Machine Comprehension

Pruthvij Thakar

Tushar Goel

1 PROBLEM STATEMENT

- Question Answering Task
- Facebook Babi Dataset
- Example: Task with single supporting fact



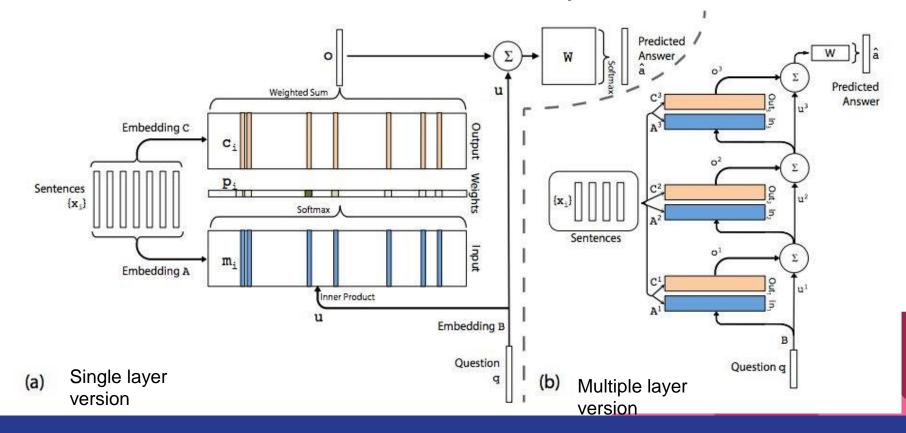
2 Memory Networks

- Memory Networks were introduced in 2014 as a work to be presented in International Conference on Learning Representations (ICLR) 2016.
- Class of models that combine large memory with learning component that can read and write to it.
- Authors of the paper: J. Weston, S. Chopra and A. Bordes
 Simple Concept:
 - Store the text in memory
 - Transform them by using embedding matrices.
 - Now do computations over them to train the model.

3 END TO END MEMORY NETWORKS

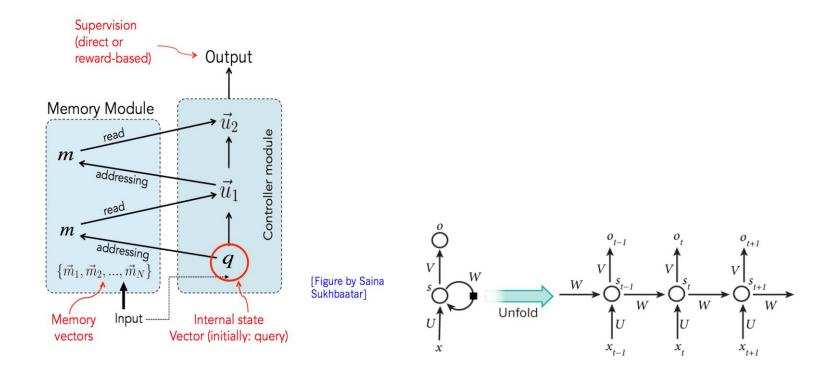
- Neural Network model with external memory.
- Reads the memory with soft attention.
- It accesses memory multiple times; each step being called a hop.
- Uses back propagation to update the model.

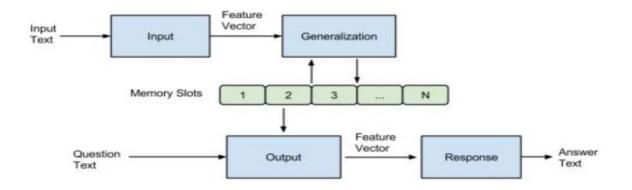
Architecture of End to End Memory Networks



4 MODEL DETAILS

- Input Sentences: X_1, X_2, \dots, X_n is taken
- Sentences are embedded into memory vectors m_i and c_i by using embedding matrices A and C.
- Question q is embedded into internal state u.
- Matching is performed between u and m_i with SoftMax function.
- Output is calculated by the relation: $o = \sum p_i c$
- Another Softmax is used to produce final predictions after summing up o with u.





- 1. I (input): converts to word embeddings X(dialog).
- 2. G (generalization): stores x in next available slot Mn()
- 3. O (output): Loops over all memories k=1 or 2 times:

a. 1st loop max: finds best match Mi with X(question).

b. 2nd loop max: finds best match Mj with (x, Mi)

c. The output o is represented with (x, Mi, Mj).

- ? (rosponso): ranks all words in the distingury given O and returns host single
- 4. R (response): ranks all words in the dictionary given O and returns best single word. (OR: use a full RNN here)

MODEL VISUALIZATION

Output Shape	Param #	Connected to
(None, 68)	0	
(None, 4)	0	
multiple	1408	input_1[0][0]
(None, 4, 64)	1408	input_2[0][0]
(None, 68, 4)	0	sequential_1[1][0] sequential_3[1][0]
(None, 68, 4)	0	merge_1[0][0]
multiple	88	input_1[0][0]
(None, 68, 4)	0	activation_1[0][0] sequential_2[1][0]
(None, 4, 68)	0	merge_2[0][0]
(None, 4, 132)	0	permute_1[0][0] sequential_3[1][0]
(None, 64)	50432	merge_3[0][0]
(None, 64)	0	lstm_1[0][0]
(None, 22)	1430	dropout_4[0][0]
(None, 22)	0	dense_1[0][0]
	(None, 68) (None, 4) multiple (None, 4, 64) (None, 68, 4) (None, 68, 4) multiple (None, 68, 4) (None, 4, 68) (None, 4, 132) (None, 64) (None, 64) (None, 62)	(None, 68) 0 (None, 4) 0 multiple 1408 (None, 4, 64) 1408 (None, 68, 4) 0 (None, 68, 4) 0 multiple 88 (None, 68, 4) 0 (None, 68, 4) 0 (None, 4, 68) 0 (None, 4, 132) 0 (None, 64) 50432 (None, 64) 0 (None, 64) 0

Layers	Dropouts	Batch-size	Epochs	Results
LSTM(32)	0.3	32	100	94.6%
LSTM(64)	0.3	32	100	96.5%
LSTM(32), LSTM(32)	(0.5,0.5)	32	100	92.4%
LSTM(32), LSTM(32)	(0.5, 0.5)	32	200	96.9%
GRU(32)	0.3	32	100	86.4%
GRU(64)	0.3	32	100	87.4%
GRU(32), GRU(32)	(0.5,0.5)	64	100	52.6%

DEMO

11 CONCLUSION

- The models with two or more layers required more training since there are more parameters that need to be set, but then have greater accuracies than the other models once trained completely.
- Overall, LSTM based models performed better than GRU based models for this task.

12 FUTURE TASKS

- There are many experiments that can be carried out such as adding neural attention layer along with the deep reinforcement approach to attain good accuracy (https://arxiv.org/pdf/1705.04304.pdf)
- We can also integrate episodic memory modules along with softGRU's and dynamic attention flow mechanism (https://arxiv.org/abs/1506.07285)

Thank you