CS 188 Project 1

January 21, 2020

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

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
- display the first few rows of the data
- drop the following columns: name, host_id, host_name, last_review
- display a summary of the statistics of the loaded data
- plot histograms for 3 features of your choice

[84]:
```
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

# 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

import os
import tarfile
```

```python
import urllib

import pandas as pd

import matplotlib.image as mpimg

from pandas.plotting import scatter_matrix

from sklearn.model_selection import StratifiedShuffleSplit

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

from sklearn.metrics import mean_squared_error

from sklearn.model_selection import train_test_split
```

[85]:
```python
DATASET_PATH = os.path.join("datasets", "airbnb")

def load_airbnb_data(airbnb_path):
    csv_path = os.path.join(airbnb_path, "AB_NYC_2019.csv")
    return pd.read_csv(csv_path)
airbnb = load_airbnb_data(DATASET_PATH)
airbnb = airbnb.drop(columns=['name','host_id','host_name','last_review'])
airbnb.head()
```

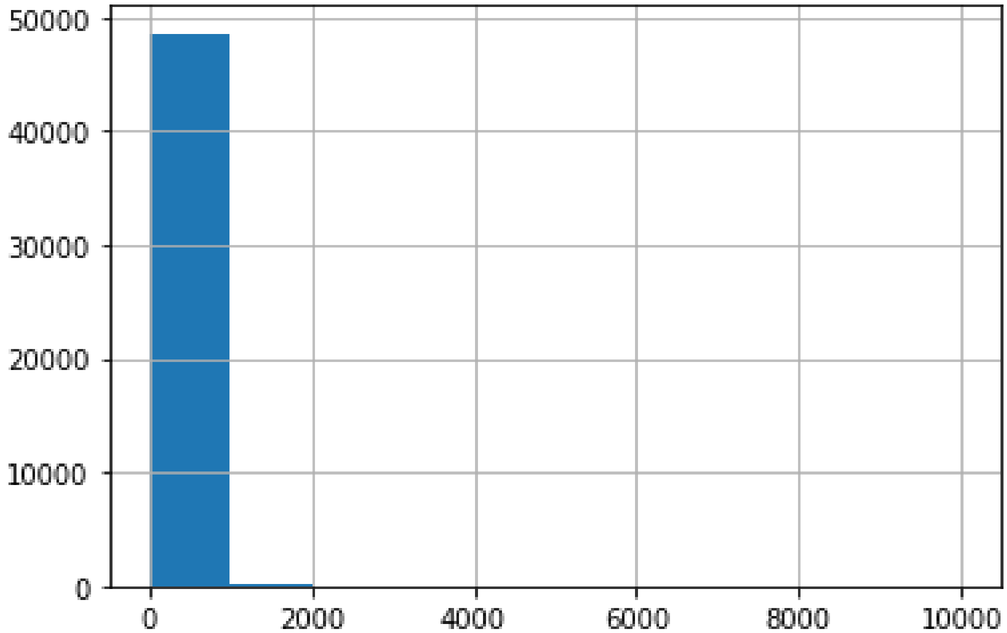
[85]:
```
     id neighbourhood_group neighbourhood  latitude  longitude  \
0  2539            Brooklyn    Kensington  40.64749  -73.97237
1  2595           Manhattan       Midtown  40.75362  -73.98377
2  3647           Manhattan        Harlem  40.80902  -73.94190
3  3831            Brooklyn  Clinton Hill  40.68514  -73.95976
4  5022           Manhattan   East Harlem  40.79851  -73.94399

         room_type  price  minimum_nights  number_of_reviews  \
0     Private room    149               1                  9
1  Entire home/apt    225               1                 45
2     Private room    150               3                  0
3  Entire home/apt     89               1                270
4  Entire home/apt     80              10                  9
```

```
   reviews_per_month  calculated_host_listings_count  availability_365
0               0.21                               6               365
1               0.38                               2               355
2                NaN                               1               365
3               4.64                               1               194
4               0.10                               1                 0
```

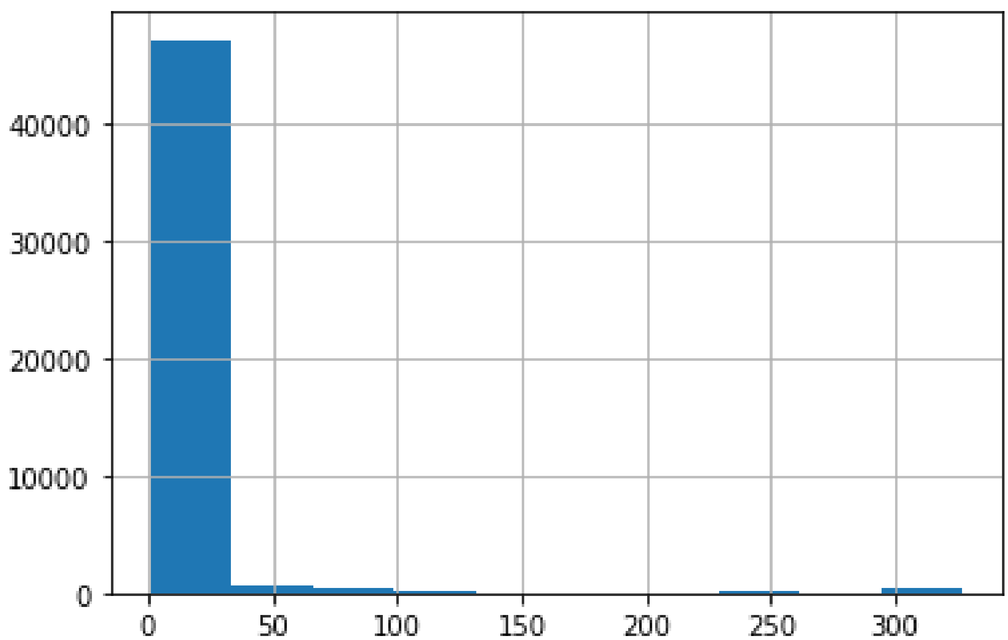
[86]:
```python
airbnb.describe()
```

[86]:
```
                 id      latitude     longitude         price  minimum_nights  \
count  4.889500e+04  48895.000000  48895.000000  48895.000000    48895.000000
mean   1.901714e+07     40.728949    -73.952170    152.720687        7.029962
std    1.098311e+07      0.054530      0.046157    240.154170       20.510550
min    2.539000e+03     40.499790    -74.244420      0.000000        1.000000
25%    9.471945e+06     40.690100    -73.983070     69.000000        1.000000
50%    1.967728e+07     40.723070    -73.955680    106.000000        3.000000
75%    2.915218e+07     40.763115    -73.936275    175.000000        5.000000
max    3.648724e+07     40.913060    -73.712990  10000.000000     1250.000000

       number_of_reviews  reviews_per_month  calculated_host_listings_count  \
count       48895.000000       38843.000000                    48895.000000
mean           23.274466           1.373221                        7.143982
std            44.550582           1.680442                       32.952519
min             0.000000           0.010000                        1.000000
25%             1.000000           0.190000                        1.000000
50%             5.000000           0.720000                        1.000000
75%            24.000000           2.020000                        2.000000
max           629.000000          58.500000                      327.000000

       availability_365
count      48895.000000
mean         112.781327
std          131.622289
min            0.000000
25%            0.000000
50%           45.000000
75%          227.000000
max          365.000000
```

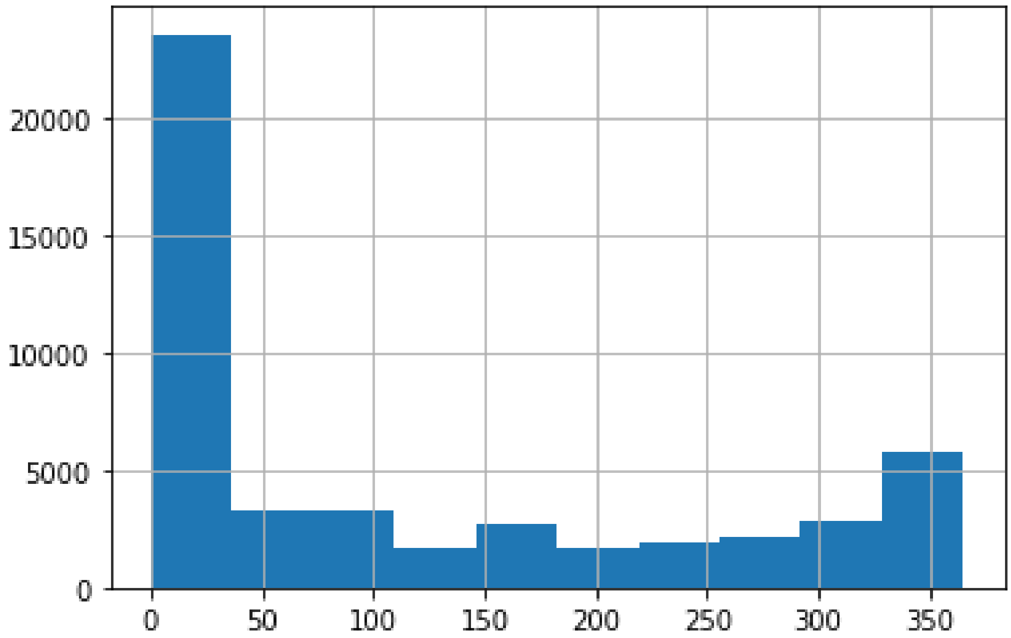
[87]:
```python
airbnb["price"].hist()
plt.show()
```



[88]:
```
airbnb["calculated_host_listings_count"].hist()
plt.show()
```



[89]:
```
airbnb["availability_365"].hist()
plt.show()
```



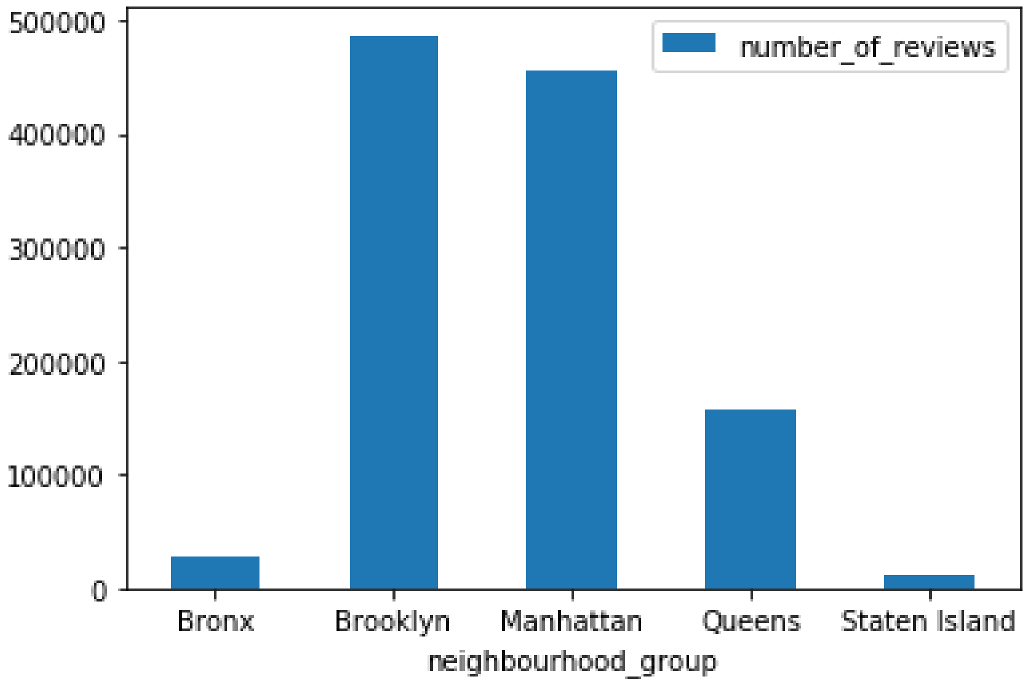
2.0.2 [5 pts] Plot total number_of_reviews per neighbourhood_group

[90]:
```
answer = airbnb.groupby("neighbourhood_group",␣
↪as_index=False)["number_of_reviews"].sum()
answer
```

[90]:

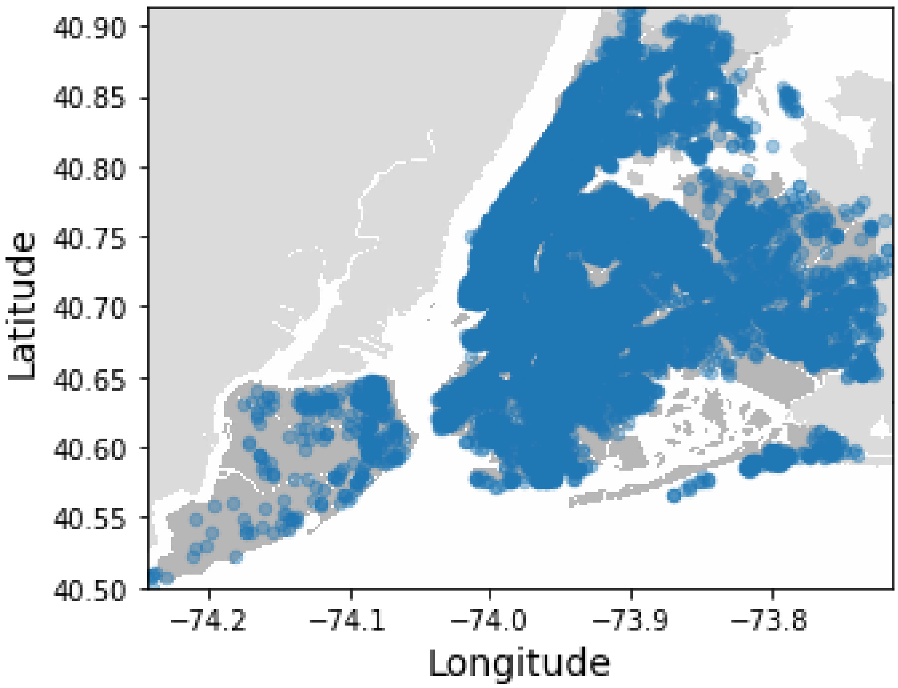
	neighbourhood_group	number_of_reviews
0	Bronx	28371
1	Brooklyn	486574
2	Manhattan	454569
3	Queens	156950
4	Staten Island	11541

[91]:
```
answer_graph = answer.plot.bar(x='neighbourhood_group', y='number_of_reviews',␣
↪rot=0)
```



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 :)).

[92]:
```
images_path = os.path.join('./', "images")
os.makedirs(images_path, exist_ok=True)
filename="newyorkcity.jpeg"
#import matplotlib.image as mpimg
newyork_img = mpimg.imread(os.path.join(images_path, filename))
ax = airbnb.plot(kind="scatter",x="longitude",y="latitude", alpha=0.4)
plt.imshow(newyork_img, extent=[-74.244420,-73.712990,40.499790,40.
↪913060],alpha=0.5)
plt.ylabel("Latitude",fontsize=14)
plt.xlabel("Longitude",fontsize=14)
plt.show()
```



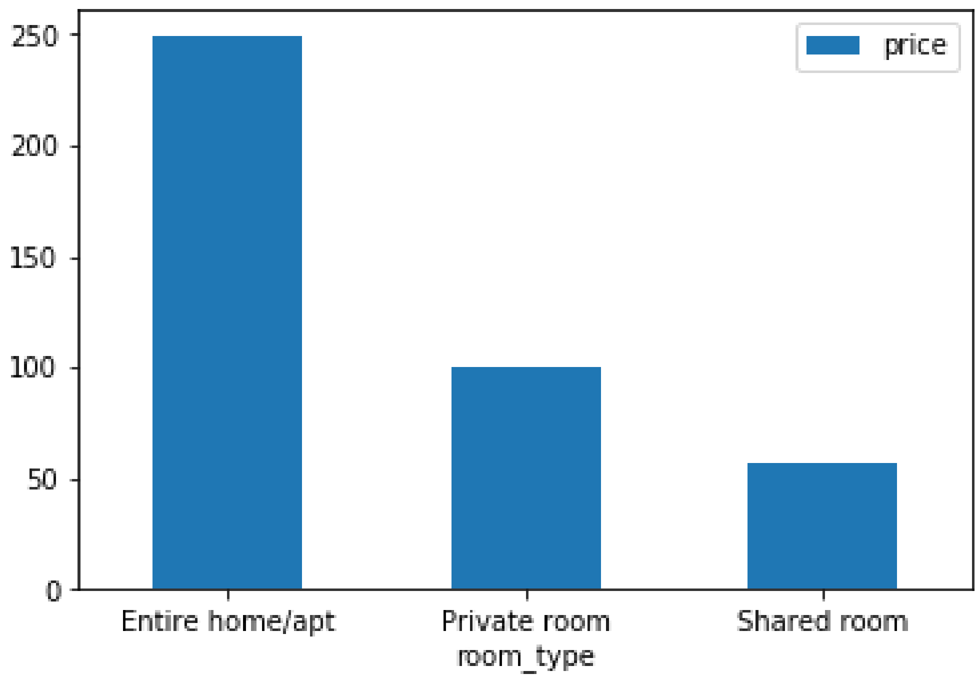
2.0.4 [5 pts] Plot average price of room types who have availability greater than 180 days.

