Final Project: Applying Python for Business Analytics

Introduction: Business problem (objective of the analysis)

The real estate industry is dynamic and influenced by various factors such as market trends, economic conditions, and location-specific dynamics. Analyzing historical real estate sales data can provide valuable insights for businesses and stakeholders in the industry. In this project, we aim to leverage a dataset containing real estate sales data from 2001 to 2020 to address key business questions and make data-driven decisions.

Business Problem/Objective:

1. Market Trends and Price Analysis: Identify and understand the overall trends and patterns in real estate within Connecticut sales over the years. Analyze changes in the assessed value, sale amount, and sales ratio to gain insights into the market dynamics and price fluctuations. This information can help businesses assess the competitiveness of different areas, track market trends, and make pricing decisions.
2. Property and Residential Type Analysis: Investigate the distribution of property types and residential types within the dataset. Determine which property types (e.g., residential, commercial, land) and residential types (e.g., single-family, multi-family, condominiums) are most prevalent in the dataset. This analysis can provide valuable information for developers, investors, and real estate agents to identify market niches and understand customer preferences.
3. Applying Models: Utilize various predictive modeling techniques such as Linear Regression, Decision Tree, and Logistic Regression to analyze the real estate sales data. By building these models, we aim to predict and understand the factors that influence the sale amount or assessed value of properties. This analysis can help businesses and stakeholders make informed decisions regarding pricing strategies, investment opportunities, and market forecasting.

0. Importing libraries

In [1]:
```
#Importing Libraries
import seaborn as sns
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import chi2_contingency
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_s
from sklearn.metrics import classification_report
```

1. Data & Data Wrangling

In [2]:
```
dtype_options = {
    'Serial Number': int,
    'List Year': int,
    'Date Recorded': str,
    'Town': str,
    'Address': str,
    'Assessed Value': float,
    'Sale Amount': float,
    'Sales Ratio': float,
    'Property Type': str,
    'Residential Type': str,
    'Non Use Code': str,
    'Assessor Remarks': str,
    'OPM remarks': str,
    'Location': str
}

df = pd.read_csv(r"C:\Users\nguye\Downloads\Real_Estate_Sales_2001-2020_GL.csv'
df['Date Recorded'] = pd.to_datetime(df['Date Recorded'])

df.head()
```

Out[2]:

	Serial Number	List Year	Date Recorded	Town	Address	Assessed Value	Sale Amount	Sales Ratio	Property Type
0	2020348	2020	2021-09-13	Ansonia	230 WAKELEE AVE	150500.0	325000.0	0.4630	Commercial
1	20002	2020	2020-10-02	Ashford	390 TURNPIKE RD	253000.0	430000.0	0.5883	Residential
2	200212	2020	2021-03-09	Avon	5 CHESTNUT DRIVE	130400.0	179900.0	0.7248	Residential
3	200243	2020	2021-04-13	Avon	111 NORTHINGTON DRIVE	619290.0	890000.0	0.6958	Residential
4	200377	2020	2021-07-02	Avon	70 FAR HILLS DRIVE	862330.0	1447500.0	0.5957	Residential

In [3]:
```
#Get the number of rows and columns
df.shape
```

Out[3]: (997213, 14)

In [4]:
```
# Check the number of missing values in each column
num_missing = df.isna().sum()

# Get the column names from the DataFrame
columns = df.columns

# Print the column names and the number of missing values
for column in columns:
    num_na = num_missing[column]
    print(f"Column: {column}, Number of missing values: {num_na}")
```

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

Since there are alot of rows and columns with NA value, we will need to get rid of them.

In [5]:
```
#Fixing Property Column
df.loc[df['Property Type'] == 'Residential', 'Property Type'] = df.loc[df['Prop

# Drop the columns from 'Residential Type' to 'Location'
df = df.drop(columns=df.columns[df.columns.get_loc('Residential Type'):df.colur
# Drop the Serial number
df = df.drop("Serial Number", axis=1)
# Drop the Address
df = df.drop("Address", axis=1)
# Drop the Recorded date
df = df.drop("Date Recorded", axis=1)

#Removing outliers
# Calculate the lower and upper boundaries for outlier detection for each colur
columns = ['Assessed Value', 'Sale Amount', 'Sales Ratio']
bounds = {}
for column in columns:
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    bounds[column] = (lower_bound, upper_bound)

# Filter and remove the rows containing outliers for each column
outliers = pd.DataFrame()
for column in columns:
    lower_bound, upper_bound = bounds[column]
    column_outliers = df[(df[column] < lower_bound) | (df[column] > upper_bounc
    outliers = pd.concat([outliers, column_outliers])
    df = df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]



# Remove rows with missing values
data_clean = df.dropna()

#Create second data copy for later use
data_log = data_clean.copy()
```

2. Preliminary Analysis

In [6]:
```
# Summary statistics for numerical columns
data_clean.describe()
```

Out[6]:

	List Year	Assessed Value	Sale Amount	Sales Ratio
count	492842.000000	492842.000000	492842.000000	492842.000000
mean	2013.894516	167776.762758	255215.867511	0.685746
std	4.530202	84902.194562	130361.174181	0.187036
min	2006.000000	190.000000	2000.000000	0.038854
25%	2010.000000	107940.000000	160000.000000	0.577300
50%	2015.000000	151360.000000	230000.000000	0.670700
75%	2018.000000	214620.000000	329000.000000	0.782143
max	2020.000000	432500.000000	702500.000000	1.233120

In [7]:
```
#correlations for numeric columns
corr_matrix = data_clean.corr(numeric_only=True)
corr_matrix
```

Out[7]:

	List Year	Assessed Value	Sale Amount	Sales Ratio
List Year	1.000000	-0.030959	0.021106	-0.093850
Assessed Value	-0.030959	1.000000	0.850676	0.172135
Sale Amount	0.021106	0.850676	1.000000	-0.296908
Sales Ratio	-0.093850	0.172135	-0.296908	1.000000

A correlation coefficient of 0.850676 indicates that there is a strong linear relationship between the "Assessed Value" and "Sale Amount" columns. As the "Assessed Value" increases, the "Sale Amount" tends to increase as well, and vice versa.

This positive correlation suggests that there is a tendency for higher assessed values to be associated with higher sale amounts, which implies that the assessed value of a property may be a good indicator of its sale price.

In [8]:
```
#Summary statistics for categorical columns:
town_counts = data_clean['Town'].value_counts()
property_type_counts = data_clean['Property Type'].value_counts()
print(town_counts)
print(property_type_counts)
```

```
Town
Waterbury        13266
Bridgeport       13126
Stamford         11454
Norwalk          11202
West Hartford    11197
                 ...
Bridgewater        185
Canaan             178
Roxbury            176
Union              100
***Unknown***        1
Name: count, Length: 170, dtype: int64
Property Type
Single Family     350890
Condo             104389
Two Family         22107
Three Family       10307
Vacant Land         2151
Four Family         1681
Commercial           949
Apartments           279
Industrial            86
Public Utility         3
Name: count, dtype: int64
```

In [9]:
```
cross_tab = pd.crosstab(data_clean['Property Type'], data_clean['Town'])
cross_tab_sorted = cross_tab.sort_values(by='Property Type', ascending=False)
print("Cross-Tabulation:")
print(cross_tab_sorted)

chi2, p, _, _ = chi2_contingency(cross_tab)
print("\nChi-square test p-value:")
print(p)

#Removing Town column as this point due to no longer needed.
data_clean = data_clean.drop("Town", axis=1)

#The chi-square test p-value is 0.0, indicating that there is a significant ass
#This suggests that the distribution of property types varies significantly acr
```

```
Cross-Tabulation:
Town            ***Unknown***  Andover  Ansonia  Ashford  Avon  Barkhamsted  \
Property Type
Vacant Land                 0        6        7        8    16           11
Two Family                  0        5      521       13     2            4
Three Family                0        0      125        0     2            1
Single Family               1      459     1690      599  2143          500
Public Utility              0        0        0        0     0            0
Industrial                  0        0        1        0     1            0
Four Family                 0        0       28        0     0            0
Condo                       0        0       81       23  1329            0
Commercial                  0        0        6        2     3            1
Apartments                  0        0        2        0     0            0

Town            Beacon Falls  Berlin  Bethany  Bethel  ...  Willington  \
Property Type                                          ...
Vacant Land                5      20        9      10  ...          15
Two Family                13      94        2     134  ...           8
Three Family               2       9        0      10  ...           1
Single Family            734    2416      740    2055  ...         578
Public Utility             0       0        0       0  ...           0
Industrial                 1       1        0       1  ...           0
Four Family                0       2        0       6  ...           1
Condo                    242     650        3     985  ...          52
Commercial                 0      14        0      11  ...           1
Apartments                 0       0        0       0  ...           0

Town            Wilton  Winchester  Windham  Windsor  Windsor Locks  Wolcott  \
Property Type
Vacant Land         17          11       11       13              0       14
Two Family           4         111      186       95             79       21
Three Family         0          38      103       13              7        1
Single Family      629        1380     2310     3912           1747     2359
Public Utility       0           0        0        0              0        0
Industrial           0           1        0        0              4        1
Four Family          0          26       12        3              1        1
Condo              326         210      108      953            632      263
Commercial           0           7       11        8              4        8
Apartments           0           0        2        1              0        0

Town            Woodbridge  Woodbury  Woodstock
Property Type
Vacant Land             10         8         29
Two Family              35        10          9
Three Family             0         1          1
Single Family         1262      1113       1411
Public Utility           0         0          0
Industrial               1         0          0
Four Family              1         1          0
Condo                   11       489        132
Commercial               0         1          4
Apartments               0         1          0

[10 rows x 170 columns]
```

```
Chi-square test p-value:
0.0
```

In [10]:

```
# Handling Text and Categorical Attributes
data_clean["Property Type"] = data_clean["Property Type"].str.strip()
data_clean["Property Type"] = data_clean["Property Type"].str.lower()
data_clean_pt = data_clean[["Property Type"]]
ordinal_encoder = OrdinalEncoder()
data_clean_pt_encoded = ordinal_encoder.fit_transform(data_clean_pt)

pt_encoder = OneHotEncoder()
data_clean_pt_1hot = pt_encoder.fit_transform(data_clean_pt)
```

In [11]:

```
#Get the encoded column
pt_encoder.categories_
```

Out[11]:

```
[array(['apartments', 'commercial', 'condo', 'four family', 'industrial',
        'public utility', 'single family', 'three family', 'two family',
        'vacant land'], dtype=object)]
```

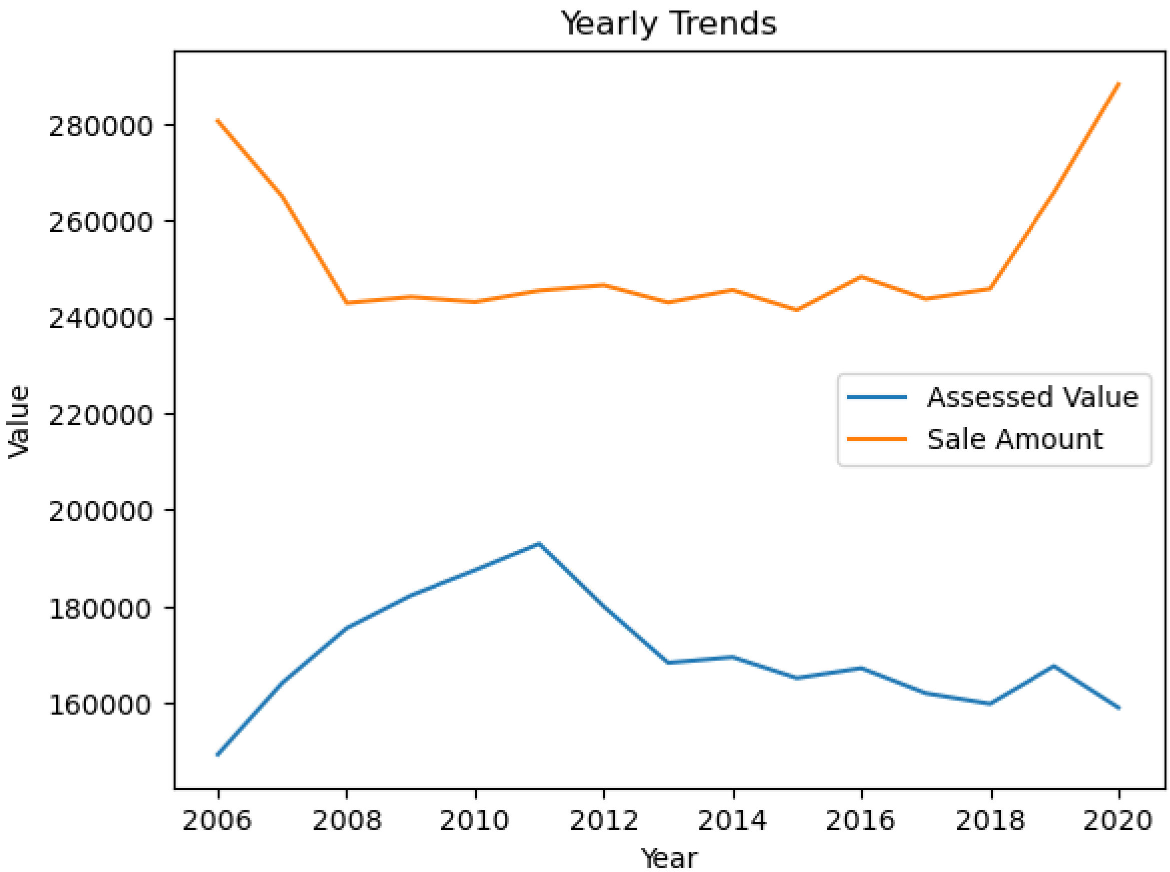
In [12]:

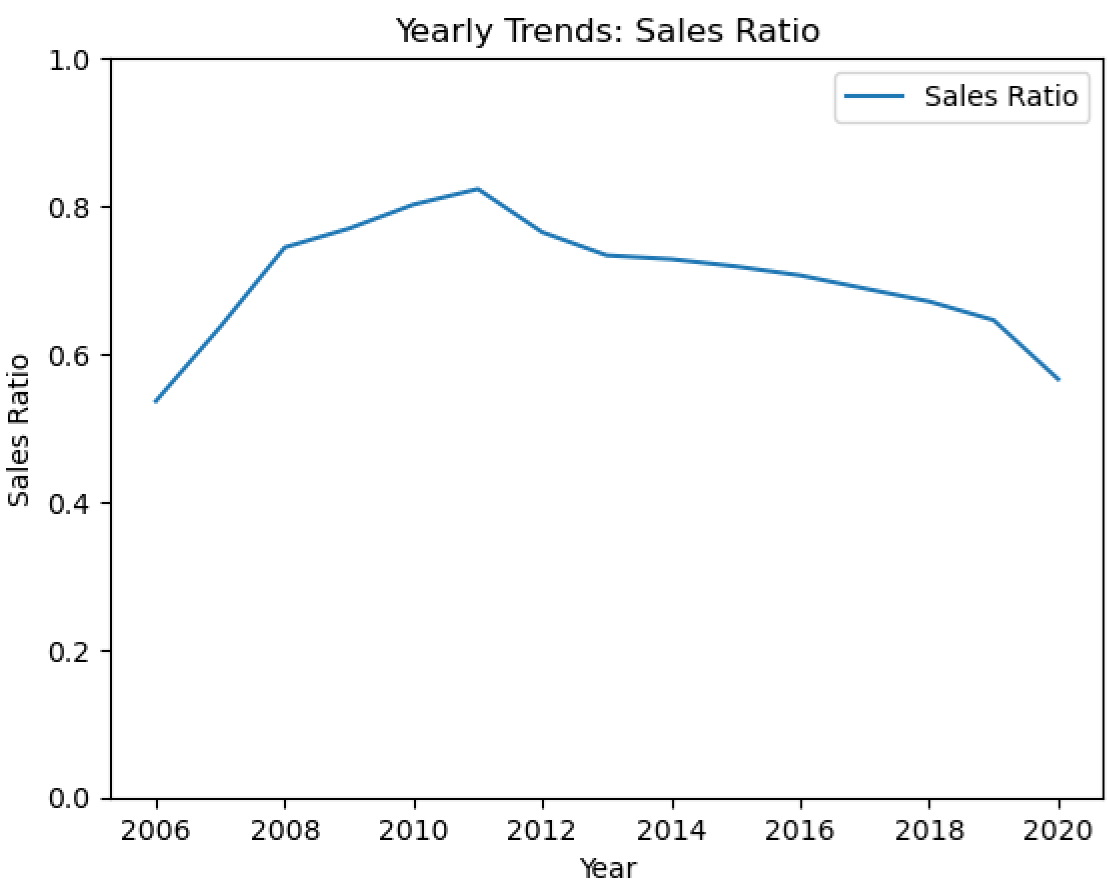
```
#Assign columsn
pt_columns = pd.DataFrame(data_clean_pt_1hot.toarray(), columns=['apartments',
        'public utility', 'single family', 'three family', 'two family',
        'vacant land'])

#Reset index to avoid missing value error
data_clean.reset_index(drop=True, inplace=True)
pt_columns.reset_index(drop=True, inplace=True)

#Joining Data
data_clean = data_clean.join(pt_columns)
data_clean = data_clean.drop("Property Type", axis=1)
```

3. Visual Inspection of the Data

In [13]:
```
cross_tab = pd.crosstab(data_log['Property Type'], data_log['Town'])
cross_tab_sorted = cross_tab.sort_values(by='Property Type', ascending=False)

# Create a heatmap of the cross-tabulation table
plt.figure(figsize=(12, 8))
sns.heatmap(cross_tab_sorted, cmap='YlGnBu')
plt.title('Cross-Tabulation: Property Type vs. Town')
plt.xlabel('Town')
plt.ylabel('Property Type')
plt.show()
```

In [14]:
```
yearly_data = data_clean[['List Year', 'Assessed Value', 'Sale Amount', 'Sales

start_year = 2006
end_year = 2020
yearly_data = yearly_data[(yearly_data['List Year'] >= start_year) & (yearly_da
yearly_data = yearly_data.groupby('List Year').mean()

# Plot the yearly trends for Assessed Value, Sale Amount, and Sales Ratio
plt.plot(yearly_data.index, yearly_data['Assessed Value'], label='Assessed Valu
plt.plot(yearly_data.index, yearly_data['Sale Amount'], label='Sale Amount')

# Customize the plot
plt.xlabel('Year')
plt.ylabel('Value')
plt.title('Yearly Trends')
plt.legend()

# Show the plot
plt.show()


# Create a separate plot for the Sales Ratio
plt.plot(yearly_data.index, yearly_data['Sales Ratio'], label='Sales Ratio')

# Customize the plot for Sales Ratio
plt.xlabel('Year')
plt.ylabel('Sales Ratio')
plt.title('Yearly Trends: Sales Ratio')
plt.ylim(0, 1)
plt.legend()

# Show the plot for Sales Ratio
plt.show()
```


Yearly Trends
280000
260000
240000
220000
200000
180000
160000
Value
Assessed Value
Sale Amount
2006
2008
2010
2012
2014
2016
2018
2020
Year


Yearly Trends: Sales Ratio
1.0
0.8
0.6
0.4
0.2
0.0
Sales Ratio
Sales Ratio
2006
2008
2010
2012
2014
2016
2018
2020
Year

4. Main analysis: Linear Regression, Decision Tree, and Logistics Regression

a. Creating training/testing data

In [15]:
```
train_set, test_set = train_test_split(data_clean, test_size=0.3, random_state=
train_set
```

Out[15]:

	List Year	Assessed Value	Sale Amount	Sales Ratio	apartments	commercial	condo	four family	industrial
169613	2010	128350.0	131600.0	0.975304	0.0	0.0	0.0	0.0	0.0
343563	2016	170240.0	308000.0	0.552727	0.0	0.0	0.0	0.0	0.0
402637	2018	97400.0	130000.0	0.749200	0.0	0.0	0.0	0.0	0.0
18456	2020	66920.0	180000.0	0.371700	0.0	0.0	0.0	0.0	0.0
446628	2019	96320.0	287000.0	0.335600	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...
338870	2015	190570.0	290000.0	0.657138	0.0	0.0	0.0	0.0	0.0
223177	2012	219900.0	263000.0	0.836122	0.0	0.0	0.0	0.0	0.0
271400	2014	135100.0	122000.0	1.107377	0.0	0.0	1.0	0.0	0.0
127718	2008	211260.0	195000.0	1.083385	0.0	0.0	0.0	0.0	0.0
369235	2016	82600.0	105000.0	0.786667	0.0	0.0	0.0	0.0	0.0

344989 rows × 14 columns

In [16]:
```
test_set
```

Out[16]:

	List Year	Assessed Value	Sale Amount	Sales Ratio	apartments	commercial	condo	four family	industrial
352561	2016	186000.0	281000.0	0.661922	0.0	0.0	0.0	0.0	0.0
314859	2015	110250.0	125000.0	0.882000	0.0	0.0	1.0	0.0	0.0
126277	2008	432100.0	525000.0	0.823048	0.0	0.0	0.0	0.0	0.0
211847	2012	335860.0	400000.0	0.839650	0.0	0.0	0.0	0.0	0.0
318933	2015	130900.0	145000.0	0.902759	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...
250064	2013	149940.0	252000.0	0.595000	0.0	0.0	0.0	0.0	0.0
274521	2014	116500.0	120000.0	0.970833	0.0	0.0	0.0	0.0	0.0
431043	2018	130800.0	215509.0	0.606900	0.0	0.0	1.0	0.0	0.0
267272	2014	73850.0	75000.0	0.984667	0.0	0.0	1.0	0.0	0.0
293582	2014	227300.0	352000.0	0.645739	0.0	0.0	0.0	0.0	0.0

147853 rows × 14 columns

In [17]:
```
data_clean_train_X = train_set.drop("Sale Amount", axis=1) # drop labels for tr
data_clean_train_y = train_set["Sale Amount"].copy()
data_clean_test_X = test_set.drop("Sale Amount", axis=1) # drop labels for tra
data_clean_test_y = test_set["Sale Amount"].copy()
```

b. Applying Linear Regression Model

In [18]:
```
lin_reg = LinearRegression()
lin_reg.fit(data_clean_train_X, data_clean_train_y)
```

Out[18]:
```
▾ LinearRegression
LinearRegression()
```

In [19]:
```
# Regression coefficients
lin_reg.coef_
```

Out[19]:
```
array([ 1.82941033e+02,  1.42293056e+00, -3.17714090e+05,  2.87781289e+04,
        5.86239845e+03, -6.54940659e+03,  5.70936212e+03,  1.88491695e+04,
       -3.82605689e+04, -3.03664087e+03, -1.62200310e+03, -1.03373297e+03,
       -8.69670655e+03])
```

In [20]:
```
pd.DataFrame(lin_reg.coef_, index = data_clean_train_X.columns)
```

Out[20]:

	0
List Year	182.941033
Assessed Value	1.422931
Sales Ratio	-317714.089600
apartments	28778.128878
commercial	5862.398445
condo	-6549.406588
four family	5709.362123
industrial	18849.169524
public utility	-38260.568899
single family	-3036.640865
three family	-1622.003103
two family	-1033.732966
vacant land	-8696.706549

In [21]:
```
#In Sample evaluation - Linear Regression
linear_train_predictions = lin_reg.predict(data_clean_train_X)
lin_mse = mean_squared_error(data_clean_train_y, linear_train_predictions)
lin_train_rmse = np.sqrt(lin_mse)
print("In Sample RMSE: ",lin_train_rmse)
```

```
In Sample RMSE:  35325.44614118062
```

In [22]:
```
# oOt-of-sample evaluation - Linear Regression
linear_predictions = lin_reg.predict(data_clean_test_X)
lin_mse = mean_squared_error(data_clean_test_y, linear_predictions)
lin_rmse = np.sqrt(lin_mse)
print("Out of Sample RMSE: ", lin_rmse)
```

```
Out of Sample RMSE:  35410.47420528373
```

In [24]:
```
actual_sales = pd.DataFrame(data_clean_train_y).reset_index(drop=True)
comparison_lin = pd.DataFrame(linear_predictions).round().join(actual_sales).re

print(comparison_lin)
```

```
        Predicted Sale Amount  Sale Amount
0                    291678.0     131600.0
1                    108270.0     308000.0
2                    587203.0     130000.0
3                    445717.0     180000.0
4                    134571.0     287000.0
...                       ...          ...
147848               259077.0     317000.0
147849                94273.0      84400.0
147850               225463.0     254000.0
147851                23674.0     438000.0
147852               353218.0     280000.0

[147853 rows x 2 columns]
```

b. Applying Decision Tree Model

In [90]:
```
#In Sample evaluation - Tree Model
tree_reg = DecisionTreeRegressor(random_state=23)
tree_reg.fit(data_clean_train_X, data_clean_train_y)
tree_train_predictions = tree_reg.predict(data_clean_train_X)
tree_mse = mean_squared_error(data_clean_train_y, tree_train_predictions)
tree_train_rmse = np.sqrt(tree_mse)
print("In Sample RMSE: ",tree_train_rmse)
```

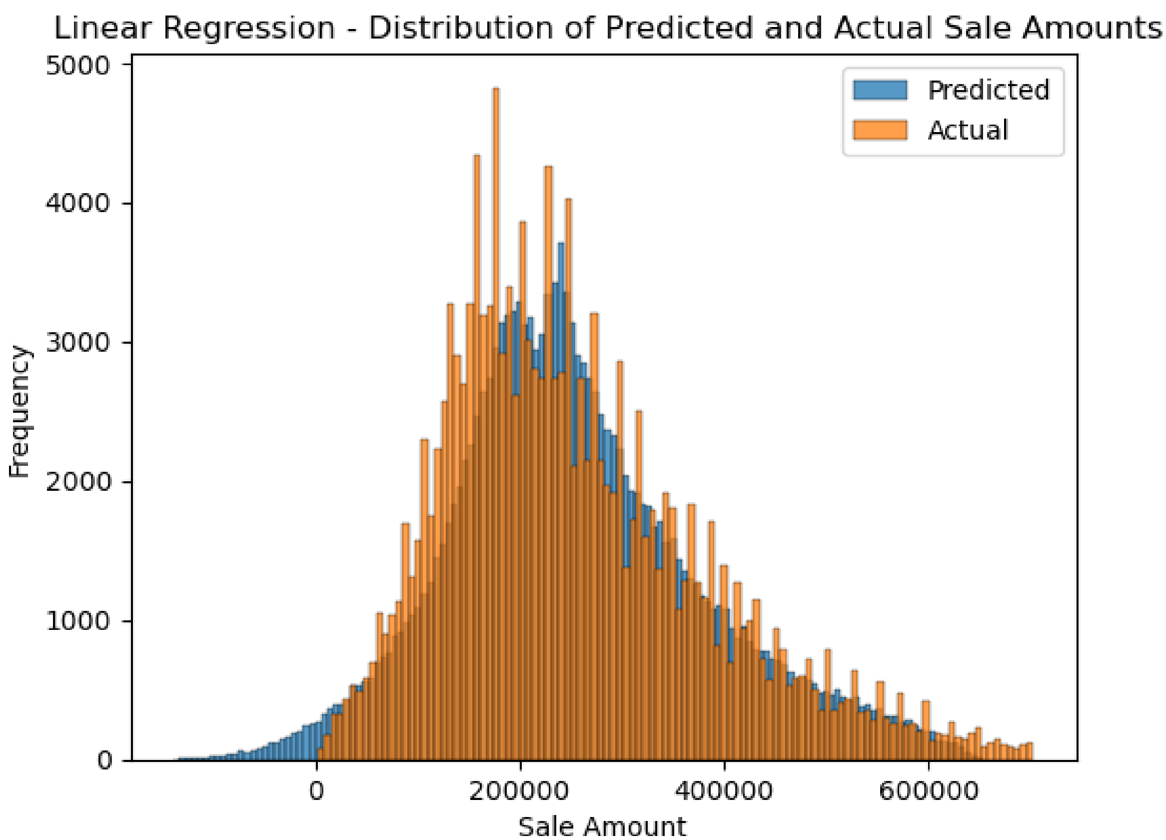
```
In Sample RMSE:  1.4924405340245084
```

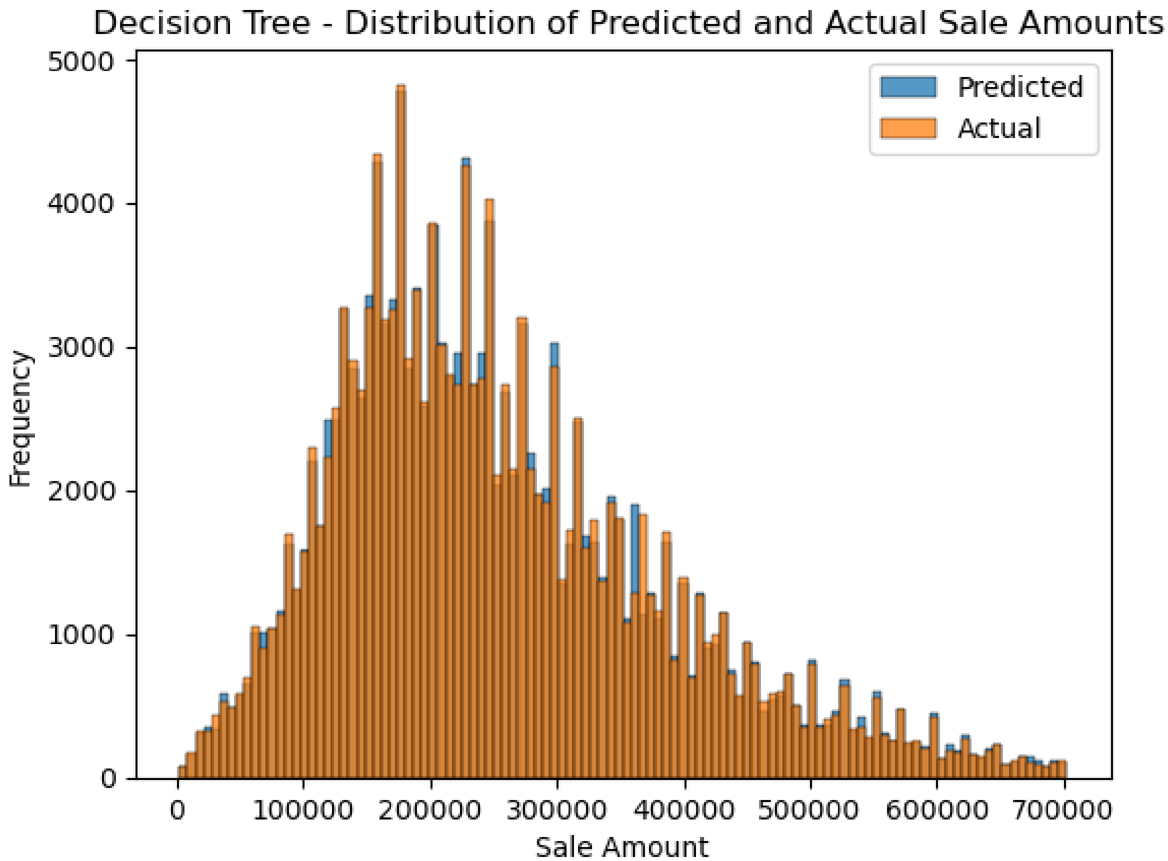
In [91]:
```
# oOt-of-sample evaluation - Tree Model
tree_predictions = tree_reg.predict(data_clean_test_X)
tree_mse = mean_squared_error(data_clean_test_y, tree_predictions)
tree_rmse = np.sqrt(tree_mse)
print("Out of Sample RMSE: ", tree_rmse)
```

```
Out of Sample RMSE:  1570.8234183711927
```

c. Comparing between Linear Regression model and Decision Tree model

In [92]:
```
comparison_tree = pd.DataFrame(tree_predictions).round().join(actual_sales).rer


import seaborn as sns
sns.histplot(comparison_lin['Predicted Sale Amount'], label='Predicted')
sns.histplot(comparison_lin['Sale Amount'], label='Actual')
plt.xlabel('Sale Amount')
plt.ylabel('Frequency')
plt.title(' Linear Regression - Distribution of Predicted and Actual Sale Amour
plt.legend()
plt.show()

sns.histplot(comparison_tree['Predicted Sale Amount'], label='Predicted')
sns.histplot(comparison_tree['Sale Amount'], label='Actual')
plt.xlabel('Sale Amount')
plt.ylabel('Frequency')
plt.title(' Decision Tree - Distribution of Predicted and Actual Sale Amounts']
plt.legend()
plt.show()
```





d. Applying Logistics Regression for categorical variable

In [93]:
```
#Perform data cleaning to group the Property Type into two values: Residential 

residential_types = ['Single Family', 'Condo', 'Two Family', 'Three Family', 'I

data_log['Property Type'] = data_log['Property Type'].map(lambda x: 'Residenti


data_log.reset_index(drop=True, inplace=True)

# Perform one-hot encoding on 'Property Type' and 'Town'
data_log_pt = data_log[["Property Type"]]
ordinal_encoder = OrdinalEncoder()
data_log_pt_encoded = ordinal_encoder.fit_transform(data_log_pt)

pt_encoder = OneHotEncoder()
data_log_pt_1hot = pt_encoder.fit_transform(data_log_pt)

pt_columns = pd.DataFrame(data_log_pt_1hot.toarray(), columns=['Residential',


data_log.reset_index(drop=True, inplace=True)
pt_columns.reset_index(drop=True, inplace=True)

data_log = data_log.join(pt_columns)

data_log["Town"] = data_log["Town"].str.strip()
data_log["Town"] = data_log["Town"].str.lower()
data_log_t = data_log[["Town"]]
ordinal_encoder = OrdinalEncoder()
data_log_t_encoded = ordinal_encoder.fit_transform(data_log_t)

t_encoder = OneHotEncoder()
data_log_t_1hot = t_encoder.fit_transform(data_log_t)
t_encoder.categories_
t_columns = pd.DataFrame(data_log_t_1hot.toarray(), columns=['***unknown***',
        'barkhamsted', 'beacon falls', 'berlin', 'bethany', 'bethel',
        'bethlehem', 'bloomfield', 'bolton', 'bozrah', 'branford',
        'bridgeport', 'bridgewater', 'bristol', 'brookfield', 'brooklyn',
        'burlington', 'canaan', 'canterbury', 'canton', 'chaplin',
        'cheshire', 'chester', 'clinton', 'colchester', 'colebrook',
        'columbia', 'cornwall', 'coventry', 'cromwell', 'danbury',
        'darien', 'deep river', 'derby', 'durham', 'east granby',
        'east haddam', 'east hampton', 'east hartford', 'east haven',
        'east lyme', 'east windsor', 'eastford', 'easton', 'ellington',
        'enfield', 'essex', 'fairfield', 'farmington', 'franklin',
        'glastonbury', 'goshen', 'granby', 'greenwich', 'griswold',
        'groton', 'guilford', 'haddam', 'hamden', 'hampton', 'hartford',
        'hartland', 'harwinton', 'hebron', 'kent', 'killingly',
        'killingworth', 'lebanon', 'ledyard', 'lisbon', 'litchfield',
        'lyme', 'madison', 'manchester', 'mansfield', 'marlborough',
        'meriden', 'middlebury', 'middlefield', 'middletown', 'milford',
        'monroe', 'montville', 'morris', 'naugatuck', 'new britain',
        'new canaan', 'new fairfield', 'new hartford', 'new haven',
        'new london', 'new milford', 'newington', 'newtown', 'norfolk',
        'north branford', 'north canaan', 'north haven',
        'north stonington', 'norwalk', 'norwich', 'old lyme',
        'old saybrook', 'orange', 'oxford', 'plainfield', 'plainville',
```

```
        'plymouth', 'pomfret', 'portland', 'preston', 'prospect', 'putnam',
        'redding', 'ridgefield', 'rocky hill', 'roxbury', 'salem',
        'salisbury', 'scotland', 'seymour', 'sharon', 'shelton', 'sherman',
        'simsbury', 'somers', 'south windsor', 'southbury', 'southington',
        'sprague', 'stafford', 'stamford', 'sterling', 'stonington',
        'stratford', 'suffield', 'thomaston', 'thompson', 'tolland',
        'torrington', 'trumbull', 'union', 'vernon', 'voluntown',
        'wallingford', 'warren', 'washington', 'waterbury', 'waterford',
        'watertown', 'west hartford', 'west haven', 'westbrook', 'weston',
        'westport', 'wethersfield', 'willington', 'wilton', 'winchester',
        'windham', 'windsor', 'windsor locks', 'wolcott', 'woodbridge',
        'woodbury', 'woodstock'])

data_log = data_log.join(t_columns)

# Step 2: Split the Data
X = data_log.drop('Town', axis=1)
X = X.drop('Property Type', axis=1)  # Independent variables
y = data_log['Property Type']  # Dependent variable

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, randor

# Step 3: Model Training
# Create and train a logistic regression model
model = LogisticRegression()
model.fit(X_train, y_train)

# Step 4: Model Evaluation
# Make predictions on the test set
y_pred = model.predict(X_test)

# Generate classification report
classification_rep = classification_report(y_test, y_pred)

print(classification_rep)
```

```
C:\Users\nguye\anaconda3\Lib\site-packages\sklearn\metrics\_classification.
py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\nguye\anaconda3\Lib\site-packages\sklearn\metrics\_classification.
py:1469: UndefinedMetricWarning: Precision and F-score are ill-defined and
being set to 0.0 in labels with no predicted samples. Use `zero_division` p
arameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))

                 precision    recall  f1-score   support

Non-Residential       0.00      0.00      0.00       986
    Residential       0.99      1.00      1.00    146867

       accuracy                           0.99    147853
      macro avg       0.50      0.50      0.50    147853
   weighted avg       0.99      0.99      0.99    147853
```