Data and Library

In [1]:
```
#pip install pmdarima
```

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pmdarima as pm

from sklearn.impute import KNNImputer
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_samples, silhouette_score
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error,
from statsmodels.tsa.holtwinters import ExponentialSmoothing, Holt
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from itertools import permutations
from datetime import datetime
import pytz
```

In [3]:
```
#Read all csv files
customer = pd.read_csv("C:\Kuliah\INTERNSHIPS\Kalbe Nutritionals Internship\Final
transaction = pd.read_csv("C:\Kuliah\INTERNSHIPS\Kalbe Nutritionals Internship\Fi
product = pd.read_csv("C:\Kuliah\INTERNSHIPS\Kalbe Nutritionals Internship\Final
store = pd.read_csv("C:\Kuliah\INTERNSHIPS\Kalbe Nutritionals Internship\Final Pr
```

In [4]:
```
customer.head()
```

Out[4]:

	CustomerID	Age	Gender	Marital Status	Income
0	1	55	1	Married	5,12
1	2	60	1	Married	6,23
2	3	32	1	Married	9,17
3	4	31	1	Married	4,87
4	5	58	1	Married	3,57

In [5]:
```
transaction.head()
```

Out[5]:

	TransactionID	CustomerID	Date	ProductID	Price	Qty	TotalAmount	StoreID
0	TR11369	328	1/1/2022	P3	7500	4	30000	12
1	TR16356	165	1/1/2022	P9	10000	7	70000	1
2	TR1984	183	1/1/2022	P1	8800	4	35200	4
3	TR35256	160	1/1/2022	P1	8800	7	61600	4
4	TR41231	386	1/1/2022	P9	10000	1	10000	4

In [6]:
```
product.head()
```

Out[6]:

	ProductID	Product Name	Price
0	P1	Choco Bar	8800
1	P2	Ginger Candy	3200
2	P3	Crackers	7500
3	P4	Potato Chip	12000
4	P5	Thai Tea	4200

In [7]:
```
store.head()
```

Out[7]:

	StoreID	StoreName	GroupStore	Type	Latitude	Longitude
0	1	Prima Tendean	Prima	Modern Trade	-6,2	106,816666
1	2	Prima Kelapa Dua	Prima	Modern Trade	-6,914864	107,608238
2	3	Prima Kota	Prima	Modern Trade	-7,797068	110,370529
3	4	Gita Ginara	Gita	General Trade	-6,966667	110,416664
4	5	Bonafid	Gita	General Trade	-7,250445	112,768845

In [8]:
```
# Merge all data into a united new dataframe
df = pd.merge(transaction,customer,on='CustomerID')
df = pd.merge(df,product,on='ProductID', suffixes=('_Customer','_Product'))
df = pd.merge(df,store,on='StoreID')
df.head()
```

Out[8]:

	TransactionID	CustomerID	Date	ProductID	Price_Customer	Qty	TotalAmount	StoreID	A
0	TR11369	328	1/1/2022	P3	7500	4	30000	12	
1	TR89318	183	17/07/2022	P3	7500	1	7500	12	
2	TR9106	123	26/09/2022	P3	7500	4	30000	12	
3	TR4331	335	8/1/2022	P3	7500	3	22500	12	
4	TR6445	181	10/1/2022	P3	7500	4	30000	12	

Data Cleaning

Check Data Type

In [9]:
```
df.dtypes
```

Out[9]:
```
TransactionID     object
CustomerID         int64
Date              object
ProductID         object
Price_Customer     int64
Qty                int64
TotalAmount        int64
StoreID            int64
Age                int64
Gender             int64
Marital Status    object
Income            object
Product Name      object
Price_Product      int64
StoreName         object
GroupStore        object
Type              object
Latitude          object
Longitude         object
dtype: object
```

Kita akan mengubah data type variabel "Date" menjadi datetime dan variabel "Income" menjadi float dengan pemisah desimal berupa "."

In [10]:
```
#Convert date and income data type
df['Date'] = pd.to_datetime(df['Date'])
df['Income'] = df['Income'].map(lambda x: float(x.replace(',','.')))

df.head()
```

```
C:\Users\ASUS Vivobook\AppData\Local\Temp\ipykernel_26532\4158832533.py:2: User
Warning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the default) w
as specified. This may lead to inconsistently parsed dates! Specify a format to
ensure consistent parsing.
  df['Date'] = pd.to_datetime(df['Date'])
```

Out[10]:

	TransactionID	CustomerID	Date	ProductID	Price_Customer	Qty	TotalAmount	StoreID	Age
0	TR11369	328	2022-01-01	P3	7500	4	30000	12	36
1	TR89318	183	2022-07-17	P3	7500	1	7500	12	27
2	TR9106	123	2022-09-26	P3	7500	4	30000	12	34
3	TR4331	335	2022-08-01	P3	7500	3	22500	12	29
4	TR6445	181	2022-10-01	P3	7500	4	30000	12	33

Drop Irrelevant Columns

In [11]:
```
# Drop irrelevant columns
df = df.drop(columns=['Latitude','Longitude'])
df.head()
```

Out[11]:

	TransactionID	CustomerID	Date	ProductID	Price_Customer	Qty	TotalAmount	StoreID	Age
0	TR11369	328	2022-01-01	P3	7500	4	30000	12	36
1	TR89318	183	2022-07-17	P3	7500	1	7500	12	27
2	TR9106	123	2022-09-26	P3	7500	4	30000	12	34
3	TR4331	335	2022-08-01	P3	7500	3	22500	12	29
4	TR6445	181	2022-10-01	P3	7500	4	30000	12	33

Check Missing Value

In [12]:
```
df.isna().sum()
```

Out[12]:
```
TransactionID      0
CustomerID         0
Date               0
ProductID          0
Price_Customer     0
Qty                0
TotalAmount        0
StoreID            0
Age                0
Gender             0
Marital Status    44
Income             0
Product Name       0
Price_Product      0
StoreName          0
GroupStore         0
Type               0
dtype: int64
```

Variabel Marital Status memiliki missing value, maka akan dilakukan imputasi terhadap missing value menggunakan K-Nearest Neighbour Method

In [13]:
```
from sklearn.preprocessing import LabelEncoder

# Create an instance of the LabelEncoder class
le = LabelEncoder()

# Fit the encoder to the Marital Status variable and transform it
df['Marital Status'] = le.fit_transform(df['Marital Status'])

# Print the encoded values
df.head()
```

Out[13]:

	TransactionID	CustomerID	Date	ProductID	Price_Customer	Qty	TotalAmount	StoreID	Age
0	TR11369	328	2022-01-01	P3	7500	4	30000	12	36
1	TR89318	183	2022-07-17	P3	7500	1	7500	12	27
2	TR9106	123	2022-09-26	P3	7500	4	30000	12	34
3	TR4331	335	2022-08-01	P3	7500	3	22500	12	29
4	TR6445	181	2022-10-01	P3	7500	4	30000	12	33

In [14]:
```
#Impute nan values using KNNImputer
#Lets use customer data to support imputer process
df_impute = df[['Age','Gender','Income','Marital Status']]

imputer = KNNImputer(n_neighbors=2)
df_impute = imputer.fit_transform(df_impute)
df_impute = pd.DataFrame(data=df_impute,columns=['Age','Gender','Income','Marital

