

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

```

```
data.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	costs	gross margin percentage	gross income	Rating
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:08	Ewallet	522.83	4.761905	26.1415	9.1
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:29	Cash	76.40	4.761905	3.8200	9.6
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:23	Credit card	324.31	4.761905	16.2155	7.4

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Time	Payment	cogs	gross margin percentage	gross income	Rating
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:33	Ewallet	465.76	4.761905	23.2880	8.4
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:37	Ewallet	604.17	4.761905	30.2085	5.3

```
data.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
```

```
data['Date']=pd.to_datetime(data['Date'])
```

```
data1=data.copy()
```

```
data1['day']=(data1['Date']).dt.day
data1['month']=(data1['Date']).dt.month
data1['year']=(data1['Date']).dt.year
```

```
data1.head()
```

	In vo ic e ID	Br an ch	City	Cus to me r typ e	Ge nd er	Pro duc t line	U ni t p ri c e	Qu ant ity	Ta x 5%	Tot al	D at e	Ti me	Pa ym ent	co gs	gros s mar gin per cen tag e	gr os s inc ome	R at ing	d ay	m o nt h	y e ar
0	75 0- 67 - 84 28	A	Yan gon	Me mb er	Fe m al e	Hea lth and bea uty	7 4. 6 9	7	26 .1 41 5	54 8.9 71 5	2 0 1 9- 0 1- 0 5	1 3: 0 8	Ew all et	52 2. 83	4.7 619 05	26 .1 41 5	9. 1	5	1	2 0 1 9

	In vo ic e ID	Br an ch	City	Cus to mer type	Ge n der	Pro duc t line	U ni t p ri ce	Qu an t ity	Ta x 5%	Tot al	D at e	Ti m e	Pa ym ent	co gs	gr os s mar gin per cen tag e	gr os s inc ome	R at ing	d a y	m o n th	y e a r
1	22 6- 31 - 30 81	C	Nay pyit aw	No rm al	Fe m al e	Elec tron ic acc ess orie s	1 5. 2 8	5	3. 82 00	80. 22 00	2 0 1 9- 0 3- 0 8	1 0: 2 9	Ca sh	76 .4 0	4.7 619 05	3. 82 00	9. 6	8	3	2 0 1 9
2	63 1- 41 - 31 08	A	Yan gon	No rm al	M al e	Ho me and lifes tyle	4 6. 3 3	7	16 .2 15 5	34 0.5 25 5	2 0 1 9- 0 3- 0 3	1 3: 2 3	Cr edi t car d	32 4. 31	4.7 619 05	16 .2 15 5	7. 4	3	3	2 0 1 9
3	12 3- 19 - 11 76	A	Yan gon	Me m ber	M al e	Hea lth and bea uty	5 8. 2 2	8	23 .2 88 0	48 9.0 48 0	2 0 1 9- 0 1- 2 7	2 0: 3 3	Ew all et	46 5. 76	4.7 619 05	23 .2 88 0	8. 4	2 7	1	2 0 1 9
4	37 3- 73 - 79 10	A	Yan gon	No rm al	M al e	Spo rts and trav el	8 6. 3 1	7	30 .2 08 5	63 4.3 78 5	2 0 1 9- 0 2-	1 0: 3 7	Ew all et	60 4. 17	4.7 619 05	30 .2 08 5	5. 3	8	2	2 0 1 9

	In vo ic e ID	Br an ch	City	Cus to mer type	Ge n der	Pro duc t line	U ni t p ri ce	Qu ant ity	Ta x 5%	Tot al	D at e	Ti m e	Pa ym ent	co gs	gross margin percentage	gross income	R at ing	d a y	m o n th	y e a r
											0 8									

```
data1.columns
```

