Aggregations: min, max, and Everything in Between

A **first step** in **exploring any dataset** is often to compute various **summary statistics.**

Perhaps the **most common summary statistics** are the **mean** and standard **deviation**.

Which allow you to **summarize** the **"typical" values** in a dataset, but other aggregations are useful as well (the sum, product, median, minimum and maximum, quantiles, etc.).

NumPy has **fast** built-in **aggregation** functions for working on arrays.

Summing the Values in an Array

As a **quick example,** consider computing **the sum of all values** in an array.

Python itself can do this using the **built-in** `sum` **function:**

```
In [7]: import numpy as np
        rng = np.random.default_rng()
```

```
In [ ]: L = rng.random(100)
        sum(L)
```

```
Out[ ]: 52.76825337322368
```

The **syntax** is quite **similar** to that of **NumPy's** `sum` **function,** and the result is the same in the simplest case:

In [ ]:
```
np.sum(L)
```

Out[ ]:
```
52.76825337322366
```

However, because it executes the operation in **compiled** code, **NumPy's version** of the operation is computed **much more quickly:**

In [ ]:
```
big_array = rng.random(1000000)
%timeit sum(big_array)
%timeit np.sum(big_array)
```

```
89.9 ms ± 233 µs per loop (mean ± std. dev. of 7 runs, 10 loops each)
521 µs ± 8.37 µs per loop (mean ± std. dev. of 7 runs, 1000 loops each)
```

Be careful, though:

- The `sum` function and the `np.sum` function are **not identical,** which can sometimes lead to confusion!
- In particular, their **optional arguments** have **different meanings** (`sum(x, 1)` initializes the sum at `1` , while `np.sum(x, 1)` sums along axis `1`), and `np.sum` is aware of multiple array dimensions.

Minimum and Maximum

Similarly, **Python** has **built-in `min` and `max`** functions, used to find the minimum value and maximum value of any given array:

In [ ]:
```
min(big_array), max(big_array)
```

Out[ ]:
```
(2.0114398036064074e-07, 0.9999997912802653)
```

NumPy's corresponding functions have **similar syntax,** and again operate **much more quickly:**

In [ ]:
```
np.min(big_array), np.max(big_array)
```

Out[ ]:
```
(2.0114398036064074e-07, 0.9999997912802653)
```

In [ ]:
```
%timeit min(big_array)
%timeit np.min(big_array)
```

```
72 ms ± 177 µs per loop (mean ± std. dev. of 7 runs, 10 loops e
ach)
564 µs ± 3.11 µs per loop (mean ± std. dev. of 7 runs, 1000 loo
ps each)
```

For `min`, `max`, `sum`, and **several other NumPy aggregates,** a **shorter syntax** is to use methods of the array object itself:

In [ ]:
```
print(big_array.min(), big_array.max(), big_array.sum())
```

```
2.0114398036064074e-07 0.9999997912802653 499854.0273321711
```

Whenever possible, **make sure that you are using the NumPy version** of these aggregates when operating on **NumPy arrays!**

Multidimensional Aggregates

One common **type** of aggregation operation is an **aggregate** along a **row** or **column.**

Example:

In [9]:
```
M = rng.integers(0, 10, (3, 4))
print(M)
```

```
[[5 1 0 7]
 [3 3 2 9]
 [1 5 2 0]]
```

NumPy **aggregations** will apply across **all elements** of a multidimensional array:

In [ ]:
```
M.sum()
```

Out[ ]:
```
45
```

Aggregation functions take an **additional argument** specifying the **axis** along which the aggregate is computed.

For example, we can find the **minimum value** within **each column** by specifying `axis=0`:

In [11]:
```
M.min(axis=0)
```

Out[11]:
```
array([1, 1, 0, 0], dtype=int64)
```

The function returns **four values,** corresponding to the **four columns of numbers.**

Similarly, we can find the **maximum value** within each row:

In [13]:
```
M.max(axis=1)
```

Out[13]:
```
array([7, 9, 5], dtype=int64)
```

The way the **axis is specified** here can be **confusing** to users coming from other languages.

The `axis` **keyword** specifies the **dimension** of the array that will be **collapsed**, rather than the dimension that will be returned.

So, specifying `axis=0` **means that axis 0 will be collapsed:** for two-dimensional arrays, values within each column will be aggregated.

Other Aggregation Functions

NumPy provides several **other aggregation functions** with a **similar API.**

Additionally **most of them** have a `NaN` **-safe counterpart** that computes the result while ignoring missing values, which are marked by the special IEEE floating-point `NaN` value (see **Handling Missing Data**).

The following table provides a **list of useful aggregation functions** available in **NumPy:**

Function name	NaN-safe version	Description
`np.sum`	`np.nansum`	Compute sum of elements
`np.prod`	`np.nanprod`	Compute product of elements
`np.mean`	`np.nanmean`	Compute mean of elements
`np.std`	`np.nanstd`	Compute standard deviation
`np.var`	`np.nanvar`	Compute variance

Function name	NaN-safe version	Description
`np.min`	`np.nanmin`	Find minimum value
`np.max`	`np.nanmax`	Find maximum value
`np.argmin`	`np.nanargmin`	Find index of minimum value
`np.argmax`	`np.nanargmax`	Find index of maximum value
`np.median`	`np.nanmedian`	Compute median of elements
`np.percentile`	`np.nanpercentile`	Compute rank-based statistics of elements
`np.any`	N/A	Evaluate whether any elements are true

Function name	NaN-safe version	Description
`np.all`	N/A	Evaluate whether all elements are true

You will see these aggregates often throughout the rest of the book.

