Exploratory Analysis

importing libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn import *
from sklearn.preprocessing import StandardScaler
from scipy import stats
```

loading dataset

In [2]:

```
df=pd.read_csv("marketplace.csv",index_col="date",parse_dates=True)
# loading the date column as index to the dataframe and parsing it as well
df.head()
```

Out[2]:

	sku_name	product_id	merchant_code	merchant_badge	product_type	merchant_city	cod	price	stock	daily_gmv	daily_sold
date											
2020-03-11	HUAWEI NOVA 5T RAM 8GB INTERNAL 128GB	E1	1.0	PM	Huawei nova 5T	Kota Kediri	False	4500000	1	0	0
2020-03-26	Huawei Nova 5T (8GB/128GB) - Crush Green	F1	2.0	OS	Huawei nova 5T	Kota Administrasi Jakarta Utara	False	4999000	5	0	0
2020-03-23	HUAWEI NOVA 5T RAM 8/128 GARANSI RESMI HUAWEI ...	F2	3.0	PM	Huawei nova 5T	Kota Administrasi Jakarta Barat	False	4589900	16	0	0
2020-04-29	HUAWEI NOVA 5T RAM 8/128GB GARANSI RESMI HUAWE...	E2	4.0	OS	Huawei nova 5T	Kota Surabaya	False	4698500	5	0	0
2020-04-15	nokia 3310 reborn	C1	5.0	RM	Nokia 1	Kab. Bangkalan	True	1000000	999999	0	0

initial description

In [3]:

```
df.describe()
```

Out[3]:

	merchant_code	price	stock	daily_gmv	daily_sold	daily_view	rating	total_review	total_sold
count	26007.000000	2.601400e+04	26014.000000	2.601400e+04	26014.000000	26014.000000	26014.000000	26014.000000	26014.000000
mean	1562.011112	3.890569e+06	344553.702083	1.582145e+06	0.737257	58.814331	98.339279	46.343969	152.429807
std	1041.170081	3.868790e+06	474104.795100	1.603716e+07	7.453432	473.091001	5.485507	91.149600	321.367828
min	1.000000	5.350000e+05	0.000000	-2.342700e+08	-82.000000	0.000000	0.000000	0.000000	0.000000
25%	854.000000	1.770000e+06	4.000000	0.000000e+00	0.000000	2.000000	98.000000	10.000000	27.000000
50%	1252.000000	2.599999e+06	37.000000	0.000000e+00	0.000000	5.000000	100.000000	24.000000	63.000000
75%	2287.000000	4.093925e+06	999972.000000	0.000000e+00	0.000000	21.000000	100.000000	44.000000	144.000000
max	4247.000000	5.000000e+07	999999.000000	9.415350e+08	441.000000	38993.000000	100.000000	2842.000000	7724.000000

In [4]:

```
df.isnull().sum()
```

Out[4]:

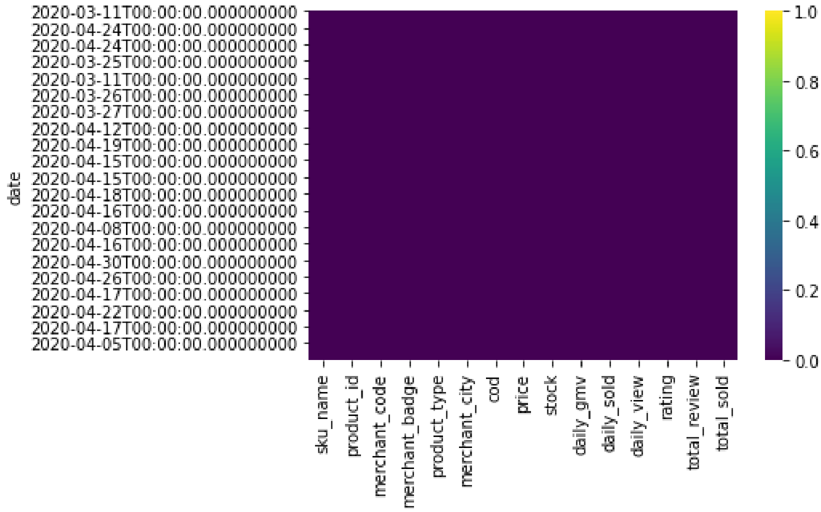
```
sku_name          0
product_id        0
merchant_code     7
merchant_badge    0
product_type      0
merchant_city     0
cod               0
price             0
stock             0
daily_gmv         0
daily_sold        0
daily_view        0
rating            0
total_review      0
total_sold        0
dtype: int64
```

In [5]:

```
# plotting heat map to show null values
sns.heatmap(df.isnull(),cmap='viridis') ## highly clean dataset with only 7 null values in a single colur
```

Out[5]:

```
<AxesSubplot:ylabel='date'>
```



No columns with dominating NULL values

no column needs to be dropped as of now

7 tuples with NULL values in field "merchant_code"

can be dropped

In [6]:

```
df=df.dropna() # dropping those tuples
df.isnull().sum()
```

Out[6]:

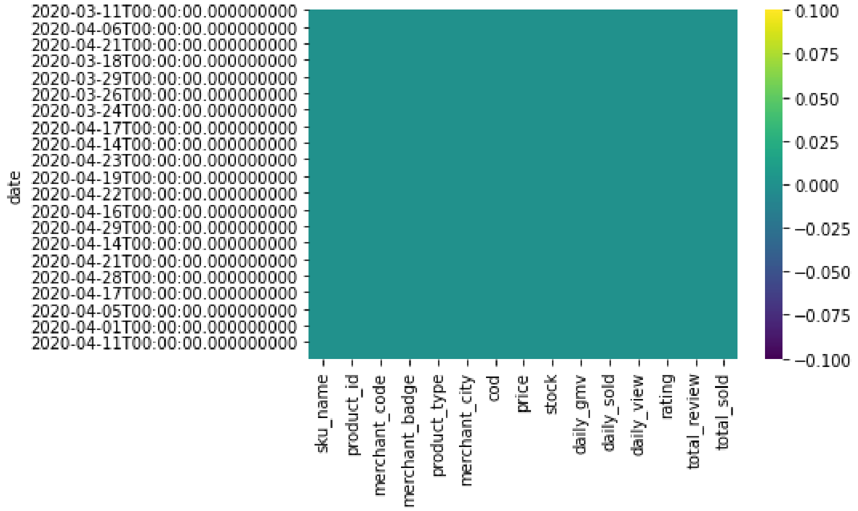
```
sku_name          0
product_id        0
merchant_code     0
merchant_badge    0
product_type      0
merchant_city     0
cod               0
price             0
stock             0
daily_gmv         0
daily_sold        0
daily_view        0
rating            0
total_review      0
total_sold        0
dtype: int64
```

In [7]:

```
sns.heatmap(df.isnull(),cmap='viridis')
```

Out[7]:

```
<AxesSubplot:ylabel='date'>
```



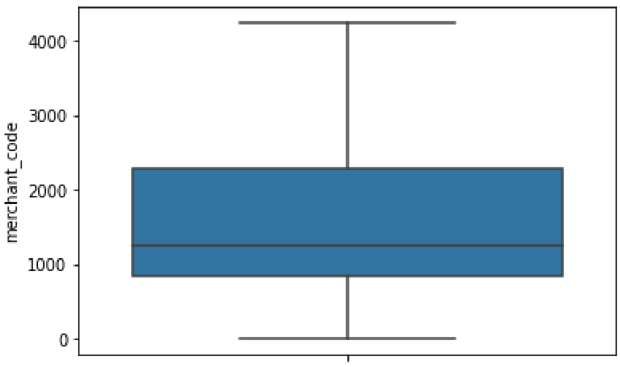
boxplots for features

In [8]:

```
sns.boxplot(y='merchant_code',data=df)
```

Out[8]:

```
<AxesSubplot:ylabel='merchant_code'>
```

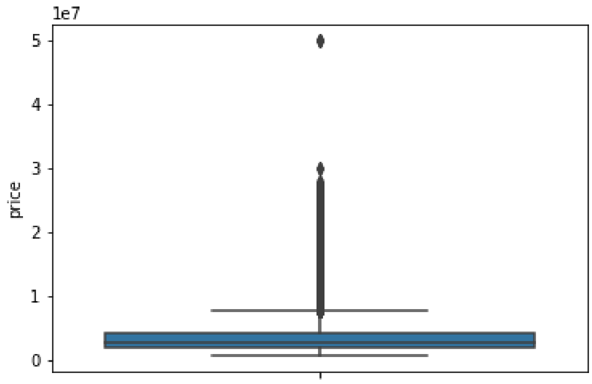


In [9]:

```
sns.boxplot(y='price',data=df)
```

Out[9]:

```
<AxesSubplot:ylabel='price'>
```

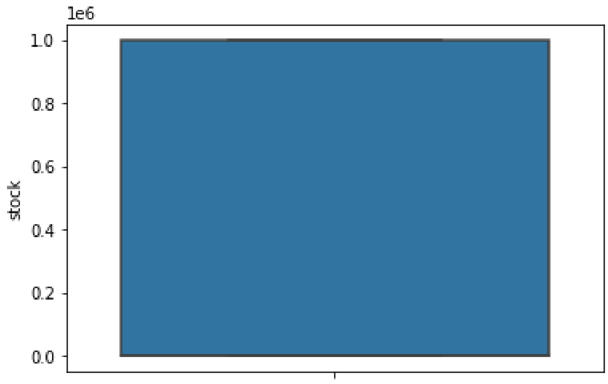


In [10]:

```
sns.boxplot(y='stock',data=df)
```

Out[10]:

```
<AxesSubplot:ylabel='stock'>
```

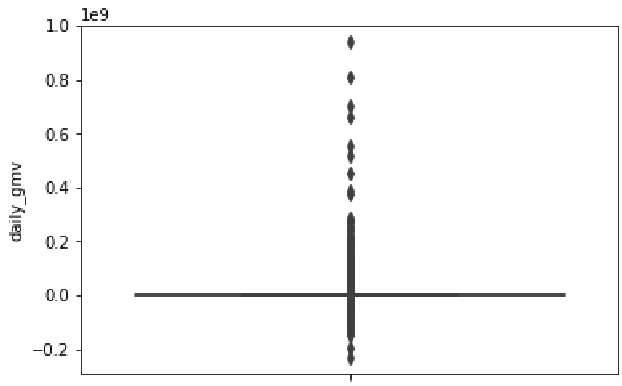


In [11]:

```
sns.boxplot(y='daily_gmv',data=df)
```

Out[11]:

```
<AxesSubplot:ylabel='daily_gmv'>
```

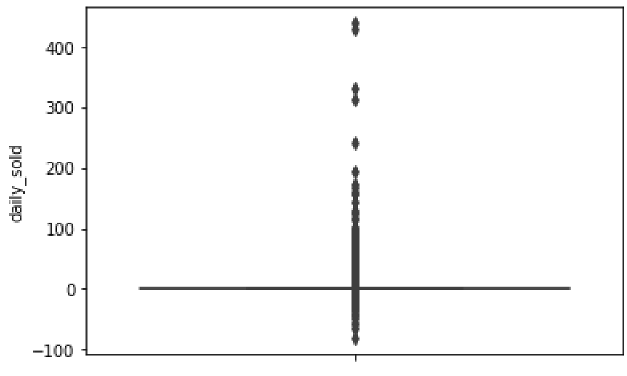


In [12]:

```
sns.boxplot(y='daily_sold',data=df)
```

Out[12]:

```
<AxesSubplot:ylabel='daily_sold'>
```

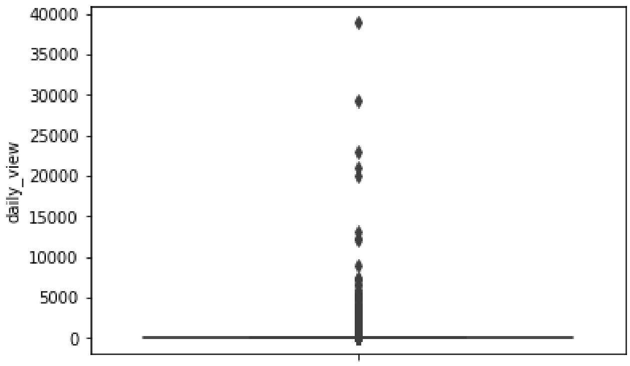


In [13]:

```
sns.boxplot(y='daily_view',data=df)
```

Out[13]:

<AxesSubplot:ylabel='daily_view'>

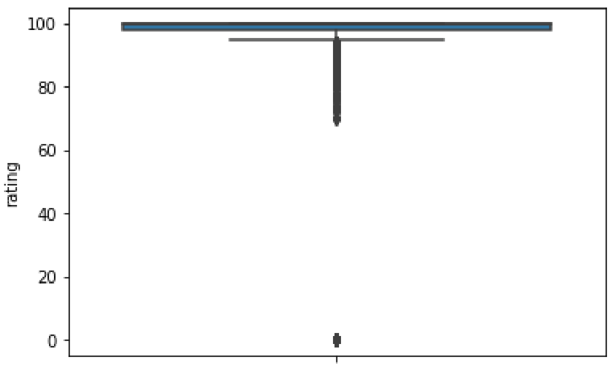


In [14]:

```
sns.boxplot(y='rating',data=df)
```

Out[14]:

<AxesSubplot:ylabel='rating'>

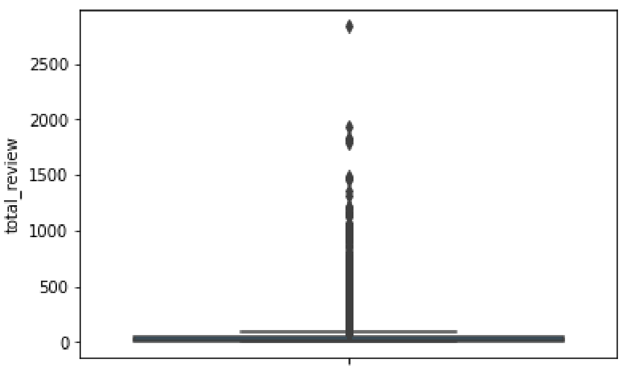


In [15]:

```
sns.boxplot(y='total_review',data=df)
```

Out[15]:

<AxesSubplot:ylabel='total_review'>



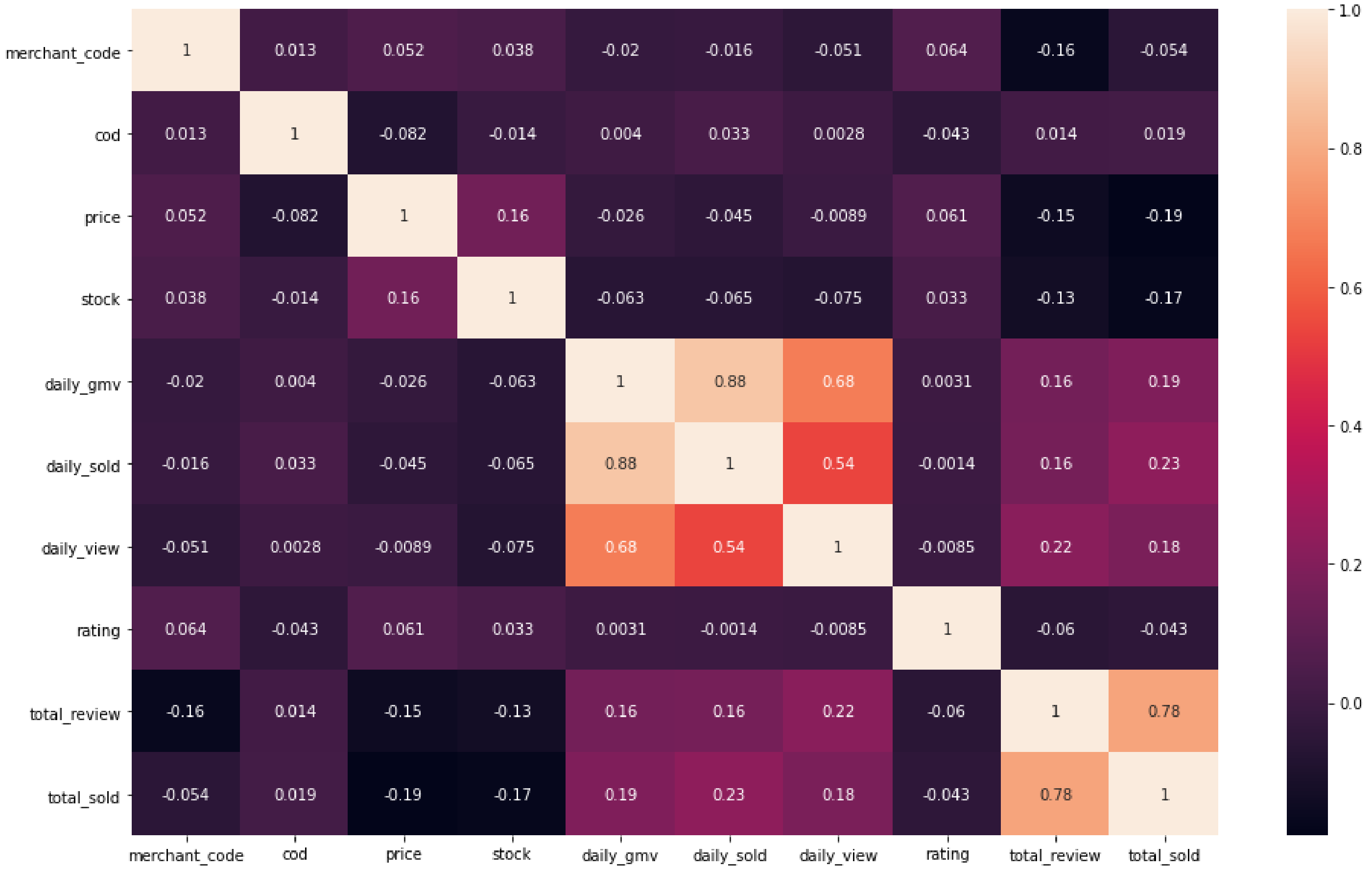
correlation matrix

In [16]:

```
corrmatrix=df.corr()
plt.figure(figsize = (16,10))
sns.heatmap(corrmatrix, annot=True)
```

Out[16]:

```
<AxesSubplot:>
```



plotting

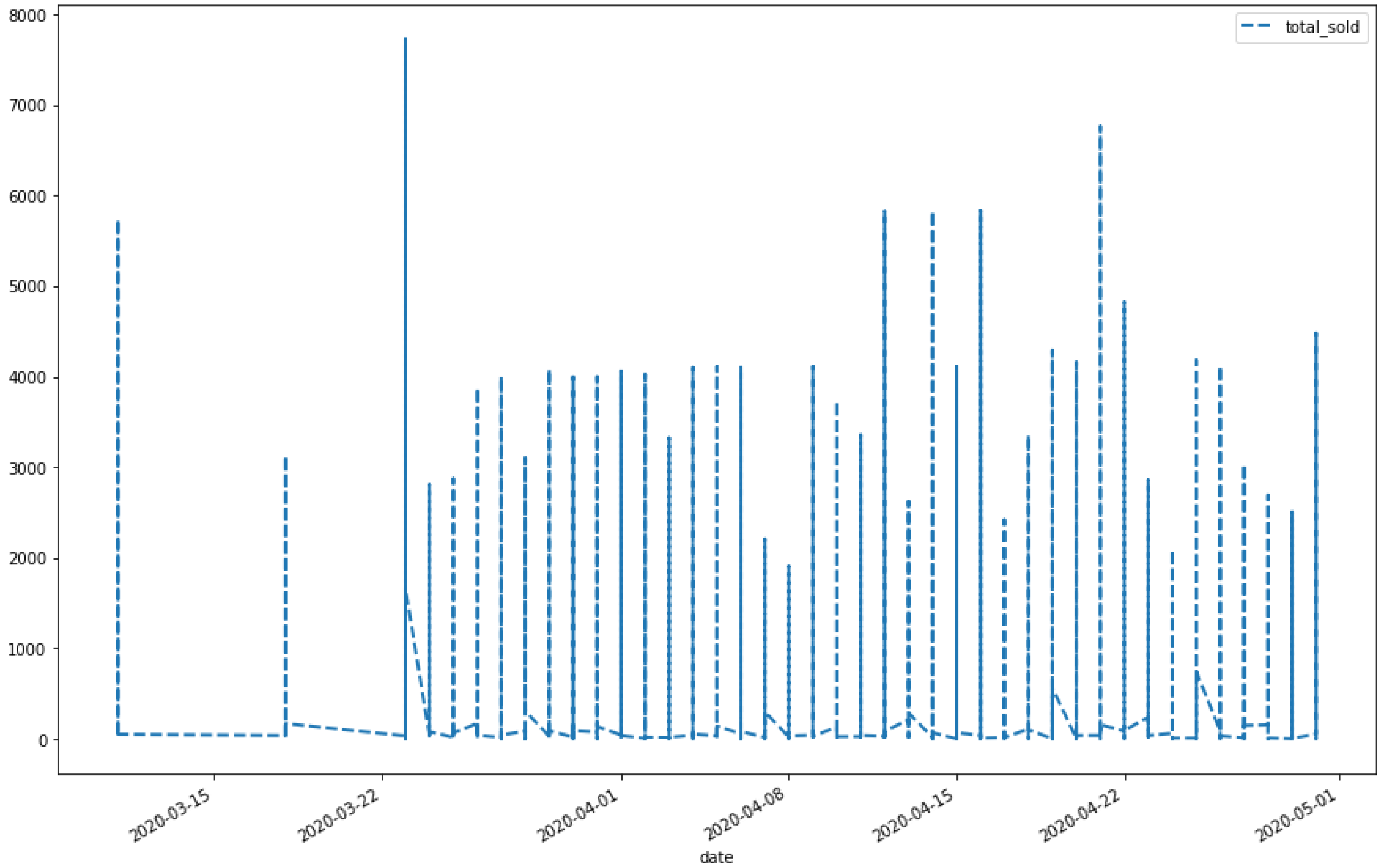
total_sold vs date

In [17]:

```
df[['total_sold']].plot(figsize=(15, 10),style=[ '--'],lw=2)
```

Out[17]:

```
<AxesSubplot:xlabel='date'>
```



plotting variables grouped by day of week

In [18]:

```
df_week = df[['daily_view','total_sold','total_review','rating']].groupby(df.index.weekday).sum()  # they
df_week
```

Out[18]:

	daily_view	total_sold	total_review	rating
date				
0	239874	575517	167742	366134
1	193305	575324	171872	396506
2	334592	782640	236245	496246
3	254878	583539	181947	352151
4	163663	467891	147168	306335
5	153819	458902	146002	316334
6	189841	521126	154557	323900

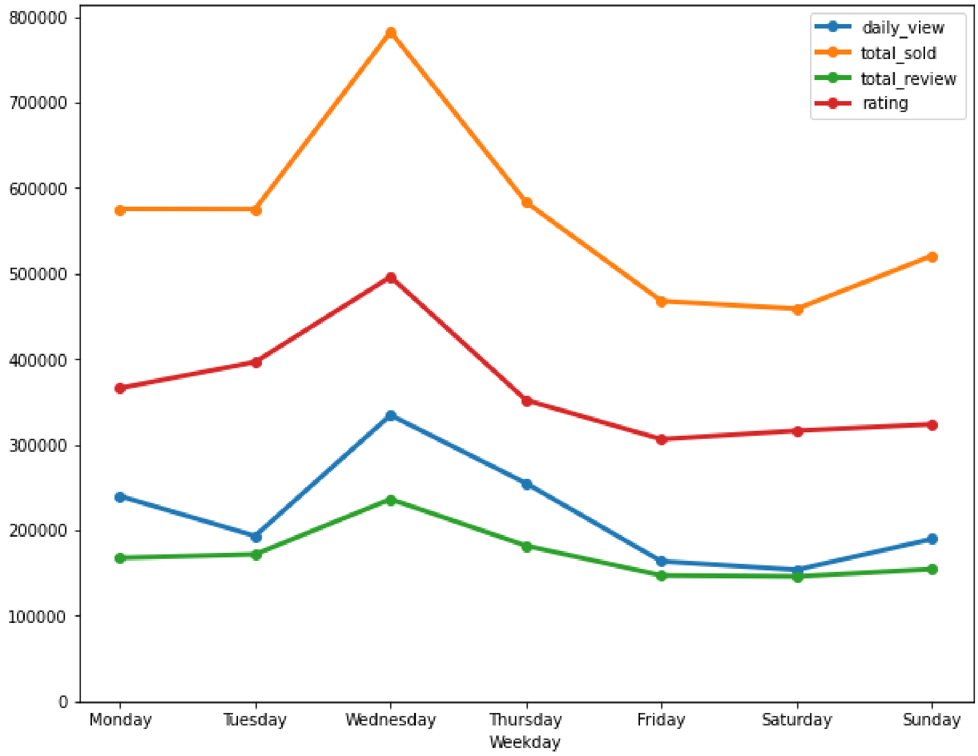
In [19]:

```
fig, ax = plt.subplots(1, 1, figsize=(10, 8))
df_week.plot(style='-o', lw=3, ax=ax)
ax.set_xlabel('Weekday')
# We replace the labels 0, 1, 2... by the weekday
# names.
ax.set_xticklabels(',Monday,Tuesday,Wednesday,Thursday,Friday,Saturday,Sunday'.split(','))
ax.set_ylim(0)  # Set the bottom axis to 0.
```

```
<ipython-input-19-5ee74aac5580>:6: UserWarning: FixedFormatter should only be used together with
FixedLocator
  ax.set_xticklabels(',Monday,Tuesday,Wednesday,Thursday,Friday,Saturday,Sunday'.split(','))
```

Out[19]:

```
(0.0, 814471.9)
```



In [20]:

```
df_week = df[['stock','price','daily_gmv']].groupby(df.index.weekday).sum() # they have similar range
df_week
```

Out[20]:

	stock	price	daily_gmv
date			
0	1209569462	13876702281	6896976128
1	1428182873	16611080428	4822291986
2	1783033796	20103019946	10863587351
3	1204889107	12868007873	4200600761
4	1050230945	12015689127	4470749054
5	1091570870	12723669029	4448481420
6	1193742519	12994420335	5455231562

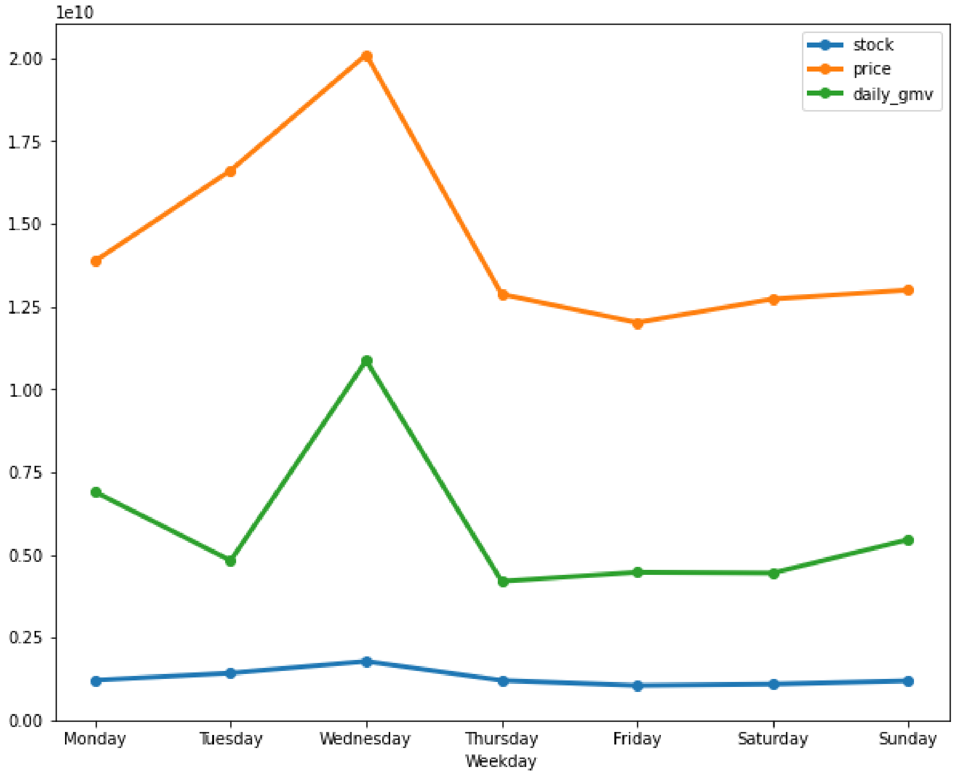
In [21]:

```
fig, ax = plt.subplots(1, 1, figsize=(10, 8))
df_week.plot(style='-o', lw=3, ax=ax)
ax.set_xlabel('Weekday')
# We replace the labels 0, 1, 2... by the weekday
# names.
ax.set_xticklabels(',Monday,Tuesday,Wednesday,Thursday,Friday,Saturday,Sunday'.split(','))
ax.set_ylim(0)  # Set the bottom axis to 0.
```

```
<ipython-input-21-5ee74aac5580>:6: UserWarning: FixedFormatter should only be used together with FixedLocator
  ax.set_xticklabels(',Monday,Tuesday,Wednesday,Thursday,Friday,Saturday,Sunday'.split(','))
```

Out[21]:

```
(0.0, 21055659396.05)
```



total_sold w.r.t the categorical variable cod

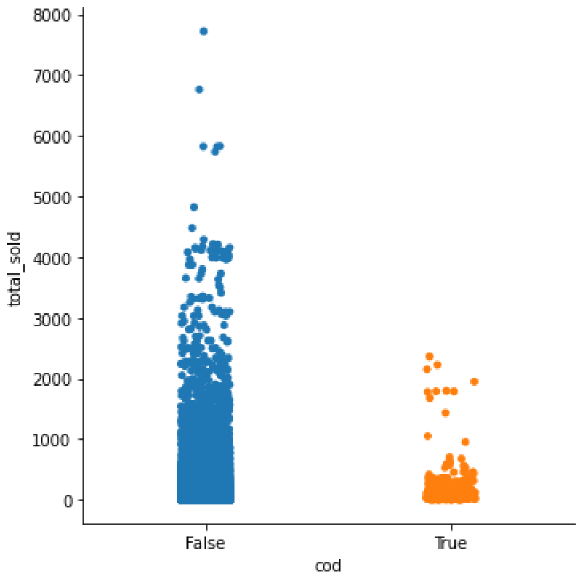
exploring how total_sold varies with the binary values of cod

In [22]:

```
sns.catplot(x="cod", y="total_sold",data=df)
```

Out[22]:

```
<seaborn.axisgrid.FacetGrid at 0x7f2e2a4bdf10>
```



exploring top 20 brands in terms of number of products

In [23]:

```
df['product_type'].value_counts()
```

Out[23]:

```
Realme 6                          2161
Samsung Galaxy A10s               1062
Xiaomi Redmi Note 8               1025
Xiaomi Redmi 7A                    858
Xiaomi Redmi 6A                    747
                                  ...
Xiaomi Mi 5c                         1
Huawei nova 7 5G                     1
vivo Y69                             1
Asus ZenFone Lite (L1) ZA551KL       1
Infinix Hot 9                        1
Name: product_type, Length: 361, dtype: int64
```

In [24]:

```
top_brands=df['product_type'].value_counts().head(20)
```

In [25]:

```
top_brands.to_frame(name="count")
```

Out[25]:

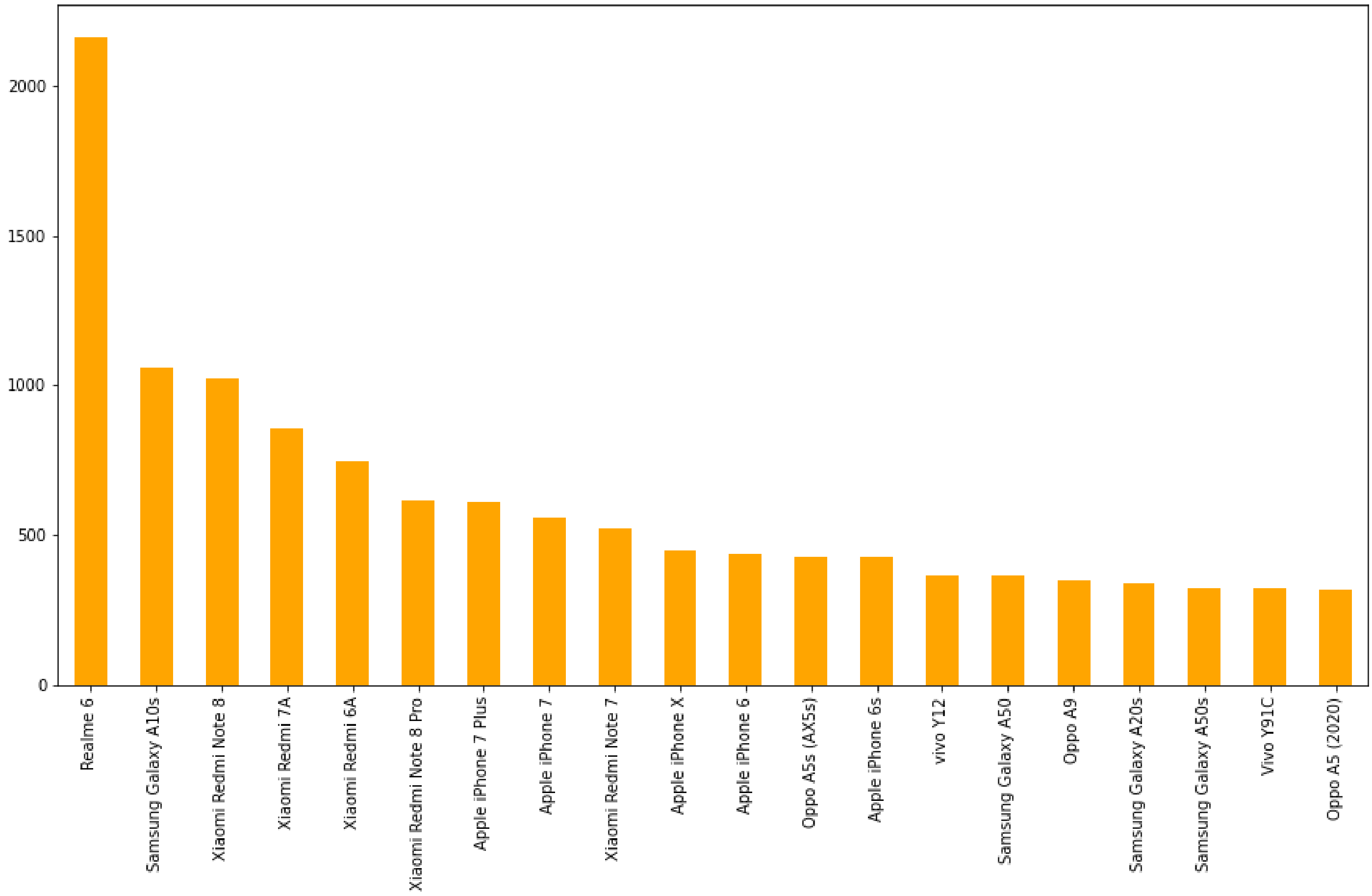
	count
Realme 6	2161
Samsung Galaxy A10s	1062
Xiaomi Redmi Note 8	1025
Xiaomi Redmi 7A	858
Xiaomi Redmi 6A	747
Xiaomi Redmi Note 8 Pro	616
Apple iPhone 7 Plus	611
Apple iPhone 7	561
Xiaomi Redmi Note 7	523
Apple iPhone X	450
Apple iPhone 6	440
Oppo A5s (AX5s)	427
Apple iPhone 6s	427
vivo Y12	367
Samsung Galaxy A50	367
Oppo A9	350
Samsung Galaxy A20s	339
Samsung Galaxy A50s	326
Vivo Y91C	326
Oppo A5 (2020)	320

In [26]:

```
top_brands.plot.bar(color="orange",figsize=(15, 8))
```

Out[26]:

```
<AxesSubplot:>
```



exploring top ten costliest w.r.t product type

In [27]:

```
bytype=df.groupby("product_type")
costliest=bytype.max("price")
costliest
```

Out[27]:

	merchant_code	cod	price	stock	daily_gmv	daily_sold	daily_view	rating	total_review	total_sold
product_type										
Apple iPhone	2756.0	False	21790000	999999	7000000	1	12	100	12	95
Apple iPhone 11	3198.0	False	18069000	999999	47850000	3	870	100	424	550
Apple iPhone 11 Pro	3670.0	False	24999000	999999	39000000	2	2118	100	256	355
Apple iPhone 11 Pro Max	4085.0	False	30000000	999999	222750000	9	6529	100	362	563
Apple iPhone 4	2796.0	True	3550000	999999	0	0	3	100	11	17
...	...	...	...	...	...	...	...	...	...	...
vivo Y93	2717.0	False	3000000	999999	9750000	6	833	100	647	974
vivo Y95	2720.0	False	4000000	999999	3000000	1	131	100	494	700
vivo Z1	2541.0	False	3000000	9982	0	0	23	92	5	29
vivo Z1Pro	2741.0	False	4000000	999999	100230000	39	3187	100	351	585
vivo iQOO Pro	2794.0	False	5200000	999999	15600000	3	63	100	363	465

361 rows × 10 columns

In [28]:

```
costliest.nlargest(10,["price"])
```

Out[28]:

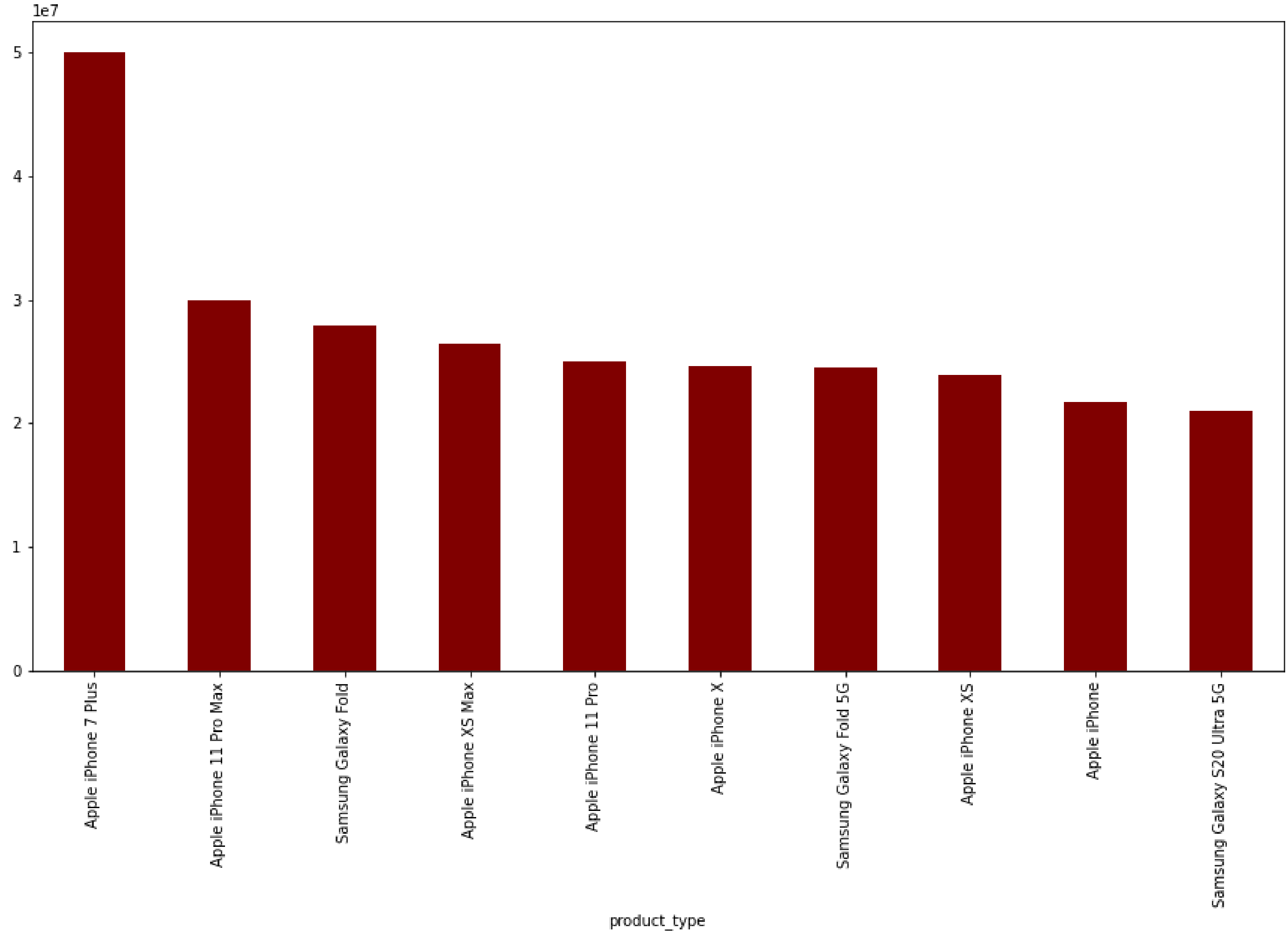
	merchant_code	cod	price	stock	daily_gmv	daily_sold	daily_view	rating	total_review	total_sold
product_type										
Apple iPhone 7 Plus	3767.0	True	50000000	999999	120275000	17	1184	100	218	607
Apple iPhone 11 Pro Max	4085.0	False	30000000	999999	222750000	9	6529	100	362	563
Samsung Galaxy Fold	1989.0	False	27885000	999978	0	0	86	100	18	24
Apple iPhone XS Max	3808.0	False	26500000	999999	14639000	1	480	100	129	306
Apple iPhone 11 Pro	3670.0	False	24999000	999999	39000000	2	2118	100	256	355
Apple iPhone X	3139.0	False	24598000	999999	12499000	1	544	100	120	233
Samsung Galaxy Fold 5G	2353.0	False	24500000	2	0	0	0	100	11	24
Apple iPhone XS	3327.0	False	23900000	999999	14645000	1	207	100	133	322
Apple iPhone	2756.0	False	21790000	999999	7000000	1	12	100	12	95
Samsung Galaxy S20 Ultra 5G	1111.0	False	20999000	45	15849000	1	1512	100	35	51

In [29]:

```
costliest=costliest.nlargest(10,["price"])["price"]
costliest.plot.bar(color="maroon",figsize=(15, 8))
```

Out[29]:

```
<AxesSubplot:xlabel='product_type'>
```



In [30]:

```
df = df.sort_values(by='date')
df
```

Out[30]:

	sku_name	product_id	merchant_code	merchant_badge	product_type	merchant_city	cod	price	stock	daily_gmv	daily_sol
date											
2020-03-11	HUAWEI NOVA 5T RAM 8GB INTERNAL 128GB	E1	1.0	PM	Huawei nova 5T	Kota Kediri	False	4500000	1	0	
2020-03-11	SAMSUNG A10S Ram 2-32 GB	E1319	2082.0	PM	Samsung Galaxy A10s	Kab. Bekasi	False	1616000	30	0	
2020-03-11	Vivo Z1 Pro 4/64 GB 64GB Garansi Resmi - Biru	E813	1295.0	PM	vivo Z1Pro	Kota Tangerang Selatan	False	2945000	2	0	
2020-03-11	Samsung A10S 2/32 Garansi Resmi Baru Segel - H...	F1176	1845.0	PM	Samsung Galaxy A10s	Kab. Sleman	False	1615000	3	0	
2020-03-11	VIVO Z1 PRO RAM 4/64 GB GARANSI RESMI VIVO IND...	E818	875.0	PM	vivo Z1Pro	Kota Administrasi Jakarta Barat	False	3279000	999999	0	
...	...	...	...	...	...	...	...	...	...	...	...
2020-04-30	VIVO Y12 RAM 3/64GB GARANSI RESMI VIVO INDONES...	E708	875.0	PM	vivo Y12	Kota Administrasi Jakarta Barat	False	1789000	9851	5367000	
2020-04-30	REALME 6 PRO 8/128 6/128 4/64 - 8GB 6GB/128GB ...	G245	976.0	PM	Realme 6	Kota Administrasi Jakarta Pusat	False	4181000	8	33448000	
2020-04-30	samsungA30	E1214	1910.0	PM	Samsung Galaxy A30	Kab. Tegal	False	3000000	96	0	
2020-04-30	Samsung Galaxy A50 Ram 4/64 Garansi Nasional S...	D1750	1254.0	PM	Samsung Galaxy A50	Kota Medan	False	3700000	999998	0	
2020-04-30	iPhone Xs Max 256gb RAM4gb GOLD SILVER GREY - ...	C1088	3802.0	PM	Apple iPhone XS Max	Kota Administrasi Jakarta Barat	False	19999000	1	0	

26007 rows × 15 columns

Processing functions and scaling of data

In [31]:

```
# importing all that is needed for training and testing
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
from sklearn.ensemble import RandomForestRegressor
from matplotlib.pyplot import figure
```

Normalising the continous variables

In [32]:

```
sc= StandardScaler()
```

```
df_new=df.copy()
column_names = ['price','stock','daily_gmv','daily_sold','daily_view','rating','total_review'] # List of
features = df_new[column_names]
scaler = sc.fit(features.values)
features = scaler.transform(features.values)
df_new[column_names] = features
unnorm_df=df # keeping track of data before normalisation , later used for chi2
df=df_new
```

In [33]:

```
# function that takes product name as parameter and returns a processed subset
def get_dataset(name, mobile_dict,data):
    #A dictionary that will contain the unique mobile phone models as keys and their corresponding sales
    #form of a dataframe as values
    if name in mobile_dict:
       # mobile_dict[name].set_index('week')
        return mobile_dict[name]

    #Getting the list of attributes needed to recreate the sales data dataframe for the individual phone
    column_list = []
    for i in data:
        column_list.append(i)


    #Creating the dataframes
    for i in data['product_type'].unique():
        mobile_dict[i] = pd.DataFrame(columns=column_list)

    #Copying information into the dataframes
    for i in mobile_dict:
        mobile_dict[i] = data.loc[data['product_type'] == i]

    # Dropping date as it isn't unifomrly distributed and dropping product_type as it already happens to
    #the key in the dictionary

    for i in mobile_dict.keys():
        for column in mobile_dict[i].columns:
            if column in ['date', 'product_type']:
                del mobile_dict[i][column]

    #Appending the week column for each of the dataframes
#     for i in mobile_dict.keys():
#         week = []
#         for j in range(1, len(mobile_dict[i]) + 1):
#             week.append(str(j))

#         mobile_dict[i].insert(1, "week", week, True)

    # removing outliers
    column_names = ['price','stock','daily_gmv','daily_sold','daily_view','rating','total_review']
    for clm_name in mobile_dict[name].columns:
        if clm_name in column_names:
            q_low = mobile_dict[name][clm_name].quantile(0.01)
            q_hi  = mobile_dict[name][clm_name].quantile(0.99)

            df_filtered = mobile_dict[name][(mobile_dict[name][clm_name] < q_hi) & (mobile_dict[name][clm

    # dropping all unnecessary columns

    df_filtered.drop(['sku_name','merchant_code','merchant_badge'],axis=1,inplace=True)
    # encoding categorical variables
    df_filtered=pd.get_dummies(data=df_filtered,columns=['cod','merchant_city','product_id'])
    mobile_dict[name]=df_filtered
    return df_filtered #mobile_dict[name]
```

In [34]:

```
mobile_dict={}
curr_data=get_dataset('Huawei nova 5T',mobile_dict,df)
curr_data
```

```
/home/sriram/.local/lib/python3.8/site-packages/pandas/core/frame.py:4162: SettingWithCopyWarning: 
A value is trying to be set on a copy of a slice from a DataFrame

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

Out[34]:

	price	stock	daily_gmv	daily_sold	daily_view	rating	total_review	total_sold	cod_False	merchant_city_Kab. Bekasi	...	product_ic
date												
2020-03-11	0.157408	-0.726784	-0.098670	-0.098930	-0.124337	-0.613162	-0.102615	74	1	0	...	
2020-03-18	0.208712	-0.726773	-0.098670	-0.098930	-0.124337	-0.062909	-0.179405	48	1	0	...	
2020-03-23	0.180643	-0.726752	-0.098670	-0.098930	-0.124337	-0.429745	-0.376864	19	1	0	...	
2020-03-23	0.180643	-0.705727	-0.098670	-0.098930	-0.124337	0.120508	-0.179405	59	1	0	...	
2020-03-24	0.177826	-0.726784	-0.098670	-0.098930	0.408270	-0.429745	-0.289104	38	1	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
2020-04-29	0.208712	-0.726775	-0.098670	-0.098930	-0.124337	0.120508	-0.047765	63	1	0	...	
2020-04-29	0.221764	-0.726746	-0.098670	-0.098930	-0.124337	-0.429745	-0.168435	58	1	0	...	
2020-04-29	0.234946	-0.726758	-0.098670	-0.098930	-0.124337	-0.062909	1.400271	326	1	0	...	
2020-04-29	0.234946	-0.726758	0.799142	0.303523	1.659473	-0.062909	1.400271	326	1	0	...	
2020-04-30	0.247610	-0.726746	-0.098670	-0.098930	0.144080	-0.429745	-0.168435	58	1	0	...	

115 rows × 42 columns

BUILDONG THE MODELS

Simple Linear Regression

Since total_review is the highly correlated with total_Sold

In [35]:

```
X=curr_data['total_review'].values.astype(float)
Y=curr_data['total_sold'].values.astype(float)
```

In [36]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 1/3, random_state = 0)
```

In [37]:

```
X_train=X_train.reshape(-1,1)
y_train=y_train.reshape(-1,1)
X_test=X_test.reshape(-1,1)
y_test=y_test.reshape(-1,1)
```

In [38]:

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[38]:

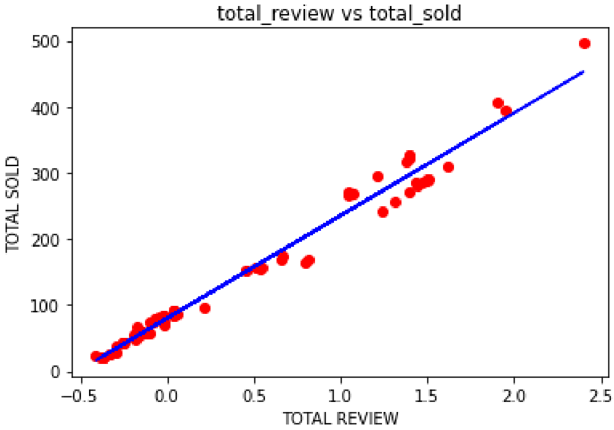
```
LinearRegression()
```

In [39]:

```
y_pred = regressor.predict(X_test)
```

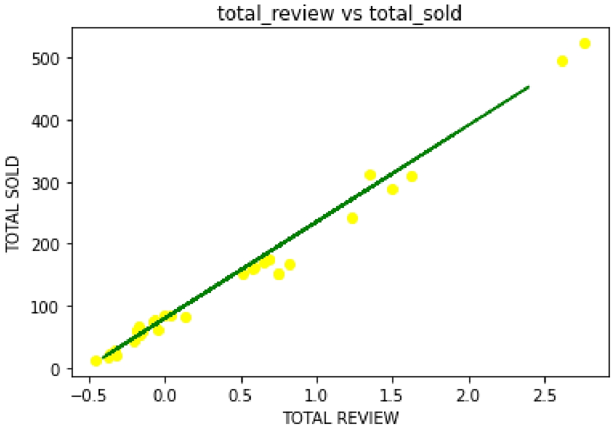
In [40]:

```
plt.scatter(X_train, y_train, color = 'red')
plt.plot(X_train, regressor.predict(X_train), color = 'blue')
plt.title('total_review vs total_sold')
plt.xlabel('TOTAL REVIEW')
plt.ylabel('TOTAL SOLD')
plt.show()
```



In [41]:

```
plt.scatter(X_test, y_test, color = 'yellow')
plt.plot(X_train, regressor.predict(X_train), color = 'green')
plt.title('total_review vs total_sold')
plt.xlabel('TOTAL REVIEW')
plt.ylabel('TOTAL SOLD')
plt.show()
```



In [42]:

```
r2_score(y_test, y_pred)
```

Out[42]:

```
0.9824359693745011
```

In [43]:

```
mean_absolute_error(y_test, y_pred)
```

Out[43]:

```
11.153096512578344
```

In [44]:

```
mean_squared_error(y_test, y_pred)
```

Out[44]:

```
247.21676809535302
```

Multiple Linear Regression

In [45]:

```
X=curr_data.copy()
X.drop(['total_sold'],axis=1,inplace=True)
Y=curr_data['total_sold'].values.astype(float)
```

In [46]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, random_state = 3)
```

In [47]:

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

Out[47]:

```
LinearRegression()
```

In [48]:

```
y_pred = regressor.predict(X_test)
```

In [49]:

```
r2_score(y_test, y_pred)
```

Out[49]:

```
0.9973128301729254
```

In [50]:

```
mean_absolute_error(y_test, y_pred)
```

Out[50]:

```
5.041849422759056
```

In [51]:

```
mean_squared_error(y_test, y_pred)
```

Out[51]:

```
42.75822596954673
```

In [52]:

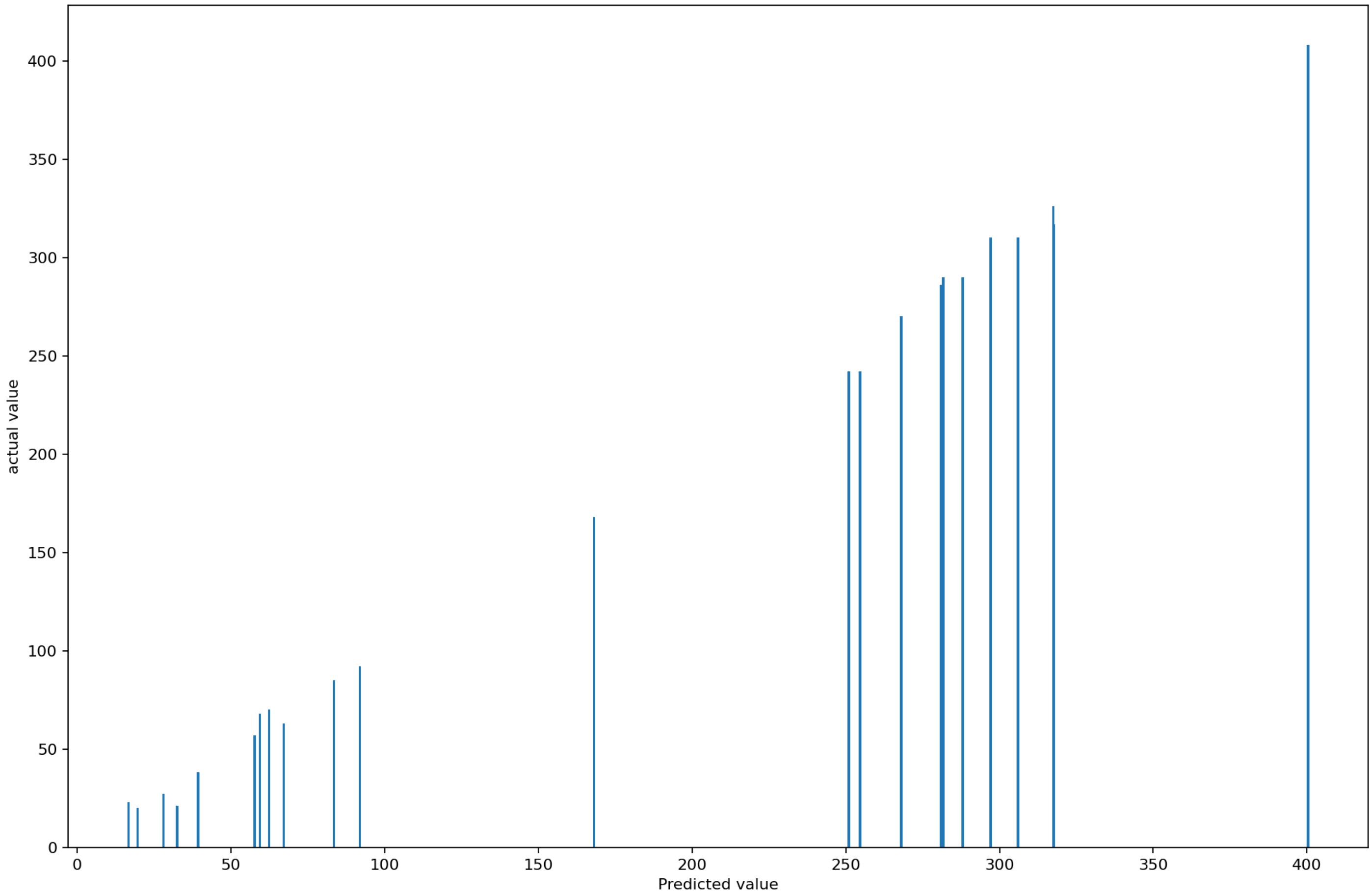
```
np.set_printoptions(precision=2)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
[[ 92.04  92.  ]
 [251.04 242.  ]
 [254.67 242.  ]
 [ 16.75  23.  ]
 [305.98 310.  ]
 [ 57.81  57.  ]
 [ 28.12  27.  ]
 [ 19.73  20.  ]
 [317.74 317.  ]
 [168.14 168.  ]
 [281.68 290.  ]
 [297.12 310.  ]
 [317.52 326.  ]
 [ 83.57  85.  ]
 [ 62.44  70.  ]
 [ 67.28  63.  ]
 [ 39.37  38.  ]
 [400.3  408.  ]
 [ 32.58  21.  ]
 [280.99 286.  ]
 [268.1  270.  ]
 [288.09 290.  ]
 [ 59.55  68.  ]]
```

In [53]:

```
figure(num=None, figsize=(15, 10), dpi=160, facecolor='w', edgecolor='k')

plt.bar(y_pred,y_test)
plt.xlabel('Predicted value')
plt.ylabel('actual value')
plt.show()
```



Random Forest

In [54]:

```
regressor = RandomForestRegressor(n_estimators = 10, random_state = 0)
```

In [55]:

```
regressor.fit(X_train, y_train)
```

Out[55]:

```
RandomForestRegressor(n_estimators=10, random_state=0)
```

In [56]:

```
y_pred = regressor.predict(X_test)
```

In [57]:

```
r2_score(y_test, y_pred)
```

Out[57]:

```
0.9744602196211687
```

In [58]:

```
mean_absolute_error(y_test, y_pred)
```

Out[58]:

```
12.460869565217397
```

In [59]:

```
mean_squared_error(y_test, y_pred)
```

Out[59]:

```
406.3887922705318
```

In [60]:

```
np.set_printoptions(precision=2)
print(np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1))
```

```
[[ 90.    92.  ]
 [284.   242.  ]
 [306.8  242.  ]
 [ 22.8   23.  ]
 [331.5  310.  ]
 [ 57.23  57.  ]
 [ 27.1   27.  ]
 [ 22.    20.  ]
 [313.7  317.  ]
 [165.9  168.  ]
 [285.7  290.  ]
 [283.4  310.  ]
 [291.   326.  ]
 [ 85.8   85.  ]
 [ 80.2   70.  ]
 [ 83.    63.  ]
 [ 32.    38.  ]
 [396.4  408.  ]
 [ 26.3   21.  ]
 [280.4  286.  ]
 [258.4  270.  ]
 [286.9  290.  ]
 [ 59.73  68.  ]]
```

trying to bring out feature importances using the trained random forest regressor

In [61]:

```
importances=regressor.feature_importances_
```

In [62]:

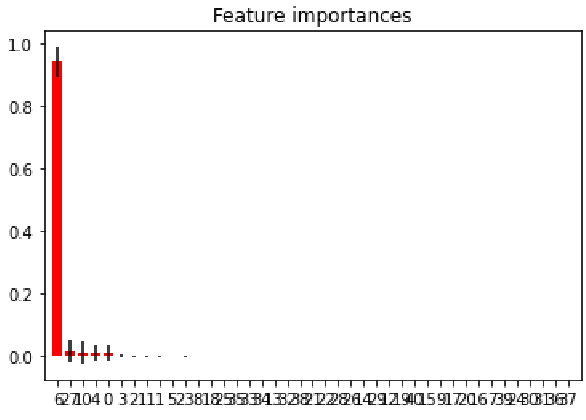
```
std = np.std([tree.feature_importances_ for tree in regressor.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(X_train.shape[1]):
    print("%d. feature %d : %s (%f)" % (f + 1,indices[f], X_train.columns[indices[f]], importances[indice

# Plot the impurity-based feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X_train.shape[1]), importances[indices],color="r", yerr=std[indices], align="center")
plt.xticks(range(X_train.shape[1]), indices)
plt.xlim([-1, X_train.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature 6 : total_review (0.940355)
2. feature 27 : product_id_E919 (0.018277)
3. feature 10 : merchant_city_Kota Administrasi Jakarta Barat (0.011484)
4. feature 4 : daily_view (0.011397)
5. feature 0 : price (0.010611)
6. feature 3 : daily_sold (0.002352)
7. feature 2 : daily_gmv (0.001594)
8. feature 11 : merchant_city_Kota Administrasi Jakarta Pusat (0.001475)
9. feature 1 : stock (0.001284)
10. feature 5 : rating (0.000368)
11. feature 23 : product_id_E3261 (0.000286)
12. feature 8 : merchant_city_Kab. Bekasi (0.000136)
13. feature 18 : product_id_E2199 (0.000110)
14. feature 25 : product_id_E3263 (0.000076)
15. feature 35 : product_id_F674 (0.000052)
16. feature 33 : product_id_F3012 (0.000041)
17. feature 34 : product_id_F3013 (0.000028)
18. feature 13 : merchant_city_Kota Kediri (0.000023)
19. feature 32 : product_id_F3011 (0.000016)
20. feature 38 : product_id_F677 (0.000011)
21. feature 21 : product_id_E286 (0.000008)
22. feature 22 : product_id_E287 (0.000005)
23. feature 28 : product_id_E920 (0.000005)
24. feature 26 : product_id_E79 (0.000002)
25. feature 14 : merchant_city_Kota Surabaya (0.000002)
26. feature 29 : product_id_F1941 (0.000002)
27. feature 12 : merchant_city_Kota Administrasi Jakarta Utara (0.000002)
28. feature 19 : product_id_E2200 (0.000000)
29. feature 40 : product_id_G50 (0.000000)
30. feature 15 : product_id_E1 (0.000000)
31. feature 9 : merchant_city_Kab. Karawang (0.000000)
32. feature 17 : product_id_E2198 (0.000000)
33. feature 20 : product_id_E2201 (0.000000)
34. feature 16 : product_id_E2 (0.000000)
35. feature 7 : cod_False (0.000000)
36. feature 39 : product_id_G335 (0.000000)
37. feature 24 : product_id_E3262 (0.000000)
38. feature 30 : product_id_F1942 (0.000000)
39. feature 31 : product_id_F2 (0.000000)
40. feature 36 : product_id_F675 (0.000000)
41. feature 37 : product_id_F676 (0.000000)
```

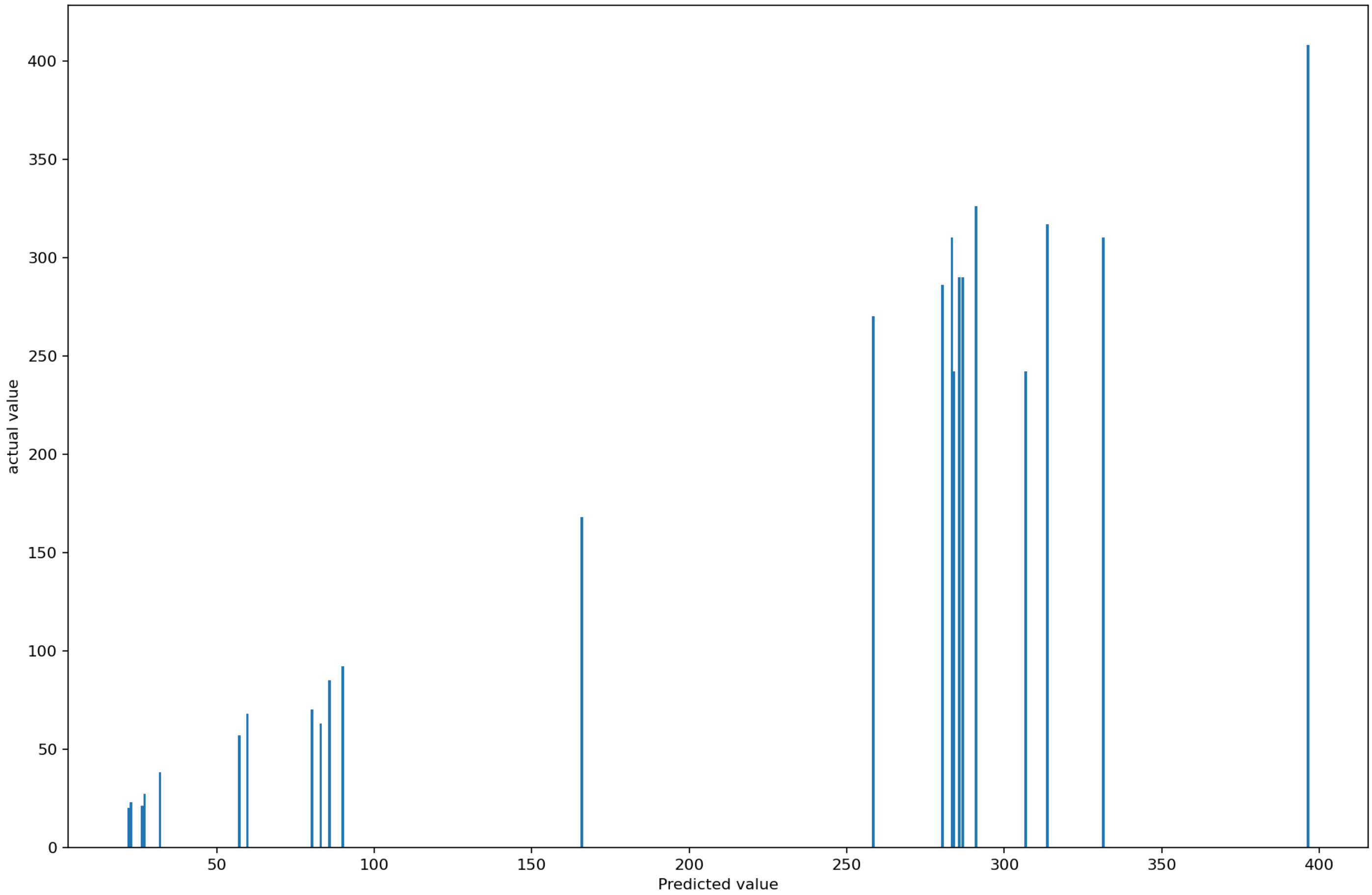


total review seems to be determining the dependant variable to a great extent

In [63]:

```
figure(num=None, figsize=(15, 10), dpi=160, facecolor='w', edgecolor='k')

plt.bar(y_pred,y_test)
plt.xlabel('Predicted value')
plt.ylabel('actual value')
plt.show()
```



Training without considering total_review

In [64]:

```
X=curr_data.copy()
X.drop(['total_sold','total_review'],axis=1,inplace=True)
Y=curr_data['total_sold'].values.astype(float)
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, random_state = 3)
```

In [65]:

```
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
r2_score(y_test, y_pred)
```

Out[65]:

```
0.8328716400674071
```

In [66]:

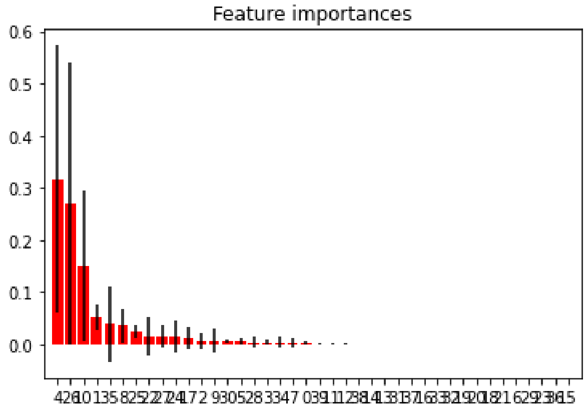
```
importances=regressor.feature_importances_
std = np.std([tree.feature_importances_ for tree in regressor.estimators_],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(X_train.shape[1]):
    print("%d. feature %d : %s (%f)" % (f + 1,indices[f], X_train.columns[indices[f]], importances[indice

# Plot the impurity-based feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X_train.shape[1]), importances[indices],color="r", yerr=std[indices], align="center")
plt.xticks(range(X_train.shape[1]), indices)
plt.xlim([-1, X_train.shape[1]])
plt.show()
```

```
Feature ranking:
1. feature 4 : daily_view (0.317270)
2. feature 26 : product_id_E919 (0.270946)
3. feature 10 : merchant_city_Kota Administrasi Jakarta Pusat (0.151379)
4. feature 1 : stock (0.052359)
5. feature 35 : product_id_F675 (0.039197)
6. feature 8 : merchant_city_Kab. Karawang (0.035491)
7. feature 25 : product_id_E79 (0.023186)
8. feature 22 : product_id_E3261 (0.015739)
9. feature 27 : product_id_E920 (0.015647)
10. feature 24 : product_id_E3263 (0.015500)
11. feature 17 : product_id_E2199 (0.012264)
12. feature 2 : daily_gmv (0.007707)
13. feature 9 : merchant_city_Kota Administrasi Jakarta Barat (0.007515)
14. feature 30 : product_id_F2 (0.007232)
15. feature 5 : rating (0.006019)
16. feature 28 : product_id_F1941 (0.004133)
17. feature 3 : daily_sold (0.004115)
18. feature 34 : product_id_F674 (0.003965)
19. feature 7 : merchant_city_Kab. Bekasi (0.003345)
20. feature 0 : price (0.003184)
21. feature 39 : product_id_G50 (0.000801)
22. feature 11 : merchant_city_Kota Administrasi Jakarta Utara (0.000728)
23. feature 12 : merchant_city_Kota Kediri (0.000703)
24. feature 38 : product_id_G335 (0.000558)
25. feature 14 : product_id_E1 (0.000550)
26. feature 13 : merchant_city_Kota Surabaya (0.000172)
27. feature 31 : product_id_F3011 (0.000126)
28. feature 37 : product_id_F677 (0.000082)
29. feature 16 : product_id_E2198 (0.000046)
30. feature 33 : product_id_F3013 (0.000030)
31. feature 32 : product_id_F3012 (0.000008)
32. feature 19 : product_id_E2201 (0.000002)
33. feature 20 : product_id_E286 (0.000002)
34. feature 18 : product_id_E2200 (0.000000)
35. feature 21 : product_id_E287 (0.000000)
36. feature 6 : cod_False (0.000000)
37. feature 29 : product_id_F1942 (0.000000)
38. feature 23 : product_id_E3262 (0.000000)
39. feature 36 : product_id_F676 (0.000000)
40. feature 15 : product_id_E2 (0.000000)
```

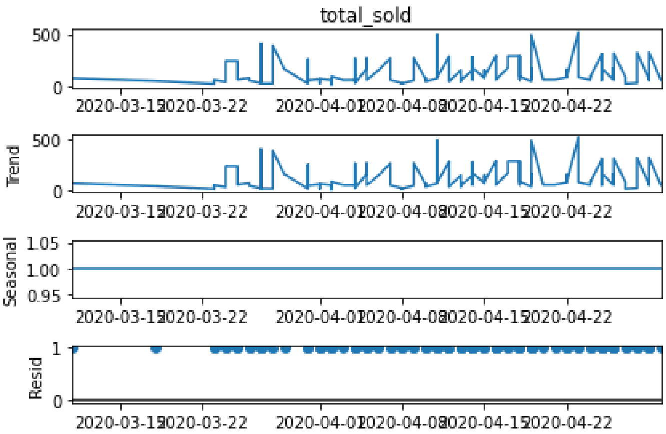


ARIMA

In [67]:

```
from statsmodels.tsa.seasonal import seasonal_decompose
from matplotlib import pyplot
curr_data=get_dataset('Huawei nova 5T',mobile_dict,df)

result = seasonal_decompose(curr_data['total_sold'], model ='multiplicative', period = 1)
result.plot()
pyplot.show()
```



In [68]:

```
from pmdarima import auto_arima

# Ignore harmless warnings
import warnings
warnings.filterwarnings("ignore")


stepwise_fit = auto_arima(curr_data['total_sold'], start_p = 1, start_q = 1,
                          max_p = 5, max_q = 5, m = 12,
                          start_P = 0, seasonal = True,
                          d = None, D = 1, trace = True,
                          error_action ='ignore',   # we don't want to know if an order does not work
                          suppress_warnings = True,  # we don't want convergence warnings
                          stepwise = True)           # set to stepwise

# To print the summary
stepwise_fit.summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(1,0,1)(0,1,1)[12] intercept   : AIC=inf, Time=1.22 sec
 ARIMA(0,0,0)(0,1,0)[12] intercept   : AIC=1355.156, Time=0.01 sec
 ARIMA(1,0,0)(1,1,0)[12] intercept   : AIC=1327.656, Time=0.51 sec
 ARIMA(0,0,1)(0,1,1)[12] intercept   : AIC=inf, Time=0.61 sec
 ARIMA(0,0,0)(0,1,0)[12]             : AIC=1353.348, Time=0.01 sec
 ARIMA(1,0,0)(0,1,0)[12] intercept   : AIC=1356.964, Time=0.11 sec
 ARIMA(1,0,0)(2,1,0)[12] intercept   : AIC=1312.662, Time=1.92 sec
 ARIMA(1,0,0)(2,1,1)[12] intercept   : AIC=1302.959, Time=2.94 sec
 ARIMA(1,0,0)(1,1,1)[12] intercept   : AIC=inf, Time=1.07 sec
 ARIMA(1,0,0)(2,1,2)[12] intercept   : AIC=inf, Time=4.78 sec
 ARIMA(1,0,0)(1,1,2)[12] intercept   : AIC=inf, Time=4.32 sec
 ARIMA(0,0,0)(2,1,1)[12] intercept   : AIC=1301.246, Time=2.06 sec
 ARIMA(0,0,0)(1,1,1)[12] intercept   : AIC=inf, Time=0.73 sec
 ARIMA(0,0,0)(2,1,0)[12] intercept   : AIC=1310.691, Time=1.33 sec
 ARIMA(0,0,0)(2,1,2)[12] intercept   : AIC=inf, Time=5.24 sec
 ARIMA(0,0,0)(1,1,0)[12] intercept   : AIC=1325.776, Time=0.51 sec
 ARIMA(0,0,0)(1,1,2)[12] intercept   : AIC=inf, Time=0.96 sec
 ARIMA(0,0,1)(2,1,1)[12] intercept   : AIC=1302.767, Time=2.59 sec
 ARIMA(1,0,1)(2,1,1)[12] intercept   : AIC=1304.840, Time=4.29 sec
 ARIMA(0,0,0)(2,1,1)[12]             : AIC=1305.511, Time=1.10 sec

Best model:  ARIMA(0,0,0)(2,1,1)[12] intercept
Total fit time: 36.329 seconds
```

Out[68]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	115
Model:	SARIMAX(2, 1, [1], 12)	**Log Likelihood**	-645.623
Date:	Mon, 30 Nov 2020	**AIC**	1301.246
Time:	12:20:41	**BIC**	1314.420
Sample:	0	**HQIC**	1306.582
	- 115		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	14.1517	5.807	2.437	0.015	2.770	25.534
ar.S.L12	-0.2620	0.144	-1.821	0.069	-0.544	0.020
ar.S.L24	-0.1904	0.133	-1.430	0.153	-0.451	0.071
ma.S.L12	-0.7685	0.210	-3.653	0.000	-1.181	-0.356
sigma2	1.365e+04	2374.579	5.748	0.000	8995.356	1.83e+04

Ljung-Box (L1) (Q):	0.31	**Jarque-Bera (JB):**	20.32
Prob(Q):	0.58	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.24	**Skew:**	0.97
Prob(H) (two-sided):	0.53	**Kurtosis:**	3.97

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

In [69]:

```
# Split data into train / test sets
train = curr_data.iloc[:len(curr_data)-40]
test = curr_data.iloc[len(curr_data)-40:] # set one year(12 months) for testing

# Fit a SARIMAX(0, 1, 1)x(2, 1, 1, 12) on the training set
from statsmodels.tsa.statespace.sarimax import SARIMAX

model = SARIMAX(train['total_sold'],
                order = (0, 0, 0),
                seasonal_order =(2, 1, 1, 12))

result = model.fit()
result.summary()
```

Out[69]:

SARIMAX Results

Dep. Variable:	total_sold	**No. Observations:**	75
Model:	SARIMAX(2, 1, [1], 12)	**Log Likelihood**	-396.330
Date:	Mon, 30 Nov 2020	**AIC**	800.659
Time:	12:20:42	**BIC**	809.232
Sample:	0	**HQIC**	804.031
	- 75		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L12	-0.1477	0.337	-0.438	0.661	-0.808	0.513
ar.S.L24	-0.2506	0.298	-0.841	0.401	-0.835	0.334
ma.S.L12	-0.7375	0.700	-1.053	0.292	-2.110	0.635
sigma2	1.33e+04	4705.861	2.826	0.005	4075.558	2.25e+04

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	13.30
Prob(Q):	0.96	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.46	**Skew:**	0.95
Prob(H) (two-sided):	0.08	**Kurtosis:**	4.21

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

In [70]:

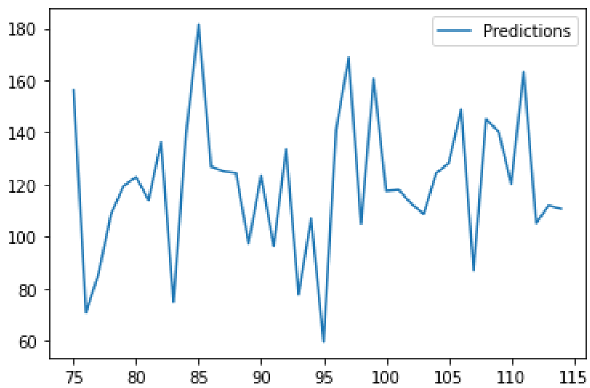
```
start = len(train)
end = len(train) + len(test) - 1

# Predictions for one-year against the test set
predictions = result.predict(start, end,typ = 'levels').rename("Predictions")

# plot predictions and actual values
predictions.plot(legend = True)
```

Out[70]:

<AxesSubplot:>

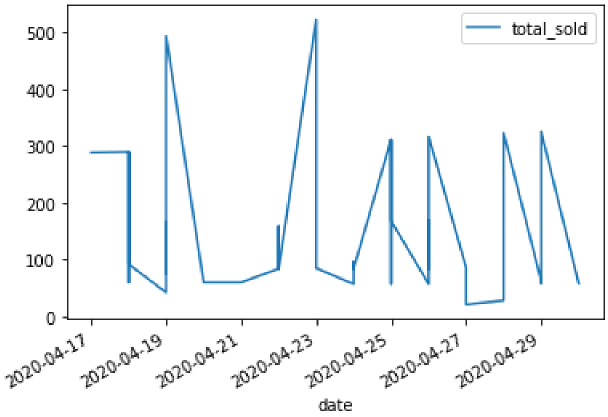


In [71]:

```
test['total_sold'].plot(legend = True)
```

Out[71]:

<AxesSubplot:xlabel='date'>



In [72]:

```
# Load specific evaluation tools
from sklearn.metrics import mean_squared_error
from statsmodels.tools.eval_measures import rmse

# Calculate root mean squared error
print("rmse : ", rmse(test["total_sold"], predictions) )

# Calculate mean squared error
print("mse : ", mean_squared_error(test["total_sold"], predictions))
```

```
rmse :  134.21321233080377
mse :  18013.186364153415
```

checkpoint

Feature importance

In [73]:

```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import  f_regression
bestfeat=SelectKBest(score_func= f_regression, k=10)
temp_x=curr_data.copy()
temp_x.drop(['total_sold'],axis=1,inplace=True)
temp_x=temp_x.to_numpy()
temp_y=curr_data['total_sold']
fit=bestfeat.fit(temp_x,temp_y)
scores=pd.DataFrame(fit.scores_)
col=pd.DataFrame(curr_data.columns)
featureScores = pd.concat([col,scores],axis=1)
featureScores.columns=["Specs","Score"]
print(featureScores.nlargest(5,'Score'))
```

```
                                        Specs        Score
6                                total_review  6105.171218
27                              product_id_E79    63.663729
11   merchant_city_Kota Administrasi Jakarta Barat    46.996206
4                                  daily_view    34.825704
23                             product_id_E287    23.212801
```

As seen above and from the importance of features extracted from the random forest model, total review seems to be determining the dependant variable to a great extent This obvious considering only those who buy products review them

K-FOLD cross validation

In [74]:

```
from sklearn.model_selection import KFold
```

In [75]:

```
kfold = KFold(7, shuffle=True, random_state=1 )
regressor = LinearRegression()
from sklearn.metrics import accuracy_score
```

with total_review column

In [76]:

```python
X=curr_data.copy()
X.drop(['total_sold'],axis=1,inplace=True)
Y=curr_data['total_sold'].values.astype(float)
i=1
for train, test in kfold.split(X):
    X_train, X_test = X.iloc[train], X.iloc[test]
    y_train, y_test = Y[train], Y[test]
    model=regressor.fit(X_train, y_train)
    r2=r2_score(y_test, model.predict(X_test))
    print(f"split number: {i},r2 score: {r2}")
    i+=1
```

```
split number: 1,r2 score: 0.996253791535193
split number: 2,r2 score: 0.998512941108337
split number: 3,r2 score: 0.9981079910226315
split number: 4,r2 score: 0.9983402225325678
split number: 5,r2 score: 0.9973601446519462
split number: 6,r2 score: 0.9980076299092491
split number: 7,r2 score: 0.9969597044767351
```

without total_review column

In [77]:

```python
X=curr_data.copy()
X.drop(['total_sold','total_review'],axis=1,inplace=True)
Y=curr_data['total_sold'].values.astype(float)
i=1
for train, test in kfold.split(X):
    X_train, X_test = X.iloc[train], X.iloc[test]
    y_train, y_test = Y[train], Y[test]
    model=regressor.fit(X_train, y_train)
    r2=r2_score(y_test, model.predict(X_test))
    print(f"split number: {i},r2 score: {r2}")
    i+=1
```

```
split number: 1,r2 score: 0.9371398639647884
split number: 2,r2 score: 0.9422389238916714
split number: 3,r2 score: 0.9827197291246527
split number: 4,r2 score: 0.7391329153551158
split number: 5,r2 score: 0.9866863676864157
split number: 6,r2 score: 0.971517601469521
split number: 7,r2 score: 0.9318330354287021
```

In [ ]:

In [ ]:

In [ ]: