pytorch_tutorial

April 3, 2024

1 ITE4052 Assignment 2-1: PyTorch Tutorial

- This material draws from EECS 498-007/598-005 (Justin Johnson)

Before we start, please put your name and HYID in following format Firstname LASTNAME, #00000000 // e.g.) Sukmin Yun, #12345678

Your Answer:
Junwoo Park, #2021006253

2 Setup Code

Before getting started we need to run some boilerplate code to set up our environment. You'll need to rerun this setup code each time you start the notebook.

First, run this cell load the autoreload extension. This allows us to edit `.py` source files, and re-import them into the notebook for a seamless editing and debugging experience.

[1]:
```
%load_ext autoreload
%autoreload 2
```

2.0.1 Google Colab Setup

Next we need to run a few commands to set up our environment on Google Colab. If you are running this notebook on a local machine you can skip this section.

Run the following cell to mount your Google Drive. Follow the link, sign in to your Google account (the same account you used to store this notebook!) and copy the authorization code into the text box that appears below.

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Now recall the path in your Google Drive where you uploaded this notebook, fill it in below. If everything is working correctly then running the folowing cell should print the filenames from the assignment:

```
['pytorch_tutorial.py', 'knn.py', 'knn.ipynb', 'ite4052', 'pytorch_tutorial.ipynb']
```

```
[3]: import os

     # TODO: Fill in the Google Drive path where you uploaded the assignment
     # Example: If you create a ITE4052 folder and put all the files under A2␣
      ↪folder, then 'ITE4052/A2'
     # GOOGLE_DRIVE_PATH_AFTER_MYDRIVE = 'ITE4052/A2'
     GOOGLE_DRIVE_PATH_AFTER_MYDRIVE = 'ITE4052/A2'
     GOOGLE_DRIVE_PATH = os.path.join('drive', 'My Drive',␣
      ↪GOOGLE_DRIVE_PATH_AFTER_MYDRIVE)
     print(os.listdir(GOOGLE_DRIVE_PATH))
```

```
['makepdf.py', 'collectSubmission.sh', 'ite4052', '__pycache__', 'knn.ipynb',
'pytorch_tutorial.py', 'knn.py', 'pytorch_tutorial.ipynb']
```

Once you have successfully mounted your Google Drive and located the path to this assignment, run the following cell to allow us to import from the `.py` files of this assignment. If it works correctly, it should print the message:

```
Hello from pytorch_tutorial.py!
```

as well as the last edit time for the file `pytorch_tutorial.py`.

```
[4]: import sys
     sys.path.append(GOOGLE_DRIVE_PATH)

     import time, os
     os.environ["TZ"] = "US/Eastern"
     time.tzset()

     from pytorch_tutorial import hello
     hello()

     pytorch_tutorial_path = os.path.join(GOOGLE_DRIVE_PATH, 'pytorch_tutorial.py')
     pytorch_tutorial_edit_time = time.ctime(os.path.getmtime(pytorch_tutorial_path))
     print('pytorch_tutorial.py last edited on %s' % pytorch_tutorial_edit_time)
```

```
Hello from pytorch_tutorial.py!
pytorch_tutorial.py last edited on Wed Apr  3 04:10:47 2024
```

3 Introduction

Python 3 and PyTorch will be used throughout the semseter, so it is important to be familiar with them. This material in this notebook draws from the Stanford CS231n and CS228 Python and numpy tutorials, but this material focuses mainly on PyTorch.

This notebook will walk you through many of the important features of PyTorch that you will need to use throughout the semester. In some cells and files you will see code blocks that look like this:

```
##############################################################################
#                     TODO: Write the equation for a line                    #
```

```
################################################################################
pass
################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

You should replace the pass statement with your own code and leave the blocks intact, like this:

```
################################################################################
#                    TODO: Write the equation for a line                       #
################################################################################
y = m * x + b
################################################################################
#                              END OF YOUR CODE                                #
################################################################################
```

When completing the notebook, please adhere to the following rules: - Do not write or modify any code outside of code blocks - Do not add or delete any cells from the notebook. You may add new cells to perform scatch work, but delete them before submitting. - Run all cells before submitting. **You will only get credit for code that has been run!**.

The last point is extremely important and bears repeating:

3.0.1 We will not re-run your notebook – you will only get credit for cells that have been run

This notebook contains many inline sanity checks for the code you write. However, **passing these sanity checks does not mean your code is correct!** During grading we may run your code on additional inputs, and we may look at your code to make sure you've followed the specific guildelines for each implementation. You are encouraged to write additional test cases for the functions you are asked to write instead of solely relying on the sanity checks in the notebook.

4 Python 3

If you're unfamiliar with Python 3, here are some of the most common changes from Python 2 to look out for.

4.0.1 Print is a function

[5]:
```
print("Hello!")
```

```
Hello!
```

Without parentheses, printing will not work.

4.0.2 Floating point division by default

[6]:
```
5 / 2
```

[6]:
```
2.5
```

To do integer division, we use two backslashes:

```
[7]: 5 // 2
```

```
[7]: 2
```

4.0.3 No xrange

The xrange from Python 2 is now merged into "range" for Python 3 and there is no xrange in Python 3. In Python 3, range(3) does not create a list of 3 elements as it would in Python 2, rather just creates a more memory efficient iterator.

Hence,
xrange in Python 3: Does not exist
range in Python 3: Has very similar behavior to Python 2's xrange

```
[8]: for i in range(3):
         print(i)
```

```
0
1
2
```

```
[9]: range(3)
```

```
[9]: range(0, 3)
```

```
[10]: # If need be, can use the following to get a similar behavior to Python 2's␣
       ↪range:
      print(list(range(3)))
```

```
[0, 1, 2]
```

5 PyTorch

PyTorch is an open source machine learning framework. At its core, PyTorch provides a few key features:

- A multidimensional **Tensor** object, similar to numpy but with GPU accelleration.
- An optimized **autograd** engine for automatically computing derivatives
- A clean, modular API for building and deploying **deep learning models**

We will use PyTorch for all programming assignments throughout the semester. This notebook will focus on the **Tensor API**, as it is the main part of PyTorch that we will use for the first few assignments.

You can find more information about PyTorch by following one of the oficial tutorials or by reading the documentation.

To use PyTorch, we first need to import the `torch` package.

We also check the version; the assignments in this course will use PyTorch verion 1.10.0, since this is the default version in Google Colab.

[11]:
```
import torch
print(torch.__version__)
```

```
2.2.1+cu121
```

5.1 Tensor Basics

5.1.1 Creating and Accessing tensors

A `torch` **tensor** is a multidimensional 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 tensor; the **shape** of a tensor is a tuple of integers giving the size of the array along each dimension.

We can initialize `torch` tensor from nested Python lists. We can access or mutate elements of a PyTorch tensor using square brackets.

Accessing an element from a PyTorch tensor returns a PyTorch scalar; we can convert this to a Python scalar using the `.item()` method:

[12]:
```
# Create a rank 1 tensor from a Python list
a = torch.tensor([1, 2, 3])
print('Here is a:')
print(a)
print('type(a): ', type(a))
print('rank of a: ', a.dim())
print('a.shape: ', a.shape)

# Access elements using square brackets
print()
print('a[0]: ', a[0])
print('type(a[0]): ', type(a[0]))
print('type(a[0].item()): ', type(a[0].item()))

# Mutate elements using square brackets
a[1] = 10
print()
print('a after mutating:')
print(a)
```

```
Here is a:
tensor([1, 2, 3])
type(a):  <class 'torch.Tensor'>
rank of a:  1
a.shape:  torch.Size([3])

a[0]:  tensor(1)
type(a[0]):  <class 'torch.Tensor'>
type(a[0].item()):  <class 'int'>

a after mutating:
tensor([ 1, 10,  3])
```

The example above shows a one-dimensional tensor; we can similarly create tensors with two or more dimensions:

[13]:
```python
# Create a two-dimensional tensor
b = torch.tensor([[1, 2, 3], [4, 5, 5]])
print('Here is b:')
print(b)
print('rank of b:', b.dim())
print('b.shape: ', b.shape)

# Access elements from a multidimensional tensor
print()
print('b[0, 1]:', b[0, 1])
print('b[1, 2]:', b[1, 2])

# Mutate elements of a multidimensional tensor
b[1, 1] = 100
print()
print('b after mutating:')
print(b)
```

```
Here is b:
tensor([[1, 2, 3],
        [4, 5, 5]])
rank of b: 2
b.shape:  torch.Size([2, 3])

b[0, 1]: tensor(2)
b[1, 2]: tensor(5)

b after mutating:
tensor([[  1,   2,   3],
        [  4, 100,   5]])
```

Now it's **your turn**. In the file `pytorch_tutorial.py`, complete the implementation of the functions `create_sample_tensor`, `mutate_tensor`, and `count_tensor_elements` to practice constructing, mutating, and thinking about the shapes of tensors.

[14]:
```python
from pytorch_tutorial import create_sample_tensor, mutate_tensor,␣
 ↪count_tensor_elements

# Create a sample tensor
x = create_sample_tensor()
print('Here is the sample tensor:')
print(x)

# Mutate the tensor by setting a few elements
indices = [(0, 0), (1, 0), (1, 1)]
values = [4, 5, 6]
mutate_tensor(x, indices, values)
print('\nAfter mutating:')
print(x)
print('\nCorrect shape: ', x.shape == (3, 2))
print('x[0, 0] correct: ', x[0, 0].item() == 4)
print('x[1, 0] correct: ', x[1, 0].item() == 5)
print('x[1, 1] correct: ', x[1, 1].item() == 6)

# Check the number of elements in the sample tensor
num = count_tensor_elements(x)
print('\nNumber of elements in x: ', num)
print('Correctly counted: ', num == 6)
```

```
Here is the sample tensor:
tensor([[  0,  10],
        [100,   0],
        [  0,   0]])

After mutating:
tensor([[ 4, 10],
        [ 5,  6],
        [ 0,  0]])

Correct shape:  True
x[0, 0] correct:  True
x[1, 0] correct:  True
x[1, 1] correct:  True

Number of elements in x:  6
Correctly counted:  True
```

5.1.2 Tensor constructors

PyTorch provides many convenience methods for constructing tensors; this avoids the need to use Python lists, which can be inefficient when manipulating large amounts of data. Some of the most commonly used tensor constructors are:

- `torch.zeros`: Creates a tensor of all zeros
- `torch.ones`: Creates a tensor of all ones
- `torch.rand`: Creates a tensor with uniform random numbers

You can find a full list of tensor creation operations in the documentation.

[15]:
```python
# Create a tensor of all zeros
a = torch.zeros(2, 3)
print('tensor of zeros:')
print(a)

# Create a tensor of all ones
b = torch.ones(1, 2)
print('\ntensor of ones:')
print(b)

# Create a 3x3 identity matrix
c = torch.eye(3)
print('\nidentity matrix:')
print(c)

# Tensor of random values
d = torch.rand(4, 5)
print('\nrandom tensor:')
print(d)
```

```
tensor of zeros:
tensor([[0., 0., 0.],
        [0., 0., 0.]])

tensor of ones:
tensor([[1., 1.]])

identity matrix:
tensor([[1., 0., 0.],
        [0., 1., 0.],
        [0., 0., 1.]])

random tensor:
tensor([[0.2685, 0.1378, 0.4314, 0.5431, 0.9150],
        [0.9099, 0.0242, 0.0952, 0.6125, 0.7767],
        [0.4783, 0.0181, 0.4891, 0.8238, 0.6290],
        [0.1349, 0.6485, 0.9199, 0.6290, 0.6474]])
```

Your turn: In the file `pytorch_tutorial.py`, complete the implementation of `create_tensor_of_pi` to practice using a tensor constructor.

Hint: `torch.full`

[16]:
```python
from pytorch_tutorial import create_tensor_of_pi

x = create_tensor_of_pi(4, 5)

print('x is a tensor:', torch.is_tensor(x))
print('x has correct shape: ', x.shape == (4, 5))
print('x is filled with pi: ', (x == 3.14).all().item() == 1)
```

```
x is a tensor: True
x has correct shape:  True
x is filled with pi:  True
```

5.1.3 Datatypes

In the examples above, you may have noticed that some of our tensors contained floating-point values, while others contained integer values.

PyTorch provides a large set of numeric datatypes that you can use to construct tensors. PyTorch tries to guess a datatype when you create a tensor; functions that construct tensors typically have a `dtype` argument that you can use to explicitly specify a datatype.

Each tensor has a `dtype` attribute that you can use to check its data type:

[17]:
```
# Let torch choose the datatype
x0 = torch.tensor([1, 2])   # List of integers
x1 = torch.tensor([1., 2.]) # List of floats
x2 = torch.tensor([1., 2])  # Mixed list
print('dtype when torch chooses for us:')
print('List of integers:', x0.dtype)
print('List of floats:', x1.dtype)
print('Mixed list:', x2.dtype)

# Force a particular datatype
y0 = torch.tensor([1, 2], dtype=torch.float32)  # 32-bit float
y1 = torch.tensor([1, 2], dtype=torch.int32)    # 32-bit (signed) integer
y2 = torch.tensor([1, 2], dtype=torch.int64)    # 64-bit (signed) integer
print('\ndtype when we force a datatype:')
print('32-bit float: ', y0.dtype)
print('32-bit integer: ', y1.dtype)
print('64-bit integer: ', y2.dtype)

# Other creation ops also take a dtype argument
z0 = torch.ones(1, 2)  # Let torch choose for us
z1 = torch.ones(1, 2, dtype=torch.int16) # 16-bit (signed) integer
z2 = torch.ones(1, 2, dtype=torch.uint8) # 8-bit (unsigned) integer
print('\ntorch.ones with different dtypes')
print('default dtype:', z0.dtype)
print('16-bit integer:', z1.dtype)
print('8-bit unsigned integer:', z2.dtype)
```

```
dtype when torch chooses for us:
List of integers: torch.int64
List of floats: torch.float32
Mixed list: torch.float32
```

```
dtype when we force a datatype:
32-bit float:  torch.float32
32-bit integer:  torch.int32
64-bit integer:  torch.int64

torch.ones with different dtypes
default dtype: torch.float32
16-bit integer: torch.int16
8-bit unsigned integer: torch.uint8
```

We can **cast** a tensor to another datatype using the `.to()` method; there are also convenience methods like `.float()` and `.long()` that cast to particular datatypes:

[18]:
```
x0 = torch.eye(3, dtype=torch.int64)
x1 = x0.float()  # Cast to 32-bit float
x2 = x0.double() # Cast to 64-bit float
x3 = x0.to(torch.float32) # Alternate way to cast to 32-bit float
x4 = x0.to(torch.float64) # Alternate way to cast to 64-bit float
print('x0:', x0.dtype)
print('x1:', x1.dtype)
print('x2:', x2.dtype)
print('x3:', x3.dtype)
print('x4:', x4.dtype)
```

```
x0: torch.int64
x1: torch.float32
x2: torch.float64
x3: torch.float32
x4: torch.float64
```

PyTorch provides several ways to create a tensor with the same datatype as another tensor:

- PyTorch provides tensor constructors such as `torch.zeros_like()` that create new tensors with the same shape and type as a given tensor
- Tensor objects have instance methods such as `.new_zeros()` that create tensors the same type but possibly different shapes
- The tensor instance method `.to()` can take a tensor as an argument, in which case it casts to the datatype of the argument.

[19]:
```
x0 = torch.eye(3, dtype=torch.float64)  # Shape (3, 3), dtype torch.float64
x1 = torch.zeros_like(x0)               # Shape (3, 3), dtype torch.float64
x2 = x0.new_zeros(4, 5)                 # Shape (4, 5), dtype torch.float64
x3 = torch.ones(6, 7).to(x0)            # Shape (6, 7), dtype torch.float64)
print('x0 shape is %r, dtype is %r' % (x0.shape, x0.dtype))
print('x1 shape is %r, dtype is %r' % (x1.shape, x1.dtype))
print('x2 shape is %r, dtype is %r' % (x2.shape, x2.dtype))
print('x3 shape is %r, dtype is %r' % (x3.shape, x3.dtype))
```

```
x0 shape is torch.Size([3, 3]), dtype is torch.float64
```

```
x1 shape is torch.Size([3, 3]), dtype is torch.float64
x2 shape is torch.Size([4, 5]), dtype is torch.float64
x3 shape is torch.Size([6, 7]), dtype is torch.float64
```

Your turn: In the file `pytorch_tutorial.py`, implement the function `multiples_of_ten` which should create and return a tensor of dtype `torch.float64` containing all the multiples of ten in a given range.

Hint: `torch.arange`

[20]:
```
from pytorch_tutorial import multiples_of_ten

start = 5
stop = 25
x = multiples_of_ten(start, stop)
print('Correct dtype: ', x.dtype == torch.float64)
print('Correct shape: ', x.shape == (2,))
print('Correct values: ', x.tolist() == [10, 20])

# If there are no multiples of ten in the given range you should return an␣
 ↪empty tensor
start = 5
stop = 7
x = multiples_of_ten(start, stop)
print('\nCorrect dtype: ', x.dtype == torch.float64)
print('Correct shape: ', x.shape == (0,))
```

```
Correct dtype:  True
Correct shape:  True
Correct values:  True

Correct dtype:  True
Correct shape:  True
```

Even though PyTorch provides a large number of numeric datatypes, the most commonly used datatypes are:

- `torch.float32`: Standard floating-point type; used to store learnable parameters, network activations, etc. Nearly all arithmetic is done using this type.
- `torch.int64`: Typically used to store indices
- `torch.bool`: Stores boolean values: 0 is false and 1 is true
- `torch.float16`: Used for mixed-precision arithmetic, usually on NVIDIA GPUs with tensor cores. You won't need to worry about this datatype in this course.

5.2 Tensor indexing

We have already seen how to get and set individual elements of PyTorch tensors. PyTorch also provides many other ways of indexing into tensors. Getting comfortable with these different options makes it easy to modify different parts of tensors with ease.

5.2.1 Slice indexing

Similar to Python lists and numpy arrays, PyTorch tensors can be **sliced** using the syntax `start:stop` or `start:stop:step`. The `stop` index is always non-inclusive: it is the first element not to be included in the slice.

Start and stop indices can be negative, in which case they count backward from the end of the tensor.

[21]:
```
a = torch.tensor([0, 11, 22, 33, 44, 55, 66])
print(0, a)        # (0) Original tensor
print(1, a[2:5])   # (1) Elements between index 2 and 5
print(2, a[2:])    # (2) Elements after index 2
print(3, a[:5])    # (3) Elements before index 5
print(4, a[:])     # (4) All elements
print(5, a[1:5:2]) # (5) Every second element between indices 1 and 5
print(6, a[:-1])   # (6) All but the last element
print(7, a[-4::2]) # (7) Every second element, starting from the fourth-last
```

```
0 tensor([ 0, 11, 22, 33, 44, 55, 66])
1 tensor([22, 33, 44])
2 tensor([22, 33, 44, 55, 66])
3 tensor([ 0, 11, 22, 33, 44])
4 tensor([ 0, 11, 22, 33, 44, 55, 66])
5 tensor([11, 33])
6 tensor([ 0, 11, 22, 33, 44, 55])
7 tensor([33, 55])
```

For multidimensional tensors, you can provide a slice or integer for each dimension of the tensor in order to extract different types of subtensors:

[22]:
```
# Create the following rank 2 tensor with shape (3, 4)
# [[ 1  2  3  4]
#  [ 5  6  7  8]
#  [ 9 10 11 12]]
a = torch.tensor([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
print('Original tensor:')
print(a)
print('shape: ', a.shape)

# Get row 1, and all columns.
print('\nSingle row:')
print(a[1, :])
print(a[1])  # Gives the same result; we can omit : for trailing dimensions
print('shape: ', a[1].shape)

print('\nSingle column:')
print(a[:, 1])
print('shape: ', a[:, 1].shape)
```

```
# Get the first two rows and the last three columns
print('\nFirst two rows, last two columns:')
print(a[:2, -3:])
print('shape: ', a[:2, -3:].shape)

# Get every other row, and columns at index 1 and 2
print('\nEvery other row, middle columns:')
print(a[::2, 1:3])
print('shape: ', a[::2, 1:3].shape)
```

```
Original tensor:
tensor([[ 1,  2,  3,  4],
        [ 5,  6,  7,  8],
        [ 9, 10, 11, 12]])
shape:  torch.Size([3, 4])

Single row:
tensor([5, 6, 7, 8])
tensor([5, 6, 7, 8])
shape:  torch.Size([4])

Single column:
tensor([ 2,  6, 10])
shape:  torch.Size([3])

First two rows, last two columns:
tensor([[2, 3, 4],
        [6, 7, 8]])
shape:  torch.Size([2, 3])

Every other row, middle columns:
tensor([[ 2,  3],
        [10, 11]])
shape:  torch.Size([2, 2])
```

There are two common ways to access a single row or column of a tensor: using an integer will reduce the rank by one, and using a length-one slice will keep the same rank. Note that this is different behavior from MATLAB.

[23]:
```
# Create the following rank 2 tensor with shape (3, 4)
a = torch.tensor([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
print('Original tensor')
print(a)

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('\nTwo ways of accessing a single row:')
print(row_r1, row_r1.shape)
print(row_r2, row_r2.shape)

# We can make the same distinction when accessing columns:
col_r1 = a[:, 1]
col_r2 = a[:, 1:2]
print('\nTwo ways of accessing a single column:')
print(col_r1, col_r1.shape)
print(col_r2, col_r2.shape)
```

```
Original tensor
tensor([[ 1,  2,  3,  4],
        [ 5,  6,  7,  8],
        [ 9, 10, 11, 12]])

Two ways of accessing a single row:
tensor([5, 6, 7, 8]) torch.Size([4])
tensor([[5, 6, 7, 8]]) torch.Size([1, 4])

Two ways of accessing a single column:
tensor([ 2,  6, 10]) torch.Size([3])
tensor([[ 2],
        [ 6],
        [10]]) torch.Size([3, 1])
```

Slicing a tensor returns a **view** into the same data, so modifying it will also modify the original tensor. To avoid this, you can use the `clone()` method to make a copy of a tensor.

[24]:
```
# Create a tensor, a slice, and a clone of a slice
a = torch.tensor([[1, 2, 3, 4], [5, 6, 7, 8]])
b = a[0, 1:]
c = a[0, 1:].clone()
print('Before mutating:')
print(a)
print(b)
print(c)

a[0, 1] = 20  # a[0, 1] and b[0] point to the same element
b[1] = 30     # b[1] and a[0, 2] point to the same element
c[2] = 40     # c is a clone, so it has its own data
print('\nAfter mutating:')
print(a)
print(b)
print(c)

print(a.storage().data_ptr() == c.storage().data_ptr())
```

```
Before mutating:
```

```
tensor([[1, 2, 3, 4],
        [5, 6, 7, 8]])
tensor([2, 3, 4])
tensor([2, 3, 4])

After mutating:
tensor([[ 1, 20, 30,  4],
        [ 5,  6,  7,  8]])
tensor([20, 30,  4])
tensor([ 2,  3, 40])
False
```

```
<ipython-input-24-ebe253bfaff2>:18: UserWarning: TypedStorage is deprecated. It
will be removed in the future and UntypedStorage will be the only storage class.
This should only matter to you if you are using storages directly.  To access
UntypedStorage directly, use tensor.untyped_storage() instead of
tensor.storage()
  print(a.storage().data_ptr() == c.storage().data_ptr())
```

Your turn: In the file `pytorch_tutorial.py`, implement the function `slice_indexing_practice` to practice indexing tensors with different types of slices.

[25]:
```
# We will use this helper function to check your results
def check(orig, actual, expected):
    if not torch.is_tensor(actual):
        return False
    expected = torch.tensor(expected)
    same_elements = (actual == expected).all().item()
    same_storage = (orig.storage().data_ptr() == actual.storage().data_ptr())
    return same_elements and same_storage
```

[26]:
```
from pytorch_tutorial import slice_indexing_practice

# Create the following rank 2 tensor of shape (3, 5)
# [[ 1  2  3  4  5]
#  [ 6  7  8  9 10]
#  [11 12 13 14 15]]
x = torch.tensor([[1, 2, 3, 4, 5], [6, 7, 8, 8, 10], [11, 12, 13, 14, 15]])
out = slice_indexing_practice(x)

last_row = out[0]
print('last_row:')
print(last_row)
correct = check(x, last_row, [11, 12, 13, 14, 15])
print('Correct: %r\n' % correct)

third_col = out[1]
print('third_col:')
print(third_col)
correct = check(x, third_col, [[3], [8], [13]])
print('Correct: %r\n' % correct)

first_two_rows_three_cols = out[2]
print('first_two_rows_three_cols:')
print(first_two_rows_three_cols)
correct = check(x, first_two_rows_three_cols, [[1, 2, 3], [6, 7, 8]])
print('Correct: %r\n' % correct)

even_rows_odd_cols = out[3]
print('even_rows_odd_cols:')
print(even_rows_odd_cols)
correct = check(x, even_rows_odd_cols, [[2, 4], [12, 14]])
print('Correct: %r\n' % correct)
```

```
last_row:
tensor([11, 12, 13, 14, 15])
Correct: True

third_col:
tensor([[ 3],
        [ 8],
        [13]])
Correct: True

first_two_rows_three_cols:
tensor([[1, 2, 3],
        [6, 7, 8]])
Correct: True

even_rows_odd_cols:
tensor([[ 2,  4],
        [12, 14]])
Correct: True
```

So far we have used slicing to **access** subtensors; we can also use slicing to **modify** subtensors by writing assignment expressions where the left-hand side is a slice expression, and the right-hand side is a constant or a tensor of the correct shape:

[27]:
```
a = torch.zeros(2, 4, dtype=torch.int64)
a[:, :2] = 1
a[:, 2:] = torch.tensor([[2, 3], [4, 5]])
print(a)
```

```
tensor([[1, 1, 2, 3],
        [1, 1, 4, 5]])
```

Your turn: in the file `pytorch_tutorial.py`, implement the function `slice_assignment_practice` to practice modifying tensors with slicing assignment statements.

This function should use slicing assignment operations to modify the first four rows and first six columns of the input tensor so they are equal to

$$\begin{bmatrix} 0 & 1 & 2 & 2 & 2 & 2 \\ 0 & 1 & 2 & 2 & 2 & 2 \\ 3 & 4 & 3 & 4 & 5 & 5 \\ 3 & 4 & 3 & 4 & 5 & 5 \end{bmatrix}$$

Your implementation must obey the following: - You should mutate the tensor x in-place and return it - You should only modify the first 4 rows and first 6 columns; all other elements should remain unchanged - You may only mutate the tensor using slice assignment operations, where you assign an integer to a slice of the tensor - You must use <= 6 slicing operations to achieve the desired result

[28]:
```python
from pytorch_tutorial import slice_assignment_practice

# note: this "x" has one extra row, intentionally
x = torch.zeros(5, 7, dtype=torch.int64)
print('Here is x before calling slice_assignment_practice:')
print(x)
slice_assignment_practice(x)
print('Here is x after calling slice assignment practice:')
print(x)

expected = [
    [0, 1, 2, 2, 2, 2, 0],
    [0, 1, 2, 2, 2, 2, 0],
    [3, 4, 3, 4, 5, 5, 0],
    [3, 4, 3, 4, 5, 5, 0],
    [0, 0, 0, 0, 0, 0, 0],
]
print('Correct: ', x.tolist() == expected)
```

```
Here is x before calling slice_assignment_practice:
tensor([[0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0],
        [0, 0, 0, 0, 0, 0, 0]])
Here is x after calling slice assignment practice:
tensor([[0, 1, 2, 2, 2, 2, 0],
        [0, 1, 2, 2, 2, 2, 0],
        [3, 4, 3, 4, 5, 5, 0],
        [3, 4, 3, 4, 5, 5, 0],
        [0, 0, 0, 0, 0, 0, 0]])
Correct:  True
```

5.2.2 Integer tensor indexing

When you index into torch tensor using slicing, the resulting tensor view will always be a subarray of the original tensor. This is powerful, but can be restrictive.

We can also use **index arrays** to index tensors; this lets us construct new tensors with a lot more flexibility than using slices.

As an example, we can use index arrays to reorder the rows or columns of a tensor:

[29]:
```
# Create the following rank 2 tensor with shape (3, 4)
# [[ 1  2  3  4]
#  [ 5  6  7  8]
#  [ 9 10 11 12]]
a = torch.tensor([[1, 2, 3, 4], [5, 6, 7, 8], [9, 10, 11, 12]])
print('Original tensor:')
print(a)

# Create a new tensor of shape (5, 4) by reordering rows from a:
# - First two rows same as the first row of a
# - Third row is the same as the last row of a
# - Fourth and fifth rows are the same as the second row from a
idx = [0, 0, 2, 1, 1]  # index arrays can be Python lists of integers
print('\nReordered rows:')
print(a[idx])

# Create a new tensor of shape (3, 4) by reversing the columns from a
idx = torch.tensor([3, 2, 1, 0])  # Index arrays can be int64 torch tensors
print('\nReordered columns:')
print(a[:, idx])
```

```
Original tensor:
tensor([[ 1,  2,  3,  4],
        [ 5,  6,  7,  8],
        [ 9, 10, 11, 12]])

Reordered rows:
tensor([[ 1,  2,  3,  4],
        [ 1,  2,  3,  4],
        [ 9, 10, 11, 12],
        [ 5,  6,  7,  8],
        [ 5,  6,  7,  8]])

Reordered columns:
tensor([[ 4,  3,  2,  1],
        [ 8,  7,  6,  5],
        [12, 11, 10,  9]])
```

More generally, given index arrays `idx0` and `idx1` with `N` elements each, `a[idx0, idx1]` is equivalent to:

```
torch.tensor([
  a[idx0[0], idx1[0]],
  a[idx0[1], idx1[1]],
  ...,
  a[idx0[N - 1], idx1[N - 1]]
])
```

(A similar pattern extends to tensors with more than two dimensions)

We can for example use this to get or set the diagonal of a tensor:

[30]:
```
a = torch.tensor([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
print('Original tensor:')
print(a)

idx = [0, 1, 2]
print('\nGet the diagonal:')
print(a[idx, idx])

# Modify the diagonal
a[idx, idx] = torch.tensor([11, 22, 33])
print('\nAfter setting the diagonal:')
print(a)
```

```
Original tensor:
tensor([[1, 2, 3],
        [4, 5, 6],
        [7, 8, 9]])

Get the diagonal:
tensor([1, 5, 9])

After setting the diagonal:
tensor([[11,  2,  3],
        [ 4, 22,  6],
        [ 7,  8, 33]])
```

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

[31]:
```
# Create a new tensor from which we will select elements
a = torch.tensor([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12]])
print('Original tensor:')
print(a)

# Take on element from each row of a:
# from row 0, take element 1;
# from row 1, take element 2;
# from row 2, take element 1;
```

```python
# from row 3, take element 0
idx0 = torch.arange(a.shape[0])  # Quick way to build [0, 1, 2, 3]
idx1 = torch.tensor([1, 2, 1, 0])
print('\nSelect one element from each row:')
print(a[idx0, idx1])

# Now set each of those elements to zero
a[idx0, idx1] = 0
print('\nAfter modifying one element from each row:')
print(a)
```

```
Original tensor:
tensor([[ 1,  2,  3],
        [ 4,  5,  6],
        [ 7,  8,  9],
        [10, 11, 12]])

Select one element from each row:
tensor([ 2,  6,  8, 10])

After modifying one element from each row:
tensor([[ 1,  0,  3],
        [ 4,  5,  0],
        [ 7,  0,  9],
        [ 0, 11, 12]])
```

Your turn: in the file `pytorch_tutorial.py`, implement the functions `shuffle_cols`, `reverse_rows`, and `take_one_elem_per_col` to practice using integer indexing to manipulate tensors. In each of these functions, your implementation should construct the output tensor **using a single indexing operation on the input**.

[32]:
```python
from pytorch_tutorial import shuffle_cols, reverse_rows, take_one_elem_per_col

# Build a tensor of shape (4, 3):
# [[ 1,  2,  3],
#  [ 4,  5,  6],
#  [ 7,  8,  9],
#  [10, 11, 12]]
x = torch.tensor([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12]])
print('Here is x:')
print(x)

y1 = shuffle_cols(x)
print('\nHere is shuffle_cols(x):')
print(y1)
expected = [[1, 1, 3, 2], [4, 4, 6, 5], [7, 7, 9, 8], [10, 10, 12, 11]]
y1_correct = torch.is_tensor(y1) and y1.tolist() == expected
print('Correct: %r\n' % y1_correct)
```

```python
y2 = reverse_rows(x)
print('Here is reverse_rows(x):')
print(y2)
expected = [[10, 11, 12], [7, 8, 9], [4, 5, 6], [1, 2, 3]]
y2_correct = torch.is_tensor(y2) and y2.tolist() == expected
print('Correct: %r\n' % y2_correct)

y3 = take_one_elem_per_col(x)
print('Here is take_one_elem_per_col(x):')
print(y3)
expected = [4, 2, 12]
y3_correct = torch.is_tensor(y3) and y3.tolist() == expected
print('Correct: %r' % y3_correct)
```

```
Here is x:
tensor([[ 1,  2,  3],
        [ 4,  5,  6],
        [ 7,  8,  9],
        [10, 11, 12]])

Here is shuffle_cols(x):
tensor([[ 1,  1,  3,  2],
        [ 4,  4,  6,  5],
        [ 7,  7,  9,  8],
        [10, 10, 12, 11]])
Correct: True

Here is reverse_rows(x):
tensor([[10, 11, 12],
        [ 7,  8,  9],
        [ 4,  5,  6],
        [ 1,  2,  3]])
Correct: True

Here is take_one_elem_per_col(x):
tensor([ 4,  2, 12])
Correct: True
```

Now implement the function `make_one_hot` that creates a matrix of **one-hot vectors** from a list of Python integers.

A one-hot vector for an integer n is a vector that has a one in its nth slot, and zeros in all other slots. One-hot vectors are commonly used to represent categorical variables in machine learning models.

For example, given a list `[1, 4, 3, 2]` of integers, your function should produce the tensor:

```
[[0 1 0 0 0],
 [0 0 0 0 1],
 [0 0 0 1 0],
 [0 0 1 0 0]]
```

Here the first row corresponds to the first element of the list: it has a one at index 1, and zeros at all other indices. The second row corresponds to the second element of the list: it has a one at index 4, and zeros at all other indices. The other rows follow the same pattern. The output has just enough columns so that none of the rows go out-of-bounds: the largest index in the input is 4, so the output matrix has 5 columns.

[33]:
```
from pytorch_tutorial import make_one_hot

def check_one_hot(x, y):
    C = y.shape[1]
    for i, n in enumerate(x):
        if n >= C: return False
        for j in range(C):
            expected = 1.0 if j == n else 0.0
            if y[i, j].item() != expected: return False
        return True

x0 = [1, 4, 3, 2]
y0 = make_one_hot(x0)
print('Here is y0:')
print(y0)
print('y0 correct: ', check_one_hot(x0, y0))

x1 = [1, 3, 5, 7, 6, 2]
y1 = make_one_hot(x1)
print('\nHere is y1:')
print(y1)
print('y1 correct: ', check_one_hot(x1, y1))
```

```
Here is y0:
tensor([[0., 1., 0., 0., 0.],
        [0., 0., 0., 0., 1.],
        [0., 0., 0., 1., 0.],
        [0., 0., 1., 0., 0.]])
y0 correct:  True

Here is y1:
tensor([[0., 1., 0., 0., 0., 0., 0., 0.],
        [0., 0., 0., 1., 0., 0., 0., 0.],
        [0., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 1.],
        [0., 0., 0., 0., 0., 0., 1., 0.],
        [0., 0., 1., 0., 0., 0., 0., 0.]])
y1 correct:  True
```

5.2.3 Boolean tensor indexing

Boolean tensor indexing lets you pick out arbitrary elements of a tensor according to a boolean mask. Frequently this type of indexing is used to select or modify the elements of a tensor that satisfy some condition.

In PyTorch, we use tensors of dtype `torch.bool` to hold boolean masks.

(Prior to version 1.2.0, there was no `torch.bool` type so instead `torch.uint8` was usually used to represent boolean data, with 0 indicating false and 1 indicating true. Watch out for this in older PyTorch code!)

[34]:
```
a = torch.tensor([[1,2], [3, 4], [5, 6]])
print('Original tensor:')
print(a)

# Find the elements of a that are bigger than 3. The mask has the same shape as
# a, where each element of mask tells whether the corresponding element of a
# is greater than three.
mask = (a > 3)
print('\nMask tensor:')
print(mask)

# We can use the mask to construct a rank-1 tensor containing the elements of a
# that are selected by the mask
print('\nSelecting elements with the mask:')
print(a[mask])

# We can also use boolean masks to modify tensors; for example this sets all
# elements <= 3 to zero:
a[a <= 3] = 0
print('\nAfter modifying with a mask:')
print(a)
```

```
Original tensor:
tensor([[1, 2],
        [3, 4],
        [5, 6]])

Mask tensor:
tensor([[False, False],
        [False,  True],
        [ True,  True]])

Selecting elements with the mask:
tensor([4, 5, 6])

After modifying with a mask:
tensor([[0, 0],
        [0, 4],
        [5, 6]])
```

Your turn: In the file `pytorch_tutorial.py`, implement the function `sum_positive_entries` which computes the sum of all positive entries in a torch tensor. You can easily accomplish this using boolean tensor indexing. Your implementation should perform only a single indexing operation on the input tensor.

[35]:
```
from pytorch_tutorial import sum_positive_entries

# Make a few test cases
torch.manual_seed(598)
x0 = torch.tensor([[-1, -1, 0], [0, 1, 2], [3, 4, 5]])
x1 = torch.tensor([-100, 0, 1, 2, 3])
x2 = torch.randn(100, 100).long()
print('Correct for x0: ', sum_positive_entries(x0) == 15)
print('Correct for x1: ', sum_positive_entries(x1) == 6)
print('Correct for x2: ', sum_positive_entries(x2) == 1871)
```

```
Correct for x0:  True
Correct for x1:  True
Correct for x2:  True
```

5.3 Reshaping operations

5.3.1 View

PyTorch provides many ways to manipulate the shapes of tensors. The simplest example is `.view()`: This returns a new tensor with the same number of elements as its input, but with a different shape.

We can use `.view()` to flatten matrices into vectors, and to convert rank-1 vectors into rank-2 row or column matrices:

[36]:
```
x0 = torch.tensor([[1, 2, 3, 4], [5, 6, 7, 8]])
print('Original tensor:')
print(x0)
print('shape:', x0.shape)

# Flatten x0 into a rank 1 vector of shape (8,)
x1 = x0.view(8)
print('\nFlattened tensor:')
print(x1)
print('shape:', x1.shape)

