Project1

January 14, 2022

1 TODO: Applying the end-to-end ML steps to a different dataset.

[42]:
```
import sys
assert sys.version_info >= (3, 5) # python>=3.5
import sklearn
assert sklearn.__version__ >= "0.20" # sklearn >= 0.20

import numpy as np #numerical package in python
import os
%matplotlib inline
import matplotlib.pyplot as plt #plotting package
import pandas as pd

# to make this notebook's output identical at every run
np.random.seed(42)

#matplotlib magic for inline figures
%matplotlib inline
import matplotlib # plotting library
import matplotlib.pyplot as plt

# Where to save the figures
ROOT_DIR = "."
IMAGES_PATH = os.path.join(ROOT_DIR, "images")
os.makedirs(IMAGES_PATH, exist_ok=True)

from sklearn.metrics import mean_squared_error
import matplotlib.image as mpimg

from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import OneHotEncoder
from sklearn.base import BaseEstimator, TransformerMixin

from sklearn.linear_model import LinearRegression
```

```python
from pandas.plotting import scatter_matrix
from sklearn.model_selection import train_test_split
```

We will apply what we've learnt to another dataset (airbnb dataset). We will predict airbnb price based on other features.

2 [25 pts] Visualizing Data

2.0.1 [5 pts] Load the data + statistics

- load the dataset (datasets/airbnb/AB_NYC_2019.csv)
- display the first 3 rows of the data
- drop the following columns: name, host_name, last_review
- display a summary of the statistics of the loaded data and determine which columns have missing values
- plot histograms for 3 features of your choice

[43]:
```python
airbnb = pd.read_csv('datasets/airbnb/AB_NYC_2019.csv') # load dataset
airbnb.head(3) # display first three rows
```

[43]:
```
     id                                name  host_id  host_name  \
0  2539  Clean & quiet apt home by the park     2787       John
1  2595               Skylit Midtown Castle     2845   Jennifer
2  3647  THE VILLAGE OF HARLEM…NEW YORK !      4632  Elisabeth

  neighbourhood_group neighbourhood  latitude  longitude        room_type  \
0            Brooklyn    Kensington  40.64749  -73.97237     Private room
1           Manhattan       Midtown  40.75362  -73.98377  Entire home/apt
2           Manhattan        Harlem  40.80902  -73.94190     Private room

   price  minimum_nights  number_of_reviews last_review  reviews_per_month  \
0    149               1                  9  2018-10-19               0.21
1    225               1                 45  2019-05-21               0.38
2    150               3                  0         NaN                NaN

   calculated_host_listings_count  availability_365
0                               6               365
1                               2               355
2                               1               365
```

[44]:
```python
airbnb = airbnb.drop("name", axis=1) # drop name
airbnb = airbnb.drop("host_name", axis=1) # drop host_name
airbnb = airbnb.drop("last_review", axis=1) # drop last_review
```

[45]:
```python
airbnb.describe() # summary of statistics
```

[45]:
```
                 id       host_id      latitude     longitude         price  \
count  4.889500e+04  4.889500e+04  48895.000000  48895.000000  48895.000000
mean   1.901714e+07  6.762001e+07     40.728949    -73.952170    152.720687
std    1.098311e+07  7.861097e+07      0.054530      0.046157    240.154170
min    2.539000e+03  2.438000e+03     40.499790    -74.244420      0.000000
25%    9.471945e+06  7.822033e+06     40.690100    -73.983070     69.000000
50%    1.967728e+07  3.079382e+07     40.723070    -73.955680    106.000000
75%    2.915218e+07  1.074344e+08     40.763115    -73.936275    175.000000
max    3.648724e+07  2.743213e+08     40.913060    -73.712990  10000.000000

       minimum_nights  number_of_reviews  reviews_per_month  \
count    48895.000000       48895.000000       38843.000000
mean         7.029962          23.274466           1.373221
std         20.510550          44.550582           1.680442
min          1.000000           0.000000           0.010000
25%          1.000000           1.000000           0.190000
50%          3.000000           5.000000           0.720000
75%          5.000000          24.000000           2.020000
max       1250.000000         629.000000          58.500000

       calculated_host_listings_count  availability_365
count                    48895.000000      48895.000000
mean                         7.143982        112.781327
std                         32.952519        131.622289
min                          1.000000          0.000000
25%                          1.000000          0.000000
50%                          1.000000         45.000000
75%                          2.000000        227.000000
max                        327.000000        365.000000
```

[46]:
```python
# rows where we have null values (col is reviews_per_month)
airbnb_incomplete = airbnb[airbnb.isnull().any(axis=1)].head()
airbnb_incomplete
```

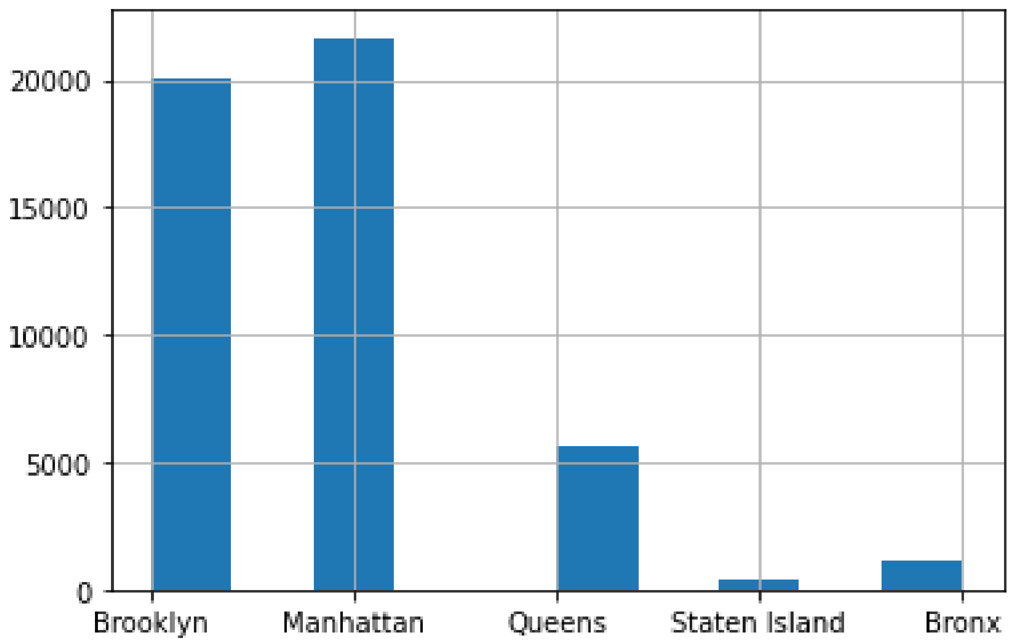
[46]:
```
       id  host_id neighbourhood_group       neighbourhood  latitude  \
2    3647     4632           Manhattan              Harlem  40.80902
19   7750    17985           Manhattan         East Harlem  40.79685
26   8700    26394           Manhattan              Inwood  40.86754
36  11452     7355            Brooklyn  Bedford-Stuyvesant  40.68876
38  11943    45445            Brooklyn            Flatbush  40.63702

    longitude        room_type  price  minimum_nights  number_of_reviews  \
2   -73.94190     Private room    150               3                  0
19  -73.94872  Entire home/apt    190               7                  0
26  -73.92639     Private room     80               4                  0
36  -73.94312     Private room     35              60                  0
38  -73.96327     Private room    150               1                  0
```

	reviews_per_month	calculated_host_listings_count	availability_365
2	NaN	1	365
19	NaN	2	249
26	NaN	1	0
36	NaN	1	365
38	NaN	1	365

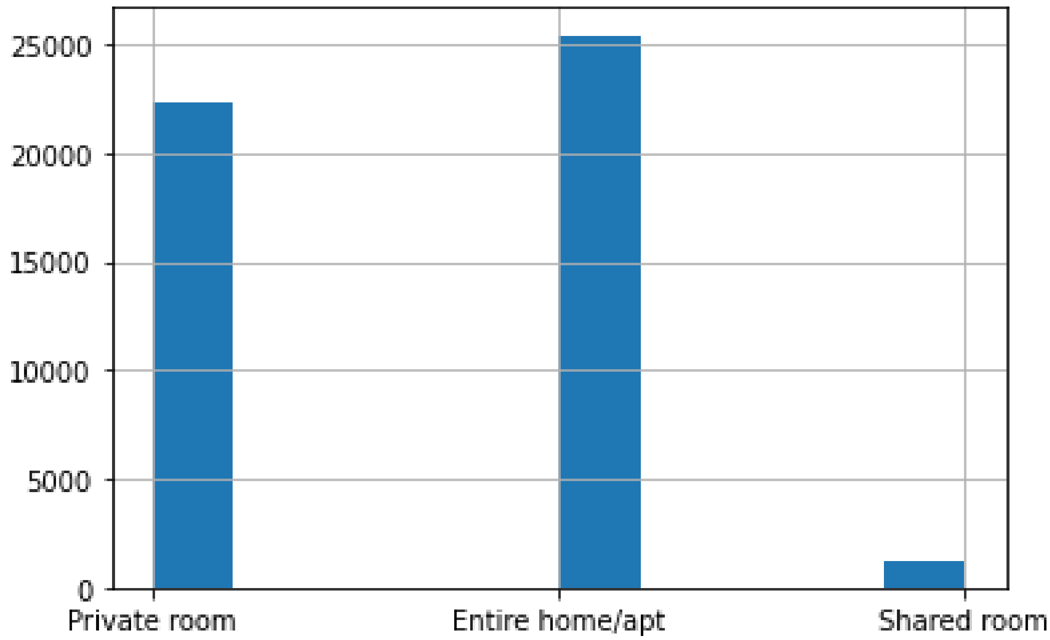
[47]:
```
airbnb["neighbourhood_group"].hist() # histogram for neighbourhood group
```

