Deep Contextualized Word representation

ELMo, (peters2018deep)

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NLP@CS reading group, 2018

Outline

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What have been done so far!

- Pretrained word representations (Mikolov et al., 2013; Pennington et al., 2014) are a key component in many neural language processing models.

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- For example:
  - The commercial bank" vs "the river bank"
  - is ..... in (interested or interesting)
  - is ..... to (interested or interesting)

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Elmo

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  - complex characteristics of word use (e.g., syntax and semantics).
  - how these uses vary across linguistic contexts (i.e., to model word senses).
- Learn a representation for each word given context (Contextualized repres).

Outline

BiLM

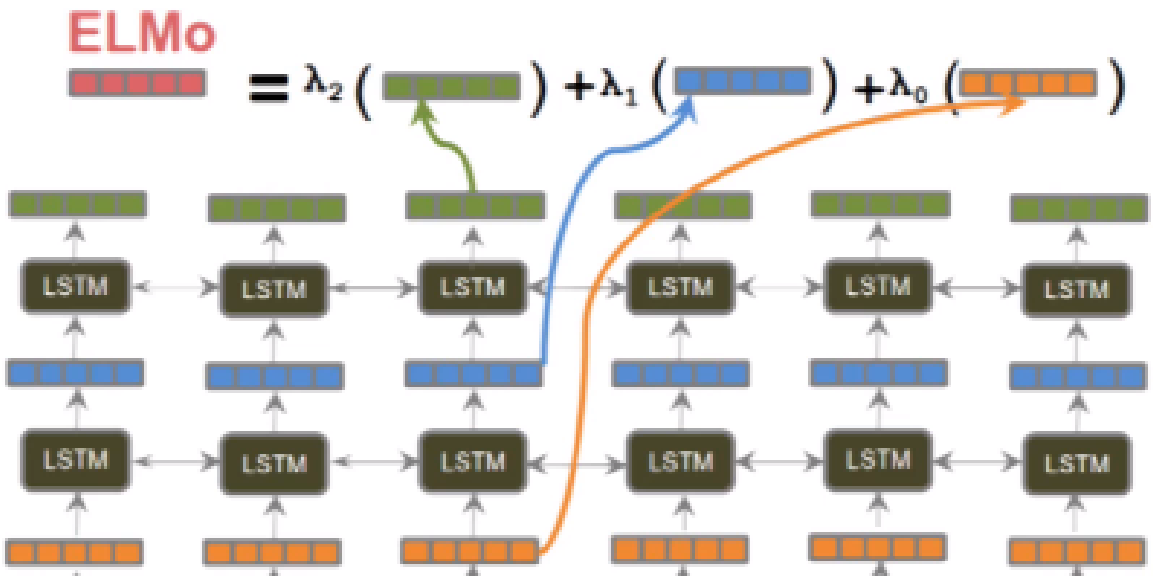
- For each token tk, biLM computes a set of 2L+1 representations.

$$R_k = \{\mathbf{x}_k^{LM}, \overrightarrow{\mathbf{h}}_{k,j}^{LM}, \overleftarrow{\mathbf{h}}_{k,j}^{LM} \mid j = 1, \ldots, L\}$$

- ELMo collapses all layers in R into a single vector.

Outline

(ELMo) Representation



Outline

(BiLM) Arch

Elmo Architecture:

- uses 2-layer BiLSTM with 4096 units.

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- also incorporated a size of 2048 character-level CNN.
- pretrained 10 epochs over a 1 billion word corpus.

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ELMO for downstream tasks

- Pass the ELMo representation into multiple layers of the supervised model.
  - Input layer
  - Output Layer
  - Both

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- Pass the ELMo representation into multiple layers of the supervised model.
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- Interestingly, Elmo is very simple model that can be combined with any type of supervised model.

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Intrinsic (POS vs WSD)

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
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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*

Outline

Textual entailment & Sentiment Analysis

TA:

Def

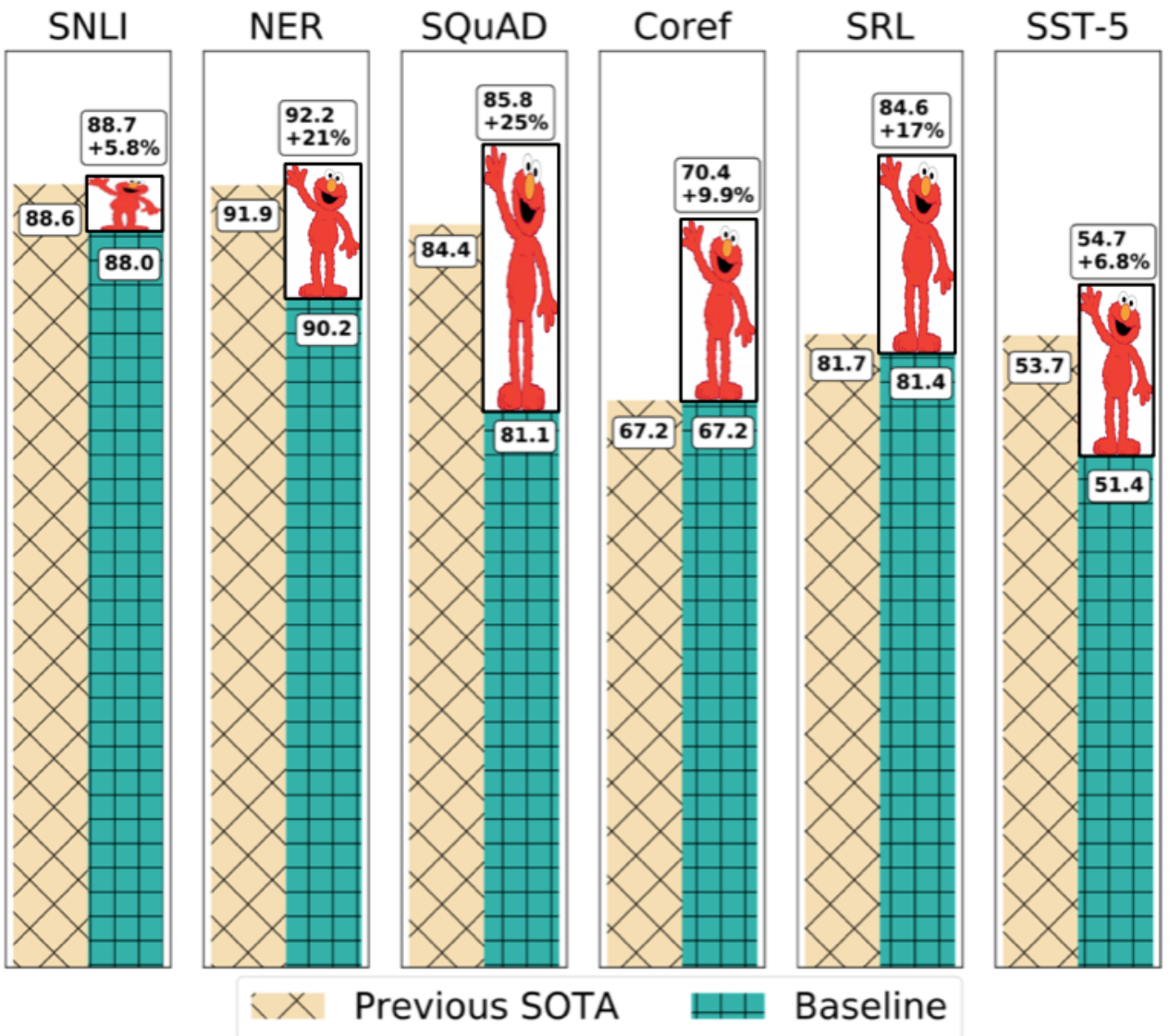
Textual entailment is the task of determining whether a hypothesis is true, given a premise.

- A known corpus for this task is "The Stanford Natural Language Inference (SNLI)" (Bowman et al., 2015), which provides approximately 550K hypothesis/premise pairs.

SA:

- Many corpora are available for SA task, but in this work, they use (SST-5: Socher et al., 2013)

Results


SNLI
NER
SQuAD
Coref
SRL
SST-5
88.7
+5.8%
88.6
88.0
92.2
+21%
91.9
90.2
85.8
+25%
84.4
81.1
70.4
+9.9%
67.2
67.2
84.6
+17%
81.7
81.4
54.7
+6.8%
53.7
51.4
Previous SOTA
Baseline

Outline

Alternate layer weighting schemes

- To assess whether it's enough to include the representation of the last layer or the representation of all layers.

Task	Baseline	Last Only	All layers	
			λ=1	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**

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Where to include ELMo?

- Previous work tends to add learned representation at the input layer, such as pre-trained embedding.
- However, in this work, it's shown that it's useful to add learned representation at both the input-level and output-level.

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

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- # epochs:
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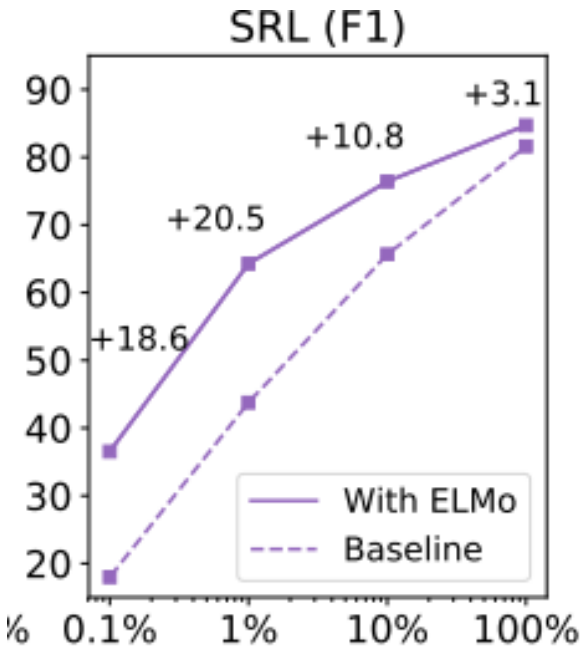

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- For more Info about implementation: visit below website `https://allennlp.org/elmo`