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 more closely 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! That may include rewatching the lectures on Data and Pandas

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 Pandas, Conceptually

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

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']`[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']`).

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).

3 Reading Data

It's always sensible to import the packages you need 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.

So in this practical we need:

```
from pathlib import Path
import numpy as np
import pandas as pd
```

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__)
```

```
2.3.2
```

[1]This is also how `[polars](https://pola.rs/)` does things

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.

3.1 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 type for each column! 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 is Polars, DuckDB, and platforms like Dask (see, eg, this) and beyond.

3.1.1 Parameterising Files

Anyway, here's where to find the data:

```
# Set download URL
ymd  = '20250615'
city = 'London'
host = 'https://orca.casa.ucl.ac.uk'
url  = f'{host}/~jreades/data/{ymd}-{city}-listings.csv.gz'
```

3.1.2 Reading CSV with Pandas

Now, what goes into the `read_csv` function below?

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 93,486 rows of data.

4 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=Fals` – 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?

4.0.1 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. Notice here how we can **subselect columns** using a list: `df[ [<names of selected columns>] ]`!

Question

```
df[
    ['latitude', 'longitude', 'accommodates', 'bathrooms', 'bedrooms', 'beds']
].describe(percentiles=[??])
```

4.0.2 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: 93486 entries, 0 to 93485
Data columns (total 75 columns):
 #    Column                                         Non-Null Count  Dtype
---   ------                                         --------------  -----
 0    id                                             93481 non-null  float64
```

1	listing_url	93485 non-null	object
2	scrape_id	93485 non-null	object
3	last_scraped	93485 non-null	object
4	source	93486 non-null	object
5	name	93486 non-null	object
6	description	90297 non-null	object
7	neighborhood_overview	46673 non-null	object
8	picture_url	93477 non-null	object
9	host_id	93486 non-null	float64
10	host_url	93486 non-null	object
11	host_name	93480 non-null	object
12	host_since	93480 non-null	object
13	host_location	72291 non-null	object
14	host_about	47802 non-null	object
15	host_response_time	62226 non-null	object
16	host_response_rate	62231 non-null	object
17	host_acceptance_rate	67455 non-null	object
18	host_is_superhost	93022 non-null	object
19	host_thumbnail_url	93475 non-null	object
20	host_picture_url	93475 non-null	object
21	host_neighbourhood	46906 non-null	object
22	host_listings_count	93475 non-null	object
23	host_total_listings_count	93475 non-null	float64
24	host_verifications	93474 non-null	object
25	host_has_profile_pic	93475 non-null	object
26	host_identity_verified	93474 non-null	object
27	neighbourhood	46675 non-null	object
28	neighbourhood_cleansed	93481 non-null	object
29	neighbourhood_group_cleansed	5 non-null	float64
30	latitude	93481 non-null	float64
31	longitude	93481 non-null	float64
32	property_type	93481 non-null	object
33	room_type	93481 non-null	object
34	accommodates	93481 non-null	float64
35	bathrooms	61355 non-null	float64
36	bathrooms_text	93331 non-null	object
37	bedrooms	81800 non-null	float64
38	beds	61289 non-null	float64
39	amenities	93481 non-null	object
40	price	61423 non-null	object
41	minimum_nights	93481 non-null	object
42	maximum_nights	93481 non-null	float64
43	minimum_minimum_nights	93480 non-null	float64
44	maximum_minimum_nights	93480 non-null	float64
45	minimum_maximum_nights	93479 non-null	object
46	maximum_maximum_nights	93479 non-null	object
47	minimum_nights_avg_ntm	93479 non-null	float64
48	maximum_nights_avg_ntm	93479 non-null	float64
49	calendar_updated	4 non-null	float64
50	has_availability	89394 non-null	object
51	availability_30	93480 non-null	float64
52	availability_60	93480 non-null	float64

```
 53   availability_90                              93480 non-null   float64
 54   availability_365                             93476 non-null   float64
 55   calendar_last_scraped                        93481 non-null   object
 56   number_of_reviews                            93481 non-null   float64
 57   number_of_reviews_ltm                        93481 non-null   float64
 58   number_of_reviews_l30d                       93481 non-null   float64
 59   first_review                                 68740 non-null   object
 60   last_review                                  68739 non-null   object
 61   review_scores_rating                         68735 non-null   float64
 62   review_scores_accuracy                       68657 non-null   float64
 63   review_scores_cleanliness                    68664 non-null   float64
 64   review_scores_checkin                        68627 non-null   float64
 65   review_scores_communication                  68652 non-null   float64
 66   review_scores_location                       68626 non-null   float64
 67   review_scores_value                          68627 non-null   float64
 68   license                                      0 non-null       float64
 69   instant_bookable                             93476 non-null   object
 70   calculated_host_listings_count               93476 non-null   float64
 71   calculated_host_listings_count_entire_homes  93476 non-null   float64
 72   calculated_host_listings_count_private_rooms 93476 non-null   float64
 73   calculated_host_listings_count_shared_rooms  93476 non-null   float64
 74   reviews_per_month                            68735 non-null   float64
dtypes: float64(36), object(39)
memory usage: 53.5+ 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 373MB.

4.0.3 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 experiencing appallingly poor performance (allowing for the amount of data you've just loaded!), then `memory_usage` is the way to go:

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