[47]: <AxesSubplot:>



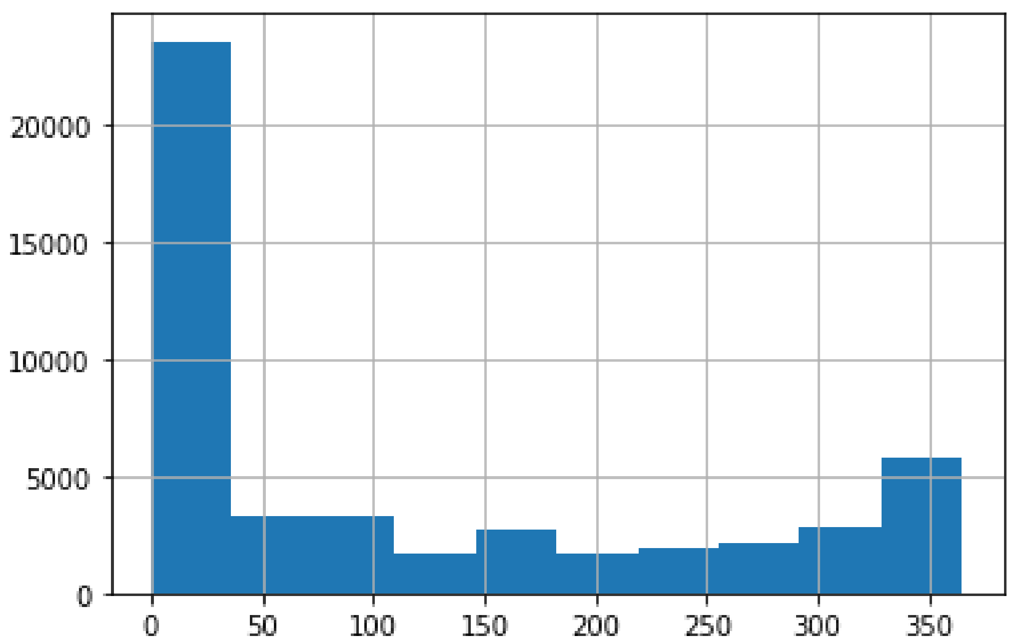
[48]:
```
airbnb["room_type"].hist() # histogram for room type
```

[48]: <AxesSubplot:>



[49]:
```
airbnb["availability_365"].hist() # histogram for availability
```

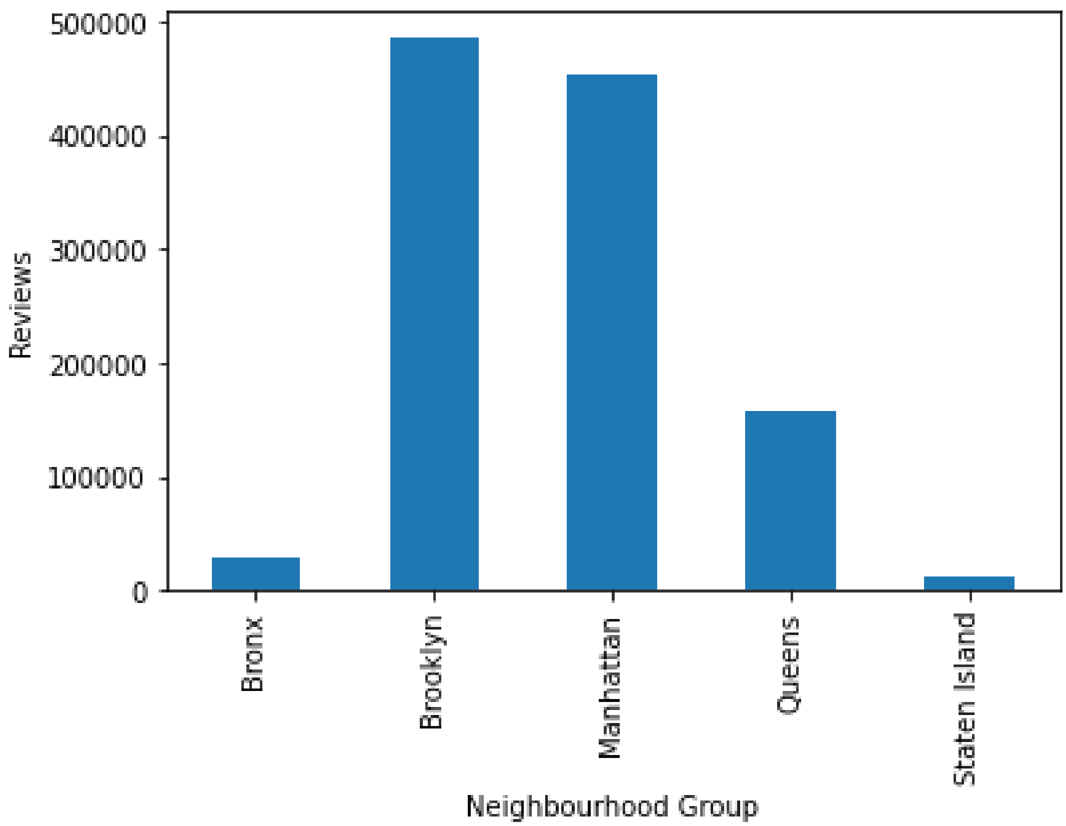
[49]: <AxesSubplot:>



2.0.2 [5 pts] Plot total number of reviews per neighbourhood_group

[50]:
```
# summing review count over neighbourhood group
reviews_per_group = airbnb.groupby(["neighbourhood_group"]).number_of_reviews.
 ↪sum().reset_index()
reviews_per_group.plot(kind="bar", x="neighbourhood_group",
                       y="number_of_reviews", xlabel="Neighbourhood Group",
                       ylabel="Reviews", legend=False)
```

[50]: <AxesSubplot:xlabel='Neighbourhood Group', ylabel='Reviews'>



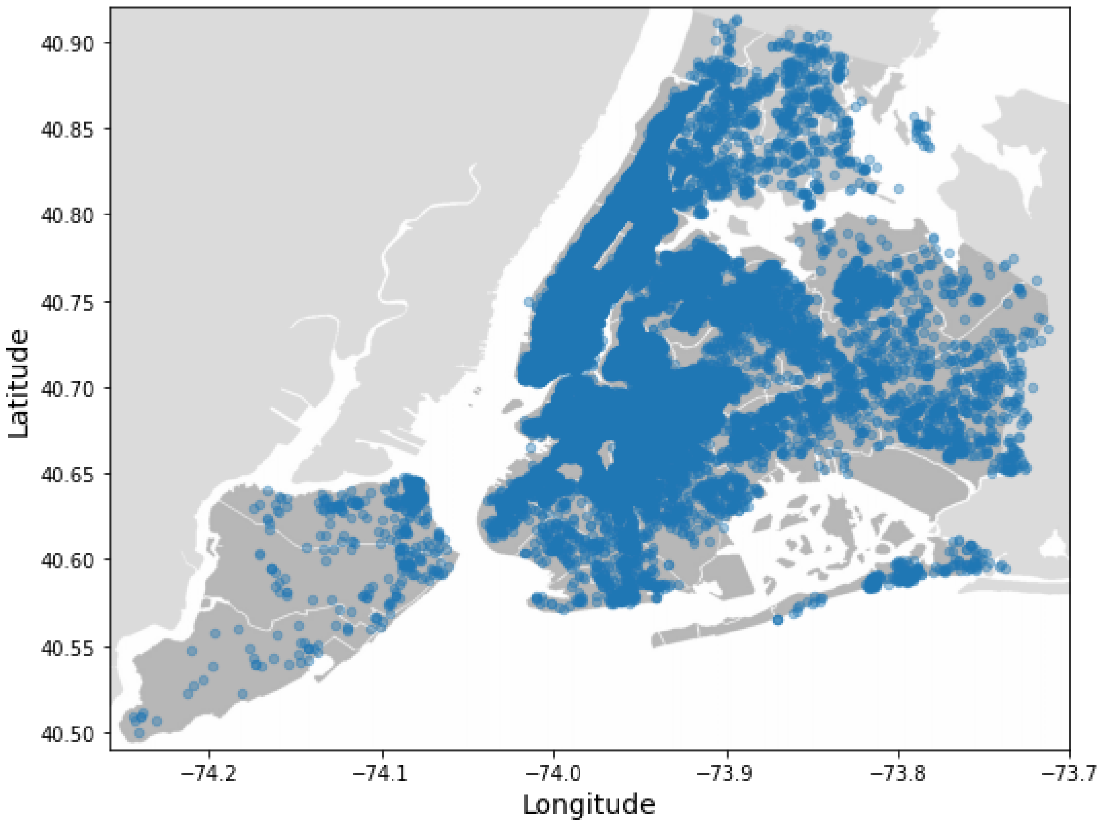
2.0.3 [5 pts] Plot map of airbnbs throughout New York (if it gets too crowded take a subset of the data, and try to make it look nice if you can :)).

If you overlay the given newyork.png image, you can use parameter extent=[-74.258, -73.7, 40.49, 40.92] with imshow() function.

[51]:
```
# load image of New York
images_path = os.path.join('./', "images")
os.makedirs(images_path, exist_ok=True)
filename = "newyork.png"
```

```
ax = airbnb.plot(kind="scatter", x="longitude",
                 y="latitude", figsize=(10, 7), alpha=0.4)
# overlay the map on the plotted scatter plot
# note: plt.imshow still refers to the most recent figure
# that hasn't been plotted yet.
newyork_img = mpimg.imread(os.path.join(images_path, filename))
plt.imshow(newyork_img, extent=[-74.258, -73.7, 40.49, 40.92], alpha=0.5)
plt.ylabel("Latitude", fontsize=14)
plt.xlabel("Longitude", fontsize=14)

plt.show()
```

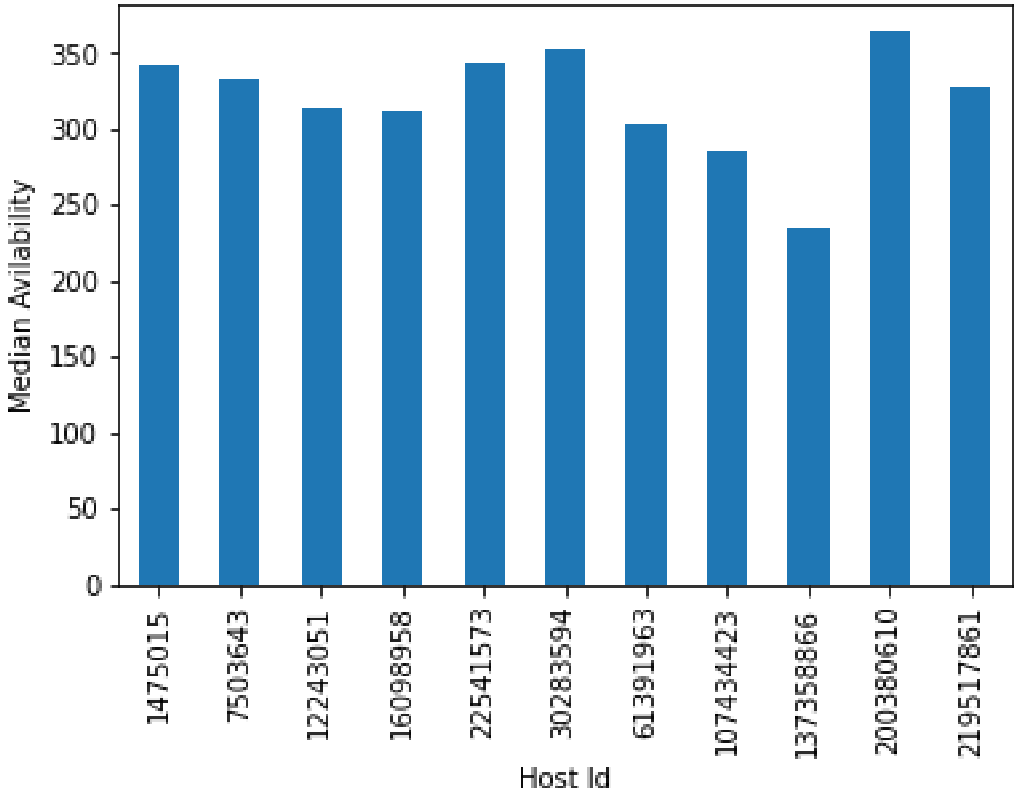


2.0.4 [5 pts] Plot median availability of hosts (host_id) who have more than 50 listings.

[52]:
```
host_50 = airbnb[airbnb["calculated_host_listings_count"] > 50]
host_50_median = host_50.groupby(by="host_id")["availability_365"].median().
 ↪reset_index()
host_50_median.plot(kind="bar", x="host_id", y="availability_365",
```

```
                xlabel="Host Id", ylabel="Median Avilability", legend=False)
```

[52]: <AxesSubplot:xlabel='Host Id', ylabel='Median Avilability'>



2.0.5 [5 pts] Plot correlation matrix

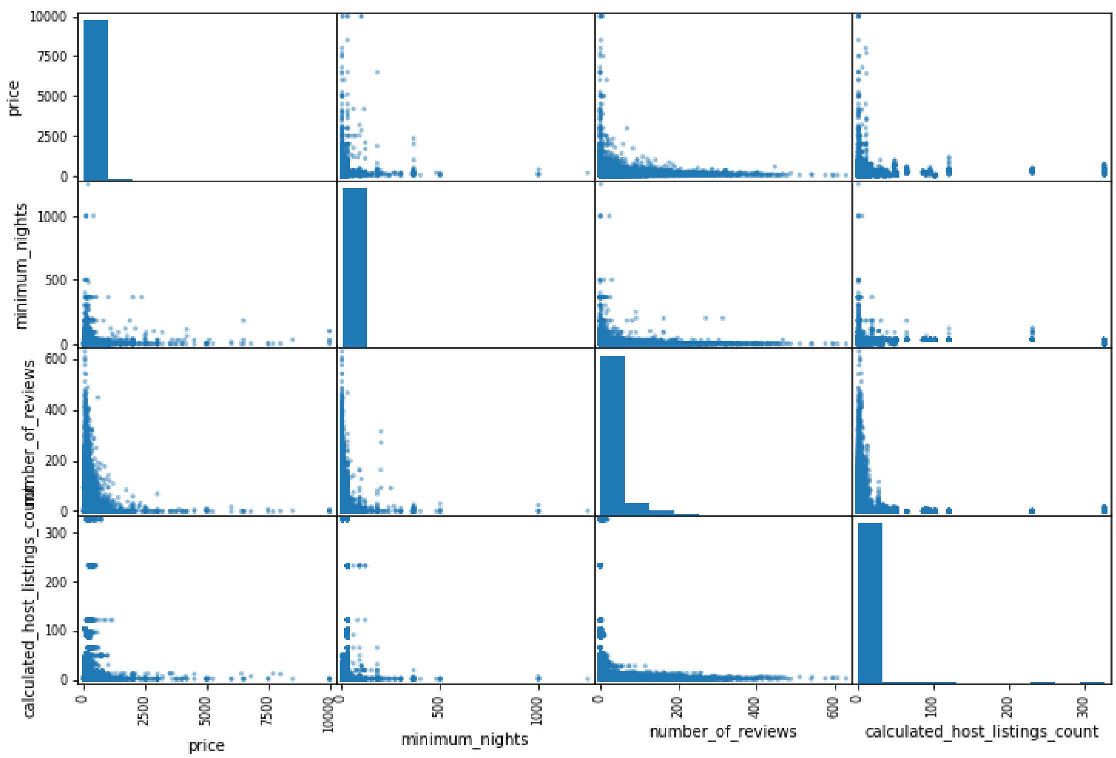
- which features have positive correlation?
- which features have negative correlation?

Negative Correlation: price and number_of_reviews, minimum_nights and number_of_reviews, number_of_reviews and calculated_host_listings_count Positive Correlation: price and minimum_nights, price and calculated_host_listings_count, minimum_nights and calculated_host_listings_count

[53]:
```
ab_corr_matrix = airbnb.corr()
ab_corr_matrix

ab_attributes = ["price", "minimum_nights",
    "number_of_reviews", "calculated_host_listings_count"]
scatter_matrix(airbnb[ab_attributes], figsize=(12, 8))
```

[53]:
```
array([[<AxesSubplot:xlabel='price', ylabel='price'>,
        <AxesSubplot:xlabel='minimum_nights', ylabel='price'>,
        <AxesSubplot:xlabel='number_of_reviews', ylabel='price'>,
        <AxesSubplot:xlabel='calculated_host_listings_count', ylabel='price'>],
       [<AxesSubplot:xlabel='price', ylabel='minimum_nights'>,
        <AxesSubplot:xlabel='minimum_nights', ylabel='minimum_nights'>,
        <AxesSubplot:xlabel='number_of_reviews', ylabel='minimum_nights'>,
        <AxesSubplot:xlabel='calculated_host_listings_count',
ylabel='minimum_nights'>],
       [<AxesSubplot:xlabel='price', ylabel='number_of_reviews'>,
        <AxesSubplot:xlabel='minimum_nights', ylabel='number_of_reviews'>,
        <AxesSubplot:xlabel='number_of_reviews', ylabel='number_of_reviews'>,
        <AxesSubplot:xlabel='calculated_host_listings_count',
ylabel='number_of_reviews'>],
       [<AxesSubplot:xlabel='price', ylabel='calculated_host_listings_count'>,
        <AxesSubplot:xlabel='minimum_nights',
ylabel='calculated_host_listings_count'>,
        <AxesSubplot:xlabel='number_of_reviews',
ylabel='calculated_host_listings_count'>,
        <AxesSubplot:xlabel='calculated_host_listings_count',
ylabel='calculated_host_listings_count'>]],
      dtype=object)
```



3 [25 pts] Prepare the Data

3.0.1 [5 pts] Set aside 30% of the data as test set (70% train, 30% test).

[54]:
```python
# splitting data
ab_train_set, ab_test_set = train_test_split(airbnb, test_size=0.3,␣
↪random_state=42)
# dropping columns I don't feel are necessary
ab_test_set.drop("host_id", axis=1)
ab_train_set.drop("host_id", axis=1)
```

[54]:
```
             id neighbourhood_group       neighbourhood  latitude  longitude  \
21681  17418006              Queens     Cambria Heights  40.69206  -73.74546
26482  21079975            Brooklyn         Sunset Park  40.66060  -73.99455
20859  16519069           Manhattan           Kips Bay  40.74227  -73.97432
45464  34773215            Brooklyn  Bedford-Stuyvesant  40.68676  -73.94593
22583  18269285           Manhattan             Midtown  40.76013  -73.96566
…           …                   …                  …       …         …
11284   8754339           Manhattan  Washington Heights  40.84650  -73.94319
44732  34383329           Manhattan             Chelsea  40.73957  -74.00082
38158  30109697           Manhattan     Upper West Side  40.78318  -73.97372
860      304799           Manhattan     Upper West Side  40.77508  -73.97990
15795  12775106              Queens    Long Island City  40.74657  -73.94555

             room_type  price  minimum_nights  number_of_reviews  \
21681  Entire home/apt    169               2                 65
26482  Entire home/apt     94               2                 24
20859     Private room    100               5                  2
45464     Private room     51               1                  4
22583      Shared room     99               3                  6
…                  …      …               …                 …
11284      Shared room     60               1                  0
44732     Private room     85               2                  4
38158  Entire home/apt    130              30                  1
860    Entire home/apt    150               2                 11
15795  Entire home/apt    120               5                  1

       reviews_per_month  calculated_host_listings_count  availability_365
21681               2.33                               1               263
26482               1.15                               1                12
20859               0.07                               1                 0
45464               2.86                               3                 0
22583               0.24                               1                 0
…                    …                             …               …
11284                NaN                               1                 0
44732               1.90                               1                76
38158               0.34                               5               261
860                 0.13                               1                 2
```

```
15795                0.03                                   1                 0

[34226 rows x 12 columns]
```

3.0.2 [5 pts] Augment the dataframe with two other features which you think would be useful

[55]:
```
ab_train_set["availabiliy_vs_min_nights"] = ab_train_set["availability_365"]/
 ↪ab_train_set["minimum_nights"]
ab_train_set["reviews_vs_listing"] = ab_train_set["number_of_reviews"]/
 ↪ab_train_set["calculated_host_listings_count"]

ab_test_set["availabiliy_vs_min_nights"] = ab_test_set["availability_365"]/
 ↪ab_test_set["minimum_nights"]
ab_test_set["reviews_vs_listing"] = ab_test_set["number_of_reviews"]/
 ↪ab_test_set["calculated_host_listings_count"]
```

3.0.3 [5 pts] Impute any missing feature with a method of your choice, and briefly discuss why you chose this imputation method

[56]:
```
ab_train_set.drop("reviews_per_month", axis=1)
ab_test_set.drop("reviews_per_month", axis=1)

# I chose to drop the missing feature because I felt that it wasn't necessary
# to include, considering we have the total number of reviews

# Remove target label from training set (i.e. don't use it as a feature)
ab_features_train = ab_train_set.drop("price", axis=1)
# Extract target labels into a separate list
ab_targets_train = ab_train_set["price"].tolist()

# Same for test data:
ab_features_test = ab_test_set.drop("price", axis=1)
ab_targets_test = ab_test_set["price"].tolist()
```

3.0.4 [10 pts] Code complete data pipeline using sklearn mixins

[57]:
```
class AugmentFeatures(BaseEstimator, TransformerMixin):
    '''
    ["availabiliy_vs_min_nights"] = ["availability_365"]/["minimum_nights"]
    ["reviews_vs_listing"] = ["number_of_reviews"]/
 ↪["calculated_host_listings_count"]
    '''
    # column index
    min_nights_ix, reviews_ix, listings_ix, availability_ix = 3, 4, 6, 7
    # min_nights_ix, reviews_ix, listings_ix, availability_ix = 4, 5, 7, 8
```

```
    def __init__(self):
        pass
    def fit(self, X, y=None):
        # This function could be used to learn something about the training␣
 ↪data, e.g.
        # what are the statistics of the data. For example, if transform()␣
 ↪function
        # is used to standardize the data, fit() function can find the mean/std␣
 ↪of the
        # training data. In this example, transform() function does not need to␣
 ↪know
        # anything about our training data, so this function is not needed.
        return self
    def transform(self, X):
        # Add three new columns to our dataset:
        availabiliy_vs_min_nights = X[:, self.availability_ix] / X[:, self.
 ↪min_nights_ix]
        reviews_vs_listing = X[:, self.reviews_ix] / X[:, self.listings_ix]
        return np.c_[X, availabiliy_vs_min_nights, reviews_vs_listing]

num_pipeline = Pipeline([
        ('imputer', SimpleImputer(strategy="median")),
        ('attribs_adder', AugmentFeatures()),
        ('std_scaler', StandardScaler()),
    ])

# Transform categorical/numerical columns using different approaches:
categorical_features = ["neighbourhood_group", "neighbourhood", "room_type"]
numerical_features = [x for x in ab_features_train.columns if x not in␣
 ↪categorical_features]

full_pipeline = ColumnTransformer([
        ("num", num_pipeline, numerical_features),
        # TODO idk if this is the right way to go about it
        ("cat", OneHotEncoder(handle_unknown='ignore'), categorical_features),
    ])

ab_features_train_transformed = full_pipeline.fit_transform(ab_features_train)
```

4 [15 pts] Fit a model of your choice

The task is to predict the price, you could refer to the housing example on how to train and evaluate your model using Root Mean Squared Error (RMSE). Provide both train and test set RMSE values. Also, plot the predictions against the actual values.

[58]:
```python
# train a linear regression model
lin_reg = LinearRegression()
lin_reg.fit(ab_features_train_transformed, ab_targets_train)

# choose a few training examples and make predictions on them
features = ab_features_train_transformed[:5, :]
targets = ab_targets_train[:5]
predictions = lin_reg.predict(features)
all_predictions = lin_reg.predict(ab_features_train_transformed)

rmse = mean_squared_error(ab_targets_train, all_predictions, squared=False)
print("Root Mean Squared Error:", rmse)

print("Predictions:", predictions)
print("Actual labels:", list(targets))
```

```
Root Mean Squared Error: 240.8604324306705
Predictions: [181.43637472 152.9449601  113.15862946  59.70053726 140.8478168 ]
Actual labels: [169, 94, 100, 51, 99]
```

[59]:
```python
# Transform test set using our pipeline
ab_features_test_transformed = full_pipeline.transform(ab_features_test)

# Make predictions on transformed data set
ab_predictions_test = lin_reg.predict(ab_features_test_transformed)

# Evaluate predictions
rmse = mean_squared_error(ab_targets_test, ab_predictions_test, squared=False)
print("Root Mean Squared Error:", rmse)

# Show a few predictions and corresponding labels
print("Sample predictions:", ab_predictions_test[:5])
print("Sample labels:", ab_targets_test[:5])
```

```
Root Mean Squared Error: 184.91353830047194
Sample predictions: [149.94828015  40.89827492 121.25452776 251.68695259
173.17605218]
Sample labels: [89, 30, 120, 470, 199]
```

[60]:
```python
# We can also visualize our predicted values against the correct values.␣
↪Ideally, our
# predictions should be very close to the correct value, i.e. the predictions␣
↪should be
# close to the red line.

plt.scatter(ab_targets_test, ab_predictions_test, alpha=0.2)
plt.plot([0,10000],[0,10000], 'r') # Draw a red line between points (0,0) and␣
↪(500000,500000)
```

```
plt.xlabel('Actual Price')
plt.ylabel('Predicted Price')
plt.show()
```