

```
import pandas as pd
df=pd.read_csv("Flight_Booking.csv")
```

```
df.head()
```

	Unnamed: 0	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	
0	0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	E
1	1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	E
2	2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	E
3	3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	E

```
df=df.drop(columns=["Unnamed: 0"])
```

```
df.head()
```

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	10h 15m
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	9h 45m
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	9h 15m
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	10h 00m

```
df.shape
```

(300153, 11)

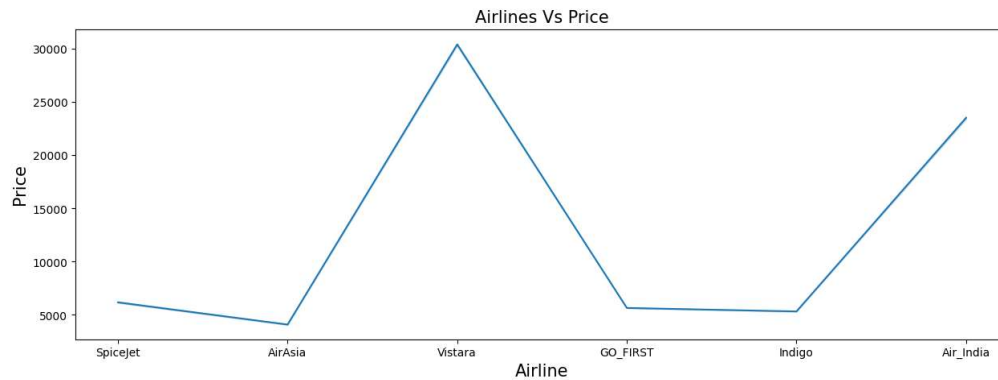
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 11 columns):
#   Column              Non-Null Count  Dtype
---  -
0   airline              300153 non-null object
1   flight               300153 non-null object
2   source_city          300153 non-null object
3   departure_time       300153 non-null object
4   stops               300153 non-null object
5   arrival_time         300153 non-null object
6   destination_city     300153 non-null object
7   class                300153 non-null object
8   duration              300153 non-null float64
9   days_left            300153 non-null int64
10  price                300153 non-null int64
dtypes: float64(1), int64(2), object(8)
memory usage: 25.2+ MB
```

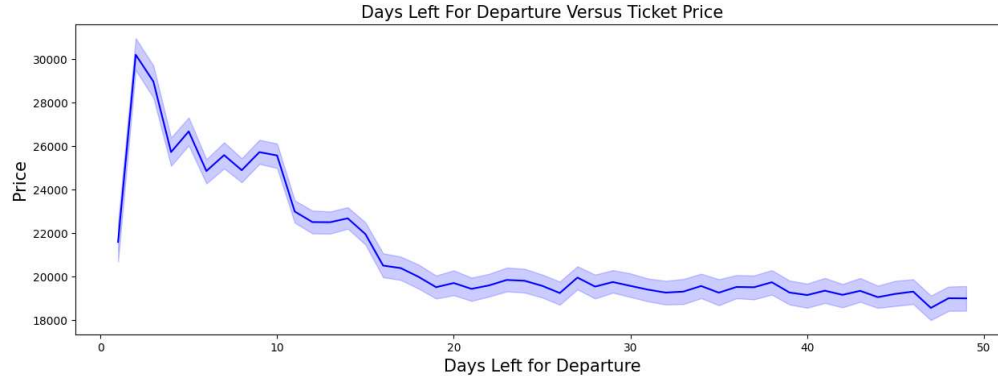
```
df.isnull().sum()
```

```
airline      0
flight       0
source_city  0
departure_time  0
stops        0
arrival_time  0
destination_city  0
class        0
duration     0
days_left   0
price        0
dtype: int64
```

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=(15,5))
sns.lineplot(x=df['airline'],y=df['price'])
plt.title('Airlines Vs Price',fontsize=15)
plt.xlabel('Airline',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```



```
plt.figure(figsize=(15,5))
sns.lineplot(data=df,x='days_left',y='price',color='blue')
plt.title('Days Left For Departure Versus Ticket Price',fontsize=15)
plt.xlabel('Days Left for Departure',fontsize=15)
plt.ylabel('Price',fontsize=15)
plt.show()
```

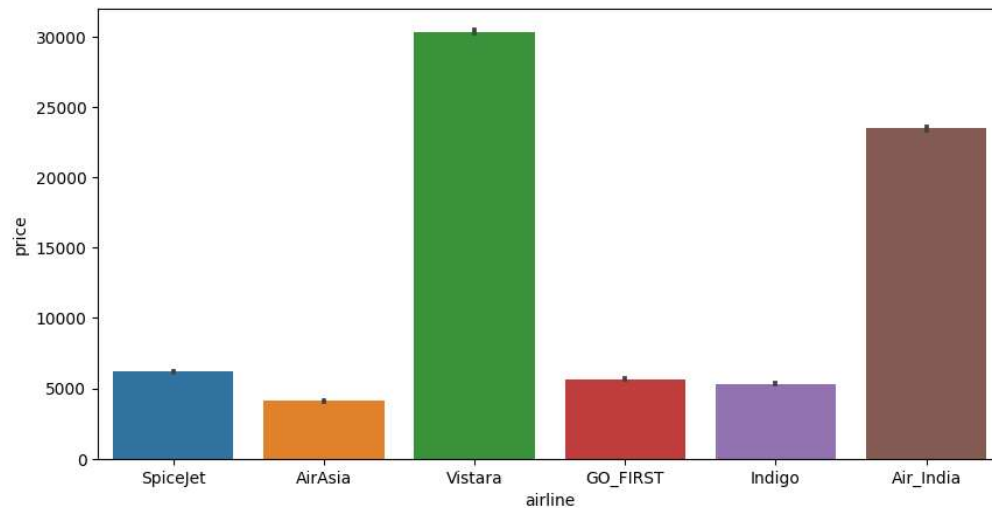


```
df["airline"].value_counts()
```

```
Vistara      127859
Air_India    80892
Indigo       43120
GO_FIRST    23173
AirAsia      16098
SpiceJet     9011
Name: airline, dtype: int64
```

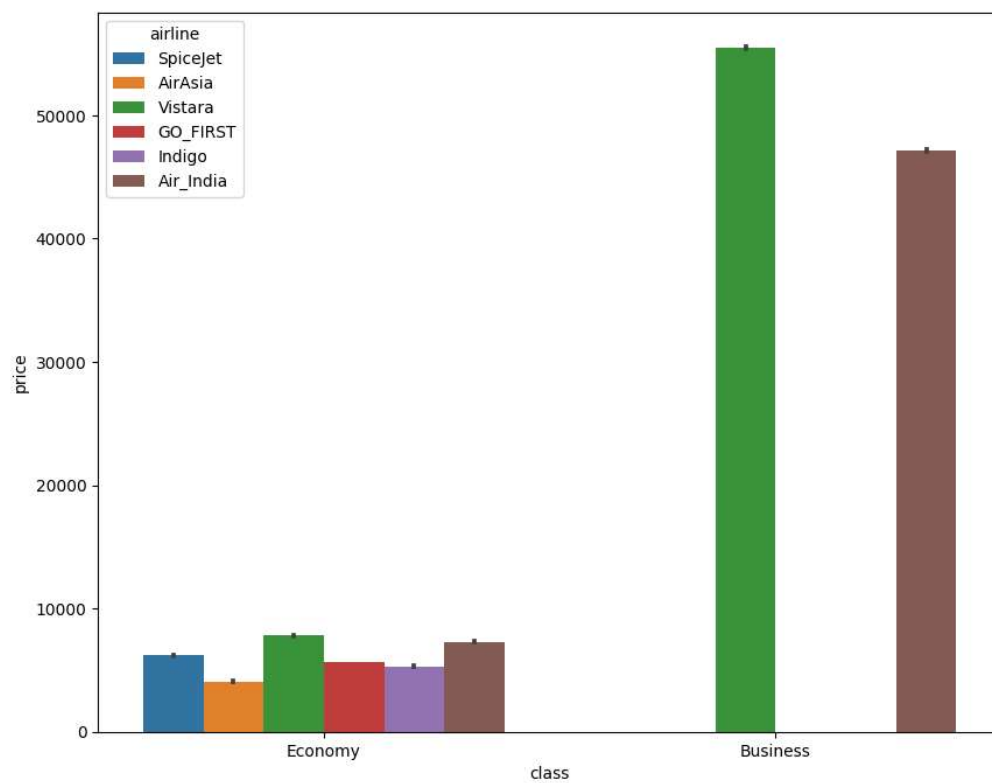
```
plt.figure(figsize=(10,5));
sns.barplot(x='airline',y='price',data=df)
```

<Axes: xlabel='airline', ylabel='price'>



```
plt.figure(figsize=(10,8));
sns.barplot(x='class',y='price',data=df,hue='airline')
```

<Axes: xlabel='class', ylabel='price'>

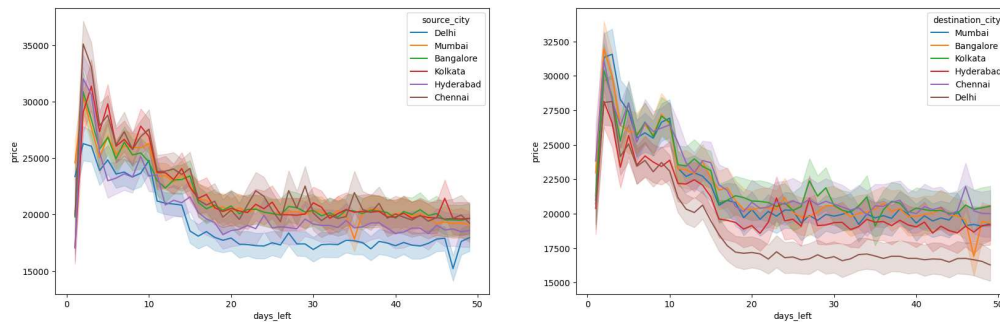


```
df1=df.loc[(df["source_city"]=="Delhi") & (df["destination_city"]=="Mumbai")]
```

```
df1.describe()
```

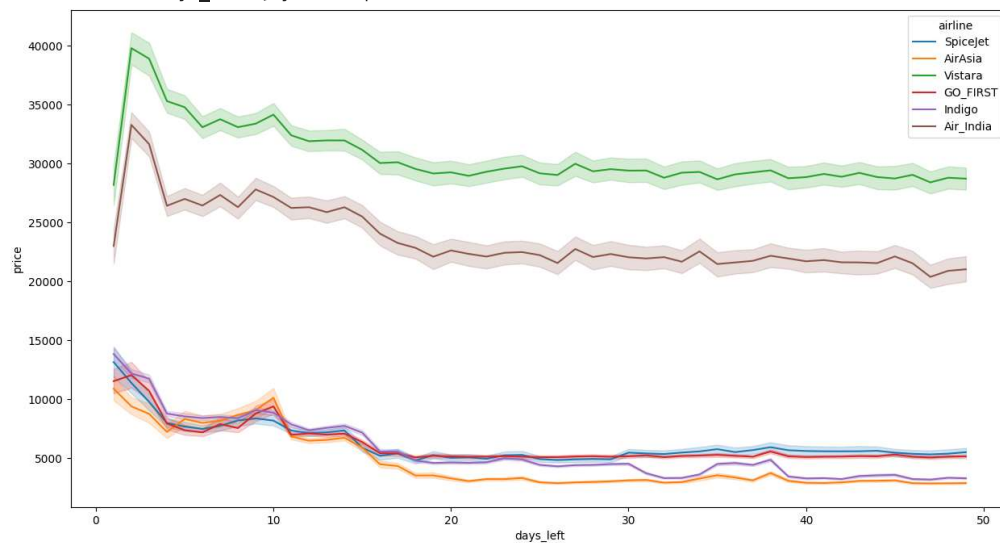
	duration	days_left	price
count	15289.000000	15289.000000	15289.000000

```
fig,ax=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(x='days_left',y='price',data=df,hue='source_city',ax=ax[0])
sns.lineplot(x='days_left',y='price',data=df,hue='destination_city',ax=ax[1])
plt.show()
```



```
plt.figure(figsize=(15,8))
sns.lineplot(x='days_left',y='price',data=df,hue='airline')
```

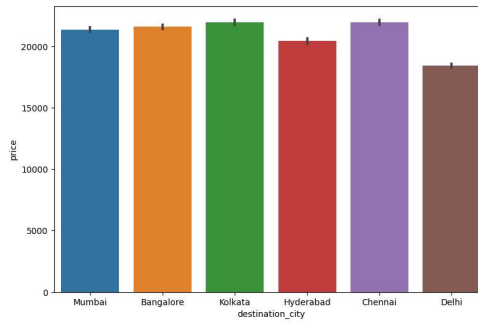
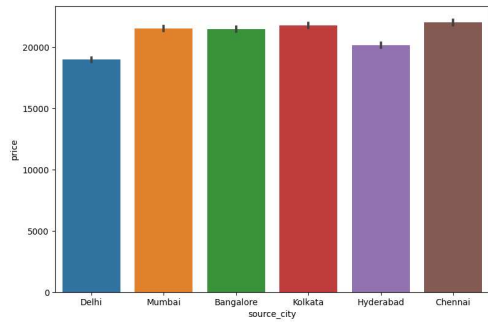
<Axes: xlabel='days\_left', ylabel='price'>



```
fig,ax=plt.subplots(1,2,figsize=(20,6))

sns.barplot(x='source_city',y='price',data=df,ax=ax[0])
sns.barplot(x='destination_city',y='price',data=df,ax=ax[1])
```

<Axes: xlabel='destination\_city', ylabel='price'>



```
# Visualizations of categoric features with countplot
plt.figure(figsize=(15,23))
```

```
plt.subplot(4, 2, 1)
sns.countplot(x=df["airline"], data=df)
plt.title("Frequency of Airline")
```

```
plt.subplot(4, 2, 2)
sns.countplot(x=df["source_city"], data=df)
plt.title("Frequency of Source City")
```

```
plt.subplot(4, 2, 3)
sns.countplot(x=df["departure_time"], data=df)
plt.title("Frequency of Departure Time")
```

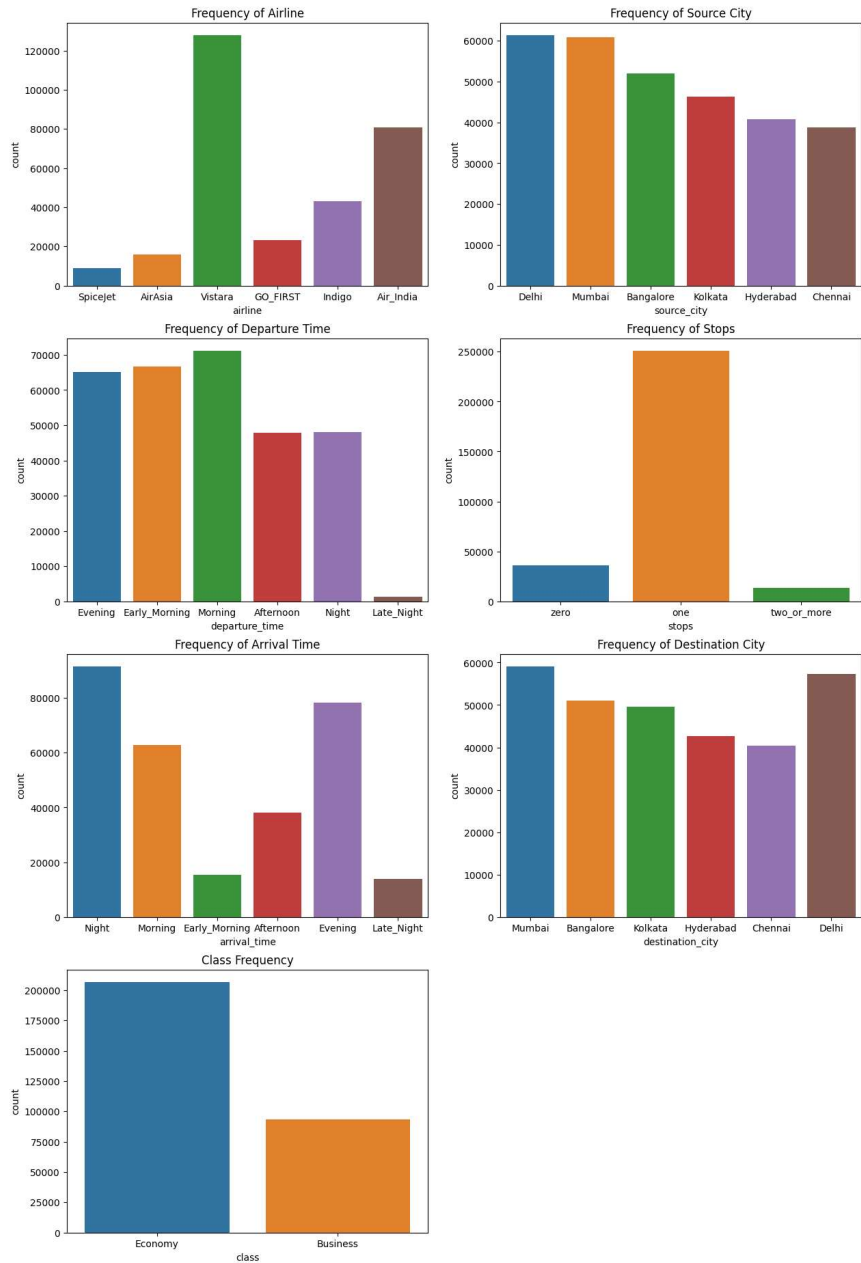
```
plt.subplot(4, 2, 4)
sns.countplot(x=df["stops"], data=df)
plt.title("Frequency of Stops")
```

