

▼ Data Analysis, Visualization and Interpretation

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```
#load file
from google.colab import drive
drive.mount('/content/drive')
```

📌 Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.moun

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
#load real estate sales dataset
df_real_estate_sales = pd.read_csv("/content/drive/My Drive/Data Science with Python Spring20
```

```
## Summarize Data
```

```
# Descriptive statistics
# shape
print(df_real_estate_sales.shape)
# types
print(df_real_estate_sales.dtypes)
# head
print(df_real_estate_sales.head(20))
```

📌

(145987, 11)

```

ID                int64
SerialNumber      int64
ListYear          int64
DateRecorded      object
Town              object
Address            object
AssessedValue     int64
SaleAmount        float64
SalesRatio        float64
PropertyType      object
ResidentialType   object
dtype: object

```

	ID	SerialNumber	ListYear	...	SalesRatio	PropertyType	ResidentialType
0	1	14046	2014	...	0.142933	Vacant Land	NaN
1	2	14011	2014	...	0.805789	Residential	Single Family
2	3	15006	2015	...	2.058000	Residential	Single Family
3	4	14044	2014	...	0.846784	Residential	Single Family
4	5	14035	2014	...	0.713043	Residential	Single Family
5	6	15051	2015	...	0.833628	Residential	Single Family
6	7	14002	2014	...	1.862500	Residential	Single Family
7	8	15011	2015	...	0.640433	Residential	Single Family
8	9	14043	2014	...	4.763636	Residential	Single Family
9	10	14029	2014	...	7.807220	Residential	Single Family
10	11	14024	2014	...	0.832827	Residential	Single Family
11	12	14030	2014	...	0.653333	Vacant Land	NaN
12	13	15024	2015	...	0.539200	Residential	Single Family
13	14	14023	2014	...	0.666667	Residential	Single Family
14	15	15038	2015	...	1.392784	Residential	Single Family
15	16	14037	2014	...	0.656044	Residential	Single Family
16	17	15026	2015	...	0.833333	Residential	Single Family
17	18	15029	2015	...	0.675780	Residential	Single Family
18	19	14008	2014	...	0.880658	Vacant Land	NaN
19	20	15004	2015	...	0.764286	Vacant Land	NaN

[20 rows x 11 columns]

#load list of towns dataset

df_list_of_towns = pd.read_csv("/content/drive/My Drive/Data Science with Python Spring2020/w

Summarize Data

Descriptive statistics

shape

print(df_list_of_towns.shape)

types

print(df_list_of_towns.dtypes)

head

print(df_list_of_towns.head(20))



(169, 7)

```

Number          int64
Town            object
Designation     object
Established Year int64
Land area (square miles) float64
Population (in 2010) object
County          object
dtype: object

```

	Number	Town	...	Population (in 2010)	County
0	1	Andover	...	3,303	Tolland County
1	2	Ansonia	...	19,249	New Haven County
2	3	Ashford	...	4,100	Windham County
3	4	Avon	...	18,098	Hartford County
4	5	Barkhamsted	...	3,620	Litchfield County
5	6	Beacon Falls	...	6,049	New Haven County
6	7	Berlin	...	19,866	Hartford County
7	8	Bethany	...	5,563	New Haven County
8	9	Bethel	...	18,584	Fairfield County
9	10	Bethlehem	...	3,607	Litchfield County
10	11	Bloomfield	...	20,486	Hartford County
11	12	Bolton	...	4,980	Tolland County
12	13	Bozrah	...	2,627	New London County
13	14	Branford	...	28,026	New Haven County
14	15	Bridgeport	...	144,229	Fairfield County
15	16	Bridgewater	...	1,727	Litchfield County
16	17	Bristol	...	60,477	Hartford County
17	18	Brookfield	...	16,452	Fairfield County
18	19	Brooklyn	...	8,210	Windham County
19	20	Burlington	...	9,301	Hartford County

[20 rows x 7 columns]

merge List of Towns file and Real Estate Sales file

```

df_result = pd.merge(df_real_estate_sales,
                      df_list_of_towns,
                      on='Town')

```

#find missing values

```

missing_values = df_result.isnull().sum(axis=0)
missing_values

```



```

ID                0
SerialNumber      0
ListYear          0
DateRecorded      6
Town              0
Address           2
AssessedValue     0
SaleAmount        5283
SalesRatio        0
PropertyType      0
ResidentialType   11905
Number            0
Designation       0
Established Year   0
Land area (square miles) 0
Population (in 2010) 0
County            0
dtype: int64

