

# numpy data types & file operations

## array review (mostly)

- `import numpy as np` to gain access to numpy functions/modules/objects with `np.something`
- generating array:
  - from a list `np.array([1, 2, 3])`, or tuple `np.array((1, 2, 3))`
  - `np.arange()`, `np.zeros()`, `np.ones()`, `np.random.random()`
  - by combining multiple lists, tuples or arrays:

```
a = [1, 2, 3]
b = 4, 5
c = np.array([6, 7, 8])
d = np.concatenate([a, b, c])
```

- indexing:
  - single value: `d[0]` `d[1]` `d[-1]` `d[10]` `d[8]`
  - fancy indexing: integer and boolean

```
a = np.arange(10)
b = a > 5 # boolean indices
```

- use `np.where()` to get integer indices from boolean indices
  - `i = np.where(a > 5)` # returns tuple of integer indices, one per dimension
  - `i = np.where(a > 5)[0]` or `i, = np.where(a > 5)` pulls out integer indices into first dimension
- vectorized math operators (`+`, `-`, `*`, `/`, `**`) and comparitors (`==`, `>`, `<`, `!=`)
  - `a = np.array([True, False, False])`
  - `b = np.array([True, True, False])`
  - normal boolean logic operators (`and`, `or`, `not`) don't work as vectorized operators on arrays
    - e.g., `a and b` gives an error
    - instead us vectorized boolean operators `&`, `|`, `~`
    - e.g. `a & b` and `a | b` and `~a` and `~b` work as you would expect
  - are all values in `a` True? `a.all()` or `np.all(a)`
  - are any values in `a` True? `a.any()` or `np.any(a)`
- common array math  
methods: `a.max()`, `a.min()`, `a.ptp()`, `a.sum()`, `a.mean()`, `a.std()`
- how can we shift all these values to have zero mean and a standard deviation of 1?

```
a -= a.mean() # now mean is very close to 0
a /= a.std() # now std is also very close to 1
```

- `a.sort()` sorts in place, `b = np.sort(a)` creates a sorted copy of `a`
- `np.diff()` finds the difference between consecutive values in `a`
  - e.g., `np.diff([1, 4, 2, -3])` gives `np.array([3, -2, -5])`

## more array exercises:

1. Create an array `a` of 10 random numbers that range from 0 to 10 at most
2. Create an array `b` that has only the 2nd, 5th and 8th entries in `a` (one line of code!)
3. Create an array `c` that has only the values in `a` greater than 5
4. Use `np.where()` to get the integer indices of where `a` is greater than 5.
5. Check that all the values in `c` really are  $> 5$  (one line of code!)
6. Create an array `d` of 10 random numbers that range from -1 to 1 at most
7. Create an array `e` that only has the values in `d` that fall between -0.5 and 0.5
8. Check that all the values in `e` really are between -0.5 and 0.5 (one line of code!)
9. Create an array `f` that has all the values of both `a` and `d`. How long do you expect it to be? Check its length.
10. Sort the values in `f` in-place. Use `np.diff()` in one line of code to check that `f` really is sorted.

### deciding between lists and arrays:

- use a list when:
  - have heterogenous data types you want to store together in a sequence
  - you don't know in advance how many entries you'll need
  - want to easily add and remove items to/from it
  - don't have to store a very large number of items, memory use isn't an issue
  - don't have to do vectorized operations on the sequence, e.g. adding two of them together
- otherwise, use an array!
- very typical use case: collect data points one by one and append them to an empty list, then convert that list to an array at the very end

```
a = []
for i in range(10):
    a.append(2*i)
a = np.array(a)
```

### memory

- what's system memory (RAM)? computer's working memory (random access memory)
- what's a byte? 8 bits
- what's a bit?
  - a Binary digit, numeric symbol for counting in base 2, can be 0 or 1
  - decimal digit: numeric symbol for counting in base 10, ranges 0 to 9
- different numeric values are expressed using different combinations of bits
  - 1 byte, 8 bits allow for  $2^8 = 256$  different numeric values to be expressed
  - `00000000, 00000001, 00000010, 00000011 ... == 0, 1, 2, 3, ...`
- how much memory does my array use, in bytes?
  - `a.nbytes`
  - memory use depends on the number of elements in the array, times the size of each element
  - element size depends on the data type (dtype) of the array - `a.dtype`
  - for 1D arrays: `a.nbytes == len(a) * a.dtype.itemsize`

