lab5_submission

February 7, 2022

1 Brooke Hunter lab 5 submission

1.1 Lab 5: Machine learning in Python

Objectives: * Engineer some features for better prediction of Seattle house prices * Train a machine learning model using scikit-learn * Evaluate our machine learning model

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1.2 Question 1 (10 points):

To start, make a **new** `jupyter notebook` called `lab5_submission.ipynb` and work through the following tasks.

The first task is answer the following questions using some of the methods we have covered in the lecture/demo.

---

[1]:
```
# Import libraries
import pandas as pd
from shapely.geometry import Point
import numpy as np
import geopandas as gpd
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
```

[2]:
```
# Import data
df = pd.read_csv('E:/GitHub/GeospatialDataAnalysis/geospatial-data-science/labs/
↪lab5/seattle_house_prices.csv')

# Read dataset
coast = gpd.read_file('E:/GitHub/GeospatialDataAnalysis/geospatial-data-science/
↪labs/lab5/Washington_coastline.shp')
```

[3]:
```
# Convert DataFrame to GeoDataFrame
gdf = gpd.GeoDataFrame(df, geometry=gpd.points_from_xy(df['long'], df['lat']))
```

```
gdf = gdf.set_crs(4326, allow_override=True)

# Reproject everything to UTM 10N (EPSG:32610)
gdf_utm = gdf.to_crs('EPSG:32610')
coast_utm = coast.to_crs('EPSG:32610')
```

- How many houses are in this dataset?

[4]:
```
num_rows = df.shape[0]
print('The number of houses in the data set is equal to the number of rows, so␣
↪there are %i houses in this dataset' % (num_rows))
```

```
The number of houses in the data set is equal to the number of rows, so there
are 19451 houses in this dataset
```

- How many **features** are there for predicting house price?

[5]:
```
df
```

[5]:
```
         price  bedrooms  bathrooms  sqft_living  sqft_lot  yr_built      lat  \
0       538000         3       2.25         2570      7242      1951  47.7210
1       180000         2       1.00          770     10000      1933  47.7379
2       604000         4       3.00         1960      5000      1965  47.5208
3       510000         3       2.00         1680      8080      1987  47.6168
4      1230000         4       4.50         5420    101930      2001  47.6561
…          …       …         …          …         …         …
19446   475000         3       2.50         1310      1294      2008  47.5773
19447   360000         3       2.50         1530      1131      2009  47.6993
19448   400000         4       2.50         2310      5813      2014  47.5107
19449   400000         3       2.50         1600      2388      2004  47.5345
19450   325000         2       0.75         1020      1076      2008  47.5941

          long                     geometry
0     -122.319  POINT (-122.31900 47.72100)
1     -122.233  POINT (-122.23300 47.73790)
2     -122.393  POINT (-122.39300 47.52080)
3     -122.045  POINT (-122.04500 47.61680)
4     -122.005  POINT (-122.00500 47.65610)
…          …                           …
19446 -122.409  POINT (-122.40900 47.57730)
19447 -122.346  POINT (-122.34600 47.69930)
19448 -122.362  POINT (-122.36200 47.51070)
19449 -122.069  POINT (-122.06900 47.53450)
19450 -122.299  POINT (-122.29900 47.59410)

[19451 rows x 9 columns]
```

[6]:
```
num_features = df.shape[1] - 2
print('The number of features in the data set for predicting house price is␣
↪equal to the number of columns (minus 2 for the price and geometry), so␣
↪there are %i features in this dataset to predict house price' %␣
↪(num_features))
```

```
The number of features in the data set for predicting house price is equal to
the number of columns (minus 2 for the price and geometry), so there are 7
features in this dataset to predict house price
```

- Are there any null values in this dataset?

There are **no** null values in this dataset.

[7]:
```
df.isnull().sum()
```

[7]:
```
price          0
bedrooms       0
bathrooms      0
sqft_living    0
sqft_lot       0
yr_built       0
lat            0
long           0
geometry       0
dtype: int64
```

1.2.1 Correlation matrix

Correlation matrix to find the best predictors of house price of `median_house_value`.

[8]:
```
# Compute correlation matrix
corr_matrix = gdf_utm.corr()

# Display just house value correlations
corr_matrix["price"].sort_values(ascending= False)
```

[8]:
```
price          1.000000
sqft_living    0.702296
bathrooms      0.524395
bedrooms       0.315804
lat            0.308082
sqft_lot       0.090125
yr_built       0.052453
long           0.020092
Name: price, dtype: float64
```

- Which three variables are best correlated with house price (include correlation coefficients)?

Best correlated three

- sqft_living: 0.702296
- bathrooms: 0.524395
- bedrooms: 0.315804

- Which three variables are least correlated with house price (include correlation coefficients)?

Least correlated three

- sqft_lot: 0.090125
- yr_built: 0.052453
- long: 0.020092

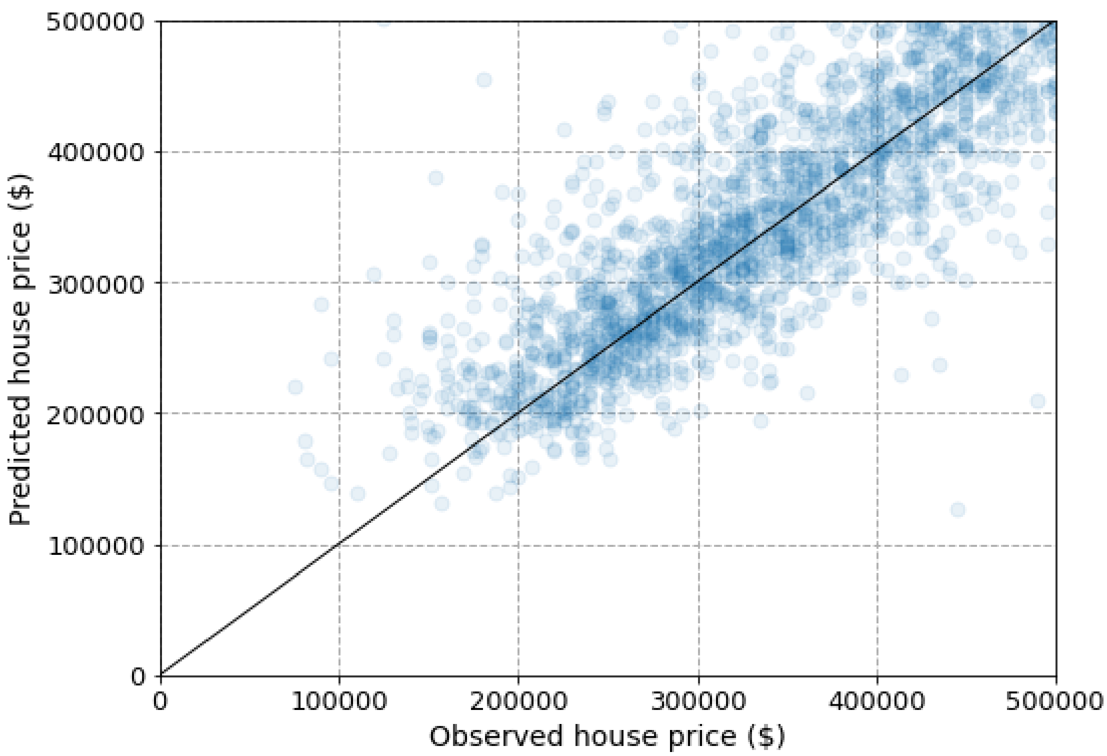
2 Base Model (no changes from example)

[9]:
```
# Define feature list
feature_list =  ['sqft_living', 'bathrooms', 'bedrooms',
                 'sqft_lot', 'yr_built', 'lat', 'long']

# Define features and labels
X = gdf_utm[feature_list]
y = gdf_utm['price']

# Standarize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split data
X_train_orig, X_test_orig, y_train_orig, y_test_orig =␣
 ↪train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Define model
forest_reg_orig = RandomForestRegressor(n_estimators = 30)

# Fit model
forest_reg_orig.fit(X_train_orig, y_train_orig)


# Predict test labels predictions
predictions_orig = forest_reg_orig.predict(X_test_orig)

# Compute mean-squared-error
final_mse_orig = mean_squared_error(y_test_orig, predictions_orig)
final_rmse_orig = np.sqrt(final_mse_orig)
final_rmse_orig
```

[9]:
```
154820.45890147457
```

[10]:
```
# Plot
fig, ax = plt.subplots(figsize=(8, 6))
ax.scatter(y_test_orig, predictions_orig, alpha=0.1, s=50, zorder=2)
ax.plot([0,500000], [0, 500000], color='k', lw=1, zorder=3)
ax.set_ylabel('Predicted house price ($)', fontsize=14)
ax.set_xlabel('Observed house price ($)', fontsize=14)
ax.tick_params(axis='both', which='major', labelsize=13)
ax.grid(ls='dashed', lw=1, zorder=1)
ax.set_ylim(0,500000)
ax.set_xlim(0,500000)
```

[10]:
```
(0.0, 500000.0)
```



2.1 Question 2 (30 points):

- Produce a model to predict house prices. You are welcome to generate new features, scale the data, and split the data into training/testing (i.e. `train_test_split`) in any way you like.

3 Model updates

3.1 I added the following features/predictors

- Distance to coastline
- Distance to Amazon Headquarters
- Distance to Microsoft Headquarters
- Distance to Nisqually entrance
- Distance to Bainbridge island Headquarters
- Distance to Capitol hill neighborhood
- Bedrooms per square foot variable

3.2 Changes to model parameters and test/train size

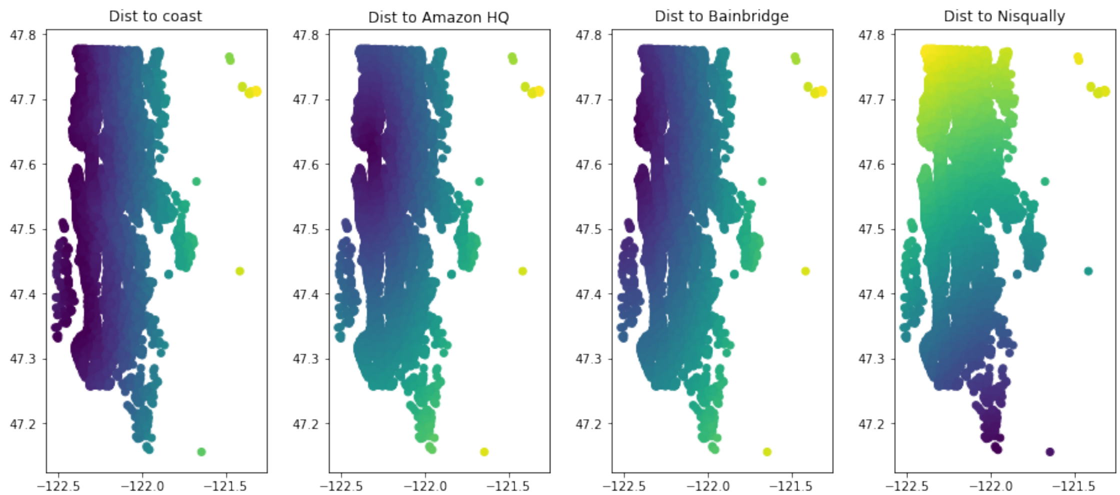
- num estimators in random forest regressor increased to 200
- increased test data to 0.25

[11]:
```
# add sqft living per bedroom
gdf_utm['sqft_liv_bedroom'] = gdf_utm['bedrooms']/gdf_utm['sqft_living']
```

[12]:
```
#compute distances to coast, amazon and microsfot headquarters
amHQ = Point(-122.337198,47.621476) #amazon headquarters
msHQ = Point(-122.192524,47.614082) #microsoft headquarters
caphill = Point(-122.314921,47.626536) #capitol hill
Nisq_ent = Point(-121.917050,46.740912) # Nisqually entrance to Mt Rainer␣
↪National Park
Bain_cent = Point(-122.533874, 47.643539) #Bainbridge island center

msHQ_gdf = gpd.GeoDataFrame(geometry = [msHQ])
msHQ_gdf = msHQ_gdf.set_crs(4326)
msHQ_gdf = msHQ_gdf.to_crs(32610)

amHQ_gdf = gpd.GeoDataFrame(geometry = [amHQ])
amHQ_gdf = amHQ_gdf.set_crs(4326)
amHQ_gdf = amHQ_gdf.to_crs(32610)

caphill_gdf = gpd.GeoDataFrame(geometry = [caphill])
caphill_gdf = caphill_gdf.set_crs(4326)
caphill_gdf = caphill_gdf.to_crs(32610)

Nisq_ent_gdf = gpd.GeoDataFrame(geometry = [Nisq_ent])
Nisq_ent_gdf = Nisq_ent_gdf.set_crs(4326)
Nisq_ent_gdf = Nisq_ent_gdf.to_crs(32610)

Bain_gdf = gpd.GeoDataFrame(geometry = [Bain_cent])
Bain_gdf = Bain_gdf.set_crs(4326)
Bain_gdf = Bain_gdf.to_crs(32610)
```

```
distance_to_amHQ = []
distance_to_msHQ = []
distance_to_coast = []
distance_to_caphill = []
distance_to_Nisq_ent = []
distance_to_Bain_cent = []
for i in range(gdf_utm.shape[0]):
    distance_to_coast.append(coast_utm.distance(gdf_utm['geometry'].iloc[i]).
 ↪min())  # Compute distance to coast for Seattle housing
    distance_to_amHQ.append(amHQ_gdf.distance(gdf_utm['geometry'].iloc[i])[0])␣
 ↪# Compute distance to amazon headquarters for Seattle housing
    distance_to_msHQ.append(amHQ_gdf.distance(gdf_utm['geometry'].iloc[i])[0]) ␣
 ↪# Compute distance to microsoft headquarters for Seattle housing
    distance_to_caphill.append(caphill_gdf.distance(gdf_utm['geometry'].
 ↪iloc[i])[0])  # Compute distance to capitol hill for Seattle housing
    distance_to_Nisq_ent.append(Nisq_ent_gdf.distance(gdf_utm['geometry'].
 ↪iloc[i])[0]) # Distance to Nisqually entrance for Mt Rainer National Park
    distance_to_Bain_cent.append(Bain_gdf.distance(gdf_utm['geometry'].
 ↪iloc[i])[0]) # Distance to Bainbrdige island center
# Add to DataFrame
gdf_utm['distance_to_amHQ'] = distance_to_amHQ
gdf_utm['distance_to_msHQ'] = distance_to_msHQ
gdf_utm['distance_to_coast'] = distance_to_coast
gdf_utm['distance_to_caphill'] = distance_to_caphill
gdf_utm['distance_to_Nisqually'] = distance_to_Nisq_ent
gdf_utm['distance_to_Bainbridge'] = distance_to_Bain_cent
```

[13]:
```
# Plot of distance to coastline for seattle
fig, ax = plt.subplots(nrows = 1, ncols = 4,figsize=(13, 6))
ax[0].scatter(gdf_utm['long'], gdf_utm['lat'], c=gdf_utm['distance_to_coast'])
ax[0].title.set_text('Dist to coast')

ax[1].scatter(gdf_utm['long'], gdf_utm['lat'], c=gdf_utm['distance_to_amHQ'])
ax[1].title.set_text('Dist to Amazon HQ')

ax[2].scatter(gdf_utm['long'], gdf_utm['lat'],␣
 ↪c=gdf_utm['distance_to_Bainbridge'])
ax[2].title.set_text('Dist to Bainbridge')

ax[3].scatter(gdf_utm['long'], gdf_utm['lat'],␣
 ↪c=gdf_utm['distance_to_Nisqually'])
ax[3].title.set_text('Dist to Nisqually')


fig.tight_layout(pad = 2.0)
```



3.3 Confusion matrix

[14]:
```
# Compute correlation matrix
corr_matrix = gdf_utm.corr()

# Display just house value correlations
corr_matrix["price"].sort_values(ascending= False)
```

[14]:
```
price                    1.000000
sqft_living              0.702296
bathrooms                0.524395
bedrooms                 0.315804
lat                      0.308082
distance_to_Nisqually    0.291833
sqft_lot                 0.090125
yr_built                 0.052453
distance_to_coast        0.027830
long                     0.020092
distance_to_Bainbridge  -0.203638
distance_to_amHQ        -0.302925
distance_to_msHQ        -0.302925
distance_to_caphill     -0.327569
sqft_liv_bedroom        -0.479228
Name: price, dtype: float64
```

3.4 Fit a model

[20]:
```
# Define feature list
feature_list =  ['sqft_living', 'bathrooms', 'bedrooms',
                 'sqft_lot', 'yr_built', 'distance_to_coast',
                 'distance_to_amHQ','distance_to_msHQ', 'lat', 'long',␣
 ↪'sqft_liv_bedroom',
              ␣
 ↪'distance_to_Bainbridge','distance_to_caphill','distance_to_Nisqually']

# Define features and labels
X = gdf_utm[feature_list]
y = gdf_utm['price']

# Standarize data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

[21]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.
 ↪25, random_state=42)
```

[22]:
```
# Define model
forest_reg_n200 = RandomForestRegressor(n_estimators = 200)

# Fit model
forest_reg_n200.fit(X_train, y_train)
```

[22]:
```
RandomForestRegressor(n_estimators=200)
```

3.5 Evaluate model

[23]:
```
# Predict test labels predictions
predictions_200 = forest_reg_n200.predict(X_test)

# Compute mean-squared-error
final_mse_200 = mean_squared_error(y_test , predictions_200)
final_rmse_200 = np.sqrt(final_mse_200)
final_rmse_200
```

[23]:
```
150389.90455120505
```

4 Compare base and new model

[24]:
```
# Plot
fig, ax = plt.subplots(1,2,figsize=(13, 6))
ax[0].scatter(y_test_orig, predictions_orig, alpha=0.1, s=50, zorder=2)
ax[0].plot([0,500000], [0, 500000], color='k', lw=1, zorder=3)
ax[0].set_ylabel('Predicted house price ($)', fontsize=14)
ax[0].set_xlabel('Observed house price ($)', fontsize=14)
ax[0].tick_params(axis='both', which='major', labelsize=13)
ax[0].grid(ls='dashed', lw=1, zorder=1)
ax[0].set_ylim(0,500000)
ax[0].set_xlim(0,500000)
ax[0].text(300000, 100000, 'rmse: ' + str(int(final_rmse_orig)), fontsize = 14)

ax[1].scatter(y_test, predictions_200, alpha=0.1, s=50, zorder=2)
ax[1].plot([0,500000], [0, 500000], color='k', lw=1, zorder=3)
ax[1].set_ylabel('Predicted house price ($)', fontsize=14)
ax[1].set_xlabel('Observed house price ($)', fontsize=14)
ax[1].tick_params(axis='both', which='major', labelsize=13)
ax[1].grid(ls='dashed', lw=1, zorder=1)
ax[1].set_ylim(0,500000)
ax[1].set_xlim(0,500000)
ax[1].text(300000, 100000, 'rmse: ' + str(int(final_rmse_200)), fontsize = 14)

fig.tight_layout(pad = 2.0)
```