Out[10]:

```
Index(['Invoice ID', 'Branch', 'City', 'Customer type', 'Gender',
      'Product line', 'Unit price', 'Quantity', 'Tax 5%', 'Total', 'Date',
      'Time', 'Payment', 'cogs', 'gross margin percentage', 'gross income',
      'Rating', 'day', 'month', 'year'],
      dtype='object')
```

```
data_col=['Branch', 'City', 'Customer type', 'Gender',
          'Product line', 'Quantity', 'Payment', 'month', 'year']
```

```
for i in data_col:
    print(i + ': ')
    print(data1[i].unique())
```

```
Branch:
['A' 'C' 'B']
City:
['Yangon' 'Naypyitaw' 'Mandalay']
Customer type:
['Member' 'Normal']
Gender:
['Female' 'Male']
```

```
Product line:
['Health and beauty' 'Electronic accessories' 'Home and lifestyle'
 'Sports and travel' 'Food and beverages' 'Fashion accessories']
Quantity:
[ 7  5  8  6 10  2  3  4  1  9]
Payment:
['Ewallet' 'Cash' 'Credit card']
month:
[1 3 2]
year:
[2019]
```

```
data2=data1.copy()
```

```
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
```

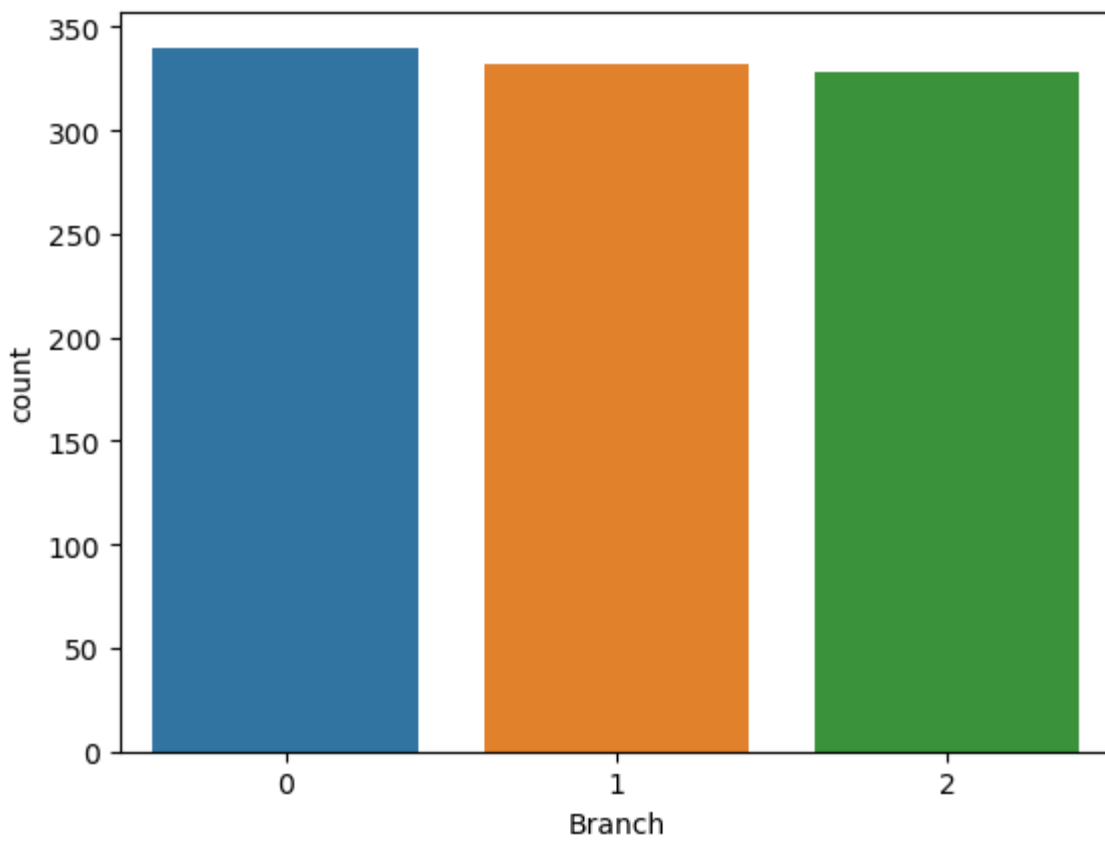
```
label_data=['Branch', 'City', 'Customer type', 'Gender',
            'Product line', 'Payment']
for j in label_data:
    data2[j]=le.fit_transform(data2[j])
```

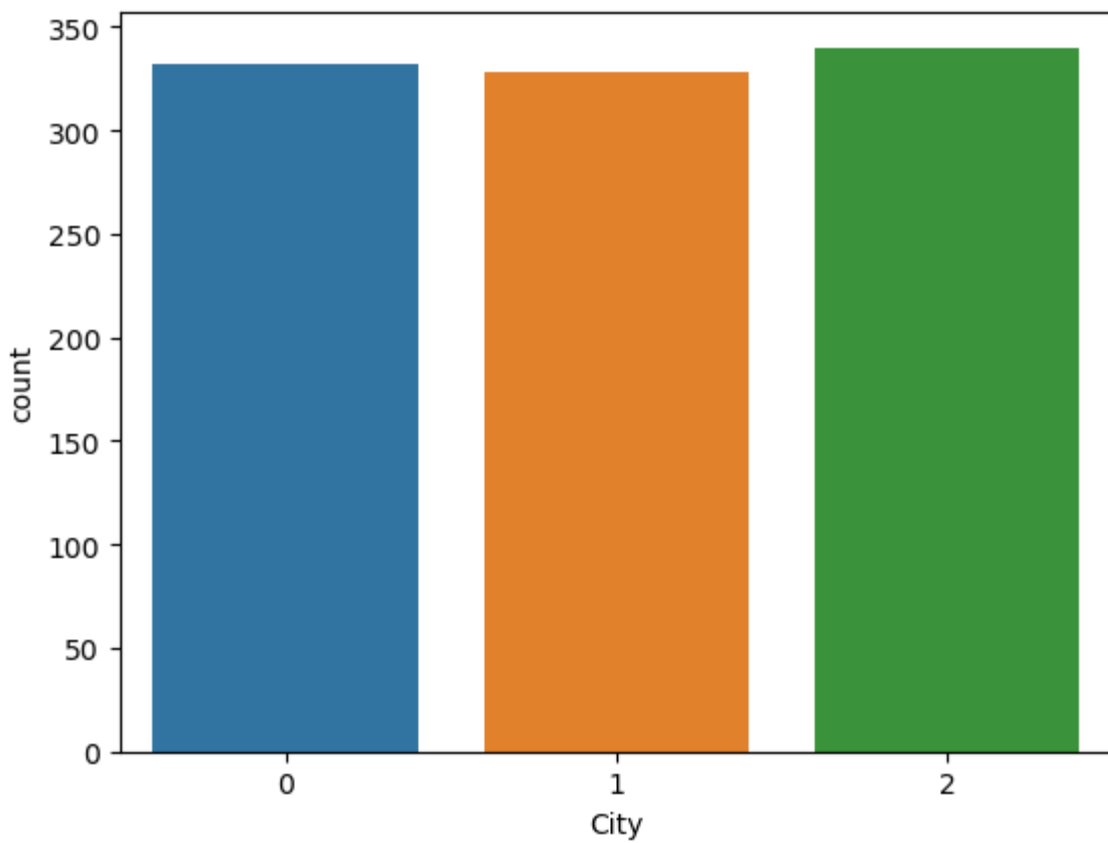
```
data2.head()
```

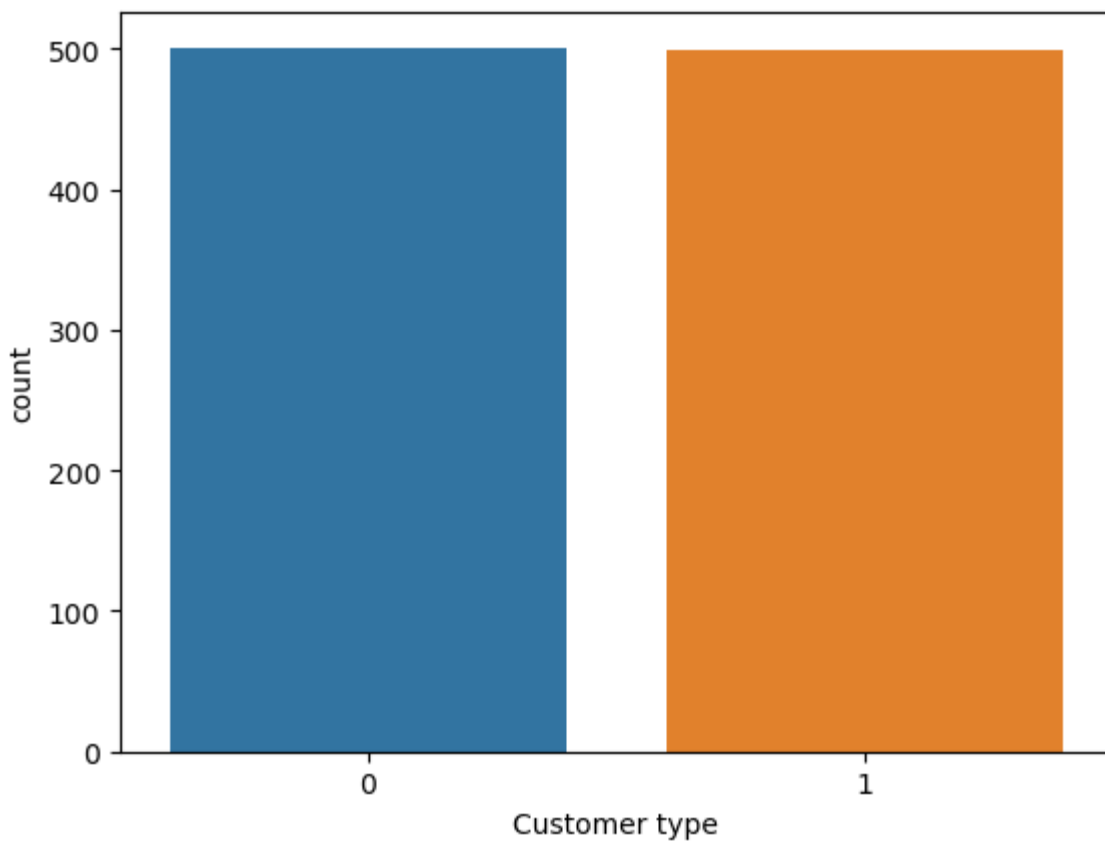
	In vo ice ID	Br an ch	C it y	Cus to mer type	Ge nder	Pr od uct line	U ni t pr ice	Qu ant ity	Tax 5%	Tot al	D ate	Time	Pay ment	co gs	gross margin percentage	gross income	Ra ti ng	day	month	year
0	75 0- 67 - 84 28	0	2	0	0	3	7 4. 6 9	7	26. 14 15	548 .97 15	2 0 1 9- 0 1- 0 5	1 3: 0 8	2	52 2. 83	4.76 190 5	26. 14 15	9. 1	5	1	2 0 1 9
1	22 6- 31 - 30 81	2	1	1	0	0	1 5. 2 8	5	3.8 20 0	80. 220 0	2 0 1 9- 0 3- 0 8	1 0: 2 9	0	76 .4 0	4.76 190 5	3.8 20 0	9. 6	8	3	2 0 1 9
2	63 1- 41 - 31 08	0	2	1	1	4	4 6. 3 3	7	16. 21 55	340 .52 55	2 0 1 9- 0 3- 0 3	1 3: 2 3	1	32 4. 31	4.76 190 5	16. 21 55	7. 4	3	3	2 0 1 9
3	12 3- 19 - 11 76	0	2	0	1	3	5 8. 2 2	8	23. 28 80	489 .04 80	2 0 1 9- 0 1- 2 7	2 0: 3 3	2	46 5. 76	4.76 190 5	23. 28 80	8. 4	2 7	1	2 0 1 9

