Deep contextualized word representations

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• Abstract

• ELMo

- 기존의 방법들이 다의어를 구분할 수 없다는 단점에서 탄생한 문맥을 반영한 워드 임베딩(Contextualized Word Embedding)
- 이전 단어 임베딩과는 다르게 BI-LSTM층들의 기능들을 이용
- 기존의 모델에 쉽게 추가될 수 있고 문제 해결, 텍스트 entailment, 감성 분석 등 6가지의 NLP 문제에 걸쳐 성능을 크게 개선할 수 있음

• Introduction

- Existing models like Word2Vec or Glove provides a single context-independent representations
- Rest of models like TagLM, utilizes representations from final layer of the model which essentially leave out information from the lower layers
- Higher-level LSTM states capture context-dependent aspects of word meaning while lower-level states model aspects of syntax

• Language Model

- 문장의 확률을 통해 다음의 단어를 예측하는 것이 목표

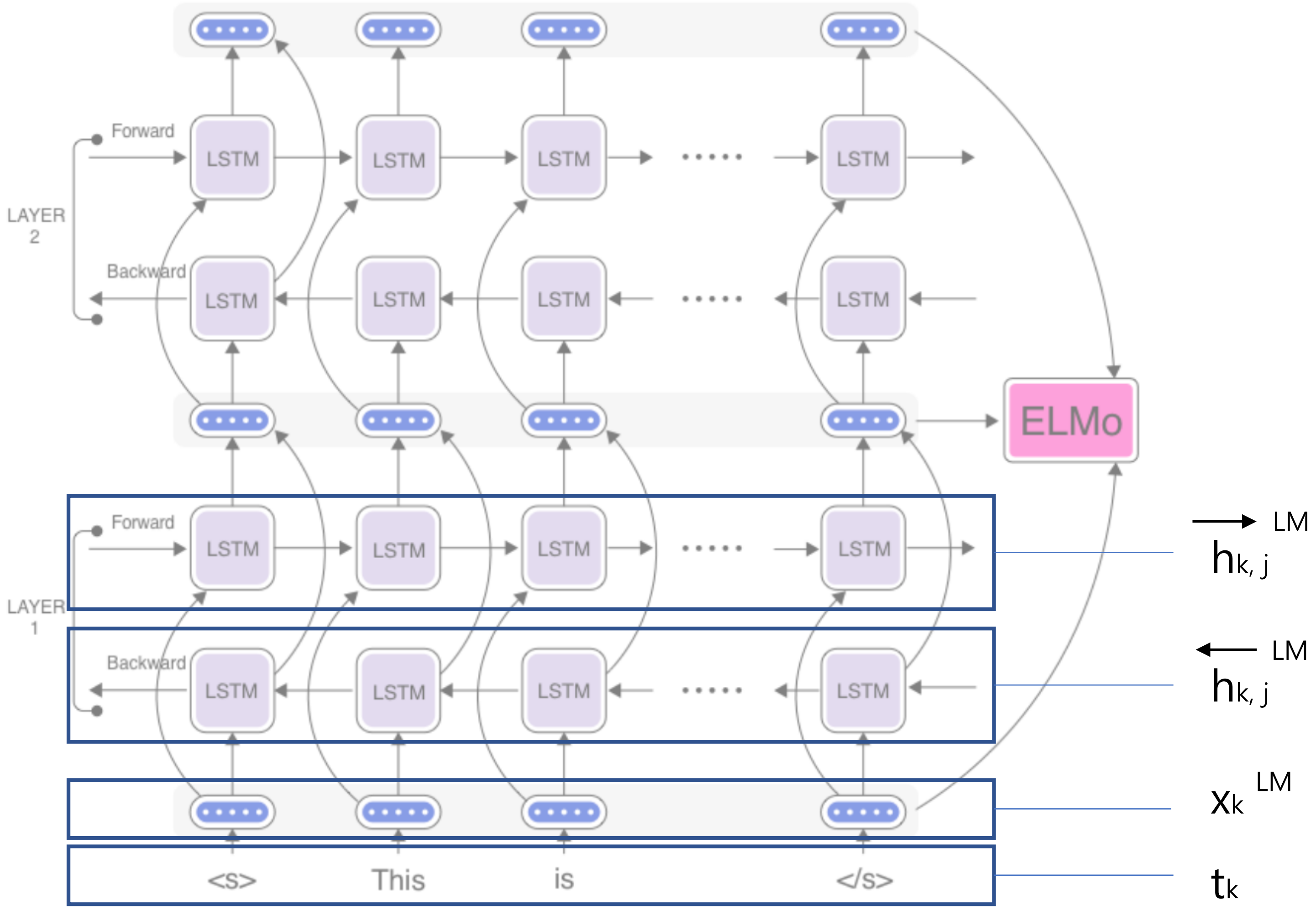
$$P(W) = P(w_1, w_2, w_3, w_4, w_5, \ldots, w_n)$$

- 기본적으론 조건부 확률을 통해 다음에 오는 단어를 구함

$$P(w_5 | w_1, w_2, w_3, w_4)$$

$$P(W) = P(w_1, w_2, w_3, w_4, w_5, \ldots w_n) = \prod_{i=1}^{n} P(w_n | w_1, \ldots, w_{n-1})$$

- **ELMo**



t_k : 토큰
k : k번째 토큰
j : j번째 레이어

• ELMo

- Bidirectional Language Models

$$p(t_1, t_2, \ldots t_N) = \sum_{k=1}^{N} p(t_k | t_1, t_2, \ldots, t_{k-1})$$

$$p(t_1, t_2, \ldots, t_N) = \sum_{k=1}^{N} p(t_k | t_{k+1}, t_{k+2}, \ldots, t_N)$$

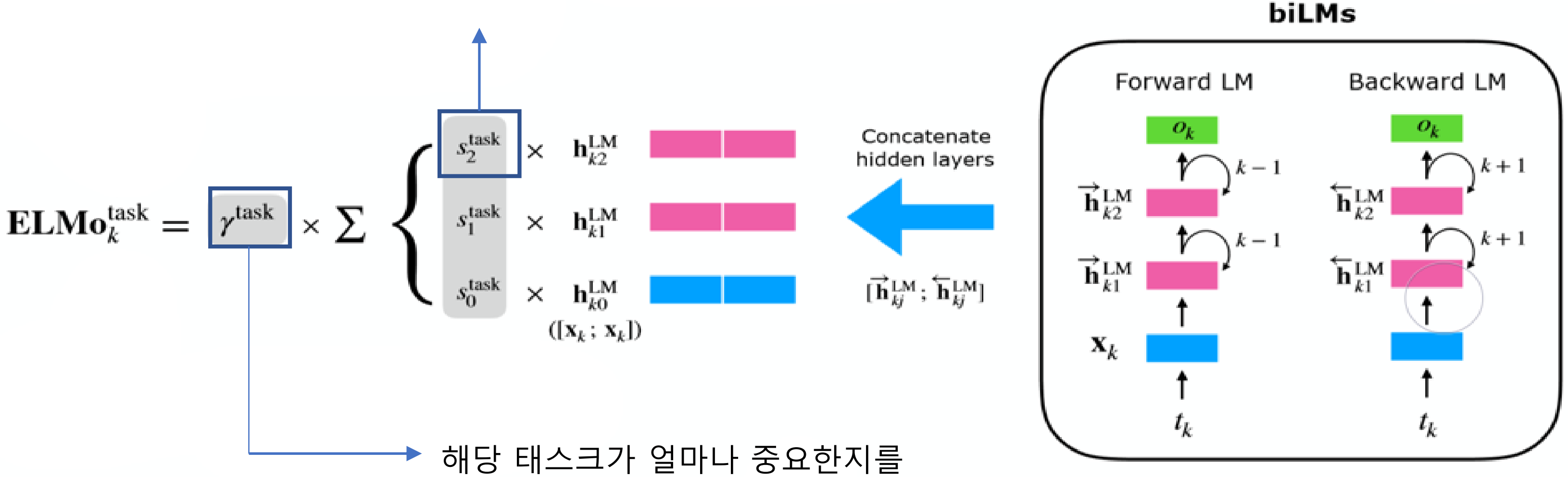
- 두 방향으로부터 나오는 로그 우도의 합을 최대화하도록 학습시킴

$$\sum_{k=1}^{N} (logp(t_k | t_1, \ldots, t_{k-1}; \boxed{\theta_x}, \overrightarrow{\theta}_{LSTM}, \boxed{\theta_s}) + logp(t_k | t_{k+1}, \ldots, t_N; \boxed{\theta_x}, \overleftarrow{\theta}_{LSTM}, \boxed{\theta_s}))$$

• ELMo

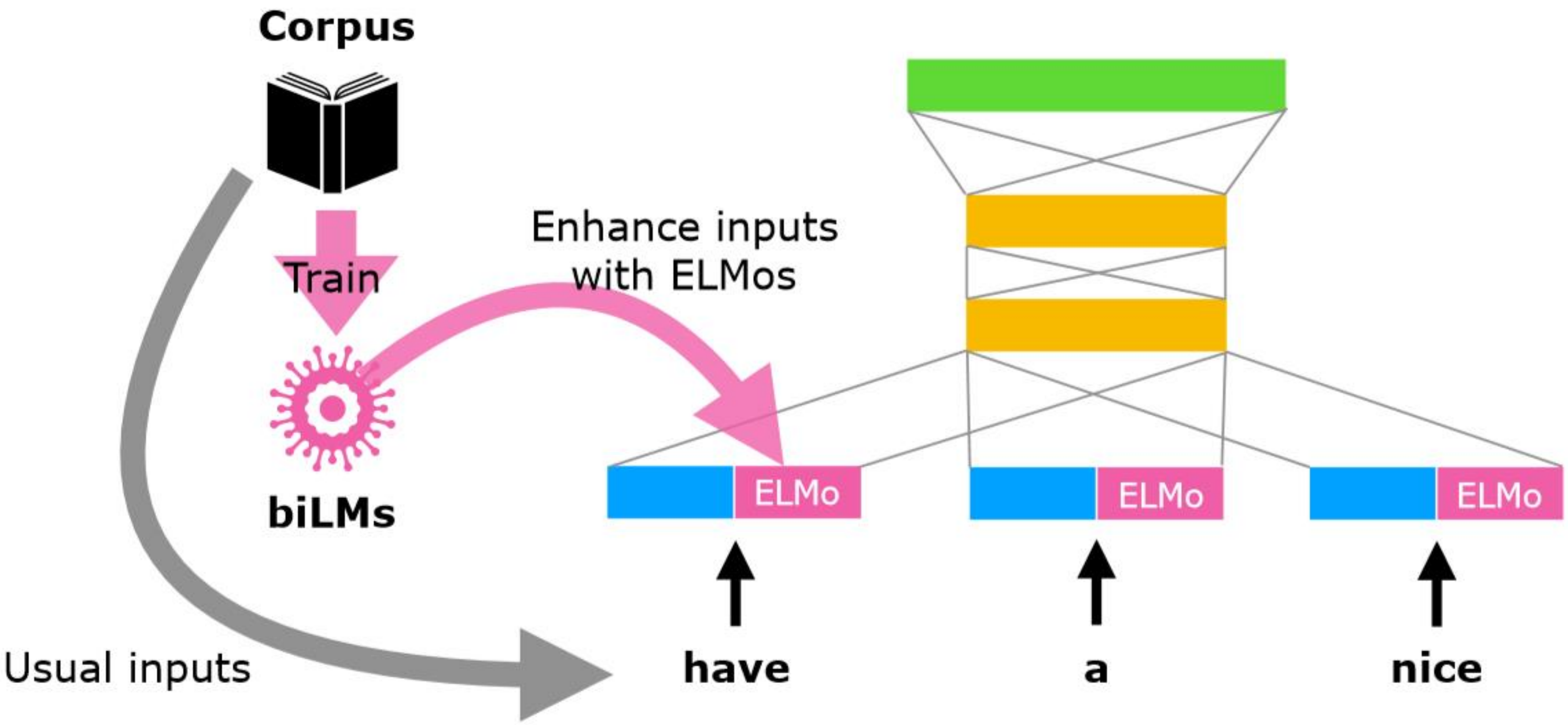
$$ELMo_k^{task} = E(R_k; \theta^{task}) = \gamma^{task} \sum_{j=0}^{L} s_j^{task} h_{k,j}^{LM}$$

j 번째 레이어가 해당 태스크 수행에 얼마나 중요한지 가리키는 스칼라값



해당 태스크가 얼마나 중요한지를
뜻하는 가중치

- **ELMo**


Corpus
Train
biLMs
Enhance inputs
with ELMos
ELMo
ELMo
ELMo
Usual inputs
have
a
nice