```
plt.subplot(4, 2, 5)
sns.countplot(x=df["arrival_time"], data=df)
plt.title("Frequency of Arrival Time")
```

```
plt.subplot(4, 2, 6)
sns.countplot(x=df["destination_city"], data=df)
plt.title("Frequency of Destination City")
```

```
plt.subplot(4, 2, 7)
sns.countplot(x=df["class"], data=df)
plt.title("Class Frequency")
```

```
plt.show()
```



```
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
```

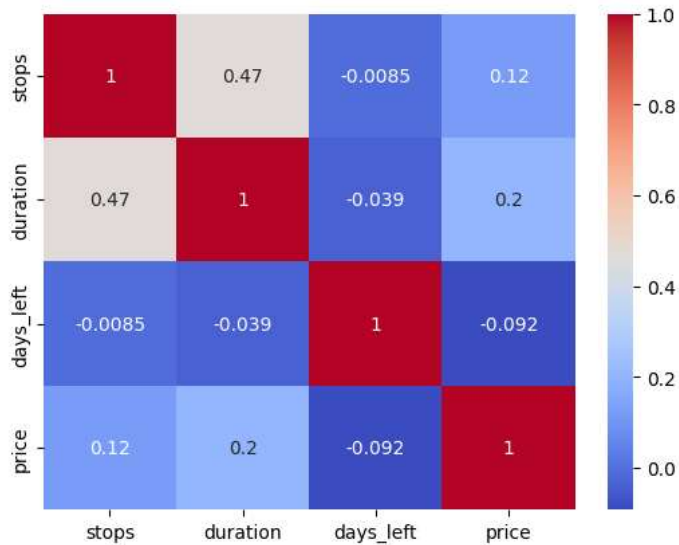
```

<ipython-input-20-0dd8dea822e2>:1: FutureWarning: The default value of numeric_only
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
<Axes: >
df["stops"]=df["stops"].replace(["zero","one","two_or_more"],[0,1,2])

sns.heatmap(df.corr(),annot=True,cmap="coolwarm")

<ipython-input-22-0dd8dea822e2>:1: FutureWarning: The default value of numeric_only in DataFrame.corr()
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
<Axes: >

```



```

from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df["airline"]=le.fit_transform(df["airline"])
df["source_city"]=le.fit_transform(df["source_city"])
df["departure_time"]=le.fit_transform(df["departure_time"])
df["arrival_time"]=le.fit_transform(df["arrival_time"])
df["destination_city"]=le.fit_transform(df["destination_city"])
df["class"]=le.fit_transform(df["class"])

```

```
df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 11 columns):
#   Column          Non-Null Count  Dtype
---  -
0   airline         300153 non-null  int64
1   flight          300153 non-null  object
2   source_city     300153 non-null  int64
3   departure_time  300153 non-null  int64
4   stops          300153 non-null  int64
5   arrival_time    300153 non-null  int64
6   destination_city 300153 non-null  int64
7   class           300153 non-null  int64
8   duration        300153 non-null  float64
9   days_left       300153 non-null  int64
10  price           300153 non-null  int64
dtypes: float64(1), int64(9), object(1)
memory usage: 25.2+ MB

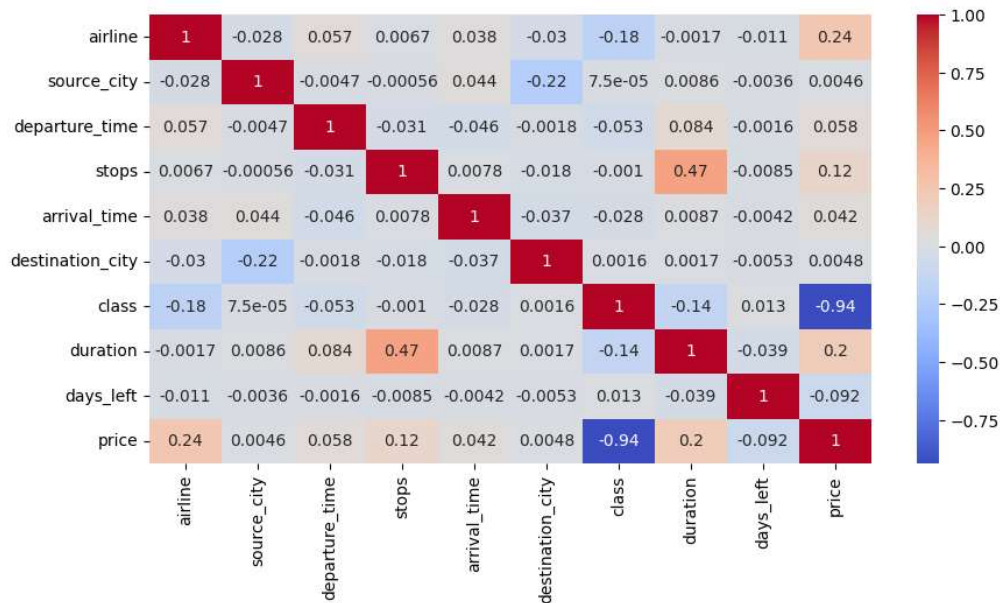
```

```
df=df.drop(columns=["flight"])
```

```
df
```

	airline	source_city	departure_time	stops	arrival_time	destination_city	class	duratic
0	4	2	2	0	5	5	1	2.1
1	4	2	1	0	4	5	1	2.3
2	0	2	1	0	1	5	1	2.1
3	5	2	4	0	0	5	1	2.2
4	5	2	4	0	4	5	1	2.3

```
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True,cmap="coolwarm")
plt.show()
```



```
from statsmodels.stats.outliers_influence import variance_inflation_factor
col_list = []
for col in df.columns:
    if ((df[col].dtype != 'object') & (col != 'price')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                    for i in range(len(X.columns))]
print(vif_data)
```

	feature	VIF
0	airline	3.461766
1	source_city	2.933064
2	departure_time	2.746367
3	stops	7.464236
4	arrival_time	3.684695
5	destination_city	2.893218
6	class	2.917521
7	duration	5.037943
8	days_left	4.035735

```
df=df.drop(columns=["stops"])
```



```

from statsmodels.stats.outliers_influence import variance_inflation_factor
col_list = []
for col in df.columns:
    if ((df[col].dtype != 'object') & (col != 'price')):
        col_list.append(col)

X = df[col_list]
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                    for i in range(len(X.columns))]
print(vif_data)

```

	feature	VIF
0	airline	3.370020
1	source_city	2.895803
2	departure_time	2.746255
3	arrival_time	3.632792
4	destination_city	2.857808
5	class	2.776721
6	duration	3.429344
7	days_left	3.950132

```

X = df.drop(columns=["price"])
y = df['price']

```

```

from sklearn.linear_model import LinearRegression

```

```

from sklearn.model_selection import train_test_split

```

```

x_train,x_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=42)

```

### **LINEAR REGRESSION**

```

lr=LinearRegression()

```

```

from sklearn.preprocessing import StandardScaler

```

```

sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.transform(x_test)

```

```

lr.fit(x_train,y_train)

```

```

LinearRegression
LinearRegression()

```

```

y_pred=lr.predict(x_test)

```

```

from sklearn.metrics import r2_score
r2result= r2_score(y_test,y_pred)
r2_score(y_test,y_pred)

```

```

0.897752737512321

```

```

from sklearn import metrics
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error

```

```

4468.426673542113

```

```

from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)

```

```

0.34765804610681816

```

```

mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error

```

```

52706651.33334208

```

```
import numpy as np
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

7259.934664536733

```
sns.distplot(y_test,label="Actual")
sns.distplot(y_pred,label="Predicted")
plt.legend()
```

<ipython-input-45-c0da3bcb0fc3>:1: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(y_test,label="Actual")
```

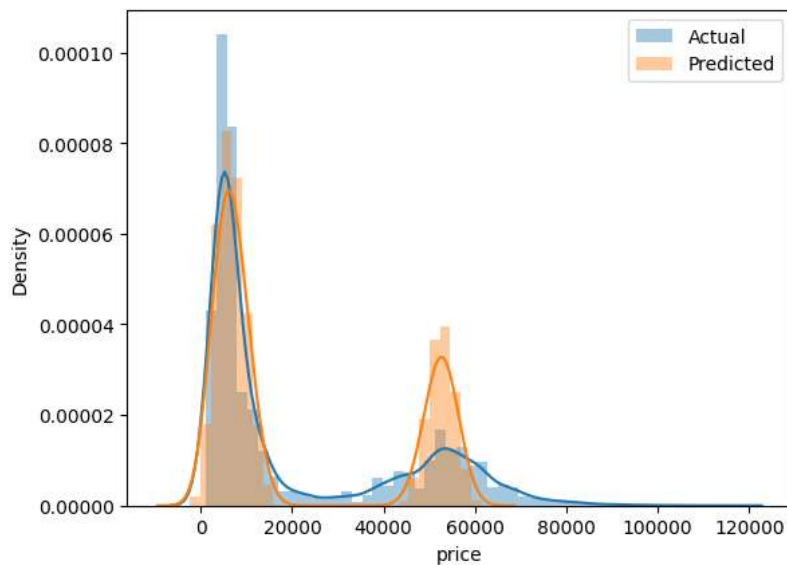
<ipython-input-45-c0da3bcb0fc3>:2: UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(y_pred,label="Predicted")
<matplotlib.legend.Legend at 0x7f3c1b2ef820>
```



### \* DECISION TREE REGRESSION MODEL\*

```
from sklearn.tree import DecisionTreeRegressor
dt=DecisionTreeRegressor()
dt.fit(x_train,y_train)
y_pred=dt.predict(x_test)
r2_score(y_test,y_pred)
```

0.9746608498709947

```
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error
```

1217.1550254590684

```
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)
```

0.07726568550667867

```
mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error
```

```
13061882.718802692
```

```
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

```
3614.122676224853
```

```
sns.distplot(y_test,label="Actual")
sns.distplot(y_pred,label="Predicted")
plt.legend()
```

```
<ipython-input-51-c0da3bcb0fc3>:1: UserWarning:
```

```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
```

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
sns.distplot(y_test,label="Actual")
```

```
<ipython-input-51-c0da3bcb0fc3>:2: UserWarning:
```

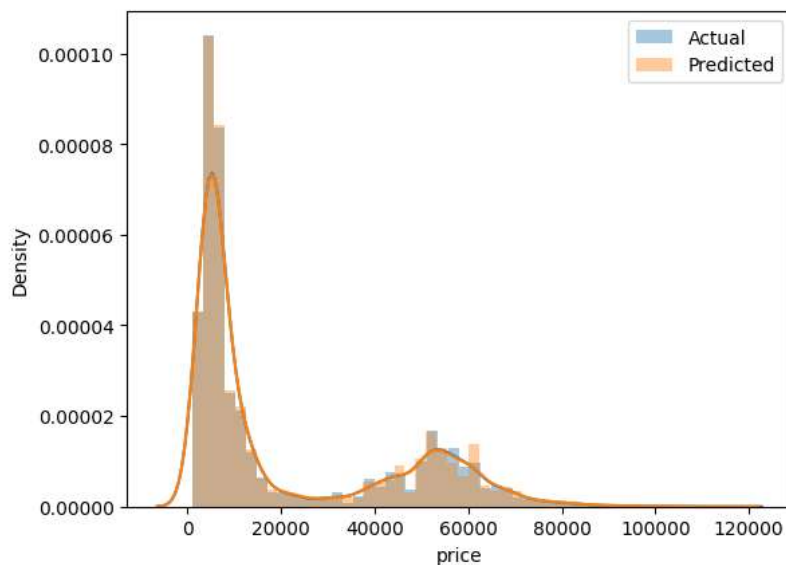
```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

```
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
```

```
For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751
```

```
sns.distplot(y_pred,label="Predicted")
```

```
<matplotlib.legend.Legend at 0x7f3c18efe3a0>
```



### RANDOM FOREST REGRESSION

```
from sklearn.ensemble import RandomForestRegressor
rfr=RandomForestRegressor()
rfr.fit(x_train,y_train)
y_pred=rfr.predict(x_test)
r2_score(y_test,y_pred)
```

```
0.9845269382287261
```

```
from sklearn import metrics
mean_abs_error= metrics.mean_absolute_error(y_test,y_pred)
mean_abs_error
```

```
1123.8247602112526
```

```
from sklearn.metrics import mean_absolute_percentage_error
mean_absolute_percentage_error(y_test, y_pred)
```

```
0.07355428620976769
```

```
mean_sq_error=metrics.mean_squared_error(y_test,y_pred)
mean_sq_error
```

```
7976089.060927906
```

```
import numpy as np
root_mean_sq_error = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
root_mean_sq_error
```

```
2824.19706481823
```

```
sns.distplot(y_test,label="Actual")
sns.distplot(y_pred,label="Predicted")
plt.legend()
```

```
<ipython-input-57-c0da3bcb0fc3>:1: UserWarning:
```

```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

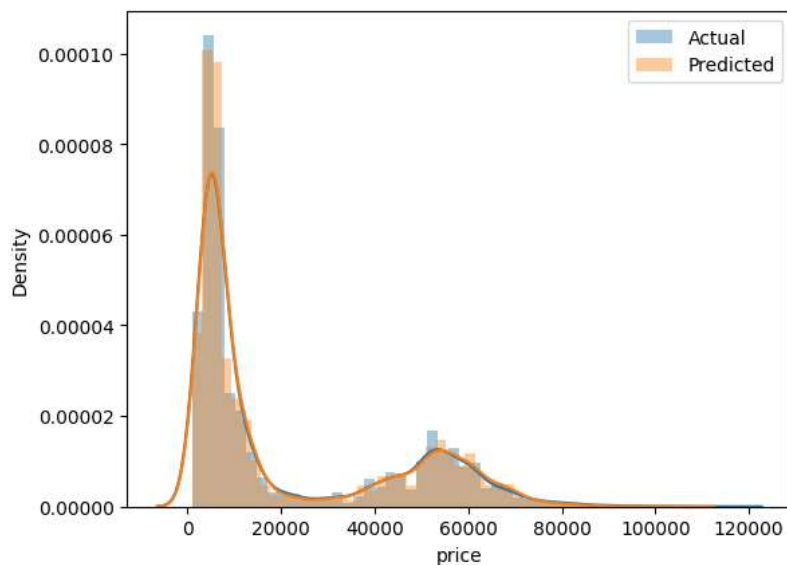
```
sns.distplot(y_test,label="Actual")
<ipython-input-57-c0da3bcb0fc3>:2: UserWarning:
```

```
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.
```

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(y_pred,label="Predicted")
<matplotlib.legend.Legend at 0x7f3c55ce3eb0>
```



#### COMPARISION OF DIFFERENT MODEL AS PER R(SQUARE)

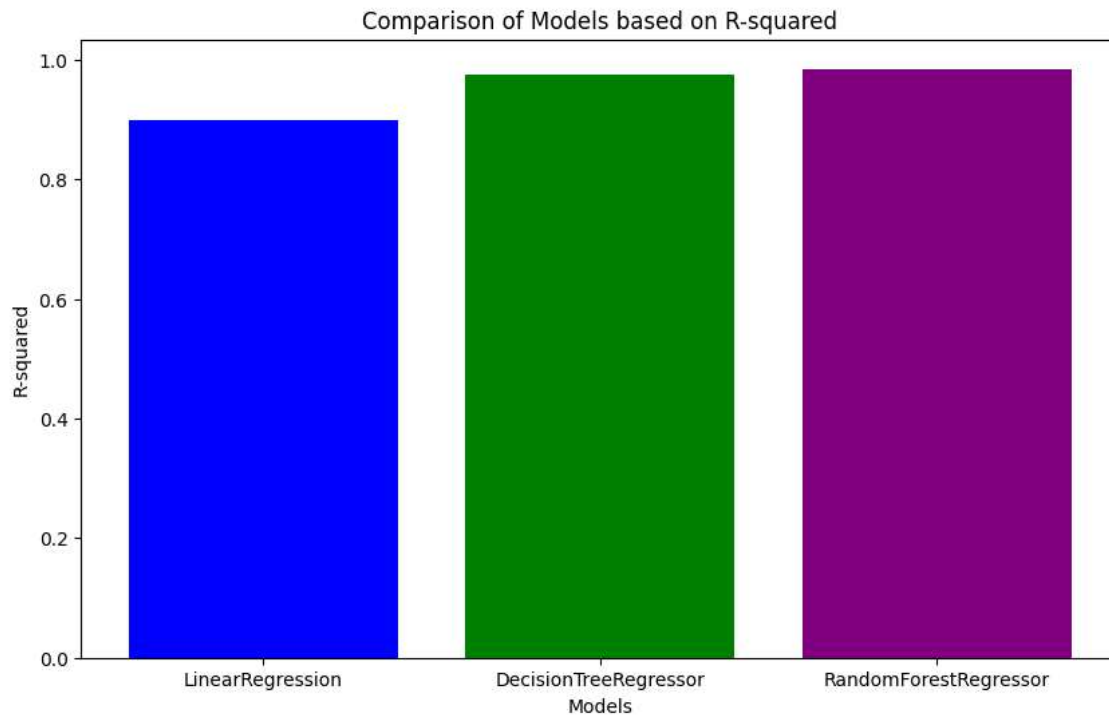
```
# R-squared values for different models
models = ['LinearRegression', 'DecisionTreeRegressor', 'RandomForestRegressor']
r_squared = [0.897752737512321, 0.9746798050021364, 0.9845174836070605]
```

```
# Set the figure size
plt.figure(figsize=(10, 6))
colors = ['blue', 'green', 'purple']
# Create a bar plot
plt.bar(models, r_squared, color=colors)
```

```
# Add labels and title
```

```
plt.xlabel('Models')
plt.ylabel('R-squared')
plt.title('Comparison of Models based on R-squared')

# Show the plot
plt.show()
```



#### COMPARISON OF DIFFERENT MODEL AS PER MEAN ABSOLUTE ERROR

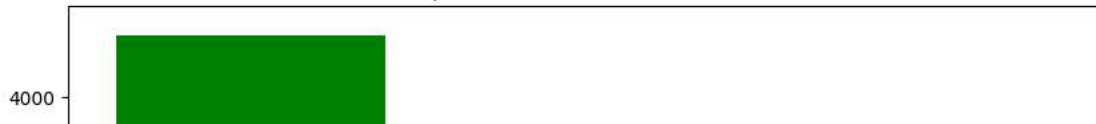
```
# MAE values for different models
models = ['LinearRegression', 'DecisionTreeRegressor', 'RandomForestRegressor' ]
MAE = [4468.426673542113, 1217.1550254590684, 1123.8247602112526]

# Set the figure size
plt.figure(figsize=(10, 6))
colors = ['green', 'pink', 'orange']
# Create a bar plot
plt.bar(models, MAE, color=colors)

# Add labels and title
plt.xlabel('Models')
plt.ylabel('MAE')
plt.title('Comparison of Models based on MAE')

# Show the plot
plt.show()
```

Comparison of Models based on MAE

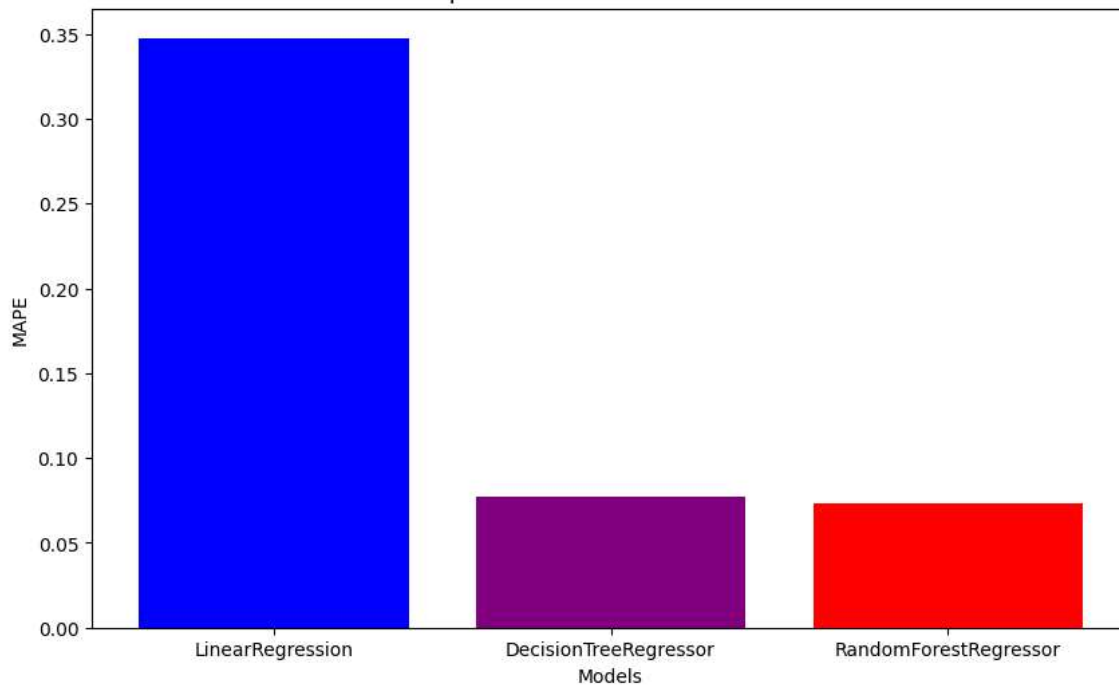
**COMPARISON OF DIFFERENT MODEL AS PER MEAN PERCENTAGE ABSOLUTE ERROR**