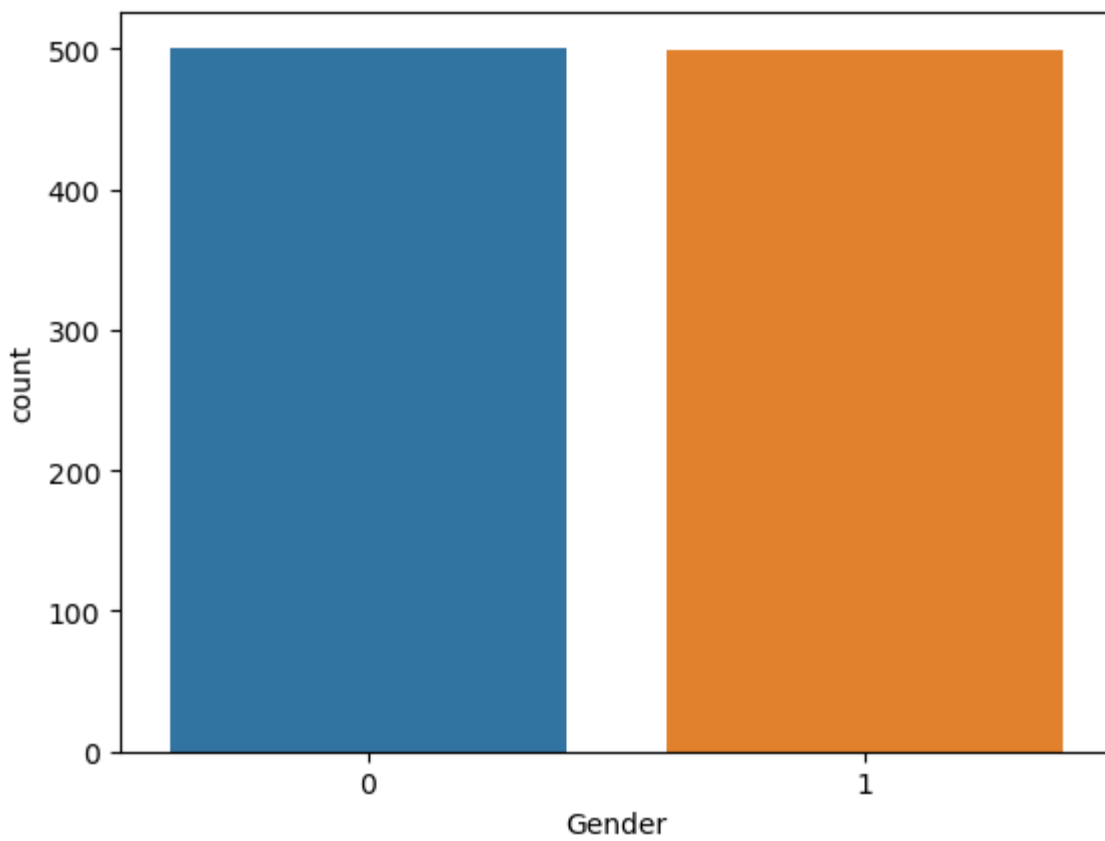
	In vo ice ID	Br an ch	C it y	Cus to mer type	Ge nder	Pr od uct line	U ni t pr ice	Qu ant ity	Ta x 5%	Tot al	D at e	Ti me	Pay me nt	co gs	gross margin percentage	gross income	Ra ti ng	day	month	year
4	37 3- 73 - 79 10	0	2	1	1	5	8 6. 3 1	7	30. 20 85	634 .37 85	2 0 1 9- 0 2- 0 8	1 0: 3 7	2	60 4. 17	4.76 190 5	30. 20 85	5. 3	8	2	2 0 1 9

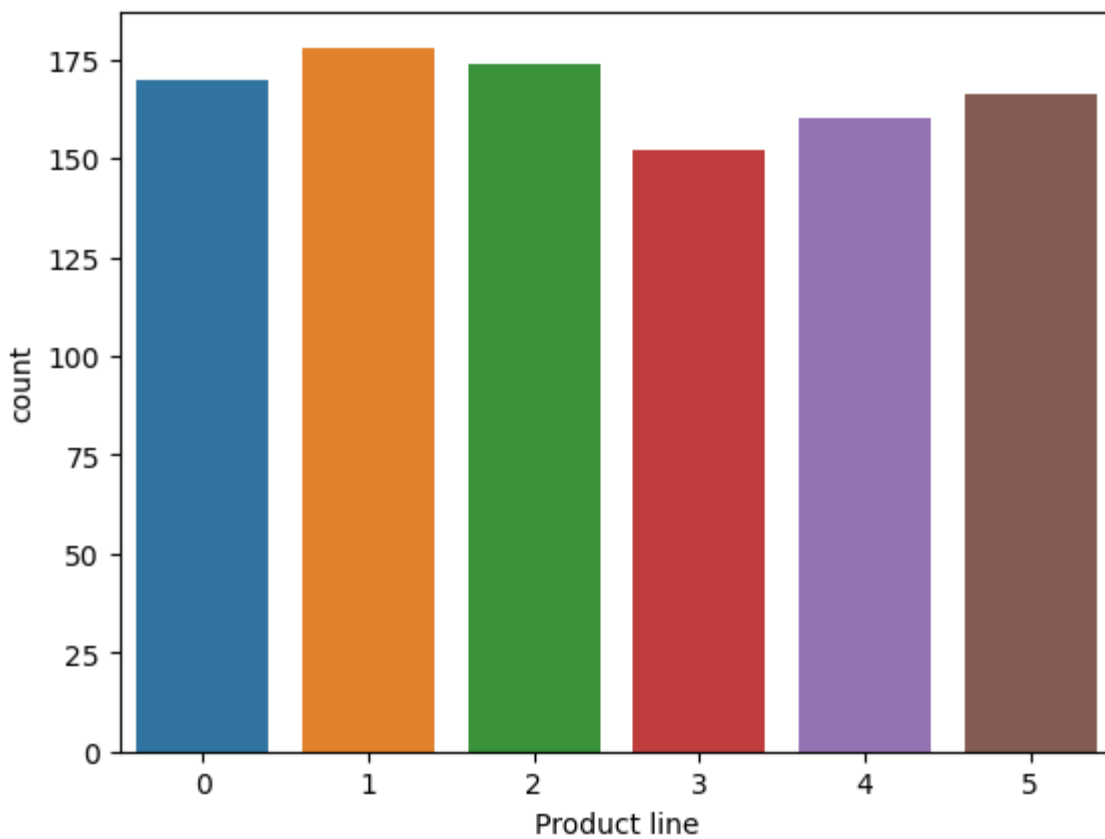
```
for k in label_data:  
    sns.countplot(x=data2[k])  
    plt.show()
```

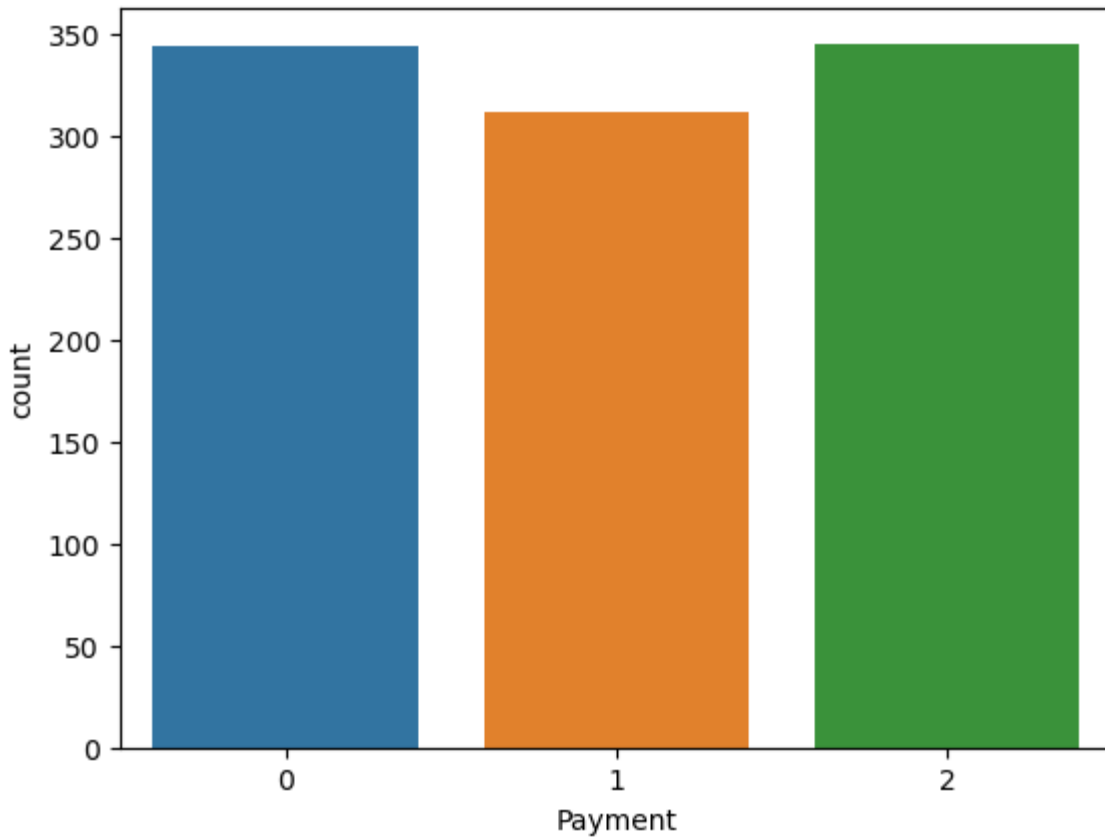







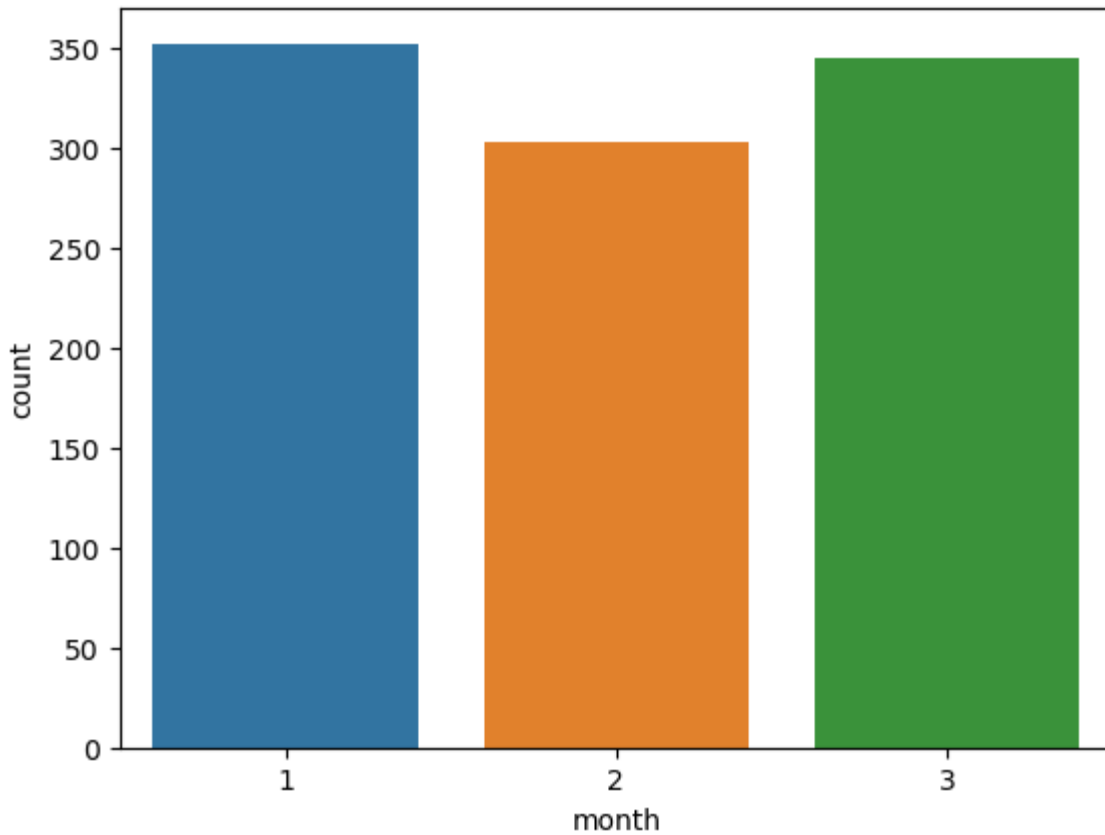






```
sns.countplot(x=data2['month'])
```

```
<AxesSubplot:xlabel='month', ylabel='count'>
```



```
data3=data2.copy()
```

```
data3.drop(['Invoice ID', 'Date',  
           'Time', 'day', 'month', 'year'],axis=1,inplace=True)
```

```
data3.head()
```

