Airline Price Prediction

Introduction

The objective of this study is to analyze the flight booking dataset obtained from the "Ease My Trip" website and
to conduct various statistical hypothesis tests to extract meaningful insights from it.

Research Questions

The aim of our study is to answer the following research questions:

1. **Does price vary with Airlines?**
2. **How is the price affected when tickets are bought just 1 or 2 days before departure?**
3. **Does ticket price change based on the departure time and arrival time?**
4. **How does the price change with the Source and Destination?**
5. **How does the ticket price vary between Economy and Business class?**

Data Collection and Methodology

The**Octoparse** scraping tool was used to extract data from the website. Data was collected in two parts: one for economy class tickets and another for business class tickets. A total of **300,261** distinct flight booking options were extracted from the site. Data collection spanned **50 days**, from **February 11th to March 31st, 2022.** Dataset contains information about flight booking options from the website "Ease My Trip" for flight travel between India's top 6 metro cities. There are 300261 datapoints and 11 features..

Features

1. **Airline:** The name of the airline company.
2. **Flight:** Stores information regarding the plane's flight code.
3. **Source City:** The city from which the flight takes off.
4. **Departure Time:** The departure time, categorized into 6 unique time labels.
5. **Stops:** The number of stops between the source and destination cities.

6. **Arrival Time:** The arrival time, also categorized into 6 unique time labels.
7. **Destination City:** The city where the flight will land.
8. **Class:** Either Business or Economy.
9. **Duration:** The overall time it takes to travel between cities, measured in hours.
10. **Days Left:** The number of days left, calculated by subtracting the trip date from the booking date.
11. **Price:** The ticket price.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings

from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn import metrics
from sklearn.model_selection import train_test_split, GridSearchCV
warnings.filterwarnings('ignore')
```

In [2]:
```
flights = pd.read_csv('flights.csv')
flights.head()
```

Out[2]:

	Unnamed: 0	airline	flight	source_city	departure_time	stops	arrival_time	destinatio
0	0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mu
1	1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mu
2	2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mu
3	3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mu
4	4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mu

In [3]:
```
flights.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 300153 entries, 0 to 300152
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Unnamed: 0        300153 non-null  int64  
 1   airline           300153 non-null  object 
 2   flight            300153 non-null  object 
 3   source_city       300153 non-null  object 
 4   departure_time    300153 non-null  object 
 5   stops             300153 non-null  object 
 6   arrival_time      300153 non-null  object 
 7   destination_city  300153 non-null  object 
 8   class             300153 non-null  object 
 9   duration          300153 non-null  float64
 10  days_left         300153 non-null  int64  
 11  price             300153 non-null  int64  
dtypes: float64(1), int64(3), object(8)
memory usage: 27.5+ MB
```

In [4]:
```
flights.columns
```

Out[4]:
```
Index(['Unnamed: 0', 'airline', 'flight', 'source_city', 'departure_time',
       'stops', 'arrival_time', 'destination_city', 'class', 'duration',
       'days_left', 'price'],
      dtype='object')
```

In [5]:
```
flights.drop('Unnamed: 0', axis=1, inplace=True)
```

In [6]:
```
flights.shape
```

Out[6]:
```
(300153, 11)
```

In [7]:
```
flights.describe()
```

Out[7]:

	duration	days_left	price
count	300153.000000	300153.000000	300153.000000
mean	12.221021	26.004751	20889.660523
std	7.191997	13.561004	22697.767366
min	0.830000	1.000000	1105.000000
25%	6.830000	15.000000	4783.000000
50%	11.250000	26.000000	7425.000000
75%	16.170000	38.000000	42521.000000
max	49.830000	49.000000	123071.000000

In [8]:
```
flights.head()
```

Out[8]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	c
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Econ
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Econ
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Econ