print('Missing Value :',df_impute.isna().sum())
```

```
Missing Value : Age               0
Gender            0
Income            0
Marital Status    0
dtype: int64
```

In [15]:
```
df['Marital Status'] = df_impute["Marital Status"].astype('int')
df.isna().sum()
```

Out[15]:
```
TransactionID     0
CustomerID        0
Date              0
ProductID         0
Price_Customer    0
Qty               0
TotalAmount       0
StoreID           0
Age               0
Gender            0
Marital Status    0
Income            0
Product Name      0
Price_Product     0
StoreName         0
GroupStore        0
Type              0
dtype: int64
```

In [16]:
```
df.dtypes
```

Out[16]:
```
TransactionID             object
CustomerID                 int64
Date              datetime64[ns]
ProductID                 object
Price_Customer             int64
Qty                        int64
TotalAmount                int64
StoreID                    int64
Age                        int64
Gender                     int64
Marital Status             int32
Income                   float64
Product Name              object
Price_Product              int64
StoreName                 object
GroupStore                object
Type                      object
dtype: object
```

Export the Merged Cleaned Data

In [17]:
```
# Export the cleaned data into a csv format
df.to_csv('C:\Kuliah\INTERNSHIPS\Kalbe Nutritionals Internship\Final Project\Data
```

Time Series Analysis (Machine Learning)

In [18]:
```
df_tsa = df.groupby('Date')[['Qty']].sum()
df_tsa
```

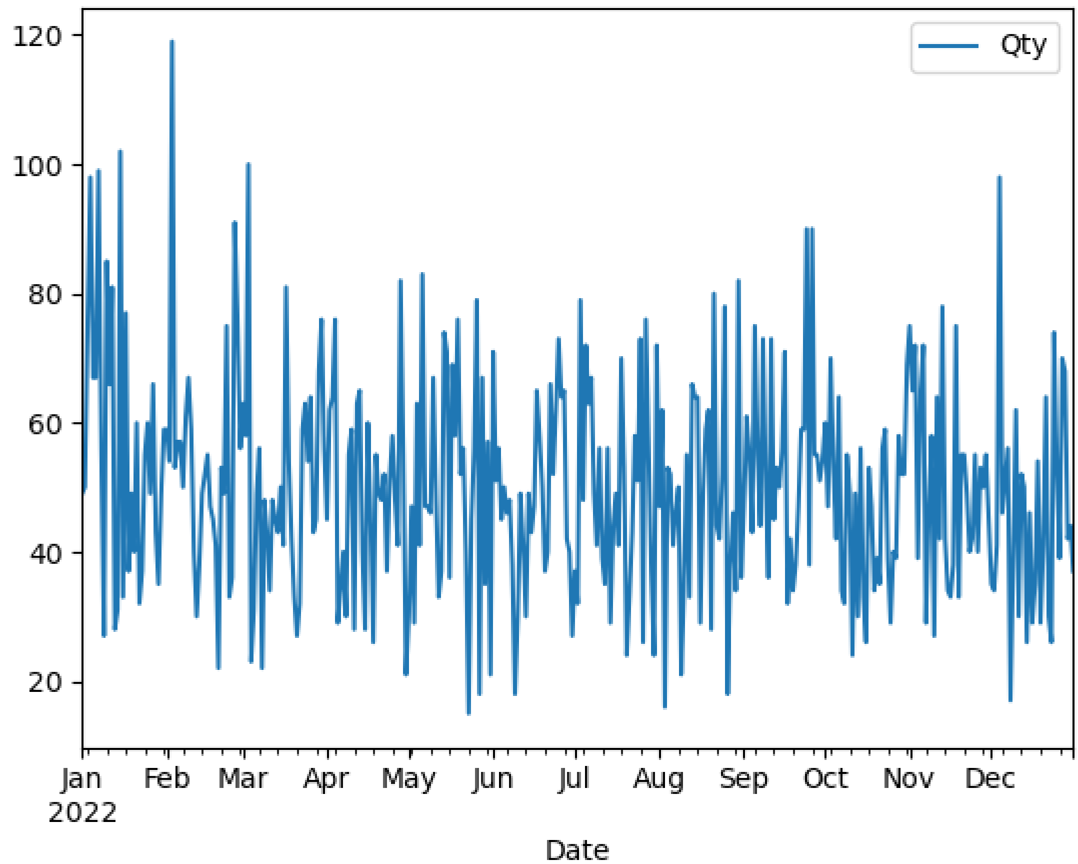
Out[18]:

	Qty
Date	
2022-01-01	49
2022-01-02	50
2022-01-03	76
2022-01-04	98
2022-01-05	67
...	...
2022-12-27	70
2022-12-28	68
2022-12-29	42
2022-12-30	44
2022-12-31	37

365 rows × 1 columns

In [19]:
```
df_tsa.plot()
```

Out[19]: <Axes: xlabel='Date'>



Training and Testing Data Split

In [20]:
```
#Split train and test
df_train = df_tsa.iloc[:-31]
df_test = df_tsa.iloc[-31:]
```

Pengecekan Stasioneritas Data

Hipotesis uji stasioner data deret waktu menggunakan Augmented Dickey-Fuller (ADF) adalah:

H0 : data tidak stasioner

H1 : data stasioner

In [21]:
```
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(df_train)
print(f'p-value: {adf_test[1]}')
```

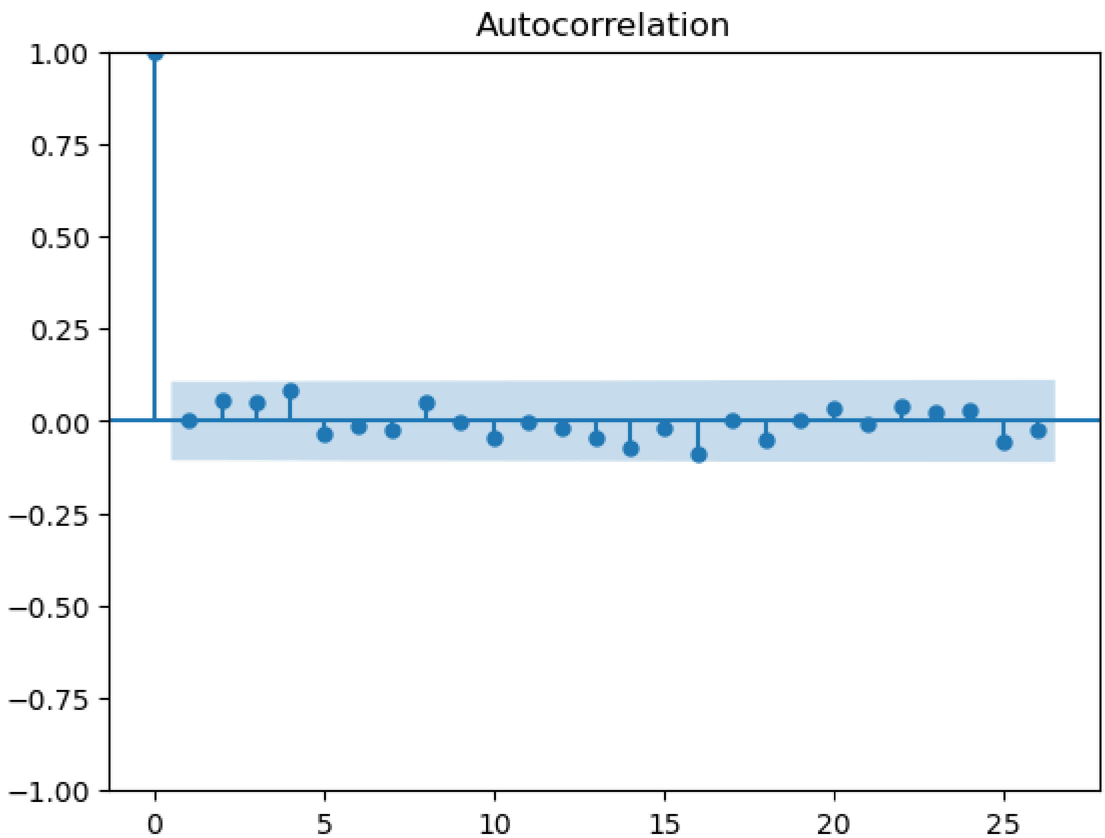
```
p-value: 2.44017311003304e-30
```

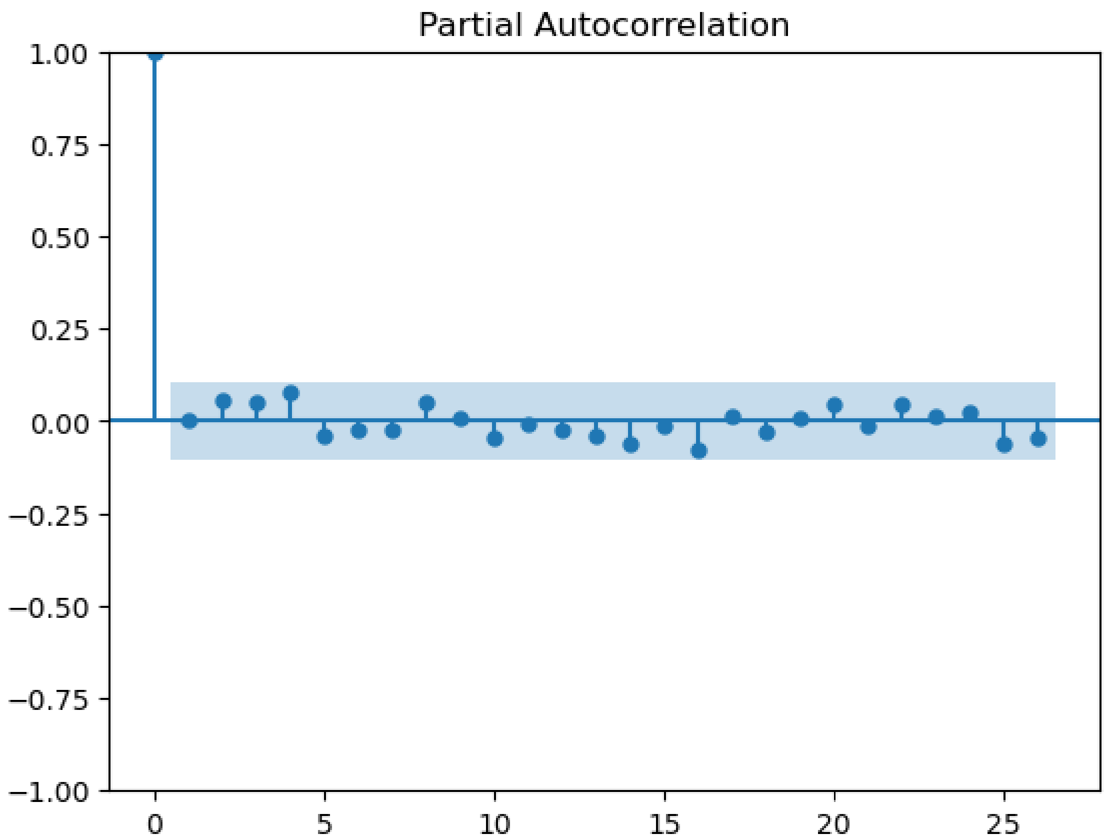
Nilai P-Value = 2.44 x 10^-30 < alpha = 0.05 sehingga tolak H0. Maka, diperoleh kesimpulan bahwa data stasioner sehingga pemodelan ARIMA dapat dilanjutkan.

In [22]:
```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