[93]:
```
is_avail = airbnb["availability_365"] > 180
airbnb_avail = airbnb[is_avail]
airbnb_avail.head()
result = airbnb_avail.groupby("room_type", as_index=False)["price"].mean()
result
```

[93]:

	room_type	price
0	Entire home/apt	248.870817
1	Private room	100.028192
2	Shared room	56.941909

[94]:
```
result_graph = result.plot.bar(x='room_type', y='price', rot=0)
```



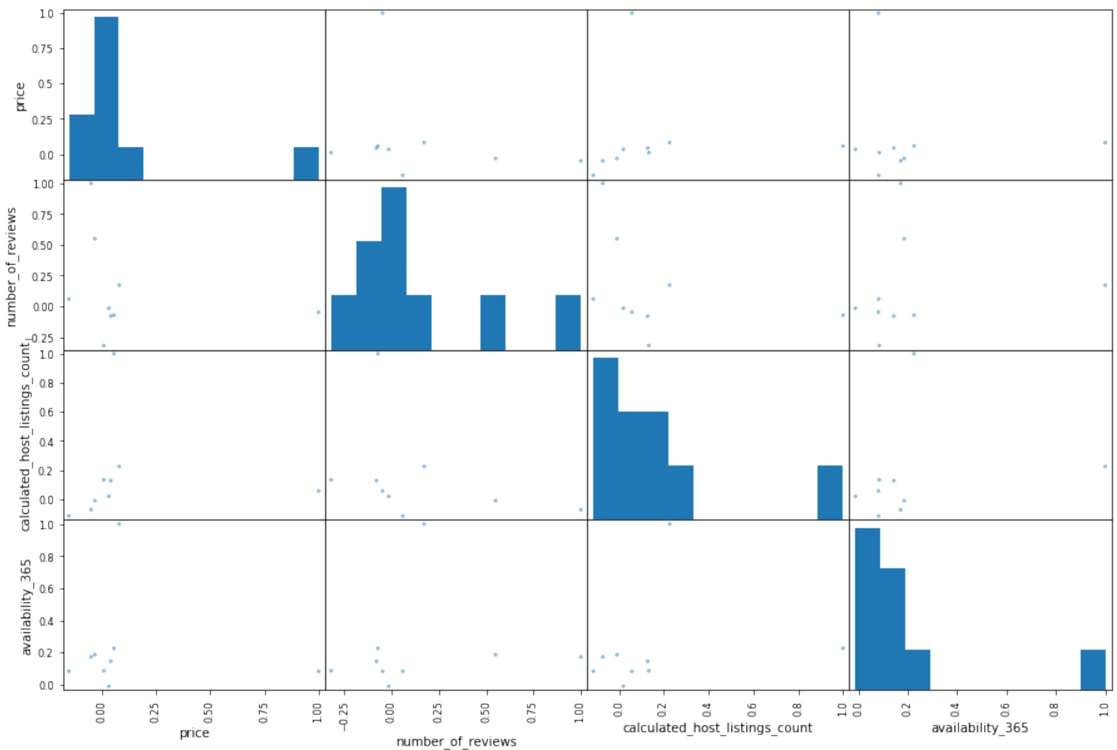
2.0.5 [5 pts] Plot correlation matrix

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

[95]:
```
airbnb_corr_matrix = airbnb.corr()
#from pandas.plotting import scatter_matrix
attributes=["price","number_of_reviews","calculated_host_listings_count","availability_365"]
scatter_matrix(airbnb_corr_matrix[attributes], figsize=(15,10))
```

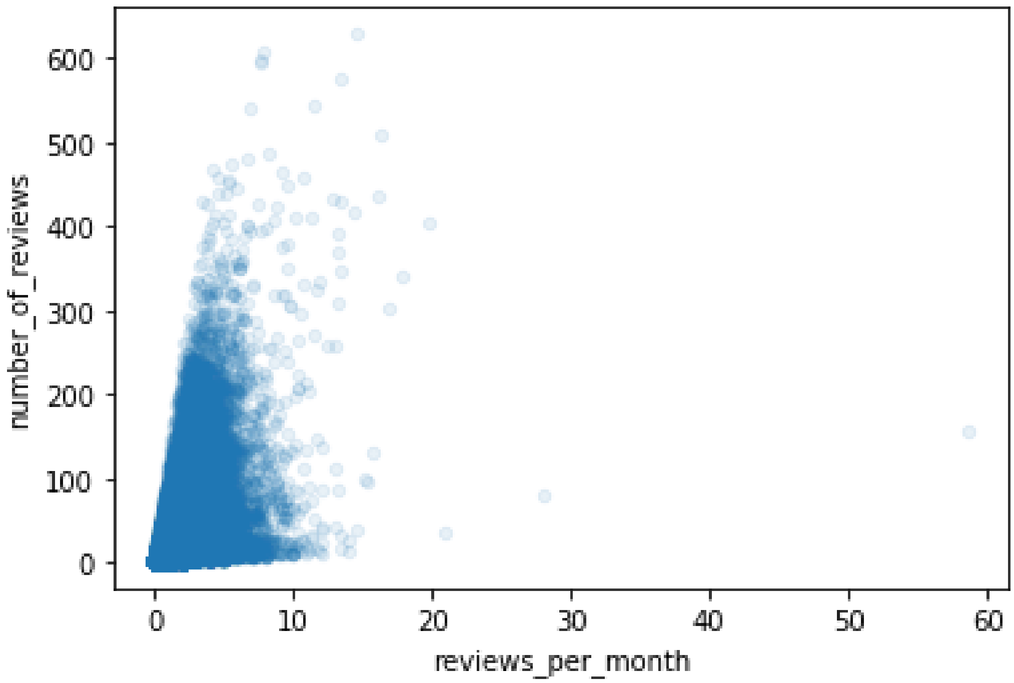
[95]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x1a28bed0b8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a274106d8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a27679c88>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2990a278>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a29939828>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2a12cdd8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a303ff5f8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a303cc5f8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a303cc780>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2df48588>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2dfceba8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a2747fd30>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x1a26acf5c0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x1a26a8d898>,
```

```
  <matplotlib.axes._subplots.AxesSubplot object at 0x1a26e8e6d8>,
  <matplotlib.axes._subplots.AxesSubplot object at 0x1a2520feb8>]],
dtype=object)
```



[96]:
```python
airbnb.plot(kind="scatter", x="reviews_per_month", y="number_of_reviews",
             alpha=0.1)
```

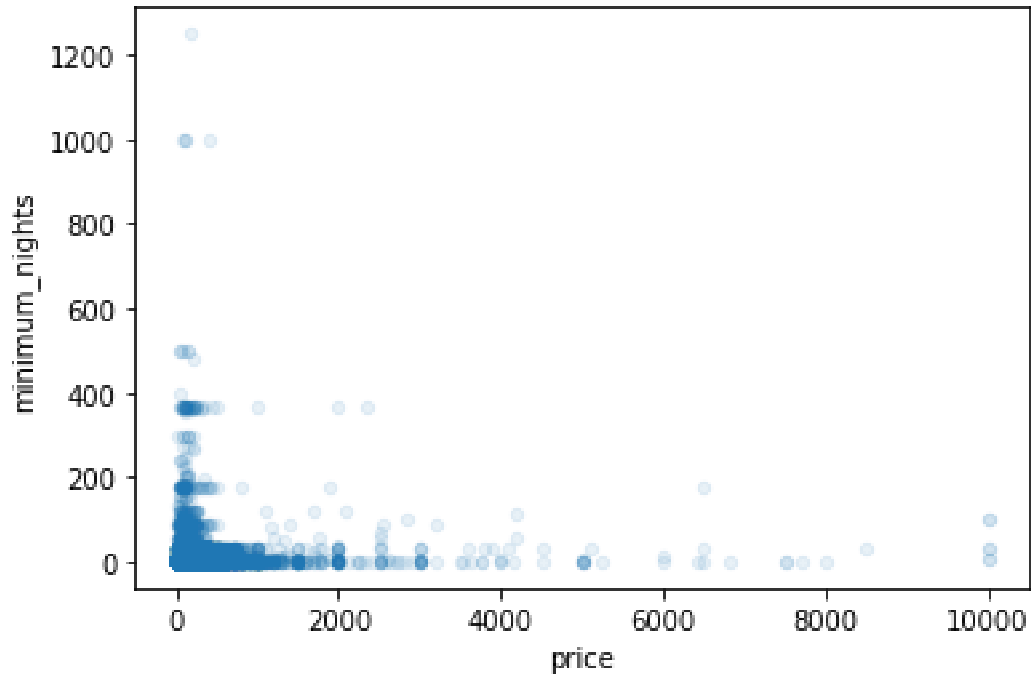
[96]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a27251748>
```



reviews_per_month and number_of_reviews: positive correlation

[97]:
```
airbnb.plot(kind="scatter", x="price", y="minimum_nights",
             alpha=0.1)
```

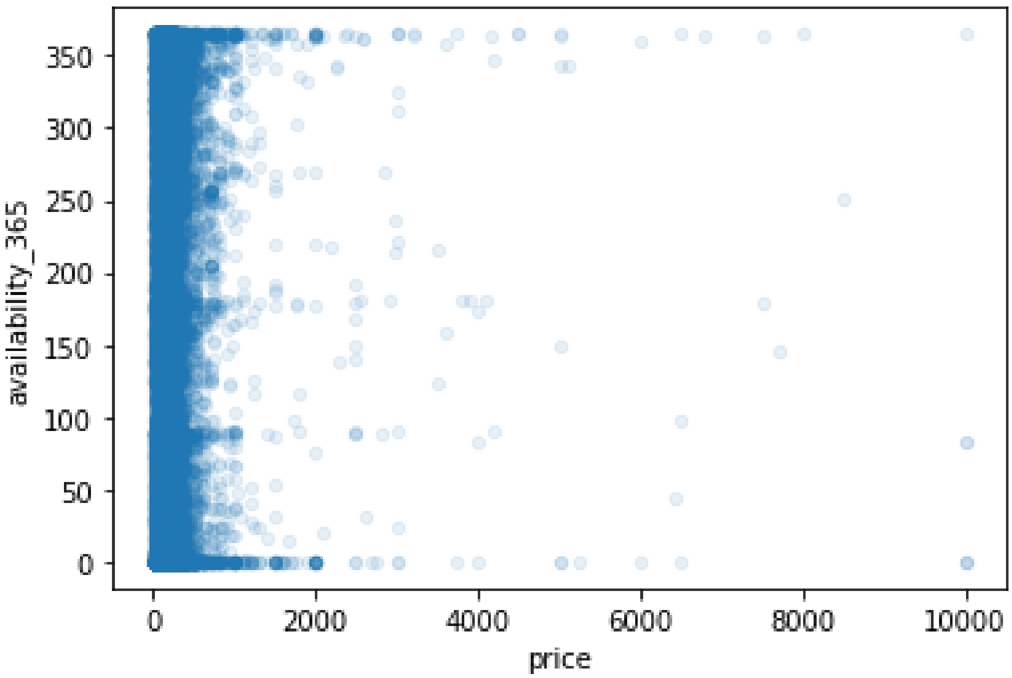
[97]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2e3db438>



price and minimum_nights: positive correlation

[98]:
```
airbnb.plot(kind="scatter", x="price", y="availability_365",
            alpha=0.1)
```

