CMPUT 328

Getting Started with Colab, Numpy and PyTorch

UNIVERSITY OF ALBERTA

Contents

- Google Colab
- Numpy
- Image Operations
- Pytorch

Google Colab

Google Colab

- Cloud based runtime environment for executing Python code
- Supports GPU, TPU and CPU acceleration
- VM like environment - allows installing python (pip) and non-python (apt) packages
- Jupyter Notebooks
    - Interactive python wrapper
    - Cells – code and markdown text
- Real time collaboration just like Google Docs
- Overview

Google Colab - Overview

Google Colab – Data Handling

Python Basics

Basic data types

Like most languages, Python has a number of basic types including integers, floats, booleans, and strings. These data types behave in ways that are familiar from other programming languages.

Numbers: Integers and floats work as you would expect from other languages:

```
x = 3
print(type(x)) # Prints "<class 'int'>"
print(x)       # Prints "3"
print(x + 1)   # Addition; prints "4"
print(x - 1)   # Subtraction; prints "2"
print(x * 2)   # Multiplication; prints "6"
print(x ** 2)  # Exponentiation; prints "9"
x += 1
print(x)  # Prints "4"
x *= 2
print(x)  # Prints "8"
y = 2.5
print(type(y)) # Prints "<class 'float'>"
print(y, y + 1, y * 2, y ** 2) # Prints "2.5 3.5 5.0 6.25"
```

Basic data types

Booleans: Python implements all of the usual operators for Boolean logic, but uses English words rather than symbols (`&&`, `||`, etc.):

```
t = True
f = False
print(type(t)) # Prints "<class 'bool'>"
print(t and f) # Logical AND; prints "False"
print(t or f)  # Logical OR; prints "True"
print(not t)   # Logical NOT; prints "False"
print(t != f)  # Logical XOR; prints "True"
```

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```

Basic data types

Strings: Python has great support for strings:

```
hello = 'hello'    # String literals can use single quotes
world = "world"    # or double quotes; it does not matter.
print(hello)       # Prints "hello"
print(len(hello))  # String length; prints "5"
hw = hello + ' ' + world  # String concatenation
print(hw)  # prints "hello world"
hw12 = '%s %s %d' % (hello, world, 12)  # sprintf style string formatting
print(hw12)  # prints "hello world 12"
```

String objects have a bunch of useful methods; for example:

```
s = "hello"
print(s.capitalize())  # Capitalize a string; prints "Hello"
print(s.upper())       # Convert a string to uppercase; prints "HELLO"
print(s.rjust(7))      # Right-justify a string, padding with spaces; prints "  hello'
print(s.center(7))     # Center a string, padding with spaces; prints " hello "
print(s.replace('l', '(ell)'))  # Replace all instances of one substring with another,
                                # prints "he(ell)(ell)o"
print('  world '.strip())  # Strip leading and trailing whitespace; prints "world"
```

Containers - List

Lists

A list is the Python equivalent of an array, but is resizeable and can contain elements of different types:

```python
xs = [3, 1, 2]    # Create a list
print(xs, xs[2])  # Prints "[3, 1, 2] 2"
print(xs[-1])     # Negative indices count from the end of the list; prints "2"
xs[2] = 'foo'     # Lists can contain elements of different types
print(xs)         # Prints "[3, 1, 'foo']"
xs.append('bar')  # Add a new element to the end of the list
print(xs)         # Prints "[3, 1, 'foo', 'bar']"
x = xs.pop()      # Remove and return the last element of the list
print(x, xs)      # Prints "bar [3, 1, 'foo']"
```

Containers – List Slicing

Slicing: In addition to accessing list elements one at a time, Python provides concise syntax to access sublists; this is known as *slicing*:

```
nums = list(range(5))     # range is a built-in function that creates a list of intege
print(nums)               # Prints "[0, 1, 2, 3, 4]"
print(nums[2:4])          # Get a slice from index 2 to 4 (exclusive); prints "[2, 3]'
print(nums[2:])           # Get a slice from index 2 to the end; prints "[2, 3, 4]"
print(nums[:2])           # Get a slice from the start to index 2 (exclusive); prints
print(nums[:])            # Get a slice of the whole list; prints "[0, 1, 2, 3, 4]"
print(nums[:-1])          # Slice indices can be negative; prints "[0, 1, 2, 3]"
nums[2:4] = [8, 9]        # Assign a new sublist to a slice
print(nums)               # Prints "[0, 1, 8, 9, 4]"
```

We will see slicing again in the context of numpy arrays.

