BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

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Agenda

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Abstract

논문에서는 양방향 context를 encoding하는 transformer기반의 language representation 모델과 이를 pre-training하고 fine-tuning하는 방법을 제시

BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

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Abstract

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

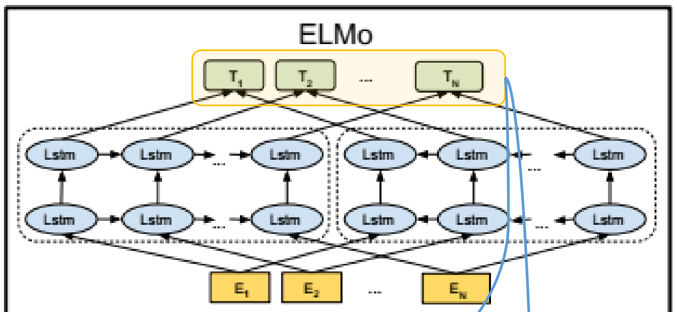
BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).

Introduction & Related Work (1/2)

Language model은 NLP의 upstream task로 pre-trained language model은 여러 downstream task에 feature-based, fine-tuning 방법등으로 적용할 수 있음

Feature-based

sequence를 구성하는 token의 embedding을 뽑고 이를 통해 데이터를 구성, task-specific한 architecture가 필요
(eg. BiDAR, BiLSTM-CRF)



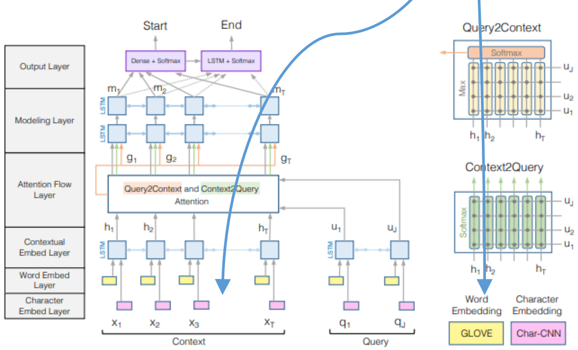
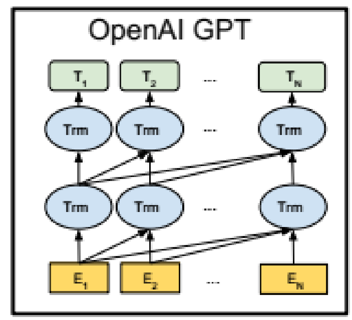


Figure 1: BiDirectional Attention Flow Model *(best viewed in color)*

Task-specific architecture (eg. BiDAF)

Fine-tuning

Sequence의 embedding을 뽑는 architecture에 task에 맞추어 fully-connected layer 한 개 정도만 활용
(minimal task-specific parameter)



minimal
task-specific parameter

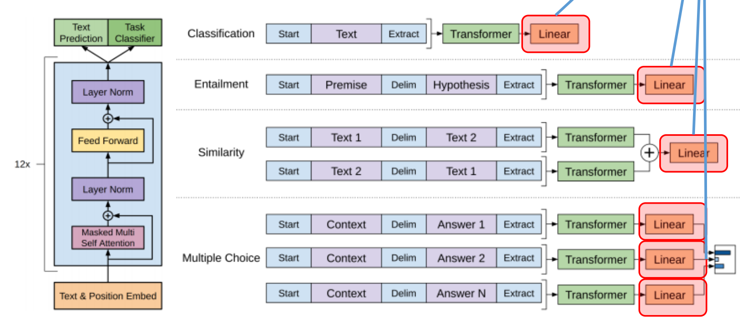


Figure 1: **(left)** Transformer architecture and training objectives used in this work. **(right)** Input transformations for fine-tuning on different tasks. We convert all structured inputs into token sequences to be processed by our pre-trained model, followed by a linear+softmax layer.

