

BERT

Bidirectional Encoder Representations from Transformers

<https://arxiv.org/pdf/1810.04805.pdf>

feature-based & fine-tuning

class	example	Task-specific model	method
Feature-based	ELMo	Need	The representation is provided as feature to tasks
fine-tuning	OpenAI GPT	Don't need	Fine tune models

Model Architecture

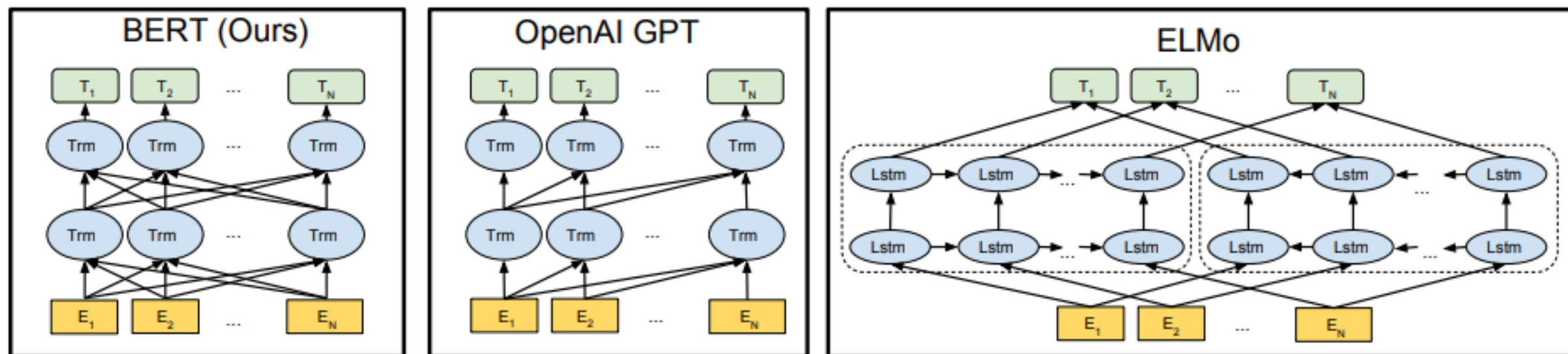


Figure 1: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTM to generate features for downstream tasks. Among three, only BERT representations are jointly conditioned on both left and right context in all layers.

Pre-trained models

- **BERT-Base, Uncased:** 12-layer, 768-hidden, 12-heads, 110M parameters
- **BERT-Large, Uncased:** 24-layer, 1024-hidden, 16-heads, 340M parameters
- **BERT-Base, Cased:** 12-layer, 768-hidden, 12-heads , 110M parameters
- **BERT-Large, Cased:** 24-layer, 1024-hidden, 16-heads, 340M parameters (Not available yet. Needs to be re-generated).
- **BERT-Base, Multilingual:** 102 languages, 12-layer, 768-hidden, 12-heads, 110M parameters
- **BERT-Base, Chinese:** Chinese Simplified and Traditional, 12-layer, 768-hidden, 12-heads, 110M parameters

Input representation

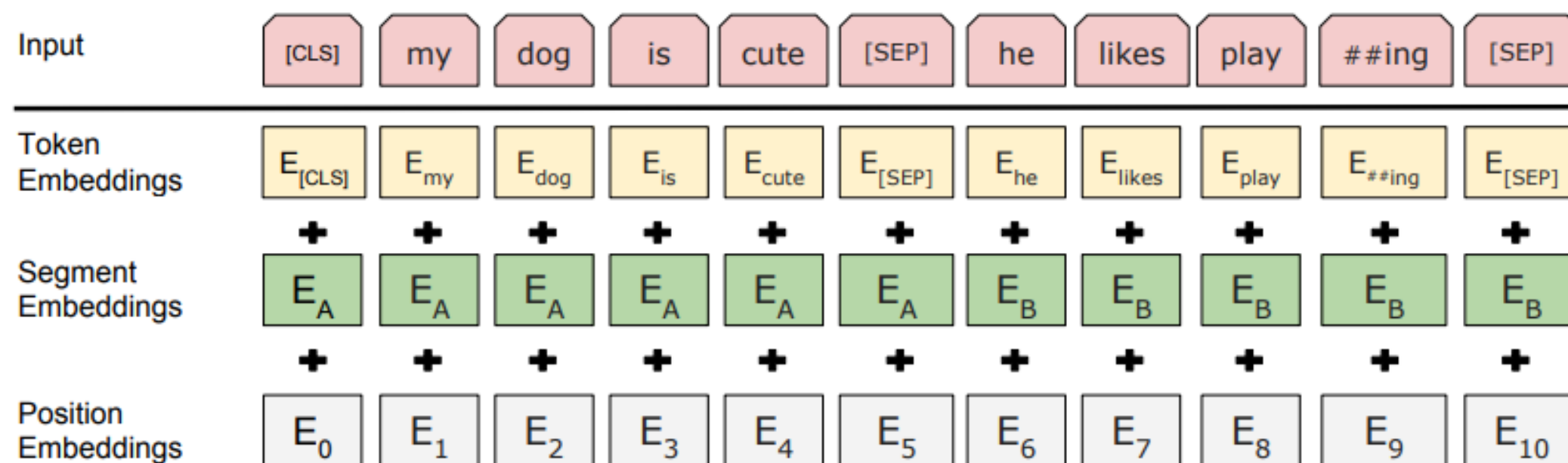


Figure 2: BERT input representation. The input embeddings is the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Pre-training tasks

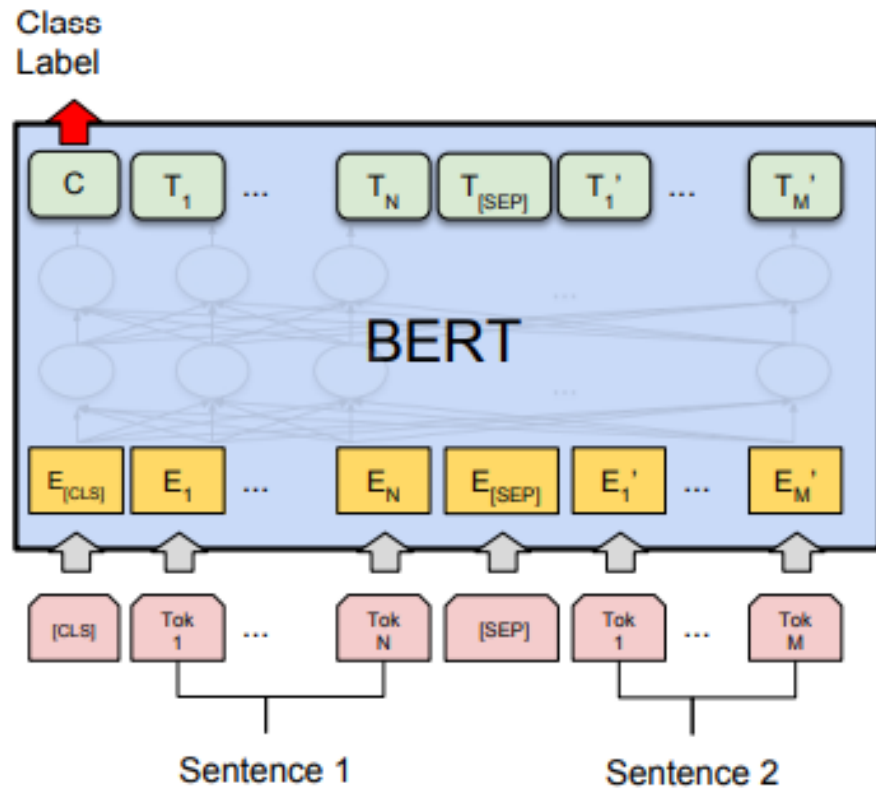
- **Task #1: Masked LM**

- 80% of the time: Replace the word with the [MASK] token,
 - e.g., my dog is hairy → my dog is [MASK]
- 10% of the time: Replace the word with a random word
 - e.g., my dog is hairy → my dog is apple
- 10% of the time: Keep the word unchanged,
 - e.g., my dog is hairy → my dog is hairy.