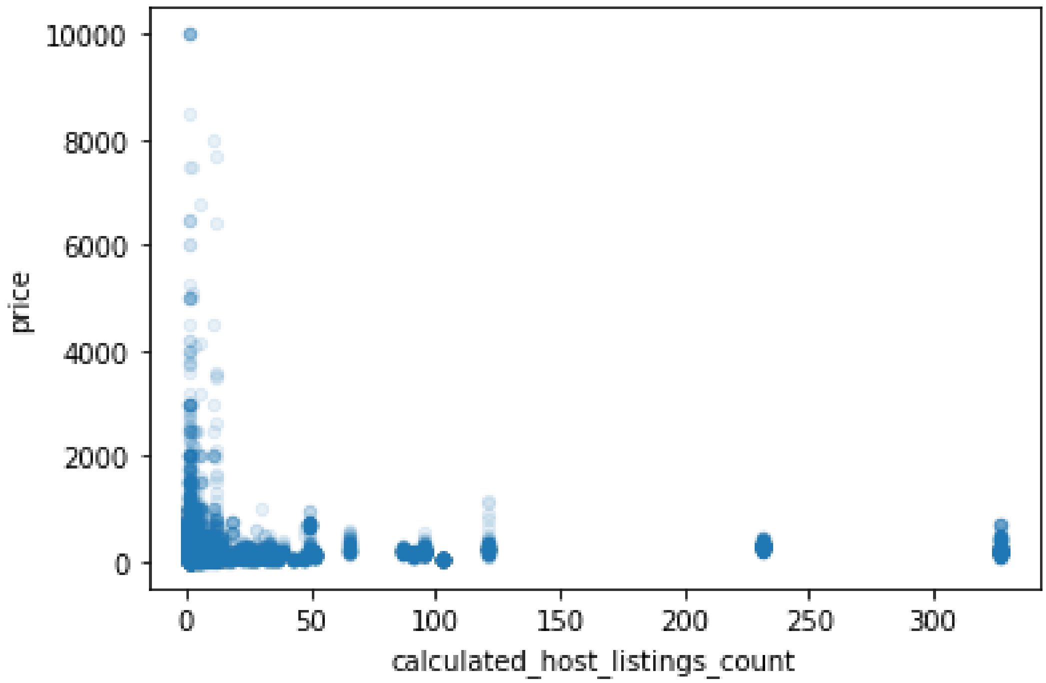
[98]: <matplotlib.axes._subplots.AxesSubplot at 0x1a28696780>



price and availability_365: no correlation

[99]:
```
airbnb.plot(kind="scatter", x="calculated_host_listings_count", y="price",
             alpha=0.1)
```

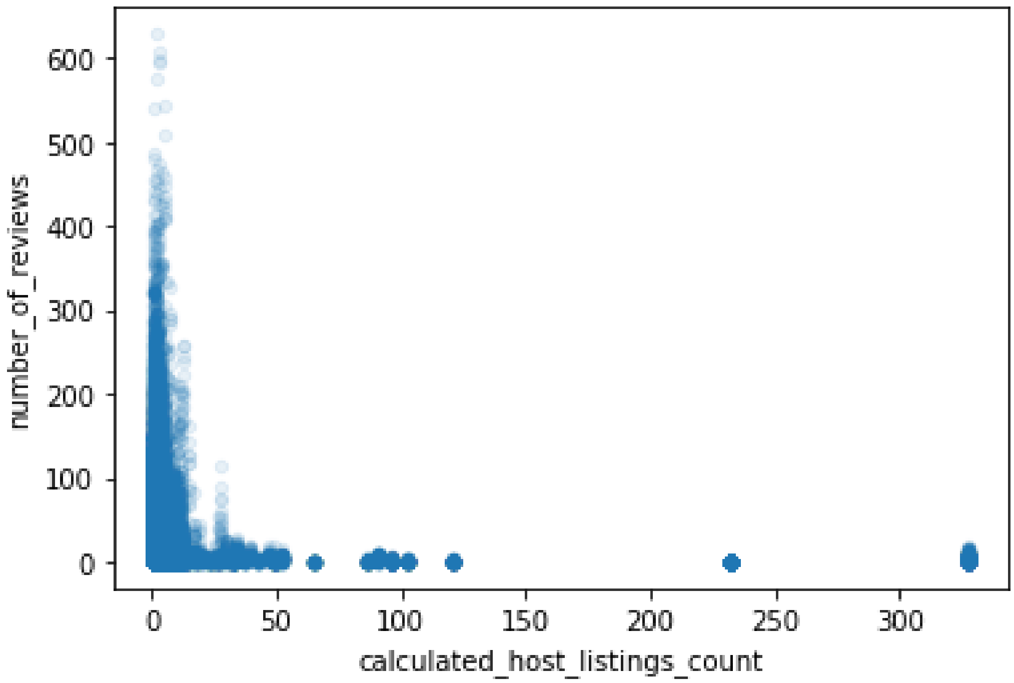
[99]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2e25a908>



calculated_host_listings_count and price: positive correlation

[100]:
```
airbnb.plot(kind="scatter", x="calculated_host_listings_count",␣
↪y="number_of_reviews",
             alpha=0.1)
```

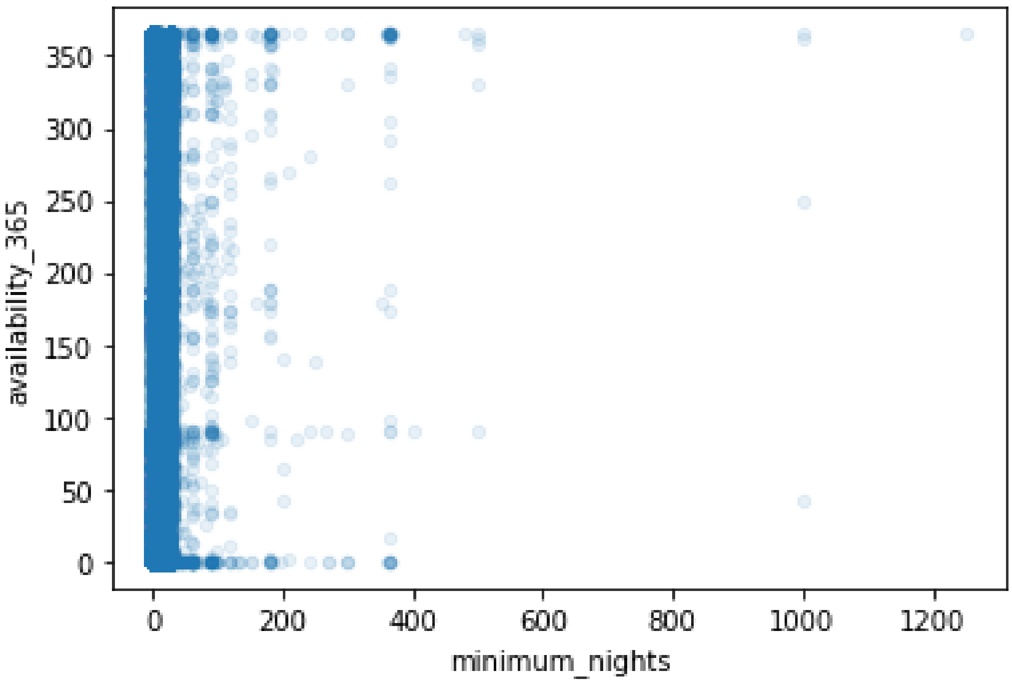
[100]: <matplotlib.axes._subplots.AxesSubplot at 0x1a289a7d68>



calculated_host_listings_count and number_of_reviews: positive correlation

[101]:
```
airbnb.plot(kind="scatter", x="minimum_nights", y="availability_365",
             alpha=0.1)
```

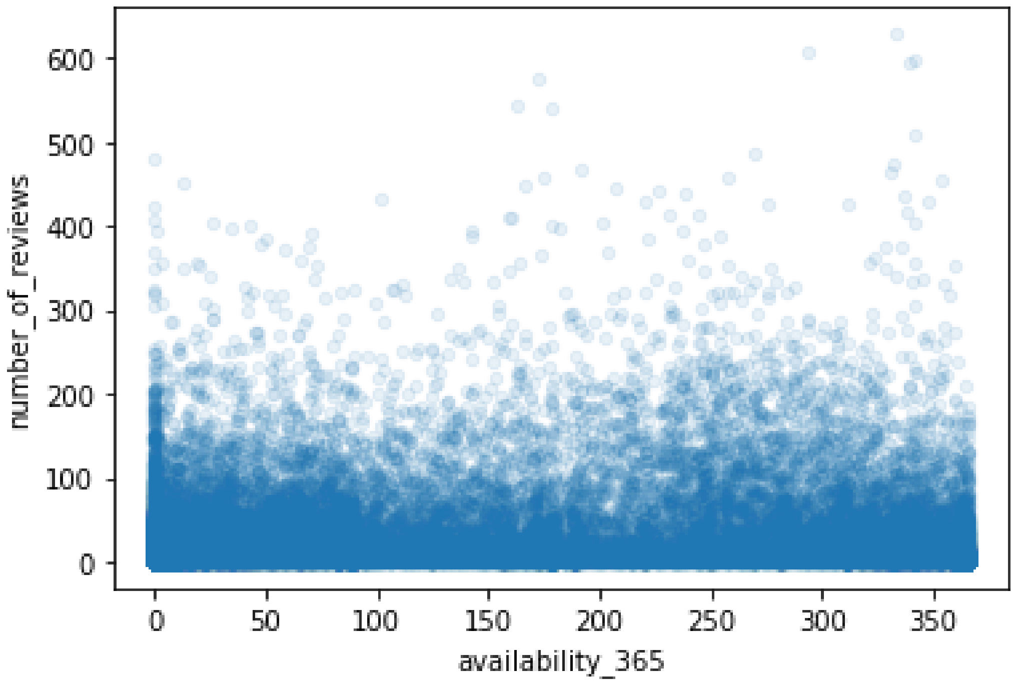
[101]: <matplotlib.axes._subplots.AxesSubplot at 0x1a2f94e588>

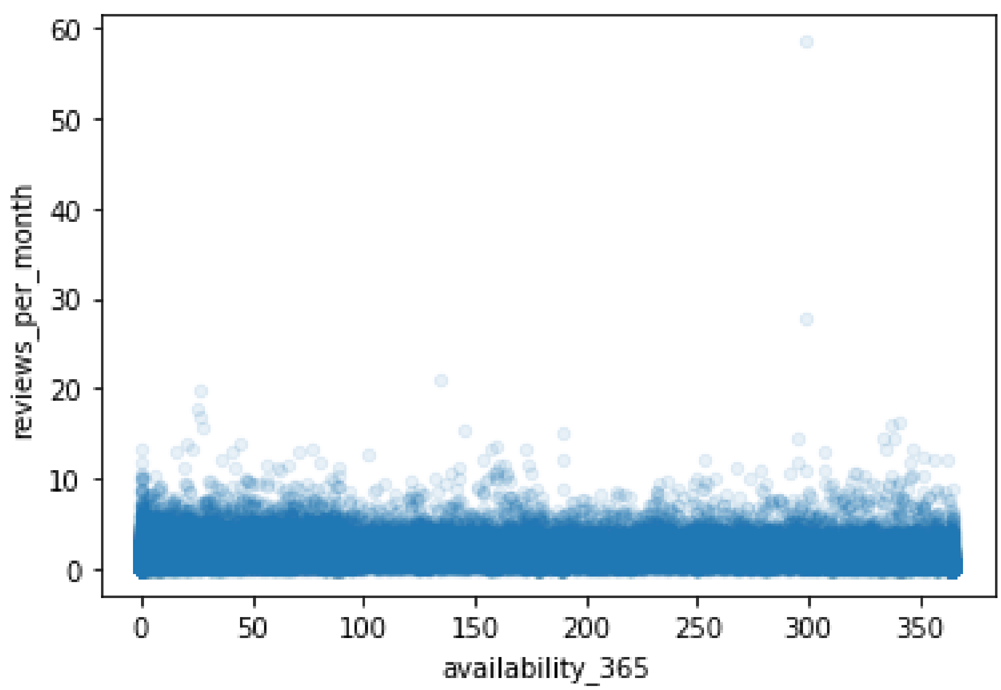


minimum_nights and availability_365: unclear correlation

[102]:
```
airbnb.plot(kind="scatter", x="availability_365", y="number_of_reviews",
            alpha=0.1)
airbnb.plot(kind="scatter", x="availability_365", y="reviews_per_month",
            alpha=0.1)
```

[102]: `<matplotlib.axes._subplots.AxesSubplot at 0x1a30e7c080>`





availability_365 and number_of_reviews: unclear correlation

availability_365 and reviews_per_month: possibly negative correlation

Reviews per month and the number of reviews appears to have a positive correlation, which makes sense given that a higher number of reviews per month would end up increasing the total number of reviews. Other pairs of features such as minimum nights and price, host listings count and price, and host listings count and number of reviews look to only have slight positive correlation. It can be hard to tell because oftentimes the data will include a density of points that look like a straight line.

There don't appear to be any features that have an overt negative correlation. A case could be made for availability and the number of reviews per month, where a higher number of available days theoretically should correlate to a low number of reviews per month. After all, a higher number of available days means people aren't reserving the listing as much, so a lower number of guests should result in a low number of reviews per month. Given there are other factors that impact the number of reviews per month, like customer dissatisfaction or laziness, the correlation between availability and number of reviews per month is very hard to see on the graph.

3 [25 pts] Prepare the Data

3.0.1 [5 pts] Augment the dataframe with two other features which you think would be useful

[103]:
```
airbnb["reviews_squared_per_month"] = airbnb["number_of_reviews"] *␣
 ↪airbnb["reviews_per_month"]
airbnb["nights_available_one_stay"] = airbnb["availability_365"] -␣
 ↪airbnb["minimum_nights"]
```

3.0.2 [5 pts] Set aside 20% of the data as test test (80% train, 20% test).

[104]:
```
airbnb = airbnb.drop(columns=['id','neighbourhood','latitude','longitude'])
airbnb_x = airbnb.drop(columns=["price"])
airbnb_y = airbnb["price"]
x_train, x_test, y_train, y_test = train_test_split(airbnb_x, airbnb_y,␣
 ↪test_size=0.2, random_state=42)
```

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

[105]:
```
incomplete_rows = airbnb[airbnb.isnull().any(axis=1)].head()
incomplete_rows
```

[105]:
```
   neighbourhood_group        room_type  price  minimum_nights  \
2            Manhattan     Private room    150               3
19           Manhattan  Entire home/apt    190               7
26           Manhattan     Private room     80               4
```

```
36           Brooklyn     Private room     35              60
38           Brooklyn     Private room    150               1

    number_of_reviews  reviews_per_month  calculated_host_listings_count  \
2                   0                NaN                               1
19                  0                NaN                               2
26                  0                NaN                               1
36                  0                NaN                               1
38                  0                NaN                               1

    availability_365  reviews_squared_per_month  nights_available_one_stay
2                365                        NaN                        362
19               249                        NaN                        242
26                 0                        NaN                         -4
36               365                        NaN                        305
38               365                        NaN                        364
```

[106]:
```python
incomplete_rows["reviews_per_month"].fillna(0, inplace=True)
incomplete_rows.head()
```

[106]:
```
   neighbourhood_group        room_type  price  minimum_nights  \
2            Manhattan     Private room    150               3
19           Manhattan  Entire home/apt    190               7
26           Manhattan     Private room     80               4
36            Brooklyn     Private room     35              60
38            Brooklyn     Private room    150               1

    number_of_reviews  reviews_per_month  calculated_host_listings_count  \
2                   0                0.0                               1
19                  0                0.0                               2
26                  0                0.0                               1
36                  0                0.0                               1
38                  0                0.0                               1

    availability_365  reviews_squared_per_month  nights_available_one_stay
2                365                        NaN                        362
19               249                        NaN                        242
26                 0                        NaN                         -4
36               365                        NaN                        305
38               365                        NaN                        364
```

I chose to replace the null values with 0. I noticed that the null values occured in the 'reviews_per_month' column and inferred that it was because the value in the 'number_of_reviews' column was 0 and whatever calculation outputted the number of reviews per month would output a null value. When the number of reviews was 0, I thought it was reasonable to set the number of reviews per month to 0 as well instead of a null value.

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

[107]:
```
airbnb_num = x_train.drop(["neighbourhood_group", "room_type"], axis=1)
airbnb_num.head()
nights_ix, num_reviews_ix, reviewspm_ix, avail_ix = 1, 2, 3, 5
```

[108]:
```
airbnb_imputer = SimpleImputer(strategy="constant", fill_value=0)

class Augment_Features1(BaseEstimator, TransformerMixin):
    def __init__(self, add_reviews_squared_per_month = True):
        self.add_reviews_squared_per_month = add_reviews_squared_per_month
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        nights_available_one_stay = X[:, avail_ix] - X[:, nights_ix]
        if self.add_reviews_squared_per_month:
            reviews_squared_per_month = X[:, num_reviews_ix] * X[:,␣
 ↪reviewspm_ix]
            return np.c_[X, nights_available_one_stay,␣
 ↪reviews_squared_per_month]
        else:
            return np.c_[X, nights_available_one_stay]
#airbnb_attr_adder = Augment_Features1()
#airbnb_extra_attribs = airbnb_attr_adder.transform(x_train.values)

airbnb_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy="constant", fill_value=1)),
    ('attribs_adder', Augment_Features1()),
    ('std_scaler', StandardScaler()),
])
airbnb_num_tr = airbnb_pipeline.fit_transform(airbnb_num)
num_features = list(airbnb_num)
cat_features = ["neighbourhood_group", "room_type"]

a_full_pipeline = ColumnTransformer([
    ("num", airbnb_pipeline, num_features),
    ("cat", OneHotEncoder(), cat_features)
])
airbnb_prepared = a_full_pipeline.fit_transform(x_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 MSE. Provide both test and train set MSE values.

[109]:

```
a_lin_reg = LinearRegression()
a_lin_reg.fit(airbnb_prepared, y_train)

a_data = x_test.iloc[:5]
a_labels = y_train.iloc[:5]
a_data_prepared = a_full_pipeline.transform(a_data)

print("Predictions:", a_lin_reg.predict(a_data_prepared))
print("Actual labels:", list(a_labels))
```

```
Predictions: [182.95703125  56.34765625 112.37890625 266.76953125 223.06640625]
Actual labels: [295, 70, 58, 75, 38]
```

[111]:

```
a_preds = a_lin_reg.predict(airbnb_prepared)
a_mse = mean_squared_error(y_train, a_preds)
a_rmse = np.sqrt(a_mse)
print("Mean squared loss:", a_rmse)
```

```
Mean squared loss: 235.7809852797133
```

[ ]:

```

```