acf_original = plot_acf(df_train)

pacf_original = plot_pacf(df_train)
```





Seperti yang terlihat pada gambar di atas, plot ACF dan PACF memiliki pola cuts off. Pada plot ACF lag yang signifikan adalah lag 1, dan pada plot PACF lag yang signifikan juga merupakan lag 1. Sehingga dapat diketahui model dugaannya adalah ARIMA (1, 0, 0) dan ARIMA (0, 0, 1).

In [23]:
```
from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(df_train, order=(1,0,0))
model_fit = model.fit()
print(model_fit.summary())
```

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                    Qty   No. Observations:                  334
Model:                 ARIMA(1, 0, 0)   Log Likelihood               -1412.447
Date:                Sat, 30 Sep 2023   AIC                           2830.895
Time:                        22:12:54   BIC                           2842.328
Sample:                    01-01-2022   HQIC                          2835.453
                         - 11-30-2022
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const         50.5329      0.970     52.076      0.000      48.631      52.435
ar.L1          0.0008      0.055      0.015      0.988      -0.107       0.109
sigma2       275.8592     19.768     13.955      0.000     237.114     314.605
===============================================================================
====
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                 2
3.89
Prob(Q):                              1.00   Prob(JB):
0.00
Heteroskedasticity (H):               0.65   Skew:
0.57
Prob(H) (two-sided):                  0.02   Kurtosis:
3.66
===============================================================================
====

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-
step).

C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
```

