

Text Classification:

Data

1. we have total of 20 types of documents(Text files) and total 18828 documents(text files).
2. You can download data from this [link](#), in that you will get documents.rar folder.
- If you unzip that, you will get total of 18828 documents. document name is defined as 'ClassLabel_DocumentNumberInThatLabel'.
- so from document name, you can extract the label for that document.
4. Now our problem is to classify all the documents into any one of the class.
5. Below we provided count plot of all the labels in our data.

```
In [1]: # changing my jupyter theme
!jt -r
```

Reset css and font defaults in:
C:\Users\sai\.jupyter\custom &
C:\Users\sai\AppData\Roaming\jupyter\nbextensions

Read the Data zip file

```
In [ ]: # Load the zip/rar file into colab
from google.colab import files
files.upload()
```

No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please

rerun this cell to enable.

Saving documents.zip to documents.zip

```
In [ ]: # To unrar/unzip the rar/zip files of documents
!unzip "/content/documents.zip" -d "/content/output_folder"
```

Obtaining the class labels & the count distribution

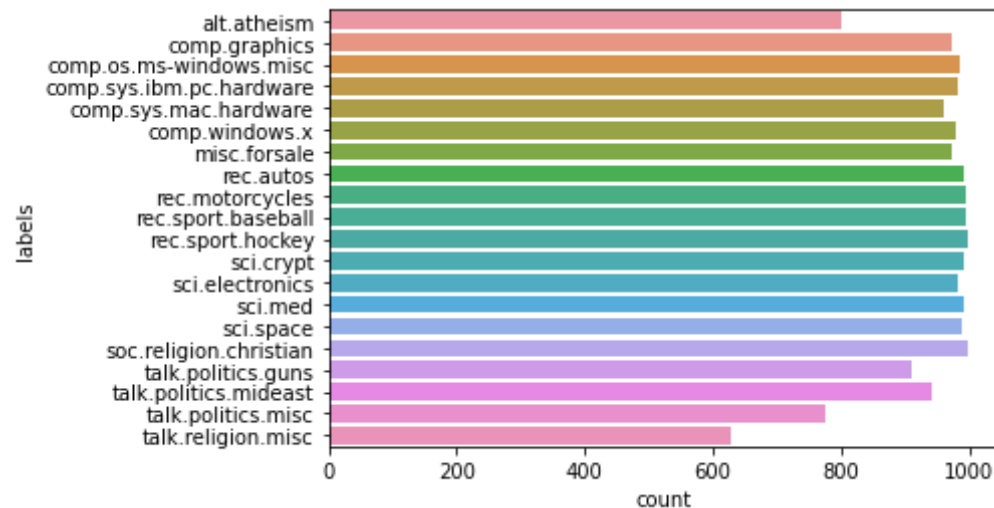
```
In [ ]: # extract class labels from the documents file name
import os ;
documents_path = '/content/output_folder/documents'
allfiles = sorted(os.listdir(documents_path))
print(allfiles[0])
print(type(allfiles))
print(len(allfiles))
```

```
# obtaining class labels
class_labels = []
for j in allfiles:
    class_labels.append(j.split("_")[0])
print(class_labels[0])
```

```
alt.atheism_49960.txt
<class 'list'>
18828
alt.atheism
```

```
In [ ]: # lets create dataframe of class labels
import pandas as pd
data_labels = pd.DataFrame(class_labels,columns = ['labels'])
data_labels.to_csv('text_classlabels.csv')
```

```
In [ ]: #count plot of labels
import seaborn as sns
import matplotlib.pyplot as plt
sns.countplot(y = 'labels',data = data_labels,orient='h')
plt.show()
```



Assignment:

sample document

Subject: A word of advice

From: jcopelan@nyx.cs.du.edu (The One and Only)

In article <65882@mimsy.umd.edu> mangoe@cs.umd.edu (Charley Wingate) writes:

>

>I've said 100 times that there is no "alternative" that should think you
>might have caught on by now. And there is no "alternative", but the point
>is, "rationality" isn't an alternative either. The problems of metaphysical
>and religious knowledge are unsolvable-- or I should say, humans cannot
>solve them.

How does that saying go: Those who say it can't be done shouldn't interrupt
those who are doing it.

Jim

--

Have you washed your brain today?

Preprocessing:

useful links: <http://www.pyregex.com/>

1. Find all emails in the document and then get the text after the "@". and then split those texts by ','

after that remove the words whose length is less than or equal to 2 and also remove 'com' word and then combine those words by space.

In one doc, if we have 2 or more mails, get all.

Eg: [test@dm1.d.com, test2@dm2.dm3.com] --> [dm1.d.com, dm3.dm4.com] --> [dm1,d,com,dm2,dm3,com] --> [dm1,dm2,dm3] --> "dm1 dm2 dm3"

append all those into one list/array. (This will give length of 18828 sentences i.e one list for each of the document).

Some sample output was shown below.

> In the above sample document there are emails [jcopelan@nyx.cs.du.edu, 65882@mimsy.umd.edu, mangoe@cs.umd.edu]

preprocessing:

```
[jcopelan@nyx.cs.du.edu, 65882@mimsy.umd.edu, mangoe@cs.umd.edu] ==> [nyx cs du edu mimsy umd edu cs umd edu] ==> [nyx edu mimsy umd edu umd edu]
```

2. Replace all the emails by space in the original text.

3. Get subject of the text i.e. get the total lines where "Subject:" occur and remove the word which are before the ":" remove the newlines, tabs, punctuations, any special chars.

Eg: if we have sentence like "Subject: Re: Gospel Dating @ \r\r\n" --> You have to get "Gospel Dating"

Save all this data into another list/array.

4. After you store it in the list, Replace those sentences in original text by space.

5. Delete all the sentences where sentence starts with "Write to:" or "From:".

> In the above sample document check the 2nd line, we should remove that

6. Delete all the tags like "< anyword >"

> In the above sample document check the 4nd line, we should remove that "< 65882@mimsy.umd.edu >"

7. Delete all the data which are present in the brackets.

In many text data, we observed that, they maintained the explanation of sentence or translation of sentence to another language in brackets so remove all those.

Eg: "AAIC-The course that gets you HIRED(AAIC - Der Kurs, der Sie anstellt)" --> "AAIC-The course that gets you HIRED"

> In the above sample document check the 4nd line, we should remove that "(Charley Wingate)"

8. Remove all the newlines('\n'), tabs('\t'), "-", "\".

9. Remove all the words which ends with ":".

Eg: "Anyword:"

> In the above sample document check the 4nd line, we should remove that "writes:"

10. Decontractions, replace words like below to full words.

please check the donors choose preprocessing for this

Eg: can't -> can not, 's -> is, i've -> i have, i'm -> i am, you're -> you are, i'll --> i will

There is no order to do point 6 to 10. but you have to get final output correctly

11. Do chunking on the text you have after above preprocessing.

Text chunking, also referred to as shallow parsing, is a task that follows Part-Of-Speech Tagging and that adds more structure to the sentence.

So it combines the some phrases, named entities into single word.

So after that combine all those phrases/named entities by separating "_".

And remove the phrases/named entities if that is a "Person".

You can use `nlk.ne_chunk` to get these.

Below we have given one example. please go through it.

useful links:

<https://www.nltk.org/book/ch07.html>

<https://stackoverflow.com/a/31837224/4084039>

<http://www.nltk.org/howto/tree.html>

<https://stackoverflow.com/a/44294377/4084039>

In []:

```
#i am living in the New York
print("i am living in the New York -->",list(chunks))
print(" ")
print("-"*50)
print(" ")
#My name is Srikanth Varma
print("My name is Srikanth Varma -->",list(chunks1))
```

```
i am living in the New York --> [('i', 'NN'), ('am', 'VBP'), ('living', 'VBG'), ('in', 'IN'), ('the', 'DT'), Tree('GP
E', [('New', 'NNP'), ('York', 'NNP')])]
```

```
My name is Srikanth Varma --> [('My', 'PRP$'), ('name', 'NN'), ('is', 'VBZ'), Tree('PERSON', [('Srikanth', 'NNP'),
('Varma', 'NNP')])]
```

We did chunking for above two lines and then We got one list where each word is mapped to a POS(parts of speech) and also if you see "New York" and "Srikanth Varma", they got combined and represented as a tree and "New York" was referred as "GPE" and "Srikanth Varma" was referred as "PERSON".

so now you have to Combine the "New York" with "_" i.e "New_York"

and remove the "Srikanth Varma" from the above sentence because it is a person.

13. Replace all the digits with space i.e delete all the digits.

> In the above sample document, the 6th line have digit 100, so we have to remove that.

14. After doing above points, we observed there might be few word's like

"_word_" (i.e starting and ending with the _), "_word" (i.e starting with the _),

"word_" (i.e ending with the _) remove the _ from these type of words.

15. We also observed some words like "OneLetter_word"- eg: d_berlin,

"TwoLetters_word" - eg: dr_berlin , in these words we remove the "OneLetter_" (d_berlin ==> berlin) and
"TwoLetters_" (de_berlin ==> berlin). i.e remove the words
which are length less than or equal to 2 after splitting those words by "_".

16. Convert all the words into lower case and lower case
and remove the words which are greater than or equal to 15 or less than or equal to 2.

17. replace all the words except "A-Za-z_" with space.

18. Now You got Preprocessed Text, email, subject. create a dataframe with those.
Below are the columns of the df.

Obtain file/doc contents

```
In [ ]: # SOME CUSTOM TERMINOLOGIES
# f_contents - > all document contents
# mail_lst - > preprocessed mails
# fg - > each document's mail contents
# sub_lst - > subject details of each document
```

```
In [ ]: # obtain all text data into f_contents list
import re
import os ;
documents_path = '/content/output_folder/documents'
allfiles = sorted(os.listdir(documents_path))
f_contents = []
for j in allfiles:
    with open(documents_path+'/'+j,'r',errors = 'ignore') as f:
        f_contents.append(f.read())

print("Total documents :- ",len(f_contents))
```

Total documents :- 18828

```
In [ ]: # create a pandas series df from class labels & text data
import pandas as pd
```

```
df1 = pd.DataFrame(list(zip(f_contents,class_labels)),columns = ['text','labels'])
df1.head()
```

```
Out[ ]:
```

	text	labels
0	From: mathew <mathew@mantis.co.uk>\nSubject: A...	alt.atheism
1	From: mathew <mathew@mantis.co.uk>\nSubject: A...	alt.atheism
2	From: l3150101@dbstu1.rz.tu-bs.de (Benedikt Ro...	alt.atheism
3	From: mathew <mathew@mantis.co.uk>\nSubject: R...	alt.atheism
4	From: strom@Watson.Ibm.Com (Rob Strom)\nSubjec...	alt.atheism

To get a data frame --> Try to Write Total Preprocessing steps in One Function Named Preprocess as below.

```
In [ ]: # required packages:-
        nltk.download('popular');
```

```
In [ ]: # MAIN
        # check for any single doc/text data
        import re; import nltk ;
        from nltk import word_tokenize,pos_tag,ne_chunk;

        #nltk.download('popular'); #--> run just one time

        # PLEASE DO CHECK FOR ANY SINGLE DOCUMENT BY CHANGING INDEX NUMBER IN f_contents[]
        #print("BEFORE PREPROCESSING:-\n",f_contents[40])

        def preprocess_text(input_text):
            # emails
            fg = re.findall(r"[a-zA-Z0-9._-]+@[a-zA-Z0-9._-]+",input_text) # list
            mail_lst = []
            empty = ''
            for each_mail in fg:
                temp = each_mail.split('@')[1].split('.')
                for word in temp:
                    if (len(word) > 2) and (word != 'com') and \
```



```
(word != 'Com') and (word != 'COM'):  
    empty = empty + ' ' + word  
mail_lst.append(empty.strip()) # we get preprocessed mail  
  
replaced = (re.sub(r"[a-zA-Z0-9._-]+@[a-zA-z0-9._-]+",'',input_text))  
  
#subject extract  
sub_lst = []  
gt = re.findall(r'Subject:\s(.*)',replaced,flags = re.I)  
#print(gt) # ['DeltaPoints Animated Desktop']  
try :  
    ind = gt[0].rindex(':')  
    gta = gt[0][ind+1:].strip()  
    gtb = re.findall(r'(\w+)',gta)  
    gtb = str(" ").join(gtb)  
    sub_lst.append(str(gtb)) # subject details extracted  
except:  
    gtb = re.findall(r'(\w+)',gt[0])  
    gtb = str(" ").join(gtb)  
    sub_lst.append(str(gtb)) # subject details extracted  
  
# Replace all the subject & from (texts) in the original text by space:-  
replaced = re.sub(r'Subject:\s(.*)','',replaced,flags = re.I)  
replaced = re.sub(r'From:\s(.*)','',replaced,flags = re.I)  
  
# general cleaning of text data  
replaced = re.sub(r'(<.*>)', '', replaced)  
replaced = re.sub(r'(\(.*\))', '', replaced)  
replaced = re.sub(r'(\s+)', ' ', replaced)  
replaced = re.sub(r'\w+[:+=]', '', replaced)  
replaced = re.sub(r'[\,\!\@\#\%\&\^_\*\_#\%;\|/+=\$\&\:\"]+', '', replaced)  
phrase = re.sub(r"won't", "will not",replaced,flags = re.I)  
phrase = re.sub(r"can't", "can not",phrase,flags = re.I)  
phrase = re.sub(r"n't", " not", phrase,flags = re.I)  
phrase = re.sub(r"\'re", " are", phrase,flags = re.I)  
phrase = re.sub(r"\'s", " is", phrase,flags = re.I)  
phrase = re.sub(r"\'d", " would", phrase,flags = re.I)  
phrase = re.sub(r"\'ll", " will", phrase,flags = re.I)  
phrase = re.sub(r"\'t", " not", phrase,flags = re.I)  
phrase = re.sub(r"\'ve", " have", phrase,flags = re.I)  
replaced = re.sub(r"\'m", " am", phrase,flags = re.I)
```

```

# chunking
replaced = " ".join(replaced.split()).strip()
chunk = ne_chunk(pos_tag(word_tokenize(replaced)), binary = False)
#print(chunk)
named_entities = []
for tagged_tree in chunk:
    #print(tagged_tree)
    if hasattr(tagged_tree, 'label'):
        entity_name = ' '.join(c[0] for c in tagged_tree.leaves()) #
        entity_type = tagged_tree.label() # get NE category
        named_entities.append((entity_name, entity_type))
#print(named_entities)
for tag in named_entities:
    if tag[1] == 'GPE': #Specify any tag which is required
        replaced = replaced.replace(tag[0], tag[0].replace(' ', '_'))
    if tag[1] == 'PERSON':
        replaced = replaced.replace(tag[0], '')

replaced = re.sub('\d+', '', replaced) # remove digits
# underscore pre-processing
gh = re.findall('(\_\w+)', replaced)
#print(gh)
jk = re.findall('(\w+_\w+)', replaced)
for m, n in enumerate(jk):
    if len(n.split('_')[0]) < 2 or len(n.split('_')[1]) == 2:
        replaced = re.sub(jk[m], n.split('_')[1], replaced, re.I)
for m, n in enumerate(gh):
    replaced = re.sub(gh[m], gh[m].replace('_', ''), replaced, re.I)

#lowercase & length preprocessing (>=15 & <=2)
replaced = replaced.lower()
hj = re.findall(r"\w+", replaced)
temp = ''
for o in hj:
    if (len(o) > 2) and (len(o) < 15):
        temp = temp + ' ' + o
replaced = temp

#final preprocessing:-
replaced = re.sub('\W+', ' ', replaced)
replaced = " ".join(replaced.split()).strip()

```

```

    return (mail_lst,sub_lst,replaced) # return results

# PLEASE DO CHECK FOR ANY SINGLE DOCUMENT BY CHANGING INDEX NUMBER IN f_contents[]
df2 = pd.DataFrame(columns=['preprocessed_emails','preprocessed_subject','preprocessed_text'])

for index,f in enumerate(f_contents):
    result = preprocess_text(f)
    df2 = df2.append({'preprocessed_emails' : result[0][0],
                    'preprocessed_subject' : result[1][0],
                    'preprocessed_text' : result[2]},ignore_index=True)

print(type(df2))
print(df2.shape)
print(df2.columns)

```

```

<class 'pandas.core.frame.DataFrame'>
(18828, 3)
Index(['preprocessed_emails', 'preprocessed_subject', 'preprocessed_text'], dtype='object')

```

```

In [ ]: # lets display our data
        df2.head()

```

```

Out[ ]:

```

	preprocessed_emails	preprocessed_subject	preprocessed_text
0	mantis netcom mantis	Atheist Resources	archive resources last december atheist resour...
1	mantis mantis mantis	Introduction to Atheism	archive introduction last april begin pgp sign...
2	dbstu1 tu-bs mimsy umd edu umd edu	Gospel Dating	article has quite different not necessarily mo...
3	mantis kepler unh edu	university violating separation of church state	recently ras have been ordered and none have r...
4	Watson Ibm harder ccr-p ida org harder ccr-p i...	soc motss et al Princeton axes matching funds ...	article however hate economic terrorism and po...

Code checking:

After Writing preprocess function. call that functoin with the input text of 'alt.atheism_49960' doc and print the output of the preprocess function

This will help us to evaluate faster, based on the output we can suggest you if there are any changes.

```
In [ ]: # lets call the preprocess function with just one text data :-
documents_path = '/content/output_folder/documents'
text_sample = 'alt.atheism_49960.txt'
p = [] #append the text of text_sample
with open(documents_path+'/'+text_sample,'r',errors = 'ignore') as f:
    p.append(f.read())
print(p)
print("Preprocessed email :-\n",preprocess_text(p[0])[0])
print("Preprocessed subject :-\n",preprocess_text(p[0])[1])
print("Preprocessed text :-\n",preprocess_text(p[0])[2])
```

```
['From: mathew <mathew@mantis.co.uk>\nSubject: Alt.Atheism FAQ: Atheist Resources\n\nArchive-name: atheism/resources\nAlt-atheism-archive-name: resources\nLast-modified: 11 December 1992\nVersion: 1.0\n\nAtheist Resources\n\nAddresses of Atheist Organizations\n\nUSA\n\nFREEDOM FROM RELIGION FOUNDATION\n\nDarwin fish bumper stickers and assorted other atheist paraphernalia are\navailable from the Freedom From Religion Foundation in the US.\n\nWrite to: FFRF, P.O. Box 750, Madison, WI 53701.\n\nTelephone: (608) 256-8900\n\nEVOLUTION DESIGNS\n\nEvolution Designs sell the "Darwin fish". It's a fish symbol, lik  
e the ones\nChristians stick on their cars, but with feet and the word "Darwin" written\ninside. The deluxe moulded  
3D plastic fish is $4.95 postpaid in the US.\n\nWrite to: Evolution Designs, 7119 Laurel Canyon #4, North Hollywoo  
d,\nCA 91605.\n\nPeople in the San Francisco Bay area can get Darwin Fish from Lynn Gold --\nentry mailing <figmo@netcom.com>. For net people who go to Lynn directly, the\nprice is $4.95 per fish.\n\nAMERICAN ATHEIST PRESS\n\nAAP publish various atheist books -- critiques of the Bible, lists of\nBiblical contradictions, and so on. One suc  
h book is:\n\n"The Bible Handbook" by W.P. Ball and G.W. Foote. American Atheist Press.\n372 pp. ISBN 0-910309-26-  
4, 2nd edition, 1986. Bible contradictions,\nabsurdities, atrocities, immoralities... contains Ball, Foote: "The Bib  
le\nContradicts Itself", AAP. Based on the King James version of the Bible.\n\nWrite to: American Atheist Press, P.  
O. Box 140195, Austin, TX 78714-0195.\n\nor: 7215 Cameron Road, Austin, TX 78752-2973.\n\nTelephone: (512) 458-124  
4\n\nFax: (512) 467-9525\n\nPROMETHEUS BOOKS\n\nSell books including Haught's "Holy Horrors" (see below).\n\nWri  
te to: 700 East Amherst Street, Buffalo, New York 14215.\n\nTelephone: (716) 837-2475.\n\nAn alternate address (which  
may be newer or older) is:\n\nPrometheus Books, 59 Glenn Drive, Buffalo, NY 14228-2197.\n\nAFRICAN-AMERICANS FOR HUMANI  
SM\n\nAn organization promoting black secular humanism and uncovering the history of\nblack freethought. They publis  
h a quarterly newsletter, AAH EXAMINER.\n\nWrite to: Norm R. Allen, Jr., African Americans for Humanism, P.O. Box 66  
4,\nBuffalo, NY 14226.\n\nUnited Kingdom\n\nRationalist Press Association  
National Secular Society\n88 Islington High Street 702 Holloway Road\nLondon N1 8EW  
London N19 3NL\n071 226 7251 071 272 1266\n\nBritish Humanist Association South P  
lace Ethical Society\n14 Lamb's Conduit Passage Conway Hall\nLondon WC1R 4RH Red  
Lion Square\n071 430 0908 London WC1R 4RL\nfax 071 430 1271 071 831 7  
723\n\nThe National Secular Society publish "The Freethinker", a monthly magazine\nfounded in 1881.\n\nGermany\n\nIBKA e.V.\n\nInternationaler Bund der Konfessionslosen und Atheisten\nPostfach 880, D-1000 Berlin 41. German  
y.\n\nIBKA publish a journal:\n\nMIZ. (Materialien und Informationen zur Zeit. Politisches\nJournal der Konfessionslose  
sn und Atheisten. Hrsg. IBKA e.V.)\n\nMIZ-Vertrieb, Postfach 880, D-1000 Berlin 41. Germany.\n\nFor atheist books, writ  
e to:\n\nIBDK, Internationaler B"ucherdienst der Konfessionslosen\nPostfach 3005, D-3000 Hannover 1. Germany.\n\nTeleph  
one: 0511/211216\n\nBooks -- Fiction\n\nTHOMAS M. DISCH\n\n"The Santa Claus Compromi  
se"\nShort story. The ultimate proof that Santa exists. All characters and \nevents are fictitious. Any similarity  
to living or dead gods -- uh, well...\n\nWALTER M. MILLER, JR\n\n"A Canticle for Leibowitz"\nOne gem in this post ato
```

mic doomsday novel is the monks who spent their lives copying blueprints from "Saint Leibowitz", filling the sheets of paper with ink and leaving white lines and letters.

EDGAR PANGBORN
"Davy"
 Post atomic doomsday novel set in clerical states. The church, for example, forbids that anyone "produce, describe or use any substance containing...atoms".

PHILIP K. DICK
 Philip K. Dick wrote many philosophical and thought-provoking short stories and novels. His stories are bizarre at times, but very approachable. He wrote mainly SF, but he wrote about people, truth and religion rather than technology. Although he often believed that he had met some sort of God, he remained sceptical. Amongst his novels, the following are of some relevance:

"Galactic Pot-Healer"
 A fallible alien deity summons a group of Earth craftsmen and women to a remote planet to raise a giant cathedral from beneath the oceans. When the deity begins to demand faith from the earthers, pot-healer Joe Fernwright is unable to comply. A polished, ironic and amusing novel.

"A Maze of Death"
 Noteworthy for its description of a technology-based religion.

"VALIS"
 The schizophrenic hero searches for the hidden mysteries of Gnostic Christianity after reality is fired into his brain by a pink laser beam of unknown but possibly divine origin. He is accompanied by his dogmatic and dismissively atheist friend and assorted other odd characters.

"The Divine Invasion"
 God invades Earth by making a young woman pregnant as she returns from another star system. Unfortunately she is terminally ill, and must be assisted by a dead man whose brain is wired to 24-hour easy listening music.

MARGARET ATWOOD
"The Handmaid's Tale"
 A story based on the premise that the US Congress is mysteriously assassinated, and fundamentalists quickly take charge of the nation to set it "right" again. The book is the diary of a woman's life as she tries to live under the new Christian theocracy. Women's right to own property is revoked, and their bank accounts are closed; sinful luxuries are outlawed, and the radio is only used for readings from the Bible. Crimes are punished retroactively: doctors who performed legal abortions in the "old world" are hunted down and hanged. Atwood's writing style is difficult to get used to at first, but the tale grows more and more chilling as it goes on.

VARIOUS AUTHORS
"The Bible"
 This somewhat dull and rambling work has often been criticized. However, it is probably worth reading, if only so that you'll know what all the fuss is about. It exists in many different versions, so make sure you get the one true version.

Books -- Non-fiction

PETER DE ROSA
"Vicars of Christ", Bantam Press, 1988
 Although de Rosa seems to be Christian or even Catholic this is a very enlightening history of papal immoralities, adulteries, fallacies etc. (German translation: "Gottes erste Diener. Die dunkle Seite des Papsttums", Droemer-Knaur, 1989)

MICHAEL MARTIN
"Atheism: A Philosophical Justification", Temple University Press, Philadelphia, USA.
 A detailed and scholarly justification of atheism. Contains an outstanding appendix defining terminology and usage in this (necessarily) tendentious area. Argues both for "negative atheism" (i.e. the "non-belief in the existence of god(s)") and also for "positive atheism" ("the belief in the non-existence of god(s)"). Includes great refutations of the most challenging arguments for god; particular attention is paid to refuting contemporary theists such as Plantinga and Swinburne. 541 pages. ISBN 0-87722-642-3 (hardcover; paperback also available)

"The Case Against Christianity", Temple University Press
 A comprehensive critique of Christianity, in which he considers the best contemporary defences of Christianity and (ultimately) demonstrates that they are unsupportable and/or incoherent. 273 pages. ISBN 0-87722-767-5

JAMES TURNER
"Without God, Without Creed", The Johns Hopkins University Press, Baltimore, MD, USA
 Subtitled "The Origins of Unbelief in America". Examines the way in which unbelief (whether agnostic or atheistic) became a mainstream alternative world-view. Focuses on the period 1770-1900, and while considering France and Britain the emphasis is on American, and particularly New England developments. "Neither a religious history of secularization or atheism, Without God, Without Creed is, rather, the intellectual history of the fate of a single idea, the belief that God exists." 316 pages. ISBN (hardcover) 0-8018-2494-X (paper) 0-8018-3407-4

GEORGE SELDES (Editor)
"The great thoughts", Ballantine Books, New York, USA
 A "dictionary of quotations" of a different kind, concentrating on statements and writings which, explicitly or implicitly, present the person's philosophy and world-view. Includes obscure (and often suppressed) opinions from many people. For some popular observations, traces the way in which various people expressed and twisted the idea over the centuries. Quite a number of the quotations are derived from Cardiff's "What Great Men Think of Religion" and Noyes' "Views of Religion".

igion".\n490 pages. ISBN (paper) 0-345-29887-X.\n\nRICHARD SWINBURNE\n\n"The Existence of God (Revised Edition)", Clarendon Paperbacks, Oxford\nThis book is the second volume in a trilogy that began with "The Coherence of\nTheism" (1977) and was concluded with "Faith and Reason" (1981). In this\nwork, Swinburne attempts to construct a series of inductive arguments for the\nexistence of God. His arguments, which are somewhat tendentious and rely\nupon the imputation of late 20th century western Christian values and\naesthetics to a God which is supposedly as simple as can be conceived, were\ndecisively rejected in Mackie's "The Miracle of Theism". In the revised\nedition of "The Existence of God", Swinburne includes an Appendix in which he\nmakes a somewhat incoherent attempt to rebut Mackie.\n\nJ. L. MAC KIE\n\n"The Miracle of Theism", Oxford\nThis (posthumous) volume contains a comprehensive review of the principal\narguments for and against the existence of God. It ranges from the classical\nphilosophical positions of Descartes, Anselm, Berkeley, Hume et al, through\nthe moral arguments of Newman, Kant and Sidgwick, to the recent restatements\nof the classical theses by Plantinga and Swinburne. It also addresses those\npositions which push the concept of God beyond the realm of the rational,\nsuch as those of Kierkegaard, Kung and Philips, as well as "replacements for\nGod" such as Lele's axiarchism. The book is a delight to read - less\nformalistic and better written than Martin's works, and refreshingly direct\nwhen compared with the hand-waving of Swinburne.\n\nJAMES A. HAUGHT\n\n"Holy Horrors: An Illustrated History of Religious Murder and Madness",\nPrometheus Books\nLooks at religious persecution from ancient times to the present day -- and\nnot only by Christians.\nLibrary of Congress Catalog Card Number 89-64079. 1990.\n\nNORM R. ALLEN, JR.\n\n"African American Humanism: an Anthology"\nSee the listing for African Americans for Humanism above.\n\nGORDON STEIN\n\n"An Anthology of Atheism and Rationalism", Prometheus Books\nAn anthology covering a wide range of subjects, including 'The Devil, Evil\nand Morality' and 'The History of Freethought'. Comprehensive bibliography.\n\nEDMUND D. COHEN\n\n"The Mind of The Bible-Believer", Prometheus Books\nA study of why people become Christian fundamentalists, and what effect it\nhas on them.\n\nNet Resources\n\nThere's a small mail-based archive server at mantis.co.uk which carries\narchives of old alt.atheism.moderated articles and assorted other files. For\nmore information, send mail to archive-server@mantis.co.uk saying\n\n help\n\n send atheism/index\n\nand it will mail back a reply.\n\n\nmathew\n\n']

Preprocessed email :-

['mantis netcom mantis']

Preprocessed subject :-

['Atheist Resources']

Preprocessed text :-

archive resources last december atheist resources addresses atheist organizations usa freedom from religion foundation fish bumper stickers and assorted other atheist paraphernalia are available from the freedom from religion foundation the write ffrf box madison evolution designs evolution designs sell the fish fish symbol like the ones stick their cars but with feet and the word written inside the deluxe moulded plastic fish postpaid the write evolution designs north hollywood people the san francisco bay area can get fish from try mailing for net people who directly the price per fish american atheist press aap publish various atheist books critiques the bible lists biblical contradictions and one such book the bible handbook ball and foote american atheist press isbn edition bible contradictions absurdities atrocities immoralities contains ball the bible contradicts itself aap based the king version the bible write american atheist press box cameron road prometheus books sell books including write east amherst street york alternate address prometheus books for humanism organization promoting black secular humanism and uncovering the history black freethought they publish quarterly newsletter aah examiner write norm allen african americans for humanism box united press association national secular society street holloway road london london british humanist association south place ethical society lamb wcr red lion square london wcr fax the national secular society publish the freethinker monthly magazine founded germany_ibka bund der und berlin germany_ibka publish miz materialien und zur zeit politisches journal der und ibka mizvertrieb postfach berlin germany for atheist books write ibdk bucherdienst der hannover germany books fiction thomas disch the claus compromise short story the ultimate proof that exists all characters and events are

e fictitious any similarity living dead gods well walter canticle for leibowitz one gem this post atomic doomsday novel the monks who spent their lives copying blueprints from filling the sheets paper with ink and leaving white lines and letters edgar pangborn atomic doomsday novel set clerical states the church for example forbids that anyone produce describe use any substance containing atoms philip dick wrote many philosophical and short stories and novels his stories are bizarre times but very approachable wrote mainly but wrote about people truth and religion rather than technology although often believed that had met some sort remained sceptical amongst his novels the following are some galactic pothealer fallible alien deity summons group craftsmen and women remote planet raise giant cathedral from beneath the oceans when the deity begins demand faith from the earthers pothealer unable comply polished ironic and amusing novel maze for its description religion valis the schizophrenic hero searches for the hidden mysteries gnostic identity after reality fired into his brain pink laser beam unknown but possibly divine origin accompanied his dogmatic and dismissively atheist friend and assorted other odd characters the divine invasion invades making young woman pregnant she returns from another star system unfortunately she terminally ill and must assisted dead man whose brain wired for easy listening music margaret atwood the handmaid story based the premise that the congress mysteriously assassinated and quickly take charge the nation set right again the book the diary woman life she tries live under the new theocracy women right own property revoked and their bank accounts are closed sinful luxuries are outlawed and the radio only used for readings from the bible crimes are punished doctors who performed legal abortions the old world are hunted down and hanged writing style difficult get used first but the tale grows more and more chilling goes various authors the bible this somewhat dull and rambling work has often been criticized however probably worth reading only that you will know what all the fuss about exists many different versions make sure you get the one true version peter rosa vicars christ bantam press although seems even catholic this very enlightening history papal immoralities adulteries fallacies etc german gottes erste dunkle seite des droemerknauer michael martin philosophical justification temple university press philadelphia usa detailed and scholarly justification atheism contains outstanding appendix defining terminology and usage this tendentious area both for negative atheism the nonbelief the existence god and also for positive atheism the belief the nonexistence god includes great refutations the most challenging arguments for god particular attention paid refuting contemporary theists such and pages isbn the case against ity temple university press comprehensive critique ity which considers the best contemporary defences ity and demonstrates that they are unsupportable and/or incoherent pages isbn james turner without the johns hopkins university press baltimore usa subtitled the origins unbelief america examines the way which unbelief became mainstream alternative worldview focusses the period and while considering france and britain the emphasis american and particularly new england developments neither religious history secularization atheism without rather the intellectual history the fate single idea the belief that exists pages isbn george selles the great thoughts usa dictionary quotations different kind concentrating statements and writings which explicitly implicitly present the person philosophy and worldview includes obscure opinions from many people for some popular observations traces the way which various people expressed and twisted the idea over the centuries quite number the quotations are derived from cardiff what religion and views religion pages isbn richard swinburne the existence clarendon paperbacks oxford this book the second volume trilogy that began with the coherence theism this work attempts construct series inductive arguments for the existence his arguments which are somewhat tendentious and rely upon the imputation late century western values and aesthetics which supposedly simple can conceived were decisively rejected mackie the miracle theism the revised edition the existence includes appendix which makes somewhat incoherent attempt rebut mackie the miracle theism oxford this volume contains comprehensive review the principal arguments for and against the existence ranges from the classical philosophical positions through the moral arguments newman kant and the recent restatements the classical theses and also addresses those positions which push the concept beyond the realm the rational such those kierkegaard kung and well replacements for such axiarchism the book delightful read less formalistic and better written than works and refreshingly direct when compared with the handwaving james haught holy illustrated history religious murder and madness prometheus books looks religious persecution from ancient times the present day and not only library congress catalog card number norm allen african american the listing for

african americans for humanism above gordon stein anthology atheism and anthology covering wide range subjects including nothe and morality and nothe history freethought comprehensive bibliography edmund cohen the mind the biblebeliever prometheus books study why people become and what effect has them net resources there small mailbased archive server mantiscouk which carries archives old articles and assorted other files for more information send mail saying help send atheisindex and will mail back reply mathew

After writing Preprocess function, call the function for each of the document(18828 docs) and then display the dataframe as mentioned in the assignment.

```
In [ ]: # Display the final dataframe using concat()
final_df = pd.concat([df1,df2],axis = 1)
final_df.head()
```

```
Out[ ]:
```

	text	labels	preprocessed_emails	preprocessed_subject	preprocessed_text
0	From: mathew <mathew@mantis.co.uk>\nSubject: A...	alt.atheism	mantis netcom mantis	Atheist Resources	archive resources last december atheist resour...
1	From: mathew <mathew@mantis.co.uk>\nSubject: A...	alt.atheism	mantis mantis mantis	Introduction to Atheism	archive introduction last april begin pgp sign...
2	From: l3150101@dbstu1.rz.tu-bs.de (Benedikt Ro...	alt.atheism	dbstu1 tu-bs mimsy umd edu umd edu	Gospel Dating	article has quite different not necessarily mo...
3	From: mathew <mathew@mantis.co.uk>\nSubject: R...	alt.atheism	mantis kepler unh edu	university violating separation of church state	recently ras have been ordered and none have r...
4	From: strom@Watson.Ibm.Com (Rob Strom)\nSubjec...	alt.atheism	Watson Ibm harder ccr-p ida org harder ccr-p i...	soc motss et al Princeton axes matching funds ...	article however hate economic terrorism and po...

```
In [ ]: # to check any null values
final_df.isnull().sum()
```

```
Out[ ]: text                0
labels                  0
preprocessed_emails     0
preprocessed_subject    0
preprocessed_text       0
dtype: int64
```

Training The models to Classify:

1. Combine "preprocessed_text", "preprocessed_subject", "preprocessed_emails" into one column. use that column to model.
2. Now Split the data into Train and test. use 25% for test also do a stratify split.
3. Analyze your text data and pad the sequence if required.
Sequence length is not restricted, you can use anything of your choice.
you need to give the reasoning
4. Do Tokenizer i.e convert text into numbers. please be careful while doing it.
if you are using tf.keras "Tokenizer" API, it removes the "_", but we need that.
5. code the model's (Model-1, Model-2) as discussed below
and try to optimize that models.
6. For every model use predefined Glove vectors.
Don't train any word vectors while Training the model.
7. Use "categorical_crossentropy" as Loss.
8. Use **Accuracy and Micro Averaged F1 score** as your as Key metrics to evaluate your model.
9. Use Tensorboard to plot the loss and Metrics based on the epoches.
10. Please save your best model weights in to '**best_model_L.h5**' (**L = 1 or 2**).
11. You are free to choose any Activation function, learning rate, optimizer.
But have to use the same architecture which we are giving below.
12. You can add some layer to our architecture but you **deletion** of layer is not acceptable.
13. Try to use **Early Stopping** technique or any of the callback techniques that you did in the previous assignments.
14. For Every model save your model to image (Plot the model) with shapes
and include those images in the notebook markdown cell,
upload those images to Classroom. You can use "plot_model"

please refer [this](#) if you don't know how to plot the model with shapes.

Final_text data for the models :-

```
In [ ]: # Obtain the data for modelling:-
df2['final_txt'] = df2[['preprocessed_text', 'preprocessed_subject', 'preprocessed_emails']].apply(lambda x: ' '.join(x), axis=1)
df2.drop(columns = ['preprocessed_text', 'preprocessed_subject', 'preprocessed_emails'], inplace = True)
df2.to_csv('final_preprocessed_text.csv')
df2.head()
```

```
Out[ ]:      final_txt
0  archive resources last december atheist resour...
1  archive introduction last april begin pgp sign...
2  article has quite different not necessarily mo...
3  recently ras have been ordered and none have r...
4  article however hate economic terrorism and po...
```

```
In [ ]: # to check gpu is running or not
import tensorflow as tf
tf.test.gpu_device_name()
```

```
Out[ ]: '/device:GPU:0'
```

```
In [ ]: # Load the classlabels file into colab
from google.colab import files
files.upload() # upload text_classlabels
# NOTE : As the uploaded file is very big, I cleared the output because of easy readeability purposes
```

```
In [ ]: # Load the final_csv file into colab
from google.colab import files
files.upload() # upload final_preprocessed_text.csv
# NOTE : As the uploaded file is very big, I cleared the output because of easy readeability purposes
```

Read the Final preprocessed datasets

```
In [2]: # lets read the dataset :-
import pandas as pd
df1 = pd.read_csv('text_classlabels.csv')
df2 = pd.read_csv('final_preprocessed_text.csv')
```

```
In [3]: # Train test split is done
from sklearn.model_selection import train_test_split
y = df1['labels']
X = df2['final_txt']
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25,random_state=170,stratify=y)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(14121,)
(4707,)
(14121,)
(4707,)
```

```
In [4]: # lets convert labels to categorical
from tensorflow.keras.utils import to_categorical
ytrain_labels = pd.get_dummies(y_train)
ytest_labels = pd.get_dummies(y_test)
```

TASK 1

Encoding of the Text --> For a given text data create a Matrix with Embedding layer as shown Below.
In the example we have considered $d = 5$, but in this assignment we will get $d =$ dimension of Word vectors we are using.
i.e if we have maximum of 350 words in a sentence and embedding of 300 dim word vector,
we result in 350×300 dimensional matrix for each sentence as output after embedding layer

I
like
this
movie
very
much
!

0.6	0.5	0.2	-0.1	0.4
0.8	0.9	0.1	0.5	0.1
0.4	0.6	0.1	-0.1	0.7
...
...
...
...

Ref: <https://i.imgur.com/kiVQuk1.png>

Reference:

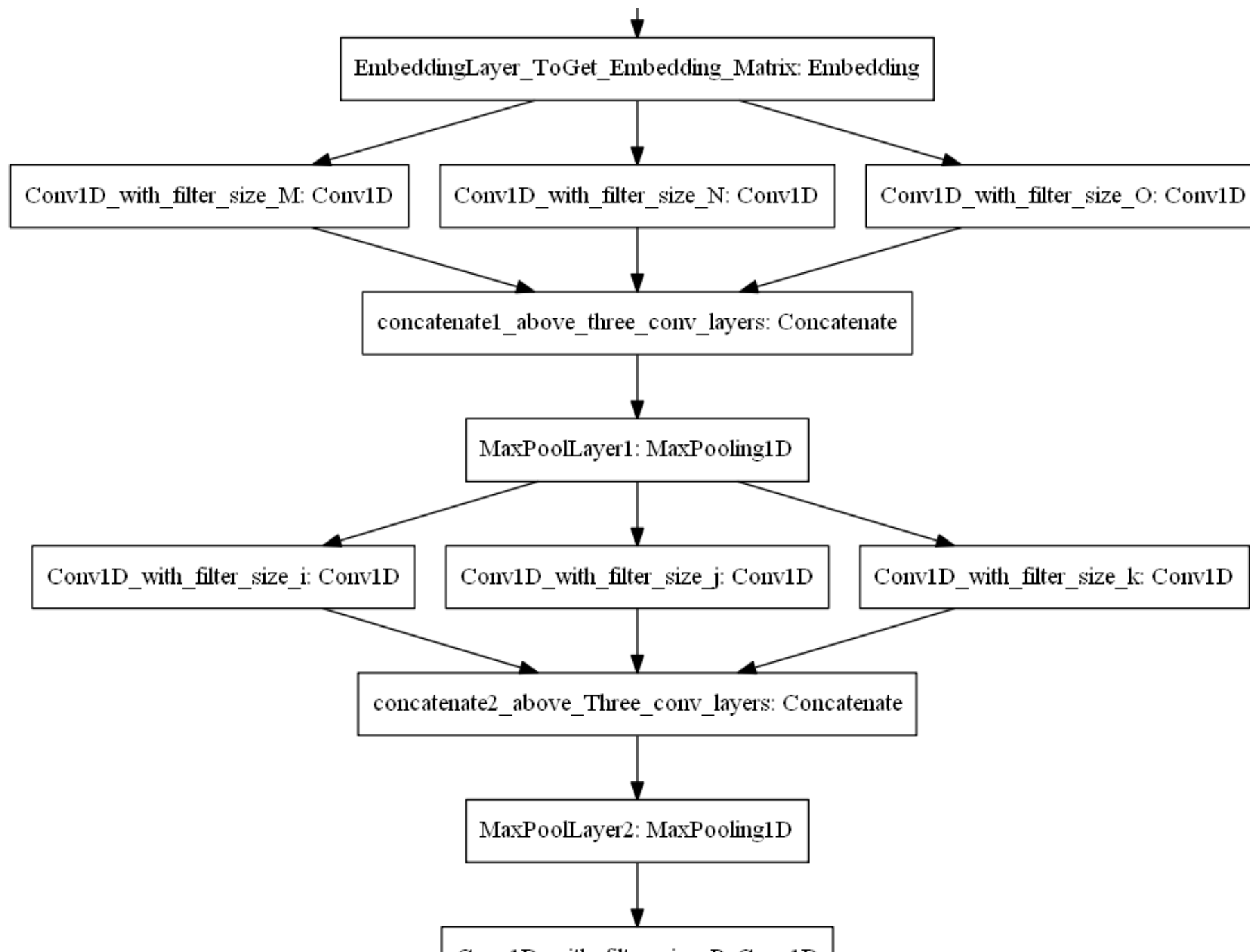
<https://stackoverflow.com/a/43399308/4084039>

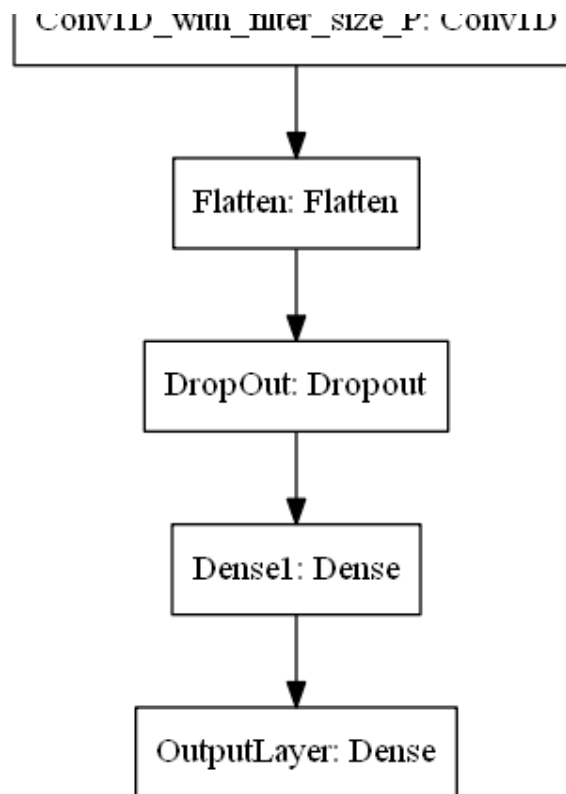
<https://missinglink.ai/guides/keras/keras-conv1d-working-1d-convolutional-neural-networks-keras/>

How EMBEDDING LAYER WORKS

Go through this blog, if you have any doubt on using predefined Embedding values in Embedding layer - <https://machinelearningmastery.com/use-word-embedding-layers-deep-learning-keras/>

Input_Text: InputLayer





ref: '<https://i.imgur.com/fv1GvFJ.png>'

1. all are Conv1D layers with any number of filter and filter sizes, there is no restriction on this.
2. use concatenate layer is to concatenate all the filters/channels.
3. You can use any pool size and stride for maxpooling layer.
4. Don't use more than 16 filters in one Conv layer because it will increase the no of params.
(Only recommendation if you have less computing power)
5. You can use any number of layers after the Flatten Layer.

Tokenizing & Padding for MODEL -1

```

In [5]: # reference : https://www.kdnuggets.com/2020/03/tensorflow-keras-tokenization-text-data-prep.html
# lets pad & tokenize the data:-
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Tokenize our training data
oov_token = '<UNK>' ;
tokenizer = Tokenizer(oov_token=oov_token, filters='!"#$%&()*+,-./:;<=>?@[\\]^`{|}~\t\n')
tokenizer.fit_on_texts(X_train)

# Get our training data word index
word_index = tokenizer.word_index
print("Length of word indices :-", len(word_index))
print('\n')
# Encode training data sentences into sequences
train_sequences = tokenizer.texts_to_sequences(X_train)

# Get max training sequence length
import statistics ; import matplotlib.pyplot as plt
lengths = [len(x) for x in train_sequences]
print("The mean length of words in the sequences :-\n", statistics.mean(lengths))
plt.hist(lengths, bins = 15)
plt.xlabel('Sequence Counts')
plt.ylabel('Word length frequency')
plt.grid()
plt.yscale('log')
plt.show()

# count of lengths
count_gr600 = 0
count_ls600 = 0
for j in lengths:
    if j > 600:
        count_gr600 += 1
    else:
        count_ls600 += 1

print("No of sentences having words > 600 :- \n", count_gr600)
print("No of sentences having words < 600 :- \n", count_ls600)
print("Contribution of lengthier sentences having > 600 words :-\n", (count_gr600)/len(lengths))

# Pad the training sequences

```

```

train_padded = pad_sequences(train_sequences,padding = 'post',maxlen= 600,truncating='post')

# tokenize & Pad the testing sequences
test_sequences = tokenizer.texts_to_sequences(X_test)
test_padded = pad_sequences(test_sequences,padding='post',maxlen = 600,truncating='post')

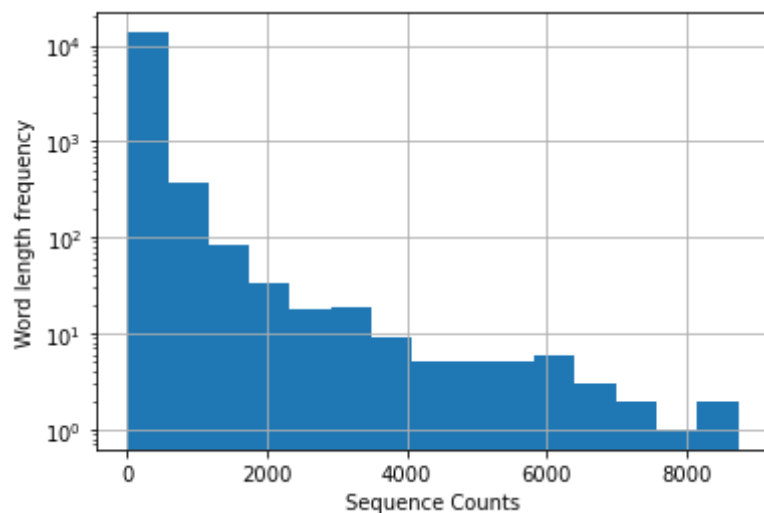
# Output the results of our work
print("\nPadded training shape:", train_padded.shape)
print("Training sequences data type:", type(train_sequences))
print("Padded Training sequences data type:", type(train_padded))

print("\nPadded testing shape:", test_padded.shape)
print("Testing sequences data type:", type(test_sequences))
print("Padded Testing sequences data type:", type(test_padded))

```

Length of word indices :- 111511

The mean length of words in the sequences :-
187.86700658593585



No of sentences having words > 600 :-
543

No of sentences having words < 600 :-
13578

Contribution of lengthier sentences having > 600 words :-
0.03845336732526025


```
Padded training shape: (14121, 600)
Training sequences data type: <class 'list'>
Padded Training sequences data type: <class 'numpy.ndarray'>
```

```
Padded testing shape: (4707, 600)
Testing sequences data type: <class 'list'>
Padded Testing sequences data type: <class 'numpy.ndarray'>
```

Observation :

From the results of tokenizing the sequence, we can understand that only 3% of total sentences contribute for greater than 600 words & also its clearly evident from the histogram plotted. therefore i chose padding length to be 600.

```
In [ ]: # Load the glove zip/rar file into colab
        from google.colab import files
        files.upload()
```

No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please

rerun this cell to enable.

Saving glove.6B.50d.txt.zip to glove.6B.50d.txt.zip

```
In [ ]: # To unrar/unzip the rar/zip files of documents
        !unzip "/content/glove.6B.50d.txt.zip" -d "/content/output_folder"
```

```
Archive: /content/glove.6B.50d.txt.zip
  creating: /content/output_folder/glove.6B.50d.txt/
  inflating: /content/output_folder/glove.6B.50d.txt/glove.6B.50d.txt
```

Model-1: Creating word embedding layer

```
In [ ]: # reference :- https://blog.keras.io/using-pre-trained-word-embeddings-in-a-keras-model.html

        # create map word indices to embeddings/vectors
        import numpy as np
        embeddings_index = {}
        with open('/content/output_folder/glove.6B.50d.txt/glove.6B.50d.txt') as f:
            for line in f:
                values = line.split()
```

```

        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_index[word] = coefs

print('No of word vectors :-\n',len(embeddings_index))
emb_dim = coefs.shape[0]
print("Dimension of word vector :-\n",emb_dim)

# embedding matrix
embeddings_matrix = np.zeros((len(word_index) + 1,emb_dim))
for word, i in word_index.items():
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        # words not found in embedding index will be all-zeros.
        embeddings_matrix[i] = embedding_vector

# embedding layer
from tensorflow.keras.layers import Embedding
embedding_layer = Embedding(len(word_index) + 1,
                             emb_dim,
                             weights = [embeddings_matrix],
                             input_length = 600,
                             trainable = False)

print('shape of embedding_matrix :-\n',embeddings_matrix.shape)

```

```

No of word vectors :-
400000
Dimension of word vector :-
50
shape of embedding_matrix :-
(111512, 50)

```

```

In [ ]: # for add-on metrics we need this library
!pip install tensorflow-addons

```

```

Collecting tensorflow-addons
  Downloading https://files.pythonhosted.org/packages/66/4b/e893d194e626c24b3df2253066aa418f46a432fdb68250cde14bf9bb0700/tensorflow_addons-0.13.0-cp37-cp37m-manylinux2010_x86_64.whl (679kB)
    |████████████████████| 686kB 3.8MB/s
Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7/dist-packages (from tensorflow-addons) (2.7.1)

```

Installing collected packages: tensorflow-addons
Successfully installed tensorflow-addons-0.13.0

Tensorboard results

```
In [ ]: # %load_ext tensorboard
        %reload_ext tensorboard
```

```
In [ ]: # Clear any logs of previous executions/runs
import shutil
# /content/best_model_1 # ./logfiles_model1
path='./logfiles_model1'
shutil.rmtree(path, ignore_errors = True)
```

```
In [ ]: import shutil
        # /content/best_model_1 # ./logfiles_model1
        path='./content/best_model_1'
        shutil.rmtree(path, ignore_errors=True)
```

```
In [ ]: !kill 558
```

```
In [ ]: # Tensorboard outputs
import os; import datetime ; #Reference :--> https://www.dlology.com/blog/how-to-run-tensorboard-in-jupyter-notebook/
logs_base_dir = "./logfiles_model1"

os.makedirs(logs_base_dir, exist_ok=True) # Creating a directory to store logs
# Launch the tensorboard & then refresh it after executing the model.
%tensorboard --logdir {logs_base_dir}
```

```
In [ ]: # Decay learning rate scheduler
import tensorflow
def scheduler(epoch, lr):
    if (epoch) % 3 == 0:
        lr = ((lr) - (lr*(0.05))) # 0.05
```

```
else:
    pass

return lr
```

APPLY MODEL 1 & DISPLAY RESULTS

In []:

```
# functional API
import tensorflow as tf
tf.keras.backend.clear_session()# For easy reset of notebook state
tf.random.set_seed(1234)
import tensorflow_addons as tfa ; import os
from tensorflow.keras import layers, Input
from tensorflow.keras import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dropout, Flatten, Dense, Conv1D, MaxPooling1D, BatchNormalization
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.callbacks import LearningRateScheduler
from tensorflow.keras.initializers import HeNormal

# inputs
x = Input(shape=(600,))
initializer = HeNormal(seed = 103)
embedded_sequences = embedding_layer(x)

x1 = Conv1D(28,3,activation='relu',padding = 'same',kernel_initializer = initializer)(embedded_sequences)
x2 = Conv1D(32,3,activation='relu',padding = 'same',kernel_initializer = initializer)(embedded_sequences)
x3 = Conv1D(28,3,activation='relu',padding = 'same',kernel_initializer = initializer)(embedded_sequences)

concat_x1 = layers.concatenate([x1,x2,x3],axis = -1)

y = MaxPooling1D(3,strides = 2)(concat_x1)

y1 = Conv1D(28,3,activation='relu',padding = 'same',kernel_initializer = initializer)(y)
y2 = Conv1D(32,3,activation='relu',padding = 'same',kernel_initializer = initializer)(y)
y3 = Conv1D(28,3,activation='relu',padding = 'same',kernel_initializer = initializer)(y)

concat_x2 = layers.concatenate([y1,y2,y3],axis = -1)
```

```

z = MaxPooling1D(3, strides = 2)(concat_x2)

h1 = Conv1D(28, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(z)
h2 = Conv1D(32, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(z)
h3 = Conv1D(28, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(z)

concat_x3 = layers.concatenate([h1, h2, h3], axis = -1)

h = MaxPooling1D(3, strides = 2)(concat_x3)

z1 = Conv1D(24, 4, activation='relu', padding = 'same', kernel_initializer = initializer)(h)

z2 = Flatten()(z1)
z3 = Dropout(0.3)(z2)
z4 = Dense(32, activation='relu', kernel_initializer = initializer)(z3)
z5 = Dense(32, activation='relu', kernel_initializer = initializer)(z4)
z6 = Dense(20, activation='softmax', kernel_initializer = 'glorot_normal')(z5)

# model
model = Model(inputs = x, outputs = z6)

# optimizer
optimizer = Adam(learning_rate = 0.001)

# save model at every epoch end if validation accuracy is improved
filepath = "best_model_1/weights-{epoch:02d}-{val_acc:.4f}.hdf5"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_acc', verbose=1, save_best_only=True, mode='auto')

# early stopping
earlystop = EarlyStopping(monitor='val_acc', patience=2, verbose=1)

# tensorboard callbacks # reference :-> https://www.dlology.com/blog/how-to-run-tensorboard-in-jupyter-notebook/
log_dir = os.path.join(logs_base_dir, datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tb_callback = TensorBoard(log_dir=log_dir, histogram_freq=1)

# Lr schedule
lrschedule = LearningRateScheduler(scheduler, verbose = 1)

# metric
f1score = tf.keras.metrics.F1Score(num_classes = 20, average = 'micro')

# Model compile

```

```

model.compile(loss='categorical_crossentropy',
              optimizer=optimizer,
              metrics=['acc', f1score])
# Model fit
model.fit(train_padded, ytrain_labels, validation_data=(test_padded, ytest_labels),
          epochs=40, batch_size=64, callbacks = [earlystop, checkpoint, lrschedule, tb_callback])

```

Epoch 1/40

Epoch 00001: LearningRateScheduler reducing learning rate to 0.0009500000451225787.
 221/221 [=====] - ETA: 0s - loss: 2.6579 - acc: 0.1270 - f1_score: 0.1270

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The name `reset_states()` has been deprecated to improve API consistency.

'consistency.' % (self.__class__.__name__,))
 221/221 [=====] - 12s 42ms/step - loss: 2.6579 - acc: 0.1270 - f1_score: 0.1270 - val_loss: 2.1459 - val_acc: 0.2233 - val_f1_score: 0.2233

Epoch 00001: val_acc improved from -inf to 0.22328, saving model to best_model_1/weights-01-0.2233.hdf5
 Epoch 2/40

Epoch 00002: LearningRateScheduler reducing learning rate to 0.0009500000160187483.
 221/221 [=====] - 7s 32ms/step - loss: 1.9126 - acc: 0.3067 - f1_score: 0.3067 - val_loss: 1.6560 - val_acc: 0.3952 - val_f1_score: 0.3952

Epoch 00002: val_acc improved from 0.22328 to 0.39516, saving model to best_model_1/weights-02-0.3952.hdf5
 Epoch 3/40

Epoch 00003: LearningRateScheduler reducing learning rate to 0.0009500000160187483.
 221/221 [=====] - 7s 32ms/step - loss: 1.5747 - acc: 0.4287 - f1_score: 0.4287 - val_loss: 1.4351 - val_acc: 0.4918 - val_f1_score: 0.4918

Epoch 00003: val_acc improved from 0.39516 to 0.49182, saving model to best_model_1/weights-03-0.4918.hdf5
 Epoch 4/40

Epoch 00004: LearningRateScheduler reducing learning rate to 0.0009025000152178108.
 221/221 [=====] - 7s 34ms/step - loss: 1.3398 - acc: 0.5229 - f1_score: 0.5229 - val_loss: 1.3026 - val_acc: 0.5509 - val_f1_score: 0.5509

Epoch 00004: val_acc improved from 0.49182 to 0.55088, saving model to best_model_1/weights-04-0.5509.hdf5
 Epoch 5/40

Epoch 00005: LearningRateScheduler reducing learning rate to 0.0009025000035762787.
 221/221 [=====] - 7s 31ms/step - loss: 1.1517 - acc: 0.5912 - f1_score: 0.5912 - val_loss:

1.2488 - val_acc: 0.5730 - val_f1_score: 0.5730

Epoch 00005: val_acc improved from 0.55088 to 0.57298, saving model to best_model_1/weights-05-0.5730.hdf5
Epoch 6/40

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0009025000035762787.
221/221 [=====] - 7s 32ms/step - loss: 1.0247 - acc: 0.6363 - f1_score: 0.6363 - val_loss:
1.1455 - val_acc: 0.6065 - val_f1_score: 0.6065

Epoch 00006: val_acc improved from 0.57298 to 0.60654, saving model to best_model_1/weights-06-0.6065.hdf5
Epoch 7/40

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0008573750033974648.
221/221 [=====] - 7s 34ms/step - loss: 0.9183 - acc: 0.6742 - f1_score: 0.6742 - val_loss:
1.1127 - val_acc: 0.6297 - val_f1_score: 0.6297

Epoch 00007: val_acc improved from 0.60654 to 0.62970, saving model to best_model_1/weights-07-0.6297.hdf5
Epoch 8/40

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0008573749801144004.
221/221 [=====] - 7s 32ms/step - loss: 0.8398 - acc: 0.7012 - f1_score: 0.7012 - val_loss:
1.0648 - val_acc: 0.6401 - val_f1_score: 0.6401

Epoch 00008: val_acc improved from 0.62970 to 0.64011, saving model to best_model_1/weights-08-0.6401.hdf5
Epoch 9/40

Epoch 00009: LearningRateScheduler reducing learning rate to 0.0008573749801144004.
221/221 [=====] - 7s 31ms/step - loss: 0.7608 - acc: 0.7246 - f1_score: 0.7246 - val_loss:
1.0477 - val_acc: 0.6550 - val_f1_score: 0.6550

Epoch 00009: val_acc improved from 0.64011 to 0.65498, saving model to best_model_1/weights-09-0.6550.hdf5
Epoch 10/40

Epoch 00010: LearningRateScheduler reducing learning rate to 0.0008145062311086804.
221/221 [=====] - 8s 34ms/step - loss: 0.6859 - acc: 0.7533 - f1_score: 0.7533 - val_loss:
1.0527 - val_acc: 0.6637 - val_f1_score: 0.6637

Epoch 00010: val_acc improved from 0.65498 to 0.66369, saving model to best_model_1/weights-10-0.6637.hdf5
Epoch 11/40

Epoch 00011: LearningRateScheduler reducing learning rate to 0.0008145062020048499.
221/221 [=====] - 7s 31ms/step - loss: 0.6317 - acc: 0.7669 - f1_score: 0.7669 - val_loss:
1.0784 - val_acc: 0.6586 - val_f1_score: 0.6586

Epoch 00011: val_acc did not improve from 0.66369

Epoch 12/40

Epoch 00012: LearningRateScheduler reducing learning rate to 0.0008145062020048499.
221/221 [=====] - 7s 34ms/step - loss: 0.5992 - acc: 0.7796 - f1_score: 0.7796 - val_loss:
1.0554 - val_acc: 0.6792 - val_f1_score: 0.6792

Epoch 00012: val_acc improved from 0.66369 to 0.67920, saving model to best_model_1/weights-12-0.6792.hdf5
Epoch 13/40

Epoch 00013: LearningRateScheduler reducing learning rate to 0.0007737808919046074.
221/221 [=====] - 7s 32ms/step - loss: 0.5176 - acc: 0.8144 - f1_score: 0.8144 - val_loss:
1.0565 - val_acc: 0.6849 - val_f1_score: 0.6849

Epoch 00013: val_acc improved from 0.67920 to 0.68494, saving model to best_model_1/weights-13-0.6849.hdf5
Epoch 14/40

Epoch 00014: LearningRateScheduler reducing learning rate to 0.000773780862800777.
221/221 [=====] - 7s 32ms/step - loss: 0.4671 - acc: 0.8301 - f1_score: 0.8301 - val_loss:
1.0962 - val_acc: 0.6936 - val_f1_score: 0.6936

Epoch 00014: val_acc improved from 0.68494 to 0.69365, saving model to best_model_1/weights-14-0.6936.hdf5
Epoch 15/40

Epoch 00015: LearningRateScheduler reducing learning rate to 0.000773780862800777.
221/221 [=====] - 7s 32ms/step - loss: 0.4348 - acc: 0.8417 - f1_score: 0.8417 - val_loss:
1.1541 - val_acc: 0.6818 - val_f1_score: 0.6818

Epoch 00015: val_acc did not improve from 0.69365
Epoch 16/40

Epoch 00016: LearningRateScheduler reducing learning rate to 0.0007350918196607382.
221/221 [=====] - 7s 32ms/step - loss: 0.3879 - acc: 0.8601 - f1_score: 0.8601 - val_loss:
1.1185 - val_acc: 0.6966 - val_f1_score: 0.6966

Epoch 00016: val_acc improved from 0.69365 to 0.69662, saving model to best_model_1/weights-16-0.6966.hdf5
Epoch 17/40

Epoch 00017: LearningRateScheduler reducing learning rate to 0.0007350918021984398.
221/221 [=====] - 7s 32ms/step - loss: 0.3483 - acc: 0.8739 - f1_score: 0.8739 - val_loss:
1.1962 - val_acc: 0.6924 - val_f1_score: 0.6924

Epoch 00017: val_acc did not improve from 0.69662
Epoch 18/40

Epoch 00018: LearningRateScheduler reducing learning rate to 0.0007350918021984398.

221/221 [=====] - 7s 32ms/step - loss: 0.3308 - acc: 0.8807 - f1_score: 0.8807 - val_loss: 1.2661 - val_acc: 0.7043 - val_f1_score: 0.7043

Epoch 00018: val_acc improved from 0.69662 to 0.70427, saving model to best_model_1/weights-18-0.7043.hdf5
Epoch 19/40

Epoch 00019: LearningRateScheduler reducing learning rate to 0.0006983372120885178.

221/221 [=====] - 8s 34ms/step - loss: 0.2883 - acc: 0.8989 - f1_score: 0.8989 - val_loss: 1.3144 - val_acc: 0.6985 - val_f1_score: 0.6985

Epoch 00019: val_acc did not improve from 0.70427
Epoch 20/40

Epoch 00020: LearningRateScheduler reducing learning rate to 0.0006983372149989009.

221/221 [=====] - 7s 32ms/step - loss: 0.2609 - acc: 0.9050 - f1_score: 0.9050 - val_loss: 1.3664 - val_acc: 0.6956 - val_f1_score: 0.6956

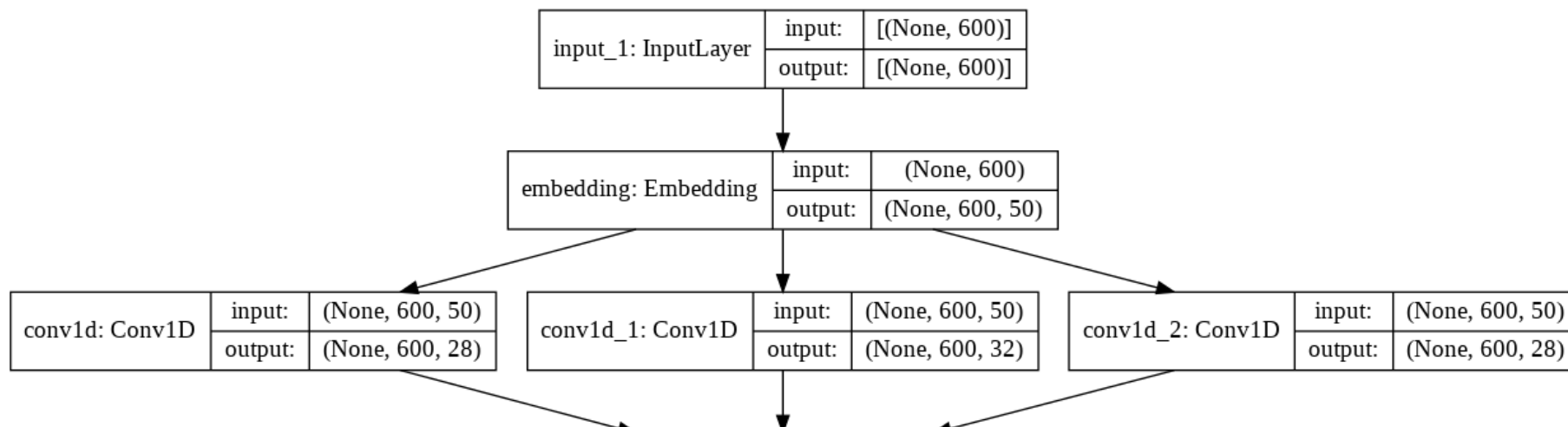
Epoch 00020: val_acc did not improve from 0.70427
Epoch 00020: early stopping

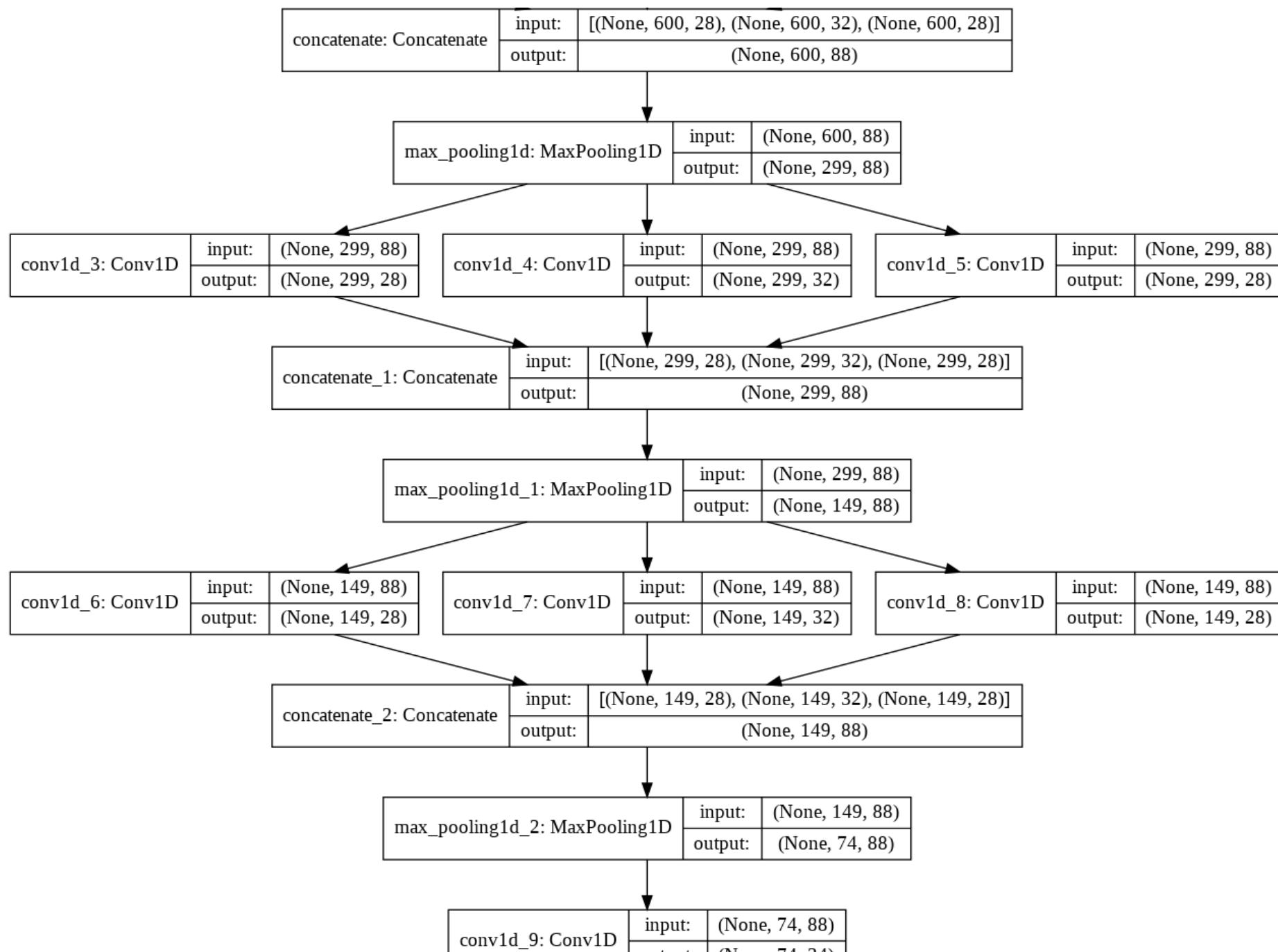
Out[]: <tensorflow.python.keras.callbacks.History at 0x7f8ffa6c5290>

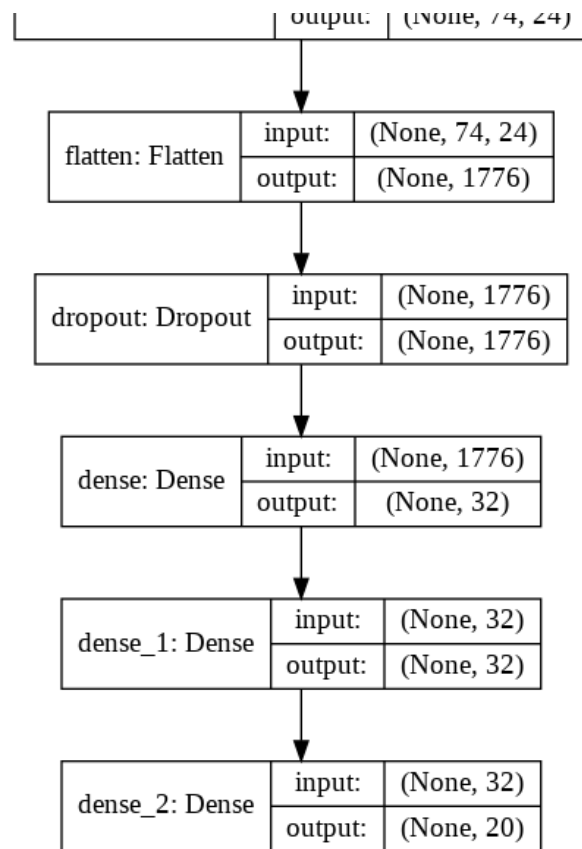
Model shapes & structure plots

```
In [ ]: from tensorflow.keras.utils import plot_model
plot_model(model, to_file='model_1_plot.png', show_shapes=True, show_layer_names=True)
#model.summary()
```

Out[]:







TASK 2

Model-2 : Using 1D convolutions with character embedding

Use 1D-convolutions!

Input tweet sliced by characters

0	0	0	0	0	0	0		0	0	0	0	0	0
1	0	0	0	0	0	0		0	0	0	0	0	0
0	0	0	0	0	0	1		0	0	0	0	0	0
0	1	0	0	1	0	0		0	0	0	0	0	0
0	0	0	0	0	0	0		0	1	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	1	0	0	0	0		1	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

Input channel = alphabet size = 70 channels

140 characters

1 1D kernel

1	0	1
---	---	---

Batch: 1 image
Input channel: 70
Output channel: 1
Output shape: (1, 1, 136)

256 1D kernels

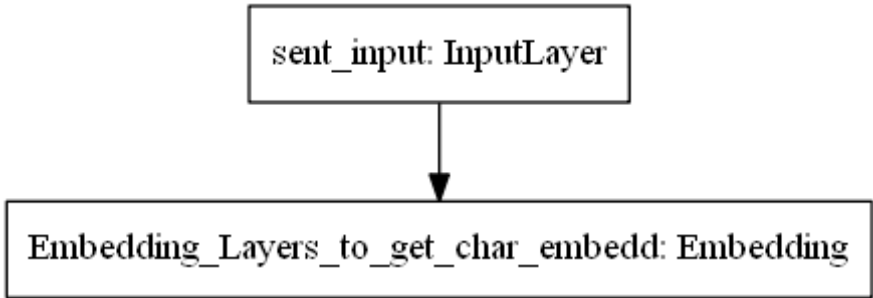
1	0	1
---	---	---

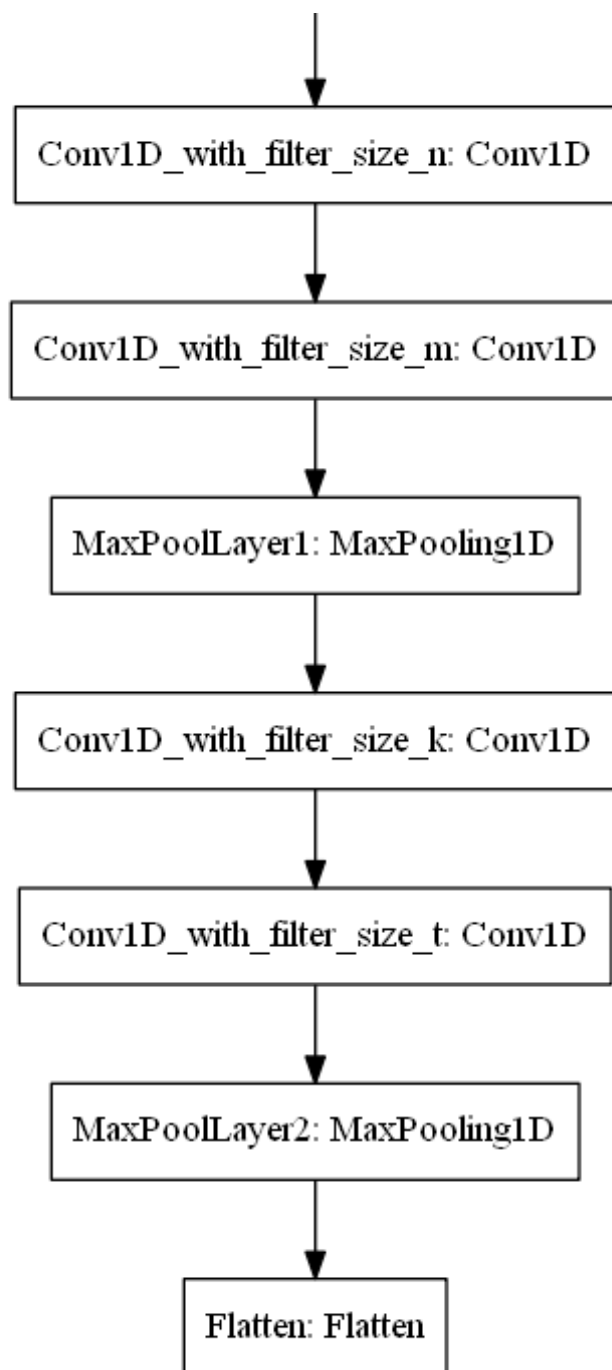
...

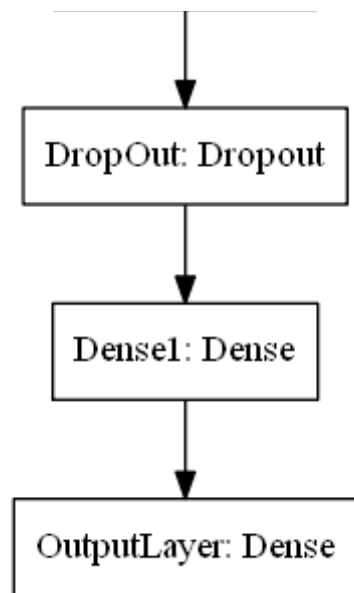
1	0	1
---	---	---

Here are the some papers based on Char-CNN

1. Xiang Zhang, Junbo Zhao, Yann LeCun. [Character-level Convolutional Networks for Text Classification](#). NIPS 2015
2. Yoon Kim, Yacine Jernite, David Sontag, Alexander M. Rush. [Character-Aware Neural Language Models](#). AAAI 2016
3. Shaojie Bai, J. Zico Kolter, Vladlen Koltun. [An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling](#)
4. Use the pretrained char embeddings <https://github.com/minimaxir/char-embeddings/blob/master/glove.840B.300d-char.txt>







Tokenizing & Padding for Model - 2

In [6]:

```
# reference : https://www.kdnuggets.com/2020/03/tensorflow-keras-tokenization-text-data-prep.html
# lets pad & tokenize the data:-
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Tokenize our training data
oov_token = '<UNK>' ;
tokenizer = Tokenizer(oov_token=oov_token, filters='!"#$%&()*+,-./:;<=>?@[\\]^`{|}~\t\n', char_level=True)
tokenizer.fit_on_texts(X_train)

# Get our training data character index
char_index = tokenizer.word_index
print("Length of character indices :-", len(char_index))
print('\n')
# Encode training data sentences into sequences
train_sequences = tokenizer.texts_to_sequences(X_train)

# Get max training sequence length
import statistics ; import matplotlib.pyplot as plt
lengths = [len(x) for x in train_sequences]
```

```

print("The median length of characters in the sequences :-\n",statistics.median(lengths))
plt.hist(lengths,bins = 15)
plt.xlabel('Sequence Counts')
plt.ylabel('Character length frequency')
plt.grid()
plt.yscale('log')
plt.show()

# count of lengths
count_gr2500 = 0
count_ls2500 = 0
for j in lengths:
    if j > 2500:
        count_gr2500 += 1
    else:
        count_ls2500 += 1

print("No of sentences having characters > 2500 :- \n",count_gr2500)
print("No of sentences having characters < 2500 :- \n",count_ls2500)
print("Contribution of lengthier sentences having > 2500 words :-\n",(count_gr2500)/len(lengths))

# Pad the training sequences
train_padded = pad_sequences(train_sequences,padding = 'post',maxlen= 2500,truncating='post')

# tokenize & Pad the testing sequences
test_sequences = tokenizer.texts_to_sequences(X_test)
test_padded = pad_sequences(test_sequences,padding='post',maxlen = 2500,truncating='post')

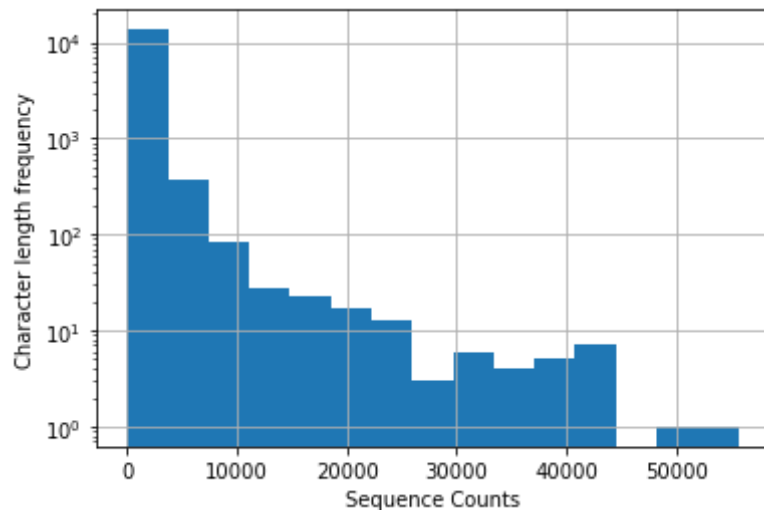
# Output the results of our work
print("\nPadded training shape:", train_padded.shape)
print("Training sequences data type:", type(train_sequences))
print("Padded Training sequences data type:", type(train_padded))

print("\nPadded testing shape:", test_padded.shape)
print("Testing sequences data type:", type(test_sequences))
print("Padded Testing sequences data type:", type(test_padded))

```

Length of character indices :- 45

The median length of characters in the sequences :-
671



No of sentences having characters > 2500 :-
1089

No of sentences having characters < 2500 :-
13032

Contribution of lengthier sentences having > 2500 words :-
0.07711918419375398

Padded training shape: (14121, 2500)
Training sequences data type: <class 'list'>
Padded Training sequences data type: <class 'numpy.ndarray'>

Padded testing shape: (4707, 2500)
Testing sequences data type: <class 'list'>
Padded Testing sequences data type: <class 'numpy.ndarray'>

Observation :

From the results of tokenizing the sequence, we can understand that only 7% of total sentences contribute for greater than 2500 characters & also its clearly evident from the histogram plotted. therefore i chose padding length to be 2500.

```
In [ ]: # Load the glove zip/rar file into colab
from google.colab import files
files.upload() # glove file for characters
# NOTE : As the uploaded file is very big, I cleared the output because of easy readeability purposes
```


Model-2: Creating character embedding layer

In []:

```
# reference :- https://blog.keras.io/using-pre-trained-word-embeddings-in-a-keras-model.html

# create map character indices to embeddings/vectors
import numpy as np
embeddings_index = {}
with open('/content/glove_300d_char.txt') as f:
    for line in f:
        values = line.split()
        _char = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_index[_char] = coefs

print('No of character vectors :-\n', len(embeddings_index))
emb_dim = coefs.shape[0]
print("Dimension of character vector :-\n", emb_dim)

# embedding matrix
embeddings_matrix = np.zeros((len(char_index) + 1, emb_dim))
for char, i in char_index.items():
    embedding_vector = embeddings_index.get(char)
    if embedding_vector is not None:
        # words not found in embedding index will be all-zeros.
        embeddings_matrix[i] = embedding_vector

# embedding layer
from tensorflow.keras.layers import Embedding
embedding_layer = Embedding(len(char_index) + 1,
                             emb_dim,
                             weights = [embeddings_matrix],
                             input_length = 2500,
                             trainable = False)

print('shape of embedding_matrix :- \n', embeddings_matrix.shape)
```

```
No of character vectors :-
94
Dimension of character vector :-
300
shape of embedding_matrix :-
(46, 300)
```

Tensorboard Results

```
In [ ]: # %load_ext tensorboard
        %reload_ext tensorboard
```

```
In [ ]: # Clear any logs of previous executions/runs
import shutil
# /content/best_model_2 # ./logfiles_model2
path='./logfiles_model2'
shutil.rmtree(path,ignore_errors=True)
```

```
In [ ]: import shutil
        # /content/best_model_1 # ./logfiles_model1
        path='./content/best_model_2'
        shutil.rmtree(path,ignore_errors=True)
```

```
In [ ]: !kill 418
```

```
In [ ]: # Tensorboard outputs
import os;import datetime ; #Reference :--> https://www.dlology.com/blog/how-to-run-tensorboard-in-jupyter-notebook/
logs_base_dir = "./logfiles_model2"
os.makedirs(logs_base_dir,exist_ok=True)# Creating a directory to store logs
# Launch the tensorboard & then refresh it after executing the model.
%tensorboard --logdir {logs_base_dir}
```

```
In [ ]: # decay learning rate scheduler
import tensorflow
def scheduler(epoch,lr):
    if ((epoch) % 4 == 0):
        lr = ((lr)-(lr*(0.05))) # 0.05
    else:
        pass
```

```
return lr
```

```
In [ ]: # for add-on metrics we need this library
!pip install tensorflow-addons
```

Collecting tensorflow-addons

Downloading https://files.pythonhosted.org/packages/66/4b/e893d194e626c24b3df2253066aa418f46a432fdb68250cde14bf9bb0700/tensorflow-addons-0.13.0-cp37-cp37m-manylinux2010_x86_64.whl (679kB)

|██| 686kB 8.8MB/s

Requirement already satisfied: typeguard>=2.7 in /usr/local/lib/python3.7/dist-packages (from tensorflow-addons) (2.7.1)

Installing collected packages: tensorflow-addons

Successfully installed tensorflow-addons-0.13.0

APPLY MODEL - 2 & DISPLAY RESULTS

```
In [ ]: # functional API
import tensorflow as tf
tf.keras.backend.clear_session()# For easy reset of notebook state
tf.random.set_seed(1234)
import tensorflow_addons as tfa ; import os
from tensorflow.keras import layers, Input
from tensorflow.keras import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dropout, Flatten, Dense, Conv1D, MaxPooling1D, BatchNormalization
from tensorflow.keras.callbacks import ModelCheckpoint
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.callbacks import LearningRateScheduler
from tensorflow.keras.initializers import HeNormal

# Inputs
x = Input(shape=(2500,))
initializer = HeNormal(seed = 32)
embedded_sequences = embedding_layer(x)

x1 = Conv1D(32,3,activation='relu',padding = 'same',kernel_initializer = initializer)(embedded_sequences)
x2 = Conv1D(32,3,activation='relu',padding = 'same',kernel_initializer = initializer)(x1)
```

```

y = MaxPooling1D(3, strides = 2)(x2)

y1 = Conv1D(24, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(y)
y2 = Conv1D(24, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(y1)

z = MaxPooling1D(3, strides = 2)(y2)

z1 = Conv1D(24, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(z)
z2 = Conv1D(24, 3, activation='relu', padding = 'same', kernel_initializer = initializer)(z1)

z3 = Flatten()(z2)
z4 = Dropout(0.3)(z3)
z5 = Dense(36, activation='relu', kernel_initializer = initializer)(z4)
z6 = Dense(20, activation='softmax', kernel_initializer = 'glorot_normal')(z5)

# model
model = Model(inputs = x, outputs = z6)

# optimizer
optimizer = Adam(learning_rate = 0.001)

# save model at every epoch end if validation accuracy is improved
filepath = "best_model_2/weights-{epoch:02d}-{val_acc:.4f}.hdf5"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val_acc', verbose=1, save_best_only=True, mode='auto')

# early stopping
earlystop = EarlyStopping(monitor='val_acc', patience=2, verbose=1)

# tensorboard callbacks # reference :-> https://www.dlology.com/blog/how-to-run-tensorboard-in-jupyter-notebook/
log_dir = os.path.join(logs_base_dir, datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
tb_callback = TensorBoard(log_dir=log_dir, histogram_freq=1)

# Lr schedule
lrschedule = LearningRateScheduler(scheduler, verbose = 1)

# metric
f1score = tf.keras.metrics.F1Score(num_classes = 20, average = 'micro')

model.compile(loss='categorical_crossentropy',
              optimizer=optimizer,
              metrics=['acc', f1score])

# Model fit

```

```
model.fit(train_padded,ytrain_labels, validation_data=(test_padded,ytest_labels),
          epochs=50, batch_size=64,callbacks = [earlystop,checkpoint,lrschedule,tb_callback])
```

Epoch 1/50

Epoch 00001: LearningRateScheduler reducing learning rate to 0.0009500000451225787.
221/221 [=====] - ETA: 0s - loss: 2.9545 - acc: 0.0795 - f1_score: 0.0795

/usr/local/lib/python3.7/dist-packages/tensorflow/python/keras/metrics.py:257: UserWarning: Metric F1Score implements a `reset_states()` method; rename it to `reset_state()` (without the final "s"). The name `reset_states()` has been deprecated to improve API consistency.

'consistency.' % (self.__class__.__name__,))
221/221 [=====] - 19s 84ms/step - loss: 2.9545 - acc: 0.0795 - f1_score: 0.0795 - val_loss: 2.9418 - val_acc: 0.0758 - val_f1_score: 0.0758

Epoch 00001: val_acc improved from -inf to 0.07584, saving model to best_model_2/weights-01-0.0758.hdf5
Epoch 2/50

Epoch 00002: LearningRateScheduler reducing learning rate to 0.0009500000160187483.
221/221 [=====] - 19s 87ms/step - loss: 2.9276 - acc: 0.0868 - f1_score: 0.0867 - val_loss: 2.9312 - val_acc: 0.0850 - val_f1_score: 0.0850

Epoch 00002: val_acc improved from 0.07584 to 0.08498, saving model to best_model_2/weights-02-0.0850.hdf5
Epoch 3/50

Epoch 00003: LearningRateScheduler reducing learning rate to 0.0009500000160187483.
221/221 [=====] - 17s 78ms/step - loss: 2.8978 - acc: 0.0969 - f1_score: 0.0969 - val_loss: 2.9213 - val_acc: 0.0865 - val_f1_score: 0.0865

Epoch 00003: val_acc improved from 0.08498 to 0.08647, saving model to best_model_2/weights-03-0.0865.hdf5
Epoch 4/50

Epoch 00004: LearningRateScheduler reducing learning rate to 0.0009500000160187483.
221/221 [=====] - 19s 87ms/step - loss: 2.8288 - acc: 0.1200 - f1_score: 0.1200 - val_loss: 2.8884 - val_acc: 0.1050 - val_f1_score: 0.1050

Epoch 00004: val_acc improved from 0.08647 to 0.10495, saving model to best_model_2/weights-04-0.1050.hdf5
Epoch 5/50

Epoch 00005: LearningRateScheduler reducing learning rate to 0.0009025000152178108.
221/221 [=====] - 17s 78ms/step - loss: 2.7206 - acc: 0.1535 - f1_score: 0.1535 - val_loss: 2.9262 - val_acc: 0.1058 - val_f1_score: 0.1058

Epoch 00005: val_acc improved from 0.10495 to 0.10580, saving model to best_model_2/weights-05-0.1058.hdf5
Epoch 6/50

Epoch 00006: LearningRateScheduler reducing learning rate to 0.0009025000035762787.
221/221 [=====] - 19s 87ms/step - loss: 2.5906 - acc: 0.1959 - f1_score: 0.1959 - val_loss:
2.9637 - val_acc: 0.1060 - val_f1_score: 0.1060

Epoch 00006: val_acc improved from 0.10580 to 0.10601, saving model to best_model_2/weights-06-0.1060.hdf5
Epoch 7/50

Epoch 00007: LearningRateScheduler reducing learning rate to 0.0009025000035762787.
221/221 [=====] - 17s 79ms/step - loss: 2.4381 - acc: 0.2309 - f1_score: 0.2309 - val_loss:
3.1042 - val_acc: 0.0992 - val_f1_score: 0.0992

Epoch 00007: val_acc did not improve from 0.10601
Epoch 8/50

Epoch 00008: LearningRateScheduler reducing learning rate to 0.0009025000035762787.
221/221 [=====] - 19s 87ms/step - loss: 2.2726 - acc: 0.2879 - f1_score: 0.2879 - val_loss:
3.2127 - val_acc: 0.0958 - val_f1_score: 0.0958

Epoch 00008: val_acc did not improve from 0.10601
Epoch 00008: early stopping

Out[]: <tensorflow.python.keras.callbacks.History at 0x7f120f75be50>

Model shapes & structure plots

```
In [ ]: from tensorflow.keras.utils import plot_model
plot_model(model, to_file='model_2_plot.png', show_shapes=True, show_layer_names=True)
#model.summary()
```

Out[]:

