Forecasting Real Estate Market with Linear Regression

Overview of Real Estate Market Dataset ¶

In [2]:
```
import pandas as pd
```

In [3]:
```
data = pd.read_csv("Real_Estate_Sales_2001-2020_GL.csv", low_memory=False)
```

In [4]:
```
data.head()
```

Out[4]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type	Residen Ty
0	2020177	2020	04/14/2021	Ansonia	323 BEAVER ST	133000.0	248400.0	0.5354	Residential	Sin Far
1	2020225	2020	05/26/2021	Ansonia	152 JACKSON ST	110500.0	239900.0	0.4606	Residential	Th Far
2	2020348	2020	09/13/2021	Ansonia	230 WAKELEE AVE	150500.0	325000.0	0.4630	Commercial	N
3	2020090	2020	12/14/2020	Ansonia	57 PLATT ST	127400.0	202500.0	0.6291	Residential	Two Far
4	200500	2020	09/07/2021	Avon	245 NEW ROAD	217640.0	400000.0	0.5441	Residential	Sin Far

In [5]:
```
data.tail()
```

Out[5]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Propert Typ
997208	190272	2019	06/24/2020	New London	4 BISHOP CT	60410.0	53100.0	1.137665	Singl Famil
997209	190284	2019	11/27/2019	Waterbury	126 PERKINS AVE	68280.0	76000.0	0.898400	Singl Famil
997210	190129	2019	04/27/2020	Windsor Locks	19 HATHAWAY ST	121450.0	210000.0	0.578300	Singl Famil
997211	190504	2019	06/03/2020	Middletown	8 BYSTREK DR	203360.0	280000.0	0.726300	Singl Famil
997212	190344	2019	12/20/2019	Milford	250 RESEARCH DR	4035970.0	7450000.0	0.541700	Nal

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 997213 entries, 0 to 997212
Data columns (total 14 columns):
 #   Column            Non-Null Count   Dtype  
---  ------            --------------   -----  
 0   Serial Number     997213 non-null  int64  
 1   List Year         997213 non-null  int64  
 2   Date Recorded     997211 non-null  object 
 3   Town              997213 non-null  object 
 4   Address           997162 non-null  object 
 5   Assessed Value    997213 non-null  float64
 6   Sale Amount       997213 non-null  float64
 7   Sales Ratio       997213 non-null  float64
 8   Property Type     614767 non-null  object 
 9   Residential Type  608904 non-null  object 
 10  Non Use Code      289681 non-null  object 
 11  Assessor Remarks  149864 non-null  object 
 12  OPM remarks       9934 non-null    object 
 13  Location          197697 non-null  object 
dtypes: float64(3), int64(2), object(9)
memory usage: 106.5+ MB
```

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

Out[7]:

	Serial Number	List Year	Assessed Value	Sale Amount	Sales Ratio
count	9.972130e+05	997213.000000	9.972130e+05	9.972130e+05	9.972130e+05
mean	4.311864e+05	2010.189829	2.791437e+05	3.911512e+05	1.044637e+01
std	6.549219e+06	6.237877	1.670610e+06	5.347270e+06	1.890192e+03
min	0.000000e+00	2001.000000	0.000000e+00	0.000000e+00	0.000000e+00
25%	3.044400e+04	2004.000000	8.760000e+04	1.400000e+05	4.867000e-01
50%	7.030300e+04	2010.000000	1.383900e+05	2.250000e+05	6.246000e-01
75%	1.518780e+05	2016.000000	2.255600e+05	3.650000e+05	7.852761e-01
max	2.000500e+09	2020.000000	8.815100e+08	5.000000e+09	1.226420e+06

In [8]:
```
data.shape
```

Out[8]:
```
(997213, 14)
```

In [9]:
```
data.columns
```

Out[9]:
```
Index(['Serial Number', 'List Year', 'Date Recorded', 'Town', 'Address',
       'Assessed Value', 'Sale Amount', 'Sales Ratio', 'Property Type',
       'Residential Type', 'Non Use Code', 'Assessor Remarks', 'OPM remarks',
       'Location'],
      dtype='object')
```

In [10]:
```
data.dtypes
```

Out[10]:
```
Serial Number          int64
List Year              int64
Date Recorded         object
Town                  object
Address               object
Assessed Value       float64
Sale Amount          float64
Sales Ratio          float64
Property Type         object
Residential Type      object
Non Use Code          object
Assessor Remarks      object
OPM remarks           object
Location              object
dtype: object
```

Cleaning Dataset

In [11]:
```
import numpy as np
```

In [12]:
```
missing_values_columns = data.isnull().sum()
print("Missing values in columns:")
print(missing_values_columns)
```

```
Missing values in columns:
Serial Number            0
List Year                0
Date Recorded            2
Town                     0
Address                 51
Assessed Value           0
Sale Amount              0
Sales Ratio              0
Property Type       382446
Residential Type    388309
Non Use Code        707532
Assessor Remarks    847349
OPM remarks         987279
Location            799516
dtype: int64
```

In [13]:
```
missing_values_rows = data.isnull().any(axis=1)
print("Missing values in rows:")
print(missing_values_rows)
```

```
Missing values in rows:
0          True
1          True
2          True
3          True
4          True
           ...
997208     True
997209     True
997210     True
997211     True
997212     True
Length: 997213, dtype: bool
```

In [14]:
```
duplicate_values = data[data.duplicated()]
print("Duplicate Rows:")
print(duplicate_values)
```

```
Duplicate Rows:
Empty DataFrame
Columns: [Serial Number, List Year, Date Recorded, Town, Address, Assessed Valu
e, Sale Amount, Sales Ratio, Property Type, Residential Type, Non Use Code, Ass
essor Remarks, OPM remarks, Location]
Index: []
```

In [15]:
```
data.dropna(axis=0,inplace=True)
```

In [16]:
```
data.head()
```

Out[16]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Propert Typ
759	200594	2020	02/16/2021	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residenti
933	200562	2020	02/03/2021	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residenti
1470	200260	2020	11/23/2020	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residenti
2107	200148	2020	01/05/2021	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residenti
2400	200000411	2020	09/10/2021	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residenti

In [17]:
```
data.shape
```

Out[17]:
```
(264, 14)
```

Detecting & Removing Potential Outliers

In [18]:
```
z_threshold = 3
z_scores = np.abs((data["Sale Amount"]-data["Sale Amount"].mean())/data["Sale Am
ount"].std())
```

In [19]:
```
data["Sale Amount Outlier"] = np.where(z_scores > z_threshold, True, False)
```

In [20]:
```
existing_outlier = data[data["Sale Amount Outlier"]]
print("Existing Outilers:")
print(existing_outlier)
```

```
Existing Outilers:
       Serial Number  List Year Date Recorded        Town          Address  \
60822       20200078       2020    07/06/2021  Willington  224 RIVER ROAD

       Assessed Value  Sale Amount  Sales Ratio Property Type  \
60822        223070.0  318790019.0       0.0007   Residential

      Residential Type Non Use Code Assessor Remarks  \
60822    Single Family    25 - Other        COLONIAL

                          OPM remarks                      Location  \
60822  INCORRECT SALE PRICE - NO MLS  POINT (-72.30341 41.86603)

       Sale Amount Outlier
60822                 True
```

In [21]:
```
data = data[data["Sale Amount Outlier"]==False]
```

In [22]:
```
data.head()
```

Out[22]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Propert Typ
759	200594	2020	02/16/2021	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residenti
933	200562	2020	02/03/2021	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residenti
1470	200260	2020	11/23/2020	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residenti
2107	200148	2020	01/05/2021	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residenti
2400	200000411	2020	09/10/2021	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residenti

Analyzing the Annual Mean and Median of Property Prices

In [23]:
```
import matplotlib.pyplot as plt
```

In [24]:
```
data.head()
```

Out[24]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Propert Typ
759	200594	2020	02/16/2021	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residenti
933	200562	2020	02/03/2021	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residenti
1470	200260	2020	11/23/2020	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residenti
2107	200148	2020	01/05/2021	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residenti
2400	200000411	2020	09/10/2021	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residenti

In [25]:
```
data["Date Recorded"] = pd.to_datetime(data["Date Recorded"])
```

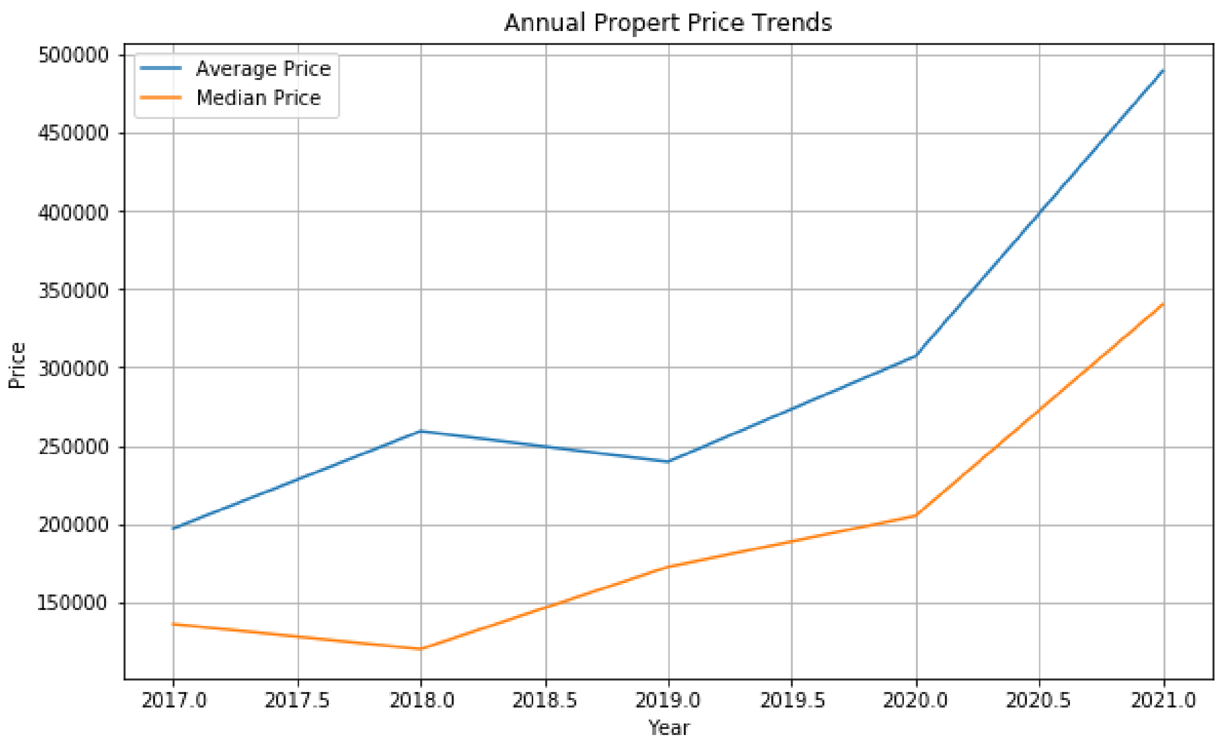
In [26]:
```
data["Year"] =data["Date Recorded"].dt.year
```

In [27]:
```
annual_average_price = data.groupby("Year")["Sale Amount"].mean()
annual_median_price = data.groupby("Year")["Sale Amount"].median()
```

In [28]:
```
print("Annual Average Sale Price")
print(annual_average_price)
print("Annual Median Sale Price")
print(annual_median_price)
```

