SEAS 6414

Spring 2024

Assignment 5, Michael Wacey

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For an easier week, that was a lot of work. Interestingly, I tried Google Gemini(Bard) for some exercises. But that did not help because things were different enough. It may have given me a starting point but there was still a lot to do.

I have embedded the graphs in this file. They are numbered the same as the problem with an A for the first one and an B for the second one, if there is a second one.

Let me know if you want to see the source file. This is the executed file and has everything in it. But I am happy to share the source file. This assignment is in GitHub at https://github.com/OwlSaver/GWU.

Execution

```
##########################################################################################
# Week 5
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# Problem 1 - Data Cleaning and Exploration
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Problem:


- Load the zillow feature sample.csv dataset using Pandas and report any missing values
  per column. Create a strategy to handle these missing values, justifying your approach.
- Generate a summary table that shows the mean, median, and standard deviation of
  taxvaluedollarcnt, structuretaxvaluedollarcnt, and landtaxvaluedollarcnt
  for properties built in each decade (1960s, 1970s, etc.).


Code:

import numpy as np
import pandas as pd

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)
print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
print(f"The Zillow Feature Sample has {ZillowFeatureSample.isnull().sum().sum()} missing values.")
print(f"The Zillow Feature Sample missing values by feature:")
print(ZillowFeatureSample.isnull().sum())
print("")
print("My strategy to address the missing values is based on the number of missing features and")
print("an understanding of the data. The steps I would go through:")
print(" 1)  For each feature, determine if there is a logical value for it, if it is missing. For")
print("     example, if the number of fireplaces is missing, then assume it is zero.")
print(" 2)  Any feature that is missing under 2% of the values and is continuous would be")
print("     replaced with the mean od the non missing values.")
print(" 3)  Any feature that is missing more than 60% of its values, would be removed.")
print(" 4)  Next I would sort the rows by the number of missing features they have. I would look")
print("     for a natural break where there are two many missing features. These rows would be")
print("     removed.")
print(" 5)  I would then compare the mean and standard deviation of each feature in the original")
```

```
print("     dataset to the one adjusted for missing values. If any large differences appear, I")
print("     look into why this happened and what can be done about it.")
print("")
ZillowFeatureSample['decadebuilt'] = ["0000" if yb != yb else str(int(yb-(yb%10))) for yb in
ZillowFeatureSample.yearbuilt]
ZillowFeatureSampleSummary = ZillowFeatureSample.groupby("decadebuilt").agg(
   row_count=("taxvaluedollarcnt", "count")
   , taxvaluedollarcnt_mean=("taxvaluedollarcnt", "mean")
   , taxvaluedollarcnt_median=("taxvaluedollarcnt", "median")
   , taxvaluedollarcnt_std=("taxvaluedollarcnt", "std")
   , structuretaxvaluedollarcnt_mean=("structuretaxvaluedollarcnt", "mean")
   , structuretaxvaluedollarcnt_median=("structuretaxvaluedollarcnt", "median")
   , structuretaxvaluedollarcnt_std=("structuretaxvaluedollarcnt", "std")
   , landtaxvaluedollarcnt_mean=("landtaxvaluedollarcnt", "mean")
   , landtaxvaluedollarcnt_median=("landtaxvaluedollarcnt", "median")
   , landtaxvaluedollarcnt_std=("landtaxvaluedollarcnt", "std")
)
print("")
print("Summary table:")
print(ZillowFeatureSampleSummary)
```

Execution:

```
The Zillow Feature Sample has 284030 missing values.
The Zillow Feature Sample missing values by feature:
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
```

My strategy to address the missing values is based on the number of missing features and an understanding of the data. The steps I would go through:

1) For each feature, determine if there is a logical value for it, if it is missing. For example, if the number of fireplaces is missing, then assume it is zero.
2) Any feature that is missing under 2% of the values and is continuous would be replaced with the mean od the non missing values.
3) Any feature that is missing more than 60% of its values, would be removed.
4) Next I would sort the rows by the number of missing features they have. I would look for a natural break where there are two many missing features. These rows would be removed.
5) I would then compare the mean and standard deviation of each feature in the original dataset to the one adjusted for missing values. If any large differences appear, I look into why this happened and what can be done about it.

Summary table:

decadebuilt	row_count	taxvaluedollarcnt_mean	taxvaluedollarcnt_median	taxvaluedollarcnt_std	structuretaxvaluedollarcnt_mean	structuretaxvaluedollarcnt_median	structuretaxvaluedollarcnt_std	landtaxvaluedollarcnt_mean	landtaxvaluedollarcnt_median	landtaxvaluedollarcnt_std
0000	148	282,547.80	40,953.50	925,541.24	158,973.64	24,109.50	508,813.27	306,692.13	119,441.50	669,489.95
1860	1	2,600,588.00	2,600,588.00	NaN	104,023.00	104,023.00	NaN	2,496,565.00	2,496,565.00	NaN
1880	4	473,815.25	450,008.00	234,392.08	141,027.25	128,322.00	83,936.50	332,788.00	283,388.50	226,589.90
1890	10	298,284.10	195,041.50	210,090.87	100,655.40	38,199.50	110,791.41	197,628.70	152,385.00	136,610.95
1900	103	294,758.97	254,328.00	232,803.52	114,436.28	75,057.00	112,924.13	180,322.69	146,301.00	148,736.98
1910	158	397,018.52	252,592.00	724,096.14	124,393.66	73,706.00	197,842.06	272,624.86	166,412.00	553,421.01
1920	673	430,727.81	279,054.00	636,701.47	135,394.68	90,315.00	185,213.51	295,534.31	172,972.00	483,498.19
1930	349	499,617.99	336,282.00	592,583.83	174,301.76	105,911.00	236,973.07	325,316.23	218,224.00	398,038.63
1940	980	366,712.86	290,323.50	333,351.21	124,400.49	96,000.00	109,412.82	242,439.30	182,391.00	252,038.49
1950	2049	357,176.30	279,139.00	459,852.41	119,710.93	94,500.00	110,366.36	237,582.22	168,412.00	393,884.50
1960	1372	395,530.76	324,814.00	390,546.73	146,786.26	118,833.00	134,046.67	248,925.93	176,199.00	301,753.31
1970	1389	391,092.63	316,000.00	318,708.58	155,448.88	130,979.00	97,463.30	235,925.52	160,378.00	258,126.44
1980	1210	463,558.15	342,899.50	776,381.84	215,180.24	166,615.50	252,129.08	249,201.72	158,589.50	548,221.89
1990	618	584,373.33	460,059.00	530,667.33	279,759.40	217,237.50	223,138.51	306,099.85	213,829.00	358,105.63
2000	660	787,722.41	572,573.00	777,851.88	385,706.62	280,808.50	376,648.70	403,237.73	272,929.50	486,368.40
2010	157	985,455.25	696,385.00	1,161,067.39	455,226.42	336,717.00	466,447.01	537,070.49	374,656.00	836,742.84

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##################################################################################
# Problem 2 - Feature Engineering
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Problem:


- Create a new feature Age that represents the age of each property from the yearbuilt
  column, considering the dataset's latest assessmentyear.
- Develop a binary feature HasPool based on the poolcnt column, where 1 indicates
  the presence of a pool and 0 or NaN indicates no pool.
- Calculate and return the descriptive statistics for the age of the properties. Specifically,
  report the median age of the properties based on the yearbuilt and the
  latest assessmentyear.
- Generate and plot a bar chart of the counts of the binary feature  HasPool  created
  earlier. Set the y-axis to a logarithmic scale to better visualize the distribution of
  properties with and without pools.


Code:

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

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)
print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
ZillowFeatureSample['Age'] = [ZillowFeatureSample["assessmentyear"].max() - yb for yb in
ZillowFeatureSample.yearbuilt]
ZillowFeatureSample['HasPool'] =  [1 if pc > 0 else 0 for pc in ZillowFeatureSample.poolcnt]

print("")
print("Summary table:")
print(ZillowFeatureSample[["Age", "yearbuilt", "poolcnt", "HasPool"]])
print("")
print(f"The medan age of the properties based on Year Built and latest assement year is
{ZillowFeatureSample["Age"].median()}.")
print("")
x = ZillowFeatureSample['HasPool'].value_counts().plot(kind='bar')
x.set_yscale('log')
plt.title(f"Problem {PNumber} A:Houses with and without pools")
plt.show()

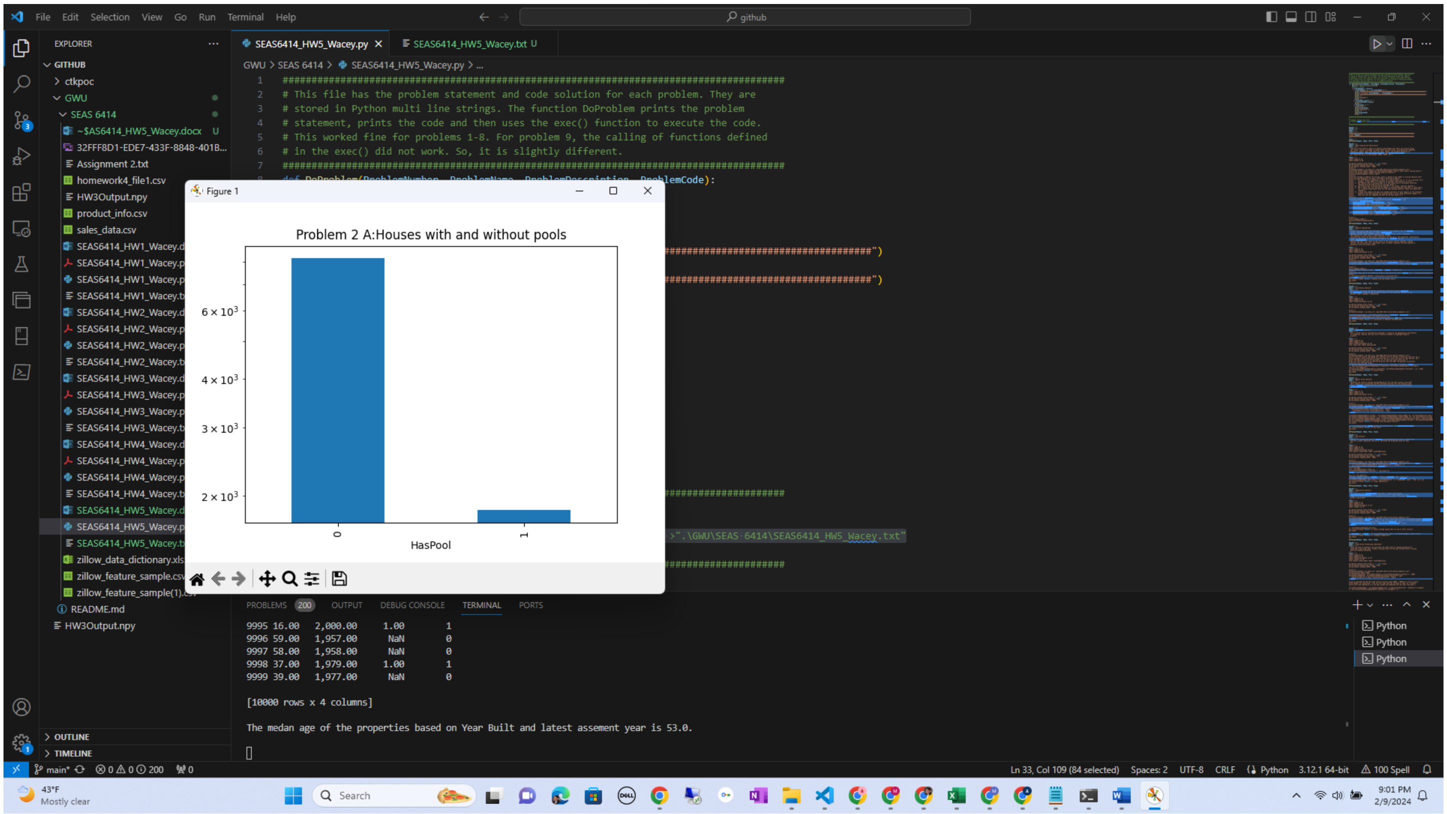
Execution:



Summary table:
       Age  yearbuilt  poolcnt  HasPool
0    61.00   1,955.00      NaN        0
1     4.00   2,012.00      NaN        0
2    59.00   1,957.00      NaN        0
3    10.00   2,006.00      NaN        0
4    29.00   1,987.00      NaN        0
...    ...        ...      ...      ...
9995 16.00   2,000.00     1.00        1
9996 59.00   1,957.00      NaN        0
9997 58.00   1,958.00      NaN        0
9998 37.00   1,979.00     1.00        1
9999 39.00   1,977.00      NaN        0

[10000 rows x 4 columns]

The medan age of the properties based on Year Built and latest assement year is 53.0.
```




```
######################################################################################
# Problem 3 - Correlation Analysis
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Problem:

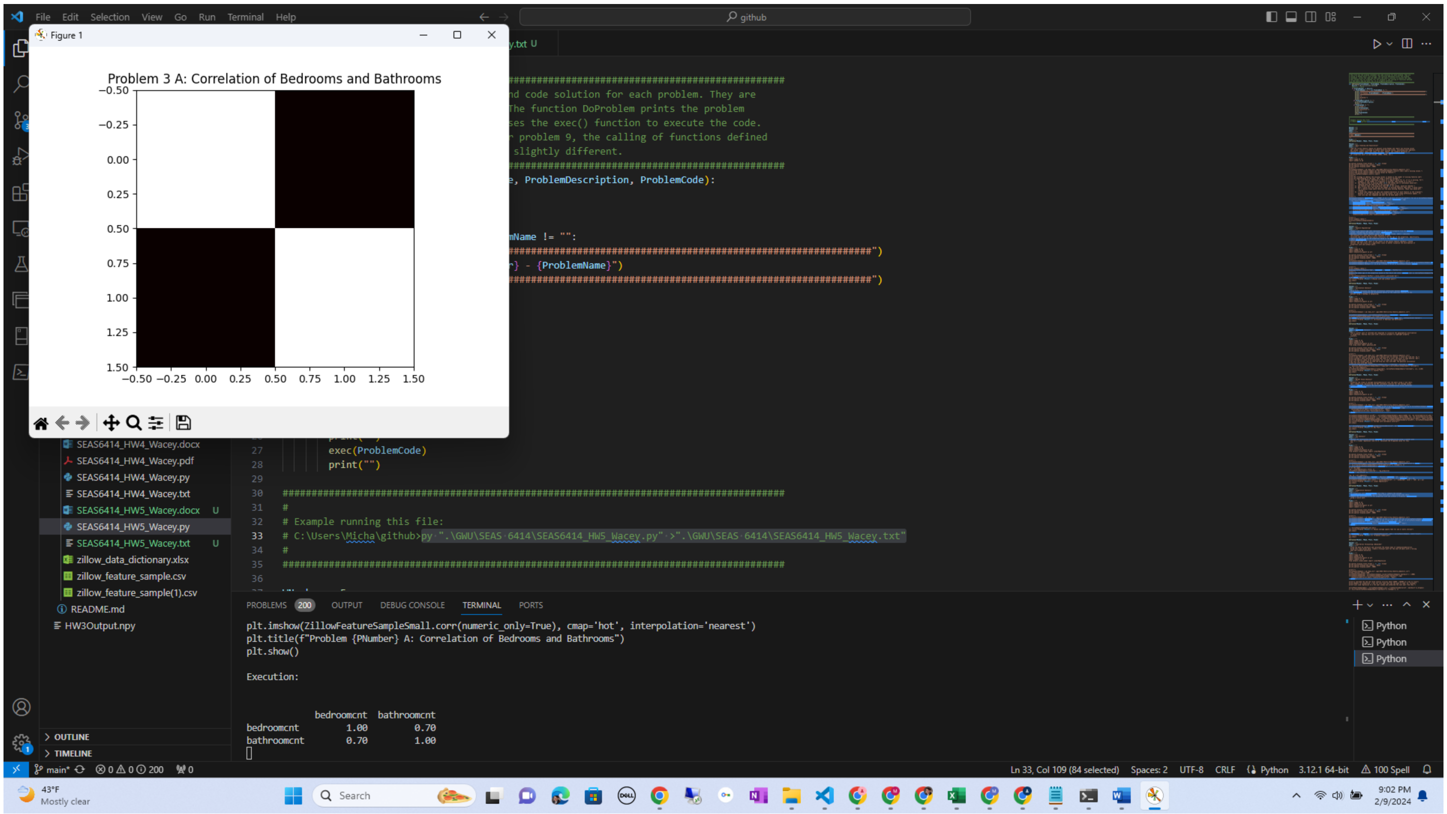
- Using NumPy, calculate the Pearson correlation coefficient between bedroomcnt and bathroomcnt. Visualize the correlation matrix of the numerical features of the dataset using a heatmap in matplotlib.

Code:

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

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")

ZillowFeatureSampleSmall = ZillowFeatureSample.loc[:,['bedroomcnt','bathroomcnt']]
print(ZillowFeatureSampleSmall.corr(numeric_only=True))
plt.imshow(ZillowFeatureSampleSmall.corr(numeric_only=True), cmap='hot', interpolation='nearest')
plt.title(f"Problem {PNumber} A: Correlation of Bedrooms and Bathrooms")
plt.show()
```

Execution:

```
             bedroomcnt  bathroomcnt
bedroomcnt         1.00         0.70
bathroomcnt        0.70         1.00
```




```
#########################################################################################
# Problem 4 - Geospatial Analysis
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```

Problem:

- Plot a scatter plot of latitude and longitude to visualize the geographical distribution of properties. Overlay this plot with a density estimate to highlight property clusters.

Code:

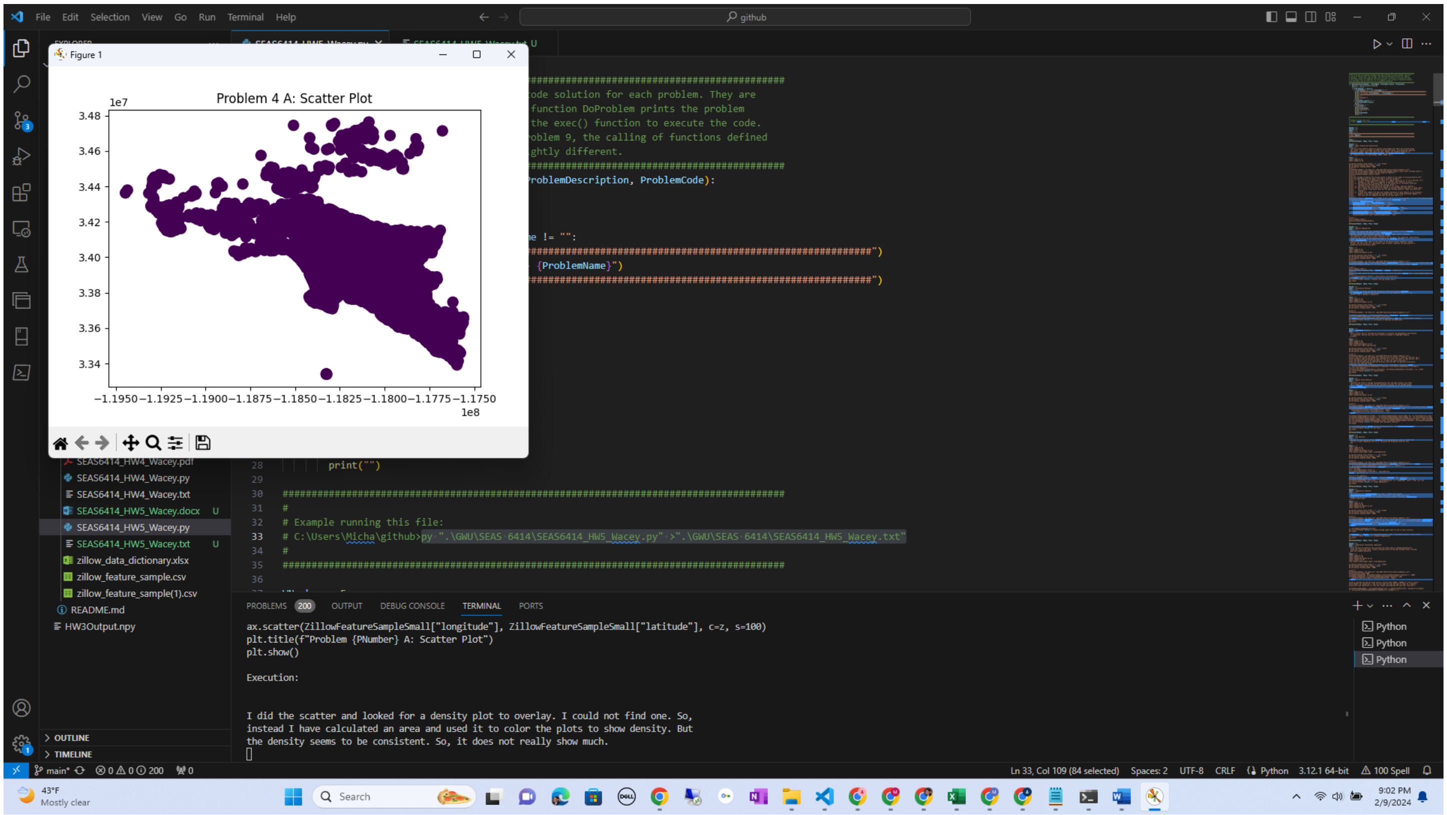
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import gaussian_kde

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
print("I did the scatter and looked for a density plot to overlay. I could not find one. So,")
print("instead I have calculated an area and used it to color the plots to show density. But")
print("the density seems to be consistent. So, it does not really show much.")
# Get just the columns that we need and drop any rows with NaN. The gaussian calculation
# does not work with NaN values.
ZillowFeatureSampleSmall = ZillowFeatureSample.loc[:,['longitude','latitude']].dropna()
z = gaussian_kde(ZillowFeatureSampleSmall["longitude"])(ZillowFeatureSampleSmall["latitude"])
fig, ax = plt.subplots()
ax.scatter(ZillowFeatureSampleSmall["longitude"], ZillowFeatureSampleSmall["latitude"], c=z, s=100)
plt.title(f"Problem {PNumber} A: Scatter Plot")
plt.show()
```

Execution:

```
I did the scatter and looked for a density plot to overlay. I could not find one. So,
instead I have calculated an area and used it to color the plots to show density. But
the density seems to be consistent. So, it does not really show much.
```




```
##################################################################################
# Problem 5 - Market Value Analysis
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Problem:


- Visualize the trend of average taxvaluedollarcnt over the years using a line chart.
  Add a shaded area representing the 95% confidence interval for the average values.
- Create a boxplot to compare the distribution of taxvaluedollarcnt across different
  buildingqualitytypeid.


Code:

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

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
ZillowFeatureSample['assessyear'] = ["0000" if ay != ay else str(int(ay)) for ay in
ZillowFeatureSample.assessmentyear]
ZillowFeatureSampleSummary = ZillowFeatureSample.groupby("assessyear").agg(
   taxvaluedollarcnt_mean=("taxvaluedollarcnt", "mean")
   , taxvaluedollarcnt_std=("taxvaluedollarcnt", "std")
).dropna()

ZillowFeatureSampleSummary['plus95'] = ZillowFeatureSampleSummary.apply(lambda row: row.taxvaluedollarcnt_mean +
(2 * row.taxvaluedollarcnt_std), axis=1)
ZillowFeatureSampleSummary['minus95'] = ZillowFeatureSampleSummary.apply(lambda row: row.taxvaluedollarcnt_mean
- (2 * row.taxvaluedollarcnt_std), axis=1)
plt.plot(ZillowFeatureSampleSummary.index, ZillowFeatureSampleSummary["taxvaluedollarcnt_mean"],
label="Average")
plt.fill_between(ZillowFeatureSampleSummary.index, ZillowFeatureSampleSummary["plus95"],
ZillowFeatureSampleSummary["minus95"], alpha=0.2, label="Confidence Interval")
plt.title(f"Problem {PNumber} A: Average with Confidence Interval")
plt.show()
```
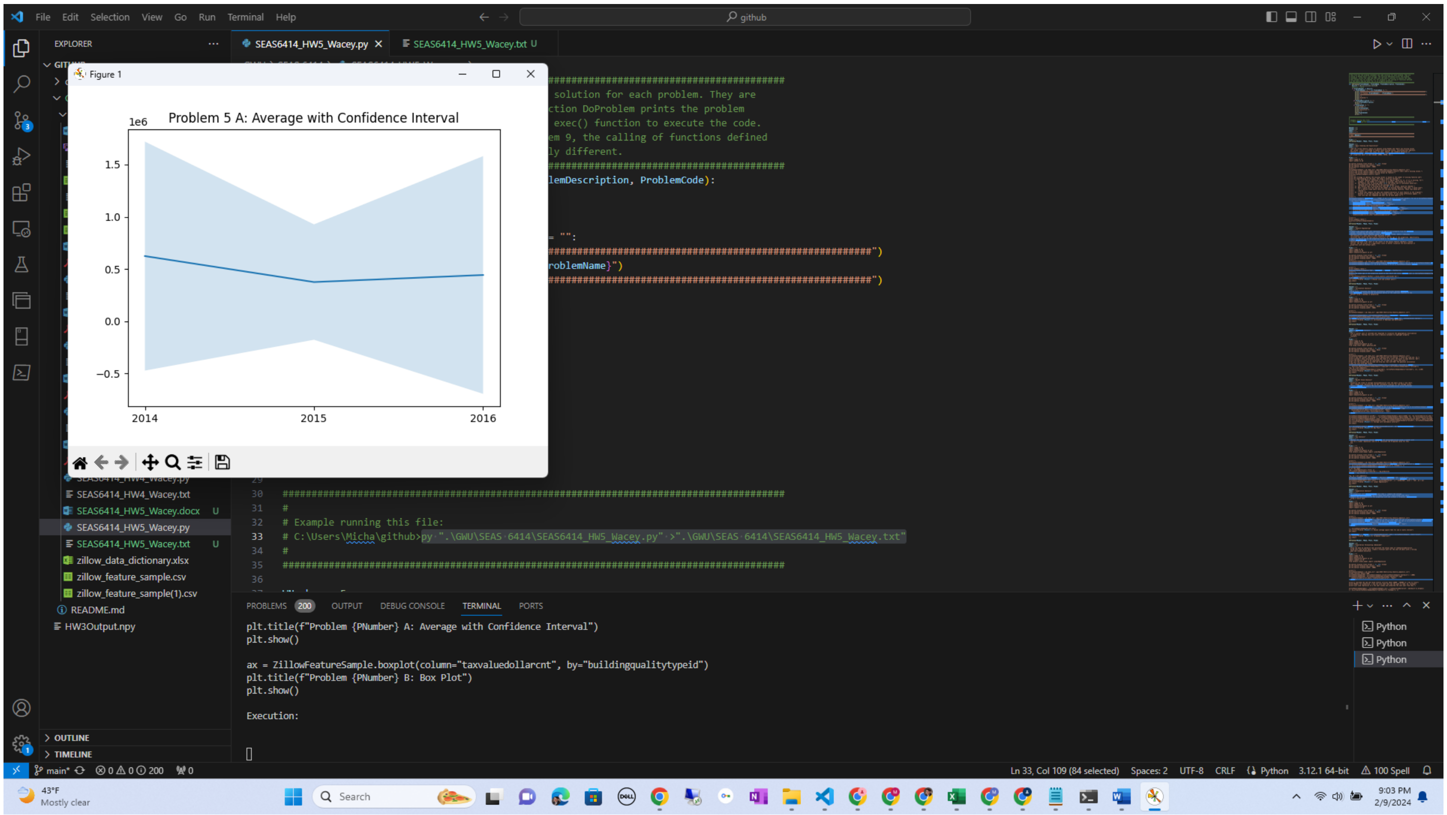
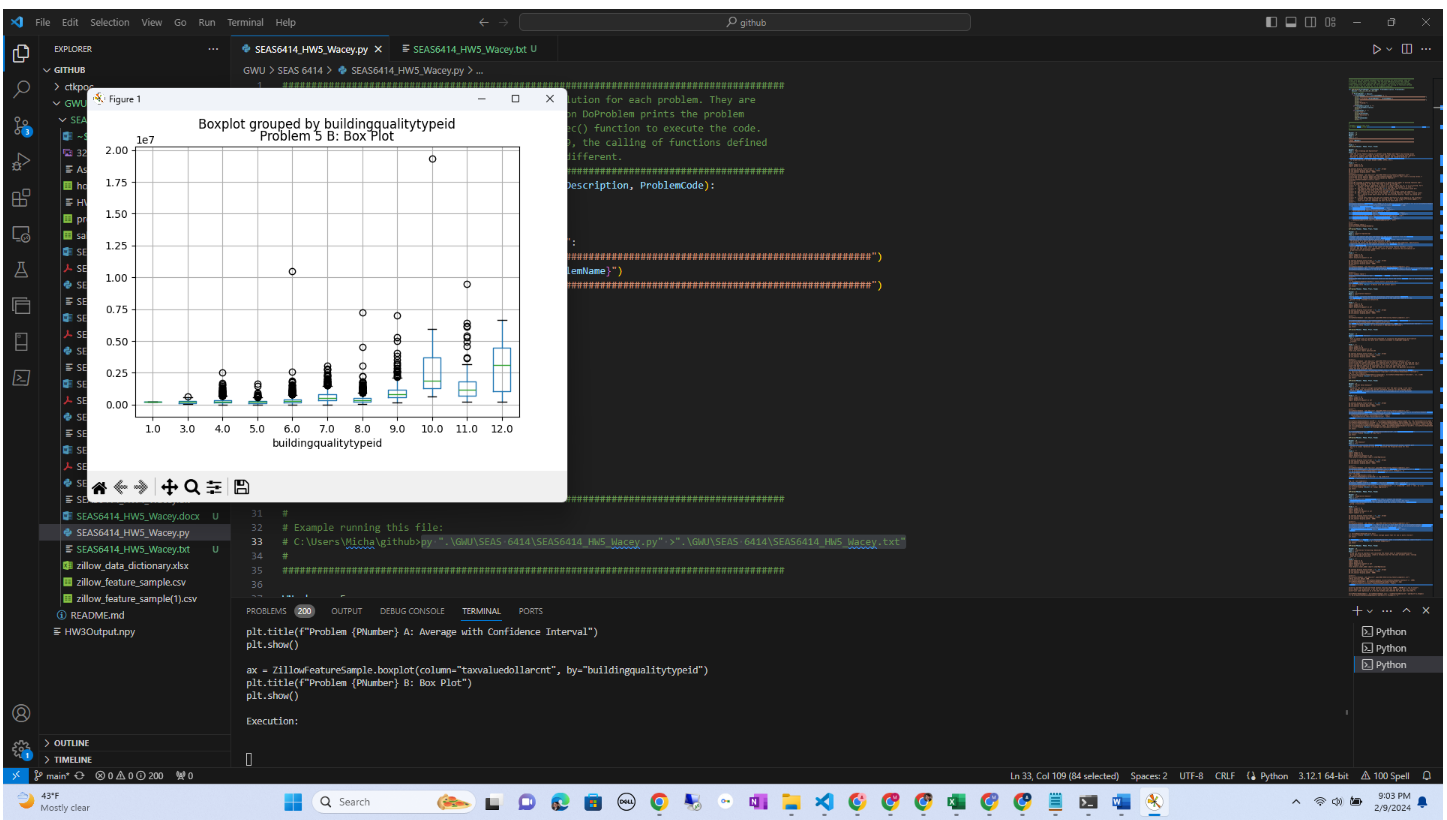

```
ax = ZillowFeatureSample.boxplot(column="taxvaluedollarcnt", by="buildingqualitytypeid")
plt.title(f"Problem {PNumber} B: Box Plot")
plt.show()
```

Execution:





```
##########################################################################################
# Problem 6 - Tax Analysis
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```

Problem:

- Analyze the relationship between taxamount and taxvaluedollarcnt using a scatter plot and fit a linear regression line to it. Calculate the R-squared value for this fit.

Code:

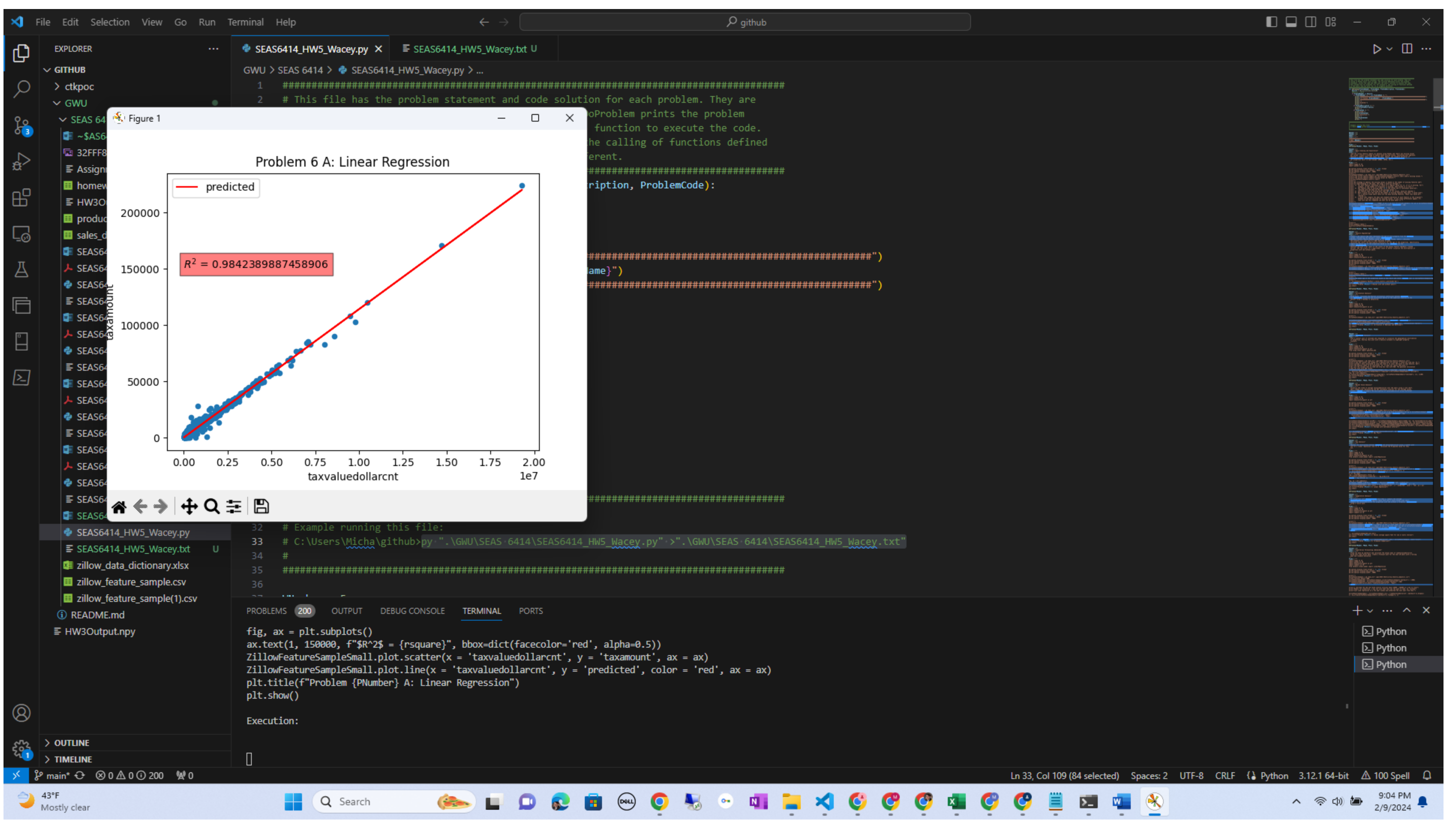
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
ZillowFeatureSampleSmall = ZillowFeatureSample.loc[:,['taxamount','taxvaluedollarcnt']].dropna()
X = np.array(ZillowFeatureSampleSmall["taxvaluedollarcnt"]).reshape(-1, 1)
y = np.array(ZillowFeatureSampleSmall["taxamount"])
# fit the model
reg = LinearRegression().fit(X, y)
ZillowFeatureSampleSmall['predicted'] = reg.predict(X)
rsquare = reg.score(X, y)

fig, ax = plt.subplots()
ax.text(1, 150000, f"$R^2$ = {rsquare}", bbox=dict(facecolor='red', alpha=0.5))
ZillowFeatureSampleSmall.plot.scatter(x = 'taxvaluedollarcnt', y = 'taxamount', ax = ax)
ZillowFeatureSampleSmall.plot.line(x = 'taxvaluedollarcnt', y = 'predicted', color = 'red', ax = ax)
plt.title(f"Problem {PNumber} A: Linear Regression")
plt.show()
```

Execution:



```
##########################################################################################
# Problem 7 - Comparative Analysis
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Problem:


- For properties with numberofstories more than 1, compare the average
  calculatedfinishedsquarefeet against those with only 1 story using a bar chart.
- Compare the taxvaluedollarcnt for properties with and without a fireplace (fireplaceflag)
  using a violin plot.


Code:

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
ZillowFeatureSample['storygroup'] = ["Multi" if nos > 1 else "One" for nos in
ZillowFeatureSample.numberofstories]
ZillowFeatureSample['fpgroup'] = ["None" if fpf != fpf else "Has" for fpf in ZillowFeatureSample.fireplaceflag]
ZillowFeatureSampleSG = ZillowFeatureSample.groupby("storygroup").agg(
   calculatedfinishedsquarefeet_mean=("calculatedfinishedsquarefeet", "mean")
).dropna()

x = ZillowFeatureSampleSG.plot.bar()
plt.title(f"Problem {PNumber} A: Houses average square feet for one or multi stories")
plt.show()

sb.violinplot(x = 'fpgroup', y = "taxvaluedollarcnt", data = ZillowFeatureSample, inner="stick")
plt.title(f"Problem {PNumber} B: Fireplace Comparison")
plt.show()

Execution:
```

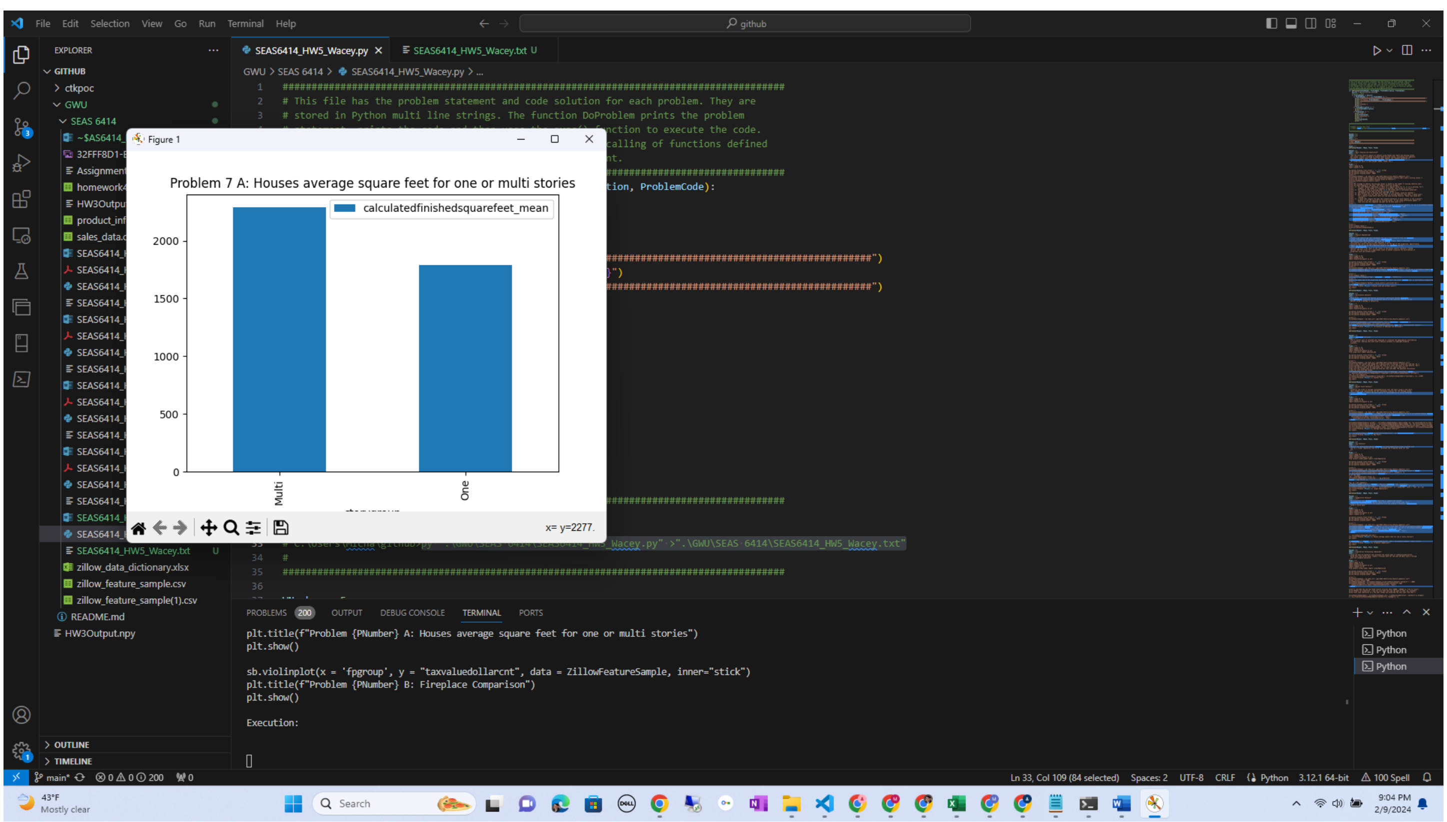

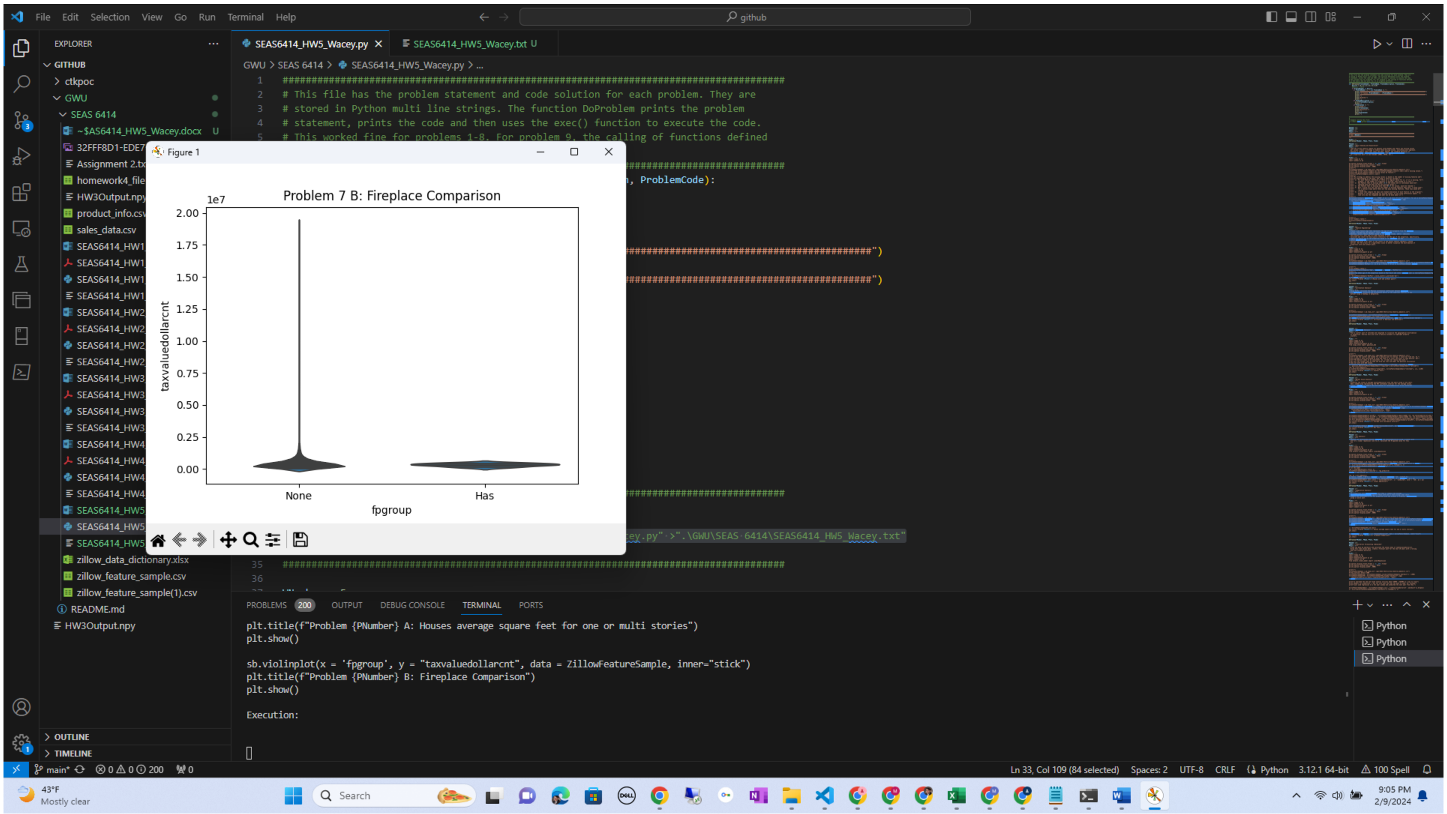


```
#######################################################################################
# Problem 8 - Time-Series Forecasting (Advanced)
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```

Problem:

- Group the data by yearbuilt and calculate the annual mean of landtaxvaluedollarcnt. Using this time series data, create a forecast plot for the next 10 years with a rolling mean and standard deviation.

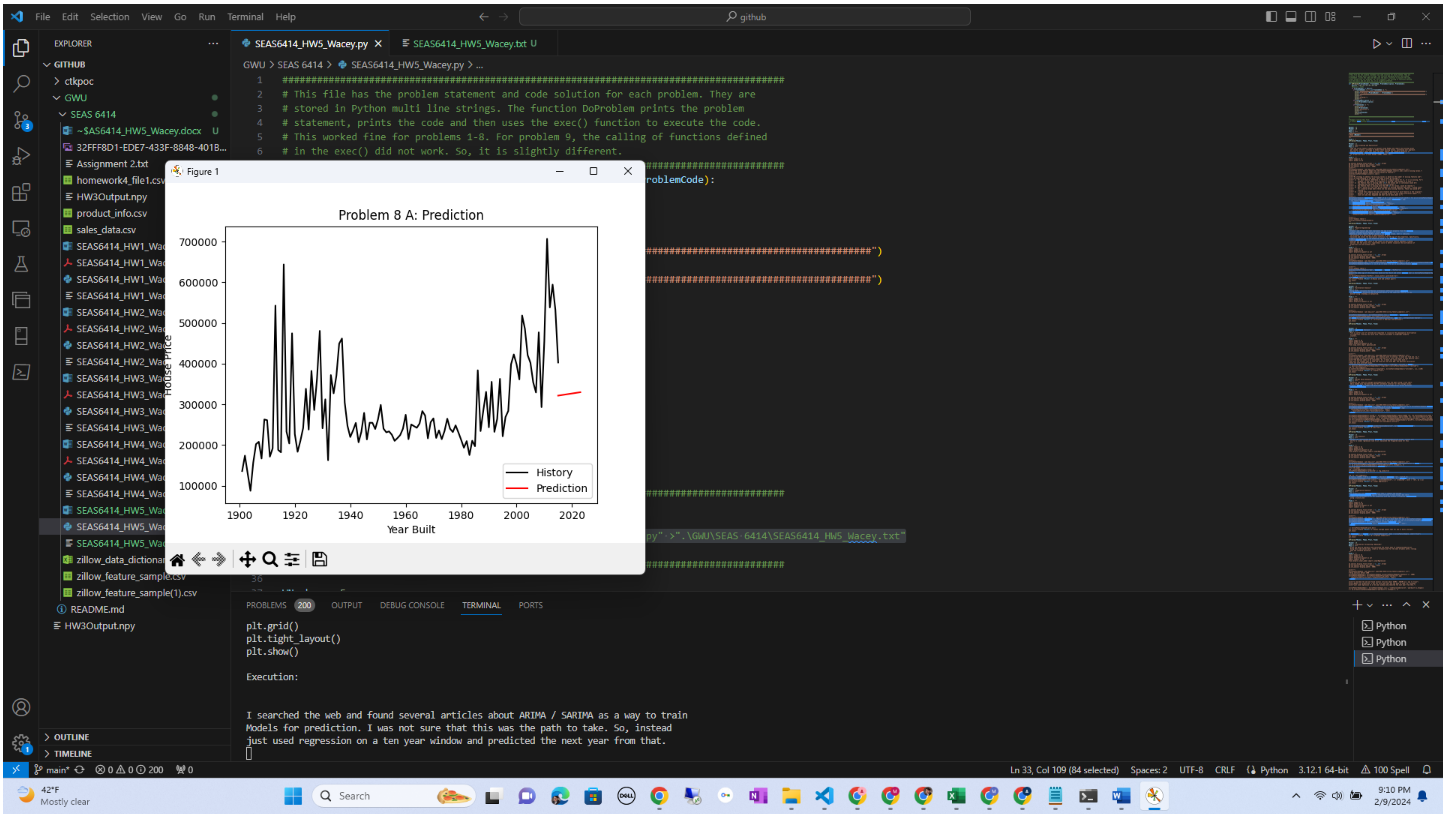
Code:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.linear_model import LinearRegression

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

print("")
ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
# Drop outliers before 1900
ZillowFeatureSampleYB = ZillowFeatureSample.loc[ZillowFeatureSample['yearbuilt'] > 1900]
ZillowFeatureSampleYB = ZillowFeatureSampleYB.groupby("yearbuilt").agg(
   landtaxvaluedollarcnt_mean=("landtaxvaluedollarcnt", "mean")
).dropna()

print("I searched the web and found several articles about ARIMA / SARIMA as a way to train")
print("Models for prediction. I was not sure that this was the path to take. So, instead")
print("just used regression on a ten year window and predicted the next year from that.")

ZillowFeatureSampleSmall = ZillowFeatureSample.loc[:,['landtaxvaluedollarcnt','yearbuilt']].dropna()
X = np.array(ZillowFeatureSampleSmall["yearbuilt"]).reshape(-1, 1)
y = np.array(ZillowFeatureSampleSmall["landtaxvaluedollarcnt"])
# fit the model
reg = LinearRegression().fit(X, y)
ZillowFeatureSampleSmall['predicted'] = reg.predict(X)
future_years = np.array(range(2015, 2024))
```

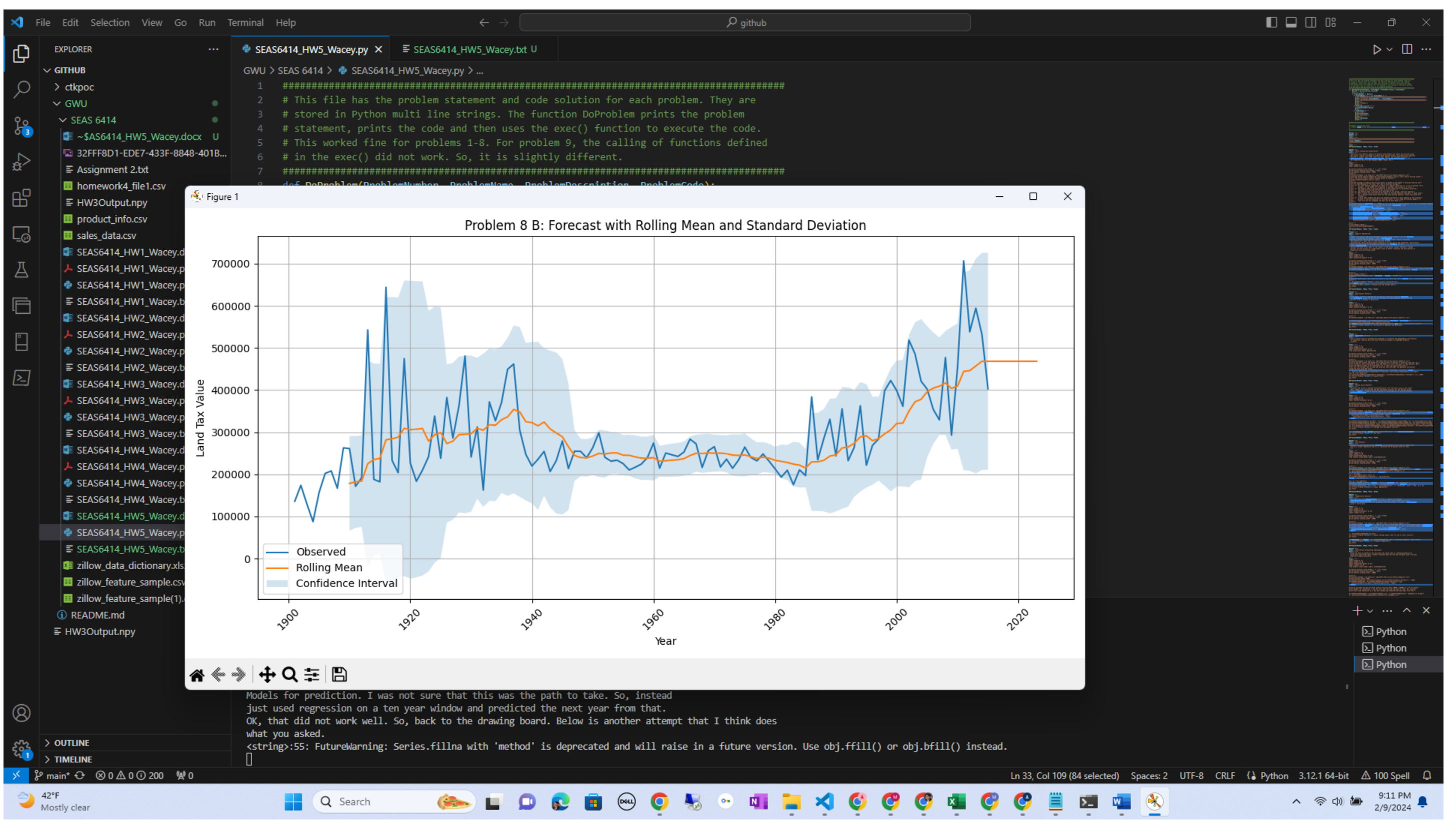
```
predicted_prices = np.array(reg.predict(future_years.reshape(-1, 1)))
predicted_data = pd.DataFrame({'yearbuilt': future_years,
'landtaxvaluedollarcnt':predicted_prices}).set_index('yearbuilt')
plt.plot(ZillowFeatureSampleYB, color = "black", label = "History")
plt.plot(predicted_data, color = "red", label = "Prediction")
plt.ylabel('House Price')
plt.xlabel('Year Built')
plt.legend()
plt.title(f"Problem {PNumber} A: Prediction")
plt.show()

print("OK, that did not work well. So, back to the drawing board. Below is another attempt that I think does")
print("what you asked.")

# Define window size for the rolling window
window_size = 10
# Calculate rolling mean
ZillowFeatureSampleYB["rolling_mean"] =
ZillowFeatureSampleYB["landtaxvaluedollarcnt_mean"].rolling(window=window_size).mean()
# Calculate rolling standard deviation
ZillowFeatureSampleYB["rolling_std"] =
ZillowFeatureSampleYB["landtaxvaluedollarcnt_mean"].rolling(window=window_size).std()
# Extend index for 10 years
future_years = np.array(range(2015, 2024))
# Extend the existing data with NaNs for future dates
ZillowFeatureSampleYB_extended = pd.concat([ZillowFeatureSampleYB,pd.DataFrame(index=future_years)])
# Fill NaN values with the last rolling mean
ZillowFeatureSampleYB_extended["rolling_mean"] =
ZillowFeatureSampleYB_extended["rolling_mean"].fillna(method="ffill")
# Calculate the upper and lower bounds based on rolling mean and standard deviation
ZillowFeatureSampleYB_extended["upper_bound"] = ZillowFeatureSampleYB_extended["rolling_mean"] + 2 *
ZillowFeatureSampleYB_extended["rolling_std"]
ZillowFeatureSampleYB_extended["lower_bound"] = ZillowFeatureSampleYB_extended["rolling_mean"] - 2 *
ZillowFeatureSampleYB_extended["rolling_std"]
# Plot observed data, rolling mean, and bounds
plt.figure(figsize=(12, 6))
plt.plot(ZillowFeatureSampleYB.index, ZillowFeatureSampleYB["landtaxvaluedollarcnt_mean"], label="Observed")
plt.plot(ZillowFeatureSampleYB_extended.index, ZillowFeatureSampleYB_extended["rolling_mean"], label="Rolling
Mean")
plt.fill_between(ZillowFeatureSampleYB_extended.index, ZillowFeatureSampleYB_extended["upper_bound"],
ZillowFeatureSampleYB_extended["lower_bound"], alpha=0.2, label="Confidence Interval")
# Add labels and title
plt.xlabel("Year")
plt.ylabel("Land Tax Value")
plt.title(f"Problem {PNumber} B: Forecast with Rolling Mean and Standard Deviation")
# Rotate x-axis labels for better readability
plt.xticks(rotation=45)
# Show the plot
plt.legend()
plt.grid()
plt.tight_layout()
plt.show()
```

Execution:

I searched the web and found several articles about ARIMA / SARIMA as a way to train Models for prediction. I was not sure that this was the path to take. So, instead just used regression on a ten year window and predicted the next year from that.

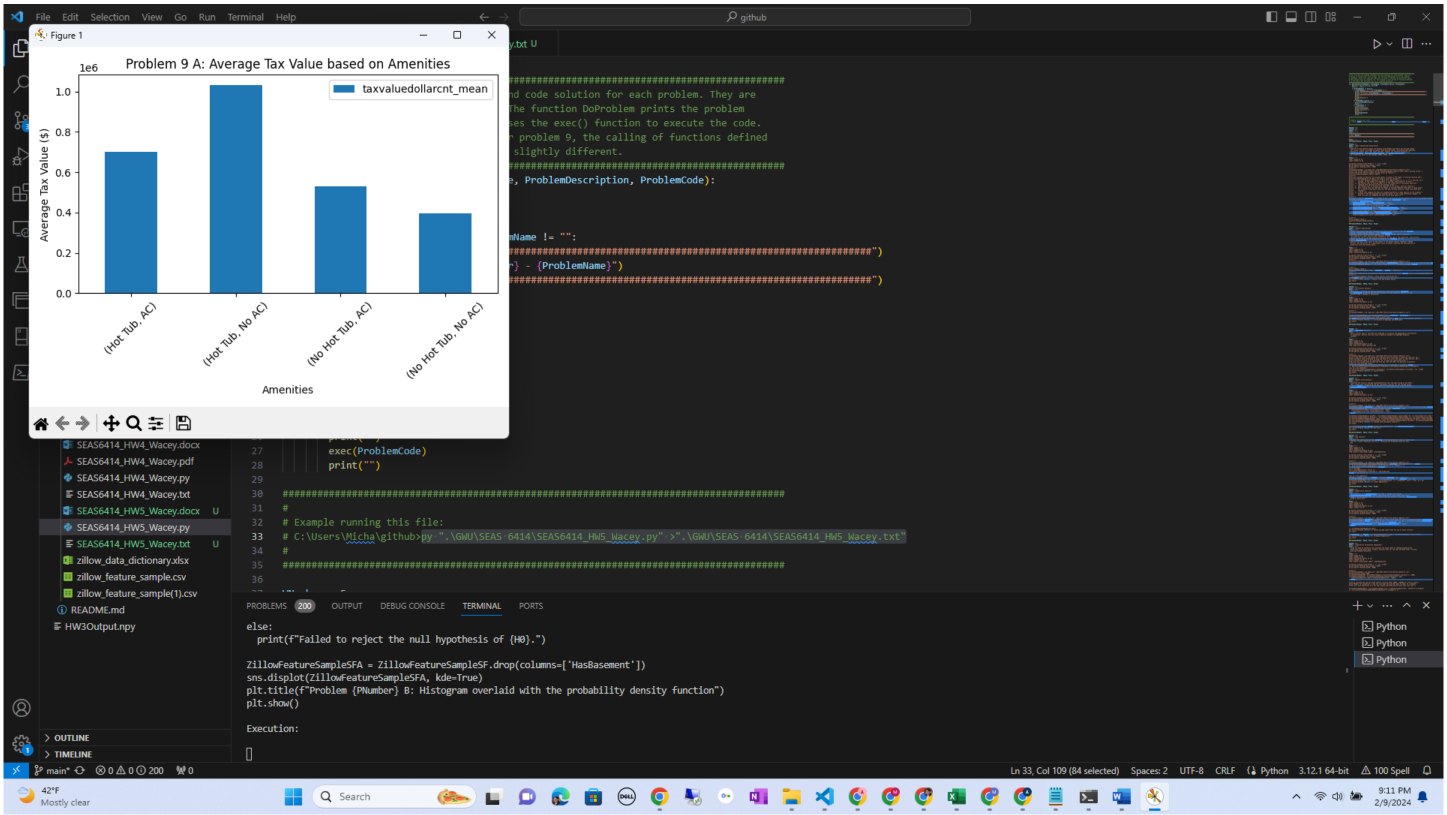


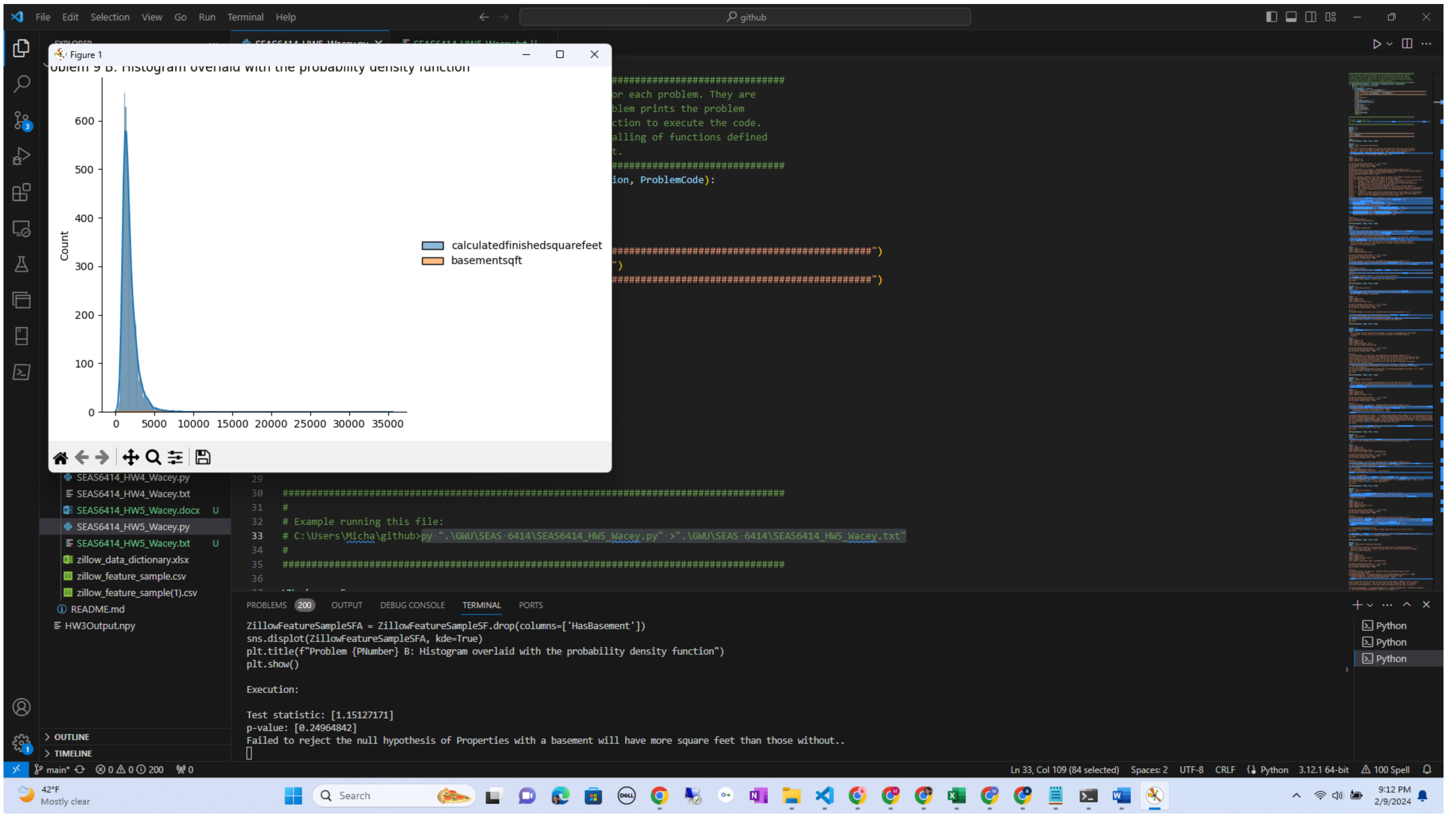
OK, that did not work well. So, back to the drawing board. Below is another attempt that I think does what you asked.



```
################################################################################
# Problem 9 - Amenities Impact Analysis
################################################################################

Problem:


- Determine how the presence of a hot tub or spa (hashottuborspa) and air conditioning (airconditioningtypeid)
  impacts the taxvaluedollarcnt. Use a grouped bar chart to represent the average taxvaluedollarcnt for
  properties with and without these amenities.
- Investigate if there is a significant difference in the calculatedfinishedsquarefeet for properties with a
  basement (basementsqft) versus those without. Perform a hypothesis test and visualize the results using a
  histogram overlaid with the probability density function.


Code:

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats
import seaborn as sns

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")
ZillowFeatureSample['HasHTS'] = ["No Hot Tub" if hhts != hhts else "Hot Tub" for hhts in
ZillowFeatureSample.hashottuborspa]
ZillowFeatureSample['HasAC'] = ["No AC" if act != act or act == 5.0 else "AC" for act in
ZillowFeatureSample.airconditioningtypeid]

ZillowFeatureSampleAM = ZillowFeatureSample.groupby(["HasHTS", "HasAC"]).agg(
   taxvaluedollarcnt_mean=("taxvaluedollarcnt", "mean")
).dropna()

x = ZillowFeatureSampleAM.plot.bar()
#x.ticklabel_format(style='plain')
plt.xlabel("Amenities")
plt.ylabel("Average Tax Value ($)")
plt.title(f"Problem {PNumber} A: Average Tax Value based on Amenities")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

ZillowFeatureSampleSF = ZillowFeatureSample.loc[:,['calculatedfinishedsquarefeet','basementsqft']]
ZillowFeatureSampleSF['HasBasement'] = ["No Basement" if bsf != bsf or bsf <= 0 else "Basement" for bsf in
ZillowFeatureSampleSF.basementsqft]
ZillowFeatureSampleHasB = ZillowFeatureSampleSF.loc[ZillowFeatureSampleSF['HasBasement'] == "Basement"]
ZillowFeatureSampleHasB = ZillowFeatureSampleHasB.drop(columns=['basementsqft','HasBasement'])
ZillowFeatureSampleNoB = ZillowFeatureSampleSF.loc[ZillowFeatureSampleSF['HasBasement'] != "Basement"]
ZillowFeatureSampleNoB = ZillowFeatureSampleNoB.drop(columns=['basementsqft','HasBasement'])

# Define the null hypothesis
H0 = "Properties with a basement will have more square feet than those without."

# Define the alternative hypothesis
H1 = "Properties with a basement will have the same or fewer square feet than those without."

# Calculate the test statistic
t_stat, p_value = stats.ttest_ind(ZillowFeatureSampleHasB, ZillowFeatureSampleNoB,nan_policy='omit')

# Print the results
print("Test statistic:", t_stat)
print("p-value:", p_value)

# Conclusion
if p_value != p_value:
  print("t Test failed.")
elif p_value < 0.05:
  print(f"Reject the null hypothesis of {H0}.")
else:
  print(f"Failed to reject the null hypothesis of {H0}.")

ZillowFeatureSampleSFA = ZillowFeatureSampleSF.drop(columns=['HasBasement'])
sns.displot(ZillowFeatureSampleSFA, kde=True)
```

```
plt.title(f"Problem {PNumber} B: Histogram overlaid with the probability density function")
plt.show()

Execution:

Test statistic: [1.15127171]
p-value: [0.24964842]
Failed to reject the null hypothesis of Properties with a basement will have more square feet than those
without..
```

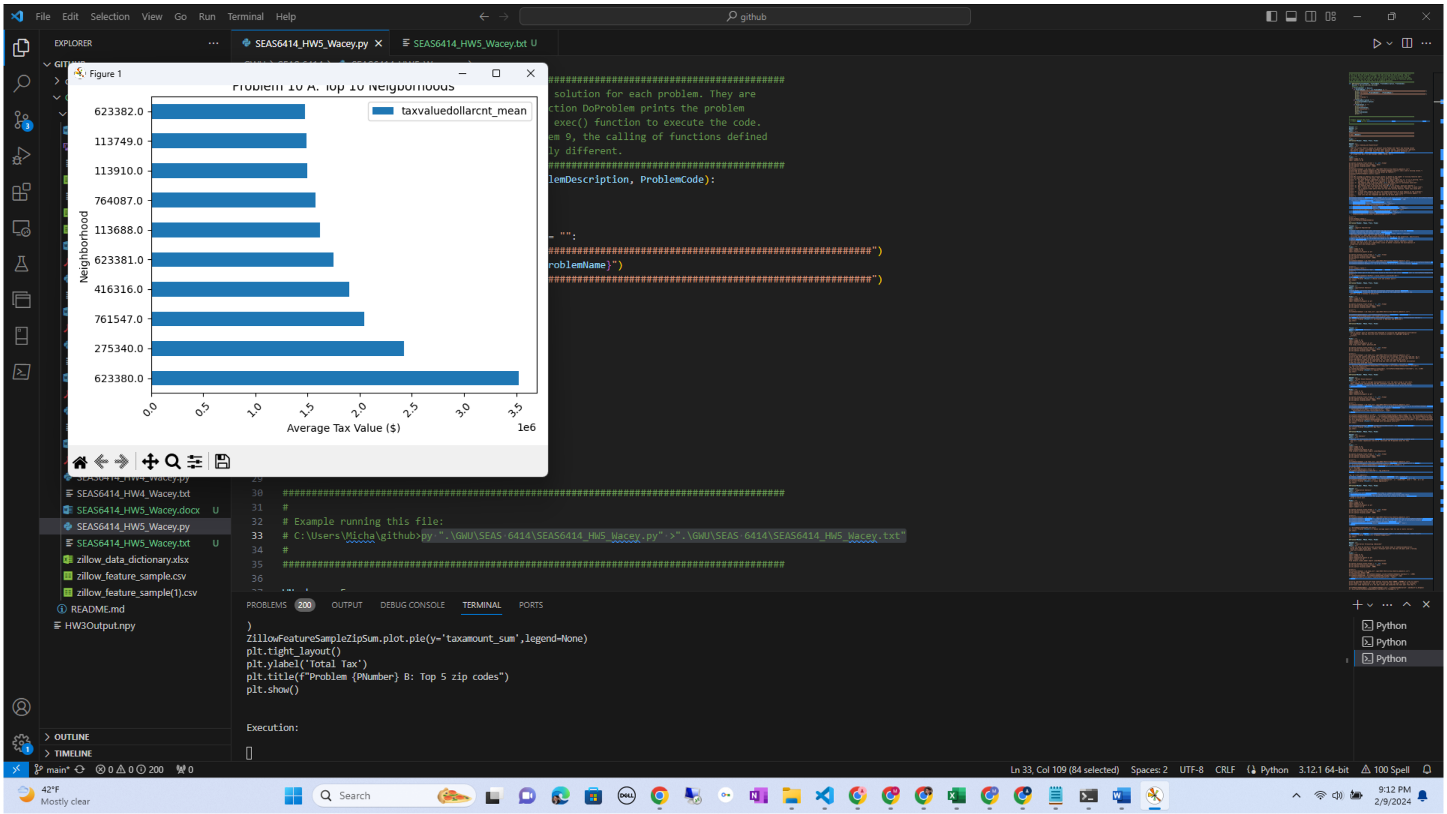


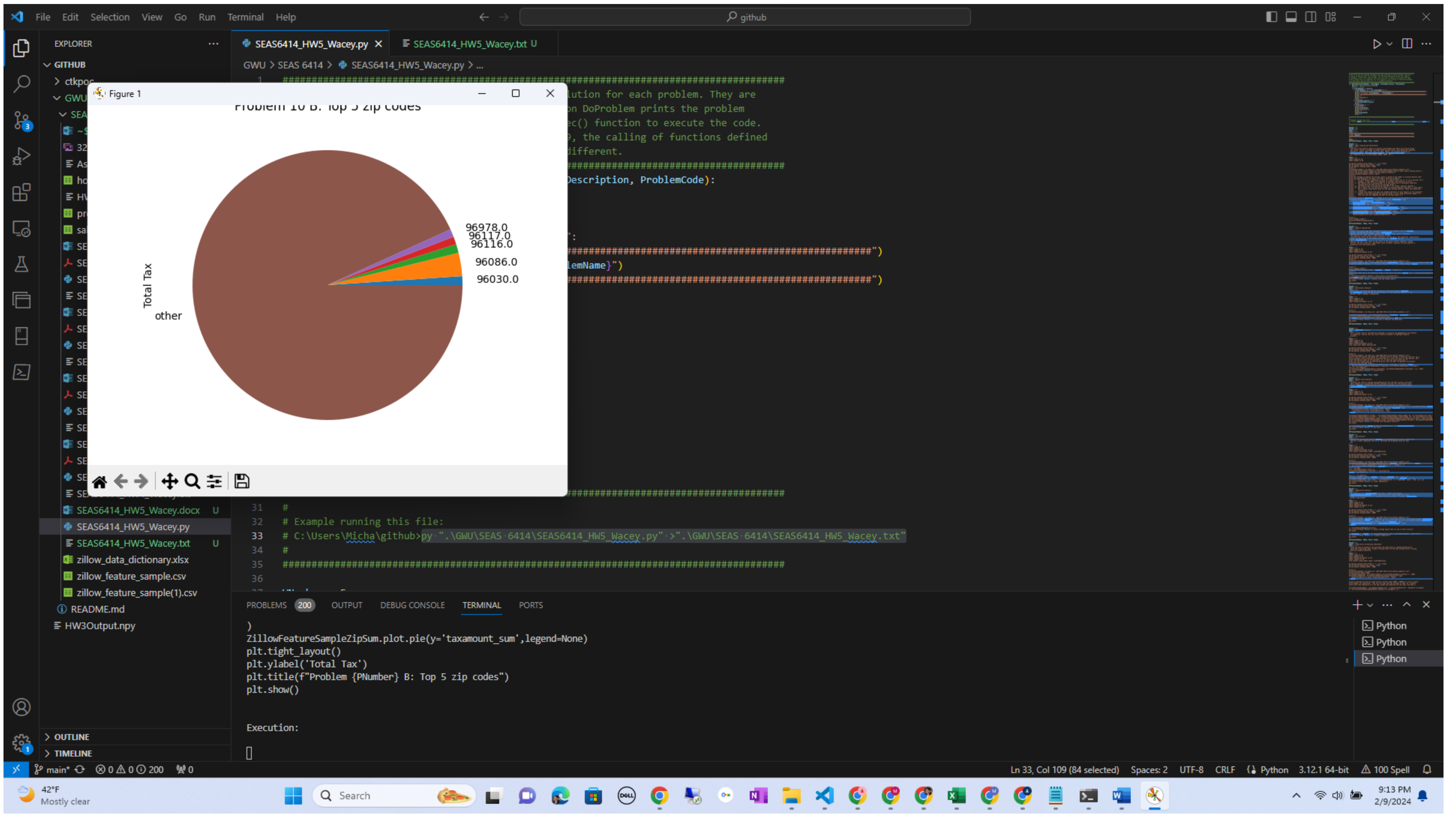



```
#######################################################################################
# Problem 10 - Neighborhood and Regional Analysis
#######################################################################################

Problem:


- Group the properties by regionidneighborhood and plot a horizontal bar chart
  showing the top 10 neighborhoods with the highest average taxvaluedollarcnt.
- Using regionidzip, create a pie chart to display the proportion of total taxamount
  contributed by the top 5 zip codes. Include a separate 'other' slice for the remaining
  zip codes.


Code:

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats

pd.options.display.float_format = '{:,.2f}'.format
pd.set_option('display.max_columns', None)
pd.set_option('display.width', 4000)

ZillowFeatureSample = pd.read_csv("./gwu/SEAS 6414/zillow_feature_sample(1).csv")

ZillowFeatureSampleAM = ZillowFeatureSample.groupby(["regionidneighborhood"]).agg(
   taxvaluedollarcnt_mean=("taxvaluedollarcnt", "mean")
)
ZillowFeatureSampleAM = ZillowFeatureSampleAM.sort_values('taxvaluedollarcnt_mean', ascending=False).head(10)
ZillowFeatureSampleAM.plot.barh()
plt.ylabel('Neighborhood')
plt.xlabel('Average Tax Value ($)')
plt.xticks(rotation=45)
plt.tight_layout()
plt.legend()
plt.title(f"Problem {PNumber} A: Top 10 Neigborhoods")
plt.show()

ZillowFeatureSampleZIP = ZillowFeatureSample.groupby(["regionidzip"]).agg(
   taxamount_sum=("taxamount", "sum")
```

```
)
ZillowFeatureSampleZipSort = ZillowFeatureSampleZIP.sort_values('taxamount_sum', ascending=False)
ZillowFeatureSampleZipTop5 = ZillowFeatureSampleZipSort.head(5).copy()
# We have to recalulate the mean, since we cannot take the mean of the mean - originally I did mean, sum is simpler
# but this works for mean witht he proper changes and so I am leaving it in the more complicated form.
ZillowFeatureSampleZipFull = ZillowFeatureSample.join(ZillowFeatureSampleZipTop5,on='regionidzip',how='outer',)
ZillowFeatureSampleZipFull['zipgroup'] = ZillowFeatureSampleZipFull.apply(lambda row: 'other' if row.taxamount_sum != row.taxamount_sum else row.regionidzip, axis=1)
ZillowFeatureSampleZipSum = ZillowFeatureSampleZipFull.groupby(["zipgroup"]).agg(
   taxamount_sum=("taxamount", "sum")
)
ZillowFeatureSampleZipSum.plot.pie(y='taxamount_sum',legend=None)
plt.tight_layout()
plt.ylabel('Total Tax')
plt.title(f"Problem {PNumber} B: Top 5 zip codes")
plt.show()
```

Execution:




Problem 10 B: Top 5 zip codes
Total Tax
other
96978.0
96117.0
96116.0
96086.0
96030.0
ZillowFeatureSampleZipSum.plot.pie(y='taxamount_sum',legend=None)
plt.tight_layout()
plt.ylabel('Total Tax')
plt.title(f"Problem {PNumber} B: Top 5 zip codes")
plt.show()
Execution: