Numeric Computations with Numpy

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Where to Find The Code and Materials?

https://github.com/iproduct/intro-python

Numpy

Working with numeric arrays and matrices

About Numpy

- Numpy is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays. If familiar with MATLAB, you might find this tutorial useful. NumPy was created in 2005 by Travis Oliphant as an open source project.
- NumPy stands for Numerical Python - library used for working with arrays.
- It also has functions for working in domain of linear algebra, fourier transform, matrices, etc.
- NumPy gives you an enormous range of fast and efficient ways of creating arrays and manipulating numerical data inside them. While a Python list can contain different data types within a single list, all of the elements in a NumPy array should be homogeneous. The mathematical operations that are meant to be performed on arrays would be extremely inefficient if the arrays weren't homogeneous.

Why Numpy

- In Python we have lists instead of arrays, but their processing is slow.
- NumPy arrays are faster and more compact than Python lists. An array consumes less memory and is convenient to use. NumPy uses much less memory to store data and it provides a mechanism of specifying the data types. This allows the code to be optimized even further.
- NumPy provides **ndarray** object – up to 50x faster than normal Python lists.
- **ndarray** provides a lot of supporting functions that make working with it very convenient.
- In data science the speed and resources are quite important, so **ndarray** is frequently used.

Why is NumPy Fast?

- vectorized code is more concise and easier to read
- fewer lines of code generally means fewer bugs
- the code more closely resembles standard mathematical notation (making it easier, typically, to correctly code mathematical constructs)
- vectorization results in more "Pythonic" code. Without vectorization, our code would be littered with inefficient and difficult to read for loops.

Broadcasting

- Broadcasting is the term used to describe the implicit element-by-element behavior of operations;
- Generally speaking, in NumPy all operations, not just arithmetic operations, but logical, bit-wise, functional, etc., behave in this implicit element-by-element fashion, i.e., they broadcast.
- Moreover, in the example above, a and b could be multidimensional arrays of the same shape, or a scalar and an array, or even two arrays of with different shapes, provided that the smaller array is "expandable" to the shape of the larger in such a way that the resulting broadcast is unambiguous.

Arrays

- A numpy array is a grid of values, all of the same type, and is indexed by a tuple of nonnegative integers. The number of dimensions is the rank of the array; the shape of an array is a tuple of integers giving the size of the array along each dimension.
- We can initialize numpy arrays from nested Python lists, and access elements using square brackets.
- Numpy also provides many functions to create arrays.

Arrays II

```
import numpy as np

a = np.array([1, 2, 3])   # Create a rank 1 array
print(type(a))            # Prints "<class 'numpy.ndarray'>"
print(a.shape)            # Prints "(3,)"
print(a[0], a[1], a[2])   # Prints "1 2 3"
a[0] = 5                  # Change an element of the array
print(a)                  # Prints "[5, 2, 3]“

b = np.array([[1,2,3],[4,5,6]])    # Create a rank 2 array
print(b.shape)                     # Prints "(2, 3)"
print(b[0, 0], b[0, 1], b[1, 0])   # Prints "1 2 4"
```

Arrays III

```
import numpy as np

a = np.zeros((2,2))   # Create an array of all zeros
print(a)              # Prints "[[ 0.  0.]
                      #          [ 0.  0.]]"

b = np.ones((1,2))    # Create an array of all ones
print(b)              # Prints "[[ 1.  1.]]"

c = np.full((2,2), 7)  # Create a constant array
print(c)               # Prints "[[ 7.  7.]
                       #          [ 7.  7.]]"

d = np.eye(2)         # Create a 2x2 identity matrix
print(d)              # Prints "[[ 1.  0.]
                      #          [ 0.  1.]]"

e = np.random.random((2,2))  # Create an array filled with random values
print(e)                     # Might print "[[ 0.91940167  0.08143941]
                             #              [ 0.68744134  0.87236687]]"
```

Array Indexing

- Slicing – similar to Python lists, numpy arrays can be sliced. Since arrays may be multidimensional, you must specify a slice for each dimension of the array:

```
# Create the following rank 2 array with shape (3, 4)
# [[ 1  2  3  4]
#  [ 5  6  7  8]
#  [ 9 10 11 12]]
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])


# Two ways of accessing the data in the middle row of the array. Mixing integer indexing with slices yields an array of lower rank, while using only slices yields an array of the same rank as the original array:
row_r1 = a[1, :]    # Rank 1 view of the second row of a
row_r2 = a[1:2, :]  # Rank 2 view of the second row of a
print(row_r1, row_r1.shape)  # Prints "[5 6 7 8] (4,)"
print(row_r2, row_r2.shape)  # Prints "[[5 6 7 8]] (1, 4)"
```

Array Indexing - Slicing

- Slicing – similar to Python lists, numpy arrays can be sliced. Since arrays may be multidimensional, you must specify a slice for each dimension of the array:

```
# We can make the same distinction when accessing columns of an array:
col_r1 = a[:, 1]
col_r2 = a[:, 1:2]
print(col_r1, col_r1.shape)  # Prints "[ 2  6 10] (3,)"
print(col_r2, col_r2.shape)  # Prints "[[ 2]
                             #         [ 6]
                             #         [10]] (3, 1)"
```

Integer Array Indexing

- Integer array indexing – when you index into numpy arrays using slicing, the resulting array view will always be a subarray of the original array. In contrast, integer array indexing allows you to construct arbitrary arrays using the data from another array. Here is an example:

```
a = np.array([[1,2], [3, 4], [5, 6]])
# An example of integer array indexing. The returned array will have shape (3,) and
print(a[[0, 1, 2], [0, 1, 0]])  # Prints "[1 4 5]"
# The above example of integer array indexing is equivalent to this:
print(np.array([a[0, 0], a[1, 1], a[2, 0]]))  # Prints "[1 4 5]"

# When using integer array indexing, you can reuse the same element from the source array:
print(a[[0, 0], [1, 1]])  # Prints "[2 2]"
# Equivalent to the previous integer array indexing example
print(np.array([a[0, 1], a[0, 1]]))  # Prints "[2 2]"
```

Array Indexing

- One useful trick with integer array indexing is selecting or mutating one element from each row of a matrix:

```
# Create a new array from which we will select elements
a = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
print(a)
# Create an array of indices
b = np.array([0, 2, 0, 1])
# Select one element from each row of a using the indices in b
print(a[np.arange(4), b])  # Prints "[ 1  6  7 11]"
# Mutate one element from each row of a using the indices in b
a[np.arange(4), b] += 10
print(a)  # prints "array([[11,  2,  3],
                 #             [ 4,  5, 16],
                 #             [17,  8,  9],
                 #             [10, 21, 12]])
```

Boolean Array Indexing

- Boolean array indexing lets you pick out arbitrary elements of an array. Frequently this type of indexing is used to select the elements of an array that satisfy some condition. Here is an example:

```
a = np.array([[1,2], [3, 4], [5, 6]])

bool_idx = (a > 2)   # Find the elements of a that are bigger than 2;
    # this returns a numpy array of Booleans of the same shape as a, where each slot of bool_idx tells
    # whether that element of a is > 2.

print(bool_idx)      # Prints "[[False False]
                     #         [ True  True]
                     #         [ True  True]]"
```

Boolean Array Indexing II

```
# We use boolean array indexing to construct a rank 1 array
# consisting of the elements of a corresponding to the True values of bool_idx
print(a[bool_idx])  # Prints "[3 4 5 6]"

# We can do all of the above in a single concise statement:
print(a[a > 2])     # Prints "[3 4 5 6]“
```

- For brevity we have left out a lot of details about numpy array indexing; if you want to know more you should read the documentation.

Datatypes

- Every numpy array is a grid of elements of the same type. Numpy provides a large set of numeric datatypes that you can use to construct arrays. Numpy tries to guess a datatype when you create an array, but functions that construct arrays usually also include an optional argument to explicitly specify the datatype. Here is an example:

```
x = np.array([1, 2])   # Let numpy choose the datatype
print(x.dtype)         # Prints "int64"

x = np.array([1.0, 2.0])   # Let numpy choose the datatype
print(x.dtype)             # Prints "float64"

x = np.array([1, 2], dtype=np.int64)   # Force a particular datatype
print(x.dtype)                         # Prints "int64"
```

Array Math I

```
x = np.array([[1,2],[3,4]], dtype=np.float64)
y = np.array([[5,6],[7,8]], dtype=np.float64)

# Elementwise sum; both produce the array
# [[ 6.0  8.0]
#  [10.0 12.0]]
print(x + y)
print(np.add(x, y))

# Elementwise difference; both produce the array
# [[-4.0 -4.0]
#  [-4.0 -4.0]]
print(x - y)
print(np.subtract(x, y))
```

Array Math II

```
# Elementwise product; both produce the array
# [[ 5.0 12.0]
#  [21.0 32.0]]
print(x * y)
print(np.multiply(x, y))

# Elementwise division; both produce the array
# [[ 0.2        0.33333333]
#  [ 0.42857143  0.5       ]]
print(x / y)
print(np.divide(x, y))

# Elementwise square root; produces the array
# [[ 1.         1.41421356]
#  [ 1.73205081  2.        ]]
print(np.sqrt(x))
```

Array Math III

```
x = np.array([[1,2],[3,4]])
y = np.array([[5,6],[7,8]])
v = np.array([9,10])
w = np.array([11, 12])
# Inner product of vectors; both produce 219
print(v.dot(w))
print(np.dot(v, w))
# Matrix / vector product; both produce the rank 1 array [29 67]
print(x.dot(v))
print(np.dot(x, v))
# Matrix / matrix product; both produce the rank 2 array
# [[19 22]
#  [43 50]]
print(x.dot(y))
print(np.dot(x, y))
```

Array Math: Sum

```
x = np.array([[1,2],[3,4]])

print(np.sum(x))  # Compute sum of all elements; prints "10"
print(np.sum(x, axis=0))  # Compute sum of each column; prints "[4 6]"
print(np.sum(x, axis=1))  # Compute sum of each row; prints "[3 7]“
```

- You can find the full list of mathematical functions provided by numpy in the documentation.

Array Math: Transposing a Matrix

```
x = np.array([[1,2], [3,4]])
print(x)    # Prints "[[1 2]
                  #         [3 4]]"
print(x.T)  # Prints "[[1 3]
                   #         [2 4]]"

# Note that taking the transpose of a rank 1 array does nothing:
v = np.array([1,2,3])
print(v)    # Prints "[1 2 3]"
print(v.T)  # Prints "[1 2 3]“
```

- Numpy provides many more functions for manipulating arrays; you can see the full list in the documentation.

Broadcasting

- Broadcasting is a powerful mechanism that allows numpy to work with arrays of different shapes when performing arithmetic operations. Frequently we have a smaller array and a larger array, and we want to use the smaller array multiple times to perform some operation on the larger array.
- For example, suppose that we want to add a constant vector to each row of a matrix.

Broadcasting: Normal Python

```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
v = np.array([1, 0, 1])
y = np.empty_like(x)   # Create an empty matrix with the same shape as x

# Add the vector v to each row of the matrix x with an explicit loop
for i in range(4):
    y[i, :] = x[i, :] + v

# Now y is the following
# [[ 2  2  4]
#  [ 5  5  7]
#  [ 8  8 10]
#  [11 11 13]]
print(y)
```

Numpy Broadcasting

```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
v = np.array([1, 0, 1])
vv = np.tile(v, (4, 1))   # Stack 4 copies of v on top of each other
print(vv)                 # Prints "[[1 0 1]
                          #         [1 0 1]
                          #         [1 0 1]
                          #         [1 0 1]]"
y = x + vv  # Add x and vv elementwise
print(y)  # Prints "[[ 2  2  4
          #         [ 5  5  7]
          #         [ 8  8 10]
          #         [11 11 13]]"
```

Numpy Broadcasting with Vector Expansion

```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
v = np.array([1, 0, 1])
y = x + v  # Add v to each row of x using broadcasting
print(y)  # Prints "[[ 2  2  4]
          #         [ 5  5  7]
          #         [ 8  8 10]
          #         [11 11 13]]"
```

Broadcasting Rules

1. If the arrays do not have the same rank, prepend the shape of the lower rank array with 1s until both shapes have the same length.
2. The two arrays are said to be compatible in a dimension if they have the same size in the dimension, or if one of the arrays has size 1 in that dimension.
3. The arrays can be broadcast together if they are compatible in all dimensions.
4. After broadcasting, each array behaves as if it had shape equal to the elementwise maximum of shapes of the two input arrays.
5. In any dimension where one array had size 1 and the other array had size greater than 1, the first array behaves as if it were copied along that dimension

If this explanation does not make sense, try reading the explanation from the documentation or this explanation.

Broadcasting Examples

```
# Compute outer product of vectors
v = np.array([1,2,3])  # v has shape (3,)
w = np.array([4,5])    # w has shape (2,)

# To compute an outer product, we first reshape v to be a column
# vector of shape (3, 1); we can then broadcast it against w to yield
# an output of shape (3, 2), which is the outer product of v and w:
# [[ 4  5]
#  [ 8 10]
#  [12 15]]
print(np.reshape(v, (3, 1)) * w)
```

Broadcasting Examples

```
# Add a vector to each row of a matrix
x = np.array([[1,2,3], [4,5,6]])
# x has shape (2, 3) and v has shape (3,) so they broadcast to (2, 3),
# giving the following matrix:
# [[2 4 6]
#  [5 7 9]]
print(x + v)
```

Broadcasting Examples

```
# Add a vector to each column of a matrix
# x has shape (2, 3) and w has shape (2,).
# If we transpose x then it has shape (3, 2) and can be broadcast
# against w to yield a result of shape (3, 2); transposing this result
# yields the final result of shape (2, 3) which is the matrix x with
# the vector w added to each column. Gives the following matrix:
# [[ 5  6  7]
#  [ 9 10 11]]
print((x.T + w).T)
# Another solution is to reshape w to be a column vector of shape (2, 1);
# we can then broadcast it directly against x to produce the same
# output.
print(x + np.reshape(w, (2, 1)))
```

Broadcasting Examples

```
# Multiply a matrix by a constant:
# x has shape (2, 3). Numpy treats scalars as arrays of shape ();
# these can be broadcast together to shape (2, 3), producing the
# following array:
# [[ 2  4  6]
#  [ 8 10 12]]
print(x * 2)
```

Functions that support broadcasting are known as *universal functions*. You can find the list of all universal functions in the documentation.

Ufunc tutorial:
https://www.w3schools.com/python/numpy/numpy_ufunc.asp

Problem: Decimal to binary

Write a NumPy program to convert a given vector of integers to a matrix of binary representation.

Sample data:

Original vector:

[0 1 3 5 7 9 11 13 15]

Binary representation of the said vector:

[[0 0 0 0 0 0 0 0]

[0 0 0 0 0 0 0 1]

.....

[0 0 0 0 1 1 1 1]]

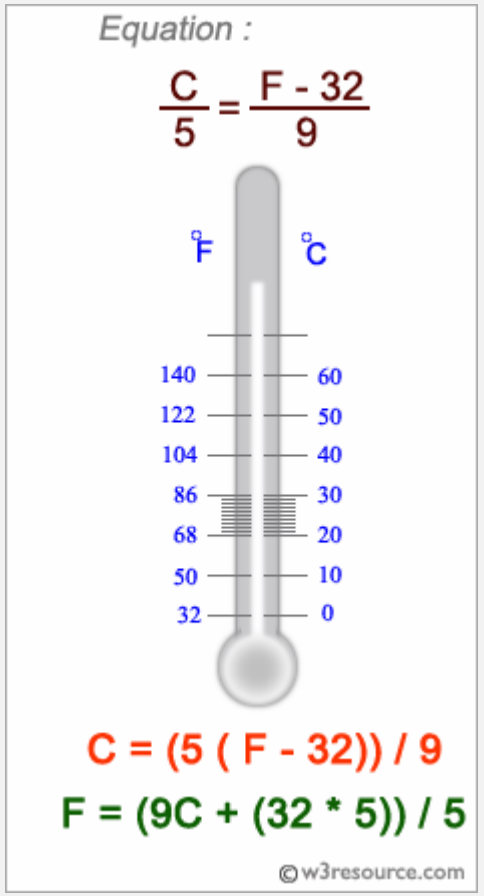
Problem: Convert values of Centigrade degrees into Fahrenheit degrees and vice versa

Write a NumPy program to convert the values of Centigrade degrees into Fahrenheit degrees and vice versa. Values are stored into a NumPy array.

Sample Array:

Values in Fahrenheit degrees [0, 12, 45.21, 34, 99.91]

Values in Centigrade degrees [-17.78, -11.11, 7.34, 1.11, 37.73, 0.]



Thank's for Your Attention!

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