### array data type (dtype)

- there are subtypes of both int and float, these are across programming languages, super important!
- **integers:** signed and unsigned
  - signed integers are symmetric around 0, unsigned integers are always  $\geq 0$ 
    - $n = 2^{*\text{nbits}}$  is the number of unique integers that can be represented by an integer data type:
    - unsigned integers range from 0 to  $n-1$
    - signed integers range from  $-n/2$  to  $n/2-1$
    - so, the bigger the integer data type (in bits and therefore bytes (  $\text{nbytes} = \text{nbits} / 8$  ), the more integer numbers it can represent
  - `np.int8`, `np.int16`, `np.int32`, `np.int64` use 1, 2, 4 and 8 bytes, **signed**
  - `np.uint8`, `np.uint16`, `np.uint32`, `np.uint64` use 1, 2, 4 and 8 bytes, **unsigned**
  - can calculate max/min values of each int dtype, or use `np.iinfo()`, e.g. `np.iinfo(np.int8)`
    - access results using `.max` and `.min` attributes
  - init arrays to the desired data type by using the `dtype` kwarg:
    - `a = np.zeros(5, dtype=np.uint8)` - smallest unsigned int
    - `b = np.zeros(5, dtype=np.int8)` - smallest signed int
  - integer overflow when assigning values:
    - `a[0] = 255` is fine, but `a[0] = 256` and `a[0] = -1` both "overflow" (wrap around)
    - `b[0] = 127` is fine, but `a[0] = -128` isn't
    - `b[0] = -128` is fine, but `b[0] = -129` isn't
  - integer overflow when doing in-place integer math:
    - `a = np.zeros(5, dtype=np.uint8)`
    - `a += 1` is fine, but then another `a += 255` isn't
  - when doing normal (not in-place) int math, numpy gives the result in the next biggest dtype if it won't fit in the existing dtypes
    - `a[0] = 200`, `b[0] = 100`, `a + b` gives result as `int16` dtype
  - when to use signed or unsigned? if in doubt, use signed!
  - how much memory (in bytes) would `a = np.zeros(1000000000000, dtype=np.uint8)` use? what would happen if I tried this on my 16 GB laptop? `MemoryError`
- **floats:** always signed, and made of `mantissa * 10exponent`, e.g. `1.23456789e02`
  - some bits that make up a float are used for the mantissa, some for the exponent
  - bigger float data types have greater resolution (mantissa) and greater range (exponent), but use more memory
  - `np.float16`, `np.float32`, `np.float64` use 2, 4 and 8 bytes. Is there a `np.float8`?
    - `a = np.zeros(5, dtype=np.float16)` uses `5*2` bytes of memory
  - float overflow:
    - `a[0] = 60000` is fine, but `a[0] = 70000` isn't (results in `inf`)
    - same for negative values
  - to get max/min/resolution of a float dtype, use `np.finfo()`
    - e.g. `np.finfo(np.float16)` gives `finfo(resolution=0.001, min=-6.55040e+04, max=6.55040e+04, dtype=float16)`
    - access results using `.max`, `.min` and `.resolution` attributes
    - note that resolution refers to the mantissa, not of the full mantissa +  $10^{\text{exponent}}$

- `np.float16(1.23456789e4)` gives `12344.0`
  - `np.float16(1.23456789)` gives `1.234`
  - `np.finfo(np.float16).tiny` gives `6.104e-05`, the smallest representable value
- special values:
  - `np.inf` and `np.nan`, i.e. "infinity" and "not a number"
    - `np.inf` is used to represent out of range float values
    - `np.nan` is used to represent invalid float values, like `1/0`
    - `inf` is signed (can be +/-), but `nan` has no sign
    - doing any math involving `inf` or `nan` always results in another `inf` or `nan`
    - `np.inf + np.nan` gives `np.nan`
    - comparing `nan` to anything, even itself, returns `False`, have to use `np.isnan()`
- numpy arrays default to the biggest dtypes, either `np.float64` or `np.int64`:
  - `a = np.array([1, 2, 3])`, `a.dtype` gives `int64`
  - `b = np.array([1.1, 2.2, 3.3])`, `b.dtype` gives `float64`
  - initialize arrays to the desired data type by using the `dtype` kwarg:
  - `a = np.zeros(10, dtype=np.int8)`
  - `b = np.zeros(10, dtype=np.int64)`
  - `c = np.zeros(10, dtype=np.float64)`
  - calculate how much memory `a`, `b` and `c` should use, then check it using `.nbytes`
- special case: `bool` dtype
  - uses one byte per entry, just like `int8` and `uint8`
  - `b = np.array([True, False, False])`
  - `b.dtype`, `b.nbytes`
  - could this be more efficient? yes, bool arrays could use single bits instead of a full byte for each value, but normal computers allocate memory no finer than a single byte
- **typecasting**: convert from one dtype to another
  - using the dtype as a function
  - `a = np.array([1, 2, 3])` has `a.dtype` of `int64`
  - `np.float64(a)` converts `a` to dtype `float64`
    - similar to basic Python: `float(val)`
  - `a = np.array([1.1, 2.2, 3.3])` has `a.dtype` of `float64`
  - `np.int64(a)` converts `a` to `int64` dtype, but it truncates!
    - this is similar to basic Python: `int(val)`
    - use `np.int64(np.round(a))` to round to the nearest integer instead
- usually only need to worry about int vs. float dtype, stick to the defaults `int64` and `float64`
  - only consider going down to smaller dtypes if you have lots of data and not enough memory on your machine
- take care when typecasting (converting between dtypes)!
  - especially from larger dtypes to smaller dtypes, and from floats to ints

- a number that can be represented in one data type might not be possible to represent in another
- dramatic example: Ariane 5 1996 failure
  - code adapted from Ariane 4 tried to convert a large float64 to int16, resulted in integer overflow, caused computer to think it was suddenly way off course, tried to correct by rapidly changing direction, high G-forces, disintegration. Cost: \$370M

### numeric data type exercises:

1. Create a sequence (tuple or a list) with the following entries: `3, 5, 1.7, -2.7, 1e2, -50` .
  - i. What are the data types of the individual values?
  - ii. What do you predict will happen if you convert this sequence to an array? What will the array's dtype be? How much memory will it use (in bytes)?
  - iii. Now check your predictions. Convert the sequence to an array and check both its `.dtype` and its `.nbytes` .
2. You have integer data whose values span -2 to 2. Normally, you would use an integer array with numpy's default int64 dtype to store this data. But, the dataset is huge (1.5 billion entries) and your laptop only has 4 GB of RAM.
  - i. How much memory would your data take up if you used the default integer dtype in numpy?
  - ii. Should you use an int or float dtype? Signed or unsigned?
  - iii. What would be the optimal dtype to minimize the amount of memory used by your dataset? Will it fit into your 4 GB of RAM?
3. Repeat question 2. for integer values that span 0 to 10000.
4. Repeat question 2. for integer values that span -1 to 50000.
5. Repeat question 2. for float values that span -60000 to 60000.