Introduction & Related Work (2/2)

기존 feature-based, fine-tuning의 방법론이 unidirectional 이었던 반면, 논문은 hidden layer에서도 bidirectional하게 정보를 encoding하는 구조와 방법을 제안

Architecture: deep bidirectional transformer (aka, stacked bidirectional transformer)

Methodology: masked language model, next sentence prediction

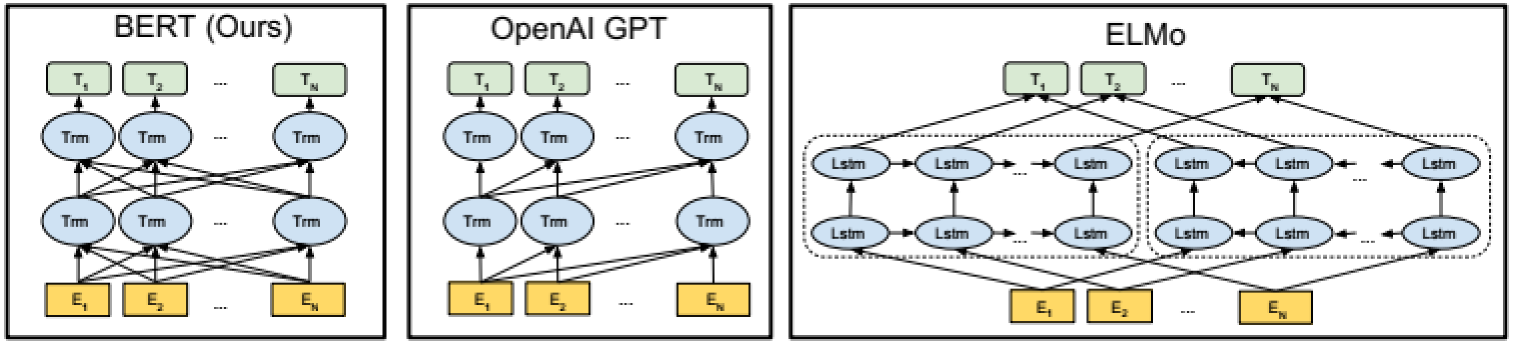


Figure 3: Differences in pre-training model architectures. BERT uses a bidirectional Transformer. OpenAI GPT uses a left-to-right Transformer. ELMo uses the concatenation of independently trained left-to-right and right-to-left LSTMs to generate features for downstream tasks. Among the three, only BERT representations are jointly conditioned on both left and right context in all layers. In addition to the architecture differences, BERT and OpenAI GPT are fine-tuning approaches, while ELMo is a feature-based approach.

BERT (1/3)

Masked language model과 next sentence prediction의 loss로 pre-training하고, 이에 task-specific하게 fully-connected layer를 붙여 fine-tuning하여 사용

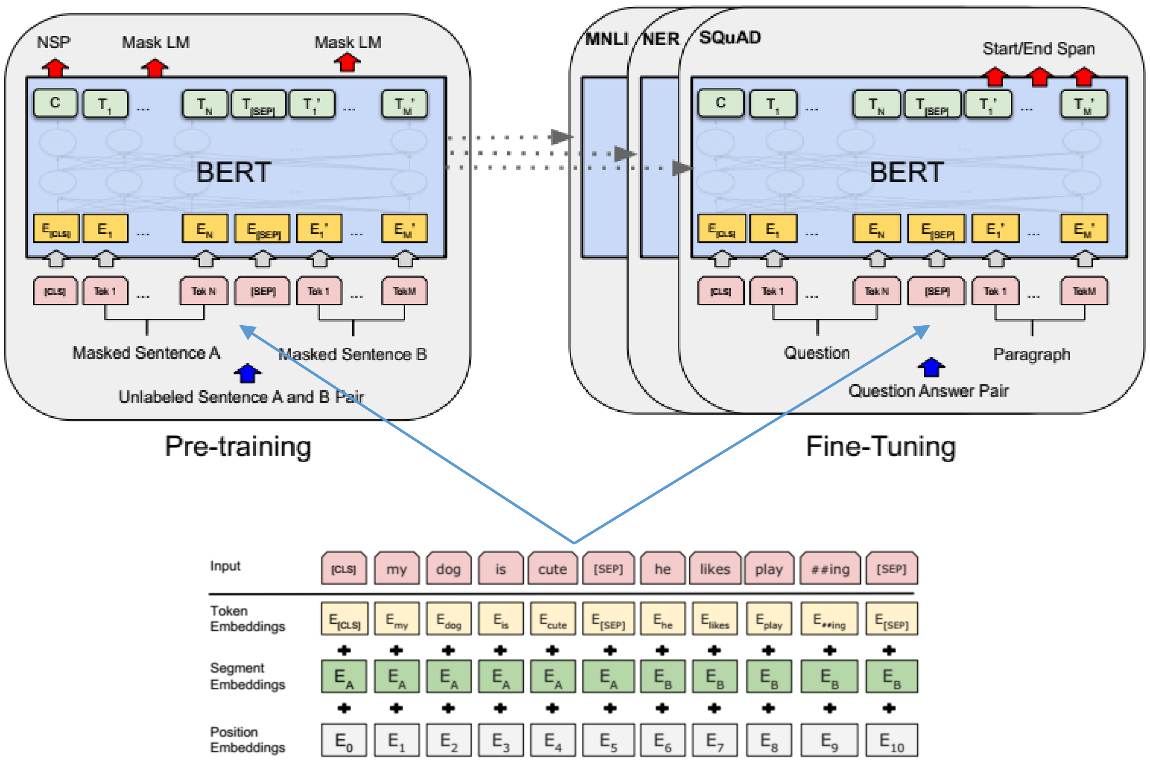


Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Model Architecture BERT's model architecture is a multi-layer bidirectional Transformer encoder based on the original implementation described in Vaswani et al. (2017) and released in the `tensor2tensor` library.[1] Because the use of Transformers has become common and our implementation is almost identical to the original, we will omit an exhaustive background description of the model architecture and refer readers to Vaswani et al. (2017) as well as excellent guides such as "The Annotated Transformer."[2]

In this work, we denote the number of layers (i.e., Transformer blocks) as L, the hidden size as H, and the number of self-attention heads as A.[3] We primarily report results on two model sizes: **$\text{BERT}_{\text{BASE}}$** (L=12, H=768, A=12, Total Parameters=110M) and **$\text{BERT}_{\text{LARGE}}$** (L=24, H=1024, A=16, Total Parameters=340M).

$\text{BERT}_{\text{BASE}}$ was chosen to have the same model size as OpenAI GPT for comparison purposes. Critically, however, the BERT Transformer uses bidirectional self-attention, while the GPT Transformer uses constrained self-attention where every token can only attend to context to its left.[4]

BERT (2/3)

Masked language model과 next sentence prediction의 loss로 pre-training하고, 이에 task-specific하게 fully-connected layer를 붙여 fine-tuning하여 사용

Input/Output Representations To make BERT handle a variety of down-stream tasks, our input representation is able to unambiguously represent both a single sentence and a pair of sentences (e.g., ⟨ Question, Answer ⟩) in one token sequence. Throughout this work, a "sentence" can be an arbitrary span of contiguous text, rather than an actual linguistic sentence. A "sequence" refers to the input token sequence to BERT, which may be a single sentence or two sentences packed together.

We use WordPiece embeddings (Wu et al., 2016) with a 30,000 token vocabulary. The first token of every sequence is always a special classification token (`[CLS]`). The final hidden state corresponding to this token is used as the aggregate sequence representation for classification tasks. Sentence pairs are packed together into a single sequence. We differentiate the sentences in two ways. First, we separate them with a special token (`[SEP]`). Second, we add a learned embedding to every token indicating whether it belongs to sentence `A` or sentence `B`. As shown in Figure 1, we denote input embedding as E, the final hidden vector of the special `[CLS]` token as $C \in \mathbb{R}^H$, and the final hidden vector for the i^{th} input token as $T_i \in \mathbb{R}^H$.

For a given token, its input representation is constructed by summing the corresponding token, segment, and position embeddings. A visualization of this construction can be seen in Figure 2.

Masked LM and the Masking Procedure Assuming the unlabeled sentence is `my dog is hairy`, and during the random masking procedure we chose the 4-th token (which corresponding to `hairy`), our masking procedure can be further illustrated by

- 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`. The purpose of this is to bias the representation towards the actual observed word.

The advantage of this procedure is that the Transformer encoder does not know which words it will be asked to predict or which have been replaced by random words, so it is forced to keep a distributional contextual representation of *every* input token. Additionally, because random replacement only occurs for 1.5% of all tokens (i.e., 10% of 15%), this does not seem to harm the model's language understanding capability. In Section C.2, we evaluate the impact this procedure.

Next Sentence Prediction The next sentence prediction task can be illustrated in the following examples.

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`

A.2 Pre-training Procedure

To generate each training input sequence, we sample two spans of text from the corpus, which we refer to as "sentences" even though they are typically much longer than single sentences (but can be shorter also). The first sentence receives the `A` embedding and the second receives the `B` embedding. 50% of the time `B` is the actual next sentence that follows `A` and 50% of the time it is a random sentence, which is done for the "next sentence prediction" task. They are sampled such that the combined length is ≤ 512 tokens. The LM masking is applied after WordPiece tokenization with a uniform masking rate of 15%, and no special consideration given to partial word pieces.

BERT (3/3)

Fine-tuning 시 sentence-level task일 경우 “[CLS]” token의 last hidden vector, token-level task의 경우 각각의 token에 해당하는 last hidden vector 사용

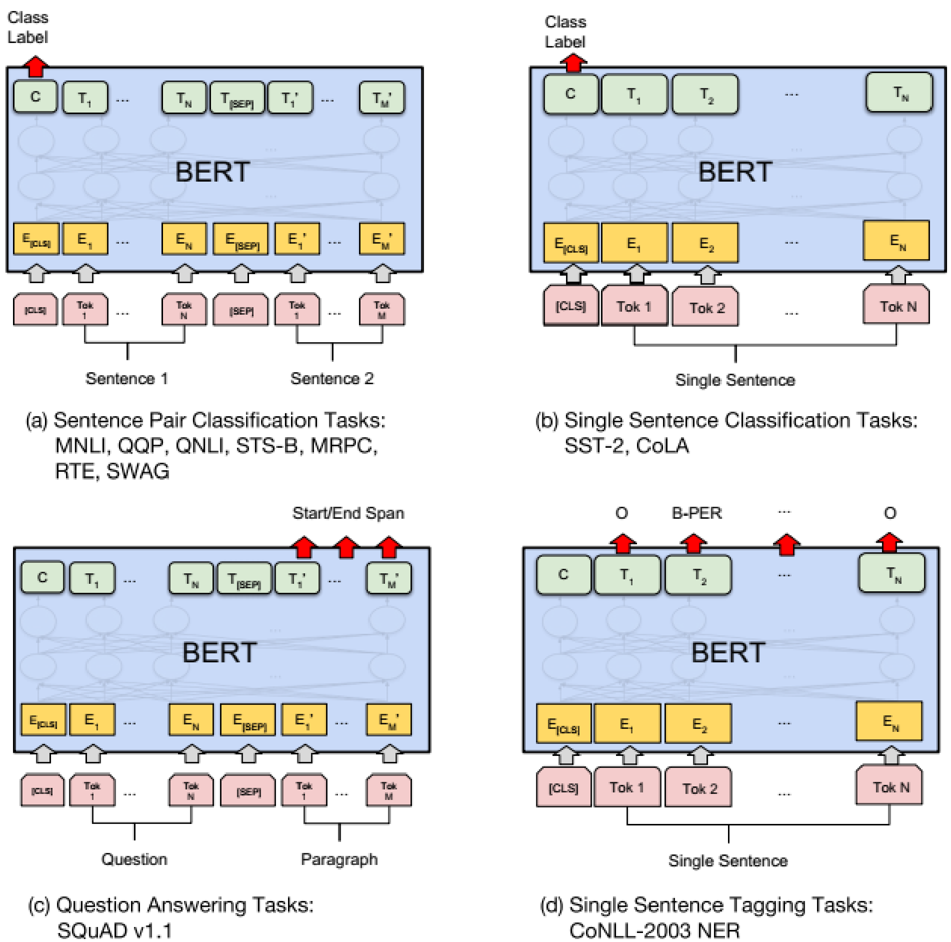


Figure 4: Illustrations of Fine-tuning BERT on Different Tasks.

A.5 Illustrations of Fine-tuning on Different Tasks

The illustration of fine-tuning BERT on different tasks can be seen in Figure 4. Our task-specific models are formed by incorporating BERT with one additional output layer, so a minimal number of parameters need to be learned from scratch. Among the tasks, (a) and (b) are sequence-level tasks while (c) and (d) are token-level tasks. In the figure, E represents the input embedding, T_i represents the contextual representation of token i, [CLS] is the special symbol for classification output, and [SEP] is the special symbol to separate non-consecutive token sequences.

Experiments

GLUE를 포함한 대부분의 task에서 SOTA를 달성

System	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	STS-B	MRPC	RTE	**Average**
	392k	363k	108k	67k	8.5k	5.7k	3.5k	2.5k	-
Pre-OpenAI SOTA	80.6/80.1	66.1	82.3	93.2	35.0	81.0	86.0	61.7	74.0
BiLSTM+ELMo+Attn	76.4/76.1	64.8	79.8	90.4	36.0	73.3	84.9	56.8	71.0
OpenAI GPT	82.1/81.4	70.3	87.4	91.3	45.4	80.0	82.3	56.0	75.1
$\text{BERT}_{\text{BASE}}$	84.6/83.4	71.2	90.5	93.5	52.1	85.8	88.9	66.4	79.6
$\text{BERT}_{\text{LARGE}}$	**86.7/85.9**	**72.1**	**92.7**	**94.9**	**60.5**	**86.5**	**89.3**	**70.1**	**82.1**

Table 1: GLUE Test results, scored by the evaluation server (https://gluebenchmark.com/leaderboard). The number below each task denotes the number of training examples. The "Average" column is slightly different than the official GLUE score, since we exclude the problematic WNLI set.[8] BERT and OpenAI GPT are single-model, single task. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. We exclude entries that use BERT as one of their components.

System	Dev EM	Dev F1	Test EM	Test F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	-	-	82.3	91.2
#1 Ensemble - nlnet	-	-	86.0	91.7
#2 Ensemble - QANet	-	-	84.5	90.5
Published				
BiDAF+ELMo (Single)	-	85.6	-	85.8
R.M. Reader (Ensemble)	81.2	87.9	82.3	88.5
Ours				
$\text{BERT}_{\text{BASE}}$ (Single)	80.8	88.5	-	-
$\text{BERT}_{\text{LARGE}}$ (Single)	84.1	90.9	-	-
$\text{BERT}_{\text{LARGE}}$ (Ensemble)	85.8	91.8	-	-
$\text{BERT}_{\text{LARGE}}$ (Sgl.+TriviaQA)	**84.2**	**91.1**	**85.1**	**91.8**
$\text{BERT}_{\text{LARGE}}$ (Ens.+TriviaQA)	**86.2**	**92.2**	**87.4**	**93.2**

Table 2: SQuAD 1.1 results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

Table 2: SQuAD 1.1 results. The BERT ensemble is 7x systems which use different pre-training checkpoints and fine-tuning seeds.

System	Dev EM	Dev F1	Test EM	Test F1
Top Leaderboard Systems (Dec 10th, 2018)				
Human	86.3	89.0	86.9	89.5
#1 Single - MIR-MRC (F-Net)	-	-	74.8	78.0
#2 Single - nlnet	-	-	74.2	77.1
Published				
unet (Ensemble)	-	-	71.4	74.9
SLQA+ (Single)	-		71.4	74.4
Ours				
$\text{BERT}_{\text{LARGE}}$ (Single)	78.7	81.9	80.0	83.1

Table 3: SQuAD 2.0 results. We exclude entries that use BERT as one of their components.

System	Dev	Test
ESIM+GloVe	51.9	52.7
ESIM+ELMo	59.1	59.2
OpenAI GPT	-	78.0
$\text{BERT}_{\text{BASE}}$	81.6	-
$\text{BERT}_{\text{LARGE}}$	**86.6**	**86.3**
Human (expert)†	-	85.0
Human (5 annotations)†	-	88.0

Table 4: SWAG Dev and Test accuracies. †Human performance is measured with 100 samples, as reported in the SWAG paper.

Ablation studies (1/2)

Pre-training 방식 중, nsp가 sentence-level task mlm이 token-level task의 성능에 영향, 잘 학습된 pre-trained BERT는 데이터셋이 적은 task에도 사용가능

Tasks	Dev Set MNLI-m (Acc)	QNLI (Acc)	MRPC (Acc)	SST-2 (Acc)	SQuAD (F1)
$\text{BERT}_{\text{BASE}}$	84.4	88.4	86.7	92.7	88.5
No NSP	83.9	84.9	86.5	92.6	87.9
LTR & No NSP	82.1	84.3	77.5	92.1	77.8
+ BiLSTM	82.1	84.1	75.7	91.6	84.9

Table 5: Ablation over the pre-training tasks using the $\text{BERT}_{\text{BASE}}$ architecture. "No NSP" is trained without the next sentence prediction task. "LTR & No NSP" is trained as a left-to-right LM without the next sentence prediction, like OpenAI GPT. "+ BiLSTM" adds a randomly initialized BiLSTM on top of the "LTR + No NSP" model during fine-tuning.

Hyperparams #L	#H	#A	Dev Set Accuracy LM (ppl)	MNLI-m	MRPC	SST-2
3	768	12	5.84	77.9	79.8	88.4
6	768	3	5.24	80.6	82.2	90.7
6	768	12	4.68	81.9	84.8	91.3
12	768	12	3.99	84.4	86.7	92.9
12	1024	16	3.54	85.7	86.9	93.3
24	1024	16	3.23	86.6	87.8	93.7

Table 6: Ablation over BERT model size. #L = the number of layers; #H = hidden size; #A = number of attention heads. "LM (ppl)" is the masked LM perplexity of held-out training data.

Only 3,600 labeled training examples, and is substantially different from the pre-training tasks.

nsp: next sentence prediction
mlm: masked language model

Ablation studies (2/2)

feature-based approach로 사용해도 fine-tuning approach에 비해서 성능 감소가 적기때문에, 상대적으로 효율적인 feature-based approach로도 사용가능

System	Dev F1	Test F1
ELMo (Peters et al., 2018a)	95.7	92.2
CVT (Clark et al., 2018)	-	92.6
CSE (Akbik et al., 2018)	-	**93.1**
Fine-tuning approach		
BERT$_{\text{LARGE}}$	96.6	92.8
BERT$_{\text{BASE}}$	96.4	92.4
Feature-based approach (BERT$_{\text{BASE}}$)		
Embeddings	91.0	-
Second-to-Last Hidden	95.6	-
Last Hidden	94.9	-
Weighted Sum Last Four Hidden	95.9	-
Concat Last Four Hidden	96.1	-
Weighted Sum All 12 Layers	95.5	-

Table 7: CoNLL-2003 Named Entity Recognition results. Hyperparameters were selected using the Dev set. The reported Dev and Test scores are averaged over 5 random restarts using those hyperparameters.

Conclusion

6 Conclusion

Recent empirical improvements due to transfer learning with language models have demonstrated that rich, unsupervised pre-training is an integral part of many language understanding systems. In particular, these results enable even low-resource tasks to benefit from deep unidirectional architectures. Our major contribution is further generalizing these findings to deep *bidirectional* architectures, allowing the same pre-trained model to successfully tackle a broad set of NLP tasks.

Q & A

감사합니다.