

CHAPTER 1

Data Tables and pandas

Much of the data that you will encounter in your career will come to you as a table. Some of these tables are spreadsheets, some are in relational databases, and some will come to you as CSV files.

Typically, each column will represent an attribute (like height or acreage) and each row will represent an entity (like a person or a farm). You might get a table like this:

property_id	bedrooms	square_meters	estimated_value
7927	3	921.4	\$ 294,393
9329	2	829.1	\$ 207,420

In most cases, one of the columns is guaranteed to be unique. We call this the *primary key*. In this table, `property_id` is the primary key; every property has one, and no two properties have the same `property_id`.

1.1 Data types

Each column in a table has a type, and these usually correspond pretty nicely with types in Python.

Here are some common datatypes:

Type	Python type	Example
Integer	int	910393
Float	float	-23.19
String	string	'Fred'
Boolean	bool	False
Date	datetime.date	2019-12-04
Timestamps	datetime.datetime	2022-06-10T14:05:22Z

Sometimes it is OK to have values missing. For example, if you had a table of data about employees, maybe one of the columns would be `retirement` — a date that tells you when the person retired. People who had not yet retired would have no value in this column. We would say that they have *null* for `retirement`.

Sometimes there are constraints on what values can appear in the column. For example, if the column were `height`, it would make no sense to have a negative value.

Sometimes a column can only be one of a few values. For example, if you ran a bike rental shop, each bicycle's status would be "available", "rented", or "broken". Any other values

in that column would not be allowed. We often call these columns *categorical*.

1.2 pandas

The Python community works with tables of data *very* often, so it created the pandas library for reading, writing, and manipulating tables of data.

When working with tables, you sometimes need to go through them row-by-row. However, for large datasets, this is very slow. pandas makes it easy (and very fast) to say things like “Delete every row that doesn’t have a value for height” instead of requiring you to step through the whole table.

In pandas, there are two datatypes that you use a lot:

- a `Series` is a single column of data.
- a `DataFrame` is a table of data: it has a `Series` for each column.

In the digital resources, you will find `bikes.csv`. If you look at it in a text editor, it will start like this:

```
bike_id,brand,size,purchase_price,purchase_date,status  
5636248,GT,57,277.99,1986-09-07,available  
4156134,Giant,56,201.52,2005-01-09,rented  
7971254,Cannondale,54,292.25,1978-02-28,available  
3600023,Canyon,57,197.62,2007-02-15,broken
```

The first line is a header; it tells you the name of each column. Next, each bike is represented by values which are separated by commas. (Thus the name: CSV stands for “Comma-Separated Values”.)

1.3 Reading a CSV with pandas

Let’s make a program that reads `bikes.csv` into a pandas dataframe. Create a file called `report.py` in the same folder as `bikes.csv`.

First, we will read in the csv file. pandas has one series that acts as the primary key; it calls this one the index. When reading in the file, we will tell it to use the `bike_id` as the index series.

If you ask a dataframe for its shape, it returns a tuple containing the number of rows and the number of columns. To confirm that we have actually read the data in, let’s print those

numbers. Add these lines to `report.py`:

```
import pandas as pd

# Read the CSV and create a dataframe
df = pd.read_csv('bikes.csv', index_col="bike_id")

# Show the shape of the dataframe
(row_count, col_count) = df.shape
print(f"*** Basics ***")
print(f"Bikes: {row_count}, ")
print(f"Columns: {col_count}")
```

Build it and run it. You should see something like this:

```
*** Basics ***
Bikes: 998
Columns: 5
```

Note that your table actually has six columns. The index series is not included in the shape.

1.4 Looking at a Series

Let's get the lowest, the highest, and the mean purchase price of the bikes. The purchase price is a series, and you can ask the dataframe for it. Add these lines to the end of your program:

```
# Purchase price stats
print("\n*** Purchase Price ***")
series = df["purchase_price"]
print(f"Lowest:{series.min()}")
print(f"Highest:{series.max()}")
print(f"Mean:{series.mean():.2f}")
```

Now when you run it, you will see a few additional lines:

```
*** Purchase Price ***
Lowest:107.37
Highest:377.7
Mean:249.01
```

What are all the brands of the bikes? Add a few more lines to your program that shows how many of each brand:

```
# Brand stats
print("\n*** Brands ***")
series = df["brand"]
series_counts = series.value_counts()
print(f"{series_counts}")
```

Now when you run it, your report will include the number of bikes for each brand from most to least common:

```
*** Brands ***
Canyon      192
BMC         173
Cannondale  170
Trek        166
GT          150
Giant       147
Name: brand, dtype: int64
```

`value_counts` returns a Series. To format this better, we need to learn about accessing individual rows in a series.

1.5 Rows and the index

In an array, you ask for data using an the location (as an int) of the item you want. You can do this in pandas using `iloc`. Add this to the end of your program:

```
# First bike
print("\n*** First Bike ***")
row = df.iloc[0]
print(f"{row}")
```

When you run it, you will see the attributes of the first row of data:

```
*** First Bike ***
brand           GT
size            57
purchase_price  277.99
purchase_date   1986-09-07
status          available
```

```
Name: 5636248, dtype: object
```

Notice that the data coming back is actually another series.

The last line says that the name (the value for the index column) for this row is 5636248. In pandas, we usually use this to locate particular rows. For example, there is a row with bike_id equal to 2969341. Let's ask for one entry from the

```
print("\n*** Some Bike ***")
brand = df.loc[2969341]['brand']
print(f"brand = {brand}")
```

Now, you will see the information about that bike:

```
*** Some Bike ***
brand = Cannondale
```

pandas has a few different ways of getting to that value. All of these get you the same thing:

```
brand = df.loc[2969341]['brand'] # Get row, then get value
brand = df['brand'][2969341]      # Get column, then get value
brand = df.loc[2969341, 'brand'] # One call with both row and value
```

1.6 Changing data

One of your attributes needs cleaning up. Every bike should have a status, and it should be one of the following strings: "available", "rented", or "broken". Get counts for each unique value in status:

```
print("\n*** Status ***")
series = df["status"]
missing = series.isnull()
print(f"{missing.sum()} bikes have no status.")
series_counts = series.value_counts()
for value in series_counts.index:
    print(f"{series_counts.loc[value]} bikes are \"{value}\")")
```

This will show you:

```
*** Status ***
```

```
7 bikes have no status.  
389 bikes are "rented"  
304 bikes are "broken"  
296 bikes are "available"  
1 bikes are "Flat tire"  
1 bikes are "Available"
```

Right away, we can see two easily fixable problems: Someone typed “Available” instead of “available”. Right after you read the CSV in, fix this in the data frame:

```
mask = df['status'] == 'Available'  
print(f"{mask}")  
df.loc[mask, 'status'] = 'available'
```

When you run this, you will see that the mask is a series with `bike_id` as the index and `False` or `True` as the value, depending on whether the row’s status was equal to “Available”.

When you use `loc` with this sort of mask, you are saying “Give me all the rows for which the mask is `True`.“ So, the assignment only happens in the one problematic row.

Let’s get rid of the mask variable and do the same for turning `Flat tire` into `Broken`:

```
df.loc[df['status'] == 'Available', 'status'] = 'available'  
df.loc[df['status'] == 'Flat tire', 'status'] = 'broken'
```

Now those problems are gone:

```
7 bikes have no status.  
389 bikes are "rented"  
305 bikes are "broken"  
297 bikes are "available"
```

What about the rows with no values for status? If we were pretty certain that the bikes were available, we could just set them to ‘available’:

```
missing_mask = df['status'].isnull()  
df.loc[missing_mask, 'status'] = 'available'
```

Or maybe we would print out the IDs of the bikes so that we could go look for them:

```
missing_mask = df['status'].isnull()
```

```
missing_ids = list(df[missing_mask].index)
print(f"These bikes have no status:{missing_ids}")
```

However, let's just keep the rows where the status is not null:

```
missing_mask = df['status'].isnull()
df = df[~missing_mask]
```

At the end of your program, write out the improved CSV:

```
df.to_csv('bikes2.csv')
```

Run the program and open `bikes2.csv` in a text editor.

1.7 Derived columns

Let's say that you want to add a column with age of the bicycle in days:

```
bike_id,brand,size,purchase_price,purchase_date,status,age_in_days
5636248,GT,57,277.99,1986-09-07,available,13061
4156134,Giant,56,201.52,2005-01-09,rented,6362
7971254,Cannondale,54,292.25,1978-02-28,available,16174
```

Your first problem is that the `purchase_date` column looks like a date, but really it is a string. So, you need to convert it to a date. You can do this by applying a function to every item in the series:

```
df['purchase_date'] = df['purchase_date'].apply(lambda s: datetime.date.fromisoformat(s))
```

(With pandas, there is often more than one way to do things. pandas has a `to_datetime` function that converts every entry in a sequence to a `datetime` object. Here is another way to convert the string column in to a date column:

```
df['purchase_date'] = pd.to_datetime(df['purchase_date']).dt.date
```

You can look up `dt` and `date` if you are curious.)

Now, we can use the same trick to create a new column with the age in days:

```
today = datetime.date.today()
df['age_in_days'] = df['purchase_date'].apply(lambda d: (today - d).days)
```

When you run this, the new `bikes.csv` will have an `age_by_date` column.

This is a draft chapter from the Kontinua Project. Please see our website (<https://kontinua.org/>) for more details.

APPENDIX A

Answers to Exercises



INDEX

datatypes, [1](#)

null, [1](#)

pandas, [2](#)