Num skip between elements

Syntax:

a[start:end:step]

Inclusive
Start from
0

exclusive

Can be
negative
or
omitted

Negative start, end: returns the nth element from the right-hand side of the list

Omitted: start = 0, end = len(a), step=1

Containers – List Slicing

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```

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Syntax:

a[start:end:step]

Inclusive
Start from
0

exclusive

Can be
negative
or
omitted

Other examples:

Even index elements: a[::2]
Special case - reverse list: a[::-1]

Containers – List Looping

Loops: You can loop over the elements of a list like this:

```
animals = ['cat', 'dog', 'monkey']
for animal in animals:
    print(animal)
# Prints "cat", "dog", "monkey", each on its own line.
```

If you want access to the index of each element within the body of a loop, use the built-in `enumerate` function:

```
animals = ['cat', 'dog', 'monkey']
for idx, animal in enumerate(animals):
    print('#%d: %s' % (idx + 1, animal))
# Prints "#1: cat", "#2: dog", "#3: monkey", each on its own line
```

Containers – List Comprehension

List comprehensions: When programming, frequently we want to transform one type of data into another. As a simple example, consider the following code that computes square numbers:

```
nums = [0, 1, 2, 3, 4]
squares = []
for x in nums:
    squares.append(x ** 2)
print(squares)   # Prints [0, 1, 4, 9, 16]
```

You can make this code simpler using a **list comprehension**:

```
nums = [0, 1, 2, 3, 4]
squares = [x ** 2 for x in nums]
print(squares)   # Prints [0, 1, 4, 9, 16]
```

List comprehensions can also contain conditions:

```
nums = [0, 1, 2, 3, 4]
even_squares = [x ** 2 for x in nums if x % 2 == 0]
print(even_squares)  # Prints "[0, 4, 16]"
```

Container - Others

- Dictionary: Stores (key, value) pairs. A map from keys to values
- Set: unordered collection of distinct elements
- Tuple: immutable ordered list of values

Functions and Classes

The syntax for defining classes in Python is straightforward:

```python
class Greeter(object):

    # Constructor
    def __init__(self, name):
        self.name = name  # Create an instance variable

    # Instance method
    def greet(self, loud=False):
        if loud:
            print('HELLO, %s!' % self.name.upper())
        else:
            print('Hello, %s' % self.name)

g = Greeter('Fred')  # Construct an instance of the Greeter class
g.greet()            # Call an instance method; prints "Hello, Fred"
g.greet(loud=True)   # Call an instance method; prints "HELLO, FRED!"
```

Functions and Classes

Python functions are defined using the `def` keyword. For example:

```
def sign(x):
    if x > 0:
        return 'positive'
    elif x < 0:
        return 'negative'
    else:
        return 'zero'

for x in [-1, 0, 1]:
    print(sign(x))
# Prints "negative", "zero", "positive"
```

We will often define functions to take optional keyword arguments, like this:

```
def hello(name, loud=False):
    if loud:
        print('HELLO, %s!' % name.upper())
    else:
        print('Hello, %s' % name)

hello('Bob') # Prints "Hello, Bob"
hello('Fred', loud=True)  # Prints "HELLO, FRED!"
```

Numpy

Array

- Grid of values, all of the same type
- 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.

Array – Array Creation

- Initialize numpy array from list

  a = np.array([1, 2, 3], dtype=np.float32)

import numpy as np

- 2D, 3D,... array from nested list:

  b = np.array([[1, 2, 3],
  [4, 5, 6],
  [7, 8, 9]])

Array – Array Creation

- Other:
  - *np.zeros((4, 4), dtype=np.uint8)*
  - *np.ones*
  - *np.full*
  - *np.eye*
  - *np.random.random*
  - *np.ones_like*
  - *np.zeros_like*
  - *np.full_like*

Array Indexing – Integer Indexing

- Access elements using square bracket:

```
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"
```

Array Indexing - Integer indexing

You can specify which element of array A to access using 2, 3, 4 one dimensional arrays depending whether A is 2D, 3D, 4D... array

Example:

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

print(a[[0, 1, 2], [0, 1, 0]])

print(np.array([a[0, 0], a[1, 1], a[2, 0]]))

Array Indexing– Boolean Indexing

- Use a boolean array B that has the same shape as array A to index array A.
- A[B] $\rightarrow$ elements in A where the same location in B equal True will be indexed
- Example: Find all element in array A that is greater than 2 and assign them to -1:
  - *A[A > 2] = -1*

Array Indexing – Slicing

- Similar to python list
- For multidimensional array:
  - Specify a slice for each dimension
  - If a dimension is omitted, it gets all elements of that dimension
  - Rank of output array is the same as input array

Array Indexing – Slicing

```
import numpy as np

# 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]])

# Use slicing to pull out the subarray consisting of the first 2 rows
# and columns 1 and 2; b is the following array of shape (2, 2):
# [[2 3]
#  [6 7]]
b = a[:2, 1:3]

# A slice of an array is a view into the same data, so modifying it
# will modify the original array.
print(a[0, 1])   # Prints "2"
b[0, 0] = 77     # b[0, 0] is the same piece of data as a[0, 1]
print(a[0, 1])   # Prints "77"
```

Array Indexing – Slicing

Mixing integer indexing and slice indexing: For each integer indexing, rank of output matrix will be decreased by 1.

```
import numpy as np

# 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)"

# 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)"
```

Mixed indexing. Output will have shape (4)

Slice indexing. Output will have shape (1, 4)

Array Indexing – Ellipsis (…)

- Indexing with unknown number of dimensions
- Ellipsis indicates a **placeholder** for the rest of the array dimensions not specified
- Think of it as indicating the full slice [:] for all the dimensions in the gap it is placed
    - *a[..., 0]* : **3D →** *a[:, :, 0]*, **4D →** *a[:, :, :, 0]*
    - *a[0, ...]* : **3D →** *a[0, :, :]*, **4D →** *a[0, : , :, :]*
    - *a[0,...,0]* : **3D →** *a[0, :, 0]*, **4D →** *a[0, :, :, 0]*
    - *a[0,1,...,0]* : **4D →** *a[0, 1, :, 2]*, **5D →** *a[0, 1, :, :, 2]*
- ***n*D →** However many colons in the middle make up the full number of dimensions

Array Indexing – Exercise

- Create a 5×5 array of random numbers between 1 and 10 → *arr1*
- Create a $6 \times 6 \times 3$ array with all 1, 2 and 3 in the respective channels → *arr2*
- Extract a 4×4 block from the center of *arr1*
- Extract a 4×4 block from bottom right corner of channel 2 of *arr2*
- Add the two blocks in such a way that:
  - *arr1* gets modified
  - *arr2* gets modified
  - neither gets modified

Numpy data types

- *np.uint8*
- *np.int32*
- *np.int64*
- *np.float16*
- *np.float32*
- *np.float64*
- ...

Array Math

- +, -, *, /

A + B, A – B, A * B, A / B

- *np.add*, *np.subtract*, *np.multiply*, *np.divide*
- All are element-wise operations
- For matrix multiplication, use *np.dot* *or* *np.matmul*:

A.dot(B)

np.dot(A, B)

np.matmul(A, B)

Array Math

- Other unary operations: sum, max, min, transpose...
- Can specify axis for some operations

Numpy provides many useful functions for performing computations on arrays; one of the most useful is `sum`:

```
import numpy as np

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]"
```

```
import numpy as np

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

Array Broadcasting

- Powerful mechanism that allows numpy to work with arrays of different shapes when performing arithmetic operations

Broadcasting two arrays together follows these 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

Array Broadcasting

- Example 1:

  image = np.random.random((400, 400, 3))

  means = np.asarray([0.1, 0.2, 0.3])

  print(image - means)

  – Shape of *image*: (400, 400, 3)

  – Shape of *means*: (1, 1, 3) ← (3)

  – Broadcasted *means*: (400, 400, 3)

  – Broadcasted *means* will have

    – [:, :, 0] = 0.1

    – [:, :, 1] = 0.2

    – [:, :, 3] = 0.3

Array Broadcasting

- Example 2:

```
>>> x = np.array([[1, 1, 1]])
>>> y = np.array([[1], [1], [1]])
>>> x.shape
(1, 3)
>>> y.shape
(3, 1)
>>> x - y
array([[0, 0, 0],
       [0, 0, 0],
       [0, 0, 0]])
```

Be careful! This can cause unnoticeable bugs in your code

Array Broadcasting – Exercise

- Create a 5×1 array of random numbers → *arr3*
- Add *arr3* to each column of *arr1*
- Subtract *arr3* from each row of *arr1*
- Reset *arr2* to its original state in a single statement
- Create a 3×3 array of all 2s → *arr4*
- Use *arr4* to add 2, 4, 6 and 8 respectively to the top left, top right, bottom right and bottom left 3×3 corners of *arr2*

Image operations

Image operations - Libraries

- **OpenCV**
  - Implemented in C++
  - Faster, more powerful and better documented
  - Slightly more buggy / less supported
  - Stores images as BGR

- **scikit-image**
  - Implemented in Python and Cython
  - Easier to use

Image operations - Read, Write, Resize

- **OpenCV**

```
import cv2
im = cv2.imread('image.jpg')
im_resized = cv2.resize(im, dsize=(0,0), fx=4, fy=4)
cv2.imwrite("im_resized.jpg", im_resized)
```

- **skimage**

```
from skimage.io import imread, imsave
from skimage.transform import resize
im = imread('image.jpg')
im_resized = resize(im, output_shape=(500, 500))
imsave("im_resized.jpg", im_resized)
```

Image operations - Show

- **OpenCV**

  # import cv2

  *# **cv2.imshow**("image", im) → causes Jupyter to crash*

  from google.colab.patches import cv2_imshow

  cv2_imshow(*im*)

- **skimage / matplotlib**

  import matplotlib.pyplot as plt

  from skimage.io import imshow

  plt.imshow(im)

  imshow(im)

Image operations - Filter

- **OpenCV**

```
import cv2
im_sobel = cv2.Sobel(im)
im_median = cv2.GaussianBlur(im)
im_median = cv2.medianBlur(im)
```

- **skimage**

```
from skimage.filters import sobel, gaussian, median
im_sobel = sobel(im)
im_gauss = gaussian(im, sigma=3)
im_median = median(im)
```

Image operations - Exercise

- Download an image from internet or use an existing image
- Upload it to Google Drive
- Mount your Google Drive and authorize
- List the contents of your Google Drive to figure out the path to that image
- Read that image and show it
- Resize it to double its original size
- Apply Sobel filtering to the resized image
- Show the resized and filtered images
- Save the resized and filtered images to Google Drive
- Download the image and open it locally

PyTorch

Overview

Numpy Interoperability

- Pytorch arrays → **tensors**
- *From Numpy:*

  import torch

  *tensor = torch.**from_numpy**(np_arr)*

  tensor = torch.tensor(np_arr)
- To numpy:
  - *np_arr = cpu_tensor.numpy()*
  - *np_arr = gpu_tensor.cpu().numpy()*
  - *np_arr = tensor_with_grad.detach().cpu().numpy()*

Running on Different Devices

- GPU:

  device = torch.device("cuda“)

  gpu_tensor = torch.tensor(np_arr, dtype=torch.float, device=device)

  gpu_tensor = tensor.to(device)

- Second GPU:

  device = torch.device("cuda:1“)

- CPU:

  device = torch.device(“cpu“)

- TPUs currently not supported

Basic operations

Close parallel with numpy functions

np.zeros → *torch.zeros*

np.ones → *torch.ones*

np.add → *torch.add*

np.matmul → *torch.matmul*

np.random.rand → *torch.rand*

Broadcasting

- Many operations support Numpy rules
- Two tensors are broadcastable if following rules hold:
  - Each tensor has at least one dimension.
  - When iterating over the dimension sizes, starting at the trailing dimension, the dimension sizes must either be equal, one of them is 1, or one of them does not exist.

Broadcasting - Examples

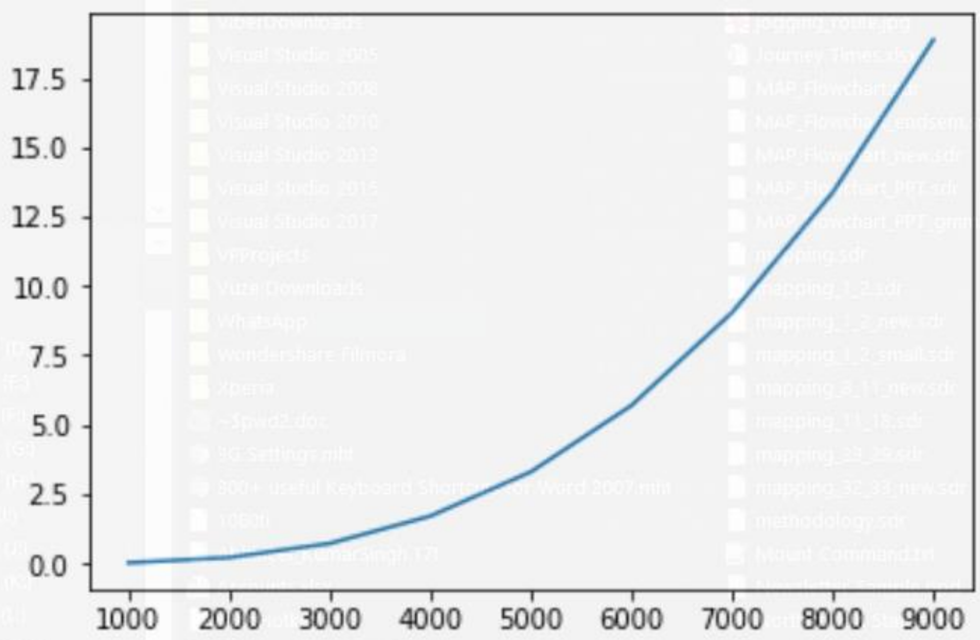
```
>>> x=torch.empty(5,7,3)
>>> y=torch.empty(5,7,3)
# same shapes are always broadcastable (i.e. the above rules always hold)

>>> x=torch.empty((0,))
>>> y=torch.empty(2,2)
# x and y are not broadcastable, because x does not have at least 1 dimension

# can line up trailing dimensions
>>> x=torch.empty(5,3,4,1)
>>> y=torch.empty(  3,1,1)
# x and y are broadcastable.
# 1st trailing dimension: both have size 1
# 2nd trailing dimension: y has size 1
# 3rd trailing dimension: x size == y size
# 4th trailing dimension: y dimension doesn't exist

# but:
>>> x=torch.empty(5,2,4,1)
>>> y=torch.empty(  3,1,1)
# x and y are not broadcastable, because in the 3rd trailing dimension 2 != 3
```

PyTorch– Exercise

- Create two 1000×1000 tensors filled with random numbers
- Multiply them together on GPU and CPU in turn and compare times
- Increase tensor size and see how the relative times change

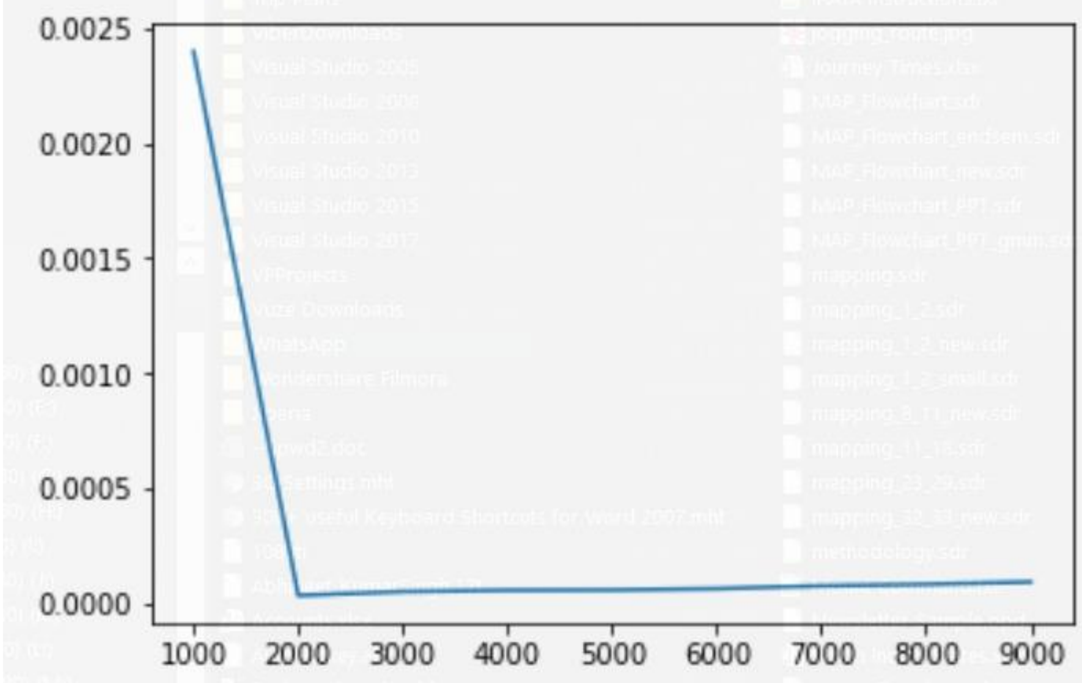
PyTorch – Training on CPU