Parameter Tuning Data Training

In [24]:
```
#Manual parameter tuning
def tune(z,y,x):
    model = ARIMA(df_train, order=(x,y,z))
    model_fit = model.fit()
    forecast_test = model_fit.forecast(len(df_test))
    df_plot = df_tsa[['Qty']].iloc[-61:]

    df_plot['forecast'] = [None]*(len(df_plot)-len(forecast_test)) + list(forecas

    MAE = mean_absolute_error(df_test, forecast_test)
    MAPE = mean_absolute_percentage_error(df_test, forecast_test)
    RMSE = np.sqrt(mean_squared_error(df_test, forecast_test))

    return MAE,MAPE,RMSE

#Parameter combinations
p = [1,0]
d = [0]
q = [0,1]

comb = []
for i in p:
    for j in d:
        for k in q:
            comb.append((i,j,k))

parameter = []
MAE_score = []
MAPE_score = []
RMSE_score = []

for i in comb:
    parameter.append(i)
    score = tune(*i)
    MAE_score.append(score[0])
    MAPE_score.append(score[1])
    RMSE_score.append(score[2])

tuning_df = pd.DataFrame({'Parameter':parameter,'MAE':MAE_score,'MAPE':MAPE_score
tuning_df.sort_values(by='MAE').head()
```

```
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
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d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
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d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
```
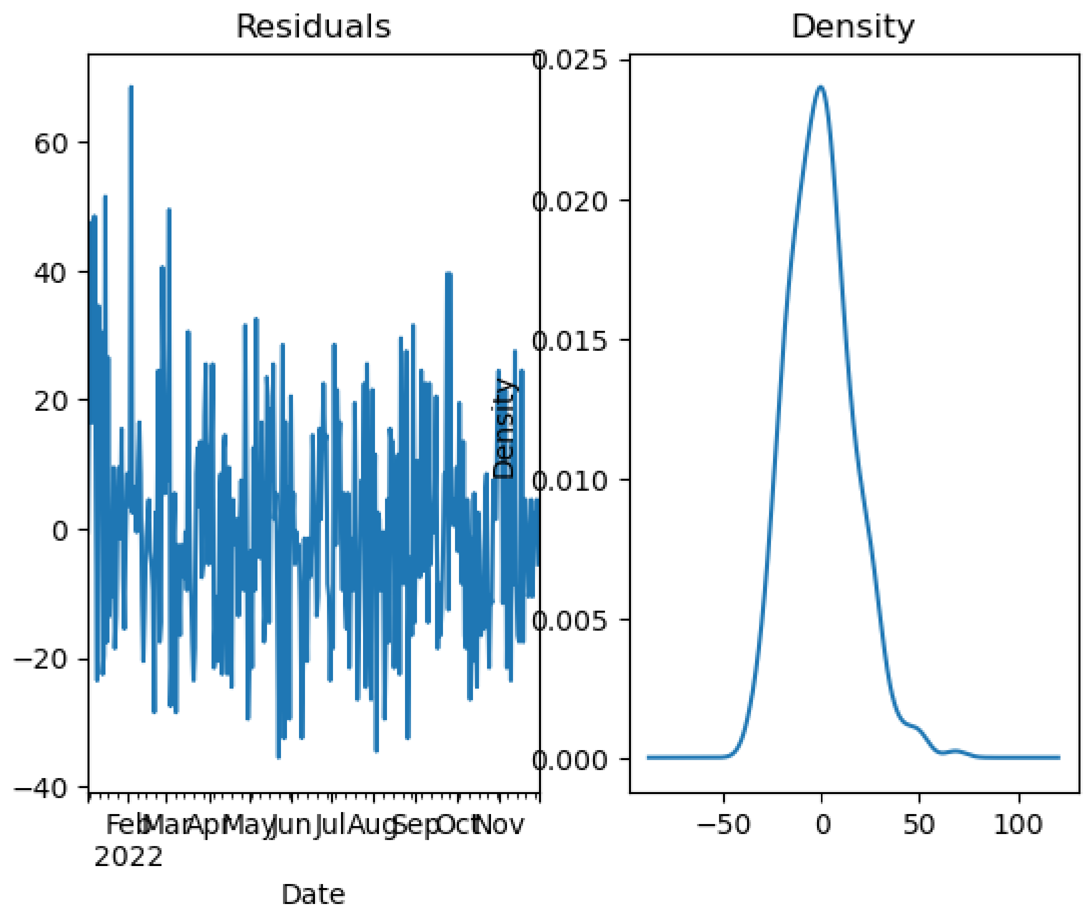

Out[24]:

	Parameter	MAE	MAPE	RMSE
1	(1, 0, 1)	14.209583	0.388313	17.496043
3	(0, 0, 1)	14.219090	0.388595	17.499637
0	(1, 0, 0)	14.219107	0.388596	17.499652
2	(0, 0, 0)	14.219237	0.388600	17.499767

Diputuskan untuk menggunakan parameter pdq ARIMA (1,0,1) karena memiliki nilai MAPE terkecil

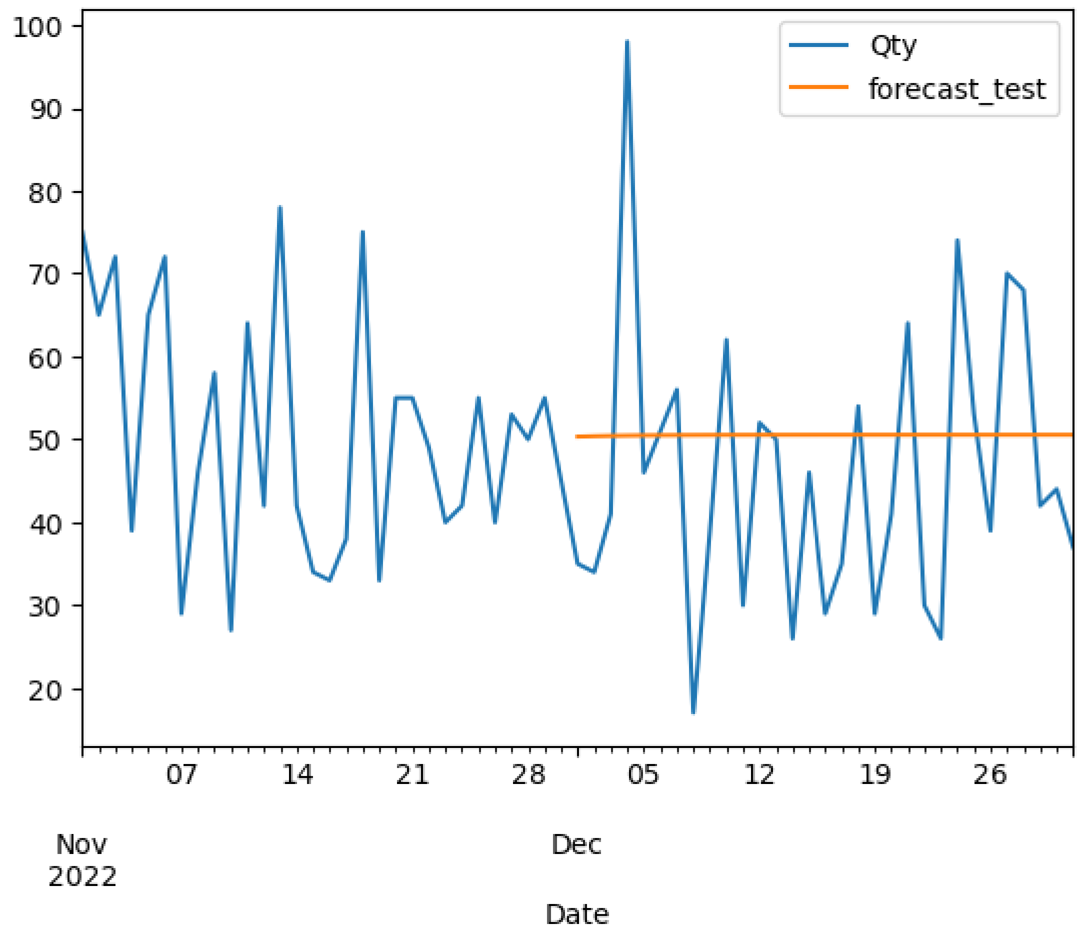
In [25]:
```
import matplotlib.pyplot as plt
residuals = model_fit.resid[1:]
fig, ax = plt.subplots(1,2)
residuals.plot(title='Residuals', ax=ax[0])
residuals.plot(title='Density', kind='kde', ax=ax[1])
plt.show()
```



In [26]:
```
#Manual parameter tuning
model = ARIMA(df_train, order=(1, 0, 1))
model_fit = model.fit()
```

```
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
```

In [27]:
```
#plot forecasting
forecast_test = model_fit.forecast(len(df_test))

df_plot = df_tsa[['Qty']].iloc[-61:]

df_plot['forecast_test'] = [None]*(len(df_plot)-len(forecast_test)) + list(foreca

df_plot.plot()
plt.show()
```

