Natural Language Processing

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Lecture 8: Language models 2 (Feb 12 2024)

Many slides & instruction ideas borrowed from:

David Bamman, Mohit Iyyer & Greg Durrett

Logistics

- Quiz 3 & HW2
- AP0 is due this Friday Feb 16
- Exam 1 is next Wednesday Feb 21
- Homework 3 will be out by Wednesday
    - Will be due Thursday Feb 22.
- Quiz 4 will be out this **Thursday (due next Sunday Feb 18)**
- Today: Neural LM

Language Model

Language modeling is the task of estimating P(w)

Language Model

$$P(w) = P(w_1, \ldots, w_n)$$

P("Call me Ishmael") =
P(w_1 = "call", w_2 = "me", w_3 = "Ishmael")

$$\sum_{w \in V^+} P(w) = 1$$

over all sequence lengths!

$$0 \leq P(w) \leq 1$$

Language Model

- Language modeling is the task of estimating P(w)
- Why is this hard?

P(“It was the best of times, it was the worst of times”)

Chain rule (of probability)

$$
\begin{aligned}
P(x_1, x_2, x_3, x_4, x_5) = P(x_1) \\
&\times P(x_2 \mid x_1) \\
&\times P(x_3 \mid x_1, x_2) \\
&\times P(x_4 \mid x_1, x_2, x_3) \\
&\times P(x_5 \mid x_1, x_2, x_3, x_4)
\end{aligned}
$$

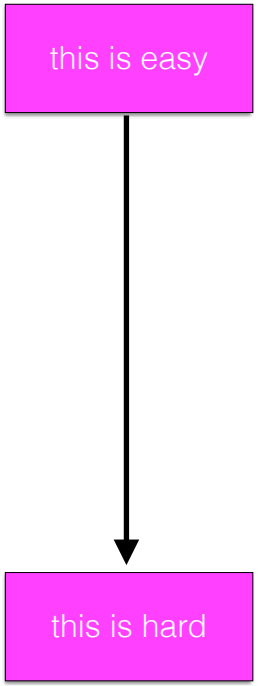
Chain rule (of probability)

P(“It was the best of times, it was the worst of times”)

Chain rule (of probability)

P(“It”)

P(“was” | “It”)



$$P(w_1)$$

$$P(w_2 \mid w_1)$$

$$P(w_3 \mid w_1, w_2)$$

$$P(w_4 \mid w_1, w_2, w_3)$$

$$P(w_n \mid w_1, \ldots, w_{n-1})$$

P(“times” | “It was the best of times, it was the worst of”)

Markov assumption

first-order

$$P(x_i \mid x_1, \ldots x_{i-1}) \approx P(x_i \mid x_{i-1})$$

second-order

$$P(x_i \mid x_1, \ldots x_{i-1}) \approx P(x_i \mid x_{i-2}, x_{i-1})$$

Ngram Models

bigram model
(first-order markov)

$$\prod_{i}^{n} P(w_i \mid w_{i-1}) \times P(\text{STOP} \mid w_n)$$

trigram model
(second-order markov)

$$\prod_{i}^{n} P(w_i \mid w_{i-2}, w_{i-1})$$

$$\times P(\text{STOP} \mid w_{n-1}, w_n)$$

"It was the best of times, it was the worst of times"

$$P(It \mid \text{START}_1, \text{START}_2)$$

$$P(was \mid \text{START}_2, It)$$

$$P(the \mid It, was)$$

...

$$P(times \mid worst, of)$$

$$P(\text{STOP} \mid of, times)$$

Estimation of N-gram model

unigram

$$\prod_{i}^{n} P(w_i) \times P(STOP)$$

bigram

$$\prod_{i}^{n} P(w_i \mid w_{i-1}) \times P(STOP \mid w_n)$$

trigram

$$\prod_{i}^{n} P(w_i \mid w_{i-2}, w_{i-1}) \times P(STOP \mid w_{n-1}, w_n)$$

Maximum likelihood estimate

$$\frac{c(w_i)}{N}$$

$$\frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

$$\frac{c(w_{i-2}, w_{i-1}, w_i)}{c(w_{i-2}, w_{i-1})}$$

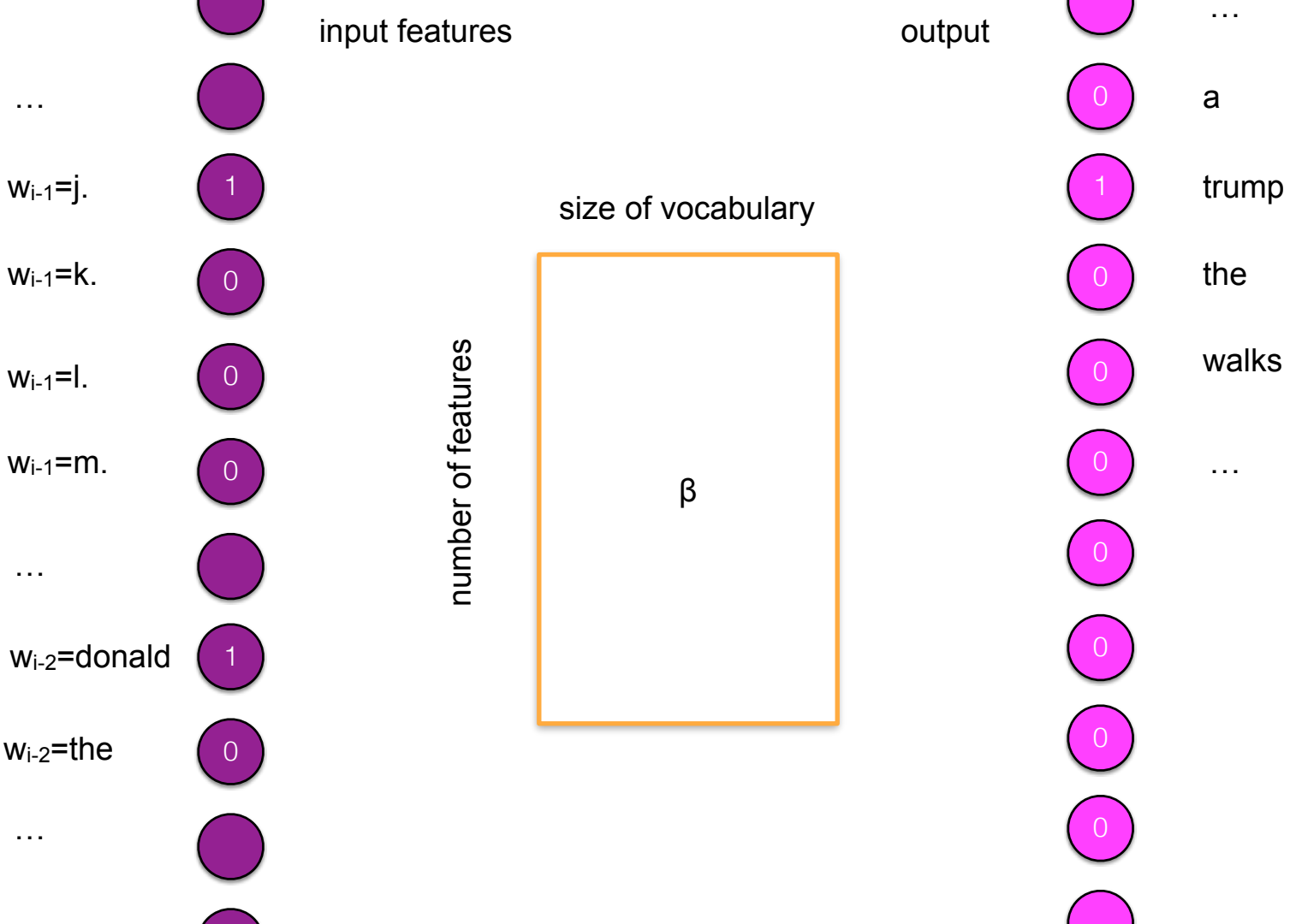
Language Model

- We can use multiclass logistic regression for language modeling by treating the vocabulary as the output space

$$\mathcal{Y} = \mathcal{V}$$

The United States Senate opens its second impeachment trial of former President Donald J. _____

feature classes	example
ngrams (w_{i-1}, w_{i-2}:w_{i-1}, w_{i-3}:w_{i-1})	w_{i-2}="donald", w_{i-1}="j."
gappy ngrams	w_1="impeachment" and w_2="donald"
spelling, capitalization	w_{i-1} is capitalized and w_i is capitalized
class/gazetteer membership	w_{i-1} in list of names and w_i in list of names


input features
output
…
w_{i-1}=j.
w_{i-1}=k.
w_{i-1}=l.
w_{i-1}=m.
…
w_{i-2}=donald
w_{i-2}=the
…
1
0
0
0
1
0
size of vocabulary
number of features
β
…
a
trump
the
walks
…
0
1
0
0
0
0
0
0
0
0

Tradeoffs

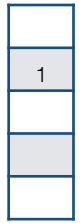
- Richer representations = more parameters, higher likelihood of overfitting
- Much slower to train than estimating the parameters of a classical model

$$P(Y = y \mid X = x; \beta) = \frac{\exp(x^\top \beta_y)}{\sum_{y' \in \mathcal{Y}} \exp(x^\top \beta_{y'})}$$

Neural LM

Simple feed-forward multilayer perceptron (e.g., one hidden layer)

input x = vector concatenation of a conditioning context of fixed size k

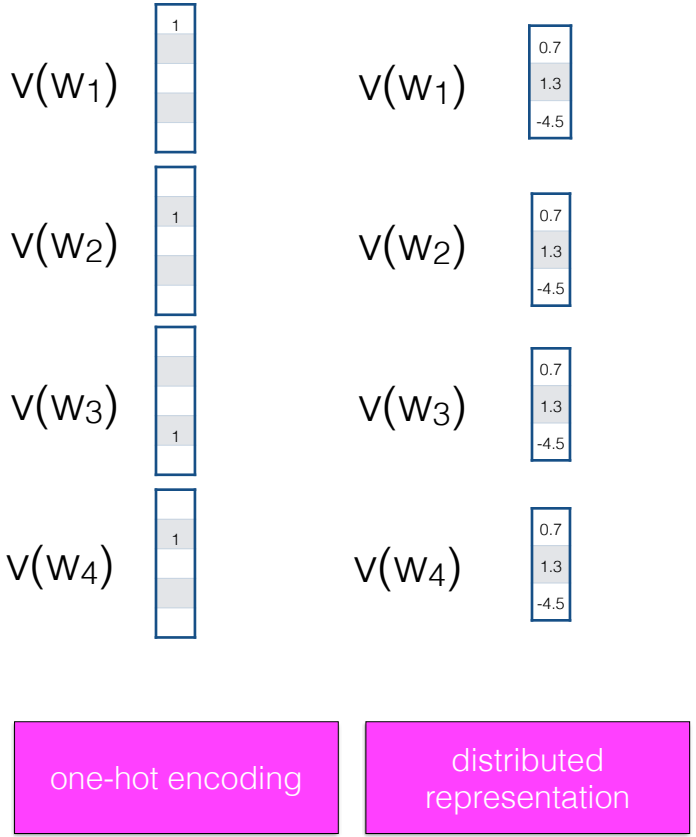


$$x = [v(w_1); \ldots; v(w_k)]$$

Bengio et al. 2003

$$x = [v(w_1); \ldots; v(w_k)]$$

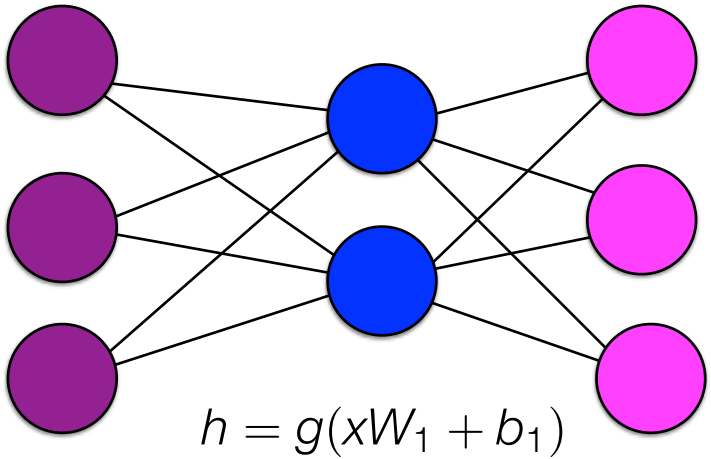
w_1 = tried
w_2 = to
w_3 = prepare
w_4 = residents



Bengio et al. 2003

$W_1 \in \mathbb{R}^{kD \times H}$ $\quad$ $W_2 \in \mathbb{R}^{H \times V}$

$b_1 \in \mathbb{R}^{H}$ $\quad$ $b_2 \in \mathbb{R}^{V}$



$h = g(xW_1 + b_1)$

$x = [v(w_1); \ldots; v(w_k)]$ $\quad$ $\hat{y} = \text{softmax}(hW_2 + b_2)$

Bengio et al. 2003

Neural LM

conditioning context

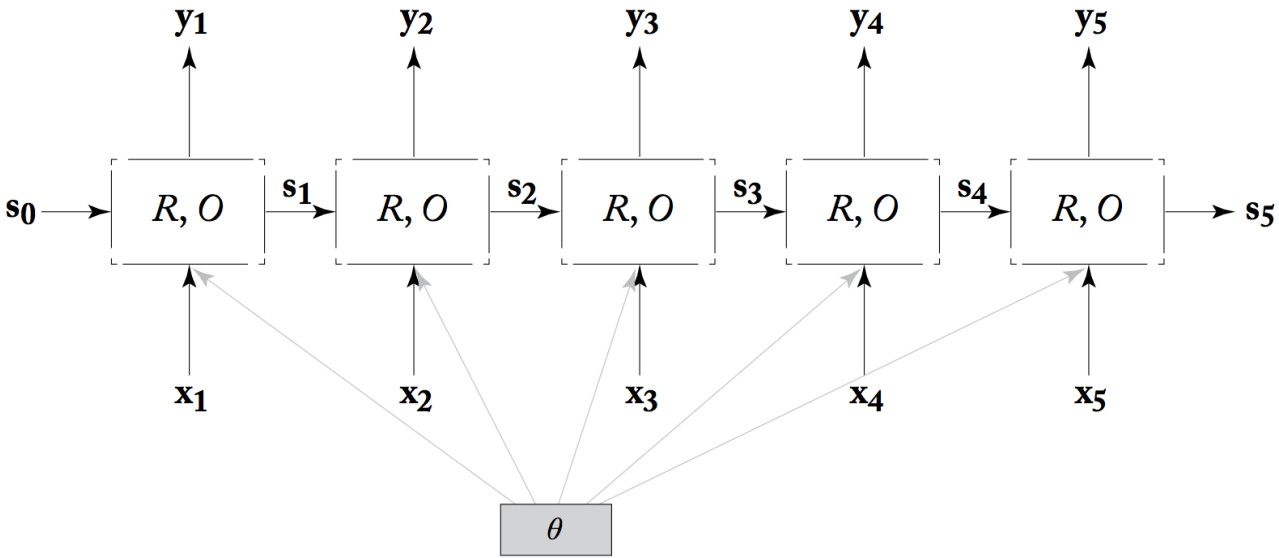
tried to prepare residents for the hardships of recovery from the

y

Recurrent neural network

- Feed Forward NN has the limits of context length.
- RNN allow arbitarily-sized conditioning contexts; condition on the entire sequence history.

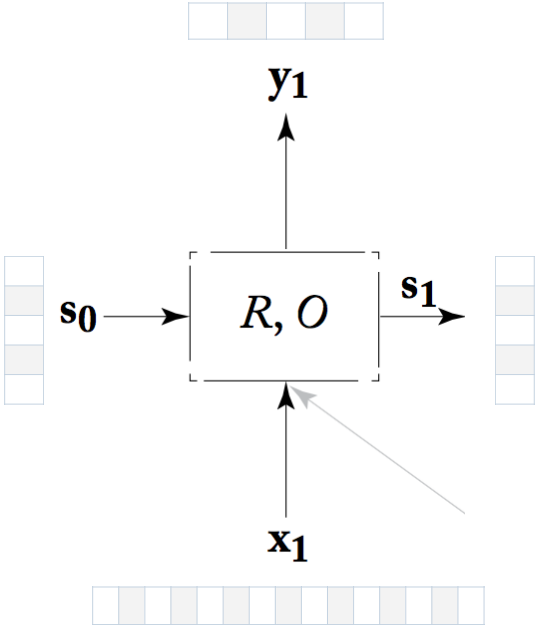
Recurrent neural network



Goldberg 2017

Recurrent neural network

- Each time step has two inputs:
  - x_i (the observation at time step i); one-hot vector, feature vector or distributed representation.
  - s_{i-1} (the output of the previous state); base case: s_0 = 0 vector



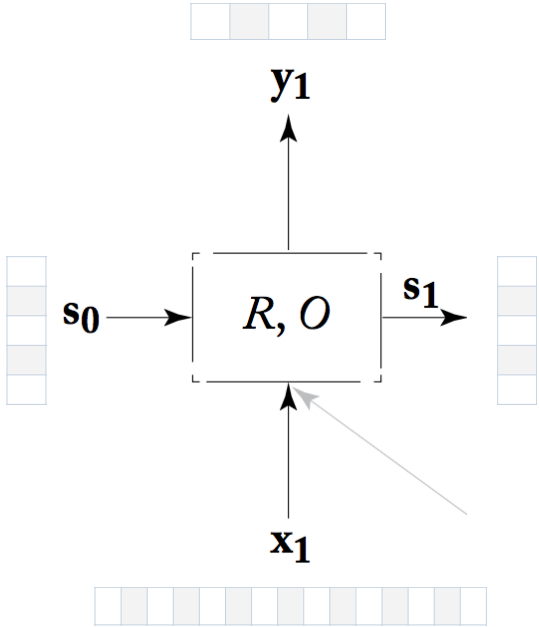
Recurrent neural network

$$s_i = R(x_i, s_{i-1})$$

R computes the output state as a function of the current input and previous state

$$y_i = O(s_i)$$

O computes the output as a function of the current output state



“Simple” RNN

g = tanh or relu

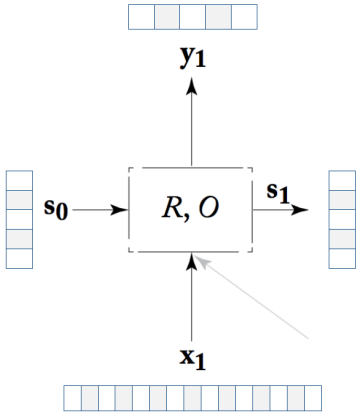
$$s_i = R(x_i, s_{i-1}) = g(s_{i-1}W^s + x_iW^x + b)$$

Different weight vectors W transform the previous state and current input before combining

$$W^s \in \mathbb{R}^{H \times H}$$

$$W^x \in \mathbb{R}^{D \times H}$$

$$b \in \mathbb{R}^H$$

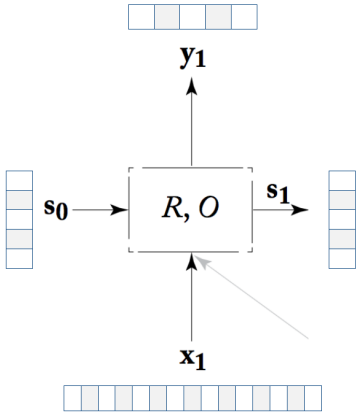


Elman 1990, Mikolov 2012

RNN LM

- The output state s_i is an H-dimensional real vector; we can transfer that into a probability by passing it through an additional linear transformation followed by a softmax

$$y_i = O(s_i) = \text{softmax}(s_i W^o + b^o)$$



Elman 1990, Mikolov 2012

Training RNNs

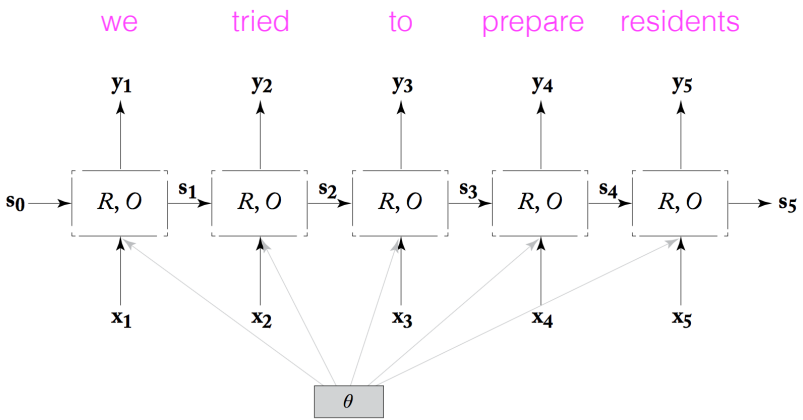
- Given this definition of an RNN:

$$s_i = R(x_i, s_{i-1}) = g(s_{i-1}W^s + x_iW^x + b)$$
$$y_i = O(s_i) = \text{softmax}(s_iW^o + b^o)$$

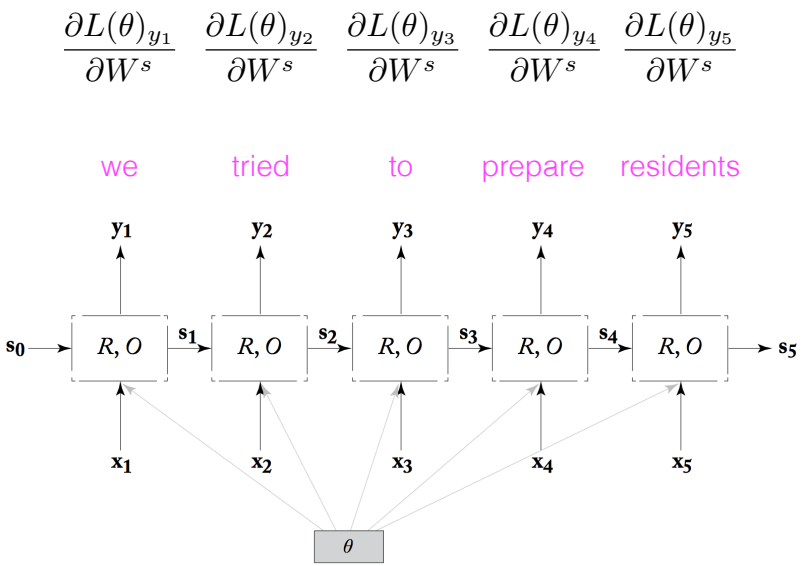
- We have five sets of parameters to learn:

$$W^s, W^x, W^o, b, b^o$$

Training RNNs

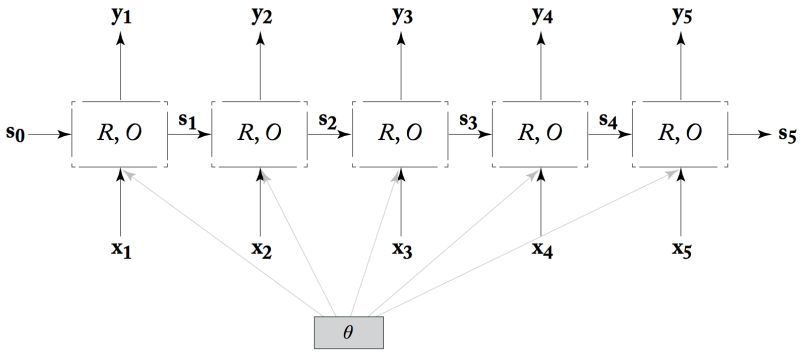


- At each time step, we make a prediction and incur a loss; we know the true y (the word we see in that position)



- Training here is standard backpropagation, taking the derivative of the loss we incur at step *t* with respect to the parameters we want to update

we tried to prepare residents



0	−2	8	−8	−1	2
0	5	−4	2	0	2
0	−2	5	−11	0	5
0	−4	−2	8	−3	−2
0	8	−4	−1	0	2

Each state *i* encodes information seen until time *i*

and its structure is optimized to predict the next word

Character LM

- Vocabulary $\mathcal{V}$ is a finite set of discrete characters
- When the output space is small, you're putting a lot of the burden on the structure of the model
- Encode long-range dependencies (suffixes depend on prefixes, word boundaries etc.)

Character LM

```
/*
 * Increment the size file of the new incorrect UI_FILTER group information
 * of the size generatively.
 */
static int indicate_policy(void)
{
  int error;
  if (fd == MARN_EPT) {
    /*
     * The kernel blank will coeld it to userspace.
     */
    if (ss->segment < mem_total)
      unblock_graph_and_set_blocked();
    else
      ret = 1;
    goto bail;
  }
  segaddr = in_SB(in.addr);
  selector = seg / 16;
  setup_works = true;
```

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Character LM

```
\begin{proof}
We may assume that $\mathcal{I}$ is an abelian sheaf on $\mathcal{C}$.
\item Given a morphism $\Delta : \mathcal{F} \to \mathcal{I}$
is an injective and let $\mathfrak q$ be an abelian sheaf on $X$.
Let $\mathcal{F}$ be a fibered complex. Let $\mathcal{F}$ be a category.
\begin{enumerate}
\item \hyperref[setain-construction-phantom]{Lemma}
\label{lemma-characterize-quasi-finite}
Let $\mathcal{F}$ be an abelian quasi-coherent sheaf on $\mathcal{C}$.
Let $\mathcal{F}$ be a coherent $\mathcal{O}_X$-module. Then
$\mathcal{F}$ is an abelian catenary over $\mathcal{C}$.
\item The following are equivalent
\begin{enumerate}
\item $\mathcal{F}$ is an $\mathcal{O}_X$-module.
\end{lemma}
```

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Character LM

```
PANDARUS:
Alas, I think he shall be come approached and the day
When little srain would be attain'd into being never fed,
And who is but a chain and subjects of his death,
I should not sleep.

Second Senator:
They are away this miseries, produced upon my soul,
Breaking and strongly should be buried, when I perish
The earth and thoughts of many states.

DUKE VINCENTIO:
Well, your wit is in the care of side and that.
```

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN Tradeoffs

- Very expensive to train (especially for large vocabulary)
- Backpropagation through long histories leads to vanishing gradients (cf. LSTMs in a few weeks).
- But they consistently have strong performances in perplexity evaluations.

Count-and-normalize

Discriminative

Neural

Model	Perplexity			Entropy reduction over baseline	
	individual	+KN5	+KN5+cache	KN5	KN5+cache
3-gram, Good-Turing smoothing (GT3)	165.2	-	-	-	-
5-gram, Good-Turing smoothing (GT5)	162.3	-	-	-	-
3-gram, Kneser-Ney smoothing (KN3)	148.3	-	-	-	-
5-gram, Kneser-Ney smoothing (KN5)	**141.2**	-	-	-	-
5-gram, Kneser-Ney smoothing + cache	**125.7**	-	-	-	-
PAQ8o10t	131.1	-	-	-	-
Maximum entropy 5-gram model	142.1	138.7	124.5	0.4%	0.2%
Random clusterings LM	170.1	126.3	115.6	2.3%	1.7%
Random forest LM	131.9	131.3	117.5	1.5%	1.4%
Structured LM	146.1	125.5	114.4	2.4%	1.9%
Within and across sentence boundary LM	116.6	110.0	108.7	5.0%	3.0%
Log-bilinear LM	144.5	115.2	105.8	4.1%	3.6%
Feedforward neural network LM [50]	140.2	116.7	106.6	3.8%	3.4%
Feedforward neural network LM [40]	141.8	114.8	105.2	4.2%	3.7%
Syntactical neural network LM	131.3	110.0	101.5	5.0%	4.4%
Recurrent neural network LM	124.7	105.7	97.5	5.8%	5.3%
Dynamically evaluated RNNLM	123.2	102.7	98.0	6.4%	5.1%
Combination of static RNNLMs	102.1	95.5	**89.4**	7.9%	7.0%
Combination of dynamic RNNLMs	101.0	**92.9**	90.0	8.5%	6.9%

Mikolov 2010

Model	Size	D	Valid	Test
Medium LSTM, Zaremba (2014)	10M	2	86.2	82.7
Large LSTM, Zaremba (2014)	24M	2	82.2	78.4
VD LSTM, Press (2016)	51M	2	75.8	73.2
VD LSTM, Inan (2016)	9M	2	77.1	73.9
VD LSTM, Inan (2016)	28M	2	72.5	69.0
VD RHN, Zilly (2016)	24M	10	67.9	65.4
NAS, Zoph (2016)	25M	-	-	64.0
NAS, Zoph (2016)	54M	-	-	62.4
LSTM	10M	1	61.8	59.6
LSTM		2	63.0	60.8
LSTM		4	62.4	60.1
RHN		5	66.0	63.5
LSTM	24M	1	61.4	59.5
LSTM		2	62.1	59.6
LSTM		4	60.9	58.3
RHN		5	64.8	62.2


Melis, Dyer and Blunsom 2017

Distributed representation

- Vector representation that encodes information about the distribution of contexts a word appears in
- Words that appear in similar contexts have similar representations (and similar meanings, by the distributional hypothesis).

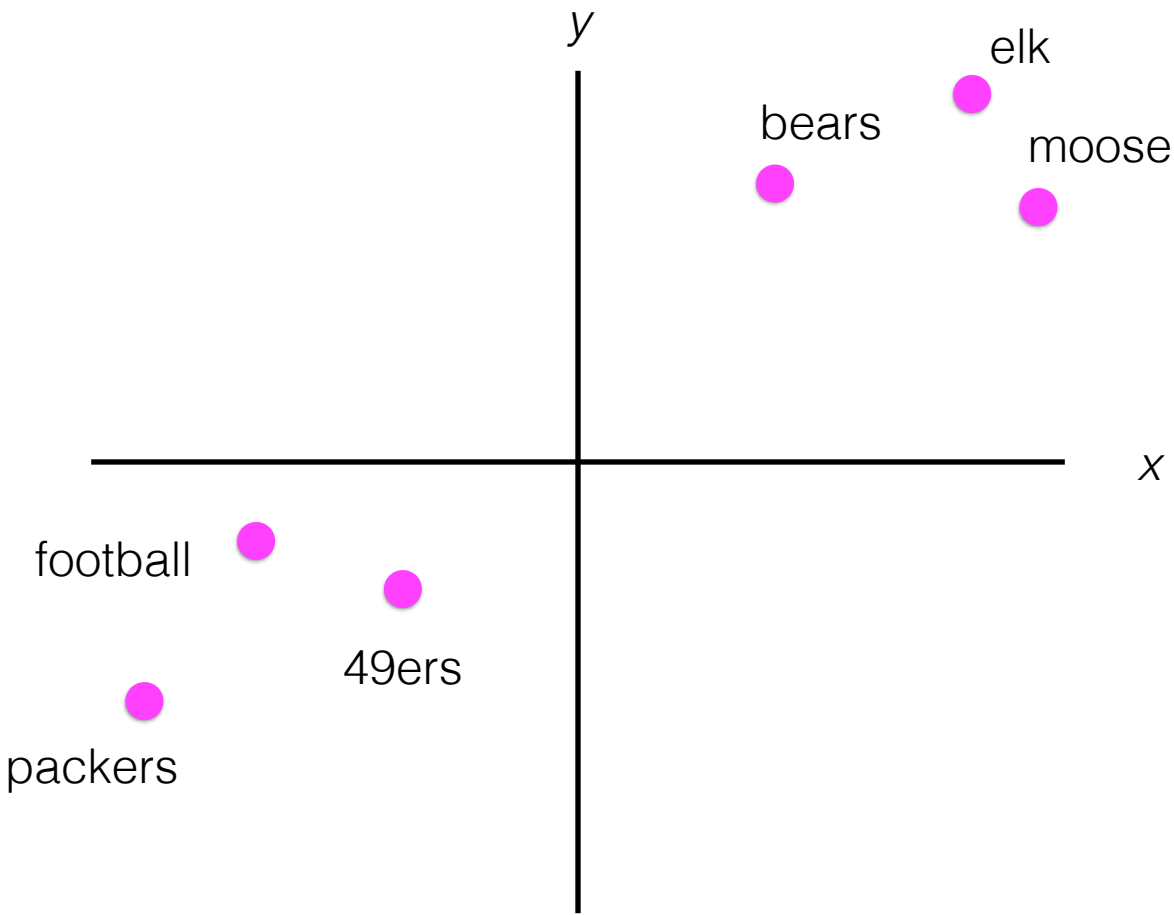
Types and tokens

- Type: bears

- Tokens:
    - The bears ate the honey
    - We spotted the bears from the highway
    - Yosemite has brown bears
    - The chicago bears didn't make the playoffs

"bears"

3.1	1.4	-2.7	0.3
3.1	1.4	-2.7	0.3
3.1	1.4	-2.7	0.3
3.1	1.4	-2.7	0.3

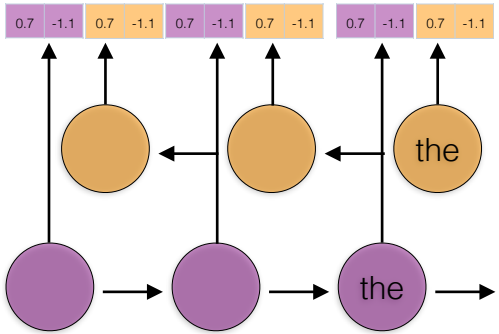

y
elk
bears
moose
x
football
49ers
packers

Contextualized word representations

- Big idea: transform the representation of a token in a sentence (e.g., from a static word embedding) to be sensitive to its local context in a sentence and trainable to be optimized for a specific NLP task.

ELMo

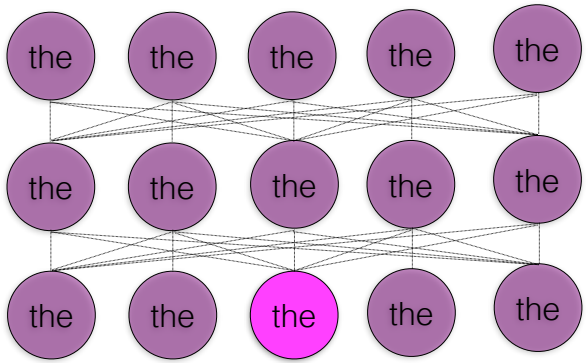
Stacked BiRNN trained to predict next word in language modeling task



Peters et al. 2018

BERT

Transformer-based model to predict masked word using bidirectional context + next sentence prediction.



Devlin et al. 2019

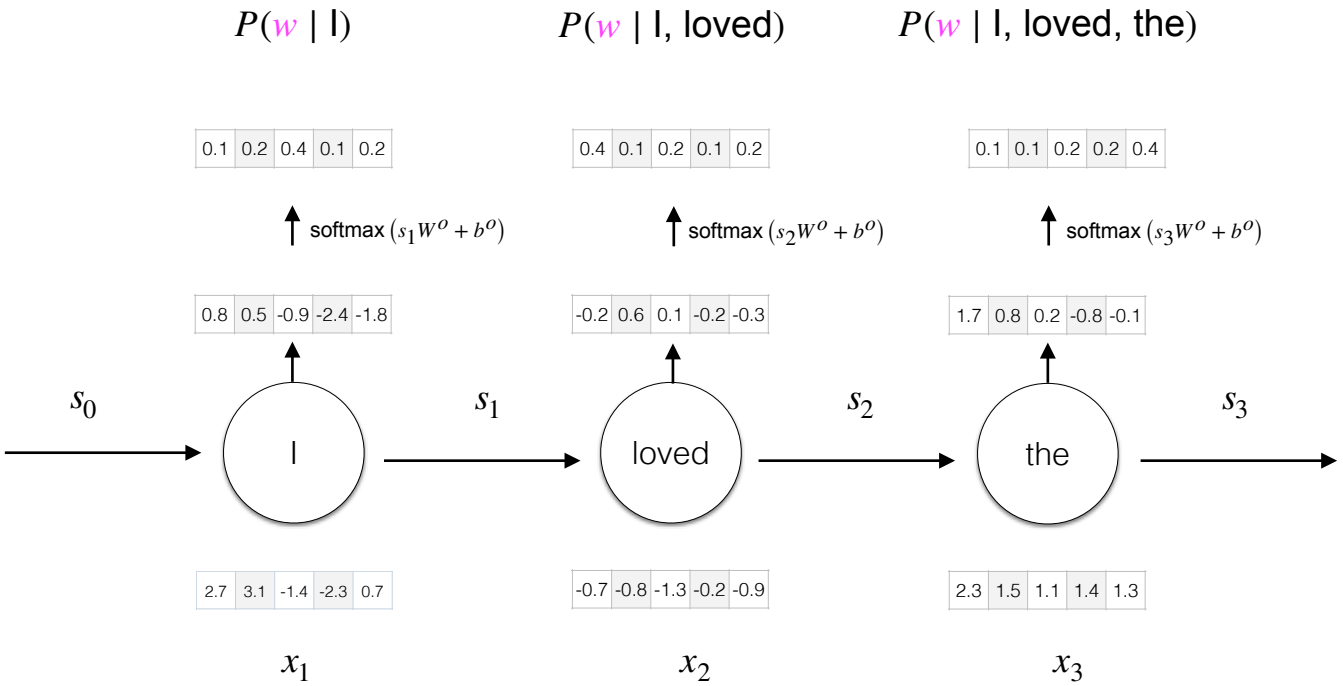
ELMo

- Peters et al. (2018), “Deep Contextualized Word Representations” (NAACL)
- Big idea: transform the representation of a word (e.g., from a static word embedding) to be sensitive to its local context in a sentence and optimized for a specific NLP task.
- Output = word representations that can be plugged into just about any architecture a word embedding can be used.

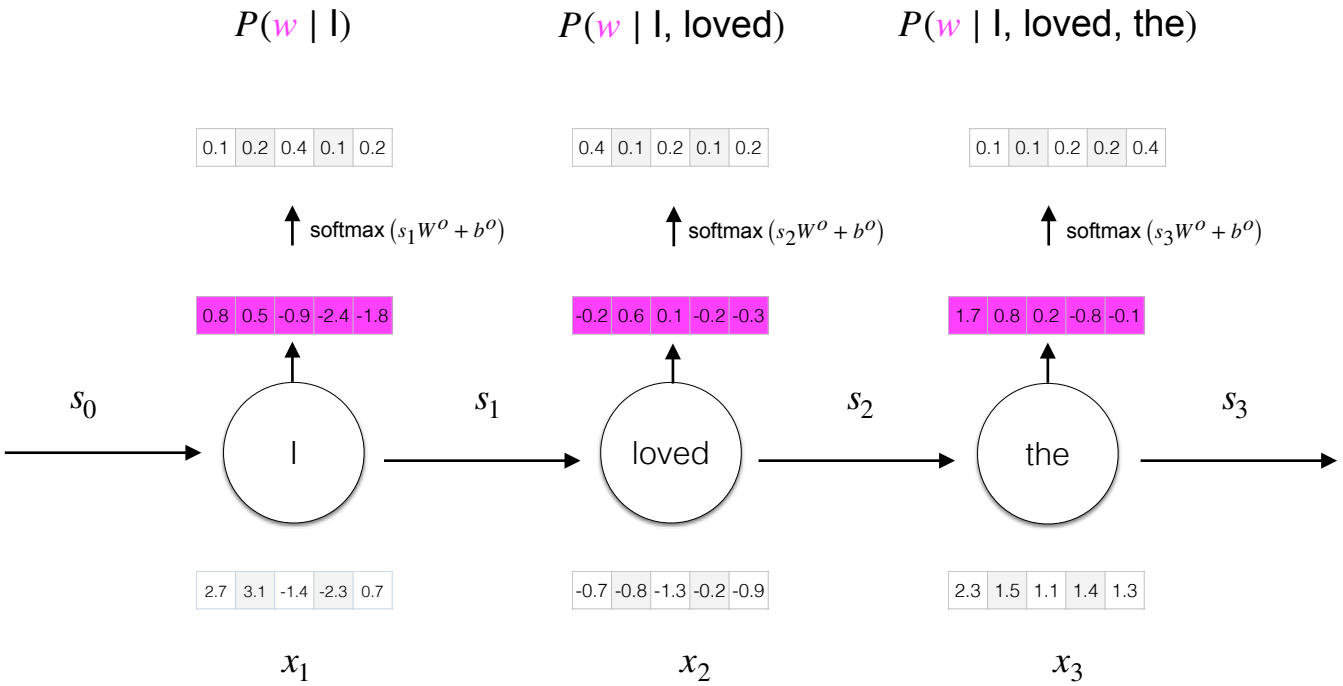
ELMo

- Train a bidirectional RNN language model with L layers on a bunch of text.
- Learn parameters to combine the RNN output across all layers for each word in a sentence for a specific task.

RNN Language model



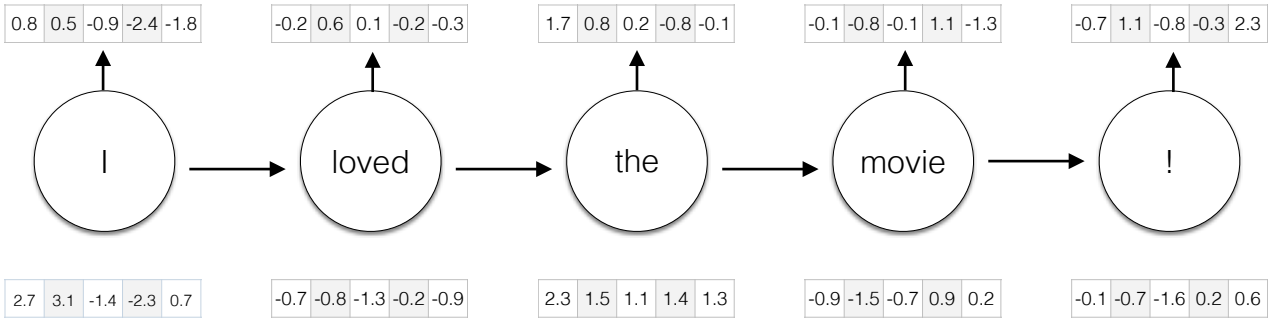
RNN Language model



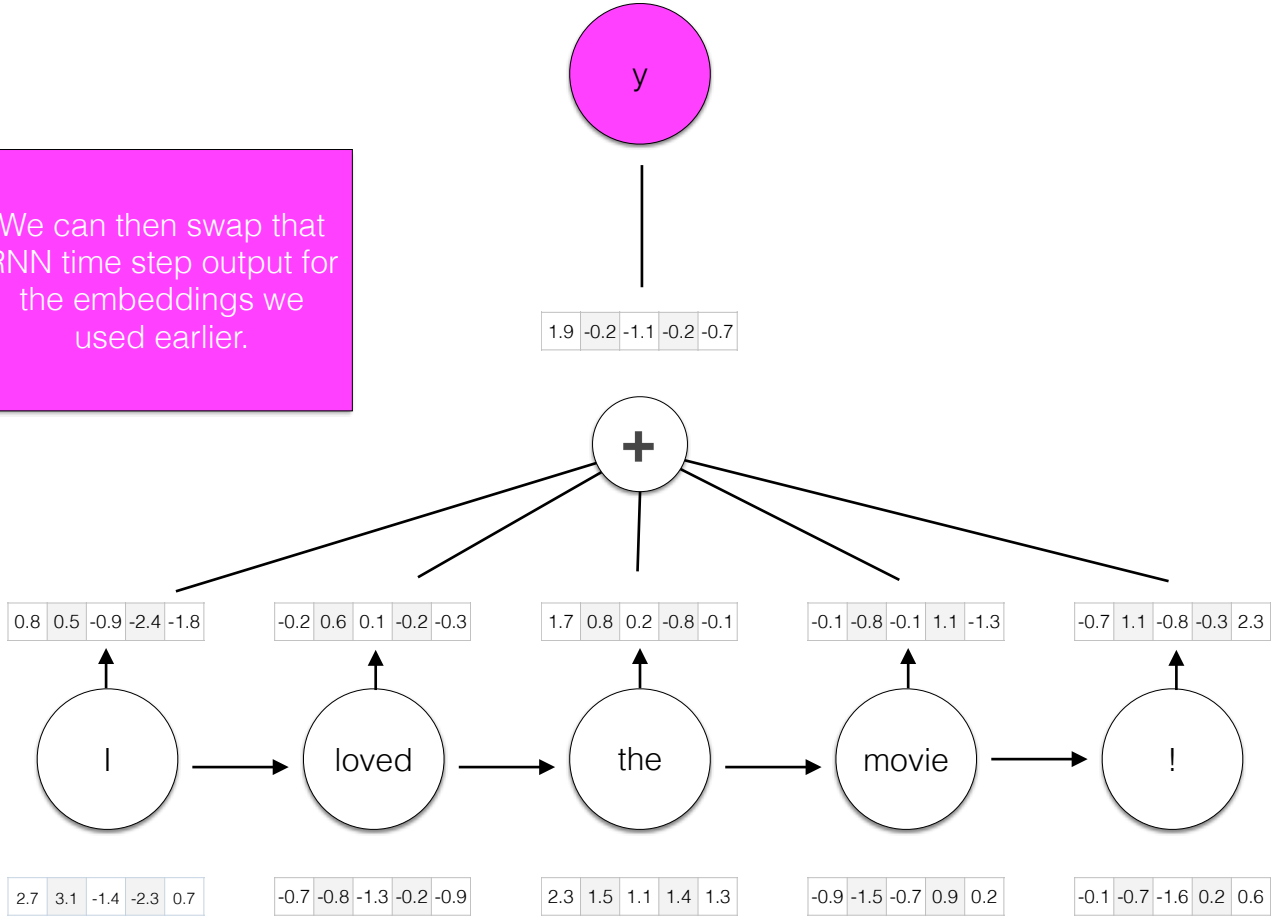
RNN

- With an RNN, we can generate a representation of the sequence as seen through time t.

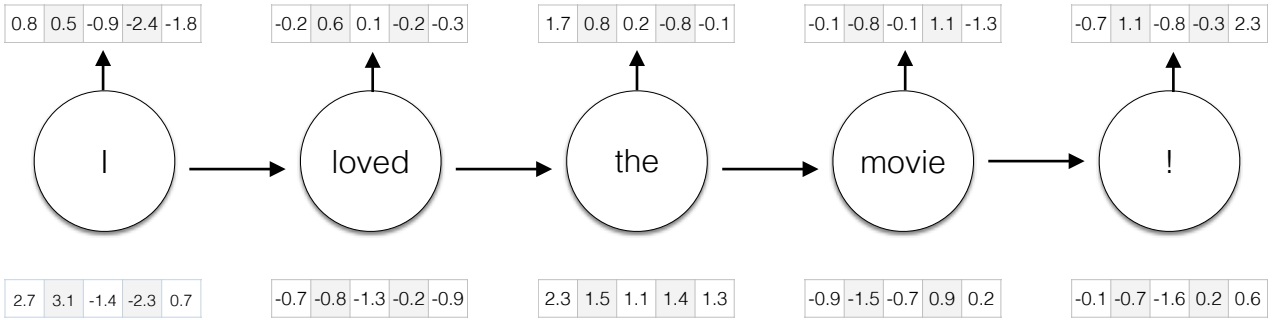
- This encodes a representation of meaning specific to the local context a word is used in.



We can then swap that RNN time step output for the embeddings we used earlier.



What about the future context?

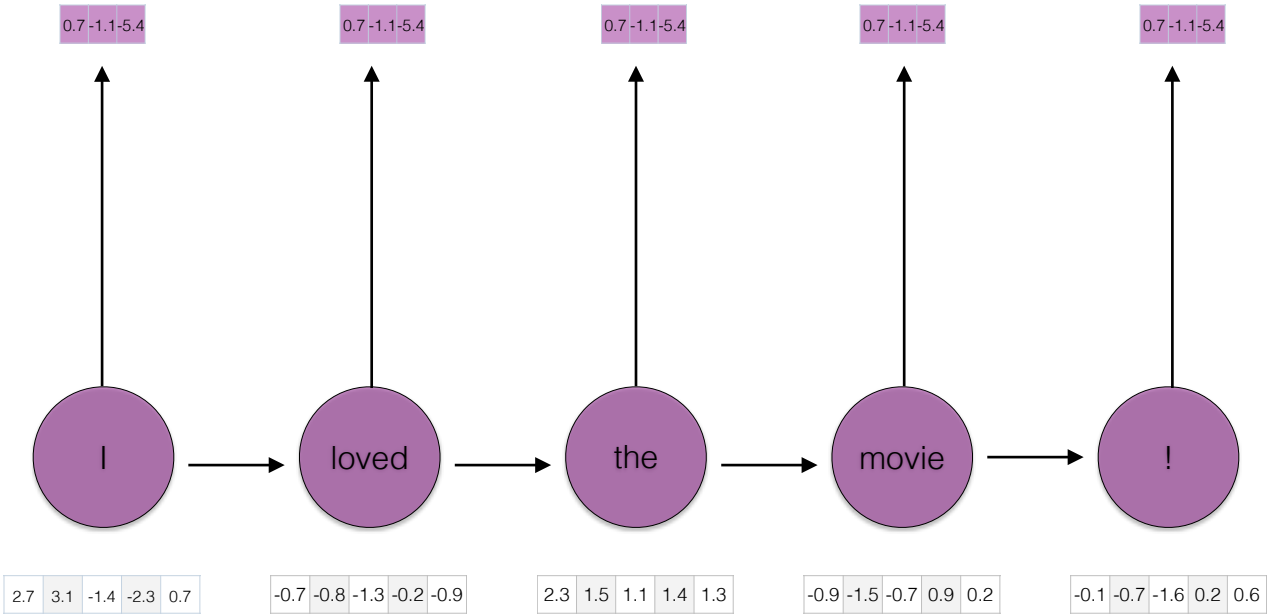


Bidirectional RNN

- A powerful alternative is make predictions conditioning both on the past and the future.
- Two RNNs
    - One running left-to-right
    - One right-to-left
- Each produces an output vector at each time step, which we concatenate

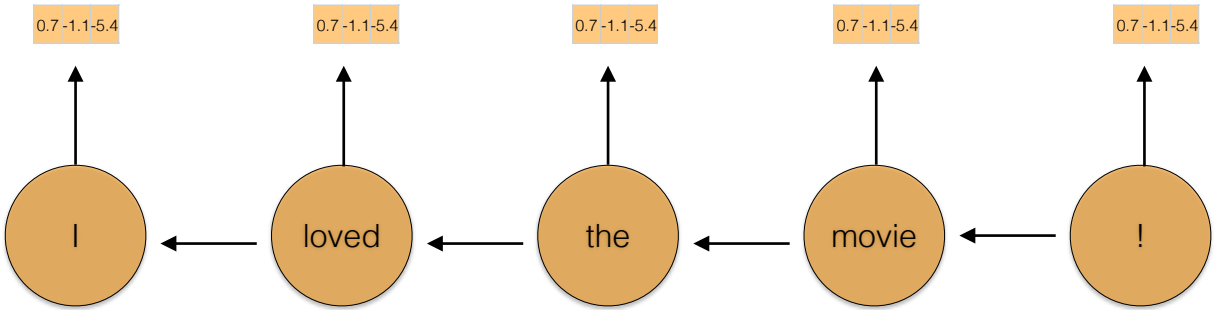
Bidirectional RNN

forward RNN



Bidirectional RNN

backward RNN



2.7	3.1	-1.4	-2.3	0.7

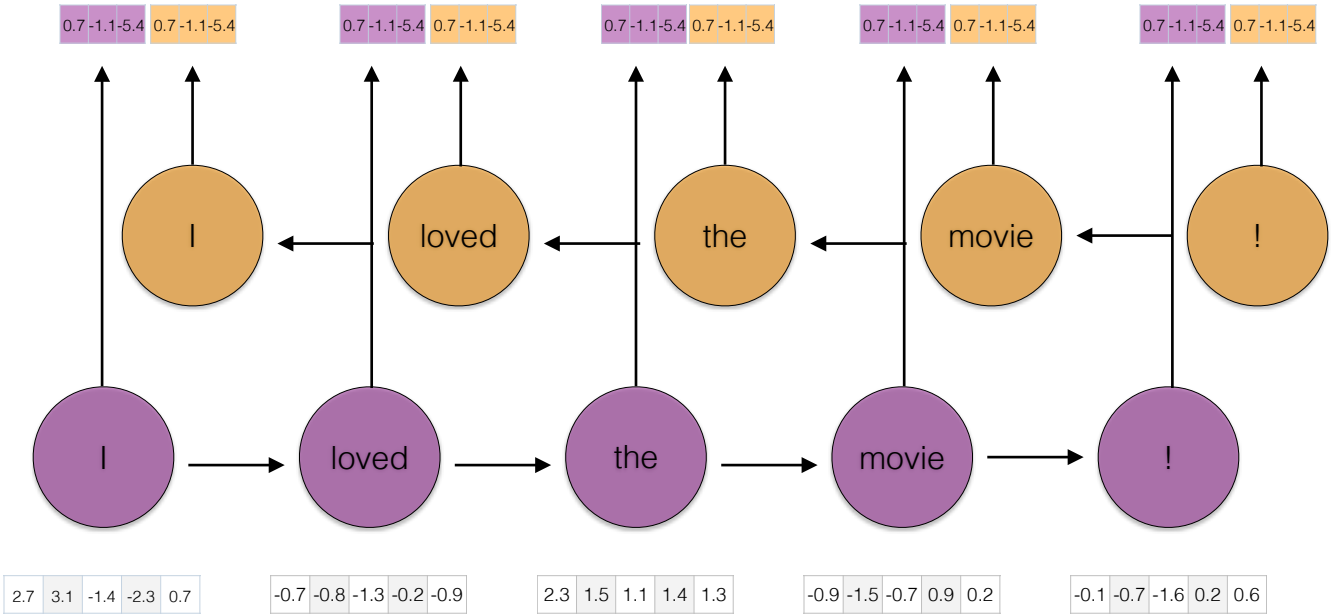
-0.7	-0.8	-1.3	-0.2	-0.9

2.3	1.5	1.1	1.4	1.3

-0.9	-1.5	-0.7	0.9	0.2

-0.1	-0.7	-1.6	0.2	0.6

Bidirectional RNN



Bidirectional RNN

- The forward RNN and backward RNN each output a vector of size H at each time step, which we concatenate into a vector of size 2H.
- The forward and backward RNN each have separate parameters to be learned during training.

Training BiRNNs

- Given this definition of an BiRNN:

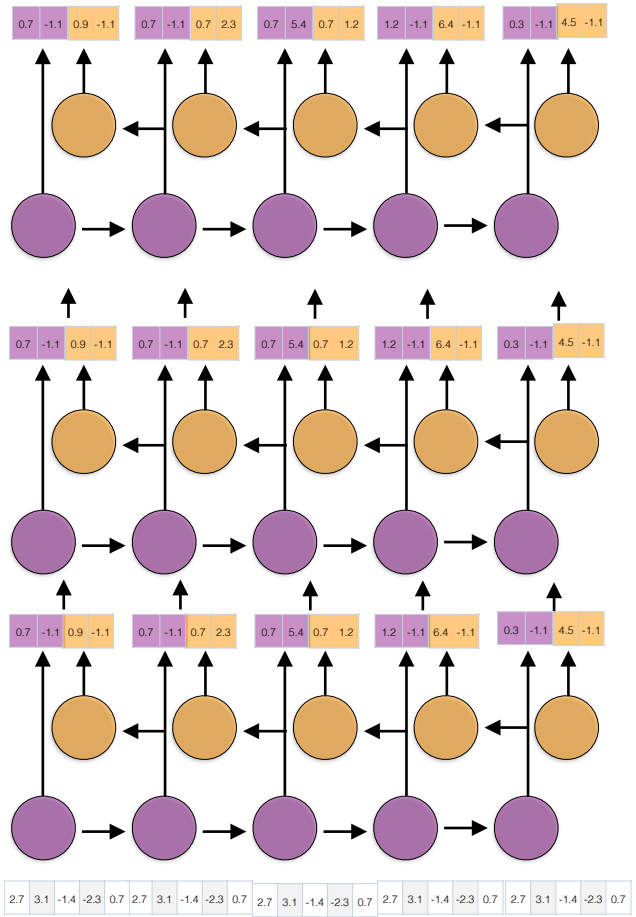
$$s_b^i = R_b(x^i, s_b^{i+1}) = g(s_b^{i+1} W_b^s + x^i W_b^x + b_b)$$
$$s_f^i = R_f(x^i, s_f^{i-1}) = g(s_f^{i-1} W_f^s + x^i W_f^x + b_f)$$

$$y_i = \text{softmax}\left([s_f^i; s_b^i] W^o + b^o\right)$$

- We have 8 sets of parameters to learn (3 for each RNN + 2 for the final layer)

Stacked RNN

- Multiple RNNs, where the output of one layer becomes the input to the next.



ELMo

- Train a bidirectional RNN language model with L layers on a bunch of text.
- Learn parameters to combine the RNN output across all layers for each word in a sentence for a specific task (NER, semantic role labeling, question answering etc.). Large improvements over SOTA for lots of NLP problems.

ELMo

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.

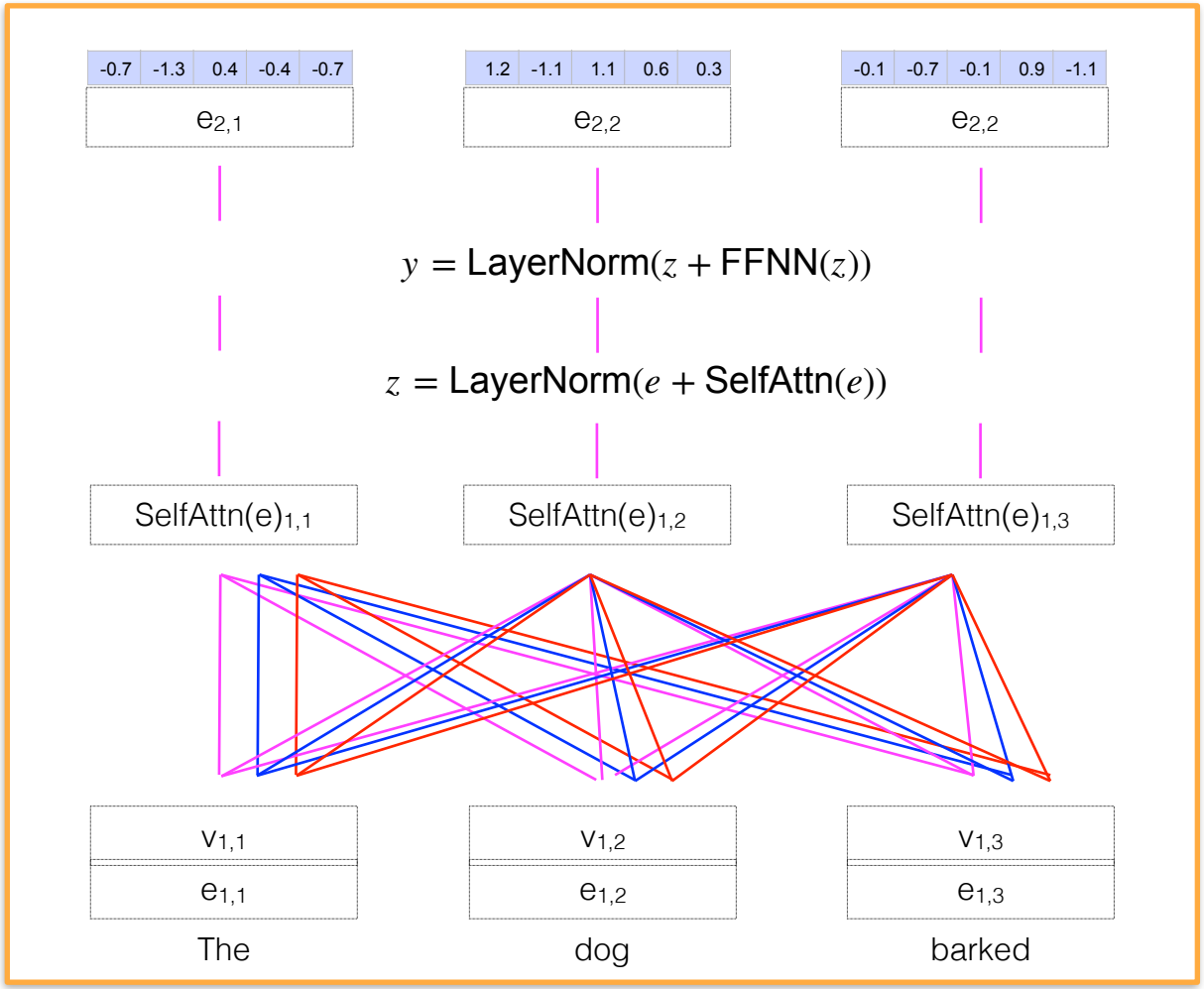
BERT

- Transformer-based model (Vaswani et al. 2017) to predict masked word using bidirectional context + next sentence prediction.
- Generates multiple layers of representations for each token sensitive to its context of use.

Output

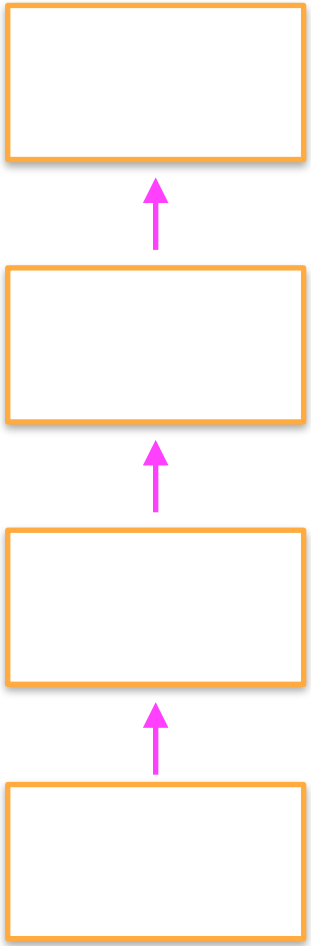
This whole process defines one attention block. The input is a sequence of (e.g. 100-dimensional) vectors; the output of each block is a sequence of (100-dimensional) vectors.

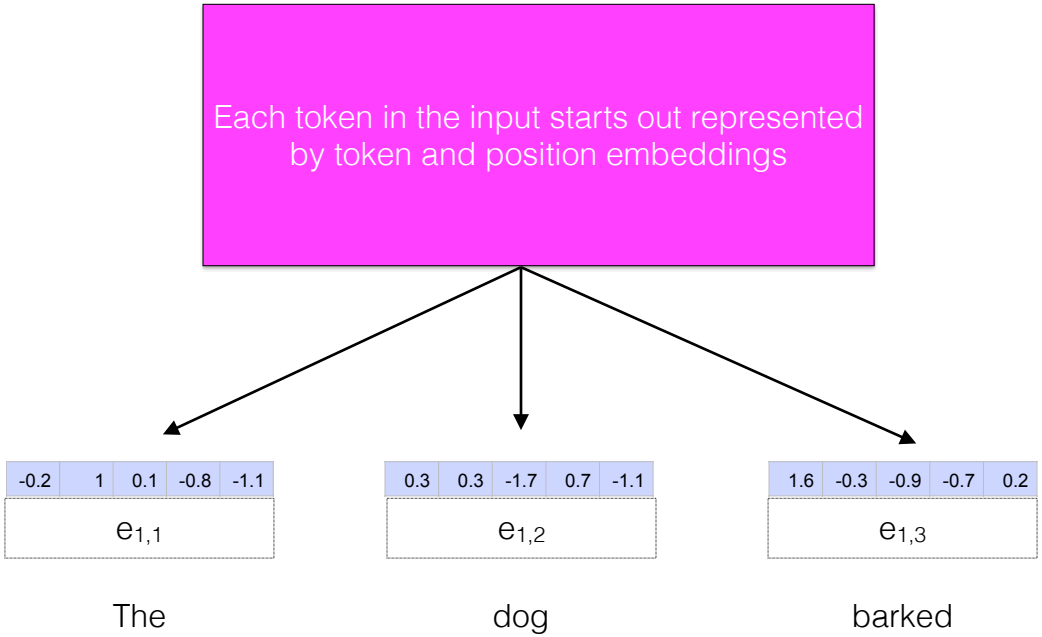
Input

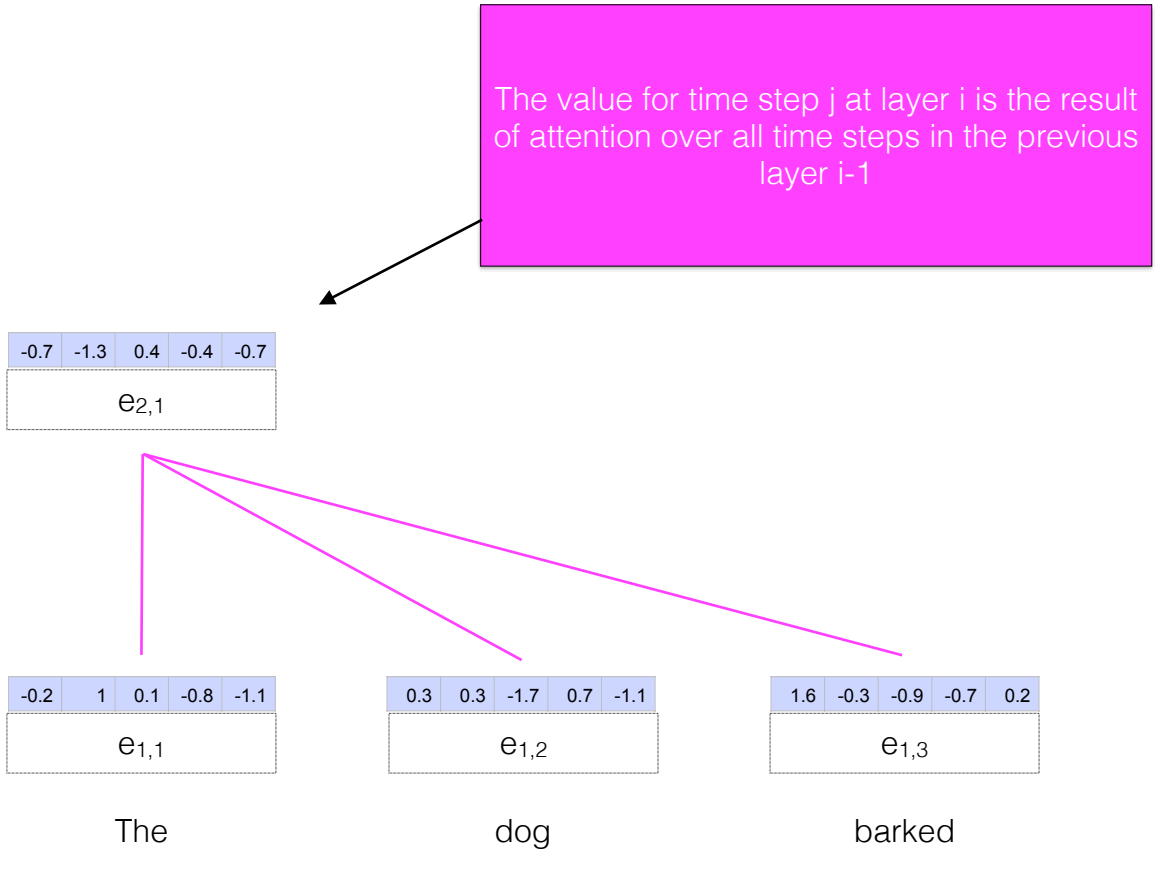


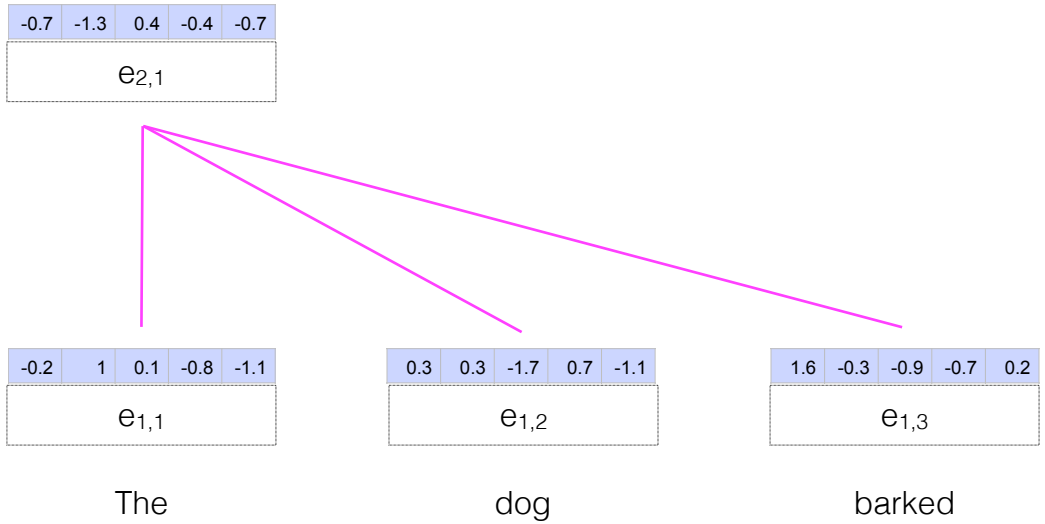
This whole process defines one attention block. The input is a sequence of (e.g. 100-dimensional) vectors; the output of each block is a sequence of (100-dimensional) vectors.

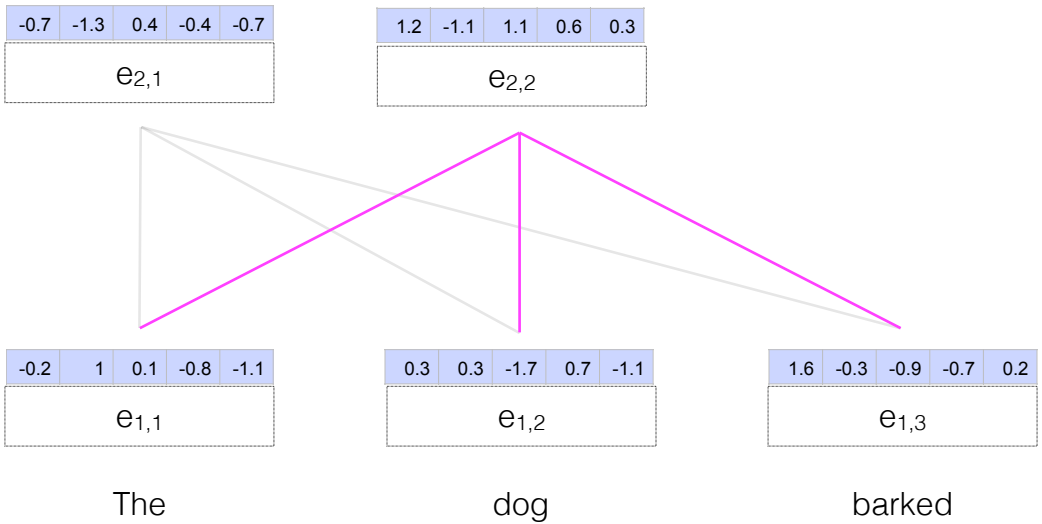
Transformers can stack many such blocks; where the output from block b is the input to block b+1.

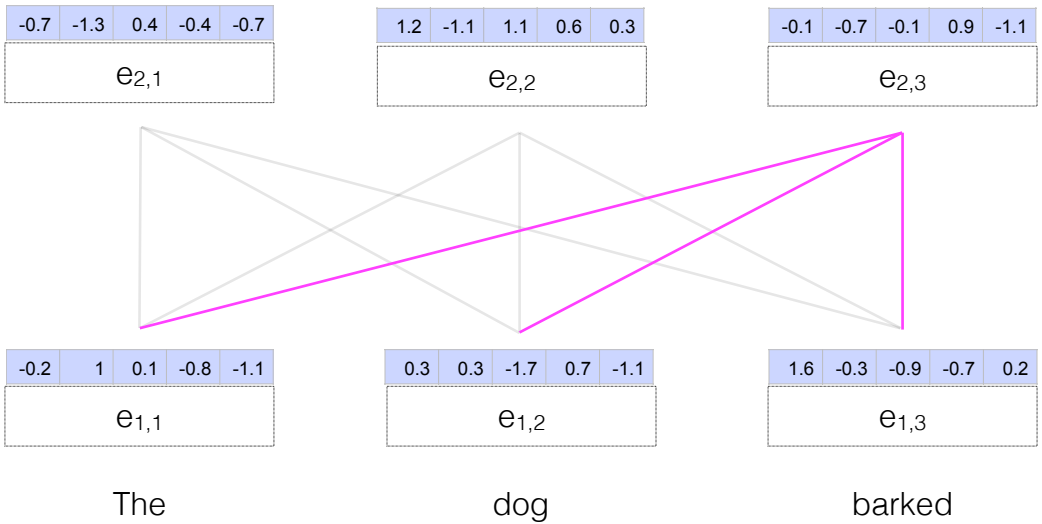


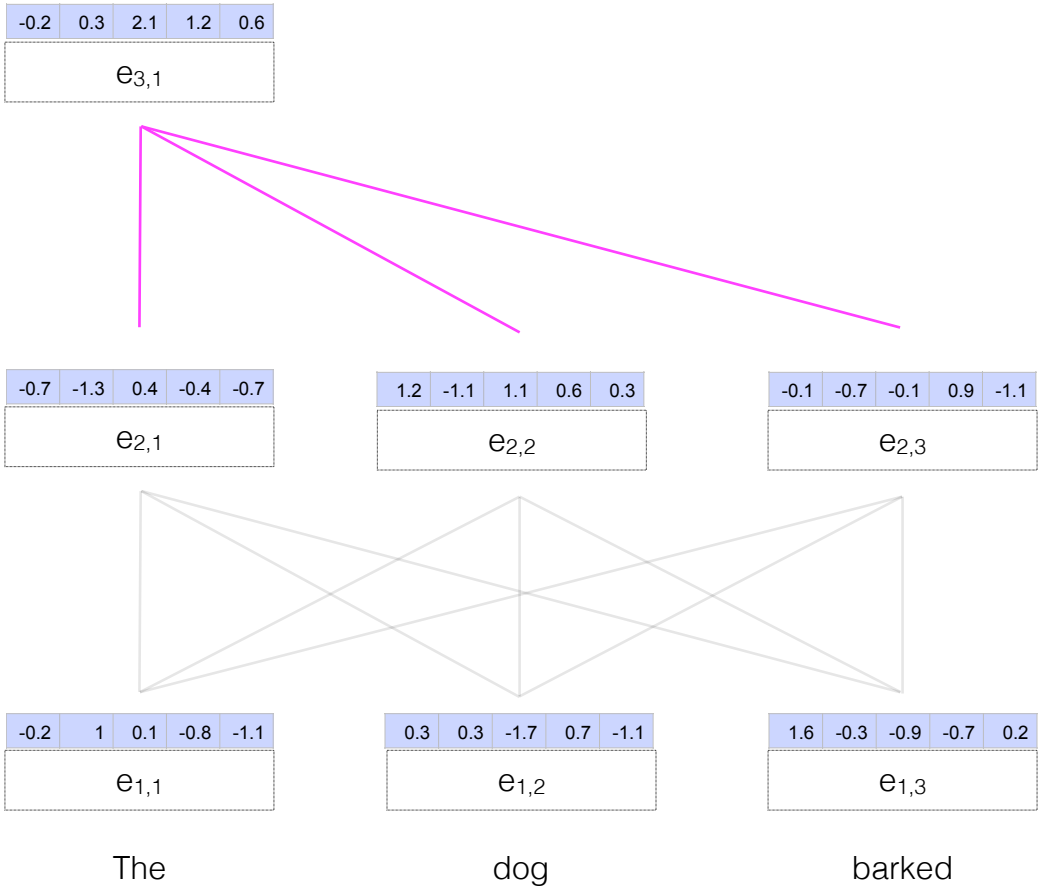

Each token in the input starts out represented by token and position embeddings
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked

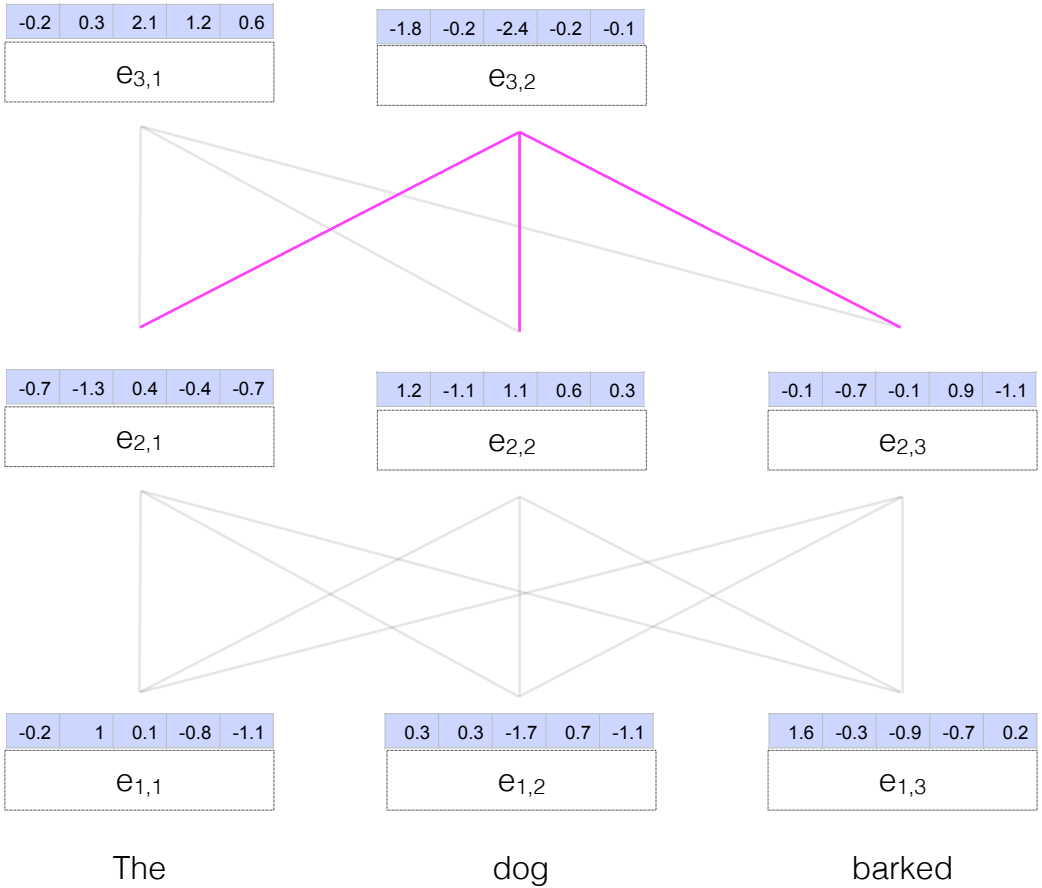

The value for time step j at layer i is the result of attention over all time steps in the previous layer i-1
-0.7 -1.3 0.4 -0.4 -0.7
e2,1
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked

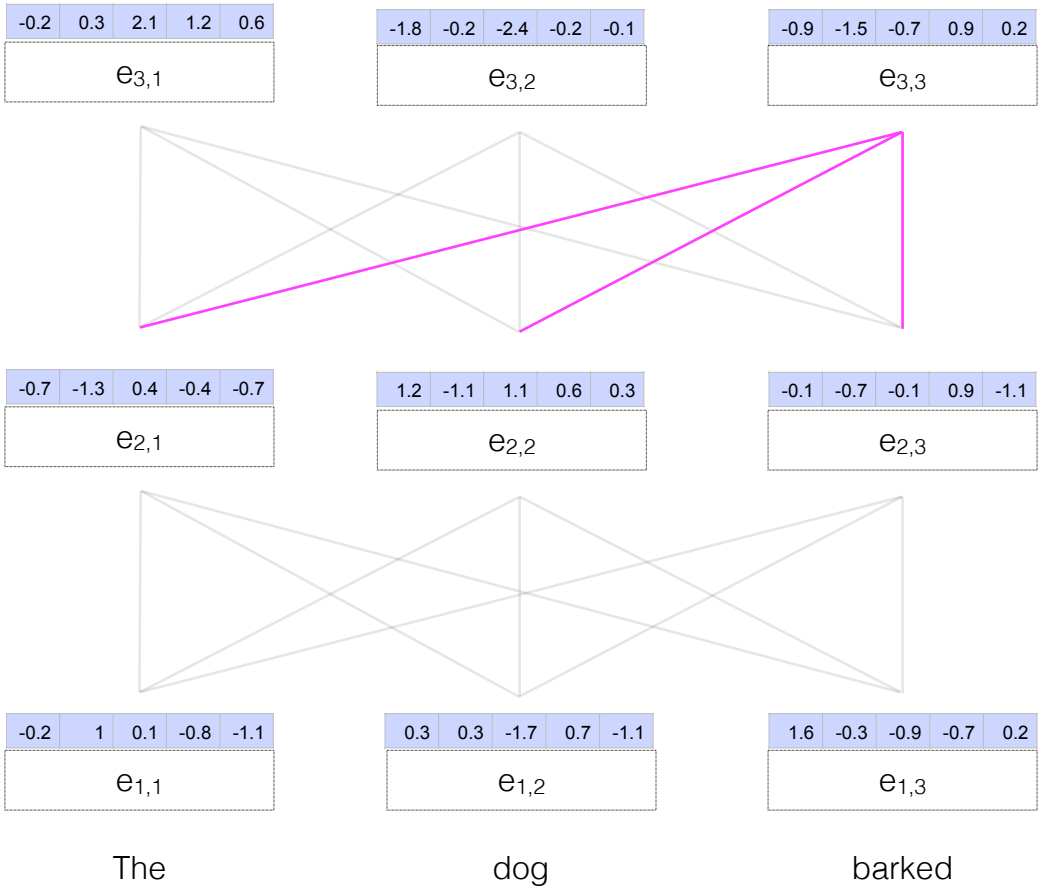

-0.7 -1.3 0.4 -0.4 -0.7
e2,1
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked


-0.7 -1.3 0.4 -0.4 -0.7
e2,1
1.2 -1.1 1.1 0.6 0.3
e2,2
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked

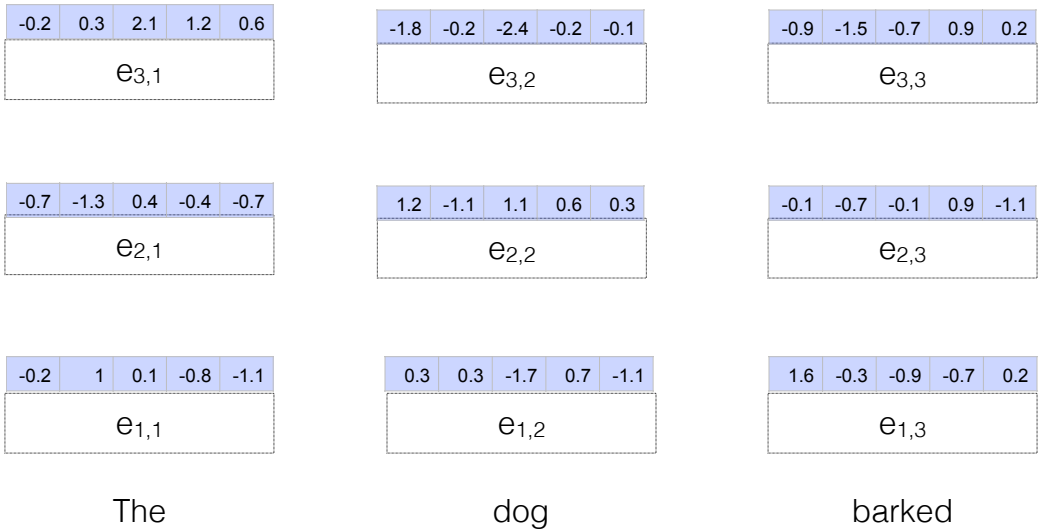

-0.7 -1.3 0.4 -0.4 -0.7
e2,1
1.2 -1.1 1.1 0.6 0.3
e2,2
-0.1 -0.7 -0.1 0.9 -1.1
e2,3
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked


-0.2 0.3 2.1 1.2 0.6
e3,1
-0.7 -1.3 0.4 -0.4 -0.7
e2,1
1.2 -1.1 1.1 0.6 0.3
e2,2
-0.1 -0.7 -0.1 0.9 -1.1
e2,3
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked


-0.2 0.3 2.1 1.2 0.6
e3,1
-1.8 -0.2 -2.4 -0.2 -0.1
e3,2
-0.7 -1.3 0.4 -0.4 -0.7
e2,1
1.2 -1.1 1.1 0.6 0.3
e2,2
-0.1 -0.7 -0.1 0.9 -1.1
e2,3
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked


-0.2 0.3 2.1 1.2 0.6
e3,1
-1.8 -0.2 -2.4 -0.2 -0.1
e3,2
-0.9 -1.5 -0.7 0.9 0.2
e3,3
-0.7 -1.3 0.4 -0.4 -0.7
e2,1
1.2 -1.1 1.1 0.6 0.3
e2,2
-0.1 -0.7 -0.1 0.9 -1.1
e2,3
-0.2 1 0.1 -0.8 -1.1
e1,1
0.3 0.3 -1.7 0.7 -1.1
e1,2
1.6 -0.3 -0.9 -0.7 0.2
e1,3
The
dog
barked

At the end of this process, we have one representation for each layer for each token



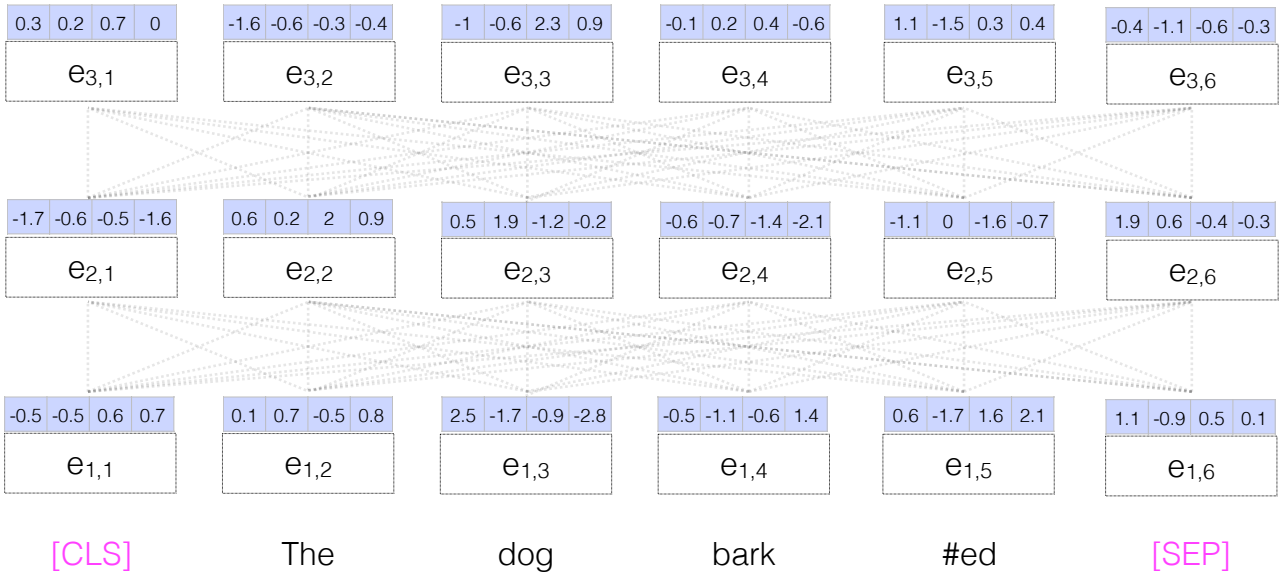
WordPiece

- BERT uses WordPiece tokenization, which segments some morphological structure of tokens
- Vocabulary size: 30,000

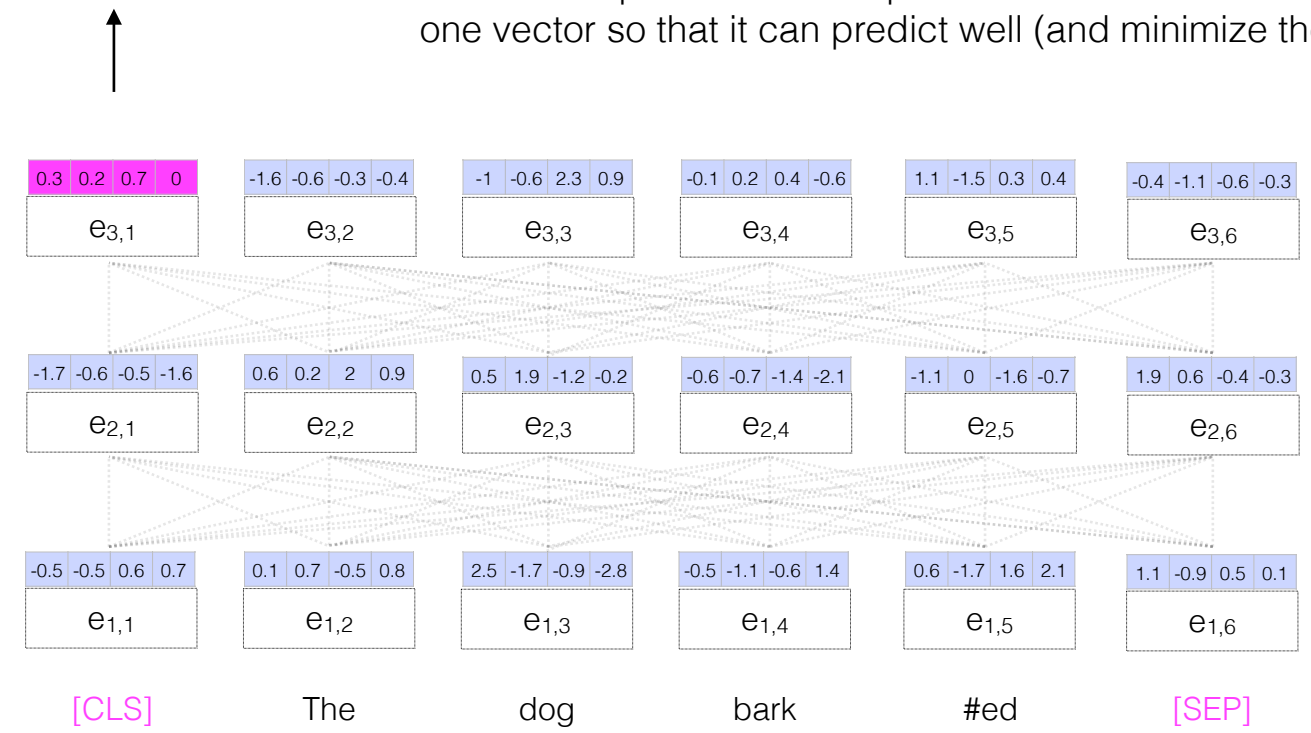
The	The
dog	dog
barked	bark #ed

- BERT also encodes each sentence by appending a special token to the beginning ([CLS]) and end ([SEP]) of each sequence.

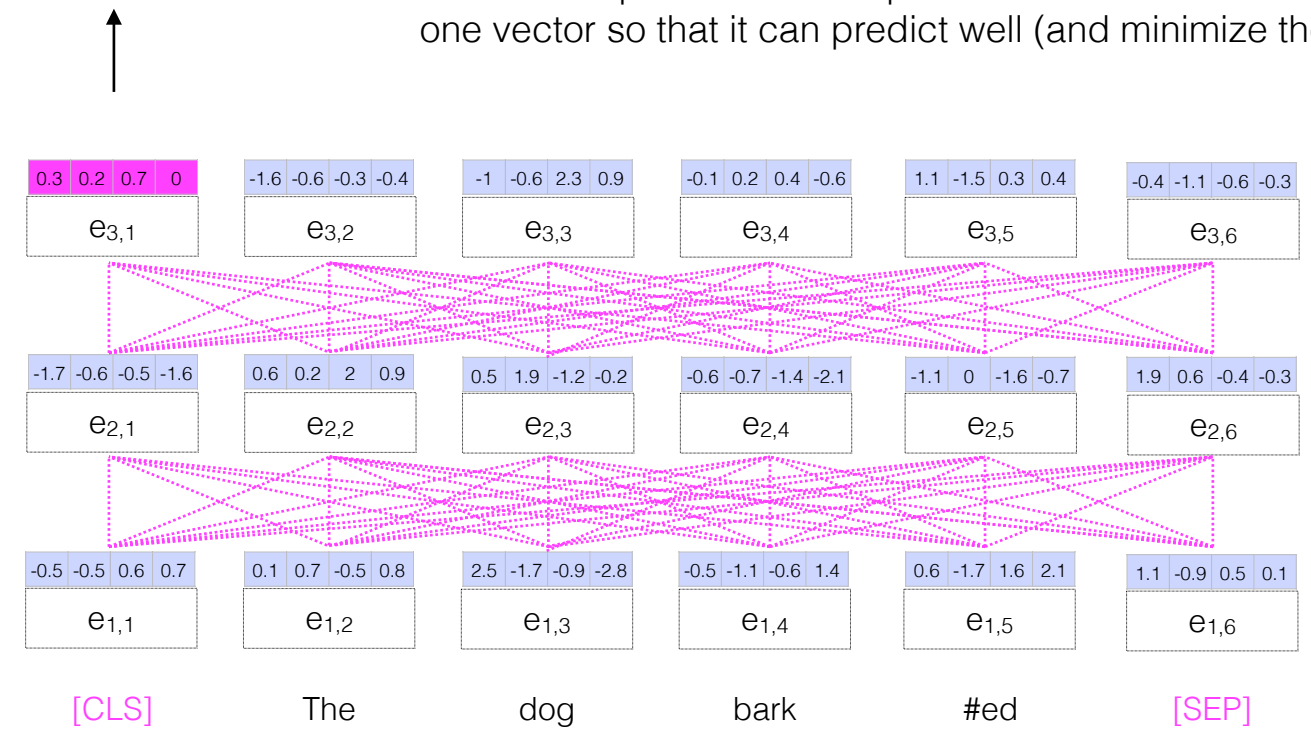
- This helps provides a single token that can be optimized to represent the entire sequence (e.g., for document classification)



- We can represent the entire document with this *one* [CLS] vector
- Why does this work? When we design our network so that a classification decision relies entirely on that one vector and allow all the parameters of the network to be updated, the parameters of the model are optimized to compress all the relevant information into that one vector so that it can predict well (and minimize the loss).



- We can represent the entire document with this *one* [CLS] vector
- Why does this work? When we design our network so that a classification decision relies entirely on that one vector and allow all the parameters of the network to be updated, the parameters of the model are optimized to compress all the relevant information into that one vector so that it can predict well (and minimize the loss).

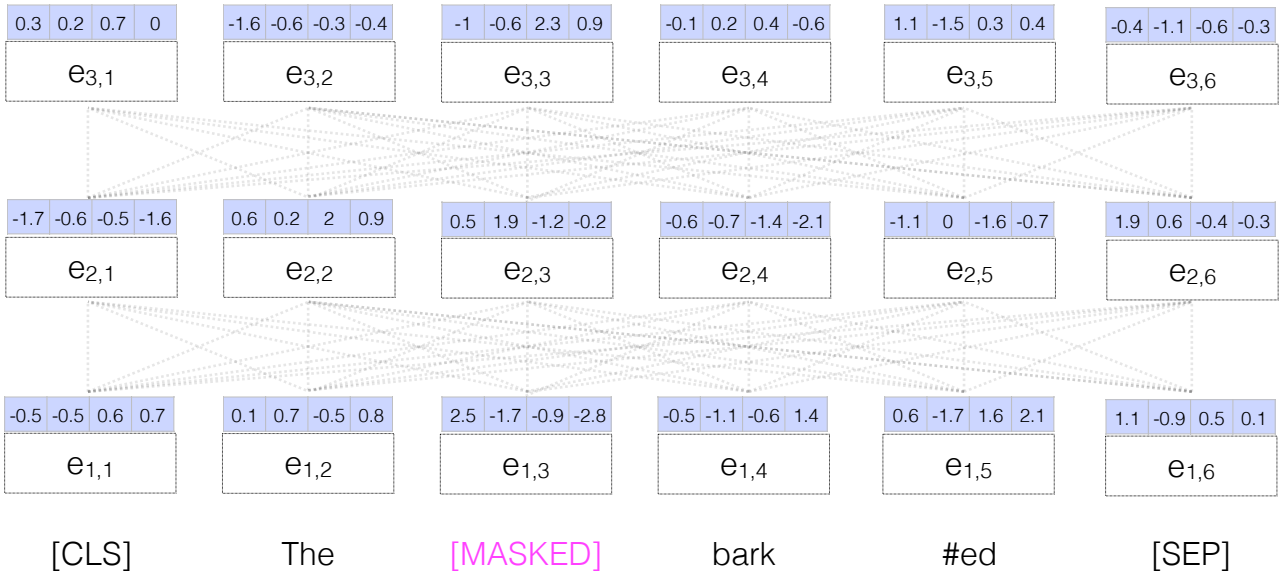


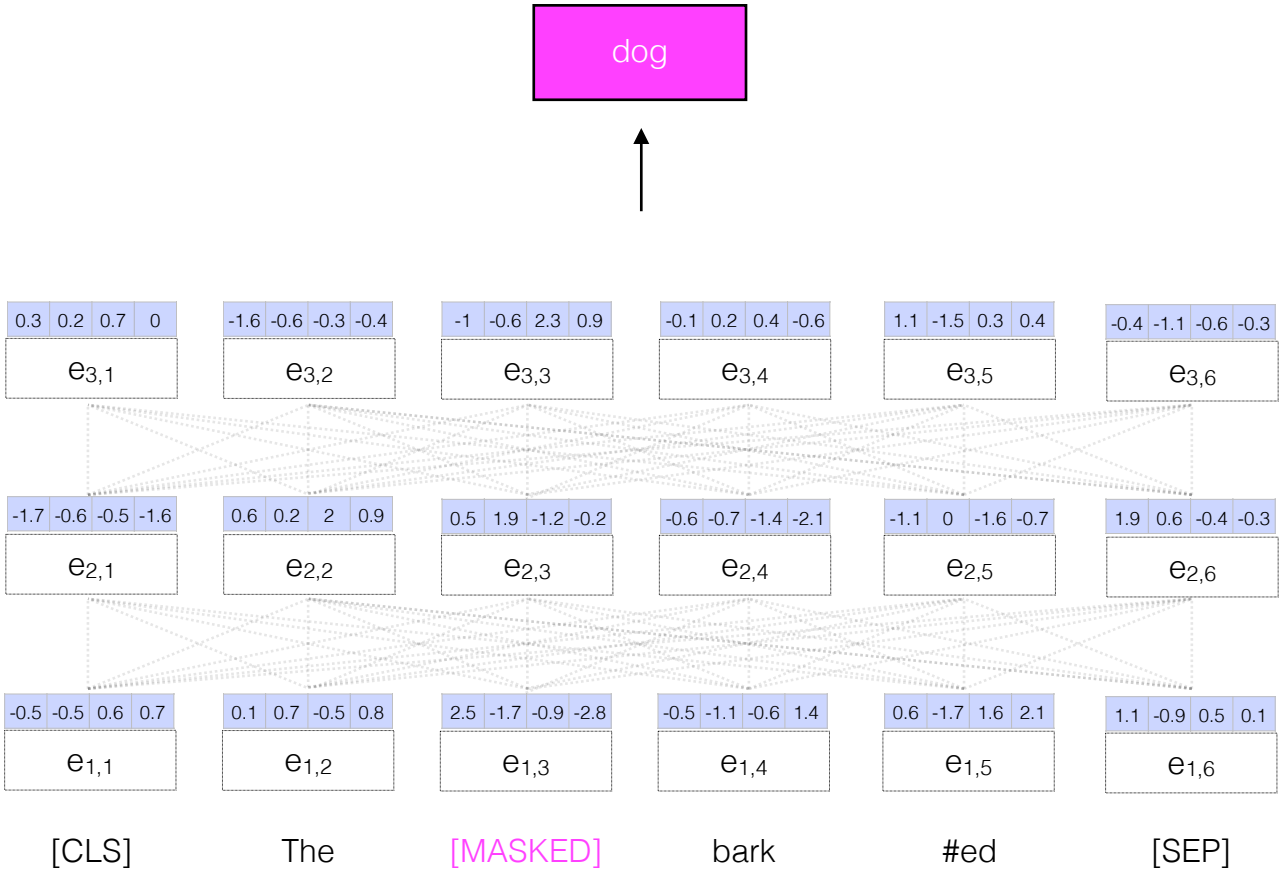
BERT

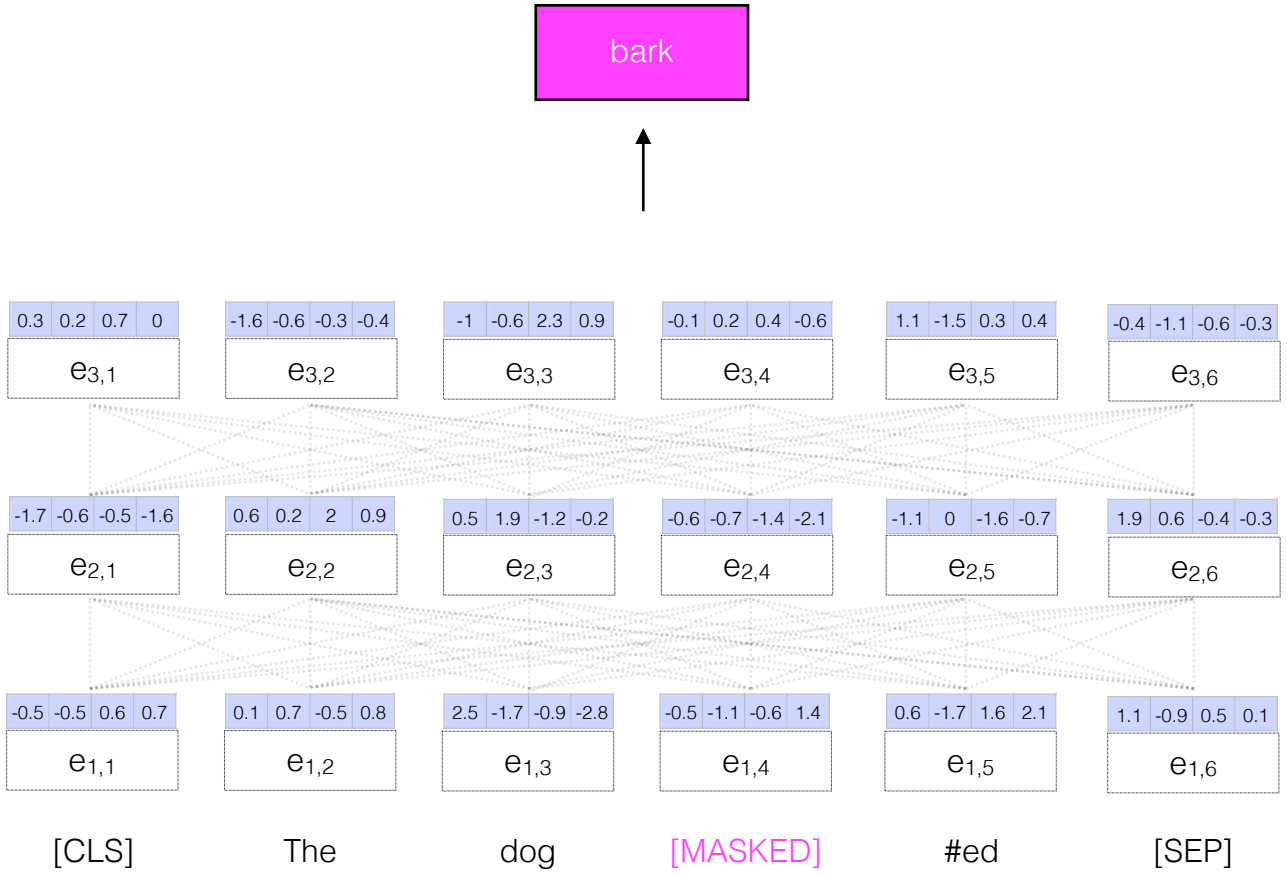
- Learn the parameters of this model with two objectives:
  - Masked language modeling
  - Next sentence prediction

Masked LM

- Mask one word from the input and try to predict that word as the output
- More powerful than an RNN LM (or even a BiRNN LM) since it can reason about context on both sides of the word being predicted.
- A BiRNN models context on both sides, but each RNN only has access to information from one direction.


0.3 0.2 0.7 0
-1.6 -0.6 -0.3 -0.4
-1 -0.6 2.3 0.9
-0.1 0.2 0.4 -0.6
1.1 -1.5 0.3 0.4
-0.4 -1.1 -0.6 -0.3
e3,1
e3,2
e3,3
e3,4
e3,5
e3,6
-1.7 -0.6 -0.5 -1.6
0.6 0.2 2 0.9
0.5 1.9 -1.2 -0.2
-0.6 -0.7 -1.4 -2.1
-1.1 0 -1.6 -0.7
1.9 0.6 -0.4 -0.3
e2,1
e2,2
e2,3
e2,4
e2,5
e2,6
-0.5 -0.5 0.6 0.7
0.1 0.7 -0.5 0.8
2.5 -1.7 -0.9 -2.8
-0.5 -1.1 -0.6 1.4
0.6 -1.7 1.6 2.1
1.1 -0.9 0.5 0.1
e1,1
e1,2
e1,3
e1,4
e1,5
e1,6
[CLS]
The
[MASKED]
bark
#ed
[SEP]


dog
0.3 0.2 0.7 0
e3,1
-1.6 -0.6 -0.3 -0.4
e3,2
-1 -0.6 2.3 0.9
e3,3
-0.1 0.2 0.4 -0.6
e3,4
1.1 -1.5 0.3 0.4
e3,5
-0.4 -1.1 -0.6 -0.3
e3,6
-1.7 -0.6 -0.5 -1.6
e2,1
0.6 0.2 2 0.9
e2,2
0.5 1.9 -1.2 -0.2
e2,3
-0.6 -0.7 -1.4 -2.1
e2,4
-1.1 0 -1.6 -0.7
e2,5
1.9 0.6 -0.4 -0.3
e2,6
-0.5 -0.5 0.6 0.7
e1,1
0.1 0.7 -0.5 0.8
e1,2
2.5 -1.7 -0.9 -2.8
e1,3
-0.5 -1.1 -0.6 1.4
e1,4
0.6 -1.7 1.6 2.1
e1,5
1.1 -0.9 0.5 0.1
e1,6
[CLS]
The
[MASKED]
bark
#ed
[SEP]


bark
0.3 0.2 0.7 0
e3,1
-1.6 -0.6 -0.3 -0.4
e3,2
-1 -0.6 2.3 0.9
e3,3
-0.1 0.2 0.4 -0.6
e3,4
1.1 -1.5 0.3 0.4
e3,5
-0.4 -1.1 -0.6 -0.3
e3,6
-1.7 -0.6 -0.5 -1.6
e2,1
0.6 0.2 2 0.9
e2,2
0.5 1.9 -1.2 -0.2
e2,3
-0.6 -0.7 -1.4 -2.1
e2,4
-1.1 0 -1.6 -0.7
e2,5
1.9 0.6 -0.4 -0.3
e2,6
-0.5 -0.5 0.6 0.7
e1,1
0.1 0.7 -0.5 0.8
e1,2
2.5 -1.7 -0.9 -2.8
e1,3
-0.5 -1.1 -0.6 1.4
e1,4
0.6 -1.7 1.6 2.1
e1,5
1.1 -0.9 0.5 0.1
e1,6
[CLS]
The
dog
[MASKED]
#ed
[SEP]

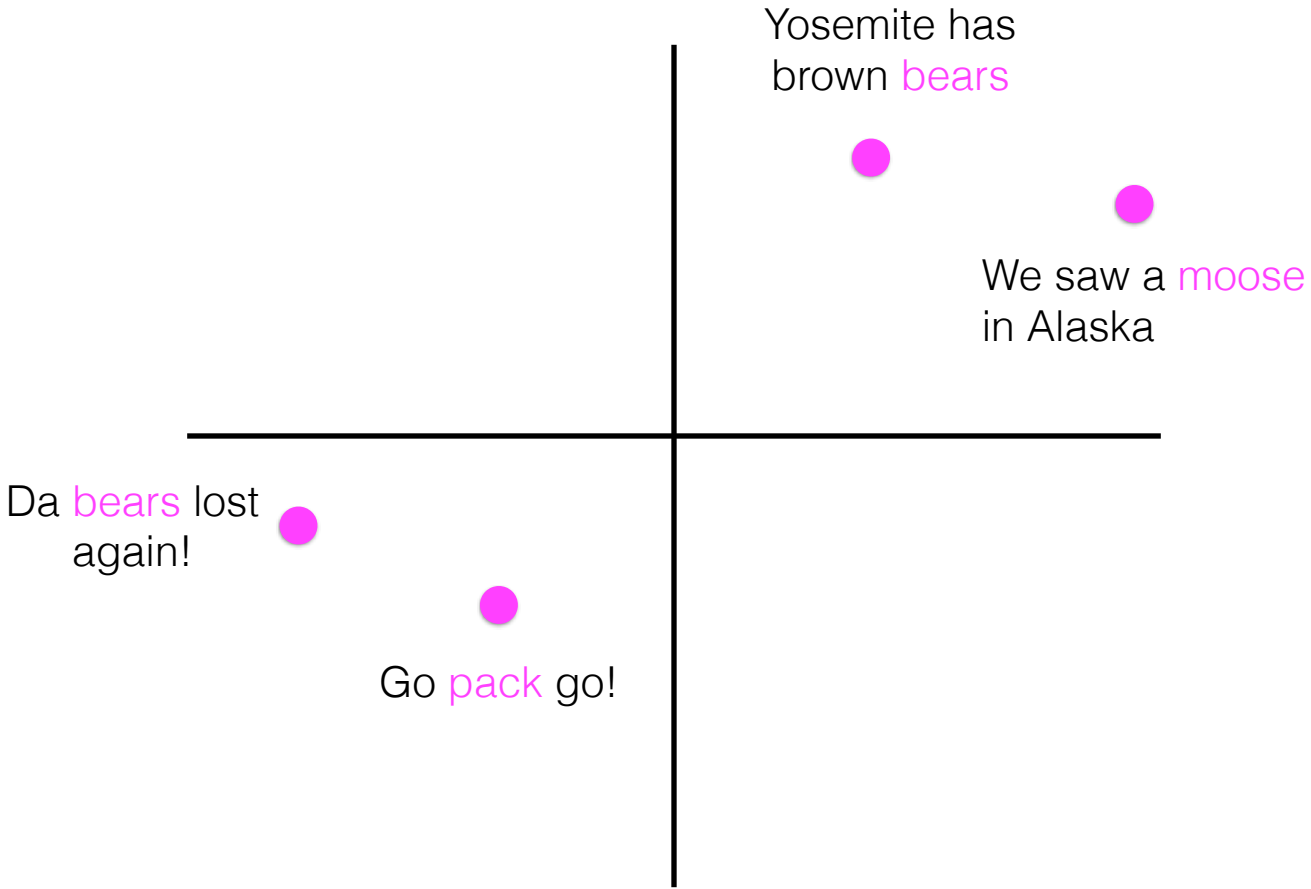
Next sentence prediction

- For a pair of sentences, predict from [CLS] representation whether they appeared sequentially in the training data:

  + [CLS] The dog bark #ed [SEP] He was hungry
  − [CLS] The dog bark #ed [SEP] Paris is in France

BERT

- Deep layers (12 for BERT base, 24 for BERT large)
- Large representation sizes (768 per layer)
- Pretrained on English Wikipedia (2.5B words) and BooksCorpus (800M words)


Yosemite has
brown bears
We saw a moose
in Alaska
Da bears lost
again!
Go pack go!

BERT

	H=128	H=256	H=512	H=768
L=2	**2/128 (BERT-Tiny)**	2/256	2/512	2/768
L=4	4/128	**4/256 (BERT-Mini)**	**4/512 (BERT-Small)**	4/768
L=6	6/128	6/256	6/512	6/768
L=8	8/128	8/256	**8/512 (BERT-Medium)**	8/768
L=10	10/128	10/256	10/512	10/768
L=12	12/128	12/256	12/512	**12/768 (BERT-Base)**

https://github.com/google-research/bert

v4.11.3 ▼

transformers

Star 52,449

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Installation

Philosophy

Glossary

USING 🤗 TRANSFORMERS

Summary of the tasks

Summary of the models

Preprocessing data

SIGN IN MODELS FORUM

Docs » Pretrained models View page source

Pretrained models

Here is a partial list of some of the available pretrained models together with a short presentation of each model.

For the full list, refer to https://huggingface.co/models.

Architecture	Model id	Details of the model
	bert-base-uncased	12-layer, 768-hidden, 12-heads, 110M parameters. Trained on lower-cased English text.
	bert-large-uncased	24-layer, 1024-hidden, 16-heads, 336M parameters. Trained on lower-cased English text.

https://huggingface.co/transformers/pretrained_models.html

Lost in (language-specific) BERT models? We are here to help!

We currently have indexed **31** BERT-based models, **19** Languages and **28** Tasks.
We have a total of **178** entries in this table; we also show **Multilingual Bert (mBERT)** results if available! (see our paper)

Curious which BERT model is the best for named entity recognition in Italian🇮🇹? Just type *"Italian NER"* in the search bar!

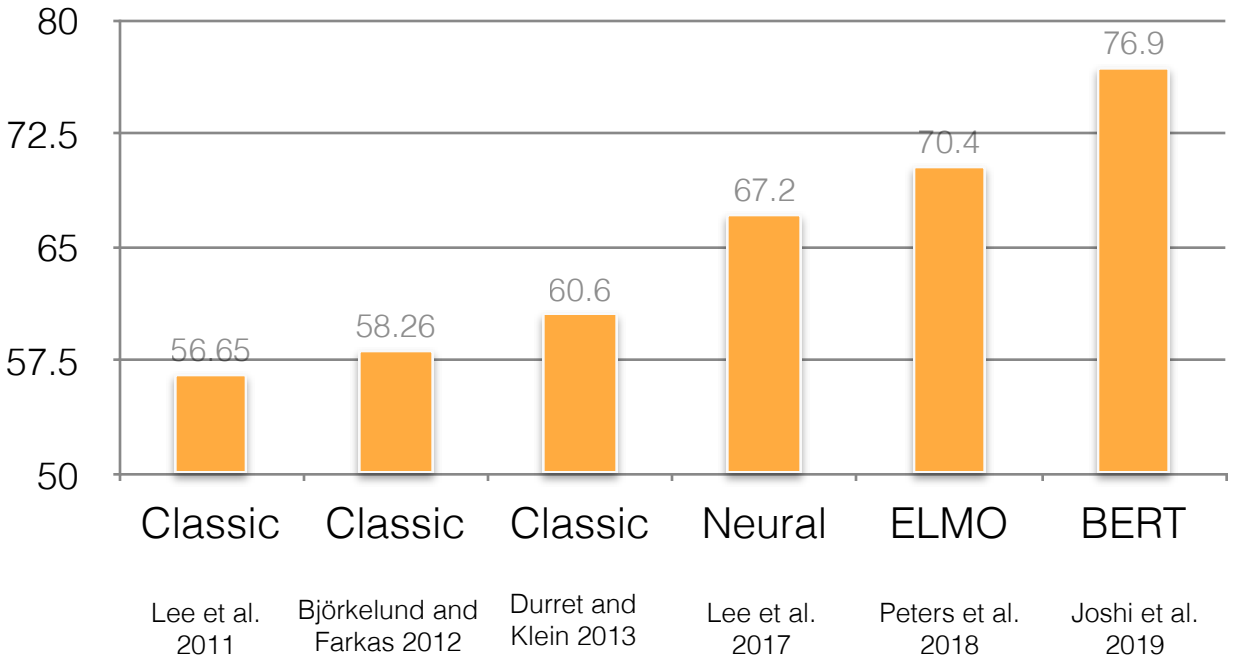
Show 10 entries

Search:

Language	Model	NLP Task	Dataset	Dataset-Domain	Measure	Performance	mBERT	Difference with mBERT	Source
Arabic	Arabert v1	SA	AJGT	twitter	Accuracy	93.8	83.6	10.2	
Arabic	Arabert v1	SA	HARD	hotel reviews	Accuracy	96.1	95.7	0.4	
Arabic	Arabert v1	SA	ASTD	twitter	Accuracy	92.6	80.1	12.5	
Arabic	Arabert v1	SA	ArSenTD-Lev	twitter	Accuracy	59.4	51.0	8.4	

https://bertlang.unibocconi.it

Progress — Coreference resolution



Bertology

- Hewitt et al. 2019
- Tenney et al. 2019
- McCoy et al. 2019
- Liu et al. 2019
- Clark et al. 2019
- Goldberg 2019
- Michel et al. 2019

Code

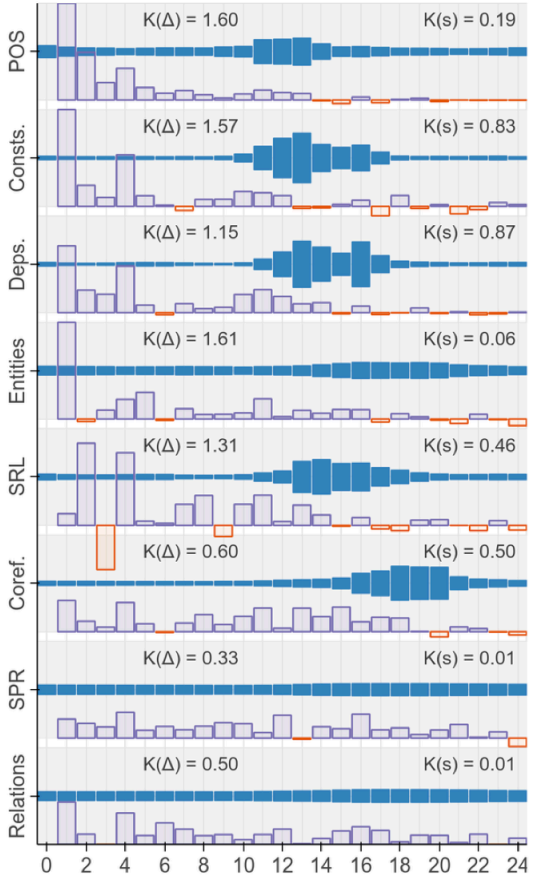
Pre-trained models for BERT, Transformer-XL, ALBERT, RoBERTa, DistilBERT, GPT-2, etc. for English, French, “Multilingual”

https://huggingface.co

Probing

- Even though BERT is mainly trained on a language modeling objective, it learns a lot about the structure of language — even without direct training data for specific linguistic tasks.

- Probing experiments uncover what—-and where (in what layers)—-pretrained BERT encodes this information.



Tenney et al. (2019), "BERT Rediscovers the Classical NLP Pipeline"