Assignment 4 NLP

Name: Devansh Mody Student Id: 1130532

Part 1 - Comprehensive Test

a. (20 points) What are the purposes of *pack_padded_sequence()* and *pad_packed_sequence()* functions used at the *get_all_hidden()* method (line 57) in the *core_nns.py* file

Answer:

pack_padded_sequence(): Packs a tensor containing padded sequences of variable length. If batch first is true then first comes batch, then length and then the input tensor. If enforce_sorted is set to true then the sequences should be sorted by the length in decreasing order and passed to the function. This function accepts any input that has at least two dimensions. You can apply it to pack the labels, and use the output of the RNN with them to compute the loss directly. Then a tensor can be retrieved from a packed sequence object by accessing its data attribute. pack_padded_sequence() function is applied before feeding into RNN. *input_lengths.cpu()* is the length of the individual sequence before padding. It is a data structure of PyTorch that allows the model to operate only up to the exact length of a given sequence without adding padding.

pad_packed_sequence(): This function is used on our packed RNN output Now we do packing so that the RNN doesn't see the unwanted padded index while processing the sequence which would affect the overall performance. It is an inverse operation to pack_padded_sequence. It pads a packed batch of variable length sequences. The returned Tensor's data will be of size T x B x *, where T is the length of the longest sequence and B is the batch size. If batch_first is True, the data will be transposed into B x T x * format. It also returns the list of lengths of each sequence in the batch. Batch elements will be reordered as they were ordered originally when the batch was passed to pack_padded_sequence or pack_sequence.

b. (20 points) Why do we need to use *sort_tensors()* and *resort_tensors()* methods at the *forward()* method (line 43) in the *core_nns.py* file Answer:

sort_tensors(input_tensor, input_lengths): Sort input tensors by their lengths in a descending order. It sorts in descending order so we get the larget sentence first so based on the number of words or tokens in the largest sentence the other sentences are then padded accordingly. Sorting is done so words can then be padded or masked accordingly based on the largest length of the sentence or document. So for example if the largest document has 200 words and other documents have less than 200 words then sorting in descending gives the largest document first so then other documents are padded to match the length of the largest document that is 200 words.

resort_tensors(inp_tensor, reorder_tensor, dim=0): Recover the original order of inp_tensor on dim dimension which orders are stored in reorder_tensor. This function is used to get the original order of the tensor is used to calculate the losss. Based on the dimension it slices the input_tensor. If dimension is equal to 1 then input_tensor= inp_tensor[reorder_tensor]. Here the reorder_tensor is the original order output with padding of the input_tensor from sort_tensor function. If dimension is equal to 1 then inp_tensor = inp_tensor[:, reorder_tensor, :], and if deimension is equal to 2 then inp_tensor = inp_tensor[:, :, reorder_tensor]

Performance comparison of the models:

UNILSTM model.py	BILSTM model.py	BILSTM with F1 Score _imp_metric.py	BILSTM with f1 score and glove embedding _imp_emb.py
	TRAINING time:	1033.77s loss 1.27	EPOCH 1: TRAINING time: 626.64s loss 1.27 documents 17495 documents/s 27.92
10.46s loss 1.23 f1	EVALUATING time: 16.80s loss 1.24 f1 6.82 documents 3749	EVALUATING time: 17.06s loss 1.24 f1	EPOCH 1: EVALUATING time: 15.14s loss 1.24 f1 8.63 documents 3749 documents/s 15.13
EPOCH 2: TRAINING time: 833.73s loss 1.23 documents 17495 documents/s 20.98	TRAINING time: 1034.88s loss 1.24 documents 17495	•	TRAINING time:
10.30s loss 1.21 f1	EVALUATING time: 16.80s loss 1.21 f1 11.72 documents 3749	16.93s loss 1.21 f1	EPOCH 2: EVALUATING time: 15.13s loss 1.21 f1 6.52 documents 3749 documents/s 15.13
	EPOCH 3: TRAINING time: 1034.27s loss 1.21 documents 17495 documents/s 16.92		TRAINING time:
	16.81s loss 1.20 f1	EVALUATING time: 16.98s loss 1.20 f1	EPOCH 3: EVALUATING time: 15.29s loss 1.20 f1 6.11 documents 3749 documents/s 15.29
EPOCH 4: TRAINING time: 847.91s loss 1.19 documents 17495 documents/s 20.63	TRAINING time:	•	EPOCH 4: TRAINING time: 630.97s loss 1.20 documents 17495 documents/s 27.73

EVALUATING time: 10.08s loss 1.18 f1 6.30 documents 3749	16.72s loss 1.18 f1	EVALUATING time: 16.90s loss 1.21 f1 11.36 documents 3749	EPOCH 4: EVALUATING time: 15.02s loss 1.18 f1 6.11 documents 3749 documents/s 15.01
TRAINING time: 852.93s loss 1.18 documents 17495	EPOCH 5: TRAINING time: 1035.49s loss 1.18 documents 17495 documents/s 16.90	1035.73s loss 1.24 documents 17495	TRAINING time: 624.95s loss 1.18
EVALUATING time: 10.10s loss 1.17 f1 6.30 documents 3749	16.89s loss 1.17 f1	EVALUATING time: 16.93s loss 1.21 f1 10.76 documents 3749	EVALUATING time: 15.25s loss 1.17 f1 6.11 documents 3749
TRAINING time: 856.10s loss 1.17 documents 17495	EPOCH 6: TRAINING time: 1032.02s loss 1.17 documents 17495 documents/s 16.95	TRAINING time: 1035.81s loss 1.24 documents 17495	TRAINING time: 629.60s loss 1.20 documents 17495
EVALUATING time: 10.18s loss 1.16 f1 6.30 documents 3749	16.79s loss 1.16 f1	EVALUATING time: 16.97s loss 1.21 f1 11.68 documents 3749	EVALUATING time: 15.22s loss 1.18 f1 6.11 documents 3749
846.52s loss 1.16	TRAINING time: 1031.63s loss 1.17	TRAINING time:	TRAINING time:
10.45s loss 1.15 f1 6.30 documents 3749	EVALUATING time: 16.84s loss 1.15 f1	EVALUATING time: 16.68s loss 1.21 f1 11.56 documents 3749	EPOCH 7: EVALUATING time: 15.66s loss 1.18 f1 6.11 documents 3749 documents/s 15.66
·	EPOCH 8: TRAINING time: 1039.09s loss 1.16 documents 17495 documents/s 16.84		EPOCH 8: TRAINING time: 630.17s loss 1.20 documents 17495 documents/s 27.76

EPOCH 8:	EPOCH 8:	EPOCH 8:	EPOCH 8:
EVALUATING time:	EVALUATING time:	EVALUATING time:	EVALUATING time:
10.24s loss 1.15 f1	16.89s loss 1.15 f1	16.99s loss 1.21 f1	15.28s loss 1.18 f1
6.30 documents 3749	7.00 documents 3749	10.82 documents 3749	6.11 documents 3749
documents/s 10.23	documents/s 16.89	documents/s 16.99	documents/s 15.28
BEST EPOCH 8:	BEST EPOCH 8:	BEST EPOCH 1:	BEST EPOCH 3:
TESTING time:	TESTING time:	TESTING time:	TESTING time:
10.89s loss 1.17 f1	17.50s loss 1.17 f1	16.95s loss 1.27 f1	15.52s loss 1.23 f1
6.65 documents 3749	6.95 documents 3749	6.60 documents 3749	6.67 documents 3749
documents/s 10.89	documents/s 17.50	documents/s 16.94	documents/s 15.51
		·	·

It can be seen with F1 score as evaluation in _imp_metric.py and F1 score as evaluation metric combined with glove embedding in _imp_emb.py the model converges faster and reaches an early stopping stage after which there are no significant improvements but it runs for 8 epochs and testing accuracy remains the same throught out the epochs. Also with glove embedding in first epoch only highest f1 score of 8.63 is achieved.

Detailed output of each model:

1) UNILSTM Model

Building dataset...

Extracting vocabulary from 21244 total samples: 21244 total labels, 5 unique labels 2265241 total tokens; 84876 unique tokens 84876 unique tokens appearing at least 1 times Writing hyperinto ./results/senti cls unilstm.args | EPOCH 1: TRAINING | time: 846.09s | loss 1.26 | documents 17495 | documents/s 20.68 | | EPOCH 1: EVALUATING | time: 10.46s | loss 1.23 | f1 6.30 | documents 3749 | documents/s 10.46 NEW **IMPROVEMENT** file Save the model | EPOCH 2: TRAINING | time: 833.73s | loss 1.23 | documents 17495 | | EPOCH 2: EVALUATING | time: 10.30s | loss 1.21 | f1 6.30 | documents 3749 | documents/s 10.29 NEW IMPROVEMENT file | EPOCH 3: TRAINING | time: 847.91s | loss 1.21 | documents 17495 | documents/s 20.63 | | EPOCH 3: EVALUATING | time: 10.12s | loss 1.19 | f1 6.30 | documents 3749 | documents/s 10.12 **NEW IMPROVEMENT** ____> Save the model file to | EPOCH 4: TRAINING | time: 847.91s | loss 1.19 | documents 17495 | documents/s 20.63 | | EPOCH 4: EVALUATING | time: 10.08s | loss 1.18 | f1 6.30 | documents 3749 | documents/s 10.07 NEW **IMPROVEMENT** Save the model file

EPOCH 5: TRA			•	•			•		•	ents/s
10.10										
	AINING	time: 856.10	s loss 1.1	•			•		•	ents/s
> 										
EPOCH 7: TRA EPOCH 7: EV 10.44	AINING ALUATII	time: 846.52 NG time: 1	ls loss 1.1 .0.45s lo	ss 1.15	f1 6	6.30 dc	cument	s 3749 d	docume	
> >	NEW	IMPROVE	EMENT		_>	Save	the 	model	to	file
	AINING	time: 826.30	s loss 1.1	•			•		•	ents/s
>								model	to	file
2)BILSTM Mod Building dataset Extracting vocal tokens; 84876 uparameters	del oulary fro	m 21244 tota kens 84876	al samples	s: 21244	total	labels, 5	5 unique	 e labels 22	265241 Iting h	total yper-
 EPOCH 1: TRA										J
EPOCH 1: EV 16.80	ALUATII	NG time: 1	.6.80s lo	ss 1.24	f1 6	5.82 do	cument	s 3749 c	docume	
>										
	AINING	time: 1034.8	88s loss 1	•			•		•	ents/s
>										
EPOCH 3: TR	 AINING	time: 1034.2	 .7s loss 1	.21 doc	umen	its 17495	5 docui	ments/s 16	5.92	

·>		IMPROV	EMENT	>	Save	the	model	to	file
EPOCH 4: TRA	 AINING	time: 1033.0	•	•		•		•	ents/s
16.72 >				>	Save	the	model	to	file
EPOCH 5: TRA EPOCH 5: EV 16.89			•	•		•		•	ents/s
>		IMPROV		>	Save	the	model	to	file
EPOCH 6: TRA EPOCH 6: EV 16.79									ents/s
!				>				to	file
			•						ents/s
·>		IMPROV		>	Save	the	model	to	file
EPOCH 8: TRA EPOCH 8: EV 16.89	/ALUATII	NG time:	16.89s lo	oss 1.15 f1	7.00 do	cument	s 3749 d	locume	
				>					file
BEST EPOCH 17.50								locume	nts/s!
3)_imp_metric. Building dataset Extracting vocal tokens; 84876 parameters	bulary from	m 21244 tot kens 84876 into	unique t	okens appea /re	ring at le sults/imp	east 1 _metric		ting h	yper-
EPOCH 1: TRA EPOCH 1: EV 17.05	AINING	time: 1033.	77s loss 1	.27 docume	nts 17495	docu			ents/s
•	NEW	IMPROV	EMENT	>	Save	the	model	to	file
EPOCH 2: TRA EPOCH 2: EV 16.93	'ALUATIN	NG time: 1	16.93s los	•	11.72 do	cument	s 3749 d	locume	

```
| EPOCH 3: TRAINING | time: 1038.09s | loss 1.21 | documents 17495 | documents/s 16.85 |
| EPOCH 3: EVALUATING | time: 16.98s | loss 1.20 | f1 7.15 | documents 3749 | documents/s
16.97
| -----> EARLY STOPPING at epoch 3
| BEST EPOCH 1: TESTING | time: 17.27s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
17.26
| EPOCH 4: TRAINING | time: 1045.07s | loss 1.24 | documents 17495 | documents/s 16.74 |
| EPOCH 4: EVALUATING | time: 16.90s | loss 1.21 | f1 11.36 | documents 3749 | documents/s
16.89
|-----> EARLY STOPPING at epoch 4
| BEST EPOCH 1: TESTING | time: 17.60s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
| EPOCH 5: TRAINING | time: 1035.73s | loss 1.24 | documents 17495 | documents/s 16.89 |
| EPOCH 5: EVALUATING | time: 16.93s | loss 1.21 | f1 10.76 | documents 3749 | documents/s
| -----> EARLY STOPPING at epoch 5
| BEST EPOCH 1: TESTING | time: 16.96s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
| EPOCH 6: TRAINING | time: 1035.81s | loss 1.24 | documents 17495 | documents/s 16.89 |
| EPOCH 6: EVALUATING | time: 16.97s | loss 1.21 | f1 11.68 | documents 3749 | documents/s
|----> EARLY STOPPING at epoch 6
| BEST EPOCH 1: TESTING | time: 17.10s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
| EPOCH 7: TRAINING | time: 1040.54s | loss 1.24 | documents 17495 | documents/s 16.81 |
| EPOCH 7: EVALUATING | time: 16.68s | loss 1.21 | f1 11.56 | documents 3749 | documents/s
|-----> EARLY STOPPING at epoch 7 | BEST EPOCH 1: TESTING | time: 17.01s | loss 1.27 |
       6.60
                        documents 3749 | documents/s 17.00
| EPOCH 8: TRAINING | time: 1036.62s | loss 1.24 | documents 17495 | documents/s 16.88 |
| EPOCH 8: EVALUATING | time: 16.99s | loss 1.21 | f1 10.82 | documents 3749 | documents/s
16.99
|-----> EARLY STOPPING at epoch 8
| BEST EPOCH 1: TESTING | time: 16.95s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
16.94 | -----
| BEST EPOCH 1: TESTING | time: 17.38s | loss 1.27 | f1 6.60 | documents 3749 | documents/s
17.38 | -----
```

4)_imp_emb.py F1 score and glove embeddings combined

Building dataset...

Extracting vocabulary from 21244 total samples: 21244 total labels, 5 unique labels 2265241 total tokens; 84876 unique tokens 84876 unique tokens appearing at least 1 times Writing hyperparameters into ./results/emb_metric_senti_cls_bilstm.args .vector_cache/glove.6B.zip: 862MB [02:43, 5.28MB/s] 100% 398366/400000 [00:14<00:00, 23542.10it/s]/content/drive/My Drive/assignment4/utils/core nns emb.pv:52: 100% 398366/400000 [00:30<00:00, 23542.10it/s]

Drive/assignment4/utils/core nns emb.py:52: 100% 398366/400000 [00:30<00:00, 23542.10it/s] -----| EPOCH 1: TRAINING | time: 626.64s | loss 1.27 | documents 17495 | documents/s 27.92 | | EPOCH 1: EVALUATING | time: 15.14s | loss 1.24 | f1 8.63 | documents 3749 | documents/s 15.13 | NEW **IMPROVEMENT** Save | EPOCH 2: TRAINING | time: 634.22s | loss 1.24 | documents 17495 | documents/s 27.59 | | EPOCH 2: EVALUATING | time: 15.13s | loss 1.21 | f1 6.52 | documents 3749 | documents/s 15.13 NEW IMPROVEMENT model file | EPOCH 3: TRAINING | time: 639.85s | loss 1.21 | documents 17495 | documents/s 27.34 | | EPOCH 3: EVALUATING | time: 15.29s | loss 1.20 | f1 6.11 | documents 3749 | documents/s 15.29 NEW **IMPROVEMENT** Save the model file | EPOCH 4: TRAINING | time: 630.97s | loss 1.20 | documents 17495 | documents/s 27.73 | EPOCH 4: EVALUATING | time: 15.02s | loss 1.18 | f1 6.11 | documents 3749 | documents/s 15.01 | EPOCH 5: TRAINING | time: 624.95s | loss 1.18 | documents 17495 | documents/s 27.99 | | EPOCH 5: EVALUATING | time: 15.25s | loss 1.17 | f1 6.11 | documents 3749 | documents/s 15.25 ----> EARLY STOPPING at epoch 5 | BEST EPOCH 3: TESTING | time: 16.13s | loss 1.23 | 3749 documents documents/s | EPOCH 6: TRAINING | time: 629.60s | loss 1.20 | documents 17495 | documents/s 27.79 | | EPOCH 6: EVALUATING | time: 15.22s | loss 1.18 | f1 6.11 | documents 3749 | documents/s 15.21 ----> EARLY STOPPING at epoch 6 | BEST EPOCH 3: TESTING | time: 15.50s | loss 1.23 | documents 3749 documents/s 15.50 | EPOCH 7: TRAINING | time: 626.32s | loss 1.20 | documents 17495 | documents/s 27.93 |

EPOC	CH 7: EVAI	LUATING	G time: 15.66s	loss 1.18 1	f1 6.11 do	ocuments 3749 c	locuments/s 1	5.66
			ING at epoch 7 NG time: 15.4	9s loss 1.2	23 f1 6.6	7 documents 37	⁷ 49 documer	nts/s
•		•	·	•		7495 documents ocuments 3749 c	•	5.28
 f1			ING at epoch 8 documents	•		ESTING time: 1 documents/s	· ·	.23
BEST 15.51			NG time: 15.5	·	•	 7 documents 37 	'49 documer	nts/s

Code and path changes that can be done:

- parser.add_argument('--bidirect', action='store_false', default=True, help='bidirectional flag') change default=False at in this argument in model.py file to train a unilstm model. By default it generates and trains a bilstm model.
- change path argument and model file in predict.py and app.py to test the results of different models.
- _imp_metric.py file is created for 5a part and it generates file with prefix "imp_metric_senti_cls_bi" for bilstm and with prefix "imp_metric_senti_cls_uni" for unilastm as bilstm model is trained so bilstm prefix will be used for files that are generated in results folder.
- Before running the _imp_emb.py file or cor_nns_emb.py download the the package pip install torchtext again. Also the file will download the glove embedding which are required in 5b part
- _imp_emb.py file is created for 5b part and it generates file with prefix "emb_metric_senti_cls_bi" for bilstm and with prefix "emb_metric_senti_cls_uni" for unilastm as bilstm model is trained so bilstm prefix will be used for files that are generated in results folder.
- core_nns_emb.py file is used for _imp_emb.py file and the code is changed to use glove embedding for training the model. Ignore the warnings that are generated.