BuildModelingDataset

August 16, 2023

1 Lab 2: Building a Modeling Data Set

[1]:
```
import os
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_theme()
```

In this lab, you will complete the following tasks to build a modeling data set:

1. Load the Airbnb "listings" data set and identify the number of rows & columns
2. Remove features that are not currently useful for analysis; Modify features to make sure they are machine-comprehensible
3. Build a new regression label column by winsorizing outliers
4. Replace all missing values with means
5. Identify two features with the highest correlation with the label
6. Build appropriate bivariate plots between the highest correlated features and the label

1.1 Part 1. Load the Data

We will once again be working with the Airbnb NYC "listings" data set. Use the specified path and name of the file to load the data. Save it as a Pandas DataFrame called `df`.

[2]:
```
# Do not remove or edit the line below:
filename = os.path.join(os.getcwd(), "data", "listings.csv.gz")
```

Task: load the data and save it to DataFrame `df`.

[3]:
```
# YOUR CODE HERE
df = pd.read_csv(filename, header = 0)
```

```
/usr/local/lib/python3.6/dist-packages/IPython/core/interactiveshell.py:2728:
DtypeWarning: Columns (67) have mixed types.Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Task: Display the shape of `df` -- that is, the number of rows and columns.

[4]:
```
# YOUR CODE HERE
df.shape
```

[4]:
```
(38277, 74)
```

Task: Get a peek at the data by displaying the first few rows, as you usually do.

[5]:
```
# YOUR CODE HERE
df.head()
```

[5]:
```
     id                          listing_url       scrape_id last_scraped  \
0  2595  https://www.airbnb.com/rooms/2595  20211204143024   2021-12-05
1  3831  https://www.airbnb.com/rooms/3831  20211204143024   2021-12-05
2  5121  https://www.airbnb.com/rooms/5121  20211204143024   2021-12-05
3  5136  https://www.airbnb.com/rooms/5136  20211204143024   2021-12-05
4  5178  https://www.airbnb.com/rooms/5178  20211204143024   2021-12-05

                                          name  \
0                           Skylit Midtown Castle
1  Whole flr w/private bdrm, bath & kitchen(pls r...
2                                BlissArtsSpace!
3          Spacious Brooklyn Duplex, Patio + Garden
4                  Large Furnished Room Near B'way

                                       description  \
0  Beautiful, spacious skylit studio in the heart...
1  Enjoy 500 s.f. top floor in 1899 brownstone, w...
2  <b>The space</b><br />HELLO EVERYONE AND THANK...
3  We welcome you to stay in our lovely 2 br dupl...
4  Please dont expect the luxury here just a bas...

                            neighborhood_overview  \
0  Centrally located in the heart of Manhattan ju...
1  Just the right mix of urban center and local n...
2                                             NaN
3                                             NaN
4   Theater district, many restaurants around here.

                                       picture_url  host_id  \
0  https://a0.muscache.com/pictures/f0813a11-40b2...     2845
1  https://a0.muscache.com/pictures/e49999c2-9fd5...     4869
2  https://a0.muscache.com/pictures/2090980c-b68e...     7356
3  https://a0.muscache.com/pictures/miso/Hosting-...     7378
4  https://a0.muscache.com/pictures/12065/f070997...     8967

                             host_url  ... review_scores_communication  \
0  https://www.airbnb.com/users/show/2845  ...                        4.79
1  https://www.airbnb.com/users/show/4869  ...                        4.80
2  https://www.airbnb.com/users/show/7356  ...                        4.91
```

```
3  https://www.airbnb.com/users/show/7378  ...                          5.00
4  https://www.airbnb.com/users/show/8967  ...                          4.42

  review_scores_location review_scores_value license instant_bookable  \
0                   4.86                4.41     NaN                 f
1                   4.71                4.64     NaN                 f
2                   4.47                4.52     NaN                 f
3                   4.50                5.00     NaN                 f
4                   4.87                4.36     NaN                 f

  calculated_host_listings_count calculated_host_listings_count_entire_homes  \
0                              3                                             3
1                              1                                             1
2                              2                                             0
3                              1                                             1
4                              1                                             0

  calculated_host_listings_count_private_rooms  \
0                                            0
1                                            0
2                                            2
3                                            0
4                                            1

  calculated_host_listings_count_shared_rooms reviews_per_month
0                                           0              0.33
1                                           0              4.86
2                                           0              0.52
3                                           0              0.02
4                                           0              3.68

[5 rows x 74 columns]
```

1.2 Part 2. Feature Selection and Engineering

We won't need the data fields that contain free, unstructured text. For example, we wont need the columns that contain apartment descriptions supplied by the host, customer reviews, or descriptions of the neighborhoods in which a listing is located.

The code cell below contains a list containing the names of *unstructured text* columns.

[6]:
```
unstr_text_colnames = ['description', 'name', 'neighborhood_overview',␣
↪'host_about', 'host_name', 'host_location']
```

Task: Drop the columns with the specified names, *in place* (that is, make sure this change applies to the original DataFrame `df`, instead of creating a temporary new DataFrame with fewer columns).

[7]:
```
# YOUR CODE HERE

```

```
# df.drop? <- explanation

# drop the columns from the list above, inplace to make changes to df
df.drop(columns = unstr_text_colnames, inplace = True)
```

Task: Display the shape of the data to verify that the new number of columns is what you expected.

[8]:
```
# YOUR CODE HERE
df.shape
```

[8]:
```
(38277, 68)
```

We will furthermore get rid of all the columns which contain website addresses (URLs).

Task: Create a list which contains the names of columns that contain URLs. Save the resulting list to variable `url_colnames`.

Tip: There are different ways to accomplish this, including using Python list comprehensions

[9]:
```
# YOUR CODE HERE

# https://www.statology.org/pandas-select-columns-containing-string/

# filter selects columns that contain url
colnames = [df.filter(regex = 'url')]
print(colnames[0])

url_colnames = ['listing_url', 'picture_url', 'host_url', 'host_thumbnail_url',␣
 ↪'host_picture_url']
```

```
                                listing_url  \
0          https://www.airbnb.com/rooms/2595
1          https://www.airbnb.com/rooms/3831
2          https://www.airbnb.com/rooms/5121
3          https://www.airbnb.com/rooms/5136
4          https://www.airbnb.com/rooms/5178
...                                      ...
38272  https://www.airbnb.com/rooms/53662330
38273  https://www.airbnb.com/rooms/53662542
38274  https://www.airbnb.com/rooms/53662772
38275  https://www.airbnb.com/rooms/53663081
38276  https://www.airbnb.com/rooms/53665099

                                             picture_url  \
0      https://a0.muscache.com/pictures/f0813a11-40b2...
1      https://a0.muscache.com/pictures/e49999c2-9fd5...
2      https://a0.muscache.com/pictures/2090980c-b68e...
3      https://a0.muscache.com/pictures/miso/Hosting-...
4      https://a0.muscache.com/pictures/12065/f070997...
...                                                  ...
38272  https://a0.muscache.com/pictures/e2d56c2f-259b...
```

```
38273  https://a0.muscache.com/pictures/05f218bd-04ff...
38274  https://a0.muscache.com/pictures/b4d3d4bf-cffa...
38275  https://a0.muscache.com/pictures/d8b633e3-0d10...
38276  https://a0.muscache.com/pictures/prohost-api/H...

                                          host_url  \
0           https://www.airbnb.com/users/show/2845
1           https://www.airbnb.com/users/show/4869
2           https://www.airbnb.com/users/show/7356
3           https://www.airbnb.com/users/show/7378
4           https://www.airbnb.com/users/show/8967
...                                            ...
38272  https://www.airbnb.com/users/show/100146245
38273  https://www.airbnb.com/users/show/100146245
38274  https://www.airbnb.com/users/show/337879004
38275  https://www.airbnb.com/users/show/337879004
38276   https://www.airbnb.com/users/show/60105727

                                     host_thumbnail_url  \
0      https://a0.muscache.com/im/pictures/user/50fc5...
1      https://a0.muscache.com/im/users/4869/profile_...
2      https://a0.muscache.com/im/pictures/user/72a61...
3      https://a0.muscache.com/im/users/7378/profile_...
4      https://a0.muscache.com/im/users/8967/profile_...
...                                                  ...
38272  https://a0.muscache.com/im/pictures/user/1c48a...
38273  https://a0.muscache.com/im/pictures/user/1c48a...
38274  https://a0.muscache.com/im/pictures/user/a83a7...
38275  https://a0.muscache.com/im/pictures/user/a83a7...
38276  https://a0.muscache.com/im/pictures/user/9b902...

                                      host_picture_url
0      https://a0.muscache.com/im/pictures/user/50fc5...
1      https://a0.muscache.com/im/users/4869/profile_...
2      https://a0.muscache.com/im/pictures/user/72a61...
3      https://a0.muscache.com/im/users/7378/profile_...
4      https://a0.muscache.com/im/users/8967/profile_...
...                                                  ...
38272  https://a0.muscache.com/im/pictures/user/1c48a...
38273  https://a0.muscache.com/im/pictures/user/1c48a...
38274  https://a0.muscache.com/im/pictures/user/a83a7...
38275  https://a0.muscache.com/im/pictures/user/a83a7...
38276  https://a0.muscache.com/im/pictures/user/9b902...

[38277 rows x 5 columns]
```

Task: Drop the columns with the specified names contained in list `url_colnames` in place (that is, make sure this change applies to the original DataFrame `df`, instead of creating a temporary

new DataFrame object with fewer columns).

[10]:
```
# YOUR CODE HERE
df.drop(columns = url_colnames, inplace = True)
```

Task: Another property of this dataset is that the `price` column contains values that are listed as <currency_name><numeric_value>. For example, it contains values that look like this: `$120`.

Let's look at the first 15 unique values of this column.

Display the first 15 unique values of the `price` column:

[11]:
```
# YOUR CODE HERE
df['price'].unique
```

[11]:
```
<bound method Series.unique of 0        $150.00
1         $75.00
2         $60.00
3        $275.00
4         $68.00
          ...
38272     $79.00
38273     $76.00
38274    $116.00
38275    $106.00
38276    $689.00
Name: price, Length: 38277, dtype: object>
```

In order for us to use the prices for modeling, we will have to transform all values of this `price` feature into regular floats. We will first need to remove the dollar signs (in this case, the platform forces the currency to be the USD, so we do not need to worry about targeting, say, the Japanese Yen sign, nor about converting the values into USD). Furthermore, we need to remove commas from all values that are in the thousands or above: for example, `$2,500$`. Here is how to do both:

[12]:
```
df['price'] = df['price'].str.replace(',', '')
df['price'] = df['price'].str.replace('$', '')
df['price'] = df['price'].astype(float)
```

Let's display the first few unique values again, to make sure they are transformed:

[13]:
```
df['price'].unique()[:15]
```

[13]:
```
array([150.,  75.,  60., 275.,  68.,  98.,  89.,  65.,  62.,  90., 199.,
        96., 299., 140., 175.])
```

Well done! Our transformed dataset looks like this:

[14]:
```
df.head()
```

[14]:
```
     id       scrape_id last_scraped  host_id  host_since  host_response_time  \
0  2595  20211204143024   2021-12-05     2845  2008-09-09        within a day
1  3831  20211204143024   2021-12-05     4869  2008-12-07  a few days or more
2  5121  20211204143024   2021-12-05     7356  2009-02-03      within an hour
3  5136  20211204143024   2021-12-05     7378  2009-02-03        within a day
4  5178  20211204143024   2021-12-05     8967  2009-03-03        within a day

