# 50.040 Natural Language Processing

Lu, Wei



#### Tasks in NLP

**POS Tagging** Chunking **Document Classification** Information Extraction Syntactic Parsing Semantic Parsing Natural Language Generation **Machine Translation** Sentiment Analysis Coreference Resolution **Question Answering** 

Word Clusters

GloVe, word2vec

**Topic Modeling** 

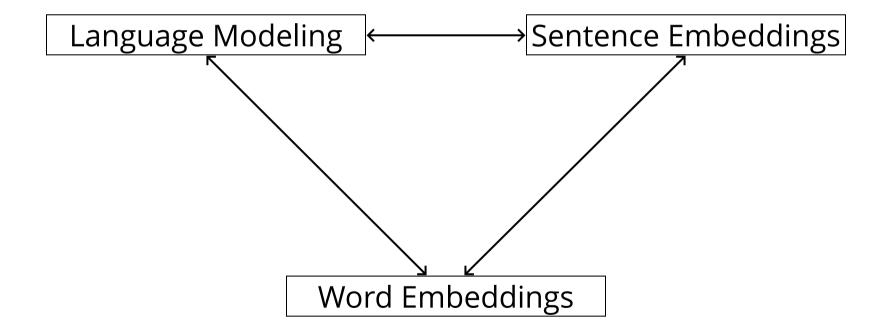
Language Modeling

ELMo, BERT

**Supervised** 

**Unsupervised** 

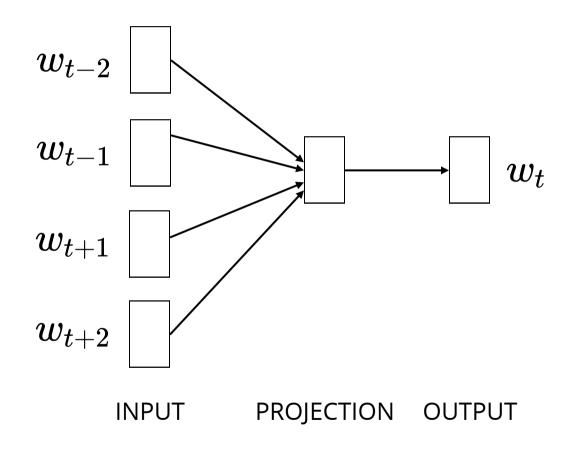
#### Three Tasks



These three tasks are closely related!

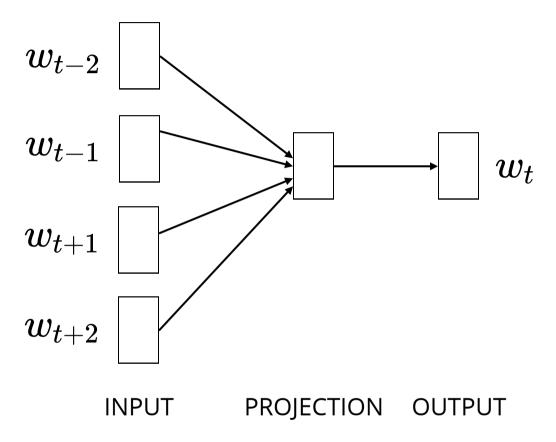
#### Word Embedding

Mikolov et al. (2013)



**CBOW** 

#### Word Embedding



One observation:

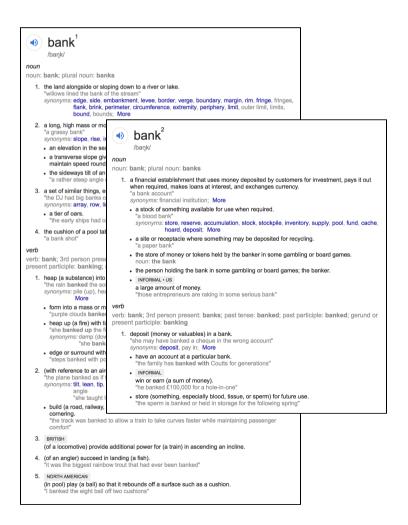
It learns for each word token a vector.

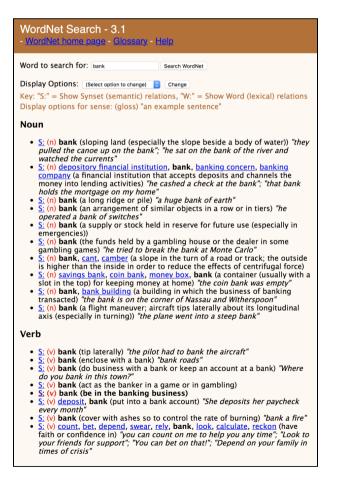


A word may have multiple senses.

#### **Word Senses**

#### A word may have multiple senses.





#### **Question**

## How do we automatically model multiple senses of a word?

Need a way to dynamically capture the specific context.

$$p(x_1,x_2,\ldots,x_m) = \prod_{i=1,\ldots,m} p(x_i|x_1,\ldots,x_{i-1})$$

We discussed:

1) n-gram language model

2) a neural language model (Bengio et al, 2003)

$$p(x_1,x_2,\ldots,x_m) = \prod_{i=1,\ldots,m} p(x_i|x_1,\ldots,x_{i-1})$$
 Context

We discussed:

1) n-gram language model

2) a neural language model (Bengio et al, 2003)

Both models rely on the Markov (independence) assumption.

$$p(x_1,x_2,\ldots,x_m) = \prod_{i=1,\ldots,m} p(x_i|x_1,\ldots,x_{i-1})$$
 Context

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Can we remove this assumption now (since we use word embeddings)?

$$p(x_1,x_2,\ldots,x_m) = \prod_{i=1,\ldots,m} p(x_i|x_1,\ldots,x_{i-1})$$
 Context

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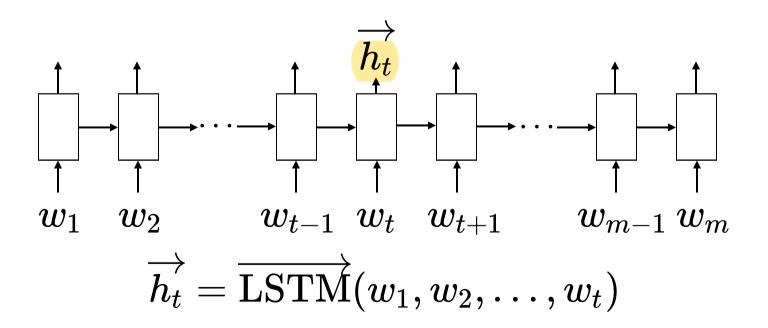
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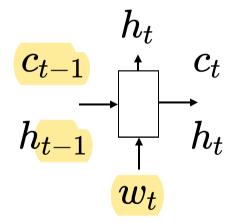
Need a way to *dynamically* capture the specific *context*.

#### Contextual Embedding

#### (Long Short-term Memory)

Hochreiter & Schmidhuber (1997)





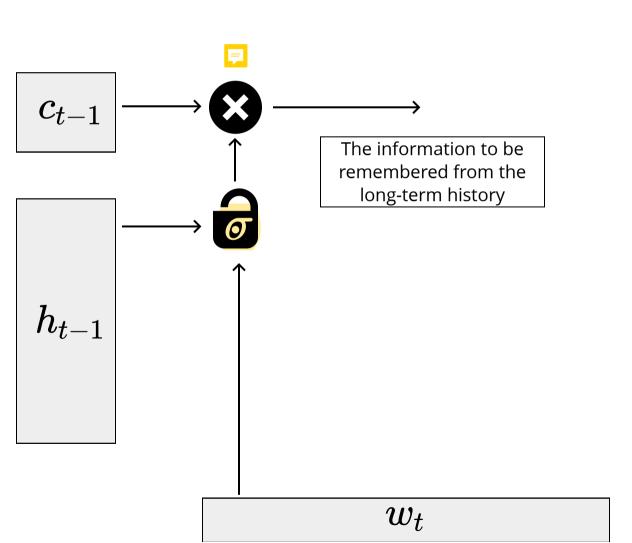
 $c_{t-1}$ 

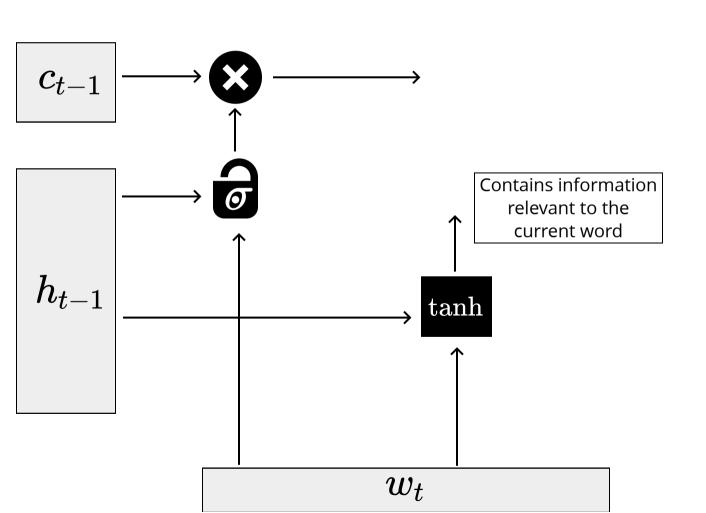
The long-term memory

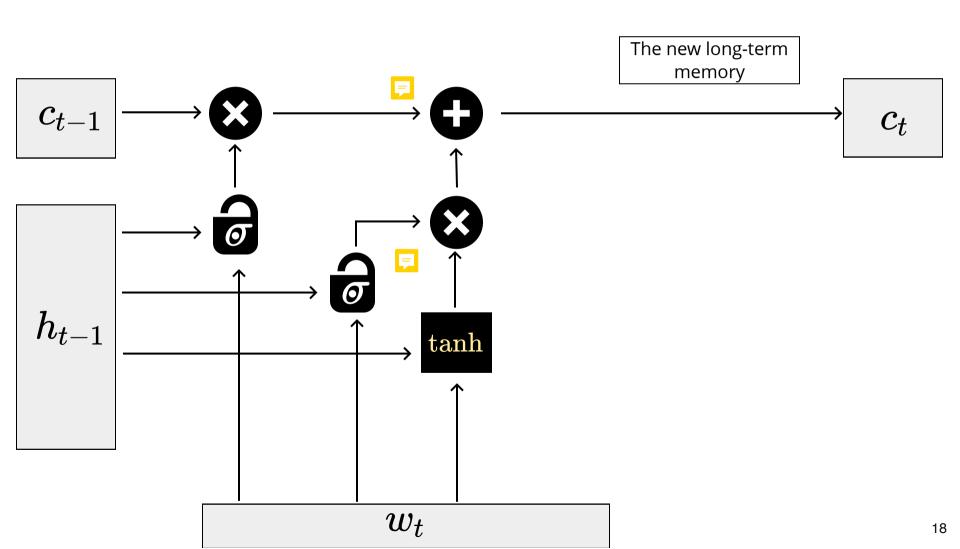
 $h_{t-1}$ 

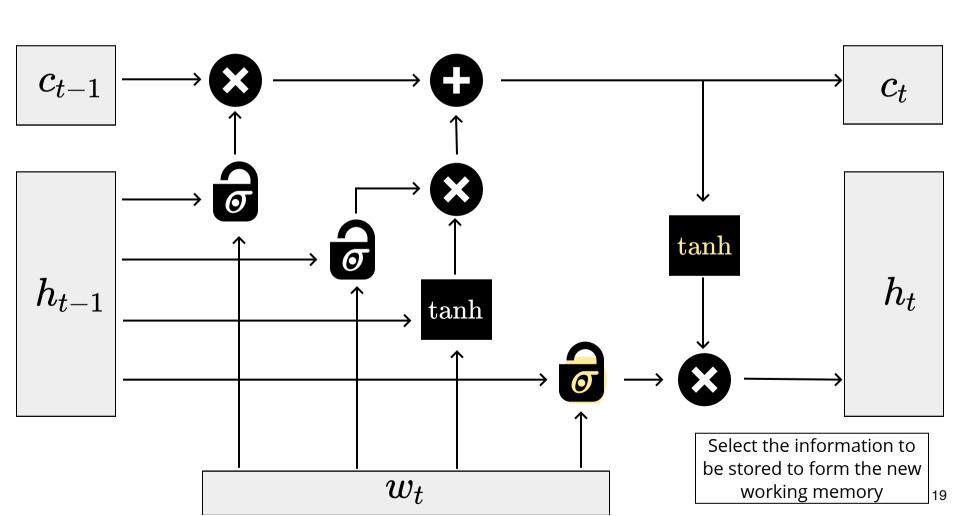
The working memory

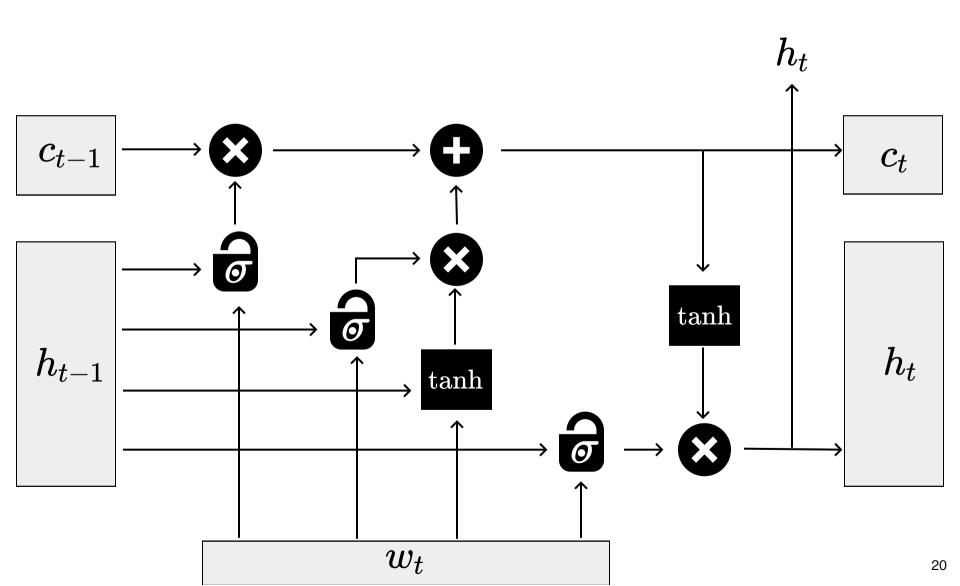
The current word

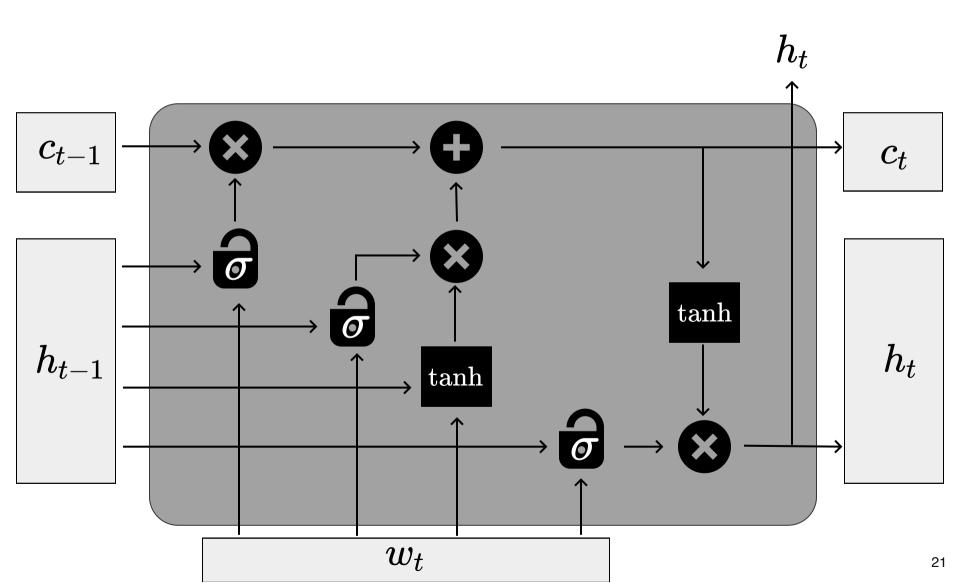




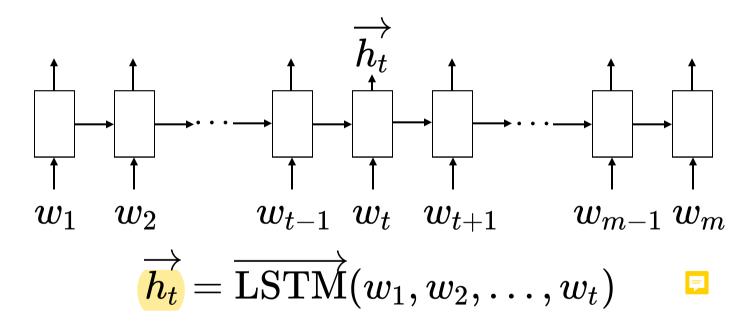








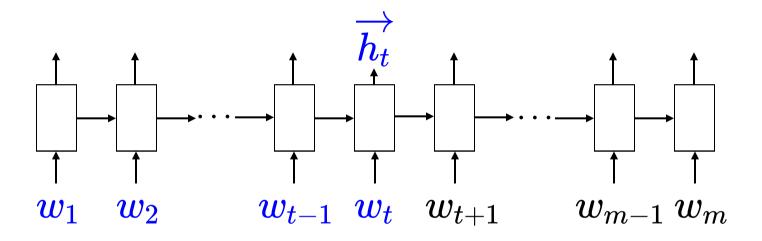
Sundermeyer et al. (2012)



Individual probability at each position:

- 1. project  $\overrightarrow{h_t}$  to a |V| dimensional space
  - 2. apply softmax on top of the vector
- 3. get the probability of generating the desired word  $w_{t+1}$

Sundermeyer et al. (2012)

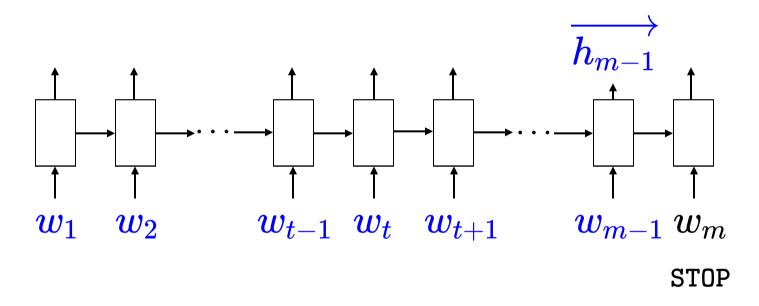


$$\overrightarrow{h_t} = \overrightarrow{ ext{LSTM}}(w_1, w_2, \dots, w_t)$$

**Context** Embedding!

A function over a sequence of word embeddings.

Sundermeyer et al. (2012)

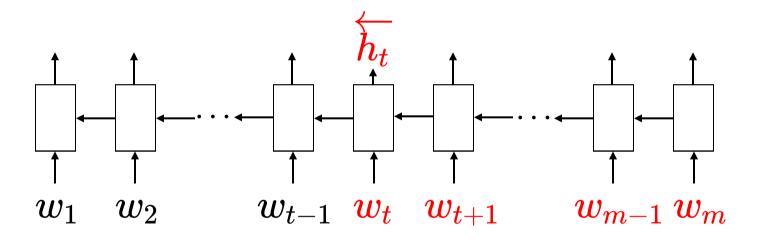


$$\overrightarrow{h_{m-1}} = \overrightarrow{ ext{LSTM}}(w_1, w_2, \dots, w_{m-1})$$

**Sentence** Embedding!

It's essentially a special context embedding.

Sundermeyer et al. (2012)



$$\overleftarrow{h_t} = \overleftarrow{ ext{LSTM}}(w_m, w_{m-1}, \dots, w_t)$$

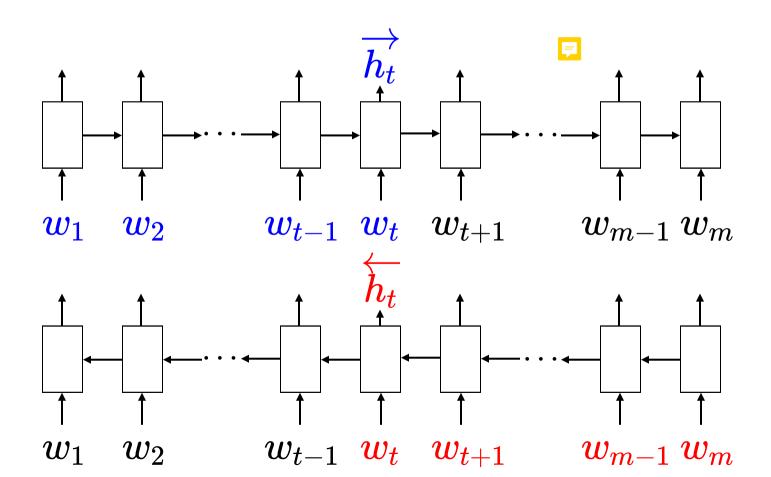
**Contextual Embedding!** 

A function over the sequence of word embeddings.

#### **Bidirectional LSTM**

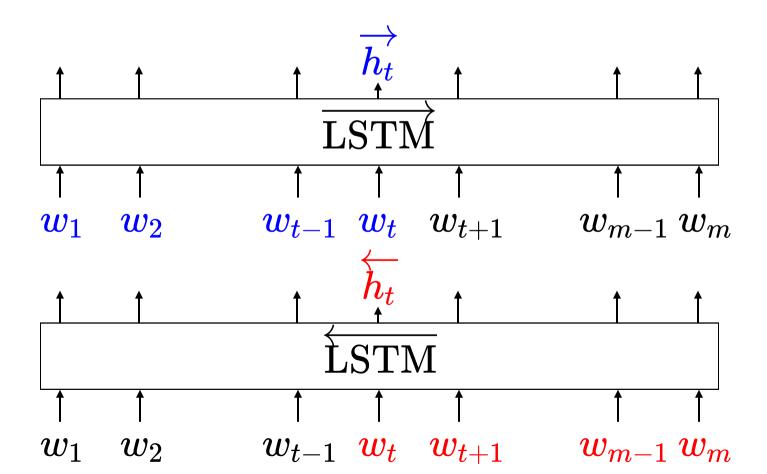
Context Embedding

$$[\overrightarrow{h_t};\overleftarrow{h_t}]$$



#### **Bidirectional LSTM**

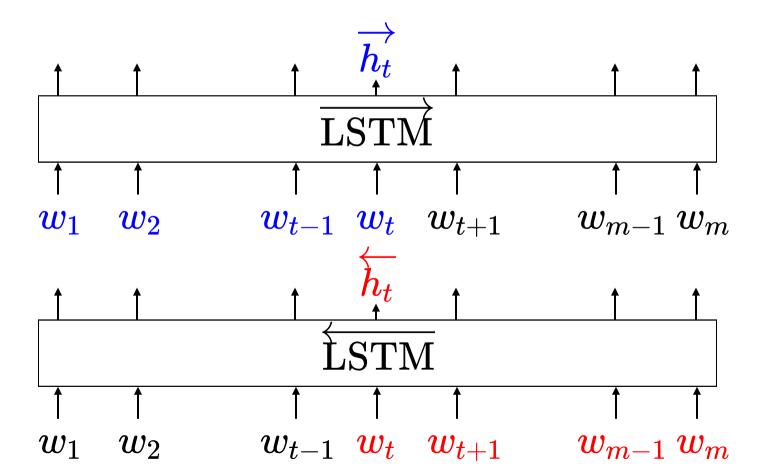
Context Embedding  $[\overrightarrow{h_t}; \overleftarrow{h_t}]$ 



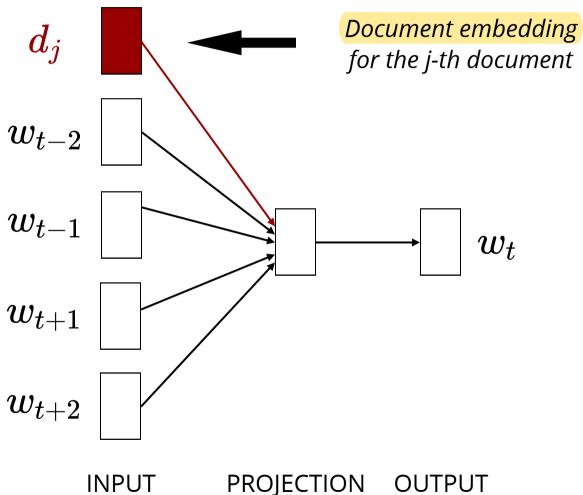
#### **Bidirectional LSTM**

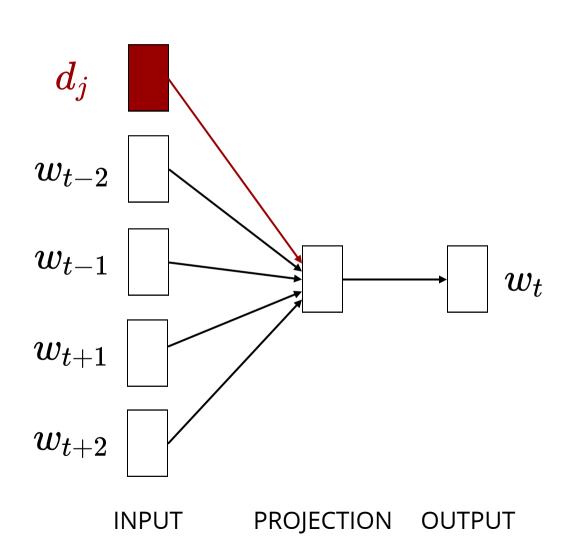
Context Embedding

$$[\overrightarrow{h_t}; \overleftarrow{h_t}] = \mathbf{h}_t$$



#### Doc2Vec Le & Mikolov (2014)

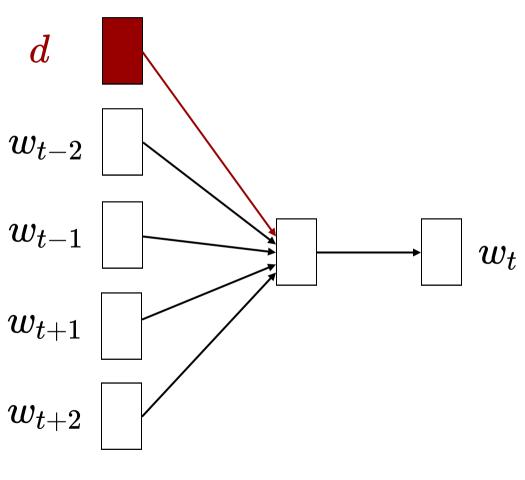




#### **Training**

Almost the same as CBOW, except that there is an additional document vector from the input layer

Concatenation was preferred (over sum/averaging) when constructing the projection layer

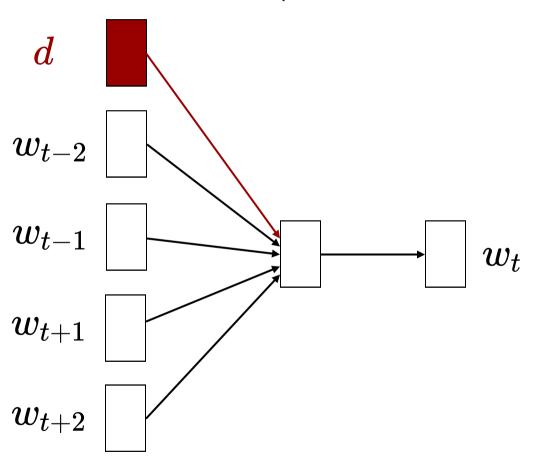


#### Inference

parameters
(including the learned word embeddings), fine tune the document embedding



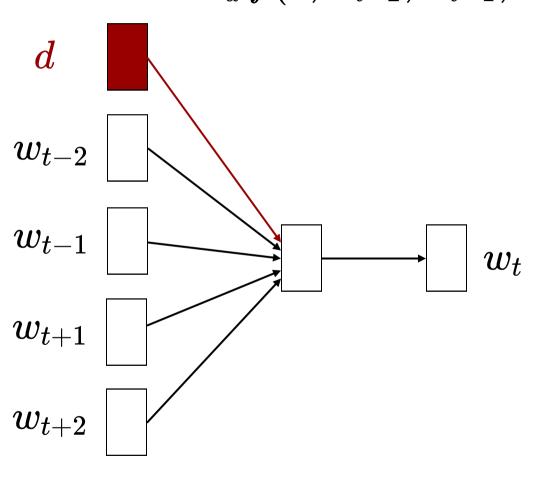
$$\min_d f(d, w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}, w_t)$$



Note that this is a simplified optimization problem!!

This is a process for finding an analytical solution to a minimization problem that involves words in the document!

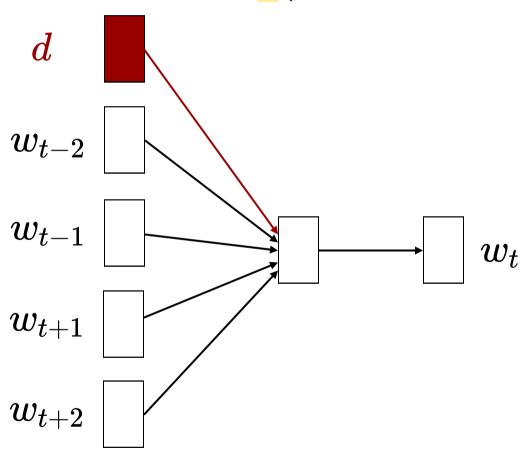
$$\min_d f(d, w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}, w_t)$$



Note that this is a simplified optimization problem!!

The sentence embedding is again a context embedding - a function of the word embeddings.

$$d = g(w_{t-2}, w_{t-1}, w_{t+1}, w_{t+2}, w_t)$$

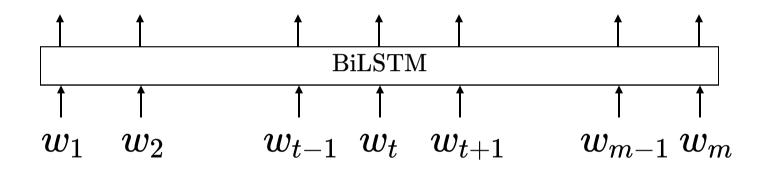


The sentence embedding is again a context embedding - a function of the word embeddings.

#### Deep Contextual Embedding

#### **ELMo**

### (Embeddings from Language Models) Peters et al. (2018)

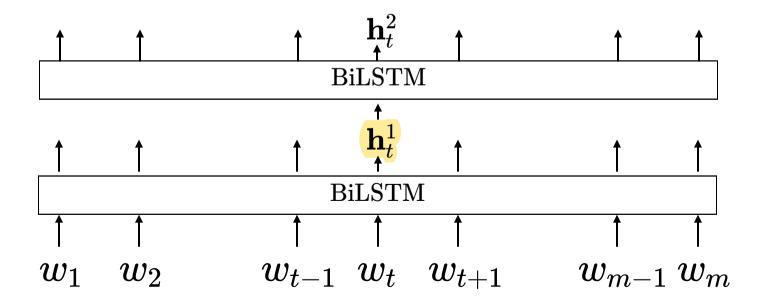


$$egin{aligned} \sum_{t=1,\ldots,m} (\log p(w_t|w_1,\ldots,w_{t-1};\Theta_x,\overrightarrow{\Theta}_{LSTM},\Theta_s) \ &+ \log p(w_t|w_{t+1},\ldots,w_m;\Theta_x,\overleftarrow{\Theta}_{LSTM},\Theta_s)) \end{aligned}$$

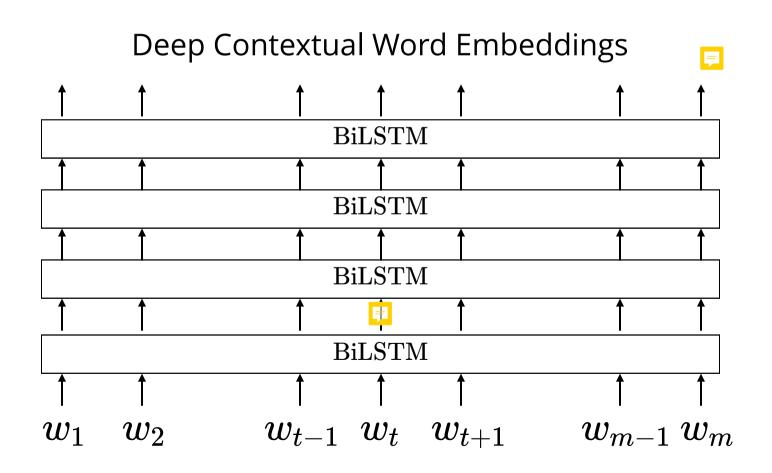
Tie the parameters for both the token representation  $(\Theta_x)$ , and softmax layer  $(\Theta_s)$ .

Separate parameters for the LSTMs in each direction.

## **ELMo**(Embeddings from Language Models)

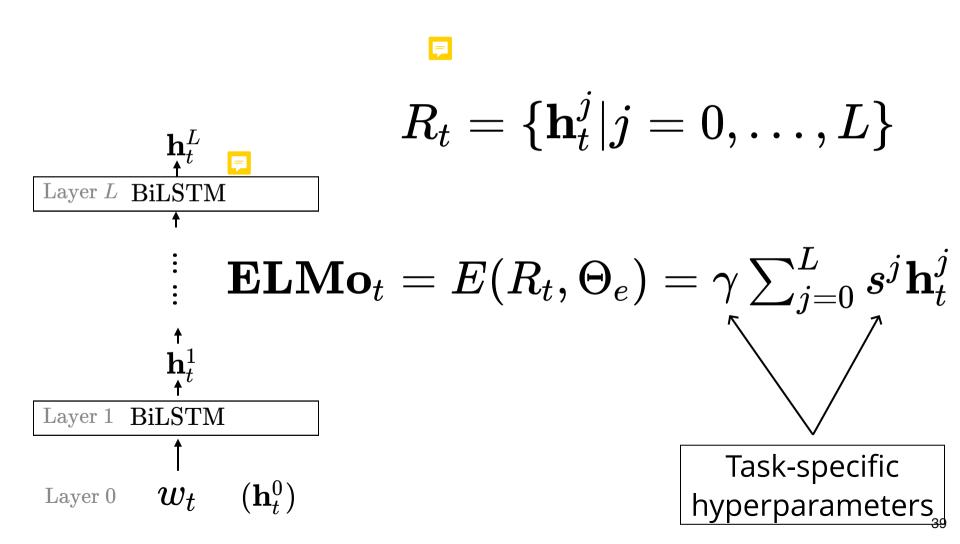


# **ELMO**(Embeddings from Language Models)

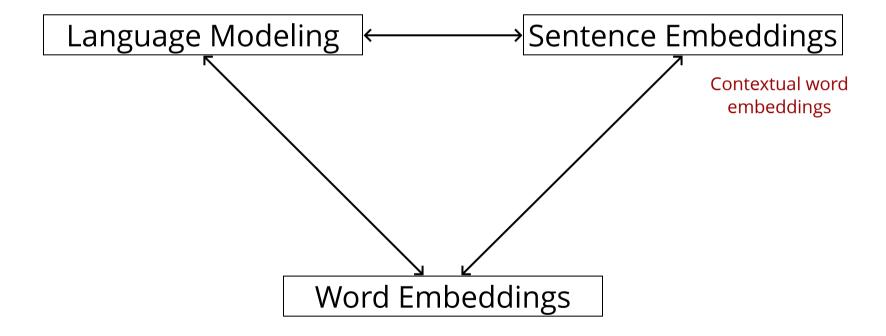


#### **ELMo**

#### (Embeddings from Language Models)



#### Three Tasks



These three tasks are closely related!

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Word Clusters
GloVe, word2vec
Topic Modeling
Language Modeling
ELMo, BERT

**Supervised** 

**Unsupervised** 

# Question What about the unsupervised HMM that we learned in the ML class?

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**Topic Modeling** 

Language Modeling

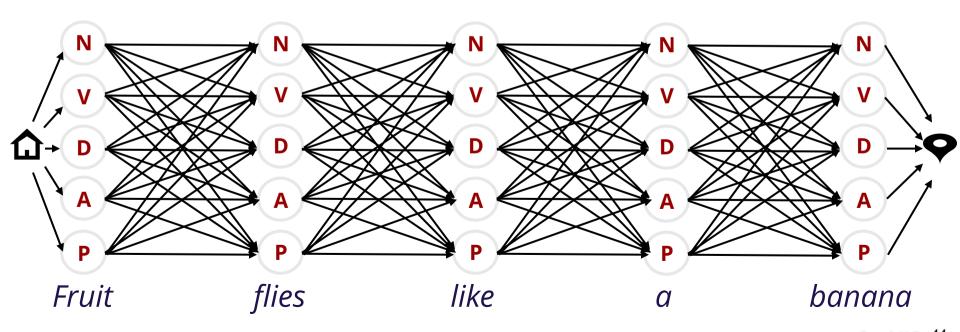
ELMo, BERT

**Supervised** 

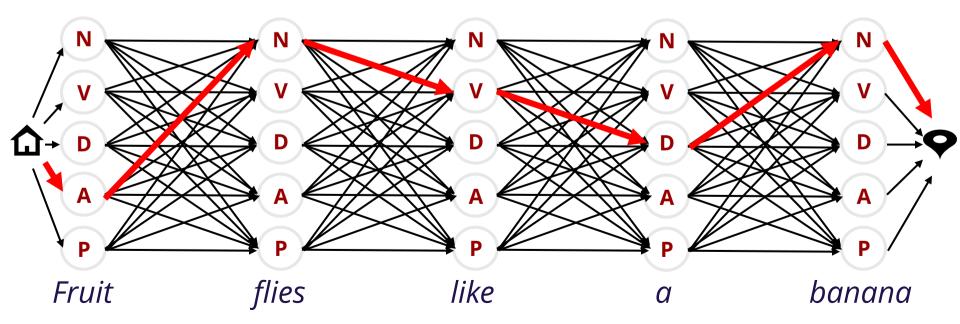
**Unsupervised** 

# Hidden Markov Model Supervised Learning

$$p(x_1,\ldots,x_m,\overset{\downarrow}{y_0},y_1,\ldots,y_m,\overset{\downarrow}{y_{m+1}})$$

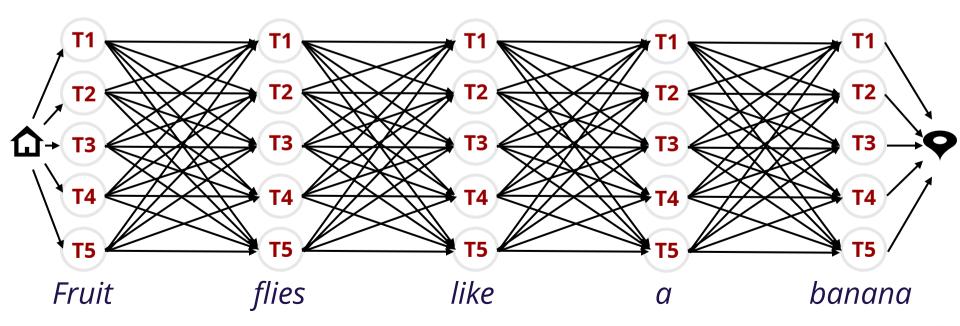


$$egin{aligned} y_1^*,\ldots,y_m^*\ &=rg\max_{y_1,\ldots,y_m}p(x_1,\ldots,x_m,y_0,y_1,\ldots,y_m,y_{m+1}) \end{aligned}$$



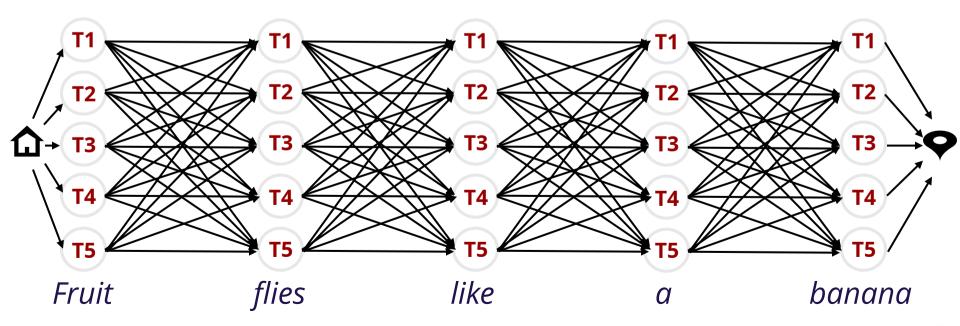
### Hidden Markov Model Unsupervised Learning

$$p(x_1,\ldots,x_m)$$

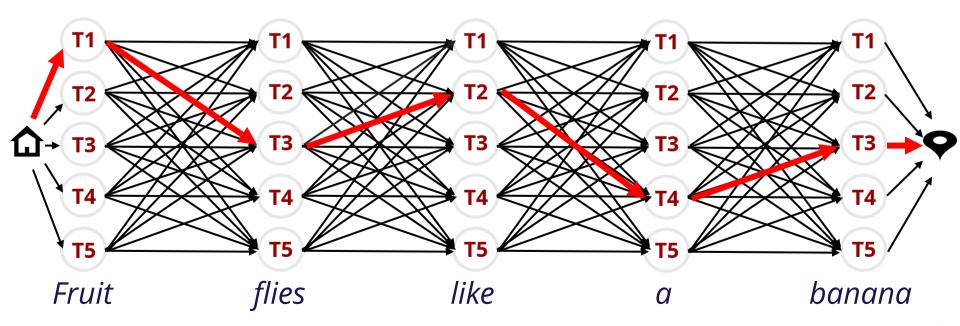


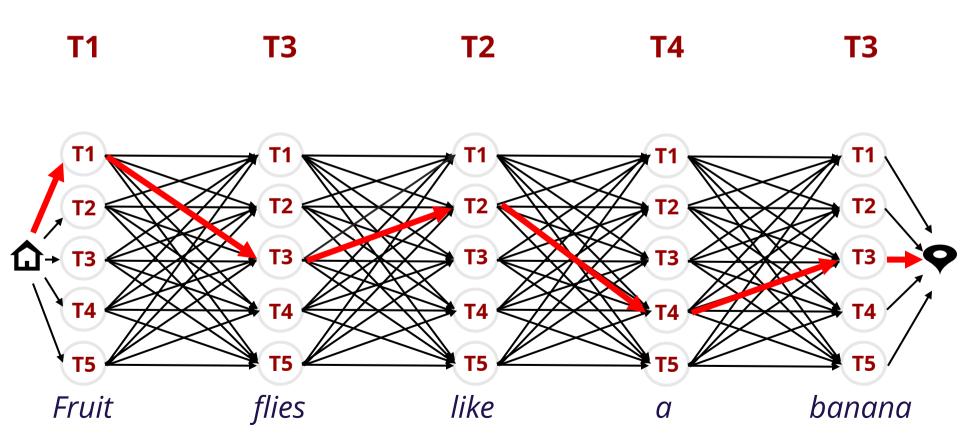
### Hidden Markov Model Unsupervised Learning