```
Annual Average Sale Price
Year
2017    197031.156250
2018    259195.272727
2019    239647.863636
2020    306981.873016
2021    489138.797101
Name: Sale Amount, dtype: float64
Annual Median Sale Price
Year
2017    136000.0
2018    120000.0
2019    172500.0
2020    205000.0
2021    340000.0
Name: Sale Amount, dtype: float64
```

In [90]:
```
plt.figure(figsize=(10,6))
plt.plot(annual_average_price.index,annual_average_price.values,label="Average P
rice")
plt.plot(annual_median_price .index,annual_median_price.values,label="Median Pri
ce")
plt.xlabel("Year")
plt.ylabel("Price")
plt.title("Annual Propert Price Trends")
plt.legend()
plt.grid(True)
plt.show()
```



Finding Correlation Between Property Type&Price

In [92]:
```
import seaborn as sns
```

In [31]:
```
data.head()
```

Out[31]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type
759	200594	2020	2021-02-16	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residentia
933	200562	2020	2021-02-03	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residentia
1470	200260	2020	2020-11-23	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residentia
2107	200148	2020	2021-01-05	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residentia
2400	200000411	2020	2021-09-10	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residentia

In [32]:
```
data["Date Recorded"] = pd.to_datetime(data["Date Recorded"])
```

In [33]:
```
data["Date Recorded"]
```

Out[33]:
```
759       2021-02-16
933       2021-02-03
1470      2020-11-23
2107      2021-01-05
2400      2021-09-10
             ...
988397    2020-08-17
988668    2020-06-17
988906    2019-10-28
989292    2020-06-08
993144    2020-01-06
Name: Date Recorded, Length: 263, dtype: datetime64[ns]
```

In [34]:
```
data["Year"] =data["Date Recorded"].dt.year
```

In [35]:
```
data["Year"]
```

Out[35]:
```
759       2021
933       2021
1470      2020
2107      2021
2400      2021
          ...
988397    2020
988668    2020
988906    2019
989292    2020
993144    2020
Name: Year, Length: 263, dtype: int64
```

In [36]:
```
annual_mean_price = data.groupby(['Year','Residential Type','Property Type'])["Sale Amount"].mean().reset_index()
```

In [37]:
```
annual_mean_price
```

Out[37]:

	Year	Residential Type	Property Type	Sale Amount
0	2017	Condo	Condo	2.844990e+05
1	2017	Single Family	Single Family	1.922292e+05
2	2017	Three Family	Three Family	1.765000e+05
3	2017	Two Family	Two Family	1.320000e+05
4	2018	Condo	Condo	1.180500e+05
5	2018	Four Family	Four Family	2.043333e+06
6	2018	Single Family	Single Family	1.771669e+05
7	2018	Three Family	Three Family	1.038333e+05
8	2018	Two Family	Two Family	1.481667e+05
9	2019	Condo	Condo	2.343595e+05
10	2019	Single Family	Single Family	2.471012e+05
11	2019	Three Family	Three Family	2.000000e+05
12	2019	Two Family	Two Family	1.895000e+05
13	2020	Condo	Condo	2.472700e+05
14	2020	Condo	Residential	2.534651e+05
15	2020	Four Family	Four Family	4.750000e+05
16	2020	Single Family	Residential	4.590909e+05
17	2020	Single Family	Single Family	3.156060e+05
18	2020	Two Family	Residential	2.380000e+05
19	2020	Two Family	Two Family	1.216667e+05
20	2021	Condo	Residential	2.748382e+05
21	2021	Single Family	Residential	5.144004e+05
22	2021	Three Family	Residential	1.080000e+06
23	2021	Two Family	Residential	6.087500e+05

In [38]:
```
pivot_table = annual_mean_price.pivot_table(values="Sale Amount",index="Year",co
lumns=['Residential Type','Property Type'])
```

In [39]:
```
pivot_table
```

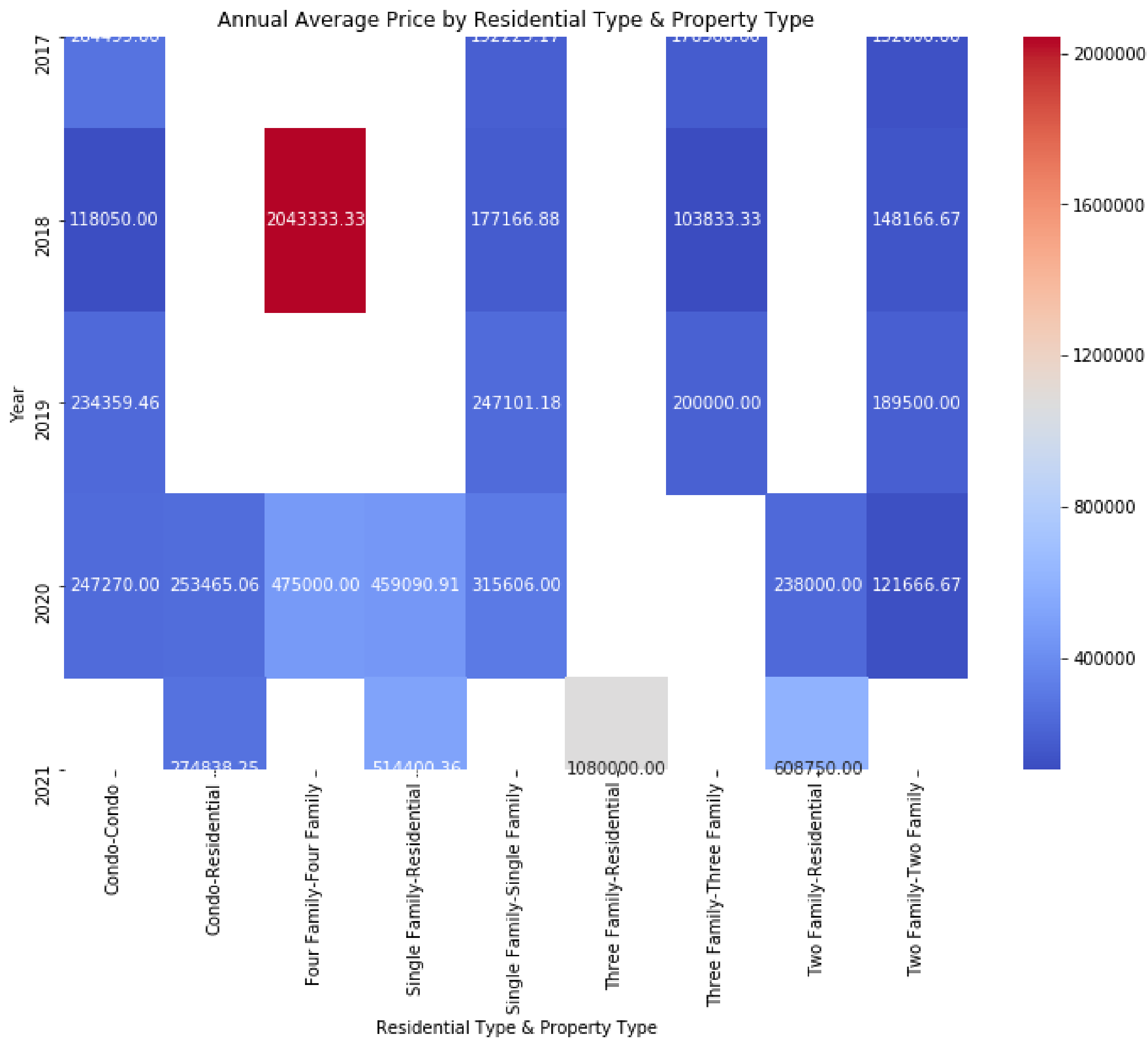
Out[39]:

Residential Type	Condo		Four Family	Single Family		Three Famil
Property Type	Condo	Residential	Four Family	Residential	Single Family	Residential
Year						
2017	284499.000000	NaN	NaN	NaN	192229.166667	NaN
2018	118050.000000	NaN	2.043333e+06	NaN	177166.875000	NaN
2019	234359.461538	NaN	NaN	NaN	247101.178571	NaN
2020	247270.000000	253465.058824	4.750000e+05	459090.909091	315606.000000	NaN
2021	NaN	274838.250000	NaN	514400.360000	NaN	1080000.0

In [40]:

```
plt.figure(figsize=(12,8))
sns.heatmap(pivot_table,cmap="coolwarm",annot=True,fmt=".2f",cbar=True)
plt.xlabel("Residential Type & Property Type")
plt.ylabel("Year")
plt.title("Annual Average Price by Residential Type & Property Type")
plt.show()

data.head(3)
```



Out[40]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type	Resi
759	200594	2020	2021-02-16	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residential	
933	200562	2020	2021-02-03	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residential	
1470	200260	2020	2020-11-23	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residential	

Analysing Real Market Trend & Finding Investment Opportunities

In [41]:
```
data.head()
```

Out[41]:

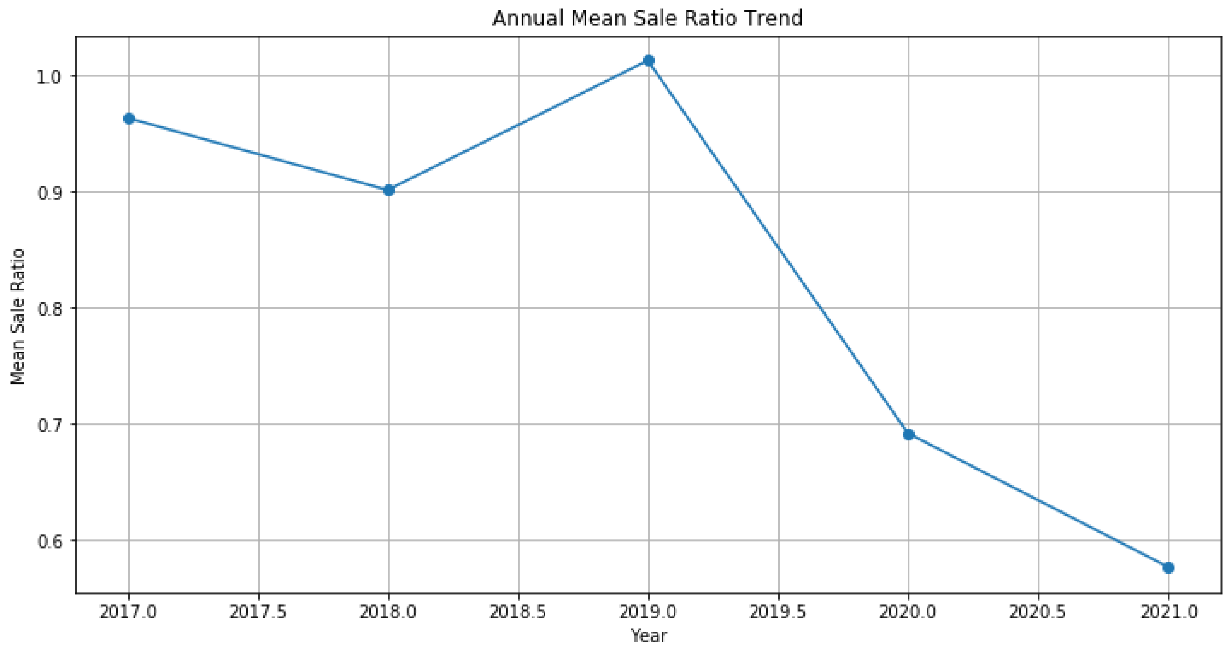
	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type
759	200594	2020	2021-02-16	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residentia
933	200562	2020	2021-02-03	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residentia
1470	200260	2020	2020-11-23	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residentia
2107	200148	2020	2021-01-05	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residentia
2400	200000411	2020	2021-09-10	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residentia

In [42]:
```
data["Date Recorded"] = pd.to_datetime(data["Date Recorded"])
```

In [43]:
```
data["Year"] =data["Date Recorded"].dt.year
```

In [44]:
```
annual_mean_sales_ratio = data.groupby("Year")["Sales Ratio"].mean()
```

In [95]:
```
plt.figure(figsize=(12,6))
plt.plot(annual_mean_sales_ratio.index,annual_mean_sales_ratio,marker='o',linest
yle='-')
plt.xlabel("Year")
plt.ylabel("Mean Sale Ratio")
plt.title("Annual Mean Sale Ratio Trend")
plt.grid(True)
plt.show()
```



In [46]:
```
threshold_ratio = 0.8
low_ratio_properties = data[data["Sales Ratio"]<threshold_ratio]
```

In [47]:
```
print("Potential Investment Opportunities:")
print(low_ratio_properties[["Address","Sale Amount","Assessed Value","Sales Rati
o"]])
```