```
Index                                               132
id                                               747888
listing_url                                     8542806
scrape_id                                       5889546
last_scraped                                    5515618
                                                 ...
calculated_host_listings_count                   747888
calculated_host_listings_count_entire_homes      747888
calculated_host_listings_count_private_rooms     747888
calculated_host_listings_count_shared_rooms      747888
reviews_per_month                                747888
Length: 76, dtype: int64
```

You should see that the data frame uses 391,099,613 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.

4.0.4 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', 'ne
```

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).

5 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 typically 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.

The purpose of the intermediate outputs is to accelerate each cycle in your development work: if you are re-running the *entire* analytics pipeline *every* time you make a small change at the tail-end of your processing pipeline then you will be drinking a lot of tea because most of your time will be spent watching the computer churn away at the data. It's also common to receive regular updates of data sets (e.g. InsideAirbnb data is updated rouhgly every six months, while Land Registry's Price Paid Data for the UK is updated monthly) and you'll need to know which release you're working with (i.e. have I already processed the September data???).

So we try to get ahead of all this by anticipating that files will be 'versioned'. I do not mean that you'll put files in Git, but that you'll need a way to track 'provenance' and 'stage of analysis' in where and how you save your data. But we also don't want to mindlessly delete the original, '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 dealing with data types 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.

So you might end up with something a bit like this (or this could be overkill):

```
|
|--project/
|   |--code/
|       |--extract/
|       |--canonicalise/
|       |--clean/
|       |--analyse/
|   |--data/
|       |--raw/
|           |--2025/
|           |--2024/
|       |--clean/
|           |--2025/
|           |--2024/
|   |--docs/
|       |--refs/
|       |--code/
|       |--data/
|   |--conf
```

There is even a coding library called cookiecutter that tries to help research groups and companies standardise how they manage their code and data.

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

5.1 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 `20250910-listings.csv.gz` then I might well specify the `url` as `{date}-listings.csv.gz` or `{year}{month}{day}-listings.csv.gz` and set up the variables that I need beforehand, possibly in a separate 'configuration' file that I read in at the start.

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 `20251111-data.csv.gz`. You save the outputs to `clean-data.csv.gz`.

Question

What happens when your boss asks you to process `20251211-data.csv.gz`?

5.2 File Saving

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 = Path(f'data/raw/{Path(url).name}') # What does this do?
print(f"Writing to: {path}")
```

```
Writing to: data/raw/20250615-London-listings.csv.gz
```

```
if not path.parent.exists(): # And what does *this* do?
    print(f"Creating {path.parent}")
    path.parent.mkdir(parents=True, exist_ok=True)

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

5.3 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.

5.3.1 Row Subsetting

Let's tackle the *rows* problem first:

Question

```python
testing = True

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

```python
testing = False
```

And:

```python
from conf import *
```

5.3.2 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.

```python
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(opath,
                low_memory=False, nrows=10000, ??)
else:
    df = pd.read_csv(path,
                low_memory=False, ??)

