]:.4f}')
sns.scatterplot(x=hour_np, y=total_np)
```

```
El factor de correlación entre la hora de compra y el total de la compra es de -0.0028
```

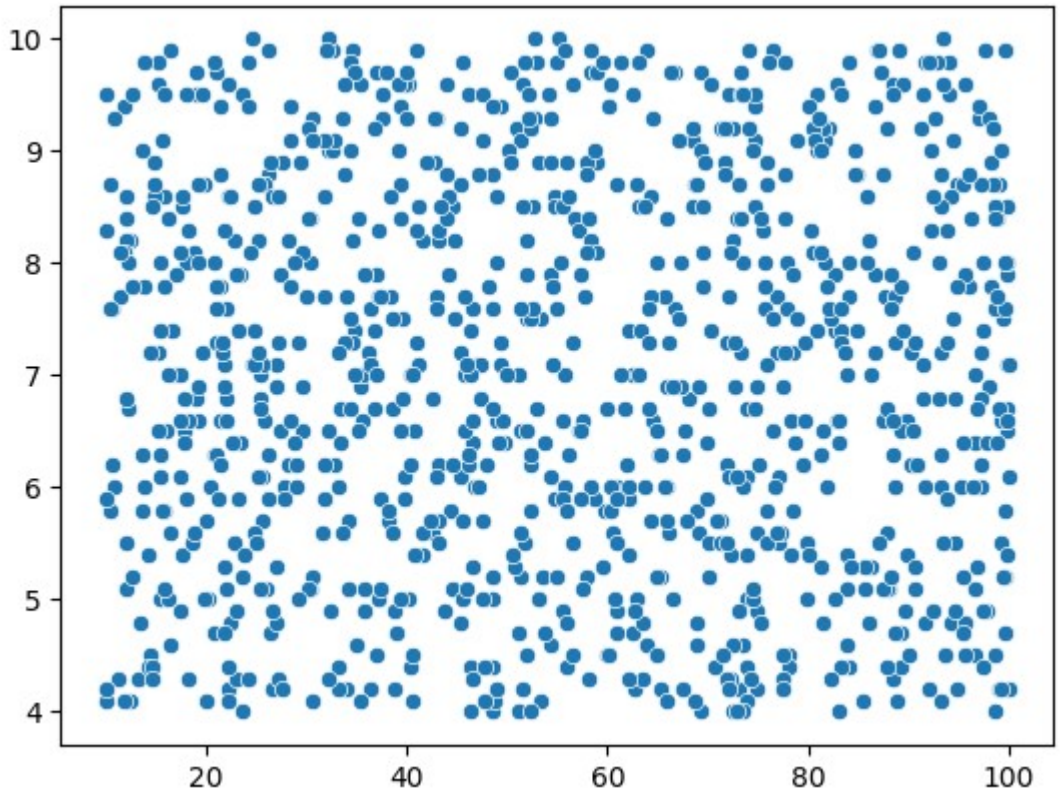
Out[ ]: <AxesSubplot: >



In [ ]:
```
# 4.2 Correlación entre el precio unitario y el rating de la transacción
rating_np = df['Rating'].to_numpy()
corr = np.corrcoef(rating_np, unit_price_np)
print(f'El factor de correlación entre el precio unitario y el rating de la transacción es de {corr[1,0]:.4f}')
sns.scatterplot(x=unit_price_np, y=rating_np)
```

```
El factor de correlación entre el precio unitario y el rating de la transacción es de -0.0088
```

Out[ ]: <AxesSubplot: >



Insights 2:

- No existe correlación alguna entre la hora de compra y el total de la compra
- No existe correlación alguna entre el precio unitario del artículo y el rating de la compra por lo que lo artículos con precio unitario más alto no necesariamente dejan una mejor ganancia