```
Potential Investment Opportunities:
                       Address  Sale Amount  Assessed Value  Sales Ratio
933                 19  MILL RD     415000.0        263600.0     0.635181
1470     32 COALPIT HILL RD #4     181778.0         84900.0     0.467053
2107         23 CHEPACHET ROAD     430000.0        165260.0     0.384326
2400           11 BRISTOL PATH     180000.0          3770.0     0.020944
2662     32 COALPIT HILL RD #6     181778.0         84900.0     0.467053
...                         ...          ...             ...          ...
967922           128 MARTIN RD     255000.0        115080.0     0.451300
973206            5108 MAIN ST     362000.0        169890.0     0.469309
975297         36 DARTMOUTH LA     320000.0        169200.0     0.528800
984216         23 WALTON STREET     520000.0        151600.0     0.291538
988906          129 CAYUGA DR     157000.0         68200.0     0.434400

[150 rows x 4 columns]
```

In [48]:
```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
import joblib
```

In [49]:
```
old_data = pd.read_csv("Real_Estate_Sales_2001-2020_GL.csv", low_memory=False)
```

In [50]:
```
old_data.head()
```

Out[50]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type	Residen Ty
0	2020177	2020	04/14/2021	Ansonia	323 BEAVER ST	133000.0	248400.0	0.5354	Residential	Sin Far
1	2020225	2020	05/26/2021	Ansonia	152 JACKSON ST	110500.0	239900.0	0.4606	Residential	Th Far
2	2020348	2020	09/13/2021	Ansonia	230 WAKELEE AVE	150500.0	325000.0	0.4630	Commercial	N
3	2020090	2020	12/14/2020	Ansonia	57 PLATT ST	127400.0	202500.0	0.6291	Residential	Two Far
4	200500	2020	09/07/2021	Avon	245 NEW ROAD	217640.0	400000.0	0.5441	Residential	Sin Far

In [51]:
```
old_data["Date Recorded"] = pd.to_datetime(data["Date Recorded"])
```

In [52]:
```
old_data.set_index("Date Recorded",inplace=True)
```

In [53]:
```
y = old_data["Sale Amount"].values
```

In [54]:
```
X = old_data[["Assessed Value"]].values
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,shuffle=Fa
lse)
```

In [56]:
```
lr_model = LinearRegression()
lr_model.fit(X_train,y_train)
```

Out[56]:
```
LinearRegression()
```

In [57]:
```
forecastedyear = 2050
forecasted_price_lr = lr_model.predict(np.array([[forecastedyear]]))
```

In [58]:
```
print(f"Year {forecastedyear}: Predicted Price: ${float(forecasted_price_lr
[0]):.2f}")
```

```
Year 2050: Predicted Price: $268736.23
```

Forecasting Real Estate with LSTM Model

In [59]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
import joblib
```

In [88]:
```
old_data = pd.read_csv("Real_Estate_Sales_2001-2020_GL.csv")
```

In [61]:
```
old_data.head()
```

Out[61]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type	Residen Ty
0	2020177	2020	04/14/2021	Ansonia	323 BEAVER ST	133000.0	248400.0	0.5354	Residential	Sin Far
1	2020225	2020	05/26/2021	Ansonia	152 JACKSON ST	110500.0	239900.0	0.4606	Residential	Th Far
2	2020348	2020	09/13/2021	Ansonia	230 WAKELEE AVE	150500.0	325000.0	0.4630	Commercial	N
3	2020090	2020	12/14/2020	Ansonia	57 PLATT ST	127400.0	202500.0	0.6291	Residential	Two Far
4	200500	2020	09/07/2021	Avon	245 NEW ROAD	217640.0	400000.0	0.5441	Residential	Sin Far

In [62]:
```
old_data["Date Recorded"] = pd.to_datetime(old_data["Date Recorded"])
```

In [63]:
```
old_data.set_index("Date Recorded",inplace=True)
```

In [64]:
```
y = old_data["Sale Amount"].values
```

In [65]:
```
X = old_data[["Assessed Value"]].values
```

In [66]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,shuffle=Fa
lse)
```

In [67]:
```
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [68]:
```
X_train_reshaped = X_train_scaled.reshape(X_train_scaled.shape[0], 1,X_train_sca
led.shape[1])
X_test_reshaped = X_test_scaled.reshape(X_test_scaled.shape[0], 1,X_test_scaled.
shape[1])
```

In [69]:
```
lstm_model = Sequential()
lstm_model.add(LSTM(50,activation='relu',input_shape=(1,X_train_scaled.shape
[1])))
lstm_model.add(Dense(1))
lstm_model.compile(optimizer='adam',loss='mse')
```

In [70]:

```
lstm_model.fit(X_train_reshaped, y_train, epochs=50, batch_size=32, verbose=1)
```

```
Epoch 1/50
24931/24931 [==============================] - 134s 5ms/step - loss: 3339139520
9216.0000
Epoch 2/50
24931/24931 [==============================] - 133s 5ms/step - loss: 3338175250
4320.0000
Epoch 3/50
24931/24931 [==============================] - 132s 5ms/step - loss: 3336450342
9120.0000
Epoch 4/50
24931/24931 [==============================] - 134s 5ms/step - loss: 3334528303
1040.0000
Epoch 5/50
24931/24931 [==============================] - 138s 6ms/step - loss: 3332629122
2528.0000
Epoch 6/50
24931/24931 [==============================] - 147s 6ms/step - loss: 3330357487
2064.0000
Epoch 7/50
24931/24931 [==============================] - 142s 6ms/step - loss: 3328140168
3968.0000
Epoch 8/50
24931/24931 [==============================] - 139s 6ms/step - loss: 3326899073
8432.0000
Epoch 9/50
24931/24931 [==============================] - 142s 6ms/step - loss: 3325866855
6288.0000
Epoch 10/50
24931/24931 [==============================] - 142s 6ms/step - loss: 3325329145
8560.0000
Epoch 11/50
24931/24931 [==============================] - 141s 6ms/step - loss: 3325043723
4688.0000
Epoch 12/50
24931/24931 [==============================] - 137s 5ms/step - loss: 3324893357
6704.0000
Epoch 13/50
24931/24931 [==============================] - 135s 5ms/step - loss: 3325030930
8416.0000
Epoch 14/50
24931/24931 [==============================] - 138s 6ms/step - loss: 3325018347
9296.0000
Epoch 15/50
24931/24931 [==============================] - 133s 5ms/step - loss: 3324819118
4896.0000
Epoch 16/50
24931/24931 [==============================] - 128s 5ms/step - loss: 3324950819
6352.0000
Epoch 17/50
24931/24931 [==============================] - 136s 5ms/step - loss: 3324739426
7136.0000
```

```
Epoch 18/50
24931/24931 [==============================] - 133s 5ms/step - loss: 3324915587
4816.0000
Epoch 19/50
24931/24931 [==============================] - 142s 6ms/step - loss: 3324684900
7616.0000
Epoch 20/50
24931/24931 [==============================] - 135s 5ms/step - loss: 3324948722
4832.0000
Epoch 21/50
24931/24931 [==============================] - 137s 5ms/step - loss: 3324619889
0496.0000
Epoch 22/50
24931/24931 [==============================] - 136s 5ms/step - loss: 3324795420
6720.0000
Epoch 23/50
24931/24931 [==============================] - 138s 6ms/step - loss: 3324818489
3440.0000
Epoch 24/50
24931/24931 [==============================] - 139s 6ms/step - loss: 3324888324
5056.0000
Epoch 25/50
24931/24931 [==============================] - 137s 5ms/step - loss: 3324871127
8592.0000
Epoch 26/50
24931/24931 [==============================] - 137s 6ms/step - loss: 3324781369
7536.0000
Epoch 27/50
24931/24931 [==============================] - 137s 5ms/step - loss: 3324584237
4656.0000
Epoch 28/50
24931/24931 [==============================] - 136s 5ms/step - loss: 3324778433
7408.0000
Epoch 29/50
24931/24931 [==============================] - 136s 5ms/step - loss: 3324612968
4480.0000
Epoch 30/50
24931/24931 [==============================] - 136s 5ms/step - loss: 3324843864
8832.0000
Epoch 31/50
24931/24931 [==============================] - 132s 5ms/step - loss: 3324759139
9424.0000
Epoch 32/50
24931/24931 [==============================] - 124s 5ms/step - loss: 3324719294
0544.0000
Epoch 33/50
24931/24931 [==============================] - 134s 5ms/step - loss: 3324708388
8640.0000
Epoch 34/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324674415
0016.0000
Epoch 35/50
```

```
24931/24931 [==============================] - 148s 6ms/step - loss: 3324582140
3136.0000
Epoch 36/50
24931/24931 [==============================] - 135s 5ms/step - loss: 3324606676
9920.0000
Epoch 37/50
24931/24931 [==============================] - 127s 5ms/step - loss: 3324597868
9536.0000
Epoch 38/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324751380
4800.0000
Epoch 39/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324796469
2480.0000
Epoch 40/50
24931/24931 [==============================] - 124s 5ms/step - loss: 3324571654
5536.0000
Epoch 41/50
24931/24931 [==============================] - 129s 5ms/step - loss: 3324627019
3664.0000
Epoch 42/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324520693
7600.0000
Epoch 43/50
24931/24931 [==============================] - 127s 5ms/step - loss: 3324681964
7488.0000
Epoch 44/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324654282
3424.0000
Epoch 45/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324571235
1232.0000
Epoch 46/50
24931/24931 [==============================] - 125s 5ms/step - loss: 3324499302
8096.0000
Epoch 47/50
24931/24931 [==============================] - 127s 5ms/step - loss: 3324771513
1392.0000
Epoch 48/50
24931/24931 [==============================] - 126s 5ms/step - loss: 3324767318
8352.0000
Epoch 49/50
24931/24931 [==============================] - 129s 5ms/step - loss: 3324689095
0656.0000
Epoch 50/50
24931/24931 [==============================] - 134s 5ms/step - loss: 3324653653
1968.0000
```

