ENVS615 - Analysis of Human Dynamics

- Dani Arribas-Bel [@darribas]

Schedule

Day 1

a. **10:00-11:00 |** Introduction: *data*, *data*, *data* (`block_1a`) b. **11:00-12:00 |** The computational building blocks of data science (GDS Ch.1)

[Lunch Break]

c. **13:00-14:30 |** Interacting with tabular data lab (Pt. I, `01_tabular_data`)

[Break]

d. **14:45-16:00 |** Interacting with tabular data lab (Pt. II, `02_tabular_data_advanced`)

Day 2

a. **10:00-12:00 |** Visualising tabular data lab (`03_tabular_data_viz`)

[Lunch Break]

b. **13:00-14:00 |** Unsupervised learning (`block_2b`)

[Break]

c. **14:15-16:00 |** Unsupervised learning lab (`04_unsupervised_learning`)

Day 3

a. **10:00-11:00 |** Supervised learning b. **11:00-12:00 |** Supervised learning lab (Pt. I, `05_supervised_learning`)

[Lunch Break]

c. **13:00-14:30 |** Supervised learning lab (Pt. II, `06_inference`)

[Break]

d. **14:45-15:30 |** Supervised learning lab (Pt. III, `07_overfitting_cv`) e. **15:30-16:00 |** Assignment details + questions + pick your favorite

Day 4

1. **10:00-12:00 |** Pick your favorite: Geo Vs APIs

[Lunch Break]

1. **13:00-14:30 |** Data Science Studio

[Break]

1. **14:45-16:00 |** Data Science Studio

Bonus

Data preparation available in `zzz_data_prep`

Collaboration

The module has a related Microsoft Teams team set up on the Liverpool cloud. You should have received an invite directly to your **Liverpool email** account but, if you have not, you can join the Team on the following link:

> https://teams.microsoft.com/l/team/19%3a1822ee5f66654039938ba7b7f7ef8715%40thread.skype/conversations?groupId=910b24fd-6449-42b5-b6f3-5f416c0b9cd2&tenantId=53255131-b129-4010-86e1-474bfd7e8076

IMPORTANT: you will need to be logged in on your Liverpool account (not your own university if you are not a Liverpool student).

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 **March 9th at 2pm**
- Electronic submission only. 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.

Further materials

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

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

Infrastructure

This course requires the following libraries installed:

- `jupyterlab`
- `pandas`
- `scikit-learn`
- `seaborn`
- `statsmodels`

You can install these through most modern Python package managers (e.g. `conda`). If you have administrative rights on your machine and are running either Windows 10 Pro, macOS, or Linux, a containerised platform is advised. The following two are good options:

- `jupyter-scipy-notebook`: the official Jupyter container for data science in Python.
- `gds`: a more comprehensive, geo-focused stack for (geographic) data science in Python and R.

You have instructions to install and run the containers at:

> http://darribas.org/gds19/software.html

Reading & Manipulating Tabular Data

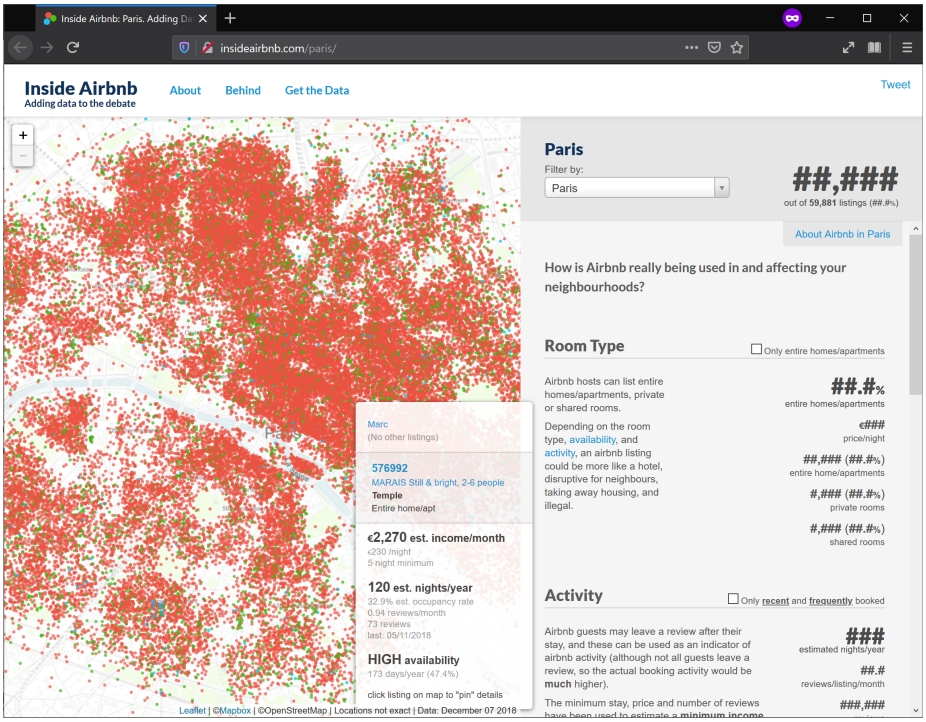

```
%matplotlib inline
from IPython.display import Image

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

To note:

- `matplotlib` magic
- Library import and alias

Data

```
Image("../figs/paris_data.png")
```



- Read in `.csv`

```
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	bathrooms	be
0	3109	Observatoire	Apartment	Entire home/apt	2	1.0	
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	1.0	
3	7964	Opéra	Apartment	Entire home/apt	2	1.0	
4	9952	Popincourt	Apartment	Entire home/apt	2	1.0	

```
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):
id       5137 non-null int64
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	bathrooms	be
0	3109	Observatoire	Apartment	Entire home/apt	2	1.0	
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	1.0	
3	7964	Opéra	Apartment	Entire home/apt	2	1.0	
4	9952	Popincourt	Apartment	Entire home/apt	2	1.0	

```
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50280 entries, 0 to 50279
Data columns (total 10 columns):
id                        50280 non-null int64
neighbourhood_cleansed    50280 non-null object
property_type             50280 non-null object
room_type                 50280 non-null object
accommodates              50280 non-null int64
bathrooms                 50280 non-null float64
bedrooms                  50280 non-null float64
beds                      50280 non-null float64
bed_type                  50280 non-null object
Price                     50280 non-null float64
dtypes: float64(4), int64(2), object(4)
memory usage: 3.8+ MB
```

```
db.describe()
```

	id	accommodates	bathrooms	bedrooms	beds	
count	5.028000e+04	50280.000000	50280.000000	50280.000000	50280.000000	5028(
mean	1.968671e+07	3.063425	1.117045	1.077804	1.664698	11(
std	1.140675e+07	1.556731	0.687370	1.001000	1.164917	157
min	3.109000e+03	1.000000	0.000000	0.000000	0.000000	(
25%	9.340209e+06	2.000000	1.000000	1.000000	1.000000	6(
50%	1.999153e+07	2.000000	1.000000	1.000000	1.000000	8(
75%	2.987492e+07	4.000000	1.000000	1.000000	2.000000	12(
max	3.858893e+07	17.000000	50.000000	50.000000	50.000000	1000(

`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	bathrooms	be
0	3109	Observatoire	Apartment	Entire home/apt	2	1.0	
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	

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

	neighbourhood_cleansed	property_type	room_type	accommodates	bathrooms	bedro
id						
3109	Observatoire	Apartment	Entire home/apt	2	1.0	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	

```
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

```
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
```

```
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

```
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
```

```
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

```
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, :]
```

id	neighbourhood_cleansed	property_type	room_type	accommodates	bathrooms	bedrc
3109	Observatoire	Apartment	Entire home/apt	2	1.0	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	
7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	1.0	
7964	Opéra	Apartment	Entire home/apt	2	1.0	
9952	Popincourt	Apartment	Entire home/apt	2	1.0	

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	accommodates	bath
12066	8876983	Luxembourg	Boutique hotel	Private room	16	
22964	18766792	Luxembourg	Boutique hotel	Private room	16	
24788	19819352	Luxembourg	Boutique hotel	Private room	16	
25798	20433587	Luxembourg	Boutique hotel	Private room	16	
26048	20691340	Luxembourg	Boutique hotel	Private room	16	
26108	20747725	Luxembourg	Boutique hotel	Private room	16	
26121	20768013	Luxembourg	Boutique hotel	Private room	16	

- 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	accommodates	bath
12066	8876983	Luxembourg	Boutique hotel	Private room	16	
22964	18766792	Luxembourg	Boutique hotel	Private room	16	
24788	19819352	Luxembourg	Boutique hotel	Private room	16	
25798	20433587	Luxembourg	Boutique hotel	Private room	16	
26048	20691340	Luxembourg	Boutique hotel	Private room	16	
26108	20747725	Luxembourg	Boutique hotel	Private room	16	
26121	20768013	Luxembourg	Boutique hotel	Private room	16	

- Concatenated queries

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

	id	neighbourhood_cleansed	property_type	room_type	accommodates	bath
12066	8876983	Luxembourg	Boutique hotel	Private room	16	
22964	18766792	Luxembourg	Boutique hotel	Private room	16	
24788	19819352	Luxembourg	Boutique hotel	Private room	16	
25798	20433587	Luxembourg	Boutique hotel	Private room	16	
26048	20691340	Luxembourg	Boutique hotel	Private room	16	
26108	20747725	Luxembourg	Boutique hotel	Private room	16	
26121	20768013	Luxembourg	Boutique hotel	Private room	16	

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

	id	neighbourhood_cleansed	property_type	room_type	accommodates	bath
8149	6088687	Temple	Apartment	Entire home/apt	2	
10113	7225849	Buttes-Montmartre	Apartment	Entire home/apt	8	
11286	8093890	Passy	Apartment	Entire home/apt	3	
25106	19974916	Buttes-Montmartre	Condominium	Entire home/apt	4	
25558	20219162	Buttes-Chaumont	Apartment	Entire home/apt	1	
25676	20291987	Passy	Apartment	Entire home/apt	3	
25697	20313940	Temple	Apartment	Entire home/apt	2	
26899	21422028	Popincourt	Apartment	Entire home/apt	3	
32190	25448670	Vaugirard	Apartment	Entire home/apt	1	
35291	27608896	Observatoire	Apartment	Private room	1	
43961	34380017	Bourse	Serviced apartment	Hotel room	8	
46767	36019554	Louvre	Serviced apartment	Hotel room	8	
47574	36402651	Batignolles-Monceau	House	Entire home/apt	12	

- 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	accommodates	bath
12066	8876983	Luxembourg	Boutique hotel	Private room	16	
22964	18766792	Luxembourg	Boutique hotel	Private room	16	
24788	19819352	Luxembourg	Boutique hotel	Private room	16	
25798	20433587	Luxembourg	Boutique hotel	Private room	16	
26048	20691340	Luxembourg	Boutique hotel	Private room	16	
26108	20747725	Luxembourg	Boutique hotel	Private room	16	
26121	20768013	Luxembourg	Boutique hotel	Private room	16	

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_dense',
 'to_dict',
 'to_excel',
 'to_feather',
 'to_gbq',
 'to_hdf',
 'to_html',
 'to_json',
 'to_latex',
 'to_msgpack',
 'to_numpy',
 'to_parquet',
 'to_period',
 'to_pickle',
 'to_records',
 'to_sparse',
 '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

Advanced Tabular Manipulation

- Sorting
- Joining
- Grouping
- `MultiIndex` Tables

```
%matplotlib inline

import pandas

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

Sorting

- By values

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

	id	neighbourhood_cleansed	property_type	room_type	accommodates	bath
25676	20291987	Passy	Apartment	Entire home/apt	3	
25697	20313940	Temple	Apartment	Entire home/apt	2	
26899	21422028	Popincourt	Apartment	Entire home/apt	3	
25558	20219162	Buttes-Chaumont	Apartment	Entire home/apt	1	
25106	19974916	Buttes-Montmartre	Condominium	Entire home/apt	4	

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

	id	neighbourhood_cleansed	property_type	room_type	accommodates	bath
47574	36402651	Batignolles-Monceau	House	Entire home/apt	12	
10113	7225849	Buttes-Montmartre	Apartment	Entire home/apt	8	
35291	27608896	Observatoire	Apartment	Private room	1	
11286	8093890	Passy	Apartment	Entire home/apt	3	
32190	25448670	Vaugirard	Apartment	Entire home/apt	1	

- By index

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

property_type	id	neighbourhood_cleansed	room_type	accommodates	bathrooms
Aparthotel	31728955	Vaugirard	Hotel room	2	1.0
Aparthotel	13003443	Vaugirard	Entire home/apt	4	1.0
Aparthotel	31733851	Temple	Hotel room	4	1.0
Aparthotel	17630233	Bourse	Hotel room	4	1.0
Aparthotel	24387710	Observatoire	Private room	12	5.0

(Useful for quick subsetting:)

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

property_type	id	neighbourhood_cleansed	Price
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_cleanliness	review_scor
0	3109	100.0	10.0	10.0	
1	5396	90.0	9.0	8.0	
2	7397	94.0	10.0	9.0	
3	7964	96.0	10.0	10.0	
4	9952	98.0	10.0	10.0	

- Join to original table:

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

	id	neighbourhood_cleansed	property_type	room_type	accommodates	bathrooms	be
0	3109	Observatoire	Apartment	Entire home/apt	2	1.0	
1	5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	
2	7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	1.0	
3	7964	Opéra	Apartment	Entire home/apt	2	1.0	
4	9952	Popincourt	Apartment	Entire home/apt	2	1.0	

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

id	neighbourhood_cleansed	property_type	room_type	accommodates	bathrooms	bedro
3109	Observatoire	Apartment	Entire home/apt	2	1.0	
5396	Hôtel-de-Ville	Apartment	Entire home/apt	2	1.0	
7397	Hôtel-de-Ville	Apartment	Entire home/apt	4	1.0	
7964	Opéra	Apartment	Entire home/apt	2	1.0	
9952	Popincourt	Apartment	Entire home/apt	2	1.0	

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")
```

room_type	Price	review_scores_rating
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")
```

neighbourhood_cleansed	Price	review_scores_rating
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				review_scores_r	
room_type	Entire home/apt	Hotel room	Private room	Shared room	Entire home/apt	Ho roo
neighbourhood_cleansed						
Batignolles-Monceau	103.501922	343.660714	58.698305	53.142857	92.484096	93
Bourse	139.618020	321.244898	71.088710	35.062500	91.608503	93
Buttes-Chaumont	82.568452	117.947368	45.866667	25.228571	93.077806	91
Buttes-Montmartre	87.478750	118.342105	55.217899	42.555556	92.940811	90
Entrepôt	101.621981	311.736842	55.144893	30.458333	92.995046	87
Gobelins	86.284188	106.961538	53.238671	35.600000	91.858974	91
Hôtel-de-Ville	154.687543	412.291667	79.372881	64.000000	93.123193	90
Louvre	165.077367	426.830508	102.828947	72.000000	91.763279	91
Luxembourg	164.863531	204.746667	87.226562	55.000000	92.269854	92
Ménilmontant	75.727787	128.200000	45.138425	34.923077	93.332795	92
Observatoire	95.354978	306.525000	90.521401	41.000000	92.864564	93
Opéra	115.688708	287.089655	75.561905	44.125000	93.126144	89
Palais-Bourbon	170.620910	450.722222	76.144144	35.400000	92.757382	93
Panthéon	129.989522	141.925000	69.246753	73.800000	92.206942	90
Passy	155.033317	331.766667	77.497674	39.785714	91.810702	92
Popincourt	95.073171	138.333333	53.348606	31.880952	93.042408	94
Reuilly	89.299656	104.727273	53.468165	30.300000	93.082090	91
Temple	150.560496	241.977273	77.474453	30.833333	92.378794	94
Vaugirard	108.483296	288.891892	58.145729	51.333333	92.632517	93
Élysée	194.715942	300.590361	94.835165	70.000000	91.547826	89

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

Visualising Tabular Data

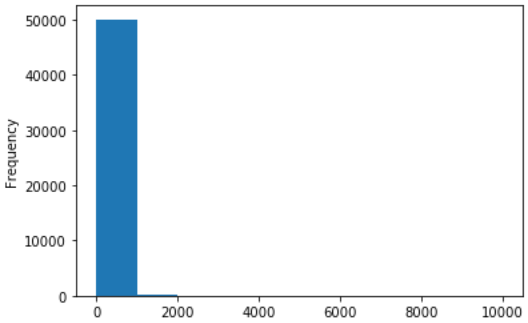
- Simple & Quick
- seaborn
- Full Control (`matplotlib`)

```
%matplotlib inline

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

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

Simple & Quick (pandas)

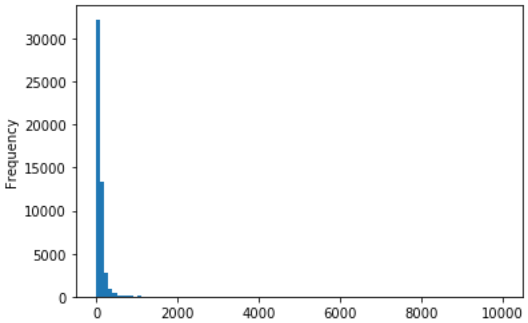
```
db["Price"].plot.hist()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ad9bf1748>
```



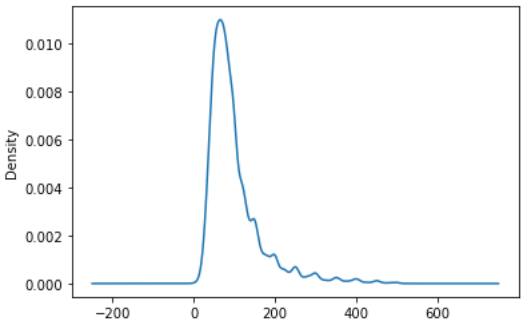

```
db["Price"].plot.hist(bins=100)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ad97fbb00>
```



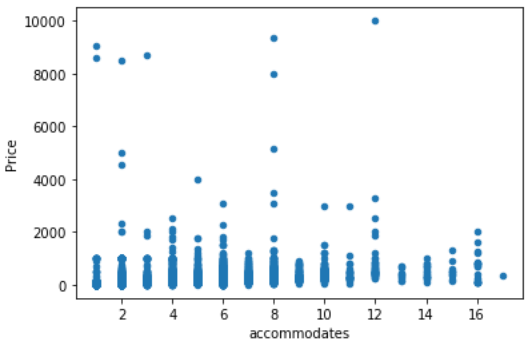

```
db.query("Price < 500")["Price"].plot.kde()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ad95e82e8>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ad83c8ac8>
```



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

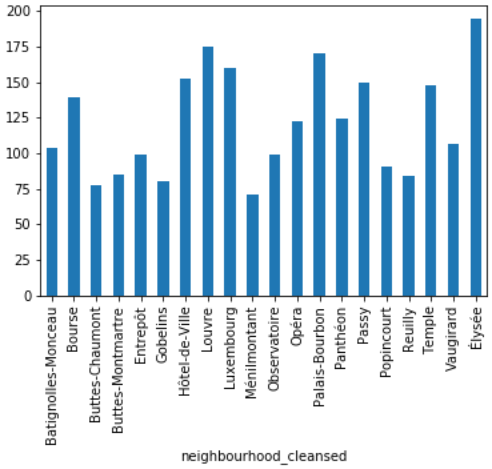
More

> 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()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f950cdfb128>
```



EXERCISE

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

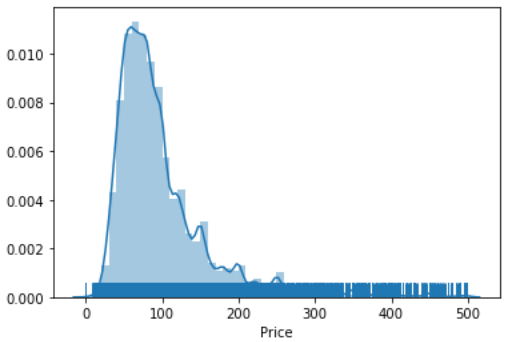
For a "pro" touch (optional), substract 90 from the reviews score before plotting.

`seaborn`

- Univariate

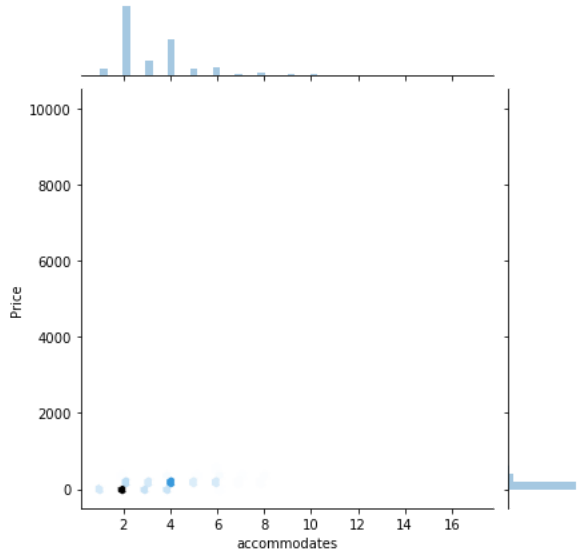
```
sns.distplot(db.query("Price < 500")["Price"],
             kde=True,
             rug=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5ad8dbf400>
```

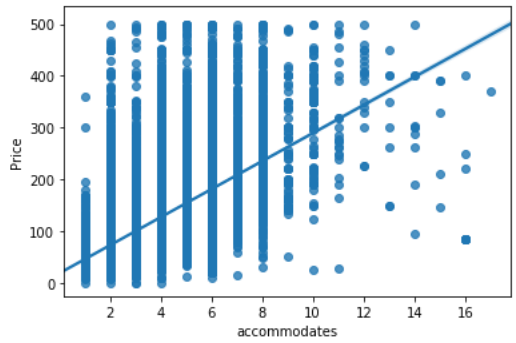


- Bivariate

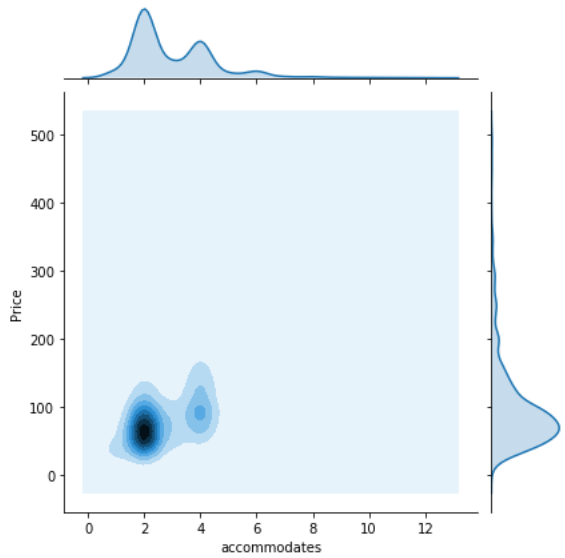
```
sns.jointplot(x = "accommodates",
              y = "Price",
              data=db,
              kind="hex"
             );
```




```
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

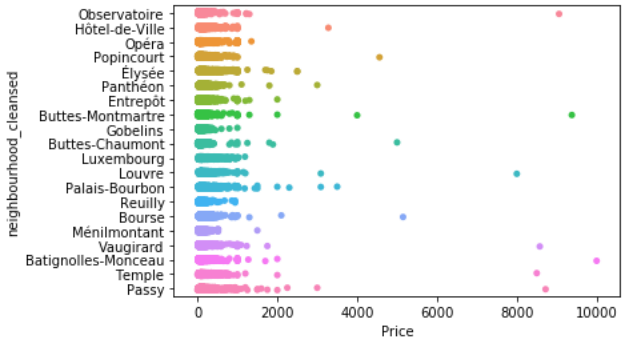
Explore the documentation of `jointplot` and create a figure similar to the one above where you replace the hexagonal binning for a KDE. Since this will probably take too long, subset your data before plotting to only properties cheaper than $500, and then randomly sample 1,000 observations (tip: check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

More

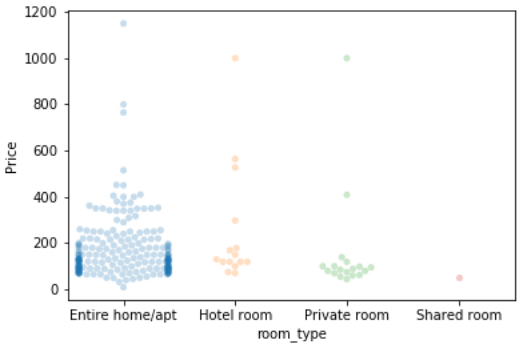
> http://seaborn.pydata.org/tutorial.html

- Categorical

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



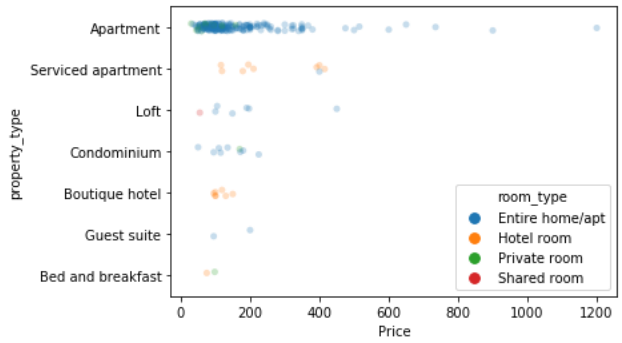

```
sns.swarmplot(x = "room_type",
              y = "Price",
              data=db.query("neighbourhood_cleansed == 'Louvre'")\
                     .sample(250),
              alpha=0.25
             );
```



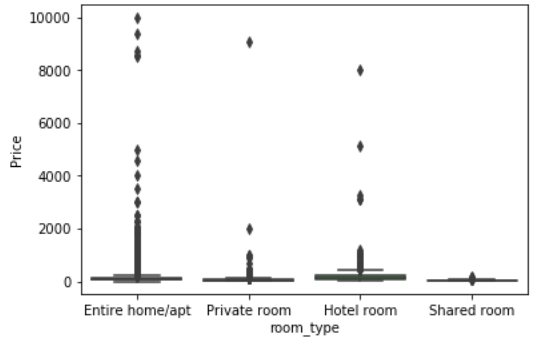
To note:

- 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

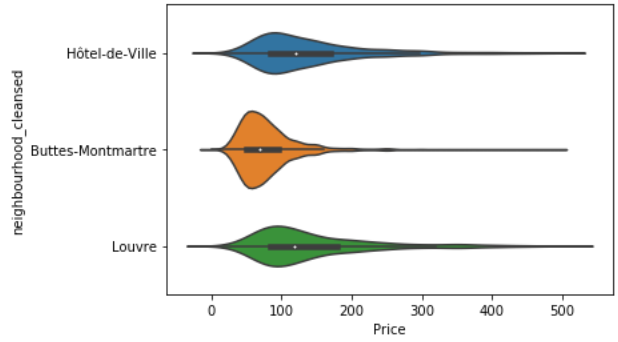
```
sns.stripplot(x = "Price",
              y = "property_type",
              hue = "room_type",
              data=db.query("neighbourhood_cleansed == 'Louvre'")\
                     .sample(250),
              alpha=0.25
             );
```




```
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")
              );
```



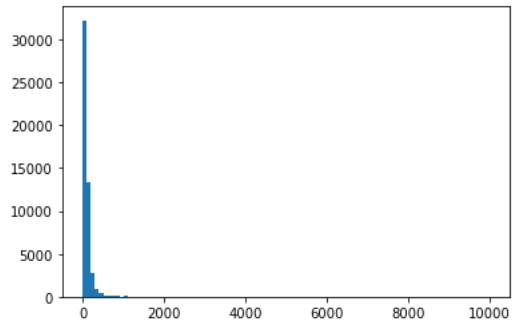
EXERCISE

Explore the distribution of price by property type

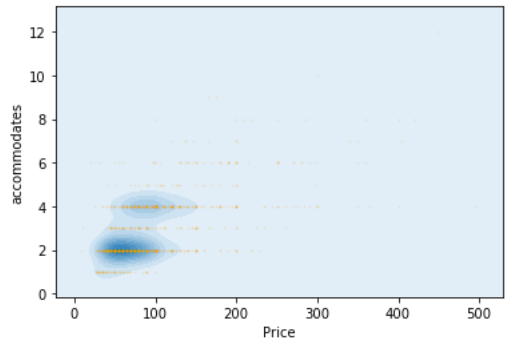
Full control (`matplotlib`)

One

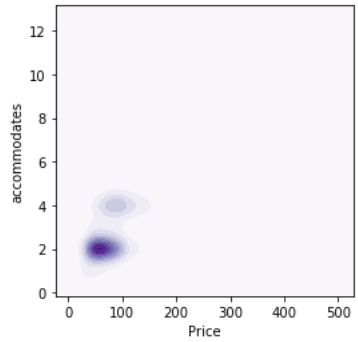
```
f, ax = plt.subplots(1)

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()
```



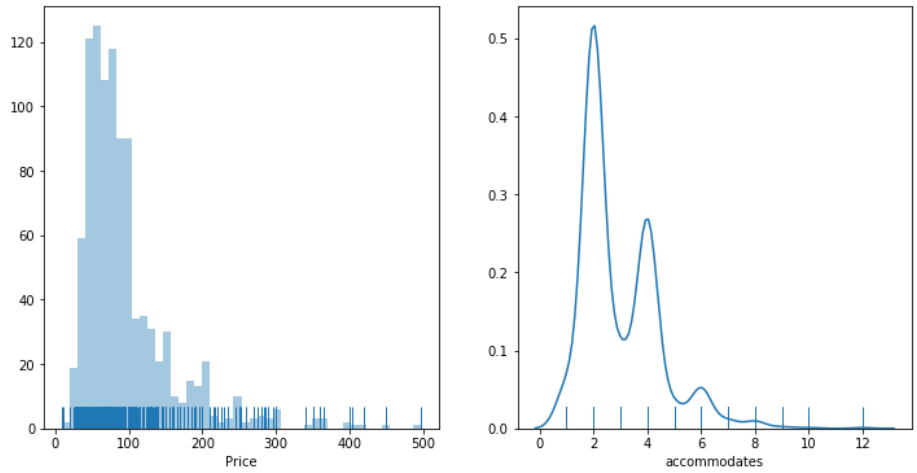

```
f, ax = plt.subplots(1, figsize=(4, 4))

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

plt.show()
```



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()
```



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

Supervised Learning

- A primer
- Explore
- Classify
- Explore the classification

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

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

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")
```

A primer

> *Everything should be made as simple as possible, but not simpler*

A. Einstein

The need to group data

- The world is complex and multidimensional
- Univariate analysis focuses on only one dimension
- Sometimes, world issues are best understood as multivariate

Grouping as simplifying

- Define a given number of categories based on many characteristics (multi-dimensional)
- Find the category where each observation fits best
- Reduce complexity, keep all the relevant information
- Produce easier-to-understand outputs

Clustering

Split a dataset into **groups** of observations that are **similar within** the group and **dissimilar between** groups, based on a series of **attributes**

`Machine learning`

The computer *learns* some of the properties of the dataset without the human specifying them

`Unsupervised`

There is no a-priori structure imposed on the classification $\rightarrow$ before the analysis, no observations is in a category

More clustering

- Hierarchical clustering
- Agglomerative clustering
- Spectral clustering
- Neural networks (e.g. Self-Organizing Maps)
- Density-based algorithms (e.g. DBScan)
- Topological Data Analysis
- ...

Examples

```
Image('../figs/05_chocolate.png')
```

Frequently Bought Together

Total price: £32.97

Add all three to Basket

ℹ These items are dispatched from and sold by different sellers. Show details

- **This item:** Green and Black's Organic Dark Chocolate 85 Percent Cocoa 100 g (Pack of 5) £11.62 (£2.32 / 100 g)
- Green and Black's Organic Ginger Dark 100 g (Pack of 5) £10.40 (£2.08 / 100 g)
- Green and Black's Organic Dark Chocolate Maya Gold 100 g (Pack of 5) £10.95 (£2.19 / 100 g)

Customers Who Bought This Item Also Bought

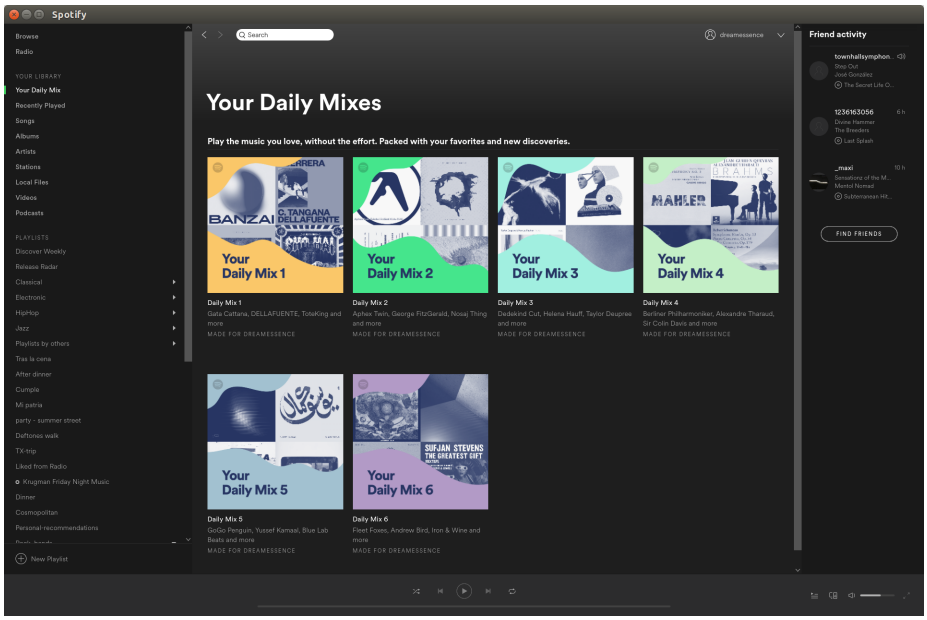
Green and Black's Organic Ginger Dark 100 g (Pack of 5)
15
£10.40

Green and Black's Organic Dark Chocolate Maya Gold 100 g (Pack of 5)
5
£10.95 Prime

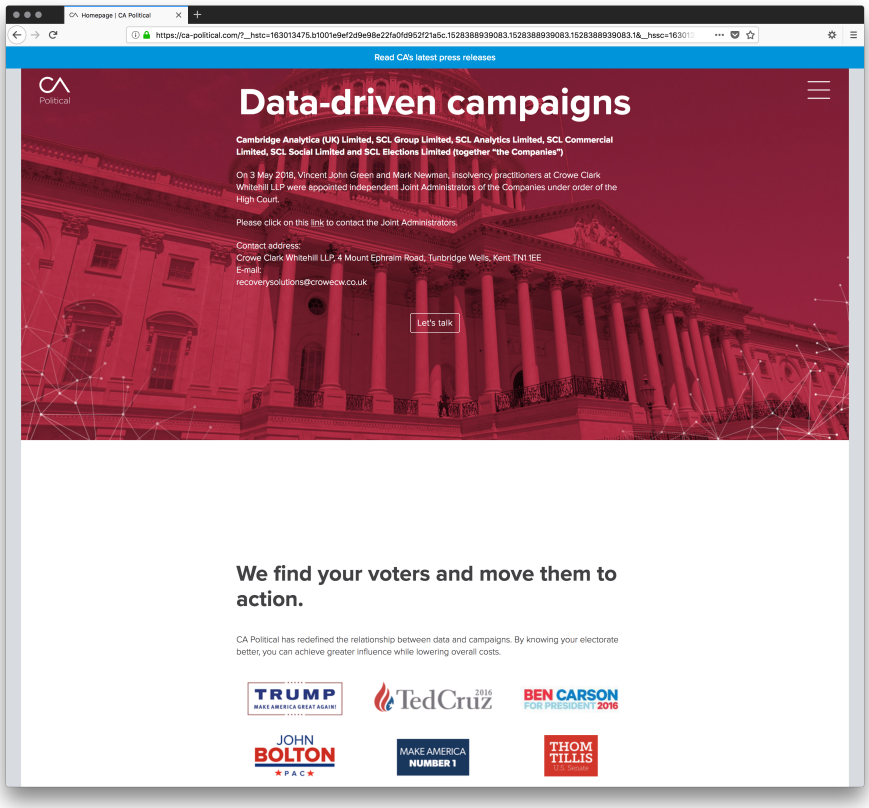
Green and Black's Organic Dark Chocolate 100 g (Pack of 5)
22
£8.20 Prime

Vivani Organic Dark Chocolate with 85% Coco 100 g (Pack of 5)
25
£11.95 Prime

```
Image('../figs/05_spotify.png')
```




```
Image('../figs/05_ca.png')
```



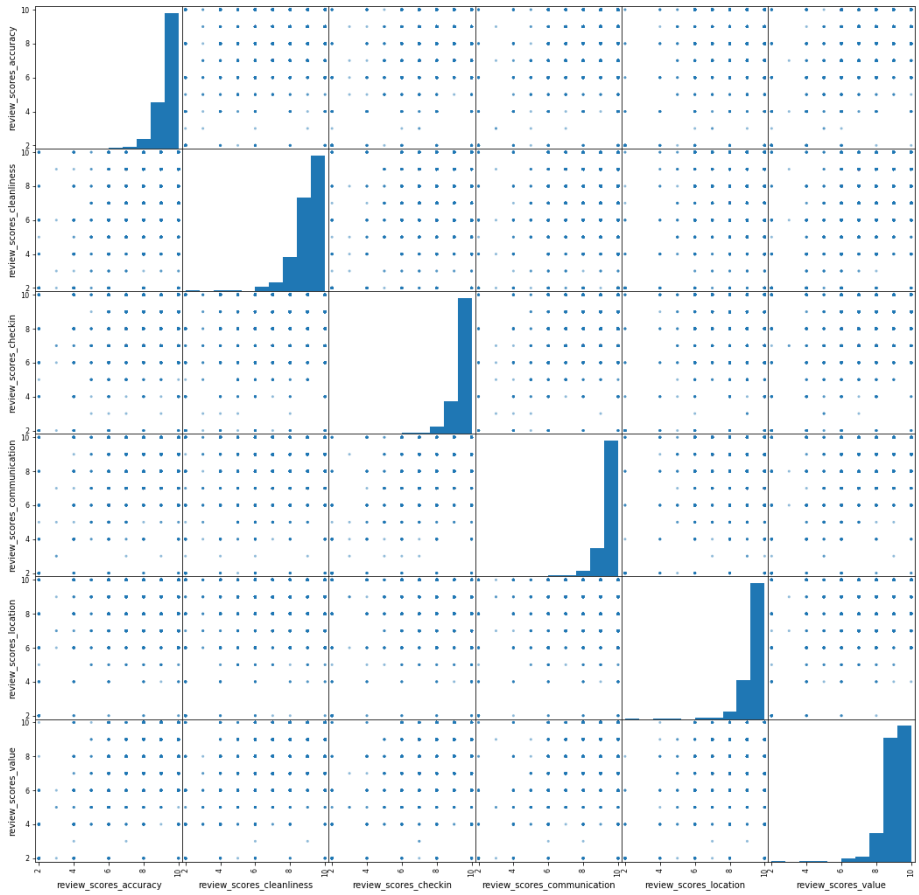
Explore

```
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%	75%	max
review_scores_accuracy	50280.0	9.576929	0.824413	2.0	9.0	10.0	10.0	10.0
review_scores_cleanliness	50280.0	9.178540	1.107574	2.0	9.0	9.0	10.0	10.0
review_scores_checkin	50280.0	9.660302	0.769064	2.0	10.0	10.0	10.0	10.0
review_scores_communication	50280.0	9.703520	0.727020	2.0	10.0	10.0	10.0	10.0
review_scores_location	50280.0	9.654018	0.696448	2.0	9.0	10.0	10.0	10.0
review_scores_value	50280.0	9.254515	0.930852	2.0	9.0	9.0	10.0	10.0

```
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

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

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=5, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

```
seed(12345)

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

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=5, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

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

```
0    0
1    3
2    0
3    0
4    0
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_checkin	review_scores
mean	4.748257e-17	2.792427e-16	-1.989746e-16	
std	1.000010e+00	1.000010e+00	1.000010e+00	

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

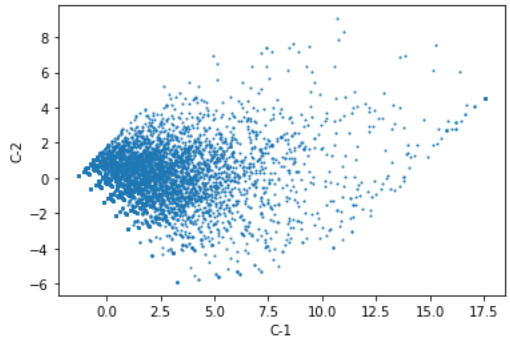
- Projected to lower dimension

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

```
PCA(copy=True, iterated_power='auto', n_components=2, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

```
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
                       );
```

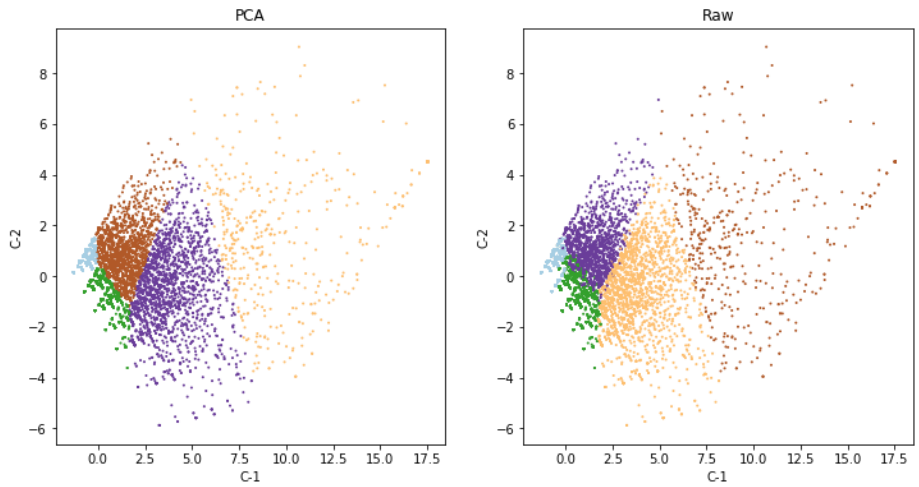


Now we cluster the two components instead of all the input variables:

```
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             16481.669537
Standardised    14732.094496
PCA             16549.690854
dtype: float64
```

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

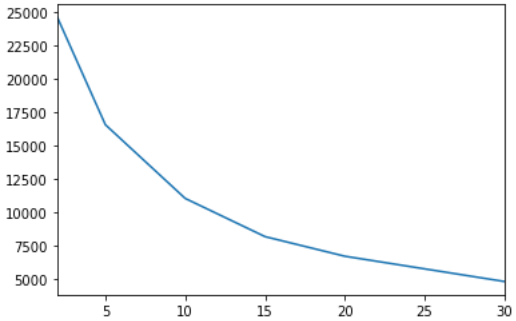
We can also use this to "optimise" (or at least explore its behaviour) the number of clusters. Let's pick the original input as the scores suggest are more desirable:

```
%%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 21.6 s, sys: 5.96 s, total: 27.6 s
Wall time: 18.4 s
```

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f9218c05390>
```



5 clusters?

- Quality of clustering (silhouette scores)

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

```
CPU times: user 1min, sys: 17.8 s, total: 1min 18s
Wall time: 1min 10s
```

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

```
CPU times: user 53.4 s, sys: 15.9 s, total: 1min 9s
Wall time: 1min 2s
```

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

```
CPU times: user 59.5 s, sys: 15.6 s, total: 1min 15s
Wall time: 1min 8s
```

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

```
Raw             0.327701
Standardised    0.305185
PCA             0.313708
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)
```

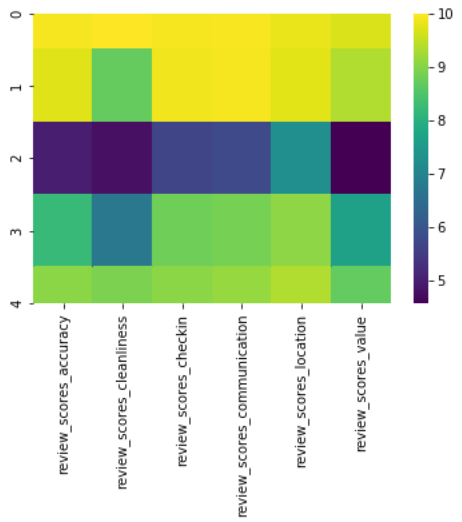
```
g.size()\
 .sort_values()
```

```
2      444
3     3046
4     8594
1    15499
0    22697
dtype: int64
```

```
g.mean()
```

	review_scores_accuracy	review_scores_cleanliness	review_scores_checkin	review_scores_coı
0	9.934485	10.000000	9.924924	
1	9.740435	8.717337	9.890832	
2	5.006757	4.788288	5.682432	
3	8.225213	6.746881	8.807945	
4	9.052944	8.929486	9.053293	

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

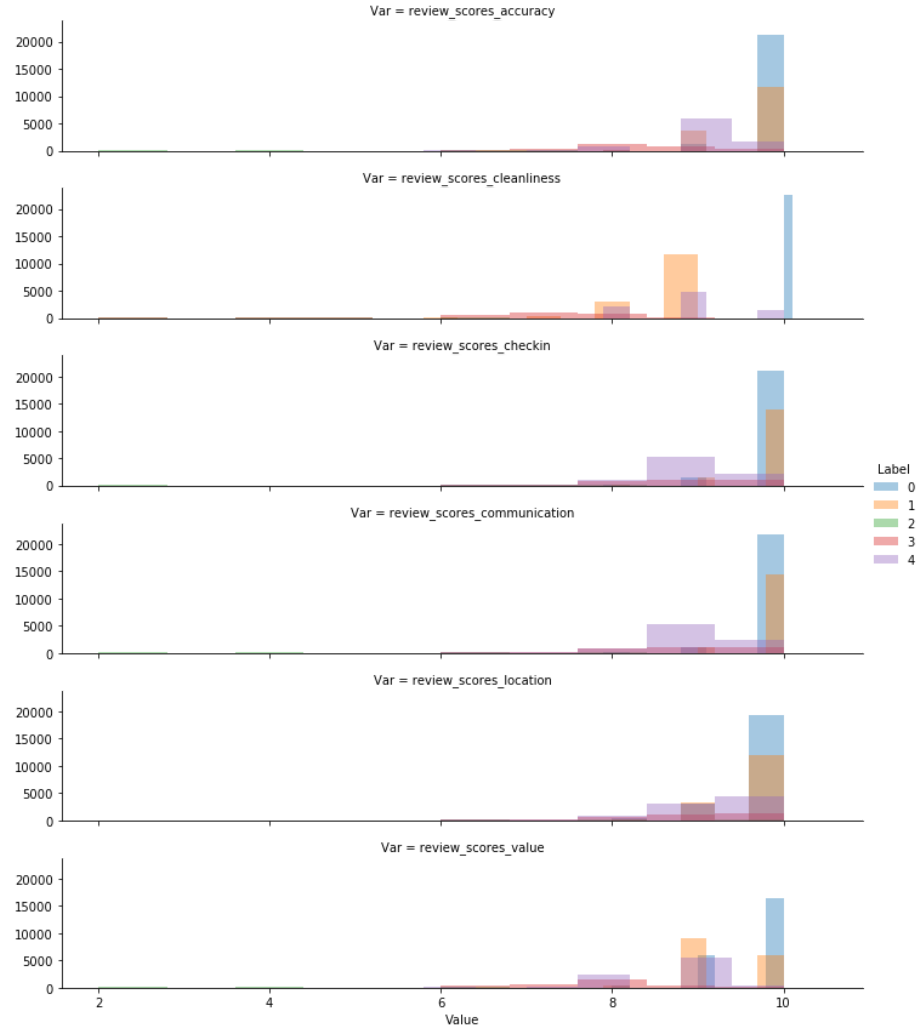


To explore the *distribution* of the values inside each cluster, rather than their mean, we can use the fancy `FaceGrid` approach:

```
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()
```

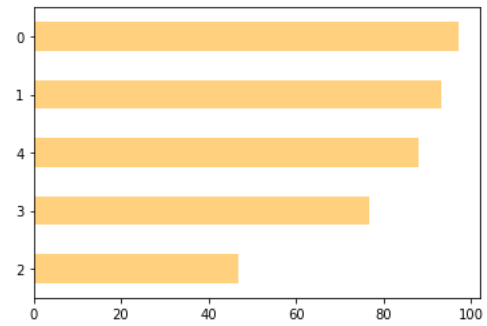
	ID	Var	Value	Label
0	0	review_scores_accuracy	10.0	0
1	0	review_scores_cleanliness	10.0	0
2	0	review_scores_checkin	10.0	0
3	0	review_scores_communication	10.0	0
4	0	review_scores_location	10.0	0

```
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();
```



Externally:

```
# 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


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

import pandas
import numpy as np

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 0x7f2f1169ad30>
```

```
lm_raw.summary()
```

Dep. Variable:	Price	**R-squared:**	0.103
Model:	OLS	**Adj. R-squared:**	0.103
Method:	Least Squares	**F-statistic:**	1151.
Date:	Sun, 01 Dec 2019	**Prob (F-statistic):**	0.00
Time:	18:30:19	**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

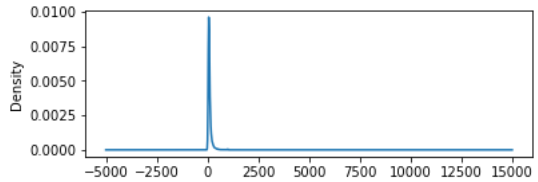
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	69.3589	1.295	53.573	0.000	66.821	71.896
room_type[T.Hotel room]	148.7074	4.779	31.120	0.000	139.341	158.073
room_type[T.Private room]	-51.5793	2.202	-23.425	0.000	-55.895	-47.264
room_type[T.Shared room]	-71.5010	8.692	-8.226	0.000	-88.537	-54.465
bathrooms	-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

Warnings:
[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 0x7f2f08a479e8>
```

```
lm_log.rsquared
```

```
0.31515872008420953
```

```
lm_raw.rsquared
```

```
0.10269412705703518
```

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

```
# 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...

```
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

```
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

```
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(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

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 1.46 s, sys: 20 ms, total: 1.48 s
Wall time: 1.48 s
```

```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=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)
```

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

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

```
array([ 72.31563706,  72.31563706, 140.81415278, ...,  93.64238832,
        72.31563706,  93.64238832])
```

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 1.19 s, sys: 20 ms, total: 1.21 s
Wall time: 1.21 s
```

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	72.315637	4.181252	60.0
1	66.950833	4.198030	72.315637	4.181252	115.0
2	153.632865	4.850742	140.814153	4.819278	119.0
3	110.291849	4.524386	93.642388	4.444827	130.0
4	110.291849	4.524386	93.642388	4.444827	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	0
1	4
2	1
3	0
4	0

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 2.9 s, sys: 0 ns, total: 2.9 s
Wall time: 2.9 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	0	0
freq	22697	49806

Inference


```
%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
```

```
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):
id                          50280 non-null int64
neighbourhood_cleansed      50280 non-null object
property_type               50280 non-null object
room_type                   50280 non-null object
accommodates                50280 non-null int64
bathrooms                   50280 non-null float64
bedrooms                    50280 non-null float64
beds                        50280 non-null float64
bed_type                    50280 non-null object
Price                       50280 non-null float64
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:	Wed, 15 Jan 2020	**Prob (F-statistic):**	0.00
Time:	10:41:37	**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

Warnings:
[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	4.522149e-17	-7.871366e-17	5.087418e-18
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:	Wed, 15 Jan 2020	**Prob (F-statistic):**	0.00
Time:	10:41:37	**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

Warnings:
[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

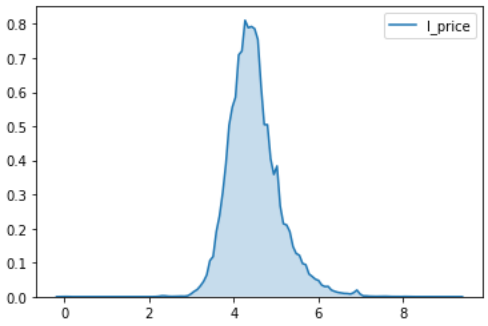
Predictive checking

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!

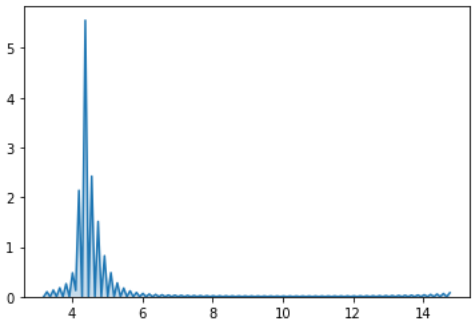
```
sns.kdeplot(db['l_price'], shade=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7019025860>
```

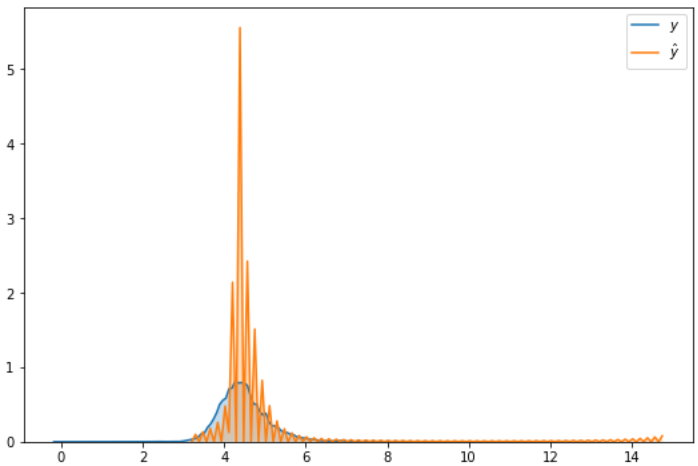



```
sns.kdeplot(m1.fittedvalues, shade=True)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7018367b00>
```




```
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:	Wed, 15 Jan 2020	**Prob (F-statistic):**	0.00
Time:	10:41:38	**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

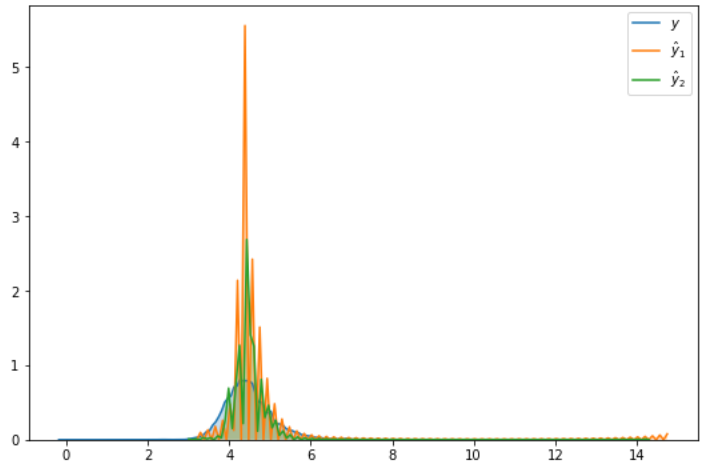
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	4.2417	0.005	899.941	0.000	4.232	4.251
room_type[T.Hotel room]	0.5548	0.016	35.619	0.000	0.524	0.585
room_type[T.Private room]	-0.4862	0.007	-66.604	0.000	-0.501	-0.472
room_type[T.Shared room]	-1.0320	0.028	-36.320	0.000	-1.088	-0.976
bedrooms	0.2388	0.004	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

Warnings:

[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:

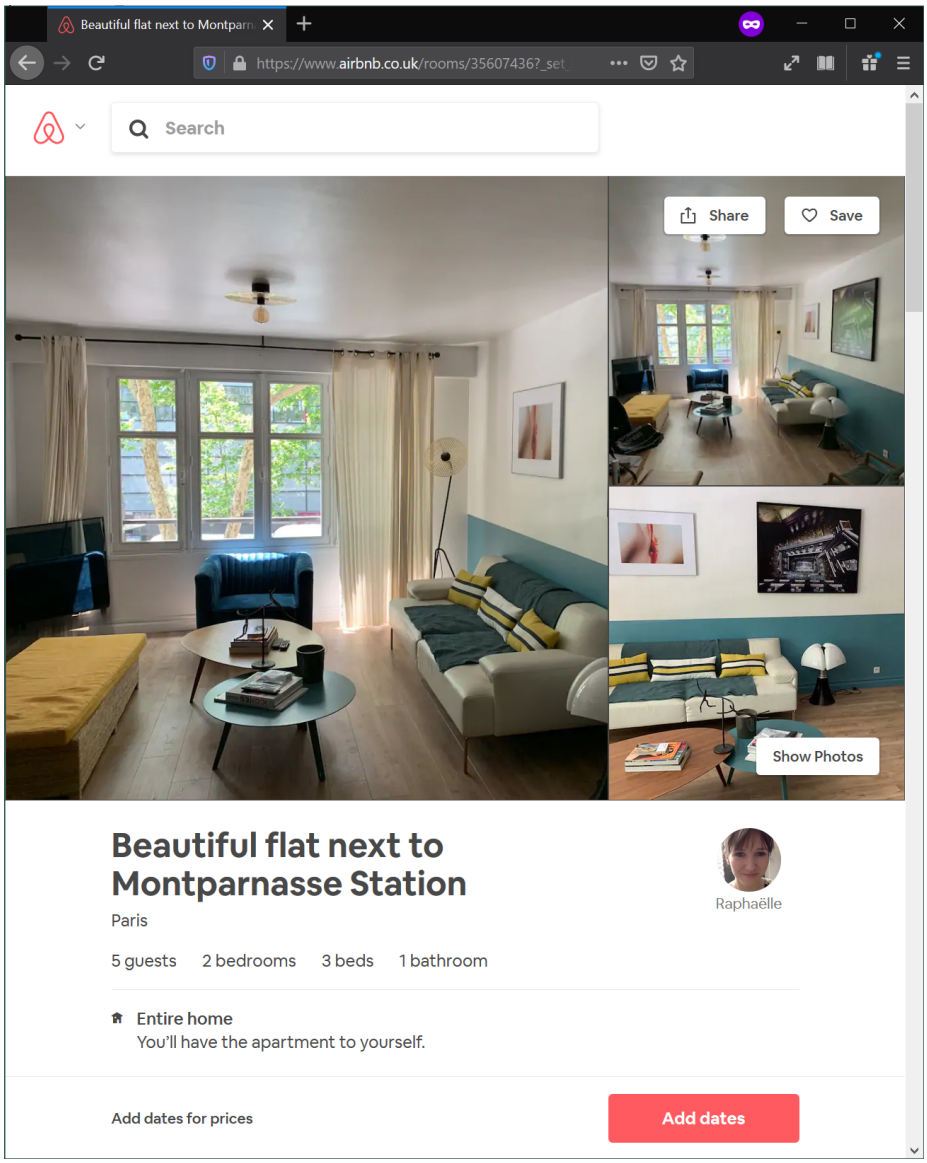
- This is better!
- But these are only point predictions. Sometimes that's good enough.
- Usually however, we want a model to capture the underlying process instead of the particular realisation observed (ie. dataset).
- Then we need to think about the uncertainty embedded in the model we are estimating

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
```

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

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

```
4.896141184855212
```

To note:

- What does `dot` do?

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

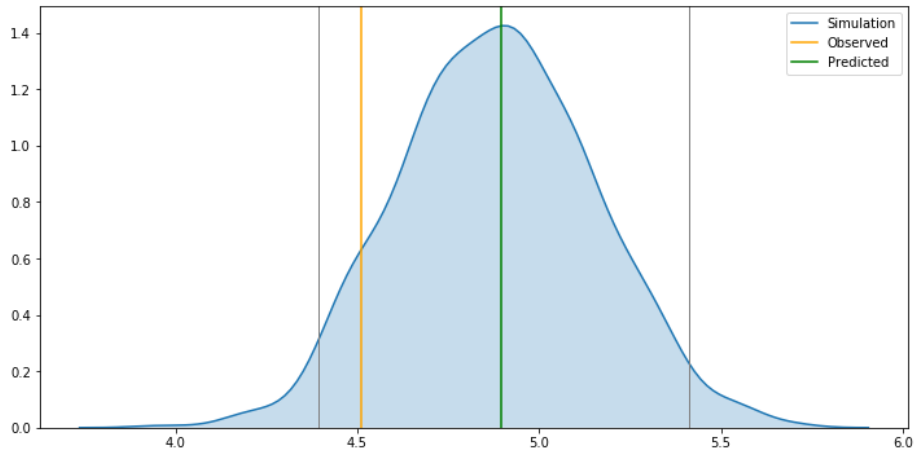
```
4.896141184855212
```

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 1.14 s, sys: 10 ms, total: 1.15 s
Wall time: 1.15 s
```

```
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+

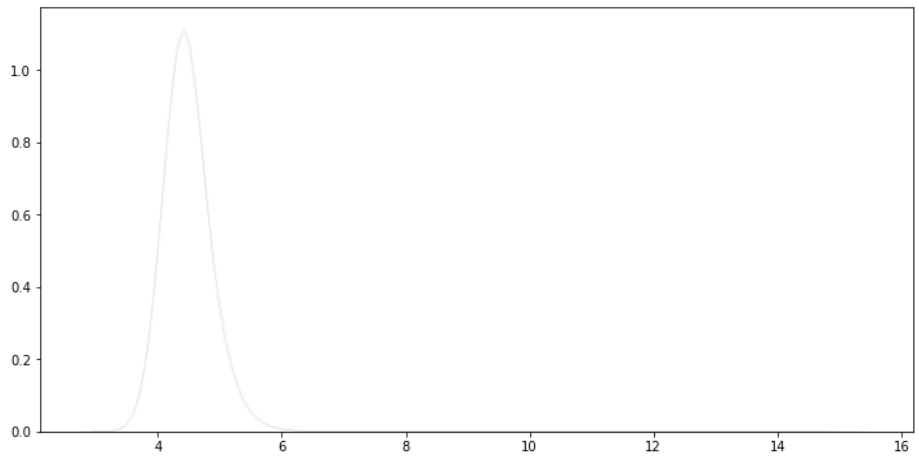
Recreate the analysis above for observation `5389821`. What happens? Why?

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

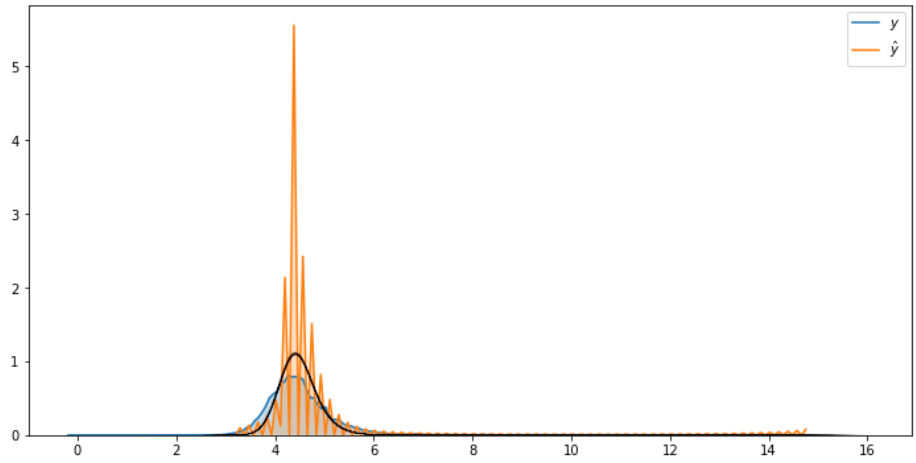
```
%%time
# Parameters
## Number of observations & simulations
n = db.shape[0]
r = 200
# Specify model engine
model = m1

# 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 4.7 s, sys: 1.54 s, total: 6.24 s
Wall time: 3.14 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.

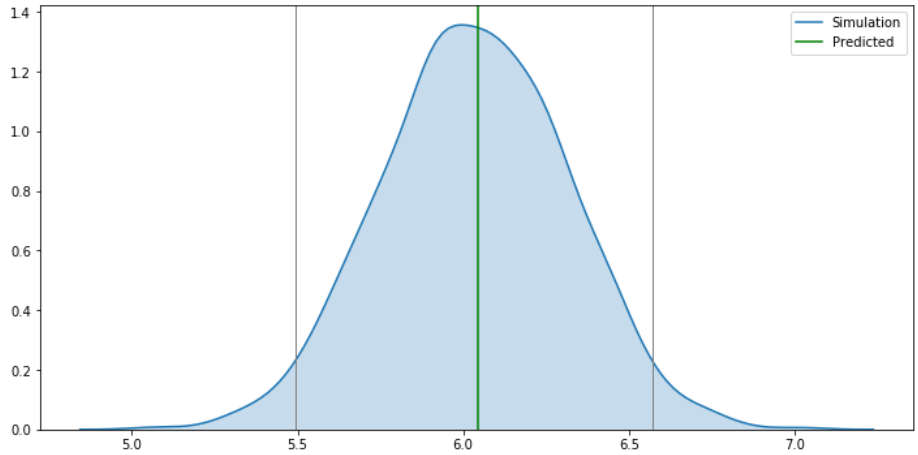
For example, let's assume our property is:

```
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
```

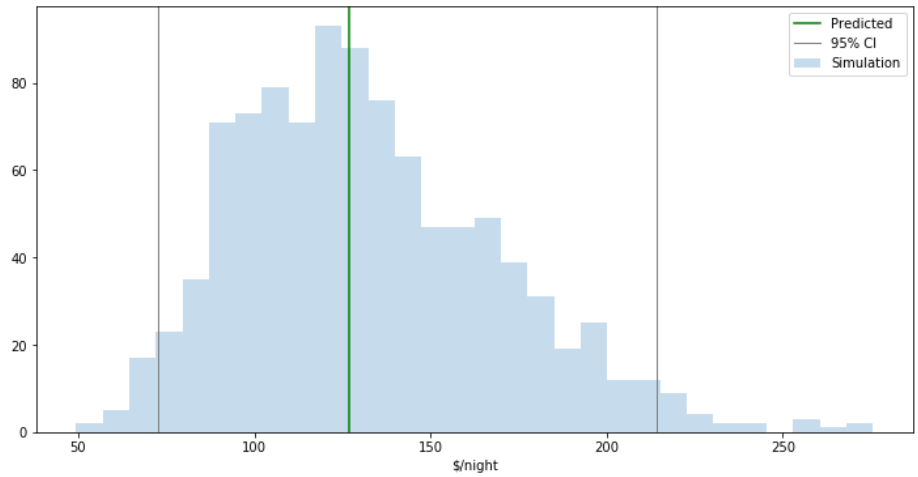
```
CPU times: user 1.1 s, sys: 50 ms, total: 1.15 s
Wall time: 1.15 s
```

```
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)
```



```
# 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

```
# 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
```

```
# 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
```

```
# 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
```

```
# 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

- Overfitting

- Cross-Validation

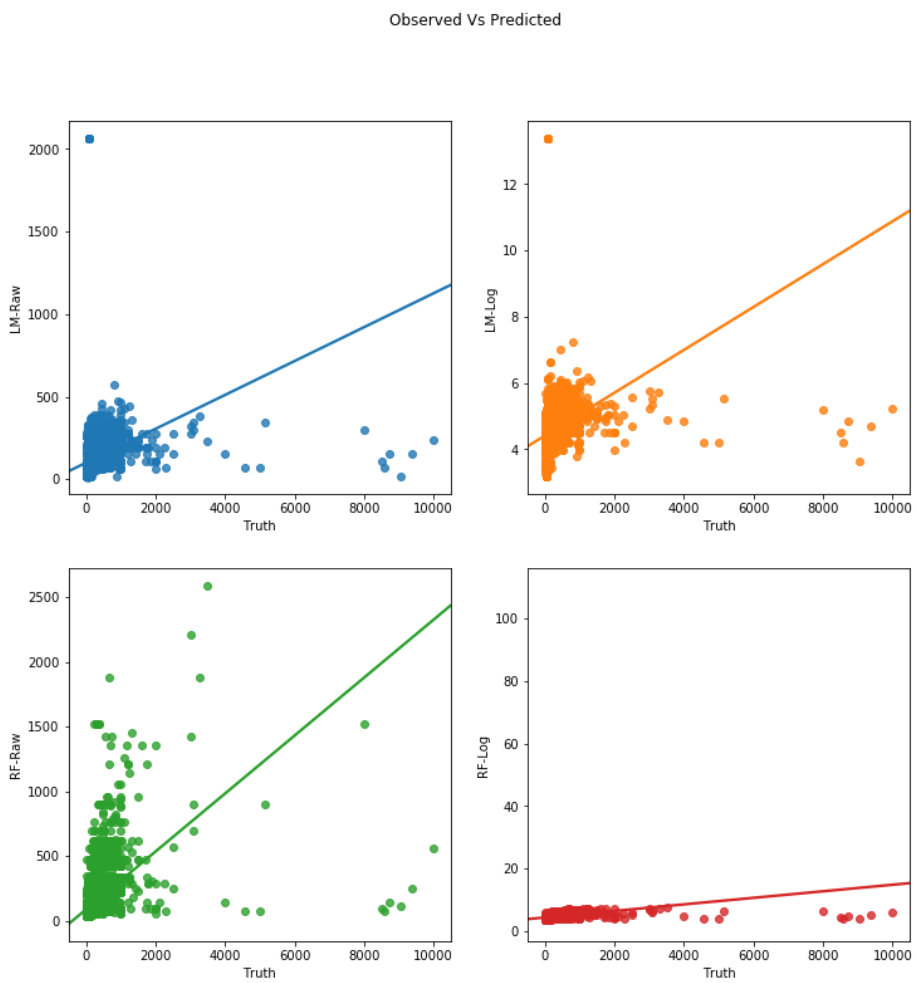
```
%matplotlib inline

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

base = 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()
```



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    0.225648
RF-Log    0.443311
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     138.900699
RF-Log     140.951982
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)
```

```
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:

```
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    134.288231
dtype: float64
```

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

```
LM-Raw    149.522153
RF-Raw    138.900699
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:

```
# 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?

```
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    218.192959
dtype: float64
```

```
mses_np
```

```
LM-Raw    144.326619
RF-Raw    134.288231
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

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

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

For the linear model:

```
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))
```

```
160.31902561005145
```

For the random forest:

```
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))
```

```
154.8768314139274
```

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

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

For the linear model:

```
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:

```
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()
```

```
142.12045777379396
```

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.

```
mses
```

```
LM-Raw     149.522153
LM-Log    7570.085725
RF-Raw     138.900699
RF-Log     140.951982
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:

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

```
{'bootstrap': True,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': 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': 'warn',
 '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 2.23 s, sys: 260 ms, total: 2.49 s
Wall time: 1min 3s
```

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='mse',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=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='warn', n_jobs=None,
                                             oob_score=False, random_state=None,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'max_features': [1, 2, 3, 4, 5],
                         'n_estimators': [5, 25, 50, 75, 100, 150]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring='neg_mean_squared_error', verbose=0)
```

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_features	param_
0	0.044183	0.004684	0.004244	0.000260	1	
1	0.189017	0.009447	0.013378	0.000627	1	
2	0.511528	0.101887	0.030065	0.005109	1	
3	0.888280	0.044405	0.055058	0.025995	1	
4	0.997883	0.174860	0.058024	0.009668	1	

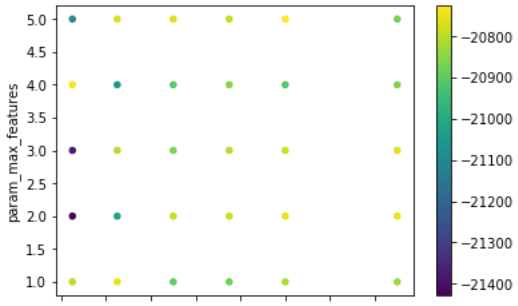
And the winner is...

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

```
28    {'max_features': 5, 'n_estimators': 100}
Name: params, dtype: object
```

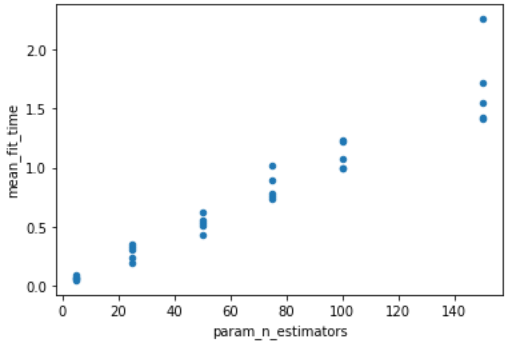
Or, we can visualise the surface generated in the grid:

```
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