

Data analysis of coffee bean sales in Saudi Arabia

Project period Starting date : 2025 03 10 Expected closing date 2025 05 06

Overview

Let's assume that a company, Saudi bean, is coffee bean supplier in Saudi Arabia. The sales manager would like to improve inventory management for 2025 and maximize sales and customer satisfaction.

Project Plan

Plan - create report at each week including next steps

1. decide what tools to use - Python,
2. data - need data containing sale amount, location, product. found data in kaggle or
3. time frame

Phase	Periods	Starting date	Ending date	Task
Plan	1 week	03 10	03-17	data, tools, sample size
Analyze	2 weeks	03 18	04 01	Data Cleaning, Descriptive Statistics
Construct	2 weeks	04 02	04 15	A/B Testing , Model Building
Execute	3 weeks	04 16	05 06	Summary, Presentation, Report

Analyze

1. Data Cleaning
2. Descriptive statistics
3. visualization (Tableau and Python) ==results==: find key insights to develop more

Construct

1. Hypothesis Test
2. Model building Results: make sure find better way to do it, check model accuracy

Execute

1. presentaiton
2. Markdown
3. Output: summary, presentaiton, code file with markdown, tableau interactive visualization

As a data Analyst, sampled 730 sales in cities of Saudi Arabia.

Data import and initial data cleaning

In [1]:

```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
# read data file and assign it to df
path = r"C:\Users\soonn\Documents\GitHub\CoffeeBeanSales\DatasetForCoffeeSales2.csv"
df = pd.read_csv(path) # Load data and assign data frame to df
```

In [3]:

```
# initially check 5 rows of data to have an idea of data.
df.head()
```

Out[3]:

	Date	Customer_ID	City	Category	Product	Unit Price	Quantity	Sales Amount	User Discount
0	1/1/2023	32	Riyadh	coffee beans	Colombian	40	14	560	
1	1/2/2023	49	Abha	coffee beans	Costa Rica	35	17	595	
2	1/3/2023	75	Tabuk	coffee beans	Costa Rica	35	19	665	
3	1/4/2023	80	Abha	coffee beans	Ethiopian	45	1	45	
4	1/5/2023	78	Hail	coffee beans	Colombian	40	46	1840	



In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
 ---  --  
 0   Date             730 non-null    object 
 1   Customer_ID     730 non-null    int64  
 2   City             730 non-null    object 
 3   Category         730 non-null    object 
 4   Product          730 non-null    object 
 5   Unit Price       730 non-null    int64  
 6   Quantity         730 non-null    int64  
 7   Sales Amount     730 non-null    int64  
 8   Used_Discount   730 non-null    bool   
 9   Discount_Amount 730 non-null    int64  
 10  Final Sales     730 non-null    int64  
dtypes: bool(1), int64(6), object(4)
memory usage: 57.9+ KB
```

```
In [5]: df.shape
```

```
Out[5]: (730, 11)
```

```
In [6]: df.size
```

```
Out[6]: 8030
```

Insight

- Data type of 'Date' is objects. Changing data type to datetime is better.
- There is no missing values in the data and it has shpe of 730 rows and 11 columns.
- there is 8030 values in the data set.

```
In [7]: df.describe(include = 'all')
```

```
Out[7]:
```

	Date	Customer_ID	City	Category	Product	Unit Price	Quantity	
count	730	730.000000	730	730	730	730.000000	730.000000	730
unique	730	NaN	10	1	5	NaN	NaN	
top	12/30/2024	NaN	Hail	coffee beans	Costa Rica	NaN	NaN	
freq	1	NaN	87	730	165	NaN	NaN	
mean	NaN	51.669863	NaN	NaN	NaN	36.794521	26.080822	95
std	NaN	29.014339	NaN	NaN	NaN	4.955104	14.480971	55
min	NaN	1.000000	NaN	NaN	NaN	30.000000	1.000000	3
25%	NaN	27.250000	NaN	NaN	NaN	35.000000	14.000000	45
50%	NaN	52.000000	NaN	NaN	NaN	35.000000	27.000000	96
75%	NaN	77.000000	NaN	NaN	NaN	40.000000	39.000000	140
max	NaN	100.000000	NaN	NaN	NaN	45.000000	49.000000	220

Insight

- 'City' has 10 unique values, which means 10 cities are sampled and the city 'Hail' counted 87 showing in 730 cities.
- 'Category' contain only one unique value,'coffee_beans'.
- 'Product' has five different names and Costa Rica is the most frequent product in five products.
- 'Unit Price' range is from 30 to 45. the spread is narrow.
- 'Quantity' range is from 1 to 49. this spread is wide compare to unit price.
- Almost half of sales have discounts on sales.

- Sold in discounted price, so final sales price is settled.

```
In [8]: # import the second data set
path = r"C:\Users\soonn\Documents\GitHub\CoffeeBeanSales\saudi_cities_geocoding.csv"
df2 = pd.read_csv(path)
```

```
In [9]: # take a look of data structure
df2.head(10)
```

Out[9]:

	City	Latitude	Longitude
0	Riyadh	24.7136	46.6753
1	Jeddah	21.2854	39.2376
2	Mecca	21.3891	39.8579
3	Medina	24.5247	39.5692
4	Dammam	26.3927	49.9777
5	Khobar	26.2172	50.1971
6	Abha	18.2465	42.5117
7	Tabuk	28.3835	36.5662
8	Hail	27.5114	41.7208
9	Buraidah	26.3259	43.9740

Insight

the dataset contains geographical information of 10 cities in Saudi Arabia. will combine df and df2 into one data set.

```
In [10]: # create a new data 'df_combined' by merging df and df2 on the same city name.
df_combined = df.merge(df2, on = 'City')
```

```
In [11]: df_combined.head(10)
df_combined.to_csv('data_combined.csv')
```

```
In [12]: df_combined.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   Date              730 non-null    object  
 1   Customer_ID       730 non-null    int64   
 2   City               730 non-null    object  
 3   Category          730 non-null    object  
 4   Product            730 non-null    object  
 5   Unit Price         730 non-null    int64   
 6   Quantity           730 non-null    int64   
 7   Sales Amount       730 non-null    int64   
 8   Used_Discount     730 non-null    bool    
 9   Discount_Amount   730 non-null    int64   
 10  Final Sales        730 non-null    int64   
 11  Latitude           730 non-null    float64 
 12  Longitude          730 non-null    float64 
dtypes: bool(1), float64(2), int64(6), object(4)
memory usage: 69.3+ KB
```

```
In [13]: # check data duplication.
df_duplicated = df_combined[df_combined.duplicated()]
df_duplicated

# add month variable
df['Date'] = pd.to_datetime(df['Date']) # change datetime

df['month'] = df['Date'].dt.month
```

Insight

- The combined dataset does not have duplication.

```
In [14]: # change data type of 'date'
df_combined['Date'] = pd.to_datetime(df_combined['Date'])
df_combined.info() # check data type changed successfully.
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 730 entries, 0 to 729
Data columns (total 13 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   Date              730 non-null    datetime64[ns] 
 1   Customer_ID       730 non-null    int64   
 2   City               730 non-null    object  
 3   Category          730 non-null    object  
 4   Product            730 non-null    object  
 5   Unit Price         730 non-null    int64   
 6   Quantity           730 non-null    int64   
 7   Sales Amount       730 non-null    int64   
 8   Used_Discount     730 non-null    bool    
 9   Discount_Amount   730 non-null    int64   
 10  Final Sales        730 non-null    int64   
 11  Latitude           730 non-null    float64 
 12  Longitude          730 non-null    float64 
dtypes: bool(1), datetime64[ns](1), float64(2), int64(6), object(3)
memory usage: 69.3+ KB
```

Optimizing inventory

Relevant variables

- Product - categorical variable
- Quantity - continuous variable
- City - categorical variable

Reasoning

I would like to build a model with one continuous dependent variable and two categorical independent variables. Dependent variable : 'Quantity' Independent variables : 'City', 'Product' I will perform Multivariate ANOVA.

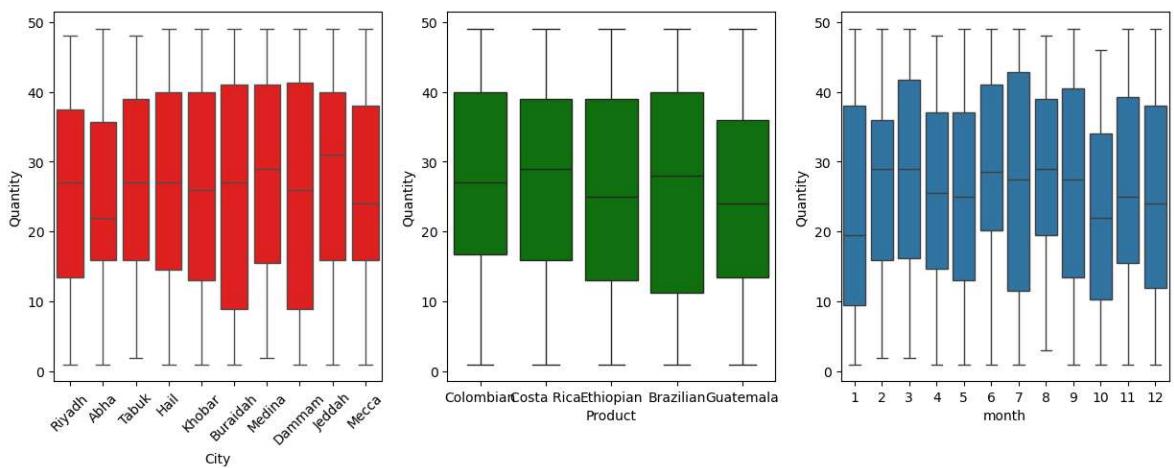
Steps

1. Build hypothesis
2. fit the model
3. check model assumptions
4. evaluate model

```
In [15]: # detect any difference on city-quantity, product-quantity, product-month
fig, axes = plt.subplots(1,3, figsize = (15,5))
sns.boxplot(data = df, x = 'City', y = 'Quantity' , ax = axes[0], color = 'red')
axes[0].tick_params(axis='x', rotation=45)
sns.boxplot(data = df, x = 'Product', y = 'Quantity',ax = axes[1], color = 'green')

sns.boxplot(data = df, x = 'month', y = 'Quantity', ax = axes[2])
```

Out[15]: <Axes: xlabel='month', ylabel='Quantity'>



```
In [16]: # Build hypothesis
h_null = 'The quantity of coffee bean sales is the same in different city'
h_alt = 'The quantity of coffee bean sales is different in different city'
print("Null hypothesis : ", h_null)
print('Althernative hypothesis : ', h_alt)
```

Null hypothesis : The quantity of coffee bean sales is the same in different city
Althernative hypothesis : The quantity of coffee bean sleas is different in different city

```
In [17]: # build formula and holdout sample
from sklearn.model_selection import train_test_split
from statsmodels.formula.api import ols

ols_formula = "Quantity~ C(City)"
x = df['City']
y = df['Quantity']

OLS = ols(formula = ols_formula, data = df)
model = OLS.fit()
print(model.summary())

from statsmodels.stats.anova import anova_lm

anova_lm(model, typ = 2)
```

OLS Regression Results

Dep. Variable:	Quantity	R-squared:	0.005		
Model:	OLS	Adj. R-squared:	-0.008		
Method:	Least Squares	F-statistic:	0.3823		
Date:	Thu, 27 Mar 2025	Prob (F-statistic):	0.944		
Time:	14:49:56	Log-Likelihood:	-2984.8		
No. Observations:	730	AIC:	5990.		
Df Residuals:	720	BIC:	6035.		
Df Model:	9				
Covariance Type:	nonrobust				
<hr/>					
<hr/>					
	coef	std err	t	P> t	[0.025 0.975]
<hr/>					
Intercept	24.4091	1.789	13.642	0.000	20.896
27.922					
C(City)[T.Buraidah]	1.5184	2.503	0.607	0.544	-3.395
6.432					
C(City)[T.Dammam]	0.8826	2.477	0.356	0.722	-3.981
5.746					
C(City)[T.Hail]	2.5219	2.373	1.063	0.288	-2.137
7.181					
C(City)[T.Jeddah]	3.3182	2.438	1.361	0.174	-1.469
8.105					
C(City)[T.Khobar]	0.7279	2.469	0.295	0.768	-4.120
5.575					
C(City)[T.Mecca]	1.7727	2.438	0.727	0.467	-3.015
6.560					
C(City)[T.Medina]	3.0275	2.486	1.218	0.224	-1.852
7.907					
C(City)[T.Riyadh]	1.1099	2.424	0.458	0.647	-3.649
5.869					
C(City)[T.Tabuk]	1.4384	2.604	0.552	0.581	-3.675
6.552					
<hr/>					
Omnibus:	539.345	Durbin-Watson:	1.973		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	45.298		
Skew:	-0.086	Prob(JB):	1.46e-10		
Kurtosis:	1.792	Cond. No.	11.4		
<hr/>					

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

	sum_sq	df	F	PR(>F)
C(City)	727.007237	9.0	0.382275	0.943814
Residual	152143.224270	720.0	NaN	NaN

All pvalue of categorical variables, city have high and this indicate each coefficient is not statistically significant and fail to reject the hypothesis the quantity of each city is the same.