```

```

#Replacing missing date recorded data with the corresponding year in ListYear column.
df_result['DateRecorded'] = df_result['DateRecorded'].astype(str)
df_result['DateRecorded'].fillna('1/1/2014', inplace = True)
missing_values = df_result.isnull().sum(axis=0)
missing_values

```

```

ID                0
SerialNumber      0
ListYear          0
DateRecorded      0
Town              0
Address           2
AssessedValue     0
SaleAmount        5283
SalesRatio        0
PropertyType      0
ResidentialType   11905
Number            0
Designation       0
Established Year   0
Land area (square miles) 0
Population (in 2010) 0
County            0
dtype: int64

```

```

#Replacing missing Sales Amount data with the corresponding assessed value column
df_result['SaleAmount'].fillna(df_result['AssessedValue'], inplace = True)
missing_values = df_result.isnull().sum(axis=0)
missing_values

```



```

ID                0
SerialNumber      0
ListYear          0
DateRecorded      0
Town              0
Address           2
AssessedValue     0
SaleAmount        0
SalesRatio        0
PropertyType      0
ResidentialType   11905
Number            0
Designation       0
Established Year   0
Land area (square miles) 0
Population (in 2010) 0
County            0
dtype: int64

```

```
#Make a column "Property Value"
```

```
#Binning AssessedValue given the conditions:
```

```
#'LowRange' if Assessed Value <=300,000
```

```
#'MidRange' if Assessed Value >300,000 and <=800,000
```

```
#'HighRange' if Assessed Value >800,000
```

```
df_result['Property Value'] = pd.cut(df_result['AssessedValue'], bins=[-100000,300000,800000],
df_result.groupby('Property Value').size())
```

```

↳ Property Value
LowRange      120076
MidRange       19486
HighRange       6425
dtype: int64

```

```
#removing , from population
```

```
df_result['Population (in 2010)'] = df_result['Population (in 2010)'].str.replace(',','')
```

```
df_result['Population (in 2010)'] = df_result['Population (in 2010)'].astype(int)
```

```
#descriptive statistics
```

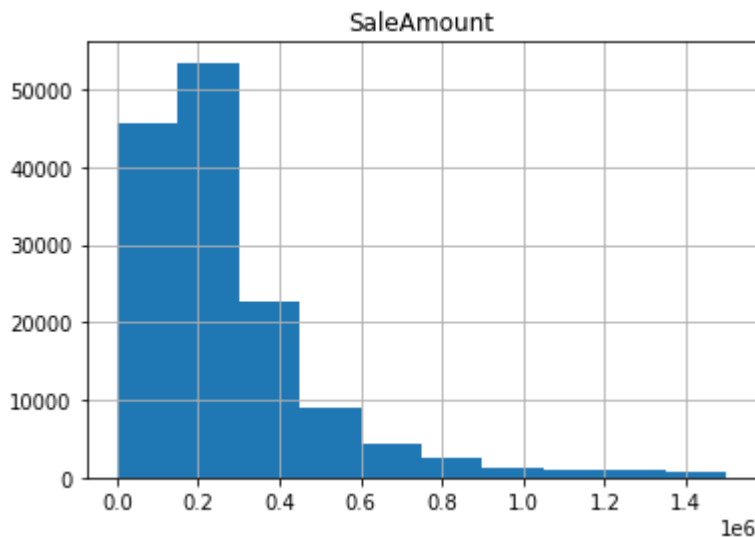
```
df_result.describe()
```

```
↳
```

	ID	SerialNumber	ListYear	AssessedValue	SaleAmount	SalesR
count	145987.000000	1.459870e+05	145987.000000	1.459870e+05	1.459870e+05	145987.00
mean	72994.000000	2.645845e+05	2015.001438	3.105082e+05	4.119349e+05	2.43
std	42142.961211	1.174402e+06	0.824892	1.546245e+06	3.376906e+06	51.83
min	1.000000	1.610000e+02	2014.000000	0.000000e+00	0.000000e+00	0.00
25%	36497.500000	1.401250e+05	2014.000000	1.038650e+05	1.289000e+05	0.61
50%	72994.000000	1.501020e+05	2015.000000	1.547000e+05	2.150000e+05	0.70
75%	109490.500000	1.601300e+05	2016.000000	2.434600e+05	3.500000e+05	0.88
max	145987.000000	1.400028e+08	2016.000000	1.389588e+08	3.955000e+08	4516.08

```
#Data visualization for Sales Amount using histogram
subData_SA = df_result[df_result['SaleAmount']<1500000]
subData_SA.hist('SaleAmount')
plt.show()
```

```
#####
#most of the sales are less 1500000
```

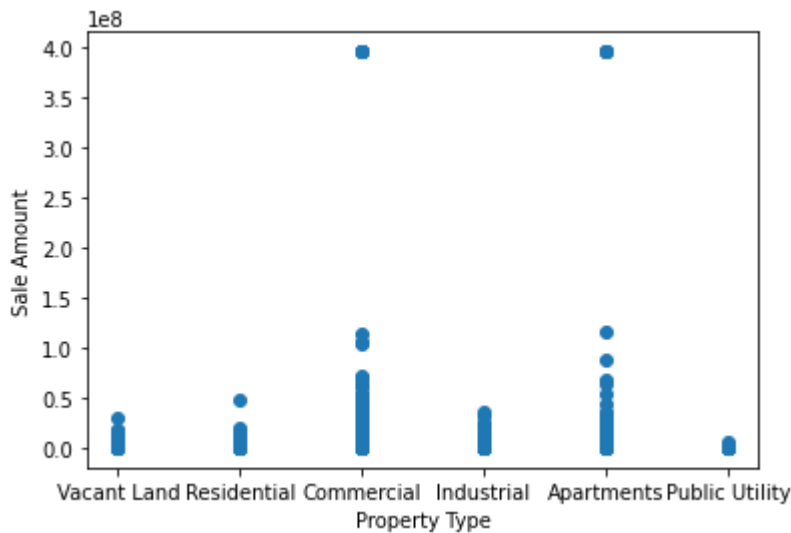


```
#Data visualization for Property Type and Sale Amount using scatter plot
plt.scatter(df_result.PropertyType,df_result.SaleAmount)
plt.xlabel('Property Type')
plt.ylabel('Sale Amount')
```

```
#####
# We can observe huge variation in the prices for 'Commercial' and 'Apartments' property type
```



Text(0, 0.5, 'Sale Amount')



#Data visualization for list year using box plot, histogram, density plot

```
import matplotlib.pyplot as plt
```

```
import numpy as np
```

```
import seaborn as sns
```

#2 rows and 2columns

```
fig, ax = plt.subplots(2,2)
```

#density plot for ListYear

```
sns.kdeplot(df_result.ListYear,
```

```
ax=ax[0,0])
```

```
ax[0,0].set_xlabel('ListYear')
```

#histogram for ListYear

```
ax[0,1].hist(df_result.ListYear, color='green')
```

```
ax[0,1].set_xlabel('ListYear')
```

```
ax[0,1].set_ylabel('Frequency')
```

#boxplot for ListYear

```
ax[1,0].boxplot(df_result.ListYear)
```

```
ax[1,0].set_ylabel('ListYear')
```

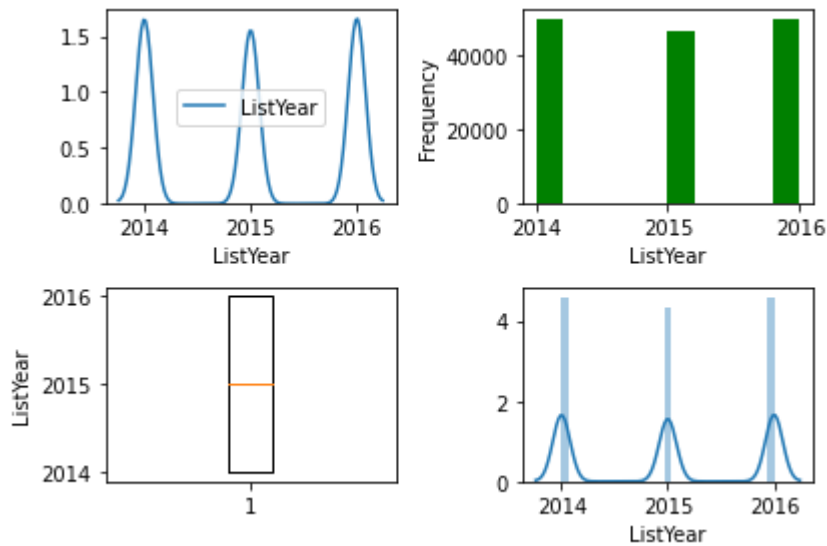
#overlapping density plot and histogram for ListYear

```
sns.distplot(df_result.ListYear,ax=ax[1,1])
```

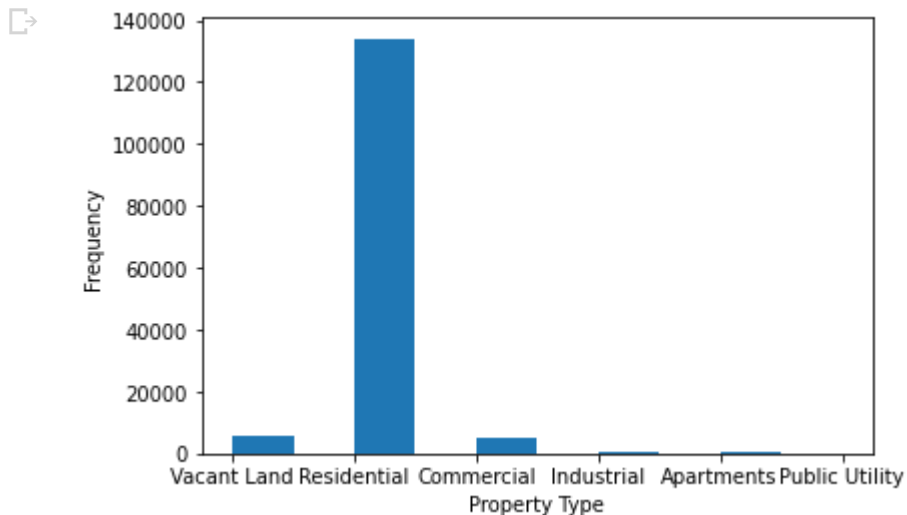
```
fig.tight_layout()
```

```
plt.show()
```





```
#Data visualization for Property Type using Bar Graph
plt.hist(df_result.PropertyType)
plt.xlabel('Property Type')
plt.ylabel('Frequency')
plt.show()
```



```
# Data visualization for County using histogram
x1 = list(df_result[df_result['County'] == 'Windham County']['Property Value'])
x2 = list(df_result[df_result['County'] == 'Fairfield County']['Property Value'])
x3 = list(df_result[df_result['County'] == 'Tolland County']['Property Value'])
x4 = list(df_result[df_result['County'] == 'Hartford County']['Property Value'])
x5 = list(df_result[df_result['County'] == 'Litchfield County']['Property Value'])
x6 = list(df_result[df_result['County'] == 'Middlesex County']['Property Value'])
x7 = list(df_result[df_result['County'] == 'New Haven County']['Property Value'])
x8 = list(df_result[df_result['County'] == 'New London County']['Property Value'])
```

```
#assigning colours and names
```

```
colors = ['#E69F00', '#56B4E9', '#F0E442', '#009E73', '#D55E00', '#9177D2', '#F882A1', '#FFEEEE']
```

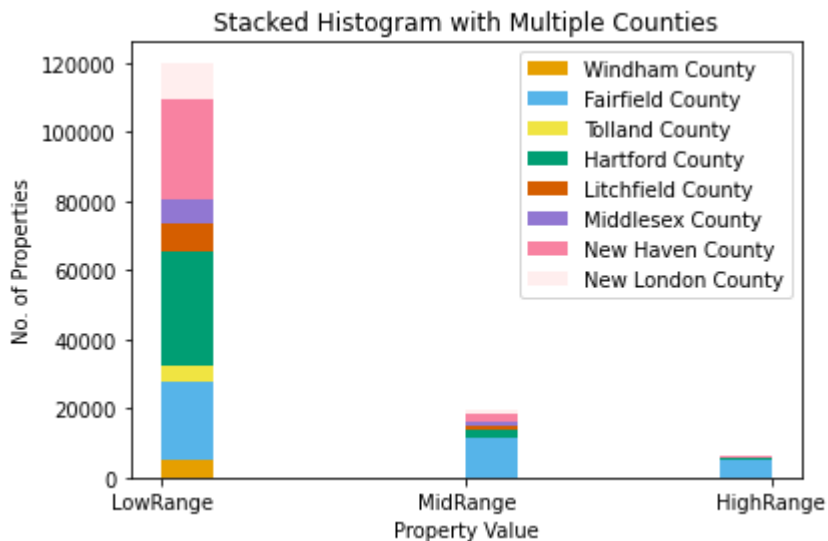


```
#Text(0, 0.5, 'Frequency')
names = ['Windham County', 'Fairfield County', 'Tolland County', 'Hartford County', 'Litchfield C

#plotting stacked histogram
plt.hist([x1, x2, x3, x4, x5, x6, x7, x8], bins = int(180/15), stacked=True, color=colors, lab
plt.legend()
plt.xlabel('Property Value')
plt.ylabel('No. of Properties')
plt.title('Stacked Histogram with Multiple Counties')

#####
#Fairfield has the maximum number of High range properties. Owning properties in the Fairfiel
#New Haven County has maximum Low range properties
```

```
Text(0.5, 1.0, 'Stacked Histogram with Multiple Counties')
```

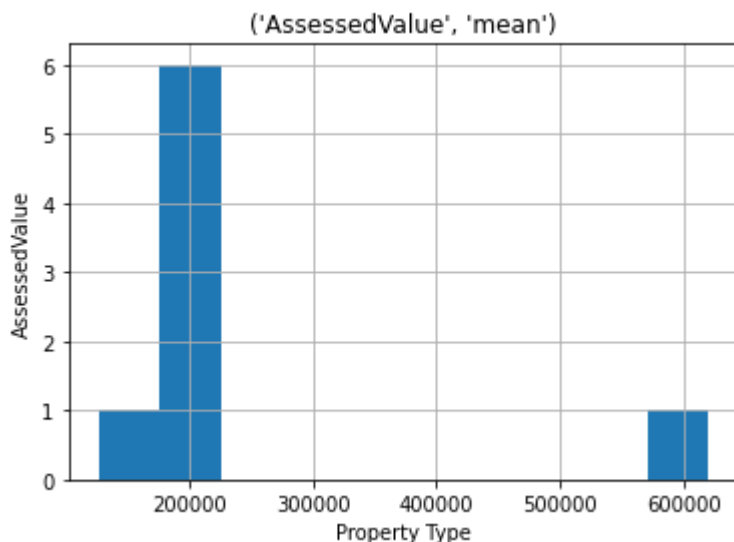


```
#Frequency table based on the average Assessed value of properties in each County
subdataAV = df_result.groupby('County').agg({'AssessedValue': ['mean']})
```

```
#Data visualization for Assessed value of County using histogram
subdataAV.hist()
plt.xlabel('Property Type')
plt.ylabel('AssessedValue')
plt.show()
```

```
#####
# Owning properties in the Fairfield county is most profitable as they have the highest avara
```





```
df_result.dtypes
```

```

ID                int64
SerialNumber      int64
ListYear          int64
DateRecorded      object
Town              object
Address           object
AssessedValue     int64
SaleAmount        float64
SalesRatio        float64
PropertyType      object
ResidentialType   object
Number            int64
Designation       object
Established Year   int64
Land area (square miles) float64
Population (in 2010) int64
County            object
Property Value    category
dtype: object

```

```
#Frequency table based on the count of properties sold in each year.
```

```
df_result.groupby('ListYear').size()
```

```
#####
```

```
#Among 2014, 2015, 2016- 2016 has highest sales
```

```

ListYear
2014    49563
2015    46651
2016    49773
dtype: int64

```

```
#Frequency table based on the average sale amount and land area of properties in each property type
subdataRT = df_result.groupby('PropertyType').agg({'SaleAmount': ['mean'], 'Land area (square miles)': ['mean']})
```

subdataR1

#####

#Average sales amount for apartments was highest

#Public Utility covers minimum land area



	SaleAmount	Land area (square miles)
	mean	mean
PropertyType		
Apartments	3.904337e+06	24.627549
Commercial	1.898054e+06	27.566583
Industrial	1.445131e+06	28.319151
Public Utility	7.433107e+05	22.816923
Residential	3.372912e+05	28.550319
Vacant Land	2.233891e+05	31.640937

multidimensional frequency table using the dataset based on Town, County and list year.

```
freq_table = pd.DataFrame(pd.crosstab([df_result.County, df_result.Town],
                                     df_result.ListYear, margins=True))
```

freq_table



	ListYear	2014	2015	2016	All
County	Town				
Fairfield County	Bethel	356	370	352	1078
	Bridgeport	1741	0	1953	3694
	Brookfield	338	346	0	684
	Danbury	1013	1127	1156	3296
	Darien	453	345	408	1206
...
Windham County	Sterling	63	82	88	233
	Thompson	0	216	227	443
	Windham	277	317	335	929
	Woodstock	156	197	0	353
All		49563	46651	49773	145987

170 rows × 4 columns

#'Property value' based on the percentages of the row and an overall total of properties in e

```
freq_table_prop_value = pd.crosstab(index=df_result['Property Value'],
```

```
columns="Number", margins=True, margins_name='Total')
freq_table_prop_value

freq_table_prop_value.columns=['Count', 'Total']
freq_table_prop_value.index=['LowRange', 'MidRange', 'HighRange', 'ColumnTotal']
freq_table_prop_value

freq_table_prop_value = (freq_table_prop_value/freq_table_prop_value.loc['ColumnTotal', 'Total']
freq_table_prop_value

#####
#Low range properties constitute 82.25% of total properties sold
```



	Count	Total
LowRange	82.251159	82.251159
MidRange	13.347764	13.347764
HighRange	4.401077	4.401077
ColumnTotal	100.000000	100.000000