  host_response_rate host_acceptance_rate host_is_superhost  \
```

```
0               80%                 17%                f
1                9%                 69%                f
2              100%                100%                f
3              100%                 25%                f
4              100%                100%                f

  host_neighbourhood  ...  review_scores_communication  \
0            Midtown  ...                        4.79
1      Clinton Hill  ...                        4.80
2  Bedford-Stuyvesant  ...                        4.91
3   Greenwood Heights  ...                        5.00
4      Hell's Kitchen  ...                        4.42

   review_scores_location review_scores_value license instant_bookable  \
0                    4.86                4.41     NaN                f
1                    4.71                4.64     NaN                f
2                    4.47                4.52     NaN                f
3                    4.50                5.00     NaN                f
4                    4.87                4.36     NaN                f

  calculated_host_listings_count calculated_host_listings_count_entire_homes  \
0                              3                                             3
1                              1                                             1
2                              2                                             0
3                              1                                             1
4                              1                                             0

  calculated_host_listings_count_private_rooms  \
0                                            0
1                                            0
2                                            2
3                                            0
4                                            1

   calculated_host_listings_count_shared_rooms  reviews_per_month
0                                            0               0.33
1                                            0               4.86
2                                            0               0.52
3                                            0               0.02
4                                            0               3.68

[5 rows x 63 columns]
```

1.3 Part 3. Create a (Winsorized) Label Column

Assume that your goal is to use this dataset to fit a regression model that predicts the price under which a given space is listed.

Task: Create a new version of the `price` column, named `label_price`, in which we replace the top and bottom 1% outlier values with the corresponding percentile value. Add this new column to the DataFrame `df`.

Remember, you will first need to load the `stats` module from the `scipy` package:

[15]:
```
# YOUR CODE HERE - import the necessary package
from scipy import stats
```

[16]:
```
# YOUR CODE HERE  - add the new column to the DataFrame
df['label_price'] = stats.mstats.winsorize(df['price'], limits = [0.01, 0.01])
```

Let's verify that a new column got added to the DataFrame:

[17]:
```
df.head()
```

[17]:

	id	scrape_id	last_scraped	host_id	host_since	host_response_time
0	2595	20211204143024	2021-12-05	2845	2008-09-09	within a day
1	3831	20211204143024	2021-12-05	4869	2008-12-07	a few days or more
2	5121	20211204143024	2021-12-05	7356	2009-02-03	within an hour
3	5136	20211204143024	2021-12-05	7378	2009-02-03	within a day
4	5178	20211204143024	2021-12-05	8967	2009-03-03	within a day

	host_response_rate	host_acceptance_rate	host_is_superhost
0	80%	17%	f
1	9%	69%	f
2	100%	100%	f
3	100%	25%	f
4	100%	100%	f

	host_neighbourhood	...	review_scores_location	review_scores_value
0	Midtown	...	4.86	4.41
1	Clinton Hill	...	4.71	4.64
2	Bedford-Stuyvesant	...	4.47	4.52
3	Greenwood Heights	...	4.50	5.00
4	Hell's Kitchen	...	4.87	4.36

	license	instant_bookable	calculated_host_listings_count
0	NaN	f	3
1	NaN	f	1
2	NaN	f	2
3	NaN	f	1
4	NaN	f	1

	calculated_host_listings_count_entire_homes
0	3
1	1
2	0
3	1
4	0

```
  calculated_host_listings_count_private_rooms  \
0                                            0
1                                            0
2                                            2
3                                            0
4                                            1

  calculated_host_listings_count_shared_rooms  reviews_per_month  label_price
0                                           0               0.33        150.0
1                                           0               4.86         75.0
2                                           0               0.52         60.0
3                                           0               0.02        275.0
4                                           0               3.68         68.0

[5 rows x 64 columns]
```

Task: Check that the values of `price` and `label_price` are *not* identical. Do this by subtracting the two columns and printing the *length* of the array (using the `len()` function) of *unique values* of the resulting difference. Note: If all values are identical, the difference would contain only one unique value -- zero. If this is the case, outlier removal did not work.

[18]:
```
# YOUR CODE HERE

noidentical = (df['price'] - df['label_price']).unique()
print(len(noidentical))
```

