In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df=pd.read_csv("/Users/tanya/Downloads/projects/Clean_Dataset.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	Unnamed: 0	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	0	SpiceJet	SG-8709	Delhi	Evening	zero	Night	Mumbai	Economy	2.17	1	5953
1	1	SpiceJet	SG-8157	Delhi	Early_Morning	zero	Morning	Mumbai	Economy	2.33	1	5953
2	2	AirAsia	I5-764	Delhi	Early_Morning	zero	Early_Morning	Mumbai	Economy	2.17	1	5956
3	3	Vistara	UK-995	Delhi	Morning	zero	Afternoon	Mumbai	Economy	2.25	1	5955
4	4	Vistara	UK-963	Delhi	Morning	zero	Morning	Mumbai	Economy	2.33	1	5955

In [4]:
```
#Dropping the first column since it isn't required.
df.drop("Unnamed: 0",axis=1,inplace=True)
```

In [5]:
```
print("There are {} observations for {} predictors.".format(df.shape[0],df.shape[1]))
```

```
There are 300153 observations for 11 predictors.
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
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
```

In [7]:
```
df.duplicated().sum()
```

Out[7]:
```
0
```

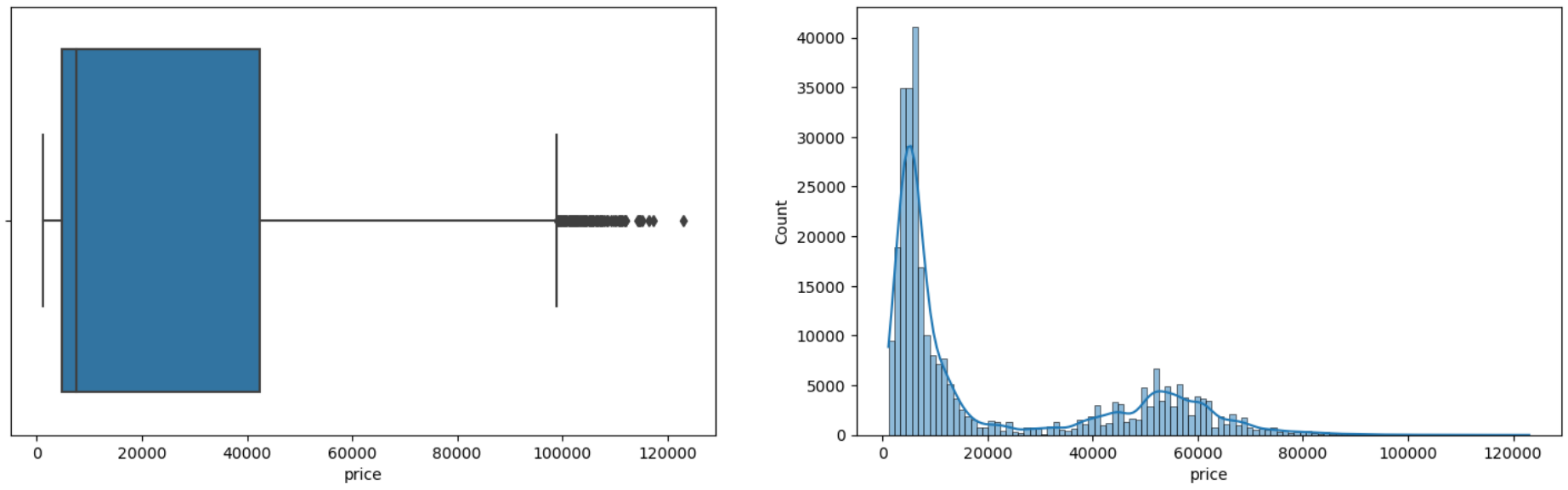
In [8]:
```
df.describe(include='all').T
```

Out[8]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
airline	300153	6	Vistara	127859	NaN	NaN	NaN	NaN	NaN	NaN	NaN
flight	300153	1561	UK-706	3235	NaN	NaN	NaN	NaN	NaN	NaN	NaN
source_city	300153	6	Delhi	61343	NaN	NaN	NaN	NaN	NaN	NaN	NaN
departure_time	300153	6	Morning	71146	NaN	NaN	NaN	NaN	NaN	NaN	NaN
stops	300153	3	one	250863	NaN	NaN	NaN	NaN	NaN	NaN	NaN
arrival_time	300153	6	Night	91538	NaN	NaN	NaN	NaN	NaN	NaN	NaN
destination_city	300153	6	Mumbai	59097	NaN	NaN	NaN	NaN	NaN	NaN	NaN
class	300153	2	Economy	206666	NaN	NaN	NaN	NaN	NaN	NaN	NaN
duration	300153.0	NaN	NaN	NaN	12.221021	7.191997	0.83	6.83	11.25	16.17	49.83
days_left	300153.0	NaN	NaN	NaN	26.004751	13.561004	1.0	15.0	26.0	38.0	49.0
price	300153.0	NaN	NaN	NaN	20889.660523	22697.767366	1105.0	4783.0	7425.0	42521.0	123071.0

In [9]:
```
plt.figure(figsize = (18,5))
plt.subplot(1,2,2)
sns.histplot(x = 'price', data = df, kde = True)
plt.subplot(1,2,1)
sns.boxplot(x = 'price', data = df)
```

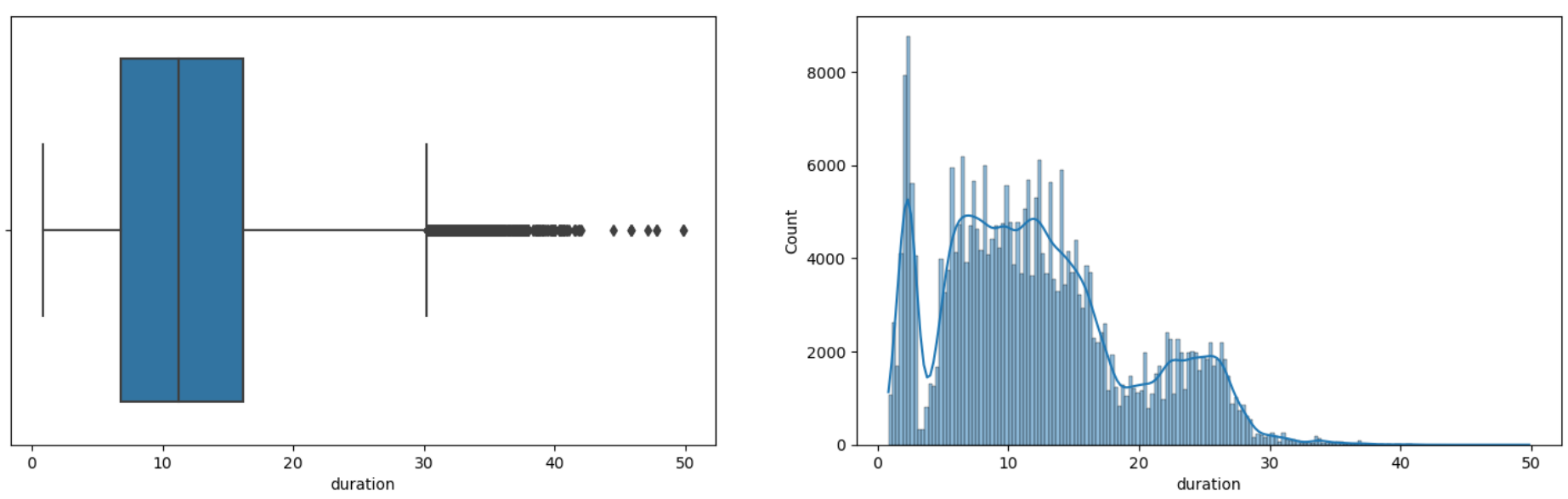
Out[9]: <AxesSubplot:xlabel='price'>



Even though the mean is around 20000, we can see here that the median is approximately 7500. This difference is explainable by the presence of two different tickets: business and economy. On the second graph, we can see that the dispersion seems to be composed by two gaussian curves.

In [10]:
```
plt.figure(figsize = (18,5))
plt.subplot(1,2,2)
sns.histplot(x = 'duration', data = df, kde = True)
plt.subplot(1,2,1)
sns.boxplot(x = 'duration', data = df)
```

Out[10]: <AxesSubplot:xlabel='duration'>



In [11]:
```
# Let's get the count values of the data corresponding to those outliers in each feature:
print ("'duration' feature Outliers:", df[df['duration']>30].count(), sep = '\n')
```

```
'duration' feature Outliers:
airline             2226
flight              2226
source_city         2226
departure_time      2226
stops               2226
arrival_time        2226
destination_city    2226
class               2226
duration            2226
days_left           2226
price               2226
dtype: int64
```

In [12]:
```
# Get the outliers (with their corresponding data) percentage:
(2226/300153)*100
```

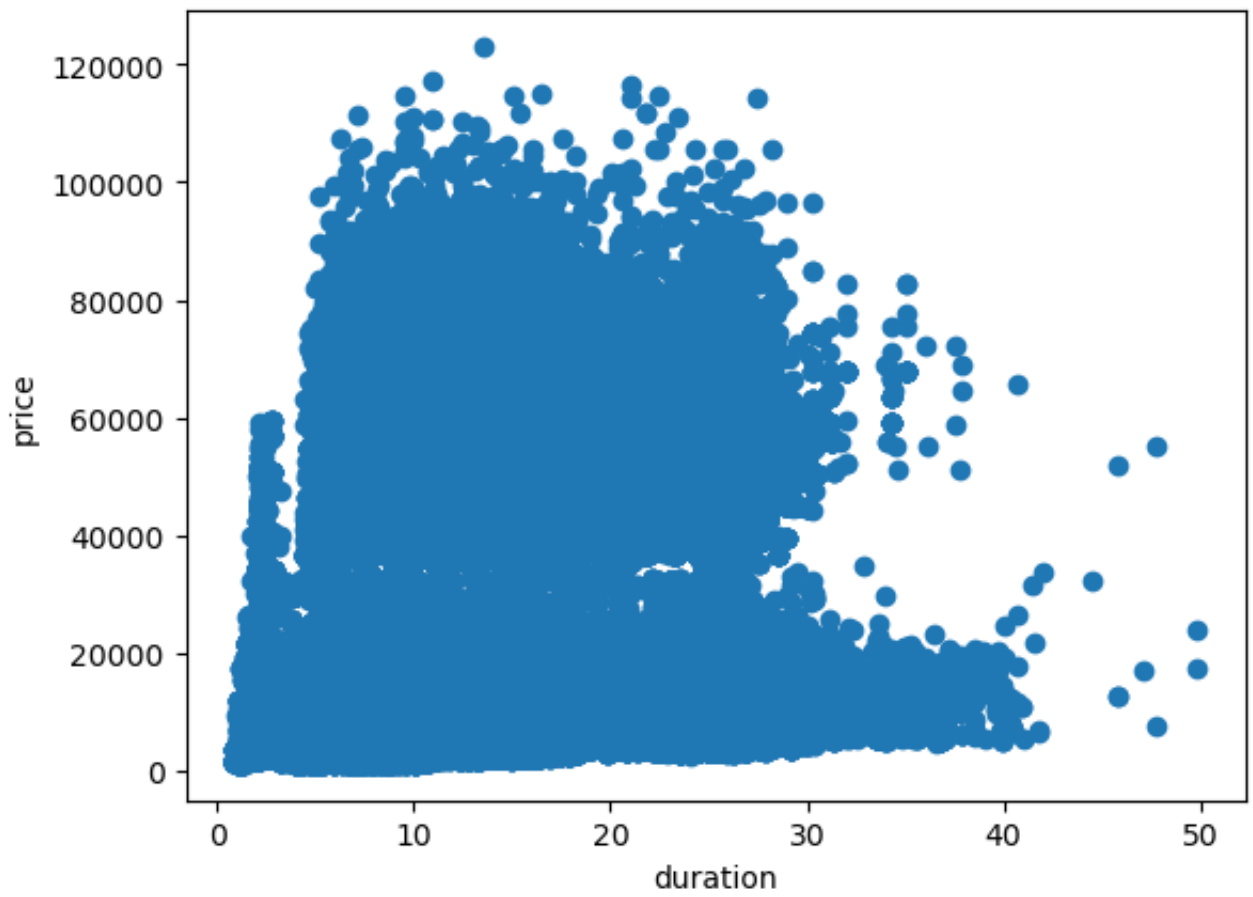
Out[12]: 0.7416217728958232

We can see that it's a very very small percentage (≈0.74%), so we can drop them with a great confidence, but because we will be dropping some critical data from the "days_left" feature; we need to double check, in case we don't want to drop those critical data from the "days_left" feature or in case the percentage was great (>10%).

So, let's use some visualizations:

In [13]:
```
plt.scatter(df['duration'] , df['price'])
plt.xlabel ("duration")
plt.ylabel ("price")
```

Out[13]:
```
Text(0, 0.5, 'price')
```



In [14]:
```
print ("'duration' feature most Outliers:", df[df['duration']>40].count(), sep = '\n')
```

```
'duration' feature most Outliers:
airline             48
flight              48
source_city         48
departure_time      48
stops               48
arrival_time        48
destination_city    48
class               48
duration            48
days_left           48
price               48
dtype: int64
```

Now we can drop those very very tiny outliers with their very very tiny corresponding data, and that if we don't want to lose much data by removing the 2226 observations.

In [15]:
```
df_new = df[df['duration']<=40]
df_new.shape
```

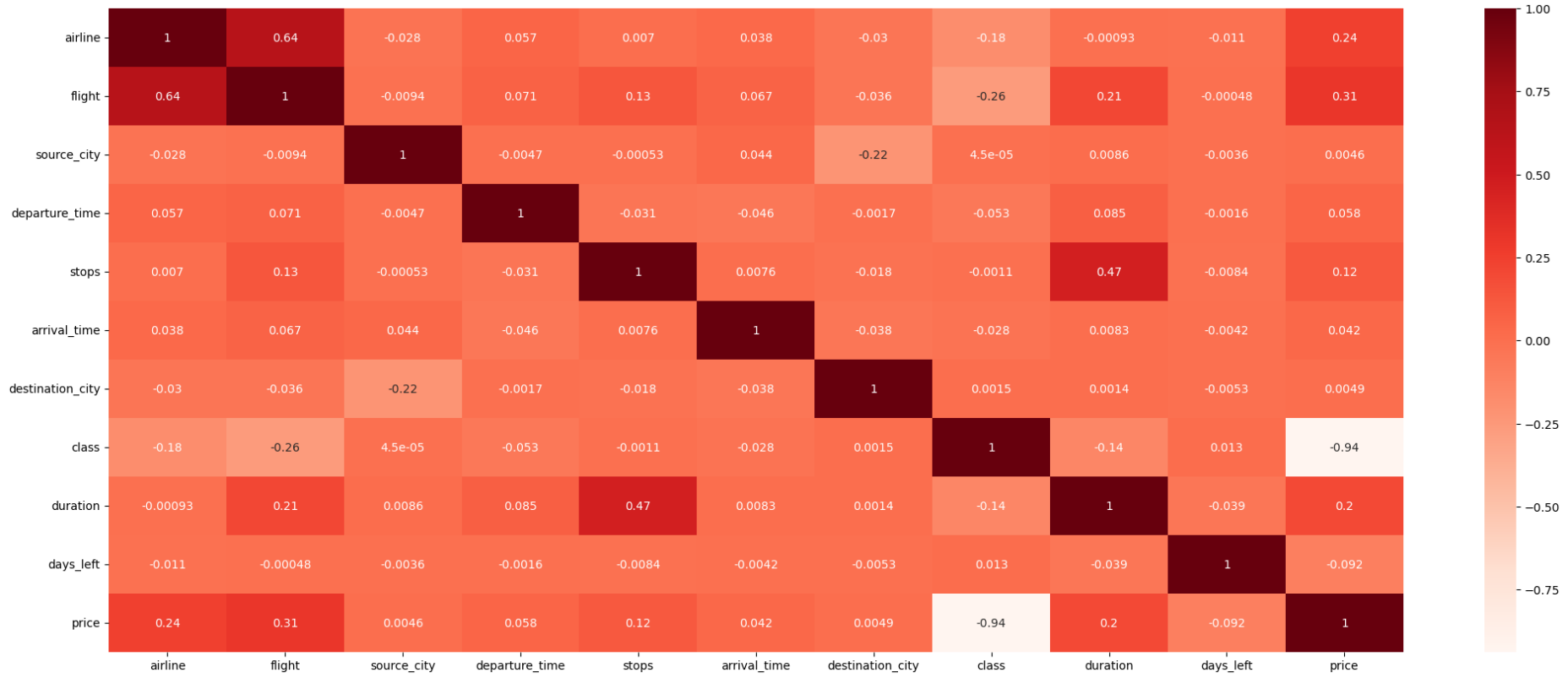
Out[15]:
```
(300105, 11)
```

In [16]:
```
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df_new['stops'] = df_new['stops'].replace({'one': 1,
                                           'zero': 0,
                                           'two_or_more': 2})
categorical = ['flight','airline','source_city','departure_time', 'arrival_time', 'destination_city','cl
df_new[categorical] = df_new[categorical].apply(label_encoder.fit_transform)
df_new.tail()
```

Out[16]:

	airline	flight	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
300148	5	1477	1	4	1	2	3	0	10.08	49	69265
300149	5	1481	1	0	1	5	3	0	10.42	49	77105
300150	5	1486	1	1	1	5	3	0	13.83	49	79099
300151	5	1483	1	1	1	2	3	0	10.00	49	81585
300152	5	1477	1	4	1	2	3	0	10.08	49	81585

In [17]:
```
plt.figure(figsize=(25,10))
cor = df_new.corr()
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```



In [18]:
```
df_new2 = df_new.drop('flight', axis = 1)
df_new2.head()
```

Out[18]:

	airline	source_city	departure_time	stops	arrival_time	destination_city	class	duration	days_left	price
0	4	2	2	0	5	5	1	2.17	1	5953
1	4	2	1	0	4	5	1	2.33	1	5953
2	0	2	1	0	1	5	1	2.17	1	5956
3	5	2	4	0	0	5	1	2.25	1	5955
4	5	2	4	0	4	5	1	2.33	1	5955

In [19]:
```
X = df_new2.drop('price', axis = 1)
y = df_new2['price']
```

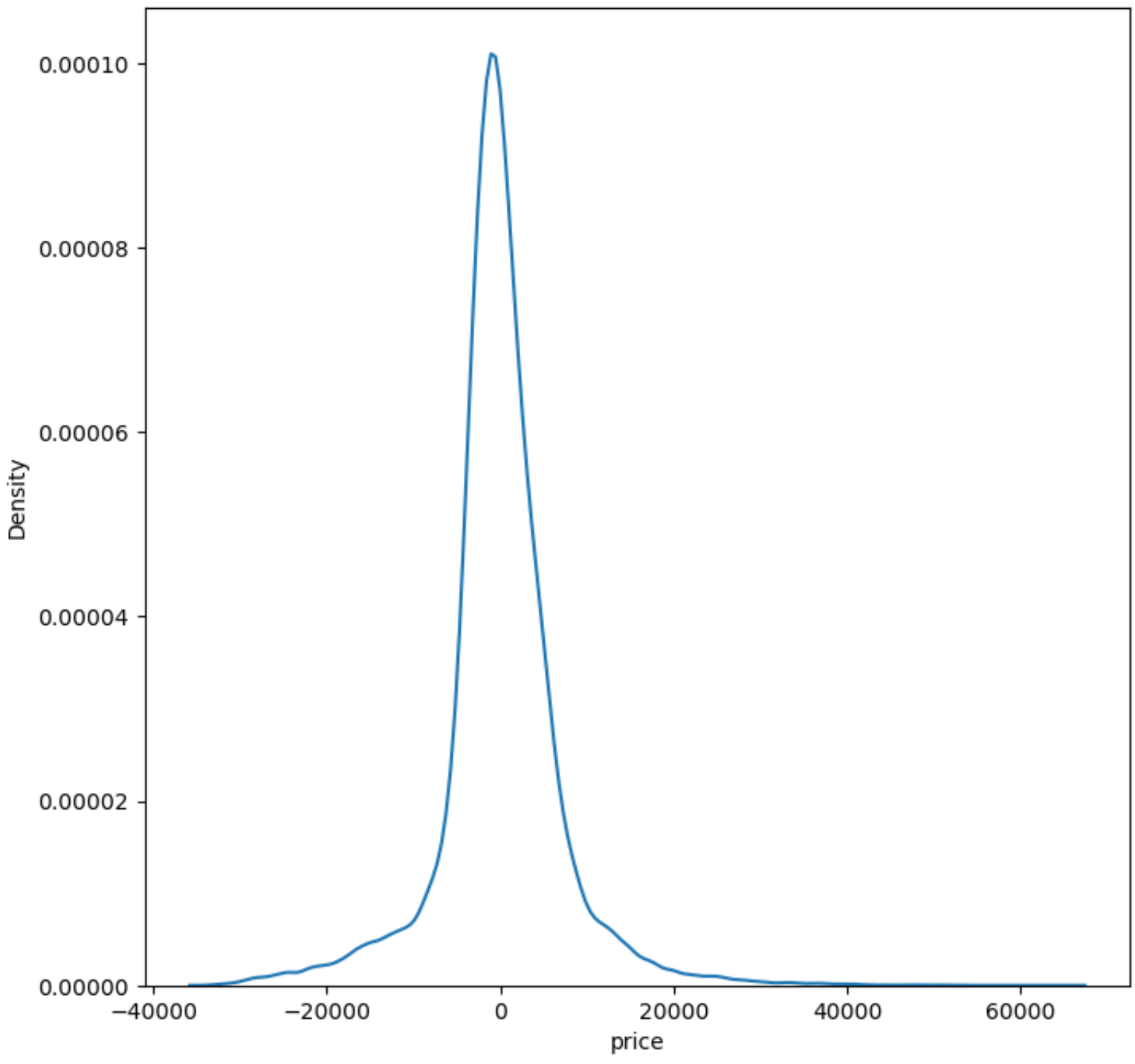
In [20]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [25]:
```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error


reg = LinearRegression().fit(X_train, y_train)


y_pred_train = reg.predict(X_train)
y_pred_test = reg.predict(X_test)
accuracy_train = reg.score(X_train, y_train)
mse_train = mean_squared_error(y_train, y_pred_train)
r2_train = r2_score(y_train, y_pred_train)
```

In [24]:
```
print("R2 Score: ",r2_score(y_test,y_pred_test))
print("Mean Squared Error: ",mean_squared_error(y_test, y_pred_test))
print('Mean Absolute Error', mean_absolute_error(y_test, y_pred_test))
print('Root Mean Squared Error:', np.sqrt(mean_squared_error(y_test, y_pred_test)))
```

```
R2 Score:  0.9072851590051217
Mean Squared Error:  47644356.167438075
Mean Absolute Error 4518.177774644642
Root Mean Squared Error: 6902.489128382462
```

In [26]:
```
plt.figure(figsize = (8,8))
sns.kdeplot(y_test-y_pred_test)
plt.show()
```



In [ ]: