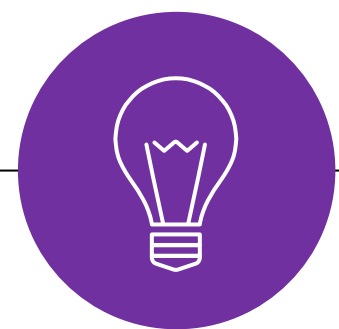


Applied Deep Learning



Contextualized Word Embeddings

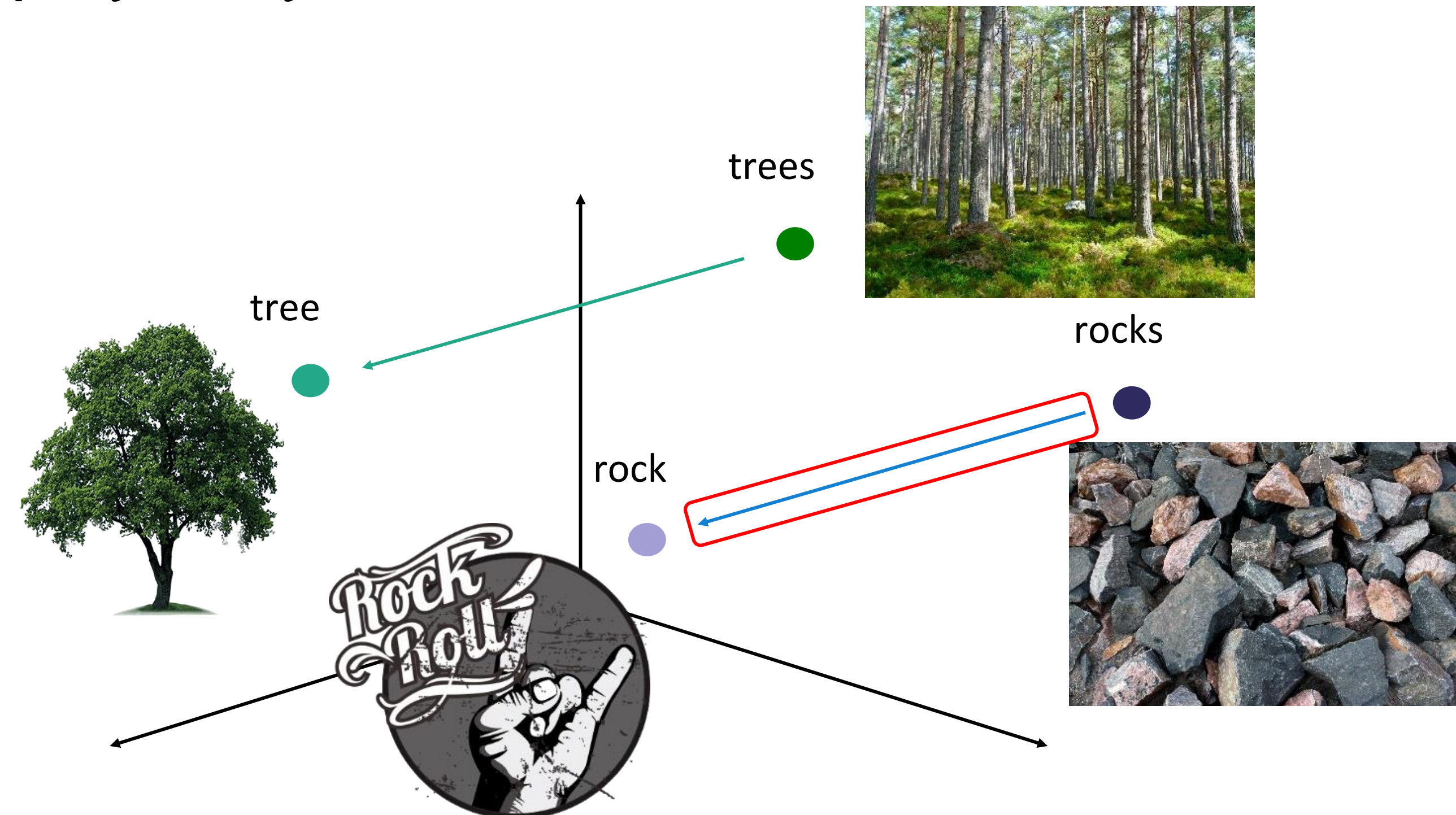
October 6th, 2022 <http://adl.miulab.tw>



2

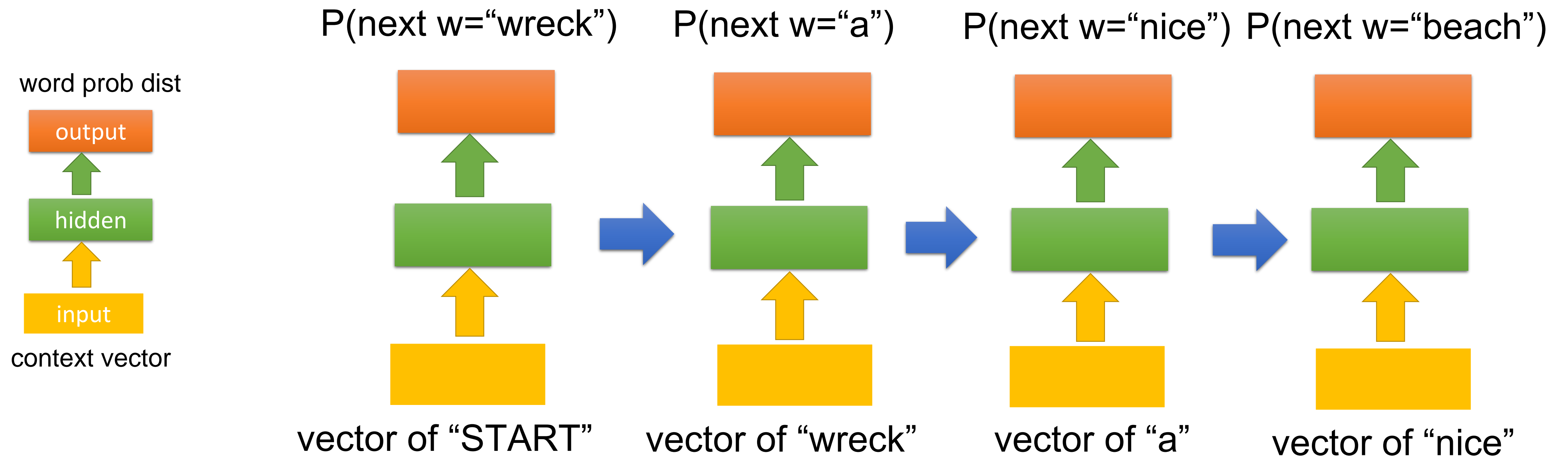
Word Embedding Polysemy Issue

- 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)



RNNLM

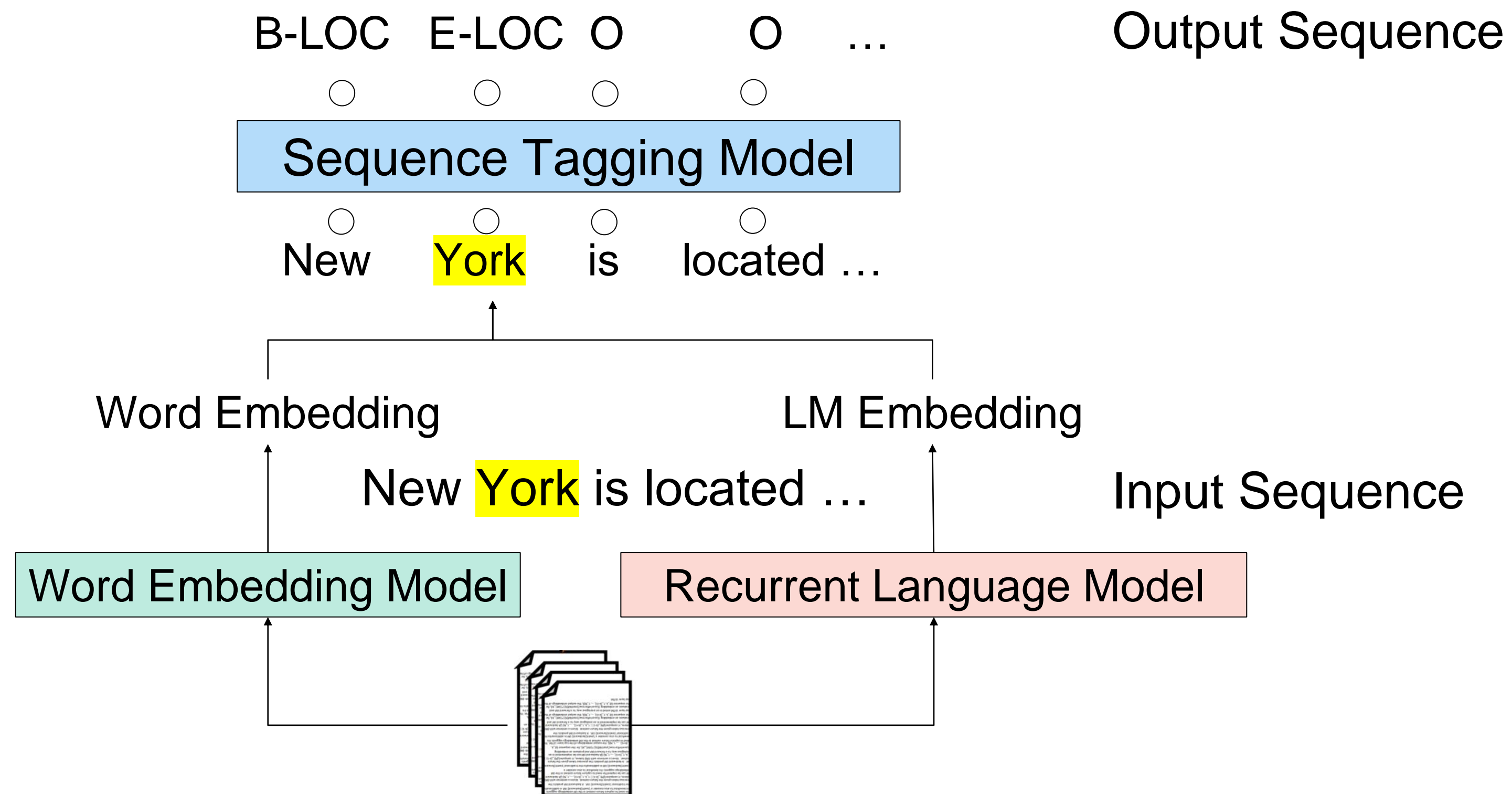
- Idea: condition the neural network on all previous words and tie the weights at each time step



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

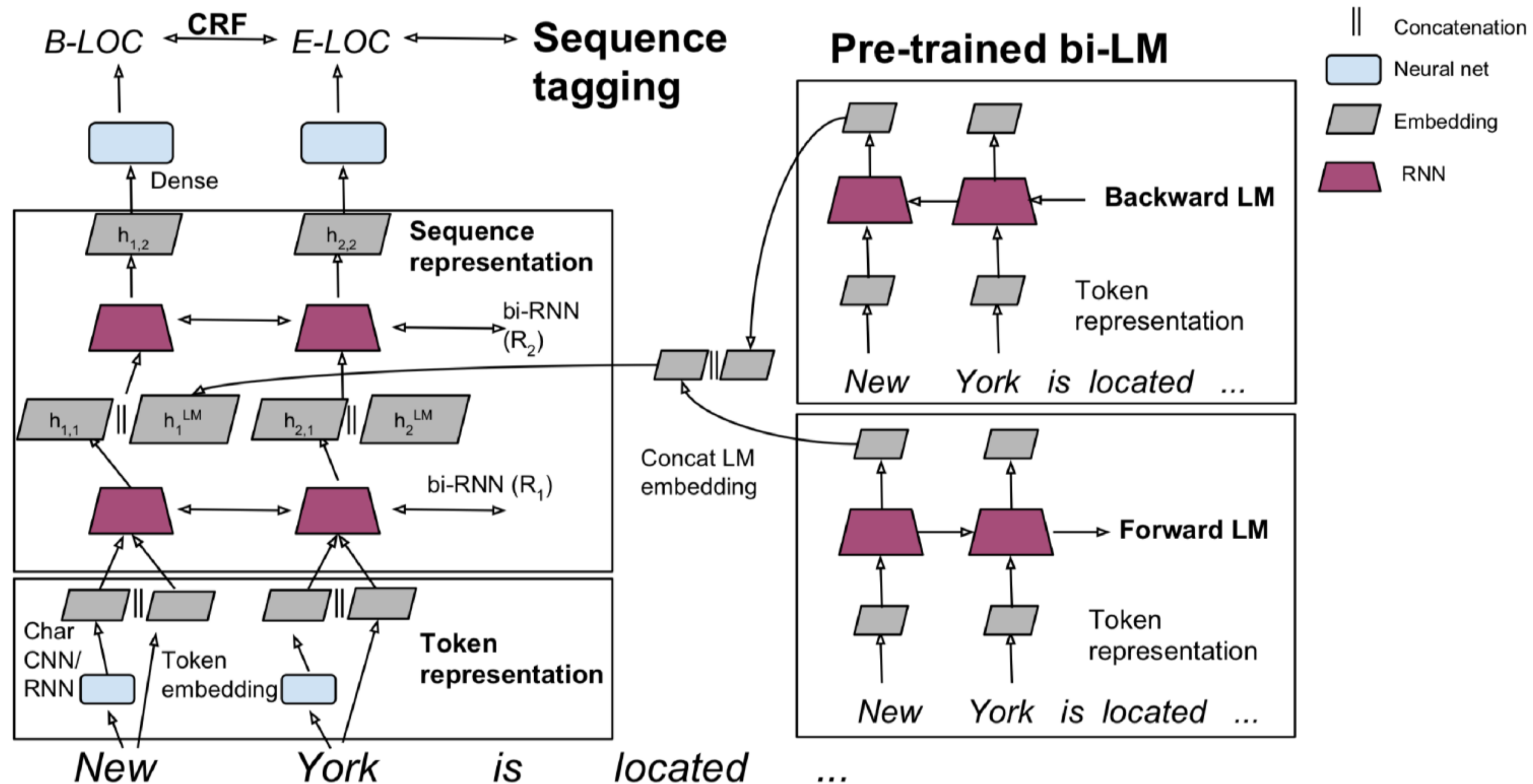
TagLM – “Pre-ELMo”

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



TagLM Model Detail

- Leveraging pre-trained LM information



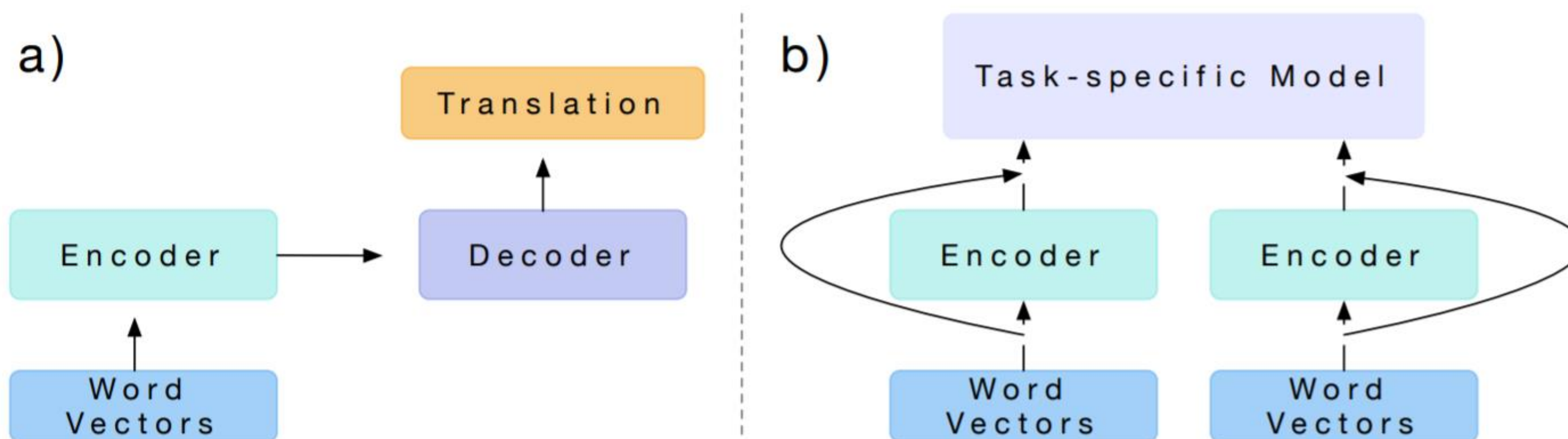
TagLM on Name Entity Recognition

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

7 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

8

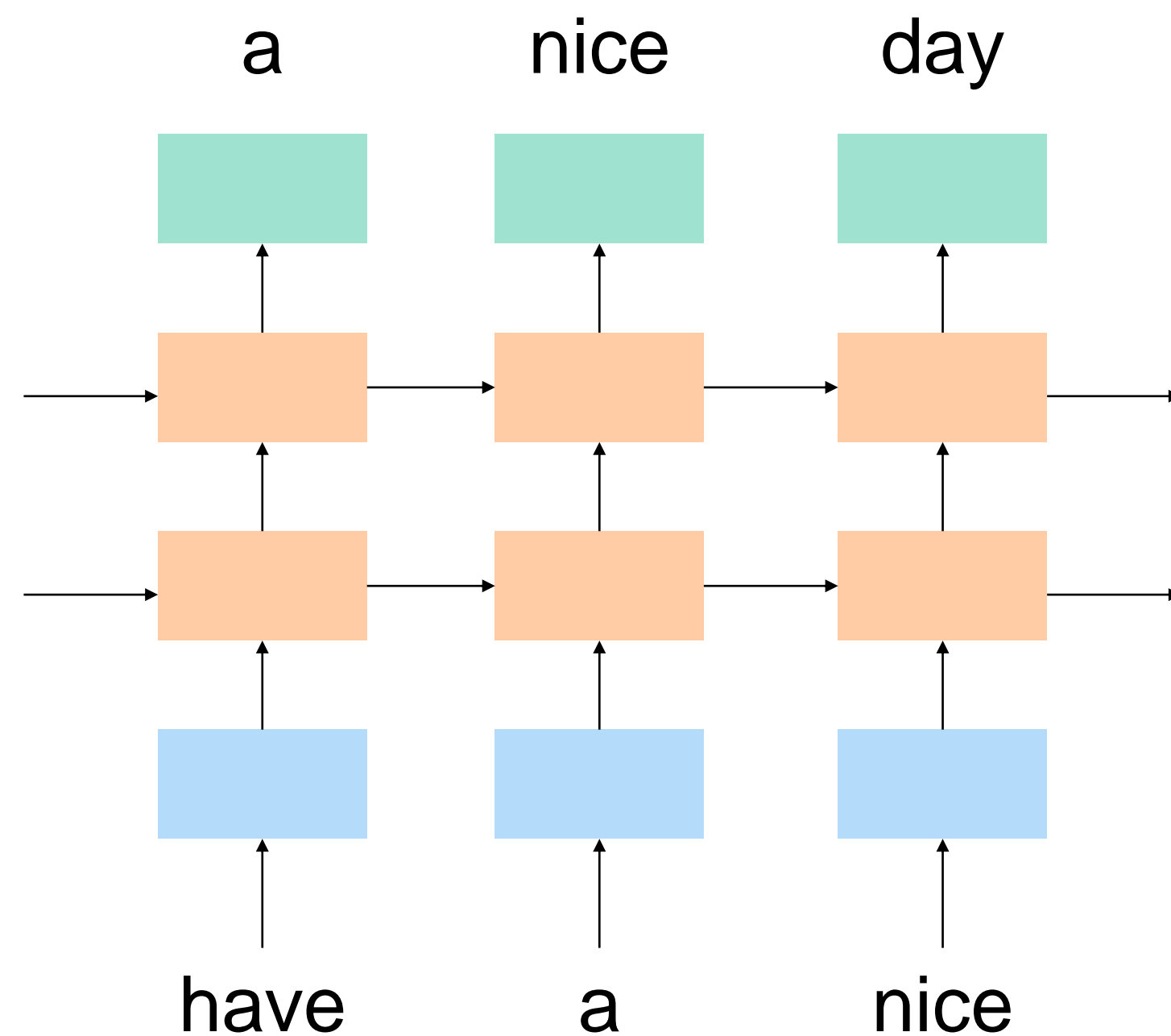
Contextualized Word Embeddings

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

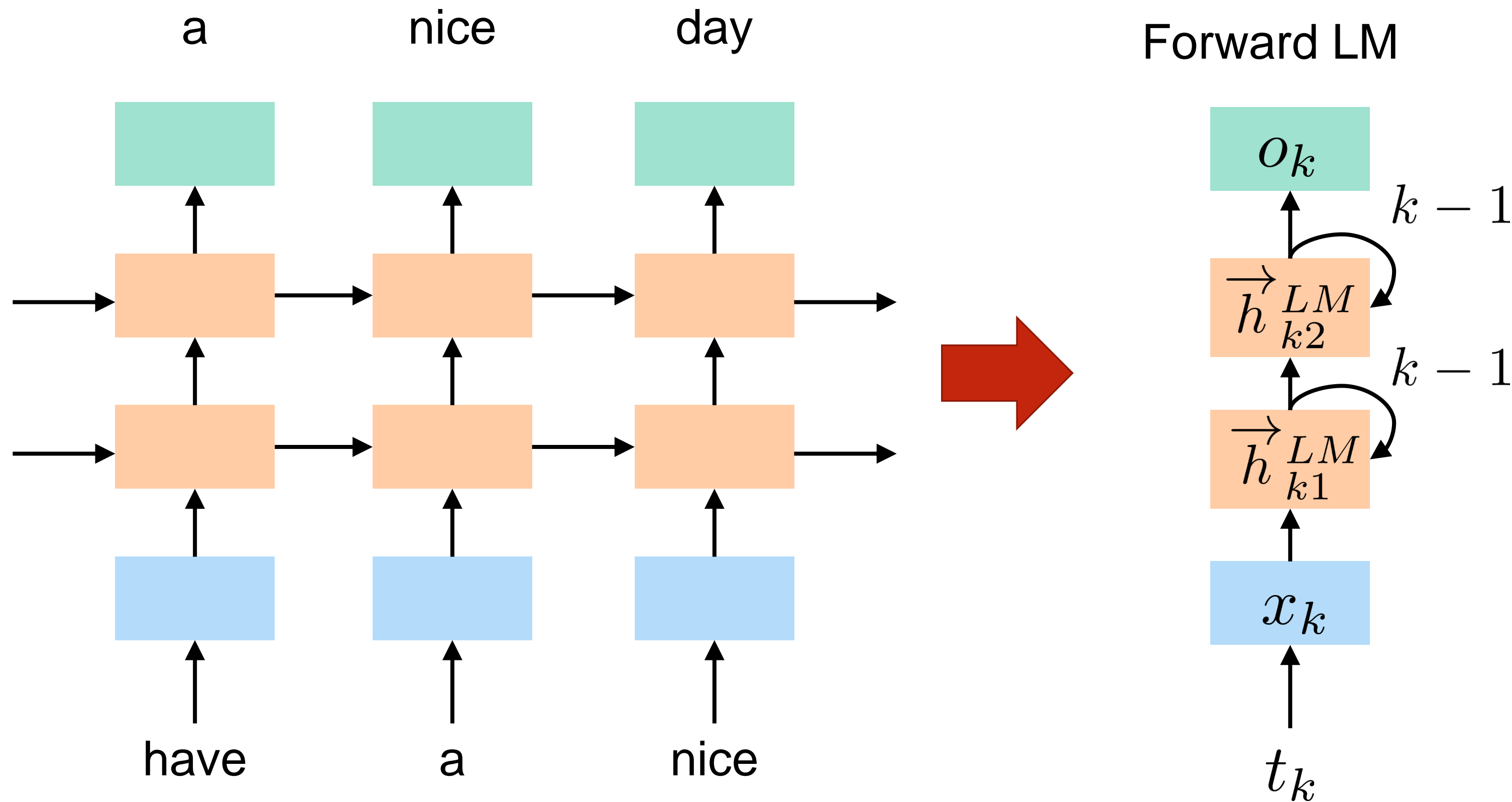


ELMo: Embeddings from Language Models



1) Bidirectional LM

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



ELMo: Embeddings from Language Models



1) Bidirectional LM

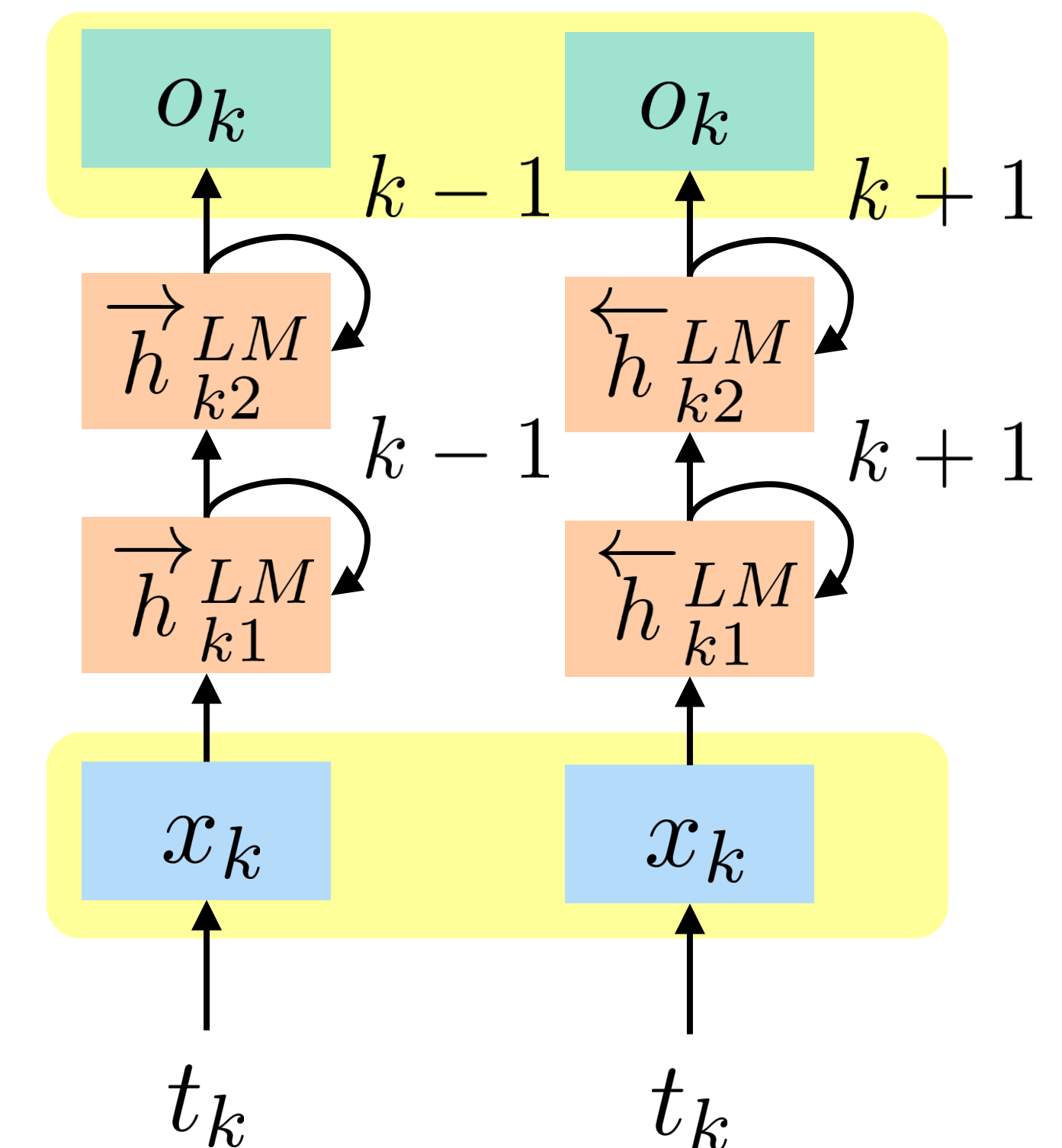
$$p(t_1, t_2, \dots, t_N) = \prod_{k=1}^N p(t_k | t_1, \dots, t_{k-1})$$

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

- 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

$$O = \sum_{k=1}^N \left(\log p(t_k | t_1, \dots, t_{k-1}; \Theta_x, \vec{\Theta}_{LSTM}, \Theta_s) \right. \\ \left. + \log p(t_k | t_{k+1}, \dots, t_N; \Theta_x, \overleftarrow{\Theta}_{LSTM}, \Theta_s) \right)$$

Forward LM Backward LM



ELMo: Embeddings from Language Models



2) ELMo

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

$$ELMo_k^{\text{task}} = \gamma^{\text{task}} \times \sum \left\{ \begin{array}{l} s_2^{\text{task}} \times h_{k2}^{LM} \\ s_1^{\text{task}} \times h_{k1}^{LM} \\ s_0^{\text{task}} \times h_{k0}^{LM} \end{array} \right.$$

\vec{h}_{k2}^{LM}

$\overleftarrow{h}_{k2}^{LM}$

\vec{h}_{k1}^{LM}

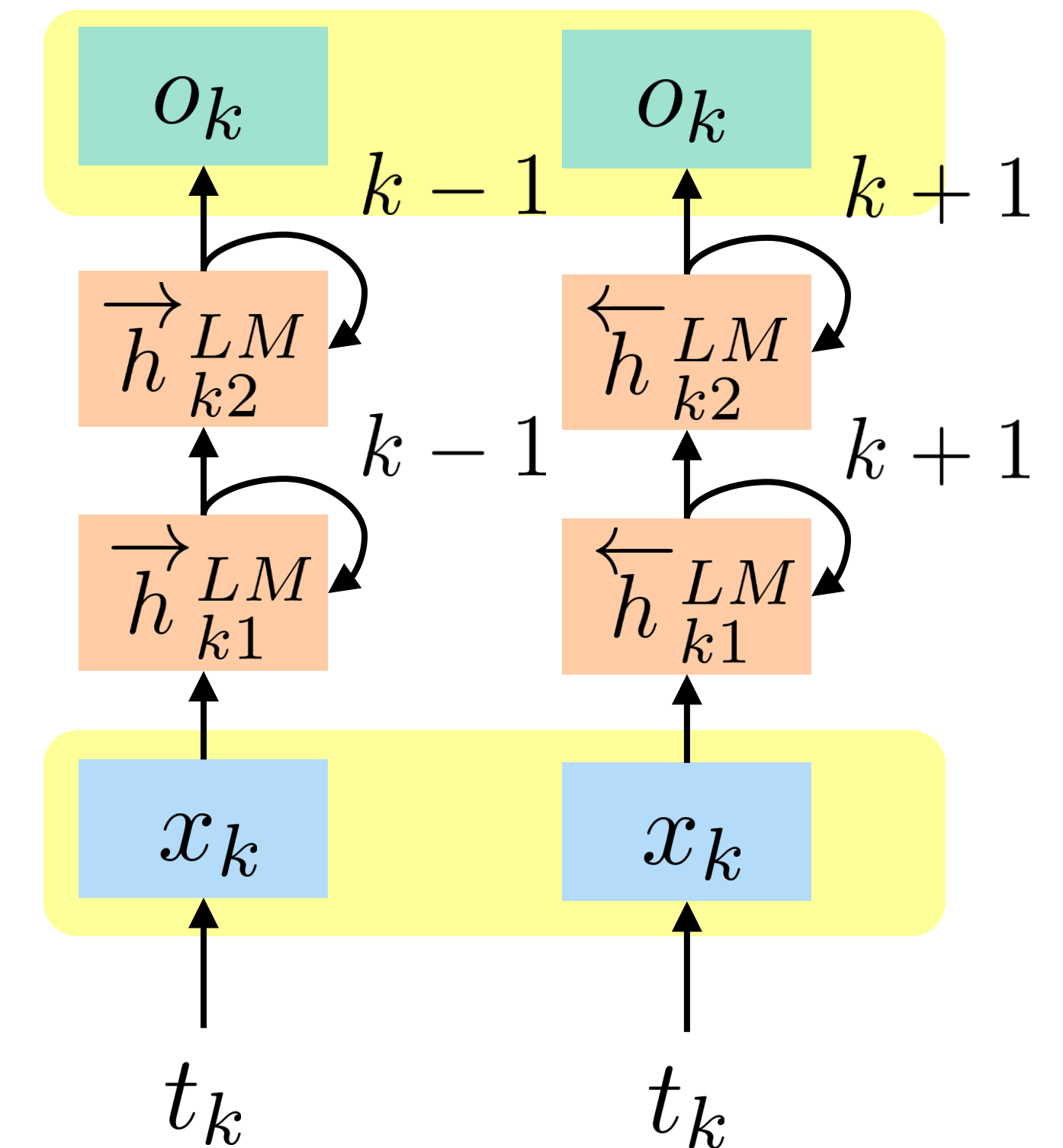
$\overleftarrow{h}_{k1}^{LM}$

x_k

x_k

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

Forward LM Backward LM



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

ELMo: Embeddings from Language Models



3) Use ELMo in Supervised NLP Tasks

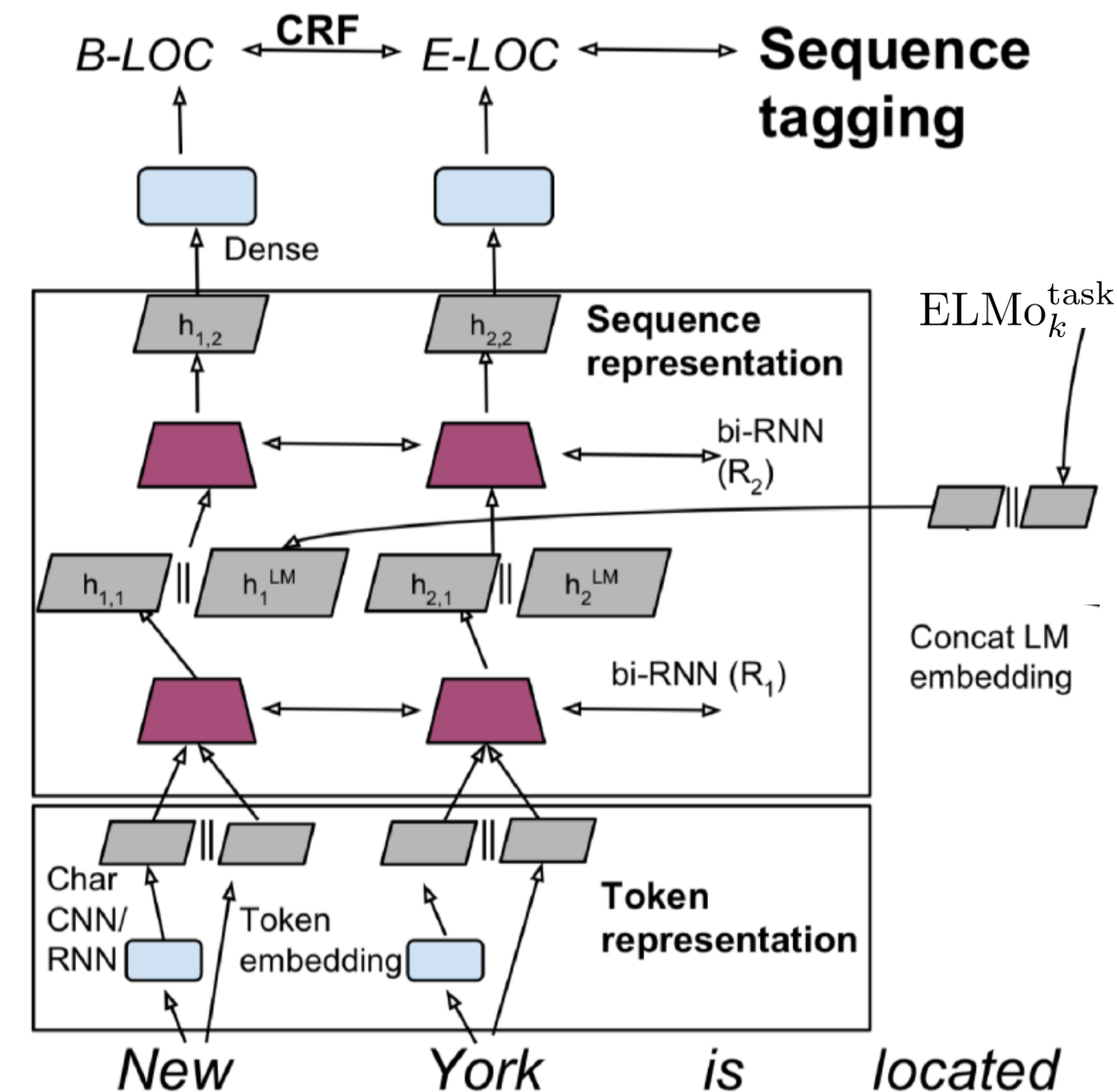
- Get LM embedding for each word
- Freeze LM weights to form ELMo enhanced embeddings

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

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

- Tricks: dropout, regularization

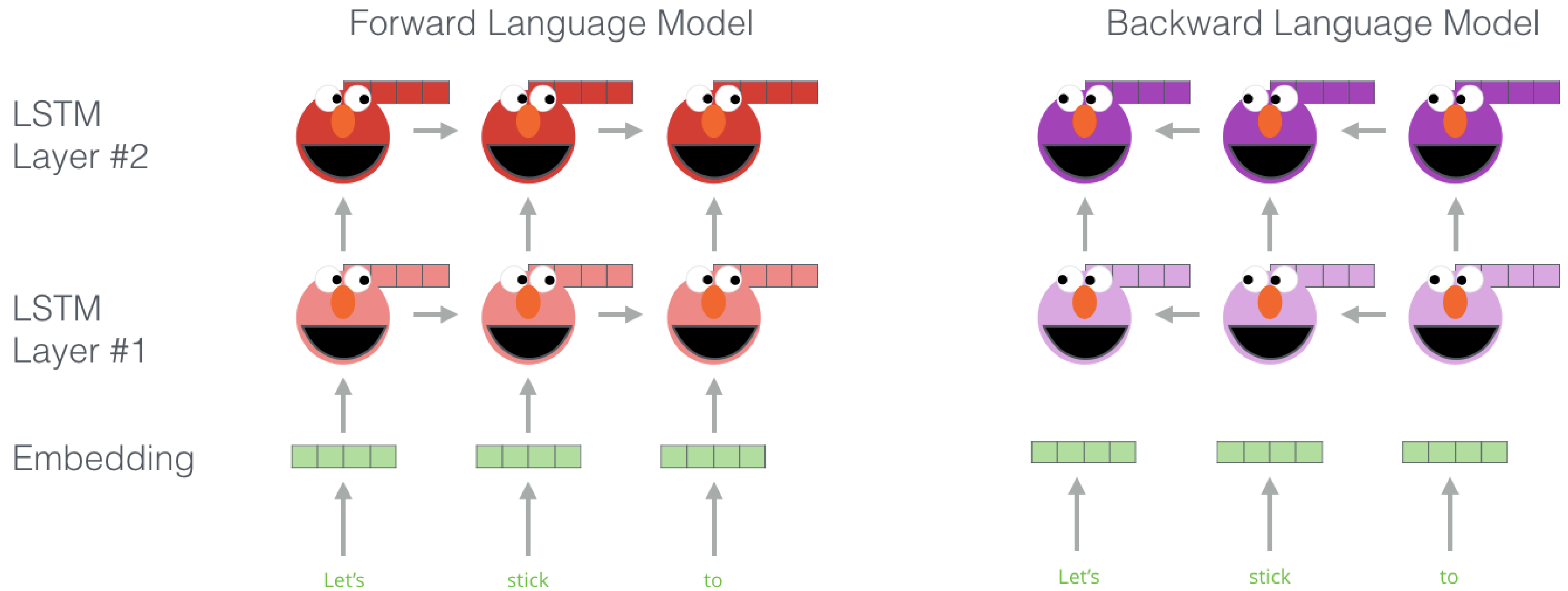
The way for concatenation depends on the task



ELMo Illustration



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

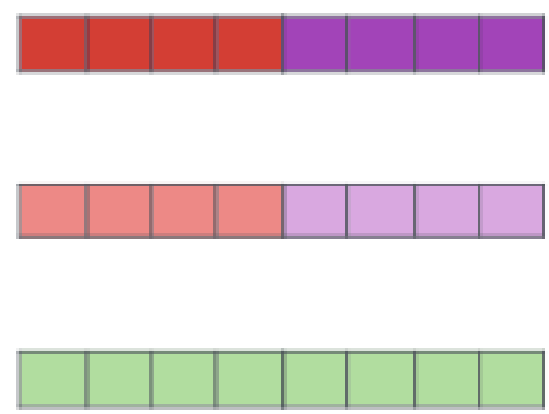


ELMo Illustration



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

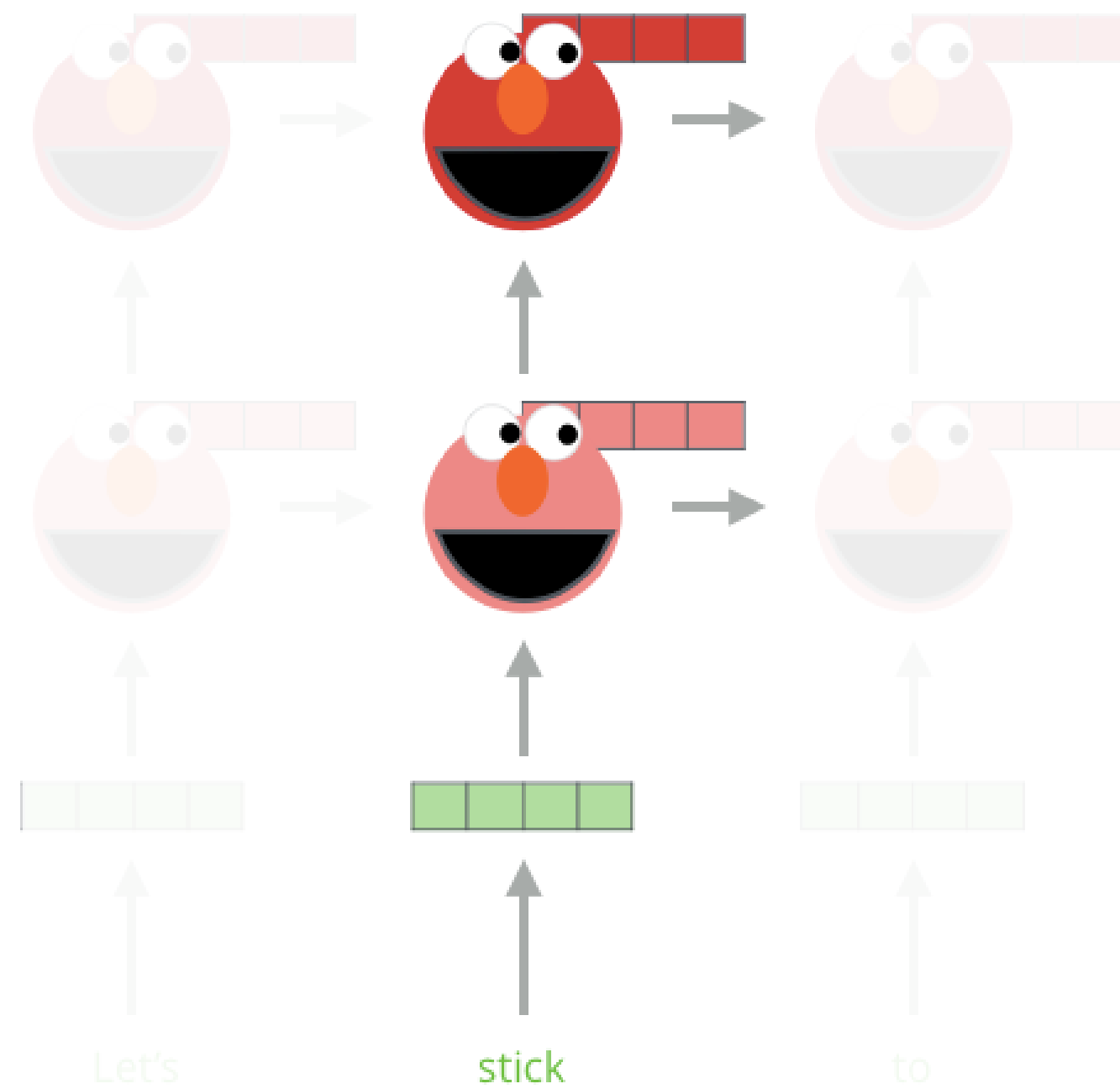


3- Sum the (now weighted) vectors

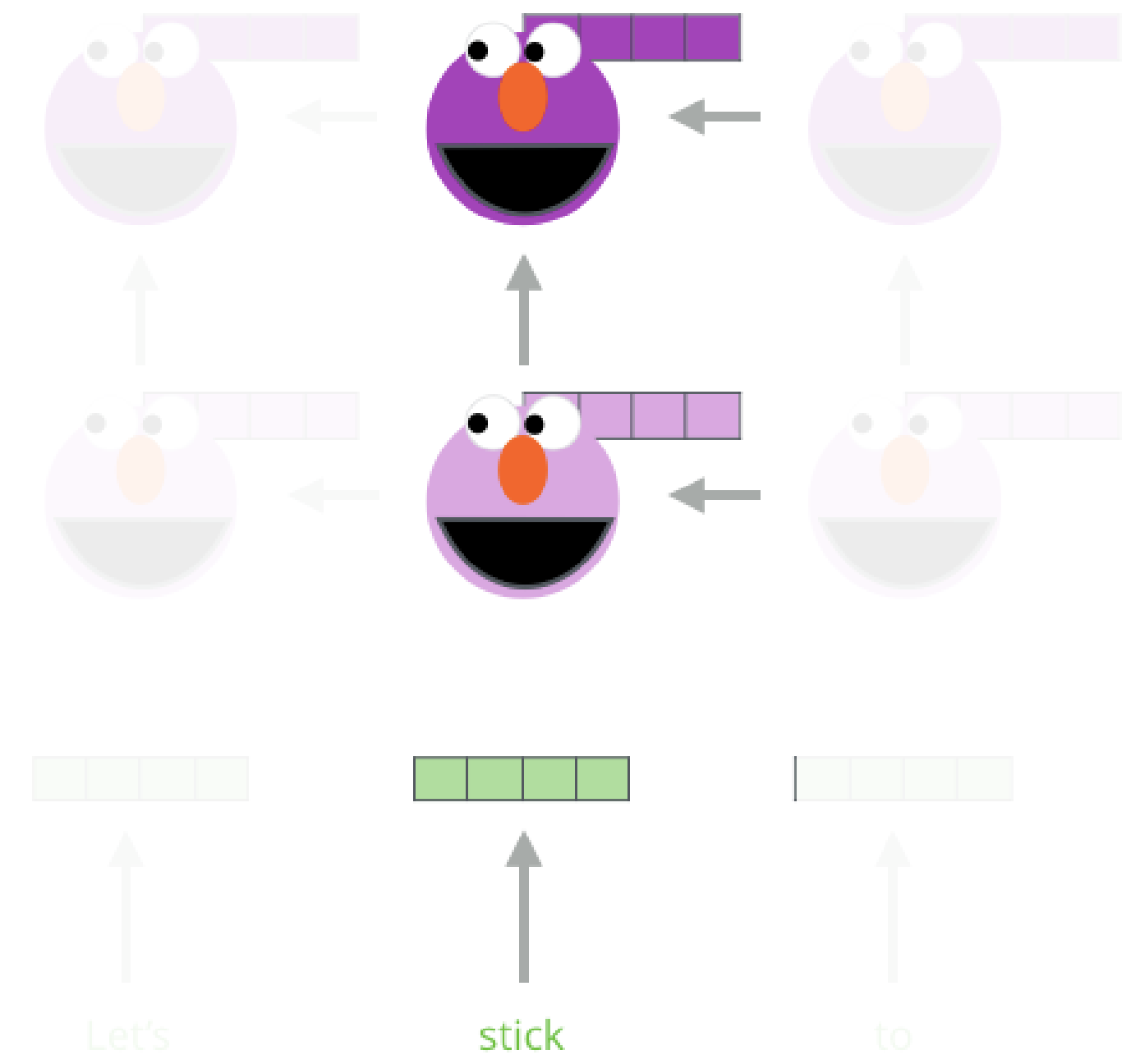


ELMo embedding of “stick” for this task in this context

Forward Language Model



Backward Language Model



ELMo on Name Entity Recognition



Model	Description	CONLL 2003 F1
Klein+, 2003	MEMM softmax markov model	86.07
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TagLM (Peters+, 2017)	LSTM BiLM in BLSTM Tagger	91.93
ELMo (Peters+, 2018)	ELMo in BLSTM	92.22

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)

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 <u>play</u> 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 <u>play</u> .
	Olivia De Havilland signed to do a Broadway <u>play</u> for Garson {...}	{...} they were actors who had been handed fat roles in a successful <u>play</u> , 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

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

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

