CITS4012 Natural Language Processing

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This Jupyter Book hosts the **lab materials** of CITS4012 Natural Language Processing offered at Department of Computer Science and Software Engineering at the University of Western Australia.

All other teaching materials of the unit can be found at UWA LMS - The University of Western Australia.

CHAPTER

ONE

LAB 01: CONDA ENVIRONMENT AND PYTHON REFRESHER

Welcome to CITS4012 Natural Language Processing. NLP is a very practical discipline that requires familiarity with Python, Numpy, Pandas and many similar yet distinctive text processing packages. So let's started by getting used to handle multiple environments as often different NLP toolkits have conflict requirement on package or Python versions. Then we will move on with some refresher of Python and Numpy.

1.1 Google Colab

For quick code testing without worrying too much about installing packages, one can use Google Colaboratory, "Colab" for short. If you are not familar with Colab, please follow the intructions to either create a Jupyter Notebook or look through the sample ones.

1.2 Bring you own device

The following two pages contain instructions on how to set up multiple "isolated" Python environments on your own computer. This is the recommended mode of study because as system adminstrator you have a lot more control on what you can install and when, and the kernerls will not disconnect with a time limit like Google Colab. Fluency in managing multiple environments is also a desired learning outcome of this unit. So despite it can be frustrating and tedious at times, it is rewarding to manage your own coding environment. Please do remember to make use of repositories such as Github for regular backups.

1. Setting up CITS4012 Base environment
2. Setting up CITS4012 MISC environment

1.3 Use Lab Machines

1. Use Lab Machines

1.4 Python Refresher

1. Python Basics
2. Iterables
3. Numpy (for math and matrix operations)
4. Matplotlib (for plotting)

Original Refresher Notebooks credit to Stanford 224n

1.5 CITS4012 Base Environment

1.5.1 IDEs and Git

Installing Visual Studio Code

- Visual Studio Code Download
- 64 bit System Installer (`VSCodeSetup-x64-1.57.1.exe` - 78KB)
- Default Installation Path (`C:\Program Files\Microsoft VS Code`)
- Installation Time (~5 mins)

Installing Extensions for Visual Studio Code

- Python Extension for VSCode Instruction
- Remote - SSH Extension
- Remote X11 (SSH) Extension

Install git

- Latest Version of Git for Windows
- Don't forget to add git to the system PATH

1.5.2 Conda and Unit Specific Packages

Installing Anaconda

- Anaconda Installation Instructions
- Individual Version (`Anaconda3-2021.05-Windows-x86_64.exe` - 488KB)
- Installation Size (2.9 GB)
- Installed for all users at `C:\ProgramData\Anaconda3`
- Installation Time (~30 mins)
- Launch Anaconda Navigator

You can start a CMD or POWERSHELL console using the navigator, or following the steps 1 and 2 in the screenshot below to start a CMD or POWERSHELL. If you are intalling packages, you can right click the arrow to bring up a pop-up menu, `run as adminstrator` (Step 3a) or `pin on taskbar` (Step 3b) for future convenience.

Install from an environment YAML file

If we install from this YAML file, then we can ignore all the following steps after this section.

First download the installation file here: cits4012.yml

```
conda env create -p c:\envs\cits4012 --file cits4012.yml
```

If this is successful, you can ignore the rest of the steps below.

Install packages step by step from scratch

Create Anaconda Environment

Need admin access to write to C drive (Run Conda Powershell as Administrator - right click on the icon)

```
conda create -p c:\envs\cits4012 python=3.8
conda activate c:\envs\cits4012
```

Use the virtual environment in VSCode

- Instructions on how to use environment in VSCode
- Test to see if the CITS4012_base environment is available from VSCode

Install Spacy

1. Go back to Conda CMD.exe, check to see if you have `pip` installed using

```
conda list
pip install -U spacy
python -m spacy download en_core_web_sm
```

1. Find the Spacy version (we want v3+):

```
# Windows CMD
C:\> conda list | findstr "spacy"`

# Windows PowerShell
C:\> conda list | Select-String "spacy"

# Linux
$ conda list | grep "spacy"
```

Install PyTorch

Check for Cuda compatible Graphics Card on Windows

1. Click Start.
2. On the Start menu, click Run.
3. In the Open box, type "dxdiag" (without the quotation marks), and then click OK.
4. The DirectX Diagnostic Tool opens. …
5. On the Display tab, information about your graphics card is shown in the Device section.

My laptop has NVIDIA GeForce MX130.

Install Pytorch

Pytorch Website

- with GPU

```
conda install pytorch torchvision torchaudio torchtext cudatoolkit=11.1 -c pytorch -c␣
↪conda-forge
```

- CPU only

```
conda install pytorch torchvision torchaudio torchtext cpuonly -c pytorch -c conda-
↪forge
```

Install Tensorboard

```
conda install -c conda-forge tensorboard
```

Install GraphViz on Windows

2.47.3 EXE installer for Windows 10 (64-bit)

Download the exe file and install, make sure it is added to the system PATH (Windows - Edit the Windows Environment Variables.

Install torchviz

```
pip install torchviz
```

Install NLTK

```
pip install nltk
```

and then download the data and models

```
python -m nltk.downloader -d c:\envs\cits4012\nltk_data all
```

Install truecase

install this after NLTK installation pls.

```
pip install truecase
```

Install Jupyterlab

```
conda install -c conda-forge jupyterlab
```

Install Scikit-learn

```
pip install -U scikit-learn
```

Verify if it works:

```
python -c "import sklearn; sklearn.show_versions()"
```

Install Matplotlib

```
pip install matplotlib
```

Install gensim

Note this will install the latest gensim 4.x

```
conda install -c conda-forge gensim
```

Install import-ipynb

This is a package to import functions from other Jupyter Notebooks.

```
pip install import-ipynb
```

Install Python Levenshtein Similarity

```
pip install python-Levenshtein
```

Install interactive visualisation bokeh

```
pip install bokeh
```

Install bs4 to get BeautifulSoup for web crawling

```
pip install bs4
```

Finally Export Environment into an YAML file

```
conda env export -p c:\envs\cits4012 --no-builds -f cits4012.yml
```

1.6 CITS4012 MISC Enviornment

1.6.1 Frequently encounted problems in Windows

1. File not found when files are actually there - this might be to do with the limitation of path length (<=260 characters) in Windows. See below for a solution

- How to set group policies in Windows to allow for long path

1. When trying to install some pip packages you may get the error stating:

   Microsoft Visual C++ 14.0 is required. Get it with "Build Tools for Visual Studio": https://visualstudio.microsoft.com/downloads/

Scroll down the page to find "All Tools", expand "Tools for Visual Studio 2019" and find "Build Tools for Visual Studio 2019", download and install as an admin for all users.

Warning: The installation of the Build Tools might take a while (~20mins).

1.6.2 Install from an environment YAML file

If we install from this YAML file, then we can ignore all the following steps after this.

Download the environment YAML file here: cits4012_py37.yml

```
conda env create -p c:\envs\cits4012_py37 --file cits4012_py37.yml
```

If this is successful, you can ignore the rest of the steps below.

1.6.3 Install step by step

Create a new environment

```
conda create -p c:\envs\cits4012_py37 python=3.7
conda activate c:\envs\cits4012_py37
```

Install Flair

Flair requires different versions of numpy and torch, so it is better to isolate it from the normal environment

```
pip install flair
```

Install Neuralcoref

Follow the "compile from source instruction" on the github page as it requires Python 3.7 and Spacy 2.0+

```
git clone https://github.com/huggingface/neuralcoref.git
cd neuralcoref
pip install -r requirements.txt
pip install -e .
```

You may run into the frequent problem 2 above. Solve it by installing C++ compiler suitable for your OS.

Install Jupyterlab

```
pip install jupyterlab
```

Install Matplotlib

```
pip install matplotlib
```

Export Environment Files

```
conda env export -p c:\envs\cits4012_py37 --no-builds -f cits4012_py37.yml
```

1.7 Use Lab Machines

Our labs support dual boot into either Window 10 or Redhat 7. Depending on which OS you prefer, you can follow the below instructions to activate the environment. However, please note these are *un-writable environments*. It is not possible to install new packages during the semester, as our IT team maintains a university-wide image. Installation during semester may disturb the global computing environment.

It is useful if you want some spare CPUs to train your model as the lab machines have decent CPU processing power, while carrying out other activities on your own devices.

Windows

1. Open the start menu and type 'Anaconda Prompt' into the search box.
2. Open 'Anaconda Prompt (Anaconda3)' or 'Anaconda Powershell Prompt (Anaconda3)'
3. Type `conda activate A:\Anaconda\envs\cits4012` for the 'cits4012' environment or `conda activate A:\Anaconda\envs\cits4012_py37` to activate the 'cits4012_py37' environment and press enter.

Red Hat Linux

1. Select 'Applications' in the top left corner and select 'CSSE' -> 'Anaconda Prompt'
2. In terminal, type `conda activate ~/anaconda/envs/cits4012` to activate the 'cits4012' environment or `conda activate ~/anaconda/envs/cits4012_py37` to activate the 'cits4012_py37' environment and press enter.

1.8 Python Basics

https://www.w3schools.com/python/

```python
# input and output
name = input()
print("hello, " + name)
```

```
hello, CITS4012 Natural Language Processing
```

```python
# print multiple variables separated by a space
print("hello", name, 1, 3.0, True)
```

```
hello CITS4012 Natural Language Processing 1 3.0 True
```

```
# line comment
"""
block
comments
"""
```

```
'\nblock \ncomments\n'
```

```
# variables don't need explicit declaration
var = "hello" # string
var = 10.0    # float
var = 10      # int
var = True    # boolean
var = [1,2,3] # pointer to list
var = None    # empty pointer
```

```
# type conversions
var = 10
print(int(var))
print(str(var))
print(float(var))
```

```
10
10
10.0
```

```
# basic math operations
var = 10
print("var + 4 =", 10 + 4)
print("var - 4 =", 10 - 4)
print("var * 4 =", 10 * 4)
print("var ^ 4=", 10 ** 4)
print("int(var) / 4 =", 10//4)   # // for int division
print("float(var) / 4 =", 10/4)  # / for float division
# All compound assignment operators available
# including += -= *= **= /= //=
# pre/post in/decrementers not available (++ --)
```

```
var + 4 = 14
var - 4 = 6
var * 4 = 40
var ^ 4= 10000
int(var) / 4 = 2
float(var) / 4 = 2.5
```

```
# basic boolean operations include "and", "or", "not"
print("not True is", not True)
print("True and False is", True and False)
print("True or False is", True or False)
```

```
not True is False
True and False is False
True or False is True
```

```python
# String operations
# '' and "" are equivalent
s = "String"
#s = 'Mary said "Hello" to John'
#s = "Mary said \"Hello\" to John"

# basic
print(len(s)) # get length of string and any iterable type
print(s[0]) # get char by index
print(s[1:3]) # [1,3)
print("This is a " + s + "!")

# handy tools
print(s.lower())
print(s*4)
print("ring" in s)
print(s.index("ring"))

# slice by delimiter
print("I am a sentence".split(" "))
# concatenate a list of string using a delimiter
print("...".join(['a','b','c']))

# formatting variables
print("Formatting a string like %.2f"%(0.12345))
print(f"Or like {s}!")
```

```
6
S
tr
This is a String!
string
StringStringStringString
True
2
['I', 'am', 'a', 'sentence']
a...b...c
Formatting a string like 0.12
Or like String!
```

```python
# control flows
# NOTE: No parentheses or curly braces
#       Indentation is used to identify code blocks
#       So never ever mix spaces with tabs
for i in range(0,5):
    for j in range(i, 5):
        print("inner loop")
    print("outer loop")
```

```python
# if-else
var = 10
if var > 10:
    print(">")
elif var == 10:
    print("=")
else:
    print("<")
```

```
=
```

```
# use "if" to check null pointer or empty arrays
var = None
if var:
    print(var)
var = []
if var:
    print(var)
var = "object"
if var:
    print(var)
```

```
object
```

```
# while-loop
var = 5
while var > 0:
    print(var)
    var -=1
```

```
5
4
3
2
1
```

```
# for-loop
for i in range(3):  # prints 0 1 2
    print(i)

"""
equivalent to
for (int i = 0; i < 3; i++)
"""
print("-------")
# range (start-inclusive, stop-exclusive, step)
for i in range(2, -3, -2):
    print(i)
"""
equivalent to
for (int i = 2; i > -3; i-=2)
"""
```

```
0
1
2
-------
2
0
-2
```

```
'\nequivalent to\nfor (int i = 2; i > -3; i-=2)\n'
```

```
# define function
def func(a, b):
    return a + b
func(1,3)
```

```
4
```

```
# use default parameters and pass values by parameter name
def rangeCheck(a, min_val = 0, max_val=10):
    return min_val < a < max_val    # syntactic sugar
rangeCheck(5, max_val=4)
```

```
False
```

```
# define class
class Foo:

    # optinal constructor
    def __init__(self, x):
        # first parameter "self" for instance reference, like "this" in JAVA
        self.x = x

    # instance method
    def printX(self): # instance reference is required for all function parameters
        print(self.x)

    # class methods, most likely you will never need this
    @classmethod
    def printHello(self):
        print("hello")

obj = Foo(6)
obj.printX()
```

```
6
```

```
# class inheritance - inherits variables and methods
# You might need this when you learn more PyTorch
class Bar(Foo):
    pass
obj = Bar(3)
obj.printX()
```

```
3
```

1.9 Iterables

```
alist = list()  # linear, size not fixed, not hashable
atuple = tuple() # linear, fixed size, hashable
adict = dict()  # hash table, not hashable, stores (key,value) pairs
aset = set()    # hash table, like dict but only stores keys
acopy = alist.copy() # shallow copy
print(len(alist)) # gets size of any iterable type
```

```
0
```

```
# examplar tuple usage
# creating a dictionary to store ngram counts
d = dict()
d[("a","cat")] = 10
d[["a","cat"]] = 11
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
<ipython-input-16-47597361a541> in <module>
      3 d = dict()
      4 d[("a","cat")] = 10
----> 5 d[["a","cat"]] = 11

TypeError: unhashable type: 'list'
```

```
"""
List: not hashable (i.e. can't use as dictionary key)
      dynamic size
      allows duplicates and inconsistent element types
      dynamic array implementation
"""
# list creation
alist = []          # empty list, equivalent to list()
alist = [1,2,3,4,5] # initialized list

print(alist[0])
alist[0] = 5
print(alist)

print("-"*10)
# list indexing
print(alist[0]) # get first element (at index 0)
print(alist[-2]) # get last element (at index len-1)
print(alist[3:]) # get elements starting from index 3 (inclusive)
print(alist[:3]) # get elements stopping at index 3 (exclusive)
print(alist[2:4]) # get elements within index range [2,4)
print(alist[6:]) # prints nothing because index is out of range
print(alist[::-1]) # returns a reversed list

print("-"*10)
# list modification
alist.append("new item") # insert at end
alist.insert(0, "new item") # insert at index 0
alist.extend([2,3,4]) # concatenate lists
```

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```
# above line is equivalent to alist += [2,3,4]
alist.index("new item") # search by content
alist.remove("new item") # remove by content
alist.pop(0) # remove by index
print(alist)

print("-"*10)
if "new item" in alist:
    print("found")
else:
    print("not found")

print("-"*10)
# list traversal
for ele in alist:
    print(ele)

print("-"*10)
# or traverse with index
for i, ele in enumerate(alist):
    print(i, ele)
```

```
1
[5, 2, 3, 4, 5]
----------
5
4
[4, 5]
[5, 2, 3]
[3, 4]
[]
[5, 4, 3, 2, 5]
----------
[2, 3, 4, 5, 'new item', 2, 3, 4]
----------
found
----------
2
3
4
5
new item
2
3
4
----------
0 2
1 3
2 4
3 5
4 new item
5 2
6 3
7 4
```

```
"""
Tuple: hashable (i.e. can use as dictionary key)
       fixed size (no insertion or deletion)
"""
# it does not make sense to create empty tuples
atuple = (1,2,3,4,5)
 # or you can cast other iterables to tuple
atuple = tuple([1,2,3])

# indexing and traversal are same as list
```

```
"""
Named tuples for readibility
"""
from collections import namedtuple
Point = namedtuple('Point', 'x y')
pt1 = Point(1.0, 5.0)
pt2 = Point(2.5, 1.5)
print(pt1.x, pt1.y)
```

```
1.0 5.0
```

```
"""
Dict: not hashable
      dynamic size
      no duplicates allowed
      hash table implementation which is fast for searching
"""
# dict creation
adict = {} # empty dict, equivalent to dict()
adict = {'a':1, 'b':2, 'c':3}
print(adict)

# get all keys in dictionary
print(adict.keys())

# get value paired with key
print(adict['a'])
key = 'e'

# NOTE: accessing keys not in the dictionary leads to exception
if key in adict:
    print(adict[key])

# add or modify dictionary entries
adict['e'] = 10 # insert new key
adict['e'] = 5  # modify existing keys

print("-"*10)
# traverse keys only
for key in adict:
    print(key, adict[key])

print("-"*10)
# or traverse key-value pairs together
for key, value in adict.items():
```

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```
    print(key, value)

print("-"*10)
# NOTE: Checking if a key exists
key = 'e'
if key in adict: # NO .keys() here please!
    print(adict[key])
else:
    print("Not found!")
```

```
{'a': 1, 'b': 2, 'c': 3}
dict_keys(['a', 'b', 'c'])
1
----------
a 1
b 2
c 3
e 5
----------
a 1
b 2
c 3
e 5
----------
5
```

```
"""
Special dictionaries
"""
# set is a dictionary without values
aset = set()
aset.add('a')

# deduplication short-cut using set
alist = [1,2,3,3,3,4,3]
alist = list(set(alist))
print(alist)

# default_dictionary returns a value computed from a default function
#     for non-existent entries
from collections import defaultdict
adict = defaultdict(lambda: 'unknown')
adict['cat'] = 'feline'
print(adict['cat'])
print(adict['dog'])
```

```
[1, 2, 3, 4]
feline
unknown
```

```
# counter is a dictionary with default value of 0
#     and provides handy iterable counting tools
from collections import Counter

# initialize and modify empty counter
```

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```
counter1 = Counter()
counter1['t'] = 10
counter1['t'] += 1
counter1['e'] += 1
print(counter1)
print("-"*10)

# initialize counter from iterable
counter2 = Counter("letters to be counted")
print(counter2)
print("-"*10)

# computations using counters
print("1", counter1 + counter2)
print("2,", counter1 - counter2)
print("3", counter1 or counter2) # or for intersection, and for union
```

```
Counter({'t': 11, 'e': 1})
----------
Counter({'e': 4, 't': 4, ' ': 3, 'o': 2, 'l': 1, 'r': 1, 's': 1, 'b': 1, 'c': 1, 'u':␣
↪1, 'n': 1, 'd': 1})
----------
1 Counter({'t': 15, 'e': 5, ' ': 3, 'o': 2, 'l': 1, 'r': 1, 's': 1, 'b': 1, 'c': 1, 'u
↪': 1, 'n': 1, 'd': 1})
2, Counter({'t': 7})
3 Counter({'t': 11, 'e': 1})
```

```
# sorting
a = [4,6,1,7,0,5,1,8,9]
a = sorted(a)
print(a)
a = sorted(a, reverse=True)
print(a)
```

```
[0, 1, 1, 4, 5, 6, 7, 8, 9]
[9, 8, 7, 6, 5, 4, 1, 1, 0]
```

```
# sorting
a = [("cat",1), ("dog", 3), ("bird", 2)]
a = sorted(a)
print(a)
a = sorted(a, key=lambda x:x[1])
print(a)
```

```
[('bird', 2), ('cat', 1), ('dog', 3)]
[('cat', 1), ('bird', 2), ('dog', 3)]
```

```
# useful in dictionary sorting
adict = {'cat':3, 'bird':1}
print(sorted(adict.items(), key=lambda x:x[1]))
```

```
[('bird', 1), ('cat', 3)]
```

```
# Syntax sugar: one-line control flow + list operation
sent = ["i am good", "a beautiful day", "HELLO FRIEND"]
"""
for i in range(len(sent)):
    sent[i] = sent[i].lower().split(" ")
"""
sent1 = [s.lower().split(" ") for s in sent]
print(sent1)

sent2 = [s.lower().split(" ") for s in sent if len(s) > 10]
print(sent2)

# Use this for deep copy!
# copy = [obj.copy() for obj in original]
```

```
[['i', 'am', 'good'], ['a', 'beautiful', 'day'], ['hello', 'friend']]
[['a', 'beautiful', 'day'], ['hello', 'friend']]
```

```
# Syntax sugar: * operator for repeating iterable elements
print("-"*10)
print([1]*10)

# Note: This only repeating by value
#       So you cannot apply the trick on reference types

# To create a double list
# DONT
doublelist = [[]]*10
doublelist[0].append(1)
print(doublelist)
# DO
doublelist = [[] for _ in range(10)]
doublelist[0].append(1)
print(doublelist)
```

```
----------
[1, 1, 1, 1, 1, 1, 1, 1, 1, 1]
[[1], [1], [1], [1], [1], [1], [1], [1], [1], [1]]
[[1], [], [], [], [], [], [], [], [], []]
```

1.10 Numpy

Very powerful python tool for handling matrices and higher dimensional arrays

```
import numpy as np
```

```
# create arrays
a = np.array([[1,2],[3,4],[5,6]])
print(a)
print(a.shape)
# create all-zero/one arrays
b = np.ones((3,4)) # np.zeros((3,4))
print(b)
```

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```
print(b.shape)
# create identity matrix
c = np.eye(5)
print(c)
print(c.shape)
```

```
[[1 2]
 [3 4]
 [5 6]]
(3, 2)
[[1. 1. 1. 1.]
 [1. 1. 1. 1.]
 [1. 1. 1. 1.]]
(3, 4)
[[1. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0.]
 [0. 0. 1. 0. 0.]
 [0. 0. 0. 1. 0.]
 [0. 0. 0. 0. 1.]]
(5, 5)
```

```
# reshaping arrays
a = np.arange(8)          # [8,] similar range() you use in for-loops
b = a.reshape((4,2))      # shape [4,2]
c = a.reshape((2,2,-1))   # shape [2,2,2] -- -1 for auto-fill
d = c.flatten()           # shape [8,]
e = np.expand_dims(a, 0)  # [1,8]
f = np.expand_dims(a, 1)  # [8,1]
g = e.squeeze()           # shape[8, ]    -- remove all unnecessary dimensions
print(a)
print(b)
```

```
[0 1 2 3 4 5 6 7]
[[0 1]
 [2 3]
 [4 5]
 [6 7]]
```

```
# concatenating arrays
a = np.ones((4,3))
b = np.ones((4,3))
c = np.concatenate([a,b], 0)
print(c.shape)
d = np.concatenate([a,b], 1)
print(d.shape)
```

```
(8, 3)
(4, 6)
```

```
# one application is to create a batch for NN
x1 = np.ones((32,32,3))
x2 = np.ones((32,32,3))
x3 = np.ones((32,32,3))
# --> to create a batch of shape (3,32,32,3)
```

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```
x = [x1, x2, x3]
x = [np.expand_dims(xx, 0) for xx in x] # xx shape becomes (1,32,32,3)
x = np.concatenate(x, 0)
print(x.shape)
```

```
(3, 32, 32, 3)
```

```
# access array slices by index
a = np.zeros([10, 10])
a[:3] = 1
a[:, :3] = 2
a[:3, :3] = 3
rows = [4,6,7]
cols = [9,3,5]
a[rows, cols] = 4
print(a)
```

```
[[3. 3. 3. 1. 1. 1. 1. 1. 1. 1.]
 [3. 3. 3. 1. 1. 1. 1. 1. 1. 1.]
 [3. 3. 3. 1. 1. 1. 1. 1. 1. 1.]
 [2. 2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 2. 0. 0. 0. 0. 0. 0. 4.]
 [2. 2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 2. 4. 0. 0. 0. 0. 0. 0.]
 [2. 2. 2. 0. 0. 4. 0. 0. 0. 0.]
 [2. 2. 2. 0. 0. 0. 0. 0. 0. 0.]
 [2. 2. 2. 0. 0. 0. 0. 0. 0. 0.]]
```

```
# transposition
a = np.arange(24).reshape(2,3,4)
print(a.shape)
print(a)
a = np.transpose(a, (2,1,0)) # swap 0th and 2nd axes
print(a.shape)
print(a)
```

```
(2, 3, 4)
[[[ 0  1  2  3]
  [ 4  5  6  7]
  [ 8  9 10 11]]

 [[12 13 14 15]
  [16 17 18 19]
  [20 21 22 23]]]
(4, 3, 2)
[[[ 0 12]
  [ 4 16]
  [ 8 20]]

 [[ 1 13]
  [ 5 17]
  [ 9 21]]

 [[ 2 14]
  [ 6 18]
```

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```
  [10 22]]

 [[ 3 15]
  [ 7 19]
  [11 23]]]
```

```
c = np.array([[1,2],[3,4]])
# pinv is pseudo inversion for stability
print(np.linalg.pinv(c))
# l2 norm by default, read documentation for more options
print(np.linalg.norm(c))
# summing a matrix
print(np.sum(c))
# the optional axis parameter
print(c)
print(np.sum(c, axis=0)) # sum along axis 0
print(np.sum(c, axis=1)) # sum along axis 1
```

```
[[-2.   1. ]
 [ 1.5 -0.5]]
5.477225575051661
10
[[1 2]
 [3 4]]
[4 6]
[3 7]
```

```
# dot product
c = np.array([1,2])
d = np.array([3,4])
print(np.dot(c,d))
```

```
11
```

```
# matrix multiplication
a = np.ones((4,3)) # 4,3
b = np.ones((3,2)) # 3,2 --> 4,2
print(a @ b)       # same as a.dot(b)
c = a @ b          # (4,2)

# automatic repetition along axis
d = np.array([1,2,3,4]).reshape(4,1)
print(c + d)
# handy for batch operation
batch = np.ones((3,32))
weight = np.ones((32,10))
bias = np.ones((1,10))
print((batch @ weight + bias).shape)
```

```
[[3. 3.]
 [3. 3.]
 [3. 3.]
 [3. 3.]]
[[4. 4.]
```

(continues on next page)

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```
 [5. 5.]
 [6. 6.]
 [7. 7.]]
(3, 10)
```

```
# speed test: numpy vs list
a = np.ones((100,100))
b = np.ones((100,100))

def matrix_multiplication(X, Y):
    result = [[0]*len(Y[0]) for _ in range(len(X))]
    for i in range(len(X)):
        for j in range(len(Y[0])):
            for k in range(len(Y)):
                result[i][j] += X[i][k] * Y[k][j]
    return result

import time

# run numpy matrix multiplication for 10 times
start = time.time()
for _ in range(10):
    a @ b
end = time.time()
print("numpy spends {} seconds".format(end-start))

# run list matrix multiplication for 10 times
start = time.time()
for _ in range(10):
    matrix_multiplication(a,b)
end = time.time()
print("list operation spends {} seconds".format(end-start))

# the difference gets more significant as matrices grow in size!
```

```
numpy spends 0.001990079879760742 seconds
list operation spends 8.681961059570312 seconds
```

```
# element-wise operations, for examples
np.log(a)
np.exp(a)
np.sin(a)
# operation with scalar is interpreted as element-wise
a * 3
```

```
array([[3., 3., 3., ..., 3., 3., 3.],
       [3., 3., 3., ..., 3., 3., 3.],
       [3., 3., 3., ..., 3., 3., 3.],
       ...,
       [3., 3., 3., ..., 3., 3., 3.],
       [3., 3., 3., ..., 3., 3., 3.],
       [3., 3., 3., ..., 3., 3., 3.]])
```

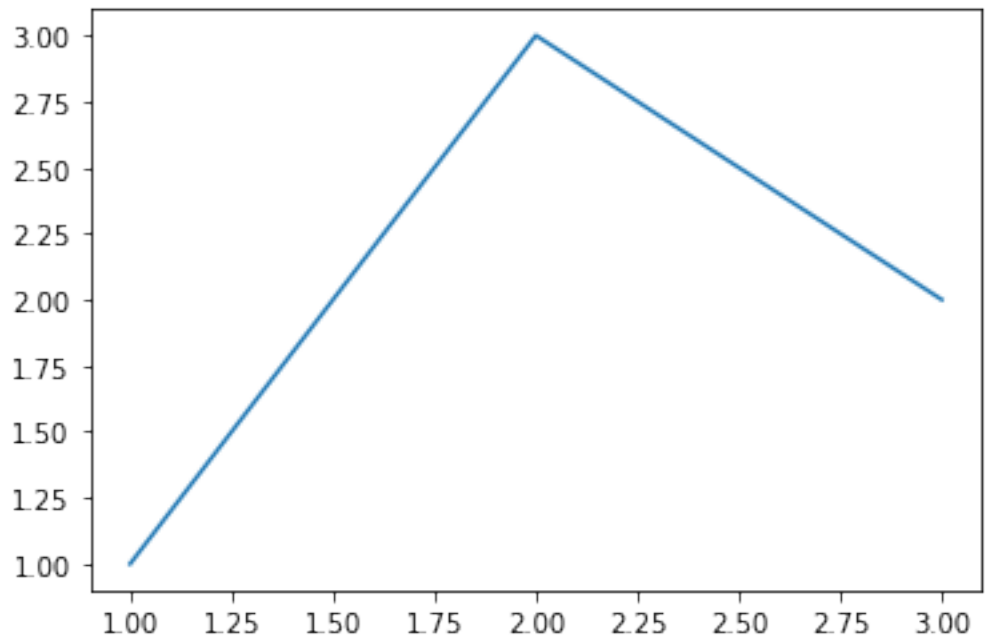
1.11 Matplotlib

Powerful tool for visualization Many tutorials online. We only go over the basics here

```
import matplotlib.pyplot as plt
```

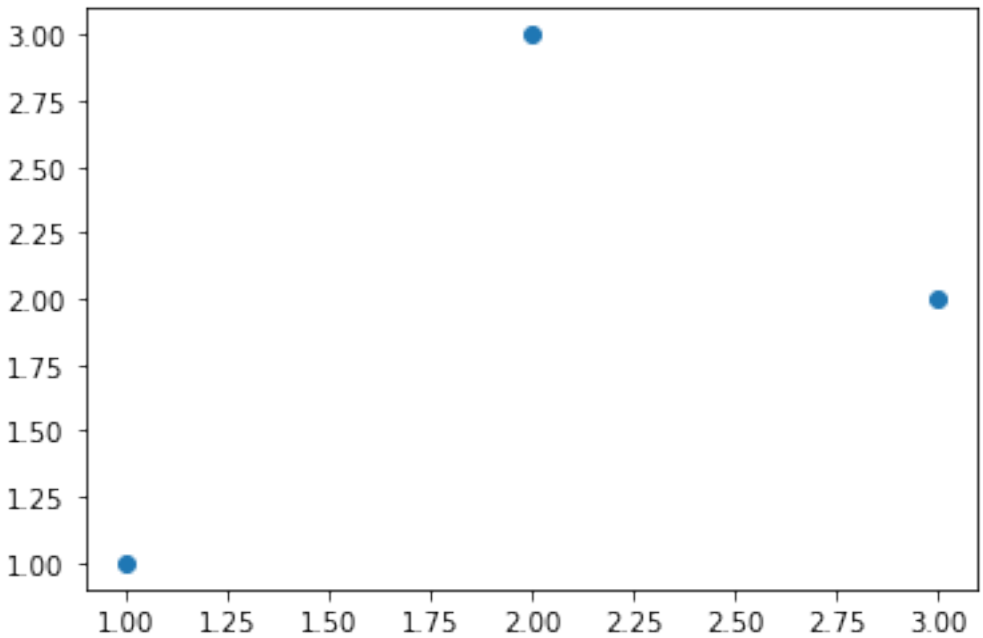
```
# line plot
x = [1,2,3]
y = [1,3,2]
plt.plot(x,y)
```

```
[<matplotlib.lines.Line2D at 0x17056d253a0>]
```



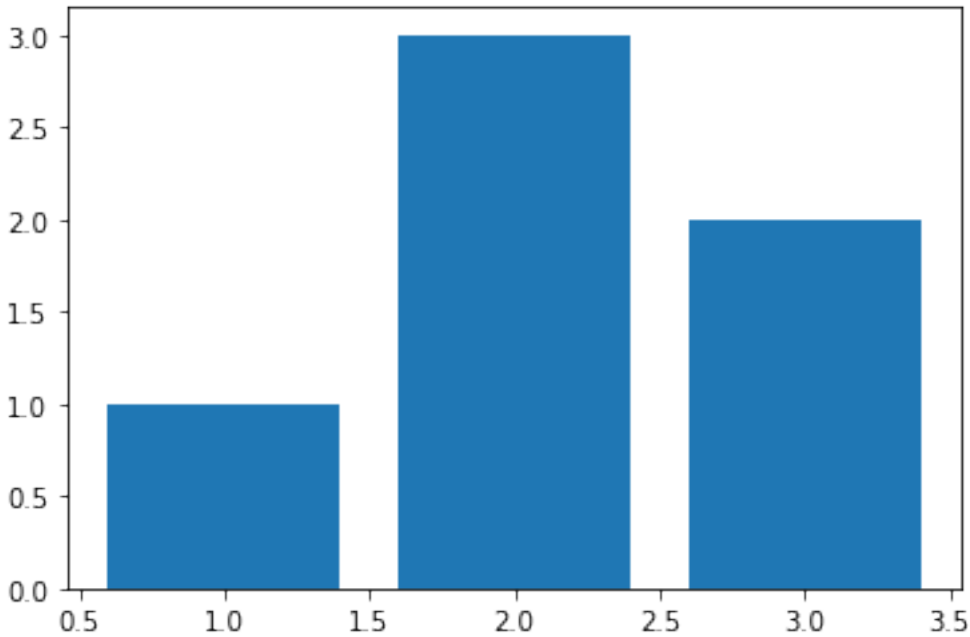

```
# scatter plot
plt.scatter(x,y)
```

```
<matplotlib.collections.PathCollection at 0x17b1b530490>
```




```
# bar plots
plt.bar(x,y)
```

```
<BarContainer object of 3 artists>
```




```
# plot configurations
x = [1,2,3]
y1 = [1,3,2]
y2 = [4,0,4]
```

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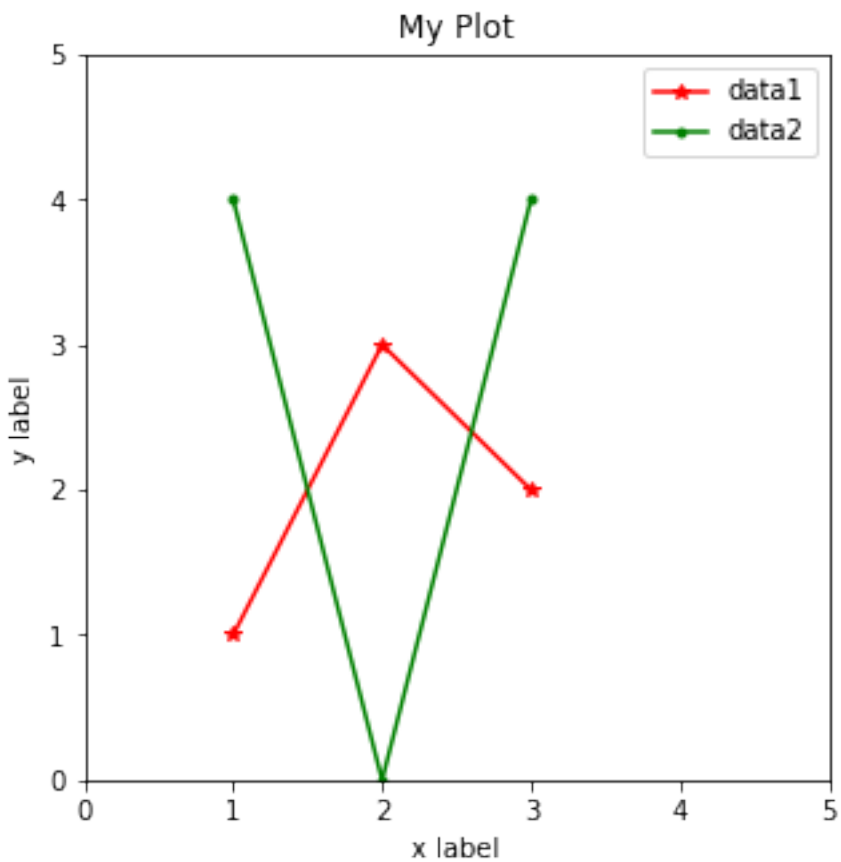
```
# set figure size
plt.figure(figsize=(5,5))

# set axes
plt.xlim(0,5)
plt.ylim(0,5)
plt.xlabel("x label")
plt.ylabel("y label")

# add title
plt.title("My Plot")

plt.plot(x,y1, label="data1", color="red", marker="*")
plt.plot(x,y2, label="data2", color="green", marker=".")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x17b1b669d00>
```



CHAPTER

TWO

LAB02: NLTK

It is easy to get our hands on millions of words of text. What can we do with it, assuming we can write some simple programs? In this chapter we'll address the following questions:

- What can we achieve by combining simple programming techniques with large quantities of text?
- How can we automatically extract key words and phrases that sum up the style and content of a text?
- What tools and techniques does the Python programming language provide for such work?
- What are some of the interesting challenges of natural language processing?

This chapter is divided into sections that skip between two quite different styles.

- In the "computing with language" sections we will take on some linguistically motivated programming tasks without necessarily explaining how they work.
- In the "closer look at Python" sections we will systematically review key programming concepts.

You can skip Section 2 and 4 if you are confident with Python, but do attempt the exercises and refer back to those sections if you find some of the questions challenging.

We'll flag the two styles in the section titles, but later labs will mix both styles without being so up-front about it. We hope this style of introduction gives you an authentic taste of what will come later, while covering a range of elementary concepts in linguistics and computer science.

Online reference material for NLTK is at http://nltk.org/.

This lab may raise more questions than it answers, we will try to address some in the rest of this unit.

Original Content Credit to Chapter 1 of the online NLTK Book

2.1 Starting with NLTK

If you have installed nltk and have downloaded the data and models, you can skip this.

```
import nltk
nltk.download()
```

Downloading the NLTK Book Collection: browse the available packages using nltk.download(). The Collections tab on the downloader shows how the packages are grouped into sets, and you should select the line labeled book to obtain all data required for the examples and exercises in this book. It consists of about 30 compressed files requiring about 100Mb disk space. The full collection of data (i.e., all in the downloader) is nearly ten times this size (at the time of writing) and continues to expand.

Once the data is downloaded to your machine, you can load some of it using the Jupyter Notebook. The first step is to type a special command which tells the interpreter to load some texts for us to explore: `from nltk.book import`

`*`. This says "from NLTK's book module, load all items." The book module contains all the data you will need as you read this chapter. After printing a welcome message, it loads the text of several books (this will take a few seconds). Here's the command again, together with the output that you will see. Take care to get spelling and punctuation right.

```
from nltk.book import *
```

```
*** Introductory Examples for the NLTK Book ***
Loading text1, ..., text9 and sent1, ..., sent9
Type the name of the text or sentence to view it.
Type: 'texts()' or 'sents()' to list the materials.
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

Any time we want to find out about these texts, we just have to enter their names at the Python prompt:

```
text1
```

```
<Text: Moby Dick by Herman Melville 1851>
```

```
text2
```

```
<Text: Sense and Sensibility by Jane Austen 1811>
```

Now that we have some data to work with, we're ready to get started.

2.1.1 Searching Text

Concordance

There are many ways to examine the context of a text apart from simply reading it. A concordance view shows us every occurrence of a given word, together with some context. Here we look up the word `monstrous` in Moby Dick:

```
text1.concordance("monstrous")
```

```
Displaying 11 of 11 matches:
ong the former , one was of a most monstrous size . ... This came towards us ,
ON OF THE PSALMS . " Touching that monstrous bulk of the whale or ork we have r
ll over with a heathenish array of monstrous clubs and spears . Some were thick
d as you gazed , and wondered what monstrous cannibal and savage could ever hav
that has survived the flood ; most monstrous and most mountainous ! That Himmal
they might scout at Moby Dick as a monstrous fable , or still worse and more de
th of Radney .'" CHAPTER 55 Of the Monstrous Pictures of Whales . I shall ere l
ing Scenes . In connexion with the monstrous pictures of whales , I am strongly
ere to enter upon those still more monstrous stories of them which are to be fo
ght have been rummaged out of this monstrous cabinet there is no telling . But
of Whale - Bones ; for Whales of a monstrous size are oftentimes cast up dead u
```

The first time you use a concordance on a particular text, it takes a few extra seconds to build an index so that subsequent searches are fast.

Your Turn

- Try searching for other words,
- You can also try searches on some of the other texts we have included. For example, search `Sense and Sensibility` for the word `affection`, using `text2`.concordance("affection").
- Search the book of `Genesis` to find out how long some people lived, using `text3.concordance("lived")`.
- You could look at `text4`, `the Inaugural Address Corpus`, to see examples of English going back to 1789, and search for words like `nation`, `terror`, `god` to see how these words have been used differently over time.
- We've also included `text5`, the `NPS Chat Corpus`: search this for unconventional words like `im`, `ur`, `lol`. (Note that this corpus is uncensored!)

Once you've spent a little while examining these texts, we hope you have a new sense of the richness and diversity of language.

Similar Words and Common Context

A concordance permits us to see words in context. For example, we saw that monstrous occurred in contexts such as the ___ pictures and a ___ size . What other words appear in a similar range of contexts? We can find out by using `similar()` function for the text object (e.g. `text1`) with the word (e.g. `monstrous`) as its argument:

```
text1.similar("monstrous")
```

```
true contemptible christian abundant few part mean careful puzzled
mystifying passing curious loving wise doleful gamesome singular
delightfully perilous fearless
```

```
text2.similar("monstrous")
```

```
very so exceedingly heartily a as good great extremely remarkably
sweet vast amazingly
```

Observe that we get different results for different texts. Austen uses this word quite differently from Melville; for her, `monstrous` has positive connotations, and sometimes functions as an intensifier like the word `very`.

The term common_contexts allows us to examine just the contexts that are shared by two or more words, such as monstrous and very. We have to enclose these words by square brackets as well as parentheses, and separate them with a comma:

```
text2.common_contexts(["monstrous", "very"])
```

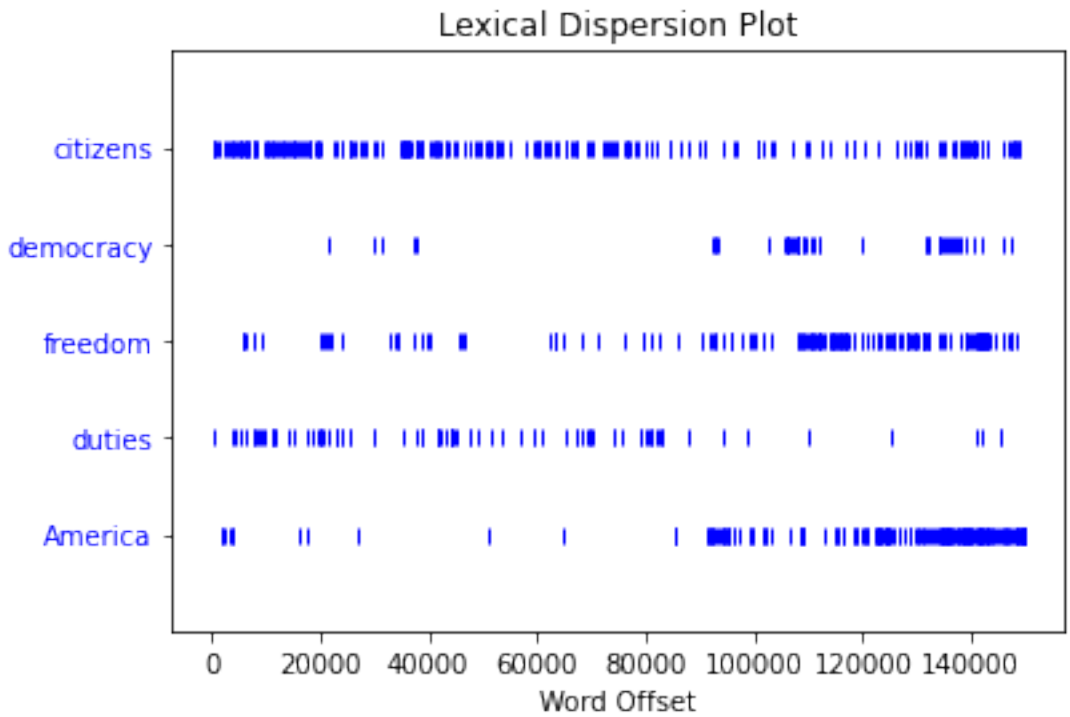
```
am_glad a_pretty a_lucky is_pretty be_glad
```

Your Turn

Pick another pair of words and compare their usage in two different texts, using the `similar()` and `common_contexts()` functions.

We have seen how to automatically detect that a particular word occurs in a text, and to display some words that appear in the same context. We can also determine the location of a word in the text: how many words from the beginning it appears. This positional information can be displayed using a dispersion plot. Each stripe represents an instance of a word, and each row represents the entire text. We can see the dispersion of words in `text4` (Inaugural Address Corpus). You can produce this plot as shown below. You might like to try more words (e.g., `liberty`, `constitution`), and different texts. Can you predict the dispersion of a word before you view it? As before, take care to get the quotes, commas, brackets and parentheses exactly right.

```
text4.dispersion_plot(["citizens", "democracy", "freedom", "duties", "America"])
```



Important: You need to have Python's NumPy and Matplotlib packages installed in order to produce the graphical plots used in this book. Please see http://nltk.org/ for installation instructions.

You can also plot the frequency of word usage through time using https://books.google.com/ngrams

Generating Text

Now, just for fun, let's try generating some random text in the various styles we have just seen. To do this, we type the name of the text followed by the term generate. (We need to include the parentheses, but there's nothing that goes between them.)

```
text3.generate()
```

```
Building ngram index...
```

```
laid by her , and said unto Cain , Where art thou , and said , Go to ,
I will not do it for ten ' s sons ; we dreamed each man according to
```

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```
their generatio the firstborn said unto Laban , Because I said , Nay ,
but Sarah shall her name be . , duke Elah , duke Shobal , and Akan .
and looked upon my affliction . Bashemath Ishmael ' s blood , but Isra
for as a prince hast thou found of all the cattle in the valley , and
the wo The
```

```
"laid by her , and said unto Cain , Where art thou , and said , Go to ,\nI will not␣
↪do it for ten ' s sons ; we dreamed each man according to\ntheir generatio the␣
↪firstborn said unto Laban , Because I said , Nay ,\nbut Sarah shall her name be . ,␣
↪duke Elah , duke Shobal , and Akan .\nand looked upon my affliction . Bashemath␣
↪Ishmael ' s blood , but Isra\nfor as a prince hast thou found of all the cattle in␣
↪the valley , and\nthe wo The"
```

2.1.2 Counting Vocabulary

The most obvious fact about texts that emerges from the preceding examples is that they differ in the vocabulary they use. In this section we will see how to use the computer to count the words in a text in a variety of useful ways. Test your understanding by modifying the examples, and trying the exercises at the end of this lab.

Text Size vs. Vocabulary Size

Let's begin by finding out the length of a text from start to finish, in terms of the words and punctuation symbols that appear. We use the term len to get the length of something, which we'll apply here to the book of `Genesis`:

```
len(text3)
```

```
44764
```

So `Genesis` has 44,764 words and punctuation symbols, or "tokens." A token is the technical name for a sequence of characters — such as `hairy`, `his`, or `:)` — that we want to treat as a group. When we count the number of tokens in a text, say, the phrase `to be or not to be`, we are counting occurrences of these sequences. Thus, in our example phrase there are two occurrences of `to`, two of `be`, and one each of `or` and `not`. But there are only four distinct vocabulary items in this phrase.

Your Turn

How many distinct words does the book of `Genesis` contain?

To work this out in Python, we have to pose the question slightly differently. The vocabulary of a text is just the set of tokens that it uses, since in a set, all duplicates are collapsed together. In Python we can obtain the vocabulary items of `text3` with the command: `set(text3)`. When you do this, many screens of words will fly past. Now try the following. By wrapping sorted() around the Python expression `set(text3)`, we obtain a sorted list of vocabulary items, beginning with various punctuation symbols and continuing with words starting with A. All capitalized words precede lowercase words. `[:20]` will list the first 20 tokens, not including the token indexed by `20`.

```
sorted(set(text3)) [:20]
```

```
['!',
 "'",
 '(',
```

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(continued from previous page)

```
 ')',
 ',',
 ',)',
 '.',
 '.)',
 ':',
 ';',
 ';)',
 '?',
 '?)',
 'A',
 'Abel',
 'Abelmizraim',
 'Abidah',
 'Abide',
 'Abimael',
 'Abimelech']
```

```
len(set(text3))
```

```
2789
```

We discover the size of the vocabulary indirectly, by asking for the number of items in the set, and again we can use len to obtain this number. Although it has 44,764 tokens, this book has only 2,789 distinct words, or "word types." A word type is the form or spelling of the word independently of its specific occurrences in a text — that is, the word considered as a unique item of vocabulary. Our count of 2,789 items will include punctuation symbols, so we will generally call these unique items types instead of word types.

Lexical Richness

Now, let's calculate a measure of the lexical richness of the text. The next example shows us that the number of distinct words is just 6% of the total number of words, or equivalently that each word is used 16 times on average.

```
len(set(text3)) / len(text3)
```

```
0.06230453042623537
```

Word Freqency

Next, let's focus on particular words. We can count how often a word occurs in a text, and compute what percentage of the text is taken up by a specific word:

```
# raw count
text3.count("smote")
```

```
5
```

```
# percentage frequency
100 * text4.count('a') / len(text4)
```

```
1.457973123627309
```

Your Turn

How many times does the word `lol` appear in `text5`? How much is this as a percentage of the total number of words in this text?

Your Turn

You may want to repeat such calculations on several texts, but it is tedious to keep retyping the formula. Instead, you can come up with your own name for a task, like "lexical_diversity" or "tf" (for term frequency), and associate it with a block of code. Now you only have to type a short name instead of one or more complete lines of Python code, and you can re-use it as often as you like. The block of code that does a task for us is called a **function**, and we define a short name for our function with the keyword def. The next example shows how to define two new functions, `lexical_diversity()` and `tf()`:

```
def lexical_diversity(text):
    return len(set(text)) / len(text)
```

```
def tf(text, token):
    count = text.count(token)
    total = len(text)
    return 100 * count / total
```

In the definition of `lexical_diversity()`, we specify a parameter named text . This parameter is a "placeholder" for the actual text whose lexical diversity we want to compute, and reoccurs in the block of code that will run when the function is used. Similarly, `tf()` is defined to take two parameters, named `text` and `token`.

Once Python knows that `lexical_diversity()` and `tf()` are the names for specific blocks of code, we can go ahead and use these functions:

```
lexical_diversity(text3)
```

```
0.06230453042623537
```

```
tf(text4, 'a')
```

```
1.457973123627309
```

To recap, we use or call a function such as `lexical_diversity()` by typing its name, followed by an open parenthesis, the name of the text, and then a close parenthesis. These parentheses will show up often; their role is to separate the name of a task — such as `lexical_diversity()` — from the data that the task is to be performed on — such as `text3`. The data value that we place in the parentheses when we call a function is an argument to the function.

You have already encountered several functions in this lab, such as `len()`, `set()`, and sorted(). By convention, we will always add an empty pair of parentheses after a function name, as in `len()`, just to make clear that what we are talking about is a function rather than some other kind of Python expression. Functions are an important concept in programming, you should consider refactoring frequently reusable blocks of code into functions.

Later we'll see how to use functions when tabulating data. Each row of the table will involve the same computation but with different data, and we'll do this repetitive work using a function.

Table 2.1: Lexical Diversity of Various Genres in the Brown Corpus

Genre	Tokens	Types	Lexical diversity
skill and hobbies	82345	11935	0.145
humor	21695	5017	0.231
fiction: science	14470	3233	0.223
press: reportage	100554	14394	0.143
fiction: romance	70022	8452	0.121
religion	39399	6373	0.162

2.2 A Closer Look at Python: Texts as Lists of Words

2.2.1 Lists

What is a text? At one level, it is a sequence of symbols on a page such as this one. At another level, it is a sequence of chapters, made up of a sequence of sections, where each section is a sequence of paragraphs, and so on. However, for our purposes, we will think of a text as nothing more than a sequence of words and punctuation. Here's how we represent text in Python, in this case the opening sentence of `Moby Dick`:

```
sent1 = ['Call', 'me', 'Ishmael', '.']
```

Here we have given a variable name we made up, `sent1`, followed by the equals sign, and then some quoted words, separated with commas, and surrounded with a pair of square brackets. This square bracketed, comma seperated content is known as a *list* in Python: it is how we store a text. We can inspect it, ask for its length and apply our own lexical_diversity() function to it.

```
sent1
```

```
['Call', 'me', 'Ishmael', '.']
```

```
len(sent1)
```

```
4
```

To use the functions we defined in another Jupyter Notebook, the best practice is to create a plain python (.py) to host all the functions, rather than import the ipython file through packages like nbimporter.

After copying the two functions into a file called `utils.py`, we can import the functions and use them in the current notebook.

```
from utils import lexical_diversity
lexical_diversity(sent1)
```

```
1.0
```

Some more lists have been defined for you, one for the opening sentence of each of our texts, sent2 … sent9. We inspect two of them here.

```
from nltk.book import *
sent2
```

```
*** Introductory Examples for the NLTK Book ***
Loading text1, ..., text9 and sent1, ..., sent9
Type the name of the text or sentence to view it.
Type: 'texts()' or 'sents()' to list the materials.
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

```
['The',
 'family',
 'of',
 'Dashwood',
 'had',
 'long',
 'been',
 'settled',
 'in',
 'Sussex',
 '.']
```

```
sent3
```

```
['In',
 'the',
 'beginning',
 'God',
 'created',
 'the',
 'heaven',
 'and',
 'the',
 'earth',
 '.']
```

Your Turn

Make up a few sentences of your own, by typing a name, equals sign, and a list of words, like this: `ex1 = ['Monty', 'Python', 'and', 'the', 'Holy', 'Grail']`. Repeat some of the other Python operations we saw earlier in 1, e.g., `sorted(ex1)`, `len(set(ex1))`, `ex1.count('the')`.

A pleasant surprise is that we can use Python's addition operator on lists. Adding two lists creates a new list with everything from the first list, followed by everything from the second list:

```
['Monty', 'Python'] + ['and', 'the', 'Holy', 'Grail']
```

```
['Monty', 'Python', 'and', 'the', 'Holy', 'Grail']
```

This special use of the addition operation is called concatenation; it combines the lists together into a single list. We can concatenate sentences to build up a text.

We don't have to literally type the lists either; we can use short names that refer to pre-defined lists.

```
sent4 + sent1
```

```
['Fellow',
 '-',
 'Citizens',
 'of',
 'the',
 'Senate',
 'and',
 'of',
 'the',
 'House',
 'of',
 'Representatives',
 ':',
 'Call',
 'me',
 'Ishmael',
 '.']
```

What if we want to add a single item to a list? This is known as appending. When we `append()` to a list, the list itself is updated as a result of the operation.

```
sent1.append("Some")
sent1
```

```
['Call', 'me', 'Ishmael', '.', 'Some']
```

2.2.2 Indexing Lists

As we have seen, a text in Python is a list of words, represented using a combination of brackets and quotes. Just as with an ordinary page of text, we can count up the total number of words in text1 with `len(text1)`, and count the occurrences in a text of a particular word — say, `'heaven'` — using `text1.count('heaven')`.

With some patience, we can pick out the 1st, 173rd, or even 14,278th word in a printed text. Analogously, we can identify the elements of a Python list by their order of occurrence in the list. The number that represents this position is the item's index. We instruct Python to show us the item that occurs at an index such as 173 in a text by writing the name of the text followed by the index inside square brackets:

```
text4[173]
```

```
'awaken'
```

We can do the converse; given a word, find the index of *when it first occurs*:

```
text4.index('awaken')
```

```
173
```

Indexes are a common way to access the words of a text, or, more generally, the elements of any list. Python permits us to access sublists as well, extracting manageable pieces of language from large texts, a technique known as *slicing*.

```
text5[16715:16735]
```

```
['U86',
 'thats',
 'why',
 'something',
 'like',
 'gamefly',
 'is',
 'so',
 'good',
 'because',
 'you',
 'can',
 'actually',
 'play',
 'a',
 'full',
 'game',
 'without',
 'buying',
 'it']
```

Indexes have some subtleties, and we'll explore these with the help of an artificial sentence:

```
sent = ['word1', 'word2', 'word3', 'word4', 'word5',
...         'word6', 'word7', 'word8', 'word9', 'word10']
sent[0]
```

```
'word1'
```

```
sent[9]
```

```
'word10'
```

Caution: Notice that our indexes start from zero: sent element zero, written sent[0], is the first word, 'word1', whereas sent element 9 is 'word10'. The reason is simple: the moment Python accesses the content of a list from the computer's memory, it is already at the first element; we have to tell it how many elements forward to go. Thus, zero steps forward leaves it at the first element.

This practice of counting from zero is initially confusing, but typical of modern programming languages. You'll quickly get the hang of it if you've mastered the system of counting centuries where 19XY is a year in the 20th century, or if you live in a country where the floors of a building are numbered from 1, and so walking up n-1 flights of stairs takes you to level n.

if we accidentally use an index that is too large, we get an error:

```
sent[10]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
<ipython-input-24-baa8b4ccd19d> in <module>
----> 1 sent[10]
```

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```
IndexError: list index out of range
```

This time it is *not a syntax error*, because the program fragment is syntactically correct. Instead, it is *a runtime error*, and it produces a Traceback message that shows the context of the error, followed by the name of the error, IndexError, and a brief explanation.

Let's take a closer look at slicing, using our artificial sentence again. Here we verify that the slice 5:8 includes sent elements at indexes 5, 6, and 7:

```
sent[5:8]
```

```
['word6', 'word7', 'word8']
```

By convention, m:n means elements m…n-1 inclusive. As the next example shows, we can omit the first number if the slice begins at the start of the list, and we can omit the second number if the slice goes to the end:

```
sent[:3]
```

```
['word1', 'word2', 'word3']
```

```
text2[141525:]
```

```
['among',
 'the',
 'merits',
 'and',
 'the',
 'happiness',
 'of',
 'Elinor',
 'and',
 'Marianne',
 ',',
 'let',
 'it',
 'not',
 'be',
 'ranked',
 'as',
 'the',
 'least',
 'considerable',
 ',',
 'that',
 'though',
 'sisters',
 ',',
 'and',
 'living',
 'almost',
 'within',
 'sight',
 'of',
 'each',
```

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```
 'other',
 ',',
 'they',
 'could',
 'live',
 'without',
 'disagreement',
 'between',
 'themselves',
 ',',
 'or',
 'producing',
 'coolness',
 'between',
 'their',
 'husbands',
 '.',
 'THE',
 'END']
```

We can modify an element of a list by assigning to one of its index values. In the next example, we put `sent[0]` on the left of the equals sign. We can also replace an entire slice with new elements. A consequence of this last change is that the list only has four elements, and accessing a later value generates an error.

```
sent[0] = 'First'
sent[9] = 'Last'
len(sent)
```

```
10
```

```
sent[1:9] = ['Second', 'Third']
sent
```

```
['First', 'Second', 'Third', 'Last']
```

```
sent[9]
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
<ipython-input-31-9d73df3f8677> in <module>
----> 1 sent[9]

IndexError: list index out of range
```

Your Turn

Take a few minutes to define a sentence of your own and modify individual words and groups of words (slices) using the same methods used earlier. Check your understanding by trying the exercises on lists at the end of this chapter.

2.3 Variables

The basic form of Python statements is: `variable = expression`. Python will evaluate the expression, and save its result to the variable. This process is called assignment. It does not generate any output; you have to type the variable on a line of its own to inspect its contents. The equals sign is slightly misleading, since information is moving from the

right side to the left. It might help to think of it as a left-arrow. The name of the variable can be anything you like, e.g., my_sent, sentence, xyzzy. It must start with a letter, and can include numbers and underscores. Here are some examples of variables and assignments:

Note: Remember that capitalized words appear before lowercase words in sorted lists.

Notice Python expressions can be split across multiple lines, so long as this happens within any kind of brackets. It doesn't matter how much indentation is used in these continuation lines, but some indentation usually makes them easier to read.

It is good to choose meaningful variable names to remind you — and to help anyone else who reads your Python code — what your code is meant to do. Python does not try to make sense of the names; it blindly follows your instructions, and does not object if you do something confusing, such as `one = 'two'` or `two = 3`. The only restriction is that a variable name cannot be any of Python's reserved words, such as `def`, `if`, `not`, and `import`. If you use a reserved word, Python will produce a syntax error:

```
not = 'Camelot'
```

```
  File "<ipython-input-32-4961bbbbef94>", line 1
    not = 'Camelot'
        ^
SyntaxError: invalid syntax
```

We will often use variables to hold intermediate steps of a computation, especially when this makes the code easier to follow. Thus `len(set(text1))` could also be written:

```
vocab = set(text1)
vocab_size = len(vocab)
vocab_size
```

```
19317
```

Caution: Take care with your choice of names (or identifiers) for Python variables. First, you should start the name with a letter, optionally followed by digits (0 to 9) or letters. Thus, abc23 is fine, but 23abc will cause a syntax error. Names are case-sensitive, which means that myVar and myvar are distinct variables. Variable names cannot contain whitespace, but you can separate words using an underscore, e.g., my_var. Be careful not to insert a hyphen instead of an underscore: my-var is wrong, since Python interprets the "-" as a minus sign.

2.2.3 Strings

Some of the methods we used to access the elements of a list also work with individual words, or strings. For example, we can assign a string to a variable [1], index a string, and slice a string:

```
name = 'Monty'
name[0]
```

```
'M'
```

```
name[:4]
```

```
'Mont'
```

We can also perform multiplication and addition with strings:

```
name * 2
```

```
'MontyMonty'
```

```
name + '!'
```

```
'Monty!'
```

We can join the words of a list to make a single string, or split a string into a list, as follows:

```
' '.join(['Monty', 'Python'])
```

```
'Monty Python'
```

```
'Monty Python'.split()
```

We now have two important building blocks — lists and strings — and are ready to get back to some language analysis.

2.3 Computing with Language: Simple Statistics

Let us return to our exploration of the ways we can bring our computational resources to bear on large quantities of text. We began this discussion in 1, and saw how to search for words in context, how to compile the vocabulary of a text, how to generate random text in the same style, and so on.

In this section we pick up the question of what makes a text distinct, and use automatic methods to find characteristic words and expressions of a text.

Before continuing further, you might like to check your understanding of the last section by predicting the output of the following code. You can use the Jupyter Notebook Code Cell to check whether you got it right. If you're not sure how to do this task, it would be a good idea to review the previous section before continuing further.

```
saying = ['After', 'all', 'is', 'said', 'and', 'done',
           'more', 'is', 'said', 'than', 'done']
tokens = set(saying)
tokens = sorted(tokens)
tokens
```

```
['After', 'all', 'and', 'done', 'is', 'more', 'said', 'than']
```

Your Turn

What output do you expect of `tokens[-2:]?

2.3.1 Frequency Distributions

How can we automatically identify the words of a text that are most informative about the topic and genre of the text? Imagine how you might go about finding the 50 most frequent words of a book. One method would be to keep a tally for each vocabulary item. The tally would need thousands of rows (the same size as the vocabulary), and it would be an exceedingly laborious process — so laborious that we would rather assign the task to a machine. Since we often need frequency distributions in language processing, NLTK provides built-in support for them. Let's use a FreqDist to find the 50 most frequent words of `Moby Dick`:

```
from nltk.book import *
```

```
*** Introductory Examples for the NLTK Book ***
Loading text1, ..., text9 and sent1, ..., sent9
Type the name of the text or sentence to view it.
Type: 'texts()' or 'sents()' to list the materials.
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

```
fdist1 = FreqDist(text1)
print(fdist1)
```

```
<FreqDist with 19317 samples and 260819 outcomes>
```

```
fdist1.most_common(50)
```

```
[(',', 18713),
 ('the', 13721),
 ('.', 6862),
 ('of', 6536),
 ('and', 6024),
 ('a', 4569),
 ('to', 4542),
 (';', 4072),
 ('in', 3916),
 ('that', 2982),
 ("'", 2684),
 ('-', 2552),
 ('his', 2459),
 ('it', 2209),
 ('I', 2124),
 ('s', 1739),
 ('is', 1695),
 ('he', 1661),
 ('with', 1659),
 ('was', 1632),
 ('as', 1620),
 ('"', 1478),
 ('all', 1462),
```

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```
 ('for', 1414),
 ('this', 1280),
 ('!', 1269),
 ('at', 1231),
 ('by', 1137),
 ('but', 1113),
 ('not', 1103),
 ('--', 1070),
 ('him', 1058),
 ('from', 1052),
 ('be', 1030),
 ('on', 1005),
 ('so', 918),
 ('whale', 906),
 ('one', 889),
 ('you', 841),
 ('had', 767),
 ('have', 760),
 ('there', 715),
 ('But', 705),
 ('or', 697),
 ('were', 680),
 ('now', 646),
 ('which', 640),
 ('?', 637),
 ('me', 627),
 ('like', 624)]
```

The tally is known as a frequency distribution, and it tells us the frequency of each vocabulary item in the text. (In general, it could count any kind of observable event.) It is a "distribution" because it tells us how the total number of word tokens in the text are distributed across the vocabulary items. Since we often need frequency distributions in language processing, NLTK provides built-in support for them. Let's use a FreqDist to find the 50 most frequent words of Moby Dick:

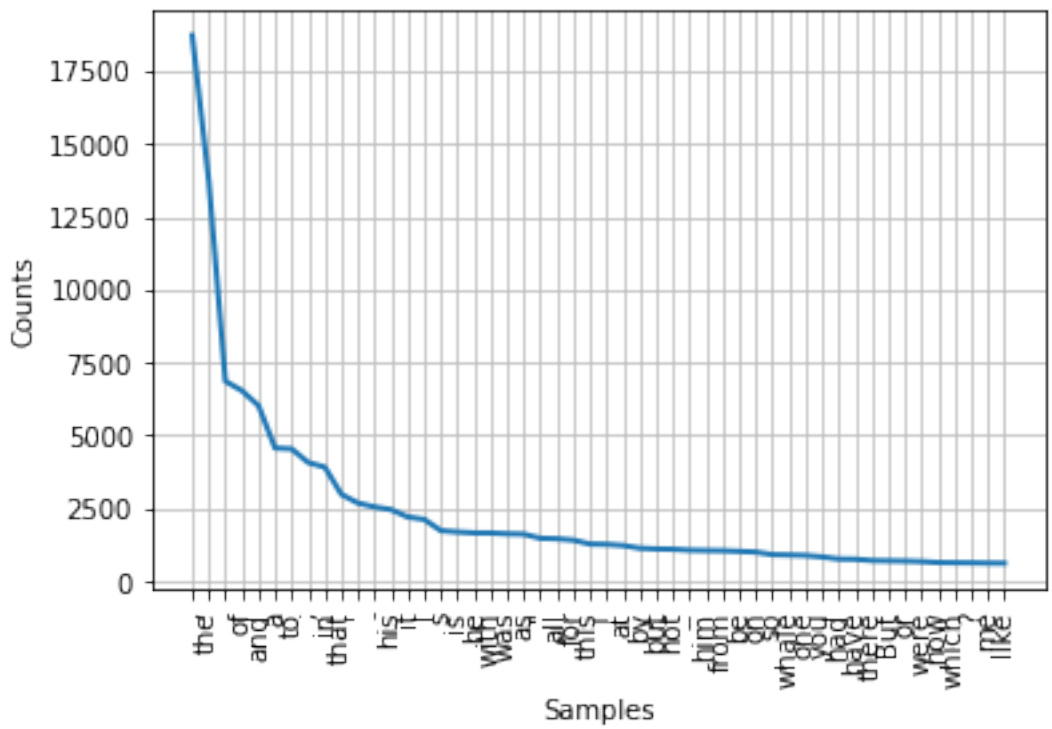
When we first invoke FreqDist, we pass the name of the text as an argument. We can inspect the total number of words ("outcomes") that have been counted up — 260,819 in the case of `Moby Dick`. The expression most_common(50) gives us a list of the 50 most frequently occurring types in the text with a raw count of each word.

Your Turn

Try the preceding frequency distribution example for yourself, for `text2`. Be careful to use the correct parentheses and uppercase letters. If you get an error message NameError: name 'FreqDist' is not defined, you need to start your work with from nltk.book import *

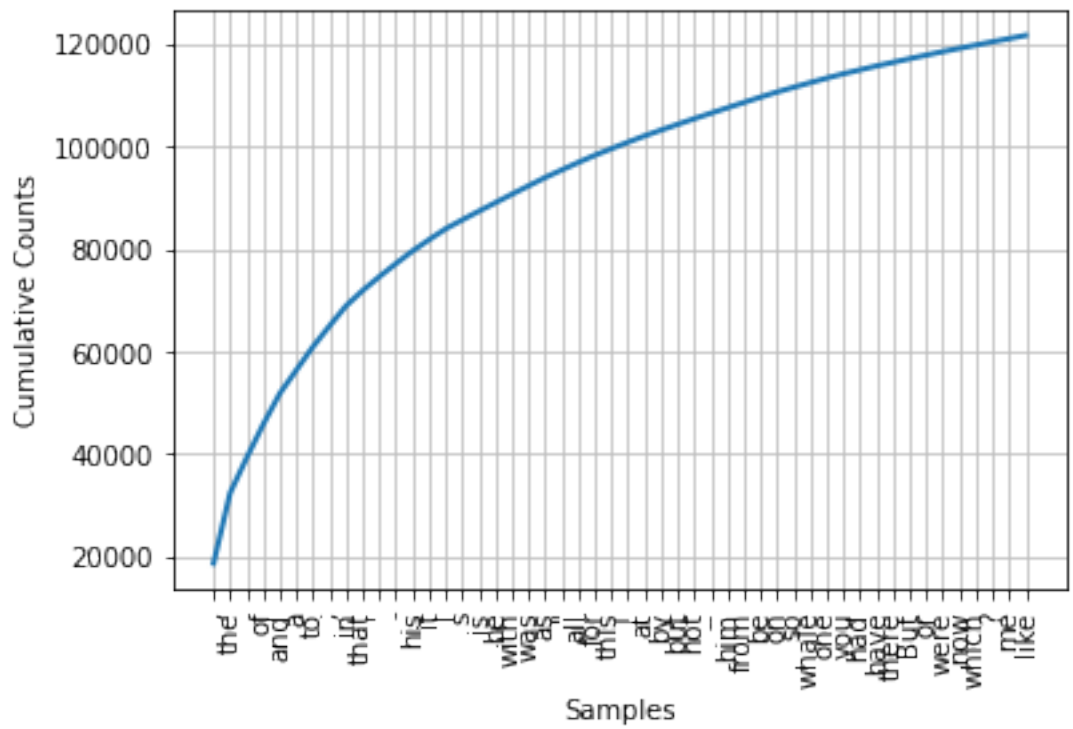
Do any words produced in the last example help us grasp the topic or genre of this text? Only one word, whale, is slightly informative! It occurs over 900 times. The rest of the words tell us nothing about the text; they're just English "plumbing." What proportion of the text is taken up with such words? We can generate a cumulative frequency plot for these words, using `fdist1.plot(50, cumulative=True)`, to produce the following graph. These 50 words account for nearly half the book!

```
# The frequency distribution
fdist1.plot(50)
```




```
<AxesSubplot:xlabel='Samples', ylabel='Counts'>
```

```
fdist1.plot(50, cumulative=True)
```



```
<AxesSubplot:xlabel='Samples', ylabel='Cumulative Counts'>
```

From the Cumulative Frequency Plot for 50 Most Frequently Words in `Moby Dick`: these account for nearly half of the tokens.

If the frequent words don't help us, how about the words that occur once only, the so-called hapaxes? View them by typing `fdist1.hapaxes()`. This list contains `lexicographer`, `cetological`, `contraband`, `expostulations`, and about 9,000 others. It seems that there are too many rare words, and without seeing the context we probably can't guess what half of the hapaxes mean in any case! Since neither frequent nor infrequent words help, we need to try something else.

```
fdist1.hapaxes()
```

```
['Herman',
 'Melville',
 ']',
 'ETYMOLOGY',
 'Late',
 'Consumptive',
 'School',
 'threadbare',
 'lexicons',
 'mockingly',
 'flags',
 'mortality',
 'signification',
 'HACKLUYT',
 'Sw',
 'HVAL',
 'roundness',
 'Dut',
 'Ger',
 'WALLEN',
 'WALW',
 'IAN',
 'RICHARDSON',
 'KETOS',
 'GREEK',
 'CETUS',
 'LATIN',
 'WHOEL',
 'ANGLO',
 'SAXON',
 'WAL',
 'HWAL',
 'SWEDISH',
 'ICELANDIC',
 'BALEINE',
 'BALLENA',
 'FEGEE',
 'ERROMANGOAN',
 'Librarian',
 'painstaking',
 'burrower',
 'grub',
 'Vaticans',
 'stalls',
```

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```
 'higgledy',
 'piggledy',
 'gospel',
 'promiscuously',
 'commentator',
 'belongest',
 'sallow',
 'Pale',
 'Sherry',
 'loves',
 'bluntly',
 'Subs',
 'thankless',
 'Hampton',
 'Court',
 'hie',
 'refugees',
 'pampered',
 'Michael',
 'Raphael',
 'unsplinterable',
 'GENESIS',
 'JOB',
 'JONAH',
 'punish',
 'ISAIAH',
 'soever',
 'cometh',
 'incontinently',
 'perisheth',
 'PLUTARCH',
 'MORALS',
 'breedeth',
 'Whirlpooles',
 'Balaene',
 'arpens',
 'PLINY',
 'Scarcely',
 'TOOKE',
 'LUCIAN',
 'TRUE',
 'catched',
 'OCTHER',
 'VERBAL',
 'TAKEN',
 'MOUTH',
 'ALFRED',
 '890',
 'gudgeon',
 'retires',
 'MONTAIGNE',
 'APOLOGY',
 'RAIMOND',
 'SEBOND',
 'Nick',
 'RABELAIS',
 'cartloads',
```

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```
 'STOWE',
 'ANNALS',
 'LORD',
 'BACON',
 'Touching',
 'ork',
 'DEATH',
 'sovereignest',
 'bruise',
 'HAMLET',
 'leach',
 'Mote',
 'availle',
 'returne',
 'againe',
 'worker',
 'Dinting',
 'paine',
 'thro',
 'maine',
 'FAERIE',
 'Immense',
 'til',
 'DAVENANT',
 'PREFACE',
 'GONDIBERT',
 'spermacetti',
 'Hosmannus',
 'Nescio',
 'VIDE',
 'Spencer',
 'Talus',
 'flail',
 'threatens',
 'jav',
 'lins',
 'WALLER',
 'SUMMER',
 'ISLANDS',
 'Commonwealth',
 'Civitas',
 'OPENING',
 'SENTENCE',
 'HOBBES',
 'LEVIATHAN',
 'Silly',
 'Mansoul',
 'chewing',
 'sprat',
 'PILGRIM',
 'PROGRESS',
 'Created',
 'PARADISE',
 'LOST',
 '---"',
 'Hugest',
 'Stretched',
```

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```
 'Draws',
 'FULLLER',
 'PROFANE',
 'HOLY',
 'STATE',
 'DRYDEN',
 'ANNUS',
 'MIRABILIS',
 'aground',
 'EDGE',
 'TEN',
 'SPITZBERGEN',
 'PURCHAS',
 'wantonness',
 'fuzzing',
 'vents',
 'HERBERT',
 'INTO',
 'ASIA',
 'AFRICA',
 'SCHOUTEN',
 'SIXTH',
 'CIRCUMNAVIGATION',
 'Elbe',
 'ducat',
 'herrings',
 'GREENLAND',
 'Several',
 'Fife',
 'Anno',
 '1652',
 'Pitferren',
 'SIBBALD',
 'FIFE',
 'KINROSS',
 'Myself',
 'Sperma',
 'ceti',
 'fierceness',
 'RICHARD',
 'STRAFFORD',
 'LETTER',
 'BERMUDAS',
 'PHIL',
 'TRANS',
 '1668',
 'PRIMER',
 'COWLEY',
 '1729',
 '"...',
 'frequendy',
 'insupportable',
 'disorder',
 'ULLOA',
 'SOUTH',
 'AMERICA',
 'sylphs',
```

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```
 'petticoat',
 'Oft',
 'Tho',
 'RAPE',
 'LOCK',
 'NAT',
 'wales',
 'JOHNSON',
 'COOK',
 'dung',
 'lime',
 'juniper',
 'UNO',
 'VON',
 'TROIL',
 'LETTERS',
 'BANKS',
 'SOLANDER',
 '1772',
 'Nantuckois',
 'JEFFERSON',
 'MEMORIAL',
 'MINISTER',
 'REFERENCE',
 'PARLIAMENT',
 'SOMEWHERE',
 'guarding',
 'protecting',
 'robbers',
 'BLACKSTONE',
 'Rodmond',
 'suspends',
 'attends',
 'FALCONER',
 'Bright',
 'roofs',
 'domes',
 'rockets',
 'Around',
 'unwieldy',
 'COWPER',
 'VISIT',
 'LONDON',
 'HUNTER',
 'DISSECTION',
 'SMALL',
 'SIZED',
 'aorta',
 'gushing',
 'PALEY',
 'THEOLOGY',
 'mammiferous',
 'hind',
 'BARON',
 'CUVIER',
 'COLNETT',
 'PURPOSE',
```

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```
 'EXTENDING',
 'SPERMACETI',
 'Floundered',
 'chace',
 'peopling',
 'Gather',
 'Led',
 'instincts',
 'trackless',
 'Assaulted',
 'voracious',
 'spiral',
 'MONTGOMERY',
 'WORLD',
 'FLOOD',
 'Paean',
 'fatter',
 'Flounders',
 'CHARLES',
 'LAMB',
 'TRIUMPH',
 '1690',
 'OBED',
 'Susan',
 'HAWTHORNE',
 'TWICE',
 'bespeak',
 'raal',
 'COOPER',
 'PILOT',
 'Berlin',
 'Gazette',
 'ECKERMANN',
 'CONVERSATIONS',
 'GOETHE',
 'ESSEX',
 'WAS',
 'ATTACKED',
 'FINALLY',
 'DESTROYED',
 'OWEN',
 'CHACE',
 'FIRST',
 'SAID',
 'VESSEL',
 'YORK',
 '1821',
 'piping',
 'dimmed',
 'phospher',
 'ELIZABETH',
 'OAKES',
 'SMITH',
 'amounted',
 '440',
 'SCORESBY',
 'Mad',
```

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```
 'agonies',
 'endures',
 'infuriated',
 'rears',
 'snaps',
 'propelled',
 'observers',
 'opportunities',
 'habitudes',
 'BEALE',
 'offensively',
 'artful',
 'mischievous',
 'FREDERICK',
 'DEBELL',
 '1840',
 'October',
 'Raise',
 'ay',
 'THAR',
 'bowes',
 'os',
 'ROSS',
 'ETCHINGS',
 'CRUIZE',
 '1846',
 'Globe',
 'transactions',
 'relate',
 'HUSSEY',
 'SURVIVORS',
 'parried',
 'MISSIONARY',
 'JOURNAL',
 'TYERMAN',
 'boldest',
 'persevering',
 'REPORT',
 'DANIEL',
 'SPEECH',
 'SENATE',
 'APPLICATION',
 'ERECTION',
 'BREAKWATER',
 'CAPTORS',
 'WHALEMAN',
 'ADVENTURES',
 'BIOGRAPHY',
 'GATHERED',
 'HOMEWARD',
 'COMMODORE',
 'PREBLE',
 'REV',
 'CHEEVER',
 'MUTINEER',
 'BROTHER',
 'ANOTHER',
```

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```
 'MCCULLOCH',
 'COMMERCIAL',
 'reciprocal',
 'clews',
 'SOMETHING',
 'UNPUBLISHED',
 'CURRENTS',
 'Pedestrians',
 'recollect',
 'gateways',
 'VOYAGER',
 'ARCTIC',
 'NEWSPAPER',
 'TAKING',
 'RETAKING',
 'HOBOMACK',
 'MIRIAM',
 'FISHERMAN',
 'appliance',
 'RIBS',
 'TRUCKS',
 'Terra',
 'Del',
 'Fuego',
 'DARWIN',
 'NATURALIST',
 ";--'",
 '!\'"',
 'WHARTON',
 'Loomings',
 'spleen',
 'regulating',
 'circulation',
 'Whenever',
 'drizzly',
 'hypos',
 'philosophical',
 'Cato',
 'Manhattoes',
 'reefs',
 'downtown',
 'gazers',
 'Circumambulate',
 'Corlears',
 'Coenties',
 'Slip',
 'Whitehall',
 'Posted',
 'sentinels',
 'spiles',
 'pier',
 'lath',
 'counters',
 'desks',
 'loitering',
 'shady',
 'Inlanders',
```

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```
 'lanes',
 'alleys',
 'attract',
 'dale',
 'dreamiest',
 'shadiest',
 'quietest',
 'enchanting',
 'Saco',
 'crucifix',
 'Deep',
 'mazy',
 'Tiger',
 'Tennessee',
 'Rockaway',
 'Persians',
 'deity',
 'Narcissus',
 'ungraspable',
 'hazy',
 'quarrelsome',
 'offices',
 'abominate',
 'toils',
 'trials',
 'barques',
 'schooners',
 'broiling',
 'buttered',
 'judgmatically',
 'peppered',
 'reverentially',
 'idolatrous',
 'dotings',
 'ibis',
 'roasted',
 'bake',
 'plumb',
 'Van',
 'Rensselaers',
 'Randolphs',
 'Hardicanutes',
 'lording',
 'tallest',
 'decoction',
 'Seneca',
 'Stoics',
 'Testament',
 'promptly',
 'rub',
 'infliction',
 'BEING',
 'PAID',
 'urbane',
 'ills',
 'monied',
 'consign',
```

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```
 'prevalent',
 'violate',
 'Pythagorean',
 'commonalty',
 'police',
 'surveillance',
 'programme',
 'solo',
 'CONTESTED',
 'ELECTION',
 'PRESIDENCY',
 'UNITED',
 'STATES',
 'ISHMAEL',
 'BLOODY',
 'AFFGHANISTAN',
 'managers',
 'genteel',
 'comedies',
 'farces',
 'cunningly',
 'disguises',
 'cajoling',
 'unbiased',
 'freewill',
 'discriminating',
 'overwhelming',
 'undeliverable',
 'itch',
 'forbidden',
 'ignoring',
 'lodges',
 'Carpet',
 'Bag',
 'Manhatto',
 'candidates',
 'penalties',
 'Tyre',
 'Carthage',
 'imported',
 'cobblestones',
 'bitingly',
 'shouldering',
 'price',
 'fervent',
 'asphaltic',
 'pavement',
 'flinty',
 'projections',
 'soles',
 'Too',
 'cheapest',
 'cheeriest',
 'invitingly',
 'particles',
 'peer',
 'Angel',
```

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```
 'Doom',
 'wailing',
 'gnashing',
 'Wretched',
 'entertainment',
 'Moving',
 'emigrant',
 'poverty',
 'creak',
 'lodgings',
 'zephyr',
 'hob',
 'toasting',
 'observest',
 'sashless',
 'glazier',
 'reasonest',
 'chinks',
 'crannies',
 'lint',
 'chattering',
 'shiverings',
 'cob',
 'redder',
 'Orion',
 'glitters',
 'conservatories',
 'president',
 'temperance',
 'blubbering',
 'straggling',
 'wainscots',
 'reminding',
 'oilpainting',
 'besmoked',
 'defaced',
 'unequal',
 'crosslights',
 'hags',
 'delineate',
 'bewitched',
 'ponderings',
 'boggy',
 'soggy',
 'squitchy',
 'froze',
 'heath',
 'icebound',
 'represents',
 'Horner',
 'foundered',
 'clubs',
 'harvesting',
 'hacking',
 'horrifying',
 'Mixed',
 'Nathan',
```

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```
 'Swain',
 'corkscrew',
 'Blanco',
 'sojourning',
 'fireplaces',
 'duskier',
 'cockpits',
 'rarities',
 'Projecting',
 'Within',
 'shelves',
 'flasks',
 'bustles',
 'deliriums',
 'Abominable',
 'tumblers',
 'cylinders',
 'goggling',
 'deceitfully',
 'tapered',
 'Parallel',
 'pecked',
 'footpads',
 'Fill',
 'shilling',
 'examining',
 'SKRIMSHANDER',
 'accommodated',
 'unoccupied',
 'haint',
 'pose',
 'whalin',
 'decidedly',
 'objectionable',
 'wander',
 'Battery',
 'ruminating',
 'adorning',
 'potatoes',
 'sartainty',
 'diabolically',
 'steaks',
 'undress',
 'looker',
 'rioting',
 'Grampus',
 'seed',
 'Feegees',
 'tramping',
 'Enveloped',
 'bedarned',
 'eruption',
 'officiating',
 'brimmers',
 'complained',
 'potion',
 'colds',
```

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```
 'catarrhs',
 'liquor',
 'arrantest',
 'topers',
 'obstreperously',
 'aloof',
 'desirous',
 'hilarity',
 'coffer',
 'Southerner',
 'mountaineers',
 'Alleghanian',
 'missed',
 'supernaturally',
 'congratulate',
 'multiply',
 'bachelor',
 'abominated',
 'tidiest',
 'bedwards',
 'shan',
 'tablecloth',
 'Skrimshander',
 'bump',
 'spraining',
 'eider',
 'yoking',
 'rickety',
 'whirlwinds',
 'knockings',
 'dismissed',
 'popped',
 'cherishing',
 'chuckled',
 'chuckle',
 'mightily',
 'catches',
 'bamboozingly',
 'overstocked',
 'toothpick',
 'rayther',
 'BROWN',
 'slanderin',
 'farrago',
 'BROKE',
 'Sartain',
 'Mt',
 'Hecla',
 'persist',
 'mystifying',
 'unsay',
 'criminal',
 'Wall',
 'purty',
 'sarmon',
 'rips',
 'tellin',
```

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```
 'bought',
 'balmed',
 'curios',
 'sellin',
 'inions',
 'fooling',
 'idolators',
 'Depend',
 'reg',
 'lar',
 'spliced',
 'Johnny',
 'sprawling',
 'Arter',
 'glim',
 'jiffy',
 'irresolute',
 'vum',
 'WON',
 'Folding',
 'scrutiny',
 'porcupine',
 'moccasin',
 'ponchos',
 'parade',
 'rainy',
 'remembering',
 'commended',
 'cobs',
 'Nod',
 'footfall',
 'unlacing',
 'blackish',
 'plasters',
 'inkling',
 'Placing',
 'crammed',
 'scalp',
 'mildewed',
 'Ignorance',
 'parent',
 'nonplussed',
 'undressing',
 'checkered',
 'Thirty',
 'frogs',
 'quaked',
 'wrapall',
 'dreadnaught',
 'fumbled',
 'Remembering',
 'manikin',
 'tenpin',
 'andirons',
 'jambs',
 'bricks',
 'appropriate',
```

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```
 'applying',
 'hastier',
 'withdrawals',
 'antics',
 'devotee',
 'extinguishing',
 'unceremoniously',
 'bagged',
 'sportsman',
 'woodcock',
 'uncomfortableness',
 'deliberating',
 'puffed',
 'sang',
 'Stammering',
 'conjured',
 'responses',
 'debel',
 'flourishing',
 'Angels',
 'flourishings',
 'peddlin',
 'sleepe',
 'grunted',
 'gettee',
 'motioning',
 'comely',
 'insured',
 'Counterpane',
 'parti',
 'triangles',
 'interminable',
 'caper',
 'supperless',
 '21st',
 'hemisphere',
 'sigh',
 'Sixteen',
 'ached',
 'coaches',
 'stockinged',
 'slippering',
 'misbehaviour',
 'unendurable',
 'stepmothers',
 'misfortunes',
 'steeped',
 'shudderingly',
 'confounding',
 'soberly',
 'recurred',
 'predicament',
 'unlock',
 'bridegroom',
 'clasp',
 'hugged',
 'rouse',
```

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```
 'snore',
 'scratch',
 'Throwing',
 'expostulations',
 'unbecomingness',
 'matrimonial',
 'dawning',
 'overture',
 'innate',
 'compliment',
 'civility',
 'rudeness',
 'toilette',
 'dressing',
 'donning',
 'gaspings',
 'booting',
 'caterpillar',
 'outlandishness',
 'manners',
 'education',
 'undergraduate',
 'dreamt',
 'cowhide',
 'pinched',
 'curtains',
 'indecorous',
 'contented',
 'restricting',
 'donned',
 'lathering',
 'unsheathes',
 'whets',
 'Rogers',
 'cutlery',
 'Afterwards',
 'baton',
 'Breakfast',
 'pleasantly',
 'bountifully',
 'laughable',
 'bosky',
 'unshorn',
 'gowns',
 'toasted',
 'lingers',
 'tarried',
 'barred',
 'Grub',
 'Park',
 'assurance',
 'polish',
 'occasioned',
 'embarrassed',
 'bashfulness',
 'duelled',
 'winking',
```

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```
 'tastes',
 'sheepishly',
 'bashful',
 'icicle',
 'admirer',
 'cordially',
 'grappling',
 'genteelly',
 'eschewed',
 'undivided',
 '6',
 'circulating',
 'nondescripts',
 'Chestnut',
 'jostle',
 'Regent',
 'Lascars',
 'Bombay',
 'Apollo',
 'Feegeeans',
 'Tongatobooarrs',
 'Erromanggoans',
 'Pannangians',
 'Brighggians',
 'weekly',
 'Vermonters',
 'stalwart',
 'frames',
 'felled',
 'strutting',
 'wester',
 'bombazine',
 'cloak',
 'mow',
 'gloves',
 'joins',
 'outfit',
 'waistcoats',
 'Hay',
 'Seed',
 'tract',
 'dearest',
 'pave',
 'eggs',
 'patrician',
 'parks',
 'scraggy',
 'scoria',
 'Herr',
 'dowers',
 'nieces',
 'reservoirs',
 'maples',
 'bountiful',
 'proffer',
 'passer',
 'cones',
```

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```
 'blossoms',
 'superinduced',
 'carnation',
 'Salem',
 'sweethearts',
 'Puritanic',
 'Whaleman',
 'Wrapping',
 'Each',
 'quote',
 'TALBOT',
 'Near',
 'Desolation',
 '1st',
 'SISTER',
 'ROBERT',
 'WILLIS',
 'ELLERY',
 'NATHAN',
 'COLEMAN',
 'WALTER',
 'CANNY',
 'SETH',
 'GLEIG',
 'Forming',
 'ELIZA',
 '31st',
 'MARBLE',
 'SHIPMATES',
 'EZEKIEL',
 'HARDY',
 'AUGUST',
 '3d',
 '1833',
 'WIDOW',
 'Shaking',
 'glazed',
 'Affected',
 'relatives',
 'unhealing',
 'sympathetically',
 'wounds',
 'bleed',
 'blanks',
 ...]
```

2.3.2 Fine-grained Selection of Words

Next, let's look at the long words of a text; perhaps these will be more characteristic and informative. For this we adapt some notation from set theory. We would like to find the words from the vocabulary of the text that are more than 15 characters long. Let's call this property `P`, so that `P(w)` is true if and only if `w` is more than 15 characters long. Now we can express the words of interest using mathematical set notation as shown in (2.1). This means "the set of all `w` such that `w` is an element of `V` (the vocabulary) and `w` has property `P`".

$$w|w \in VP(w) \tag{2.1}$$

[w for w in V if p(w)]

The corresponding Python expression is given in

```
[w for w in V if p(w)]
```

Note that it produces a list, not a set, which means that duplicates are possible. Observe how similar the two notations are. Let's go one more step and write executable Python code:

```
V = set(text1)
long_words = [w for w in V if len(w) > 15]
sorted(long_words)
```

```
['CIRCUMNAVIGATION',
 'Physiognomically',
 'apprehensiveness',
 'cannibalistically',
 'characteristically',
 'circumnavigating',
 'circumnavigation',
 'circumnavigations',
 'comprehensiveness',
 'hermaphroditical',
 'indiscriminately',
 'indispensableness',
 'irresistibleness',
 'physiognomically',
 'preternaturalness',
 'responsibilities',
 'simultaneousness',
 'subterraneousness',
 'supernaturalness',
 'superstitiousness',
 'uncomfortableness',
 'uncompromisedness',
 'undiscriminating',
 'uninterpenetratingly']
```

Your Turn

Try out the previous statements in the Jupyter Notebook, and experiment with changing the text and changing the length condition. Does it make a difference to your results if you change the variable names, e.g., using `[word for word in vocab if ...]`?

Let's return to our task of finding words that characterize a text. Notice that the long words in `text4` reflect its national focus — constitutionally, transcontinental — whereas those in `text5` reflect its informal content: boooooooooooglyyyyyy

and yuuuuuuuuuuuummmmmmmmmmmm. Have we succeeded in automatically extracting words that typify a text? Well, these very long words are often *hapaxes* (i.e., unique) and perhaps it would be better to find frequently occurring long words. This seems promising since it eliminates frequent short words (e.g., the) and infrequent long words (e.g. antiphilosophists). Here are all words from the chat corpus that are longer than seven characters, that occur more than seven times:

```
fdist5 = FreqDist(text5)
sorted(w for w in set(text5) if len(w) > 7 and fdist5[w] > 7)
```

```
['#14-19teens',
 '#talkcity_adults',
 '((((((((((',
 '........',
 'Question',
 'actually',
 'anything',
 'computer',
 'cute.-ass',
 'everyone',
 'football',
 'innocent',
 'listening',
 'remember',
 'seriously',
 'something',
 'together',
 'tomorrow',
 'watching']
```

Notice how we have used two conditions: `len(w) > 7` ensures that the words are longer than seven letters, and `fdist5[w] > 7` ensures that these words occur more than seven times. At last we have managed to automatically identify the frequently-occurring content-bearing words of the text. It is a modest but important milestone: a tiny piece of code, processing tens of thousands of words, produces some informative output.

2.3.3 Collocations and Bigrams

A collocation is a sequence of words that occur together unusually often. Thus `red wine` is a collocation, whereas `the wine` is not. A characteristic of collocations is that they are resistant to substitution with words that have similar senses; for example, `maroon wine` sounds definitely odd.

To get a handle on collocations, we start off by extracting from a text a list of word pairs, also known as bigrams. This is easily accomplished with the function `bigrams()`:

```
list(bigrams(['more', 'is', 'said', 'than', 'done']))
```

```
[('more', 'is'), ('is', 'said'), ('said', 'than'), ('than', 'done')]
```

If you omitted list() above, and just typed bigrams(['more', …]), you would have seen output of the form <generator object bigrams at 0x10fb8b3a8>. This is Python's way of saying that it is ready to compute a sequence of items, in this case, bigrams. For now, you just need to know to tell Python to convert it into a list, using list().

Here we see that the pair of words `than-done` is a bigram, and we write it in Python as ('than', 'done'). Now, collocations are essentially just frequent bigrams, except that we want to pay more attention to the cases that involve rare words. In particular, we want to find bigrams that occur more often than we would expect based on the frequency of the individual words. The collocations() function does this for us. We will see how it works later.

```
text4.collocations()
```

```
United States; fellow citizens; four years; years ago; Federal
Government; General Government; American people; Vice President; God
bless; Chief Justice; Old World; Almighty God; Fellow citizens; Chief
Magistrate; every citizen; one another; fellow Americans; Indian
tribes; public debt; foreign nations
```

```
text8.collocations()
```

```
would like; medium build; social drinker; quiet nights; non smoker;
long term; age open; Would like; easy going; financially secure; fun
times; similar interests; Age open; weekends away; poss rship; well
presented; never married; single mum; permanent relationship; slim
build
```

The collocations that emerge are very specific to the genre of the texts. In order to find red wine as a collocation, we would need to process a much larger body of text.

2.3.4 Counting Other Things

Counting words is useful, but we can count other things too. For example, we can look at the distribution of word lengths in a text, by creating a FreqDist out of a long list of numbers, where each number is the length of the corresponding word in the text:

```
fdist = FreqDist(len(w) for w in text1)
print(fdist)
```

```
<FreqDist with 19 samples and 260819 outcomes>
```

```
fdist
```

```
FreqDist({3: 50223, 1: 47933, 4: 42345, 2: 38513, 5: 26597, 6: 17111, 7: 14399, 8:␣
↪9966, 9: 6428, 10: 3528, ...})
```

We start by deriving a list of the lengths of words in text1, and the FreqDist then counts the number of times each of these occurs. The result is a distribution containing a quarter of a million items, each of which is a number corresponding to a word token in the text. But there are at most only 20 distinct items being counted, the numbers 1 through 20, because there are only 20 different word lengths. That is, there are words consisting of just one character, two characters, …, twenty characters, but none with twenty one or more characters. One might wonder how frequent the different lengths of word are (e.g., how many words of length four appear in the text, are there more words of length five than length four, etc). We can do this as follows:

```
fdist.most_common()
```

```
[(3, 50223),
 (1, 47933),
 (4, 42345),
 (2, 38513),
 (5, 26597),
 (6, 17111),
 (7, 14399),
```

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```
 (8, 9966),
 (9, 6428),
 (10, 3528),
 (11, 1873),
 (12, 1053),
 (13, 567),
 (14, 177),
 (15, 70),
 (16, 22),
 (17, 12),
 (18, 1),
 (20, 1)]
```

```
fdist.max()
```

```
3
```

```
fdist[3]
```

```
50223
```

```
fdist.freq(3)
```

```
0.19255882431878046
```

From this we see that the most frequent word length is 3, and that words of length 3 account for roughly 50,000 (or 20%) of the words making up the book. Although we will not pursue it here, further analysis of word length might help us understand differences between authors, genres, or languages.

3.1 summarizes the functions defined in frequency distributions.

Table 2.2: Functions Defined for NLTK's Frequency Distributions

Example	Description
fdist = FreqDist(samples)	create a frequency distribution containing the given samples
fdist[sample] += 1	increment the count for this sample
fdist['monstrous']	count of the number of times a given sample occurred
fdist.freq('monstrous')	frequency of a given sample
fdist.N()	total number of samples
fdist.most_common(n)	the n most common samples and their frequencies
for sample in fdist:	iterate over the samples
fdist.max()	sample with the greatest count
fdist.tabulate()	tabulate the frequency distribution
fdist.plot()	graphical plot of the frequency distribution
fdist.plot(cumulative=True)	cumulative plot of the frequency distribution
fdist1 |= fdist2	update fdist1 with counts from fdist2
fdist1 < fdist2	test if samples in fdist1 occur less frequently than in fdist2

Our discussion of frequency distributions has introduced some important Python concepts, and we will look at them systematically.

2.4 Back to Python: Making Decisions and Taking Control

So far, our little programs have had some interesting qualities: the ability to work with language, and the potential to save human effort through automation. A key feature of programming is the ability of machines to make decisions on our behalf, executing instructions when certain conditions are met, or repeatedly looping through text data until some condition is satisfied. This feature is known as control, and is the focus of this section.

4.1 Conditionals Python supports a wide range of operators, such as < and >=, for testing the relationship between values. The full set of these relational operators is shown in 4.1.

Table 2.3: Numerical Comparison Operators

Operator	Relationship
<	less than
<=	less than or equal to
==	equal to (note this is two "=" signs, not one)
!=	not equal to
>	greater than
>=	greater than or equal to

We can use these to select different words from a sentence of news text. Here are some examples — only the operator is changed from one line to the next. They all use `sent7`, the first sentence from text7 (Wall Street Journal). As before, if you get an error saying that `sent7` is undefined, you need to first type: `from nltk.book import *`

```
from nltk.book import *
```

```
*** Introductory Examples for the NLTK Book ***
Loading text1, ..., text9 and sent1, ..., sent9
Type the name of the text or sentence to view it.
Type: 'texts()' or 'sents()' to list the materials.
text1: Moby Dick by Herman Melville 1851
text2: Sense and Sensibility by Jane Austen 1811
text3: The Book of Genesis
text4: Inaugural Address Corpus
text5: Chat Corpus
text6: Monty Python and the Holy Grail
text7: Wall Street Journal
text8: Personals Corpus
text9: The Man Who Was Thursday by G . K . Chesterton 1908
```

```
sent7
```

```
['Pierre',
 'Vinken',
 ',',
 '61',
 'years',
 'old',
 ',',
 'will',
 'join',
 'the',
 'board',
 'as',
 'a',
```

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```
 'nonexecutive',
 'director',
 'Nov.',
 '29',
 '.']
```

```
[w for w in sent7 if len(w) < 4]
```

```
[',', '61', 'old', ',', 'the', 'as', 'a', '29', '.']
```

```
[w for w in sent7 if len(w) <= 4]
```

```
[',', '61', 'old', ',', 'will', 'join', 'the', 'as', 'a', 'Nov.', '29', '.']
```

```
[w for w in sent7 if len(w) == 4]
```

```
['will', 'join', 'Nov.']
```

```
[w for w in sent7 if len(w) != 4]
```

```
['Pierre',
 'Vinken',
 ',',
 '61',
 'years',
 'old',
 ',',
 'the',
 'board',
 'as',
 'a',
 'nonexecutive',
 'director',
 '29',
 '.']
```

There is a common pattern to all of these examples: `[w for w in text if condition ]`, where condition is a Python "test" that yields either true or false. In the cases shown in the previous code example, the condition is always a numerical comparison.

Instead of writing your own Regex, we can test various properties of words, using the functions for a string object listed below.

Table 2.4: Some Word Comparison Operators

Function	Meaning
s.startswith(t)	test if s starts with t
s.endswith(t)	test if s ends with t
t in s	test if t is a substring of s
s.islower()	test if s contains cased characters and all are lowercase
s.isupper()	test if s contains cased characters and all are uppercase
s.isalpha()	test if s is non-empty and all characters in s are alphabetic
s.isalnum()	test if s is non-empty and all characters in s are alphanumeric
s.isdigit()	test if s is non-empty and all characters in s are digits
s.istitle()	test if s contains cased characters and is titlecased (i.e. all words in s have initial capitals)

Here are some examples of these operators being used to select words from our texts: words ending with `-ableness`; words containing `gnt`; words having an initial capital; and words consisting entirely of digits.

```
sorted(w for w in set(text1) if w.endswith('ableness'))
```

```
['comfortableness',
 'honourableness',
 'immutableness',
 'indispensableness',
 'indomitableness',
 'intolerableness',
 'palpableness',
 'reasonableness',
 'uncomfortableness']
```

```
sorted(term for term in set(text4) if 'gnt' in term)
```

```
['Sovereignty', 'sovereignties', 'sovereignty']
```

```
sorted(item for item in set(text6) if item.istitle())[-5:]
```

```
['Yes', 'You', 'Your', 'Yup', 'Zoot']
```

```
sorted(item for item in set(sent7) if item.isdigit())
```

```
['29', '61']
```

We can also create more complex conditions. If `c` is a condition, then `not c` is also a condition. If we have two conditions `c1` and `c2`, then we can combine them to form a new condition using conjunction and disjunction: `c1 and c2`, `c1 or c2`.

Your Turn

Run the following examples and try to explain what is going on in each one. Next, try to make up some conditions of your own.

```
sorted(w for w in set(text7) if '-' in w and 'index' in w)
sorted(wd for wd in set(text3) if wd.istitle() and len(wd) > 10)
```

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```
sorted(w for w in set(sent7) if not w.islower())
sorted(t for t in set(text2) if 'cie' in t or 'cei' in t)
```

2.4.1 Operating on Every Element

We saw some examples of counting items other than words. Let's take a closer look at the notation we used:

Note: These expressions have the form [f(w) for …] or [w.f() for …], where f is a function that operates on a word to compute its length, or to convert it to uppercase. For now, you don't need to understand the difference between the notations f(w) and w.f(). Instead, simply learn this Python idiom which performs the same operation on every element of a list. In the preceding examples, it goes through each word in text1, assigning each one in turn to the variable w and performing the specified operation on the variable.

The notation just described is called a **list comprehension**." This is a Python idiom, a fixed notation that we use habitually without bothering to analyze each time. Mastering such idioms is an important part of becoming a fluent Python programmer.

Let's return to the question of vocabulary size, and apply the same idiom here:

```
len(text1)
```

```
260819
```

```
len(set(text1))
```

```
len(set(word.lower() for word in text1))
```

```
17231
```

Now that we are not double-counting words like This and this, which differ only in capitalization, we've wiped 2,000 off the vocabulary count! We can go a step further and eliminate numbers and punctuation from the vocabulary count by filtering out any non-alphabetic items:

```
len(set(word.lower() for word in text1 if word.isalpha()))
```

```
16948
```

This example is slightly complicated: it lowercases all the purely alphabetic items. Perhaps it would have been simpler just to count the lowercase-only items, but this gives the wrong answer (why?).

2.4.2 Nested Code Blocks

Most programming languages permit us to execute a block of code when a conditional expression, or if statement, is satisfied. We already saw examples of conditional tests in code like `[w for w in sent7 if len(w) < 4]`. In the following program, we have created a variable called word containing the string value 'cat'. The if statement checks whether the test `len(word) < 5` is true. It is, so the body of the if statement is invoked and the print statement is executed, displaying a message to the user. Remember to indent the print statement by typing four spaces.

```
word = 'cat'
if len(word) < 5:
    print('word length is less than 5')
else:
    print('word length is greater than or equal to 5')
```

```
word length is less than 5
```

An if statement is known as a control structure because it controls whether the code in the indented block will be run. Another control structure is the `for` loop. Try the following, and remember to include the colon and the four spaces:

```
for word in ['Call', 'me', 'Ishmael', '.']:
   print(word)
```

```
Call
me
Ishmael
.
```

This is called a loop because Python executes the code in circular fashion. It starts by performing the assignment word = 'Call', effectively using the word variable to name the first item of the list. Then, it displays the value of word to the user. Next, it goes back to the for statement, and performs the assignment word = 'me', before displaying this new value to the user, and so on. It continues in this fashion until every item of the list has been processed.

Tip: If we want to create a list by iterating through a list, "list comprehension" is a Pythonic way and preferred than a loop.

2.4.3 Looping with Conditions

Now we can combine the if and for statements. We will loop over every item of the list, and print the item only if it ends with the letter l. We'll pick another name for the variable to demonstrate that Python doesn't try to make sense of variable names.

```
sent1 = ['Call', 'me', 'Ishmael', '.']
for xyzzy in sent1:
    if xyzzy.endswith('l'):
        print(xyzzy)
```

```
Call
Ishmael
```

You will notice that if and for statements have a colon at the end of the line, before the indentation begins. In fact, all Python control structures end with a colon. The colon indicates that the current statement relates to the indented block that follows.

We can also specify an action to be taken if the condition of the if statement is not met. Here we see the elif (else if) statement, and the else statement. Notice that these also have colons before the indented code.

```
for token in sent1:
    if token.islower():
        print(token, 'is a lowercase word')
    elif token.istitle():
```

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```
        print(token, 'is a titlecase word')
    else:
        print(token, 'is punctuation')
```

```
Call is a titlecase word
me is a lowercase word
Ishmael is a titlecase word
. is punctuation
```

As you can see, even with this small amount of Python knowledge, you can start to build multiline Python programs. It's important to develop such programs in pieces, testing that each piece does what you expect before combining them into a program. This is why the Python interactive interpreter is so invaluable, and why you should get comfortable using it.

Finally, let's combine the idioms we've been exploring. First, we create a list of cie and cei words, then we loop over each item and print it. Notice the extra information given in the print statement: end=' '. This tells Python to print a space (not the default newline) after each word.

```
tricky = sorted(w for w in set(text2) if 'cie' in w or 'cei' in w)
for word in tricky:
    print(word, end=' ')
```

```
ancient ceiling conceit conceited conceive conscience conscientious conscientiously␣
↪deceitful deceive deceived deceiving deficiencies deficiency deficient delicacies␣
↪excellencies fancied insufficiency insufficient legacies perceive perceived␣
↪perceiving prescience prophecies receipt receive received receiving society species␣
↪sufficient sufficiently undeceive undeceiving
```

2.5 Exercises

1. Try using the Python interpreter as a calculator, and typing expressions like `12 / (4 + 1)`.
2. Given an alphabet of 26 letters, there are 26 to the power 10, or `26 ** 10`, ten-letter strings we can form. That works out to 141167095653376. How many hundred-letter strings are possible?
3. The Python multiplication operation can be applied to lists. What happens when you type `['Monty', 'Python'] * 20`, or `3 * sent1`?
4. How many words are there in `text2`? How many distinct words are there?
5. Compare the lexical diversity scores for humor and romance fiction in 1.1. Which genre is more lexically diverse?
6. Produce a dispersion plot of the four main protagonists in `Sense and Sensibility`: `Elinor`, `Marianne`, `Edward`, and `Willoughby`. What can you observe about the different roles played by the males and females in this novel? Can you identify the couples?
7. Find the collocations in text5.
8. Consider the following Python expression: `len(set(text4))`. State the purpose of this expression. Describe the two steps involved in performing this computation.
9. Define a string and assign it to a variable, e.g., `my_string = 'My String'` (but put something more interesting in the string).
    - Print the contents of this variable in two ways, first by simply typing the variable name and pressing enter, then by using the print statement.

- Try adding the string to itself using `my_string + my_string`, or multiplying it by a number, e.g.,`my_string * 3`.
- Notice that the strings are joined together without any spaces. How could you fix this?

10. Define a variable `my_sent` to be a list of words, using the syntax `my_sent = ["My", "sent"]` (but with your own words, or a favorite saying).
    - Use `' '.join(my_sent)` to convert this into a string.
    - Use split() to split the string back into the list form you had to start with.
11. Define several variables containing lists of words, e.g., `phrase1`, `phrase2`, and so on. Join them together in various combinations (using the plus operator) to form whole sentences. What is the relationship between `len(phrase1 + phrase2)` and `len(phrase1) + len(phrase2)`?
12. Consider the following two expressions, which have the same value. Which one will typically be more relevant in NLP? Why?

```
"Monty Python"[6:12]
["Monty", "Python"][1]
```

13. We have seen how to represent a sentence as a list of words, where each word is a sequence of characters. What does `sent1[2][2]` do? Why? Experiment with other index values.
14. The first sentence of `text3` is provided to you in the variable sent3. The index of `the` in `sent3` is 1, because `sent3[1]` gives us 'the'. What are the indexes of the two other occurrences of this word in `sent3`?
15. Find all words in the `Chat Corpus` (`text5`) starting with the letter `b`. Show them in alphabetical order.
16. Type the expression `list(range(10))` at the interpreter prompt. Now try `list(range(10, 20))`, `list(range(10, 20, 2))`, and `list(range(20, 10, -2))`. We will see a variety of uses for this built-in function in later part of the unit.
17. Use `text9.index()` to find the index of the word `sunset`. You'll need to insert this word as an argument between the parentheses. By a process of trial and error, find the slice for the complete sentence that contains this word.
    - Using list addition, and the set and sorted operations, compute the vocabulary of the sentences `sent1 ... sent8`.
18. What is the difference between the following two lines? Which one will give a larger value? Will this be the case for other texts?

```
sorted(set(w.lower() for w in text1))
sorted(w.lower() for w in set(text1))
```

19. What is the difference between the following two tests: `w.isupper()` and `not w.islower()`?
20. Write the slice expression that extracts the last two words of `text2`.
21. Find all the four-letter words in `the Chat Corpus` (`text5`). With the help of a frequency distribution (FreqDist), show these words in decreasing order of frequency.
22. Review the discussion of looping with conditions. Use a combination of `for` and `if` statements to loop over the words of the movie script for `Monty Python and the Holy Grail` (`text6`) and print all the uppercase words, one per line.
23. Write expressions for finding all words in `text6` that meet the conditions listed below. The result should be in the form of a list of words: `['word1', 'word2', ...]`.
    - Ending in ise
    - Containing the letter z

- Containing the sequence of letters pt
- Having all lowercase letters except for an initial capital (i.e., titlecase)

24. Define sent to be the list of words ['she', 'sells', 'sea', 'shells', 'by', 'the', 'sea', 'shore']. Now write code to perform the following tasks:
    - Print all words beginning with sh
    - Print all words longer than four characters
25. What does the following Python code do? `sum(len(w) for w in text1)` Can you use it to work out the average word length of a text?
26. Define a function called `vocab_size(text)` that has a single parameter for the text, and which returns the vocabulary size of the text.
27. Define a function percent(word, text) that calculates how often a given word occurs in a text, and expresses the result as a percentage.
28. We have been using sets to store vocabularies. Try the following Python expression: `set(sent3) < set(text1)`. Experiment with this using different arguments to `set()`. What does it do? Can you think of a practical application for this?

CHAPTER

THREE

LAB03: SPACY NLP PIPELINES

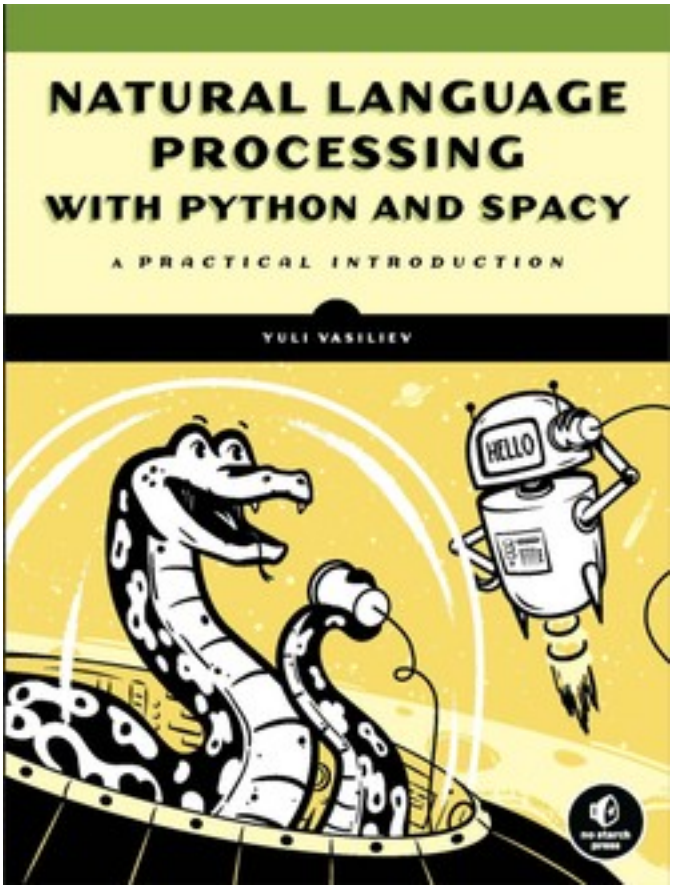
spaCy makes use of two core types of objects to support various NLP tasks.

A **container** object in spaCy groups multiple elements into a single unit. It can be a collection of objects, like tokens or sentences, or a set of annotations related to a single object.

Pipeline components objects that process the text input to create containers and fill them with relevant data, such as a part-of-speech tagger, a dependency parser and an entity recogniser.

In this lab, we will look at these two types of objects in spaCy to get a more in-depth understanding of how spaCy NLP code works. The we will test out our information extraction skills by deploying a simple rule-based chatbot.

Reference: (The book code works with spaCy v2.2, our lab code is compiled on spaCy v3.0.5)



3.1 Container Objects in spaCy

Container objects in spaCy mimic the structure of natural language texts: a text is composed of sentences, and each sentence contains tokens. Token, Span, and Doc, the most widely used container objects in spaCy from a user's standpoint, represent a token, a phrase or sentence, and a text, respectively. A container can contain other containers - for example, a Doc contains Tokens. In this section, we'll explore working with these container objects.

3.1.1 Doc

The `Doc()` constructor, requires two parameters:

- a vocab object, which is a storage container that provides vocabulary data, such as lexical types (adjective, verb, noun …);
- a list of tokens to add to the Doc object being created.

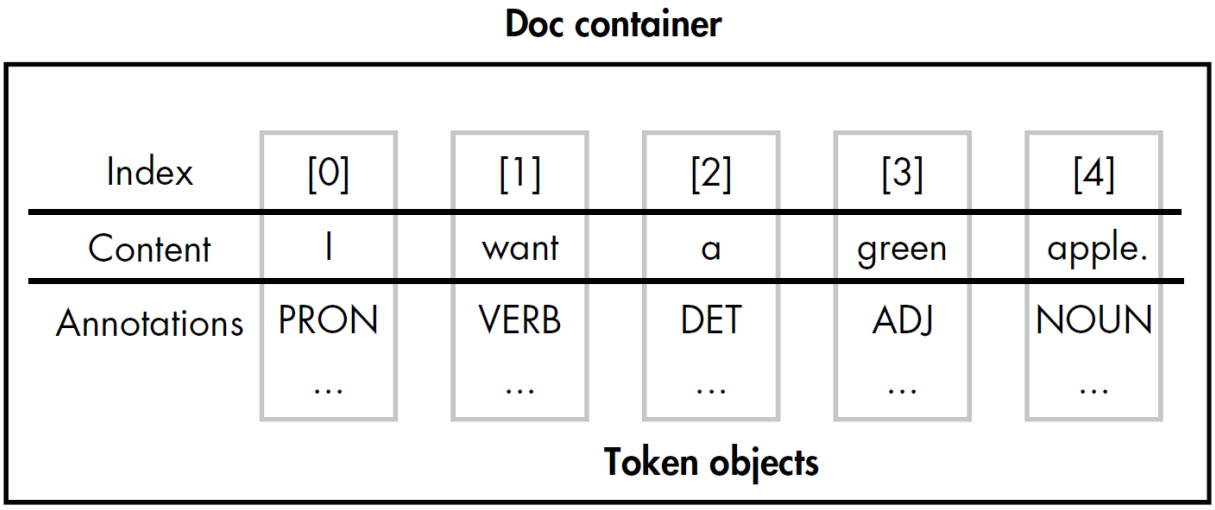
```
from spacy.tokens.doc import Doc
from spacy.vocab import Vocab

"""
create a spacy.tokens.doc.Doc object
using its constructor
"""
doc = Doc(Vocab(), words = [u'Hello', u'World!'])
print(doc)
print(type(doc))
```

```
Hello World!
<class 'spacy.tokens.doc.Doc'>
```

3.1.2 Token

spaCy's Token object is a container for a set of annotations related to a single token, such as that token's part of speech.

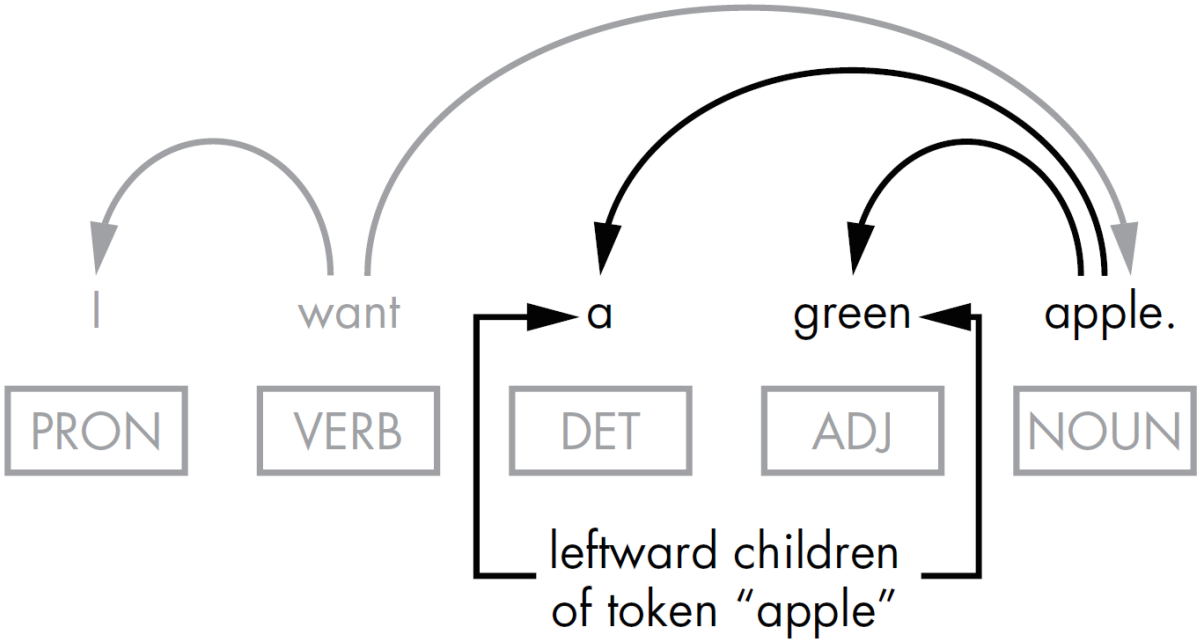
A Doc object contains a collection of the Token objects generated as a result of the tokenization performed on a submitted text. These tokens have indices, allowing you to access them based on their positions in the text.




```
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp(u'I want a green apple.')
# token_text1 and token_text2 produce the same results
token_text1 = [token.text for token in doc]
token_text2 = [doc[i].text for i in range(len(doc))]
print(token_text1)
print(token_text2)
```

```
['I', 'want', 'a', 'green', 'apple', '.']
['I', 'want', 'a', 'green', 'apple', '.']
```

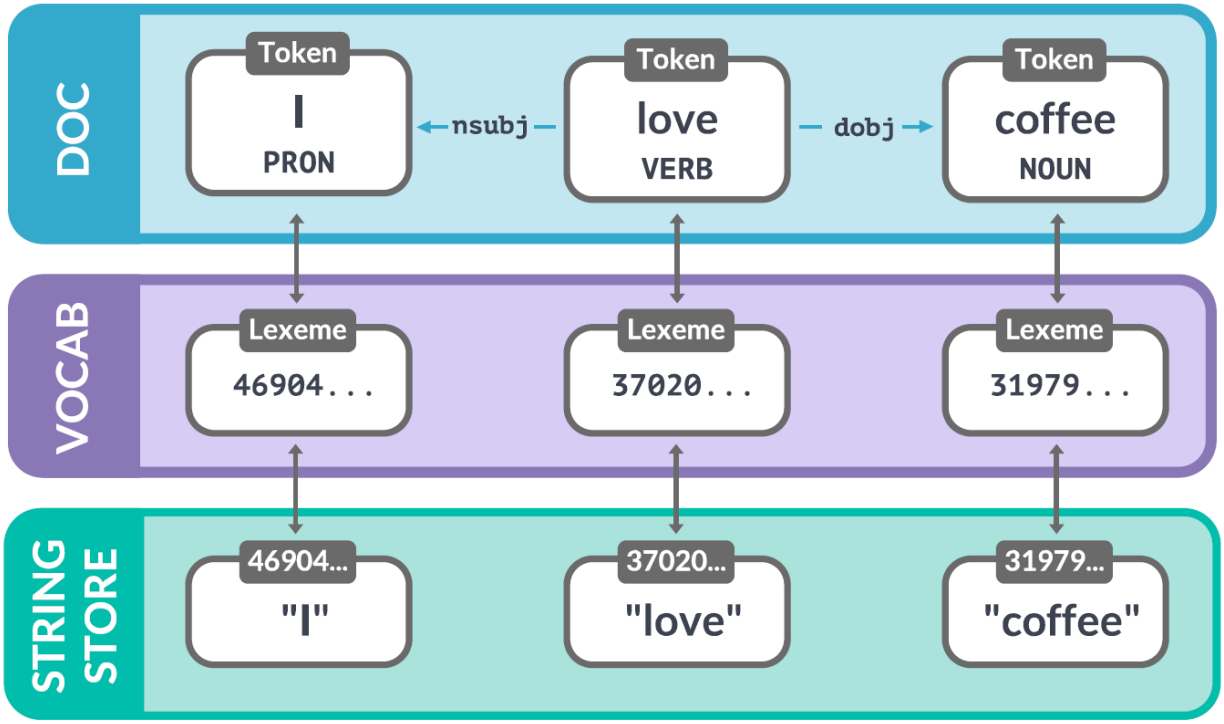
3.1.3 `Token.lefts` `Token.rights` and `Token.children`




```
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp(u'I want a green apple.')
print([t for t in doc[4].lefts])
print([t for t in doc[4].children])
print([t for t in doc[1].rights])
```

```
[a, green]
[a, green]
[apple, .]
```

3.1.4 Vocab



- Whenever possible, spaCy tries to store data in a vocabulary, the Vocab storage class, that will be shared by multiple documents;
- To save memory, spaCy also encodes all strings to hash values. For example, "coffee" has the hash 3197928453018144401.
- Entity labels like "ORG" and part-of-speech tags like "VERB" are also encoded.

spaCy 101

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp('I love coffee!')
for token in doc:
    lexeme = doc.vocab[token.text]
    print(lexeme.text, lexeme.orth, lexeme.shape_,
          lexeme.prefix_, lexeme.suffix_, lexeme.is_alpha,
          lexeme.is_digit, lexeme.is_title, lexeme.lang_)

print(doc.vocab.strings["coffee"]) # 3197928453018144401
print(doc.vocab.strings[3197928453018144401]) # 'coffee'
```

```
I 4690420944186131903 X I I True False True en
love 3702023516439754181 xxxx l ove True False False en
coffee 3197928453018144401 xxxx c fee True False False en
! 17494803046312582752 ! ! ! False False False en
3197928453018144401
coffee
```

3.1.5 Span

Span can be obtained as simple as doc[start:end] where start and end are the index of starting token and the ending token, respectively. The two indices can be

- manually specified; or
- computed through pattern matching

```
import spacy
from spacy.matcher import Matcher
from spacy.tokens import Doc, Span, Token
nlp = spacy.load("en_core_web_sm")
matcher = Matcher(nlp.vocab)
# A dependency label pattern that matches a word sequence
pattern = [{"DEP": "nsubj"},{"DEP": "aux"},{"DEP": "ROOT"}]
matcher.add("NsubjAuxRoot", [pattern])
doc = nlp(u"We can overtake them.")
# 1. Return (match_id, start, end) tuples
matches = matcher(doc)
for match_id, start, end in matches:
    span = doc[start:end]
    print("Span: ", span.text)
    print("The positions in the doc are: ", start, "-", end)
# 2. Return Span objects directly
matches = matcher(doc, as_spans=True)
for span in matches:
    print(span.text, span.label_)
```

```
Span:  We can overtake
The positions in the doc are:  0 - 3
We can overtake NsubjAuxRoot
```

3.1.6 Doc.noun_chunks and Retokenising

A **noun chunk** is a phrase that has a noun as its head.

```
import spacy
nlp = spacy.load('en_core_web_sm')

doc = nlp(u'The Golden Gate Bridge is an iconic landmark in San Francisco.')

# Retokenize to treat each noun_chunk as a single token
with doc.retokenize() as retokenizer:
  for chunk in doc.noun_chunks:
    print(chunk.text + ' ' + str(type(chunk)))
    retokenizer.merge(chunk)
    #doc.retokenize().merge(chunk)

for token in doc:
  print(token)
```

```
The Golden Gate Bridge <class 'spacy.tokens.span.Span'>
an iconic landmark <class 'spacy.tokens.span.Span'>
San Francisco <class 'spacy.tokens.span.Span'>
The Golden Gate Bridge
```

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```
is
an iconic landmark
in
San Francisco
.
```

3.1.7 Doc.sents

the Doc object's doc.sents property is an iterator over the sentences in a Doc object. For this reason, you can't use this property to refer to sentences by index, but you can iterate over them in a loop or create a list of Span objects where each span represents a sentence.

- Doc object's `doc.sents` property is an `generator` object, i.e. an iterator over the sentences in a Doc object. You can use for each in loop, but not subset indexing.
- Each member of the generator object is a Span of type spacy.tokens.span.Span.

Tip

`spans = list(doc.sents)` will return a list of span objects that each represent a sentence.

```python
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp(u'A storm hit the beach. It started to rain.')
for sent in doc.sents:
  print(type(sent))
  # Sentence level index
  [sent[i] for i in range(len(sent))]
# Doc level index
[doc[i] for i in range(len(doc))]
```

```
<class 'spacy.tokens.span.Span'>
<class 'spacy.tokens.span.Span'>
```

```
[A, storm, hit, the, beach, ., It, started, to, rain, .]
```

3.2 NLP Pipelines

3.2.1 Traditional NLP Pipeline in NLTK

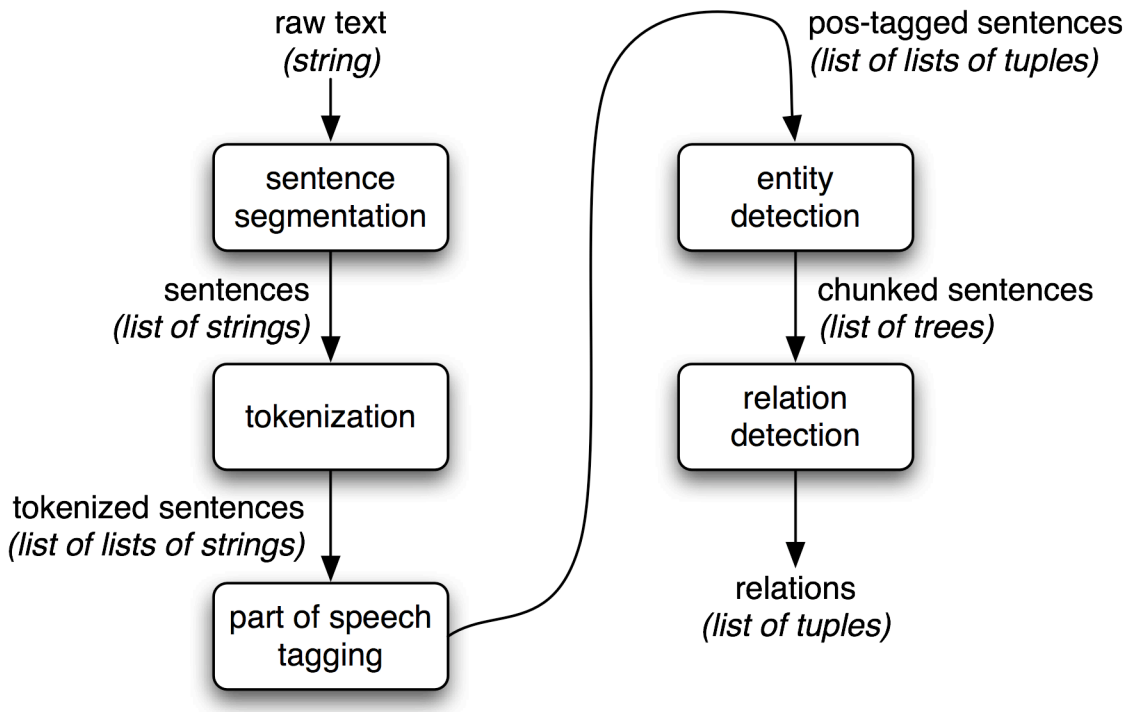

Image credit of Information Extraction in NLTK

```
import nltk
nltk.download('punkt') # Sentence Tokenize
nltk.download('averaged_perceptron_tagger') # POS Tagging
nltk.download('maxent_ne_chunker') # Named Entity Chunking
nltk.download('words') # Word Tokenize

# texts is a collection of documents.
# Here is a single document with two sentences.
texts = [u"A storm hit the beach in Perth. It started to rain."]
for text in texts:
    sentences = nltk.sent_tokenize(text)
    for sentence in sentences:
      words = nltk.word_tokenize(sentence)
      tagged_words = nltk.pos_tag(words)
      ne_tagged_words = nltk.ne_chunk(tagged_words)
      print(ne_tagged_words)
```

```
(S A/DT storm/NN hit/VBD the/DT beach/NN in/IN (GPE Perth/NNP) ./.)
(S It/PRP started/VBD to/TO rain/VB ./.)
```

```
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
```

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```
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package maxent_ne_chunker to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package maxent_ne_chunker is already up-to-date!
[nltk_data] Downloading package words to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package words is already up-to-date!
```

3.2.2 Visualising NER in spaCy

We can use the `Doc.user_data` *attribute* to set a title for the visualisation.

```
from spacy import displacy
doc.user_data['title'] = "An example of an entity visualization"
displacy.render(doc, style='ent')
```

```
<IPython.core.display.HTML object>
```

3.2.3 Write the visualisation to a file

We can inform the render to not display the visualisation in the Jupyter Notebook instead write into a file by calling the render with two extra argument:

```
jupyter=False, page=True
```

```
from pathlib import Path
# the page=True indicates that we want to write to a file
html = displacy.render(doc, style='ent', jupyter=False, page=True)
output_path = Path("C:\\Users\\wei\\CITS4012\\ent_visual.html")
output_path.open("w", encoding="utf-8").write(html)
```

```
758
```

3.2.4 NLP pipeline in spaCy

Recall that spaCy's container objects represent linguistic units, suchas a text (i.e. document), a sentence and an individual token withlinguistic features already extracted for them.

How does spaCy create these containers and fill them withrelevant data?

A spaCy pipeline include, by default, a part-of-speech tagger (`tagger`), a dependency parser (`parser`), a lemmatizer (`lemmatizer`), an entity recognizer (`ner`), an attribute ruler (`attribute_ruler` and a word vectorisation model (`tok2vec`)).

```
import spacy
nlp = spacy.load('en_core_web_sm')
nlp.pipe_names
```

```
['tok2vec', 'tagger', 'parser', 'ner', 'attribute_ruler', 'lemmatizer']
```

spaCy allows you to load a selected set of pipeline components, dis-abling those that aren't necessary.

You can do this either when creating a nlp object or disable it after the nlp object is created.

Disabling when create

```
nlp = spacy.load('en_core_web_sm',disable=['parser'])
```

Disabling after creation

```
nlp.disable_pipes('tagger')
nlp.disable_pipes('parser')
```

3.2.5 Customising a NLP pipe in spaCy

```
import spacy
nlp = spacy.load('en_core_web_sm')

doc = nlp(u'I need a taxi to Cottesloe.')
for ent in doc.ents:
    print(ent.text, ent.label_)
```

```
Cottesloe GPE
```

What if?

If we would like to introduce a new entity type `SUBURB` for `Cottesloe` and other suburb names, how should we informthe NER component about it?

Steps of Customising a spaCy NER pipe

1. Create a training example to show the entity recognizer so it will learn what to apply the SUBURB label to;
2. Add a new label called SUBURB to the list of supported entitytypes;
3. Disable other pipe to ensure that only the entity recogniser will beupdated during training;
4. Start training;
5. Test your new NER pipe;
6. Serialise the pipe to disk;
7. Load the customised NER

```
import spacy
nlp = spacy.load('en_core_web_sm')
```

```
# Specify new label and training data
LABEL = 'SUBURB'
TRAIN_DATA = [('I need a taxi to Cottesloe',
                { 'entities': [(17, 26, 'SUBURB')] }),
              ('I like red oranges', { 'entities': []})]
```

```
# Add new label to the ner pipe
ner = nlp.get_pipe('ner')
ner.add_label(LABEL)
```

```
1
```

```
# Train
optimizer = nlp.create_optimizer()
import random
from spacy.tokens import Doc
from spacy.training import Example
for i in range(25):
  random.shuffle(TRAIN_DATA)
  for text, annotations in TRAIN_DATA:
    doc = Doc(nlp.vocab, words=text.split(" "))
    # We need to create a training example object
    example = Example.from_dict(doc, annotations)
    nlp.update([example], sgd=optimizer)
```

```
# Test
doc = nlp(u'I need a taxi to Crawley')
for ent in doc.ents:
  print(ent.text, ent.label_)
```

```
Crawley SUBURB
```

```
# Serialize the entire model to disk
nlp.to_disk('C:\\Users\\wei\\CITS4012') # Windows Path
```

```
# Load spacy model from disk
import spacy
nlp_updated = spacy.load('C:\\Users\\wei\\CITS4012')
```

```
# Test
doc = nlp_updated(u'I need a taxi to Subiaco')
for ent in doc.ents:
  print(ent.text, ent.label_)
```

```
Subiaco SUBURB
```

Your Turn

- Replace the suburb name with a few others, for example 'Claremont', 'Western Australia' and see what the the entity label is.
- Take a look at the directory and see how the `nlp` model is stored.
- This blog post on How to Train spaCy to Autodetect New Entities (NER) [Complete Guide] has more extensive examples on how to train a ner model with more data.

3.3 Finding Patterns

Imagine you are building a chat bot and we are trying to find utterances in user input that express one of the following:

What's Expressed

ability, possibility, permission, or obligation (as opposed to utterances that describe real actions that have occurred, are occurring, or occur regularly)

Example Sentences

For instance, we want to find "I can do it." but not "I've done it."

Linguistic Pattern

`subject + auxiliary + verb + . . . + direct object + ...`

The ellipses indicate that the direct object isn't necessarily located immediately behind the verb, there might be other words in between.

3.3.1 Check spaCy version

```
!pip show spacy
```

```
Name: spacy
Version: 3.0.5
Summary: Industrial-strength Natural Language Processing (NLP) in Python
Home-page: https://spacy.io
Author: Explosion
Author-email: contact@explosion.ai
License: MIT
Location: c:\programdata\anaconda3\envs\lda\lib\site-packages
Requires: cymem, blis, spacy-legacy, numpy, preshed, srsly, murmurhash, jinja2, thinc,
 ↪ tqdm, wasabi, requests, pydantic, setuptools, typer, catalogue, packaging, pathy
Required-by: en-core-web-sm
```

3.3.2 Hard-coded pattern discovery

To look for the `subject + auxiliary + verb + . . . + direct object + ...` pattern programmably, we need to go through each token's dependency label (*not part of speech label*) to first find the sequence of `nsubj aux ROOT` where `ROOT` indicate the root verb, then for each of children of the root verb (`ROOT`) we check to see if it is a direct object (`dobj`) of the verb.

```
import spacy
nlp = spacy.load('en_core_web_sm')
def dep_pattern(doc):
    for i in range(len(doc)-1):
        if doc[i].dep_ == 'nsubj' and doc[i+1].dep_ == 'aux' and doc[i+2].dep_ ==
↪'ROOT':
            for tok in doc[i+2].children:
                if tok.dep_ == 'dobj':
                    return True

    return False
```

```
# doc = nlp(u'We can overtake them.')
doc = nlp(u'I might send them a card as a reminder.')
```

Use displaycy to visualise the dependency

```
from spacy import displacy
displacy.render(doc, style='dep')
```

```
<IPython.core.display.HTML object>
```

```
options = {'compact': True, 'font': 'Tahoma'}
displacy.render(doc, style='dep', options=options)
```

```
<IPython.core.display.HTML object>
```

```
if dep_pattern(doc):
    print('Found')
else:
    print('Not found')
```

```
Found
```

Code Explanation

The `dep_pattern` function above takes a Doc object as parameter and returns a binary value `True` if the hard-coded pattern `subject + auxiliary + verb + . . . + direct object + ...` is found, otherwise `False`. The function iterates over the Doc object's tokens, searching for a `subject + auxiliary + verb`, where the `verb` is the `root` of the dependency tree. If the pattern is found, then we check whether the verb has a direct object among its syntactic children. Finally, if we find a direct object, the function returns `True`. Otherwise, it returns `False`.

3.3.3 Using spaCy pattern matcher

spaCy has a predefined tool called `Matcher`, that is specially designed to find sequences of tokens based on pattern rules. An implementation of the "subject + auxiliary + verb" pattern with `Matcher` might look like this:

```
import spacy
from spacy.matcher import Matcher
nlp = spacy.load("en_core_web_sm")
matcher = Matcher(nlp.vocab)
pattern = [{"DEP": "nsubj"}, {"DEP": "aux"}, {"DEP": "ROOT"}]
matcher.add("NsubjAuxRoot", [pattern])
doc = nlp("We can overtake them.")
matches = matcher(doc)
for match_id, start, end in matches:
    span = doc[start:end]
    print("Span: ", span.text)
    print("The positions in the doc are: ", start, "-", end)
    print("Match ID ", match_id)
    print(doc.vocab.strings[match_id])
    for tok in doc[end-1].children:
        if tok.dep_ == 'dobj':
            print("The direct object of {} is {}".format(doc[end-1], tok.dep_))
```

```
Span:  We can overtake
The positions in the doc are:  0 - 3
Match ID  10599197345289971701
NsubjAuxRoot
The direct object of overtake is dobj
```

Code Explanation

spaCy `Matcher` class takes a model's vocabulary as input and creates a matcher object named `matcher`. Then we need to define a pattern of interest. The pattern is specified in a dictionary object, and the order of the key value pairs indicate the desired sequence we are trying to find a match for. Once the pattern is found, a list of tuples in the form of `(match_id, start, end)` is returned. The `match_id` is the hash value of the string ID "NsubjAuxRoot". To get the string value, you can look up the ID in the StringStore.

3.3.4 Summary of Rule-based Matching

Steps for using the Matcher class:

1. Create a Matcher instance by passing in a shared Vocab object;
2. Specify the pattern as an list of dependency labels;
3. Add the pattern to the a Matcher object;
4. Input a Doc object to the matcher;
5. Go through each match $\langle match_id, start, end \rangle$.

We have seen a *Dependency Matcher* just now, there are more Rule-based matching support in spaCy:

- Token Matcher: regex, and patterns such as

- Phrase Matcher: PhraseMatcher class
- Entity Ruler
- Combining models with rules

For more information of different types of matchers, see spaCy Documentation on Rule Based Matching.

Reference: Chapter 6 of NATURAL LANGUAGE PROCESSING WITH PYTHON AND SPACY

3.4 Your first chatbot

A typical chatbot app consists of multiple tiers. After you've implemented the logic for processing user input on your machine, you'll need a messenger app (e.g. Skype, Facebook Messenger or Telegram) that allows you to create accounts that your programs operate. Users won't interact with the bot implementation on your machine directly; instead, they'll chat with the bot through the messenger API. Apart from a messenger, your chatbot might require some additional services, such as a database or other storage.

3.4.1 Creating a Telegram Account and Authorizing Your Bot

Note: You'll need a smartphone or tablet that runs either iOS or Android to create a Telegram account. A PC version of Telegram won't work for this operation. However, once you create a Telegram account, you can use it on a PC.

On your smartphone or tablet go to an app store, and install the `Telegram app`. Then you need to enter your `phone number` to access the app.

1. In the Telegram app, perform a search for @BotFather (note: case sensitive) or open the URL https://telegram.me/botfather/. BotFather is a Telegram bot that manages all the other bots in your account.
2. On the BotFather page, click the Start button to see the list of commands that you can use to set up your Telegram bots.
3. To create a new bot, enter the `/newbot` command in the Write a message box. You'll be prompted for a name and a username for your bot. Then you'll be given an authorization token for the new bot. Note down the token in a secure place as people who have access to the token can manipulate your new bot.

3.4.2 Install the `python-telegram-bot` Library

To connect chatbot functionality implemented in Python, you'll need the python-telegram-bot library, which is built on top of the Telegram Bot API. The library provides an easy-to-use interface for bot programmers developing apps for Telegram.

```
pip install python-telegram-bot --upgrade
```

Once you've installed the library, use the following lines of code to perform a quick test to verify that you can access your Telegram bot from Python. You must have an internet connection for this test to work.

```
import telegram
TOKEN = 'YOUR TOKEN'
bot = telegram.Bot(token=TOKEN)
```

```
print(bot.get_me())
```

```
{'first_name': 'Pizza2me', 'is_bot': True, 'supports_inline_queries': False, 'id':␣
↪1947674606, 'username': 'Pizza2meBot', 'can_join_groups': True, 'can_read_all_group_
↪messages': False}
```

3.4.3 A copy-cat chatbot

A chatbot simply echoing the input message.

```
from telegram.ext import Updater, MessageHandler, Filters
#function that implements the message handler
def echo(update, context):
    update.message.reply_text(update.message.text)
#creating an Updater instance
updater = Updater(TOKEN, use_context=True)
#registering a handler to handle input text messages
updater.dispatcher.add_handler(MessageHandler(Filters.text, echo))
#starting polling updates from the messenger
updater.start_polling()
updater.idle()
```

Click the `run` button for the above cell, it will start the bot. You can then go to your smartphone or tablet's Telegram app to chat with your bot.

Note: You can use the Interrupt button in your notebook to stop the bot after testing.

3.4.4 Chatbot that uses spaCy code

```
import spacy
from telegram.ext import Updater, MessageHandler, Filters
#the callback function that uses spaCy
def utterance(update, context):
    msg = update.message.text
    nlp = spacy.load('en_core_web_sm')
    doc = nlp(msg)
    for token in doc:
        if token.dep_ == 'dobj':
            update.message.reply_text('We are processing your request...')
            return
    update.message.reply_text('Please rephrase your request. Be as specific as␣
↪possible!')

#the code responsible for interactions with Telegram
updater = Updater(TOKEN, use_context=True)
updater.dispatcher.add_handler(MessageHandler(Filters.text, utterance))
updater.start_polling()
updater.idle()
```

Your Turn

Integrte some more patterns to handle more varieties of requests. For example, extracting the type of pizza by finding its left children, if you are handling pizza ordering.

Reference: Chapter 11 of NATURAL LANGUAGE PROCESSING WITH PYTHON AND SPACY

3.5 Exercise

Extend a `to` + `GPE` NER pattern

Let's consider a travel assistant here. Write a function that uses the entity type `GPE` to find the desired destination of a user. The code below is capable of very simple parsing, but not able to handle sentences like `I am going to a conference in Berlin.`

- Modify the code to make it work for more cases.
- Incoporate that into your Telgram booking bot.

```
import spacy
nlp = spacy.load('en_core_web_sm')
```

```
# Here's the function that figures out the destination
def det_destination(doc):
    for i, token in enumerate(doc):
        if token.ent_type != 0 and token.ent_type_ == 'GPE':
            while True:
                token = token.head
                if token.text == 'to':
                    return doc[i].text
                if token.head == token:
                    return 'Failed to determine'
    return 'Failed to determine'
```

```
# Testing the det_destination function
doc = nlp(u'I am going to Berlin.')
# doc = nlp(u'I am going to the conference in Berlin.')
for token in doc:
    print(token.text, token.ent_type_, token.head)
```

```
I  going
am  going
going  going
to  going
Berlin GPE to
.  going
```

```
dest = det_destination(doc)
print('It seems the user wants a ticket to ' + dest)
```

```
It seems the user wants a ticket to Berlin
```

CHAPTER

FOUR

LAB04: COUNT-BASED MODELS

In this lab, we will look at how to process natural language text to build two different types of count-based matrices, one for word characterisation (i.e. word co-occurence matrix), one for document characterisation (i.e. document term matrix).

While putting the theory into practice, we will also introduce two more packages that are excelled at count-based methods, namely `scikit learn` and `gensim`. After introducing the basics using small toy corpus, we demonstrate how `tf-idf` can be used for document classification in `scikit learn`.

Work on your project after you finish this lab.

4.1 TF-IDF in scikit-learn and Gensim

In a large text corpus, some words will be very present (e.g. "the", "a", "is" in English) hence carrying very little meaningful information about the actual contents of the document. If we were to feed the raw count data directly to a classifier those very frequent terms would shadow the frequencies of rarer yet more interesting terms. In other words, frequent words may not provide descriminative or similarity information for

- scoring/ranking documents with regard to a query document, in the context of information retrieval used in search engines;
- separating documents into different categories, in the context of documen classification (sentiment detection, spam detection).

In this lab, we will focus on document classification. In order to re-weight the count features into floating point values suitable for usage by a classifier it is very common to use the tf–idf transform.

TF-IDF was originally a term weighting scheme developed for information retrieval (as a ranking function for search engines results) that has also found good use in document classification and clustering.

Term Frequency

Denoted $tf_{d,t}$, which means term-frequency of term t in document d, can be referred to as the *raw count*, i.e. the number of times term term t occurs in document d; or the raw count normalised (divided) by the total number of words in document d.

Document Frequency

Denoted df_t, which means the number of times that term t occurs across the entire collection of documents (i.e. corpus). It is a value specific to each term but not specific to each document.

Inverse Document Frequency

Denoted idf_t, which is defined as

$$idf_t = \log_2 \frac{N}{df_t}$$

where N is total number of documents in the collection. It is a value specific to each term but not specific to each document.

TF-IDF is the term frequency discounted by the document freqency. In other words, a frequent term in a document needs to be infrequent across documents to acquire a high tf-idf value. There are several variations of TF-IDF implementations. Gensim's implementation is more closer to the original definition. scikit-learn's implementation normalises the resulting vector to ensure the values are between 0 and 1, which is better for classification tasks.

```
text = ["It was the best of times",
"it was the worst of times",
"it was the age of wisdom",
"it was the age of foolishness"]
```

4.1.1 TF-IDF in Gensim

Gensim is yet another popular libray specialising in statistical analysis of natural language text, in particular useful for Topic Modelling, which we will cover later in the unit.

Note: You will need to activate the cits4012_py37 environment to use gensim.

```
import gensim
import gensim.downloader as api
from gensim.models import TfidfModel
from gensim.corpora import Dictionary
```

Step 1: Preprocessing

Gensim has a different routine in preparing text. It uses `gensim.utils.simple_preprocess()` to tokenise while removing punctuation and turn the tokens into lower cases.

```
def sent_to_words(sentences):
    for sentence in sentences:
        # deacc=True removes punctuations
        yield(gensim.utils.simple_preprocess(str(sentence), deacc=True))
```

Step 2: Create a corpus with counts

Gensim has a built-in class `gensim.corpora.Dictionary` that has a function `doc2bow` that implements the bag of words idea, which processes the document collection, assigning an id to each unique token, while counting the term frequency of each token in each document. The following code returns each document as a list of tuples, in the form of `(term_id, count)`

```
doc_tokenized = list(sent_to_words(text))
dictionary = Dictionary()
BoW_corpus = [dictionary.doc2bow(doc, allow_update=True) for doc in doc_tokenized]
BoW_corpus
```

```
[[(0, 1), (1, 1), (2, 1), (3, 1), (4, 1), (5, 1)],
 [(1, 1), (2, 1), (3, 1), (4, 1), (5, 1), (6, 1)],
 [(1, 1), (2, 1), (3, 1), (5, 1), (7, 1), (8, 1)],
 [(1, 1), (2, 1), (3, 1), (5, 1), (7, 1), (9, 1)]]
```

We can examine the Bag of Words corpus obtained. You can think of the dictionary object is a vocabulary of the collection, mapping a term id to its lexical form (i.e. the word form) of the term.

```
for doc in BoW_corpus:
   print([[dictionary[id], freq] for id, freq in doc])
```

```
[['best', 1], ['it', 1], ['of', 1], ['the', 1], ['times', 1], ['was', 1]]
[['it', 1], ['of', 1], ['the', 1], ['times', 1], ['was', 1], ['worst', 1]]
[['it', 1], ['of', 1], ['the', 1], ['was', 1], ['age', 1], ['wisdom', 1]]
[['it', 1], ['of', 1], ['the', 1], ['was', 1], ['age', 1], ['foolishness', 1]]
```

Step 3: Calculating the tfidf values

A `gensim.models.TfidfModel` object can be constructed using the processed BoW corpus. The `smartirs` parameter stands for SMART information retrieval system, where SMART is an acronym for "System for the Mechanical Analysis and Retrieval of Text". If interested, you can read more about SMART on Wikipedia, which contains a rather comprehensive list of TF-IDF variants. `smartirs = ntc` means the model will use `n` raw term freqency, `t` zero-corrected idf, and `c` cosine for document vector nomalisation. For a list of other letter codes for each of the three tf-idf components, see the tabs or refer to the original documentation. You do not need to memorise all these variants, but just be aware of the many alternatives in calculating such a seemingly simple value. You can even define your own way of calculating tf and idf to feed into the model constructor.

Term frequency weighing

- b - binary,
- t or n - raw,
- a - augmented,
- l - logarithm,
- d - double logarithm,
- L - log average.

Document frequency weighting

- x or n - none,
- f - idf,
- t - zero-corrected idf,
- p - probabilistic idf.

Document normalization

- x or n - none,
- c - cosine,
- u - pivoted unique,
- b - pivoted character length.

Example Code

```
import numpy as np
tfidf = TfidfModel(BoW_corpus, smartirs='ntc')

# Get the tfidf vector representation of the second sentence
tfidf[BoW_corpus[1]]
```

```
[(1, 0.11713529839512132),
 (2, 0.11713529839512132),
 (3, 0.11713529839512132),
 (4, 0.48099076877929253),
 (5, 0.11713529839512132),
 (6, 0.8448462391634637)]
```

```
# Get the tfidf transformed corpus,
# then the vector of the second sentence.
tfidf[BoW_corpus][1]
```

```
[(1, 0.11713529839512132),
 (2, 0.11713529839512132),
 (3, 0.11713529839512132),
 (4, 0.48099076877929253),
 (5, 0.11713529839512132),
 (6, 0.8448462391634637)]
```

```
# Now a friendlier print out
for doc in tfidf[BoW_corpus]:
   print([[dictionary[id], np.around(freq,decimals=2)] for id, freq in doc])
```

```
[['best', 0.84], ['it', 0.12], ['of', 0.12], ['the', 0.12], ['times', 0.48], ['was',␣
↪0.12]]
[['it', 0.12], ['of', 0.12], ['the', 0.12], ['times', 0.48], ['was', 0.12], ['worst',␣
↪0.84]]
```

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```
[['it', 0.12], ['of', 0.12], ['the', 0.12], ['was', 0.12], ['age', 0.48], ['wisdom',␣
↪0.84]]
[['it', 0.12], ['of', 0.12], ['the', 0.12], ['was', 0.12], ['age', 0.48], [
↪'foolishness', 0.84]]
```

How do we get the document-term matrix

```
vocab = [dictionary[i] for i in range(len(dictionary))]
vocab
```

```
['best',
 'it',
 'of',
 'the',
 'times',
 'was',
 'worst',
 'age',
 'wisdom',
 'foolishness']
```

```
index = list(range(len(BoW_corpus)))
index
```

```
[0, 1, 2, 3]
```

```
import pandas as pd
df = pd.DataFrame(data=np.zeros((len(BoW_corpus), len(vocab)), dtype=np.float16),
                  index=index,
                  columns=vocab)
```

```
for idx in index:
    for id, freq in tfidf[BoW_corpus[idx]]:
        df[dictionary[id]][idx] = freq
```

```
df
```

```
       best        it        of       the     times       was     worst  \
0  0.844727  0.117126  0.117126  0.117126  0.480957  0.117126  0.844727
1  5.000000  0.117126  0.117126  0.117126  0.480957  0.117126  0.844727
2  0.000000  0.117126  0.117126  0.117126  0.000000  0.117126  0.000000
3  0.000000  0.117126  0.117126  0.117126  0.000000  0.117126  0.000000

        age    wisdom  foolishness
0  0.480957  0.844727     0.844727
1  0.000000  0.000000     0.000000
2  0.480957  0.844727     0.000000
3  0.480957  0.000000     0.844727
```

4.1.2 TF-IDF in scikit-learn

In scikit-learn, the TF-IDF is caculated using the `TfidfTransformer`. Its default settings, `TfidfTransformer(norm='l2', use_idf=True, smooth_idf=True, sublinear_tf=False)` the term frequency, the number of times a term occurs in a given document, is multiplied with idf component, which is computed as

TF-IDF with `smooth_idf=True`

$$idf_t = \log_2 \frac{1+n}{1+df_t} + 1$$

The default parameter `smooth_idf=True` adds "1" to the numerator and denominator as if an extra document was seen containing every term in the collection exactly once, which prevents zero divisions.

TF-IDF with `smooth_idf=False`

$$idf_t = \log_2 \frac{n}{df_t} + 1$$

With `smooth_idf=False`, the "1" count is added to the idf instead of the idf's denominator:

Then the resulting tf-idf vectors are then normalized by the Euclidean norm

$$v_{norm} = \frac{v}{||v||} = \frac{v}{\sqrt{v_1^2 + ... + v_n^2}}$$

See scikit-learn Documenation on Feature Extraction (Section 6.2.3.4) for more details.

`TfidfTransformer` vs `TfidfVectorizer`

With `TfidfTransformer` you will systematically compute word counts using `CountVectorizer` and then compute the Inverse Document Frequency (IDF) values and only then compute the Tf-idf scores.

With `TfidfVectorizer` on the contrary, you will do all three steps at once. Under the hood, it computes the word counts, IDF values, and Tf-idf scores all using the same dataset.

Use `TfidfTransformer` if you need to obtain term frequency (i.e. term counts). We will illustrate the TF-IDF calculation using `TfidfVectorizer` in this notebook and `TfidfTransformer` in the classification notebook after this.

Example Code

```
from sklearn.feature_extraction.text import TfidfVectorizer
```

```
tfidf_vectorizer = TfidfVectorizer()
tfidf = tfidf_vectorizer.fit_transform(text).toarray()
tfidf
```

```
array([[0.        , 0.60735961, 0.        , 0.31694544, 0.31694544,
        0.31694544, 0.4788493 , 0.31694544, 0.        , 0.        ],
       [0.        , 0.        , 0.        , 0.31694544, 0.31694544,
        0.31694544, 0.4788493 , 0.31694544, 0.        , 0.60735961],
```

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```
       [0.4788493 , 0.        , 0.        , 0.31694544, 0.31694544,
        0.31694544, 0.        , 0.31694544, 0.60735961, 0.        ],
       [0.4788493 , 0.        , 0.60735961, 0.31694544, 0.31694544,
        0.31694544, 0.        , 0.31694544, 0.        , 0.        ]])
```

```
import numpy as np
# Define labels for the x and y axis
nrows = np.shape(tfidf)[0]
xlabels = tfidf_vectorizer.get_feature_names()
ylabels = ['D' + str(idx) for idx in list(np.arange(nrows))]
```

```
['D0', 'D1', 'D2', 'D3']
```

```
xlabels
```

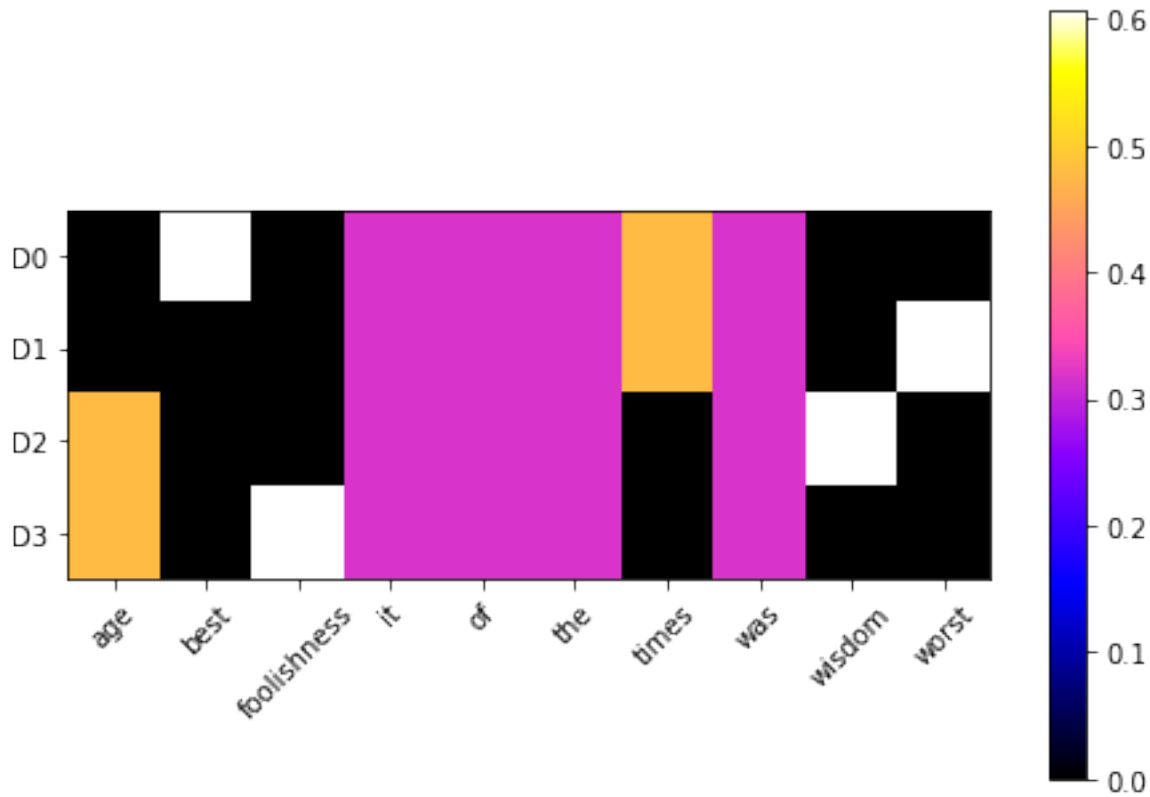
```
['age',
 'best',
 'foolishness',
 'it',
 'of',
 'the',
 'times',
 'was',
 'wisdom',
 'worst']
```

```
ylabels
```

```
['D0', 'D1', 'D2', 'D3']
```

```
import matplotlib.pyplot as plt

plt.figure()
plt.axes([0, 0, 1, 1])
plt.imshow(tfidf, interpolation='nearest',
          cmap=plt.cm.gnuplot2, vmin=0)
plt.xticks(range(len(xlabels)), xlabels, rotation=45)
plt.yticks(range(nrows), ylabels)
plt.colorbar()
plt.tight_layout()
plt.show()
```

```
<ipython-input-10-4c5527a74677>:10: UserWarning: This figure includes Axes that are␣
↪not compatible with tight_layout, so results might be incorrect.
  plt.tight_layout()
```



Note, this is a document-term matrix, with tf-idf values for each cell, not a similarity or distance plot.

Your Turn

You can refer to the code for similarity calculation in Resturant Example (Lecture 3) to work out the cosine similarities between these documents. Note this will require `pytorch`.

4.2 Document Classification

Now that we have a good understanding of TF-IDF term document matrix, we can treat each term as a feature, and each document (row) as an instance or a training sample to train a classifier. The classifier can be any traditional supervised learning models that deals with tabular shaped data, where one column stores the labels of each sample. All other columns are feature variables, in this case, each term/word is a feature. An illustration table is shown below.

ID	best	it	of	the	times	was	worst	age	wis-dom	foolish-ness	class label
0	0.844727	0.117126	0.117126	0.117126	0.480957	0.117126	0.844727	0.480957	0.844727	0.844727	positive
1	5.000000	0.117126	0.117126	0.117126	0.480957	0.117126	0.844727	0.000000	0.000000	0.000000	negative
2	0.000000	0.117126	0.117126	0.117126	0.000000	0.117126	0.000000	0.480957	0.844727	0.000000	positive
3	0.000000	0.117126	0.117126	0.117126	0.000000	0.117126	0.000000	0.480957	0.000000	0.844727	negative

The goal of this guide is to explore some of the main 'scikit-learn' tools on a popular classification task: analyzing a collection of text documents (newsgroups posts) and classify them into one of the twenty different topics.

In this notebook we will see how to:

- load the file contents and the categories
- extract feature vectors suitable for machine learning
- train a linear model to perform categorization
- use a grid search strategy to find a good configuration of both the feature extraction components and the classifier

Original Notebook Credit to scikit-learn tutorial on Working with Text Data

4.2.1 Loading the 20 newsgroups dataset

The dataset is called "Twenty Newsgroups". Here is the official description:

> The 20 Newsgroups data set is a collection of approximately 20,000 newsgroup documents, partitioned (nearly) evenly across 20 different newsgroups. To the best of our knowledge, it was originally collected by Ken Lang, probably for his paper "Newsweeder: Learning to filter netnews," though he does not explicitly mention this collection. The 20 newsgroups collection has become a popular data set for experiments in text applications of machine learning techniques, such as text classification and text clustering.

In the following we will use the built-in dataset loader for 20 newsgroups from scikit-learn.

In order to get faster execution times for this first example we will work on a partial dataset with only 4 categories out of the 20 available in the dataset:

```
categories = ['alt.atheism', 'soc.religion.christian',
               'comp.graphics', 'sci.med']
```

We can now load the list of files matching those categories as follows (this may take a while - 65.1s on a desktop computer - AMD 16 core, 32GB RAM):

```
from sklearn.datasets import fetch_20newsgroups
twenty_train = fetch_20newsgroups(subset='train',
      categories=categories, shuffle=True, random_state=42)
```

The returned dataset is a `scikit-learn` "bunch": a simple holder object with fields that can be both accessed as python `dict` keys or `object` attributes for convenience, for instance the `target_names` holds the list of the requested category names::

```
twenty_train.target_names
```

```
['alt.atheism', 'comp.graphics', 'sci.med', 'soc.religion.christian']
```

The files themselves are loaded in memory in the `data` attribute. For reference the filenames are also available:

```
len(twenty_train.data)
```

```
2257
```

```
twenty_train.filenames[0]
```

```
'C:\\Users\\wei\\scikit_learn_data\\20news_home\\20news-bydate-train\\comp.graphics\\
↪38440'
```

Let's print the first three lines of the first loaded file:

```
print("\n".join(twenty_train.data[0].split("\n")[:3]))
```

```
From: sd345@city.ac.uk (Michael Collier)
Subject: Converting images to HP LaserJet III?
Nntp-Posting-Host: hampton
```

Below is how to access the class label (i.e. target column) of the first document.

```
print(twenty_train.target_names[twenty_train.target[0]])
```

```
comp.graphics
```

Supervised learning algorithms will require a category label for each document in the training set. In this case the category is the name of the newsgroup which also happens to be the name of the folder holding the individual documents.

For speed and space efficiency reasons `scikit-learn` loads the target attribute as an array of integers that corresponds to the index of the category name in the `target_names` list. The category integer id of each sample is stored in the `target` attribute:

```
twenty_train.target[:10]
```

```
array([1, 1, 3, 3, 3, 3, 3, 2, 2, 2], dtype=int64)
```

It is possible to get back the category names as follows:

```
for t in twenty_train.target[:10]:
    print(twenty_train.target_names[t])
```

```
comp.graphics
comp.graphics
soc.religion.christian
soc.religion.christian
soc.religion.christian
soc.religion.christian
soc.religion.christian
sci.med
sci.med
sci.med
```

You might have noticed that the samples were shuffled randomly when we called `fetch_20newsgroups(..., shuffle=True, random_state=42)`: this is useful if you wish to select only a subset of samples to quickly train a model and get a first idea of the results before re-training on the complete dataset later.

4.2.2 Extracting features from text files

In order to perform machine learning on text documents, we first need to turn the text content into numerical feature vectors.

Bags of words

The most intuitive way to do so is to use a bags of words representation:

1. Assign a fixed integer id to each word occurring in any document of the training set (for instance by building a dictionary from words to integer indices).
2. For each document `#i`, count the number of occurrences of each word `w` and store it in `X[i, j]` as the value of feature `#j` where `j` is the index of word `w` in the dictionary.

The bags of words representation implies that `n_features` is the number of distinct words in the corpus: this number is typically larger than 100,000.

If `n_samples == 10000`, storing `X` as a NumPy array of type float32 would require 10000 x 100000 x 4 bytes = **4GB in RAM** which is barely manageable on today's computers.

Fortunately, **most values in X will be zeros** since for a given document less than a few thousand distinct words will be used. For this reason we say that bags of words are typically **high-dimensional sparse datasets**. We can save a lot of memory by only storing the non-zero parts of the feature vectors in memory.

`scipy.sparse` matrices are data structures that do exactly this, and `scikit-learn` has built-in support for these structures.

Tokenizing text with `scikit-learn`

Text preprocessing, tokenizing and filtering of stopwords are all included in class: `CountVectorizer`, which builds a dictionary of features and transforms documents to feature vectors:

```
from sklearn.feature_extraction.text import CountVectorizer

count_vect = CountVectorizer()
X_train_counts = count_vect.fit_transform(twenty_train.data)
X_train_counts.shape
```

```
(2257, 35788)
```

Class `CountVectorizer` supports counts of N-grams of words or consecutive characters. Once fitted, the vectorizer has built a dictionary of feature indices:

```
# The number of times the word 'algorithm' occurs
count_vect.vocabulary_.get(u'algorithm')
```

```
4690
```

The index value of a word in the vocabulary is linked to its frequency in the whole training corpus.

Note: The method `count_vect.fit_transform` performs two actions: it learns the vocabulary and transforms the documents into count vectors. It's possible to separate these steps by calling `count_vect.fit(twenty_train.data)` followed by `X_train_counts = count_vect.transform(twenty_train.data)`, but doing so would tokenize and vectorize each text file twice.

From occurrences to frequencies

Occurrence count is a good start but there is an issue: longer documents will have higher average count values than shorter documents, even though they might talk about the same topics.

To avoid these potential discrepancies it suffices to divide the number of occurrences of each word in a document by the total number of words in the document: these new features are called `tf` for Term Frequencies.

Another refinement on top of tf is to downscale weights for words that occur in many documents in the corpus and are therefore less informative than those that occur only in a smaller portion of the corpus.

This downscaling is the `tf-idf` - "Term Frequency times Inverse Document Frequency" we discussed earlier.

As dicussed in the previous notebooks, both **tf** and **tf–idf** can be computed as follows using class `TfidfTransformer`:

```
from sklearn.feature_extraction.text import TfidfTransformer

tf_transformer = TfidfTransformer(use_idf=False).fit(X_train_counts)
X_train_tf = tf_transformer.transform(X_train_counts)
X_train_tf.shape
```

```
(2257, 35788)
```

In the above example-code, we firstly use the `fit(..)` method to fit our estimator to the data and secondly the `transform(..)` method to transform our count-matrix to a tf-idf representation. These two steps can be combined to achieve the same end result faster by skipping redundant processing. This is done through using the `fit_transform(..)` method as shown below, and as mentioned in the note in the previous section:

```
tfidf_transformer = TfidfTransformer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
X_train_tfidf.shape
```

```
(2257, 35788)
```

```
X_train_tfidf.toarray()
```

```
array([[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., 0.]])
```

4.2.3 Training a classifier

Now that we have our features, we can train a classifier to try to predict the category of a post. Let's start with a `naïve Bayes <naive_bayes>` classifier, which provides a nice baseline for this task. `scikit-learn` includes several variants of this classifier; the one most suitable for word counts is the multinomial variant:

```
from sklearn.naive_bayes import MultinomialNB

clf = MultinomialNB().fit(X_train_tfidf, twenty_train.target)
```

To try to predict the outcome on a new document we need to extract the features using almost the same feature extracting chain as before. The difference is that we call `transform` instead of `fit_transform` on the transformers, since they have already been fit to the training set:

```
docs_new = ['God is love', 'OpenGL on the GPU is fast']
X_new_counts = count_vect.transform(docs_new)
X_new_tfidf = tfidf_transformer.transform(X_new_counts)

predicted = clf.predict(X_new_tfidf)

for doc, category in zip(docs_new, predicted):
  print('%r => %s' % (doc, twenty_train.target_names[category]))
```

```
'God is love' => soc.religion.christian
'OpenGL on the GPU is fast' => comp.graphics
```

4.2.4 Building a pipeline

In order to make the vectorizer => transformer => classifier easier to work with, `scikit-learn` provides a class `~sklearn.pipeline.Pipeline` that behaves like a compound classifier:

```
from sklearn.pipeline import Pipeline
text_clf = Pipeline([
     ('vect', CountVectorizer()),
     ('tfidf', TfidfTransformer()),
     ('clf', MultinomialNB())])
```

The names `vect`, `tfidf` and `clf` (classifier) are arbitrary. We will use them to perform grid search for suitable hyperparameters below. We can now train the model with a single command:

```
text_clf.fit(twenty_train.data, twenty_train.target)
```

```
Pipeline(steps=[('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('clf', MultinomialNB())])
```

4.2.5 Evaluation of the performance on the test set

Evaluating the predictive accuracy of the model is simply a comparision of the predicted and the actual labels.

```
import numpy as np
twenty_test = fetch_20newsgroups(subset='test',
              categories=categories, shuffle=True, random_state=42)
docs_test = twenty_test.data
predicted = text_clf.predict(docs_test)
np.mean(predicted == twenty_test.target)
```

```
0.8348868175765646
```

We achieved 83.5% accuracy. Let's see if we can do better with a linear `support vector machine (SVM) <svm>`, which is widely regarded as one of the best text classification algorithms (although it's also a bit slower than naïve Bayes). We can change the learner by simply plugging a different classifier object into our pipeline:

```
from sklearn.linear_model import SGDClassifier
text_clf = Pipeline([
     ('vect', CountVectorizer()),
     ('tfidf', TfidfTransformer()),
     ('clf', SGDClassifier(loss='hinge', penalty='l2',
                           alpha=1e-3, random_state=42,
                           max_iter=5, tol=None))])

text_clf.fit(twenty_train.data, twenty_train.target)
```

```
Pipeline(steps=[('vect', CountVectorizer()), ('tfidf', TfidfTransformer()),
                ('clf',
                 SGDClassifier(alpha=0.001, max_iter=5, random_state=42,
                               tol=None))])
```

```
predicted = text_clf.predict(docs_test)
np.mean(predicted == twenty_test.target)
```

```
0.9101198402130493
```

We achieved 91.3% accuracy using the SVM. `scikit-learn` provides further utilities for more detailed performance analysis of the results:

```
from sklearn import metrics
print(metrics.classification_report(twenty_test.target, predicted,
      target_names=twenty_test.target_names))
```

```
                        precision    recall  f1-score   support

           alt.atheism       0.95      0.80      0.87       319
         comp.graphics       0.87      0.98      0.92       389
               sci.med       0.94      0.89      0.91       396
soc.religion.christian       0.90      0.95      0.93       398

              accuracy                           0.91      1502
             macro avg       0.91      0.91      0.91      1502
          weighted avg       0.91      0.91      0.91      1502
```

```
metrics.confusion_matrix(twenty_test.target, predicted)
```

```
array([[256,  11,  16,  36],
       [  4, 380,   3,   2],
       [  5,  35, 353,   3],
       [  5,  11,   4, 378]], dtype=int64)
```

As expected the confusion matrix shows that posts from the newsgroups on atheism and Christianity are more often confused for one another than with computer graphics.

Note: SGD stands for Stochastic Gradient Descent. This is a simple optimization algorithms that is known to be scalable when the dataset has many samples.

By setting `loss="hinge"` and `penalty="l2"` we are configuring the classifier model to tune its parameters for the linear Support Vector Machine cost function.

Alternatively we could have used `sklearn.svm.LinearSVC` (Linear Support Vector Machine Classifier) that provides an alternative optimizer for the same cost function based on the liblinear_ C++ library.

4.2.6 Parameter tuning using grid search

We've already encountered some parameters such as `use_idf` in the `TfidfTransformer`. Classifiers tend to have many parameters as well; e.g., `MultinomialNB` includes a smoothing parameter `alpha` and `SGDClassifier` has a penalty parameter `alpha` and configurable loss and penalty terms in the objective function (see the module documentation, or use the Python `help` function to get a description of these).

Instead of tweaking the parameters of the various components of the chain, it is possible to run an exhaustive search of the best parameters on a grid of possible values. We try out all classifiers on either words or bigrams, with or without idf, and with a penalty parameter of either 0.01 or 0.001 for the linear SVM:

```
from sklearn.model_selection import GridSearchCV
parameters = {
    'vect__ngram_range': [(1, 1), (1, 2)],
    'tfidf__use_idf': (True, False),
    'clf__alpha': (1e-2, 1e-3),
}
```

Obviously, such an exhaustive search can be expensive. If we have multiple CPU cores at our disposal, we can tell the grid searcher to try these eight parameter combinations in parallel with the `n_jobs` parameter. If we give this parameter a value of `-1`, grid search will detect how many cores are installed and use them all:

```
gs_clf = GridSearchCV(text_clf, parameters, cv=5, n_jobs=-1)
```

The grid search instance behaves like a normal `scikit-learn` model. Let's perform the search on a smaller subset of the training data to speed up the computation:

```
gs_clf = gs_clf.fit(twenty_train.data[:400], twenty_train.target[:400])
```

After calling `fit` on a `GridSearchCV` object, we now obtained a classifier that we can use to `predict`:

```
twenty_train.target_names[gs_clf.predict(['God is love'])[0]]
```

```
'soc.religion.christian'
```

The object's `best_score_` and `best_params_` attributes store the best mean score and the parameters setting corresponding to that score:

```
gs_clf.best_score_
```

```
0.9175000000000001
```

```
for param_name in sorted(parameters.keys()):
    print("%s: %r" % (param_name, gs_clf.best_params_[param_name]))
```

```
clf__alpha: 0.001
tfidf__use_idf: True
vect__ngram_range: (1, 1)
```

A more detailed summary of the search is available at `gs_clf.cv_results_`.

The `cv_results_` parameter can be easily imported into pandas as a `DataFrame` for further inspection.

Note: A `GridSearchCV` object also stores the best classifier that it trained as its `best_estimator_` attribute. In this case, that isn't much use as we trained on a small, 400-document subset of our full training set.

The index value of a word in the vocabulary is linked to its frequency in the whole training corpus.

Your Turn

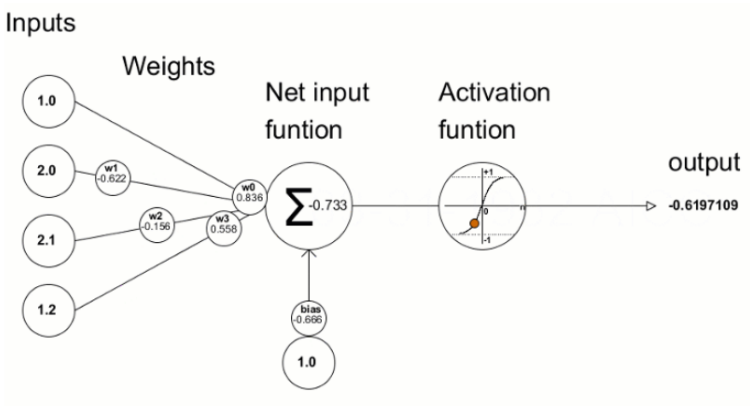
1. Build classifiers using the `raw count`, or `term frequency` to compare the performance against `tf-idf`.
2. Update the code to use TfidfVectorisor.
3. Think about how a classification model or a similarity/distance calculation using `tf-idf` might help your chatbot.

CHAPTER

FIVE

LAB05: INTRODUCTION TO NEURAL NETWORKS AND PYTORCH

In this lab, we will introduce the basic training steps of neural networks by starting with simple linear models in Numpy. Then we will introduce basic Pytorch data types, and re-implement the linear model in Pytorch. A number of important Pytorch functions are introduced in this lab.



The Linear Models in Numpy/Pytorch notebooks are adapted from: Deep Learning in Pytorch Step by Step Chapter 1 notebook on Github

5.1 Linear Models in Numpy

Despite the simplicity, linear models can be applicable in many scenarios. For example, a traditional model for document sentiment classification can be achieved by collecting a set of features (e.g. fequency of positive and negative words by looking up SentiWordNet, and model the sentiment score as a linear combination of the features. Linear models can be seen as the simplest type of neural networks without non-linear activation functions.

Notebook adapted from Github of Deep Learning with Pytorch: Step by Step

```
import numpy as np
import matplotlib.pyplot as plt
```

5.1.1 Data Preparation

Generating a synthetic dataset

We define a linear line $y = 2x + 1$ and add random small guassian noise for the synthetic dataset.

```
true_b = 1
true_w = 2
N = 100
# Data Generation
np.random.seed(42)
x = np.random.rand(N, 1)
# Guassian noise to add some randomness to y
epsilon = (.1 * np.random.randn(N, 1))
y = true_b + true_w * x + epsilon
```

```
print("The epsilon is in the range of [%3.2f, %3.2f]" % (min(epsilon), max(epsilon)))
```

```
The epsilon is in the range of [-0.20, 0.25]
```

Splitting the dataset to training and validation

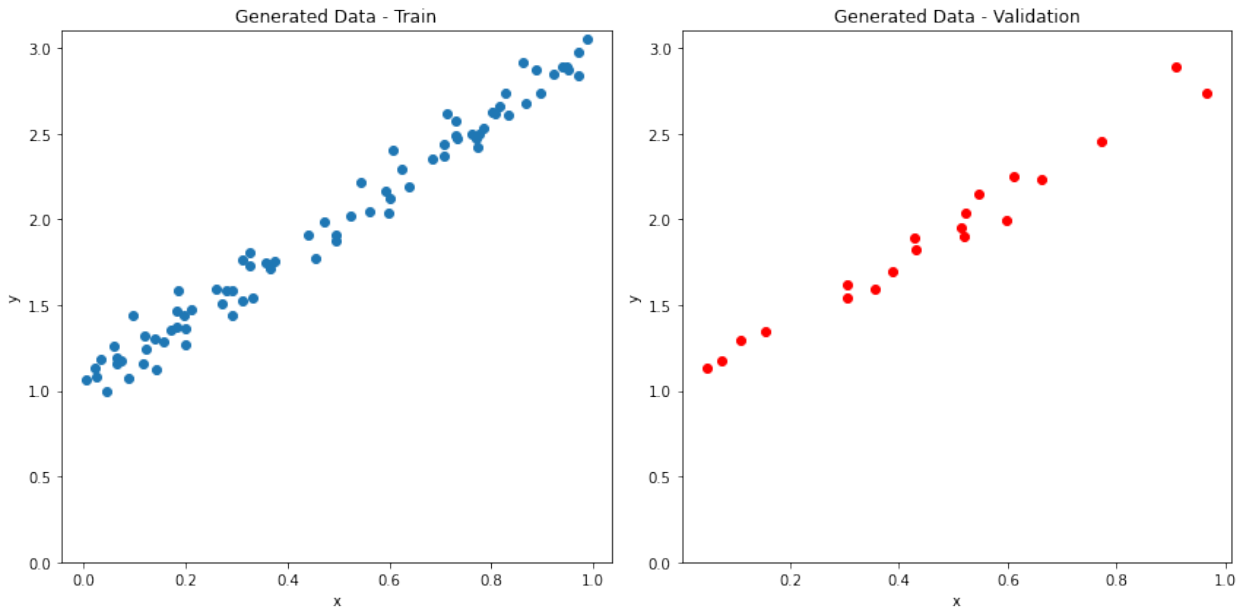
Next, let's split our synthetic data into train and validation sets, shuffling the array of indexes and using the first 80 shuffled points for training, the rest of 20 for validation.

```
# Shuffles the indices
idx = np.arange(N)
np.random.shuffle(idx)
# Uses first 80 random indices for train
train_idx = idx[:int(N*.8)]
# Uses the remaining indices for validation
val_idx = idx[int(N*.8):]
# Generates train and validation sets
x_train, y_train = x[train_idx], y[train_idx]
x_val, y_val = x[val_idx], y[val_idx]
```

```
def figure1(x_train, y_train, x_val, y_val):
    fig, ax = plt.subplots(1, 2, figsize=(12, 6))

    ax[0].scatter(x_train, y_train)
    ax[0].set_xlabel('x')
    ax[0].set_ylabel('y')
    ax[0].set_ylim([0, 3.1])
    ax[0].set_title('Generated Data - Train')

    ax[1].scatter(x_val, y_val, c='r')
    ax[1].set_xlabel('x')
    ax[1].set_ylabel('y')
    ax[1].set_ylim([0, 3.1])
    ax[1].set_title('Generated Data - Validation')
    fig.tight_layout()

    return fig, ax
```

```
figure1(x_train, y_train, x_val, y_val)
```

```
(<Figure size 864x432 with 2 Axes>,
 array([<AxesSubplot:title={'center':'Generated Data - Train'}, xlabel='x', ylabel='y
↪'>,
        <AxesSubplot:title={'center':'Generated Data - Validation'}, xlabel='x',␣
↪ylabel='y'>],
       dtype=object))
```



5.1.2 Gradient Descent

Step 0: Random Initialization

For training a model, you need to randomly initialize the parameters/weights (we have only two, b and w).

```
# Step 0 - Initializes parameters "b" and "w" randomly
np.random.seed(42)
b = np.random.randn(1)
w = np.random.randn(1)
print(b, w)
```

```
[0.49671415] [-0.1382643]
```

Step 1: Compute Predication

```
# Step 1 - Computes our model's predicted output - forward pass
yhat = b + w * x_train
yhat
```

```
array([[0.390075  ],
       [0.4879263 ],
       [0.37737776],
       [0.4931996 ],
       [0.39550552],
       [0.48647642],
       [0.46923887],
       [0.4537164 ],
       [0.43142369],
       [0.36265521],
       [0.47984062],
       [0.38954095],
       [0.38579895],
       [0.39583566],
       [0.48320959],
       [0.47115538],
       [0.47514234],
       [0.49386805],
       [0.36026292],
       [0.41053427],
       [0.39881299],
       [0.41404593],
       [0.36925186],
       [0.40856271],
       [0.45787094],
       [0.46093412],
       [0.48017854],
       [0.39591849],
       [0.36551716],
       [0.41271239],
       [0.41910955],
       [0.42843985],
       [0.47157425],
       [0.45919627],
       [0.36261025],
       [0.46735523],
       [0.47135586],
       [0.37695291],
       [0.44492863],
       [0.45644756],
       [0.38494166],
       [0.48868326],
       [0.38161705],
       [0.42167866],
       [0.38994027],
       [0.3740443 ],
       [0.4844788 ],
       [0.49046083],
       [0.41480437],
       [0.40210915],
       [0.39809786],
```

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```
       [0.49195945],
       [0.41360141],
       [0.38396495],
       [0.43585678],
       [0.45175291],
       [0.38815235],
       [0.39152474],
       [0.42824886],
       [0.4691064 ],
       [0.3652643 ],
       [0.45632098],
       [0.47742713],
       [0.45361564],
       [0.39898102],
       [0.4806936 ],
       [0.44715114],
       [0.49595064],
       [0.46961672],
       [0.37299147],
       [0.43365596],
       [0.42415907],
       [0.47722936],
       [0.48771984],
       [0.47313675],
       [0.38212934],
       [0.45173258],
       [0.36681499],
       [0.45096277],
       [0.44605939]])
```

Step 2 - Compute the Loss

For a regression problem, the loss is given by the Mean Squared Error (MSE), that is, the average of all squared errors, that is, the average of all squared differences between labels (y) and predictions ($b + wx$).

For a regression problem, the loss is given by the Mean Squared Error (MSE), that is, the average of all squared errors, that is, the average of all squared differences between labels (y) and predictions (b + wx).

$$
\begin{aligned}
MSE &= \frac{1}{n}\sum_{i=1}^{n} error_i^2 && (5.1)\\
&= \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 && (5.2)\\
&= \frac{1}{n}\sum_{i=1}^{n}(b + wx_i - y_i)^2 && (5.3)\\
& && (5.4)
\end{aligned}
$$

In the code below, we are using all data points of the training set to compute the loss, so $n = N = 80$, meaning we are performing batch gradient descent.

```
# Step 2 - Computing the loss
# We are using ALL data points, so this is BATCH gradient
# descent.
```

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```
# How wrong is our model? This is the error!
error = (yhat - y_train)
# It is a regression, so it computes mean squared error (MSE)
loss = (error ** 2).mean()
print(loss)
```

```
2.7421577700550976
```

Batch, Mini-batch, and Stochastic Gradient Descent

- if we use all points in the training set (n = N) to compute the loss, we are performing a batch gradient descent
- if we were to use a single point (n = 1) each time, it would be a stochastic gradient descent
- anything else (n) in-between 1 and N characterizes a minibatch gradient descent

Step 3 - Compute the gradient

A gradient is a partial derivative — why partial? Because one computes it with respect to (w.r.t.) a single parameter. We have two parameters, b and w, so we must compute two partial derivatives.

A derivative tells you how much a given quantity changes when you slightly vary some other quantity. In our case, how much does our MSE loss change when we vary each one of our two parameters separately?

```
# Step 3 - Computes gradients for both "b" and "w" parameters
b_grad = 2 * error.mean()
w_grad = 2 * (x_train * error).mean()
print(b_grad, w_grad)
```

```
-3.044811379650508 -1.8337537171510832
```

Step 4 - Update the Parameters

In the final step, we use the gradients to update the parameters. Since we are trying to minimize our losses, we reverse the sign of the gradient for the update. There is still another (hyper-)parameter to consider: the learning rate, denoted by the Greek letter alpha, which is the multiplicative factor that we need to apply to the gradient for the parameter update.

```
# Sets learning rate - this is "eta" ~ the "n"-like Greek letter
lr = 0.1
print(b, w)
# Step 4 - Updates parameters using gradients and
# the learning rate
b = b - lr * b_grad
w = w - lr * w_grad
print(b, w)
```

```
[0.49671415] [-0.1382643]
[0.80119529] [0.04511107]
```

Step 5 - Rinse and Repeat!

Now we use the updated parameters to go back to Step 1 and restart the process.

Definition of Epoch

An epoch is complete whenever every point in the training set (N) has already been used in all steps: forward pass, computing loss, computing gradients, and updating parameters.

```
n_epochs = 1000

for epoch in range(n_epochs):
    # Step 1 - Computes model's predicted output - forward pass
    yhat = b + w * x_train

    # Step 2 - Computes the loss
    # We are using ALL data points, so this is BATCH gradient
    # descent.
    # How wrong is our model? This is the error!
    error = (yhat - y_train)
    # It is a regression, so it computes mean squared error (MSE)
    loss = (error ** 2).mean()

    # Step 3 - Computes gradients for both "b" and "w" parameters
    b_grad = 2 * error.mean()
    w_grad = 2 * (x_train * error).mean()

    # Step 4 - Updates parameters using gradients and
    # the learning rate
    b = b - lr * b_grad
    w = w - lr * w_grad

print(b, w)
```

```
[1.02354093] [1.96896412]
```

5.1.3 Sanity Check using Scikit-Learn

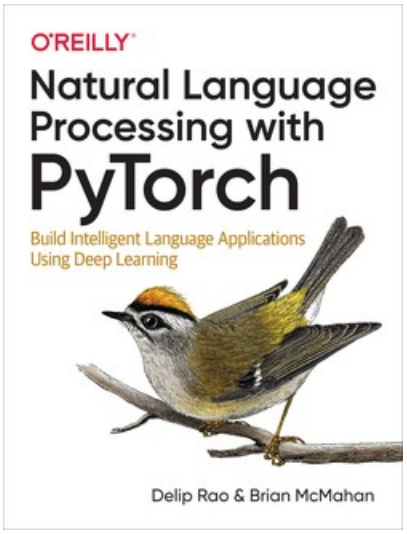
Just to make sure we haven't done any mistakes in our code, we can use Scikit- Learn's Linear Regression to fit the model and compare the coefficients.

```
from sklearn.linear_model import LinearRegression
# Sanity Check: do we get the same results as our
# gradient descent?
linr = LinearRegression()
linr.fit(x_train, y_train)
print(linr.intercept_, linr.coef_[0])
```

```
[1.02354075] [1.96896447]
```

5.2 Introduction to Pytorch Tensors

Pytorch is an optimised `tensor` manipulation library that offers an array of packages for deep learning. As compared to static frameworks such as Theano, Caffe and Tensorflow, Pytorch is in the family of dynamic frameworks, which does not require pre-defined computational graphs. This allows for a more flexible, imperative style of development, as it does not require the computational graphs to be first declared, compiled, and then excuted. However, this is potentially at the cost of computational efficiency, which makes it not as advantageous for production and mobile settings, but extremely useful during research and development.



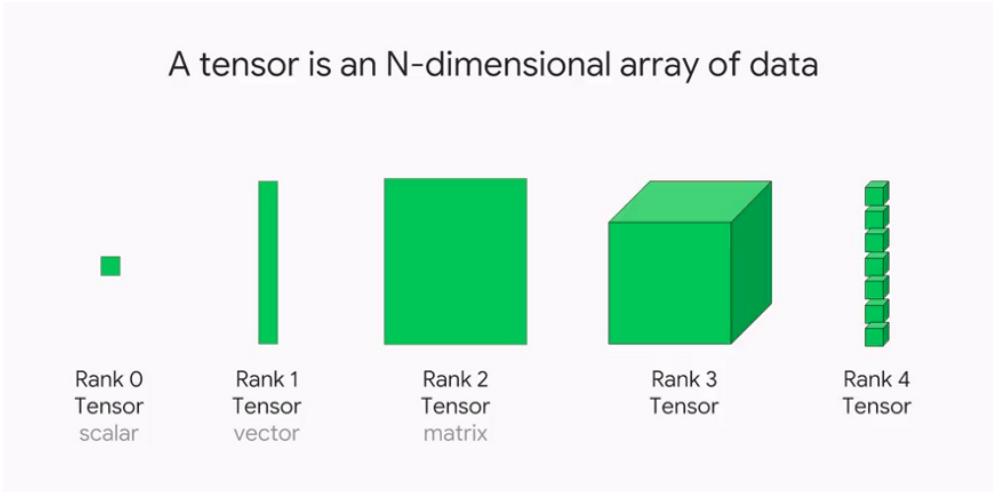
PyTorch

Reference: *Natural Lanuage Processing with PyTorch* - Building intelligent lanaguage applications using deep learning, by Delip Rao and Brian McMahan (copyright O'REILLY Feb 2019)

5.2.1 Tensors

Tensor

A tensor is a mathematical object holding some multidimensional data.



- A tensor of order zero is just a number, or a `scalar`.
- A tensor of order one (1st-order tensor) is an array of numbers, or a `vector`.
- A tensor of order two (2nd-order tensor) is an array of vectors, or a `matrix`.
- A tenosr of order n (nth-order tensor) is a generalised n-dimensional array of scalars.

5.2.2 Creating Tensors

You can create tensors in PyTorch pretty much the same way you create arrays in *Numpy*. Using `tensor()` you can create either a scalar or a tensor. PyTorch's tensors have equivalent functions as its Numpy counterparts, like: `ones()`, `zeros()`, `rand()`, `randn()` and many more. In the example below, we create one of each: scalar, vector, matrix and tensor or, saying it differently, one scalar and three tensors.

```
import torch
```

```
scalar = torch.tensor(3.14159)
vector = torch.tensor([1, 2, 3])
matrix = torch.ones((2, 3), dtype=torch.float)
# two (2) 3x4 matrices
tensor = torch.randn((2, 3, 4), dtype=torch.float)
print(scalar)
print(vector)
print(matrix)
print(tensor)
```

```
tensor(3.1416)
tensor([1, 2, 3])
tensor([[1., 1., 1.],
        [1., 1., 1.]])
tensor([[[-0.1062,  0.0259,  1.0003,  1.7506],
         [ 1.5519,  0.5936,  0.0977,  1.0550],
         [-0.8436, -0.2855,  0.0348, -1.2236]],

        [[-0.7193, -1.7311,  0.3547, -2.5190],
         [ 0.6258, -0.6508, -0.4601, -0.4112],
         [ 0.6510,  0.2963, -0.1989,  0.3999]]])
```

A helper function `describe(x)`

Given a torch tensor `x`, we can use either `x.size()` function or `x.shape` property to look at the dimensionality of the torch tensor.

Note: `tensor.shape` is a property, not a callable function, whereas `tensor.size()` is a function.

```
def describe(x):
    print("Type:{}".format(x.type()))
    print("Shape:{}".format(x.shape))
    print("Size():{}".format(x.size()))
    print("Values: \n{}".format(x))
```

```
describe(scalar)
```

```
Type:torch.FloatTensor
Shape:torch.Size([])
Size():torch.Size([])
Values:
3.141590118408203
```

```
describe(vector)
```

```
Type:torch.LongTensor
Shape:torch.Size([3])
Size():torch.Size([3])
Values:
tensor([1, 2, 3])
```

```
describe(matrix)
```

```
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[1., 1., 1.],
        [1., 1., 1.]])
```

```
describe(tensor)
```

```
Type:torch.FloatTensor
Shape:torch.Size([2, 3, 4])
Size():torch.Size([2, 3, 4])
Values:
tensor([[[-0.1062,  0.0259,  1.0003,  1.7506],
         [ 1.5519,  0.5936,  0.0977,  1.0550],
         [-0.8436, -0.2855,  0.0348, -1.2236]],

        [[-0.7193, -1.7311,  0.3547, -2.5190],
         [ 0.6258, -0.6508, -0.4601, -0.4112],
         [ 0.6510,  0.2963, -0.1989,  0.3999]]])
```

Creating a tensor with `torch.Tensor()`

```
describe(torch.Tensor(2,3))
```

```
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[0.0000e+00, 0.0000e+00, 2.1019e-44],
        [0.0000e+00, 1.4013e-45, 0.0000e+00]])
```

Warning: You might have noted that we can create tensors using both `torch.tensor()` and `torch.Tensor()`, note the subtle difference between the case of letter "t".

`torch.Tensor` is an alias for `torch.FloatTensor`, which creates tensors of float type.

`torch.tensor` on the other hand, infers the `dtype` automatically, and allows explicit specification of `dtype` during creation.

So let's stick to `torch.tensor` instead.

Creating a randomly initialized tensor

```
import torch

describe(torch.rand(2,3))    # uniform random
describe(torch.randn(2,3))   # normal random
```

```
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[0.2609, 0.1867, 0.2250],
        [0.7788, 0.2673, 0.5694]])
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[ 0.5022, -1.1496, -0.6783],
        [ 0.7880, -0.0197,  1.7654]])
```

Creating a filled tensor

```
import torch

describe(torch.zeros(2,3))

x = torch.ones(2,3)
describe(x)

x.fill_(5)
describe(x)
```

```
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[0., 0., 0.],
        [0., 0., 0.]])
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[1., 1., 1.],
        [1., 1., 1.]])
Type:torch.FloatTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[5., 5., 5.],
        [5., 5., 5.]])
```

Creating and initialising a tensor from lists

Observe the type difference between the `torch.tensor()` and `torch.Tensor()`.

```
x = torch.tensor([[1, 2, 3],
                  [4, 5, 6]])
describe(x)
```

```
Type:torch.LongTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[1, 2, 3],
        [4, 5, 6]])
```

```
x = torch.tensor([[1, 2, 3],
                  [4, 5, 6]])
describe(x)
```

```
Type:torch.LongTensor
Shape:torch.Size([2, 3])
Size():torch.Size([2, 3])
Values:
tensor([[1, 2, 3],
        [4, 5, 6]])
```

Creating and initialising a tensor from Numpy

`from_numpy()` automatically inherits input array dtype. On the other hand, `torch.Tensor` is an alias for `torch.FloatTensor`.

Therefore, if you pass int32 array to torch.Tensor, output tensor is float tensor and they wouldn't share the storage. torch.from_numpy gives you torch.LongTensor as expected.

```
import torch
import numpy as np

a = np.arange(10)
```

```
describe(torch.from_numpy(a))
```

```
Type:torch.IntTensor
Shape:torch.Size([10])
Size():torch.Size([10])
Values:
tensor([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=torch.int32)
```

```
describe(torch.Tensor(a))
```

```
Type:torch.FloatTensor
Shape:torch.Size([10])
Size():torch.Size([10])
Values:
tensor([0., 1., 2., 3., 4., 5., 6., 7., 8., 9.])
```

```
describe(torch.tensor(a))
```

```
Type:torch.IntTensor
Shape:torch.Size([10])
Size():torch.Size([10])
Values:
tensor([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=torch.int32)
```

Subtleties in Torch Memory Model

Another way of creating tensor is to use `torch.as_tensor()`. What's the difference between `torch.as_tensor()` and `torch.tensor()`?

<literal>torch.tensor()</literal>

`torch.tensor` always copies the data. For example, `torch.tensor(x)` is equivalent to `x.clone().detach()`.

<literal>torch.as_tensor()</literal>

`torch.as_tensor` always tries to avoid copies of the data. One of the cases where `as_tensor` avoids copying the data is if the original data is a numpy array.

It is not always necessary or a good idea to copy and create a new tensor, especially when the tensor is large.

Reshaping a tensor

The same subtle difference exists between the methods that change the shape of a tensor, i.e. `view()` and `reshape()`.

Important: The `view()` method only returns a tensor with the desired shape that shares the underlying data with the original tensor - it **DOES NOT** create a new, independent, tensor!

The `reshape()` method **may or may not** create a copy! The reasons behind this apparently weird behavior are beyond the scope of this section - but this behavior is the reason why view() is preferred :-)

Why does it matter? Using `view()`, we get the same tensor with a different shape, any modification to the reshaped tensor will change the original tensor.

```
# We get a tensor with a different shape but it still is
# the SAME tensor
same_matrix = matrix.view(1, 6)
# If we change one of its elements...
same_matrix[0, 1] = 2.
# It changes both variables: matrix and same_matrix
print(matrix)
print(same_matrix)
```

```
tensor([[1., 2., 1.],
        [1., 1., 1.]])
tensor([[1., 2., 1., 1., 1., 1.]])
```

To copy all data into a separate independent tensor in the memory, so future operations will not affect the orignal, we will need to use `new_tensor()` or `clone()` methods.

```
# We can use "new_tensor" method to REALLY copy it into a new one
different_matrix = matrix.new_tensor(matrix.view(1, 6))
# Now, if we change one of its elements...
different_matrix[0, 1] = 3.
# The original tensor (matrix) is left untouched!
# But we get a "warning" from PyTorch telling us
# to use "clone()" instead!
print(matrix)
print(different_matrix)
```

```
tensor([[1., 2., 1.],
        [1., 1., 1.]])
tensor([[1., 3., 1., 1., 1., 1.]])
```

```
C:\Users\wei\AppData\Local\Temp/ipykernel_10816/887542709.py:2: UserWarning: To copy␣
↪construct from a tensor, it is recommended to use sourceTensor.clone().detach() or␣
↪sourceTensor.clone().detach().requires_grad_(True), rather than tensor.new_
↪tensor(sourceTensor).
  different_matrix = matrix.new_tensor(matrix.view(1, 6))
```

Warning: As from the warning message, we in fact should use `matrix.clone().detach()` to copy a tensor into a new duplicate, rather than `matrix.new_tensor()`.

In summary, the preferred functions are:

- from a list of values, use `torch.tensor(values, dtype="")`
- from numpy, use `torch.from_numpy()` or `torch.as_tensor()` to avoid data copying.
- from numpy, use `torch.tensor()` to copy it into a new tensor.
- from an existing tensor, `sourceTensor.view()` to avoid copying.
- from an existing tensor, `sourceTensor.clone().detach()` for a fresh duplicate.

5.2.3 Tensor Slicing, Indexing and Joining

```
import torch
from functions import describe

x = torch.arange(6).view(2,3)
describe(x)
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2, 3])
Values:
tensor([[0, 1, 2],
        [3, 4, 5]])
```

Contiguous Indexing using `[:a, :b]`

The code below accesses up to row 1 but not including row 1, and up to col 2, but no including col 2.

```
describe(x[:1, :2])
```

```
Type:torch.LongTensor
Shape/size:torch.Size([1, 2])
Values:
tensor([[0, 1]])
```

Noncontiguous Indexing

Using function `torch.index_select()`, the code below accesses column (`dim=1`) indexed by 0 and 2.

```
indices = torch.LongTensor([0, 2])
describe(torch.index_select(x, dim=1, index=indices))
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2, 2])
Values:
tensor([[0, 2],
        [3, 5]])
```

You can duplicate the same row or column multiple times, by specifying the same index multiple times.

```
indices = torch.LongTensor([0, 0, 0])
describe(torch.index_select(x, dim=0, index=indices))
```

```
Type:torch.LongTensor
Shape/size:torch.Size([3, 3])
Values:
tensor([[0, 1, 2],
        [0, 1, 2],
        [0, 1, 2]])
```

Use indices directly `[inices_list, indices_list]` can also achieve the same outcome.

```
row_indices = torch.arange(2).long()
col_indices = torch.LongTensor([0,2])
describe(x[row_indices, col_indices])
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2])
Values:
tensor([0, 5])
```

```
describe(x[[0,1], [0,2]])
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2])
Values:
tensor([0, 5])
```

Concatenating Tensors

```
x = torch.arange(6).view(2,3)
describe(x)
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2, 3])
Values:
tensor([[0, 1, 2],
        [3, 4, 5]])
```

```
describe(torch.cat([x, x], dim=0))
```

```
Type:torch.LongTensor
Shape/size:torch.Size([4, 3])
Values:
tensor([[0, 1, 2],
        [3, 4, 5],
        [0, 1, 2],
        [3, 4, 5]])
```

```
describe(torch.cat([x, x], dim=1))
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2, 6])
Values:
tensor([[0, 1, 2, 0, 1, 2],
        [3, 4, 5, 3, 4, 5]])
```

```
describe(torch.stack([x, x], dim=1))
```

```
Type:torch.LongTensor
Shape/size:torch.Size([2, 2, 3])
Values:
tensor([[[0, 1, 2],
         [0, 1, 2]],

        [[3, 4, 5],
         [3, 4, 5]]])
```

Linear Algebra on tensors: multiplication

```
x1 = torch.arange(6).view(2,3).float()
describe(x1)
```

```
Type:torch.FloatTensor
Shape/size:torch.Size([2, 3])
Values:
tensor([[0., 1., 2.],
        [3., 4., 5.]])
```

Warning: `torch.arange()` creates LongTensor, for `torch.mm()`, we need to convert the LongTensor to FloatTensor by using `x.float()`.

```
x2 = torch.ones(3,2)
x2[:, 1] += 1
describe(x2)
```

```
Type:torch.FloatTensor
Shape/size:torch.Size([3, 2])
Values:
tensor([[1., 2.],
        [1., 2.],
        [1., 2.]])
```

```
describe(torch.mm(x1, x2))
```

```
Type:torch.FloatTensor
Shape/size:torch.Size([2, 2])
Values:
tensor([[ 3.,  6.],
        [12., 24.]])
```

5.2.4 CUDA tensors

So far, we have only created CPU tensors. What does it mean? It means the data in the tensor is stored in the computer's main memory and any operations performed on it are going to be handled by its CPU (the Central Processing Unit, for instance, an Intel® Core™ i7 Processor). So, although the data is, technically speaking, in the memory, we're still calling this kind of tensor a CPU tensor.

A GPU (which stands for Graphics Processing Unit) is the processor of a graphics card. These tensors store their data in the graphics card's memory and operations on top of them are performed by the GPU.

If you have a graphics card from NVIDIA, you can use the power of its GPU to speed up model training. PyTorch supports the use of these GPUs for model training using CUDA (Compute Unified Device Architecture), which needs to be previously installed and configured (please refer to the Setup Guide for more information on this).

If you do have a GPU (and you managed to install CUDA), we're getting to the part where you get to use it with PyTorch. But, even if you do not have a GPU, you should stick around in this section anyway… why? First, you can use a free GPU from Google Colab and, second, you should always make your code GPU-ready, that is, it should automatically run in a GPU, if one is available.

```
print(torch.cuda.is_available())
```

```
True
```

```
# prefered method: device agnostic tensor instantiation

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda
```

So, if you don't have a GPU, your device is called cpu. If you do have a **GPU**, your device is called **cuda** or **cuda:0**.

If you have multiple GPUs, and want to check how many GPUs it has, or which model they are, you can figure it out using `cuda.device_count()` and `cuda.get_device_name()`:

```
n_cudas = torch.cuda.device_count()
for i in range(n_cudas):
    print(torch.cuda.get_device_name(i))
```

```
NVIDIA GeForce RTX 3080
```

We can use `.to(device)` to turn our tensor to a GPU tensor if you have a GPU device.

```
x = torch.rand(3,2).to(device)
describe(x)
```

```
Type:torch.cuda.FloatTensor
Shape/size:torch.Size([3, 2])
Values:
tensor([[0.3817, 0.3665],
        [0.9877, 0.7927],
        [0.9034, 0.5782]], device='cuda:0')
```

Warning: Mixing CUDA tensors with CPU-bound tensors will lead to errors. This is because we need to ensure the tensors are on the same device.

```
y = torch.rand(3,2)
x + y
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_10816/1126695582.py in <module>
      1 y = torch.rand(3,2)
----> 2 x + y

RuntimeError: Expected all tensors to be on the same device, but found at least two␣
↪devices, cuda:0 and cpu!
```

```
cpu_device = torch.device("cpu")
x = x.to(cpu_device)
y = y.to(cpu_device)
x + y
```

```
tensor([[0.6276, 0.9583],
        [0.7592, 1.2605],
        [1.0946, 0.9480]])
```

Note: It is expensive to move data back and forth from the GPU. Best practice is to carry out as much computation on GPU as possible and then just transfering the final results to CPU.

5.3 Linear Models in Pytorch

Now that we have some basic knowledge of Torch tensors, let's see how we can implement the linear model earlier using Pytorch.

5.3.1 Data Preparation

Let's first repeat the same data preparation process, first generating a synthetic dataset of 100 data points, then perform an 80%:20% split as training and validation dataset, respectively.

```
import numpy as np
import torch
```

```
true_b = 1
true_w = 2
N = 100
# Data Generation
np.random.seed(42)
x = np.random.rand(N, 1)
# Guassian noise to add some randomness to y
epsilon = (.1 * np.random.randn(N, 1))
y = true_b + true_w * x + epsilon

# Shuffles the indices
idx = np.arange(N)
```

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```
np.random.shuffle(idx)
# Uses first 80 random indices for train
train_idx = idx[:int(N*.8)]
# Uses the remaining indices for validation
val_idx = idx[int(N*.8):]
# Generates train and validation sets
x_train, y_train = x[train_idx], y[train_idx]
x_val, y_val = x[val_idx], y[val_idx]
```

No matter you have a GPU or not, the best practice is to use `.to(device)` method to make your code GPU ready.

```
device = 'cuda' if torch.cuda.is_available() else 'cpu'
# Our data was in Numpy arrays, but we need to transform them
# into PyTorch's Tensors and then we send them to the
# chosen device
x_train_tensor = torch.as_tensor(x_train).float().to(device)
y_train_tensor = torch.as_tensor(y_train).float().to(device)
```

```
# Here we can see the difference - notice that .type() is more
# useful since it also tells us WHERE the tensor is (device)
print(type(x_train), type(x_train_tensor), x_train_tensor.type())
```

```
<class 'numpy.ndarray'> <class 'torch.Tensor'> torch.cuda.FloatTensor
```

We normally can turn a tensor back to a *Numpy* array using `sourceTensor.numpy()`, but now we have GPU tensor, which cannot be directly handled by Numpy. We have turn it back to a CPU tensor first before converting to a Numpy array.

```
back_to_numpy = x_train_tensor.cpu().numpy()
```

Good Practice

It is a good practice to always first `cpu()` and then `numpy()`, even if you are using a CPU. It follows the same principle of to(device): you may share your code with others who may be using a GPU.

5.3.2 Creating Parameters

What distinguishes a tensor used for training data (or validation, or test) — like the ones we've just created — from a tensor used as a (trainable) parameter/weight?

The latter (a parameter) requires the computation of its gradients, so we can update their values (the parameters' values).

In Pytorch, we use the `requires_grad=True` argument to tell PyTorch to compute gradients for us.

A tensor for a learnable parameter requires a gradient!

Good Practice

To make GPU ready code, we should specify the device at the moment of creation to avoid shadowing the gradient requirement.

```
# We can specify the device at the moment of creation
# RECOMMENDED!
# Step 0 - Initializes parameters "b" and "w" randomly
torch.manual_seed(42)
b = torch.randn(1, requires_grad=True, dtype=torch.float, device=device)
w = torch.randn(1, requires_grad=True, dtype=torch.float, device=device)
print(b, w)
```

```
tensor([0.1940], device='cuda:0', requires_grad=True) tensor([0.1391], device='cuda:0
↪', requires_grad=True)
```

Note: Notice that even with the same seed value, because *Pytorch* and *Numpy* are two different packages, they have different implemenations of the `randn()` method, thus different results.

5.3.3 Autograd

In Pytorch, we don't need to worry about partial derivatives, chain rule, or anything like it. Autograd is PyTorch's automatic differentiation package.

backward()

To tell PyTorch to compute all gradients, we use the `backward()` method. It will compute gradients for all (requiring gradient) tensors involved in the computation of a given variable.

Recall that we need to compute the partial derivatives of the loss function w.r.t. our parameters. Hence, we need to invoke the `backward()` method from the corresponding Python variable: `loss.backward()`.

```
# Step 1 - Computes our model's predicted output - forward pass
yhat = b + w * x_train_tensor
# Step 2 - Computes the loss
# We are using ALL data points, so this is BATCH gradient
# descent. How wrong is our model? That's the error!
error = (yhat - y_train_tensor)
# It is a regression, so it computes mean squared error (MSE)
loss = (error ** 2).mean()
# Step 3 - Computes gradients for both "b" and "w" parameters
# No more manual computation of gradients!
# b_grad = 2 * error.mean()
# w_grad = 2 * (x_tensor * error).mean()
loss.backward()
```

We have set `requires_grad=True` to both `b` and `w`, so they are obviously included in the list of gradient calculation. We use them both to compute `yhat`, so it will also make it to the list. Then we use `yhat` to compute the `error`, so `error` is also on the list.

`x_train_tensor` and `y_train_tensor` however, are not gradient-requiring tensors, so `backward()` does not care about them.

```
print(error.requires_grad, yhat.requires_grad, b.requires_grad, w.requires_grad)
print(y_train_tensor.requires_grad, x_train_tensor.requires_grad)
```

```
True True True True
False False
```

grad

We can inspect the actual values of the gradients by looking at the `grad` attribute of a tensor.

```
print(b.grad, w.grad)
```

```
tensor([-3.3881], device='cuda:0') tensor([-1.9439], device='cuda:0')
```

Accumulated Gradients

Let's run the backward function again:

```
# Step 1 - Computes our model's predicted output - forward pass
yhat = b + w * x_train_tensor
# Step 2 - Computes the loss
# We are using ALL data points, so this is BATCH gradient
# descent. How wrong is our model? That's the error!
error = (yhat - y_train_tensor)
# It is a regression, so it computes mean squared error (MSE)
loss = (error ** 2).mean()
# Step 3 - Computes gradients for both "b" and "w" parameters
# No more manual computation of gradients!
# b_grad = 2 * error.mean()
# w_grad = 2 * (x_tensor * error).mean()
loss.backward()
```

```
print(b.grad, w.grad)
```

```
tensor([-6.7762], device='cuda:0') tensor([-3.8878], device='cuda:0')
```

Note: If we ran this above code again, the gradient of b and w exactly doubled. This is because Pytorch implements an accumlated gradients to circumvent hardware limitations. If a minibatch is still too big to fit in memory, we can split it further into "subminibatch", that's when the aggregated gradients become useful.

zero_

For training problem that does not have memory limitations, every time we use the gradients to update the parameters, we need to zero the gradients afterward. This what `zero_()` is good for.

```
# This code will be placed _after_ Step 4
# (updating the parameters)
b.grad.zero_(), w.grad.zero_()
```

```
(tensor([0.], device='cuda:0'), tensor([0.], device='cuda:0'))
```

Important: In PyTorch, every method that ends with an underscore (_), like the `requires_grad_()` and `zero_()` method above, makes changes in-place, in other words, they will modify the underlying variable.

5.3.4 Put it all together

```
# Sets learning rate - this is "eta" ~ the "n"-like Greek letter
lr = 0.1

# Step 0 - Initializes parameters "b" and "w" randomly
torch.manual_seed(42)
b = torch.randn(1, requires_grad=True, dtype=torch.float, device=device)
w = torch.randn(1, requires_grad=True, dtype=torch.float, device=device)

# Defines number of epochs
n_epochs = 1000

for epoch in range(n_epochs):
    # Step 1 - Computes model's predicted output - forward pass
    yhat = b + w * x_train_tensor

    # Step 2 - Computes the loss
    # We are using ALL data points, so this is BATCH gradient
    # descent. How wrong is our model? That's the error!
    error = (yhat - y_train_tensor)
    # It is a regression, so it computes mean squared error (MSE)
    loss = (error ** 2).mean()

    # Step 3 - Computes gradients for both "b" and "w"
    # parameters. No more manual computation of gradients!
    # b_grad = 2 * error.mean()
    # w_grad = 2 * (x_tensor * error).mean()
    # We just tell PyTorch to work its way BACKWARDS
    # from the specified loss!
    loss.backward()

    # Step 4 - Updates parameters using gradients and
    # the learning rate. But not so fast...
    # FIRST ATTEMPT - just using the same code as before
    # AttributeError: 'NoneType' object has no attribute 'zero_'
    # b = b - lr * b.grad
    # w = w - lr * w.grad
    # print(b)

    # SECOND ATTEMPT - using in-place Python assingment
    # RuntimeError: a leaf Variable that requires grad
    # has been used in an in-place operation.
    # b -= lr * b.grad
    # w -= lr * w.grad

    # THIRD ATTEMPT - NO_GRAD for the win!
    # We need to use NO_GRAD to keep the update out of
    # the gradient computation. Why is that? It boils
    # down to the DYNAMIC GRAPH that PyTorch uses...
    with torch.no_grad():
```

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```
        b -= lr * b.grad
        w -= lr * w.grad

    # PyTorch is "clingy" to its computed gradients, we
    # need to tell it to let it go...
    b.grad.zero_()
    w.grad.zero_()

print(b, w)
```

```
tensor([1.0235], device='cuda:0', requires_grad=True) tensor([1.9690], device='cuda:0
↪', requires_grad=True)
```

In the first attempt, if we use the same update structure as in our Numpy code, we'll get a weird error but we can get a hint of what's going on by looking at the tensor itself — once again, we "lost" the gradient while reassigning the update results to our parameters. Thus, the grad attribute turns out to be None, and it raises the error…

Important: We use `with torch.no_grad():` to ensure the update is not tracked by the *dyanmic computation graph* mechanism of Pytorch. We will talk about compuation graph next lab.

CHAPTER

SIX

LAB06: NEURAL NETWORK BUILDING BLOCKS

Each node in a neural network is called a **perceptron** unit, which has three "knobs", a set of weights (w), a bias (b), and an activation function (f). The weights and bias are learned from the data, and the activation function is hand picked depending on the network designer's intuition of the network and its target outputs. Mathematically,

$y = f(wx + b)$

Listing 6.1: A skeleton of a Perceptron

```
class Perceptron(nn.Module):
    """
    A perceptron is one linear layer
    """

    def __init__(self, input_dim):
        """
        Args:
            input_dim (int): size of the input features
        """
        super(Perceptron, self).__init__()
        self.fc1 = nn.Linear(input_dim, 1)

    def forward(self, x_in):
        """The forward pass of the perceptron

        Args:
            x_in (torch.Tensor): an input data tensor
                x_in.shape should be (batch, num_features)
        Returns:
            the resulting tensor. tensor.shape should be (batch,).
        """
        return torch.sigmoid(self.fc1(x_in))
```

In this lab, we will look at the activation functions, and loss functions in more detail, and finish with building and train a simple neural network in PyTorch for simulating the XOR binary operator with Object-orientation in mind.

Reference: *Deep Learning in PyTorch, Step by Step A Beginner's Guide* by Daniel Voigt Godoy - Chapter 2 and 3.

6.1 Activation Functions and their derivatives

Activation functions are salient to provide the important non-linearities to Neural Networks, which turn a linear model into powerful scalable models that are fundamental to modern neural computation.

This notebook visualises the popular activation functions and their derivatives, adapted from this reference blog on activation functions

6.1.1 Sigmoid Function

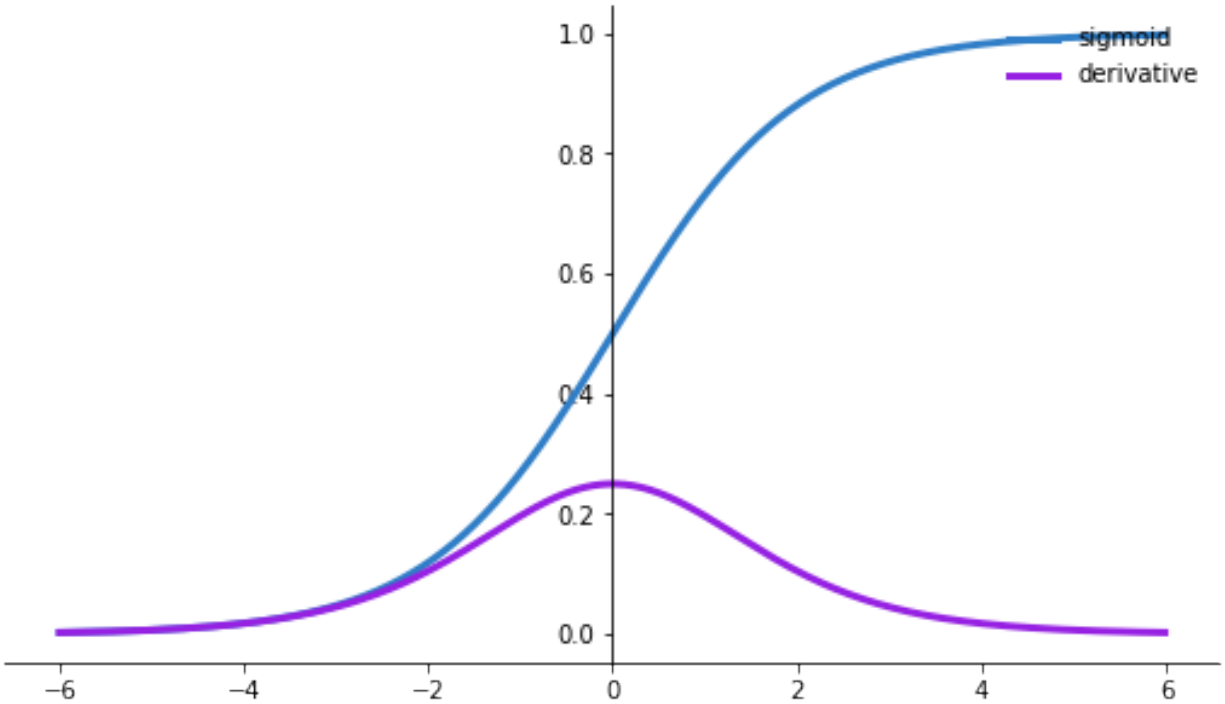
$$t = f(z) = \frac{1}{1+e^{-z}}$$
$$\frac{dt}{dz} = \frac{e^{-z}}{(1+e^{-z})^2} = t * (1-t)$$

In Plain Python with Numpy

```
import matplotlib.pyplot as plt
import numpy as np

def sigmoid(x):
    s=1/(1+np.exp(-x))
    ds=s*(1-s)
    return s,ds
x=np.arange(-6,6,0.01)
sigmoid(x)
# Setup centered axes
fig, ax = plt.subplots(figsize=(9, 5))
ax.spines['left'].set_position('center')
ax.spines['right'].set_color('none')
ax.spines['top'].set_color('none')
ax.xaxis.set_ticks_position('bottom')
ax.yaxis.set_ticks_position('left')
# Create and show plot
ax.plot(x,sigmoid(x)[0], color="#307EC7", linewidth=3, label="sigmoid")
ax.plot(x,sigmoid(x)[1], color="#9621E2", linewidth=3, label="derivative")
ax.legend(loc="upper right", frameon=False)
fig.show()
```

```
C:\Users\wei\AppData\Local\Temp/ipykernel_15812/3857614770.py:21: UserWarning:␣
↪Matplotlib is currently using module://matplotlib_inline.backend_inline, which is a␣
↪non-GUI backend, so cannot show the figure.
  fig.show()
```



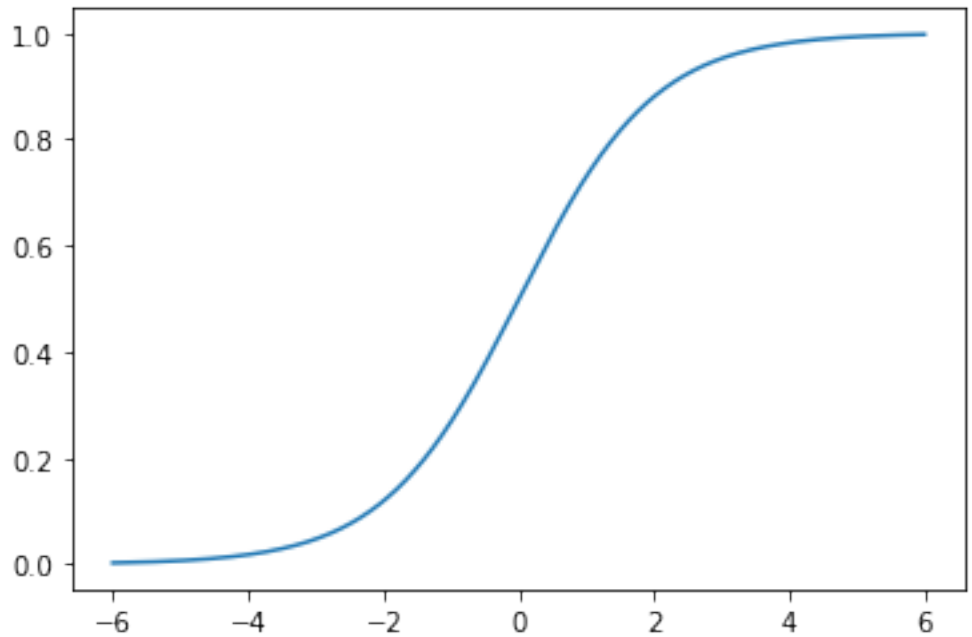
In Pytorch with `torch.sigmoid()`

> **Warning:** `torch.range` is deprecated and will be removed in a future release because its behavior is inconsistent with Python's range builtin. Instead, use torch.arange, which produces values in [start, end). Do not use: `x = torch.range(-6,6,0.01)`

```
import torch
import numpy
import matplotlib.pyplot as plt

x = torch.arange(-6,6,0.01)
y = torch.sigmoid(x)

plt.plot(x.numpy(), y.numpy())
plt.show()
```



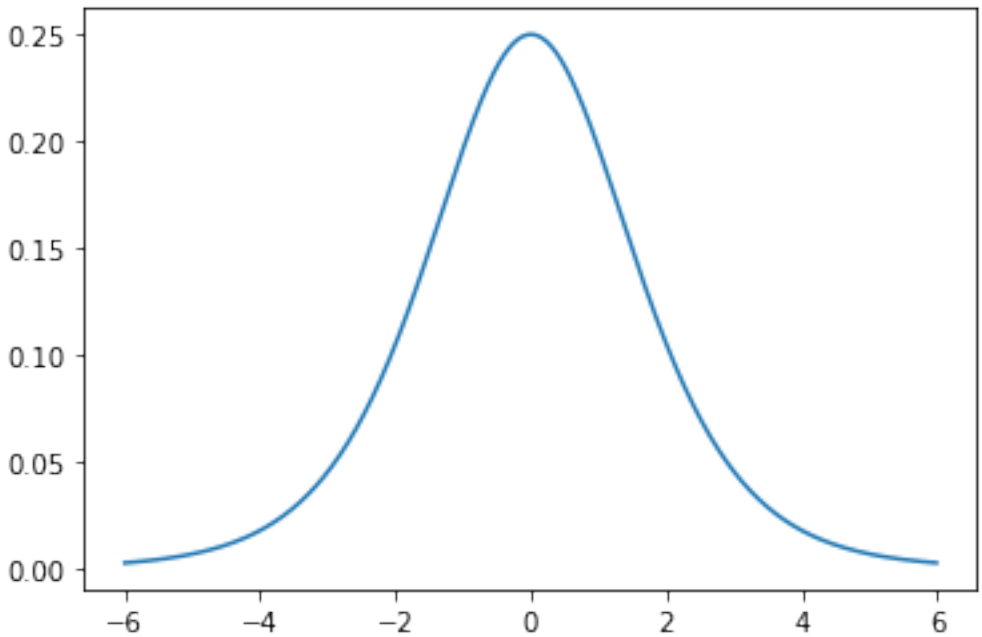
[AUTOGRAD] (https://pytorch.org/tutorials/beginner/former_torchies/autograd_tutorial.html) is a core Torch package for automatic differentiation.

```
x = torch.arange(-6,6,0.01)
x.requires_grad_()
print(x[1:10])
t = torch.sigmoid(x)

t.backward(torch.ones(x.shape))

# x.grad the gradient at each x with respect to function t
dt = x.grad
plt.plot(x.detach().numpy(), dt.detach().numpy())
plt.show()
```

```
tensor([-5.9900, -5.9800, -5.9700, -5.9600, -5.9500, -5.9400, -5.9300, -5.9200,
        -5.9100], grad_fn=<SliceBackward>)
```




```
x
```

```
tensor([-6.0000, -5.9900, -5.9800,  ...,  5.9700,  5.9800,  5.9900],
       requires_grad=True)
```

6.1.2 Hyperbolic tanh

$$t = tanh(z) = \frac{e^z - e^{-z}}{e^z - e^{-z}}$$

$$\frac{dt}{dz} = 1 - t^2$$

In Plain Python and Numpy

```
import matplotlib.pyplot as plt
import numpy as np

def tanh(x):
    t=(np.exp(x)-np.exp(-x))/(np.exp(x)+np.exp(-x))
    dt=1-t**2
    return t,dt


z=np.arange(-4,4,0.01)
# print(tanh(z)[0])
tanh(z)[0].size,tanh(z)[1].size
# Setup centered axes
fig, ax = plt.subplots(figsize=(9, 5))
ax.spines['left'].set_position('center')
ax.spines['bottom'].set_position('center')
```

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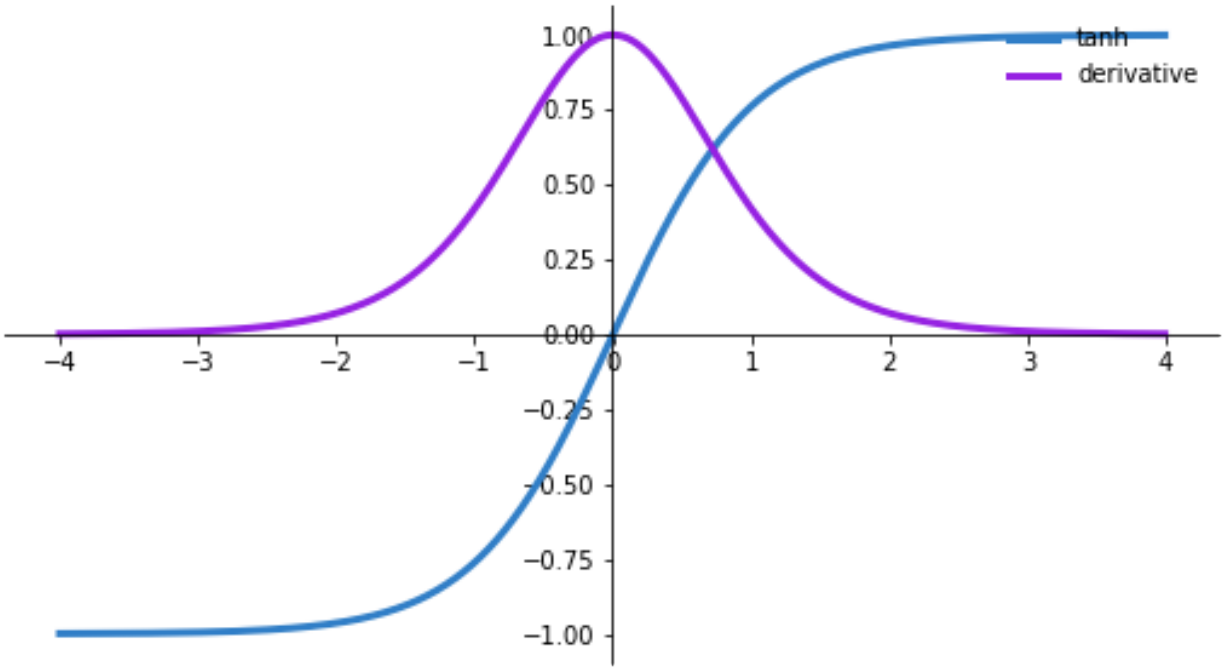
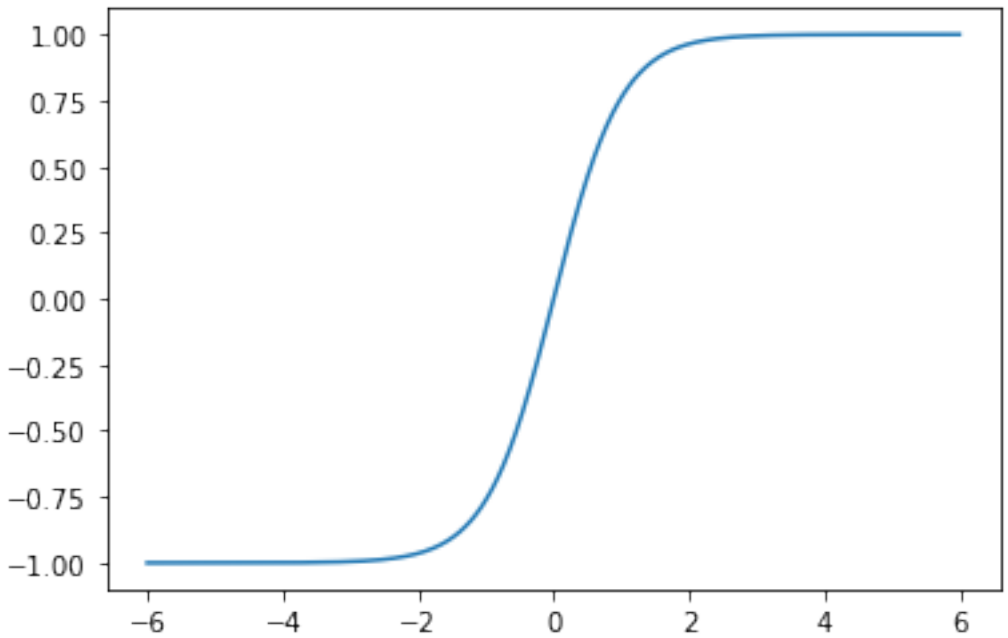
```
ax.spines['right'].set_color('none')
ax.spines['top'].set_color('none')
ax.xaxis.set_ticks_position('bottom')
ax.yaxis.set_ticks_position('left')
# Create and show plot
ax.plot(z,tanh(z)[0], color="#307EC7", linewidth=3, label="tanh")
ax.plot(z,tanh(z)[1], color="#9621E2", linewidth=3, label="derivative")
ax.legend(loc="upper right", frameon=False)
fig.show()
```

```
C:\Users\wei\AppData\Local\Temp/ipykernel_15812/1006845169.py:25: UserWarning:␣
↪Matplotlib is currently using module://matplotlib_inline.backend_inline, which is a␣
↪non-GUI backend, so cannot show the figure.
  fig.show()
```

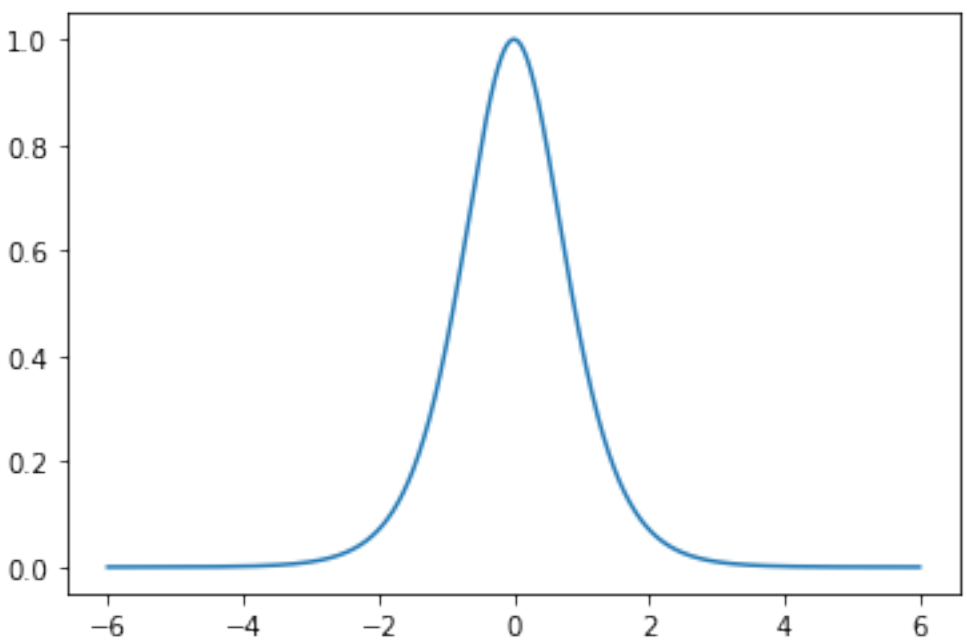


In Pytorch with `torch.tanh()`

```
import torch
import matplotlib.pyplot as pyplot

x = torch.arange(-6, 6, 0.01)
y = torch.tanh(x)

plt.plot(x.numpy(), y.numpy())
plt.show()
```




```
x = torch.arange(-6,6,0.01)
x.requires_grad_()
y = torch.tanh(x)

y.backward(torch.ones(x.shape))

plt.plot(x.detach().numpy(), x.grad.detach().numpy())
plt.show()
```



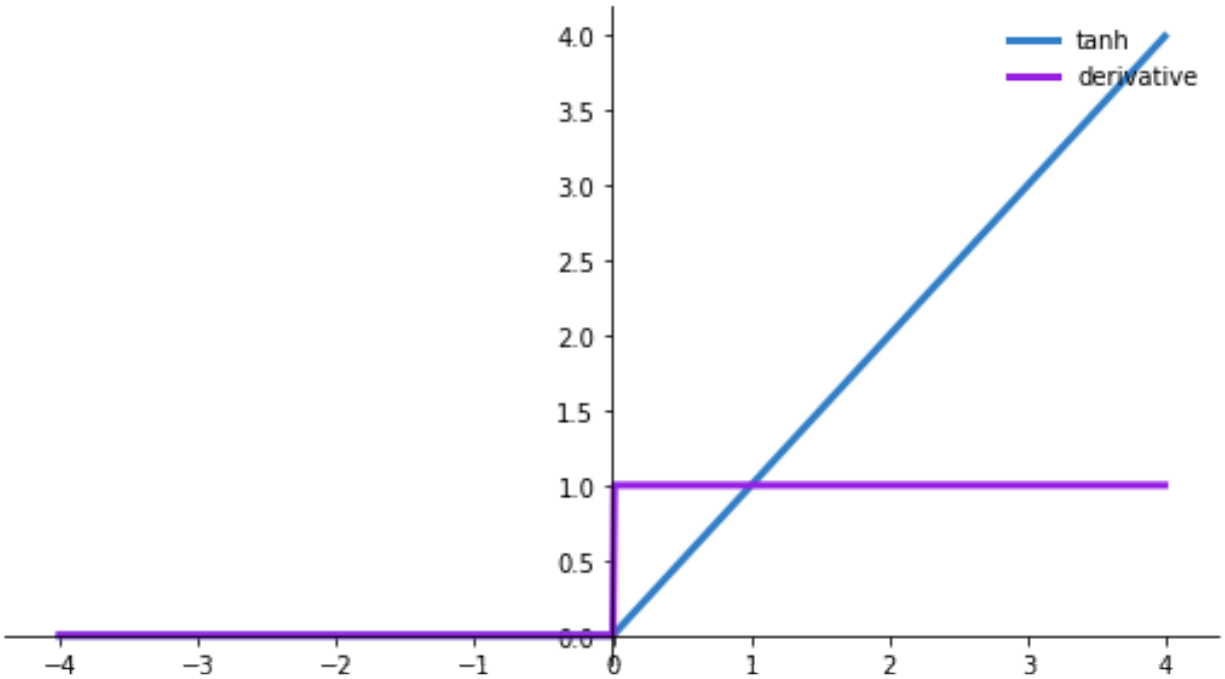
6.1.3 Relu

$$t = f(z) = max(0, z)$$

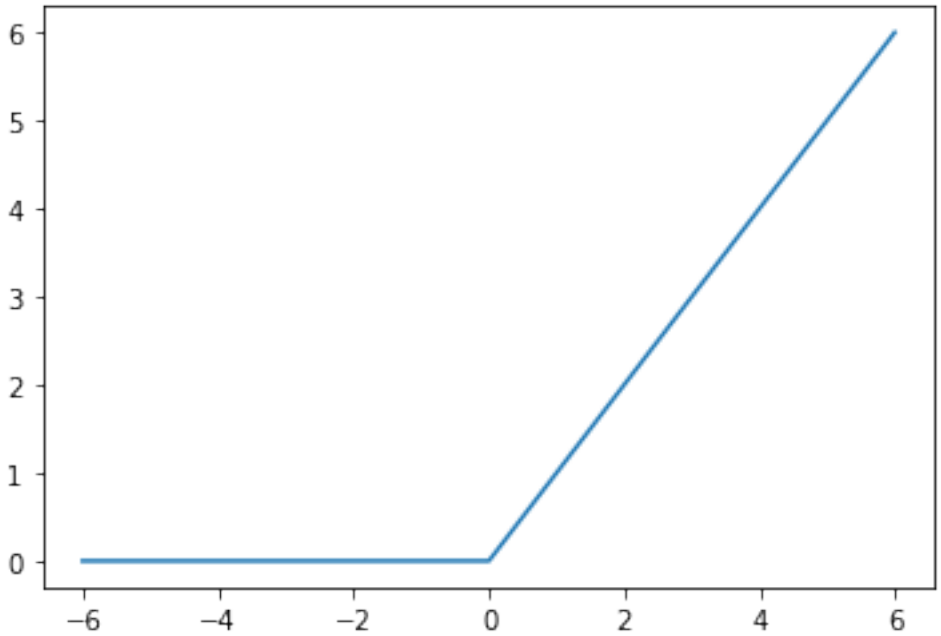
$$\frac{dt}{dz} = \begin{cases} 1 & \text{if } z \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

```
import matplotlib.pyplot as plt
import numpy as np

def relu(x):
    t = [v if v >= 0 else 0 for v in x]
    dt = [1 if v >= 0 else 0 for v in x]
    t = np.array(t)
    dt = np.array(dt)
    return t,dt

z=np.arange(-4,4,0.01)
#print(relu(z)[0])
relu(z)[0].size,relu(z)[1].size
# Setup centered axes
fig, ax = plt.subplots(figsize=(9, 5))
ax.spines['left'].set_position('center')
ax.spines['bottom'].set_position('zero')
ax.spines['right'].set_color('none')
ax.spines['top'].set_color('none')
ax.xaxis.set_ticks_position('bottom')
ax.yaxis.set_ticks_position('left')
# Create and show plot
ax.plot(z,relu(z)[0], color="#307EC7", linewidth=3, label="tanh")
ax.plot(z,relu(z)[1], color="#9621E2", linewidth=3, label="derivative")
ax.legend(loc="upper right", frameon=False)
fig.show()
```

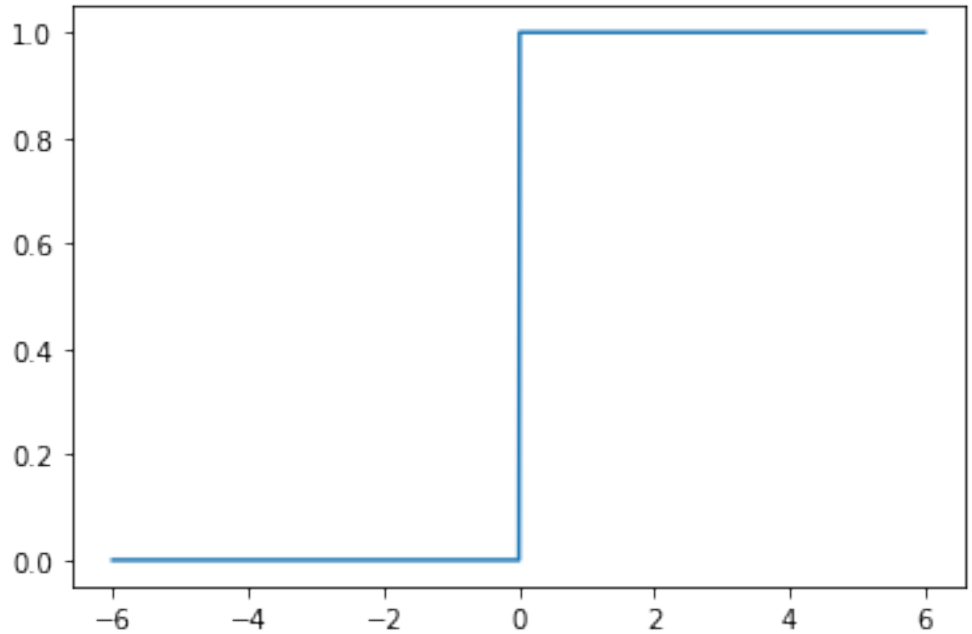
```
C:\Users\wei\AppData\Local\Temp/ipykernel_15812/1318022484.py:26: UserWarning:␣
↪Matplotlib is currently using module://matplotlib_inline.backend_inline, which is a␣
↪non-GUI backend, so cannot show the figure.
  fig.show()
```




```
import torch
import matplotlib.pyplot as plt

relu = torch.nn.ReLU()
x = torch.arange(-6, 6, 0.01)
y = relu(x)

plt.plot(x.numpy(), y.numpy())
plt.show()
```



```
x = torch.arange(-6,6,0.01)
x.requires_grad_()
# y = torch.nn.ReLU not working
y = torch.nn.functional.relu(x)

y.backward(torch.ones(x.shape))

plt.plot(x.detach().numpy(), x.grad.detach().numpy())
plt.show()
```



6.1.4 Parametric and Leaky Relu

Dying ReLU

The clipping effect of ReLU that helps with the vanishing gradient problem can also become an issue. Over time, certain ouputs in the network can simply vecome zero and never revive again. The is called the *dying ReLU* problem.

The Prametric ReLU (PReLU) is introduced to address the dying ReLU, where the leak coefficient a is a learned parameter.

$$t = max(z, a * z) = f(a, z) \begin{cases} z & \text{if } z \geq 0 \\ a * z & \text{otherwise} \end{cases}$$

$$\frac{dt}{dz} = \begin{cases} 1 & \text{if } z \geq 0 \\ a & \text{otherwise} \end{cases}$$

```
import matplotlib.pyplot as plt
import numpy as np
```

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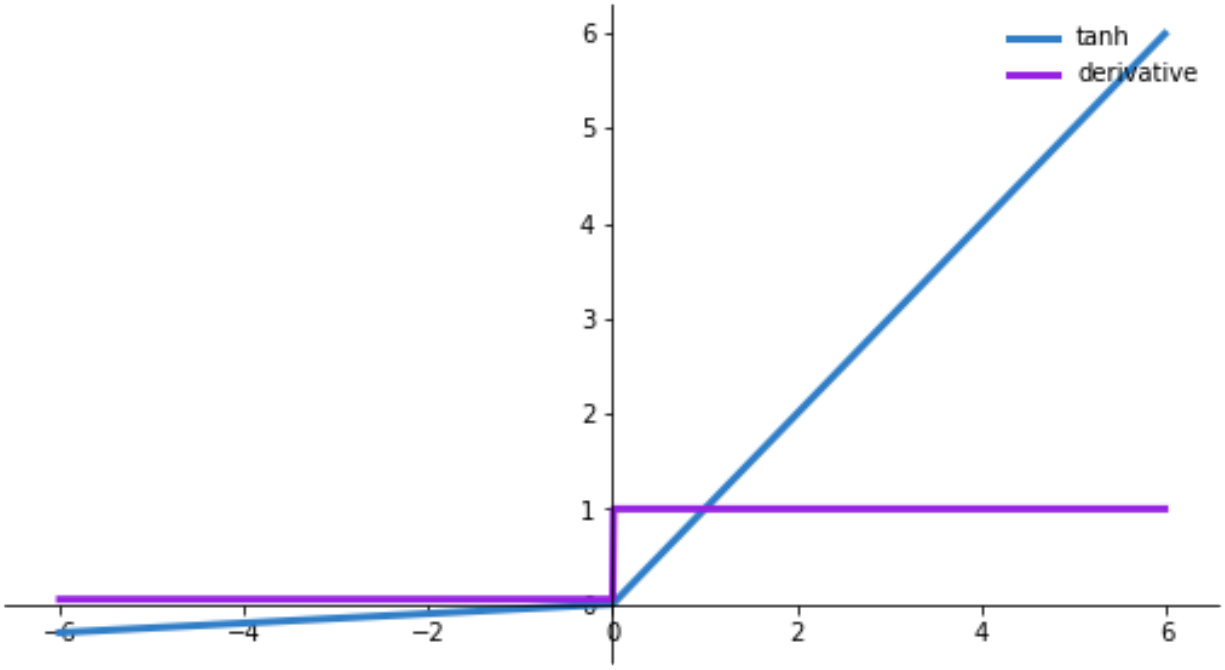
```
def parametric_relu(a, x):
    t = [v if v >= 0 else a*v for v in x]
    dt = [1 if v >= 0 else a for v in x]
    t = np.array(t)
    dt = np.array(dt)
    return t,dt

z=np.arange(-6,6,0.01)
#print(relu(z)[0])
t=parametric_relu(0.05,z)
# Setup centered axes
fig, ax = plt.subplots(figsize=(9, 5))
ax.spines['left'].set_position('center')
ax.spines['bottom'].set_position('zero')
ax.spines['right'].set_color('none')
ax.spines['top'].set_color('none')
ax.xaxis.set_ticks_position('bottom')
ax.yaxis.set_ticks_position('left')
# Create and show plot
ax.plot(z,t[0], color="#307EC7", linewidth=3, label="tanh")
ax.plot(z,t[1], color="#9621E2", linewidth=3, label="derivative")
ax.legend(loc="upper right", frameon=False)
fig.show()
```

```
C:\Users\wei\AppData\Local\Temp/ipykernel_15812/586447431.py:26: UserWarning:␣
↪Matplotlib is currently using module://matplotlib_inline.backend_inline, which is a␣
↪non-GUI backend, so cannot show the figure.
  fig.show()
```




```
import torch
import matplotlib.pyplot as plt
```

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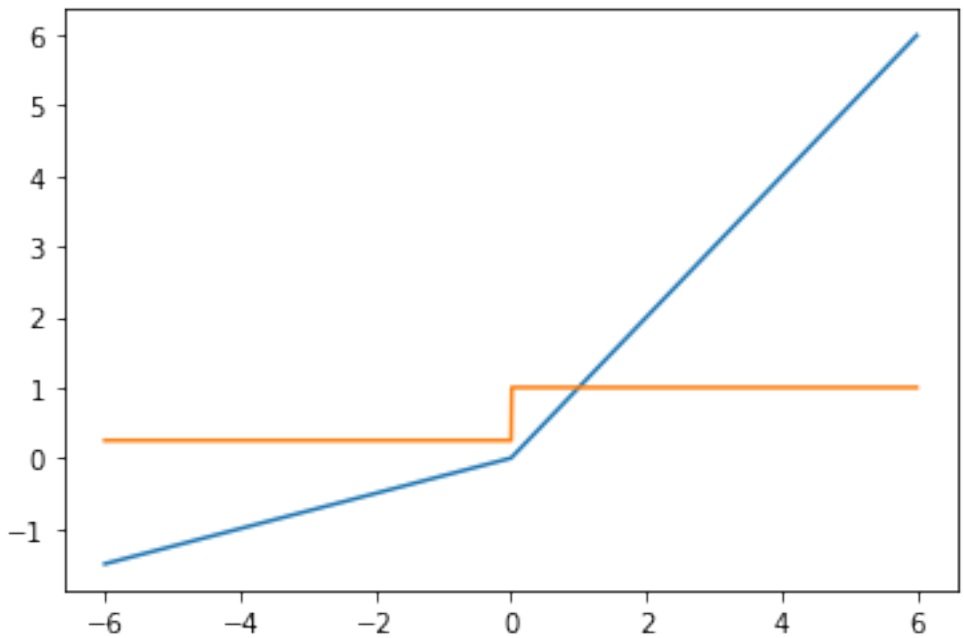
```
prelu = torch.nn.PReLU(num_parameters=1)
x = torch.arange(-6, 6, 0.01)
x.requires_grad_()
y = prelu(x)
y.backward(torch.ones(x.shape))
plt.plot(x.detach().numpy(), y.detach().numpy())
plt.plot(x.detach().numpy(), x.grad.detach().numpy())
plt.show()
```



6.1.5 Softmax

The softmax function squahses the output of each unit to be between 0 and 1, like sigmod function. However, the softmax operation also divides each output by the sum of all outputs, which gives a discrete probabilty distribution over k possible classes.

$$softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_j}}$$

```
import torch.nn as nn
import torch

softmax = nn.Softmax(dim=1)
x_input = torch.randn(1, 3)
y_output = softmax(x_input)
print(x_input)
print(y_output)
print(torch.sum(y_output, dim=1))
```

```
tensor([[-0.0027,  1.0101, -0.9370]])
tensor([[0.2412, 0.6641, 0.0947]])
tensor([1.])
```

For more, see this blog on Activation Functions in Neural Networks.

6.2 Loss Functions

```
import numpy as np
import torch
import torch.nn as nn

seed = 42

torch.manual_seed(seed)
torch.cuda.manual_seed_all(seed)
np.random.seed(seed)

%matplotlib inline
```

6.2.1 Perceptron

Each node in a neural network is called a perceptron unit, which has three "knobs", a set of weights (w), a bias (b), and an activation function (f). The weights and bias are learned from the data, and the activation function is hand picked depending on the network designer's intuition of the network and its target outputs. Mathematically,

$y = f(wx + b)$

```
class Perceptron(nn.Module):
    """
    A perceptron is one linear layer
    """

    def __init__(self, input_dim):
        """
        Args:
            input_dim (int): size of the input features
        """
        super(Perceptron, self).__init__()
        self.fc1 = nn.Linear(input_dim, 1)

    def forward(self, x_in):
        """The forward pass of the perceptron

        Args:
            x_in (torch.Tensor): an input data tensor
                x_in.shape should be (batch, num_features)
        Returns:
            the resulting tensor. tensor.shape should be (batch,).
        """
        return torch.sigmoid(self.fc1(x_in)).squeeze()
```

What does .squeeze() do in Python?

```
# Python program explaining
# numpy.squeeze function

import numpy as np
```

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```
in_arr = np.array([[[2, 2, 2], [2, 2, 2]]])

print ("Input array : ", in_arr)
print("Shape of input array : ", in_arr.shape)

out_arr = np.squeeze(in_arr)

print ("output squeezed array : ", out_arr)
print("Shape of output array : ", out_arr.shape)
```

```
Input array :  [[[2 2 2]
  [2 2 2]]]
Shape of input array :  (1, 2, 3)
output squeezed array :  [[2 2 2]
 [2 2 2]]
Shape of output array :  (2, 3)
```

6.2.2 Softmax

```
softmax = nn.Softmax(dim=1)
x_input = torch.randn(1, 3)
y_output = softmax(x_input)
print(x_input)
print(y_output)
print(torch.sum(y_output, dim=1))
```

```
tensor([[0.3367, 0.1288, 0.2345]])
tensor([[0.3683, 0.2992, 0.3325]])
tensor([1.])
```

6.2.3 MSELoss

```
import torch
import torch.nn as nn

mse_loss = nn.MSELoss()
torch.manual_seed(42)
yhat = torch.randn(3, 5, requires_grad=True)
y = torch.randn(3, 5)
loss = mse_loss(yhat, y)
loss.backward()
print(loss)
```

```
tensor(1.0192, grad_fn=<MseLossBackward>)
```

6.2.4 MAE Loss - L1Loss

```
import torch
import torch.nn as nn

mse_loss = nn.L1Loss()
torch.manual_seed(42)
yhat = torch.randn(3, 5, requires_grad=True)
y = torch.randn(3, 5)
loss = mse_loss(yhat, y)
print(yhat)
print(y)
loss.backward()
print(loss)
```

```
tensor([[ 0.3367,  0.1288,  0.2345,  0.2303, -1.1229],
        [-0.1863,  2.2082, -0.6380,  0.4617,  0.2674],
        [ 0.5349,  0.8094,  1.1103, -1.6898, -0.9890]], requires_grad=True)
tensor([[ 0.9580,  1.3221,  0.8172, -0.7658, -0.7506],
        [ 1.3525,  0.6863, -0.3278,  0.7950,  0.2815],
        [ 0.0562,  0.5227, -0.2384, -0.0499,  0.5263]])
tensor(0.8502, grad_fn=<L1LossBackward>)
```

6.2.5 RMSE Loss

```
class RMSELoss(nn.Module):
    def __init__(self):
        super().__init__()
        self.mse = nn.MSELoss()

    def forward(self,yhat,y):
        eps = 1e-7
        return torch.sqrt(self.mse(yhat,y) + eps)

criterion = RMSELoss()

torch.manual_seed(42)
yhat = torch.randn(3, 5, requires_grad=True)
y = torch.randn(3, 5)
loss = criterion(yhat,y)
print(loss)
```

```
tensor(1.0096, grad_fn=<SqrtBackward>)
```

6.2.6 CrossEntropyLoss

```
import torch
import torch.nn as nn

ce_loss = nn.CrossEntropyLoss()

torch.manual_seed(42)
outputs = torch.randn(3, 5, requires_grad=True)
targets = torch.tensor([1, 0, 3], dtype=torch.int64)
loss = ce_loss(outputs, targets)
loss.backward()
print (loss)
```

```
tensor(2.6812, grad_fn=<NllLossBackward>)
```

Cross Entropy Loss - Manual Calculation

```
labels = torch.tensor([1.0, 0.0])
predictions = torch.tensor([.9, .2])
# Positive class (labels == 1)
positive_pred = predictions[labels == 1]
first_summation = torch.log(positive_pred).sum()
# Negative class (labels == 0)
negative_pred = predictions[labels == 0]
second_summation = torch.log(1 - negative_pred).sum()
# n_total = n_pos + n_neg
n_total = labels.size(0)
loss = -(first_summation + second_summation) / n_total
loss
```

```
tensor(0.1643)
```

```
positive_pred = predictions[labels == 1]
print(labels == 1)
print(positive_pred)
```

```
tensor([ True, False])
tensor([0.9000])
```

```
summation = torch.sum(labels * torch.log(predictions) + (1 - labels) * torch.log(1 -␣
↪predictions))
loss = -summation / n_total
loss
```

```
tensor(0.1643)
```

Binary Cross Entropy Loss - PyTorch

```
bce_loss = nn.BCELoss()
sigmoid = nn.Sigmoid()

torch.manual_seed(42)
probabilities = sigmoid(torch.randn(4, 1, requires_grad=True))
print(probabilities)

targets = torch.tensor([1, 0, 1, 0], dtype=torch.float32).view(4, 1)
loss = bce_loss(probabilities, targets)
loss.backward()
print(loss)
```

```
tensor([[0.5834],
        [0.5322],
        [0.5583],
        [0.5573]], grad_fn=<SigmoidBackward>)
tensor(0.6741, grad_fn=<BinaryCrossEntropyBackward>)
```

```
labels = torch.tensor([1.0, 0.0])
predictions = torch.tensor([.9, .2])
# RIGHT
right_loss = bce_loss(predictions, labels)
# WRONG
wrong_loss = bce_loss(labels, predictions)
print(right_loss, wrong_loss)
```

```
tensor(0.1643) tensor(15.0000)
```

BCE with Logits Loss

```
import numpy as np
import torch.nn as nn

def log_odds_ratio(prob):
    return np.log(prob/(1-prob))
```

```
logit1 = log_odds_ratio(.9)
logit2 = log_odds_ratio(.2)
labels = torch.tensor([1.0, 0.0])
logits = torch.tensor([logit1, logit2])
print(logits)
loss_fn_logits = nn.BCEWithLogitsLoss()
loss = loss_fn_logits(logits, labels)
loss
```

```
tensor([ 2.1972, -1.3863], dtype=torch.float64)
```

```
tensor(0.1643)
```

6.2.7 Negative Log-Likelihood Loss

Log Softmax

```
import torch.nn as nn
import torch.nn.functional as F
```

```
logits = torch.tensor([ 1.3863, 0.0000, -0.6931])
```

Compute Softmax Manually

```
# e^z is odds ratios
odds_ratios = torch.exp(logits)
odds_ratios
```

```
tensor([4.0000, 1.0000, 0.5000])
```

```
softmaxed = odds_ratios/odds_ratios.sum()
softmaxed
```

```
tensor([0.7273, 0.1818, 0.0909])
```

Compute Softmax in PyTorch

PyTorch provide the typical implementations both as a function (`F.softmax`) and as a module (`nn.Softmax`), which both take in logits (the log odds) as input. We need to tell the softmax function which dimension should be applied to.

In general, our models will produce logits with the shape `(number of data points, number of classes)`, so the right dimension to apply softmax to is the last one (dim=-1).

```
## Using module
softmaxed_torch = nn.Softmax(dim=-1)(logits)
softmaxed_torch
```

```
tensor([0.7273, 0.1818, 0.0909])
```

```
# Using functional
softmaxed_torch = F.softmax(logits, dim=-1)
softmaxed_torch
```

```
tensor([0.7273, 0.1818, 0.0909])
```

6.2.8 LogSoftmax

```
torch.log(softmaxed)
```

```
tensor([-0.3185, -1.7048, -2.3979])
```

```
# Use functional
log_probs = F.log_softmax(logits, dim=-1)
log_probs
```

```
tensor([-0.3185, -1.7048, -2.3979])
```

```
# Use module
log_probs = nn.LogSoftmax(dim=-1)(logits)
log_probs
```

```
tensor([-0.3185, -1.7048, -2.3979])
```

6.2.9 Negative Loglikelihood Loss

NLL loss is a summation of the negative log probilities (log softmax) for all classes over the data points.

Let's take a look at the following 3 classes, 5 data points' NLL loss calculation.

logits → log softmax (log probability) → NLL

```
# manual implementation

torch.manual_seed(11)
logits = torch.randn((5, 3))
labels = torch.tensor([0, 0, 1, 2, 1])
log_probs = F.log_softmax(logits, dim=-1)
log_probs
```

```
tensor([[-1.5229, -0.3146, -2.9600],
        [-1.7934, -1.0044, -0.7607],
        [-1.2513, -1.0136, -1.0471],
        [-2.6799, -0.2219, -2.0367],
        [-1.0728, -1.9098, -0.6737]])
```

NLL is a negated sum of log probabilities.

Manual Calculation

```
#indices = torch.tensor([[0], [0], [1], [2], [1]])
indices = torch.tensor([[idx] for idx in labels])
log_probs_cls = log_probs.gather(1, indices)
```

```
# for each data point, we select the log_probs of corresponding class
-log_probs_cls.mean()
```

```
tensor(1.6553)
```

Using PyTorch

```
F.nll_loss(log_probs, labels)
```

```
tensor(1.6553)
```

```
loss_fn = nn.NLLLoss()
loss_fn(log_probs, labels)
```

```
tensor(1.6553)
```

The preferred module implementation `nn.NLLLoss` loss function is a higher-order function, and this one takes three optional arguments (the others are deprecated and you can safely ignore them).

reduction: it takes either `mean`, `sum`, or `none`. The default, `mean`, corresponds to our equation above. As expected, `sum` will return the sum of the errors, instead of the average. The last option, `none`, corresponds to the unreduced form, that is, it returns the full array of errors.

weight: it takes a tensor of length C, that is, containing as many weights as there are classes.

Important: this weight argument can be used to handle imbalanced datasets, unlike the weight argument in the binary cross-entropy losses we've seen before. Also, unlike the pos_weight argument of BCEWithLogitsLoss, the NLLLoss computes a true weighted average when this argument is used.

---

ignore_index: it takes one integer, corresponding to the one (and only one) class index that should be ignored when computing the loss. It can be used to mask a particular label that is not relevant to the classification task.

Example of Using Weight

What if we want to balance our dataset, giving data points with label (y=2) double the weight of the other classes?

```
loss_fn = nn.NLLLoss(weight=torch.tensor([1., 1., 2.]))
loss_fn(log_probs, labels)
```

```
tensor(1.7188)
```

Example of Using ignore_index

What if we want to simply ignore data points with label (y=2)?

```
loss_fn = nn.NLLLoss(ignore_index=2)
loss_fn(log_probs, labels)
```

```
tensor(1.5599)
```

6.3 Dynamic Computational Graph in PyTorch

Computational Graphs allow a deep learning framework to do additional bookkeeping to implement automatic gradient differentiation needed to obtain gradients of parameters during training. A computational graph is a DAG (directed acyclic graph), where the nodes are the mathematical operations, such as multiplication and addition. The inputs to the operations are the incoming edges and the output of each operation is the outgoing edge.

Static frameworks such as Teano, Caffe and TensorFlow (< v1.7) require the computational graphs to be first declared , compiled and the excuted. Although this leads to extremely efficient implementations (useful in production and mobile settings), it can become quite cumberson during research and development. Modern frames like Chainer, DyNet and Pytorch, implement Dynamic Computational Graphs to allow for a more flexible, imperative style of development, without needing to compile the models before every excution. Dynamic computational graphs are especially useful in modelling NLP tasks as each input could potentially result in a different graph structure. As of Version 1.7, TensorFlow has an eager excution that `tf.Tensor` objects reference concrete values instead of symbolic handles to nodes in a computational graph. This is a similar to the PyTorch's dynamic computational graph idea.

```
import torch
import numpy as np

device = 'cuda' if torch.cuda.is_available() else 'cpu'
```

6.3.1 Training Data Preparation

We use the same linear model data preparation process here.

```
true_b = 1
true_w = 2
N = 100
# Data Generation
np.random.seed(42)
x = np.random.rand(N, 1)
epsilon = (.1 * np.random.randn(N, 1))
y = true_b + true_w * x + epsilon

# Shuffles the indices
idx = np.arange(N)
np.random.shuffle(idx)
# Uses first 80 random indices for train
train_idx = idx[:int(N*.8)]
# Uses the remaining indices for validation
val_idx = idx[int(N*.8):]
# Generates train and validation sets
x_train, y_train = x[train_idx], y[train_idx]
x_val, y_val = x[val_idx], y[val_idx]

# Our data was in Numpy arrays, but we need to transform them
# into PyTorch's Tensors and then we send them to the
# chosen device
x_train_tensor = torch.as_tensor(x_train).float().to(device)
y_train_tensor = torch.as_tensor(y_train).float().to(device)
```

6.3.2 Using `torchviz` to visualise computation graph

```
from torch import nn
from torchviz import make_dot, make_dot_from_trace
```

```
# Step 0 - Initializes parameters "b" and "w" randomly
torch.manual_seed(42)
b = torch.randn(1, requires_grad=True, \
    dtype=torch.float, device=device)
w = torch.randn(1, requires_grad=True, \
    dtype=torch.float, device=device)
# Step 1 - Computes our model's predicted output
#        - forward pass
yhat = b + w * x_train_tensor
# Step 2 - Computes the loss
error = (yhat - y_train_tensor)
loss = (error ** 2).mean()
# We can try plotting the graph for any python variable:
# yhat, error, loss...
make_dot(yhat)
```

```
<graphviz.dot.Digraph at 0x1cd4650f580>
```

Let's take a closer look at its components:

- blue boxes ((1)s): these boxes correspond to the tensors we use as parameters, the ones we're asking PyTorch to compute gradients for
- gray boxes (MulBackward0 and AddBackward0): a Python operation that involves a gradient-computing tensor or its dependencies
- green box ((80, 1)): the tensor used as the starting point for the computation of gradients (assuming the backward() method is called from the variable used to visualize the graph) — they are computed from the bottom-up in a graph

Now, take a closer look at the gray box (AddBackward0) at the bottom of the graph: two arrows are pointing to it since it is adding up two variables, b, and $w \times x$. But the gray box (MulBackward0) of the same graph: it is performing a multiplication, namely, $w \times x$. But there is only one arrow pointing to it! The arrow comes from the blue box that corresponds to our parameter w.

"Why don't we have a box for our data (x)?"

The answer is: we do not compute gradients for it!

6.3.3 No gradient tracking for `b`

Important: Even though there are more tensors involved in the operations performed by the computation graph, it only shows **gradient-computing tensors** and its dependencies.

Let's try to set b to be a non-gradient computing tensor and visualise the computational graph.

```
b_nograd = torch.randn(1, requires_grad=False, \
dtype=torch.float, device=device)
w = torch.randn(1, requires_grad=True, \
```

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```
dtype=torch.float, device=device)
yhat = b_nograd + w * x_train_tensor
make_dot(yhat)
```

```
<graphviz.dot.Digraph at 0x1cd4c14b910>
```

6.3.4 Computational Graph with branches

Let's look at how computational graph deals with if statement. Note the code does not do anything sensible, purely for visualisation and demonstration purposes.

```
b = torch.randn(1, requires_grad=True, \
dtype=torch.float, device=device)
w = torch.randn(1, requires_grad=True, \
dtype=torch.float, device=device)
yhat = b + w * x_train_tensor
error = yhat - y_train_tensor
loss = (error ** 2).mean()
# this makes no sense!!
if loss > 0:
    yhat2 = w * x_train_tensor
    error2 = yhat2 - y_train_tensor
# neither does this :-)
loss += error2.mean()
make_dot(loss)
```

```
<graphviz.dot.Digraph at 0x1cd4c17b1c0>
```

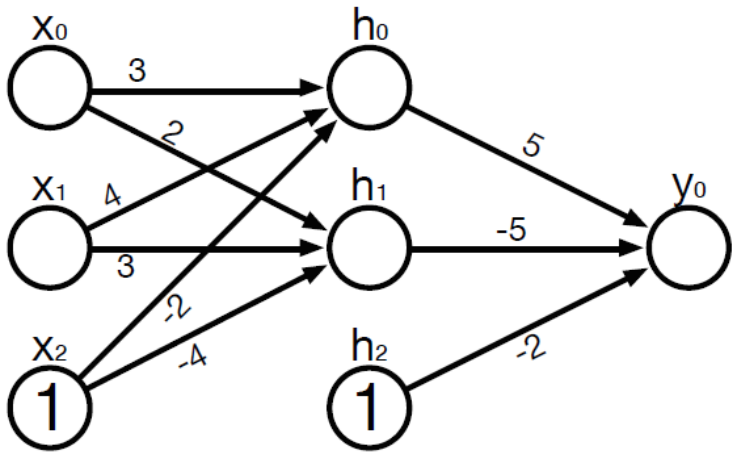
6.4 Neural Networks in PyTorch

6.4.1 A neural network with one hidden layer

Extending the simple perceptron in the openning page of this lab, let's build a simple neural network that takes two binary inputs, and simulate the logical operation of XOR. The network has two sets of weights and biases, one set between the input and the hidden layer with two nodes, another set between the hidden layer and the single output, as shown in the figure below.

Note: Compare the code below with the `Perceptron` code at the front page of this lab to have a better understanding of the building blocks.

```
import torch
import torch.nn as nn
import torch.optim as optim
```



Defining the model class

Let's define the XOR neural network model inherited from the `torch.nn.Module` class using an Object Oriented approach.

```
class XOR(nn.Module):
    """
    An XOR is similuated using neural network with
    two fully connected linear layers
    """

    def __init__(self, input_dim, output_dim):
        """
        Args:
            input_dim (int): size of the input features
            output_dim (int): size of the output
        """
        super(XOR, self).__init__()
        self.fc1 = nn.Linear(input_dim, 2)
        self.fc2 = nn.Linear(2, output_dim)

    def forward(self, x_in):
        """The forward pass of the perceptron

        Args:
            x_in (torch.Tensor): an input data tensor
                x_in.shape should be (batch, num_features)
        Returns:
            the resulting tensor. tensor.shape should be (batch,).
        """
        hidden = torch.sigmoid(self.fc1(x_in))
        yhat = torch.sigmoid(self.fc2(hidden))
        return yhat
```

Object Orientation in PyTorch

In PyTorch, a model (e.g. the `XOR` model) is represented by a regular Python class that inherits from the Module class.

Important: IMPORTANT: If you are uncomfortable with object-oriented programming (OOP) concepts like *classes*, *constructors*, *methods/class methods*, *instances*, and *attributes*, it is strongly recommended to follow tutorials such as Real Python's Objected-Oriented Programming (OOP) in Python 3

The most fundamental methods a model class needs to implement are:

- `__init__(self)`: it defines the parts that make up the model — in our case, two parameters, b and w.
- `forward(self, x)`: it performs the actual computation, that is, it outputs a prediction, given the input x.

Note: Do not forget to include `super().__init__()` to execute the `__init__()` method of the parent class `(nn.Module)` before your own.

6.4.2 XOR Model

Now let's create a Linear Model with two inputs (features) and one output.

Calling the XOR constructor with an `input_dim=2` and `output_dim=1`, namely `XOR(2,1)` results in two fully connected linear models, one `nn.Linear(2,2)` and ``nn.Linear(2,1)`, which will create a model with two input features, one output feature with biases at the input layer, hidden layer and output layer.

```
model = XOR(2,1)
```

Obtain all model parameters using `state_dict()`

We can get the current values of all parameters using our model's state_dict() method.

```
model.state_dict()
```

```
OrderedDict([('fc1.weight',
              tensor([[ 0.5827,  0.0717],
                      [-0.2969, -0.1214]])),
             ('fc1.bias', tensor([-0.5186, -0.6406])),
             ('fc2.weight', tensor([[0.3564, 0.5904]])),
             ('fc2.bias', tensor([0.3660]))])
```

We used to manually assign random values to these weights and biases. Now PyTorch does it for us automatically.

The `state_dict()` of a given model is simply a Python dictionary that maps each attribute/parameter to its corresponding tensor. But only learnable parameters are included, as its purpose is to keep track of parameters that are going to be updated by the optimizer.

The optimizer itself has a `state_dict()` too, which contains its internal state, as well as other hyper-parameters. Let's take a quick look at it:

```
lr = 0.01
optimizer = optim.SGD(model.parameters(), lr=lr)
optimizer.state_dict()
```

```
{'state': {},
 'param_groups': [{'lr': 0.01,
   'momentum': 0,
   'dampening': 0,
   'weight_decay': 0,
   'nesterov': False,
   'params': [0, 1, 2, 3]}]}
```

Model and Data need to be on the same device

Important: We need to send our model to the same device where the data is. If our data is made of GPU tensors, our model must "live" inside the GPU as well.

```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

```
model = model.to(device)
```

6.4.3 Training XOR

Now let's put it all together to train an neural XOR model.

Training Data Preparation

```
# Training data preparation

x_train_tensor = torch.tensor([[0,0],[0,1],[1,1],[1,0]], device=device).float()
y_train_tensor = torch.tensor([0,1,1,0], device=device).view(4,1).float()

x_val_tensor = torch.clone(x_train_tensor)
y_val_tensor = torch.clone(y_train_tensor)
```

```
# Verify the shape of the output tensor
y_train_tensor.shape
```

```
torch.Size([4, 1])
```

Hyperparameter setup

We need to set up the learning rate and the number of epochs, and then select the three key compoenents of a neural model: model, optimiser and loss function before training.

```
# Sets learning rate - this is "eta" ~ the "n" like
# Greek letter
lr = 0.01

# Step 0 - Initializes parameters "b" and "w" randomly
torch.manual_seed(42)
```

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```
# Now we can create a model and send it at once to the device
model = XOR(2,1)
model = model.to(device)

# Defines a SGD optimizer to update the parameters
# (now retrieved directly from the model)
optimizer = optim.SGD(model.parameters(), lr=lr)

# Defines a MSE loss function
loss_fn = nn.MSELoss(reduction='mean')

# Defines number of epochs
n_epochs = 100000
```

Training

Now we are ready to train.

```
for epoch in range(n_epochs):
    #for j in range(steps):
    model.train() # What is this?!?

    # Step 1 - Computes model's predicted output - forward pass
    # No more manual prediction!
    yhat = model(x_train_tensor)

    # Step 2 - Computes the loss
    loss = loss_fn(yhat, y_train_tensor)

    # Step 3 - Computes gradients for both "b" and "w" parameters
    loss.backward()

    # Step 4 - Updates parameters using gradients and
    # the learning rate
    optimizer.step()
    optimizer.zero_grad()
    if (epoch % 500 == 0):
        print("Epoch: {0}, Loss: {1}, ".format(epoch, loss.to("cpu").detach().
↪numpy()))

# We can also inspect its parameters using its state_dict
print(model.state_dict())
```

```
Epoch: 0, Loss: 0.27375736832618713,
Epoch: 500, Loss: 0.2555079460144043,
Epoch: 1000, Loss: 0.25011080503463745,
Epoch: 1500, Loss: 0.24655020236968994,
Epoch: 2000, Loss: 0.24295492470264435,
Epoch: 2500, Loss: 0.238966703414917,
Epoch: 3000, Loss: 0.23448437452316284,
Epoch: 3500, Loss: 0.22930260002613068,
Epoch: 4000, Loss: 0.2232476770877838,
Epoch: 4500, Loss: 0.21623794734477997,
Epoch: 5000, Loss: 0.20812170207500458,
Epoch: 5500, Loss: 0.19883160293102264,
```

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```
Epoch: 6000, Loss: 0.18850544095039368,
Epoch: 6500, Loss: 0.1771014928817749,
Epoch: 7000, Loss: 0.16488364338874817,
Epoch: 7500, Loss: 0.15211743116378784,
Epoch: 8000, Loss: 0.139143705368042,
Epoch: 8500, Loss: 0.12626223266124725,
Epoch: 9000, Loss: 0.11392521113157272,
Epoch: 9500, Loss: 0.10234947502613068,
Epoch: 10000, Loss: 0.09172774851322174,
Epoch: 10500, Loss: 0.08199518918991089,
Epoch: 11000, Loss: 0.0733182281255722,
Epoch: 11500, Loss: 0.06560301780700684,
Epoch: 12000, Loss: 0.05884382501244545,
Epoch: 12500, Loss: 0.05294763296842575,
Epoch: 13000, Loss: 0.04782135412096977,
Epoch: 13500, Loss: 0.04328809678554535,
Epoch: 14000, Loss: 0.039366669952869415,
Epoch: 14500, Loss: 0.03590844199061394,
Epoch: 15000, Loss: 0.03286368399858475,
Epoch: 15500, Loss: 0.030230185016989708,
Epoch: 16000, Loss: 0.02787426859140396,
Epoch: 16500, Loss: 0.025831308215856552,
Epoch: 17000, Loss: 0.02391224540770054,
Epoch: 17500, Loss: 0.02228483371436596,
Epoch: 18000, Loss: 0.02080184407532215,
Epoch: 18500, Loss: 0.019479243084788322,
Epoch: 19000, Loss: 0.018279727548360825,
Epoch: 19500, Loss: 0.017226679250597954,
Epoch: 20000, Loss: 0.01625426858663559,
Epoch: 20500, Loss: 0.01537842396646738,
Epoch: 21000, Loss: 0.014549647457897663,
Epoch: 21500, Loss: 0.01378196757286787,
Epoch: 22000, Loss: 0.01309845969080925,
Epoch: 22500, Loss: 0.01248301099985838,
Epoch: 23000, Loss: 0.011914841830730438,
Epoch: 23500, Loss: 0.011366013437509537,
Epoch: 24000, Loss: 0.01088915579020977,
Epoch: 24500, Loss: 0.010406192392110825,
Epoch: 25000, Loss: 0.010014466941356659,
Epoch: 25500, Loss: 0.009598497301340103,
Epoch: 26000, Loss: 0.009224366396665573,
Epoch: 26500, Loss: 0.008882050402462482,
Epoch: 27000, Loss: 0.008561154827475548,
Epoch: 27500, Loss: 0.008238466456532478,
Epoch: 28000, Loss: 0.007974416017532349,
Epoch: 28500, Loss: 0.007680158130824566,
Epoch: 29000, Loss: 0.0074332160875201225,
Epoch: 29500, Loss: 0.007197014521807432,
Epoch: 30000, Loss: 0.006972037721425295,
Epoch: 30500, Loss: 0.0067596533335745335,
Epoch: 31000, Loss: 0.006562951020896435,
Epoch: 31500, Loss: 0.006372722331434488,
Epoch: 32000, Loss: 0.006173261906951666,
Epoch: 32500, Loss: 0.005995258688926697,
Epoch: 33000, Loss: 0.005834578536450863,
Epoch: 33500, Loss: 0.005697771906852722,
Epoch: 34000, Loss: 0.005533096380531788,
```

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```
Epoch: 34500, Loss: 0.005399664863944054,
Epoch: 35000, Loss: 0.005252258852124214,
Epoch: 35500, Loss: 0.0051279375329613686,
Epoch: 36000, Loss: 0.005004711449146271,
Epoch: 36500, Loss: 0.00487515376880765,
Epoch: 37000, Loss: 0.004761365242302418,
Epoch: 37500, Loss: 0.004653751850128174,
Epoch: 38000, Loss: 0.004538621753454208,
Epoch: 38500, Loss: 0.004451357759535313,
Epoch: 39000, Loss: 0.004348565824329853,
Epoch: 39500, Loss: 0.004250797443091869,
Epoch: 40000, Loss: 0.0041722762398421764,
Epoch: 40500, Loss: 0.00408073328435421,
Epoch: 41000, Loss: 0.004001058172434568,
Epoch: 41500, Loss: 0.003916418645530939,
Epoch: 42000, Loss: 0.0038418788462877274,
Epoch: 42500, Loss: 0.0037747276946902275,
Epoch: 43000, Loss: 0.003688385244458914,
Epoch: 43500, Loss: 0.003622728865593672,
Epoch: 44000, Loss: 0.0035602175630629063,
Epoch: 44500, Loss: 0.003489775350317359,
Epoch: 45000, Loss: 0.003426765091717243,
Epoch: 45500, Loss: 0.003366705495864153,
Epoch: 46000, Loss: 0.0033056712709367275,
Epoch: 46500, Loss: 0.0032519223168492317,
Epoch: 47000, Loss: 0.0031912513077259064,
Epoch: 47500, Loss: 0.0031480954494327307,
Epoch: 48000, Loss: 0.003087468910962343,
Epoch: 48500, Loss: 0.0030377130024135113,
Epoch: 49000, Loss: 0.0029869868885725737,
Epoch: 49500, Loss: 0.0029457740020006895,
Epoch: 50000, Loss: 0.0028982609510421753,
Epoch: 50500, Loss: 0.0028544270899146795,
Epoch: 51000, Loss: 0.0028089506085962057,
Epoch: 51500, Loss: 0.0027682341169565916,
Epoch: 52000, Loss: 0.0027215657755732536,
Epoch: 52500, Loss: 0.0026850481517612934,
Epoch: 53000, Loss: 0.002641090890392661,
Epoch: 53500, Loss: 0.0026040119118988514,
Epoch: 54000, Loss: 0.0025728303007781506,
Epoch: 54500, Loss: 0.0025344102177768946,
Epoch: 55000, Loss: 0.0024971726816147566,
Epoch: 55500, Loss: 0.002462733769789338,
Epoch: 56000, Loss: 0.002433920744806528,
Epoch: 56500, Loss: 0.002397480420768261,
Epoch: 57000, Loss: 0.0023658026475459337,
Epoch: 57500, Loss: 0.002332453615963459,
Epoch: 58000, Loss: 0.002302789594978094,
Epoch: 58500, Loss: 0.002273410093039274,
Epoch: 59000, Loss: 0.002243262715637684,
Epoch: 59500, Loss: 0.0022170250304043293,
Epoch: 60000, Loss: 0.002190019004046917,
Epoch: 60500, Loss: 0.002158280462026596,
Epoch: 61000, Loss: 0.0021350218448787928,
Epoch: 61500, Loss: 0.0021104959305375814,
Epoch: 62000, Loss: 0.0020827956032007933,
Epoch: 62500, Loss: 0.002065179403871298,
```

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```
Epoch: 63000, Loss: 0.002039001788944006,
Epoch: 63500, Loss: 0.0020126295275986195,
Epoch: 64000, Loss: 0.0019906111992895603,
Epoch: 64500, Loss: 0.0019670012407004833,
Epoch: 65000, Loss: 0.0019415951101109385,
Epoch: 65500, Loss: 0.0019239818211644888,
Epoch: 66000, Loss: 0.0019025187939405441,
Epoch: 66500, Loss: 0.001879572868347168,
Epoch: 67000, Loss: 0.0018573695560917258,
Epoch: 67500, Loss: 0.0018442103173583746,
Epoch: 68000, Loss: 0.0018211827846243978,
Epoch: 68500, Loss: 0.0017985039157792926,
Epoch: 69000, Loss: 0.0017842620145529509,
Epoch: 69500, Loss: 0.001763233682140708,
Epoch: 70000, Loss: 0.0017411105800420046,
Epoch: 70500, Loss: 0.0017304448410868645,
Epoch: 71000, Loss: 0.0017097863601520658,
Epoch: 71500, Loss: 0.001695991144515574,
Epoch: 72000, Loss: 0.0016756795812398195,
Epoch: 72500, Loss: 0.0016603447729721665,
Epoch: 73000, Loss: 0.0016442921478301287,
Epoch: 73500, Loss: 0.0016290463972836733,
Epoch: 74000, Loss: 0.0016133070457726717,
Epoch: 74500, Loss: 0.0015992799308151007,
Epoch: 75000, Loss: 0.001579604228027165,
Epoch: 75500, Loss: 0.0015679539646953344,
Epoch: 76000, Loss: 0.0015530944801867008,
Epoch: 76500, Loss: 0.0015387125313282013,
Epoch: 77000, Loss: 0.0015230522258207202,
Epoch: 77500, Loss: 0.0015115310670807958,
Epoch: 78000, Loss: 0.0014988419134169817,
Epoch: 78500, Loss: 0.0014816472539678216,
Epoch: 79000, Loss: 0.0014696801081299782,
Epoch: 79500, Loss: 0.00145495415199548,
Epoch: 80000, Loss: 0.0014449709560722113,
Epoch: 80500, Loss: 0.001434221281670034,
Epoch: 81000, Loss: 0.0014170538634061813,
Epoch: 81500, Loss: 0.0014048947487026453,
Epoch: 82000, Loss: 0.001396734151057899,
Epoch: 82500, Loss: 0.0013808537041768432,
Epoch: 83000, Loss: 0.0013706223107874393,
Epoch: 83500, Loss: 0.001362814218737185,
Epoch: 84000, Loss: 0.0013511404395103455,
Epoch: 84500, Loss: 0.0013351887464523315,
Epoch: 85000, Loss: 0.0013270438648760319,
Epoch: 85500, Loss: 0.0013187713921070099,
Epoch: 86000, Loss: 0.0013084793463349342,
Epoch: 86500, Loss: 0.0012941481545567513,
Epoch: 87000, Loss: 0.0012852461077272892,
Epoch: 87500, Loss: 0.0012746803695335984,
Epoch: 88000, Loss: 0.0012681942898780107,
Epoch: 88500, Loss: 0.0012594859581440687,
Epoch: 89000, Loss: 0.0012420803541317582,
Epoch: 89500, Loss: 0.0012359283864498138,
Epoch: 90000, Loss: 0.0012270398437976837,
Epoch: 90500, Loss: 0.001218495424836874,
Epoch: 91000, Loss: 0.0012108510127291083,
```

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```
Epoch: 91500, Loss: 0.0012005458120256662,
Epoch: 92000, Loss: 0.001190779497846961,
Epoch: 92500, Loss: 0.001179547980427742,
Epoch: 93000, Loss: 0.001171827781945467,
Epoch: 93500, Loss: 0.001165188499726355,
Epoch: 94000, Loss: 0.0011571240611374378,
Epoch: 94500, Loss: 0.001148390700109303,
Epoch: 95000, Loss: 0.0011400426737964153,
Epoch: 95500, Loss: 0.001132698031142354,
Epoch: 96000, Loss: 0.0011260239407420158,
Epoch: 96500, Loss: 0.0011176535626873374,
Epoch: 97000, Loss: 0.0011106508318334818,
Epoch: 97500, Loss: 0.0011001934763044119,
Epoch: 98000, Loss: 0.0010945061221718788,
Epoch: 98500, Loss: 0.0010835299035534263,
Epoch: 99000, Loss: 0.001077619381248951,
Epoch: 99500, Loss: 0.0010701098944991827,
OrderedDict([('fc1.weight', tensor([[ 0.2956, -2.3485],
        [-0.1467,  4.8632]], device='cuda:0')), ('fc1.bias', tensor([ 0.7222, -2.
↪1771], device='cuda:0')), ('fc2.weight', tensor([[-2.9656,  6.3072]], device='cuda:0
↪')), ('fc2.bias', tensor([-1.8895], device='cuda:0'))])
```

Important: In PyTorch, models have a train() method which, somewhat disappointingly, does NOT perform a training step. Its only purpose is to set the model to **training mode**. Why is this important? Some models may use mechanisms like Dropout, for instance, which have distinct behaviors during training and evaluation phases.

It is good practice to call `model.train()` in the training loop. It is also possible to set a model to evaluation mode. We will see this in later labs.

Your Turn

Put the returned weights and biases into the XOR neural network diagram and try to work out the output when the input is `[0,0]`.

Inference (Forward Pass)

Instead of verifying it maually, we can test out our XOR model, with input [0,1] by called the model with the input. Note we do not call the forward function directly, instead we provide input to the model.

```
model(torch.tensor([0.,1.]).to(device))
```

```
tensor([0.9715], device='cuda:0', grad_fn=<SigmoidBackward>)
```

6.4.4 Logging the model training for Visualisation in TensorBoard

TensorBoard by TensorFlow is a very useful tool for visualising training progress and model architectures, despite being a competiting platform, PyTorch provides classes and methods for us to integrate it with our model.

TensorBoard can be loaded inside Jupyter notebooks, or can be started externally from a command line. Before we run TensorBoard, we need to change to the directory of your model code, and create a folder, e.g. `runs` to keep a log of the training progress.

The examples in this lab are running Tensorboard inside a notebook, but it is a good idea to run TensorBoard on the command line by giving the log directory. Assuming you are one level up the `runs` directory:

```
tensorboard --logdir runs
```

If successful, it will say that `TensorBoard 2.6.0 at http://localhost:6006/ (Press CTRL+C to quit)`, copy and paste the URL to your browser to see TensorBoard in action.

```
%load_ext tensorboard
```

TensorBoard running in Jupyter Notebook

```
%tensorboard --logdir runs
```

SummaryWriter

It all starts with the creation of a SummaryWriter. TensorBoard to look for logs inside the `runs` folder, it only makes sense to actually log to that folder. Moreover, to be able to distinguish between different experiments or models, we should also specify a sub-folder: test.

If we do not specify any folder, TensorBoard will default to `runs/CURRENT_DATETIME_HOSTNAME`, which is not such a great name if you'd be looking for your experiment results in the future.

So, it is recommended to try to name it in a more meaningful way, like runs/test or runs/simple_linear_regression. It will then create a subfolder inside runs (the folder we specified when we started TensorBoard).

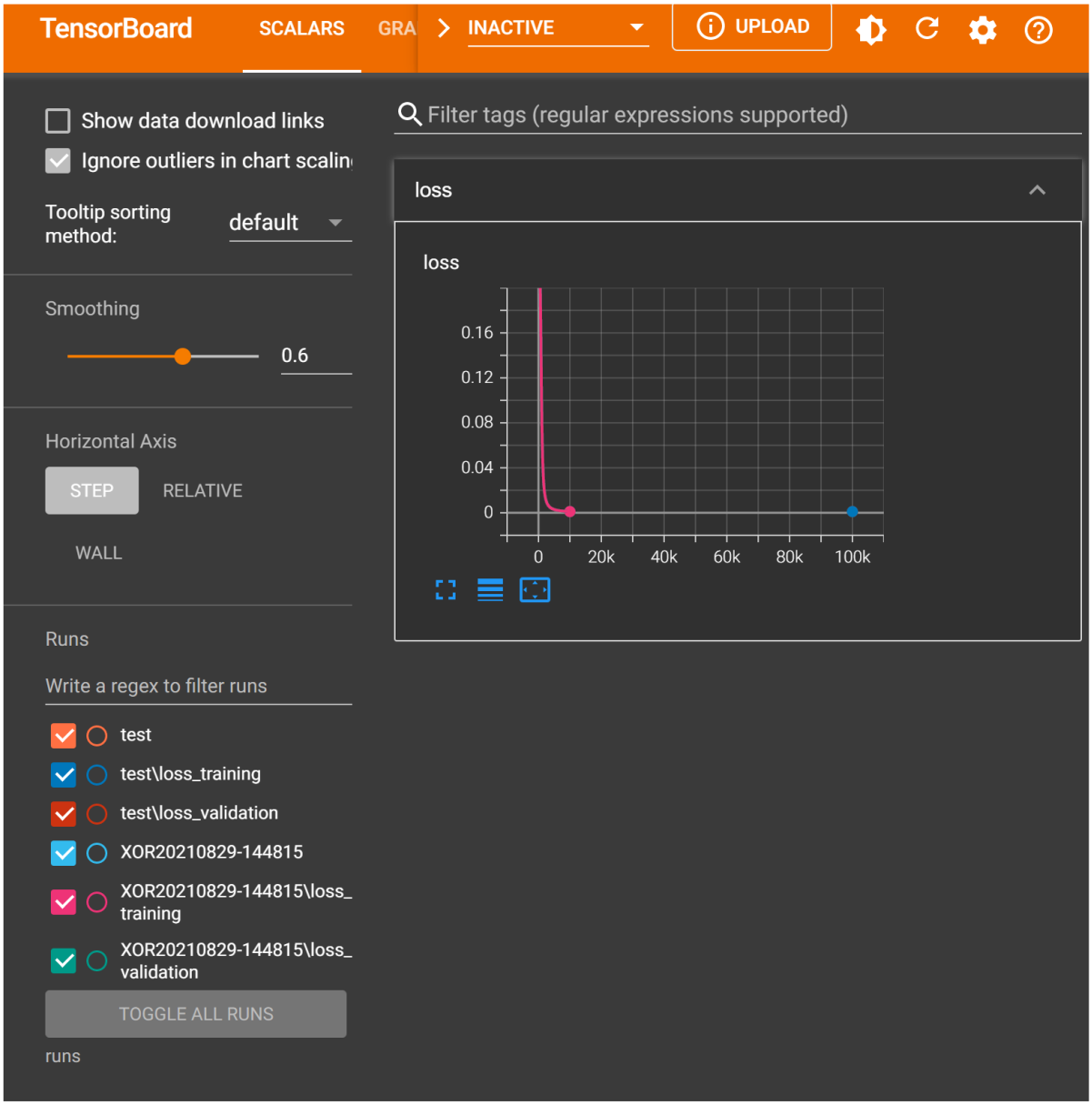
Even better, you should name it in a meaningful way and add datetime or a sequential number as a suffix, like `runs/test_001` or `runs/test_20200502172130`, to avoid writing data of multiple runs into the same folder (we'll see why this is bad in the add_scalars section below).

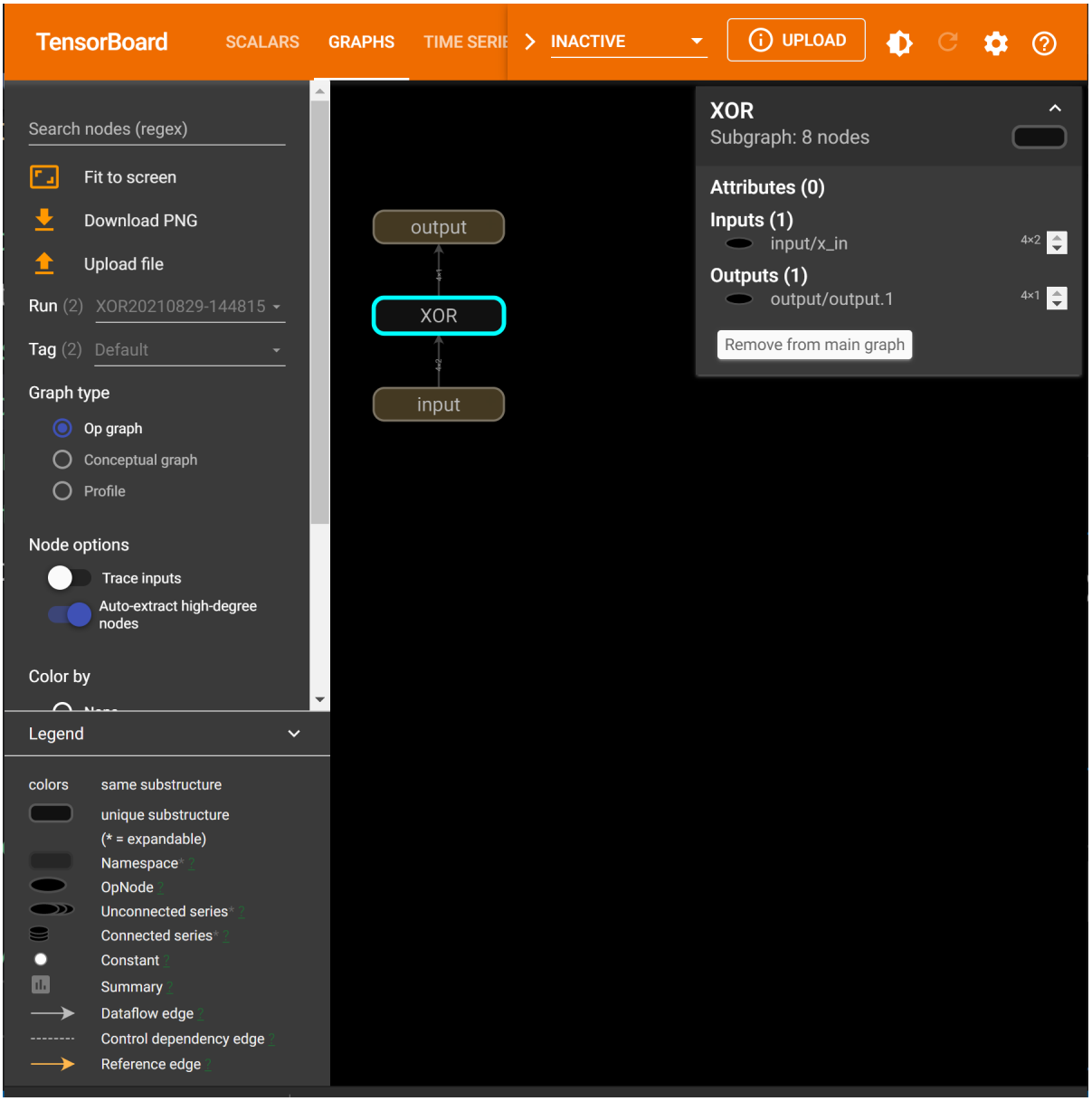
```
from torch.utils.tensorboard import SummaryWriter
writer = SummaryWriter('runs/test')
```

add_graph

It will produce an input-output graph that allows you to interactively inspect parameters, which is different from the TorchViz's computation graph (a static visualisation - not interactive).

```
writer.add_graph(model, x_train_tensor)
%tensorboard --logdir runs
```


TensorBoard
SCALARS
GRA
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scalin
Tooltip sorting method:
default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
test
test\loss_training
test\loss_validation
XOR20210829-144815
XOR20210829-144815\loss_training
XOR20210829-144815\loss_validation
TOGGLE ALL RUNS
runs
Filter tags (regular expressions supported)
loss
loss
0.16
0.12
0.08
0.04
0
0
20k
40k
60k
80k
100k


TensorBoard
SCALARS
GRAPHS
TIME SERIE
INACTIVE
UPLOAD
Search nodes (regex)
Fit to screen
Download PNG
Upload file
Run (2)
XOR20210829-144815
Tag (2)
Default
Graph type
Op graph
Conceptual graph
Profile
Node options
Trace inputs
Auto-extract high-degree nodes
Color by
Legend
colors
same substructure
unique substructure
(* = expandable)
Namespace*
OpNode
Unconnected series*
Connected series*
Constant
Summary
Dataflow edge
Control dependency edge
Reference edge
output
XOR
input
XOR
Subgraph: 8 nodes
Attributes (0)
Inputs (1)
input/x_in
4×2
Outputs (1)
output/output.1
4×1
Remove from main graph

add_scalar

We can send the loss values to TensorBoard using the `add_scalars` method to send multiple scalar values at once, and it needs three arguments:

- main_tag: the parent name of the tags or, the "group tag"
- tag_scalar_dict: the dictionary containing the key: value pairs for the scalars you want to keep track of (can be training and validation losses)
- global_step: step value, that is, the index you're associating with the values you're sending in the dictionary - the epoch comes to mind in our case, as losses are computed for each epoch

```
writer.add_scalars(main_tag='loss',
    tag_scalar_dict={'training': loss,
                     'validation': loss},
    global_step=epoch
)
```

If you run the code above after performing the model training, it will just send both loss values computed for the last epoch.

```
%tensorboard --logdir runs
```

```
from datetime import datetime
# Sets learning rate - this is "eta" ~ the "n" like
# Greek letter
lr = 0.1

# Step 0 - Initializes parameters "b" and "w" randomly
torch.manual_seed(42)
# Now we can create a model and send it at once to the device
model = XOR(2,1)
model = model.to(device)

# Defines a SGD optimizer to update the parameters
# (now retrieved directly from the model)
optimizer = optim.SGD(model.parameters(), lr=lr)

# Defines a MSE loss function
loss_fn = nn.MSELoss(reduction='mean')

# Tensorboard setup
writer = SummaryWriter('runs/XOR' + datetime.now().strftime("%Y%m%d-%H%M%S"))
writer.add_graph(model, x_train_tensor.to(device))

# Defines number of epochs
n_epochs = 10000

losses = []
val_losses = [] # note we did not use the validation data
for epoch in range(n_epochs):
    #for j in range(steps):
    model.train() # What is this?!?

    # Step 1 - Computes model's predicted output - forward pass
    # No more manual prediction!
    yhat = model(x_train_tensor)
```

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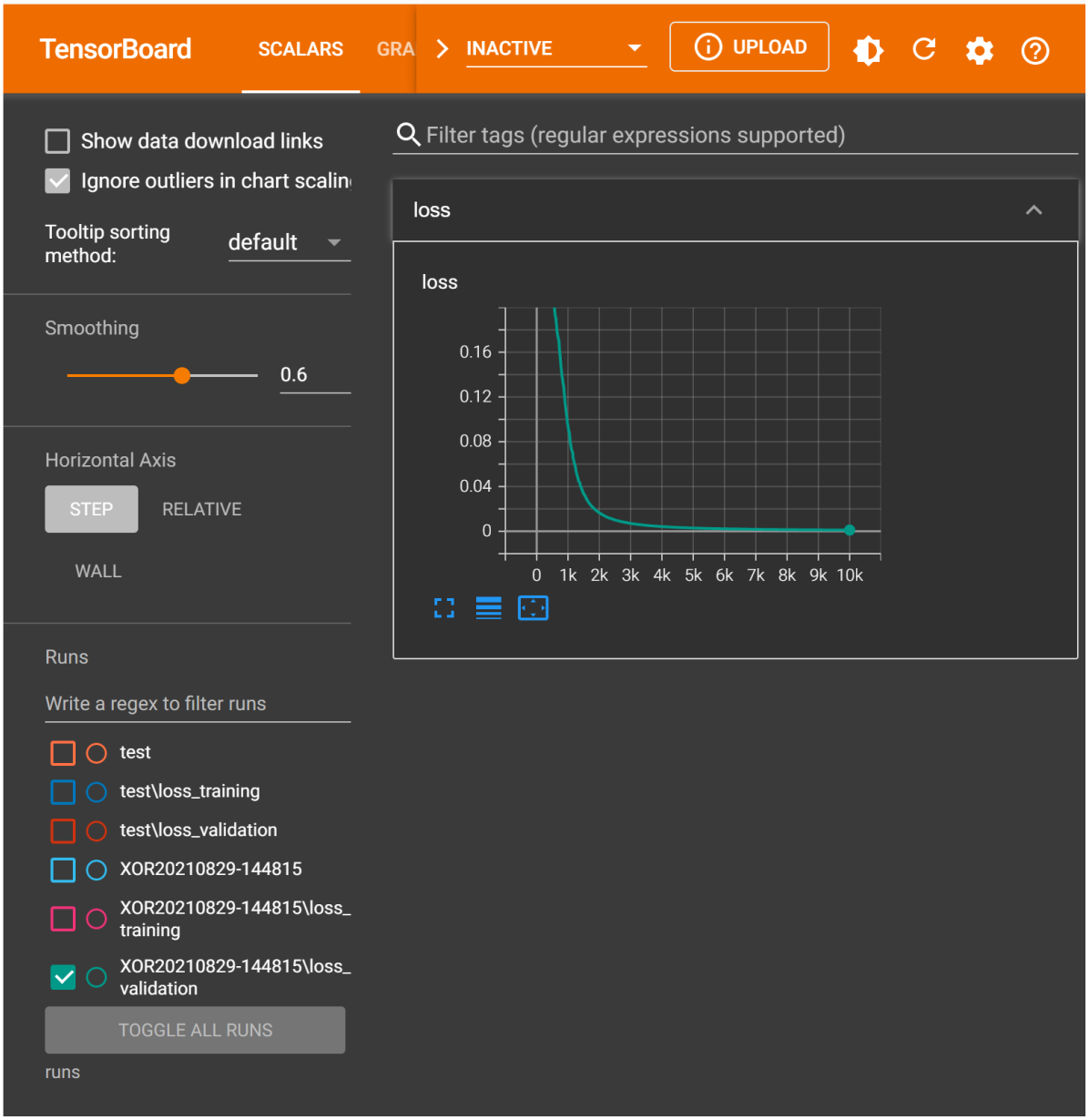
TensorBoard
SCALARS
GRA
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scalin
Tooltip sorting method:
default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
test
test\loss_training
test\loss_validation
XOR20210829-144815
XOR20210829-144815\loss_training
XOR20210829-144815\loss_validation
TOGGLE ALL RUNS
runs
Filter tags (regular expressions supported)
loss
loss
0.16
0.12
0.08
0.04
0
0 1k 2k 3k 4k 5k 6k 7k 8k 9k 10k

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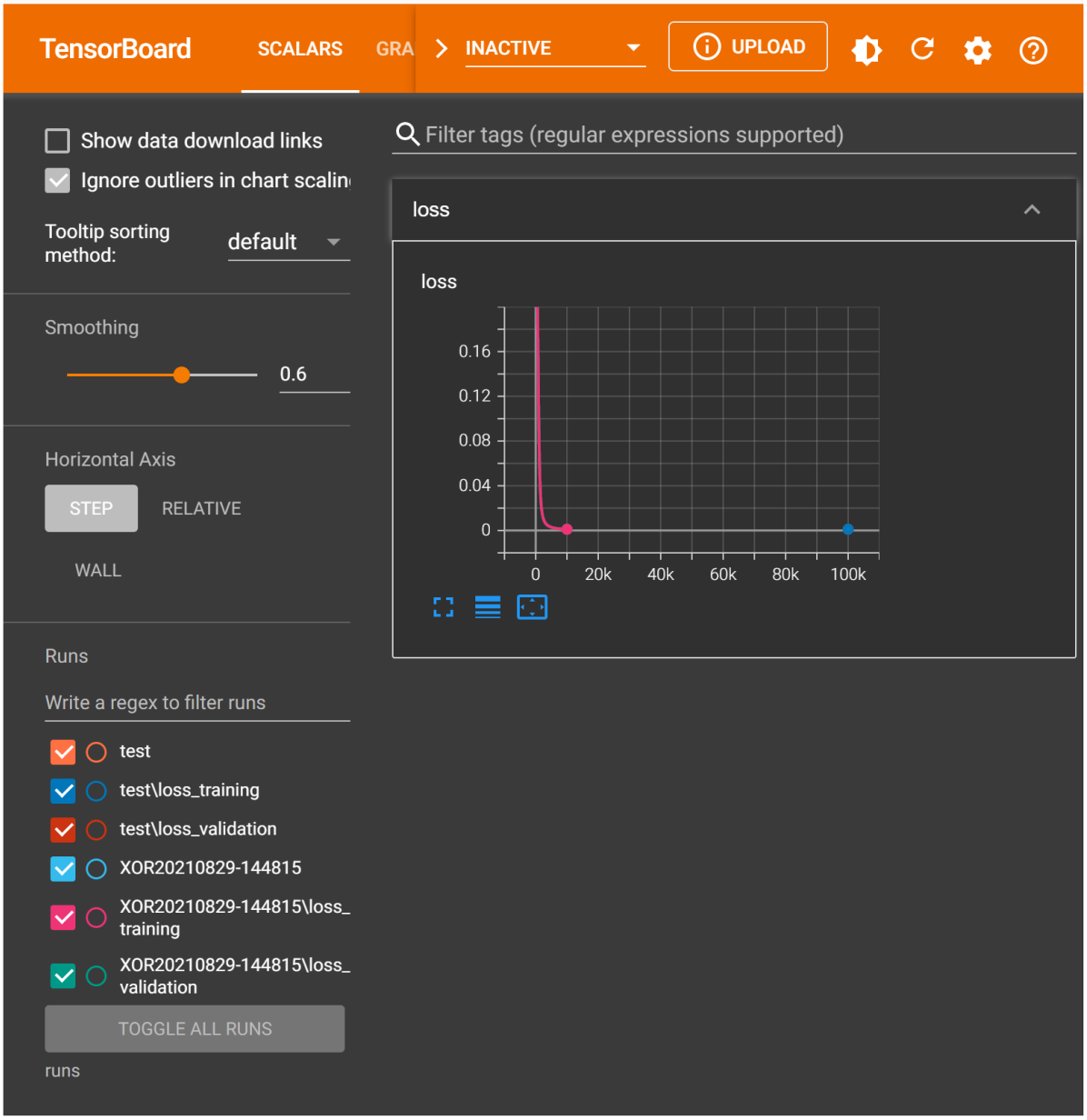
```
    # Step 2 - Computes the loss
    loss = loss_fn(yhat, y_train_tensor)

    # Step 3 - Computes gradients for both "b" and "w" parameters
    loss.backward()

    # Step 4 - Updates parameters using gradients and
    # the learning rate
    optimizer.step()
    optimizer.zero_grad()
    if (epoch % 500 == 0):
        print("Epoch: {0}, Loss: {1}, ".
            format(epoch, loss.to("cpu").detach().numpy()))

    losses.append(loss)
    writer.add_scalars(main_tag='loss',
                       tag_scalar_dict={'training': loss,
                                        'validation': loss},
                       global_step=epoch)

writer.close()
```

```
Epoch: 0, Loss: 0.27375736832618713,
Epoch: 500, Loss: 0.2081705629825592,
Epoch: 1000, Loss: 0.09176724404096603,
Epoch: 1500, Loss: 0.03289078176021576,
Epoch: 2000, Loss: 0.016263967379927635,
Epoch: 2500, Loss: 0.009998900815844536,
Epoch: 3000, Loss: 0.006978640332818031,
Epoch: 3500, Loss: 0.005261328537017107,
Epoch: 4000, Loss: 0.00416548689827323,
Epoch: 4500, Loss: 0.0034290249459445477,
Epoch: 5000, Loss: 0.002894176635891199,
Epoch: 5500, Loss: 0.002497166395187378,
Epoch: 6000, Loss: 0.0021936693228781223,
Epoch: 6500, Loss: 0.0019435270223766565,
Epoch: 7000, Loss: 0.0017444714903831482,
Epoch: 7500, Loss: 0.0015824229922145605,
Epoch: 8000, Loss: 0.001446553273126483,
Epoch: 8500, Loss: 0.0013299942947924137,
Epoch: 9000, Loss: 0.00122724543325603,
Epoch: 9500, Loss: 0.0011413537431508303,
```

```
%tensorboard --logdir runs
```

Note: In the TensorBoard logged run, we increased the learning rate and shortened the number of epochs. Play with these two parameters to see what you can get. Or change the loss function to BCE or BCEWithLogits to see how your training loss changes.


TensorBoard
SCALARS
GRA
INACTIVE
UPLOAD
Show data download links
Ignore outliers in chart scalin
Tooltip sorting method:
default
Smoothing
0.6
Horizontal Axis
STEP
RELATIVE
WALL
Runs
Write a regex to filter runs
test
test\loss_training
test\loss_validation
XOR20210829-144815
XOR20210829-144815\loss_training
XOR20210829-144815\loss_validation
TOGGLE ALL RUNS
runs
Filter tags (regular expressions supported)
loss
loss
0.16
0.12
0.08
0.04
0
0
20k
40k
60k
80k
100k

CHAPTER

SEVEN

LAB07: WORD EMBEDDINGS

Word Vectors are often used as a fundamental component for downstream NLP tasks, e.g. question answering, text generation, translation, etc., so it is important to build some intuitions as to their strengths and weaknesses. Here, you will explore two types of word vectors: those derived from *co-occurrence matrices*, and those derived via *GloVe*.

Note: The terms "word vectors" and "word embeddings" are often used interchangeably. The term "embedding" refers to the fact that we are encoding aspects of a word's meaning in a lower dimensional space. As Wikipedia states, "*conceptually it involves a mathematical embedding from a space with one dimension per word (one-hot encoding) to a continuous vector space with a much lower dimension*".

In this lab, we will look at how to use SVD on Word-Word co-ocurrence matrix to obtain word embeddings, and then visualising pretrained word embeddings using Matplotlib and TSNE, finally we train our own embeddings using a document crawled from the Web, and copmare with the pre-trained embeddings.

Credit: the notebooks are adapted from the Stanford CS224N Assignment on Exploring Word Vectors.

7.1 Environment Update with more packages

7.1.1 Install gensim

Note this will install the latest gensim 4.x

```
conda install -c conda-forge gensim
```

7.1.2 Install import-ipynb

This is a package to import functions from other Jupyter Notebooks.

```
pip install import-ipynb
```

7.1.3 Install Python Levenshtein Similarity

```
pip install python-Levenshtein
```

7.1.4 Install interactive visualisation bokeh

```
pip install bokeh
```

7.1.5 Install bs4 to get BeautifulSoup for web crawling

```
pip install bs4
```

7.2 Word Vectors from Word-Word Coocurrence Matrix

Let's take a look at how to use SVD on Word Coocurrence Matrix to obtain word vectors.

```
# All Import Statements Defined Here
# ----------------

import sys
assert sys.version_info[0]==3
assert sys.version_info[1] >= 5

from gensim.models import KeyedVectors
from gensim.test.utils import datapath
import pprint
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10, 5]
import nltk
nltk.download('reuters')
from nltk.corpus import reuters
import numpy as np
import random
import scipy as sp
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import PCA

START_TOKEN = '<START>'
END_TOKEN = '<END>'

np.random.seed(0)
random.seed(0)
# ----------------
```

```
C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\gensim\similarities\__init__.
↪py:15: UserWarning: The gensim.similarities.levenshtein submodule is disabled,␣
↪because the optional Levenshtein package <https://pypi.org/project/python-
↪Levenshtein/> is unavailable. Install Levenhstein (e.g. `pip install python-
↪Levenshtein`) to suppress this warning.
 warnings.warn(msg)
```

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```
[nltk_data] Downloading package reuters to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package reuters is already up-to-date!
```

Most word vector models start from the following idea:

You shall know a word by the company it keeps (Firth, J. R. 1957:11)

Many word vector implementations are driven by the idea that similar words, i.e., (near) synonyms, will be used in similar contexts. As a result, similar words will often be spoken or written along with a shared subset of words, i.e., contexts. By examining these contexts, we can try to develop embeddings for our words. With this intuition in mind, many "old school" approaches to constructing word vectors relied on word counts. Here we elaborate upon one of those strategies, *co-occurrence matrices* (for more information, see here or here).

7.2.1 Co-Occurrence Matrix - Revisited

A co-occurrence matrix counts how often things co-occur in some environment. Given some word w_i occurring in the document, we consider the *context window* surrounding w_i. Supposing our fixed window size is n, then this is the n preceding and n subsequent words in that document, i.e. words $w_{i-n} \dots w_{i-1}$ and $w_{i+1} \dots w_{i+n}$. We build a *co-occurrence matrix* M, which is a symmetric word-by-word matrix in which M_{ij} is the number of times w_j appears inside w_i's window among all documents.

Example: Co-Occurrence with Fixed Window of n=1:

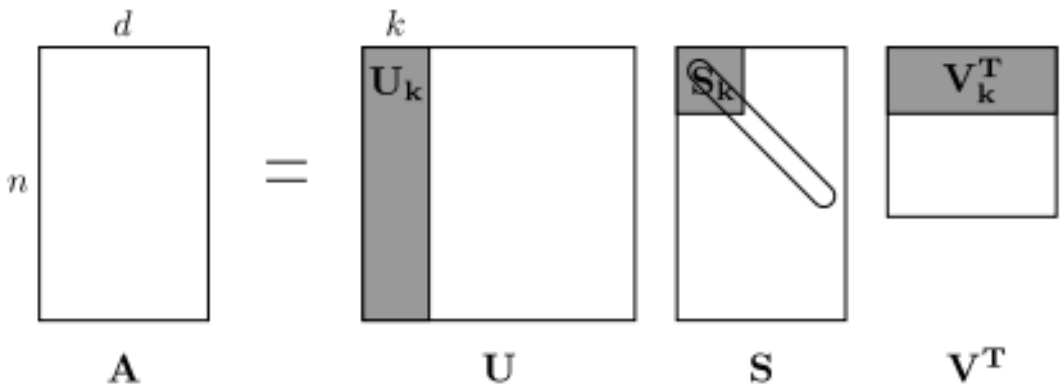
Document 1: "all that glitters is not gold"

Document 2: "all is well that ends well"

*	<START>	all	that	glitters	is	not	gold	well	ends	<END>
<START>	0	2	0	0	0	0	0	0	0	0
all	2	0	1	0	1	0	0	0	0	0
that	0	1	0	1	0	0	0	1	1	0
glitters	0	0	1	0	1	0	0	0	0	0
is	0	1	0	1	0	1	0	1	0	0
not	0	0	0	0	1	0	1	0	0	0
gold	0	0	0	0	0	1	0	0	0	1
well	0	0	1	0	1	0	0	0	1	1
ends	0	0	1	0	0	0	0	1	0	0
<END>	0	0	0	0	0	0	1	1	0	0

Note: In NLP, we often add <START> and <END> tokens to represent the beginning and end of sentences, paragraphs or documents. In thise case we imagine <START> and <END> tokens encapsulating each document, e.g., "<START> All that glitters is not gold <END>", and include these tokens in our co-occurrence counts.

The rows (or columns) of this matrix provide one type of word vectors (those based on word-word co-occurrence), but the vectors will be large in general (linear in the number of distinct words in a corpus). Thus, our next step is to run *dimensionality reduction*. In particular, we will run *SVD (Singular Value Decomposition)*, which is a kind of generalized *PCA (Principal Components Analysis)* to select the top k principal components. Here's a visualization of dimensionality reduction with SVD. In this picture our co-occurrence matrix is A with n rows corresponding to n words. We obtain a full matrix decomposition, with the singular values ordered in the diagonal S matrix, and our new, shorter length-k word vectors in U_k.



This reduced-dimensionality co-occurrence representation preserves semantic relationships between words, e.g. *doctor* and *hospital* will be closer than *doctor* and *dog*.

Note: If you can barely remember what an eigenvalue is, here's a slow, friendly introduction to SVD. If you want to learn more thoroughly about PCA or SVD, feel free to check out lectures 7, 8, and 9 of CS168. These course notes provide a great high-level treatment of these general purpose algorithms. Though, for the purpose of this class, you only need to know how to extract the k-dimensional embeddings by utilizing pre-programmed implementations of these algorithms from the numpy, scipy, or sklearn python packages. In practice, it is challenging to apply full SVD to large corpora because of the memory needed to perform PCA or SVD. However, if you only want the top k vector components for relatively small k — known as Truncated SVD — then there are reasonably scalable techniques to compute those iteratively.

7.2.2 Plotting Co-Occurrence Word Embeddings

Here, we will be using the Reuters (business and financial news) corpus. If you haven't run the import cell at the top of this page, please run it now (click it and press SHIFT-RETURN). The corpus consists of 10,788 news documents totaling 1.3 million words. These documents span 90 categories and are split into train and test. For more details, please see https://www.nltk.org/book/ch02.html. We provide a `read_corpus` function below that pulls out only articles from the "crude" (i.e. news articles about oil, gas, etc.) category. The function also adds `<START>` and `<END>` tokens to each of the documents, and lowercases words. You do **not** have to perform any other kind of pre-processing.

```
def read_corpus(category="crude"):
    """ Read files from the specified Reuter's category.
        Params:
            category (string): category name
        Return:
            list of lists, with words from each of the processed files
    """
    files = reuters.fileids(category)
    return [[START_TOKEN] + [w.lower() for w in list(reuters.words(f))] + [END_TOKEN]␣
↪for f in files]
```

Let's have a look what these documents are like….

```
reuters_corpus = read_corpus()
pprint.pprint(reuters_corpus[:3], compact=True, width=100)
```

```
[['<START>', 'japan', 'to', 'revise', 'long', '-', 'term', 'energy', 'demand',
↪'downwards', 'the',
 'ministry', 'of', 'international', 'trade', 'and', 'industry', '(', 'miti', ')',
↪'will', 'revise',
 'its', 'long', '-', 'term', 'energy', 'supply', '/', 'demand', 'outlook', 'by',
↪'august', 'to',
 'meet', 'a', 'forecast', 'downtrend', 'in', 'japanese', 'energy', 'demand', ',',
↪'ministry',
 'officials', 'said', '.', 'miti', 'is', 'expected', 'to', 'lower', 'the',
↪'projection', 'for',
 'primary', 'energy', 'supplies', 'in', 'the', 'year', '2000', 'to', '550', 'mln',
↪'kilolitres',
 '(', 'kl', ')', 'from', '600', 'mln', ',', 'they', 'said', '.', 'the', 'decision',
↪'follows',
 'the', 'emergence', 'of', 'structural', 'changes', 'in', 'japanese', 'industry',
↪'following',
 'the', 'rise', 'in', 'the', 'value', 'of', 'the', 'yen', 'and', 'a', 'decline', 'in
↪', 'domestic',
 'electric', 'power', 'demand', '.', 'miti', 'is', 'planning', 'to', 'work', 'out',
↪'a', 'revised',
 'energy', 'supply', '/', 'demand', 'outlook', 'through', 'deliberations', 'of',
↪'committee',
 'meetings', 'of', 'the', 'agency', 'of', 'natural', 'resources', 'and', 'energy', ',
↪', 'the',
 'officials', 'said', '.', 'they', 'said', 'miti', 'will', 'also', 'review', 'the',
↪'breakdown',
 'of', 'energy', 'supply', 'sources', ',', 'including', 'oil', ',', 'nuclear', ',',
↪'coal', 'and',
 'natural', 'gas', '.', 'nuclear', 'energy', 'provided', 'the', 'bulk', 'of', 'japan
↪', "'", 's',
 'electric', 'power', 'in', 'the', 'fiscal', 'year', 'ended', 'march', '31', ',',
↪'supplying',
 'an', 'estimated', '27', 'pct', 'on', 'a', 'kilowatt', '/', 'hour', 'basis', ',',
↪'followed',
 'by', 'oil', '(', '23', 'pct', ')', 'and', 'liquefied', 'natural', 'gas', '(', '21',
↪ 'pct', '),',
 'they', 'noted', '.', '<END>'],
['<START>', 'energy', '/', 'u', '.', 's', '.', 'petrochemical', 'industry', 'cheap',
↪'oil',
 'feedstocks', ',', 'the', 'weakened', 'u', '.', 's', '.', 'dollar', 'and', 'a',
↪'plant',
 'utilization', 'rate', 'approaching', '90', 'pct', 'will', 'propel', 'the',
↪'streamlined', 'u',
 '.', 's', '.', 'petrochemical', 'industry', 'to', 'record', 'profits', 'this', 'year
↪', ',',
 'with', 'growth', 'expected', 'through', 'at', 'least', '1990', ',', 'major',
↪'company',
 'executives', 'predicted', '.', 'this', 'bullish', 'outlook', 'for', 'chemical',
↪'manufacturing',
 'and', 'an', 'industrywide', 'move', 'to', 'shed', 'unrelated', 'businesses', 'has',
↪ 'prompted',
 'gaf', 'corp', '&', 'lt', ';', 'gaf', '>,', 'privately', '-', 'held', 'cain',
↪'chemical', 'inc',
 ',', 'and', 'other', 'firms', 'to', 'aggressively', 'seek', 'acquisitions', 'of',
↪'petrochemical',
 'plants', '.', 'oil', 'companies', 'such', 'as', 'ashland', 'oil', 'inc', '&', 'lt',
↪ ';', 'ash',
```

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```
 '>,', 'the', 'kentucky', '-', 'based', 'oil', 'refiner', 'and', 'marketer', ',',
↪'are', 'also',
 'shopping', 'for', 'money', '-', 'making', 'petrochemical', 'businesses', 'to', 'buy
↪', '.', '"',
 'i', 'see', 'us', 'poised', 'at', 'the', 'threshold', 'of', 'a', 'golden', 'period',
↪ ',"', 'said',
 'paul', 'oreffice', ',', 'chairman', 'of', 'giant', 'dow', 'chemical', 'co', '&',
↪'lt', ';',
 'dow', '>,', 'adding', ',', '"', 'there', "'", 's', 'no', 'major', 'plant',
↪'capacity', 'being',
 'added', 'around', 'the', 'world', 'now', '.', 'the', 'whole', 'game', 'is',
↪'bringing', 'out',
 'new', 'products', 'and', 'improving', 'the', 'old', 'ones', '."', 'analysts', 'say
↪', 'the',
 'chemical', 'industry', "'", 's', 'biggest', 'customers', ',', 'automobile',
↪'manufacturers',
 'and', 'home', 'builders', 'that', 'use', 'a', 'lot', 'of', 'paints', 'and',
↪'plastics', ',',
 'are', 'expected', 'to', 'buy', 'quantities', 'this', 'year', '.', 'u', '.', 's', '.
↪',
 'petrochemical', 'plants', 'are', 'currently', 'operating', 'at', 'about', '90',
↪'pct',
 'capacity', ',', 'reflecting', 'tighter', 'supply', 'that', 'could', 'hike',
↪'product', 'prices',
 'by', '30', 'to', '40', 'pct', 'this', 'year', ',', 'said', 'john', 'dosher', ',',
↪'managing',
 'director', 'of', 'pace', 'consultants', 'inc', 'of', 'houston', '.', 'demand', 'for
↪', 'some',
 'products', 'such', 'as', 'styrene', 'could', 'push', 'profit', 'margins', 'up', 'by
↪', 'as',
 'much', 'as', '300', 'pct', ',', 'he', 'said', '.', 'oreffice', ',', 'speaking', 'at
↪', 'a',
 'meeting', 'of', 'chemical', 'engineers', 'in', 'houston', ',', 'said', 'dow',
↪'would', 'easily',
 'top', 'the', '741', 'mln', 'dlrs', 'it', 'earned', 'last', 'year', 'and',
↪'predicted', 'it',
 'would', 'have', 'the', 'best', 'year', 'in', 'its', 'history', '.', 'in', '1985',
↪',', 'when',
 'oil', 'prices', 'were', 'still', 'above', '25', 'dlrs', 'a', 'barrel', 'and',
↪'chemical',
 'exports', 'were', 'adversely', 'affected', 'by', 'the', 'strong', 'u', '.', 's', '.
↪', 'dollar',
 ',', 'dow', 'had', 'profits', 'of', '58', 'mln', 'dlrs', '.', '"', 'i', 'believe',
↪'the',
 'entire', 'chemical', 'industry', 'is', 'headed', 'for', 'a', 'record', 'year', 'or
↪', 'close',
 'to', 'it', ',"', 'oreffice', 'said', '.', 'gaf', 'chairman', 'samuel', 'heyman',
↪'estimated',
 'that', 'the', 'u', '.', 's', '.', 'chemical', 'industry', 'would', 'report', 'a',
↪'20', 'pct',
 'gain', 'in', 'profits', 'during', '1987', '.', 'last', 'year', ',', 'the',
↪'domestic',
 'industry', 'earned', 'a', 'total', 'of', '13', 'billion', 'dlrs', ',', 'a', '54',
↪'pct', 'leap',
 'from', '1985', '.', 'the', 'turn', 'in', 'the', 'fortunes', 'of', 'the', 'once', '-
↪', 'sickly',
 'chemical', 'industry', 'has', 'been', 'brought', 'about', 'by', 'a', 'combination',
↪ 'of', 'luck',
```

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```
 'and', 'planning', ',', 'said', 'pace', "'", 's', 'john', 'dosher', '.', 'dosher',
↪'said', 'last',
 'year', "'", 's', 'fall', 'in', 'oil', 'prices', 'made', 'feedstocks', 'dramatically
↪', 'cheaper',
 'and', 'at', 'the', 'same', 'time', 'the', 'american', 'dollar', 'was', 'weakening',
↪ 'against',
 'foreign', 'currencies', '.', 'that', 'helped', 'boost', 'u', '.', 's', '.',
↪'chemical',
 'exports', '.', 'also', 'helping', 'to', 'bring', 'supply', 'and', 'demand', 'into',
↪ 'balance',
 'has', 'been', 'the', 'gradual', 'market', 'absorption', 'of', 'the', 'extra',
↪'chemical',
 'manufacturing', 'capacity', 'created', 'by', 'middle', 'eastern', 'oil', 'producers
↪', 'in',
 'the', 'early', '1980s', '.', 'finally', ',', 'virtually', 'all', 'major', 'u', '.',
↪ 's', '.',
 'chemical', 'manufacturers', 'have', 'embarked', 'on', 'an', 'extensive', 'corporate
↪',
 'restructuring', 'program', 'to', 'mothball', 'inefficient', 'plants', ',', 'trim',
↪'the',
 'payroll', 'and', 'eliminate', 'unrelated', 'businesses', '.', 'the', 'restructuring
↪', 'touched',
 'off', 'a', 'flurry', 'of', 'friendly', 'and', 'hostile', 'takeover', 'attempts', '.
↪', 'gaf', ',',
 'which', 'made', 'an', 'unsuccessful', 'attempt', 'in', '1985', 'to', 'acquire',
↪'union',
 'carbide', 'corp', '&', 'lt', ';', 'uk', '>,', 'recently', 'offered', 'three',
↪'billion', 'dlrs',
 'for', 'borg', 'warner', 'corp', '&', 'lt', ';', 'bor', '>,', 'a', 'chicago',
↪'manufacturer',
 'of', 'plastics', 'and', 'chemicals', '.', 'another', 'industry', 'powerhouse', ',',
↪ 'w', '.',
 'r', '.', 'grace', '&', 'lt', ';', 'gra', '>', 'has', 'divested', 'its', 'retailing
↪', ',',
 'restaurant', 'and', 'fertilizer', 'businesses', 'to', 'raise', 'cash', 'for',
↪'chemical',
 'acquisitions', '.', 'but', 'some', 'experts', 'worry', 'that', 'the', 'chemical',
↪'industry',
 'may', 'be', 'headed', 'for', 'trouble', 'if', 'companies', 'continue', 'turning',
↪'their',
 'back', 'on', 'the', 'manufacturing', 'of', 'staple', 'petrochemical', 'commodities
↪', ',', 'such',
 'as', 'ethylene', ',', 'in', 'favor', 'of', 'more', 'profitable', 'specialty',
↪'chemicals',
 'that', 'are', 'custom', '-', 'designed', 'for', 'a', 'small', 'group', 'of',
↪'buyers', '.', '"',
 'companies', 'like', 'dupont', '&', 'lt', ';', 'dd', '>', 'and', 'monsanto', 'co',
↪'&', 'lt', ';',
 'mtc', '>', 'spent', 'the', 'past', 'two', 'or', 'three', 'years', 'trying', 'to',
↪'get', 'out',
 'of', 'the', 'commodity', 'chemical', 'business', 'in', 'reaction', 'to', 'how',
↪'badly', 'the',
 'market', 'had', 'deteriorated', ',"', 'dosher', 'said', '.', '"', 'but', 'i',
↪'think', 'they',
 'will', 'eventually', 'kill', 'the', 'margins', 'on', 'the', 'profitable',
↪'chemicals', 'in',
 'the', 'niche', 'market', '."', 'some', 'top', 'chemical', 'executives', 'share',
↪'the',
```

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```
 'concern', '.', '"', 'the', 'challenge', 'for', 'our', 'industry', 'is', 'to', 'keep
↪', 'from',
 'getting', 'carried', 'away', 'and', 'repeating', 'past', 'mistakes', ',"', 'gaf', "
↪'", 's',
 'heyman', 'cautioned', '.', '"', 'the', 'shift', 'from', 'commodity', 'chemicals',
↪'may', 'be',
 'ill', '-', 'advised', '.', 'specialty', 'businesses', 'do', 'not', 'stay', 'special
↪', 'long',
 '."', 'houston', '-', 'based', 'cain', 'chemical', ',', 'created', 'this', 'month',
↪'by', 'the',
 'sterling', 'investment', 'banking', 'group', ',', 'believes', 'it', 'can',
↪'generate', '700',
 'mln', 'dlrs', 'in', 'annual', 'sales', 'by', 'bucking', 'the', 'industry', 'trend',
↪ '.',
 'chairman', 'gordon', 'cain', ',', 'who', 'previously', 'led', 'a', 'leveraged',
↪'buyout', 'of',
 'dupont', "'", 's', 'conoco', 'inc', "'", 's', 'chemical', 'business', ',', 'has',
↪'spent', '1',
 '.', '1', 'billion', 'dlrs', 'since', 'january', 'to', 'buy', 'seven',
↪'petrochemical', 'plants',
 'along', 'the', 'texas', 'gulf', 'coast', '.', 'the', 'plants', 'produce', 'only',
↪'basic',
 'commodity', 'petrochemicals', 'that', 'are', 'the', 'building', 'blocks', 'of',
↪'specialty',
 'products', '.', '"', 'this', 'kind', 'of', 'commodity', 'chemical', 'business',
↪'will', 'never',
 'be', 'a', 'glamorous', ',', 'high', '-', 'margin', 'business', ',"', 'cain', 'said
↪', ',',
 'adding', 'that', 'demand', 'is', 'expected', 'to', 'grow', 'by', 'about', 'three',
↪'pct',
 'annually', '.', 'garo', 'armen', ',', 'an', 'analyst', 'with', 'dean', 'witter',
↪'reynolds', ',',
 'said', 'chemical', 'makers', 'have', 'also', 'benefitted', 'by', 'increasing',
↪'demand', 'for',
 'plastics', 'as', 'prices', 'become', 'more', 'competitive', 'with', 'aluminum', ',
↪', 'wood',
 'and', 'steel', 'products', '.', 'armen', 'estimated', 'the', 'upturn', 'in', 'the',
↪ 'chemical',
 'business', 'could', 'last', 'as', 'long', 'as', 'four', 'or', 'five', 'years', ',',
↪ 'provided',
 'the', 'u', '.', 's', '.', 'economy', 'continues', 'its', 'modest', 'rate', 'of',
↪'growth', '.',
 '<END>'],
['<START>', 'turkey', 'calls', 'for', 'dialogue', 'to', 'solve', 'dispute', 'turkey',
↪ 'said',
 'today', 'its', 'disputes', 'with', 'greece', ',', 'including', 'rights', 'on', 'the
↪',
 'continental', 'shelf', 'in', 'the', 'aegean', 'sea', ',', 'should', 'be', 'solved',
↪ 'through',
 'negotiations', '.', 'a', 'foreign', 'ministry', 'statement', 'said', 'the', 'latest
↪', 'crisis',
 'between', 'the', 'two', 'nato', 'members', 'stemmed', 'from', 'the', 'continental',
↪ 'shelf',
 'dispute', 'and', 'an', 'agreement', 'on', 'this', 'issue', 'would', 'effect', 'the
↪', 'security',
 ',', 'economy', 'and', 'other', 'rights', 'of', 'both', 'countries', '.', '"', 'as',
↪ 'the',
```

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```
 'issue', 'is', 'basicly', 'political', ',', 'a', 'solution', 'can', 'only', 'be',
↪'found', 'by',
 'bilateral', 'negotiations', ',"', 'the', 'statement', 'said', '.', 'greece', 'has',
↪ 'repeatedly',
 'said', 'the', 'issue', 'was', 'legal', 'and', 'could', 'be', 'solved', 'at', 'the',
 'international', 'court', 'of', 'justice', '.', 'the', 'two', 'countries',
↪'approached', 'armed',
 'confrontation', 'last', 'month', 'after', 'greece', 'announced', 'it', 'planned',
↪'oil',
 'exploration', 'work', 'in', 'the', 'aegean', 'and', 'turkey', 'said', 'it', 'would
↪', 'also',
 'search', 'for', 'oil', '.', 'a', 'face', '-', 'off', 'was', 'averted', 'when',
↪'turkey',
 'confined', 'its', 'research', 'to', 'territorrial', 'waters', '.', '"', 'the',
↪'latest',
 'crises', 'created', 'an', 'historic', 'opportunity', 'to', 'solve', 'the',
↪'disputes', 'between',
 'the', 'two', 'countries', ',"', 'the', 'foreign', 'ministry', 'statement', 'said',
↪'.', 'turkey',
 "'", 's', 'ambassador', 'in', 'athens', ',', 'nazmi', 'akiman', ',', 'was', 'due',
↪'to', 'meet',
 'prime', 'minister', 'andreas', 'papandreou', 'today', 'for', 'the', 'greek', 'reply
↪', 'to', 'a',
 'message', 'sent', 'last', 'week', 'by', 'turkish', 'prime', 'minister', 'turgut',
↪'ozal', '.',
 'the', 'contents', 'of', 'the', 'message', 'were', 'not', 'disclosed', '.', '<END>
↪']]
```

7.2.3 Find `distinct_words`

Let's write a method to work out the distinct words (word types) that occur in the corpus. You can do this with `for` loops, but it's more efficient to do it with **Python list comprehensions**. In particular, this may be useful to flatten a list of lists. If you're not familiar with Python list comprehensions in general, here's more information.

You may find it useful to use Python sets to remove duplicate words.

```
def distinct_words(corpus):
    """ Determine a list of distinct words for the corpus.
        Params:
            corpus (list of list of strings): corpus of documents
        Return:
            corpus_words (list of strings): list of distinct words across the corpus,␣
↪sorted (using python 'sorted' function)
            num_corpus_words (integer): number of distinct words across the corpus
    """
    corpus_words = []
    num_corpus_words = -1

    # ------------------
    # Write your implementation here.
    corpus_words = sorted(list(set([y for x in corpus for y in x])))
#     corpus_words = [y for x in corpus for y in x]
#     corpus_words = list(set(corpus_words)) # unique words
#     corpus_words = sorted(corpus_words) # sorts
    num_corpus_words = len(corpus_words)
```

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```
    # ------------------

    return corpus_words, num_corpus_words
```

{Test-driven coding practice}

A good practice is to write test code to validate your program output against expected output.

```
# ---------------------
# Run this sanity check
# Note that this not an exhaustive check for correctness.
# Very simple tokenization using the Python string split
# with space - string.split(" ").
# ---------------------

# Define toy corpus
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TOKEN).
 ↪split(" "), "{} All's well that ends well {}".format(START_TOKEN, END_TOKEN).split(
 ↪" ")]
test_corpus_words, num_corpus_words = distinct_words(test_corpus)

# Correct answers
ans_test_corpus_words = sorted([START_TOKEN, "All", "ends", "that", "gold", "All's",
 ↪"glitters", "isn't", "well", END_TOKEN])
ans_num_corpus_words = len(ans_test_corpus_words)

# Test correct number of words
assert(num_corpus_words == ans_num_corpus_words), "Incorrect number of distinct words.
 ↪ Correct: {}. Yours: {}".format(ans_num_corpus_words, num_corpus_words)

# Test correct words
assert (test_corpus_words == ans_test_corpus_words), "Incorrect corpus_words.\
 ↪nCorrect: {}\nYours:   {}".format(str(ans_test_corpus_words), str(test_corpus_
 ↪words))

# Print Success
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
```

7.2.4 compute_co_occurrence_matrix

Write a method that constructs a co-occurrence matrix for a certain window-size n (with a default of 4), considering words n before and n after the word in the center of the window. Here, we start to use `numpy (np)` to represent vectors, matrices, and tensors. If you're not familiar with NumPy, there's a NumPy tutorial Python NumPy tutorial.

```
def compute_co_occurrence_matrix(corpus, window_size=4):
    """ Compute co-occurrence matrix for the given corpus and window_size (default of␣
↪4).

        Note: Each word in a document should be at the center of a window. Words near␣
↪edges will have a smaller
              number of co-occurring words.

              For example, if we take the document "<START> All that glitters is not␣
↪gold <END>" with window size of 4,
              "All" will co-occur with "<START>", "that", "glitters", "is", and "not".

        Params:
            corpus (list of list of strings): corpus of documents
            window_size (int): size of context window
        Return:
            M (a symmetric numpy matrix of shape (number of unique words in the␣
↪corpus , number of unique words in the corpus)):
                Co-occurence matrix of word counts.
                The ordering of the words in the rows/columns should be the same as␣
↪the ordering of the words given by the distinct_words function.
            word2Ind (dict): dictionary that maps word to index (i.e. row/column␣
↪number) for matrix M.
    """
    words, num_words = distinct_words(corpus)
    M = None
    word2Ind = {}

    # ------------------
    M = np.zeros((num_words, num_words))
    word2Ind = {w : i for i, w in enumerate(words)}


    for sentence in corpus:
        for cen_w_i, cen_w in enumerate(sentence): # center word
            for con_w_i in range(cen_w_i-window_size, cen_w_i+window_size+1): #␣
↪context word
                if(cen_w_i!=con_w_i and con_w_i>=0 and con_w_i<len(sentence)):

                    ce = word2Ind[cen_w]
                    co = word2Ind[sentence[con_w_i]]

                    M[ce][co] = M[ce][co] + 1

    # ------------------

    return M, word2Ind
```

```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness.
```

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```
# ---------------------

# Define toy corpus and get student's co-occurrence matrix
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TOKEN).
 ↪split(" "), "{} All's well that ends well {}".format(START_TOKEN, END_TOKEN).split(
 ↪" ")]
M_test, word2Ind_test = compute_co_occurrence_matrix(test_corpus, window_size=1)

# Correct M and word2Ind
M_test_ans = np.array(
    [[0., 0., 0., 0., 0., 0., 1., 0., 0., 1.,],
     [0., 0., 1., 1., 0., 0., 0., 0., 0., 0.,],
     [0., 1., 0., 0., 0., 0., 0., 0., 1., 0.,],
     [0., 1., 0., 0., 0., 0., 0., 0., 0., 1.,],
     [0., 0., 0., 0., 0., 0., 0., 0., 1., 1.,],
     [0., 0., 0., 0., 0., 0., 0., 1., 1., 0.,],
     [1., 0., 0., 0., 0., 0., 0., 1., 0., 0.,],
     [0., 0., 0., 0., 0., 1., 1., 0., 0., 0.,],
     [0., 0., 1., 0., 1., 1., 0., 0., 0., 1.,],
     [1., 0., 0., 1., 1., 0., 0., 0., 1., 0.,]]
)
ans_test_corpus_words = sorted([START_TOKEN, "All", "ends", "that", "gold", "All's",
 ↪"glitters", "isn't", "well", END_TOKEN])
word2Ind_ans = dict(zip(ans_test_corpus_words, range(len(ans_test_corpus_words))))

# Test correct word2Ind
assert (word2Ind_ans == word2Ind_test), "Your word2Ind is incorrect:\nCorrect: {}\
 ↪nYours: {}".format(word2Ind_ans, word2Ind_test)

# Test correct M shape
assert (M_test.shape == M_test_ans.shape), "M matrix has incorrect shape.\nCorrect: {}
 ↪\nYours: {}".format(M_test.shape, M_test_ans.shape)

# Test correct M values
for w1 in word2Ind_ans.keys():
    idx1 = word2Ind_ans[w1]
    for w2 in word2Ind_ans.keys():
        idx2 = word2Ind_ans[w2]
        student = M_test[idx1, idx2]
        correct = M_test_ans[idx1, idx2]
        if student != correct:
            print("Correct M:")
            print(M_test_ans)
            print("Your M: ")
            print(M_test)
            raise AssertionError("Incorrect count at index ({}, {})=({}, {}) in␣
 ↪matrix M. Yours has {} but should have {}.".format(idx1, idx2, w1, w2, student,␣
 ↪correct))

# Print Success
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
```

7.2.5 Using SVD to `reduce_to_k_dim`

Now let's construct a method that performs dimensionality reduction on the matrix to produce k-dimensional embeddings. Use SVD to take the top k components and produce a new matrix of k-dimensional embeddings.

Note: All of numpy, scipy, and scikit-learn (`sklearn`) provide *some* implementation of SVD, but only scipy and sklearn provide an implementation of Truncated SVD, and only sklearn provides an efficient randomized algorithm for calculating large-scale Truncated SVD. So please use sklearn.decomposition.TruncatedSVD.

```
import sklearn
def reduce_to_k_dim(M, k=2):
    """ Reduce a co-occurence count matrix of dimensionality (num_corpus_words, num_
 ↪corpus_words)
        to a matrix of dimensionality (num_corpus_words, k) using the following SVD␣
 ↪function from Scikit-Learn:
            - http://scikit-learn.org/stable/modules/generated/sklearn.decomposition.
 ↪TruncatedSVD.html

        Params:
            M (numpy matrix of shape (number of unique words in the corpus , number␣
 ↪of unique words in the corpus)): co-occurence matrix of word counts
            k (int): embedding size of each word after dimension reduction
        Return:
            M_reduced (numpy matrix of shape (number of corpus words, k)): matrix of␣
 ↪k-dimensioal word embeddings.
                    In terms of the SVD from math class, this actually returns U * S
    """
    n_iters = 10     # Use this parameter in your call to `TruncatedSVD`
    M_reduced = None
    print("Running Truncated SVD over %i words..." % (M.shape[0]))

        # ------------------
        # Write your implementation here.
    M_r = sklearn.decomposition.TruncatedSVD(n_components=k,
                                             algorithm='randomized',
                                             n_iter=n_iters,
                                             random_state=None,
                                             tol=0.0)
    M_reduced = M_r.fit_transform(M)
        # ------------------

    print("Done.")
    return M_reduced
```

```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness
# In fact we only check that your M_reduced has the right dimensions.
# ---------------------

# Define toy corpus and run student code
test_corpus = ["{} All that glitters isn't gold {}".format(START_TOKEN, END_TOKEN).
 ↪split(" "), "{} All's well that ends well {}".format(START_TOKEN, END_TOKEN).split(
 ↪" ")]
M_test, word2Ind_test = compute_co_occurrence_matrix(test_corpus, window_size=1)
```

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```
M_test_reduced = reduce_to_k_dim(M_test, k=2)

# Test proper dimensions
assert (M_test_reduced.shape[0] == 10), "M_reduced has {} rows; should have {}".
↪format(M_test_reduced.shape[0], 10)
assert (M_test_reduced.shape[1] == 2), "M_reduced has {} columns; should have {}".
↪format(M_test_reduced.shape[1], 2)

# Print Success
print ("-" * 80)
print("Passed All Tests!")
print ("-" * 80)
```

```
Running Truncated SVD over 10 words...
Done.
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
```

7.2.6 Visualise the embeddings using `plot_embeddings`

We can now write a function to plot a set of 2D vectors in 2D space. For graphs, we will use Matplotlib (`plt`).

For this example, you may find it useful to adapt this code. In the future, a good way to make a plot is to look at the Matplotlib gallery, find a plot that looks somewhat like what you want, and adapt the code they give.

```
def plot_embeddings(M_reduced, word2Ind, words):
    """ Plot in a scatterplot the embeddings of the words specified in the list "words
↪".
        NOTE: do not plot all the words listed in M_reduced / word2Ind.
        Include a label next to each point.

        Params:
            M_reduced (numpy matrix of shape (number of unique words in the corpus ,␣
↪2)): matrix of 2-dimensioal word embeddings
            word2Ind (dict): dictionary that maps word to indices for matrix M
            words (list of strings): words whose embeddings we want to visualize
    """

    # ------------------
    import matplotlib.pyplot as plt
    x_coords = M_reduced[:,0]
    y_coords = M_reduced[:,1]

    for word in words:
        i = word2Ind[word]
        x = x_coords[i]
        y = y_coords[i]
        plt.scatter(x, y, color='r', marker='x')
        plt.annotate(word, (x, y))
    plt.show()

    # ------------------
```

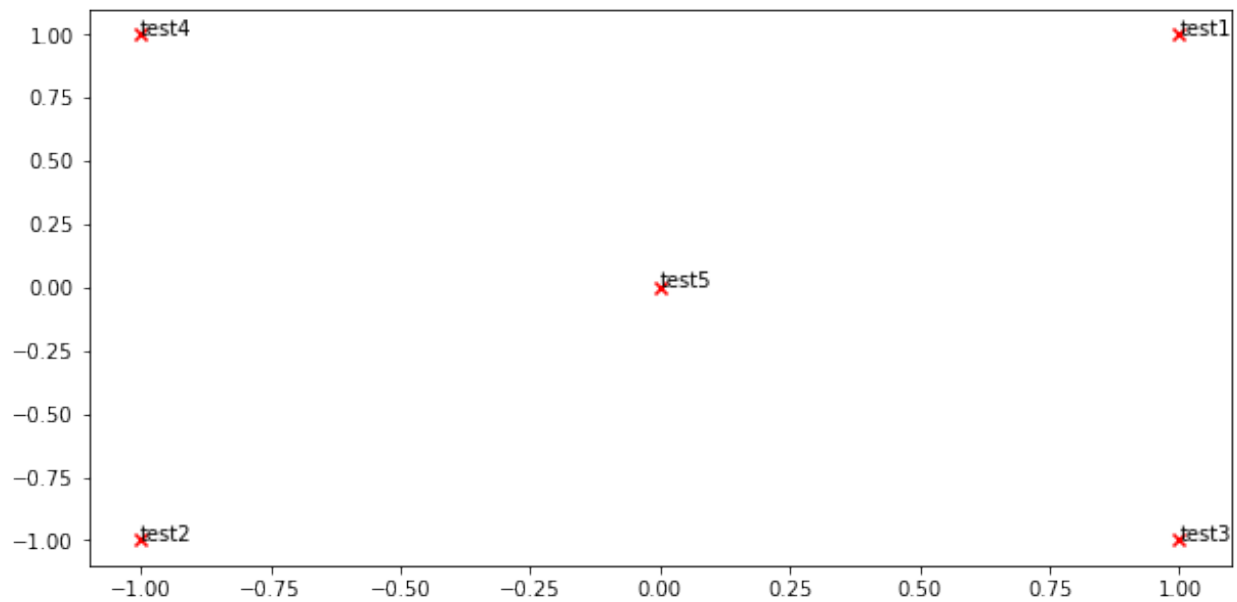
```
# ---------------------
# Run this sanity check
# Note that this is not an exhaustive check for correctness.
# The plot produced should look like the "test solution plot" depicted below.
# ---------------------

print ("-" * 80)
print ("Outputted Plot:")

M_reduced_plot_test = np.array([[1, 1], [-1, -1], [1, -1], [-1, 1], [0, 0]])
word2Ind_plot_test = {'test1': 0, 'test2': 1, 'test3': 2, 'test4': 3, 'test5': 4}
words = ['test1', 'test2', 'test3', 'test4', 'test5']
plot_embeddings(M_reduced_plot_test, word2Ind_plot_test, words)

print ("-" * 80)
```

```
--------------------------------------------------------------------------------
Outputted Plot:
```




```
--------------------------------------------------------------------------------
```

7.3 GloVe: Global Vectors for Word Representation

As discussed in the lecture, more recently prediction-based word vectors have demonstrated better performance, such as word2vec and GloVe (which also utilizes the benefit of counts). Here, we will explore the embeddings produced by GloVe. Please revisit the lecture slides for more details on the word2vec and GloVe algorithms. If you're feeling adventurous, challenge yourself and try reading GloVe's original paper.

Run the following cells to load the GloVe vectors into memory.

Note: If this is your first time to run these cells, i.e. download the embedding model, it will take about 15 minutes to run. If you've run these cells before, rerunning them will load the model without redownloading it, which will take about

1 to 2 minutes.

Important: The code in this notebook is updated to work with Gensim v4.0.

```
# All Import Statements Defined Here
# Note: Do not add to this list.
# ----------------

import sys
assert sys.version_info[0]==3
assert sys.version_info[1] >= 5

from gensim.models import KeyedVectors
from gensim.test.utils import datapath
import pprint
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = [10, 5]
import nltk
nltk.download('reuters')
from nltk.corpus import reuters
import numpy as np
import random
import scipy as sp
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import PCA

START_TOKEN = '<START>'
END_TOKEN = '<END>'

np.random.seed(0)
random.seed(0)
# ----------------
```

```
C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\gensim\similarities\__init__.
↪py:15: UserWarning: The gensim.similarities.levenshtein submodule is disabled,␣
↪because the optional Levenshtein package <https://pypi.org/project/python-
↪Levenshtein/> is unavailable. Install Levenhstein (e.g. `pip install python-
↪Levenshtein`) to suppress this warning.
  warnings.warn(msg)
[nltk_data] Downloading package reuters to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package reuters is already up-to-date!
```

```
def load_embedding_model():
    """ Load GloVe Vectors
        Return:
            wv_from_bin: All 400000 embeddings, each lengh 200
    """
    import gensim.downloader as api
    wv_pretrained = api.load("glove-wiki-gigaword-200")
    print("Loaded vocab size %i" % len(wv_pretrained))
    print("The loaded object is of type %s" % str(type(wv_pretrained)))
    return wv_pretrained
```

```
# ----------------------------------
# Run Cell to Load Word Vectors
# Note: This will take several minutes
# (8 mins in my case )
# ----------------------------------
wv_pretrained = load_embedding_model()
```

```
Loaded vocab size 400000
The loaded object is of type <class 'gensim.models.keyedvectors.KeyedVectors'>
```

Important: Gensim 4.0 has made some significant changes to its syntax and object oragnisation. For more information see Magrating from Gensim 3.x to 4

The `KeyedVectors` object has a dictionary property (`.key_to_index`) that returns a disctionary mapping of words to indices.

```
{key:value for key, value in wv_pretrained.key_to_index.items() if value<10}
```

```
{'the': 0,
 ',': 1,
 '.': 2,
 'of': 3,
 'to': 4,
 'and': 5,
 'in': 6,
 'a': 7,
 '"': 8,
 "'s": 9}
```

```
wv_pretrained.get_vector('engineering')
```

```
array([-5.1938e-02,  1.7635e-01,  1.8786e-01, -4.7958e-01,  1.0851e+00,
       -2.8156e-01, -2.8066e-02,  9.1940e-02, -7.6533e-02,  3.4757e-02,
       -5.2543e-02,  3.4220e-01, -3.3942e-01,  1.2675e-01,  3.4639e-02,
       -2.7710e-01, -1.1907e-01, -2.2184e-01,  7.1293e-01, -2.9338e-01,
       -4.2741e-01,  2.1376e+00,  1.0362e+00, -1.7944e-01,  6.5682e-01,
        5.7012e-01, -1.8262e-01,  4.5973e-01,  7.9056e-01, -8.7835e-01,
        7.9399e-01,  3.0741e-02, -1.3160e-01, -2.8041e-01,  1.3836e-01,
        4.1736e-01,  8.1038e-05, -5.7410e-01, -5.9988e-02,  1.2367e-01,
       -6.9972e-01, -3.6496e-01, -2.8456e-01, -4.4996e-01,  3.0715e-01,
       -6.0679e-01,  2.5705e-01, -3.8619e-01, -4.6077e-02, -1.7457e-01,
        3.8706e-01,  4.0831e-01, -1.7162e-01, -2.3532e-02, -3.5146e-01,
       -3.1349e-01,  2.8886e-02,  5.0182e-01,  3.4199e-01, -3.4627e-01,
        7.0743e-01,  1.5336e-01,  5.5904e-01,  4.0061e-01, -2.4110e-01,
       -3.8127e-01, -3.7064e-01,  1.1633e+00, -2.7004e-01,  3.4658e-01,
        2.3165e-01, -8.0207e-01,  3.9961e-01,  1.3949e-01, -2.1591e-01,
       -1.7998e-01,  7.4177e-01,  4.7986e-02, -2.5916e-01, -3.4934e-01,
        6.1844e-01,  1.9083e-03, -4.6262e-01,  7.7001e-01,  3.2828e-01,
       -3.2410e-01, -4.4820e-01,  4.7219e-01,  1.6762e+00,  3.1895e-01,
        5.2878e-01, -5.3253e-01,  1.3662e-01,  3.6778e-01, -7.2084e-01,
       -6.4639e-01,  2.8320e-01, -2.6098e-01,  7.2896e-01,  5.0380e-01,
        1.1000e-01, -1.0159e-01, -4.8650e-01,  1.0542e+00, -6.7540e-02,
        4.6954e-01, -6.2859e-02,  8.7161e-01,  2.6370e-01,  4.8938e-01,
       -1.0615e-02,  1.9904e-01,  9.3244e-02,  6.9493e-01, -2.6162e-01,
```

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```
        3.7821e-01,  8.9474e-02,  4.8153e-01,  4.5557e-02,  8.0432e-02,
        1.0388e-01, -9.1506e-01, -4.7667e-01,  1.7653e-02, -2.0044e-01,
        1.1785e-01, -1.6728e-01, -4.9748e-02, -9.6106e-02, -3.5579e-02,
       -1.4029e+00,  1.4633e-01, -3.3947e-02, -1.0846e+00, -7.8798e-01,
        8.8403e-02, -3.0667e-01,  8.8800e-01, -6.6901e-02,  7.8241e-01,
        6.1223e-02,  8.2684e-03, -2.9807e-01, -1.0423e-01,  4.9161e-01,
       -2.1850e-01, -1.2854e-01, -2.8894e-02,  1.1280e+00, -3.7454e-01,
        2.6395e-01, -7.8308e-01,  2.5786e-01, -8.8650e-01,  1.3409e-01,
       -3.8980e-01,  2.5154e-01, -6.2761e-02, -1.7067e-02, -7.6850e-01,
        7.6643e-01,  2.0544e-01, -2.2464e-01,  1.9980e-01, -3.8998e-01,
        7.6401e-01, -5.1074e-01, -3.2532e-01,  1.7820e-01,  9.8373e-01,
        9.9213e-01,  2.4715e-01,  1.3402e-01,  2.7492e-01, -5.4361e-02,
       -1.8243e-01,  2.1020e-02, -2.6531e-01, -1.8704e-01,  4.5575e-01,
        7.4159e-01, -1.2683e-02,  2.7622e-01,  3.3264e-01,  4.9330e-01,
       -1.2482e-01, -5.5854e-01,  4.4076e-01,  6.5997e-01,  2.7176e-01,
        2.2405e-01,  6.3891e-01,  4.1986e-01,  3.5628e-01,  2.1770e-01,
        2.9551e-01,  3.1118e-01, -7.8597e-02,  5.5859e-01, -1.4067e-04],
      dtype=float32)
```

7.3.1 Note: If you are receiving reset by peer error, rerun the cell to restart the download.

7.3.2 Reducing dimensionality of Word Embeddings

Let's directly compare the GloVe embeddings to those of the co-occurrence matrix. In order to avoid running out of memory, we will work with a sample of 10000 GloVe vectors instead. Run the following cells to:

1. Put 10000 Glove vectors into a matrix M
2. Run reduce_to_k_dim (your Truncated SVD function) to reduce the vectors from 200-dimensional to 2-dimensional.

To import functions from another Jupyter notebook, we will use the `import_ipynb package`. You will need to install this into your environment. " pip install import_ipynb "

```
def get_matrix_of_vectors(wv_pretrained, required_words=['barrels', 'bpd', 'ecuador',
↪'energy', 'industry', 'kuwait', 'oil', 'output', 'petroleum', 'venezuela']):
    """ Put the GloVe vectors into a matrix M.
        Param:
            wv_pretrained: KeyedVectors object; the 400000 GloVe vectors loaded from␣
↪file
        Return:
            M: numpy matrix shape (num words, 200) containing the vectors
            word2Ind: dictionary mapping each word to its row number in M
    """
    import random
    words = list(wv_pretrained.key_to_index.keys())
    print("Shuffling words ...")
    random.seed(224)
    random.shuffle(words)
    words = words[:10000]
    print("Putting %i words into word2Ind and matrix M..." % len(words))
    word2Ind = {}
    M = []
    curInd = 0
```

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```
    for w in words:
        try:
            M.append(wv_pretrained.get_vector(w, norm=True))
            word2Ind[w] = curInd
            curInd += 1
        except KeyError:
            continue
    for w in required_words:
        if w in words:
            continue
        try:
            M.append(wv_pretrained.get_vector(w, norm=True))
            word2Ind[w] = curInd
            curInd += 1
        except KeyError:
            continue
    M = np.stack(M)
    print("Done.")
    return M, word2Ind
```

```
import import_ipynb
from svd import reduce_to_k_dim

# ----------------------------------------------------------------
# Run Cell to Reduce 200-Dimensional Word Embeddings to k Dimensions
# Note: This should be quick to run
# ----------------------------------------------------------------
M, word2Ind = get_matrix_of_vectors(wv_pretrained)
M_reduced = reduce_to_k_dim(M, k=2)

# Rescale (normalize) the rows to make them each of unit-length
M_lengths = np.linalg.norm(M_reduced, axis=1)
M_reduced_normalized = M_reduced / M_lengths[:, np.newaxis] # broadcasting
```

```
importing Jupyter notebook from svd.ipynb
```

```
[nltk_data] Downloading package reuters to
[nltk_data]     C:\Users\wei\AppData\Roaming\nltk_data...
[nltk_data]   Package reuters is already up-to-date!
```

```
[['<START>', 'japan', 'to', 'revise', 'long', '-', 'term', 'energy', 'demand',
 ↪'downwards', 'the',
  'ministry', 'of', 'international', 'trade', 'and', 'industry', '(', 'miti', ')',
 ↪'will', 'revise',
  'its', 'long', '-', 'term', 'energy', 'supply', '/', 'demand', 'outlook', 'by',
 ↪'august', 'to',
  'meet', 'a', 'forecast', 'downtrend', 'in', 'japanese', 'energy', 'demand', ',',
 ↪'ministry',
  'officials', 'said', '.', 'miti', 'is', 'expected', 'to', 'lower', 'the',
 ↪'projection', 'for',
  'primary', 'energy', 'supplies', 'in', 'the', 'year', '2000', 'to', '550', 'mln',
 ↪'kilolitres',
  '(', 'kl', ')', 'from', '600', 'mln', ',', 'they', 'said', '.', 'the', 'decision',
 ↪'follows',
  'the', 'emergence', 'of', 'structural', 'changes', 'in', 'japanese', 'industry',
 ↪'following',
```

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```
 'the', 'rise', 'in', 'the', 'value', 'of', 'the', 'yen', 'and', 'a', 'decline', 'in
↪', 'domestic',
 'electric', 'power', 'demand', '.', 'miti', 'is', 'planning', 'to', 'work', 'out',
↪'a', 'revised',
 'energy', 'supply', '/', 'demand', 'outlook', 'through', 'deliberations', 'of',
↪'committee',
 'meetings', 'of', 'the', 'agency', 'of', 'natural', 'resources', 'and', 'energy', ',
↪', 'the',
 'officials', 'said', '.', 'they', 'said', 'miti', 'will', 'also', 'review', 'the',
↪'breakdown',
 'of', 'energy', 'supply', 'sources', ',', 'including', 'oil', ',', 'nuclear', ',',
↪'coal', 'and',
 'natural', 'gas', '.', 'nuclear', 'energy', 'provided', 'the', 'bulk', 'of', 'japan
↪', "'", 's',
 'electric', 'power', 'in', 'the', 'fiscal', 'year', 'ended', 'march', '31', ',',
↪'supplying',
 'an', 'estimated', '27', 'pct', 'on', 'a', 'kilowatt', '/', 'hour', 'basis', ',',
↪'followed',
 'by', 'oil', '(', '23', 'pct', ')', 'and', 'liquefied', 'natural', 'gas', '(', '21',
↪ 'pct', '),',
 'they', 'noted', '.', '<END>'],
['<START>', 'energy', '/', 'u', '.', 's', '.', 'petrochemical', 'industry', 'cheap',
↪'oil',
 'feedstocks', ',', 'the', 'weakened', 'u', '.', 's', '.', 'dollar', 'and', 'a',
↪'plant',
 'utilization', 'rate', 'approaching', '90', 'pct', 'will', 'propel', 'the',
↪'streamlined', 'u',
 '.', 's', '.', 'petrochemical', 'industry', 'to', 'record', 'profits', 'this', 'year
↪', ',',
 'with', 'growth', 'expected', 'through', 'at', 'least', '1990', ',', 'major',
↪'company',
 'executives', 'predicted', '.', 'this', 'bullish', 'outlook', 'for', 'chemical',
↪'manufacturing',
 'and', 'an', 'industrywide', 'move', 'to', 'shed', 'unrelated', 'businesses', 'has',
↪ 'prompted',
 'gaf', 'corp', '&', 'lt', ';', 'gaf', '>,', 'privately', '-', 'held', 'cain',
↪'chemical', 'inc',
 ',', 'and', 'other', 'firms', 'to', 'aggressively', 'seek', 'acquisitions', 'of',
↪'petrochemical',
 'plants', '.', 'oil', 'companies', 'such', 'as', 'ashland', 'oil', 'inc', '&', 'lt',
↪ ';', 'ash',
 '>,', 'the', 'kentucky', '-', 'based', 'oil', 'refiner', 'and', 'marketer', ',',
↪'are', 'also',
 'shopping', 'for', 'money', '-', 'making', 'petrochemical', 'businesses', 'to', 'buy
↪', '.', '"',
 'i', 'see', 'us', 'poised', 'at', 'the', 'threshold', 'of', 'a', 'golden', 'period',
↪ ',"', 'said',
 'paul', 'oreffice', ',', 'chairman', 'of', 'giant', 'dow', 'chemical', 'co', '&',
↪'lt', ';',
 'dow', '>,', 'adding', ',', '"', 'there', "'", 's', 'no', 'major', 'plant',
↪'capacity', 'being',
 'added', 'around', 'the', 'world', 'now', '.', 'the', 'whole', 'game', 'is',
↪'bringing', 'out',
 'new', 'products', 'and', 'improving', 'the', 'old', 'ones', '."', 'analysts', 'say
↪', 'the',
 'chemical', 'industry', "'", 's', 'biggest', 'customers', ',', 'automobile',
↪'manufacturers',
```

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```
 'and', 'home', 'builders', 'that', 'use', 'a', 'lot', 'of', 'paints', 'and',
↪'plastics', ',',
 'are', 'expected', 'to', 'buy', 'quantities', 'this', 'year', '.', 'u', '.', 's', '.
↪',
 'petrochemical', 'plants', 'are', 'currently', 'operating', 'at', 'about', '90',
↪'pct',
 'capacity', ',', 'reflecting', 'tighter', 'supply', 'that', 'could', 'hike',
↪'product', 'prices',
 'by', '30', 'to', '40', 'pct', 'this', 'year', ',', 'said', 'john', 'dosher', ',',
↪'managing',
 'director', 'of', 'pace', 'consultants', 'inc', 'of', 'houston', '.', 'demand', 'for
↪', 'some',
 'products', 'such', 'as', 'styrene', 'could', 'push', 'profit', 'margins', 'up', 'by
↪', 'as',
 'much', 'as', '300', 'pct', ',', 'he', 'said', '.', 'oreffice', ',', 'speaking', 'at
↪', 'a',
 'meeting', 'of', 'chemical', 'engineers', 'in', 'houston', ',', 'said', 'dow',
↪'would', 'easily',
 'top', 'the', '741', 'mln', 'dlrs', 'it', 'earned', 'last', 'year', 'and',
↪'predicted', 'it',
 'would', 'have', 'the', 'best', 'year', 'in', 'its', 'history', '.', 'in', '1985',
↪',', 'when',
 'oil', 'prices', 'were', 'still', 'above', '25', 'dlrs', 'a', 'barrel', 'and',
↪'chemical',
 'exports', 'were', 'adversely', 'affected', 'by', 'the', 'strong', 'u', '.', 's', '.
↪', 'dollar',
 ',', 'dow', 'had', 'profits', 'of', '58', 'mln', 'dlrs', '.', '"', 'i', 'believe',
↪'the',
 'entire', 'chemical', 'industry', 'is', 'headed', 'for', 'a', 'record', 'year', 'or
↪', 'close',
 'to', 'it', ',"', 'oreffice', 'said', '.', 'gaf', 'chairman', 'samuel', 'heyman',
↪'estimated',
 'that', 'the', 'u', '.', 's', '.', 'chemical', 'industry', 'would', 'report', 'a',
↪'20', 'pct',
 'gain', 'in', 'profits', 'during', '1987', '.', 'last', 'year', ',', 'the',
↪'domestic',
 'industry', 'earned', 'a', 'total', 'of', '13', 'billion', 'dlrs', ',', 'a', '54',
↪'pct', 'leap',
 'from', '1985', '.', 'the', 'turn', 'in', 'the', 'fortunes', 'of', 'the', 'once', '-
↪', 'sickly',
 'chemical', 'industry', 'has', 'been', 'brought', 'about', 'by', 'a', 'combination',
↪ 'of', 'luck',
 'and', 'planning', ',', 'said', 'pace', "'", 's', 'john', 'dosher', '.', 'dosher',
↪'said', 'last',
 'year', "'", 's', 'fall', 'in', 'oil', 'prices', 'made', 'feedstocks', 'dramatically
↪', 'cheaper',
 'and', 'at', 'the', 'same', 'time', 'the', 'american', 'dollar', 'was', 'weakening',
↪ 'against',
 'foreign', 'currencies', '.', 'that', 'helped', 'boost', 'u', '.', 's', '.',
↪'chemical',
 'exports', '.', 'also', 'helping', 'to', 'bring', 'supply', 'and', 'demand', 'into',
↪ 'balance',
 'has', 'been', 'the', 'gradual', 'market', 'absorption', 'of', 'the', 'extra',
↪'chemical',
 'manufacturing', 'capacity', 'created', 'by', 'middle', 'eastern', 'oil', 'producers
↪', 'in',
 'the', 'early', '1980s', '.', 'finally', ',', 'virtually', 'all', 'major', 'u', '.',
↪ 's', '.',
```

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```
 'chemical', 'manufacturers', 'have', 'embarked', 'on', 'an', 'extensive', 'corporate
↪',
 'restructuring', 'program', 'to', 'mothball', 'inefficient', 'plants', ',', 'trim',
↪'the',
 'payroll', 'and', 'eliminate', 'unrelated', 'businesses', '.', 'the', 'restructuring
↪', 'touched',
 'off', 'a', 'flurry', 'of', 'friendly', 'and', 'hostile', 'takeover', 'attempts', '.
↪', 'gaf', ',',
 'which', 'made', 'an', 'unsuccessful', 'attempt', 'in', '1985', 'to', 'acquire',
↪'union',
 'carbide', 'corp', '&', 'lt', ';', 'uk', '>,', 'recently', 'offered', 'three',
↪'billion', 'dlrs',
 'for', 'borg', 'warner', 'corp', '&', 'lt', ';', 'bor', '>,', 'a', 'chicago',
↪'manufacturer',
 'of', 'plastics', 'and', 'chemicals', '.', 'another', 'industry', 'powerhouse', ',',
↪ 'w', '.',
 'r', '.', 'grace', '&', 'lt', ';', 'gra', '>', 'has', 'divested', 'its', 'retailing
↪', ',',
 'restaurant', 'and', 'fertilizer', 'businesses', 'to', 'raise', 'cash', 'for',
↪'chemical',
 'acquisitions', '.', 'but', 'some', 'experts', 'worry', 'that', 'the', 'chemical',
↪'industry',
 'may', 'be', 'headed', 'for', 'trouble', 'if', 'companies', 'continue', 'turning',
↪'their',
 'back', 'on', 'the', 'manufacturing', 'of', 'staple', 'petrochemical', 'commodities
↪', ',', 'such',
 'as', 'ethylene', ',', 'in', 'favor', 'of', 'more', 'profitable', 'specialty',
↪'chemicals',
 'that', 'are', 'custom', '-', 'designed', 'for', 'a', 'small', 'group', 'of',
↪'buyers', '.', '"',
 'companies', 'like', 'dupont', '&', 'lt', ';', 'dd', '>', 'and', 'monsanto', 'co',
↪'&', 'lt', ';',
 'mtc', '>', 'spent', 'the', 'past', 'two', 'or', 'three', 'years', 'trying', 'to',
↪'get', 'out',
 'of', 'the', 'commodity', 'chemical', 'business', 'in', 'reaction', 'to', 'how',
↪'badly', 'the',
 'market', 'had', 'deteriorated', ',"', 'dosher', 'said', '.', '"', 'but', 'i',
↪'think', 'they',
 'will', 'eventually', 'kill', 'the', 'margins', 'on', 'the', 'profitable',
↪'chemicals', 'in',
 'the', 'niche', 'market', '."', 'some', 'top', 'chemical', 'executives', 'share',
↪'the',
 'concern', '.', '"', 'the', 'challenge', 'for', 'our', 'industry', 'is', 'to', 'keep
↪', 'from',
 'getting', 'carried', 'away', 'and', 'repeating', 'past', 'mistakes', ',"', 'gaf', "
↪'", 's',
 'heyman', 'cautioned', '.', '"', 'the', 'shift', 'from', 'commodity', 'chemicals',
↪'may', 'be',
 'ill', '-', 'advised', '.', 'specialty', 'businesses', 'do', 'not', 'stay', 'special
↪', 'long',
 '."', 'houston', '-', 'based', 'cain', 'chemical', ',', 'created', 'this', 'month',
↪'by', 'the',
 'sterling', 'investment', 'banking', 'group', ',', 'believes', 'it', 'can',
↪'generate', '700',
 'mln', 'dlrs', 'in', 'annual', 'sales', 'by', 'bucking', 'the', 'industry', 'trend',
↪ '.',
 'chairman', 'gordon', 'cain', ',', 'who', 'previously', 'led', 'a', 'leveraged',
↪'buyout', 'of',
```

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```
 'dupont', "'", 's', 'conoco', 'inc', "'", 's', 'chemical', 'business', ',', 'has',
↪'spent', '1',
 '.', '1', 'billion', 'dlrs', 'since', 'january', 'to', 'buy', 'seven',
↪'petrochemical', 'plants',
 'along', 'the', 'texas', 'gulf', 'coast', '.', 'the', 'plants', 'produce', 'only',
↪'basic',
 'commodity', 'petrochemicals', 'that', 'are', 'the', 'building', 'blocks', 'of',
↪'specialty',
 'products', '.', '"', 'this', 'kind', 'of', 'commodity', 'chemical', 'business',
↪'will', 'never',
 'be', 'a', 'glamorous', ',', 'high', '-', 'margin', 'business', ',"', 'cain', 'said
↪', ',',
 'adding', 'that', 'demand', 'is', 'expected', 'to', 'grow', 'by', 'about', 'three',
↪'pct',
 'annually', '.', 'garo', 'armen', ',', 'an', 'analyst', 'with', 'dean', 'witter',
↪'reynolds', ',',
 'said', 'chemical', 'makers', 'have', 'also', 'benefitted', 'by', 'increasing',
↪'demand', 'for',
 'plastics', 'as', 'prices', 'become', 'more', 'competitive', 'with', 'aluminum', ',
↪', 'wood',
 'and', 'steel', 'products', '.', 'armen', 'estimated', 'the', 'upturn', 'in', 'the',
↪ 'chemical',
 'business', 'could', 'last', 'as', 'long', 'as', 'four', 'or', 'five', 'years', ',',
↪ 'provided',
 'the', 'u', '.', 's', '.', 'economy', 'continues', 'its', 'modest', 'rate', 'of',
↪'growth', '.',
 '<END>'],
['<START>', 'turkey', 'calls', 'for', 'dialogue', 'to', 'solve', 'dispute', 'turkey',
↪ 'said',
 'today', 'its', 'disputes', 'with', 'greece', ',', 'including', 'rights', 'on', 'the
↪',
 'continental', 'shelf', 'in', 'the', 'aegean', 'sea', ',', 'should', 'be', 'solved',
↪ 'through',
 'negotiations', '.', 'a', 'foreign', 'ministry', 'statement', 'said', 'the', 'latest
↪', 'crisis',
 'between', 'the', 'two', 'nato', 'members', 'stemmed', 'from', 'the', 'continental',
↪ 'shelf',
 'dispute', 'and', 'an', 'agreement', 'on', 'this', 'issue', 'would', 'effect', 'the
↪', 'security',
 ',', 'economy', 'and', 'other', 'rights', 'of', 'both', 'countries', '.', '"', 'as',
↪ 'the',
 'issue', 'is', 'basicly', 'political', ',', 'a', 'solution', 'can', 'only', 'be',
↪'found', 'by',
 'bilateral', 'negotiations', ',"', 'the', 'statement', 'said', '.', 'greece', 'has',
↪ 'repeatedly',
 'said', 'the', 'issue', 'was', 'legal', 'and', 'could', 'be', 'solved', 'at', 'the',
 'international', 'court', 'of', 'justice', '.', 'the', 'two', 'countries',
↪'approached', 'armed',
 'confrontation', 'last', 'month', 'after', 'greece', 'announced', 'it', 'planned',
↪'oil',
 'exploration', 'work', 'in', 'the', 'aegean', 'and', 'turkey', 'said', 'it', 'would
↪', 'also',
 'search', 'for', 'oil', '.', 'a', 'face', '-', 'off', 'was', 'averted', 'when',
↪'turkey',
 'confined', 'its', 'research', 'to', 'territorrial', 'waters', '.', '"', 'the',
↪'latest',
 'crises', 'created', 'an', 'historic', 'opportunity', 'to', 'solve', 'the',
↪'disputes', 'between',
```

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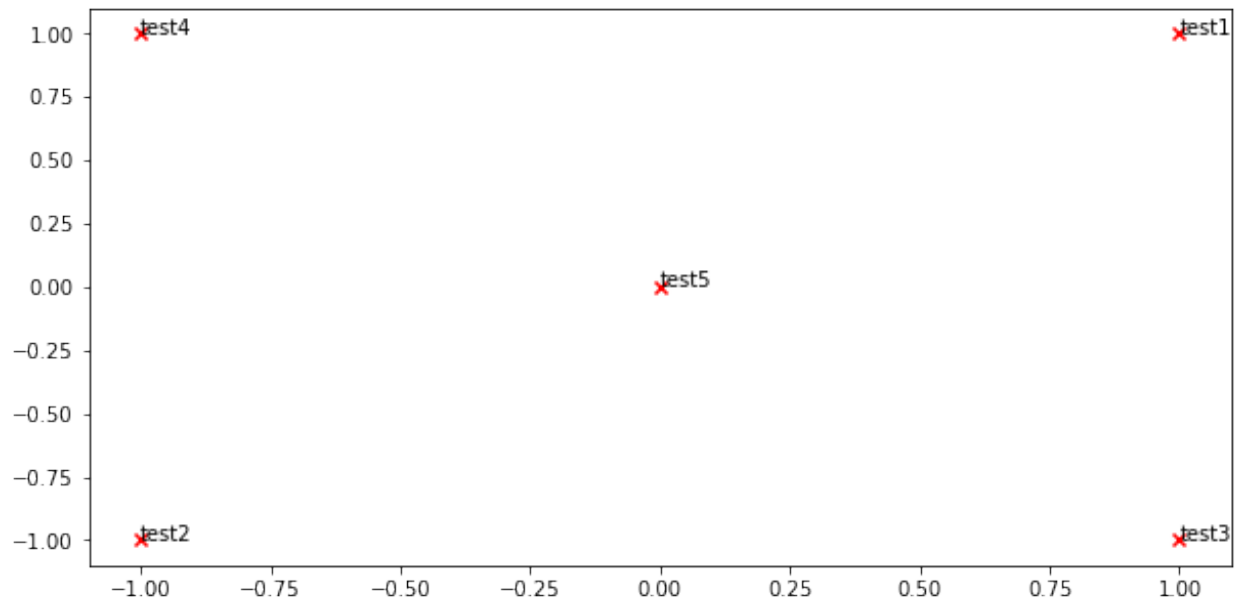
```
 'the', 'two', 'countries', ',"', 'the', 'foreign', 'ministry', 'statement', 'said',
↪'.', 'turkey',
 "'", 's', 'ambassador', 'in', 'athens', ',', 'nazmi', 'akiman', ',', 'was', 'due',
↪'to', 'meet',
 'prime', 'minister', 'andreas', 'papandreou', 'today', 'for', 'the', 'greek', 'reply
↪', 'to', 'a',
 'message', 'sent', 'last', 'week', 'by', 'turkish', 'prime', 'minister', 'turgut',
↪'ozal', '.',
 'the', 'contents', 'of', 'the', 'message', 'were', 'not', 'disclosed', '.', '<END>
↪']]
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
Running Truncated SVD over 10 words...
Done.
--------------------------------------------------------------------------------
Passed All Tests!
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
Outputted Plot:
```




```
--------------------------------------------------------------------------------
Shuffling words ...
Putting 10000 words into word2Ind and matrix M...
Done.
Running Truncated SVD over 10010 words...
Done.
```

Note: If you are receiving out of memory issues on your local machine, try closing other applications to free more memory on your device. You may want to try restarting your machine so that you can free up extra memory. Then

immediately run the jupyter notebook and see if you can load the word vectors properly.

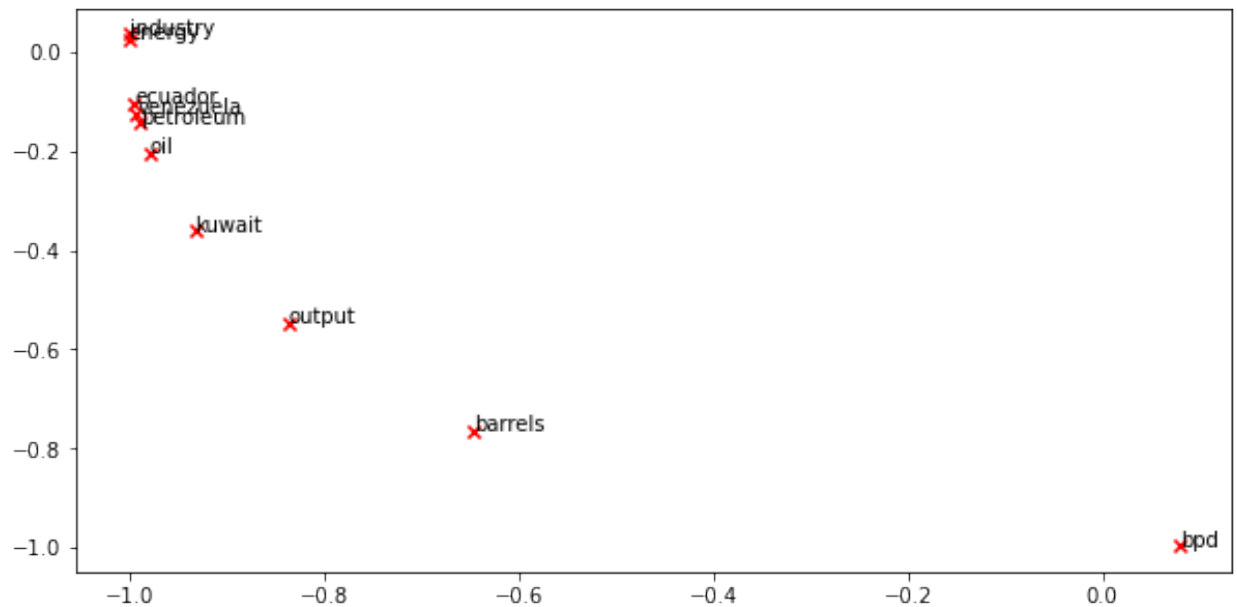
7.3.3 GloVe Plot Analysis

Run the cell below to plot the 2D GloVe embeddings for `['barrels', 'bpd', 'ecuador', 'energy', 'industry', 'kuwait', 'oil', 'output', 'petroleum', 'venezuela']`.

What clusters together in 2-dimensional embedding space? What doesn't cluster together that you might think should have? How is the plot different from the one generated earlier from the co-occurrence matrix? What is a possible reason for causing the difference?

```
from svd import plot_embeddings

words = ['barrels', 'bpd', 'ecuador', 'energy', 'industry', 'kuwait', 'oil', 'output',
 ↪ 'petroleum', 'venezuela']
plot_embeddings(M_reduced_normalized, word2Ind, words)
```



7.4 Word2Vec

7.4.1 Using Pretrained Word2Vec Vectors

Gensim has functions to support the downloading of pretrained Word2Vec vectors. Let's use another visualisation tool (`sklearn.manifold.TSNE`) to see how the word embeddings can help us identify clusters of words with similar meaning.

```
from sklearn.manifold import TSNE
import numpy as np
import matplotlib.pyplot as plt
```

```
import gensim.downloader as api
wv = api.load('word2vec-google-news-300')
```

Analogy Test: A is to B as C is to D

```
king - man + woman = ?
```

Google has released a analogy test set, you can use it to evaluate the performance of word embeddings.

Your Turn

Try some other set of words and see how well the pretrained embeddings perform. Consider writing an evaluation function using the analogy test set. If the first word returned by the analogy test matches what's in the test set, it's a HIT. As we only consider the most similar for comparison, this evaluation is called HIT@1.

```
wv.most_similar(positive=["king", "woman"], negative=["man"])
```

```
[('queen', 0.7118193507194519),
 ('monarch', 0.6189674735069275),
 ('princess', 0.5902431011199951),
 ('crown_prince', 0.5499460697174072),
 ('prince', 0.5377322435379028),
 ('kings', 0.5236844420433044),
 ('Queen_Consort', 0.5235945582389832),
 ('queens', 0.5181134939193726),
 ('sultan', 0.5098593235015869),
 ('monarchy', 0.5087411403656006)]
```

Plot using TSNE

```
def display_closestwords_tsnescatterplot(model, word):

    arr = np.empty((0,300), dtype='f')
    word_labels = [word]

    # get close words
    close_words = model.similar_by_word(word)

    # add the vector for each of the closest words to the array
    arr = np.append(arr, np.array([model[word]]), axis=0)
    for wrd_score in close_words:
        wrd_vector = model[wrd_score[0]]
        word_labels.append(wrd_score[0])
        arr = np.append(arr, np.array([wrd_vector]), axis=0)

    # find tsne coords for 2 dimensions
    tsne = TSNE(n_components=2, random_state=0)
    np.set_printoptions(suppress=True)
    Y = tsne.fit_transform(arr)

    x_coords = Y[:, 0]
```

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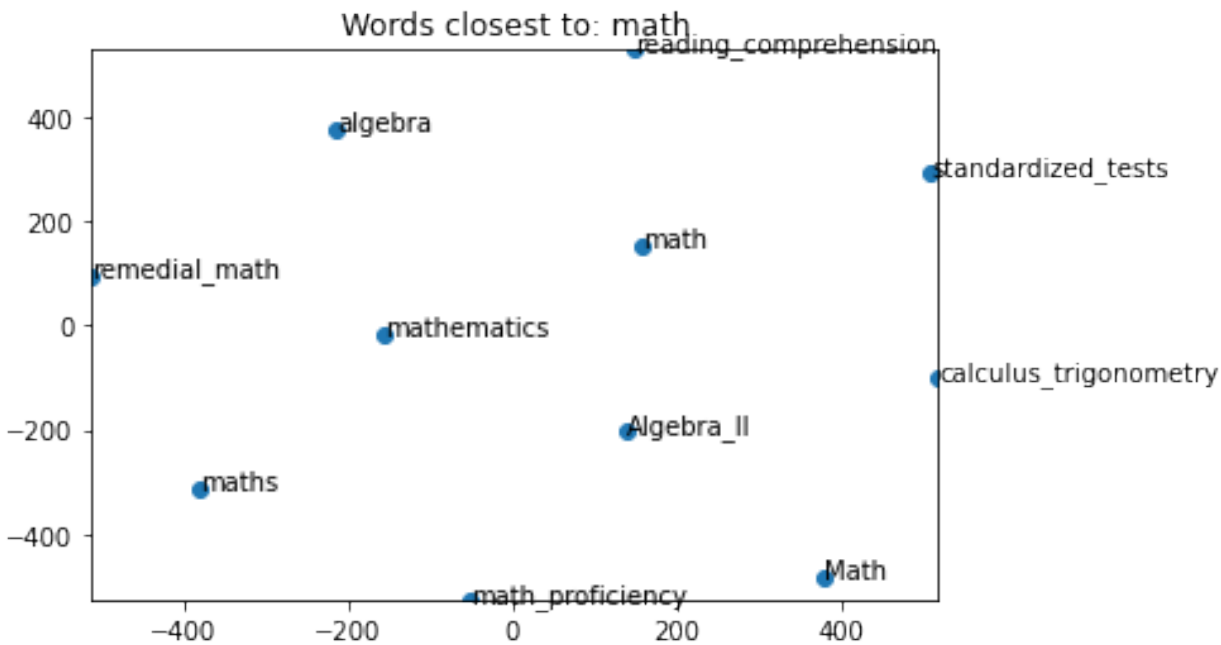
```
    y_coords = Y[:, 1]
    # display scatter plot
    plt.scatter(x_coords, y_coords)

    for label, x, y in zip(word_labels, x_coords, y_coords):
        plt.annotate(label, xy=(x, y), xytext=(0, 0), textcoords='offset points')
    plt.xlim(x_coords.min()+0.00005, x_coords.max()+0.00005)
    plt.ylim(y_coords.min()+0.00005, y_coords.max()+0.00005)
    plt.title(f'Words closest to: {word}')
    plt.show()
```

```
display_closestwords_tsnescatterplot(wv, "math")
```



Interactive Visualisation using bokeh

```
from bokeh.plotting import figure, show
from bokeh.io import push_notebook, output_notebook
from bokeh.models import ColumnDataSource, LabelSet
from bokeh.plotting import figure, show
from bokeh.io import push_notebook, output_notebook
from bokeh.models import ColumnDataSource, LabelSet
import pandas as pd
```

```
def interactive_tsne(text_labels, tsne_array):
    '''makes an interactive scatter plot with text labels for each point'''

    # Define a dataframe to be used by bokeh context
    bokeh_df = pd.DataFrame(tsne_array, text_labels, columns=['x','y'])
    bokeh_df['text_labels'] = bokeh_df.index
```

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```
    # interactive controls to include to the plot
    TOOLS="hover, zoom_in, zoom_out, box_zoom, undo, redo, reset, box_select"

    p = figure(tools=TOOLS, plot_width=700, plot_height=700)

    # define data source for the plot
    source = ColumnDataSource(bokeh_df)

    # scatter plot
    p.scatter('x', 'y', source=source, fill_alpha=0.6,
              fill_color="#8724B5",
              line_color=None)

    # text labels
    labels = LabelSet(x='x', y='y', text='text_labels', y_offset=8,
                      text_font_size="8pt", text_color="#555555",
                      source=source, text_align='center')

    p.add_layout(labels)

    # show plot inline
    output_notebook()
    show(p)
```

```
vocab = ['math', 'computing', 'physics']
input_vocab =  [word for word in vocab if word in wv.key_to_index.keys()]
X = wv[input_vocab]
# find tsne coords for 2 dimensions
tsne = TSNE(n_components=2, random_state=0)
X_tsne = tsne.fit_transform(X)

print(input_vocab)

points = len(input_vocab)
interactive_tsne(list(input_vocab)[:points], X_tsne)
```

```
['math', 'computing', 'physics']
```

7.4.2 Training your own Word2Vec Embeddings

Data Crawling from the Web

```
from __future__ import division, unicode_literals
import codecs
from bs4 import BeautifulSoup
import urllib

f = urllib.request.urlopen("https://en.wikipedia.org/wiki/Natural_language_processing
↪")

document= BeautifulSoup(f.read()).get_text()
print(document)
```

```
Natural language processing - Wikipedia
```

```
Natural language processing

From Wikipedia, the free encyclopedia



Jump to navigation
Jump to search
This article is about natural language processing done by computers. For the natural␣
↪language processing done by the human brain, see Language processing in the brain.
Field of computer science and linguistics
 An automated online assistant providing customer service on a web page, an example␣
↪of an application where natural language processing is a major component.[1]
Natural language processing (NLP) is a subfield of linguistics, computer science, and␣
↪artificial intelligence concerned with the interactions between computers and human␣
↪language, in particular how to program computers to process and analyze large␣
↪amounts of natural language data.  The goal is a computer capable of "understanding
↪" the contents of documents, including the contextual nuances of the language␣
↪within them. The technology can then accurately extract information and insights␣
↪contained in the documents as well as categorize and organize the documents␣
↪themselves.
Challenges in natural language processing frequently involve speech recognition,␣
↪natural language understanding, and natural language generation.
```

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```
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3.3 Syntactic analysis
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4 General tendencies and (possible) future directions

4.1 Cognition and NLP


5 See also
6 References
7 Further reading


History[edit]
Further information: History of natural language processing
Natural language processing has its roots in the 1950s. Already in 1950, Alan Turing␣
↪published an article titled "Computing Machinery and Intelligence" which proposed␣
↪what is now called the Turing test as a criterion of intelligence, a task that␣
↪involves the automated interpretation and generation of natural language, but at␣
↪the time not articulated as a problem separate from artificial intelligence.

Symbolic NLP (1950s - early 1990s)[edit]
The premise of symbolic NLP is well-summarized by John Searle's Chinese room␣
↪experiment: Given a collection of rules (e.g., a Chinese phrasebook, with questions␣
↪and matching answers), the computer emulates natural language understanding (or␣
↪other NLP tasks) by applying those rules to the data it is confronted with.

1950s: The Georgetown experiment in 1954 involved fully automatic translation of more␣
↪than sixty Russian sentences into English. The authors claimed that within three or␣
↪five years, machine translation would be a solved problem.[2]  However, real␣
↪progress was much slower, and after the ALPAC report in 1966, which found that ten-
↪year-long research had failed to fulfill the expectations, funding for machine␣
↪translation was dramatically reduced.  Little further research in machine␣
↪translation was conducted until the late 1980s when the first statistical machine␣
↪translation systems were developed.
```

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```
1960s: Some notably successful natural language processing systems developed in the␣
↪1960s were SHRDLU, a natural language system working in restricted "blocks worlds"␣
↪with restricted vocabularies, and ELIZA, a simulation of a Rogerian psychotherapist,
↪ written by Joseph Weizenbaum between 1964 and 1966.  Using almost no information␣
↪about human thought or emotion, ELIZA sometimes provided a startlingly human-like␣
↪interaction. When the "patient" exceeded the very small knowledge base, ELIZA might␣
↪provide a generic response, for example, responding to "My head hurts" with "Why do␣
↪you say your head hurts?".
1970s: During the 1970s, many programmers began to write "conceptual ontologies",␣
↪which structured real-world information into computer-understandable data. ␣
↪Examples are MARGIE (Schank, 1975), SAM (Cullingford, 1978), PAM (Wilensky, 1978),␣
↪TaleSpin (Meehan, 1976), QUALM (Lehnert, 1977), Politics (Carbonell, 1979), and␣
↪Plot Units (Lehnert 1981).  During this time, the first many chatterbots were␣
↪written (e.g., PARRY).
1980s: The 1980s and early 1990s mark the hey-day of symbolic methods in NLP. Focus␣
↪areas of the time included research on rule-based parsing (e.g., the development of␣
↪HPSG as a computational operationalization of generative grammar), morphology (e.g.,
↪ two-level morphology[3]), semantics (e.g., Lesk algorithm), reference (e.g.,␣
↪within Centering Theory[4]) and other areas of natural language understanding (e.g.,
↪ in the Rhetorical Structure Theory). Other lines of research were continued, e.g.,␣
↪the development of chatterbots with Racter and Jabberwacky. An important␣
↪development (that eventually led to the statistical turn in the 1990s) was the␣
↪rising importance of quantitative evaluation in this period.[5]
Statistical NLP (1990s-2010s)[edit]
Up to the 1980s, most natural language processing systems were based on complex sets␣
↪of hand-written rules.  Starting in the late 1980s, however, there was a revolution␣
↪in natural language processing with the introduction of machine learning algorithms␣
↪for language processing.  This was due to both the steady increase in computational␣
↪power (see Moore's law) and the gradual lessening of the dominance of Chomskyan␣
↪theories of linguistics (e.g. transformational grammar), whose theoretical␣
↪underpinnings discouraged the sort of corpus linguistics that underlies the machine-
↪learning approach to language processing.[6]

1990s: Many of the notable early successes on statistical methods in NLP occurred in␣
↪the field of machine translation, due especially to work at IBM Research.  These␣
↪systems were able to take advantage of existing multilingual textual corpora that␣
↪had been produced by the Parliament of Canada and the European Union as a result of␣
↪laws calling for the translation of all governmental proceedings into all official␣
↪languages of the corresponding systems of government.  However, most other systems␣
↪depended on corpora specifically developed for the tasks implemented by these␣
↪systems, which was (and often continues to be) a major limitation in the success of␣
↪these systems. As a result, a great deal of research has gone into methods of more␣
↪effectively learning from limited amounts of data.
2000s: With the growth of the web, increasing amounts of raw (unannotated) language␣
↪data has become available since the mid-1990s. Research has thus increasingly␣
↪focused on unsupervised and semi-supervised learning algorithms.  Such algorithms␣
↪can learn from data that has not been hand-annotated with the desired answers or␣
↪using a combination of annotated and non-annotated data.  Generally, this task is␣
↪much more difficult than supervised learning, and typically produces less accurate␣
↪results for a given amount of input data.  However, there is an enormous amount of␣
↪non-annotated data available (including, among other things, the entire content of␣
↪the World Wide Web), which can often make up for the inferior results if the␣
↪algorithm used has a low enough time complexity to be practical.
Neural NLP (present)[edit]
In the 2010s, representation learning and deep neural network-style machine learning␣
↪methods became widespread in natural language processing, due in part to a flurry␣
↪of results showing that such techniques[7][8] can achieve state-of-the-art results␣
↪in many natural language tasks, for example in language modeling,[9] parsing,
↪[10][11] and many others. This is increasingly important in medicine and healthcare,
↪ where NLP is being used to analyze notes and text in electronic health records␣
↪that would otherwise be inaccessible for study when seeking to improve care.[12]
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Methods: Rules, statistics, neural networks[edit]
In the early days, many language-processing systems were designed by symbolic methods,
 ↪ i.e., the hand-coding of a set of rules, coupled with a dictionary lookup:[13][14]␣
 ↪such as by writing grammars or devising heuristic rules for stemming.
More recent systems based on machine-learning algorithms have many advantages over␣
 ↪hand-produced rules:

The learning procedures used during machine learning automatically focus on the most␣
 ↪common cases, whereas when writing rules by hand it is often not at all obvious␣
 ↪where the effort should be directed.
Automatic learning procedures can make use of statistical inference algorithms to␣
 ↪produce models that are robust to unfamiliar input (e.g. containing words or␣
 ↪structures that have not been seen before) and to erroneous input (e.g. with␣
 ↪misspelled words or words accidentally omitted). Generally, handling such input␣
 ↪gracefully with handwritten rules, or, more generally, creating systems of␣
 ↪handwritten rules that make soft decisions, is extremely difficult, error-prone and␣
 ↪time-consuming.
Systems based on automatically learning the rules can be made more accurate simply by␣
 ↪supplying more input data. However, systems based on handwritten rules can only be␣
 ↪made more accurate by increasing the complexity of the rules, which is a much more␣
 ↪difficult task. In particular, there is a limit to the complexity of systems based␣
 ↪on handwritten rules, beyond which the systems become more and more unmanageable.␣
 ↪However, creating more data to input to machine-learning systems simply requires a␣
 ↪corresponding increase in the number of man-hours worked, generally without␣
 ↪significant increases in the complexity of the annotation process.
Despite the popularity of machine learning in NLP research, symbolic methods are␣
 ↪still (2020) commonly used:

when the amount of training data is insufficient to successfully apply machine␣
 ↪learning methods, e.g., for the machine translation of low-resource languages such␣
 ↪as provided by the Apertium system,
for preprocessing in NLP pipelines, e.g., tokenization, or
for postprocessing and transforming the output of NLP pipelines, e.g., for knowledge␣
 ↪extraction from syntactic parses.
Statistical methods[edit]
Since the so-called "statistical revolution"[15][16] in the late 1980s and mid-1990s,␣
 ↪much natural language processing research has relied heavily on machine learning.␣
 ↪The machine-learning paradigm calls instead for using statistical inference to␣
 ↪automatically learn such rules through the analysis of large corpora (the plural␣
 ↪form of corpus, is a set of documents, possibly with human or computer annotations)␣
 ↪of typical real-world examples.
Many different classes of machine-learning algorithms have been applied to natural-
 ↪language-processing tasks. These algorithms take as input a large set of "features"␣
 ↪that are generated from the input data. Increasingly, however, research has focused␣
 ↪on statistical models, which make soft, probabilistic decisions based on attaching␣
 ↪real-valued weights to each input feature (complex-valued embeddings,[17] and␣
 ↪neural networks in general have also been proposed, for e.g. speech[18]). Such␣
 ↪models have the advantage that they can express the relative certainty of many␣
 ↪different possible answers rather than only one, producing more reliable results␣
 ↪when such a model is included as a component of a larger system.
Some of the earliest-used machine learning algorithms, such as decision trees,␣
 ↪produced systems of hard if-then rules similar to existing hand-written rules. ␣
 ↪However, part-of-speech tagging introduced the use of hidden Markov models to␣
 ↪natural language processing, and increasingly, research has focused on statistical␣
 ↪models, which make soft, probabilistic decisions based on attaching real-valued␣
 ↪weights to the features making up the input data. The cache language models upon␣
 ↪which many speech recognition systems now rely are examples of such statistical␣
 ↪models.  Such models are generally more robust when given unfamiliar input,␣
 ↪especially input that contains errors (as is very common for real-world data), and␣
 ↪produce more reliable results when integrated into a larger system comprising␣
 ↪multiple subtasks.
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Since the neural turn, statistical methods in NLP research have been largely replaced␣
 ↪by neural networks. However, they continue to be relevant for contexts in which␣
 ↪statistical interpretability and transparency is required.

Neural networks[edit]
Further information: Artificial neural network
A major drawback of statistical methods is that they require elaborate feature␣
 ↪engineering. Since 2015,[19] the field has thus largely abandoned statistical␣
 ↪methods and shifted to neural networks for machine learning. Popular techniques␣
 ↪include the use of word embeddings to capture semantic properties of words, and an␣
 ↪increase in end-to-end learning of a higher-level task (e.g., question answering)␣
 ↪instead of relying on a pipeline of separate intermediate tasks (e.g., part-of-
 ↪speech tagging and dependency parsing). In some areas, this shift has entailed␣
 ↪substantial changes in how NLP systems are designed, such that deep neural network-
 ↪based approaches may be viewed as a new paradigm distinct from statistical natural␣
 ↪language processing. For instance, the term neural machine translation (NMT)␣
 ↪emphasizes the fact that deep learning-based approaches to machine translation␣
 ↪directly learn sequence-to-sequence transformations, obviating the need for␣
 ↪intermediate steps such as word alignment and language modeling that was used in␣
 ↪statistical machine translation (SMT). Latest works tend to use non-technical␣
 ↪structure of a given task to build proper neural network.[20]

Common NLP tasks[edit]
The following is a list of some of the most commonly researched tasks in natural␣
 ↪language processing. Some of these tasks have direct real-world applications, while␣
 ↪others more commonly serve as subtasks that are used to aid in solving larger tasks.
Though natural language processing tasks are closely intertwined, they can be␣
 ↪subdivided into categories for convenience. A coarse division is given below.

Text and speech processing[edit]
Optical character recognition (OCR)
Given an image representing printed text, determine the corresponding text.
Speech recognition
Given a sound clip of a person or people speaking, determine the textual␣
 ↪representation of the speech.  This is the opposite of text to speech and is one of␣
 ↪the extremely difficult problems colloquially termed "AI-complete" (see above).  In␣
 ↪natural speech there are hardly any pauses between successive words, and thus␣
 ↪speech segmentation is a necessary subtask of speech recognition (see below). In␣
 ↪most spoken languages, the sounds representing successive letters blend into each␣
 ↪other in a process termed coarticulation, so the conversion of the analog signal to␣
 ↪discrete characters can be a very difficult process. Also, given that words in the␣
 ↪same language are spoken by people with different accents, the speech recognition␣
 ↪software must be able to recognize the wide variety of input as being identical to␣
 ↪each other in terms of its textual equivalent.
Speech segmentation
Given a sound clip of a person or people speaking, separate it into words.  A subtask␣
 ↪of speech recognition and typically grouped with it.
Text-to-speech
Given a text, transform those units and produce a spoken representation. Text-to-
 ↪speech can be used to aid the visually impaired.[21]
Word segmentation (Tokenization)
Separate a chunk of continuous text into separate words. For a language like English,␣
 ↪this is fairly trivial, since words are usually separated by spaces. However, some␣
 ↪written languages like Chinese, Japanese and Thai do not mark word boundaries in␣
 ↪such a fashion, and in those languages text segmentation is a significant task␣
 ↪requiring knowledge of the vocabulary and morphology of words in the language.␣
 ↪Sometimes this process is also used in cases like bag of words (BOW) creation in␣
 ↪data mining.
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Morphological analysis[edit]
Lemmatization
The task of removing inflectional endings only and to return the base dictionary form␣
↪of a word which is also known as a lemma. Lemmatization is another technique for␣
↪reducing words to their normalized form. But in this case, the transformation␣
↪actually uses a dictionary to map words to their actual form.[22]
Morphological segmentation
Separate words into individual morphemes and identify the class of the morphemes. The␣
↪difficulty of this task depends greatly on the complexity of the morphology (i.e.,␣
↪the structure of words) of the language being considered. English has fairly simple␣
↪morphology, especially inflectional morphology, and thus it is often possible to␣
↪ignore this task entirely and simply model all possible forms of a word (e.g.,
↪"open, opens, opened, opening") as separate words. In languages such as Turkish or␣
↪Meitei,[23] a highly agglutinated Indian language, however, such an approach is not␣
↪possible, as each dictionary entry has thousands of possible word forms.
Part-of-speech tagging
Given a sentence, determine the part of speech (POS) for each word. Many words,␣
↪especially common ones, can serve as multiple parts of speech. For example, "book"␣
↪can be a noun ("the book on the table") or verb ("to book a flight"); "set" can be␣
↪a noun, verb or adjective; and "out" can be any of at least five different parts of␣
↪speech.
Stemming
The process of reducing inflected (or sometimes derived) words to a base form (e.g.,
↪"close" will be the root for "closed", "closing", "close", "closer" etc.). Stemming␣
↪yields similar results as lemmatization, but does so on grounds of rules, not a␣
↪dictionary.
Syntactic analysis[edit]
Grammar induction[24]
Generate a formal grammar that describes a language's syntax.
Sentence breaking (also known as "sentence boundary disambiguation")
Given a chunk of text, find the sentence boundaries. Sentence boundaries are often␣
↪marked by periods or other punctuation marks, but these same characters can serve␣
↪other purposes (e.g., marking abbreviations).
Parsing
Determine the parse tree (grammatical analysis) of a given sentence. The grammar for␣
↪natural languages is ambiguous and typical sentences have multiple possible␣
↪analyses: perhaps surprisingly, for a typical sentence there may be thousands of␣
↪potential parses (most of which will seem completely nonsensical to a human). There␣
↪are two primary types of parsing: dependency parsing and constituency parsing.␣
↪Dependency parsing focuses on the relationships between words in a sentence␣
↪(marking things like primary objects and predicates), whereas constituency parsing␣
↪focuses on building out the parse tree using a probabilistic context-free grammar␣
↪(PCFG) (see also stochastic grammar).
Lexical semantics (of individual words in context)[edit]
Lexical semantics
What is the computational meaning of individual words in context?
Distributional semantics
How can we learn semantic representations from data?
Named entity recognition (NER)
Given a stream of text, determine which items in the text map to proper names, such␣
↪as people or places, and what the type of each such name is (e.g. person, location,␣
↪organization). Although capitalization can aid in recognizing named entities in␣
↪languages such as English, this information cannot aid in determining the type of␣
↪named entity, and in any case, is often inaccurate or insufficient.  For example,␣
↪the first letter of a sentence is also capitalized, and named entities often span␣
↪several words, only some of which are capitalized.  Furthermore, many other␣
↪languages in non-Western scripts (e.g. Chinese or Arabic) do not have any␣
↪capitalization at all, and even languages with capitalization may not consistently␣
↪use it to distinguish names. For example, German capitalizes all nouns, regardless␣
↪of whether they are names, and French and Spanish do not capitalize names that␣
↪serve as adjectives.
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Sentiment analysis (see also Multimodal sentiment analysis)
Extract subjective information usually from a set of documents, often using online␣
↪reviews to determine "polarity" about specific objects. It is especially useful for␣
↪identifying trends of public opinion in social media, for marketing.
Terminology extraction
The goal of terminology extraction is to automatically extract relevant terms from a␣
↪given corpus.
Word sense disambiguation
Many words have more than one meaning; we have to select the meaning which makes the␣
↪most sense in context.  For this problem, we are typically given a list of words␣
↪and associated word senses, e.g. from a dictionary or an online resource such as␣
↪WordNet.
Relational semantics (semantics of individual sentences)[edit]
Relationship extraction
Given a chunk of text, identify the relationships among named entities (e.g. who is␣
↪married to whom).
Semantic parsing
Given a piece of text (typically a sentence), produce a formal representation of its␣
↪semantics, either as a graph (e.g., in AMR parsing) or in accordance with a logical␣
↪formalism (e.g., in DRT parsing). This challenge typically includes aspects of␣
↪several more elementary NLP tasks from semantics (e.g., semantic role labelling,␣
↪word sense disambiguation) and can be extended to include full-fledged discourse␣
↪analysis (e.g., discourse analysis, coreference; see Natural language understanding␣
↪below).
Semantic role labelling (see also implicit semantic role labelling below)
Given a single sentence, identify and disambiguate semantic predicates (e.g., verbal␣
↪frames), then identify and classify the frame elements (semantic roles).
Discourse (semantics beyond individual sentences)[edit]
Coreference resolution
Given a sentence or larger chunk of text, determine which words ("mentions") refer to␣
↪the same objects ("entities"). Anaphora resolution is a specific example of this␣
↪task, and is specifically concerned with matching up pronouns with the nouns or␣
↪names to which they refer. The more general task of coreference resolution also␣
↪includes identifying so-called "bridging relationships" involving referring␣
↪expressions. For example, in a sentence such as "He entered John's house through␣
↪the front door", "the front door" is a referring expression and the bridging␣
↪relationship to be identified is the fact that the door being referred to is the␣
↪front door of John's house (rather than of some other structure that might also be␣
↪referred to).
Discourse analysis
This rubric includes several related tasks.  One task is discourse parsing, i.e.,␣
↪identifying the discourse structure of a connected text, i.e. the nature of the␣
↪discourse relationships between sentences (e.g. elaboration, explanation, contrast).
↪  Another possible task is recognizing and classifying the speech acts in a chunk␣
↪of text (e.g. yes-no question, content question, statement, assertion, etc.).
Implicit semantic role labelling
Given a single sentence, identify and disambiguate semantic predicates (e.g., verbal␣
↪frames) and their explicit semantic roles in the current sentence (see Semantic␣
↪role labelling above). Then, identify semantic roles that are not explicitly␣
↪realized in the current sentence, classify them into arguments that are explicitly␣
↪realized elsewhere in the text and those that are not specified, and resolve the␣
↪former against the local text. A closely related task is zero anaphora resolution,␣
↪i.e., the extension of coreference resolution to pro-drop languages.
Recognizing textual entailment
Given two text fragments, determine if one being true entails the other, entails the␣
↪other's negation, or allows the other to be either true or false.[25]
Topic segmentation and recognition
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Given a chunk of text, separate it into segments each of which is devoted to a topic,␣
↪and identify the topic of the segment.
Argument mining
The goal of argument mining is the automatic extraction and identification of␣
↪argumentative structures from natural language text with the aid of computer␣
↪programs.[26] Such argumentative structures include the premise, conclusions, the␣
↪argument scheme and the relationship between the main and subsidiary argument, or␣
↪the main and counter-argument within discourse.[27][28]
Higher-level NLP applications[edit]
Automatic summarization (text summarization)
Produce a readable summary of a chunk of text.  Often used to provide summaries of␣
↪the text of a known type, such as research papers, articles in the financial␣
↪section of a newspaper.
Book generation
Not an NLP task proper but an extension of natural language generation and other NLP␣
↪tasks is the creation of full-fledged books. The first machine-generated book was␣
↪created by a rule-based system in 1984 (Racter, The policeman's beard is half-
↪constructed).[29] The first published work by a neural network was published in␣
↪2018, 1 the Road, marketed as a novel, contains sixty million words. Both these␣
↪systems are basically elaborate but non-sensical (semantics-free) language models.␣
↪The first machine-generated science book was published in 2019 (Beta Writer,␣
↪Lithium-Ion Batteries, Springer, Cham).[30] Unlike Racter and 1 the Road, this is␣
↪grounded on factual knowledge and based on text summarization.
Dialogue management
Computer systems intended to converse with a human.
Document AI
A Document AI platform sits on top of the NLP technology enabling users with no prior␣
↪experience of artificial intelligence, machine learning or NLP to quickly train a␣
↪computer to extract the specific data they need from different document types. NLP-
↪powered Document AI enables non-technical teams to quickly access information␣
↪hidden in documents, for example, lawyers, business analysts and accountants.[31]
Grammatical error correction
Grammatical error detection and correction involves a great band-width of problems on␣
↪all levels of linguistic analysis (phonology/orthography, morphology, syntax,␣
↪semantics, pragmatics). Grammatical error correction is impactful since it affects␣
↪hundreds of millions of people that use or acquire English as a second language. It␣
↪has thus been subject to a number of shared tasks since 2011.[32][33][34] As far as␣
↪orthography, morphology, syntax and certain aspects of semantics are concerned, and␣
↪due to the development of powerful neural language models such as GPT-2, this can␣
↪now (2019) be considered a largely solved problem and is being marketed in various␣
↪commercial applications.
Machine translation
Automatically translate text from one human language to another.  This is one of the␣
↪most difficult problems, and is a member of a class of problems colloquially termed
↪"AI-complete", i.e. requiring all of the different types of knowledge that humans␣
↪possess (grammar, semantics, facts about the real world, etc.) to solve properly.
Natural language generation (NLG):
Convert information from computer databases or semantic intents into readable human␣
↪language.
Natural language understanding (NLU)
Convert chunks of text into more formal representations such as first-order logic␣
↪structures that are easier for computer programs to manipulate. Natural language␣
↪understanding involves the identification of the intended semantic from the␣
↪multiple possible semantics which can be derived from a natural language expression␣
↪which usually takes the form of organized notations of natural language concepts.␣
↪Introduction and creation of language metamodel and ontology are efficient however␣
↪empirical solutions. An explicit formalization of natural language semantics␣
↪without confusions with implicit assumptions such as closed-world assumption (CWA)␣
↪vs. open-world assumption, or subjective Yes/No vs. objective True/False is␣
↪expected for the construction of a basis of semantics formalization.[35]
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Question answering
Given a human-language question, determine its answer. Typical questions have a␣
↪specific right answer (such as "What is the capital of Canada?"), but sometimes␣
↪open-ended questions are also considered (such as "What is the meaning of life?").
General tendencies and (possible) future directions[edit]
Based on long-standing trends in the field, it is possible to extrapolate future␣
↪directions of NLP. As of 2020, three trends among the topics of the long-standing␣
↪series of CoNLL Shared Tasks can be observed:[36]

Interest on increasingly abstract, "cognitive" aspects of natural language (1999-
↪2001: shallow parsing, 2002-03: named entity recognition, 2006-09/2017-18:␣
↪dependency syntax, 2004-05/2008-09 semantic role labelling, 2011-12 coreference,␣
↪2015-16: discourse parsing, 2019: semantic parsing).
Increasing interest in multilinguality, and, potentially, multimodality (English␣
↪since 1999; Spanish, Dutch since 2002; German since 2003; Bulgarian, Danish,␣
↪Japanese, Portuguese, Slovenian, Swedish, Turkish since 2006; Basque, Catalan,␣
↪Chinese, Greek, Hungarian, Italian, Turkish since 2007; Czech since 2009; Arabic␣
↪since 2012; 2017: 40+ languages; 2018: 60+/100+ languages)
Elimination of symbolic representations (rule-based over supervised towards weakly␣
↪supervised methods, representation learning and end-to-end systems)
Cognition and NLP[edit]
Most higher-level NLP applications involve aspects that emulate intelligent behaviour␣
↪and apparent comprehension of natural language. More broadly speaking, the␣
↪technical operationalization of increasingly advanced aspects of cognitive␣
↪behaviour represents one of the developmental trajectories of NLP (see trends among␣
↪CoNLL shared tasks above).
Cognition refers to "the mental action or process of acquiring knowledge and␣
↪understanding through thought, experience, and the senses."[37] Cognitive science␣
↪is the interdisciplinary, scientific study of the mind and its processes.[38]␣
↪Cognitive linguistics is an interdisciplinary branch of linguistics, combining␣
↪knowledge and research from both psychology and linguistics.[39] Especially during␣
↪the age of symbolic NLP, the area of computational linguistics maintained strong␣
↪ties with cognitive studies.
As an example, George Lakoff offers a methodology to build natural language␣
↪processing (NLP) algorithms through the perspective of cognitive science, along␣
↪with the findings of cognitive linguistics,[40] with two defining aspects:

Apply the theory of conceptual metaphor, explained by Lakoff as “the understanding of␣
↪one idea, in terms of another” which provides an idea of the intent of the author.
↪[41] For example, consider the English word “big”. When used in a comparison (“That␣
↪is a big tree”), the author's intent is to imply that the tree is ”physically␣
↪large” relative to other trees or the authors experience.  When used metaphorically␣
↪(”Tomorrow is a big day”), the author’s intent to imply ”importance”.  The intent␣
↪behind other usages, like in ”She is a big person” will remain somewhat ambiguous␣
↪to a person and a cognitive NLP algorithm alike without additional information.
Assign relative measures of meaning to a word, phrase, sentence or piece of text␣
↪based on the information presented before and after the piece of text being␣
↪analyzed, e.g., by means of a probabilistic context-free grammar (PCFG). The␣
↪mathematical equation for such algorithms is presented in US patent 9269353 :




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{\displaystyle {RMM(token_{N})}={PMM(token_{N})}\times {\frac {1}{2d}}\left(\sum _{i=-
↪d}^{d}{((PMM(token_{N-1})}\times {PF(token_{N},token_{N-1}))_{i}}\right)}


Where,
RMM, is the Relative Measure of Meaning
token, is any block of text, sentence, phrase or word
N, is the number of tokens being analyzed
PMM, is the Probable Measure of Meaning based on a corpora
d, is the location of the token along the sequence of N-1 tokens
PF, is the Probability Function specific to a language
Ties with cognitive linguistics are part of the historical heritage of NLP, but they␣
↪have been less frequently addressed since the statistical turn during the 1990s.␣
↪Nevertheless, approaches to develop cognitive models towards technically␣
↪operationalizable frameworks have been pursued in the context of various frameworks,
↪ e.g., of cognitive grammar,[42] functional grammar,[43] construction grammar,[44]␣
↪computational psycholinguistics and cognitive neuroscience (e.g., ACT-R), however,␣
↪with limited uptake in mainstream NLP (as measured by presence on major␣
↪conferences[45] of the ACL). More recently, ideas of cognitive NLP have been␣
↪revived as an approach to achieve explainability, e.g., under the notion of
↪"cognitive AI".[46] Likewise, ideas of cognitive NLP are inherent to neural models␣
↪multimodal NLP (although rarely made explicit).[47]

See also[edit]

1 the Road
Automated essay scoring
Biomedical text mining
Compound term processing
Computational linguistics
Computer-assisted reviewing
Controlled natural language
Deep learning
Deep linguistic processing
Distributional semantics
Foreign language reading aid
Foreign language writing aid
Information extraction
Information retrieval
Language and Communication Technologies
Language technology
Latent semantic indexing
Native-language identification
Natural language programming
Natural language search
Outline of natural language processing
Query expansion
Query understanding
Reification (linguistics)
Speech processing
Spoken dialogue systems
Text-proofing
Text simplification
```

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Transformer (machine learning model)
Truecasing
Question answering
Word2vec

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↪the limits of its theoretical models (comparable to pathological phenomena in␣
↪mathematics), typically created using thought experiments, rather than the␣
↪systematic investigation of typical phenomena that occur in real-world data, as is␣
↪the case in corpus linguistics.  The creation and use of such corpora of real-world␣
↪data is a fundamental part of machine-learning algorithms for natural language␣
↪processing.  In addition, theoretical underpinnings of Chomskyan linguistics such␣
↪as the so-called "poverty of the stimulus" argument entail that general learning␣
↪algorithms, as are typically used in machine learning, cannot be successful in␣
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Sentiment analysis
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Word-sense induction
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Speech synthesis
Natural language generation
Optical character recognition
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Document classification
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Pachinko allocation
Computer-assistedreviewing
Automated essay scoring
Concordancer
Grammar checker
Predictive text
Spell checker
Syntax guessing
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Chatbot
Interactive fiction
Question answering
Virtual assistant
Voice user interface
Other software
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spaCy

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United States
Japan

Language portal




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Pre-processing

```
import gensim
import re
from gensim.corpora import Dictionary
```

```
doc_tokenized = gensim.utils.simple_preprocess(str(document), deacc=True)
doc_tokenized[:10]
```

```
['natural',
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 'the']
```

```
dictionary = Dictionary()
BoW_corpus = dictionary.doc2bow(doc_tokenized, allow_update=True)
BoW_corpus = [(dictionary[id], freq) for id, freq in BoW_corpus]
BoW_corpus[:10]
```

```
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 ('abelson', 1),
 ('able', 2),
 ('about', 5),
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 ('accents', 1)]
```

```
def convert(tup, dict):
    for a, b in tup:
        dict[a] = b
    return dict
BoW_corpus_dict = dict()
convert(BoW_corpus, BoW_corpus_dict)
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```

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```

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```

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```

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 'must': 1,
 'my': 1,
 'name': 1,
 'named': 7,
 'names': 5,
 'namespaces': 1,
 'national': 2,
 'native': 1,
 'natural': 66,
 ...}
```

Visualisation of Pre-trained Embeddings

We only look at the non-stopwords that are in the Word2Vec vocabulary.

```
import nltk
from nltk.corpus import stopwords

vocab_sorted = dict(sorted(BoW_corpus_dict.items(), key=lambda item: item[1],␣
↪reverse=True))
#print(vocab_sorted)

stopwords = stopwords.words('english')
input_vocab =  [word for word in vocab_sorted if word in wv.key_to_index.keys() and␣
↪word not in stopwords]
points = len(input_vocab)
X = wv[input_vocab]
X_tsne = tsne.fit_transform(X[:points])

#print(input_vocab)

#points = len(input_vocab)

interactive_tsne(list(input_vocab)[:points], X_tsne)
```

Training your own Word2Vec

```
from gensim.models import Word2Vec

cores = 16
model = Word2Vec(min_count=1,
                     window=2,
                     vector_size=100,
                     sample=6e-5,
                     alpha=0.03,
                     min_alpha=0.0007,
                     negative=20,
                     workers=cores-1)
```

```
from time import time

t = time()

model.build_vocab([doc_tokenized], progress_per=10)

print('Time to build vocab: {} mins'.format(round((time() - t) / 60, 2)))
```

```
Time to build vocab: 0.0 mins
```

```
t = time()

model.train(doc_tokenized, total_examples=model.corpus_count, epochs=1000, report_
↪delay=1)

print('Time to train the model: {} mins'.format(round((time() - t) / 60, 2)))
```

```
Time to train the model: 0.16 mins
```

```
model.wv.key_to_index.keys()
```

```
dict_keys(['the', 'of', 'and', 'to', 'language', 'in', 'is', 'natural', 'for', 'as',
↪'processing', 'text', 'nlp', 'on', 'that', 'learning', 'or', 'machine', 'with',
↪'such', 'speech', 'words', 'are', 'linguistics', 'be', 'this', 'systems', 'from',
↪'statistical', 'semantic', 'semantics', 'data', 'given', 'by', 'neural', 'more', 'an
↪', 'can', 'which', 'word', 'based', 'edit', 'sentence', 'cognitive', 'rules', 'other
↪', 'analysis', 'tasks', 'parsing', 'models', 'information', 'task', 'grammar',
↪'retrieved', 'computer', 'into', 'computational', 'methods', 'have', 'research',
↪'recognition', 'understanding', 'has', 'since', 'not', 'languages', 'also', 'was',
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↪'discourse', 'example', 'it', 'human', 'deep', 'possible', 'been', 'using',
↪'segmentation', 'world', 'when', 'morphology', 'extraction', 'most', 'real', 'doi',
↪'one', 'often', 'determine', 'document', 'knowledge', 'www', 'some', 'role', 'part',
↪ 'but', 'at', 'use', 'separate', 'its', 'dictionary', 'english', 'being', 'they',
↪'system', 'symbolic', 'mining', 'science', 'networks', 'arxiv', 'sentences',
↪'context', 'meaning', 'individual', 'all', 'ai', 'network', 'aid', 'typically', 'pdf
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↪'generation', 'error', 'early', 'level', 'syntax', 'labelling', 'documents',
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↪'thus', 'typical', 'proceedings', 'complexity', 'sense', 'trends', 'corpora', 'press
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↪'published', 'during', 'chinese', 'then', 'field', 'major', 'about', 'artificial',
```

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Comparing the purposely trained and the pre-trained vectors

We can see that due to the lack of data in training our own embeddings, the semantic information captured by the embeddings are not as meaningful as the the pre-trained ones.

```
# Our trained domain specific embeddings
model.wv.most_similar(positive=["language"])
```

```
[('generated', 0.3286932706832886),
 ('cache', 0.29854971170425415),
 ('charge', 0.27286359667778015),
 ('segmentation', 0.26987093687057495),
 ('assisted', 0.26623496413230896),
 ('drop', 0.2609272599220276),
 ('on', 0.25290459394454956),
 ('successfully', 0.2467595636844635),
 ('any', 0.24194024503231049),
 ('easier', 0.2374984174966812)]
```

```
# Pretrained embeddings
wv.most_similar(positive=["language"])
```

```
[('langauge', 0.747669517993927),
 ('Language', 0.6695358157157898),
 ('languages', 0.6341331601142883),
 ('English', 0.6120712757110596),
 ('CMPB_Spanish', 0.6083105802536011),
 ('nonnative_speakers', 0.6063110828399658),
 ('idiomatic_expressions', 0.5889802575111389),
 ('verb_tenses', 0.5841568112373352),
 ('Kumeyaay_Diegueno', 0.5798824429512024),
 ('dialect', 0.5724599957466125)]
```

CHAPTER

EIGHT

LAB08: DOCUMENT CLASSIFICATION

In this labe we will

- first use a toy example to *revisit a simple perceptron* (one hidden layer neural network) in PyTorch to illustrate many fundamental concepts (activation functions, hidden layers, backpropogation, training routines) with visualisation.
- then by introducing *the PyTorch built-in* `Dataset` *and* `Dataloader` *classes*, we take an object oriented coding approach to factorise our earlier code into a better more modulised style. This new code not only allows for the separation of data preparation from training, it also enables the transition from whole dataset training (batch gradient decent) to mini-batch gradient decent.
- lastly, we repeat the above exercises, but this time with a realworld task and* natural language dataset*: to classify whether restaurant reviews on Yelp are positive or negative using a perceptron for supervised training.

Credit: the notebooks are adapted from Chapter 3 of Natural Language Processing with PyTorch

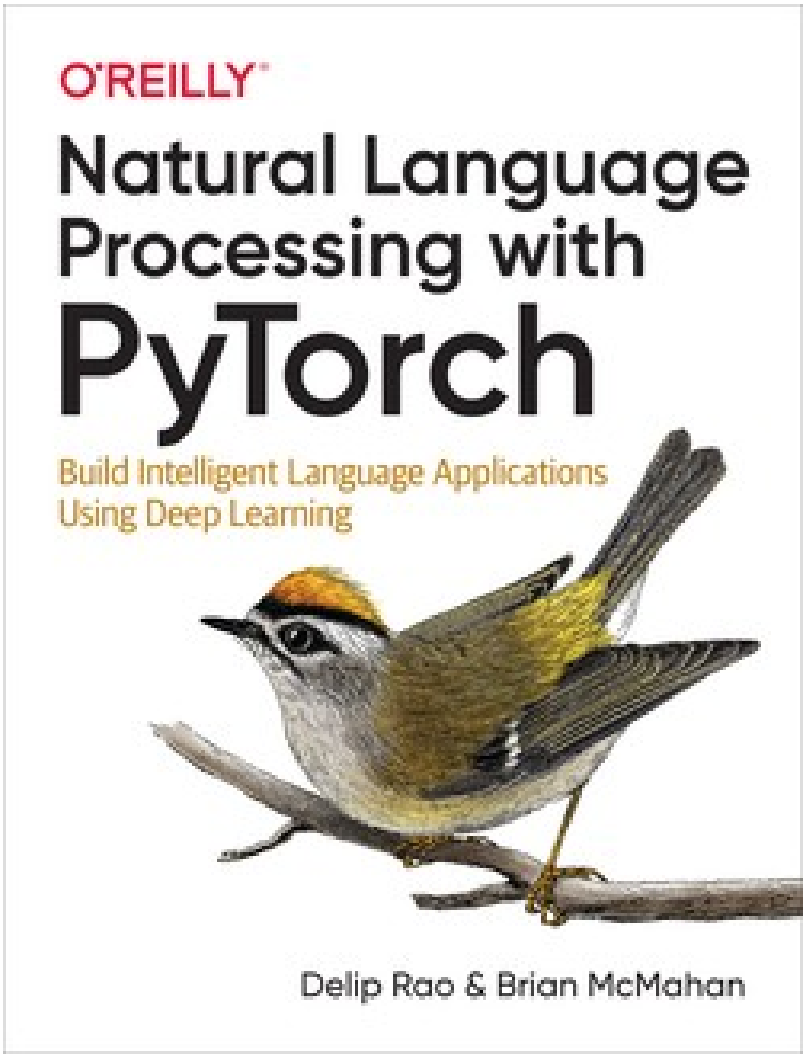
8.1 Perceptron

```
import matplotlib.pyplot as plt
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

%matplotlib inline
```

8.1.1 Global Settings

```
LEFT_CENTER = (3, 3)
RIGHT_CENTER = (3, -2)
```


O'REILLY
Natural Language Processing with PyTorch
Build Intelligent Language Applications Using Deep Learning
Delip Rao & Brian McMahan

8.1.2 Defining the Model

```
class Perceptron(nn.Module):
    """ A Perceptron is one Linear layer """

    def __init__(self, input_dim):
        """
        Args:
            input_dim (int): size of the input features
        """
        super(Perceptron, self).__init__()
        self.fc1 = nn.Linear(input_dim, 1)

    def forward(self, x_in):
        """The forward pass of the MLP

        Args:
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, input_dim)
        Returns:
            the resulting tensor. tensor.shape should be (batch, 1)
        """
        return torch.sigmoid(self.fc1(x_in))
```

8.1.3 Get Data Function

```
def get_toy_data(batch_size, left_center=LEFT_CENTER, right_center=RIGHT_CENTER):
    seed = 1337

    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    np.random.seed(seed)

    x_data = []
    y_targets = np.zeros(batch_size)
    for batch_i in range(batch_size):
        if np.random.random() > 0.5:
            x_data.append(np.random.normal(loc=left_center))
        else:
            x_data.append(np.random.normal(loc=right_center))
            y_targets[batch_i] = 1
    return torch.tensor(x_data, dtype=torch.float32), torch.tensor(y_targets,␣
↪dtype=torch.float32)
```

8.1.4 Visualizing Results Function

```
def visualize_results(perceptron, x_data, y_truth, n_samples=1000, ax=None,␣
↪epoch=None,
                      title='', levels=[0.3, 0.4, 0.5], linestyles=['--', '-', '--']):
    y_pred = perceptron(x_data)
    y_pred = (y_pred > 0.5).long().data.numpy().astype(np.int32)

    x_data = x_data.data.numpy()
```

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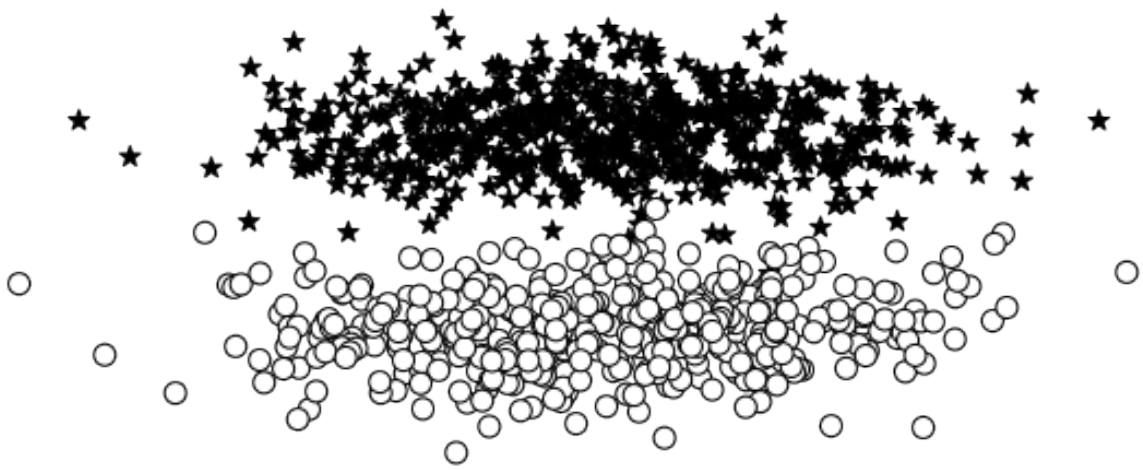
```
    y_truth = y_truth.data.numpy().astype(np.int32)

    n_classes = 2

    all_x = [[] for _ in range(n_classes)]
    all_colors = [[] for _ in range(n_classes)]

    colors = ['black', 'white']
    markers = ['o', '*']

    for x_i, y_pred_i, y_true_i in zip(x_data, y_pred, y_truth):
        all_x[y_true_i].append(x_i)
        if y_pred_i == y_true_i:
            all_colors[y_true_i].append("white")
        else:
            all_colors[y_true_i].append("black")
        #all_colors[y_true_i].append(colors[y_pred_i])

    all_x = [np.stack(x_list) for x_list in all_x]

    if ax is None:
        _, ax = plt.subplots(1, 1, figsize=(10,10))

    for x_list, color_list, marker in zip(all_x, all_colors, markers):
        ax.scatter(x_list[:, 0], x_list[:, 1], edgecolor="black", marker=marker,␣
↪facecolor=color_list, s=300)


    xlim = (min([x_list[:,0].min() for x_list in all_x]),
            max([x_list[:,0].max() for x_list in all_x]))

    ylim = (min([x_list[:,1].min() for x_list in all_x]),
            max([x_list[:,1].max() for x_list in all_x]))

    # hyperplane

    xx = np.linspace(xlim[0], xlim[1], 30)
    yy = np.linspace(ylim[0], ylim[1], 30)
    YY, XX = np.meshgrid(yy, xx)
    xy = np.vstack([XX.ravel(), YY.ravel()]).T

    Z = perceptron(torch.tensor(xy, dtype=torch.float32)).detach().numpy().reshape(XX.
↪shape)
    ax.contour(XX, YY, Z, colors='k', levels=levels, linestyles=linestyles)

    plt.suptitle(title)

    if epoch is not None:
        plt.text(xlim[0], ylim[1], "Epoch = {}".format(str(epoch)))
```

8.1.5 Initial Data Plot

```
seed = 1337

torch.manual_seed(seed)
torch.cuda.manual_seed_all(seed)
np.random.seed(seed)

x_data, y_truth = get_toy_data(batch_size=1000)

x_data = x_data.data.numpy()
y_truth = y_truth.data.numpy()

left_x = []
right_x = []
left_colors = []
right_colors =  []

for x_i, y_true_i in zip(x_data, y_truth):
    color = 'black'

    if y_true_i == 0:
        left_x.append(x_i)
        left_colors.append(color)

    else:
        right_x.append(x_i)
        right_colors.append(color)

left_x = np.stack(left_x)
right_x = np.stack(right_x)

_, ax = plt.subplots(1, 1, figsize=(10,4))

ax.scatter(left_x[:, 0], left_x[:, 1], color=left_colors, marker='*', s=100)
ax.scatter(right_x[:, 0], right_x[:, 1], facecolor='white', edgecolor=right_colors,␣
↪marker='o', s=100)

plt.axis('off')
```

```
(-0.6789941847324372, 6.3322738468647, -5.551233220100403, 6.149525094032287)
```



8.1.6 The Training + intermittent data plots

```
lr = 0.01
input_dim = 2

batch_size = 1000
n_epochs = 12
n_batches = 5

perceptron = Perceptron(input_dim=input_dim)
optimizer = optim.Adam(params=perceptron.parameters(), lr=lr)
bce_loss = nn.BCELoss()

losses = []

x_data_static, y_truth_static = get_toy_data(batch_size)
fig, ax = plt.subplots(1, 1, figsize=(10,5))
visualize_results(perceptron, x_data_static, y_truth_static, ax=ax, title='Initial␣
↪Model State')
plt.axis('off')
#plt.savefig('initial.png')

change = 1.0
last = 10.0
epsilon = 1e-3
epoch = 0
while change > epsilon or epoch < n_epochs or last > 0.3:
#for epoch in range(n_epochs):
    for _ in range(n_batches):

        optimizer.zero_grad()
        x_data, y_target = get_toy_data(batch_size)
        y_pred = perceptron(x_data).squeeze()
        loss = bce_loss(y_pred, y_target)
        loss.backward()
        optimizer.step()
```

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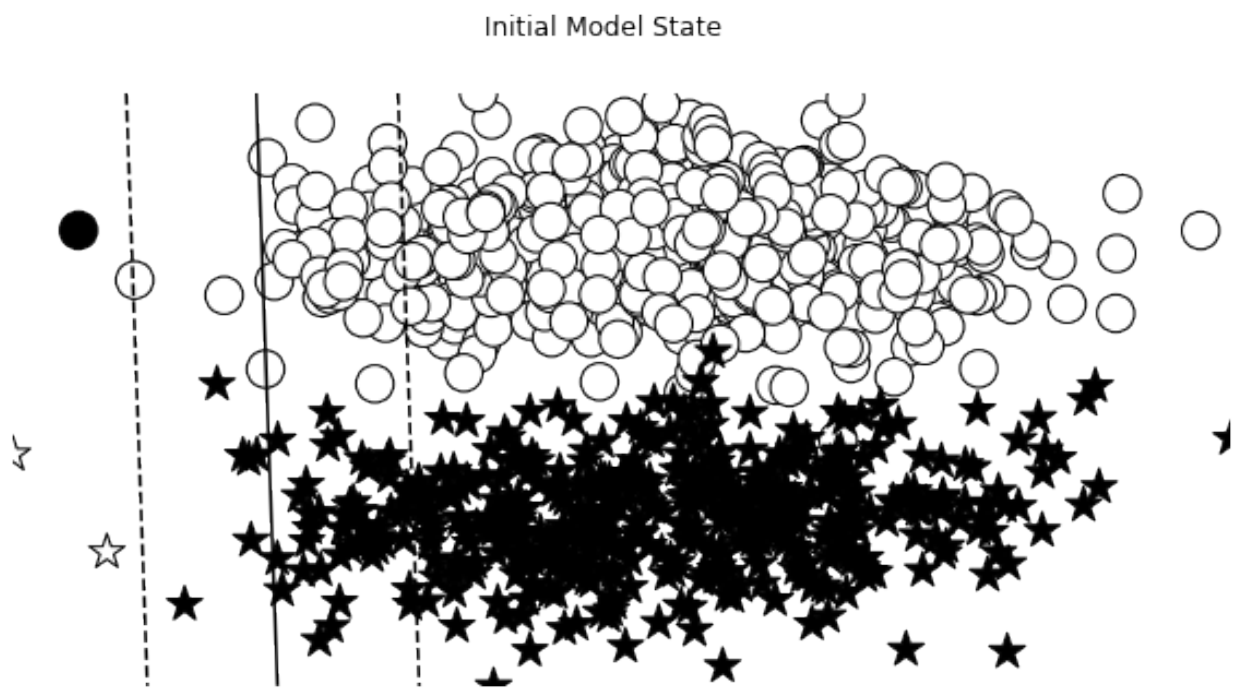
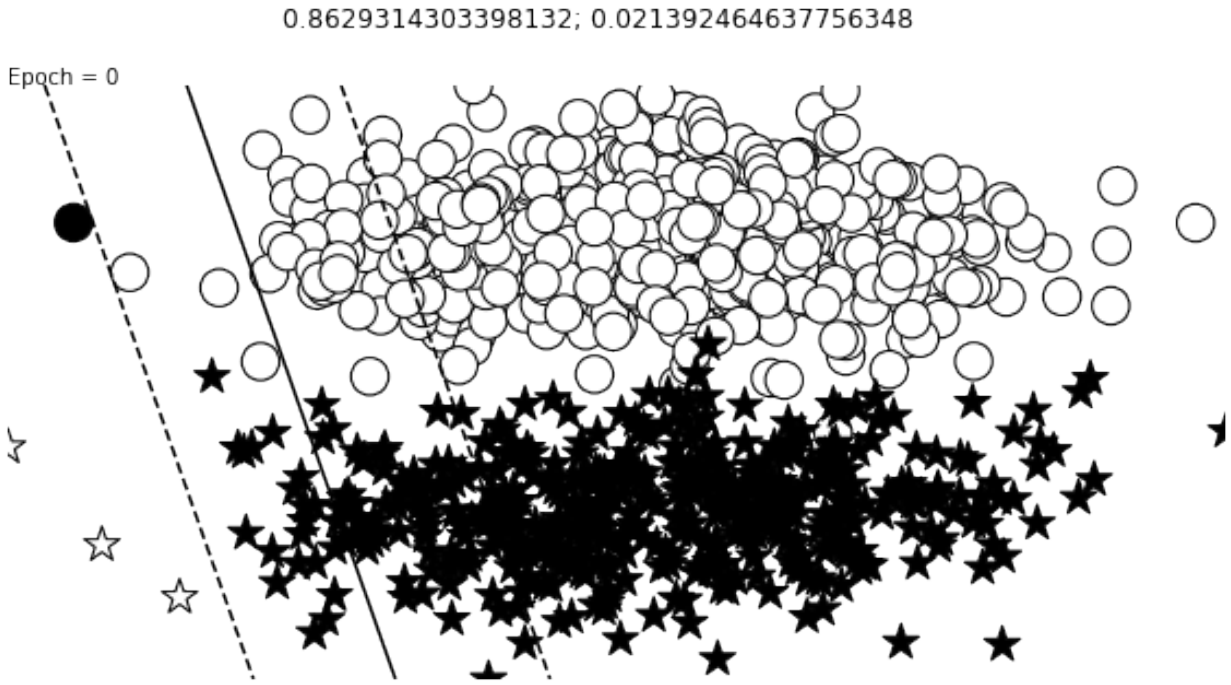
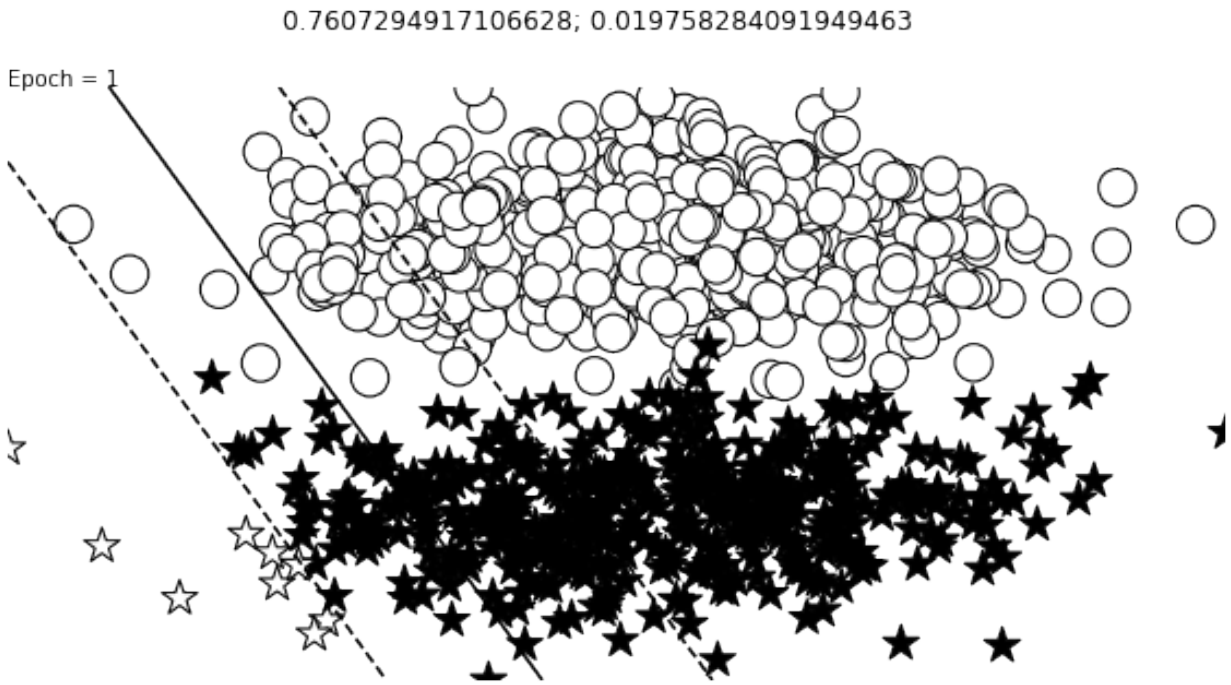
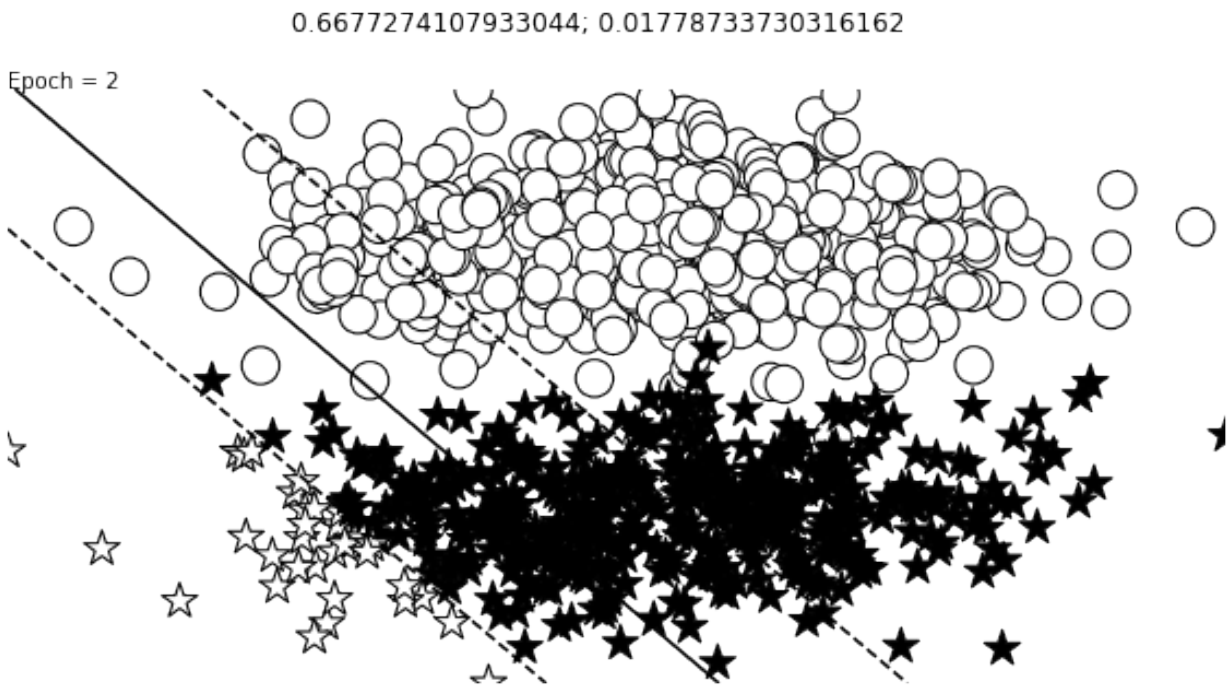
```
        loss_value = loss.item()
        losses.append(loss_value)