Out[70]:
```
<keras.callbacks.History at 0x159416ba748>
```

In [71]:
```
y_pred_lstm = lstm_model.predict(X_test_reshaped)
```

```
6233/6233 [==============================] - 24s 4ms/step
```

In [72]:
```
y_pred_lstm = scaler.inverse_transform(y_pred_lstm)
y_test_original = scaler.inverse_transform(y_test.reshape(-1,1))
```

In [73]:
```
forecastedyear = 2030
input_data = np.array([[forecastedyear]])
input_data_scaled = scaler.transform(input_data )
input_data_reshaped = input_data_scaled.reshape(1,1,1)
forecasted_price_lstm = lstm_model.predict(input_data_reshaped)
forecasted_price_lstm = scaler.inverse_transform(forecasted_price_lstm )
print(f"Year {forecastedyear}: Forecasted price: ${forecasted_price_lstm[0][0]:.
2f}")
```

```
1/1 [==============================] - 0s 69ms/step
Year 2030: Forecasted price: $52262772670464.00
```

Evaluating the Accuracy of Forecasting Models

Performing R-squared Analysis

In [74]:
```
data.head()
```

Out[74]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type
759	200594	2020	2021-02-16	Danbury	8 HICKORY ST	121600.0	146216.0	0.831646	Residentia
933	200562	2020	2021-02-03	Danbury	19 MILL RD	263600.0	415000.0	0.635181	Residentia
1470	200260	2020	2020-11-23	Danbury	32 COALPIT HILL RD #4	84900.0	181778.0	0.467053	Residentia
2107	200148	2020	2021-01-05	Avon	23 CHEPACHET ROAD	165260.0	430000.0	0.384326	Residentia
2400	200000411	2020	2021-09-10	Brookfield	11 BRISTOL PATH	3770.0	180000.0	0.020944	Residentia

In [75]:
```
data["Date Recorded"] = pd.to_datetime(data["Date Recorded"])
```

In [76]:
```
data.set_index("Date Recorded",inplace=True)
```

In [77]:
```
y = data["Sale Amount"].values
```

In [78]:
```
X = data[["Assessed Value"]].values
```

In [79]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,shuffle=Fa
lse)
```

In [80]:
```
lr_model = LinearRegression()
lr_model.fit(X_train,y_train)
```

Out[80]: LinearRegression()

In [81]:
```
forecastedyear = 2050
forecasted_price_lr = lr_model.predict(np.array([[forecastedyear]]))
```

In [82]:
```
print(f"Year {forecastedyear}: Predicted Price: ${float(forecasted_price_lr
[0]):.2f}")
```

```
Year 2050: Predicted Price: $-91054.01
```

In [83]:
```
y_pred_lr = lr_model.predict(X_test)
```

In [84]:
```
from sklearn.metrics import r2_score
```

In [85]:
```
r_squared_lr = r2_score(y_test,y_pred_lr)
print("Linear Regression R-squared value:", r_squared_lr)
```

```
Linear Regression R-squared value: 0.5682004023398247
```

Performing Directional Symmetry Analysis

In [86]:
```
def directional_symmetry(predictions):
    upward_changes = np.sum(np.diff(predictions) > 0)
    total_changes = len(predictions) - 1
    ds_score = upward_changes / total_changes
    return ds_score

ds_lstm = directional_symmetry(y_pred_lstm)
print("Direcational Symmetry(DS) for LSTM forecasting model:", ds_lstm)
```

```
Direcational Symmetry(DS) for LSTM forecasting model: 0.0
```