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

5.4 Releasing Memory

Two risks when working with Jupyter notebooks are:

1. You have run code in an order *other* than the order shown in the notebook; or
2. You have made edits to code but *not* re-run the changed code.

So you're still working from code that is no longer visible or where the a step (or five) has been missed/changed since you ran it! 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.

6 Using Indexes

So let's start over from the saved data:

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

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 and 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 also change these at any time.

6.1 Numeric Indexing

You can always access rows and columns by their **integer location** as if it is a 2D list and you want to access the 3rd to 5th columns and the 9th to 425th rows. So if you remember that `iloc` means you're using the index location that will help you to work out what's going on.

So can you read this:

```
df.iloc[
    4552:4557, # <- rows
    14:19      # <- columns
]
```

	latitude	longitude	property_type	room_type	accommodates
4552	51.59074	-0.07300	Entire home	Entire home/apt	2.0
4553	51.53624	-0.10740	Entire rental unit	Entire home/apt	4.0
4554	51.55775	0.00173	Entire guest suite	Entire home/apt	2.0
4555	51.49577	-0.18463	Entire rental unit	Entire home/apt	3.0
4556	51.50581	-0.03495	Private room in home	Private room	1.0

We're accessing the 4552nd through 4556th rows, and the 14th through 18th columns.

6.2 Label Indexing

Where it can get confusing is when you see this:

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

	latitude	longitude	property_type	room_type	price
4552	51.59074	-0.07300	Entire home	Entire home/apt	NaN
4553	51.53624	-0.10740	Entire rental unit	Entire home/apt	NaN
4554	51.55775	0.00173	Entire guest suite	Entire home/apt	NaN
4555	51.49577	-0.18463	Entire rental unit	Entire home/apt	NaN
4556	51.50581	-0.03495	Private room in home	Private room	NaN
4557	51.53649	-0.04638	Entire rental unit	Entire home/apt	NaN

This code *seems* similar, but why does this use `loc` and not `iloc`, and why doesn't it actually return the same data??? In this case, the **index** (the numbers down the left-hand side in bold) is numeric, so we can treat it as either a *label* (which allows us to use `df.loc`) *or* a list-type index (which allows us to use `df.iloc`). So with `loc` the value `4557` is treated as a 'key' so it's retrieved, whereas with `.iloc` it's treated like a list index accessed with `range` and so *isn't* returned. It's a bit weird, but hopefully makes *some* sense now.

6.3 Non-numeric Indexes

Notice the 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]
```

	latitude	longitude	property_type
listing_url			
https://www.airbnb.com/rooms/1126718007114818431	51.535030	-0.394000	Private room in home
https://www.airbnb.com/rooms/702589406864297985	51.554232	-0.037135	Private room in casa parti
https://www.airbnb.com/rooms/1122535727514526769	51.412310	0.026380	Entire rental unit

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

```
df.set_index('listing_url').loc[
    :, # <- Special syntax that means 'all rows' (or all columns)
    ['latitude','longitude','property_type','room_type','accommodates']
].head(3)
```

	latitude	longitude	property_type
listing_url			
https://www.airbnb.com/rooms/1126718007114818431	51.535030	-0.394000	Private room in home
https://www.airbnb.com/rooms/702589406864297985	51.554232	-0.037135	Private room in casa parti
https://www.airbnb.com/rooms/1122535727514526769	51.412310	0.026380	Entire rental unit

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()
```

```
np.float64(51.500523858482154)
```

7 Exploring Your Data

Let's start over *again* from the saved data:

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

7.1 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	name
85253	9.315566e+17	https://www.airbnb.com/rooms/931556581909292236	2024-06-14	2 bed hous
13830	4.546130e+05	https://www.airbnb.com/rooms/454613	2024-06-16	Double+Br
70153	1.061544e+18	https://www.airbnb.com/rooms/1061543573711193281	2024-06-16	Comfort 5

