Comparative Analysis of Neural Networks and General NLP Methods on An Academic Journal Article Database

Self-collected database; NLP methods used; FNN tuned; DNN constructed and compared, thourough analysis

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Template I Use

- **CM3015-Machine Learning and Neural Network**.
- I have combined the two templates (1. Deep Learning on a public dataset; 2. Gather your own dataset) in this course provided, to do my own project.
- I have done a deep learning classification project, on a topic - **academic journal articles**, **use the whole article body text as the data**.

Features of My Project

- Collect dataset on my own (using an API)
- Outstanding text-cleansing work
- Tune hyperparameters in FNN using controlled experiments
- Try to find the best FNN using GridSearchCV
- Have constructed DNN based on pre-trained existing models, including CNN, RNN with LSTM layer, etc.
- Use different combinations of 3 vectorizers (TF-IDF, Count Vectorizer, Bigram) and 4 classifiers (SVC, MNB, Random Forest, KNN) in NLP and compare their performance
- Have attempted to use the methods in literature review (AWD-LSTM, ULMFiT FastAI, Wikipedia2Vec, BERT-for-Task, ...)

Literature Review – Text Classification

Previous Methods	01	02	03
Paper	*Large Scale Subject Category Classification of Scholarly Papers with Deep Attentive Neural Networks*	*Regularizing and optimizing LSTM language models*	*Universal Language Model Fine-Tuning for Text Classification*
Author	Kandimalla et al.	Merity, Keskar, and Socher	Howard and Ruder
Data Source	Web of Science (WoS), year 2015	2 datasets: Penn Treebank; WikiText-2	6 datasets: TREC-6; IMDb; Yelp-bi; Yelp-full; AG; DBpedia
Main Idea	Propose a deep attentive neural network (DANN) that classifies scholarly papers using only their abstracts	Weight-dropped LSTM; introduce various regularization techniques in LSTM	Propose a new model - universal LSTM model fine-tuning for classification (ULMFiT)
Methods	The proposed network consists of two bidirectional recurrent neural networks followed by an attention layer. Compare their models and others.	Uses a method called 'DropConnect' to subtitute the Dropout neurons in regularization, since Dropouts will weaken the long-distance ability. Other than dropouts, they do not use SGD here, but investigate ASGD (averaged SGD)	Phase 1: General-domain LM pretraining; Phase 2: Target task LM fine-tuning – skills: (1) Discrivinative fine-tuning, (2) Slanted triangular learning rate; Phase 3: Target task classifier fine-tuning – skills: (1) Concat pooling, (2) Gradual unfreezing, (3) BPT3C, (4) Bidirectional language model;
Results	(1) The combination of word vectors with TFIDF outperforms character and sentence level embedding models; (2) FastText + BiGRU + Attn and FastText+BiLSTM + Attn (micro-F1 =0.76); (3) Retraining FastText and GloVe improves the performance; (4) Character-level embedding models often perform worse than word-level embedding models; (5) The best machine learning model (LR) is outperformed by the best DANN model by roughly 10%.	ASGD has a better effect. 'DropConnect' is effective.	ULMFiT significantly outperformed existing transfer learning techniques and the stateof-the-art on six representative text classification tasks.

Justified Based on Domain and Users

- (1) real journal platforms in academia (e.g. Nature, Science, etc.) to classify newly received articles and therefore simplify the procedure before posting new articles, and will make the news being published more timely without manual work; may stimulate an interdisciplinary collaboration between these platforms and data science platforms to add comprehensive metadata for information retrieval;
- (2) librarianship field, by boosting the development of computer-based technologies to do part of the librarian jobs, and to stimulate the debate of human work vs. computer work;
- (3) real journal platforms if I can find any obstacles or difficulties when developing my project, and will contribute furthermore if I could possibly propose methods to solve them;
- (4) philosophical field, by exploring potential difficulties and proposing possible solutions, since classification is a very basic concept in philosophy;
- (5) students studying in academia (e.g. postgraduate applicants, doctoral students) who have a strong pressure or focus on publishing papers, by receiving stimulation and inspirations found from my project. For instance, the top list of keywords shown in each academic subject can be a hint to expand the students' academic vocabulary set;
- (6) teachers working in academia who need a timely update for the recent research trend, to stimulate their own research and to give their students a prospective working direction;
- (7) data scientists and computer scientists who are also interested in text classification methods. If my models are well-tuned, they may be applied more widely as a transfer learning example, not only in my own dataset, but also in other label-classifications in NLP field, such as sentiment classification, or even image classification. Data scientists may find new inspirations on labelling articles.

Collect Data – from EventRegistry.org

- Their API: https://www.newsapi.ai/documentation/sandbox?tab=searchArticles
- I copied their codes from the sandbox to my own Jupyter Notebook file, and output the retrieved data into JSON files.

In [4]:
```
import json

er = EventRegistry(apiKey = '5d9ca3e2-04a6-4cf5-b47c-4346d55c385a')
qStr = """
{
    "$query": {
        "$and": [
            {
                "categoryUri": "dmoz/Science/Earth_Sciences"
            },
            {
                "sourceGroupUri": "science/top15"
            },
            {
                "lang": "eng"
            }
        ]
    },
    "$filter": {
        "forceMaxDataTimeWindow": "31",
        "dataType": [
            "news"
        ]
    }
}
"""
q = QueryArticlesIter.initWithComplexQuery(qStr)
# change maxItems to get the number of results that you want
for article in q.execQuery(er, maxItems=100):
    with open('D:/University-of-London-2020/CM3070-Computer-Science-Final-Project/datasets/Event_registry_search_results/API/output.js
        f.write(json.dumps(article,ensure_ascii=True))
```

Collect Data – from EventRegistry.org

- Then I convert those JSON files into EXCEL format, and combine them. The following is the snapshot for the combined file.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC
1		record	uri	lang	isDuplicate	date	time	dateTime	lateTimePu	dataType	sim	url	title	body	source	uri.1	dataType.1	title.1	image	eventUri	sentiment	wgt	relevance	authors	uri.2	name	type	isAgency	category
2	0		7.22E+09	eng	FALSE	2022-10-0	17:31:00	2022-10-0	2022-10-0	news	0	https://wv	Towards a	When studying physic		nature.con	news	Nature	https://media.springe		0.011765	25	25						biology
3	1		7.23E+09	eng	FALSE	2022-10-1	16:35:00	2022-10-1	2022-10-1	news	0	https://wv	Efficient ar	Human pluripotent ste		nature.con	news	Nature	https://media.springe		0.223529	24	24						biology
4	2		7.21E+09	eng	FALSE	2022-10-0	15:56:00	2022-10-0	2022-10-0	news	0.729412	https://wv	c-Myb red	When worn out, most		nature.con	news	Nature	https://me	eng-80682	-0.02745	24	24						biology
5	3		7.22E+09	eng	FALSE	2022-10-1	14:17:00	2022-10-1	2022-10-1	news	0.619608	https://wv	Co-express	Here, to examine the		nature.con	news	Nature	https://me	eng-80994	0.137255	23	23						biology
6	4		7.21E+09	eng	FALSE	2022-09-2	10:31:00	2022-09-2	2022-09-2	news	0.54902	https://wv	Changes in	In our work, we have		nature.con	news	Nature	https://me	eng-80570	-0.05098	23	23						biology
7	5		7.23E+09	eng	FALSE	2022-10-1	15:14:00	2022-10-1	2022-10-1	news	0.533333	https://wv	scRNA-seq	Here, in our study, we		nature.con	news	Nature	https://me	eng-81077	-0.27059	22	22						biology
8	6		7.22E+09	eng	FALSE	2022-10-1	04:22:00	2022-10-1	2022-10-1	news	0	https://wv	Epigenetic	Epigenetic modificatic		nature.con	news	Nature	https://media.springe		0.160784	22	22						biology
9	7		7.21E+09	eng	FALSE	2022-09-2	15:55:00	2022-09-2	2022-09-2	news	0	https://wv	Rigid tumo	The ability for cancer c		nature.con	news	Nature	https://media.springe		-0.09804	22	22						biology
10	8		7.23E+09	eng	FALSE	2022-10-1	16:12:00	2022-10-1	2022-10-1	news	0.580392	https://wv	Establishm	During early mammal		nature.con	news	Nature	https://me	eng-80994	0.207843	21	21						biology
11	9		7.22E+09	eng	FALSE	2022-10-1	10:04:00	2022-10-1	2022-10-1	news	0.678431	https://wv	Naive pluri	Cells positive for SSEA		nature.con	news	Nature	https://me	eng-80994	0.145098	21	21						biology
12	10		7.21E+09	eng	FALSE	2022-09-2	20:28:00	2022-09-2	2022-09-2	news	0	https://wv	Autosis an	Historical Perspective		nature.con	news	Nature	https://media.springe		-0.30196	21	21						biology
13	11		7.23E+09	eng	FALSE	2022-10-2	15:37:00	2022-10-2	2022-10-2	news	0	https://wv	Multiplexe	In this study, we used		nature.con	news	Nature	https://media.springe		-0.2549	20	20						biology
14	12		7.23E+09	eng	FALSE	2022-10-2	15:35:00	2022-10-2	2022-10-2	news	0	https://wv	Unapprecia	CD40 has long been k		nature.con	news	Nature	https://media.springe		-0.05882	20	20						biology
15	13		7.23E+09	eng	FALSE	2022-10-1	17:01:00	2022-10-1	2022-10-1	news	0	https://wv	Characteri	Induced pluripotent st		nature.con	news	Nature	https://media.springe		0.176471	20	20						biology
16	14		7.23E+09	eng	FALSE	2022-10-1	08:22:00	2022-10-1	2022-10-1	news	0	https://wv	Online sing	SCALEX implements a		nature.con	news	Nature	https://media.springe		0.035294	20	20						biology
17	15		7.23E+09	eng	FALSE	2022-10-1	17:18:00	2022-10-1	2022-10-1	news	0.592157	https://wv	VASA prot	Our studies aimed to a		nature.con	news	Nature	https://me	eng-80994	0.113725	20	20						biology
18	16		7.22E+09	eng	FALSE	2022-10-1	08:19:00	2022-10-1	2022-10-1	news	0	https://wv	Drug toxici	Different response of		nature.con	news	Nature	https://media.springe		0.2	20	20						biology
19	17		7.22E+09	eng	FALSE	2022-10-1	16:27:00	2022-10-1	2022-10-1	news	0	https://wv	Deep learn	Constructing single-ce		nature.con	news	Nature	https://media.springernature.cor			20	20						biology
20	18		7.22E+09	eng	FALSE	2022-10-1	10:19:00	2022-10-1	2022-10-1	news	0	https://wv	Corynoxine	In this study, we aime		nature.con	news	Nature	https://media.springe		-0.05882	20	20						biology
21	19		7.22E+09	eng	FALSE	2022-10-1	17:22:00	2022-10-1	2022-10-1	news	0	https://wv	Clinical imp	More definitive conclu		nature.con	news	Nature	https://media.springe		-0.07451	20	20						biology
22	20		7.21E+09	eng	FALSE	2022-10-0	16:45:00	2022-10-0	2022-10-0	news	0.72549	https://wv	Mouse em	For more than 100 yea		nature.con	news	Nature	https://me	eng-80719	0.160784	20	20						biology
23	21		7.21E+09	eng	FALSE	2022-10-0	14:06:00	2022-10-0	2022-10-0	news	0.619608	https://wv	Local immu	Overwhelming systen		nature.con	news	Nature	https://me	eng-80682	-0.08235	20	20						biology
24	22		7.21E+09	eng	FALSE	2022-09-2	13:10:00	2022-09-2	2022-09-2	news	0.490196	https://wv	In vivo lab	Cell neighbourhoods a		nature.con	news	Nature		eng-80570	-0.19216	20	20						biology
25	23		7.2E+09	eng	FALSE	2022-09-2	21:00:00	2022-09-2	2022-09-2	news	0	https://wv	Decipherin	Evolutionary theory h		nature.con	news	Nature	https://media.springe		-0.22353	20	20						biology
26	24		7.2E+09	eng	FALSE	2022-09-2	15:36:00	2022-09-2	2022-09-2	news	0	https://wv	Advancing	The workshop focused		nature.con	news	Nature	https://media.springe		0.207843	20	20						biology
27	25		7.23E+09	eng	FALSE	2022-10-2	00:05:00	2022-10-2	2022-10-2	news	0	https://wv	New insigh	HESC cultures have be		nature.con	news	Nature	https://media.springe		-0.06667	19	19						biology
28	26		7.23E+09	eng	FALSE	2022-10-2	20:09:00	2022-10-2	2022-10-2	news	0	https://wv	Impact of t	We generated human		nature.con	news	Nature	https://media.springe		0.035294	19	19						biology

The article body (full content)

Feature X

The academic news platform

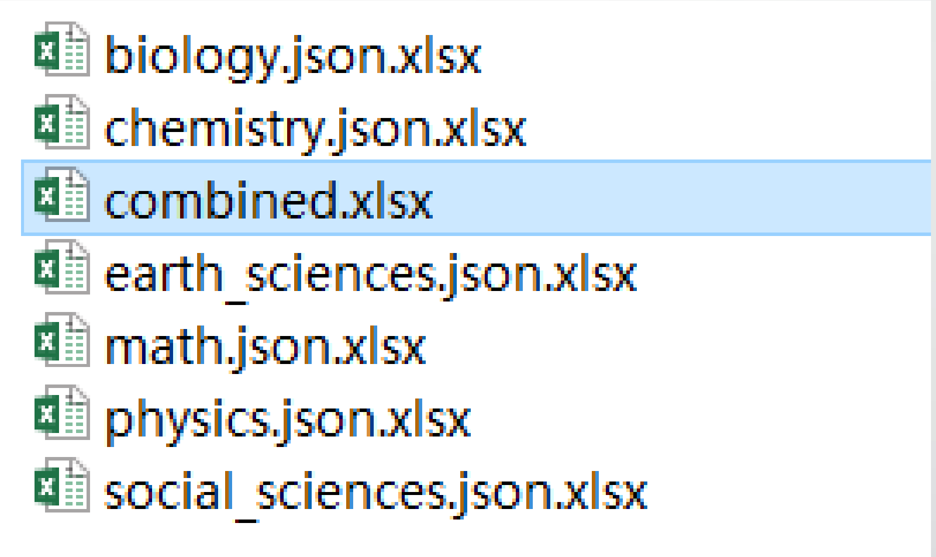
The subject col

(here it is 'biology')

Target Y

Collect Data – from EventRegistry.org

- 6 classes:
  - Biology
  - Chemistry
  - Earth Sciences
  - Math
  - Physics
  - Social Sciences



- Commonsense baseline = 1/6 = 0.167

Codes Implemented

- Preprocessing: **Remove unwanted characters; Lowercase and expand contractions; Remove stopwords & lemmatisation.**

```
In [33]: def stopword_lemmatizing(word_list):
             '''
             Remove Stopwords, Punctuations, and also Lemmatize the Original Input
             I will do two steps of lemmatization - the verb version, and the noun version.

             Parameters:
                 A list which contains many word strings.

             Returns:
                 The stopwords-removed and lemmatized version of this list, also containing word strings.
             '''
             result = []
             # Below order is important! We should always firstly remove stopwords
             # Otherwise, stopwords would change their form!

             for word in word_list:  # for each string in the list
                 word = word.lower()   # to get the lower form of each w
                 if not word in stop_words:   # to remove stop words.
                     if not word in string.punctuation:   # Notice: her
                         word_n = wnl.lemmatize(word, pos='n')   # to le
                         word_v = wnl.lemmatize(word_n, pos='v')   # to

                         result.append(word_v)

             return result
```

Algorithm 4.2-2: Expand Contractions & Lowercase

Input: a text string *text*

contractions ← set rules for contractions; *new_text* ← an empty list to store future list of word strings
for each character *char* in *text*:
  if *char* is not space:
    read the *char*, and append it into a temporary variable
  else if *char* is space:
    join each character to form the word, and lowercase the word
    if that word is in the *contractions*:
      append the full version to *new_text*
    else:
      just append this word to *new_text*
text ← use space to join these words, then delete spaces at beginning and the end

Output: the new version of that string of *text*

- I have also output my cleansed text data into files, for later to use.

Codes Implemented

- Control randomness

```
In [43]: # Set the random seeds,
         # of the variables.
         import random
         random.seed(15)
         np.random.seed(15)
         tf.random.set_seed(15)
```

- Transform and feed data to Keras
- Text data ⟶ numerical data

```
In [50]: # Below codes are from https://github.com/codehax41/BBC-Text-Classification/blob/master/BBC%20usi
         num_words_input = 600 # We should set the max number of crucial words to be identified.
         # Notice that Keras does not input all of the texts. It only uses important words.
         tok = keras.preprocessing.text.Tokenizer(num_words=num_words_input,
                                                   lower=True,    # convert to lowercase
                                                   char_level=False)
         # The above process will filter default punctuations.

         tok.fit_on_texts(X_train_pre)  # fit tokenizer to our training text data

         X_train = tok.texts_to_matrix(X_train_pre)
         X_test = tok.texts_to_matrix(X_test_pre)
```

```
In [53]: # This cell of codes is from: https://github.com/codehax41/BBC-
         #Use sklearn utility to convert label strings to numbered index
         encoder = LabelEncoder()
         encoder.fit(Y_train_pre)
         Y_train = encoder.transform(Y_train_pre)
         Y_test = encoder.transform(Y_test_pre)
         # Converts the labels to a one-hot representation
         num_classes = np.max(Y_train) + 1
         Y_train = keras.utils.to_categorical(Y_train, num_classes)
         Y_test = keras.utils.to_categorical(Y_test, num_classes)
```

```
In [54]: Y_train[300]   # check. It should be a one-hot encoding array

Out[54]: array([0., 0., 0., 1., 0., 0.], dtype=float32)
```

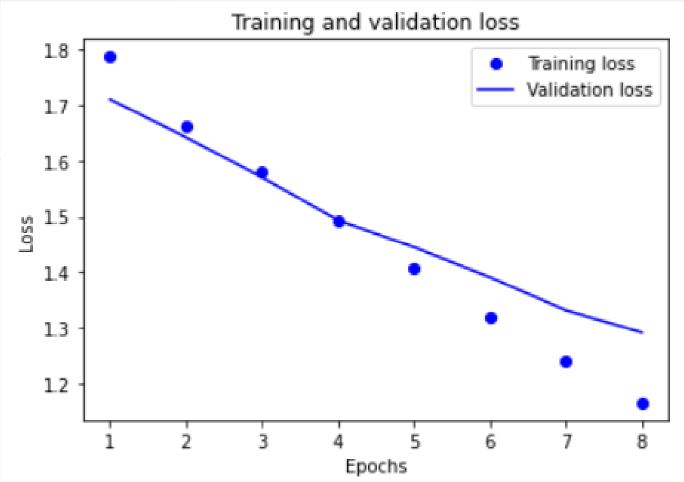
Codes Implemented

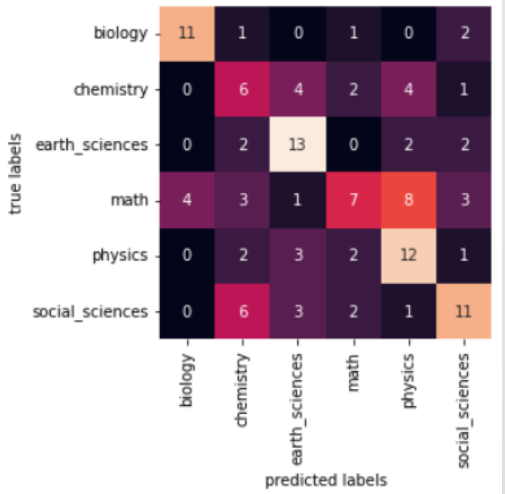
- A small underfitting ML model (Chollet Step 5)

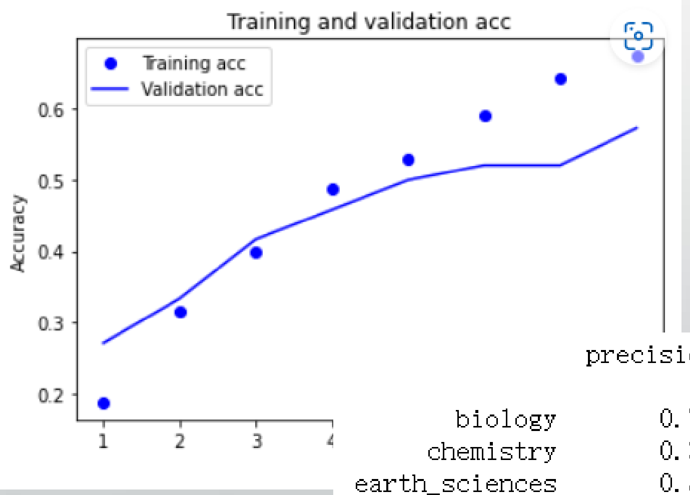
In [82]:
```
# This cell of codes is from our lecture material, the lab REUTERS.
from tensorflow.keras import models
from tensorflow.keras import layers

model_small = models.Sequential()
model_small.add(layers.Dense(16, activation = 'relu', input_shape = (num_words_input, ))) # input 600
model_small.add(layers.Dense(16, activation = 'relu'))
model_small.add(layers.Dense(6, activation = 'softmax'))
# Notice that for multi-class classification task, the last layer should choose 'softmax' as the
# activation function.

model_small.compile(optimizer = 'rmsprop',
              loss = 'categorical_crossentropy',
              # Notice that the Chollet book emphasizes that 'categorical_crossentropy' is always used
              # because 'It minimizes the distance between the probability distributions output by
              # the model and the true distribution of the targets'.
              metrics = ['accuracy'])
```

In [83]:
```
# train-validation splitting
X_train_partial2, X_val2, Y_train_partial2, Y_val2 = train_test_split(
    X_train2, Y_train2, test_size=0.20, random_state=15)
# we set a random state in order to repeat the experiment later

history_small = model_small.fit(X_train_partial2,
                    Y_train_partial2,
                    batch_size=64,
                    epochs=8,   # we set a small epoch
                    validation_data=(X_val2, Y_val2))
```

```
Epoch 1/8
6/6 [==============================] - 1s 68ms/step - loss: 1.7867 - accuracy: 0.1875 - val_loss: 1.70
98 - val_accuracy: 0.2708
Epoch 2/8
6/6 [==============================] - 0s 10ms/step - loss: 1.6607 - accuracy: 0.3151 - val_loss: 1.64
19 - val_accuracy: 0.3333
Epoch 3/8
6/6 [==============================] - 0s 11ms/step - loss: 1.5810 - accuracy: 0.3984 - val_loss: 1.57
02 - val_accuracy: 0.4167
Epoch 4/8
```





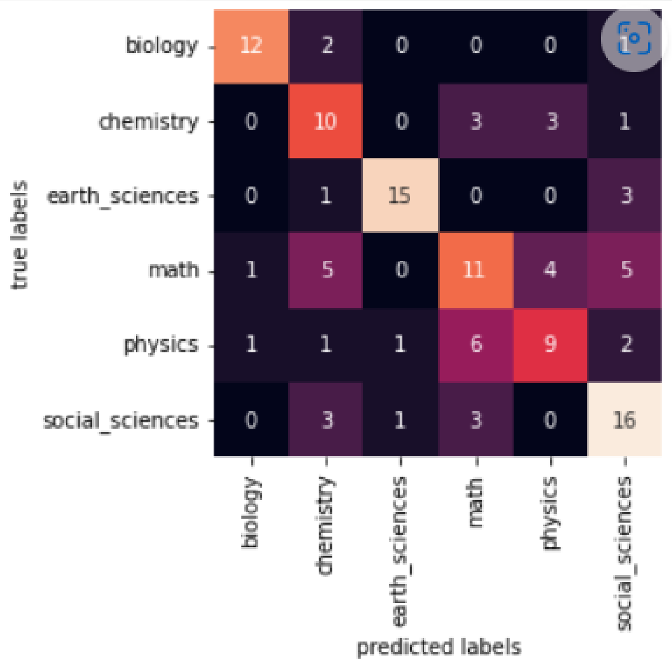


	precision	recall	f1-score	support
biology	0.73	0.73	0.73	15
chemistry	0.30	0.35	0.32	17
earth_sciences	0.54	0.68	0.60	19
math	0.50	0.27	0.35	26
physics	0.44	0.60	0.51	20
social_sciences	0.55	0.48	0.51	23
accuracy			0.50	120
macro avg	0.51	0.52	0.51	120
weighted avg	0.51	0.50	0.49	120

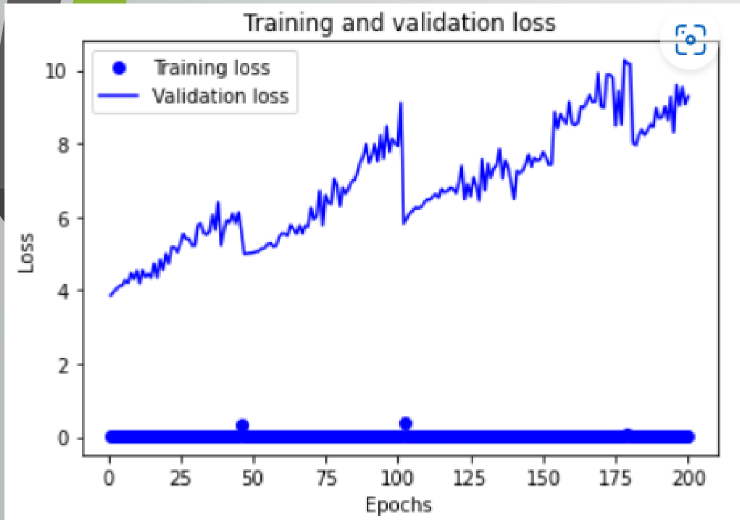
Codes Implemented

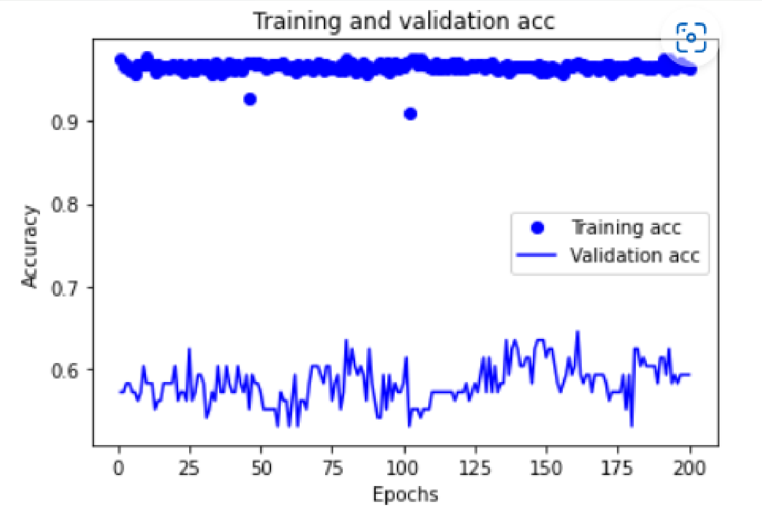
- An overfitting ML model (Chollet Step 6)

```
In [67]: # This cell of codes is from our lecture material, the lab REUTERS.
from tensorflow.keras import models
from tensorflow.keras import layers

model_overfit = models.Sequential()
model_overfit.add(layers.Dense(16, activation = 'relu', input_shape = (num_words_input, ))) # input 600
model_overfit.add(layers.Dense(128, activation = 'relu'))
model_overfit.add(layers.Dense(256, activation = 'relu'))
model_overfit.add(layers.Dense(256, activation = 'relu'))
model_overfit.add(layers.Dense(16, activation = 'relu'))
model_overfit.add(layers.Dense(6, activation = 'softmax'))
# Notice that for multi-class classification task, the last layer should choose 'softmax' as the
# activation function.

model_overfit.compile(optimizer = 'rmsprop',
              loss = 'categorical_crossentropy',
              # Notice that the Chollet book emphasizes that 'categorical_crossentropy' is always used
              # because 'It minimizes the distance between the probability distributions output by
              # the model and the true distribution of the targets'.
              metrics = ['accuracy'])
```



	precision	recall	f1-score	support
biology	0.86	0.80	0.83	15
chemistry	0.45	0.59	0.51	17
earth_sciences	0.88	0.79	0.83	19
math	0.48	0.42	0.45	26
physics	0.56	0.45	0.50	20
social_sciences	0.57	0.70	0.63	23
accuracy			0.61	120
macro avg	0.63	0.62	0.63	120
weighted avg	0.62	0.61	0.61	120





Controlled experiments results – batch size

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	**Batch size**	# hidden layers	Neuron nums	Activation functions	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Dec 09	Cleansed	15	15	15	600	20	**1024**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.5667	1.1342
Dec 09	Cleansed	15	15	15	600	20	**512**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.5750	1.1667
Dec 09	Cleansed	15	15	15	600	20	**256**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.6250	1.0836
Dec 09	Cleansed	15	15	15	600	20	**128**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.6333	1.0605
Dec 09	Cleansed	15	15	15	600	20	**64**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	**0.6750**	1.1273
Dec 09	Cleansed	15	15	15	600	20	**32**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.6250	1.2453
Dec 09	Cleansed	15	15	15	600	20	**16**	1	64-64-6	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.5500	1.3784

Based on my controlled settings, the best performing **batch size is 64** when operated on Feb 09, with accuracy=0.675. I have found an increasing-then-decreasing pattern of the accuracies when the batch size goes down.

- Controlled experiments results – number of layers

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	**# hidden layers**	Neuron nums	Activation functions	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Jan 31	Clean sed	15	15	15	600	20	**64**	**1**	**256-256-6**	relu-relu-softmax	rmsprop	categorical_crossentropy	-	**0.6916666626930237**	1.1270121335983276
Jan 31	Clean sed	15	15	15	600	20	**256**	**3**	**128-128-128-128-6**	relu-relu- relu-relu-softmax	rmsprop	categorical_crossentropy	-	**0.699999988079071**	1.0144932270050049
Jan 31	Clean sed	15	15	15	600	20	**128**	**0**	**128-6**	relu-softmax	rmsprop	categorical_crossentropy	-	**0.699999988079071**	0.9842715859413147
Jan 31	Clean sed	15	15	15	600	20	**128**	**1**	**128-128-6**	relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.6583333611488342	1.0232696533203125
Jan 31	Clean sed	15	15	15	600	20	**128**	**2**	**128-128-128-6**	relu- relu-relu-softmax	rmsprop	categorical_crossentropy	-	**0.699999988079071**	0.9746896624565125

I have run 7 records * (3 settings * 2 repetitions) = 42 experiments, using different settings. The best numbers of layers are quite unpredictable.
The best layer number covers all from 0 to 4 in my 6 groups of experiments.

Controlled experiments results – activation functions

Experiments Records – activation functions

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	**Activation functions**	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-relu-softmax**	rmsprop	categorical_crossentropy	-	0.65	1.0465116818745932
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-softmax-softmax**	rmsprop	categorical_crossentropy	-	0.49166667	1.6607657194137573
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-sigmoid-softmax**	rmsprop	categorical_crossentropy	-	0.675	0.9671117067337036
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-tanh-softmax**	rmsprop	categorical_crossentropy	-	0.6333333	1.1139755964279174
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-selu-softmax**	rmsprop	categorical_crossentropy	-	0.6666667	1.0172423601150513
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-softsign-softmax**	rmsprop	categorical_crossentropy	-	0.68333334	0.9269145607948304
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-hard_sigmoid-softmax**	rmsprop	categorical_crossentropy	-	**0.69166666**	0.9540115276972453
Feb 03	Cleansed	15	15	15	600	20	128	1	64-128-6	**relu-exponential-softmax**	rmsprop	categorical_crossentropy	-	0.6666667	1.493983308474223

Experiments Records – activation functions

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	**Activation functions**	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-relu-relu-softmax**	rmsprop	categorical_crossentropy	-	0.625	1.0755352258682251
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-softmax-softmax-softmax**	rmsprop	categorical_crossentropy	-	0.29166666	1.7877373139063517
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-sigmoid-sigmoid-softmax**	rmsprop	categorical_crossentropy	-	0.6166667	1.104865050315857
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-tanh-tanh-softmax**	rmsprop	categorical_crossentropy	-	**0.6666667**	1.0579676866531371
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-selu-selu-softmax**	rmsprop	categorical_crossentropy	-	0.64166665	1.2318978706995647
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-softsign-softsign-softmax**	rmsprop	categorical_crossentropy	-	0.625	1.1883386691411337
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu—hard_sigmoid-hard_sigmoid-softmax**	rmsprop	categorical_crossentropy	-	0.6333333	1.1228162209192911
Feb 03	Cleansed	15	15	15	600	20	128	2	64-128-128-6	**relu-exponential-exponential-softmax**	rmsprop	categorical_crossentropy	-	0.55833334	1.981887149810791

From the two groups of experiment, I find that putting **hard_sigmoid** inside the inner layer achieves the best accuracy, and softsign and sigmoid perform the second and third best;
If using two same activation functions inside the inner layers, then use **tanh**.
Never try to put softmax inside inner layers, since it has got 0.49 and 0.29 when using once and twice. Others are just viable as well.

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	Activation functions	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Feb 03	Cleansed	15	15	15	600	15	512	2	32-32-32-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.575	1.281682046254476
Feb 03	Cleansed	15	15	15	600	15	512	2	32-64-64-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.5416667	1.2656379699707032
Feb 03	Cleansed	15	15	15	600	15	512	2	64-64-64-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.625	1.1398384332656861
Feb 03	Cleansed	15	15	15	600	15	512	2	64-64-32-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.55	1.1970116376876831
Feb 03	Cleansed	15	15	15	600	15	512	2	64-128-128-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.55	1.1849392811457315
Feb 03	Cleansed	15	15	15	600	15	512	2	64-128-64-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.55833334	1.1169984579086303
Feb 03	Cleansed	15	15	15	600	15	512	2	128-128-256-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.68333334	0.9293365836143493
Feb 03	Cleansed	15	15	15	600	15	512	2	128-128-128-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.53333336	1.320115900039673
Feb 03	Cleansed	15	15	15	600	15	512	2	128-128-64-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.6	1.1395802736282348
Feb 03	Cleansed	15	15	15	600	15	512	2	128-256-128-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.6166667	1.1106221596399943
Feb 03	Cleansed	15	15	15	600	15	512	2	128-256-64-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.56666666	1.1338408788045247
Feb 03	Cleansed	15	15	15	600	15	512	2	512-256-128-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.68333334	0.9334465821584066
Feb 03	Cleansed	15	15	15	600	15	512	2	512-512-256-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.65833336	0.9807055513064067
Feb 03	Cleansed	15	15	15	600	15	512	2	512-1024-512-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.53333336	1.1604699532190959
Feb 03	Cleansed	15	15	15	600	15	512	2	1024-1024-512-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.65833336	0.9688995122909546
Feb 03	Cleansed	15	15	15	600	15	512	2	1024-512-256-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.55	1.2143640756607055
Feb 03	Cleansed	15	15	15	600	15	512	2	1024-512-128-6	relu-tanh-tanh-softmax	rmsprop	categorical_crossentropy	-	0.55833334	1.0940533717473349

- Controlled experiments results – neuron numbers

It seems that, with the same settings, **128-128-256-6 neurons**, and **512-256-128-6 neurons** perfoms the best, with accuracy=0.68333334. The second best are 512-512-256-6 and 1024-1024-512-6.

Less neurons or bottleneck effects (128-128-128-6) indeed cannot get a high score.

Controlled experiments results – optimizer

Experiments Records – optimizers

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	Activation functions	**optimizer**	loss	regulerisation	Accuracy (test)	Loss (test)
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**rmsprop**	categorical_crossentropy	-	0.65833336	1.137278159459432
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adam**	categorical_crossentropy	-	**0.7083333**	1.2403667132059732
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**sgd**	categorical_crossentropy	-	0.425	1.4351878404617309
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adagrad**	categorical_crossentropy	-	0.35833332	1.663960321744283
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adamax**	categorical_crossentropy	-	0.69166666	1.0454886635144551
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adadelta**	categorical_crossentropy	-	0.175	1.8860424121220907

Adam performs really well, with accuracy of nearly 0.708. Adamax and RMSprop are both good to use. Never try to use AdaDelta or AdaGrad. SGD performs with a rather low score as well.

Controlled experiments results – regularizer

Experiments Records – regularisation

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	Activation functions	optimizer	loss	Regulerisation (same for all 4 layers)	Accuracy (test)	Loss (test)
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**None**	0.6583333611488342	1.2913317680358887
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1(0.00001)**	0.6666666865348816	1.4933713674545288
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1(0.0001)**	0.6833333373069763	2.9563088417053223
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1(0.001)**	0.6583333611488342	7.4965000152587 89
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1(0.01)**	0.1666666716337204	20.8071060180664 06
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1(0.1)**	0.2083333283662796	186.671417236328 12
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l2(0.00001)**	**0.6916666626930237**	1.3007627725601196
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l2(0.0001)**	0.6833333373069763	1.4108805656433105
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l2(0.001)**	0.6666666865348816	2.1059288978576 6
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l2(0.01)**	**0.6916666626930237**	3.8480386734008 79
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l2(0.1)**	0.4416666626930237	10.2590351104736 33
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.00001, l2=0.00001)**	0.6499999761581421	1.4778742790222168
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.0001, l2=0.0001)**	0.6583333611488342	2.9277451038360596
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.001, l2=0.001)**	**0.6916666626930237**	7.6063089370727 54
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.1, l2=0.1)**	0.19166666269302368	200.353195190429 7
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.00001, l2=0.1)**	0.4749999940395355	10.3081378936767 58
Feb 08	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	adam	categorical_crossentropy	**l1_l2(l1=0.1, l2=0.00001)**	0.19166666269302368	186.403411865234 38

I have settled 17 experiments. I find that, there are three sets of regularizers perform the best, with test accuracy of 0.6916666626930237. They are:

```
all layers use l2(0.00001)
all layers use l2(0.01)
all layers use l1_l2(l1=0.001, l2=0.001)
```

Notice: should never use l1(0.01) or l1(0.1) or l1_l2(l1=0.1, l2=0.1) or l1_l2(l1=0.1, l2=0.00001) in all layers.

L2 can be allowed to be big, but l1 can never be big.

Codes

- Sklearn.model_selection.GridSearchCV on FNN

```python
def my_model3(act_func, neuron_num1, neuron_num2, num_layers, loss_f, layers_num):
    # train the model:
    model = models.Sequential()
    # just pick any parameters here to control the other variables:
    model.add(layers.Dense(neuron_num1, activation = act_func, input_shape = (600,)))

    # append identical inner layers:
    i = 0
    while i < num_layers:
        model.add(layers.Dense(neuron_num2, activation =act_func))
        i += 1

    # the output layer:
    model.add(layers.Dense(6, activation = 'softmax'))  # must be 6 categories, should use softmax
    model.compile(optimizer = 'adam', loss = loss_f, metrics = ['accuracy'])

    return model
from sklearn.model_selection import GridSearchCV
# from tensorflow.keras.wrappers.scikit_learn import KerasRegressor
import scikeras
from scikeras.wrappers import KerasClassifier, KerasRegressor

# SciKeras renamed the constructor argument build_fn to model
classifier3 = KerasClassifier(model = my_model3, act_func='relu', neuron_num1=32,
                              neuron_num2=128, num_layers=0, loss_f='categorical_crossentropy',
                             layers_num=3)

# hyperparameters:
hyperparameters3 = {
    'neuron_num1': [32, 64],
    'neuron_num2': [128, 256, 512],
    'num_layers': [0, 1, 2, 3],
    'act_func': ['relu', 'tanh', 'selu'],
    'batch_size': [128, 256, 512],
    'epochs': [20, 40, 60],
    'loss_f': ['categorical_crossentropy', 'mean_absolute_error'],
    'optimizer': ['adam', 'rmsprop', 'adamax']
}
```

```
Best hyperparameters are: {'act_func': 'relu', 'batch_size': 256, 'epochs': 60, 'loss_f': 'mean_absolute_error', 'neuron_num1': 64, 'neuron_num2': 256, 'num_layers': 0, 'optimizer': 'adam'} Best score is: 0.5625
```

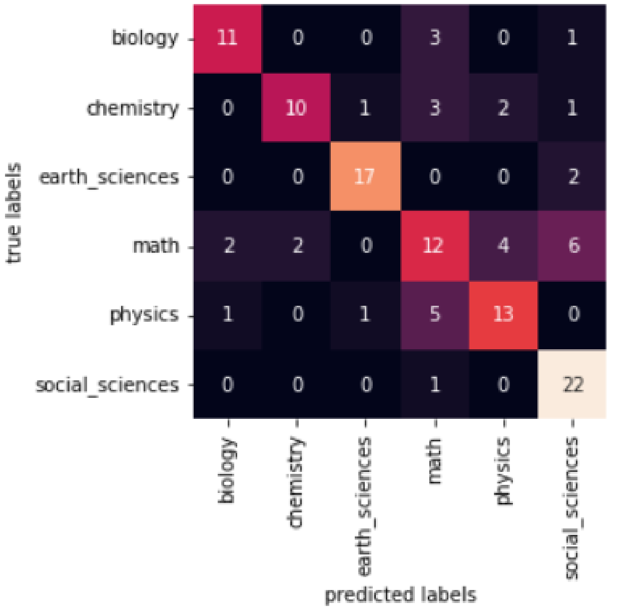
```python
# train-validation splitting:
from sklearn.model_selection import train_test_split
# this time I use the cleansed dataset
X_train_partial2, X_val2, Y_train_partial2, Y_val2 = train_test_split(
    X_train2, Y_train2, test_size=0.20, random_state=15)
# we set a random state in order to repeat the experiment later

grid_search_trial3 = GridSearchCV(estimator = classifier3, param_grid = hyperparameters3, scoring = 'accu
# In sklearn, any machine learning model is an estimator. estimator.get_params()
```

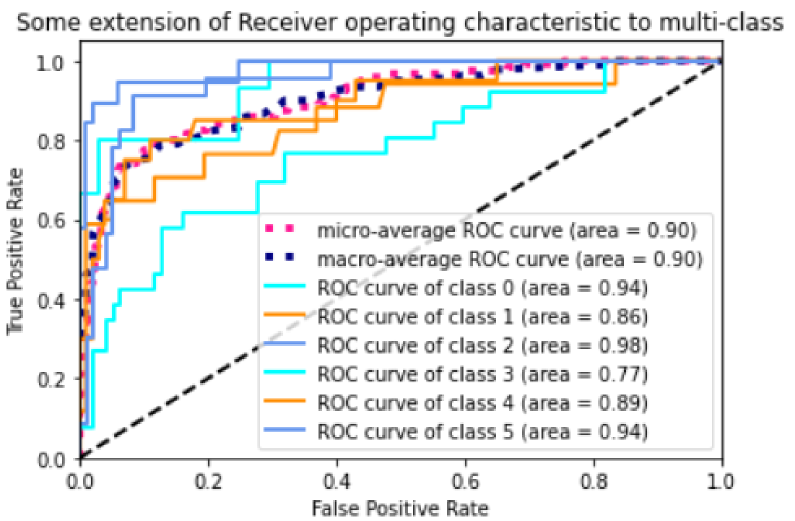
```python
# run on Feb 02
grid_search_fit3 = grid_search_trial3.fit(X_train_partial2, Y_train_partial2, verbose=0, validation_data=

best_parameters3 = grid_search_fit3.best_params_
best_score3 = grid_search_fit3.best_score_

print("Best hyperparameters are: " + str(best_parameters3), "Best score is: ", best_score3)
```

Repetition of The Best FCNN Model

Table 5.1.1-2 Repetition for the High-Performing FNN Models Using K-Fold Cross Validation

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hid layers	Neuron nums	Activation functions	optimizer	loss	regulerisation	Accuracy Holdout (test)	Avg Accuracy 10-Fold (val)
Feb 28	Cleansed	15	15	15	600	20	**64**	**0**	**256-6**	relu-softmax	rmsprop	categorical_crossentropy	-	0.7083333134651184	60.63% (+/- 4.79%)
Feb 23	Cleansed	15	15	15	600	20	**64**	**0**	**256-6**	relu-softmax	rmsprop	categorical_crossentropy	Dropout(0.3)	0.7083333134651184	63.54% (+/- 6.67%)
Feb 28	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adam**	categorical_crossentropy	-	0.6833333373069763	60.21% (+/- 5.70%)
Feb 28	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adam**	categorical_crossentropy	2 Dropout	-	61.04% (+/- 6.85%)
Feb 28	Cleansed	15	15	15	600	20	**256**	**3**	**128-128-128-128-6**	relu-relu-relu-relu-softmax	rmsprop	categorical_crossentropy	3 Dropout	0.699999988079071	59.38% (+/- 6.86%)





- Accuracy is different, may caused by randomness of Dropout, randomness of weight, …
- Dropout layers can increase the K-Fold accuracy
- Best Hold-Out accuracy is about 0.708; Best K-Fold accuracy is about 0.635

```
In [68]: # convert to a numerical vector
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.svm import LinearSVC
from sklearn.pipeline import make_pipeline

model_TFIDFSVC = make_pipeline(TfidfVectorizer(), LinearSVC(random_state=0, tol=1e-5))
```

```
In [70]: # Apply model to the training data, then predict labels for test data
model_TFIDFSVC.fit(X_train_pre2, Y_train_pre2)
labels_TFIDFSVC = model_TFIDFSVC.predict(X_test_pre2)
```

Codes Implemented

- Classification Using Classical NLP methods

Table 5.1.2-3 Performances of My NLP Models Using Hold-Out Cross Validation vs. K-Fold Cross Validation

They score really high!

Vectorizer	Classifier	Avg Accuracy using Hold-out	Avg Accuracy using 5-Fold
TF-IDF	Support Vector Classifier	0.86	0.84 (+/- 0.05)
Count Vectorizer	Support Vector Classifier	0.86	0.75 (+/- 0.09)
Bigram	Support Vector Classifier	0.68	0.66 (+/- 0.05)
TF-IDF	Multinomial Naive Bayes	0.78	0.74 (+/- 0.08)
Count Vectorizer	Multinomial Naive Bayes	0.78	0.75 (+/- 0.08)
Bigram	Multinomial Naive Bayes	0.74	0.70 (+/- 0.03)
TF-IDF	Random Forest	0.73	0.64 (+/- 0.02)
Count Vectorizer	Random Forest	0.69	0.65 (+/- 0.04)
Bigram	Random Forest	0.54	0.51 (+/- 0.08)
TF-IDF	K-Nearest Neighbors	0.82	0.81 (+/- 0.07)
Count Vectorizer	K-Nearest Neighbors	0.55	0.59 (+/- 0.14)
Bigram	K-Nearest Neighbors	0.26	0.20 (+/- 0.03)

- (1) Classifier: SVC is No.1, MNB is No.2, both are impressive. Random Forest provides just a passing performance; while KNN must combine with TF-IDF vectorizer to be outstanding.
- (2) Vectorizer: TF-IDF is always excellent with all classifiers; Count Vectorizer almost the same but should not combine with KNN; Bigram performs always the worst, and should never combine with KNN.

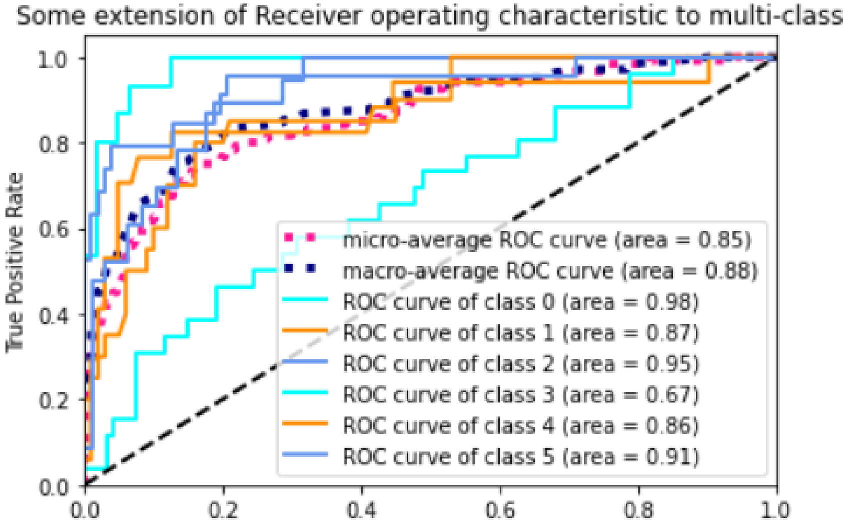
Pre-trained model source: Bilibili video tutorial
https://www.bilibili.com/video/BV1u7411d7zU/?share_source=copy_web&vd_source=296c14837e03501f00801a512d70f87e

Codes Implemented

```
model_1DCNN.add(layers.Embedding(input_dim=2000,     # size of the vocabulary
                                 output_dim=128,
                                 input_length=600))
model_1DCNN.add(layers.Conv1D(256,     # output size
                              3,     # conv core size
                              padding='same',
                              activation='relu'))
# The above layer creates a convolution kernel that is convolved with the layer input over
# spatial (or temporal) dimension to produce a tensor of outputs.
model_1DCNN.add(layers.MaxPooling1D(3, 3, padding='same'))
model_1DCNN.add(layers.Conv1D(32, 3, padding='same', activation='relu'))
model_1DCNN.add(layers.Flatten())
model_1DCNN.add(layers.Dropout(0.3))
model_1DCNN.add(layers.BatchNormalization())    # the layer of batch normalization
model_1DCNN.add(layers.Dense(256, activation='relu'))
model_1DCNN.add(layers.Dropout(0.2))

model_1DCNN.add(layers.Dense(6, activation='softmax'))

model_1DCNN.compile(optimizer='rmsprop', loss='categorical_crossentropy',

model_1DCNN.summary()

# train-validation splitting
X_train_partial2, X_val2, Y_train_partial2, Y_val2 = train_test_split(
        X_train2, Y_train2, test_size=0.20, random_state=15)
# we set a random state in order to repeat the experiment later

history_1DCNN = model_1DCNN.fit(X_train_partial2,
                                Y_train_partial2,
                                batch_size=64, # set a fixed batch size
                                epochs=31,   # we just set any fixed number fo
                                validation_data=(X_val2, Y_val2))
```

conv1d_16 (Conv1D)	(None, 600, 256)	98560
max_pooling1d_8 (MaxPooling1D)	(None, 200, 256)	0
conv1d_17 (Conv1D)	(None, 200, 32)	24608
flatten_8 (Flatten)	(None, 6400)	0
dropout_16 (Dropout)	(None, 6400)	0
batch_normalization_8 (BatchNormalization)	(None, 6400)	25600
dense_16 (Dense)	(None, 256)	1638656
dropout_17 (Dropout)	(None, 256)	0
dense_17 (Dense)	(None, 6)	1542

```
results_1DCNN = model_1DCNN.evaluate(X_test2, Y_test2)
results_1DCNN
```



loss: 1.3253 - accuracy: 0.6333

- The best CNN

Hold-Out Accuracy=0.633

K-Fold Accuracy=0.531

Codes Implemented

- RNN with LSTM layer

```
model_RNN = Sequential()
# the embedding layer has the shape of (samples, input_length, 8):
model_RNN.add(Embedding(600, 128))
# model_RNN.add(SimpleRNN(64))
model_RNN.add(LSTM(64, activation='tanh',
                    recurrent_activation='hard_sigmoid',
                    use_bias=True,
                    kernel_initializer='glorot_uniform',
                    recurrent_initializer='orthogonal',
                    bias_initializer='zeros',
                    unit_forget_bias=True,
                    dropout=0.0, recurrent_dropout=0.0,
                    return_sequences=True))
model_RNN.add(Dropout(0.4))
model_RNN.add(LSTM(64, activation='tanh'))
model_RNN.add(Dropout(0.4))

model_RNN.add(Dense(6, activation='softmax'))

model_RNN.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])
model_RNN.summary()
```

```
final_LSTM = model_RNN.evaluate(X_test2, Y_test2)
final_LSTM
```

```
4/4 [==============================] - 0s 98ms/step - loss: 1.7375 - accuracy: 0.2667

[1.7375144958496094, 0.2666666805744171]
```

Accuracy=0.267

```
# train-validation splitting
_train_partial2, X_val2, Y_train_partial2, Y_val2 = train_test_split(
        X_train2, Y_train2, test_size=0.20, random_state=15)
# we set a random state in order to repeat the experiment later

istory_RNN = model_RNN.fit(X_train_partial2,
                           Y_train_partial2,
                           batch_size=128, # set a fixed batch size
                           epochs=15,  # we just set any fixed number for co
                           validation_data=(X_val2, Y_val2))
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_7 (Embedding)      (None, None, 128)         76800

lstm_10 (LSTM)               (None, None, 64)          49408

dropout_6 (Dropout)          (None, None, 64)          0

lstm_11 (LSTM)               (None, 64)                33024

dropout_7 (Dropout)          (None, 64)                0

dense_3 (Dense)              (None, 6)                 390
```

Pre-trained model source: Chollet's ML book Ch.6

Codes Implemented

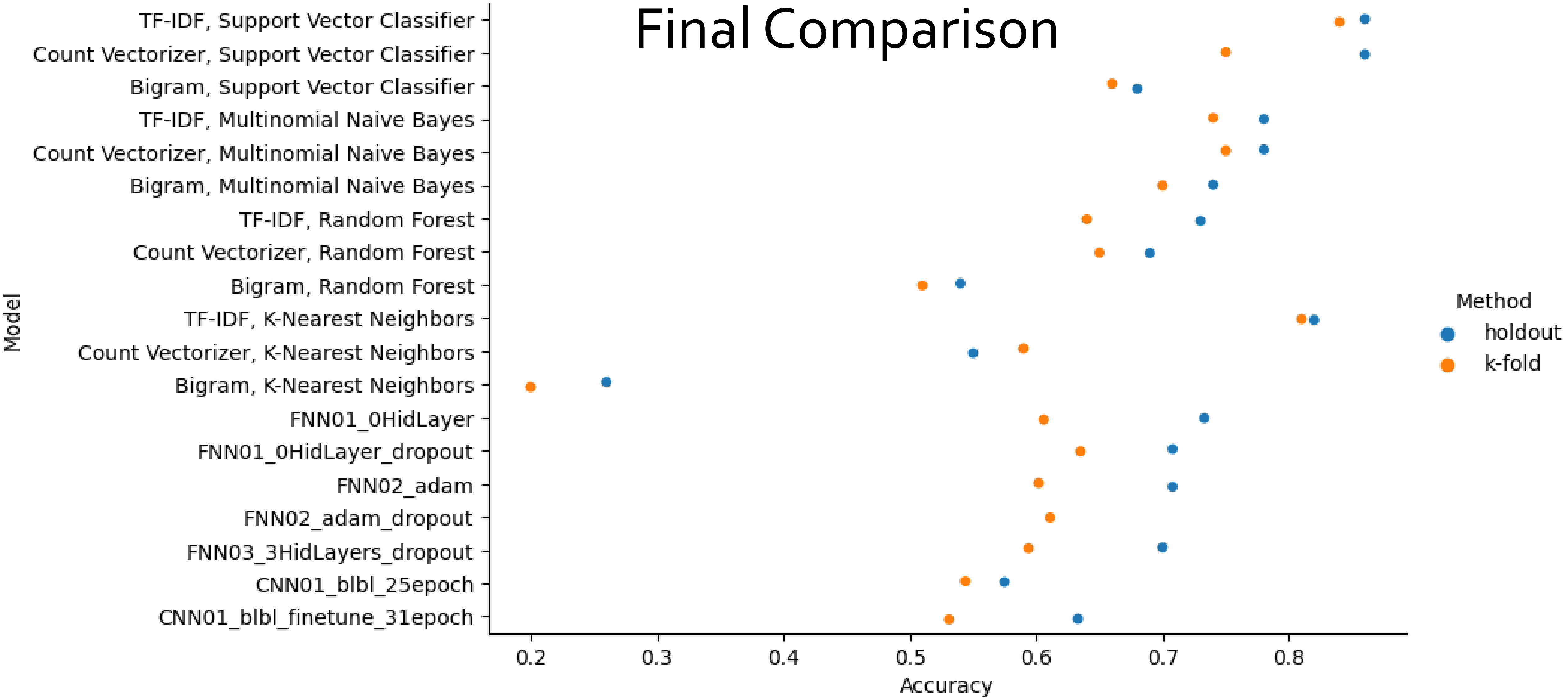
- Latent Dirichlet Allocation

(Oct 25)

```
Topic 0
        ['study', 'year', 'research', 'one', 'university', 'say', 'find', 'also', 'social', 'people']
Topic 1
        ['cell', 'fig', 'expression', 'gene', 'study', 'also', 'show', 'result', 'group', 'level']
Topic 2
        ['quantum', 'state', 'phase', 'fig', 'show', 'system', 'two', 'time', 'use', 'energy']
Topic 3
        ['use', 'cell', '10', 'sample', 'min', 'flow', 'perform', 'mm', 'study', 'medium']
Topic 4
        ['hurricane', 'storm', 'water', 'flood', 'change', 'increase', 'crystal', 'temperature', 'sho
w', 'plasma']
Topic 5
        ['data', 'use', 'model', 'method', 'fig', 'structure', 'magnetic', 'result', 'field', 'stud
y']
```

(Fig 5.1.5-1 LDA Result)

Final Comparison



(Fig 5.2-1 Accuracy Comparison for Each Good Model Using Hold-Out vs. K-Fold)

- The best Neural Network models cannot compare with other NLP models. The best Neural Network models in general can achieve an accuracy of 0.733 using Hold-Out (0.635 using K-Fold), while the best NLP models can get 0.86 using Hold-Out (0.84 using K-Fold). Among the Neural Networks, the best FCNN win against the best CNN models. Among the Neural Networks, using Dropout can slightly improve accuracy.

Final Comparison

- The best FCNN I can bring to you is with Hold-Out accuracy=0.733, K-Fold accuracy=0.606, which has no hidden layers.

Settings						Tuning parameters								Evaluations	
Date	Data	sys_seed	np_seed	tf_seed	words	Epochs	Batch size	# hidden layers	Neuron nums	Activation functions	optimizer	loss	regularisation	Accuracy (test)	Loss (test)
Feb 03	Cleansed	15	15	15	600	20	**64**	**0**	**256-6**	relu-softmax	rmsprop	categorical_crossentropy	-	0.7333333492279053	0.9777682423591614
Feb 03	Cleansed	15	15	15	600	20	128	2	512-256-128-6	relu-tanh-tanh-softmax	**adam**	categorical_crossentropy	-	0.7083333	1.2403667132059732
Jan 31	Cleansed	15	15	15	600	20	**256**	**3**	**128-128-128-128-6**	relu-relu- relu-relu-softmax	rmsprop	categorical_crossentropy	-	0.699999988079071	1.0144932270050049

Settings 4.9-1: 1D CNN
Layer types: (1) Embedding(2000, 128, 600); (2) Conv1D(256, 3); (3) MaxPooling1D(3, 3); (4) Conv1D(32, 3, 'relu'); (5) Flatten; (6) Dropout(0.3); (7) BatchNormalization; (8) Dense(256, 'relu'); (9) Dropout(0.2); (10) Dense(6, 'softmax').
np_seed: 15; tf_seed: 15; words: 600; batch size: 64; epoch: 31

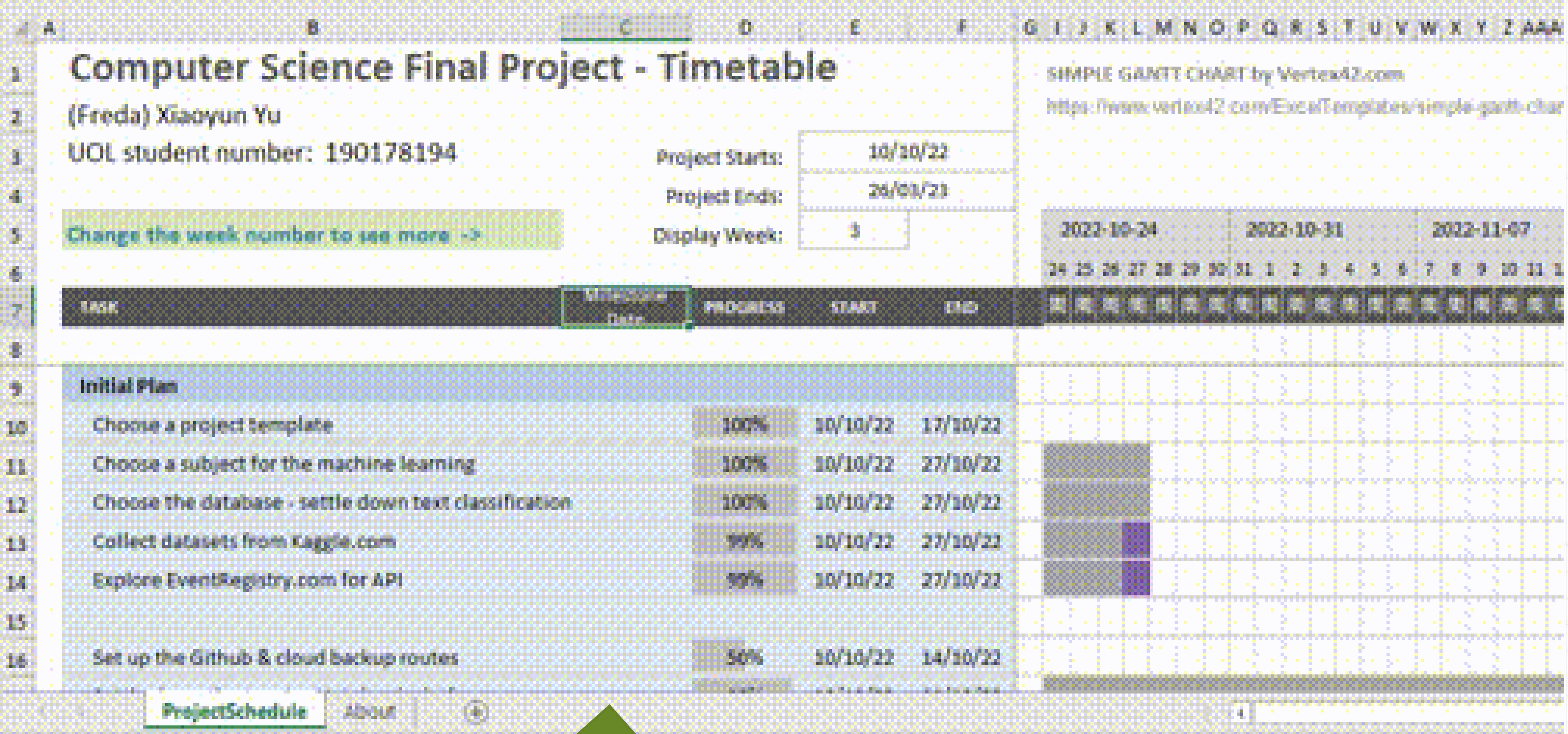
- The best DNN model is a CNN model for which I get Hold-Out accuracy=0.633, fine-tuned by a pre-trained model mentioned by a video in Bilibili website.

- The best model is the 'TF-IDF with SVC' model, with both the Hold-Out and K-Fold accuracy about 0.85.
- The second-best: the 'Count Vectorizer with SVC' model, and 'TF-IDF with KNN'. The former has a very high accuracy using Hold-Out (0.86), but has a lower accuracy using K-Fold (0.75). The latter has both Hold-Out and K-Fold accuracy=0.82.
- The third-best: the 'TF-IDF with MNB ', and the 'Count Vectorizer with MNB' model, with accuracy of above 0.75.

Discussions

- It is interesting why SVC and MNB Classifiers outperform all the Neural Network models.
- TF-IDF and Count Vectorizer apparently help its model to get a high accuracy. Can I implement them into a NN as a layer?
- Inspired by LDA result, can I purify my subject-classification scheme by eliminating the classification based on research methods?
- Journal editors may adapt my model(s), but should manually scan for errors. Editors’ work is irreplaceable.

Arrangement - Gantt Chart, Milestone Tasks



Milestone dates

Milestone tasks

Literature papers and books collected	Dec 01	Done
Literature Review file	Dec 20	Done before midterm
Project Design file	Dec 19	
Slides for pitch video	Dec 25	Done, on Dec 19
Pitch video for midterm	Dec 31	Done before midterm
Prototype: use a vectoriser and a classifier	Dec 10	Done, on Dec 09. Built 3 NLP models for SVC
Prototype: use > 5 NLP methods	Dec 31	
Prototype: use a small neural network	Dec 01	Done.
Prototype: use a larger neural network	Dec 28	Done, on Dec 09
*Tuning hyper-parameters: plan (grid search?)	Dec 15	Done, on Dec 09 by installing NNI, Feb 01-02 run GridSearchCV
Tuning hyper-parameters: practice	Dec 25	
Try LSTM	Feb 10	LSTM layer on Feb 03
Try CNN	Dec 17	Tried on Dec 09
*CNN learning	Jan 20	
*RNN learning	Jan 20	
Report: write methods intro	Jan 31	
Report: experiment record	Keep along all the way till the end	
GridSearchCV codes	Feb 05	Done on Feb 01-02
Build a strong CNN	Feb 10	Feb 03, 0.57 accuracy
Try ULMFiT (FastAI)	Feb 18	Feb 02-04 stuck
Try AWD-LSTM	Feb 18	Feb 03, stuck on cuda
Try Wikipedia2vec	Feb 18	Feb 05-06 too slow stuck
Try Bert-for-Task	Feb 18	Feb 06 reform data, meet utf-8 decoding error
At least one pre-training	Feb 13	?
Report: write implementation	Feb 12	
Report: write evaluations	Feb 12	
Report: write key techs	Feb 12	
Report: change references to ACM style	Mar 12	
Exam: prepare	Mar 04	
Video: slides	Feb 25	

Thank You for reviewing my project!