        change = abs(last - loss_value)
        last = loss_value

    fig, ax = plt.subplots(1, 1, figsize=(10,5))
    visualize_results(perceptron, x_data_static, y_truth_static, ax=ax, epoch=epoch,
                      title=f"{loss_value}; {change}")
    plt.axis('off')
    epoch += 1
    #plt.savefig('epoch{}_toylearning.png'.format(epoch))
```

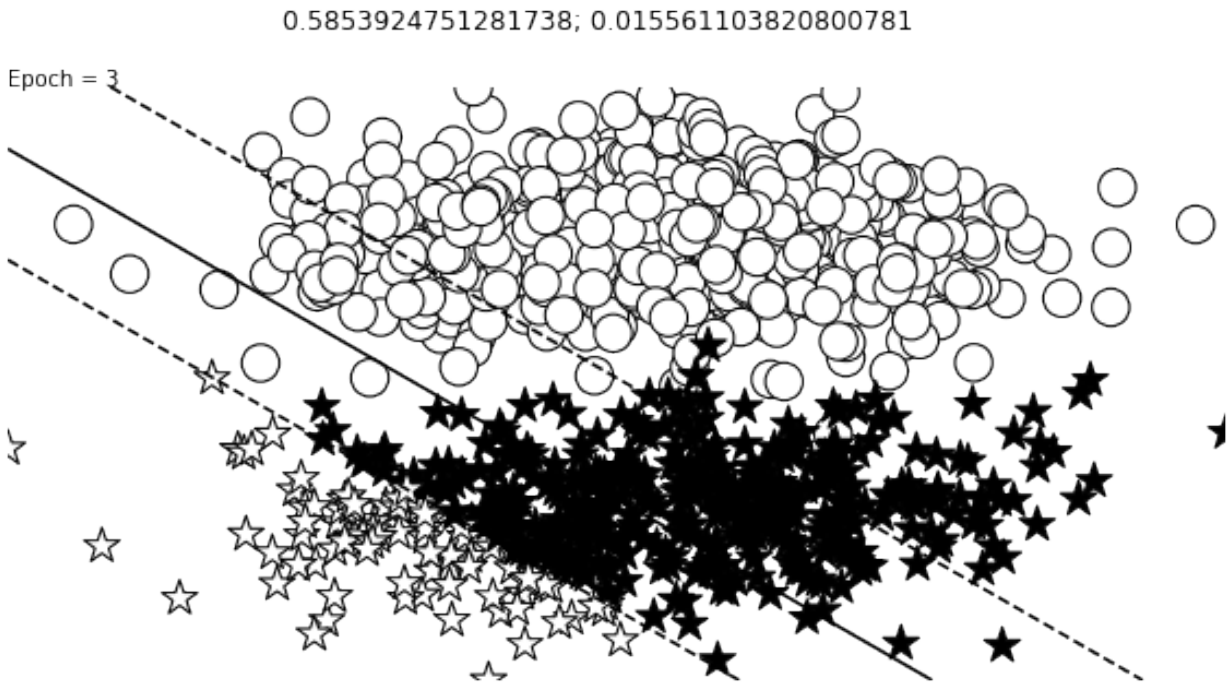
```
C:\Users\wei\AppData\Local\Temp/ipykernel_8888/1489453434.py:48: RuntimeWarning: More␣
↪than 20 figures have been opened. Figures created through the pyplot interface␣
↪(`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume␣
↪too much memory. (To control this warning, see the rcParam `figure.max_open_
↪warning`).
  fig, ax = plt.subplots(1, 1, figsize=(10,5))
```



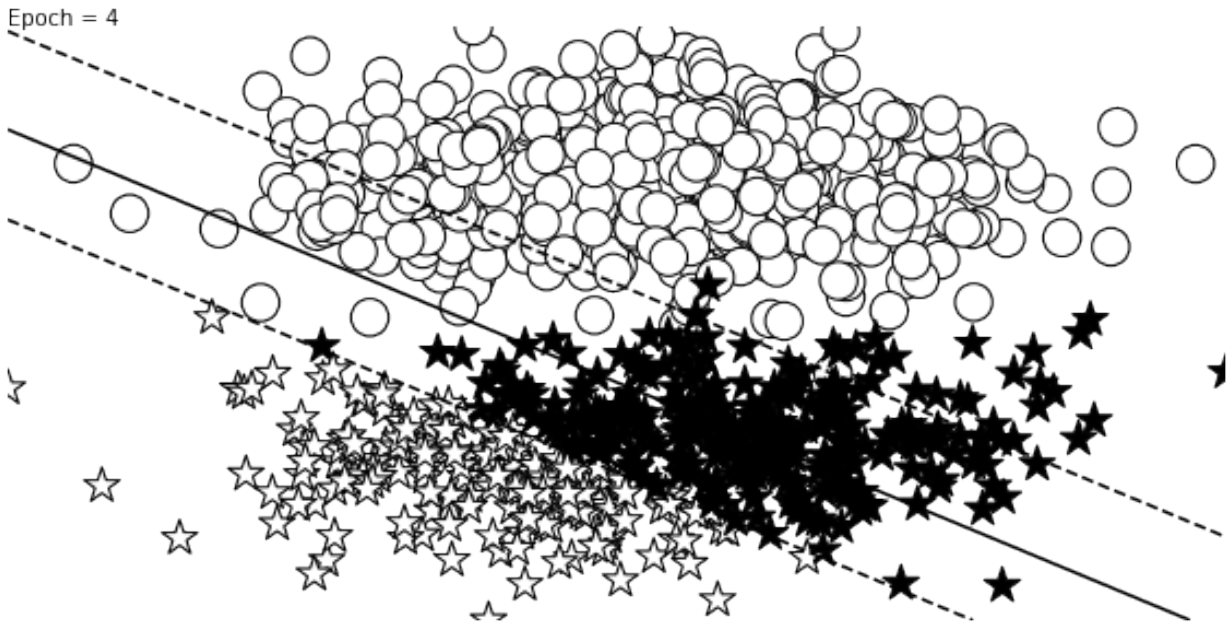

0.8629314303398132; 0.021392464637756348
Epoch = 0


0.7607294917106628; 0.019758284091949463
Epoch = 1

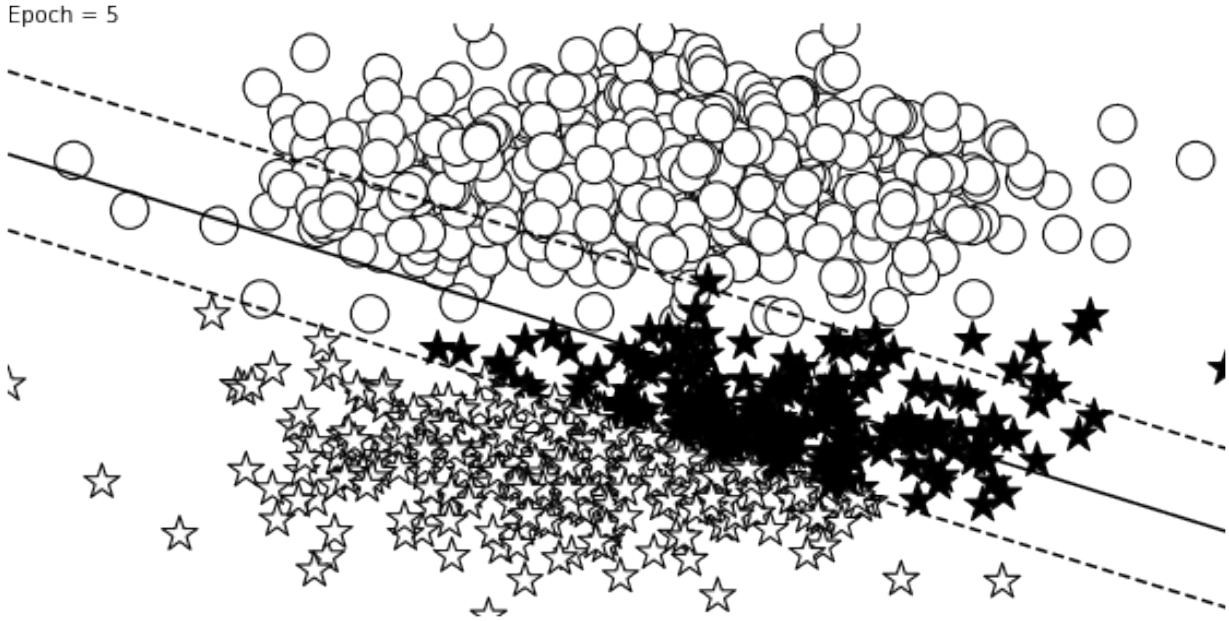

0.6677274107933044; 0.01778733730316162
Epoch = 2

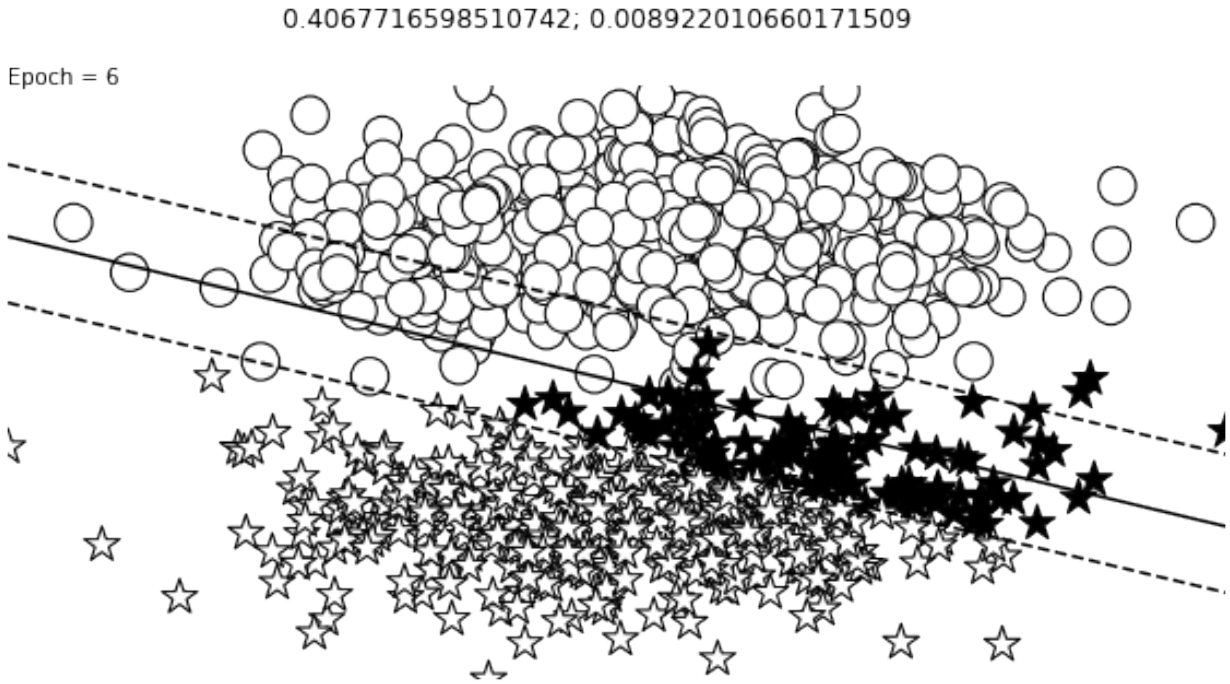

0.5853924751281738; 0.015561103820800781
Epoch = 3

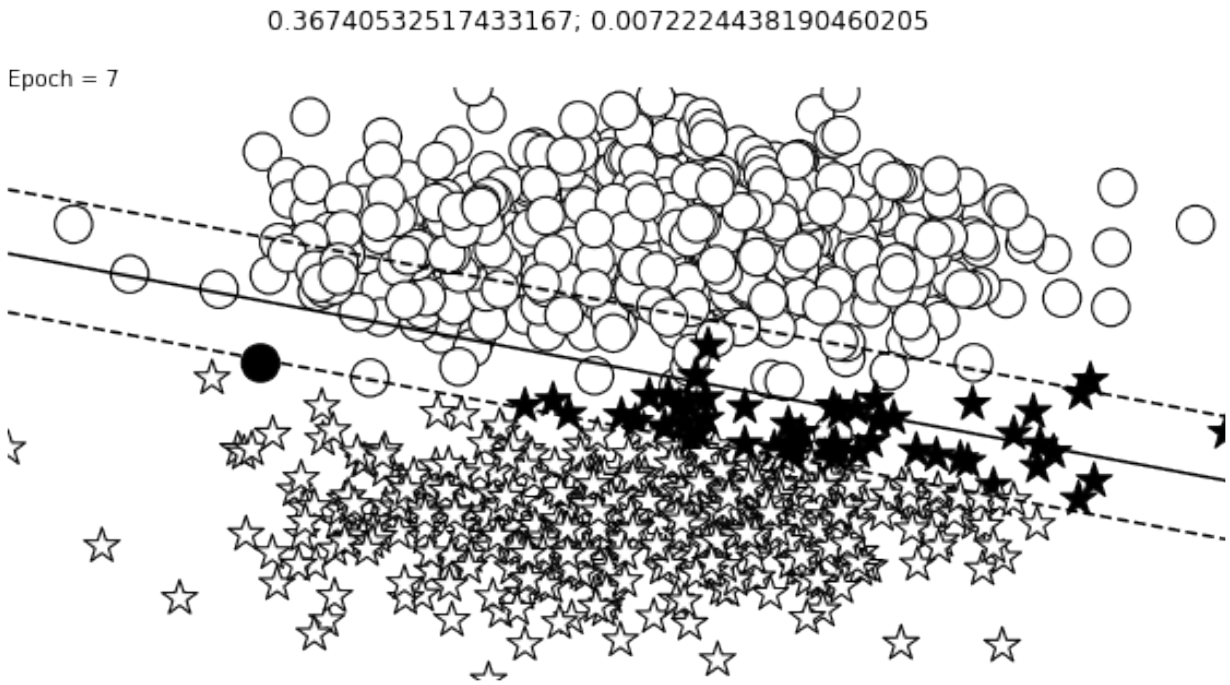
0.5145881175994873; 0.013224363327026367

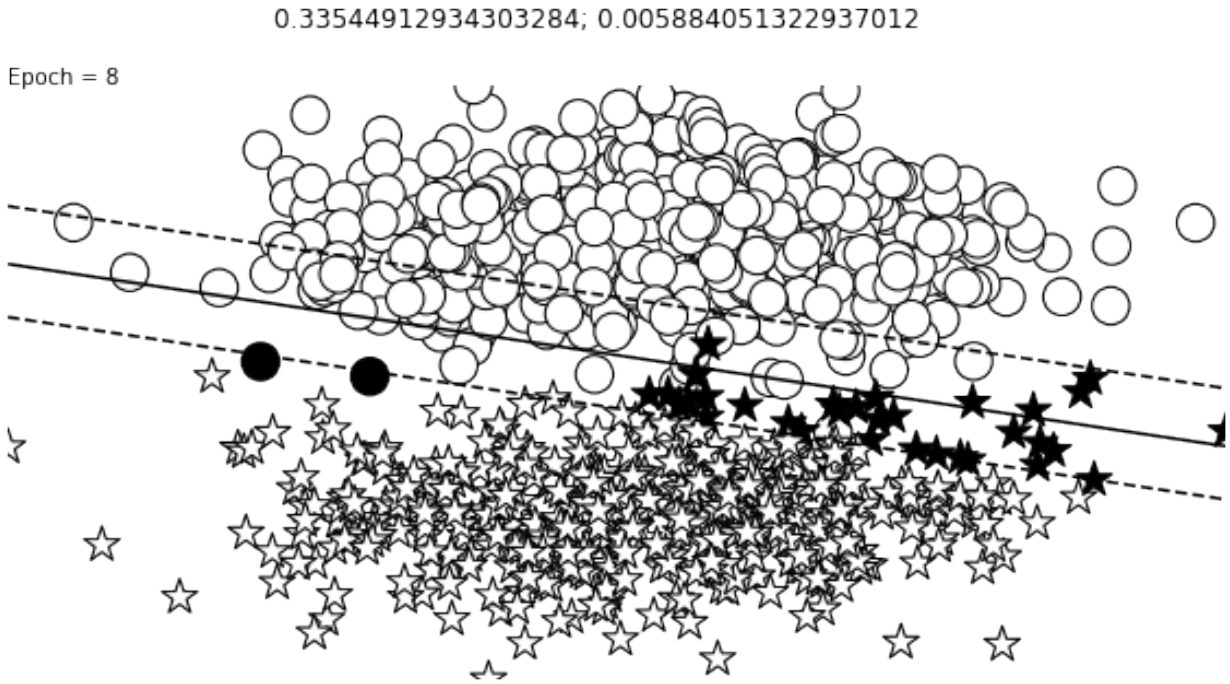


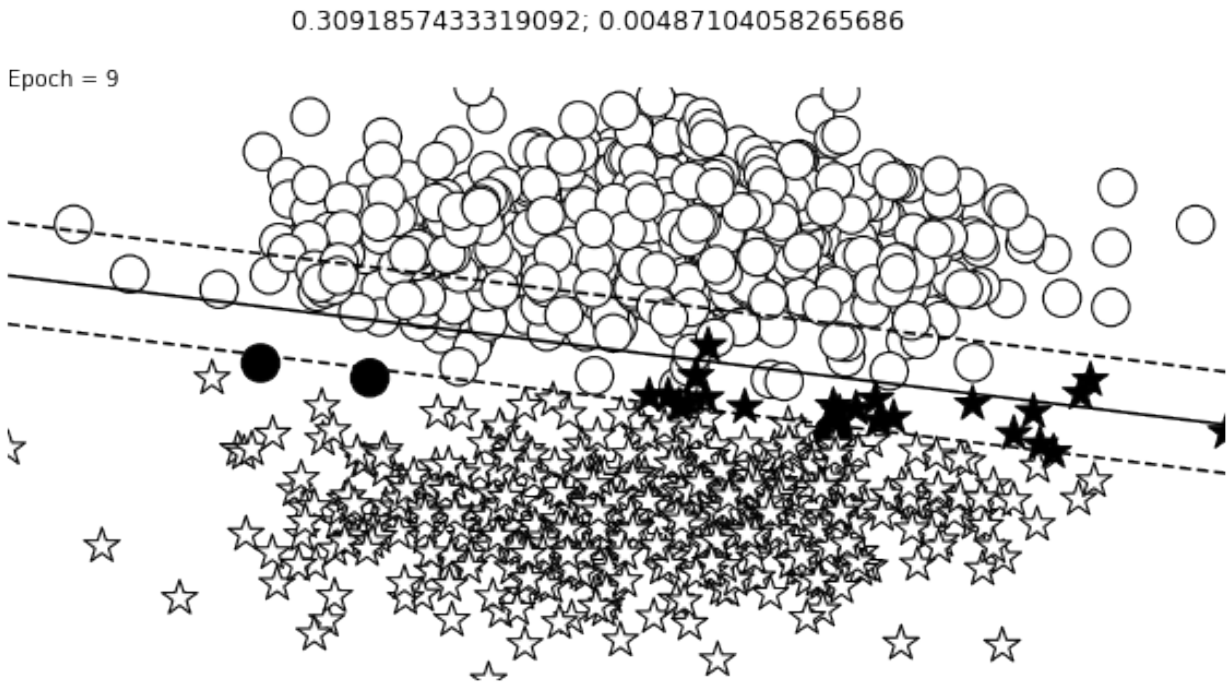
0.4553321599960327; 0.01095685362815857

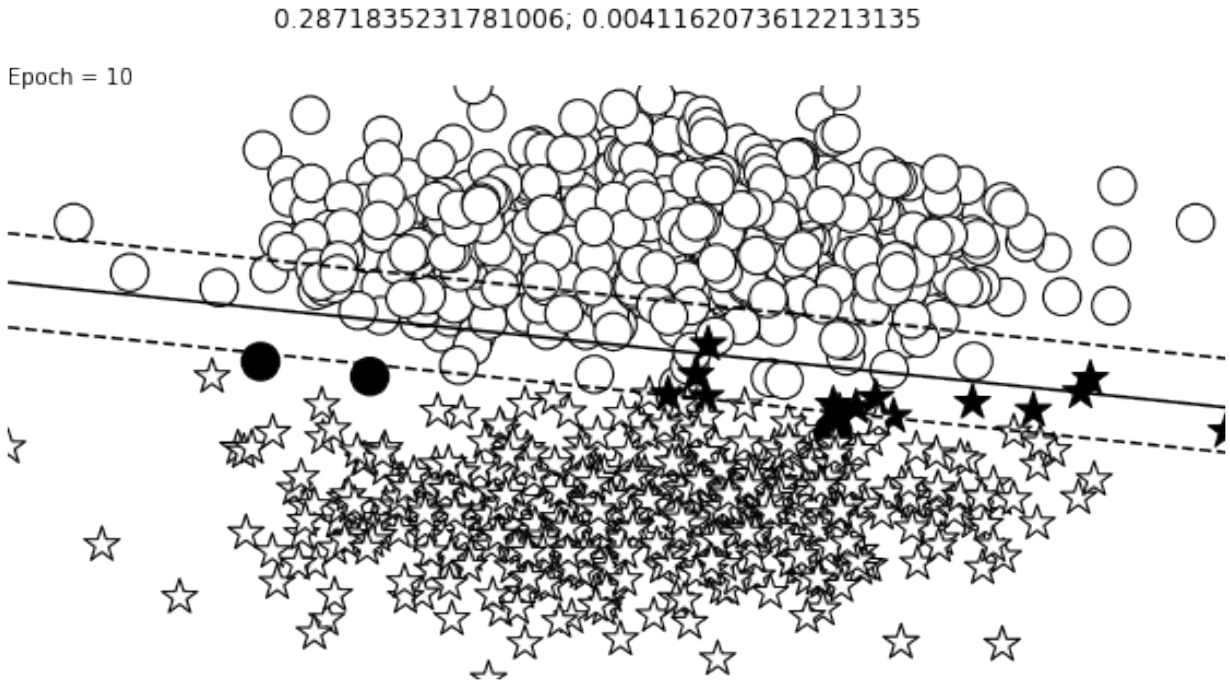


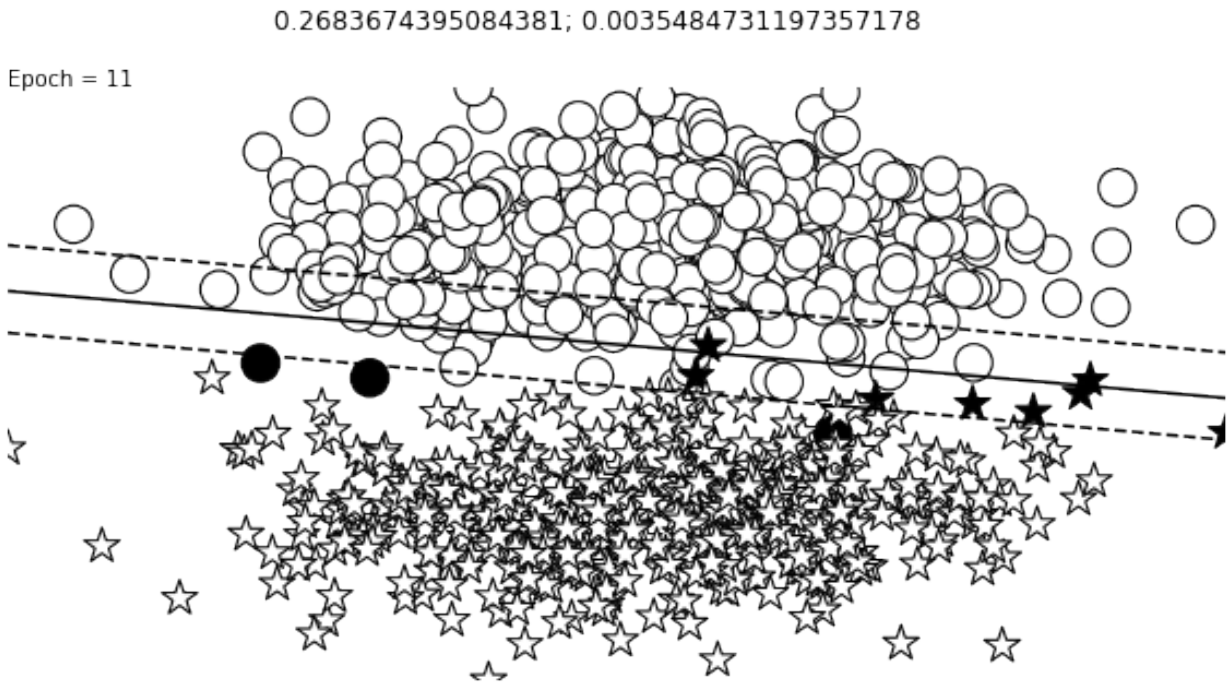

0.4067716598510742; 0.008922010660171509
Epoch = 6

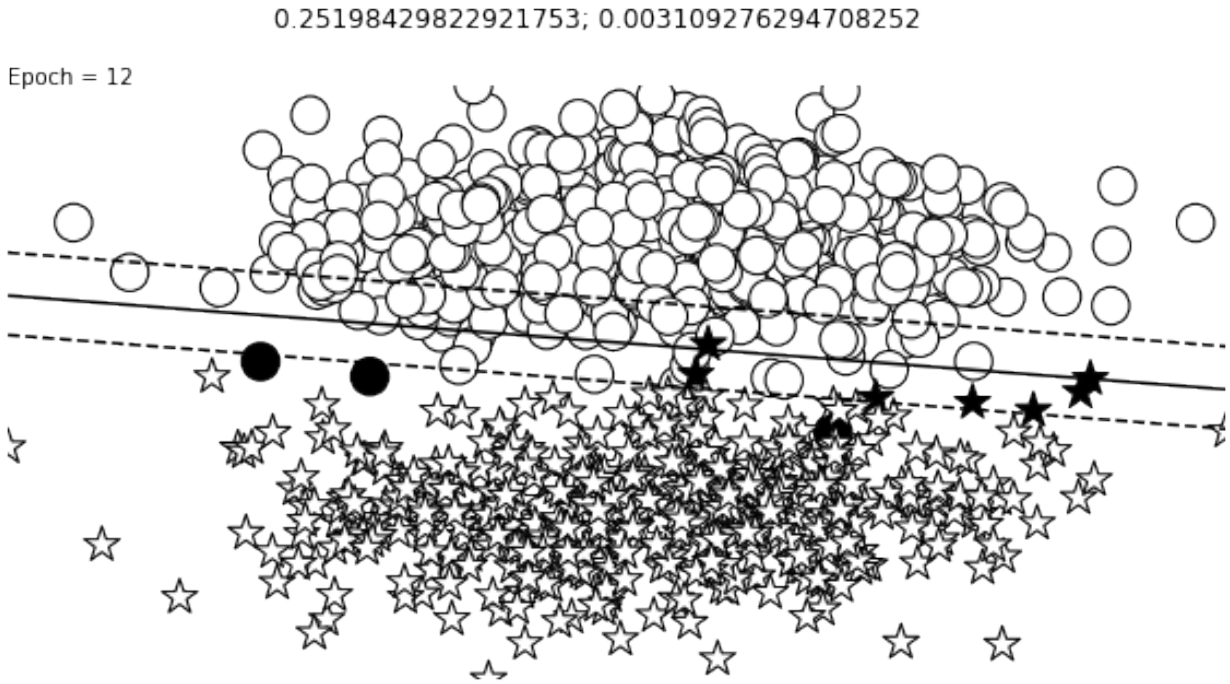

0.36740532517433167; 0.0072224438190460205
Epoch = 7

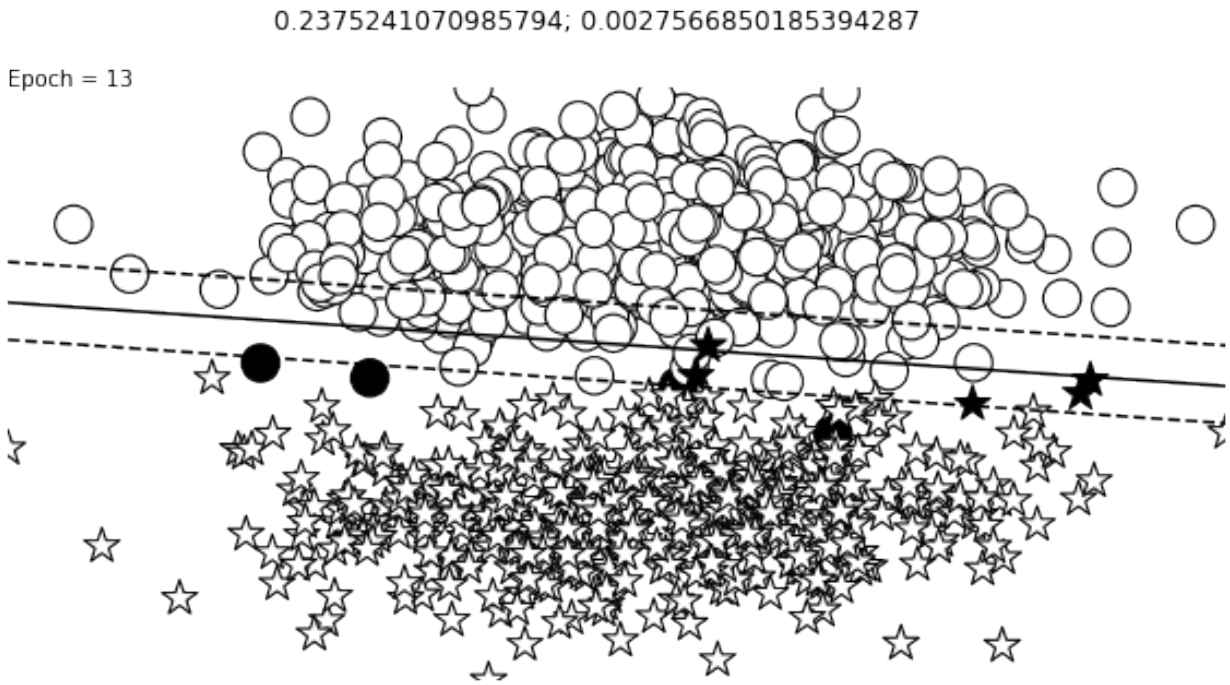

0.33544912934303284; 0.005884051322937012
Epoch = 8

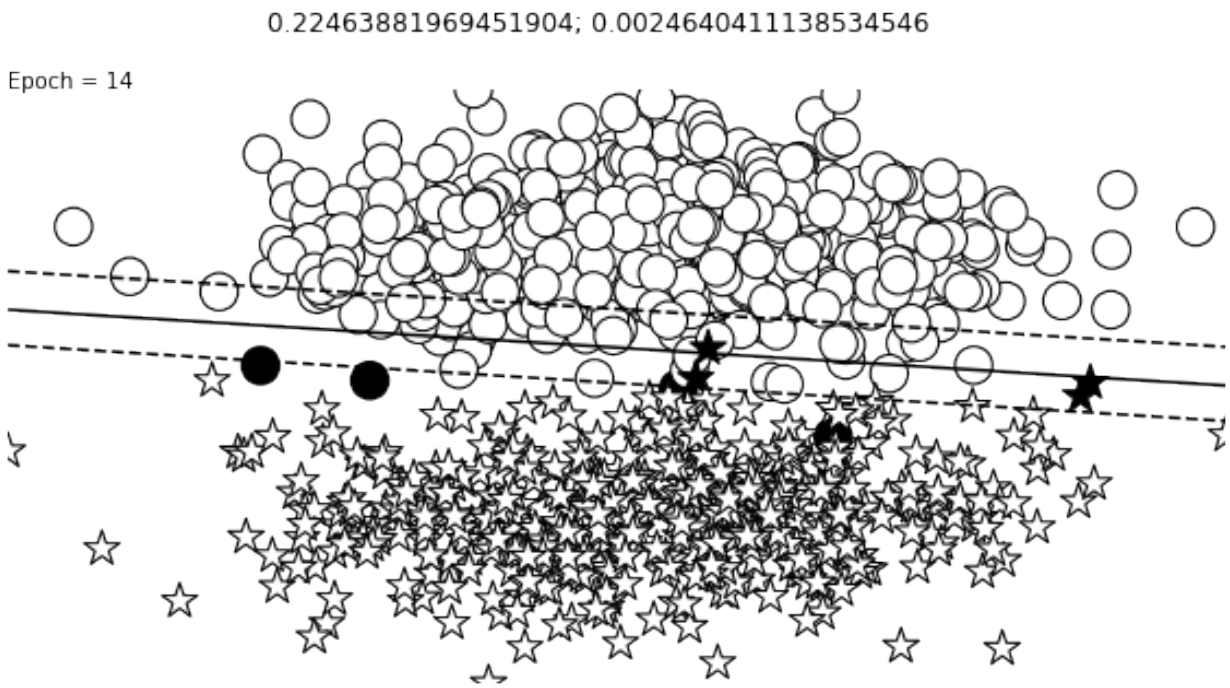

0.3091857433319092; 0.00487104058265686
Epoch = 9

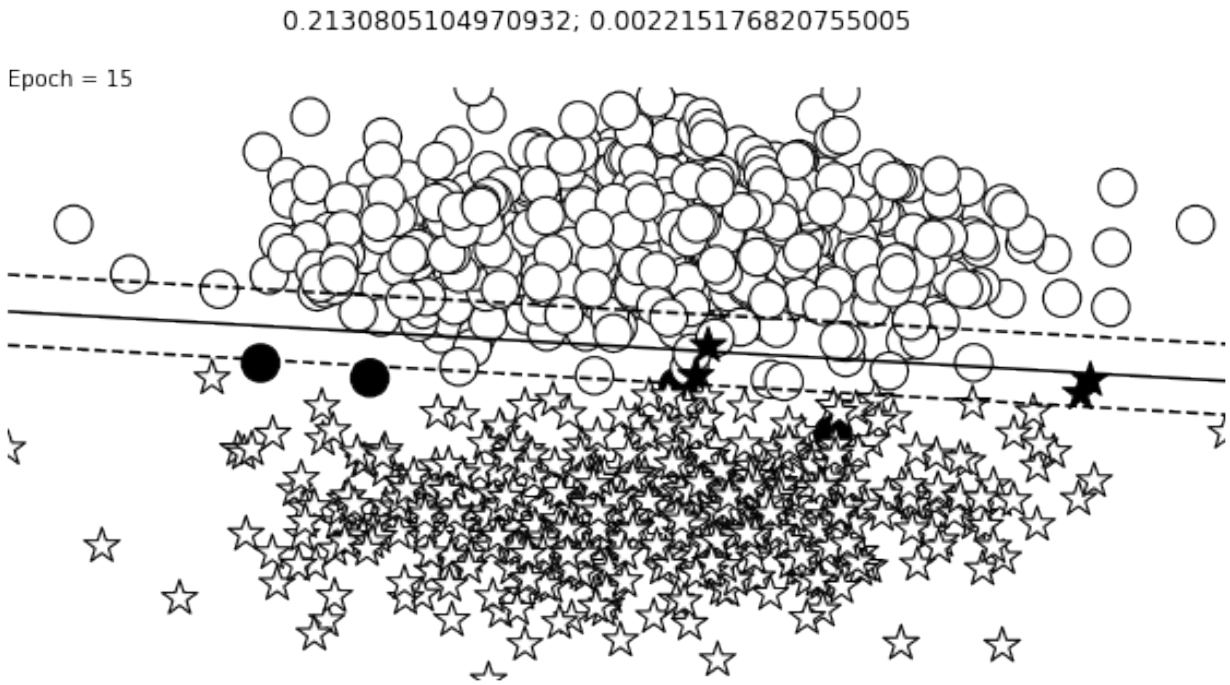

0.2871835231781006; 0.0041162073612213135
Epoch = 10

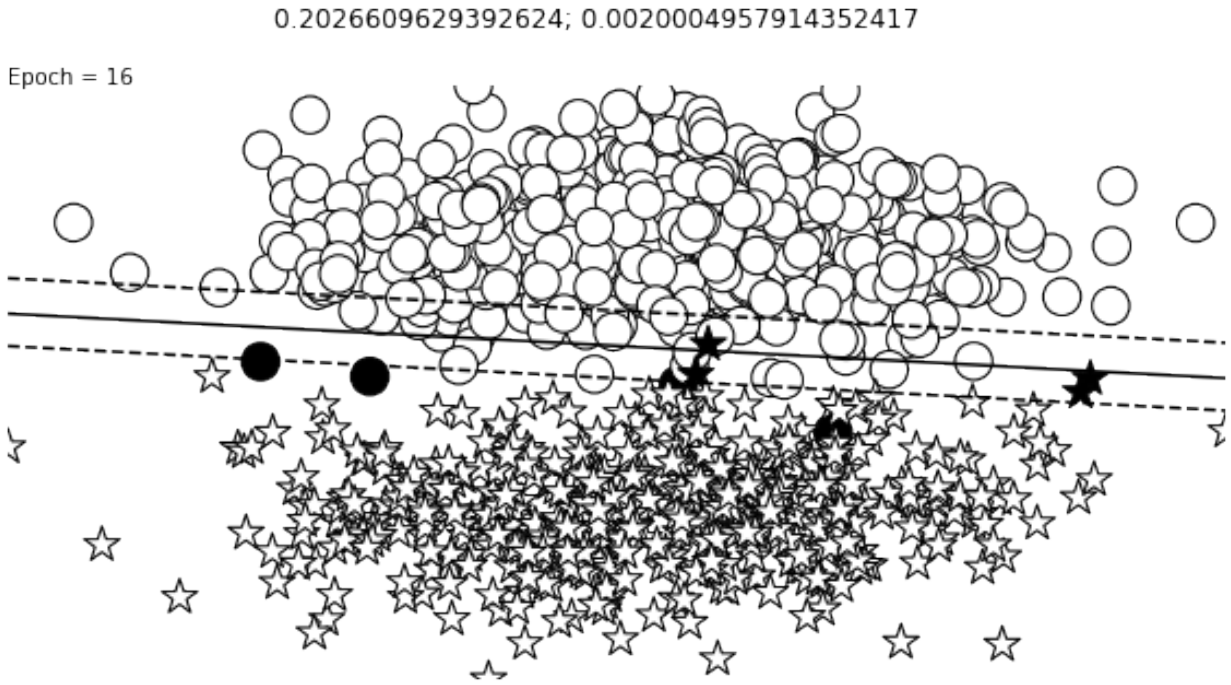

0.2683674395084381; 0.0035484731197357178
Epoch = 11

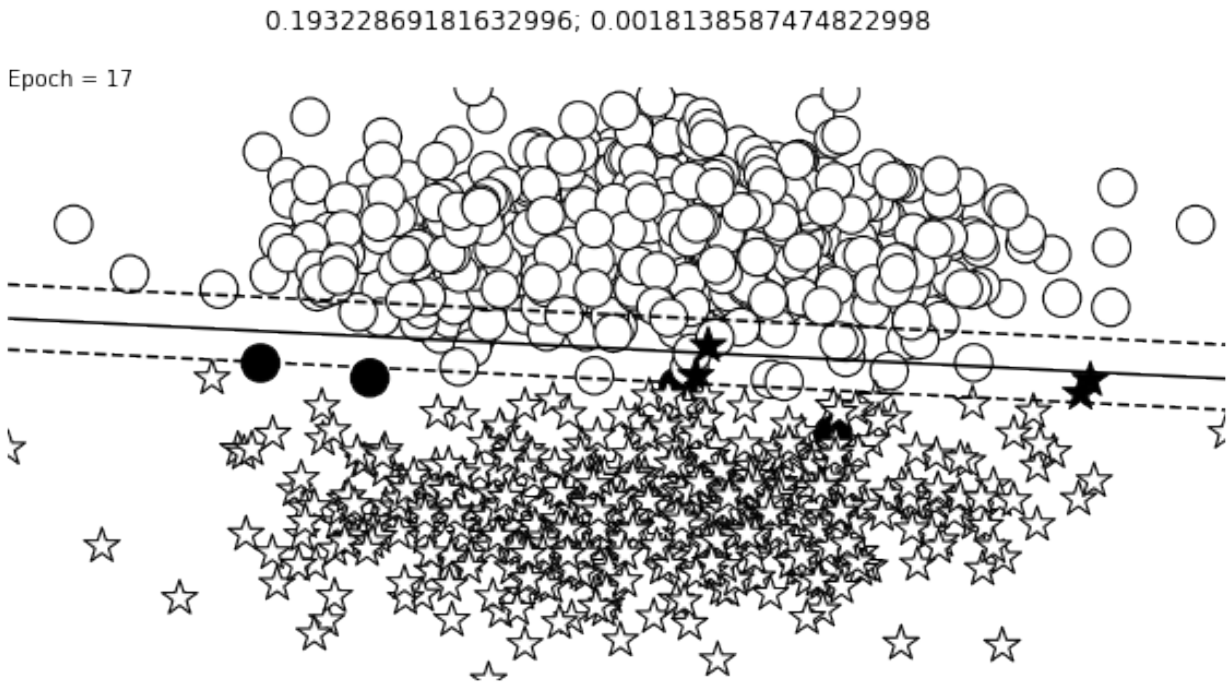

0.25198429822921753; 0.003109276294708252
Epoch = 12

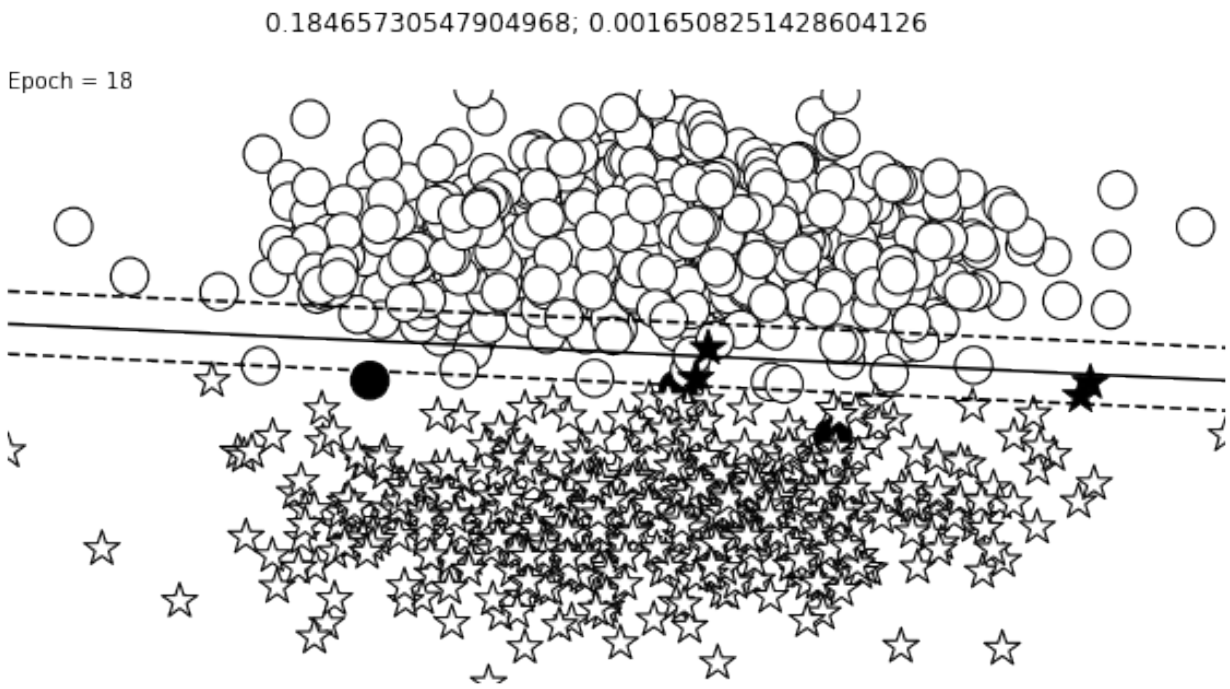

0.2375241070985794; 0.0027566850185394287
Epoch = 13

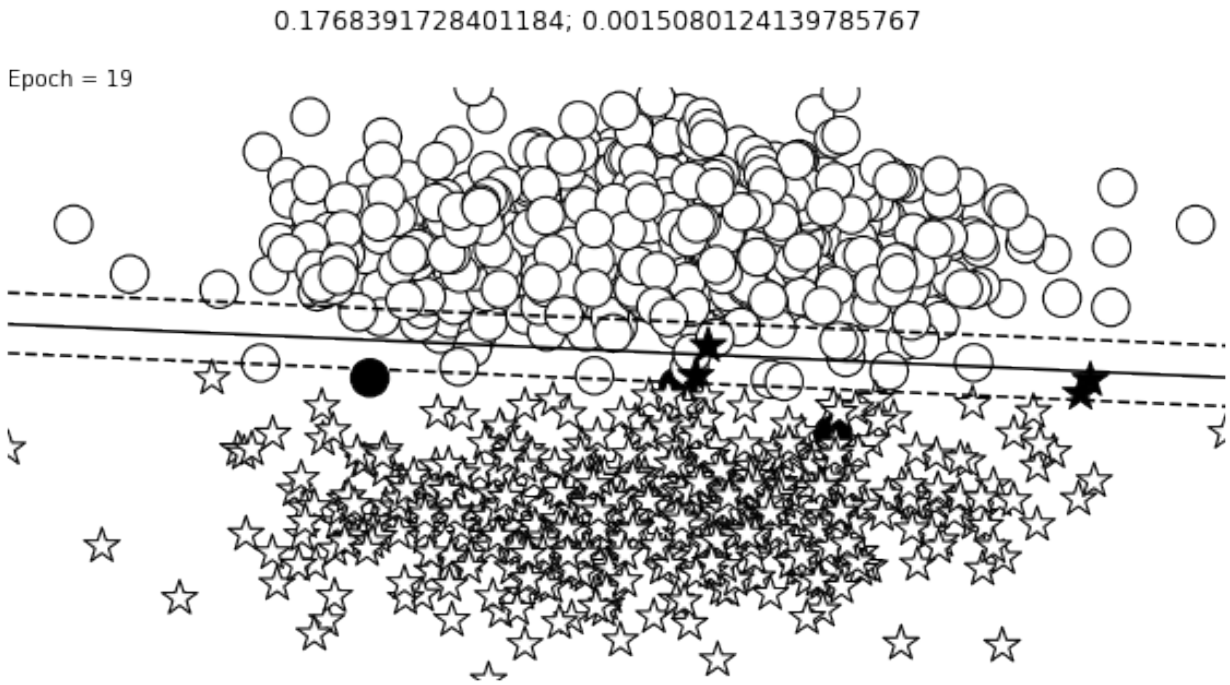

0.22463881969451904; 0.0024640411138534546
Epoch = 14

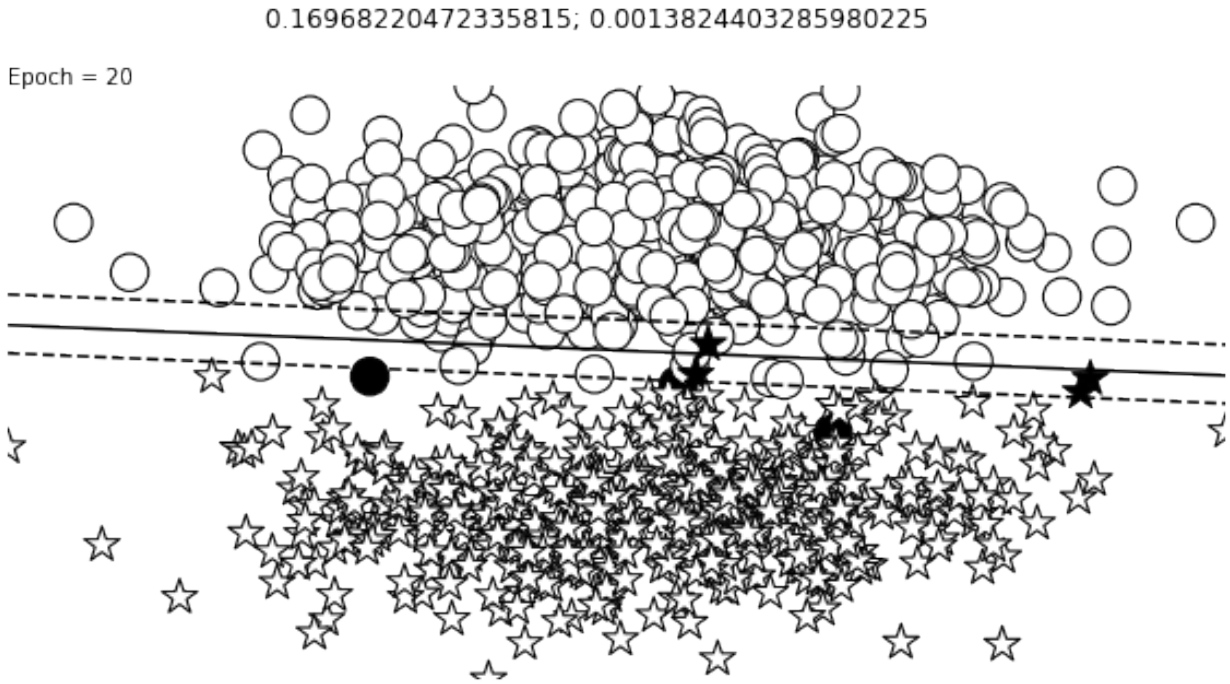

0.2130805104970932; 0.002215176820755005
Epoch = 15

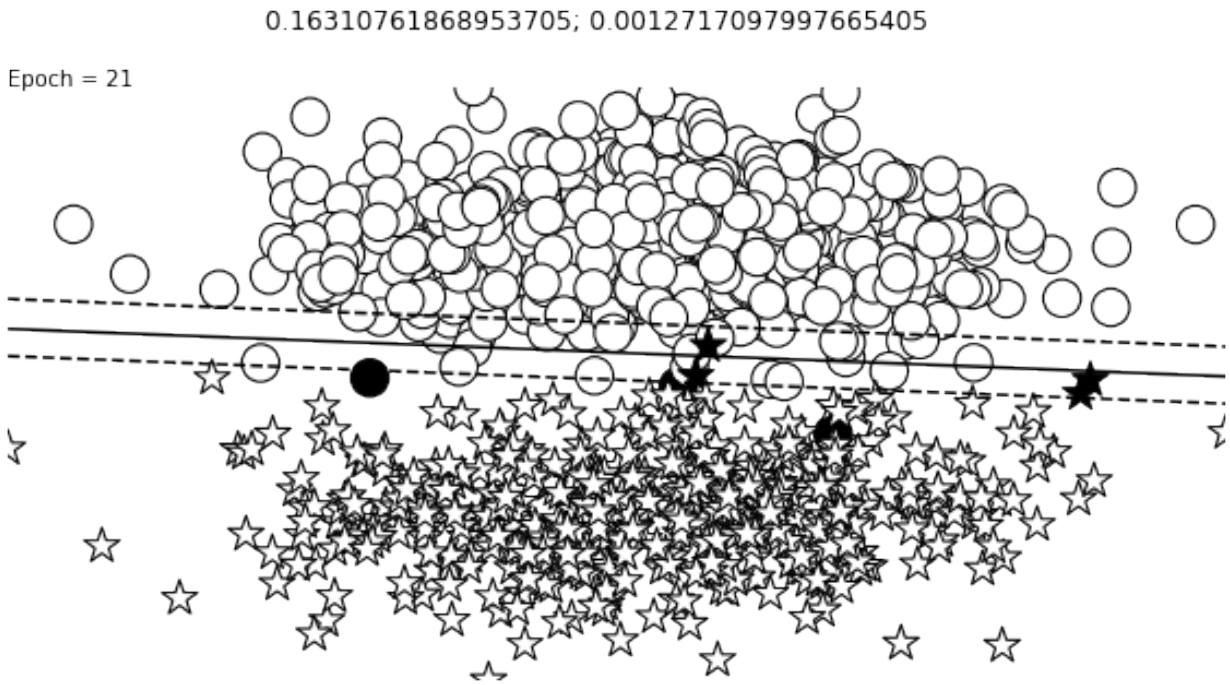

0.2026609629392624; 0.0020004957914352417
Epoch = 16

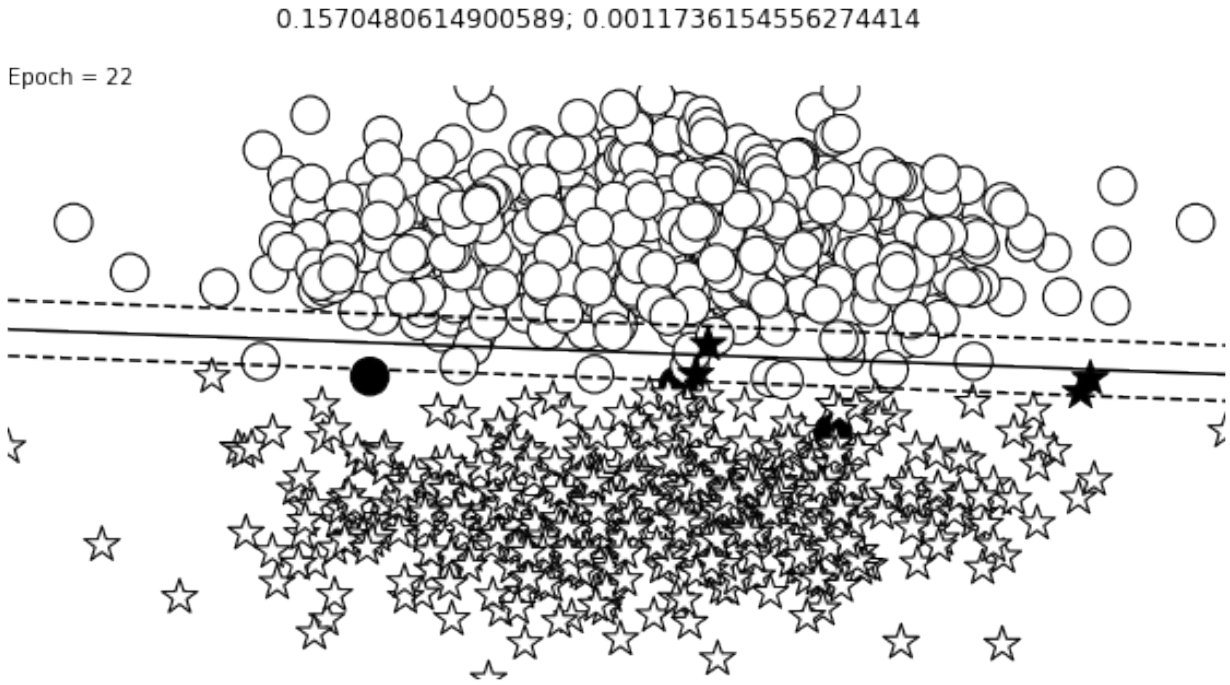

0.19322869181632996; 0.0018138587474822998
Epoch = 17

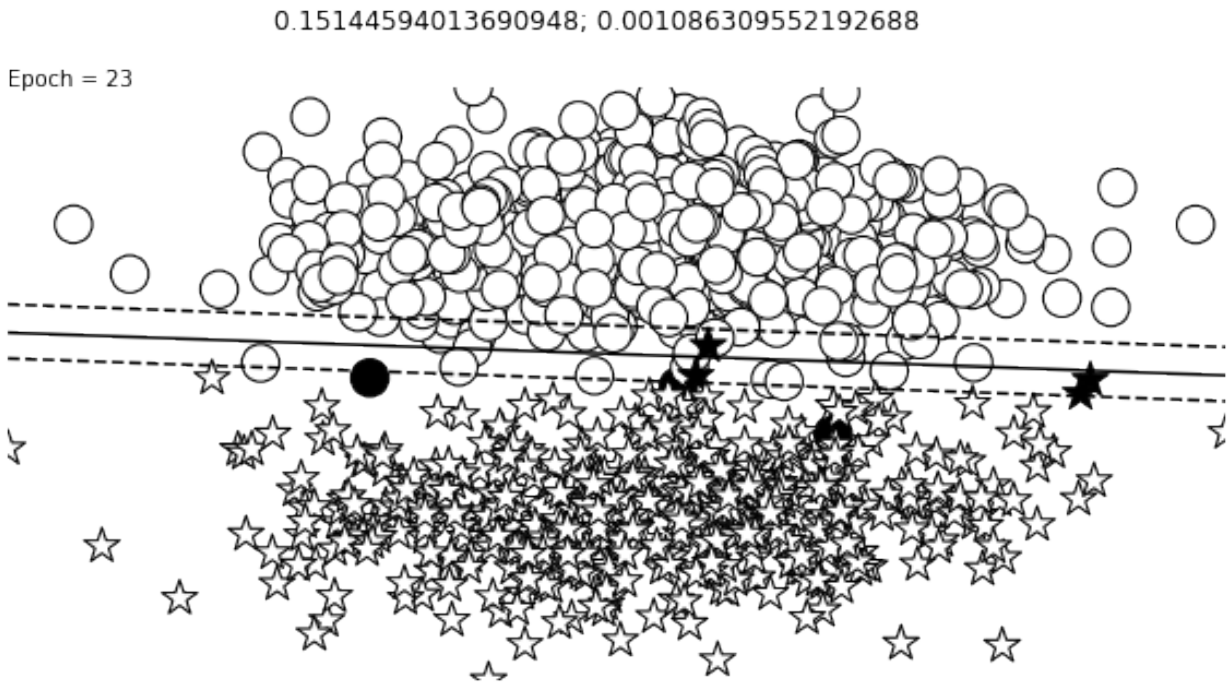

0.18465730547904968; 0.0016508251428604126
Epoch = 18

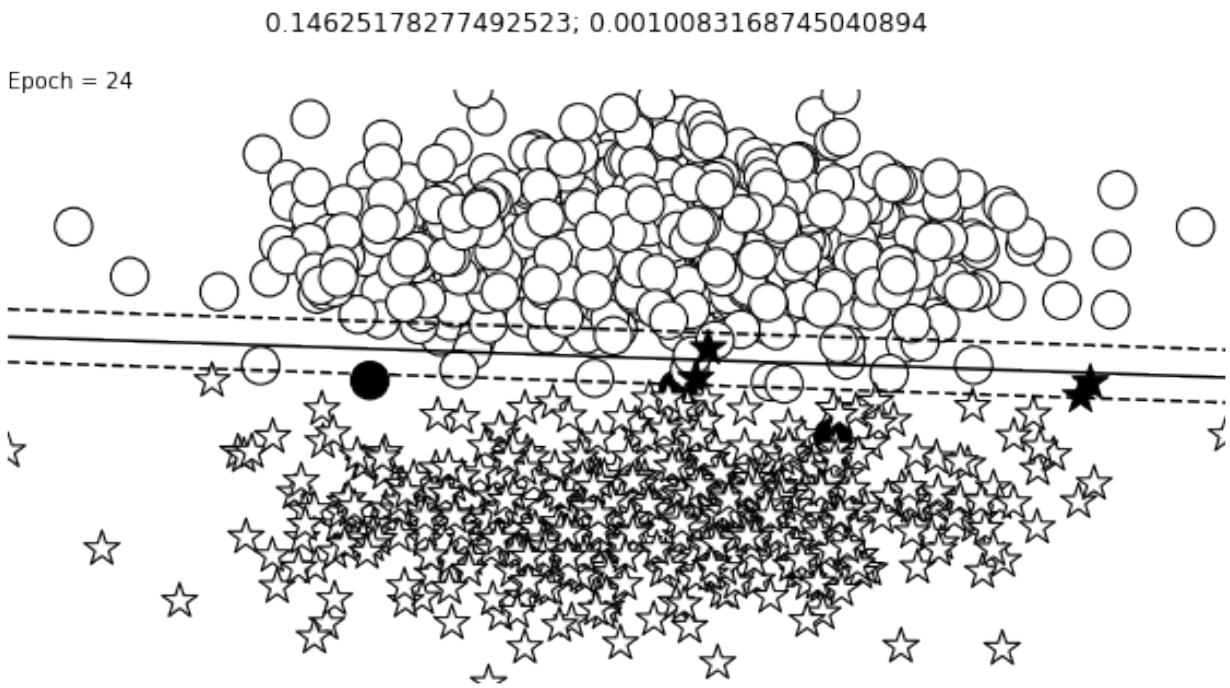

0.1768391728401184; 0.0015080124139785767
Epoch = 19

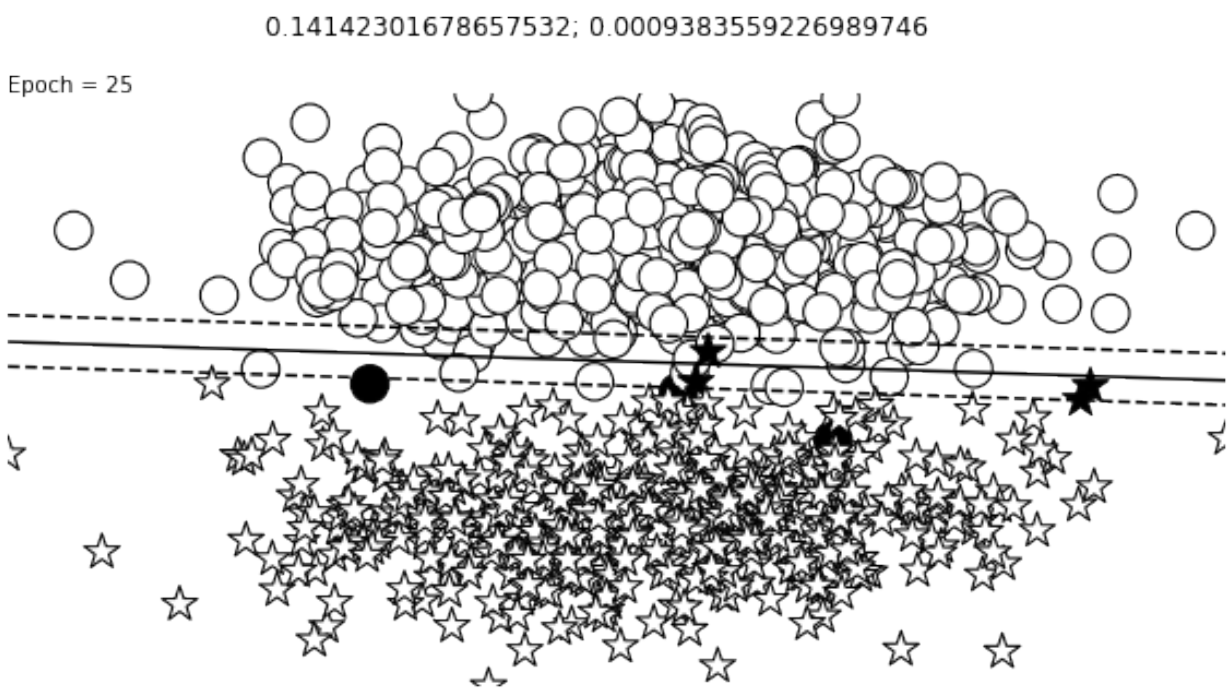

0.16968220472335815; 0.0013824403285980225
Epoch = 20


0.16310761868953705; 0.0012717097997665405
Epoch = 21


0.1570480614900589; 0.0011736154556274414
Epoch = 22


0.15144594013690948; 0.001086309552192688
Epoch = 23






```
_, axes = plt.subplots(1,2,figsize=(12,4))


axes[0].scatter(left_x[:, 0], left_x[:, 1], facecolor='white',edgecolor='black',␣
↪marker='o', s=300)
axes[0].scatter(right_x[:, 0], right_x[:, 1], facecolor='white', edgecolor='black',␣
↪marker='*', s=300)
axes[0].axis('off')
```

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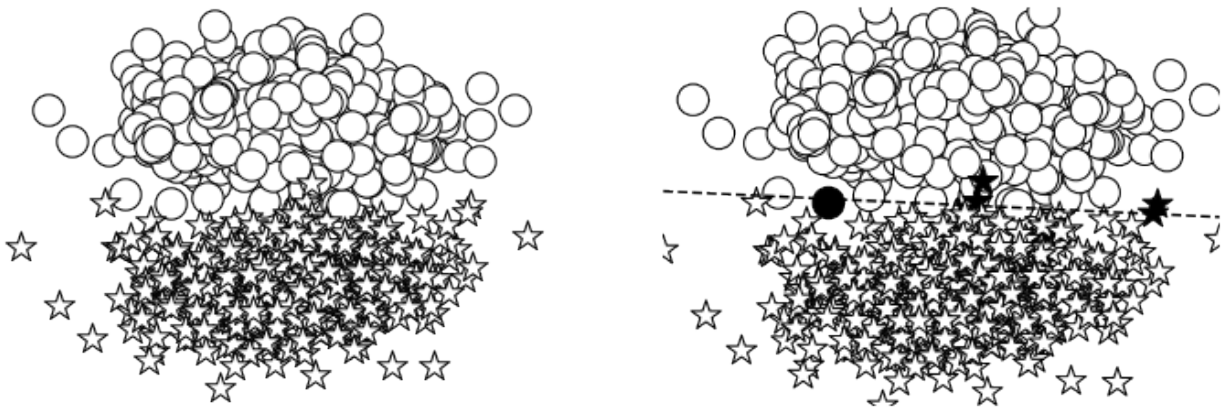
```
visualize_results(perceptron, x_data_static, y_truth_static, epoch=None, levels=[0.5],
 ↪ ax=axes[1])
axes[1].axis('off')
plt.savefig('perceptron_final.png')
plt.savefig('perceptron_final.pdf')
```



8.2 Dataset and DataLoader

8.2.1 Dataset

In PyTorch, a dataset is represented by a regular Python class that inherits from the `Dataset` class. You can think of it as a list of tuples, each tuple corresponding to one data point (features, label).

The most fundamental methods it needs to implement are:

- `__init__(self)`: it takes arguments needed to build a list of tuples, for example
  - the name of a CSV file that will be loaded and processed; or
  - two tensors, one for features, another one for labels; or
  - or anything else, depending on the task at hand.

Important: There is no need to load the whole dataset in the constructor method (`__init__`). If your dataset is big (tens of thousands of files, for instance), loading it at once would **not** be memory efficient. It is recommended to load them on demand (whenever `__get_item__` is called).

- `__get_item__(self, index)`: this function allows the dataset to be indexed so that it can work like a list (`dataset[i]`)
  - it must return a tuple (features, label) corresponding to the requested data point.
  - We can either return the corresponding slices of our pre-loaded dataset or, as mentioned above, load them on demand.
- `__len__(self)`: it should simply return the size of the *whole dataset*. This is useful to ensure when sampling, the indexing is bouned by the size of the data.

Building a `Dataset` class with Two Tensors

Let's build a simple custom dataset that takes two tensors as arguments: one for the features, one for the labels.

Let's first get the generated data from the `perceptron.ipynb` notebook.

```
import import_ipynb
from perceptron import get_toy_data

data_size = 1000
x_data, y_truth = get_toy_data(data_size);
```

```
import torch
from torch.utils.data import Dataset
class CustomDataset(Dataset):
    def __init__(self, x_tensor, y_tensor):
        self.x = x_tensor
        self.y = y_tensor

    def __getitem__(self, index):
        return (self.x[index], self.y[index])

    def __len__(self):
        return len(self.x)

# Wait, is this a CPU tensor now? Why? Where is .to(device)?
x_train_tensor = torch.as_tensor(x_data).float()
y_train_tensor = torch.as_tensor(y_truth).float()

train_data = CustomDataset(x_train_tensor, y_train_tensor)

# Now we can iterate through our data points using simple indices
print(train_data[0])
```

```
(tensor([ 2.5058, -2.7603]), tensor(1.))
```

Why do we not sending the Numpy arrays to GPU?

We don't want our whole training data to be loaded into GPU tensors, as we have been doing in our example so far, because it takes up space in our precious graphics card's RAM.

Use `TensorDataset`

Why go through all this trouble to wrap a couple of tensors in a class?

If the dataset is more than a couple of tensors, we can use PyTorch's `TensorDataset` class, which will do pretty much the same as our custom dataset above.

The full-fledged custom dataset class may seem like a stretch, but this is a design pattern that we will use repeatedly in later chapters.

```
from torch.utils.data import TensorDataset
train_data = TensorDataset(x_train_tensor, y_train_tensor)
print(train_data[0])
```

```
(tensor([ 2.5058, -2.7603]), tensor(1.))
```

8.2.2 DataLoader

Until now, we have used one data point training data at every training step. So we have been doing **stochastic gradient descent** all along. This is fine for small dataset, but if we want to go with large dataset, we must use **mini-batch gradient descent**. Thus, we need mini-batches. Thus, we need to slice our dataset accordingly. `DataLoader` saves us from doing it manually! All we need to do is to tell the `DataLoader`:

- the dataset
- the size of the mini-batch
- whether we want to shuffle it or not

Your Turn

Recall what's *batch*, *mini-batch* and *stochastic* gradient decent.

A data loader will behave like an iterator, so we can loop over it and fetch a different mini-batch every time.

How do I choose my mini-batch size?

It is typical to use powers of two for mini-batch sizes, like 16, 32, 64 or 128, and 32 or 64 are popular choices.

```
from torch.utils.data import DataLoader
train_loader = DataLoader(dataset=train_data, batch_size=1000, shuffle=True)
```

To retrieve a mini-batch, one can simply run the command below — it will return a list containing two tensors, one for the features, another one for the labels:

```
next(iter(train_loader))
```

```
[tensor([[ 3.6587, -1.7854],
         [ 1.2505, -2.9371],
         [ 3.3038,  2.9329],
         ...,
         [ 3.9159,  3.5062],
         [ 3.3351, -2.6869],
         [ 3.7338,  2.9684]]),
 tensor([1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 1., 0., 1., 0., 1.,
         0., 1., 0., 1., 0., 0., 1., 0., 0., 0., 0., 1., 1., 1., 0., 0., 1., 1.,
         1., 1., 1., 1., 0., 1., 0., 0., 0., 1., 1., 1., 1., 1., 1., 1., 1., 0.,
         0., 1., 1., 0., 0., 1., 1., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1.,
         0., 1., 0., 1., 0., 1., 1., 0., 1., 1., 1., 0., 1., 0., 1., 0., 1., 0.,
         0., 0., 1., 0., 1., 1., 1., 1., 0., 1., 1., 0., 1., 1., 0., 1., 1., 1.,
         0., 1., 1., 0., 1., 0., 1., 1., 1., 1., 1., 0., 0., 0., 0., 0., 1., 0.,
         0., 1., 1., 1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 1., 0., 1., 1.,
         1., 0., 1., 1., 0., 1., 1., 0., 1., 0., 0., 1., 1., 0., 1., 0., 0., 1.,
```

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```
        0., 1., 1., 0., 0., 0., 0., 1., 1., 0., 1., 1., 0., 1., 1., 1., 0., 0.,
        1., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 1., 1., 1., 1., 1., 1., 0.,
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        1., 1., 0., 0., 0., 1., 1., 0., 0., 1., 1., 0., 0., 1., 1., 0., 1., 0.,
        0., 0., 0., 0., 1., 0., 1., 1., 0., 1., 1., 0., 1., 1., 1., 1., 1., 1.,
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        1., 1., 1., 1., 0., 0., 1., 1., 0., 1., 0., 0., 1., 0., 0., 1., 1., 0.,
        1., 1., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 0., 0., 0., 0., 1., 0.,
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        0., 1., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0., 1., 1., 0.,
        0., 0., 1., 1., 0., 0., 0., 0., 0., 1., 1., 1., 1., 1., 0., 1., 0., 1.,
        0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0.,
        0., 1., 0., 1., 0., 1., 0., 0., 0., 0., 1., 1., 0., 1., 1., 1., 0., 1.,
        0., 0., 0., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0.,
        1., 0., 1., 0., 0., 0., 1., 1., 1., 0., 1., 0., 0., 0., 1., 0., 1., 1.,
        1., 1., 1., 1., 0., 0., 1., 0., 1., 0., 1., 0., 0., 0., 1., 0., 0., 1.,
        0., 0., 0., 1., 1., 0., 1., 0., 1., 0., 1., 0., 0., 0., 1., 1., 0., 0.,
        0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 1., 0., 1., 1., 1., 1., 0., 1.,
        1., 0., 1., 1., 0., 1., 1., 1., 1., 1., 0., 1., 0., 0., 1., 0., 0., 1.,
        0., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
        0., 0., 0., 1., 0., 1., 0., 1., 0., 0., 1., 1., 0., 1., 0., 0., 0., 0.,
        1., 0., 1., 0., 1., 0., 0., 1., 1., 1., 0., 0., 0., 0., 0., 1., 1., 1.,
        1., 1., 1., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 1., 0.,
        0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 1.,
        0., 0., 0., 0., 1., 0., 1., 1., 0., 0., 1., 1., 1., 1., 1., 0., 0., 0.,
        0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 1., 1., 0., 1., 0., 1.,
        0., 1., 0., 1., 0., 1., 1., 0., 1., 0., 1., 0., 0., 0., 1., 1., 0., 0.,
        0., 0., 0., 0., 0., 1., 0., 1., 1., 0., 1., 0., 0., 1., 1., 1., 1., 0.,
        0., 1., 0., 0., 0., 1., 0., 1., 1., 0., 1., 0., 0., 1., 0., 0., 1., 0.,
        1., 1., 1., 1., 1., 0., 1., 0., 1., 0., 0., 1., 1., 1., 1., 1., 1., 0.,
        0., 1., 1., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 1., 1.,
        0., 1., 0., 0., 0., 0., 0., 1., 1., 1., 0., 0., 0., 0., 0., 1., 0., 0.,
        0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 1., 1., 1., 1.,
        0., 1., 0., 0., 0., 1., 1., 0., 0., 1., 1., 1., 0., 1., 0., 1., 0., 1.,
        1., 0., 0., 1., 0., 0., 1., 0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 1.,
        1., 0., 1., 0., 0., 1., 1., 1., 0., 1., 1., 1., 0., 1., 1., 0., 1., 1.,
        0., 0., 1., 1., 0., 1., 0., 0., 1., 0., 1., 0., 0., 1., 0., 1., 0., 1.,
        0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0.,
        1., 0., 1., 1., 0., 0., 0., 1., 1., 0., 1., 0., 1., 0., 1., 0., 1., 1.,
        1., 0., 0., 0., 0., 1., 1., 0., 1., 1., 0., 0., 0., 0., 1., 1., 1., 0.,
        0., 0., 0., 1., 1., 1., 1., 1., 0., 1., 0., 0., 0., 1., 0., 1., 0., 0.,
        0., 0., 0., 1., 1., 1., 1., 0., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0.,
        0., 1., 0., 0., 1., 0., 0., 1., 0., 0., 1., 1., 0., 1., 0., 1., 1., 0.,
        1., 0., 0., 1., 1., 0., 0., 0., 1., 1., 0., 0., 0., 1., 0., 1., 1., 0.,
        1., 0., 0., 1., 0., 0., 1., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 1.,
        0., 1., 0., 0., 0., 0., 1., 0., 1., 0.])]
```

```
len(train_loader)
```

```
1
```

To shuffle or not to shuffle

In the absolute majority of cases, you should set `shuffle=True` for your training set to improve the performance of gradient descent. There are a few exceptions, though, like time series problems, where shuffling actually leads to data

leakage.

So, always ask yourself: "do I have a reason NOT to shuffle the data?"

"What about the validation and test sets?" There is no need to shuffle them since we are not computing gradients with them.

There is more to a DataLoader, for example, it is also possible to use it together with a `sampler` to fetch mini-batches that compensate for imbalanced classes, for instance.

Your Turn

Note we put all data in one "mini-batch" because we set `batch_size=1000`. Set `batch_size` to a smaller number and observe the training time and performance.

8.2.3 Putting it all together

```
import torch
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

A higher order function is a function returns a function, for example

The key elements of our training loop: `model`, `loss`, and `optimizer`. The actual training step function to be returned will have

- input: two arguments, namely, *features* and *labels*, and
- return: the corresponding loss value.

```
def make_train_step(model, loss_fn, optimizer):
    # Builds function that performs a step in the train loop
    def perform_train_step(x_batch, y_batch):
        # Sets model to TRAIN mode
        model.train()

        # Step 1 - Computes model's predictions - forward pass
        yhat = model(x_batch).squeeze()
        y_batch = y_batch.squeeze()

        # Step 2 - Computes the loss
        loss = loss_fn(yhat, y_batch)
        # Step 3 - Computes gradients for parameters
        loss.backward()
        # Step 4 - Updates parameters using gradients and
        # the learning rate
        optimizer.step()
        optimizer.zero_grad()
        # Returns the loss
        return loss.item()

    # Returns the function that will be called inside the
    # train loop
    return perform_train_step
```

```
import import_ipynb
from perceptron import Perceptron
import torch.nn as nn
import torch.optim as optim
import numpy as np

input_dim = 2
lr = 0.01
n_epochs = 60

perceptron = Perceptron(input_dim=input_dim).to(device)
optimizer = optim.Adam(params=perceptron.parameters(), lr=lr)
bce_loss = nn.BCELoss()
train_step = make_train_step(perceptron, bce_loss, optimizer)
losses = []

change = 1.0
last = 10.0
epsilon = 1e-3
epoch = 0
while change > epsilon or epoch < n_epochs or last > 0.3:
# For each epoch...
# for epoch in range(n_epochs):
    # inner loop
    mini_batch_losses = []
    for x_batch, y_batch in train_loader:
        # the dataset "lives" in the CPU, so do our mini-batches
        # therefore, we need to send those mini-batches to the
        # device where the model "lives"
        x_batch = x_batch.to(device)
        y_batch = y_batch.to(device)

        # Performs one train step and returns the
        # corresponding loss for this mini-batch

        mini_batch_loss = train_step(x_batch, y_batch)
        mini_batch_losses.append(mini_batch_loss)

    # Computes average loss over all mini-batches
    # That's the epoch loss
    loss = np.mean(mini_batch_losses)
    change = abs(last - loss)
    last = loss
    epoch += 1

losses.append(loss)
```

```
print(loss)
```

```
0.10094598680734634
```

```
perceptron = perceptron.to('cpu')
```

```
import import_ipynb
from perceptron import visualize_results
import matplotlib.pyplot as plt
```

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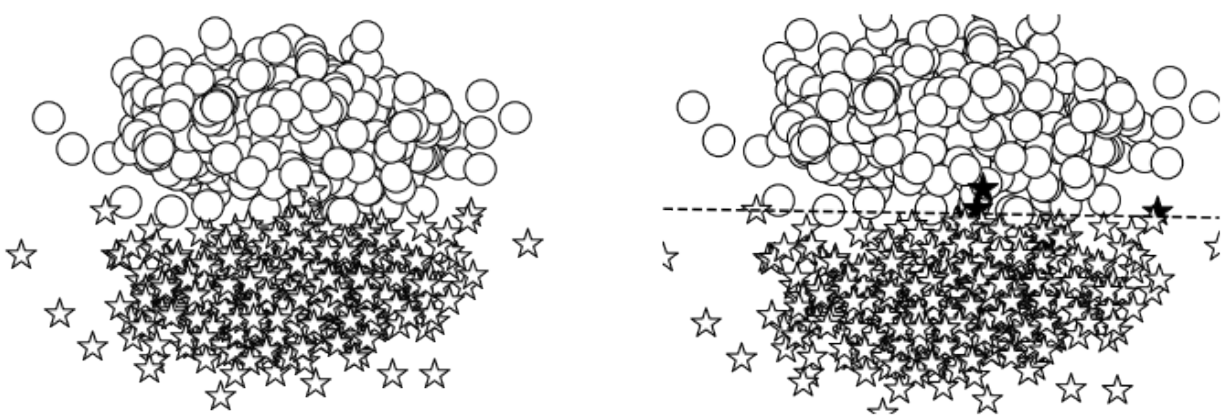
```
left_x = []
right_x = []
left_colors = []
right_colors =  []

# Construct a stack of values and colors
for x_i, y_true_i in zip(x_data, y_truth):
    color = 'black'

    if y_true_i == 0:
        left_x.append(x_i)
        left_colors.append(color)

    else:
        right_x.append(x_i)
        right_colors.append(color)

left_x = np.stack(left_x)
right_x = np.stack(right_x)

_, axes = plt.subplots(1,2,figsize=(12,4))

axes[0].scatter(left_x[:, 0], left_x[:, 1], facecolor='white',edgecolor='black',␣
↪marker='o', s=300)
axes[0].scatter(right_x[:, 0], right_x[:, 1], facecolor='white', edgecolor='black',␣
↪marker='*', s=300)
axes[0].axis('off')
visualize_results(perceptron, x_data, y_truth, epoch=None, levels=[0.5], ax=axes[1])
axes[1].axis('off')
```

```
(-0.3603001832962036, 6.013579845428467, -5.019380569458008, 5.617672443389893)
```



8.3 Yelp Dataset at a glance

The Yelp dataset, pairs review texts with their sentiment labels (positive or negative). In this notebook, we take a look at the dataset by loading a csv file into a Pandas Data Frame, which will give us the foundation of motivating a more object-oriented data handling in PyTorch.

```
import collections
import numpy as np
import pandas as pd
import re

from argparse import Namespace
```

8.3.1 Group all initial settings together

```
args = Namespace(
    raw_train_dataset_csv="../data/yelp/raw_train.csv",
    raw_test_dataset_csv="../data/yelp/raw_test.csv",
    train_proportion=0.7,
    val_proportion=0.3,
    output_munged_csv="../data/yelp/reviews_with_splits_full.csv",
    seed=1337
)
```

8.3.2 Use `pandas.read_csv` to process CSV files

```
# Read raw data
train_reviews = pd.read_csv(args.raw_train_dataset_csv, header=None, names=['rating',
 ↪'review'])
train_reviews = train_reviews[~pd.isnull(train_reviews.review)]
test_reviews = pd.read_csv(args.raw_test_dataset_csv, header=None, names=['rating',
 ↪'review'])
test_reviews = test_reviews[~pd.isnull(test_reviews.review)]
```

```
train_reviews.head()
```

```
   rating                                             review
0       1  Unfortunately, the frustration of being Dr. Go...
1       2  Been going to Dr. Goldberg for over 10 years. ...
2       1  I don't know what Dr. Goldberg was like before...
3       1  I'm writing this review to give you a heads up...
4       2  All the food is great here. But the best thing...
```

```
test_reviews.head()
```

```
   rating                                             review
0       1  Ordered a large Mango-Pineapple smoothie. Stay...
1       2  Quite a surprise!  \n\nMy wife and I loved thi...
2       1  First I will say, this is a nice atmosphere an...
3       2  I was overall pretty impressed by this hotel. ...
4       1  Video link at bottom review. Worst service I h...
```

```
# Unique classes
set(train_reviews.rating)
```

```
{1, 2}
```

8.3.3 Splitting the training dataset

For turning the hyper-parameters, we often want to retain a small proportion of validation data from the original training data.

```
# Splitting train by rating
# Create dict
by_rating = collections.defaultdict(list)
for _, row in train_reviews.iterrows():
    by_rating[row.rating].append(row.to_dict())
```

```
# Create split data
final_list = []
np.random.seed(args.seed)

for _, item_list in sorted(by_rating.items()):

    np.random.shuffle(item_list)

    n_total = len(item_list)
    n_train = int(args.train_proportion * n_total)
    n_val = int(args.val_proportion * n_total)

    # Give data point a split attribute
    for item in item_list[:n_train]:
        item['split'] = 'train'

    for item in item_list[n_train:n_train+n_val]:
        item['split'] = 'val'

    # Add to final list
    final_list.extend(item_list)
```

```
for _, row in test_reviews.iterrows():
    row_dict = row.to_dict()
    row_dict['split'] = 'test'
    final_list.append(row_dict)
```

8.3.4 Simple preprocessing and Write to file

```
final_reviews = pd.DataFrame(final_list)
final_reviews.split.value_counts()
```

```
train    392000
val      168000
test      38000
Name: split, dtype: int64
```

```
final_reviews.review.head()
```

```
0    The entrance was the #1 impressive thing about...
1    I'm a Mclover, and I had no problem\nwith the ...
2    Less than good here, not terrible, but I see n...
3    I don't know if I can ever bring myself to go ...
4    Food was OK/Good but the service was terrible....
Name: review, dtype: object
```

```
final_reviews[pd.isnull(final_reviews.review)]
```

```
Empty DataFrame
Columns: [rating, review, split]
Index: []
```

```
# Preprocess the reviews
# You can come up with better pre-processing
def preprocess_text(text):
    if type(text) == float:
        print(text)
    text = text.lower()
    text = re.sub(r"([.,!?])", r" \1 ", text)
    text = re.sub(r"[^a-zA-Z.,!?]+", r" ", text)
    return text

final_reviews.review = final_reviews.review.apply(preprocess_text)
```

```
final_reviews['rating'] = final_reviews.rating.apply({1: 'negative', 2: 'positive'}.
 ↪get)
```

```
final_reviews.head()
```

```
     rating                                            review  split
0  negative  the entrance was the impressive thing about th...  train
1  negative  i m a mclover , and i had no problem nwith the...  train
2  negative  less than good here , not terrible , but i see...  train
3  negative  i don t know if i can ever bring myself to go ...  train
4  negative  food was ok good but the service was terrible ...  train
```

```
final_reviews.to_csv(args.output_munged_csv, index=False)
```

8.4 Yelp Review Dataset - Document Classification

8.4.1 Converting Text Inputs to Vectorized Minibatches

The `Vocabulary`, the `Vectorizer`, and the `DataLoader` are three classes to perform a crucial pipeline for PyTorch based NLP tasks: converting text inputs to vectorized minibatches. The pipeline starts with preprocessed text; each data point is a collection of tokens. In this example, the tokens happen to be words, but tokens can also be characters.

The three classes presented in this notebook are responsible for

- mapping each token to an integer to create a `Vocabulary`,

- applying this mapping to each data point to create a vectorized form using `Vectorizer`, and
- grouping the vectorized data points into a minibatch for the model through `DataLoader`.

Dataset

```
from torch.utils.data import Dataset
class ReviewDataset(Dataset):
    def __init__(self, review_df, vectorizer):
        """
        Args:
        review_df (pandas.DataFrame): the dataset
        vectorizer (ReviewVectorizer): vectorizer instantiated from dataset
        """
        self.review_df = review_df
        self._vectorizer = vectorizer
        self.train_df = self.review_df[self.review_df.split=='train']
        self.train_size = len(self.train_df)
        self.val_df = self.review_df[self.review_df.split=='val']
        self.validation_size = len(self.val_df)
        self.test_df = self.review_df[self.review_df.split=='test']
        self.test_size = len(self.test_df)
        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}
        self.set_split('train')
    @classmethod
    def load_dataset_and_make_vectorizer(cls, review_csv):
        """Load dataset and make a new vectorizer from scratch
        Args:
            review_csv (str): location of the dataset
        Returns:
            an instance of ReviewDataset
        """
        review_df = pd.read_csv(review_csv)
        return cls(review_df, ReviewVectorizer.from_dataframe(review_df))
    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer
    def set_split(self, split="train"):
        """ selects the splits in the dataset using a column in the dataframe
        Args:
        split (str): one of "train", "val", or "test"
        """
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]
    def __len__(self):
        return self._target_size
    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets
        Args:
        index (int): the index to the data point
        Returns:
        a dict of the data point's features (x_data) and label (y_target)
        """
        row = self._target_df.iloc[index]
        review_vector = \
```

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```
        self._vectorizer.vectorize(row.review)
        rating_index = \
        self._vectorizer.rating_vocab.lookup_token(row.rating)
        return {'x_data': review_vector,
                'y_target': rating_index}
    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset
        Args:
        batch_size (int)
        Returns:
        number of batches in the dataset
        """
        return len(self) // batch_size
```

The `Vocabulary` Class

The first stage to map each token to a numerical version of itself. The standard methodology is to have a bijection - a mapping that can be reversed between the tokens and integers. In Python, this is simply two dictionaries.

```
class Vocabulary(object):
    """Class to process text and extract Vocabulary for mapping"""
    def __init__(self, token_to_idx=None, add_unk=True, unk_token="<UNK>"):
        """
        Args:
            token_to_idx (dict): a pre-existingmap of tokens to indices
            add_unk (bool): a flag that indicates whether to add the UNK token
            unk_token (str): the UNK token to add into the Vocabulary
        """
        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx
        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}
        self._add_unk = add_unk
        self._unk_token = unk_token
        self.unk_index = 1
        if add_unk:
            self.unk_index = self.add_token(unk_token)
    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx,
                'add_unk': self._add_unk,
                'unk_token': self._unk_token}
    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)
    def add_token(self, token):
        """Update mapping dicts based on the token.
        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
```

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```
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index
    def lookup_token(self, token):
        """Retrieve the index associated with the token
        or the UNK index if token isn't present.
        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
            for the UNK functionality
        """
        if self._add_unk:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
    def lookup_index(self, index):
        """Return the token associated with the index
        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
        KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]
    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)
    def __len__(self):
        return len(self._token_to_idx)
```

Vectorizer

The second stage of going from a text dataset to a vectorized minibatch is to iterate through the tokens of an input data point and convert each token to its integer form. The result of this iteration should be a vector. Because this vector will be combined with vectors from other data points, there is a constraint that the vectors produced by the Vectorizer should always have the same length.

```
from collections import Counter
import string
class ReviewVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, review_vocab, rating_vocab):
        """
        Args:
            review_vocab (Vocabulary): maps words to integers
            rating_vocab (Vocabulary): maps class labels to integers
        """
```

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```
        self.review_vocab = review_vocab
        self.rating_vocab = rating_vocab
    def vectorize(self, review):
        """Create a collapsed one hot vector for the review
        Args:
            review (str): the review
        Returns:
            one_hot (np.ndarray): the collapsed onehot encoding
        """
        one_hot = np.zeros(len(self.review_vocab), dtype=np.float32)
        for token in review.split(" "):
            if token not in string.punctuation:
                one_hot[self.review_vocab.lookup_token(token)] = 1
        return one_hot
    @classmethod
    def from_dataframe(cls, review_df, cutoff=25):
        """Instantiate the vectorizer from the dataset dataframe
        Args:
            review_df (pandas.DataFrame): the review dataset
            cutoff (int): the parameter for frequency based filtering
        Returns:
            an instance of the ReviewVectorizer
        """
        review_vocab = Vocabulary(add_unk=True)
        rating_vocab = Vocabulary(add_unk=False)
        # Add ratings
        for rating in sorted(set(review_df.rating)):
            rating_vocab.add_token(rating)
        # Add top words if count > provided count
        word_counts = Counter()
        for review in review_df.review:
            for word in review.split(" "):
                if word not in string.punctuation:
                    word_counts[word] += 1
        for word, count in word_counts.items():
            if count > cutoff:
                review_vocab.add_token(word)
        return cls(review_vocab, rating_vocab)
    @classmethod
    def from_serializable(cls, contents):
        """Intantiate a ReviewVectorizer from a serializable dictionary
        Args:
            contents (dict): the serializable dictionary
        Returns:
            an instance of the ReviewVectorizer class
        """
        review_vocab = Vocabulary.from_serializable(contents['review_vocab'])
        rating_vocab = Vocabulary.from_serializable(contents['rating_vocab'])
        return cls(review_vocab=review_vocab, rating_vocab=rating_vocab)
    def to_serializable(self):
        """Create the serializable dictionary for caching
        Returns:
            contents (dict): the serializable dictionary
        """
        return {'review_vocab': self.review_vocab.to_serializable(),
                'rating_vocab': self.rating_vocab.to_serializable()}
```

Dataloader

The final stage of the text to vectorized minibatch pipeline is to actually group the vectorized data points.

```
from torch.utils.data import DataLoader
def generate_batches(dataset, batch_size, shuffle=True, drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
    ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)
    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

8.4.2 A perceptron classifier

This is a simple one hidden layer Perceptron that we have seen many times by now.

```
import torch.nn as nn
import torch.nn.functional as F
class ReviewClassifier(nn.Module):
    """ a simple perceptron-based classifier """
    def __init__(self, num_features):
        """
        Args:
            num_features (int): the size of the input feature vector
        """
        super(ReviewClassifier, self).__init__()
        self.fc1 = nn.Linear(in_features=num_features, out_features=1)

    def forward(self, x_in, apply_sigmoid=False):
        """The forward pass of the classifier
        Args:
            x_in (torch.Tensor): an input data tensor
                    x_in.shape should be (batch, num_features)
            apply_sigmoid (bool): a flag for the sigmoid activation
                    should be false if used with the cross-entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch,).
        """
        y_out = self.fc1(x_in).squeeze()

        if apply_sigmoid:
            y_out = torch.sigmoid(y_out)
        return y_out
```

8.4.3 Training

Initial Setup

```
from argparse import Namespace
args = Namespace(
    # Data and path information
    frequency_cutoff=25,
    model_state_file='model.pth',
    review_csv='../data/yelp/reviews_with_splits_full.csv',
    save_dir='model_storage/yelp/',
    vectorizer_file='vectorizer.json',
    # No model hyperparameters
    # Training hyperparameters
    batch_size=128,
    early_stopping_criteria=5,
    learning_rate=0.001,
    num_epochs=100,
    seed=1337,
    # Runtime options
    cuda=True,
    device='cuda',
)
```

Training Preparation

Recall that three key components that we need prepare for a training are:

- model
- loss function
- optimizer

```
import torch
import torch.optim as optim
import pandas as pd

def make_train_state(args):
    return {'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': 1,
            'test_acc': 1}

train_state = make_train_state(args)
if not torch.cuda.is_available():
    args.cuda = False
args.device = torch.device("cuda" if args.cuda else "cpu")

# dataset and vectorizer
dataset = ReviewDataset.load_dataset_and_make_vectorizer(args.review_csv)
vectorizer = dataset.get_vectorizer()
# model
```

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```
classifier = ReviewClassifier(num_features=len(vectorizer.review_vocab))
classifier = classifier.to(args.device)
# loss and optimizer
loss_func = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(classifier.parameters(), lr=args.learning_rate)
```

```
def compute_accuracy(y_pred, y_target):
    y_target = y_target.cpu()
    y_pred_indices = (torch.sigmoid(y_pred)>0.5).cpu().long()#.max(dim=1)[1]
    n_correct = torch.eq(y_pred_indices, y_target).sum().item()
    return n_correct / len(y_pred_indices) * 100
```

Training

This is the most time-consuming cell. Training on a NVIDIA RTX3070 GPU with the full dataset took 9237.4 seconds (rougly 3 hours). You should changes the `args` settings to use the LITE dataset first with a reduced number of epochs.

```
9237.4/60/60
```

```
2.5659444444444444
```

```
import numpy as np
for epoch_index in range(args.num_epochs):
    train_state['epoch_index'] = epoch_index
    # Iterate over training dataset
    # setup: batch generator, set loss and acc to 0, set train mode on
    dataset.set_split('train')
    batch_generator = generate_batches(dataset, batch_size=args.batch_size,␣
↪device=args.device)
    running_loss = 0.0
    running_acc = 0.0
    classifier.train()
    for batch_index, batch_dict in enumerate(batch_generator):
        # the training routine is 5 steps:
        # step 1. zero the gradients
        optimizer.zero_grad()
        # step 2. compute the output
        y_pred = classifier(x_in=batch_dict['x_data'].float())
        # step 3. compute the loss
        loss = loss_func(y_pred, batch_dict['y_target'].float())
        loss_batch = loss.item()
        running_loss += (loss_batch-running_loss) / (batch_index + 1)
        # step 4. use loss to produce gradients
        loss.backward()
        # step 5. use optimizer to take gradient step
        optimizer.step()
        # compute the accuracy
        acc_batch = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_batch - running_acc) / (batch_index + 1)

    train_state['train_loss'].append(running_loss)
    train_state['train_acc'].append(running_acc)

    # Iterate over val dataset
```

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```
    # setup: batch generator, set loss and acc to 0, set eval mode on
    dataset.set_split('val')
    batch_generator = generate_batches(dataset, batch_size=args.batch_size,␣
↪device=args.device)
    running_loss = 0.
    running_acc = 0.
    classifier.eval()

    for batch_index, batch_dict in enumerate(batch_generator):
        # step 1. compute the output
        y_pred = classifier(x_in=batch_dict['x_data'].float())
        # step 2. compute the loss
        loss = loss_func(y_pred, batch_dict['y_target'].float())
        loss_batch = loss.item()
        running_loss += (loss_batch - running_loss) / (batch_index + 1)
        # step 3. compute the accuracy
        acc_batch = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_batch - running_acc) / (batch_index + 1)
    train_state['val_loss'].append(running_loss)
    train_state['val_acc'].append(running_acc)
```

8.4.4 Evaluation, Inference, and Inspection

After you have a trained model, the next steps are to either evaluate how it did against some heldout portion of the data, use it to do inference on new data, or inspect the model weights to see what it is has learned. In this section, we will show you all three steps.

EVALUATING ON TEST DATA

To evaluate the data on the heldout test set, the code is exactly the same as the validation loop in the training routine we saw in the previous example, but with one minor difference: the split is set to be 'test' rather than 'val'. The difference between the two partitions of the dataset comes from the fact that the test set should be run as little as possible. Each time you run a trained model on the test set, make a new model decision (such as changing the size of the layers), and remeasure the new retrained model on the test set, you are biasing your modeling decisions toward the test data. In other words, if you repeat that process often enough, the test set will become meaningless as an accurate measure of truly heldout data.

```
dataset.set_split('test')
batch_generator = generate_batches(dataset,batch_size=args.batch_size,device=args.
↪device)
running_loss = 0.
running_acc = 0.
classifier.eval()
for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred = classifier(x_in=batch_dict['x_data'].float())
    # compute the loss
    loss = loss_func(y_pred, batch_dict['y_target'].float())
    loss_batch = loss.item()
    running_loss += (loss_batch - running_loss) / (batch_index + 1)
    # compute the accuracy
    acc_batch = compute_accuracy(y_pred, batch_dict['y_target'])
    running_acc += (acc_batch - running_acc) / (batch_index + 1)
```

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```
train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {:.3f}".format(train_state['test_loss']))
print("Test Accuracy: {:.2f}".format(train_state['test_acc']))
```

```
Test loss: 0.243
Test Accuracy: 92.45
```

INFERENCE AND CLASSIFYING NEW DATA POINTS

Another method for evaluating the model is to do inference on new data and make qualitative judgments about whether the model is working.

```
import re
# Preprocess the reviews
def preprocess_text(text):
    if type(text) == float:
        print(text)
    text = text.lower()
    text = re.sub(r"([.,!?])", r" \1 ", text)
    text = re.sub(r"[^a-zA-Z.,!?]+", r" ", text)
    return text

def predict_rating(review, classifier, vectorizer,decision_threshold=0.5):
    """Predict the rating of a review
    Args:
        review (str): the text of the review
        classifier (ReviewClassifier): the trained model
        vectorizer (ReviewVectorizer): the corresponding vectorizer
        decision_threshold (float): The numerical boundary which
                                    separates the rating classes
    """
    review = preprocess_text(review)
    vectorized_review = torch.tensor(vectorizer.vectorize(review)).to(args.device)
    result = classifier(vectorized_review.view(1, -1))
    probability_value = torch.sigmoid(result).item()
    index = 1
    if probability_value < decision_threshold:
        index = 0
    return vectorizer.rating_vocab.lookup_index(index)
```

```
test_review = "NLP is pretty awesome"
prediction = predict_rating(test_review, classifier, vectorizer)
print("{} > {}".format(test_review, prediction))
```

```
NLP is pretty awesome > positive
```

INSPECTING MODEL WEIGHTS

Finally, the last way to understand whether a model is doing well after it has finished training is to inspect the weights and make qualitative judgments about whether they seem correct.

```
# Sort weights
fc1_weights = classifier.fc1.weight.to('cpu').detach()[0]
_, indices = torch.sort(fc1_weights, dim=0, descending=True)
indices = indices.numpy().tolist()
```

Top 20 Influential Words in Positive Reviews

```
# Top 20 words
print("Influential words in Positive Reviews:")
print("")
for i in range(20):
    print(vectorizer.review_vocab.lookup_index(indices[i]))
```

```
Influential words in Positive Reviews:

pastys
excellentes
mmmmmmmm
yummo
teau
excellents
reina
besten
nhats
soulful
bovine
nsupport
bottling
abel
emplacement
recyclable
couleurs
kouign
whimsy
couverte
```

Top 20 Influential Words in Negative Reviews

```
# Top 20 negative words
print("Influential words in Negative Reviews:")
print("")
indices.reverse()
for i in range(20):
    print(vectorizer.review_vocab.lookup_index(indices[i]))
```

```
Influential words in Negative Reviews:
```

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```
ception
nlame
nworse
nnasty
discusting
discriminates
ewwwww
disputing
crook
demerits
acrid
scab
nyuck
nbland
dishonesty
unfresh
lecturing
poorest
grossest
condescendingly
```

8.4.5 Your Turn

Your Turn

Modify the vectorizer to use Word Embeddings (e.g. GloVe) to replace one-hot encoding. Observe the performance change. You may need to handle unknown words.

CHAPTER

NINE

LAB09: CNN FOR NLP

In this lab, we will first use a small dataset (Frankenstein) to illustrate how to train CBOW from scratch.

We then introduce the basic building blocks of Convolutional Neural Networks (CNNs), and finally demontrate the use of CNN as a featurizer for news title classification, using pretrained GloVe embeddings as the input layer to CNN.

The pipeline from text to vectorized minibatch is mostly standard. Therefore in the past couple of labs we decompose the task of turning text into vectorized minibatch by writing resuable classes (`Dataset`, `DataLoader`, `Vocabulary` and `Vectorizer`). However, the object-oriented code is not as easy to read as pure procedule based programming style. Below is an illustration of the pipeline using the news title classification to demonstrate how the program control flows. To understand the code in Section 5 better, for example,we should start from the Initialization Step (Section 5.4.3). As you can see, this pipeline for text dataset preparation is a general pattern used in most neural language model training.

Credit: the notebooks are adapted from Chapter 5 of Natural Language Processing with PyTorch

9.1 Frankenstein Dataset At a Glance

Here we will build a text dataset from a digitized version of Mary Shelley's novel *Frankenstein*, available via *Project Gutenberg*. This section walks through the preprocessing; building a PyTorch Dataset class for this text dataset; and finally splitting the dataset into training, validation, and test sets.

9.1.1 Import

```
import os

from argparse import Namespace
import collections
import nltk.data
import numpy as np
import pandas as pd
import re
import string
from tqdm.notebook import tqdm
```

9.1.2 Setting up

```
args = Namespace(
    raw_dataset_txt="../data/books/frankenstein.txt",
    window_size=5,
    train_proportion=0.7,
    val_proportion=0.15,
    test_proportion=0.15,
    output_munged_csv="../data/books/frankenstein_with_splits.csv",
    seed=1337
)
```

9.1.3 Preprocessing - Tokenizer

Starting with the raw text file that Project Gutenberg distributes, the preprocessing is minimal: we use NLTK's Punkt tokenizer to split the text into separate sentences, then each sentence is converted to lowercase and the punctuation is completely removed. This preprocessing allows for us to later split strings on whitespace in order to retrieve a list of tokens.

```
# Split the raw text book into sentences
tokenizer = nltk.data.load('tokenizers/punkt/english.pickle')
with open(args.raw_dataset_txt) as fp:
    book = fp.read()
sentences = tokenizer.tokenize(book)
```

```
print (len(sentences), "sentences")
print ("Sample:", sentences[100])
```

```
3427 sentences
Sample: No incidents have hitherto befallen us that would make a figure in a
letter.
```

```
# Clean sentences
def preprocess_text(text):
    text = ' '.join(word.lower() for word in text.split(" "))
    text = re.sub(r"([.,!?])", r" \1 ", text)
    text = re.sub(r"[^a-zA-Z.,!?]+", r" ", text)
    return text
```

```
cleaned_sentences = [preprocess_text(sentence) for sentence in sentences]
```

9.1.4 CBOW training data preparation

As we know that CBOW is to use context in a specified window to predict the center word. We need to then to the list of tokens in each sentence and group them into context words in a specified window size, for each token as a center word.

Note: tqdm instantly make your loops show a smart progress meter - just wrap any iterable with `tqdm(iterable)` in your `for` loop, and you'll see a progress bar when run the loop.

```
# Global vars
MASK_TOKEN = "<MASK>"
```

```
# Create windows based on the window_size
flatten = lambda outer_list: [item for inner_list in outer_list for item in inner_
↪list]
windows = flatten([list(nltk.ngrams([MASK_TOKEN] * args.window_size + sentence.split(
↪' ') + \
    [MASK_TOKEN] * args.window_size, args.window_size * 2 + 1)) \
    for sentence in tqdm(cleaned_sentences)])

# Create cbow data (extract target center word and context words)
data = []
for window in tqdm(windows):
    target_token = window[args.window_size]
    context = []
    for i, token in enumerate(window):
        if token == MASK_TOKEN or i == args.window_size:
            continue
        else:
            context.append(token)
    data.append([' '.join(token for token in context), target_token])


# Convert to dataframe
cbow_data = pd.DataFrame(data, columns=["context", "target"])
```

```
  0%|          | 0/3427 [00:00<?, ?it/s]
```

```
  0%|          | 0/90698 [00:00<?, ?it/s]
```

9.1.5 Training, Validation and Test data split

```
# Create split data
n = len(cbow_data)
def get_split(row_num):
    if row_num <= n*args.train_proportion:
        return 'train'
    elif (row_num > n*args.train_proportion) and (row_num <= n*args.train_proportion␣
↪+ n*args.val_proportion):
```

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```
        return 'val'
    else:
        return 'test'
cbow_data['split']= cbow_data.apply(lambda row: get_split(row.name), axis=1)
```

```
cbow_data.head()
```

```
                                              context        target  split
0                          , or the modern prometheus  frankenstein  train
1            frankenstein or the modern prometheus by             ,  train
2        frankenstein , the modern prometheus by mary            or  train
3  frankenstein , or modern prometheus by mary wo...           the  train
4  frankenstein , or the prometheus by mary wolls...        modern  train
```

```
# Write split data to file
cbow_data.to_csv(args.output_munged_csv, index=False)
```

9.2 Learning Embeddings with Continuous Bag of Words (CBOW)

The pipeline from text to vectorized minibatch is mostly standard: both the Vocabulary and the DataLoader function exactly as they did in Example: Classifying Sentiment of Restaurant Reviews. However, unlike the Vectorizers we saw there, the Vectorizer in this section does not construct onehot vectors. Instead, a vector of integers representing the indices of the context is constructed and returned.

9.2.1 Imports

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm import tqdm_notebook
from tqdm.notebook import tqdm
```

9.2.2 Data Vectorization classes (from text to vectorized minibatches)

The Vocabulary

A `Vocabulary` object allows the lookup of index by a token, and the lookup of token by index, and add tokens to the vocabulary.

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None, mask_token="<MASK>", add_unk=True, unk_
↪token="<UNK>"):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
            mask_token (str): the MASK token to add into the Vocabulary; indicates
                a position that will not be used in updating the model's parameters
            add_unk (bool): a flag that indicates whether to add the UNK token
            unk_token (str): the UNK token to add into the Vocabulary

        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

        self._add_unk = add_unk
        self._unk_token = unk_token
        self._mask_token = mask_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = -1
        if add_unk:
            self.unk_index = self.add_token(unk_token)

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx,
                'add_unk': self._add_unk,
                'unk_token': self._unk_token,
                'mask_token': self._mask_token}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
```

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```
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

Vectorizer

The Vectorizer class build a vocabulary from the data frame using its class method `from_dataframe()`, then the `vectorize()` methods look up the input `contex` tokens, returns a list of indices of these tokens.

```
class CBOWVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, cbow_vocab):
        """
        Args:
            cbow_vocab (Vocabulary): maps words to integers
        """
        self.cbow_vocab = cbow_vocab

    def vectorize(self, context, vector_length=-1):
        """
        Args:
            context (str): the string of words separated by a space
            vector_length (int): an argument for forcing the length of index vector
        """

        indices = [self.cbow_vocab.lookup_token(token) for token in context.split('
↪')]
        if vector_length < 0:
            vector_length = len(indices)

        out_vector = np.zeros(vector_length, dtype=np.int64)
        out_vector[:len(indices)] = indices
        out_vector[len(indices):] = self.cbow_vocab.mask_index

        return out_vector

    @classmethod
    def from_dataframe(cls, cbow_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            cbow_df (pandas.DataFrame): the target dataset
        Returns:
            an instance of the CBOWVectorizer
        """
        cbow_vocab = Vocabulary()
        for index, row in cbow_df.iterrows():
            for token in row.context.split(' '):
                cbow_vocab.add_token(token)
            cbow_vocab.add_token(row.target)

        return cls(cbow_vocab)

    @classmethod
    def from_serializable(cls, contents):
        cbow_vocab = \
            Vocabulary.from_serializable(contents['cbow_vocab'])
        return cls(cbow_vocab=cbow_vocab)

    def to_serializable(self):
        return {'cbow_vocab': self.cbow_vocab.to_serializable()}
```

The Dataset with DataLoader

The `Dataset` class uses class method `load_dataset_and_make_vectorizer()` to read the input data into a data frame, then pass the data frame to the `Vectorizer` class to populate a Vocabulary object such that when the `vectorize()` method is called, it will perform the appropriate vectorization, in this case, return the vocabulary indices of the input context words.

Note: The `generate_batches()` method uses PyTorch build in `DataLoader` class to create mini-batches.

```
class CBOWDataset(Dataset):
    def __init__(self, cbow_df, vectorizer):
        """
        Args:
            cbow_df (pandas.DataFrame): the dataset
            vectorizer (CBOWVectorizer): vectorizer instatiated from dataset
        """
        self.cbow_df = cbow_df
        self._vectorizer = vectorizer

        measure_len = lambda context: len(context.split(" "))
        self._max_seq_length = max(map(measure_len, cbow_df.context))

        self.train_df = self.cbow_df[self.cbow_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.cbow_df[self.cbow_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.cbow_df[self.cbow_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}

        self.set_split('train')

    @classmethod
    def load_dataset_and_make_vectorizer(cls, cbow_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            cbow_csv (str): location of the dataset
        Returns:
            an instance of CBOWDataset
        """
        cbow_df = pd.read_csv(cbow_csv)
        train_cbow_df = cbow_df[cbow_df.split=='train']
        return cls(cbow_df, CBOWVectorizer.from_dataframe(train_cbow_df))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, cbow_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
```

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```
            cbow_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of CBOWDataset
        """
        cbow_df = pd.read_csv(cbow_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(cbow_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of CBOWVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return CBOWVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer

    def set_split(self, split="train"):
        """ selects the splits in the dataset using a column in the dataframe """
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point's features (x_data) and label (y_
↪target)
        """
        row = self._target_df.iloc[index]

        context_vector = \
            self._vectorizer.vectorize(row.context, self._max_seq_length)
        target_index = self._vectorizer.cbow_vocab.lookup_token(row.target)
```

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```
        return {'x_data': context_vector,
                'y_target': target_index}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size

def generate_batches(dataset, batch_size, shuffle=True,
                     drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
      ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

9.2.3 The Model: CBOW

The CBOW model uses an embedding layer `nn.Embedding()` which will have weights to be intialised randomly and updated through training. These weights will be the embeddings for each token after training. The model is a simple one hidden layer fully connected network.

```
class CBOWClassifier(nn.Module): # Simplified cbow Model
    def __init__(self, vocabulary_size, embedding_size, padding_idx=0):
        """
        Args:
            vocabulary_size (int): number of vocabulary items, controls the
                number of embeddings and prediction vector size
            embedding_size (int): size of the embeddings
            padding_idx (int): default 0; Embedding will not use this index
        """
        super(CBOWClassifier, self).__init__()

        self.embedding =  nn.Embedding(num_embeddings=vocabulary_size,
                                       embedding_dim=embedding_size,
                                       padding_idx=padding_idx)
        self.fc1 = nn.Linear(in_features=embedding_size,
                             out_features=vocabulary_size)

    def forward(self, x_in, apply_softmax=False):
        """The forward pass of the classifier

        Args:
```

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```
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, input_dim)
            apply_softmax (bool): a flag for the softmax activation
                should be false if used with the Cross Entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch, output_dim)
        """
        x_embedded_sum = F.dropout(self.embedding(x_in).sum(dim=1), 0.3)
        y_out = self.fc1(x_embedded_sum)

        if apply_softmax:
            y_out = F.softmax(y_out, dim=1)

        return y_out
```

9.2.4 Training Routine

Helper functions

```
def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.

    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
```

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```
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= train_state['early_stopping_best_val']:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state

def compute_accuracy(y_pred, y_target):
    _, y_pred_indices = y_pred.max(dim=1)
    n_correct = torch.eq(y_pred_indices, y_target).sum().item()
    return n_correct / len(y_pred_indices) * 100
```

general utilities

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)
```

Settings and some prep work

```
args = Namespace(
    # Data and Path information
    cbow_csv="../data/books/frankenstein_with_splits.csv",
    vectorizer_file="vectorizer.json",
    model_state_file="model.pth",
    save_dir="model_storage\cbow",
    # Model hyper parameters
    embedding_size=50,
    # Training hyper parameters
    seed=1337,
    num_epochs=100,
    learning_rate=0.0001,
```

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```
    batch_size=32,
    early_stopping_criteria=5,
    # Runtime options
    cuda=True,
    catch_keyboard_interrupt=True,
    reload_from_files=False,
    expand_filepaths_to_save_dir=True
)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))


# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))


# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage\cbow\vectorizer.json
        model_storage\cbow\model.pth
Using CUDA: True
```

Initializations

```
if args.reload_from_files:
    print("Loading dataset and loading vectorizer")
    dataset = CBOWDataset.load_dataset_and_load_vectorizer(args.cbow_csv,
                                                           args.vectorizer_file)
else:
    print("Loading dataset and creating vectorizer")
    dataset = CBOWDataset.load_dataset_and_make_vectorizer(args.cbow_csv)
    dataset.save_vectorizer(args.vectorizer_file)

vectorizer = dataset.get_vectorizer()
```

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```
classifier = CBOWClassifier(vocabulary_size=len(vectorizer.cbow_vocab),
                            embedding_size=args.embedding_size)
```

```
Loading dataset and creating vectorizer
```

Training loop

This takes 904 seconds (15 mins).

```
classifier = classifier.to(args.device)

loss_func = nn.CrossEntropyLoss()
optimizer = optim.Adam(classifier.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)
train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                         total=args.num_epochs,
                         position=0)

dataset.set_split('train')
train_bar = tqdm(desc='split=train',
                         total=dataset.get_num_batches(args.batch_size),
                         position=1,
                         leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
                       total=dataset.get_num_batches(args.batch_size),
                       position=1,
                       leave=True)

try:
    for epoch_index in range(args.num_epochs):
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on

        dataset.set_split('train')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        classifier.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()
```

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```
        # step 2. compute the output
        y_pred = classifier(x_in=batch_dict['x_data'])

        # step 3. compute the loss
        loss = loss_func(y_pred, batch_dict['y_target'])
        loss_t = loss.item()
        running_loss += (loss_t - running_loss) / (batch_index + 1)

        # step 4. use loss to produce gradients
        loss.backward()

        # step 5. use optimizer to take gradient step
        optimizer.step()
        # -----------------------------------------
        # compute the accuracy
        acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_t - running_acc) / (batch_index + 1)

        # update bar
        train_bar.set_postfix(loss=running_loss, acc=running_acc,
                              epoch=epoch_index)
        train_bar.update()

    train_state['train_loss'].append(running_loss)
    train_state['train_acc'].append(running_acc)

    # Iterate over val dataset

    # setup: batch generator, set loss and acc to 0; set eval mode on
    dataset.set_split('val')
    batch_generator = generate_batches(dataset,
                                       batch_size=args.batch_size,
                                       device=args.device)
    running_loss = 0.
    running_acc = 0.
    classifier.eval()

    for batch_index, batch_dict in enumerate(batch_generator):

        # compute the output
        y_pred =  classifier(x_in=batch_dict['x_data'])

        # step 3. compute the loss
        loss = loss_func(y_pred, batch_dict['y_target'])
        loss_t = loss.item()
        running_loss += (loss_t - running_loss) / (batch_index + 1)

        # compute the accuracy
        acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_t - running_acc) / (batch_index + 1)
        val_bar.set_postfix(loss=running_loss, acc=running_acc,
                            epoch=epoch_index)
        val_bar.update()

    train_state['val_loss'].append(running_loss)
    train_state['val_acc'].append(running_acc)
```

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```
        train_state = update_train_state(args=args, model=classifier,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])

        if train_state['stop_early']:
            break

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.update()
except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/1984 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/425 [00:00<?, ?it/s]
```

```
# compute the loss & accuracy on the test set using the best available model

classifier.load_state_dict(torch.load(train_state['model_filename']))
classifier = classifier.to(args.device)
loss_func = nn.CrossEntropyLoss()

dataset.set_split('test')
batch_generator = generate_batches(dataset,
                                   batch_size=args.batch_size,
                                   device=args.device)
running_loss = 0.
running_acc = 0.
classifier.eval()

for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred =  classifier(x_in=batch_dict['x_data'])

    # compute the loss
    loss = loss_func(y_pred, batch_dict['y_target'])
    loss_t = loss.item()
    running_loss += (loss_t - running_loss) / (batch_index + 1)

    # compute the accuracy
    acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
    running_acc += (acc_t - running_acc) / (batch_index + 1)

train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {};".format(train_state['test_loss']))
print("Test Accuracy: {}".format(train_state['test_acc']))
```

```
Test loss: 8.131561214222629;
Test Accuracy: 11.551470588235299
```

Warning: The accuracy is pretty low, this is largely to do with the small training set - only one book. In reality, the model needs to be trained with at least terabytes of data. We have shown in the lectures on how model performace are significantly affected by the data size. The larger the dataset, the better the performance.

Trained Embeddings

```
def pretty_print(results):
    """
    Pretty print embedding results.
    """
    for item in results:
        print ("...[%.2f] - %s"%(item[1], item[0]))

def get_closest(target_word, word_to_idx, embeddings, n=5):
    """
    Get the n closest
    words to your word.
    """

    # Calculate distances to all other words

    word_embedding = embeddings[word_to_idx[target_word.lower()]]
    distances = []
    for word, index in word_to_idx.items():
        if word == "<MASK>" or word == target_word:
            continue
        distances.append((word, torch.dist(word_embedding, embeddings[index])))

    results = sorted(distances, key=lambda x: x[1])[1:n+2]
    return results
```

```
word = 'monster'
embeddings = classifier.embedding.weight.data
word_to_idx = vectorizer.cbow_vocab._token_to_idx
pretty_print(get_closest(word, word_to_idx, embeddings, n=5))
```

```
...[7.32] - cares
...[7.58] - griefs
...[7.63] - sickness
...[7.66] - trifling
...[7.69] - saw
...[7.70] - prolong
```

```
target_words = ['frankenstein', 'monster', 'science', 'sickness', 'lonely', 'happy']

embeddings = classifier.embedding.weight.data
word_to_idx = vectorizer.cbow_vocab._token_to_idx

for target_word in target_words:
```

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```
    print(f"========{target_word}=======")
    if target_word not in word_to_idx:
        print("Not in vocabulary")
        continue
    pretty_print(get_closest(target_word, word_to_idx, embeddings, n=5))
```

```
=======frankenstein=======
...[6.93] - discrimination
...[6.99] - slight
...[7.02] - oppressive
...[7.05] - spurned
...[7.11] - illustrate
...[7.11] - wandering
=======monster=======
...[7.32] - cares
...[7.58] - griefs
...[7.63] - sickness
...[7.66] - trifling
...[7.69] - saw
...[7.70] - prolong
=======science=======
...[6.85] - mutual
...[6.93] - mist
...[6.95] - swelling
...[7.01] - impression
...[7.06] - darkened
...[7.06] - nearly
=======sickness=======
...[6.37] - while
...[6.45] - foundations
...[6.61] - awoke
...[6.65] - consoles
...[6.70] - literally
...[6.74] - depend
=======lonely=======
...[6.74] - unveiled
...[6.88] - moonlight
...[7.05] - ought
...[7.08] - bed
...[7.14] - superhuman
...[7.14] - therefore
=======happy=======
...[6.25] - bottom
...[6.42] - injury
...[6.49] - chivalry
...[6.50] - altered
...[6.51] - penetrated
...[6.54] - danger
```

9.3 Convolution Basics

9.3.1 Convolution in Raw Numpy Code

There is one image, one channel, six by six pixels in size (shape $1\times 1\times 1 \times 6 \times 6). There is one filter, one channel, three by three pixels in size.

```
import numpy as np
```

```
single = np.array(
    [[[[5, 0, 8, 7, 8, 1],
    [1, 9, 5, 0, 7, 7],
    [6, 0, 2, 4, 6, 6],
    [9, 7, 6, 6, 8, 4],
    [8, 3, 8, 5, 1, 3],
    [7, 2, 7, 0, 1, 0]]]]
)
single.shape
```

```
(1, 1, 6, 6)
```

```
filter = np.array(
    [[[[0, 0, 0],
    [0, 1, 0],
    [0, 0, 0]]]]
    )
filter.shape
```

```
(1, 1, 3, 3)
```

```
region = single[:, :, 0:3, 0:3]
filtered_region = region * filter
total = filtered_region.sum()
total
```

```
9
```

```
new_region = single[:, :, 0:3, (0+1):(3+1)]
```

```
new_filtered_region = new_region * filter
new_total = new_filtered_region.sum()
new_total
```

```
5
```

```
last_horizontal_region = single[:, :, 0:3, (0+4):(3+4)]
```

```
last_horizontal_region * filter
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_10920/1958888837.py in <module>
```

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```
----> 1 last_horizontal_region * filter

ValueError: operands could not be broadcast together with shapes (1,1,3,2) (1,1,3,3)
```

```
last_horizontal_region = single[:, :, 0:3, (0+4):(3+4)]
```

Applying a filter always produces a single value, the reduction is equal to the filter size minus one when stride is 1. For example, the above matrix is 6×6, the filter size is 3×3, the reduction is $3 - 1 = 2$, the the resulting matrix is 4×4.

How do we generalise this to a $n \times m$ matrix, with a filter size $k \times l$ and a stride d. The shape of the newly reduced matrix is then:

$$h \times w = n - (k - 1) - (d - 1) \times m - (l - 1) - (d - 1)$$

Your Turn

Based on the code above, write a function conv() that takes Arguments: input - a matrix to be convertedfilter - a filter matrix stride - the number of places to move during convolution Returns: result - the resulting matrix after convolution

Make sure you take the border conditions into account.

```
def conv(input, filter, stride):
    # Setting up
    m, n = input.shape[2:4]
    k, l = filter.shape[2:4]
    result = np.zeros([1,1,(m-(k-1))//stride, (n-(l-1))//stride])
    h, w = result.shape[2:4]
    print(result.shape)
    row_idx = 0 # keep track of the row index of the output
    col_idx = 0 # keep track of the column index of the output
    for i in range(0, n, stride):
        for j in range(0, m, stride):
            if((i+k)<=n and (j+l)<=m and col_idx<w and row_idx<h ):
                result[:,:,row_idx,col_idx] = (input[:, :, i:i+k, j:j+l]*filter).sum()
                col_idx = col_idx + 1
        row_idx = row_idx + 1
        col_idx = 0
    return result
```

```
conv(single, filter, 1)
```

```
(1, 1, 4, 4)
```

```
array([[[[9., 5., 0., 7.],
         [0., 2., 4., 6.],
         [7., 6., 6., 8.],
         [3., 8., 5., 1.]]]])
```

```
conv(single, filter, 2)
```

```
(1, 1, 2, 2)
```

```
array([[[[9., 0.],
         [7., 6.]]]])
```

9.3.2 Convolving in PyTorch

`kernel` and `filter` are often used interchangably to refer to the matrix that will be applied over the original input matrix.

Just like the activation functions and loss functions we've seen in earlier labs, convolutions also come in two flavors: functional and module. There is a fundamental difference between the two, though: the functional convolution takes the kernel/filter as an argument while the module has weights to represent the kernel/filter. Let's use the functional convolution, `F.conv2d`, to apply the filter to our input matrix (notice we're using stride=1 since we moved the region around one pixel at a time.

Note: We need to convert Numpy arrays into Torch Tensors before we can make use the `F.conv2d` function.

```
import torch
import torch.nn.functional as F
image = torch.as_tensor(single).float()
kernel = torch.as_tensor(filter).float()
convolved = F.conv2d(image, kernel, stride=1)
convolved
```

```
tensor([[[[9., 5., 0., 7.],
          [0., 2., 4., 6.],
          [7., 6., 6., 8.],
          [3., 8., 5., 1.]]]])
```

Now, let's turn our attention to PyTorch's convolution module, `nn.Conv2d`. It has many arguments, let's focus on the first four of them:

- `in_channels`: number of channels of the input image
- `out_channels`: number of channels produced by the convolution
- `kernel_size`: size of the (square) convolution filter/kernel
- `stride`: the size of the movement of the selected region

Important:

- First, there is no argument for the kernel/filter itself, there is only a `kernel_size` argument. This is because the actual filter is learned through training rather than specified.
- Second, it is possible to produce multiple channels as output. It simply means the module is going to learn multiple filters. Each filter is going to produce a different result, which is being called a channel here.

For a single channel matrix (you can think of 2D matrices are images) as input, and applying one filter (size three by three) to it, moving one pixel at a time, resulting in one output/channel. This is what it looks like in `nn.Conv2d` code:

```
import torch.nn as nn
conv = nn.Conv2d(in_channels=1, out_channels=1, kernel_size=3, stride=1)
conv(image)
```

```
tensor([[[[-1.0575, -2.6052, -2.2154, -1.7589],
          [ 1.7594,  0.5861,  1.2595,  0.6742],
          [ 1.0704,  1.4473,  1.1077, -2.0348],
          [-1.6991, -1.5751, -1.4593, -3.0604]]]],
       grad_fn=<ThnnConv2DBackward>)
```

Important: These results are randomly initalised weights representing the kernel/filter. Yours will be different from this.

This is the whole point of the convolutional module: it will learn the kernel/filter on its own. In traditional computer vision, people would develop different filters for different purposes: blurring, sharpening, edge detection, and so on. But, instead of being clever and trying to manually devise a filter that does the trick for a given problem, why not outsource the filter definition to the neural network as well? This way the network will come up with filters that highlight features that are relevant to the task at hand.

Note: The resulting matrix shows a grad_fn attribute now: it will be used to compute gradients so the network can actually learn how to change the weights representing the filter.

Your Turn

Try changing the output channels to 2, and see how many filters have been randomly initialised.

Force to use a pre-defined filter

We can also force a convolutional module to use a particular filter by setting its weights.

Important: Setting the weights is a strictly no-gradient operation, so you should always use the no_grad context manager.

```
with torch.no_grad():
    conv.weight[0] = kernel
    conv.bias[0] = 0

conv(image)
```

```
tensor([[[[9., 5., 0., 7.],
          [0., 2., 4., 6.],
          [7., 6., 6., 8.],
          [3., 8., 5., 1.]]]], grad_fn=<ThnnConv2DBackward>)
```

9.3.3 Key hyperparameters in convolution

Dilation

Instead of a *contiguous* kernel, **dilation** controls the number of rows and columns to skip when the convolutional kernel is applied to the input matrix. In the code below, a dilation of two stretch the 2 kernel into a `holed` 3×3 kernel. The shape of the output feature map is therefore 4×4.

```
conv_dilated = nn.Conv2d(in_channels=1, out_channels=1,
          kernel_size=2, dilation=2, bias=False, stride=1)
conv_dilated(image)  # [1x1x6x6] tensor as input
```

```
tensor([[[[ 2.0450, -0.8075,  2.1801,  1.3727],
          [-1.0471,  2.2050,  0.2247, -0.7972],
          [ 0.4034, -1.2558,  0.9169,  1.2028],
          [ 2.2282,  3.4014,  2.7813,  2.8520]]]],
       grad_fn=<SlowConvDilated2DBackward>)
```

Padding

By adding columns and rows of zeros around it, we expand the input image such that the gray region starts centered in the actual top left corner of the input image. This simple trick can be used to preserve the original size of the image. In code, as usual, PyTorch gives us two options: functional (F.pad) and module (nn.ConstantPad2d). Let's start with the module version this time:

```
constant_padder = nn.ConstantPad2d(padding=1, value=0)
constant_padder(image)
```

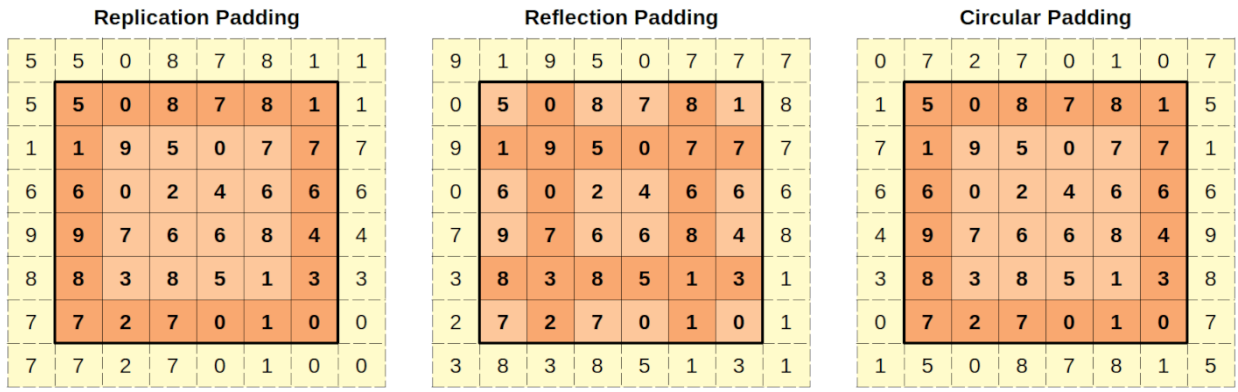
```
tensor([[[[0., 0., 0., 0., 0., 0., 0., 0.],
          [0., 5., 0., 8., 7., 8., 1., 0.],
          [0., 1., 9., 5., 0., 7., 7., 0.],
          [0., 6., 0., 2., 4., 6., 6., 0.],
          [0., 9., 7., 6., 6., 8., 4., 0.],
          [0., 8., 3., 8., 5., 1., 3., 0.],
          [0., 7., 2., 7., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 0., 0., 0.]]]])
```

One can also do asymmetric padding, by specifying a tuple in the padding argument representing (left, right, top, bottom). So, if we were to stuff our image on left and right sides only, the argument would go like this: (1, 1, 0, 0).

```
padded = F.pad(image, pad=(1, 1, 1, 1), mode='constant', value=0)
padded
```

```
tensor([[[[0., 0., 0., 0., 0., 0., 0., 0.],
          [0., 5., 0., 8., 7., 8., 1., 0.],
          [0., 1., 9., 5., 0., 7., 7., 0.],
          [0., 6., 0., 2., 4., 6., 6., 0.],
          [0., 9., 7., 6., 6., 8., 4., 0.],
          [0., 8., 3., 8., 5., 1., 3., 0.],
          [0., 7., 2., 7., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 0., 0., 0.]]]])
```

There are three other modes: replicate, reflect, and circular.



Replication Padding

In the replication padding, the padded pixels will have the same value as the closest real pixel. The padded corners will have the same value as the real corners. The other columns (left and right) and rows (top and bottom) will replicate the corresponding values of the original image. The values used in the replication are in a darker shade of orange.

In PyTorch, one can use the functional form `F.pad` with `mode="replicate"`, or use the module version `nn.ReplicationPad2d`:

```
replication_padder = nn.ReplicationPad2d(padding=1)
replication_padder(image)
```

```
tensor([[[[5., 5., 0., 8., 7., 8., 1., 1.],
          [5., 5., 0., 8., 7., 8., 1., 1.],
          [1., 1., 9., 5., 0., 7., 7., 7.],
          [6., 6., 0., 2., 4., 6., 6., 6.],
          [9., 9., 7., 6., 6., 8., 4., 4.],
          [8., 8., 3., 8., 5., 1., 3., 3.],
          [7., 7., 2., 7., 0., 1., 0., 0.],
          [7., 7., 2., 7., 0., 1., 0., 0.]]]])
```

```
F.pad(image, pad=(1, 1, 1, 1), mode='replicate')
```

```
tensor([[[[5., 5., 0., 8., 7., 8., 1., 1.],
          [5., 5., 0., 8., 7., 8., 1., 1.],
          [1., 1., 9., 5., 0., 7., 7., 7.],
          [6., 6., 0., 2., 4., 6., 6., 6.],
          [9., 9., 7., 6., 6., 8., 4., 4.],
          [8., 8., 3., 8., 5., 1., 3., 3.],
          [7., 7., 2., 7., 0., 1., 0., 0.],
          [7., 7., 2., 7., 0., 1., 0., 0.]]]])
```

Reflection Padding

In the reflection padding, the outer columns and rows are used as axes for the reflection. So, the left padded column (forget about the corners for now) will reflect the second column (since the first column is the axis of reflection). The same reasoning goes for the right padded column. Similarly, the top padded row will reflect the second row (since the first row is the axis of reflection), and the same reasoning goes for the bottom padded row. The values used in the reflection are in a darker shade of orange. The corners will have the same values as the intersection of the reflected rows and columns of the original image, or the diagnol value when the original corners are used as a reflection point.

In PyTorch, you can use the functional form `F.pad` with `mode="reflect"`, or use the module version `nn.ReflectionPad2d`.

```
reflection_padder = nn.ReflectionPad2d(padding=1)
reflection_padder(image)
```

```
tensor([[[[9., 1., 9., 5., 0., 7., 7., 7.],
          [0., 5., 0., 8., 7., 8., 1., 8.],
          [9., 1., 9., 5., 0., 7., 7., 7.],
          [0., 6., 0., 2., 4., 6., 6., 6.],
          [7., 9., 7., 6., 6., 8., 4., 8.],
          [3., 8., 3., 8., 5., 1., 3., 1.],
          [2., 7., 2., 7., 0., 1., 0., 1.],
          [3., 8., 3., 8., 5., 1., 3., 1.]]]])
```

```
F.pad(image, pad=(1, 1, 1, 1), mode='reflect')
```

```
tensor([[[[9., 1., 9., 5., 0., 7., 7., 7.],
          [0., 5., 0., 8., 7., 8., 1., 8.],
          [9., 1., 9., 5., 0., 7., 7., 7.],
          [0., 6., 0., 2., 4., 6., 6., 6.],
          [7., 9., 7., 6., 6., 8., 4., 8.],
          [3., 8., 3., 8., 5., 1., 3., 1.],
          [2., 7., 2., 7., 0., 1., 0., 1.],
          [3., 8., 3., 8., 5., 1., 3., 1.]]]])
```

Circular Padding

In the circular padding, the left-most (right-most) column gets copied as the right (left) padded column (forget about the corners for now too). Similarly, the topmost (bottom-most) row gets copied as the bottom (top) padded row. The corners will receive the values of the diametrically opposed corner: the top-left padded pixel receives the value of the bottom-right corner of the original image. Once again, the values used in the padding are in a darker shade of orange.

In PyTorch, you must use the functional form `F.pad` with `mode="circular"` since there is no module version of the circular padding (at time of writing):

```
F.pad(image, pad=(1, 1, 1, 1), mode='circular')
```

```
tensor([[[[0., 7., 2., 7., 0., 1., 0., 7.],
          [1., 5., 0., 8., 7., 8., 1., 5.],
          [7., 1., 9., 5., 0., 7., 7., 1.],
          [6., 6., 0., 2., 4., 6., 6., 6.],
          [4., 9., 7., 6., 6., 8., 4., 9.],
          [3., 8., 3., 8., 5., 1., 3., 8.],
```

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```
          [0., 7., 2., 7., 0., 1., 0., 7.],
          [1., 5., 0., 8., 7., 8., 1., 5.]]]])
```

Pooling to Shrink Images

Another way of shrinking images is to use **pooling**. It is different from the former operations: it splits the image into tiny chunks, performs an operation on each chunk (that yields a single value), and puts the chunks together as the resulting image. For example, a 6×6 image can be reduced to 3×3 by splitting the original image to 9 chunks.

In PyTorch, as usual, we have both forms: `F.max_pool2d` and `nn.MaxPool2d`.

```
pooled = F.max_pool2d(padded, kernel_size=2)
pooled
```

```
C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\nn\functional.py:718:␣
↪UserWarning: Named tensors and all their associated APIs are an experimental␣
↪feature and subject to change. Please do not use them for anything important until␣
↪they are released as stable. (Triggered internally at  ..\c10/core/TensorImpl.
↪h:1156.)
 return torch.max_pool2d(input, kernel_size, stride, padding, dilation, ceil_mode)
```

```
tensor([[[[5., 8., 8., 1.],
          [6., 9., 7., 7.],
          [9., 8., 8., 4.],
          [7., 7., 1., 0.]]]])
```

- A pooling kernel of two-by-two results in an image whose dimensions are half of the original.
- A pooling kernel of three-by-three makes the resulting image one third the size of the original, and so on.

Important: only full chunks count: if we try a kernel of five-by-five in our eight-by-eight image, only one chunk fits, and the resulting image would have a single pixel.

```
maxpool5 = nn.MaxPool2d(kernel_size=5)
pooled5 = maxpool5(padded)
pooled5
```

```
tensor([[[[9.]]]])
```

Besides max-pooling, average pooling is also fairly common. As the name suggests, it will output the average pixel value for each chunk. In PyTorch, we have `F.avg_pool2d` and `nn.AvgPool2d`.

You can also use a stride greater than 1 just like applying a convolution kernel:

```
padded
```

```
tensor([[[[0., 0., 0., 0., 0., 0., 0., 0.],
          [0., 5., 0., 8., 7., 8., 1., 0.],
          [0., 1., 9., 5., 0., 7., 7., 0.],
          [0., 6., 0., 2., 4., 6., 6., 0.],
          [0., 9., 7., 6., 6., 8., 4., 0.],
          [0., 8., 3., 8., 5., 1., 3., 0.],
```

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```
          [0., 7., 2., 7., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 0., 0., 0.]]]])
```

```
F.max_pool2d(padded, kernel_size=2, stride=2)
```

```
tensor([[[[5., 8., 8., 1.],
          [6., 9., 7., 7.],
          [9., 8., 8., 4.],
          [7., 7., 1., 0.]]]])
```

Flatterning

It simply flattens a tensor, by appending the values of each row to its previous row. It has a module version `nn.Flatten()`. There is no functional version of it, as it can achieved by the `view()` function.

```
pooled
```

```
tensor([[[[5., 8., 8., 1.],
          [6., 9., 7., 7.],
          [9., 8., 8., 4.],
          [7., 7., 1., 0.]]]])
```

```
flatterned = nn.Flatten()(pooled)
flatterned
```

```
tensor([[5., 8., 8., 1., 6., 9., 7., 7., 9., 8., 8., 4., 7., 7., 1., 0.]])
```

```
pooled.view(1,-1)
```

```
tensor([[5., 8., 8., 1., 6., 9., 7., 7., 9., 8., 8., 4., 7., 7., 1., 0.]])
```

9.3.4 1D Convolution

Give a sequence of daily temperature readings, let's use a window (filter) of size five, like in the figure below. In its first step, the window is over days one to five. In the next step, since it can only move to the right, it will be over days two to six. The size of our movement to the right is, the stride.

Now, let's assign the same value ($0.2 = \frac{1}{5}$) for every weight in our filter and use PyTorch's F.conv1d to convolve the filter with our sequence (the shape is the NCL: the **N**umber of sequences, the number of **C**hannels and the **L**ength of the sequence.):

```
import torch.nn.functional as F
import numpy as np
import torch

temperatures = np.array([5, 11, 15, 6, 5, 3, 3, 0, 0, 3, 4, 2, 1])
size = 5
weight = torch.ones(size) * 0.2
F.conv1d(torch.as_tensor(temperatures).float().view(1, 1, -1),
         weight=weight.view(1, 1, -1))
```

```
tensor([[[8.4000, 8.0000, 6.4000, 3.4000, 2.2000, 1.8000, 2.0000, 1.8000,
          2.0000]]])
```

This is a moving average, as we have the same weight ($\frac{1}{window_size}$) for the weighted sum.

```
weight
```

```
tensor([0.2000, 0.2000, 0.2000, 0.2000, 0.2000])
```

```
import torch.nn as nn
torch.manual_seed(17)
conv_seq = nn.Conv1d(in_channels=10, out_channels=100,
    kernel_size=2, bias=False)
conv_seq.weight, conv_seq.weight.shape
```

```
(Parameter containing:
 tensor([[[-0.0294,  0.0157],
          [ 0.1477, -0.1682],
          [-0.2105,  0.0221],
          ...,
          [-0.0651, -0.1261],
          [-0.2236, -0.1607],
          [ 0.0448,  0.0294]],

         [[-0.1812, -0.1802],
          [-0.0575, -0.2116],
          [-0.1365,  0.1271],
          ...,
          [ 0.2072,  0.0923],
          [ 0.1267,  0.1031],
          [-0.0246, -0.0949]],

         [[-0.1262, -0.1012],
          [ 0.1101, -0.0824],
          [-0.0500,  0.1758],
          ...,
          [-0.1602,  0.0048],
          [ 0.1420, -0.1564],
          [ 0.1490, -0.1395]],

         ...,

         [[ 0.1480, -0.1971],
          [-0.1273,  0.0995],
          [-0.0726, -0.1250],
          ...,
          [ 0.1296,  0.1590],
          [-0.0313,  0.1204],
          [-0.1540, -0.0166]],

         [[ 0.1235,  0.2034],
          [ 0.0404, -0.0861],
          [ 0.0900, -0.1462],
          ...,
          [ 0.0307,  0.1345],
          [-0.1840, -0.1889],
```

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```
          [-0.0731,  0.0381]],

         [[ 0.1546, -0.0249],
          [-0.1551,  0.0903],
          [-0.0173, -0.1090],
          ...,
          [ 0.1704,  0.2202],
          [-0.2147,  0.2092],
          [-0.1115,  0.1248]]], requires_grad=True),
 torch.Size([100, 10, 2]))
```

9.4 AG News Dataset at A Glance

The **AG News** dataset is a collection of more than one million news articles collected in 2005 by academics for experimenting with data mining and information extraction methods. The goal of this example is to illustrate the effectiveness of pretrained word embeddings in classifying texts. For this example, we use a slimmed down version consisting of 120,000 news articles that are split evenly between four categories:

- Sports,
- Science/Technology,
- World, and
- Business.

In addition to slimming down the dataset, we focus on the article headlines as our observations and create the multiclass classification task of predicting the category given the headline.

9.4.1 Imports

```
import collections
import numpy as np
import pandas as pd
import re

from argparse import Namespace
```

9.4.2 Setting up

```
args = Namespace(
    raw_dataset_csv="../data/ag_news/news.csv",
    train_proportion=0.7,
    val_proportion=0.15,
    test_proportion=0.15,
    output_munged_csv="../data/ag_news/news_with_splits.csv",
    seed=1337
)
```

9.4.3 Read Data

```
# Read raw data
news = pd.read_csv(args.raw_dataset_csv, header=0)
```

```
news.head()
```

```
   category                                                title
0  Business  Wall St. Bears Claw Back Into the Black (Reuters)
1  Business  Carlyle Looks Toward Commercial Aerospace (Reu...
2  Business    Oil and Economy Cloud Stocks' Outlook (Reuters)
3  Business  Iraq Halts Oil Exports from Main Southern Pipe...
4  Business  Oil prices soar to all-time record, posing new...
```

```
# Unique classes
set(news.category)
```

```
{'Business', 'Sci/Tech', 'Sports', 'World'}
```

```
# Splitting train by category
# Create dict
by_category = collections.defaultdict(list)
for _, row in news.iterrows():
    by_category[row.category].append(row.to_dict())
```

9.4.4 Create training, validation and test split

```
# Create split data
final_list = []
np.random.seed(args.seed)
for _, item_list in sorted(by_category.items()):
    np.random.shuffle(item_list)
    n = len(item_list)
    n_train = int(args.train_proportion*n)
    n_val = int(args.val_proportion*n)
    n_test = int(args.test_proportion*n)

    # Give data point a split attribute
    for item in item_list[:n_train]:
        item['split'] = 'train'
    for item in item_list[n_train:n_train+n_val]:
        item['split'] = 'val'
    for item in item_list[n_train+n_val:]:
        item['split'] = 'test'

    # Add to final list
    final_list.extend(item_list)
```

```
# Write split data to file
final_news = pd.DataFrame(final_list)
```

```
final_news.split.value_counts()
```

```
train    84000
val      18000
test     18000
Name: split, dtype: int64
```

```
# Preprocess the reviews
def preprocess_text(text):
    text = ' '.join(word.lower() for word in text.split(" "))
    text = re.sub(r"([.,!?])", r" \1 ", text)
    text = re.sub(r"[^a-zA-Z.,!?]+", r" ", text)
    return text

final_news.title = final_news.title.apply(preprocess_text)
```

```
final_news.head()
```

```
   category                                title  split
0  Business  jobs , tax cuts key issues for bush  train
1  Business    jarden buying mr . coffee s maker  train
2  Business    retail sales show festive fervour  train
3  Business  intervoice s customers come calling  train
4  Business    boeing expects air force contract  train
```

```
# Write munged data to CSV
final_news.to_csv(args.output_munged_csv, index=False)
```

9.5 Using CNN for Document Classification with Embeddings

The CBOW example used an Embedding layer to do simple classification. This example builds on that in three ways:

- first by loading pretrained word embeddings, then
- by finetuning these pretrained embeddings by classifying entire news articles, and
- finally by using a convolutional neural network to capture the spatial relationships between words.

Transfer Learning

In machine learning, using a model trained on one task as an initializer for another task is called *transfer learning*.

In this example, we use the AG News dataset. To model the sequences of words in AG News, we introduce a variant of the `Vocabulary` class `SequenceVocabulary`, to bundle several tokens vital for modeling sequences. The `Vectorizer` demonstrates how to use this class.

Download GloVe Pretrained Embeddings - glove.6B.zip

9.5.1 Imports

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm.notebook import tqdm
```

9.5.2 Data Vectorization classes

The Standard `Vocabulary` Class

A `Vocabulary` object is able to look up an index for a token and vice versa, useful for constructing a one-hot vector for each word.

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
```

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```
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

SequenceVocabulary

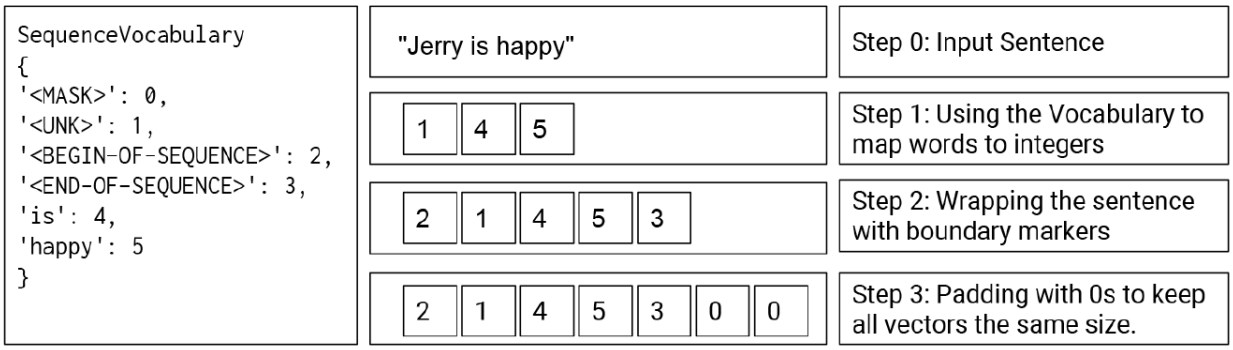
When we deal with a sequence of words, it is often useful to have four special tokens

- the `UNK` token,
- the `MASK` token,
- the `BEGINOFSEQUENCE` token, and
- the `ENDOFSEQUENCE` token.

They serve three different purposes.

- The `UNK` token (short for unknown), allows the model to learn a representation for rare words so that it can accommodate words that it has never seen at test time.
- The `MASK` token serves as a sentinel for Embedding layers and loss calculations when we have sequences of variable length (padding in the context of sequence modelling).
- Finally, the `BEGINOFSEQUENCE` and `ENDOFSEQUENCE` tokens give the neural network hints about the sequence boundaries.

The figure below shows the result of using these special tokens in the broader vectorization pipeline.




```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):

        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
```

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```
                        'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

The Vectorizer

The `Vectorizer`, instantiates and encapsulates the use of the `SequenceVocabulary`. In this example, the Vectorizer follows the pattern we demonstrated before of restricting the total set of words allowed in the Vocabulary by counting and thresholding on a certain frequency (`cutoff`). The core purpose of this action is to improve the signal quality for the model and limit the memory model's memory usage by removing noisy, lowfrequency words.

After instantiation, the `Vectorizer`'s `vectorize()` method takes as input a news title and returns a vector that is as long as the longest title in the dataset. It has two key behaviors.

- The first is that it stores the maximum sequence length locally. Normally, the dataset tracks the maximum sequence length, and at inference time, the length of the test sequence is taken as the length of the vector, for example in a Recurrent Neural Network (RNN) model. However, because we have a CNN model, it is important to maintain a static size even at inference time.
- The second key behavior, it outputs a zeropadded vector of integers (indices), which represent the words in the sequence.
- Additionally, this vector of integers has the integer for the BEGINOFSEQUENCE token prepended to the beginning and the integer for the ENDOFSEQUENCE token appended to the end.

From the classifier's perspective, these special tokens provide evidence of the sequence boundaries, allowing it to react to words near the boundary differently than to words near the center.

```
class NewsVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, title_vocab, category_vocab):
        self.title_vocab = title_vocab
        self.category_vocab = category_vocab

    def vectorize(self, title, vector_length=-1):
        """
        Args:
            title (str): the string of words separated by a space
            vector_length (int): an argument for forcing the length of index vector
        Returns:
```

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```
            the vetorized title (numpy.array)
        """
        indices = [self.title_vocab.begin_seq_index]
        indices.extend(self.title_vocab.lookup_token(token)
                       for token in title.split(" "))
        indices.append(self.title_vocab.end_seq_index)

        if vector_length < 0:
            vector_length = len(indices)

        out_vector = np.zeros(vector_length, dtype=np.int64)
        out_vector[:len(indices)] = indices
        out_vector[len(indices):] = self.title_vocab.mask_index

        return out_vector

    @classmethod
    def from_dataframe(cls, news_df, cutoff=25):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            news_df (pandas.DataFrame): the target dataset
            cutoff (int): frequency threshold for including in Vocabulary
        Returns:
            an instance of the NewsVectorizer
        """
        category_vocab = Vocabulary()
        for category in sorted(set(news_df.category)):
            category_vocab.add_token(category)

        word_counts = Counter()
        for title in news_df.title:
            for token in title.split(" "):
                if token not in string.punctuation:
                    word_counts[token] += 1

        title_vocab = SequenceVocabulary()
        for word, word_count in word_counts.items():
            if word_count >= cutoff:
                title_vocab.add_token(word)

        return cls(title_vocab, category_vocab)

    @classmethod
    def from_serializable(cls, contents):
        title_vocab = \
            SequenceVocabulary.from_serializable(contents['title_vocab'])
        category_vocab =  \
            Vocabulary.from_serializable(contents['category_vocab'])

        return cls(title_vocab=title_vocab, category_vocab=category_vocab)

    def to_serializable(self):
        return {'title_vocab': self.title_vocab.to_serializable(),
                'category_vocab': self.category_vocab.to_serializable()}
```

The Dataset

```
class NewsDataset(Dataset):
    def __init__(self, news_df, vectorizer):
        """
        Args:
            news_df (pandas.DataFrame): the dataset
            vectorizer (NewsVectorizer): vectorizer instatiated from dataset
        """
        self.news_df = news_df
        self._vectorizer = vectorizer

        # +1 if only using begin_seq, +2 if using both begin and end seq tokens
        measure_len = lambda context: len(context.split(" "))
        self._max_seq_length = max(map(measure_len, news_df.title)) + 2


        self.train_df = self.news_df[self.news_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.news_df[self.news_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.news_df[self.news_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}

        self.set_split('train')

        # Class weights
        class_counts = news_df.category.value_counts().to_dict()
        def sort_key(item):
            return self._vectorizer.category_vocab.lookup_token(item[0])
        sorted_counts = sorted(class_counts.items(), key=sort_key)
        frequencies = [count for _, count in sorted_counts]
        self.class_weights = 1.0 / torch.tensor(frequencies, dtype=torch.float32)


    @classmethod
    def load_dataset_and_make_vectorizer(cls, news_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            news_csv (str): location of the dataset
        Returns:
            an instance of NewsDataset
        """
        news_df = pd.read_csv(news_csv)
        train_news_df = news_df[news_df.split=='train']
        return cls(news_df, NewsVectorizer.from_dataframe(train_news_df))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, news_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
```

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```
        Used in the case in the vectorizer has been cached for re-use

        Args:
            news_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of NewsDataset
        """
        news_df = pd.read_csv(news_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(news_csv, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of NewsVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return NameVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer

    def set_split(self, split="train"):
        """ selects the splits in the dataset using a column in the dataframe """
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point's features (x_data) and label (y_
↪target)
        """
        row = self._target_df.iloc[index]

        title_vector = \
```

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```
            self._vectorizer.vectorize(row.title, self._max_seq_length)

        category_index = \
            self._vectorizer.category_vocab.lookup_token(row.category)

        return {'x_data': title_vector,
                'y_target': category_index}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size

def generate_batches(dataset, batch_size, shuffle=True,
                     drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
      ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

9.5.3 The Model: NewsClassifier

In this example, we demonstrate how to use pretrained word embeddings with CNN. Specifically, we use the Embedding layer, which maps the input token indices to a vector representation. We use the pretrained embedding subset by replacing the Embedding layer's weight matrix. The embedding is then used in the forward() method to map from the indices to the vectors.

The model uses a series of one-dimensional convolutions to compute incrementally more features that result in a single feature vector.

Note: The `Sequential` module is a convenience wrapper that encapsulates a linear sequence of operations. In this case, we use it to encapsulate the application of the Conv1d sequence.

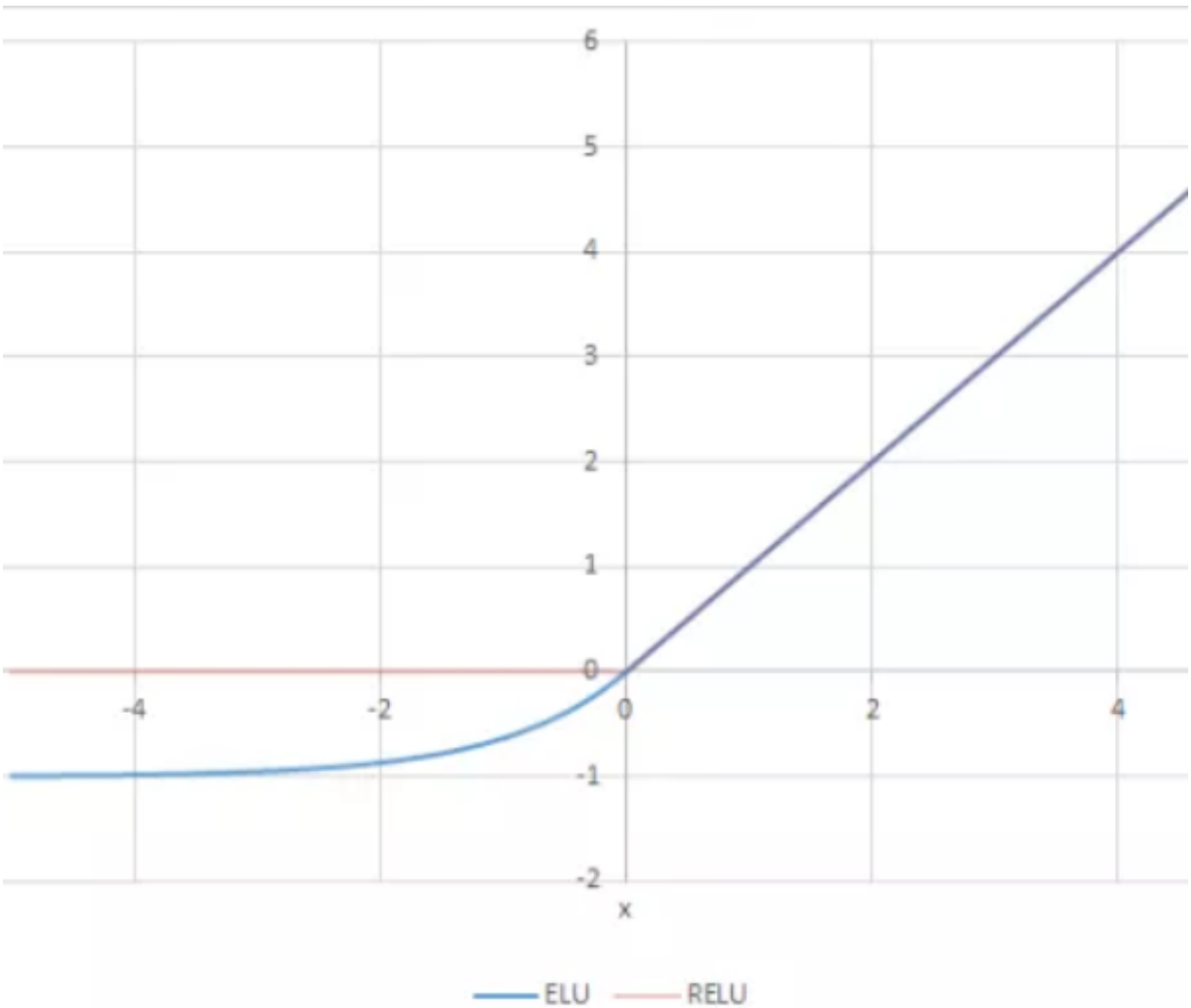
ELU is a nonlinearity similar to the ReLU activation function, but rather than clipping values below 0, it exponentiates them. ELU has been shown to be a promising nonlinearity to use between convolutional layers (Clevert et al., 2015).

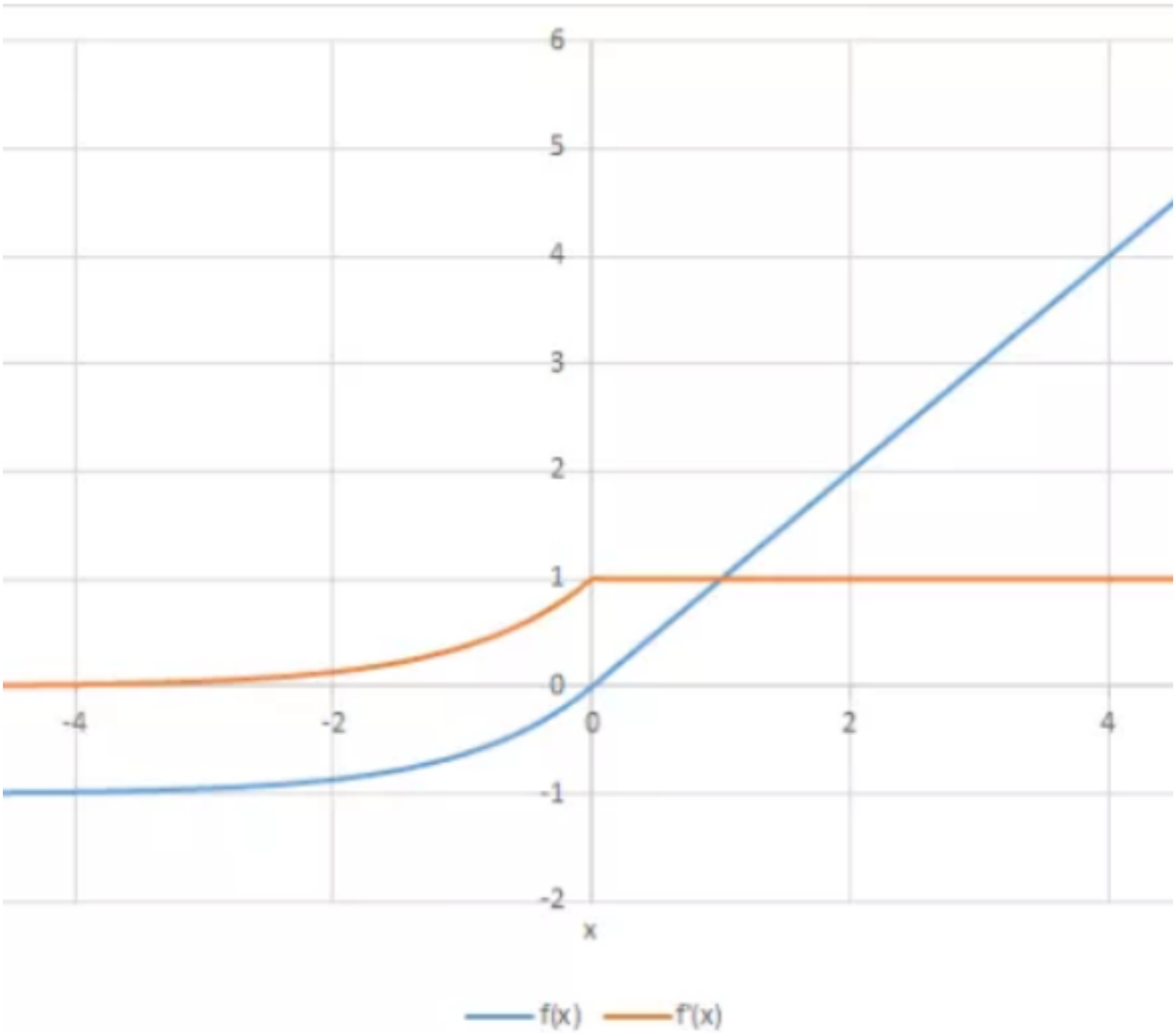
The ELU activation function

ELU, Exponential Linear Unit, is a variation of the ReLU (Rectified Linear Unit) Actvation Function. ELU is very similiar to RELU except negative inputs. They are both in identity function form for non-negative inputs. On the other hand, ELU becomes smooth slowly until its output equal to -α whereas RELU sharply smoothes. It is based on the mathematical function:

Once you see the shape it will become familar:

$$ELU(x) = \begin{cases} 1 & \text{if } x > 0 \\ \alpha \times e^x & \text{if } x < 0 \end{cases}$$





>-12.4pt>-12.4pthllines=, 3, 11, 12, 23,

The ELU function tends to converge cost to zero faster and produce more accurate results. Different to other activation functions, ELU has a extra alpha constant which should be positive number.

Pros

- ELU becomes smooth slowly until its output equal to -α whereas RELU sharply smoothes.
- ELU is a strong alternative to ReLU.
- Unlike ReLU, ELU can produce negative outputs.

Cons

- For $x > 0$, same as ReLU it can blow up the activation with the output range of [0, inf].

A summary of pros and cons of Activation Functions

Torch Documentation on `torch.nn.ELU`

```
class NewsClassifier(nn.Module):
    def __init__(self, embedding_size, num_embeddings, num_channels,
                 hidden_dim, num_classes, dropout_p,
                 pretrained_embeddings=None, padding_idx=0):
        """
        Args:
            embedding_size (int): size of the embedding vectors
            num_embeddings (int): number of embedding vectors
            filter_width (int): width of the convolutional kernels
            num_channels (int): number of convolutional kernels per layer
            hidden_dim (int): the size of the hidden dimension
            num_classes (int): the number of classes in classification
            dropout_p (float): a dropout parameter
            pretrained_embeddings (numpy.array): previously trained word embeddings
                default is None. If provided,
            padding_idx (int): an index representing a null position
        """
        super(NewsClassifier, self).__init__()

        if pretrained_embeddings is None:

            self.emb = nn.Embedding(embedding_dim=embedding_size,
                                    num_embeddings=num_embeddings,
                                    padding_idx=padding_idx)
        else:
            pretrained_embeddings = torch.from_numpy(pretrained_embeddings).float()
            self.emb = nn.Embedding(embedding_dim=embedding_size,
                                    num_embeddings=num_embeddings,
                                    padding_idx=padding_idx,
                                    _weight=pretrained_embeddings)


        self.convnet = nn.Sequential(
            nn.Conv1d(in_channels=embedding_size,
                      out_channels=num_channels, kernel_size=3),
            nn.ELU(),
            nn.Conv1d(in_channels=num_channels, out_channels=num_channels,
                      kernel_size=3, stride=2),
            nn.ELU(),
            nn.Conv1d(in_channels=num_channels, out_channels=num_channels,
                      kernel_size=3, stride=2),
            nn.ELU(),
            nn.Conv1d(in_channels=num_channels, out_channels=num_channels,
                      kernel_size=3),
            nn.ELU()
        )

        self._dropout_p = dropout_p
        self.fc1 = nn.Linear(num_channels, hidden_dim)
        self.fc2 = nn.Linear(hidden_dim, num_classes)

    def forward(self, x_in, apply_softmax=False):
        """The forward pass of the classifier

        Args:
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, dataset._max_seq_length)
```

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```
            apply_softmax (bool): a flag for the softmax activation
                should be false if used with the Cross Entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch, num_classes)
        """

        # embed and permute so features are channels
        x_embedded = self.emb(x_in).permute(0, 2, 1)

        features = self.convnet(x_embedded)

        # average and remove the extra dimension
        remaining_size = features.size(dim=2)
        features = F.avg_pool1d(features, remaining_size).squeeze(dim=2)
        features = F.dropout(features, p=self._dropout_p)

        # mlp classifier
        intermediate_vector = F.relu(F.dropout(self.fc1(features), p=self._dropout_p))
        prediction_vector = self.fc2(intermediate_vector)

        if apply_softmax:
            prediction_vector = F.softmax(prediction_vector, dim=1)

        return prediction_vector
```

9.5.4 Training Routine

Helper functions

```
def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.

    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
```

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```
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= train_state['early_stopping_best_val']:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state

def compute_accuracy(y_pred, y_target):
    _, y_pred_indices = y_pred.max(dim=1)
    n_correct = torch.eq(y_pred_indices, y_target).sum().item()
    return n_correct / len(y_pred_indices) * 100
```

general utilities

The process for using word embeddings as the initial embedding matrix involves first loading the embeddings from the disk (see the utlility function `load_glove_from_disk()` function), then selecting the correct subset of embeddings for the words that are actually present in the data, and finally setting the Embedding layer's weight matrix as the loaded subset.

Important: How to deal with words that do not have pretrained word embeddings? One issue that commonly arises is the existence of words that are in the dataset but are not among the pretrained GloVe embeddings. One common method for handling this is to use an initialization method from the PyTorch library, such as the Xavier Uniform method (Glorot and Bengio, 2010). See the `make_embedding_matrix()` function.

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
```

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```
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)

def load_glove_from_file(glove_filepath):
    """
    Load the GloVe embeddings

    Args:
        glove_filepath (str): path to the glove embeddings file
    Returns:
        word_to_index (dict), embeddings (numpy.ndarary)
    """

    word_to_index = {}
    embeddings = []
    with open(glove_filepath, encoding="utf8") as fp:
        for index, line in enumerate(fp):
            line = line.split(" ") # each line: word num1 num2 ...
            word_to_index[line[0]] = index # word = line[0]
            embedding_i = np.array([float(val) for val in line[1:]])
            embeddings.append(embedding_i)
    return word_to_index, np.stack(embeddings)

def make_embedding_matrix(glove_filepath, words):
    """
    Create embedding matrix for a specific set of words.

    Args:
        glove_filepath (str): file path to the glove embeddigns
        words (list): list of words in the dataset
    """
    word_to_idx, glove_embeddings = load_glove_from_file(glove_filepath)
    embedding_size = glove_embeddings.shape[1]

    final_embeddings = np.zeros((len(words), embedding_size))

    for i, word in enumerate(words):
        if word in word_to_idx:
            final_embeddings[i, :] = glove_embeddings[word_to_idx[word]]
        else:
            embedding_i = torch.ones(1, embedding_size)
            torch.nn.init.xavier_uniform_(embedding_i)
            final_embeddings[i, :] = embedding_i

    return final_embeddings
```

Settings and some prep work

```
from argparse import Namespace
```

```
args = Namespace(
    # Data and Path hyper parameters
    news_csv="../data/ag_news/news_with_splits.csv",
    vectorizer_file="vectorizer.json",
    model_state_file="model.pth",
    save_dir="model_storage\document_classification",
    # Model hyper parameters
    glove_filepath='../data/glove.6B/glove.6B.100d.txt',
    use_glove=False,
    embedding_size=100,
    hidden_dim=100,
    num_channels=100,
    # Training hyper parameter
    seed=1337,
    learning_rate=0.001,
    dropout_p=0.1,
    batch_size=128,
    num_epochs=100,
    early_stopping_criteria=5,
    # Runtime option
    cuda=True,
    catch_keyboard_interrupt=True,
    reload_from_files=False,
    expand_filepaths_to_save_dir=True
)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))

# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")
print("Using CUDA: {}".format(args.cuda))

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage\document_classification\vectorizer.json
        model_storage\document_classification\model.pth
```

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```
Using CUDA: True
```

Initializations

```
args.use_glove = True
```

```
if args.reload_from_files:
    # training from a checkpoint
    dataset = NewsDataset.load_dataset_and_load_vectorizer(args.news_csv,
                                                           args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = NewsDataset.load_dataset_and_make_vectorizer(args.news_csv)
    dataset.save_vectorizer(args.vectorizer_file)
vectorizer = dataset.get_vectorizer()

# Use GloVe or randomly initialized embeddings
if args.use_glove:
    words = vectorizer.title_vocab._token_to_idx.keys()
    embeddings = make_embedding_matrix(glove_filepath=args.glove_filepath,
                                       words=words)
    print("Using pre-trained embeddings")
else:
    print("Not using pre-trained embeddings")
    embeddings = None

classifier = NewsClassifier(embedding_size=args.embedding_size,
                            num_embeddings=len(vectorizer.title_vocab),
                            num_channels=args.num_channels,
                            hidden_dim=args.hidden_dim,
                            num_classes=len(vectorizer.category_vocab),
                            dropout_p=args.dropout_p,
                            pretrained_embeddings=embeddings,
                            padding_idx=0)
```

```
Using pre-trained embeddings
```

```
# Number of Classes
len(vectorizer.category_vocab)
```

```
4
```

Training loop

Training routines consist of the following now familiar sequence of operations: instantiate the dataset, instantiate the model, instantiate the loss function, instantiate the optimizer, iterate over the dataset's training partition and update the model parameters, iterate over the dataset's validation partition and measure the performance, and then repeat the dataset iterations a certain number of times.

This takes 1008 seconds (around 17 mins).

```
classifier = classifier.to(args.device)
dataset.class_weights = dataset.class_weights.to(args.device)

loss_func = nn.CrossEntropyLoss(dataset.class_weights)
optimizer = optim.Adam(classifier.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)

train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                 total=args.num_epochs,
                 position=0)

dataset.set_split('train')
train_bar = tqdm(desc='split=train',
                 total=dataset.get_num_batches(args.batch_size),
                 position=1,
                 leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
               total=dataset.get_num_batches(args.batch_size),
               position=1,
               leave=True)

try:
    for epoch_index in range(args.num_epochs):
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on

        dataset.set_split('train')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        classifier.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = classifier(batch_dict['x_data'])

            # step 3. compute the loss
            loss = loss_func(y_pred, batch_dict['y_target'])
            loss_t = loss.item()
            running_loss += (loss_t - running_loss) / (batch_index + 1)
```

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```
        # step 4. use loss to produce gradients
        loss.backward()

        # step 5. use optimizer to take gradient step
        optimizer.step()
        # ----------------------------------------
        # compute the accuracy
        acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_t - running_acc) / (batch_index + 1)

        # update bar
        train_bar.set_postfix(loss=running_loss, acc=running_acc,
                              epoch=epoch_index)
        train_bar.update()

    train_state['train_loss'].append(running_loss)
    train_state['train_acc'].append(running_acc)

    # Iterate over val dataset

    # setup: batch generator, set loss and acc to 0; set eval mode on
    dataset.set_split('val')
    batch_generator = generate_batches(dataset,
                                       batch_size=args.batch_size,
                                       device=args.device)
    running_loss = 0.
    running_acc = 0.
    classifier.eval()

    for batch_index, batch_dict in enumerate(batch_generator):

        # compute the output
        y_pred =  classifier(batch_dict['x_data'])

        # step 3. compute the loss
        loss = loss_func(y_pred, batch_dict['y_target'])
        loss_t = loss.item()
        running_loss += (loss_t - running_loss) / (batch_index + 1)

        # compute the accuracy
        acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
        running_acc += (acc_t - running_acc) / (batch_index + 1)
        val_bar.set_postfix(loss=running_loss, acc=running_acc,
                            epoch=epoch_index)
        val_bar.update()

    train_state['val_loss'].append(running_loss)
    train_state['val_acc'].append(running_acc)

    train_state = update_train_state(args=args, model=classifier,
                                     train_state=train_state)

    scheduler.step(train_state['val_loss'][-1])

    if train_state['stop_early']:
        break
```

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```
        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.update()
except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/656 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/140 [00:00<?, ?it/s]
```

```
# compute the loss & accuracy on the test set using the best available model

classifier.load_state_dict(torch.load(train_state['model_filename']))

classifier = classifier.to(args.device)
dataset.class_weights = dataset.class_weights.to(args.device)
loss_func = nn.CrossEntropyLoss(dataset.class_weights)

dataset.set_split('test')
batch_generator = generate_batches(dataset,
                                   batch_size=args.batch_size,
                                   device=args.device)
running_loss = 0.
running_acc = 0.
classifier.eval()

for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred =  classifier(batch_dict['x_data'])

    # compute the loss
    loss = loss_func(y_pred, batch_dict['y_target'])
    loss_t = loss.item()
    running_loss += (loss_t - running_loss) / (batch_index + 1)

    # compute the accuracy
    acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
    running_acc += (acc_t - running_acc) / (batch_index + 1)

train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {};".format(train_state['test_loss']))
print("Test Accuracy: {}".format(train_state['test_acc']))
```

```
Test loss: 0.5580926260777882;
Test Accuracy: 83.09151785714283
```

Inference

```
# Preprocess the reviews
def preprocess_text(text):
    text = ' '.join(word.lower() for word in text.split(" "))
    text = re.sub(r"([.,!?])", r" \1 ", text)
    text = re.sub(r"[^a-zA-Z.,!?]+", r" ", text)
    return text
```

```
def predict_category(title, classifier, vectorizer, max_length):
    """Predict a News category for a new title

    Args:
        title (str): a raw title string
        classifier (NewsClassifier): an instance of the trained classifier
        vectorizer (NewsVectorizer): the corresponding vectorizer
        max_length (int): the max sequence length
            Note: CNNs are sensitive to the input data tensor size.
                  This ensures to keep it the same size as the training data
    """
    title = preprocess_text(title)
    vectorized_title = \
        torch.tensor(vectorizer.vectorize(title, vector_length=max_length))
    result = classifier(vectorized_title.unsqueeze(0), apply_softmax=True)
    probability_values, indices = result.max(dim=1)
    predicted_category = vectorizer.category_vocab.lookup_index(indices.item())

    return {'category': predicted_category,
            'probability': probability_values.item()}
```

```
def get_samples():
    samples = {}
    for cat in dataset.val_df.category.unique():
        samples[cat] = dataset.val_df.title[dataset.val_df.category==cat].tolist()[:5]
    return samples

val_samples = get_samples()
```

```
#title = input("Enter a news title to classify: ")
classifier = classifier.to("cpu")

for truth, sample_group in val_samples.items():
    print(f"True Category: {truth}")
    print("="*30)
    for sample in sample_group:
        prediction = predict_category(sample, classifier,
                                      vectorizer, dataset._max_seq_length + 1)
        print("Prediction: {} (p={:0.2f})".format(prediction['category'],
                                                  prediction['probability']))
        print("\t + Sample: {}".format(sample))
    print("-"*30 + "\n")
```

```
True Category: Business
==============================
Prediction: Business (p=0.93)
         + Sample: az suspends marketing of cancer drug
```

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```
Prediction: Business (p=0.63)
         + Sample: business world has mixed reaction to perez move
Prediction: Sports (p=0.65)
         + Sample: betting against bombay
Prediction: Business (p=0.94)
         + Sample: malpractice insurers face a tough market
Prediction: Business (p=0.50)
         + Sample: nvidia is vindicated
------------------------------

True Category: Sci/Tech
==============================
Prediction: World (p=0.79)
         + Sample: spies prize webcam s eyes
Prediction: Sci/Tech (p=1.00)
         + Sample: sober worm causes headaches
Prediction: Sci/Tech (p=0.95)
         + Sample: local search missing pieces falling into place
Prediction: Sci/Tech (p=1.00)
         + Sample: hackers baiting internet users with beckham pix
Prediction: Sci/Tech (p=0.95)
         + Sample: nokia adds blackberry support to series handsets
------------------------------

True Category: Sports
==============================
Prediction: Sports (p=0.99)
         + Sample: is meyer the man to get irish up ?
Prediction: Sports (p=0.99)
         + Sample: who ? who ? and clemens
Prediction: Sports (p=0.99)
         + Sample: baseball today ap
Prediction: Sports (p=1.00)
         + Sample: mark kreidler yao ming epitomizes the chinese athlete who is lt b␣
 ↪gt . . . lt b gt
Prediction: Sports (p=0.97)
         + Sample: no . miami rebounds to beat fsu in overtime
------------------------------

True Category: World
==============================
Prediction: World (p=1.00)
         + Sample: arafat in pain but expected to recover shaath
Prediction: World (p=1.00)
         + Sample: maoist rebels bomb kathmandu building , no injuries reuters
Prediction: World (p=1.00)
         + Sample: son running for ill . rep . s house seat ap
Prediction: World (p=0.99)
         + Sample: strong quake hits in japan
Prediction: World (p=1.00)
         + Sample: israel assassinates hamas militant in damascus
------------------------------
```

CHAPTER

TEN

LAB10: RNN FOR NLP

This set of notebooks introduce the vanilla Elman Recurrent Neural Networks (RNNs) and how to use an Elman RNN as the featuriser for classification tasks.

We first introduce the basics of an Elman RNN in PyTorch, and illustrate how it can be used in a binary classification of simple synthetic sequences. Then we apply this a character sequence modelling for surname nationality classification with the objective of introducing general sequence modelling - where the last hidden state represent the sequence in the general sense:

- A word is a sequence of characters
- A sentence is a sequence of words
- A document is a sequence of sentences

Credit: the notebooks are adapted from:

- Chpater 8 of Deep Learning with PyTorch Step-by-Step
- Chapter 6 of Natural Language Processing with PyTorch

10.1 Recurrent Neural Networks - Introduction

In this notebook, we will look at the basics of how to use `nn.RNNCell` and `nn.RNN` to create RNN Cells and RNN layers, and illustrate the important tensor shape expectation of RNN.

10.1.1 Imports

```
import torch
import torch.nn as nn
```

10.1.2 RNN Cell

Given an input feature n, and a hidden dimension d, if the transformed dimension is m, then the dimensionality of W_{ih} should be $m \times n$, and the W_{hh} should be $m \times d$.

The following code randomly initialised a (2×2) hidden to hidden matrix, and a (2×2) input to hidden matrix.

```
n_features = 2
hidden_dim = 2
```

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```
torch.manual_seed(19)
rnn_cell = nn.RNNCell(input_size=n_features, hidden_size=hidden_dim)
rnn_cell.state_dict()
```

```
OrderedDict([('weight_ih',
              tensor([[ 0.6627, -0.4245],
                      [ 0.5373,  0.2294]])),
             ('weight_hh',
              tensor([[-0.4015, -0.5385],
                      [-0.1956, -0.6835]])),
             ('bias_ih', tensor([0.4954, 0.6533])),
             ('bias_hh', tensor([-0.3565, -0.2904]))])
```

Your Turn

Modify the input feature and hidden dimension, to observe how the weight matrices change.

10.1.3 RNN Layer

RNN cell requires us manually feed the cell hidden layer as one of the two inputs (previous hidden state and current input) to the same RNN cell in a for loop. See the `forward()` method in the ElmanRNN model class as an example. Luckily PyTorch has a `nn.RNN()` function that looks after this recurrent behaviour for us.

The example below creates the same set of weights, but with `l0` suffix for the weight matrix keys, to indicate these weights are the first layer of RNN.

```
n_features = 2
hidden_dim = 2

torch.manual_seed(19)
rnn = nn.RNN(input_size=n_features, hidden_size=hidden_dim)
rnn.state_dict()
```

```
OrderedDict([('weight_ih_l0',
              tensor([[ 0.6627, -0.4245],
                      [ 0.5373,  0.2294]])),
             ('weight_hh_l0',
              tensor([[-0.4015, -0.5385],
                      [-0.1956, -0.6835]])),
             ('bias_ih_l0', tensor([0.4954, 0.6533])),
             ('bias_hh_l0', tensor([-0.3565, -0.2904]))])
```

10.1.4 Sequence-first shape default in RNN

Generate some synthetic data

The code below generate random sequences of four points (`points` e.g. A, B, C, D) Each point has two values, which can be think of a data point in a 2D space. The sequence are points in sequence that are ordered either clock-wise or counter-wise (`direction`). This is a simplified version of sentences,

- sentences are sequences (of words);
- the order or direction of the above sequence is analogus to classes, e.g. sentiment or news categories
- words are elements in the sequence, representing as vectors with dimensions.

The example data points has a feature space of two dimensions, so they can be easily visualised using a x-y Cartesian coordinate system, whereas words may be in 50, 100, 300 etc. dimensions depending on the embedding methods.

```
import numpy as np

def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

```
points, directions = generate_sequences(n=128, seed=13)
```

Batch-first tensor

We now take three (N=3) sequences, each sequence has four data points (L=4), with two features (F=2) representing each data point. This is an example of batch-first input tensor (N,L,F), as shown in the example below.

```
batch = torch.as_tensor(points[:3]).float()
batch.shape
```

```
torch.Size([3, 4, 2])
```

How to use RNN with correctly shaped tensors

However, RNN uses *sequence-first* by default (L,N,F), we need to make our tensor **RNN friendly**. Two options:

1. We could explicitly change the shape of the batch using `permute()` to flip the first two dimensions.
2. We could use the `batch_first` argument in the RNN layer construction.

Option 1

```
# From a batch-first tensor to sequence-first
permuted_batch = batch.permute(1, 0, 2)
permuted_batch.shape
```

```
torch.Size([4, 3, 2])
```

Once the data is in an "RNN-friendly" shape and we can run it through a regular RNN to get two sequence-first tensors back:

```
torch.manual_seed(19)
rnn = nn.RNN(input_size=n_features, hidden_size=hidden_dim)
out, final_hidden = rnn(permuted_batch)
out.shape, final_hidden.shape
```

```
(torch.Size([4, 3, 2]), torch.Size([1, 3, 2]))
```

Once we're done with the RNN we can turn the data back to our familiar batchfirst shape:

```
batch_hidden = final_hidden.permute(1, 0, 2)
batch.shape
```

```
torch.Size([3, 4, 2])
```

Your Turn

In the code above, the hidden state dimension (`hidden_dim`) happens to be the same as the number of input features (`n_features`), which is 2. These two do not have to agree. For example, the word embedding dimension can be 100 (e.g. `n_features=100`), the hidden dimension can be 50 (`hidden_dim=50`). Change these two parameters to observe the shape change and get familar with the sequence-first and batch-first tensor shapes.

Option 2

Option 1 is a lot of work to keep track of, we can instead set RNN's `batch_first` argument to True so we can use the batch above without any modifications.

> **Warning:** But you get these two distinct shapes as a result: batch-first (N,L,H) for the output and sequence-first (1,N,H) for the final hidden state.

On the one hand, this can lead to confusion. On the other hand, most of the time we would not be handling the hidden state, and we will handle the *batch-first* output instead. So, we can stick with batch-first for now and, when it comes the time we have to handle the hidden state, we will highlight the difference in shapes once again.

```
torch.manual_seed(19)
rnn_batch_first = nn.RNN(input_size=n_features, hidden_size=hidden_dim, batch_
↪first=True)
out, final_hidden = rnn_batch_first(batch)
out.shape, final_hidden.shape
```

```
(torch.Size([3, 4, 2]), torch.Size([1, 3, 2]))
```

Note: For simple RNNs, the last element of the output IS the final hidden state!

```
out = out.permute(1,0,2)
(out[-1] == final_hidden).all()
```

```
tensor(True)
```

Summary

The RNN's default behavior is to handle tensors having the shape (L,N,H) for hidden states and (L,N,F) for sequences of data points.

Datasets and data loaders, unless customized otherwise, will produce data points in the shape (N,L,F).

To address this difference, we'll be using OPTION 2 the `batch_first` argument to turn both inputs and outputs into this familiar batch-first shape. But be aware of the shape difference between hidden state and output state. In other words, with `batch_first` argument to be true, we have input and output "batch-first", but the hidden states are still "sequence-first".

10.1.5 Stacked RNN with Two Layers

```
torch.manual_seed(19)
rnn_stacked = nn.RNN(input_size=2, hidden_size=2,
        num_layers=2, batch_first=True)
state = rnn_stacked.state_dict()
state
```

```
OrderedDict([('weight_ih_l0',
              tensor([[ 0.6627, -0.4245],
                      [ 0.5373,  0.2294]])),
             ('weight_hh_l0',
              tensor([[-0.4015, -0.5385],
                      [-0.1956, -0.6835]])),
             ('bias_ih_l0', tensor([0.4954, 0.6533])),
             ('bias_hh_l0', tensor([-0.3565, -0.2904])),
             ('weight_ih_l1',
              tensor([[-0.6701, -0.5811],
                      [-0.0170, -0.5856]])),
             ('weight_hh_l1',
              tensor([[ 0.1159, -0.6978],
                      [ 0.3241, -0.0983]])),
             ('bias_ih_l1', tensor([-0.3163, -0.2153])),
             ('bias_hh_l1', tensor([ 0.0722, -0.3242]))])
```

Manually Stacking Two RNNs

Let's replicate the above with two RNNs, "manually" stacked together.

```
list(state.items())
```

```
[('weight_ih_l0',
  tensor([[ 0.6627, -0.4245],
          [ 0.5373,  0.2294]])),
 ('weight_hh_l0',
  tensor([[-0.4015, -0.5385],
          [-0.1956, -0.6835]])),
 ('bias_ih_l0', tensor([0.4954, 0.6533])),
 ('bias_hh_l0', tensor([-0.3565, -0.2904])),
 ('weight_ih_l1',
  tensor([[-0.6701, -0.5811],
          [-0.0170, -0.5856]])),
 ('weight_hh_l1',
  tensor([[ 0.1159, -0.6978],
          [ 0.3241, -0.0983]])),
 ('bias_ih_l1', tensor([-0.3163, -0.2153])),
 ('bias_hh_l1', tensor([ 0.0722, -0.3242]))]
```

Your Turn

Give a string `k`, what does `k[:-1]` do?

```
str = 'test'
str[:-2]
```

```
'te'
```

```
dict([(k[:-1]+'0', v) for k, v in list(state.items())[4:]])
```

```
{'weight_ih_l0': tensor([[-0.6701, -0.5811],
         [-0.0170, -0.5856]]),
 'weight_hh_l0': tensor([[ 0.1159, -0.6978],
         [ 0.3241, -0.0983]]),
 'bias_ih_l0': tensor([-0.3163, -0.2153]),
 'bias_hh_l0': tensor([ 0.0722, -0.3242])}
```

```
# Create two RNNs
rnn_layer0 = nn.RNN(input_size=2, hidden_size=2, batch_first=True)
rnn_layer1 = nn.RNN(input_size=2, hidden_size=2, batch_first=True)
# Load the same weights from above
rnn_layer0.load_state_dict(dict(list(state.items())[:4]))
# Note the layer label (keys) need to change
rnn_layer1.load_state_dict(dict([(k[:-1]+'0', v) for k, v in list(state.
↪items())[4:]]))
```

```
<All keys matched successfully>
```

Step 0: A batch sequence from the sample (N=1, L=4, F=2)

```
x = torch.as_tensor(points[0:1]).float()
```

Step 1: Feed the input to the first RNN layer

```
out0, h0 = rnn_layer0(x)
```

Step 2: Feed the output of the first layer to the second RNN layer

```
out1, h1 = rnn_layer1(out0)
```

The overall output of the stacked RNN must have two elements as well:

- a sequence of hidden states, those produced by the last layer (`out1`)
- the concatenation of final hidden states of all layers

```
out1, torch.cat([h0, h1])
```

```
(tensor([[[-0.7533, -0.7711],
          [-0.0566, -0.5960],
          [ 0.4324, -0.2908],
          [ 0.1563, -0.5152]]], grad_fn=<TransposeBackward1>),
 tensor([[[-0.5297,  0.3551]],

         [[ 0.1563, -0.5152]]], grad_fn=<CatBackward>))
```

This should be the same as running a stacked RNN, as shown below.

```
out, hidden = rnn_stacked(x)
out, hidden
```

```
(tensor([[[-0.7533, -0.7711],
          [-0.0566, -0.5960],
          [ 0.4324, -0.2908],
          [ 0.1563, -0.5152]]], grad_fn=<TransposeBackward1>),
 tensor([[[-0.5297,  0.3551]],

         [[ 0.1563, -0.5152]]], grad_fn=<StackBackward>))
```

Important: For stacked RNNs, the last element of the output is the final hidden state of the LAST LAYER!

But, since we're using a batch_first layer, we need to permute the hidden state's dimensions to batch-first as well:

```
(out[:, -1] == hidden.permute(1, 0, 2)[:, -1]).all()
```

```
tensor(True)
```

10.1.6 Bidirectional RNN

```
torch.manual_seed(19)
rnn_bidirect = nn.RNN(input_size=2, hidden_size=2,
            bidirectional=True, batch_first=True)
state = rnn_bidirect.state_dict()
state
```

```
OrderedDict([('weight_ih_l0',
              tensor([[ 0.6627, -0.4245],
                      [ 0.5373,  0.2294]])),
             ('weight_hh_l0',
              tensor([[-0.4015, -0.5385],
                      [-0.1956, -0.6835]])),
             ('bias_ih_l0', tensor([0.4954, 0.6533])),
             ('bias_hh_l0', tensor([-0.3565, -0.2904])),
             ('weight_ih_l0_reverse',
              tensor([[-0.6701, -0.5811],
                      [-0.0170, -0.5856]])),
             ('weight_hh_l0_reverse',
              tensor([[ 0.1159, -0.6978],
                      [ 0.3241, -0.0983]])),
             ('bias_ih_l0_reverse', tensor([-0.3163, -0.2153])),
             ('bias_hh_l0_reverse', tensor([ 0.0722, -0.3242]))])
```

Manually Created Bidirectional RNN

Once again, we can create two simple RNNs, and use the weights and biases above to set their weights accordingly. Each RNN will behave as one of the layers from the bidirectional one:

```
rnn_forward = nn.RNN(input_size=2, hidden_size=2, batch_first=True)
rnn_reverse = nn.RNN(input_size=2, hidden_size=2, batch_first=True)
rnn_forward.load_state_dict(dict(list(state.items())[:4]))
rnn_reverse.load_state_dict(dict([(k[:-8], v) for k, v in list(state.items())[4:]]))
```

```
<All keys matched successfully>
```

Step 0: A batch sequence and its reverse

```
x = torch.as_tensor(points[0:1]).float()
print(x)
x_rev = torch.flip(x, dims=[1]) #N, L, F
print(x_rev)
```

```
tensor([[[ 1.0349,  0.9661],
         [ 0.8055, -0.9169],
         [-0.8251, -0.9499],
         [-0.8670,  0.9342]]])
tensor([[[-0.8670,  0.9342],
         [-0.8251, -0.9499],
         [ 0.8055, -0.9169],
         [ 1.0349,  0.9661]]])
```

Step 1: Feed each RNN with its corresponding sequence

Since there is no dependency between the two layers, we just need to feed each layer its corresponding sequence (regular and reversed) and remember to reverse back the sequence of hidden states.

```
out, h = rnn_forward(x)
out_rev, h_rev = rnn_reverse(x_rev)
out_rev_back = torch.flip(out_rev, dims=[1])
```

Step 2: Tidy up the output

The overall output of the bidirectional RNN must have two elements as well:

- a concatenation side-by-side of both sequences of hidden states (out and out_rev_back)
- the concatenation of final hidden states of both layers

```
out
```

```
tensor([[[ 0.3924,  0.8146],
         [ 0.4347, -0.0481],
         [-0.1521, -0.3367],
         [-0.5297,  0.3551]]], grad_fn=<TransposeBackward1>)
```

```
out_rev_back
```

```
tensor([[[-0.9355, -0.8353],
         [-0.1766,  0.2596],
         [ 0.8829,  0.0425],
         [-0.2032, -0.7901]]], grad_fn=<FlipBackward>)
```

```
torch.cat([out, out_rev_back], dim=2), torch.cat([h, h_rev])
```

```
(tensor([[[ 0.3924,  0.8146, -0.9355, -0.8353],
          [ 0.4347, -0.0481, -0.1766,  0.2596],
          [-0.1521, -0.3367,  0.8829,  0.0425],
          [-0.5297,  0.3551, -0.2032, -0.7901]]], grad_fn=<CatBackward>),
 tensor([[[-0.5297,  0.3551]],

         [[-0.9355, -0.8353]]], grad_fn=<CatBackward>))
```

Double check the results with the bi-directional RNN itself

```
out, hidden = rnn_bidirect(x)
out, hidden
```

```
(tensor([[[ 0.3924,  0.8146, -0.9355, -0.8353],
          [ 0.4347, -0.0481, -0.1766,  0.2596],
          [-0.1521, -0.3367,  0.8829,  0.0425],
          [-0.5297,  0.3551, -0.2032, -0.7901]]], grad_fn=<TransposeBackward1>),
 tensor([[[-0.5297,  0.3551]],

         [[-0.9355, -0.8353]]], grad_fn=<StackBackward>))
```

Important: For bidirectional RNNs, the last element of the output **ISN'T** the final hidden state! Once again, since we're using a `batch_first` layer, we need to permute the hidden state's dimensions to batch-first as well:

```
out[:, -1] == hidden.permute(1, 0, 2).view(1, -1)
```

```
tensor([[ True,  True, False, False]])
```

Bidirectional RNNs are different because the final hidden state corresponds to the last element in the sequence for the forward layer and to the first element in the sequence for the reverse layer. The output, on the other hand, is aligned to sequence, hence the difference.

10.2 Classifying Synthetic Sequences - The Square Model

This is a simplified example of sequence modelling for classification. In this example, each sequence contains exactly four symbols, A, B, C, D, which can be ordered either clockwise or counter clockwise. Given a collection of sequences, the task is to classify if the symbols are in clockwise order (target variable $y = 1$) or counter clockwise (target variable $y = 0$).

The simplifications made include:

- binary classification (a slightly more complex scenario is multi-class classification);
- uniform sequence length, all sequences are of the same length 4, so no padding is needed;
- the vocabulary size is tiny, 4 in this case;
- the feature/embeding space for each symbol/token is 2 so that we can visualise in a Cartesian coordinate system. Word Embeddings are at 50+ dimensions.
- similarly for convenience of visualisation, the hidden dimension chosen is also 2.

10.2.1 Download Untility Files for Plotting and Data Generation

Download these utility functions first and place them in the same directory as this notebook.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\rnn\plots.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\rnn\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\rnn\replay.py
```

10.2.2 Imports

```
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F

from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from torch.nn.utils import rnn as rnn_utils
from util import StepByStep
from plots import *
```

10.2.3 Synthetic Data Generation

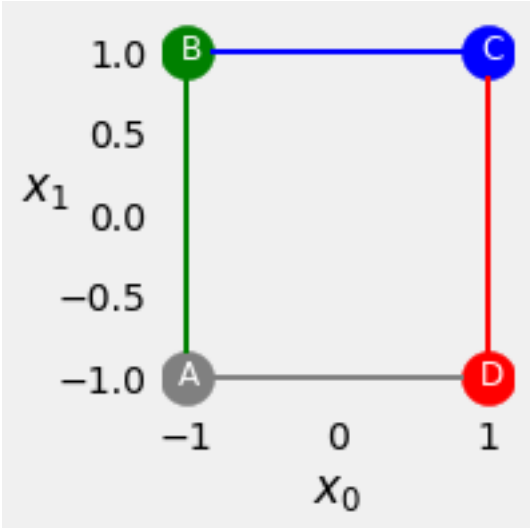
Sequence Generation Function

This function generate sequences, each of four data points, located close to a perfect square with four corners at `[-1, -1], [-1, 1], [1, 1], [1, -1]`, respectively.

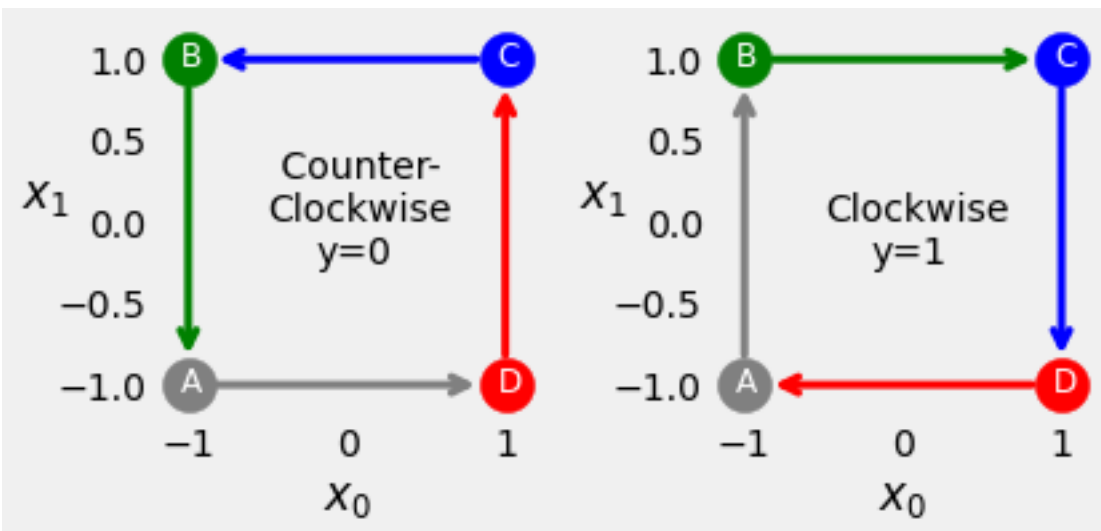
```
import numpy as np

def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

How does the sequence data look like

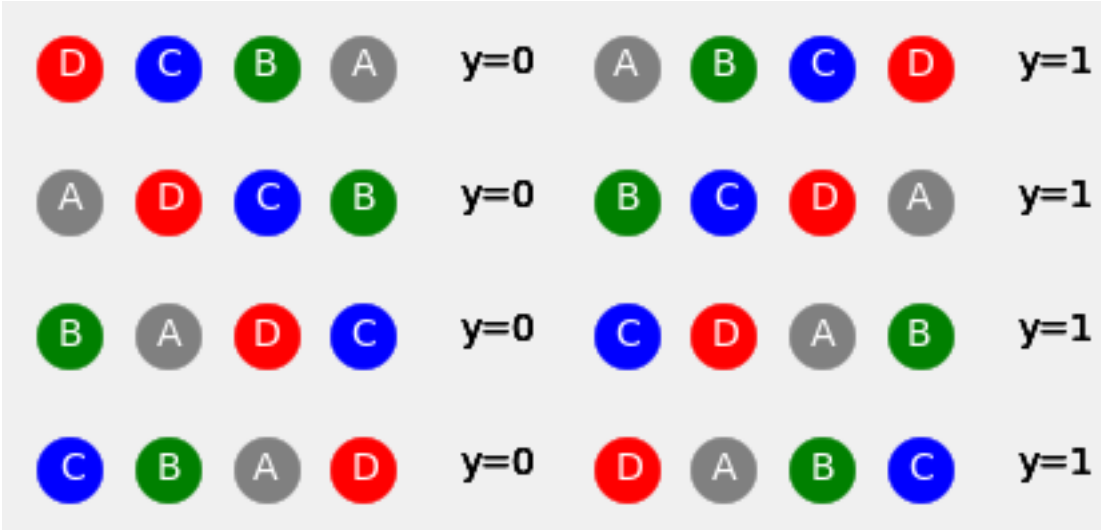
```
fig = counter_vs_clock(draw_arrows=False)
```




```
fig = counter_vs_clock()
```

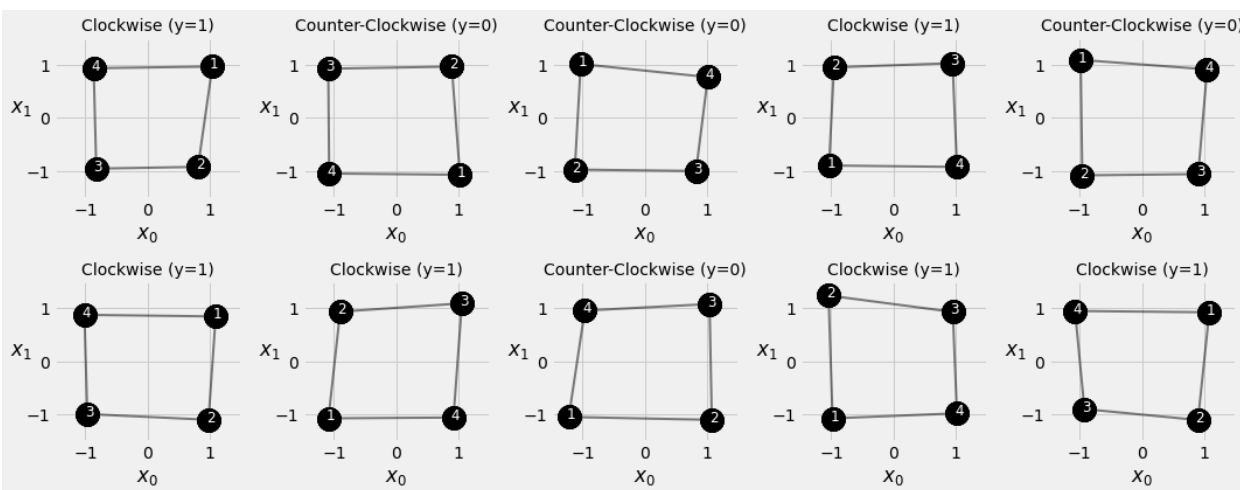



```
fig = plot_sequences()
```




```
points, directions = generate_sequences(n=128, seed=13)
```

```
fig = plot_data(points, directions)
```



10.2.4 Square Model

Dataset Preparation

```
test_points, test_directions = generate_sequences(seed=19)
```

Data Preparation

```
train_data = TensorDataset(torch.as_tensor(points).float(),
                           torch.as_tensor(directions).view(-1, 1).float())
test_data = TensorDataset(torch.as_tensor(test_points).float(),
                          torch.as_tensor(test_directions).view(-1, 1).float())

train_loader = DataLoader(train_data, batch_size=16, shuffle=True)
test_loader = DataLoader(test_data, batch_size=16)
```

Model Configuration

The `SquareModel` creates a single layered RNN with fully connected layer as classifier.

Your Turn

Note in the model, we did not use a sigmoid function, so what loss function should we use for binary classification?

```
class SquareModel(nn.Module):
    def __init__(self, n_features, hidden_dim, n_outputs):
        super(SquareModel, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.n_outputs = n_outputs
        self.hidden = None
        # Simple RNN
        self.basic_rnn = nn.RNN(self.n_features, self.hidden_dim, batch_first=True)
        # Classifier to produce as many logits as outputs
        self.classifier = nn.Linear(self.hidden_dim, self.n_outputs)

    def forward(self, X):
        # X is batch first (N, L, F)
        # output is (N, L, H)
        # final hidden state is (1, N, H)
        batch_first_output, self.hidden = self.basic_rnn(X)

        # only last item in sequence (N, 1, H)
        last_output = batch_first_output[:, -1]
        # classifier will output (N, 1, n_outputs)
        out = self.classifier(last_output)

        # final output is (N, n_outputs)
        return out.view(-1, self.n_outputs)
```

Tip: Note the `BCEWithLogitsLoss()` loss function. Modify the model and change the loss function, and see if you can still achieve the same results.

```
torch.manual_seed(21)
model = SquareModel(n_features=2, hidden_dim=2, n_outputs=1)
loss = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

Model Training

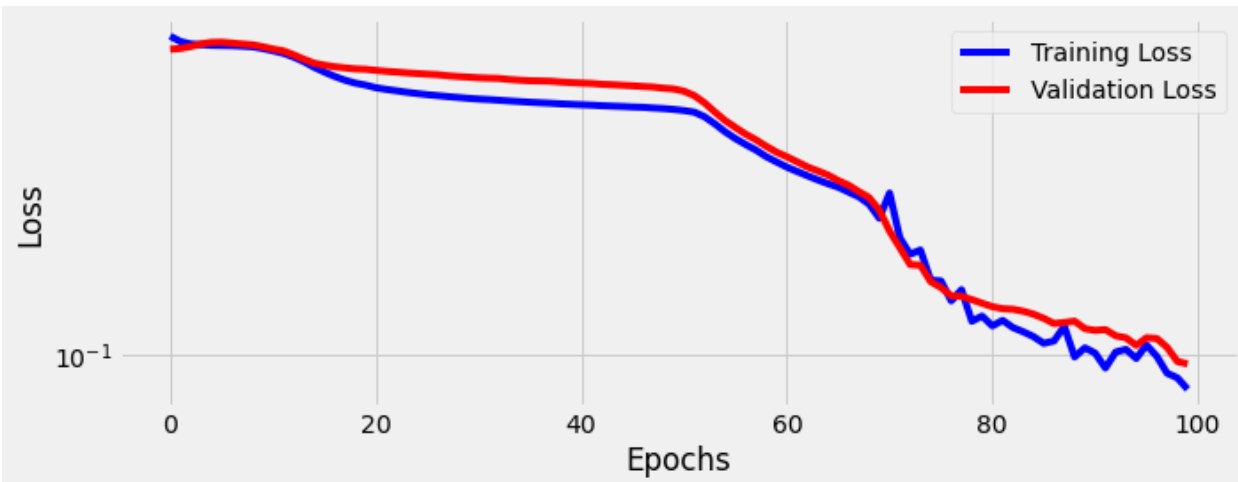
The StepByStep class encapsulated the training routine as well as the data loading into methods such as:

- `_mini_batch`
- `_make_train_step`
- `_make_val_step`

You may want to take a closer look at the `StepByStep` in the `util.py` file to learn how to factorize your code into a reusable blocks.

```
sbs_rnn = StepByStep(model, loss, optimizer)
sbs_rnn.set_loaders(train_loader, test_loader)
sbs_rnn.train(100)
```

```
fig = sbs_rnn.plot_losses()
```




```
StepByStep.loader_apply(test_loader, sbs_rnn.correct)
```

```
tensor([[50, 53],
        [75, 75]])
```

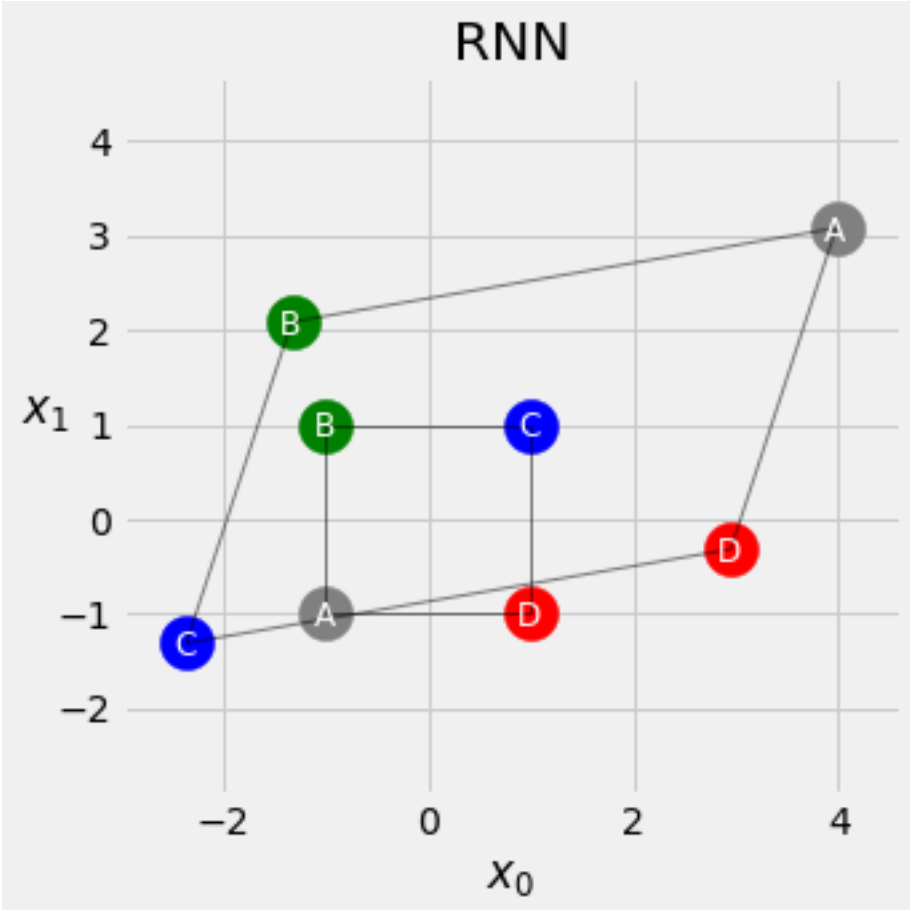
10.2.5 Visualizing the Model

Transformed Inputs

```
state = model.basic_rnn.state_dict()
state['weight_ih_l0'], state['bias_ih_l0']
```

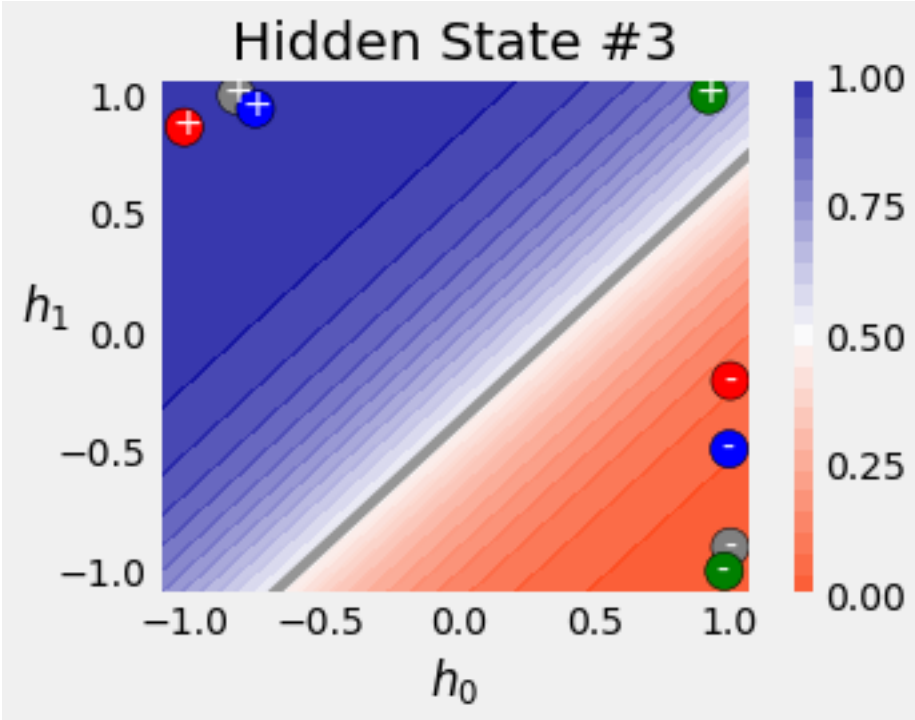
```
(tensor([[-0.5153, -2.6577],
         [-1.7006, -0.4970]], device='cuda:0'),
 tensor([0.8069, 0.8827], device='cuda:0'))
```

```
fig = figure13(model.basic_rnn)
```

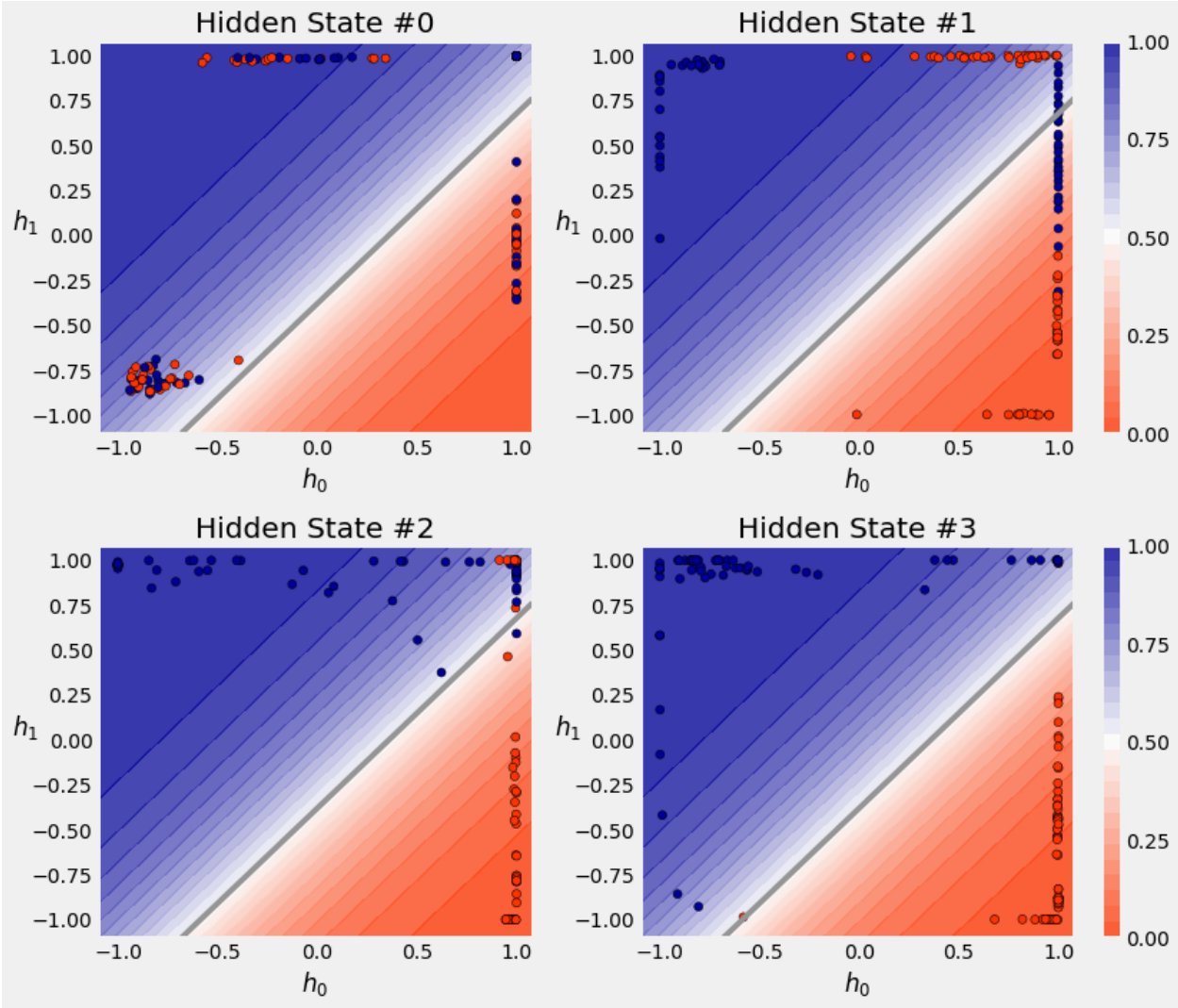


Hidden States

```
fig = canonical_contour(model)
```

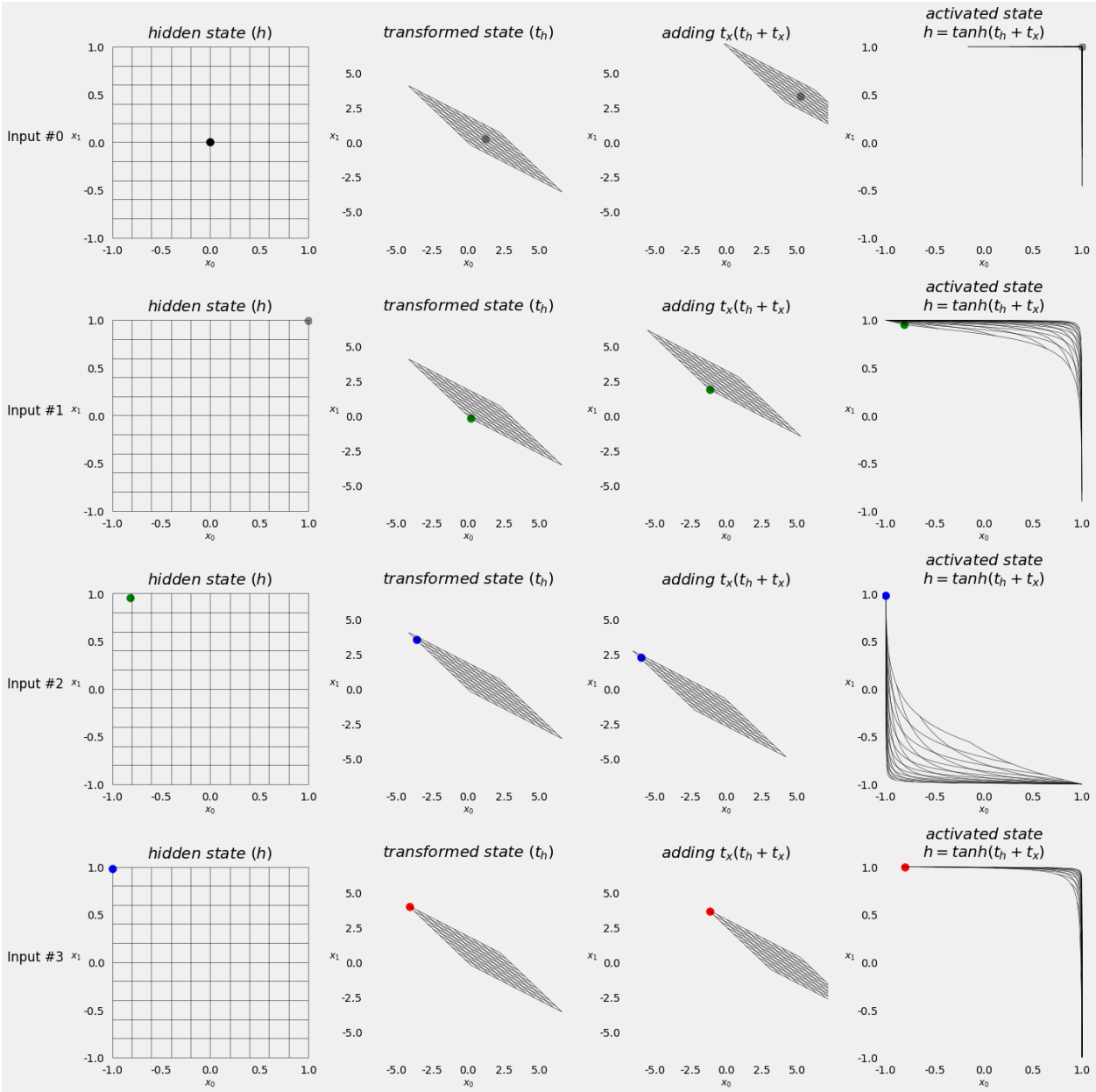



```
fig = hidden_states_contour(model, points, directions)
```



The Journey of a Hidden State

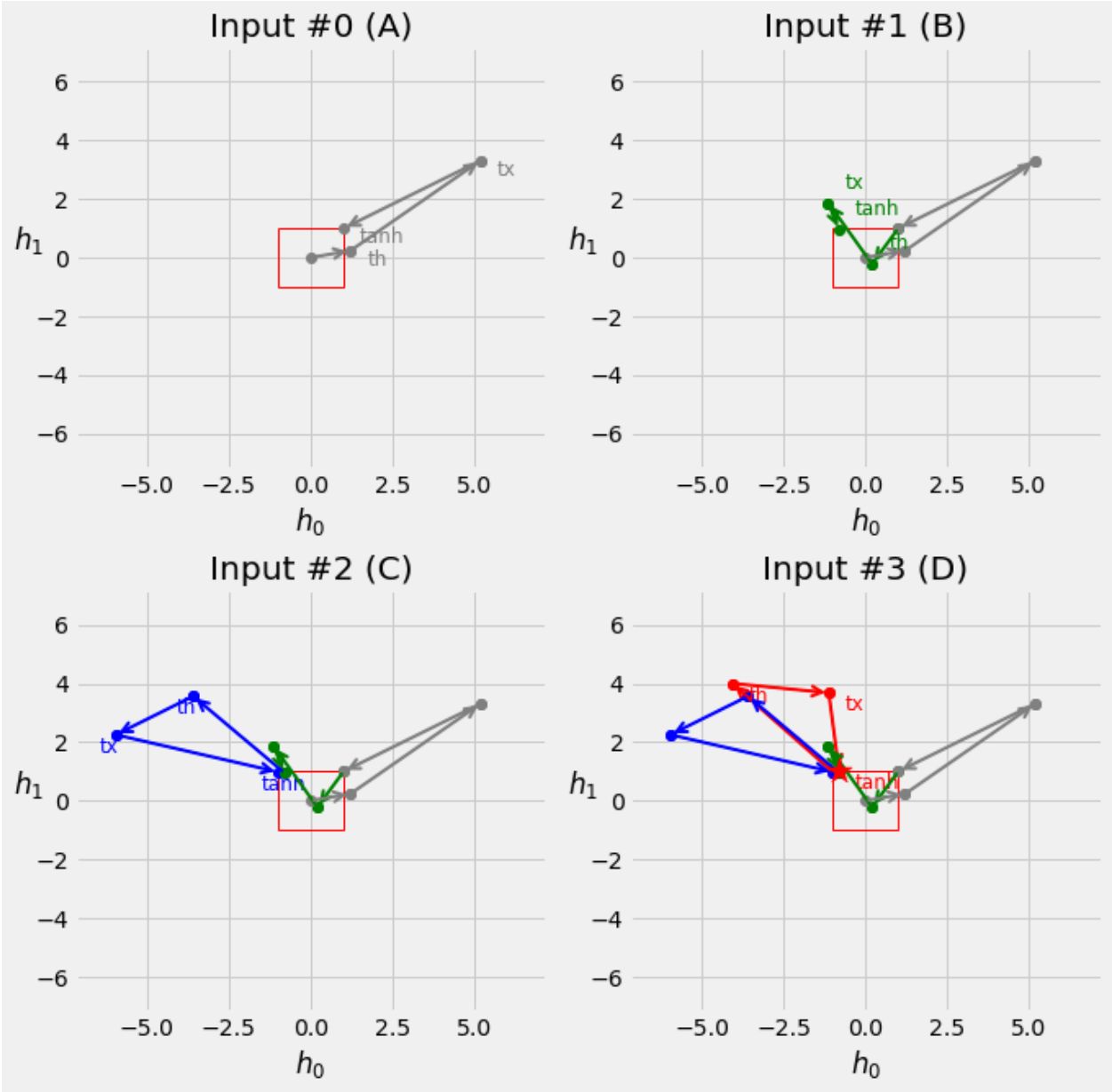
```
fig = figure16(model.basic_rnn)
```




```
square = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
model(square.to(sbs_rnn.device))
model.hidden
```

```
tensor([[[-0.8091,  0.9987]]], device='cuda:0', grad_fn=<CudnnRnnBackward>)
```

```
fig = figure17(model.basic_rnn)
```



10.3 Surname Dataset Processing

In this example, we introduce the surnames dataset, a collection of 10,000 surnames from 18 different nationalities collected by the authors from different name sources on the internet. This dataset has several properties that make it interesting.

- The first property is that it is fairly imbalanced. The top three classes account for more than 60% of the data: 27% are English, 21% are Russian, and 14% are Arabic. The remaining 15 nationalities have decreasing frequency - a property that is endemic to language, as well.
- The second property is that there is a valid and intuitive relationship between nationality of origin and surname orthography (spelling). There are spelling variations that are strongly tied to nation of origin (such in `O'Neill`, `Antonopoulos`, `Nagasawa`, or `Zhu`).

10.3.1 Imports

```
import collections
import numpy as np
import pandas as pd
import re

from argparse import Namespace
```

```
args = Namespace(
    raw_dataset_csv="../data/surnames/surnames.csv",
    train_proportion=0.7,
    val_proportion=0.15,
    test_proportion=0.15,
    output_munged_csv="../data/surnames/surnames_with_splits.csv",
    seed=1337
)
```

```
# Read raw data
surnames = pd.read_csv(args.raw_dataset_csv, header=0)
```

```
surnames.head()
```

```
    surname nationality
0  Woodford     English
1      Coté      French
2      Kore     English
3     Koury      Arabic
4    Lebzak     Russian
```

```
# Unique classes
set(surnames.nationality)
```

```
{'Arabic',
 'Chinese',
 'Czech',
 'Dutch',
 'English',
 'French',
 'German',
 'Greek',
 'Irish',
 'Italian',
 'Japanese',
 'Korean',
 'Polish',
 'Portuguese',
 'Russian',
 'Scottish',
 'Spanish',
 'Vietnamese'}
```

```
# Splitting train by nationality
# Create dict
by_nationality = collections.defaultdict(list)
```

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```
for _, row in surnames.iterrows():
    by_nationality[row.nationality].append(row.to_dict())
```

```
# Create split data
final_list = []
np.random.seed(args.seed)
for _, item_list in sorted(by_nationality.items()):
    np.random.shuffle(item_list)
    n = len(item_list)
    n_train = int(args.train_proportion*n)
    n_val = int(args.val_proportion*n)
    n_test = int(args.test_proportion*n)

    # Give data point a split attribute
    for item in item_list[:n_train]:
        item['split'] = 'train'
    for item in item_list[n_train:n_train+n_val]:
        item['split'] = 'val'
    for item in item_list[n_train+n_val:]:
        item['split'] = 'test'

    # Add to final list
    final_list.extend(item_list)
```

```
# Write split data to file
final_surnames = pd.DataFrame(final_list)
```

```
final_surnames.split.value_counts()
```

```
train    7680
test     1660
val      1640
Name: split, dtype: int64
```

```
final_surnames.head()
```

```
   surname nationality  split
0   Gerges      Arabic  train
1   Nassar      Arabic  train
2   Kanaan      Arabic  train
3    Hadad      Arabic  train
4  Tannous      Arabic  train
```

```
# Write munged data to CSV
final_surnames.to_csv(args.output_munged_csv, index=False)
```

Your Turn

Visualise the distribution of nationalities to observe the class imbalance in this dataset. What can you do to create a balanced dataset?

10.4 Surname Classification with RNN

In this example, we see surname classification in which character sequences (surnames) are classified to nationality of origin.

Inferring demographic information (like nationality) from publicly observable data has applications from product recommendations to ensuring fair outcomes for users across different demographics. However, demographic and other self--identifying attributes are collectively called "protected attributes". We must exercise care in the use of such attributes in modeling and in products. We begin by splitting the characters of each surname and treating them the same way we treated words. Aside from the data difference, character level models are mostly similar to wordbased models in structure and implementation.

```
from argparse import Namespace
import os
import json

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm.notebook import tqdm
```

10.4.1 Vocabulary, Vectorizer, Dataset

We treat each surname as a sequence of characters. As usual, we implement a dataset class, that returns the vectorized surname as well as the integer representing its nationality. Additionally returned is the length of the sequence, which is used in downstream computations to know where the final vector in the sequence is located. This is a part of the familiar sequence of steps - implementing Dataset, a Vectorizer, and a Vocabulary before the actual training can take place.

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
```

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```
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

The first stage in the vectorization pipeline is to map each character token in the surname to a unique integer. To accomplish this, we use the `SequenceVocabulary` data structure, which we first introduced and described in Section 5.2.2 of Document Classification using CNN and GloVe Embeddings. Recall that this data structure not only maps characters in the names to integers, but also utilizes four specialpurpose tokens:

- the `UNK` token,
- the `MASK` token,
- the BEGINOFSEQUENCE token, and
- the ENDOFSEQUENCE token.

The first two tokens are vital for language data: the `UNK` token is used for unseen OutOfVocabulary (OOV) tokens in the input and the `MASK` token enables handling variable-length inputs. The latter two tokens provide the model with sentence boundary features and are prepended and appended to the sequence, respectively.

```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):

        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
                         'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

The overall vectorizer is `SurnameVectorizer`, which populates the `SequenceVocabulary` by surname charac-

ters, and the normal `Vocabulary` for nationalities.

```
class SurnameVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, char_vocab, nationality_vocab):
        """
        Args:
            char_vocab (Vocabulary): maps characters to integers
            nationality_vocab (Vocabulary): maps nationalities to integers
        """
        self.char_vocab = char_vocab
        self.nationality_vocab = nationality_vocab

    def vectorize(self, surname, vector_length=-1):
        """
        Args:
            title (str): the string of characters
            vector_length (int): an argument for forcing the length of index vector
        """
        indices = [self.char_vocab.begin_seq_index]
        indices.extend(self.char_vocab.lookup_token(token)
                       for token in surname)
        indices.append(self.char_vocab.end_seq_index)

        if vector_length < 0:
            vector_length = len(indices)

        out_vector = np.zeros(vector_length, dtype=np.int64)
        out_vector[:len(indices)] = indices
        out_vector[len(indices):] = self.char_vocab.mask_index

        return out_vector, len(indices)

    @classmethod
    def from_dataframe(cls, surname_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            surname_df (pandas.DataFrame): the surnames dataset
        Returns:
            an instance of the SurnameVectorizer
        """
        char_vocab = SequenceVocabulary()
        nationality_vocab = Vocabulary()

        for index, row in surname_df.iterrows():
            for char in row.surname:
                char_vocab.add_token(char)
            nationality_vocab.add_token(row.nationality)

        return cls(char_vocab, nationality_vocab)

    @classmethod
    def from_serializable(cls, contents):
        char_vocab = SequenceVocabulary.from_serializable(contents['char_vocab'])
        nat_vocab =  Vocabulary.from_serializable(contents['nationality_vocab'])

        return cls(char_vocab=char_vocab, nationality_vocab=nat_vocab)
```

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```
    def to_serializable(self):
        return {'char_vocab': self.char_vocab.to_serializable(),
                'nationality_vocab': self.nationality_vocab.to_serializable()}
```

```
class SurnameDataset(Dataset):
    def __init__(self, surname_df, vectorizer):
        """
        Args:
            surname_df (pandas.DataFrame): the dataset
            vectorizer (SurnameVectorizer): vectorizer instatiated from dataset
        """
        self.surname_df = surname_df
        self._vectorizer = vectorizer

        self._max_seq_length = max(map(len, self.surname_df.surname)) + 2

        self.train_df = self.surname_df[self.surname_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.surname_df[self.surname_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.surname_df[self.surname_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}

        self.set_split('train')

        # Class weights
        class_counts = self.train_df.nationality.value_counts().to_dict()
        def sort_key(item):
            return self._vectorizer.nationality_vocab.lookup_token(item[0])
        sorted_counts = sorted(class_counts.items(), key=sort_key)
        frequencies = [count for _, count in sorted_counts]
        self.class_weights = 1.0 / torch.tensor(frequencies, dtype=torch.float32)


    @classmethod
    def load_dataset_and_make_vectorizer(cls, surname_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            surname_csv (str): location of the dataset
        Returns:
            an instance of SurnameDataset
        """
        surname_df = pd.read_csv(surname_csv)
        train_surname_df = surname_df[surname_df.split=='train']
        return cls(surname_df, SurnameVectorizer.from_dataframe(train_surname_df))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, surname_csv, vectorizer_filepath):
```

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```
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
            surname_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of SurnameDataset
        """
        surname_df = pd.read_csv(surname_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(surname_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of SurnameVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return SurnameVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer

    def set_split(self, split="train"):
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point's:
                features (x_data)
                label (y_target)
                feature length (x_length)
        """
        row = self._target_df.iloc[index]
```

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```
        surname_vector, vec_length = \
            self._vectorizer.vectorize(row.surname, self._max_seq_length)

        nationality_index = \
            self._vectorizer.nationality_vocab.lookup_token(row.nationality)

        return {'x_data': surname_vector,
                'y_target': nationality_index,
                'x_length': vec_length}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size



def generate_batches(dataset, batch_size, shuffle=True,
                     drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
      ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

10.4.2 Model

The `SurnameClassifier` model is composed of an Embedding layer, the ElmanRNN, and a Linear layer. We assume that the input to the model is tokens represented as a set of integers after they have been mapped to integers by the `SequenceVocabulary`. The model first embeds the integers using the embedding layer. Then, using the RNN, sequence representation vectors are computed. These vectors represent the hidden state for each character in the surname. Because the goal is to classify each surname,** the vector corresponding to the final character position in each surname is extracted**. One way to think about this vector is that the final vector is a result of passing over the entire sequence input, and hence it's a summary vector for the surname. These summary vectors are passed through the Linear layer to compute a prediction vector. The prediction vector is used in the training loss, or we can apply the softmax function to create a probability distribution over surnames.

The arguments to the model are

- the size of the embeddings - *hyperparameter*,
- the number of embeddings (i.e., vocabulary size) - determined by the data,

- the number of classes - determined by the data, and
- the hidden state size of the RNN - *hyperparameter*.

Important: Although the two hyperparameters can take on any value, it is usually good to start with something small that ensures fast training, as a way verifying that the model actually works.

Retrieving the last vector of each sequence

You will notice that the `forward()` function in the model requires the lengths of the sequences. The lengths are used to retrieve the final vector of each sequence in the tensor that is returned from the RNN with a function named `column_gather()`, shown below. The function iterates over batch row indices and retrieves the vector that's at the position indicated by the corresponding length of sequence.

```
def column_gather(y_out, x_lengths):
    '''Get a specific vector from each batch datapoint in `y_out`.

    More precisely, iterate over batch row indices, get the vector that's at
    the position indicated by the corresponding value in `x_lengths` at the row
    index.

    Args:
        y_out (torch.FloatTensor, torch.cuda.FloatTensor)
            shape: (batch, sequence, feature)
        x_lengths (torch.LongTensor, torch.cuda.LongTensor)
            shape: (batch,)

    Returns:
        y_out (torch.FloatTensor, torch.cuda.FloatTensor)
            shape: (batch, feature)
    '''
    x_lengths = x_lengths.long().detach().cpu().numpy() - 1

    out = []
    for batch_index, column_index in enumerate(x_lengths):
        out.append(y_out[batch_index, column_index])

    return torch.stack(out)
```

The ElmanRNN model

```
class ElmanRNN(nn.Module):
    """ an Elman RNN built using the RNNCell """
    def __init__(self, input_size, hidden_size, batch_first=False):
        """
        Args:
            input_size (int): size of the input vectors
            hidden_size (int): size of the hidden state vectors
            bathc_first (bool): whether the 0th dimension is batch
        """
        super(ElmanRNN, self).__init__()

        self.rnn_cell = nn.RNNCell(input_size, hidden_size)
```

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```
        self.batch_first = batch_first
        self.hidden_size = hidden_size

    def _initial_hidden(self, batch_size):
        return torch.zeros((batch_size, self.hidden_size))

    def forward(self, x_in, initial_hidden=None):
        """The forward pass of the ElmanRNN

        Args:
            x_in (torch.Tensor): an input data tensor.
                If self.batch_first: x_in.shape = (batch, seq_size, feat_size)
                Else: x_in.shape = (seq_size, batch, feat_size)
            initial_hidden (torch.Tensor): the initial hidden state for the RNN
        Returns:
            hiddens (torch.Tensor): The outputs of the RNN at each time step.
                If self.batch_first: hiddens.shape = (batch, seq_size, hidden_size)
                Else: hiddens.shape = (seq_size, batch, hidden_size)
        """
        if self.batch_first:
            batch_size, seq_size, feat_size = x_in.size()
            x_in = x_in.permute(1, 0, 2)
        else:
            seq_size, batch_size, feat_size = x_in.size()

        hiddens = []

        if initial_hidden is None:
            initial_hidden = self._initial_hidden(batch_size)
            initial_hidden = initial_hidden.to(x_in.device)

        hidden_t = initial_hidden

        for t in range(seq_size):
            hidden_t = self.rnn_cell(x_in[t], hidden_t)
            hiddens.append(hidden_t)

        hiddens = torch.stack(hiddens)

        if self.batch_first:
            hiddens = hiddens.permute(1, 0, 2)

        return hiddens


class SurnameClassifier(nn.Module):
    """ A Classifier with an RNN to extract features and an MLP to classify """
    def __init__(self, embedding_size, num_embeddings, num_classes,
                 rnn_hidden_size, batch_first=True, padding_idx=0):
        """
        Args:
            embedding_size (int): The size of the character embeddings
            num_embeddings (int): The number of characters to embed
            num_classes (int): The size of the prediction vector
                Note: the number of nationalities
```

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```
            rnn_hidden_size (int): The size of the RNN's hidden state
            batch_first (bool): Informs whether the input tensors will
                have batch or the sequence on the 0th dimension
            padding_idx (int): The index for the tensor padding;
                see torch.nn.Embedding
        """
        super(SurnameClassifier, self).__init__()

        self.emb = nn.Embedding(num_embeddings=num_embeddings,
                                embedding_dim=embedding_size,
                                padding_idx=padding_idx)
        self.rnn = ElmanRNN(input_size=embedding_size,
                            hidden_size=rnn_hidden_size,
                            batch_first=batch_first)
        self.fc1 = nn.Linear(in_features=rnn_hidden_size,
                             out_features=rnn_hidden_size)
        self.fc2 = nn.Linear(in_features=rnn_hidden_size,
                             out_features=num_classes)

    def forward(self, x_in, x_lengths=None, apply_softmax=False):
        """The forward pass of the classifier

        Args:
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, input_dim)
            x_lengths (torch.Tensor): the lengths of each sequence in the batch.
                They are used to find the final vector of each sequence
            apply_softmax (bool): a flag for the softmax activation
                should be false if used with the Cross Entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch, output_dim)
        """
        x_embedded = self.emb(x_in)
        y_out = self.rnn(x_embedded)

        if x_lengths is not None:
            y_out = column_gather(y_out, x_lengths)
        else:
            y_out = y_out[:, -1, :]

        y_out = F.relu(self.fc1(F.dropout(y_out, 0.5)))
        y_out = self.fc2(F.dropout(y_out, 0.5))

        if apply_softmax:
            y_out = F.softmax(y_out, dim=1)

        return y_out
```

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)
```

10.4.3 Settings

```
args = Namespace(
    # Data and path information
    surname_csv="../data/surnames/surnames_with_splits.csv",
    vectorizer_file="vectorizer.json",
    model_state_file="model.pth",
    save_dir="model_storage/ch6/surname_classification",
    # Model hyper parameter
    char_embedding_size=100,
    rnn_hidden_size=64,
    # Training hyper parameter
    num_epochs=100,
    learning_rate=1e-3,
    batch_size=64,
    seed=1337,
    early_stopping_criteria=5,
    # Runtime hyper parameter
    cuda=True,
    catch_keyboard_interrupt=True,
    reload_from_files=False,
    expand_filepaths_to_save_dir=True,
)

# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))


if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Using CUDA: True
```

```
if args.reload_from_files and os.path.exists(args.vectorizer_file):
    # training from a checkpoint
    dataset = SurnameDataset.load_dataset_and_load_vectorizer(args.surname_csv,
                                                              args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = SurnameDataset.load_dataset_and_make_vectorizer(args.surname_csv)
    dataset.save_vectorizer(args.vectorizer_file)
```

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```
vectorizer = dataset.get_vectorizer()

classifier = SurnameClassifier(embedding_size=args.char_embedding_size,
                               num_embeddings=len(vectorizer.char_vocab),
                               num_classes=len(vectorizer.nationality_vocab),
                               rnn_hidden_size=args.rnn_hidden_size,
                               padding_idx=vectorizer.char_vocab.mask_index)
```

10.4.4 Training Routine

The training routine follows the standard formula. For a single batch of data, apply the model and compute the prediction vectors. Use the `CrossEntropyLoss()` loss function and the ground truth to compute a loss value. Using the loss value and an optimizer, compute the gradients and update the weights of the model using those gradients. Repeat this for each batch in the training data. Proceed similarly with the validation data, but set the model in eval mode so as to prevent backpropagating. Instead, the validation data is used only to give a lessbiased sense of how the model is performing. Repeat this routine for a specific number of epochs or a stopping condition (e.g. loss is less than a threshold, or loss stoped changing in the most recent two epochs) is met.

```
def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
            'model_filename': args.model_state_file}


def update_train_state(args, model, train_state):
    """Handle the training state updates.

    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
```

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```
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= loss_tm1:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])
                train_state['early_stopping_best_val'] = loss_t

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state


def compute_accuracy(y_pred, y_target):
    _, y_pred_indices = y_pred.max(dim=1)
    n_correct = torch.eq(y_pred_indices, y_target).sum().item()
    return n_correct / len(y_pred_indices) * 100
```

```
classifier = classifier.to(args.device)
dataset.class_weights = dataset.class_weights.to(args.device)

loss_func = nn.CrossEntropyLoss(dataset.class_weights)
optimizer = optim.Adam(classifier.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)

train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                 total=args.num_epochs,
                 position=0)

dataset.set_split('train')
train_bar = tqdm(desc='split=train',
                 total=dataset.get_num_batches(args.batch_size),
                 position=1,
                 leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
               total=dataset.get_num_batches(args.batch_size),
               position=1,
               leave=True)

try:
    for epoch_index in range(args.num_epochs):
```

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```
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on
        dataset.set_split('train')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        classifier.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = classifier(x_in=batch_dict['x_data'],
                                x_lengths=batch_dict['x_length'])

            # step 3. compute the loss
            loss = loss_func(y_pred, batch_dict['y_target'])

            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            # step 4. use loss to produce gradients
            loss.backward()

            # step 5. use optimizer to take gradient step
            optimizer.step()
            # ----------------------------------------
            # compute the accuracy
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # update bar
            train_bar.set_postfix(loss=running_loss, acc=running_acc, epoch=epoch_
↪index)
            train_bar.update()

        train_state['train_loss'].append(running_loss)
        train_state['train_acc'].append(running_acc)

        # Iterate over val dataset

        # setup: batch generator, set loss and acc to 0; set eval mode on

        dataset.set_split('val')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.
        running_acc = 0.
```

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```
        classifier.eval()

        for batch_index, batch_dict in enumerate(batch_generator):
            # compute the output
            y_pred = classifier(x_in=batch_dict['x_data'],
                                x_lengths=batch_dict['x_length'])

            # step 3. compute the loss
            loss = loss_func(y_pred, batch_dict['y_target'])
            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            # compute the accuracy
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
            running_acc += (acc_t - running_acc) / (batch_index + 1)
            val_bar.set_postfix(loss=running_loss, acc=running_acc, epoch=epoch_index)
            val_bar.update()

        train_state['val_loss'].append(running_loss)
        train_state['val_acc'].append(running_acc)

        train_state = update_train_state(args=args, model=classifier,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.update()

        if train_state['stop_early']:
            break

except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/120 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/25 [00:00<?, ?it/s]
```

```
# compute the loss & accuracy on the test set using the best available model

classifier.load_state_dict(torch.load(train_state['model_filename']))

classifier = classifier.to(args.device)
dataset.class_weights = dataset.class_weights.to(args.device)
loss_func = nn.CrossEntropyLoss(dataset.class_weights)

dataset.set_split('test')
batch_generator = generate_batches(dataset,
                                   batch_size=args.batch_size,
                                   device=args.device)
running_loss = 0.
running_acc = 0.
```

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```
classifier.eval()

for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred =  classifier(batch_dict['x_data'],
                         x_lengths=batch_dict['x_length'])

    # compute the loss
    loss = loss_func(y_pred, batch_dict['y_target'])
    loss_t = loss.item()
    running_loss += (loss_t - running_loss) / (batch_index + 1)

    # compute the accuracy
    acc_t = compute_accuracy(y_pred, batch_dict['y_target'])
    running_acc += (acc_t - running_acc) / (batch_index + 1)

train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {};".format(train_state['test_loss']))
print("Test Accuracy: {}".format(train_state['test_acc']))
```

```
Test loss: 1.8524044704437257;
Test Accuracy: 41.06249999999999
```

Inference

```
def predict_nationality(surname, classifier, vectorizer):
    vectorized_surname, vec_length = vectorizer.vectorize(surname)
    vectorized_surname = torch.tensor(vectorized_surname).unsqueeze(dim=0)
    vec_length = torch.tensor([vec_length], dtype=torch.int64)

    result = classifier(vectorized_surname, vec_length, apply_softmax=True)
    probability_values, indices = result.max(dim=1)

    index = indices.item()
    prob_value = probability_values.item()

    predicted_nationality = vectorizer.nationality_vocab.lookup_index(index)

    return {'nationality': predicted_nationality, 'probability': prob_value, 'surname
↪': surname}
```

```
# surname = input("Enter a surname: ")
classifier = classifier.to("cpu")
for surname in ['McMahan', 'Nakamoto', 'Wan', 'Cho']:
    print(predict_nationality(surname, classifier, vectorizer))
```

```
{'nationality': 'Irish', 'probability': 0.4722009301185608, 'surname': 'McMahan'}
{'nationality': 'Japanese', 'probability': 0.7476573586463928, 'surname': 'Nakamoto'}
{'nationality': 'Chinese', 'probability': 0.6742308139801025, 'surname': 'Wan'}
{'nationality': 'Korean', 'probability': 0.3817710876464844, 'surname': 'Cho'}
```

Your Turn

- Play with the hyperparameters to get a sense of what affects performance and by how much, and to tabulate the results.
- The model implemented in here is general and not restricted to characters. The embedding layer in the model can map any discrete item in a sequence of discrete items. Consider reuse the code here for sentence or document classification.

CHAPTER

ELEVEN

LAB11: GRU, LSTM AND SEQ2SEQ

In this lab we introduce two more powerful variants of RNNs, namely, Gated Recurrent Units (GRUs) and Long Short Term Memorys (LSTMs). We then compare their performance with Elman RNN in the same square sequence direction binary classification task.

The second part of this lab focuses on the Sequence to Sequence models, first introduced by Ilya Sutskever, Oriol Vinyals, Quoc V. Le from Google at NeurIPS 2014. Then we will forcus on the decoder part for a Surname Generation task unconditioned and conditioned.

Credit: the notebooks are adapted from:

- Chpater 8 of Deep Learning with PyTorch Step-by-Step
- Chpater 9 of Deep Learning with PyTorch Step-by-Step
- Chapter 7 of Natural Language Processing with PyTorch

11.1 Gated Recurrent Units (GRUs)

GRU addressed two fundamental limitations of Elman RNN, by introducing

- **Update Gate**: Weights between old and new (candidate) hidden state

Update Gate

- **Reset Gate**: Weights between input and hidden state

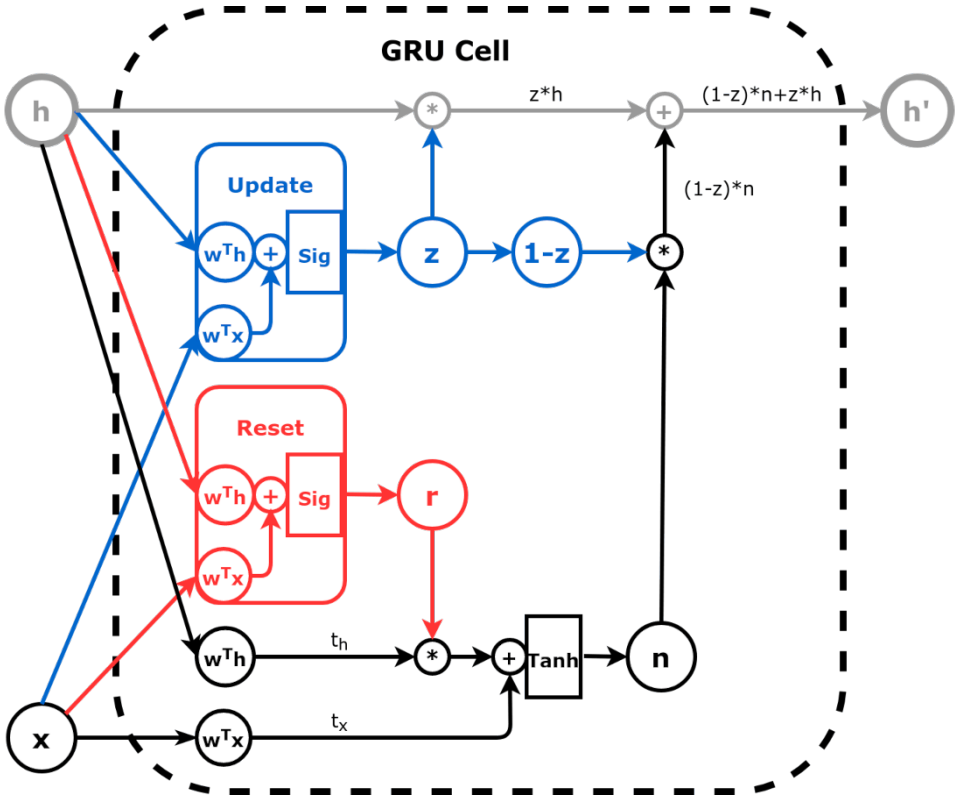
Reset Gate

$h_{new} = tanh(r * t_h + t_x)$

Both gates can be learned through linear layer followed by sigmoid to ensure they are values in the range [0,1]. Put them together, we have a GRU cell.

GRU Cell

$h' = tanh(r * t_h + t_x) * (1 - z) + h * z$



11.1.1 GRU Cell

RNN is a special case of GRU when $r = 1$ and $z = 0$.

$$
\begin{aligned}
RNN : h' &= tanh(t_h + t_x) \\
GRU : h' &= \underbrace{\underbrace{tanh(r * t_{hn} + t_{xn})}_{n} * (1 - z) + h * z}_{weighted\ average\ of\ n\ and\ h}
\end{aligned}
$$

$$
\begin{aligned}
r(reset\ gate) &= \sigma(t_{hr} + t_{xr}) \\
z(update\ gate) &= \sigma(t_{hz} + t_{xz}) \\
n(hidden\ state) &= tanh(t_{hn} + t_{xn})
\end{aligned}
$$

$$
\begin{array}{rlll}
r\ (hidden): t_{hr} & = W_{hr} & h + & b_{hr} \\
r\ (input): t_{xr} & = W_{ir} & x + & b_{ir} \\
z\ (hidden): t_{hz} & = W_{hz} & h + & b_{hz} \\
z\ (input): t_{xz} & = W_{iz} & x + & b_{iz} \\
n\ (hidden) : t_{hn} & = W_{hn} & h + & b_{hn} \\
n\ (input) : t_{xn} & = W_{in} & x + & b_{in}
\end{array}
$$

To really understand the flow of information inside the GRU cell, I suggest you try these exercises:

- first, learn to look past (or literally ignore) the internals of the gates: both `r` and `z` are simply values between zero and one (for each hidden dimension)
- pretend `r=1`; can you see that the resulting n is equivalent to the output of a simple RNN?
- keep `r=1` and now pretend `z=0`; can you see that the new hidden state `h'` is equivalent to the output of a simple RNN?

- now pretend `z=1`; can you see that the new hidden state `h'` is simply a copy of the old hidden state (in other words, the data (`x`) does not have any effect)?
- if you decrease `r` all the way to zero, the resulting `n` is less and less influenced by the old hidden state
- if you decrease `z` all the way to zero, the new hidden state `h'` is closer and closer to `n`
- for `r=0` and `z=0`, the cell becomes equivalent to a linear layer followed by a Tanh activation function (in other words, the old hidden state (`h`) does not have any effect)

11.1.2 Imports

```
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F

from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from torch.nn.utils import rnn as rnn_utils
```

11.1.3 GRU Cell

```
n_features = 2
hidden_dim = 2
torch.manual_seed(17)
gru_cell = nn.GRUCell(input_size=n_features, hidden_size=hidden_dim)
gru_state = gru_cell.state_dict()
gru_state
```

```
OrderedDict([('weight_ih',
              tensor([[-0.0930,  0.0497],
                      [ 0.4670, -0.5319],
                      [-0.6656,  0.0699],
                      [-0.1662,  0.0654],
                      [-0.0449, -0.6828],
                      [-0.6769, -0.1889]])),
             ('weight_hh',
              tensor([[-0.4167, -0.4352],
                      [-0.2060, -0.3989],
                      [-0.7070, -0.5083],
                      [ 0.1418,  0.0930],
                      [-0.5729, -0.5700],
                      [-0.1818, -0.6691]])),
             ('bias_ih',
              tensor([-0.4316,  0.4019,  0.1222, -0.4647, -0.5578,  0.4493])),
             ('bias_hh',
              tensor([-0.6800,  0.4422, -0.3559, -0.0279,  0.6553,  0.2918]))])
```

```
Wi, bi = gru_state['weight_ih'], gru_state['bias_ih']
Wh, bh = gru_state['weight_hh'], gru_state['bias_hh']
print(Wi.shape, Wh.shape)
print(bi.shape, bh.shape)
```

```
torch.Size([6, 2]) torch.Size([6, 2])
torch.Size([6]) torch.Size([6])
```

Splitting up the `weight_ih` as an example

$$W_{ir} = \begin{cases} -0.0930, & 0.0497, \\ 0.4670, & -0.5319, \end{cases}$$

$$W_{iz} = \begin{cases} -0.6656, & 0.0699, \\ -0.1662, & 0.0654, \end{cases}$$

$$W_{in} = \begin{cases} -0.0449, & -0.6828, \\ -0.6769, & -0.1889 \end{cases}$$

$$\underbrace{-0.4316, 0.4019}_{b_{ir}}, \underbrace{0.1222, -0.4647}_{b_{iz}}, \underbrace{-0.5578, 0.4493}_{b_{in}}$$

```
Wir, Wiz, Win = Wi.split(hidden_dim, dim=0)
bir, biz, bin = bi.split(hidden_dim, dim=0)
Whr, Whz, Whn = Wh.split(hidden_dim, dim=0)
bhr, bhz, bhn = bh.split(hidden_dim, dim=0)
Wxr, bxr
```

```
(tensor([[-0.0930,  0.0497],
         [ 0.4670, -0.5319]]),
 tensor([-0.4316,  0.4019]))
```

11.1.4 Creating the Linear Layers

We can use the weights and biases to create the corresponding linear layers:

```
def linear_layers(Wi, bi, Wh, bh):
    hidden_dim, n_features = Wi.size()
    lin_input = nn.Linear(n_features, hidden_dim)
    lin_input.load_state_dict({'weight': Wi, 'bias': bi})
    lin_hidden = nn.Linear(hidden_dim, hidden_dim)
    lin_hidden.load_state_dict({'weight': Wh, 'bias': bh})
    return lin_hidden, lin_input

# reset gate - red
```

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```
r_hidden, r_input = linear_layers(Wir, bir, Whr, bhr)
# update gate - blue
z_hidden, z_input = linear_layers(Wiz, biz, Whz, bhz)
# candidate state - black
n_hidden, n_input = linear_layers(Win, bin, Whn, bhn)
```

```
def reset_gate(h, x):
    thr = r_hidden(h)
    txr = r_input(x)
    r = torch.sigmoid(thr + txr)
    return r  # red

def update_gate(h, x):
    thz = z_hidden(h)
    txz = z_input(x)
    z = torch.sigmoid(thz + txz)
    return z  # blue

def candidate_n(h, x, r):
    thn = n_hidden(h)
    txn = n_input(x)
    n = torch.tanh(r * thn + txn)
    return n  # black
```

11.1.5 Data Generation

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

```
points, directions = generate_sequences(n=128, seed=13)
```

```
initial_hidden = torch.zeros(1, hidden_dim)
X = torch.as_tensor(points[0]).float()
first_corner = X[0:1]
```

```
r = reset_gate(initial_hidden, first_corner)
r
```

```
tensor([[0.2387, 0.6928]], grad_fn=<SigmoidBackward>)
```

Important: The reset gate scales each hidden dimension independently. It can completely suppress the values from one

of the hidden dimensions while letting the other pass unchallenged. In geometrical terms, it means that the hidden space may shrink in one direction while stretching in the other.

```
z = update_gate(initial_hidden, first_corner)
z
```

```
tensor([[0.2984, 0.3540]], grad_fn=<SigmoidBackward>)
```

The reset gate is an input for the candidate hidden state (`n`)

```
n = candidate_n(initial_hidden, first_corner, r)
n
```

```
tensor([[-0.8032, -0.2275]], grad_fn=<TanhBackward>)
```

The update gate is telling us to keep 29.84% of the first and 35.40% of the second dimensions of the initial hidden state. The remaining 60.16% and 64.6%, respectively, are coming from the candidate hidden state (`n`).

```
h_prime = n*(1-z) + initial_hidden*z
h_prime
```

```
tensor([[-0.5635, -0.1470]], grad_fn=<AddBackward0>)
```

Verify against GRU Cell

We can see the `nn.GRUCell()` had encapsulated all the above steps. Effectively, a GRU consists of six linear layers, with

- four of them require sigmoid action to learn
  - two reset gates, each for hidden state and input respectively, and
  - two update gates, each for hidden state and input respectively
- two require tanh() activation for learning the new candidate hidden state.

```
gru_cell(first_corner)
```

```
tensor([[-0.5635, -0.1470]], grad_fn=<AddBackward0>)
```

11.2 Long Short Term Memories (LSTMs)

In addtion to the bounded hidden state (between [-1,1]), LSTM introduced an unbounded **cell state**, which is mimic the "long term memory". This allows more past information to be kept and thus passed to the current cell, because the gradient is not squashed to approach zero as fast as `tanh`, so it is also refered to as a "gradient highway". In contrast, the hidden state keeps more recent information, thus responsible for the "short term memory".

The candidate hidden state

$$g = tanh(t_{hg} + t_{xg})$$

Cell state is an unbounded weighted sum of the candidate hidden state g and previous cell state c, weighted by learnt input gate i and forget gate f, respectively.

The candidate hidden state

$$c' = g * i + c * f$$

The new hidden state is obtained by bounding the new cell state (c') before applying output gate weights (o)::: $h' = tanh(c') * o$

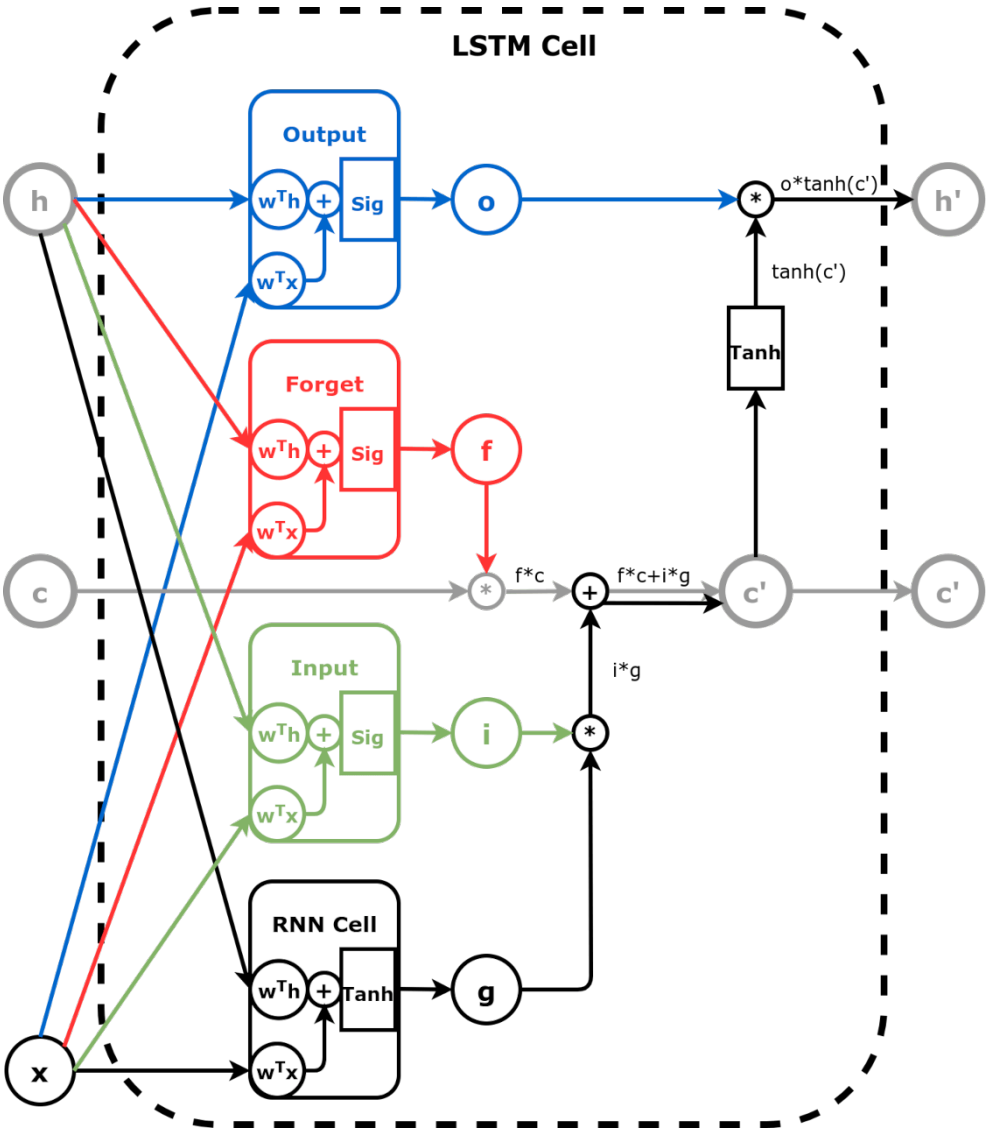
11.2.1 Imports

```
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F

from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from torch.nn.utils import rnn as rnn_utils
```

11.2.2 LSTM Cell

There are two sets of weights for each type of gates, one for hidden state, one for input. They are learnt through a linear layer followed by sigmoid like in a GRU cell.

$$\begin{array}{rcccc}
i\ (hidden): t_{hi} & =W_{hi} & h+ & b_{hi} & \\
i\ (input): t_{xi} & =W_{ii} & x+ & & b_{ii} \\
f\ (hidden): t_{hf} & =W_{hf} & h+ & & b_{hf} \\
f\ (input): t_{xf} & =W_{if} & x+ & & b_{if} \\
g\ (hidden) : t_{hg} & =W_{hg} & h+ & & b_{hg} \\
g\ (input) : t_{xg} & =W_{ig} & x+ & & b_{ig} \\
o\ (hidden): t_{ho} & =W_{ho} & h+ & & b_{ho} \\
o\ (input): t_{xo} & =W_{io} & x+ & & b_{io}
\end{array}$$



nn.LSTMCell

Let's take a look at the weights generated by `nn.LSTMCell`.

```
n_features = 2
hidden_dim = 2

torch.manual_seed(17)
lstm_cell = nn.LSTMCell(input_size=n_features, hidden_size=hidden_dim)
lstm_state = lstm_cell.state_dict()
lstm_state
```

```
OrderedDict([('weight_ih',
              tensor([[-0.0930,  0.0497],
                      [ 0.4670, -0.5319],
                      [-0.6656,  0.0699],
                      [-0.1662,  0.0654],
```

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```
                        [-0.0449, -0.6828],
                        [-0.6769, -0.1889],
                        [-0.4167, -0.4352],
                        [-0.2060, -0.3989]])),
              ('weight_hh',
               tensor([[-0.7070, -0.5083],
                        [ 0.1418,  0.0930],
                        [-0.5729, -0.5700],
                        [-0.1818, -0.6691],
                        [-0.4316,  0.4019],
                        [ 0.1222, -0.4647],
                        [-0.5578,  0.4493],
                        [-0.6800,  0.4422]])),
              ('bias_ih',
               tensor([-0.3559, -0.0279,  0.6553,  0.2918,  0.4007,  0.3262, -0.0778, -
↪0.3002])),
              ('bias_hh',
               tensor([-0.3991, -0.3200,  0.3483, -0.2604, -0.1582,  0.5558,  0.5761, -
↪0.3919]))])
```

Replicate a LSTMCell Manually

The code below tries to use the above the weights, manually create the linear layers for learning the gates.

```
def linear_layers(Wi, bi, Wh, bh):
    hidden_dim, n_features = Wi.size()
    lin_input = nn.Linear(n_features, hidden_dim)
    lin_input.load_state_dict({'weight': Wi, 'bias': bi})
    lin_hidden = nn.Linear(hidden_dim, hidden_dim)
    lin_hidden.load_state_dict({'weight': Wh, 'bias': bh})
    return lin_hidden, lin_input
```

Split the weights and the create the linear layers for input, forget and output gate. Note the candidate hidden state is an Elman RNN.

```
Wx, bx = lstm_state['weight_ih'], lstm_state['bias_ih']
Wh, bh = lstm_state['weight_hh'], lstm_state['bias_hh']

# Split weights and biases for data points
Wxi, Wxf, Wxg, Wxo = Wx.split(hidden_dim, dim=0)
bxi, bxf, bxg, bxo = bx.split(hidden_dim, dim=0)
# Split weights and biases for hidden state
Whi, Whf, Whg, Who = Wh.split(hidden_dim, dim=0)
bhi, bhf, bhg, bho = bh.split(hidden_dim, dim=0)

# Creates linear layers for the components
i_hidden, i_input = linear_layers(Wxi, bxi, Whi, bhi) # input gate - green
f_hidden, f_input = linear_layers(Wxf, bxf, Whf, bhf) # forget gate - red
o_hidden, o_input = linear_layers(Wxo, bxo, Who, bho) # output gate - blue
g_cell = nn.RNNCell(n_features, hidden_dim) # black
g_cell.load_state_dict({'weight_ih': Wxg, 'bias_ih': bxg,
                        'weight_hh': Whg, 'bias_hh': bhg})
```

```
<All keys matched successfully>
```

```
def forget_gate(h, x):
    thf = f_hidden(h)
    txf = f_input(x)
    f = torch.sigmoid(thf + txf)
    return f  # red

def output_gate(h, x):
    tho = o_hidden(h)
    txo = o_input(x)
    o = torch.sigmoid(tho + txo)
    return o  # blue

def input_gate(h, x):
    thi = i_hidden(h)
    txi = i_input(x)
    i = torch.sigmoid(thi + txi)
    return i  # green
```

Data Generation

Same square sequence is used here to verify that our manual LSTM produces the same result as `nn.LSTMCell`.

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

```
points, directions = generate_sequences(n=128, seed=13)
```

```
initial_hidden = torch.zeros(1, hidden_dim)
initial_cell = torch.zeros(1, hidden_dim)

X = torch.as_tensor(points[0]).float()
first_corner = X[0:1]
```

```
g = g_cell(first_corner)
i = input_gate(initial_hidden, first_corner)
gated_input = g * i
gated_input
```

```
tensor([[-0.1340, -0.0004]], grad_fn=<MulBackward0>)
```

```
f = forget_gate(initial_hidden, first_corner)
gated_cell = initial_cell * f
gated_cell
```

```
tensor([[0., 0.]], grad_fn=<MulBackward0>)
```

```
c_prime = gated_cell + gated_input
c_prime
```

```
tensor([[-0.1340, -0.0004]], grad_fn=<AddBackward0>)
```

```
o = output_gate(initial_hidden, first_corner)
h_prime = o * torch.tanh(c_prime)
h_prime
```

```
tensor([[-5.4936e-02, -8.3810e-05]], grad_fn=<MulBackward0>)
```

LSTM Cell output hidden state and cell state.

```
(h_prime, c_prime)
```

```
(tensor([[-5.4936e-02, -8.3810e-05]], grad_fn=<MulBackward0>),
 tensor([[-0.1340, -0.0004]], grad_fn=<AddBackward0>))
```

Verify the result against `nn.LSTMCell`

```
lstm_cell(first_corner)
```

```
(tensor([[-5.4936e-02, -8.3810e-05]], grad_fn=<MulBackward0>),
 tensor([[-0.1340, -0.0004]], grad_fn=<AddBackward0>))
```

BiLSTM Layer

Find out how to create a Bidirectional LSTM Layer in PyTorch? What's the output look like?

11.3 The Square Model Using GRU and LSTM

In this notebook, we put GRU and LSTM in the same square sequence direction classification that we have seen before with Elman RNN. The Elman RNN model is also included for performance comparision.

You can see that LSTM achieves the best result, but GRU being a simpler model also has similar performance. So when there is a trade-off between performance and computational efficiency, GRU is often a prefered model.

11.3.1 Download Untility Files for Plotting and Data Generation

Download these utility functions first and place them in the same directory as this notebook.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\plots.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\replay.py
```

11.3.2 Imports

```
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F

from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from torch.nn.utils import rnn as rnn_utils
from util import StepByStep
from plots import *
```

11.3.3 Synthetic Data Generation

Sequence Generation Function

This function generate sequences, each of four data points, located close to a perfect square with four corners at `[-1, -1], [-1, 1], [1, 1], [1, -1]`, respectively.

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
```

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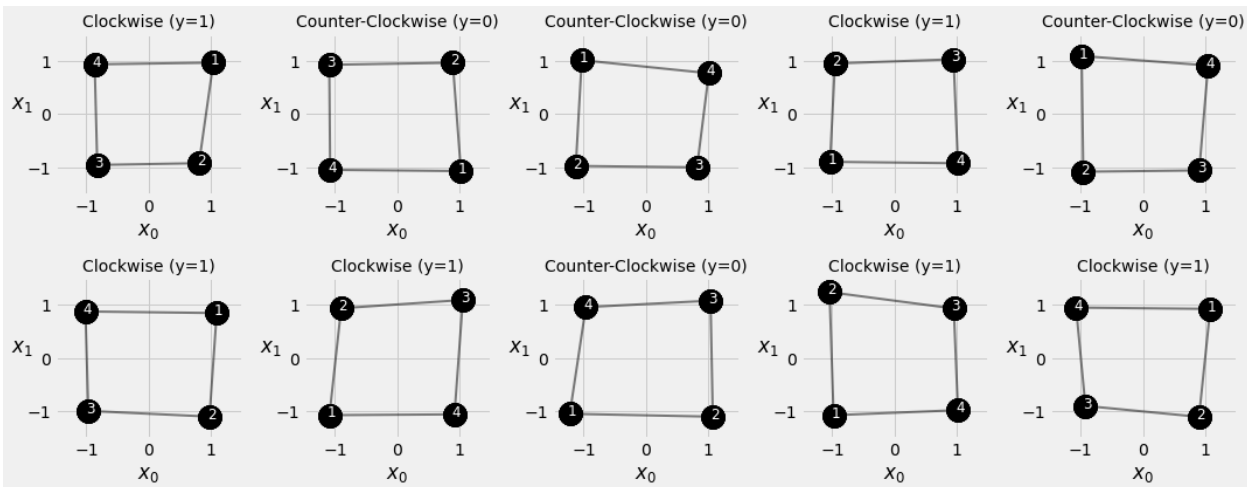
```
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

Training data Generation

```
points, directions = generate_sequences(n=128, seed=13)
```

```
fig = plot_data(points, directions)
```



11.3.4 Square Model

Test Data Generation

```
test_points, test_directions = generate_sequences(seed=19)
```

Data Preparation

```
train_data = TensorDataset(torch.as_tensor(points).float(),
                           torch.as_tensor(directions).view(-1, 1).float())
test_data = TensorDataset(torch.as_tensor(test_points).float(),
                          torch.as_tensor(test_directions).view(-1, 1).float())

train_loader = DataLoader(train_data, batch_size=16, shuffle=True)
test_loader = DataLoader(test_data, batch_size=16)
```

Model Configuration

```
class SquareModel(nn.Module):
    def __init__(self, n_features, hidden_dim, n_outputs):
        super(SquareModel, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.n_outputs = n_outputs
        self.hidden = None
        # Simple RNN
        self.basic_rnn = nn.RNN(self.n_features, self.hidden_dim, batch_first=True)
        # Classifier to produce as many logits as outputs
        self.classifier = nn.Linear(self.hidden_dim, self.n_outputs)

    def forward(self, X):
        # X is batch first (N, L, F)
        # output is (N, L, H)
        # final hidden state is (1, N, H)
        batch_first_output, self.hidden = self.basic_rnn(X)

        # only last item in sequence (N, 1, H)
        last_output = batch_first_output[:, -1]
        # classifier will output (N, 1, n_outputs)
        out = self.classifier(last_output)

        # final output is (N, n_outputs)
        return out.view(-1, self.n_outputs)
```

```
torch.manual_seed(21)
model = SquareModel(n_features=2, hidden_dim=2, n_outputs=1)
loss = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

Model Training

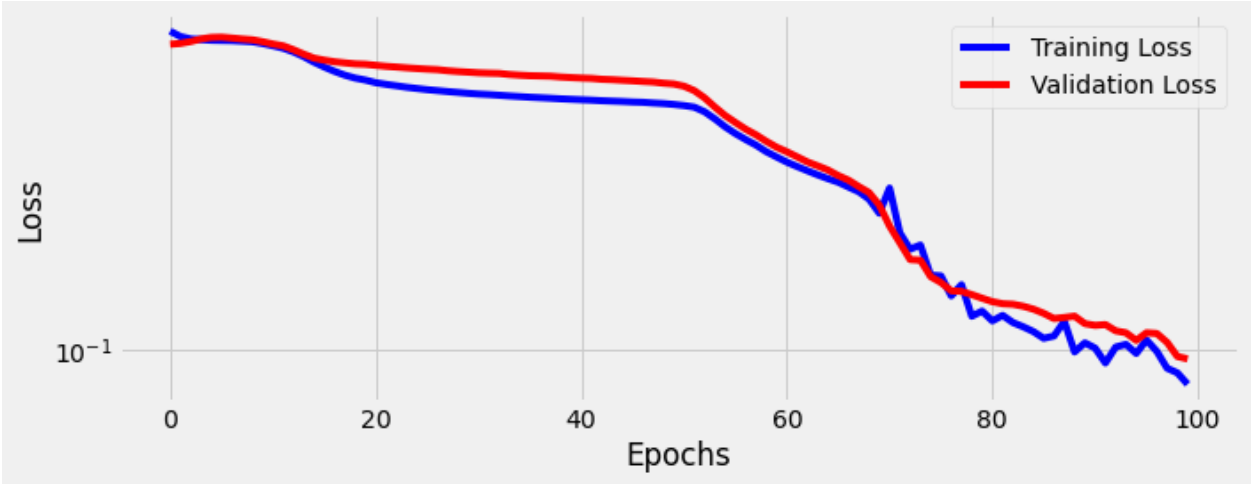
The StepByStep class encapsulated the training routine as well as the data loading into methods such as:

- `_mini_batch`
- `_make_train_step`
- `_make_val_step`

You may want to take a closer look at the `StepByStep` in the `util.py` file to learn how to factorize your code into a reusable blocks.

```
sbs_rnn = StepByStep(model, loss, optimizer)
sbs_rnn.set_loaders(train_loader, test_loader)
sbs_rnn.train(100)
```

```
fig = sbs_rnn.plot_losses()
```




```
StepByStep.loader_apply(test_loader, sbs_rnn.correct)
```

```
tensor([[50, 53],
        [75, 75]])
```

Transformed Inputs

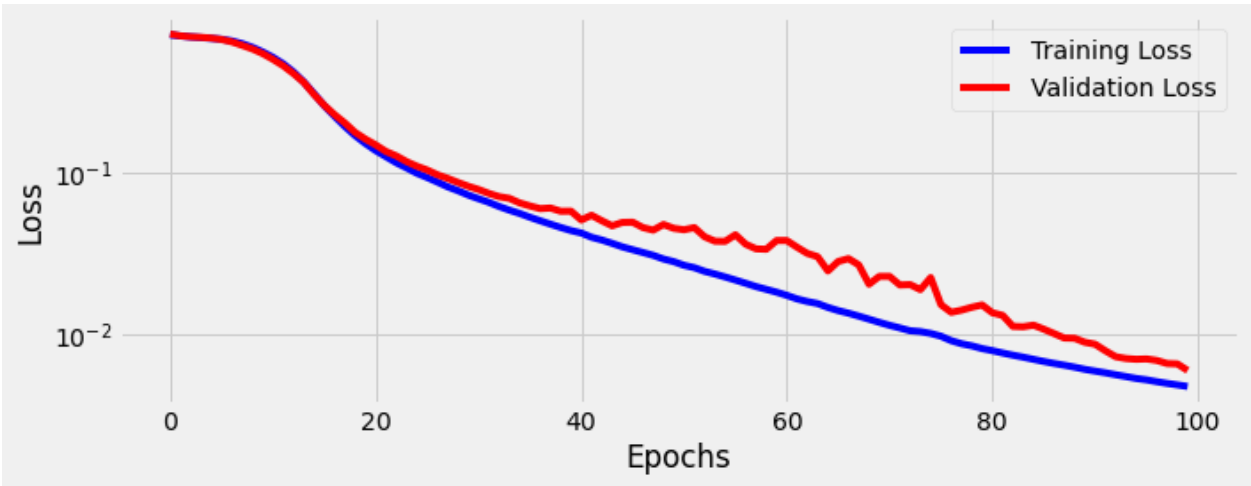
```
class SquareModelGRU(nn.Module):
    def __init__(self, n_features, hidden_dim, n_outputs):
        super(SquareModelGRU, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.n_outputs = n_outputs
        self.hidden = None
        # Simple GRU
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)
        # Classifier to produce as many logits as outputs
        self.classifier = nn.Linear(self.hidden_dim, self.n_outputs)

    def forward(self, X):
        # X is batch first (N, L, F)
        # output is (N, L, H)
        # final hidden state is (1, N, H)
        batch_first_output, self.hidden = self.basic_rnn(X)

        # only last item in sequence (N, 1, H)
        last_output = batch_first_output[:, -1]
        # classifier will output (N, 1, n_outputs)
        out = self.classifier(last_output)

        # final output is (N, n_outputs)
        return out.view(-1, self.n_outputs)
```

Model Configuration & Training

```
torch.manual_seed(21)
model = SquareModelGRU(n_features=2, hidden_dim=2, n_outputs=1)
loss = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
sbs_gru = StepByStep(model, loss, optimizer)
sbs_gru.set_loaders(train_loader, test_loader)
sbs_gru.train(100)
```

```
fig = sbs_gru.plot_losses()
```



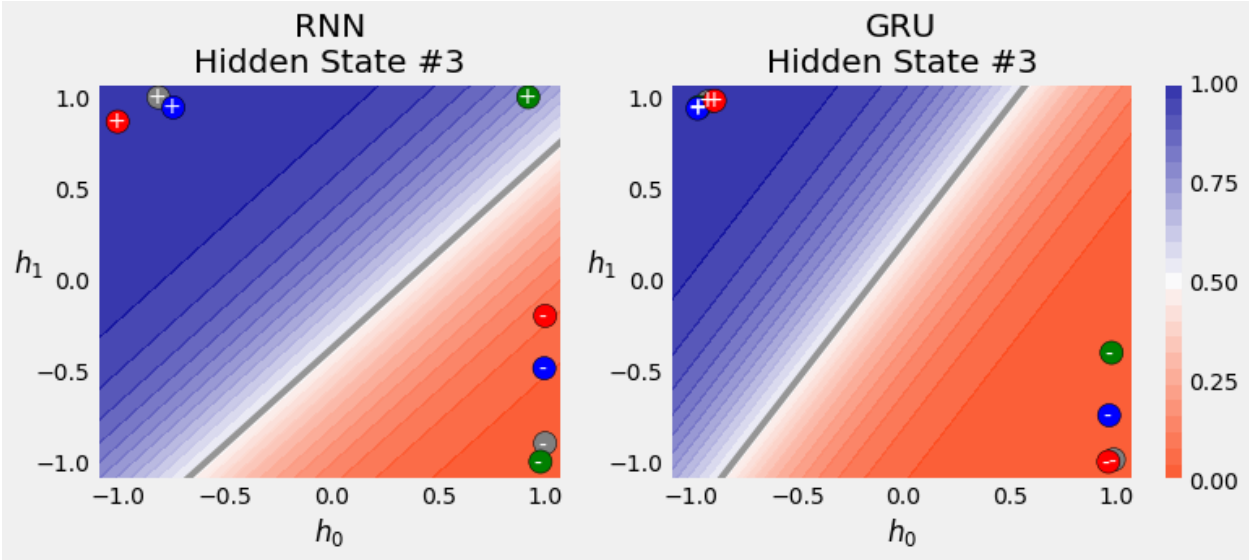

```
StepByStep.loader_apply(test_loader, sbs_gru.correct)
```

```
tensor([[53, 53],
        [75, 75]])
```

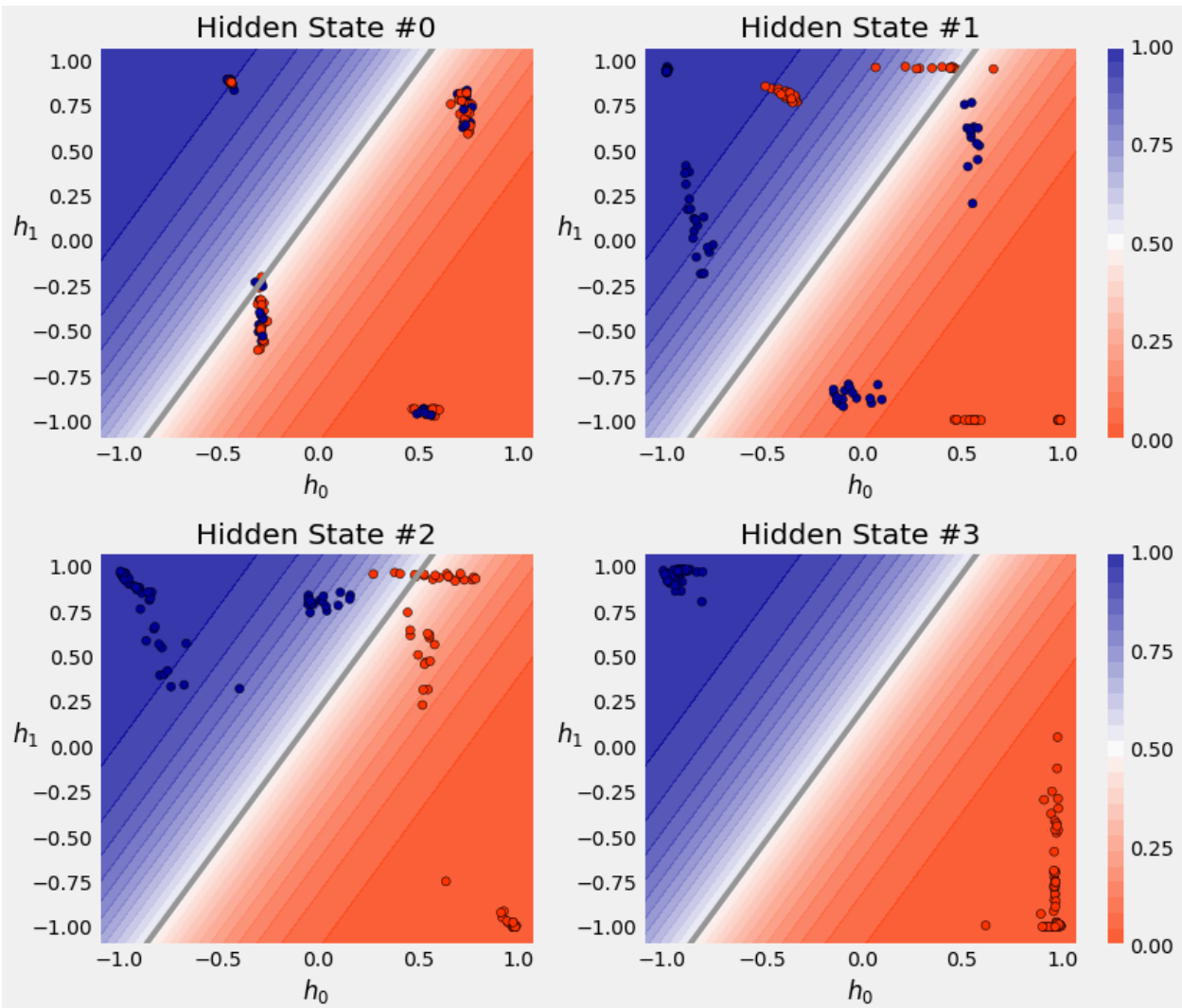
11.3.5 Visualizing the Model

Hidden States

```
fig = figure20(sbs_rnn.model, sbs_gru.model)
```

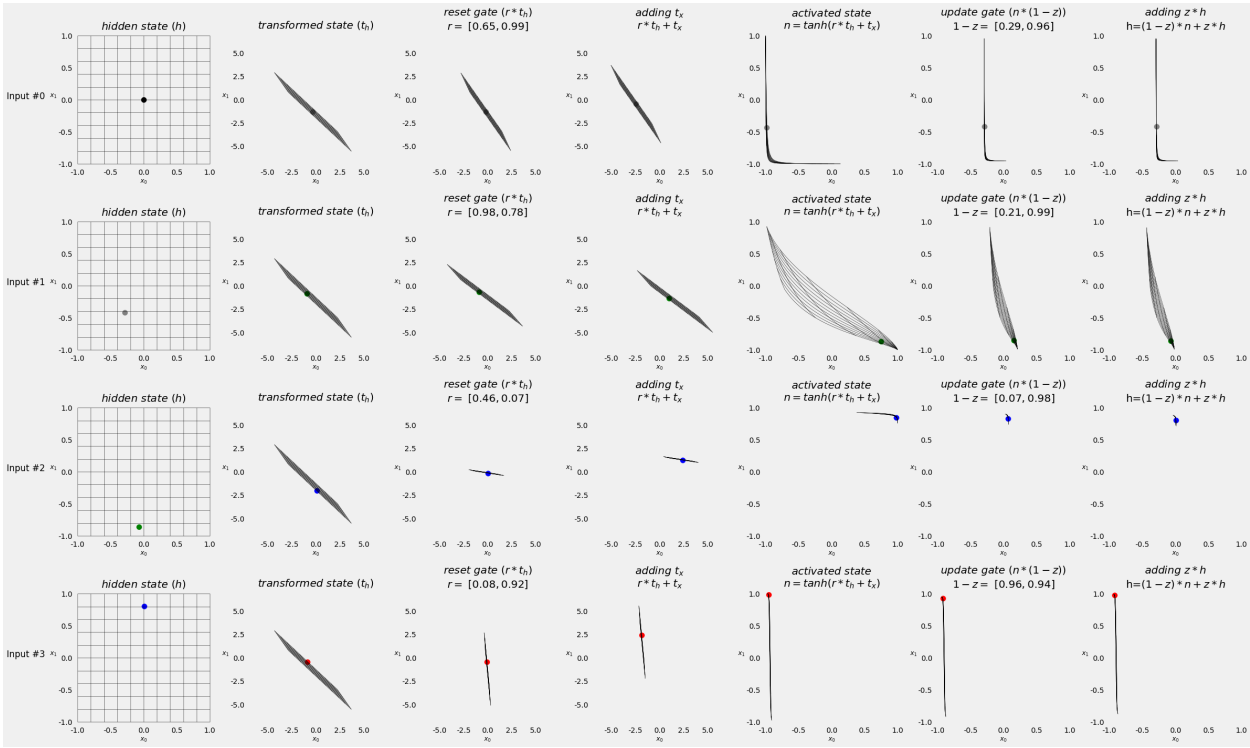



```
fig = hidden_states_contour(model, points, directions)
```



Journey of a GATED Hidden State

```
fig = figure22(model.basic_rnn)
```



11.3.6 Square Model: LSTM

Model Configuration

```
class SquareModelLSTM(nn.Module):
    def __init__(self, n_features, hidden_dim, n_outputs):
        super(SquareModelLSTM, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.n_outputs = n_outputs
        self.hidden = None
        self.cell = None
        # Simple LSTM
        self.basic_rnn = nn.LSTM(self.n_features, self.hidden_dim, batch_first=True)
        # Classifier to produce as many logits as outputs
        self.classifier = nn.Linear(self.hidden_dim, self.n_outputs)

    def forward(self, X):
        # X is batch first (N, L, F)
        # output is (N, L, H)
        # final hidden state is (1, N, H)
        # final cell state is (1, N, H)
        batch_first_output, (self.hidden, self.cell) = self.basic_rnn(X)

        # only last item in sequence (N, 1, H)
```

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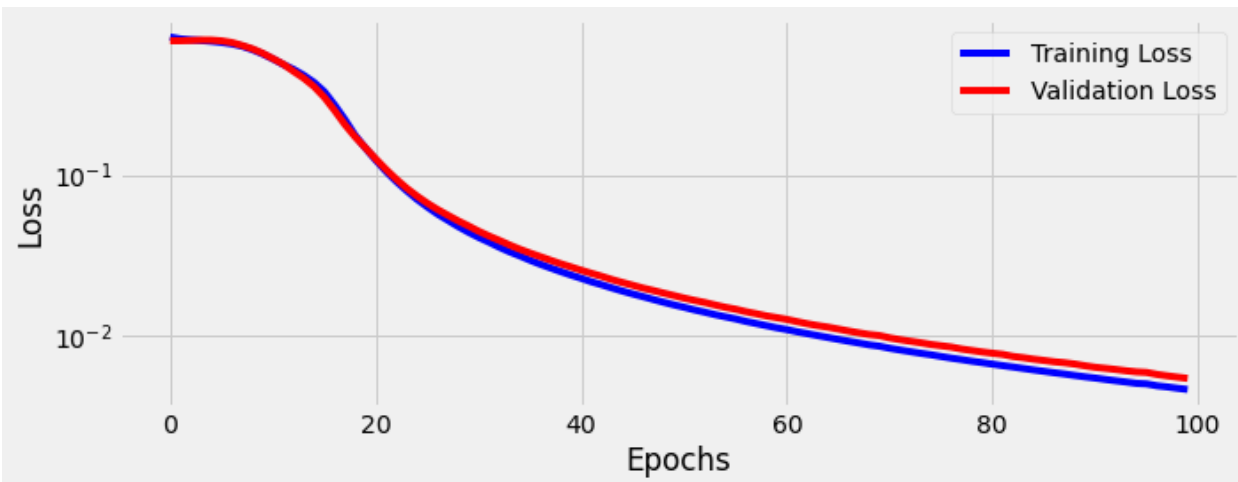
```
        last_output = batch_first_output[:, -1]
        # classifier will output (N, 1, n_outputs)
        out = self.classifier(last_output)

        # final output is (N, n_outputs)
        return out.view(-1, self.n_outputs)
```

Model Configuration & Training

```
torch.manual_seed(21)
model = SquareModelLSTM(n_features=2, hidden_dim=2, n_outputs=1)
loss = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
sbs_lstm = StepByStep(model, loss, optimizer)
sbs_lstm.set_loaders(train_loader, test_loader)
sbs_lstm.train(100)
```

```
fig = sbs_lstm.plot_losses()
```

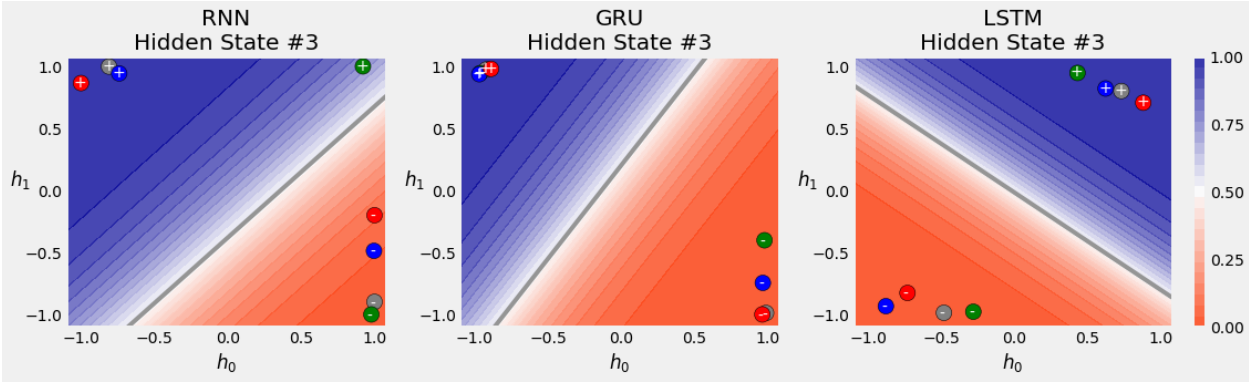



```
StepByStep.loader_apply(test_loader, sbs_lstm.correct)
```

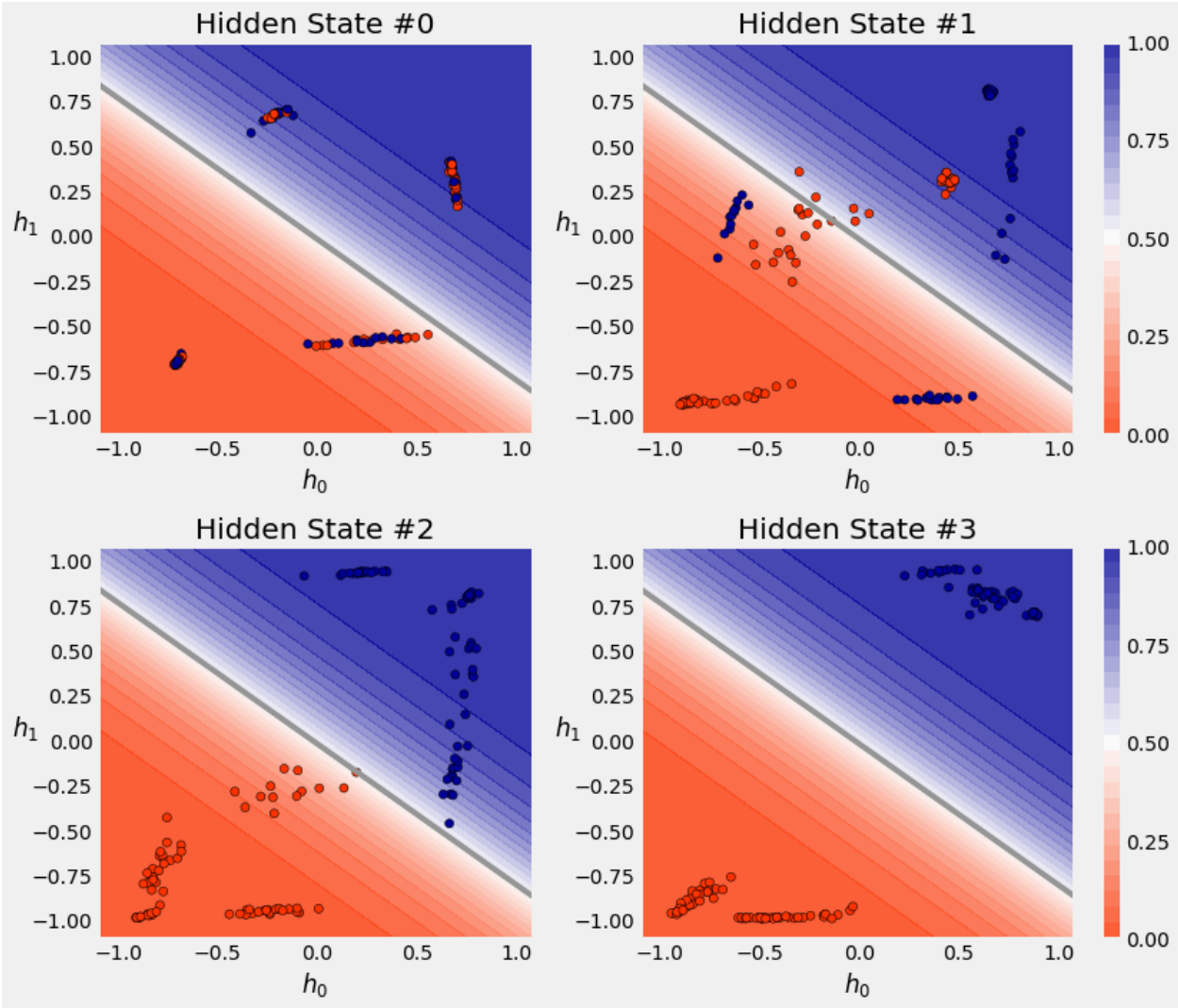
```
tensor([[53, 53],
        [75, 75]])
```

11.3.7 Visualizing the Hidden States

```
fig = figure25(sbs_rnn.model, sbs_gru.model, sbs_lstm.model)
```




```
fig = hidden_states_contour(model, points, directions)
```



11.3.8 Variable-Length Sequences

```
s0 = points[0]       # 4 data points
s1 = points[1][2:]   # 2 data points
s2 = points[2][1:]   # 3 data points

s0.shape, s1.shape, s2.shape
```

```
((4, 2), (2, 2), (3, 2))
```

Padding

```
all_seqs = [s0, s1, s2]
torch.as_tensor(all_seqs)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_13432/1816182238.py in <module>
      1 all_seqs = [s0, s1, s2]
----> 2 torch.as_tensor(all_seqs)

ValueError: expected sequence of length 4 at dim 1 (got 2)
```

```
seq_tensors = [torch.as_tensor(seq).float() for seq in all_seqs]
padded = rnn_utils.pad_sequence(seq_tensors, batch_first=True)
padded
```

```
tensor([[[ 1.0349,  0.9661],
         [ 0.8055, -0.9169],
         [-0.8251, -0.9499],
         [-0.8670,  0.9342]],

        [[-1.0911,  0.9254],
         [-1.0771, -1.0414],
         [ 0.0000,  0.0000],
         [ 0.0000,  0.0000]],

        [[-1.1247, -0.9683],
         [ 0.8182, -0.9944],
         [ 1.0081,  0.7680],
         [ 0.0000,  0.0000]]])
```

```
torch.manual_seed(11)
rnn = nn.RNN(2, 2, batch_first=True)
```

```
output_padded, hidden_padded = rnn(padded)
output_padded
```

```
tensor([[[-0.6388,  0.8505],
         [-0.4215,  0.8979],
         [ 0.3792,  0.3432],
         [ 0.3161, -0.1675]],
```

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```
        [[ 0.2911, -0.1811],
         [ 0.3051,  0.7055],
         [ 0.0052,  0.5819],
         [-0.0642,  0.6012]],

        [[ 0.3385,  0.5927],
         [-0.3875,  0.9422],
         [-0.4832,  0.6595],
         [-0.1007,  0.5349]]], grad_fn=<TransposeBackward1>)
```

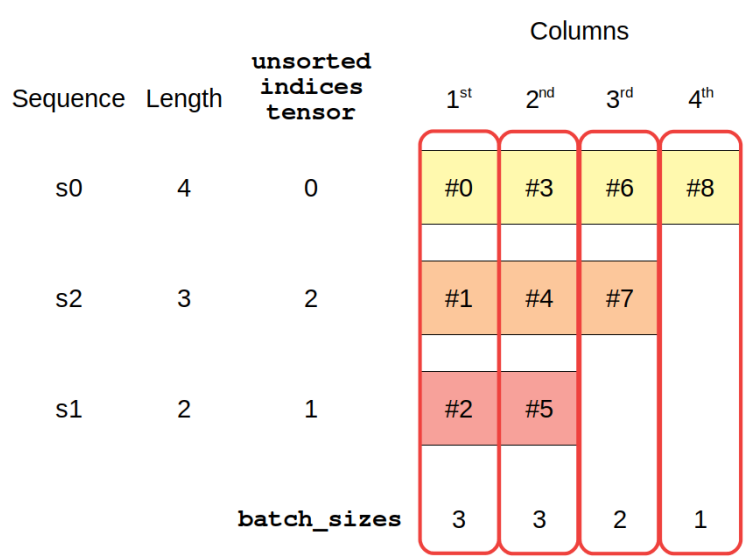
```
hidden_padded.permute(1, 0, 2)
```

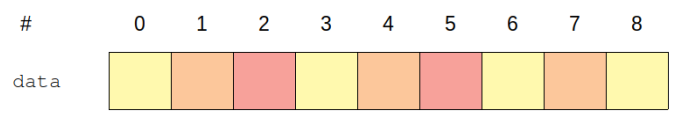
```
tensor([[[ 0.3161, -0.1675]],

        [[-0.0642,  0.6012]],

        [[-0.1007,  0.5349]]], grad_fn=<PermuteBackward>)
```

Packing

```
packed = rnn_utils.pack_sequence(seq_tensors, enforce_sorted=False)
packed
```

```
PackedSequence(data=tensor([[ 1.0349,  0.9661],
        [-1.1247, -0.9683],
        [-1.0911,  0.9254],
        [ 0.8055, -0.9169],
        [ 0.8182, -0.9944],
        [-1.0771, -1.0414],
        [-0.8251, -0.9499],
        [ 1.0081,  0.7680],
        [-0.8670,  0.9342]]), batch_sizes=tensor([3, 3, 2, 1]), sorted_
↪indices=tensor([0, 2, 1]), unsorted_indices=tensor([0, 2, 1]))
```






```
(packed.data[[0, 3, 6, 8]] == seq_tensors[0]).all()
```

```
tensor(True)
```

```
output_packed, hidden_packed = rnn(packed)
output_packed, hidden_packed
```

```
(PackedSequence(data=tensor([[-0.6388,  0.8505],
         [ 0.3385,  0.5927],
         [ 0.2911, -0.1811],
         [-0.4215,  0.8979],
         [-0.3875,  0.9422],
         [ 0.3051,  0.7055],
         [ 0.3792,  0.3432],
         [-0.4832,  0.6595],
         [ 0.3161, -0.1675]], grad_fn=<CatBackward>), batch_sizes=tensor([3, 3, 2,␣
↪1]), sorted_indices=tensor([0, 2, 1]), unsorted_indices=tensor([0, 2, 1])),
 tensor([[[ 0.3161, -0.1675],
          [ 0.3051,  0.7055],
          [-0.4832,  0.6595]]], grad_fn=<IndexSelectBackward>))
```

```
hidden_packed == hidden_padded
```

```
tensor([[[ True,  True],
         [False, False],
         [False, False]]])
```

```
output_packed.data[[2, 5]] # x1 sequence
```

```
tensor([[ 0.2911, -0.1811],
        [ 0.3051,  0.7055]], grad_fn=<IndexBackward>)
```

Unpacking (to padded)

```
output_unpacked, seq_sizes = rnn_utils.pad_packed_sequence(output_packed, batch_
↪first=True)
output_unpacked, seq_sizes
```

```
(tensor([[[-0.6388,  0.8505],
          [-0.4215,  0.8979],
          [ 0.3792,  0.3432],
          [ 0.3161, -0.1675]],

         [[ 0.2911, -0.1811],
          [ 0.3051,  0.7055],
          [ 0.0000,  0.0000],
          [ 0.0000,  0.0000]],
```

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```
         [[ 0.3385,  0.5927],
          [-0.3875,  0.9422],
          [-0.4832,  0.6595],
          [ 0.0000,  0.0000]]], grad_fn=<IndexSelectBackward>),
 tensor([4, 2, 3]))
```

```
output_unpacked[:, -1]
```

```
tensor([[ 0.3161, -0.1675],
        [ 0.0000,  0.0000],
        [ 0.0000,  0.0000]], grad_fn=<SelectBackward>)
```

```
seq_idx = torch.arange(seq_sizes.size(0))
output_unpacked[seq_idx, seq_sizes-1]
```

```
tensor([[ 0.3161, -0.1675],
        [ 0.3051,  0.7055],
        [-0.4832,  0.6595]], grad_fn=<IndexBackward>)
```

Packing (from padded)

```
len_seqs = [len(seq) for seq in all_seqs]
len_seqs
```

```
[4, 2, 3]
```

```
packed = rnn_utils.pack_padded_sequence(padded, len_seqs, enforce_sorted=False, batch_
 ↪first=True)
packed
```

```
PackedSequence(data=tensor([[ 1.0349,  0.9661],
        [-1.1247, -0.9683],
        [-1.0911,  0.9254],
        [ 0.8055, -0.9169],
        [ 0.8182, -0.9944],
        [-1.0771, -1.0414],
        [-0.8251, -0.9499],
        [ 1.0081,  0.7680],
        [-0.8670,  0.9342]]), batch_sizes=tensor([3, 3, 2, 1]), sorted_
 ↪indices=tensor([0, 2, 1]), unsorted_indices=tensor([0, 2, 1]))
```

Variable-Length Dataset

```
var_points, var_directions = generate_sequences(variable_len=True)
var_points[:2]
```

```
[array([[ 1.12636495,  1.1570899 ],
        [ 0.87384513, -1.00750892],
        [-0.9149893 , -1.09150317],
```

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```
        [-1.0867348 ,  1.07731667]]),
 array([[ 0.92250954, -0.89887678],
        [ 1.0941646 ,  0.92300589]])]
```

11.3.9 Data Preparation

```
class CustomDataset(Dataset):
    def __init__(self, x, y):
        self.x = [torch.as_tensor(s).float() for s in x]
        self.y = torch.as_tensor(y).float().view(-1, 1)

    def __getitem__(self, index):
        return (self.x[index], self.y[index])

    def __len__(self):
        return len(self.x)

train_var_data = CustomDataset(var_points, var_directions)
```

```
train_var_loader = DataLoader(train_var_data, batch_size=16, shuffle=True)
next(iter(train_var_loader))
```

```
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_13432/3135847152.py in <module>
      1 train_var_loader = DataLoader(train_var_data, batch_size=16, shuffle=True)
----> 2 next(iter(train_var_loader))

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\dataloader.
 ↪py in __next__(self)
    519             if self._sampler_iter is None:
    520                 self._reset()
--> 521             data = self._next_data()
    522             self._num_yielded += 1
    523             if self._dataset_kind == _DatasetKind.Iterable and \

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\dataloader.
 ↪py in _next_data(self)
    559     def _next_data(self):
    560         index = self._next_index()  # may raise StopIteration
--> 561         data = self._dataset_fetcher.fetch(index)  # may raise StopIteration
    562         if self._pin_memory:
    563             data = _utils.pin_memory.pin_memory(data)

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\_utils\
 ↪fetch.py in fetch(self, possibly_batched_index)
     45         else:
     46             data = self.dataset[possibly_batched_index]
---> 47         return self.collate_fn(data)

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\_utils\
 ↪collate.py in default_collate(batch)
     82             raise RuntimeError('each element in list of batch should be of␣
 ↪equal size')
```

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```
     83         transposed = zip(*batch)
---> 84         return [default_collate(samples) for samples in transposed]
     85
     86     raise TypeError(default_collate_err_msg_format.format(elem_type))

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\_utils\
 ↪collate.py in <listcomp>(.0)
     82             raise RuntimeError('each element in list of batch should be of␣
 ↪equal size')
     83         transposed = zip(*batch)
---> 84         return [default_collate(samples) for samples in transposed]
     85
     86     raise TypeError(default_collate_err_msg_format.format(elem_type))

C:\ProgramData\Anaconda3\envs\cits4012\lib\site-packages\torch\utils\data\_utils\
 ↪collate.py in default_collate(batch)
     54             storage = elem.storage()._new_shared(numel)
     55             out = elem.new(storage)
---> 56         return torch.stack(batch, 0, out=out)
     57     elif elem_type.__module__ == 'numpy' and elem_type.__name__ != 'str_' \
     58             and elem_type.__name__ != 'string_':

RuntimeError: stack expects each tensor to be equal size, but got [4, 2] at entry 0␣
 ↪and [2, 2] at entry 1
```

Collate Function

```
def pack_collate(batch):
    X = [item[0] for item in batch]
    y = [item[1] for item in batch]
    X_pack = rnn_utils.pack_sequence(X, enforce_sorted=False)

    return X_pack, torch.as_tensor(y).view(-1, 1)
```

```
# list of tuples returned by the dataset
dummy_batch = [train_var_data[0], train_var_data[1]]
dummy_x, dummy_y = pack_collate(dummy_batch)
dummy_x
```

```
PackedSequence(data=tensor([[ 1.1264,  1.1571],
        [ 0.9225, -0.8989],
        [ 0.8738, -1.0075],
        [ 1.0942,  0.9230],
        [-0.9150, -1.0915],
        [-1.0867,  1.0773]]), batch_sizes=tensor([2, 2, 1, 1]), sorted_
 ↪indices=tensor([0, 1]), unsorted_indices=tensor([0, 1]))
```

```
train_var_loader = DataLoader(train_var_data, batch_size=16, shuffle=True, collate_
 ↪fn=pack_collate)
x_batch, y_batch = next(iter(train_var_loader))
```

11.3.10 Square Model IV: Packed

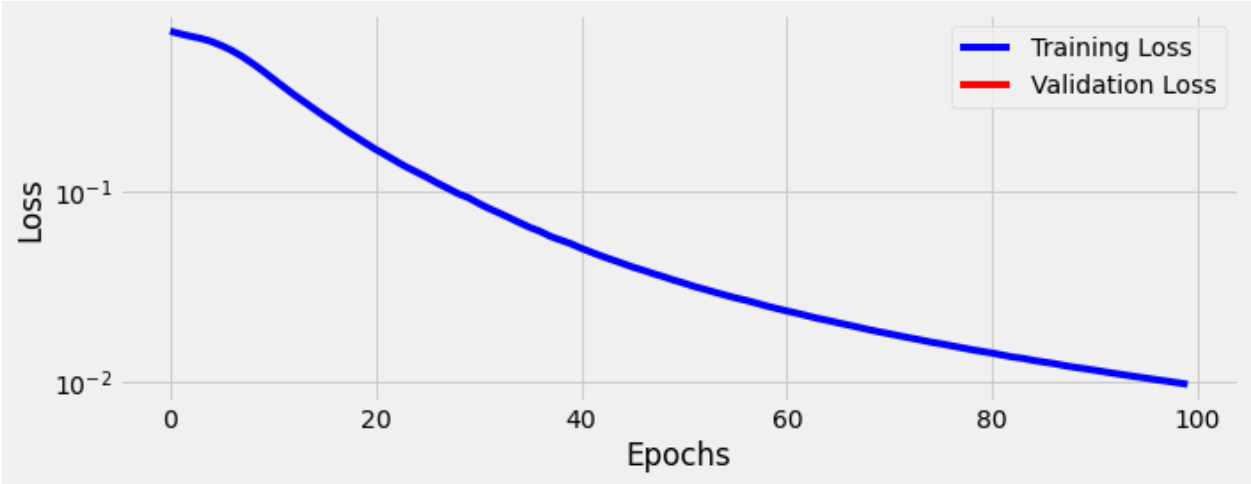
```
class SquareModelPacked(nn.Module):
    def __init__(self, n_features, hidden_dim, n_outputs):
        super(SquareModelPacked, self).__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.n_outputs = n_outputs
        self.hidden = None
        self.cell = None
        # Simple LSTM
        self.basic_rnn = nn.LSTM(self.n_features, self.hidden_dim, bidirectional=True)
        # Classifier to produce as many logits as outputs
        self.classifier = nn.Linear(2 * self.hidden_dim, self.n_outputs)

    def forward(self, X):
        # X is a PACKED sequence now

        # output is PACKED
        # final hidden state is (2, N, H) - bidirectional
        # final cell state is (2, N, H) - bidirectional
        rnn_out, (self.hidden, self.cell) = self.basic_rnn(X)
        # unpack the output (N, L, 2*H)
        batch_first_output, seq_sizes = rnn_utils.pad_packed_sequence(rnn_out, batch_
↪first=True)

        # only last item in sequence (N, 1, 2*H)
        seq_idx = torch.arange(seq_sizes.size(0))
        last_output = batch_first_output[seq_idx, seq_sizes-1]
        # classifier will output (N, 1, n_outputs)
        out = self.classifier(last_output)

        # final output is (N, n_outputs)
        return out.view(-1, self.n_outputs)
```

11.3.11 Model Configuration & Training

```
torch.manual_seed(21)
model = SquareModelPacked(n_features=2, hidden_dim=2, n_outputs=1)
loss = nn.BCEWithLogitsLoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
sbs_packed = StepByStep(model, loss, optimizer)
sbs_packed.set_loaders(train_var_loader)
sbs_packed.train(100)
```

```
fig = sbs_packed.plot_losses()
```




```
StepByStep.loader_apply(train_var_loader, sbs_packed.correct)
```

```
tensor([[66, 66],
        [62, 62]])
```

11.4 Sequence to Sequence Models

In this notebook, we will be using the same squares as before, but this time know the first two corners (the source sequence) and ask our model to predict the next two corners (the target sequence). As with every sequence-related problem, the order is important, so it is not enough to get the corner's coordinates right, but they should follow the same direction (clockwise or counter-clockwise).

11.4.1 Download Plotting and Helper Functions

Download the followings files and place them in the same folder as the notebook before proceed further. These files contain the utility functions and plotting functions needed for this notebook.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\plots.py
```

```
FileLink('plots_seq2seq.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\plots_seq2seq.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\LSTM\replay.py
```

11.4.2 Imports

```
import copy
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from util import StepByStep
from plots import *
from plots_seq2seq import *
```

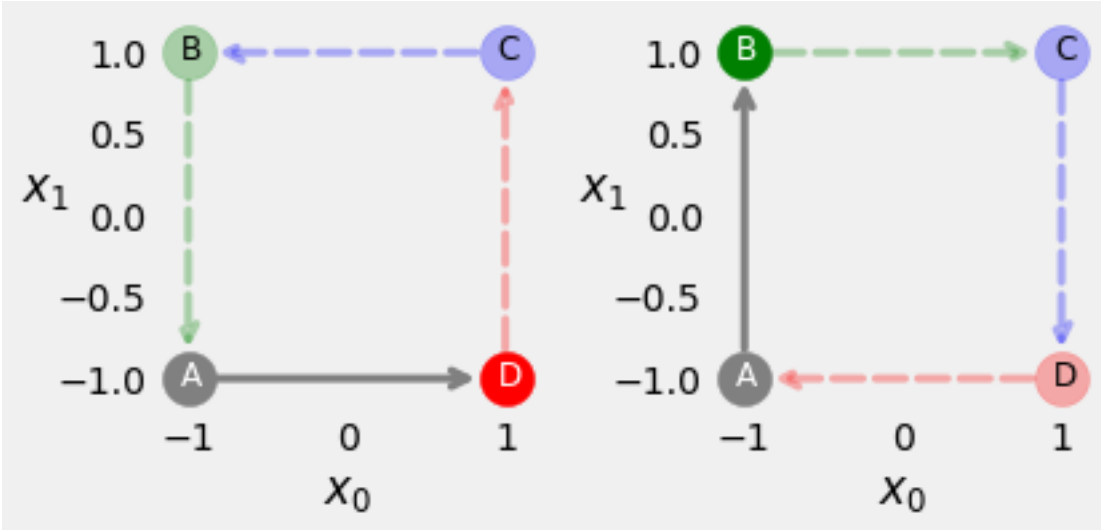
11.4.3 Data Generation

Same method as before for generating noisy squares.

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

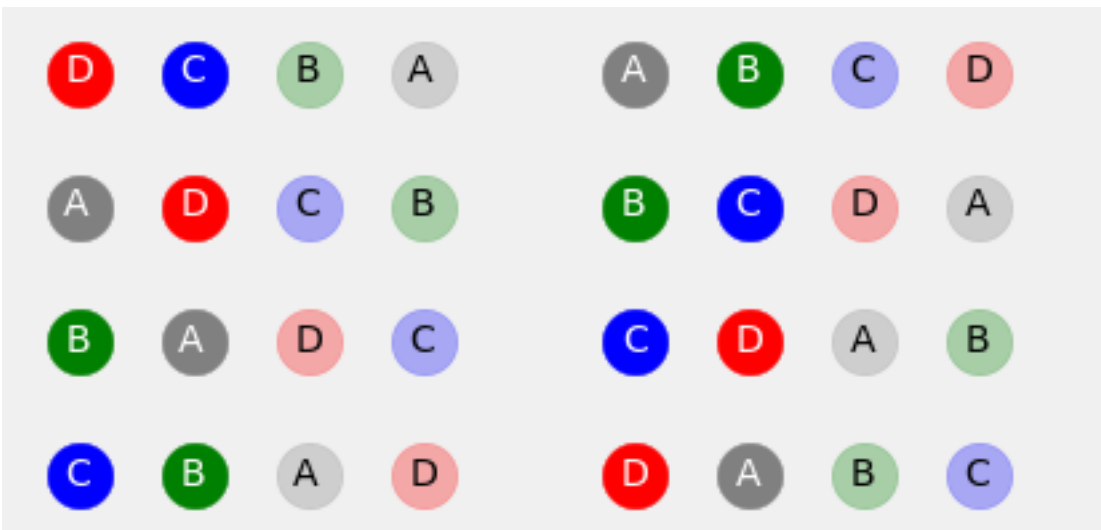
Visualise an counter clock-wise perfect square and a clock-wise one.

```
fig = counter_vs_clock(binary=False)
```



Since there are four corners to start from and two directions to follow, there are effectively eight possible sequences.

```
fig = plot_sequences(binary=False, target_len=2)
```

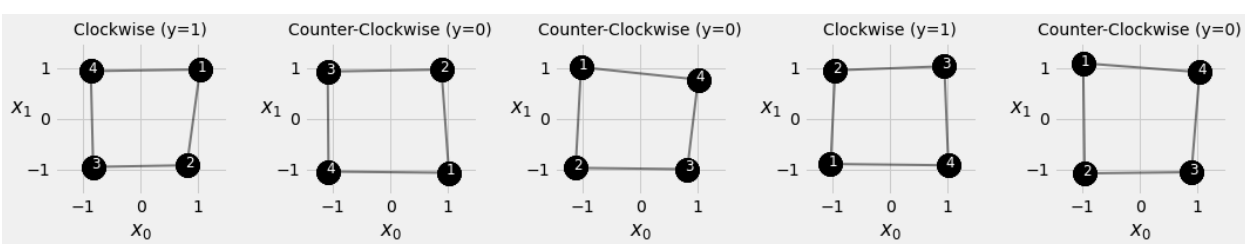


Generate 128 random noisy squares:

```
points, directions = generate_sequences(n=128, seed=13)
```

Visualize the first five squares.

```
fig = plot_data(points, directions, n_rows=1)
```



11.4.4 Encoder-Decoder Architecture

The encoder-decoder is a combination of two models: the **encoder** and the **decoder**.

Encoder

The encoder's goal is to generate a vector representation ψ of the source sequence, that is, to encode it.

An encoder can be any of the featuriser we have seen before, e.g. a Conv1D, an Elman RNN, a GRU, an LSTM or their stacked and bidirectional variances. Here we use a GRU, ψ is the hidden state of the last cell.

Note: We kept the outputs of all cells in the `Encoder` code, to make the code more extendable to future "attention-based" models.

```
class Encoder(nn.Module):
    def __init__(self, n_features, hidden_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.hidden = None
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)

    def forward(self, X):
        rnn_out, self.hidden = self.basic_rnn(X)

        return rnn_out # N, L, F
```

A perfect square with two corners as source, and two coners target.

```
full_seq = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
source_seq = full_seq[:, :2] # first two corners
target_seq = full_seq[:, 2:] # last two corners
```

We use the un-trained `Encoder` to encode the source sequence. If trained the output vector is expected to caputre the source seqence's intrinsic positional thus directional information.

```
torch.manual_seed(21)
encoder = Encoder(n_features=2, hidden_dim=2)
hidden_seq = encoder(source_seq) # output is N, L, F
hidden_final = hidden_seq[:, -1:]   # takes last hidden state
hidden_final
```

```
tensor([[[ 0.3105, -0.5263]]], grad_fn=<SliceBackward>)
```

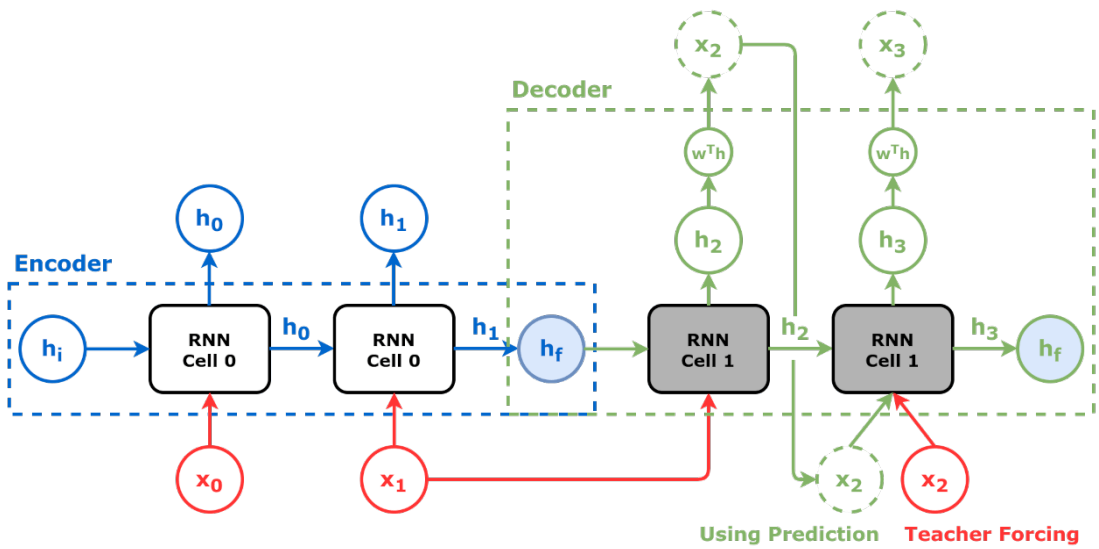
Decoder

The decoder's goal is to generate the target sequence from an initial representation, that is, to decode it.

Very often the decorder takes the encoder's output of last cell, as its initial hidden state, and use last input the encoder as its first input, to generate a sequence of desired length. The output of each cell through a linear transformantion (*regression*) to obtain the output sequence of the decoder So the encoder can be realised through an RNN or its variants as well.

The code below uses a GRU layer as a decoder.

Note: Since we are generating numerical values that represent the coordinates of the corners, we are dealing with a regression problem. So in the later model training, we use MSE as loss function.




```
class Decoder(nn.Module):
    def __init__(self, n_features, hidden_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.hidden = None
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)
        self.regression = nn.Linear(self.hidden_dim, self.n_features)

    def init_hidden(self, hidden_seq):
        # We only need the final hidden state
        hidden_final = hidden_seq[:, -1:] # N, 1, H
        # But we need to make it sequence-first
        self.hidden = hidden_final.permute(1, 0, 2) # 1, N, H

    def forward(self, X):
        # X is N, 1, F
        batch_first_output, self.hidden = self.basic_rnn(X, self.hidden)

        last_output = batch_first_output[:, -1:]
        out = self.regression(last_output)

        # N, 1, F
        return out.view(-1, 1, self.n_features)
```

Decoder is often considered as a generator. Here the `decoder` is intialised with the last hidden state of the encoder first. The initial input is the last element of the source sequence. Then it takes the previous cell output as input, in a for loop, until it generate a specified number (*target sequence length*) of elements.

```
torch.manual_seed(21)
decoder = Decoder(n_features=2, hidden_dim=2)

# Initial hidden state will be encoder's final hidden state
decoder.init_hidden(hidden_seq)
# Initial data point is the last element of source sequence
inputs = source_seq[:, -1:]

target_len = 2
for i in range(target_len):
    print(f'Hidden: {decoder.hidden}')
    out = decoder(inputs)   # Predicts coordinates
    print(f'Output: {out}\n')
    # Predicted coordinates are next step's inputs
    inputs = out
```

```
Hidden: tensor([[[ 0.3105, -0.5263]]], grad_fn=<PermuteBackward>)
Output: tensor([[[-0.2339,  0.4702]]], grad_fn=<ViewBackward>)

Hidden: tensor([[[ 0.3913, -0.6853]]], grad_fn=<StackBackward>)
Output: tensor([[[-0.0226,  0.4628]]], grad_fn=<ViewBackward>)
```

Teacher Forcing

There is one problem with the approach above, an untrained model will make really bad predictions, and these predictions will still be used as inputs for subsequent steps. This makes model training unnecessarily hard because the prediction error in one step is caused by both the (untrained) model and the prediction error in the previous step.

Tip: We can use the actual target sequence instead! This technique is called **teacher forcing**. We can ignore the predictions and use the real data from the target sequence instead.

```
# Initial hidden state will be encoder's final hidden state
decoder.init_hidden(hidden_seq)
# Initial data point is the last element of source sequence
inputs = source_seq[:, -1:]

target_len = 2
for i in range(target_len):
    print(f'Hidden: {decoder.hidden}')
    out = decoder(inputs) # Predicts coordinates
    print(f'Output: {out}\n')
    # But completely ignores the predictions and uses real data instead
    inputs = target_seq[:, i:i+1]
```

```
Hidden: tensor([[[ 0.3105, -0.5263]]], grad_fn=<PermuteBackward>)
Output: tensor([[[-0.2339,  0.4702]]], grad_fn=<ViewBackward>)

Hidden: tensor([[[ 0.3913, -0.6853]]], grad_fn=<StackBackward>)
Output: tensor([[[0.2265, 0.4529]]], grad_fn=<ViewBackward>)
```

Put the two cases together:

```
# Initial hidden state is encoder's final hidden state
decoder.init_hidden(hidden_seq)
# Initial data point is the last element of source sequence
inputs = source_seq[:, -1:]

teacher_forcing_prob = 0.5
target_len = 2
for i in range(target_len):
    print(f'Hidden: {decoder.hidden}')
    out = decoder(inputs)
    print(f'Output: {out}\n')
    # If it is teacher forcing
    if torch.rand(1) <= teacher_forcing_prob:
        # Takes the actual element
        inputs = target_seq[:, i:i+1]
    else:
        # Otherwise uses the last predicted output
        inputs = out
```

```
Hidden: tensor([[[ 0.3105, -0.5263]]], grad_fn=<PermuteBackward>)
Output: tensor([[[-0.2339,  0.4702]]], grad_fn=<ViewBackward>)

Hidden: tensor([[[ 0.3913, -0.6853]]], grad_fn=<StackBackward>)
Output: tensor([[[-0.0226,  0.4628]]], grad_fn=<ViewBackward>)
```

Encoder + Decoder

We can assemble a **boilerplate** that integrates a encoder and a decoder. Given an encoder and a decoder model, the code below implements a forward method that splits the input into the source and target sequences, loops over the generation of the target sequence, and implements teacher forcing in training mode.

```
class EncoderDecoder(nn.Module):
    def __init__(self, encoder, decoder, input_len, target_len, teacher_forcing_
↪prob=0.5):
        super().__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.input_len = input_len
        self.target_len = target_len
        self.teacher_forcing_prob = teacher_forcing_prob
        self.outputs = None

    def init_outputs(self, batch_size):
        device = next(self.parameters()).device
        # N, L (target), F
        self.outputs = torch.zeros(batch_size,
                                   self.target_len,
                                   self.encoder.n_features).to(device)

    def store_output(self, i, out):
        # Stores the output
        self.outputs[:, i:i+1, :] = out

    def forward(self, X):
```

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```
        # splits the data in source and target sequences
        # the target seq will be empty in testing mode
        # N, L, F
        source_seq = X[:, :self.input_len, :]
        target_seq = X[:, self.input_len:, :]
        self.init_outputs(X.shape[0])

        # Encoder expected N, L, F
        hidden_seq = self.encoder(source_seq)
        # Output is N, L, H
        self.decoder.init_hidden(hidden_seq)

        # The last input of the encoder is also
        # the first input of the decoder
        dec_inputs = source_seq[:, -1:, :]

        # Generates as many outputs as the target length
        for i in range(self.target_len):
            # Output of decoder is N, 1, F
            out = self.decoder(dec_inputs)
            self.store_output(i, out)

            prob = self.teacher_forcing_prob
            # In evaluation/test the target sequence is
            # unknown, so we cannot use teacher forcing
            if not self.training:
                prob = 0

            # If it is teacher forcing
            if torch.rand(1) <= prob:
                # Takes the actual element
                dec_inputs = target_seq[:, i:i+1, :]
            else:
                # Otherwise uses the last predicted output
                dec_inputs = out

        return self.outputs
```

```
encdec = EncoderDecoder(encoder, decoder, input_len=2, target_len=2, teacher_forcing_
↪prob=1.0)
```

```
encdec.train()
encdec(full_seq)
```

```
tensor([[[-0.2339,  0.4702],
         [ 0.2265,  0.4529]]], grad_fn=<CopySlices>)
```

```
encdec.eval()
encdec(source_seq)
```

```
tensor([[[-0.2339,  0.4702],
         [-0.0226,  0.4628]]], grad_fn=<CopySlices>)
```

Data Preparation

The first two corners of the square `data[:, :2]` are the source sequences; the last two corners `data[:, 2:]` are the target sequences.

```
points, directions = generate_sequences()
full_train = torch.as_tensor(points).float()
target_train = full_train[:, 2:]
```

```
test_points, test_directions = generate_sequences(seed=19)
full_test = torch.as_tensor(points).float()
source_test = full_test[:, :2]
target_test = full_test[:, 2:]
```

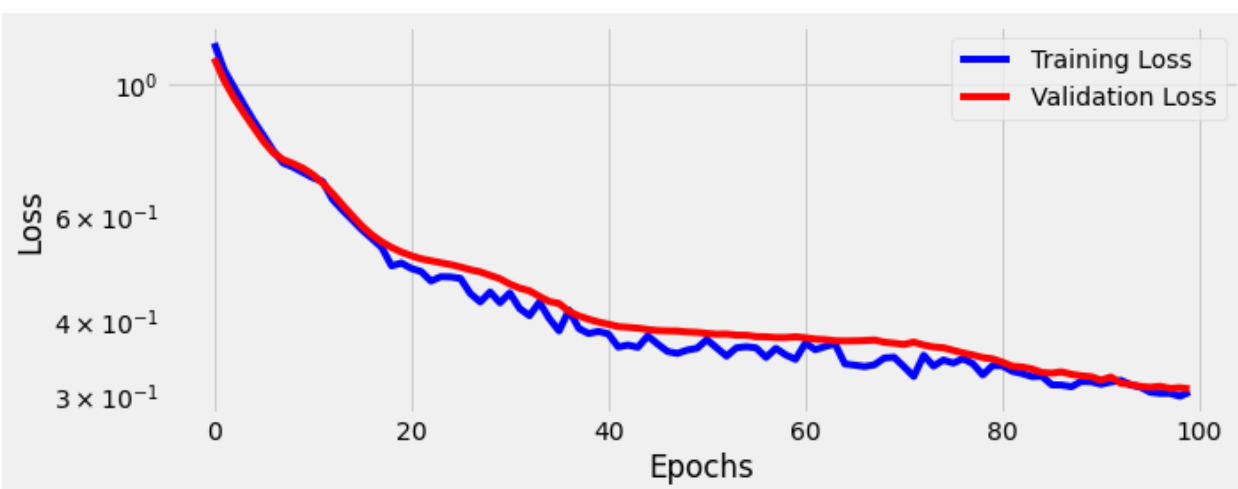
```
train_data = TensorDataset(full_train, target_train)
test_data = TensorDataset(source_test, target_test)

generator = torch.Generator()
train_loader = DataLoader(train_data, batch_size=16, shuffle=True,␣
 ↪generator=generator)
test_loader = DataLoader(test_data, batch_size=16)
```

Model Training & Configuration

```
torch.manual_seed(23)
encoder = Encoder(n_features=2, hidden_dim=2)
decoder = Decoder(n_features=2, hidden_dim=2)
model = EncoderDecoder(encoder, decoder, input_len=2, target_len=2, teacher_forcing_
 ↪prob=0.5)
loss = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

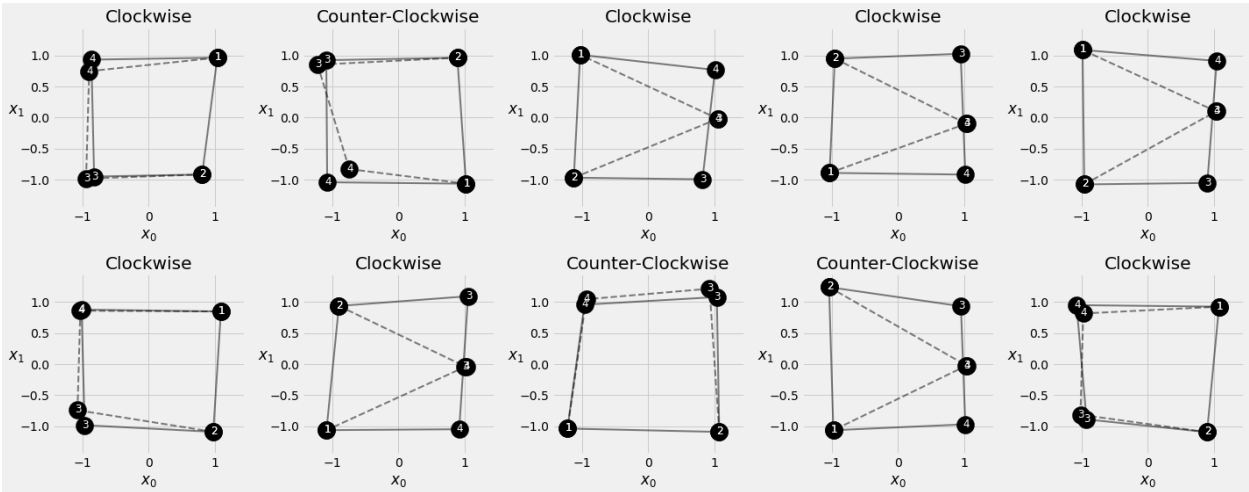
```
sbs_seq = StepByStep(model, loss, optimizer)
sbs_seq.set_loaders(train_loader, test_loader)
sbs_seq.train(100)
```

```
fig = sbs_seq.plot_losses()
```



Visualizing Predictions

```
fig = sequence_pred(sbs_seq, full_test, test_directions)
```

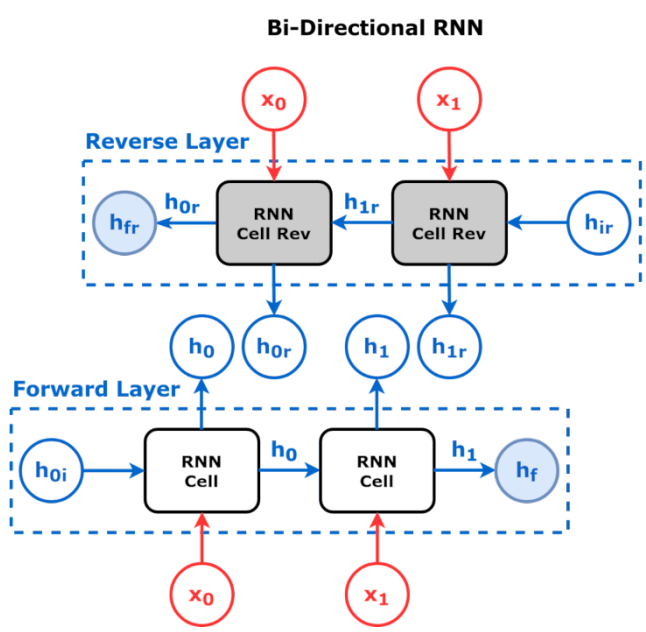


11.4.5 Bidirectional LSTM as an Encoder

We have been using the output of GRU above to exact the last hidden state as the representation vector ψ betwen the encoder and decoder. Note that despite the output and hidden state of a GRU cell is the same, we still used the output, rather than the hidden state. This is because the bidirectional variations outputs are hidden states are not the same. Recall that the overall output of the bidirectional RNN must have two elements:

- a concatenation side-by-side of both sequences of hidden states (input aligned)
- the concatenation of final hidden states of both layers, the last of the forward layer is corresponding to the last element of the sequence, the last of the backward layer is corresponding to the first element of the sequence (i.e. not input aligned).

See the figure below for clarification.



For Sequence to Sequence model, we will need an input aligned output, so the code above largely should still work (the dimenionality changed though), but conceptually we need to be clear of what's happening.

Your Turn

Change the code above to use BiLSTM as an encoder.

11.5 Surname Generation - Unconditioned

In this notebook, we use the same `Surname` dataset, but not for nationality classification. The RNN here is used as a decoder that generates sequences of characters (i.e. a generated surname) instead of a featurizer for the classification task we have seen before.

The model in this notebook is **unconditioned**: it does not observe the nationality before generating a surname. In practice, being unconditioned means the GRU does not bias its computations toward any nationality. In PyTorch code, this means we use a vector of all `0`s so that the initial hidden state vector does not contribute to the computations. In the next notebook, the computational bias is introduced through the initial hidden vector.

11.5.1 Imports

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
from torch.nn import functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm.notebook import tqdm
```

11.5.2 Data Vectorization classes

Vocabulary

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
```

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```
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
```

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```
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):

        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
                         'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

Vectorizer

```
class SurnameVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, char_vocab, nationality_vocab):
        """
        Args:
            char_vocab (Vocabulary): maps words to integers
            nationality_vocab (Vocabulary): maps nationalities to integers
        """
        self.char_vocab = char_vocab
        self.nationality_vocab = nationality_vocab

    def vectorize(self, surname, vector_length=-1):
        """Vectorize a surname into a vector of observations and targets

        The outputs are the vectorized surname split into two vectors:
            surname[:-1] and surname[1:]
        At each timestep, the first vector is the observation and the second vector␣
↪is the target.

        Args:
            surname (str): the surname to be vectorized
            vector_length (int): an argument for forcing the length of index vector
        Returns:
            a tuple: (from_vector, to_vector)
            from_vector (numpy.ndarray): the observation vector
            to_vector (numpy.ndarray): the target prediction vector
        """
        indices = [self.char_vocab.begin_seq_index]
        indices.extend(self.char_vocab.lookup_token(token) for token in surname)
        indices.append(self.char_vocab.end_seq_index)

        if vector_length < 0:
            vector_length = len(indices) - 1

        from_vector = np.empty(vector_length, dtype=np.int64)
        from_indices = indices[:-1]
        from_vector[:len(from_indices)] = from_indices
        from_vector[len(from_indices):] = self.char_vocab.mask_index

        to_vector = np.empty(vector_length, dtype=np.int64)
        to_indices = indices[1:]
        to_vector[:len(to_indices)] = to_indices
        to_vector[len(to_indices):] = self.char_vocab.mask_index

        return from_vector, to_vector

    @classmethod
    def from_dataframe(cls, surname_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            surname_df (pandas.DataFrame): the surname dataset
        Returns:
            an instance of the SurnameVectorizer
        """
```

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```
        char_vocab = SequenceVocabulary()
        nationality_vocab = Vocabulary()

        for index, row in surname_df.iterrows():
            for char in row.surname:
                char_vocab.add_token(char)
            nationality_vocab.add_token(row.nationality)

        return cls(char_vocab, nationality_vocab)

    @classmethod
    def from_serializable(cls, contents):
        """Instantiate the vectorizer from saved contents

        Args:
            contents (dict): a dict holding two vocabularies for this vectorizer
                This dictionary is created using `vectorizer.to_serializable()`
        Returns:
            an instance of SurnameVectorizer
        """
        char_vocab = SequenceVocabulary.from_serializable(contents['char_vocab'])
        nat_vocab =  Vocabulary.from_serializable(contents['nationality_vocab'])

        return cls(char_vocab=char_vocab, nationality_vocab=nat_vocab)

    def to_serializable(self):
        """ Returns the serializable contents """
        return {'char_vocab': self.char_vocab.to_serializable(),
                'nationality_vocab': self.nationality_vocab.to_serializable()}
```

Dataset

```
class SurnameDataset(Dataset):
    def __init__(self, surname_df, vectorizer):
        """
        Args:
            surname_df (pandas.DataFrame): the dataset
            vectorizer (SurnameVectorizer): vectorizer instatiated from dataset
        """
        self.surname_df = surname_df
        self._vectorizer = vectorizer

        self._max_seq_length = max(map(len, self.surname_df.surname)) + 2

        self.train_df = self.surname_df[self.surname_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.surname_df[self.surname_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.surname_df[self.surname_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
```

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```
                                'test': (self.test_df, self.test_size)}

        self.set_split('train')

    @classmethod
    def load_dataset_and_make_vectorizer(cls, surname_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            surname_csv (str): location of the dataset
        Returns:
            an instance of SurnameDataset
        """

        surname_df = pd.read_csv(surname_csv)
        return cls(surname_df, SurnameVectorizer.from_dataframe(surname_df))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, surname_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
            surname_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of SurnameDataset
        """
        surname_df = pd.read_csv(surname_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(surname_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of SurnameVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return SurnameVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer
```

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```
    def set_split(self, split="train"):
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point: (x_data, y_target, class_index)
        """
        row = self._target_df.iloc[index]

        from_vector, to_vector = \
            self._vectorizer.vectorize(row.surname, self._max_seq_length)

        nationality_index = \
            self._vectorizer.nationality_vocab.lookup_token(row.nationality)

        return {'x_data': from_vector,
                'y_target': to_vector,
                'class_index': nationality_index}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size

def generate_batches(dataset, batch_size, shuffle=True,
                     drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
      ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

11.5.3 The Model: SurnameGenerationModel

The *SurnameGenerationModel* embeds character indices, computes their sequential state using a GRU, and computes the probability of token predictions using a Linear layer. More explicitly, the unconditioned `SurnameGenerationModel` starts with initializing an Embedding layer, a GRU, and a Linear layer. Similar to the sequence models for classification, when a matrix of integers is input to the model:

- We first use a PyTorch Embedding instance, the `char_embedding`, to convert the integers to a three dimensional tensor (a sequence of vectors for each batch item);
- This tensor is passed to the GRU, which computes a hidden state vector for each character in each sequence.

The primary difference between the sequence classification tasks and sequence prediction tasks of this chapter is how the state vectors computed by the RNN are handled. In classification, we retrieved a single vector per batch index and performed predictions using those single vectors. In this example, we reshape our three-dimensional tensor `(N,L,F)` into a two-dimensional tensor (a matrix `(NxL,F)`) with each row represents a character (batch and sequence index) and the columns of each row are features (embedding for the character). Using this matrix and the Linear layer, we compute prediction vectors for every character. We finish the computation by reshaping the matrix back into a threedimensional tensor. Because the ordering information is preserved with reshaping operations, each batch and sequence index is still in the same position. The reason why we needed to reshape is because the Linear layer requires a matrix as input.

```
class SurnameGenerationModel(nn.Module):
    def __init__(self, char_embedding_size, char_vocab_size, rnn_hidden_size,
                 batch_first=True, padding_idx=0, dropout_p=0.5):
        """
        Args:
            char_embedding_size (int): The size of the character embeddings
            char_vocab_size (int): The number of characters to embed
            rnn_hidden_size (int): The size of the RNN's hidden state
            batch_first (bool): Informs whether the input tensors will
                have batch or the sequence on the 0th dimension
            padding_idx (int): The index for the tensor padding;
                see torch.nn.Embedding
            dropout_p (float): the probability of zeroing activations using
                the dropout method.  higher means more likely to zero.
        """
        super(SurnameGenerationModel, self).__init__()

        self.char_emb = nn.Embedding(num_embeddings=char_vocab_size,
                                     embedding_dim=char_embedding_size,
                                     padding_idx=padding_idx)

        self.rnn = nn.GRU(input_size=char_embedding_size,
                          hidden_size=rnn_hidden_size,
                          batch_first=batch_first)

        self.fc = nn.Linear(in_features=rnn_hidden_size,
                            out_features=char_vocab_size)

        self._dropout_p = dropout_p

    def forward(self, x_in, apply_softmax=False):
        """The forward pass of the model

        Args:
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, input_dim)
            apply_softmax (bool): a flag for the softmax activation
```

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```
                should be false if used with the Cross Entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch, char_vocab_size)
        """
        x_embedded = self.char_emb(x_in)

        y_out, _ = self.rnn(x_embedded)

        batch_size, seq_size, feat_size = y_out.shape
        y_out = y_out.contiguous().view(batch_size * seq_size, feat_size)

        y_out = self.fc(F.dropout(y_out, p=self._dropout_p))

        if apply_softmax:
            y_out = F.softmax(y_out, dim=1)

        new_feat_size = y_out.shape[-1]
        y_out = y_out.view(batch_size, seq_size, new_feat_size)

        return y_out
```

Even though the percharacter accuracy of the predictions is a measure of model performance, it is better in this example to do qualitative evaluation by inspecting what kinds of surnames the model will generate. To do this, we write a new loop over a modified version of the steps in the `forward()` method to compute predictions at each time step and use those predictions as the input to the following time step. Please see the code in the `sample_from_model()` function.

The output of the model at each time step is a prediction vector which is turned into a probability distribution using the softmax function. Using the probability distribution, we take advantage of the `torch.multinomial()` sampling function, which selects an index at a rate proportional to the probability of the index. Sampling is a stochastic procedure that produces different outputs each time.

```
def sample_from_model(model, vectorizer, num_samples=1, sample_size=20,
                      temperature=1.0):
    """Sample a sequence of indices from the model

    Args:
        model (SurnameGenerationModel): the trained model
        vectorizer (SurnameVectorizer): the corresponding vectorizer
        num_samples (int): the number of samples
        sample_size (int): the max length of the samples
        temperature (float): accentuates or flattens
            the distribution.
            0.0 < temperature < 1.0 will make it peakier.
            temperature > 1.0 will make it more uniform
    Returns:
        indices (torch.Tensor): the matrix of indices;
        shape = (num_samples, sample_size)
    """
    begin_seq_index = [vectorizer.char_vocab.begin_seq_index
                       for _ in range(num_samples)]
    begin_seq_index = torch.tensor(begin_seq_index,
                                   dtype=torch.int64).unsqueeze(dim=1)
    indices = [begin_seq_index]
    h_t = None

    for time_step in range(sample_size):
```

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```
        x_t = indices[time_step]
        x_emb_t = model.char_emb(x_t)
        rnn_out_t, h_t = model.rnn(x_emb_t, h_t)
        prediction_vector = model.fc(rnn_out_t.squeeze(dim=1))
        probability_vector = F.softmax(prediction_vector / temperature, dim=1)
        indices.append(torch.multinomial(probability_vector, num_samples=1))
    indices = torch.stack(indices).squeeze().permute(1, 0)
    return indices
```

We need to transform the sampled indices from the `sample_from_model()` function into a string for humanreadable output. The `decode_sample()` function demonstrates, to do this, we use the `SequenceVocabulary` that was used to vectorize the surnames. In creating the string, we use only the indices up to the `ENDOFSEQUENCE` index. This assumes that the model learns some sense of when surnames should end.

```
def decode_samples(sampled_indices, vectorizer):
    """Transform indices into the string form of a surname

    Args:
        sampled_indices (torch.Tensor): the inidces from `sample_from_model`
        vectorizer (SurnameVectorizer): the corresponding vectorizer
    """
    decoded_surnames = []
    vocab = vectorizer.char_vocab

    for sample_index in range(sampled_indices.shape[0]):
        surname = ""
        for time_step in range(sampled_indices.shape[1]):
            sample_item = sampled_indices[sample_index, time_step].item()
            if sample_item == vocab.begin_seq_index:
                continue
            elif sample_item == vocab.end_seq_index:
                break
            else:
                surname += vocab.lookup_index(sample_item)
        decoded_surnames.append(surname)
    return decoded_surnames
```

11.5.4 Training Routine

Helper functions

```
def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
```

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```
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.
    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= loss_tm1:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])
                train_state['early_stopping_best_val'] = loss_t

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state

def normalize_sizes(y_pred, y_true):
    """Normalize tensor sizes

    Args:
        y_pred (torch.Tensor): the output of the model
            If a 3-dimensional tensor, reshapes to a matrix
        y_true (torch.Tensor): the target predictions
            If a matrix, reshapes to be a vector
    """
    if len(y_pred.size()) == 3:
        y_pred = y_pred.contiguous().view(-1, y_pred.size(2))
    if len(y_true.size()) == 2:
        y_true = y_true.contiguous().view(-1)
```

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```
    return y_pred, y_true

def compute_accuracy(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)

    _, y_pred_indices = y_pred.max(dim=1)

    correct_indices = torch.eq(y_pred_indices, y_true).float()
    valid_indices = torch.ne(y_true, mask_index).float()

    n_correct = (correct_indices * valid_indices).sum().item()
    n_valid = valid_indices.sum().item()

    return n_correct / n_valid * 100

def sequence_loss(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)
    return F.cross_entropy(y_pred, y_true, ignore_index=mask_index)
```

General utilities

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)
```

Settings and some prep work

```
args = Namespace(
    # Data and Path information
    surname_csv="../data/surnames/surnames_with_splits.csv",
    vectorizer_file="vectorizer.json",
    model_state_file="model.pth",
    save_dir="model_storage/model1_unconditioned_surname_generation",
    # Model hyper parameters
    char_embedding_size=32,
    rnn_hidden_size=32,
    # Training hyper parameters
    seed=1337,
    learning_rate=0.001,
    batch_size=128,
    num_epochs=100,
    early_stopping_criteria=5,
    # Runtime options
    catch_keyboard_interrupt=True,
    cuda=True,
    expand_filepaths_to_save_dir=True,
    reload_from_files=False,
```

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```
)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))


# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage/model1_unconditioned_surname_generation\vectorizer.json
        model_storage/model1_unconditioned_surname_generation\model.pth
Using CUDA: True
```

Initializations

```
if args.reload_from_files:
    # training from a checkpoint
    dataset = SurnameDataset.load_dataset_and_load_vectorizer(args.surname_csv,
                                                              args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = SurnameDataset.load_dataset_and_make_vectorizer(args.surname_csv)
    dataset.save_vectorizer(args.vectorizer_file)

vectorizer = dataset.get_vectorizer()

model = SurnameGenerationModel(char_embedding_size=args.char_embedding_size,
                               char_vocab_size=len(vectorizer.char_vocab),
                               rnn_hidden_size=args.rnn_hidden_size,
                               padding_idx=vectorizer.char_vocab.mask_index)
```

Training loop

```
mask_index = vectorizer.char_vocab.mask_index

model = model.to(args.device)


optimizer = optim.Adam(model.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)
train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                 total=args.num_epochs,
                 position=0)

dataset.set_split('train')
train_bar = tqdm(desc='split=train',
                 total=dataset.get_num_batches(args.batch_size),
                 position=1,
                 leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
               total=dataset.get_num_batches(args.batch_size),
               position=1,
               leave=True)

try:
    for epoch_index in range(args.num_epochs):
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on
        dataset.set_split('train')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        model.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = model(x_in=batch_dict['x_data'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)
```

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```
            # step 4. use loss to produce gradients
            loss.backward()

            # step 5. use optimizer to take gradient step
            optimizer.step()
            # -----------------------------------------
            # compute the  running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # update bar
            train_bar.set_postfix(loss=running_loss,
                                  acc=running_acc,
                                  epoch=epoch_index)
            train_bar.update()

        train_state['train_loss'].append(running_loss)
        train_state['train_acc'].append(running_acc)

        # Iterate over val dataset

        # setup: batch generator, set loss and acc to 0; set eval mode on
        dataset.set_split('val')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.
        running_acc = 0.
        model.eval()

        for batch_index, batch_dict in enumerate(batch_generator):
            # compute the output
            y_pred = model(x_in=batch_dict['x_data'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # compute the  running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # Update bar
            val_bar.set_postfix(loss=running_loss, acc=running_acc,
                                epoch=epoch_index)
            val_bar.update()

        train_state['val_loss'].append(running_loss)
        train_state['val_acc'].append(running_acc)

        train_state = update_train_state(args=args, model=model,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])

        if train_state['stop_early']:
```

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```
            break

        # move model to cpu for sampling
        model = model.cpu()
        sampled_surnames = decode_samples(
            sample_from_model(model, vectorizer, num_samples=2),
            vectorizer)
        epoch_bar.set_postfix(sample1=sampled_surnames[0],
                              sample2=sampled_surnames[1])
        # move model back to whichever device it should be on
        model = model.to(args.device)

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.update()

except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/60 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/12 [00:00<?, ?it/s]
```

```
np.random.choice(np.arange(len(vectorizer.nationality_vocab)), replace=True, size=2)
```

```
array([8, 7])
```

```
# compute the loss & accuracy on the test set using the best available model

model.load_state_dict(torch.load(train_state['model_filename']))

model = model.to(args.device)

dataset.set_split('test')
batch_generator = generate_batches(dataset,
                                   batch_size=args.batch_size,
                                   device=args.device)
running_acc = 0.
model.eval()

for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred = model(x_in=batch_dict['x_data'])

    # compute the loss
    loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

    # compute the accuracy
    running_loss += (loss.item() - running_loss) / (batch_index + 1)

    acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
    running_acc += (acc_t - running_acc) / (batch_index + 1)
```

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```
train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {};".format(train_state['test_loss']))
print("Test Accuracy: {}".format(train_state['test_acc']))
```

```
Test loss: 2.6623813112576804;
Test Accuracy: 23.699346354510485
```

11.5.5 Inference

```
# number of names to generate
num_names = 10
model = model.cpu()
# Generate nationality hidden state
sampled_surnames = decode_samples(
    sample_from_model(model, vectorizer, num_samples=num_names),
    vectorizer)
# Show results
print ("-"*15)
for i in range(num_names):
    print (sampled_surnames[i])
```

```
---------------
Clan
Turkuek
Srigbo
T
Gchare
Wagil
Noélaveyo
Faiausmeiduz
Spylik
Wardhin
```

Using the functions `sample_from_model()` and `decode_samples()`, we can inspect the output of the model above, to get a sense of whether the model is learning to generate sensible surnames.

What can we learn from inspecting the output?

We can see that although the surnames appear to follow several morphological patterns, the names don't appear distinctly to be of one nationality or another. One possibility is that learning a general model of surnames confuses the character distributions between different nationalities. The conditioned `SurnameGenerationModel` is meant to handle this kind of situation.

11.6 Surname Generation Conditioned

The difference in the conditioned `SurnameGenerationModel`, is that an extra Embedding is introduced to map the nationality indices to vectors the same size as the RNN's hidden layer. Then, in the forward function, nationality indices are embedded and simply passed in as the initial hidden layer of the RNN. Although this is a very simple modification to the first model, it has a profound effect in letting the RNN change its behavior based on the nationality of the surname being generated.

The `sample_from_model()` function is also modified to accept a list of nationality indices rather than a specified number of samples. The modified function uses the nationality indices with the nationality embedding to construct the initial hidden state of the GRU. After that, the sampling procedure is exactly the same as with the unconditioned model.

Your Turn

Find the relevant code section and try to understand the changes.

11.6.1 Imports

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
from torch.nn import functional as F
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm.notebook import tqdm
```

11.6.2 Data Vectorization classes

Vocabulary

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx
```

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```
        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
```

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```
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):

        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
                         'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

Vectorizer

```
class SurnameVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, char_vocab, nationality_vocab):
        """
        Args:
            char_vocab (SequenceVocabulary): maps words to integers
            nationality_vocab (Vocabulary): maps nationalities to integers
        """
        self.char_vocab = char_vocab
        self.nationality_vocab = nationality_vocab

    def vectorize(self, surname, vector_length=-1):
        """Vectorize a surname into a vector of observations and targets

        The outputs are the vectorized surname split into two vectors:
            surname[:-1] and surname[1:]
        At each timestep, the first vector is the observation and the second vector␣
↪is the target.

        Args:
            surname (str): the surname to be vectorized
            vector_length (int): an argument for forcing the length of index vector
        Returns:
            a tuple: (from_vector, to_vector)
            from_vector (numpy.ndarray): the observation vector
            to_vector (numpy.ndarray): the target prediction vector
        """
        indices = [self.char_vocab.begin_seq_index]
        indices.extend(self.char_vocab.lookup_token(token) for token in surname)
        indices.append(self.char_vocab.end_seq_index)

        if vector_length < 0:
            vector_length = len(indices) - 1

        from_vector = np.zeros(vector_length, dtype=np.int64)
        from_indices = indices[:-1]
        from_vector[:len(from_indices)] = from_indices
        from_vector[len(from_indices):] = self.char_vocab.mask_index

        to_vector = np.zeros(vector_length, dtype=np.int64)
        to_indices = indices[1:]
        to_vector[:len(to_indices)] = to_indices
        to_vector[len(to_indices):] = self.char_vocab.mask_index

        return from_vector, to_vector

    @classmethod
    def from_dataframe(cls, surname_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            surname_df (pandas.DataFrame): the surname dataset
        Returns:
            an instance of the SurnameVectorizer
        """
```

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```
        char_vocab = SequenceVocabulary()
        nationality_vocab = Vocabulary()

        for index, row in surname_df.iterrows():
            for char in row.surname:
                char_vocab.add_token(char)
            nationality_vocab.add_token(row.nationality)

        return cls(char_vocab, nationality_vocab)

    @classmethod
    def from_serializable(cls, contents):
        """Instantiate the vectorizer from saved contents

        Args:
            contents (dict): a dict holding two vocabularies for this vectorizer
                This dictionary is created using `vectorizer.to_serializable()`
        Returns:
            an instance of SurnameVectorizer
        """
        char_vocab = SequenceVocabulary.from_serializable(contents['char_vocab'])
        nat_vocab =  Vocabulary.from_serializable(contents['nationality_vocab'])

        return cls(char_vocab=char_vocab, nationality_vocab=nat_vocab)

    def to_serializable(self):
        """ Returns the serializable contents """
        return {'char_vocab': self.char_vocab.to_serializable(),
                'nationality_vocab': self.nationality_vocab.to_serializable()}
```

Dataset

```
class SurnameDataset(Dataset):
    def __init__(self, surname_df, vectorizer):
        """
        Args:
            surname_df (pandas.DataFrame): the dataset
            vectorizer (SurnameVectorizer): vectorizer instatiated from dataset
        """
        self.surname_df = surname_df
        self._vectorizer = vectorizer

        self._max_seq_length = max(map(len, self.surname_df.surname)) + 2

        self.train_df = self.surname_df[self.surname_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.surname_df[self.surname_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.surname_df[self.surname_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
```

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```
                                'test': (self.test_df, self.test_size)}

        self.set_split('train')

    @classmethod
    def load_dataset_and_make_vectorizer(cls, surname_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            surname_csv (str): location of the dataset
        Returns:
            an instance of SurnameDataset
        """

        surname_df = pd.read_csv(surname_csv)
        return cls(surname_df, SurnameVectorizer.from_dataframe(surname_df))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, surname_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
            surname_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of SurnameDataset
        """
        surname_df = pd.read_csv(surname_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(surname_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of SurnameVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return SurnameVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer
```

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```
    def set_split(self, split="train"):
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point: (x_data, y_target, class_index)
        """
        row = self._target_df.iloc[index]

        from_vector, to_vector = \
            self._vectorizer.vectorize(row.surname, self._max_seq_length)

        nationality_index = \
            self._vectorizer.nationality_vocab.lookup_token(row.nationality)

        return {'x_data': from_vector,
                'y_target': to_vector,
                'class_index': nationality_index}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size

def generate_batches(dataset, batch_size, shuffle=True,
                     drop_last=True, device="cpu"):
    """
    A generator function which wraps the PyTorch DataLoader. It will
      ensure each tensor is on the write device location.
    """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name].to(device)
        yield out_data_dict
```

```
x = torch.ones(5, 5)
```

```
x = x.to("cuda")
```

```
y = torch.zeros(5)
y
```

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

```
y.to(x.device)
```

```
tensor([0., 0., 0., 0., 0.], device='cuda:0')
```

11.6.3 The Model: SurnameGenerationModel

```
class SurnameGenerationModel(nn.Module):
    def __init__(self, char_embedding_size, char_vocab_size, num_nationalities,
                 rnn_hidden_size, batch_first=True, padding_idx=0, dropout_p=0.5):
        """
        Args:
            char_embedding_size (int): The size of the character embeddings
            char_vocab_size (int): The number of characters to embed
            num_nationalities (int): The size of the prediction vector
            rnn_hidden_size (int): The size of the RNN's hidden state
            batch_first (bool): Informs whether the input tensors will
                have batch or the sequence on the 0th dimension
            padding_idx (int): The index for the tensor padding;
                see torch.nn.Embedding
            dropout_p (float): the probability of zeroing activations using
                the dropout method.  higher means more likely to zero.
        """
        super(SurnameGenerationModel, self).__init__()

        self.char_emb = nn.Embedding(num_embeddings=char_vocab_size,
                                     embedding_dim=char_embedding_size,
                                     padding_idx=padding_idx)

        self.nation_emb = nn.Embedding(num_embeddings=num_nationalities,
                                       embedding_dim=rnn_hidden_size)

        self.rnn = nn.GRU(input_size=char_embedding_size,
                          hidden_size=rnn_hidden_size,
                          batch_first=batch_first)

        self.fc = nn.Linear(in_features=rnn_hidden_size,
                            out_features=char_vocab_size)

        self._dropout_p = dropout_p

    def forward(self, x_in, nationality_index, apply_softmax=False):
        """The forward pass of the model

        Args:
            x_in (torch.Tensor): an input data tensor.
                x_in.shape should be (batch, max_seq_size)
            nationality_index (torch.Tensor): The index of the nationality for each␣
↪data point
                Used to initialize the hidden state of the RNN
```

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```
            apply_softmax (bool): a flag for the softmax activation
                should be false if used with the Cross Entropy losses
        Returns:
            the resulting tensor. tensor.shape should be (batch, char_vocab_size)
        """
        x_embedded = self.char_emb(x_in)

        # hidden_size: (num_layers * num_directions, batch_size, rnn_hidden_size)
        # L,N,F
        nationality_embedded = self.nation_emb(nationality_index).unsqueeze(0)

        y_out, _ = self.rnn(x_embedded, nationality_embedded)

        # N,L,F
        batch_size, seq_size, feat_size = y_out.shape
        y_out = y_out.contiguous().view(batch_size * seq_size, feat_size)

        y_out = self.fc(F.dropout(y_out, p=self._dropout_p))

        if apply_softmax:
            y_out = F.softmax(y_out, dim=1)

        new_feat_size = y_out.shape[-1]
        y_out = y_out.view(batch_size, seq_size, new_feat_size)

        return y_out
```

```
def sample_from_model(model, vectorizer, nationalities, sample_size=20,
                      temperature=1.0):
    """Sample a sequence of indices from the model

    Args:
        model (SurnameGenerationModel): the trained model
        vectorizer (SurnameVectorizer): the corresponding vectorizer
        nationalities (list): a list of integers representing nationalities
        sample_size (int): the max length of the samples
        temperature (float): accentuates or flattens
            the distribution.
            0.0 < temperature < 1.0 will make it peakier.
            temperature > 1.0 will make it more uniform
    Returns:
        indices (torch.Tensor): the matrix of indices;
        shape = (num_samples, sample_size)
    """
    num_samples = len(nationalities)
    begin_seq_index = [vectorizer.char_vocab.begin_seq_index
                       for _ in range(num_samples)]
    begin_seq_index = torch.tensor(begin_seq_index,
                                   dtype=torch.int64).unsqueeze(dim=1)
    indices = [begin_seq_index]
    nationality_indices = torch.tensor(nationalities, dtype=torch.int64).
↪unsqueeze(dim=0)
    h_t = model.nation_emb(nationality_indices)

    for time_step in range(sample_size):
        x_t = indices[time_step]
```

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```
        x_emb_t = model.char_emb(x_t)
        rnn_out_t, h_t = model.rnn(x_emb_t, h_t)
        prediction_vector = model.fc(rnn_out_t.squeeze(dim=1))
        probability_vector = F.softmax(prediction_vector / temperature, dim=1)
        indices.append(torch.multinomial(probability_vector, num_samples=1))
    indices = torch.stack(indices).squeeze().permute(1, 0)
    return indices
```

```
def decode_samples(sampled_indices, vectorizer):
    """Transform indices into the string form of a surname

    Args:
        sampled_indices (torch.Tensor): the inidces from `sample_from_model`
        vectorizer (SurnameVectorizer): the corresponding vectorizer
    """
    decoded_surnames = []
    vocab = vectorizer.char_vocab

    for sample_index in range(sampled_indices.shape[0]):
        surname = ""
        for time_step in range(sampled_indices.shape[1]):
            sample_item = sampled_indices[sample_index, time_step].item()
            if sample_item == vocab.begin_seq_index:
                continue
            elif sample_item == vocab.end_seq_index:
                break
            else:
                surname += vocab.lookup_index(sample_item)
        decoded_surnames.append(surname)
    return decoded_surnames
```

11.6.4 Training Routine

Computing the loss in this example requires two changes when compared with previous examples because we are making predictions at every time step in the sequence.

1. We reshape three-dimensional tensors to two-dimensional tensors (matrices) to satisfy computational constraints.
2. We coordinate the masking index, which allows for variable length sequences, with the loss function so that the loss does not use the masked positions in its computations.

The `normalize_sizes()` function below normalize the predictions and the targets to sizes that the loss function expects (two dimensions for the predictions and one dimension for the targets). After size normalization, each row represents a single sample: one time step in one sequence.

The `equence_loss()` function ensures that the crossentropy loss is used with the `ignore_index` set to the `mask_index`. This has the effect of the loss function ignoring any position in the targets that matches the `ignore_index`.

Helper functions

```
def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.
    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= loss_tm1:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])
                train_state['early_stopping_best_val'] = loss_t

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state
```

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```
def normalize_sizes(y_pred, y_true):
    """Normalize tensor sizes

    Args:
        y_pred (torch.Tensor): the output of the model
            If a 3-dimensional tensor, reshapes to a matrix
        y_true (torch.Tensor): the target predictions
            If a matrix, reshapes to be a vector
    """
    if len(y_pred.size()) == 3:
        y_pred = y_pred.contiguous().view(-1, y_pred.size(2))
    if len(y_true.size()) == 2:
        y_true = y_true.contiguous().view(-1)
    return y_pred, y_true

def compute_accuracy(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)

    _, y_pred_indices = y_pred.max(dim=1)

    correct_indices = torch.eq(y_pred_indices, y_true).float()
    valid_indices = torch.ne(y_true, mask_index).float()

    n_correct = (correct_indices * valid_indices).sum().item()
    n_valid = valid_indices.sum().item()

    return n_correct / n_valid * 100

def sequence_loss(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)
    return F.cross_entropy(y_pred, y_true, ignore_index=mask_index)
```

General utilities

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)
```

Settings and some prep work

```
args = Namespace(
    # Data and Path information
    surname_csv="../data/surnames/surnames_with_splits.csv",
    vectorizer_file="vectorizer.json",
    model_state_file="model.pth",
    save_dir="model_storage/model2_conditioned_surname_generation",
    # Model hyper parameters
    char_embedding_size=32,
    rnn_hidden_size=32,
    # Training hyper parameters
    seed=1337,
    learning_rate=0.001,
    batch_size=128,
    num_epochs=100,
    early_stopping_criteria=5,
    # Runtime options
    catch_keyboard_interrupt=True,
    cuda=True,
    expand_filepaths_to_save_dir=True,
    reload_from_files=False,
)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))

# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage/model2_conditioned_surname_generation\vectorizer.json
        model_storage/model2_conditioned_surname_generation\model.pth
Using CUDA: True
```

Initializations

```
if args.reload_from_files:
    # training from a checkpoint
    dataset = SurnameDataset.load_dataset_and_load_vectorizer(args.surname_csv,
                                                              args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = SurnameDataset.load_dataset_and_make_vectorizer(args.surname_csv)
    dataset.save_vectorizer(args.vectorizer_file)

vectorizer = dataset.get_vectorizer()

model = SurnameGenerationModel(char_embedding_size=args.char_embedding_size,
                               char_vocab_size=len(vectorizer.char_vocab),
                               num_nationalities=len(vectorizer.nationality_vocab),
                               rnn_hidden_size=args.rnn_hidden_size,
                               padding_idx=vectorizer.char_vocab.mask_index,
                               dropout_p=0.5)
```

Training loop

```
mask_index = vectorizer.char_vocab.mask_index

model = model.to(args.device)


optimizer = optim.Adam(model.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)
train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                 total=args.num_epochs,
                 position=0)

dataset.set_split('train')
train_bar = tqdm(desc='split=train',
                 total=dataset.get_num_batches(args.batch_size),
                 position=1,
                 leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
               total=dataset.get_num_batches(args.batch_size),
               position=1,
               leave=True)

try:
    for epoch_index in range(args.num_epochs):
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on
```

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```
        dataset.set_split('train')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        model.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = model(x_in=batch_dict['x_data'],
                           nationality_index=batch_dict['class_index'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)


            # step 4. use loss to produce gradients
            loss.backward()

            # step 5. use optimizer to take gradient step
            optimizer.step()
            # ----------------------------------------
            # compute the  running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # update bar
            train_bar.set_postfix(loss=running_loss,
                                  acc=running_acc,
                                  epoch=epoch_index)
            train_bar.update()

        train_state['train_loss'].append(running_loss)
        train_state['train_acc'].append(running_acc)

        # Iterate over val dataset

        # setup: batch generator, set loss and acc to 0; set eval mode on
        dataset.set_split('val')
        batch_generator = generate_batches(dataset,
                                           batch_size=args.batch_size,
                                           device=args.device)
        running_loss = 0.
        running_acc = 0.
        model.eval()

        for batch_index, batch_dict in enumerate(batch_generator):
            # compute the output
            y_pred = model(x_in=batch_dict['x_data'],
```

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```
                            nationality_index=batch_dict['class_index'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # compute the  running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)
            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # Update bar
            val_bar.set_postfix(loss=running_loss, acc=running_acc,
                                epoch=epoch_index)
            val_bar.update()

        train_state['val_loss'].append(running_loss)
        train_state['val_acc'].append(running_acc)

        train_state = update_train_state(args=args, model=model,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])

        if train_state['stop_early']:
            break

        # move model to cpu for sampling

        nationalities = np.random.choice(np.arange(len(vectorizer.nationality_vocab)),
↪ replace=True, size=2)
        model = model.cpu()
        sampled_surnames = decode_samples(
            sample_from_model(model, vectorizer, nationalities=nationalities),
            vectorizer)

        sample1 = "{}->{}".format(vectorizer.nationality_vocab.lookup_
↪index(nationalities[0]),
                                  sampled_surnames[0])
        sample2 = "{}->{}".format(vectorizer.nationality_vocab.lookup_
↪index(nationalities[1]),
                                  sampled_surnames[1])
        epoch_bar.set_postfix(sample1=sample1,
                              sample2=sample2)
        # move model back to whichever device it should be on
        model = model.to(args.device)

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.update()

except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/60 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/12 [00:00<?, ?it/s]
```

```
# compute the loss & accuracy on the test set using the best available model

model.load_state_dict(torch.load(train_state['model_filename']))

model = model.to(args.device)

dataset.set_split('test')
batch_generator = generate_batches(dataset,
                                   batch_size=args.batch_size,
                                   device=args.device)
running_acc = 0.
model.eval()

for batch_index, batch_dict in enumerate(batch_generator):
    # compute the output
    y_pred = model(x_in=batch_dict['x_data'],
                   nationality_index=batch_dict['class_index'])

    # compute the loss
    loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

    # compute the running loss and running accuracy
    running_loss += (loss.item() - running_loss) / (batch_index + 1)
    acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
    running_acc += (acc_t - running_acc) / (batch_index + 1)

train_state['test_loss'] = running_loss
train_state['test_acc'] = running_acc
```

```
print("Test loss: {};".format(train_state['test_loss']))
print("Test Accuracy: {}".format(train_state['test_acc']))
```

```
Test loss: 2.4188760916392007;
Test Accuracy: 28.964094993312216
```

11.6.5 Sampling

```
model = model.cpu()
for index in range(len(vectorizer.nationality_vocab)):
    nationality = vectorizer.nationality_vocab.lookup_index(index)
    print("Sampled for {}: ".format(nationality))
    sampled_indices = sample_from_model(model, vectorizer,
                                        nationalities=[index] * 3,
                                        temperature=0.7)
    for sampled_surname in decode_samples(sampled_indices, vectorizer):
        print("-  " + sampled_surname)
```

```
Sampled for Arabic:
-  Bohama
```

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```
-  Badol
-  Setar
Sampled for Chinese:
-  Anga
-  Anfo
-  Mini
Sampled for Czech:
-  Chakabins
-  Fringo
-  Altrora
Sampled for Dutch:
-  Harlach
-  Himtell
-  Methabel
Sampled for English:
-  Storel
-  Hurin
-  Fiente
Sampled for French:
-  Dirnis
-  Piin
-  Malbello
Sampled for German:
-  Wesnen
-  Tinnit
-  Kachark
Sampled for Greek:
-  Minusha
-  Yichekse
-  Alelagon
Sampled for Irish:
-  Solley
-  Warahin
-  Ciwene
Sampled for Italian:
-  Aceahe
-  Ansatea
-  Hyras
Sampled for Japanese:
-  Vosani
-  Tunago
-  Staroka
Sampled for Korean:
-  Co
-  Ded
-  Tes
Sampled for Polish:
-  Sovzon
-  Povourov
-  Haera
Sampled for Portuguese:
-  Giagori
-  Neara
-  Firnou
Sampled for Russian:
-  Kavanon
-  Askanek
```

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```
-  Turendov
Sampled for Scottish:
-  Miwodr
-  Korothrin
-  Teneitin
Sampled for Spanish:
-  Arnkir
-  Ccille
-  Barn
Sampled for Vietnamese:
-  Na
-  Kinno
-  Lan
```

CHAPTER

TWELVE

LAB12: SEQUENCE TO SEQUENCE LEARNING WITH ATTENTION

In this lab we introduce the basic attention (cross-attention) and the self-attention mechansim, applying them to the same square sequence predication problem we have seen in Lab11's Sequence to Sequence Model.

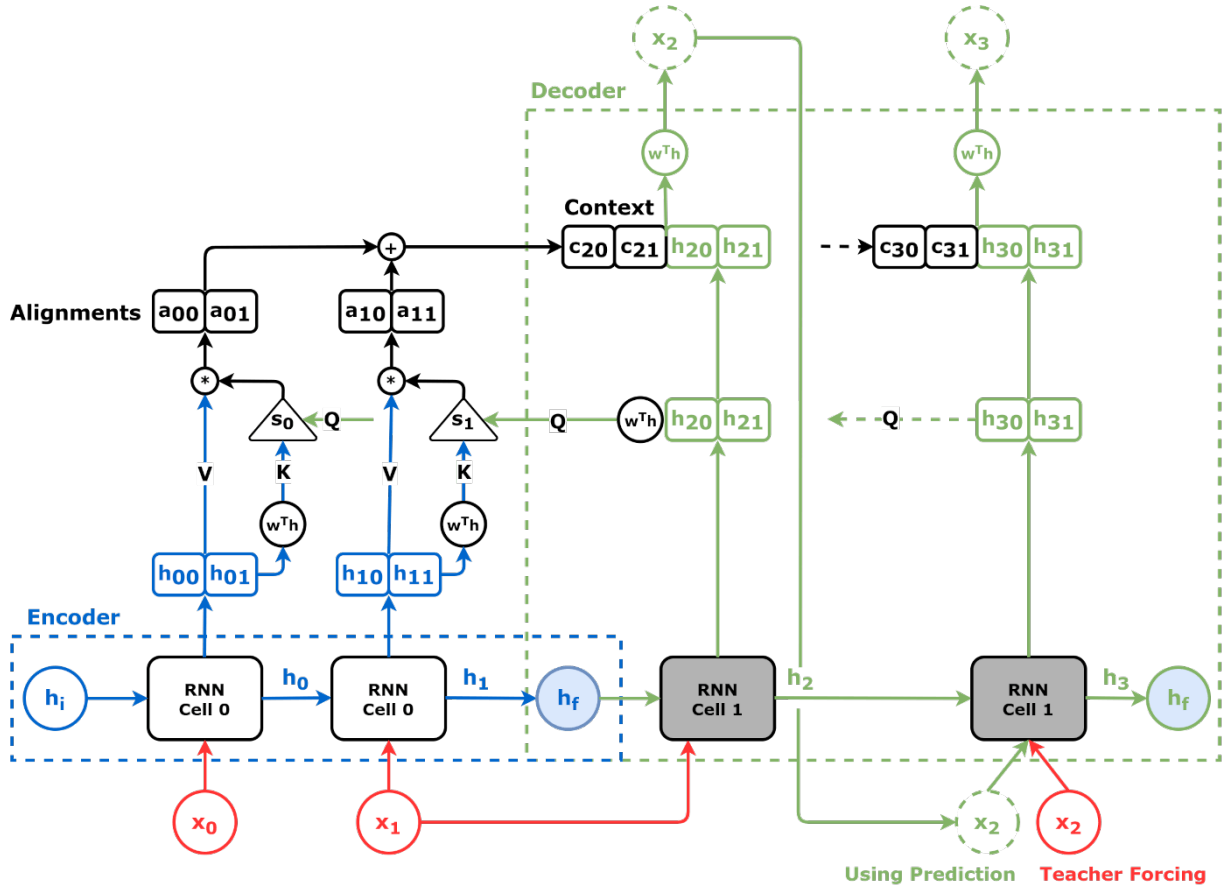
The second part of this lab focuses on a real neural machine translation task to build attention based models, one with no sampling (i.e. using teacher forcing 100% of the time), and another with scheduled sampling (i.e. using teacher forcing only sometimes). Since we have biGRU for the Encoder, the masked padded sequence in the backward layer would affect the results. So here we take the opportunity to introduce the `PackedSequence` in PyTorch to handle variable length sequences.

Credit: the notebooks are adapted from:

- Chpater 9 of Deep Learning with PyTorch Step-by-Step
- Chapter 8 of Natural Language Processing with PyTorch

12.1 Attention Mechanism

In this notebook, we introduce the attention mechanism to our plain sequence to sequence model, as illustrated in the diagram below:



12.1.1 Download Untility Files for Plotting and Data Generation

Download these utility functions first and place them in the same directory as this notebook. These files are the same as the ones in Lab11 Sequence to Sequence Model.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\plots.py
```

```
FileLink('plots_seq2seq.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\plots_seq2seq.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\replay.py
```

12.1.2 Imports

```
import copy
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from util import StepByStep
from plots import *
from plots_seq2seq import *
```

12.1.3 Data Generation

We still make use of the Square Sequences, using the first two corners to predict the last two. Same method as before for generating noisy squares.

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

12.1.4 Plain Encoder-Decoder

We use exactly the same encoder-decoder from Lab11's sequence to sequence notebook.

```
class Encoder(nn.Module):
    def __init__(self, n_features, hidden_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.hidden = None
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)

    def forward(self, X):
```

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```
        rnn_out, self.hidden = self.basic_rnn(X)

        return rnn_out # N, L, F
```

```
class Decoder(nn.Module):
    def __init__(self, n_features, hidden_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.hidden = None
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)
        self.regression = nn.Linear(self.hidden_dim, self.n_features)

    def init_hidden(self, hidden_seq):
        # We only need the final hidden state
        hidden_final = hidden_seq[:, -1:] # N, 1, H
        # But we need to make it sequence-first
        self.hidden = hidden_final.permute(1, 0, 2) # 1, N, H

    def forward(self, X):
        # X is N, 1, F
        batch_first_output, self.hidden = self.basic_rnn(X, self.hidden)

        last_output = batch_first_output[:, -1:]
        out = self.regression(last_output)

        # N, 1, F
        return out.view(-1, 1, self.n_features)
```

```
class EncoderDecoder(nn.Module):
    def __init__(self, encoder, decoder, input_len, target_len, teacher_forcing_
↪prob=0.5):
        super().__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.input_len = input_len
        self.target_len = target_len
        self.teacher_forcing_prob = teacher_forcing_prob
        self.outputs = None

    def init_outputs(self, batch_size):
        device = next(self.parameters()).device
        # N, L (target), F
        self.outputs = torch.zeros(batch_size,
                                   self.target_len,
                                   self.encoder.n_features).to(device)

    def store_output(self, i, out):
        # Stores the output
        self.outputs[:, i:i+1, :] = out

    def forward(self, X):
        # splits the data in source and target sequences
        # the target seq will be empty in testing mode
        # N, L, F
        source_seq = X[:, :self.input_len, :]
```

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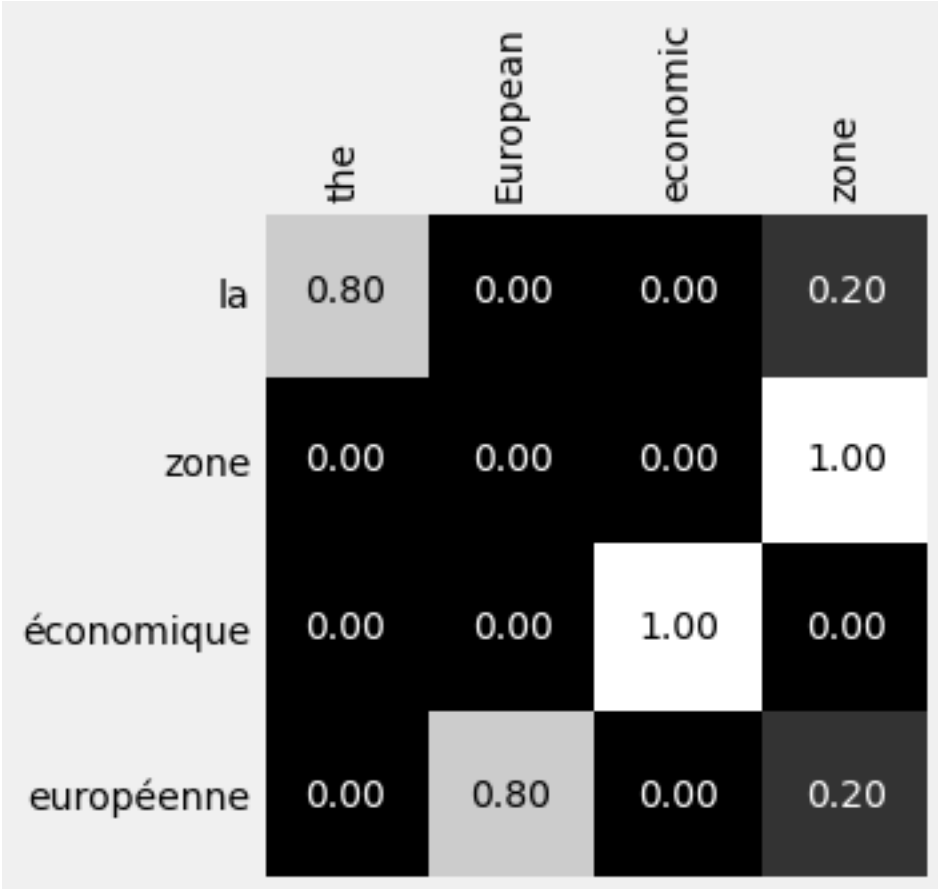
```
        target_seq = X[:, self.input_len:, :]
        self.init_outputs(X.shape[0])

        # Encoder expected N, L, F
        hidden_seq = self.encoder(source_seq)
        # Output is N, L, H
        self.decoder.init_hidden(hidden_seq)

        # The last input of the encoder is also
        # the first input of the decoder
        dec_inputs = source_seq[:, -1:, :]

        # Generates as many outputs as the target length
        for i in range(self.target_len):
            # Output of decoder is N, 1, F
            out = self.decoder(dec_inputs)
            self.store_output(i, out)

            prob = self.teacher_forcing_prob
            # In evaluation/test the target sequence is
            # unknown, so we cannot use teacher forcing
            if not self.training:
                prob = 0

            # If it is teacher forcing
            if torch.rand(1) <= prob:
                # Takes the actual element
                dec_inputs = target_seq[:, i:i+1, :]
            else:
                # Otherwise uses the last predicted output
                dec_inputs = out

        return self.outputs
```

12.1.5 Attention Mechanism Explained

An illustration of Attention Scores

```
fig = figure9()
```



Context Vector

The context vector is the weighted average of encoder hidden states.

$$context\ vector = \underbrace{\alpha_0 * h_0}_{alignment\ vector_0} + \underbrace{\alpha_1 * h_1}_{alignment\ vector_1} = 0.8 * value_{the} + 0.2 * value_{zone}$$

But how do we compute alphas - attention scores?

Let's use our own sequence-to-sequence problem, and the "perfect" square as input to illustrate how the context vector is computed.

A sequence `full_seq` is splitted into source and target sequences.

```
full_seq = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
source_seq = full_seq[:, :2]
target_seq = full_seq[:, 2:]
```

"Values" and "Keys"

The source sequence is the input of the encoder. The hidden states the encoder outputs are going to be both "values" (V) and "keys" (K):

```
torch.manual_seed(21)
encoder = Encoder(n_features=2, hidden_dim=2)
hidden_seq = encoder(source_seq)

values = hidden_seq # N, L, H
values
```

```
tensor([[[ 0.0832, -0.0356],
         [ 0.3105, -0.5263]]], grad_fn=<TransposeBackward1>)
```

```
keys = hidden_seq # N, L, H
keys
```

```
tensor([[[ 0.0832, -0.0356],
         [ 0.3105, -0.5263]]], grad_fn=<TransposeBackward1>)
```

Query

The encoder-decoder dynamics stay exactly the same: despite that we are sending the entire sequence of hidden states to the decoder, we still use the encoder's final hidden state as the decoder's initial hidden state.

In this example of using the first two corners to predict the last two, we still use the last element of the source sequence as input to the first step of the decoder:

```
torch.manual_seed(21)
decoder = Decoder(n_features=2, hidden_dim=2)
decoder.init_hidden(hidden_seq)

inputs = source_seq[:, -1:]
out = decoder(inputs)
```

The first "query" (Q) is the decoder's hidden state (remember, hidden states are always sequence-first, so we permute it to batch-first):

```
query = decoder.hidden.permute(1, 0, 2)  # N, 1, H
query
```

```
tensor([[[ 0.3913, -0.6853]]], grad_fn=<PermuteBackward>)
```

Compute the Attention Score

Once we have the "keys" and a "query", we can compute attention scores (alphas) using them. This is for illustration only, we will progressively develop the `calc_alphas()` to reflect the true processing in the digram.

Note: The alphas here do not make use of the values of keys and query, they are simply ones averaged by the sequence length.

```
def calc_alphas(ks, q):
    N, L, H = ks.size()
    alphas = torch.ones(N, 1, L).float() * 1/L
    return alphas

alphas = calc_alphas(keys, query)
alphas
```

```
tensor([[[0.5000, 0.5000]]])
```

We had to make sure alphas had the right shape (N, 1, L) so that, when multiplied by the "values" with shape (N, L, H), it will result in a weighted sum of the alignment vectors with shape (N, 1, H). We can use batch matrix multiplication (torch.bmm) for that:

$$(N, 1, L) \times (N, L, H) = (N, 1, H)$$

We can simply ignore the first dimension and PyTorch will go over all the elements in the mini-batch for us.

Warning: Why are we spending so much time on shapes and matrix multiplication?

Although it seems a fairly basic topic, getting the shapes and dimensions right is of utmost importance for the correct implementation of an algorithm or technique. Worst case is when using the wrong dimensions in an operation, PyTorch *may not raise an explicit error*, causing the almost undetectable Logical Error. This will ultimately damage the model's ability to learn.

```
# N, 1, L x N, L, H -> 1, L x L, H -> 1, H
context_vector = torch.bmm(alphas, values)
context_vector
```

```
tensor([[[ 0.1968, -0.2809]]], grad_fn=<BmmBackward0>)
```

Once the context vector is ready, we can concatenate it to the "query" (the decoder's hidden state) and use it as the input for the linear layer that actually generates the predicted coordinates:

```
concatenated = torch.cat([context_vector, query], axis=-1)
concatenated
```

```
tensor([[[ 0.1968, -0.2809,  0.3913, -0.6853]]], grad_fn=<CatBackward>)
```

In summary, the above can be summarised into the following steps of a typical attention mechanism:

- encoder to get hidden states, which are used as `"values"` as well as `"keys"`
- decoder to get the first hidden state, which is used as `"query"`
- query and keys to work out attention scores, `alphas`

- "values" weighted by alphas to get alignment vectors
- summing up alignment vectors to get the context vector
- concatenate context vector with the decoder hidden state (in this simplest case, the same as query), for output predication.

12.1.6 Scoring Method

In the calc_alpha() function above, we used the simple $\frac{1}{L}$ as weights, which produces an average of the hidden states. Below we show the use of dot product between Q and K as a scoring method.

Dot product

$$cos\ \theta = \frac{\sum_i q_i k_i}{\sqrt{\sum_j q_j^2}\sqrt{\sum_j k_j^2}}$$

$$cos\ \theta \sqrt{\sum_j q_j^2}\sqrt{\sum_j k_j^2} = \sum_i q_i k_i$$

$$cos\theta\ ||Q||\ ||K|| = Q \cdot K$$

```
# N, 1, H x N, H, L -> N, 1, L
products = torch.bmm(query, keys.permute(0, 2, 1))
products
```

```
tensor([[[0.0569, 0.4821]]], grad_fn=<BmmBackward0>)
```

Attention Scores

```
alphas = F.softmax(products, dim=-1)
alphas
```

```
tensor([[[0.3953, 0.6047]]], grad_fn=<SoftmaxBackward>)
```

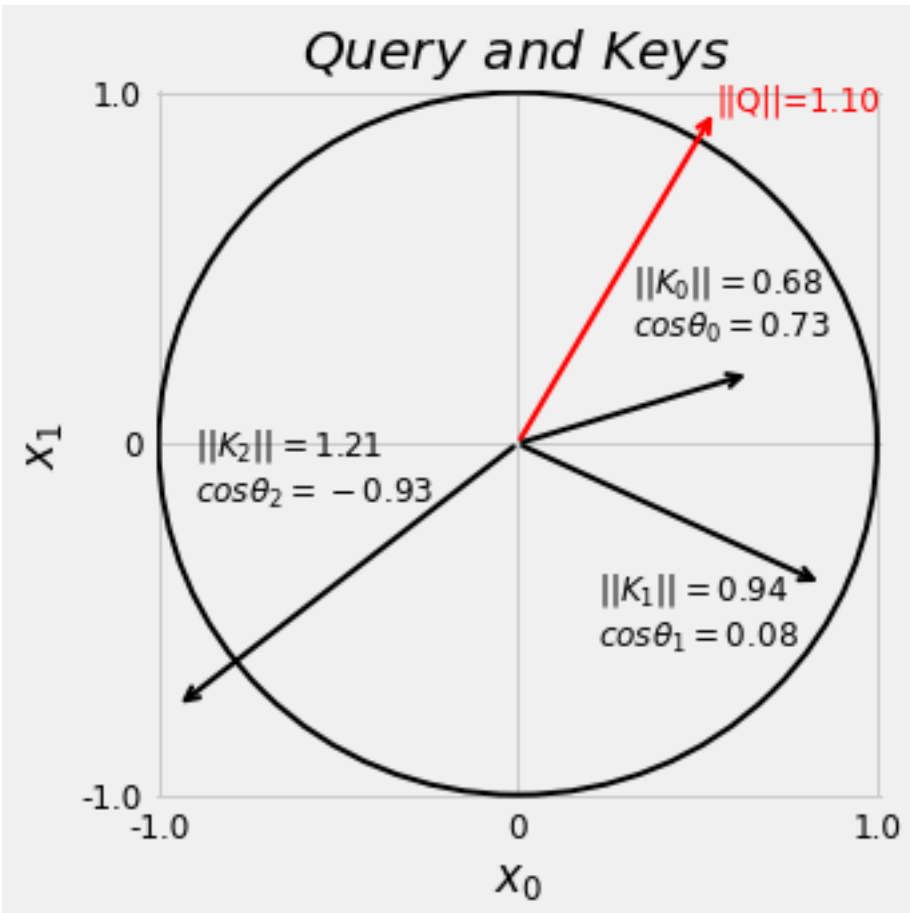
```
def calc_alphas(ks, q):
    # N, 1, H x N, H, L -> N, 1, L
    products = torch.bmm(q, ks.permute(0, 2, 1))
    alphas = F.softmax(products, dim=-1)
    return alphas
```

Visualizing the Context

Here we use a single query (`q`) and three keys (`k`) to illustrate the idea of using dot products in measuring vector similarity. Visually, the red query vector (Q) is closer to K_0.

```
q = torch.tensor([.55, .95]).view(1, 1, 2) # N, 1, H
k = torch.tensor([[.65, .2],
                  [.85, -.4],
                  [-.95, -.75]]).view(1, 3, 2) # N, L, H
```

```
fig = query_and_keys(q.squeeze(), k.view(3, 2))
```



$$
\begin{array}{lllll}
Q \cdot K_0 = cos\theta_0\ ||Q||\ ||K_0|| = & 0.73* & 1.10* & 0.68 = & 0.54 \\
Q \cdot K_1 = cos\theta_1\ ||Q||\ ||K_1|| = & 0.08* & 1.10* & 0.94 = & 0.08 \\
Q \cdot K_2 = cos\theta_2\ ||Q||\ ||K_2|| = - & 0.93* & 1.10* & 1.21 = - & 1.23
\end{array}
$$

```
# N, 1, H x N, H, L -> N, 1, L
prod = torch.bmm(q, k.permute(0, 2, 1))
prod
```

```
tensor([[[ 0.5475,  0.0875, -1.2350]]])
```

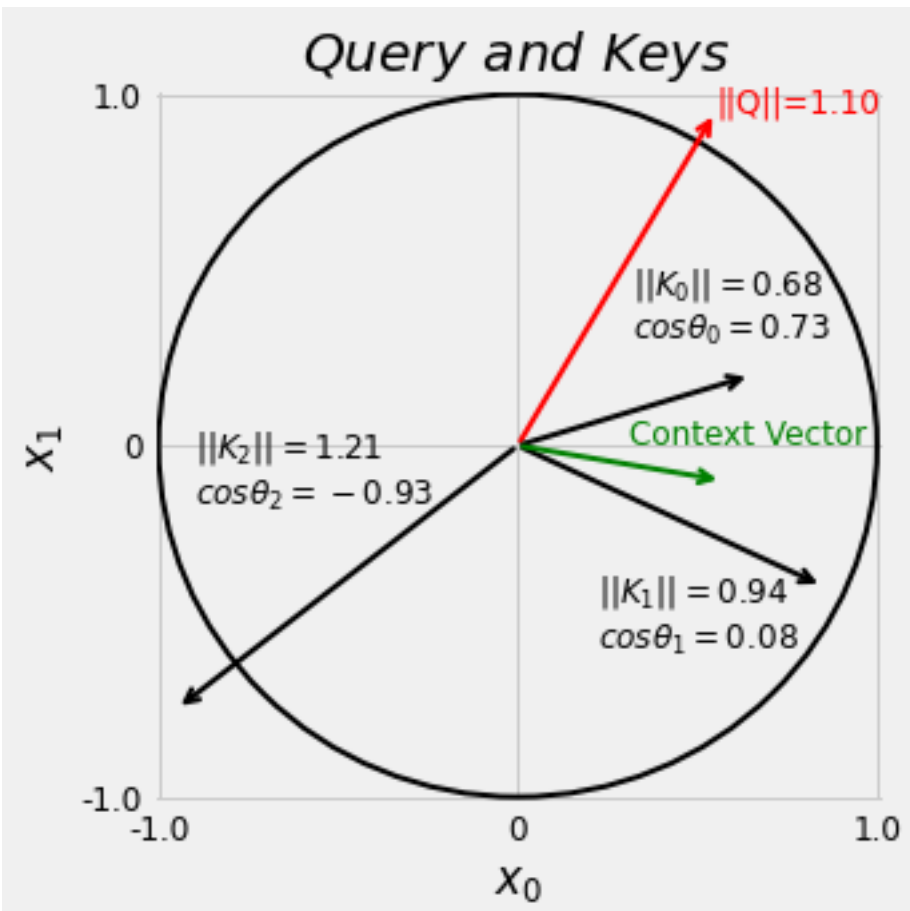
```
scores = F.softmax(prod, dim=-1)
scores
```

```
tensor([[[0.5557, 0.3508, 0.0935]]])
```

```
v = k
context = torch.bmm(scores, v)
context
```

```
tensor([[[ 0.5706, -0.0993]]])
```

```
fig = query_and_keys(q.squeeze(), k.view(3, 2), context)
```



Scaled Dot

The dot product score is sensitive to the length of the vectors, and we can normalise using the standard deviation, which is roughly the sequare root of the dimension of vector as verified using randomly generated normally distributed data.

Variance of a batch dot product is roughly the same as the dimension of the vector

```
n_dims = 10
dummy_qs = torch.randn(10000, 1, n_dims)
dummy_ks = torch.randn(10000, 1, n_dims).permute(0, 2, 1)
torch.bmm(dummy_qs, dummy_ks).squeeze().var()
```

```
tensor(9.7670)
```

$$Var(Q \cdot K) = d_q = d_k$$
$$\sigma(Q \cdot K) = \sqrt{d_q} = \sqrt{d_k}$$

```
dummy_product = torch.tensor([4.0, 1.0])
F.softmax(dummy_product, dim=-1), F.softmax(100*dummy_product, dim=-1)
```

```
(tensor([0.9526, 0.0474]), tensor([1., 0.]))
```

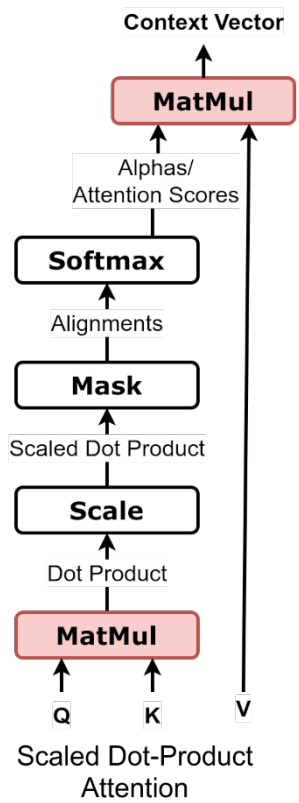
$$scaled\ dot\ product = \frac{Q \cdot K}{\sqrt{d_k}}$$

```
scaled_products = products / np.sqrt(2)
scaled_products
```

```
tensor([[[0.0403, 0.3409]]], grad_fn=<DivBackward0>)
```

```
alphas = F.softmax(scaled_products, dim=-1)
alphas
```

```
tensor([[[0.4254, 0.5746]]], grad_fn=<SoftmaxBackward>)
```




```
def calc_alphas(ks, q):
    dims = q.size(-1)
    # N, 1, H x N, H, L -> N, 1, L
    products = torch.bmm(q, ks.permute(0, 2, 1))
    scaled_products = products / np.sqrt(dims)
    alphas = F.softmax(scaled_products, dim=-1)
    return alphas
```

```
alphas = calc_alphas(keys, query)
# N, 1, L x N, L, H -> 1, L x L, H -> 1, H
context_vector = torch.bmm(alphas, values)
context_vector
```

```
tensor([[[ 0.2138, -0.3175]]], grad_fn=<BmmBackward0>)
```

12.1.7 Encoder Decoder with Attention Mechanism

Attention Class

```
class Attention(nn.Module):
    def __init__(self, hidden_dim, input_dim=None, proj_values=False):
        super().__init__()
        self.d_k = hidden_dim
        self.input_dim = hidden_dim if input_dim is None else input_dim
        self.proj_values = proj_values
        # Affine transformations for Q, K, and V
```

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```
        self.linear_query = nn.Linear(self.input_dim, hidden_dim)
        self.linear_key = nn.Linear(self.input_dim, hidden_dim)
        self.linear_value = nn.Linear(self.input_dim, hidden_dim)
        self.alphas = None

    def init_keys(self, keys):
        self.keys = keys
        self.proj_keys = self.linear_key(self.keys)
        self.values = self.linear_value(self.keys) \
                      if self.proj_values else self.keys

    def score_function(self, query):
        proj_query = self.linear_query(query)
        # scaled dot product
        # N, 1, H x N, H, L -> N, 1, L
        dot_products = torch.bmm(proj_query, self.proj_keys.permute(0, 2, 1))
        scores =  dot_products / np.sqrt(self.d_k)
        return scores

    def forward(self, query, mask=None):
        # Query is batch-first N, 1, H
        scores = self.score_function(query) # N, 1, L
        if mask is not None:
            scores = scores.masked_fill(mask == 0, -1e9)
        alphas = F.softmax(scores, dim=-1) # N, 1, L
        self.alphas = alphas.detach()

        # N, 1, L x N, L, H -> N, 1, H
        context = torch.bmm(alphas, self.values)
        return context
```

Source Mask

```
source_seq = torch.tensor([[[-1., 1.], [0., 0.]]])
# pretend there's an encoder here...
keys = torch.tensor([[[-.38, .44], [.85, -.05]]])
query = torch.tensor([[[-1., 1.]]])
```

```
source_mask = (source_seq != 0).all(axis=2).unsqueeze(1)
source_mask # N, 1, L
```

```
tensor([[[ True, False]]])
```

```
torch.manual_seed(11)
attnh = Attention(2)
attnh.init_keys(keys)

context = attnh(query, mask=source_mask)
attnh.alphas
```

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

Decoder with Attention

```
class DecoderAttn(nn.Module):
    def __init__(self, n_features, hidden_dim):
        super().__init__()
        self.hidden_dim = hidden_dim
        self.n_features = n_features
        self.hidden = None
        self.basic_rnn = nn.GRU(self.n_features, self.hidden_dim, batch_first=True)
        self.attn = Attention(self.hidden_dim)
        self.regression = nn.Linear(2 * self.hidden_dim, self.n_features)

    def init_hidden(self, hidden_seq):
        # the output of the encoder is N, L, H
        # and init_keys expects batch-first as well
        self.attn.init_keys(hidden_seq)
        hidden_final = hidden_seq[:, -1:]
        self.hidden = hidden_final.permute(1, 0, 2)    # L, N, H

    def forward(self, X, mask=None):
        # X is N, 1, F
        batch_first_output, self.hidden = self.basic_rnn(X, self.hidden)

        query = batch_first_output[:, -1:]
        # Attention
        context = self.attn(query, mask=mask)
        concatenated = torch.cat([context, query], axis=-1)
        out = self.regression(concatenated)

        # N, 1, F
        return out.view(-1, 1, self.n_features)
```

```
full_seq = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
source_seq = full_seq[:, :2]
target_seq = full_seq[:, 2:]
```

```
torch.manual_seed(21)
encoder = Encoder(n_features=2, hidden_dim=2)
decoder_attn = DecoderAttn(n_features=2, hidden_dim=2)

# Generates hidden states (keys and values)
hidden_seq = encoder(source_seq)
decoder_attn.init_hidden(hidden_seq)

# Target sequence generation
inputs = source_seq[:, -1:]
target_len = 2
for i in range(target_len):
    out = decoder_attn(inputs)
    print(f'Output: {out}')
    inputs = out
```

```
Output: tensor([[[-0.3555, -0.1220]]], grad_fn=<ViewBackward>)
Output: tensor([[[-0.2641, -0.2521]]], grad_fn=<ViewBackward>)
```

Encoder + Decoder + Attention

We can safely use the orginal code for grouping the encoder and decoder (in this case, the decoder with attention), and create a valid model, but we would like to store the output to visualise attention scores.

```
encdec = EncoderDecoder(encoder, decoder_attn, input_len=2, target_len=2, teacher_
↪forcing_prob=0.0)
encdec(full_seq)
```

```
tensor([[[-0.3555, -0.1220],
         [-0.2641, -0.2521]]], grad_fn=<CopySlices>)
```

```
class EncoderDecoderAttn(EncoderDecoder):
    def __init__(self, encoder, decoder, input_len, target_len, teacher_forcing_
↪prob=0.5):
        super().__init__(encoder, decoder, input_len, target_len, teacher_forcing_
↪prob)
        self.alphas = None

    def init_outputs(self, batch_size):
        device = next(self.parameters()).device
        # N, L (target), F
        self.outputs = torch.zeros(batch_size,
                                   self.target_len,
                                   self.encoder.n_features).to(device)
        # N, L (target), L (source)
        self.alphas = torch.zeros(batch_size,
                                  self.target_len,
                                  self.input_len).to(device)

    def store_output(self, i, out):
        # Stores the output
        self.outputs[:, i:i+1, :] = out
        self.alphas[:, i:i+1, :] = self.decoder.attn.alphas
```

Data Preparation

Training data of the square sequences generated.

```
points, directions = generate_sequences()
full_train = torch.as_tensor(points).float()
target_train = full_train[:, 2:]
```

```
test_points, test_directions = generate_sequences(seed=19)
full_test = torch.as_tensor(points).float()
source_test = full_test[:, :2]
target_test = full_test[:, 2:]
```

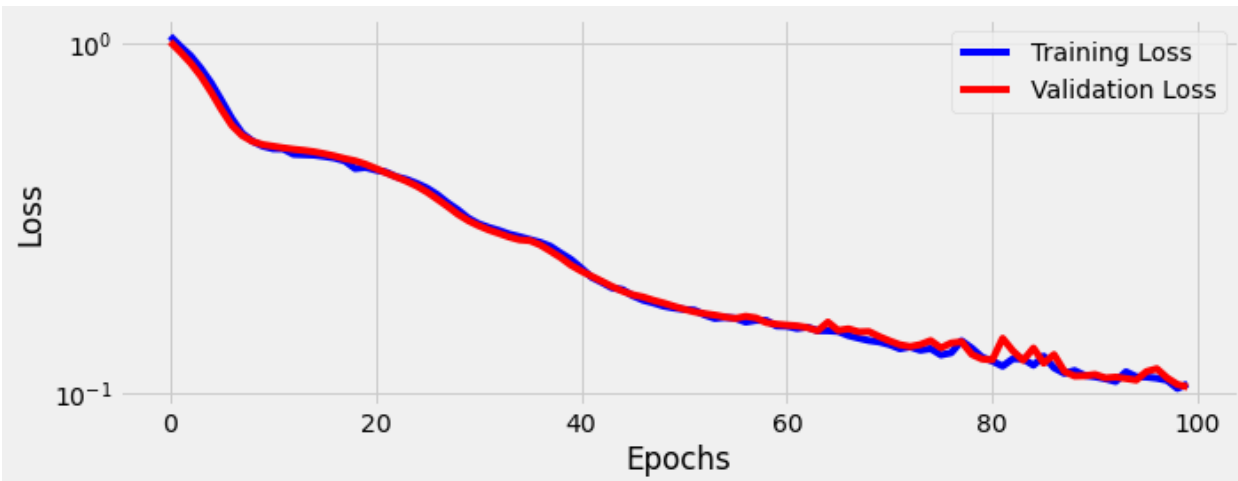
```
train_data = TensorDataset(full_train, target_train)
test_data = TensorDataset(source_test, target_test)

generator = torch.Generator()
train_loader = DataLoader(train_data, batch_size=16, shuffle=True,␣
↪generator=generator)
test_loader = DataLoader(test_data, batch_size=16)
```

Model Configuration & Training

```
torch.manual_seed(23)
encoder = Encoder(n_features=2, hidden_dim=2)
decoder_attn = DecoderAttn(n_features=2, hidden_dim=2)
model = EncoderDecoderAttn(encoder, decoder_attn, input_len=2, target_len=2, teacher_
↪forcing_prob=0.5)
loss = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

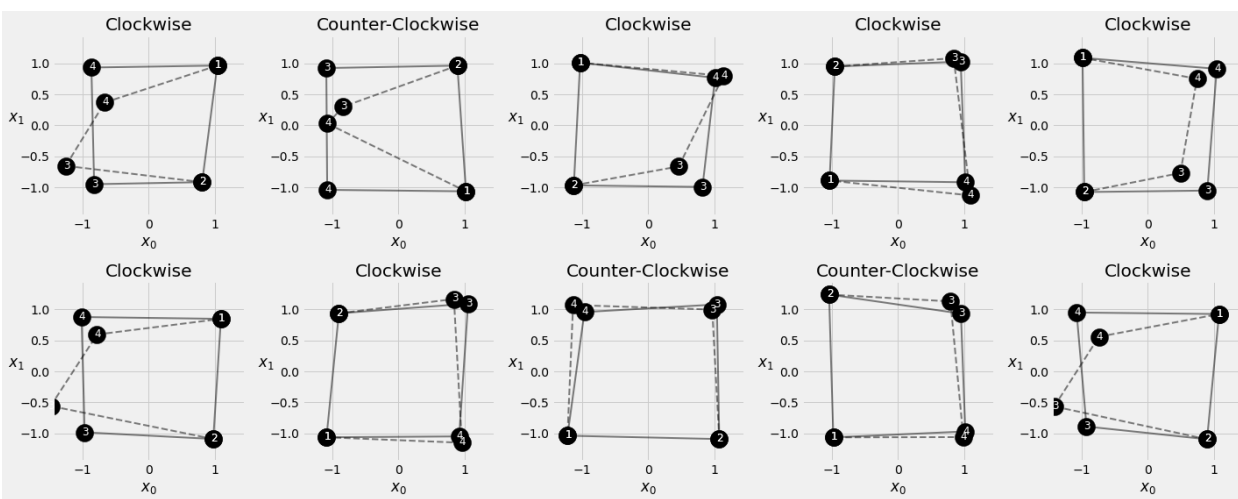
```
sbs_seq_attn = StepByStep(model, loss, optimizer)
sbs_seq_attn.set_loaders(train_loader, test_loader)
sbs_seq_attn.train(100)
```

```
fig = sbs_seq_attn.plot_losses()
```



Visualizing Predictions

```
fig = sequence_pred(sbs_seq_attn, full_test, test_directions)
```



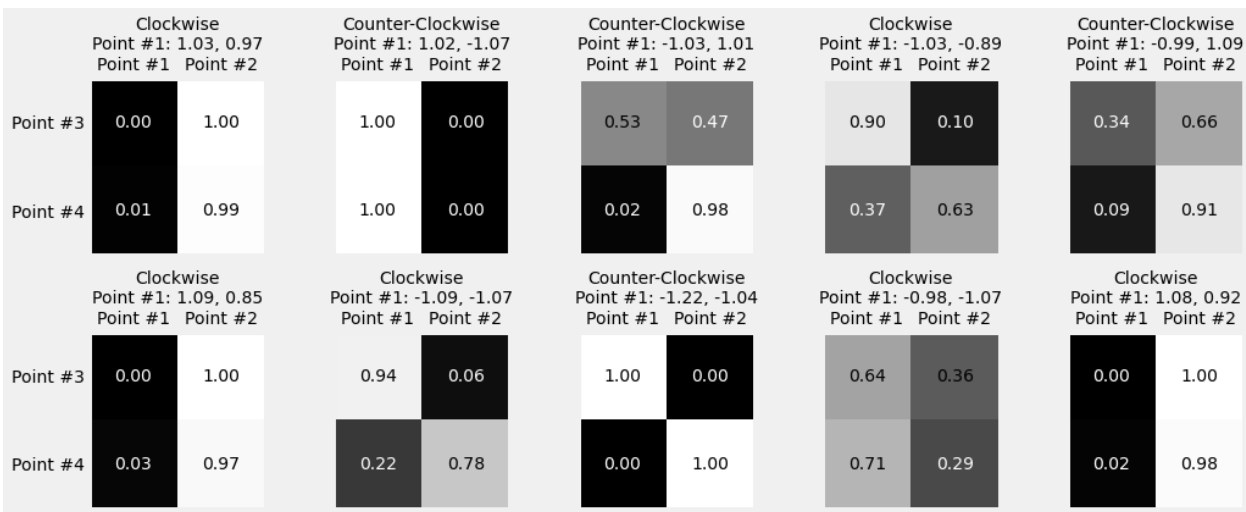
Visualizing Attention

```
inputs = full_train[:1, :2]
out = sbs_seq_attn.predict(inputs)
sbs_seq_attn.model.alphas
```

```
tensor([[[7.8848e-04, 9.9921e-01],
         [1.0210e-02, 9.8979e-01]]], device='cuda:0')
```

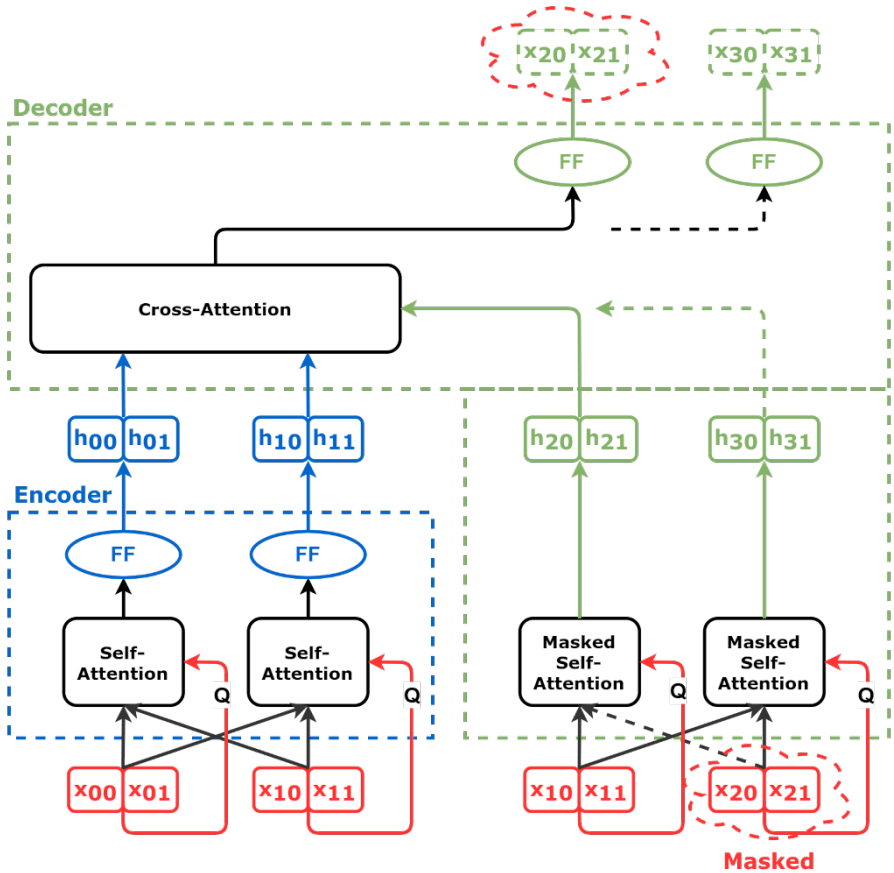
$$\begin{array}{c|cc} & source & \\ target & x_0 & x_1 \\ \hline x_2 & \alpha_{20} & \alpha_{21} \\ x_3 & \alpha_{30} & \alpha_{31} \end{array} \Longrightarrow \begin{array}{c|cc} & source & \\ target & x_0 & x_1 \\ \hline x_2 & 0.0011 & 0.9989 \\ x_3 & 0.0146 & 0.9854 \end{array}$$

```
inputs = full_train[:10, :2]
source_labels = ['Point #1', 'Point #2']
target_labels = ['Point #3', 'Point #4']
point_labels = [f'{"Counter-" if not directions[i] else ""}Clockwise\nPoint #1:
 ↪{inp[0, 0]:.2f}, {inp[0, 1]:.2f}' for i, inp in enumerate(inputs)]
fig = plot_attention(model, inputs, point_labels, source_labels, target_labels)
```



12.2 Self-Attention

In this notebook, we look at how self-attention works. In other words, no RNN, but simply self attention of source sequence for the encoder, attention (both self and cross) of the **shifted target sequence** for the decoder.



12.2.1 Download Untility Files for Plotting and Data Generation

Download these utility functions first and place them in the same directory as this notebook. These files are the same as the ones in Lab11 Sequence to Sequence Model.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\plots.py
```

```
FileLink('plots_seq2seq.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\plots_seq2seq.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\attention\replay.py
```

12.2.2 Imports

```
import copy
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from util import StepByStep
from plots import *
from plots_seq2seq import *
```

12.2.3 Data Generation

We still make use of the Square Sequences, using the first two corners to predict the last two. Same method as before for generating noisy squares.

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

12.2.4 Multi-Headed Attention

```
class Attention(nn.Module):
    def __init__(self, hidden_dim, input_dim=None, proj_values=False):
        super().__init__()
        self.d_k = hidden_dim
        self.input_dim = hidden_dim if input_dim is None else input_dim
        self.proj_values = proj_values
        # Affine transformations for Q, K, and V
        self.linear_query = nn.Linear(self.input_dim, hidden_dim)
        self.linear_key = nn.Linear(self.input_dim, hidden_dim)
        self.linear_value = nn.Linear(self.input_dim, hidden_dim)
        self.alphas = None

    def init_keys(self, keys):
        self.keys = keys
        self.proj_keys = self.linear_key(self.keys)
        self.values = self.linear_value(self.keys) \
                      if self.proj_values else self.keys

    def score_function(self, query):
        proj_query = self.linear_query(query)
        # scaled dot product
        # N, 1, H x N, H, L -> N, 1, L
        dot_products = torch.bmm(proj_query, self.proj_keys.permute(0, 2, 1))
        scores =  dot_products / np.sqrt(self.d_k)
        return scores

    def forward(self, query, mask=None):
        # Query is batch-first N, 1, H
        scores = self.score_function(query) # N, 1, L
        if mask is not None:
            scores = scores.masked_fill(mask == 0, -1e9)
        alphas = F.softmax(scores, dim=-1) # N, 1, L
        self.alphas = alphas.detach()

        # N, 1, L x N, L, H -> N, 1, H
        context = torch.bmm(alphas, self.values)
        return context
```

```
class MultiHeadAttention(nn.Module):
    def __init__(self, n_heads, d_model, input_dim=None, proj_values=True):
        super().__init__()
        self.linear_out = nn.Linear(n_heads * d_model, d_model)
        self.attn_heads = nn.ModuleList([Attention(d_model,
                                                   input_dim=input_dim,
                                                   proj_values=proj_values)
                                         for _ in range(n_heads)])

    def init_keys(self, key):
        for attn in self.attn_heads:
            attn.init_keys(key)

    @property
    def alphas(self):
        # Shape: n_heads, N, 1, L (source)
        return torch.stack([attn.alphas for attn in self.attn_heads], dim=0)
```

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```
    def output_function(self, contexts):
        # N, 1, n_heads * D
        concatenated = torch.cat(contexts, axis=-1)
        # Linear transf. to go back to original dimension
        out = self.linear_out(concatenated) # N, 1, D
        return out

    def forward(self, query, mask=None):
        contexts = [attn(query, mask=mask) for attn in self.attn_heads]
        out = self.output_function(contexts)
        return out
```

12.2.5 Self-Attention

Instead of using RNN to generate the hidden states, we use attention mechanism to generate hidden states for inputs. This is called self-attention, i.e. attention on the input data points themselves. Each input will have its own context vector. All context vectors are concatenated and transformed through a linear layer, as an input to the feedforward network as hidden state for the corresponding input.

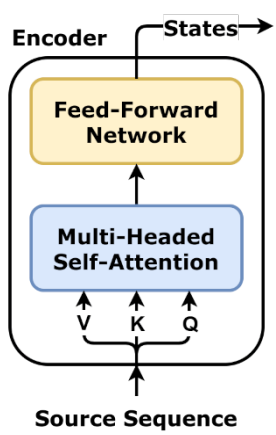
Attention Scores from Input

Inputs or their affine transformations are used as Keys, Values and Queries.

$$\alpha_{00}, \alpha_{01} = softmax(\frac{Q_0 \cdot K_0}{\sqrt{2}}, \frac{Q_0 \cdot K_1}{\sqrt{2}})$$
$$context\ vector_0 = \alpha_{00} V_0 + \alpha_{01} V_1$$

$$\alpha_{10}, \alpha_{11} = softmax(\frac{Q_1 \cdot K_0}{\sqrt{2}}, \frac{Q_1 \cdot K_1}{\sqrt{2}})$$
$$context\ vector_1 = \alpha_{10} V_0 + \alpha_{11} V_1$$

	source	
target	x_0	x_1
h_0	α_{00}	α_{01}
h_1	α_{10}	α_{11}



Encoder with Self-Attention

As you can see from the code below, each input has its own attention head, so it makes use of the multi-headed attention above. Check the code against the diagram for better understanding.

```
class EncoderSelfAttn(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.n_features = n_features
        self.self_attn_heads = MultiHeadAttention(n_heads, d_model, input_dim=n_
↪features)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
            nn.ReLU(),
            nn.Linear(ff_units, d_model),
        )

    def forward(self, query, mask=None):
        self.self_attn_heads.init_keys(query)
        att = self.self_attn_heads(query, mask)
        out = self.ffn(att)
        return out
```

Encoder the Square Sequence

The perfect sequare with four corners, is split into a source sequence of two corners and a target sequence of two corners.

```
full_seq = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
source_seq = full_seq[:, :2]
target_seq = full_seq[:, 2:]
```

```
torch.manual_seed(11)
encself = EncoderSelfAttn(n_heads=3, d_model=2, ff_units=10, n_features=2)
query = source_seq
encoder_states = encself(query)
encoder_states
```

```
tensor([[[-0.0498,  0.2193],
         [-0.0642,  0.2258]]], grad_fn=<AddBackward0>)
```

Decoder

This decoder has both self attention and cross-attention, which uses the decoder hidden state as query.

```
class DecoderSelfAttn(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.n_features = d_model if n_features is None else n_features
```

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```
        self.self_attn_heads = MultiHeadAttention(n_heads, d_model, input_dim=self.n_
↪features)
        self.cross_attn_heads = MultiHeadAttention(n_heads, d_model)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
            nn.ReLU(),
            nn.Linear(ff_units, self.n_features),
        )

    def init_keys(self, states):
        self.cross_attn_heads.init_keys(states)

    def forward(self, query, source_mask=None, target_mask=None):
        self.self_attn_heads.init_keys(query)
        att1 = self.self_attn_heads(query, target_mask)
        att2 = self.cross_attn_heads(att1, source_mask)
        out = self.ffn(att2)
        return out
```

Subsequent Inputs and Teacher Forcing

The **shifted target sequence** containes the last element of the source sequence, and everything but the last element of the target sequence.

```
shifted_seq = torch.cat([source_seq[:, -1:], target_seq[:, :-1]], dim=1)
```

Attention Scores

Because we feed the entire shifted target sequence to the decoder, we need to be careful not to allow the model to peek into the future.

The attention score α_{22} is problematic, because we are using the K_2 and V_2 which the model should not have seen yet for calculation. So we need **target mask** to ensure that it is not computed.

$$\alpha_{21}, \alpha_{22} = softmax(\frac{Q_1 \cdot K_1}{\sqrt{2}}, \frac{Q_1 \cdot K_2}{\sqrt{2}})$$
$$context\ vector_2 = \alpha_{21} V_1 + \alpha_{22} V_2$$

Below, it is fine for us to use K_2 and V_2 to caluate α_3.

$$\alpha_{31}, \alpha_{32} = softmax(\frac{Q_2 \cdot K_1}{\sqrt{2}}, \frac{Q_2 \cdot K_2}{\sqrt{2}})$$
$$context\ vector_3 = \alpha_{31} V_1 + \alpha_{32} V_2$$

Any values in the attention score matrix that are above the diagnal line needs to be masked. Here we need to mask α_{22} to 0. $

	$source$	
$target$	x_1	x_2
h_2	α_{21}	α_{22}
h_3	α_{31}	α_{32}

$

Target Mask (Training)

The masked scoreing matrix should look like this:

	source	
target	x_1	x_2
h_2	α_{21}	0
h_3	α_{31}	α_{32}

```
def subsequent_mask(size):
    attn_shape = (1, size, size)
    subsequent_mask = (1 - torch.triu(torch.ones(attn_shape), diagonal=1)).bool()
    return subsequent_mask
```

```
subsequent_mask(2) # 1, L, L
```

```
tensor([[[ True, False],
         [ True,  True]]])
```

Important: Subsequent Mask We must use this mask while querying the decoder to prevent it from cheating. You can choose to use an additional mask to "hide" more data from the decoder if you wish, but the subsequent mask is a strong requirement of the self-attention decoder.

```
torch.manual_seed(13)
decself = DecoderSelfAttn(n_heads=3, d_model=2, ff_units=10, n_features=2)
decself.init_keys(encoder_states)

query = shifted_seq
out = decself(query, target_mask=subsequent_mask(2))

decself.self_attn_heads.alphas
```

```
tensor([[[[1.0000, 0.0000],
          [0.4011, 0.5989]]],


        [[[1.0000, 0.0000],
          [0.4264, 0.5736]]],


        [[[1.0000, 0.0000],
          [0.6304, 0.3696]]]])
```

Target Mask (Evaluation/Prediction)

The only difference between training and evaluation, concerning the target mask, is that we'll be using larger masks as we go. The very first mask is actually trivial since there are no elements above the diagonal:

$$1^{st}\ Step \left\{ \begin{array}{c|c} target & source \\ & x_1 \\ \hline h_2 & \alpha_{21} \end{array} \right.$$

In evaluation/prediction time we only have the source sequence and, in our example, we use its last element as input for the decoder:

```
inputs = source_seq[:, -1:]
trg_masks = subsequent_mask(1)
out = decself(inputs, trg_masks)
out
```

```
tensor([[[0.4132, 0.3728]]], grad_fn=<AddBackward0>)
```

The mask is not actually masking anything in this case, and we get a prediction for the coordinates of x_2 as expected. In RNN based seq2seq models, this prediction would be used directly as the next input, but the self-attention decoder expects the full sequence as "query", so we concatenate the prediction to the previous "query".

```
inputs = torch.cat([inputs, out[:, -1:, :]], dim=-2)
inputs
```

```
tensor([[[-1.0000,  1.0000],
         [ 0.4132,  0.3728]]], grad_fn=<CatBackward>)
```

Now there are two data points for querying the decoder, so we adjust the mask accordingly.

$$2^{nd}\ Step \left\{ \begin{array}{c|cc} target & source & \\ & x_1 & x_2 \\ \hline h_2 & \alpha_{21} & 0 \\ h_3 & \alpha_{31} & \alpha_{32} \end{array} \right.$$

```
trg_masks = subsequent_mask(2)
out = decself(inputs, trg_masks)
out
```

```
tensor([[[0.4137, 0.3727],
         [0.4132, 0.3728]]], grad_fn=<AddBackward0>)
```

Important: The mask guarantees that the predicted x_2 (in the first step) won't change the predicted x_2 (in the second step) because predictions are made based on past data points only

The last prediction is, once again, concatenated to the previous "query".

```
inputs = torch.cat([inputs, out[:, -1:, :]], dim=-2)
inputs
```

```
tensor([[[-1.0000,  1.0000],
         [ 0.4132,  0.3728],
         [ 0.4132,  0.3728]]], grad_fn=<CatBackward>)
```

But, since we're actually done with the predictions (the desired target sequence has a length of two), we simply exclude the first data point in the query (the one coming from the source sequence) and that's the predicted target sequence

```
inputs[:, 1:]
```

```
tensor([[[0.4132, 0.3728],
         [0.4132, 0.3728]]], grad_fn=<SliceBackward>)
```

Encoder + Decoder + Self-Attention

```
class EncoderDecoderSelfAttn(nn.Module):
    def __init__(self, encoder, decoder, input_len, target_len):
        super().__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.input_len = input_len
        self.target_len = target_len
        self.trg_masks = self.subsequent_mask(self.target_len)

    @staticmethod
    def subsequent_mask(size):
        attn_shape = (1, size, size)
        subsequent_mask = (1 - torch.triu(torch.ones(attn_shape), diagonal=1))
        return subsequent_mask

    def encode(self, source_seq, source_mask):
        # Encodes the source sequence and uses the result
        # to initialize the decoder
        encoder_states = self.encoder(source_seq, source_mask)
        self.decoder.init_keys(encoder_states)

    def decode(self, shifted_target_seq, source_mask=None, target_mask=None):
        # Decodes/generates a sequence using the shifted (masked)
        # target sequence - used in TRAIN mode
        outputs = self.decoder(shifted_target_seq,
                               source_mask=source_mask,
                               target_mask=target_mask)
        return outputs

    def predict(self, source_seq, source_mask):
        # Decodes/generates a sequence using one input
        # at a time - used in EVAL mode
        inputs = source_seq[:, -1:]
        for i in range(self.target_len):
            out = self.decode(inputs, source_mask, self.trg_masks[:, :i+1, :i+1])
            out = torch.cat([inputs, out[:, -1:, :]], dim=-2)
            inputs = out.detach()
        outputs = inputs[:, 1:, :]
        return outputs

    def forward(self, X, source_mask=None):
```

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```
        # Sends the mask to the same device as the inputs
        self.trg_masks = self.trg_masks.type_as(X).bool()
        # Slices the input to get source sequence
        source_seq = X[:, :self.input_len, :]
        # Encodes source sequence AND initializes decoder
        self.encode(source_seq, source_mask)
        if self.training:
            # Slices the input to get the shifted target seq
            shifted_target_seq = X[:, self.input_len-1:-1, :]
            # Decodes using the mask to prevent cheating
            outputs = self.decode(shifted_target_seq, source_mask, self.trg_masks)
        else:
            # Decodes using its own predictions
            outputs = self.predict(source_seq, source_mask)

        return outputs
```

Data Preparation

```
points, directions = generate_sequences()
full_train = torch.as_tensor(points).float()
target_train = full_train[:, 2:]
```

```
test_points, test_directions = generate_sequences(seed=19)
full_test = torch.as_tensor(points).float()
source_test = full_test[:, :2]
target_test = full_test[:, 2:]
```

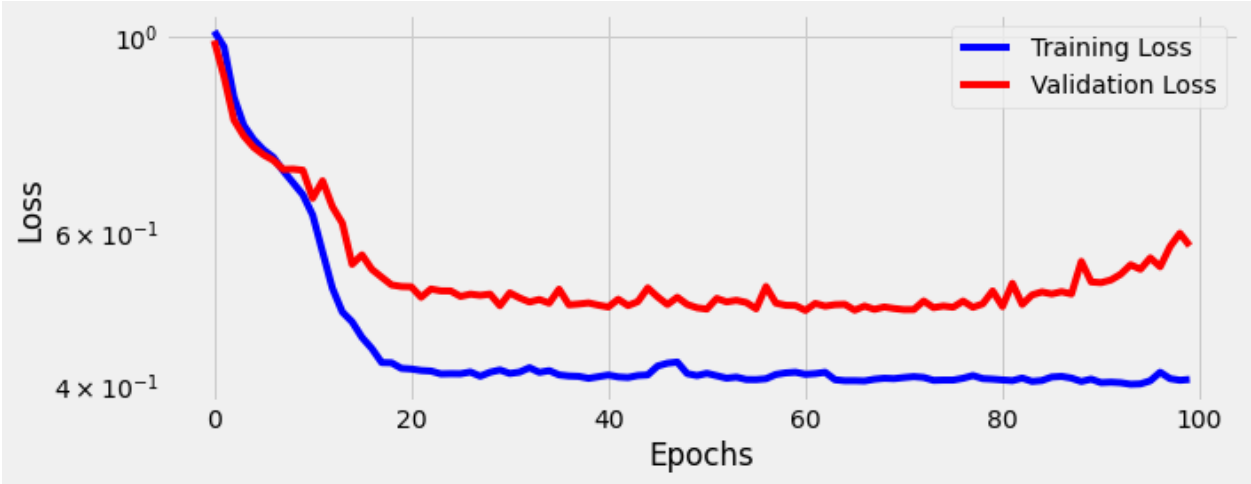
```
train_data = TensorDataset(full_train, target_train)
test_data = TensorDataset(source_test, target_test)

generator = torch.Generator()
train_loader = DataLoader(train_data, batch_size=16, shuffle=True,␣
 ↪generator=generator)
test_loader = DataLoader(test_data, batch_size=16)
```

Model Configuration & Training

```
torch.manual_seed(23)
encself = EncoderSelfAttn(n_heads=3, d_model=2, ff_units=10, n_features=2)
decself = DecoderSelfAttn(n_heads=3, d_model=2, ff_units=10, n_features=2)
model = EncoderDecoderSelfAttn(encself, decself, input_len=2, target_len=2)
loss = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

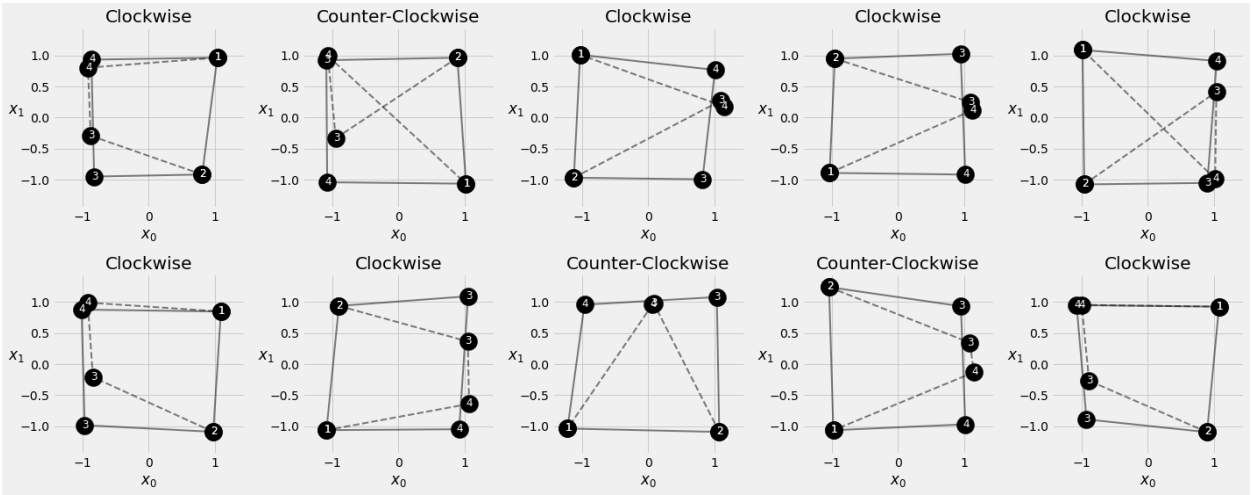
```
sbs_seq_selfattn = StepByStep(model, loss, optimizer)
sbs_seq_selfattn.set_loaders(train_loader, test_loader)
sbs_seq_selfattn.train(100)
```

```
fig = sbs_seq_selfattn.plot_losses()
```



Visualizing Predictions

```
fig = sequence_pred(sbs_seq_selfattn, full_test, test_directions)
```



12.3 Neual Machine Translation

For the following two notebooks, we use a dataset of English–French sentence pairs from the Tatoeba Project. Such paired dataset is referred to as a **parallel corpus**. This dataset is composed of pairs of English sentences and their corresponding French translations.

12.3.1 Imports

```
from argparse import Namespace
from nltk.tokenize import word_tokenize
import numpy as np
import pandas as pd
```

```
args = Namespace(
    source_data_path="../data/nmt/eng-fra.txt",
    output_data_path="../data/nmt/simplest_eng_fra.csv",
    perc_train=0.7,
    perc_val=0.15,
    perc_test=0.15,
    seed=1337
)

assert args.perc_test > 0 and (args.perc_test + args.perc_val + args.perc_train == 1.
↪0)
```

12.3.2 Preprocessing

The data preprocessing begins by reading the lines in and making all sentences lowercase and applying NLTK's English and French tokenizers to each of the sentence pairs.

```
with open(args.source_data_path, encoding="utf-8") as fp:
    lines = fp.readlines()

lines = [line.replace("\n", "").lower().split("\t") for line in lines]
```

Next, we apply NLTK's language-specific word tokenizer to create a list of tokens. Even though we do further computations, which we describe next, this list of tokens is a preprocessed dataset.

```
data = []
for english_sentence, french_sentence in lines:
    data.append({"english_tokens": word_tokenize(english_sentence, language="english
↪"),
                 "french_tokens": word_tokenize(french_sentence, language="french")})
```

12.3.3 Selecting a subset of data

Here we select a subset of the data we select consists of the English sentences that begin with "i am", "he is", "she is", "they are", "you are", or "we are". This reduces the dataset from 135,842 sentence pairs to just 13,062 sentence pairs, a factor of 10.

```
filter_phrases = (
    ("i", "am"), ("i", "'m"),
    ("he", "is"), ("he", "'s"),
    ("she", "is"), ("she", "'s"),
    ("you", "are"), ("you", "'re"),
    ("we", "are"), ("we", "'re"),
    ("they", "are"), ("they", "'re")
)
```

Creating empty lists as place holders for each filter phrase.

```
data_subset = {phrase: [] for phrase in filter_phrases}
data_subset
```

```
{('i', 'am'): [],
 ('i', "'m"): [],
 ('he', 'is'): [],
 ('he', "'s"): [],
 ('she', 'is'): [],
 ('she', "'s"): [],
 ('you', 'are'): [],
 ('you', "'re"): [],
 ('we', 'are'): [],
 ('we', "'re"): [],
 ('they', 'are'): [],
 ('they', "'re"): []}
```

Get the first two tokens of the English sentence as a key, if it is in the prepared data_subset keys, append the datum into the list of that key.

```
for datum in data:
    key = tuple(datum['english_tokens'][:2])
    if key in data_subset:
        data_subset[key].append(datum)
```

```
counts = {k: len(v) for k,v in data_subset.items()}
counts, sum(counts.values())
```

```
({('i', 'am'): 805,
  ('i', "'m"): 4760,
  ('he', 'is'): 1069,
  ('he', "'s"): 787,
  ('she', 'is'): 504,
  ('she', "'s"): 316,
  ('you', 'are'): 449,
  ('you', "'re"): 2474,
  ('we', 'are'): 181,
  ('we', "'re"): 1053,
  ('they', 'are'): 194,
  ('they', "'re"): 470},
 13062)
```

12.3.4 Training, Test, Validation Split

To finalize the learning setup, we split the subset of 13,062 sentence pairs into 70% training, 15% validation, and 15% test sets. The proportion of each sentence beginning with the just listed syntax is held constant by first grouping by sentence beginning, creating the splits from those groups, and then merging the splits from each group.

```
np.random.seed(args.seed)

dataset_stage3 = []
for phrase, datum_list in sorted(data_subset.items()):
    np.random.shuffle(datum_list)
    n_train = int(len(datum_list) * args.perc_train)
    n_val = int(len(datum_list) * args.perc_val)
```

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```
    for datum in datum_list[:n_train]:
        datum['split'] = 'train'

    for datum in datum_list[n_train:n_train+n_val]:
        datum['split'] = 'val'

    for datum in datum_list[n_train+n_val:]:
        datum['split'] = 'test'

    dataset_stage3.extend(datum_list)
```

```
# here we pop and assign into the dictionary, thus modifying in place
for datum in dataset_stage3:
    datum['source_language'] = " ".join(datum.pop('english_tokens'))
    datum['target_language'] = " ".join(datum.pop('french_tokens'))
```

12.3.5 A glimpse of the processed dataset

```
nmt_df = pd.DataFrame(dataset_stage3)
```

```
nmt_df.head()
```

```
   split                    source_language  \
0  train     he 's the cutest boy in town .
1  train                he 's a nonsmoker .
2  train            he 's smarter than me .
3  train         he 's a lovely young man .
4  train  he 's three years older than me .

                            target_language
0  c'est le garçon le plus mignon en ville .
1                       il est non-fumeur .
2          il est plus intelligent que moi .
3            c'est un adorable jeune homme .
4           il a trois ans de plus que moi .
```

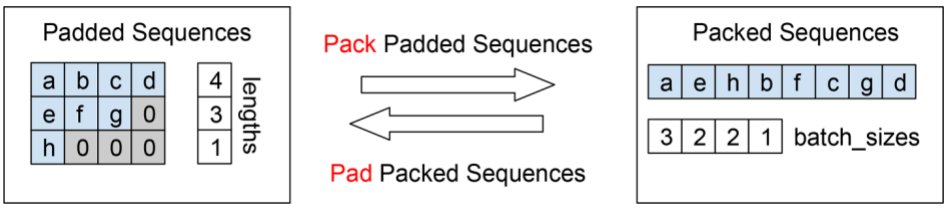
12.3.6 Write the processed dataset to disk

```
nmt_df.to_csv(args.output_data_path)
```

12.4 Packed Sequences

Normally, a minibatch of *variable-length* sequences is represented numerically as rows in a matrix of integers in which each sequence is left aligned and *zero-padded* to accommodate the variable lengths.

The `PackedSequence` data structure represents variable-length sequences as an array by concatenating the data for the sequences at each time step, one after another, and knowing the number of sequences at each time step, as shown in the figure below.



A matrix of padded sequences and its lengths are shown on the left. The padded matrix is the standard way of representing variable-length sequences, by righ-padding them with zeroes and stacking them as row vectors.

In PyTorch, we can pack the padded sequences into a terser representation, the `PackedSequence`, shown on the right along with the batch sizes. This representation allows the GPU to step through the sequence by keeping track of how many sequences are in each time step (the batch sizes). Using the example above,

- The longest sequence is 4, so the maximum time step is 4.
- The first time step, we have three sequences (`a`,`e`, and `h`).
- The second time step, we have two sequences (`b`, and `f`).
- The third time step, we have two sequences (`c`, and `g`).
- The final time step, we have one sequence (`d`).

```
import torch
import torch.nn as nn
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence
```

```
def describe(x):
    print("Type: {}".format(x.type()))
    print("Shape/size: {}".format(x.shape))
    print("Values: \n{}".format(x))
```

12.4.1 From padded to packed

```
abcd_padded = torch.tensor([1, 2, 3, 4], dtype=torch.float32)
efg_padded = torch.tensor([5, 6, 7, 0], dtype=torch.float32)
h_padded = torch.tensor([8, 0, 0, 0], dtype=torch.float32)

padded_tensor = torch.stack([abcd_padded, efg_padded, h_padded])

describe(padded_tensor)
```

```
Type: torch.FloatTensor
Shape/size: torch.Size([3, 4])
Values:
tensor([[1., 2., 3., 4.],
        [5., 6., 7., 0.],
        [8., 0., 0., 0.]])
```

```
lengths = [4, 3, 1]
packed_tensor = pack_padded_sequence(padded_tensor, lengths,
                                     batch_first=True)
packed_tensor
```

```
PackedSequence(data=tensor([1., 5., 8., 2., 6., 3., 7., 4.]), batch_sizes=tensor([3,␣
↪2, 2, 1]), sorted_indices=None, unsorted_indices=None)
```

12.4.2 From packed to padded

You can also turn packed sequence back to padded sequence

```
unpacked_tensor, unpacked_lengths = pad_packed_sequence(packed_tensor, batch_
↪first=True)
describe(unpacked_tensor)
describe(unpacked_lengths)
```

```
Type: torch.FloatTensor
Shape/size: torch.Size([3, 4])
Values:
tensor([[1., 2., 3., 4.],
        [5., 6., 7., 0.],
        [8., 0., 0., 0.]])
Type: torch.LongTensor
Shape/size: torch.Size([3])
Values:
tensor([4, 3, 1])
```

12.5 Neural Machine Translation - No Sampling

Vectorizing the source English and target French sentences requires a more complex pipeline than we have seen in pervious labs. There are two reasons for the increase in complexity.

- First, the source and target sequences have different roles in the model, belong to different languages, and are vectorized in two different ways. Therefore,
  - the *NMTVectorizer* is instantiated with two separate `SequenceVocabulary` objects and two measurements of max sequence length, as shown in the constructor `__init__` function below.
- Second, we use PyTorch's `PackedSequence` data structure to handle variable length sequences in a more compact way than padded sequences. See a separate short notebook introducing `PackedSequence`. As a prerequisite to use PyTorch's `PackedSequences`, we must sort each minibatch by the length of the source sentences.
  - To address this complexity, the `generate_batches()` function is modified to become the `generate_nmt_batches()` function, which produces a DataLoader that sort the minibatch into decending order of the sequence length, and then used in the `NMTEncoder` forward function.

Encoder and `PackedSequence`

The **encoder** in our model uses a bidirectional gated recurrent unit (biGRU) to compute vectors for each position in the source sequence that are informed by all parts of the sequence.

In general, the encoder takes as input a sequence of integers and creates a feature vector for each position. The output of the encoder in this example is these vectors and the final hidden state of the biGRU that is used to make the feature vectors. This hidden state is used to initialize the hidden state of the decoder.

Diving deeper into the encoder, we first embed the input sequence using an embedding layer. Usually, just by setting the `padding_idx` flag on the embedding layer, we enable the model to handle variablelength sequences because any position that equals `padding_idx` is given a zero-valued vector, which does not update during optimization. Recall that this is called the `mask`.

However, in this encoder–decoder model, masked positions need to be handled differently because we use a biGRU to encode the source sequence. The primary reason is that the backward component can be influenced by the masked positions, with a factor proportional to the number of masked positions it encounters before it starts on the sequence.

To handle the masked positions of variablelength sequences in the biGRU, we use PyTorch's PackedSequence data structure. `PackedSequences` are derived from how CUDA allows for the handling of variablelength sequences in a batched format. Any zero-padded sequence, such as the embedded source sequence in the encoder can be converted to a `PackedSequence` if two conditions are met:

- the length of each sequence is provided, and
- the minibatch is sorted according to the length of those sequences.

Decoder and Attentional Mechanism

The encoder maps each source sequence to a sequence of vector states with a biGRU and a final hidden state. The final hidden state is used as the decoder's inital hidden state for a decoder, which uses attention mechanism to select different information in the source sequence to generate an output sequence.

12.5.1 Imports

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
from torch.nn import functional as F
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm.notebook import tqdm
```

12.5.2 From sentences to vectorised tokens (Vocabulary, Dataset, DataLoader, Vectorizer)

`Vocabulary` and `SequenceVocabulary`

These two classes are standard as we have seen earlier.

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}

    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
```

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```
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):
```

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```
        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
                         'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

NMTVectorizer

Important: Vectorization of the source sequence The source sequence is vectorized with the `BEGINOFSEQUENCE` token inserted at the beginning and the `ENDOFSEQUENCE` token added to the end. The model uses a biGRU to create summary vectors for each token in the source sentence, and these summary vectors greatly benefit from having an indication of sentence boundaries.

Important: Vectorization of the target sequence The target sequence is vectorized as two copies offset by one token: the first copy needs the `BEGINOFSEQUENCE` token and the second copy needs the `ENDOFSEQUENCE` token.

recall that sequence prediction tasks require observations of the input token and output token at every time step. The decoder in an seq2seq model is performing this task, but with the added availability of the encoder context. To address this complexity,

- We make the core vectorization method, `_vectorize()`, indifferent to whether it is the source or target indices.
- Then, two methods are written to handle the source and target indices separately.
- Finally, these sets of indices are coordinated by using the `NMTVectorizer.vectorize` method, which is the method invoked by the dataset.

```
class NMTVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, source_vocab, target_vocab, max_source_length, max_target_
↪length):
        """
        Args:
            source_vocab (SequenceVocabulary): maps source words to integers
            target_vocab (SequenceVocabulary): maps target words to integers
            max_source_length (int): the longest sequence in the source dataset
            max_target_length (int): the longest sequence in the target dataset
        """
        self.source_vocab = source_vocab
        self.target_vocab = target_vocab

        self.max_source_length = max_source_length
        self.max_target_length = max_target_length


    def _vectorize(self, indices, vector_length=-1, mask_index=0):
        """Vectorize the provided indices

        Args:
            indices (list): a list of integers that represent a sequence
            vector_length (int): an argument for forcing the length of index vector
            mask_index (int): the mask_index to use; almost always 0
        """
        if vector_length < 0:
            vector_length = len(indices)

        vector = np.zeros(vector_length, dtype=np.int64)
        vector[:len(indices)] = indices
        vector[len(indices):] = mask_index

        return vector

    def _get_source_indices(self, text):
        """Return the vectorized source text

        Args:
            text (str): the source text; tokens should be separated by spaces
        Returns:
            indices (list): list of integers representing the text
        """
        indices = [self.source_vocab.begin_seq_index]
        indices.extend(self.source_vocab.lookup_token(token) for token in text.split(
↪" "))
        indices.append(self.source_vocab.end_seq_index)
        return indices

    def _get_target_indices(self, text):
        """Return the vectorized source text
```

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```
        Args:
            text (str): the source text; tokens should be separated by spaces
        Returns:
            a tuple: (x_indices, y_indices)
                x_indices (list): list of integers representing the observations in␣
↪target decoder
                y_indices (list): list of integers representing predictions in target␣
↪decoder
        """
        indices = [self.target_vocab.lookup_token(token) for token in text.split(" ")]
        x_indices = [self.target_vocab.begin_seq_index] + indices
        y_indices = indices + [self.target_vocab.end_seq_index]
        return x_indices, y_indices

    def vectorize(self, source_text, target_text, use_dataset_max_lengths=True):
        """Return the vectorized source and target text

        The vetorized source text is just the a single vector.
        The vectorized target text is split into two vectors in a similar style to
            the surname modeling in Chapter 7.
        At each timestep, the first vector is the observation and the second vector␣
↪is the target.


        Args:
            source_text (str): text from the source language
            target_text (str): text from the target language
            use_dataset_max_lengths (bool): whether to use the global max vector␣
↪lengths
        Returns:
            The vectorized data point as a dictionary with the keys:
                source_vector, target_x_vector, target_y_vector, source_length
        """
        source_vector_length = -1
        target_vector_length = -1

        if use_dataset_max_lengths:
            source_vector_length = self.max_source_length + 2
            target_vector_length = self.max_target_length + 1

        source_indices = self._get_source_indices(source_text)
        source_vector = self._vectorize(source_indices,
                                        vector_length=source_vector_length,
                                        mask_index=self.source_vocab.mask_index)

        target_x_indices, target_y_indices = self._get_target_indices(target_text)
        target_x_vector = self._vectorize(target_x_indices,
                                        vector_length=target_vector_length,
                                        mask_index=self.target_vocab.mask_index)
        target_y_vector = self._vectorize(target_y_indices,
                                        vector_length=target_vector_length,
                                        mask_index=self.target_vocab.mask_index)
        return {"source_vector": source_vector,
                "target_x_vector": target_x_vector,
                "target_y_vector": target_y_vector,
                "source_length": len(source_indices)}
```

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```
    @classmethod
    def from_dataframe(cls, bitext_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            bitext_df (pandas.DataFrame): the parallel text dataset
        Returns:
            an instance of the NMTVectorizer
        """
        source_vocab = SequenceVocabulary()
        target_vocab = SequenceVocabulary()

        max_source_length = 0
        max_target_length = 0

        for _, row in bitext_df.iterrows():
            source_tokens = row["source_language"].split(" ")
            if len(source_tokens) > max_source_length:
                max_source_length = len(source_tokens)
            for token in source_tokens:
                source_vocab.add_token(token)

            target_tokens = row["target_language"].split(" ")
            if len(target_tokens) > max_target_length:
                max_target_length = len(target_tokens)
            for token in target_tokens:
                target_vocab.add_token(token)

        return cls(source_vocab, target_vocab, max_source_length, max_target_length)

    @classmethod
    def from_serializable(cls, contents):
        source_vocab = SequenceVocabulary.from_serializable(contents["source_vocab"])
        target_vocab = SequenceVocabulary.from_serializable(contents["target_vocab"])

        return cls(source_vocab=source_vocab,
                   target_vocab=target_vocab,
                   max_source_length=contents["max_source_length"],
                   max_target_length=contents["max_target_length"])

    def to_serializable(self):
        return {"source_vocab": self.source_vocab.to_serializable(),
                "target_vocab": self.target_vocab.to_serializable(),
                "max_source_length": self.max_source_length,
                "max_target_length": self.max_target_length}
```

NMTDataset

```
class NMTDataset(Dataset):
    def __init__(self, text_df, vectorizer):
        """
        Args:
            surname_df (pandas.DataFrame): the dataset
            vectorizer (SurnameVectorizer): vectorizer instatiated from dataset
        """
        self.text_df = text_df
        self._vectorizer = vectorizer

        self.train_df = self.text_df[self.text_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.text_df[self.text_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.text_df[self.text_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}

        self.set_split('train')

    @classmethod
    def load_dataset_and_make_vectorizer(cls, dataset_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            surname_csv (str): location of the dataset
        Returns:
            an instance of SurnameDataset
        """
        text_df = pd.read_csv(dataset_csv)
        train_subset = text_df[text_df.split=='train']
        return cls(text_df, NMTVectorizer.from_dataframe(train_subset))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, dataset_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
            surname_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of SurnameDataset
        """
        text_df = pd.read_csv(dataset_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(text_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
```

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```
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of SurnameVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return NMTVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer

    def set_split(self, split="train"):
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]

    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point: (x_data, y_target, class_index)
        """
        row = self._target_df.iloc[index]

        vector_dict = self._vectorizer.vectorize(row.source_language, row.target_
↪language)

        return {"x_source": vector_dict["source_vector"],
                "x_target": vector_dict["target_x_vector"],
                "y_target": vector_dict["target_y_vector"],
                "x_source_length": vector_dict["source_length"]}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size
```

DataLoader - Generate NMT Batches using PackedSequence

There are two prerequisites for creating a `PackedSequence`:

1. knowing the length of each sequence, and
2. sorting the sequences in descending order by the length of the source sequence.

To reflect this newly sorted matrix, the remaining tensors in the minibatch are sorted in the same order so that they stay aligned with the source sequence encoding. The actual packing and unpacking of `PackedSequences` happens in the `forward()` function of the NMTEncoder model .

```
def generate_nmt_batches(dataset, batch_size, shuffle=True,
                         drop_last=True, device="cpu"):
    """A generator function which wraps the PyTorch DataLoader.  The NMT Version """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                         shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        lengths = data_dict['x_source_length'].numpy()
        # Get the indices according to sorted length
        sorted_length_indices = lengths.argsort()[::-1].tolist()

        # Sort the minibatch
        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name][sorted_length_indices].to(device)
        yield out_data_dict
```

12.5.3 Neural Machine Translation Model

Components:

1. NMTEncoder
    - accepts as input a source sequence to be embedded and fed through a bi-directional GRU
2. NMTDecoder
    - using the encoder state and attention, the decoder generates a new sequence
    - the ground truth target sequence is used as input to the decoder at each time step
    - an alternative formulation would allow some of the decoder's own choices to be used as input
    - this is referred to as curriculum learning, learning to search
3. NMTModel
    - Combines the encoder and decoder into a single class.

NMTEncoder

In the `forward()` function, PyTorch's `pack_padded_sequence()` function is evoked by passing the embedded sequences, the lengths of the sequences, and a Boolean flag indicating a batch-first tensor. The output of this function is a `PackedSequence`. The resulting `PackedSequence` is input into the `biGRU` to create hidden state vectors for the downstream decoder.

The output of the `biGRU` is **unpacked** into a full tensor. The unpacking operation, sets each masked position to be a zero-valued vector, preserving the integrity for downstream computations.

```
class NMTEncoder(nn.Module):
    def __init__(self, num_embeddings, embedding_size, rnn_hidden_size):
        """
        Args:
            num_embeddings (int): number of embeddings is the size of source␣
↪vocabulary
            embedding_size (int): size of the embedding vectors
            rnn_hidden_size (int): size of the RNN hidden state vectors
        """
        super(NMTEncoder, self).__init__()

        self.source_embedding = nn.Embedding(num_embeddings, embedding_size, padding_
↪idx=0)
        self.birnn = nn.GRU(embedding_size, rnn_hidden_size, bidirectional=True,␣
↪batch_first=True)

    def forward(self, x_source, x_lengths):
        """The forward pass of the model

        Args:
            x_source (torch.Tensor): the input data tensor.
                x_source.shape is (batch, seq_size)
            x_lengths (torch.Tensor): a vector of lengths for each item in the batch
        Returns:
            a tuple: x_unpacked (torch.Tensor), x_birnn_h (torch.Tensor)
                x_unpacked.shape = (batch, seq_size, rnn_hidden_size * 2)
                x_birnn_h.shape = (batch, rnn_hidden_size * 2)
        """
        x_embedded = self.source_embedding(x_source)
        # create PackedSequence; x_packed.data.shape=(number_items, embeddign_size)
        x_packed = pack_padded_sequence(x_embedded, x_lengths.detach().cpu().numpy(),
                                        batch_first=True)

        # x_birnn_h.shape = (num_rnn, batch_size, feature_size)
        x_birnn_out, x_birnn_h  = self.birnn(x_packed)
        # permute to (batch_size, num_rnn, feature_size)
        x_birnn_h = x_birnn_h.permute(1, 0, 2)

        # flatten features; reshape to (batch_size, num_rnn * feature_size)
        #  (recall: -1 takes the remaining positions,
        #           flattening the two RNN hidden vectors into 1)
        x_birnn_h = x_birnn_h.contiguous().view(x_birnn_h.size(0), -1)

        x_unpacked, _ = pad_packed_sequence(x_birnn_out, batch_first=True)

        return x_unpacked, x_birnn_h
```

Attention Mechanism

The attention mechanism can be described as the decoder uses `queries`, to match with `keys` in the encoder in order to work out the distribution of the `values` that contributes to the *context vector*. A score function takes as input the `query` vector and the `key` vectors to compute a set of weights that select among the `value` vectors.

In this example, we use the `dot product` scoring function, but it is not the only one. In this example, the decoder's hidden state is used as the query vector, and the set of encoder state vectors are both the key and value vectors. The dot product of the decoder's hidden state with the vectors in the encoder state creates a scalar for each item in the encoded sequence. Upon using the softmax function, these scalars become a probability distribution over the vectors in the encoder state. These probabilities are used to weight the encoder state vectors before they are added together to result in a single vector (i.e. the context vector) for each batch item.

Note: To summarize, the decoder hidden state is allowed to preferentially weight the encoder state at each time step.

This is like a **spotlight**, giving the model the ability to learn how to highlight the information it needs to generate an output sequence. We demonstrate this version of the attention mechanism in `verbose_attention()`. This function tries to verbosely spell out the operations. Additionally, it uses the `view()` operation to insert dimensions with size 1 so that the tensor can be broadcast against another tensor.

In the `terse_attention()` version, the `view()` operation is replaced with the more commonly accepted practice, `unsqueeze()`. In addition, rather than multiplying elementwise and summing, the more efficient `matmul()` operation is used.

Your Turn

Modify the code below to use `torch.bmm()`.

```
def verbose_attention(encoder_state_vectors, query_vector):
    """A descriptive version of the neural attention mechanism

    Args:
        encoder_state_vectors (torch.Tensor): 3dim tensor from bi-GRU in encoder
        query_vector (torch.Tensor): hidden state in decoder GRU
    Returns:

    """
    batch_size, num_vectors, vector_size = encoder_state_vectors.size()
    vector_scores = torch.sum(encoder_state_vectors * query_vector.view(batch_size, 1,
 ↪ vector_size),
                              dim=2)
    vector_probabilities = F.softmax(vector_scores, dim=1)
    weighted_vectors = encoder_state_vectors * vector_probabilities.view(batch_size,␣
 ↪num_vectors, 1)
    context_vectors = torch.sum(weighted_vectors, dim=1)
    return context_vectors, vector_probabilities, vector_scores

def terse_attention(encoder_state_vectors, query_vector):
    """A shorter and more optimized version of the neural attention mechanism

    Args:
        encoder_state_vectors (torch.Tensor): 3dim tensor from bi-GRU in encoder
        query_vector (torch.Tensor): hidden state
    """
```

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```
    vector_scores = torch.matmul(encoder_state_vectors, query_vector.
↪unsqueeze(dim=2)).squeeze()
    vector_probabilities = F.softmax(vector_scores, dim=-1)
    context_vectors = torch.matmul(encoder_state_vectors.transpose(-2, -1),
                                   vector_probabilities.unsqueeze(dim=2)).squeeze()
    return context_vectors, vector_probabilities
```

NMTDecoder

After the encoder creates the state vectors with its biGRU and packing-unpacking coordination, the decoder iterates over the time steps to generate an output sequence. Functionally, this loop should seem very similar to the generation loop we have seen before, but with a few differences that are distinctly the methodological choices of Luong, Pham, and Manning's (2015) style of attention.

- First, a target sequence is provided as observations at each time step.
- Hidden states are computed by using a GRUCell.
- The initial hidden state is computed by applying a Linear layer to *the concatenated final hidden states of the encoder biGRU*.
- The input to the decoder GRU at each time step is a concatenated vector of *an embedded input token* and *the last time step's context vector*.
  - The context vector is intended to capture information that is useful for that time step and acts to condition the output of the model.
  - For the first time step, the context vector is all 0s to represent no context and mathematically allow only the input to contribute to the GRU computation.
  - Using the new hidden state as a query vector, a new set of context vectors are created using the attention mechanism for the current time step.
  - These context vectors are concatenated with the hidden state to create a vector representing the decoding information at that time step.

This decoding information state vector is used in a classifier (in this case, a simple Linear layer) to create a prediction vector, `score_for_y_t_index`. These prediction vectors can be turned into probability distributions over the output vocabulary using the softmax function, or they can be used with cross-entropy loss to optimize for ground truth targets.

```
class NMTDecoder(nn.Module):
    def __init__(self, num_embeddings, embedding_size, rnn_hidden_size, bos_index):
        """
        Args:
            num_embeddings (int): number of embeddings is also the number of
                unique words in target vocabulary
            embedding_size (int): the embedding vector size
            rnn_hidden_size (int): size of the hidden rnn state
            bos_index(int): begin-of-sequence index
        """
        super(NMTDecoder, self).__init__()
        self._rnn_hidden_size = rnn_hidden_size
        self.target_embedding = nn.Embedding(num_embeddings=num_embeddings,
                                             embedding_dim=embedding_size,
                                             padding_idx=0)
        self.gru_cell = nn.GRUCell(embedding_size + rnn_hidden_size,
                                   rnn_hidden_size)
```

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```
        self.hidden_map = nn.Linear(rnn_hidden_size, rnn_hidden_size)
        self.classifier = nn.Linear(rnn_hidden_size * 2, num_embeddings)
        self.bos_index = bos_index

    def _init_indices(self, batch_size):
        """ return the BEGIN-OF-SEQUENCE index vector """
        return torch.ones(batch_size, dtype=torch.int64) * self.bos_index

    def _init_context_vectors(self, batch_size):
        """ return a zeros vector for initializing the context """
        return torch.zeros(batch_size, self._rnn_hidden_size)

    def forward(self, encoder_state, initial_hidden_state, target_sequence):
        """The forward pass of the model

        Args:
            encoder_state (torch.Tensor): the output of the NMTEncoder
            initial_hidden_state (torch.Tensor): The last hidden state in the ␣
↪NMTEncoder
            target_sequence (torch.Tensor): the target text data tensor
        Returns:
            output_vectors (torch.Tensor): prediction vectors at each output step
        """
        # We are making an assumption there: The batch is on first
        # The input is (Batch, Seq)
        # We want to iterate over sequence so we permute it to (S, B)
        target_sequence = target_sequence.permute(1, 0)
        output_sequence_size = target_sequence.size(0)

        # use the provided encoder hidden state as the initial hidden state
        h_t = self.hidden_map(initial_hidden_state)

        batch_size = encoder_state.size(0)
        # initialize context vectors to zeros
        context_vectors = self._init_context_vectors(batch_size)
        # initialize first y_t word as BOS
        y_t_index = self._init_indices(batch_size)

        h_t = h_t.to(encoder_state.device)
        y_t_index = y_t_index.to(encoder_state.device)
        context_vectors = context_vectors.to(encoder_state.device)

        output_vectors = []
        self._cached_p_attn = []
        self._cached_ht = []
        self._cached_decoder_state = encoder_state.cpu().detach().numpy()

        for i in range(output_sequence_size):
            y_t_index = target_sequence[i]

            # Step 1: Embed word and concat with previous context
            y_input_vector = self.target_embedding(y_t_index)
            rnn_input = torch.cat([y_input_vector, context_vectors], dim=1)

            # Step 2: Make a GRU step, getting a new hidden vector
            h_t = self.gru_cell(rnn_input, h_t)
            self._cached_ht.append(h_t.cpu().detach().numpy())
```

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```
            # Step 3: Use the current hidden to attend to the encoder state
            context_vectors, p_attn, _ = verbose_attention(encoder_state_
↪vectors=encoder_state,
                                                           query_vector=h_t)

            # auxillary: cache the attention probabilities for visualization
            self._cached_p_attn.append(p_attn.cpu().detach().numpy())

            # Step 4: Use the current hidden and context vectors to make a prediction␣
↪to the next word
            prediction_vector = torch.cat((context_vectors, h_t), dim=1)
            score_for_y_t_index = self.classifier(F.dropout(prediction_vector, 0.3))

            # auxillary: collect the prediction scores
            output_vectors.append(score_for_y_t_index)

        output_vectors = torch.stack(output_vectors).permute(1, 0, 2)

        return output_vectors
```

NMTModel

The model that connects `NMTdecoder` with `NMTEncoder`.

```
class NMTModel(nn.Module):
    """ The Neural Machine Translation Model """
    def __init__(self, source_vocab_size, source_embedding_size,
                 target_vocab_size, target_embedding_size, encoding_size,
                 target_bos_index):
        """
        Args:
            source_vocab_size (int): number of unique words in source language
            source_embedding_size (int): size of the source embedding vectors
            target_vocab_size (int): number of unique words in target language
            target_embedding_size (int): size of the target embedding vectors
            encoding_size (int): the size of the encoder RNN.
        """
        super(NMTModel, self).__init__()
        self.encoder = NMTEncoder(num_embeddings=source_vocab_size,
                                  embedding_size=source_embedding_size,
                                  rnn_hidden_size=encoding_size)
        decoding_size = encoding_size * 2
        self.decoder = NMTDecoder(num_embeddings=target_vocab_size,
                                  embedding_size=target_embedding_size,
                                  rnn_hidden_size=decoding_size,
                                  bos_index=target_bos_index)

    def forward(self, x_source, x_source_lengths, target_sequence):
        """The forward pass of the model

        Args:
            x_source (torch.Tensor): the source text data tensor.
                x_source.shape should be (batch, vectorizer.max_source_length)
```

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```
            x_source_lengths torch.Tensor): the length of the sequences in x_source
            target_sequence (torch.Tensor): the target text data tensor
        Returns:
            decoded_states (torch.Tensor): prediction vectors at each output step
        """
        encoder_state, final_hidden_states = self.encoder(x_source, x_source_lengths)
        decoded_states = self.decoder(encoder_state=encoder_state,
                                      initial_hidden_state=final_hidden_states,
                                      target_sequence=target_sequence)
        return decoded_states
```

12.5.4 Training Routine and Bookkeeping Functions

The training routine for this example is nearly identical to the training routines seen previously.

However, each minibatch here is composed of four tensors:

- a matrix of integers for the **source sequence**,
- two matrices of integers for the **target sequence**, and
- a vector of integers for the **source sequence lengths**.

The two target sequence matrices are

- the target sequence offset by one and padded with either `BEGINOFSEQUENCE` tokens to act as target sequence observations or
- ENDOSEQUENCE tokens to act as target sequence prediction labels.

The model takes as input the source sequence and the target sequence observations to produce target sequence predictions. The target sequence prediction labels are used in the loss function to compute the **crossentropy loss**, which is then backpropagated to each model parameter so that it knows its gradient. The optimizer is then invoked and updates each model parameter by some amount proportional to the gradient.

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)

def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
```

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```
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.
    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= loss_tm1:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])
                train_state['early_stopping_best_val'] = loss_t

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria

    return train_state

def normalize_sizes(y_pred, y_true):
    """Normalize tensor sizes

    Args:
        y_pred (torch.Tensor): the output of the model
            If a 3-dimensional tensor, reshapes to a matrix
        y_true (torch.Tensor): the target predictions
            If a matrix, reshapes to be a vector
    """
    if len(y_pred.size()) == 3:
        y_pred = y_pred.contiguous().view(-1, y_pred.size(2))
    if len(y_true.size()) == 2:
        y_true = y_true.contiguous().view(-1)
```

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```
    return y_pred, y_true

def compute_accuracy(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)

    _, y_pred_indices = y_pred.max(dim=1)

    correct_indices = torch.eq(y_pred_indices, y_true).float()
    valid_indices = torch.ne(y_true, mask_index).float()

    n_correct = (correct_indices * valid_indices).sum().item()
    n_valid = valid_indices.sum().item()

    return n_correct / n_valid * 100

def sequence_loss(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)
    return F.cross_entropy(y_pred, y_true, ignore_index=mask_index)
```

```
torch.cuda.is_available()
```

```
True
```

```
args = Namespace(dataset_csv="../data/nmt/simplest_eng_fra.csv",
                 vectorizer_file="vectorizer.json",
                 model_state_file="model.pth",
                 save_dir="model_storage/nmt_luong_no_sampling",
                 reload_from_files=True,
                 expand_filepaths_to_save_dir=True,
                 cuda=True,
                 seed=1337,
                 learning_rate=5e-4,
                 batch_size=64,
                 num_epochs=100,
                 early_stopping_criteria=5,
                 source_embedding_size=64,
                 target_embedding_size=64,
                 encoding_size=64,
                 catch_keyboard_interrupt=True)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
                                         args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))

# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False
```

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```
args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage/nmt_luong_no_sampling\vectorizer.json
        model_storage/nmt_luong_no_sampling\model.pth
Using CUDA: True
```

```
if args.reload_from_files and os.path.exists(args.vectorizer_file):
    # training from a checkpoint
    dataset = NMTDataset.load_dataset_and_load_vectorizer(args.dataset_csv,
                                                          args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = NMTDataset.load_dataset_and_make_vectorizer(args.dataset_csv)
    dataset.save_vectorizer(args.vectorizer_file)

vectorizer = dataset.get_vectorizer()
```

```
model = NMTModel(source_vocab_size=len(vectorizer.source_vocab),
                 source_embedding_size=args.source_embedding_size,
                 target_vocab_size=len(vectorizer.target_vocab),
                 target_embedding_size=args.target_embedding_size,
                 encoding_size=args.encoding_size,
                 target_bos_index=vectorizer.target_vocab.begin_seq_index)

if args.reload_from_files and os.path.exists(args.model_state_file):
    model.load_state_dict(torch.load(args.model_state_file))
    print("Reloaded model")
else:
    print("New model")
```

```
New model
```

```
model = model.to(args.device)

optimizer = optim.Adam(model.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
                                                 mode='min', factor=0.5,
                                                 patience=1)
mask_index = vectorizer.target_vocab.mask_index
train_state = make_train_state(args)

epoch_bar = tqdm(desc='training routine',
                 total=args.num_epochs,
                 position=0)

dataset.set_split('train')
```

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```
train_bar = tqdm(desc='split=train',
                         total=dataset.get_num_batches(args.batch_size),
                         position=1,
                         leave=True)
dataset.set_split('val')
val_bar = tqdm(desc='split=val',
                       total=dataset.get_num_batches(args.batch_size),
                       position=1,
                       leave=True)

try:
    for epoch_index in range(args.num_epochs):
        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on
        dataset.set_split('train')
        batch_generator = generate_nmt_batches(dataset,
                                               batch_size=args.batch_size,
                                               device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        model.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = model(batch_dict['x_source'],
                           batch_dict['x_source_length'],
                           batch_dict['x_target'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # step 4. use loss to produce gradients
            loss.backward()

            # step 5. use optimizer to take gradient step
            optimizer.step()
            # ----------------------------------------
            # compute the running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # update bar
            train_bar.set_postfix(loss=running_loss, acc=running_acc,
                                  epoch=epoch_index)
            train_bar.update()
```

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```
        train_state['train_loss'].append(running_loss)
        train_state['train_acc'].append(running_acc)

        # Iterate over val dataset

        # setup: batch generator, set loss and acc to 0; set eval mode on
        dataset.set_split('val')
        batch_generator = generate_nmt_batches(dataset,
                                               batch_size=args.batch_size,
                                               device=args.device)
        running_loss = 0.
        running_acc = 0.
        model.eval()

        for batch_index, batch_dict in enumerate(batch_generator):
            # compute the output
            y_pred = model(batch_dict['x_source'],
                           batch_dict['x_source_length'],
                           batch_dict['x_target'])

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # compute the running loss and accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # Update bar
            val_bar.set_postfix(loss=running_loss, acc=running_acc,
                                epoch=epoch_index)
            val_bar.update()

        train_state['val_loss'].append(running_loss)
        train_state['val_acc'].append(running_acc)

        train_state = update_train_state(args=args, model=model,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])

        if train_state['stop_early']:
            break

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.set_postfix(best_val=train_state['early_stopping_best_val'] )
        epoch_bar.update()

except KeyboardInterrupt:
    print("Exiting loop")
```

```
training routine:   0%|          | 0/100 [00:00<?, ?it/s]
```

```
split=train:   0%|          | 0/142 [00:00<?, ?it/s]
```

```
split=val:   0%|          | 0/30 [00:00<?, ?it/s]
```

```
model.eval()
```

```
NMTModel(
  (encoder): NMTEncoder(
    (source_embedding): Embedding(3025, 64, padding_idx=0)
    (birnn): GRU(64, 64, batch_first=True, bidirectional=True)
  )
  (decoder): NMTDecoder(
    (target_embedding): Embedding(4902, 64, padding_idx=0)
    (gru_cell): GRUCell(192, 128)
    (hidden_map): Linear(in_features=128, out_features=128, bias=True)
    (classifier): Linear(in_features=256, out_features=4902, bias=True)
  )
)
```

12.5.5 Inference and Evaluation

Important: Measuring the performance is an important and nontrivial problem in Machine Translation.

Several sequence generation evaluation metrics (including manual human assessment) exist, but metrics such as `BLEU` which measure the ngram overlap between predicted sentences and reference sentences have become a standard for the machine translation field. In the code below, the model's outputs are aggregated with the source sentence, the reference target sentence, and the attention probability matrix for that example. Finally, BLEU4 is computed for each pair of source and generated sentences.

To qualitatively assess how well the model is working, we visualize the attention probability matrix as alignments between the source and generated text. It is important to note, however, that recent research has shown attention-based alignments are not exactly the same as they are in classical machine translation. Instead of the alignments between words and phrases being indicative of translation synonymy, attention-based alignment scores could indicate useful information for the decoder, such as attending to the sentence"'s subject when generating the output verb (Koehn and Knowles, 2017).

```
from nltk.translate import bleu_score
import seaborn as sns
import matplotlib.pyplot as plt

chencherry = bleu_score.SmoothingFunction()
```

```
def sentence_from_indices(indices, vocab, strict=True, return_string=True):
    ignore_indices = set([vocab.mask_index, vocab.begin_seq_index, vocab.end_seq_
↪index])
    out = []
    for index in indices:
        if index == vocab.begin_seq_index and strict:
            continue
        elif index == vocab.end_seq_index and strict:
            break
        else:
            out.append(vocab.lookup_index(index))
```

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```
    if return_string:
        return " ".join(out)
    else:
        return out

class NMTSampler:
    def __init__(self, vectorizer, model):
        self.vectorizer = vectorizer
        self.model = model

    def apply_to_batch(self, batch_dict):
        self._last_batch = batch_dict
        y_pred = self.model(x_source=batch_dict['x_source'],
                            x_source_lengths=batch_dict['x_source_length'],
                            target_sequence=batch_dict['x_target'])
        self._last_batch['y_pred'] = y_pred

        attention_batched = np.stack(self.model.decoder._cached_p_attn).transpose(1,␣
↪0, 2)
        self._last_batch['attention'] = attention_batched

    def _get_source_sentence(self, index, return_string=True):
        indices = self._last_batch['x_source'][index].cpu().detach().numpy()
        vocab = self.vectorizer.source_vocab
        return sentence_from_indices(indices, vocab, return_string=return_string)

    def _get_reference_sentence(self, index, return_string=True):
        indices = self._last_batch['y_target'][index].cpu().detach().numpy()
        vocab = self.vectorizer.target_vocab
        return sentence_from_indices(indices, vocab, return_string=return_string)

    def _get_sampled_sentence(self, index, return_string=True):
        _, all_indices = torch.max(self._last_batch['y_pred'], dim=2)
        sentence_indices = all_indices[index].cpu().detach().numpy()
        vocab = self.vectorizer.target_vocab
        return sentence_from_indices(sentence_indices, vocab, return_string=return_
↪string)

    def get_ith_item(self, index, return_string=True):
        output = {"source": self._get_source_sentence(index, return_string=return_
↪string),
                  "reference": self._get_reference_sentence(index, return_
↪string=return_string),
                  "sampled": self._get_sampled_sentence(index, return_string=return_
↪string),
                  "attention": self._last_batch['attention'][index]}

        reference = output['reference']
        hypothesis = output['sampled']

        if not return_string:
            reference = " ".join(reference)
            hypothesis = " ".join(hypothesis)

        output['bleu-4'] = bleu_score.sentence_bleu(references=[reference],
                                                    hypothesis=hypothesis,
                                                    smoothing_function=chencherry.
↪method1)
```

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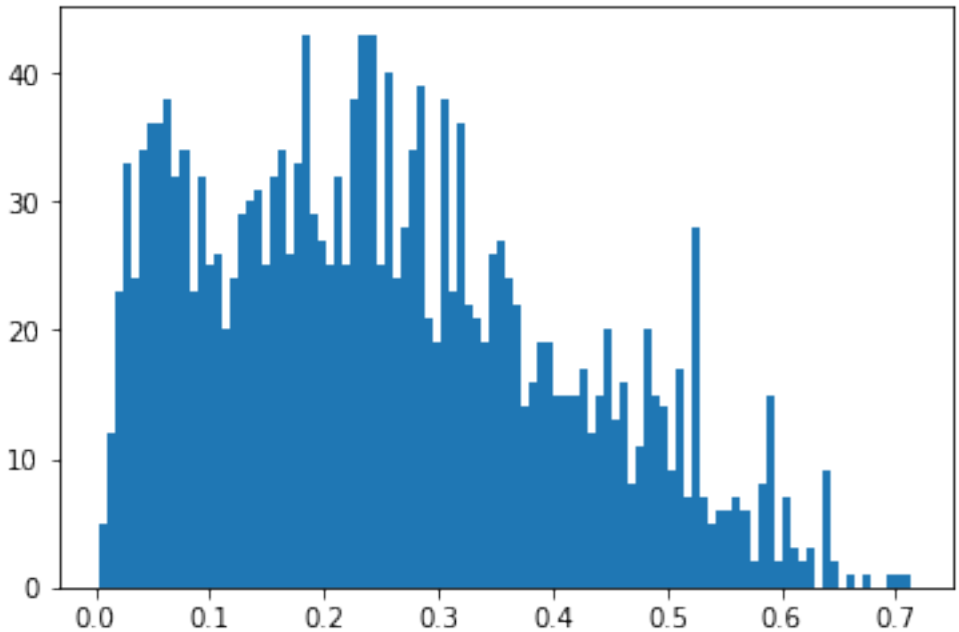
```
        return output
```

```
model = model.eval().to(args.device)

sampler = NMTSampler(vectorizer, model)

dataset.set_split('test')
batch_generator = generate_nmt_batches(dataset,
                                       batch_size=args.batch_size,
                                       device=args.device)

test_results = []
for batch_dict in batch_generator:
    sampler.apply_to_batch(batch_dict)
    for i in range(args.batch_size):
        test_results.append(sampler.get_ith_item(i, False))
```

```
plt.hist([r['bleu-4'] for r in test_results], bins=100);
np.mean([r['bleu-4'] for r in test_results]), np.median([r['bleu-4'] for r in test_
↪results])
```

```
(0.25407270926974085, 0.238016853527947)
```




```
dataset.set_split('val')
batch_generator = generate_nmt_batches(dataset,
                                       batch_size=args.batch_size,
                                       device=args.device)
batch_dict = next(batch_generator)

model = model.eval().to(args.device)
```

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```
sampler = NMTSampler(vectorizer, model)
sampler.apply_to_batch(batch_dict)
```

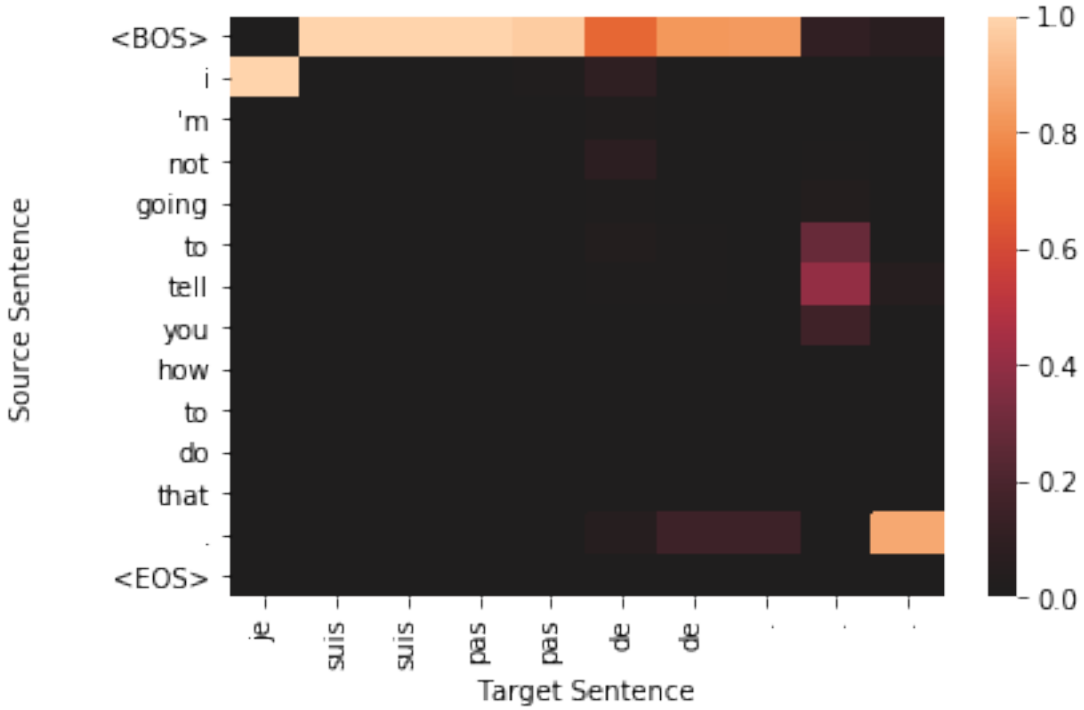
```
all_results = []
for i in range(args.batch_size):
    all_results.append(sampler.get_ith_item(i, False))
```

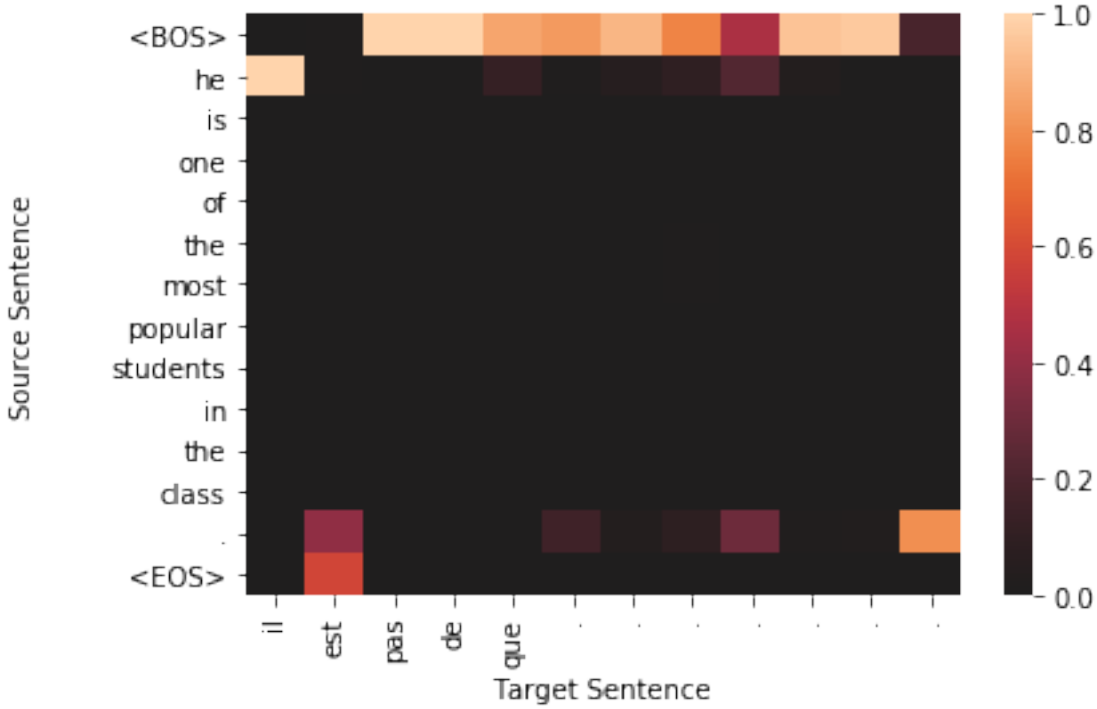
```
top_results = [x for x in all_results if x['bleu-4']>0.1]
len(top_results)
```

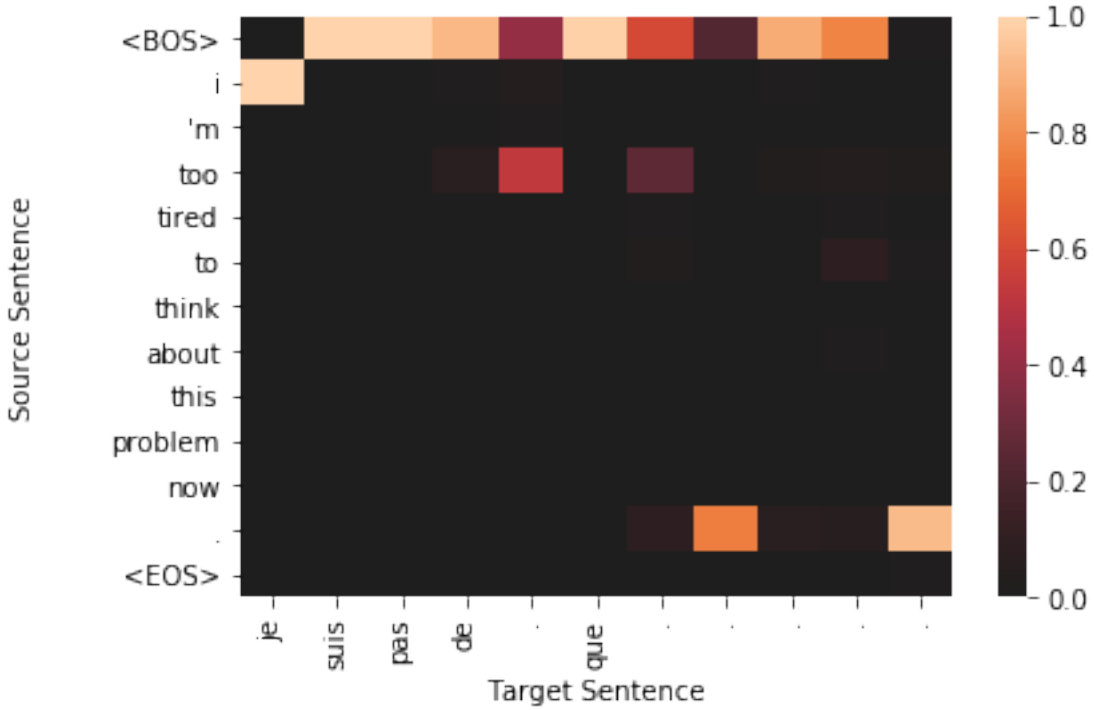
```
54
```

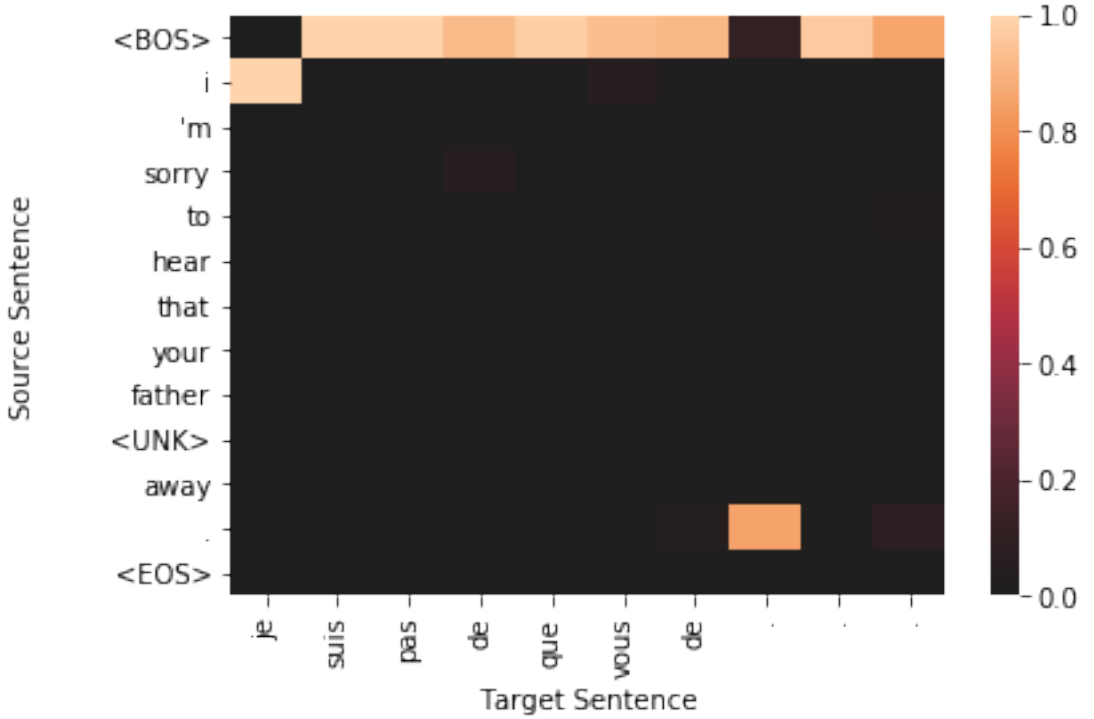
```
for sample in top_results:
    plt.figure()
    target_len = len(sample['sampled'])
    source_len = len(sample['source'])

    attention_matrix = sample['attention'][:target_len, :source_len+2].transpose()
 ↪#[::-1]
    ax = sns.heatmap(attention_matrix, center=0.0)
    ylabs = ["<BOS>"]+sample['source']+["<EOS>"]
    #ylabs = sample['source']
    #ylabs = ylabs[::-1]
    ax.set_yticklabels(ylabs, rotation=0)
    ax.set_xticklabels(sample['sampled'], rotation=90)
    ax.set_xlabel("Target Sentence")
    ax.set_ylabel("Source Sentence\n\n")
```

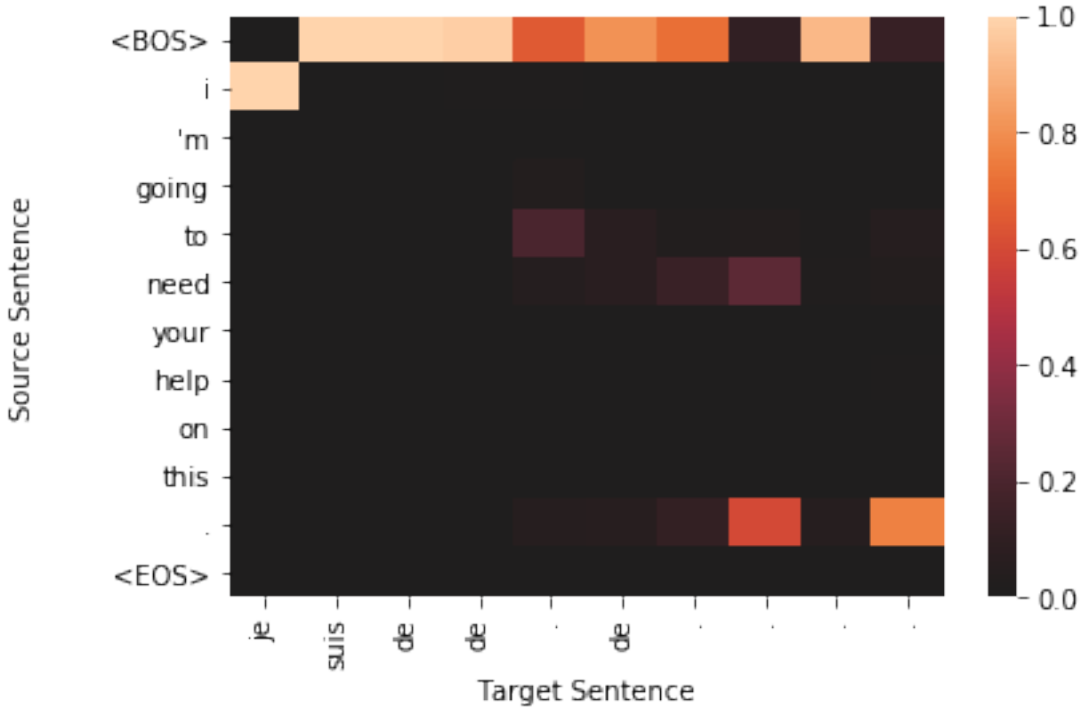
```
/home/brian/anaconda3/envs/nlpbook/lib/python3.7/site-packages/matplotlib/pyplot.
 ↪py:514: RuntimeWarning: More than 20 figures have been opened. Figures created␣
 ↪through the pyplot interface (`matplotlib.pyplot.figure`) are retained until␣
 ↪explicitly closed and may consume too much memory. (To control this warning, see␣
 ↪the rcParam `figure.max_open_warning`).
  max_open_warning, RuntimeWarning)
```

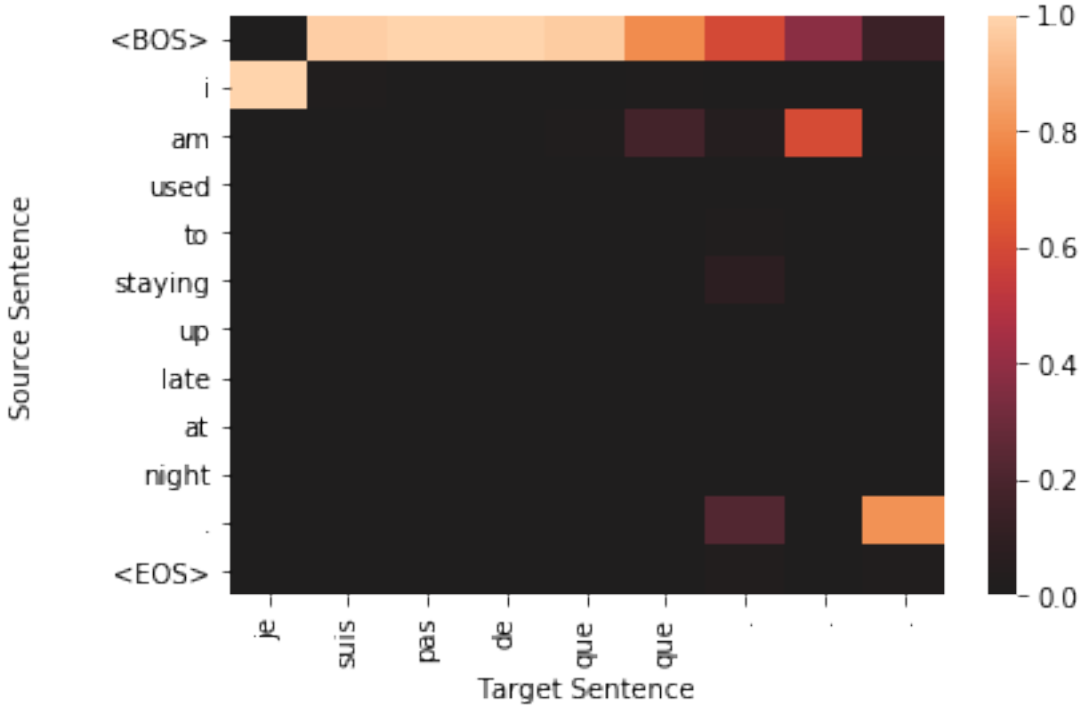

<BOS>
i
'm
not
going
to
tell
you
how
to
do
that
.
<EOS>
Source Sentence
je
suis
suis
pas
pas
de
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

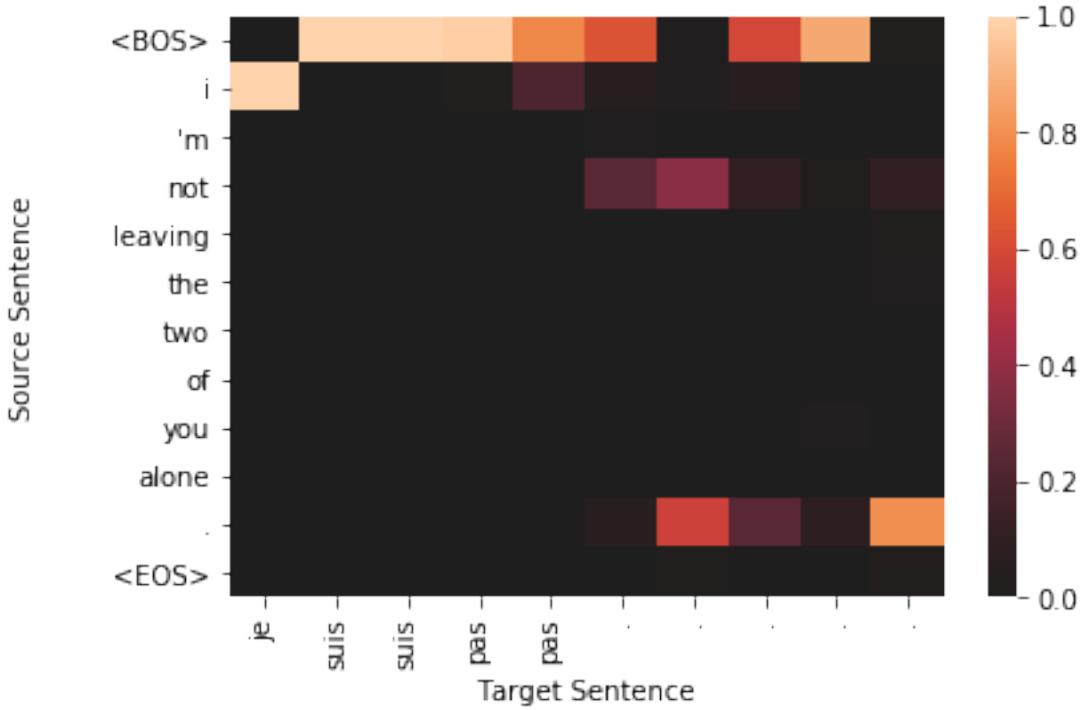

<BOS>
he
is
one
of
the
most
popular
students
in
the
class
.
<EOS>
Source Sentence
il
est
pas
de
que
.
.
.
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

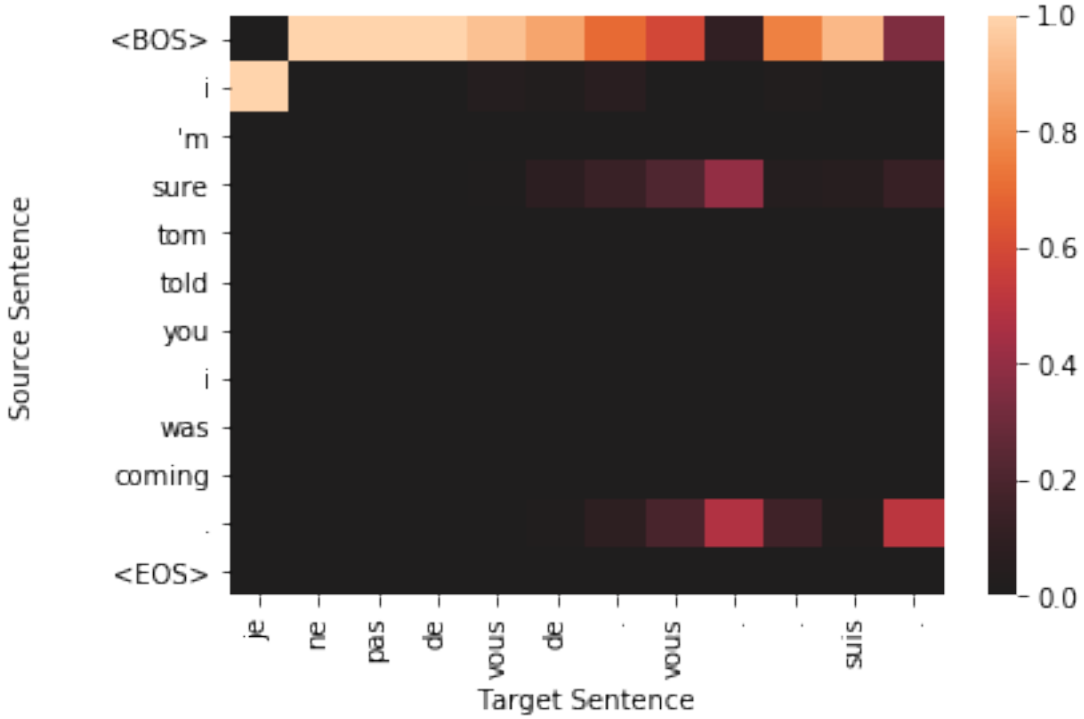

<BOS>
i
'm
too
tired
to
think
about
this
problem
now
.
<EOS>
Source Sentence
je
suis
pas
de
.
que
.
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

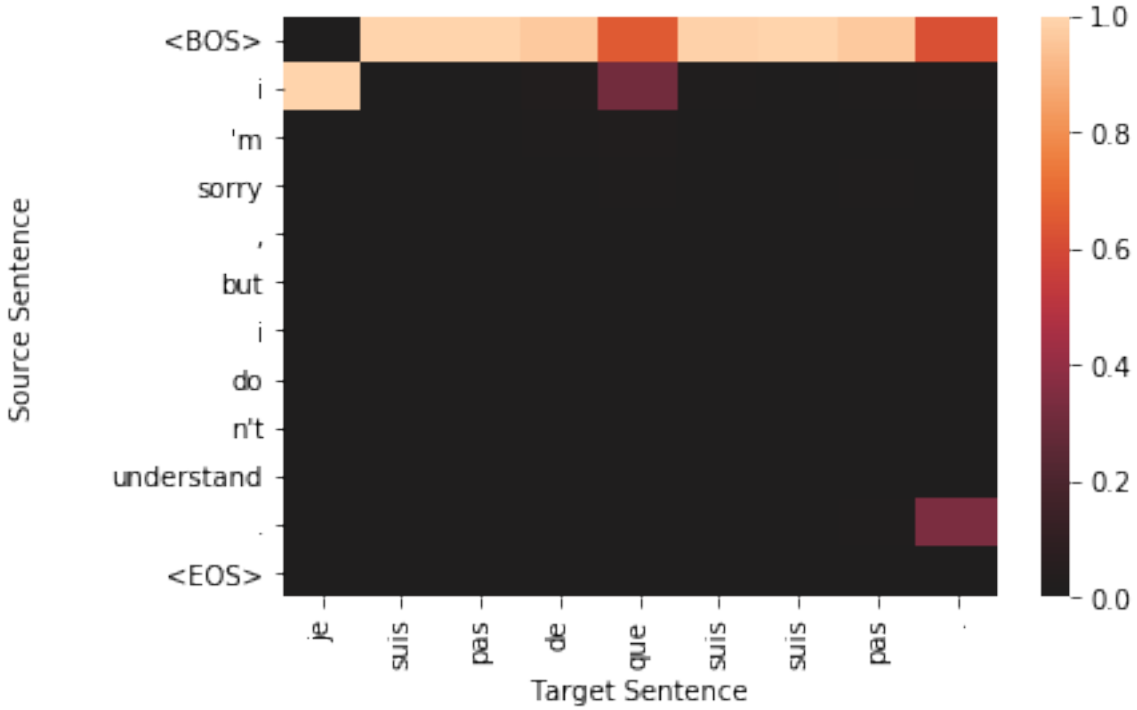

<BOS>
i
'm
sorry
to
hear
that
your
father
<UNK>
away
.
<EOS>
Source Sentence
je
suis
pas
de
que
vous
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

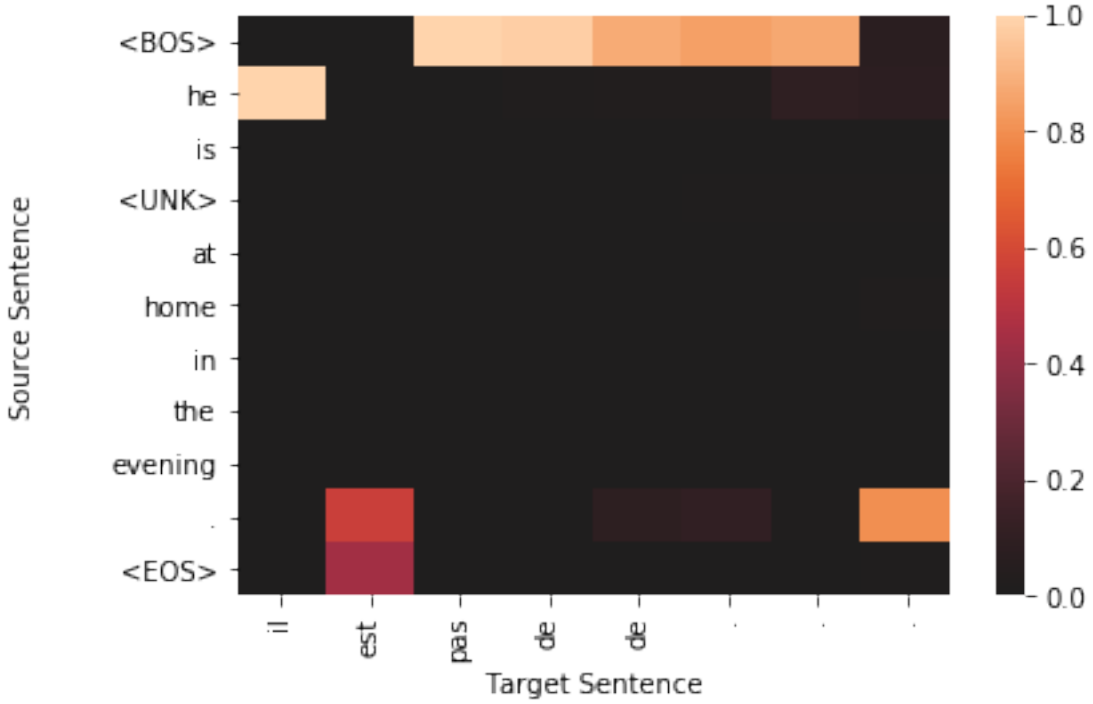

Source Sentence
<BOS>
i
'm
going
to
need
your
help
on
this
.
<EOS>
je
suis
de
de
.
de
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

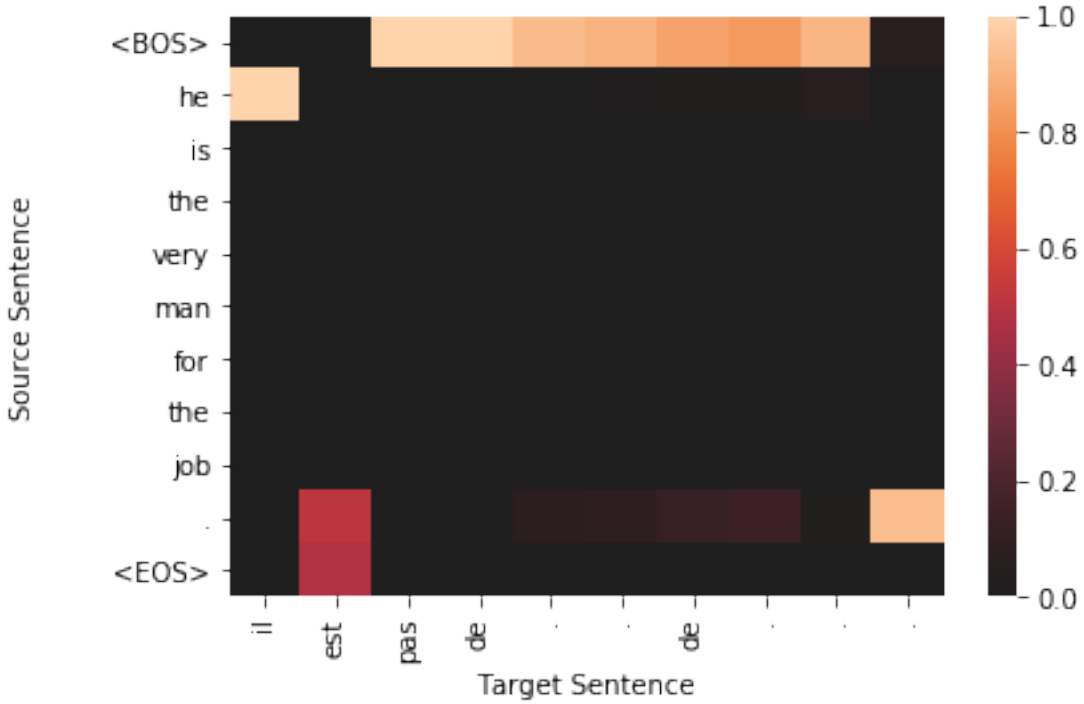

Source Sentence
<BOS>
i
am
used
to
staying
up
late
at
night
.
<EOS>
je
suis
pas
de
que
que
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

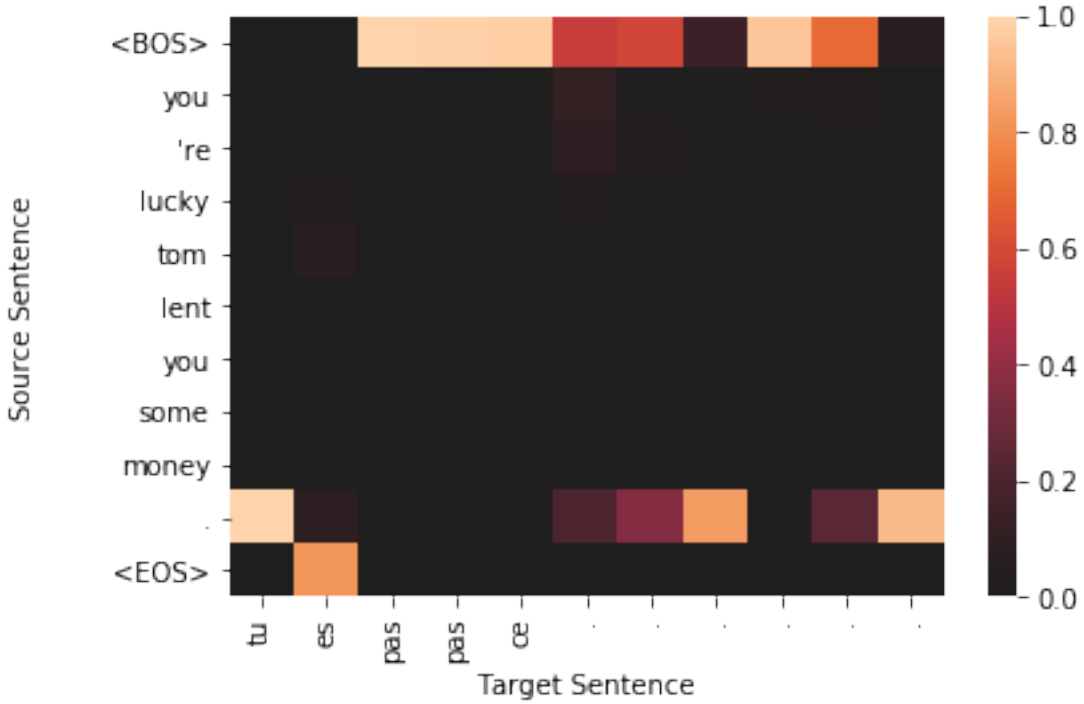

Source Sentence
<BOS>
i
'm
not
leaving
the
two
of
you
alone
.
<EOS>
je
suis
suis
pas
pas
.
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

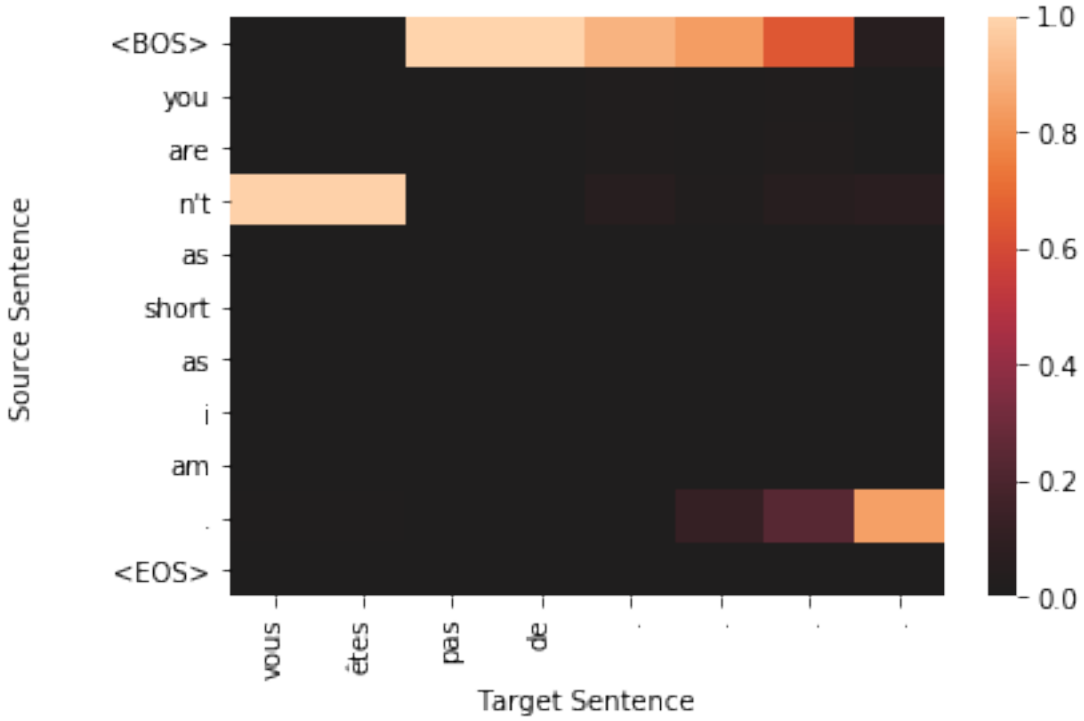

Source Sentence
<BOS>
i
'm
sure
tom
told
you
i
was
coming
.
<EOS>
je
ne
pas
de
vous
de
.
vous
.
.
suis
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

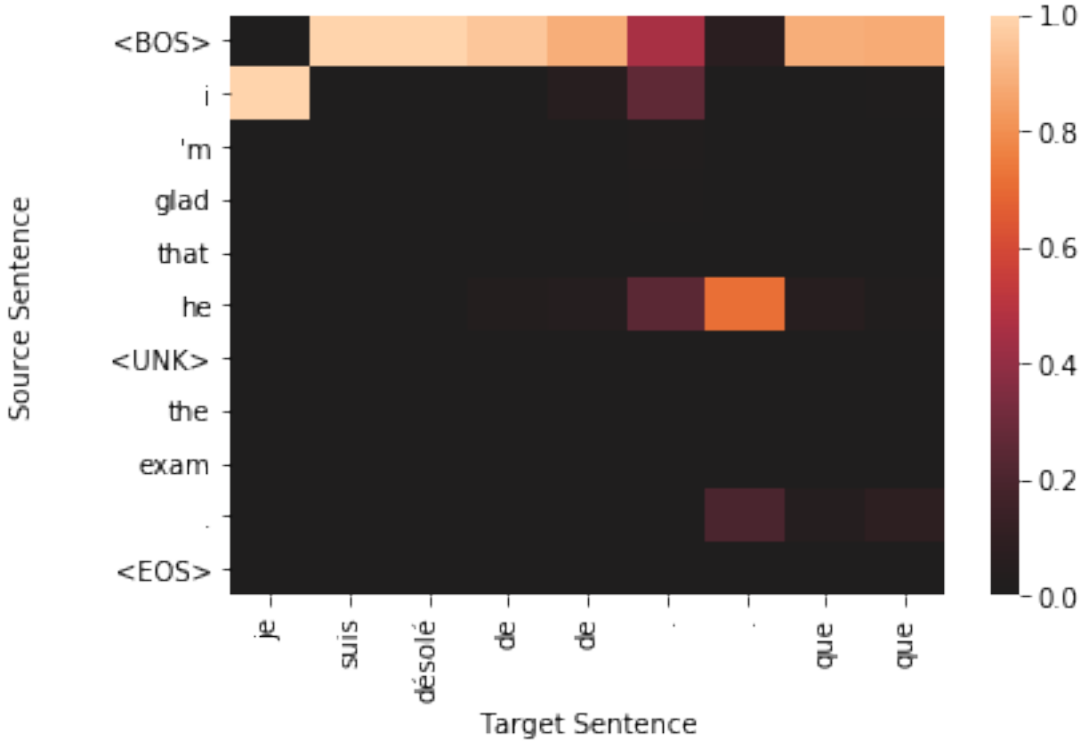

<BOS>
i
'm
sorry
,
but
i
do
n't
understand
.
<EOS>
Source Sentence
je
suis
pas
de
que
suis
suis
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

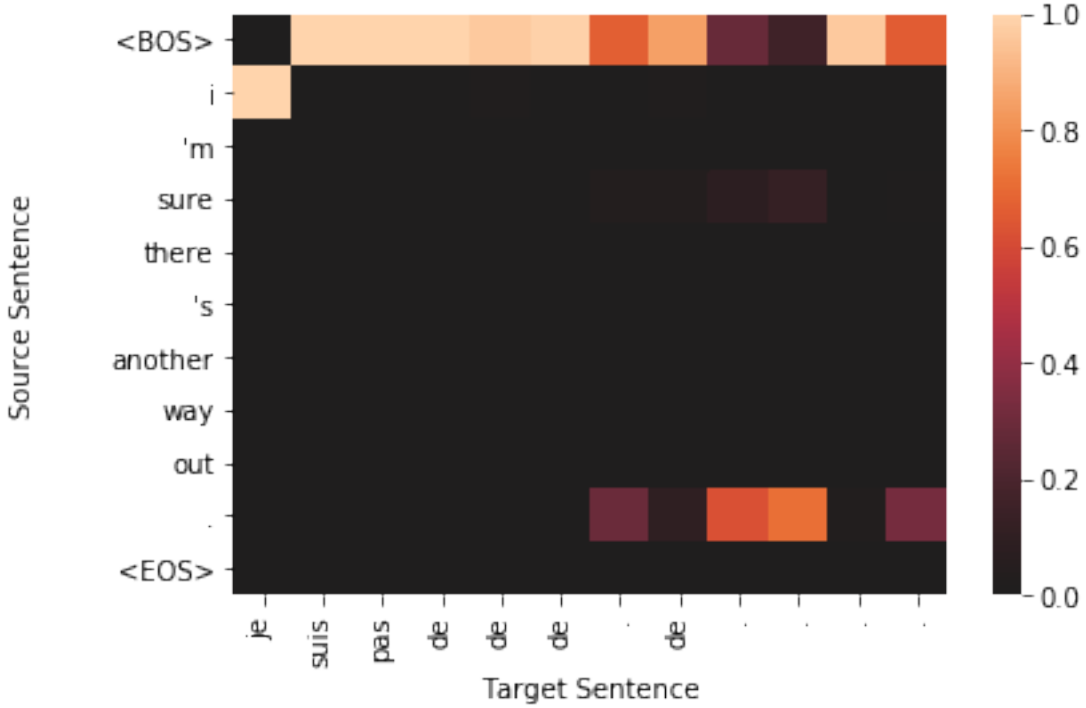

<BOS>
he
is
<UNK>
at
home
in
the
evening
.
<EOS>
Source Sentence
il
est
pas
de
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

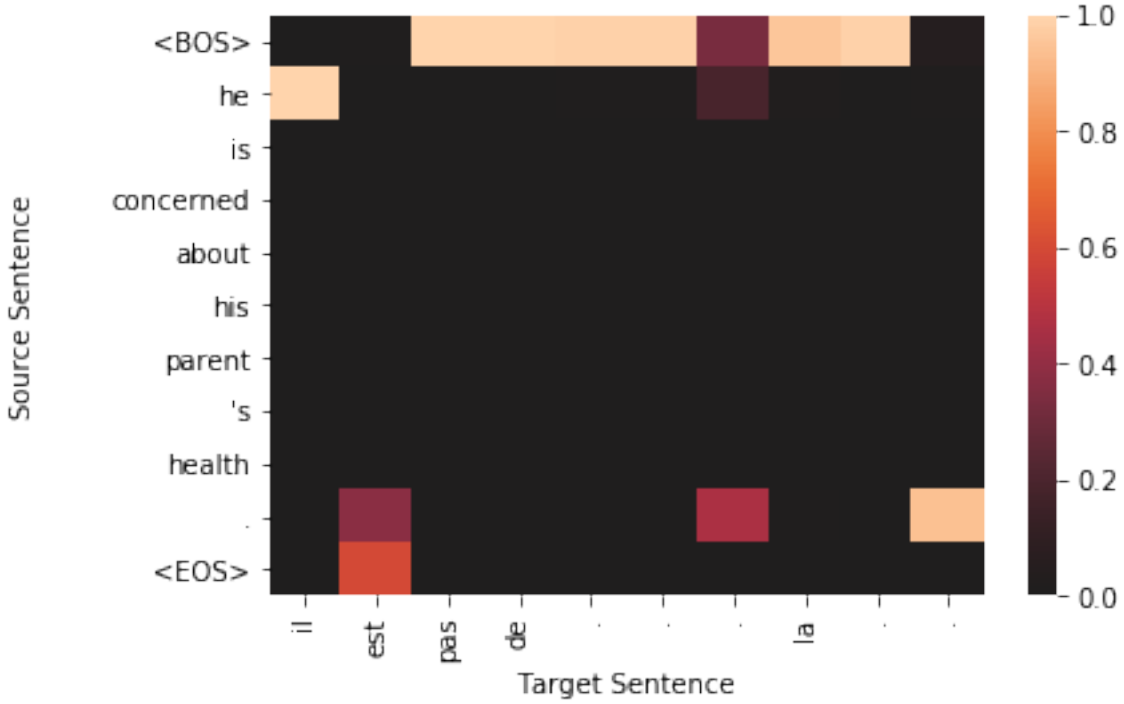

Source Sentence
<BOS>
he
is
the
very
man
for
the
job
.
<EOS>
il
est
pas
de
.
.
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

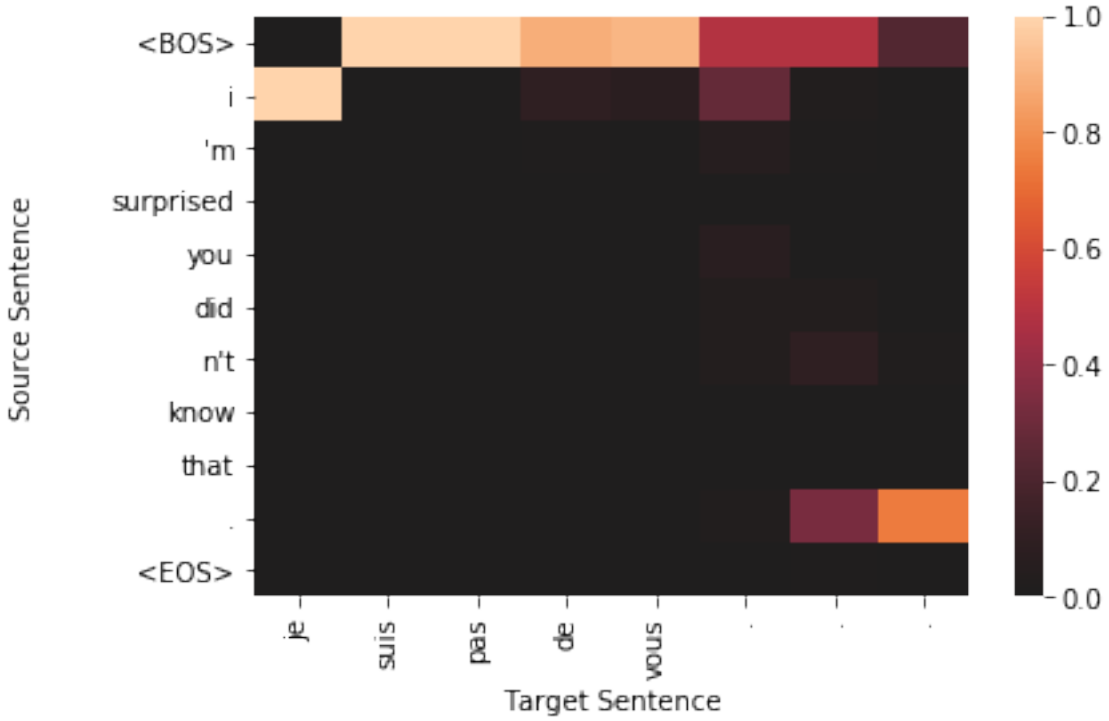

Source Sentence
<BOS>
you
're
lucky
tom
lent
you
some
money
.
<EOS>
tu
es
pas
pas
ce
.
.
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

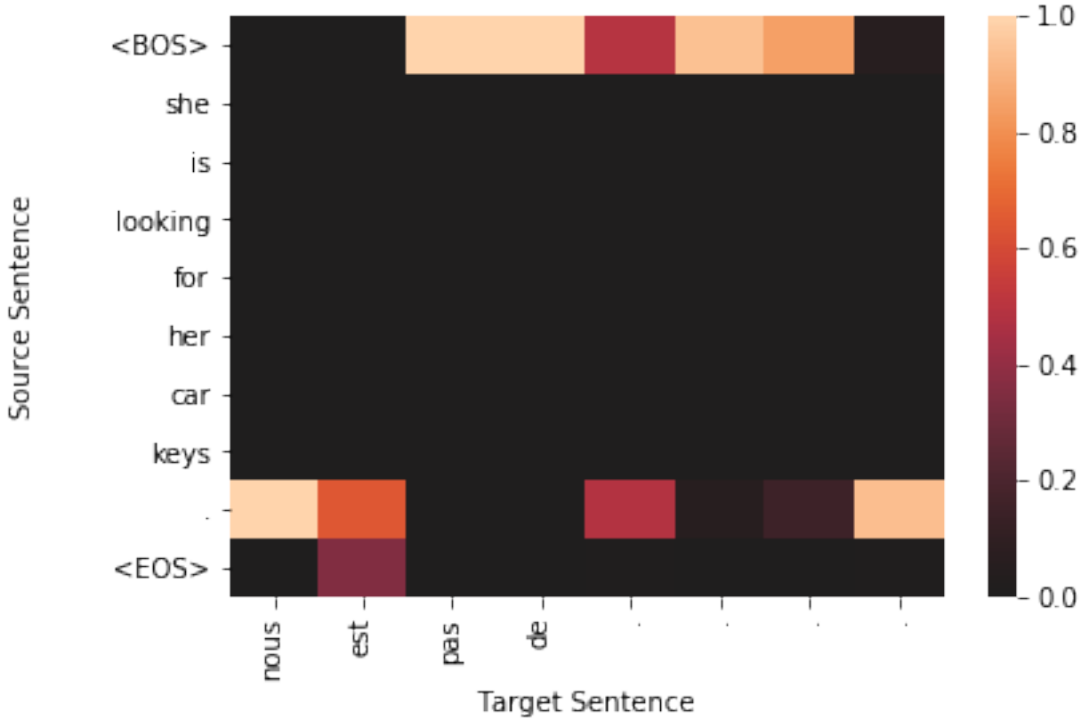

Source Sentence
<BOS>
you
are
n't
as
short
as
i
am
.
<EOS>
vous
êtes
pas
de
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

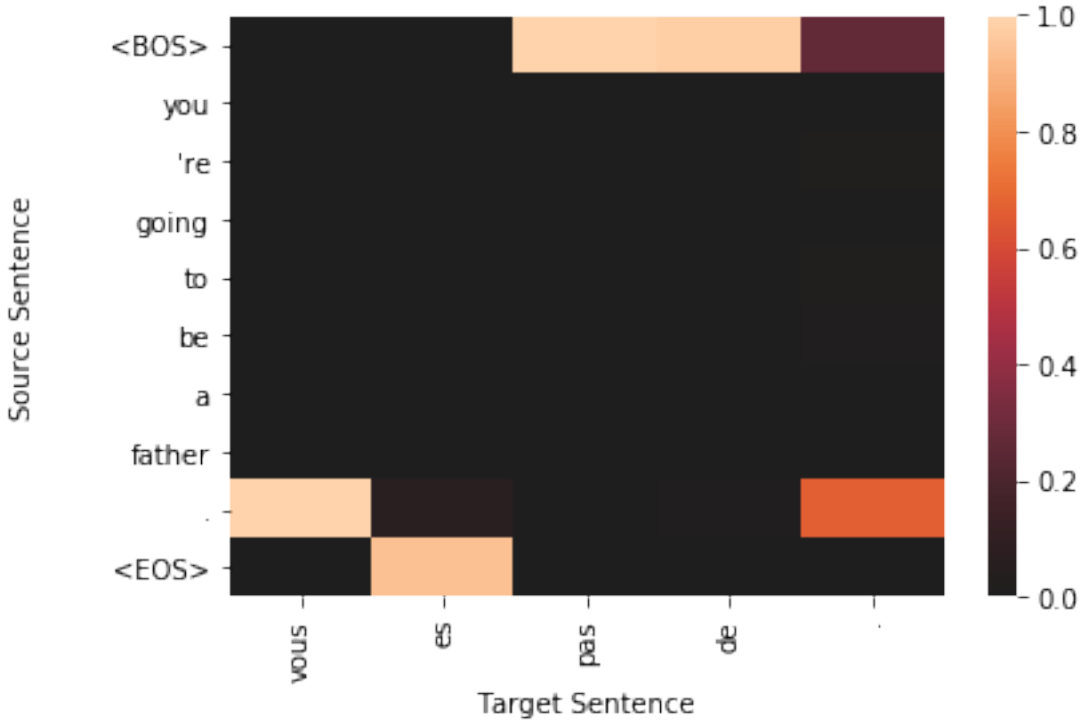

Source Sentence
<BOS>
i
'm
glad
that
he
<UNK>
the
exam
.
<EOS>
je
suis
désolé
de
de
.
.
que
que
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

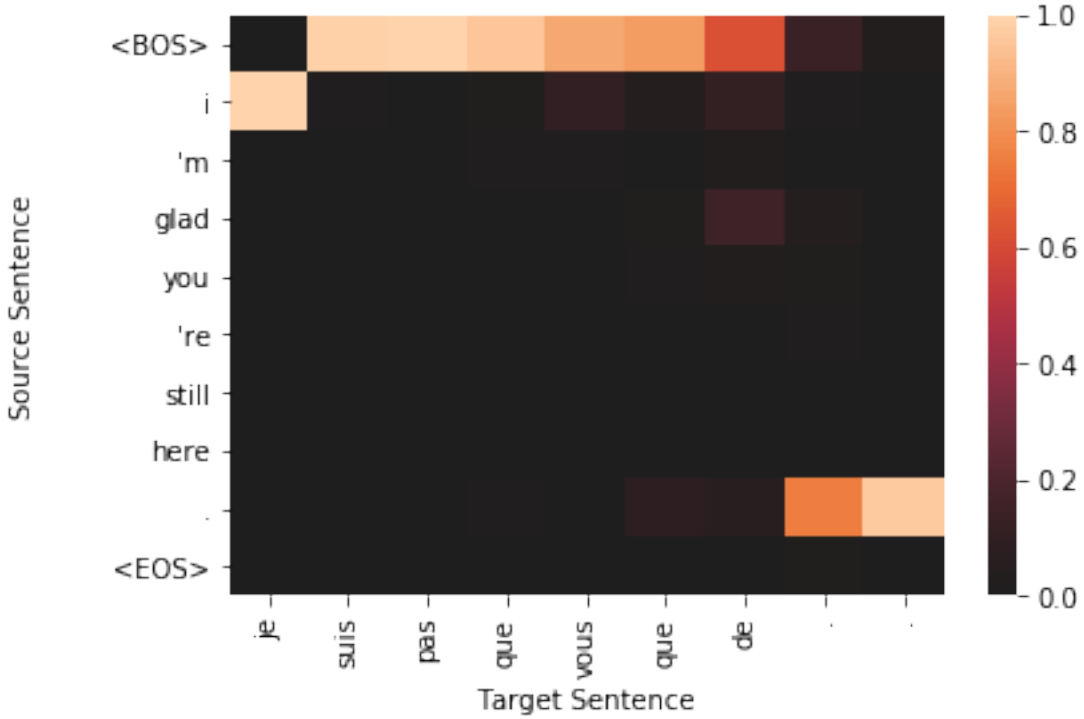

Source Sentence
<BOS>
i
'm
sure
there
's
another
way
out
.
<EOS>
je
suis
pas
de
de
de
.
de
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

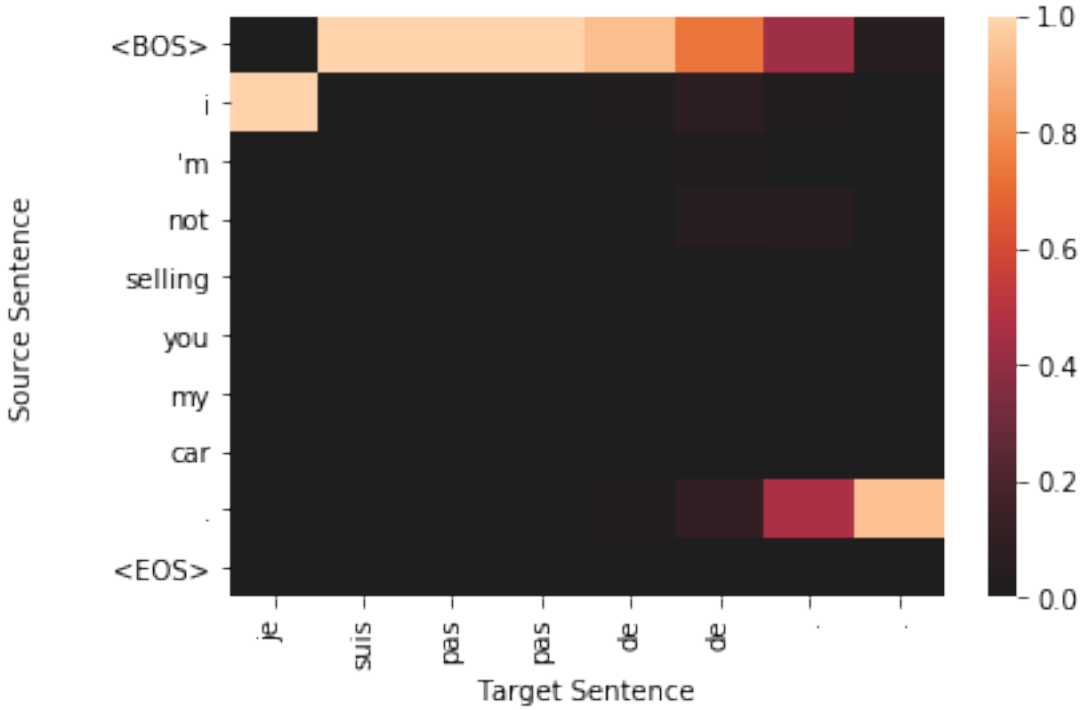

Source Sentence
<BOS>
he
is
concerned
about
his
parent
's
health
.
<EOS>
il
est
pas
de
.
.
.
la
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

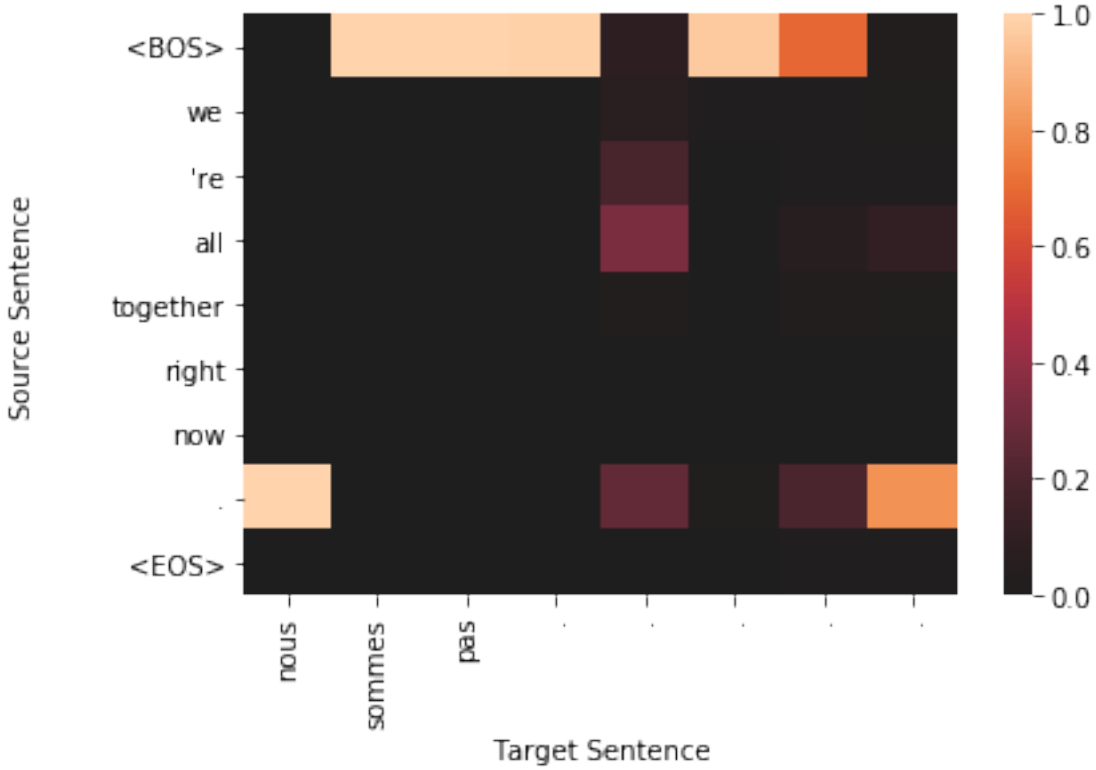

Source Sentence
<BOS>
i
'm
surprised
you
did
n't
know
that
.
<EOS>
je
suis
pas
de
vous
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

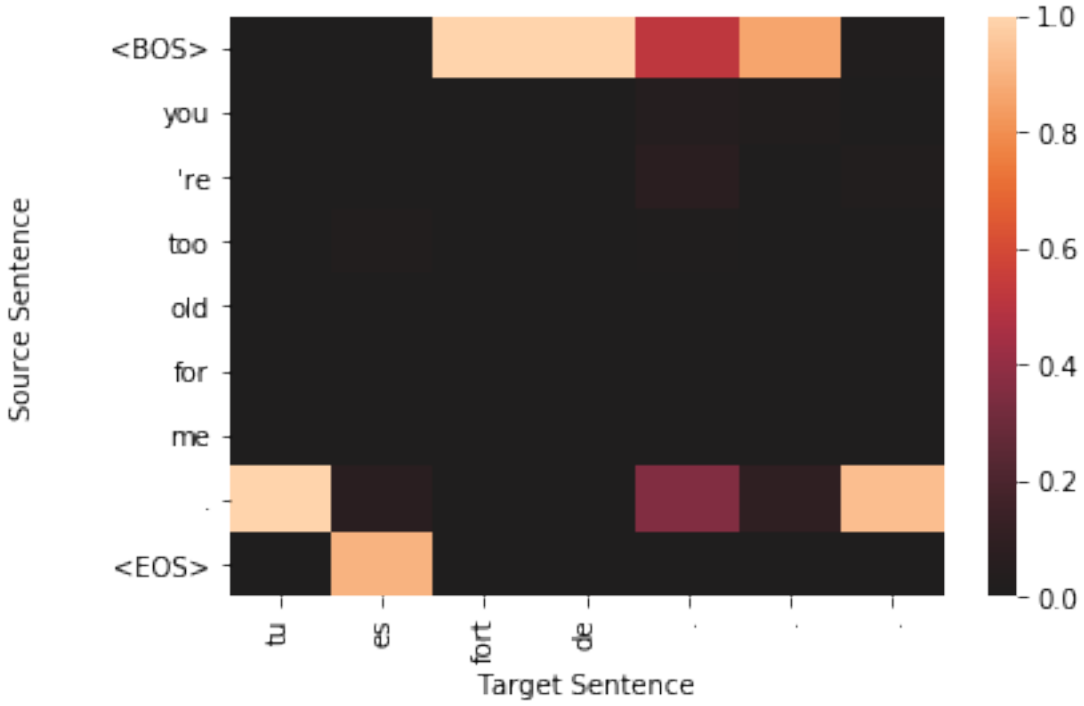

Source Sentence
<BOS>
she
is
looking
for
her
car
keys
.
<EOS>
nous
est
pas
de
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

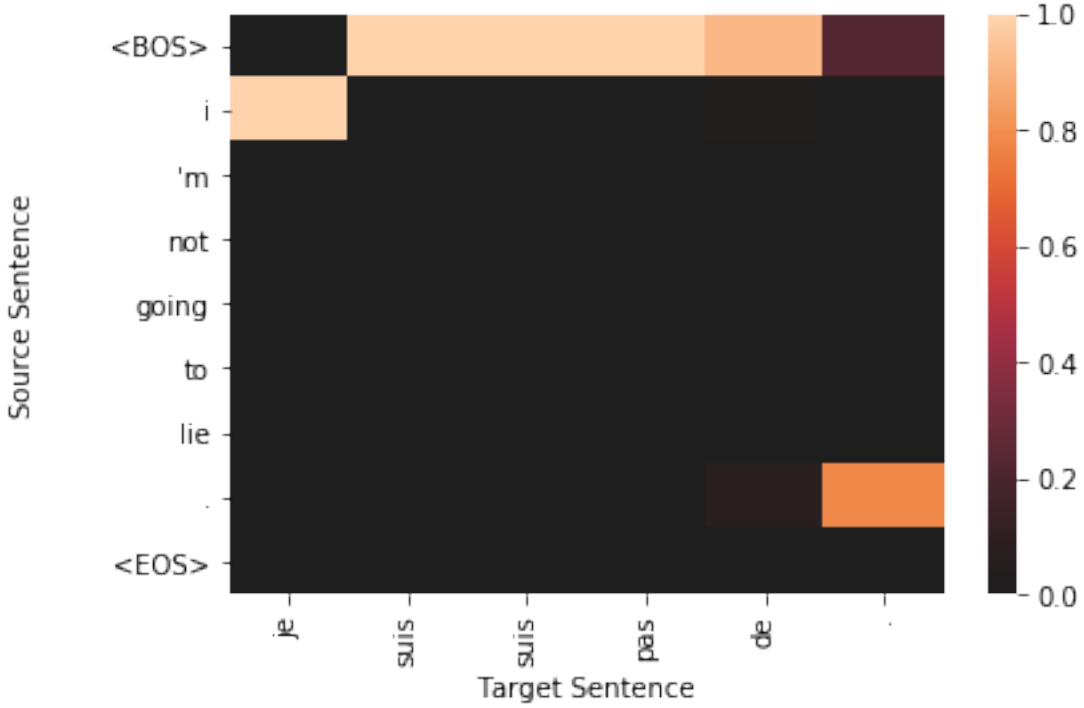

Source Sentence
<BOS>
you
're
going
to
be
a
father
.
<EOS>
vous
es
pas
de
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

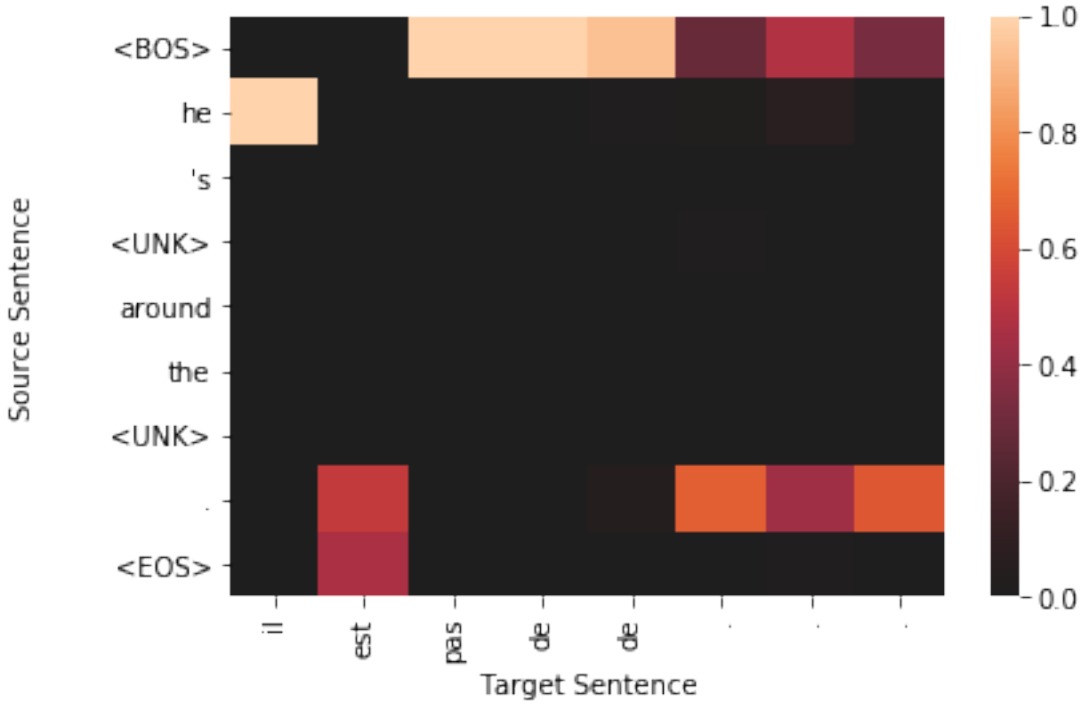

Source Sentence
<BOS>
i
'm
glad
you
're
still
here
.
<EOS>
je
suis
pas
que
vous
que
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

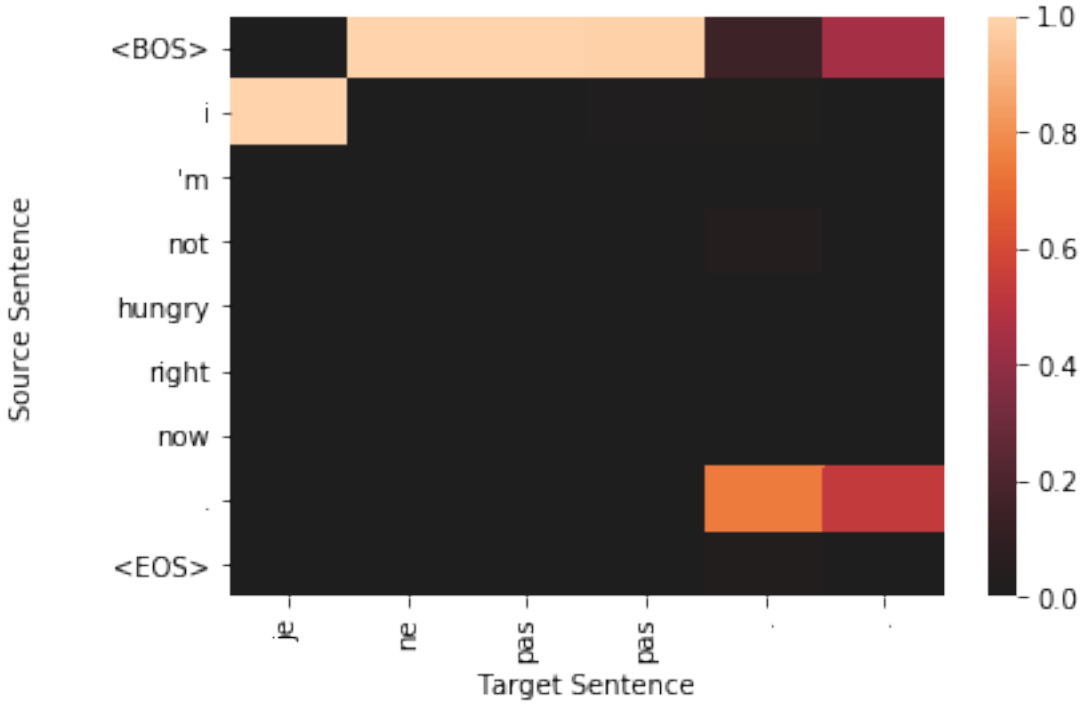

Source Sentence
<BOS>
i
'm
not
selling
you
my
car
.
<EOS>
je
suis
pas
pas
de
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

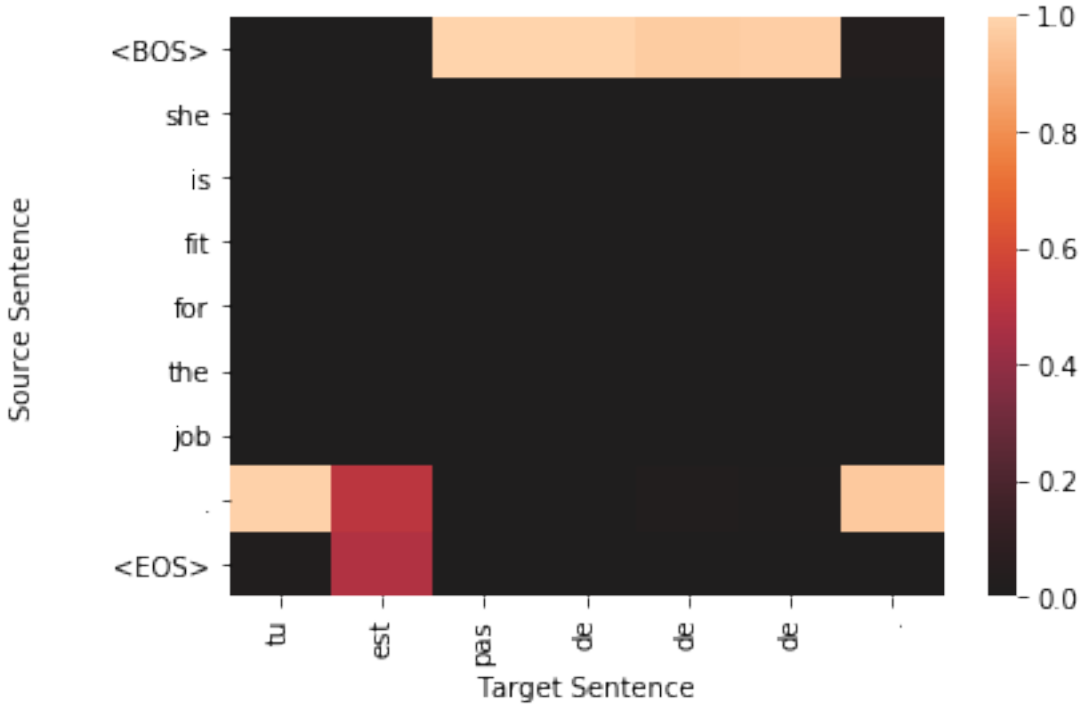

Source Sentence
<BOS>
we
're
all
together
right
now
.
<EOS>
nous
sommes
pas
.
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

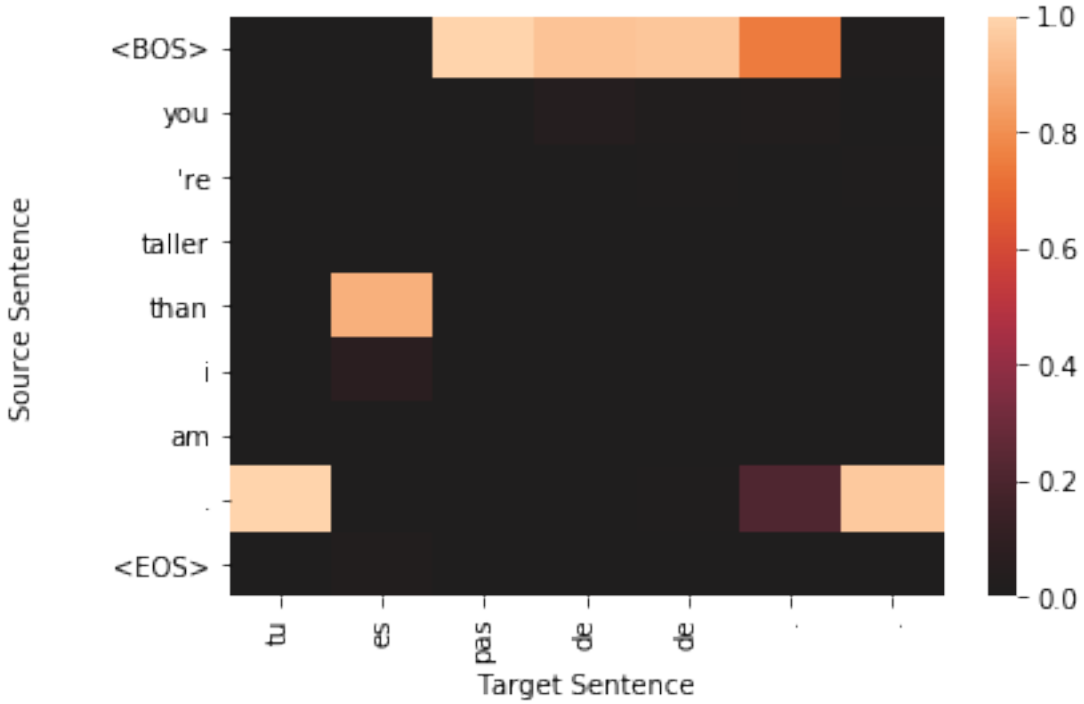

Source Sentence
<BOS>
you
're
too
old
for
me
.
<EOS>
tu
es
fort
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

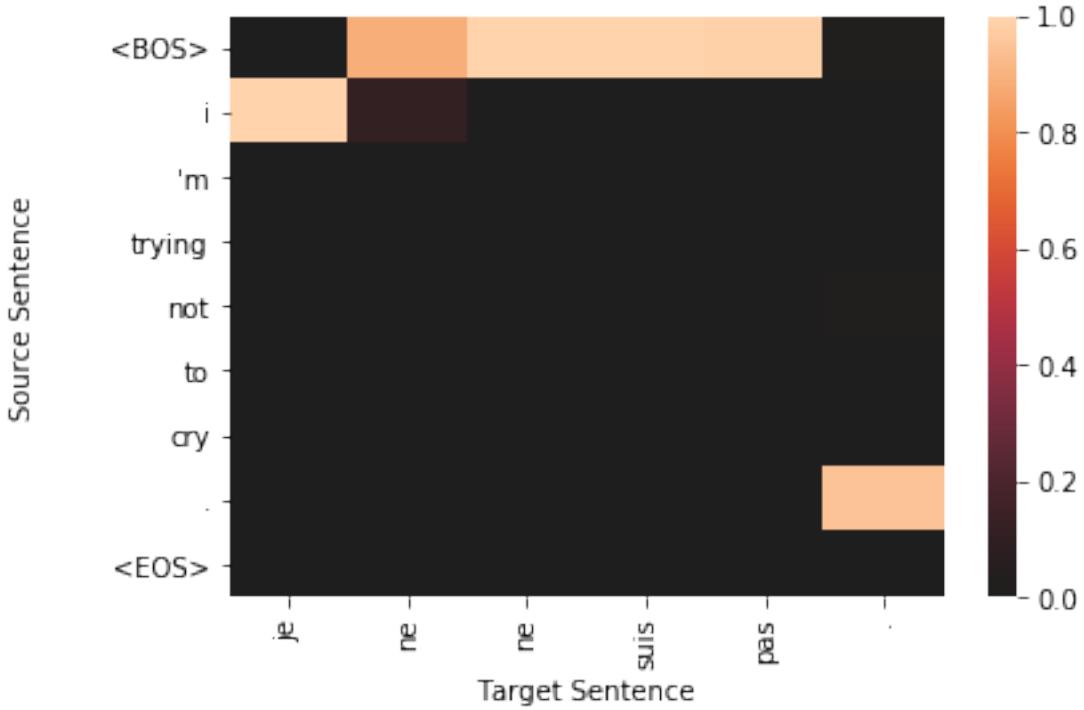

Source Sentence
<BOS>
i
'm
not
going
to
lie
.
<EOS>
je
suis
suis
pas
de
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

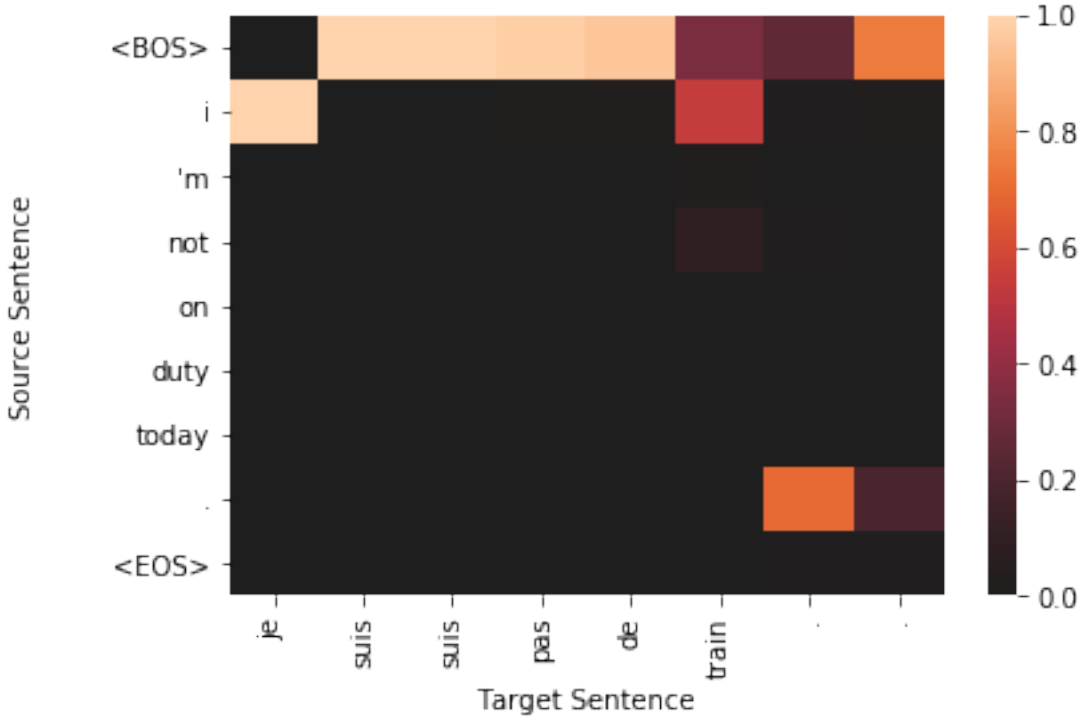

Source Sentence
<BOS>
he
's
<UNK>
around
the
<UNK>
.
<EOS>
il
est
pas
de
de
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

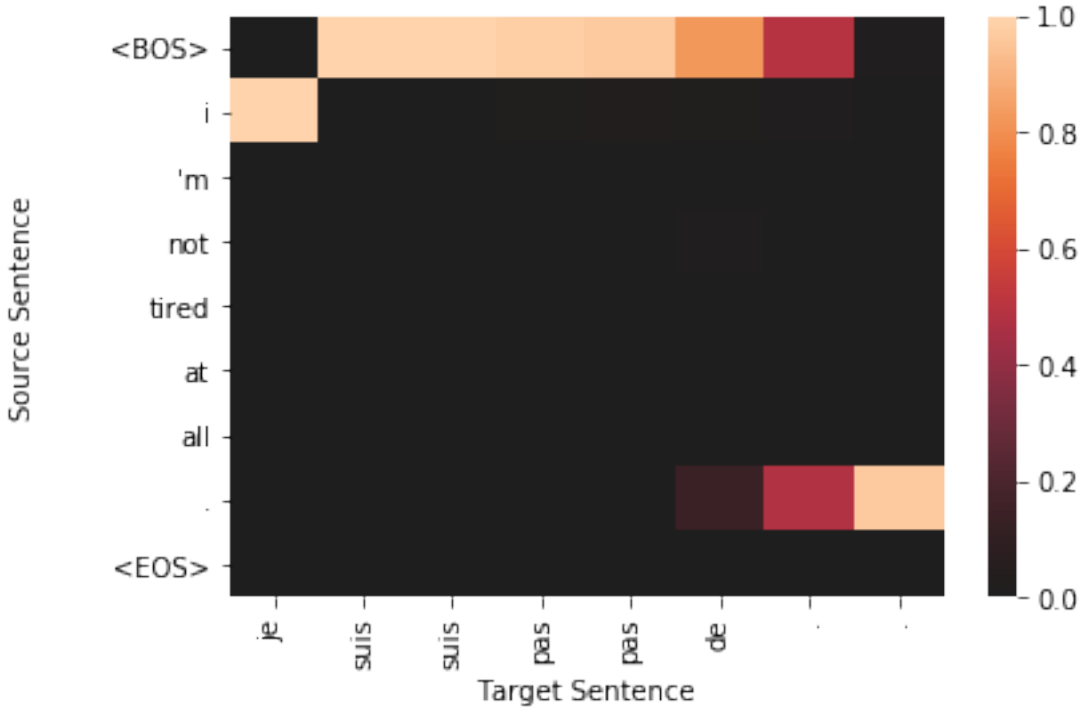

Source Sentence
<BOS>
i
'm
not
hungry
right
now
.
<EOS>
je
ne
pas
pas
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

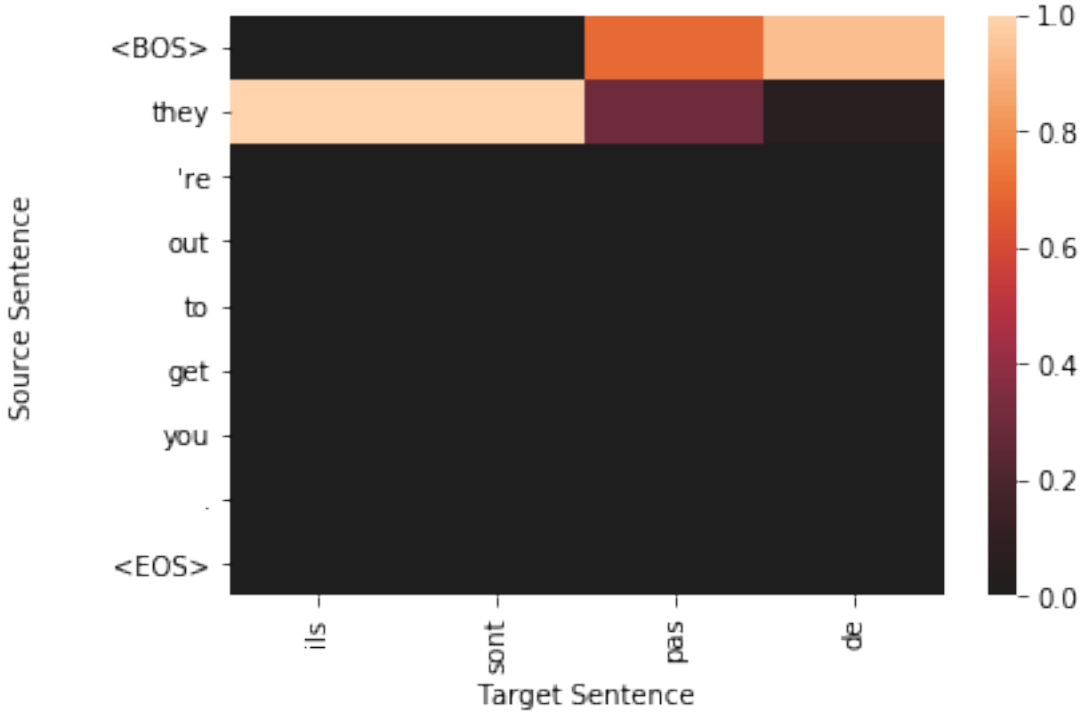

Source Sentence
<BOS>
she
is
fit
for
the
job
.
<EOS>
tu
est
pas
de
de
de
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

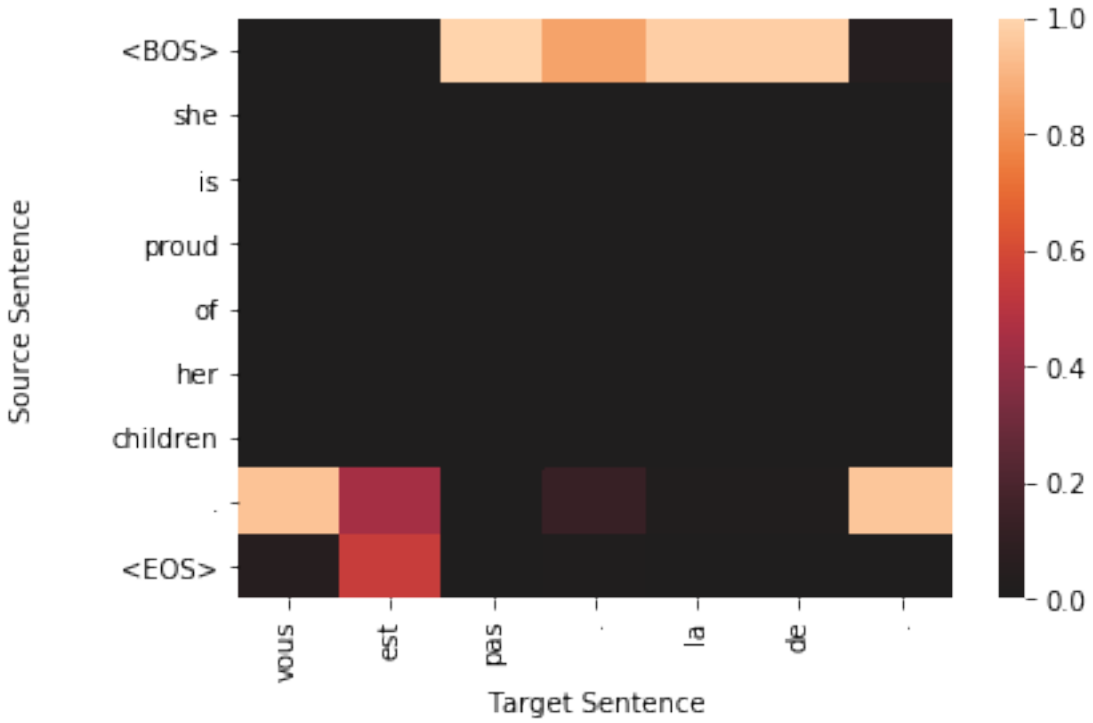

Source Sentence
<BOS>
you
're
taller
than
i
am
.
<EOS>
tu
es
pas
de
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

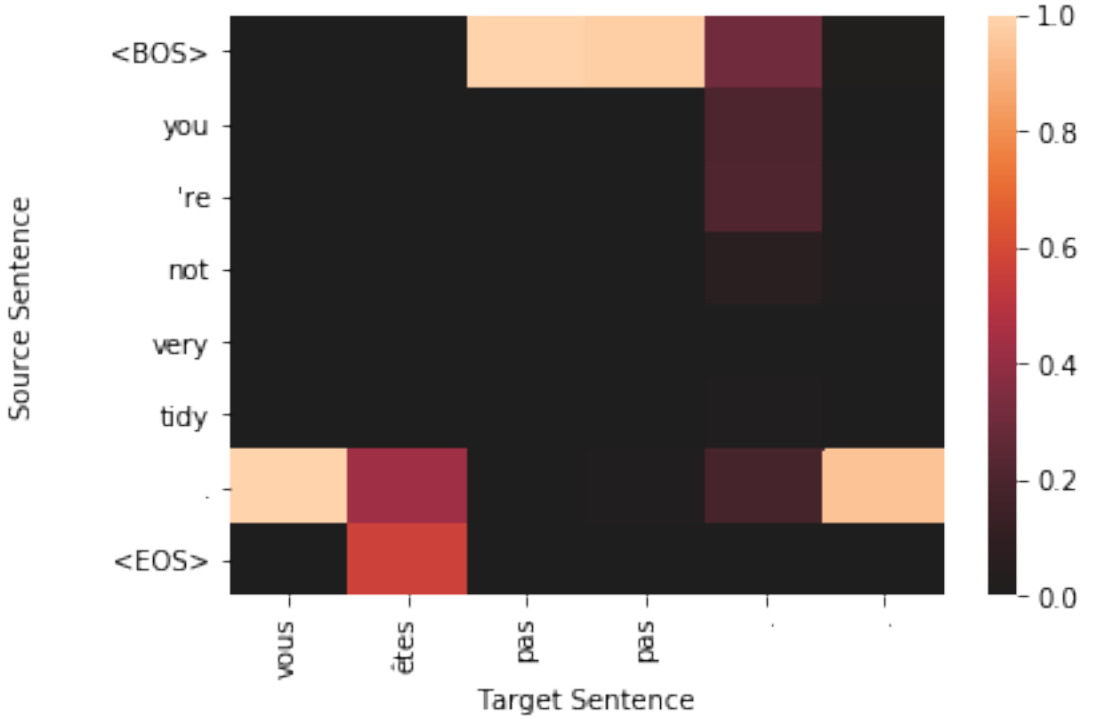

Source Sentence
<BOS>
i
'm
trying
not
to
cry
.
<EOS>
je
ne
ne
suis
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

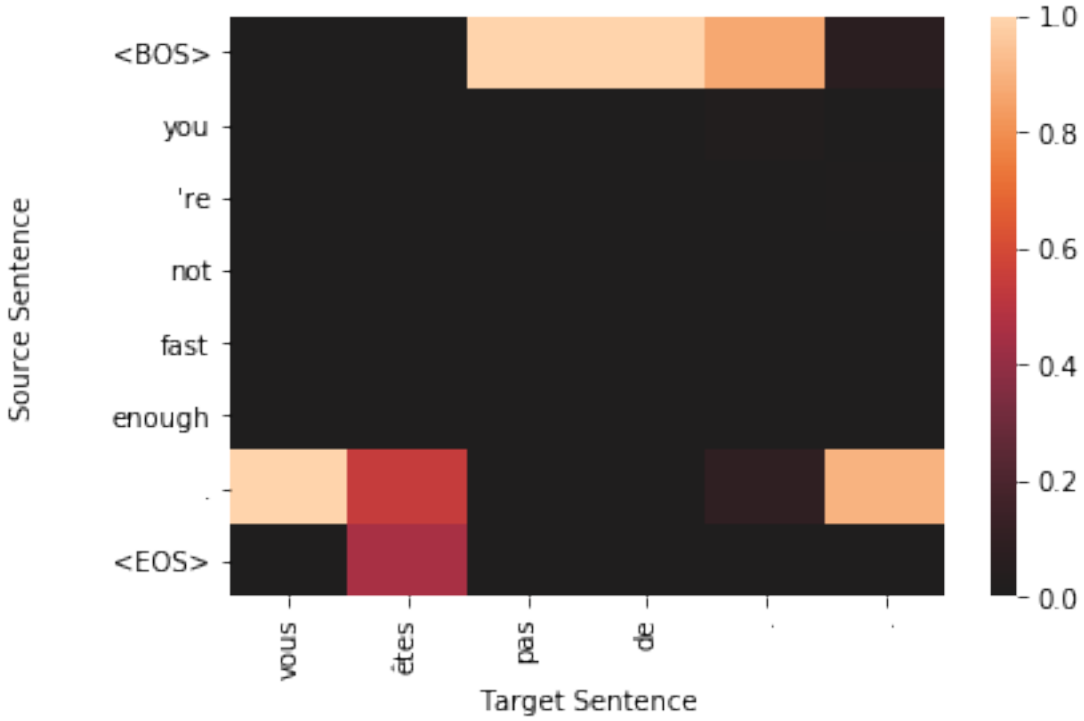

Source Sentence
<BOS>
i
'm
not
on
duty
today
.
<EOS>
je
suis
suis
pas
de
train
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

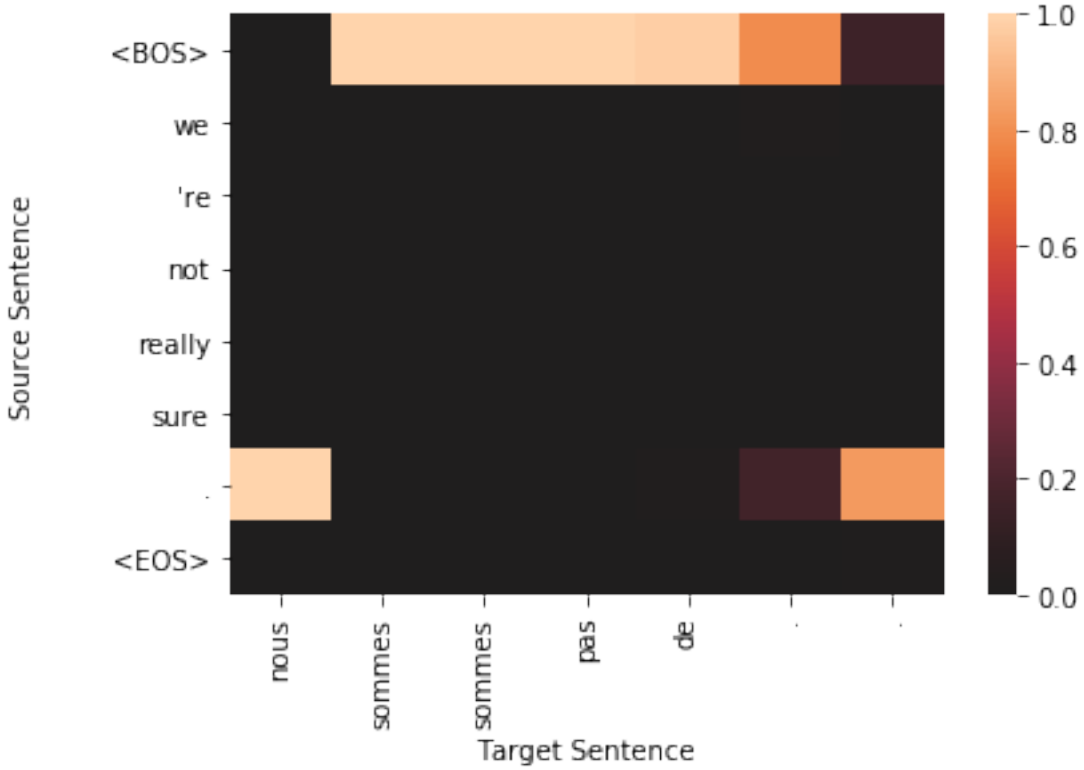

Source Sentence
<BOS>
i
'm
not
tired
at
all
.
<EOS>
je
suis
suis
pas
pas
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

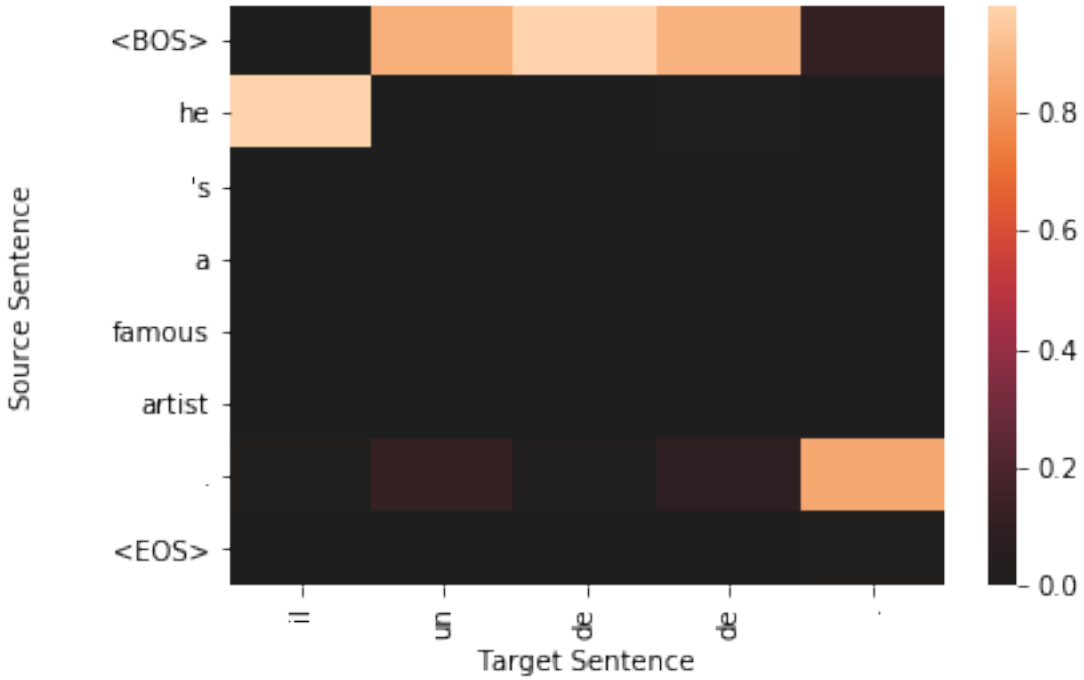

Source Sentence
<BOS>
they
're
out
to
get
you
.
<EOS>
ils
sont
pas
de
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

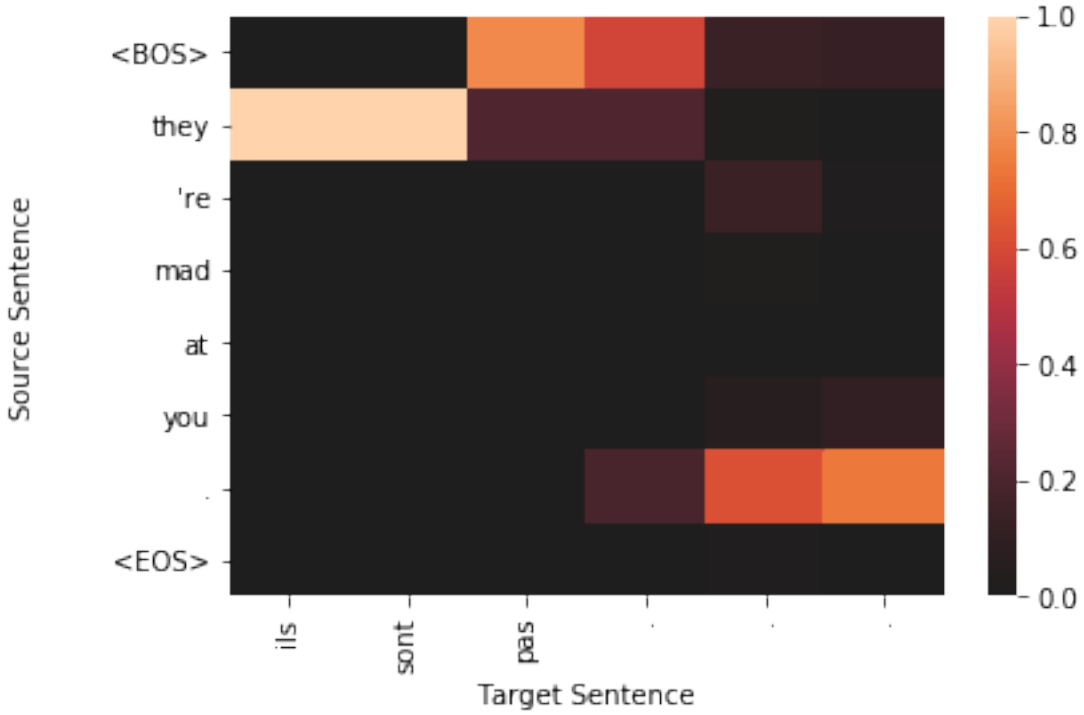

Source Sentence
<BOS>
she
is
proud
of
her
children
.
<EOS>
vous
est
pas
.
la
de
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

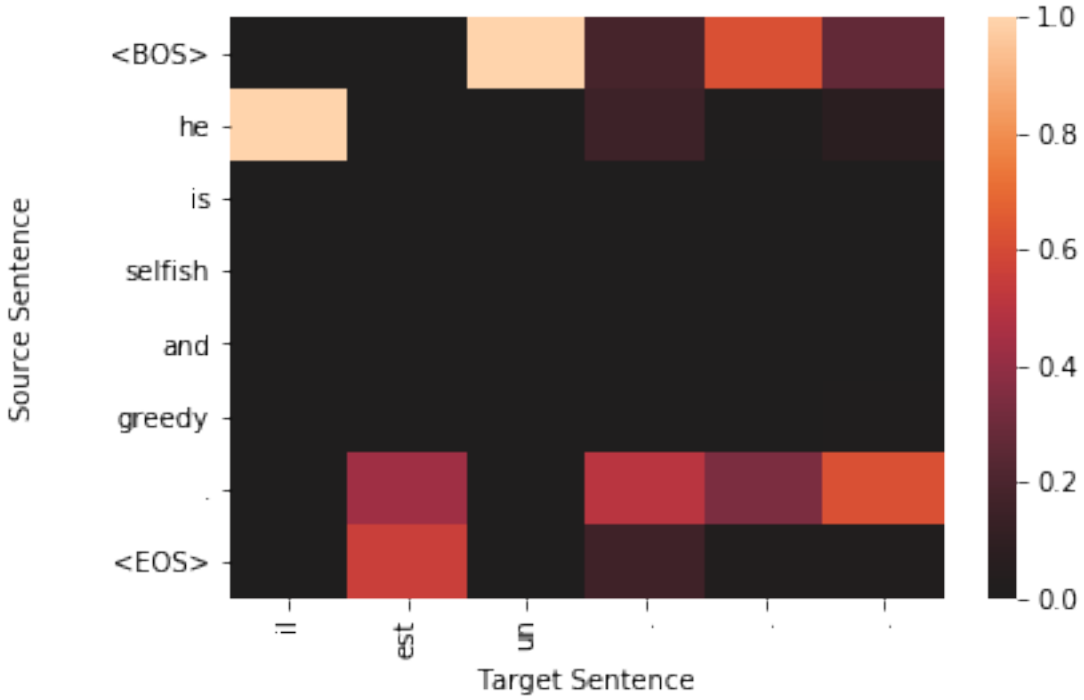

Source Sentence
<BOS>
you
're
not
very
tidy
.
<EOS>
vous
êtes
pas
pas
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

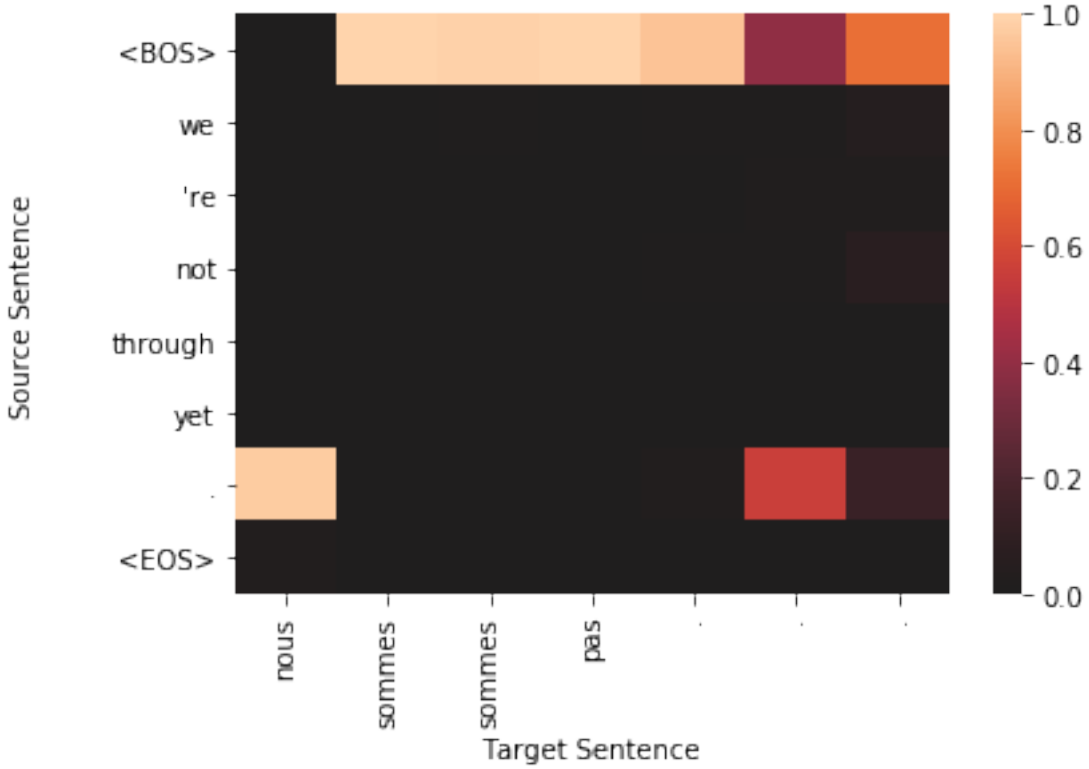

Source Sentence
<BOS>
you
're
not
fast
enough
.
<EOS>
vous
êtes
pas
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

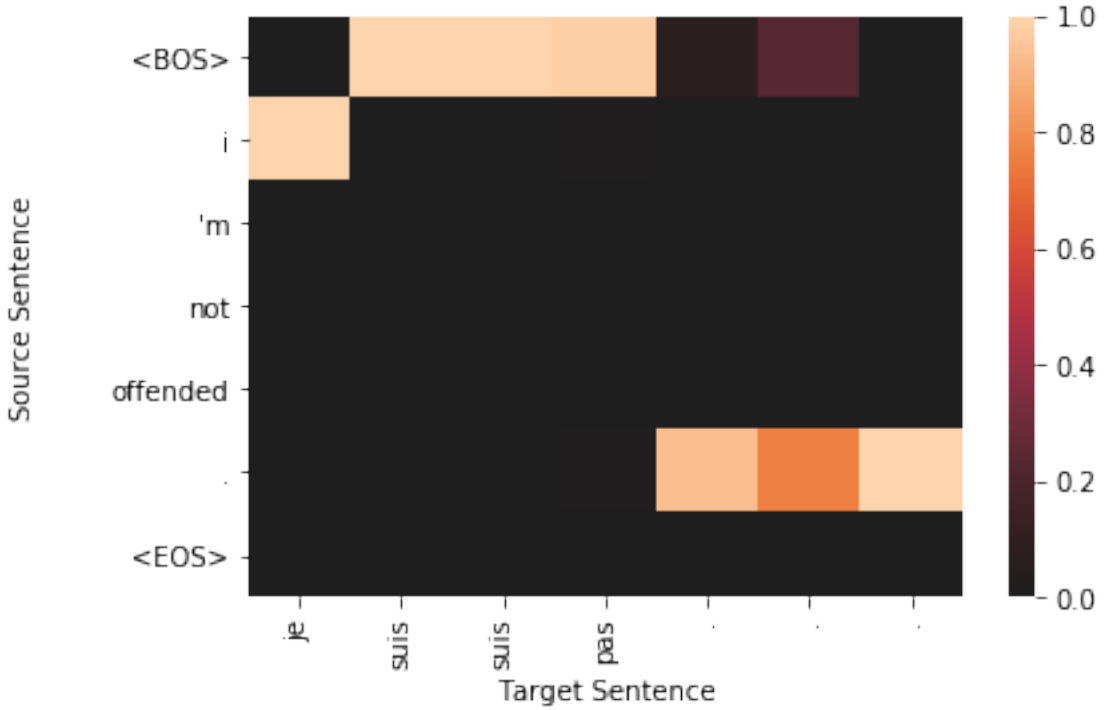

Source Sentence
<BOS>
we
're
not
really
sure
.
<EOS>
nous
sommes
sommes
pas
de
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

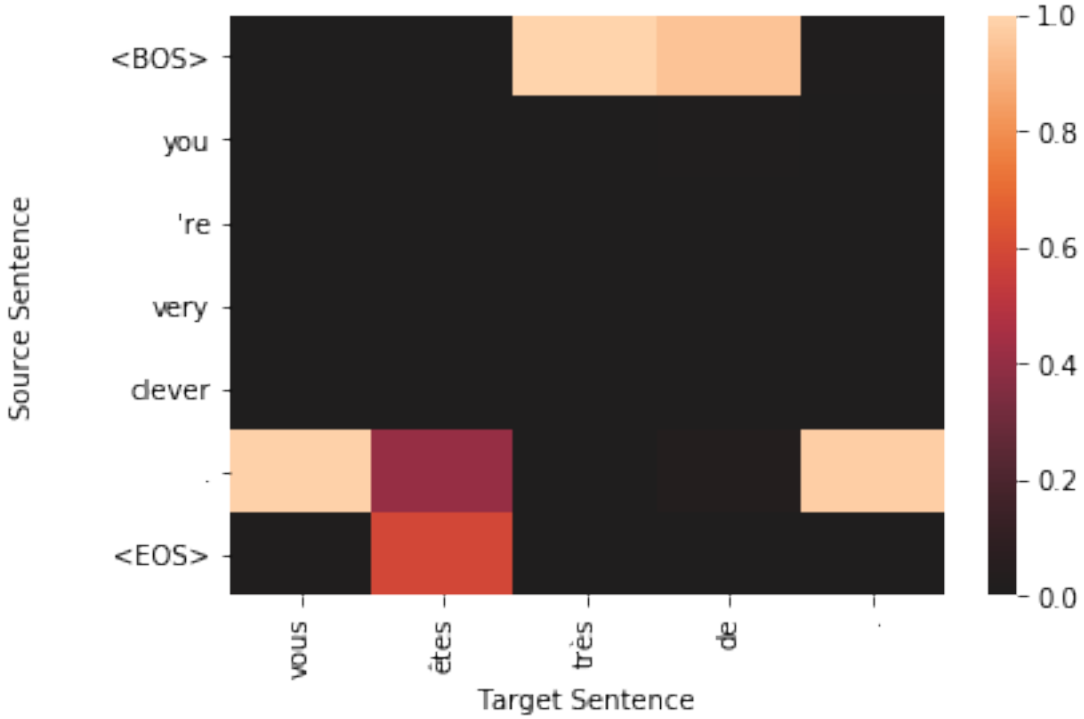

Source Sentence
<BOS>
he
's
a
famous
artist
.
<EOS>
il
un
de
de
.
Target Sentence
0.8
0.6
0.4
0.2
0.0

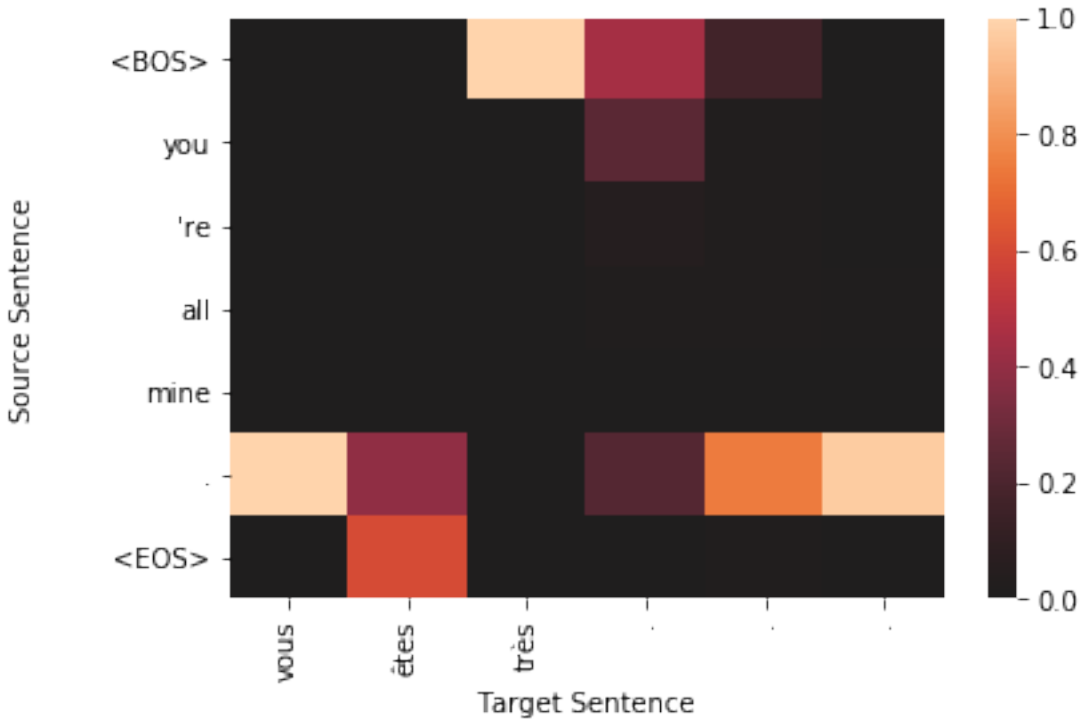

Source Sentence
<BOS>
they
're
mad
at
you
.
<EOS>
ils
sont
pas
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

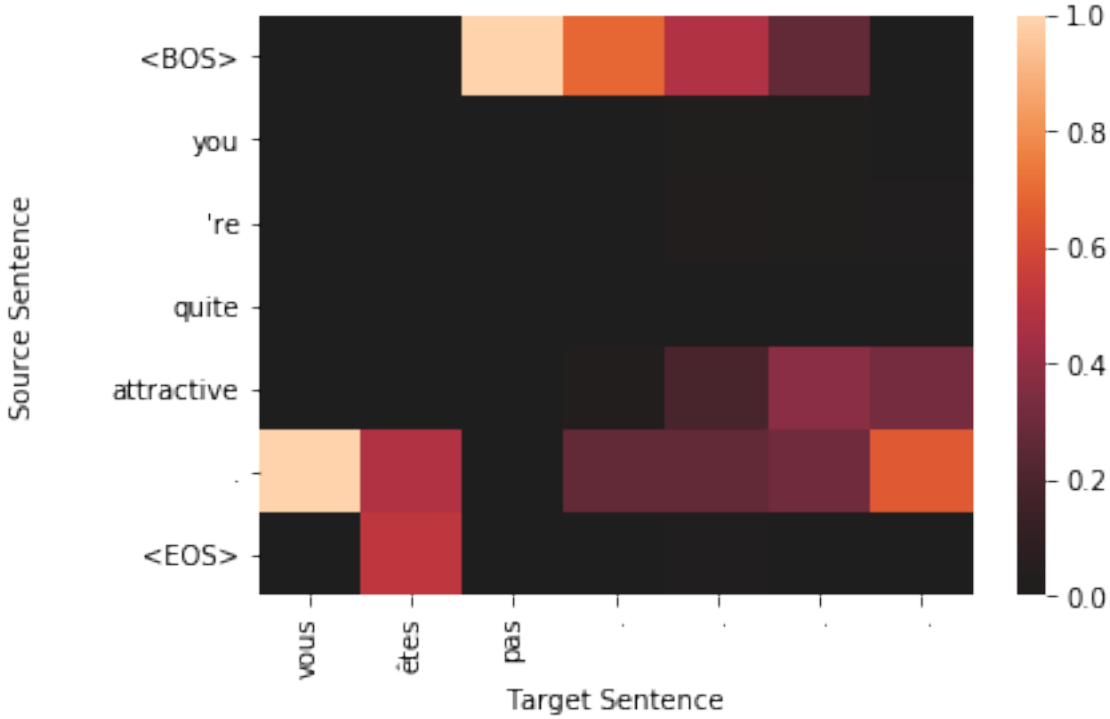

Source Sentence
<BOS>
he
is
selfish
and
greedy
.
<EOS>
il
est
un
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

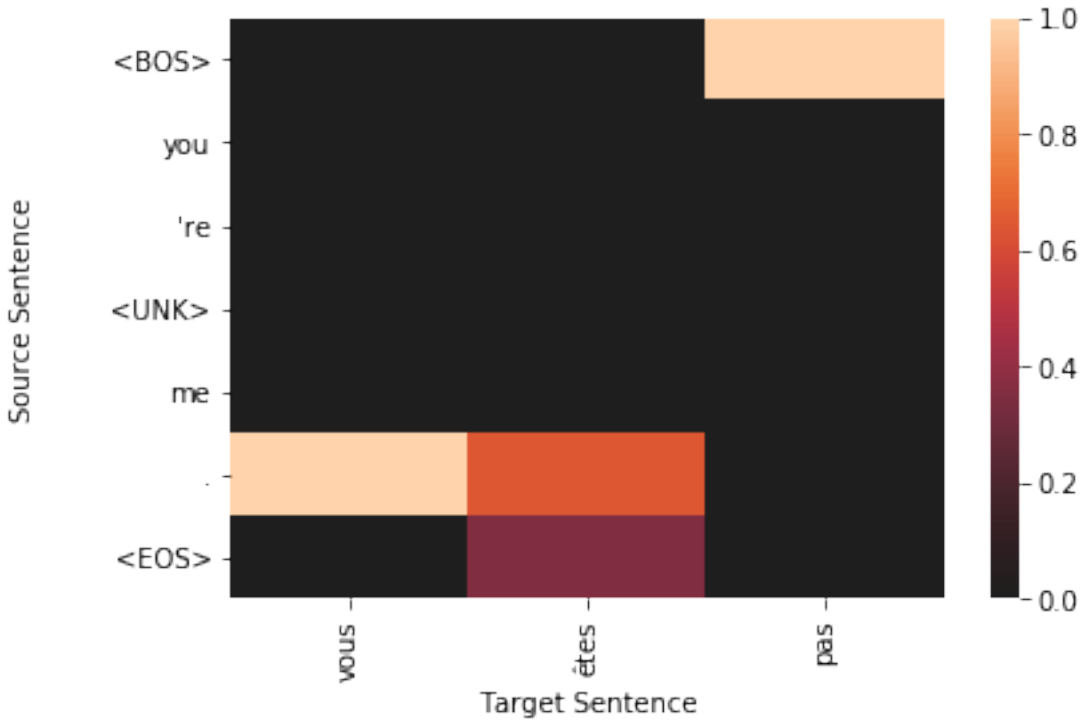

Source Sentence
<BOS>
we
're
not
through
yet
.
<EOS>
nous
sommes
sommes
pas
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

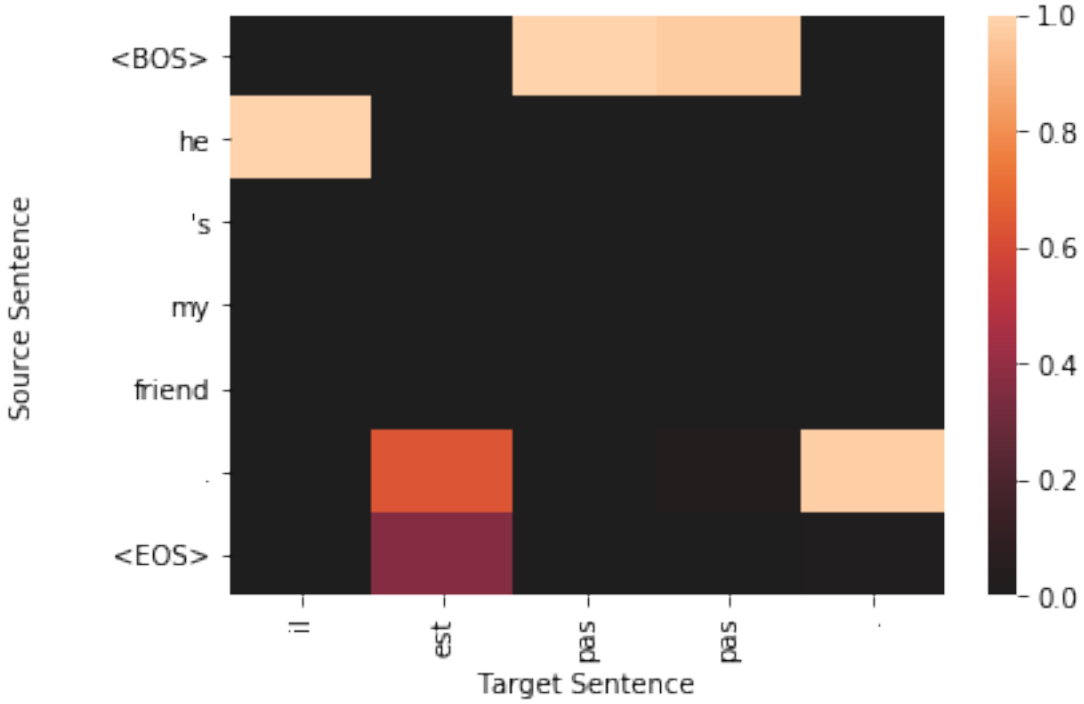

Source Sentence
<BOS>
i
'm
not
offended
.
<EOS>
je
suis
suis
pas
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

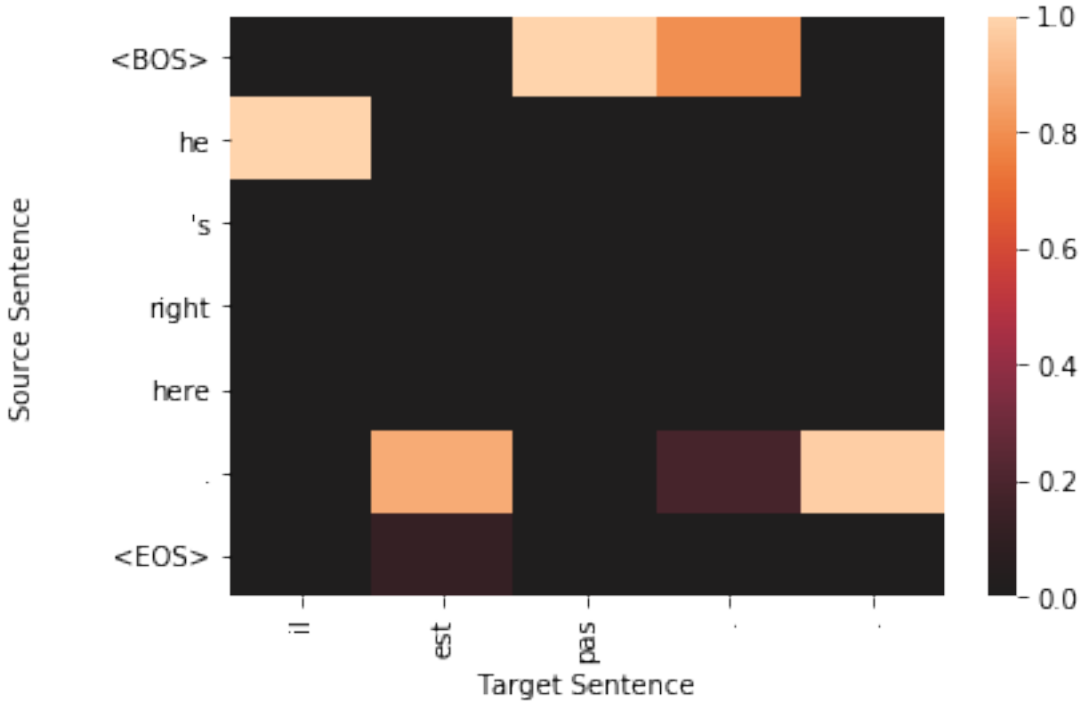

Source Sentence
<BOS>
you
're
very
clever
.
<EOS>
vous
êtes
très
de
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

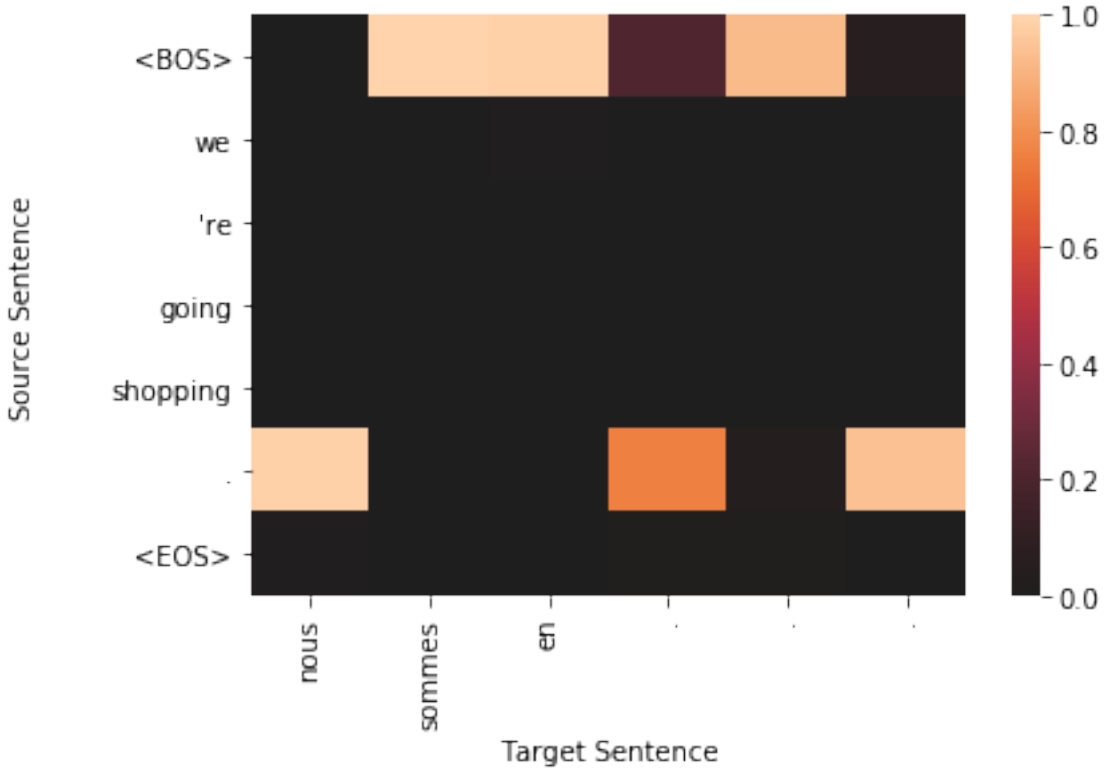

Source Sentence
<BOS>
you
're
all
mine
.
<EOS>
vous
êtes
très
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

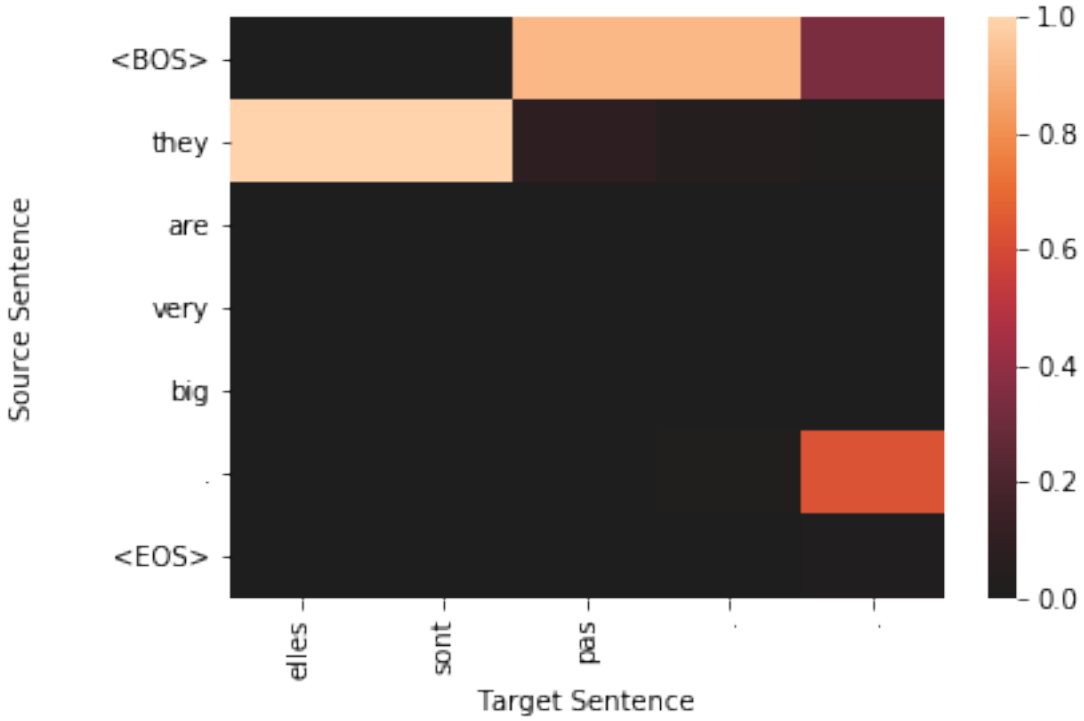

Source Sentence
<BOS>
you
're
quite
attractive
.
<EOS>
vous
êtes
pas
.
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

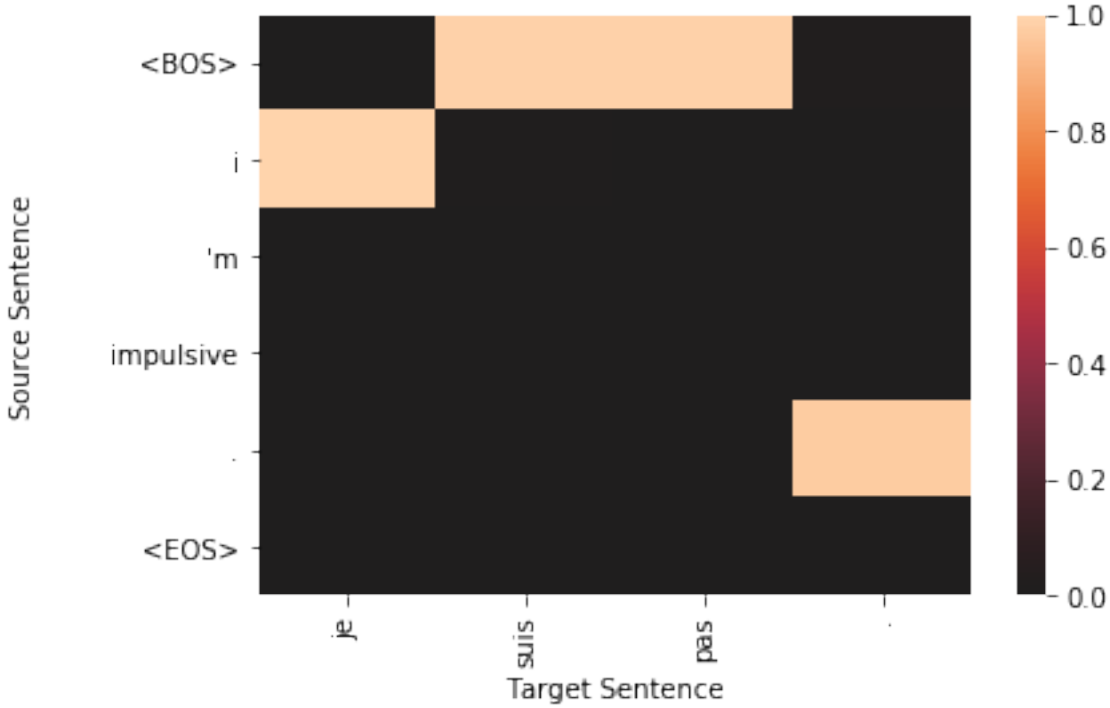

Source Sentence
<BOS>
you
're
<UNK>
me
.
<EOS>
vous
êtes
pas
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

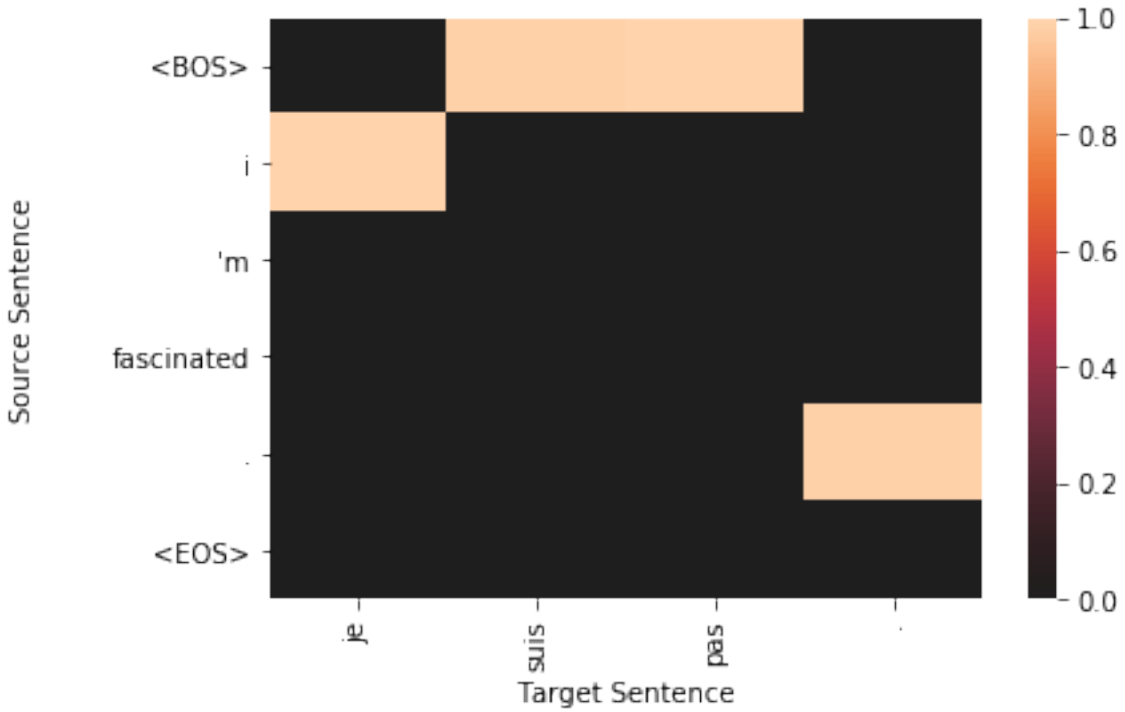

Source Sentence
<BOS>
he
's
my
friend
.
<EOS>
il
est
pas
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

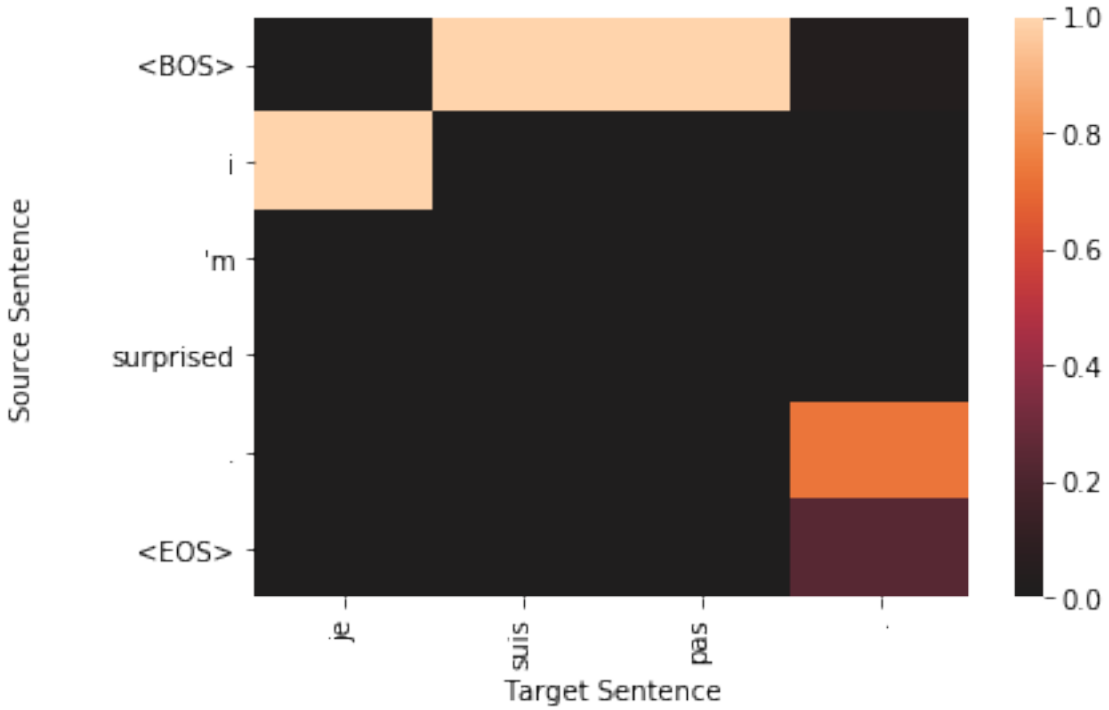

Source Sentence
<BOS>
he
's
right
here
.
<EOS>
il
est
pas
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

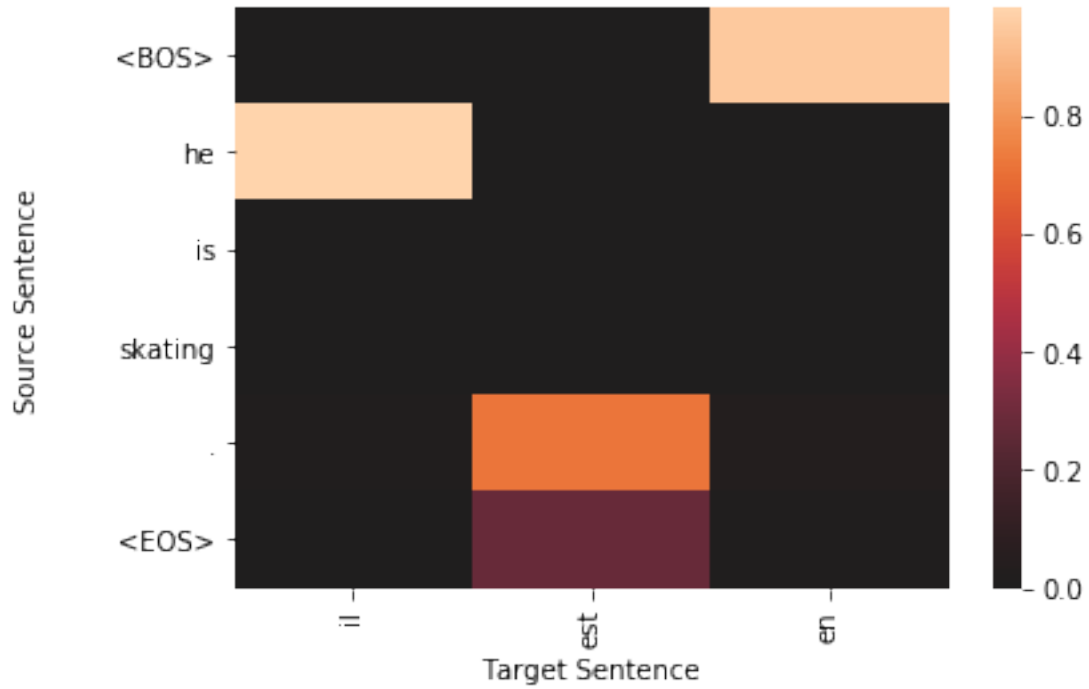

Source Sentence
<BOS>
we
're
going
shopping
.
<EOS>
nous
sommes
en
.
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0

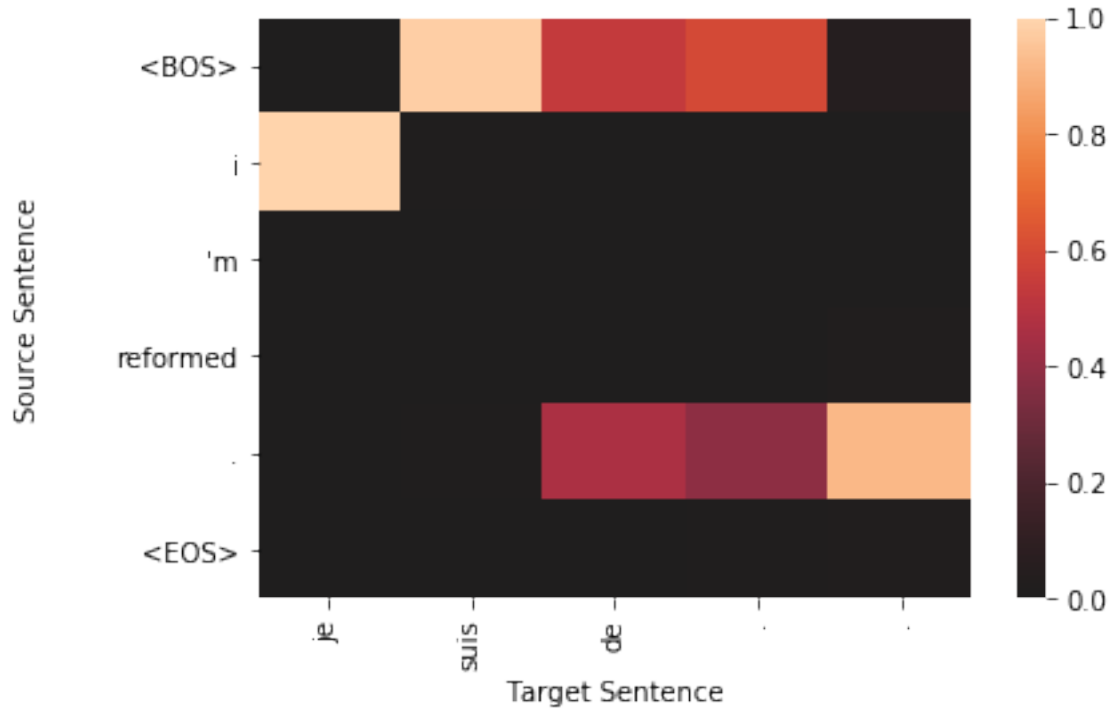

Source Sentence
<BOS>
they
are
very
big
.
<EOS>
elles
sont
pas
.
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0


Source Sentence
<BOS>
i
'm
impulsive
.
<EOS>
je
suis
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0


Source Sentence
<BOS>
i
'm
fascinated
.
<EOS>
je
suis
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0


Source Sentence
<BOS>
i
'm
surprised
.
<EOS>
je
suis
pas
.
Target Sentence
1.0
0.8
0.6
0.4
0.2
0.0






```
def get_source_sentence(vectorizer, batch_dict, index):
    indices = batch_dict['x_source'][index].cpu().data.numpy()
    vocab = vectorizer.source_vocab
    return sentence_from_indices(indices, vocab)

def get_true_sentence(vectorizer, batch_dict, index):
```

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```
    return sentence_from_indices(batch_dict['y_target'].cpu().data.numpy()[index],␣
↪vectorizer.target_vocab)

def get_sampled_sentence(vectorizer, batch_dict, index):
    y_pred = model(x_source=batch_dict['x_source'],
                   x_source_lengths=batch_dict['x_source_length'],
                   target_sequence=batch_dict['x_target'])
    return sentence_from_indices(torch.max(y_pred, dim=2)[1].cpu().data.
↪numpy()[index], vectorizer.target_vocab)

def get_all_sentences(vectorizer, batch_dict, index):
    return {"source": get_source_sentence(vectorizer, batch_dict, index),
            "truth": get_true_sentence(vectorizer, batch_dict, index),
            "sampled": get_sampled_sentence(vectorizer, batch_dict, index)}

def sentence_from_indices(indices, vocab, strict=True):
    ignore_indices = set([vocab.mask_index, vocab.begin_seq_index, vocab.end_seq_
↪index])
    out = []
    for index in indices:
        if index == vocab.begin_seq_index and strict:
            continue
        elif index == vocab.end_seq_index and strict:
            return " ".join(out)
        else:
            out.append(vocab.lookup_index(index))
    return " ".join(out)

results = get_all_sentences(vectorizer, batch_dict, 1)
results
```

```
{'source': "i 'm not going to tell you how to do that .",
 'truth': 'je ne vais pas te dire comment le faire .',
 'sampled': 'je suis suis pas de de de . . .'}
```

12.6 Neural Machine Translation - Scheduled Sampling

In the previous notebook (no sampling), the model assumes that the target sequence is provided and will be used as the input at each time step in the decoder. In other words, we use teacher forcing with 100% probability.

At test time, this assumption is violated because the model cannot cheat and know the sequence it is trying to generate. To accommodate this fact, one technique is to allow the model to use its own predictions during training. This is a technique explored in the literature as "learning to search" and "scheduled sampling", or simply without tearcher forcing.

One intuitive way to understand this technique is to think of the prediction problem as a search problem. At each time step, the model has many paths from which to choose (the number of choices is the size of the target vocabulary) and the target sequence is observations of correct paths.

At test time, the model is finally allowed to go "off path" because it is not provided the correct path from which it should be computing probability distributions. Thus, the technique of letting the model sample its own path provides a way in which you can optimize the model for having better probability distributions when it deviates from target sequences in the dataset.

There are three primary modifications to the code to have the model sample its own predictions during training.

- First, the initial indices are made more explicit as the `BEGINOFSEQUENCE` token indices.
- Second, a random sample is drawn for each step in the generation loop, and if the random sample is smaller than the sample probability, it uses the model's predictions during that iteration.
- Finally, the actual sampling itself is done under the conditional `if use_sample`.

In the `NMTDecoder`, a commented line shows how you could use the maximum prediction, whereas the uncommented line shows how to actually sample indices at rates proportional to their probability.

```
if use_sample:
    p_y_t_index = F.softmax(score_for_y_t_index * self._sampling_temperature, dim=1)
    # _, y_t_index = torch.max(p_y_t_index, 1)
    y_t_index = torch.multinomial(p_y_t_index, 1).squeeze()
```

12.6.1 Import

```
import os
from argparse import Namespace
from collections import Counter
import json
import re
import string

import numpy as np
import pandas as pd
import torch
import torch.nn as nn
from torch.nn import functional as F
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader
from tqdm import tqdm_notebook
```

12.6.2 Data Prepration (Vocabulary, Verctorizer, DataLoader)

```
class Vocabulary(object):
    """Class to process text and extract vocabulary for mapping"""

    def __init__(self, token_to_idx=None):
        """
        Args:
            token_to_idx (dict): a pre-existing map of tokens to indices
        """

        if token_to_idx is None:
            token_to_idx = {}
        self._token_to_idx = token_to_idx

        self._idx_to_token = {idx: token
                              for token, idx in self._token_to_idx.items()}

    def to_serializable(self):
        """ returns a dictionary that can be serialized """
        return {'token_to_idx': self._token_to_idx}
```

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```
    @classmethod
    def from_serializable(cls, contents):
        """ instantiates the Vocabulary from a serialized dictionary """
        return cls(**contents)

    def add_token(self, token):
        """Update mapping dicts based on the token.

        Args:
            token (str): the item to add into the Vocabulary
        Returns:
            index (int): the integer corresponding to the token
        """
        if token in self._token_to_idx:
            index = self._token_to_idx[token]
        else:
            index = len(self._token_to_idx)
            self._token_to_idx[token] = index
            self._idx_to_token[index] = token
        return index

    def add_many(self, tokens):
        """Add a list of tokens into the Vocabulary

        Args:
            tokens (list): a list of string tokens
        Returns:
            indices (list): a list of indices corresponding to the tokens
        """
        return [self.add_token(token) for token in tokens]

    def lookup_token(self, token):
        """Retrieve the index associated with the token

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        """
        return self._token_to_idx[token]

    def lookup_index(self, index):
        """Return the token associated with the index

        Args:
            index (int): the index to look up
        Returns:
            token (str): the token corresponding to the index
        Raises:
            KeyError: if the index is not in the Vocabulary
        """
        if index not in self._idx_to_token:
            raise KeyError("the index (%d) is not in the Vocabulary" % index)
        return self._idx_to_token[index]

    def __str__(self):
```

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```
        return "<Vocabulary(size=%d)>" % len(self)

    def __len__(self):
        return len(self._token_to_idx)
```

```
class SequenceVocabulary(Vocabulary):
    def __init__(self, token_to_idx=None, unk_token="<UNK>",
                 mask_token="<MASK>", begin_seq_token="<BEGIN>",
                 end_seq_token="<END>"):

        super(SequenceVocabulary, self).__init__(token_to_idx)

        self._mask_token = mask_token
        self._unk_token = unk_token
        self._begin_seq_token = begin_seq_token
        self._end_seq_token = end_seq_token

        self.mask_index = self.add_token(self._mask_token)
        self.unk_index = self.add_token(self._unk_token)
        self.begin_seq_index = self.add_token(self._begin_seq_token)
        self.end_seq_index = self.add_token(self._end_seq_token)

    def to_serializable(self):
        contents = super(SequenceVocabulary, self).to_serializable()
        contents.update({'unk_token': self._unk_token,
                         'mask_token': self._mask_token,
                         'begin_seq_token': self._begin_seq_token,
                         'end_seq_token': self._end_seq_token})
        return contents

    def lookup_token(self, token):
        """Retrieve the index associated with the token
          or the UNK index if token isn't present.

        Args:
            token (str): the token to look up
        Returns:
            index (int): the index corresponding to the token
        Notes:
            `unk_index` needs to be >=0 (having been added into the Vocabulary)
              for the UNK functionality
        """
        if self.unk_index >= 0:
            return self._token_to_idx.get(token, self.unk_index)
        else:
            return self._token_to_idx[token]
```

```
class NMTVectorizer(object):
    """ The Vectorizer which coordinates the Vocabularies and puts them to use"""
    def __init__(self, source_vocab, target_vocab, max_source_length, max_target_
↪length):
        """
        Args:
            source_vocab (SequenceVocabulary): maps source words to integers
            target_vocab (SequenceVocabulary): maps target words to integers
            max_source_length (int): the longest sequence in the source dataset
```

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```
            max_target_length (int): the longest sequence in the target dataset
        """
        self.source_vocab = source_vocab
        self.target_vocab = target_vocab

        self.max_source_length = max_source_length
        self.max_target_length = max_target_length


    def _vectorize(self, indices, vector_length=-1, mask_index=0):
        """Vectorize the provided indices

        Args:
            indices (list): a list of integers that represent a sequence
            vector_length (int): an argument for forcing the length of index vector
            mask_index (int): the mask_index to use; almost always 0
        """
        if vector_length < 0:
            vector_length = len(indices)

        vector = np.zeros(vector_length, dtype=np.int64)
        vector[:len(indices)] = indices
        vector[len(indices):] = mask_index

        return vector

    def _get_source_indices(self, text):
        """Return the vectorized source text

        Args:
            text (str): the source text; tokens should be separated by spaces
        Returns:
            indices (list): list of integers representing the text
        """
        indices = [self.source_vocab.begin_seq_index]
        indices.extend(self.source_vocab.lookup_token(token) for token in text.split(
↪" "))
        indices.append(self.source_vocab.end_seq_index)
        return indices

    def _get_target_indices(self, text):
        """Return the vectorized source text

        Args:
            text (str): the source text; tokens should be separated by spaces
        Returns:
            a tuple: (x_indices, y_indices)
                x_indices (list): list of integers representing the observations in␣
↪target decoder
                y_indices (list): list of integers representing predictions in target␣
↪decoder
        """
        indices = [self.target_vocab.lookup_token(token) for token in text.split(" ")]
        x_indices = [self.target_vocab.begin_seq_index] + indices
        y_indices = indices + [self.target_vocab.end_seq_index]
        return x_indices, y_indices
```

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```
    def vectorize(self, source_text, target_text, use_dataset_max_lengths=True):
        """Return the vectorized source and target text

        The vetorized source text is just the a single vector.
        The vectorized target text is split into two vectors in a similar style to
            the surname modeling in Chapter 7.
        At each timestep, the first vector is the observation and the second vector␣
↪is the target.


        Args:
            source_text (str): text from the source language
            target_text (str): text from the target language
            use_dataset_max_lengths (bool): whether to use the global max vector␣
↪lengths
        Returns:
            The vectorized data point as a dictionary with the keys:
                source_vector, target_x_vector, target_y_vector, source_length
        """
        source_vector_length = -1
        target_vector_length = -1

        if use_dataset_max_lengths:
            source_vector_length = self.max_source_length + 2
            target_vector_length = self.max_target_length + 1

        source_indices = self._get_source_indices(source_text)
        source_vector = self._vectorize(source_indices,
                                        vector_length=source_vector_length,
                                        mask_index=self.source_vocab.mask_index)

        target_x_indices, target_y_indices = self._get_target_indices(target_text)
        target_x_vector = self._vectorize(target_x_indices,
                                        vector_length=target_vector_length,
                                        mask_index=self.target_vocab.mask_index)
        target_y_vector = self._vectorize(target_y_indices,
                                        vector_length=target_vector_length,
                                        mask_index=self.target_vocab.mask_index)
        return {"source_vector": source_vector,
                "target_x_vector": target_x_vector,
                "target_y_vector": target_y_vector,
                "source_length": len(source_indices)}

    @classmethod
    def from_dataframe(cls, bitext_df):
        """Instantiate the vectorizer from the dataset dataframe

        Args:
            bitext_df (pandas.DataFrame): the parallel text dataset
        Returns:
            an instance of the NMTVectorizer
        """
        source_vocab = SequenceVocabulary()
        target_vocab = SequenceVocabulary()

        max_source_length = 0
        max_target_length = 0
```

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```
        for _, row in bitext_df.iterrows():
            source_tokens = row["source_language"].split(" ")
            if len(source_tokens) > max_source_length:
                max_source_length = len(source_tokens)
            for token in source_tokens:
                source_vocab.add_token(token)

            target_tokens = row["target_language"].split(" ")
            if len(target_tokens) > max_target_length:
                max_target_length = len(target_tokens)
            for token in target_tokens:
                target_vocab.add_token(token)

        return cls(source_vocab, target_vocab, max_source_length, max_target_length)

    @classmethod
    def from_serializable(cls, contents):
        source_vocab = SequenceVocabulary.from_serializable(contents["source_vocab"])
        target_vocab = SequenceVocabulary.from_serializable(contents["target_vocab"])

        return cls(source_vocab=source_vocab,
                   target_vocab=target_vocab,
                   max_source_length=contents["max_source_length"],
                   max_target_length=contents["max_target_length"])

    def to_serializable(self):
        return {"source_vocab": self.source_vocab.to_serializable(),
                "target_vocab": self.target_vocab.to_serializable(),
                "max_source_length": self.max_source_length,
                "max_target_length": self.max_target_length}
```

```
class NMTDataset(Dataset):
    def __init__(self, text_df, vectorizer):
        """
        Args:
            surname_df (pandas.DataFrame): the dataset
            vectorizer (SurnameVectorizer): vectorizer instatiated from dataset
        """
        self.text_df = text_df
        self._vectorizer = vectorizer

        self.train_df = self.text_df[self.text_df.split=='train']
        self.train_size = len(self.train_df)

        self.val_df = self.text_df[self.text_df.split=='val']
        self.validation_size = len(self.val_df)

        self.test_df = self.text_df[self.text_df.split=='test']
        self.test_size = len(self.test_df)

        self._lookup_dict = {'train': (self.train_df, self.train_size),
                             'val': (self.val_df, self.validation_size),
                             'test': (self.test_df, self.test_size)}

        self.set_split('train')
```

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```
    @classmethod
    def load_dataset_and_make_vectorizer(cls, dataset_csv):
        """Load dataset and make a new vectorizer from scratch

        Args:
            surname_csv (str): location of the dataset
        Returns:
            an instance of SurnameDataset
        """
        text_df = pd.read_csv(dataset_csv)
        train_subset = text_df[text_df.split=='train']
        return cls(text_df, NMTVectorizer.from_dataframe(train_subset))

    @classmethod
    def load_dataset_and_load_vectorizer(cls, dataset_csv, vectorizer_filepath):
        """Load dataset and the corresponding vectorizer.
        Used in the case in the vectorizer has been cached for re-use

        Args:
            surname_csv (str): location of the dataset
            vectorizer_filepath (str): location of the saved vectorizer
        Returns:
            an instance of SurnameDataset
        """
        text_df = pd.read_csv(dataset_csv)
        vectorizer = cls.load_vectorizer_only(vectorizer_filepath)
        return cls(text_df, vectorizer)

    @staticmethod
    def load_vectorizer_only(vectorizer_filepath):
        """a static method for loading the vectorizer from file

        Args:
            vectorizer_filepath (str): the location of the serialized vectorizer
        Returns:
            an instance of SurnameVectorizer
        """
        with open(vectorizer_filepath) as fp:
            return NMTVectorizer.from_serializable(json.load(fp))

    def save_vectorizer(self, vectorizer_filepath):
        """saves the vectorizer to disk using json

        Args:
            vectorizer_filepath (str): the location to save the vectorizer
        """
        with open(vectorizer_filepath, "w") as fp:
            json.dump(self._vectorizer.to_serializable(), fp)

    def get_vectorizer(self):
        """ returns the vectorizer """
        return self._vectorizer

    def set_split(self, split="train"):
        self._target_split = split
        self._target_df, self._target_size = self._lookup_dict[split]
```

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```
    def __len__(self):
        return self._target_size

    def __getitem__(self, index):
        """the primary entry point method for PyTorch datasets

        Args:
            index (int): the index to the data point
        Returns:
            a dictionary holding the data point: (x_data, y_target, class_index)
        """
        row = self._target_df.iloc[index]

        vector_dict = self._vectorizer.vectorize(row.source_language, row.target_
↪language)

        return {"x_source": vector_dict["source_vector"],
                "x_target": vector_dict["target_x_vector"],
                "y_target": vector_dict["target_y_vector"],
                "x_source_length": vector_dict["source_length"]}

    def get_num_batches(self, batch_size):
        """Given a batch size, return the number of batches in the dataset

        Args:
            batch_size (int)
        Returns:
            number of batches in the dataset
        """
        return len(self) // batch_size

def generate_nmt_batches(dataset, batch_size, shuffle=True,
                         drop_last=True, device="cpu"):
    """A generator function which wraps the PyTorch DataLoader.  The NMT Version """
    dataloader = DataLoader(dataset=dataset, batch_size=batch_size,
                            shuffle=shuffle, drop_last=drop_last)

    for data_dict in dataloader:
        lengths = data_dict['x_source_length'].numpy()
        sorted_length_indices = lengths.argsort()[::-1].tolist()

        out_data_dict = {}
        for name, tensor in data_dict.items():
            out_data_dict[name] = data_dict[name][sorted_length_indices].to(device)
        yield out_data_dict
```

12.6.3 Neural Machine Translation Model

Components:

1. NMTEncoder
   - accepts as input a source sequence to be embedded and fed through a bi-directional GRU
2. NMTDecoder
   - using the encoder state and attention, the decoder generates a new sequence
   - the ground truth target sequence is used as input to the decoder at each time step
   - an alternative formulation would allow some of the decoder's own choices to be used as input
   - this is referred to as curriculum learning, learning to search
3. NMTModel
   - Combines the encoder and decoder into a single class.

NMTEncoder

```
class NMTEncoder(nn.Module):
    def __init__(self, num_embeddings, embedding_size, rnn_hidden_size):
        """
        Args:
            num_embeddings (int): number of embeddings is the size of source␣
↪vocabulary
            embedding_size (int): size of the embedding vectors
            rnn_hidden_size (int): size of the RNN hidden state vectors
        """
        super(NMTEncoder, self).__init__()

        self.source_embedding = nn.Embedding(num_embeddings, embedding_size, padding_
↪idx=0)
        self.birnn = nn.GRU(embedding_size, rnn_hidden_size, bidirectional=True,␣
↪batch_first=True)

    def forward(self, x_source, x_lengths):
        """The forward pass of the model

        Args:
            x_source (torch.Tensor): the input data tensor.
                x_source.shape is (batch, seq_size)
            x_lengths (torch.Tensor): a vector of lengths for each item in the batch
        Returns:
            a tuple: x_unpacked (torch.Tensor), x_birnn_h (torch.Tensor)
                x_unpacked.shape = (batch, seq_size, rnn_hidden_size * 2)
                x_birnn_h.shape = (batch, rnn_hidden_size * 2)
        """
        x_embedded = self.source_embedding(x_source)
        # create PackedSequence; x_packed.data.shape=(number_items, embeddign_size)
        x_packed = pack_padded_sequence(x_embedded, x_lengths.detach().cpu().numpy(),
                                        batch_first=True)

        # x_birnn_h.shape = (num_rnn, batch_size, feature_size)
        x_birnn_out, x_birnn_h  = self.birnn(x_packed)
```

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```
        # permute to (batch_size, num_rnn, feature_size)
        x_birnn_h = x_birnn_h.permute(1, 0, 2)

        # flatten features; reshape to (batch_size, num_rnn * feature_size)
        #  (recall: -1 takes the remaining positions,
        #           flattening the two RNN hidden vectors into 1)
        x_birnn_h = x_birnn_h.contiguous().view(x_birnn_h.size(0), -1)

        x_unpacked, _ = pad_packed_sequence(x_birnn_out, batch_first=True)

        return x_unpacked, x_birnn_h
```

Attention

```
def verbose_attention(encoder_state_vectors, query_vector):
    """A descriptive version of the neural attention mechanism

    Args:
        encoder_state_vectors (torch.Tensor): 3dim tensor from bi-GRU in encoder
        query_vector (torch.Tensor): hidden state in decoder GRU
    Returns:

    """
    batch_size, num_vectors, vector_size = encoder_state_vectors.size()
    vector_scores = torch.sum(encoder_state_vectors * query_vector.view(batch_size, 1,
 ↪ vector_size),
                              dim=2)
    vector_probabilities = F.softmax(vector_scores, dim=1)
    weighted_vectors = encoder_state_vectors * vector_probabilities.view(batch_size,␣
 ↪num_vectors, 1)
    context_vectors = torch.sum(weighted_vectors, dim=1)
    return context_vectors, vector_probabilities, vector_scores

def terse_attention(encoder_state_vectors, query_vector):
    """A shorter and more optimized version of the neural attention mechanism

    Args:
        encoder_state_vectors (torch.Tensor): 3dim tensor from bi-GRU in encoder
        query_vector (torch.Tensor): hidden state
    """
    vector_scores = torch.matmul(encoder_state_vectors, query_vector.
 ↪unsqueeze(dim=2)).squeeze()
    vector_probabilities = F.softmax(vector_scores, dim=-1)
    context_vectors = torch.matmul(encoder_state_vectors.transpose(-2, -1),
                                   vector_probabilities.unsqueeze(dim=2)).squeeze()
    return context_vectors, vector_probabilities
```

NMTDecoder with Scheduled Sampling

```
class NMTDecoder(nn.Module):
    def __init__(self, num_embeddings, embedding_size, rnn_hidden_size, bos_index):
        """
        Args:
            num_embeddings (int): number of embeddings is also the number of
                unique words in target vocabulary
            embedding_size (int): the embedding vector size
            rnn_hidden_size (int): size of the hidden rnn state
            bos_index(int): begin-of-sequence index
        """
        super(NMTDecoder, self).__init__()
        self._rnn_hidden_size = rnn_hidden_size
        self.target_embedding = nn.Embedding(num_embeddings=num_embeddings,
                                             embedding_dim=embedding_size,
                                             padding_idx=0)
        self.gru_cell = nn.GRUCell(embedding_size + rnn_hidden_size,
                                   rnn_hidden_size)
        self.hidden_map = nn.Linear(rnn_hidden_size, rnn_hidden_size)
        self.classifier = nn.Linear(rnn_hidden_size * 2, num_embeddings)
        self.bos_index = bos_index
        self._sampling_temperature = 3

    def _init_indices(self, batch_size):
        """ return the BEGIN-OF-SEQUENCE index vector """
        return torch.ones(batch_size, dtype=torch.int64) * self.bos_index

    def _init_context_vectors(self, batch_size):
        """ return a zeros vector for initializing the context """
        return torch.zeros(batch_size, self._rnn_hidden_size)

    def forward(self, encoder_state, initial_hidden_state, target_sequence, sample_
↪probability=0.0):
        """The forward pass of the model

        Args:
            encoder_state (torch.Tensor): the output of the NMTEncoder
            initial_hidden_state (torch.Tensor): The last hidden state in the ␣
↪NMTEncoder
            target_sequence (torch.Tensor): the target text data tensor
            sample_probability (float): the schedule sampling parameter
                probabilty of using model's predictions at each decoder step
        Returns:
            output_vectors (torch.Tensor): prediction vectors at each output step
        """
        if target_sequence is None:
            sample_probability = 1.0
        else:
            # We are making an assumption there: The batch is on first
            # The input is (Batch, Seq)
            # We want to iterate over sequence so we permute it to (S, B)
            target_sequence = target_sequence.permute(1, 0)
            output_sequence_size = target_sequence.size(0)

        # use the provided encoder hidden state as the initial hidden state
        h_t = self.hidden_map(initial_hidden_state)
```

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```
        batch_size = encoder_state.size(0)
        # initialize context vectors to zeros
        context_vectors = self._init_context_vectors(batch_size)
        # initialize first y_t word as BOS
        y_t_index = self._init_indices(batch_size)

        h_t = h_t.to(encoder_state.device)
        y_t_index = y_t_index.to(encoder_state.device)
        context_vectors = context_vectors.to(encoder_state.device)

        output_vectors = []
        self._cached_p_attn = []
        self._cached_ht = []
        self._cached_decoder_state = encoder_state.cpu().detach().numpy()

        for i in range(output_sequence_size):
            # Schedule sampling is whe
            use_sample = np.random.random() < sample_probability
            if not use_sample:
                y_t_index = target_sequence[i]

            # Step 1: Embed word and concat with previous context
            y_input_vector = self.target_embedding(y_t_index)
            rnn_input = torch.cat([y_input_vector, context_vectors], dim=1)

            # Step 2: Make a GRU step, getting a new hidden vector
            h_t = self.gru_cell(rnn_input, h_t)
            self._cached_ht.append(h_t.cpu().detach().numpy())

            # Step 3: Use the current hidden to attend to the encoder state
            context_vectors, p_attn, _ = verbose_attention(encoder_state_
↪vectors=encoder_state,
                                                           query_vector=h_t)

            # auxillary: cache the attention probabilities for visualization
            self._cached_p_attn.append(p_attn.cpu().detach().numpy())

            # Step 4: Use the current hidden and context vectors to make a prediction␣
↪to the next word
            prediction_vector = torch.cat((context_vectors, h_t), dim=1)
            score_for_y_t_index = self.classifier(F.dropout(prediction_vector, 0.3))

            if use_sample:
                p_y_t_index = F.softmax(score_for_y_t_index * self._sampling_
↪temperature, dim=1)
                # _, y_t_index = torch.max(p_y_t_index, 1)
                y_t_index = torch.multinomial(p_y_t_index, 1).squeeze()

            # auxillary: collect the prediction scores
            output_vectors.append(score_for_y_t_index)

        output_vectors = torch.stack(output_vectors).permute(1, 0, 2)

        return output_vectors
```

NMTModel

```
class NMTModel(nn.Module):
    """ The Neural Machine Translation Model """
    def __init__(self, source_vocab_size, source_embedding_size,
                 target_vocab_size, target_embedding_size, encoding_size,
                 target_bos_index):
        """
        Args:
            source_vocab_size (int): number of unique words in source language
            source_embedding_size (int): size of the source embedding vectors
            target_vocab_size (int): number of unique words in target language
            target_embedding_size (int): size of the target embedding vectors
            encoding_size (int): the size of the encoder RNN.
        """
        super(NMTModel, self).__init__()
        self.encoder = NMTEncoder(num_embeddings=source_vocab_size,
                                  embedding_size=source_embedding_size,
                                  rnn_hidden_size=encoding_size)
        decoding_size = encoding_size * 2
        self.decoder = NMTDecoder(num_embeddings=target_vocab_size,
                                  embedding_size=target_embedding_size,
                                  rnn_hidden_size=decoding_size,
                                  bos_index=target_bos_index)

    def forward(self, x_source, x_source_lengths, target_sequence, sample_
↪probability=0.0):
        """The forward pass of the model

        Args:
            x_source (torch.Tensor): the source text data tensor.
                x_source.shape should be (batch, vectorizer.max_source_length)
            x_source_lengths torch.Tensor): the length of the sequences in x_source
            target_sequence (torch.Tensor): the target text data tensor
            sample_probability (float): the schedule sampling parameter
                probabilty of using model's predictions at each decoder step
        Returns:
            decoded_states (torch.Tensor): prediction vectors at each output step
        """
        encoder_state, final_hidden_states = self.encoder(x_source, x_source_lengths)
        decoded_states = self.decoder(encoder_state=encoder_state,
                                      initial_hidden_state=final_hidden_states,
                                      target_sequence=target_sequence,
                                      sample_probability=sample_probability)
        return decoded_states
```

12.6.4 Training Routine and Bookkeeping Functions

```
def set_seed_everywhere(seed, cuda):
    np.random.seed(seed)
    torch.manual_seed(seed)
    if cuda:
        torch.cuda.manual_seed_all(seed)

def handle_dirs(dirpath):
```

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```
    if not os.path.exists(dirpath):
        os.makedirs(dirpath)

def make_train_state(args):
    return {'stop_early': False,
            'early_stopping_step': 0,
            'early_stopping_best_val': 1e8,
            'learning_rate': args.learning_rate,
            'epoch_index': 0,
            'train_loss': [],
            'train_acc': [],
            'val_loss': [],
            'val_acc': [],
            'test_loss': -1,
            'test_acc': -1,
            'model_filename': args.model_state_file}

def update_train_state(args, model, train_state):
    """Handle the training state updates.
    Components:
     - Early Stopping: Prevent overfitting.
     - Model Checkpoint: Model is saved if the model is better

    :param args: main arguments
    :param model: model to train
    :param train_state: a dictionary representing the training state values
    :returns:
        a new train_state
    """

    # Save one model at least
    if train_state['epoch_index'] == 0:
        torch.save(model.state_dict(), train_state['model_filename'])
        train_state['stop_early'] = False

    # Save model if performance improved
    elif train_state['epoch_index'] >= 1:
        loss_tm1, loss_t = train_state['val_loss'][-2:]

        # If loss worsened
        if loss_t >= loss_tm1:
            # Update step
            train_state['early_stopping_step'] += 1
        # Loss decreased
        else:
            # Save the best model
            if loss_t < train_state['early_stopping_best_val']:
                torch.save(model.state_dict(), train_state['model_filename'])
                train_state['early_stopping_best_val'] = loss_t

            # Reset early stopping step
            train_state['early_stopping_step'] = 0

        # Stop early ?
        train_state['stop_early'] = \
            train_state['early_stopping_step'] >= args.early_stopping_criteria
```

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```
    return train_state

def normalize_sizes(y_pred, y_true):
    """Normalize tensor sizes

    Args:
        y_pred (torch.Tensor): the output of the model
            If a 3-dimensional tensor, reshapes to a matrix
        y_true (torch.Tensor): the target predictions
            If a matrix, reshapes to be a vector
    """
    if len(y_pred.size()) == 3:
        y_pred = y_pred.contiguous().view(-1, y_pred.size(2))
    if len(y_true.size()) == 2:
        y_true = y_true.contiguous().view(-1)
    return y_pred, y_true

def compute_accuracy(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)

    _, y_pred_indices = y_pred.max(dim=1)

    correct_indices = torch.eq(y_pred_indices, y_true).float()
    valid_indices = torch.ne(y_true, mask_index).float()

    n_correct = (correct_indices * valid_indices).sum().item()
    n_valid = valid_indices.sum().item()

    return n_correct / n_valid * 100

def sequence_loss(y_pred, y_true, mask_index):
    y_pred, y_true = normalize_sizes(y_pred, y_true)
    return F.cross_entropy(y_pred, y_true, ignore_index=mask_index)
```

```
args = Namespace(dataset_csv="data/nmt/simplest_eng_fra.csv",
                 vectorizer_file="vectorizer.json",
                 model_state_file="model.pth",
                 save_dir="model_storage/ch8/nmt_luong_sampling",
                 reload_from_files=False,
                 expand_filepaths_to_save_dir=True,
                 cuda=True,
                 seed=1337,
                 learning_rate=5e-4,
                 batch_size=32,
                 num_epochs=100,
                 early_stopping_criteria=5,
                 source_embedding_size=24,
                 target_embedding_size=24,
                 encoding_size=32,
                 catch_keyboard_interrupt=True)

if args.expand_filepaths_to_save_dir:
    args.vectorizer_file = os.path.join(args.save_dir,
                                        args.vectorizer_file)

    args.model_state_file = os.path.join(args.save_dir,
```

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```
                                        args.model_state_file)

    print("Expanded filepaths: ")
    print("\t{}".format(args.vectorizer_file))
    print("\t{}".format(args.model_state_file))

# Check CUDA
if not torch.cuda.is_available():
    args.cuda = False

args.device = torch.device("cuda" if args.cuda else "cpu")

print("Using CUDA: {}".format(args.cuda))

# Set seed for reproducibility
set_seed_everywhere(args.seed, args.cuda)

# handle dirs
handle_dirs(args.save_dir)
```

```
Expanded filepaths:
        model_storage/ch8/nmt_luong_sampling/vectorizer.json
        model_storage/ch8/nmt_luong_sampling/model.pth
Using CUDA: True
```

```
if args.reload_from_files and os.path.exists(args.vectorizer_file):
    # training from a checkpoint
    dataset = NMTDataset.load_dataset_and_load_vectorizer(args.dataset_csv,
                                                          args.vectorizer_file)
else:
    # create dataset and vectorizer
    dataset = NMTDataset.load_dataset_and_make_vectorizer(args.dataset_csv)
    dataset.save_vectorizer(args.vectorizer_file)

vectorizer = dataset.get_vectorizer()
```

```
model = NMTModel(source_vocab_size=len(vectorizer.source_vocab),
                 source_embedding_size=args.source_embedding_size,
                 target_vocab_size=len(vectorizer.target_vocab),
                 target_embedding_size=args.target_embedding_size,
                 encoding_size=args.encoding_size,
                 target_bos_index=vectorizer.target_vocab.begin_seq_index)

if args.reload_from_files and os.path.exists(args.model_state_file):
    model.load_state_dict(torch.load(args.model_state_file))
    print("Reloaded model")
else:
    print("New model")
```

```
New model
```

```
model = model.to(args.device)

optimizer = optim.Adam(model.parameters(), lr=args.learning_rate)
scheduler = optim.lr_scheduler.ReduceLROnPlateau(optimizer=optimizer,
```

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```
                                          mode='min', factor=0.5,
                                          patience=1)
mask_index = vectorizer.target_vocab.mask_index
train_state = make_train_state(args)

epoch_bar = tqdm_notebook(desc='training routine',
                          total=args.num_epochs,
                          position=0)

dataset.set_split('train')
train_bar = tqdm_notebook(desc='split=train',
                          total=dataset.get_num_batches(args.batch_size),
                          position=1,
                          leave=True)
dataset.set_split('val')
val_bar = tqdm_notebook(desc='split=val',
                        total=dataset.get_num_batches(args.batch_size),
                        position=1,
                        leave=True)

try:
    for epoch_index in range(args.num_epochs):
        sample_probability = (20 + epoch_index) / args.num_epochs

        train_state['epoch_index'] = epoch_index

        # Iterate over training dataset

        # setup: batch generator, set loss and acc to 0, set train mode on
        dataset.set_split('train')
        batch_generator = generate_nmt_batches(dataset,
                                               batch_size=args.batch_size,
                                               device=args.device)
        running_loss = 0.0
        running_acc = 0.0
        model.train()

        for batch_index, batch_dict in enumerate(batch_generator):
            # the training routine is these 5 steps:

            # --------------------------------------
            # step 1. zero the gradients
            optimizer.zero_grad()

            # step 2. compute the output
            y_pred = model(batch_dict['x_source'],
                           batch_dict['x_source_length'],
                           batch_dict['x_target'],
                           sample_probability=sample_probability)

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # step 4. use loss to produce gradients
            loss.backward()

            # step 5. use optimizer to take gradient step
```

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```
            optimizer.step()

            # ----------------------------------------
            # compute the running loss and running accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # update bar
            train_bar.set_postfix(loss=running_loss, acc=running_acc,
                                  epoch=epoch_index)
            train_bar.update()

        train_state['train_loss'].append(running_loss)
        train_state['train_acc'].append(running_acc)

        # Iterate over val dataset

        # setup: batch generator, set loss and acc to 0; set eval mode on
        dataset.set_split('val')
        batch_generator = generate_nmt_batches(dataset,
                                               batch_size=args.batch_size,
                                               device=args.device)
        running_loss = 0.
        running_acc = 0.
        model.eval()

        for batch_index, batch_dict in enumerate(batch_generator):
            # compute the output
            y_pred = model(batch_dict['x_source'],
                           batch_dict['x_source_length'],
                           batch_dict['x_target'],
                           sample_probability=sample_probability)

            # step 3. compute the loss
            loss = sequence_loss(y_pred, batch_dict['y_target'], mask_index)

            # compute the running loss and accuracy
            running_loss += (loss.item() - running_loss) / (batch_index + 1)

            acc_t = compute_accuracy(y_pred, batch_dict['y_target'], mask_index)
            running_acc += (acc_t - running_acc) / (batch_index + 1)

            # Update bar
            val_bar.set_postfix(loss=running_loss, acc=running_acc,
                                epoch=epoch_index)
            val_bar.update()

        train_state['val_loss'].append(running_loss)
        train_state['val_acc'].append(running_acc)

        train_state = update_train_state(args=args, model=model,
                                         train_state=train_state)

        scheduler.step(train_state['val_loss'][-1])
```

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```
        if train_state['stop_early']:
            break

        train_bar.n = 0
        val_bar.n = 0
        epoch_bar.set_postfix(best_val=train_state['early_stopping_best_val'])
        epoch_bar.update()

except KeyboardInterrupt:
    print("Exiting loop")
```

```
HBox(children=(IntProgress(value=0, description='training routine',␣
↪style=ProgressStyle(description_width='ini…
```

```
HBox(children=(IntProgress(value=0, description='split=train', max=285,␣
↪style=ProgressStyle(description_width=…
```

```
HBox(children=(IntProgress(value=0, description='split=val', max=61,␣
↪style=ProgressStyle(description_width='in…
```

```
Exiting loop
```

12.6.5 Inference and Evaluation

```
from nltk.translate import bleu_score
import seaborn as sns
import matplotlib.pyplot as plt

chencherry = bleu_score.SmoothingFunction()
```

```
def sentence_from_indices(indices, vocab, strict=True, return_string=True):
    ignore_indices = set([vocab.mask_index, vocab.begin_seq_index, vocab.end_seq_
↪index])
    out = []
    for index in indices:
        if index == vocab.begin_seq_index and strict:
            continue
        elif index == vocab.end_seq_index and strict:
            break
        else:
            out.append(vocab.lookup_index(index))
    if return_string:
        return " ".join(out)
    else:
        return out

class NMTSampler:
    def __init__(self, vectorizer, model):
        self.vectorizer = vectorizer
        self.model = model

    def apply_to_batch(self, batch_dict):
```

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```
        self._last_batch = batch_dict
        y_pred = self.model(x_source=batch_dict['x_source'],
                            x_source_lengths=batch_dict['x_source_length'],
                            target_sequence=batch_dict['x_target'])
        self._last_batch['y_pred'] = y_pred

        attention_batched = np.stack(self.model.decoder._cached_p_attn).transpose(1,␣
↪0, 2)
        self._last_batch['attention'] = attention_batched

    def _get_source_sentence(self, index, return_string=True):
        indices = self._last_batch['x_source'][index].cpu().detach().numpy()
        vocab = self.vectorizer.source_vocab
        return sentence_from_indices(indices, vocab, return_string=return_string)

    def _get_reference_sentence(self, index, return_string=True):
        indices = self._last_batch['y_target'][index].cpu().detach().numpy()
        vocab = self.vectorizer.target_vocab
        return sentence_from_indices(indices, vocab, return_string=return_string)

    def _get_sampled_sentence(self, index, return_string=True):
        _, all_indices = torch.max(self._last_batch['y_pred'], dim=2)
        sentence_indices = all_indices[index].cpu().detach().numpy()
        vocab = self.vectorizer.target_vocab
        return sentence_from_indices(sentence_indices, vocab, return_string=return_
↪string)

    def get_ith_item(self, index, return_string=True):
        output = {"source": self._get_source_sentence(index, return_string=return_
↪string),
                  "reference": self._get_reference_sentence(index, return_
↪string=return_string),
                  "sampled": self._get_sampled_sentence(index, return_string=return_
↪string),
                  "attention": self._last_batch['attention'][index]}

        reference = output['reference']
        hypothesis = output['sampled']

        if not return_string:
            reference = " ".join(reference)
            hypothesis = " ".join(hypothesis)

        output['bleu-4'] = bleu_score.sentence_bleu(references=[reference],
                                                    hypothesis=hypothesis,
                                                    smoothing_function=chencherry.
↪method1)

        return output
```

```
model = model.eval().to(args.device)

sampler = NMTSampler(vectorizer, model)

dataset.set_split('test')
batch_generator = generate_nmt_batches(dataset,
```

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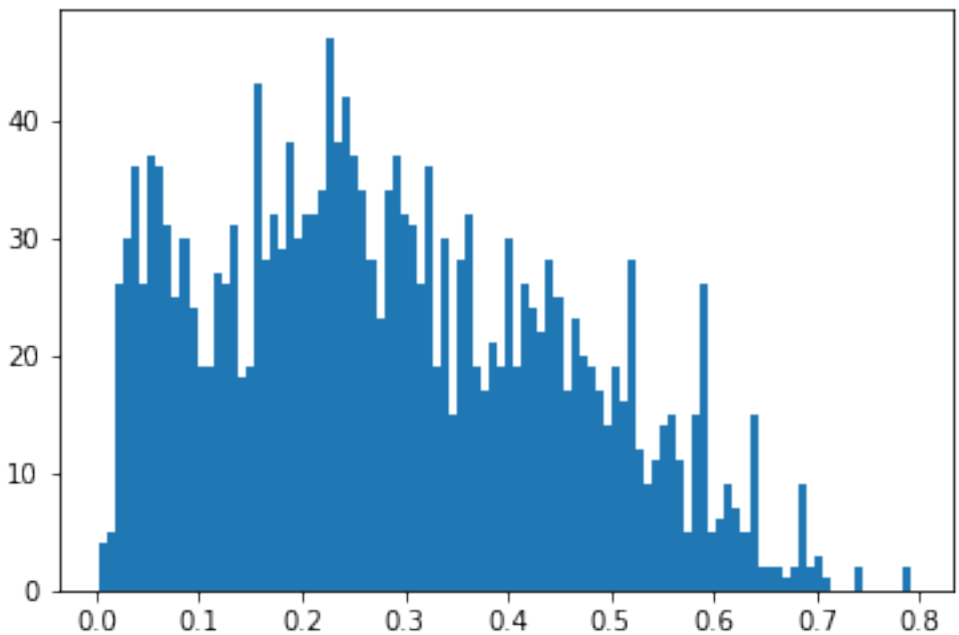
```
                                        batch_size=args.batch_size,
                                        device=args.device)

test_results = []
for batch_dict in batch_generator:
    sampler.apply_to_batch(batch_dict)
    for i in range(args.batch_size):
        test_results.append(sampler.get_ith_item(i, False))
```

```
plt.hist([r['bleu-4'] for r in test_results], bins=100);
np.mean([r['bleu-4'] for r in test_results]), np.median([r['bleu-4'] for r in test_
↪results])
```

```
(0.28705687208416497, 0.26730098289088333)
```




```
dataset.set_split('val')
batch_generator = generate_nmt_batches(dataset,
                                        batch_size=args.batch_size,
                                        device=args.device)
batch_dict = next(batch_generator)

model = model.eval().to(args.device)
sampler = NMTSampler(vectorizer, model)
sampler.apply_to_batch(batch_dict)
```

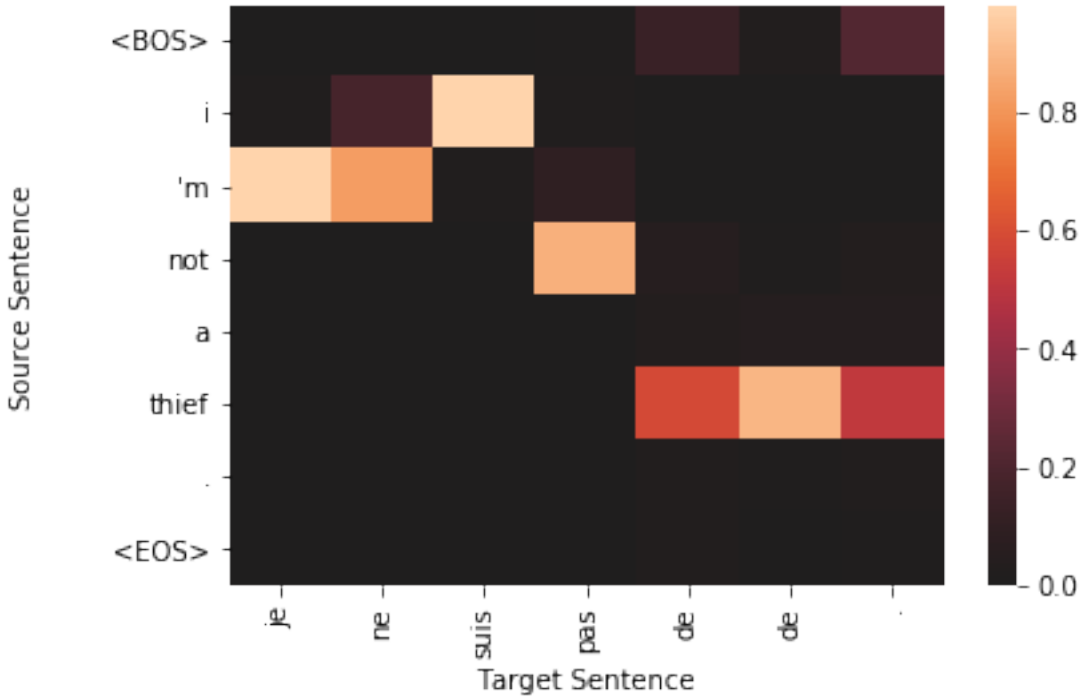
```
all_results = []
for i in range(args.batch_size):
    all_results.append(sampler.get_ith_item(i, False))
```

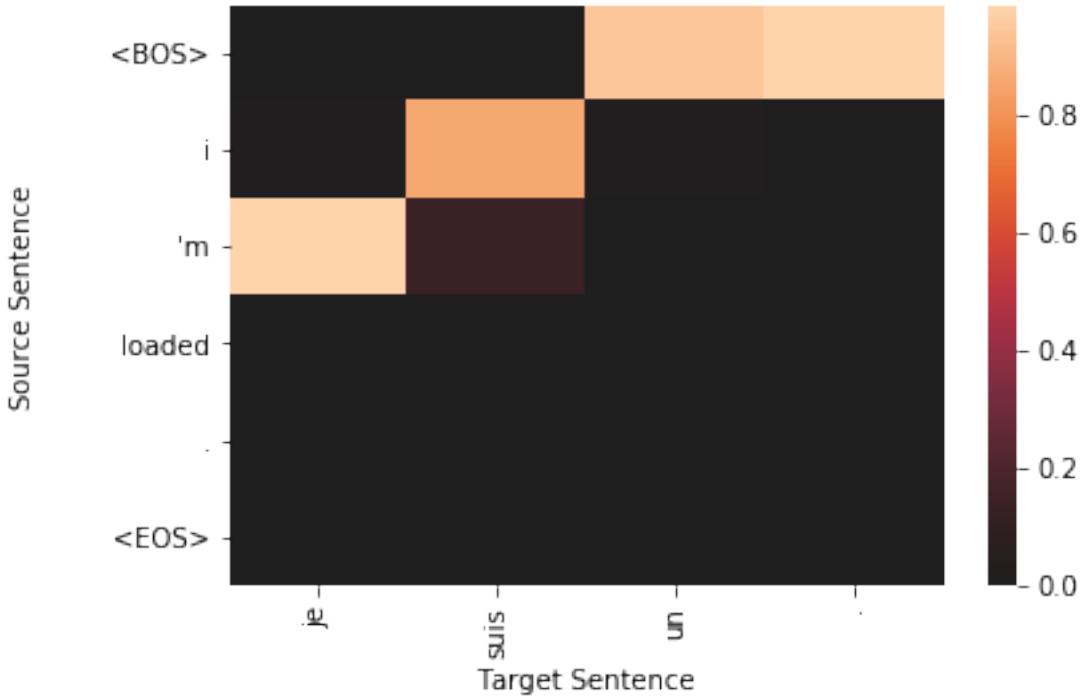
```
top_results = [x for x in all_results if x['bleu-4']>0.5]
len(top_results)
```

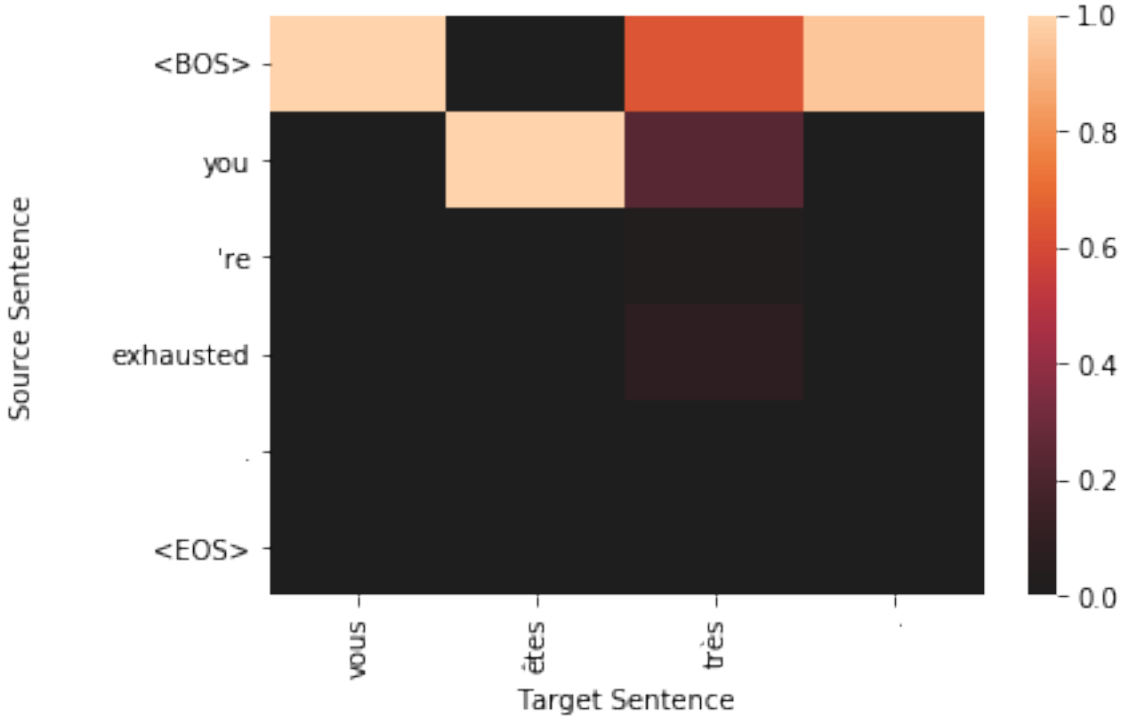
```
3
```

```
for sample in top_results:
    plt.figure()
    target_len = len(sample['sampled'])
    source_len = len(sample['source'])

    attention_matrix = sample['attention'][:target_len, :source_len+2].transpose()
↪#[::-1]
    ax = sns.heatmap(attention_matrix, center=0.0)
    ylabs = ["<BOS>"]+sample['source']+["<EOS>"]
    #ylabs = sample['source']
    #ylabs = ylabs[::-1]
    ax.set_yticklabels(ylabs, rotation=0)
    ax.set_xticklabels(sample['sampled'], rotation=90)
    ax.set_xlabel("Target Sentence")
    ax.set_ylabel("Source Sentence\n\n")
```








```
def get_source_sentence(vectorizer, batch_dict, index):
    indices = batch_dict['x_source'][index].cpu().data.numpy()
    vocab = vectorizer.source_vocab
    return sentence_from_indices(indices, vocab)

def get_true_sentence(vectorizer, batch_dict, index):
```

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```
    return sentence_from_indices(batch_dict['y_target'].cpu().data.numpy()[index],␣
↪vectorizer.target_vocab)

def get_sampled_sentence(vectorizer, batch_dict, index):
    y_pred = model(x_source=batch_dict['x_source'],
                   x_source_lengths=batch_dict['x_source_length'],
                   target_sequence=batch_dict['x_target'],
                   sample_probability=1.0)
    return sentence_from_indices(torch.max(y_pred, dim=2)[1].cpu().data.
↪numpy()[index], vectorizer.target_vocab)

def get_all_sentences(vectorizer, batch_dict, index):
    return {"source": get_source_sentence(vectorizer, batch_dict, index),
            "truth": get_true_sentence(vectorizer, batch_dict, index),
            "sampled": get_sampled_sentence(vectorizer, batch_dict, index)}

def sentence_from_indices(indices, vocab, strict=True):
    ignore_indices = set([vocab.mask_index, vocab.begin_seq_index, vocab.end_seq_
↪index])
    out = []
    for index in indices:
        if index == vocab.begin_seq_index and strict:
            continue
        elif index == vocab.end_seq_index and strict:
            return " ".join(out)
        else:
            out.append(vocab.lookup_index(index))
    return " ".join(out)

results = get_all_sentences(vectorizer, batch_dict, 1)
results
```

```
{'source': "you 're not as good as you think you are .",
 'truth': "vous n'êtes pas aussi bonnes que vous pensez l'être .",
 'sampled': "vous n'êtes pas très pas vous vous vous vous ?"}
```

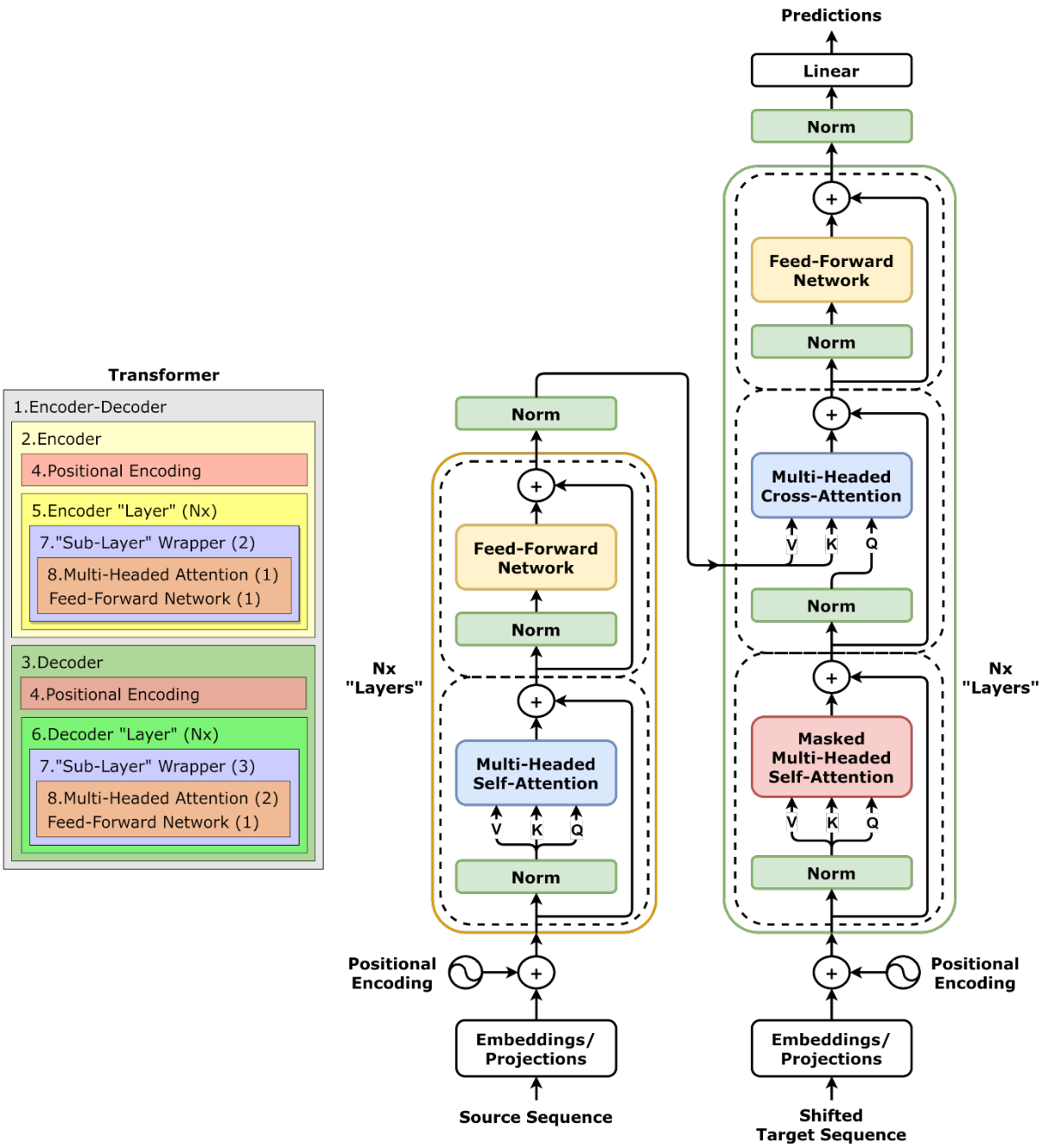
CHAPTER

THIRTEEN

EXTRA: TRANSFORMERS

This set of notebooks first introduces the key elements for building a transformer encoder-decoder modle, namely, multi-headed narrow attention, layer normalisation, and position encoding.

Then finally, we assemble them together to build our own Transformer Model, and compare it with the PyTorch `nn.Tranformer` class in the transform and roll out notebook. The picture below provides a good mapping of classes we implemented to the components used in a Transformer Encoder-Decoder Model.



Credit: the notebooks are adapted from:

- Chpater 9 of Deep Learning with PyTorch Step-by-Step
- Chpater 10 of Deep Learning with PyTorch Step-by-Step

13.1 Positional Encoding

We loose positional information when using self-attention, as compared to RNNs with cross-attention. The idea of positional encoding is to capture the position information and use that to augument the input vectors.

Three key requirements of positional encoding vectors:

- The values need to be bounded.
- Each position should have its own vector. The same position should have the same values.
- They need to be unique. No two positions should share the same encoding vectors.
- The euclidean distance between two vectors needs to reflect the positional distance between the correponding two position indices. Take position `3` for example, the vector distance between position `1` and `3`, needs to be the same as `3` and `5`, as both `1` and `5` are two positions away from `3`.

13.1.1 Helper Files

Download these files and place them in the same directory as the current notebook before you start.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots_transformer.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\plots_transformer.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\util.py
```

```
FileLink('replay.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\replay.py
```

13.1.2 Imports

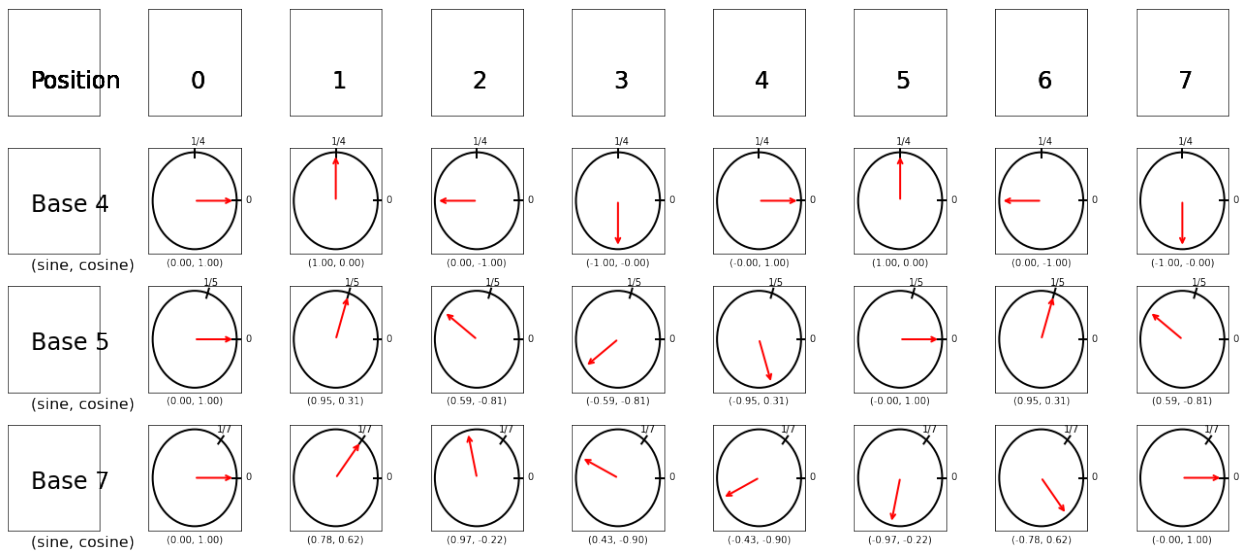
```
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from util import StepByStep
from plots_transformer import *
```

13.1.3 Angular Speed

Fixed Based Positional Encoding

Visualisation of base 4, 5 and 7. Each base corresponds to an angular speed of $(\frac{360}{4}, \frac{360}{5}, \frac{360}{7})$ per position, indicating how many degrees to move along the circle at each position. For example, at position 3, the corresponding degrees to move for each base is $\frac{360}{4} * 3, \frac{360}{5} * 3, \frac{360}{7} * 3$, respectively. We use sine and cosine of these degrees along a unit circle to get the position encodings. The values under each position index is a vector encode the position.

```
fig = encoding_degrees(dims=3, seqs=(4, 5, 7), tot=8)
```



Position	0	1	2	3	4	5	6	7
sine (base 4)	0.00	1.00	0.00	-1.00	0.00	1.00	0.00	-1.00
cosine (base 4)	1.00	0.00	-1.00	0.00	1.00	0.00	-1.00	0.00
sine (base 5)	0.00	0.95	0.59	-0.59	-0.95	0.00	0.95	0.59
cosine (base 5)	1.00	0.31	-0.81	-0.81	0.31	1.00	0.31	-0.81
sine (base 7)	0.00	0.78	0.97	0.43	-0.43	-0.97	-0.78	0.00
cosine (base 7)	1.00	0.62	-0.22	-0.90	-0.90	-0.22	0.62	1.00

3		2		Diff
-1.00		0.00		-1.00
0.00		-1.00		1.00
-0.59	-	0.59	=	-1.18
-0.81		-0.81		0.00
0.43		0.97		-0.54
-0.90		-0.22		-0.68

Distance = ||Diff|| = 2.03

4		3		Diff
0.00		-1.00		1.00
1.00		0.00		1.00
-0.95	-	-0.59	=	-0.36
0.31		-0.81		1.12
-0.43		0.43		-0.87
-0.90		-0.90		0.00

Distance = ||Diff|| = 2.03

As shown above the position encoding above meets the requirements we listed above.

Your Turn

Implement a position encoding using the above bases (4,5,7), and verify the distance between positions is maintained by the positional encodings.

General Exponential Bases

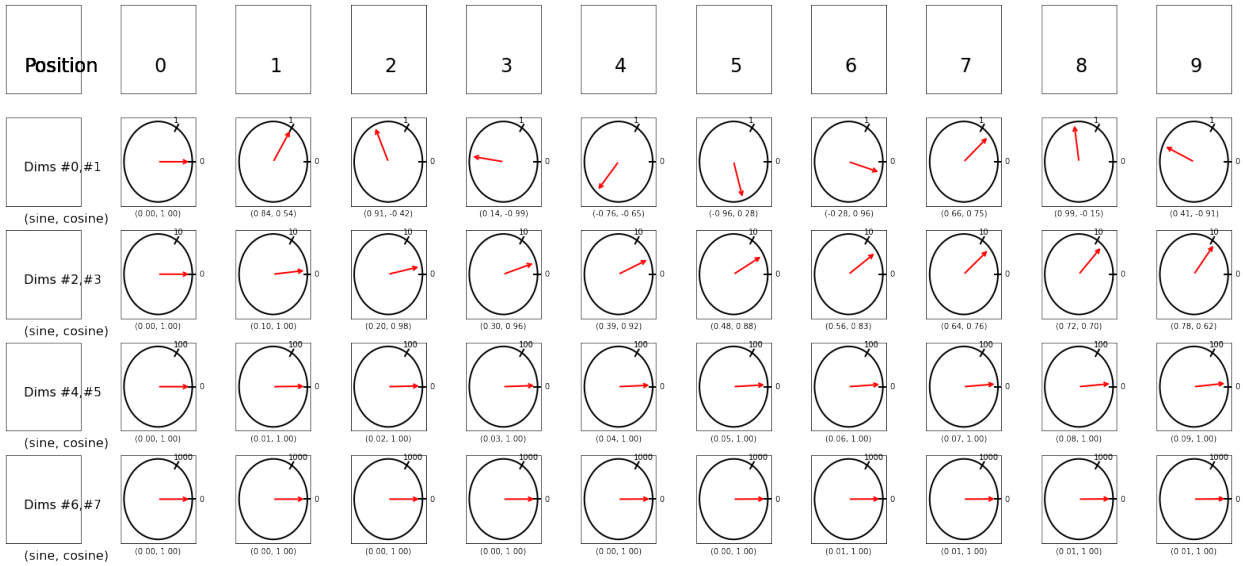
In real implementation, we do not need to worry about choosing the right bases.

As the first vector, we can simply move along the circle as many radians as the index of the position (one radian is approximately $\frac{360}{2\pi} = 57.3$ degrees). Then, for each new vector we add to the encoding, we move along the circle with exponentially slower angular speeds. For example, in the second vector, we would move only one-tenth of a radian (approximately 5.73 degrees) for each new position. In the third vector we would move only one-hundredth of a radian, and so on and so forth. Figure below depicts the red arrow moving at increasingly slower angular speeds, for an eight dimensional positional encoding. For eight dimensions, we need four speeds and to get the four speeds, we can use the exponential power of 10000 like below to get speed multipliers (in this case, $[1, 0.1, 0.01, 0.001]$). $\$\left(\frac{1}{10000^{\frac{0}{8}}}, \frac{1}{10000^{\frac{2}{8}}}, \frac{1}{10000^{\frac{4}{8}}}, \frac{1}{10000^{\frac{6}{8}}}\right) = (1, 0.1, 0.01, 0.001)\$$

$$PE_{pos,\ 2d} = sin\left(\frac{1}{10000^{\frac{2d}{d_{model}}}} pos\right);$$

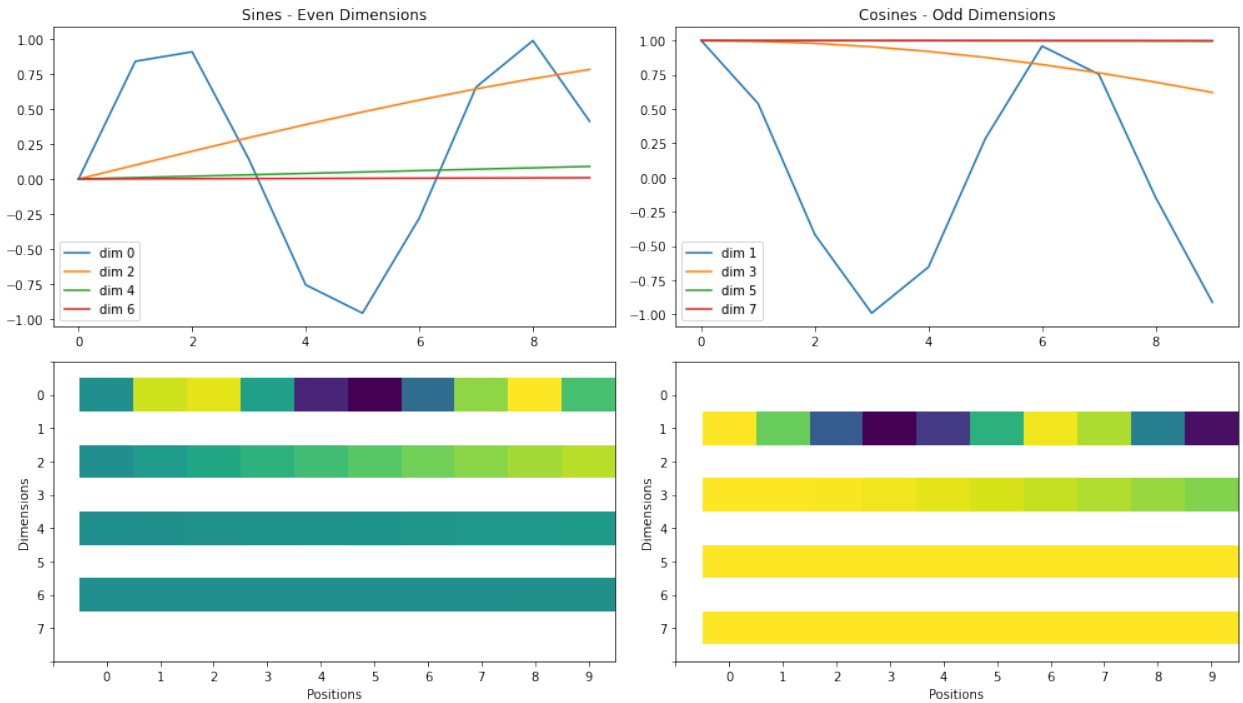
$$PE_{pos,\ 2d+1} = cos\left(\frac{1}{10000^{\frac{2d}{d_{model}}}} pos\right)$$

```
fig = exponential_dials(d_model=8, max_len=10)
```




```
max_len = 10
d_model = 8

position = torch.arange(0, max_len).float().unsqueeze(1)
angular_speed = torch.exp(torch.arange(0, d_model, 2).float() * (-np.log(10000.0) / d_
↪model))

encoding = torch.zeros(max_len, d_model)
encoding[:, 0::2] = torch.sin(angular_speed * position)
encoding[:, 1::2] = torch.cos(angular_speed * position)
```

```
fig = encoding_heatmap(d_model=8, max_len=10)
```




```
np.round(encoding[0:4], 4) # first four positions
```

```
tensor([[ 0.0000,  1.0000,  0.0000,  1.0000,  0.0000,  1.0000,  0.0000,  1.0000],
        [ 0.8415,  0.5403,  0.0998,  0.9950,  0.0100,  1.0000,  0.0010,  1.0000],
        [ 0.9093, -0.4161,  0.1987,  0.9801,  0.0200,  0.9998,  0.0020,  1.0000],
        [ 0.1411, -0.9900,  0.2955,  0.9553,  0.0300,  0.9996,  0.0030,  1.0000]])
```

A Note on Encoded Distances

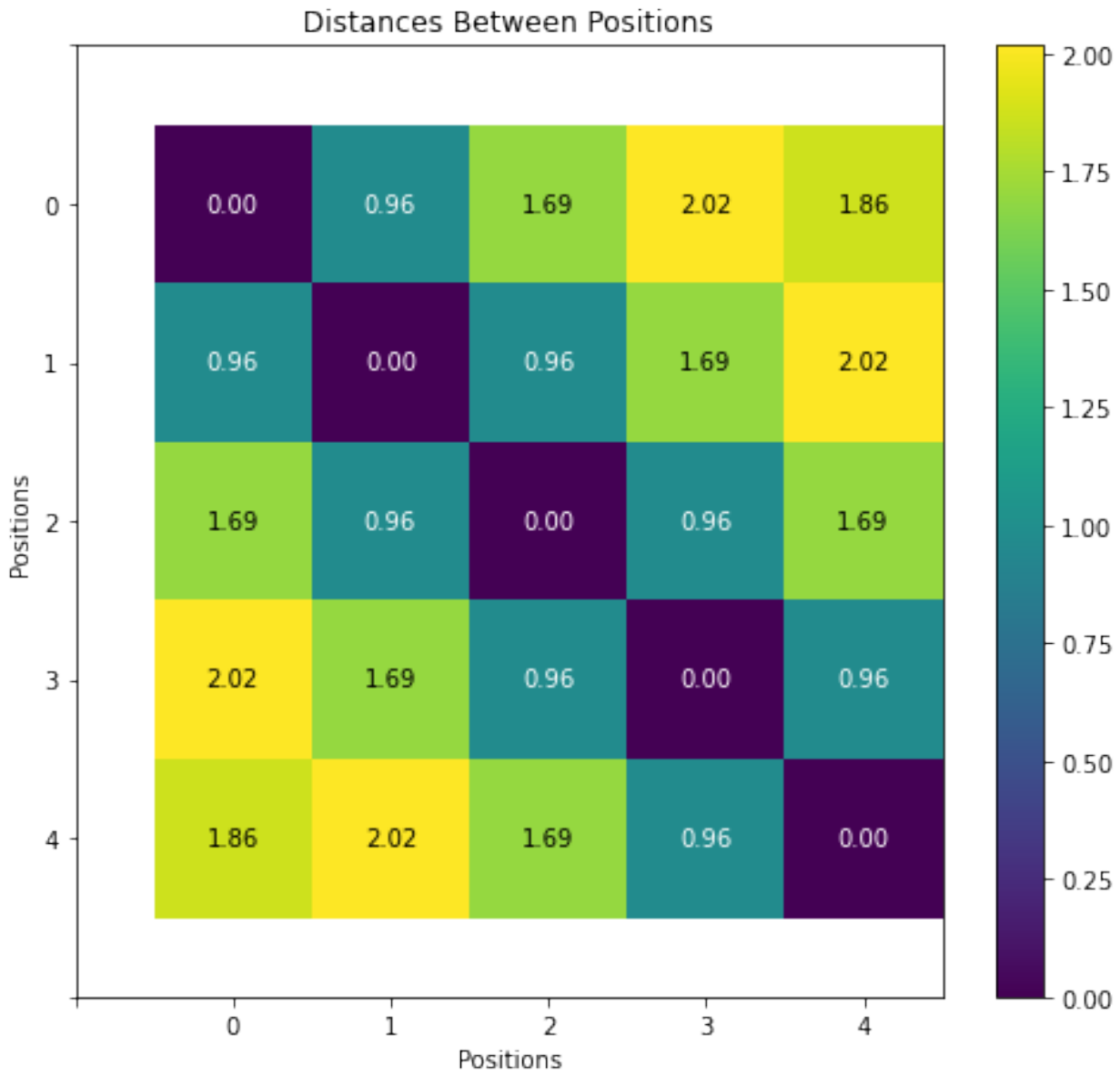
We have already seen:

- the encoded distance is defined by the Euclidean distance between two vectors or, in other words, it is the norm (size) of the difference between two encoding vectors
- the encoded distance between positions zero and two (T=2) should be exactly the same as the encoded distance between positions one and three, two and four, and so on

In other words, the encoded distance between any two positions T steps apart remains constant. Let's illustrate this by computing the encoded distances among the first five positions (by the way, we are using the encoding with eight dimensions.)

```
distances = np.zeros((5, 5))
for i, v1 in enumerate(encoding[:5]):
    for j, v2 in enumerate(encoding[:5]):
        distances[i, j] = np.linalg.norm(v1 - v2)
```

```
fig, ax = plt.subplots(1, 1, figsize=(7, 6.5))
ax.set_title('Distances Between Positions')
fig = plot_mesh(distances, ax, showvals=True, colorbar=True, ylabel='Positions')
```



13.1.4 The positional encoding class

There is a couple of things about this class to highlight:

- in the constructor, it uses `register_buffer` to define an attribute of the module
- in the forward method, it is scaling the input before adding the positional encoding

register_buffer

Important: `register_buffer` The `register_buffer` is used to define an attribute that is part of the module's state, yet not a parameter. In other words, it is the recorded in `state_dict` but is not updated or tracked by the dynamic computational graph for gradient calculation.

The positional encoding is a good example: its values are computed according to the dimension and length used by the model, and even though these values are going to be used during training, they shouldn not be updated by gradient descent.

```
class PositionalEncoding(nn.Module):
    def __init__(self, max_len, d_model):
        super().__init__()
        self.d_model = d_model
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len).float().unsqueeze(1)
        angular_speed = torch.exp(torch.arange(0, d_model, 2).float() * (-np.
↪log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * angular_speed) # even dimensions
        pe[:, 1::2] = torch.cos(position * angular_speed) # odd dimensions
        self.register_buffer('pe', pe.unsqueeze(0))

    def forward(self, x):
        # x is N, L, D
        # pe is 1, maxlen, D
        scaled_x = x * np.sqrt(self.d_model)
        encoded = scaled_x + self.pe[:, :x.size(1), :]
        return encoded
```

Reverse Input Scaling

Warning: "crowded-out" effect As shown below, the original coordinates are "crowded-out" by the addition of the positional encoding (especially the first row). This may happen if the data points have values roughly in the same range as the positional encoding.

Unfortunately, this is fairly common: both standardized inputs and word embeddings are likely to have most of their values inside the `[-1, 1]` range of the positional encoding.

Note: "How can we handle "crowded-out"?" The scaling in the forward method "reverses the standardization" of the inputs (using a standard deviation equals the square root of their dimensionality) to retrieve the hypothetical "raw" inputs.

$$\text{standardized } x = \frac{\text{``raw''} \ x}{\sqrt{d_x}} \implies \text{``raw''} x = \sqrt{d_x} \text{ standardized } x$$

```
posenc = PositionalEncoding(2, 2)
```

```
list(posenc.parameters()), posenc.state_dict()
```

```
([],
 OrderedDict([('pe', tensor([[[0.0000, 1.0000],
                         [0.8415, 0.5403]]]))]))
```

```
posenc.pe
```

```
tensor([[[0.0000, 1.0000],
         [0.8415, 0.5403]]])
```

```
full_seq = torch.tensor([[-1, -1], [-1, 1], [1, 1], [1, -1]]).float().view(1, 4, 2)
source_seq = full_seq[:, :2]
target_seq = full_seq[:, 2:]
```

```
source_seq # 1, L, D
```

```
tensor([[[-1., -1.],
         [-1.,  1.]]])
```

```
source_seq + posenc.pe
```

```
tensor([[[-1.0000,  0.0000],
         [-0.1585,  1.5403]]])
```

```
posenc(source_seq)
```

```
tensor([[[-1.4142, -0.4142],
         [-0.5727,  1.9545]]])
```

The results above (after the encoding) illustrate the effect of scaling the inputs: it seems to have lessened the crowding-out effect of the positional encoding.

> **Warning:** Reverse standardisation is bad for the model, when the input dimension is large
>
> For inputs with many dimensions, the effect of reverse standardisation will be much more pronounced: a 300-dimensions embedding will have a scaling factor around 17, for example. Another normalization trick: layer normalization, will counter-act it.

13.1.5 Encoder and Decoder with Self Attention

These are the same code we have seen earlier in the Week 12 lab.

```
class Attention(nn.Module):
    def __init__(self, hidden_dim, input_dim=None, proj_values=False):
        super().__init__()
        self.d_k = hidden_dim
        self.input_dim = hidden_dim if input_dim is None else input_dim
        self.proj_values = proj_values
        # Affine transformations for Q, K, and V
        self.linear_query = nn.Linear(self.input_dim, hidden_dim)
        self.linear_key = nn.Linear(self.input_dim, hidden_dim)
        self.linear_value = nn.Linear(self.input_dim, hidden_dim)
```

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```
        self.alphas = None

    def init_keys(self, keys):
        self.keys = keys
        self.proj_keys = self.linear_key(self.keys)
        self.values = self.linear_value(self.keys) \
                      if self.proj_values else self.keys

    def score_function(self, query):
        proj_query = self.linear_query(query)
        # scaled dot product
        # N, 1, H x N, H, L -> N, 1, L
        dot_products = torch.bmm(proj_query, self.proj_keys.permute(0, 2, 1))
        scores =  dot_products / np.sqrt(self.d_k)
        return scores

    def forward(self, query, mask=None):
        # Query is batch-first N, 1, H
        scores = self.score_function(query) # N, 1, L
        if mask is not None:
            scores = scores.masked_fill(mask == 0, -1e9)
        alphas = F.softmax(scores, dim=-1) # N, 1, L
        self.alphas = alphas.detach()

        # N, 1, L x N, L, H -> N, 1, H
        context = torch.bmm(alphas, self.values)
        return context
```

```
class MultiHeadAttention(nn.Module):
    def __init__(self, n_heads, d_model, input_dim=None, proj_values=True):
        super().__init__()
        self.linear_out = nn.Linear(n_heads * d_model, d_model)
        self.attn_heads = nn.ModuleList([Attention(d_model,
                                                   input_dim=input_dim,
                                                   proj_values=proj_values)
                                         for _ in range(n_heads)])

    def init_keys(self, key):
        for attn in self.attn_heads:
            attn.init_keys(key)

    @property
    def alphas(self):
        # Shape: n_heads, N, 1, L (source)
        return torch.stack([attn.alphas for attn in self.attn_heads], dim=0)

    def output_function(self, contexts):
        # N, 1, n_heads * D
        concatenated = torch.cat(contexts, axis=-1)
        # Linear transf. to go back to original dimension
        out = self.linear_out(concatenated) # N, 1, D
        return out

    def forward(self, query, mask=None):
        contexts = [attn(query, mask=mask) for attn in self.attn_heads]
        out = self.output_function(contexts)
        return out
```

```
class EncoderSelfAttn(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.n_features = n_features
        self.self_attn_heads = MultiHeadAttention(n_heads, d_model, input_dim=n_
↪features)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
            nn.ReLU(),
            nn.Linear(ff_units, d_model),
        )

    def forward(self, query, mask=None):
        self.self_attn_heads.init_keys(query)
        att = self.self_attn_heads(query, mask)
        out = self.ffn(att)
        return out
```

```
class DecoderSelfAttn(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.n_features = d_model if n_features is None else n_features
        self.self_attn_heads = MultiHeadAttention(n_heads, d_model, input_dim=self.n_
↪features)
        self.cross_attn_heads = MultiHeadAttention(n_heads, d_model)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
            nn.ReLU(),
            nn.Linear(ff_units, self.n_features),
        )

    def init_keys(self, states):
        self.cross_attn_heads.init_keys(states)

    def forward(self, query, source_mask=None, target_mask=None):
        self.self_attn_heads.init_keys(query)
        att1 = self.self_attn_heads(query, target_mask)
        att2 = self.cross_attn_heads(att1, source_mask)
        out = self.ffn(att2)
        return out
```

13.1.6 Encoder + Decoder + PE

The new encoder and decoder classes are just wrapping their self-attention counterparts by assigning the latter as the layer attribute (`self.layer`) of the former, and encoding the inputs prior to calling the corresponding layer in the `forward()` method:

```
class EncoderPe(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None, max_len=100):
        super().__init__()
        pe_dim = d_model if n_features is None else n_features
        self.pe = PositionalEncoding(max_len, pe_dim)
        self.layer = EncoderSelfAttn(n_heads, d_model, ff_units, n_features)

    def forward(self, query, mask=None):
        query_pe = self.pe(query)
        out = self.layer(query_pe, mask)
        return out

class DecoderPe(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, n_features=None, max_len=100):
        super().__init__()
        pe_dim = d_model if n_features is None else n_features
        self.pe = PositionalEncoding(max_len, pe_dim)
        self.layer = DecoderSelfAttn(n_heads, d_model, ff_units, n_features)

    def init_keys(self, states):
        self.layer.init_keys(states)

    def forward(self, query, source_mask=None, target_mask=None):
        query_pe = self.pe(query)
        out = self.layer(query_pe, source_mask, target_mask)
        return out
```

```
class EncoderDecoderSelfAttn(nn.Module):
    def __init__(self, encoder, decoder, input_len, target_len):
        super().__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.input_len = input_len
        self.target_len = target_len
        self.trg_masks = self.subsequent_mask(self.target_len)

    @staticmethod
    def subsequent_mask(size):
        attn_shape = (1, size, size)
        subsequent_mask = (1 - torch.triu(torch.ones(attn_shape), diagonal=1))
        return subsequent_mask

    def encode(self, source_seq, source_mask):
        # Encodes the source sequence and uses the result
        # to initialize the decoder
        encoder_states = self.encoder(source_seq, source_mask)
        self.decoder.init_keys(encoder_states)

    def decode(self, shifted_target_seq, source_mask=None, target_mask=None):
        # Decodes/generates a sequence using the shifted (masked)
        # target sequence - used in TRAIN mode
```

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```
        outputs = self.decoder(shifted_target_seq,
                               source_mask=source_mask,
                               target_mask=target_mask)
        return outputs

    def predict(self, source_seq, source_mask):
        # Decodes/generates a sequence using one input
        # at a time - used in EVAL mode
        inputs = source_seq[:, -1:]
        for i in range(self.target_len):
            out = self.decode(inputs, source_mask, self.trg_masks[:, :i+1, :i+1])
            out = torch.cat([inputs, out[:, -1:, :]], dim=-2)
            inputs = out.detach()
        outputs = inputs[:, 1:, :]
        return outputs

    def forward(self, X, source_mask=None):
        # Sends the mask to the same device as the inputs
        self.trg_masks = self.trg_masks.type_as(X).bool()
        # Slices the input to get source sequence
        source_seq = X[:, :self.input_len, :]
        # Encodes source sequence AND initializes decoder
        self.encode(source_seq, source_mask)
        if self.training:
            # Slices the input to get the shifted target seq
            shifted_target_seq = X[:, self.input_len-1:-1, :]
            # Decodes using the mask to prevent cheating
            outputs = self.decode(shifted_target_seq, source_mask, self.trg_masks)
        else:
            # Decodes using its own predictions
            outputs = self.predict(source_seq, source_mask)

        return outputs
```

13.1.7 Data Preparation

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

```
points, directions = generate_sequences()
full_train = torch.as_tensor(points).float()
target_train = full_train[:, 2:]
```

```
test_points, test_directions = generate_sequences(seed=19)
full_test = torch.as_tensor(points).float()
source_test = full_test[:, :2]
target_test = full_test[:, 2:]
```

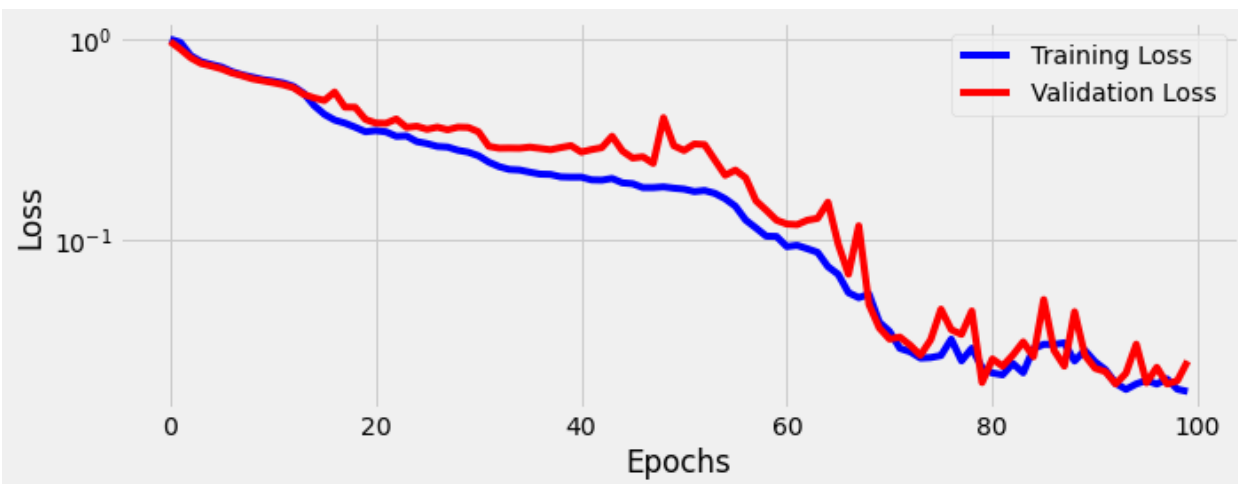
```
train_data = TensorDataset(full_train, target_train)
test_data = TensorDataset(source_test, target_test)

generator = torch.Generator()
train_loader = DataLoader(train_data, batch_size=16, shuffle=True,␣
↪generator=generator)
test_loader = DataLoader(test_data, batch_size=16)
```

13.1.8 Model Configuration & Training

```
torch.manual_seed(43)
encpe = EncoderPe(n_heads=3, d_model=2, ff_units=10, n_features=2)
decpe = DecoderPe(n_heads=3, d_model=2, ff_units=10, n_features=2)

model = EncoderDecoderSelfAttn(encpe, decpe, input_len=2, target_len=2)
loss = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

```
sbs_seq_selfattnpe = StepByStep(model, loss, optimizer)
sbs_seq_selfattnpe.set_loaders(train_loader, test_loader)
sbs_seq_selfattnpe.train(100)
```

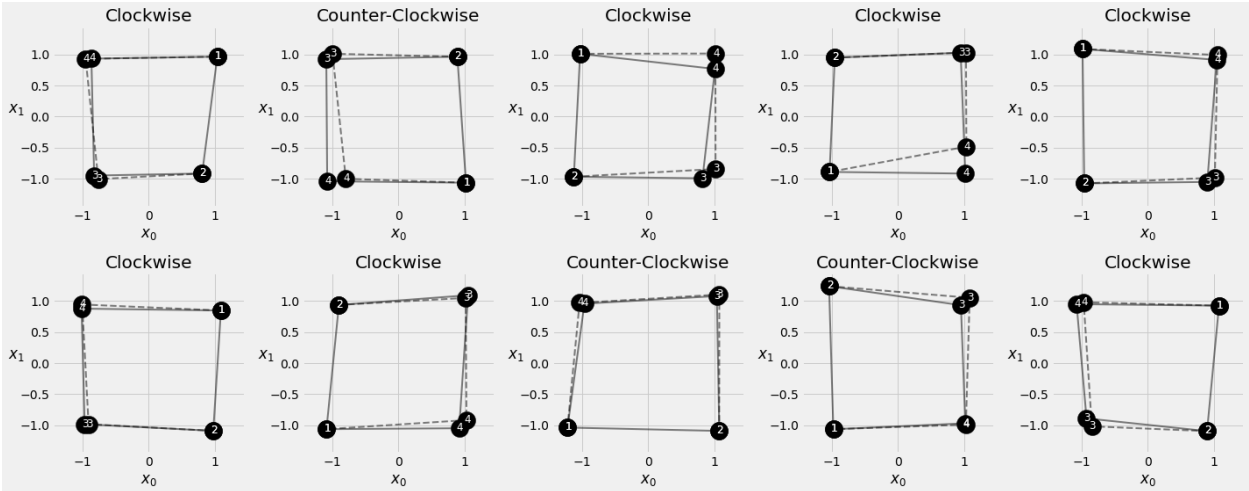
```
fig = sbs_seq_selfattnpe.plot_losses()
```



13.1.9 Visualizing Results

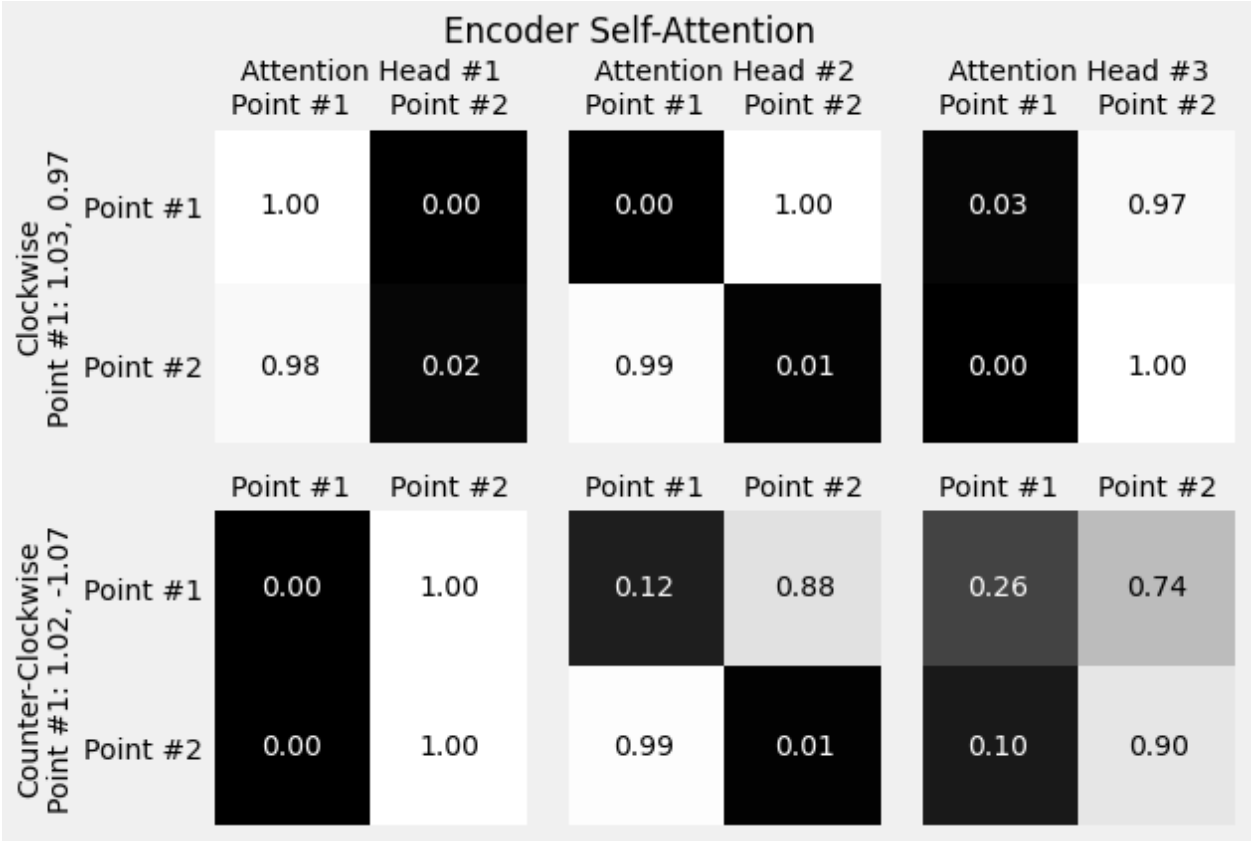
Visualizing Predictions

```
fig = sequence_pred(sbs_seq_selfattnpe, full_test, test_directions)
```

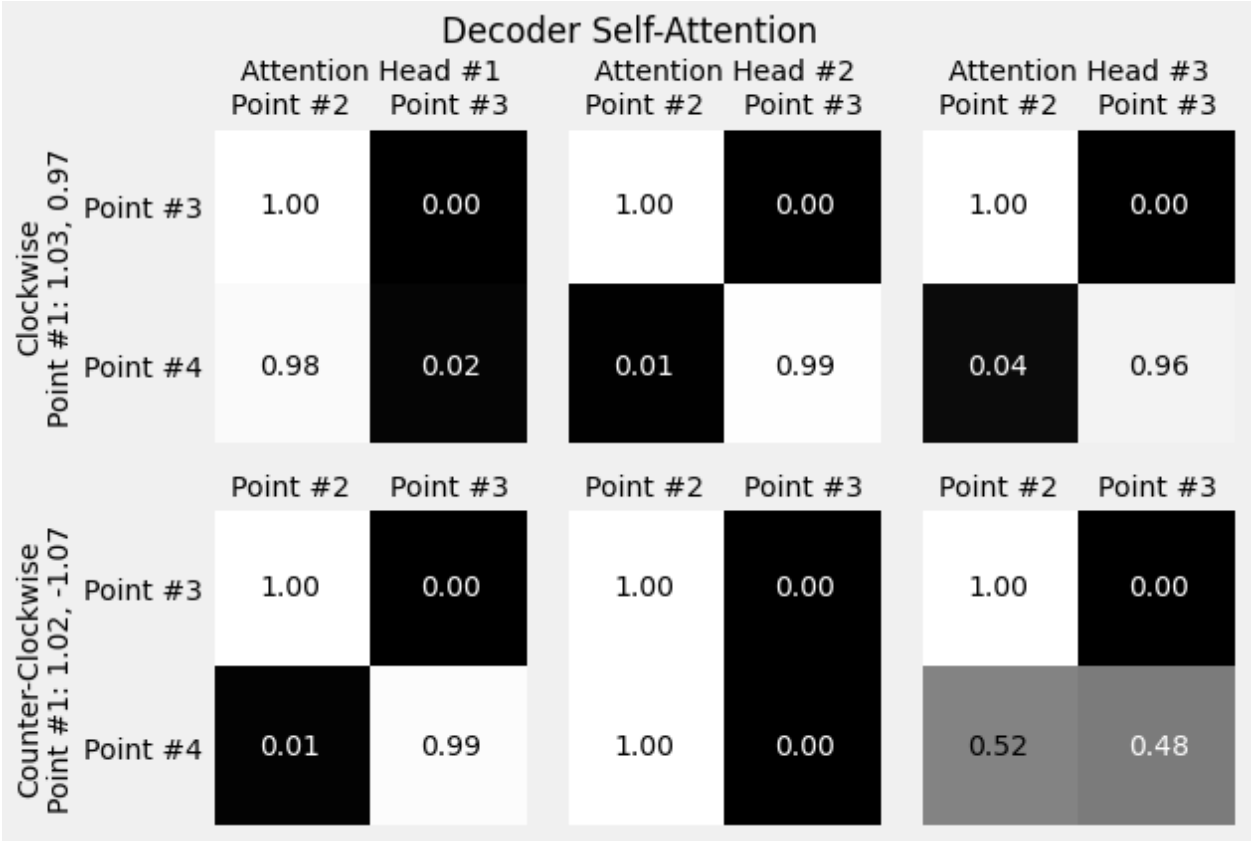


Visualizing Attention

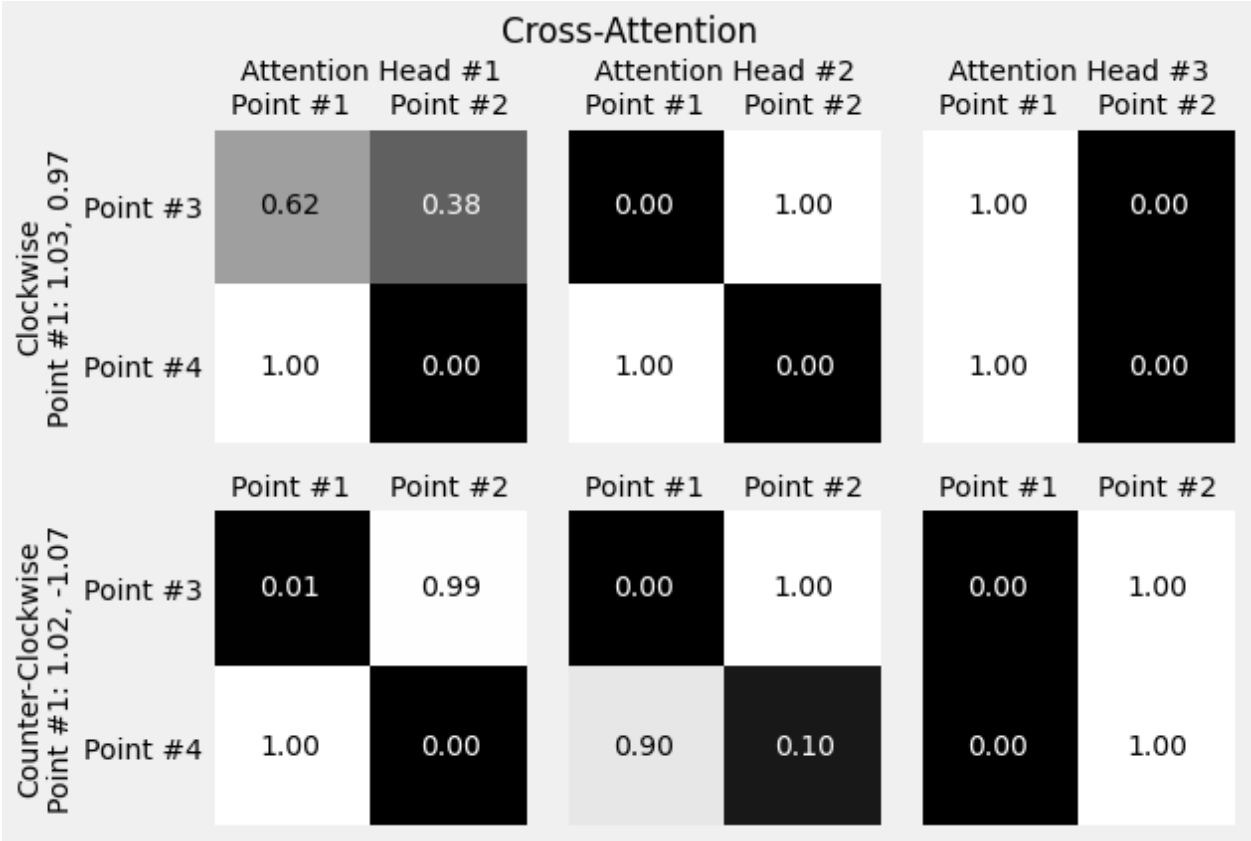
```
inputs = full_test[:2, :2]
source_labels = ['Point #1', 'Point #2']
target_labels = ['Point #3', 'Point #4']
point_labels = [f'{"Counter-" if not directions[i] else ""}Clockwise\nPoint #1:
 ↪{inp[0, 0]:.2f}, {inp[0, 1]:.2f}' for i, inp in enumerate(inputs)]

fig = plot_attention(model, inputs, point_labels, source_labels, target_labels,␣
 ↪decoder=False, self_attn=True, alphas_attr='encoder.layer.self_attn_heads.alphas')
fig.suptitle('Encoder Self-Attention')
fig.subplots_adjust(top=0.85)
```




```
fig = plot_attention(model, inputs, point_labels, source_labels, target_labels,
                     decoder=True, self_attn=True, alphas_attr='decoder.layer.self_
↪attn_heads.alphas')
fig.suptitle('Decoder Self-Attention')
fig.subplots_adjust(top=0.85)
```




```
fig = plot_attention(model, inputs, point_labels, source_labels, target_labels, self_
↪attn=False, alphas_attr='decoder.layer.cross_attn_heads.alphas')
fig.suptitle('Cross-Attention')
fig.subplots_adjust(top=0.85)
```

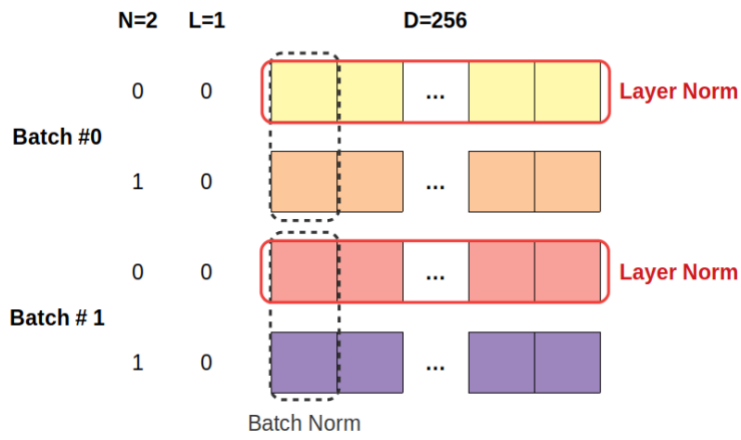


13.2 Layer Normalization

Layer normalization was introduced by Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffery E. Hinton in their 2016 paper Layer Normalization, but it only got really popular after being used in the hugely successful Transformer architecture.

Simply put: layer normalization standardizes individual data points, not features. This is completely different than the standardizations we've performed so far. Before, each feature, either in the whole training set (using Scikit-learn's `StandardScaler` or in a mini-batch (using batch norm), was standardized to have zero mean and unit standard deviation. In a tabular dataset, we were standardizing the columns.

Important: Layer normalization Layer normalization, in a tabular dataset, standardizes the rows. Each data point will have the average of its features equals zero, and the standard deviation of its features equals one.



13.2.1 imports

```
import torch
import torch.nn as nn
import numpy as np
import matplotlib.pyplot as plt
```

13.2.2 Positional Encoding

```
class PositionalEncoding(nn.Module):
    def __init__(self, max_len, d_model):
        super().__init__()
        self.d_model = d_model
        pe = torch.zeros(max_len, d_model)
        position = torch.arange(0, max_len).float().unsqueeze(1)
        angular_speed = torch.exp(torch.arange(0, d_model, 2).float() * (-np.
↪log(10000.0) / d_model))
        pe[:, 0::2] = torch.sin(position * angular_speed) # even dimensions
        pe[:, 1::2] = torch.cos(position * angular_speed) # odd dimensions
        self.register_buffer('pe', pe.unsqueeze(0))

    def forward(self, x):
        # x is N, L, D
        # pe is 1, maxlen, D
        scaled_x = x * np.sqrt(self.d_model)
        encoded = scaled_x + self.pe[:, :x.size(1), :]
        return encoded
```

13.2.3 Step-by-step Layer Normalization

- Calculating the mean of data point
- Calculating the standard deviation of the data point
- Computing the standardized data point

```
d_model = 4
seq_len = 2
n_points = 3

torch.manual_seed(34)
data = torch.randn(n_points, seq_len, d_model)
pe = PositionalEncoding(seq_len, d_model)
inputs = pe(data)
inputs
```

```
tensor([[[-3.8049,  1.9899, -1.7325,  2.1359],
         [ 1.7854,  0.8155,  0.1116, -1.7420]],

        [[-2.4273,  1.3559,  2.8615,  2.0084],
         [-1.0353, -1.2766, -2.2082, -0.6952]],

        [[-0.8044,  1.9707,  3.3704,  2.0587],
         [ 4.2256,  6.9575,  1.4770,  2.0762]]])
```

$$\overline{X}_{n,l} = \frac{1}{D}\sum_{d=1}^{D} x_{n,l,d}$$

```
inputs_mean = inputs.mean(axis=2).unsqueeze(2)
inputs_mean
```

```
tensor([[[-0.3529],
         [ 0.2426]],

        [[ 0.9496],
         [-1.3038]],

        [[ 1.6489],
         [ 3.6841]]])
```

$$\sigma_{n,l}(X) = \sqrt{\frac{1}{D}\sum_{d=1}^{D}(x_{n,l,d} - \overline{X}_{n,l})^2}$$

```
inputs_var = inputs.var(axis=2, unbiased=False).unsqueeze(2)
inputs_var
```

```
tensor([[[6.3756],
         [1.6661]],

        [[4.0862],
         [0.3153]],

        [[2.3135],
         [4.6163]]])
```

$$standardized\ x_{n,l,d} = \frac{x_{n,l,d} - \overline{X}_{n,l}}{\sigma_{n,l}(X) + \epsilon}$$

```
(inputs - inputs_mean)/torch.sqrt(inputs_var+1e-5)
```

```
tensor([[[-1.3671,  0.9279, -0.5464,  0.9857],
         [ 1.1953,  0.4438, -0.1015, -1.5376]],

        [[-1.6706,  0.2010,  0.9458,  0.5238],
         [ 0.4782,  0.0485, -1.6106,  1.0839]],

        [[-1.6129,  0.2116,  1.1318,  0.2695],
         [ 0.2520,  1.5236, -1.0272, -0.7484]]])
```

```
layer_norm = nn.LayerNorm(d_model)
layer_norm.state_dict()
```

```
OrderedDict([('weight', tensor([1., 1., 1., 1.])),
             ('bias', tensor([0., 0., 0., 0.]))])
```

13.2.4 PyTorch's `nn.LayerNorm` function

```
layer_norm = nn.LayerNorm(d_model)
normalized = layer_norm(inputs)

normalized[0][0].mean(), normalized[0][0].std(unbiased=False)
```

```
(tensor(-1.4901e-08, grad_fn=<MeanBackward0>),
 tensor(1.0000, grad_fn=<StdBackward>))
```

```
layer_norm.state_dict()
```

```
OrderedDict([('weight', tensor([1., 1., 1., 1.])),
             ('bias', tensor([0., 0., 0., 0.]))])
```

$$layer\ normed\ x_{n,l,d} = b_d + w_d\ standardized\ x_{n,l,d}$$

$$layer\ normed\ x_{n,l,d} = standardized\ x_{n,l,d}\ \gamma_d + \beta_d$$

13.2.5 Layer Normalization of Positionally Encoded Dummy

The size of the mini-batch strongly impacts the running statistics of the batch normalization. We also learned that batch norms oscillating statistics may introduce a regularizing effect.

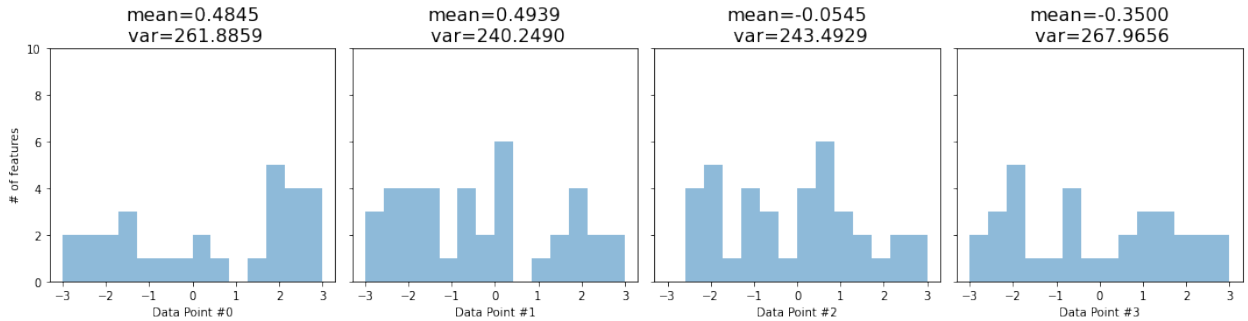
None of this happens with layer normalization: it steadily delivers data points with zero mean and unit standard deviation regardless of our choice of mini-batch size or anything else.

```
torch.manual_seed(23)
dummy_points = torch.randn(4, 1, 256)
dummy_pe = PositionalEncoding(1, 256)
dummy_enc = dummy_pe(dummy_points)
dummy_enc
```

```
tensor([[[-14.4193,  10.0495,  -7.8116,  ..., -15.4844, -18.0732,  -3.9566]],

        [[  2.6628,  -3.5462, -23.6461,  ...,  -0.9403, -18.4375, -37.4197]],

        [[-24.6397,  -1.9127, -16.4244,  ..., -17.3708, -26.0550, -14.0706]],

        [[ 13.7988,  21.4612,  10.4125,  ...,  -3.2333, -17.0188,   3.9237]]])
```

```
def hist_encoding(encoding):
    encoding = encoding.cpu().detach().numpy()
    fig, axs = plt.subplots(1, 4, figsize=(15, 4))
    axs = axs.flatten()
    for i in range(4):
        data_point = encoding[i][0]
        axs[i].hist(data_point, bins=np.linspace(-3, 3, 15), alpha=.5)
        axs[i].set_xlabel(f'Data Point #{i}')
        axs[i].set_ylabel('# of features')
        axs[i].set_title(f'mean={data_point.mean():.4f}\n var={data_point.var():.4f}',
 ↪ fontsize=16)
        axs[i].set_ylim([0, 10])
        axs[i].label_outer()
    fig.tight_layout()
    return fig

def hist_layer_normed(encoding, normed):
    encoding = encoding.cpu().detach().numpy()
    normed = normed.cpu().detach()
    fig, axs = plt.subplots(1, 4, figsize=(15, 4))
    for i in range(4):
        data_point = encoding[i][0]
        normed_point = normed.detach()[i][0]
        axs[i].hist(data_point, bins=np.linspace(-3, 3, 15), alpha=.5, label='Original
 ↪')
        axs[i].hist(normed_point.numpy(), bins=np.linspace(-3, 3, 15), alpha=.5,␣
 ↪label='Standardized')
        axs[i].set_xlabel(f'Data Point #{i}')
        axs[i].set_ylabel('# of features')
        axs[i].set_title(f'mean={normed.mean().numpy():.4f}\n std={normed.
 ↪std(unbiased=False).numpy():.4f}', fontsize=16)
        axs[i].legend()
        axs[i].set_ylim([0, 80])
        axs[i].label_outer()
    fig.tight_layout()
    return fig
```

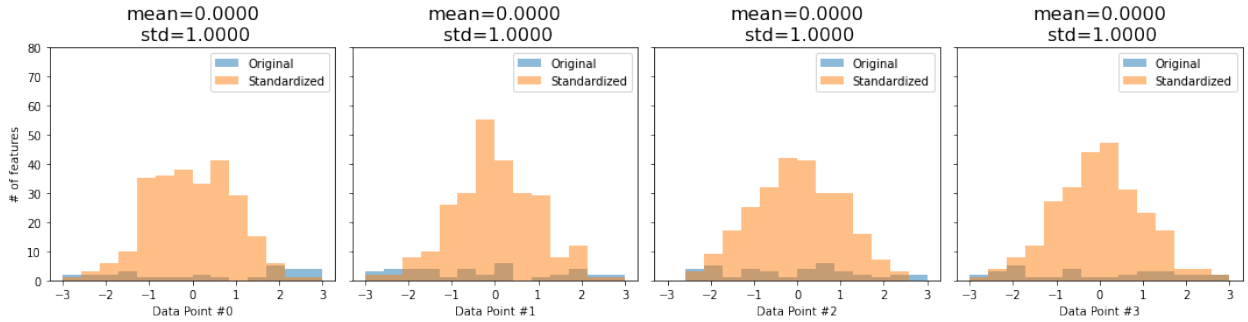
```
fig = hist_encoding(dummy_enc)
```




```
layer_normalizer = nn.LayerNorm(256)
dummy_normed = layer_normalizer(dummy_enc)
dummy_normed
```

```
tensor([[[-0.9210,  0.5911, -0.5127,  ..., -0.9868, -1.1467, -0.2744]],

        [[ 0.1399, -0.2607, -1.5574,  ..., -0.0925, -1.2214, -2.4460]],

        [[-1.5755, -0.1191, -1.0491,  ..., -1.1097, -1.6662, -0.8982]],

        [[ 0.8643,  1.3324,  0.6575,  ..., -0.1761, -1.0183,  0.2611]]],
       grad_fn=<NativeLayerNormBackward>)
```

```
fig = hist_layer_normed(dummy_enc, dummy_normed)
```



13.2.6 Our Seq2Seq Problem

So far, we have been using dummy examples to illustrate how layer normalization works. Let's go back to our sequence-to-sequence problem, where the source sequence had two data points, each data point representing the coordinates of two corners. As usual, we are adding positional encoding to it

```
pe = PositionalEncoding(max_len=2, d_model=2)

source_seq = torch.tensor([[[ 1.0349,  0.9661], [ 0.8055, -0.9169]]])
source_seq_enc = pe(source_seq)
source_seq_enc
```

```
tensor([[[ 1.4636,  2.3663],
         [ 1.9806, -0.7564]]])
```

```
norm = nn.LayerNorm(2)
norm(source_seq_enc)
```

```
tensor([[[-1.0000,  1.0000],
         [ 1.0000, -1.0000]]], grad_fn=<NativeLayerNormBackward>)
```

Warning: When one tries to layer normalize two features only: they become either minus one or one. Even worse, it will be the same for every data point. These values will not get us anywhere.

We need projections (for numerical values) or embeddings (for categorical values) to get us from 2 dimensions to a different dimensionality.

13.2.7 Projections or Embeddings

Note: Sometimes projections and embeddings are used interchangeably. Here, we are sticking with embeddings for categorical values and projections for numerical values. }

Projections/Embeddings are referring to using a simple linear layer to project our pair of coordinates into a higher-dimensional feature space.

```
torch.manual_seed(11)
proj_dim = 6
linear_proj = nn.Linear(2, proj_dim)
pe = PositionalEncoding(2, proj_dim)

source_seq_proj = linear_proj(source_seq)
source_seq_proj_enc = pe(source_seq_proj)
source_seq_proj_enc
```

```
tensor([[[-2.0934,  1.5040,  1.8742,  0.0628,  0.3034,  2.0190],
         [-0.8853,  2.8213,  0.5911,  2.4193, -2.5230,  0.3599]]],
       grad_fn=<AddBackward0>)
```

```
norm = nn.LayerNorm(proj_dim)
norm(source_seq_proj_enc)
```

```
tensor([[[-1.9061,  0.6287,  0.8896, -0.3868, -0.2172,  0.9917],
         [-0.7362,  1.2864,  0.0694,  1.0670, -1.6299, -0.0568]]],
       grad_fn=<NativeLayerNormBackward>)
```

13.3 Transform and Roll Out

We will finally put everything together in this notebook to implement the famious Transformer model.

13.3.1 Helper Files

Download these files and place them in the same directory as the current notebook before you start.

```
from IPython.display import FileLink, FileLinks
```

```
FileLink('plots_transformer.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\plots_transformer.py
```

```
FileLink('util.py')
```

```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\util.py
```

```
FileLink('replay.py')
```

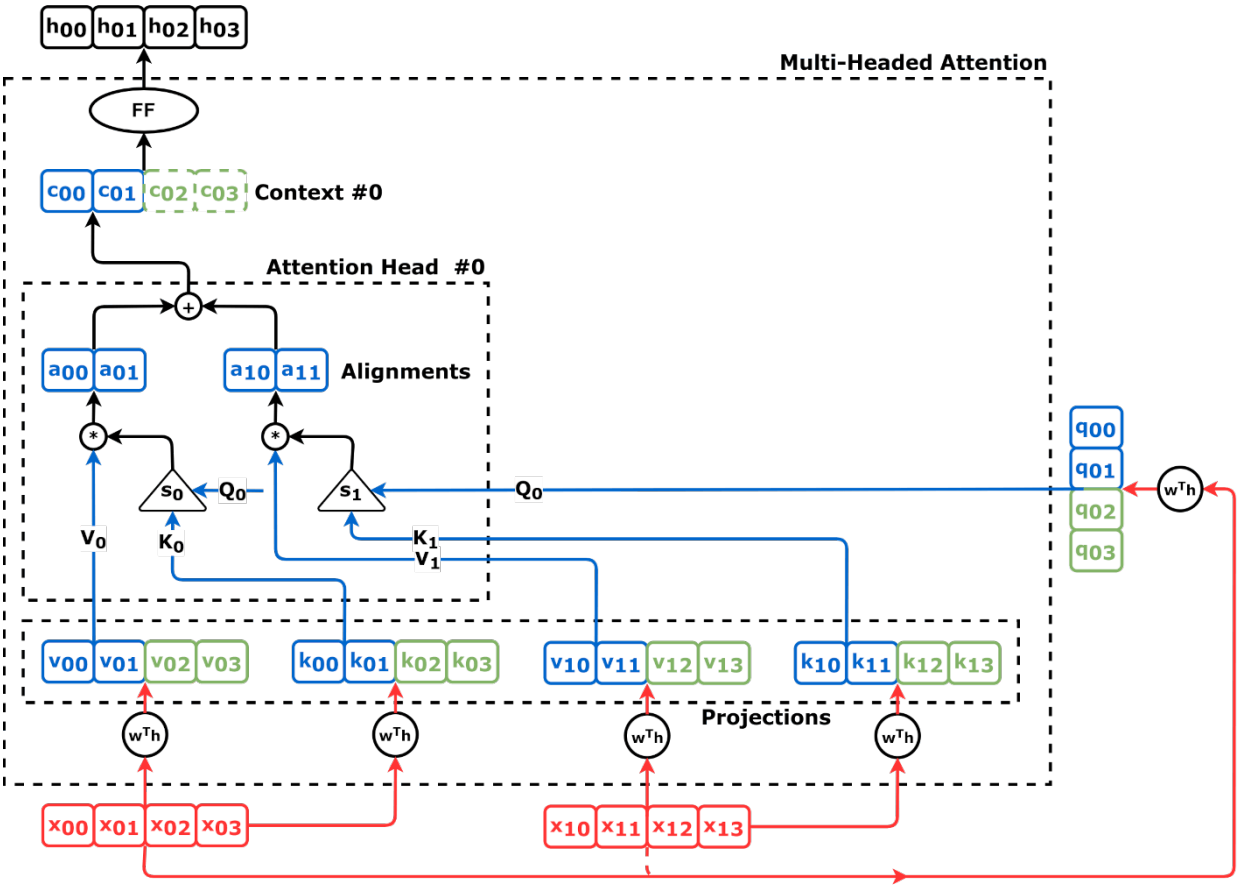
```
c:\Users\wei\jupyter_book\cits4012\cits4012_natural_language_processing\cits4012_
↪natural_language_processing\transformer\replay.py
```

13.3.2 Imports

```
import copy
import numpy as np

import torch
import torch.optim as optim
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader, Dataset, random_split, TensorDataset
from plots_transformer import *
from util import *
```

We need `PositionalEncoding`, `subsequent_mask` and `EncoderDecoderSelfAttn` that we built earlier. They are copied here for clarity and completeness, and demonstrating when they are needed, but for better software engineering, you should consider putting them in a separate .py file, so they can be imported.

13.3.3 Narrow Attention



Multiheaded Attention

```
class MultiHeadedAttention(nn.Module):
    def __init__(self, n_heads, d_model, dropout=0.1):
        super(MultiHeadedAttention, self).__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.d_k = int(d_model / n_heads)
        self.linear_query = nn.Linear(d_model, d_model)
        self.linear_key = nn.Linear(d_model, d_model)
        self.linear_value = nn.Linear(d_model, d_model)
        self.linear_out = nn.Linear(d_model, d_model)
        self.dropout = nn.Dropout(p=dropout)
        self.alphas = None

    def make_chunks(self, x):
        batch_size, seq_len = x.size(0), x.size(1)
        # N, L, D -> N, L, n_heads * d_k
        x = x.view(batch_size, seq_len, self.n_heads, self.d_k)
        # N, n_heads, L, d_k
        x = x.transpose(1, 2)
        return x
```

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```
    def init_keys(self, key):
        # N, n_heads, L, d_k
        self.proj_key = self.make_chunks(self.linear_key(key))
        self.proj_value = self.make_chunks(self.linear_value(key))

    def score_function(self, query):
        # scaled dot product
        # N, n_heads, L, d_k x # N, n_heads, d_k, L -> N, n_heads, L, L
        proj_query = self.make_chunks(self.linear_query(query))
        dot_products = torch.matmul(proj_query,
                                    self.proj_key.transpose(-2, -1))
        scores =  dot_products / np.sqrt(self.d_k)
        return scores

    def attn(self, query, mask=None):
        # Query is batch-first: N, L, D
        # Score function will generate scores for each head
        scores = self.score_function(query) # N, n_heads, L, L
        if mask is not None:
            scores = scores.masked_fill(mask == 0, -1e9)
        alphas = F.softmax(scores, dim=-1) # N, n_heads, L, L
        alphas = self.dropout(alphas)
        self.alphas = alphas.detach()

        # N, n_heads, L, L x N, n_heads, L, d_k -> N, n_heads, L, d_k
        context = torch.matmul(alphas, self.proj_value)
        return context

    def output_function(self, contexts):
        # N, L, D
        out = self.linear_out(contexts) # N, L, D
        return out

    def forward(self, query, mask=None):
        if mask is not None:
            # N, 1, L, L - every head uses the same mask
            mask = mask.unsqueeze(1)

        # N, n_heads, L, d_k
        context = self.attn(query, mask=mask)
        # N, L, n_heads, d_k
        context = context.transpose(1, 2).contiguous()
        # N, L, n_heads * d_k = N, L, d_model
        context = context.view(query.size(0), -1, self.d_model)
        # N, L, d_model
        out = self.output_function(context)
        return out
```

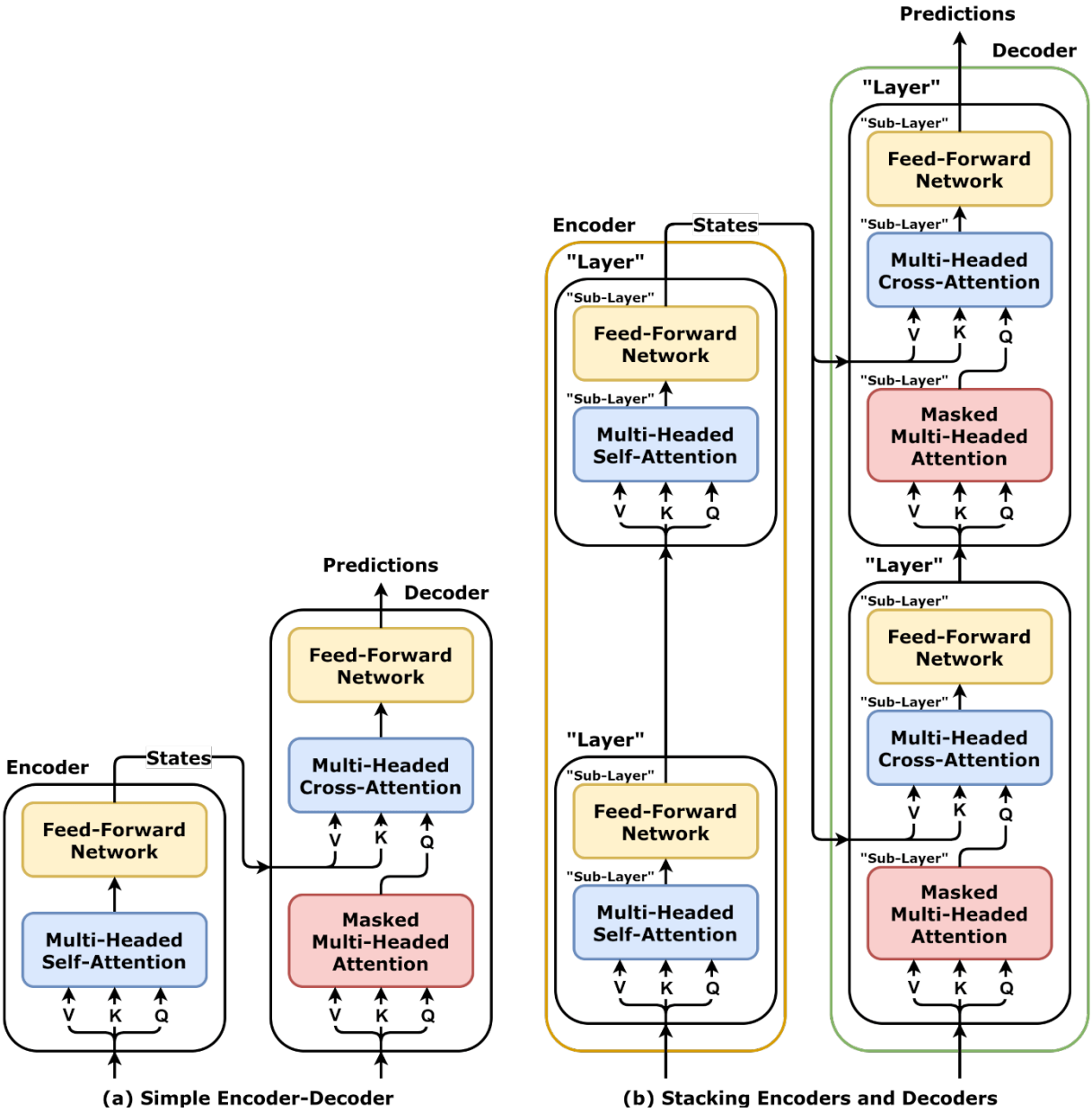
```
dummy_points = torch.randn(16, 2, 4) # N, L, F
mha = MultiHeadedAttention(n_heads=2, d_model=4, dropout=0.0)
mha.init_keys(dummy_points)
out = mha(dummy_points) # N, L, D
out.shape
```

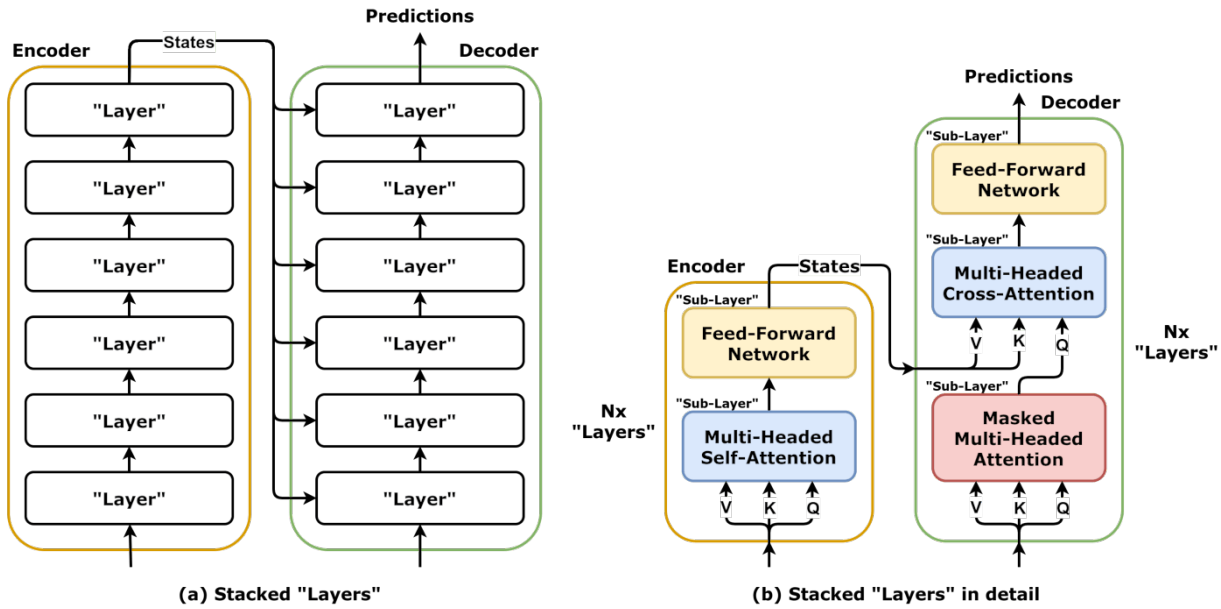
```
torch.Size([16, 2, 4])
```

13.3.4 Stacking Encoders and Decoders

The output of one encoder feeds the next, and the last encoder outputs states as usual. These states will feed the cross-attention mechanism of all stacked decoders. The output of one decoder feeds the next, and the last decoder outputs predictions as usual.

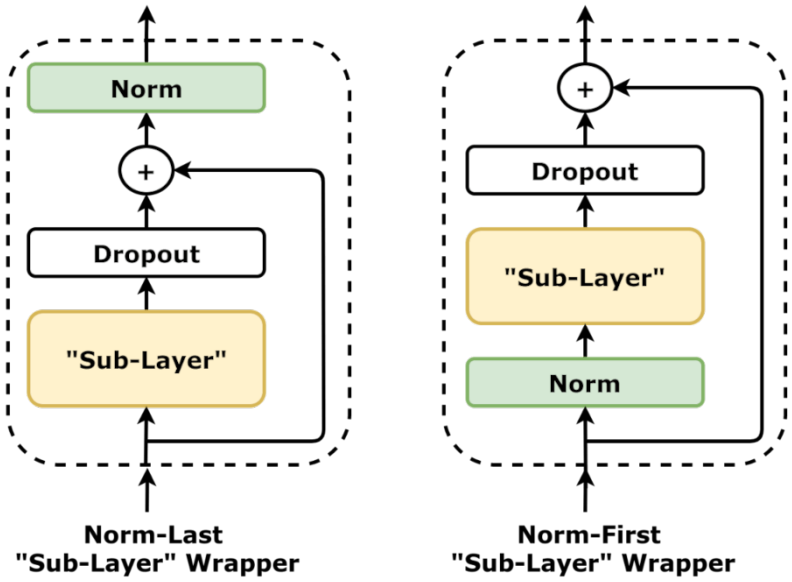
The former encoder is now a so-called "layer", and a stack of "layers" compose the new, deeper, encoder. The same holds true for the decoder. Moreover, each operation (multi-headed self- and cross-attention mechanisms and feed-forward networks) inside a "layer" is now a "sub-layer".





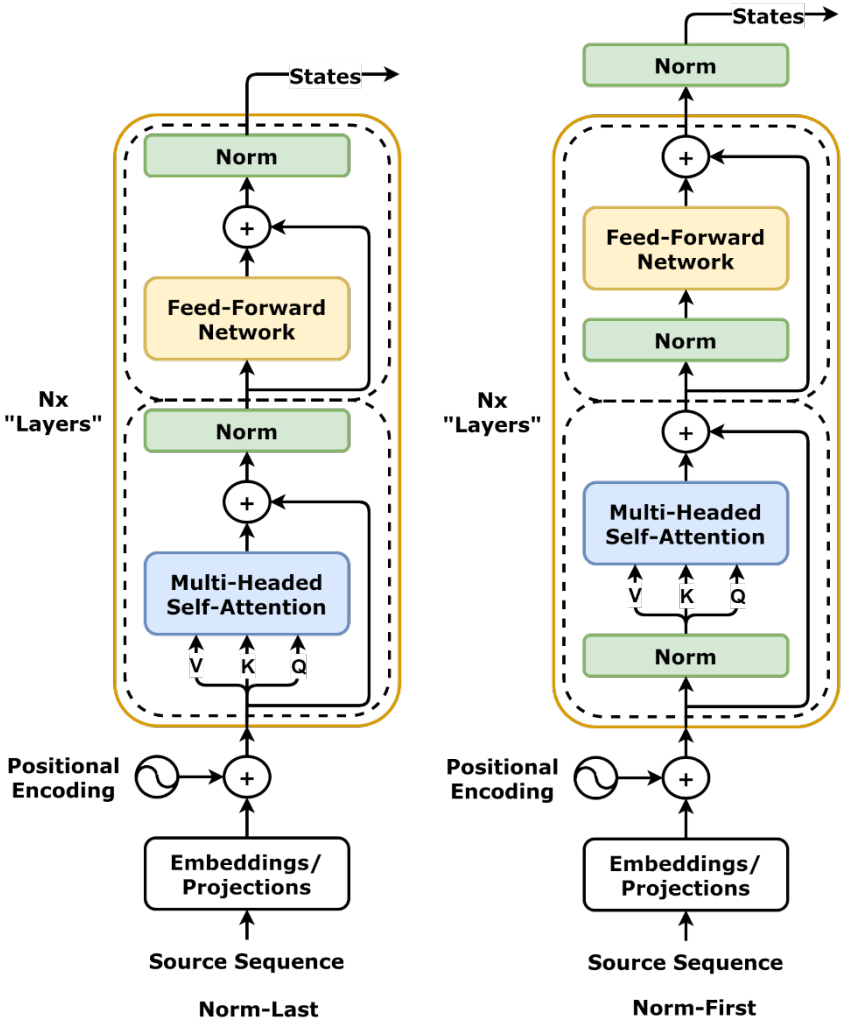
13.3.5 Wrapping "Sub-Layers"

As our models grows deeper with many stacked "layers", we are running into familiar issues, like the vanishing gradients problem. we can add batch and layer normalization, residual connections, introduce dropout to our model. We can wrap each and every "sub-layer" with them in either a norm-first or norm-last manner.



$$outputs_{norm-last} = \quad norm(inputs + dropout(sublayer(inputs))$$
$$outputs_{norm-first} = \quad inputs + dropout(sublayer(norm(inputs)))$$

13.3.6 Transformer Encoder



$$outputs_{norm-last} = norm(\underbrace{norm(inputs + att(inputs))}_{Output\ of\ SubLayer_0} + ffn(\underbrace{norm(inputs + att(inputs))}_{Output\ of\ SubLayer_0}))$$

$$outputs_{norm-first} = \underbrace{inputs + att(norm(inputs))}_{Output\ of\ SubLayer_0} + ffn(norm(\underbrace{inputs + att(norm(inputs))}_{Output\ of\ SubLayer_0}))$$

```
class EncoderLayer(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, dropout=0.1):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.self_attn_heads = MultiHeadedAttention(n_heads, d_model,
                                                    dropout=dropout)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
```

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```
            nn.ReLU(),
            nn.Dropout(dropout),
            nn.Linear(ff_units, d_model),
        )

        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.drop1 = nn.Dropout(dropout)
        self.drop2 = nn.Dropout(dropout)

    def forward(self, query, mask=None):
        # Sublayer #0
        # Norm
        norm_query = self.norm1(query)
        # Multi-headed Attention
        self.self_attn_heads.init_keys(norm_query)
        states = self.self_attn_heads(norm_query, mask)
        # Add
        att = query + self.drop1(states)

        # Sublayer #1
        # Norm
        norm_att = self.norm2(att)
        # Feed Forward
        out = self.ffn(norm_att)
        # Add
        out = att + self.drop2(out)
        return out
```

```
class EncoderTransf(nn.Module):
    def __init__(self, encoder_layer, n_layers=1, max_len=100):
        super().__init__()
        self.d_model = encoder_layer.d_model
        self.pe = PositionalEncoding(max_len, self.d_model)
        self.norm = nn.LayerNorm(self.d_model)
        self.layers = nn.ModuleList([copy.deepcopy(encoder_layer)
                                     for _ in range(n_layers)])

    def forward(self, query, mask=None):
        # Positional Encoding
        x = self.pe(query)
        for layer in self.layers:
            x = layer(x, mask)
        # Norm
        return self.norm(x)
```

```
enclayer = nn.TransformerEncoderLayer(d_model=6, nhead=3, dim_feedforward=20)
enctransf = nn.TransformerEncoder(enclayer, num_layers=1, norm=nn.LayerNorm)
```

13.3.7 Transformer Decoder

```
class DecoderLayer(nn.Module):
    def __init__(self, n_heads, d_model, ff_units, dropout=0.1):
        super().__init__()
        self.n_heads = n_heads
        self.d_model = d_model
        self.ff_units = ff_units
        self.self_attn_heads = MultiHeadedAttention(n_heads, d_model,
                                                    dropout=dropout)
        self.cross_attn_heads = MultiHeadedAttention(n_heads, d_model,
```

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```
                                                    dropout=dropout)
        self.ffn = nn.Sequential(
            nn.Linear(d_model, ff_units),
            nn.ReLU(),
            nn.Dropout(dropout),
            nn.Linear(ff_units, d_model),
        )

        self.norm1 = nn.LayerNorm(d_model)
        self.norm2 = nn.LayerNorm(d_model)
        self.norm3 = nn.LayerNorm(d_model)
        self.drop1 = nn.Dropout(dropout)
        self.drop2 = nn.Dropout(dropout)
        self.drop3 = nn.Dropout(dropout)

    def init_keys(self, states):
        self.cross_attn_heads.init_keys(states)

    def forward(self, query, source_mask=None, target_mask=None):
        # Sublayer #0
        # Norm
        norm_query = self.norm1(query)
        # Masked Multi-head Attention
        self.self_attn_heads.init_keys(norm_query)
        states = self.self_attn_heads(norm_query, target_mask)
        # Add
        att1 = query + self.drop1(states)

        # Sublayer #1
        # Norm
        norm_att1 = self.norm2(att1)
        # Multi-head Attention
        encoder_states = self.cross_attn_heads(norm_att1, source_mask)
        # Add
        att2 = att1 + self.drop2(encoder_states)

        # Sublayer #2
        # Norm
        norm_att2 = self.norm3(att2)
        # Feed Forward
        out = self.ffn(norm_att2)
        # Add
        out = att2 + self.drop3(out)
        return out
```

```
class DecoderTransf(nn.Module):
    def __init__(self, decoder_layer, n_layers=1, max_len=100):
        super(DecoderTransf, self).__init__()
        self.d_model = decoder_layer.d_model
        self.pe = PositionalEncoding(max_len, self.d_model)
        self.norm = nn.LayerNorm(self.d_model)
        self.layers = nn.ModuleList([copy.deepcopy(decoder_layer)
                                     for _ in range(n_layers)])

    def init_keys(self, states):
        for layer in self.layers:
```

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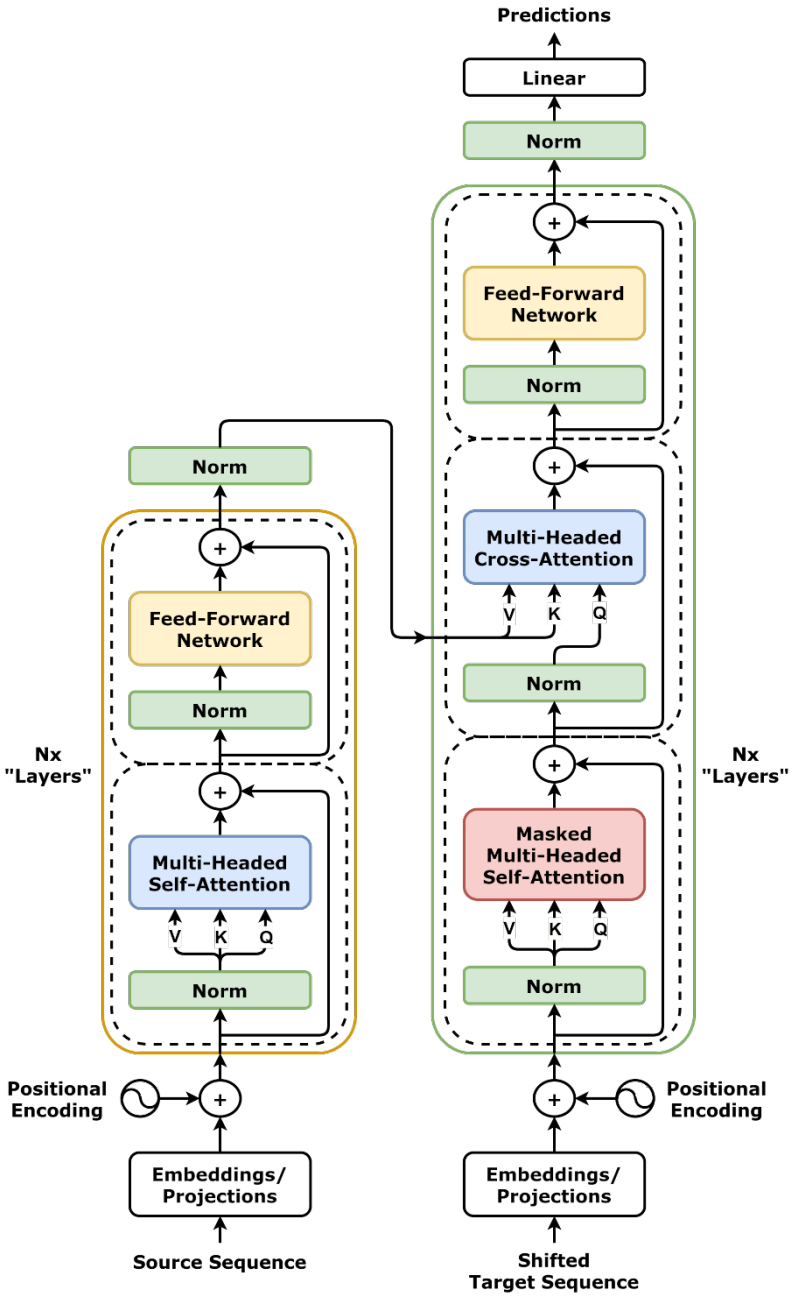
```
            layer.init_keys(states)

    def forward(self, query, source_mask=None, target_mask=None):
        # Positional Encoding
        x = self.pe(query)
        for layer in self.layers:
            x = layer(x, source_mask, target_mask)
        # Norm
        return self.norm(x)
```

```
declayer = nn.TransformerDecoderLayer(d_model=6, nhead=3, dim_feedforward=20)
dectransf = nn.TransformerDecoder(declayer, num_layers=1, norm=nn.LayerNorm)
```

13.3.8 The Transformer



The Transformer still is an encoder-decoder architecture like the one we developed in the previous chapter, so it should be no surprise that we can actually use our former `EncoderDecoderSelfAttn` class as a parent class and add two extra components to it:

- a projection layer to map our original features (`n_features`) to the dimensionality of both encoder and decoder (`d_model`)
- a final linear layer to map the decoder's outputs back to the original feature space (the coordinates we're trying to predict)

```
class EncoderDecoderSelfAttn(nn.Module):
    def __init__(self, encoder, decoder, input_len, target_len):
        super(EncoderDecoderSelfAttn, self).__init__()
        self.encoder = encoder
        self.decoder = decoder
        self.input_len = input_len
        self.target_len = target_len
        self.trg_masks = self.subsequent_mask(self.target_len)

    @staticmethod
    def subsequent_mask(size):
        attn_shape = (1, size, size)
        subseque_mask = (1 - torch.triu(torch.ones(attn_shape), diagonal=1))
        return subseque_mask

    def encode(self, source_seq, source_mask):
        encoder_states = self.encoder(source_seq, source_mask)
        self.decoder.init_keys(encoder_states)

    def decode(self, shifted_target_seq, source_mask=None, target_mask=None):
        outputs = self.decoder(shifted_target_seq,
                               source_mask=source_mask,
                               target_mask=target_mask)
        return outputs

    def predict(self, source_seq, source_mask):
        inputs = source_seq[:, -1:]
        for i in range(self.target_len):
            out = self.decode(inputs, source_mask, self.trg_masks[:, :i+1, :i+1])
            out = torch.cat([inputs, out[:, -1:, :]], dim=-2)
            inputs = out.detach()
        outputs = inputs[:, 1:, :]
        return outputs

    def forward(self, X, source_mask=None):
        self.trg_masks = self.trg_masks.type_as(X).bool()
        source_seq = X[:, :self.input_len, :]

        self.encode(source_seq, source_mask)
        if self.training:
            shifted_target_seq = X[:, self.input_len-1:-1, :]
            outputs = self.decode(shifted_target_seq, source_mask, self.trg_masks)
        else:
            outputs = self.predict(source_seq, source_mask)

        return outputs
```

```
class EncoderDecoderTransf(EncoderDecoderSelfAttn):
    def __init__(self, encoder, decoder, input_len, target_len, n_features):
        super(EncoderDecoderTransf, self).__init__(encoder, decoder, input_len,␣
↪target_len)
        self.n_features = n_features
        self.proj = nn.Linear(n_features, encoder.d_model)
        self.linear = nn.Linear(encoder.d_model, n_features)

    def encode(self, source_seq, source_mask=None):
        # Projection
```

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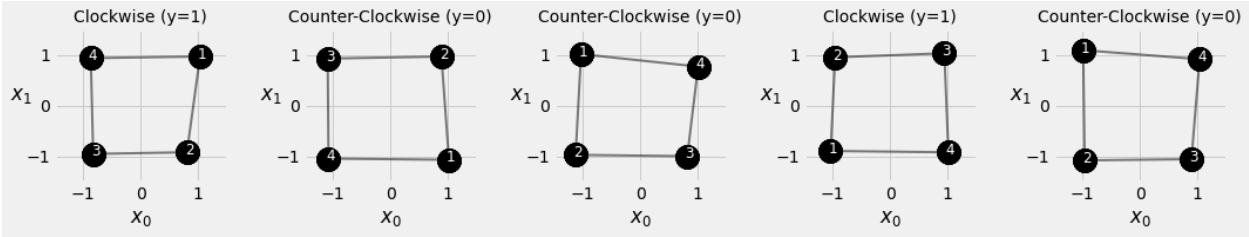
```
        source_proj = self.proj(source_seq)
        encoder_states = self.encoder(source_proj, source_mask)
        self.decoder.init_keys(encoder_states)

    def decode(self, shifted_target_seq, source_mask=None, target_mask=None):
        # Projection
        target_proj = self.proj(shifted_target_seq)
        outputs = self.decoder(target_proj,
                               source_mask=source_mask,
                               target_mask=target_mask)
        # Linear
        outputs = self.linear(outputs)
        return outputs
```

Data Preparation

```
def generate_sequences(n=128, variable_len=False, seed=13):
    basic_corners = np.array([[-1, -1], [-1, 1], [1, 1], [1, -1]])
    np.random.seed(seed)
    bases = np.random.randint(4, size=n)
    if variable_len:
        lengths = np.random.randint(3, size=n) + 2
    else:
        lengths = [4] * n
    directions = np.random.randint(2, size=n)
    points = [basic_corners[[(b + i) % 4 for i in range(4)]][slice(None, None, d*2-
↪1)][:l] + np.random.randn(l, 2) * 0.1 for b, d, l in zip(bases, directions,␣
↪lengths)]
    return points, directions
```

```
# Generating training data
points, directions = generate_sequences()
full_train = torch.as_tensor(points).float()
target_train = full_train[:, 2:]
# Generating test data
test_points, test_directions = generate_sequences(seed=17)
full_test = torch.as_tensor(points).float()
source_test = full_test[:, :2]
target_test = full_test[:, 2:]
# Datasets and data loaders
train_data = TensorDataset(full_train, target_train)
test_data = TensorDataset(source_test, target_test)
generator = torch.Generator()
train_loader = DataLoader(train_data, batch_size=16, shuffle=True,␣
↪generator=generator)
test_loader = DataLoader(test_data, batch_size=16)
```

```
fig = plot_data(points, directions, n_rows=1)
```



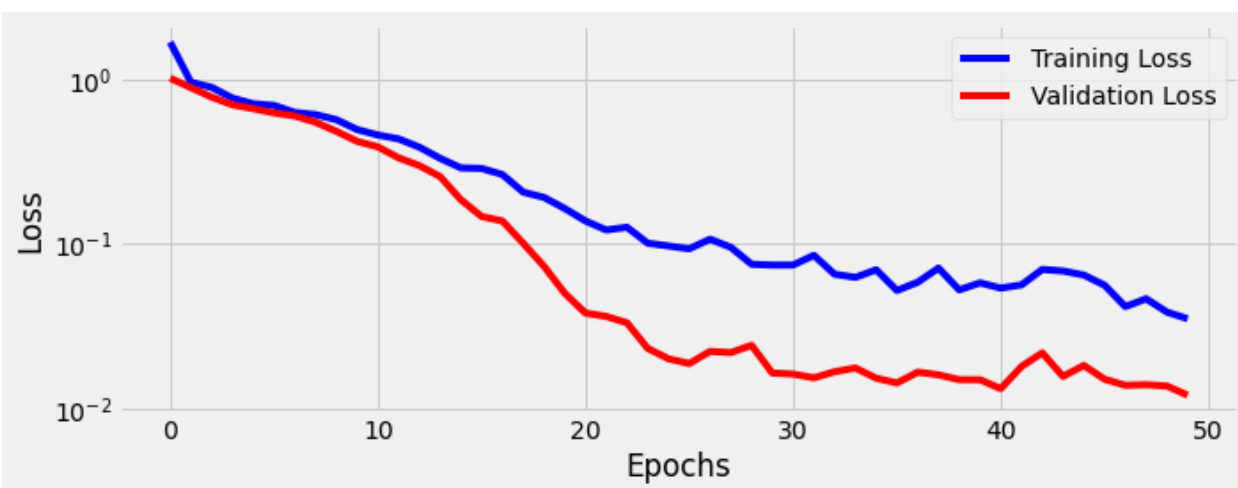
Model Configuration & Training

```
torch.manual_seed(42)
# Layers
enclayer = EncoderLayer(n_heads=3, d_model=6, ff_units=10, dropout=0.1)
declayer = DecoderLayer(n_heads=3, d_model=6, ff_units=10, dropout=0.1)
# Encoder and Decoder
enctransf = EncoderTransf(enclayer, n_layers=2)
dectransf = DecoderTransf(declayer, n_layers=2)
# Transformer
model_transf = EncoderDecoderTransf(enctransf, dectransf, input_len=2, target_len=2,␣
↪n_features=2)
loss = nn.MSELoss()
optimizer = torch.optim.Adam(model_transf.parameters(), lr=0.01)
```

```
for p in model_transf.parameters():
    if p.dim() > 1:
        nn.init.xavier_uniform_(p)
```

```
sbs_seq_transf = StepByStep(model_transf, loss, optimizer)
sbs_seq_transf.set_loaders(train_loader, test_loader)
sbs_seq_transf.train(50)
```

```
fig = sbs_seq_transf.plot_losses()
```



Note: Why is the validation loss so much better than the training loss? This phenomenon may happen for a variety of reasons, from an easier validation set to a "side effect" of regularization (e.g. dropout) in our current model. The regularization makes it harder for the model to learn or, in other words, yields higher losses. In our Transformer model,

there are many dropout layers, so it gets increasingly more difficult for the model to learn.

Let's observe this effect by using the same mini-batch to compute the loss using the trained model both in train and eval modes:

```
torch.manual_seed(11)
x, y = next(iter(train_loader))
device = sbs_seq_transf.device
# Training
model_transf.train()
loss(model_transf(x.to(device)), y.to(device))
```

```
tensor(0.0456, device='cuda:0', grad_fn=<MseLossBackward>)
```

```
# Validation
model_transf.eval()
loss(model_transf(x.to(device)), y.to(device))
```

```
tensor(0.0101, device='cuda:0')
```

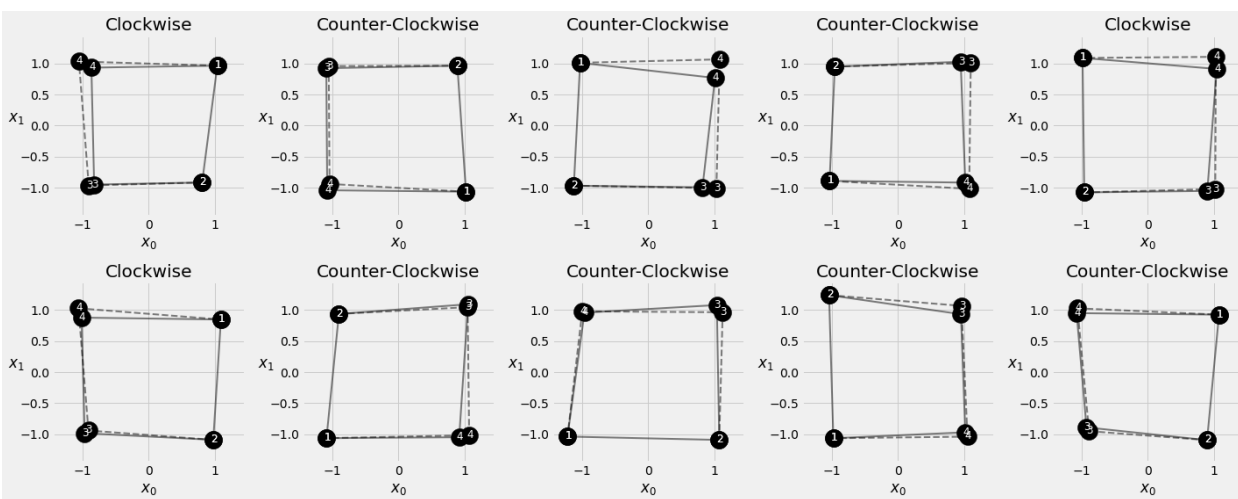
The loss is roughly three times larger in training mode.

Your Turn

You can set dropout to zero and retrain the model to verify that both loss curves get much closer to each other (by the way, the overall loss level gets better without dropout, but that's just because our sequence-to-sequence problem is actually quite simple).

Visualizing Predictions

```
fig = sequence_pred(sbs_seq_transf, full_test, test_directions)
```



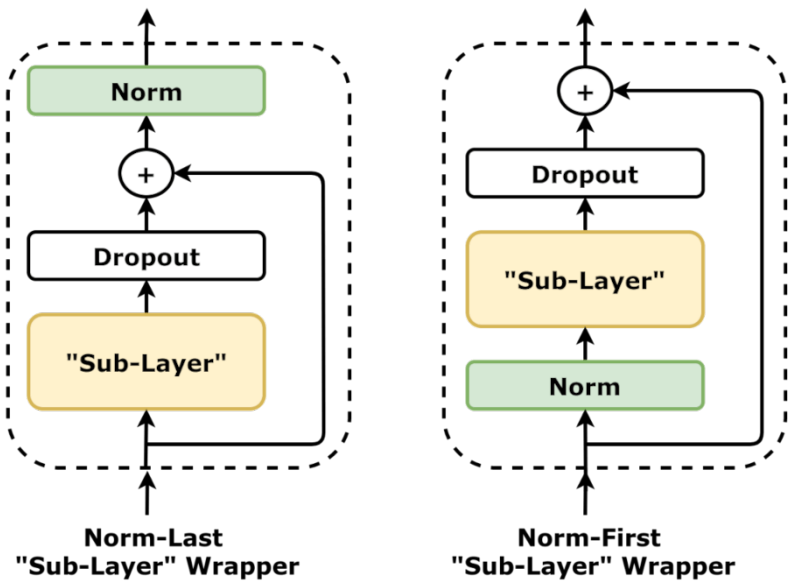
13.3.9 The PyTorch Transformer

PyTorch implements a full-fledged Transformer class of its own: `nn.Transformer`.

There are some differences between PyTorch's implementation and our own:

- first, and most importantly, PyTorch implements norm-last "sub-layer" wrappers, normalizing the output of each "sub-layer"
- it does not implement positional encoding, the final linear layer, and the projection layer, so we have to handle those ourselves.

The constructor expects many arguments because PyTorch's Transformer actually builds both encoder and decoder by itself.




```
def encode_decode(self, source, target, source_mask=None, target_mask=None):
    # Projections
    # PyTorch Transformer expects L, N, F
    src = self.preprocess(source).permute(1, 0, 2)
    tgt = self.preprocess(target).permute(1, 0, 2)

    out = self.transf(src, tgt,
                      src_key_padding_mask=source_mask,
                      tgt_mask=target_mask)

    # Linear
    # Back to N, L, D
    out = out.permute(1, 0, 2)
    out = self.linear(out) # N, L, F
    return out
```

```
class TransformerModel(nn.Module):
    def __init__(self, transformer, input_len, target_len, n_features):
        super().__init__()
        self.transf = transformer
        self.input_len = input_len
        self.target_len = target_len
```

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```
        self.trg_masks = self.transf.generate_square_subsequent_mask(self.target_len)
        self.n_features = n_features
        self.proj = nn.Linear(n_features, self.transf.d_model)
        self.linear = nn.Linear(self.transf.d_model, n_features)

        max_len = max(self.input_len, self.target_len)
        self.pe = PositionalEncoding(max_len, self.transf.d_model)
        self.norm = nn.LayerNorm(self.transf.d_model)

    def preprocess(self, seq):
        seq_proj = self.proj(seq)
        seq_enc = self.pe(seq_proj)
        return self.norm(seq_enc)

    def encode_decode(self, source, target, source_mask=None, target_mask=None):
        # Projections
        # PyTorch Transformer expects L, N, F
        src = self.preprocess(source).permute(1, 0, 2)
        tgt = self.preprocess(target).permute(1, 0, 2)

        out = self.transf(src, tgt,
                          src_key_padding_mask=source_mask,
                          tgt_mask=target_mask)

        # Linear
        # Back to N, L, D
        out = out.permute(1, 0, 2)
        out = self.linear(out) # N, L, F
        return out

    def predict(self, source_seq, source_mask=None):
        inputs = source_seq[:, -1:]
        for i in range(self.target_len):
            out = self.encode_decode(source_seq, inputs,
                                     source_mask=source_mask,
                                     target_mask=self.trg_masks[:i+1, :i+1])
            out = torch.cat([inputs, out[:, -1:, :]], dim=-2)
            inputs = out.detach()
        outputs = out[:, 1:, :]
        return outputs

    def forward(self, X, source_mask=None):
        self.trg_masks = self.trg_masks.type_as(X)
        source_seq = X[:, :self.input_len, :]

        if self.training:
            shifted_target_seq = X[:, self.input_len-1:-1, :]
            outputs = self.encode_decode(source_seq, shifted_target_seq,
                                         source_mask=source_mask,
                                         target_mask=self.trg_masks)
        else:
            outputs = self.predict(source_seq, source_mask)

        return outputs
```

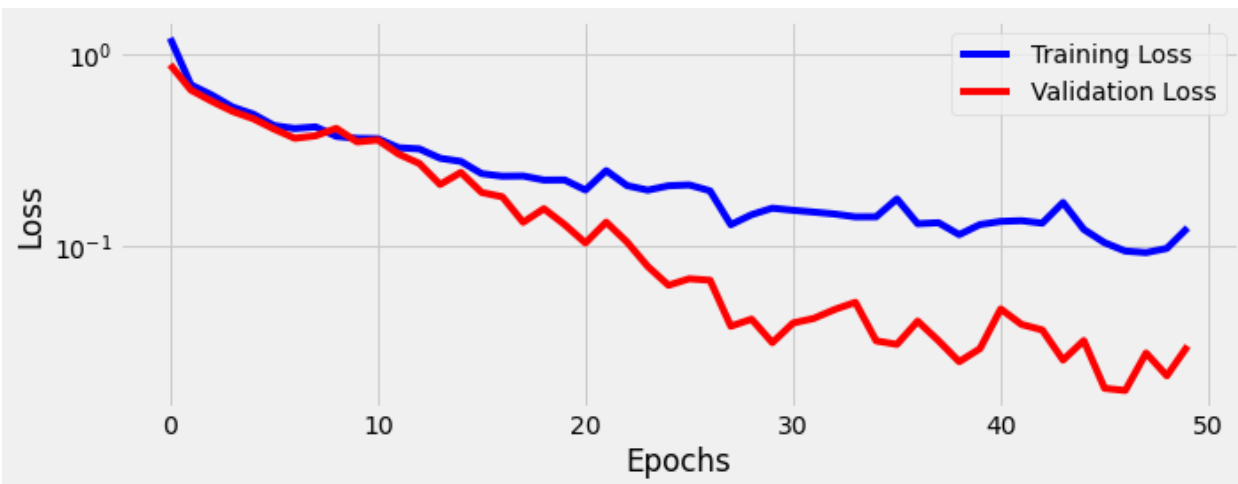
Model Configuration & Training

```
torch.manual_seed(42)
transformer = nn.Transformer(d_model=6, nhead=3,
                             num_encoder_layers=1, num_decoder_layers=1,
                             dim_feedforward=20, dropout=0.1)
model_transformer = TransformerModel(transformer, input_len=2, target_len=2, n_
↪features=2)
loss = nn.MSELoss()
optimizer = torch.optim.Adam(model_transformer.parameters(), lr=0.01)
```

```
for p in model_transformer.parameters():
    if p.dim() > 1:
        nn.init.xavier_uniform_(p)
```

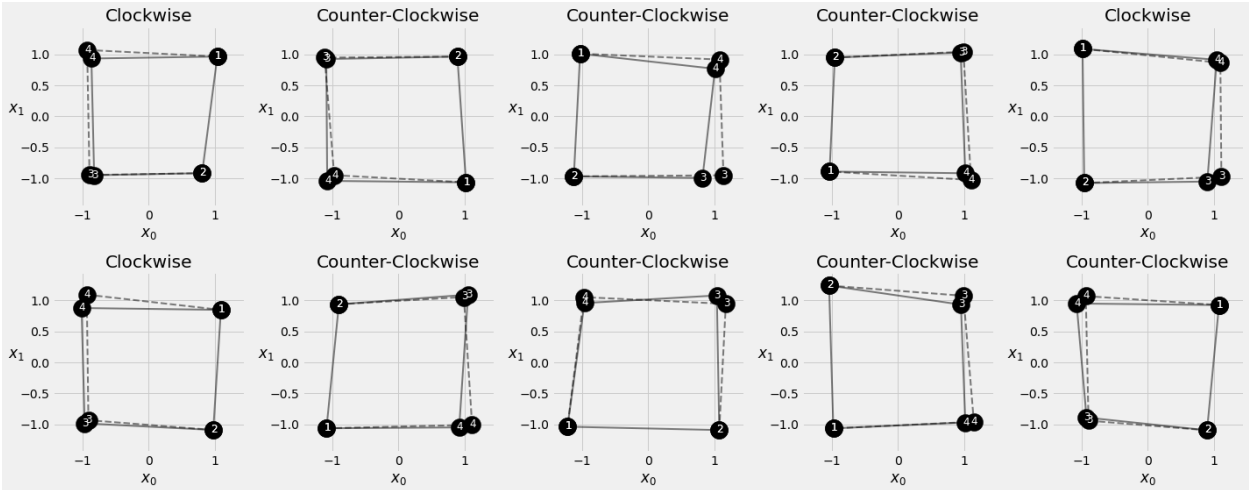
```
sbs_seq_transformer = StepByStep(model_transformer, loss, optimizer)
sbs_seq_transformer.set_loaders(train_loader, test_loader)
sbs_seq_transformer.train(50)
```

```
fig = sbs_seq_transformer.plot_losses()
```



Visualizing Predictions

```
fig = sequence_pred(sbs_seq_transformer, full_test, test_directions)
```


Clockwise
Counter-Clockwise
Counter-Clockwise
Counter-Clockwise
Clockwise
Clockwise
Counter-Clockwise
Counter-Clockwise
Counter-Clockwise
Counter-Clockwise
x_0
x_1