Example: What Is the Average Height of US Presidents?

Aggregates available in NumPy can act as **summary statistics** for a set of values.

As a small example, let's consider **the heights of all US presidents.**

This data is available in the file **president_heights.csv**, which is a **comma-separated list** of labels and values:

In [ ]:

```
!head -4 data/president_heights.csv
```

```
order,name,height(cm)
1,George Washington,189
2,John Adams,170
3,Thomas Jefferson,189
```

We'll use the **Pandas package,** which we'll explore more fully in **Part 3,** to **read** the file and **extract this information** (note that the heights are measured in centimeters):

In [ ]:

```
import pandas as pd
data = pd.read_csv('data/president_heights.csv')
heights = np.array(data['height(cm)'])
print(heights)
```

```
[189 170 189 163 183 171 185 168 173 183 173 173 175 178 183 19
3 178 173
 174 183 183 168 170 178 182 180 183 178 182 188 175 179 183 19
3 182 183
 177 185 188 188 182 185 191 182]
```

Now that we have this data array, we can **compute a variety of summary statistics:**

In [ ]:
```
print("Mean height:         ", heights.mean())
print("Standard deviation:", heights.std())
print("Minimum height:     ", heights.min())
print("Maximum height:     ", heights.max())
```

```
Mean height:        180.04545454545453
Standard deviation: 6.983599441335736
Minimum height:     163
Maximum height:     193
```

Note that in each case, the **aggregation** operation **reduced the entire array to a single summarizing value,** which gives us information about the **distribution** of values.

We may also wish to compute **quantiles:**

In [ ]:
```
print("25th percentile:   ", np.percentile(heights, 25))
print("Median:            ", np.median(heights))
print("75th percentile:   ", np.percentile(heights, 75))
```

```
25th percentile:    174.75
Median:             182.0
75th percentile:    183.5
```

We see that the **median height of US presidents is 182 cm,** or just shy of six feet.

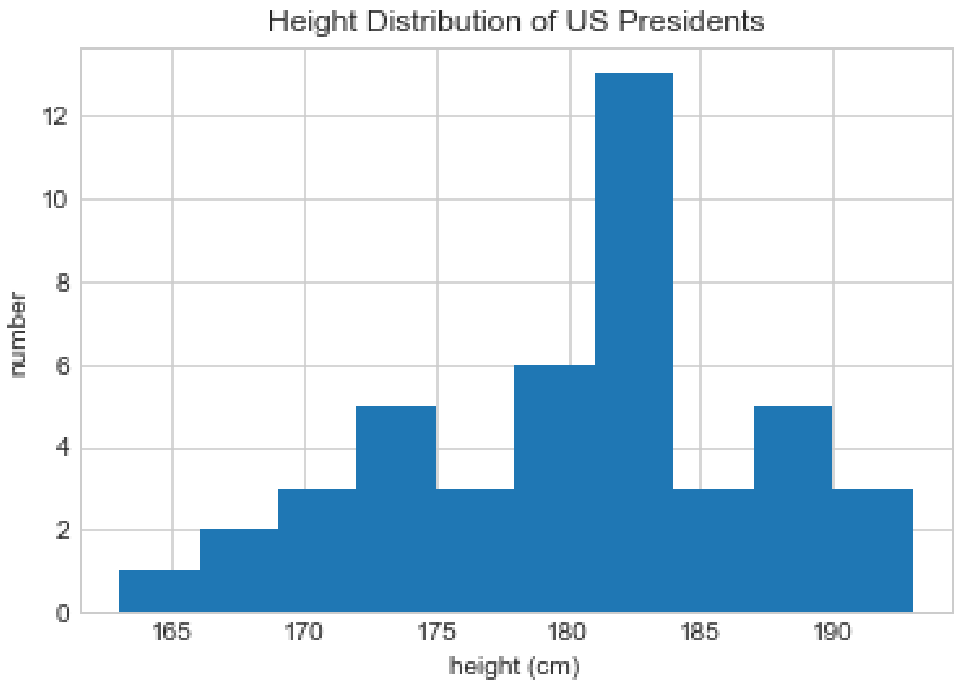
Of course, sometimes it's **more useful** to see a **visual representation** of this data.

Which we can accomplish using tools in **Matplotlib** (we'll discuss Matplotlib more fully in **Part 4.**

For example, this code generates the following chart:

In [ ]:
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn-whitegrid')
```

In [ ]:
```
plt.hist(heights)
plt.title('Height Distribution of US Presidents')
plt.xlabel('height (cm)')
plt.ylabel('number');
```


Height Distribution of US Presidents
number
0
2
4
6
8
10
12
165
170
175
180
185
190
height (cm)