Understanding Data Types in Python

- **Effective data-driven science** and computation requires understanding how **data is stored and manipulated.**
- This chapter outlines and contrasts how **arrays of data** are handled in the **Python language itself**, and how **NumPy improves** on this.
- Understanding this difference is **fundamental** to understanding much of the material throughout the rest of the book.

Users of **Python** are often drawn in by its **ease of use**, one piece of which is **dynamic typing.**

While a **statically typed** language like C or Java requires each variable to be **explicitly declared,** a dynamically typed language like Python **skips** this specification.

For example, in C you might specify a particular operation as follows:

```c
/* C code */
int result = 0;
for(int i=0; i<100; i++){
    result += i;
}
```

While in **Python** the equivalent operation could be written this way:

```python
# Python code
result = 0
for i in range(100):
    result += i
```

Notice one **main difference:**

In C, the data types of each variable are **explicitly** declared.

While in **Python** the types are **dynamically inferred**.

This means, for example, that we can **assign any kind of data to any variable:**

```python
# Python code
x = 4
x = "four"
```

Here we've **switched the contents** of `x` from an integer to a string.

The same thing **in C** would lead (depending on compiler settings) to a **compilation error** or other unintended consequences:

```c
/* C code */
int x = 4;
x = "four";  // FAILS
```

This sort of **flexibility** is one element that makes Python and other **dynamically** typed languages **convenient** and easy to use.

Understanding **how** this works is an important piece of **learning to analyze data efficiently** and effectively with Python.

But what this type flexibility also points to is the fact that **Python variables are more than just their values:**

They also contain extra information about the **type** of the value.

A Python Integer Is More Than Just an Integer

The **standard** Python implementation is **written in C.**

This means that every **Python object** is simply a **cleverly disguised C structure,** which contains not only its **value,** but **other information** as well.

For example, when we define an **integer** in Python, such as `x = 10000`, `x` is **not just a "raw" integer.**

It's actually a **pointer to a compound C structure,** which contains several values.

Looking through the **Python 3.10 source code,** we find that the integer (long) **type definition** effectively looks like this (once the C macros are expanded):

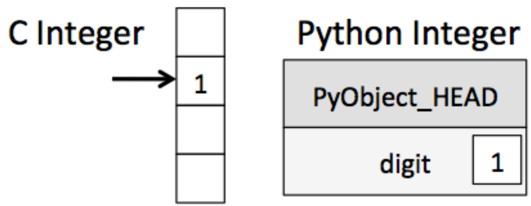
```
struct _longobject {
    long ob_refcnt;
    PyTypeObject *ob_type;
    size_t ob_size;
    long ob_digit[1];
};
```

A **single integer** in Python 3.10 actually contains **four pieces:**

- `ob_refcnt`, a reference count that helps Python silently handle memory allocation and deallocation
- `ob_type`, which encodes the type of the variable

- `ob_size`, which specifies the size of the following data members
- `ob_digit`, which contains the actual integer value that we expect the Python variable to represent

This means that there is some **overhead involved** in storing an integer in Python as compared to a **compiled language** like C:



Here, `PyObject_HEAD` is the part of the **structure** containing the reference count, type code, and other pieces mentioned before.

Notice the difference here: a **C integer is essentially a label** for a position in memory whose bytes encode an **integer value.**

A **Python integer is a pointer** to a position in memory containing **all the Python object information,** including the bytes that contain the integer value.

This **extra information** in the **Python** integer structure is what allows Python to be coded so **freely and dynamically**.

All this **additional information** in Python types comes at **a cost,** however, which becomes **especially apparent** in structures that **combine many of these objects.**

A Python List Is More Than Just a List

Consider **what happens when we use** a Python data **structure that holds many Python objects.**

The standard mutable multielement container in Python is the list. We can **create a list of integers** as follows:

In [ ]:
```
L = list(range(10))
L
```

Out[ ]:
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

In [ ]:
```
type(L[0])
```

Out[ ]:
```
int
```

Or, similarly, a list of strings:

In [ ]:
```
L2 = [str(c) for c in L]
L2
```

Out[ ]:
```
['0', '1', '2', '3', '4', '5', '6', '7', '8', '9']
```

In [ ]:
```
type(L2[0])
```

Out[ ]:
```
str
```

Because of **Python's dynamic typing,** we can even create **heterogeneous lists:**

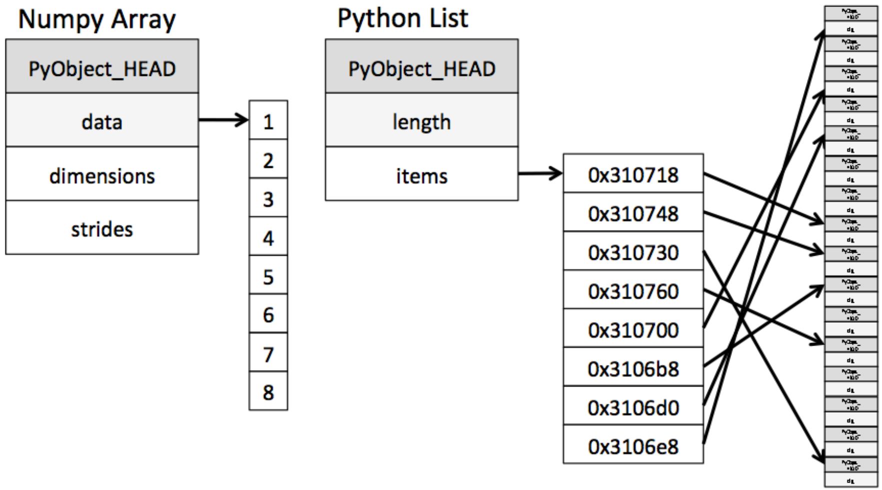
In [ ]:
```
L3 = [True, "2", 3.0, 4]
[type(item) for item in L3]
```

Out[ ]:
```
[bool, str, float, int]
```

But this **flexibility** comes at a **cost:**

- To allow these flexible types, **each item** in the list **must contain** its own **type, reference count,** and **other information.**
- That is, **each item** is a **complete Python object.**
- In the **special case** that **all variables** are of the **same type,** much of this information is **redundant.**
- So it can be much **more efficient** to store the data in a **fixed-type array.**

- The difference between a **dynamic-type list** and a **fixed-type** (NumPy-style) **array** is illustrated in the following figure:



At the implementation level, **the array** essentially contains a **single pointer** to one **contiguous block of data.**

The **Python list,** on the other hand, contains **a pointer to a block of pointers,** each of which in turn points to a **full Python object** like the Python integer we saw earlier.

Again, the **advantage** of the **list** is **flexibility.**
(because each list element is a full structure containing both data and type information, the list can be filled with data of any desired type.)

Fixed-type NumPy-style arrays **lack this flexibility,** but are much **more efficient for storing and manipulating data.**

Fixed-Type Arrays in Python

Python offers several **different options** for **storing** data in efficient, **fixed-type** data buffers.

The **built-in** `array` module (available since Python 3.3) can be used to create dense arrays of a uniform type:

In [ ]:

```
import array
L = list(range(10))
A = array.array('i', L)
A
```

Out[ ]:

```
array('i', [0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

Here, `'i'` is a **type** code indicating the contents are **integers.**

Much more useful, however, is the `ndarray` object of the **NumPy** package.

While Python's `array` object provides efficient storage of array-based data, **NumPy** adds to this **efficient operations** on that data.

Creating Arrays from Python Lists

We'll start with the standard NumPy import, under the alias `np`:

In [ ]:
```python
import numpy as np
```

Now we can use `np.array` to create arrays from Python lists:

In [ ]:
```python
# Integer array
np.array([1, 4, 2, 5, 3])
```

Out[ ]:
```
array([1, 4, 2, 5, 3])
```

Remember that unlike Python lists, **NumPy arrays** can only contain data of the **same type.**

If the **types do not match,** NumPy will **upcast** them according to its **type promotion rules;** here, integers are upcast to floating point:

In [ ]:
```python
np.array([3.14, 4, 2, 3])
```

Out[ ]:
```
array([3.14, 4.  , 2.  , 3.  ])
```

If we want to **explicitly set the data type** of the resulting array, we can use the `dtype` keyword:

In [ ]:
```
np.array([1, 2, 3, 4], dtype=np.float32)
```

Out[ ]:
```
array([1., 2., 3., 4.], dtype=float32)
```

Finally, **unlike Python lists,** which are always **one-dimensional** sequences, **NumPy arrays** can be **multidimensional.** Here's one way of initializing a multidimensional array using a list of lists:

In [106…
```
[range(i, i + 3) for i in [2, 4, 6]]
```

Out[106…
```
[range(2, 5), range(4, 7), range(6, 9)]
```

In [ ]:
```
# Nested lists result in multidimensional arrays
np.array([range(i, i + 3) for i in [2, 4, 6]])
```

Out[ ]:
```
array([[2, 3, 4],
       [4, 5, 6],
       [6, 7, 8]])
```

The **inner lists** are treated as **rows** of the resulting two-dimensional array.

Creating Arrays from Scratch

Especially for **larger arrays,** it is more **efficient** to create arrays from **scratch** using routines built into NumPy.

Here are several examples:

In [ ]:
```
# Create a length-10 integer array filled with 0s
np.zeros(10, dtype=int)
```

Out[ ]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

```
In [ ]: # Create a 3x5 floating-point array filled with 1s
        np.ones((3, 5), dtype=float)
```

```
Out[ ]: array([[1., 1., 1., 1., 1.],
               [1., 1., 1., 1., 1.],
               [1., 1., 1., 1., 1.]])
```

```
In [ ]: # Create a 3x5 array filled with 3.14
        np.full((3, 5), 3.14)
```

```
Out[ ]: array([[3.14, 3.14, 3.14, 3.14, 3.14],
               [3.14, 3.14, 3.14, 3.14, 3.14],
               [3.14, 3.14, 3.14, 3.14, 3.14]])
```

```
In [ ]: # Create an array filled with a linear sequence
        # starting at 0, ending at 20, stepping by 2
        # (this is similar to the built-in range function)
        np.arange(0, 20, 2)
```

```
Out[ ]: array([ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18])
```

In [ ]:
```python
# Create an array of five values evenly spaced between 0 and 1
np.linspace(0, 1, 5)
```

Out[ ]:
```
array([0.  , 0.25, 0.5 , 0.75, 1.  ])
```

In [ ]:
```python
# Create a 3x3 array of uniformly distributed
# pseudorandom values between 0 and 1
np.random.random((3, 3))
```

Out[ ]:
```
array([[0.09610171, 0.88193001, 0.70548015],
       [0.35885395, 0.91670468, 0.8721031 ],
       [0.73237865, 0.09708562, 0.52506779]])
```

In [ ]:
```python
# Create a 3x3 array of normally distributed pseudorandom
# values with mean 0 and standard deviation 1
np.random.normal(0, 1, (3, 3))
```

Out[ ]:
```
array([[-0.46652655, -0.59158776, -1.05392451],
       [-1.72634268,  0.03194069, -0.51048869],
       [ 1.41240208,  1.77734462, -0.43820037]])
```

In [ ]:
```
# Create a 3x3 identity matrix
np.eye(3)
```

Out[ ]:
```
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

In [ ]:
```
# Create an uninitialized array of three integers; the values w
# whatever happens to already exist at that memory location
np.empty(3)
```

Out[ ]:
```
array([1., 1., 1.])
```

NumPy Standard Data Types

NumPy arrays contain values of a **single type,** so it is important to have detailed **knowledge** of those **types** and their limitations.

Because **NumPy is built in C,** the types will be familiar to users of C, Fortran, and other related languages.

The **standard NumPy data types** are listed in the **following table.**

Note that when **constructing an array,** they can be specified using a **string:**

```
np.zeros(10, dtype='int16')
```

Or using the associated **NumPy object:**

```
np.zeros(10, dtype=np.int16)
```

Data type	Description
`bool_`	Boolean (True or False) stored as a byte
`int_`	Default integer type (same as C `long`; normally either `int64` or `int32`)
`intc`	Identical to C `int` (normally `int32` or `int64`)
`intp`	Integer used for indexing (same as C `ssize_t`; normally either `int32` or `int64`)

Data type	Description
`int8`	Byte (–128 to 127)
`int16`	Integer (–32768 to 32767)
`int32`	Integer (–2147483648 to 2147483647)
`int64`	Integer (–9223372036854775808 to 9223372036854775807)
`uint8`	Unsigned integer (0 to 255)
`uint16`	Unsigned integer (0 to 65535)
`uint32`	Unsigned integer (0 to 4294967295)
`uint64`	Unsigned integer (0 to 18446744073709551615)
`float_`	Shorthand for `float64`
`float16`	Half-precision float: sign bit, 5 bits exponent, 10 bits mantissa

Data type	Description
`float32`	Single-precision float: sign bit, 8 bits exponent, 23 bits mantissa
`float64`	Double-precision float: sign bit, 11 bits exponent, 52 bits mantissa
`complex_`	Shorthand for `complex128`
`complex64`	Complex number, represented by two 32-bit floats
`complex128`	Complex number, represented by two 64-bit floats

More **advanced type specification** is possible:

- Such as specifying **big- or little-endian** numbers; for more information, refer to the NumPy documentation.
- NumPy also supports **compound data types,** which will be covered in Structured Data: NumPy's Structured Arrays.