```
In [18]: # build hypothesis
h_null = "The sales quantity of coffee bean is the same in product"
h_alt = "The sales quantity of coffee bean is different in product"
print("Null hypothesis : ", h_null)
print('Althernative hypothesis : ', h_alt)
```

Null hypothesis : The sales quantity of coffee bean is the same in product
 Althernative hypothesis : The sales quantity of coffee bean is different in product

```
In [19]: # build formula and ols
ols_formula = "Quantity ~ C(Product)"
OLS = ols(formula = ols_formula, data = df)
model = OLS.fit()
print(model.summary())
```

OLS Regression Results						
Dep. Variable:	Quantity	R-squared:	0.003			
Model:	OLS	Adj. R-squared:	-0.002			
Method:	Least Squares	F-statistic:	0.6105			
Date:	Thu, 27 Mar 2025	Prob (F-statistic):	0.655			
Time:	14:49:56	Log-Likelihood:	-2985.3			
No. Observations:	730	AIC:	5981.			
Df Residuals:	725	BIC:	6004.			
Df Model:	4					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	
0.975]						
Intercept	25.9726	1.200	21.649	0.000	23.617	
28.328						
C(Product)[T.Colombian]	0.8169	1.680	0.486	0.627	-2.481	
4.115						
C(Product)[T.Costa Rica]	1.0092	1.647	0.613	0.540	-2.224	
4.243						
C(Product)[T.Ethiopian]	-0.2070	1.755	-0.118	0.906	-3.653	
3.239						
C(Product)[T.Guatemala]	-1.3323	1.718	-0.776	0.438	-4.705	
2.040						
Omnibus:	548.281	Durbin-Watson:	1.985			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	45.503			
Skew:	-0.089	Prob(JB):	1.32e-10			
Kurtosis:	1.790	Cond. No.	5.84			

Notes:

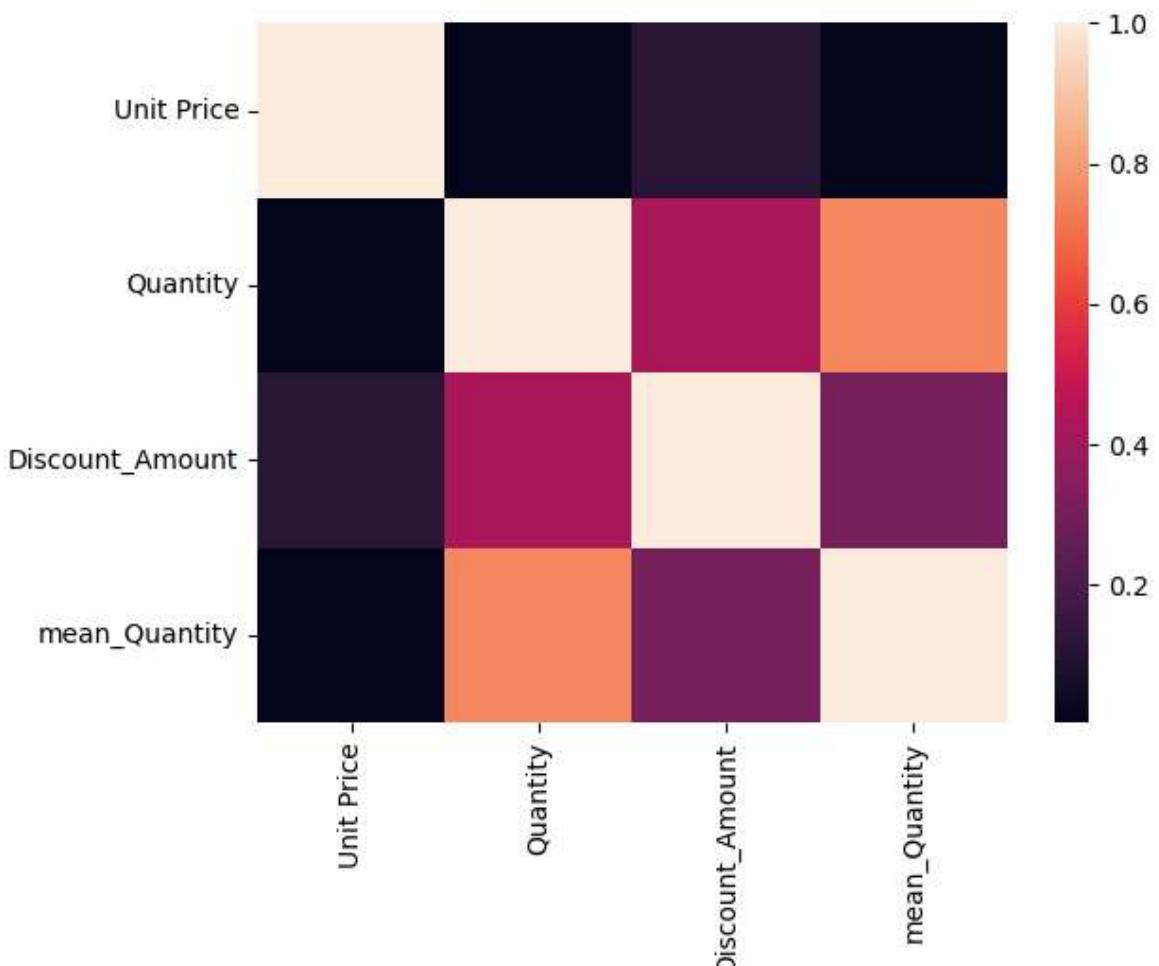
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

All pvalue of categorical variables, product have high and this indicate each coefficient is not statistically significant and fail to reject the hypothesis the quantity of each product is the same.

```
In [20]: # adding mean of city,month,product
df['city_product_month'] = df['City'].astype(str) + ' ' + df['Product'].astype(str)
grouped = df.groupby('city_product_month').mean(numeric_only = True)[['Quantity']]
grouped_dict = grouped.to_dict()
grouped_dict = grouped_dict['Quantity']
df['mean_Quantity'] = df['city_product_month']
df['mean_Quantity'] = df['mean_Quantity'].map(grouped_dict)

df_corr = df[['Unit Price', 'Quantity', 'Discount_Amount', 'mean_Quantity']].corr()
sns.heatmap(df_corr)
```

Out[20]: <Axes: >



Customer_ID and Sales

1. Check Customer_ID and find big customers
2. check big customers' sales, frequency, order size and discount amount
3. build strategies for big customers.

```
In [21]: df_sales_ID = df_combined[['Customer_ID', 'Final Sales']].groupby(['Customer_ID'])
df_sales_ID = df_sales_ID.sort_values(by = 'Final Sales', ascending = False)
print(df_sales_ID)
print(df_sales_ID.describe())
sns.boxplot(data = df_sales_ID, x = 'Final Sales')
```

```

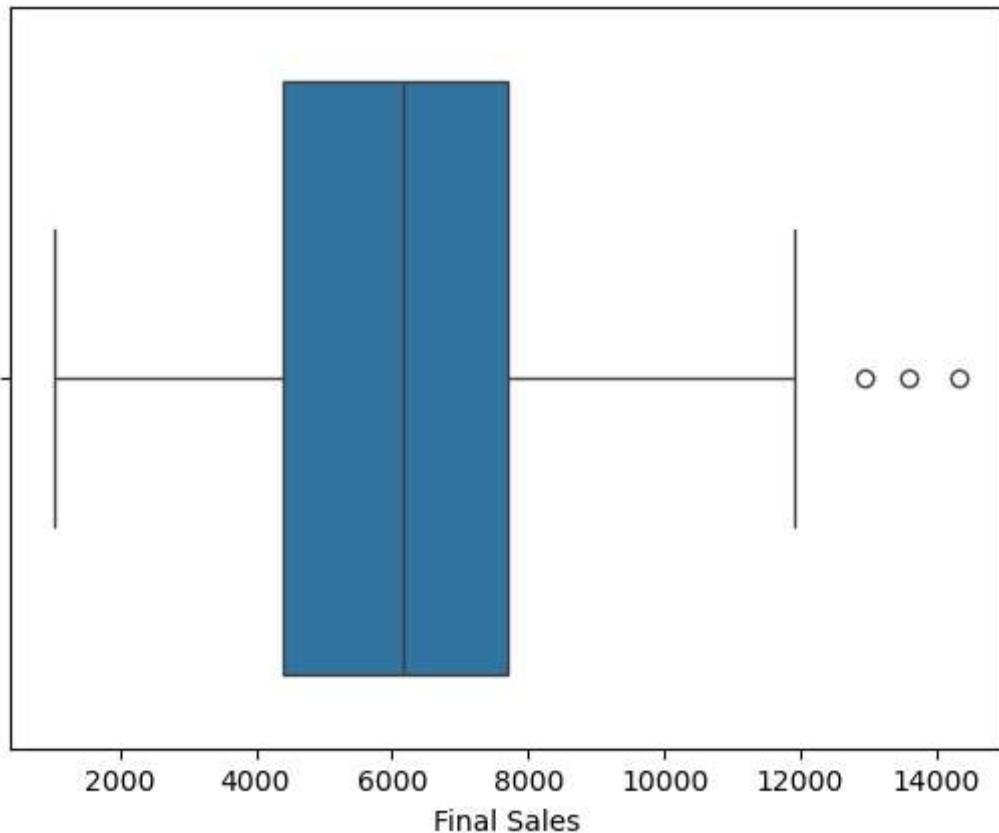
Customer_ID  Final Sales
1             2           14334
96            97          13602
81             82          12932
80             81          11903
49             50          11285
..             ...
11             12          2813
32             33          2548
19             20          1826
86             87          1440
69             70          1050

```

[100 rows x 2 columns]

	Customer_ID	Final Sales
count	100.000000	100.000000
mean	50.500000	6296.480000
std	29.011492	2586.040359
min	1.000000	1050.000000
25%	25.750000	4403.500000
50%	50.500000	6161.000000
75%	75.250000	7687.250000
max	100.000000	14334.000000

Out[21]: <Axes: xlabel='Final Sales'>



In [22]: # there are three big customers
a special promotion on the big three will and make a deal with them will boost
find frequency of orders and date will help to prepare stocks to supply faster
calculate discounts rate

In [23]: big_three = df_sales_ID[df_sales_ID['Final Sales'] >= 12000] # make a data frame
big_three_ID = big_three['Customer_ID'].tolist() # save customer ids of top three
big_three_df = df_combined[df_combined['Customer_ID'].isin(big_three_ID)] # build

```
# add year and month to dataset
big_three_df['year'] = big_three_df['Date'].dt.year
big_three_df['month'] = big_three_df['Date'].dt.month_name().str[:3]
# check the columns are added to
big_three_df.head()
```

C:\Users\soonn\AppData\Local\Temp\ipykernel_19168\229075286.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
big_three_df['year'] = big_three_df['Date'].dt.year
C:\Users\soonn\AppData\Local\Temp\ipykernel_19168\229075286.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
big_three_df['month'] = big_three_df['Date'].dt.month_name().str[:3]

Out[23]:

	Date	Customer_ID	City	Category	Product	Unit Price	Quantity	Sales Amount	User
9	2023-01-10	82	Dammam	coffee beans	Costa Rica	35	4	140	
19	2023-01-20	2	Riyadh	coffee beans	Ethiopian	45	18	810	
34	2023-02-04	82	Riyadh	coffee beans	Colombian	40	35	1400	
41	2023-02-11	2	Dammam	coffee beans	Colombian	40	43	1720	
51	2023-02-21	97	Dammam	coffee beans	Guatemala	35	36	1260	

Sales by month

In order to prepare inventory for the sales, want to know the sales of each month and based on this will build predictive model to answer question. From this process i will achieve

1. sum of quantity by month for each product with visualization
2. predictive model for 2020 to maintain inventory

In [24]:

```
df_combined['year'] = df_combined['Date'].dt.year
df_combined['month'] = df_combined['Date'].dt.month_name().str[:3]
products = df_combined['Product'].unique().tolist()
products # check products
```