```
# MAPE values for different models
models = ['LinearRegression', 'DecisionTreeRegressor', 'RandomForestRegressor' ]
MAPE = [0.34765804610681816, 0.07726568550667867, 0.07355428620976769]
# Set the figure size
plt.figure(figsize=(10, 6))
colors = ['blue', 'purple', 'red']
# Create a bar plot
plt.bar(models, MAPE, color=colors)

# Add labels and title
plt.xlabel('Models')
plt.ylabel('MAPE')
plt.title('Comparison of Models based on MAPE')

# Show the plot
plt.show()
```

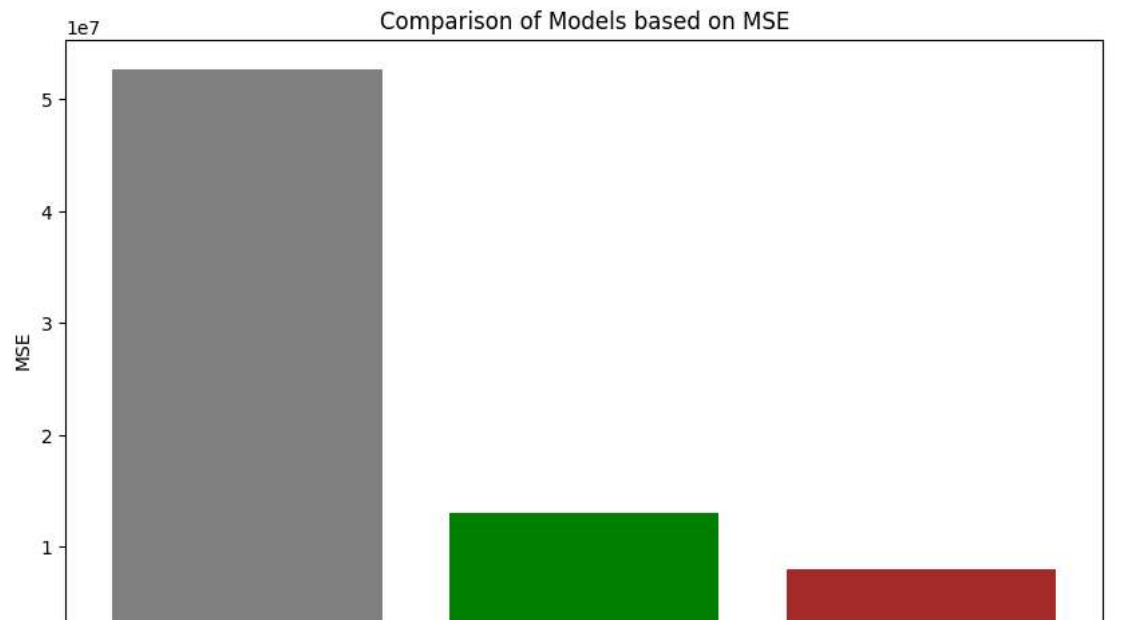
Comparison of Models based on MAPE

**COMPARISON OF DIFFERENT MODEL AS PER MEAN SQUARE ERROR**

```
# MSE values for different models
models = ['LinearRegression', 'DecisionTreeRegressor', 'RandomForestRegressor' ]
MSE = [52706651.33334208, 13061882.718802692, 7976089.060927906]
# Set the figure size
plt.figure(figsize=(10, 6))
colors = ['grey', 'green', 'brown']
# Create a bar plot
plt.bar(models, MSE, color=colors)

# Add labels and title
plt.xlabel('Models')
plt.ylabel('MSE')
plt.title('Comparison of Models based on MSE')

# Show the plot
plt.show()
```



COMPARISION OF DIFFERENT MODEL AS PER ROOT MEAN SQUARE ERROR

LinearRegression DecisionTreeRegressor RandomForestRegressor

```
# RMSE values for different models
models = ['LinearRegression', 'DecisionTreeRegressor', 'RandomForestRegressor' ]
RMSE = [7259.934664536733, 3614.122676224853, 2824.19706481823]
# Set the figure size
plt.figure(figsize=(10, 6))
colors = ['red', 'orange', 'yellow']
# Create a bar plot
plt.bar(models, RMSE, color=colors)

# Add labels and title
plt.xlabel('Models')
plt.ylabel('RMSE')
plt.title('Comparison of Models based on RMSE')

# Show the plot
plt.show()
```