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, ??)
```

7.2 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!

> **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.

7.2.1 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','name','price','room_type']].head(4)
```

	id	name	price	room_type
236	20256005.0	Suitable for travel and evection.	NaN	Entire home/apt
238	7377571.0	double room, near brixton,london	NaN	Private room
239	38519592.0	Heart of the east London. Room 3 with Cable TV	NaN	Private room
240	6761407.0	Private room in Shoreditch	NaN	Private room

```
df[df.room_type.isna()][['id','name','price','room_type']].head(4)
```

	id	name	price	room_type
50162	1.359431e+07	Beautiful & bright in Queen's Park	NaN	NaN
52260	8.446589e+17	Designer Notting Hill Flat	NaN	NaN
56508	1.066257e+18	Haggerston Artists condo x2 bed	NaN	NaN
77222	5.342282e+07	Central 1-bed flat in Trendy Zone 2 East London	NaN	NaN

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

	id	name	price	room_type
236	20256005.0	Suitable for travel and evection.	NaN	Entire home/apt
238	7377571.0	double room, near brixton,london	NaN	Private room
239	38519592.0	Heart of the east London. Room 3 with Cable TV	NaN	Private room
240	6761407.0	Private room in Shoreditch	NaN	Private room

If I had to guess, I'd say that it's the result 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','name','price','room_type']]
```

	id	name	price	room_type
50163	NaN	https://a0.muscache.com/im/pictures/user/User-...	0	3.0
52261	NaN	https://a0.muscache.com/im/pictures/user/7d57d...	364	5.0
56509	NaN	https://a0.muscache.com/im/pictures/user/652bf...	4	2.0
77223	NaN	https://a0.muscache.com/im/pictures/user/3a51c...	174	2.0
78241	NaN	https://a0.muscache.com/im/users/11520835/prof...	19	4.5

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):

```
print(f"Data frame contains {df.shape[0]:,} rows.")
df.drop(df[df.id.isna()].index.array, axis=0, inplace=True)
print(f"Data frame contains {df.shape[0]:,} rows.")
```

```
Data frame contains 93,486 rows.
Data frame contains 93,481 rows.
```

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.

7.2.2 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]
```

```
license                 93481
host_about              45684
beds                    32197
bathrooms               32126
price                   32063
first_review            24746
reviews_per_month       24746
last_review             24746
review_scores_rating    24746
host_location           21192
bedrooms                11686
description              3189
dtype: int64
```

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

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

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

7.2.3 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(10)
```

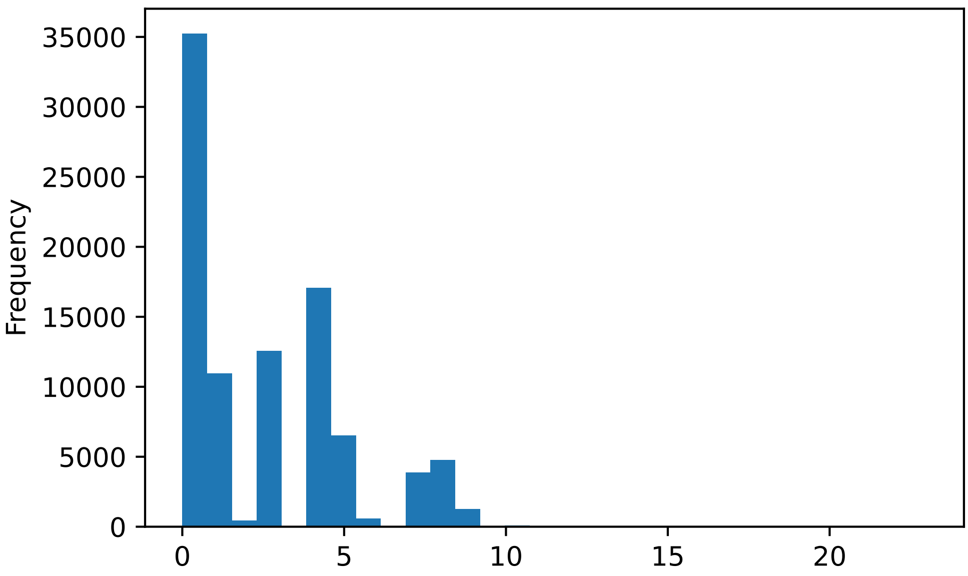
```
78240    23
56508    23
52260    23
50162    23
77222    23
4801     14
8322     14
45832    14
13539    14
4684     14
dtype: int64
```

So that `Series` shows how many `NaN` values there are by index value (i.e. the row number). The first column is the row id, the second is the number of NaNs in that row.

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

```
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, I would think about dropping rows missing more than about 5 values on the basis that they are the 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:

```
print(f"df contains {df.shape[0]:,} rows.")
cutoff = 5
df.drop(probs[probs > cutoff].index, inplace=True)
print(f"df contains {df.shape[0]:,} rows.")
```

```
df contains 93,481 rows.
df contains 82,856 rows.
```

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`.