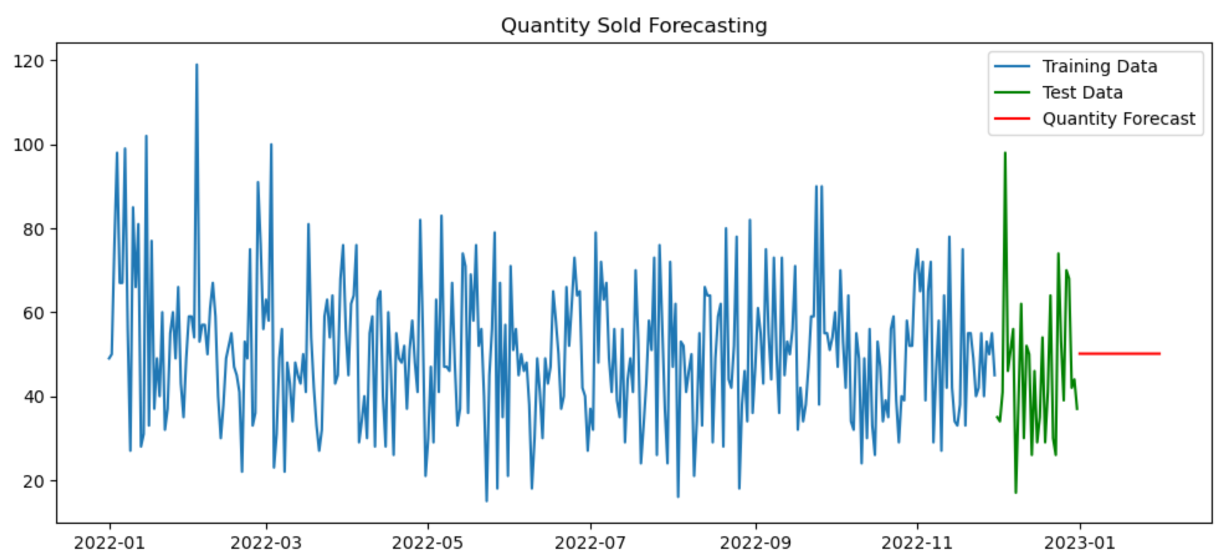


Overall Quantity of Product Sold Forecasting

In [28]:
```
#Overall Quantity Forecasting
model = ARIMA(df_tsa, order=(1, 0, 1))
model_fit = model.fit()
forecast = model_fit.forecast(steps=31)
```

```
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarni
ng: No frequency information was provided, so inferred frequency D will be use
d.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:966: UserWa
rning: Non-stationary starting autoregressive parameters found. Using zeros as
starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Anaconda\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:978: UserWa
rning: Non-invertible starting MA parameters found. Using zeros as starting par
ameters.
  warn('Non-invertible starting MA parameters found.'
```

In [29]:
```
#Plot forecasting
plt.figure(figsize=(12,5))
plt.plot(df_train, label='Training Data')
plt.plot(df_test, color='green', label='Test Data')
plt.plot(forecast,color='red', label= 'Quantity Forecast')
plt.title('Quantity Sold Forecasting')
plt.legend()
plt.show()
```



In [30]:
```
forecast.mean()
```

Out[30]:
```
50.1262232207751
```

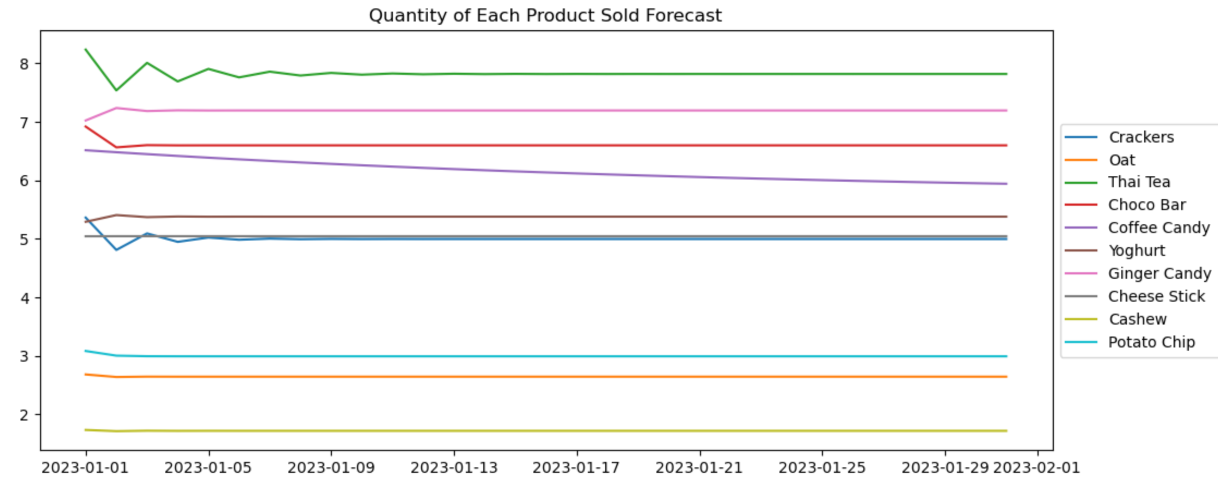
Berdasarkan hasil forecast di atas, diketahui bahwa estimasi kuantitas penjualan harian pada bulan januari 2023 adalah sekitar 51 pcs produk per hari (50.1262 dibulatkan ke atas).

