Open in Colab

In [0]:

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
from torchvision import transforms
from torch.utils.data import Dataset, DataLoader

from tqdm.autonotebook import tqdm

import time
from datetime import datetime
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.pyplot import imshow
from collections import Counter
from sklearn.metrics import accuracy_score

import gzip
import gensim
import os
import sys
import json
import shutil
import re
import tarfile
import zipfile


import re
import string
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
nltk.download('punkt')
from nltk.tokenize import word_tokenize
!pip install wget
import wget
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
Collecting wget
  Downloading
https://files.pythonhosted.org/packages/47/6a/62e288da7bcda82b935ff0c6cfe542970f04e29c756b0e147251b
51f/wget-3.2.zip
Building wheels for collected packages: wget
  Building wheel for wget (setup.py) ... done
  Created wheel for wget: filename=wget-3.2-cp36-none-any.whl size=9682
sha256=4b048c7418df45469d2da910e232334f94d8a0aa306f4076061dde1adcaae150
  Stored in directory:
/root/.cache/pip/wheels/40/15/30/7d8f7cea2902b4db79e3fea550d7d7b85ecb27ef992b618f3f
Successfully built wget
Installing collected packages: wget
Successfully installed wget-3.2
```

1.Create a dataset loader for the IMDB reviews dataset here (You will need to write some python code to download and extract it in your notebook!). Use it to load the training/testing set, and break reviews up by words. (i.e., "This movie was terrible!" -> ["this", "movie", "was", "terrible"] -> torch.tensor([1, 8, 2, 9])

In [0]:

```
from google.colab import drive
drive.mount('/content/gdrive/',force_remount=True)

import sys
sys.path.append('/content/gdrive/My Drive/MPDL/')

from mpdl import train_simple_network, Flatten, weight_reset
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%
b&response_type=code&scope=email%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2
www.googleapis.com%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.readonly
ttps%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
··········
Mounted at /content/gdrive/
```

In [0]:

```
device = torch.device("cuda") if torch.cuda.is_available() else torch.device("cpu")
device
```

Out[0]:

```
device(type='cuda')
```

In [0]:

```
os.makedirs('/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta')
```

In [0]:

```
os.chdir('/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta')
!ls
```

Python code to download extract IMDB Reviews Dataset

In [0]:

```
data_source_url = "https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz"
print('Data source url : ',data_source_url)
```

```
Data source url :  https://ai.stanford.edu/~amaas/data/sentiment/aclImdb_v1.tar.gz
```

In [0]:

```
def check_if_file_exists(file):
    '''
    Checks if 'file' exists
    '''
    try:
        tarfh = tarfile.open(file)
        return True
    except FileNotFoundError:
        print('Please make sure file: ' + file + ' is present before continuing')
        return False

def check_if_dir_exists(directory):
    '''
    Checks if 'directory' exists
    '''
    return(os.path.isdir(directory))
```

In [0]:

```
data_file_path='/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb_v1.tar.gz'
if not check_if_file_exists(data_file_path):
    print('Start of data download')
```

```
    wget.download(url=data_source_url, out='/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta')
    print('Download complete')
else:
    print('Data file already exists. Not downloading again!')
```

```
Please make sure file: /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb_v1.tar.gz is
present before continuing
Start of data download
Download complete
```

In [0]:

```
data_folder='/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb'
if not check_if_dir_exists(data_folder):
    startTime = time.time()
    tar = tarfile.open(data_file_path)
    print('Extracting all the files now...')
    tar.extractall()
    tar.close()
    print('Done!')
    total_time=time.time()-startTime
    print('Time Taken for extracting all files : ',total_time/60,'minutes')
else:
    print('Data foler exists. Won\'t copy again!')
```

```
Extracting all the files now...
Done!
Time Taken for extracting all files :  25.22191904783249 minutes
```

Loading the training/testing set, and breaking reviews up by words.

[Load Data Link]

In [0]:

```
def review_preprocess(review):
    """
    Takes in a string of review, then performs the following:
    1. Remove HTML tag from review
    2. Remove URLs from review
    3. Make entire review lowercase
    4. Split the review in words
    5. Remove all punctuation
    6. Remove empty strings from review
    7. Remove all stopwords
    8. Returns a list of the cleaned review after jioning them back to a sentence
    """
    en_stops = set(stopwords.words('english'))

    """
    Removing HTML tag from review
    """
    clean = re.compile('<.*?>')
    review_without_tag = re.sub(clean, '', review)


    """
    Removing URLs
    """
    review_without_tag_and_url = re.sub(r"http\S+", "", review_without_tag)

    review_without_tag_and_url = re.sub(r"www\S+", "", review_without_tag)

    """
    Make entire string lowercase
    """
    review_lowercase = review_without_tag_and_url.lower()

    """
    Split string into words
    """
    list_of_words = word_tokenize(review_lowercase)
```

```
    """
    Remove punctuation
    Checking characters to see if they are in punctuation
    """

    list_of_words_without_punctuation=[''.join(this_char for this_char in this_string if
(this_char in string.ascii_lowercase))for this_string in list_of_words]


    """
    Remove empty strings
    """
    list_of_words_without_punctuation = list(filter(None, list_of_words_without_punctuation))


    """
    Remove any stopwords
    """

    filtered_word_list = [w for w in list_of_words_without_punctuation if w not in en_stops]

    """
    Returns a list of the cleaned review after jioning them back to a sentence
    """
    return ' '.join(filtered_word_list)


"""
Load file into memory
"""
def load_file(filename):
    """
    Open the file as read only
    """
    file = open(filename, 'r')
    """
    Read all text
    """
    text = file.read()
    """
    Close the file
    """
    file.close()
    return text

def get_data(directory, vocab, is_trian):
    """
    Reading train test directory
    """
    review_dict={'neg':[],'pos':[]}
    if is_trian:
        directory = os.path.join(directory+'/train')
    else:
        directory = os.path.join(directory+'/test')
    print('Directory : ',directory)
    for label_type in ['neg', 'pos']:
            data_folder=os.path.join(directory, label_type)
            print('Data Folder : ',data_folder)
            for root, dirs, files in os.walk(data_folder):
                for fname in files:
                    if fname.endswith(".txt"):
                        file_name_with_full_path=os.path.join(root, fname)
                        review=load_file(file_name_with_full_path)
                        clean_review=review_preprocess(review)
                        if label_type == 'neg':
                            review_dict['neg'].append(clean_review)
                        else:
                            review_dict['pos'].append(clean_review)
                        """
                        Update counts
                        """
                        vocab.update(clean_review.split())

    return review_dict
```

In [0]:

```python
"""
Define vocab
"""
startTime = time.time()
vocab = Counter()
directory='/content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb'
train_review_dict=get_data(directory, vocab, True)
test_review_dict=get_data(directory, vocab, False)
total_time=time.time()-startTime
print('Time Taken : ',total_time/60,'minutes')
```

```
Directory :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/train
Data Folder :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/train/neg
Data Folder :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/train/pos
Directory :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/test
Data Folder :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/test/neg
Data Folder :  /content/gdrive/My Drive/HW2_Datasets_Sofia_Dutta/aclImdb/test/pos
Time Taken :  2.894369538625081 minutes
```

In [0]:

```python
print('Number of negative reviews in train set :',len(train_review_dict['neg']))
print('Number of positive reviews in train set :',len(train_review_dict['pos']))

print('\nNumber of negative reviews in test set :',len(test_review_dict['neg']))
print('Number of positive reviews in test set :',len(test_review_dict['pos']))
```

```
Number of negative reviews in train set : 12500
Number of positive reviews in train set : 12500

Number of negative reviews in test set : 12500
Number of positive reviews in test set : 12500
```

In [0]:

```python
print('First five entires : ')
print(train_review_dict['pos'][:5])
print(train_review_dict['neg'][:5])
print(test_review_dict['pos'][:5])
print(test_review_dict['neg'][:5])
```

```
First five entires :
['zentropa much common third man another noirlike film set among rubble postwar europe like ttm mu
ch inventive camera work innocent american gets emotionally involved woman nt really understand wh
ose naivety striking contrast nativesbut say third man wellcrafted storyline zentropa bit disjoint
ed respect perhaps intentional presented dreamnightmare making coherent would spoil effect movie u
nrelentingly grim noir one sense one never sees sun shine grim intriguing frightening', 'zentropa
original movie seen years like unique thrillers influenced film noir right cure hollywood summer b
lockbusters clogging theaters days von trier followups like breaking waves gotten acclaim really b
est work flashy without distracting offers perfect combination suspense dark humor bad decided han
dheld cameras wave future hard say talked away style exhibits everyone loss went heavily
theoretical dogma direction instead', 'lars von trier never backward trying new techniques
original others best forgottenhe depicts postwar germany nightmarish train journey many cities lyi
ng ruins leo kessler young american german descent feels obliged help restoration simple task quic
kly finds outhis uncle finds job night conductor zentropa railway line job attend needs passengers
shoes polished chalk mark made soles terrible argument ensues passenger shoes chalked despite fact
polished many allusions german fanaticism adherence stupid detailsthe railway journey like
allegory representing man procession life trials tribulations one sequence leo dashes back carriag
es discover filled halfstarved bodies appearing escaped auschwitz images horrible fleeting dream t
errible impact yet unconnectedat station called urmitz leo jumps train parceled bomb view many bys
tanders connects bomb underside carriage returns cabin makes connection time clock later jumps
train high speed lies cool grass river bank looking stars decides job build destroy subsequently
sees train approaching giant bridge runs breakneck speed board train stop clock care analyse
situation completely impossible task quite ridiculous fact could happen dreamit strange one
remembers little details row cups hanging hooks rattling away swaying traindespite fact film widel
y acclaimed prefer lars von trier later films breaking waves idiots bomb scene described really pu
t perhaps realist', 'contains spoilers due describe film techniques read risk loved film use tinti
ng scenes makes seem like old photograph come life also enjoyed projection people back screen inst
ance one scene leopold calls wife projected behind rather typical split screen face huge back leo
foregroundone best uses young boys kill ravensteins train scene shot almost political poster style
facial close ups reminded battleship potemkin intense constant style coupled spray red convey tons
```

horror without much gore scene katharina finds father dead bathtub see red water side one things l
ove von trier understatement horror ends making creepythe use text film unique like leo character
pushed word werewolf never seen anything like filmthe use black comedy film well done ernsthugo jr
egrd great leo uncle brings snickers got role kingdom riget humor makes plotline absurd anal reten
tiveness train conductors terrible backdrop ww chaos easier take reminds riget way hospital
administrator trying maintain normalcy end part one everything going crazy shows people truly obli
vious awful things happening around yet people like leo tuned nothing positive itthe voice done ex
pertly well max von sydow amusing draws story makes jump leo head times scary place bethe movie
brings point one coward nt choose side see idea used dancer dark bjork character nt speak ends des
truction actually one time von trier seemed antiwoman making breaking waves dancer know male chara
cters nt fare well either found place end dancer seriously want main character rethink actions cou
rse never', 'first thing sprang mind watched closing credits europa make across screen never
entire life seen film technical genius visuals europa impressive film watch wake pale comparison f
orget michael bay ridley scott slick hollywood cinematography europa ethereal beauty anything two
could conjure million years first hail lars von trier genius back films breaking waves dancer dark
stupid fact europa gone unnoticed film experts long crime cinema whilst overrated rubbish like cro
uching tiger hidden dragon life beautiful clean academy awards know europa hidden away absent form
video stores recently british tv channels visuals europa mtv gloss case style substance case subst
ance dictating style much like first film element crime von trier uses perspective main character
draw us world much like element film begins main character case europa audience hypnotized move tr
acks voice narrator max von sydow counts us deep sleep awake europa allows von trier three
cinematographers pay conventions time imagery many scenes europa character background black white
interact person foreground colour von trier trying show us much precedence coloured item person pl
ot instance surprise first shot leopold kessler jeanmarc barr colour since character actions super
iority film performances good may par performances later von trier films images sometimes
distracting nt really pick first time round would like point fantastic performance jeanmarc barr l
ead role whose blind idealism slowly warn two opposing sides erupts films final act muck like elem
ent crime film ends hero unable wake nightmare state left terrible place continuing narration von
sydow seal fate europa tremendous film cant help thinking shame von trier abandoned way filming si
nce clearly one talented visual directors working time europa much like rest cinematic cannon fill
ed wealth iconic scenes dedication composition miseenscene unrivalled mention use sound production
design since nofrills melodramas turned breaking waves dancer dark argue seems like waste
imaginative talent']
['rented curiousyellow video store controversy surrounded first released also heard first seized
us customs ever tried enter country therefore fan films considered controversial really see
myselfthe plot centered around young swedish drama student named lena wants learn everything life
particular wants focus attentions making sort documentary average swede thought certain political
issues vietnam war race issues united states asking politicians ordinary denizens stockholm opinio
ns politics sex drama teacher classmates married menwhat kills curiousyellow years ago considered
pornographic really sex nudity scenes far even shot like cheaply made porno countrymen mind find s
hocking reality sex nudity major staple swedish cinema even ingmar bergman arguably answer good ol
d boy john ford sex scenes filmsi commend filmmakers fact sex shown film shown artistic purposes r
ather shock people make money shown pornographic theaters america curiousyellow good film anyone w
anting study meat potatoes pun intended swedish cinema really film nt much plot', 'curious yellow
risible pretentious steaming pile nt matter one political views film hardly taken seriously level
claim frontal male nudity automatic nc nt true seen rrated films male nudity granted offer
fleeting views rrated films gaping vulvas flapping labia nowhere nt exist goes crappy cable shows
schlongs swinging breeze clitoris sight pretentious indie movies like brown bunny treated site vin
cent gallo throbbing johnson trace pink visible chloe sevigny crying implying doublestandard
matters nudity mentally obtuse take account one unavoidably obvious anatomical difference men wome
n genitals display actresses appears nude said man fact generally wo nt see female genitals americ
an film anything short porn explicit erotica alleged doublestandard less double standard
admittedly depressing ability come terms culturally insides women bodies', 'avoid making type film
future film interesting experiment tells cogent storyone might feel virtuous sitting thru touches
many important issues without discernable motive viewer comes away new perspectives unless one com
es one one mind wanders invariably pointless film one might better spend one time staring window t
ree growing', 'film probably inspired godard masculin fminin urge see film insteadthe film two str
ong elements realistic acting impressive undeservedly good photo apart strikes endless stream
silliness lena nyman annoying actress world acts stupid nudity film unattractive comparing godard
film intellectuality replaced stupidity without going far subject would say follows difference ide
als french swedish societya movie time place', 'oh brother hearing ridiculous film umpteen years t
hink old peggy lee song early teen smoked fish hit us young get theater although manage sneak good
bye columbus screening local film museum beckoned finally could see film except old parents schlep
ped see reason film condemned anonymous sands time obscenity case sparked us release millions peop
le flocked stinker thinking going see sex film instead got lots closeups gnarly repulsive swedes o
nstreet interviews bland shopping malls asinie political pretension feeble whocares simulated sex
scenes saggy pale actorscultural icon holy grail historic artifactwhatever thing shred burn stuff
ashes lead box elite esthetes still scrape find value boring pseudo revolutionary political
spewingsbut nt censorship scandal would ignored forgotteninstead blank blank rhythymed title
repeated endlessly years titilation porno films curious lavender gay films curious black
blaxploitation films etc every ten years thing rises dead viewed new generation suckers want see n
aughty sex film revolutionized film industry yeesh avoid like plagueor must see rent video fast fo
rward dirty parts get']
['previous reviewer claudio carvalho gave much better recap film plot details could recall mostly
beautiful every sense emotionally visually editorially gorgeousif like movies wonderful look also
emotional content beauty relevant think glad seen extraordinary unusual work arton scale give
reason shy away mood piece mood really artistic romantic film definitely think mustsee none us moo

d time overall', 'contains spoiler information watch director film earth point better film one nt
bad differenta rare feminist point view indian filmmaker tradition rituals duty secrets portrayal
strict sex roles make engaging culturally dynamic film viewing experience married characters lack
fire marriage bed respective spouses one husband celibate commits form spiritual adultery giving l
ove honor time respect religious swami guru wife lonely yearns intimacy tenderness eventually
finds closeted lesbian sisterinlaw comes live house unfaithful husband unfaithful husband openly l
ove chinese mistress forced marriage unbeknownest lesbian sex closet lesbian wife loses virginitya
servant lives house eventually reveals secret two women lovers another significant character
elderly matriarch unable speak care due stroke however uses ringing bell communicate needs well di
spleasure family members lets know bell pounding fist knows exacly going house much disapprovesin
end truth everybody comes two female lovers end running away together emotional scene
swamiaddicted husband formerly straight wife sari catches fire first think going die however see t
wo women united last scene moviethe writerdirector film challenges culture traditions shows us
individual human beings trapped culture gender come really care characters nt see stereotypes surp
rises us humanity vulgarity tenderness anger spirit', 'first deepa mehta film saw film tv hindi ve
rsion sita character presented nita also note radha underwent allegorical trial fire film nitasita
yet loved film screenplay ms mehta direction characters big small welldeveloped seemed quixotic
towards end somewhat like end mazursky unmarried woman brave women surrounded cardboard men one ca
rdboard man ashok seems come alive last shot see carrying invalid mother biji seems finally take f
uture responsibility beyond celibacy adherance religion ms mehta seems fumble director however com
pared indian mainstream cinema would seem brilliant use script go beyond microscopic joint family
presenting except presenting glimpse chinese microminority social milieu india even dedicates film
mother daughter father yet radha reminesces halcyon days parents mustard field compare mrinal sen
adoor gopalakrishnan muzaffar ali dwarfed giants given competent canadian production team
financial resources mehta film two bisexual ladies indian middleclass household may sacrilege mere
ly captures atrophy middleclass homes seem aspire something better immediate survival limited soci
al space kannada malayalam bengali films touched parallel themes india publicity surrounded film t
herefore seen wide segment knowledgeable cinemagoersms das ms azmi mr jafri mr kharbanda credible
outstanding ms azmi talented actress gave superb performances good directors mrinal sen khandar ga
utam ghose paar benegal ankur brilliance notably absent film ms das sparkled due screen presence r
ather acting capability film strength remains structure screenplay average terms international
cinema sure ms mehta hone writing talents future screenplays', 'great film every sense word
tackles subject tribadism society quite intolerant deviations norm criticises great many indian
customs many find oppressive arranging marriages others importance status face religious hypocrisy
sexism valuation women terms babymaking capacity binding concepts duty heart film touching love st
ory goes beyond limitations society two protagonists find film wellacted genuine completely
believable beginning end unlike bollywood flicks main faults film saw first two lovers seem drawn
one another necessarily natural affinity much fact stuck deadend marriages passion rewards may pla
y part sexual awakening characters people stuck situation turn homosexual seems clear beginning
film two characters quite heterosexual radha scene end movie aashok makes quite clear without
desire dead implication desired could fulfilled quite completely also sita seemed disappointed
husband seemed like situations turn people homosexuals may seek comfort others position inthe film
made clear lesbians beginning quite opposite people bisexual true tend either hetero homosexual ca
se ladies film insensitive jerks husbands case would naturally found need express desire
relationship may otherwise considered film ignores fault naming characters names sita radha seem c
ontrived deliberately shock outrage imagine film america depicting gay relationship man named
jesus another named paul using names associated various hindoo scriptures film strong enough stand
needs devices opinion rate faults take much away power movie indeed touching powerful story images
characters stay long time leave theatre', 'stunningly wellmade film exceptional acting directing w
riting photographya newlywed finds married life expected starts question duty versus duty society
together sister inlaw makes radical departures conventional roles mores']
['love scifi willing put lot scifi moviestv usually underfunded underappreciated misunderstood tri
ed like really good tv scifi babylon star trek original silly prosthetics cheap cardboard sets sti
lted dialogues cg nt match background painfully onedimensional characters overcome scifi setting s
ure think babylon good scifi tv clichd uninspiring us viewers might like emotion character
development scifi genre take seriously cf star trek may treat important issues yet serious
philosophy really difficult care characters simply foolish missing spark life actions reactions wo
oden predictable often painful watch makers earth know rubbish always say gene roddenberry earth o
therwise people would continue watching roddenberry ashes must turning orbit dull cheap poorly edi
ted watching without advert breaks really brings home trudging trabant show lumbers space spoiler
kill main character bring back another actor jeeez dallas', 'worth entertainment value rental
especially like action movies one features usual car chases fights great van damme kick style shoo
ting battles shell load shotgun even terrorist style bombs entertaining competently handled
nothing really blows away seen share beforethe plot made interesting inclusion rabbit clever hardl
y profound many characters heavily stereotyped angry veterans terrified illegal aliens crooked cop
s indifferent feds bitchy tough lady station head crooked politician fat federale looks like
typecast mexican hollywood movie passably acted nothing speciali thought main villains pretty well
done fairly well acted end movie certainly knew good guys nt emotional lift really bad ones got de
serts simplistic nt expecting hamlet right thing found really annoying constant cuts vds daughter
last fight scenenot bad good passable', 'totally average film semialright action sequences make pl
ot seem little better remind viewer classic van dam films parts plot nt make sense seem added use
time end plot basic type nt leave viewer guessing twists obvious beginning end scene flask backs n
t make sense added seem little relevance history van dam character really worth watching bit disap
pointed end production even though apparent shot low budget certain shots sections film poor direc
ted quality', 'star rating saturday night friday night friday morning sunday night monday morning
former new orleans homicide cop jack robideaux jean claude van damme reassigned columbus small vio
lent town mexico help police efforts stop major heroin smuggling operation town culprits turn exmi

```
tent town mexico help police efforts stop major heroin smuggling operation town culprits turn exmi
litary lead former commander benjamin meyers stephen lord otherwise known jase east enders using s
pecial method learned afghanistan fight opponents jack personal reason taking draws two men explos
ive final showdown one walk away aliveafter death van damme appeared high showing could make best
straight video films action market far drama oriented film shepherd returned highkicking brainer a
ction first made famous sadly produced worst film since derailed nowhere near bad film said still
standsa dull predictable film little way exciting action little mainly consists limp fight scenes
trying look cool trendy cheap slomosped effects added sadly instead make look desperate mexican
set film director isaac florentine tried give film robert rodriguezdesperado sort feel adds
desperationvd gives particularly uninspired performance given never robert de niro sort actor ca
nt good villain lord nt expect leave beeb anytime soon gets little dialogue beginning struggles mu
ster american accent gets mysteriously better towards end supporting cast equally bland nothing ra
ise films spirits allthis one shepherd strayed right flock', 'first let say nt enjoyed van damme m
ovie since bloodsport probably like movie movies may best plots best actors enjoy kinds movies mov
ie much better movies action guys segal dolph thought putting past years van damme good movie
movie worth watching van damme fans good wake death highly recommend anyone likes van damme hell o
pinion worth watching type feel nowhere run good fun stuff']
```

In [0]:

```
word_list = sorted(vocab, key = vocab.get, reverse = True)
vocab_to_int = {word:idx+1 for idx, word in enumerate(word_list)}
int_to_vocab = {idx:word for word, idx in vocab_to_int.items()}
```

Creating a dataset loader for the IMDB reviews dataset

In [0]:

```
class IMDBReviewDataset(Dataset):

    def __init__(self, review_dict, alphabet):

        self.data = review_dict
        self.labels = [x for x in review_dict.keys()]
        self.alphabet = alphabet

    def __len__(self):
        return sum([len(x) for x in self.data.values()])

    def __getitem__(self, idx):
        label = 0
        while idx >= len(self.data[self.labels[label]]):
            idx -= len(self.data[self.labels[label]])
            label += 1
        reviewText = self.data[self.labels[label]][idx]



        label_vec = torch.zeros((1), dtype=torch.long)
        label_vec[0] = label
        return self.reviewText2InputVec(reviewText), label

    def reviewText2InputVec(self, review_text):
        T = len(review_text)

        review_text_vec = torch.zeros((T), dtype=torch.long)
        encoded_review=[]
        for pos,word in enumerate(review_text.split()):
            if word not in vocab_to_int.keys():
                """
                If word is not available in vocab_to_int dict puting 0 in that place
                """
                review_text_vec[pos]=0
            else:
                review_text_vec[pos]=vocab_to_int[word]

        return review_text_vec
```

Down Sampling

- Need to down sample the training set to make training faster.
- Training set contains balanced number of positive and negative reviews.(12500 positive and 12500 negative reviews.)

- For Fatser taraining as RNN is computational expensive I downsampled the data.I Took 50% of the positive reviews of trainig set(6250 positive reviews) and 50% of the negative reviews of trainig set(6250 negative reviews).That way, reduced or down sampled training set contains balanced number of positive and negative reviews and would not create the unbalabced data point issues.Learning of the model is unbisaed as there will be no issue like learning one class gives maximum accuracy.

In [0]:

```
train_review_dict['pos']=train_review_dict['pos'][:int(len(train_review_dict['pos'])*.5)]
train_review_dict['neg']=train_review_dict['neg'][:int(len(train_review_dict['neg'])*.5)]
print('After Down Sampling the training set :')
print('Number of negative reviews in train set :',len(train_review_dict['neg']))
print('Number of positive reviews in train set :',len(train_review_dict['pos']))
```

```
After Down Sampling the training set :
Number of negative reviews in train set : 6250
Number of positive reviews in train set : 6250
```

In [0]:

```
def pad_and_pack(batch):
    input_tensors = []
    labels = []
    lengths = []
    for x, y in batch:
        input_tensors.append(x)
        labels.append(y)
        lengths.append(x.shape[0]) #Assume shape is (T, *)
    longest = max(lengths)
    #We need to pad all the inputs up to 'longest', and combine into a batch ourselves
    if len(input_tensors[0].shape) == 1:
        x_padded = torch.nn.utils.rnn.pad_sequence(input_tensors, batch_first=False)
    else:
        raise Exception('Current implementation only supports (T) shaped data')

    x_packed = torch.nn.utils.rnn.pack_padded_sequence(x_padded, lengths, batch_first=False, enforc
e_sorted=False)

    y_batched = torch.as_tensor(labels, dtype=torch.long)

    return x_packed, y_batched
```

In [0]:

```
B = 24
train_dataset=IMDBReviewDataset(train_review_dict,vocab)
test_dataset=IMDBReviewDataset(test_review_dict,vocab)

train_loader = DataLoader(train_dataset, batch_size=B, shuffle=True, collate_fn=pad_and_pack)
test_loader = DataLoader(test_dataset, batch_size=32, shuffle=False, collate_fn=pad_and_pack)
```

2.Train some form of RNN model on the dataset. Its up to you to select the type, single-bidirectional, number of layers, etc. Explain your choices and show the comparisons that lead you to your conclusions! If you need to down sample the training set to make training faster, that is OK. Just explain why!

In [0]:

```
class EmbeddingPackable(nn.Module):
    """
    The embedding layer in PyTorch does not support Packed Sequence objects.
    This wrapper class will fix that. If a normal input comes in, it will
    use the regular Embedding layer. Otherwise, it will work on the packed
    sequence to return a new Packed sequence of the appropriate result.
    """
    def __init__(self, embd_layer):
        super(EmbeddingPackable, self).__init__()
        self.embd_layer = embd_layer

    def forward(self, input):
        if type(input) == torch.nn.utils.rnn.PackedSequence:
```

```
            # we need to unpack the input,
            sequences, lengths = torch.nn.utils.rnn.pad_packed_sequence(input.cpu(), batch_first=Tr
ue)
            #Embed it
            sequences = self.embd_layer(sequences.to(input.data.device))
            #And pack it into a new sequence
            return torch.nn.utils.rnn.pack_padded_sequence(sequences, lengths.to(input.data.device)
,
                                                           batch_first=True, enforce_sorted=False)
        else:#apply to normal data
            return self.embd_layer(input)
```

In [0]:

```
class LastTimeStep(nn.Module):
    """
    A class for extracting the hidden activations of the last time step following
    the output of a PyTorch RNN module.
    """
    def __init__(self, rnn_layers=1, bidirectional=False):
        super(LastTimeStep, self).__init__()
        self.rnn_layers = rnn_layers
        if bidirectional:
            self.num_driections = 2
        else:
            self.num_driections = 1

    def forward(self, input):
        #Result is either a tupe (out, h_t)
        #or a tuple (out, (h_t, c_t))
        rnn_output = input[0]
        last_step = input[1]
        if(type(last_step) == tuple):
            last_step = last_step[0]
        batch_size = last_step.shape[1] #per docs, shape is: '(num_layers * num_directions, batch,
hidden_size)'

        last_step = last_step.view(self.rnn_layers, self.num_driections, batch_size, -1)
        #We want the last layer's results
        last_step = last_step[self.rnn_layers-1]
        #Re order so batch comes first
        last_step = last_step.permute(1, 0, 2)
        #Finally, flatten the last two dimensions into one
        return last_step.reshape(batch_size, -1)
```

In [0]:

```
def train_network(model, loss_func, train_loader, val_loader=None, score_funcs=None,
                         epochs=50, device="cpu", checkpoint_file=None,
                         lr_schedule=None, optimizer=None, disable_tqdm=False
                        ):
    """Train simple neural networks

    Keyword arguments:
    model -- the PyTorch model / "Module" to train
    loss_func -- the loss function that takes in batch in two arguments, the model outputs and the
labels, and returns a score
    train_loader -- PyTorch DataLoader object that returns tuples of (input, label) pairs.
    val_loader -- Optional PyTorch DataLoader to evaluate on after every epoch
    score_funcs -- A dictionary of scoring functions to use to evalue the performance of the model
    epochs -- the number of training epochs to perform
    device -- the compute lodation to perform training

    """
    if score_funcs == None:
        score_funcs = {}#Empty set

    to_track = ["epoch", "total time", "train loss"]
    if val_loader is not None:
        to_track.append("val loss")
    for eval_score in score_funcs:
        to_track.append("train " + eval_score )
        if val_loader is not None:
            to_track.append("val " + eval_score )
```

```
    total_train_time = 0 #How long have we spent in the training loop?
    results = {}
    #Initialize every item with an empty list
    for item in to_track:
        results[item] = []

    if optimizer == None:
        #The AdamW optimizer is a good default optimizer
        optimizer = torch.optim.AdamW(model.parameters())

    #Place the model on the correct compute resource (CPU or GPU)
    model.to(device)
    for epoch in tqdm(range(epochs), desc="Epoch", disable=disable_tqdm):

        model = model.train()#Put our model in training mode
        running_loss = 0.0

        y_true = []
        y_pred = []

        start = time.time()
        for inputs, labels in tqdm(train_loader, desc="Train Batch", leave=False, disable=disable_t
qdm):

            #Move the batch to the device we are using.
            inputs = inputs.to(device)
            labels = labels.to(device)

            batch_size = labels.shape[0]

            # PyTorch stores gradients in a mutable data structure. So we need to set it to a clean
state before we use it.
            #Otherwise, it will have old information from a previous iteration
            optimizer.zero_grad()

            y_hat = model(inputs) #this just computed f_Θ(x(i))

            # Compute loss.
            loss = loss_func(y_hat, labels)

            loss.backward()# ∇_Θ just got computed by this one call!

            #Now we just need to update all the parameters!
            optimizer.step()# Θ_{k+1} = Θ_k − η * ∇_Θ ℓ(y_hat, y)

            #Now we are just grabbing some information we would like to have
            running_loss += loss.item() * batch_size

            #moving labels & predictions back to CPU for computing / storing predictions
            labels = labels.detach().cpu().numpy()
            y_hat = y_hat.detach().cpu().numpy()
            for i in range(batch_size):
                y_true.append(labels[i])
                y_pred.append(y_hat[i,:])
        #end training epoch
        end = time.time()
        total_train_time += (end-start)

        results["epoch"].append( epoch )
        results["total time"].append( total_train_time )
        results["train loss"].append( running_loss )

        y_pred = np.asarray(y_pred)

        if y_pred.shape[1] > 1: #We have a classification problem, convert to labels
            y_pred = np.argmax(y_pred, axis=1)

        for name, score_func in score_funcs.items():
            results["train " + name].append( score_func(y_true, y_pred) )

        if val_loader is None:
            pass
        else:#Lets find out validation performance as we go!
            model = model.eval() #Set the model to "evaluation" mode, b/c we don't want to make any
updates!

            y_true = []
            y_pred = []
```

```
            y_pred = []

            val_running_loss = 0.0

            for inputs, labels in val_loader:

                #Move the batch to the device we are using.
                inputs = inputs.to(device)
                labels = labels.to(device)

                batch_size = labels.shape[0]

                y_hat = model(inputs)

                loss = loss_func(y_hat, labels)

                #Now we are just grabbing some information we would like to have
                val_running_loss += loss.item() * batch_size

                #moving labels & predictions back to CPU for computing / storing predictions
                labels = labels.detach().cpu().numpy()
                y_hat = y_hat.detach().cpu().numpy()
                for i in range(batch_size):
                    y_true.append(labels[i])
                    y_pred.append(y_hat[i,:])

            results["val loss"].append( running_loss )

            y_pred = np.asarray(y_pred)

            if y_pred.shape[1] > 1: #We have a classification problem, convert to labels
                y_pred = np.argmax(y_pred, axis=1)

            for name, score_func in score_funcs.items():
                results["val " + name].append( score_func(y_true, y_pred) )

        #In PyTorch, the convention is to update the learning rate after every epoch
        if not lr_schedule is None:
            if isinstance(lr_schedule, torch.optim.lr_scheduler.ReduceLROnPlateau):
                lr_schedule.step(val_running_loss)
            else:
                lr_schedule.step()

        if checkpoint_file is not None:
            torch.save({
                'epoch': epoch,
                'model_state_dict': model.state_dict(),
                'optimizer_state_dict': optimizer.state_dict(),
                'results' : results
                }, checkpoint_file)

    return pd.DataFrame.from_dict(results)
```

RNN 3 Layer Bidirectional Model

In [0]:

```
D = 32
alphabet_size = len(vocab)+1
hidden_nodes = 64
classes = len(train_dataset.labels)

rnn_3layer_bidir = nn.Sequential(
  EmbeddingPackable(nn.Embedding(alphabet_size, D)), #(B, T) -> (B, T, D)
  nn.RNN(D, hidden_nodes, num_layers=3, batch_first=True, bidirectional=True), #(B, T, D) -> ( (B,T
,D) , (S, B, D)  )
  LastTimeStep(rnn_layers=3, bidirectional=True), #We need to take the RNN output and reduce it to
one item, (B, D)
  nn.Linear(hidden_nodes*2, classes), #(B, D) -> (B, classes)
)

rnn_3layer_bidir.to(device)
loss_func = nn.CrossEntropyLoss()
optimizer = torch.optim.AdamW(rnn_3layer_bidir.parameters(), lr=0.001*B)
epochs=10
```

```
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, epochs)
```

In [0]:

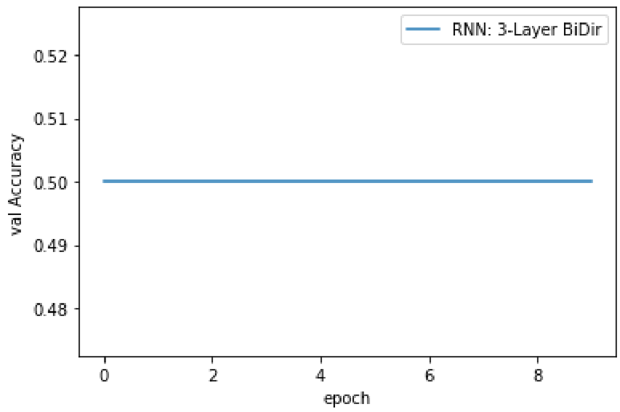
```
rnn_3layer_bidir_results = train_network(rnn_3layer_bidir, loss_func, train_loader,
val_loader=test_loader,
                                         epochs=epochs, optimizer=optimizer, lr_schedule=scheduler,
                                         score_funcs={'Accuracy': accuracy_score}, checkpoint_file=
model_rnn_3layer_bidir.pt', device=device)
```

In [0]:

```
sns.lineplot(x='epoch', y='val Accuracy', data=rnn_3layer_bidir_results, label='RNN: 3-Layer BiDir'
)
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2d43787c18>
```

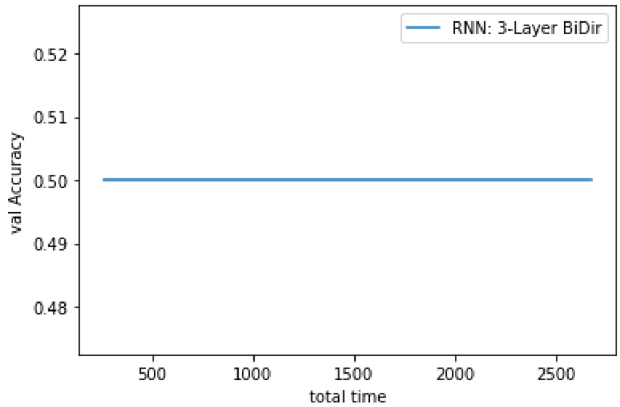


In [0]:

```
sns.lineplot(x='total time', y='val Accuracy', data=rnn_3layer_bidir_results, label='RNN: 3-Layer B
iDir')
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2d433820b8>
```



In [0]:

```
device
```

Out[0]:

```
device(type='cuda')
```

In [0]:

```
with torch.no_grad():
    correct = 0
    for X_test, y_test in test_loader:
        X_test=X_test.to(device)
        y_test=y_test.to(device)
        y_val = rnn_3layer_bidir(X_test)
        predicted = torch.max(y_val,1)[1]
        correct += (predicted == y_test).sum()
print(f'Test accuracy: {correct.item()}/{len(test_dataset)} = {correct.item()*100/(len(test_dataset
)):7.3f}%')
```

```
Test accuracy: 12500/25000 =  50.000%
```

LSTM 3 Layer Bidirectional Model

In [0]:

```
lstm = nn.Sequential(
  EmbeddingPackable(nn.Embedding(alphabet_size, D)), #(B, T) -> (B, T, D)
  nn.LSTM(D, hidden_nodes, num_layers=3, batch_first=True, bidirectional=True), #(B, T, D) -> ( (B,
T,D) , (S, B, D)  )
  LastTimeStep(rnn_layers=3, bidirectional=True), #We need to take the RNN output and reduce it to
one item, (B, D)
  nn.Linear(hidden_nodes*2, classes), #(B, D) -> (B, classes)
)

lstm.to(device)
optimizer = torch.optim.AdamW(lstm.parameters(), lr=0.001*B)
scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, epochs)
```

In [0]:

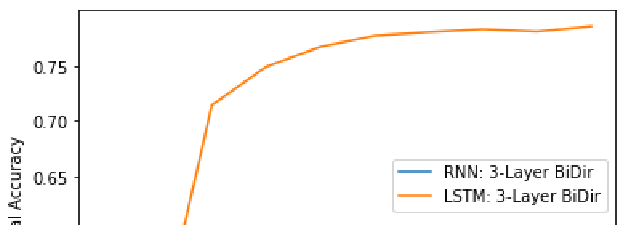
```
lstm_results = train_network(lstm, loss_func, train_loader, val_loader=test_loader,
                             epochs=epochs, optimizer=optimizer, lr_schedule=scheduler,
                             score_funcs={'Accuracy': accuracy_score}, checkpoint_file='model_l
tm.pt', device=device)
```

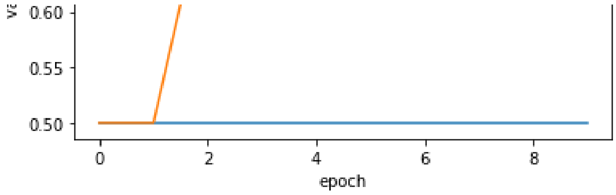
In [0]:

```
sns.lineplot(x='epoch', y='val Accuracy', data=rnn_3layer_bidir_results, label='RNN: 3-Layer BiDir'
)
sns.lineplot(x='epoch', y='val Accuracy', data=lstm_results, label='LSTM: 3-Layer BiDir')
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2d40188780>
```



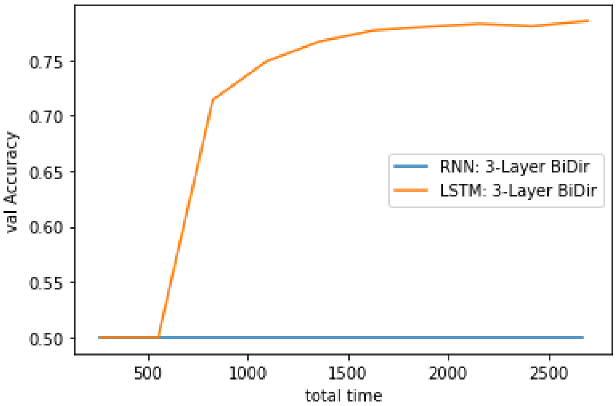


In [0]:

```
sns.lineplot(x='total time', y='val Accuracy', data=rnn_3layer_bidir_results, label='RNN: 3-Layer B
iDir')
sns.lineplot(x='total time', y='val Accuracy', data=lstm_results, label='LSTM: 3-Layer BiDir')
```

Out[0]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2cdbb3a668>
```



In [0]:

```
model_name = 'LSTM_Three_Layer_BiDir.pt'
torch.save(lstm.state_dict(),model_name)
```

In [0]:

```
model_name = 'LSTM_Three_Layer_BiDir.pt'
lstm_model_new=nn.Sequential(
  EmbeddingPackable(nn.Embedding(alphabet_size, D)), #(B, T) -> (B, T, D)
  nn.LSTM(D, hidden_nodes, num_layers=3, batch_first=True, bidirectional=True), #(B, T, D) -> ( (B,
T,D) , (S, B, D)  )
  LastTimeStep(rnn_layers=3, bidirectional=True), #We need to take the RNN output and reduce it to
one item, (B, D)
  nn.Linear(hidden_nodes*2, classes), #(B, D) -> (B, classes)
)
lstm_model_new.load_state_dict(torch.load(model_name))
lstm_model_new.eval()
```

Out[0]:

```
Sequential(
  (0): EmbeddingPackable(
    (embd_layer): Embedding(180673, 32)
  )
  (1): LSTM(32, 64, num_layers=3, batch_first=True, bidirectional=True)
  (2): LastTimeStep()
  (3): Linear(in_features=128, out_features=2, bias=True)
)
```

In [0]:

```
with torch.no_grad():
   correct = 0
   for X_test, y_test in test_loader:
       X_test=X_test.to(device)
       y_test=y_test.to(device)
```

```
        y_val = lstm(x_test)
        predicted = torch.max(y_val,1)[1]
        correct += (predicted == y_test).sum()
print(f'Test accuracy: {correct.item()}/{len(test_dataset)} = {correct.item()*100/(len(test_dataset
)):7.3f}%')
```

```
Test accuracy: 19635/25000 =  78.540%
```

- Tensors need all dimensions to be consistent and the same, but our time dimension due to varying length reviews are inconsistent. In order to not preventing an RNN in working with inputs of varying lengths of time used PyTorch's Packed Sequence abstraction.
- The embedding layer in PyTorch does not support Packed Sequence objects. Created EmbeddingPackable wrapper class to resolve the issue. For normal input, it will use the regular Embedding layer. Otherwise, it will work on the packed sequence to return a new Packed sequence of the appropriate result.
- For Training, I used AdamW optimizer and CosineAnnealingLR LR scheduler. AdamW uses unbiased estimates of the mean and variance, both together to update the weights of the parameters, gives better performance. It's an optimizer that, using the default values, will usually perform well. CosineAnnealingLR is one of the best ways to adjusting the learning rate which eventually increases the performance of the model.
- The essence of deep learning is to create multiple hidden layers for getting better performance so implemented multi-layer(3 Layers) RNN and LSTM.
- Created a bi-directional RNN and LSTM, so that, it can traverse the input in both directions at once, and share this information with the next layer of the model. This starts to accumulate information about time more evenly through the model and can make learning easier.
- The tried-and-true option that seems to always work well with sequence data is called a Long Short Term Memory (LSTM) network.LSTM using the gate functionality can decide which information to keep track of or forget. It uses forget gate to control whether or not the old context should be forgotten. It uses an input gate to control whether or not to add to the current context. It uses an output gate to control the next hidden state based on the current context. In this way, it can capture the long term dependencies in text and work well with sequence data, which is why I used it.
- LSTM 3-layer bidirectional model is the best performing model with a test accuracy of 78.54%