HW5

February 10, 2024

0.1 Question 1

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from scipy.stats import ttest_ind, gaussian_kde
```

[2]:
```
df = pd.read_csv('zillow_feature_sample.csv')
```

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

[3]:
```
   parcelid  airconditioningtypeid  architecturalstyletypeid  basementsqft  \
0  12833975                    NaN                       NaN           NaN
1  11070096                    1.0                       NaN           NaN
2  12752672                    1.0                       NaN           NaN
3  11338563                    NaN                       NaN           NaN
4  17098704                    NaN                       NaN           NaN

   bathroomcnt  bedroomcnt  buildingclasstypeid  buildingqualitytypeid  \
0          3.0         4.0                  NaN                    6.0
1          4.0         4.0                  NaN                    7.0
2          2.0         3.0                  NaN                    6.0
3          3.0         4.0                  NaN                    7.0
4          0.0         3.0                  NaN                    NaN

   calculatedbathnbr  decktypeid  …  numberofstories  fireplaceflag  \
0                3.0         NaN  …              NaN            NaN
1                4.0         NaN  …              NaN            NaN
2                2.0         NaN  …              NaN            NaN
3                3.0         NaN  …              NaN            NaN
4                NaN         NaN  …              1.0            NaN

   structuretaxvaluedollarcnt  taxvaluedollarcnt  assessmentyear  \
0                    155403.0           304592.0          2016.0
1                    493070.0           821783.0          2016.0
2                    126695.0           247962.0          2016.0
```

```
3                    130500.0           308900.0          2016.0
4                    142271.0           223101.0          2016.0

   landtaxvaluedollarcnt  taxamount  taxdelinquencyflag  taxdelinquencyyear  \
0               149189.0    3708.29                 NaN                 NaN
1               328713.0   10087.59                 NaN                 NaN
2               121267.0    3377.86                 NaN                 NaN
3               178400.0    3578.92                 NaN                 NaN
4                80830.0    2564.86                 NaN                 NaN

   censustractandblock
0         6.037409e+13
1         6.037108e+13
2         6.037504e+13
3         6.037920e+13
4         6.111000e+13

[5 rows x 58 columns]
```

[4]:
```
df.shape
```

[4]:
```
(10000, 58)
```

[5]:
```
missing_values = df.isnull().sum()
```

[6]:
```
missing_values
```

[6]:
```
parcelid                           0
airconditioningtypeid           7219
architecturalstyletypeid        9987
basementsqft                    9996
bathroomcnt                       13
bedroomcnt                        13
buildingclasstypeid             9961
buildingqualitytypeid           3530
calculatedbathnbr                388
decktypeid                      9932
finishedfloor1squarefeet        9305
calculatedfinishedsquarefeet     149
finishedsquarefeet12             859
finishedsquarefeet13            9974
finishedsquarefeet15            9388
finishedsquarefeet50            9305
finishedsquarefeet6             9928
fips                              13
fireplacecnt                    8953
fullbathcnt                      388
```

```
garagecarcnt                    6978
garagetotalsqft                 6978
hashottuborspa                  9827
heatingorsystemtypeid           3757
latitude                          13
longitude                         13
lotsizesquarefeet                925
poolcnt                         8162
poolsizesum                     9894
pooltypeid10                    9937
pooltypeid2                     9890
pooltypeid7                     8275
propertycountylandusecode         14
propertylandusetypeid             13
propertyzoningdesc              3411
rawcensustractandblock            13
regionidcity                     210
regionidcounty                    13
regionidneighborhood            6078
regionidzip                       42
roomcnt                           13
storytypeid                     9996
threequarterbathnbr             8929
typeconstructiontypeid          9980
unitcnt                         3400
yardbuildingsqft17              9746
yardbuildingsqft26              9988
yearbuilt                        166
numberofstories                 7655
fireplaceflag                   9989
structuretaxvaluedollarcnt       144
taxvaluedollarcnt                119
assessmentyear                    13
landtaxvaluedollarcnt            210
taxamount                         66
taxdelinquencyflag              9816
taxdelinquencyyear              9816
censustractandblock              240
dtype: int64
```

[7]:

```
df[['taxvaluedollarcnt', 'structuretaxvaluedollarcnt', 'landtaxvaluedollarcnt',␣
↪'yearbuilt']]
```

[7]:

```
     taxvaluedollarcnt  structuretaxvaluedollarcnt  landtaxvaluedollarcnt  \
0             304592.0                    155403.0               149189.0
1             821783.0                    493070.0               328713.0
2             247962.0                    126695.0               121267.0
```

```
3             308900.0                     130500.0                  178400.0
4             223101.0                     142271.0                   80830.0
…                  …                          …                       …
9995          399915.0                     259395.0                  140520.0
9996           98658.0                      73738.0                   24920.0
9997          520000.0                     130500.0                  389500.0
9998          167805.0                     112656.0                   55149.0
9999          129147.0                     101845.0                   27302.0

      yearbuilt
0        1955.0
1        2012.0
2        1957.0
3        2006.0
4        1987.0
…          …
9995     2000.0
9996     1957.0
9997     1958.0
9998     1979.0
9999     1977.0

[10000 rows x 4 columns]
```

[8]:
```
# Fill missing numerical values with the median
for column in ['taxvaluedollarcnt', 'structuretaxvaluedollarcnt',␣
 ↪'landtaxvaluedollarcnt']:
    df[column].fillna(df[column].median(), inplace=True)

df['decade'] = (df['yearbuilt'] // 10) * 10
summary_table = df.groupby('decade')[['taxvaluedollarcnt',␣
 ↪'structuretaxvaluedollarcnt',
                                      'landtaxvaluedollarcnt']].agg(['mean',␣
 ↪'median', 'std'])
summary_table
```

[8]:
```
       taxvaluedollarcnt                          structuretaxvaluedollarcnt  \
                    mean     median          std                        mean
decade
1860.0      2.600588e+06  2600588.0          NaN               104023.000000
1880.0      4.738152e+05   450008.0  2.343921e+05              141027.250000
1890.0      2.982841e+05   195041.5  2.100909e+05              100655.400000
1900.0      2.947590e+05   254328.0  2.328035e+05              114436.281553
1910.0      3.970185e+05   252592.0  7.240961e+05              124393.658228
1920.0      4.307278e+05   279054.0  6.367015e+05              135383.991085
1930.0      4.996180e+05   336282.0  5.925838e+05              174301.759312
1940.0      3.666715e+05   290651.0  3.331836e+05              124408.232416
```

1950.0	3.571612e+05	279524.0	4.597407e+05	119723.350732
1960.0	3.950789e+05	326192.0	3.893111e+05	146665.118030
1970.0	3.895420e+05	319514.0	3.150314e+05	154778.619817
1980.0	4.605599e+05	336441.0	7.681176e+05	213281.678254
1990.0	5.798582e+05	448403.0	5.270886e+05	277108.885533
2000.0	7.761330e+05	565401.0	7.714013e+05	379240.373708
2010.0	9.812827e+05	695630.0	1.158552e+06	453156.620253

			landtaxvaluedollarcnt		\
	median	std	mean	median	
decade					
1860.0	104023.0	NaN	2.496565e+06	2496565.0	
1880.0	128322.0	83936.496493	3.327880e+05	283388.5	
1890.0	38199.5	110791.408959	1.976287e+05	152385.0	
1900.0	75057.0	112924.130537	1.803227e+05	146301.0	
1910.0	73706.0	197842.060825	2.726249e+05	166412.0	
1920.0	90344.0	185075.855143	2.955343e+05	172972.0	
1930.0	105911.0	236973.065579	3.253162e+05	218224.0	
1940.0	96446.0	109301.246999	2.423761e+05	182248.0	
1950.0	94593.5	110286.009524	2.375543e+05	168479.0	
1960.0	119182.0	133617.226417	2.484299e+05	176607.0	
1970.0	128733.0	96348.946041	2.345602e+05	164449.0	
1980.0	164501.0	249683.993876	2.474779e+05	164252.0	
1990.0	215433.0	222067.519580	3.033025e+05	207846.0	
2000.0	277159.0	374061.966060	3.969843e+05	265066.0	
2010.0	332221.0	465686.462670	5.302986e+05	369210.0	

	std
decade	
1860.0	NaN
1880.0	226589.896822
1890.0	136610.951629
1900.0	148736.981612
1910.0	553421.014607
1920.0	483498.193651
1930.0	398038.632866
1940.0	251917.652893
1950.0	393790.398199
1960.0	300714.159256
1970.0	255075.031439
1980.0	541410.137313
1990.0	354577.358541
2000.0	480896.876449
2010.0	830147.326747

0.2 Question 2

[9]:
```
df['poolcnt']
```

[9]:
```
0       NaN
1       NaN
2       NaN
3       NaN
4       NaN
       …
9995    1.0
9996    NaN
9997    NaN
9998    1.0
9999    NaN
Name: poolcnt, Length: 10000, dtype: float64
```

[10]:
```
latest_assessment_year = df['assessmentyear'].max()  # Find the latest␣
 ↪assessment year
df['Age'] = latest_assessment_year - df['yearbuilt']  # Calculate the age of␣
 ↪each property

# Develop a binary feature 'HasPool'
df['HasPool'] = df['poolcnt'].apply(lambda x: 1 if x > 0 else 0)  # 1 if there␣
 ↪is a pool, else 0

# Display the head of the dataframe to confirm the new features
df['HasPool'].value_counts()
```

[10]:
```
0    8162
1    1838
Name: HasPool, dtype: int64
```

[13]:
```
df['assessmentyear'].value_counts()
```

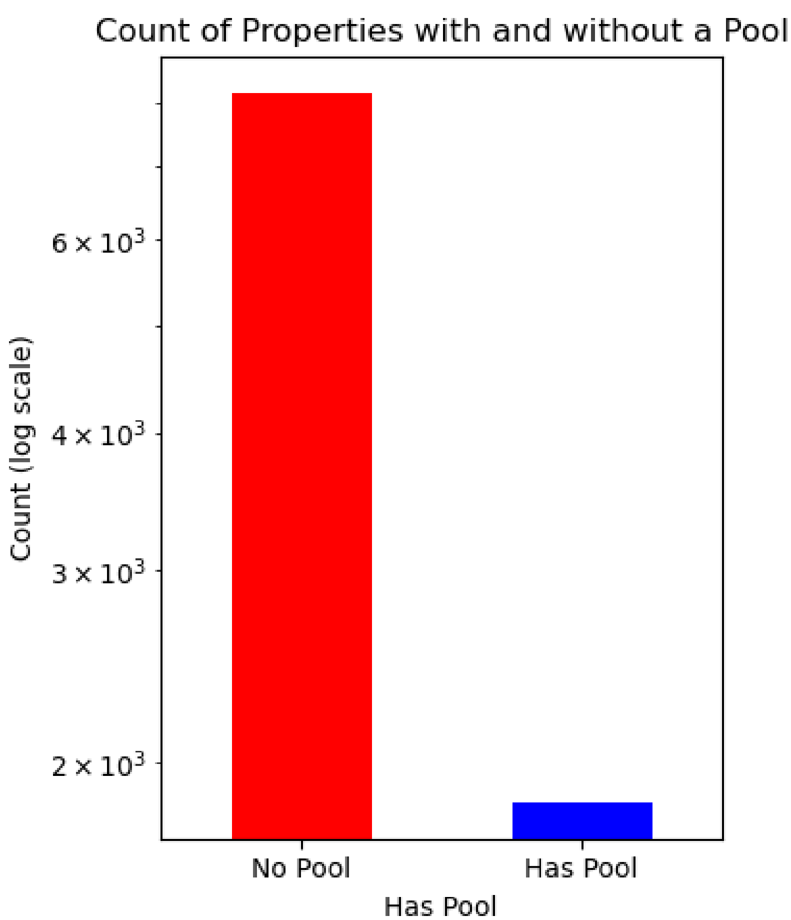
[13]:
```
2016.0    9976
2014.0       6
2015.0       5
Name: assessmentyear, dtype: int64
```

[14]:
```
df['Age'].describe()
```

[14]:
```
count    9834.000000
mean       51.467562
std        23.690129
min         1.000000
25%        35.000000
```

```
50%         53.000000
75%         66.000000
max        155.000000
Name: Age, dtype: float64
```

[12]:
```
pool_counts = df['HasPool'].value_counts()

# Plotting the bar chart
plt.figure(figsize=(4, 5))
pool_counts.plot(kind='bar', logy=True, color = ['red', 'blue'])  # Set log
 ↪scale for y-axis
plt.title('Count of Properties with and without a Pool')
plt.xlabel('Has Pool')
plt.ylabel('Count (log scale)')
plt.xticks(ticks=[0, 1], labels=['No Pool', 'Has Pool'], rotation=0)  # Set
 ↪custom x-axis labels
plt.tight_layout()
plt.show()
```



0.3 Question 3

[15]:
```python
# Step 1: Calculate the Pearson correlation coefficient
for column in ['bedroomcnt', 'bathroomcnt']:
    df[column].fillna(df[column].median(), inplace=True)