• **Evaluation**

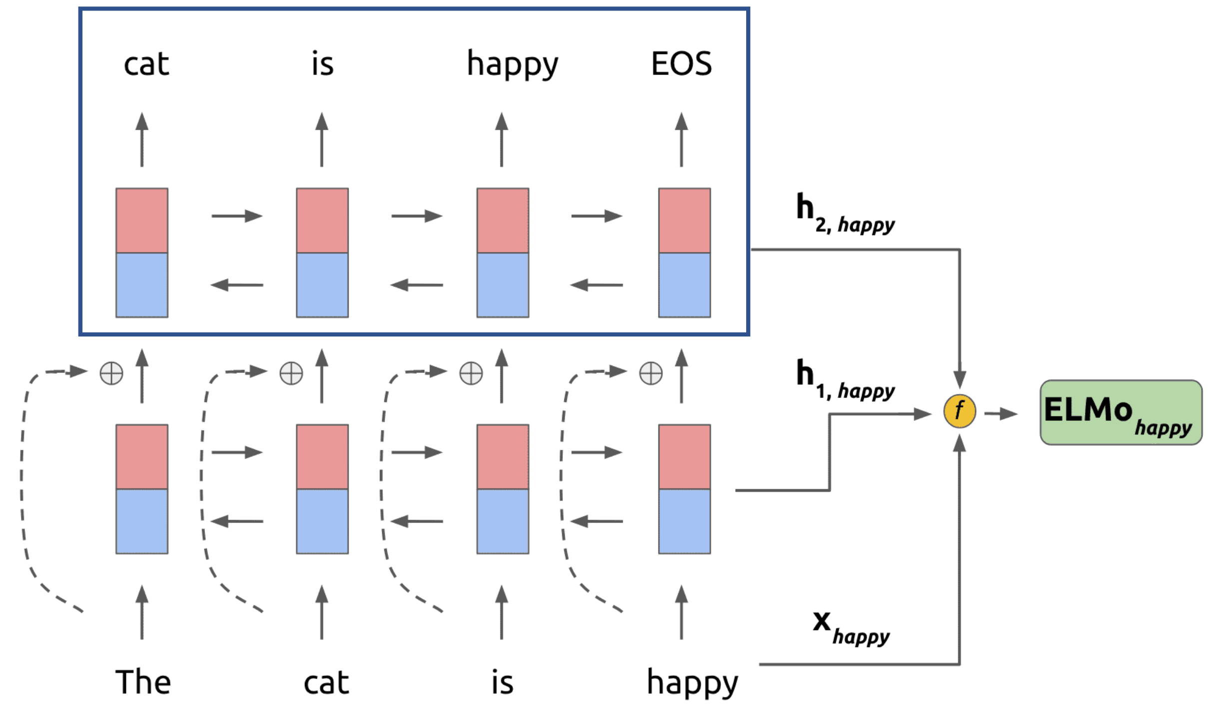
TASK	PREVIOUS SOTA		OUR BASELINE	ELMO + BASELINE	INCREASE (ABSOLUTE/ RELATIVE)
SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

Table 1: Test set comparison of ELMo enhanced neural models with state-of-the-art single model baselines across six benchmark NLP tasks. The performance metric varies across tasks – accuracy for SNLI and SST-5; F_1 for SQuAD, SRL and NER; average F_1 for Coref. Due to the small test sizes for NER and SST-5, we report the mean and standard deviation across five runs with different random seeds. The "increase" column lists both the absolute and relative improvements over our baseline.

• Analysis

Task	Baseline	Last Only	All layers λ=1	All layers λ=0.001
SQuAD	80.8	84.7	85.0	**85.2**
SNLI	88.1	89.1	89.3	**89.5**
SRL	81.6	84.1	84.6	**84.8**

Table 2: Development set performance for SQuAD, SNLI and SRL comparing using all layers of the biLM (with different choices of regularization strength λ) to just the top layer.



• Analysis

- **ELMo의 위치**

Task	Input Only	Input & Output	Output Only
SQuAD	85.1	**85.6**	84.8
SNLI	88.9	**89.5**	88.7
SRL	**84.7**	84.3	80.9

Table 3: Development set performance for SQuAD, SNLI and SRL when including ELMo at different locations in the supervised model.

• Analysis

• 기존 워드 임베딩과의 비교

	Source	Nearest Neighbors
GloVe	play	playing, game, games, played, players, plays, player, Play, football, multiplayer
biLM	Chico Ruiz made a spectacular play on Alusik 's grounder {...}	Kieffer , the only junior in the group , was commended for his ability to hit in the clutch , as well as his all-round excellent play .
	Olivia De Havilland signed to do a Broadway play for Garson {...}	{...} they were actors who had been handed fat roles in a successful play , and had talent enough to fill the roles competently , with nice understatement .

Table 4: Nearest neighbors to "play" using GloVe and the context embeddings from a biLM.

• Analysis

• **ELMo에서 representation이 내포하는 것**

Second Layer가 semantic한 정보를 더 잘 알아냄

Model	F_1
WordNet 1st Sense Baseline	65.9
Raganato et al. (2017a)	69.9
Iacobacci et al. (2016)	**70.1**
CoVe, First Layer	59.4
CoVe, Second Layer	*64.7*
biLM, First layer	67.4
biLM, Second layer	*69.0*

Table 5: All-words fine grained WSD F_1. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

First Layer는 syntactic한 정보를 더 내포함

Model	Acc.
Collobert et al. (2011)	97.3
Ma and Hovy (2016)	97.6
Ling et al. (2015)	**97.8**
CoVe, First Layer	*93.3*
CoVe, Second Layer	92.8
biLM, First Layer	*97.3*
biLM, Second Layer	96.8

Table 6: Test set POS tagging accuracies for PTB. For CoVe and the biLM, we report scores for both the first and second layer biLSTMs.

• Conclusion

- biLMs로부터 높은 성능의 문맥 의존적인 representations를 제안
- 기존의 워드 임베딩에 ELMo 표현을 더해주는 것만으로 높은 성능을 보임
- 모든 BiLM 레이어들을 이용해 정보 손실을 최소화하여 syntactic한 정보와 semantic한 정보를 얻음