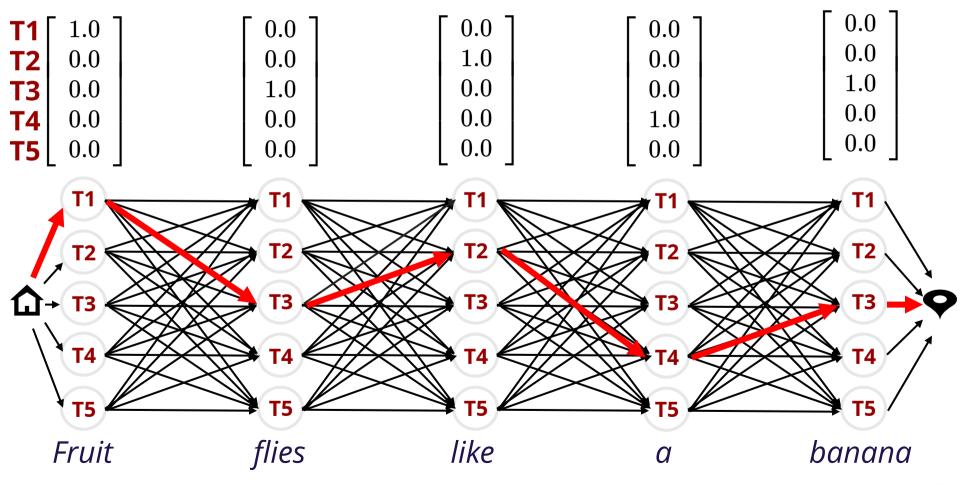
$$p(x_1,\ldots,x_m) \ = \sum_{m{x}_1,\ldots,m{x}_m,y_1,\ldots,y_m} p(x_1,\ldots,x_m,y_0,y_1,\ldots,y_m,y_{m+1})$$



$$egin{aligned} y_1^*,\dots,y_m^* \ &= rg\max_{y_1,\dots,y_m} p(x_1,\dots,x_m,y_0,y_1,\dots,y_m,y_{m+1}) \end{aligned}$$



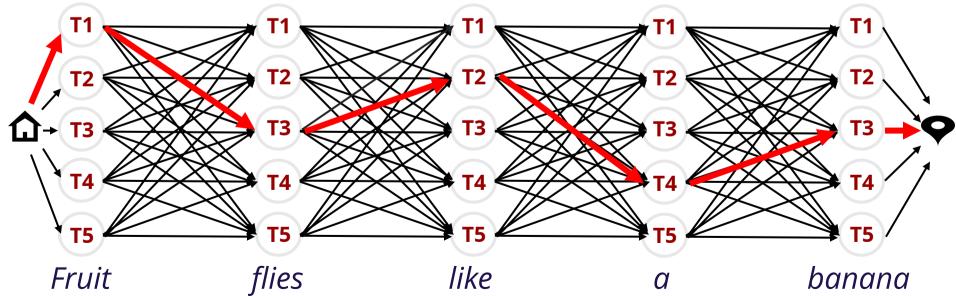




### Contextual Embedding

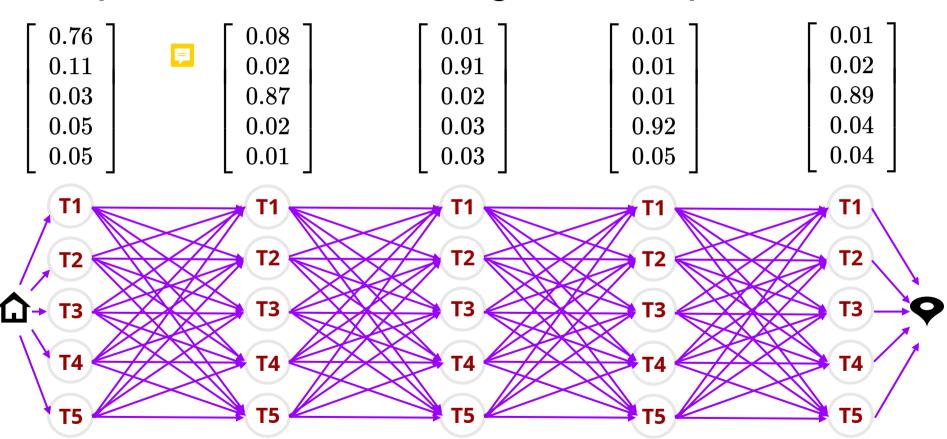
Low-Dimensional One-hot Vectors Similar to Brown Clusters (Brown et al. 1992)





### Contextual Embedding

Use Forward-backward Algorithm to find probabilities for all tags at each position



like

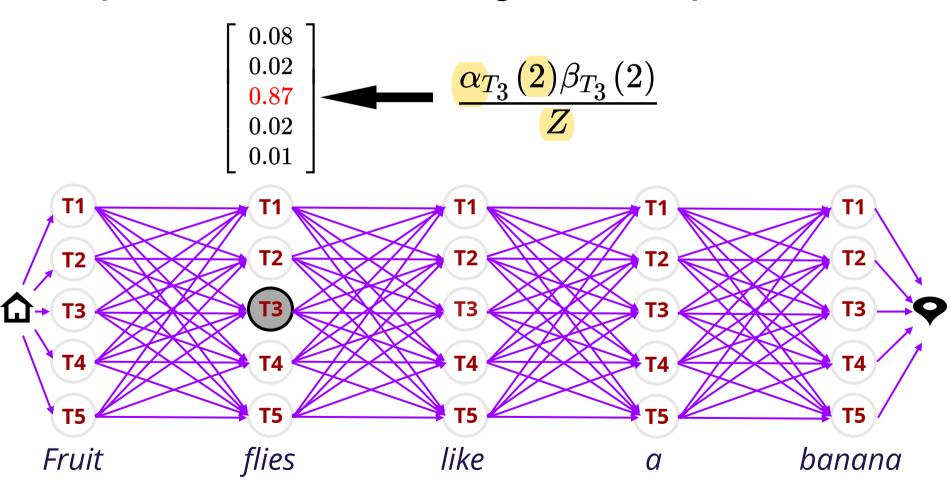
flies

Fruit

banana

### Contextual Embedding

Use Forward-backward Algorithm to find probabilities for all tags at each position



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**POS Tagging** Chunking **Document Classification** Information Extraction Syntactic Parsing **Semantic Parsing** Natural Language Generation **Machine Translation** Sentiment Analysis Next Class Coreference Resolution **Question Answering**