Quantity of Each Product Forecast

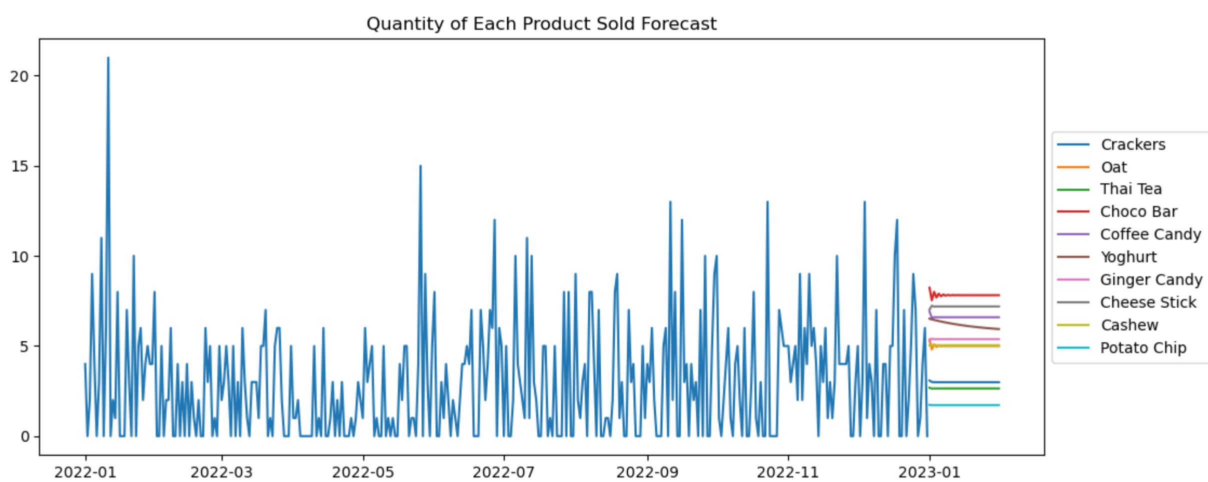
In [31]:
```
#Forecasting the quantity of each product for the next 31 days (January 2023 have
product_name = df['Product Name'].unique()

dfprod = pd.DataFrame({'Date':pd.date_range(start='2023-01-01',end='2023-01-31')]
dfprod = dfprod.set_index('Date')
for i in product_name:
    df1 = df[['Date','Product Name','Qty']]
    df1 = df1[df1['Product Name']==i]
    df1 = df1.groupby('Date')[['Qty']].sum()
    df1 = df1.reset_index()
    df_prod = pd.DataFrame({'Date':pd.date_range(start='2022-01-01',end='2022-12-
    df_prod = df_prod.merge(df1, how='left', on='Date')
    df_prod = df_prod.fillna(0)
    df_prod = df_prod.set_index('Date')

    model1 = ARIMA(df_prod, order=(1,0,1))
    model1_fit = model1.fit()
    forecast1 = model1_fit.forecast(steps=31)
    dfprod[i] = forecast1.values

dfprod.head()
```

```
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency D will be used.
  self._init_dates(dates, freq)
C:\Anaconda\Lib\site-packages\statsmodels\tsa\base\tsa_model.py:473: ValueWarning: No frequency information was provided, so inferred frequency D will be
```

In [32]:
```
#Forecasting Plot
plt.figure(figsize=(12,5))
plt.plot(dfprod)
plt.legend(dfprod.columns,loc='center left', bbox_to_anchor=(1, 0.5))
plt.title('Quantity of Each Product Sold Forecast')
plt.show()
```



In [33]:
```
#Plot forecasting
plt.figure(figsize=(12,5))
plt.plot(df_prod)
plt.plot(dfprod, label= 'Quantity of Each Product Forecast')
plt.title('Quantity of Each Product Sold Forecast')
plt.legend(dfprod.columns, loc='center left', bbox_to_anchor=(1,0.5))
plt.show()
```



In [34]:
```
#Quantity of Each Product Sold forecast
round(dfprod.describe().T['mean'],0)
```

Out[34]:
```
Crackers         5.0
Oat              3.0
Thai Tea         8.0
Choco Bar        7.0
Coffee Candy     6.0
Yoghurt          5.0
Ginger Candy     7.0
Cheese Stick     5.0
Cashew           2.0
Potato Chip      3.0
Name: mean, dtype: float64
```

Dari forecasting terhadap tiap produk yang terjual, diperkirakan pada bulan depan rata-rata produk Crackers akan terjual sebanyak 5 pcs per hari, Oat terjual sebanyak 3 pcs per hari, Thai Tea sebanyak 8 pcs per hari, Choco Bar sebanyak 7 pcs per hari, Coffee Candy sebanyak 6 pcs per hari, Yoghurt sebanyak 5 pcs per hari, Ginger Candy sebanyak 7 pcs per hari, Cheese Stick sebanyak 5 pcs per hari, Cashew sebanyak 2 pcs per hari, dan Potato Chip sebanyak 3 pcs per hari. Informasi ini dapat digunakan sebagai insight terhadap tim inventory untuk membuat stock persediaan harian yang cukup dan efektif.

In [ ]: