Multiple Linear Regression and Geospatial

```
In [1]: # Check the dataset directory
        %pwd
```

Out[1]: 'C:\\Users\\SK\\Desktop\\Python\\Python Project\\5. Multiple Linear R egression and Geospatial'

```
In [2]: # Change the working directory
        import os
        os.chdir("/Users/SK/Desktop/SK/NUS EBA/Semester 2/Statistical BootCamp/WK4")
```

```
In [3]: # Import the functions
        import pandas as pd
        import numpy as np
        from pandas import DataFrame, read_csv
```

```
In [4]: # Read the csv file
        housing = pd.read_csv("housing.csv")
```

In [5]: housing.head()

Out[5]:

	Iongitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households
0	- 122.23	37.88	41.0	880.0	129.0	322.0	126.0
1	- 122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0
2	- 122.24	37.85	52.0	1467.0	190.0	496.0	177.0
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0
4							>

```
In [6]:
        housing.describe()
```

Out[6]:

```
longitude
                           latitude
                                    housing median age
                                                            total rooms
                                                                         total bedrooms
                                                                                             popul
       20640.000000
                     20640.000000
                                            20640.000000
                                                           20640.000000
                                                                            20433.000000
                                                                                          20640.00
count
mean
         -119.569704
                         35.631861
                                               28.639486
                                                            2635.763081
                                                                              537.870553
                                                                                            1425.47
           2.003532
                          2.135952
                                               12.585558
                                                            2181.615252
                                                                              421.385070
                                                                                            1132.46
  std
 min
         -124.350000
                         32.540000
                                                 1.000000
                                                               2.000000
                                                                                1.000000
                                                                                               3.00
 25%
        -121.800000
                                                                                            787.00
                         33.930000
                                               18.000000
                                                            1447.750000
                                                                              296.000000
 50%
         -118.490000
                         34.260000
                                               29.000000
                                                            2127.000000
                                                                              435.000000
                                                                                            1166.00
 75%
         -118.010000
                         37.710000
                                               37.000000
                                                            3148.000000
                                                                              647.000000
                                                                                            1725.00
         -114.310000
                         41.950000
                                               52.000000
                                                          39320.000000
                                                                             6445.000000
                                                                                          35682.00
 max
```

```
In [7]:
        housing.shape
```

Out[7]: (20640, 10)

```
In [8]:
        # Check the missing value
        housing.isnull().sum()
```

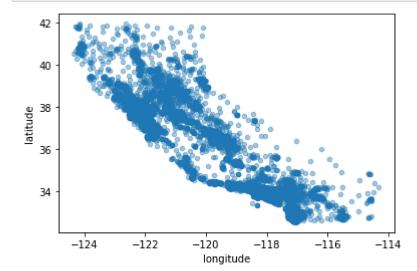
Out[8]: longitude 0 latitude 0 housing_median_age 0 total_rooms 0 total bedrooms 207 population 0 households 0 median income 0 median_house_value 0 ocean proximity 0 dtype: int64

```
In [13]:
         # Remove the missing value from the dataset
         house no missing = housing.dropna()
```

```
In [14]:
         house_no_missing.isnull().sum()
```

```
Out[14]: longitude
                                 0
                                 0
          latitude
                                 0
          housing median age
          total_rooms
                                 0
          total bedrooms
                                 0
          population
                                 0
          households
                                 0
          median income
                                 0
          median house value
                                 0
          ocean_proximity
                                 0
          dtype: int64
```

```
In [16]:
         import matplotlib.pyplot as plt
         house_no_missing.plot(kind="scatter", x="longitude", y="latitude", alpha=0.4)
         plt.show()
```



```
In [18]: | house_no_missing.plot(kind="scatter", x="longitude", y="latitude",
              s=house_no_missing['population']/100, label="population",
             c="median_house_value", cmap=plt.get_cmap("jet"),
             colorbar=True, alpha=0.4, figsize=(10,7),
         plt.legend()
         plt.show()
```

C:\Users\SK\Anaconda3\lib\site-packages\pandas\plotting\ tools.py:307: Matplo tlibDeprecationWarning:

The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().rowspan.start instead.

layout[ax.rowNum, ax.colNum] = ax.get visible()

C:\Users\SK\Anaconda3\lib\site-packages\pandas\plotting_tools.py:307: Matplo tlibDeprecationWarning:

The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().colspan.start instead.

layout[ax.rowNum, ax.colNum] = ax.get_visible()

C:\Users\SK\Anaconda3\lib\site-packages\pandas\plotting_tools.py:313: Matplo tlibDeprecationWarning:

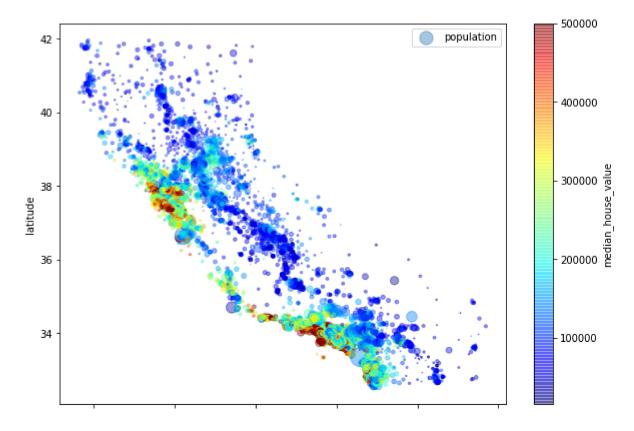
The rowNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get_subplotspec().rowspan.start instead.

if not layout[ax.rowNum + 1, ax.colNum]:

C:\Users\SK\Anaconda3\lib\site-packages\pandas\plotting_tools.py:313: Matplo tlibDeprecationWarning:

The colNum attribute was deprecated in Matplotlib 3.2 and will be removed two minor releases later. Use ax.get subplotspec().colspan.start instead.

if not layout[ax.rowNum + 1, ax.colNum]:



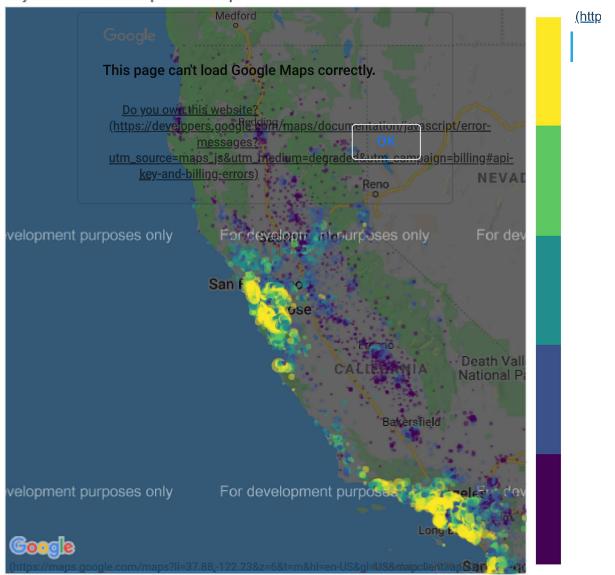
```
from bokeh.io import output_file, output_notebook, show
In [19]:
         from bokeh.models import (
             GMapPlot, GMapOptions, ColumnDataSource, Circle, LogColorMapper, BasicTick
         er,
         ColorBar, Range1d, PanTool, WheelZoomTool, BoxSelectTool)
         from bokeh.models.mappers import ColorMapper, LinearColorMapper
         from bokeh.palettes import Viridis5
```

```
In [20]: map_options = GMapOptions(lat=37.88, lng=-122.23, map_type="roadmap", zoom=6)
         plot = GMapPlot(
             x_range=Range1d(), y_range=Range1d(),
             map_options=map_options
         plot.title.text = "Hey look! It's a scatter plot on a map!"
```

```
In [21]: # For GMaps to function, Google requires you obtain and enable an API key:
               https://developers.google.com/maps/documentation/javascript/get-api-key
         # Replace the value below with your personal API key:
         plot.api_key = "AIzaSyBYrbp340ohAHsX1cub8ZeHlMEFajv15fY"
         source = ColumnDataSource(
             data=dict(
                 lat=house_no_missing.latitude.tolist(),
                 lon=house_no_missing.longitude.tolist(),
                 size=house_no_missing.median_income.tolist(),
                 color=house_no_missing.median_house_value.tolist()
             )
         )
         max_median_house_value = house_no_missing.loc[house_no_missing['median_house_v
         alue'].idxmax()]['median house value']
         min_median_house_value = house_no_missing.loc[house_no_missing['median_house_v
         alue'].idxmin()]['median_house_value']
         #color_mapper = CategoricalColorMapper(factors=['hi', 'lo'], palette=[RdBu3
         [2], RdBu3[0]])
         #color_mapper = LogColorMapper(palette="Viridis5", low=min_median_house value,
         high=max_median_house_value)
         color_mapper = LinearColorMapper(palette=Viridis5)
         circle = Circle(x="lon", y="lat", size="size", fill color={'field': 'color',
         'transform': color_mapper}, fill_alpha=0.5, line_color=None)
         plot.add_glyph(source, circle)
         color_bar = ColorBar(color_mapper=color_mapper, ticker=BasicTicker(),
                               label_standoff=12, border_line_color=None, location=(0,0
         ))
         plot.add layout(color bar, 'right')
         plot.add_tools(PanTool(), WheelZoomTool(), BoxSelectTool())
         #output file("gmap plot.html")
         output notebook()
         show(plot)
```

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Hey look! It's a scatter plot on a map!



```
## Check the Correlation between variable
In [22]:
         house_no_missing.corr()
```

Out[22]:

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	р
longitude	1.000000	-0.924616	-0.109357	0.045480	0.069608	
latitude	-0.924616	1.000000	0.011899	-0.036667	-0.066983	-
housing_median_age	-0.109357	0.011899	1.000000	-0.360628	-0.320451	-
total_rooms	0.045480	-0.036667	-0.360628	1.000000	0.930380	
total_bedrooms	0.069608	-0.066983	-0.320451	0.930380	1.000000	
population	0.100270	-0.108997	-0.295787	0.857281	0.877747	
households	0.056513	-0.071774	-0.302768	0.918992	0.979728	
median_income	-0.015550	-0.079626	-0.118278	0.197882	-0.007723	
median_house_value	-0.045398	-0.144638	0.106432	0.133294	0.049686	-

```
## Multiple Linear Regression
In [51]:
         x = house_no_missing.drop(['median_house_value', 'ocean_proximity'], axis =1)
         y = house_no_missing['median_house_value']
```

```
In [52]:
         from sklearn.linear model import LinearRegression
         import statsmodels.formula.api as smf
         model = smf.ols('y~x', data = house_no_missing).fit()
         model.summary()
```

Out[52]:

OLS Regression Results

Covariance Type:

Dep. Variable: 0.637 R-squared: У Model: OLS Adj. R-squared: 0.637 Method: **Least Squares** F-statistic: 4478. Date: Wed, 15 Jul 2020 Prob (F-statistic): 0.00 Time: 23:46:43 Log-Likelihood: -2.5682e+05 No. Observations: 20433 AIC: 5.137e+05 Df Residuals: 20424 BIC: 5.137e+05 Df Model: 8

nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-3.585e+06	6.29e+04	-57.001	0.000	-3.71e+06	-3.46e+06
x[0]	-4.273e+04	717.087	-59.588	0.000	-4.41e+04	-4.13e+04
x[1]	-4.251e+04	676.952	-62.796	0.000	-4.38e+04	-4.12e+04
x[2]	1157.9003	43.389	26.687	0.000	1072.855	1242.945
x[3]	- 8.2497	0.794	-10.387	0.000	-9.807	- 6.693
x[4]	113.8207	6.931	16.423	0.000	100.236	127.405
x[5]	-38.3856	1.084	-35.407	0.000	-40.511	-36.261
x[6]	47.7014	7.547	6.321	0.000	32.909	62.493
x[7]	4.03e+04	337.207	119.504	0.000	3.96e+04	4.1e+04

Omnibus: 4898.534 **Durbin-Watson:** 0.975 Prob(Omnibus): 0.000 Jarque-Bera (JB): 18260.733 Skew: 1.166 Prob(JB): 0.00 7.002 Kurtosis: Cond. No. 5.10e+05

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 5.1e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [55]: ## Check the VIF
    from statsmodels.stats.outliers_influence import variance_inflation_factor
    x['Intercept'] = 1

    vif = pd.DataFrame()
    vif["variables"] = x.columns
    vif['VIF'] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1
])]

    print(vif)
```

```
variables
                                 VIF
0
            longitude
                            8.713740
             latitude
1
                            8.828919
2
  housing_median_age
                            1.260015
          total_rooms
3
                          12.717000
4
       total_bedrooms
                           36.003726
5
           population
                           6.371238
6
           households
                           35.136045
7
        median_income
                            1.731511
            Intercept 16702.386835
8
```

```
In [56]: ## Eliminate 'total_bedrooms' variable due to high VIF value
    x = house_no_missing.drop(['median_house_value', 'ocean_proximity' ,'total_bed
    rooms'], axis =1)
    y = house_no_missing['median_house_value']
```

```
In [57]: model = smf.ols('y~x', data = house_no_missing).fit()
model.summary()
```

Out[57]:

OLS Regression Results

0.632	R-squared:	у	Dep. Variable:
0.632	Adj. R-squared:	OLS	Model:
5014.	F-statistic:	Least Squares	Method:
0.00	Prob (F-statistic):	Wed, 15 Jul 2020	Date:
-2.5695e+05	Log-Likelihood:	23:51:44	Time:
5.139e+05	AIC:	20433	No. Observations:
5.140e+05	BIC:	20425	Df Residuals:
		7	Df Model:

Df Model:

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-3.497e+06	6.31e+04	- 55.434	0.000	-3.62e+06	-3.37e+06
x[0]	-4.197e+04	720.300	- 58.273	0.000	-4.34e+04	-4.06e+04
x[1]	-4.222e+04	681.159	-61.983	0.000	-4.36e+04	-4.09e+04
x[2]	1126.4985	43.631	25.819	0.000	1040.979	1212.018
x[3]	-1.7751	0.694	-2.558	0.011	-3.135	-0.415
x[4]	-43.0960	1.052	- 40.952	0.000	- 45.159	-41.033
x[5]	148.9776	4.378	34.025	0.000	140.396	157.560
x[6]	3.838e+04	318.479	120.518	0.000	3.78e+04	3.9e+04

Omnibus: 5263.565 **Durbin-Watson:** 0.941

Prob(Omnibus): 0.000 **Jarque-Bera (JB):** 20453.770

 Skew:
 1.241
 Prob(JB):
 0.00

 Kurtosis:
 7.227
 Cond. No.
 5.01e+05

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 5.01e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [58]: ## Check the VIF
    x['Intercept'] = 1

    vif = pd.DataFrame()
    vif["variables"] = x.columns
    vif['VIF'] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1 ])]
    print(vif)
```

```
variables
                                 VIF
0
            longitude
                            8.677840
1
             latitude
                            8.822928
   housing_median_age
2
                            1.257568
3
          total_rooms
                            9.583814
4
           population
                            5.925295
5
           households
                           11.673860
        median_income
                            1.524467
6
7
            Intercept 16579.355378
```

```
In [59]: ## Eliminate 'households' variable due to high VIF value
    x = house_no_missing.drop(['median_house_value', 'ocean_proximity' ,'total_bed
    rooms', 'households'], axis =1)
    y = house_no_missing['median_house_value']
```

```
In [60]: model = smf.ols('y~x', data = house_no_missing).fit()
model.summary()
```

Out[60]:

OLS Regression Results

Dep. Variable:	у	R-squared:	0.611
Model:	OLS	Adj. R-squared:	0.611
Method:	Least Squares	F-statistic:	5353.
Date:	Wed, 15 Jul 2020	Prob (F-statistic):	0.00
Time:	23:53:28	Log-Likelihood:	-2.5752e+05
No. Observations:	20433	AIC:	5.150e+05
Df Residuals:	20426	BIC:	5.151e+05
B	•		

Df Model: 6

Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
Intercept	-3.968e+06	6.33e+04	-62.723	0.000	-4.09e+06	-3.84e+06
x[0]	-4.774e+04	719.613	-66.345	0.000	-4.92e+04	-4.63e+04
x[1]	-4.777e+04	679.805	-70.271	0.000	-4.91e+04	-4.64e+04
x[2]	1118.2926	44.848	24.935	0.000	1030.386	1206.199
x[3]	15.0384	0.501	30.020	0.000	14.057	16.020
x[4]	-25.4074	0.941	-27.014	0.000	-27.251	-23.564
x[5]	3.431e+04	303.318	113.100	0.000	3.37e+04	3.49e+04

Omnibus: 4604.156 **Durbin-Watson:** 0.816

Prob(Omnibus): 0.000 **Jarque-Bera (JB):** 12192.156

 Skew:
 1.215
 Prob(JB):
 0.00

 Kurtosis:
 5.902
 Cond. No.
 4.83e+05

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 4.83e+05. This might indicate that there are strong multicollinearity or other numerical problems.

```
In [61]: ## Check the VIF
x['Intercept'] = 1

vif = pd.DataFrame()
vif["variables"] = x.columns
vif['VIF'] = [variance_inflation_factor(x.values, i) for i in range(x.shape[1])]

print(vif)
```

```
variables
                                 VIF
0
            longitude
                            8.197084
             latitude
                            8.316903
1
2
  housing_median_age
                            1.257530
          total_rooms
3
                            4.725402
           population
4
                            4.479289
5
        median_income
                            1.308668
6
            Intercept 15780.636633
```