Practical 6: Numeric Data

Easing into EDA with Pandas

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This session is a tour-de-`pandas`; since this is Python's equivalent of the `tidyverse` meets `data.tables` it is fundamental to the data science ecosystem and is probably one of the most-widely used libraries in the language as a whole. I get more than 286,000 questions tagged with pandas on StackOverflow.

This week we are also going to start looking at the **InsideAirbnb** data which forms the core of the work that we do over the rest of the term. The focus of *this* notebook is simple numeric data: no mapping or text data... yet... and direct manipulation of data types, derivation of summary statistics, and simple plotting.

We hope that you will be able to draw on the past few practical sessions to develop a more intuitive understanding of how to interact with pandas since it supports both a 'dictionary-of-lists' style of interaction *and* a methods-based style of interaction with the 'Data Frame'.

> ⚠ Important
>
> Conceptually, this practical links together *all* of the preceding ones; you will find data structures, classes and methods, reading CSV files from a remote location, `numpy`, and more than you ever wanted to know about data types in Python.

> Making these connections will make the remainder of term much, much easier, so it might be worth **revising this practical** over Reading Week so make sure it all makes sense!

1 The Importance of EDA

After a few weeks getting to grips with Python, we're now going to start working with some real data. One of the first things that we do when working with any new data set is to familiarise ourselves with it. There are a *huge* number of ways to do this, but there are no shortcuts to:

1. Reading about the data (how it was collected, what the sample size was, etc.)
2. Reviewing any accompanying metadata (data about the data, column specs, etc.)
3. Looking at the data itself at the row- and column-levels
4. Producing descriptive statistics
5. Visualising the data using plots

You should use *all* of these together to really understand where the data came from, how it was handled, and whether there are gaps or other problems. If you're wondering which comes first, the concept of *start with a chart* is always good… though we've obviously not *quite* gotten there yet! This week we want you to get a handle on pandas itself, so although we will do some plotting of charts, we'll focus on 3-4 with a tiny bit of 5. There will be much more on plotting charts next week, and you should be looking into 1 and 2 yourself based on what's been written both on the Inside Airbnb web site and in the suggested readings.

So although they don't need to be done now, you probably want to add both those links to your reading list!

2 Preamble

> **i** Connections
>
> This is why we spent time talking about Packages, Methods Classes in the lectures… because now we're going to be making *intensive* use of them.

It's always sensible to import packages these at the top of the notebook:

1. Because it lets everyone know what they need to have installed to run your code.
2. It's easy to run this and then skip further down the notebook if you have already done *some* of the work and saved an intermediate output.

```
import os
import numpy as np
import pandas as pd
```

Beyond what we provide below there are numerous useful introductions; one of our favourites is from Greg Reda, and there are some good videos on our YouTube channel. And of course, there's TONS of stuff on StackOverflow. If you want an actual physical book, you might try McKinney (2017).

However, one thing you will really want to bookmark is the official documentation since you will undoubtedly need to refer to it fairly regularly. *Note*: this link is to the most recent release. Over time there will be updates published and you *may* find that you no longer have the most up-to-date version. If you find that you are now using an older version of pandas and the methods have changed then you'll need to track down the *specific* version of the documentation that you need from the home page.

You can always check what version you have installed like this:

```
print(pd.__version__)
```

```
2.2.2
```

> **Tip**
>
> The `<package_name>.__version__` approach isn't guaranteed to work with *every* package, but it will work with most of them. Remember that variables and methods starting and ending with '__' are **private** and any interaction with them should be approached very, very carefully.

3 Reading and Writing Data

> **Connections**
>
> You will *really* need to get to grips with Pandas through the lectures on Data and Pandas.

Pandas can do a *lot*, and you might be feeling a little intimidated by this, but here's the thing: we were already writing something like pandas from scratch! That's because pandas takes a **column-view of data** in the same way that our **Dictionary-of-Lists** did, it's just that it's got a lot more features than our 'simple' tool did. That's why the documentation is so much more forbidding and why pandas is so much more powerful.

But at its heart, a pandas `Data Frame` (`df` for short) is a collection of `Data Series` objects (i.e. columns) with an index. Each Series is like one of our column-lists from the last notebook. And the `df` is like the dictionary that held the data together. So you've seen this before and you already *know* what's going on… or at least you now have an *analogy* that you can use to make sense of pandas:

```
myDataFrame = {
    '<column_name_1>': <Series_1>,
    '<column_name_2>': <Series_2>,
```

```
    '<column_name_3>': <Series_3>
}
```

And pandas gives us two ways to access that data:

1. Using a method syntax: `myDataFrame.column_name_1`
2. Using a dictionary syntax: `myDataFrame['column_name_1']`

Depending on which syntax you prefer, you can use these interchangeably. The only times you *have* to choose one over the other are:

- Assignment (e.g. `myDataFrame['column_name_1'] = ...`);
- Columns with spaces in their names (e.g. `myDataFrame['Column Name 1']`).

3.1 Reading Remote Data

Difficulty: Low (this time around).

You will need to do several things here to read the remote, compressed CSV file specified by `url` into a data frame called `df`. Setting `low_memory=False` ensures that pandas will try to load the entire data set *before* guessing the data format! Obviously, with very large files this is probably a bad idea and it's possible to force a particular column type while readng in the data as well. For larger data sets there are platforms like Dask (see, eg, this), and beyond that are other options.

```
# Set download URL
ymd  = '20240614'
city = 'London'
host = 'https://orca.casa.ucl.ac.uk'
url  = f'{host}/~jreades/data/{ymd}-{city}-listings.csv.gz'
```

Question

```
# your code here
df = pd.read_csv(??, compression='gzip', low_memory=False)
print(f"Data frame is {df.shape[0]:,} x {df.shape[1]}")
```

You should get a data frame containing 75 columns and 87,953 rows of data.

3.2 Inspecting the Data Frame

Difficulty: Low.

Let's get a general sense of the data by printing out information *about* the data frame. There are several ways to do this (and we'll see another futher on):

- `df.describe(percentiles=None, include=None, exclude=None, datetime_is_numeric=False` – descriptive stats for all **numeric** columns
- `df.info(verbose=None, buf=None, max_cols=None, memory_usage=None, show_counts=None)` – summarises all columns, but without distribution information
- `df.memory_usage(index=True, deep=True)` – memory usage details about each column (can be quite slow as it's doing a *lot* of digging)

Question

What is another term for the 0.5 percentile?

3.2.1 Describing

Describing a data frame provides general information about *numeric* columns, such as the median, IQR, or number of discrete values.

So to show the 5th and 95th percentiles you need to pass an argument to `describe` to override the default report from pandas:

Question

```
df.describe(percentiles=[??])
```

3.2.2 Info

The `info` method provides a more system-oriented view of the data frame, helping you to understand what each column is composed of, how many NAs there might be, and some high-level (but often incomplete) data on performance.

```
df.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87953 entries, 0 to 87952
Data columns (total 75 columns):
 #   Column                                        Non-Null Count  Dtype
---  ------                                        --------------  -----
 0   id                                            87946 non-null  float64
 1   listing_url                                   87950 non-null  object
 2   scrape_id                                     87950 non-null  object
 3   last_scraped                                  87951 non-null  object
 4   source                                        87953 non-null  object
 5   name                                          87953 non-null  object
 6   description                                   86686 non-null  object
 7   neighborhood_overview                         47194 non-null  object
 8   picture_url                                   87950 non-null  object
 9   host_id                                       87953 non-null  float64
 10  host_url                                      87953 non-null  object
```

```
11  host_name                                     87948 non-null  object
12  host_since                                    87948 non-null  object
13  host_location                                 69172 non-null  object
14  host_about                                    45913 non-null  object
15  host_response_time                            59024 non-null  object
16  host_response_rate                            59031 non-null  object
17  host_acceptance_rate                          62760 non-null  object
18  host_is_superhost                             87014 non-null  object
19  host_thumbnail_url                            87941 non-null  object
20  host_picture_url                              87941 non-null  object
21  host_neighbourhood                            48075 non-null  object
22  host_listings_count                           87941 non-null  object
23  host_total_listings_count                     87941 non-null  float64
24  host_verifications                            87941 non-null  object
25  host_has_profile_pic                          87941 non-null  object
26  host_identity_verified                        87941 non-null  object
27  neighbourhood                                 47194 non-null  object
28  neighbourhood_cleansed                        87946 non-null  object
29  neighbourhood_group_cleansed                  7 non-null      float64
30  latitude                                      87946 non-null  float64
31  longitude                                     87946 non-null  float64
32  property_type                                 87946 non-null  object
33  room_type                                     87946 non-null  object
34  accommodates                                  87946 non-null  float64
35  bathrooms                                     0 non-null      float64
36  bathrooms_text                                87843 non-null  object
37  bedrooms                                      55172 non-null  float64
38  beds                                          86812 non-null  float64
39  amenities                                     87946 non-null  object
40  price                                         87946 non-null  object
41  minimum_nights                                87946 non-null  object
42  maximum_nights                                87946 non-null  float64
43  minimum_minimum_nights                        87945 non-null  float64
44  maximum_minimum_nights                        87945 non-null  float64
45  minimum_maximum_nights                        87944 non-null  object
46  maximum_maximum_nights                        87944 non-null  object
47  minimum_nights_avg_ntm                        87944 non-null  float64
48  maximum_nights_avg_ntm                        87944 non-null  float64
49  calendar_updated                              6 non-null      float64
50  has_availability                              87945 non-null  object
51  availability_30                               87945 non-null  float64
52  availability_60                               87945 non-null  float64
53  availability_90                               87945 non-null  float64
54  availability_365                              87939 non-null  float64
55  calendar_last_scraped                         87946 non-null  object
56  number_of_reviews                             87946 non-null  float64
57  number_of_reviews_ltm                         87946 non-null  float64
58  number_of_reviews_l30d                        87946 non-null  float64
59  first_review                                  65789 non-null  object
60  last_review                                   65788 non-null  object
61  review_scores_rating                          65782 non-null  float64
62  review_scores_accuracy                        64847 non-null  float64
```

```
 63   review_scores_cleanliness                     64859 non-null   float64
 64   review_scores_checkin                         64815 non-null   float64
 65   review_scores_communication                   64845 non-null   float64
 66   review_scores_location                        64815 non-null   float64
 67   review_scores_value                           64814 non-null   float64
 68   license                                       1 non-null       object
 69   instant_bookable                              87939 non-null   object
 70   calculated_host_listings_count                87939 non-null   float64
 71   calculated_host_listings_count_entire_homes   87939 non-null   float64
 72   calculated_host_listings_count_private_rooms  87939 non-null   float64
 73   calculated_host_listings_count_shared_rooms   87939 non-null   float64
 74   reviews_per_month                             65782 non-null   float64
dtypes: float64(35), object(40)
memory usage: 50.3+ MB
```

You should get that the data frame has a mix of `float64`, `int`, and `object` (text) columns and that some columns contain many nulls. You will also get an *estimate* of memory usage that may differ substantially from the more complete picture provided below, which suggests a 'true' value of 396MB.

3.2.3 Memory Usage

If you really need to get into the 'weeds' and profile your data frame because you are crashing Python and seeing messages about 'core dumped', or seeing appallingly poor performance, then `memory_usage` is the way to go:

```
df.memory_usage(index=True, deep=True)
```

```
Index                                               132
id                                               703624
listing_url                                     7940958
scrape_id                                       5540904
last_scraped                                    5189137
                                                 ...
calculated_host_listings_count                   703624
calculated_host_listings_count_entire_homes      703624
calculated_host_listings_count_private_rooms     703624
calculated_host_listings_count_shared_rooms      703624
reviews_per_month                                703624
Length: 76, dtype: int64
```

You should see that the data frame uses 415,086,430 bytes of memory, but the *really* important thing to note here is the difference between `string` and other types of data: keeping data as raw strings (instead of converting to categories, for instance) uses up a *lot* more memory and this can have a huge impact on the performance of your code.

3.2.4 Printing the Columns

Finally, I find it *very* useful to be able to quickly print out a list of the **columns** without all of the details shown above. You just need to *print* the *columns* as a *list*:

```
print(df.columns.to_list())
```

```
['id', 'listing_url', 'scrape_id', 'last_scraped', 'source', 'name', 'description', 'neig
```

You should get a list showing every single column. If you get `Index(['id', 'listing_url',...], dtype='object')` then you have printed the column *index* object and you to need to tell the object to convert its output **to a list** (*hint*: Google).

3.3 Saving the File Locally

Difficulty: Low

Now save the file somewhere local so that you don't have to keep downloading 40MB of compressed data every time you want to start the practical. We'll be using this data for the rest of term, so you might as well save yourself some time and bandwidth! We'll talk more about data processing pipelines over the course of the term, but I'd suggest putting this data set into a `data/raw` folder because then you can have directories like `data/clean` and `data/analytical` as you move through the process of cleaning and prepping your data for analysis.

```
path = os.path.join('data','raw') # A default location to save raw data
fn   = url.split('/')[-1]         # What does this do?
print(f"Writing to: {fn}")
```

```
Writing to: 20240614-London-listings.csv.gz
```

```
if not os.path.exists(path):      # And what does *this* do?
    print(f"Creating {path} under {os.getcwd()}")
    os.makedirs(path)

if not os.path.exists(os.path.join(path,fn)):
    df.to_csv(os.path.join(path,fn), index=False)
    print("Done.")
```

4 Managing Your Data

When starting out it's common to think in terms of there being one input (the raw data) and one output (the results) to an analysis. In practice, you will have many intermediate outputs used as 'milestones' in the overall analysis:

- You might have a 'canonical' data file that has dealt with formatting issues and converted the columns to appropriate data types.
- You might have a 'clean' data file that has dealt with observations that seem to be incomplete or otherwise improperly formatted.
- You might generate subsets by region or area.
- You might produce an 'analytical' or 'final' data set appropriate to a specific analysis.

Most importantly, if you are going to run the same analysis multiple times using data from different time periods (e.g. Land Registry's Price Paid Data is updated every month) then you will *multiple* versions of each of each of the above.

But, *in addition*, you might also be working with such a large data set that processing the *entire* thing every time you want to do some development work is impractical: do you want to load 1 billion rows only to find out that you needed 1,000 of them or that one of your columns is incorrectly formatted?

So although you *could* do the next few steps as part of loading the *raw* data, I always prefer to keep the original data set handy since I almost always discover that there are fields I didn't realise I needed when I started my work.

So my approach to coding is usually:

1. Download the raw file and save it locally in a `data/raw` directory.
2. Load the first `nrows` of data so that I can quickly:
    - Check that the specification matches the data and select columns/rows accordingly.
    - Identify obviously invalid rows/columns and investigate further.
    - Check the code to fix data types and (where relevant) values works.
    - Write this new, smaller file ($m` << m$ and $n` << n$) out to a `data/clean` or `data/canonical` directory (depending on whether formatting the columns is so complex or takes so long on a large data set that it needs to be separated out from actual cleaning).
    - Test out some initial ideas for further analysis.
3. Re-run the code (remove the `nrows` limit) using the full data set.

> ⚠ Difficulty: Moderate
>
> Although the code here is simple, the logic is not.

4.1 File Names

You should always be looking for ways to *avoid* hard-coding values that might change over time, especially those linked to the date of the data file.

In this case you might try to work out how to make it easy to update the code to download the latest file. For instance, if the file looks like `2022-09-10-listings.csv.gz` then I might well specify the `url` as `{date}-listings.csv.gz` or `{year}-{month}-{day}-listings.cs` and set up the variables that I need beforehand or in a separate file.

Using parameters makes it easier to write robust code that doesn't have unwanted side-effects. Here's a common one: you write code to download and process a file named `20221111-data.csv.gz`. After doing all the steps in Tasks 2 and 3 below you save it to `clean-data.csv.gz`.

Question

What happens when your boss asks you to process `20221211-data.csv.gz`?

4.2 File Loading

Now let's write something that will allow us to more quickly write our code and validate the results in exploratory phase. For simplicity I've called this 'testing', but you could also think of it as 'dev' mode. What we want is to be able to easily swap between testing and operational contexts using a 'switch' (typically, a Boolean value) and limit the data load in testing mode.

To achieve this you could set pandas to:

- Load only the first 10,000 rows using `nrows` *if* we are testing
- Use the columns specified in `cols`
- Allow pandas to load the entire data set before deciding on the column type by setting `low_memory` appropriately.

4.2.1 Row Subsetting

Let's tackle the *rows* problem first:

Question

```
testing = True

if testing:
    df = pd.read_csv(os.path.join(path,fn),
                low_memory=??, ??)
else:
    df = pd.read_csv(os.path.join(path,fn),
                low_memory=??)

print(f"Data frame is {df.shape[0]:,} x {df.shape[1]}")
```

So notice how this code deliberately works the same for either testing *or* operational execution – we just flip between the option by changing the `testing` variable from `True` to `False`!

To make this more robust and useful we could use this `testing` variable *throughout* our code if we wanted to change other behaviours based on development/deployment context. The state of the switch could then be set globally using an external configuration file (usually just called a 'conf file'). The easiest way to do this is to have a `conf.py` which contains your global parameters and then every script or notebook file reads in the configuration and sets these variables.

Something like:

```
testing = False
```

And:

```
from conf import *
```

4.2.2 Column Subsetting

Now let's tackle the column problem... In order to avoid having to load lots of data that we aren't sure we need yet, we can restrict the columns that we load. We got `cols` below by copying the output of (`df.columns.to_list()` and then removing the fields that we thought we *weren't* interested in.

```
cols = ['id', 'listing_url', 'last_scraped', 'name', 'description', 'host_id',
        'host_name', 'host_since', 'host_location', 'host_about', 'host_is_superhost
        'host_listings_count', 'host_total_listings_count', 'host_verifications',
        'latitude', 'longitude', 'property_type', 'room_type', 'accommodates',
        'bathrooms', 'bathrooms_text', 'bedrooms', 'beds', 'amenities', 'price',
        'minimum_nights', 'maximum_nights', 'availability_365', 'number_of_reviews',
        'first_review', 'last_review', 'review_scores_rating', 'license',
        'reviews_per_month']
print(f"Cols contains {len(cols)} columns.")
```

```
Cols contains 34 columns.
```

So let's extend our previous answer

Question

```
testing = True

if testing:
    df = pd.read_csv(os.path.join(path,fn),
                low_memory=False, nrows=10000, ??)
else:
    df = pd.read_csv(os.path.join(path,fn),
                low_memory=False, ??)

print(f"Data frame is {df.shape[0]:,} x {df.shape[1]}")
```

4.3 Releasing Memory

A particular risk when working with Jupyter notebooks is that you either: a) have run code in an order *other* than the order shown in the notebook; or b) have made edits to code but *not* re-run the changed code. So you're still working from code that is no longer visible!

When that happens you can get *very* confusing issues because what you *see* doesn't square with what the computer has *executed*. To resolve this without having to re-run the entire notebook (though that can *also* be a good choice!) you might want to 'delete' the current object and re-load or re-run the relevant data or code.

```
del(df)
```

So we use `del(df)` to ensure that we aren't accidentally using the 'old' data frame. But another good reason to delete data you're no longer using is to free up memory.

5 Exploring Your Data

Let's start over from the saved data:

```
df = pd.read_csv(os.path.join(path,fn),
                low_memory=False, usecols=cols)
```

5.1 Selecting Rows

Connections

You will want to refer to the Randomness lecture to understand how we can select the *same* random sample each time and to the session on Logic lecture to cover `NaN`s and `NA`s.

Difficulty: Low

I often like to start my EDA by simply printing out randomly-selected rows to get a feel for what's in the data. Does what I see square with what I read in the documentation? What does the `name` look like? What do I see in `last_scraped` and is it a sensible? What's the `id` field for?

```
df.sample(3)
```

	id	listing_url	last_scraped	nar
64436	7.968150e+17	https://www.airbnb.com/rooms/796814963031833805	2023-09-06	Rer
20834	2.136226e+07	https://www.airbnb.com/rooms/21362262	2023-09-06	Hor
23592	2.360948e+07	https://www.airbnb.com/rooms/23609479	2023-09-06	Rer

See if you can work out from the documentation (Google search time!) how to get the same 'random' sample every time you re-run this code block:

Question

```
df.sample(3, ??)
```

5.2 Selecting Columns

If you look very closely, you'll see that pandas isn't showing you the *full* range of columns since there are 34! If you'd like to only look at specific columns then you can specify them after the sample method call using what looks like a nested list: `[[<column names as strings>]]`.

I'd like you to sample 3 random rows, selecting the 'latitude', 'longitude', 'license', 'property_type', 'room_type' and 'price' columns only.

Question

```
df.sample(??)[??]
```

Your answer should look like this:

	latitude	longitude	license	property_type	room_type	price
38092	51.491470	-0.144230	NaN	Private room in home	Private room	$70.00
75620	51.536788	-0.183432	NaN	Entire rental unit	Entire home/apt	$238.00
53212	51.499500	-0.299260	NaN	Entire rental unit	Entire home/apt	$1,570.00

	latitude	longitude	license	property_type	room_type	price
38092	51.491470	-0.144230	NaN	Private room in home	Private room	$70.00
75620	51.536788	-0.183432	NaN	Entire rental unit	Entire home/apt	$238.00
53212	51.499500	-0.299260	NaN	Entire rental unit	Entire home/apt	$1,570.00

5.3 Dealing with NaNs and Nulls

Difficulty: Hard.

There is a *lot* going on here and you should be paying close attention.

If you really dig into the data you will see that a number of data types that aren't 'appropriate' for their contents: the id columns are floats; the dates aren't dates; there's a boolean that's not a boolean… It would be nice to fix these!

```
# Add some columns here...
```

Note

I had intended to ask you to fix these by combining code from previous weeks with information provided in the lecture, but it turns out that the InsideAirbnb data set is *dirty*. There are a lot of `NaN` values and some of these are *deeply* problematic for some of the column types in pandas. There are also a number of challenges with other columns so, instead, I've opted to show you how I would clean this data as a *first pass* to get it into a format where it's tractable for further cleaning.

5.3.1 Identifying Problem Rows

The reason I'm not asking you to do this part yourselves is that it took me nearly an hour just to work out why I couldn't convert some of the columns to the right data types; then I started finding rows like these:

```
df[df.price.isna()]
```

	id	listing_url	last_scraped	na
8668	1.012818e+07	https://www.airbnb.com/rooms/10128178	2023-09-06	Lo
11814	1.359431e+07	https://www.airbnb.com/rooms/13594306	2023-09-06	Re
21912	2.206322e+07	https://www.airbnb.com/rooms/22063217	2023-09-07	Re
48138	5.342282e+07	https://www.airbnb.com/rooms/53422816	2023-09-06	Co
48765	5.389986e+07	https://www.airbnb.com/rooms/53899858	2023-09-06	Lo
68884	8.446589e+17	https://www.airbnb.com/rooms/844658929307006668	2023-09-06	Re
74896	8.971145e+17	https://www.airbnb.com/rooms/897114471991989638	2023-09-06	Re

```
df[df.room_type.isna()]
```

	id	listing_url	last_scraped	na
8668	1.012818e+07	https://www.airbnb.com/rooms/10128178	2023-09-06	Lo
11814	1.359431e+07	https://www.airbnb.com/rooms/13594306	2023-09-06	Re
21912	2.206322e+07	https://www.airbnb.com/rooms/22063217	2023-09-07	Re
48138	5.342282e+07	https://www.airbnb.com/rooms/53422816	2023-09-06	Co
48765	5.389986e+07	https://www.airbnb.com/rooms/53899858	2023-09-06	Lo
68884	8.446589e+17	https://www.airbnb.com/rooms/844658929307006668	2023-09-06	Re
74896	8.971145e+17	https://www.airbnb.com/rooms/897114471991989638	2023-09-06	Re

```
df[~(df.price.str.startswith('$', na=False))]
```

	id	listing_url	last_scraped	na
8668	1.012818e+07	https://www.airbnb.com/rooms/10128178	2023-09-06	Lo
8669	NaN	within an hour	71%	htt
11814	1.359431e+07	https://www.airbnb.com/rooms/13594306	2023-09-06	Re
11815	NaN	NaN	NaN	htt
21912	2.206322e+07	https://www.airbnb.com/rooms/22063217	2023-09-07	Re

	id	listing_url	last_scraped	na
21913	NaN	NaN	NaN	htt
48138	5.342282e+07	https://www.airbnb.com/rooms/53422816	2023-09-06	Co
48139	NaN	NaN	83%	htt
48765	5.389986e+07	https://www.airbnb.com/rooms/53899858	2023-09-06	Lo
48766	NaN	within an hour	71%	htt
68884	8.446589e+17	https://www.airbnb.com/rooms/844658929307006668	2023-09-06	Re
68885	NaN	a few days or more	6%	htt
74896	8.971145e+17	https://www.airbnb.com/rooms/897114471991989638	2023-09-06	Re
74897	NaN	within an hour	80%	htt

If I had to guess, I'd say that it's some kind of partial extract/write process because there *are* elements in some of the problem row(s) that look right but they are in the wrong columns. So we can *probably* drop some of these rows, but one thing to do is look at the frequency of NaNs across the data frame *first*. So we need to look for NaNs and Nulls, but it's quite obvious that a `NaN` in the listing id is a basic problem and we should drop these.

```
df[df.id.isna()][['id','listing_url','name','description','host_id','host_name','pri
```

	id	listing_url	name	descrip
8669	NaN	within an hour	https://a0.muscache.com/im/pictures/user/652bf...	https:/
11815	NaN	NaN	https://a0.muscache.com/im/pictures/user/User-...	https:/
21913	NaN	NaN	https://a0.muscache.com/defaults/user_pic-50x5...	https:/
48139	NaN	NaN	https://a0.muscache.com/im/pictures/user/3a51c...	https:/
48766	NaN	within an hour	https://a0.muscache.com/im/pictures/user/652bf...	https:/
68885	NaN	a few days or more	https://a0.muscache.com/im/pictures/user/7d57d...	https:/
74897	NaN	within an hour	https://a0.muscache.com/im/users/11520835/prof...	https:/

As always, if you don't know that's going on, break it down:

- You have seen how column works (`[[<column names>]]`), so that's just selecting the columns that we want to show;
- You know how row selection works (`df[<selection criteria>]`), so that isn't anything really new either;
- So the only really new part is `df.id.isna()`: `df.id` is the `id` column (we could have written this `df['id']` if we wanted) and `isna()` is a test for whether or not a value is NaN.

So this shows that only one row in the 10,000 row sub-sample has a NaN for its id.

If you're not sure what the next line does, try breaking it down by running the inner bits before you run the `drop` command; and also try looking online for examples of how to use `df.drop` (e.g. just up above):

```
df.drop(df[df.id.isna()].index.array, axis=0, inplace=True)
```

With that really troublesome data out of the way, you can now turn to counting NaNs or Nulls in the remaining data with a view to identifying other rows that can probably be dropped.

5.3.2 Counting Nulls by Column

As a starting point I would look to drop the columns that contain only NaNs. Remember that we've dropped a row from the data frame so our maximum is now $n-1$)! Notice how this next command works:

```
# returns a data frame with all values set to True/False according to Null status
df.isnull()
# counts these values by column (we'll see another option in a moment)
df.isnull.sum(axis=0)
# Sort results in descending order
df.isnull.sum(axis=0).sort_values(ascending=False)
```

```
df.isnull().sum(axis=0).sort_values(ascending=False)[:12]
```

```
bathrooms               87946
license                 87945
host_about              42040
bedrooms                32781
first_review            22164
reviews_per_month       22164
last_review             22164
review_scores_rating    22164
host_location           18778
description              1267
beds                     1141
host_is_superhost         939
dtype: int64
```

The most obvious ones here are: bathrooms, license, and host_about.

```
df.drop(columns=['bathrooms','license','host_about'], inplace=True)
```

Because we have dropped everything `inplace` the code simply runs and doesn't return anything.

5.3.3 Counting Nulls by Row

We now know that there *are* still quite a few problems, but we do still need a way to identify the rows that are causing most of the problems.

Notice here that the change from `axis=0` to `axis=1` changes the 'direction' of the `sum` from columns to rows. And we are getting back a data series because the summing operation reduces it to just one column.

```
df.isnull().sum(axis=1).sort_values(ascending=False).head(20)
```

```
48765     22
8668      22
```

```
21912    22
68884    22
48138    22
11814    22
74896    22
7003     11
6042     11
5353     11
4274     11
6694     11
2412      9
39141     8
39082     8
40686     8
27778     8
39023     8
1134      8
611       8
dtype: int64
```

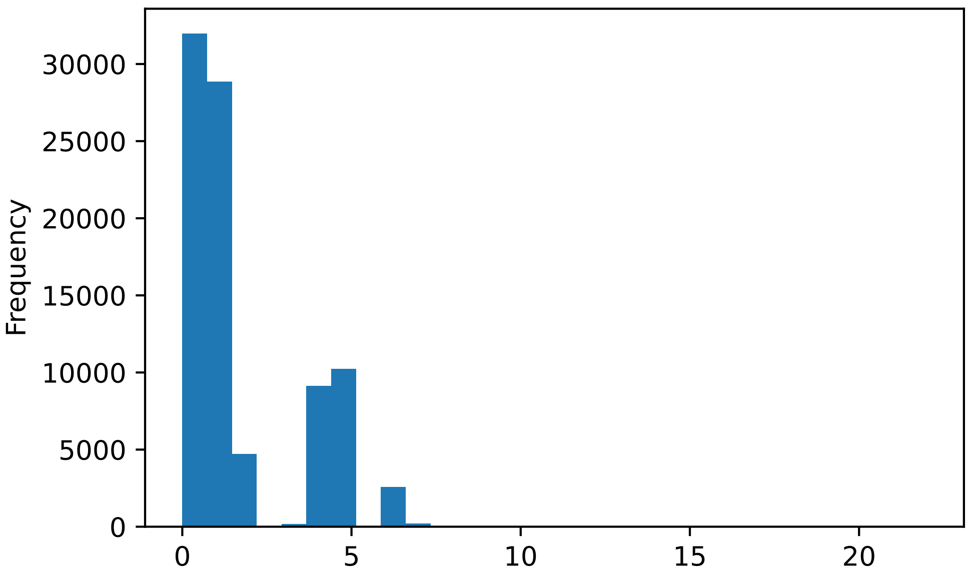
So that is Series showing how many NaN values there are by index value. You should see two columns of numbers: the first is the row id, the second is the number of Nulls in that row.

If we save the results to a variable called `probs` (i.e. problems) then we can decide what to do next.

> **Warning**
>
> There's a chance that Python will complain why you try to run the third line of code. This is particularly likely if you are using Anaconda Python directly (i.e. not Docker). In that case you need to add the code listed at the start of Task 5.

```
probs = df.isnull().sum(axis=1)
print(type(probs))       # Note that this has returned a series!
probs.plot.hist(bins=30) # Oooooooh, check out what we can do with a series!
```

```
<class 'pandas.core.series.Series'>
```



Looking at this histogram, these look like two groups in the data so I would start there. I would take values greater than 3–5 as being ones that are most likely be problematic. We can use the index from `probs` to select out the rows we want to inspect from the main data frame.

Here's another bit of code that bears unpacking:

```
cutoff = 5
df.drop(probs[probs > cutoff].index, inplace=True)
```

1. `probs > 5`: this selects only those rows in the 'probs' series whose value is greater than 5
2. `probs[...].index` returns the index values from the Series, which we will then pass to the `drop` command.
3. `df.drop(..., inplace=True)` will then drop the rows selected by `probs[probs>5].index`.

```
print(f"Have reduced data frame to: {df.shape[0]:,} rows and {df.shape[1]:,} columns
```

```
Have reduced data frame to: 85,127 rows and 31 columns
```

6 Using Indexes

To recap, when we use the `[[...]]` syntax we're taking a short-cut through the data by column (keeping all rows). The *full* syntax is `df[<row_selection>,<col_selection>]`. Only when we *don't* specify both does it then default to `df[<col_selection>]`.

To make the most of pandas you will need to get to grips with the logic than underpins this syntax. This is embedded in the idea of there being row and column indexes. These are *like* the columns `A`..`ZZ` and the rows 1..n in Excel. As you'll have seen in the video, these aren't considered *data*, they are ways to *access the data*. Unlike Excel, while every data frame must *have* an index, in pandas you can 'promote' or 'demote' any column to be used *as* an index.

The default row index is just the row number — this will be created for you if you don't specify something else when you create the data frame. The default column index is created from a file's column names (works for many types of data) but you can change these at any time.

6.1 Label and Numeric Indexing

Perhaps this will (eventually) help to make it more clear:

```
df.loc[
    [4552, 4554, 4556, 4557],
    ['latitude','longitude','property_type','room_type','price']
]
```

	latitude	longitude	property_type	room_type	price
4552	51.531070	-0.186060	Private room in rental unit	Private room	$95.00
4554	51.476640	-0.215200	Entire rental unit	Entire home/apt	$250.00
4556	51.400162	-0.076788	Private room in home	Private room	$56.00
4557	51.408920	-0.180910	Entire rental unit	Entire home/apt	$150.00

And compare *that* with:

```
df.iloc[
    4552:4557,
    14:19
]
```

	longitude	property_type	room_type	accommodates	bathrooms_te
4655	-0.15610	Private room in home	Private room	1.0	1 shared bath
4656	-0.11470	Private room in rental unit	Private room	1.0	1 bath
4657	-0.06745	Private room in rental unit	Private room	1.0	1 shared bath
4658	-0.24050	Entire rental unit	Entire home/apt	4.0	1 bath
4659	-0.18325	Private room in home	Private room	2.0	1 bath

This code *seems* similar, but what are `iloc` and `loc`? The way I remember it is that `iloc` means *integer* location (as you would with *list indexing*), while `loc` means *label* location (as you would with *dictionary keys* or labels). I guess that should therefore be `lloc`, but you get the idea).

6.2 Numeric Indexes

In this case, the **index** (the numbers down the left-hand side in bold) is numeric, so we can treat it as a *label* (which allows us to use `df.loc`) *or* a list-type index (which allows us to use `df.iloc`). So with `loc` we refer to the columns by *label*, whereas with `iloc` we refer to them by *location*; as well, `loc` allows us to access rows and columns non-sequentially/randomly by label, while `iloc` allows us to access them as a numeric range.

6.3 Non-numeric Indexes

Notice how this works differently if we specify a **non-numeric index**:

```
df.set_index('listing_url')[
    ['latitude','longitude','property_type','room_type','price']
].sample(3)
```

listing_url	latitude	longitude	property_type
https://www.airbnb.com/rooms/760992559868916706	51.571028	0.077365	Private room in ho
https://www.airbnb.com/rooms/32511071	51.485810	0.038030	Private room in ren
https://www.airbnb.com/rooms/12324271	51.455420	-0.197130	Entire rental unit

Notice change in indexing because 'listing_url' is no longer a column, it's the index now!

```
df.set_index('listing_url').iloc[0:3,13:18]
```

listing_url	longitude	property_type	room_type
https://www.airbnb.com/rooms/92644	-0.18739	Private room in rental unit	Private room
https://www.airbnb.com/rooms/93015	-0.21707	Entire rental unit	Entire home/apt
https://www.airbnb.com/rooms/13913	-0.11270	Private room in rental unit	Private room

Caution

It's vital that you understand how this code *works*. By which I mean *why* it does something at all, not exactly how to use `loc` and `iloc` (though that is also useful).

`df.set_index(...)` changes the index from the default row number to another field in the data frame. This operation *returns* a new data frame with `listing_url` as its index. Because set index returned a data frame, we can simply add *another* method call (`iloc` or `loc`) on to the end of that line and *it* returns a new data frame in turn!

The fact that each operation returns a new data frame (or data series) is why you can even do this:

```
df.set_index('listing_url').iloc[0:3].latitude.mean()
```

```
51.50351666666666
```

7 Fixing Data Types

If you want to challenge yourself, then I'd suggest trying to work out how to adapt what we saw in previous weeks using the data type dictionary to map column names to column types; however, a more straightforward way to do this is to create different for loops for each:

7.1 Profiling (Optional)

> Difficulty: Low.

The Pandas Profiling tool (rebranded a year or so back as ydata-profiling) offers an alternative way of understanding what's going on in your data. The output looks rather nice and you might be tempted to ask why we didn't use this straight away on the full data set – well, if you really want to know, see what happens when you profile all 70,000-odd rows and 70-odd columns in the raw data frame... in effect: while it's 'nice to have', the likelihood of crashing your computer increases significantly and it's a bit of a tangent, so that's why it's no longer included in the Docker image.

If you *do* want to explore this then you'll need to install the library, and **this is a good chance to look at a quite sophisiticated way to install software on another machine**:

```
from ydata_profiling import ProfileReport
```

7.1.1 Specify the Profiling Columns

Looking back over earlier code see if you can work out how to profile `latitude`, `longitude`,and `review_scores_rating` together.

Question

```
profile = ProfileReport(??, title="Pandas Profiling Report")
```

7.1.2 Profiling Targets

You can write the profile either directly into the Jupyter notebook (this file) or into a separate HTML (i.e. Web) page.

```
profile.to_notebook_iframe()
# You can also write this profile to a web page:
# profile.to_file("your_report.html")
```

7.2 Managing Memory

Difficulty: Low.

As to *why* you'd want to fix your data types, there are two reasons: 1) to ensure that you can make the *most* of your data; 2) to ensure that it takes up as little space as possible in memory. Some simple examples:

- A column containing only `'True'` (4 bytes) and `'False'` (5 bytes) will take up much more space than a column containing only `True` and `False` (1 bit each).
- A column containing only `'Red'`, `'Green'`, and `'Blue'` (3, 5, and 4 bytes each respectively) will take up much more space that a column where we use the numbers `1, 2, 3` to represent these values and have a map that tells us `1==Red`, `2==Blue`, and `3==Green`.

Let's test this idea out:

```
rtm = df.room_type.memory_usage(deep=True) # Room Type Memory
ctm = df.room_type.astype('category').memory_usage(deep=True) # Categorical Type Mem

print(f"The raw memory usage of `room_type` is {rtm/1024:,.0f} Kb.")
print(f"The categorical memory usage of `room_type` is {ctm/1024:,.0f} Kb.")
print(f"That's {(ctm/rtm)*100:.0f}% of the original!")
```

```
The raw memory usage of `room_type` is 7,958 Kb.
The categorical memory usage of `room_type` is 2,813 Kb.
That's 35% of the original!
```

```
shm = df.host_is_superhost.memory_usage(deep=True) # Super Host Memory
bhm = df.host_is_superhost.replace({'f':False, 't':True}).astype('bool').memory_usag

print(f"The raw memory usage of `host_is_superhost` is {shm/1024:,.0f} Kb.")
print(f"The boolean memory usage of `host_is_superhost` is {bhm/1024:,.0f} Kb.")
print(f"That's {(bhm/shm)*100:.0f}% of the original!")
```

```
The raw memory usage of `host_is_superhost` is 6,870 Kb.
The boolean memory usage of `host_is_superhost` is 2,812 Kb.
That's 41% of the original!
```

7.3 Boolean Values

Difficulty: Moderate.

Let's start with columns that are likely to be boolean:

```python
bools = ['host_is_superhost']
df.sample(5, random_state=43)[bools]
```

	host_is_superhost
55197	f
24505	f
44546	f
16312	t
66564	f

Here we have to `map` 't' to True and 'f' to False *before* converting the column to a boolean type. If you simply tried to replace them with the strings 'True' and 'False', then the conversion would run into the same problem as Week 3: any string that is not `None` will convert a True boolean.

```python
# This approach requires us to map 't'
# and 'f' to True and False
for b in bools:
    print(f"Converting {b}")
    df[b] = df[b].replace({'f':False, 't':True}).astype('bool')
```

```
Converting host_is_superhost
```

```python
df.sample(5, random_state=43)[bools]
```

	host_is_superhost
55197	False
24505	False
44546	False
16312	True
66564	False

7.4 Dates

Difficulty: Hard.

I've found dates to be particularly challenging, though pandas has *tried* to make this process less painful than it was a few years ago. What can be particularly frustrating is if *one* row has a non-sensical date value (e.g. a `t`, as happened in 2019/20) then the entire type conversion will fail. When that happens, pandas is not great about communicating where the problem occurred and I had to work it out by trying to convert *parts* of each series (using `.iloc`) to the datetime type until I had a block that failed. I then knew that I could narrow this down further using integer location indexing.

```python
dates = ['last_scraped','host_since','first_review','last_review']

print(f"Currently {dates[1]} is of type '{df[dates[1]].dtype}'", "\n")
df.sample(5, random_state=43)[dates]
```

```
Currently host_since is of type 'object'
```

	last_scraped	host_since	first_review	last_review
55197	2023-09-07	2015-02-11	NaN	NaN
24505	2023-09-06	2012-12-18	2019-01-05	2020-01-05
44546	2023-09-06	2016-05-26	2021-08-15	2023-01-10
16312	2023-09-07	2017-04-02	2017-04-04	2023-08-26
66564	2023-09-06	2017-05-07	NaN	NaN

```python
for d in dates:
    print("Converting " + d)
    df[d] = pd.to_datetime(df[d])
```

```
Converting last_scraped
Converting host_since
Converting first_review
Converting last_review
```

```python
df.sample(5, random_state=43)[dates]
```

	last_scraped	host_since	first_review	last_review
55197	2023-09-07	2015-02-11	NaT	NaT
24505	2023-09-06	2012-12-18	2019-01-05	2020-01-05
44546	2023-09-06	2016-05-26	2021-08-15	2023-01-10
16312	2023-09-07	2017-04-02	2017-04-04	2023-08-26
66564	2023-09-06	2017-05-07	NaT	NaT

Of course, it's not actually clear there what has changed! But if you dig a little more deeply:

```python
print(f"Now {dates[1]} is of type '{df[dates[1]].dtype}'", "\n")
df.sample(5, random_state=45)[dates[1]].dt.strftime('%A %B %d, %Y')
# Try some other formats!
```

```
Now host_since is of type 'datetime64[ns]'

45006     Sunday December 15, 2013
11882        Monday April 13, 2015
74675      Wednesday July 16, 2014
```

```
80039          Friday May 06, 2022
84399        Friday April 22, 2022
Name: host_since, dtype: object
```

In that line of code we:

- Took a random sample (setting the state to 45),
- Took the second column from the dates list (`dates[1]`),
- Used the *date* 'accessor method' (`.dt`),
- And called `string format time` with the format `%A %B %d, %Y` (Full Day of Week, Month Name, Date, 4-digit Year)

7.5 Categories

> ⚠ Difficulty: Moderate.

We know that these are likely to be categories because there'd be no other way to allow users to effectively search Airbnb.

```
cats = ['property_type','room_type']

print(f"Currently {cats[1]} is of type '{df[cats[1]].dtype}'", "\n")
df.sample(5, random_state=42)[cats]
```

```
Currently room_type is of type 'object'
```

	property_type	room_type
18050	Private room in home	Private room
86868	Private room in home	Private room
54798	Private room in bed and breakfast	Private room
74233	Entire rental unit	Entire home/apt
87242	Entire rental unit	Entire home/apt

This next piece of code is quite useful for grouping and counting operations: we are counting the occurences of each unique value in part particular column or combination of columns:

```
df[cats[0]].value_counts()
```

```
property_type
Entire rental unit                  33450
Private room in rental unit         13278
Private room in home                 9795
Entire condo                         8656
Entire home                          7530
```

```
                                          ...
Yurt                                        1
Private room in island                      1
Shared room in villa                        1
Shared room in serviced apartment           1
Treehouse                                   1
Name: count, Length: 99, dtype: int64
```

```
df[cats[1]].value_counts()
```

```
room_type
Entire home/apt    54203
Private room       30366
Shared room          340
Hotel room           218
Name: count, dtype: int64
```

Tip

One column has *many* different values (including Campers/RVs and Yurts!), the other has just four. If I were looking to conduct research I'd probably *start* with the `room_type` column since I may not care about hotels and therefore never even need to decide whether I care about boutique ones!

```
for c in cats:
    print(f"Converting {c}")
    df[c] = df[c].astype('category')
```

```
Converting property_type
Converting room_type
```

```
print(f"Now {cats[1]} is of type '{df[cats[1]].dtype}'", "\n")
print(df[cats[1]].cat.categories.values)
```

```
Now room_type is of type 'category'

['Entire home/apt' 'Hotel room' 'Private room' 'Shared room']
```

```
df.sample(5, random_state=42)[cats]
```

	property_type	room_type
18050	Private room in home	Private room
86868	Private room in home	Private room
54798	Private room in bed and breakfast	Private room
74233	Entire rental unit	Entire home/apt

	property_type	room_type
87242	Entire rental unit	Entire home/apt

7.6 Dealing with Strings

Difficulty: Hard.

We'll have to put some more work into deal with the description and other more free-from text fields later in the term, but for now let's just deal with a straightforward one: price!

```
money = ['price']
df.sample(5, random_state=42)[money]
```

	price
18050	$51.00
86868	$56.00
54798	$45.00
74233	$104.00
87242	$126.00

You will get an error when you run the next code block, that's because I want you to do a little thinking about how to extend the code to fix the data. You've already got the code you need to fix it, you just need to do a bit of thinking about 'method chaining'!

```
for m in money:
    print(f"Converting {m}")
    try:
        df[m] = df[m].str.replace('$','', regex=False).astype('float')
    except ValueError as e:
        print(f"    xxxx Unable to convert {m} to float xxxx")
        print(e)
```

```
Converting price
    xxxx Unable to convert price to float xxxx
could not convert string to float: '1,000.00'
```

Look closely at the error and then think about what you need to add to the code below:

Note

For now don't worry about what `regex=False` means. It will all make sense when we get to *dealing with text*.

Question

```
for m in money:
    print(f"Converting {m}")
    df[m] = df[m].str.replace('$','', regex=False).str.replace(??).astype('float')
```

```
df.sample(5, random_state=42)[money]
```

	price
18050	51.0
86868	56.0
54798	45.0
74233	104.0
87242	126.0

```
df.sort_values(by='price', ascending=False).head(3)[['id','name','price','minimum_ni
```

	id	name	price	minimum_ni
36168	3.845268e+07	Guesthouse in Dagenham · ?5.0 · 1 bedroom · 1 ...	80100.0	2
11249	1.325477e+07	Rental unit in London · ?4.85 · 1 bedroom · 1 ...	53588.0	3
53708	6.454631e+17	Serviced apartment in Greater London · 4 bedro...	36000.0	28

7.7 Dealing with Integers

Difficulty: Hard.

This is the issue that made me abandon the idea of making you clean the data yourselves. Although *floats* have no issues with `np.nan` in the Series, by default there are no numpy integer arrays that can cope with NaNs. This was such a major issue for Pandas that they've actually created their *own* data type that does support NaN values in integer columns. There are a lot of integer columns, but only one of them seems to be a problem.

```
ints  = ['id','host_id','host_listings_count','host_total_listings_count','accommoda
         'beds','minimum_nights','maximum_nights','availability_365']
for i in ints:
    print(f"Converting {i}")
    try:
        df[i] = df[i].astype('float').astype('int')
    except ValueError as e:
        print("  - !!!Converting to unsigned 16-bit integer!!!")
        df[i] = df[i].astype('float').astype(pd.UInt16Dtype())
```

```
Converting id
```

```
Converting host_id
Converting host_listings_count
Converting host_total_listings_count
Converting accommodates
Converting beds
  - !!!Converting to unsigned 16-bit integer!!!
Converting minimum_nights
Converting maximum_nights
Converting availability_365
```

So we convert the column but using a `try / except` approach that allows to trap `ValueError` exceptions triggered by the presence of NaNs in the column. The following code tells us that there are just eight of these in the 10k sample, but they're enough to cause the code to fail if you don't trap them. The alternatives would be to: a) drop those rows; or b) leave the data as floats. For some reason the latter offends my sense of order, and the former feels like avoiding the problem rather than dealing with it.

```
df.beds.isna().value_counts()
```

```
beds
False    84326
True       801
Name: count, dtype: int64
```

7.8 Validation

Difficulty: Low.

Ordinarily, at this point I would then output information to confirm that all of the opeations I *think* I've undertaken were correctly applied.

```
df.info()
```

7.9 Saving

Also at this point I would save a copy of the cleaned data, though I would only consider this data *partially* cleaned since we've not made it any further than just ensuring that each column is in an appropriate format and that some particularly problematic rows have been dropped!

```
path = os.path.join('data','clean')

if not os.path.exists(path):
    print(f"Creating {path} under {os.getcwd()}")
    os.makedirs(path)
```

```
df.to_csv(os.path.join(path,fn), index=False)
print("Done.")
```

```
Done.
```

Feather is an alternative format (gradually being replaced by parquet, which is more widely supported) for data interchange between R and Python: it's fast, it preserves data types, it's compressed, and it will avoid the kinds of the problems that come up when you move to/from CSV as a default.

8 Selection using Criteria

So far we've been taking primarily a row and column view of the data, now we want to think about selecting ranges from within the data set...

8.1 Selecting using Data Types

Difficulty: Low.

If we wanted to filter in/out certain columns pandas can do that! Let's try for floats and ints (*hint*: these are 64-bit data types).

Question

```
df.select_dtypes(include=[??])
```

8.2 Selecting using Conditions

Difficulty: Hard.

What if we wanted to find whole homes listings for more than $100/night?

To do this we use a combination of the selection approaches above in combination with conditionals, but first we need to see what sort of properties there are in the data set! `groupby` is a really useful function that we'll come back to later in the term, but for now notice that it helps us to group the analysis by `room_type` so that subsequently asking for the `property_type` value counts allows the same `property_type` to appear in more than once place if it's associated with more than one `room_type`.

```
df.groupby('room_type', observed=True)['property_type'].value_counts()
```

```
room_type        property_type
Entire home/apt  Entire rental unit          33450
                 Entire condo                 8656
                 Entire home                  7530
                 Entire serviced apartment    2021
                 Entire townhouse             1153
                                              ...
Shared room      Tent                            0
                 Tiny home                       0
                 Tower                           0
                 Treehouse                       0
                 Yurt                            0
Name: count, Length: 396, dtype: int64
```

Now try to select only the `Entire home/apt` room type:

Question

```
df[df.??=='??']['property_type'].value_counts().head(10)
```

Your output should be:

```
property_type
Entire rental unit           33450
Entire condo                  8656
Entire home                   7530
Entire serviced apartment     2021
Entire townhouse              1153
Entire loft                    389
Entire guesthouse              205
Entire guest suite             178
Entire vacation home           102
Boat                            68
Name: count, dtype: int64
```

8.3 Arbitrary Selection Criteria

> ⚠ Difficulty: Moderate, if the previous section made sense to you.

OK, now let's look for the Entire home/apt listings that are more expected than average... to do *that* let's get a sense of where the mean and median value fall:

Question

```
print(f"The mean price is ${df.price.??():0.2f}")
print(f"The median price is ${df.price.??():0.2f}")
```

You should see that the mean is higher than the median price but both are *very* roughly plausible values. Given your understanding of distributions from, say, Quantitative Methods, what can you say about the pricing distribution of Airbnb units?

You might want to have a look at the documentation: it's rather a long list, but most of your descriptive stats are on that page in the Cumulative / Descriptive Stats section, and there's also lots of information about methods for strings and categorical data.

8.3.1 Filtering: it's 'logical'

So we want to take `Entire home/apt` and filter the data set *together with* the price per night from the `price` column. For that, let's use the mean price/night of $183.63 (*note*: this is totally arbitrary)?

Question

So here we want to filter on two values in the data set using `&`:

```
pricey = df[(??) & (df.price>df.price.??)]
print(f"Selected {pricey.shape[0]:,} rows")
```

In the code above we see two things:

1. The use of the bitwise `&` (it's *not* the same as `and`).
2. The fact that you need parentheses around the selection in order to make the the `&` work.

8.4 Selection with an Aggregate

Difficulty: Low.

Let's find the cheapest and most expensive listings using `min` and `max` methods:

Question

Least expensive:

```
df[df.price==df.price.??()][['price','id','listing_url','room_type','description']]
```

Most expensive:

```
df[df.price==df.price.??()][['price','id','listing_url','room_type','description']]
```

You should see one or more units priced at exceedingly high levels… and here's a way to see a few more of these budget-busting options.

```
df.sort_values(by='price', ascending=False).head(3)[
    ['price','listing_url','room_type','description']
]
```

	price	listing_url	room_type	descri
36168	80100.0	https://www.airbnb.com/rooms/38452677	Entire home/apt	Bouqu
11249	53588.0	https://www.airbnb.com/rooms/13254774	Private room	PLEAS
53708	36000.0	https://www.airbnb.com/rooms/645463113262447532	Entire home/apt	Enjoy

Stop: Ask yourself if the result is *plausible*.

Question

What do you make of this result?

8.5 Selection with a Range

Difficulty: Moderate

Perhaps we aren't just looking for extremes... how about all of the properties falling within the middle of the distribution? We can ask for any abitrary quantile we like, so let's go with the 25th and 75th percentile to get the middle 50% of the data. Google how to get percentiles from pandas.

Question

```
dfr = df[
            (df.price > df.price.quantile(??)) &
            (df.price < df.price.quantile(??)) ]

print(f"Lower Quartile: {df.price.quantile(??):>6.2f}")
print(f"Upper Quartile: {df.price.quantile(??):>6.2f}")
print()
print(f"Range selected contains {dfr.shape[0]:,} rows.")
print(f"Minimum price: {dfr.price.??():>6.2f}")
print(f"Maximum price: {dfr.price.??():>6.2f}")
```

That example contains a few things to which you need to pay attention:

1. *Again* you can see that, with mutiple selections, we had to put parentheses around each one – this forces Python to...
2. Process the `&` (bit-wise AND) that asks pandas to "Find all the rows where condition 1 *and* condition 2 are both `True`". So it calculates the `True`/`False` for the left side and the `True`/`False` for the right side of the `&`, and then combines them.

9 Enhancing our Understanding

9.1 Deriving a New Variable

Difficulty: ?

Let's try calculating several derived measures of distribution for the price... these deliberately demonstrate different ways of handling this process (and notice also the little call to `apply` that can perform additional tasks).

9.1.1 The z-Score

The z-score is given by $z = (x - \bar{x})/\sigma$.

Question

```
df['z'] = (df.?? - df.??.??()) / df.??.??()
df.z.describe().apply(lambda x: f"{x:5.5f}")
```

9.1.2 Inter-Quartile Standardisation

The IQR-standardised score is given by $i = (x - Q_1)/(Q_3 - Q_1)$

Question

```
df['iqs'] = (df.price - ??)/(??-??)
df.iqs.describe().apply(lambda x: f"{x:5.5f}")
```

9.1.3 Log-Normalisation

The natural log of the price is gven by $ln(x)$

Question

```
df['lnprice'] = np.log(??)
df.lnprice.describe().apply(lambda x: f"{x:5.5f}")
```

9.2 Quick (and Dirty) Plotting

One of the first things we should do when exploring a new dataset is plot (aka graph) the data. We've left plotting until a little later in this practical so that we could see some other basic attributes of how pandas stores data. We'll look at plotting and exploratory data analyses in much more detail next week, including using packages other than pandas.

For now, let's look at the basic plotting functionality pandas provides - in conjunctions with the online documentation for both DataFrames and Series. There are also examples of all the different types of plots pandas can produce.

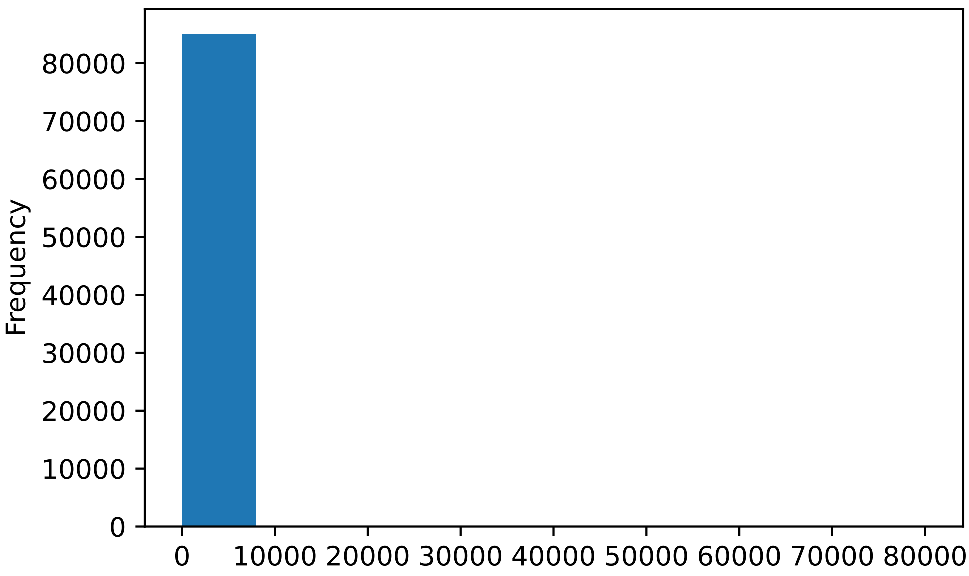
> ⚠ MacOS plotting *without* Docker
>
> MacOS users who are *not* using Docker will need to do certain things in a specific order at the start of any notebook in order to show maps or graphs. Please make a copy of the following code for any notebook that you create and make it the *first* code that you run in the notebook...
>
> ```
> # Needed on a Mac
> import matplotlib as mpl
> mpl.use('TkAgg')
> %matplotlib inline
> import matplotlib.pyplot as plt
> ```

9.2.1 Histograms

> Difficulty: Low

First, let's see some of the ways we could visualise the distribution of the `Series` in the dataset:

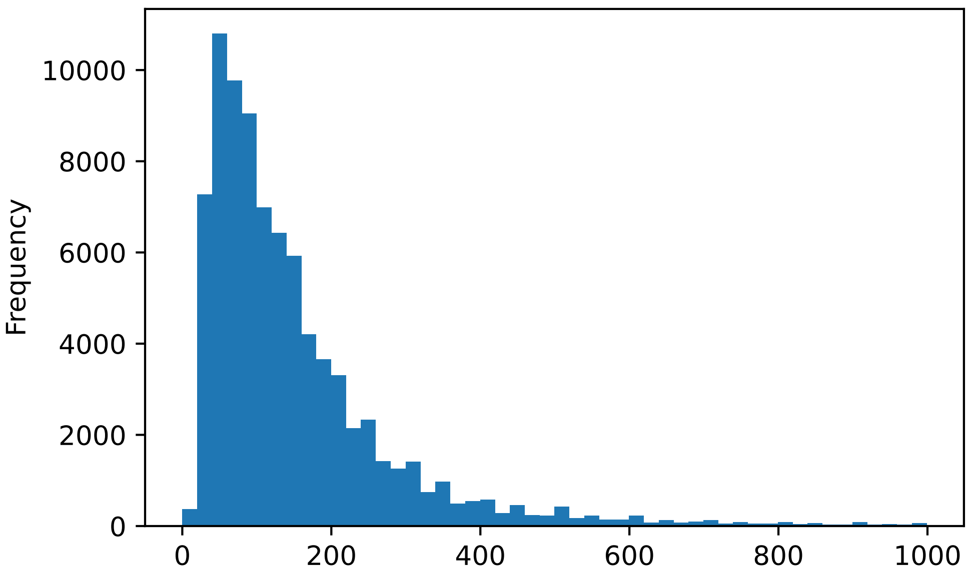
```
df.price.plot.hist() # histogram
```



If the code worked properly you should have just created a standard histogram plot (if you can't see one, ask for help). However, a basic problem here may be the range of the data: if your maximum price is much more than £5,000 then you'll find the majority of your data plotted in one bar, which isn't very helpful.

You can filter the data *and* pass in some simple options to improve the plotting:

```
# Notice the ';' here to suppress `<AxesSubplot...>`
# That information doesn't *always* appear, but whenever
# you have unwanted textual output above your plot just
# add a ';' on the end of the line of code!
df[df.price < 1000].price.plot.hist(bins=50);
```



9.2.2 KDE Plots

> Difficulty: Low

Similarly, we can produce a Kernel Density Estimate plot. This time, instead of dropping data just before calling `plot` we're going to modify the *limits* of the x-axis using `xlim`:

Question

Look for information about using `xlim`:

```
df.price.plot.kde(xlim=(??)); #kernel density estimate plot
```

Kind of handy, no? These aren't the *best* looking plots, but they are all being generated on-the-fly for you by pandas with no more than a cheery `DataFrame.Series.plot.<plot type>`! Since those plots are all just method calls, many of them take optional parameters to change the colour, the notation (scientific or not), and other options. For example, many of the documentation pages linked to above are rather brief, but include a link to the general options that can be applied to all `Series.plot` calls.

This is why we like pandas: it allows us to be *constructively lazy*. We don't need to know *how* a draw a KDE plot (though it always helps if you don't see what you expected), we just need to know that pandas provides a method that will do it for you. And *that* is why it's always worth having a look at the documentation.

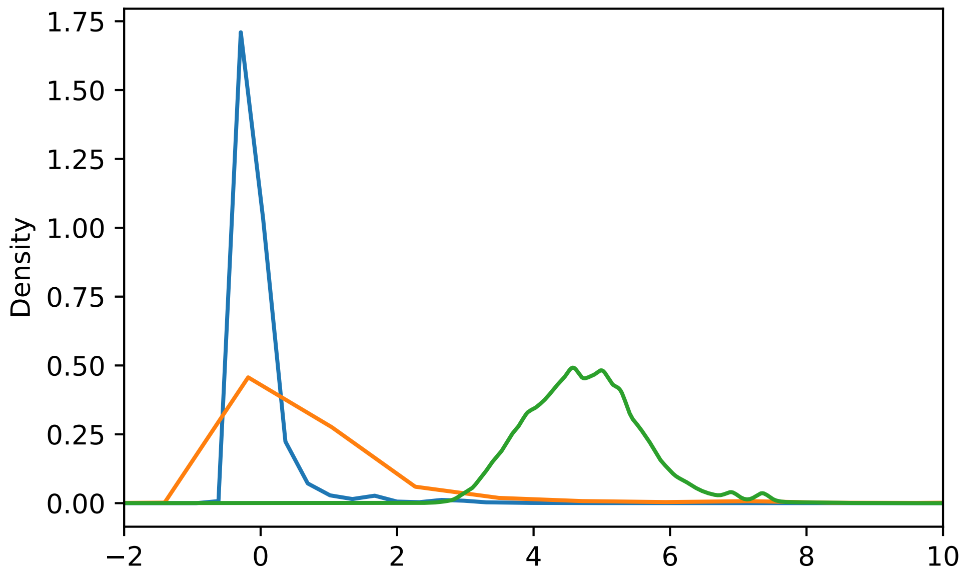
9.2.3 A Slight Case of Over-Plotting

Generally, Jupyter is clever enough to overlay plots one on top of the other if you call them all in the same cell. We'll see ways to gain more control later, but this is still a good start! Note that here we also need to get rid of the `-inf` values from rows that had a price of £0.

> **Bug Alert**
>
> The more we use pandas to sort and filter data the more you will start to see a `SettingWithCopyWarning`. This happens because of an interaction between how Pandas works and how Python works: when you are working with a very large data set you don't want to make a 'deep copy' of the data structure every time you make a change to the data. Instead, you get a 'view' into the data using a reference, which is a just a lightweight shortcut. So what happens when you try to modify that lightweight copy? Well, if you want to drop rows or columns then you either want to make a `copy()` at that point, or you will have to accept the warning *and* the computational risks that go with it.

```
# Calling copy() ensures the index is updated
# and note that all subsequent plots will have
```

```python
# these £0 rows removed!
df = df[df.price > 0].copy()
df.z.plot.kde(xlim=[-2, 10])
df.iqs.plot.kde(xlim=[-2, 10])
df.lnprice.plot.kde();
```

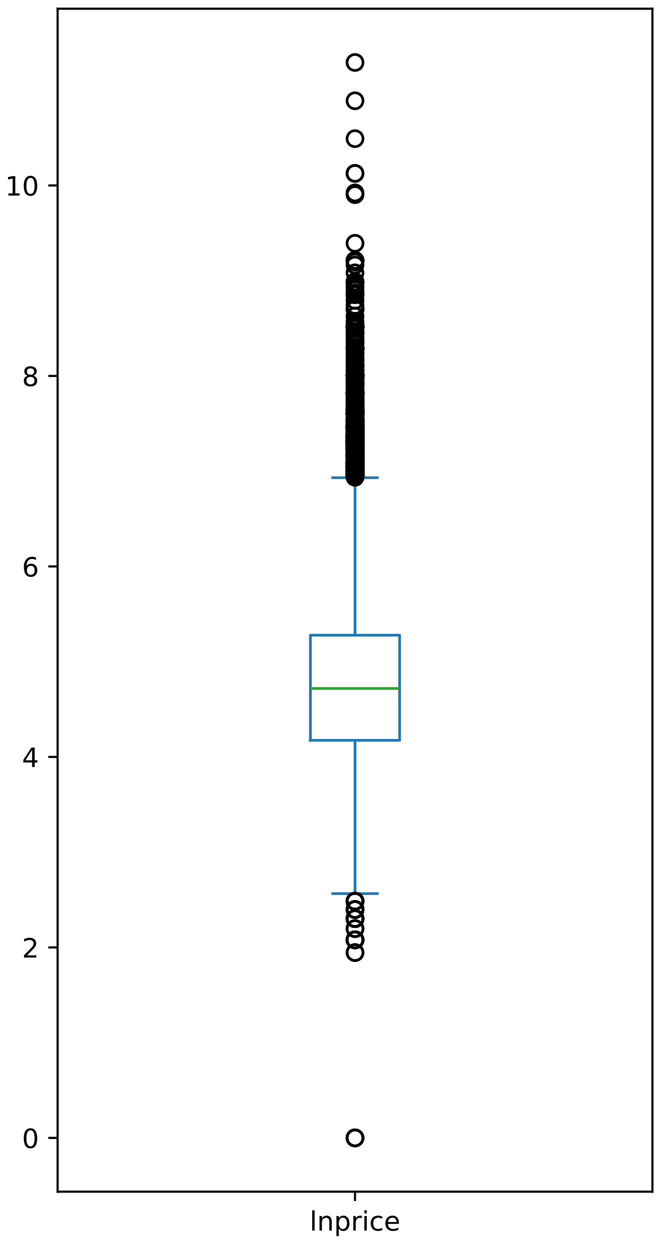


9.2.4 Boxplots

> Difficulty: Low

A standard boxplot:

```python
df.lnprice.plot.box(figsize=(4, 8));
```

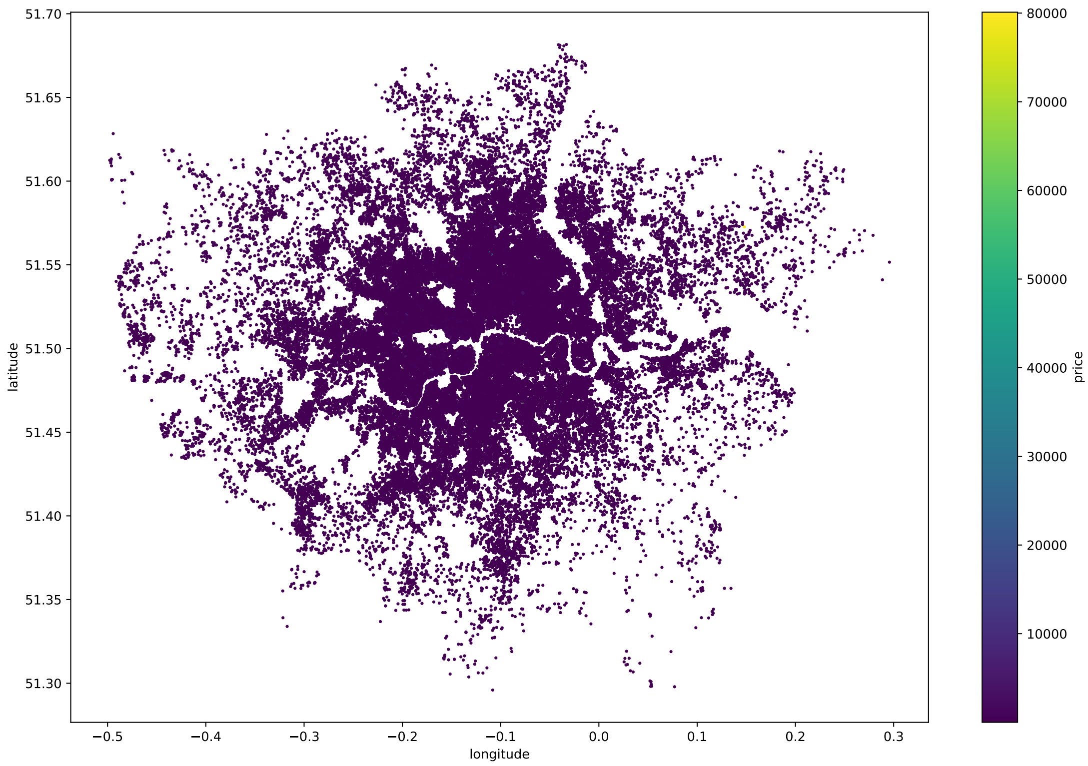


9.2.5 Scatterplots

> **Difficulty: Low**

We can also plot two variables in a scatter plot by applying a plot method to the `DataFrame` (not an individual `Series`):

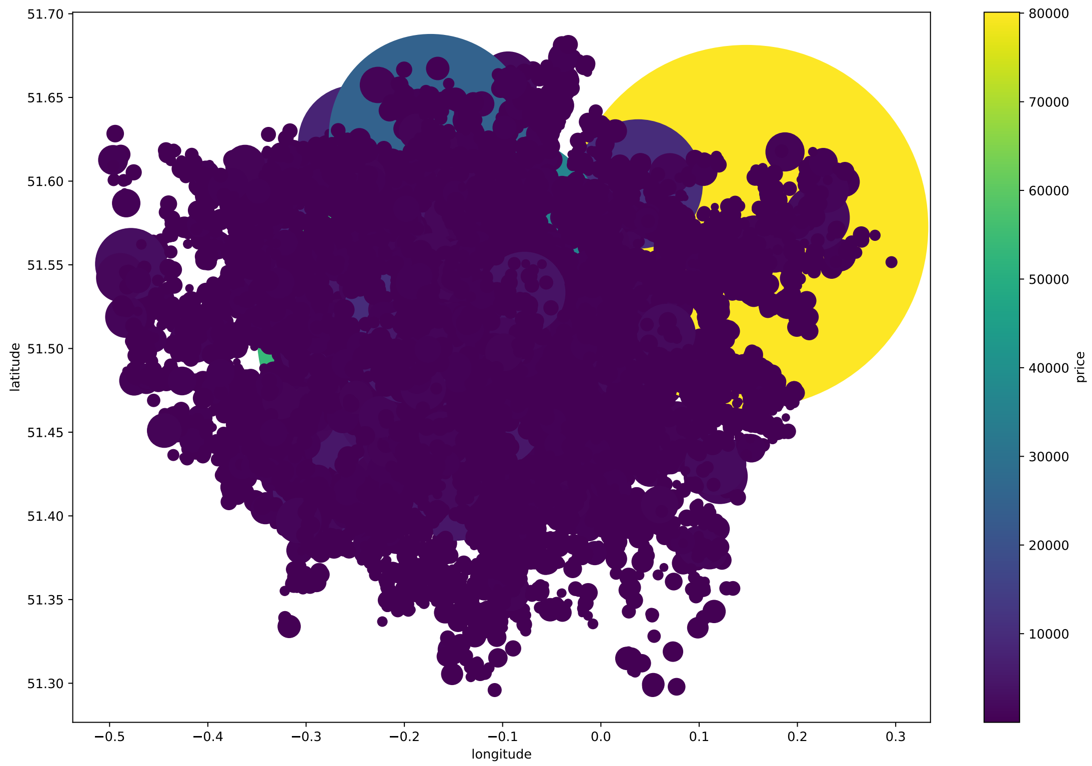
```
df.plot.scatter(x='longitude', y='latitude', c='price', s=2, cmap='viridis', figsize
```



Note how the code above has the form `DataFrame.plot.<plot type>`, not `DataFrame.Series.plot.<plot type>` as in the prior plots. Think about why this then means we need the `x` and `y` arguments.

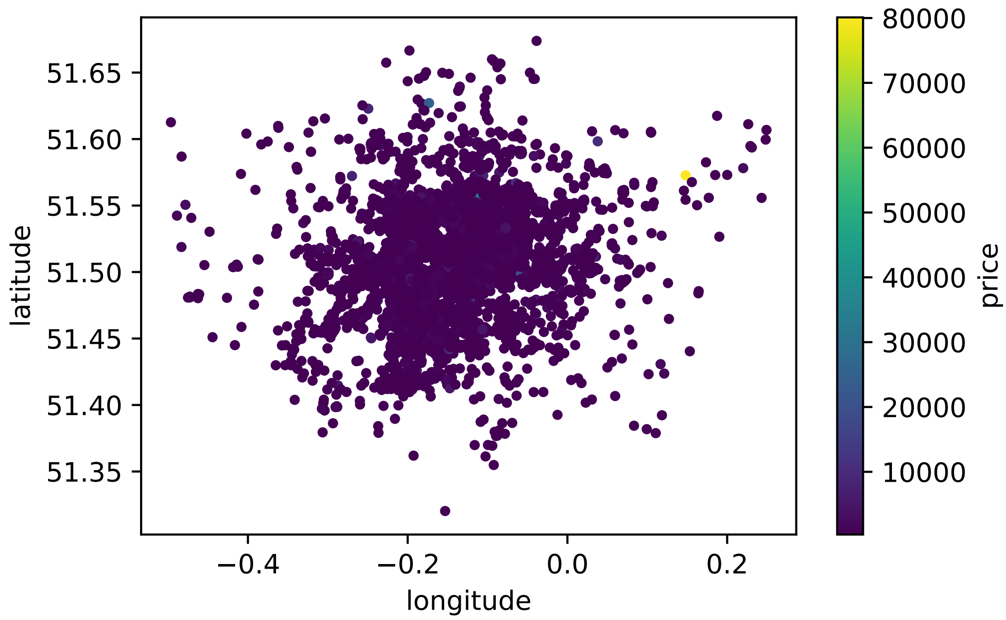
Looking at the plot produced, it's hard to see where the high values are, so we might want to think about ways that we could make it easier to spot the big numbers... We could, for instance, also vary the size of the point in a plot by some variable, but why does the following not really work?

```
df.plot.scatter(x='longitude', y='latitude', c='price', s=(df.price/df.price.min()),
```



And we can plot subsets of our data without creating a new object. See if you can work out what the following code is doing that is different from the last plot:

```
df[df.price > df.price.quantile(0.90)].plot.scatter(x='longitude', y='latitude', c='
```

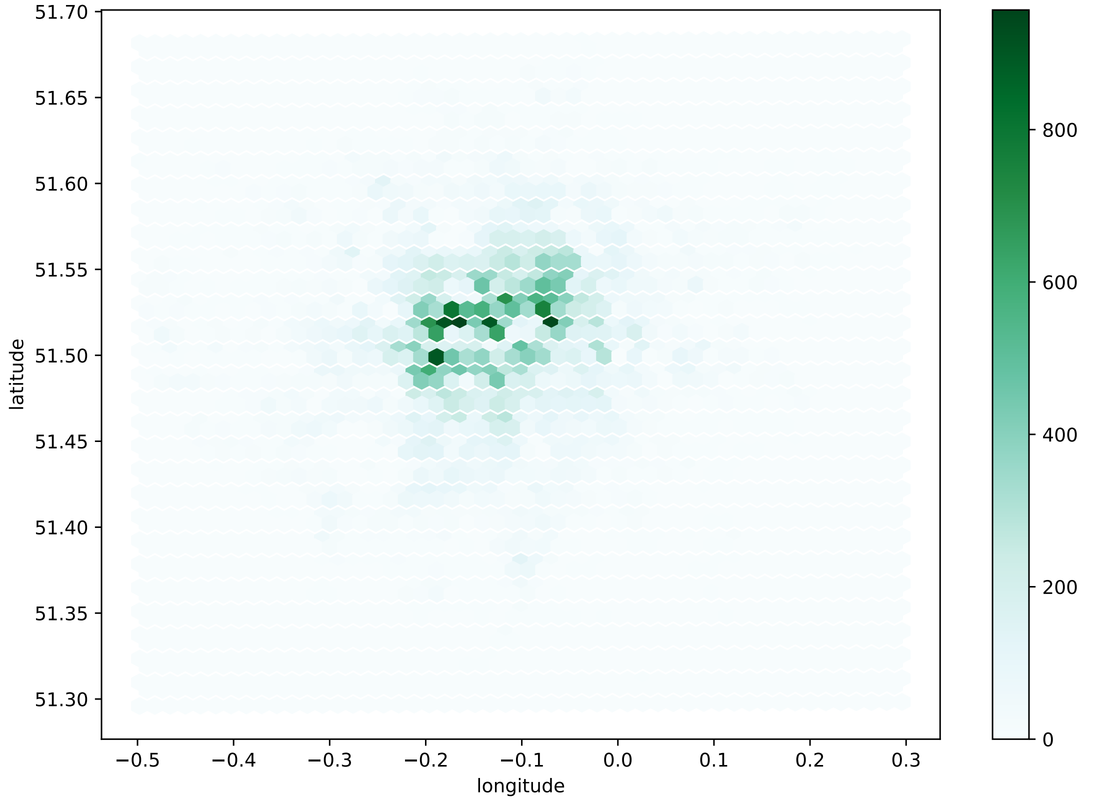


9.2.6 Hex Bin Plots

> Difficulty: Low

And pandas allows us to create 'less standard' plots, like a hex bin plot:

```
df.plot.hexbin(x='longitude', y='latitude', gridsize=50, figsize=(10,7))
```



That's just a taste of what the basic plotting functionality of pandas can do. Feel free to explore more yourself and we'll also see the seaborn package later.

10 Credits!

License

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Potential Dependencies:

This notebook may depend on the following libraries: pandas, matplotlib