bed_bath_pears_corr = np.corrcoef(df['bedroomcnt'], df['bathroomcnt'])[0,1]
print(f"Pearson correlation coefficient between bedrooms and bathrooms: 
 ↪{bed_bath_pears_corr}")
```

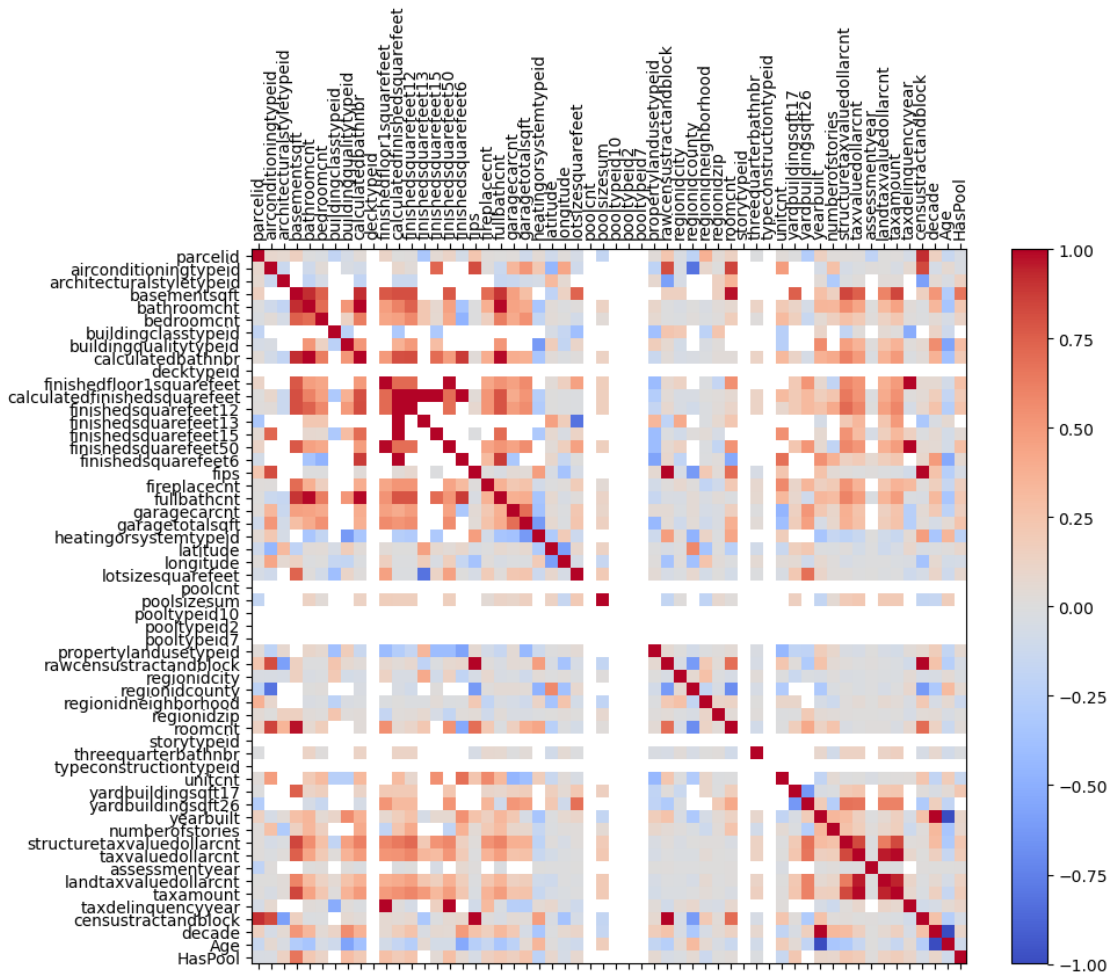
```
Pearson correlation coefficient between bedrooms and bathrooms:
0.6995759331687951
```

[17]:
```python
df['bedroomcnt'].value_counts()
```

[17]:
```
3.0     3981
4.0     2431
2.0     2009
5.0      612
0.0      393
1.0      299
6.0      162
7.0       49
8.0       42
9.0       13
11.0       4
10.0       4
12.0       1
Name: bedroomcnt, dtype: int64
```

[18]:
```python
# Select only the numerical features from your DataFrame. This list might 
 ↪change based on your actual DataFrame.
numerical_features = df.select_dtypes(include=[np.number]).columns.tolist()

# Calculate the correlation matrix
corr_matrix = df[numerical_features].corr()

# Now, let's use matplotlib to plot a heatmap
fig, ax = plt.subplots(figsize=(10, 8))
cax = ax.matshow(corr_matrix, cmap='coolwarm')
fig.colorbar(cax)

# Set ticks and labels
ax.set_xticks(np.arange(len(corr_matrix.columns)))
ax.set_yticks(np.arange(len(corr_matrix.columns)))
ax.set_xticklabels(corr_matrix.columns, rotation=90)
ax.set_yticklabels(corr_matrix.columns)
```

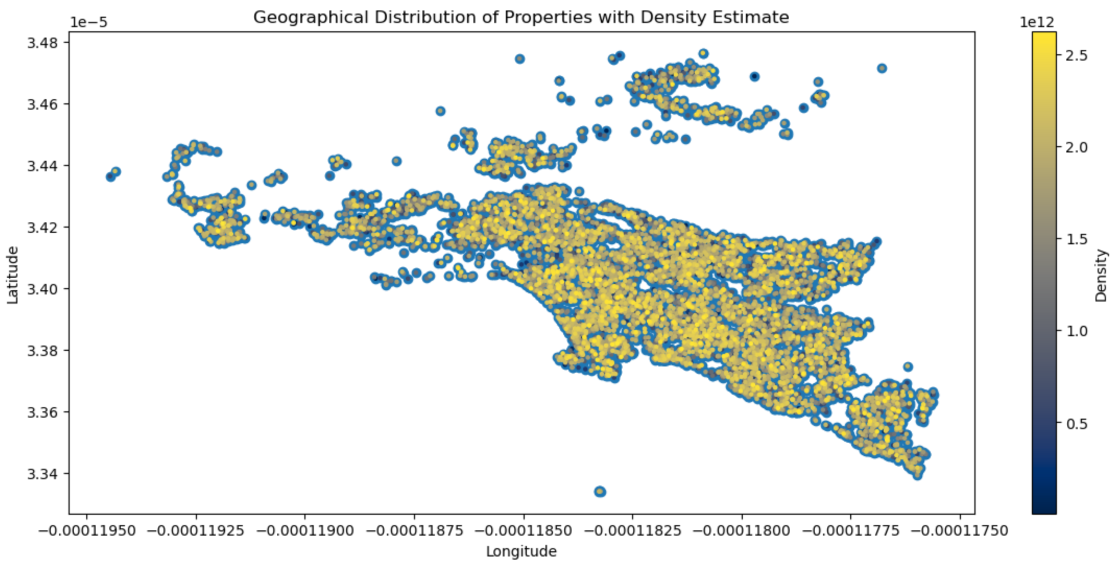
```
# Display the heatmap
plt.show()
```



0.4 Question 4

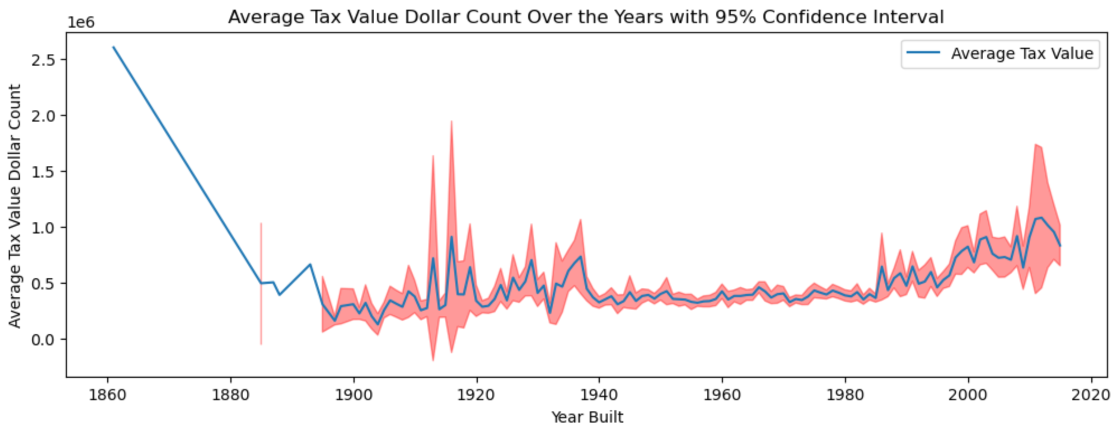
[20]:
```
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import gaussian_kde


# Convert latitude and longitude from e6 format to standard format if needed
df['latitude'] = df['latitude'] / 1e6
df['longitude'] = df['longitude'] / 1e6

# Create a scatter plot of latitude and longitude
```

```python
plt.figure(figsize=(14, 6))
plt.scatter(df['longitude'], df['latitude'])

# Calculate the point density
xy = np.vstack([df['longitude'].dropna(), df['latitude'].dropna()])
z = gaussian_kde(xy)(xy)

# Sort the points by density, so that the densest points are plotted last
sorted_idx = z.argsort()
x, y, z = df['longitude'][sorted_idx], df['latitude'][sorted_idx], z[sorted_idx]

# Overlay the density estimate
plt.scatter(x, y, c=z, s=5, cmap='cividis')

# Add labels and title
plt.colorbar(label='Density')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Geographical Distribution of Properties with Density Estimate')

# Show the plot
plt.show()
```



0.5 Question 5

[21]:
```
# Group the data by 'yearbuilt' and calculate the mean and standard deviation
grouped_year = df.groupby('yearbuilt')['taxvaluedollarcnt'].agg(['mean', 'std',␣
↪'count'])
grouped_year['mean_se'] = grouped_year['std'] / np.sqrt(grouped_year['count']) ␣
↪# Standard error of the mean
grouped_year['ci95'] = 1.96 * grouped_year['mean_se']  # 95% confidence interval

# Plotting the line chart with confidence intervals
plt.figure(figsize=(12, 4))
plt.plot(grouped_year.index, grouped_year['mean'], label='Average Tax Value')
plt.fill_between(grouped_year.index, grouped_year['mean'] -␣
↪grouped_year['ci95'], grouped_year['mean'] + grouped_year['ci95'],␣
↪color='r', alpha=0.4)
plt.xlabel('Year Built')
plt.ylabel('Average Tax Value Dollar Count')
plt.title('Average Tax Value Dollar Count Over the Years with 95% Confidence␣
↪Interval')
plt.legend()
plt.show()
```



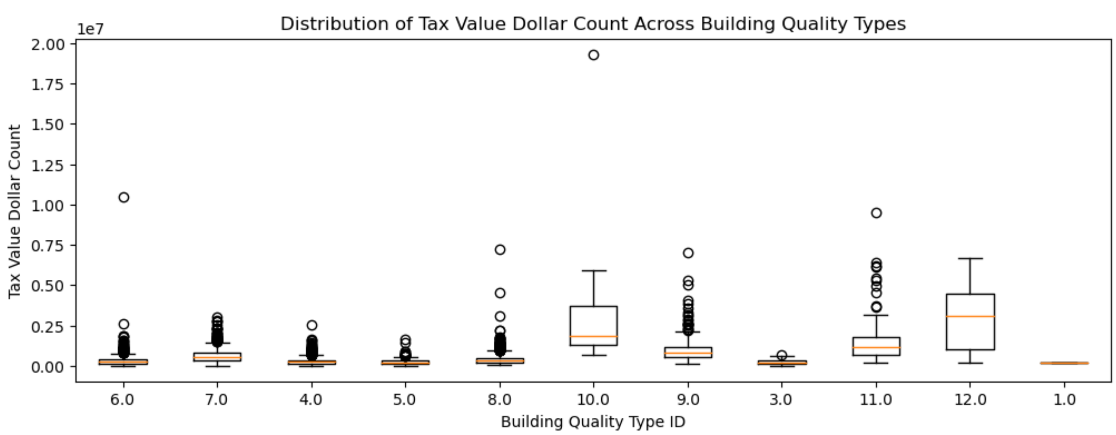
[22]:
```
grouped_year
```

[22]:

	mean	std	count	mean_se	ci95
yearbuilt					
1861.0	2.600588e+06	NaN	1	NaN	NaN
1885.0	4.976225e+05	3.952960e+05	2	279516.500000	547852.340000
1887.0	5.061010e+05	NaN	1	NaN	NaN
1888.0	3.939150e+05	NaN	1	NaN	NaN
1893.0	6.657420e+05	NaN	1	NaN	NaN
…	…	…	…	…	…

```
2011.0     1.070881e+06  1.663184e+06     24  339495.927502  665412.017904
2012.0     1.082261e+06  1.777329e+06     31  319217.684178  625666.660989
2013.0     1.014304e+06  9.253842e+05     23  192955.945296  378193.652781
2014.0     9.550477e+05  6.840317e+05     30  124886.524420  244777.587864
2015.0     8.346949e+05  4.227476e+05     21   92251.090585  180812.137548

[124 rows x 5 columns]
```

[23]:
```python
# Creating a boxplot for 'taxvaluedollarcnt' across different␣
↪'buildingqualitytypeid'
plt.figure(figsize=(12, 4))

# Extract unique building quality types
building_quality_types = df['buildingqualitytypeid'].dropna().unique()

# Collect the tax values for each building quality type
tax_values = [df[df['buildingqualitytypeid'] == bqt]['taxvaluedollarcnt'] for␣
↪bqt in building_quality_types]

plt.boxplot(tax_values, labels=building_quality_types)
plt.xlabel('Building Quality Type ID')
plt.ylabel('Tax Value Dollar Count')
plt.title('Distribution of Tax Value Dollar Count Across Building Quality␣
↪Types')
plt.show()
```

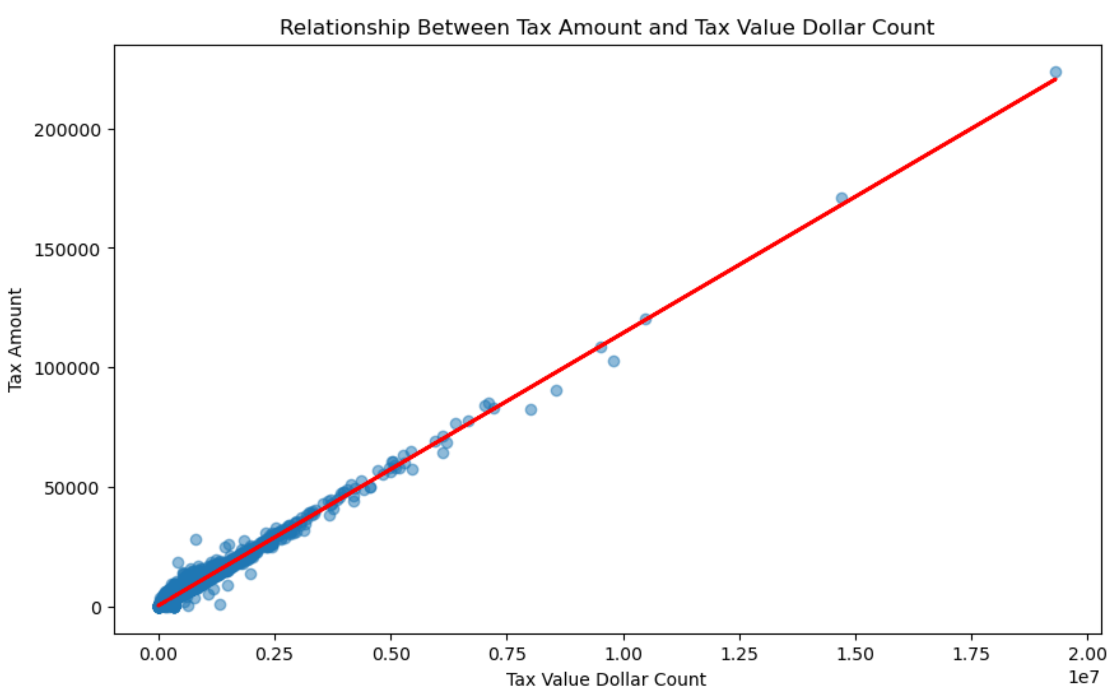


0.6 Question 6

[24]:
```python
# Scatter plot of 'taxvaluedollarcnt' vs 'taxamount'
plt.figure(figsize=(10, 6))
plt.scatter(df['taxvaluedollarcnt'], df['taxamount'], alpha=0.5)
```

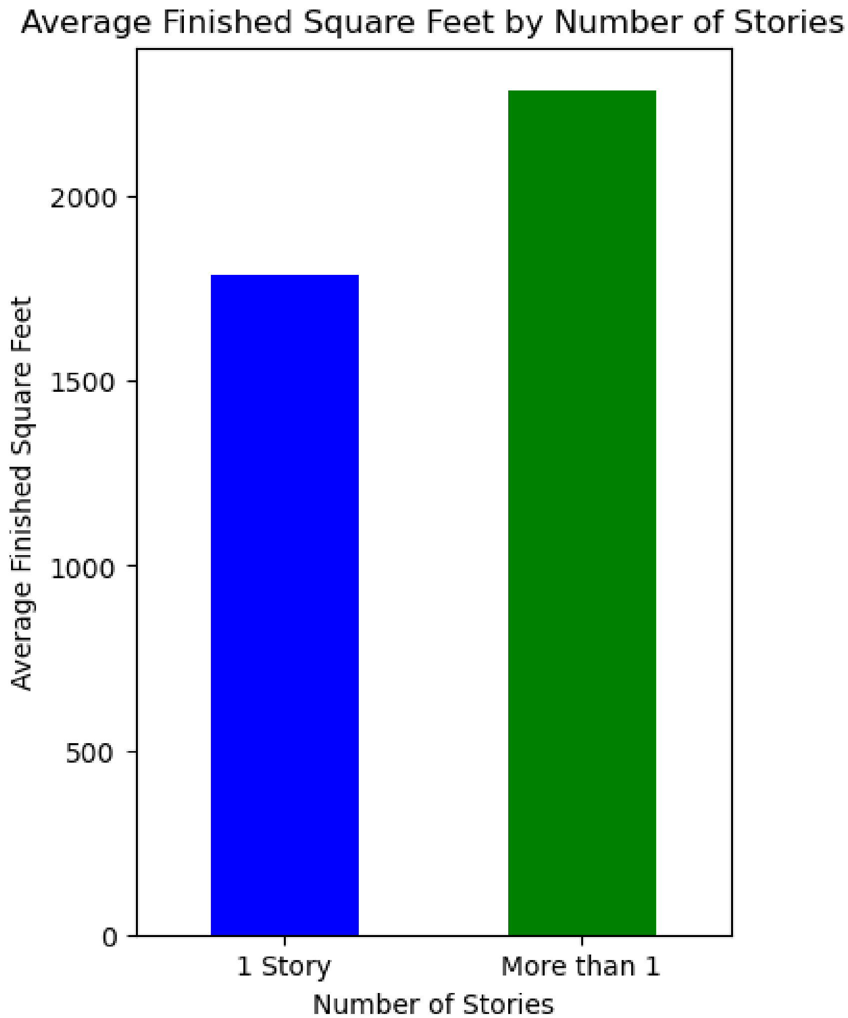
```python
# Fit a linear regression line
m, b = np.polyfit(df['taxvaluedollarcnt'].fillna(0), df['taxamount'].fillna(0),␣
↪1)
plt.plot(df['taxvaluedollarcnt'], m * df['taxvaluedollarcnt'] + b, color='red',␣
↪linewidth = 2)

plt.xlabel('Tax Value Dollar Count')
plt.ylabel('Tax Amount')
plt.title('Relationship Between Tax Amount and Tax Value Dollar Count')

# Show the plot
#plt.show()

# Calculate the R-squared value
correlation_matrix = np.corrcoef(df['taxvaluedollarcnt'].
↪fillna(df['taxvaluedollarcnt'].median()),
                                 df['taxamount'].fillna(df['taxamount'].
↪median()))
correlation_xy = correlation_matrix[0,1]
r_squared = correlation_xy**2

print(f'R-squared: {r_squared}')
```

```
R-squared: 0.9807457707605431
```

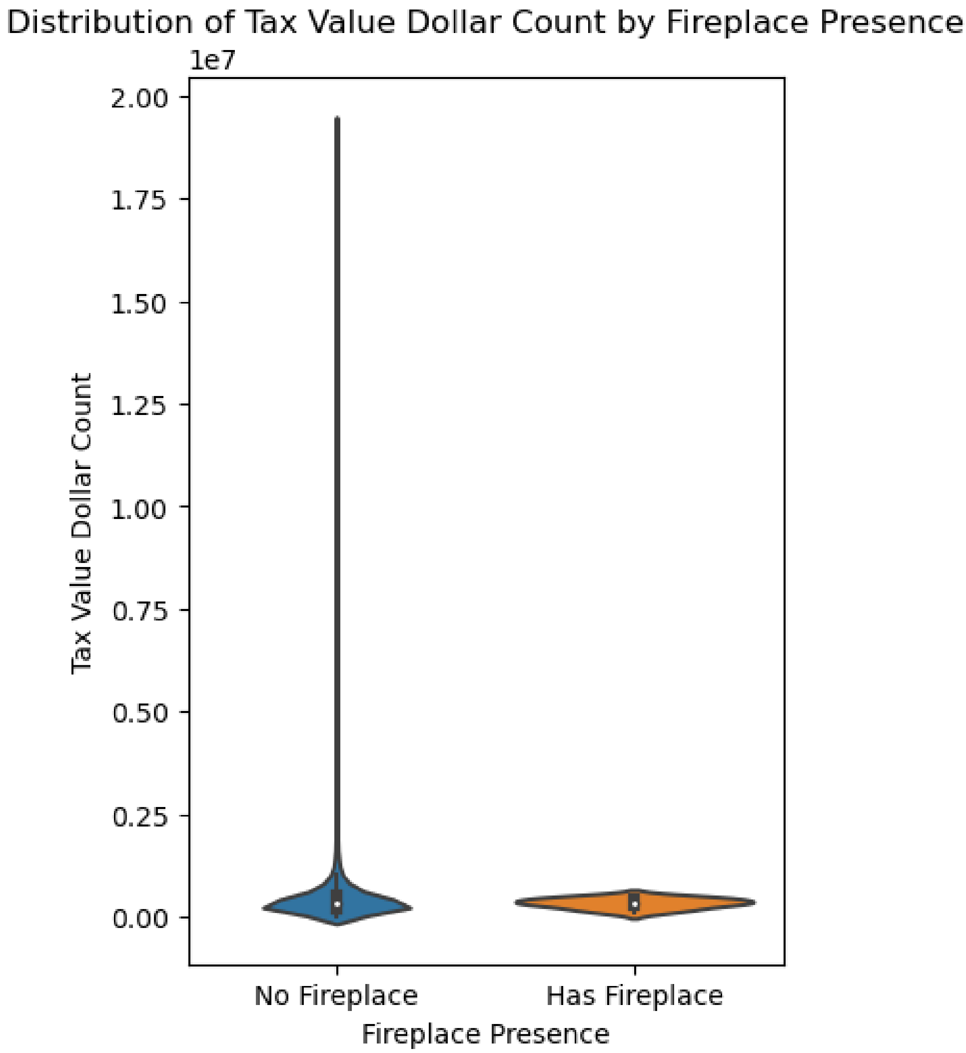


0.7 Question 7

[25]:
```
# Compare the average calculatedfinishedsquarefeet for properties with␣
↪different number of stories using a bar chart
df['StoryCategory'] = df['numberofstories'].apply(lambda x: 'More than 1' if x␣
↪> 1 else '1 Story')
average_sqft_by_story = df.
↪groupby('StoryCategory')['calculatedfinishedsquarefeet'].mean()

plt.figure(figsize=(4, 6))
average_sqft_by_story.plot(kind='bar', color = ['b', 'g'])
plt.xlabel('Number of Stories')
plt.ylabel('Average Finished Square Feet')
plt.title('Average Finished Square Feet by Number of Stories')
plt.xticks(rotation=0)
plt.show()
```



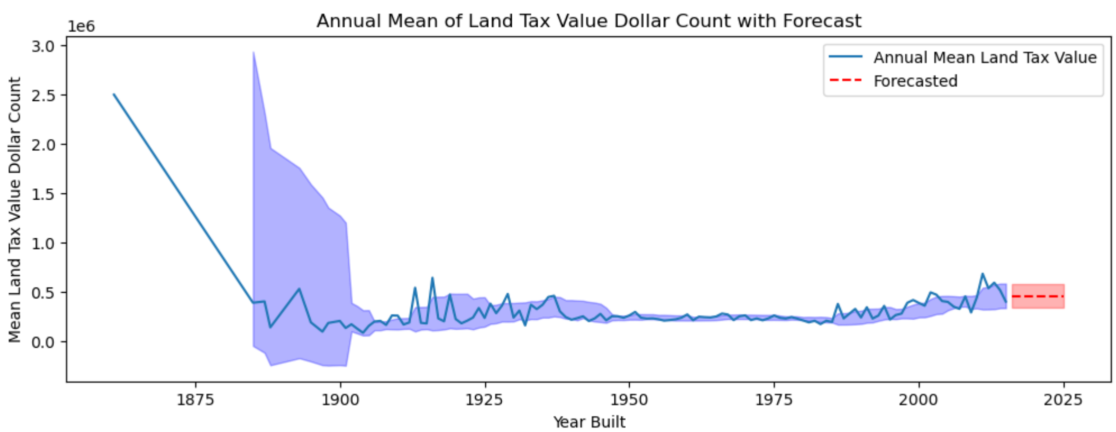

```
[26]: # Compare the taxvaluedollarcnt for properties with and without a fireplace␣
      ↪using a violin plot
      df['HasFireplace'] = df['fireplaceflag'].apply(lambda x: 'Has Fireplace' if x␣
      ↪== 1 else 'No Fireplace')
      plt.figure(figsize=(4, 6))
      sns.violinplot(x='HasFireplace', y='taxvaluedollarcnt', data=df)
      plt.xlabel('Fireplace Presence')
      plt.ylabel('Tax Value Dollar Count')
      plt.title('Distribution of Tax Value Dollar Count by Fireplace Presence')
      plt.show()
```



0.8 Question 8

[27]:
```
# Group data by 'yearbuilt' and calculate the annual mean of
 ↪'landtaxvaluedollarcnt'
annual_mean = df.groupby('yearbuilt')['landtaxvaluedollarcnt'].mean()

# Rolling mean and standard deviation
rolling_mean = annual_mean.rolling(window=10, min_periods=1).mean()
rolling_std = annual_mean.rolling(window=10, min_periods=1).std()

# Forecast plot for the next 10 years
years = np.arange(annual_mean.index.max() + 1, annual_mean.index.max() + 11)
future_mean = np.repeat(rolling_mean.iloc[-1], len(years))
future_std = np.repeat(rolling_std.iloc[-1], len(years))
```

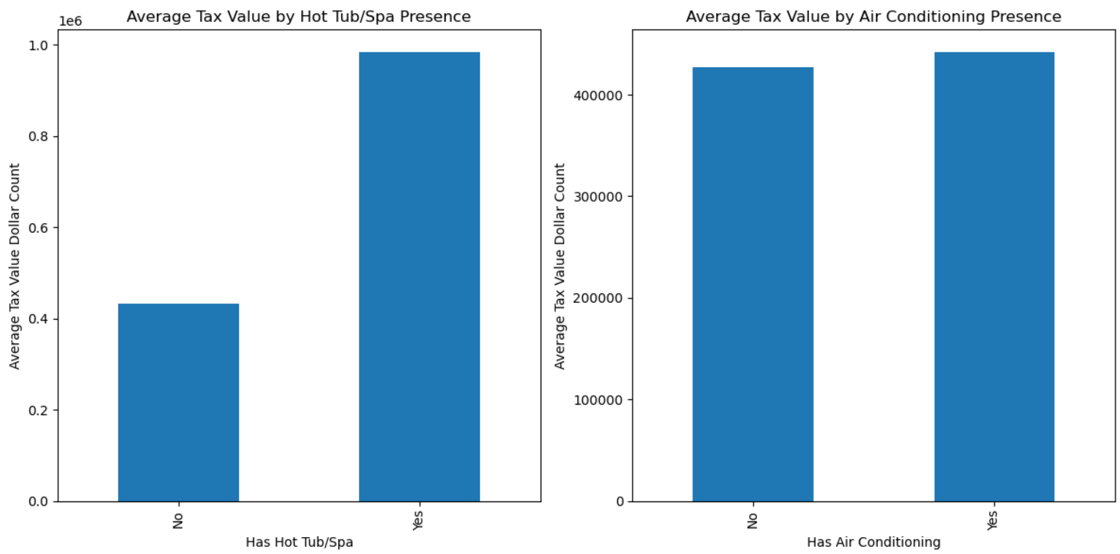
```
# Create a plot
plt.figure(figsize=(12, 4))

# Plotting the historical data
plt.plot(annual_mean.index, annual_mean, label='Annual Mean Land Tax Value')
plt.fill_between(annual_mean.index, rolling_mean - rolling_std, rolling_mean +␣
↪rolling_std, color='blue', alpha=0.3)

# Plotting the forecast
plt.plot(years, future_mean, label='Forecasted', linestyle='--', color='red')
plt.fill_between(years, future_mean - future_std, future_mean + future_std,␣
↪color='red', alpha=0.3)

plt.xlabel('Year Built')
plt.ylabel('Mean Land Tax Value Dollar Count')
plt.title('Annual Mean of Land Tax Value Dollar Count with Forecast')
plt.legend()
plt.show()
```



0.9 Question 9

[29]:
```
# Create binary features for the presence of hot tub/spa and air conditioning
df['HasHotTubOrSpa'] = df['hashottuborspa'].apply(lambda x: 'Yes' if x == True␣
↪else 'No')
df['HasAirConditioning'] = df['airconditioningtypeid'].apply(lambda x: 'No' if␣
↪x == 5 or x is None else 'Yes')

# Calculate average taxvaluedollarcnt for each group
avg_taxval_by_hot_tub = df.groupby('HasHotTubOrSpa')['taxvaluedollarcnt'].mean()
avg_taxval_by_ac = df.groupby('HasAirConditioning')['taxvaluedollarcnt'].mean()
```

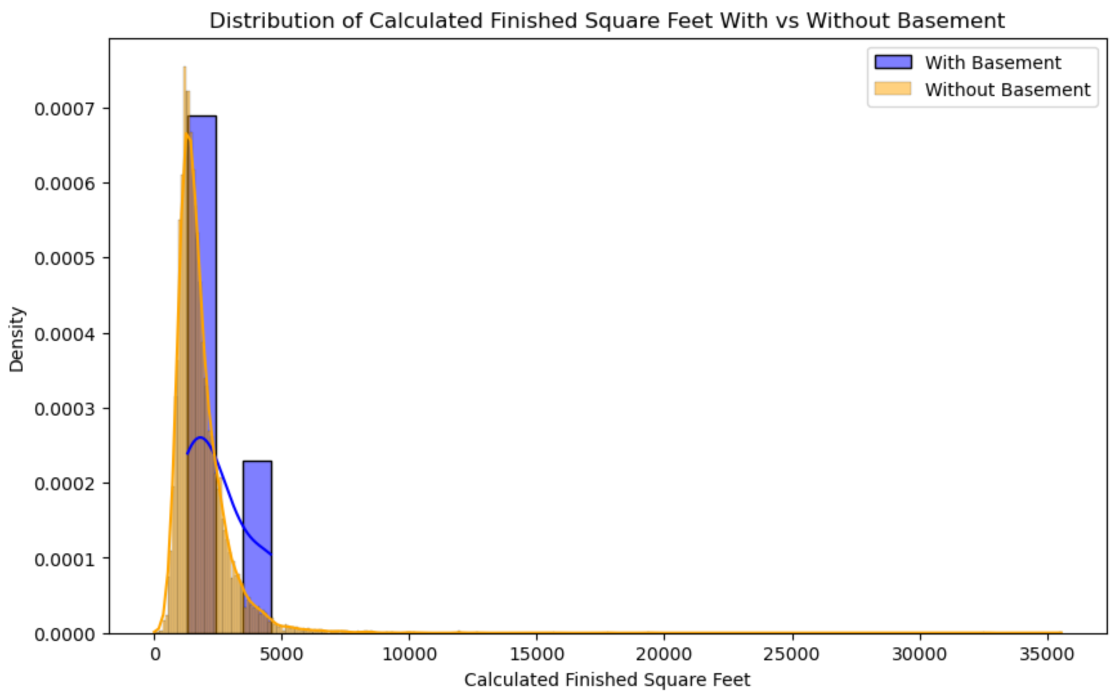
```python
# Plot grouped bar chart
fig, ax = plt.subplots(1, 2, figsize=(12, 6))

# Plot for hot tub/spa
avg_taxval_by_hot_tub.plot(kind='bar', ax=ax[0])
ax[0].set_title('Average Tax Value by Hot Tub/Spa Presence')
ax[0].set_xlabel('Has Hot Tub/Spa')
ax[0].set_ylabel('Average Tax Value Dollar Count')

# Plot for air conditioning
avg_taxval_by_ac.plot(kind='bar', ax=ax[1])
ax[1].set_title('Average Tax Value by Air Conditioning Presence')
ax[1].set_xlabel('Has Air Conditioning')
ax[1].set_ylabel('Average Tax Value Dollar Count')

plt.tight_layout()
plt.show()
```



[30]:
```python
df['HasBasement'] = df['basementsqft'].apply(lambda x: 'Yes' if x > 0 else 'No')

# Perform a hypothesis test
with_basement = df[df['HasBasement'] == 'Yes']['calculatedfinishedsquarefeet']
without_basement = df[df['HasBasement'] == 'No']['calculatedfinishedsquarefeet']
t_stat, p_val = ttest_ind(with_basement.dropna(), without_basement.dropna())

print(f"T-statistic: {t_stat}, P-value: {p_val}")
```

```
# Visualize the results using a histogram overlaid with the probability density
  ↪function
plt.figure(figsize=(10, 6))
sns.histplot(with_basement, color='blue', kde=True, label='With Basement',
  ↪stat="density")
sns.histplot(without_basement, color='orange', kde=True, label='Without
  ↪Basement', stat="density")
plt.xlabel('Calculated Finished Square Feet')
plt.ylabel('Density')
plt.title('Distribution of Calculated Finished Square Feet With vs Without
  ↪Basement')
plt.legend()
plt.show()
```

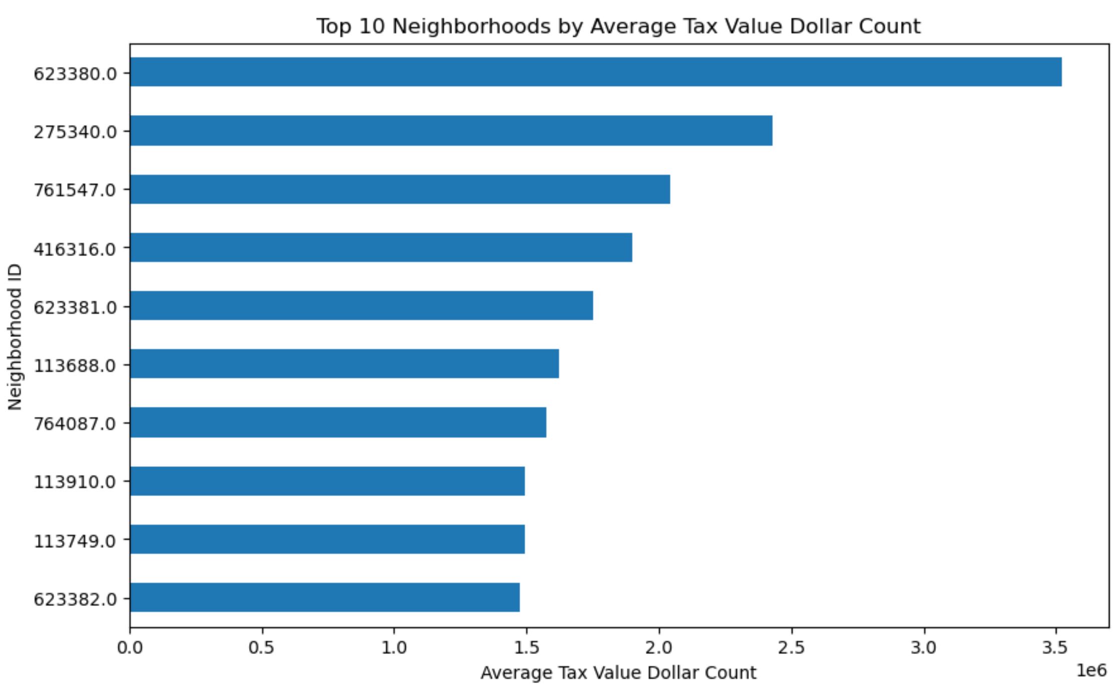
```
T-statistic: 1.1512717067318656, P-value: 0.24964842071351181
```

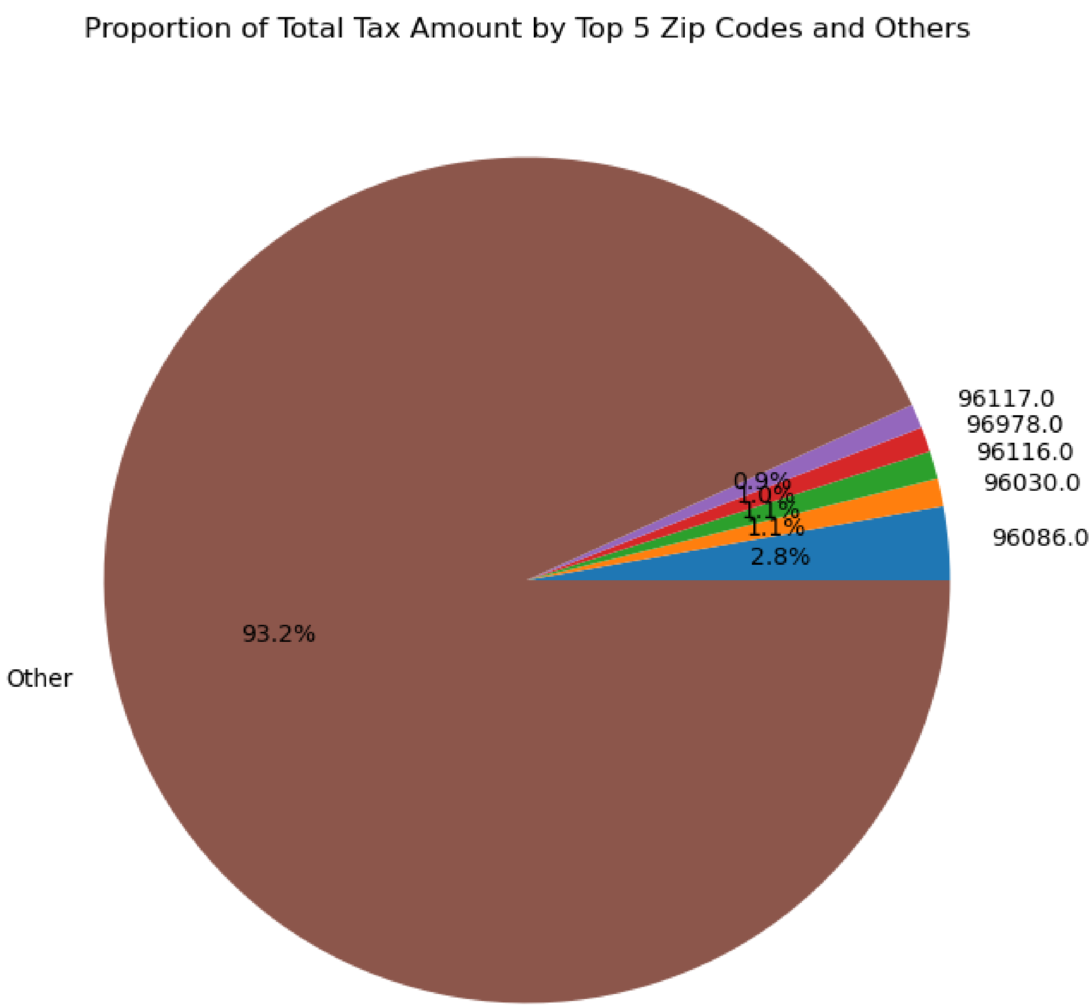


0.10 Question 10

[31]:
```
# Group properties by 'regionidneighborhood' and calculate the average
  ↪'taxvaluedollarcnt'
avg_taxval_by_neighborhood = df.
  ↪groupby('regionidneighborhood')['taxvaluedollarcnt'].mean().
  ↪sort_values(ascending=False)
```

```python
# Plot a horizontal bar chart for the top 10 neighborhoods
top_10_neighborhoods = avg_taxval_by_neighborhood.head(10)
plt.figure(figsize=(10, 6))
top_10_neighborhoods.plot(kind='barh')
plt.xlabel('Average Tax Value Dollar Count')
plt.ylabel('Neighborhood ID')
plt.title('Top 10 Neighborhoods by Average Tax Value Dollar Count')
plt.gca().invert_yaxis()  # Invert y-axis to have the highest value on top
plt.show()

# Group properties by 'regionidzip' and calculate the total 'taxamount'
total_tax_by_zip = df.groupby('regionidzip')['taxamount'].sum().
    sort_values(ascending=False)

# Get the top 5 zip codes and the sum of the rest
top_5_zip = total_tax_by_zip.head(5)
other_zip = total_tax_by_zip.iloc[5:].sum()
top_5_zip['Other'] = other_zip

# Plot a pie chart
plt.figure(figsize=(8, 8))
top_5_zip.plot(kind='pie', autopct='%1.1f%%')
plt.title('Proportion of Total Tax Amount by Top 5 Zip Codes and Others')
plt.ylabel('')  # Hide y-label
plt.show()
```





[32]:
```
top_5_zip
```

[32]:
```
regionidzip
96086.0     1495212.79
96030.0      566045.70
96116.0      564857.89
96978.0      507861.38
96117.0      495607.22
Other      49704544.40
Name: taxamount, dtype: float64
```

[ ]:
```

```