```
print("Product Nama: ", str(products), "\nNumber of Product Type : ",len(product
df_combined.head())
```

Product Nama: ['Colombian', 'Costa Rica', 'Ethiopian', 'Brazilian', 'Guatemala']
Number of Product Type : 5

Out[24]:

	Date	Customer_ID	City	Category	Product	Unit Price	Quantity	Sales Amount	Used_D
0	2023-01-01	32	Riyadh	coffee beans	Colombian	40	14	560	
1	2023-01-02	49	Abha	coffee beans	Costa Rica	35	17	595	
2	2023-01-03	75	Tabuk	coffee beans	Costa Rica	35	19	665	
3	2023-01-04	80	Abha	coffee beans	Ethiopian	45	1	45	
4	2023-01-05	78	Hail	coffee beans	Colombian	40	46	1840	

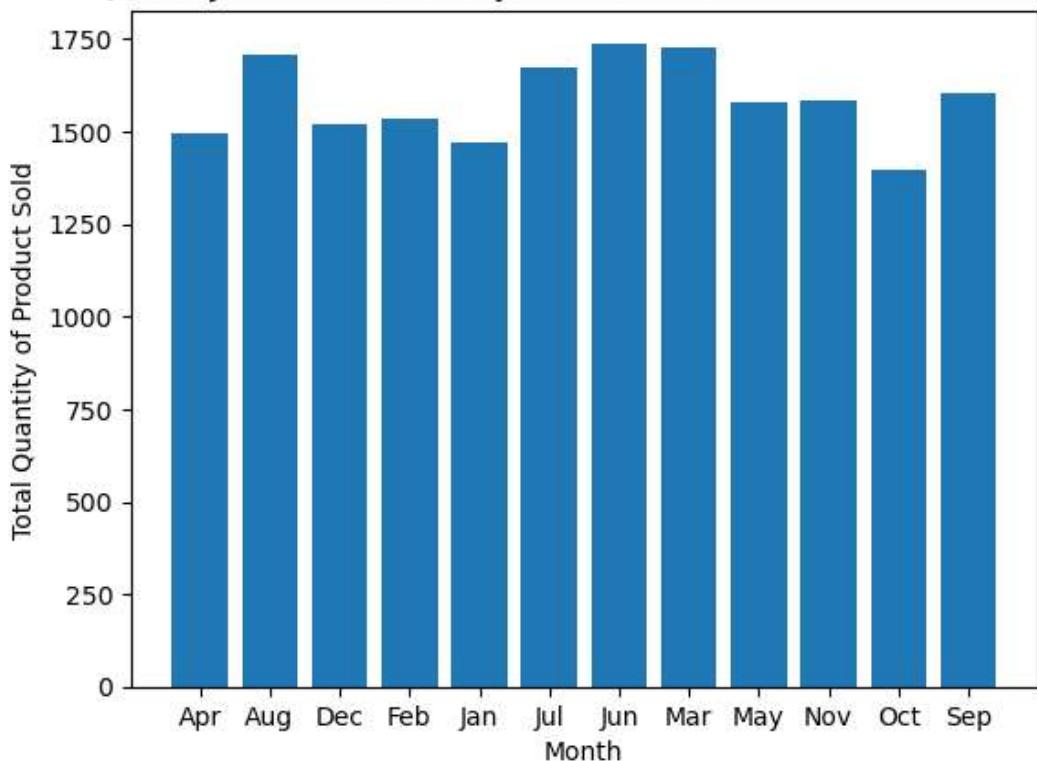


In []:

```
In [25]: df_month = df_combined[['month','Quantity']].groupby('month').sum().reset_index()
df_month.head()
plt.bar(df_month['month'],df_month['Quantity'])
plt.xlabel('Month')
plt.ylabel('Total Quantity of Product Sold')
plt.title('Total Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024')
```

Out[25]: Text(0.5, 1.0, 'Total Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024')

Total Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024

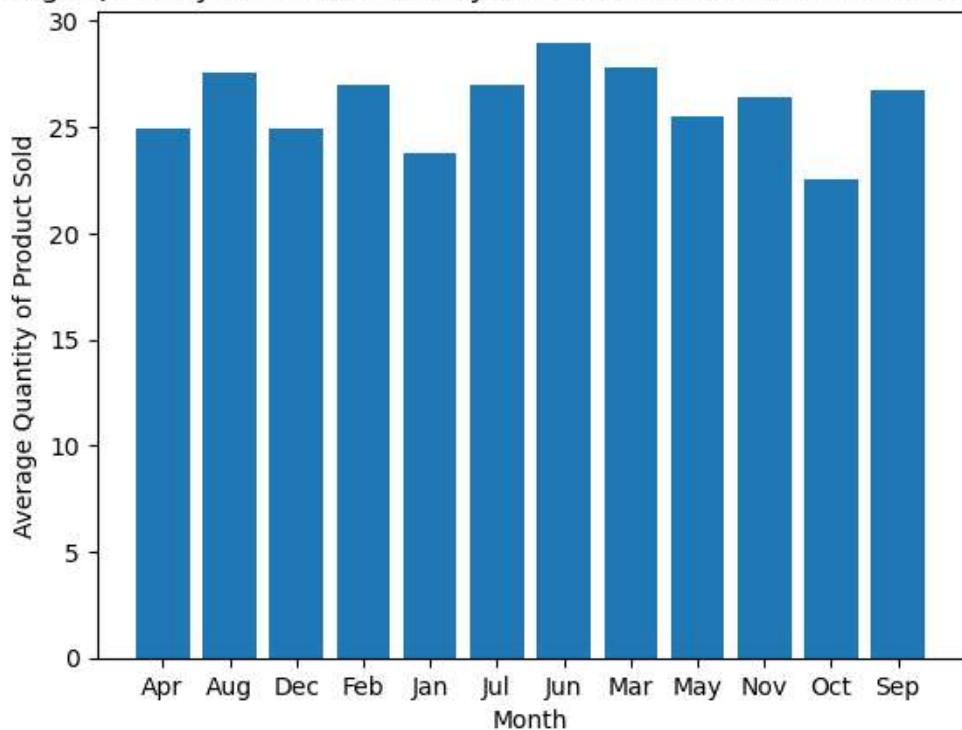


In []:

```
In [26]: df_month_mean = df_combined[['month', 'Quantity']].groupby('month').mean().reset_index()
df_month_mean.head()
plt.bar(df_month_mean['month'], df_month_mean['Quantity'])
plt.xlabel('Month')
plt.ylabel('Average Quantity of Product Sold')
plt.title('Average Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024')
```

Out[26]: Text(0.5, 1.0, 'Average Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024')

Average Quantity of Product Sold by month in Saudi Arabia from 2023 to 2024



Null hypothesis: expected quantity of each month is not different from expected value of Quantity over year. Alternative hypothesis: expected quantity of each month is different from expected value of Quantity over year.

Significance level: 0.05

```
In [27]: df_combined['month'] = df_combined['Date'].dt.month
from scipy.stats import ttest_1samp
q_mean = df_combined['Quantity'].mean()
print("The average value of Quantity : ", q_mean)
for i in range(len(df_combined['month'].unique())+1):
    if i ==0:
        print()
    else:
        m = df_combined[df_combined['month'] == i]
        t_statistics, pval = ttest_1samp( m['Quantity'], q_mean)
        print("t_statistics of month {} ".format(i), t_statistics,
              "\n P value of month {} : ".format(i), pval)
        print("")
```

```
The average value of Quantity : 26.08082191780822
```

```
t_statistics of month 1 -1.1609607374750097
```

```
P value of month 1 : 0.2501810118116579
```

```
t_statistics of month 2 0.504358591195905
```

```
P value of month 2 : 0.615988197284021
```

```
t_statistics of month 3 0.9055409606551041
```

```
P value of month 3 : 0.368741774957579
```

```
t_statistics of month 4 -0.6673483658000391
```

```
P value of month 4 : 0.5071515059120049
```

```
t_statistics of month 5 -0.3229309033146611
```

```
P value of month 5 : 0.7478519360413689
```

```
t_statistics of month 6 1.693154605061607
```

```
P value of month 6 : 0.0957003622508075
```

```
t_statistics of month 7 0.4437180812089893
```

```
P value of month 7 : 0.6588163899701915
```

```
t_statistics of month 8 0.9066707766955214
```

```
P value of month 8 : 0.3681486174937507
```

```
t_statistics of month 9 0.31722394903817847
```

```
P value of month 9 : 0.7521935547436993
```

```
t_statistics of month 10 -1.9782319906710595
```

```
P value of month 10 : 0.0524237519856854
```

```
t_statistics of month 11 0.17035780170193698
```

```
P value of month 11 : 0.8653116019052833
```

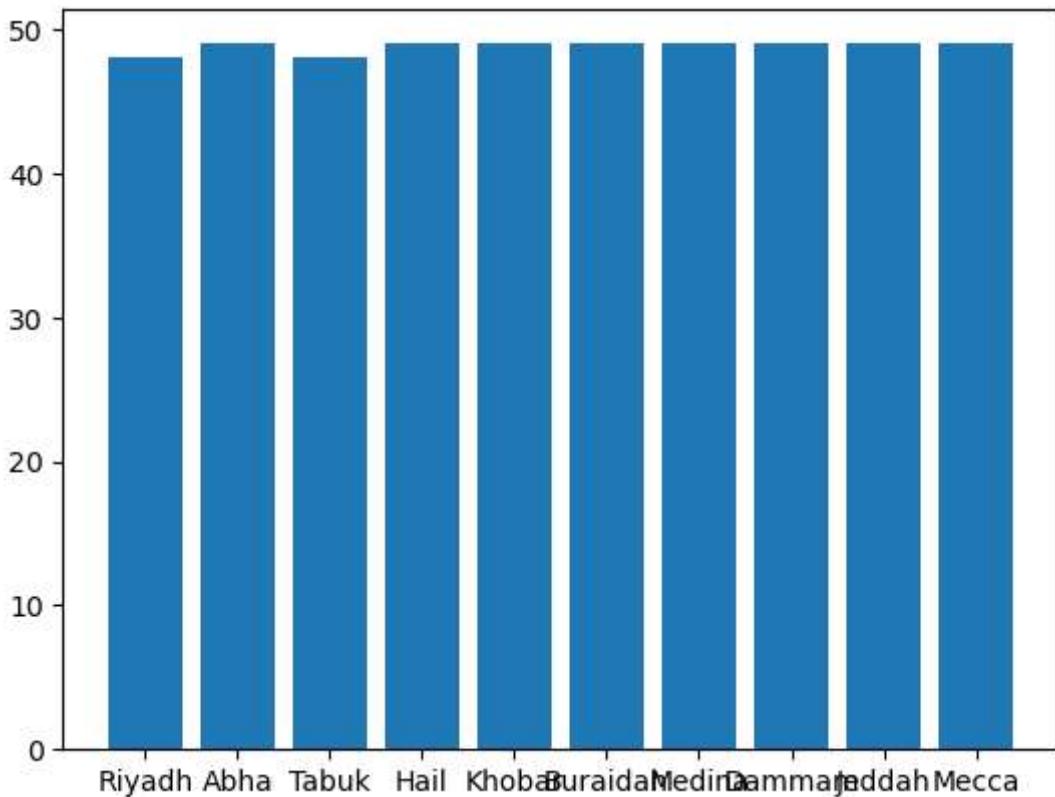
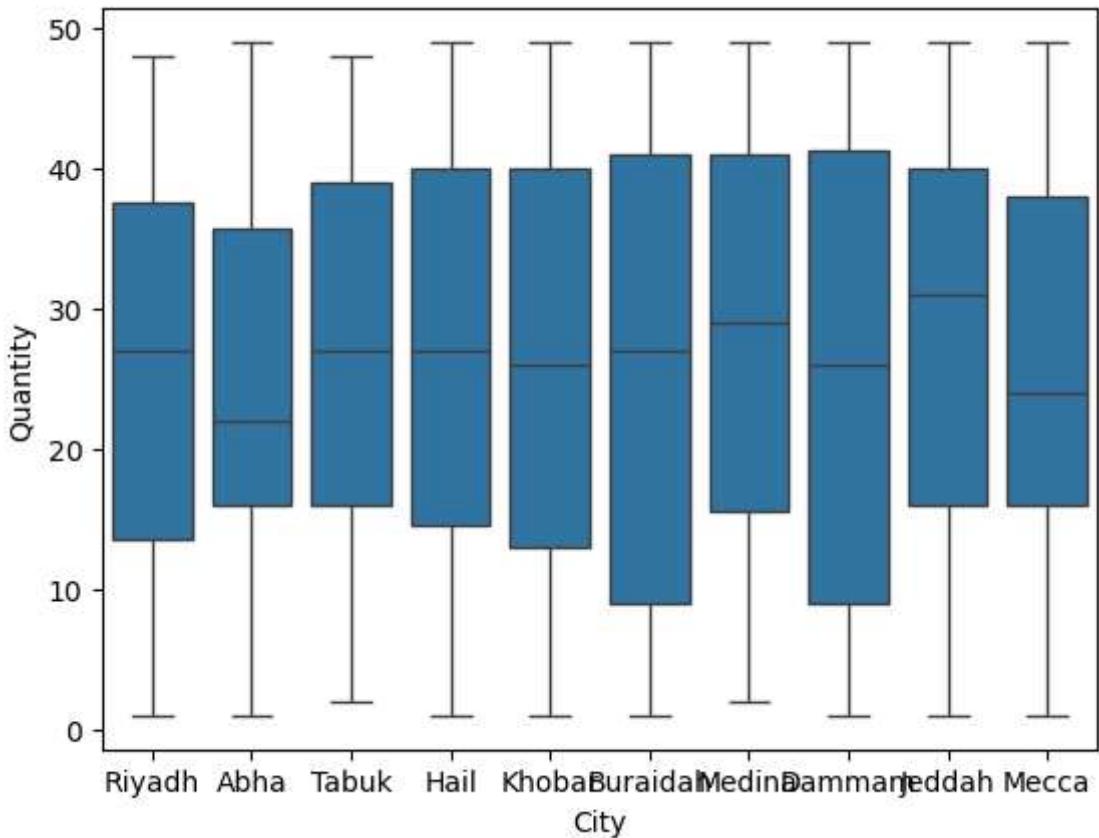
```
t_statistics of month 12 -0.594192937039002
```

```
P value of month 12 : 0.5546169836055441
```

Calculated t-statistics and pvalue of each month to check significance difference between expected quantity of month and expected quantity of year. Month 6 and 10 have the lower p value compare to other month, but they are insignificant with 5% significant level. Fail to reject the Null hypothesis: expected quantity of each month is not different from expected value of Quantity over year and average quantity sold in a u

Quantity by city

```
In [28]: sns.boxplot(data = df_combined, x = 'City', y = 'Quantity')
plt.show()
plt.bar(df_combined['City'], df_combined['Quantity'])
plt.show()
```



Quantity by product and month

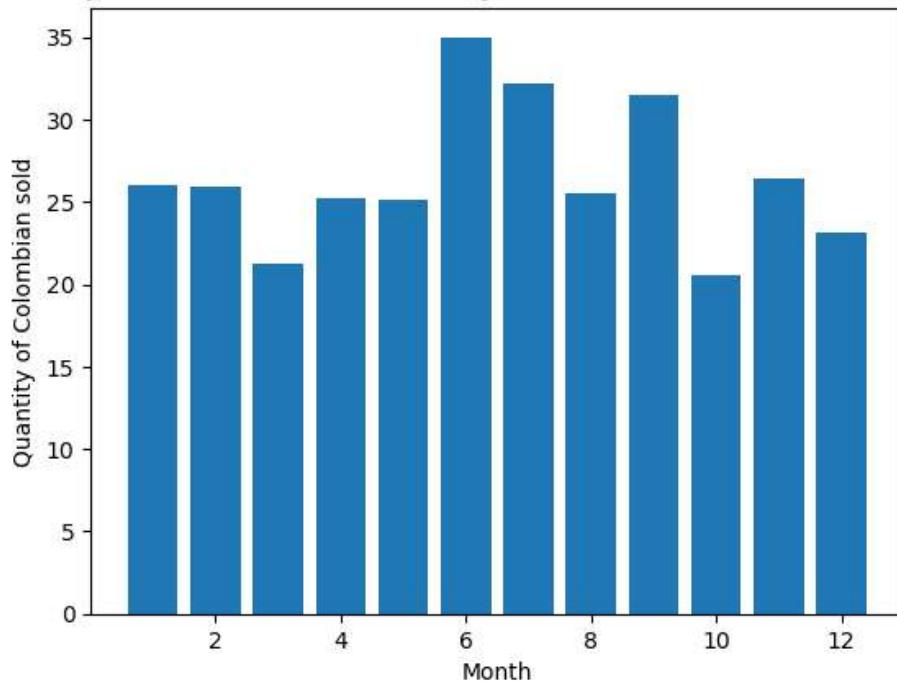
```
In [29]: q_p_m = df_combined[['Quantity','Product','month']]  
q_p_m.head()  
q_p_m.groupby(['Product','month']).mean().reset_index()  
  
df_month_product = df_combined[['Product','month','Quantity']].groupby(['Product',
```

```

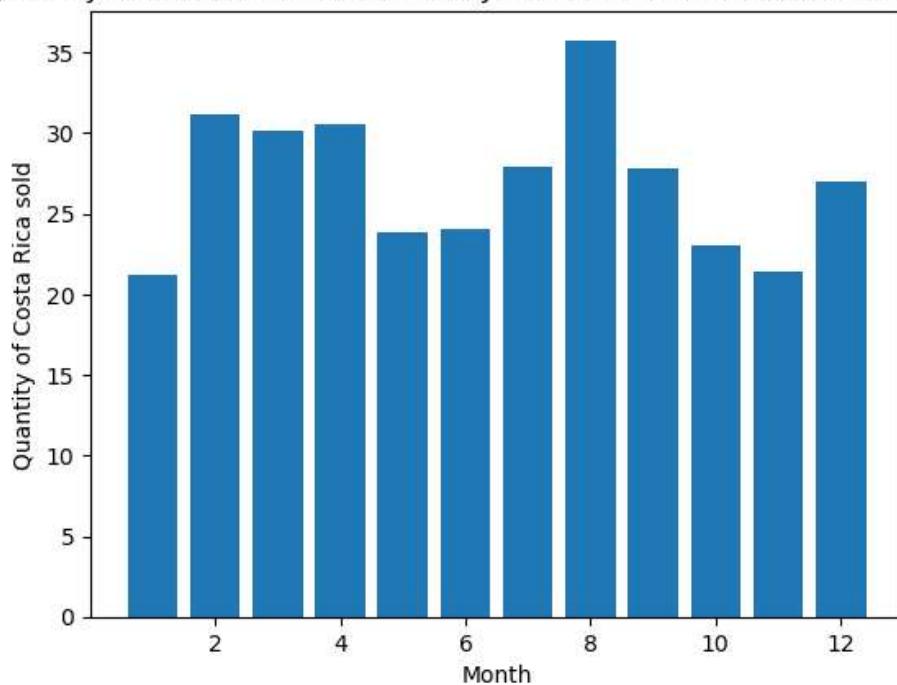
for i in range(len(products)):
    df_products = df_month_product[df_month_product['Product'] == products[i]]
    plt.bar(df_products['month'], df_products['Quantity'])
    plt.xlabel("Month")
    plt.ylabel('Quantity of {} sold'.format(products[i]))
    plt.title('The Quantity of {} Coffee Sold by Month in Saudi Arabia from 2023 to 2024')
    plt.show()

```

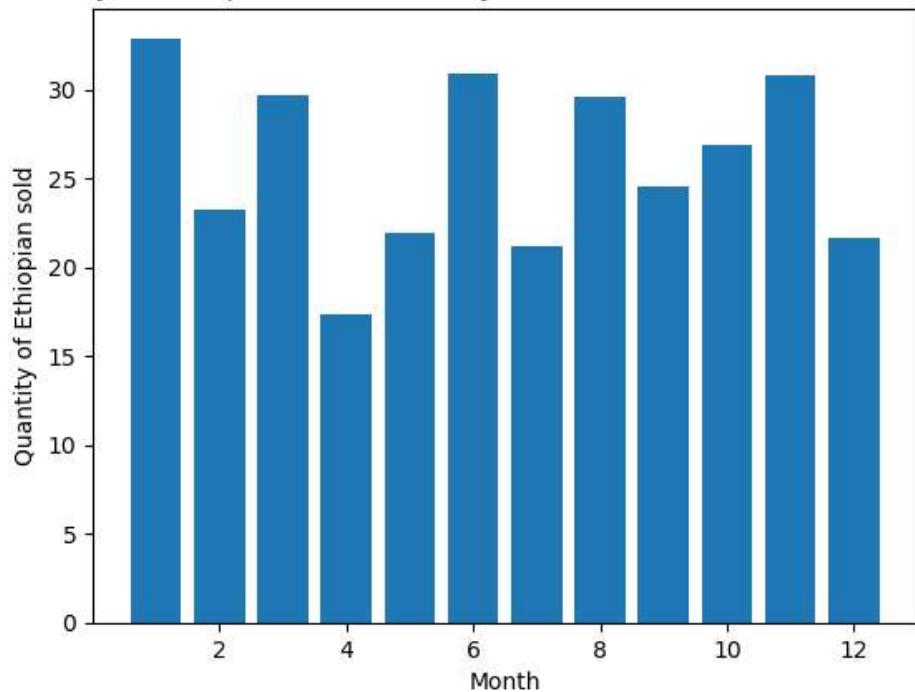
The Quantity of Colombian Coffee Sold by Month in Saudi Arabia from 2023 to 2024



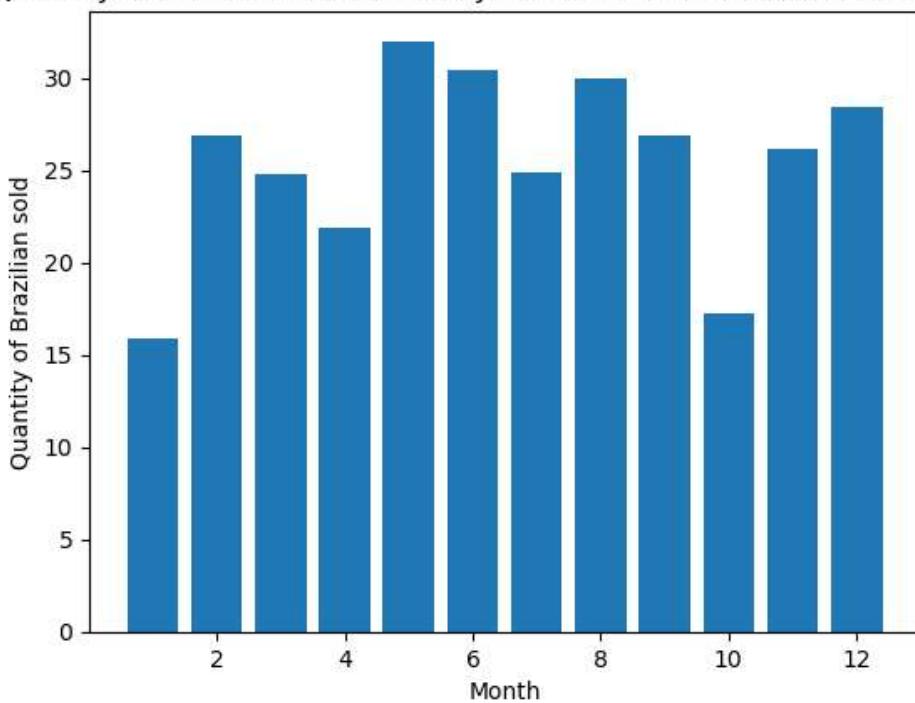
The Quantity of Costa Rica Coffee Sold by Month in Saudi Arabia from 2023 to 2024



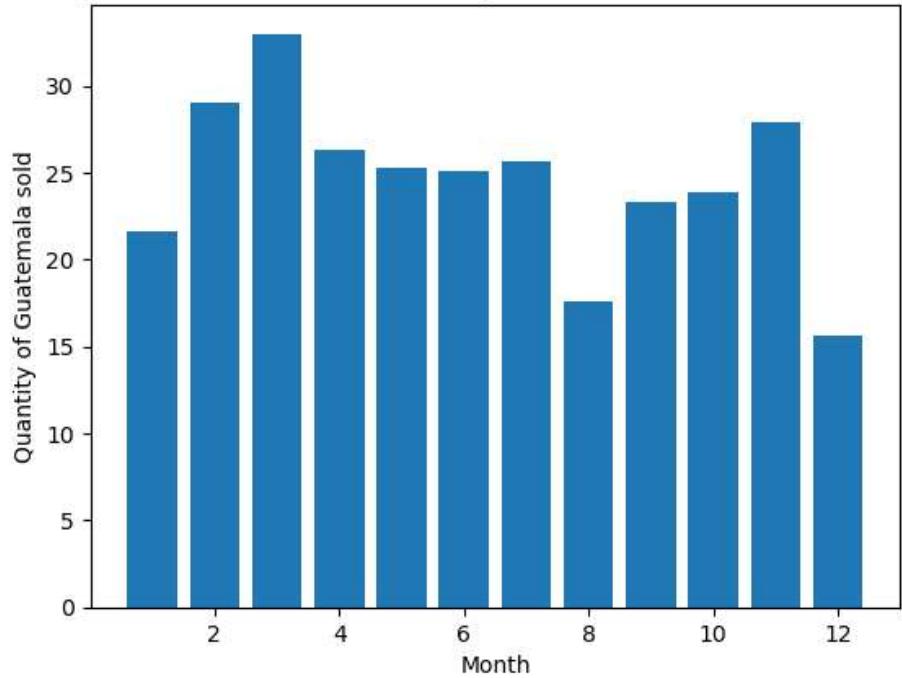
The Quantity of Ethiopian Coffee Sold by Month in Saudi Arabia from 2023 to 2024



The Quantity of Brazilian Coffee Sold by Month in Saudi Arabia from 2023 to 2024



The Quantity of Guatemala Coffee Sold by Month in Saudi Arabia from 2023 to 2024



Quantity by City and Product

```
In [30]: df_qpc = df_combined[['Quantity','City','Product']]
df_qpc.head()
df_col = df_qpc[df_qpc['Product'] == products[0]]
df_col_sum = df_col[['Quantity','City']].groupby('City').sum().reset_index()
df_col_sum.rename(columns = {'Quantity' : 'Colombia_Quantity'}, inplace = True)
print(df_col_sum)

df_col = df_qpc[df_qpc['Product'] == products[1]]
df_1_sum = df_col[['Quantity','City']].groupby('City').sum().reset_index()
df_1_sum.rename(columns = {'Quantity' : '{}_Quantity'.format(str(products[1]))}, 
print(df_1_sum)
df_col_sum = pd.concat([df_col_sum,df_1_sum['Costa Rica_Quantity']], axis = 1)

df_col = df_qpc[df_qpc['Product'] == products[2]]
df_1_sum = df_col[['Quantity','City']].groupby('City').sum().reset_index()
df_1_sum.rename(columns = {'Quantity' : '{}_Quantity'.format(str(products[2]))}, 
df_col_sum = pd.concat([df_col_sum,df_1_sum['{}_Quantity'.format(str(products[2]))]])

df_col = df_qpc[df_qpc['Product'] == products[3]]
df_1_sum = df_col[['Quantity','City']].groupby('City').sum().reset_index()
df_1_sum.rename(columns = {'Quantity' : '{}_Quantity'.format(str(products[3]))}, 
df_col_sum = pd.concat([df_col_sum,df_1_sum['{}_Quantity'.format(str(products[3]))]])

df_col = df_qpc[df_qpc['Product'] == products[4]]
df_1_sum = df_col[['Quantity','City']].groupby('City').sum().reset_index()
df_1_sum.rename(columns = {'Quantity' : '{}_Quantity'.format(str(products[4]))}, 
df_col_sum = pd.concat([df_col_sum,df_1_sum['{}_Quantity'.format(str(products[4]))]])

df_col_sum
```

	City	Colombia_Quantity
0	Abha	286
1	Buraidah	291
2	Dammam	590
3	Hail	497
4	Jeddah	212
5	Khobar	465
6	Mecca	369
7	Medina	502
8	Riyadh	374
9	Tabuk	486

	City	Costa Rica_Quantity
0	Abha	591
1	Buraidah	304
2	Dammam	456
3	Hail	409
4	Jeddah	520
5	Khobar	293
6	Mecca	326
7	Medina	592
8	Riyadh	632
9	Tabuk	329

Out[30]:

	City	Colombia_Quantity	Costa Rica_Quantity	Ethiopian_Quantity	Brazilian_Quantity
0	Abha	286	591	220	312
1	Buraidah	291	304	401	516
2	Dammam	590	456	185	295
3	Hail	497	409	339	477
4	Jeddah	212	520	515	323
5	Khobar	465	293	327	386
6	Mecca	369	326	475	484
7	Medina	502	592	187	370
8	Riyadh	374	632	475	317
9	Tabuk	486	329	174	312

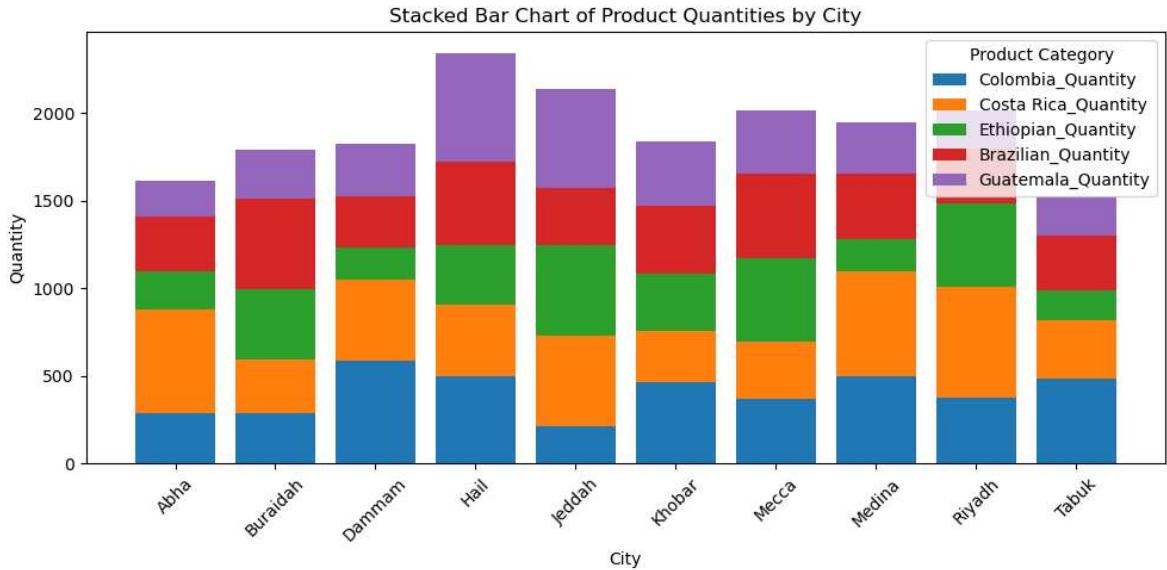
In [31]:

```
# Set up the figure and axis
plt.figure(figsize=(10, 5))

# Plot the stacked bar chart
cities = df_col_sum['City']
cities
categories = ["Colombia_Quantity", "Costa Rica_Quantity", "Ethiopian_Quantity",

# Stacking the bars
bottom_values = [0] * len(cities)
for category in categories:
    plt.bar(cities, df_col_sum[category], label=category, bottom=bottom_values)
    bottom_values = [bottom_values[i] + df_col_sum[category][i] for i in range(10)]
```

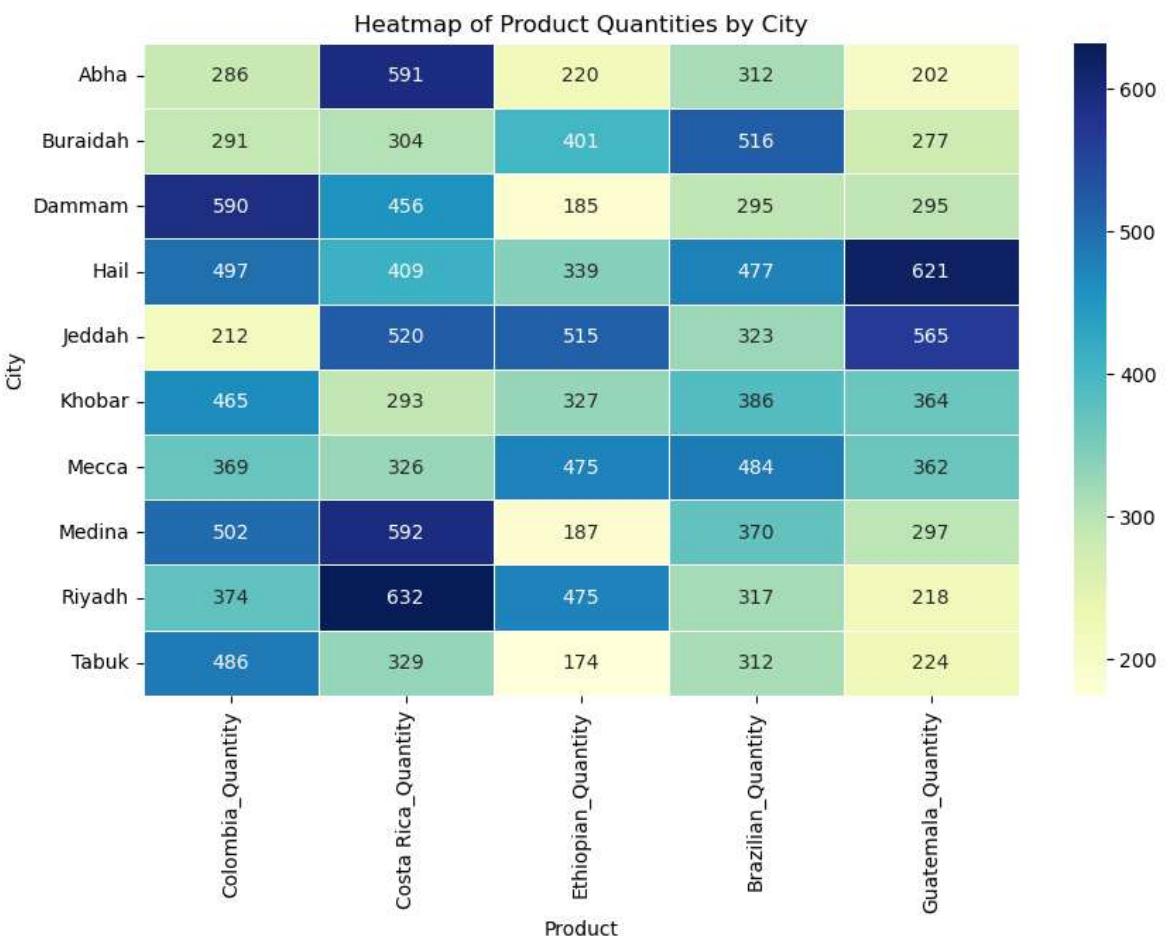
```
# Customizing the chart
plt.title("Stacked Bar Chart of Product Quantities by City")
plt.xlabel("City")
plt.ylabel("Quantity")
plt.xticks(rotation=45)
plt.legend(title="Product Category")
plt.tight_layout()
```



In []:

```
In [32]: # Set 'City' as the index
df_col_sum.set_index("City", inplace=True)

# Create the heatmap
plt.figure(figsize=(10, 6)) # Adjust the size of the plot
sns.heatmap(df_col_sum, annot=True, fmt="d", cmap="YlGnBu", linewidths=0.5)
plt.title("Heatmap of Product Quantities by City")
plt.xlabel("Product")
plt.ylabel("City")
plt.show()
```



```
In [33]: df_col_sum = df_col_sum.T
for col in df_col_sum.columns.tolist() :
    print((df_col_sum.loc[df_col_sum[col] >= 500, col]))
    print("")
```

```
Costa Rica_Quantity      591
Name: Abha, dtype: int64

Brazilian_Quantity      516
Name: Buraidah, dtype: int64

Colombia_Quantity      590
Name: Dammam, dtype: int64

Guatemala_Quantity     621
Name: Hail, dtype: int64

Costa Rica_Quantity      520
Ethiopian_Quantity      515
Guatemala_Quantity      565
Name: Jeddah, dtype: int64

Series([], Name: Khobar, dtype: int64)

Series([], Name: Mecca, dtype: int64)

Colombia_Quantity      502
Costa Rica_Quantity      592
Name: Medina, dtype: int64

Costa Rica_Quantity      632
Name: Riyadh, dtype: int64

Series([], Name: Tabuk, dtype: int64)
```

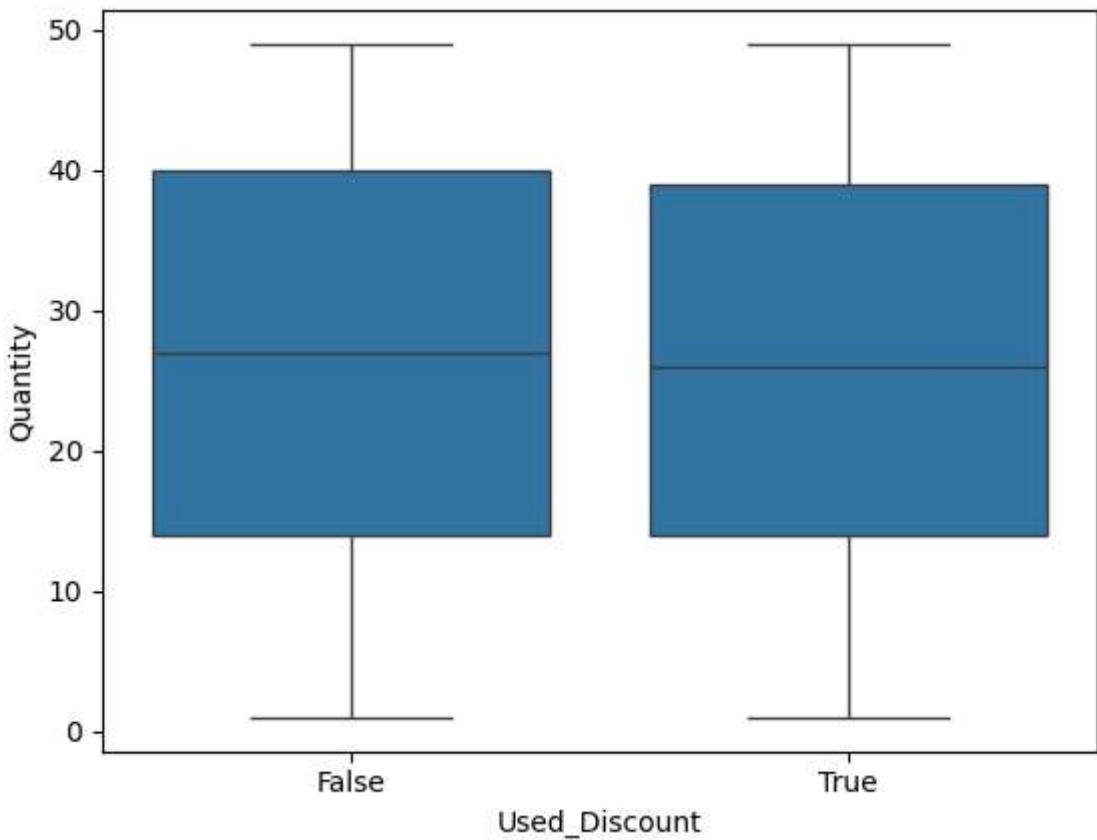
Each city has popular products, so manage inventory well.

Quantity and discounts

```
In [34]: print(df[['Quantity', 'Used_Discount']].groupby('Used_Discount').sum())
sns.boxplot(x= df['Used_Discount'],y= df['Quantity'])
```

Used_Discount	Quantity
False	9398
True	9641

```
Out[34]: <Axes: xlabel='Used_Discount', ylabel='Quantity'>
```



```
In [35]: df[['Final Sales','Used_Discount']].groupby('Used_Discount').sum()
#sns.boxplot(x= df['Used_Discount'],y= df['Final Sales'])
```

Out[35]:

Final Sales	
Used_Discount	
False	345260
True	284388

```
In [36]: from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
x = df[['Quantity']]
y = df['Used_Discount'].astype(int)

x_train,x_test, y_train,y_test = train_test_split(x, y, test_size = 0.3, random_
clf = clf.fit(x_train,y_train)

print(clf.coef_)
print(clf.intercept_)

# sns.regplot(x= x,y = y, logistic = True)

y_pred = clf.predict(x_test)

y_pred_pro = clf.predict_proba(x_test)[:, -1]

import sklearn.metrics as metrics

cm = metrics.confusion_matrix(y_test, y_pred, labels = clf.classes_)
```

```

disp = metrics.ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = cl)
disp.plot()

precision = metrics.precision_score(y_test,y_pred)
recall = metrics.recall_score(y_test,y_pred)
accuracy = metrics.accuracy_score(y_test,y_pred)

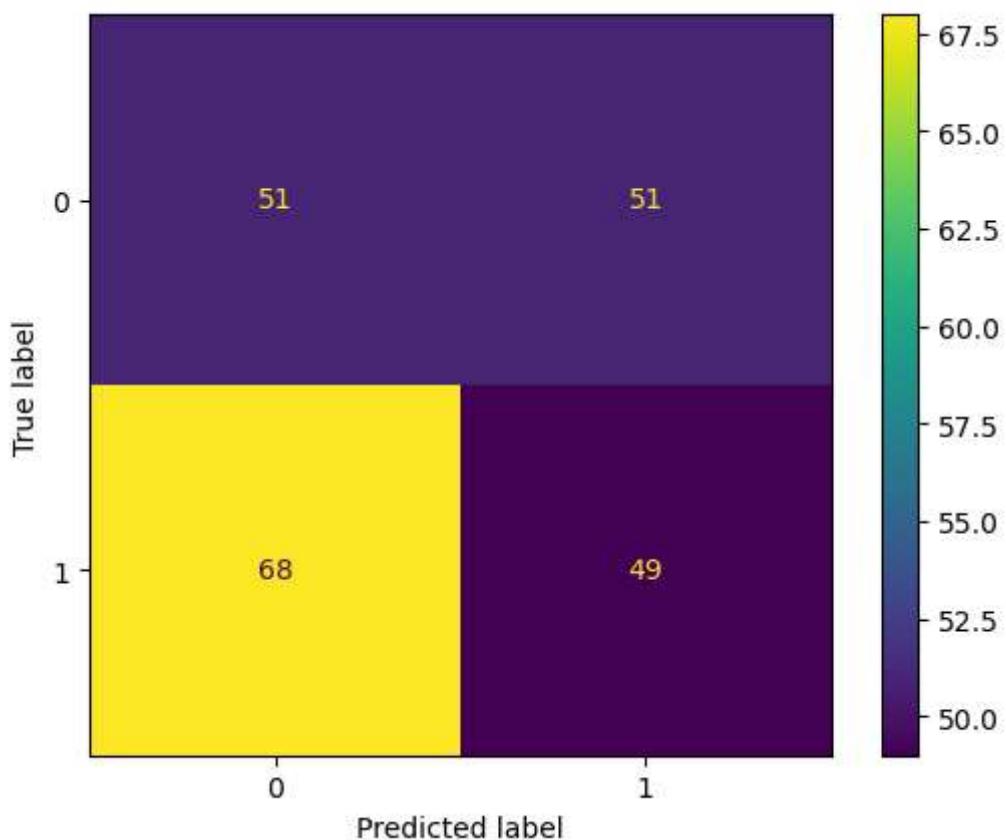
print( precision, recall, accuracy)

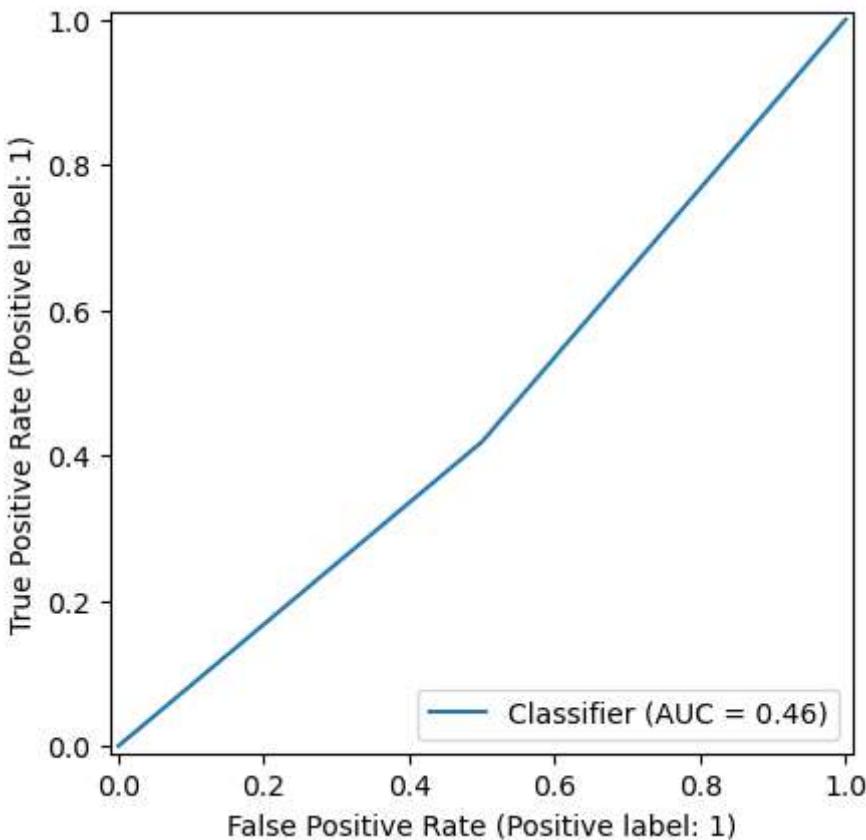
import matplotlib.pyplot as plt
from sklearn.metrics import RocCurveDisplay

RocCurveDisplay.from_predictions(y_test, y_pred)
plt.show()

```

$[-0.00584148]$
 $[0.1419348]$
 $0.49 \ 0.4188034188034188 \ 0.45662100456621$





```
In [37]: from sklearn.linear_model import LogisticRegression
clf = LogisticRegression()
x = df[['Final Sales']]
y = df['Used_Discount'].astype(int)

x_train,x_test, y_train,y_test = train_test_split(x, y, test_size = 0.3, random_
clf = clf.fit(x_train,y_train)

print(clf.coef_)
print(clf.intercept_)

# sns.regplot(x= x,y = y, logistic = True)

y_pred = clf.predict(x_test)

y_pred_pro = clf.predict_proba(x_test)[:, -1]

import sklearn.metrics as metrics

cm = metrics.confusion_matrix(y_test, y_pred, labels = clf.classes_)
disp = metrics.ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = cl
disp.plot()

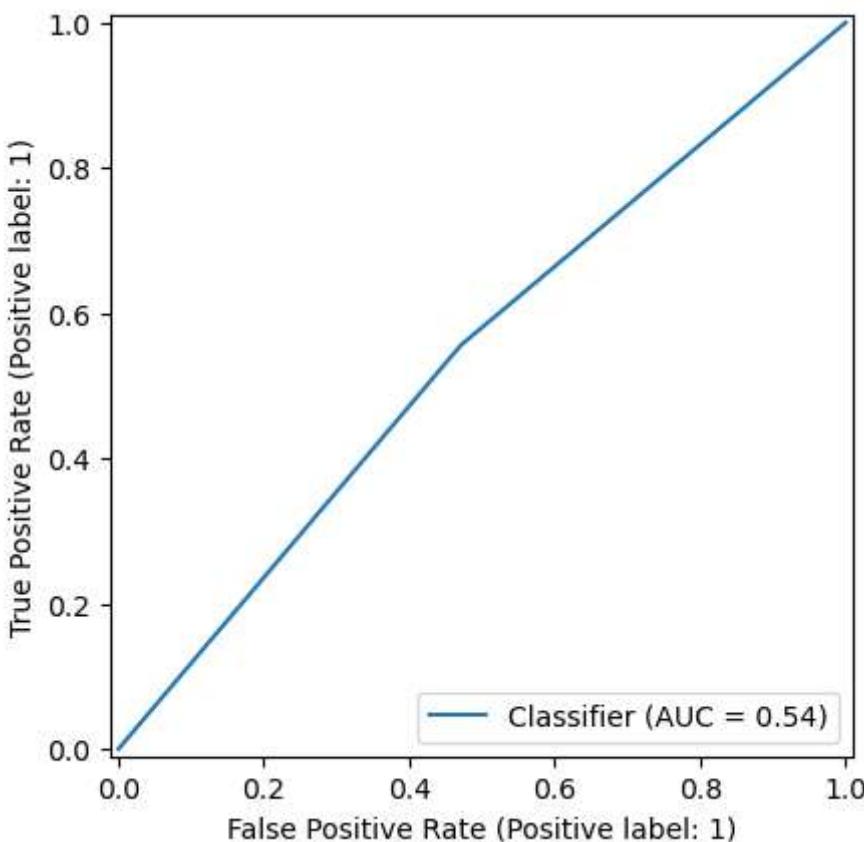
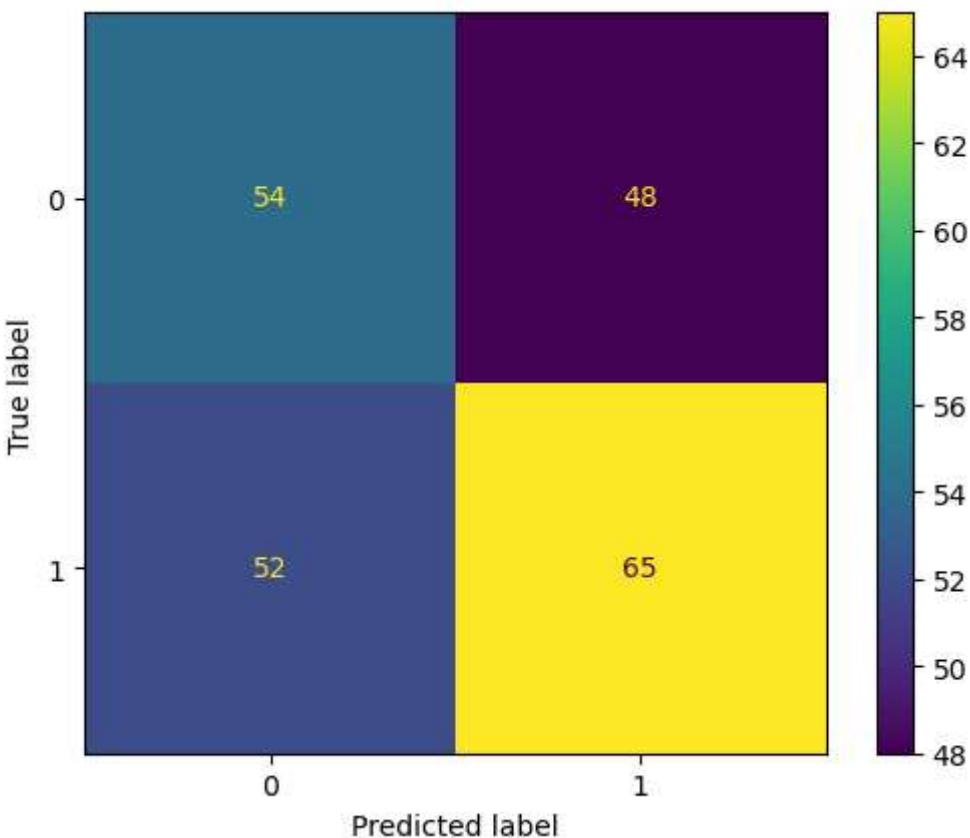
precision = metrics.precision_score(y_test,y_pred)
recall = metrics.recall_score(y_test,y_pred)
accuracy = metrics.accuracy_score(y_test,y_pred)

print( precision, recall, accuracy)

import matplotlib.pyplot as plt
from sklearn.metrics import RocCurveDisplay
```

```
RocCurveDisplay.from_predictions(y_test, y_pred)  
plt.show()
```

```
[[ -0.00088866]]  
[0.76885301]  
0.5752212389380531 0.5555555555555556 0.54337899543379
```

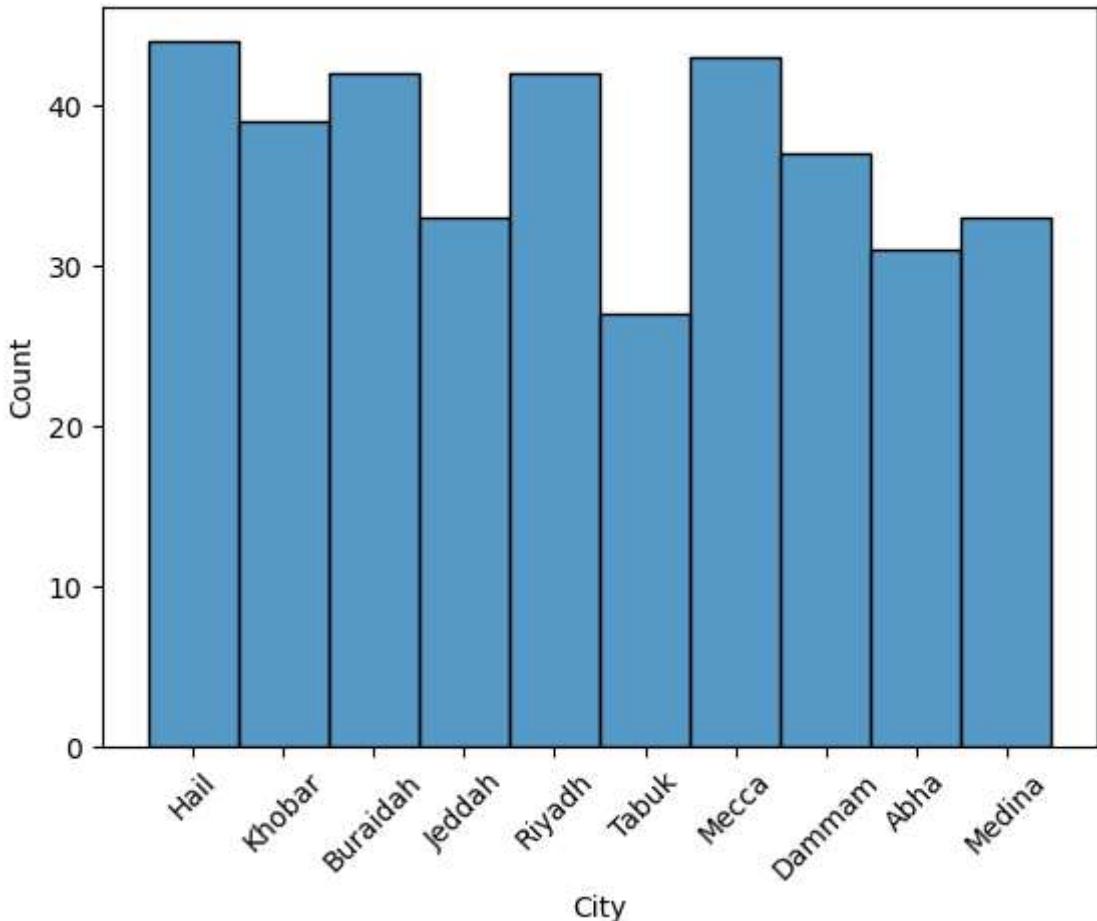


Now i want to figure out why?

1. expary date is coming. so give discount price. -> check the which city have the high discount rate

2. big sum of purchase.

```
In [38]: df_dis = df_combined[['Used_Discount','City']]  
  
df_dis = df_dis[df_dis['Used_Discount'] == True]  
df_dis.head()  
  
sns.histplot(df_dis['City'])  
plt.xticks(rotation = 45)  
plt.show()  
city_fre = df_dis.value_counts().tolist()  
city_mean = np.mean(city_fre)  
  
df_grp = df_dis.groupby('City').sum().reset_index()  
mask = df_grp['Used_Discount'] >= city_mean  
df_grp= df_grp[mask]  
df_grp = df_grp['City'].tolist()  
  
print("Cities with high discount number : ", df_grp)  
#for column in df_dis['City'].tolist():  
#    if city_fre[df_dis['City'] == column] >= city_mean:  
#        print("")  
#        print(city_fre[city_fre['City'] == column].mean())
```



```
Cities with high discount number : ['Buraidah', 'Hail', 'Khobar', 'Mecca', 'Riyadh']
```

['Buraidah', 'Hail', 'Khobar', 'Mecca', 'Riyadh'] have high discount rate and It is possible the might have more products in stock.

2. big sum of purchase.

3.

```
In [39]: df_grp = df_combined[['Quantity', 'Used_Discount']]
bins = np.linspace(min(df_grp['Quantity']), max(df_grp['Quantity']), 4)
head = ['small', 'middle', 'high']
df_grp['Quantity_grp'] = pd.cut(df_grp['Quantity'], bins = bins, labels = head,
                                 df_grp.head()
df_grp = df_grp[df_grp['Used_Discount'] == True]

sns.histplot(df_grp['Quantity_grp'])
```

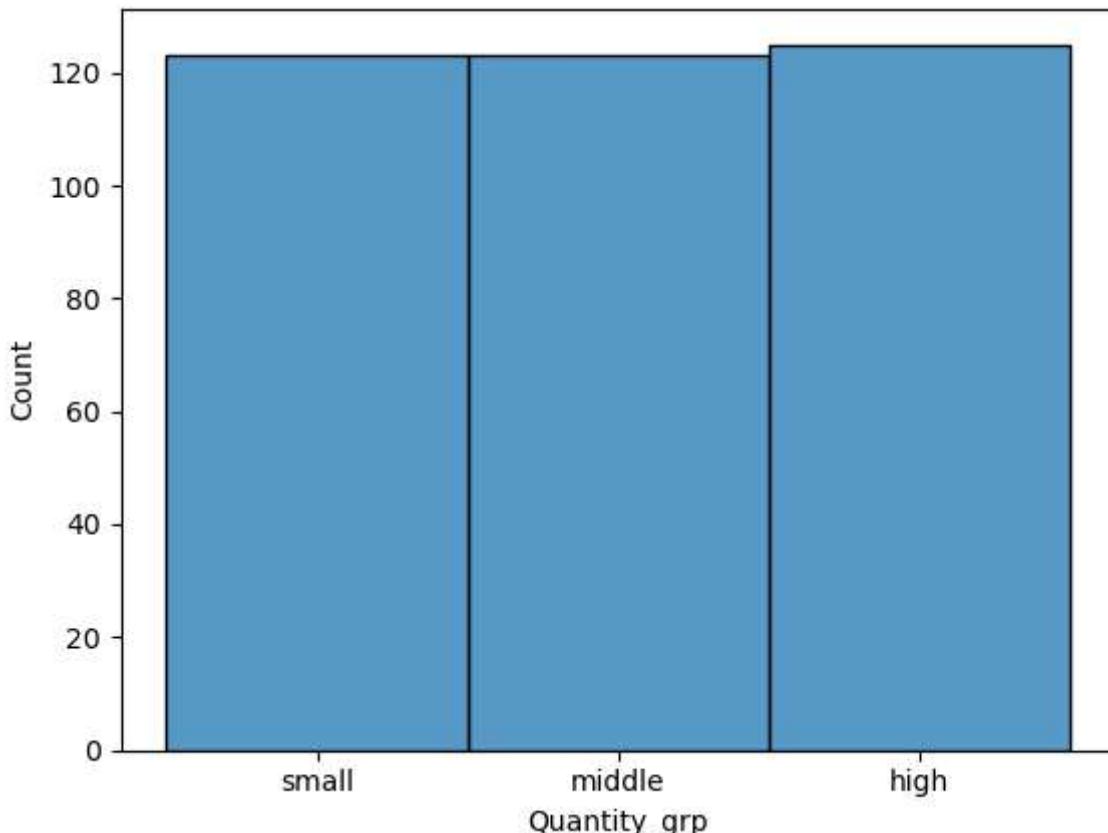
C:\Users\soonn\AppData\Local\Temp\ipykernel_19168\1719746665.py:4: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
df_grp['Quantity_grp'] = pd.cut(df_grp['Quantity'], bins = bins, labels = head,
                                 include_lowest = True)
```

Out[39]: <Axes: xlabel='Quantity_grp', ylabel='Count'>



Althohgh the quantity of sales at a time is small, the discount was applied, which means the discount is not applied by quantity of order.

```
In [40]: # hypothesis
# Null hypothesis : sales of bean from Jun to Sep is higher than other month
# alternative hypothesis : sales of bean from Jun to Sep is the same or less than
df['month'] = df['Date'].dt.month # assign month with integer
df['compare'] = df['month']
df.loc[df['compare'].isin([6,7,8,9]),'compare'] = 99
df.loc[df['compare'].isin([1,2,3,4,5,10,11,12]),'compare'] = 1
df['compare'] = df['compare'].astype(str)
df.loc[df['compare'] == '99','compare'] = 'high'
df.loc[df['compare'] == '1','compare'] = 'others'

df.head()

import pandas as pd
from scipy.stats import ttest_ind

# Split data by city
summer_q = df[df['compare'] == 'high']['Quantity']
other_q = df[df['compare'] == 'others']['Quantity']

# Perform independent t-test
t_stat, p_value = ttest_ind(summer_q, other_q)
print(f"T-statistic: {t_stat}, P-value: {p_value}")

# Interpret results
if p_value < 0.05:
    print("There is a significant difference in sales between summer months and")
else:
    print("No significant difference in sales between summer months and other mo
```

T-statistic: 1.955825526815722, P-value: 0.05086781138757017
 No significant difference in sales between summer months and other months.

Sales trends from 2023 Jan to 2024 Dec

Overview : find sales trends of sales and see any increase and decrease. consider model variables

```
In [41]: df.head()
```

Out[41]:

	Date	Customer_ID	City	Category	Product	Unit Price	Quantity	Sales Amount	Used_D
0	2023-01-01	32	Riyadh	coffee beans	Colombian	40	14	560	
1	2023-01-02	49	Abha	coffee beans	Costa Rica	35	17	595	
2	2023-01-03	75	Tabuk	coffee beans	Costa Rica	35	19	665	
3	2023-01-04	80	Abha	coffee beans	Ethiopian	45	1	45	
4	2023-01-05	78	Hail	coffee beans	Colombian	40	46	1840	

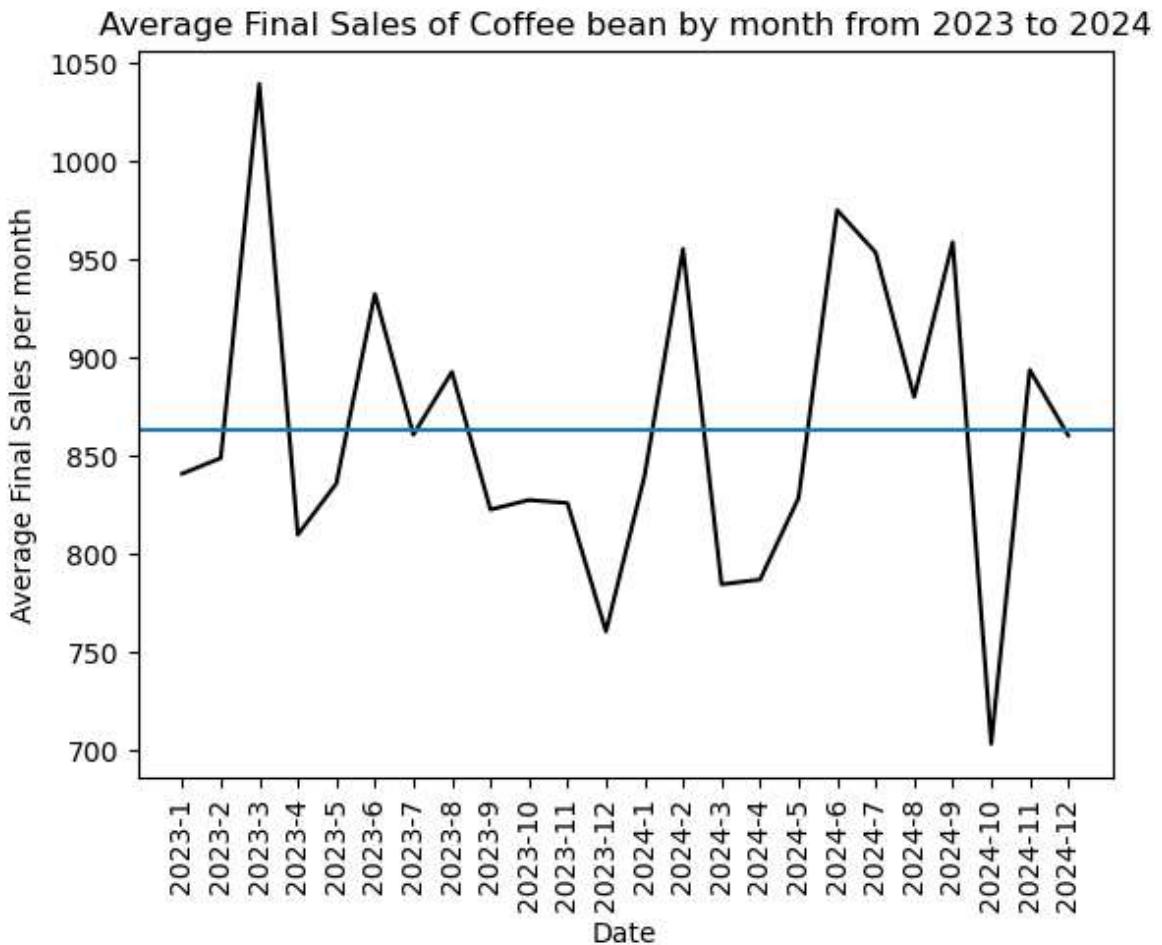


In [42]:

```
df['year'] = df['Date'].dt.year
mean_sales_date = df.groupby(['year','month']).mean(numeric_only = True)[['Final Sales']]
mean_sales_date = mean_sales_date.reset_index()

mean_sales_date['year_month'] = mean_sales_date['year'].astype(str) + '-' + mean_sales_date['month'].astype(str)
mean_sales_date.drop(['month','year'], axis = 1)
mean_sales = mean_sales_date['Final Sales'].mean()
sns.lineplot(data = mean_sales_date, x = 'year_month', y = 'Final Sales', color = 'red')
plt.xticks(rotation = 90)
plt.axhline(y = mean_sales)
plt.xlabel('Date')
plt.ylabel('Average Final Sales per month')
plt.title('Average Final Sales of Coffee bean by month from 2023 to 2024')
```

Out[42]: Text(0.5, 1.0, 'Average Final Sales of Coffee bean by month from 2023 to 2024')



the average sales of coffee beans has fluctuate over the years. the sales tend to go up in the beginning of the year go down and goes up in summer time then go down again. one possible reason of decrease from march to april is Ramadan, which people does not eat daytime.

Consider variables for model

Target variables: Quantity or Final sales independent variables : other variables

```
In [43]: df.head()
df_model = df[['Date', 'Unit Price', 'Sales Amount', 'Discount_Amount', 'Final S
```

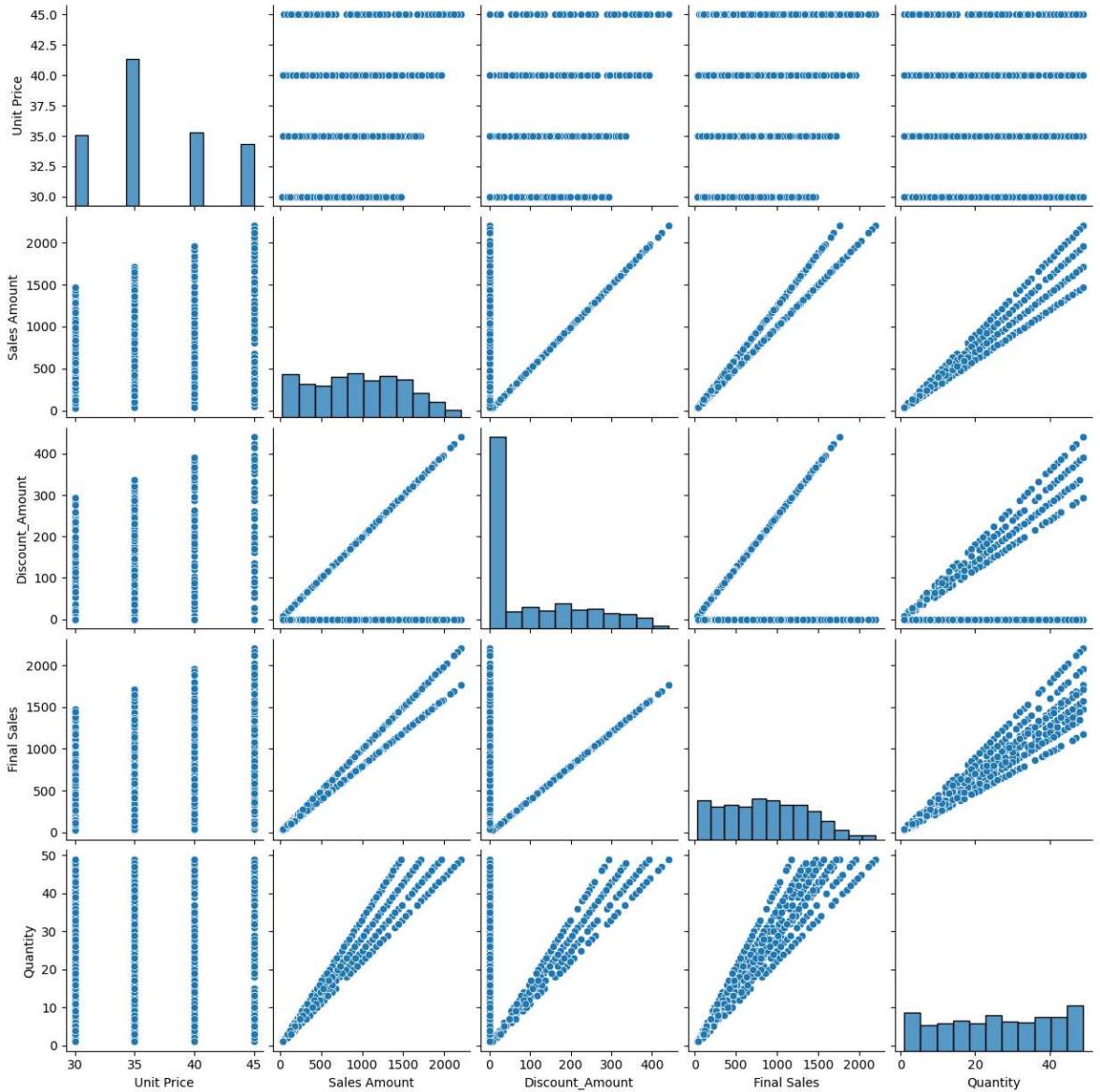
```
In [44]: df_model.head()
```

```
Out[44]:
```

	Date	Unit Price	Sales Amount	Discount_Amount	Final Sales	Quantity
0	2023-01-01	40	560	0	560	14
1	2023-01-02	35	595	0	595	17
2	2023-01-03	35	665	0	665	19
3	2023-01-04	45	45	0	45	1
4	2023-01-05	40	1840	368	1472	46

```
In [45]: sns.pairplot(df_model)
```

```
Out[45]: <seaborn.axisgrid.PairGrid at 0x22be4650140>
```



```
In [46]: df_model['Discount_Rate'] = df_model['Discount_Amount']/df_model['Final Sales']
df_model.head()
```

C:\Users\soonn\AppData\Local\Temp\ipykernel_19168\1974359409.py:1: SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
df_model['Discount_Rate'] = df_model['Discount_Amount']/df_model['Final Sales']

Out[46]:

	Date	Unit Price	Sales Amount	Discount_Amount	Final Sales	Quantity	Discount_Rate
0	2023-01-01	40	560	0	560	14	0.00
1	2023-01-02	35	595	0	595	17	0.00
2	2023-01-03	35	665	0	665	19	0.00
3	2023-01-04	45	45	0	45	1	0.00
4	2023-01-05	40	1840	368	1472	46	0.25

In []: `sns.pairplot(df_model)`

Out[]: <seaborn.axisgrid.PairGrid at 0x22be4195790>

In []: `df_model['year'] = df_model['Date'].dt.year`
`df_model_2023 = df_model[df_model['year'] == 2023]`
`df_model_2024 = df_model[df_model['year'] == 2024]`

In []: `x = df_model[['Quantity', 'Sales Amount']]`
`y = df_model['Final Sales']`
`x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3, random_state=42)`
`df_model.rename(columns = {'Sales Amount': 'Sales_Amount', 'Final Sales': 'Final_Sales'}, inplace=True)`
`df_model.info()`

In []: `from sklearn.linear_model import LinearRegression`
`from sklearn.preprocessing import StandardScaler`
`from sklearn.metrics import mean_squared_error`

`# Initialize the scaler`
`scaler = StandardScaler()`

`# Scale the training and test data`
`x_train_scaled = scaler.fit_transform(x_train)`
`x_test_scaled = scaler.transform(x_test)`

`# Fit the Linear Regression model on the scaled training data`
`lr = LinearRegression()`
`lr.fit(x_train_scaled, y_train)`

`# Predict on the scaled test data`
`y_pred_test = lr.predict(x_test_scaled)`

`# Calculate residuals for the test set`
`residuals_test = y_test - y_pred_test`

`# Display residuals`
`print("Residuals for test set:", residuals_test)`

In []: `import seaborn as sns`
`import matplotlib.pyplot as plt`

```

# Residuals vs Fitted Values (Linearity & Homoscedasticity Test)
sns.scatterplot(x=y_pred_test, y=residuals_test) # Predicted values vs residual
plt.axhline(0, color='red', linestyle='--', linewidth=1) # Reference Line at y=
plt.xlabel('Predicted Values (Fitted Values)')
plt.ylabel('Residuals')
plt.title('Residuals vs. Fitted Values')
plt.show()

import statsmodels.api as sm
import matplotlib.pyplot as plt

# Q-Q Plot for Normality Check
sm.qqplot(residuals_test, line='s') # Residuals Q-Q plot
plt.title('Q-Q Plot of Residuals')
plt.show()

```

In []: lr.score(x_test_scaled,y_test)

In []: print(df_model.corr())
sns.heatmap(df_model.corr())

model building variables

I worked extensively on both binomial logistic regression and linear regression models. For the logistic regression model, I used Used_discount as the dependent variable. Initially, I built a model with Quantity as the independent variable, but the results were not promising. I then created a second model using Final_Sales as the independent variable, which yielded a slightly better confusion matrix. However, the AUC remained at 0.54, with recall, accuracy, and precision indicators hovering around 0.55. Despite these efforts, I was unable to build a robust logistic regression model with the available data. Next, I shifted my focus to building a multivariable linear regression model to predict Final_Sales. The variables Quantity and Sales_Amount showed clear relationships with Final_Sales, resulting in a model with an impressive R-squared value of 0.95—indicating that 95% of the variance in the dependent variable was explained by the independent variables. However, the model failed to satisfy critical linear regression assumptions, such as linearity and normality. Thus, the model building process was ultimately unsuccessful. Recognizing the limitations of the given data, I sought open data sources related to coffee sales in Saudi Arabia from 2023 to 2024 but was unable to locate relevant datasets. Given this situation, I recommend collecting additional data to enhance the modeling process. Specifically, collecting sales/inventory data, market/customer data, and geographic/location data could prove valuable for building better predictive models in the future.

a) Sales and Inventory Data

1. Historical Inventory Levels: Add information on past inventory amounts and stock-outs to capture supply-demand dynamics.

2. Waste/Expiration Data: Include the number of products that spoiled or went unsold to refine inventory predictions.
3. Sales Time Data: Record timestamps more granularly (e.g., daily/hourly sales) to account for short-term trends.

b) Market/Customer Data

1. Promotions/Events: Track promotional activities and local events, which could impact sales spikes.
2. Customer Feedback: Add review/rating data or customer preferences for specific products

c) Geographic/Location Data

1. Foot Traffic: If sales locations are physical stores, include data on customer foot traffic
2. Regional Patterns: Consider adding broader regional economic indicators, such as population or income