**ABOUT PRICE OF CINEMA TICKETS PROJECT**

objective: About movie ticket pricing system using python and machine learning By using kaggle source we uploaded cinemaTickets_Ref.csv

By importing these libraries we can done these project

In [2]:

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

To read the given data

**EDA

In [3]:

```
sc = pd.read_csv('cinemaTicket_Ref.csv')
```

To print five five rows

In [4]:

```
sc.head()
```

Out[4]:

| | film_code | cinema_code | total_sales | tickets_sold | tickets_out | show_time | occu_perc | ticket_p |
|---|---|---|---|---|---|---|---|---|
| **0** | 1492 | 304 | 3900000 | 26 | 0 | 4 | 4.26 | 150 |
| **1** | 1492 | 352 | 3360000 | 42 | 0 | 5 | 8.08 | 80 |
| **2** | 1492 | 489 | 2560000 | 32 | 0 | 4 | 20.00 | 80 |
| **3** | 1492 | 429 | 1200000 | 12 | 0 | 1 | 11.01 | 100 |
| **4** | 1492 | 524 | 1200000 | 15 | 0 | 3 | 16.67 | 80 |

To print last five rows

In [5]:

```
sc.tail()
```

Out[5]:

| | film_code | cinema_code | total_sales | tickets_sold | tickets_out | show_time | occu_perc | ti |
|---|---|---|---|---|---|---|---|---|
| **142519** | 1569 | 495 | 1320000 | 22 | 0 | 2 | 3.86 | |
| **142520** | 1569 | 474 | 1200000 | 15 | 0 | 1 | 65.22 | |
| **142521** | 1569 | 524 | 1060000 | 8 | 0 | 3 | 9.20 | |
| **142522** | 1569 | 529 | 600000 | 5 | 0 | 2 | 5.00 | |
| **142523** | 1569 | 486 | 250000 | 5 | 0 | 1 | 1.79 | |

To print the size of given data

In [6]:

```
sc.shape
```

Out[6]:

```
(142524, 14)
```

To show is there any null values present because to understand is there any need to do data cleaning

In [7]:

```
sc.isnull()
```

Out[7]:

| | film_code | cinema_code | total_sales | tickets_sold | tickets_out | show_time | occu_perc | ti |
|---|---|---|---|---|---|---|---|---|
| **0** | False | False | False | False | False | False | False | |
| **1** | False | False | False | False | False | False | False | |
| **2** | False | False | False | False | False | False | False | |
| **3** | False | False | False | False | False | False | False | |
| **4** | False | False | False | False | False | False | False | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **142519** | False | False | False | False | False | False | False | |
| **142520** | False | False | False | False | False | False | False | |
| **142521** | False | False | False | False | False | False | False | |
| **142522** | False | False | False | False | False | False | False | |
| **142523** | False | False | False | False | False | False | False | |

142524 rows × 14 columns

To show the total sum of null values present in given data

In [8]:

```
sc.isnull().sum()
```

Out[8]:

```
film_code         0
cinema_code       0
total_sales       0
tickets_sold      0
tickets_out       0
show_time         0
occu_perc       125
ticket_price      0
ticket_use        0
capacity        125
date              0
month             0
quarter           0
day               0
dtype: int64
```

In [ ]:

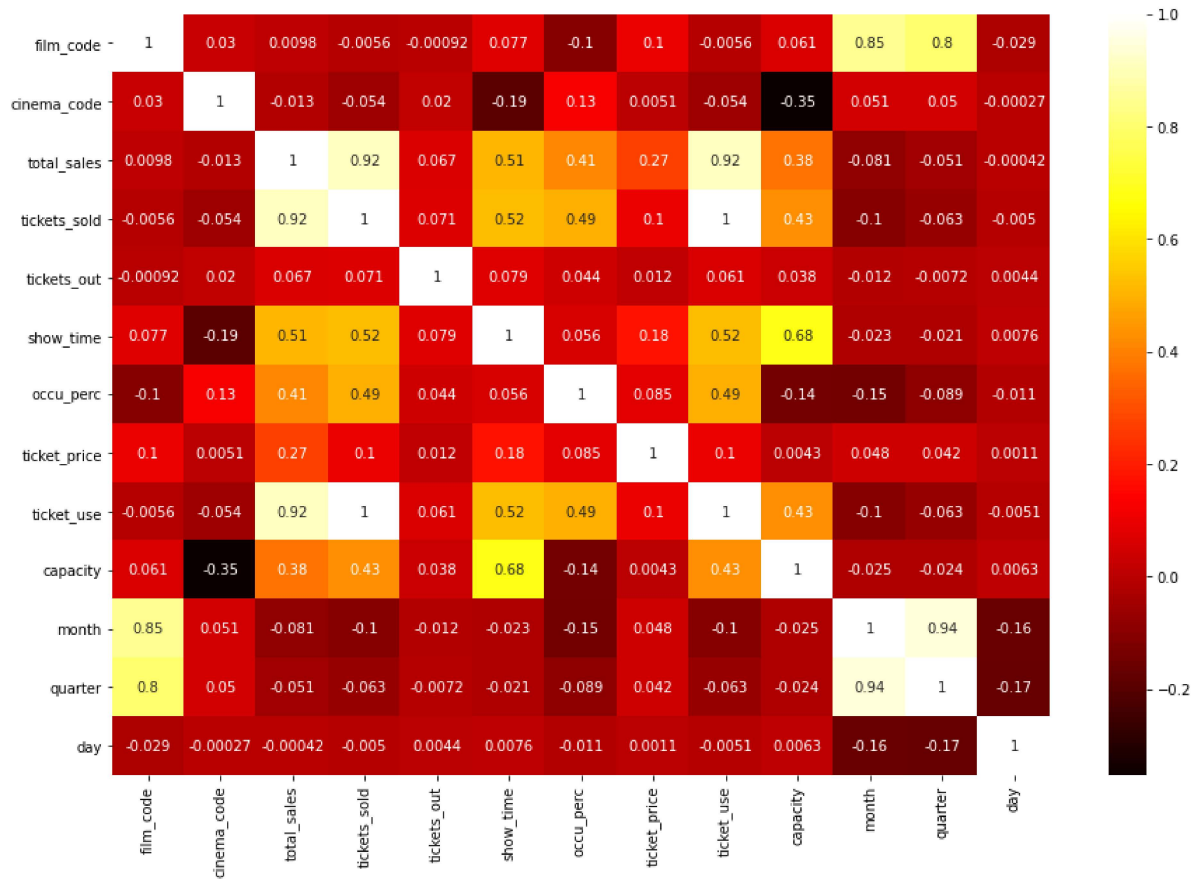
```
```

In [9]:

```
plt.figure(figsize=(15, 10))
sns.heatmap(sc.corr(), annot=True, cmap='hot')
```

Out[9]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a791e16790>
```

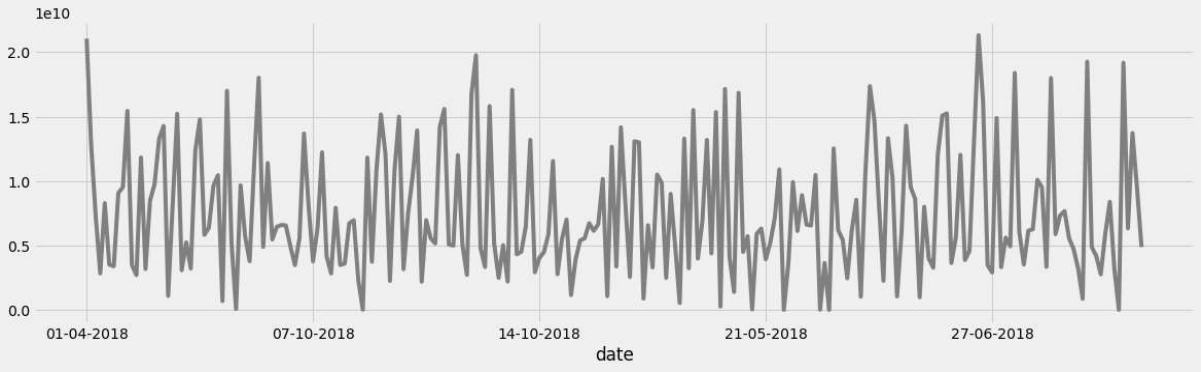


In [17]:

```
plt.style.use('fivethirtyeight')
sc.groupby('date')['total_sales'].sum().plot(figsize=(18, 5), color='grey')
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a7aeb6f790>
```



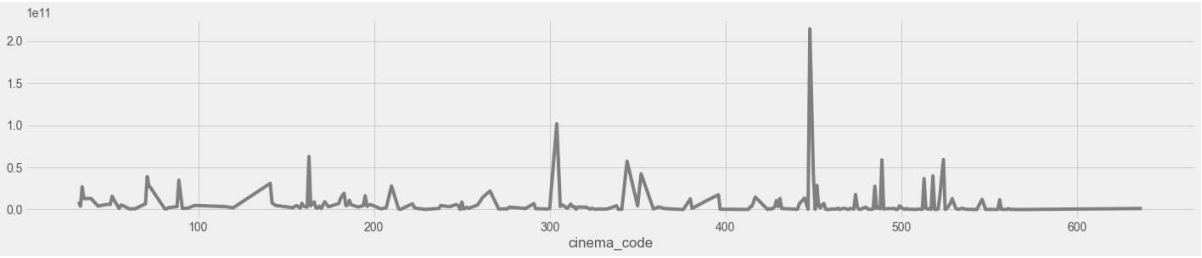

TOTAL SALE PER DAY

In [123]:

```
plt.style.use('fivethirtyeight')
sc.groupby('cinema_code')['total_sales'].sum().plot(figsize=(22, 4), color='grey')
```

Out[123]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26716b66400>
```



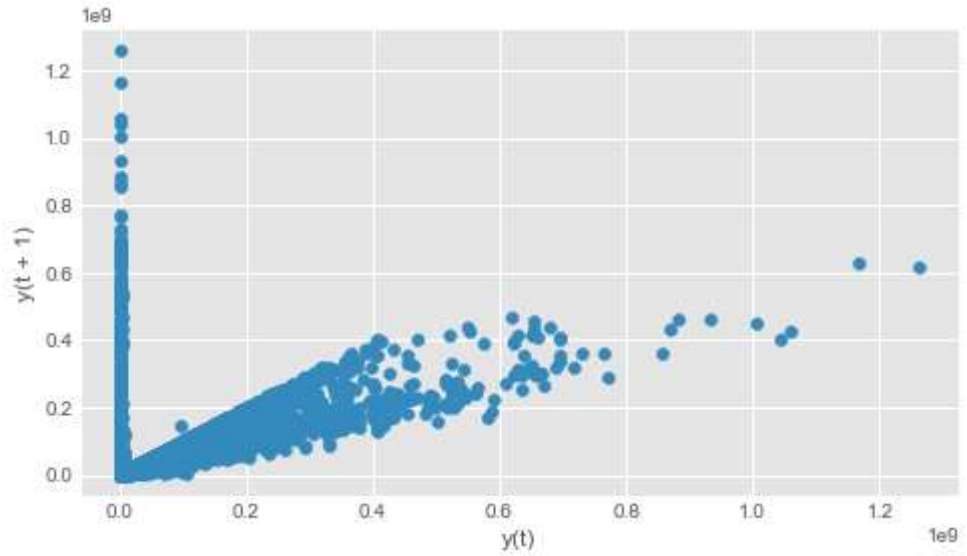

SCATTER PLOT

In [124]:

```
plt.style.use('ggplot')
plt.figure(figsize=(7, 4))
pd.plotting.lag_plot(sc['total_sales'], lag=1)
```

Out[124]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26712075a90>
```



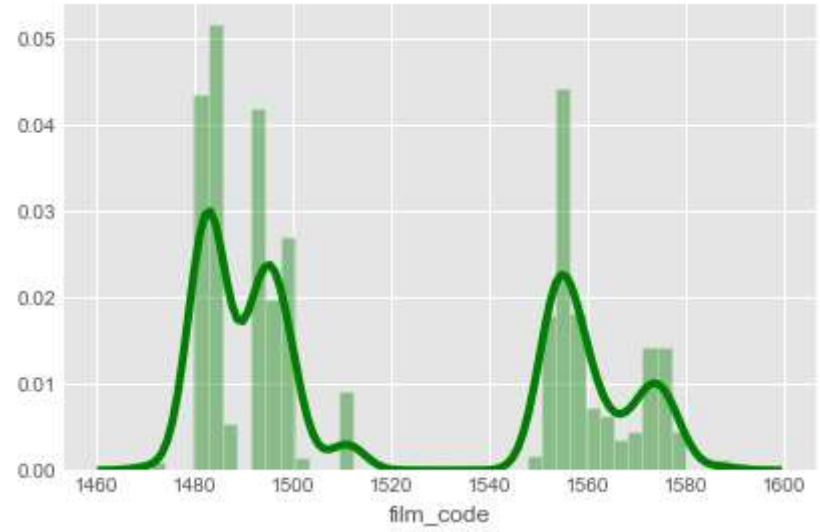

DIST PLOT

In [125]:

```
sns.distplot(sc['film_code'],color='Green',bins=40)
```

Out[125]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2671205bc40>
```



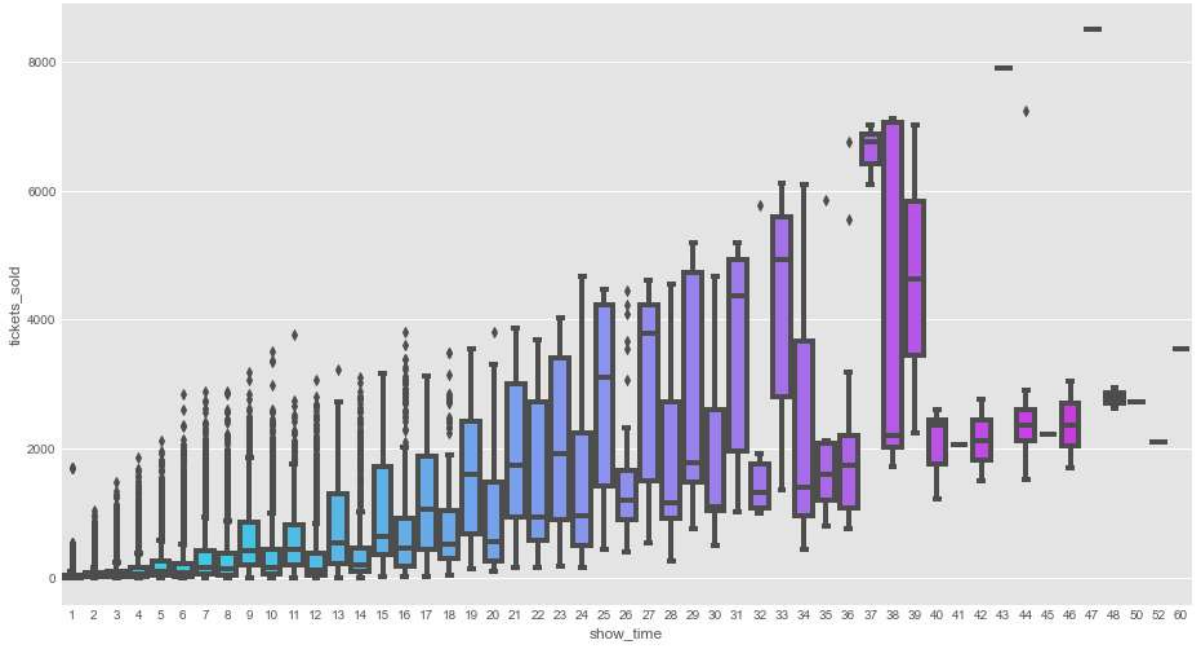

BOX PLOT

In [126]:

```
plt.figure(figsize=(14,8))
sns.boxplot(x='show_time',y='tickets_sold',data=sc,palette='cool')
```

Out[126]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26712195160>
```




DATA CLEANING

In [128]:

```
# to delete the rows having null values
sc.dropna()
# to delete the date column
sc.drop('date', inplace=True, axis=1)
print(sc)
```

```
        film_code  cinema_code  total_sales  tickets_sold  tickets_out  \
0            1492          304      3900000            26            0
1            1492          352      3360000            42            0
2            1492          489      2560000            32            0
3            1492          429      1200000            12            0
4            1492          524      1200000            15            0
...           ...          ...          ...           ...          ...
142519       1569          495      1320000            22            0
142520       1569          474      1200000            15            0
142521       1569          524      1060000             8            0
142522       1569          529       600000             5            0
142523       1569          486       250000             5            0

        show_time  occu_perc  ticket_price  ticket_use    capacity  month  \
0               4       4.26      150000.0          26  610.328639      5
1               5       8.08       80000.0          42  519.801980      5
2               4      20.00       80000.0          32  160.000000      5
3               1      11.01      100000.0          12  108.991826      5
4               3      16.67       80000.0          15   89.982004      5
...           ...        ...           ...         ...         ...    ...
142519          2       3.86       60000.0          22  569.948187     11
142520          1      65.22       80000.0          15   22.999080     11
142521          3       9.20      132500.0           8   86.956522     11
142522          2       5.00      120000.0           5  100.000000     11
142523          1       1.79       50000.0           5  279.329609     11

        quarter  day
0             2    5
1             2    5
2             2    5
3             2    5
4             2    5
...         ...  ...
142519        4    4
142520        4    4
142521        4    4
142522        4    4
142523        4    4

[142524 rows x 13 columns]
```

To delete the columns having null values

In [130]:

```
sc = sc.dropna(axis=1)
print(sc)
```

```
        film_code  cinema_code  total_sales  tickets_sold  tickets_out  \
0            1492          304      3900000            26            0
1            1492          352      3360000            42            0
2            1492          489      2560000            32            0
3            1492          429      1200000            12            0
4            1492          524      1200000            15            0
...           ...          ...          ...           ...          ...
142519       1569          495      1320000            22            0
142520       1569          474      1200000            15            0
142521       1569          524      1060000             8            0
142522       1569          529       600000             5            0
142523       1569          486       250000             5            0

        show_time  ticket_price  ticket_use  month  quarter  day
0               4      150000.0          26      5        2    5
1               5       80000.0          42      5        2    5
2               4       80000.0          32      5        2    5
3               1      100000.0          12      5        2    5
4               3       80000.0          15      5        2    5
...           ...           ...         ...    ...      ...  ...
142519          2       60000.0          22     11        4    4
142520          1       80000.0          15     11        4    4
142521          3      132500.0           8     11        4    4
142522          2      120000.0           5     11        4    4
142523          1       50000.0           5     11        4    4

[142524 rows x 11 columns]
```

To check whether null values are deleted or not

In [131]:

```
sc.isnull().sum()
```

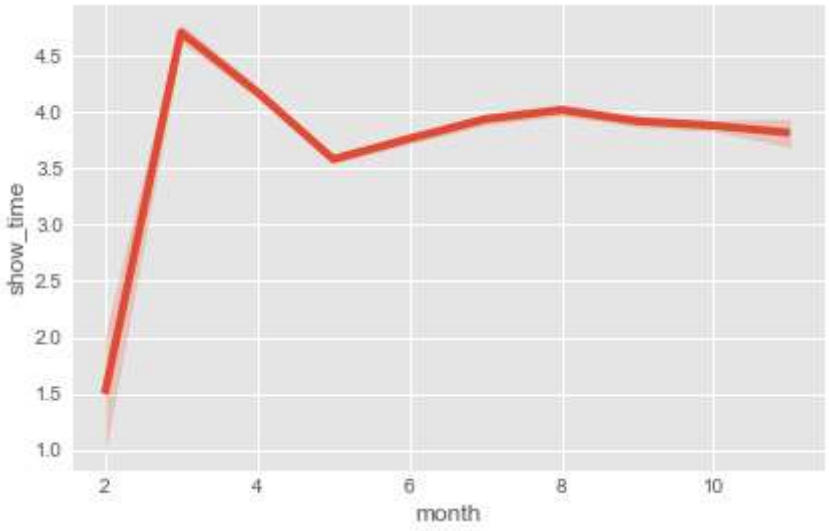
Out[131]:

```
film_code       0
cinema_code     0
total_sales     0
tickets_sold    0
tickets_out     0
show_time       0
ticket_price    0
ticket_use      0
month           0
quarter         0
day             0
dtype: int64
```

lineplot

In [76]:

```
sns.lineplot(data=sc,x="month",y="show_time")
plt.show()
```



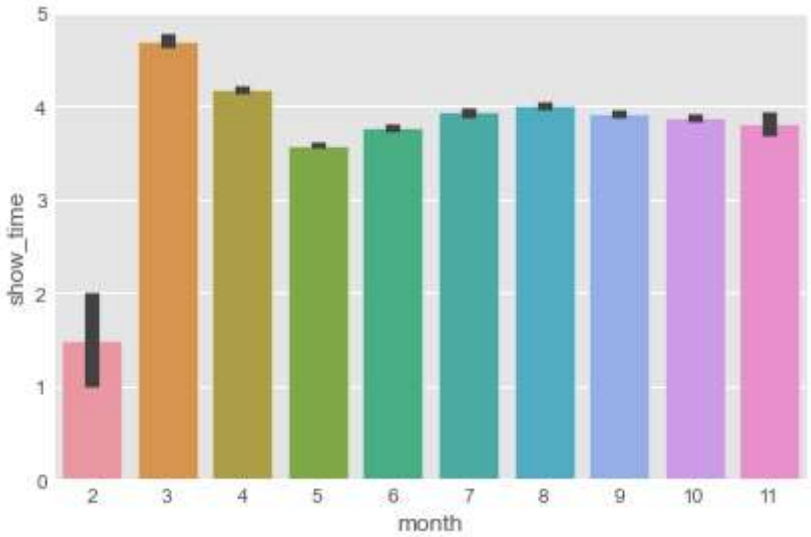

BAR PLOT

In [133]:

```
sns.barplot(data=sc,x="month",y="show_time")
```

Out[133]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26716c55b20>
```



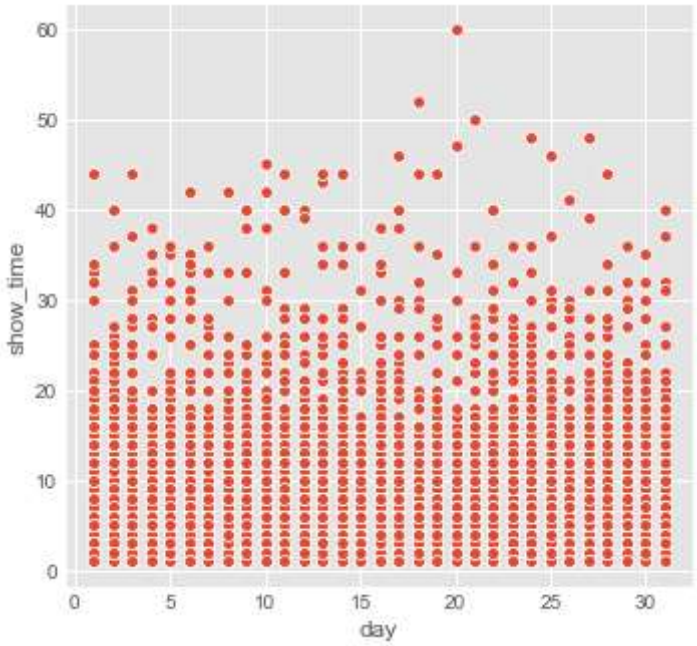

scatter plot

In [135]:

```
plt.figure(figsize=(5,5))
sns.scatterplot(x='day',y='show_time',data=sc,palette='rocket_r')
```

Out[135]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x26712080340>
```




**First machine learning model 1.K NEAREST NEIGHBOUR

In [136]:

```
import sklearn
#features
X = sc.iloc[:, [2,3,6,7]].values
#target
y = sc.iloc[:, 4].values
```

In [137]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:,0] = le.fit_transform(X[:,0])
```

**splitting our data into 80 to 20 percentage

In [138]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state =
0)
```

In [139]:

```
from sklearn.preprocessing import StandardScaler
s = StandardScaler()
X_train = s.fit_transform(X_train)
X_test = s.transform(X_test)
```

**FITTING

In [140]:

```
#FITTING
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)
```

Out[140]:

```
KNeighborsClassifier()
```

**PREDICTION

In [141]:

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

In [142]:

```
y_test
```

Out[142]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [143]:

```
y_pred
```

Out[143]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

**ACCURACY

In [144]:

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
print(cm)
print("accuracy=",ac)
```

```
[[27276     0     1 ...     0     0     0]
 [  283     5     1 ...     0     0     0]
 [  319     7    17 ...     0     0     0]
 ...
 [    0     0     0 ...     0     0     0]
 [    1     0     0 ...     0     0     0]
 [    0     0     0 ...     0     0     0]]
accuracy= 0.9579372039992984
```