# Convert x1 to a rank 2 "row vector" of shape (1, 8)
x2 = x1.view(1, 8)
print('\nRow vector:')
print(x2)
print('shape:', x2.shape)
```

```
# Convert x1 to a rank 2 "column vector" of shape (8, 1)
x3 = x1.view(8, 1)
print('\nColumn vector:')
print(x3)
print('shape:', x3.shape)

# Convert x1 to a rank 3 tensor of shape (2, 2, 2):
x4 = x1.view(2, 2, 2)
print('\nRank 3 tensor:')
print(x4)
print('shape:', x4.shape)
```

```
Original tensor:
tensor([[1, 2, 3, 4],
        [5, 6, 7, 8]])
shape: torch.Size([2, 4])

Flattened tensor:
tensor([1, 2, 3, 4, 5, 6, 7, 8])
shape: torch.Size([8])

Row vector:
tensor([[1, 2, 3, 4, 5, 6, 7, 8]])
shape: torch.Size([1, 8])

Column vector:
tensor([[1],
        [2],
        [3],
        [4],
        [5],
        [6],
        [7],
        [8]])
shape: torch.Size([8, 1])

Rank 3 tensor:
tensor([[[1, 2],
         [3, 4]],

        [[5, 6],
         [7, 8]]])
shape: torch.Size([2, 2, 2])
```

As a convenience, calls to `.view()` may include a single -1 argument; this puts enough elements on that dimension so that the output has the same number of elements as the input. This makes it easy to write some reshape operations in a way that is agnostic to the shape of the tensor:

[37]:
```
# We can reuse these functions for tensors of different shapes
def flatten(x):
    return x.view(-1)

def make_row_vec(x):
    return x.view(1, -1)

x0 = torch.tensor([[1, 2, 3], [4, 5, 6]])
x0_flat = flatten(x0)
x0_row = make_row_vec(x0)
print('x0:')
print(x0)
print('x0_flat:')
print(x0_flat)
print('x0_row:')
print(x0_row)

x1 = torch.tensor([[1, 2], [3, 4]])
x1_flat = flatten(x1)
x1_row = make_row_vec(x1)
print('\nx1:')
print(x1)
print('x1_flat:')
print(x1_flat)
print('x1_row:')
print(x1_row)
```

```
x0:
tensor([[1, 2, 3],
        [4, 5, 6]])
x0_flat:
tensor([1, 2, 3, 4, 5, 6])
x0_row:
tensor([[1, 2, 3, 4, 5, 6]])

x1:
tensor([[1, 2],
        [3, 4]])
x1_flat:
tensor([1, 2, 3, 4])
x1_row:
tensor([[1, 2, 3, 4]])
```

As its name implies, a tensor returned by `.view()` shares the same data as the input, so changes to one will affect the other and vice-versa:

[38]:
```
x = torch.tensor([[1, 2, 3], [4, 5, 6]])
x_flat = x.view(-1)
```

```
print('x before modifying:')
print(x)
print('x_flat before modifying:')
print(x_flat)

x[0, 0] = 10   # x[0, 0] and x_flat[0] point to the same data
x_flat[1] = 20 # x_flat[1] and x[0, 1] point to the same data

print('\nx after modifying:')
print(x)
print('x_flat after modifying:')
print(x_flat)
```

```
x before modifying:
tensor([[1, 2, 3],
        [4, 5, 6]])
x_flat before modifying:
tensor([1, 2, 3, 4, 5, 6])

x after modifying:
tensor([[10, 20,  3],
        [ 4,  5,  6]])
x_flat after modifying:
tensor([10, 20,  3,  4,  5,  6])
```

5.3.2 Swapping axes

Another common reshape operation you might want to perform is transposing a matrix. You might be surprised if you try to transpose a matrix with `.view()`: The `view()` function takes elements in row-major order, so **you cannot transpose matrices with `.view()`**.

In general, you should only use `.view()` to add new dimensions to a tensor, or to collapse adjacent dimensions of a tensor.

For other types of reshape operations, you usually need to use a function that can swap axes of a tensor. The simplest such function is `.t()`, specificially for transposing matrices. It is available both as a function in the `torch` module, and as a tensor instance method:

[39]:
```
x = torch.tensor([[1, 2, 3], [4, 5, 6]])
print('Original matrix:')
print(x)
print('\nTransposing with view DOES NOT WORK!')
print(x.view(3, 2))
print('\nTransposed matrix:')
print(torch.t(x))
print(x.t())
```

```
Original matrix:
tensor([[1, 2, 3],
        [4, 5, 6]])

Transposing with view DOES NOT WORK!
tensor([[1, 2],
        [3, 4],
        [5, 6]])

Transposed matrix:
tensor([[1, 4],
        [2, 5],
        [3, 6]])
tensor([[1, 4],
        [2, 5],
        [3, 6]])
```

For tensors with more than two dimensions, we can use the function `torch.transpose` (or its instance method variant) to swap arbitrary dimensions.

If you want to swap multiple axes at the same time, you can use `torch.permute` (or its instance method variant) method to arbitrarily permute dimensions:

[40]:
```
# Create a tensor of shape (2, 3, 4)
x0 = torch.tensor([
     [[1,  2,  3,  4],
      [5,  6,  7,  8],
      [9, 10, 11, 12]],
     [[13, 14, 15, 16],
      [17, 18, 19, 20],
      [21, 22, 23, 24]]])
print('Original tensor:')
print(x0)
print('shape:', x0.shape)

# Swap axes 1 and 2; shape is (2, 4, 3)
x1 = x0.transpose(1, 2)
print('\nSwap axes 1 and 2:')
print(x1)
print(x1.shape)

# Permute axes; the argument (1, 2, 0) means:
# - Make the old dimension 1 appear at dimension 0;
# - Make the old dimension 2 appear at dimension 1;
# - Make the old dimension 0 appear at dimension 2
# This results in a tensor of shape (3, 4, 2)
x2 = x0.permute(1, 2, 0)
print('\nPermute axes')
print(x2)
print('shape:', x2.shape)
```

```
Original tensor:
tensor([[[ 1,  2,  3,  4],
         [ 5,  6,  7,  8],
         [ 9, 10, 11, 12]],

        [[13, 14, 15, 16],
         [17, 18, 19, 20],
         [21, 22, 23, 24]]])
shape: torch.Size([2, 3, 4])

Swap axes 1 and 2:
tensor([[[ 1,  5,  9],
         [ 2,  6, 10],
         [ 3,  7, 11],
         [ 4,  8, 12]],

        [[13, 17, 21],
         [14, 18, 22],
         [15, 19, 23],
         [16, 20, 24]]])
torch.Size([2, 4, 3])

Permute axes
tensor([[[ 1, 13],
         [ 2, 14],
         [ 3, 15],
         [ 4, 16]],

        [[ 5, 17],
         [ 6, 18],
         [ 7, 19],
         [ 8, 20]],

        [[ 9, 21],
         [10, 22],
         [11, 23],
         [12, 24]]])
shape: torch.Size([3, 4, 2])
```

5.3.3 Contiguous tensors

Some combinations of reshaping operations will fail with cryptic errors. The exact reasons for this have to do with the way that tensors and views of tensors are implemented, and are beyond the scope of this assignment. However if you're curious, this blog post by Edward Yang gives a clear explanation of the problem.

What you need to know is that you can typically overcome these sorts of errors by either by calling `.contiguous()` before `.view()`, or by using `.reshape()` instead of `.view()`.

[41]:
```python
x0 = torch.randn(2, 3, 4)

try:
  # This sequence of reshape operations will crash
  x1 = x0.transpose(1, 2).view(8, 3)
except RuntimeError as e:
  print(type(e), e)

# We can solve the problem using either .contiguous() or .reshape()
x1 = x0.transpose(1, 2).contiguous().view(8, 3)
x2 = x0.transpose(1, 2).reshape(8, 3)
print('x1 shape: ', x1.shape)
print('x2 shape: ', x2.shape)
```

```
<class 'RuntimeError'> view size is not compatible with input tensor's size and
stride (at least one dimension spans across two contiguous subspaces). Use
.reshape(…) instead.
x1 shape:  torch.Size([8, 3])
x2 shape:  torch.Size([8, 3])
```

5.3.4 Your turn

In the file `pytorch_tutorial.py`, implement the function `reshape_practice` to practice using reshape operations on tensors. Given the 1-dimensional input tensor `x` containing the numbers 0 through 23 in order, it should the following output tensor `y` of shape `(3, 8)` by using reshape operations on x:

```
y = tensor([[ 0,  1,  2,  3, 12, 13, 14, 15],
            [ 4,  5,  6,  7, 16, 17, 18, 19],
            [ 8,  9, 10, 11, 20, 21, 22, 23]])
```

Hint: You will need to create an intermediate tensor of rank 3

[42]:
```python
from pytorch_tutorial import reshape_practice

x = torch.arange(24)
print('Here is x:')
print(x)
y = reshape_practice(x)
print('Here is y:')
print(y)

expected = [
    [0, 1,  2,  3, 12, 13, 14, 15],
    [4, 5,  6,  7, 16, 17, 18, 19],
    [8, 9, 10, 11, 20, 21, 22, 23]]
print('Correct:', y.tolist() == expected)
```

```
Here is x:
```

```
tensor([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
        18, 19, 20, 21, 22, 23])
Here is y:
tensor([[ 0,  1,  2,  3, 12, 13, 14, 15],
        [ 4,  5,  6,  7, 16, 17, 18, 19],
        [ 8,  9, 10, 11, 20, 21, 22, 23]])
Correct: True
```

5.4 Tensor operations

So far we have seen how to construct, access, and reshape tensors. But one of the most important reasons to use tensors is for performing computation! PyTorch provides many different operations to perform computations on tensors.

5.4.1 Elementwise operations

Basic mathematical functions operate elementwise on tensors, and are available as operator overloads, as functions in the `torch` module, and as instance methods on torch objects; all produce the same results:

[43]:
```python
x = torch.tensor([[1, 2, 3, 4]], dtype=torch.float32)
y = torch.tensor([[5, 6, 7, 8]], dtype=torch.float32)

# Elementwise sum; all give the same result
print('Elementwise sum:')
print(x + y)
print(torch.add(x, y))
print(x.add(y))

# Elementwise difference
print('\nElementwise difference:')
print(x - y)
print(torch.sub(x, y))
print(x.sub(y))

# Elementwise product
print('\nElementwise product:')
print(x * y)
print(torch.mul(x, y))
print(x.mul(y))

# Elementwise division
print('\nElementwise division')
print(x / y)
print(torch.div(x, y))
print(x.div(y))

# Elementwise power
```

```
print('\nElementwise power')
print(x ** y)
print(torch.pow(x, y))
print(x.pow(y))
```

```
Elementwise sum:
tensor([[ 6.,  8., 10., 12.]])
tensor([[ 6.,  8., 10., 12.]])
tensor([[ 6.,  8., 10., 12.]])

Elementwise difference:
tensor([[-4., -4., -4., -4.]])
tensor([[-4., -4., -4., -4.]])
tensor([[-4., -4., -4., -4.]])

Elementwise product:
tensor([[ 5., 12., 21., 32.]])
tensor([[ 5., 12., 21., 32.]])
tensor([[ 5., 12., 21., 32.]])

Elementwise division
tensor([[0.2000, 0.3333, 0.4286, 0.5000]])
tensor([[0.2000, 0.3333, 0.4286, 0.5000]])
tensor([[0.2000, 0.3333, 0.4286, 0.5000]])

Elementwise power
tensor([[1.0000e+00, 6.4000e+01, 2.1870e+03, 6.5536e+04]])
tensor([[1.0000e+00, 6.4000e+01, 2.1870e+03, 6.5536e+04]])
tensor([[1.0000e+00, 6.4000e+01, 2.1870e+03, 6.5536e+04]])
```

Torch also provides many standard mathematical functions; these are available both as functions in the `torch` module and as instance methods on tensors:

You can find a full list of all available mathematical functions in the documentation; many functions in the `torch` module have corresponding instance methods on tensor objects.

[44]:
```
x = torch.tensor([[1, 2, 3, 4]], dtype=torch.float32)

print('Square root:')
print(torch.sqrt(x))
print(x.sqrt())

print('\nTrig functions:')
print(torch.sin(x))
print(x.sin())
print(torch.cos(x))
print(x.cos())
```

```
Square root:
```

```
tensor([[1.0000, 1.4142, 1.7321, 2.0000]])
tensor([[1.0000, 1.4142, 1.7321, 2.0000]])

Trig functions:
tensor([[ 0.8415,  0.9093,  0.1411, -0.7568]])
tensor([[ 0.8415,  0.9093,  0.1411, -0.7568]])
tensor([[ 0.5403, -0.4161, -0.9900, -0.6536]])
tensor([[ 0.5403, -0.4161, -0.9900, -0.6536]])
```

5.4.2 Reduction operations

So far we've seen basic arithmetic operations on tensors that operate elementwise. We may sometimes want to perform operations that aggregate over part or all of a tensor, such as a summation; these are called **reduction** operations.

Like the elementwise operations above, most reduction operations are available both as functions in the `torch` module and as instance methods on `tensor` objects.

The simplest reduction operation is summation. We can use the `.sum()` method (or eqivalently `torch.sum`) to reduce either an entire tensor, or to reduce along only one dimension of the tensor using the `dim` argument:

[45]:
```
x = torch.tensor([[1, 2, 3],
                  [4, 5, 6]], dtype=torch.float32)
print('Original tensor:')
print(x)

print('\nSum over entire tensor:')
print(torch.sum(x))
print(x.sum())

# We can sum over the first dimension:
print('\nSum over the first dimension:')
print(torch.sum(x, dim=0))
print(x.sum(dim=0))

# Sum over the second dimension:
print('\nSum over the second dimension:')
print(torch.sum(x, dim=1))
print(x.sum(dim=1))
```

```
Original tensor:
tensor([[1., 2., 3.],
        [4., 5., 6.]])

Sum over entire tensor:
tensor(21.)
tensor(21.)
```

```
Sum over the first dimension:
tensor([5., 7., 9.])
tensor([5., 7., 9.])

Sum over the second dimension:
tensor([ 6., 15.])
tensor([ 6., 15.])
```

Students often get confused by the `dim` argument in reduction operations – how do I sum over rows vs columns?

The easiest way to remember is to think about the shapes of the tensors involved. After summing with `dim=d`, the dimension at index `d` of the input is **eliminated** from the shape of the output tensor:

[46]:
```
# Create a tensor of shape (3, 4, 5, 6)
x = torch.randn(3, 4, 5, 6)
print('x.shape: ', x.shape)

# Summing over dim=0 eliminates the dimension at index 0 (of size 3):
print('x.sum(dim=0).shape: ', x.sum(dim=0).shape)

# Summing with dim=1 eliminates the dimension at index 1 (of size 4):
print('x.sum(dim=1).shape: ', x.sum(dim=1).shape)

# Summing with dim=2 eliminates the dimension at index 2 (of size 5):
print('x.sum(dim=2).shape: ', x.sum(dim=2).shape)

# Summing with dim=3 eliminates the dimension at index 3 (of size 6):
print('x.sum(dim=3).shape: ', x.sum(dim=3).shape)
```

```
x.shape:  torch.Size([3, 4, 5, 6])
x.sum(dim=0).shape:  torch.Size([4, 5, 6])
x.sum(dim=1).shape:  torch.Size([3, 5, 6])
x.sum(dim=2).shape:  torch.Size([3, 4, 6])
x.sum(dim=3).shape:  torch.Size([3, 4, 5])
```

Other useful reduction operations include `mean`, `min`, and `max`. You can find a full list of all available reduction operations in the documentation.

Some reduction operations return more than one value; for example `min` returns both the minimum value over the specified dimension, as well as the index where the minimum value occurs:

[47]:
```
x = torch.tensor([[2, 4, 3, 5], [3, 3, 5, 2]], dtype=torch.float32)
print('Original tensor:')
print(x, x.shape)

# Finding the overall minimum only returns a single value
print('\nOverall minimum: ', x.min())
```

```
# Compute the minimum along each column; we get both the value and location:
# The minimum of the first column is 2, and it appears at index 0;
# the minimum of the second column is 3 and it appears at index 1; etc
col_min_vals, col_min_idxs = x.min(dim=0)
print('\nMinimum along each column:')
print('values:', col_min_vals)
print('idxs:', col_min_idxs)

# Compute the minimum along each row; we get both the value and the minimum
row_min_vals, row_min_idxs = x.min(dim=1)
print('\nMinimum along each row:')
print('values:', row_min_vals)
print('idxs:', row_min_idxs)
```

```
Original tensor:
tensor([[2., 4., 3., 5.],
        [3., 3., 5., 2.]]) torch.Size([2, 4])

Overall minimum:  tensor(2.)