	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Payment	cogs	gross margin percentage	gross income	Rating
0	0	2	0	0	3	74.69	7	26.1415	548.9715	2	522.83	4.761905	26.1415	9.1
1	2	1	1	0	0	15.28	5	3.8200	80.2200	0	76.40	4.761905	3.8200	9.6
2	0	2	1	1	4	46.33	7	16.2155	340.5255	1	324.31	4.761905	16.2155	7.4
3	0	2	0	1	3	58.22	8	23.2880	489.0480	2	465.76	4.761905	23.2880	8.4
4	0	2	1	1	5	86.31	7	30.2085	634.3785	2	604.17	4.761905	30.2085	5.3

```
data3.columns
```

```
Index(['Branch', 'City', 'Customer type', 'Gender', 'Product line',
      'Unit price', 'Quantity', 'Tax 5%', 'Total', 'Payment', 'cogs',
      'gross margin percentage', 'gross income', 'Rating'],
      dtype='object')
```

```
data3 = data3.reindex(columns=['Branch', 'City', 'Customer type', 'Gender',
                              'Product line',
                              'Unit price', 'Quantity', 'Tax 5%', 'Payment', 'cogs',
                              'gross margin percentage', 'gross income', 'Rating', 'Total'])
```



```
x=data3.drop(['Total'],axis=1)
y=data3[['Total']]
```

```
x.shape,y.shape, data3.shape
```

```
((1000, 13), (1000, 1), (1000, 14))
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.4,random_state=42)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((600, 13), (400, 13), (600, 1), (400, 1))
```

```
from sklearn.preprocessing import StandardScaler
stand= StandardScaler()
x_train=stand.fit_transform(x_train)
x_test=stand.transform(x_test)
```

```
from sklearn.ensemble import RandomForestRegressor
rfc=RandomForestRegressor(n_estimators=100)
```

```
rfc.fit(x_train,y_train)
```

```
RandomForestRegressor()
```

```
from sklearn.metrics import r2_score
```

```
rfc_y_predict=rfc.predict(x_test)
```

```
r2_score(y_test, rfc_y_predict)
```

0.9999350661657065

```
for z in range(0,20):  
    diff=y_test.values[z]-rfc_y_predict[z]  
    print(y_test.values[z] , ' ', rfc_y_predict[z], ' ', diff )
```

```
[523.971]    521.2057199999999    [2.76528]  
[616.98]    616.4257049999995    [0.554295]  
[408.7335]    408.61380000000014    [0.1197]  
[135.3555]    135.63669000000002    [-0.28119]  
[45.927]    44.609250000000004    [1.31775]  
[618.975]    620.2895999999995    [-1.3146]  
[127.827]    127.36531499999994    [0.461685]  
[731.6925]    731.7491999999995    [-0.0567]  
[450.1035]    451.34858999999994    [-1.24509]  
[138.1275]    137.48920500000008    [0.638295]  
[422.73]    422.38307999999995    [0.34692]  
[463.428]    462.1820699999998    [1.24593]  
[212.7825]    213.20018999999982    [-0.41769]  
[252.252]    252.18563999999998    [0.06636]  
[290.0835]    289.80965999999984    [0.27384]  
[331.128]    329.26487999999995    [1.86312]  
[587.664]    587.83557    [-0.17157]  
[216.846]    216.92013000000009    [-0.07413]  
[757.365]    757.3464150000001    [0.018585]  
[185.094]    185.0490599999999    [0.04494]
```