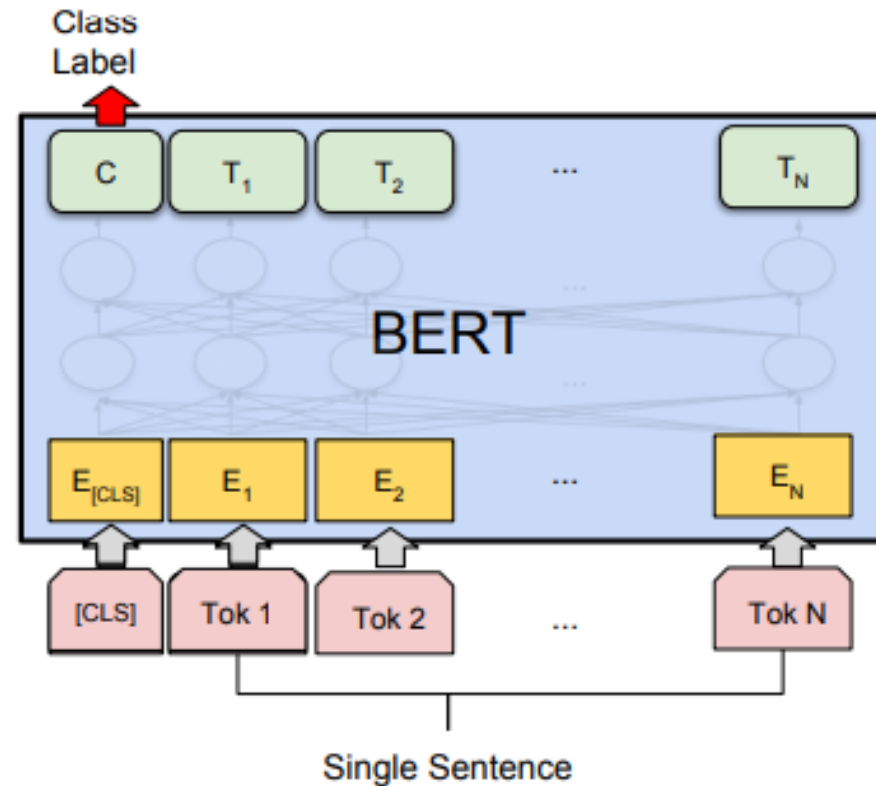
- **Task #2: Next Sentence Prediction**

- Input = [CLS] the man went to [MASK] store [SEP] he bought a gallon [MASK] milk [SEP]
Label = IsNext
- Input = [CLS] the man [MASK] to the store [SEP] penguin [MASK] are flight ##less birds [SEP]
Label = NotNext

Fine-tuning Procedure



(a) Sentence Pair Classification Tasks:
MNLI, QQP, QNLI, STS-B, MRPC,
RTE, SWAG



(b) Single Sentence Classification Tasks:
SST-2, CoLA

Task — datasets

名称	全名	用途
MNLI	Multi-Genre NLI	蕴含关系推断
QQP	Quora Question Pairs	问题对是否等价
QNLI	Question NLI	句子是否回答问句
SST-2	Stanford Sentiment Treebank	情感分析
CoLA	Corpus of Linguistic Acceptability	句子语言性判断
STS-B	Semantic Textual Similarity	语义相似
MRPC	Microsoft Research Paraphrase Corpus	句子对是否语义等价
RTE	Recognizing Textual Entailment	蕴含关系推断
WNLI	Winograd NLI	蕴含关系推断

Task — MRPC(sentence-pair)

Quality	#1 ID	#2 ID	#1 String	#2 String
1	702876	702977	<u>Amrozi</u> accused his brother , whom he called " the witness " , of deliberately distorting his evidence . Referring	
0	2108705	2108831	<u>Yucaipa</u> owned Dominick 's before selling the chain to Safeway in 1998 for \$ 2.5 billion . <u>Yucaipa</u> bought Domini	
1	1330381	1330521	They had published an advertisement on the Internet on June 10 , offering the cargo for sale , he added . On Ju	
0	3344667	3344648	Around 0335 GMT , Tab shares were up 19 cents , or 4.4 % , at A \$ 4.56 , having earlier set a record high of A \$	
1	1236820	1236712	The stock rose \$ 2.11 , or about 11 percent , to close Friday at \$ 21.51 on the New York Stock Exchange . PG &	
1	738533	737951	Revenue in the first quarter of the year dropped 15 percent from the same period a year earlier . With the scar	
0	264589	264502	The Nasdaq had a weekly gain of 17.27 , or 1.2 percent , closing at 1,520.15 on Friday . The tech-laced Nasdaq	
1	579975	579810	The DVD-CCA then appealed to the state Supreme Court . The DVD CCA appealed that decision to the U.S. Supreme Co	
0	3114205	3114194	That compared with \$ 35.18 million , or 24 cents per share , in the year-ago period . Earnings were affected by	
0	222621	222514	Shares of <u>Genentech</u> , a much larger company with several products on the market , rose more than 2 percent . S	
0	3131772	3131625	Legislation making it harder for consumers to erase their debts in bankruptcy court won overwhelming House approv	
0	58747	58516	The Nasdaq composite index increased 10.73 , or 0.7 percent , to 1,514.77 . The Nasdaq Composite index , full of	

Training: loading train.tsv—>tokenization—>print 5 train examples—>loading model—>create model_fn(fn+softmax) —>training & save checkpoints

evaluate: loading dev.tsv—>tokenization—>print 5 dev examples—>loading model—>create model_fn(fn+softmax) —>loading checkpoints & evaluation

Task — MRPC(sentence-pair)

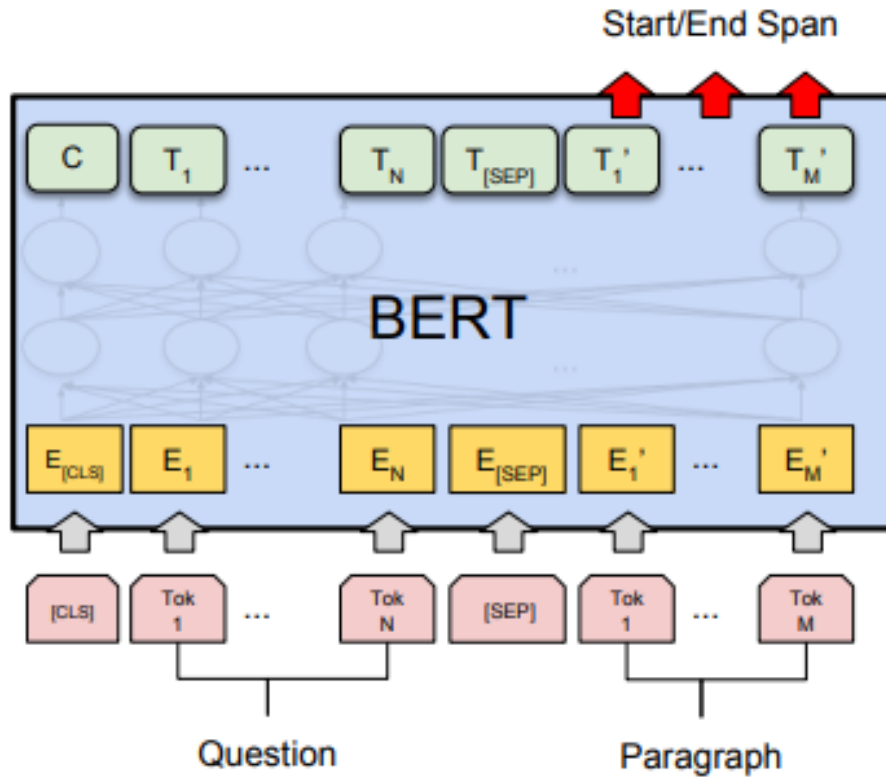
[illegible]

Task — MRPC(sentence-pair)

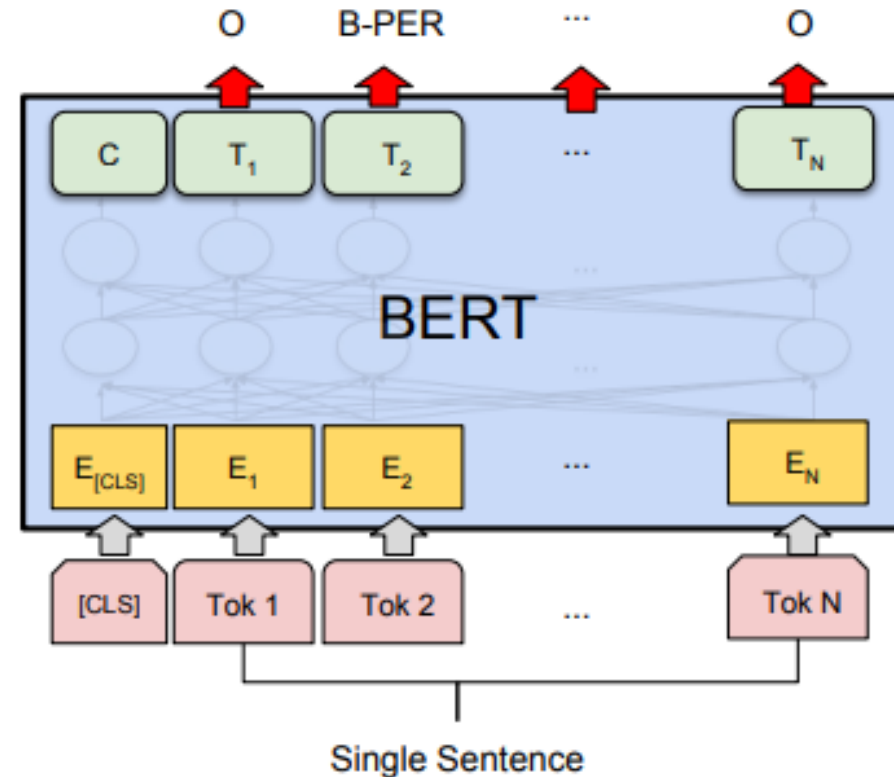
Steps = $\text{len}(\text{train_examples}) / \text{train_batch_size} * \text{num_train_epochs}$

```
INFO:tensorflow:***** Running training *****
INFO:tensorflow:  Num examples = 3668
INFO:tensorflow:  Batch size = 32
INFO:tensorflow:  Num steps = 343
INFO:tensorflow:Calling model_fn.
INFO:tensorflow:Running train on CPU
INFO:tensorflow:*** Features ***
INFO:tensorflow:  name = input_ids, shape = (32, 128)
INFO:tensorflow:  name = input_mask, shape = (32, 128)
INFO:tensorflow:  name = label_ids, shape = (32,)
INFO:tensorflow:  name = segment_ids, shape = (32, 128)
INFO:tensorflow:**** Trainable Variables ****
INFO:tensorflow:  name = bert/embeddings/word_embeddings:0, shape = (30522, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/embeddings/token_type_embeddings:0, shape = (2, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/embeddings/position_embeddings:0, shape = (512, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/embeddings/LayerNorm/beta:0, shape = (768,), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/embeddings/LayerNorm/gamma:0, shape = (768,), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/query/kernel:0, shape = (768, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/query/bias:0, shape = (768,), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/key/kernel:0, shape = (768, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/key/bias:0, shape = (768,), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/value/kernel:0, shape = (768, 768), *INIT_FROM_CKPT*
INFO:tensorflow:  name = bert/encoder/layer_0/attention/self/value/bias:0, shape = (768,), *INIT_FROM_CKPT*
INFO:tensorflow:***** Eval results *****
INFO:tensorflow:  eval_accuracy = 0.85784316
INFO:tensorflow:  eval_loss = 0.45819566
INFO:tensorflow:  global_step = 343
INFO:tensorflow:  loss = 0.45819566
```

Fine-tuning Procedure



(c) Question Answering Tasks:
SQuAD v1.1



(d) Single Sentence Tagging Tasks:
CoNLL-2003 NER

Task — SQuAD(span)

- **Input Question:**

`Where do water droplets collide with ice
crystals to form precipitation?`

- **Input Paragraph:**

`... Precipitation forms as smaller droplets
coalesce via collision with other rain drops
or ice crystals within a cloud. ...`

- **Output Answer:**

`within a cloud`

Evaluate:

- EM: the results must exact match the answer
- F1: Cut the phrase of the results into words, and calculate the recall, Precision and F1 together with the answer of the person

out-of-memory: change `train_batch_size=6`

Task — SQuAD(span)

```
INFO:tensorflow:*** Example ***
INFO:tensorflow:unique_id: 1000000009
INFO:tensorflow:example_index: 9
INFO:tensorflow:doc_span_index: 0
INFO:tensorflow:tokens: [CLS] what race has a very low rate of holding public office in brazil ? [SEP] though brazilian ##s of
  at least partial african heritage make up a large percentage of the population , few blacks have been elected as politicians
. the city of salvador , bahia , for instance , is 80 % people of color , but voters have not elected a mayor of color . journ
alists like to say that us cities with black major ##ities , such as detroit and new orleans , have not elected white mayors s
ince after the civil rights movement , when the voting rights act of 1965 protected the franchise for minorities , and blacks
in the south regained the power to vote for the first time since the turn of the 20th century . new orleans elected its first
black mayor in the 1970s . new orleans elected a white mayor after the wide ##sca ##le disruption and damage of hurricane katr
ina in 2005 . [SEP]
INFO:tensorflow:token_to_orig_map: 16:0 17:1 18:1 19:2 20:3 21:4 22:5 23:6 24:7 25:8 26:9 27:10 28:11 29:12 30:13 31:14 32:15
33:15 34:16 35:17 36:18 37:19 38:20 39:21 40:22 41:22 42:23 43:24 44:25 45:26 46:26 47:27 48:27 49:28 50:29 51:29 52:30 53:31
54:31 55:32 56:33 57:34 58:34 59:35 60:36 61:37 62:38 63:39 64:40 65:41 66:42 67:43 68:43 69:44 70:45 71:46 72:47 73:48 74:49
75:50 76:51 77:52 78:53 79:53 80:53 81:54 82:55 83:56 84:57 85:58 86:59 87:59 88:60 89:61 90:62 91:63 92:64 93:65 94:66 95:67
96:68 97:69 98:70 99:70 100:71 101:72 102:73 103:74 104:75 105:76 106:77 107:78 108:79 109:80 110:81 111:82 112:82 113:83 114:
84 115:85 116:86 117:87 118:88 119:89 120:90 121:91 122:92 123:93 124:94 125:95 126:96 127:97 128:98 129:99 130:100 131:101 13
2:102 133:103 134:103 135:104 136:105 137:106 138:107 139:108 140:109 141:110 142:111 143:112 144:113 145:113 146:114 147:115
148:116 149:117 150:118 151:119 152:120 153:121 154:122 155:122 156:122 157:123 158:124 159:125 160:126 161:127 162:128 163:12
9 164:130 165:130
INFO:tensorflow:token_is_max_context: 16:True 17:True 18:True 19:True 20:True 21:True 22:True 23:True 24:True 25:True 26:True
27:True 28:True 29:True 30:True 31:True 32:True 33:True 34:True 35:True 36:True 37:True 38:True 39:True 40:True 41:True 42:Tru
e 43:True 44:True 45:True 46:True 47:True 48:True 49:True 50:True 51:True 52:True 53:True 54:True 55:True 56:True 57:True 58:T
rue 59:True 60:True 61:True 62:True 63:True 64:True 65:True 66:True 67:True 68:True 69:True 70:True 71:True 72:True 73:True 74
:True 75:True 76:True 77:True 78:True 79:True 80:True 81:True 82:True 83:True 84:True 85:True 86:True 87:True 88:True 89:True
90:True 91:True 92:True 93:True 94:True 95:True 96:True 97:True 98:True 99:True 100:True 101:True 102:True 103:True 104:True 1
05:True 106:True 107:True 108:True 109:True 110:True 111:True 112:True 113:True 114:True 115:True 116:True 117:True 118:True 1
19:True 120:True 121:True 122:True 123:True 124:True 125:True 126:True 127:True 128:True 129:True 130:True 131:True 132:True 1
33:True 134:True 135:True 136:True 137:True 138:True 139:True 140:True 141:True 142:True 143:True 144:True 145:True 146:True 1
```

Todo list

- Transformer : Set the **hyperparameter** and select the words to connect to each node
- pre_training : add another tasks;
- final hidden state : Like ELMo, learning the linear combination of the representations of **each** layer;
- Fine-tune : Add a deep network model