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Econ
4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Econ

In [9]:
```
flights.isnull().any()
```

Out[9]:
```
airline             False
flight              False
source_city         False
departure_time      False
stops               False
arrival_time        False
destination_city    False
class               False
duration            False
days_left           False
price               False
dtype: bool
```

💻 **Rename class name to flight_class to avoid conflicts with the reserved Python keyword class.**

In [10]:
```
flights.rename(columns={'class' : 'flight_class'}, inplace=True)
```

In [11]:
```
flights.head()
```

Out[11]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	fligh
0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Ec
1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Ec
2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Ec
3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Ec
4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Ec

In [12]:
```
flights.columns
```

Out[12]:
```
Index(['airline', 'flight', 'source_city', 'departure_time', 'stops',
       'arrival_time', 'destination_city', 'flight_class', 'duration',
       'days_left', 'price'],
      dtype='object')
```

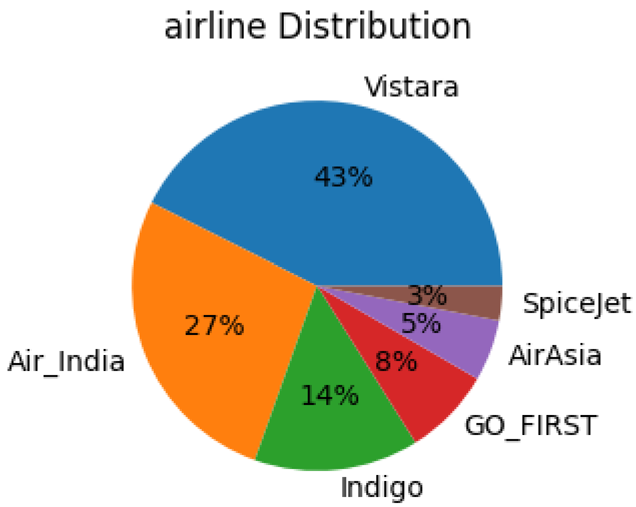
💻 **Flight name is like a ID, so its not nessasary for modeling and will drop from dataframe.**

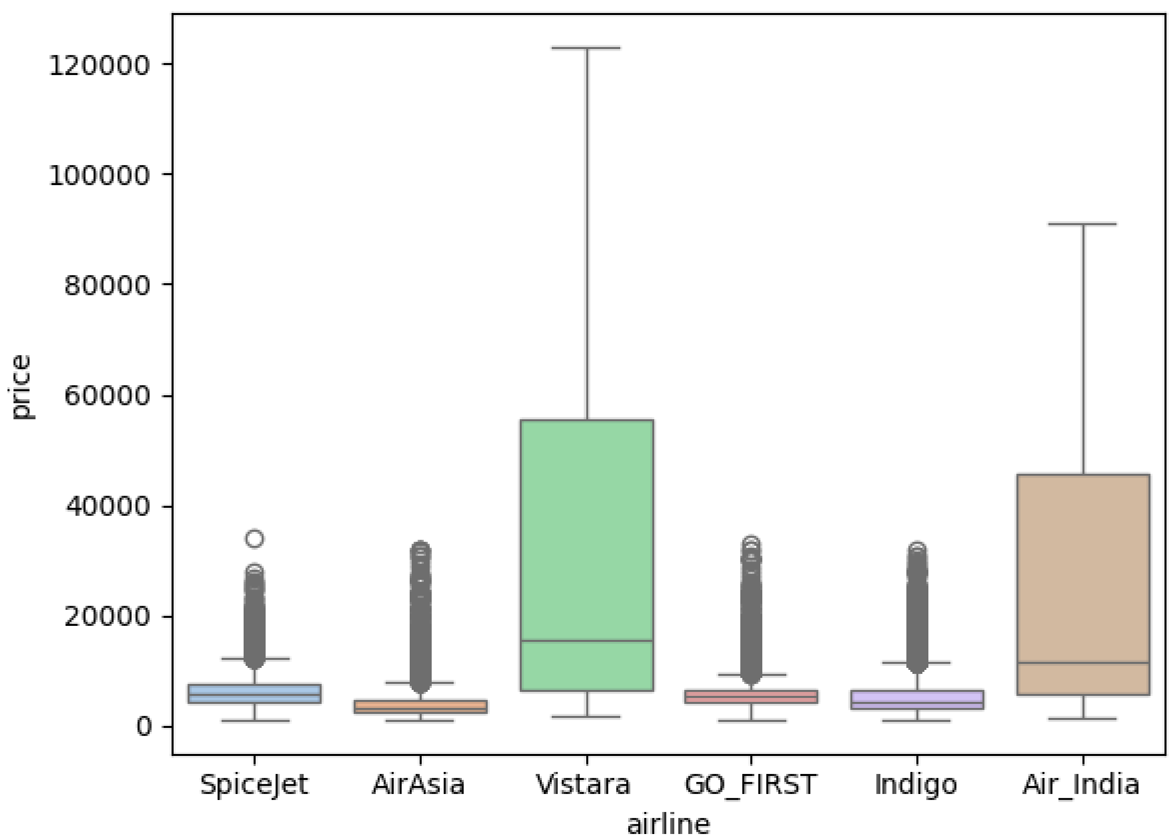
In [13]:
```
flights.drop('flight', axis=1, inplace=True)
```

In [14]:
```
num_features = ['duration', 'days_left']
cat_features = ['airline', 'source_city', 'departure_time', 'stops', 'arrival_time'
```

In [15]:
```
def pie_chart(data, feature):
    plt.figure(figsize=(3, 3))
    feature_counts = data[feature].value_counts()
    plt.pie(feature_counts, labels=feature_counts.index, autopct='%.0f%%')
    plt.title(feature + ' Distribution')
    plt.show()
```

In [16]:
```
pie_chart(flights, 'airline')
sns.boxplot(x='airline', y='price', data=flights, palette='pastel')
plt.show()
```



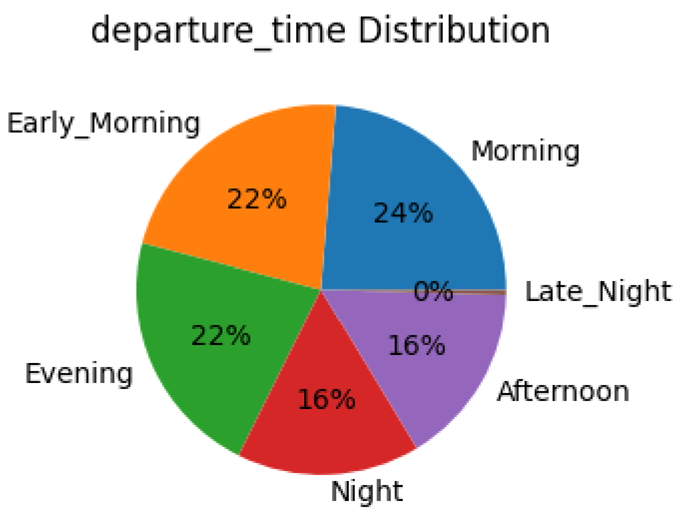


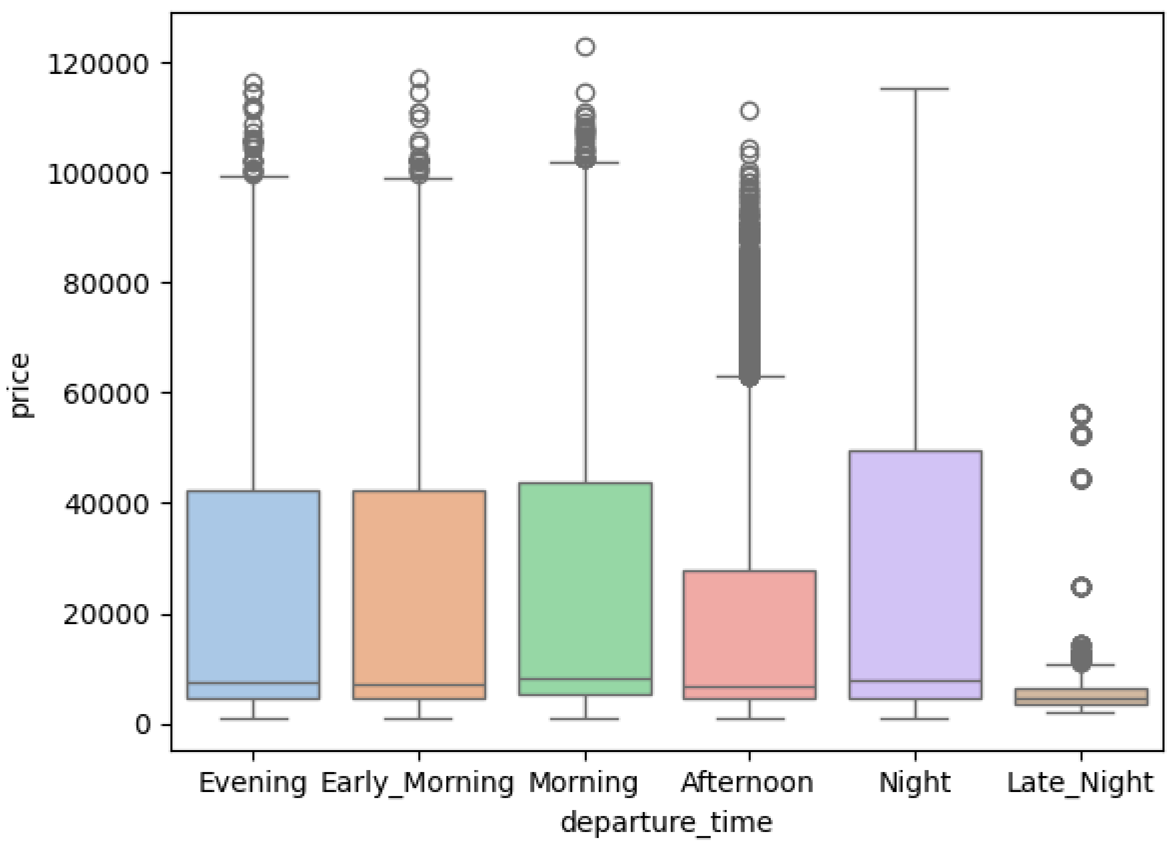
Airline Usage Statistics.

1. **Most used airline:** Vistara
   - **43%** of all flights
   - **127,859 flights**
2. **Second most used airline:** Air India
   - **27%** of all flights
   - **80,892 flights**
3. **Least used airline:** SpiceJet

- **3%** of all flights
- **9,011 flights**

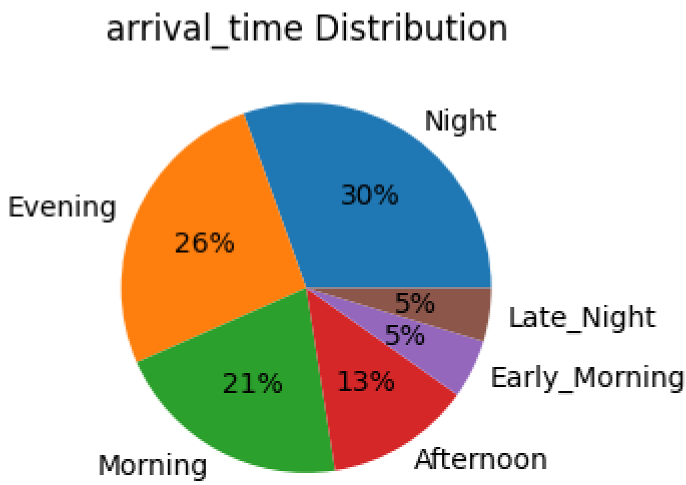
In [17]:
```
pie_chart(flights, 'departure_time')
sns.boxplot(x='departure_time', y='price', data=flights, palette='pastel')
plt.show()
```

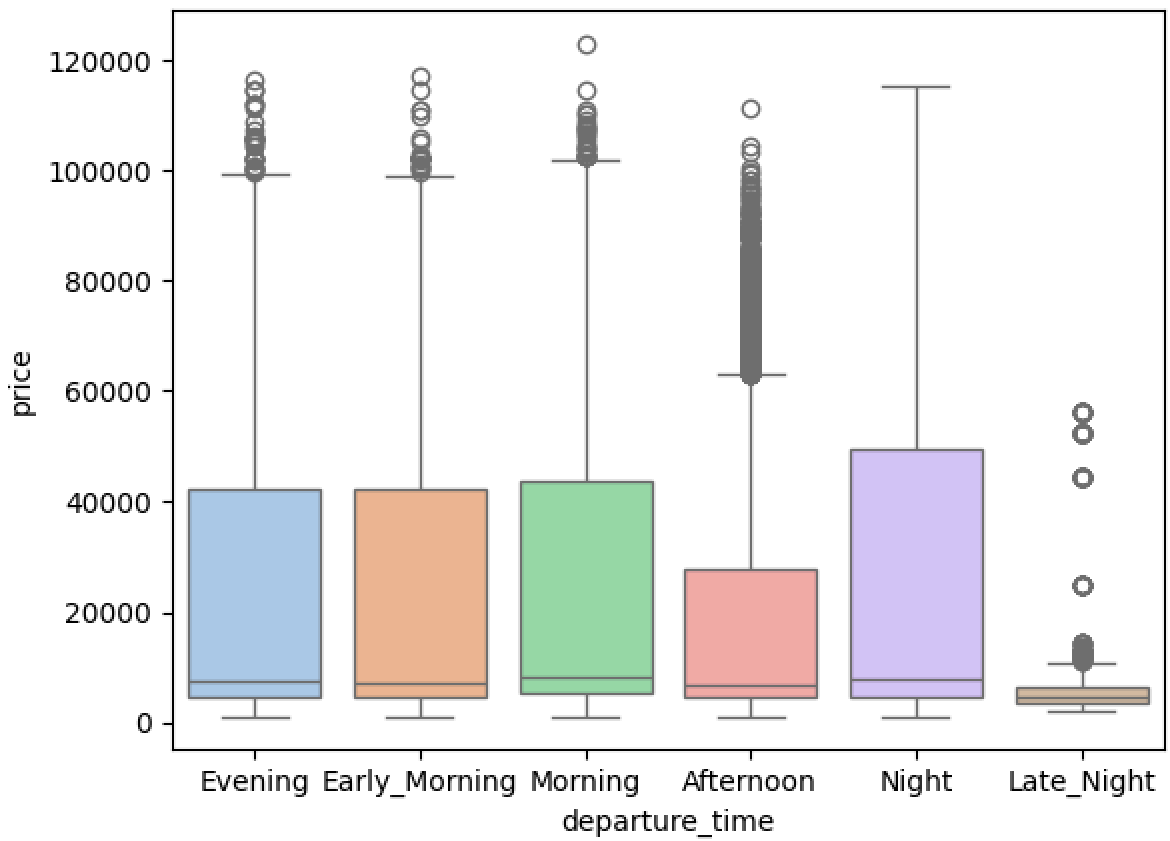




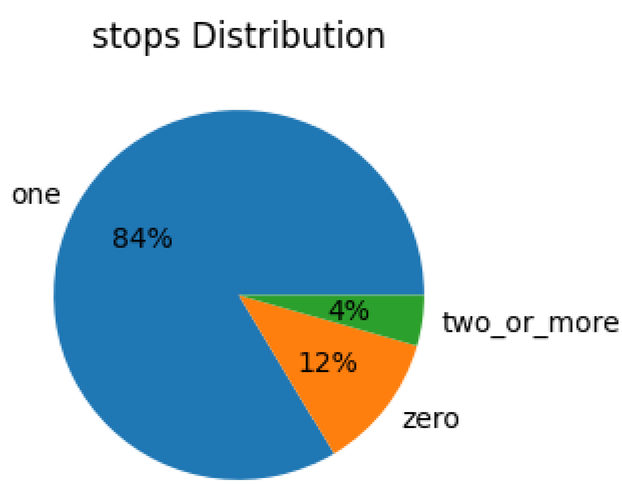
ℹ️ **Except at the end of Late_Night, the frequency of the rest of the departure_time is almost equal.**

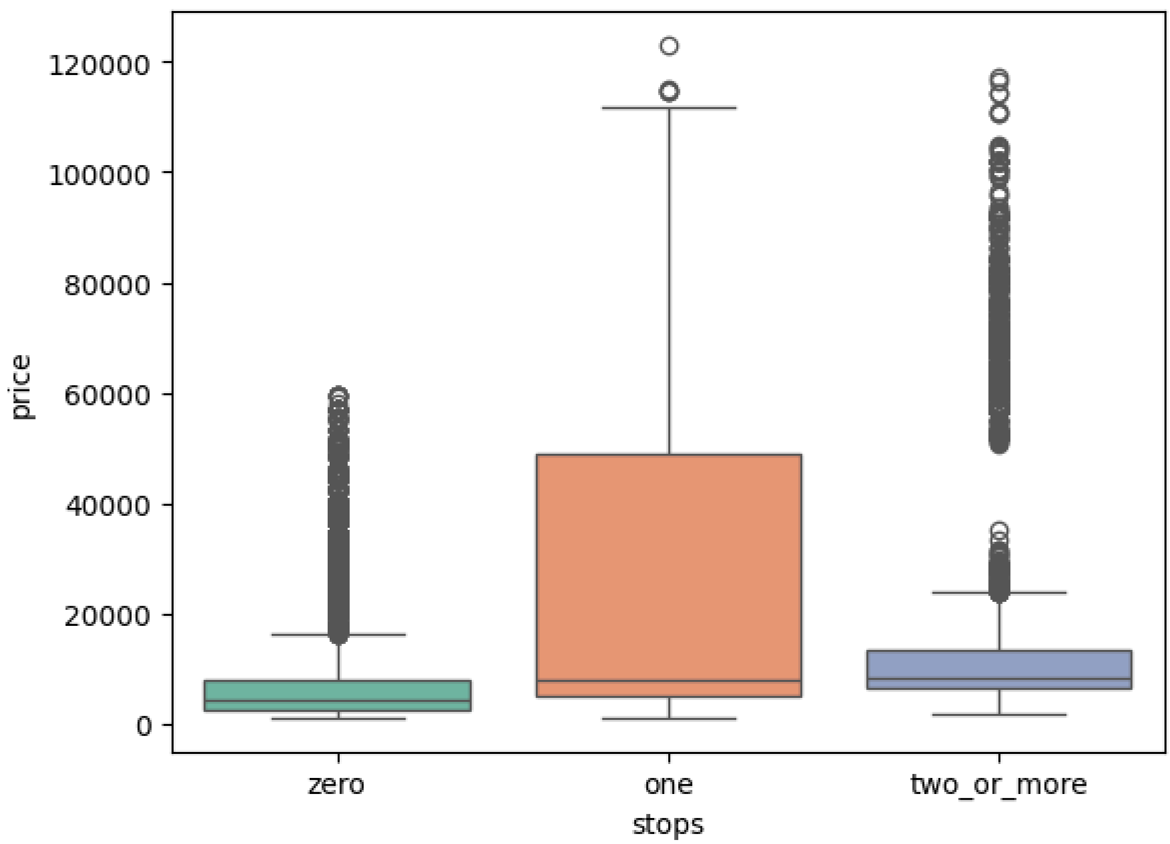
In [18]:
```
pie_chart(flights, 'arrival_time')
sns.boxplot(x='departure_time', y='price', data=flights, palette='pastel')
plt.show()
```





In [19]:
```
pie_chart(flights, 'stops')
sns.boxplot(x='stops', y='price', data=flights, palette='Set2')
plt.show()
```



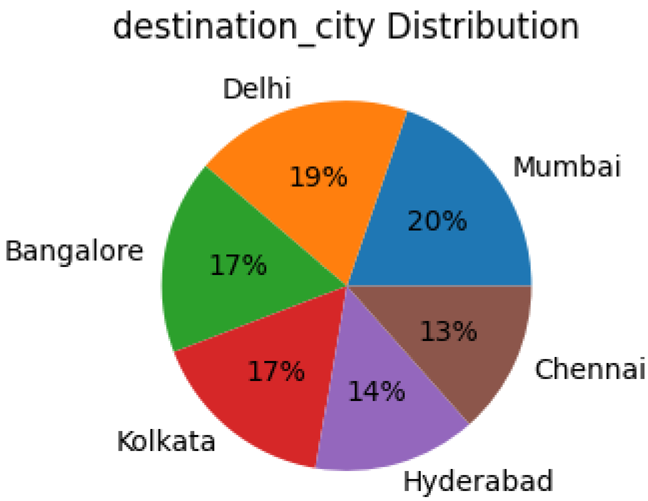


Flight Stopover Statistics.

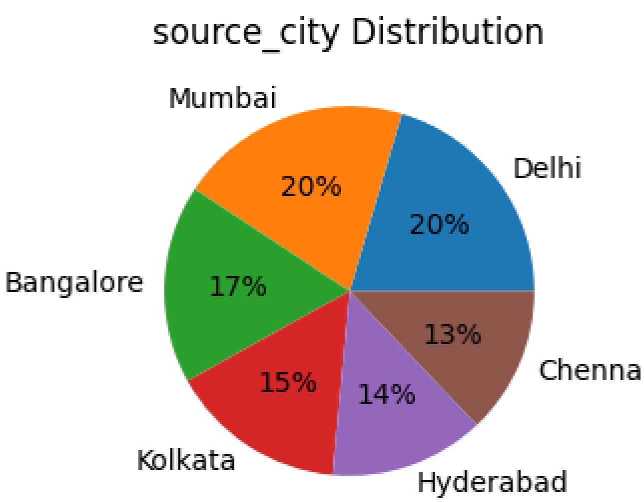
1. **Majority of flights have 1 stop:**
    - **Approximately 84%** of flights
    - **250,863 flights**
2. **Flights with 2 or more stops:**
    - **Just 4%** of flights
3. **Flights with no stops:**

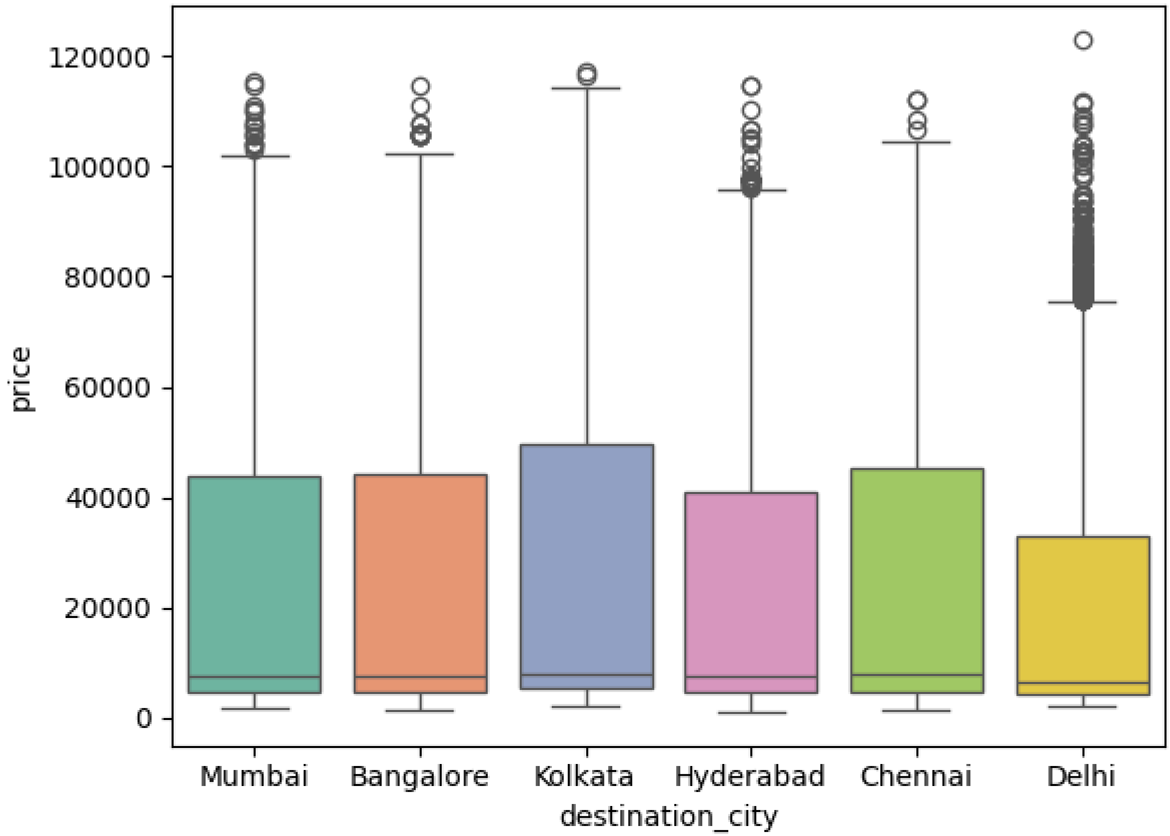
- **Approximately 12%** of flights
- **13,286 flights**

In [20]:
```
pie_chart(flights, 'destination_city')
```



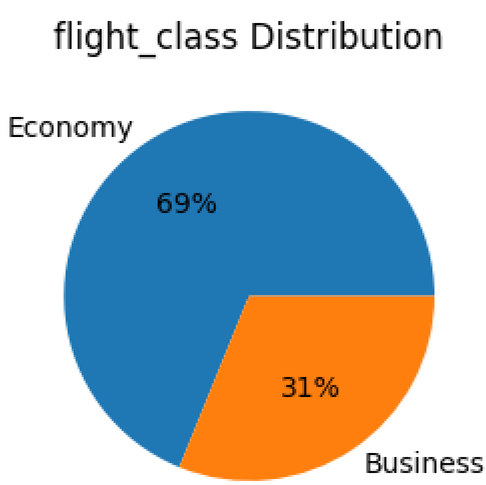
In [21]:
```
pie_chart(flights, 'source_city')
sns.boxplot(x='destination_city', y='price', data=flights, palette='Set2')
plt.show()
```

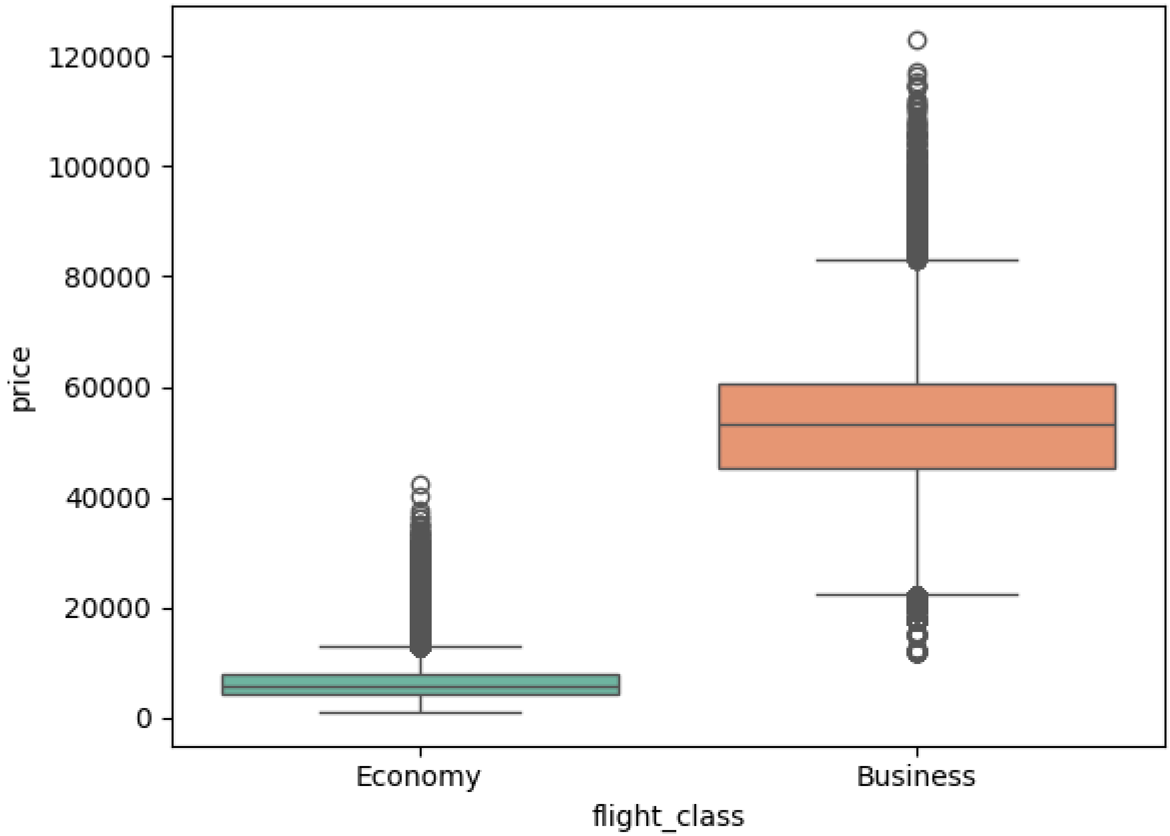




ℹ️ Almost number of all flights source and distination are equal.

In [22]:
```
pie_chart(flights, 'flight_class')
sns.boxplot(x='flight_class', y='price', data=flights, palette='Set2')
plt.show()
```





Flight Class Distribution and Pricing

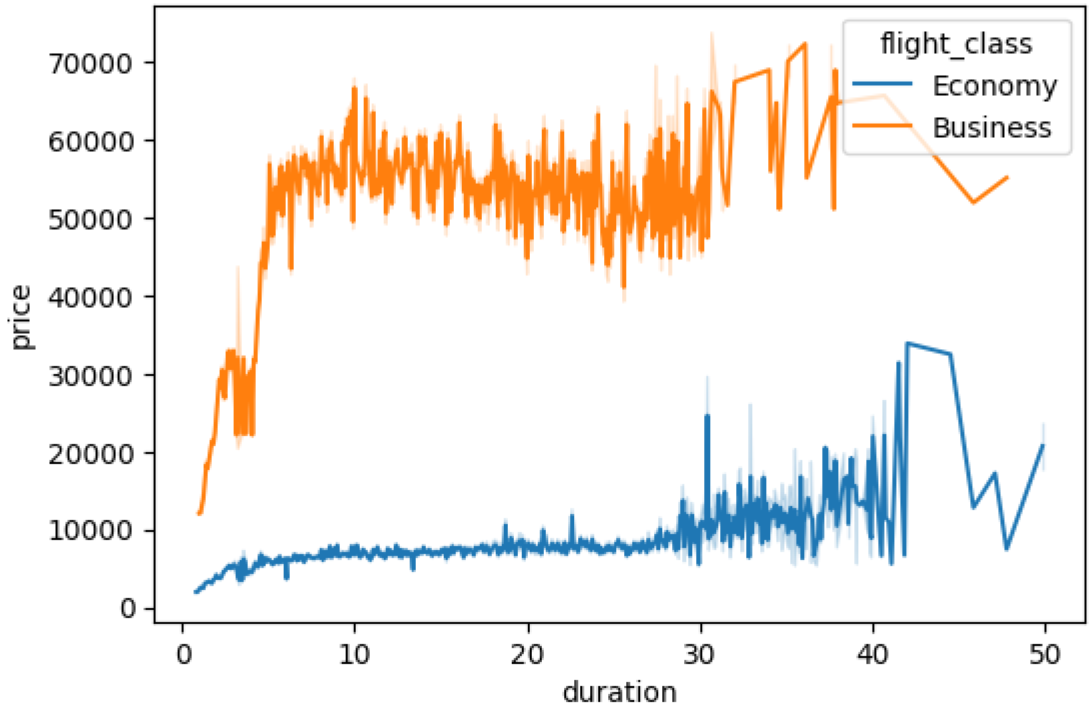
1. **Business class flights** are **obviously more expensive** than Economy class flights.

2. **Most flights are in Economy class:**

   - **Approximately 69%** of all flights

In [23]:
```
plt.figure(figsize=(6, 4))
sns.lineplot(data=flights, x='duration', y='price', hue='flight_class')
```

Out[23]:
```
<Axes: xlabel='duration', ylabel='price'>
```



ℹ️ Price Trends by Flight Class and Duration

1. **Business Class:**

   - For flight durations between **1 to 5 hours**, prices **grow sharply**.
   - For durations **more than 5 hours**, prices remain within a **range of 45,000 to 60,000**.

2. **Economy Class:**

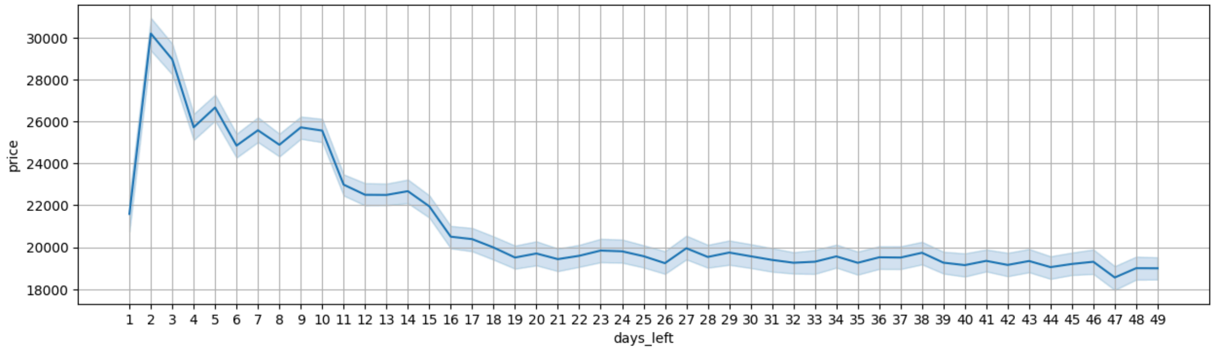
   - Price shows a **linear growth** with increasing flight duration.
   - A **sharp price increase** is observed for flights with a duration of **47 hours**.

In [24]:

```
plt.figure(figsize=(15, 4))
sns.lineplot(data=flights, x='days_left', y='price')
plt.grid(True)

# Increase the number of ticks on the x-axis
plt.xticks(ticks=range(flights['days_left'].min(), flights['days_left'].max()+1, 1)

plt.show()
```



ℹ️ The earlier you book your ticket, the less you will pay(for values greater than 2)

⚠️ Adjustment only for prediction

Important: When a ticket is purchased **one day before the flight** (`days_left = 1`), it will be treated as if it were purchased **15 days in advance** (`days_left = 15`).
This adjustment accounts for the typical **reduction in ticket prices** observed the day before the flight. Conversely, tickets purchased **two days before the flight** tend to be **more expensive**.

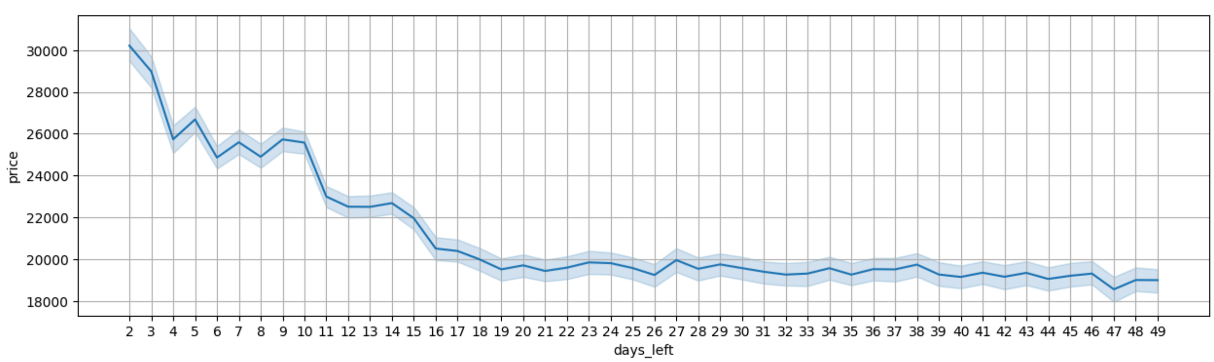
Note: Data for tickets purchased one day before the flight has been excluded from the model due to its limited quantity and its negative impact on accuracy.

In [25]:
```
flights = flights[flights['days_left'] != 1]
```

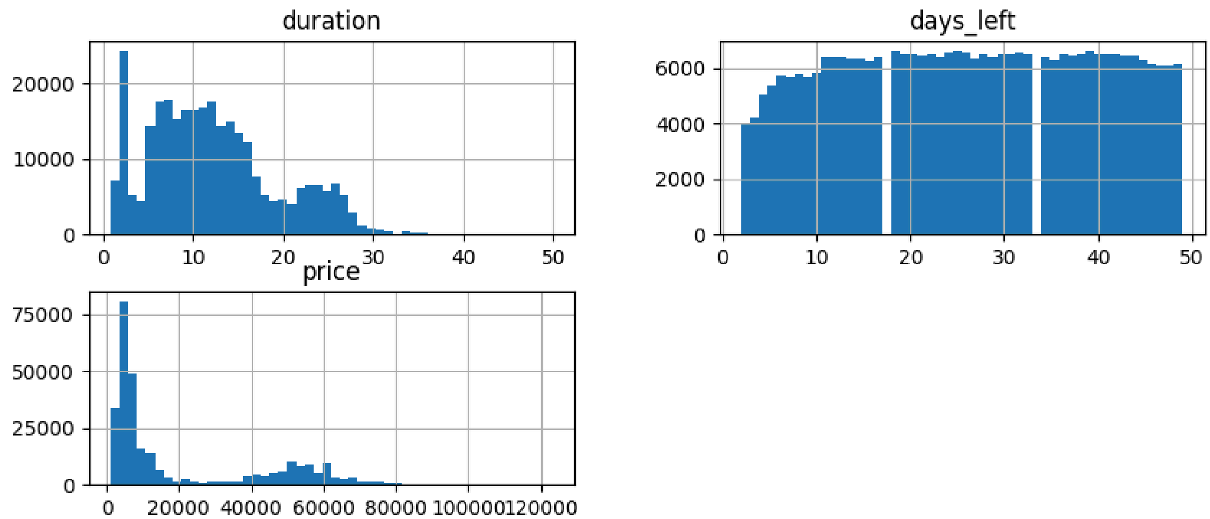
In [26]:
```
plt.figure(figsize=(15, 4))
sns.lineplot(data=flights, x='days_left', y='price')
plt.grid(True)

plt.xticks(ticks=range(flights['days_left'].min(), flights['days_left'].max()+1, 1)

plt.show()
```



In [27]:
```
flights.hist(bins=50, figsize=(10, 4))
plt.show()
```



In [28]:
```python
df = flights.copy()
df.head()
```

Out[28]:

	airline	source_city	departure_time	stops	arrival_time	destination_city	flight_class
118	SpiceJet	Delhi	Early_Morning	zero	Morning	Mumbai	Economy
119	SpiceJet	Delhi	Evening	zero	Night	Mumbai	Economy
120	Vistara	Delhi	Morning	zero	Morning	Mumbai	Economy
121	Vistara	Delhi	Evening	zero	Night	Mumbai	Economy
122	Vistara	Delhi	Evening	zero	Night	Mumbai	Economy

In [29]:
```python
df.airline = df.airline.replace(
    {
        'Vistara' : 1,
        'Air_India' : 2,
        'Indigo' : 3,
        'GO_FIRST' : 4,
        'AirAsia': 5,
        'SpiceJet' : 6
    }
)
```

In [30]:
```python
df.source_city = df.source_city.replace(
    {
        'Delhi' : 1,
        'Mumbai' : 2,
        'Bangalore' : 3,
        'Kolkata' : 4,
        'Hyderabad'  : 5,
        'Chennai' : 6
    }
)
```

In [31]:
```
df.departure_time = df.departure_time.replace(
    {
        'Morning' : 1,
        'Early_Morning' : 2,
        'Evening' : 3,
        'Night' : 4,
        'Afternoon' : 5,
        'Late_Night' : 6
    }
)
```

In [32]:
```
df.stops = df.stops.replace(
    {
        'one' : 1,
        'zero' : 2,
        'two_or_more' : 3
    }
)
```

In [33]:
```
df.arrival_time = df.arrival_time.replace(
    {
        'Night' : 1,
        'Evening' : 2,
        'Morning' : 3,
        'Afternoon' : 4,
        'Early_Morning' : 5,
        'Late_Night' : 6
    }
)
```

In [34]:
```
df.destination_city = df.destination_city.replace(
    {
        'Mumbai' : 1,
        'Delhi' : 2,
        'Bangalore' : 3,
        'Kolkata' : 4,
        'Hyderabad' : 5,
        'Chennai' : 6
    }
)
```

In [35]:
```
df.flight_class = df.flight_class.replace(
    {
        'Economy' : 1,
        'Business' :2
    }
)
```

In [36]:
```
flights.head()
```

Out[36]:

	airline	source_city	departure_time	stops	arrival_time	destination_city	flight_class
118	SpiceJet	Delhi	Early_Morning	zero	Morning	Mumbai	Economy
119	SpiceJet	Delhi	Evening	zero	Night	Mumbai	Economy
120	Vistara	Delhi	Morning	zero	Morning	Mumbai	Economy
121	Vistara	Delhi	Evening	zero	Night	Mumbai	Economy
122	Vistara	Delhi	Evening	zero	Night	Mumbai	Economy

In [37]:

```
df.head()
```

Out[37]:

	airline	source_city	departure_time	stops	arrival_time	destination_city	flight_class
118	6	1	2	2	3	1	1
119	6	1	3	2	1	1	1
120	1	1	1	2	3	1	1
121	1	1	3	2	1	1	1
122	1	1	3	2	1	1	1

In [38]:

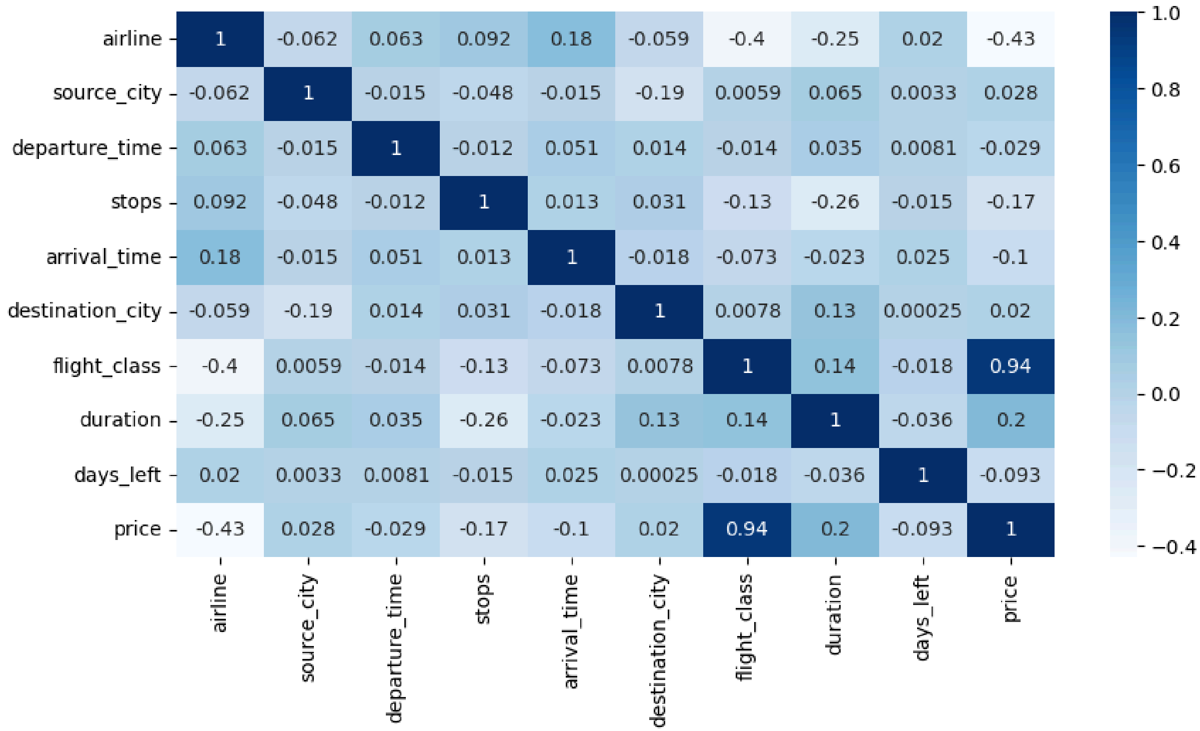
```
df.describe()
```

Out[38]:

	airline	source_city	departure_time	stops	arrival_time	destin
count	298226.000000	298226.000000	298226.000000	298226.000000	298226.000000	2982
mean	2.152773	3.206471	2.793720	1.208194	2.499500	
std	1.348692	1.685961	1.401818	0.503329	1.408574	
min	1.000000	1.000000	1.000000	1.000000	1.000000	
25%	1.000000	2.000000	2.000000	1.000000	1.000000	
50%	2.000000	3.000000	3.000000	1.000000	2.000000	
75%	3.000000	5.000000	4.000000	1.000000	3.000000	
max	6.000000	6.000000	6.000000	3.000000	6.000000	

In [39]:

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

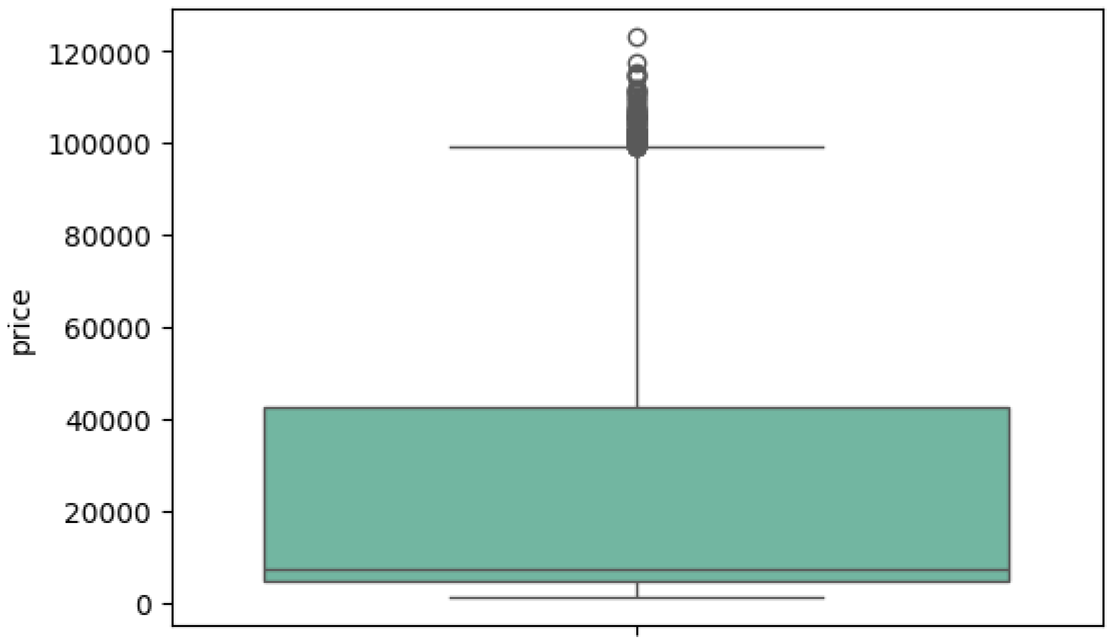


In [40]:
```
corr_matrix = df.corr()
corr_matrix["price"].sort_values(ascending=False)
```

Out[40]:
```
price               1.000000
flight_class        0.938535
duration            0.203875
source_city         0.027728
destination_city    0.019599
departure_time     -0.029063
days_left          -0.092818
arrival_time       -0.101622
stops              -0.173789
airline            -0.428987
Name: price, dtype: float64
```

💻 **Removing Some Outliers.**

In [41]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(df['price'], palette='Set2')
plt.show()
```

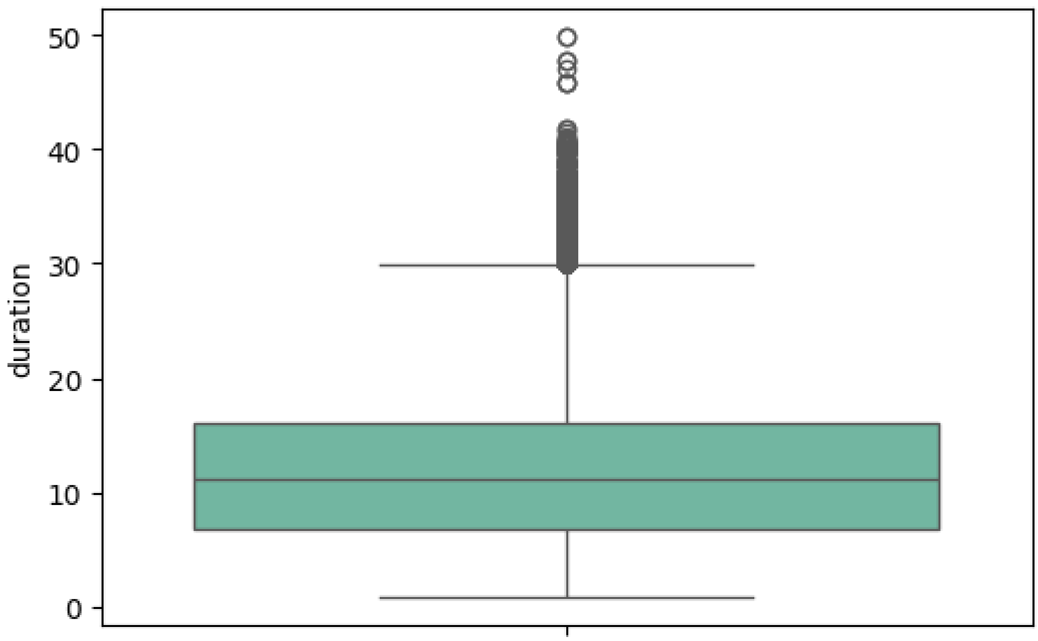


In [42]:
```
def iqr(df, var):
    q1 = np.quantile(df[var], 0.25)
    q3 = np.quantile(df[var], 0.75)
    diff = q3 - q1
    lower_v = q1 - (1.5 * diff)
    upper_v = q3 + (1.5 * diff)
    return df[(df[var] < lower_v) | (df[var] > upper_v)]
```

In [43]:
```
oul2 = iqr(df, 'price')
```

In [44]:
```
df = df.drop(oul2.index)
```

In [45]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(df['duration'], palette='Set2')
plt.show()
```



In [46]:
```
oul3 = iqr(df, 'duration')
```

In [47]:
```
df = df.drop(oul3.index)
```

In [48]:
```
num_features = ['duration', 'days_left']
cat_features = ['airline', 'source_city', 'departure_time', 'stops', 'arrival_time'
```

In [49]:
```
X = df.drop(["price"], axis=1)
y = df["price"].copy()
```

In [50]:
```
X.shape
```

Out[50]: (295824, 9)

In [51]:
```
y.shape
```

Out[51]: (295824,)

In [52]:
```
from sklearn.ensemble import IsolationForest

isolation_forest = IsolationForest(random_state=42)
outlier_pred = isolation_forest.fit_predict(X)

X = X.iloc[outlier_pred == 1]
y = y.iloc[outlier_pred == 1]
```

In [53]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
```

In [54]:
```
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import MinMaxScaler, RobustScaler
```

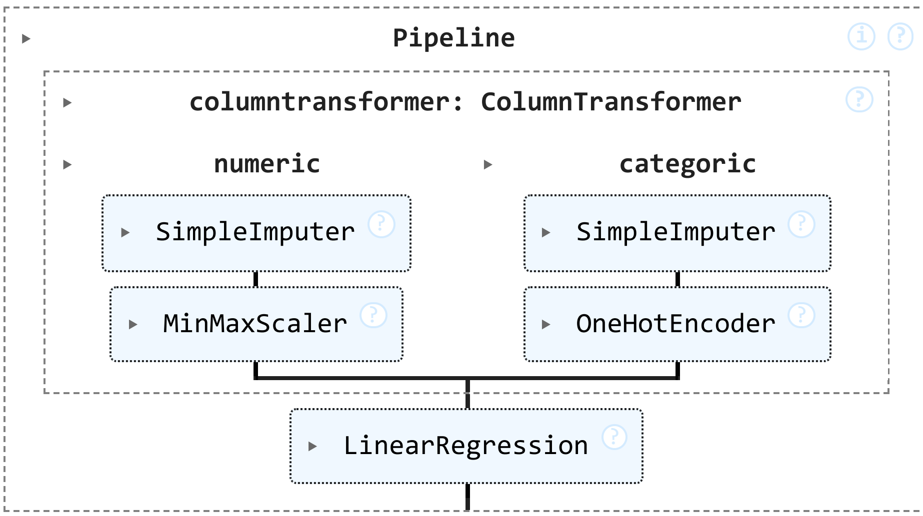
```python
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import PolynomialFeatures
from sklearn.model_selection import cross_val_score
```

In [55]:
```python
num_pipeline = make_pipeline(SimpleImputer(strategy="mean"), MinMaxScaler())
cat_pipeline = make_pipeline(SimpleImputer(strategy="most_frequent"), OneHotEncoder
```

In [56]:
```python
preprocessing = ColumnTransformer([
    ("numeric", num_pipeline, num_features),
    ("categoric", cat_pipeline, cat_features),
])
```

In [57]:
```python
lin_reg = make_pipeline(preprocessing, LinearRegression())
lin_reg.fit(X_train, y_train)
```

Out[57]:



In [58]:
```python
lin_pred = lin_reg.predict(X_test)
```

In [59]:
```python
from sklearn.metrics import mean_squared_error, root_mean_squared_error

lin_rmse = root_mean_squared_error(y_test, lin_pred)
lin_rmse
```

Out[59]:
```
4316.087168220243
```

In [60]:
```python
lr_r2 = metrics.r2_score(y_test, lin_pred)
lr_r2
```

Out[60]:
```
0.9486607117696843
```

In [61]:
```python
lin_rmses = -cross_val_score(lin_reg, X_train, y_train,
                              scoring="neg_root_mean_squared_error", cv=10)
```

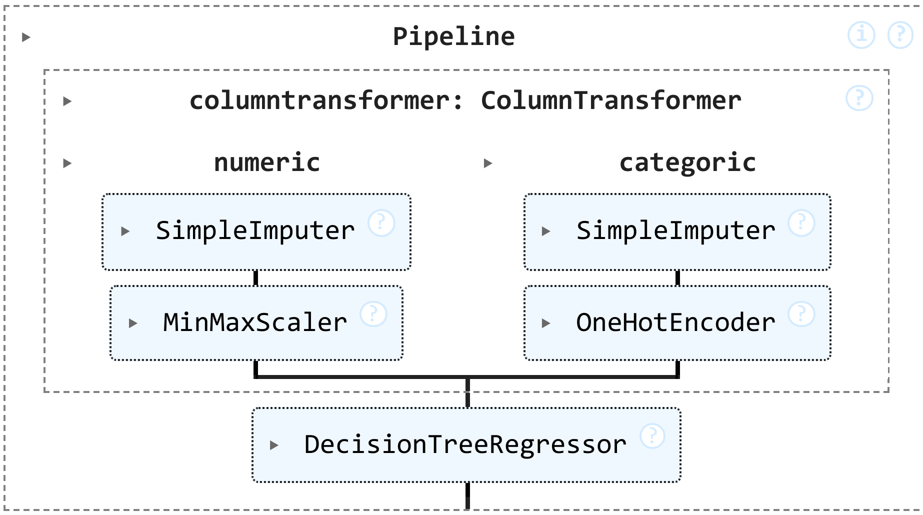
In [62]:
```python
pd.Series(lin_rmses).describe()
```

Out[62]:
```
count      10.000000
mean     4305.040040
std        74.163968
min      4213.487470
25%      4252.438566
50%      4295.852937
75%      4323.932350
max      4460.821909
dtype: float64
```

In [63]:
```python
from sklearn.tree import DecisionTreeRegressor

tree_reg = make_pipeline(preprocessing, DecisionTreeRegressor(random_state=42))
tree_reg.fit(X_train, y_train)
```

Out[63]:



In [64]:
```python
tree_pred = tree_reg.predict(X_test)
tree_rmse = root_mean_squared_error(y_test, tree_pred)
tree_rmse
```

Out[64]: 2643.2800928393667

In [65]:
```python
from sklearn.model_selection import cross_val_score

tree_rmses = -cross_val_score(tree_reg, X_train, y_train,
                              scoring="neg_root_mean_squared_error", cv=10)
```

In [66]:
```python
pd.Series(tree_rmses).describe()
```

Out[66]:
```
count      10.000000
mean     2721.584530
std        96.517436
min      2550.199636
25%      2659.242781
50%      2722.069611
75%      2791.196251
max      2862.080045
dtype: float64
```

In [67]:
```python
tree_r2 = metrics.r2_score(y_test, tree_pred)
tree_r2
```

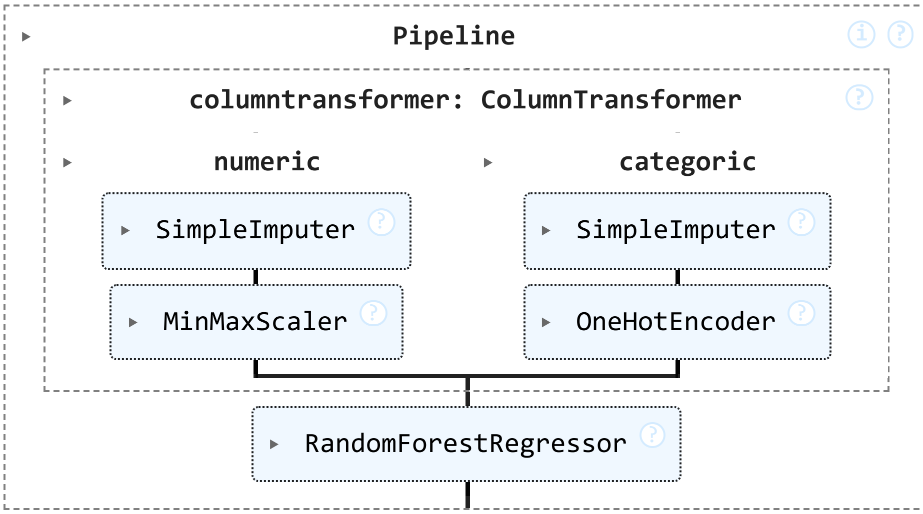
Out[67]: 0.9807444557015719

In [68]:
```python
from sklearn.ensemble import RandomForestRegressor

forest_reg = make_pipeline(preprocessing, RandomForestRegressor())
```

In [69]:
```python
forest_reg.fit(X_train, y_train)
```

Out[69]:



In [70]:
```python
forest_pred = forest_reg.predict(X_test)
forest_rmse = root_mean_squared_error(y_test, forest_pred)
forest_rmse
```

Out[70]: 2172.748605062864

In [71]:
```python
forest_rmses = -cross_val_score(forest_reg, X_train, y_train,
                                scoring="neg_root_mean_squared_error", cv=10)
```

In [72]:
```python
pd.Series(forest_rmses).describe()
```

Out[72]:
```
count      10.000000
mean     2179.664301
std        61.129308
min      2104.951761
25%      2134.534854
50%      2173.703057
75%      2216.589980
max      2295.686023
dtype: float64
```

In [73]:
```python
forest_r2 = metrics.r2_score(y_test, forest_pred)
forest_r2
```

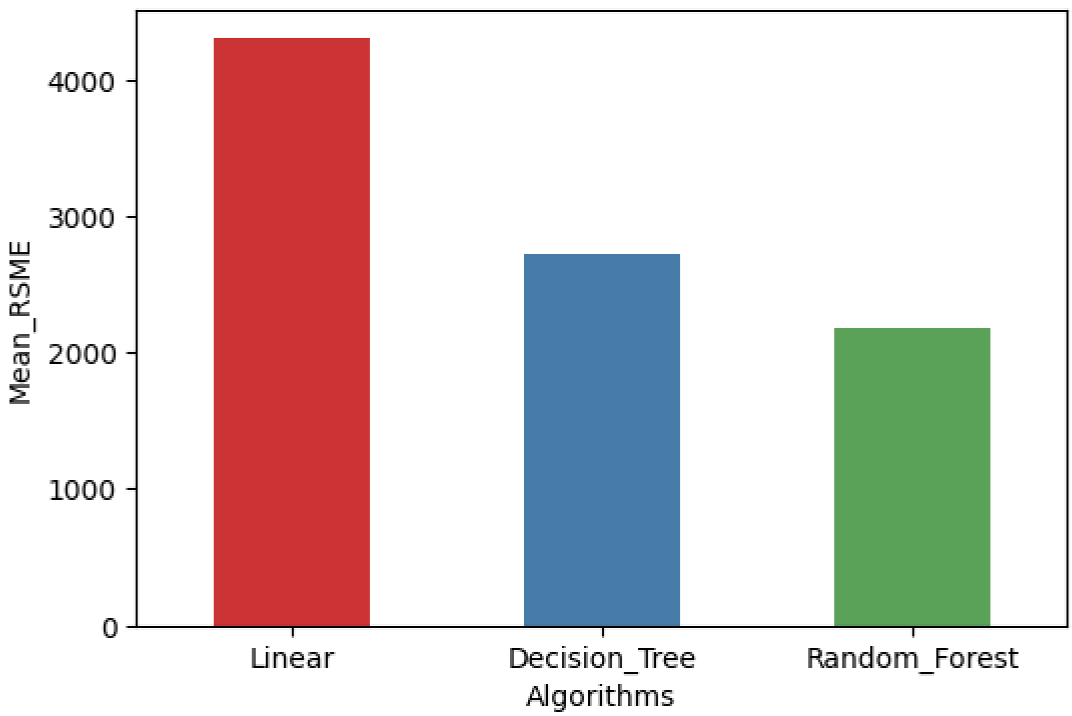
Out[73]: 0.9869896677180315

In [74]:
```python
result = pd.DataFrame({
    'Algorithms' : ['Linear', 'Decision_Tree', 'Random_Forest'],
    'Mean_RSME' : [lin_rmses.mean(), tree_rmses.mean(), forest_rmses.mean()],
    'R2_Scores' : [lr_r2, tree_r2, forest_r2]
})
```

In [75]:
```python
print(result.to_markdown(index=False))
```

```
| Algorithms    |   Mean_RSME |   R2_Scores |
|:--------------|------------:|------------:|
| Linear        |     4305.04 |    0.948661 |
| Decision_Tree |     2721.58 |    0.980744 |
| Random_Forest |     2179.66 |    0.98699  |
```

In [76]:
```python
plt.figure(figsize=(6, 4))
sns.barplot(data=result, x='Algorithms', y='Mean_RSME', palette="Set1", width=0.5)
plt.show()
```



Random Forest Regressor Performance

- **Random Forest Regressor** is the **best model** with the **highest accuracy of 98%**.
- It also achieved the **lowest RMSE of 2,179**.

In [79]:
```python
from scipy import stats

confidence = 0.95
squared_errors = (forest_pred - y_test) ** 2
lower_bound, upper_bound = np.sqrt(stats.t.interval(confidence, len(squared_errors)
```

```
                              loc=squared_errors.mean(),
                              scale=stats.sem(squared_errors)))
```

In [80]:
```
print(f"Lower Bound: {lower_bound:.2f}")
print(f"Upper Bound: {upper_bound:.2f}")
```

```
Lower Bound: 2075.01
Upper Bound: 2266.28
```

95% confidence

- **Lower Bound :** 2034.67
- **Upper Bound :** 2201.53

Answers Research Questions

1. **Does price vary with Airlines?**
   Yes It Does.
   Vistara and **Air India** are notably more expensive compared to other airlines.

2. **How is the price affected when tickets are bought just 1 or 2 days before departure?**
   1 Day Before: Potential for a price drop(same as 15 days Before).
   2 Days Before: Prices typically increase due to high demand and limited availability.

3. **Does ticket price change based on the departure time and arrival time?**
   Late-Night Flights: Typically have the **lowest prices**.
   Afternoon Flights: Generally have the **second lowest prices**.
   Other Times: Prices are **almost equal** across different times of the day.

   This pricing trend reflects the demand for flight times, with late-night and afternoon departures often being less desirable for most travelers.

4. **How does the price change with the Source and Destination?**
   Ticket prices **do not significantly change** based on the source and destination.
   Prices **do change** based on the **distance traveled**.

5. **How does the ticket price vary between Economy and Business class?**
   Business class flights are **obviously more expensive** than Economy class flights.

- **Business Class:**
  - For flight durations between **1 to 5 hours**, prices **grow sharply**.

        - For durations **more than 5 hours**, prices remain within a **range of 45,000 to 60,000**.

- **Economy Class:**

    - Price shows a **linear growth** with increasing flight duration.
    - A **sharp price increase** is observed for flights with a duration of **47 hours**.

In [ ]:

```

```

In [ ]:

```

```