CIS41_Project

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0.1 CISD41 Introduction to Data Science by Sohair Zaki

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US Real Estate Market and Economics (YEAR 2020)

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0.1.1 Overview

Purpose & Questions

Importing/Clearning Data

Importing Libraries, Loading Data, Reading Data

Functions, Lambda, and Cleaning

Organizing Sub-Datasets

Merge Sub-Datasets and create House_df

Data Visualization

Pivot Tables and Groupby Table

Additional Cleaning and Organizing to create State_df

House_df

Quantitative Data Exploratory

Visualization

State_df

Quantitative Data Exploratory

Visualization

Testing Hypothesis, ANOVA

Pearson Correlation, Z-test, ANOVA, Chisquare

Conclusion

Questions and Answers

Interesting Findings

Main Takeaways

References

0.1.2 1. Purpose & Questions

Purpose Real Estate is a huge investment throughout individual's life. This will enhance individual's knowledge of United States real estate market and related economic information. Learn Python data analysis tools.

Questions

What is average and median house price across all USA? (Jack)

Is Size highly correlated with Price? If not what's most correlated with Price? (Jack)

What's the primary type of houses people prefer in each state? (Jack)

What states have the largest and smallest avg size? (Jack)

What states have the highest and lowest $ perSqFt? (Jack)

Find out each State's: Price, Size, perSqft, Annual Income, SavingsRate,Years of Savings to Buy a House(20% down). (Jack)

Since I live in California, what's California house avg like? (Jack)

Is there Significant relationship between Regions and Price. (Jack)

Is there huge difference between House Type and Price? (Jack)

0.1.3 2. Importing/Cleaning Data

Importing Libraries, Loading Data, Reading Data

[ ]:
```
# Import modules
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objs as go
from plotly.offline import init_notebook_mode,iplot
import scipy.stats as st
from scipy.stats import norm
%matplotlib inline

# filter warnings
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

# Display plotly plots offline in notebook mode
init_notebook_mode(connected=True)
```

[ ]:
```python
# Loading Data              # FOR YEAR 2020

# "main" data for housing
df = pd.read_csv('data/data_house.csv')

# subdata sets
spending_df = pd.read_csv('data/data_spending.csv')         # need 1 column of␣
↪spending per state
gdp_df = pd.read_csv('data/data_gdp.csv')                   # need 1 column of␣
↪gdp per state
population_df = pd.read_csv('data/data_population.csv')     # need 1 column of␣
↪population per state
income_df = pd.read_csv('data/data_income.csv')             # need 1 column of␣
↪income per state
```

[ ]:
```python
# Read the shape of df
df.shape
```

[ ]:
```
(85509, 8)
```

[ ]:
```python
# Reading the housing data
df.info()
df.tail()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 85509 entries, 0 to 85508
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Price        85509 non-null  object
 1   Address      85509 non-null  object
 2   Bedrooms     64999 non-null  object
 3   Bathrooms    69439 non-null  object
 4   Size         73698 non-null  object
 5   Sale Status  69960 non-null  object
 6   URL          85509 non-null  object
 7   Raw Price    85509 non-null  float64
dtypes: float64(1), object(7)
memory usage: 5.2+ MB
```

[ ]:
```
              Price                                        Address Bedrooms  \
85504   $79,000,000                 2 Park Pl, New York, NY 10007      NaN
85505   $90,000,000          432 Park Ave #82, New York, NY 10022    6 bds
85506   $95,000,000         1441 Angelo Dr, Los Angeles, CA 90210      NaN
85507   $99,000,000         908 Bel Air Rd, Los Angeles, CA 90077    9 bds
85508  $110,000,000  30 Beverly Park Ter, Beverly Hills, CA 90210    8 bds

       Bathrooms          Size          Sale Status  \
```

```
85504      1 ba   9,680 sqft       Condo for sale
85505      8 ba   8,054 sqft       Condo for sale
85506       NaN          NaN  Lot / Land for sale
85507     20 ba  34,000 sqft       House for sale
85508     12 ba      -- sqft       House for sale

                                                    URL    Raw Price
85504  https://www.zillow.com/homedetails/2-Park-Pl-N…   79000000.0
85505  https://www.zillow.com/homedetails/432-Park-Av…   90000000.0
85506  https://www.zillow.com/homedetails/1441-Angelo…   95000000.0
85507  https://www.zillow.com/homedetails/908-Bel-Air…   99000000.0
85508  https://www.zillow.com/homedetails/30-Beverly-…  110000000.0
```

[ ]:
```python
# read df head
df.head()
```

[ ]:
```
  Price                                        Address Bedrooms Bathrooms  \
0    $1                  Airpark N, Loveland, CO 80538      NaN       NaN
1    $1            2940 W Sunset Ave, Springdale, AR 72762      NaN       NaN
2    $1  2392 SE Fruit Ave, Port Saint Lucie, FL 34952    3 bds      2 ba
3    $1              0 SW 38th Ter, Gainesville, FL 32605      NaN       NaN
4    $1                 75th St NW, Rochester, MN 55901      NaN       NaN

         Size          Sale Status  \
0         NaN  Lot / Land for sale
1         NaN  Lot / Land for sale
2  1,649 sqft                  NaN
3         NaN  Lot / Land for sale
4         NaN                  NaN

                                                 URL  Raw Price
0  https://www.zillow.com/homedetails/Airpark-N-L…        1.0
1  https://www.zillow.com/homedetails/2940-W-Suns…        1.0
2  https://www.zillow.com/homedetails/2392-SE-Fru…        1.0
3  https://www.zillow.com/homedetails/0-SW-38th-T…        1.0
4  https://www.zillow.com/homedetails/75th-St-NW-…        1.0
```

Functions, Lambda, and Cleaning

[ ]:
```python
# Function #1
# drop NaN, Price, URL, and assign to df1
def metric_deletion(x):
    x.dropna(axis='rows',inplace=True)                # drop NA
    x = x[x.Bedrooms != '-- bds']                     # drop -- bds
    x = x[x.Bathrooms != '-- ba']                     # drop -- ba
    x = x[x.Size != '-- sqft']                        # drop -- sqft
    x.drop(['URL', 'Price'], axis=1,inplace=True)     # drop URL and Price␣
 ↪column since we dont need them, there is raw price in float
```

```
    return x
df1 = metric_deletion(df)                                  # applying the function␣
↪to the df and assign df1
df1.head()
```

```
[ ]:                                       Address Bedrooms Bathrooms  \
5        3515 W Thompson Rd, Indianapolis, IN 46217    2 bds      1 ba
53        3713 Hillside Ave, Indianapolis, IN 46218    2 bds      1 ba
65   1337 W Livingston St APT 1, Allentown, PA 18102    3 bds      1 ba
70                 1788 Westwood Dr, Troy, MI 48083    3 bds      2 ba
72        390 Rosado Springs St, Henderson, NV 89014    2 bds      2 ba

         Size         Sale Status  Raw Price
5     814 sqft      House for sale        1.0
53  1,728 sqft      House for sale      775.0
65  1,000 sqft      House for sale     1050.0
70  1,418 sqft      House for sale     1600.0
72  1,060 sqft  Townhouse for sale     1700.0
```

```
[ ]: # Converting Bathrooms into float
df1.Bathrooms = df1.Bathrooms.str.replace(' ba','').astype('float')      #␣
↪remove the " ba" and assign the remaining number to float
# Converting Bedrooms into float
df1.Bedrooms = df1.Bedrooms.str.replace(' bds','').astype('float')      #␣
↪remove the " bds" and assign the remaining number to float
```

```
[ ]: # Function #2
# Converting Size to float
def filt_size(s):
    s= s.replace(',','')                        # remove the , in size
    s =s.replace(' sqft','')                    # remove the " sqft" in size
    return float(s)                             # convert it to float
df1.Size = df1.Size.apply(filt_size)        # applying the function
```

```
[ ]: # Spliting Address into Street, City, State, ZipCode, and drop the Address
df1.Address = df1.Address.astype('str')                                         ␣
↪     # convert Address to string
df1['Street']= df1.Address.apply(lambda x: x.split(', ')[0])                    ␣
↪     # splitting address into list and assign each value to the corresponding␣
↪columns
df1['City']= df1.Address.apply(lambda x: x.split(', ')[1])                      ␣
↪     # splitting address into list and assign each value to the corresponding␣
↪columns
df1['State']= df1.Address.apply(lambda x: (x.split(', ')[-1]).split(' ')[0])    ␣
↪     # splitting address into list and assign each value to the corresponding␣
↪columns
```

```
df1['ZipCode']= df1.Address.apply(lambda x: (x.split(', ')[-1]).split(' ')[1]) ␣
↪     # splitting address into list and assign each value to the corresponding␣
↪columns
# Assign to df2
df2 = df1.drop(['Address'],axis=1)                                              ␣
↪     # since we have the columns, we dont need address anymore
# Reset the index
df2.reset_index(inplace=True,drop=True)                                         ␣
↪     # resetting index, and drop original index
df2.head()
```

```
[ ]:    Bedrooms  Bathrooms    Size          Sale Status  Raw Price  \
0       2.0        1.0   814.0      House for sale        1.0
1       2.0        1.0  1728.0      House for sale      775.0
2       3.0        1.0  1000.0      House for sale     1050.0
3       3.0        2.0  1418.0      House for sale     1600.0
4       2.0        2.0  1060.0  Townhouse for sale     1700.0

                      Street          City State ZipCode
0          3515 W Thompson Rd  Indianapolis    IN   46217
1            3713 Hillside Ave  Indianapolis    IN   46218
2  1337 W Livingston St APT 1     Allentown    PA   18102
3             1788 Westwood Dr          Troy    MI   48083
4        390 Rosado Springs St     Henderson    NV   89014
```

```
[ ]: # Found two rows of abnormal values, so found exact address on google and␣
↪replace with the right values
df2.loc[28709:28711, 'State']= 'AZ'                # the two rows are missing␣
↪state and zip, after googling found exact address
df2.loc[28709:28711, 'ZipCode']= '85260'           # df2.loc[ (index values) ,␣
↪column names] = assigned value
```

```
[ ]: # Converting the columns as strings for further cleaning
df2[['Street','City','State','ZipCode']].astype('str')          # since they␣
↪are object type, convert them to string
```

```
[ ]:                          Street          City State ZipCode
0              3515 W Thompson Rd  Indianapolis    IN   46217
1               3713 Hillside Ave  Indianapolis    IN   46218
2      1337 W Livingston St APT 1     Allentown    PA   18102
3                1788 Westwood Dr          Troy    MI   48083
4           390 Rosado Springs St     Henderson    NV   89014
…                             …           …   …     …
45394  111 W 57th St PENTHOUSE 72      New York    NY   10019
45395             0 Del Valle Rd     Livermore    CA   94550
45396          1060 Brooklawn Dr   Los Angeles    CA   90077
45397             432 Park Ave #82      New York    NY   10022
```

```
45398              908 Bel Air Rd   Los Angeles    CA   90077

[45399 rows x 4 columns]
```

[ ]:
```
# Finding the weird ZipCode, it is in Canada
df2.loc[df2.ZipCode == 'N9V']
```

[ ]:
```
       Bedrooms  Bathrooms    Size     Sale Status  Raw Price          Street  \
38379       4.0        4.0  2800.0  House for sale   865000.0  349 Benson Ct

              City State ZipCode
38379  Amherstburg    ON     N9V
```

[ ]:
```
# Dropping the canada row
df2.drop(df2.iloc[38379].name,inplace=True)
```

[ ]:
```
# Now the ZipCode can be converted to Integer
df2.ZipCode = df2.ZipCode.astype('int')
```

[ ]:
```
# convert Sale Status into house Types
# first we make a list
house_status = list(df2['Sale Status'].unique())
house_status
```

[ ]:
```
['House for sale',
 'Townhouse for sale',
 'Multifamily home for sale',
 'Condo for sale',
 'Home for sale',
 'Apartment for sale']
```

[ ]:
```
# Make a list of house types
house_type = ['House','Townhouse','Multifamily', 'Condo', 'Others', 'Apartment']

# Replacing house_status with house_type using .map
df2['Sale Status'] = df2['Sale Status'].map(dict(zip(house_status,house_type)))

# Rename column sale status to type
df2.rename(columns={"Sale Status": "Type"}, inplace=True)
```

[ ]:
```
# Street column is not useful so we drop it and assign new df3
df3 = df2.drop(['Street'], axis=1)
df3.head()
```

[ ]:
```
   Bedrooms  Bathrooms    Size      Type  Raw Price          City State  \
0       2.0        1.0   814.0     House        1.0  Indianapolis    IN
1       2.0        1.0  1728.0     House      775.0  Indianapolis    IN
2       3.0        1.0  1000.0     House     1050.0     Allentown    PA
```

```
3       3.0         2.0  1418.0      House      1600.0          Troy     MI
4       2.0         2.0  1060.0  Townhouse      1700.0     Henderson     NV

   ZipCode
0    46217
1    46218
2    18102
3    48083
4    89014
```

[ ]:
```
# Change Raw Price column name to Price
df3.rename(columns={"Raw Price":"Price"}, inplace=True)

# Column - create perSqft column
df3['perSqFt'] = df3.Price / df3.Size
```

[ ]:
```
# Visualize the last value counts per state
df3.State.value_counts().tail(5)

# HI NH is below 30 counts, so dropping HI and NH
df3 = df3[(df3['State'] != 'HI') & (df3['State'] != 'NH')]

# drop Type: Others
# because it is not the majority and has weird type of lots/houses/other asset␣
↪types
df3 = df3[df3['Type'] != 'Others']
```

[ ]:
```
# Due to previously dropping rows, reset index again
# West Virginia and Wyoming not in data
df3 = df3.reset_index(drop=True)

# Check how many states we have
len(df3.State.unique())
```

[ ]: 46

[ ]:
```
# Function #3 find_region()
# Assign Regions, also need to drop Wyoming and West Virgina since the dataset␣
↪does not contain them
# listings for that certain State in the initial DataFrame
#                this is created manually
west = ['CA', 'NV', 'AK', 'WA' , 'OR', 'ID', 'MT', 'UT', 'CO', 'AZ', 'NM']
midwest = ['ND', 'WI','SD', 'NE', 'KS', 'MN', 'IA', 'MO', 'IL', 'IN', 'OH','MI']
north = ['PA', 'NY', 'MA', 'CT', 'ME', 'DC', 'NJ', 'RI']
south = ['TX', 'OK', 'AR', 'LA', 'MS', 'AL', 'TN', 'KY', 'VA', 'MD', 'DE',␣
↪'NC', 'SC', 'GA', 'FL']
```

```python
# List - full state list other than the df
full_state_list = west + midwest + north + south

# Creating function to assign regions
def find_region(state):
    if state in west:
        state = 'West'
    elif state in north:
        state = 'North'
    elif state in south:
        state = 'South'
    elif state in midwest:
        state = 'MidWest'
    return state

# Create Region column by using find_region function
df3['Region'] = df3.State.apply(find_region)
```

[ ]:
```python
# Sort the full state list
full_state_list.sort()
full_state_list

# List - states from df
comparator = df3['State'].unique().tolist()
comparator.sort()
comparator

# compare full_state_list and our df-state-list,
compare_dict = dict(zip(full_state_list,comparator))
compare_dict

# Check our list of states and dataframe states are in sync
# df3 is fully cleaned, now we are making a "state_df"
```

[ ]:
```
{'AK': 'AK',
 'AL': 'AL',
 'AR': 'AR',
 'AZ': 'AZ',
 'CA': 'CA',
 'CO': 'CO',
 'CT': 'CT',
 'DC': 'DC',
 'DE': 'DE',
 'FL': 'FL',
 'GA': 'GA',
 'IA': 'IA',
 'ID': 'ID',
```

```
 'IL': 'IL',
 'IN': 'IN',
 'KS': 'KS',
 'KY': 'KY',
 'LA': 'LA',
 'MA': 'MA',
 'MD': 'MD',
 'ME': 'ME',
 'MI': 'MI',
 'MN': 'MN',
 'MO': 'MO',
 'MS': 'MS',
 'MT': 'MT',
 'NC': 'NC',
 'ND': 'ND',
 'NE': 'NE',
 'NJ': 'NJ',
 'NM': 'NM',
 'NV': 'NV',
 'NY': 'NY',
 'OH': 'OH',
 'OK': 'OK',
 'OR': 'OR',
 'PA': 'PA',
 'RI': 'RI',
 'SC': 'SC',
 'SD': 'SD',
 'TN': 'TN',
 'TX': 'TX',
 'UT': 'UT',
 'VA': 'VA',
 'WA': 'WA',
 'WI': 'WI'}
```

Organizing Sub-Datasets

[ ]:
```
# Read gdp_df
gdp_df.head()
```

[ ]:
```
   Unnamed: 0  GeoFips        GeoName        2020
0           0        0  United States  18384687.0
1           1     1000        Alabama    196906.1
2           2     2000         Alaska     50161.0
3           3     4000        Arizona    320550.6
4           4     5000       Arkansas    114943.5
```

[ ]:
```
# Checking the States in gdp_df
gdp_df.GeoName.unique()
```

[ ]:
```
array(['United States', 'Alabama', 'Alaska', 'Arizona', 'Arkansas',
       'California', 'Colorado', 'Connecticut', 'Delaware',
       'District of Columbia', 'Florida', 'Georgia', 'Hawaii', 'Idaho',
       'Illinois', 'Indiana', 'Iowa', 'Kansas', 'Kentucky', 'Louisiana',
       'Maine', 'Maryland', 'Massachusetts', 'Michigan', 'Minnesota',
       'Mississippi', 'Missouri', 'Montana', 'Nebraska', 'Nevada',
       'New Hampshire', 'New Jersey', 'New Mexico', 'New York',
       'North Carolina', 'North Dakota', 'Ohio', 'Oklahoma', 'Oregon',
       'Pennsylvania', 'Rhode Island', 'South Carolina', 'South Dakota',
       'Tennessee', 'Texas', 'Utah', 'Vermont', 'Virginia', 'Washington',
       'West Virginia', 'Wisconsin', 'Wyoming', 'New England', 'Mideast',
       'Great Lakes', 'Plains', 'Southeast', 'Southwest',
       'Rocky Mountain', 'Far West'], dtype=object)
```

[ ]:
```
# Drop the non-used States/Regions and none used attributes
gdp_df = gdp_df[(gdp_df.GeoName != 'United States') & (gdp_df.GeoName !=␣
↪'Southwest') & (gdp_df.GeoName != 'Southeast') & (gdp_df.GeoName !=␣
↪'Plains') & (gdp_df.GeoName != 'Mideast') & (gdp_df.GeoName != 'Great␣
↪Lakes') & (gdp_df.GeoName != 'Rocky Mountain') & (gdp_df.GeoName != 'Far␣
↪West') & (gdp_df.GeoName != 'New England') & (gdp_df.GeoName != 'West␣
↪Virginia') & (gdp_df.GeoName != 'Wyoming') & (gdp_df.GeoName != 'Hawaii') &␣
↪(gdp_df.GeoName != 'New Hampshire')]

# rename the columns
gdp_df.rename(columns={'GeoName':'State','2020':'GDP'},inplace=True)

# pick out the columns we need
gdp_df = gdp_df[['State', 'GDP']]

# reset index
gdp_df.reset_index(inplace=True,drop=True)

# reading last part to see if index match with ours
gdp_df.tail()
```

[ ]:

	State	GDP
42	Utah	171370.1
43	Vermont	28648.5
44	Virginia	473817.5
45	Washington	532861.9
46	Wisconsin	291715.8

[ ]:
```
# Read population_df
population_df.head()
```

[ ]:

	rank	State	Pop	Growth	Pop2018	Pop2010	growthSince2010	\
0	1	California	39613493	0.0038	39461588	37319502	0.0615	

```
1     2         Texas  29730311  0.0385  28628666  25241971            0.1778
2     3       Florida  21944577  0.0330  21244317  18845537            0.1644
3     4      New York  19299981 -0.0118  19530351  19399878           -0.0051
4     5  Pennsylvania  12804123  0.0003  12800922  12711160            0.0073

   Percent   density
0   0.1184  254.2929
1   0.0889  113.8081
2   0.0656  409.2229
3   0.0577  409.5400
4   0.0383  286.1704
```

[ ]:
```
# Checking states in population_df
population_df.State.unique()
```

[ ]:
```
array(['California', 'Texas', 'Florida', 'New York', 'Pennsylvania',
       'Illinois', 'Ohio', 'Georgia', 'North Carolina', 'Michigan',
       'New Jersey', 'Virginia', 'Washington', 'Arizona', 'Tennessee',
       'Massachusetts', 'Indiana', 'Missouri', 'Maryland', 'Colorado',
       'Wisconsin', 'Minnesota', 'South Carolina', 'Alabama', 'Louisiana',
       'Kentucky', 'Oregon', 'Oklahoma', 'Connecticut', 'Utah',
       'Puerto Rico', 'Nevada', 'Iowa', 'Arkansas', 'Mississippi',
       'Kansas', 'New Mexico', 'Nebraska', 'Idaho', 'West Virginia',
       'Hawaii', 'New Hampshire', 'Maine', 'Montana', 'Rhode Island',
       'Delaware', 'South Dakota', 'North Dakota', 'Alaska',
       'District of Columbia', 'Vermont', 'Wyoming'], dtype=object)
```

[ ]:
```
# Filter out some regions and states, Grabbing State and Pop columns, reset␣
 ↪index
population_df = population_df[(population_df.State != 'Wyoming') &␣
 ↪(population_df.State != 'West Virginia') & (population_df.State != 'Puerto␣
 ↪Rico') & (population_df.State != 'Hawaii') & (population_df.State != 'New␣
 ↪Hampshire')]

# picking out the columns we want
population_df = population_df[['State','Pop']]

# sort by state
population_df.sort_values(by=['State'],inplace=True)

# replace index
population_df.reset_index(inplace=True,drop=True)

# read last part of df
population_df.tail()
```

[ ]:
```
          State      Pop
42         Utah  3310774
43      Vermont   623251
44     Virginia  8603985
45   Washington  7796941
46    Wisconsin  5852490
```

[ ]:
```
# Check GeoName/States
income_df.GeoName.unique()
```

[ ]:
```
array(['United States', 'Alabama', 'Alaska *', 'Arizona', 'Arkansas',
       'California', 'Colorado', 'Connecticut', 'Delaware',
       'District of Columbia', 'Florida', 'Georgia', 'Hawaii *', 'Idaho',
       'Illinois', 'Indiana', 'Iowa', 'Kansas', 'Kentucky', 'Louisiana',
       'Maine', 'Maryland', 'Massachusetts', 'Michigan', 'Minnesota',
       'Mississippi', 'Missouri', 'Montana', 'Nebraska', 'Nevada',
       'New Hampshire', 'New Jersey', 'New Mexico', 'New York',
       'North Carolina', 'North Dakota', 'Ohio', 'Oklahoma', 'Oregon',
       'Pennsylvania', 'Rhode Island', 'South Carolina', 'South Dakota',
       'Tennessee', 'Texas', 'Utah', 'Vermont', 'Virginia', 'Washington',
       'West Virginia', 'Wisconsin', 'Wyoming', 'New England', 'Mideast',
       'Great Lakes', 'Plains', 'Southeast', 'Southwest',
       'Rocky Mountain', 'Far West'], dtype=object)
```

[ ]:
```
# found astrious * in States, such as hawaii, so made a function to remove it
def conv_state(a):
    if '*' in a:
        a=a.replace(' *', '')
    return a

# rename the columns
income_df.rename(columns={'GeoName':'State','2020':'income'},inplace=True)

# pick the used columns
income_df = income_df[['State', 'income']]

# convert into string type
income_df.State.astype('str')

# applying the conv_state function
income_df.State = income_df.State.apply(conv_state)

# Drop unused States/Region, rename GeoName to State and 2020 to income, filter␣
↪out other columns, reset index
```

```python
income_df = income_df[(income_df.State != 'United States') & (income_df.State !
↪= 'Southwest') & (income_df.State != 'Southeast') & (income_df.State !=␣
↪'Plains') & (income_df.State != 'Mideast') & (income_df.State != 'Great␣
↪Lakes') & (income_df.State != 'Rocky Mountain') & (income_df.State != 'Far␣
↪West') & (income_df.State != 'New England') & (income_df.State != 'West␣
↪Virginia') & (income_df.State != 'Wyoming') & (income_df.State != 'Hawaii')␣
↪& (income_df.State != 'New Hampshire')]

# reset index
income_df.reset_index(inplace=True,drop=True)

# read the tail of df
income_df.tail()
```

[ ]:

```
         State    income
42        Utah  169656.3
43     Vermont   36894.2
44    Virginia  532256.2
45  Washington  516441.1
46   Wisconsin  324252.0
```

[ ]:

```python
# Reading spending_df
spending_df.head(15)
```

[ ]:

```
    Unnamed: 0  GeoFips        GeoName  LineCode  \
0            0        0  United States         1
1            1        0  United States         2
2            2        0  United States         3
3            3        0  United States         4
4            4        0  United States         5
5            5        0  United States         6
6            6        0  United States         7
7            7        0  United States         8
8            8        0  United States         9
9            9        0  United States        10
10          10        0  United States        11
11          11        0  United States        12
12          12        0  United States        13
13          13        0  United States        14
14          14        0  United States        15

                                 Description        2020
0             Personal consumption expenditures  14047565.0
1                                         Goods   4653822.0
2                                 Durable goods   1616408.0
3                        Motor vehicles and parts    541265.0
4     Furnishings and durable household equipment    390382.0
```

```
5                        Recreational goods and vehicles    476217.0
6                                    Other durable goods    208545.0
7                                       Nondurable goods   3037413.0
8          Food and beverages purchased for off-pre…   1146676.0
9                                  Clothing and footwear    362435.0
10                       Gasoline and other energy goods    246757.0
11                                Other nondurable goods   1281545.0
12                                              Services   9393744.0
13      Household consumption expenditures (for se…   8872868.0
14                                 Housing and utilities   2668144.0
```

[ ]:
```python
# Personal consumption expenditure is the total of the sub categories, so we␣
↪only want the total per state
spending_df = spending_df[spending_df['Description'] == 'Personal consumption␣
↪expenditures']

# Dropping un-used region/State
spending_df = spending_df[(spending_df.GeoName != 'United States') &␣
↪(spending_df.GeoName != 'Southwest') & (spending_df.GeoName != 'Southeast')␣
↪& (spending_df.GeoName != 'Plains') & (spending_df.GeoName != 'Mideast') &␣
↪(spending_df.GeoName != 'Great Lakes') & (spending_df.GeoName != 'Rocky␣
↪Mountain') & (spending_df.GeoName != 'Far West') & (spending_df.GeoName !=␣
↪'New England') & (spending_df.GeoName != 'West Virginia') & (spending_df.
↪GeoName != 'Wyoming') & (spending_df.GeoName != 'Hawaii') & (spending_df.
↪GeoName != 'New Hampshire')]

# Rename column names
spending_df.rename(columns={'GeoName':'State','2020':'spending'},inplace=True)

# Filter out needed columns
spending_df = spending_df[['State', 'spending']]

# Reset index
spending_df.reset_index(inplace=True,drop=True)

# reading last 5 rows of column
spending_df.tail()
```

[ ]:

	State	spending
42	Utah	121445.4
43	Vermont	29544.8
44	Virginia	367302.7
45	Washington	354219.1
46	Wisconsin	238923.0

1. **Merge the Sub-Datasets for future use 2. Create main - house_df**

[ ]:
```
# Making a merge_df and merge all the data by state
merged_df = gdp_df.merge(spending_df, how = 'inner', on = 'State')
merged_df = merged_df.merge(population_df, how = 'inner', on = 'State')
merged_df = merged_df.merge(income_df, how = 'inner', on = 'State')

# Renaming columns, renaming to fullState is because we will insert␣
↪abbreviations later, and merge with future data.
merged_df.rename(columns={'State':'fullState','spending':'Spending', 'Pop':
↪'Population', 'income': 'Income'},inplace=True)
merged_df.tail()
```

[ ]:
```
     fullState       GDP  Spending  Population    Income
42        Utah  171370.1  121445.4     3310774  169656.3
43     Vermont   28648.5   29544.8      623251   36894.2
44    Virginia  473817.5  367302.7     8603985  532256.2
45  Washington  532861.9  354219.1     7796941  516441.1
46   Wisconsin  291715.8  238923.0     5852490  324252.0
```

[ ]:
```
# sort df3 by state, reset index and set to our Final house_df
df3= df3.sort_values(by='State')

# reset index
df3.reset_index(inplace=True,drop=True)

# Drop - zipcode since we dont need it
df4=df3.drop('ZipCode', axis=1)

# assign a new df
df5 = df4
df5.head()
```

[ ]:
```
   Bedrooms  Bathrooms    Size         Type     Price         City State  \
0       8.0        4.0  3264.0  Multifamily  459900.0    Anchorage    AK
1       2.0        1.0   778.0        Condo   89900.0    Anchorage    AK
2       8.0        4.0  3880.0  Multifamily  590000.0  Eagle River    AK
3       6.0        5.0  4640.0        House  589900.0      Chugiak    AK
4       2.0        2.0  1152.0        Condo  184000.0    Anchorage    AK

      perSqFt Region
0  140.900735   West
1  115.552699   West
2  152.061856   West
3  127.133621   West
4  159.722222   West
```

[ ]:
```
# removing Vermont from df since we dont need that, now we have 46 instead of␣
↪47 in the subdatasets
```

```python
merged_df = merged_df[(merged_df['fullState'] != 'Vermont')]

# List - making a state list from our main df
list1 = list(df5.State.unique())

# List - making a state list from sub dataset
list2 = list(merged_df.fullState)

# Dict - make dict from list1 and list2
state_dict = dict(zip(list1,list2))

# read and see if they are correct
state_dict
```

[ ]:
```
{'AK': 'Alabama',
 'AL': 'Alaska',
 'AR': 'Arizona',
 'AZ': 'Arkansas',
 'CA': 'California',
 'CO': 'Colorado',
 'CT': 'Connecticut',
 'DC': 'Delaware',
 'DE': 'District of Columbia',
 'FL': 'Florida',
 'GA': 'Georgia',
 'IA': 'Idaho',
 'ID': 'Illinois',
 'IL': 'Indiana',
 'IN': 'Iowa',
 'KS': 'Kansas',
 'KY': 'Kentucky',
 'LA': 'Louisiana',
 'MA': 'Maine',
 'MD': 'Maryland',
 'ME': 'Massachusetts',
 'MI': 'Michigan',
 'MN': 'Minnesota',
 'MO': 'Mississippi',
 'MS': 'Missouri',
 'MT': 'Montana',
 'NC': 'Nebraska',
 'ND': 'Nevada',
 'NE': 'New Jersey',
 'NJ': 'New Mexico',
 'NM': 'New York',
 'NV': 'North Carolina',
 'NY': 'North Dakota',
```

```
 'OH': 'Ohio',
 'OK': 'Oklahoma',
 'OR': 'Oregon',
 'PA': 'Pennsylvania',
 'RI': 'Rhode Island',
 'SC': 'South Carolina',
 'SD': 'South Dakota',
 'TN': 'Tennessee',
 'TX': 'Texas',
 'UT': 'Utah',
 'VA': 'Virginia',
 'WA': 'Washington',
 'WI': 'Wisconsin'}
```

[ ]:

```
# since many are not correct, we update them
# state_dict will be used later
state_dict.update({'AK': 'Alaska',
 'AL': 'Alabama',
 'AR': 'Arkansas',
 'AZ': 'Arizona',
 'CA': 'California',
 'CO': 'Colorado',
 'CT': 'Connecticut',
 'DC': 'District of Columbia',
 'DE': 'Delaware',
 'FL': 'Florida',
 'GA': 'Georgia',
 'IA': 'Iowa',
 'ID': 'Idaho',
 'IL': 'Illinois',
 'IN': 'Indiana',
 'KS': 'Kansas',
 'KY': 'Kentucky',
 'LA': 'Louisiana',
 'MA': 'Massachusetts',
 'MD': 'Maryland',
 'ME': 'Maine',
 'MI': 'Michigan',
 'MN': 'Minnesota',
 'MO': 'Missouri',
 'MS': 'Mississippi',
 'MT': 'Montana',
 'NC': 'North Carolina',
 'ND': 'North Dakota',
 'NE': 'Nebraska',
 'NJ': 'New Jersey',
 'NM': 'New Mexico',
```

```
 'NV': 'Nevada',
 'NY': 'New York',
 'OH': 'Ohio',
 'OK': 'Oklahoma',
 'OR': 'Oregon',
 'PA': 'Pennsylvania',
 'RI': 'Rhode Island',
 'SC': 'South Carolina',
 'SD': 'South Dakota',
 'TN': 'Tennessee',
 'TX': 'Texas',
 'UT': 'Utah',
 'VA': 'Virginia',
 'WA': 'Washington',
 'WI': 'Wisconsin'}, inplace=True)
```

[ ]:
```
# Creating a for loop to remove outliers based on Price

# list of states in df
state_list = list(df5['State'].unique())

# create empty dataframe
df6 = pd.DataFrame(columns=df5.columns)

# loop each state from state_list
for a in state_list:
    df = df5[df5['State'] == a]
    # calculating quantiles and IQR
    q1 = df['Price'].quantile(0.25)
    q3 = df['Price'].quantile(0.75)
    iqr = q3-q1
    fence_low  = q1-1.5*iqr
    fence_high = q3+1.5*iqr
    # filtering out the outliers
    df_out = df.loc[(df['Price'] > fence_low) & (df['Price'] < fence_high)]
    # append to the empty df6
    df6 = df6.append(df_out)
```

[ ]:
```
# Creating a for loop to remove outliers based on perSqFt
house_df = pd.DataFrame(columns=df6.columns)
for a in state_list:
    df = df6[df6['State'] == a]
    # calculating quantiles and IQR
    q1 = df['perSqFt'].quantile(0.25)
    q3 = df['perSqFt'].quantile(0.75)
    iqr = q3-q1
    fence_low  = q1-1.5*iqr
```

```
    fence_high = q3+1.5*iqr
    # filtering out the outliers
    df_out = df.loc[(df['perSqFt'] > fence_low) & (df['perSqFt'] < fence_high)]
    # append to empty df house_df
    house_df = house_df.append(df_out)

# Filter out size over 15,000 square feet
house_df = house_df[house_df.Size < 15000]

# Produce the main house_df and reset index
house_df = house_df.reset_index(drop=True)
```

[ ]:
```
# # Function to calculate z-score for each row.

# def create_val(a,b):
#     df = house_df[house_df['State'] == b]
#     avg = df['perSqFt'].mean()
#     std = df['perSqFt'].std()
#     z = (a - avg) / std
#     return z

# # creating z_score by applying function with lambda
# house_df['z_score'] = house_df.apply(lambda x: create_val(x.perSqFt, x.
↪State), axis = 1)
# house_df = house_df[(house_df.z_score < 3) & (house_df.z_score > -3)]
```

[ ]:
```
# Function to assign Size into categories
def find_sizeCat(size):
    if size > 4500:
        size = "4500 and higher"
    elif 3501 < size <= 4500:
        size = "3501 to 4500"
    elif 2501 < size < 3500:
        size = "2501 to 3500"
    elif 1501 < size <= 2500:
        size = "1501 to 2500"
    elif 801 < size <= 1500:
        size = "801 to 1500"
    else:
        size = "800 and under"
    return size
house_df["SizeCat"] = house_df.Size.apply(find_sizeCat)
```

0.1.4 3. Data Visualization

Pivot Tables and Groupby Table

[ ]:
```python
# Pivot Table #1 - by Region

# setting format display to float with 2 decimal places
pd.set_option('display.float_format', '{:.2f}'.format)

# by region (big picture/general overview), shows the region's average␣
↪Bedrooms, Batherooms, Price, Size, and per SqFt
pd.pivot_table(house_df,␣
↪values=['perSqFt','Size','Bedrooms','Bathrooms','Price'], index=['Region'])
```

[ ]:
```
         Bathrooms  Bedrooms     Price    Size  perSqFt
Region
MidWest       2.11      3.16 232389.06 1851.80   126.30
North         2.26      3.50 458599.63 1793.98   281.09
South         2.51      3.26 313300.11 2026.79   156.33
West          2.59      3.46 624722.63 2052.39   326.17
```

West Region average Price, Size, and perSqFt are highest

[ ]:
```python
# Piviot Tabel #2 - by State

# setting format display to float with 2 decimal places
pd.set_option('display.float_format', '{:.2f}'.format)

# by state, shows the region's average Bedrooms, Batherooms, Price, Size, and␣
↪per SqFt
pivot_state = pd.pivot_table(house_df,␣
↪values=['perSqFt','Size','Bedrooms','Bathrooms','Price'],␣
↪index=['Region','State'])
pivot_state.head(15)
```

[ ]:
```
               Bathrooms  Bedrooms     Price    Size  perSqFt
Region  State
MidWest IA          1.95      3.13 149252.38 1686.97    90.80
        IL          2.24      2.99 268614.69 1756.19   159.48
        IN          2.13      3.09 216826.92 2076.28    98.88
        KS          2.55      3.41 259040.19 2287.53   108.62
        MI          1.81      3.13 142267.57 1587.69    86.42
        MN          2.18      3.11 369010.68 1850.69   205.52
        MO          2.23      2.97 238783.35 1944.31   123.43
        ND          2.22      3.58 259991.39 2286.61   112.95
        NE          2.45      3.38 276671.76 2150.49   127.82
        OH          1.84      3.35 134835.39 1721.55    79.80
        SD          2.40      3.44 362883.80 2031.12   181.82
        WI          2.32      3.25 297997.15 1906.92   161.82
North   CT          2.57      4.15 365254.44 2359.92   177.04
        DC          2.47      2.78 732301.21 1525.06   500.22
        MA          2.37      3.44 800828.82 1826.08   501.47
```

[ ]:
```python
# Made a groupby table so data can be viewed by Region then State
house_df.groupby(['Region','State']).mean()
```

[ ]:

Region	State	Bedrooms	Bathrooms	Size	Price	perSqFt
MidWest	IA	3.13	1.95	1686.97	149252.38	90.80
	IL	2.99	2.24	1756.19	268614.69	159.48
	IN	3.09	2.13	2076.28	216826.92	98.88
	KS	3.41	2.55	2287.53	259040.19	108.62
	MI	3.13	1.81	1587.69	142267.57	86.42
	MN	3.11	2.18	1850.69	369010.68	205.52
	MO	2.97	2.23	1944.31	238783.35	123.43
	ND	3.58	2.22	2286.61	259991.39	112.95
	NE	3.38	2.45	2150.49	276671.76	127.82
	OH	3.35	1.84	1721.55	134835.39	79.80
	SD	3.44	2.40	2031.12	362883.80	181.82
	WI	3.25	2.32	1906.92	297997.15	161.82
North	CT	4.15	2.57	2359.92	365254.44	177.04
	DC	2.78	2.47	1525.06	732301.21	500.22
	MA	3.44	2.37	1826.08	800828.82	501.47
	ME	2.83	2.14	1673.86	713430.86	437.12
	NJ	3.86	2.28	1780.86	381615.45	240.69
	NY	3.56	2.19	1771.99	393834.38	232.72
	PA	3.22	2.13	1633.04	279879.74	177.84
	RI	3.14	1.98	1750.53	305050.04	191.57
South	AL	3.38	2.62	2319.30	305048.89	124.37
	AR	3.64	2.96	2804.81	337014.73	117.71
	DE	3.11	1.83	1537.86	192903.10	121.23
	FL	2.94	2.28	1596.70	322036.59	201.74
	GA	3.32	2.41	1969.07	253325.04	125.18
	KY	3.32	2.77	2387.65	394384.46	165.15
	LA	3.28	2.32	2040.95	281259.07	123.74
	MD	2.98	2.28	1577.91	240832.79	157.61
	MS	3.30	2.29	1907.25	181302.03	90.56
	NC	3.26	2.84	2235.15	478810.32	221.57
	OK	3.41	2.57	2511.43	354887.77	131.90
	SC	3.48	2.65	2039.93	378263.16	185.20
	TN	3.26	2.58	2130.56	427594.91	203.61
	TX	3.42	2.62	2170.51	277502.48	128.98
	VA	3.23	2.52	1806.27	291610.56	161.60
West	AK	4.59	2.97	2392.84	363202.40	165.54
	AZ	3.34	2.51	2070.79	466962.46	224.66
	CA	3.44	2.56	1965.24	776273.37	424.09
	CO	3.26	2.64	2114.61	581882.04	289.85
	ID	3.91	2.75	2321.74	571593.22	253.87
	MT	3.45	2.48	2464.15	417416.81	168.74
	NM	3.37	2.46	2096.72	315167.86	152.91

```
NV          3.32       2.71 1999.47 400673.05   202.44
OR          3.44       2.83 2299.38 556123.87   250.94
UT          4.15       2.73 2524.02 470316.15   200.74
WA          3.60       2.49 2240.48 485569.83   230.23
```

Additional Cleaning and Organizing to create State_df

```
[ ]: # count house data per state in house_df

# Create a column for house counts per State by making a valuecount_df
valuecount_df = pd.DataFrame(house_df['State'].value_counts())

# reset index
valuecount_df2 = valuecount_df.reset_index()

# rename column
valuecount_df2 = valuecount_df2.rename(columns={"State": "HouseCount", 'index':
 ↪'State'})

# sort by state
valuecount_df2 = valuecount_df2.sort_values(by = "State")

# reset index
valuecount_df2 = valuecount_df2.reset_index(drop=True)
```

```
[ ]: # Creating state_df, Step #1, from pivot table

# Converting pivot_state into DF and reset index
pivot_df =pd.DataFrame(pivot_state)
pivot_df = pivot_df.reset_index()

# create function to insert fullState name for merge
def insert_fullState(a):
    a = state_dict[a]
    return a

# Merge with pivot df
pivot_df = pivot_df.merge(valuecount_df2, how = 'inner', on = 'State')

# insert both fullState and Region
pivot_df['fullState'] = pivot_df.State.apply(insert_fullState)
pivot_df['Region'] = pivot_df.State.apply(find_region)

# insert fullState into house_df
house_df['fullState'] = house_df.State.apply(insert_fullState)

# read pivot df
pivot_df.head(15)
```

[ ]:
```
      Region State  Bathrooms  Bedrooms      Price     Size  perSqFt  HouseCount  \
0    MidWest    IA       1.95      3.13  149252.38  1686.97    90.80         117
1    MidWest    IL       2.24      2.99  268614.69  1756.19   159.48        1467
2    MidWest    IN       2.13      3.09  216826.92  2076.28    98.88         990
3    MidWest    KS       2.55      3.41  259040.19  2287.53   108.62         283
4    MidWest    MI       1.81      3.13  142267.57  1587.69    86.42         871
5    MidWest    MN       2.18      3.11  369010.68  1850.69   205.52         848
6    MidWest    MO       2.23      2.97  238783.35  1944.31   123.43         343
7    MidWest    ND       2.22      3.58  259991.39  2286.61   112.95         151
8    MidWest    NE       2.45      3.38  276671.76  2150.49   127.82         266
9    MidWest    OH       1.84      3.35  134835.39  1721.55    79.80        1182
10   MidWest    SD       2.40      3.44  362883.80  2031.12   181.82          25
11   MidWest    WI       2.32      3.25  297997.15  1906.92   161.82         320
12     North    CT       2.57      4.15  365254.44  2359.92   177.04         406
13     North    DC       2.47      2.78  732301.21  1525.06   500.22         102
14     North    MA       2.37      3.44  800828.82  1826.08   501.47        1068

               fullState
0                   Iowa
1               Illinois
2                Indiana
3                 Kansas
4               Michigan
5              Minnesota
6               Missouri
7           North Dakota
8               Nebraska
9                   Ohio
10          South Dakota
11             Wisconsin
12           Connecticut
13  District of Columbia
14         Massachusetts
```

[ ]:
```python
# Creating state_df, Step #2, now we have both state_df and house_df
state_df = merged_df.merge(pivot_df, how = 'inner', on = 'fullState')
state_df.head()
```

[ ]:
```
    fullState         GDP    Spending  Population      Income Region State  \
0     Alabama   196906.10   176479.80     4934193   228748.80  South    AL
1      Alaska    50161.00    35635.70      724357    46430.30   West    AK
2     Arizona   320550.60   287090.10     7520103   368458.60   West    AZ
3    Arkansas   114943.50   104488.80     3033946   143147.90  South    AR
4  California 2663665.90 1835980.60    39613493 2763312.00   West    CA

   Bathrooms  Bedrooms      Price     Size  perSqFt  HouseCount
0       2.62      3.38  305048.89  2319.30   124.37         892
```

```
1        2.97      4.59 363202.40 2392.84   165.54          403
2        2.51      3.34 466962.46 2070.79   224.66         1998
3        2.96      3.64 337014.73 2804.81   117.71          280
4        2.56      3.44 776273.37 1965.24   424.09         5696
```

```
[ ]: # Column - calculate savings rate per state
     state_df['SavingsRate'] = (state_df['Income']-state_df['Spending'])/
      ↪state_df['Income']
     state_df.head()
```

```
[ ]:    fullState        GDP   Spending  Population     Income Region State  \
     0     Alabama  196906.10  176479.80     4934193  228748.80  South    AL
     1      Alaska   50161.00   35635.70      724357   46430.30   West    AK
     2     Arizona  320550.60  287090.10     7520103  368458.60   West    AZ
     3    Arkansas  114943.50  104488.80     3033946  143147.90  South    AR
     4  California 2663665.90 1835980.60    39613493 2763312.00   West    CA

        Bathrooms  Bedrooms     Price    Size  perSqFt  HouseCount  SavingsRate
     0       2.62      3.38 305048.89 2319.30   124.37         892         0.23
     1       2.97      4.59 363202.40 2392.84   165.54         403         0.23
     2       2.51      3.34 466962.46 2070.79   224.66        1998         0.22
     3       2.96      3.64 337014.73 2804.81   117.71         280         0.27
     4       2.56      3.44 776273.37 1965.24   424.09        5696         0.34
```

```
[ ]: # Calculate year of savings to buy a house with 20% down payment
     state_df['Years_of_Savings'] = (state_df['Price'] * 0.2) / ((state_df['Income']␣
      ↪- state_df['Spending']) * 1000000 / state_df['Population'])
     state_df.sort_values(by='Years_of_Savings',ascending=True).head(5)
```

```
[ ]:      fullState       GDP  Spending  Population    Income   Region State  \
     14         Iowa 169420.30 118904.60     3167974 169181.60  MidWest    IA
     33         Ohio 589897.70 466159.70    11714618 627231.30  MidWest    OH
     19     Maryland 353052.50 268456.80     6065436 404520.70    South    MD
     21     Michigan 445682.60 411364.20     9992427 530808.60  MidWest    MI
     6   Connecticut 235888.60 179405.90     3552821 279612.40    North    CT

         Bathrooms  Bedrooms     Price    Size  perSqFt  HouseCount  SavingsRate  \
     14       1.95      3.13 149252.38 1686.97    90.80         117         0.30
     33       1.84      3.35 134835.39 1721.55    79.80        1182         0.26
     19       2.28      2.98 240832.79 1577.91   157.61         505         0.34
     21       1.81      3.13 142267.57 1587.69    86.42         871         0.23
     6        2.57      4.15 365254.44 2359.92   177.04         406         0.36

         Years_of_Savings
     14              1.88
     33              1.96
     19              2.15
```

```
21              2.38
6               2.59
```

[ ]:
```
# Calculate per Annual Income
state_df['perAnnualIncome'] = (state_df['Income'] * 1000000 /␣
 ↪state_df['Population'])
state_df.sort_values(by='perAnnualIncome',ascending=True).head(5)
```

[ ]:
```
      fullState        GDP   Spending  Population     Income Region State  \
23  Mississippi   99667.50   95998.30     2966407  124988.20  South    MS
0       Alabama  196906.10  176479.80     4934193  228748.80  South    AL
29   New Mexico   92696.50   74276.40     2105005   97603.50   West    NM
3      Arkansas  114943.50  104488.80     3033946  143147.90  South    AR
16     Kentucky  185535.10  163749.90     4480713  211947.60  South    KY

    Bathrooms  Bedrooms     Price    Size  perSqFt  HouseCount  SavingsRate  \
23       2.29      3.30 181302.03 1907.25    90.56         376         0.23
0        2.62      3.38 305048.89 2319.30   124.37         892         0.23
29       2.46      3.37 315167.86 2096.72   152.91         235         0.24
3        2.96      3.64 337014.73 2804.81   117.71         280         0.27
16       2.77      3.32 394384.46 2387.65   165.15         361         0.23

    Years_of_Savings  perAnnualIncome
23              3.71         42134.54
0               5.76         46359.92
29              5.69         46367.35
3               5.29         47182.09
16              7.33         47302.20
```

[ ]:
```
#######

# Mortgage Amount - Calculating avg mortgage amount with avg price
state_df['mortAmount'] = state_df['Price']*.8
```

[ ]:
```
# NOTE: We assume 20% down payment, 30yr loan, 4% interest for whole project


# Variables
i = 0.04         # interest rate
yrs = 30         # years of mortgage
mth = 12         # month per year

divided_rate = (i/12)    #monthly rates
thirty_total = yrs*mth   # total number of months

# Column - Calculating mortgage payment per month for each state
```

```
state_df['mortPayment'] = (state_df['mortAmount']* ((i/12) * (1 + (i/
↪12))**(yrs*mth))) / ((1 + (i/12))**(yrs*mth) - 1)
```

[ ]:
```
# Desired Annual Income - income calculated using mortgage,
# to live comfortably, paying off mortgage, have savings, and money to spend.
state_df['desiredAnnualIncome'] = (((state_df['mortPayment']  / 20) * 100) *␣
↪12) / 2
```

[ ]:
```
# Column - Calculate Annual Income After Mortgage
state_df['annualIncomeAfterMortgage'] = state_df['perAnnualIncome'] -␣
↪((state_df['mortPayment']) * 12)
```

House_Df

Descriptive Statistics

[ ]:
```
house_df.head()
```

[ ]:
```
   Bedrooms  Bathrooms    Size         Type     Price         City State  \
0      8.00       4.00 3264.00  Multifamily 459900.00    Anchorage    AK
1      2.00       1.00  778.00        Condo  89900.00    Anchorage    AK
2      8.00       4.00 3880.00  Multifamily 590000.00  Eagle River    AK
3      6.00       5.00 4640.00        House 589900.00      Chugiak    AK
4      2.00       2.00 1152.00        Condo 184000.00    Anchorage    AK

   perSqFt Region          SizeCat fullState
0   140.90   West     2501 to 3500    Alaska
1   115.55   West    800 and under    Alaska
2   152.06   West     3501 to 4500    Alaska
3   127.13   West  4500 and higher    Alaska
4   159.72   West      801 to 1500    Alaska
```

[ ]:
```
house_df.describe()
```

[ ]:
```
       Bedrooms  Bathrooms     Size      Price  perSqFt
count  38479.00   38479.00 38479.00   38479.00 38479.00
mean       3.33       2.43  1973.83  407007.46   215.65
std        1.31       1.08  1036.53  326193.75   159.11
min        2.00       1.00   397.00       1.00     0.00
25%        3.00       2.00  1243.00  190000.00   118.15
50%        3.00       2.00  1701.00  324900.00   172.27
75%        4.00       3.00  2405.00  525000.00   256.68
max       84.00      16.00 13776.00 2500000.00  1293.53
```

Across US Median are: 3 Bedrooms, 2 Bathrooms, 1702 SqFt, Price of 325,000 Average are: 3.3 Bedrooms, 2.5 Bathrooms, 2000 SqFt, Price of 407,000

[ ]:
```
# Correlation - of variables
house_df.corr()
```

[ ]:

```
           Bedrooms  Bathrooms  Size  Price  perSqFt
Bedrooms       1.00       0.55  0.62   0.29    -0.10
Bathrooms      0.55       1.00  0.76   0.49     0.03
Size           0.62       0.76  1.00   0.48    -0.11
Price          0.29       0.49  0.48   1.00     0.73
perSqFt       -0.10       0.03 -0.11   0.73     1.00
```

Price and Bedrooms have correlationof 29% Price and Size have correlation of 30% Price and Bathrooms have correlation of 49% Bedroom and Bathrooms have correlation of 56% Price and Bathrooms have a higher correlation than Price and Bedrooms. So the higher the price the number Bathrooms will increase faster than bedrooms you will have. BAM!!!

[ ]:

```
############

#filter the house_df table by creating a seperate table where price is in the␣
↪range of 2.5 to 3 times the the income
houseFilter = house_df[house_df['Type'] == 'House']
houseMin = 55000 * 2.5
houseMax = 55000 * 3
houseRangeMin = houseFilter[houseFilter['Price']>= houseMin]
houseRanges = houseRangeMin[houseRangeMin['Price']<= houseMax]
houseRanges.head(2)
```

[ ]:

```
    Bedrooms  Bathrooms   Size   Type      Price       City State  perSqFt  \
9       2.00       1.00 836.00  House 140000.00  Anchorage    AK   167.46
12      3.00       2.00 830.00  House 165000.00  Anchorage    AK   198.80

   Region      SizeCat fullState
9    West  801 to 1500    Alaska
12   West  801 to 1500    Alaska
```

[ ]:

```
#using the monthly payment formula, grab the table price and apply the function.
twentyPercentDown = houseRanges['Price'] * .8
indMonthlyPayment = (twentyPercentDown * (divided_rate * (1 +␣
↪divided_rate)**thirty_total)) / ((1 + divided_rate)**thirty_total - 1)
indMonthlyPayment.head(2)
```

[ ]:

```
9    534.71
12   630.19
Name: Price, dtype: float64
```

[ ]:

```
#add estimated montly morgage payment
houseRanges['accuredInterestPayMonth'] = indMonthlyPayment
houseRanges.head(2)
```

```
/var/folders/fy/_jcf8bdn3hbccf_yk638qvkw0000gn/T/ipykernel_16201/3317195810.py:2
: SettingWithCopyWarning:
```

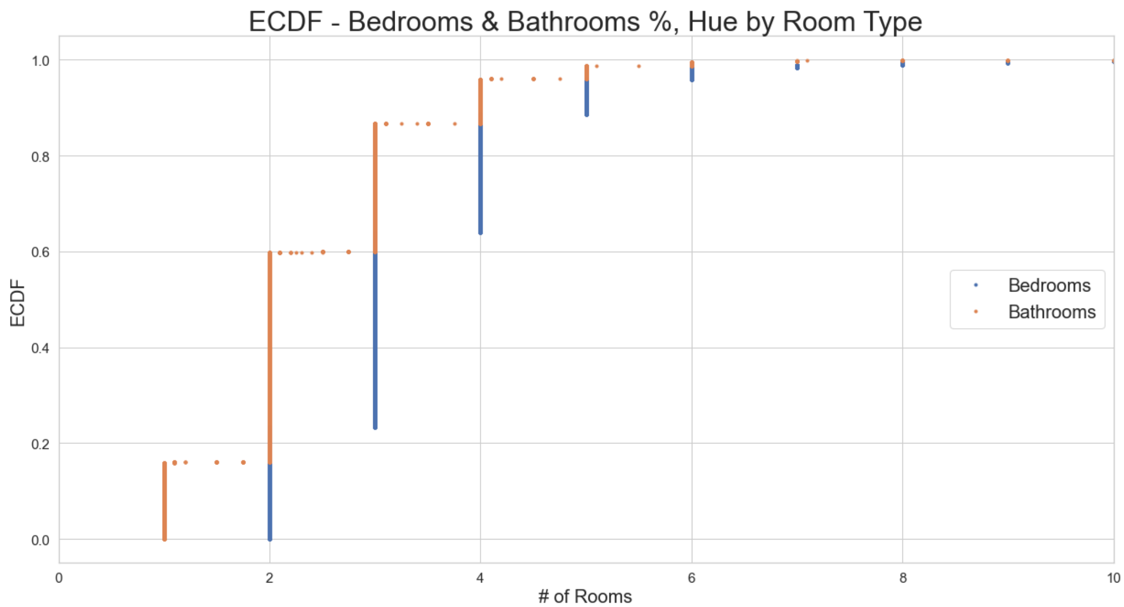
```
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```

[ ]:
```
    Bedrooms  Bathrooms   Size   Type      Price       City State  perSqFt  \
9       2.00       1.00 836.00  House 140000.00  Anchorage    AK   167.46
12      3.00       2.00 830.00  House 165000.00  Anchorage    AK   198.80

   Region       SizeCat fullState  accuredInterestPayMonth
9    West  801 to 1500    Alaska                   534.71
12   West  801 to 1500    Alaska                   630.19
```

House_df visulizations

[ ]:
```
# Setting Theme
sns.set_theme(style="whitegrid") # all charts will have a light grid

# Function to convert x to array, y to the count %
def ecdf(data):
    n = len(data)
    x = np.sort(data)
    y = np.arange(1,1+n)/n
    return x, y

# Figure size and axis
fig = plt.figure(figsize=(20,10))
axes = fig.add_axes([0.1,0.1,0.8,0.8])

# Calculate x and y
x_1, y_1 = ecdf(house_df['Bedrooms'])
x_2, y_2 = ecdf(house_df['Bathrooms'])

# Plot ECDFs
axes.plot(x_1,y_1,marker ='.',linestyle='none')
axes.plot(x_2,y_2,marker ='.',linestyle='none')

# Legend
plt.legend(('Bedrooms','Bathrooms'),loc=7, prop={'size': 20})

# Annotation, Label, Tick, Title
plt.xlabel('# of Rooms', fontsize=20)
plt.ylabel('ECDF', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('ECDF - Bedrooms & Bathrooms %, Hue by Room Type', fontsize=30)
```

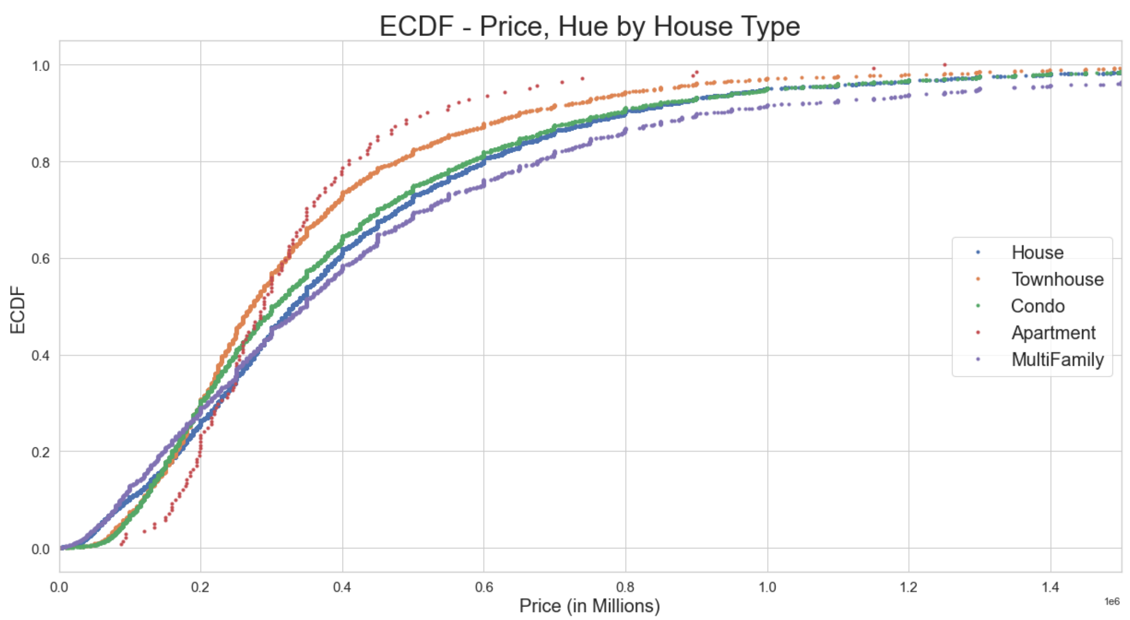
```
# Set limit for x
axes.set_xlim(0,10)

# Show plot
plt.show()
```



According to ECDF, there are more Bedrooms than Bathrooms.

[ ]:
```
# Figure size and axis
fig = plt.figure(figsize=(20,10))
axes = fig.add_axes([0.1,0.1,0.8,0.8])

# Calculate x and y
x_1, y_1 = ecdf(house_df[house_df['Type'] == 'House']['Price'])
x_2, y_2 = ecdf(house_df[house_df['Type'] == 'Townhouse']['Price'])
x_3, y_3 = ecdf(house_df[house_df['Type'] == 'Condo']['Price'])
x_4, y_4 = ecdf(house_df[house_df['Type'] == 'Apartment']['Price'])
x_5, y_5 = ecdf(house_df[house_df['Type'] == 'Multifamily']['Price'])

# Plot ECDFs
axes.plot(x_1,y_1,marker ='.',linestyle='none')
axes.plot(x_2,y_2,marker ='.',linestyle='none')
axes.plot(x_3,y_3,marker ='.',linestyle='none')
axes.plot(x_4,y_4,marker ='.',linestyle='none')
axes.plot(x_5,y_5,marker ='.',linestyle='none')

# Legend
```

```
plt.legend(('House','Townhouse', 'Condo','Apartment','MultiFamily'),loc=7,␣
↪prop={'size': 20})

# Annotation, Label, Tick, Title
plt.xlabel('Price (in Millions)', fontsize=20)
plt.ylabel('ECDF', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('ECDF - Price, Hue by House Type', fontsize=30)

# Set limit for x
axes.set_xlim(0,1500000)

# Show plot
plt.show()
```



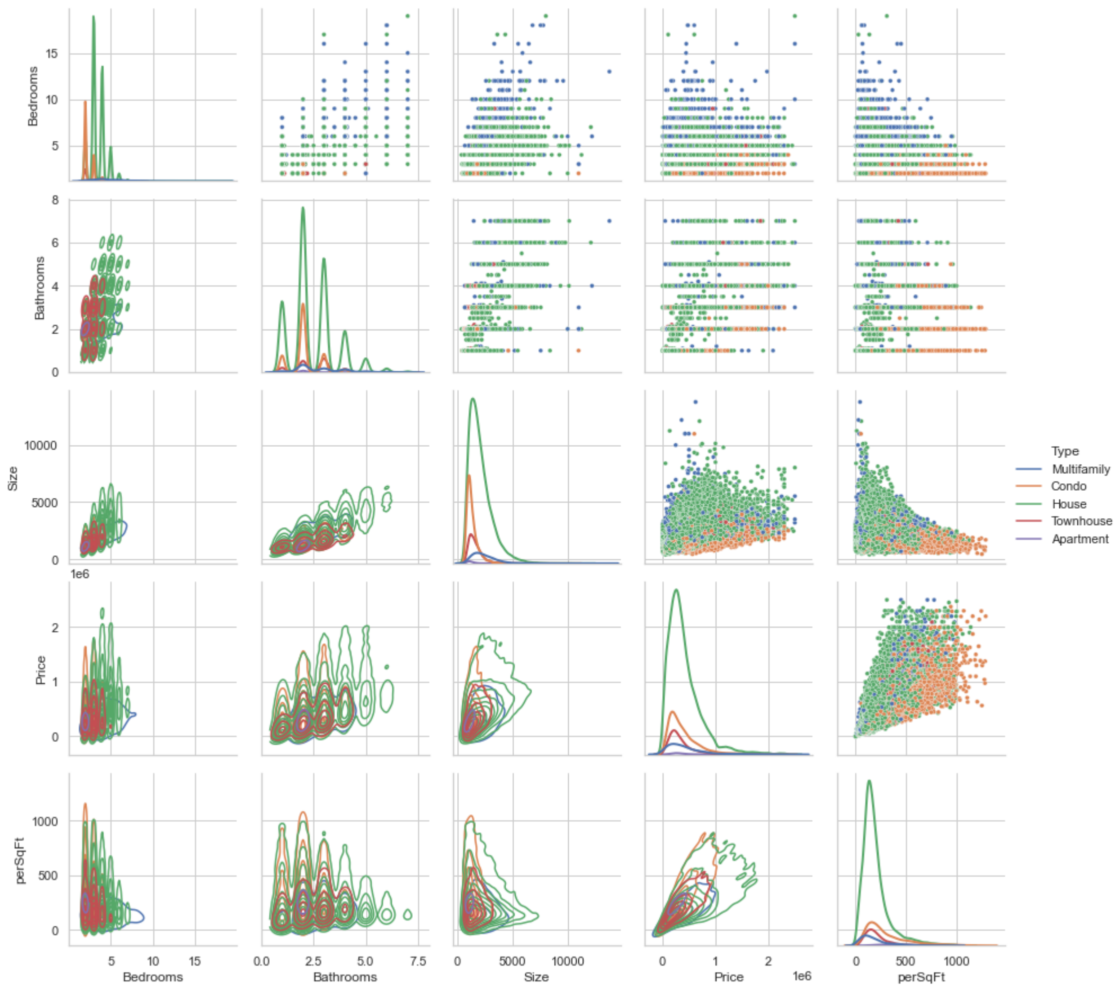
Apartments near 200k range, have a clear premium/higher price than all other types of homes.

Appartments Prices drastrically change near 350k to 400k and becomes a lot lower comparing to others

[ ]:
```
# DataFrame - sorting custom df for the plot
room_sorted_df = house_df[(house_df['Bedrooms']<=20) & (house_df["Bathrooms"]␣
↪<= 7)]

# PairGrid - with the sorted data frame with hue
g = sns.PairGrid(room_sorted_df, diag_sharey=False, hue="Type")
# Upper side of grid is scatter
```

```
g.map_upper(sns.scatterplot, s=15)
# Lower side is KDE
g.map_lower(sns.kdeplot)
# Diagonal is also KDE
g.map_diag(sns.kdeplot, lw=2)
# Adding legend
g.add_legend()
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7fdcbdc438e0>



Top right side of graph, Orange - Condos has clearly smaller size

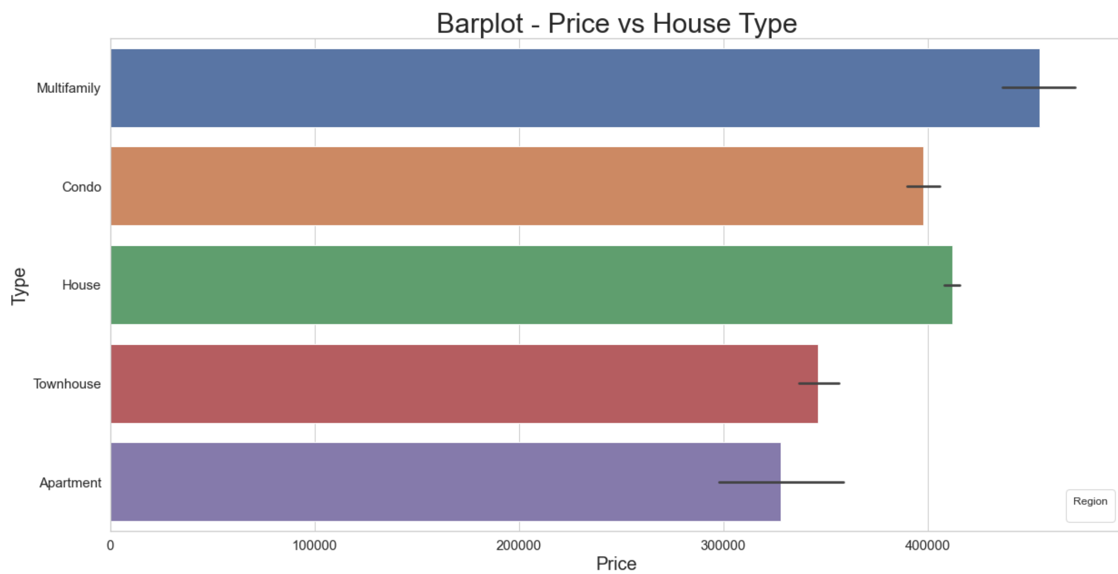
Bottom left side of graph, - Higher perSqFt has lessor Bedrooms

[ ]:
```
# Figure Size
plt.figure(figsize=(20,10))
# Countplot by state, how many data we have for each state
```

```
sns.barplot(data=house_df, x="Price", y="Type", palette="deep")

# Annotation, Label, Tick, Title
plt.xlabel('Price', fontsize=20)
plt.ylabel('Type', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Barplot - Price vs House Type', fontsize=30)
plt.legend(title="Region", loc="lower right", fontsize=20)
```

```
No handles with labels found to put in legend.
```

[ ]:
```
<matplotlib.legend.Legend at 0x7fdcc07d0f10>
```



Multifamily - Most expensive

Condo - is close to House

House - is second highest for price

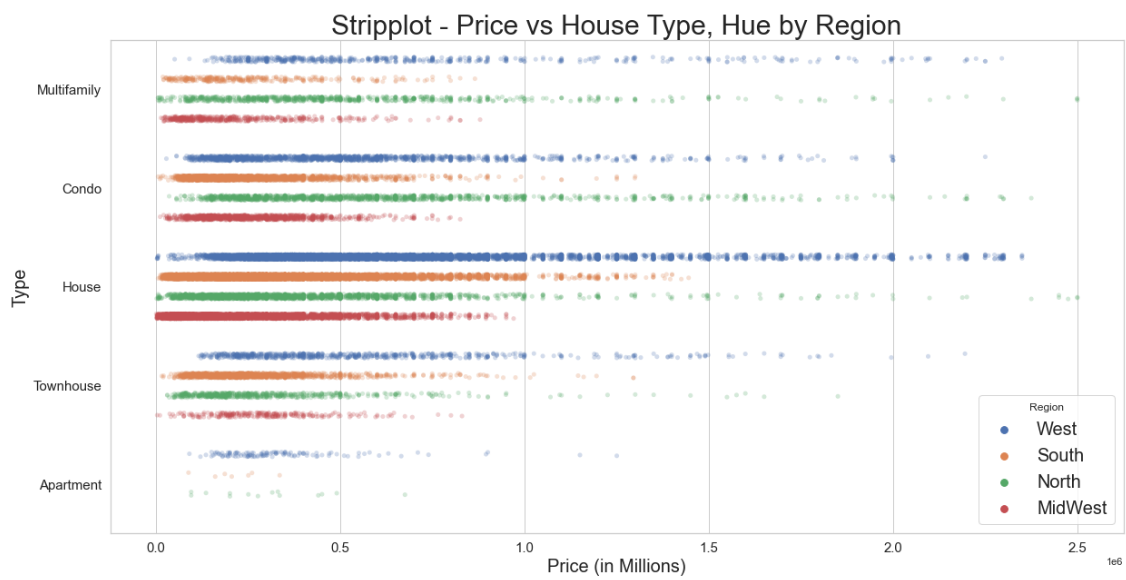
Townhouses - is a lot lower than house and condo, closer to apartment. - This data is useful, because in theory, Townhouses should worth more than condos because they dont have common walls and have independent units. When shopping for homes, Townhouses might have higher chance to get a bargain or have higher values.

Apartments - lowest Price compare to others.

[ ]:
```
# Figure Size
plt.figure(figsize=(20,10))

# Stripplot
```

```
# Dodge is not to mix the color together. (if False, all the dots will be mixed␣
↪together)
sns.stripplot(x="Price", y="Type", hue="Region", data=house_df, dodge=True,␣
↪alpha=.25, zorder=1)

# Annotation
plt.xlabel('Price (in Millions)', fontsize=20)
plt.ylabel('Type', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Stripplot - Price vs House Type, Hue by Region', fontsize=30)
plt.legend(title="Region", loc="lower right", fontsize=20)
```

[ ]: <matplotlib.legend.Legend at 0x7fdcc08d8910>



Stripplot can clearly see where most data is focused in for each Type of house via Region.

Multifamily - West Regions is clearly higher than all other regions

Condo - North and West Regions is clearly higher than all other regions

House - West Region is clearly higher than all other regions, lowest for MidWest

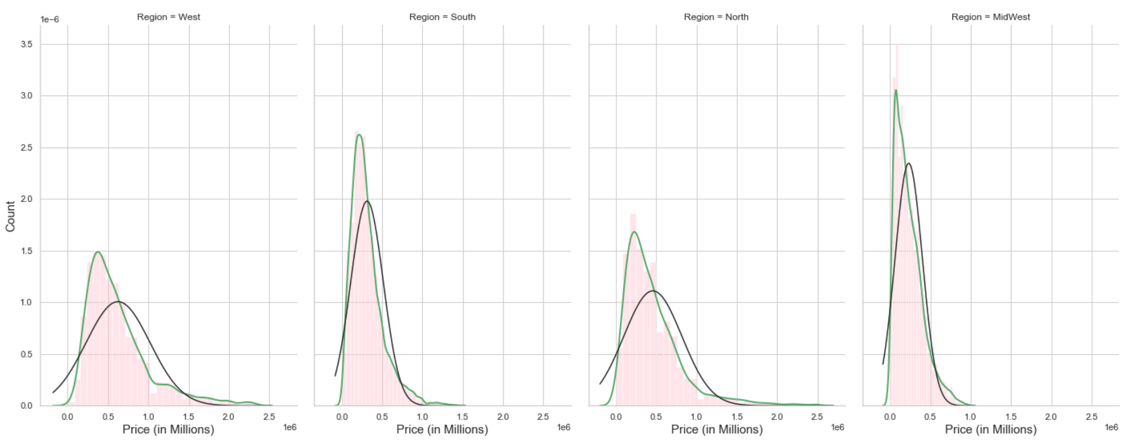
Townhouses - West Region is clearly higher than all other regions, the prices for other regions are extremely close

Apartments - All Region's price all relatively close to each other

MidWest has few/no Apartments

[ ]:
```
# FacetGrid - distribution by Price in Region
g = sns.FacetGrid(col='Region', data=house_df)
g.map(sns.distplot, 'Price', bins = 30, color='pink',kde=True,fit=stats.
 ↪norm,kde_kws={"color": "g", "lw": 2, "label": "KDE"}, hist_kws={"color":␣
 ↪"pink"})
# Annotations
g.fig.set_figheight(10)
g.fig.set_figwidth(20)
g.set_xlabels("Price (in Millions)", fontsize=15)
g.set_ylabels("Count", fontsize=15)

# # Distribution plot of Prices divide into type of houses, hue of region.
# plt.figure(figsize=(20,10))
# sns.histplot(house_df,x='Price', hue='Region', edgecolor='0.5',␣
 ↪bins=150,palette='bright', alpha=0.3)
# # Annotation
# plt.title('Histplot - Price, Hue by Region', fontsize=12)
# plt.xlabel('Price(in Millions)', fontsize=20)
# plt.ylabel('House Data Count', fontsize = 20)
# plt.yticks(fontsize=15)
# plt.xticks(fontsize=15)
```

[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7ffc7abd03d0>
```

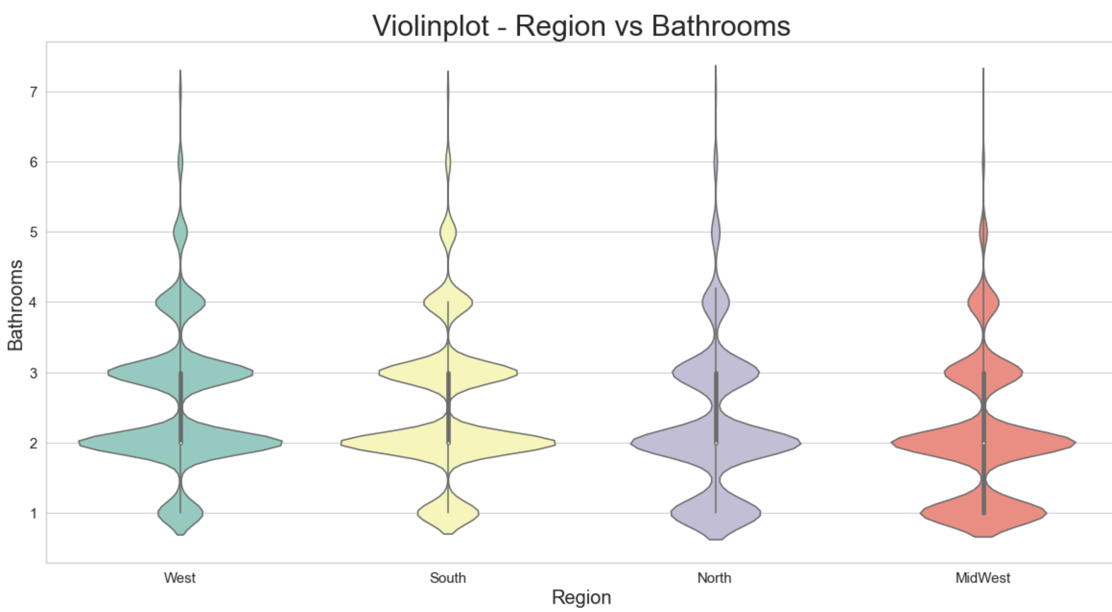


- West Region's most data is around 500k, comparing with other region, West have higher Price mean.
- South Region has most data points. Price is more focused around 250k, half of West Region.
- MidWest has lowest Price mean, where most data is focused on the left side of Price
- Most distribution are positively skewed towards to the right.

[ ]:
```
# Figure Size
plt.figure(figsize=(20,10))
```

```
bath_sorted_df = house_df[house_df["Bathrooms"] <= 7]
sns.violinplot(data=bath_sorted_df, x='Region',y='Bathrooms',palette="Set3")


# Annotation
plt.xlabel('Region', fontsize=20)
plt.ylabel('Bathrooms', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Violinplot - Region vs Bathrooms', fontsize=30)
```

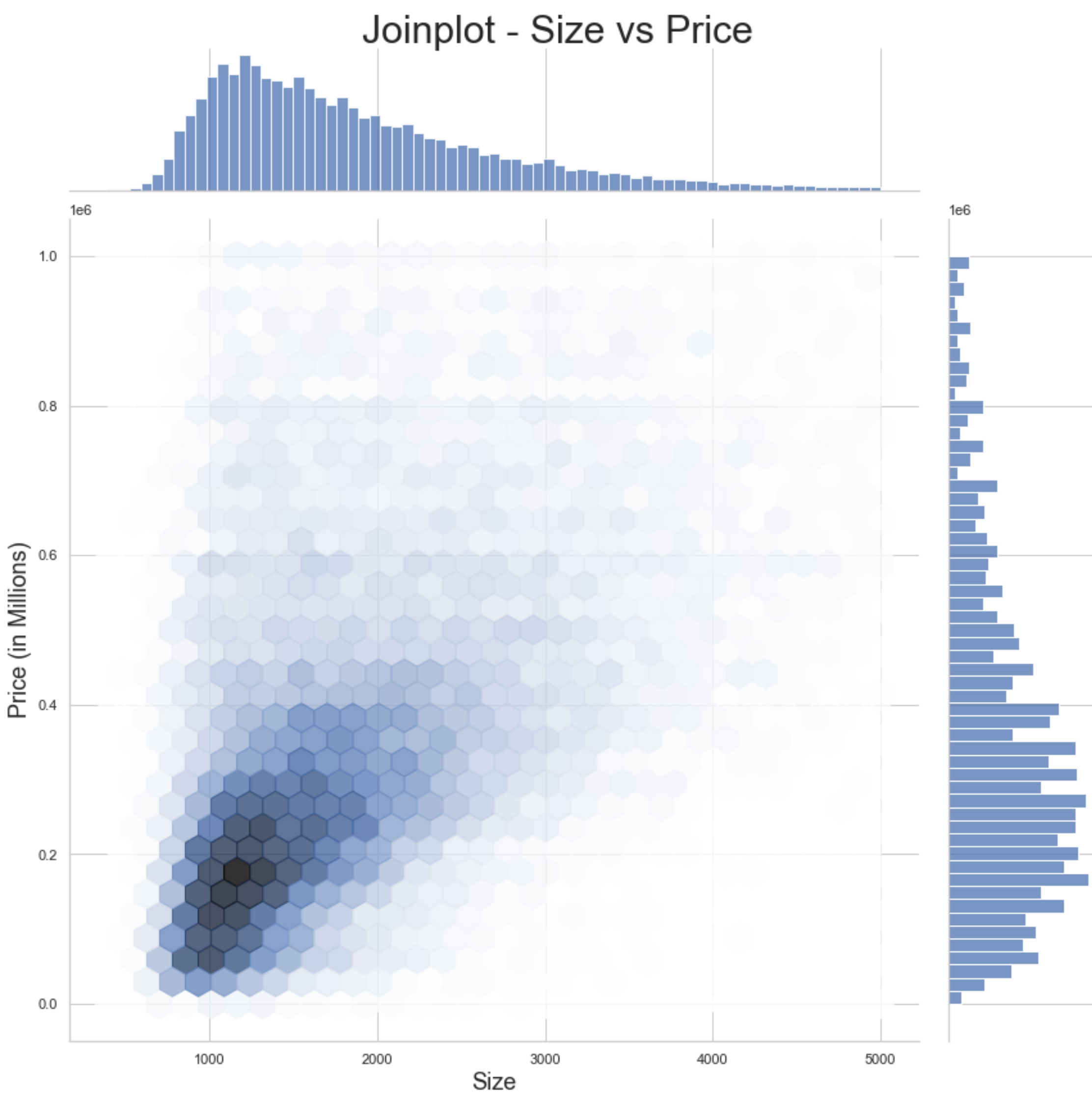
[ ]: Text(0.5, 1.0, 'Violinplot - Region vs Bathrooms')



Violinplot to see each Region's number of bathrooms and how are data focused. Overall, most data are around 2 and 3 Bathrooms. MidWest also have many houses with 1 Bathroom.

[ ]:
```
# DataFrame sorting custom df for graphing
price_sorted_df = house_df[(house_df["Price"] <= 1000000) & (house_df["Size"]␣
 ↪<= 5000)]

# joint_kws is the hex size
_ = sns.jointplot(y='Price', x='Size',data=price_sorted_df, alpha=0.
 ↪8,kind="hex",joint_kws=dict(gridsize=30),height=12)

# Labels for jointplot
_.set_axis_labels("Size", "Price (in Millions)", fontsize = 18)
```

```
# Set title
_.fig.suptitle('Joinplot - Size vs Price', fontsize = 30)
# Adjusting jointplot size to 95%, to leave room for title
_.fig.subplots_adjust(top=0.95)
```

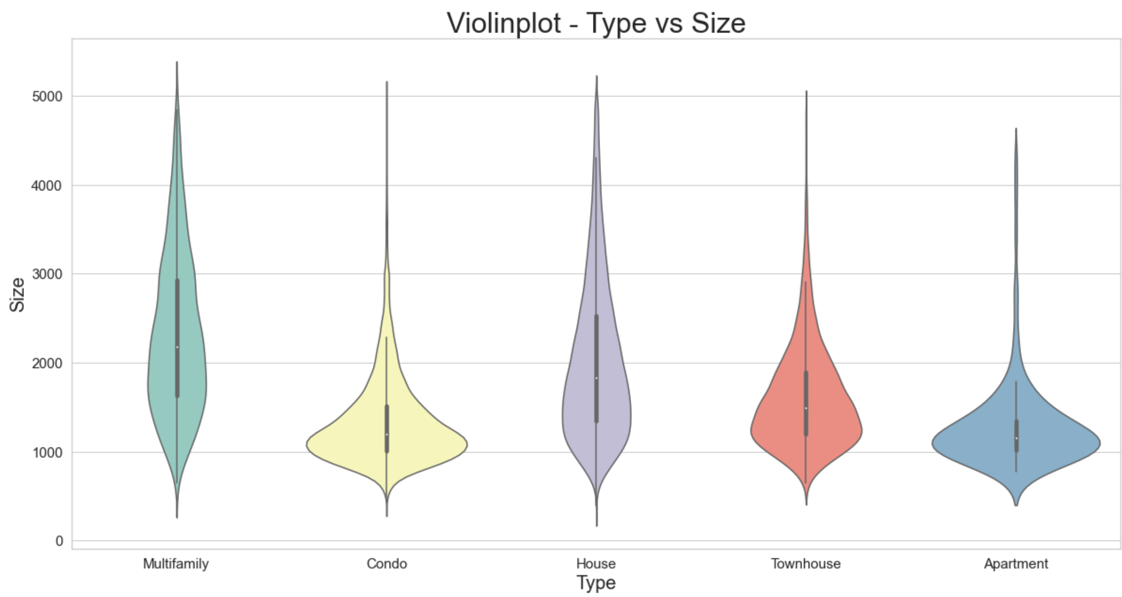


- Price: most data is around $200,000
- Size: most data is between early 1,000 to 2,000 SqFt

[ ]:
```
# Figure Size
plt.figure(figsize=(20,10))
# Dataframe sort custom df for graph
bath_sorted_df = house_df[house_df["Size"] <= 5000]
sns.violinplot(data=bath_sorted_df, x='Type',y='Size',palette="Set3")
```

```
# Annotation
plt.xlabel('Type', fontsize=20)
plt.ylabel('Size', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Violinplot - Type vs Size', fontsize=30)
```

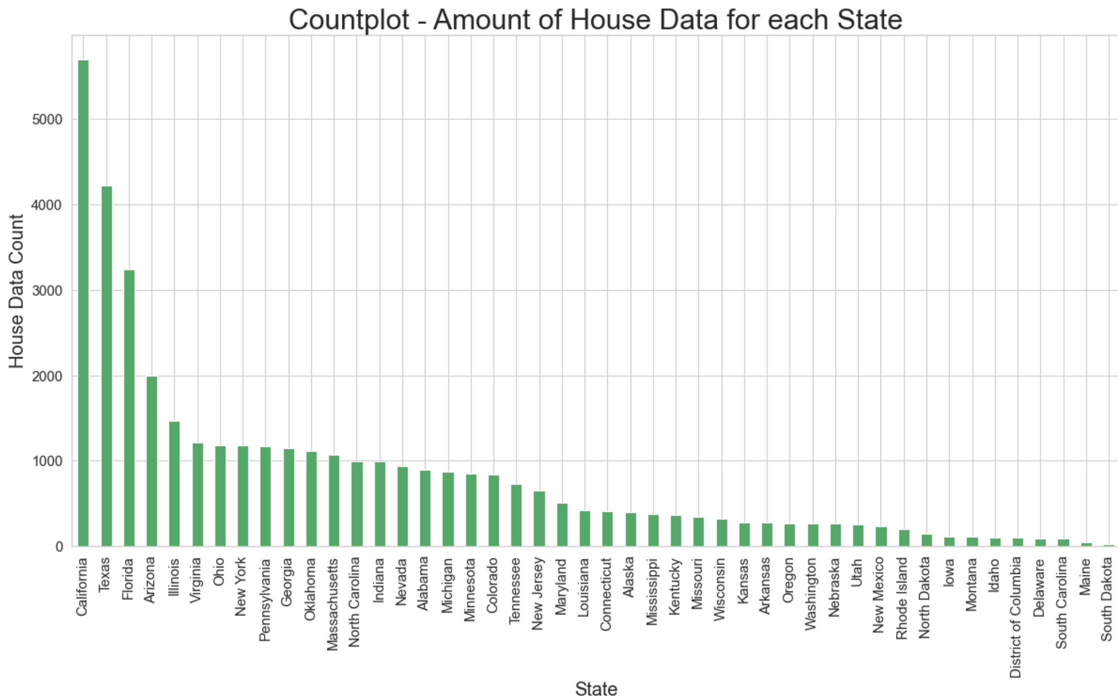
[ ]: Text(0.5, 1.0, 'Violinplot - Type vs Size')



Condo and Apartment are wider around 1000 SqFt. Multifamily and House are slimmer where all data is spread between 1k and 4k, clearly multifamily have larger sizes. Townhouse is in between Condos vs Multifamilies

[ ]:
```
# Countplot by state, how many data we have for each state
plt.figure(figsize=(20,10))
house_df['fullState'].value_counts().plot(kind='bar',color='g')

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('House Data Count', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Countplot - Amount of House Data for each State', fontsize=30)
```

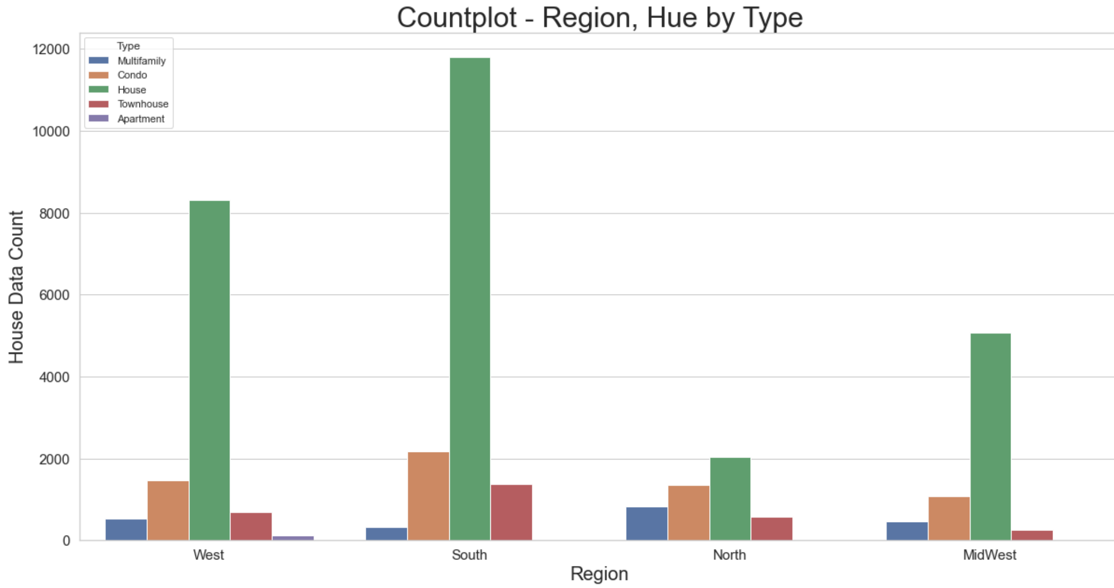
[ ]: Text(0.5, 1.0, 'Countplot - Amount of House Data for each State')



We have most data in California, Texas, and Florida. Partial indicator that these states have more real estate activities.

[ ]:
```
# Count plot x is region and hue is Type of houses
plt.figure(figsize=(20,10))
g=sns.countplot(x='Region',data=house_df,hue='Type')
g.set(ylim=(0, None))

# Annotation
plt.xlabel('Region', fontsize=20)
plt.ylabel('House Data Count', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Countplot - Region, Hue by Type' , fontsize=30)
```

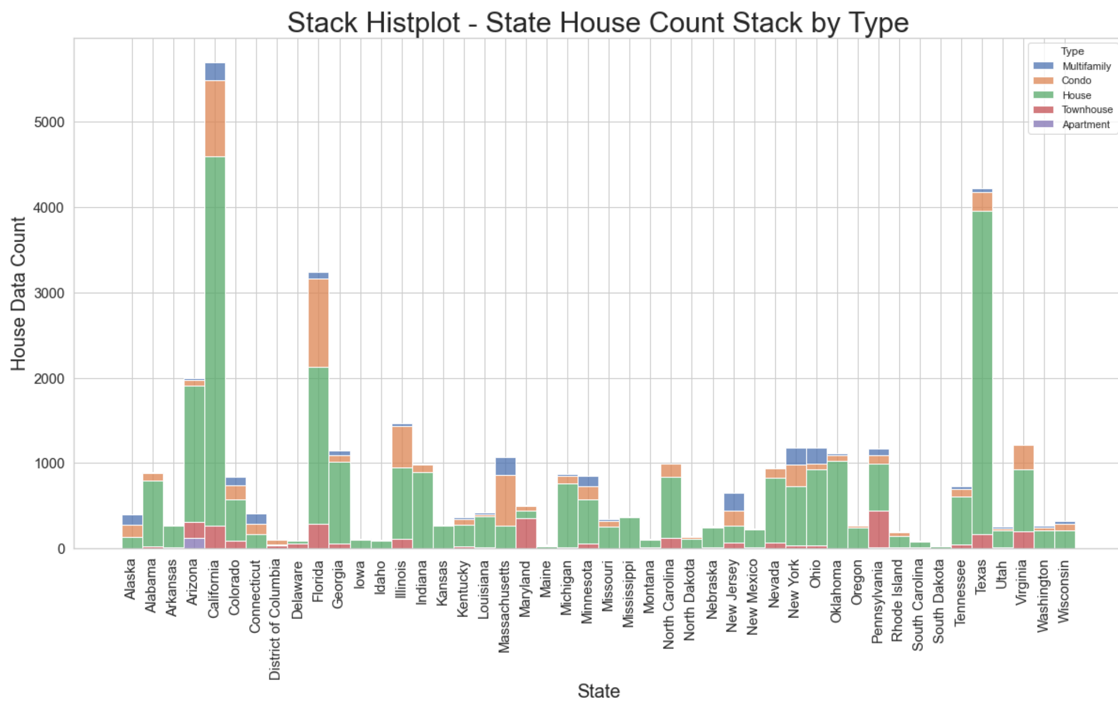
[ ]:
```
Text(0.5, 1.0, 'Countplot - Region, Hue by Type')
```



Countplot by Region and Hue by Property Types. 1. Single Family Residence are primary market for United States2. Condos are 2nd, follow by Townhouses as 3rd The North Region has a high percentage of Condos and Townhouses relative to the houses.

[ ]:
```
# Histplot stacked by type
plt.figure(figsize=(20,10))
sns.
 ↪histplot(data=house_df,x='fullState',hue='Type',multiple='stack',edgecolor='white')

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('House Data Count', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Stack Histplot - State House Count Stack by Type', fontsize=30)
```

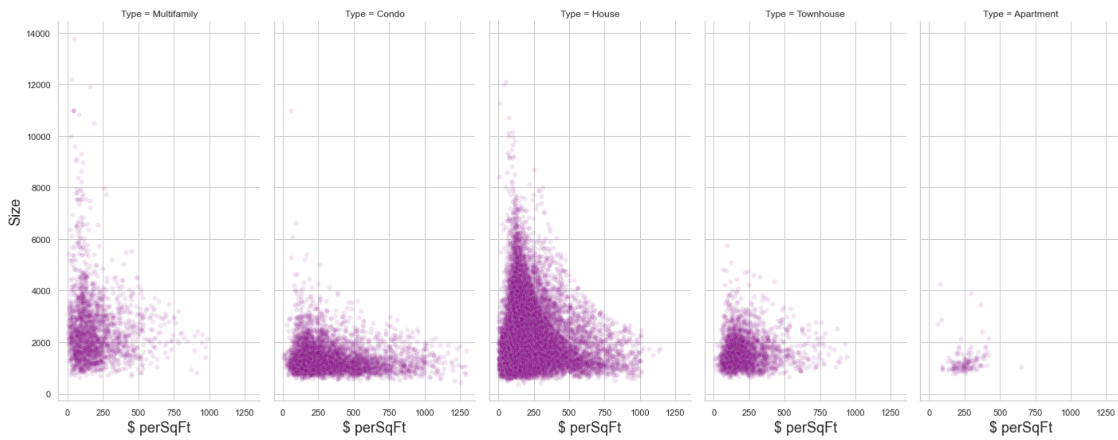
[ ]:
```
Text(0.5, 1.0, 'Stack Histplot - State House Count Stack by Type')
```



- Massachusetts, Alaska, District of Columbia are primarily Condos.
- Maryland, Pennylvania, Delaware are primarily Townhouses or have huge % in Townhouses.

[ ]:
```
# FacetGrid
g = sns.FacetGrid(col='Type', data=house_df)
# Map out with scatter plot X perSqFt, y Size, Columns by Type
g.map(sns.scatterplot, "perSqFt", 'Size', alpha=0.1, color='purple')

# Figsize
g.fig.set_figheight(10)
g.fig.set_figwidth(20)
g.set_xlabels('$ perSqFt', fontsize = 18)
g.set_ylabels('Size', fontsize = 18)
```

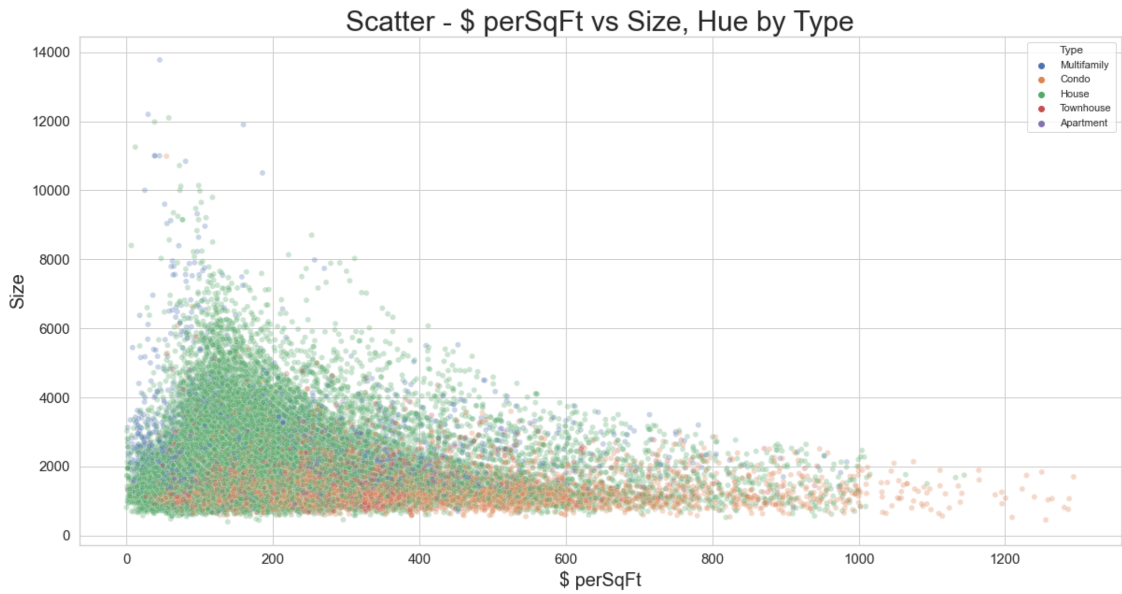
[ ]:
```
<seaborn.axisgrid.FacetGrid at 0x7ffc907e2100>
```



Multifamily perSqFt are mostly focused between $0 - $250. Condo Size are clearly smaller. Most focused under 2000 SqFt House is everywhere, but theres clearly negative relationship between Size and perSqFt. Townhouse and Apartment is focused under 2000 SqFt and between $0 - $250 perSqFt

[ ]:
```
# Scatterplot perSqFt, Size, hue by Type
plt.figure(figsize=(20,10))

# Scatterplot
sns.scatterplot(data=house_df,x='perSqFt',y='Size',hue='Type', alpha=0.3)

# Annotation
plt.xlabel('$ perSqFt', fontsize=20)
plt.ylabel('Size', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Scatter - $ perSqFt vs Size, Hue by Type', fontsize=30)
```

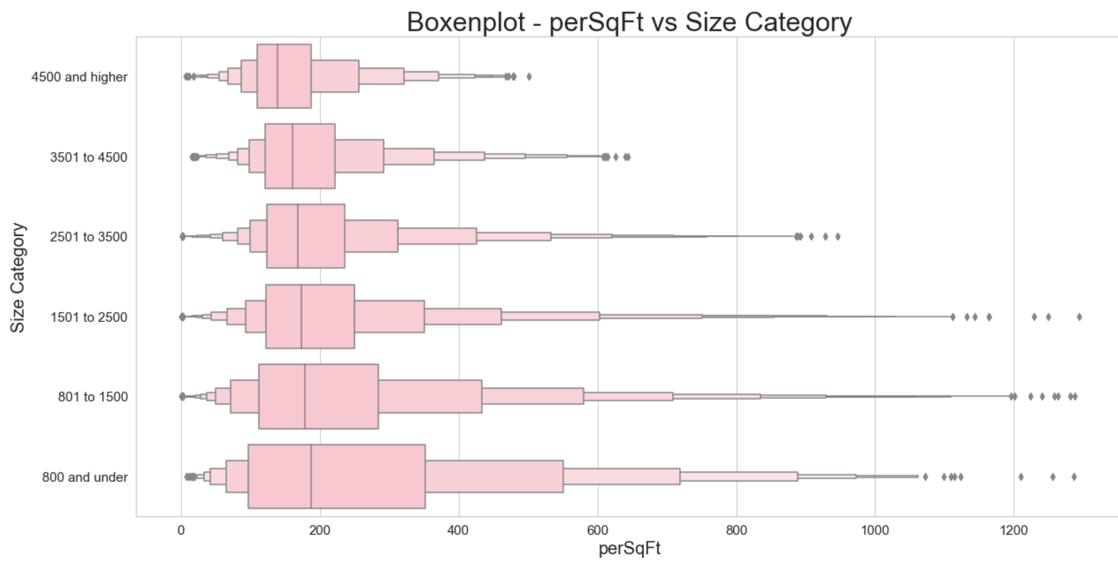
[ ]:
```
Text(0.5, 1.0, 'Scatter - $ perSqFt vs Size, Hue by Type')
```



- The higher the perSqFt the smaller the house Size.
- Most Condos have higher perSqFt prices.

[ ]:
```
# List - Making Size Category list, so we can sort it later
sizeCat_list = list(house_df['SizeCat'].unique())
sizeCat_list

# Figure Size
plt.figure(figsize=(20,10))
# List - Sort the Size Category
sizeCat_list_sorted =['800 and under','801 to 1500', '1501 to 2500','2501 to␣
↪3500','3501 to 4500','4500 and higher'][::-1]
# Boxenplot
sns.boxenplot(y="SizeCat", x="perSqFt", color="pink",␣
↪order=sizeCat_list_sorted, data=house_df)


# Annotation
plt.xlabel('$ perSqFt', fontsize=20)
plt.ylabel('Size Category', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Boxenplot - $ perSqFt vs Size Category', fontsize=30)
```

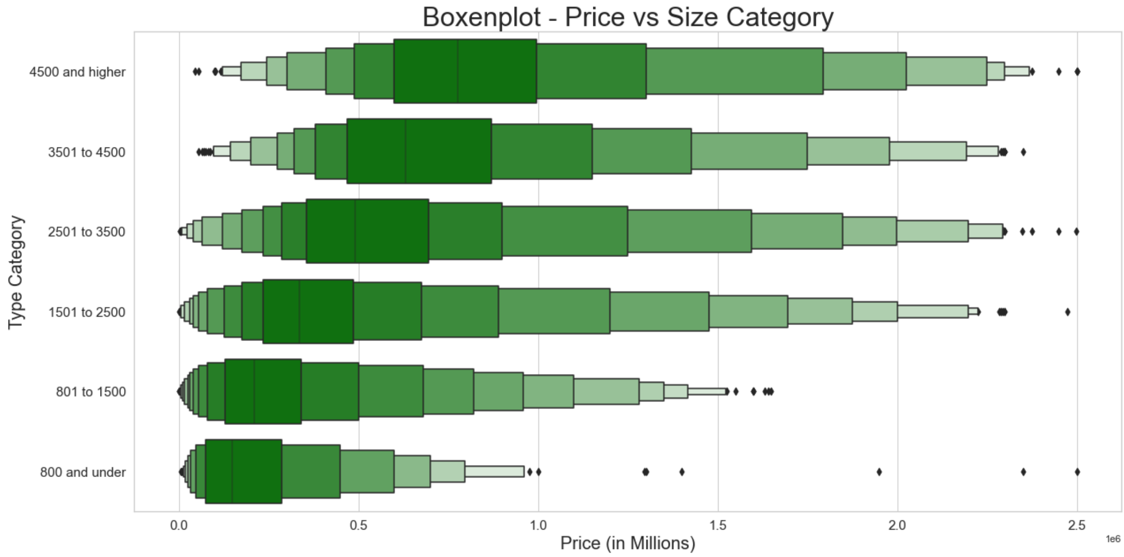
[ ]:
```
Text(0.5, 1.0, 'Boxenplot - perSqFt vs Size Category')
```



Steady increase of $ perSqFt as Size decreases. (Negatively Correlated)

[ ]:
```
# List - Making Size Category list, so we can sort it later
sizeCat_list = list(house_df['SizeCat'].unique())
sizeCat_list

# Figure Size
plt.figure(figsize=(20,10))
# List - Sort the Size Category
sizeCat_list_sorted =['800 and under','801 to 1500', '1501 to 2500','2501 to␣
↪3500','3501 to 4500','4500 and higher',][::-1]
# Boxenplot
sns.boxenplot(y="SizeCat", x="Price",color="green",␣
↪scale='linear',order=sizeCat_list_sorted, data=house_df)


# Annotation
plt.xlabel('Price (in Millions)', fontsize=20)
plt.ylabel('Type Category', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Boxenplot - Price vs Size Category', fontsize=30)
```

[ ]:
```
Text(0.5, 1.0, 'Boxenplot - Price vs Size Category')
```



Exact Opposite with Price, as Size get larger Price is larger. (Positively Correlated)

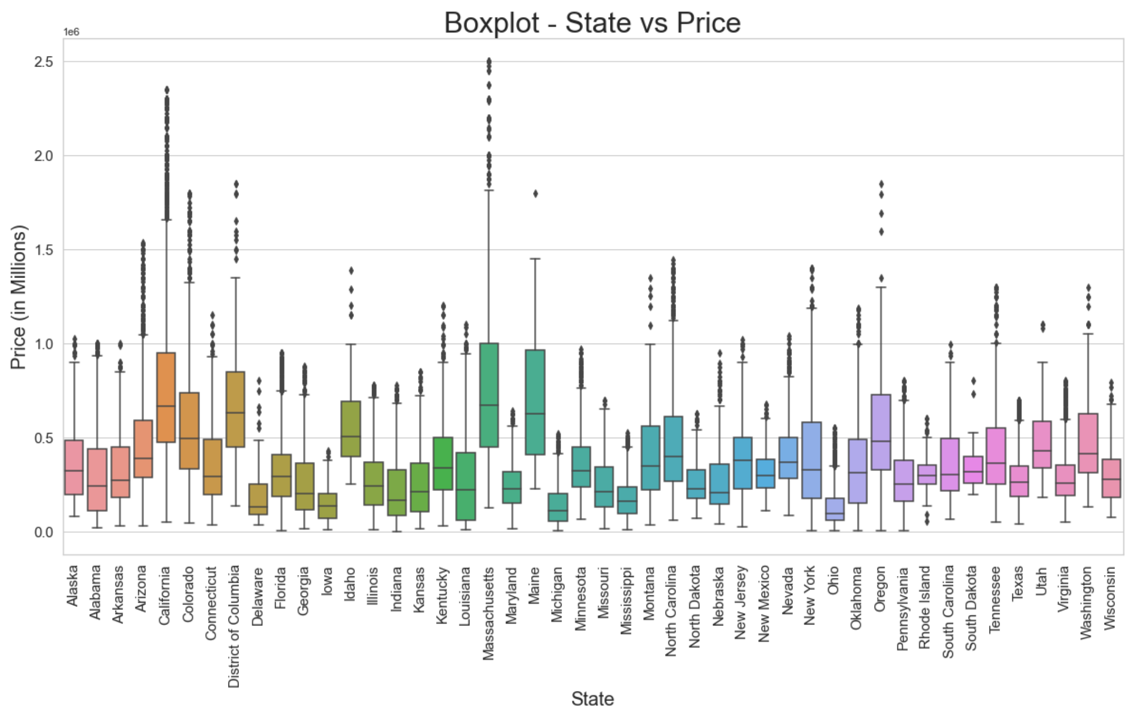
[ ]:
```
# Scatterplot perSqFt, Size, hue by Type
plt.figure(figsize=(20,10))
sns.scatterplot(data=house_df,x='Price',y='Size',hue='Type', alpha=0.4)

# Annotation
plt.xlabel('Price (in Millions)', fontsize=20)
plt.ylabel('Size', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Scatter - Price vs Size, Hue by Type', fontsize=30)
```

[ ]:
```
Text(0.5, 1.0, 'Scatter - Price vs Size, Hue by Type')
```

- Slight correlation between Price and Size. The larger the house the price will be slightly increased.
- Condo size is at the bottom of chart

[ ]:
```
# Boxplot of States by House price
plt.figure(figsize=(20,10))
ax = sns.boxplot(data = house_df, x = 'fullState' , y = 'Price')

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('Price (in Millions)', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Boxplot - State vs Price', fontsize=30)
```

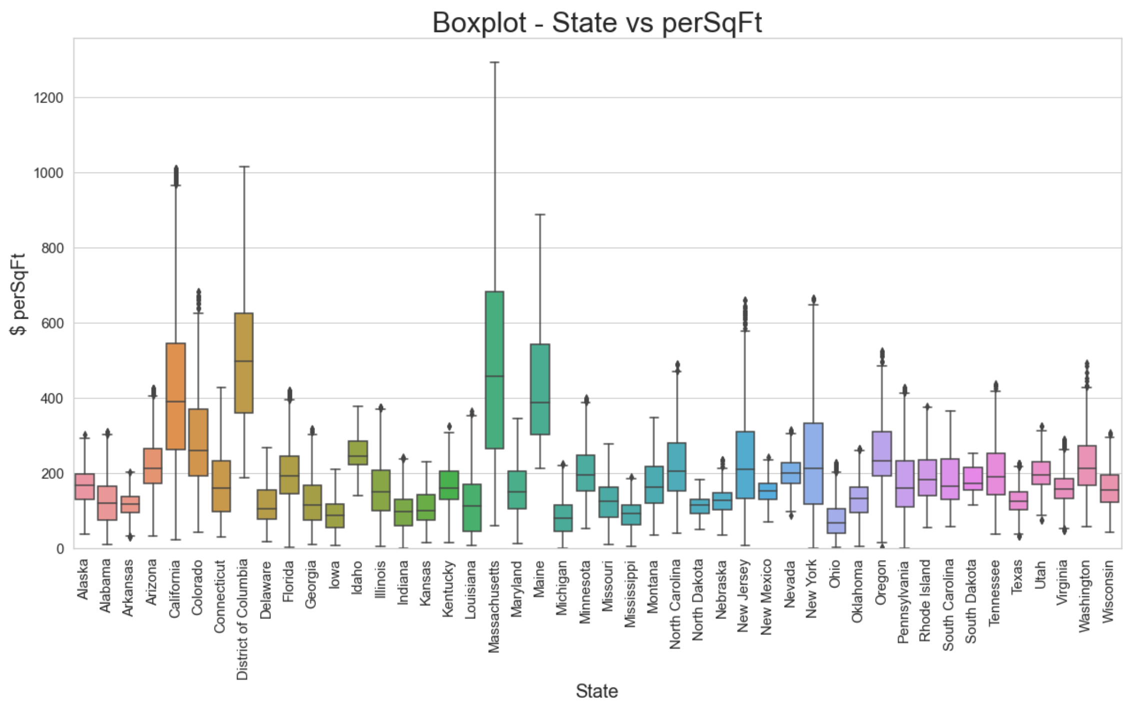
[ ]:
```
Text(0.5, 1.0, 'Boxplot - State vs Price')
```



- The house price for California, District of Columbia, Maine, Massachusetts are fairly high. there are extreme outliers in many states.
- Rich people are everywhere! Double BAM!!

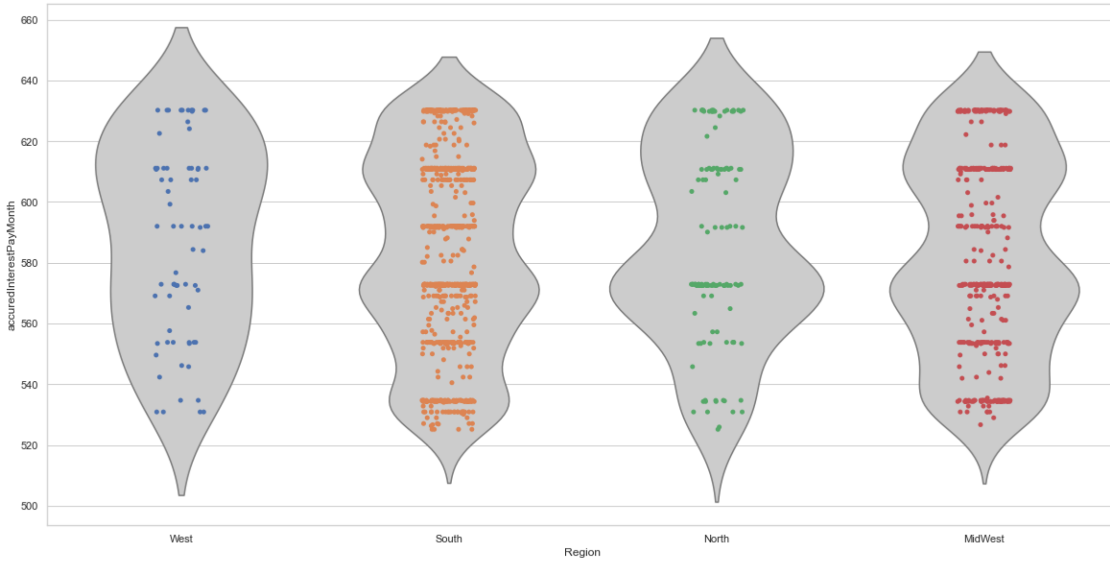
[ ]:
```
# Boxplot of States by $ perSqFt
plt.figure(figsize=(20,10))
ax = sns.boxplot(data = house_df, x = 'fullState' , y = 'perSqFt')
ax.set_ylim(0,None)

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('$ perSqFt', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Boxplot - State vs $ perSqFt', fontsize=30)
```

[ ]:
```
Text(0.5, 1.0, 'Boxplot - State vs perSqFt')
```



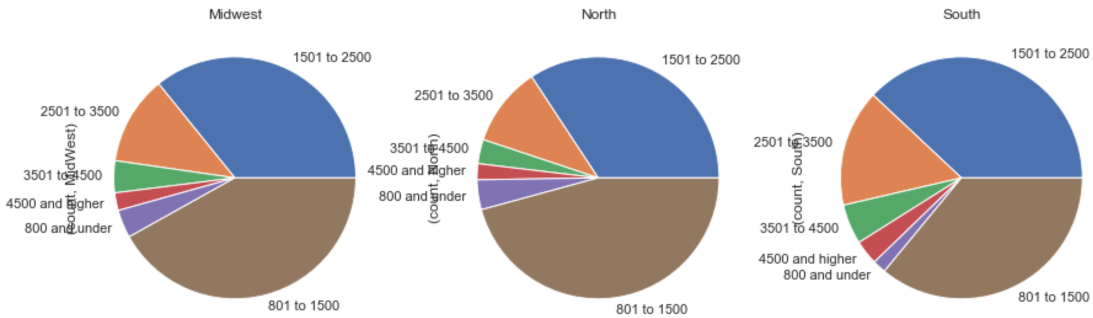
- The $ perSqFt for the same states; California, District of Columbia, Massachusetts, Maine are clearly top 4 again.
- Comparing with the Price boxplot, Maine has higher Prices, lower perSqFt. So the house Size there should be proportionally larger. This is exact opposite for District of Columbia lower Prices, higher perSqFt. So house Size should be proportionally smaller.

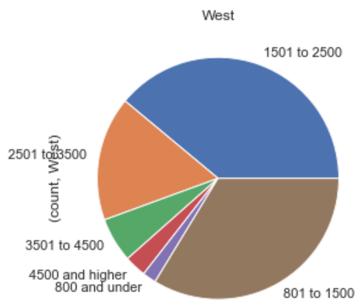
[ ]:
```
#########

#graph the distribution and see where the most of data points land using a␣
↪violin plot and strip plot
plt.figure(figsize=(20,10))
ax = sns.violinplot(x="Region", y="accuredInterestPayMonth",␣
↪data=houseRanges,inner=None, color=".8")
ax = sns.stripplot(x="Region", y="accuredInterestPayMonth", data=houseRanges)
```



Markdown: It seems that you are more likely to find a house in the South and Midwest, due to amount of distribution compared to the North and West Regions. in the South you have plenty of options from ranges of $560 to $580 and $600 and $620; In the Midwest, you also have plenty of options as well, from ranges of $560 to $580 and $600 and $620.

[ ]:
```python
# Dataframe - create a multi-index dataframe for Pie Chart
regionSize_df = house_df.groupby(['Region', 'SizeCat']).size()
regionCounts= regionSize_df.to_frame(name = 'count')

#create the pir chart subplots
ax = regionCounts.unstack(level=0).plot(kind='pie', subplots=True, figsize=(15,
 ↪30), layout=(4, 3), legend = False, title = ['Midwest', 'North', 'South',
 ↪'West'], sharex = False, sharey = False)
plt.show()
```





Interesting points is that the Midwest and North Regions have a larger distributions of properties that are 800 sqft and lower.

State_df

Descriptive for State_df

[ ]:
```
state_df.head()
```

[ ]:

	fullState	GDP	Spending	Population	Income	Region	State
0	Alabama	196906.10	176479.80	4934193	228748.80	South	AL
1	Alaska	50161.00	35635.70	724357	46430.30	West	AK
2	Arizona	320550.60	287090.10	7520103	368458.60	West	AZ
3	Arkansas	114943.50	104488.80	3033946	143147.90	South	AR
4	California	2663665.90	1835980.60	39613493	2763312.00	West	CA

	Bathrooms	Bedrooms	Price	Size	perSqFt	HouseCount	SavingsRate
0	2.62	3.38	305048.89	2319.30	124.37	892	0.23
1	2.97	4.59	363202.40	2392.84	165.54	403	0.23
2	2.51	3.34	466962.46	2070.79	224.66	1998	0.22
3	2.96	3.64	337014.73	2804.81	117.71	280	0.27

```
4       2.56      3.44 776273.37 1965.24   424.09        5696          0.34

   Years_of_Savings  perAnnualIncome
0              5.76         46359.92
1              4.87         64098.64
2              8.63         48996.48
3              5.29         47182.09
4              6.63         69756.84
```

[ ]:
```
state_df.describe()
```

[ ]:
```
             GDP    Spending   Population     Income  Bathrooms  Bedrooms  \
count      46.00       46.00        46.00      46.00      46.00     46.00
mean   390208.88   299606.37   7078103.24  419131.06       2.42      3.37
std    482294.66   340567.83   7600879.42  496796.28       0.29      0.34
min     46158.10    33631.30    714153.00   46430.30       1.81      2.78
25%    118834.20    98120.93   2929519.75  129528.12       2.23      3.16
50%    229092.70   187682.30   5106011.50  265093.00       2.46      3.33
75%    492387.12   365095.10   8402224.00  531894.30       2.61      3.44
max   2663665.90  1835980.60  39613493.00 2763312.00       2.97      4.59

          Price    Size  perSqFt  HouseCount  SavingsRate  Years_of_Savings  \
count     46.00   46.00    46.00       46.00        46.00             46.00
mean  371094.07 2024.62   191.74      836.50         0.27              5.02
std   160612.69  304.99    99.39     1081.74         0.04              2.52
min   134835.39 1525.06    79.80       25.00         0.16              1.88
25%   270628.96 1774.21   124.58      255.50         0.23              3.28
50%   345951.25 2035.53   167.14      415.50         0.27              4.20
75%   425050.39 2275.08   217.56     1050.50         0.30              6.44
max   800828.82 2804.81   501.47     5696.00         0.36             16.01

       perAnnualIncome
count            46.00
mean          57397.29
std            9664.06
min           42134.54
25%           51108.37
50%           54791.33
75%           61796.02
max           86404.59
```

[ ]:
```
# Finding Highest/Lowest 3 States of per square footage and size
sqft_top = state_df.sort_values(by='perSqFt',ascending=False).
 ↪head(3)[['State','perSqFt']]
sqft_bot = state_df.sort_values(by='perSqFt',ascending=True).
 ↪head(3)[['State','perSqFt']]
```

```
size_top = state_df.sort_values(by='Size',ascending=False).
 ↪head(3)[['State','Size']]
size_bot = state_df.sort_values(by='Size',ascending=True).
 ↪head(3)[['State','Size']]
# For loop to print the output for $ perSqFt
print('Top 3 Highest and Lowest $ perSqFt')
dflist = sqft_top, sqft_bot
for d in dflist:
    dict_d = dict(zip(d.iloc[:,0],d.iloc[:,1]))
    for k in dict_d:
        print('State {} have average of ${:.2f} per square feet'.
 ↪format(k,dict_d[k]))

# For loop to print the output for Size
print('\nTop 3 Largest and Smallest House Size')
dflist2 = size_top, size_bot
for d in dflist2:
    dict_d = dict(zip(d.iloc[:,0],d.iloc[:,1]))
    for k in dict_d:
        print('State {} have average of {:.0f} square feet.'.
 ↪format(k,dict_d[k]))
```

```
Top 3 Highest and Lowest $ perSqFt
State MA have average of $501.47 per square feet
State DC have average of $500.22 per square feet
State ME have average of $437.12 per square feet
State OH have average of $79.80 per square feet
State MI have average of $86.42 per square feet
State MS have average of $90.56 per square feet

Top 3 Largest and Smallest House Size
State AR have average of 2805 square feet.
State UT have average of 2524 square feet.
State OK have average of 2511 square feet.
State DC have average of 1525 square feet.
State DE have average of 1538 square feet.
State MD have average of 1578 square feet.
```

[ ]:
```
# Groupby table #2
state_df.groupby(['Region']).mean()
```

[ ]:

	GDP	Spending	Population	Income	Bathrooms	Bedrooms	\
Region							
MidWest	295767.66	233952.69	5709479.67	319849.12	2.19	3.24	
North	450836.24	333676.30	6821733.50	487617.51	2.27	3.37	
South	409233.81	327572.71	8341364.40	443628.85	2.50	3.29	
West	423199.96	308314.50	7034969.00	444224.20	2.65	3.62	

```
            Price     Size  perSqFt  HouseCount  SavingsRate  Years_of_Savings  \
Region
MidWest 248014.61 1940.53   128.11      571.92         0.27              3.18
North   496524.37 1790.17   307.33      602.12         0.29              5.59
South   314451.73 2069.02   150.68     1045.67         0.26              4.95
West    491380.10 2226.31   233.09     1010.36         0.26              6.70

         perAnnualIncome
Region
MidWest         56367.56
North           70962.55
South           51799.11
West            56288.87
```

- Years of Saving to buy a house is highest in West Region than other regions and Lowest in MidWest Region.
- Individual's Income highest in North Region, lowest in South Region.
- perSqFt highest in North lowest in MidWest.

[ ]:
```
# Top income states after paying mortgage
state_df[['fullState','annualIncomeAfterMortgage']].
↪sort_values(by='annualIncomeAfterMortgage',ascending=False).head()
```

[ ]:
```
               fullState  annualIncomeAfterMortgage
6            Connecticut                   61961.22
30              New York                   56563.87
28            New Jersey                   56034.83
19              Maryland                   55654.95
8   District of Columbia                   52841.86
```

[ ]:
```
# compare that to the savings rate table
state_df[['fullState','SavingsRate']].
↪sort_values(by='SavingsRate',ascending=False).head()
```

[ ]:
```
        fullState  SavingsRate
6     Connecticut         0.36
20  Massachusetts         0.34
19       Maryland         0.34
4      California         0.34
30       New York         0.33
```

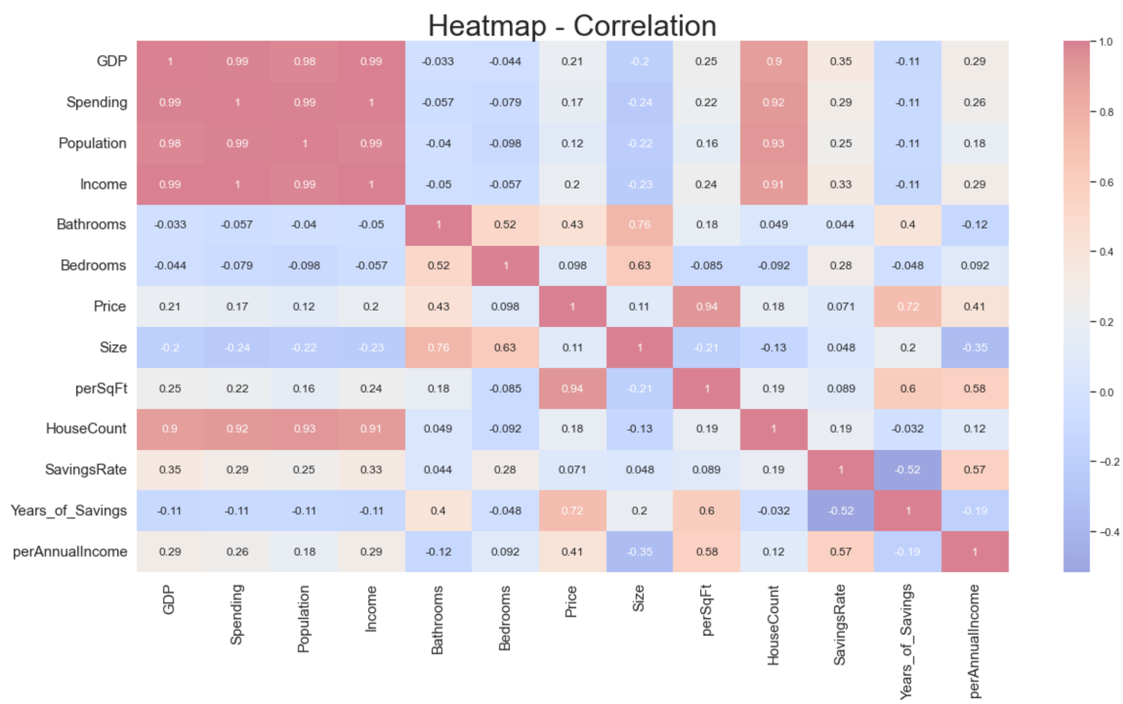
Because SavingsRate didnt account for different mortgage payments,there are some states that do not match. Conneticut, NY, and MD seem like the best states to live in for economic savings.

Visualization for state_df

[ ]:
```
# Figure Size
plt.figure(figsize=(20,10))
```

```python
# Heatmap plotting
sns.heatmap(state_df.corr(),cmap='coolwarm' ,annot=True, alpha=0.5)

# Annotations
plt.xticks(rotation=30)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Heatmap - Correlation', fontsize=30)
```

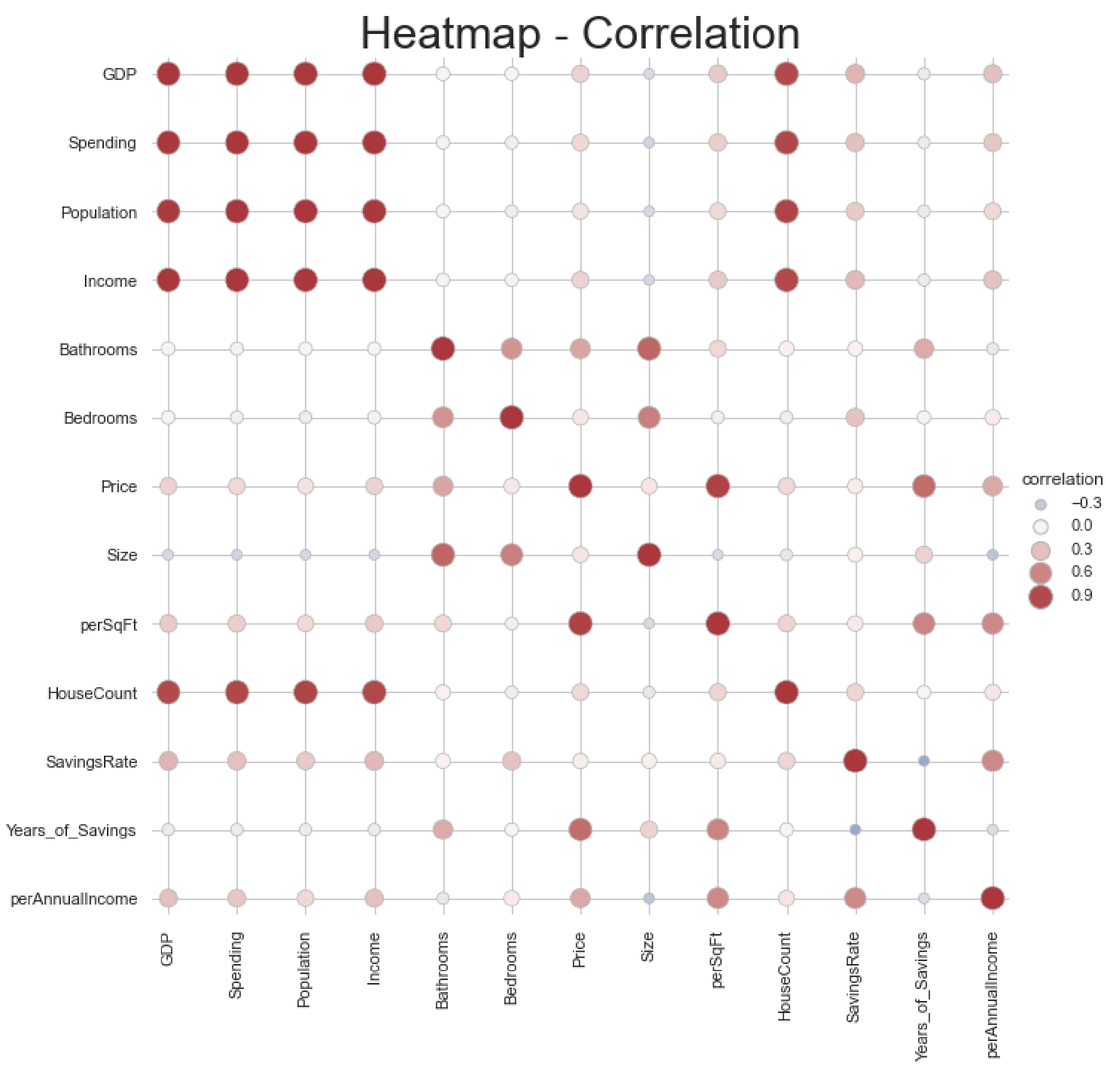
[ ]: Text(0.5, 1.0, 'Heatmap - Correlation')



[ ]:
```python
# Heat Scatter
# Source: https://seaborn.pydata.org/examples/heat_scatter.html
# Note: this map is literally from the source, i really liked it thats why i want to plot it.

# Compute a correlation matrix and convert to long-form
corr_mat = state_df.corr().stack().reset_index(name="correlation")

# Draw each cell as a scatter point with varying size and color
g = sns.relplot(data=corr_mat,x="level_0", y="level_1", hue="correlation", size="correlation",palette="vlag", hue_norm=(-1, 1), edgecolor=".7",height=10, sizes=(50, 250), size_norm=(-.2, .8),)
```

```
# Tweak the figure to finalize
g.set(xlabel="", ylabel="", aspect="equal")
g.despine(left=True, bottom=True)
g.ax.margins(.02)
for label in g.ax.get_xticklabels():
    label.set_rotation(90)
for artist in g.legend.legendHandles:
    artist.set_edgecolor(".7")
plt.title('Heatmap - Correlation', fontsize=30)
```

[ ]: Text(0.5, 1.0, 'Heatmap - Correlation')



Savings Rate is correlated highest with GDP and Income.

The house count is highly correlated with population. More population, more housing activity.

The $ perSqFt has highest correlation with GDP

Size is highest correlated with Bedrooms, second correlated with Bathrooms. It is negatively correlated with GDP, Population, Income, Spending, $ perSqFt, and HouseCount.

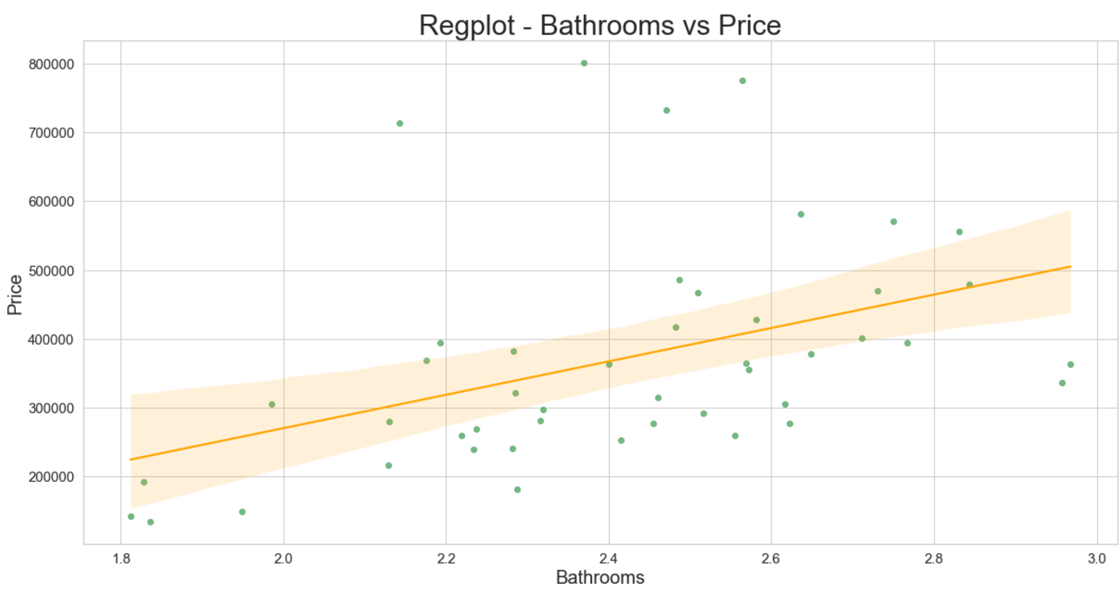
Bedrooms almost same relationship correlations as Size

Unlike Bedrooms and Size, Bathrooms has a high correlation with Price.

Higher per Annual Income, smaller the Size

[ ]:
```
# Fig Size
plt.figure(figsize=(20,10))

# Regplot line_kws is the reg line
sns.regplot(data=state_df,y="Price", x="Bathrooms", color="g",line_kws={'color':
↪'orange'})

# Annotation
plt.xlabel('Bathrooms', fontsize=20)
plt.ylabel('Price', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Regplot - Bathrooms vs Price', fontsize=30)
```

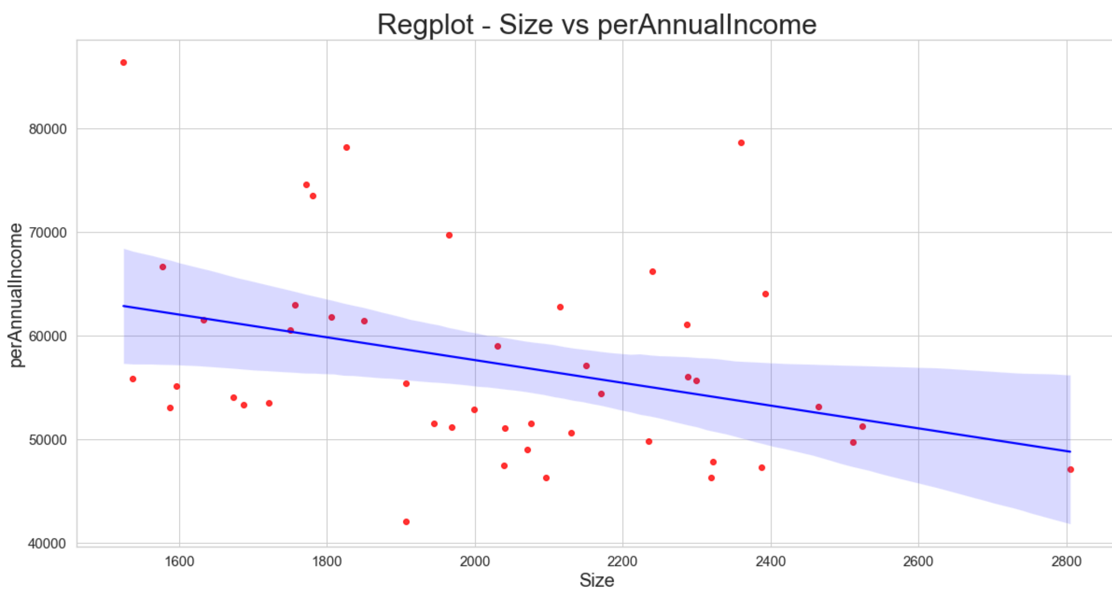
[ ]:
```
Text(0.5, 1.0, 'Regplot - Bathrooms vs Price')
```



[ ]:
```
# Regression plot of SavingsRate vs perSqFt
plt.figure(figsize=(20,10))
```

```
g = sns.regplot(data = state_df, y = 'perAnnualIncome', x = 'Size',␣
↪color='red', line_kws={'color':'blue'})
plt.ticklabel_format(style='plain', axis='y')
plt.ticklabel_format(style='plain', axis='x')
# The States that have higher SavingRate will pay higher perSqFt for the houses.
↪ Note: perSqFt vs House price is two different things.

# Annotation
plt.xlabel('Size', fontsize=20)
plt.ylabel('perAnnualIncome', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Regplot - Size vs perAnnualIncome', fontsize=30)
```

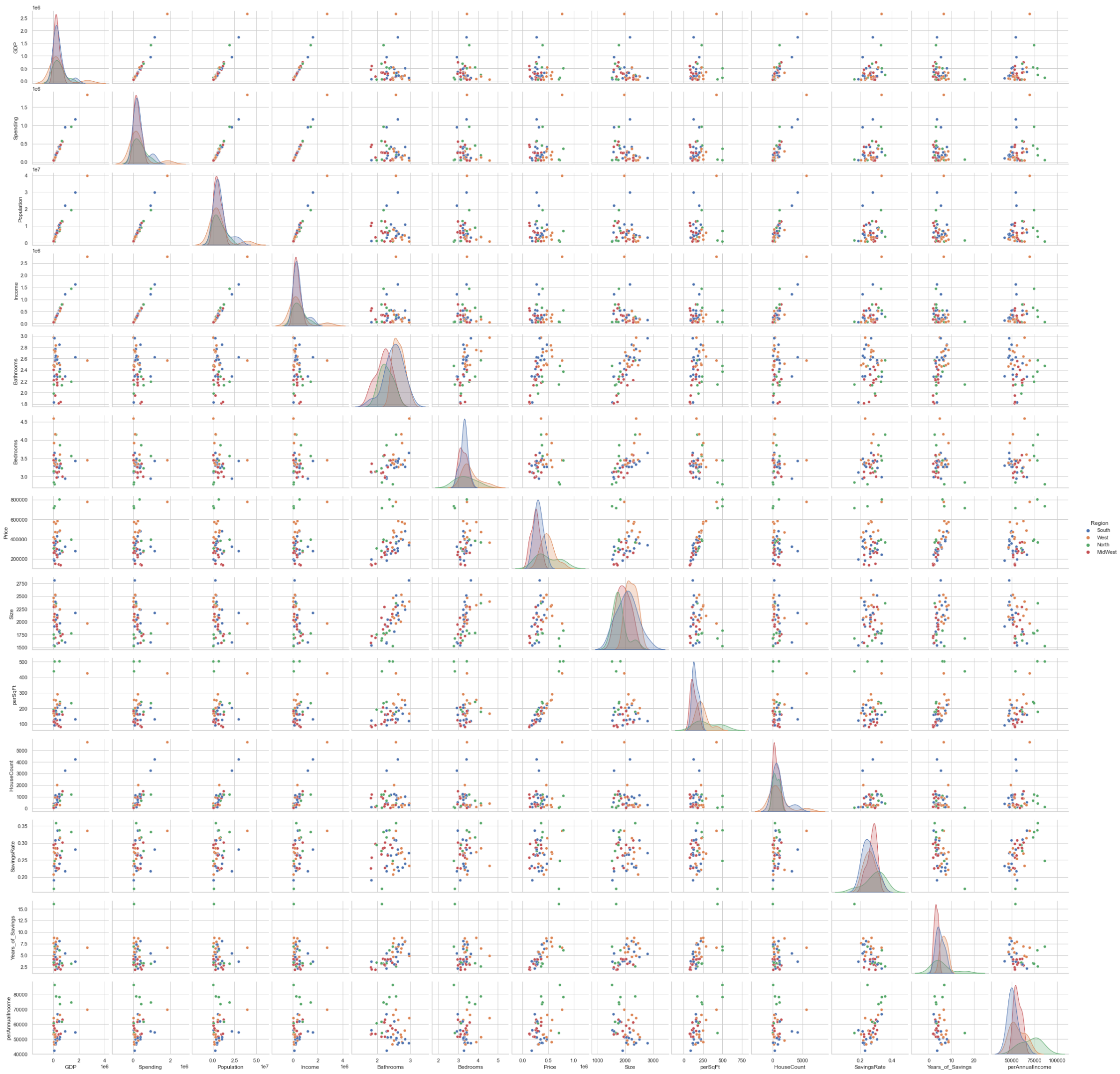
[ ]: Text(0.5, 1.0, 'Regplot - Size vs perAnnualIncome')



The more you make, the smaller place you get!! TRIPPLE BAMMMM

[ ]:
```
# Print pairplot to visualize the correlations.
sns.pairplot(data=state_df, hue="Region")
# the more money you have the more bathrooms you will get.
```

[ ]: <seaborn.axisgrid.PairGrid at 0x7ffc968da6a0>

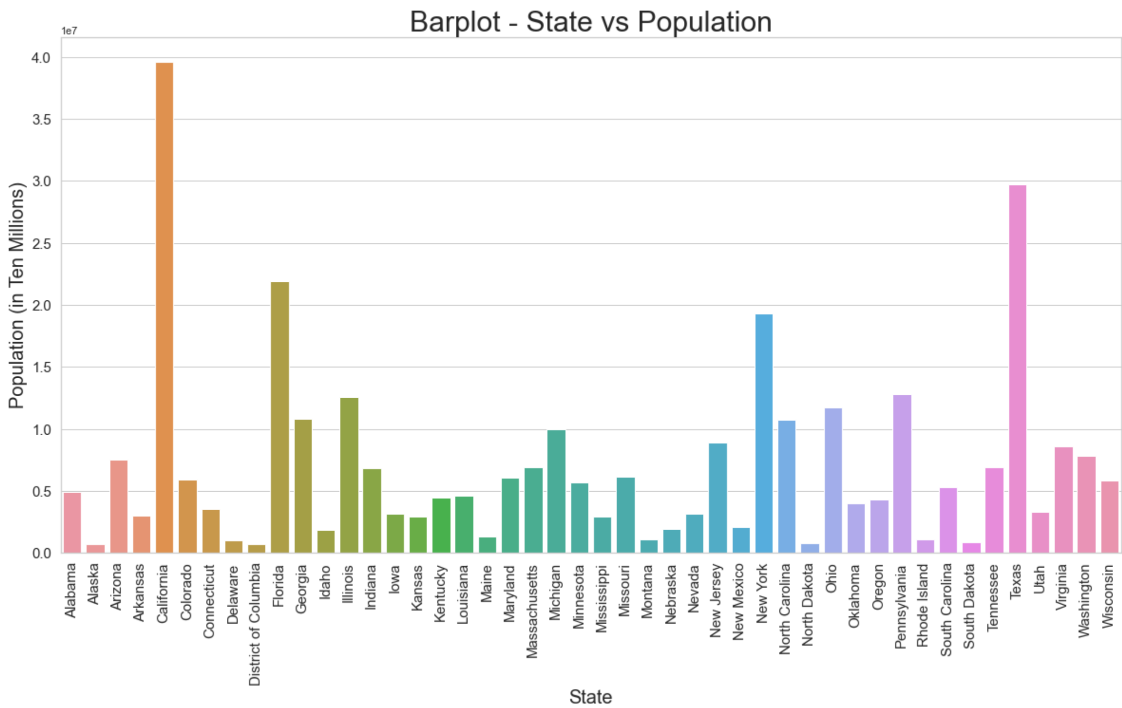


GDP Income Spending and Population have a strong correlation. Additionally, number of houses sold also have a strong correlation with these. So more real estate activity with higher GDP Income Spending and Population SavingsRate and Bedrooms are slightly, the more you save the more bedrooms you are going to get. Of course the bigger the house, the more Bedrooms and Bathrooms you will have. SavingsRate and HouseCount has a slight correlation, the more you save, the more real estate activities there will be.

[ ]:
```
# Barplot
plt.figure(figsize=(20,10))
sorted_df = state_df.sort_values(by='Population',ascending=False)
sns.barplot(data=state_df, x='fullState',y='Population')

# Annotation
plt.xlabel('State', fontsize=20)
```

```
plt.ylabel('Population (in Ten Millions)', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Barplot - State vs Population', fontsize=30)
```

[ ]: Text(0.5, 1.0, 'Barplot - State vs Population')

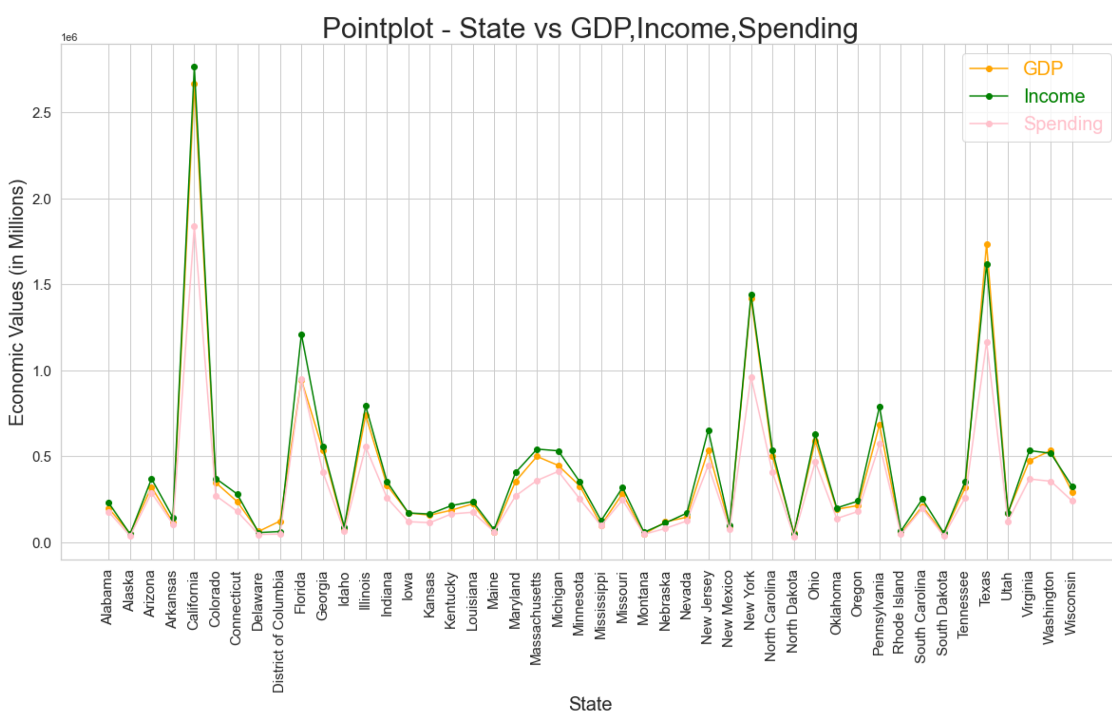


- Sorting states by population. Interesting enough that CA TX FL have most housing activities too.
- AZ has the 4th housing count, but the population is 14th. So AZ has a lot more real estate activities per person.

[ ]:
```
# Figure size
plt.figure(figsize=(20,10))
# Pointplot
# _ = sns.pointplot(data=state_df,x="fullState",y="GDP", color='orange',␣
↪label='GDP')
# _ = sns.pointplot(data=state_df,x="fullState",y="Spending",␣
↪color='red',label="Spending")
# _ = sns.pointplot(data=state_df,x="fullState",y="Income", color='Green',␣
↪label="Income")
# https://stackoverflow.com/questions/69933566/
↪multiple-seaborn-pointplots-not-showing-the-right-color-on-the-legend?
↪noredirect=1
```

```
# for pointplots legend doesnt show the right color, does not have label, so␣
↪you have to iterate through each to draw manually, source provided above

# using matplotlib to draw
plt.plot(state_df.fullState, state_df.GDP, 'o-', label="GDP", color='orange')
plt.plot(state_df.fullState, state_df.Income, 'o-', label="Income",␣
↪color='green')
plt.plot(state_df.fullState, state_df.Spending, 'o-', label="Spending",␣
↪color='pink')

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('Economic Values (in Millions)', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Pointplot - State vs GDP,Income,Spending', fontsize=30)
plt.
↪legend(labels=['GDP','Income','Spending'],labelcolor=['orange','green','pink'],loc="upper␣
↪right", prop={'size': 20})
```

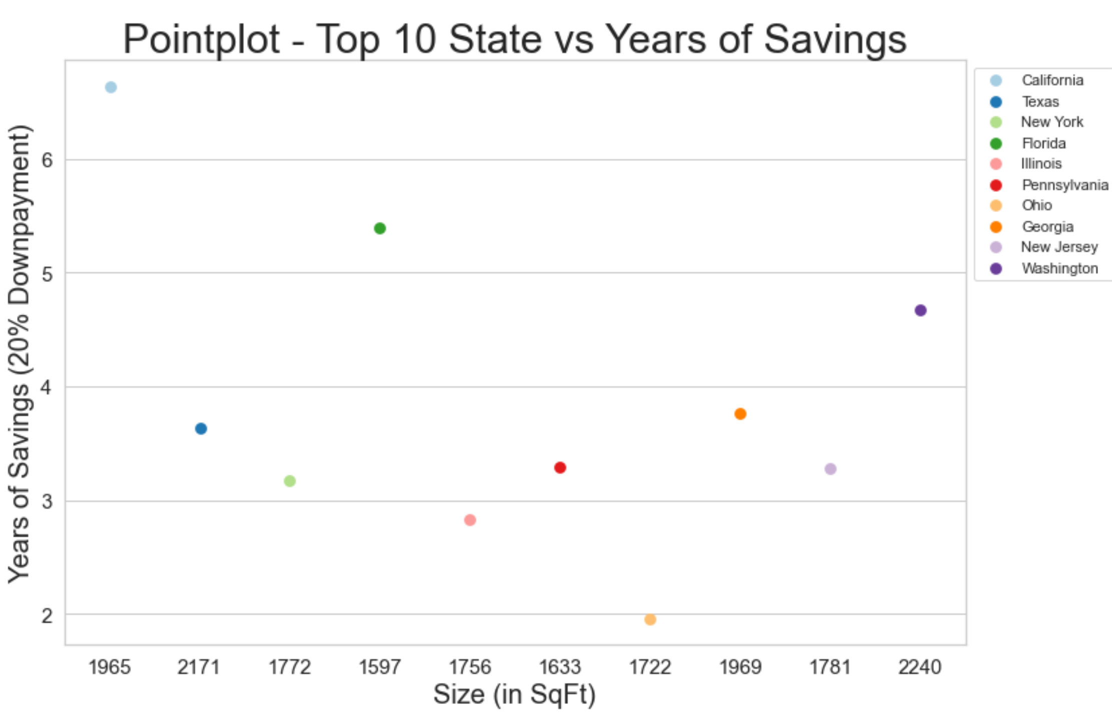
[ ]: <matplotlib.legend.Legend at 0x7ffc74800b20>



California have more Income, less GDP. So produce less goods and earn more. Texas have more GDP and lessor Income. So produce more goods and earn less.

```
[ ]: # Dataframe - top 10 GDP states and reset index
top_gdp_df = state_df.sort_values(by='GDP',ascending=False).head(10).
 ↪reset_index(drop=True)
top_gdp_df['Size']=top_gdp_df['Size'].apply(round)
top_gdp_size_list=list(top_gdp_df.Size.unique())

#Fig size
plt.figure(figsize=(12,8))

# Pointplot
a = sns.pointplot(data=top_gdp_df, x='Size', y="Years_of_Savings",␣
 ↪hue="fullState", palette="Paired", order=top_gdp_size_list, s=200)

# Annotation
plt.xlabel('Size (in SqFt)', fontsize=20)
plt.ylabel('Years of Savings (20% Downpayment)', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Pointplot - Top 10 State vs Years of Savings', fontsize=30)
plt.legend(bbox_to_anchor=(1.175,1))
# for i in range(len(top_gdp_size_list)):
#     plt.text(x=top_gdp_df.Size[i], y = top_gdp_df.Years_of_Savings[i],␣
 ↪s=top_gdp_df.fullState[i], fontdict=dict(color='black', size=20),␣
 ↪bbox=dict(facecolor='grey', alpha=0.4))
```

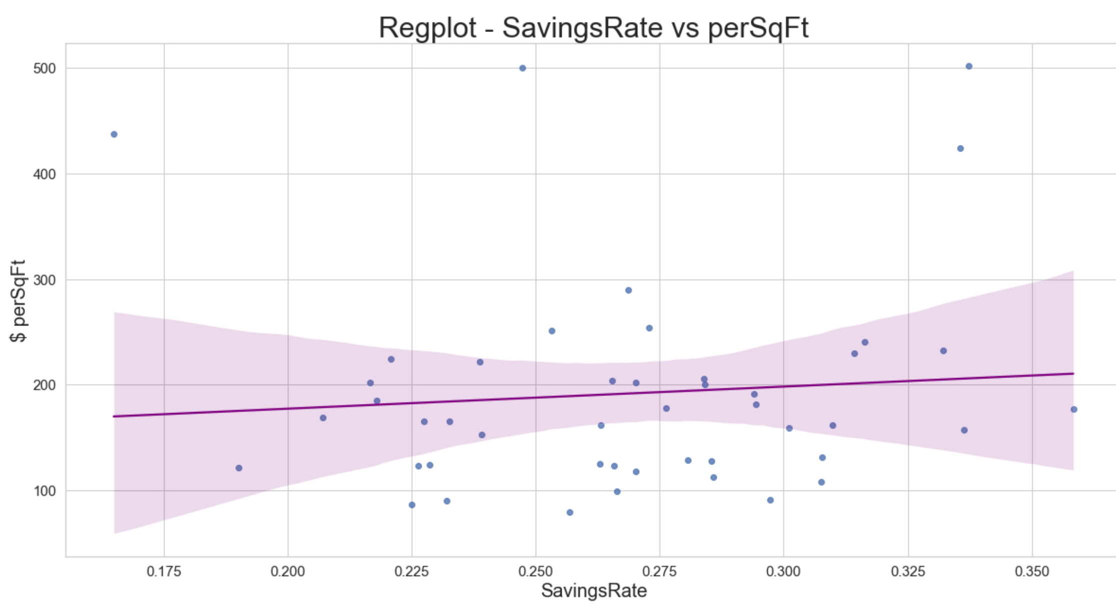
```
[ ]: <matplotlib.legend.Legend at 0x7ffc6da6f040>
```



(Sorted by State GDP, Left to Right : #1 to #10) Years of Savings of top 10 States with highest GDP (Strong Economy)

[ ]:
```
# Regression plot of SavingsRate vs perSqFt
plt.figure(figsize=(20,10))
g = sns.regplot(data = state_df, y = 'perSqFt', x = 'SavingsRate',␣
↪line_kws={'color':'purple'})
plt.ticklabel_format(style='plain', axis='y')
plt.ticklabel_format(style='plain', axis='x')
# The States that have higher SavingRate will pay higher perSqFt for the houses.
↪ Note: perSqFt vs House price is two different things.

# Annotation
plt.xlabel('SavingsRate', fontsize=20)
plt.ylabel('$ perSqFt', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Regplot - SavingsRate vs $ perSqFt', fontsize=30)
```

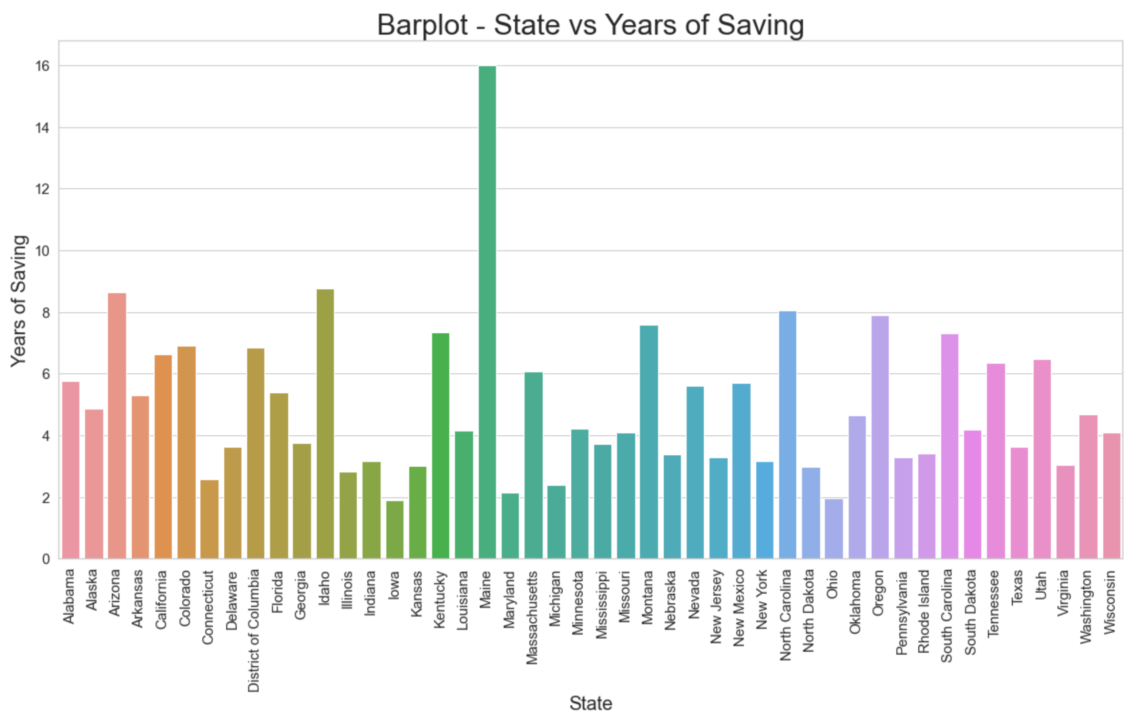
[ ]:
```
Text(0.5, 1.0, 'Regplot - SavingsRate vs perSqFt')
```



- There is slight correlation between SavingsRate and perSqFt.
- As people saves more money, they pay higher perSqFt for the house. Note: This doesnt mean they will be better furnished houses, it may be geographic area. We dont have enough data/evidence to prove this.

[ ]:
```
# Barplot
plt.figure(figsize=(20,10))

# sorted_df = state_df.sort_values(by='Years_of_Savings',ascending=True)
sns.barplot(data=state_df,x='fullState',y='Years_of_Savings')

# Annotation
plt.xlabel('State', fontsize=20)
plt.ylabel('Years of Saving', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15,rotation=90)
plt.title('Barplot - State vs Years of Saving', fontsize=30)

# value_array = state_df['Years_of_Savings'].to_list()
# for i in range(len(value_array)):
#     plt.text(x=state_df['fullState'][i],y=state_df["Years_of_Savings"][i]+0.
↪1, s=state_df["fullState"][i], fontdict=dict(color='black', size=12),␣
↪bbox=dict(facecolor='grey', alpha=0.3))
```

[ ]: Text(0.5, 1.0, 'Barplot - State vs Years of Saving')



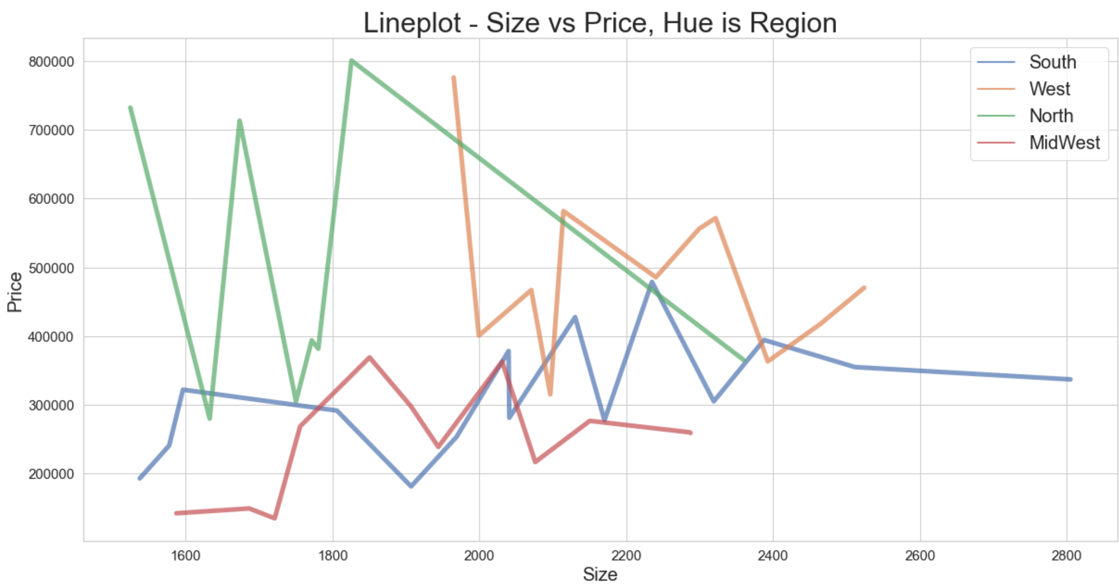
- Number of years to save in order to purchase a house with 20% down payment.

[ ]:
```
state_df.head()
```

```
[ ]:      fullState         GDP    Spending  Population     Income Region State  \
     0     Alabama   196906.10   176479.80     4934193   228748.80  South    AL
     1      Alaska    50161.00    35635.70      724357    46430.30   West    AK
     2     Arizona   320550.60   287090.10     7520103   368458.60   West    AZ
     3    Arkansas   114943.50   104488.80     3033946   143147.90  South    AR
     4  California  2663665.90  1835980.60    39613493  2763312.00   West    CA

        Bathrooms  Bedrooms      Price     Size  perSqFt  HouseCount  SavingsRate  \
     0       2.62      3.38  305048.89  2319.30   124.37         892         0.23
     1       2.97      4.59  363202.40  2392.84   165.54         403         0.23
     2       2.51      3.34  466962.46  2070.79   224.66        1998         0.22
     3       2.96      3.64  337014.73  2804.81   117.71         280         0.27
     4       2.56      3.44  776273.37  1965.24   424.09        5696         0.34

        Years_of_Savings  perAnnualIncome
     0              5.76         46359.92
     1              4.87         64098.64
     2              8.63         48996.48
     3              5.29         47182.09
     4              6.63         69756.84
```

```
[ ]: # Lineplot Size vs Price
     plt.figure(figsize=(20,10))
     sns.lineplot(x="Size", y='Price', hue='Region', data=state_df, lw=5, alpha=0.7)

     # Annotation
     plt.xlabel('Size', fontsize=20)
     plt.ylabel('Price', fontsize = 20)
     plt.yticks(fontsize=15)
     plt.xticks(fontsize=15)
     plt.title('Lineplot - Size vs Price, Hue is Region', fontsize=30)
     plt.legend(prop={'size': 20})
```

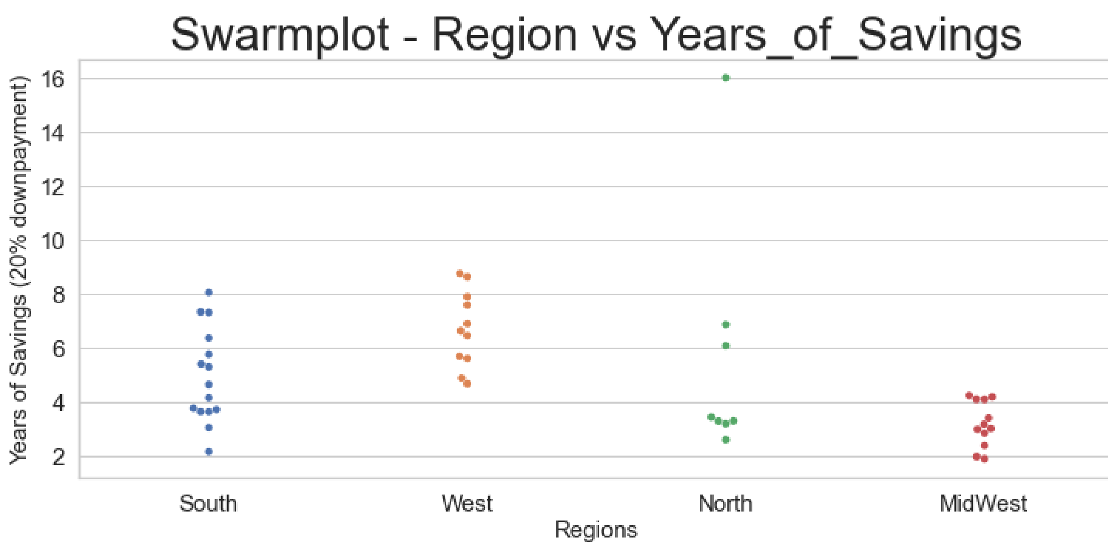
```
[ ]: <matplotlib.legend.Legend at 0x7ffc83dffdf0>
```



- Blue - South Region is kind of positive correlated, but Price does not exceed $500k and have all kinds of Sizes
- Orange - West Region has higher prices and larger Sizes
- Green - North Region has high prices in smaller Sizes
- Red - MidWest has low prices and smaller Sizes

[ ]:
```
plt.figure(figsize=(12,5))
sns.swarmplot(x='Region',y='Years_of_Savings',data=state_df)
# sns.
↪violinplot(data=state_df['Years_of_Savings'],orient='horizontal',palette='Set2')


# Annotation
plt.xlabel('Regions', fontsize=15)
plt.ylabel('Years of Savings (20% downpayment)', fontsize=15)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Swarmplot - Region vs Years_of_Savings', fontsize=30)
```

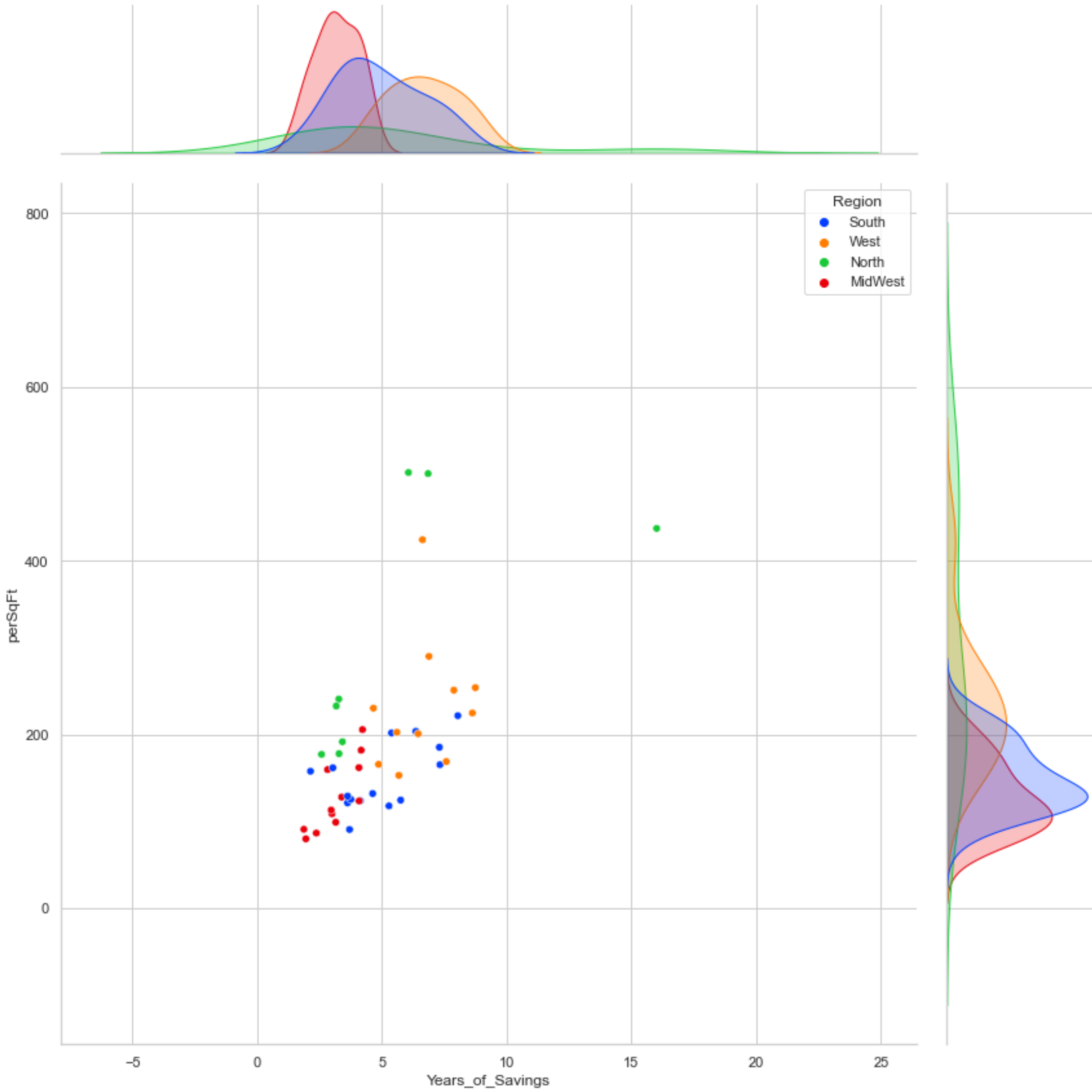
[ ]:
```
Text(0.5, 1.0, 'Swarmplot - Region vs Years_of_Savings')
```



- South Region is around 3 to 8 Years of Saving
- West Region have higher 4.5 to 9 Years of Saving
- North Region have outliers, but most are almost near 4 Years of Saving
- MidWest Region have overall lowest, and are around 1-4 Years of Saving

[ ]:
```
# sns.jointplot(data=state_df,x='Years_of_Savings',y='Price',size='Population')
plt.figure(figsize=(20,10))
sns.jointplot(data=state_df,y='perSqFt',x='Years_of_Savings', hue='Region',␣
↪palette='bright',height=12)
```

[ ]:
```
<seaborn.axisgrid.JointGrid at 0x7ffc82f943d0>

<Figure size 1440x720 with 0 Axes>
```



Year of Savings are mostly around 5 years. Price is around 200k to 600k. West has higher price range around 600k to 800k

Preview the distribution of data and where they lie mostly.

```
[ ]: # Choropleth graph
data = dict(type = 'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states', z=state_df['Price'],text=state_df['Price'], colorbar={'title':'Price'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope': 'usa'},title_text='<b>House Price of each State</b><br>(Hover for Avg Price)'))

iplot(choromap,validate=False)
```

CA, MA have highest housing price across the United States. Additionally most western regions are pretty high.

```
[ ]: # Choropleth graph
data = dict(type =␣
 ↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
 ↪z=state_df['Size'],text=state_df['Size'], colorbar={'title':'Size'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
 ↪'usa'},title_text='<b>House Size of each State</b><br>(Hover for Avg Size)'))

iplot(choromap,validate=False)
```

The Western Region is overall larger in size for living. The Eastern Region is smaller in size for living.

```
[ ]: # Choropleth graph
data = dict(type =␣
 ↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
 ↪z=state_df['perSqFt'],text=state_df['perSqFt'], colorbar={'title':'perSqFt'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
 ↪'usa'},title_text='<b>perSqFt of each State</b><br>(Hover for Avg perSqFt)'))

iplot(choromap,validate=False)
```

From a $ perSqFt point of view, the nation is actually pretty similar. Besides MA, ME, CA, and CO.

```
[ ]: # Choropleth graph
data = dict(type =␣
 ↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
 ↪z=state_df['SavingsRate'],text=state_df['SavingsRate'], colorbar={'title':
 ↪'SavingsRate'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
 ↪'usa'},title_text='<b>SavingsRate of each State</b><br>(Hover for Avg␣
 ↪SavingsRate)'))

iplot(choromap,validate=False)
```

The whole country's SavingsRate is relatively similar, in the range of 25 to 35 %.

```
[ ]: # Choropleth graph
data = dict(type =␣
 ↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
 ↪z=state_df['Years_of_Savings'],text=state_df['Years_of_Savings'],␣
 ↪colorbar={'title':'Years_of_Savings'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
 ↪'usa'},title_text='<b>Years_of_Savings of each State</b><br>(Hover for␣
 ↪Years_of_Savings)'))
```

```
iplot(choromap,validate=False)
```

- West Region are mostly brighter/higher than other regions.

[ ]:
```
# Choropleth graph
data = dict(type =␣
↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
↪z=state_df['perAnnualIncome'],text=state_df['perAnnualIncome'],␣
↪colorbar={'title':'perAnnualIncome'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
↪'usa'},title_text='<b>Avg Individual\'s Annual Income of each State</
↪b><br>(Hover for per Annual Income)'))

iplot(choromap,validate=False)
```

Colorado and Illinoise are proportionally higher for rural areas.

[ ]:
```
# Regplot for GDP vs Price
plt.figure(figsize=(20,10))
g = sns.regplot(data = state_df, x = 'GDP', y = 'Price', color='orange',␣
↪line_kws={'color':'teal'})
plt.ticklabel_format(style='plain', axis='y')
plt.ticklabel_format(style='plain', axis='x')
# g.set(xlim = (0,1000000))

# Annotation
plt.xlabel('GDP', fontsize=20)
plt.ylabel('Price', fontsize = 20)
plt.yticks(fontsize=15)
plt.xticks(fontsize=15)
plt.title('Regplot - GDP vs Price', fontsize=30)
```

[ ]:
```
Text(0.5, 1.0, 'Regplot - GDP vs Price')
```

- There is slight correlation between GDP and House Price.

[ ]:
```
########

#Choropleth Graph of Desired Annual Income per Individual
data = dict(type =␣
↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
↪z=state_df['desiredAnnualIncome'],text= state_df['desiredAnnualIncome'],␣
↪colorbar={'title':'Desired Annual Income'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
↪'usa'},title_text='<b>Desired Annual Income of each State</b><br>(Hover for␣
↪Desired Annual Income)'))

iplot(choromap,validate=False)
```

For highest desired income: California, New York, and Maine stand out on the top of this list.

[ ]:
```
#Choropleth Graph of Desired Annual Income per Individual
data = dict(type =␣
↪'choropleth',colorscale='Portland',locations=state_df['State'],locationmode='USA-states',␣
↪z=state_df['mortPayment'],text= state_df['mortPayment'], colorbar={'title':
↪'Monthly Mortgage Payment'})
choromap = go.Figure(data = [data],layout = dict(geo = {'scope':
↪'usa'},title_text='<b>Desired Annual Income of each State</b><br>(Hover for␣
↪Monthly Mortgage Payment)'))

iplot(choromap,validate=False)
```

For highest average monthly payment: California, New York, and Maine stand out on the top of this list.

0.1.5 4. Testing Hypothesis, ANOVA

Importing Libraries

```
[ ]: # Importing Libraries
from scipy.stats import normaltest
from statsmodels.stats.weightstats import ztest
import scipy.stats as stats
from scipy.stats import chi2_contingency
```

Pearson Coefficient vs P-Value – using correlation to test if variables are statistically significant

```
[ ]: # Calculate pearson coefficient and pvalue
pearson_coef, p_value = stats.pearsonr(house_df['Bathrooms'], house_df['Price'])

# print out results
print(f'The Pearson Correlation Coefficient is {pearson_coef:.4f} with a␣
↪P-value of {p_value:.4f}')
if p_value < 0.001:
    print('Since p-value is < 0.001, the correlation between Bathrooms and␣
↪Price is statistically significant, although the linear relationship isn\'t␣
↪extreamely strong.')
else:
    print('Since p-value is > 0.001, the correlation between Bathrooms and␣
↪Price is not statistically significant.')
```

```
The Pearson Correlation Coefficient is 0.4857 with a P-value of 0.0000
Since p-value is < 0.001, the correlation between Bathrooms and Price is
statistically significant, although the linear relationship isn't extreamely
strong.
```

Z-Test Hypothesis – Hypothesis and statistical test that assumes normal distribution to determine whether two population means are different. Variances are known and sample size is large.

H0 : u <= u0 California house prices is higher than 600k

H1 : u > u0 California house prices is lower than 600k

Confidence Interval = 99%, since it is one tailed test, alpha = 0.01

```
[ ]: # Calculate test statistic and pvalue
(test_statistic, p_value) = ztest(house_df[house_df['State'] == 'CA']['Price'],␣
↪value=600000, alternative='smaller',ddof=1)

# print out results
print(f'The Test Statistic is {test_statistic:.4f} with a P-value of {p_value:.
↪4f}')
```

```
if p_value < 0.005:
    print('Since p-value is < 0.01, we do not retain the null hypothesis.')
else:
    print('Since p-value is > 0.01, we retain the null hypothesis')
```

```
The Test Statistic is 30.5485 with a P-value of 1.0000
Since p-value is > 0.01, we retain the null hypothesis
```

ANOVA – determine whether the differences between groups of data are statistically significant.

H0 : Region and House Prices are not statistically different.

H1 : Region and House Prices are statistically different.

[ ]:
```
anova_df = house_df[['Region', 'Price']]
groupby_anova = anova_df.groupby(['Region'])
F_oneway, p_value = stats.f_oneway(groupby_anova.get_group('West')['Price'],␣
 ↪groupby_anova.get_group('MidWest')['Price'])
print('ANOVA results: F-Oneway = {:.4f}, P-Value = {:.4f}.'.
 ↪format(F_oneway,p_value))

F_oneway, p_value = stats.f_oneway(groupby_anova.get_group('North')['Price'],␣
 ↪groupby_anova.get_group('MidWest')['Price'])
print('ANOVA results: F-Oneway = {:.4f}, P-Value = {:.4f}.'.
 ↪format(F_oneway,p_value))

F_oneway, p_value = stats.f_oneway(groupby_anova.get_group('South')['Price'],␣
 ↪groupby_anova.get_group('North')['Price'])
print('ANOVA results: F-Oneway = {:.4f}, P-Value = {:.4f}.'.
 ↪format(F_oneway,p_value))


F_oneway, p_value = stats.f_oneway(groupby_anova.get_group('South')['Price'],␣
 ↪groupby_anova.get_group('West')['Price'])
print('ANOVA results: F-Oneway = {:.4f}, P-Value = {:.4f}.'.
 ↪format(F_oneway,p_value))

F_oneway, p_value = stats.f_oneway(groupby_anova.get_group('West')['Price'],␣
 ↪groupby_anova.get_group('North')['Price'])
print('ANOVA results: F-Oneway = {:.4f}, P-Value = {:.4f}.'.
 ↪format(F_oneway,p_value))
```

```
ANOVA results: F-Oneway = 6028.2917, P-Value = 0.0000.
ANOVA results: F-Oneway = 2060.2618, P-Value = 0.0000.
ANOVA results: F-Oneway = 1265.6909, P-Value = 0.0000.
ANOVA results: F-Oneway = 7083.4905, P-Value = 0.0000.
ANOVA results: F-Oneway = 623.1008, P-Value = 0.0000.
```

As you can see all P-Value < 0.05, all region house prices are statistically different. Strong correlation between region variable and price.

Chi-Squared Test – determine whether there is a statistically significant and dependent on each other.

H0 : SavingsRate and Bedrooms are not statistically different.

H1 : SavingsRate and Bedrooms are statistically different.

[ ]:
```
# See if Savings Rate and Bedrooms are dependent
chi2_df = state_df[['SavingsRate', 'Bedrooms']]
stat, p, dof,expected = chi2_contingency(chi2_df)

# HO = SavingsRate and Bedrooms are independent
# Ha = SavingsRate and Bedrooms are dependent

# print out results
print(f'The Test Statistic is {stat:.4f} with a P-value of {p:.4f}')
if p_value < 0.05:
    print('Since p-value is < 0.05, they are dependent.') # We Reject HO,␣
 ↪statistically significant
else:
    print('Since p-value is > 0.05, they are independent')
```

```
The Test Statistic is 0.2829 with a P-value of 1.0000
Since p-value is < 0.05, they are dependent.
```

0.1.6 5. Conclusion

Questions and Answers What is average and median house price across all USA? (Jack)

- Median are: 3 Bedrooms, 2 Bathrooms, 1702 SqFt, Price of 325,000
- Average are: 3.3 Bedrooms, 2.5 Bathrooms, 2000 SqFt, Price of 407,000
  Is Size highly correlated with Price? If not what's most correlated with Price. (Jack)
- Size and Price correlation is 48%
- Highest correlation is Bathroom, 49%
  What's the primary type of houses people prefer in each state? (Graph answer, house_df graph) (Jack)
- Primary Type is Single Family Residence Massachusetts, Alaska, District of Columbia are primarily Condos. Maryland, Pennylvania, Delaware are primarily Townhouses or have huge % in Townhouses.
  What states have the largest and smallest avg size? (Jack)
- States with Largest House Size State AR have average of 2805 square feet. State UT have average of 2524 square feet. State OK have average of 2511 square feet.
- States with Smallest House Size State DC have average of 1525 square feet. State DE have average of 1538 square feet. State MD have average of 1578 square feet.
  What states have the highest and lowest $ perSqFt? (Jack)
- Highest States $ perSqFt State MA have average of $501.47 per square feet State DC have average of $500.22 per square feet State ME have average of $437.12 per square feet

- Lowest States $ perSqFt State OH have average of $79.80 per square feet State MI have average of $86.42 per square feet State MS have average of $90.56 per square feet
  Find out each State's: Price, Size, perSqft, Annual Income, SavingsRate,Years of Savings to Buy a House(20% down). (Jack)
- See choropleth map
  Since I live in California, what's California house avg like? (Jack)
  6.6 years of saving to purchase a house with 20% down at 33.5% Savings Rate 70k perAnnualIncome nearly 2000 SqFt at 421 perSqFt 770k Avg House Price No.1 in GDP across USA
  Relationship between Regions and Price. (Jack)
  Yes, different Regions have clear Price difference and Size difference.
  Is there huge difference between House Type and Price? (Jack)
  Yes, most Townhouses across US may be under-valued.
  Lets say you are a prospective buyer with a salary of $55,000; which different regions are you more likely to buy in and how much are you paying (assuming you put 20% down and have a 4% interest rate)? (Alec) General rule of thumb for for calculating how much house you can buy with your salary is to multiply by the minimum of 2.5 and max of 3, where the house you can afford can fall into the range of these two houses
  What does the distribution of the size of houses in each region? (Alec) Knowing the Size categories, we can create a multi-index dataframe with regions and size categories.

Interesting Findings The $ perSqFt and Savings rate are positively correlated. The more people save, the higher they will spend more money on $ perSqFt in houses. (Jack)

There is a negative correlation between Individual's Annual Income and Size of House So the more you make the smaller place you live?! Make less money so you live in a big house! (Jack)

(Good to target ad) Country's savings rate is mostly 25-35%, since i know how much is in your wallet/savings, i can calculate what kind/price-range of items are appropriate for you to spend on. (Jack)

For some states, you only need work 2-4 years to buy a house. Ex: Iowa (Jack)

With higher $ perSqFt, Size will be smaller, seems negatively correlated. (Jack)

The West Region has higher real estate prices. (Jack)

In AZ, there are a lot more house activities per person than other states. (Jack)

Colorado has a high $ perSqFt compared to average. From another student's project, it indicated that CO has a higher education level. (So it match the findings) (Jack)

Maine has high house Price vs Income difference. (Jack)

Data can be used for many other exploratories

Main Takeaways Townhouses should worth more than condos because they dont have common walls and have independent units. Since Townhouses price is cheaper than Condos, for home buyers, Townhouses might have higher chance to get a bargain/ buyers may obtain more value. (Jack)

Try to buy houses with more bathrooms, apparently it will have higher prices. For house flippers, it is good to find cheap houses with more bathrooms, then you can re-sell for more profit after flipping it. (Jack)

Top ten strong economies with savings rate and size. (Jack)

Given the average price of homes in each state, calculate the average monthly morgage payments that one has to pay (Assuming that it is 4% interest rate and 20% down) (Alec) Since we know the average price for homes in each state, we can use the monthly morgage formula P= L[c (1 + c)n] / [(1+c)n - 1].

Given that the rule of thumb that you should not spend no more than 30% percent of you income in housing, calculate the desired average yearly income per individual. (Alec) Given the Average Monthly Payment of each state, you can use the Unitary Method in order to calculate the desired yearly income.

Given the average morgage payments and average salary of each state, which state has the highest savings after morgage payments? (Alec) Using annual salary and morgage payments per household we can create a bar plot visualization showing the two differences and we can use column subtraction to find the actual values.

0.1.7 6. References

Data of: Housing Price Data https://www.kaggle.com/dataranch/zillow-1 Data of: Population https://worldpopulationreview.com/states Data of: 1-GDP, 2-Income, 3-Spending https://apps.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=1&isuri=1&acrd