```
Training on CPU
tensor_size: 1000        time_per_run: 0.027797651290893555 sec
tensor_size: 2000        time_per_run: 0.217865228652954l sec
tensor_size: 3000        time_per_run: 0.7244607925415039 sec
tensor_size: 4000        time_per_run: 1.710223913192749 sec
tensor_size: 5000        time_per_run: 3.3055325508117677 sec
tensor_size: 6000        time_per_run: 5.694778609275818 sec
tensor_size: 7000        time_per_run: 9.0444904088974 sec
tensor_size: 8000        time_per_run: 13.364873147010803 sec
tensor_size: 9000        time_per_run: 18.858213233947755 sec
[<matplotlib.lines.Line2D at 0x7f3cb9b66908>]
```



PyTorch – Training on GPU

```
Training on GPU: Tesla K80
tensor_size: 1000        time_per_run: 0.002401423454284668 sec
tensor_size: 2000        time_per_run: 3.24249267578125e-05 sec
tensor_size: 3000        time_per_run: 4.935264587402344e-05 sec
tensor_size: 4000        time_per_run: 5.507469177246094e-05 sec
tensor_size: 5000        time_per_run: 5.614757537841797e-05 sec
tensor_size: 6000        time_per_run: 6.191730499267578e-05 sec
tensor_size: 7000        time_per_run: 7.419586181640625e-05 sec
tensor_size: 8000        time_per_run: 8.080005645751953e-05 sec
tensor_size: 9000        time_per_run: 9.114742279052735e-05 sec
[<matplotlib.lines.Line2D at 0x7fb9aa727a58>]
```



Torchvision

- "popular datasets, model architectures, and common image transformations for computer vision"
- torchvision.transforms, torchvision.transforms.functional
- Combine transforms*:* *Compose*
- Cropping: *CenterCrop*,
- Conversion: *Grayscale*
- Size change: *Pad*, *Resize*
- Augmentation: *RandomCrop*, *RandomAffine*, *RandomHorizontalFlip*, *RandomRotation*

TensorBoardX

- **Installation**

  !pip install tensorboardX

- **Basic use**

from tensorboardX import SummaryWriter

*writer = **SummaryWriter**(logdir=dir_path)*

*writer.**add_scalar**('train/total_loss', loss, iteration)*

- **Advanced use**

*writer.**add_scalars**, writer.**add_image**, writer.**add_text**, writer.**add_histogram**, writer.**add_pr_curve**, writer.**add_audio***

TensorBoardX – YOLO Example

```
lxy, lwh, lconf, lcls, _loss = loss_items.cpu().numpy()
_iter = i + (nb - 1) * epoch
writer.add_scalar('train/total_loss', _loss, _iter)
writer.add_scalar('train/xy_loss', lxy, _iter)
writer.add_scalar('train/wh_loss', lwh, _iter)
writer.add_scalar('train/conf_loss', lconf, _iter)
writer.add_scalar('train/class_loss', lcls, _iter)
writer.add_scalar('train/mean_loss', mloss[-1], _iter)
```

Thanks !