Applied Deep Learning

Contextualized Word Embeddings

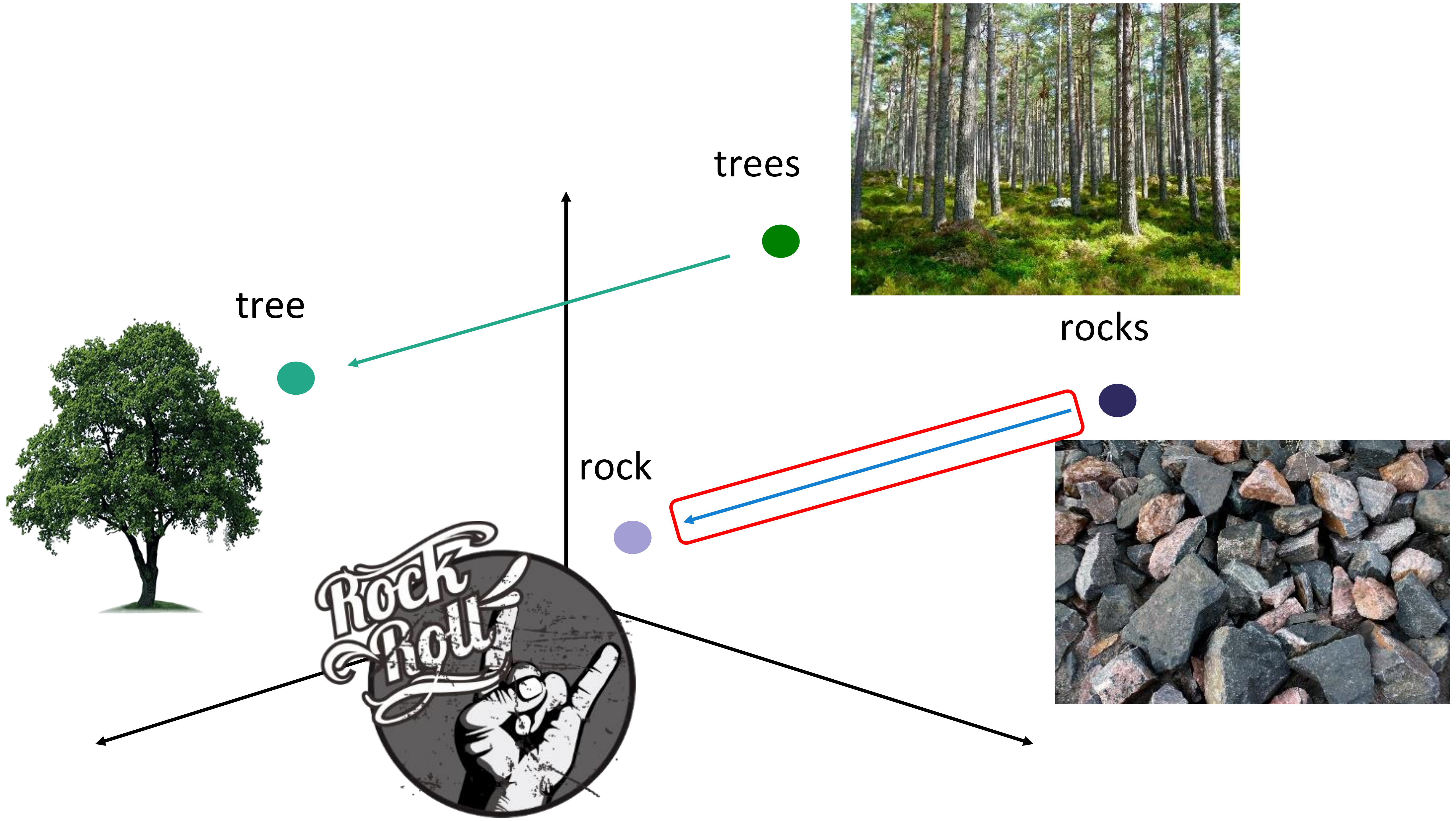
March 14th, 2022 **http://adl.miulab.tw**

National Taiwan University
國立臺灣大學

2

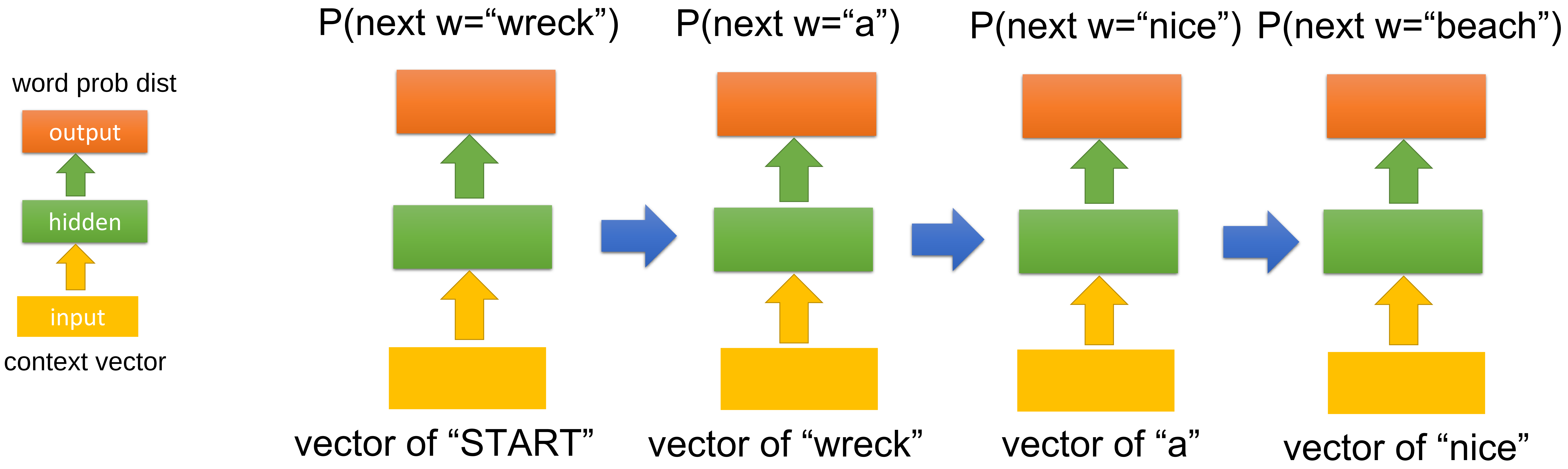
Word Embedding Polysemy Issue

- Words are polysemy
  - ✓ An apple a day, keeps the doctor away.
  - ✓ Smartphone companies including apple, …
- However, their embeddings are NOT polysemy
- Issue
  - ✓ Multi-senses (polysemy)
  - ✓ Multi-aspects (semantics, syntax)



3 RNNLM

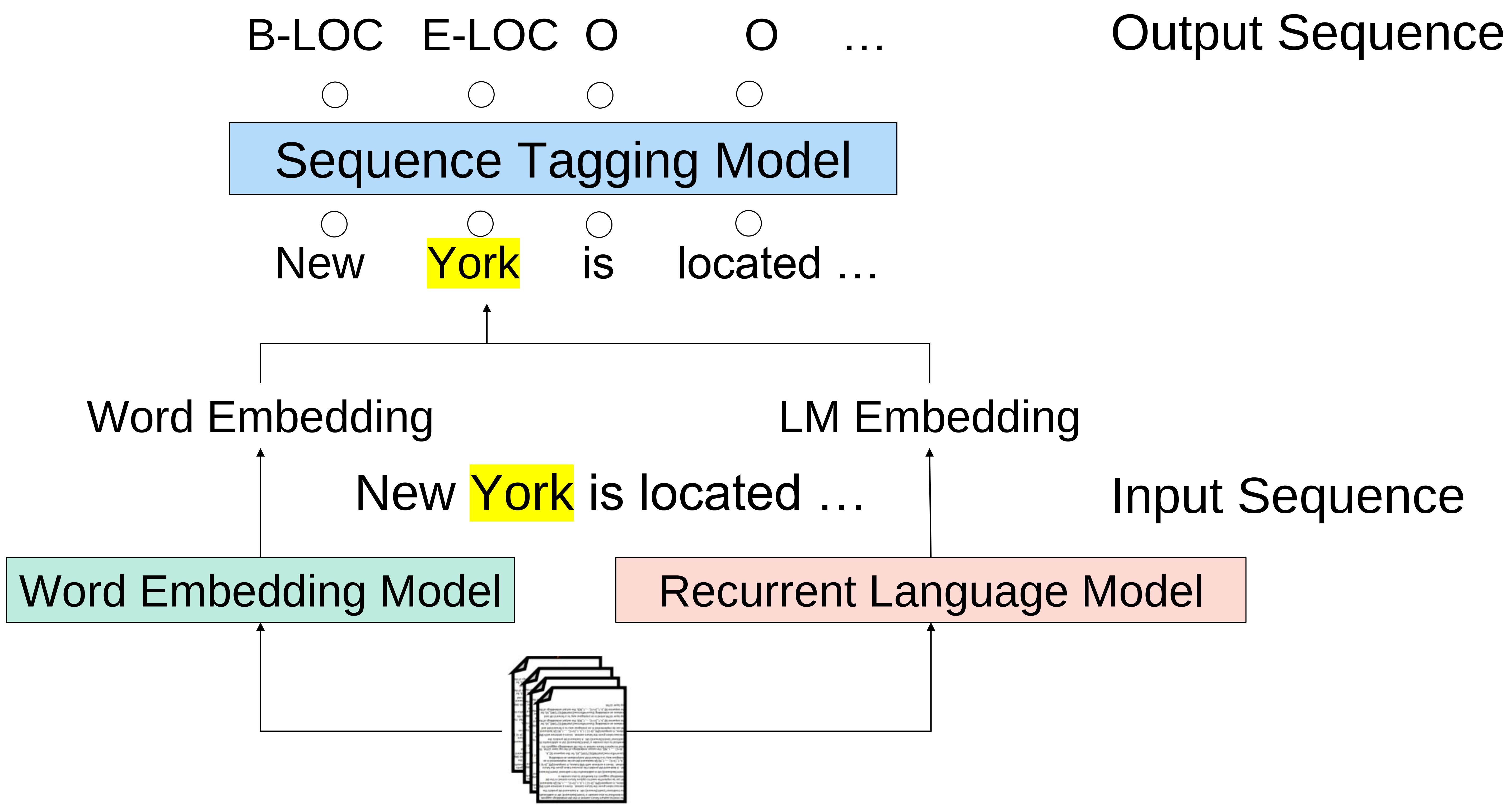
- Idea: condition the neural network on <u>all previous words</u> and <u>tie the weights</u> at each time step



This LM producing **context-specific word representations** at each position

TagLM – “Pre-ELMo”

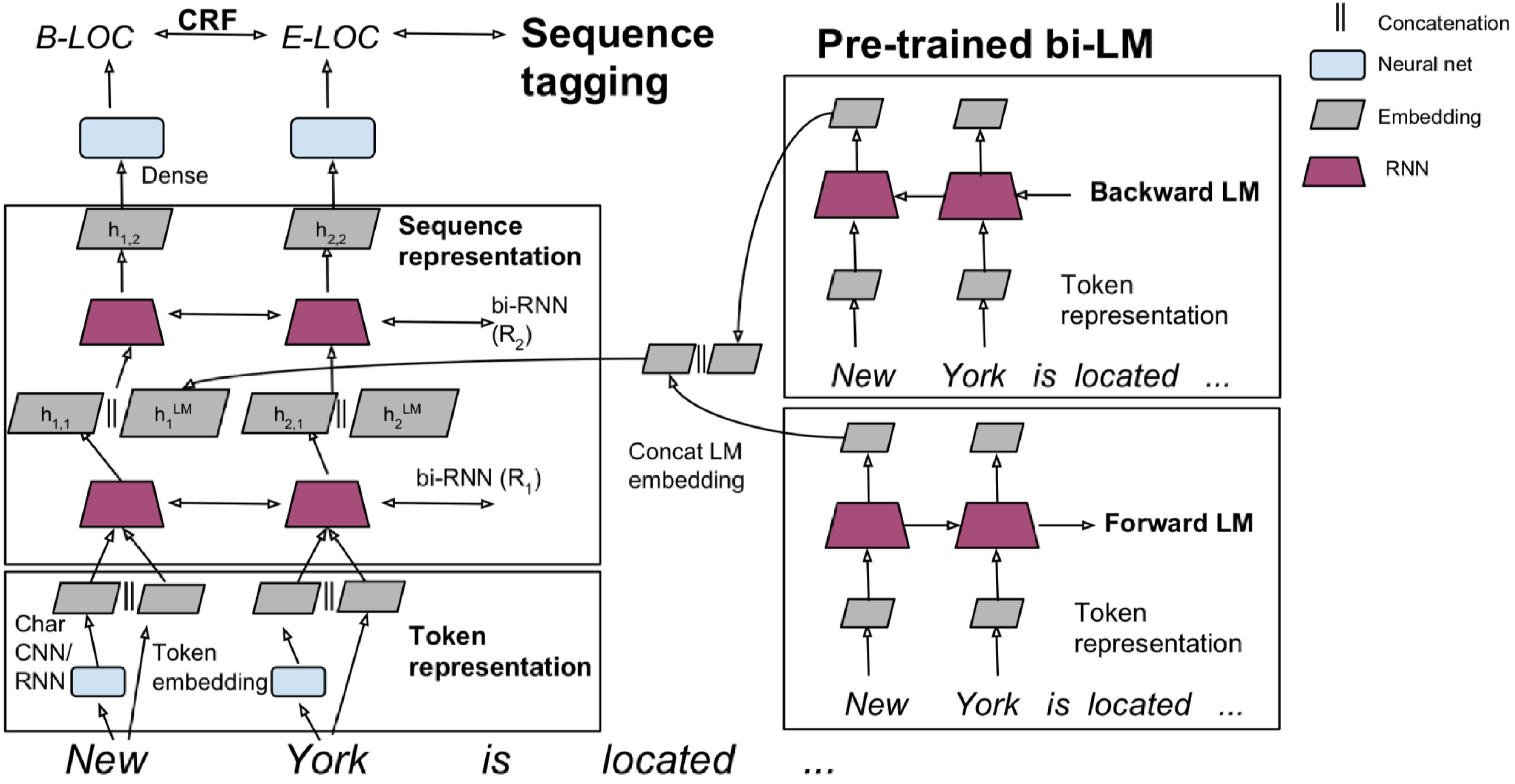
- Idea: train NLM on big unannotated data and provide the <u>context-specific embeddings</u> for the target task → **semi-supervised learning**



Peters et al., “Semi-supervised sequence tagging with bidirectional language models,” in *ACL*, 2017.

5 TagLM Model Detail

- Leveraging pre-trained LM information



Peters et al., "Semi-supervised sequence tagging with bidirectional language models," in *ACL*, 2017.

TagLM on Name Entity Recognition

The decision by the independent MP Andrew Wilkie to withdraw his support for the minority Labor government sounded dramatic but it should not further threaten its stability. When, after the 2010 election, Wilkie, Rob Oakeshott, Tony Windsor and the Greens agreed to support Labor, they gave just two guarantees: confidence and supply.

Model	Description	CONLL 2003 F1
Klein+, 2003	MEMM softmax markov model	86.07
Florian+, 2003	Linear/softmax/TBL/HMM	88.76
Finkel+, 2005	Categorical feature CRF	86.86
Ratinov and Roth, 2009	CRF+Wiki+Word cls	90.80
Peters+, 2017	BLSTM + char CNN + CRF	90.87
Ma and Hovy, 2016	BLSTM + char CNN + CRF	91.21
TagLM (Peters+, 2017)	LSTM BiLM in BLSTM Tagger	**91.93**

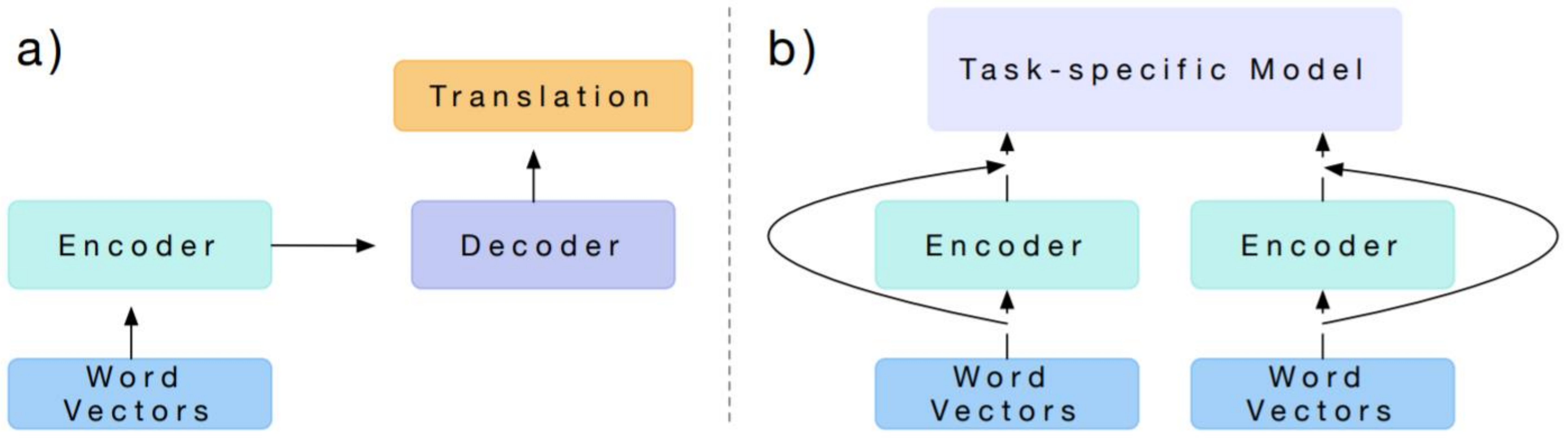
Peters et al., "Semi-supervised sequence tagging with bidirectional language models," in *ACL*, 2017.

CoVe

- Idea: use trained sequence model to provide contexts to other NLP tasks

a) MT is to capture the meaning of a sequence

b) NMT provides the context for target tasks



CoVe vectors outperform GloVe vectors on various tasks

The results are not as strong as the simpler NLM training

McCann et al., "Learned in Translation: Contextualized Word Vectors", in *NIPS*, 2017.

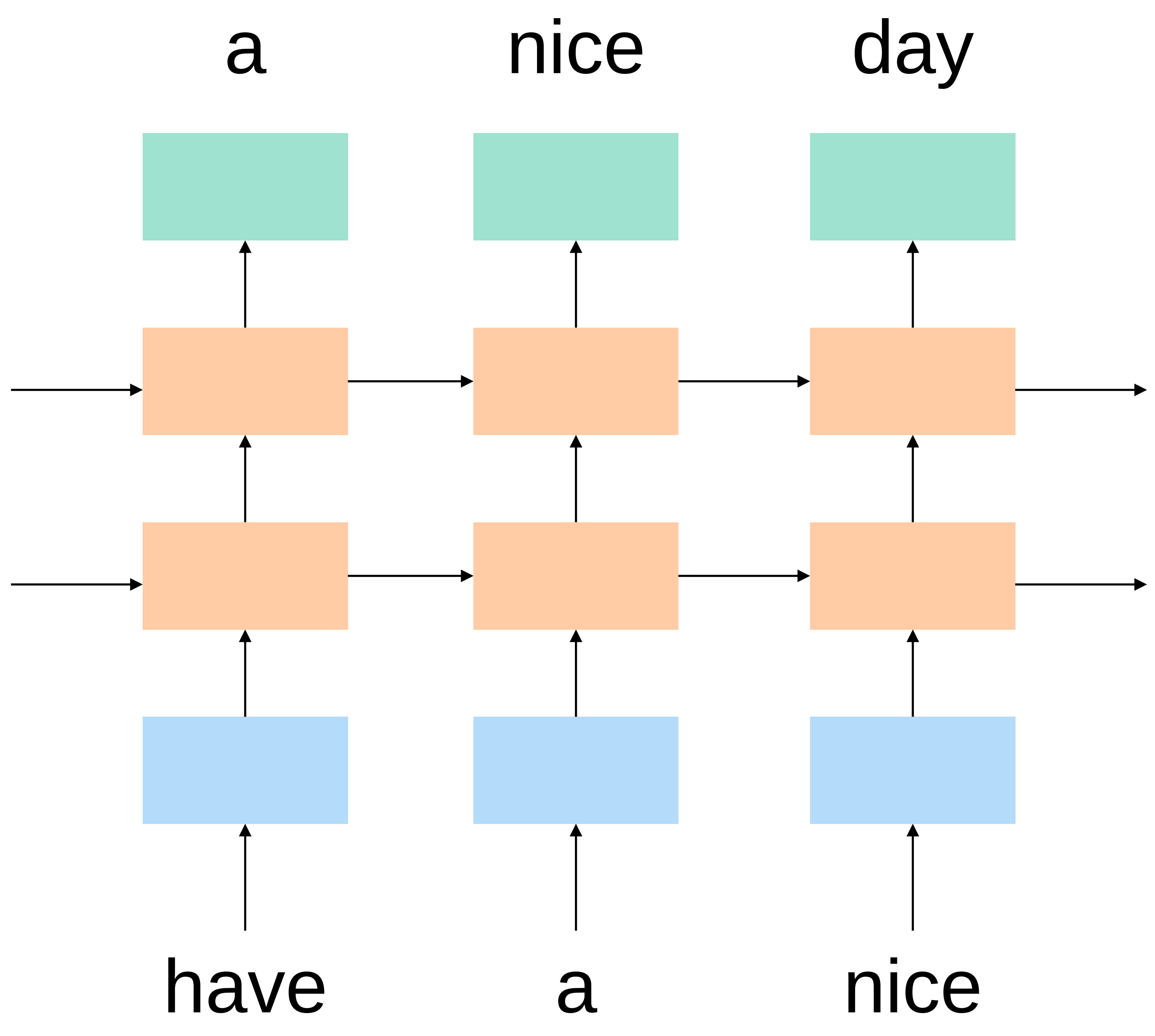
8

Contextualized Word Embeddings

ELMo

ELMo: Embeddings from Language Models

- Idea: contextualized word representations
  - ✓ Learn word vectors using long contexts instead of a context window
  - ✓ Learn a deep Bi-NLM and use all its layers in prediction

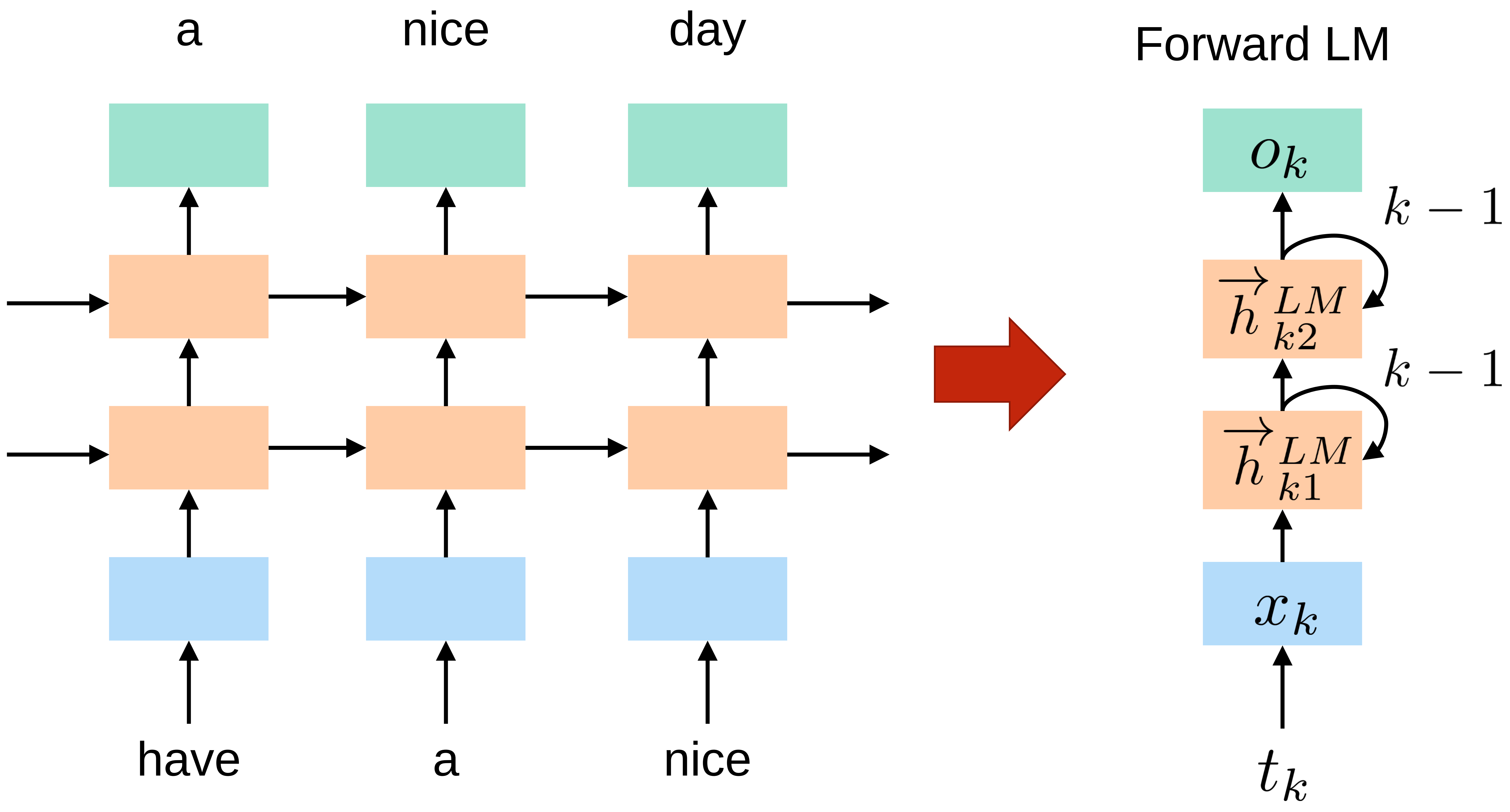


Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

ELMo: Embeddings from **L**anguage **Mo**dels

1) Bidirectional LM

$$p(t_1, t_2, \cdots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_1, \cdots, t_{k-1})$$



Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

ELMo: Embeddings from **L**anguage **Mo**dels

1) Bidirectional LM

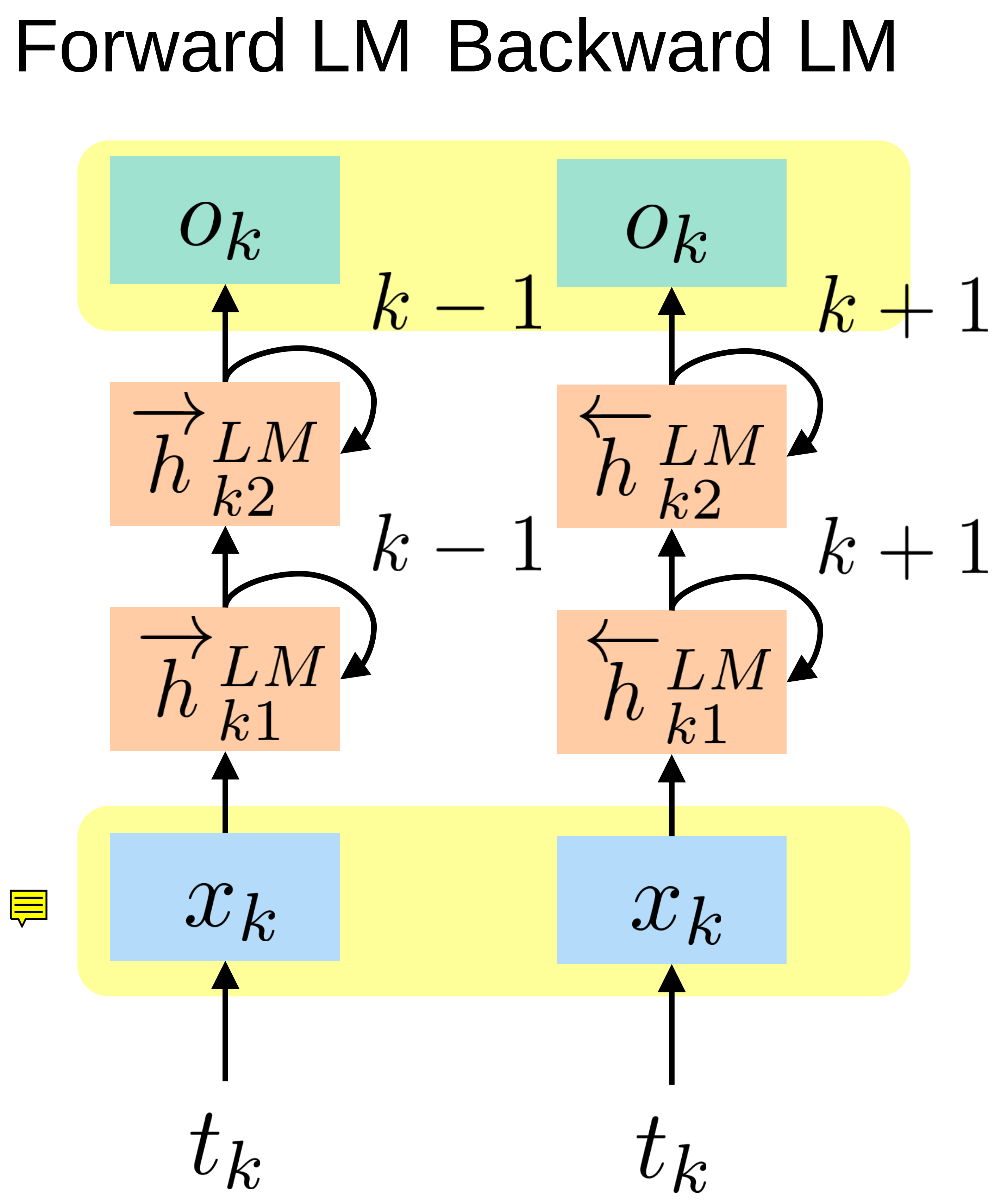
$$p(t_1, t_2, \cdots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_1, \cdots, t_{k-1})$$

$$p(t_1, t_2, \cdots, t_N) = \prod_{k=1}^{N} p(t_k \mid t_{k+1}, \cdots, t_N)$$

- Character CNN for initial word embeddings

  2048 n-gram filters, 2 highway layers, 512 dim projection
- 2 BLSTM layers
- Parameter tying for input/output layers

$$O = \sum_{k=1}^{N} \Big(\log p(t_k \mid t_1, \cdots, t_{k-1}; \Theta_x, \overrightarrow{\Theta}_{LSTM}, \Theta_s) + \log p(t_k \mid t_{k+1}, \cdots, t_N; \Theta_x, \overleftarrow{\Theta}_{LSTM}, \Theta_s) \Big)$$



Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

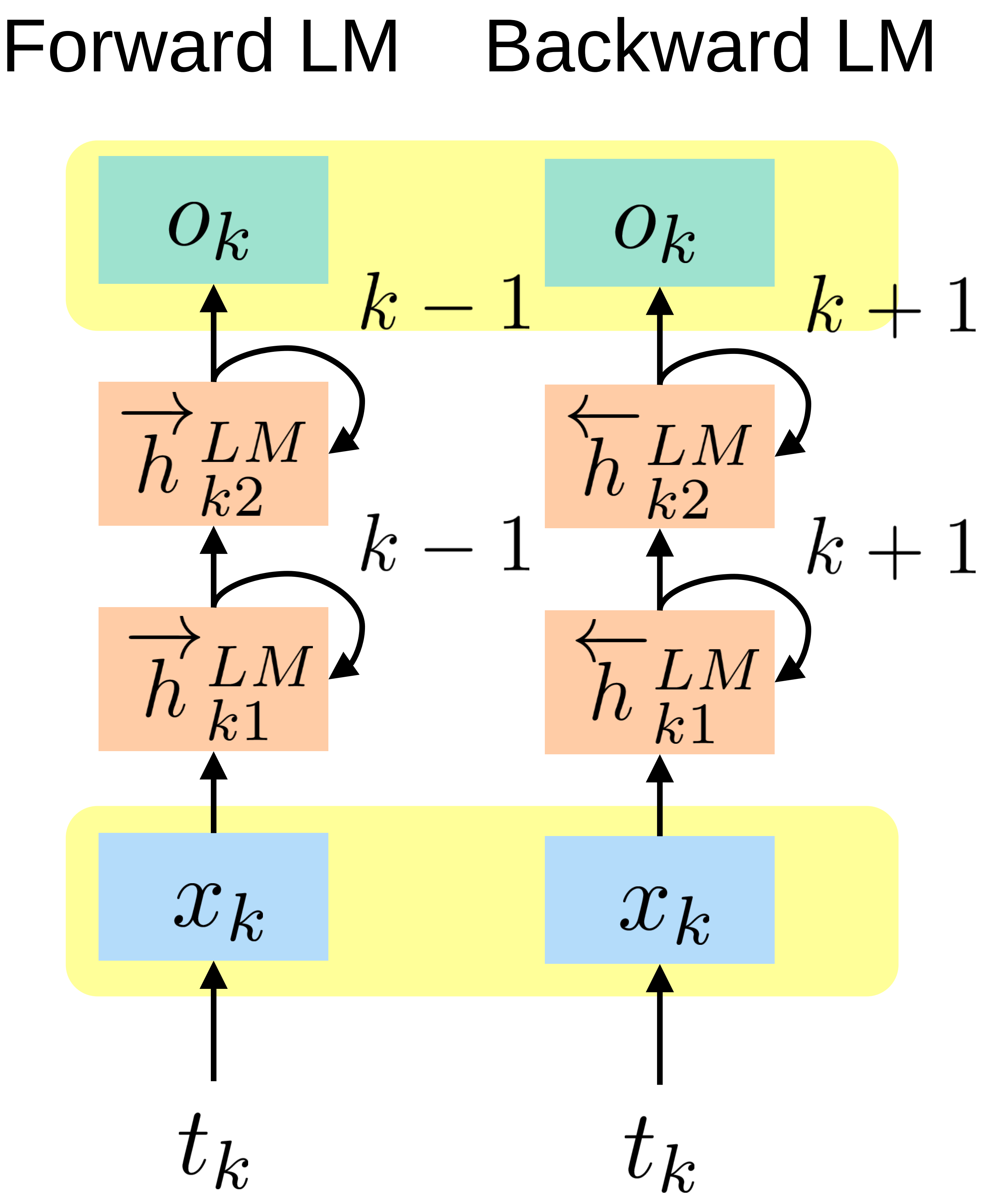
ELMo: Embeddings from Language Models

2) ELMo

- Learn <u>task-specific linear combination</u> of LM embeddings
- Use multiple layers in LSTM instead of top one

$$\text{ELMo}_k^{\text{task}} = \gamma^{\text{task}} \times \sum \begin{cases} s_2^{\text{task}} \times h_{k2}^{LM} & \overrightarrow{h}_{k2}^{LM} \quad \overleftarrow{h}_{k2}^{LM} \\ s_1^{\text{task}} \times h_{k1}^{LM} & \overrightarrow{h}_{k1}^{LM} \quad \overleftarrow{h}_{k1}^{LM} \\ s_0^{\text{task}} \times h_{k0}^{LM} & x_k \quad x_k \end{cases}$$

- γ^{task} scales overall usefulness of ELMo to task
- s^{task} are softmax-normalized weights
- optional layer normalization



A task-specific embedding with combining weights learned from a downstream task

ELMo: **E**mbeddings from **L**anguage **Mo**dels

3) Use ELMo in Supervised NLP Tasks

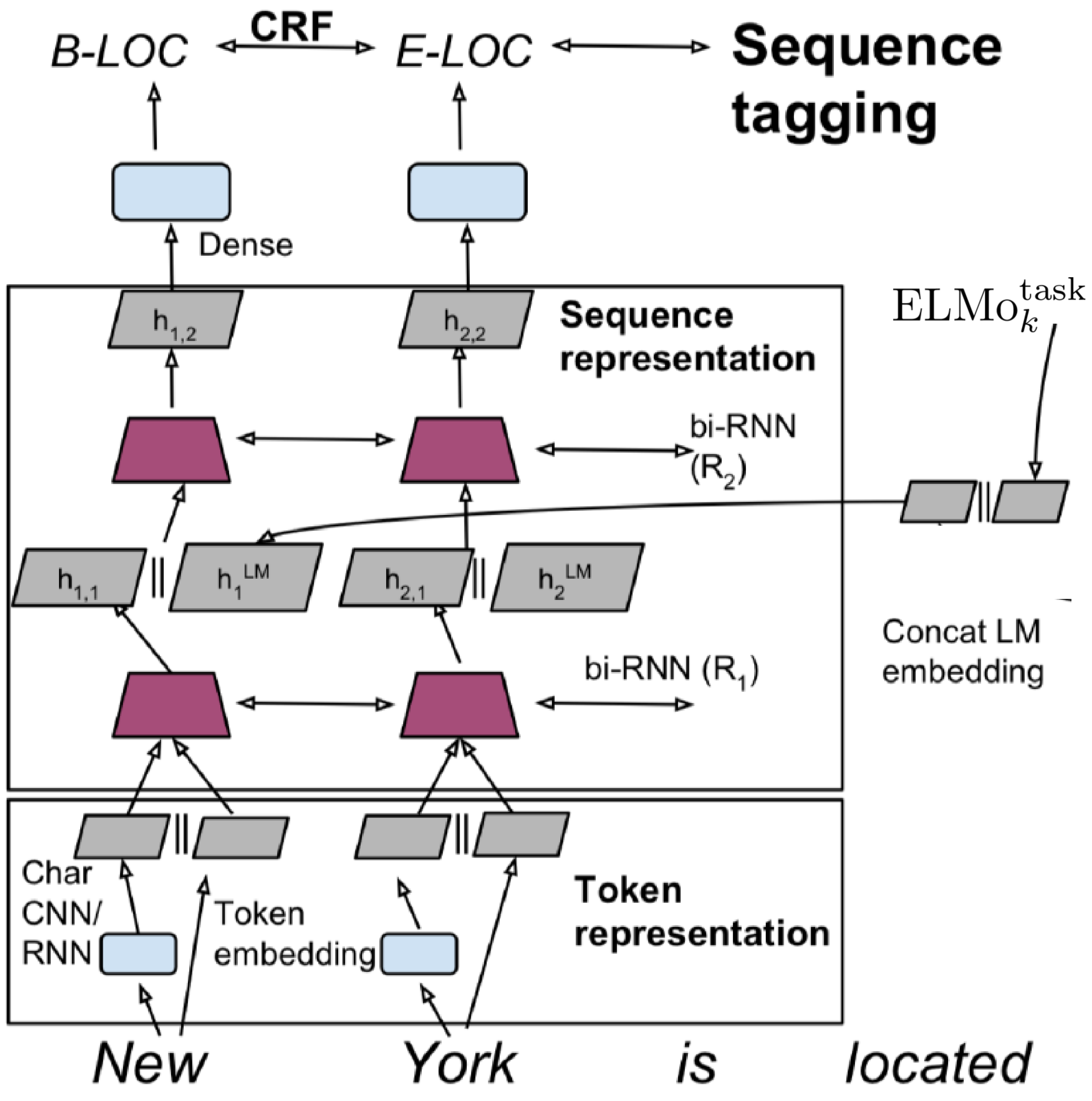
- Get LM embedding for each word
- Freeze LM weights to form ELMo enhanced embeddings

$[h_k; \mathrm{ELMo}_k^{\mathrm{task}}]$: concatenate ELMo into the intermediate layer

$[x_k; \mathrm{ELMo}_k^{\mathrm{task}}]$: concatenate ELMo into the input layer

- Tricks: dropout, regularization

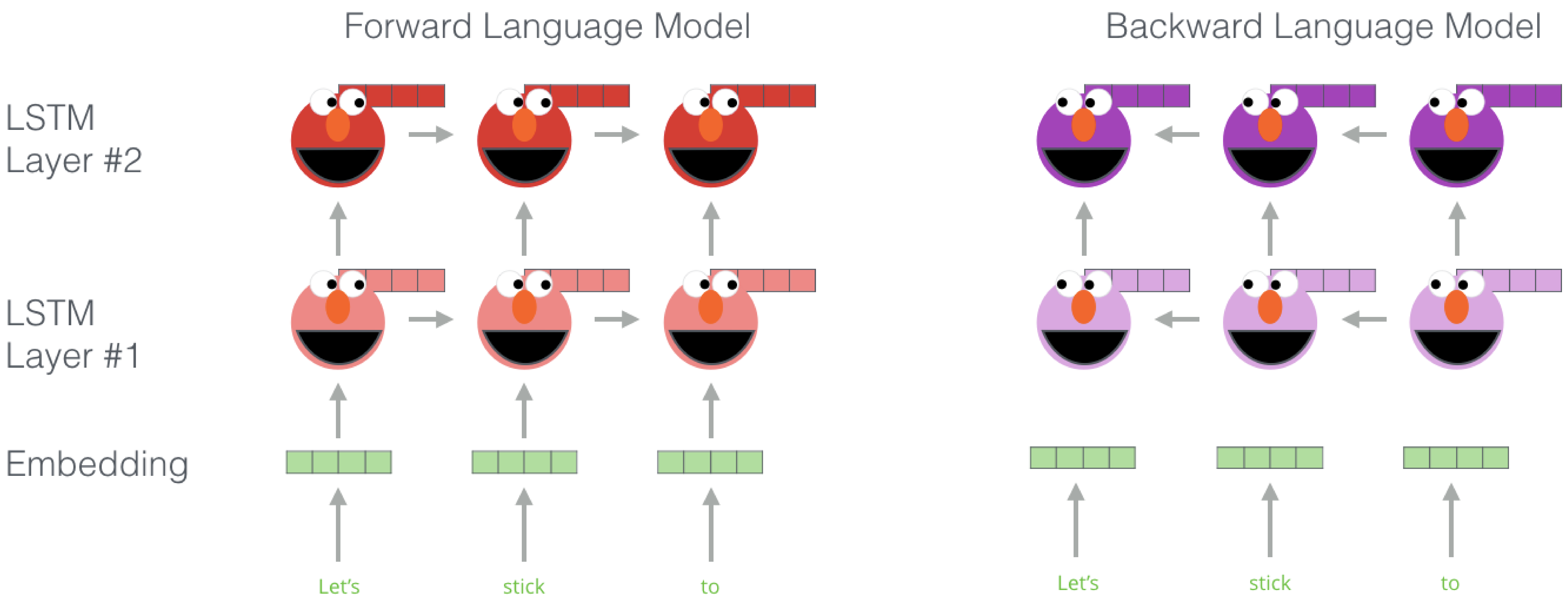
The way for concatenation depends on the task



Peters et al., "Deep Contextualized Word Representations", in *NAACL-HLT*, 2018.

ELMo Illustration

Embedding of “stick” in “Let’s stick to” - Step #1

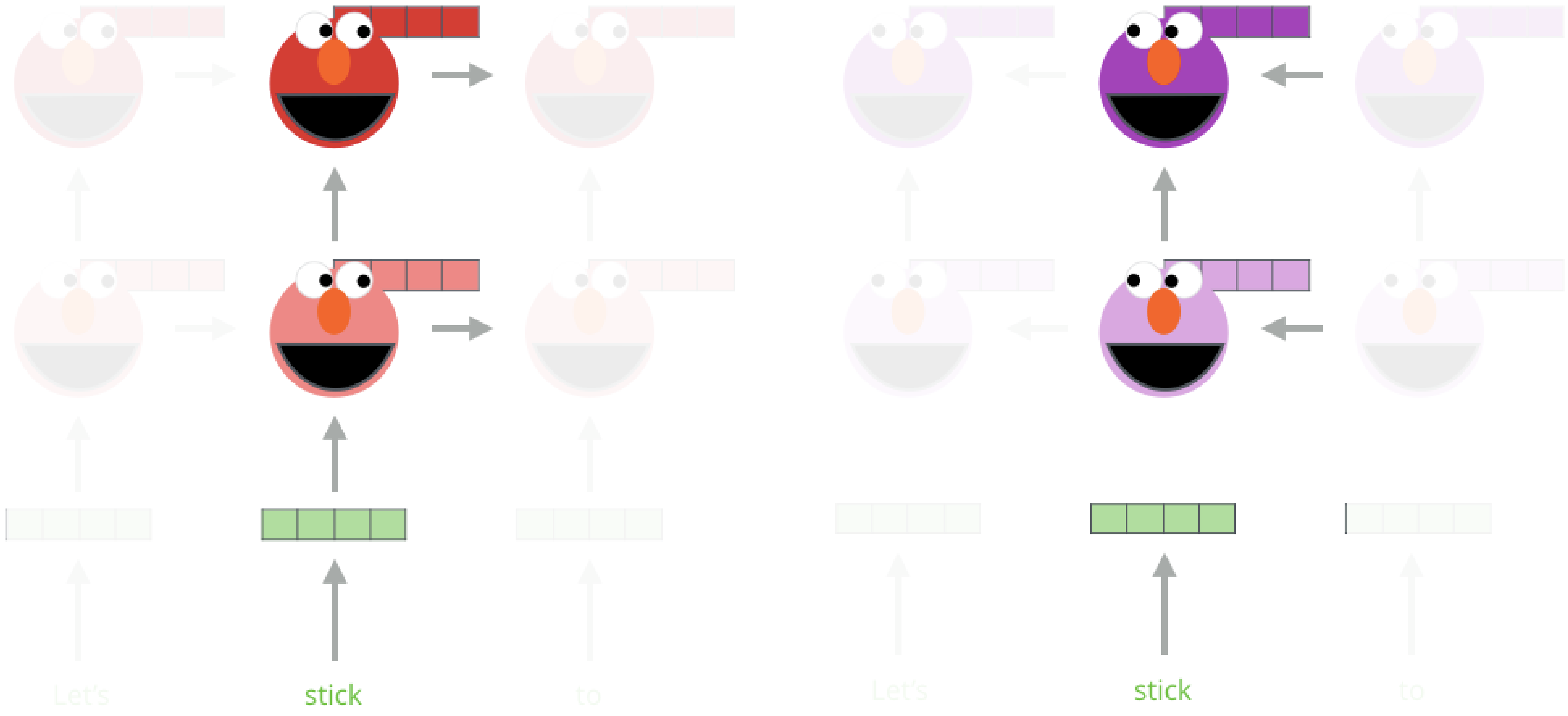


Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

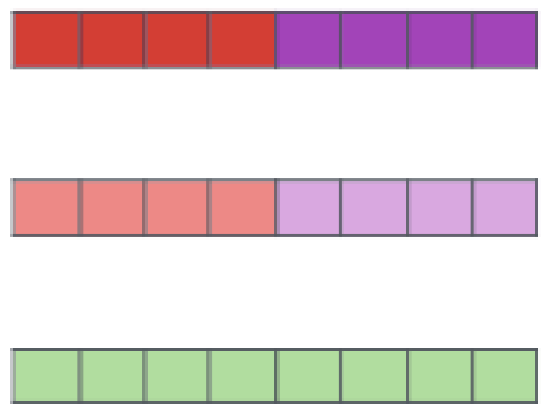
ELMo Illustration

Embedding of “stick” in “Let’s stick to” - Step #2

1- Concatenate hidden layers



2- Multiply each vector by a weight based on the task

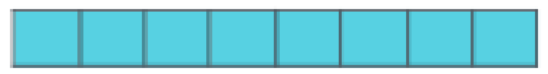


x s_2

x s_1

x s_0

3- Sum the (now weighted) vectors



ELMo embedding of “stick” for this task in this context

Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

ELMo on Name Entity Recognition

Model	Description	CONLL 2003 F1
Klein+, 2003	MEMM softmax markov model	86.07
Florian+, 2003	Linear/softmax/TBL/HMM	88.76
Finkel+, 2005	Categorical feature CRF	86.86
Ratinov and Roth, 2009	CRF+Wiki+Word cls	90.80
Peters+, 2017	BLSTM + char CNN + CRF	90.87
Ma and Hovy, 2016	BLSTM + char CNN + CRF	91.21
TagLM (Peters+, 2017)	LSTM BiLM in BLSTM Tagger	91.93
ELMo (Peters+, 2018)	ELMo in BLSTM	**92.22**

Peters et al., "Deep Contextualized Word Representations", in *NAACL-HLT*, 2018.

ELMo Results

- Improvement on various NLP tasks

	Task	Previous SOTA		Our baseline	ELMo + baseline	Increase (absolute/ relative)
Machine Comprehension	SQuAD	Liu et al. (2017)	84.4	81.1	85.8	4.7 / 24.9%
Textual Entailment	SNLI	Chen et al. (2017)	88.6	88.0	88.7 ± 0.17	0.7 / 5.8%
Semantic Role Labeling	SRL	He et al. (2017)	81.7	81.4	84.6	3.2 / 17.2%
Coreference Resolution	Coref	Lee et al. (2017)	67.2	67.2	70.4	3.2 / 9.8%
Name Entity Recognition	NER	Peters et al. (2017)	91.93 ± 0.19	90.15	92.22 ± 0.10	2.06 / 21%
Sentiment Analysis	SST-5	McCann et al. (2017)	53.7	51.4	54.7 ± 0.5	3.3 / 6.8%

Good transfer learning in NLP (similar to computer vision)

Peters et al., “Deep Contextualized Word Representations”, in *NAACL-HLT*, 2018.

ELMo Analysis

- Word embeddings v.s. contextualized embeddings

	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 .

The biLM is able to disambiguate both the PoS and word sense in the source sentence

Peters et al., "Deep Contextualized Word Representations", in *NAACL-HLT*, 2018.

ELMo Analysis

- The two NLM layers have differentiated uses/meanings
  - ✓ Lower layer is better for lower-level **syntax**, etc. (e.g. Part-of-speech tagging, syntactic dependencies, NER)
  - ✓ Higher layer is better for higher-level **semantics** (e.g. sentiment, semantic role labeling, question answering, SNLI)

PoS Tagging

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

Word Sense Disambiguation

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*

Peters et al., "Deep Contextualized Word Representations", in *NAACL-HLT*, 2018.

Concluding Remarks

- Contextualized embeddings learned from LM provide informative cues
- ELMo – a general approach for learning high-quality deep context-dependent representations from biLMs
  - ✓ Pre-trained ELMo: https://allennlp.org/elmo
  - ✓ ELMo can process the character-level inputs