8 Fixing Data Types

When we fix the data types we are undertaking a kind of data 'profiling': working out what kind of data we are working with and how it should be represented at the level of observations and columns. There are *huge* benefits to computer memory and diskspace usage to profiling and, consequently, huge gains to be made in the speed of data analysis.

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.

8.1 Profiling (Not Supported)

> 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 Podman 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 how to install software on another machine**:

```
from ydata_profiling import ProfileReport
```

8.2 Managing Memory

> Difficulty: Low.

So 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 the strings `'True'` (4 bytes) and `'False'` (5 bytes) will take up vastly 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 before looking more closely at how to convert each type of data:

```
# String type memory usage
rtm = df.room_type.memory_usage(deep=True)
# Categorical type memory usage
ctm = df.room_type.astype('category').memory_usage(deep=True)

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 5,741 Kb.
The categorical memory usage of `room_type` is 729 Kb.
That's 13% of the original!
```

```python
# String type memory usage
shm = df.host_is_superhost.memory_usage(deep=True)
# Boolean type memory usage
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 4,686 Kb.
The boolean memory usage of `host_is_superhost` is 728 Kb.
That's 16% of the original!
```

8.3 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
45788	f
36397	f
37218	f
13743	f
7179	f

Here we have to map `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 any string that is not `None` would convert to 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
```

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

	host_is_superhost
45788	False
36397	False
37218	False
13743	False
7179	False

8.4 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.

```
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
45788	2024-06-16	2011-10-03	2014-12-30	2017-08-28
36397	2024-06-16	2014-12-31	2022-10-10	2022-10-10
37218	2024-06-16	2021-12-30	2024-06-02	2024-06-02
13743	2024-06-16	2016-06-09	2016-07-24	2016-07-24
7179	2024-06-16	2019-07-19	2023-01-13	2024-01-05

```
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
```

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

	last_scraped	host_since	first_review	last_review
45788	2024-06-16	2011-10-03	2014-12-30	2017-08-28
36397	2024-06-16	2014-12-31	2022-10-10	2022-10-10
37218	2024-06-16	2021-12-30	2024-06-02	2024-06-02
13743	2024-06-16	2016-06-09	2016-07-24	2016-07-24
7179	2024-06-16	2019-07-19	2023-01-13	2024-01-05

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

```
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]'
```

```
90719      Tuesday August 25, 2015
86895      Thursday April 04, 2024
23856    Tuesday February 06, 2024
11538      Monday October 14, 2019
21073    Tuesday December 03, 2019
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)

8.5 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
63675	Entire rental unit	Entire home/apt
29219	Entire rental unit	Entire home/apt
15274	Private room in condo	Private room
82638	Entire rental unit	Entire home/apt
27097	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              34289
Private room in rental unit     11681
Private room in home             9833
Entire condo                     8412
Entire home                      7437
                                ...
Religious building                  1
Shared room in villa                1
Minsu                               1
Private room in nature lodge        1
Private room in floor               1
Name: count, Length: 94, dtype: int64
```

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

```
room_type
Entire home/apt    54157
Private room       28197
Shared room          327
Hotel room           175
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
63675	Entire rental unit	Entire home/apt
29219	Entire rental unit	Entire home/apt
15274	Private room in condo	Private room
82638	Entire rental unit	Entire home/apt
27097	Entire rental unit	Entire home/apt

8.6 Dealing with Strings

Difficulty: Hard.

We'll have to put some more work into dealing with the description and other '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
63675	$1,047.00
29219	$249.00
15274	$61.00
82638	NaN
27097	$150.00

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')
```

```python
    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

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

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

	price
63675	1047.0
29219	249.0
15274	61.0
82638	NaN
27097	150.0

And here's a final thing to note that looks… a little odd:

```python
df.sort_values(by='price', ascending=False).head(5)[['id','name','price','minimum_ni
```

	id	name	price	minimum_nights
2220	1.069627e+18	Close To London Bridge	80000.0	2
39737	9.364490e+17	Close To Waterloo & London Eye (CHA)	80000.0	2
42956	1.040471e+18	Room In Zone 1 (TOB)	80000.0	2
53426	2.261002e+07	CLOSE TO LONDON EYE AND TUBE (PANA)	78679.0	2
54526	4.155799e+07	Close To London Eye (HED)	75000.0	2

8.7 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    60769
True     22087
Name: count, dtype: int64
```

8.8 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()
```

8.9 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!

```
csv_out = Path(f'data/clean/{path.name}')
pq_out  = Path(f'data/clean/{path.name.replace('.csv.gz','.parquet')}')

if not csv_out.parent.exists():
    print(f"Creating {csv_out.parent}")
    csv_out.parent.mkdir(parents=True, exist_ok=True)

df.to_csv(csv_out, index=False)
df.to_parquet(pq_out, index=False)
print(f"Saved {df.shape[0]:,} rows of {df.shape[1]:,} columns to {csv_out.resolve()}
print("Done.")
```

```
Saved 82,856 rows of 32 columns to /home/jovyan/work/practicals/data/clean/20250615-
London-listings.csv.gz
Done.
```

We'll shortly begin to look at the `parquet` file format because 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; however, for now let's keep working with what we understand.

9 Selection using Criteria

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

9.1 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=[??])
```

9.2 Selecting using Conditions

Difficulty: Hard.

Conditional selection is usally done as a combination of the selection approaches above in combination with conditionals. So to try to select only the `Entire home/apt` room type we are testing for cases where the `room_type` equals our target term (`Entire home/apt`):

Question

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

Your output should be:

```
property_type
Entire rental unit           34289
Entire condo                  8412
Entire home                   7437
Entire serviced apartment     1653
Entire townhouse              1041
Entire loft                    352
Entire guesthouse              217
Name: count, dtype: int64
```

9.3 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 cost more than the average price of all listings… 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 get:

- The mean price is $209.56
- The median price is $137.00

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.

9.3.1 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 $209.56. *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")
```

You should get 16,257 rows.

In the code above we see two things:

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

9.4 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	description
2220	80000.0	https://www.airbnb.com/rooms/1069626776402758037	Private room	7 minutes walk t
39737	80000.0	https://www.airbnb.com/rooms/936449020154835053	Private room	10 minutes walk
42956	80000.0	https://www.airbnb.com/rooms/1040471243366946776	Private room	* ZONE 1

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

Question

What do you make of this result?

9.5 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.

I find this parentheses business annoying and frequently get an error when I forget to add them, but I'm guessing it's tied to operator precedence and how the various operations are interpreted by Python.

10 Deriving New Variables

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).

10.0.1 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}")
```

10.0.2 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}")
```

10.0.3 Log-Normalisation

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

Question

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

11 Quick (and Dirty) Plotting

Although we've spent a lot of time grappling with pandas code and cleaning/filtering/selecting data, one of the first things we should really do when exploring a new dataset is plot (aka graph) the data. We've left plotting until late 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 across the following weeks, 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* Podman
>
> MacOS users who are *not* using Podman 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…
>
> ```python
> # Needed on a Mac
> import matplotlib as mpl
> mpl.use('TkAgg')
> %matplotlib inline
> import matplotlib.pyplot as plt
> ```

11.0.1 Histograms

> Difficulty: Low

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

```python
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:

```python
# 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);
```

11.0.2 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.

11.0.3 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
# 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();
```

11.0.4 Boxplots

Difficulty: Low

A standard boxplot:

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

11.0.5 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='
```

11.0.6 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.

12 Credits!

License

Acknowledgements:

Supported by the Royal Geographical Society (with the Institute of British Geographers) with a Ray Y Gildea Jr Award.

Potential Dependencies:

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