Home

`ENVS615` - *Data Science Studio*

- [Dani Arribas-Bel `[@darribas]`]

Contact

> Dani Arribas-Bel - `D.Arribas-Bel [at] liverpool.ac.uk`
> Senior Lecturer in Geographic Data Science
> Office 508, Roxby Building,
> University of Liverpool - 74 Bedford St S,
> Liverpool, L69 7ZT,
> United Kingdom.

Overview

Delivery modes

The course is delivered following a flipped, hybrid model by which some of the content is available to students *before* class time, and some is delivered in group sessions together with the instructor. The former is called *asynchronous* delivery, while the latter is referred to as *synchronous*.

Throughout the course content, each learning object (typically subsections in the materials) is tagged with one of the following two labels for reference:

- `[Async]` To be completed asynchronously, on your own, and *before* class
- `[Sync]` To be completed synchronously, with course instructor, remotely through video link

Similarly, the overview below contains them for a quick, general sense at what is expected from you before we meet in synchronous sessions.

Schedule

Day 1 - Introduction

- `[Async]` Introduction to the course: *data, data, data*
- `[Async]` Computational building blocks

Day 2 - Tabular data

- `[Sync]` Manipulation
- `[Sync]` Visualisation
- `[Sync]` Advanced manipulation

Day 3 - Unsupervised learning

- Unsupervised learning

Contents

- [Async] Overview
- [Sync] Hands-on

Day 4 - Supervised learning

- Introduction
  - [Async] Overview
  - [Sync] Hands-on
- [Sync] Inference
- [Sync] Overfitting & cross-validation

Day 5

- Data Studio
  - [Async] Assignment brief
  - [Sync] Studio time

Programming Language

This course is entirely taught in the Python programming language.

Source: XKCD

There are several reasons why we have made this choice. Many of them are summarised nicely in this article by The Economist.

Infrastructure

This page covers a few technical aspects on how the course is built, kept up to date, and how you can create a computational environment to run all the code it includes.

Software stack

This course is best followed if you can not only read its content but also interact with its code and even branch out to write your own code and play on your own. For that, you will need to have installed on your computer a series of interconnected software packages; this is what we call a *stack*.

Instructions on how to install a software stack that allows you to run the materials of this course depend on the operating system you are using. Detailed guides are available for the main systems on the following resource, provided by the Geographic Data Science Lab:

@gdsl-ul/soft_install

Github repository

All the materials for this course and this website are available on the following Github repository:

@darribas/data_science_studio

If you are interested, you can download a compressed `.zip` file with the most up-to-date version of all the materials, including the HTML for this website at:

Icon made by Freepik from www.flaticon.com

@darribas/data_science_studio_zip

Containerised backend

The course is developed, built and tested using the `gds_env`, a containerised platform for Geographic Data Science. You can read more about the `gds_env` project at:

env

Binder

Binder is service that allows you to run scientific projects in the cloud for free. Binder can spin up *"ephemeral"* instances that allow you to run code on the browser without any local setup. It is possible to run the course on Binder by clicking on the button below:

launch binder

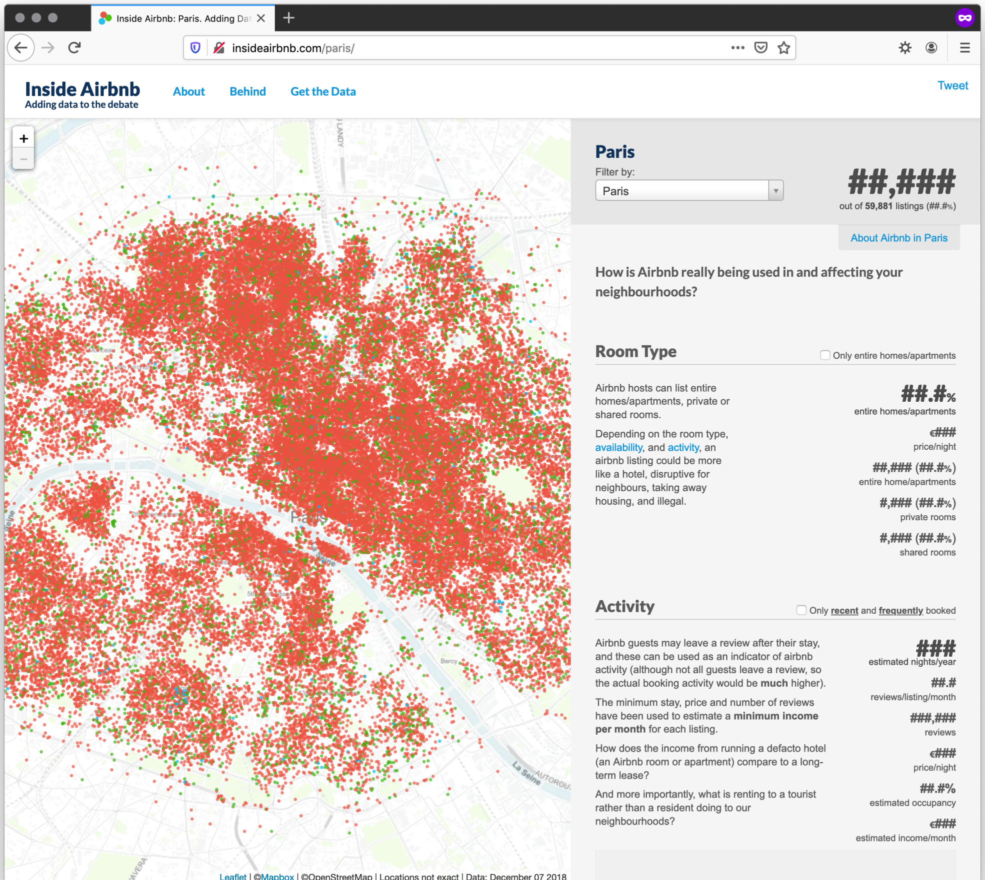
> **Warning**
>
> It is important to note Binder instances are *ephemeral* in the sense that the data and content created in a session is **NOT** saved anywhere and is deleted as soon as the browser tab is closed.

Binder is also the backend this website relies on when you click on the rocket icon () on a page with code. Remember, you can play with the code interactively but, once you close the tab, all the changes are lost.

Data

What

To maintain consistency and allow you to focus on the concepts we will be exploring throughout this course, we will stick to the same data throughout.



Source

The dataset we will use comes from [InsideAirBnb](#) and contains real estate properties listed for the area of Paris (France). Essentially every bit of information you can inquire about an AirBnb property is recorded in the original dataset. From there, we have processed it to simplify it so it is easier to illustrates the concepts we will be learning in the course.

Access

All the data files required for this course is contained in the zip compressed [bundled download](#) provided via Github.

Prep code

Data preparation code is available, if you are so inclined, for you to peruse over [here](#).

Assessment

Key information:

- Type: Coursework
- [Equivalent to 5,000 words] Up to five figures and three tables + code + comments + up to 2,000
- Chance to be reassessed
- Due on **14:00, March 9th 2021**
- Electronic submission through Turnitin/CANVAS. Static HTML with NO interactive cells

This module is assessed through a *computational essay*. To complete it successfully, you will need to demonstrate aptitude in at least three areas:

1. Data audacity
2. Python data skills
3. Machine learning and inference literacy

These translate in the following components of the computational essay:

1 - Find, prepare & explore a dataset

Find a dataset you are excited about and that meets the following characteristics:

- It contains several characteristics (features) for a number of observations (samples)
- At least two characteristics are continuous and at least two are categorical
- You can think of ways in which clustering the observations based on their characteristics could tell an interesting story
- You can imagine a situation in which one of the continuous characteristics can be explained in a supervised model as a function of some of the other characteristics

NOTE: please discuss with Dani the choice of dataset before the course finishes

With the dataset at hand:

1. Prepare it for analysis
2. Explore the dataset visually, identifying interesting patterns

2 - Unsupervised learning

Perform a clustering exercise & analyse the results. You are expected to try several clustering models, choose a preferred one, and present a critical argument about why that is your choice. To build your argument, you may rely on graphics, performance scores, and substantive reasoning. Demonstrate that you understand not only how the mechanics of the algorithms work but that you are able to translate those into an applied context to make sense of data.

3 - Supervised learning

Finally, build a predictive model based on linear regression and:

- Interpret the coefficient
- Evaluate its predictive performance both with and without cross-validation
- Reflect on the differences between assessing the performance of a model cross-validating and not.

Similarly to the previous point, demonstrate that you both understand the workings of the algorithms and techniques but also how you can make the most of it to learn about your data. Critical thinking is critical.

Bibliography

References

[B+01]
Leo Breiman and others. Statistical modeling: the two cultures (with comments and a rejoinder by the author). *Statistical science*, 16(3):199–231, 2001.

[Don17]
David Donoho. 50 years of data science. *Journal of Computational and Graphical Statistics*, 26(4):745–766, 2017.

[MS17]
Sendhil Mullainathan and Jann Spiess. Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, 31(2):87–106, 2017.

[RABWng]
Sergio J. Rey, Daniel Arribas-Bel, and Levi J. Wolf. *Geographic Data Science with PySAL and the PyData stack*. CRC press, forthcoming.

Further materials

A list of further materials where you can continue learning is available at:

```
http://darribas.org/gds19/further_resources.html
```

"Data, data, data"

[Async]

We kick off the course with an overview of what Data Science, as a discipline, is. There are two tasks for you to do ahead of class:

- Watch the following introductory clip:

Slides

The slides used in the clip are available at:

- `[HTML]`
- `[PDF]`

Although not required, the clip mentions Lazer & Radford (2017) [lazer14032014] which, although not fully required for this course, is well worth your time if you are interested in new forms of data in the Social Sciences.

- Read *"50 Years of Data Science"*, by David Donoho [Don17].

The paper, published under an Open Access license, is available here

Once you have read Donoho [Don17], the following table below will show you how the outline of this course can be mapped to his "Greater Data Science" goals:

Donoho's Greater Data Science

1. Data Gathering, Preparation, and Exploration

Course Blocks	Goal
Computational building blocks	GDS3
Data Manipulation (Intro + Advanced)	GDS1 + GDS2
Exploring data visually	GDS4
Unsupervised learning	GDS5
[Supervised learning (Overview + Inference + Cross-Validation)	GDS5

2. Data Representation and Transformation
3. Computing with Data
4. Data Visualisation and Presentation
5. Data Modeling
6. Science about Data Science

Computational building blocks

_[Async]

Background

Data Science is as much a process as it is an outcome. And *how* that process gets done matters. In this section, we cover the main practices and tools on top of which this course is built.

There are three sets of materials you are expected to go over to complete this section:

1. `[Read]` *"Geospatial Computational Environment"*, Chapter 2 of the upcoming book by [RABWng].
2. `[Watch]` Go over the three videos in Block A of the GDS course ([URL]), covering an overview of the main tools we will use in the course.

The chapter can be read online here

Software stack

Attention

Before you move on to the next section, make sure you have all the software stack installed, up and running on your computer so you can follow on the rest of the course interactively

Let's install everything you will need to successfully complete this course! To do so, please follow the appropriate guide for your case from those offered at:

> https://gdsl-ul.github.io/soft_install/

They will all help you install the same software, but they vary based on the operating system you are running (Windows/macOS/Linux).

Reading & Manipulating Tabular Data

_[Sync]

```
import pandas
import numpy as np
from sqlalchemy import create_engine
```

To note:

- `matplotlib` magic

- Library import and alias

Data

- Read in `.csv`

Local files   Online read

Assuming you have the file downloaded on the path `../data/`:

```
db = pandas.read_csv("../data/paris_abb.csv.zip")
```

- Connect to `SQLite` and query

```
engine = create_engine("sqlite:///../data/paris_abb_mini.db")
```

```
qry = """
SELECT *
FROM db
LIMIT 5;
"""
dbs = pandas.read_sql(qry, engine)
dbs
```

	id	neighbourhood_cleansed	property_type	room_type	accommodates
0	3109	Observatoire	Apartment	Entire home/apt	2
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4
3	7964	Opéra	Apartment	Entire home/apt	2
4	9952	Popincourt	Apartment	Entire home/apt	2

```
qry = """
SELECT id, Price
FROM db
WHERE neighbourhood_cleansed = 'Popincourt';
"""
dbs = pandas.read_sql(qry, engine)
dbs.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5137 entries, 0 to 5136
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   id      5137 non-null   int64  
 1   Price   5137 non-null   float64
dtypes: float64(1), int64(1)
memory usage: 80.4 KB
```

- Explore

```
db.head()
```

	id	neighbourhood_cleansed	property_type	room_type	accommodates
0	3109	Observatoire	Apartment	Entire home/apt	2
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4
3	7964	Opéra	Apartment	Entire home/apt	2
4	9952	Popincourt	Apartment	Entire home/apt	2

```
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50280 entries, 0 to 50279
Data columns (total 10 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   id                      50280 non-null  int64  
 1   neighbourhood_cleansed  50280 non-null  object 
 2   property_type           50280 non-null  object 
 3   room_type               50280 non-null  object 
 4   accommodates            50280 non-null  int64  
 5   bathrooms               50280 non-null  float64
 6   bedrooms                50280 non-null  float64
 7   beds                    50280 non-null  float64
 8   bed_type                50280 non-null  object 
 9   Price                   50280 non-null  float64
dtypes: float64(4), int64(2), object(4)
memory usage: 3.8+ MB
```

```
db.describe()
```

	id	accommodates	bathrooms	bedrooms	b
count	5.028000e+04	50280.000000	50280.000000	50280.000000	50280.000
mean	1.968671e+07	3.063425	1.117045	1.077804	1.664
std	1.140675e+07	1.556731	0.687370	1.001000	1.164
min	3.109000e+03	1.000000	0.000000	0.000000	0.000
25%	9.340209e+06	2.000000	1.000000	1.000000	1.000
50%	1.999153e+07	2.000000	1.000000	1.000000	1.000
75%	2.987492e+07	4.000000	1.000000	1.000000	2.000
max	3.858893e+07	17.000000	50.000000	50.000000	50.000

`DataFrame` objects can hold different types of data

- "Whole" numbers (`int`)
- Decimals (`float`)
- Categorical (`pandas.Category`)
- Dates (`pandas.Timestamp`)
- Geo (`geopandas.GeoDataFrame`)
- …

Indices

```
db.head(2)
```

	id	neighbourhood_cleansed	property_type	room_type	accommodates
0	3109	Observatoire	Apartment	Entire home/apt	2
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2

```
db.set_index("id").head(2)
```

	neighbourhood_cleansed	property_type	room_type	accommodates	bat
id					
3109	Observatoire	Apartment	Entire home/apt	2	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	

```
dbi = db.set_index("id")
```

```
dbi.index
```

```
Int64Index([    3109,     5396,     7397,     7964,     9952,    10710,
               11170,    11213,    11265,    11798,
            ...
            38485563, 38489275, 38513797, 38516223, 38516341, 38517692,
            38520175, 38537044, 38546594, 38588929],
           dtype='int64', name='id', length=50280)
```

```
dbi.columns
```

```
Index(['neighbourhood_cleansed', 'property_type', 'room_type', 'accommodates',
       'bathrooms', 'bedrooms', 'beds', 'bed_type', 'Price'],
      dtype='object')
```

Slicing and Dicing Data

Index-based queries

- Columns

```
db["Price"].head()
```

```
0     60.0
1    115.0
2    119.0
3    130.0
4     75.0
Name: Price, dtype: float64
```

- Generic point-querying

```
db.loc[0, "Price"]
```

```
60.0
```

- Full slice of one dimension

```python
db.loc[0, :]
```

```
id                                   3109
neighbourhood_cleansed       Observatoire
property_type                   Apartment
room_type                 Entire home/apt
accommodates                            2
bathrooms                               1
bedrooms                                0
beds                                    1
bed_type                         Real Bed
Price                                  60
Name: 0, dtype: object
```

```python
db.loc[:, "Price"]
```

```
0         60.0
1        115.0
2        119.0
3        130.0
4         75.0
         ...
50275    250.0
50276     40.0
50277     60.0
50278     65.0
50279     69.0
Name: Price, Length: 50280, dtype: float64
```

- Range queries

```python
db.loc[0:5, "neighbourhood_cleansed"]
```

```
0      Observatoire
1    Hôtel-de-Ville
2    Hôtel-de-Ville
3             Opéra
4        Popincourt
5            Élysée
Name: neighbourhood_cleansed, dtype: object
```

```python
db.loc[5, "property_type":"bed_type"]
```

```
property_type          Apartment
room_type        Entire home/apt
accommodates                   4
bathrooms                      1
bedrooms                       1
beds                           2
bed_type                Real Bed
Name: 5, dtype: object
```

- List-based queries

```python
db.loc[[0, 49, 19, 29, 39, 9], ["Price", "id"]]
```

	Price	id
0	60.0	3109
49	128.0	32082
19	65.0	17919
29	80.0	21264
39	49.0	26567
9	120.0	11798

Order-based queries

```
dbi.iloc[0:5, :]
```

	neighbourhood_cleansed	property_type	room_type	accommodates	bat
id					
3109	Observatoire	Apartment	Entire home/apt	2	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	
7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	
7964	Opéra	Apartment	Entire home/apt	2	
9952	Popincourt	Apartment	Entire home/apt	2	

EXERCISE:

- Slice the dataset to keep only properties with the following IDs, in that order: `38520175`, `619716`, and `37847454`
- Extract the section of the dataset that includes the 50th to the 100th rows, and the `room_type` and `bedrooms` columns

---

Conditional queries

- Using `loc`

```
db.loc[db["neighbourhood_cleansed"] == "Observatoire",
       ["neighbourhood_cleansed", "Price"]]\
  .head()
```

	neighbourhood_cleansed	Price
0	Observatoire	60.0
47	Observatoire	90.0
52	Observatoire	150.0
104	Observatoire	84.0
144	Observatoire	140.0

```
db.loc[db["Price"] < 100, ["id", "neighbourhood_cleansed"]].head()
```

	id	neighbourhood_cleansed
0	3109	Observatoire
4	9952	Popincourt
5	10710	Élysée
6	11170	Panthéon
10	11848	Popincourt

```
db.loc[(db["Price"] < 100) & \
       (db["bathrooms"] >= 8),
       :]
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
12066	8876983	Luxembourg	Boutique hotel	Private room	
22964	18766792	Luxembourg	Boutique hotel	Private room	
24788	19819352	Luxembourg	Boutique hotel	Private room	
25798	20433587	Luxembourg	Boutique hotel	Private room	
26048	20691340	Luxembourg	Boutique hotel	Private room	
26108	20747725	Luxembourg	Boutique hotel	Private room	
26121	20768013	Luxembourg	Boutique hotel	Private room	

- Conditional filters

```
fltr = db["bathrooms"] > 8
fltr.head()
```

```
0    False
1    False
2    False
3    False
4    False
Name: bathrooms, dtype: bool
```

```
db[fltr]
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
12066	8876983	Luxembourg	Boutique hotel	Private room	
22964	18766792	Luxembourg	Boutique hotel	Private room	
24788	19819352	Luxembourg	Boutique hotel	Private room	
25798	20433587	Luxembourg	Boutique hotel	Private room	
26048	20691340	Luxembourg	Boutique hotel	Private room	
26108	20747725	Luxembourg	Boutique hotel	Private room	
26121	20768013	Luxembourg	Boutique hotel	Private room	

- Concatenated queries

```
db.loc[(db["Price"] < 100) & \
       (db["bathrooms"] >= 8),
       :]
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
12066	8876983	Luxembourg	Boutique hotel	Private room	
22964	18766792	Luxembourg	Boutique hotel	Private room	
24788	19819352	Luxembourg	Boutique hotel	Private room	
25798	20433587	Luxembourg	Boutique hotel	Private room	
26048	20691340	Luxembourg	Boutique hotel	Private room	
26108	20747725	Luxembourg	Boutique hotel	Private room	
26121	20768013	Luxembourg	Boutique hotel	Private room	

```
db.loc[(db["Price"] < 5) | \
       (db["Price"] > 5000),
       :]
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
8149	6088687	Temple	Apartment	Entire home/apt	
10113	7225849	Buttes-Montmartre	Apartment	Entire home/apt	
11286	8093890	Passy	Apartment	Entire home/apt	
25106	19974916	Buttes-Montmartre	Condominium	Entire home/apt	
25558	20219162	Buttes-Chaumont	Apartment	Entire home/apt	
25676	20291987	Passy	Apartment	Entire home/apt	
25697	20313940	Temple	Apartment	Entire home/apt	
26899	21422028	Popincourt	Apartment	Entire home/apt	
32190	25448670	Vaugirard	Apartment	Entire home/apt	
35291	27608896	Observatoire	Apartment	Private room	
43961	34380017	Bourse	Serviced apartment	Hotel room	
46767	36019554	Louvre	Serviced apartment	Hotel room	
47574	36402651	Batignolles-Monceau	House	Entire home/apt	

- Using `query`

```
db.query("neighbourhood_cleansed == 'Observatoire'")\
  [["neighbourhood_cleansed", "Price"]]\
  .head()
```

	neighbourhood_cleansed	Price
0	Observatoire	60.0
47	Observatoire	90.0
52	Observatoire	150.0
104	Observatoire	84.0
144	Observatoire	140.0

```
db.query("Price < 100")\
  [["id", "neighbourhood_cleansed"]]\
  .head()
```

	id	neighbourhood_cleansed
0	3109	Observatoire
4	9952	Popincourt
5	10710	Élysée
6	11170	Panthéon
10	11848	Popincourt

```
db.query("(Price < 100) & (bathrooms >= 8)")
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
12066	8876983	Luxembourg	Boutique hotel	Private room	
22964	18766792	Luxembourg	Boutique hotel	Private room	
24788	19819352	Luxembourg	Boutique hotel	Private room	
25798	20433587	Luxembourg	Boutique hotel	Private room	
26048	20691340	Luxembourg	Boutique hotel	Private room	
26108	20747725	Luxembourg	Boutique hotel	Private room	
26121	20768013	Luxembourg	Boutique hotel	Private room	

Editing tables

- Modifying single values

```
db.loc[1, "bed_type"]
```

```
'Pull-out Sofa'
```

```
db.loc[1, "bed_type"] = "Pullout Sofa"
```

```
db.loc[1, "bed_type"]
```

```
'Pullout Sofa'
```

- Modifying blocks of values

```
db.neighbourhood_cleansed.unique()
```

```
array(['Observatoire', 'Hôtel-de-Ville', 'Opéra', 'Popincourt', 'Élysée',
       'Panthéon', 'Entrepôt', 'Buttes-Montmartre', 'Gobelins',
       'Buttes-Chaumont', 'Luxembourg', 'Louvre', 'Palais-Bourbon',
       'Reuilly', 'Bourse', 'Ménilmontant', 'Vaugirard',
       'Batignolles-Monceau', 'Temple', 'Passy'], dtype=object)
```

```
db.loc[db["neighbourhood_cleansed"] == "Hôtel-de-Ville",
       "neighbourhood_cleansed"] = "City Council"
```

```
db.neighbourhood_cleansed.unique()
```

```
array(['Observatoire', 'City Council', 'Opéra', 'Popincourt', 'Élysée',
       'Panthéon', 'Entrepôt', 'Buttes-Montmartre', 'Gobelins',
       'Buttes-Chaumont', 'Luxembourg', 'Louvre', 'Palais-Bourbon',
       'Reuilly', 'Bourse', 'Ménilmontant', 'Vaugirard',
       'Batignolles-Monceau', 'Temple', 'Passy'], dtype=object)
```

- Creating new columns and rows

```
db["more_beds_than_accomodates"] = db["beds"] > db["accommodates"]
```

EXERCISE

- Find how many properties have more than ten bathrooms
- Can you rent an AirBnb in Paris with only one bed but three bedrooms?
- In which neighbourhoods can you rent an "Airbed"?

Writing Data

```
[i for i in dir(db) if i[:3]=="to_"]
```

```
['to_clipboard',
 'to_csv',
 'to_dict',
 'to_excel',
 'to_feather',
 'to_gbq',
 'to_hdf',
 'to_html',
 'to_json',
 'to_latex',
 'to_markdown',
 'to_numpy',
 'to_parquet',
 'to_period',
 'to_pickle',
 'to_records',
 'to_sql',
 'to_stata',
 'to_string',
 'to_timestamp',
 'to_xarray']
```

Further Resources

Similar introduction:

> http://darribas.org/gds19/content/labs/lab_01.html

More stuff on indices:

> http://pandas.pydata.org/pandas-docs/stable/indexing.html

And for the pros:

> http://pandas.pydata.org/pandas-docs/stable/advanced.html

Visualising Tabular Data

_[Sync]

```
%matplotlib inline

import pandas
import seaborn as sns
import matplotlib.pyplot as plt
```

Local files   Online read

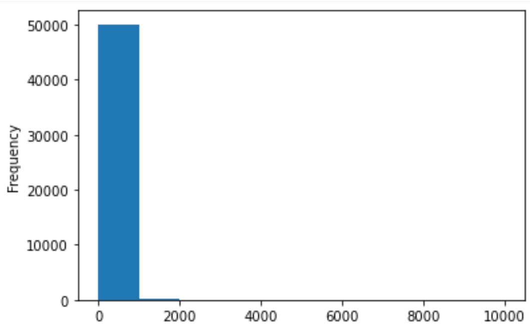
Assuming you have the file downloaded on the path `../data/`:

```
db = pandas.read_csv("../data/paris_abb.csv.zip")
```

Simple & Quick (pandas)

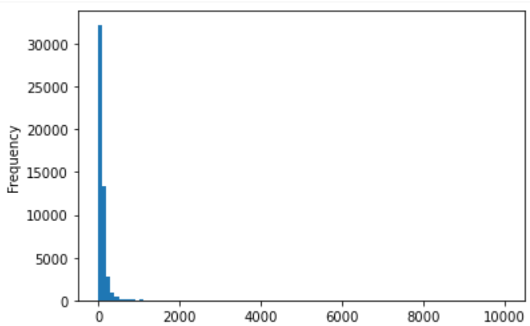
```
db["Price"].plot.hist()
```

```
<AxesSubplot:ylabel='Frequency'>
```



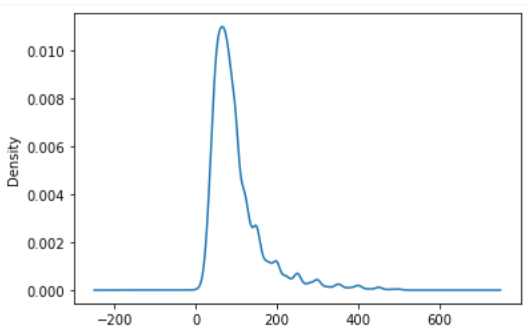

```
db["Price"].plot.hist(bins=100)
```

```
<AxesSubplot:ylabel='Frequency'>
```



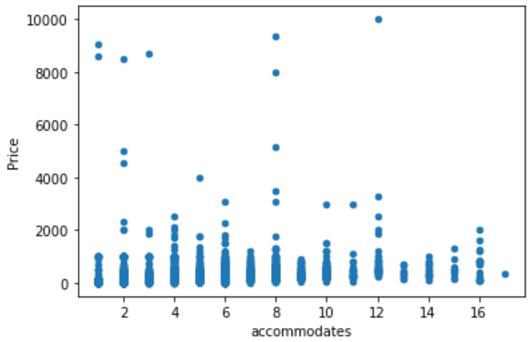

```
db.query("Price < 500")["Price"].plot.kde()
```

```
<AxesSubplot:ylabel='Density'>
```



```
db.plot.scatter("accommodates", "Price")
```

```
<AxesSubplot:xlabel='accommodates', ylabel='Price'>
```



EXERCISE

- Create a histogram of the distribution of number of people a property accommodates (`accommodates`)
- Create a scatter plot of the number of beds and number of bedrooms

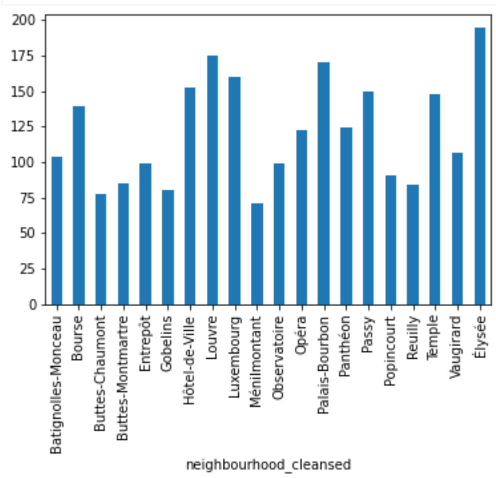
More

> https://pandas.pydata.org/pandas-docs/stable/user_guide/visualization.html

We can also combine this with groupings from the previous notebook:

```
db.groupby("neighbourhood_cleansed")\
  ["Price"]\
  .mean()\
  .plot.bar()
```

```
<AxesSubplot:xlabel='neighbourhood_cleansed'>
```



EXERCISE

Create a bar plot of the average `review_scores_rating` by neighbourhood, sorted by average price.

For a "pro" touch (optional), substract 90 from the reviews score before plotting.

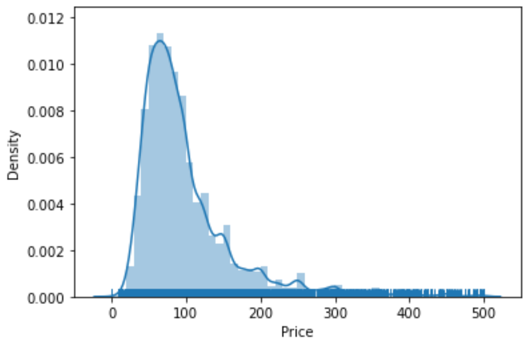
`seaborn`

- Univariate

```
sns.distplot(db.query("Price < 500")["Price"],
             kde=True,
             rug=True)
```

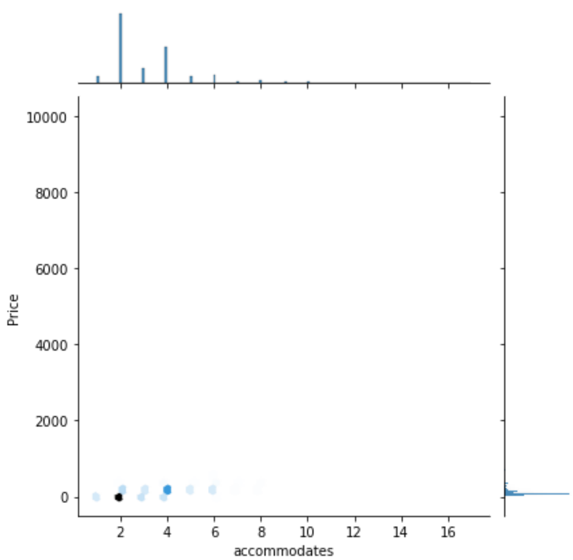
```
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2055: FutureWarning:
The `axis` variable is no longer used and will be removed. Instead, assign variables
directly to `x` or `y`.
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```

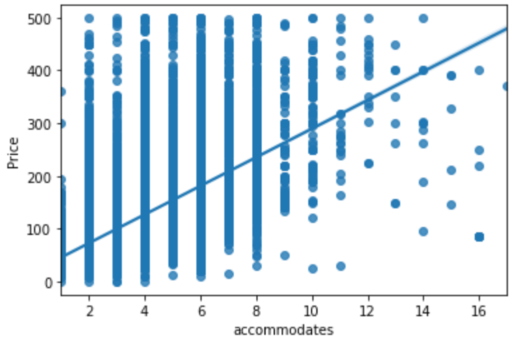


- Bivariate

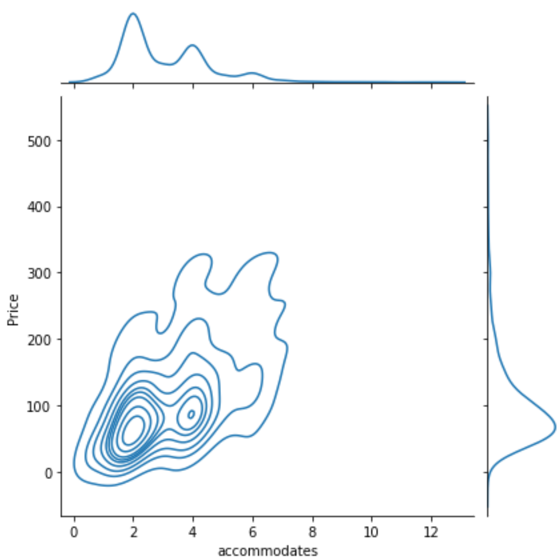
```
sns.jointplot(x = "accommodates",
              y = "Price",
              data=db,
              kind="hex"
             );
```




```
sns.regplot(x = "accommodates",
            y = "Price",
            data=db.query("Price < 500")
           );
```




```
sns.jointplot(x = "accommodates",
              y = "Price",
              data=db.query("Price < 500")\
                     .sample(1000),
              kind="kde"
             );
```



EXERCISE

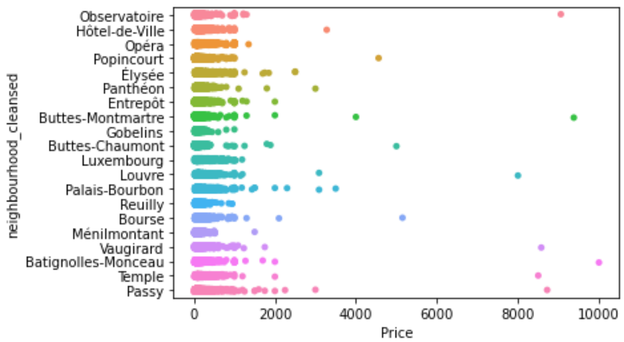
Explore the documentation of `jointplot` and create a figure similar to the one above where you replace the hexagonal binning for a KDE. Since this will probably take too long, subset your data before plotting to only properties cheaper than $500, and then randomly sample 1,000 observations (tip: check out the [`sample`](#) method).

More

```
http://seaborn.pydata.org/tutorial.html
```

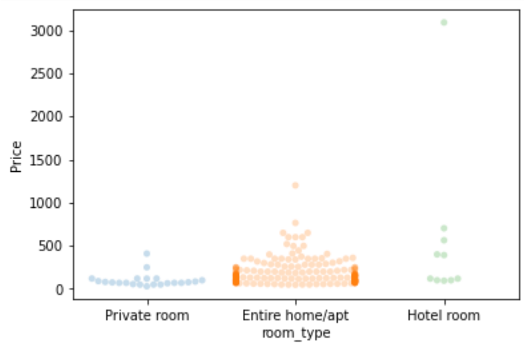
- Categorical

```
sns.stripplot(x = "Price",
              y = "neighbourhood_cleansed",
              data=db
             );
```




```
sns.swarmplot(x = "room_type",
              y = "Price",
              data=db.query("neighbourhood_cleansed == 'Louvre'")\
                     .sample(250),
              alpha=0.25
             );
```

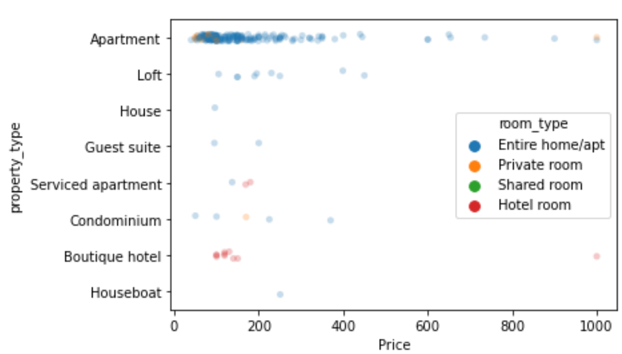
```
/opt/conda/lib/python3.8/site-packages/seaborn/categorical.py:1296: UserWarning:
58.3% of the points cannot be placed; you may want to decrease the size of the
markers or use stripplot.
  warnings.warn(msg, UserWarning)
```



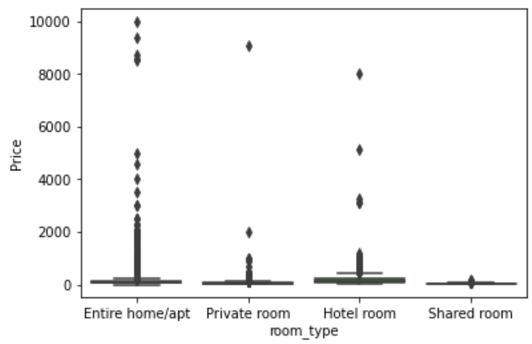
To note:

- With larger datasets, it's hard to see any pattern
- This is true even if you jitter the points around to avoid overlap and/or you play with transparency (`alpha`)
- Algorithms to separate out dots exist but they're computationally intensive and can only do so much

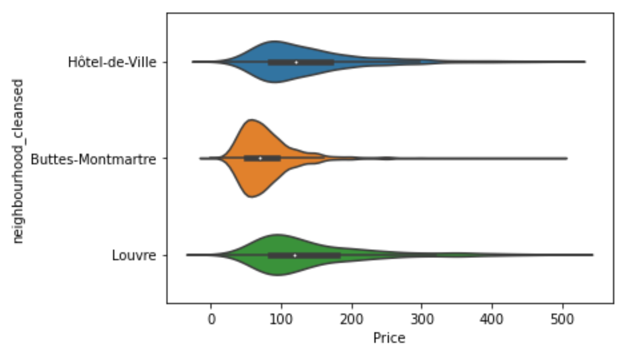
```
sns.stripplot(x = "Price",
              y = "property_type",
              hue = "room_type",
              data=db.query("neighbourhood_cleansed == 'Louvre'")\
                     .sample(250),
              alpha=0.25
             );
```



```
sns.boxplot(x = "room_type",
            y = "Price",
            data = db
           );
```




```
nei_list = ["Hôtel-de-Ville", "Louvre", "Buttes-Montmartre"]
sub = db["neighbourhood_cleansed"].isin(nei_list)

sns.violinplot(x = "Price",
               y = "neighbourhood_cleansed",
               data = db[sub].query("Price < 500")
              );
```



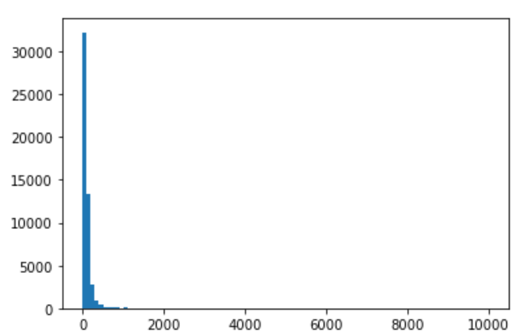
EXCERCISE

Explore the distribution of price by property type

Full control (`matplotlib`)

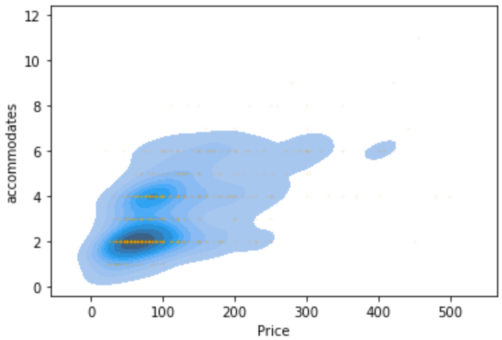
One

```
f, ax = plt.subplots(1)

ax.hist(db['Price'], bins=100)

plt.show()
```



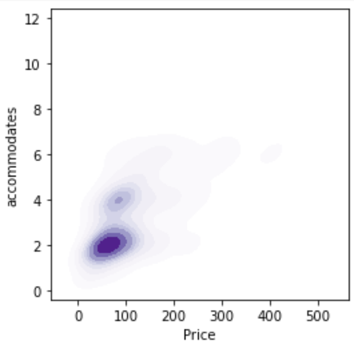
```
sub = db.query("Price < 500")\
        .sample(1000)

f, ax = plt.subplots(1)

sns.kdeplot(sub['Price'], sub['accommodates'],
            shade=True, ax=ax)
ax.scatter(sub['Price'], sub['accommodates'],
           alpha=0.1, s=0.75, color='orange')

plt.show()
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: y. From version 0.12, the only valid
positional argument will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
f, ax = plt.subplots(1, figsize=(4, 4))

sns.kdeplot(sub['Price'],
            sub['accommodates'],
            shade=True, ax=ax, cmap='Purples')

plt.show()
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: y. From version 0.12, the only valid
positional argument will be `data`, and passing other arguments without an explicit
keyword will result in an error or misinterpretation.
  warnings.warn(
```

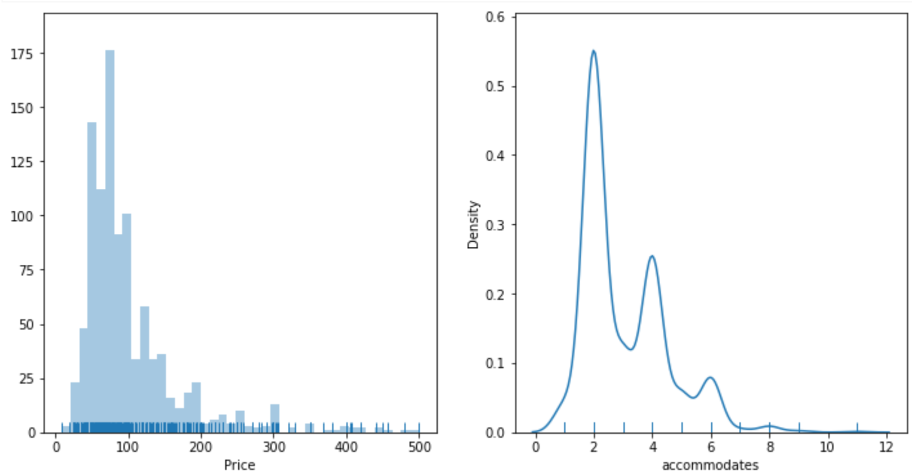


CHALLENGE - Create a visualisation that includes a KDE and a scatter plot and that explores the relationship between number of beds and number of people it accommodates, for a random sample of 500 properties.

Two or more

```
f, axs = plt.subplots(1, 2, figsize=(12, 6))

sns.distplot(sub['Price'],
             kde=False,
             rug=True,
             ax=axs[0]
            )

sns.distplot(sub['accommodates'],
             hist=False,
             kde=True,
             rug=True,
             ax=axs[1]
            )

plt.show()
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2055: FutureWarning:
The `axis` variable is no longer used and will be removed. Instead, assign variables
directly to `x` or `y`.
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar
flexibility) or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2055: FutureWarning:
The `axis` variable is no longer used and will be removed. Instead, assign variables
directly to `x` or `y`.
  warnings.warn(msg, FutureWarning)
```



CHALLENGE - Create a visualisation for all of the properties with three subplots:

1. Histogram of price
2. Scatter plot of price Vs number of people it accommodates
3. Histogram of number of people the property accommodates

Advanced Tabular Manipulation

[Sync]

```
%matplotlib inline

import pandas
```

Local files Online read

Assuming you have the file downloaded on the path `../data/`:

```python
db = pandas.read_csv("../data/paris_abb.csv.zip")
```

Sorting

- By values

```python
# Top-5 cheapes properties
db.sort_values("Price")\
  .head(5)
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
25676	20291987	Passy	Apartment	Entire home/apt	
25697	20313940	Temple	Apartment	Entire home/apt	
26899	21422028	Popincourt	Apartment	Entire home/apt	
25558	20219162	Buttes-Chaumont	Apartment	Entire home/apt	
25106	19974916	Buttes-Montmartre	Condominium	Entire home/apt	

```python
# Top-5 most expensive properties
db.sort_values("Price", ascending=False)\
  .head(5)
```

	id	neighbourhood_cleansed	property_type	room_type	accomr
47574	36402651	Batignolles-Monceau	House	Entire home/apt	
10113	7225849	Buttes-Montmartre	Apartment	Entire home/apt	
35291	27608896	Observatoire	Apartment	Private room	
11286	8093890	Passy	Apartment	Entire home/apt	
32190	25448670	Vaugirard	Apartment	Entire home/apt	

- By index

```python
tmp = db.set_index("property_type")\
        .sort_index()
tmp.head()
```

	id	neighbourhood_cleansed	room_type	accommodates
property_type				
Aparthotel	31728955	Vaugirard	Hotel room	2
Aparthotel	13003443	Vaugirard	Entire home/apt	4
Aparthotel	31733851	Temple	Hotel room	4
Aparthotel	17630233	Bourse	Hotel room	4
Aparthotel	24387710	Observatoire	Private room	12

(Useful for quick subsetting:)

```
tmp.loc["Tiny house",
       ["id", "neighbourhood_cleansed", "Price"]
       ]
```

	id	neighbourhood_cleansed	Price
property_type			
Tiny house	20976623	Panthéon	110.0
Tiny house	6838781	Entrepôt	60.0
Tiny house	29322690	Passy	30.0
Tiny house	18919023	Louvre	100.0
Tiny house	4191080	Louvre	80.0
Tiny house	9582468	Popincourt	80.0
Tiny house	37312602	Ménilmontant	40.0
Tiny house	2555221	Buttes-Montmartre	114.0
Tiny house	34572791	Passy	35.0
Tiny house	37174177	Vaugirard	50.0
Tiny house	26292760	Ménilmontant	75.0
Tiny house	36864294	Passy	38.0
Tiny house	20273867	Panthéon	100.0
Tiny house	34816113	Observatoire	40.0
Tiny house	768986	Temple	79.0
Tiny house	13220094	Buttes-Chaumont	160.0
Tiny house	5699102	Buttes-Montmartre	71.0
Tiny house	36048024	Buttes-Montmartre	70.0
Tiny house	20688679	Buttes-Montmartre	73.0
Tiny house	15157047	Temple	42.0
Tiny house	12588228	Passy	75.0

Joinning

- Additional data (linked through ID!)

```
reviews = pandas.read_csv("../data/paris_abb_review.csv.zip")
reviews.head()
```

	id	review_scores_rating	review_scores_accuracy	review_scores_cleanline
0	3109	100.0	10.0	1(
1	5396	90.0	9.0	ε
2	7397	94.0	10.0	ς
3	7964	96.0	10.0	1(
4	9952	98.0	10.0	1(

- Join to original table:

```
dbj1 = db.join(reviews.set_index("id"),
              on = "id"
             )
dbj1.head()
```

	id	neighbourhood_cleansed	property_type	room_type	accommodates
0	3109	Observatoire	Apartment	Entire home/apt	2
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4
3	7964	Opéra	Apartment	Entire home/apt	2
4	9952	Popincourt	Apartment	Entire home/apt	2

```
dbj2 = db.set_index("id")\
        .join(reviews.set_index("id"))
dbj2.head()
```

	neighbourhood_cleansed	property_type	room_type	accommodates	bat
id					
3109	Observatoire	Apartment	Entire home/apt	2	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	
7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	
7964	Opéra	Apartment	Entire home/apt	2	
9952	Popincourt	Apartment	Entire home/apt	2	

Note:

- Left can choose index/column, right needs to be index (results "almost" the same)
- For more flexibility, check out `merge`:

> https://pandas.pydata.org/pandas-docs/stable/user_guide/merging.html

Grouping

- Get the mean price for "Louvre":

```
db.query("neighbourhood_cleansed == 'Louvre'")\
  ["Price"]\
  .mean()
```

```
175.2634194831014
```

- Get the mean price for "Luxembourg":

```
db.query("neighbourhood_cleansed == 'Luxembourg'")\
  ["Price"]\
  .mean()
```

```
160.02262142381903
```

- Get the mean price for "Palais-Bourbon":

```
db.query("neighbourhood_cleansed == 'Palais-Bourbon'")\
  ["Price"]\
  .mean()
```

```
169.8526690391459
```

- For every neighbourhood???

```
db.groupby("neighbourhood_cleansed")\
  ["Price"]\
  .mean()
```

```
neighbourhood_cleansed
Batignolles-Monceau    103.355239
Bourse                 138.898017
Buttes-Chaumont         76.971745
Buttes-Montmartre       84.867211
Entrepôt                99.130493
Gobelins                80.000000
Hôtel-de-Ville         152.547723
Louvre                 175.263419
Luxembourg             160.022621
Ménilmontant            71.074504
Observatoire            98.907340
Opéra                  122.495921
Palais-Bourbon         169.852669
Panthéon               124.683662
Passy                  149.237946
Popincourt              90.832782
Reuilly                 84.225256
Temple                 147.904592
Vaugirard              106.269580
Élysée                 194.158416
Name: Price, dtype: float64
```

`MultiIndex` Tables

Grouping can be based on more than one variable only…

```
nr = dbj1.groupby(["neighbourhood_cleansed", "room_type"])\
       [["Price", "review_scores_rating"]]\
       .mean()
```

This generates a `MultiIndex`:

```
nr.head()
```

		Price	review_scores_rating
neighbourhood_cleansed	**room_type**		
Batignolles-Monceau	**Entire home/apt**	103.501922	92.484096
	Hotel room	343.660714	93.607143
	Private room	58.698305	95.064407
	Shared room	53.142857	90.214286
Bourse	**Entire home/apt**	139.618020	91.608503

```
nr.index
```

```
MultiIndex([('Batignolles-Monceau', 'Entire home/apt'),
            ('Batignolles-Monceau',      'Hotel room'),
            ('Batignolles-Monceau',    'Private room'),
            ('Batignolles-Monceau',     'Shared room'),
            (             'Bourse', 'Entire home/apt'),
            (             'Bourse',      'Hotel room'),
            (             'Bourse',    'Private room'),
            (             'Bourse',     'Shared room'),
            (    'Buttes-Chaumont', 'Entire home/apt'),
            (    'Buttes-Chaumont',      'Hotel room'),
            (    'Buttes-Chaumont',    'Private room'),
            (    'Buttes-Chaumont',     'Shared room'),
            (  'Buttes-Montmartre', 'Entire home/apt'),
            (  'Buttes-Montmartre',      'Hotel room'),
            (  'Buttes-Montmartre',    'Private room'),
            (  'Buttes-Montmartre',     'Shared room'),
            (           'Entrepôt', 'Entire home/apt'),
            (           'Entrepôt',      'Hotel room'),
            (           'Entrepôt',    'Private room'),
            (           'Entrepôt',     'Shared room'),
            (           'Gobelins', 'Entire home/apt'),
            (           'Gobelins',      'Hotel room'),
            (           'Gobelins',    'Private room'),
            (           'Gobelins',     'Shared room'),
            (     'Hôtel-de-Ville', 'Entire home/apt'),
            (     'Hôtel-de-Ville',      'Hotel room'),
            (     'Hôtel-de-Ville',    'Private room'),
            (     'Hôtel-de-Ville',     'Shared room'),
            (             'Louvre', 'Entire home/apt'),
            (             'Louvre',      'Hotel room'),
            (             'Louvre',    'Private room'),
            (             'Louvre',     'Shared room'),
            (         'Luxembourg', 'Entire home/apt'),
            (         'Luxembourg',      'Hotel room'),
            (         'Luxembourg',    'Private room'),
            (         'Luxembourg',     'Shared room'),
            (       'Ménilmontant', 'Entire home/apt'),
            (       'Ménilmontant',      'Hotel room'),
            (       'Ménilmontant',    'Private room'),
            (       'Ménilmontant',     'Shared room'),
            (       'Observatoire', 'Entire home/apt'),
            (       'Observatoire',      'Hotel room'),
            (       'Observatoire',    'Private room'),
            (       'Observatoire',     'Shared room'),
            (              'Opéra', 'Entire home/apt'),
            (              'Opéra',      'Hotel room'),
            (              'Opéra',    'Private room'),
            (              'Opéra',     'Shared room'),
            (     'Palais-Bourbon', 'Entire home/apt'),
            (     'Palais-Bourbon',      'Hotel room'),
            (     'Palais-Bourbon',    'Private room'),
            (     'Palais-Bourbon',     'Shared room'),
            (           'Panthéon', 'Entire home/apt'),
            (           'Panthéon',      'Hotel room'),
            (           'Panthéon',    'Private room'),
            (           'Panthéon',     'Shared room'),
            (              'Passy', 'Entire home/apt'),
            (              'Passy',      'Hotel room'),
            (              'Passy',    'Private room'),
            (              'Passy',     'Shared room'),
            (         'Popincourt', 'Entire home/apt'),
            (         'Popincourt',      'Hotel room'),
            (         'Popincourt',    'Private room'),
            (         'Popincourt',     'Shared room'),
            (            'Reuilly', 'Entire home/apt'),
            (            'Reuilly',      'Hotel room'),
            (            'Reuilly',    'Private room'),
            (            'Reuilly',     'Shared room'),
            (             'Temple', 'Entire home/apt'),
            (             'Temple',      'Hotel room'),
            (             'Temple',    'Private room'),
            (             'Temple',     'Shared room'),
            (          'Vaugirard', 'Entire home/apt'),
            (          'Vaugirard',      'Hotel room'),
            (          'Vaugirard',    'Private room'),
            (          'Vaugirard',     'Shared room'),
            (             'Élysée', 'Entire home/apt'),
            (             'Élysée',      'Hotel room'),
            (             'Élysée',    'Private room'),
            (             'Élysée',     'Shared room')],
           names=['neighbourhood_cleansed', 'room_type'])
```

These indices allow us to do several more things than single index objects. For example:

- One-level queries:

```
nr.xs("Bourse", level="neighbourhood_cleansed")
```

	Price	review_scores_rating
room_type		
Entire home/apt	139.618020	91.608503
Hotel room	321.244898	93.367347
Private room	71.088710	93.225806
Shared room	35.062500	90.875000

```
nr.xs("Shared room", level="room_type")
```

	Price	review_scores_rating
neighbourhood_cleansed		
Batignolles-Monceau	53.142857	90.214286
Bourse	35.062500	90.875000
Buttes-Chaumont	25.228571	90.400000
Buttes-Montmartre	42.555556	89.333333
Entrepôt	30.458333	90.458333
Gobelins	35.600000	92.533333
Hôtel-de-Ville	64.000000	95.375000
Louvre	72.000000	93.400000
Luxembourg	55.000000	88.666667
Ménilmontant	34.923077	90.730769
Observatoire	41.000000	97.142857
Opéra	44.125000	94.500000
Palais-Bourbon	35.400000	95.000000
Panthéon	73.800000	95.200000
Passy	39.785714	93.785714
Popincourt	31.880952	89.261905
Reuilly	30.300000	93.200000
Temple	30.833333	92.833333
Vaugirard	51.333333	94.750000
Élysée	70.000000	96.000000

```
nr.loc[("Bourse", "Shared room"), :]
```

```
Price                   35.0625
review_scores_rating    90.8750
Name: (Bourse, Shared room), dtype: float64
```

But also “unstack” it so we can cross-tab:

```
unstacked = nr.unstack()
unstacked
```

	Price				rev
room_type	Entire home/apt	Hotel room	Private room	Shared room	Ent hor
neighbourhood_cleansed					
Batignolles-Monceau	103.501922	343.660714	58.698305	53.142857	92.
Bourse	139.618020	321.244898	71.088710	35.062500	91.
Buttes-Chaumont	82.568452	117.947368	45.866667	25.228571	93.
Buttes-Montmartre	87.478750	118.342105	55.217899	42.555556	92.
Entrepôt	101.621981	311.736842	55.144893	30.458333	92.
Gobelins	86.284188	106.961538	53.238671	35.600000	91.
Hôtel-de-Ville	154.687543	412.291667	79.372881	64.000000	93.
Louvre	165.077367	426.830508	102.828947	72.000000	91.
Luxembourg	164.863531	204.746667	87.226562	55.000000	92.
Ménilmontant	75.727787	128.200000	45.138425	34.923077	93.
Observatoire	95.354978	306.525000	90.521401	41.000000	92.
Opéra	115.688708	287.089655	75.561905	44.125000	93.
Palais-Bourbon	170.620910	450.722222	76.144144	35.400000	92.
Panthéon	129.989522	141.925000	69.246753	73.800000	92.
Passy	155.033317	331.766667	77.497674	39.785714	91.
Popincourt	95.073171	138.333333	53.348606	31.880952	93.
Reuilly	89.299656	104.727273	53.468165	30.300000	93.
Temple	150.560496	241.977273	77.474453	30.833333	92.
Vaugirard	108.483296	288.891892	58.145729	51.333333	92.
Élysée	194.715942	300.590361	94.835165	70.000000	91.

This in turn creates a `MultiIndex` on the columns instead, which works similarly:

```
unstacked["Price"]
```

room_type	Entire home/apt	Hotel room	Private room	Shared room
neighbourhood_cleansed				
Batignolles-Monceau	103.501922	343.660714	58.698305	53.142857
Bourse	139.618020	321.244898	71.088710	35.062500
Buttes-Chaumont	82.568452	117.947368	45.866667	25.228571
Buttes-Montmartre	87.478750	118.342105	55.217899	42.555556
Entrepôt	101.621981	311.736842	55.144893	30.458333
Gobelins	86.284188	106.961538	53.238671	35.600000
Hôtel-de-Ville	154.687543	412.291667	79.372881	64.000000
Louvre	165.077367	426.830508	102.828947	72.000000
Luxembourg	164.863531	204.746667	87.226562	55.000000
Ménilmontant	75.727787	128.200000	45.138425	34.923077
Observatoire	95.354978	306.525000	90.521401	41.000000
Opéra	115.688708	287.089655	75.561905	44.125000
Palais-Bourbon	170.620910	450.722222	76.144144	35.400000
Panthéon	129.989522	141.925000	69.246753	73.800000
Passy	155.033317	331.766667	77.497674	39.785714
Popincourt	95.073171	138.333333	53.348606	31.880952
Reuilly	89.299656	104.727273	53.468165	30.300000
Temple	150.560496	241.977273	77.474453	30.833333
Vaugirard	108.483296	288.891892	58.145729	51.333333
Élysée	194.715942	300.590361	94.835165	70.000000

EXERCISE

Create a table that shows the average price for properties by room and property type

More at:

> https://pandas.pydata.org/pandas-docs/stable/user_guide/advanced.html

Unsupervised Learning

To do before…

_[Async]

Before we jump on the action, we are going to get some background on unsupervised learning. Please complete watching the following three clips, all sourced from the Geographic Data Science course:

1. *The need to group data*, which describes *why* unsupervised learning is useful
2. *Non-spatial clustering*, which describes *what* unsupervised learning is and illustrates it

3. *K-Means*, which introduces the technique we'll use in class and, by far, most popular one to cluster data

Action!

[Sync]

```
import pandas
from numpy.random import seed

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, calinski_harabasz_score
from sklearn.decomposition import PCA
from sklearn.preprocessing import scale, MinMaxScaler

import seaborn as sns
import matplotlib.pyplot as plt
```

Local files Online read

Assuming you have the files downloaded on the path `../data/`:

```
orig = pandas.read_csv("../data/paris_abb.csv.zip")
reviews = pandas.read_csv("../data/paris_abb_review.csv.zip")
```

```
db = orig.join(reviews.set_index("id"), on="id")
```

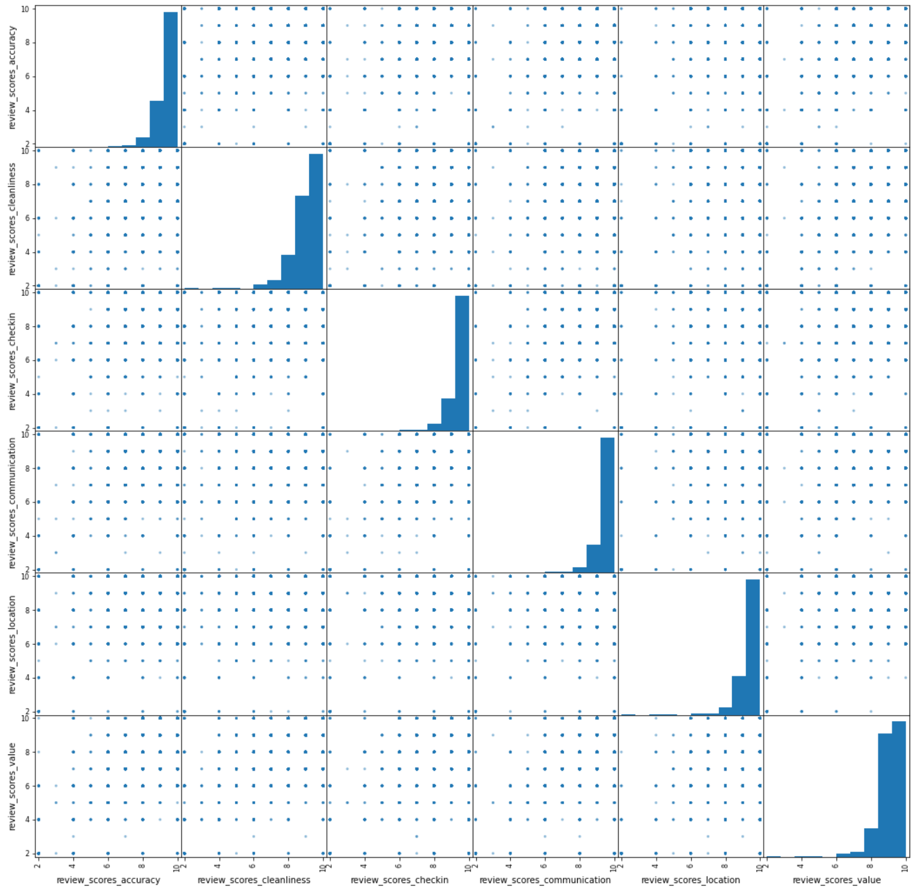
Explore

```
review_areas = ["review_scores_accuracy",
                "review_scores_cleanliness",
                "review_scores_checkin",
                "review_scores_communication",
                "review_scores_location",
                "review_scores_value"
               ]
```

```
db[review_areas].describe().T
```

	count	mean	std	min	25%	50%
review_scores_accuracy	50280.0	9.576929	0.824413	2.0	9.0	10.0
review_scores_cleanliness	50280.0	9.178540	1.107574	2.0	9.0	9.0
review_scores_checkin	50280.0	9.660302	0.769064	2.0	10.0	10.0
review_scores_communication	50280.0	9.703520	0.727020	2.0	10.0	10.0
review_scores_location	50280.0	9.654018	0.696448	2.0	9.0	10.0
review_scores_value	50280.0	9.254515	0.930852	2.0	9.0	9.0

```
pandas.plotting.scatter_matrix(db[review_areas],
                               figsize=(18, 18));
```



This , into a composite index.

Classify

`scikit-learn` has a very consistent API (learn it once, use it across). It comes in a few flavors:

```
- `fit`
- `fit_transform`
- Direct method
```

- All raw

```python
estimator = KMeans(n_clusters = 5)
estimator
```

```
KMeans(n_clusters=5)
```

```python
seed(12345)

estimator.fit(db[review_areas])
```

```
KMeans(n_clusters=5)
```

```python
k5_raw = pandas.Series(estimator.labels_,
                       index=db.index
                      )
k5_raw.head()
```

```
0    3
1    0
2    1
3    3
4    3
dtype: int32
```

NOTE `fit`

- All standardised

```
# Minus mean, divided by std
db_stded = scale(db[review_areas])
pandas.DataFrame(db_stded,
                 index = db.index,
                 columns = review_areas
                ).describe()\
                 .reindex(["mean", "std"])
```

	review_scores_accuracy	review_scores_cleanliness	review_scores_checki
mean	2.450638e-14	1.191311e-14	-3.519940e-1
std	1.000010e+00	1.000010e+00	1.000010e+0

NOTE `scale` API

```
# Range scale
range_scaler = MinMaxScaler()
db_scaled = range_scaler.fit_transform(db[review_areas])
pandas.DataFrame(db_scaled,
                 index = db.index,
                 columns = review_areas
                ).describe()\
                 .reindex(["min", "max"])
```

	review_scores_accuracy	review_scores_cleanliness	review_scores_checkin
min	0.0	0.0	0.0
max	1.0	1.0	1.0

NOTE `fit_transform`

```
seed(12345)

estimator = KMeans(n_clusters = 5)

estimator.fit(db_stded)

k5_std = pandas.Series(estimator.labels_,
                       index=db.index
                      )
k5_std.head()
```

```
0    0
1    4
2    0
3    0
4    0
dtype: int32
```

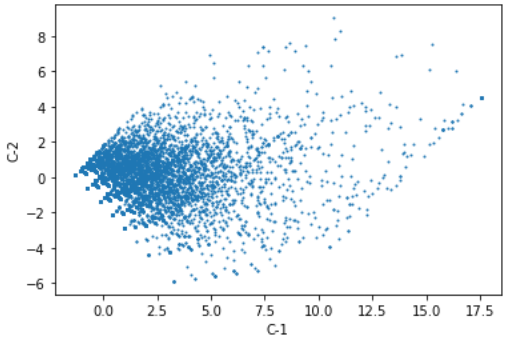
- Projected to lower dimension

```
pca_estimator = PCA(n_components=2)
pca_estimator
```

```
PCA(n_components=2)
```

```
components = pca_estimator.fit_transform(db[review_areas])
components = pandas.DataFrame(components,
                              index = db.index,
                              columns = ["C-1", "C-2"]
                             )
```

```
components.plot.scatter("C-1",
                        "C-2",
                        s=1
                       );
```

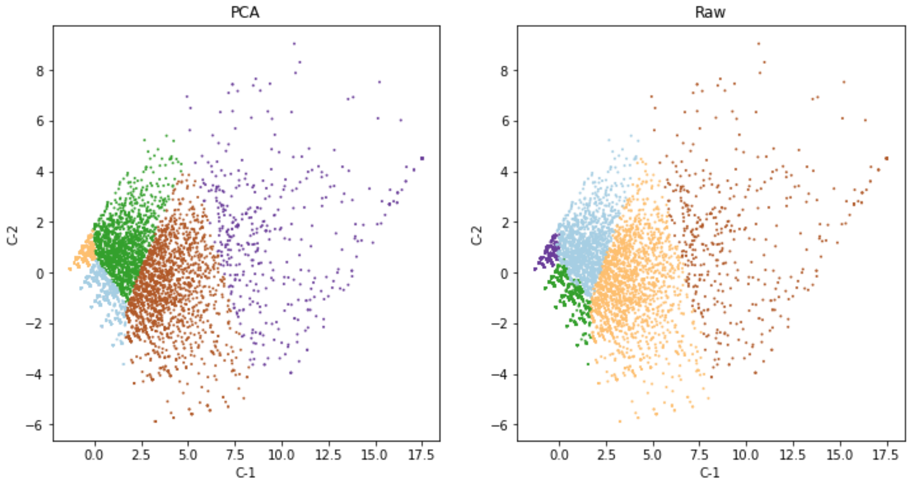


Now we cluster the two components instead of all the input variables:

```
seed(12345)
estimator = KMeans(n_clusters = 5)
estimator.fit(components)
k5_pca = pandas.Series(estimator.labels_,
                       index=components.index
                      )
```

We can compare how both solutions relate to each other (or not):

```
f, axs = plt.subplots(1, 2, figsize=(12, 6))

ax = axs[0]
components.assign(labels=k5_pca)\
          .plot.scatter("C-1",
                        "C-2",
                        c="labels",
                        s=1,
                        cmap="Paired",
                        colorbar=False,
                        ax=ax
                       )
ax.set_title("PCA")

ax = axs[1]
components.assign(labels=k5_raw)\
          .plot.scatter("C-1",
                        "C-2",
                        c="labels",
                        s=1,
                        cmap="Paired",
                        colorbar=False,
                        ax=ax
                       )
ax.set_title("Raw")

plt.show()
```



Actually pretty similar (which is good!). But remember that our original input was expressed in the same units anyway, so it makes sense.

EXERCISE: Add a third plot to the figure above visualising the labels with the range-scaled transformation.

Explore the classification

- Quality of clustering (Calinski and Harabasz score, the ratio of between over within dispersion)

```
chs_raw = calinski_harabasz_score(db[review_areas],
                                  k5_raw
                                 )
```

```
chs_std = calinski_harabasz_score(db[review_areas],
                                  k5_std
                                 )
```

```
chs_pca = calinski_harabasz_score(db[review_areas],
                                  k5_pca
                                 )
```

```
pandas.Series({"Raw": chs_raw,
               "Standardised": chs_std,
               "PCA": chs_pca,
              })
```

```
Raw             16548.489419
Standardised    14674.706963
PCA             16519.822001
dtype: float64
```

The higher, the better, so either the original or PCA.

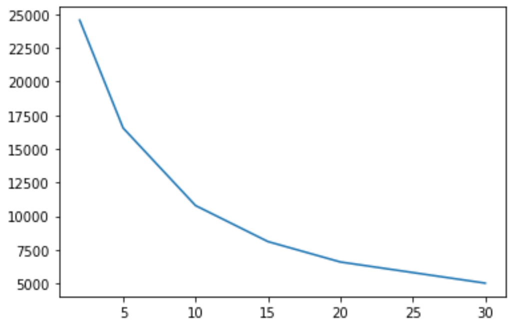
We can also use this to "optimise" (or at least explore its behaviour) the number of clusters. Let's pick the original input as the scores suggest are more desirable:

```
%%time
seed(12345)

chss = {}
for i in [2, 5, 10, 15, 20, 30]:
    estimator = KMeans(n_clusters=i)
    estimator.fit(components)
    chs = calinski_harabasz_score(db[review_areas],
                                  estimator.labels_
                                 )
    chss[i] = chs
chss = pandas.Series(chss)
```

```
CPU times: user 2min 32s, sys: 1min 9s, total: 3min 42s
Wall time: 14.6 s
```

```
chss.plot.line()
```

```
<AxesSubplot:>
```



5 clusters?

- Quality of clustering (silhouette scores)

```
%%time
sil_raw = silhouette_score(db[review_areas],
                           k5_raw,
                           metric="euclidean"
                          )
```

```
CPU times: user 1min 3s, sys: 4min 38s, total: 5min 41s
Wall time: 41.5 s
```

```
%%time
sil_std = silhouette_score(db[review_areas],
                           k5_std,
                           metric="euclidean"
                          )
```

```
CPU times: user 1min 4s, sys: 4min 28s, total: 5min 33s
Wall time: 41.3 s
```

```
%%time
sil_pca = silhouette_score(db[review_areas],
                           k5_pca,
                           metric="euclidean"
                          )
```

```
CPU times: user 1min 5s, sys: 4min 22s, total: 5min 28s
Wall time: 41 s
```

```
pandas.Series({"Raw": sil_raw,
               "Standardised": sil_std,
               "PCA": sil_pca,
              })
```

```
Raw             0.314448
Standardised    0.304222
PCA             0.314263
dtype: float64
```

For a graphical analysis of silhouette scores, see here:

> https://scikit-learn.org/stable/auto_examples/cluster/plot_kmeans_silhouette_analysis.html

---

EXERCISE Compare silhouette scores across our three original approaches for three and 20 clusters

---

- Characterise

Internally:

```
g = db[review_areas]\
      .groupby(k5_pca)
```

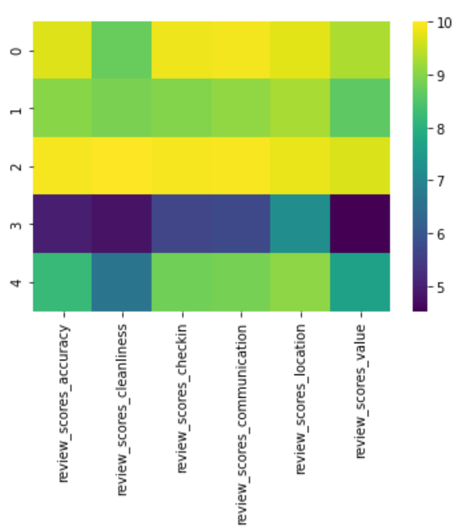
```
g.size()\
 .sort_values()
```

```
3      437
4     2850
1     7752
0    16468
2    22773
dtype: int64
```

```
g.mean()
```

	review_scores_accuracy	review_scores_cleanliness	review_scores_checkin	r
0	9.705186	8.728564	9.867379	
1	9.020253	8.901961	8.986068	
2	9.931366	10.000000	9.923989	
3	4.993135	4.789474	5.665904	
4	8.220702	6.640000	8.803158	

```
sns.heatmap(g.mean(), cmap='viridis');
```



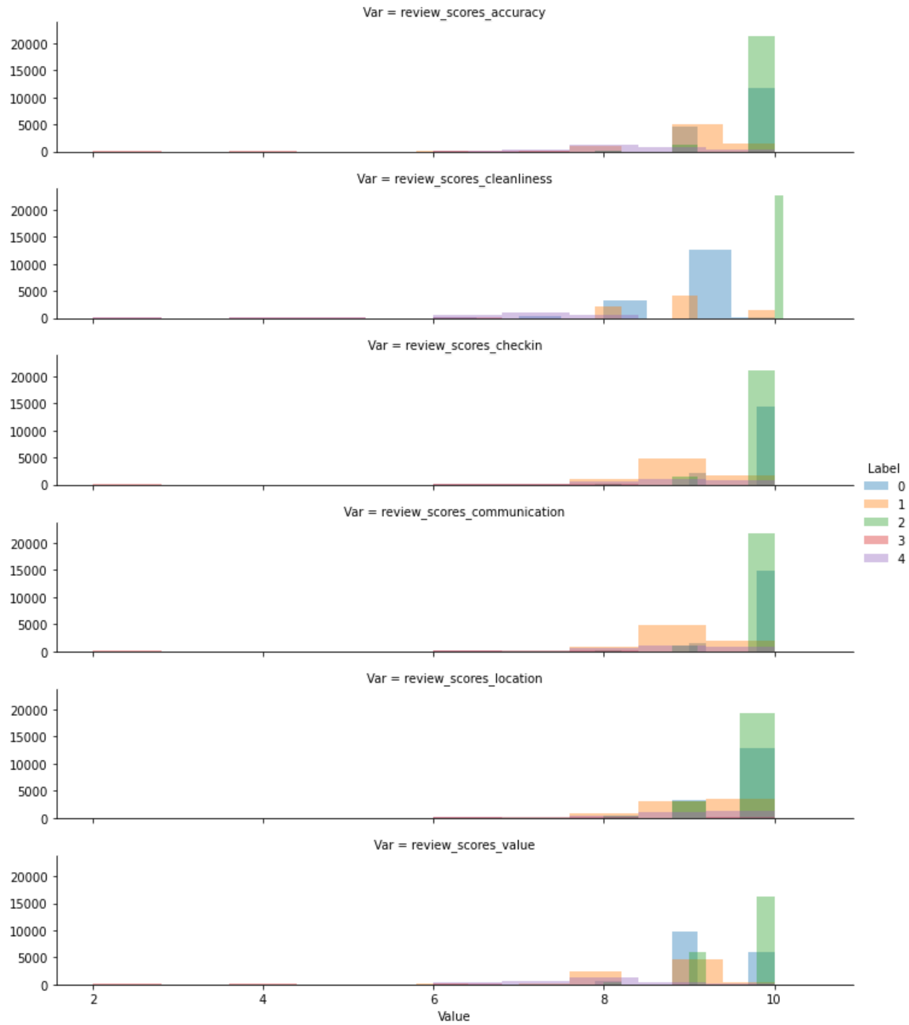
To explore the *distribution* of the values inside each cluster, rather than their mean, we can use the fancy `FaceGrid` approach:

```
tidy_db = db[review_areas]\
            .stack()\
            .reset_index()\
            .rename(columns={"level_1": "Var",
                             "level_0": "ID",
                             0: "Value"
                            })\
            .join(pandas.DataFrame({"Label": k5_pca}),
                  on="ID")
tidy_db.head()
```

	ID	Var	Value	Label
0	0	review_scores_accuracy	10.0	2
1	0	review_scores_cleanliness	10.0	2
2	0	review_scores_checkin	10.0	2
3	0	review_scores_communication	10.0	2
4	0	review_scores_location	10.0	2

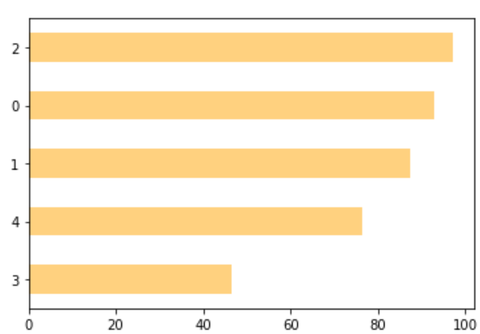
```
g = sns.FacetGrid(tidy_db,
                  row="Var",
                  hue="Label",
                  height=2,
                  aspect=5
                 )
g.map(sns.distplot,
      "Value",
      hist=True,
      bins=10,
      kde=False,
      rug=False
     )
g.add_legend();
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please
adapt your code to use either `displot` (a figure-level function with similar
flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



Externally:

```python
# Cross with review_scores_rating
db.groupby(k5_pca)\
  ["review_scores_rating"]\
  .mean()\
  .sort_values()\
  .plot.barh(color="orange",
             alpha=0.5
            );
```



EXERCISE Can you cross the clustering results with property prices? Create:

- A bar plot with the average price by cluster
- A plot with the distribution (KDE/hist) of prices within cluster

---

Before we move on, let's also save the labels of the results:

```
pandas.DataFrame({"k5_pca": k5_pca})\
      .to_parquet("../data/k5_pca.parquet")
```

Supervised Learning

To do before...

[Async]

Background

Here is a taster for supervised learning to make you want more, which we'll do on the live session. To prepare for this part of the course (which includes the section below, as well as the one on inference and overfitting/CV), here are two tasks you will need to complete *before* the live session:

First, watch the following clip which sets up the scene for what will be to come

Slides

The slides used in the clip are available at:

- `[HTML]`
- `[PDF]`

Second, read the following two articles, all mentioned in the clip:

- *Statistical Modeling: the Two Cultures* ([B+01])

An open access, PDF version is available here

- *Machine Learning*: An Applied Econometric Approach* ([MS17])

An open access, PDF version is available here

Regression trees

Most of this block relies on linear regression. Linear regression is one of the simplest but also most powerful supervised algorithms. Later in the section, we will contrast its use with another technique that has gained much popularity since its inception at the turn of the millenium: random forests. A detailed understanding of random forests goes beyond the scope of this course. However, its intuition will be useful and will be covered here.

To understand random forests, we first need to learn about regression trees:

A forest is no more than a collection of trees. A random forest thus will "grow" several trees, and then aggregate the predictions of each into a single, better prediction. This is what we call "bagging":

Building on these two ideas, the notion of a "random" forest makes a bit more sense:

Action!

[Sync]

```
%matplotlib inline
from IPython.display import Image

import pandas
import numpy as np
```

Local files Online read

Assuming you have the file downloaded on the path `../data/`:

```
db = pandas.read_csv("../data/paris_abb.csv.zip")
```

Linear Regression

$$P_i = \alpha + \beta X + \epsilon$$

The Econometrician way

```
import statsmodels.formula.api as sm
```

- Raw price

```
f = "Price ~ bathrooms + bedrooms + room_type"
lm_raw = sm.ols(f, db)\
       .fit()
lm_raw
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7f458e6d1cd0>
```

```
lm_raw.summary()
```

Dep. Variable:	Price	**R-squared:**	0.103
Model:	OLS	**Adj. R-squared:**	0.103
Method:	Least Squares	**F-statistic:**	1151.
Date:	Thu, 07 Jan 2021	**Prob (F-statistic):**	0.00
Time:	17:24:33	**Log-Likelihood:**	-3.2312e+05
No. Observations:	50280	**AIC:**	6.462e+05
Df Residuals:	50274	**BIC:**	6.463e+05
Df Model:	5		
Covariance Type:	nonrobust		

OLS Regression Results

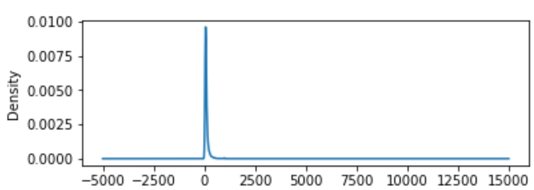
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	69.3589	1.295	53.573	0.000	66.821	71.896
room_type[T.Hotel room]	148.7074	4.779	31.120	0.000	139.341	158.073
room_type[T.Private room]	-51.5793	2.202	-23.425	0.000	-55.895	-47.264
room_type[T.Shared room]	-71.5010	8.692	-8.226	0.000	-88.537	-54.465
bathrooms	-2.4081	1.367	-1.762	0.078	-5.087	0.271
bedrooms	43.3410	0.939	46.174	0.000	41.501	45.181

Omnibus:	135133.909	**Durbin-Watson:**	1.923
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	6632879884.203
Skew:	32.680	**Prob(JB):**	0.00
Kurtosis:	1781.140	**Cond. No.**	27.2

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Now, $Price$ is rather skewed:

```
db.Price.plot.kde(figsize=(6, 2));
```



We could take the log to try to obtain a better fit:

```
f = "np.log1p(Price) ~ bathrooms + bedrooms + room_type"
lm_log = sm.ols(f, db)\
       .fit()
lm_log
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7f458e1484c0>
```

```python
lm_log.rsquared
```

```
0.31515872008420753
```

```python
lm_raw.rsquared
```

```
0.10269412705703151
```

That is *inference* though. We're here to "machine learn"!

```python
# Get predictions
yp_raw = lm_raw.fittedvalues
yp_raw.head()
```

```
0     66.950833
1     66.950833
2    153.632865
3    110.291849
4    110.291849
dtype: float64
```

Or…

```python
lm_raw.predict(db[["bathrooms",
                   "bedrooms",
                   "room_type"
                  ]])\
      .head()
```

```
0     66.950833
1     66.950833
2    153.632865
3    110.291849
4    110.291849
dtype: float64
```

The Machine Learner way

We need to:

- Get the dummies ourselves first

```python
room_type_ds = pandas.get_dummies(db["room_type"])
room_type_ds.head(2)
```

	Entire home/apt	Hotel room	Private room	Shared room
0	1	0	0	0
1	1	0	0	0

- Prep X and y

```python
X = pandas.concat([db[["bathrooms", "bedrooms"]],
                   room_type_ds.drop("Entire home/apt",
                                     axis=1)
                  ], axis=1
                 )
X.head()
```

	bathrooms	bedrooms	Hotel room	Private room	Shared room
0	1.0	0.0	0	0	0
1	1.0	0.0	0	0	0
2	1.0	2.0	0	0	0
3	1.0	1.0	0	0	0
4	1.0	1.0	0	0	0

- Set up a model

```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()
```

- Train the model (see the use of `fit`)

```
regressor.fit(X, db["Price"])
```

```
LinearRegression()
```

And voila, we have our results!

```
pandas.Series(regressor.coef_,
              index=X.columns
             )
```

```
bathrooms        -2.408064
bedrooms         43.341016
Hotel room      148.707387
Private room    -51.579347
Shared room     -71.501010
dtype: float64
```

```
regressor.intercept_
```

```
69.35889717336228
```

```
lm_raw.params
```

```
Intercept                      69.358897
room_type[T.Hotel room]       148.707387
room_type[T.Private room]     -51.579347
room_type[T.Shared room]      -71.501010
bathrooms                      -2.408064
bedrooms                       43.341016
dtype: float64
```

Tree-based approaches: the Random Forest

```
from sklearn.ensemble import RandomForestRegressor
```

Very similar API (as throughout `sklearn`). Two parameters to set (see here for guidance):

```
rf_raw = RandomForestRegressor(n_estimators=100,
                               max_features=None
                              )

%time rf_raw.fit(X, db["Price"])
```

```
CPU times: user 750 ms, sys: 0 ns, total: 750 ms
Wall time: 749 ms
```

```
RandomForestRegressor(max_features=None)
```

To recover the predictions, we need to rely on `predict`:

```
rf_raw_lbls = rf_raw.predict(X)
rf_raw_lbls
```

```
array([ 71.98778067,  71.98778067, 140.74061093, ...,  93.62649936,
        71.98778067,  93.62649936])
```

For completeness, let's quickly fit a Random Forest on the log of price:

```
rf_log = RandomForestRegressor(n_estimators=100,
                               max_features=None
                              )

%time rf_log.fit(X, np.log1p(db["Price"]))

rf_log_lbls = rf_log.predict(X)
```

```
CPU times: user 590 ms, sys: 0 ns, total: 590 ms
Wall time: 589 ms
```

EXERCISE

- Train a random forest on the price using the number of beds and the property type instead

---

Before we move on, let's record all the predictions in a single table for convenience:

```
res = pandas.DataFrame({"LM-Raw": lm_raw.fittedvalues,
                        "LM-Log": lm_log.fittedvalues,
                        "RF-Raw": rf_raw_lbls,
                        "RF-Log": rf_log_lbls,
                        "Truth": db["Price"]
                       })
res.head()
```

	LM-Raw	LM-Log	RF-Raw	RF-Log	Truth
0	66.950833	4.198030	71.987781	4.181397	60.0
1	66.950833	4.198030	71.987781	4.181397	115.0
2	153.632865	4.850742	140.740611	4.817468	119.0
3	110.291849	4.524386	93.626499	4.444683	130.0
4	110.291849	4.524386	93.626499	4.444683	75.0

And write it out to a file:

```
res.to_parquet("../data/lm_results.parquet")
```

An example with categorical outcomes

Let's bring back the classification we did in the previous session:

```
k5_pca = pandas.read_parquet("../data/k5_pca.parquet")\
               .reindex(db.index)
k5_pca.head()
```

	k5_pca
0	2
1	1
2	0
3	2
4	2

Now we might conceive cases where we want to build a model to predict these classes based on some house characteristics. To illustrate it, let's consider the same variables as above. In this case, however, we want a *classifier* rather than a *regressor*, as the response is categorical.

```
from sklearn.ensemble import RandomForestClassifier
```

But the training is very similar:

```
%%time

classifier = RandomForestClassifier(n_estimators=100,
                                    max_features="sqrt"
                                   )
classifier.fit(X, k5_pca["k5_pca"])

pred_lbls = pandas.Series(classifier.predict(X),
                          index=k5_pca.index
                         )
```

```
CPU times: user 1.23 s, sys: 0 ns, total: 1.23 s
Wall time: 1.23 s
```

```
class_res = pandas.DataFrame({"Truth": k5_pca["k5_pca"],
                              "Predicted": pred_lbls
                             }
                            ).apply(pandas.Categorical)
class_res.describe()
```

	Truth	Predicted
count	50280	50280
unique	5	5
top	2	2
freq	22773	49801

Inference

_[Sync]

```
%matplotlib inline
from IPython.display import Image

import pandas
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as sm
from sklearn.preprocessing import scale
from sklearn import metrics
```

Local files   Online read

Assuming you have [the file]() downloaded on the path `../data/`:

```
db = pandas.read_csv("../data/paris_abb.csv.zip")
```

```
db['l_price'] = np.log1p(db['Price'])
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50280 entries, 0 to 50279
Data columns (total 11 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   id                      50280 non-null  int64  
 1   neighbourhood_cleansed  50280 non-null  object 
 2   property_type           50280 non-null  object 
 3   room_type               50280 non-null  object 
 4   accommodates            50280 non-null  int64  
 5   bathrooms               50280 non-null  float64
 6   bedrooms                50280 non-null  float64
 7   beds                    50280 non-null  float64
 8   bed_type                50280 non-null  object 
 9   Price                   50280 non-null  float64
 10  l_price                 50280 non-null  float64
dtypes: float64(5), int64(2), object(4)
memory usage: 4.2+ MB
```

Baseline model

$$\log(P) = \alpha + X\beta + \epsilon$$

X:

- Bathrooms
- Bedrooms
- Beds
- Room type

```
m1 = sm.ols('l_price ~ bedrooms + bathrooms + beds', db).fit()
m1.summary()
```

Dep. Variable:	l_price	**R-squared:**	0.245
Model:	OLS	**Adj. R-squared:**	0.245
Method:	Least Squares	**F-statistic:**	5433.
Date:	Thu, 07 Jan 2021	**Prob (F-statistic):**	0.00
Time:	17:25:24	**Log-Likelihood:**	-38592.
No. Observations:	50280	**AIC:**	7.719e+04
Df Residuals:	50276	**BIC:**	7.723e+04
Df Model:	3		
Covariance Type:	nonrobust		

OLS Regression Results

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	4.1806	0.005	852.126	0.000	4.171	4.190
bedrooms	0.2253	0.004	57.760	0.000	0.218	0.233
bathrooms	-0.1544	0.005	-32.373	0.000	-0.164	-0.145
beds	0.1398	0.003	50.554	0.000	0.134	0.145

Omnibus:	11384.882	**Durbin-Watson:**	1.846
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	585415.122
Skew:	-0.096	**Prob(JB):**	0.00
Kurtosis:	19.715	**Cond. No.**	7.94

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

To note:

- Decent R^2 (although that's not holy truth)
- Every variable significant and related as expected
- Interpret coefficients

```
cols = ['bedrooms', 'bathrooms', 'beds']
scX = pandas.DataFrame(scale(db[cols]),
                       index=db.index,
                       columns=cols)
scX.describe()
```

	bedrooms	bathrooms	beds
count	5.028000e+04	5.028000e+04	5.028000e+04
mean	1.748138e-14	1.621070e-15	-5.895298e-15
std	1.000010e+00	1.000010e+00	1.000010e+00
min	-1.076738e+00	-1.625116e+00	-1.429042e+00
25%	-7.772733e-02	-1.702805e-01	-5.706025e-01
50%	-7.772733e-02	-1.702805e-01	-5.706025e-01
75%	-7.772733e-02	-1.702805e-01	2.878366e-01
max	4.887380e+01	7.111664e+01	4.149292e+01

```
m2 = sm.ols('l_price ~ bedrooms + bathrooms + beds',
            data=scX.join(db['l_price']))\
       .fit()
m2.summary()
```

Dep. Variable:	l_price	**R-squared:**	0.245
Model:	OLS	**Adj. R-squared:**	0.245
Method:	Least Squares	**F-statistic:**	5433.
Date:	Thu, 07 Jan 2021	**Prob (F-statistic):**	0.00
Time:	17:25:24	**Log-Likelihood:**	-38592.
No. Observations:	50280	**AIC:**	7.719e+04
Df Residuals:	50276	**BIC:**	7.723e+04
Df Model:	3		
Covariance Type:	nonrobust		

OLS Regression Results

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4.4837	0.002	1928.462	0.000	4.479	4.488
bedrooms	0.2255	0.004	57.760	0.000	0.218	0.233
bathrooms	-0.1061	0.003	-32.373	0.000	-0.113	-0.100
beds	0.1628	0.003	50.554	0.000	0.156	0.169

Omnibus:	11384.882	**Durbin-Watson:**	1.846
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	585415.122
Skew:	-0.096	**Prob(JB):**	0.00
Kurtosis:	19.715	**Cond. No.**	3.11

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Let's bring both sets of results together:

```
pandas.DataFrame({"Baseline": m1.params,
                  "X Std.": m2.params
                 })
```

	Baseline	X Std.
Intercept	4.180599	4.483657
bedrooms	0.225325	0.225548
bathrooms	-0.154385	-0.106119
beds	0.139759	0.162806

To note:

How does interpretation of the coefficients change?

- Meaning of intecept when X is demeanded
- Units in which β are interpreted

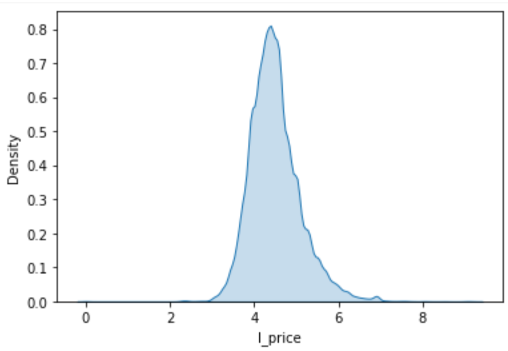
Predictive checking

Is the model picking up the overall "shape of data"?

- Important to know how much we should trust our inferences
- Crucial if we want to use the model to predict!

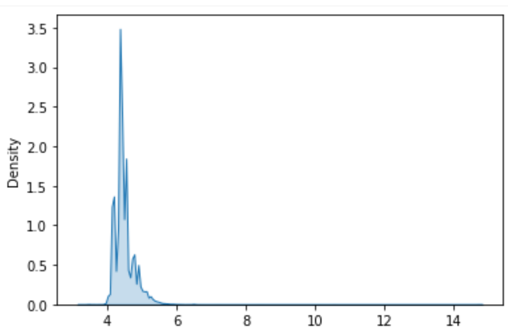
```
sns.kdeplot(db['l_price'], shade=True)
```

```
<AxesSubplot:xlabel='l_price', ylabel='Density'>
```

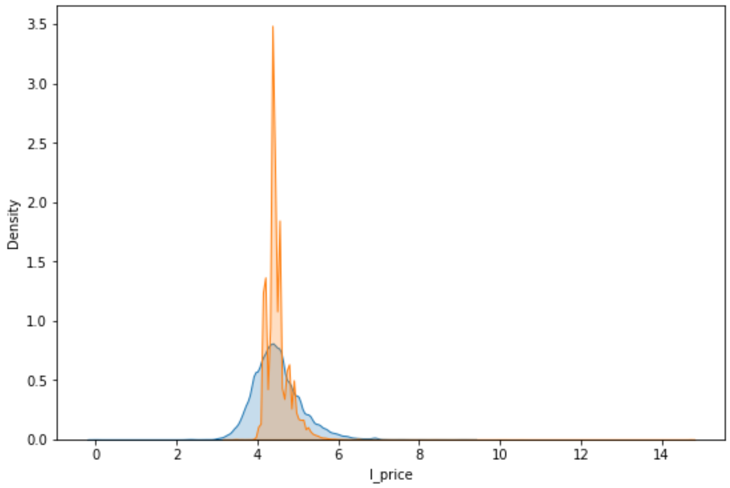



```
sns.kdeplot(m1.fittedvalues, shade=True)
```

```
<AxesSubplot:ylabel='Density'>
```




```
f, ax = plt.subplots(1, figsize=(9, 6))
sns.kdeplot(db['l_price'], shade=True, ax=ax, label='$y$')
sns.kdeplot(m1.fittedvalues, shade=True, ax=ax, label='$\hat{y}$')
plt.show()
```



To note:

- Not a terrible start
- How could we improve it?

```
m3 = sm.ols('l_price ~ bedrooms + bathrooms + beds + room_type', db).fit()
m3.summary()
```

Dep. Variable:	l_price	**R-squared:**	0.340
Model:	OLS	**Adj. R-squared:**	0.340
Method:	Least Squares	**F-statistic:**	4314.
Date:	Thu, 07 Jan 2021	**Prob (F-statistic):**	0.00
Time:	17:25:25	**Log-Likelihood:**	-35210.
No. Observations:	50280	**AIC:**	7.043e+04
Df Residuals:	50273	**BIC:**	7.050e+04
Df Model:	6		
Covariance Type:	nonrobust		

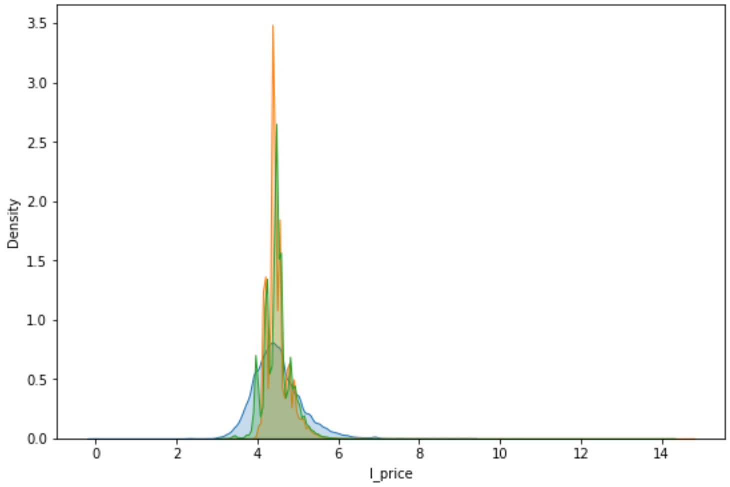
OLS Regression Results

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	4.2417	0.005	899.941	0.000	4.232	4.251
room_type[T.Hotel room]	0.5548	0.016	35.619	0.000	0.524	0.585
room_type[T.Private room]	-0.4862	0.007	-66.604	0.000	-0.501	-0.472
room_type[T.Shared room]	-1.0320	0.028	-36.320	0.000	-1.088	-0.976
bedrooms	0.2388	0.004	65.134	0.000	0.232	0.246
bathrooms	-0.1440	0.004	-32.285	0.000	-0.153	-0.135
beds	0.1144	0.003	43.386	0.000	0.109	0.120

Omnibus:	11695.728	**Durbin-Watson:**	1.878
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	680804.847
Skew:	-0.027	**Prob(JB):**	0.00
Kurtosis:	21.027	**Cond. No.**	37.2

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

```
f, ax = plt.subplots(1, figsize=(9, 6))
sns.kdeplot(db['l_price'], shade=True, ax=ax, label='$y$')
sns.kdeplot(m1.fittedvalues, shade=True, ax=ax, label='$\hat{y}_1$')
sns.kdeplot(m3.fittedvalues, shade=True, ax=ax, label='$\hat{y}_2$')
plt.show()
```



To note:

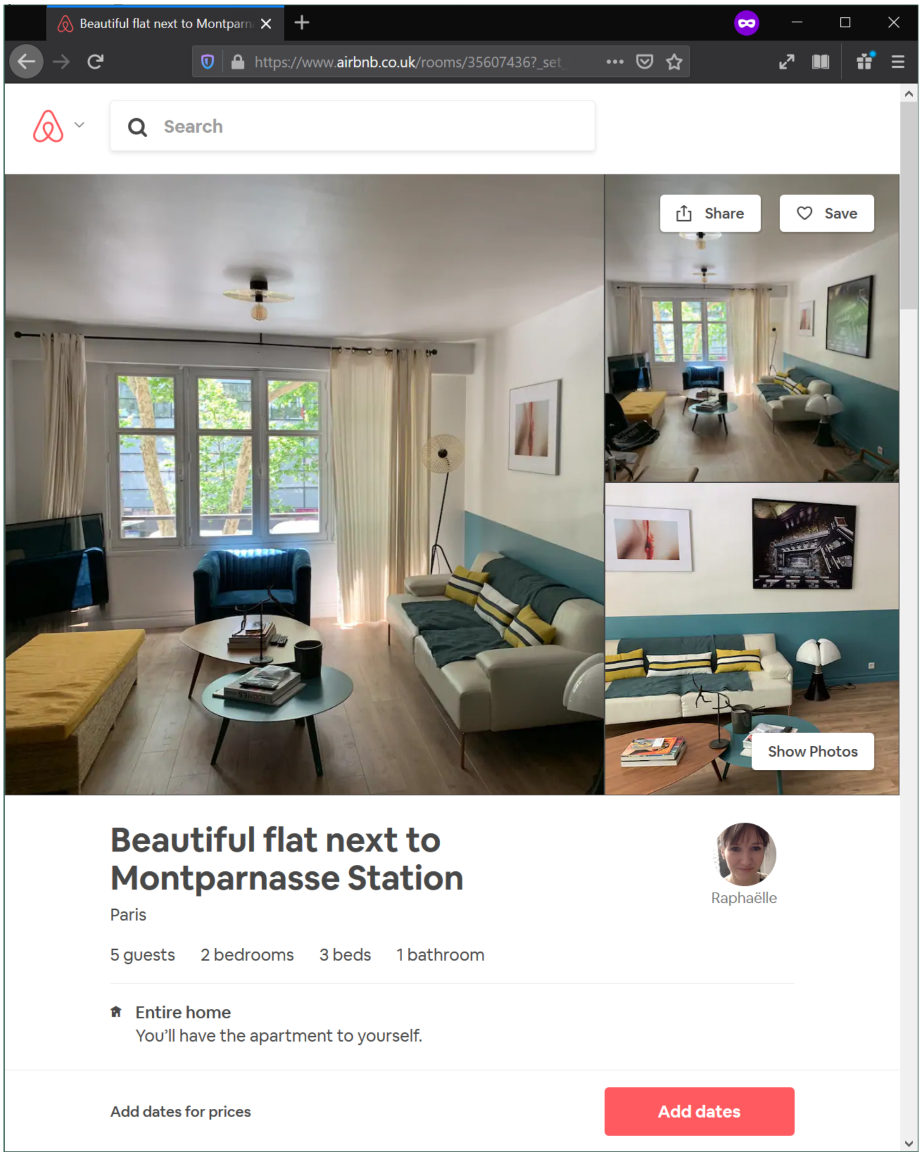
- This is better!
- But these are only point predictions. Sometimes that's good enough.
- Usually however, we want a model to capture the underlying process instead of the particular realisation observed (ie. dataset).
- Then we need to think about the uncertainty embedded in the model we are estimating

Inferential Vs Predictive uncertainty

[See more in Chapter 7.2 of Gelman & Hill 2006]

- Two types of uncertainty in our model
  - Predictive (ϵ)
  - Inferential (β)
- Both affect the final predictions we make

```
Image("../figs/abb_room.png", retina=True)
```




```
room = db.loc[db['id']==35607436, :]
room.T
```

	45979
id	35607436
neighbourhood_cleansed	Luxembourg
property_type	Apartment
room_type	Entire home/apt
accommodates	5
bathrooms	1
bedrooms	2
beds	3
bed_type	Real Bed
Price	90
l_price	4.51086

```
rid = room.index[0]
db.loc[rid, :]
```

```
id                                35607436
neighbourhood_cleansed          Luxembourg
property_type                    Apartment
room_type                  Entire home/apt
accommodates                             5
bathrooms                                1
bedrooms                                 2
beds                                     3
bed_type                          Real Bed
Price                                   90
l_price                            4.51086
Name: 45979, dtype: object
```

$$\log(\hat{P_i}) = \alpha + \sum_k \beta_k * X_k$$

```
m1.params['Intercept'] + db.loc[rid, cols].dot(m1.params[cols])
```

```
4.896141184855212
```

To note:

- What does `dot` do?

```
m1.fittedvalues[rid]
```

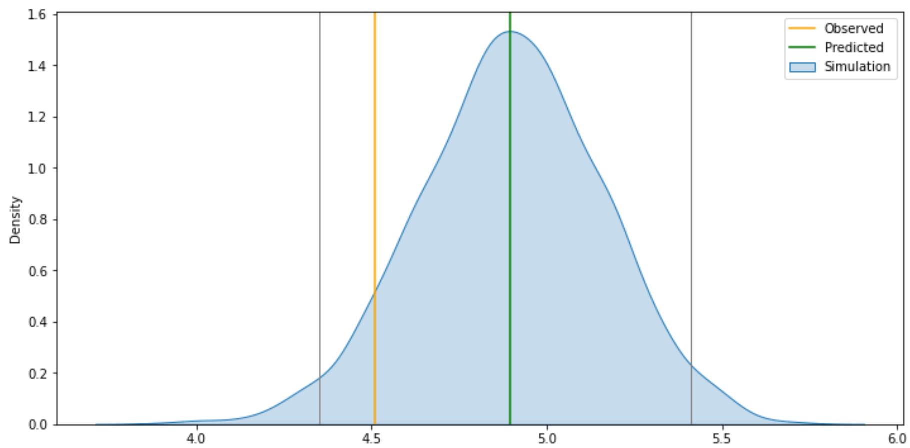
```
4.896141184855212
```

Point predictive simulation

```
%%time
# Parameters
## Number of simulations
r = 2000
# Pull out characteristics for house of interest
x_i = db.loc[rid, cols]
# Specify model engine
model = m1

# Place-holder
sims = np.zeros(r)
# Loop over number of replications
for i in range(r):
    # Get a random draw of betas
    rbs = np.random.normal(model.params, model.bse)
    # Get a random draw of epsilon
    re = np.random.normal(0, model.scale)
    # Obtain point estimate
    y_hr = rbs[0] + np.dot(x_i, rbs[1:]) + re
    # Store estimate
    sims[i] = y_hr
```

```
CPU times: user 637 ms, sys: 35.1 ms, total: 672 ms
Wall time: 632 ms
```

```
f, ax = plt.subplots(1, figsize=(12, 6))

sns.kdeplot(sims, shade=True, ax=ax, label='Simulation')
ax.axvline(db.loc[rid, 'l_price'], c='orange', label='Observed')
ax.axvline(model.fittedvalues[rid], c='green', label='Predicted')

lo, up = pandas.Series(sims)\
               .sort_values()\
               .iloc[[int(np.round(0.025 * r)), int(np.round(0.975 * r))]]
ax.axvline(lo, c='grey', linewidth=1)
ax.axvline(up, c='grey', linewidth=1)

plt.legend()
plt.show()
```



To note:

- Intuition of the simulation
- The `for` loop, deconstructed
- The graph, bit by bit
- If we did this for every observation, we'd expect 95% to be within the 95% bands

---

Exercise

Explore with the code above and try to generate similar plots for:

- Different houses across locations and characteristics
- Different model

Exercise+

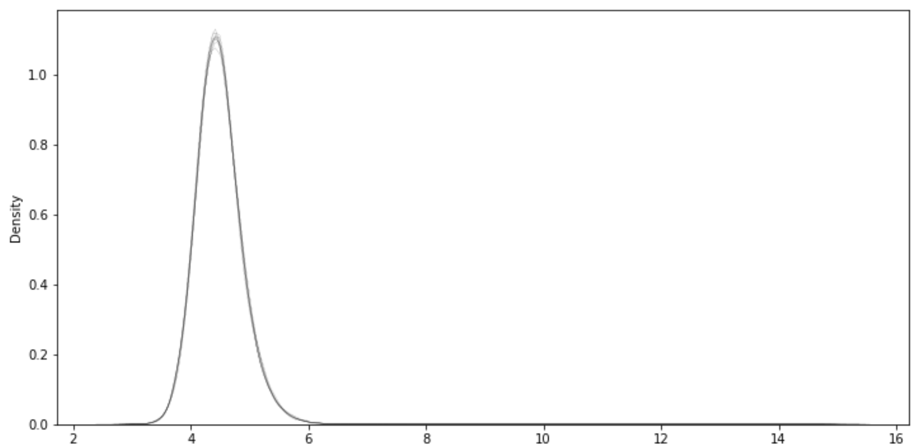
Recreate the analysis above for observation `5389821`. What happens? Why?

Now, we could do this for ***all*** the observations and get a sense of the overall distribution to be expected

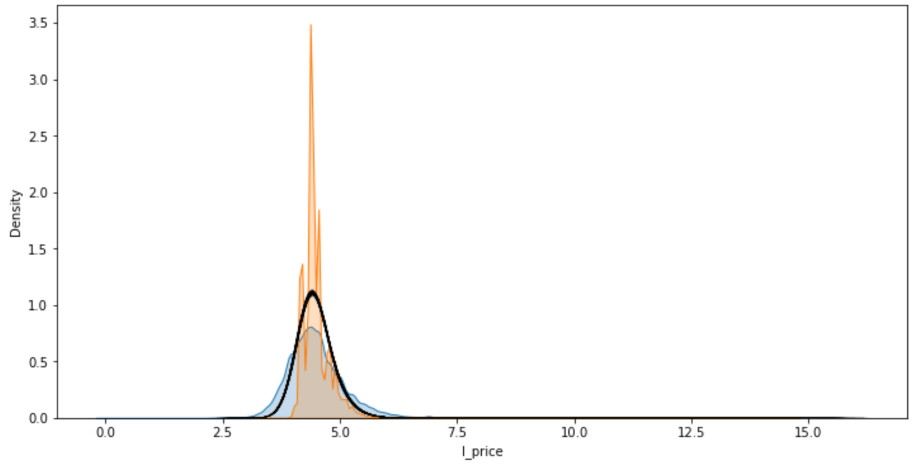
```
%%time
# Parameters
## Number of observations & simulations
n = db.shape[0]
r = 200
# Specify model engine
model = m1

# Place-holder (N, r)
sims = np.zeros((n, r))
# Loop over number of replications
for i in range(r):
    # Get a random draw of betas
    rbs = np.random.normal(model.params, model.bse)
    # Get a random draw of epsilon
    re = np.random.normal([0]*n, model.scale)
    # Obtain point estimate
    y_hr = rbs[0] + np.dot(db[cols], rbs[1:]) + re
    # Store estimate
    sims[:, i] = y_hr
```

```
CPU times: user 5.61 s, sys: 27.3 s, total: 32.9 s
Wall time: 2.08 s
```

```
f, ax = plt.subplots(1, figsize=(12, 6))

for i in range(10):
    sns.kdeplot(sims[:, i], ax=ax, linewidth=0.1, alpha=0.1, color='k')

plt.show()
```




```
f, ax = plt.subplots(1, figsize=(12, 6))

sns.kdeplot(db['l_price'], shade=True, ax=ax, label='$y$')
sns.kdeplot(m1.fittedvalues, shade=True, ax=ax, label='$\hat{y}$')

for i in range(r):
    sns.kdeplot(sims[:, i], ax=ax, linewidth=0.1, alpha=0.1, color='k')

plt.show()
```



To note:

- Black line contains r thin lines that collectively capture the uncertainty behind the model

New data

Imagine we are trying to figure out how much should we charge for a property we want to put on AirBnb.

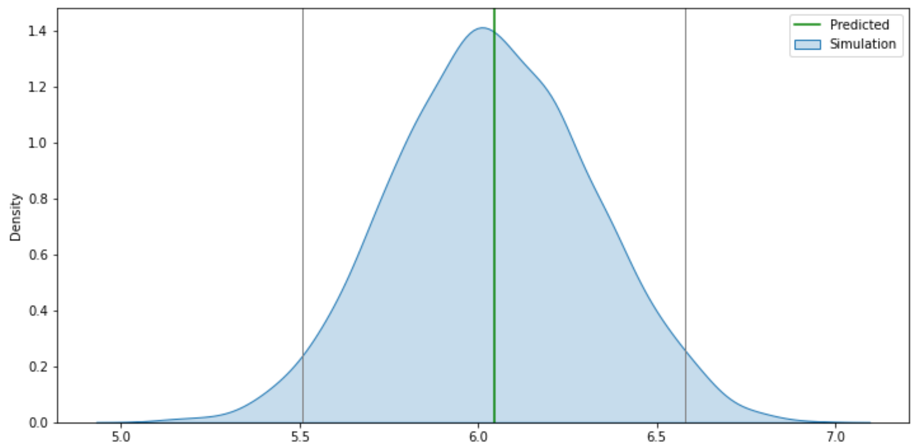
For example, let's assume our property is:

```
new = pandas.Series({'bedrooms': 4,
                     'bathrooms': 1,
                     'beds': 8})
```

```
%%time
# Parameters
## Number of simulations
r = 2000
# Pull out characteristics for house of interest
x_i = new
# Specify model engine
model = m1

# Place-holder
sims = np.zeros(r)
# Loop over number of replications
for i in range(r):
    # Get a random draw of betas
    rbs = np.random.normal(model.params, model.bse)
    # Get a random draw of epsilon
    re = np.random.normal(0, model.scale)
    # Obtain point estimate
    y_hr = rbs[0] + np.dot(x_i, rbs[1:]) + re
    # Store estimate
    sims[i] = y_hr
```

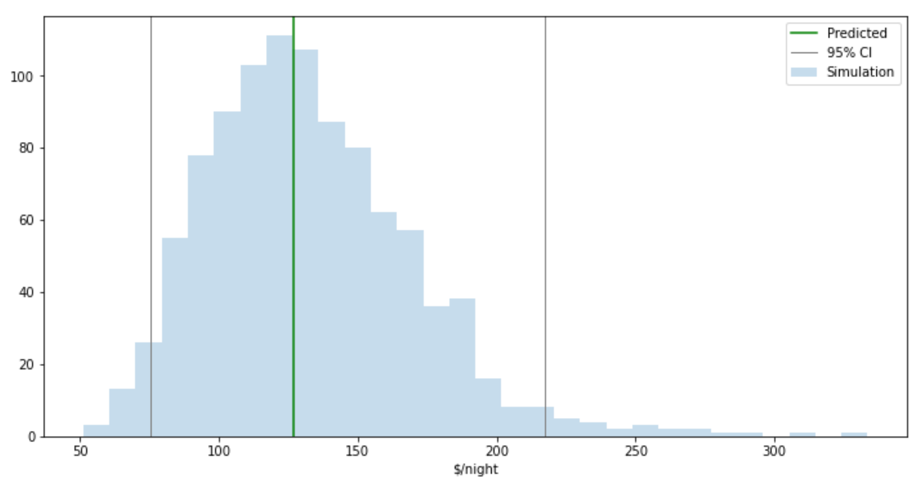
```
CPU times: user 640 ms, sys: 4.53 ms, total: 644 ms
Wall time: 643 ms
```

```
f, ax = plt.subplots(1, figsize=(12, 6))

sns.kdeplot(sims, shade=True, ax=ax, label='Simulation')
ax.axvline(model.params.iloc[0] + np.dot(new, model.params.iloc[1:]), \
           c='green', label='Predicted')

lo, up = pandas.Series(sims)\
               .sort_values()\
               .iloc[[int(np.round(0.025 * r)), int(np.round(0.975 * r))]]
ax.axvline(lo, c='grey', linewidth=1)
ax.axvline(up, c='grey', linewidth=1)

plt.legend()
plt.show()
```



[Pro]

```
def predictor(bedrooms, bathrooms, beds):
    new = pandas.Series({'bedrooms': bedrooms,
                         'bathrooms': bathrooms,
                         'beds': beds
                        })
    r = 1000
    x_i = new
    model = m1
    y_hat = model.params.iloc[0] + np.dot(new, model.params.iloc[1:])
    # Simulation
    sims = np.zeros(r)
    for i in range(r):
        rbs = np.random.normal(model.params, model.bse)
        re = np.random.normal(0, model.scale)
        y_hr = rbs[0] + np.dot(x_i, rbs[1:]) + re
        sims[i] = y_hr
    sims = np.exp(sims)
    y_hat = np.exp(y_hat)
    # Bands
    lo, up = pandas.Series(sims)\
               .sort_values()\
               .iloc[[int(np.round(0.025 * r)), int(np.round(0.975 * r))]]
    # Setup'n'draw figure
    f, ax = plt.subplots(1, figsize=(12, 6))
    ax.hist(sims, label='Simulation', alpha=0.25, bins=30)
    ax.axvline(y_hat, c='green', label='Predicted')
    ax.axvline(lo, c='grey', linewidth=1, label='95% CI')
    ax.axvline(up, c='grey', linewidth=1)
    #ax.set_xlim((0, 10))
    # Dress up
    ax.set_xlabel("$/night")
    plt.legend()
    return plt.show()

predictor(3, 1, 1)
```



```python
# You might have to run this to make interactives work
# jupyter labextension install @jupyter-widgets/jupyterlab-manager
# From https://ipywidgets.readthedocs.io/en/latest/user_install.html#installing-the-jupyterlab-extension
# Then restart Jupyter Lab
from ipywidgets import interact, IntSlider

interact(predictor,
         bedrooms=IntSlider(min=1, max=10), \
         bathrooms=IntSlider(min=0, max=10), \
         beds=IntSlider(min=1, max=20)
        );
```

Model performance

To note:

- Switch from inference to prediction
- Overall idea of summarising model performance
- R^2
- Error-based measures

```python
# R^2
r2 = pandas.Series({'Baseline': metrics.r2_score(db['l_price'],
                                                 m1.fittedvalues),
                    'Augmented': metrics.r2_score(db['l_price'],
                                                  m3.fittedvalues)})
r2
```

```
Baseline     0.244826
Augmented    0.339876
dtype: float64
```

```python
# MSE
mse = pandas.Series({'Baseline': metrics.mean_squared_error(db['l_price'],
                                                            m1.fittedvalues),
                     'Augmented': metrics.mean_squared_error(db['l_price'],
                                                             m3.fittedvalues)})
mse
```

```
Baseline     0.271771
Augmented    0.237565
dtype: float64
```

```python
# MAE
mae = pandas.Series({'Baseline': metrics.mean_absolute_error(db['l_price'],
                                                             m1.fittedvalues),
                     'Augmented': metrics.mean_absolute_error(db['l_price'],
                                                              m3.fittedvalues)})
mae
```

```
Baseline     0.379119
Augmented    0.357287
dtype: float64
```

```python
# All
perf = pandas.DataFrame({'MAE': mae,
                         'MSE': mse,
                         'R^2': r2})
perf
```

	MAE	MSE	R^2
Baseline	0.379119	0.271771	0.244826
Augmented	0.357287	0.237565	0.339876

Overfitting & Cross-Validation

[Sync]

```
%matplotlib inline

import pandas
import seaborn as sns
import matplotlib.pyplot as plt
from numpy import exp, log1p, sqrt
```

Local files Online read

Assuming you have the files downloaded on the path `../data/`:

```
orig = pandas.read_csv("../data/paris_abb.csv.zip")
res = pandas.read_parquet("../data/lm_results.parquet")
```

```
db = base.join(res)
```

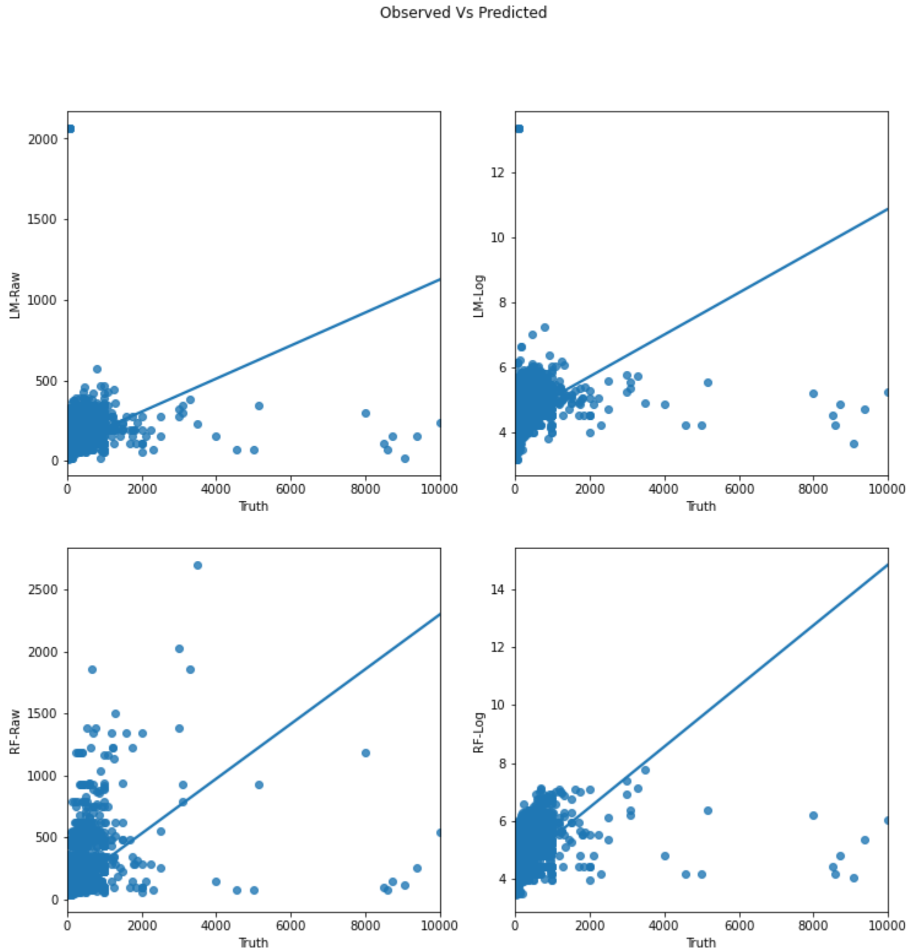
Overfitting

So we have models but, are they any good?

Model evaluation the ML is all about predictive performance (remember the $\hat{\beta}$ Vs $\hat{y}$, this is all about $\hat{y}$).

```
f, axs = plt.subplots(2, 2, figsize=(12, 12))
axs = axs.flatten()
for i, m in enumerate(res.columns.drop("Truth")):
    ax = axs[i]
    sns.regplot("Truth",
                m,
                res,
                ci=None,
                ax=ax
               )
f.suptitle(f"Observed Vs Predicted")
plt.show()
```

```
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y, data. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y, data. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y, data. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/opt/conda/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass
the following variables as keyword args: x, y, data. From version 0.12, the only
valid positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



There are several measures, we'll use two:

- R^2

```
from sklearn.metrics import r2_score
```

Let's compare apparent performance:

```
r2s = pandas.Series({"LM-Raw": r2_score(db["Truth"],
                                        db["LM-Raw"]
                                       ),
                     "LM-Log": r2_score(log1p(db["Truth"]),
                                        db["LM-Log"]
                                       ),
                     "RF-Raw": r2_score(db["Truth"],
                                        db["RF-Raw"]
                                       ),
                     "RF-Log": r2_score(log1p(db["Truth"]),
                                        db["RF-Log"]
                                       ),
                    })
r2s
```

```
LM-Raw    0.102694
LM-Log    0.315159
RF-Raw    0.225217
RF-Log    0.443318
dtype: float64
```

- (R)MSE

```
from sklearn.metrics import mean_squared_error as mse
```

And a similar comparison (where we can convert all predictions to price units):

```
mses = pandas.Series({"LM-Raw": mse(db["Truth"],
                                    db["LM-Raw"]
                                   ),
                      "LM-Log": mse(db["Truth"],
                                    exp(db["LM-Log"])
                                   ),
                      "RF-Raw": mse(db["Truth"],
                                    db["RF-Raw"]
                                   ),
                      "RF-Log": mse(db["Truth"],
                                    exp(db["RF-Log"])
                                   ),
                     }).apply(sqrt)
mses
```

```
LM-Raw     149.522153
LM-Log    7570.085725
RF-Raw     138.939346
RF-Log     140.904608
dtype: float64
```

Now this is great news for the random forest!

... or is it?

Let's do a thought experiment. Imagine that AirBnb, for some reason, did not initially move into the Passy neighbourhood.

Let's quickly retrain our models for that world. For convenience, let's focus on the raw models, not those based on logs:

```
room_type_ds = pandas.get_dummies(db["room_type"])
X = pandas.concat([db[["bathrooms", "bedrooms"]],
                   room_type_ds.drop("Entire home/apt",
                                     axis=1)
                  ], axis=1
                 )
# Passy IDs
pi = db.query("neighbourhood_cleansed == 'Passy'").index
# Non Passy IDs
npi = db.index.difference(pi)

# Non Passy data (same as in previous notebook)
X_np = X.reindex(npi)
```

```python
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import LinearRegression

# Linear model
lm_raw_np_model = LinearRegression().fit(X_np,
                                         db.loc[npi, "Price"]
                                        )
lm_raw_np = lm_raw_np_model.predict(X_np)
# RF
rf_raw_np_model = RandomForestRegressor(n_estimators=100,
                                        max_features=None
                                       )\
                                      .fit(X_np,
                                           db.loc[npi, "Price"]
                                          )
rf_raw_np = rf_raw_np_model.predict(X_np)
```

The *apparent* performance of our model is similar, a bit better if anything:

```python
mses_np = pandas.Series({"LM-Raw": mse(db.loc[npi, "Truth"],
                                       lm_raw_np
                                      ),
                         "RF-Raw": mse(db.loc[npi, "Truth"],
                                       rf_raw_np
                                      ),
                        }).apply(sqrt)
mses_np
```

```
LM-Raw    144.326619
RF-Raw    134.277649
dtype: float64
```

```python
mses.reindex(mses_np.index)
```

```
LM-Raw    149.522153
RF-Raw    138.939346
dtype: float64
```

Now imagine that Passy comes on the AirBnb market and we need to provide price estimates for its properties. We can use our model to make predictions:

```python
# Linear predictions
lm_raw_passy_pred = lm_raw_np_model.predict(X.reindex(pi))
lm_raw_passy_pred = pandas.Series(lm_raw_passy_pred,
                                  index=pi
                                 )
# RF predictions
rf_raw_passy_pred = rf_raw_np_model.predict(X.reindex(pi))
fr_raw_passy_pred = pandas.Series(rf_raw_passy_pred,
                                  index=pi
                                 )
```

How's our model doing now?

```python
mses_p = pandas.Series({"LM-Raw": mse(db.loc[pi, "Truth"],
                                      lm_raw_passy_pred
                                     ),
                        "RF-Raw": mse(db.loc[pi, "Truth"],
                                      fr_raw_passy_pred
                                     ),
                       }).apply(sqrt)
mses_p
```

```
LM-Raw    235.291495
RF-Raw    218.293239
dtype: float64
```

```python
mses_np
```

```
LM-Raw    144.326619
RF-Raw    134.277649
dtype: float64
```

Not that great on data the models have not seen before.

Linear regression is a particular case in that, given the features chosen, one cannot tweak much more; but the RF does allow us to tweak things slightly differently. How is a matter of (computational) brute force and a bit of savvy-ness in designing the data split.

Cross-Validation to the rescue

- What it does: give you a better sense of the actual performance of your model
- What it doesn't (estimate a better model per-se)

Train/test split

```python
from sklearn.model_selection import train_test_split
```

```python
x_train, x_test, y_train, y_test = train_test_split(X,
                                                    db["Price"],
                                                    test_size=0.8
                                                   )
```

For the linear model:

```python
lm_estimator = LinearRegression()
# Fit on X/Y train
lm_estimator.fit(x_train, y_train)
# Predict on X test
lm_y_pred = lm_estimator.predict(x_test)
# Evaluate on Y test
sqrt(mse(y_test, lm_y_pred))
```

```
146.63691841889124
```

For the random forest:

```python
rf_estimator = RandomForestRegressor(n_estimators=100,
                                     max_features=None
                                    )
# Train on X/Y train
rf_estimator.fit(x_train, y_train)
# Predict on X test
rf_y_pred = rf_estimator.predict(x_test)
# Evaluate on Y test
sqrt(mse(y_test, rf_y_pred))
```

```
140.59053185334008
```

Worse than in-testing, but better than on an entirely new set of data with (potentially) different structure.

Now, the splitting that `train_test_split` does is random. What if it happens to be very particular? Can we trust the performance scores we recover?

k-fold CV

```python
from sklearn.model_selection import cross_val_score
```

For the linear model:

```python
lm_kcv_mses = cross_val_score(LinearRegression(),
                              X,
                              db["Price"],
                              cv=5,
                              scoring="neg_mean_squared_error"
                             )
# sklearn uses neg to optimisation is alway maximisation
sqrt(-lm_kcv_mses).mean()
```

```
156.0444939069434
```

And for the random forest:

```python
rf_estimator = RandomForestRegressor(n_estimators=100,
                                     max_features=None
                                    )
rf_kcv_mses = cross_val_score(rf_estimator,
                              X,
                              db["Price"],
                              cv=5,
                              scoring="neg_mean_squared_error"
                             )
# sklearn uses neg to optimisation is alway maximisation
sqrt(-rf_kcv_mses).mean()
```

```
141.65779397663923
```

These would be more reliable measures of model performance. The difference between CV'ed estimates and original ones can be seen as an indication of overfitting.

```python
mses
```

```
LM-Raw     149.522153
LM-Log    7570.085725
RF-Raw     138.939346
RF-Log     140.904608
dtype: float64
```

In our case, since we're using very few features, both models probably already feature enough "regularisation" and the changes are not very dramatic. In other contexts, this can be a drastic change (e.g. [Arribas-Bel, Patino & Duque; 2017]()).

Parameter optimisation in `scikit-learn`

Random Forests really can be optimised over two key parameters, `n_estimators` and `max_features`, although there are more to tweak around:

```python
RandomForestRegressor().get_params()
```

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 100,
 'n_jobs': None,
 'oob_score': False,
 'random_state': None,
 'verbose': 0,
 'warm_start': False}
```

Here we'll exhaustively test each combination for several values of the parameters:

```
param_grid = {
    "n_estimators": [5, 25, 50, 75, 100, 150],
    "max_features": [1, 2, 3, 4, 5]
}
```

We will use `GridSearchCV` to automatically work over every combination, create cross-validated scores (MSE), and pick the preferred one.

```
from sklearn.model_selection import GridSearchCV
```

This can get fairly computationally intensive, and it is also "embarrasingly parallel", so it's a good candidate to parallelise.

```
grid = GridSearchCV(RandomForestRegressor(),
                    param_grid,
                    scoring="neg_mean_squared_error",
                    cv=5,
                    n_jobs=-1
                   )
```

Once defined, we `fit` to actually execute computations on a given set of data:

```
%%time
grid.fit(X, db["Price"])
```

```
CPU times: user 631 ms, sys: 165 ms, total: 796 ms
Wall time: 10.5 s
```

```
GridSearchCV(cv=5, estimator=RandomForestRegressor(), n_jobs=-1,
             param_grid={'max_features': [1, 2, 3, 4, 5],
                         'n_estimators': [5, 25, 50, 75, 100, 150]},
             scoring='neg_mean_squared_error')
```

And we can explore the output from the same `grid` object:

```
grid_res = pandas.DataFrame(grid.cv_results_)
grid_res.head()
```

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_fe
0	0.059308	0.002531	0.007023	0.000338	
1	0.260195	0.003964	0.019304	0.000458	
2	0.519160	0.003526	0.035556	0.000450	
3	0.818000	0.017073	0.054218	0.002030	
4	1.071697	0.034987	0.065108	0.001701	

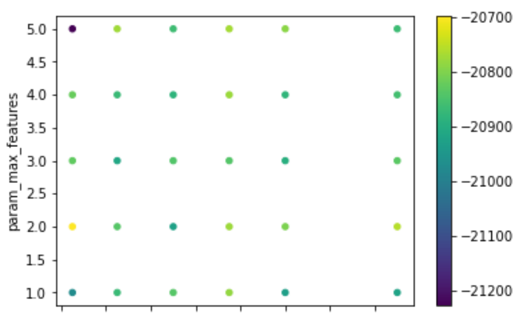
And the winner is…

```
grid_res[grid_res["mean_test_score"] \
         == \
         grid_res["mean_test_score"].max()
        ]["params"]
```

```
6    {'max_features': 2, 'n_estimators': 5}
Name: params, dtype: object
```

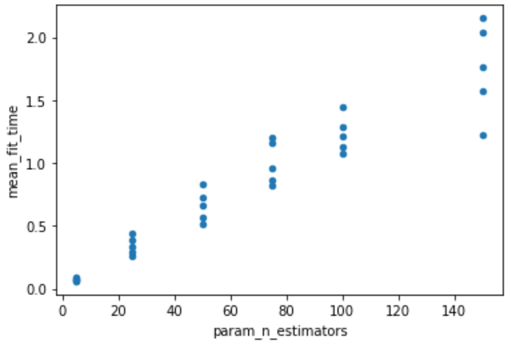
Or, we can visualise the surface generated in the grid:

```
grid_res[["param_n_estimators", "param_max_features"]]\
        .astype(float)\
        .plot.scatter("param_n_estimators",
                      "param_max_features",
                      c=grid_res["mean_test_score"],
                      cmap="viridis"
                     );
```



It is also possible to see that, as expected, the more trees, the longer it takes to compute:

```
grid_res[["param_n_estimators", "mean_fit_time"]]\
        .astype(float)\
        .plot.scatter("param_n_estimators",
                      "mean_fit_time"
                     );
```



EXERCISE What's the model performance (R/MSE) of the random forest setup we've used with the optimised set of parameters from the experiment above?

More at:

> https://scikit-learn.org/stable/modules/grid_search.html

By Dani Arribas-Bel