```
206
```

1.4 Part 4. Replace the Missing Values With Means

1.4.1 a. Identifying missingness

Task: Check if a given value in any data cell is missing, and sum up the resulting values (`True/False`) by columns. Save this sum to variable `nan_count`. Print the results.

[19]:
```
nan_count = np.sum(df.isnull())
nan_count
```

[19]:
```
id                                              0
scrape_id                                       0
last_scraped                                    0
host_id                                         0
host_since                                     34
                                              ...
calculated_host_listings_count_entire_homes     0
calculated_host_listings_count_private_rooms    0
calculated_host_listings_count_shared_rooms     0
reviews_per_month                            9504
label_price                                     0
Length: 64, dtype: int64
```

Those are more columns than we can eyeball! For this exercise, we don't care about the number of missing values -- we just want to get a list of columns that have *any*.

Task: From variable `nan_count`, create a new series called `nan_detected` that contains `True/False` values that indicate whether the number of missing values is *not zero*:

[20]:
```
nan_detected = nan_count != 0
nan_detected
```

[20]:
```
id                                                False
scrape_id                                         False
last_scraped                                      False
host_id                                           False
host_since                                         True
                                                  ...
calculated_host_listings_count_entire_homes       False
calculated_host_listings_count_private_rooms      False
calculated_host_listings_count_shared_rooms       False
reviews_per_month                                  True
label_price                                       False
Length: 64, dtype: bool
```

Since replacing the missing values with the mean only makes sense for the numerically valued columns (and not for strings, for example), let us create another condition: the *type* of the column must be `int` or `float`.

Task: Create a series that contains `True` if the type of the column is either `int64` or `float64`. Save the result to variable `is_int_or_float`.

[21]:
```
# get columns of nan_count
print(nan_count.index)

print("\n")

# dtypes of the columns
is_int_or_float = df[nan_count.index].dtypes

# stores true/false values to see if the dtype is int or float
is_int_or_float = (is_int_or_float == int) | (is_int_or_float == float)
is_int_or_float
```

```
Index(['id', 'scrape_id', 'last_scraped', 'host_id', 'host_since',
       'host_response_time', 'host_response_rate', 'host_acceptance_rate',
       'host_is_superhost', 'host_neighbourhood', 'host_listings_count',
       'host_total_listings_count', 'host_verifications',
       'host_has_profile_pic', 'host_identity_verified', 'neighbourhood',
       'neighbourhood_cleansed', 'neighbourhood_group_cleansed', 'latitude',
       'longitude', 'property_type', 'room_type', 'accommodates', 'bathrooms',
       'bathrooms_text', 'bedrooms', 'beds', 'amenities', 'price',
       'minimum_nights', 'maximum_nights', 'minimum_minimum_nights',
       'maximum_minimum_nights', 'minimum_maximum_nights',
       'maximum_maximum_nights', 'minimum_nights_avg_ntm',
```

```
 'maximum_nights_avg_ntm', 'calendar_updated', 'has_availability',
 'availability_30', 'availability_60', 'availability_90',
 'availability_365', 'calendar_last_scraped', 'number_of_reviews',
 'number_of_reviews_ltm', 'number_of_reviews_l30d', 'first_review',
 'last_review', 'review_scores_rating', 'review_scores_accuracy',
 'review_scores_cleanliness', 'review_scores_checkin',
 'review_scores_communication', 'review_scores_location',
 'review_scores_value', 'license', 'instant_bookable',
 'calculated_host_listings_count',
 'calculated_host_listings_count_entire_homes',
 'calculated_host_listings_count_private_rooms',
 'calculated_host_listings_count_shared_rooms', 'reviews_per_month',
 'label_price'],
dtype='object')
```

[21]:
```
id                                               True
scrape_id                                        True
last_scraped                                    False
host_id                                          True
host_since                                      False
                                                ...
calculated_host_listings_count_entire_homes      True
calculated_host_listings_count_private_rooms     True
calculated_host_listings_count_shared_rooms      True
reviews_per_month                                True
label_price                                      True
Length: 64, dtype: bool
```

Task: Combine the two binary series values into a new series named `to_impute`. It will contain the value `True` if a column contains missing values *and* is of type 'int' or 'float'

[22]:
```
to_impute = nan_detected & is_int_or_float
to_impute
```

[22]:
```
id                                              False
scrape_id                                       False
last_scraped                                    False
host_id                                         False
host_since                                      False
                                                ...
calculated_host_listings_count_entire_homes     False
calculated_host_listings_count_private_rooms    False
calculated_host_listings_count_shared_rooms     False
reviews_per_month                                True
label_price                                     False
Length: 64, dtype: bool
```

Finally, let's display a list that contains just the selected column names:

[23]:
```
df.columns[to_impute]
```

[23]:
```
Index(['host_listings_count', 'host_total_listings_count', 'bathrooms',
       'bedrooms', 'beds', 'minimum_minimum_nights', 'maximum_minimum_nights',
       'minimum_maximum_nights', 'maximum_maximum_nights',
       'minimum_nights_avg_ntm', 'maximum_nights_avg_ntm', 'calendar_updated',
       'review_scores_rating', 'review_scores_accuracy',
       'review_scores_cleanliness', 'review_scores_checkin',
       'review_scores_communication', 'review_scores_location',
       'review_scores_value', 'reviews_per_month'],
      dtype='object')
```

We just identified and displayed the list of candidate columns for potentially replacing missing values with the column mean.

Assume that you have decided that it is safe to impute the values for `host_listings_count`, `host_total_listings_count`, `bathrooms`, `bedrooms`, and `beds`:

[24]:
```
to_impute_selected = ['host_listings_count', 'host_total_listings_count',␣
↪'bathrooms',
      'bedrooms', 'beds']
```

1.4.2 b. Keeping record of the missingness: creating dummy variables

As a first step, you will now create dummy variables indicating missingness of the values.

Task: Store the `True/False` series that indicate missingness of any value in a given column as a new variable called `<original-column-name>_na`.

[25]:
```
for colname in to_impute_selected:
    # YOUR CODE HERE - complete the loop
    df['to_impute_selected_na'] = colname
```

Check that the DataFrame contains the new variables:

[26]:
```
df.head()
```

[26]:

	id	scrape_id	last_scraped	host_id	host_since	host_response_time	host_response_rate	host_acceptance_rate	host_is_superhost	host_neighbourhood	...	review_scores_value	license	instant_bookable
0	2595	20211204143024	2021-12-05	2845	2008-09-09	within a day	80%	17%	f	Midtown	...	4.41	NaN	f
1	3831	20211204143024	2021-12-05	4869	2008-12-07	a few days or more	9%	69%	f					
2	5121	20211204143024	2021-12-05	7356	2009-02-03	within an hour	100%	100%	f					
3	5136	20211204143024	2021-12-05	7378	2009-02-03	within a day	100%	25%	f					
4	5178	20211204143024	2021-12-05	8967	2009-03-03	within a day	100%	100%	f					

```
1        Clinton Hill  ...                 4.64      NaN                f
2  Bedford-Stuyvesant  ...                 4.52      NaN                f
3   Greenwood Heights  ...                 5.00      NaN                f
4      Hell's Kitchen  ...                 4.36      NaN                f

  calculated_host_listings_count calculated_host_listings_count_entire_homes  \
0                              3                                            3
1                              1                                            1
2                              2                                            0
3                              1                                            1
4                              1                                            0

  calculated_host_listings_count_private_rooms  \
0                                            0
1                                            0
2                                            2
3                                            0
4                                            1

  calculated_host_listings_count_shared_rooms reviews_per_month  label_price  \
0                                           0              0.33        150.0
1                                           0              4.86         75.0
2                                           0              0.52         60.0
3                                           0              0.02        275.0
4                                           0              3.68         68.0

   to_impute_selected_na
0                   beds
1                   beds
2                   beds
3                   beds
4                   beds

[5 rows x 65 columns]
```

1.4.3 c. Replacing the missing values with mean values of the column

Task: Fill the missing values of the selected few columns with the corresponding mean value.

[27]:
```
# replace the null values with the mean for each column
for colname in to_impute_selected:
    df[colname].fillna(value = df[colname].mean(), inplace = True)
```

Check your results below. The code displays the count of missing values for each of the selected columns.

[28]:
```
for colname in to_impute_selected:
    print("{} missing values count :{}".format(colname, np.sum(df[colname].
 ↪isnull(), axis = 0)))
```

```
host_listings_count missing values count :0
host_total_listings_count missing values count :0
bathrooms missing values count :38277
bedrooms missing values count :0
beds missing values count :0
```

Why did the `bathrooms` column retain missing values after our imputation?

Task: List the unique values of the `bathrooms` column.

[29]:
```
# YOUR CODE HERE - returning unique values of bathroom
df['bathrooms'].unique()
```

[29]:
```
array([nan])
```

The column did not contain a single value (except the `NaN` indicator) to begin with.

1.5 Part 5. Identify Features With the Highest Correlation With the Label

Your next goal is to figure out which features in the data correlate most with the label.

In the next few cells, we will demonstrate how to use the Pandas `corr()` method to get a list of correlation coefficients between `label` and all other (numerical) features.

Let's first glance at what the `corr()` method does:

[30]:
```
df.corr().head()
```

[30]:
```
                                  id     scrape_id       host_id  \
id                      1.000000e+00 -4.269620e-13  5.861676e-01
scrape_id              -4.269620e-13  1.000000e+00  2.367225e-13
host_id                 5.861676e-01  2.367225e-13  1.000000e+00
host_listings_count     1.298621e-01 -2.061273e-14  3.189206e-02
host_total_listings_count  1.298621e-01 -2.061273e-14  3.189206e-02

                          host_listings_count  host_total_listings_count  \
id                               1.298621e-01               1.298621e-01
scrape_id                       -2.061273e-14              -2.061273e-14
host_id                          3.189206e-02               3.189206e-02
host_listings_count              1.000000e+00               1.000000e+00
host_total_listings_count        1.000000e+00               1.000000e+00

                              latitude     longitude  accommodates  \
id                        1.000083e-02  8.708041e-02  3.540148e-02
scrape_id                 7.448373e-13 -1.544987e-11  1.251408e-14
host_id                   4.148254e-02  1.162017e-01  2.722884e-02
host_listings_count       3.475008e-02 -8.842627e-02 -2.620826e-02
host_total_listings_count  3.475008e-02 -8.842627e-02 -2.620826e-02

                          bathrooms      bedrooms  ...  \
id                              NaN  4.502641e-02  ...
scrape_id                       NaN  1.094740e-13  ...
host_id                         NaN  2.201904e-02  ...
host_listings_count             NaN -1.709828e-02  ...
```

```
host_total_listings_count        NaN -1.709828e-02  ...

                          review_scores_checkin  review_scores_communication  \
id                             -9.156486e-02               -1.195007e-01
scrape_id                       1.379149e-13                9.055966e-14
host_id                        -1.488953e-01               -1.742021e-01
host_listings_count            -1.701258e-02               -5.031839e-02
host_total_listings_count      -1.701258e-02               -5.031839e-02

                          review_scores_location  review_scores_value  \
id                              3.222227e-03        -7.080059e-02
scrape_id                       1.895615e-13         9.019724e-14
host_id                        -7.863950e-02        -1.333992e-01
host_listings_count             6.381593e-03        -7.390664e-02
host_total_listings_count       6.381593e-03        -7.390664e-02

                          calculated_host_listings_count  \
id                                          2.366733e-01
scrape_id                                  -5.055182e-14
host_id                                     1.575424e-01
host_listings_count                         4.294398e-01
host_total_listings_count                   4.294398e-01

                          calculated_host_listings_count_entire_homes  \
id                                                        1.371325e-01
scrape_id                                                 2.212092e-14
host_id                                                   2.524284e-02
host_listings_count                                       5.418772e-01
host_total_listings_count                                 5.418772e-01

                          calculated_host_listings_count_private_rooms  \
id                                                         2.118813e-01
scrape_id                                                 -4.315383e-14
host_id                                                    1.931984e-01
host_listings_count                                        1.491464e-01
host_total_listings_count                                  1.491464e-01

                          calculated_host_listings_count_shared_rooms  \
id                                                        4.671123e-02
scrape_id                                                -9.152507e-15
host_id                                                   7.830736e-02
host_listings_count                                      -1.594956e-02
host_total_listings_count                                -1.594956e-02

                          reviews_per_month   label_price
id                             2.316854e-01  7.906593e-02
scrape_id                      5.899236e-15 -3.138348e-14
```

```
host_id                          2.084392e-01  4.053291e-02
host_listings_count             -2.095984e-02  1.310429e-01
host_total_listings_count       -2.095984e-02  1.310429e-01

[5 rows x 41 columns]
```

The result is a computed *correlation matrix*. The values on the diagonal are all equal to 1, and the matrix is symmetrical with respect to the diagonal (note that we are only printing the first five lines of it).

We only need to observe correlations of all features with *the label* (as opposed to every possible pairwise correlation).

Task: Save the `label_price` column of the correlation matrix to the variable `corrs`:

[31]:
```
# corr has the row examples of label_price
corrs = df.corr()['label_price']
corrs
```

[31]:
```
id                                7.906593e-02
scrape_id                        -3.138348e-14
host_id                           4.053291e-02
host_listings_count               1.310429e-01
host_total_listings_count         1.310429e-01
latitude                          4.329905e-02
longitude                        -2.069501e-01
accommodates                      5.006227e-01
bathrooms                                  NaN
bedrooms                          4.199613e-01
beds                              3.736971e-01
price                             7.111249e-01
minimum_nights                   -7.589208e-02
maximum_nights                   -9.728756e-04
minimum_minimum_nights           -3.803776e-02
maximum_minimum_nights            6.553784e-02
minimum_maximum_nights            6.581829e-02
maximum_maximum_nights            1.116868e-01
minimum_nights_avg_ntm            6.387517e-02
maximum_nights_avg_ntm            8.209898e-02
calendar_updated                           NaN
availability_30                   1.456894e-01
availability_60                   1.470082e-01
availability_90                   1.439066e-01
availability_365                  1.235559e-01
number_of_reviews                -4.197310e-02
number_of_reviews_ltm             2.757416e-02
number_of_reviews_l30d            2.158982e-02
review_scores_rating              4.319689e-02
review_scores_accuracy            5.358322e-03
review_scores_cleanliness         8.254405e-02
review_scores_checkin            -3.665125e-03
```

```
review_scores_communication                      1.206558e-04
review_scores_location                           9.724051e-02
review_scores_value                             -4.816654e-03
calculated_host_listings_count                  -1.581634e-02
calculated_host_listings_count_entire_homes      9.508782e-02
calculated_host_listings_count_private_rooms    -9.977978e-02
calculated_host_listings_count_shared_rooms     -4.333734e-02
reviews_per_month                                3.113557e-02
label_price                                      1.000000e+00
Name: label_price, dtype: float64
```

Task: Sort the values of the series we just obtained in the descending order.

[32]:
```
corrs_sorted = corrs.sort_values(ascending = False)
corrs_sorted
```

[32]:
```
label_price                                      1.000000e+00
price                                            7.111249e-01
accommodates                                     5.006227e-01
bedrooms                                         4.199613e-01
beds                                             3.736971e-01
availability_60                                  1.470082e-01
availability_30                                  1.456894e-01
availability_90                                  1.439066e-01
host_listings_count                              1.310429e-01
host_total_listings_count                        1.310429e-01
availability_365                                 1.235559e-01
maximum_maximum_nights                           1.116868e-01
review_scores_location                           9.724051e-02
calculated_host_listings_count_entire_homes      9.508782e-02
review_scores_cleanliness                        8.254405e-02
maximum_nights_avg_ntm                           8.209898e-02
id                                               7.906593e-02
minimum_maximum_nights                           6.581829e-02
maximum_minimum_nights                           6.553784e-02
minimum_nights_avg_ntm                           6.387517e-02
latitude                                         4.329905e-02
review_scores_rating                             4.319689e-02
host_id                                          4.053291e-02
reviews_per_month                                3.113557e-02
number_of_reviews_ltm                            2.757416e-02
number_of_reviews_l30d                           2.158982e-02
review_scores_accuracy                           5.358322e-03
review_scores_communication                      1.206558e-04
scrape_id                                       -3.138348e-14
maximum_nights                                  -9.728756e-04
review_scores_checkin                           -3.665125e-03
review_scores_value                             -4.816654e-03
calculated_host_listings_count                  -1.581634e-02
```

```
minimum_minimum_nights                          -3.803776e-02
number_of_reviews                               -4.197310e-02
calculated_host_listings_count_shared_rooms     -4.333734e-02
minimum_nights                                  -7.589208e-02
calculated_host_listings_count_private_rooms    -9.977978e-02
longitude                                       -2.069501e-01
bathrooms                                                 NaN
calendar_updated                                          NaN
Name: label_price, dtype: float64
```

Task: In the code cell below, save the *column names* for the top-2 correlation values to the list `top_two_corr` (not counting the correlation of `label` column with itself, nor the `price` column -- which is the `label` column prior to outlier removal). Add the column names to the list in the order in which they appear in the output above. Tip: `corrs_sorted` is a Pandas `Series` object, in which column names are the *index*.

[33]:
```
top_two_corr = [corrs_sorted.index[2], corrs_sorted.index[3]]
top_two_corr
```

[33]:
```
['accommodates', 'bedrooms']
```

1.6 Part 6. Produce Bivariate Plots for the Label and Its Top Correlates

We will use the `pairplot()` function in `seaborn` to plot the relationships between the two features we identified and the label.

Task: Create a DataFrame `df_sub` that contains only the selected three columns: the label, and the two columns which correlate with it the most.

[34]:
```
# Do not remove or edit the line below:
top_two_corr.append('label_price')
print(top_two_corr)


df_sub = df[top_two_corr]
df_sub
```

```
['accommodates', 'bedrooms', 'label_price']
```

[34]:

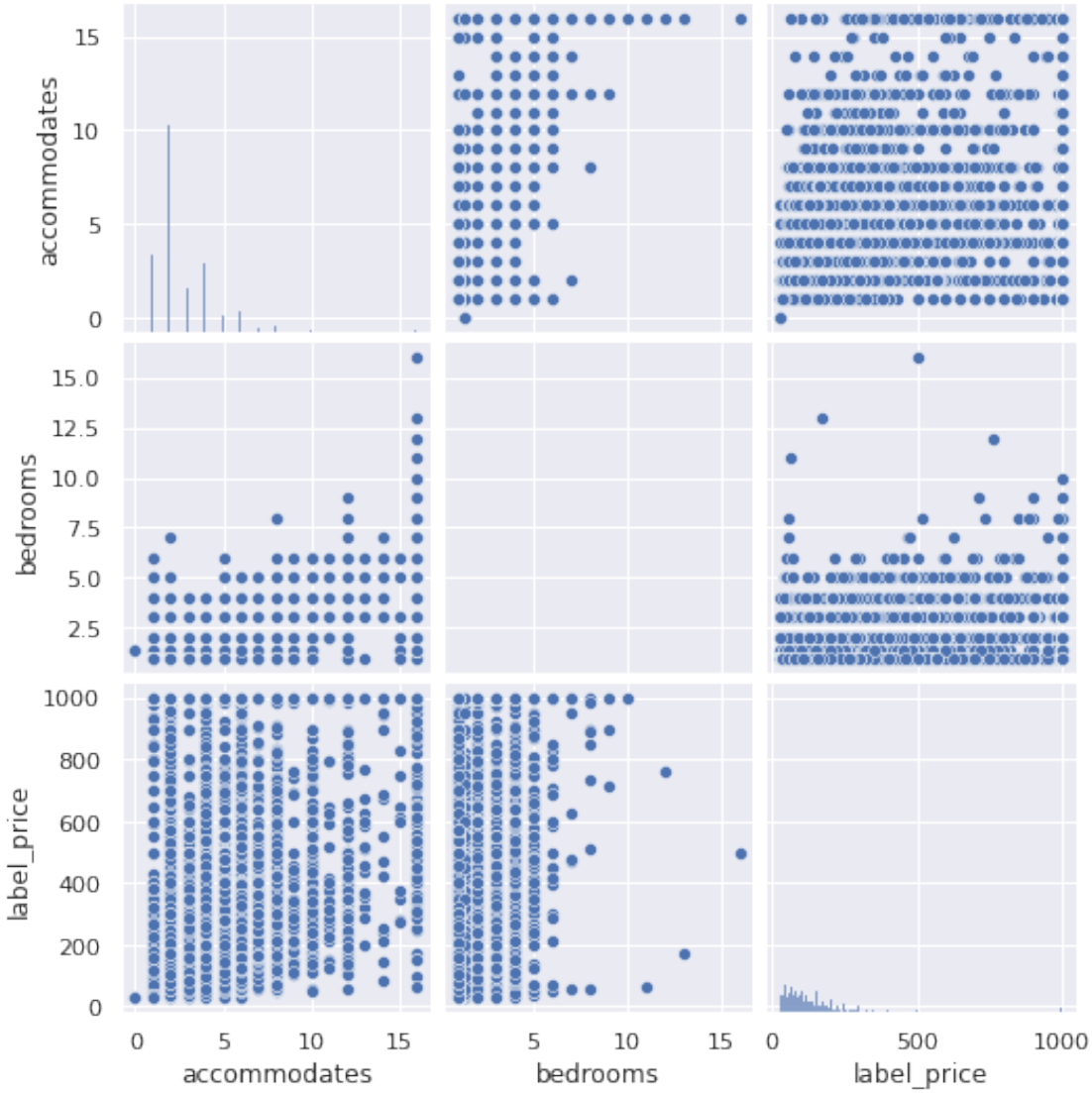
	accommodates	bedrooms	label_price
0	1	1.323567	150.0
1	3	1.000000	75.0
2	2	1.000000	60.0
3	4	2.000000	275.0
4	2	1.000000	68.0
...	...	...	...
38272	2	1.000000	79.0
38273	2	1.000000	76.0
38274	2	1.000000	116.0
38275	2	1.000000	106.0
38276	14	6.000000	689.0

```
[38277 rows x 3 columns]
```

Task: Create a `seaborn` pairplot of the data subset you just created

[35]:
```
# YOUR CODE HERE
sns.pairplot(data = df_sub)
```

[35]:
```
<seaborn.axisgrid.PairGrid at 0x7f49bcb829b0>
```

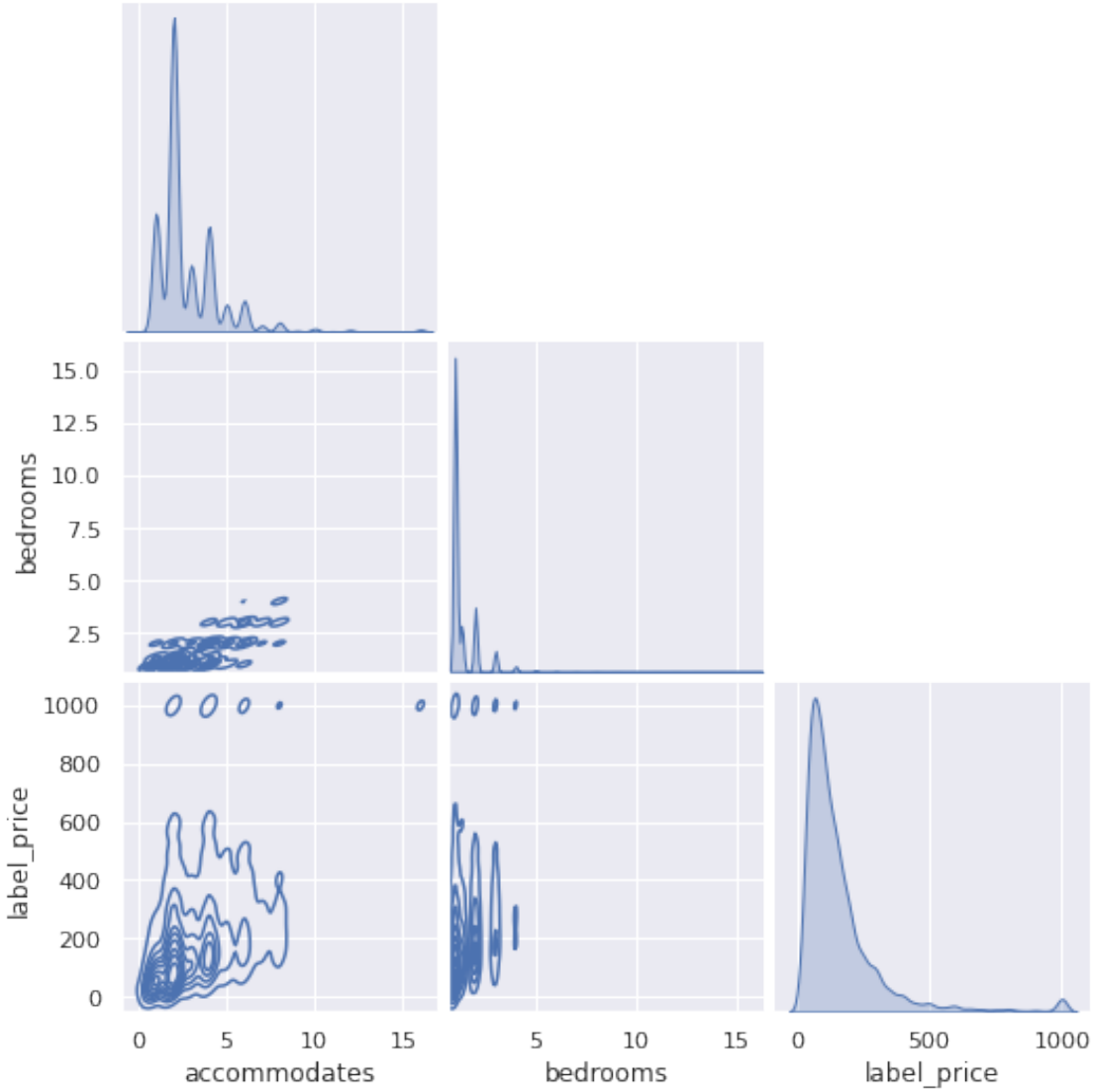


This one is not very easy to make sense of: the points overlap, but we do not have visibility into how densely they are stacked together.

Task: Repeat the `pairplot` exercise, this time specifying the *kernel density estimator* as the *kind* of the plot. Tip: use `kind = 'kde'` as a parameter of the `pairplot()` function. You could also specify `corner=True` to make sure you don't plot redundant (symmetrical) plots. Note: this one may take a while!

[36]:
```
# YOUR CODE HERE
sns.pairplot(data = df_sub, kind = 'kde', corner = True)
```

[36]:
```
<seaborn.axisgrid.PairGrid at 0x7f49b92a0278>
```



Analysis: Think about the possible interpretations of these plots. (Recall that our label encodes the listing price). What kind of stories does this data seem to be telling? Is the relationship what you thought it would be? Is there anything surprising or, on the contrary, reassuring about the plots? For example, how would you explain the relationship between the label and 'accommodates'? Is there a slight tilt to the points cluster, as the price goes up? What other patterns do you observe?

With the first pairplots, there seems to be an increasing pattern between accomodates and bathrooms. There is also a pattern betweem bathrooms and accomodates as majority of the points is on the left side. However, with accomodates and label_prices, there seems to be no correlation.

The same follows with the axis switched. It seems like no matter what, the price varies for each accomodation, with no specific pattern.

With the second pairplots, all the markings seem to be staying by the left side. With accomodates and label_price, the price seems to stay under $200, with accomodations under 5. There is outliers with $1000. There is one weird outlier where the accomodation passes 15. With the bedrooms and label_price, the price majorly stays under $400. No one seems to book a airbnb with more than 5 bedrooms, which makes sense. For both graphs, there are outliers where it is at a $1000. I wonder if these are from the same airbnb.

Overall, most air-bnbs seem to be similair in price and when it comes to bedrooms. Accommodates may vary.