Minimum along each column:
values: tensor([2., 3., 3., 2.])
idxs: tensor([0, 1, 0, 1])

Minimum along each row:
values: tensor([2., 2.])
idxs: tensor([0, 3])
```

Reduction operations *reduce* the rank of tensors: the dimension over which you perform the reduction will be removed from the shape of the output. If you pass `keepdim=True` to a reduction operation, the specified dimension will not be removed; the output tensor will instead have a shape of 1 in that dimension.

When you are working with multidimensional tensors, thinking about rows and columns can become confusing; instead it's more useful to think about the shape that will result from each operation. For example:

[48]:
```
# Create a tensor of shape (128, 10, 3, 64, 64)
x = torch.randn(128, 10, 3, 64, 64)
print(x.shape)

# Take the mean over dimension 1; shape is now (128, 3, 64, 64)
x = x.mean(dim=1)
print(x.shape)

# Take the sum over dimension 2; shape is now (128, 3, 64)
x = x.sum(dim=2)
print(x.shape)
```

```python
# Take the mean over dimension 1, but keep the dimension from being eliminated
# by passing keepdim=True; shape is now (128, 1, 64)
x = x.mean(dim=1, keepdim=True)
print(x.shape)
```

```
torch.Size([128, 10, 3, 64, 64])
torch.Size([128, 3, 64, 64])
torch.Size([128, 3, 64])
torch.Size([128, 1, 64])
```

Your turn: In the file `pytorch_tutorial.py`, implement the function `zero_row_min` which sets the minimum value along each row of a tensor to zero. You should use reduction and indexing operations, and you should not use any explicit loops.

Hint: `clone`, `argmin`

[49]:
```python
from pytorch_tutorial import zero_row_min

x0 = torch.tensor([[10, 20, 30], [2, 5, 1]])
print('Here is x0:')
print(x0)
y0 = zero_row_min(x0)
print('Here is y0:')
print(y0)
expected = [[0, 20, 30], [2, 5, 0]]
y0_correct = torch.is_tensor(y0) and y0.tolist() == expected
print('y0 correct: ', y0_correct)

x1 = torch.tensor([[2, 5, 10, -1], [1, 3, 2, 4], [5, 6, 2, 10]])
print('\nHere is x1:')
print(x1)
y1 = zero_row_min(x1)
print('Here is y1:')
print(y1)
expected = [[2, 5, 10, 0], [0, 3, 2, 4], [5, 6, 0, 10]]
y1_correct = torch.is_tensor(y1) and y1.tolist() == expected
print('y1 correct: ', y1_correct)
```

```
Here is x0:
tensor([[10, 20, 30],
        [ 2,  5,  1]])
Here is y0:
tensor([[ 0, 20, 30],
        [ 2,  5,  0]])
y0 correct:  True

Here is x1:
tensor([[ 2,  5, 10, -1],
        [ 1,  3,  2,  4],
        [ 5,  6,  2, 10]])
Here is y1:
tensor([[ 2,  5, 10,  0],
        [ 0,  3,  2,  4],
        [ 5,  6,  0, 10]])
y1 correct:  True
```

5.4.3 Matrix operations

Note that unlike MATLAB, * is elementwise multiplication, not matrix multiplication. PyTorch provides a number of linear algebra functions that compute different types of vector and matrix products. The most commonly used are:

- `torch.dot`: Computes inner product of vectors
- `torch.mm`: Computes matrix-matrix products
- `torch.mv`: Computes matrix-vector products
- `torch.addmm` / `torch.addmv`: Computes matrix-matrix and matrix-vector multiplications plus a bias
- `torch.bmm` / `torch.baddmm`: Batched versions of `torch.mm` and `torch.addmm`, respectively
- `torch.matmul`: General matrix product that performs different operations depending on the rank of the inputs. Confusingly, this is similar to `np.dot` in numpy.

You can find a full list of the available linear algebra operators in the documentation. All of these functions are also available as Tensor instance methods, e.g. `Tensor.dot` instead of `torch.dot`.

Here is an example of using `torch.dot` to compute inner products. Like the other mathematical operators we've seen, most linear algebra operators are available both as functions in the `torch` module and as instance methods of tensors:

[50]:
```
v = torch.tensor([9,10], dtype=torch.float32)
w = torch.tensor([11, 12], dtype=torch.float32)

# Inner product of vectors
print('Dot products:')
print(torch.dot(v, w))
print(v.dot(w))

# dot only works for vectors -- it will give an error for tensors of rank > 1
x = torch.tensor([[1,2],[3,4]], dtype=torch.float32)
y = torch.tensor([[5,6],[7,8]], dtype=torch.float32)
try:
  print(x.dot(y))
except RuntimeError as e:
  print(e)

# Instead we use mm for matrix-matrix products:
print('\nMatrix-matrix product:')
print(torch.mm(x, y))
print(x.mm(y))
```

```
Dot products:
tensor(219.)
tensor(219.)
1D tensors expected, but got 2D and 2D tensors

Matrix-matrix product:
tensor([[19., 22.],
        [43., 50.]])
tensor([[19., 22.],
        [43., 50.]])
```

With all the different linear algebra operators that PyTorch provides, there is usually more than one way to compute something. For example to compute matrix-vector products we can use `torch.mv`; we can reshape the vector to have rank 2 and use `torch.mm`; or we can use `torch.matmul`. All give the same results, but the outputs might have different ranks:

[51]:
```
print('Here is x (rank 2):')
print(x)
print('\nHere is v (rank 1):')
print(v)

# Matrix-vector multiply with torch.mv produces a rank-1 output
print('\nMatrix-vector product with torch.mv (rank 1 output)')
print(torch.mv(x, v))
print(x.mv(v))

# We can reshape the vector to have rank 2 and use torch.mm to perform
# matrix-vector products, but the result will have rank 2
print('\nMatrix-vector product with torch.mm (rank 2 output)')
print(torch.mm(x, v.view(2, 1)))
print(x.mm(v.view(2, 1)))

print('\nMatrix-vector product with torch.matmul (rank 1 output)')
print(torch.matmul(x, v))
print(x.matmul(v))
```

```
Here is x (rank 2):
tensor([[1., 2.],
        [3., 4.]])

Here is v (rank 1):
tensor([ 9., 10.])

Matrix-vector product with torch.mv (rank 1 output)
tensor([29., 67.])
tensor([29., 67.])
```

```
Matrix-vector product with torch.mm (rank 2 output)
tensor([[29.],
        [67.]])
tensor([[29.],
        [67.]])

Matrix-vector product with torch.matmul (rank 1 output)
tensor([29., 67.])
tensor([29., 67.])
```

Your turn: In the file `pytorch_tutorial.py`, look at the function `batched_matrix_multiply`.

You should implement the two variants `batched_matrix_multiply_loop` and `batched_matrix_multiply_noloop`; the first should use an explicit Python loop over the batch dimension, and the second should perform batched matrix multiplication using a single PyTorch operation with no explicit loops.

Hint: `torch.stack`, `torch.bmm` may be useful.

[52]:
```
from pytorch_tutorial import batched_matrix_multiply

B, N, M, P = 2, 3, 5, 4
x = torch.randn(B, N, M)
y = torch.randn(B, M, P)
z_expected = torch.stack([x[0] @ y[0], x[1] @ y[1]])

# The two may not return exactly the same result; different linear algebra
# routines often return slightly different results due to the fact that
# floating-point math is non-exact and non-associative.
z1 = batched_matrix_multiply(x, y, use_loop=True)
z1_diff = (z1 - z_expected).abs().max().item()
print('z1 difference: ', z1_diff)
print('z1 difference within tolerance: ', z1_diff < 1e-6)

z2 = batched_matrix_multiply(x, y, use_loop=False)
z2_diff = (z2 - z_expected).abs().max().item()
print('\nz2 difference: ', z2_diff)
print('z2 difference within tolerance: ', z2_diff < 1e-6)
```

```
z1 difference:  0.0
z1 difference within tolerance:  True

z2 difference:  4.76837158203125e-07
z2 difference within tolerance:  True
```

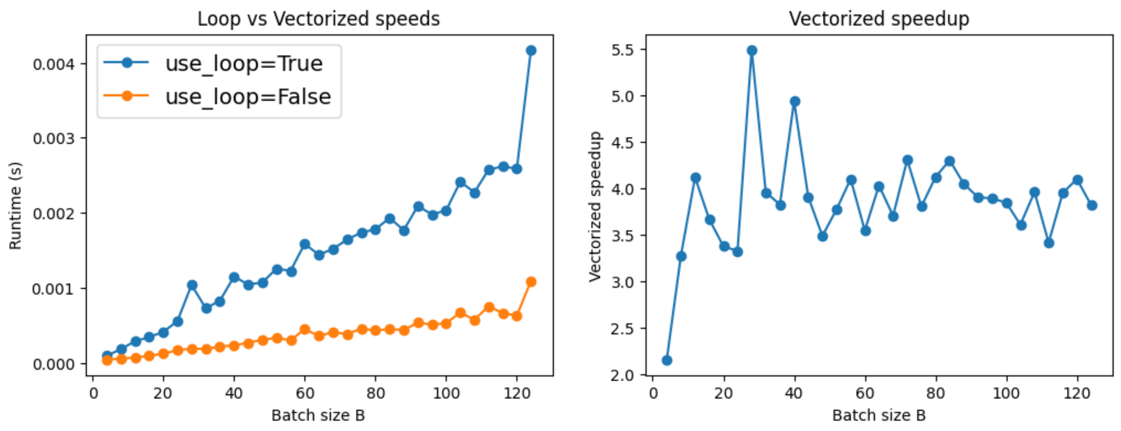
5.4.4 Vectorization

In many cases, avoiding explicit Python loops in your code and instead using PyTorch operators to handle looping internally will cause your code to run a lot faster. This style of writing code, called

vectorization, avoids overhead from the Python interpreter, and can also better parallelize the computation (e.g. across CPU cores, on on GPUs). Whenever possible you should strive to write vectorized code.

Run the following the compare the speed of the `batched_matrix_multiply` with `use_loop=True` and with `use_loop=False`.

[53]:
```python
import time
import matplotlib.pyplot as plt
from pytorch_tutorial import batched_matrix_multiply

N, M, P = 64, 64, 64
loop_times = []
no_loop_times = []
no_loop_speedup = []
Bs = list(range(4, 128, 4))
num_trials = 20
for B in Bs:
    loop_trials = []
    no_loop_trials = []
    for trial in range(num_trials):
        x = torch.randn(B, N, M)
        y = torch.randn(B, M, P)
        t0 = time.time()
        z1 = batched_matrix_multiply(x, y, use_loop=True)
        t1 = time.time()
        z2 = batched_matrix_multiply(x, y, use_loop=False)
        t2 = time.time()
        loop_trials.append(t1 - t0)
        no_loop_trials.append(t2 - t1)
    loop_mean = torch.tensor(loop_trials).mean().item()
    no_loop_mean = torch.tensor(no_loop_trials).mean().item()
    loop_times.append(loop_mean)
    no_loop_times.append(no_loop_mean)
    no_loop_speedup.append(loop_mean / no_loop_mean)

plt.subplot(1, 2, 1)
plt.plot(Bs, loop_times, 'o-', label='use_loop=True')
plt.plot(Bs, no_loop_times, 'o-', label='use_loop=False')
plt.xlabel('Batch size B')
plt.ylabel('Runtime (s)')
plt.legend(fontsize=14)
plt.title('Loop vs Vectorized speeds')

plt.subplot(1, 2, 2)
plt.plot(Bs, no_loop_speedup, '-o')
plt.title('Vectorized speedup')
plt.xlabel('Batch size B')
plt.ylabel('Vectorized speedup')

plt.gcf().set_size_inches(12, 4)
plt.show()
```



5.5 Broadcasting

Broadcasting is a powerful mechanism that allows PyTorch to work with arrays of different shapes when performing arithmetic operations. Frequently we have a smaller tensor and a larger tensor, and we want to use the smaller tensor multiple times to perform some operation on the larger tensor.

For example, suppose that we want to add a constant vector to each row of a tensor. We could do it like this:

[54]:
```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = torch.tensor([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
v = torch.tensor([1, 0, 1])
y = torch.zeros_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

print(y)
```

```
tensor([[ 2,  2,  4],
        [ 5,  5,  7],
        [ 8,  8, 10],
        [11, 11, 13]])
```

This works; however when the tensor x is very large, computing an explicit loop in Python could be slow. Note that adding the vector v to each row of the tensor x is equivalent to forming a tensor vv by stacking multiple copies of v vertically, then performing elementwise summation of x and vv. We could implement this approach like this:

[55]:
```
vv = v.repeat((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]]"
```

```
tensor([[1, 0, 1],
        [1, 0, 1],
        [1, 0, 1],
        [1, 0, 1]])
```

[56]:
```
y = x + vv  # Add x and vv elementwise
print(y)
```

```
tensor([[ 2,  2,  4],
        [ 5,  5,  7],
        [ 8,  8, 10],
        [11, 11, 13]])
```

PyTorch broadcasting allows us to perform this computation without actually creating multiple copies of v. Consider this version, using broadcasting:

[57]:
```
# We will add the vector v to each row of the matrix x,
# storing the result in the matrix y
x = torch.tensor([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
v = torch.tensor([1, 0, 1])
y = x + v  # Add v to each row of x using broadcasting
print(y)
```

```
tensor([[ 2,  2,  4],
        [ 5,  5,  7],
        [ 8,  8, 10],
        [11, 11, 13]])
```

The line y = x + v works even though x has shape (4, 3) and v has shape (3,) due to broadcasting; this line works as if v actually had shape (4, 3), where each row was a copy of v, and the sum was performed elementwise.

Broadcasting two tensors together follows these rules:

1. If the tensors 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 tensors are said to be *compatible* in a dimension if they have the same size in the dimension, or if one of the tensors has size 1 in that dimension.
3. The tensors can be broadcast together if they are compatible in all dimensions.
4. After broadcasting, each tensor behaves as if it had shape equal to the elementwise maximum of shapes of the two input tensors.

5. In any dimension where one tensor had size 1 and the other tensor had size greater than 1, the first tensor behaves as if it were copied along that dimension

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

Broadcasting usually happens implicitly inside many PyTorch operators. However we can also broadcast explicitly using the function `torch.broadcast_tensors`:

[58]:
```
x = torch.tensor([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12]])
v = torch.tensor([1, 0, 1])
print('Here is x (before broadcasting):')
print(x)
print('x.shape: ', x.shape)
print('\nHere is v (before broadcasting):')
print(v)
print('v.shape: ', v.shape)

xx, vv = torch.broadcast_tensors(x, v)
print('Here is xx (after) broadcasting):')
print(xx)
print('xx.shape: ', x.shape)
print('\nHere is vv (after broadcasting):')
print(vv)
print('vv.shape: ', vv.shape)
```

```
Here is x (before broadcasting):
tensor([[ 1,  2,  3],
        [ 4,  5,  6],
        [ 7,  8,  9],
        [10, 11, 12]])
x.shape:  torch.Size([4, 3])

Here is v (before broadcasting):
tensor([1, 0, 1])
v.shape:  torch.Size([3])
Here is xx (after) broadcasting):
tensor([[ 1,  2,  3],
        [ 4,  5,  6],
        [ 7,  8,  9],
        [10, 11, 12]])
xx.shape:  torch.Size([4, 3])

Here is vv (after broadcasting):
tensor([[1, 0, 1],
        [1, 0, 1],
        [1, 0, 1],
        [1, 0, 1]])
vv.shape:  torch.Size([4, 3])
```

Notice that after broadcasting, `x` remains the same but `v` has an extra dimension prepended to its shape, and it is duplicated to have the same shape as `x`; since they have the same shape after broadcasting they can be added elementwise.

All elementwise functions support broadcasting. Some non-elementwise functions (such as linear algebra routines) also support broadcasting; you can check the documentation to tell whether any particular function supports broadcasting. For example `torch.mm` does not support broadcasting, but `torch.matmul` does.

Broadcasting can let us easily implement many different operations. For example we can compute an outer product of vectors:

[59]:
```
# Compute outer product of vectors
v = torch.tensor([1, 2, 3])  # v has shape (3,)
w = torch.tensor([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:
print(v.view(3, 1) * w)
```

```
tensor([[ 4,  5],
        [ 8, 10],
        [12, 15]])
```

We can add a vector to each row of a matrix:

[60]:
```
x = torch.tensor([[1, 2, 3], [4, 5, 6]])  # x has shape (2, 3)
v = torch.tensor([1, 2, 3])               # v has shape (3,)
print('Here is the matrix:')
print(x)
print('\nHere is the vector:')
print(v)

# x has shape (2, 3) and v has shape (3,) so they broadcast to (2, 3),
# giving the following matrix:
print('\nAdd the vector to each row of the matrix:')
print(x + v)
```

```
Here is the matrix:
tensor([[1, 2, 3],
        [4, 5, 6]])

Here is the vector:
tensor([1, 2, 3])

Add the vector to each row of the matrix:
tensor([[2, 4, 6],
        [5, 7, 9]])
```

We can add a vector to each column of a matrix:

```
[61]: x = torch.tensor([[1, 2, 3], [4, 5, 6]])  # x has shape (2, 3)
      w = torch.tensor([4, 5])                    # w has shape (2,)
      print('Here is the matrix:')
      print(x)
      print('\nHere is the vector:')
      print(w)

      # x has shape (2, 3) and w has shape (2,). We reshape w to (2, 1);
      # then when we add the two the result broadcasts to (2, 3):
      print('\nAdd the vector to each column of the matrix:')
      print(x + w.view(-1, 1))

      # Another solution is the following:
      # 1. Transpose x so it has shape (3, 2)
      # 2. Since w has shape (2,), adding will broadcast to (3, 2)
      # 3. Transpose the result, resulting in a shape (2, 3)
      print((x.t() + w).t())
```

```
Here is the matrix:
tensor([[1, 2, 3],
        [4, 5, 6]])

Here is the vector:
tensor([4, 5])

Add the vector to each column of the matrix:
tensor([[ 5,  6,  7],
        [ 9, 10, 11]])
tensor([[ 5,  6,  7],
        [ 9, 10, 11]])
```

Multiply a tensor by a set of constants:

```
[62]: x = torch.tensor([[1, 2, 3], [4, 5, 6]])  # x has shape (2, 3)
      c = torch.tensor([1, 10, 11, 100])          # c has shape (4)
      print('Here is the matrix:')
      print(x)
      print('\nHere is the vector:')
      print(c)

      # We do the following:
      # 1. Reshape c from (4,) to (4, 1, 1)
      # 2. x has shape (2, 3). Since they have different ranks, when we multiply the
      #    two, x behaves as if its shape were (1, 2, 3)
      # 3. The result of the broadcast multiplication between tensor of shape
      #    (4, 1, 1) and (1, 2, 3) has shape (4, 2, 3)
      # 4. The result y has shape (4, 2, 3), and y[i] (shape (2, 3)) is equal to
      #    c[i] * x
```

```
y = c.view(-1, 1, 1) * x
print('\nMultiply x by a set of constants:')
print(y)
```

```
Here is the matrix:
tensor([[1, 2, 3],
        [4, 5, 6]])

Here is the vector:
tensor([  1,  10,  11, 100])

Multiply x by a set of constants:
tensor([[[  1,   2,   3],
         [  4,   5,   6]],

        [[ 10,  20,  30],
         [ 40,  50,  60]],

        [[ 11,  22,  33],
         [ 44,  55,  66]],

        [[100, 200, 300],
         [400, 500, 600]]])
```

Your turn: In the file `pytorch_tutorial.py`, implement the function `normalize_columns` that normalizes the columns of a matrix. It should compute the mean and standard deviation of each column, then subtract the mean and divide by the standard deviation for each element in the column.

Example:

```
x = [[ 0,  30,  600],
     [ 1,  10,  200],
     [-1,  20,  400]]
```

- The first column has mean 0 and std 1
- The second column has mean 20 and std 10
- The third column has mean 400 and std 200

After normalizing the columns, the result should be:

```
y = [[ 0,  1,  1],
     [ 1, -1, -1],
     [-1,  0,  0]]
```

Recall that given scalars $x_1, \ldots, x_M$ the mean μ and standard deviation σ are given by

$$\mu = \frac{1}{M}\sum_{i=1}^{M} x_i \qquad \sigma = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}(x_i - \mu)^2}$$

```
[63]: from pytorch_tutorial import normalize_columns

x = torch.tensor([[0., 30., 600.], [1., 10., 200.], [-1., 20., 400.]])
y = normalize_columns(x)
print('Here is x:')
print(x)
print('Here is y:')
print(y)

x_expected = [[0., 30., 600.], [1., 10., 200.], [-1., 20., 400.]]
y_expected = [[0., 1., 1.], [1., -1., -1.], [-1., 0., 0.]]
y_correct = y.tolist() == y_expected
x_correct = x.tolist() == x_expected
print('y correct: ', y_correct)
print('x unchanged: ', x_correct)
```

```
Here is x:
tensor([[  0.,  30., 600.],
        [  1.,  10., 200.],
        [ -1.,  20., 400.]])
Here is y:
tensor([[ 0.,  1.,  1.],
        [ 1., -1., -1.],
        [-1.,  0.,  0.]])
y correct:  True
x unchanged:  True
```

5.5.1 Out-of-place vs in-place operators

Most PyTorch operators are classified into one of two categories: - **Out-of-place operators:** return a new tensor. Most PyTorch operators behave this way. - **In-place operators:** modify and return the input tensor. Instance methods that end with an underscore (such as `add_()` are in-place. Operators in the `torch` namespace can be made in-place using the `out=` keyword argument.

For example:

```
[64]: # Out-of-place addition creates and returns a new tensor without modifying the␣
       ↪inputs:
x = torch.tensor([1, 2, 3])
y = torch.tensor([3, 4, 5])
print('Out-of-place addition:')
print('Before addition:')
print('x: ', x)
print('y: ', y)
z = x.add(y)  # Same as z = x + y or z = torch.add(x, y)
print('\nAfter addition (x and y unchanged):')
print('x: ', x)
print('y: ', y)
```

```python
print('z: ', z)
print('z is x: ', z is x)
print('z is y: ', z is y)

# In-place addition modifies the input tensor:
print('\n\nIn-place Addition:')
print('Before addition:')
print('x: ', x)
print('y: ', y)
x.add_(y)  # Same as x += y or torch.add(x, y, out=x)
print('\nAfter addition (x is modified):')
print('x: ', x)
print('y: ', y)
print('z: ', z)
print('z is x: ', z is x)
print('z is y: ', z is y)
```

```
Out-of-place addition:
Before addition:
x:  tensor([1, 2, 3])
y:  tensor([3, 4, 5])

After addition (x and y unchanged):
x:  tensor([1, 2, 3])
y:  tensor([3, 4, 5])
z:  tensor([4, 6, 8])
z is x:  False
z is y:  False


In-place Addition:
Before addition:
x:  tensor([1, 2, 3])
y:  tensor([3, 4, 5])

After addition (x is modified):
x:  tensor([4, 6, 8])
y:  tensor([3, 4, 5])
z:  tensor([4, 6, 8])
z is x:  False
z is y:  False
```

In general, **you should avoid in-place operations** since they can cause problems when computing gradients using autograd (which we will cover in a future assignment).

5.6 Running on GPU

Note: this section requires a GPU! If you do not have a computer with a CUDA-enabled GPU, you can complete this portion of the notebook on Google Colab.

One of the most important features of PyTorch is that it can use graphics processing units (GPUs) to accelerate its tensor operations.

We can easily check whether PyTorch is configured to use GPUs:

Tensors can be moved onto any device using the .to method.

[65]:
```
import torch

if torch.cuda.is_available():
  print('PyTorch can use GPUs!')
else:
  print('PyTorch cannot use GPUs.')
```

```
PyTorch can use GPUs!
```

You can enable GPUs in Colab via Runtime -> Change Runtime Type -> Hardware Accelerator -> GPU.

This may cause the Colab runtime to restart, so we will re-import torch in the next cell.

We have already seen that PyTorch tensors have a `dtype` attribute specifying their datatype. All PyTorch tensors also have a `device` attribute that specifies the device where the tensor is stored – either CPU, or CUDA (for NVIDA GPUs). A tensor on a CUDA device will automatically use that device to accelerate all of its operations.

Just as with datatypes, we can use the `.to()` method to change the device of a tensor. We can also use the convenience methods `.cuda()` and `.cpu()` methods to move tensors between CPU and GPU.

[66]:
```
# Construct a tensor on the CPU
x0 = torch.tensor([[1, 2], [3, 4]], dtype=torch.float32)
print('x0 device:', x0.device)

# Move it to the GPU using .to()
x1 = x0.to('cuda')
print('x1 device:', x1.device)

# Move it to the GPU using .cuda()
x2 = x0.cuda()
print('x2 device:', x2.device)

# Move it back to the CPU using .to()
x3 = x1.to('cpu')
print('x3 device:', x3.device)

# Move it back to the CPU using .cpu()
```

```
x4 = x2.cpu()
print('x4 device:', x4.device)

# We can construct tensors directly on the GPU as well
y = torch.tensor([[1, 2, 3], [4, 5, 6]], dtype=torch.float64, device='cuda')
print('y device / dtype:', y.device, y.dtype)

# Calling x.to(y) where y is a tensor will return a copy of x with the same
# device and dtype as y
x5 = x0.to(y)
print('x5 device / dtype:', x5.device, x5.dtype)
```

```
x0 device: cpu
x1 device: cuda:0
x2 device: cuda:0
x3 device: cpu
x4 device: cpu
y device / dtype: cuda:0 torch.float64
x5 device / dtype: cuda:0 torch.float64
```

Performing large tensor operations on a GPU can be **a lot faster** than running the equivalent operation on CPU.

Here we compare the speed of adding two tensors of shape (10000, 10000) on CPU and GPU:

(Note that GPU code may run asynchronously with CPU code, so when timing the speed of operations on the GPU it is important to use `torch.cuda.synchronize` to synchronize the CPU and GPU.)

[71]:
```
import time

a_cpu = torch.randn(10000, 10000, dtype=torch.float32)
b_cpu = torch.randn(10000, 10000, dtype=torch.float32)

a_gpu = a_cpu.cuda()
b_gpu = b_cpu.cuda()
torch.cuda.synchronize()

t0 = time.time()
c_cpu = a_cpu + b_cpu
t1 = time.time()
c_gpu = a_gpu + b_gpu
torch.cuda.synchronize()
t2 = time.time()

# Check that they computed the same thing
diff = (c_gpu.cpu() - c_cpu).abs().max().item()
print('Max difference between c_gpu and c_cpu:', diff)
```

```
cpu_time = 1000.0 * (t1 - t0)
gpu_time = 1000.0 * (t2 - t1)
print('CPU time: %.2f ms' % cpu_time)
print('GPU time: %.2f ms' % gpu_time)
print('GPU speedup: %.2f x' % (cpu_time / gpu_time))
```

```
Max difference between c_gpu and c_cpu: 0.0
CPU time: 254.33 ms
GPU time: 5.01 ms
GPU speedup: 50.75 x
```

You should see that running the same computation on the GPU was more than 10~30 times faster than on the CPU! Due to the massive speedups that GPUs offer, we will use GPUs to accelerate much of our machine learning code starting in Assignment 2.

Your turn: Use the GPU to accelerate the following matrix multiplication operation. You should see 5~10x speedup by using the GPU.

[74]:
```
import time
from pytorch_tutorial import mm_on_cpu, mm_on_gpu

x = torch.rand(512, 4096)
w = torch.rand(4096, 4096)

t0 = time.time()
y0 = mm_on_cpu(x, w)
t1 = time.time()

y1 = mm_on_gpu(x, w)
torch.cuda.synchronize()
t2 = time.time()

print('y1 on CPU:', y1.device == torch.device('cpu'))
diff = (y0 - y1).abs().max().item()
print('Max difference between y0 and y1:', diff)
print('Difference within tolerance:', diff < 5e-2)

cpu_time = 1000.0 * (t1 - t0)
gpu_time = 1000.0 * (t2 - t1)
print('CPU time: %.2f ms' % cpu_time)
print('GPU time: %.2f ms' % gpu_time)
print('GPU speedup: %.2f x' % (cpu_time / gpu_time))
```

```
y1 on CPU: True
Max difference between y0 and y1: 0.001220703125
Difference within tolerance: True
CPU time: 237.70 ms
GPU time: 32.68 ms
GPU speedup: 7.27 x
```

Done! Now you can move to kNN.ipynb. Before you move, please check whether you generated any additional cell in every ipynb file (e.g. empty cell after very last code cell).

knn

April 3, 2024

1 ITE4052 Assignment 2-2: K-Nearest Neighbors (k-NN)

- This material draws from EECS 498-007/598-005 (Justin Johnson)

Before we start, please put your name and HYID in following format Firstname LASTNAME, #00000000 // e.g.) Sukmin Yun, #12345678

Your Answer:
Junwoo Park, #2021006253

In this notebook you will implement a K-Nearest Neighbors classifier on the CIFAR-10 dataset.

Recall that the K-Nearest Neighbor classifier does the following: - During training, the classifier simply memorizes the training data - During testing, test images are compared to each training image; the predicted label is the majority vote among the K nearest training examples.

After implementing the K-Nearest Neighbor classifier, you will use *cross-validation* to find the best value of K.

The goals of this exercise are to go through a simple example of the data-driven image classification pipeline, and also to practice writing efficient, vectorized code in PyTorch.

2 Setup Code

Before getting started we need to run some boilerplate code to set up our environment. You'll need to rerun this setup code each time you start the notebook.

First, run this cell load the autoreload extension. This allows us to edit `.py` source files, and re-import them into the notebook for a seamless editing and debugging experience.

[1]:
```
%load_ext autoreload
%autoreload 2
```

2.0.1 Google Colab Setup

Next we need to run a few commands to set up our environment on Google Colab. If you are running this notebook on a local machine you can skip this section.

Run the following cell to mount your Google Drive. Follow the link, sign in to your Google account (the same account you used to store this notebook!) and copy the authorization code into the text box that appears below.

[2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Now recall the path in your Google Drive where you uploaded this notebook, fill it in below. If everything is working correctly then running the folowing cell should print the filenames from the assignment:

```
['pytorch_tutorial.py', 'knn.py', 'knn.ipynb', 'ite4052', 'pytorch_tutorial.ipynb']
```

[3]:
```
import os

# TODO: Fill in the Google Drive path where you uploaded the assignment
# Example: If you create a ITE4052 folder and put all the files under A2␣
  ↪folder, then 'ITE4052/A2'
# GOOGLE_DRIVE_PATH_AFTER_MYDRIVE = 'ITE4052/A2'
GOOGLE_DRIVE_PATH_AFTER_MYDRIVE = 'ITE4052/A2'
GOOGLE_DRIVE_PATH = os.path.join('drive', 'My Drive',␣
  ↪GOOGLE_DRIVE_PATH_AFTER_MYDRIVE)
print(os.listdir(GOOGLE_DRIVE_PATH))
```

```
['makepdf.py', 'collectSubmission.sh', 'ite4052', '__pycache__',
'pytorch_tutorial.py', 'knn.py', 'pytorch_tutorial.ipynb', 'knn.ipynb']
```

Once you have successfully mounted your Google Drive and located the path to this assignment, run th following cell to allow us to import from the `.py` files of this assignment. If it works correctly, it should print the message:

```
Hello from knn.py!
```

as well as the last edit time for the file `knn.py`.

[4]:
```
import sys
sys.path.append(GOOGLE_DRIVE_PATH)

import time, os
os.environ["TZ"] = "US/Eastern"
time.tzset()

from knn import hello
hello()

knn_path = os.path.join(GOOGLE_DRIVE_PATH, 'knn.py')
knn_edit_time = time.ctime(os.path.getmtime(knn_path))
print('knn.py last edited on %s' % knn_edit_time)
```

```
Hello from knn.py!
knn.py last edited on Wed Apr  3 04:10:49 2024
```

3 Data preprocessing / Visualization

3.1 Setup code

Run some setup code for this notebook: Import some useful packages and increase the default figure size.

[5]:
```
import ite4052
import torch
import torchvision
import matplotlib.pyplot as plt
import statistics

plt.rcParams['figure.figsize'] = (10.0, 8.0)
plt.rcParams['font.size'] = 16
```

3.2 Load the CIFAR-10 dataset

The utility function `ite4052.data.cifar10()` returns the entire CIFAR-10 dataset as a set of four **Torch tensors**:

- `x_train` contains all training images (real numbers in the range $[0, 1]$)
- `y_train` contains all training labels (integers in the range $[0, 9]$)
- `x_test` contains all test images
- `y_test` contains all test labels

This function automatically downloads the CIFAR-10 dataset the first time you run it.

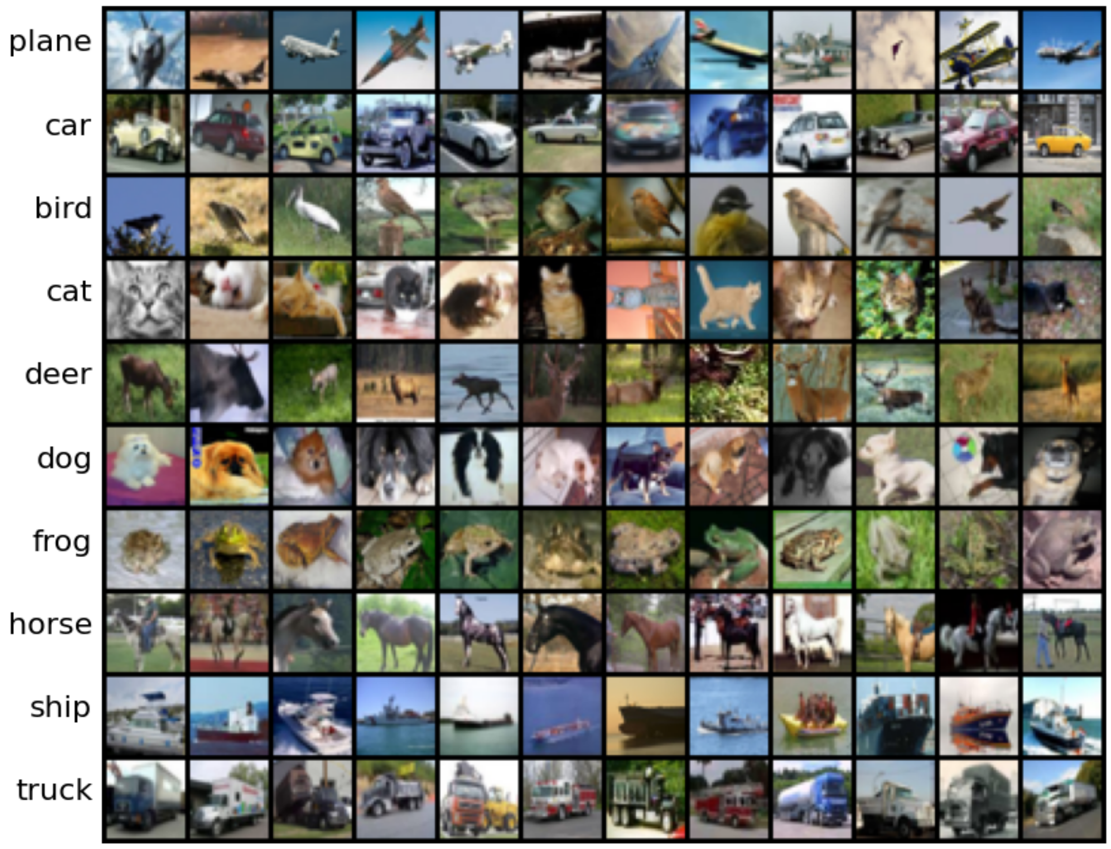
[6]:
```
x_train, y_train, x_test, y_test = ite4052.data.cifar10()

print('Training set:', )
print('  data shape:', x_train.shape)
print('  labels shape: ', y_train.shape)
print('Test set:')
print('  data shape: ', x_test.shape)
print('  labels shape', y_test.shape)
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./cifar-10-python.tar.gz

100%|     | 170498071/170498071 [00:13<00:00, 12494414.34it/s]

Extracting ./cifar-10-python.tar.gz to .
Training set:
  data shape: torch.Size([50000, 3, 32, 32])
  labels shape:  torch.Size([50000])
Test set:
  data shape:  torch.Size([10000, 3, 32, 32])
  labels shape torch.Size([10000])
```

3.3 Visualize the dataset

To give you a sense of the nature of the images in CIFAR-10, this cell visualizes some random examples from the training set.

```
[7]: import random
     from torchvision.utils import make_grid

     classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
      ↪'ship', 'truck']
     samples_per_class = 12
     samples = []
     for y, cls in enumerate(classes):
         plt.text(-4, 34 * y + 18, cls, ha='right')
         idxs, = (y_train == y).nonzero(as_tuple=True)
         for i in range(samples_per_class):
             idx = idxs[random.randrange(idxs.shape[0])].item()
             samples.append(x_train[idx])
     img = torchvision.utils.make_grid(samples, nrow=samples_per_class)
     plt.imshow(ite4052.tensor_to_image(img))
     plt.axis('off')
     plt.show()
```



3.4 Subsample the dataset

When implementing machine learning algorithms, it's usually a good idea to use a small sample of the full dataset. This way your code will run much faster, allowing for more interactive and efficient development. Once you are satisfied that you have correctly implemented the algorithm, you can then rerun with the entire dataset.

The function `ite4052.data.cifar10()` can automatically subsample the CIFAR10 dataset for us. To see how to use it, we can check the documentation using the built-in `help` command:

[8]:
```
help(ite4052.data.cifar10)
```

```
Help on function cifar10 in module ite4052.data:

cifar10(num_train=None, num_test=None, x_dtype=torch.float32)
    Return the CIFAR10 dataset, automatically downloading it if necessary.
    This function can also subsample the dataset.

    Inputs:
    - num_train: [Optional] How many samples to keep from the training set.
      If not provided, then keep the entire training set.
    - num_test: [Optional] How many samples to keep from the test set.
      If not provided, then keep the entire test set.
    - x_dtype: [Optional] Data type of the input image

    Returns:
    - x_train: `x_dtype` tensor of shape (num_train, 3, 32, 32)
    - y_train: int64 tensor of shape (num_train, 3, 32, 32)
    - x_test: `x_dtype` tensor of shape (num_test, 3, 32, 32)
    - y_test: int64 tensor of shape (num_test, 3, 32, 32)
```

We will subsample the data to use only 500 training examples and 250 test examples:

[9]:
```
num_train = 500
num_test = 250

x_train, y_train, x_test, y_test = ite4052.data.cifar10(num_train, num_test)

print('Training set:', )
print('  data shape:', x_train.shape)
print('  labels shape: ', y_train.shape)
print('Test set:')
print('  data shape: ', x_test.shape)
print('  labels shape', y_test.shape)
```

```
Training set:
  data shape: torch.Size([500, 3, 32, 32])
  labels shape:  torch.Size([500])
Test set:
  data shape:  torch.Size([250, 3, 32, 32])
  labels shape torch.Size([250])
```

4 K-Nearest Neighbors (k-NN)

4.1 Compute distances: Naive implementation

Now that we have examined and prepared our data, it is time to implement the kNN classifier. We can break the process down into two steps:

1. Compute the (squared Euclidean) distances between all training examples and all test examples
2. Given these distances, for each test example find its k nearest neighbors and have them vote for the label to output

Lets begin with computing the distance matrix between all training and test examples. First we will implement a naive version of the distance computation, using explicit loops over the training and test sets. In the file `knn.py`, implement the function `compute_distances_two_loops`.

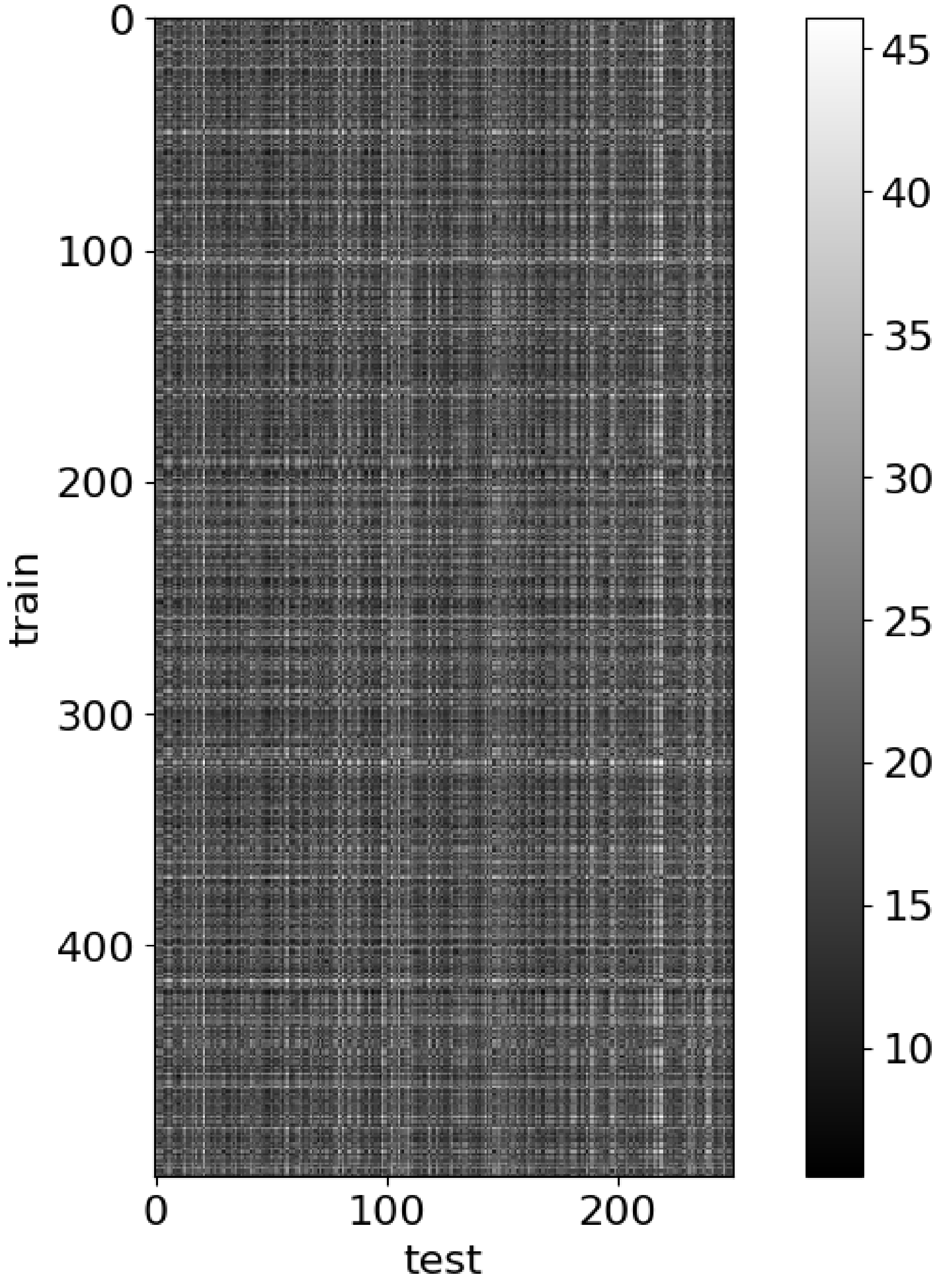
NOTE: When implementing distance functions for this assignment, you may not use functions `torch.norm` or `torch.dist` (or their instance method variants `x.norm` / `x.dist`); you may not use any functions from `torch.nn` or `torch.nn.functional`.

[10]:
```python
from knn import compute_distances_two_loops

torch.manual_seed(0)
num_train = 500
num_test = 250
x_train, y_train, x_test, y_test = ite4052.data.cifar10(num_train, num_test)

dists = compute_distances_two_loops(x_train, x_test)
print('dists has shape: ', dists.shape)
```

```
dists has shape:  torch.Size([500, 250])
```

As a visual debugging step, we can visualize the distance matrix, where each row is a test example and each column is a training example.

[11]:
```python
plt.imshow(dists.numpy(), cmap='gray', interpolation='none')
plt.colorbar()
plt.xlabel('test')
plt.ylabel('train')
plt.show()
```



4.2 Compute distances: Vectorization

Our implementation of the distance computation above is fairly inefficient since it uses nested Python loops over the training and test sets.

When implementing algorithms in PyTorch, it's best to avoid loops in Python if possible. Instead it is preferable to implement your computation so that all loops happen inside PyTorch functions. This will usually be much faster than writing your own loops in Python, since PyTorch functions can be internally optimized to iterate efficiently, possibly using multiple threads. This is especially important when using a GPU to accelerate your code.

The process of eliminating explict loops from your code is called **vectorization**. Sometimes it is straighforward to vectorize code originally written with loops; other times vectorizing requires thinking about the problem in a new way. We will use vectorization to improve the speed of our distance computation function.

As a first step toward vectorizing our distance computation, you will implement a version that uses only a single Python loop over the training data. In the file `knn.py`, complete the implementation of the function `compute_distances_one_loop`.

We can check the correctness of our one-loop implementation by comparing it with our two-loop implementation on some randomly generated data.

Note that we do the comparison with 64-bit floating points for increased numeric precision.

[12]:
```
from knn import compute_distances_one_loop
from knn import compute_distances_two_loops

torch.manual_seed(0)
x_train_rand = torch.randn(100, 3, 16, 16, dtype=torch.float64)
x_test_rand = torch.randn(100, 3, 16, 16, dtype=torch.float64)

dists_one = compute_distances_one_loop(x_train_rand, x_test_rand)
dists_two = compute_distances_two_loops(x_train_rand, x_test_rand)
difference = (dists_one - dists_two).pow(2).sum().sqrt().item()
print('Difference: ', difference)
if difference < 1e-4:
    print('Good! The distance matrices match')
else:
    print('Uh-oh! The distance matrices are different')
```

```
Difference:  0.0
Good! The distance matrices match
```

You will now implement a fully vectorized version of the distance computation function that does not use any Python loops. In the file `knn.py`, implement the function `compute_distances_no_loops`.

As before, we can check the correctness of our implementation by comparing the fully vectorized version against the original naive version:

[13]:
```
from knn import compute_distances_two_loops
from knn import compute_distances_no_loops

torch.manual_seed(0)
x_train_rand = torch.randn(100, 3, 16, 16, dtype=torch.float64)
x_test_rand = torch.randn(100, 3, 16, 16, dtype=torch.float64)

dists_two = compute_distances_two_loops(x_train_rand, x_test_rand)
dists_none = compute_distances_no_loops(x_train_rand, x_test_rand)
```

```
difference = (dists_two - dists_none).pow(2).sum().sqrt().item()
print('Difference: ', difference)
if difference < 1e-4:
  print('Good! The distance matrices match')
else:
  print('Uh-oh! The distance matrices are different')
```

```
Difference:  3.428322680126376e-13
Good! The distance matrices match
```

We can now compare the speed of our three implementations. If you've implemented everything properly, the one-loop implementation should take less than 4 seconds to run, and the fully vectorized implementation should take less than 0.1 seconds to run.

[14]:
```
import time
from knn import compute_distances_two_loops
from knn import compute_distances_one_loop
from knn import compute_distances_no_loops

def timeit(f, *args):
    tic = time.time()
    f(*args)
    toc = time.time()
    return toc - tic

torch.manual_seed(0)
x_train_rand = torch.randn(500, 3, 32, 32)
x_test_rand = torch.randn(500, 3, 32, 32)

two_loop_time = timeit(compute_distances_two_loops, x_train_rand, x_test_rand)
print('Two loop version took %.2f seconds' % two_loop_time)

one_loop_time = timeit(compute_distances_one_loop, x_train_rand, x_test_rand)
speedup = two_loop_time / one_loop_time
print('One loop version took %.2f seconds (%.1fX speedup)'
      % (one_loop_time, speedup))

no_loop_time = timeit(compute_distances_no_loops, x_train_rand, x_test_rand)
speedup = two_loop_time / no_loop_time
print('No loop version took %.2f seconds (%.1fX speedup)'
      % (no_loop_time, speedup))
```

```
Two loop version took 10.73 seconds
One loop version took 0.69 seconds (15.4X speedup)
No loop version took 0.03 seconds (384.7X speedup)
```

4.3 Predict labels

Now that we have a method for computing distances between training and test examples, we need to implement a function that uses those distances together with the training labels to predict labels for test samples.

In the file `knn.py`, implement the function `predict_labels`.

[15]:
```
from knn import predict_labels

torch.manual_seed(0)
dists = torch.tensor([
    [0.3, 0.4, 0.1],
    [0.1, 0.5, 0.5],
    [0.4, 0.1, 0.2],
    [0.2, 0.2, 0.4],
    [0.5, 0.3, 0.3],
])
y_train = torch.tensor([0, 1, 0, 1, 2])
y_pred_expected = torch.tensor([1, 0, 0])
y_pred = predict_labels(dists, y_train, k=3)
correct = y_pred.tolist() == y_pred_expected.tolist()
print('Correct: ', correct)
```

```
Correct:  True
```

Now we have implemented all the required functionality for the K-Nearest Neighbor classifier. In the file `knn.py`, complete the implementation of the `KnnClassifer` class.

We can get some intuition into the KNN classifier by visualizing its predictions on toy 2D data. Here we will generate some random training and test points in 2D, and assign random labels to the training points. We can then make predictions for the test points, and visualize both training and test points. Training points are shown as stars, and tet points are shown as small transparent circles. The color of each point denots its label – ground-truth label for training points, and predicted label for test points.

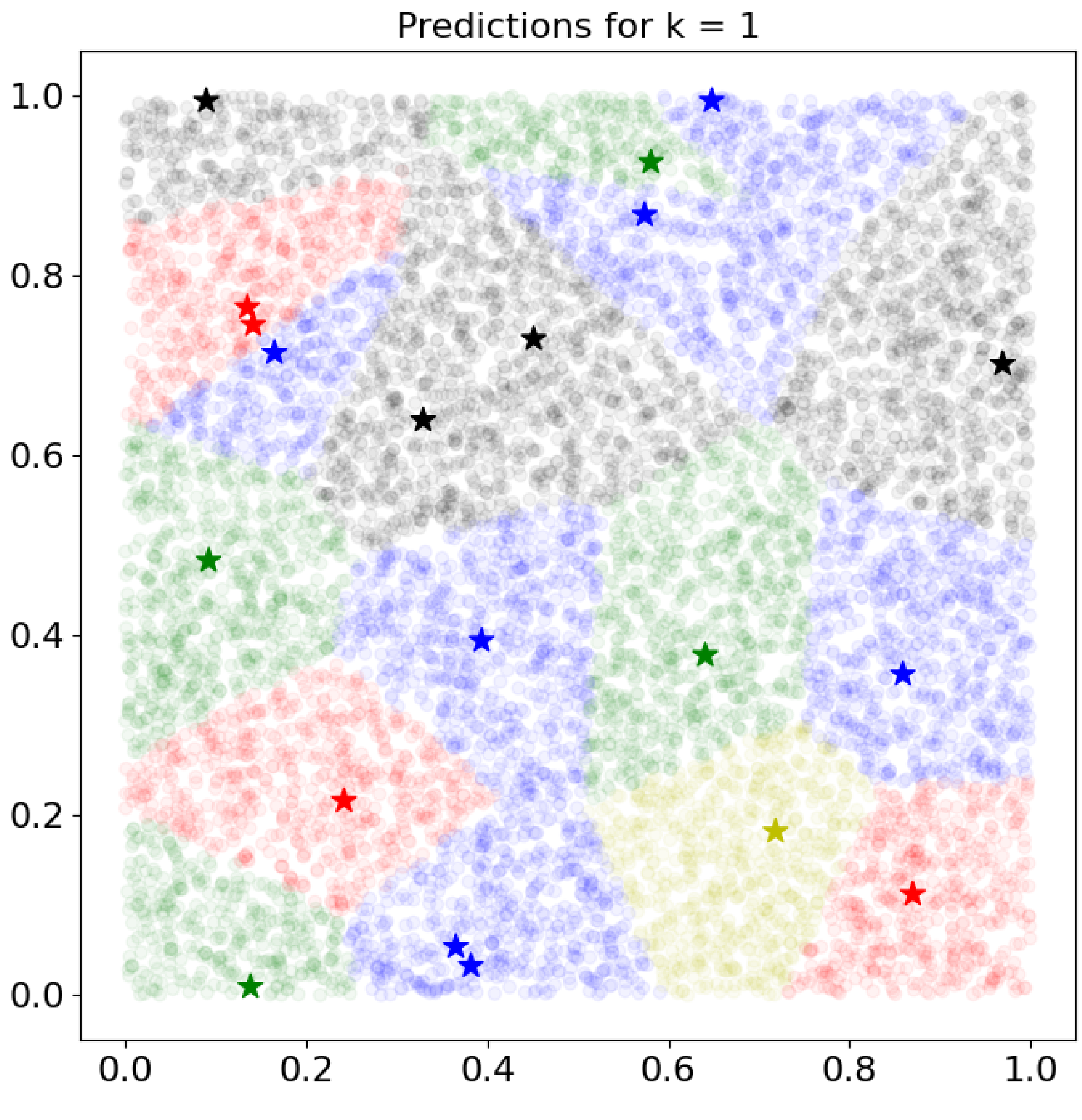
[16]:
```
from knn import KnnClassifier

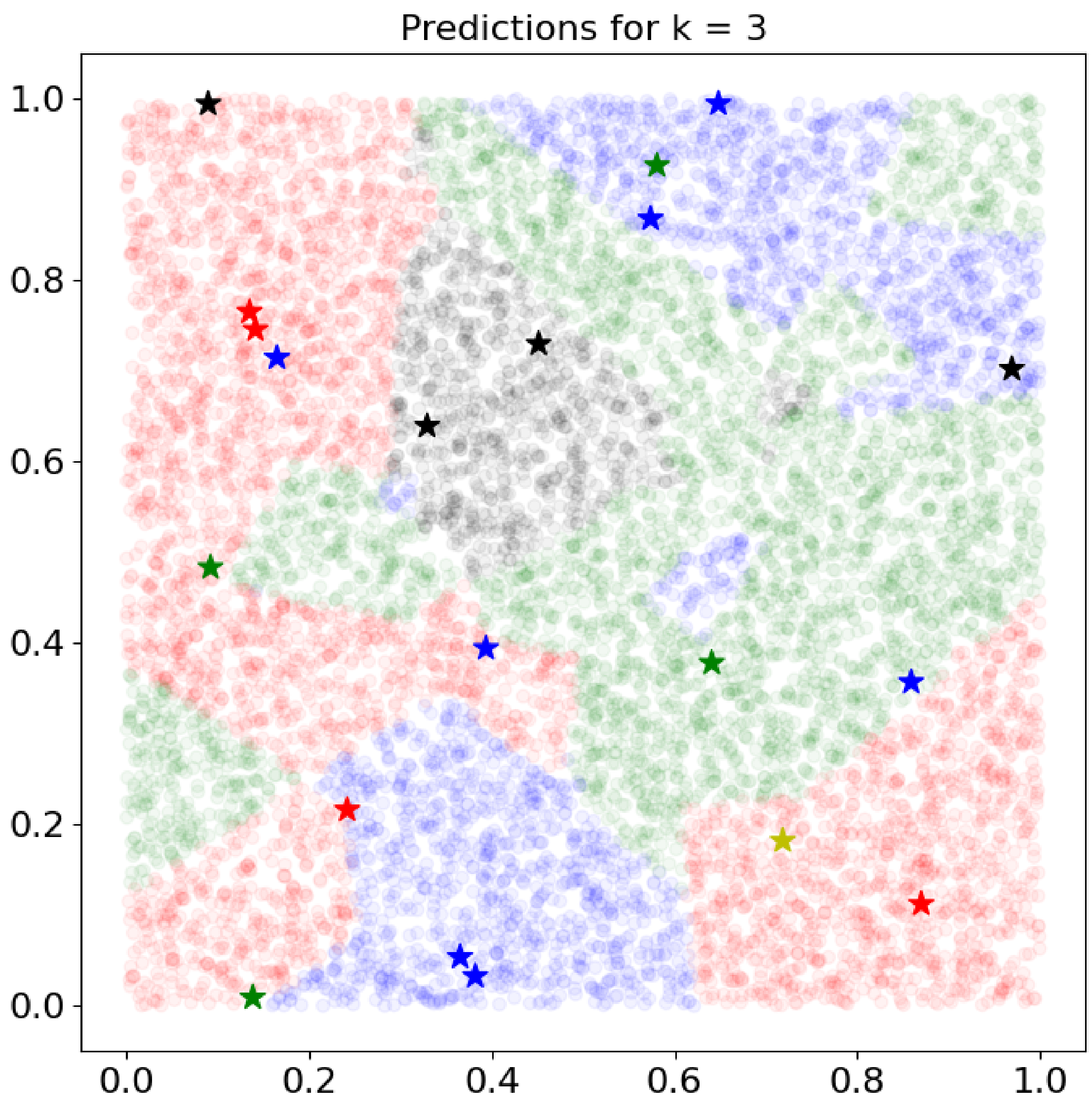
num_test = 10000
num_train = 20
num_classes = 5

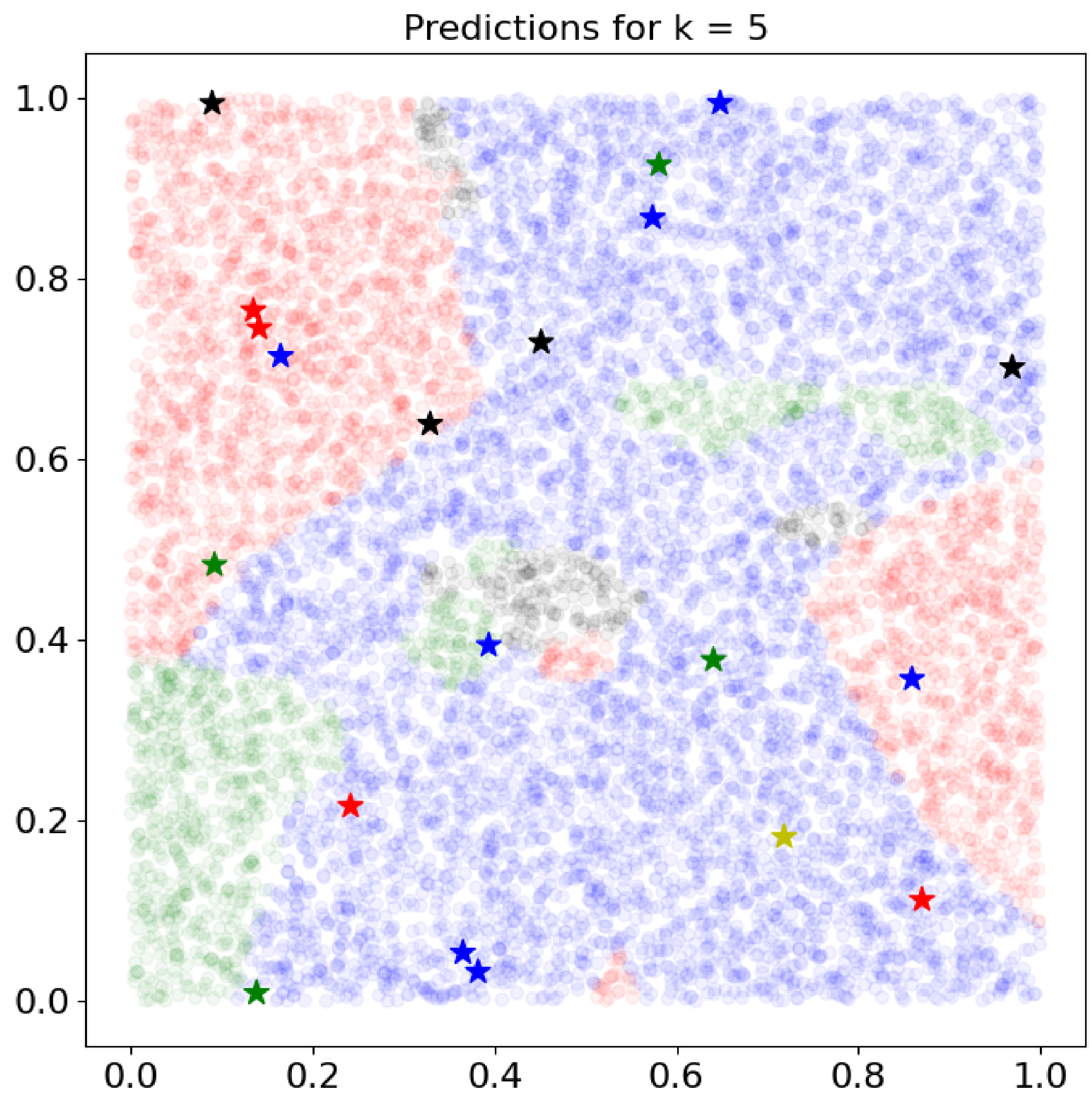
# Generate random training and test data
torch.manual_seed(128)
x_train = torch.rand(num_train, 2)
y_train = torch.randint(num_classes, size=(num_train,))
x_test = torch.rand(num_test, 2)
classifier = KnnClassifier(x_train, y_train)

# Plot predictions for different values of k
```

```
for k in [1, 3, 5]:
    y_test = classifier.predict(x_test, k=k)
    plt.gcf().set_size_inches(8, 8)
    class_colors = ['r', 'g', 'b', 'k', 'y']
    train_colors = [class_colors[c] for c in y_train]
    test_colors = [class_colors[c] for c in y_test]
    plt.scatter(x_test[:, 0], x_test[:, 1],
                color=test_colors, marker='o', s=32, alpha=0.05)
    plt.scatter(x_train[:, 0], x_train[:, 1],
                color=train_colors, marker='*', s=128.0)
    plt.title('Predictions for k = %d' % k, size=16)
    plt.show()
```




Predictions for k = 3
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0



We can use the exact same KNN code to perform image classification on CIFAR-10!

Now lets put everything together and test our K-NN clasifier on a subset of CIFAR-10, using k=1:

If you've implemented everything correctly you should see an accuracy of about 27%.

[17]:
```
from knn import KnnClassifier

torch.manual_seed(0)
num_train = 5000
num_test = 500
x_train, y_train, x_test, y_test = ite4052.data.cifar10(num_train, num_test)

classifier = KnnClassifier(x_train, y_train)
```

```
classifier.check_accuracy(x_test, y_test, k=1)
```

```
Got 137 / 500 correct; accuracy is 27.40%
```

[17]:
```
27.4
```

Now lets increase to k=5. You should see a slightly higher accuracy than k=1:

[18]:
```
from knn import KnnClassifier

torch.manual_seed(0)
num_train = 5000
num_test = 500
x_train, y_train, x_test, y_test = ite4052.data.cifar10(num_train, num_test)

classifier = KnnClassifier(x_train, y_train)
classifier.check_accuracy(x_test, y_test, k=5)
```

```
Got 139 / 500 correct; accuracy is 27.80%
```

[18]:
```
27.8
```

4.4 Cross-validation

We have not implemented the full k-Nearest Neighbor classifier, but the choice of $k = 5$ was arbitrary. We will use **cross-validation** to set this hyperparameter in a more principled manner.

In the file `knn.py`, implement the function `knn_cross_validate` to perform cross-validation on k.

[19]:
```
from knn import knn_cross_validate

torch.manual_seed(0)
num_train = 5000
num_test = 500
x_train, y_train, x_test, y_test = ite4052.data.cifar10(num_train, num_test)

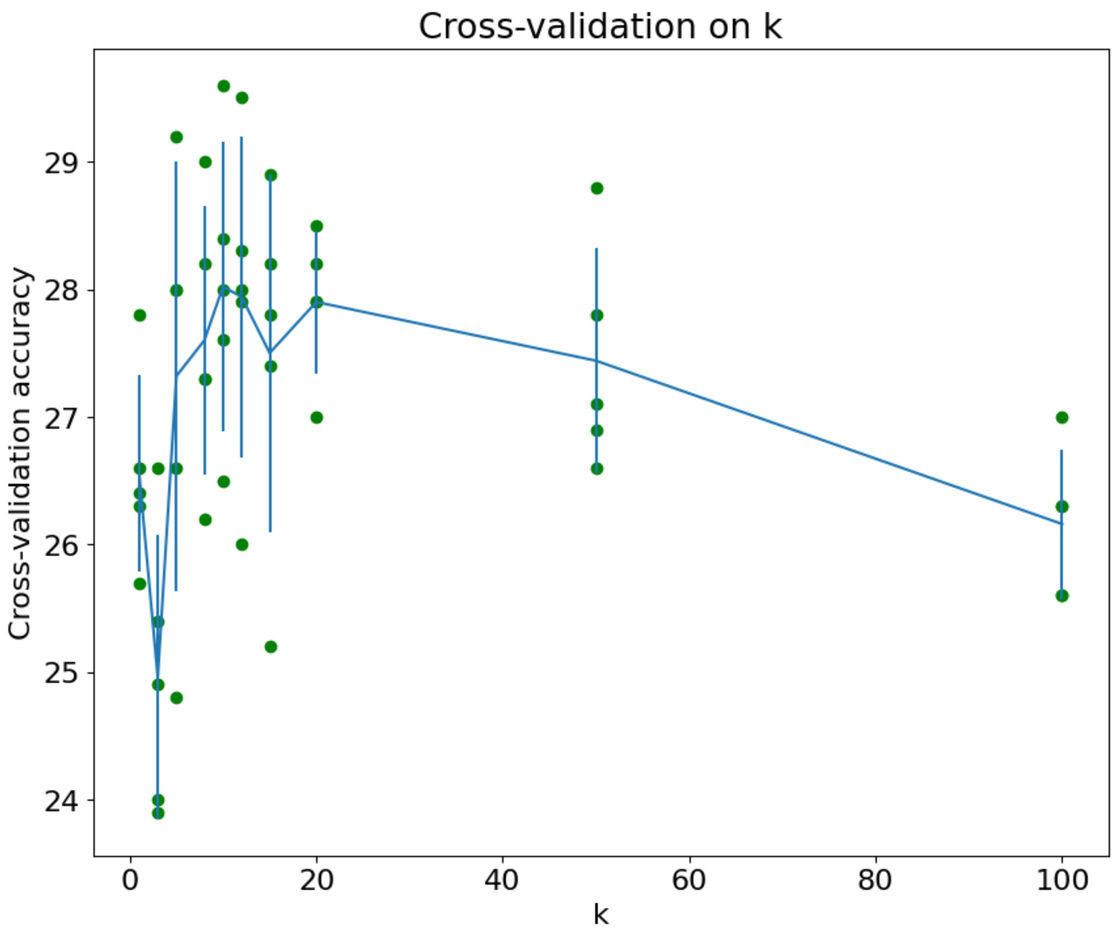
k_to_accuracies = knn_cross_validate(x_train, y_train, num_folds=5)

for k, accs in sorted(k_to_accuracies.items()):
  print('k = %d got accuracies: %r' % (k, accs))
```

```
Got 263 / 1000 correct; accuracy is 26.30%
Got 257 / 1000 correct; accuracy is 25.70%
Got 264 / 1000 correct; accuracy is 26.40%
Got 278 / 1000 correct; accuracy is 27.80%
Got 266 / 1000 correct; accuracy is 26.60%
Got 239 / 1000 correct; accuracy is 23.90%
Got 249 / 1000 correct; accuracy is 24.90%
Got 240 / 1000 correct; accuracy is 24.00%
Got 266 / 1000 correct; accuracy is 26.60%
Got 254 / 1000 correct; accuracy is 25.40%
Got 248 / 1000 correct; accuracy is 24.80%
Got 266 / 1000 correct; accuracy is 26.60%
Got 280 / 1000 correct; accuracy is 28.00%
Got 292 / 1000 correct; accuracy is 29.20%
Got 280 / 1000 correct; accuracy is 28.00%
Got 262 / 1000 correct; accuracy is 26.20%
Got 282 / 1000 correct; accuracy is 28.20%
Got 273 / 1000 correct; accuracy is 27.30%
Got 290 / 1000 correct; accuracy is 29.00%
Got 273 / 1000 correct; accuracy is 27.30%
Got 265 / 1000 correct; accuracy is 26.50%
Got 296 / 1000 correct; accuracy is 29.60%
Got 276 / 1000 correct; accuracy is 27.60%
Got 284 / 1000 correct; accuracy is 28.40%
Got 280 / 1000 correct; accuracy is 28.00%
Got 260 / 1000 correct; accuracy is 26.00%
Got 295 / 1000 correct; accuracy is 29.50%
Got 279 / 1000 correct; accuracy is 27.90%
Got 283 / 1000 correct; accuracy is 28.30%
Got 280 / 1000 correct; accuracy is 28.00%
Got 252 / 1000 correct; accuracy is 25.20%
Got 289 / 1000 correct; accuracy is 28.90%
Got 278 / 1000 correct; accuracy is 27.80%
Got 282 / 1000 correct; accuracy is 28.20%
Got 274 / 1000 correct; accuracy is 27.40%
Got 270 / 1000 correct; accuracy is 27.00%
Got 279 / 1000 correct; accuracy is 27.90%
Got 279 / 1000 correct; accuracy is 27.90%
Got 282 / 1000 correct; accuracy is 28.20%
Got 285 / 1000 correct; accuracy is 28.50%
Got 271 / 1000 correct; accuracy is 27.10%
Got 288 / 1000 correct; accuracy is 28.80%
Got 278 / 1000 correct; accuracy is 27.80%
Got 269 / 1000 correct; accuracy is 26.90%
Got 266 / 1000 correct; accuracy is 26.60%
Got 256 / 1000 correct; accuracy is 25.60%
Got 270 / 1000 correct; accuracy is 27.00%
Got 263 / 1000 correct; accuracy is 26.30%
Got 256 / 1000 correct; accuracy is 25.60%
Got 263 / 1000 correct; accuracy is 26.30%
k = 1 got accuracies: [26.3, 25.7, 26.4, 27.8, 26.6]
k = 3 got accuracies: [23.9, 24.9, 24.0, 26.6, 25.4]
k = 5 got accuracies: [24.8, 26.6, 28.0, 29.2, 28.0]
k = 8 got accuracies: [26.2, 28.2, 27.3, 29.0, 27.3]
k = 10 got accuracies: [26.5, 29.6, 27.6, 28.4, 28.0]
k = 12 got accuracies: [26.0, 29.5, 27.9, 28.3, 28.0]
```

```
k = 15 got accuracies: [25.2, 28.9, 27.8, 28.2, 27.4]
k = 20 got accuracies: [27.0, 27.9, 27.9, 28.2, 28.5]
k = 50 got accuracies: [27.1, 28.8, 27.8, 26.9, 26.6]
k = 100 got accuracies: [25.6, 27.0, 26.3, 25.6, 26.3]
```

[20]:
```
ks, means, stds = [], [], []
torch.manual_seed(0)
for k, accs in sorted(k_to_accuracies.items()):
  plt.scatter([k] * len(accs), accs, color='g')
  ks.append(k)
  means.append(statistics.mean(accs))
  stds.append(statistics.stdev(accs))
plt.errorbar(ks, means, yerr=stds)
plt.xlabel('k')
plt.ylabel('Cross-validation accuracy')
plt.title('Cross-validation on k')
plt.show()
```



Now we can use the results of cross-validation to select the best value for k, and rerun the classifier on our full 5000 set of training examples.

You should get an accuracy above 28%.

```
[21]: from knn import KnnClassifier
      from knn import knn_get_best_k

      best_k = 1
      torch.manual_seed(0)

      best_k = knn_get_best_k(k_to_accuracies)
      print('Best k is ', best_k)

      classifier = KnnClassifier(x_train, y_train)
      classifier.check_accuracy(x_test, y_test, k=best_k)
```

```
Best k is  10
Got 141 / 500 correct; accuracy is 28.20%
```

```
[21]: 28.2
```

Finally, we can use our chosen value of k to run on the entire training and test sets.

This may take a while to run, since the full training and test sets have 50k and 10k examples respectively. You should get an accuracy above 33%.

Run this only once!

```
[22]: from knn import KnnClassifier

      torch.manual_seed(0)
      x_train_all, y_train_all, x_test_all, y_test_all = ite4052.data.cifar10()
      classifier = KnnClassifier(x_train_all, y_train_all)
      classifier.check_accuracy(x_test_all, y_test_all, k=best_k)
```

```
Got 3386 / 10000 correct; accuracy is 33.86%
```

```
[22]: 33.86
```

4.5 Submit Your Work - Zip + Generate PDF

1. After completing both notebooks for this assignment (`pytorch_tutorial.ipynb` and this notebook, `knn.ipynb`), run the following cell to create a `.zip` file for you to download and turn in. **Please MANUALLY SAVE every `*.ipynb` and `*.py` files before executing the following cell:**
2. Convert all notebooks into a single PDF file called a2_inline_submission.pdf. If your submission for this step was successful, you should see the following display message: `### Done! Please submit a2_inline_submission.pdf to LMS. ###`. **Please MANUALLY change your `a2_inline_submission.pdf` to your unique filename (e.g., `sukminyun_12345678_A2.pdf`)**

Make sure to download the zip and pdf file locally to your computer, then submit to LMS. Congrats on succesfully completing the assignment!

[23]:
```
from ite4052.submit import make_a2_submission

make_a2_submission(GOOGLE_DRIVE_PATH)
```

```
Enter your uniquename (e.g. sukminyun): JunwooPark
Enter your hyid (e.g. 12345678): 2021006253
Writing zip file to:  drive/My Drive/ITE4052/A2/JunwooPark_2021006253_A2.zip
```

[ ]:
```
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
 ↪texlive-plain-generic
!pip install PyPDF2
%cd $GOOGLE_DRIVE_PATH
!bash collectSubmission.sh
```

```
Reading package lists… Done
Building dependency tree… Done
Reading state information… Done
The following additional packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono
  fonts-texgyre fonts-urw-base35 libapache-pom-java libcommons-logging-java
  libcommons-parent-java libfontbox-java libfontenc1 libgs9 libgs9-common
  libidn12 libijs-0.35 libjbig2dec0 libkpathsea6 libpdfbox-java libptexenc1
  libruby3.0 libsynctex2 libteckit0 libtexlua53 libtexluajit2 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby
  ruby-net-telnet ruby-rubygems ruby-webrick ruby-xmlrpc ruby3.0
  rubygems-integration t1utils teckit tex-common tex-gyre texlive-base
  texlive-binaries texlive-latex-base texlive-latex-extra
  texlive-latex-recommended texlive-pictures tipa xfonts-encodings
  xfonts-utils
Suggested packages:
  fonts-noto fonts-freefont-otf | fonts-freefont-ttf libavalon-framework-java
  libcommons-logging-java-doc libexcalibur-logkit-java liblog4j1.2-java
  poppler-utils ghostscript fonts-japanese-mincho | fonts-ipafont-mincho
  fonts-japanese-gothic | fonts-ipafont-gothic fonts-arphic-ukai
  fonts-arphic-uming fonts-nanum ri ruby-dev bundler debhelper gv
  | postscript-viewer perl-tk xpdf | pdf-viewer xzdec
  texlive-fonts-recommended-doc texlive-latex-base-doc python3-pygments
  icc-profiles libfile-which-perl libspreadsheet-parseexcel-perl
  texlive-latex-extra-doc texlive-latex-recommended-doc texlive-luatex
  texlive-pstricks dot2tex prerex texlive-pictures-doc vprerex
  default-jre-headless tipa-doc
The following NEW packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono
  fonts-texgyre fonts-urw-base35 libapache-pom-java libcommons-logging-java
  libcommons-parent-java libfontbox-java libfontenc1 libgs9 libgs9-common
  libidn12 libijs-0.35 libjbig2dec0 libkpathsea6 libpdfbox-java libptexenc1
  libruby3.0 libsynctex2 libteckit0 libtexlua53 libtexluajit2 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby
  ruby-net-telnet ruby-rubygems ruby-webrick ruby-xmlrpc ruby3.0
  rubygems-integration t1utils teckit tex-common tex-gyre texlive-base
  texlive-binaries texlive-fonts-recommended texlive-latex-base
  texlive-latex-extra texlive-latex-recommended texlive-pictures
  texlive-plain-generic texlive-xetex tipa xfonts-encodings xfonts-utils
0 upgraded, 54 newly installed, 0 to remove and 45 not upgraded.
Need to get 182 MB of archives.
After this operation, 571 MB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-droid-fallback all
1:6.0.1r16-1.1build1 [1,805 kB]
Get:2 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-lato all 2.0-2.1
[2,696 kB]
Get:3 http://archive.ubuntu.com/ubuntu jammy/main amd64 poppler-data all
0.4.11-1 [2,171 kB]
Get:4 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tex-common all 6.17
[33.7 kB]
Get:5 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-urw-base35 all
20200910-1 [6,367 kB]
Get:6 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9-common
all 9.55.0~dfsg1-0ubuntu5.6 [751 kB]
Get:7 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libidn12 amd64
1.38-4ubuntu1 [60.0 kB]
Get:8 http://archive.ubuntu.com/ubuntu jammy/main amd64 libijs-0.35 amd64
0.35-15build2 [16.5 kB]
Get:9 http://archive.ubuntu.com/ubuntu jammy/main amd64 libjbig2dec0 amd64
0.19-3build2 [64.7 kB]
Get:10 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9 amd64
9.55.0~dfsg1-0ubuntu5.6 [5,031 kB]
Get:11 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libkpathsea6
amd64 2021.20210626.59705-1ubuntu0.2 [60.4 kB]
Get:12 http://archive.ubuntu.com/ubuntu jammy/main amd64 libwoff1 amd64
1.0.2-1build4 [45.2 kB]
Get:13 http://archive.ubuntu.com/ubuntu jammy/universe amd64 dvisvgm amd64
2.13.1-1 [1,221 kB]
Get:14 http://archive.ubuntu.com/ubuntu jammy/universe amd64 fonts-lmodern all
2.004.5-6.1 [4,532 kB]
Get:15 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-noto-mono all
20201225-1build1 [397 kB]
Get:16 http://archive.ubuntu.com/ubuntu jammy/universe amd64 fonts-texgyre all
20180621-3.1 [10.2 MB]
Get:17 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libapache-pom-java
all 18-1 [4,720 B]
Get:18 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libcommons-parent-
java all 43-1 [10.8 kB]
Get:19 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libcommons-logging-
```

```
java all 1.2-2 [60.3 kB]
Get:20 http://archive.ubuntu.com/ubuntu jammy/main amd64 libfontenc1 amd64
1:1.1.4-1build3 [14.7 kB]
Get:21 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libptexenc1
amd64 2021.20210626.59705-1ubuntu0.2 [39.1 kB]
Get:22 http://archive.ubuntu.com/ubuntu jammy/main amd64 rubygems-integration
all 1.18 [5,336 B]
Get:23 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 ruby3.0 amd64
3.0.2-7ubuntu2.4 [50.1 kB]
Get:24 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby-rubygems all
3.3.5-2 [228 kB]
Get:25 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby amd64 1:3.0~exp1
[5,100 B]
Get:26 http://archive.ubuntu.com/ubuntu jammy/main amd64 rake all 13.0.6-2 [61.7
kB]
Get:27 http://archive.ubuntu.com/ubuntu jammy/main amd64 ruby-net-telnet all
0.1.1-2 [12.6 kB]
Get:28 http://archive.ubuntu.com/ubuntu jammy/universe amd64 ruby-webrick all
1.7.0-3 [51.8 kB]
Get:29 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 ruby-xmlrpc all
0.3.2-1ubuntu0.1 [24.9 kB]
Get:30 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libruby3.0
amd64 3.0.2-7ubuntu2.4 [5,113 kB]
Get:31 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libsynctex2
amd64 2021.20210626.59705-1ubuntu0.2 [55.6 kB]
Get:32 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libteckit0 amd64
2.5.11+ds1-1 [421 kB]
Get:33 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libtexlua53
amd64 2021.20210626.59705-1ubuntu0.2 [120 kB]
Get:34 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libtexluajit2
amd64 2021.20210626.59705-1ubuntu0.2 [267 kB]
Get:35 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libzzip-0-13 amd64
0.13.72+dfsg.1-1.1 [27.0 kB]
Get:36 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-encodings all
1:1.0.5-0ubuntu2 [578 kB]
Get:37 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-utils amd64
1:7.7+6build2 [94.6 kB]
Get:38 http://archive.ubuntu.com/ubuntu jammy/universe amd64 lmodern all
2.004.5-6.1 [9,471 kB]
Get:39 http://archive.ubuntu.com/ubuntu jammy/universe amd64 preview-latex-style
all 12.2-1ubuntu1 [185 kB]
Get:40 http://archive.ubuntu.com/ubuntu jammy/main amd64 t1utils amd64
1.41-4build2 [61.3 kB]
Get:41 http://archive.ubuntu.com/ubuntu jammy/universe amd64 teckit amd64
2.5.11+ds1-1 [699 kB]
Get:42 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tex-gyre all
20180621-3.1 [6,209 kB]
Get:43 http://archive.ubuntu.com/ubuntu jammy-updates/universe amd64 texlive-
```

```
binaries amd64 2021.20210626.59705-1ubuntu0.2 [9,860 kB]
Get:44 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-base all
2021.20220204-1 [21.0 MB]
Get:45 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-fonts-
recommended all 2021.20220204-1 [4,972 kB]
Get:46 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-base
all 2021.20220204-1 [1,128 kB]
Get:47 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libfontbox-java all
1:1.8.16-2 [207 kB]
Get:48 http://archive.ubuntu.com/ubuntu jammy/universe amd64 libpdfbox-java all
1:1.8.16-2 [5,199 kB]
Get:49 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-
recommended all 2021.20220204-1 [14.4 MB]
Get:50 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-pictures
all 2021.20220204-1 [8,720 kB]
Get:51 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-latex-extra
all 2021.20220204-1 [13.9 MB]
Get:52 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-plain-
generic all 2021.20220204-1 [27.5 MB]
Get:53 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tipa all 2:1.3-21
[2,967 kB]
Get:54 http://archive.ubuntu.com/ubuntu jammy/universe amd64 texlive-xetex all
2021.20220204-1 [12.4 MB]
Fetched 182 MB in 18s (10.3 MB/s)
debconf: unable to initialize frontend: Dialog
debconf: (No usable dialog-like program is installed, so the dialog based
frontend cannot be used. at /usr/share/perl5/Debconf/FrontEnd/Dialog.pm line 78,
<> line 54.)
debconf: falling back to frontend: Readline
debconf: unable to initialize frontend: Readline
debconf: (This frontend requires a controlling tty.)
debconf: falling back to frontend: Teletype
dpkg-preconfigure: unable to re-open stdin:
Selecting previously unselected package fonts-droid-fallback.
(Reading database … 121753 files and directories currently installed.)
Preparing to unpack …/00-fonts-droid-fallback_1%3a6.0.1r16-1.1build1_all.deb
…
Unpacking fonts-droid-fallback (1:6.0.1r16-1.1build1) …
Selecting previously unselected package fonts-lato.
Preparing to unpack …/01-fonts-lato_2.0-2.1_all.deb …
Unpacking fonts-lato (2.0-2.1) …
Selecting previously unselected package poppler-data.
Preparing to unpack …/02-poppler-data_0.4.11-1_all.deb …
Unpacking poppler-data (0.4.11-1) …
Selecting previously unselected package tex-common.
Preparing to unpack …/03-tex-common_6.17_all.deb …
Unpacking tex-common (6.17) …
Selecting previously unselected package fonts-urw-base35.
```

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Preparing to unpack …/04-fonts-urw-base35_20200910-1_all.deb …
Unpacking fonts-urw-base35 (20200910-1) …
Selecting previously unselected package libgs9-common.
Preparing to unpack …/05-libgs9-common_9.55.0~dfsg1-0ubuntu5.6_all.deb …
Unpacking libgs9-common (9.55.0~dfsg1-0ubuntu5.6) …
Selecting previously unselected package libidn12:amd64.
Preparing to unpack …/06-libidn12_1.38-4ubuntu1_amd64.deb …
Unpacking libidn12:amd64 (1.38-4ubuntu1) …
Selecting previously unselected package libijs-0.35:amd64.
Preparing to unpack …/07-libijs-0.35_0.35-15build2_amd64.deb …
Unpacking libijs-0.35:amd64 (0.35-15build2) …
Selecting previously unselected package libjbig2dec0:amd64.
Preparing to unpack …/08-libjbig2dec0_0.19-3build2_amd64.deb …
Unpacking libjbig2dec0:amd64 (0.19-3build2) …
Selecting previously unselected package libgs9:amd64.
Preparing to unpack …/09-libgs9_9.55.0~dfsg1-0ubuntu5.6_amd64.deb …
Unpacking libgs9:amd64 (9.55.0~dfsg1-0ubuntu5.6) …
Selecting previously unselected package libkpathsea6:amd64.
Preparing to unpack …/10-libkpathsea6_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libkpathsea6:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libwoff1:amd64.
Preparing to unpack …/11-libwoff1_1.0.2-1build4_amd64.deb …
Unpacking libwoff1:amd64 (1.0.2-1build4) …
Selecting previously unselected package dvisvgm.
Preparing to unpack …/12-dvisvgm_2.13.1-1_amd64.deb …
Unpacking dvisvgm (2.13.1-1) …
Selecting previously unselected package fonts-lmodern.
Preparing to unpack …/13-fonts-lmodern_2.004.5-6.1_all.deb …
Unpacking fonts-lmodern (2.004.5-6.1) …
Selecting previously unselected package fonts-noto-mono.
Preparing to unpack …/14-fonts-noto-mono_20201225-1build1_all.deb …
Unpacking fonts-noto-mono (20201225-1build1) …
Selecting previously unselected package fonts-texgyre.
Preparing to unpack …/15-fonts-texgyre_20180621-3.1_all.deb …
Unpacking fonts-texgyre (20180621-3.1) …
Selecting previously unselected package libapache-pom-java.
Preparing to unpack …/16-libapache-pom-java_18-1_all.deb …
Unpacking libapache-pom-java (18-1) …
Selecting previously unselected package libcommons-parent-java.
Preparing to unpack …/17-libcommons-parent-java_43-1_all.deb …
Unpacking libcommons-parent-java (43-1) …
Selecting previously unselected package libcommons-logging-java.
Preparing to unpack …/18-libcommons-logging-java_1.2-2_all.deb …
Unpacking libcommons-logging-java (1.2-2) …
Selecting previously unselected package libfontenc1:amd64.
Preparing to unpack …/19-libfontenc1_1%3a1.1.4-1build3_amd64.deb …
Unpacking libfontenc1:amd64 (1:1.1.4-1build3) …
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Selecting previously unselected package libptexenc1:amd64.
Preparing to unpack …/20-libptexenc1_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libptexenc1:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package rubygems-integration.
Preparing to unpack …/21-rubygems-integration_1.18_all.deb …
Unpacking rubygems-integration (1.18) …
Selecting previously unselected package ruby3.0.
Preparing to unpack …/22-ruby3.0_3.0.2-7ubuntu2.4_amd64.deb …
Unpacking ruby3.0 (3.0.2-7ubuntu2.4) …
Selecting previously unselected package ruby-rubygems.
Preparing to unpack …/23-ruby-rubygems_3.3.5-2_all.deb …
Unpacking ruby-rubygems (3.3.5-2) …
Selecting previously unselected package ruby.
Preparing to unpack …/24-ruby_1%3a3.0~exp1_amd64.deb …
Unpacking ruby (1:3.0~exp1) …
Selecting previously unselected package rake.
Preparing to unpack …/25-rake_13.0.6-2_all.deb …
Unpacking rake (13.0.6-2) …
Selecting previously unselected package ruby-net-telnet.
Preparing to unpack …/26-ruby-net-telnet_0.1.1-2_all.deb …
Unpacking ruby-net-telnet (0.1.1-2) …
Selecting previously unselected package ruby-webrick.
Preparing to unpack …/27-ruby-webrick_1.7.0-3_all.deb …
Unpacking ruby-webrick (1.7.0-3) …
Selecting previously unselected package ruby-xmlrpc.
Preparing to unpack …/28-ruby-xmlrpc_0.3.2-1ubuntu0.1_all.deb …
Unpacking ruby-xmlrpc (0.3.2-1ubuntu0.1) …
Selecting previously unselected package libruby3.0:amd64.
Preparing to unpack …/29-libruby3.0_3.0.2-7ubuntu2.4_amd64.deb …
Unpacking libruby3.0:amd64 (3.0.2-7ubuntu2.4) …
Selecting previously unselected package libsynctex2:amd64.
Preparing to unpack …/30-libsynctex2_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libsynctex2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libteckit0:amd64.
Preparing to unpack …/31-libteckit0_2.5.11+ds1-1_amd64.deb …
Unpacking libteckit0:amd64 (2.5.11+ds1-1) …
Selecting previously unselected package libtexlua53:amd64.
Preparing to unpack …/32-libtexlua53_2021.20210626.59705-1ubuntu0.2_amd64.deb
…
Unpacking libtexlua53:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libtexluajit2:amd64.
Preparing to unpack
…/33-libtexluajit2_2021.20210626.59705-1ubuntu0.2_amd64.deb …
Unpacking libtexluajit2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package libzzip-0-13:amd64.
Preparing to unpack …/34-libzzip-0-13_0.13.72+dfsg.1-1.1_amd64.deb …
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Unpacking libzzip-0-13:amd64 (0.13.72+dfsg.1-1.1) …
Selecting previously unselected package xfonts-encodings.
Preparing to unpack …/35-xfonts-encodings_1%3a1.0.5-0ubuntu2_all.deb …
Unpacking xfonts-encodings (1:1.0.5-0ubuntu2) …
Selecting previously unselected package xfonts-utils.
Preparing to unpack …/36-xfonts-utils_1%3a7.7+6build2_amd64.deb …
Unpacking xfonts-utils (1:7.7+6build2) …
Selecting previously unselected package lmodern.
Preparing to unpack …/37-lmodern_2.004.5-6.1_all.deb …
Unpacking lmodern (2.004.5-6.1) …
Selecting previously unselected package preview-latex-style.
Preparing to unpack …/38-preview-latex-style_12.2-1ubuntu1_all.deb …
Unpacking preview-latex-style (12.2-1ubuntu1) …
Selecting previously unselected package t1utils.
Preparing to unpack …/39-t1utils_1.41-4build2_amd64.deb …
Unpacking t1utils (1.41-4build2) …
Selecting previously unselected package teckit.
Preparing to unpack …/40-teckit_2.5.11+ds1-1_amd64.deb …
Unpacking teckit (2.5.11+ds1-1) …
Selecting previously unselected package tex-gyre.
Preparing to unpack …/41-tex-gyre_20180621-3.1_all.deb …
Unpacking tex-gyre (20180621-3.1) …
Selecting previously unselected package texlive-binaries.
Preparing to unpack …/42-texlive-
binaries_2021.20210626.59705-1ubuntu0.2_amd64.deb …
Unpacking texlive-binaries (2021.20210626.59705-1ubuntu0.2) …
Selecting previously unselected package texlive-base.
Preparing to unpack …/43-texlive-base_2021.20220204-1_all.deb …
Unpacking texlive-base (2021.20220204-1) …
Selecting previously unselected package texlive-fonts-recommended.
Preparing to unpack …/44-texlive-fonts-recommended_2021.20220204-1_all.deb …
Unpacking texlive-fonts-recommended (2021.20220204-1) …
Selecting previously unselected package texlive-latex-base.
Preparing to unpack …/45-texlive-latex-base_2021.20220204-1_all.deb …
Unpacking texlive-latex-base (2021.20220204-1) …
Selecting previously unselected package libfontbox-java.
Preparing to unpack …/46-libfontbox-java_1%3a1.8.16-2_all.deb …
Unpacking libfontbox-java (1:1.8.16-2) …
Selecting previously unselected package libpdfbox-java.
Preparing to unpack …/47-libpdfbox-java_1%3a1.8.16-2_all.deb …
Unpacking libpdfbox-java (1:1.8.16-2) …
Selecting previously unselected package texlive-latex-recommended.
Preparing to unpack …/48-texlive-latex-recommended_2021.20220204-1_all.deb …
Unpacking texlive-latex-recommended (2021.20220204-1) …
Selecting previously unselected package texlive-pictures.
Preparing to unpack …/49-texlive-pictures_2021.20220204-1_all.deb …
Unpacking texlive-pictures (2021.20220204-1) …
Selecting previously unselected package texlive-latex-extra.
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Preparing to unpack …/50-texlive-latex-extra_2021.20220204-1_all.deb …
Unpacking texlive-latex-extra (2021.20220204-1) …
Selecting previously unselected package texlive-plain-generic.
Preparing to unpack …/51-texlive-plain-generic_2021.20220204-1_all.deb …
Unpacking texlive-plain-generic (2021.20220204-1) …
Selecting previously unselected package tipa.
Preparing to unpack …/52-tipa_2%3a1.3-21_all.deb …
Unpacking tipa (2:1.3-21) …
Selecting previously unselected package texlive-xetex.
Preparing to unpack …/53-texlive-xetex_2021.20220204-1_all.deb …
Unpacking texlive-xetex (2021.20220204-1) …
Setting up fonts-lato (2.0-2.1) …
Setting up fonts-noto-mono (20201225-1build1) …
Setting up libwoff1:amd64 (1.0.2-1build4) …
Setting up libtexlua53:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libijs-0.35:amd64 (0.35-15build2) …
Setting up libtexluajit2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libfontbox-java (1:1.8.16-2) …
Setting up rubygems-integration (1.18) …
Setting up libzzip-0-13:amd64 (0.13.72+dfsg.1-1.1) …
Setting up fonts-urw-base35 (20200910-1) …
Setting up poppler-data (0.4.11-1) …
Setting up tex-common (6.17) …
debconf: unable to initialize frontend: Dialog
debconf: (No usable dialog-like program is installed, so the dialog based
frontend cannot be used. at /usr/share/perl5/Debconf/FrontEnd/Dialog.pm line
78.)
debconf: falling back to frontend: Readline
update-language: texlive-base not installed and configured, doing nothing!
Setting up libfontenc1:amd64 (1:1.1.4-1build3) …
Setting up libjbig2dec0:amd64 (0.19-3build2) …
Setting up libteckit0:amd64 (2.5.11+ds1-1) …
Setting up libapache-pom-java (18-1) …
Setting up ruby-net-telnet (0.1.1-2) …
Setting up xfonts-encodings (1:1.0.5-0ubuntu2) …
Setting up t1utils (1.41-4build2) …
Setting up libidn12:amd64 (1.38-4ubuntu1) …
Setting up fonts-texgyre (20180621-3.1) …
Setting up libkpathsea6:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up ruby-webrick (1.7.0-3) …
Setting up fonts-lmodern (2.004.5-6.1) …
Setting up fonts-droid-fallback (1:6.0.1r16-1.1build1) …
Setting up ruby-xmlrpc (0.3.2-1ubuntu0.1) …
Setting up libsynctex2:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up libgs9-common (9.55.0~dfsg1-0ubuntu5.6) …
Setting up teckit (2.5.11+ds1-1) …
Setting up libpdfbox-java (1:1.8.16-2) …
Setting up libgs9:amd64 (9.55.0~dfsg1-0ubuntu5.6) …
Setting up preview-latex-style (12.2-1ubuntu1) …
Setting up libcommons-parent-java (43-1) …
Setting up dvisvgm (2.13.1-1) …
Setting up libcommons-logging-java (1.2-2) …
Setting up xfonts-utils (1:7.7+6build2) …
Setting up libptexenc1:amd64 (2021.20210626.59705-1ubuntu0.2) …
Setting up texlive-binaries (2021.20210626.59705-1ubuntu0.2) …
update-alternatives: using /usr/bin/xdvi-xaw to provide /usr/bin/xdvi.bin
(xdvi.bin) in auto mode
update-alternatives: using /usr/bin/bibtex.original to provide /usr/bin/bibtex
(bibtex) in auto mode
Setting up lmodern (2.004.5-6.1) …
Setting up texlive-base (2021.20220204-1) …
/usr/bin/ucfr
/usr/bin/ucfr
/usr/bin/ucfr
/usr/bin/ucfr
mktexlsr: Updating /var/lib/texmf/ls-R-TEXLIVEDIST…
mktexlsr: Updating /var/lib/texmf/ls-R-TEXMFMAIN…
mktexlsr: Updating /var/lib/texmf/ls-R…
mktexlsr: Done.
tl-paper: setting paper size for dvips to a4:
/var/lib/texmf/dvips/config/config-paper.ps
tl-paper: setting paper size for dvipdfmx to a4:
/var/lib/texmf/dvipdfmx/dvipdfmx-paper.cfg
tl-paper: setting paper size for xdvi to a4: /var/lib/texmf/xdvi/XDvi-paper
tl-paper: setting paper size for pdftex to a4: /var/lib/texmf/tex/generic/tex-
ini-files/pdftexconfig.tex
debconf: unable to initialize frontend: Dialog
debconf: (No usable dialog-like program is installed, so the dialog based
frontend cannot be used. at /usr/share/perl5/Debconf/FrontEnd/Dialog.pm line
78.)
debconf: falling back to frontend: Readline
Setting up tex-gyre (20180621-3.1) …
Setting up texlive-plain-generic (2021.20220204-1) …
Setting up texlive-latex-base (2021.20220204-1) …
Setting up texlive-latex-recommended (2021.20220204-1) …
Setting up texlive-pictures (2021.20220204-1) …
Setting up texlive-fonts-recommended (2021.20220204-1) …
Setting up tipa (2:1.3-21) …
Setting up texlive-latex-extra (2021.20220204-1) …
Setting up texlive-xetex (2021.20220204-1) …
Setting up rake (13.0.6-2) …
Setting up libruby3.0:amd64 (3.0.2-7ubuntu2.4) …
Setting up ruby3.0 (3.0.2-7ubuntu2.4) …
Setting up ruby (1:3.0~exp1) …
Setting up ruby-rubygems (3.3.5-2) …
Processing triggers for man-db (2.10.2-1) …
Processing triggers for fontconfig (2.13.1-4.2ubuntu5) …
Processing triggers for libc-bin (2.35-0ubuntu3.4) …
/sbin/ldconfig.real: /usr/local/lib/libtbb.so.12 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_5.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_0.so.3 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc.so.2 is not a symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc_proxy.so.2 is not a symbolic
link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind.so.3 is not a symbolic link

Processing triggers for tex-common (6.17) …
debconf: unable to initialize frontend: Dialog
debconf: (No usable dialog-like program is installed, so the dialog based
frontend cannot be used. at /usr/share/perl5/Debconf/FrontEnd/Dialog.pm line
78.)
debconf: falling back to frontend: Readline
Running updmap-sys. This may take some time… done.
Running mktexlsr /var/lib/texmf … done.
Building format(s) --all.
        This may take some time… done.
Collecting PyPDF2
  Downloading pypdf2-3.0.1-py3-none-any.whl (232 kB)
                           232.6/232.6

kB 4.2 MB/s eta 0:00:00
Installing collected packages: PyPDF2
Successfully installed PyPDF2-3.0.1
/content/drive/My Drive/ITE4052/A2
### Creating PDFs ###
```

```
[ ]:
```