

Python Debugging & Numpy Basics


CS 5670

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1. PyCharm Debugging Techniques

See [here](#) for basic tutorials

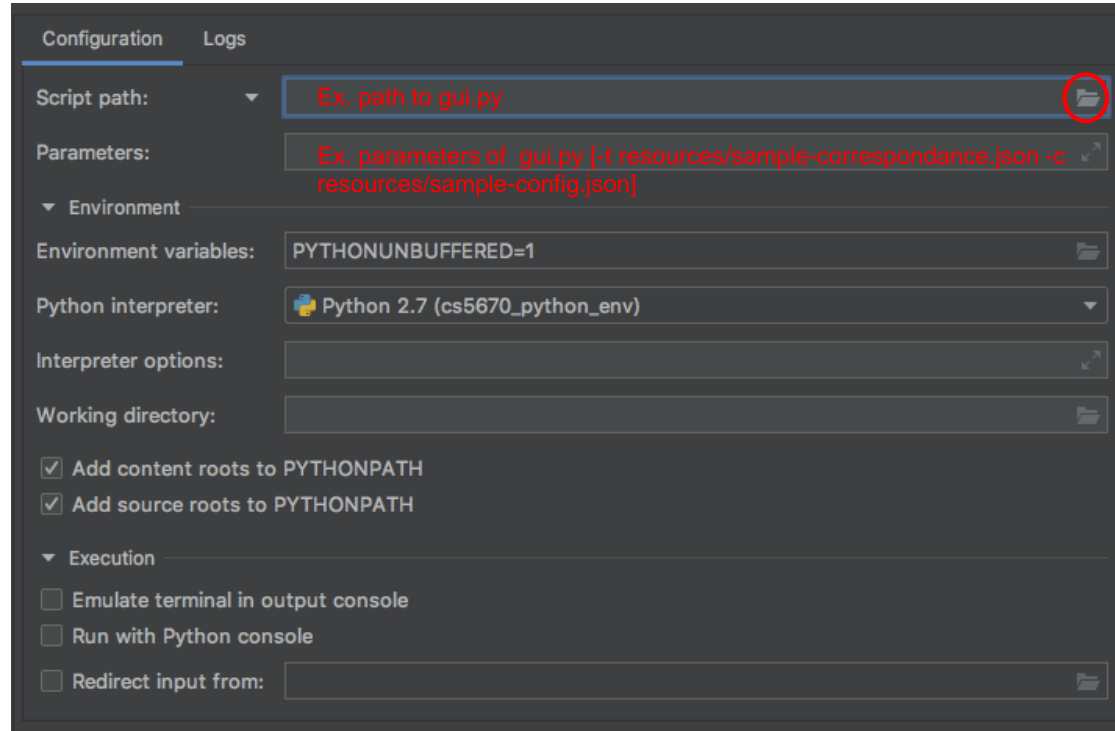
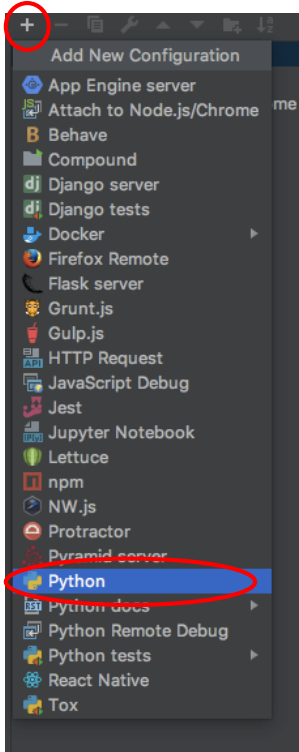
Virtualenv Environment Configurations

1. In **Settings/Preferences** dialog (⌘,), select **Project: <project name> | Project Interpreter**.
2. In the Project Interpreter page, click  and select **Add**.
3. In the left-hand pane of the Add Python Interpreter dialog box, select **Virtualenv Environment**.
4. Select **Existing environment**, Specify the virtual environment in your file system, e.g., `{full path to}/cs5670_python_env/bin/python2.7`

Reference: [Pycharm Help Page](#)

Run/Debug Configurations

1. Open the Run/Debug Configuration dialog [via **Run** | **Edit Configurations**]



Reference:
[Pycharm Help Page](#)

Use Pycharm Debugger

1. Set **breakpoints**: just click in the left gutter
2. Click **Debug** Button
3. Start Debugging!

a. Step through your program

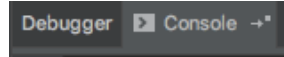


b. Create a watch

c. Evaluate an expression



or enable the Python console



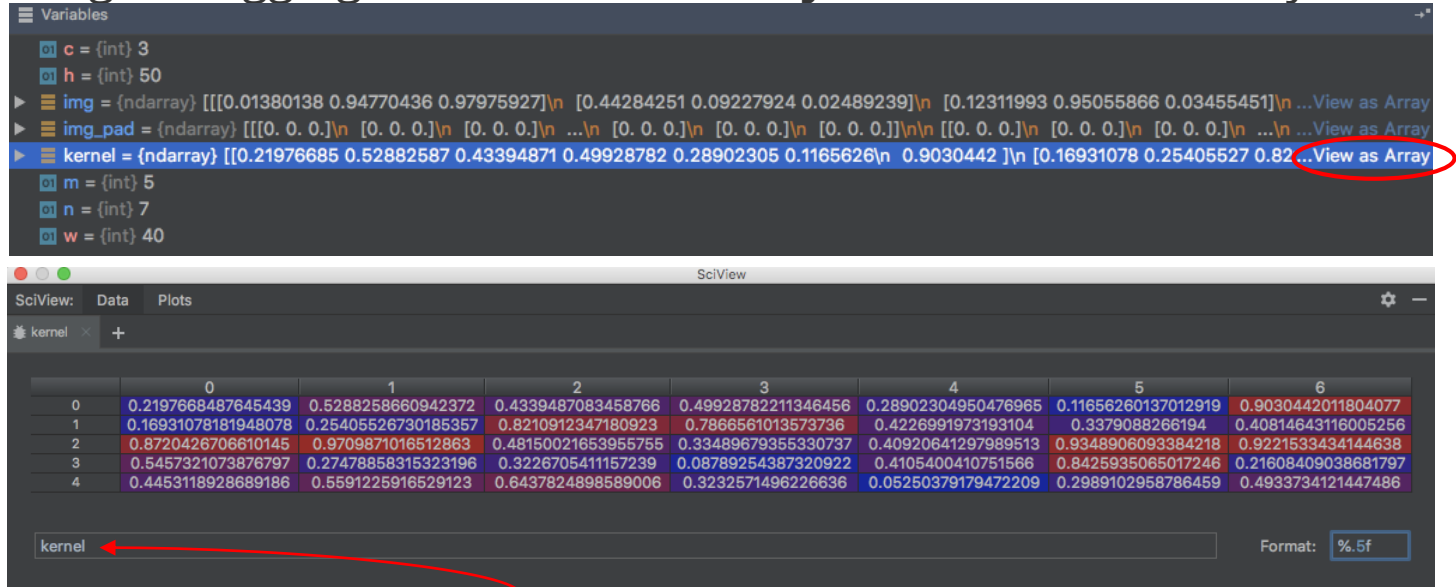
in the

Debugger

Reference: [Pycharm Help Page](#)

Numpy array visualization

1. During debugging, click '**View as Array**' to visualize the array



The image shows a debugger's 'Variables' window and a 'SciView' window. The 'Variables' window lists several variables: `c` (int 3), `h` (int 50), `img` (ndarray), `img_pad` (ndarray), `kernel` (ndarray), `m` (int 5), `n` (int 7), and `w` (int 40). The `kernel` variable is selected, and its value is shown as a 2D array of floating-point numbers. The 'SciView' window displays this array as a grid of colored cells. A red circle highlights the 'View as Array' link for the `kernel` variable in the 'Variables' window. A red arrow points from this circle to the 'kernel' label in the 'SciView' window.

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| 0 | 0.2197668487645439 | 0.5288258660942372 | 0.4339487083458766 | 0.49928782211346456 | 0.28902304950476965 | 0.11656260137012919 | 0.9030442011804077 |
| 1 | 0.16931078181948078 | 0.25405526730185357 | 0.8210912347180923 | 0.7866561013573736 | 0.4226991973193104 | 0.3379088266194 | 0.40814643116005256 |
| 2 | 0.8720426706610145 | 0.9709871016512863 | 0.48150021653955755 | 0.33489679355330737 | 0.40920641297989513 | 0.9348906093384218 | 0.9221533434144638 |
| 3 | 0.5457321073876797 | 0.27478858315323196 | 0.3226705411157239 | 0.08789254387320922 | 0.4105400410751566 | 0.8425935065017246 | 0.21608409038681797 |
| 4 | 0.44531189286889186 | 0.5591225916529123 | 0.6437824898589006 | 0.3232571496226636 | 0.05250379179472209 | 0.2989102958786459 | 0.4933734121447486 |

Want to visualize high-dimensional array? Try proper slicing

**2. Virtual Machine
vs.
Python Virtual Environment**

1. Different levels of isolation:
 - a. Python Virtual Environment: isolate only python packages
 - b. VMs: isolate everything
2. Applications running in a **virtual environment** share an underlying operating system, while **VM** systems can run different operating systems.

3. Numpy Basics

Slicing [[Manual](#)]

What is an N Dimensional array?

Write explicitly, $X[\theta:m_1, \theta:m_2, \dots, \theta:m_N]$

N: number of dimensions (axes)

m_1, m_2, \dots, m_N : length of each dimension (axis)

Tips:

- Slicing is simply setting **an ordered subset**.
 - **range**: $a:b$, ':' is a special character that represents the range
 - **logical mask**
 - **any subset**
- Indexing a single element can be viewed as slicing.
 - Compare $X[a, b, c]$ with $X[a:a+1, b:b+1, c:c+1]$.
- Dimension loss and expansion.
 - Loss:
 - set the slicing range for a dimension to a single scalar
 - `np.sum`, `np.mean`, `np.median`, ...
 - Expansion:
 - `np.newaxis`, `np.reshape`, ...

Slicing Examples

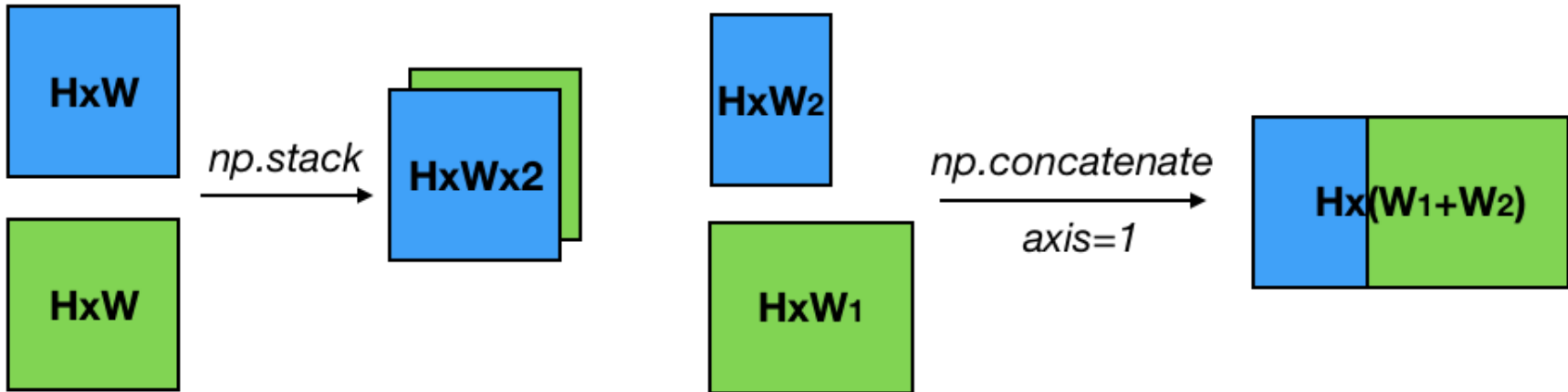
```
>>> import numpy as np
>>> grey = np.random.rand(4, 5)
>>> grey
array([[0.53843361, 0.57248719, 0.15094141, 0.25546857, 0.24077735],
       [0.30343379, 0.27474219, 0.39006497, 0.13884071, 0.30546357],
       [0.01240259, 0.14430918, 0.94647453, 0.32942122, 0.35585103],
       [0.82999887, 0.7653893 , 0.37365659, 0.6500917 , 0.28086595]])
>>> grey[2,3]
0.3294212171303872
>>> grey[2:3,3:4]
array([[0.32942122]])
>>> grey[:, 1]
array([0.57248719, 0.27474219, 0.14430918, 0.7653893 ])
>>> grey[1:3, 2:4]
array([[0.39006497, 0.13884071],
       [0.94647453, 0.32942122]])
>>> np.sum(grey, axis=0)
array([1.68426886, 1.75692786, 1.86113749, 1.37382219, 1.18295791])
>>> mask = grey > 0.5
>>> mask
array([[ True,  True, False, False, False],
       [False, False, False, False, False],
       [False, False,  True, False, False],
       [ True,  True, False,  True, False]])
>>> grey[mask]
array([0.53843361, 0.57248719, 0.94647453, 0.82999887, 0.7653893 ,
       0.6500917 ])
>>> grey[mask].reshape(2,3)
array([[0.53843361, 0.57248719, 0.94647453],
       [0.82999887, 0.7653893 , 0.6500917 ]])
```

Examples:

- Given an RGB image $X[0:h, 0:w, 0:3]$
- Get G channel of a RGB image:
 $X[:, :, 1]$
- RGB to BGR
 $X[:, :, [2, 1, 0]]$
- Center-crop an RGB image
 $X[r_1:r_2, c_1:c_2, :]$
- Downsample an RGB image by 2x
 $X[0:h:2, 0:w:2, :]$

Stacking [[Manual](#)] and Concatenating [[Manual](#)]

1. `np.stack()`, `np.concatenate()`
2. `np.stack()` requires that all input array must have the **same shape**, and the stacked array has **one more dimension** than the input arrays.
3. `np.concatenate()` requires that the input arrays must have the same shape, **except in the dimension** corresponding to *axis*



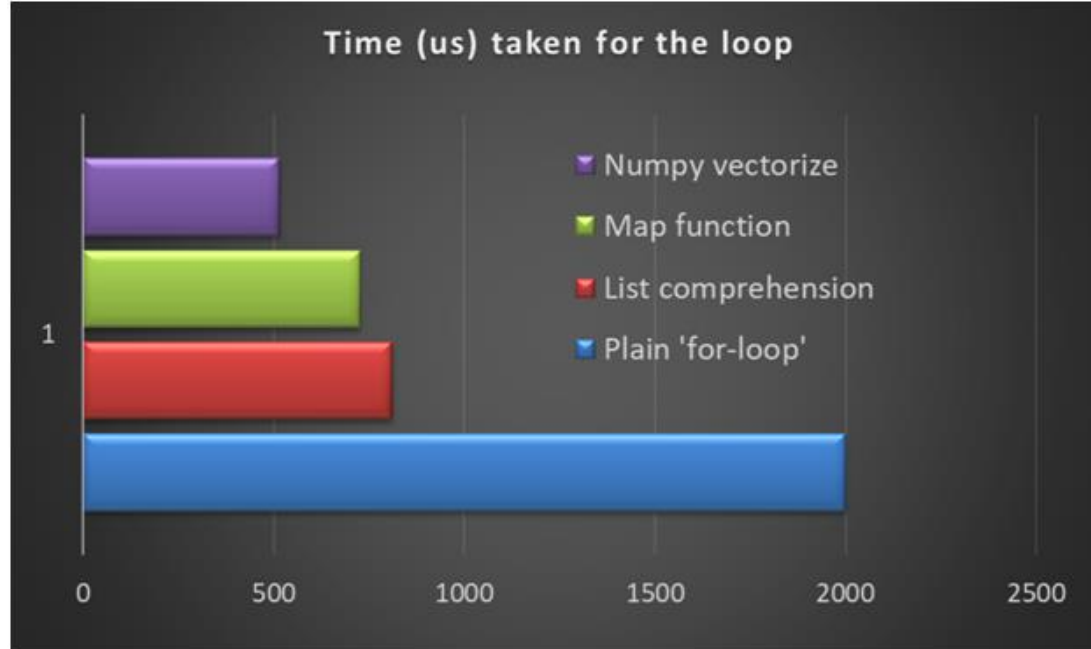
Concatenation Examples

```
>>> R=np.random.randn(300, 400)
>>> G=np.random.randn(300, 400)
>>> B=np.random.randn(300, 400)
>>> RGB=np.concatenate((R[:, :, np.newaxis], G[:, :, np.newaxis], B[:, :, np.newaxis]), axis=2)
>>>
>>>
>>> R.shape
(300, 400)
>>> G.shape
(300, 400)
>>> B.shape
(300, 400)
>>> RGB.shape
(300, 400, 3)
>>> █
```

```
>>> another_RGB=np.concatenate((R[np.newaxis, :, :], G[np.newaxis, :, :], B[np.newaxis, :, :]), axis=0)
>>> another_RGB.shape
(3, 300, 400)
>>>
```

Vectorization

1. Turn your loops to Numpy vector manipulation
2. Vectorization enables fast **parallel computation**



Vectorization

Example 1: element-wise multiplication

For-Loop -- Inefficient

```
>>> a = [1, 2, 3, 4, 5]
>>> b = [6, 7, 8, 9, 10]
>>> [x * y for x, y in zip(a, b)]
[6, 14, 24, 36, 50]
```

Numpy Vector -- Efficient!

```
>>> import numpy as np
>>> a = np.array([1, 2, 3, 4, 5])
>>> b = np.array([6, 7, 8, 9, 10])
>>> a * b
array([ 6, 14, 24, 36, 50])
```

Vectorization

Example 2: compute gaussian kernel

| | |
|--------------|---|
| For Loop | <pre>hc = height // 2 wc = width // 2 gaussian = np.zeros((height, width)) for i in range(height): for j in range(width): gaussian[i, j] = np.exp(-((i - hc)**2 + (j - wc)**2)/(2.0*sigma**2)) gaussian /= np.sum(gaussian)</pre> |
| Numpy Vector | <pre>hc = height // 2 wc = width // 2 grid = np.mgrid[-hc:hc+1, -wc:wc+1] # 2 x height x width gaussian = np.exp(-np.sum(grid**2, axis=0)/(2.0*sigma**2)) gaussian /= np.sum(gaussian)</pre> |

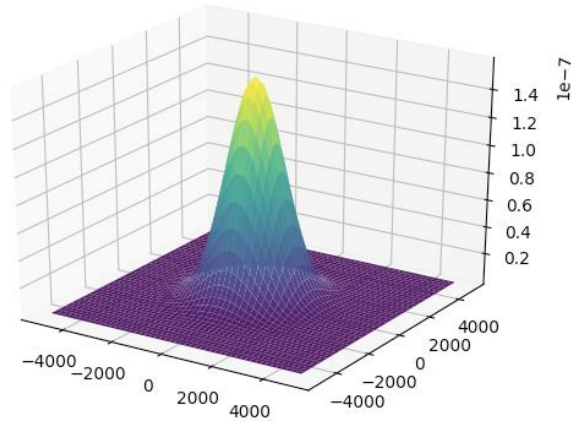
Vectorization

Example 2: compute gaussian kernel and plot

Height = width = 9999, sigma = 1000

For Loop: ~106s

Vectorization: ~12s



Other useful functions:

1. vector operations: inner product [`np.inner()`], outer product [`np.outer()`], cross product [`np.cross()`], matrix multiplication [`np.dot()`], matrix inverse [`np.linalg.inv()`]
 2. special matrices/vectors: `np.zeros()`, `np.ones()`, `np.identity()`, `np.linspace()`, `np.arange()`
 3. matrix reshaping: `np.reshape()`, `np.transpose()`
(`row_axis, column_axis, channel_axis`) → (`channel_axis, row_axis, column_axis`): `np.transpose(X, [2, 0, 1])`
1. statistics: `np.min()`, `np.max()`, `np.mean()`, `np.median()`, `np.sum()`
 2. logical arrays: `np.logical_and()`, `np.logical_or()`, `np.logical_not()`