**second machine learning model 2.NAIVE BAYES

**selecting features and target

In [145]:

```
X = sc.iloc[:, [2, 3 ,6,7]].values
y = sc.iloc[:, 4].values
```

In [146]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:,0] = le.fit_transform(X[:,0])
```

**splitting our data

In [147]:

```
#splitting our data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state =
0)
```

In [148]:

```
from sklearn.preprocessing import StandardScaler
s = StandardScaler()
X_train = s.fit_transform(X_train)
X_test = s.transform(X_test)
```

**fitting

In [149]:

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

Out[149]:

```
GaussianNB()
```

**prediction

In [150]:

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

In [151]:

```
y_pred
```

Out[151]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [152]:

```
y_test
```

Out[152]:

```
array([0, 0, 0, ..., 0, 0, 0], dtype=int64)
```

In [166]:

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
print(cm)
```

```
[[26418     0    26 ...     0     0     0]
 [  260     0     1 ...     0     0     0]
 [  314     0     0 ...     0     0     0]
 ...
 [    1     0     0 ...     0     0     0]
 [    0     0     0 ...     0     0     0]
 [    0     0     0 ...     0     0     0]]
```

**accuracy

In [167]:

```
print("accuracy=",ac)
```

```
accuracy= 0.9269251008594983
```

**Third machine learning model

**3.LOGISTIC REGRESSION

In [ ]:

```
from sklearn.linear_model import LogisticRegression
#splitting our data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state =
0)
# Define model. Specify a number for random_state to ensure same results each run
sc_model = LogisticRegression(random_state=1)
# Fit model
X_train = sc.iloc[:,[2,7]]
Y_train = sc.iloc[:,4]
sc_model.fit(X_train,Y_train)
```

prediction and accuracy

In [169]:

```
LogisticRegression_score = sc_model.score(X_train,Y_train)
print('Accuracy obtained by LogisticRegression_sc_model',LogisticRegression_score*100)
```

```
Accuracy obtained by LogisticRegression_sc_model 95.6821307288597
```

**summary:** Cinema industry is not excluded of getting advantage of predictive modeling. Like other industry e.g. retail , banking and restaurants , sale forecastcan help cinemas for cost reduction and better ROI. By forecasting sale, screening in different location could be optimized as well as effective market targeting and pricing.Also historical data of sale and movies details e.g. cost, cast and crews, and other project details like schedule, could help producers to select high performance cast and crews and planning for better projects ROI . Also it helps to assign screening location on hot spots and areas. **1.EDA**

In statistics, exploratory data analysis is an approach of analyzing data sets to summarize their main characteristics, often using statistical graphics and other data visualization methods. A statistical model can be used or not, but primarily EDA is for seeing what the data can tell us beyond the formal modeling or hypothesis testing task. Exploratory data analysis was promoted by John Tukey to encourage statisticians to explore the data, and possibly formulate hypothese that could lead to new data collection and experiments. EDA is different from initial data analysis which focuses more narrowly on checking assumptions required for model fitting and hypothesis testing, and handling missing values and making transformations of variables as needed.

**2.DATA CLEANING**

Data cleaning is the process of fixing or removing incorrect, corrupted, incorrectly formatted, duplicate, or incomplete data within a dataset. When combining multiple data sources, there are many opportunities for data to be duplicated or mislabeled.

**3.splitting our data into 80 percent for training and 20 perecent for testing**

The procedure involves taking a dataset and dividing it into two subsets. The first subset is used to fit the model and is referred to as the training dataset. The second subset is not used to train the model; instead, the input element of the dataset is provided to the model, then predictions are made and compared to the expected values. This second dataset is referred to as the test dataset. Train Dataset: Used to fit the machine learning model. Test Dataset: Used to evaluate the fit machine learning model.

**4.BUILDING THREE MACHINE LEARNING MODELS**

1.K nearest neighbour The k-nearest neighbors (KNN) algorithm is a simple, supervised machine learning algorithm that can be used to solve both classification and regression problems. It's easy to implement and understand, but has a major drawback of becoming significantly slows as the size of that data in use grows.

2.Naive bayes It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. 3.Logistic Regression Logistic Regression is a Machine Learning classification algorithm that is used to predict the probability of a categorical dependent variable. In logistic regression, the dependent variable is a binary variable that contains data coded as 1 (yes, success, etc.) or 0 (no, failure, etc.).