Neural Networks part 2

JURAFSKY AND MARTIN CHAPTERS 7 AND 9

Reminders

HOMEWORK 5 IS DUE TONIGHT BY 11:50PM

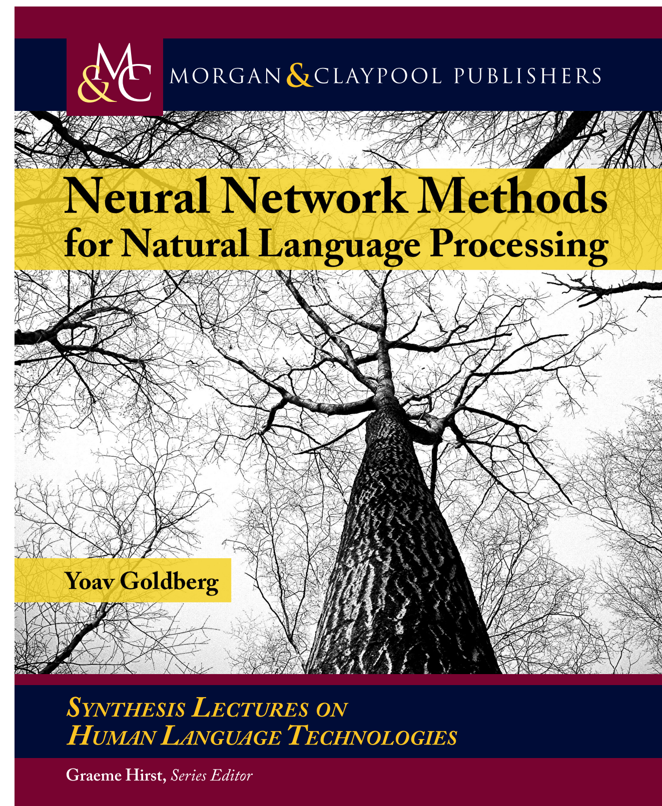
HW6 (NN-LM) HAS BEEN RELEASED

QUIZZES DON'T HAVE LATE DAYS

Neural Network LMs part 2

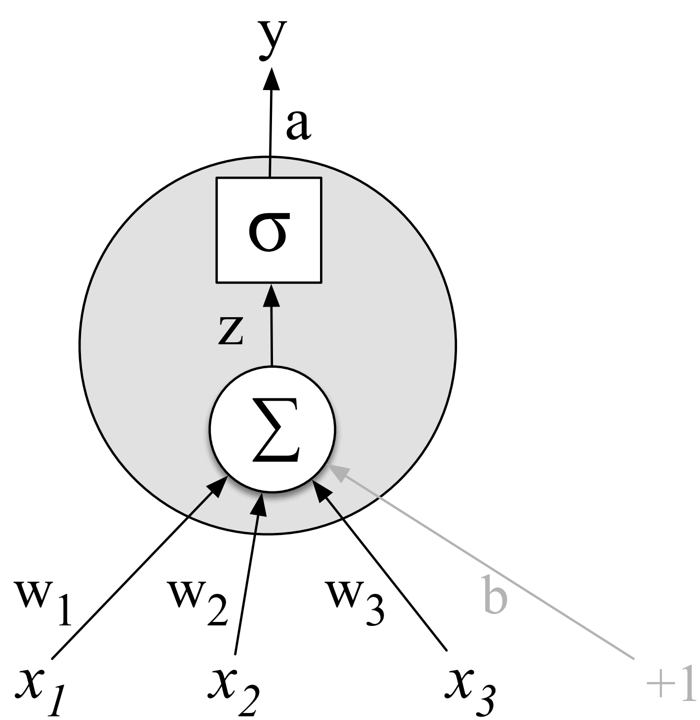
READ CHAPTERS 7 AND 9 IN JURAFSKY AND MARTIN

READ CHAPTER 4 AND 14 FROM YOAV GOLDBERG'S BOOK **NEURAL NETWORKS METHODS FOR NLP**



Recap: Neural Networks

The building block of a neural network is a single computational unit. A unit takes a set of real valued numbers as input, performs some computation.

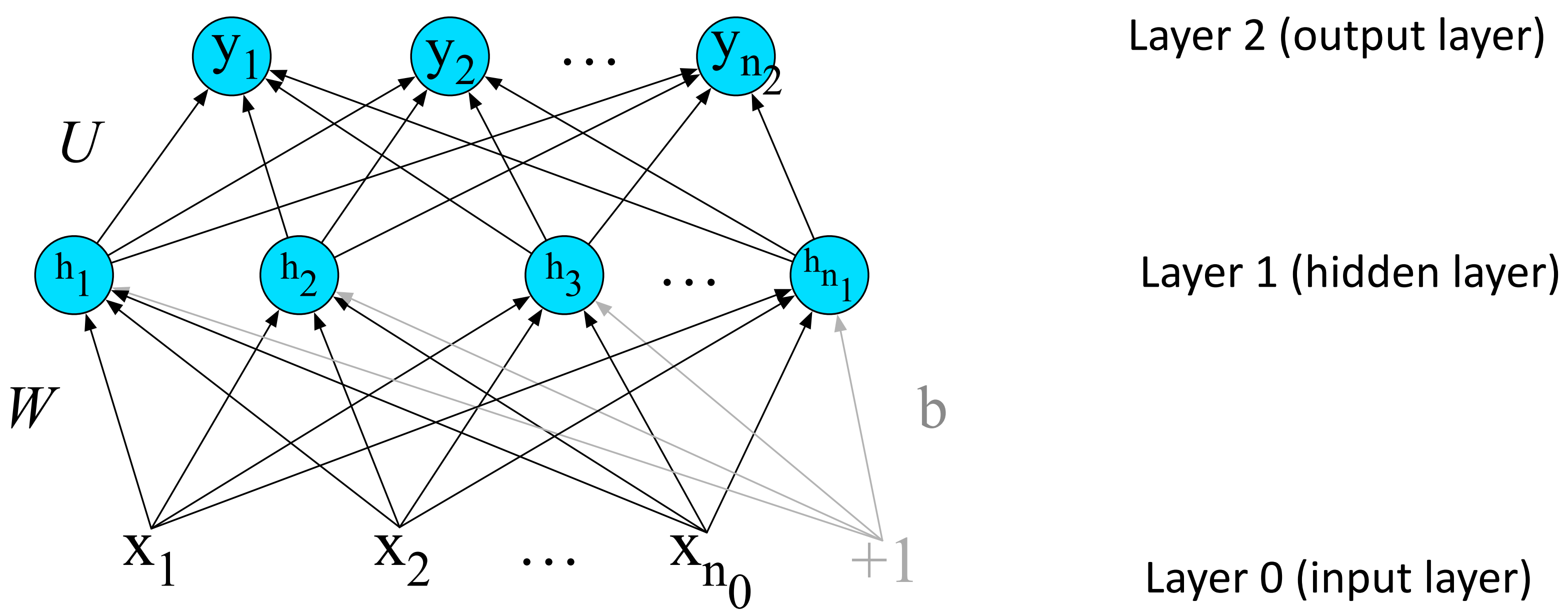


Recap: Feed-Forward NN

The simplest kind of NN is the **Feed-Forward Neural Network**

Multilayer network, all units are usually **fully-connected**, and **no cycles**.

The outputs from each layer are passed to units in the next higher layer, and no outputs are passed back to lower layers.



Recap: Language Modeling

Goal: Learn a **function** that returns the joint probability

Primary difficulty:

1. There are too many parameters to accurately estimate.
2. In n-gram-based models we fail to generalize to related words / word sequences that we <u>have</u> observed.

Recap: Curse of dimensionality AKA sparse statistics

Suppose we want a joint distribution over 10 words.
Suppose we have a vocabulary of size 100,000.

$$100{,}000^{10} = 10^{50} \text{ parameters}$$

This is too high to estimate from data.

Recap: Chain rule

In LMs we use the chain rule to get the conditional probability of the next word in the sequence given all of the previous words:

$$P(w_1 w_2 w_3 \ldots w_t) = \prod_{t=1}^{T} P(w_t | w_1 \ldots w_{t-1})$$

What assumption do we make in n-gram LMs to simplify this?

The probability of the next word only depends on the previous *n*-1 words.

A small *n* makes it easier for us to get an estimate of the probability from data.

Recap: N-gram LMs

Estimate the probability of the next word in a sequence, given the entire prior context $P(w_t | w_1^{t-1})$. We use the Markov assumption approximate the probability based on the n-1 previous words.

$$P(w_t|w_1^{t-1}) \approx P(w_t|w_{t-N+1}^{t-1})$$

For a 4-gram model, we use MLE estimate the probability a large corpus.

$$P(w_t|w_{t-3}, w_{t-2}, w_{t-1}) = \frac{count(w_{t-3}\, w_{t-2} w_{t-1}\, w_t)}{count(w_{t-3}\, w_{t-2} w_{t-1})}$$

Probability tables

We construct tables to look up the probability of seeing a word given a history.

curse of	$P(w_t \mid w_{t-n} \ldots w_{t-1})$
dimensionality	
azure	
knowledge	
oak	

The tables only store observed sequences.

What happens when we have a new (unseen) combination of n words?

Unseen sequences

What happens when we have a new (unseen) combination of n words?

1. Back-off
2. Smoothing / interpolation

We are basically just stitching together short sequences of observed words.

Alternate idea

Let's try **generalizing**.

Intuition: Take a sentence like

The cat is walking in the bedroom

And use it when we assign probabilities to similar sentences like

The dog is running around the room

Similarity of words / contexts

Use word embeddings!

sim (cat , dog)

Vector for *cat*

Vector for *dog*

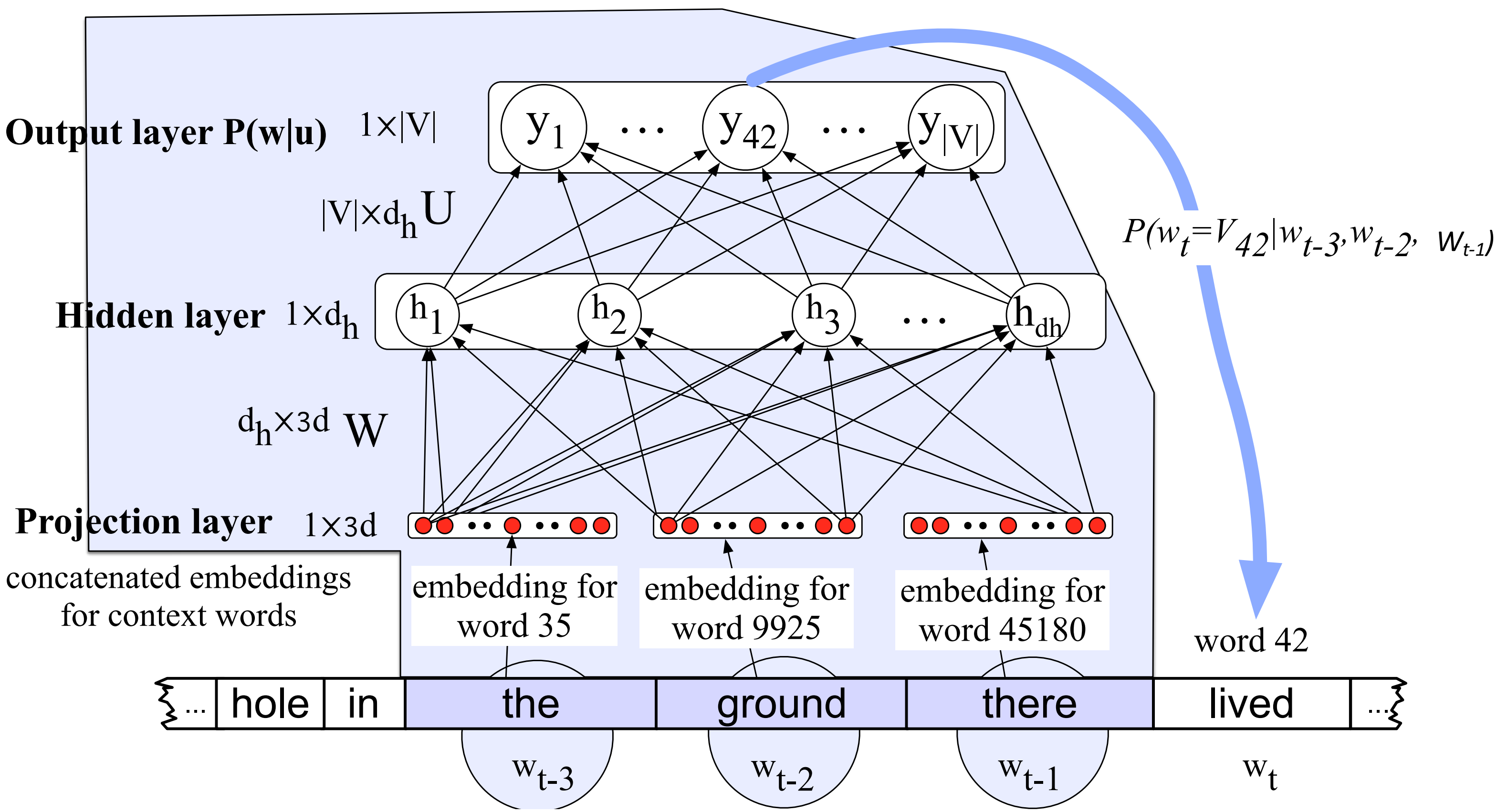
How can we use embeddings to estimate language model probabilities?

p(cat | please feed the)

Concatenate these 3 vectors together, use that as input vector to a feed forward neural network

Compute the probability of all words in the vocabulary with a softmax on the output layer

Neural network with embeddings as input



A Neural Probabilistic LM

In NIPS 2003, Yoshua Begio and his colleagues introduced a neural probabilistic language model

1. They used a vector space model where the words are vectors with real values $\mathbb{R}^m$. m=30, 60, 100. This gave a way to compute word similarity.
2. They defined a function that returns a joint probability of words in a sequence based on a sequence of these vectors.
3. Their model simultaneously learned the word representations **and** the probability function from data.

Seeing one of the cat/dog sentences allows them to increase the probability for that sentence **and** its combinatorial # of **"neighbor" sentences** in vector space.

A Neural Probabilistic LM

Given:

A training set $w_1 \dots w_t$ where $w_t \in V$

Learn:

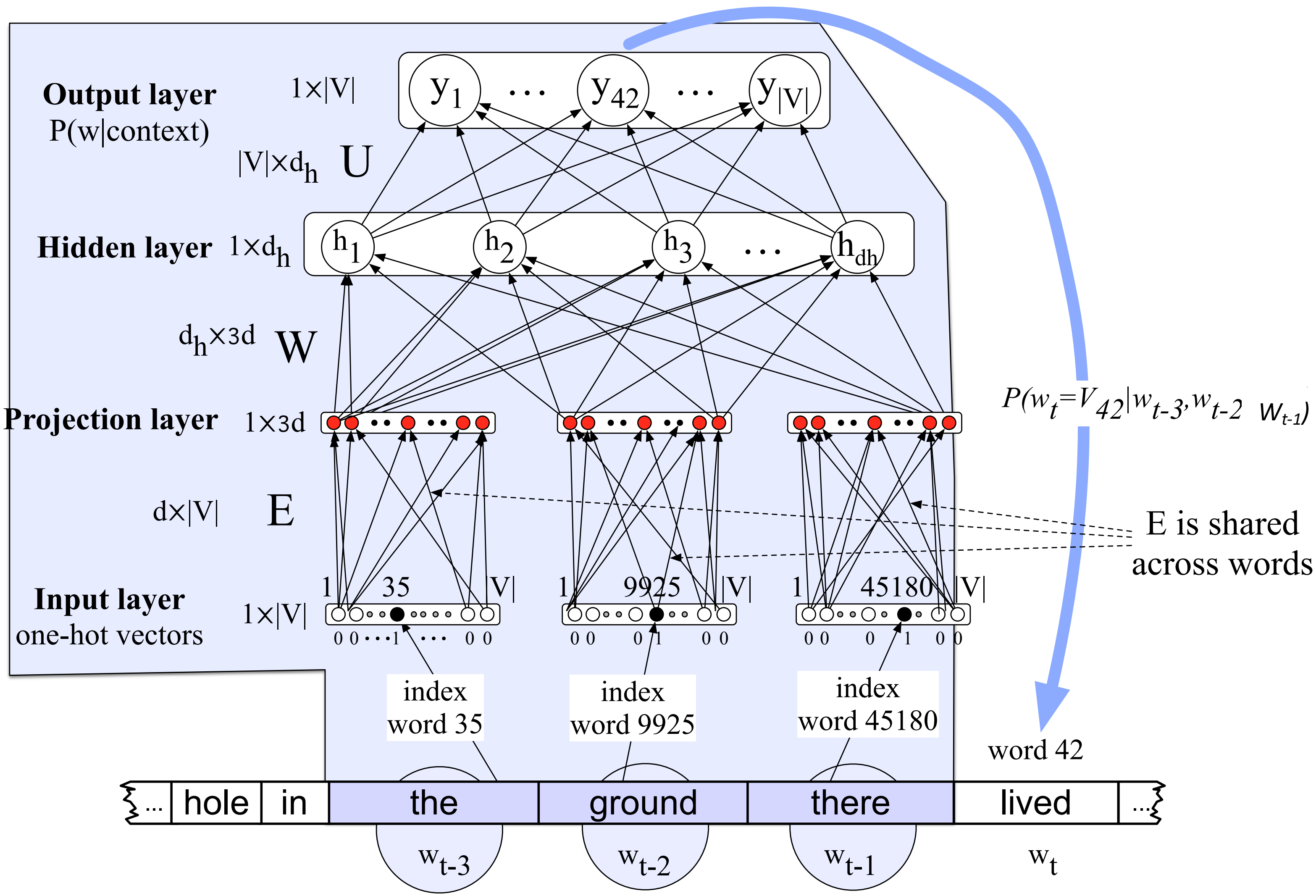
$f(w_1 \dots w_t) = P(w_t | w_1 \dots w_{t-1})$

Subject to giving a high probability to an unseen text/dev set (e.g. minimizing the perplexity)

Constraint:

Create a proper probability distribution (e.g. sums to 1) so that we can take the product of conditional probabilities to get the joint probability of a sentence

Neural net that learns embeddings



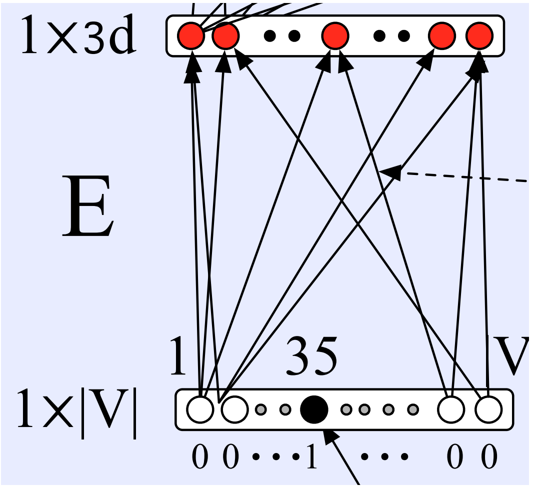
One-hot vectors

To learn the embeddings, we added an extra layer to the network. Instead of pre-trained embeddings as the input layer, we instead use **one-hot vectors.**

```
[0 0 0 0 1 0 0 ... 0 0 0 0]
 1 2 3 4 5 6 7 ...   ... |V|
```

These are then used to look up a **row vector** in the embedding matrix **E**, which is of size d by |V|.

With this small change, we now can learn the emebddings of words.



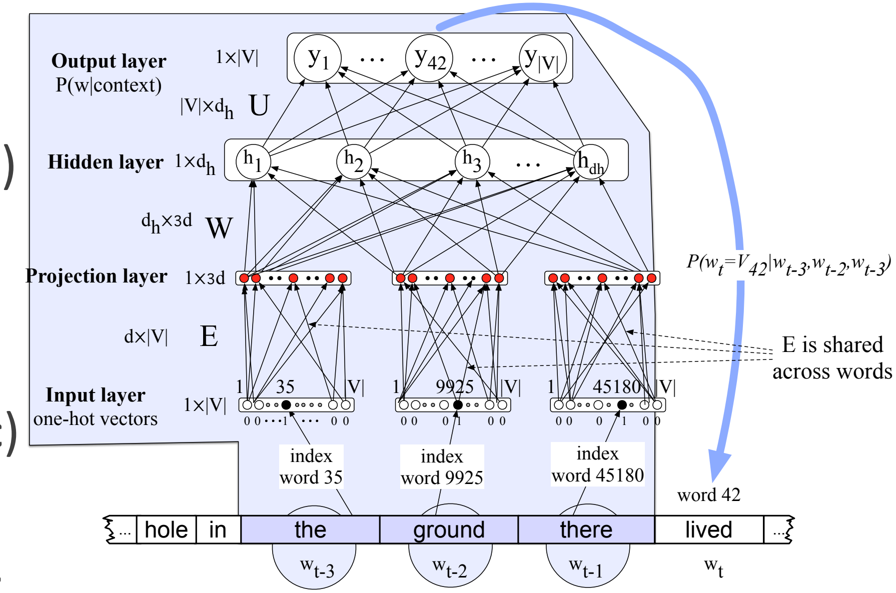
Forward pass

1. Select embeddings from **E** for the three context words (*the ground there*) and concatenate them together

2. Multiply by **W** and add **b** (not shown), and pass it through an activation function (sigmoid, ReLU, etc) to get the hidden layer **h**.

3. Multiply by **U** (the weight matrix for the hidden layer) to get the output layer, which is of size **1 by |V|**.

4. Apply **softmax** to get the probability. Each node *i* in the output layer estimates the probability $P(w_t = i | w_{t-1}, w_{t-2}, w_{t-3})$



$$
\begin{aligned}
e &= (Ex_1, Ex_2, \ldots, Ex) \\
h &= \sigma(We + b) \\
z &= Uh \\
y &= softmax(z)
\end{aligned}
$$

Training with backpropagation

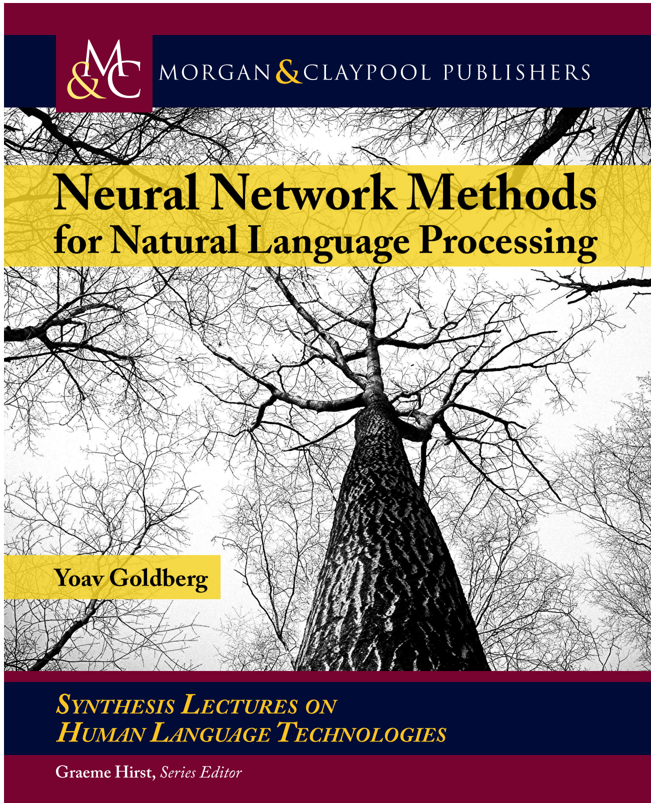
To train the models we need to find good settings for all of the parameters θ = ***E,W,U,b***.

How do we do it? ***Gradient descent using error backpropagation*** on the computation graph to compute the gradient.

Since the final prediction depends on many intermediate layers, and since each layer has its own weights, we need to know how much to update each layer.

Error backpropagation allows us to assign proportional blame (compute the error term) back to the previous hidden layers.

For information about backpropogation, check out Chapter 5 of this book →



Training data

The training examples are simply word k-grams from the corpus

The identities of the first k-1 words are used as features, and the last word is used as the target label for the classification.

Conceptually, the model is trained using cross-entropy loss.

Training the Neural LM

Use a large text to train. Start with random weights Iteratively moving through the text predicting each word w_t .

At each word w_t, the cross-entropy (negative log likelihood) loss is:

$$L = -\log p(w_t \,|w_{t-1}, \dots, w_{t-n+1})$$

The gradient for the loss is:

$$\theta_{t+1} = \theta_t \; - \; \eta \frac{\partial -\log p(w_t \,|w_{t-1},\dots,w_{t-n+1})}{\partial \theta}$$

The gradient can be computed in any standard neural network framework which will then backpropagate through ***U* , *W* , *b*, *E***.

The model learns both a function to predict the probability of the next word, **and it learns word embeddings** too!

Learned embeddings

When the ~50 dimensional vectors that result from training a neural LM are projected down to 2-dimensions, we see a lot of words that are intuitively similar are close together.

Advantages of NN LMs

Better results. They achieve better perplexity scores than SOTA n-gram LMs.

Larger N. NN LMs can scale to much larger orders of n. This is achievable because parameters are associated only with individual words, and not with n-grams.

They generalize across contexts. For example, by observing that the words *blue, green, red, black*, etc. appear in similar contexts, the model will be able to assign a reasonable score to the *green car* even though it never observed in training, because it did observe *blue car* and *red car*.

A by-product of training are word embeddings!

Disadvantage of Feedforward Neural Networks

Bengio (2003) used a **Feedfoward neural network** for their language model. This means is that it operates only on **fixed size inputs**.

For sequences longer than that size, it slides a window over the input, and makes predictions as it goes.

The decision for one window **has no impact** on the later decisions.

This shares the **weakness of Markov** approaches, because it limits the context to the window size.

To fix this, we're going to look at **recurrent neural networks**.

Current state of the art neural LMs

[ELMo]

[GPT]

[BERT]

[GPT-2]

Recurrent Neural Networks

Language is an inherently temporal phenomenon.

Logistic regression and Feedforward NNs are not temporal in nature. They use fixed size vectors that have simultaneous access to the full input all at once.

Work-arounds like a sliding window aren't great, because

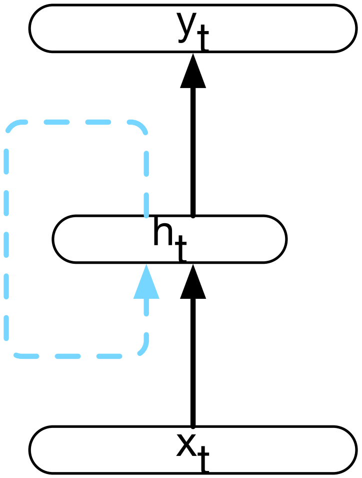
1. The decision made for one window has no impact on later decisions
2. It limits the context being used
3. Fails to capture important aspects of language like consistency and long distance dependencies

Recurrent Neural Networks

A recurrent neural network (RNN) is any network that contains a cycle within its network.

In such networks the value of a unit can be dependent on earlier outputs as an input.

RNNs have proven extremely effective when applied to NLP.



Memory

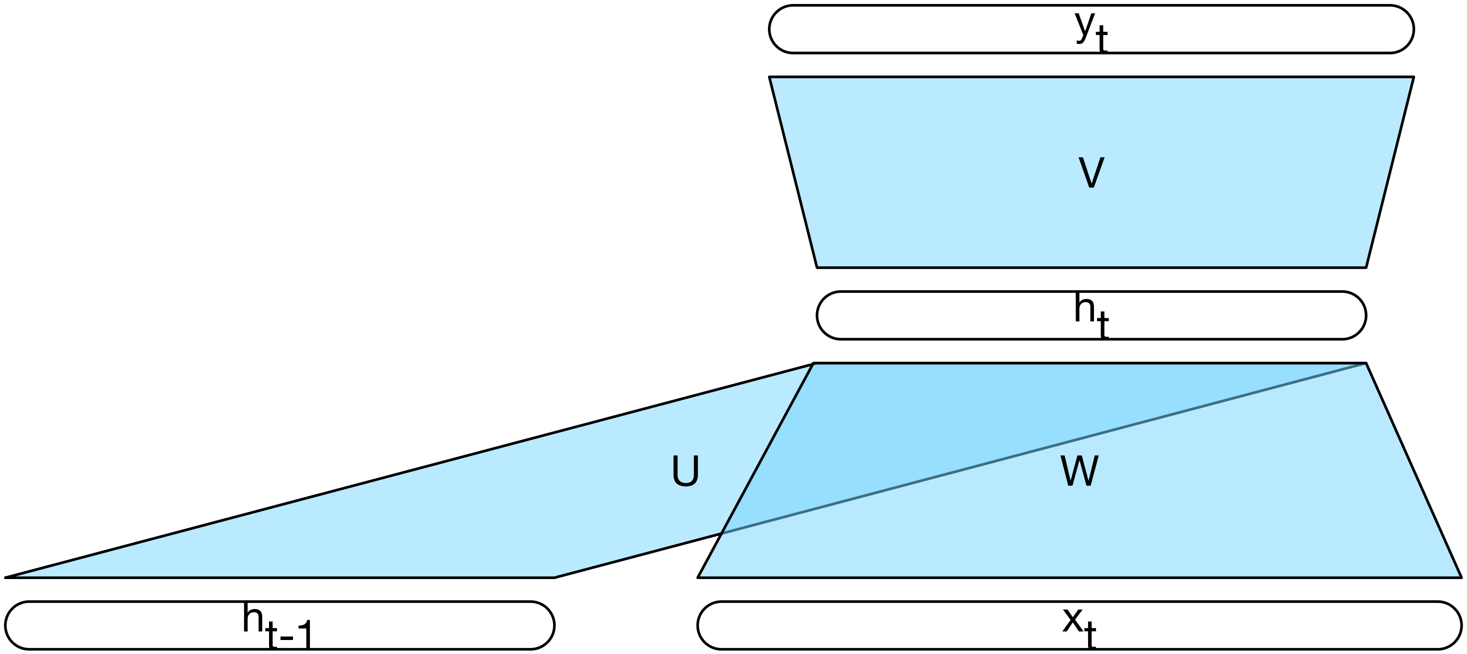
We use a hidden layer from a **preceding point in time** to augment the input layer.

This hidden layer from the preceding point in time provides a form of **memory** or context.

This architecture **does not impose a fixed-length limit** on its prior context.

As a result, information can come from all the way back at the beginning of the input sequence.   Thus we get away from the Markov assumption.

RNN as a feedforward network



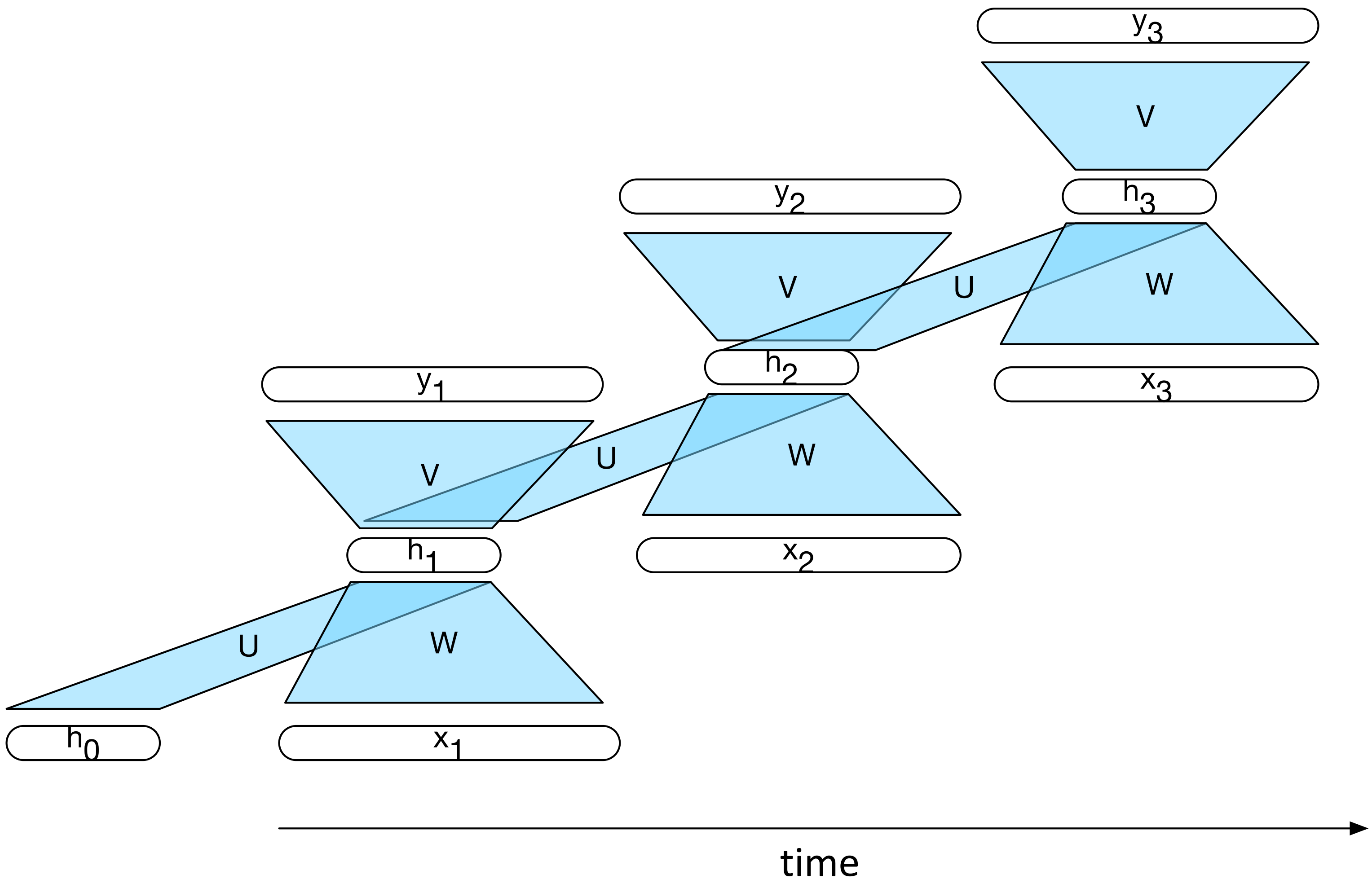
Forward inference

function FORWARDRNN(x, $network$) **returns** output sequence y

$h_0 \leftarrow 0$
for $i \leftarrow 1$ **to** LENGTH(x) **do**
  $h_i \leftarrow g(U\ h_{i-1}\ +\ W\ x_i)$
  $y_i \leftarrow f(V\ \ h_i)$
return y

This allows us to have an output sequence equal in length to the input sequence.

Unrolled RNN



Training RNNs

Just like with feedforward networks, we'll use a training set, a loss function, and back-propagation to get the gradients needed to adjust the weights in an RNN.

The weights we need to update are:

W – the weights from the input layer to the hidden layer
U – the weights from the previous hidden layer to the current hidden layer
V – the weights from the hidden layer to the output layer

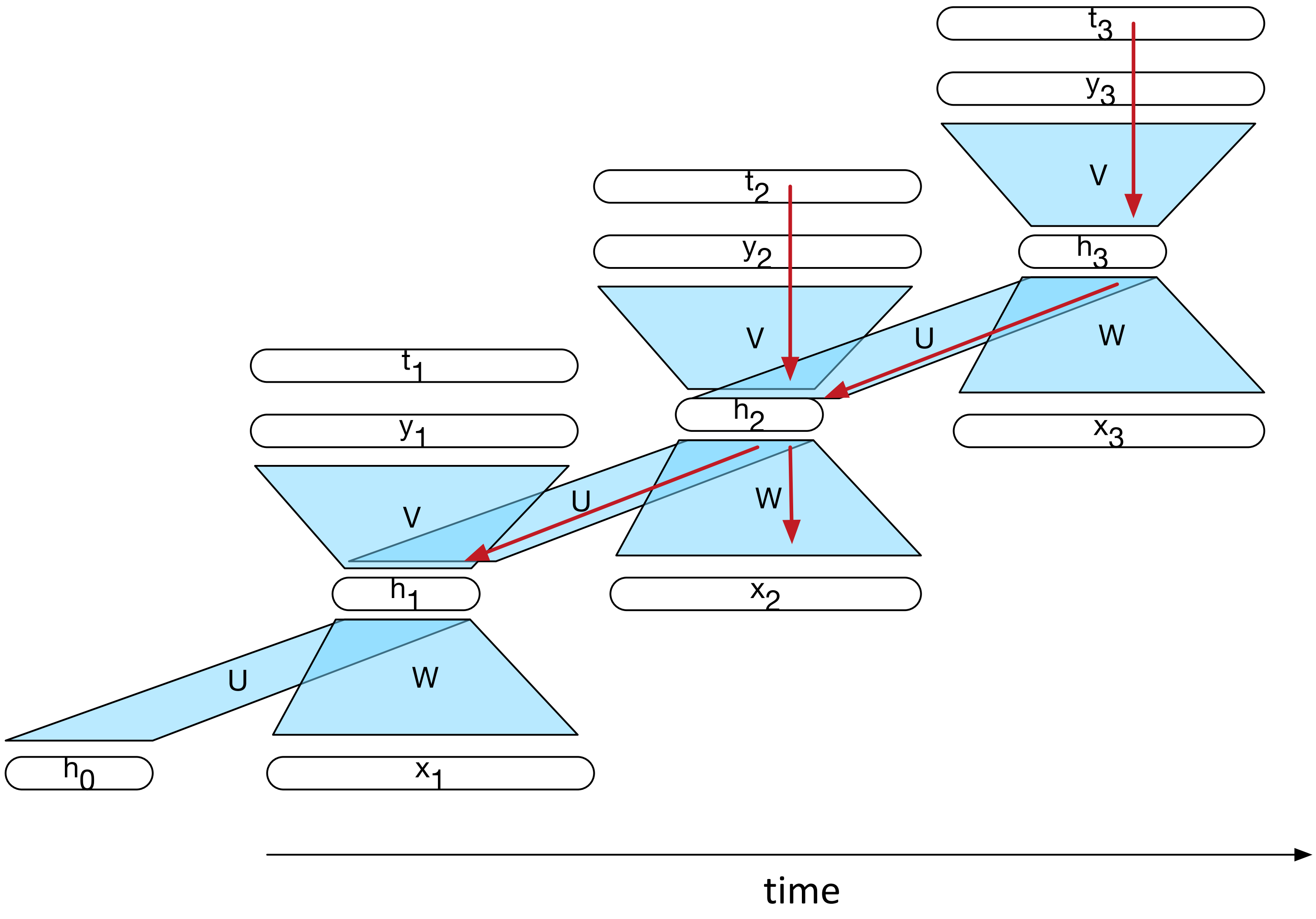
Training RNNs

New considerations:

1. to compute the loss function for the output at time t we need the hidden layer from time $t - 1$.
2. The hidden layer at time t influences both the output at time t and the hidden layer at time $t + 1$ (and hence the output and loss at t+1)

To assess the error accruing to h_t , we'll need to know its influence on both the current output *as well as the ones that follow*.

Backpropagation of errors



Vanishing/Exploding Gradients

In deep networks, it is common for the error gradients to either vanish or explode as they backpropagate. The problem is more severe in deeper networks, especially in RNNs.

Dealing with vanishing gradients is still an open research question. Solutions include:

1. making the networks shallower
2. step-wise training where first layers are trained and then fixed
3. performing batch-normalization
4. using specialized NN architectures like LSTM and GRU

Recurrent Neural Language Models

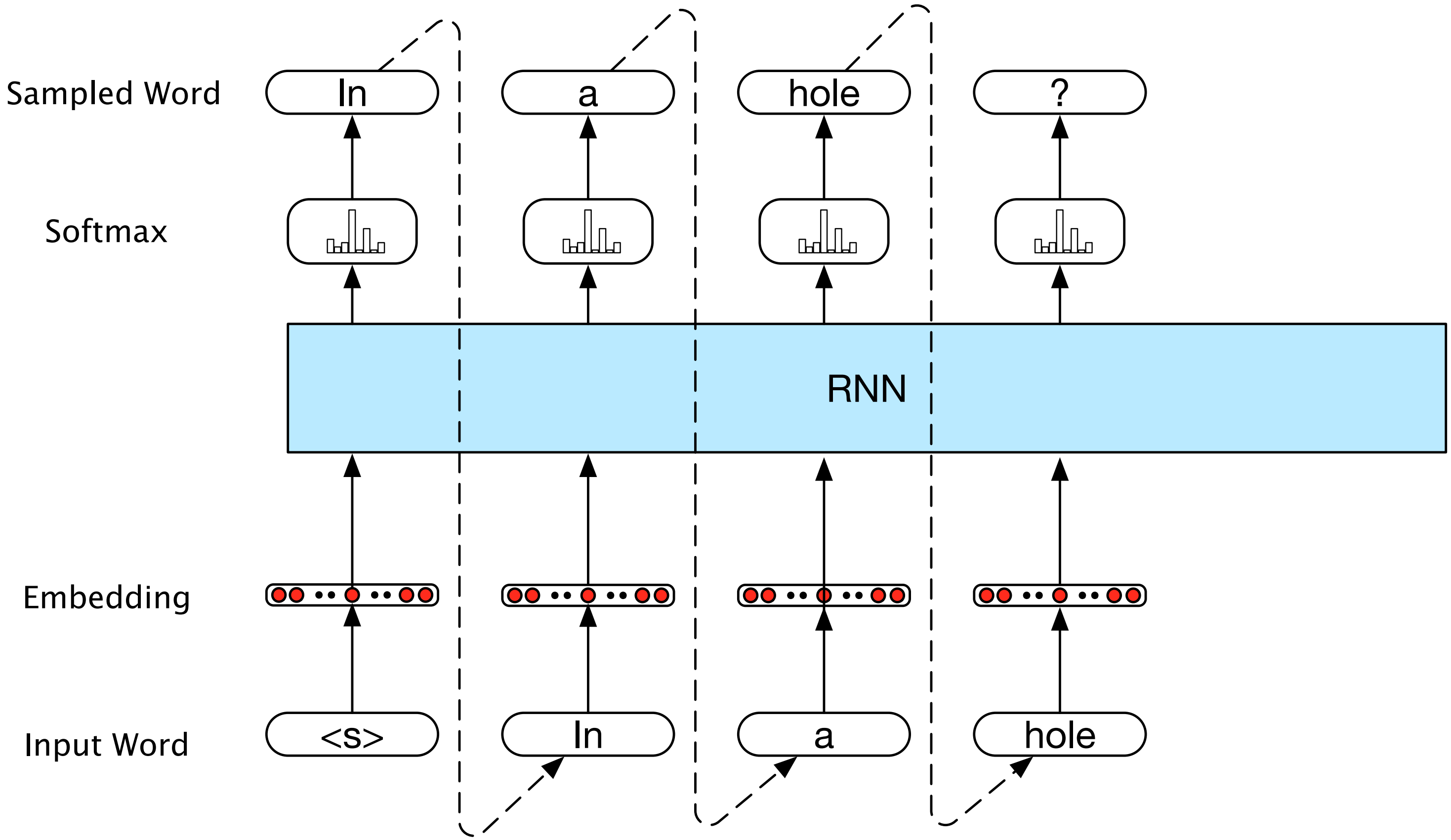
Unlike n-gram LMs and feedforward networks with sliding windows, RNN LMs don’t use a fixed size context window.

They predict the next word in a sequence by using the current word and the previous hidden state as input.

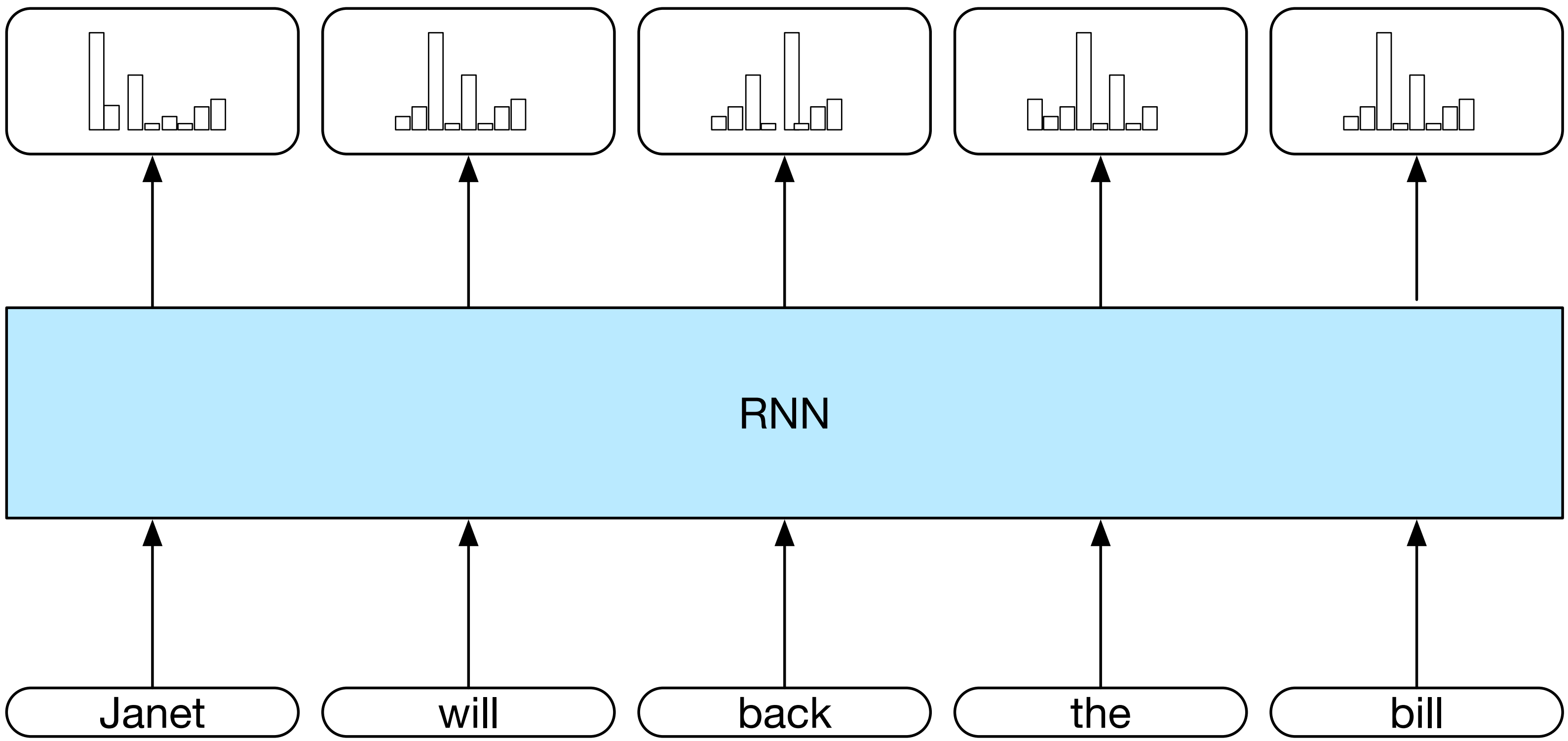
The hidden state embodies information about all of the preceding words all the way back to the beginning of the sequence.

Thus they can potentially take more context into account than n-gram LMs and NN LMs that use a sliding window.

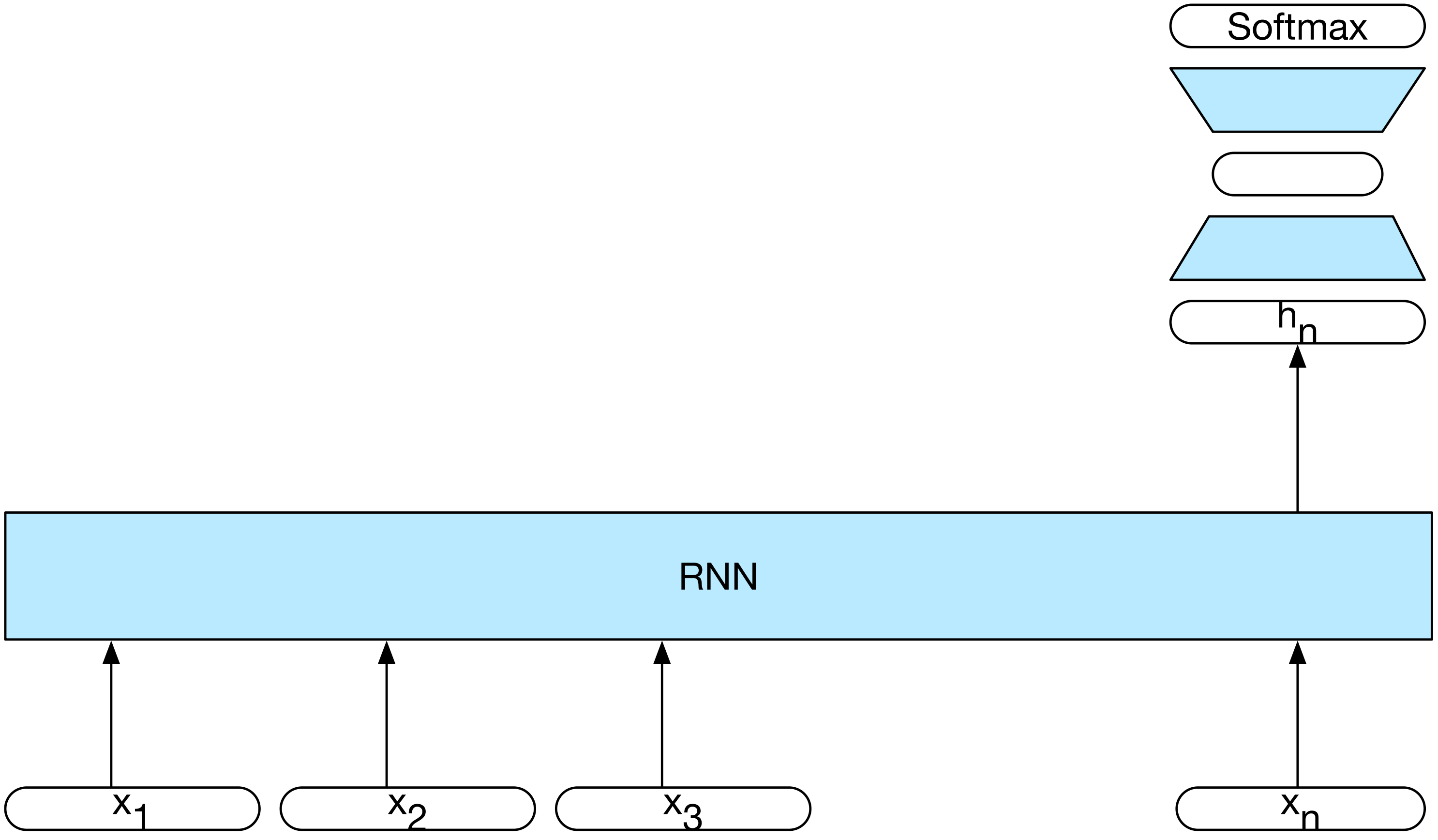
Autoregressive generation with an RNN LM



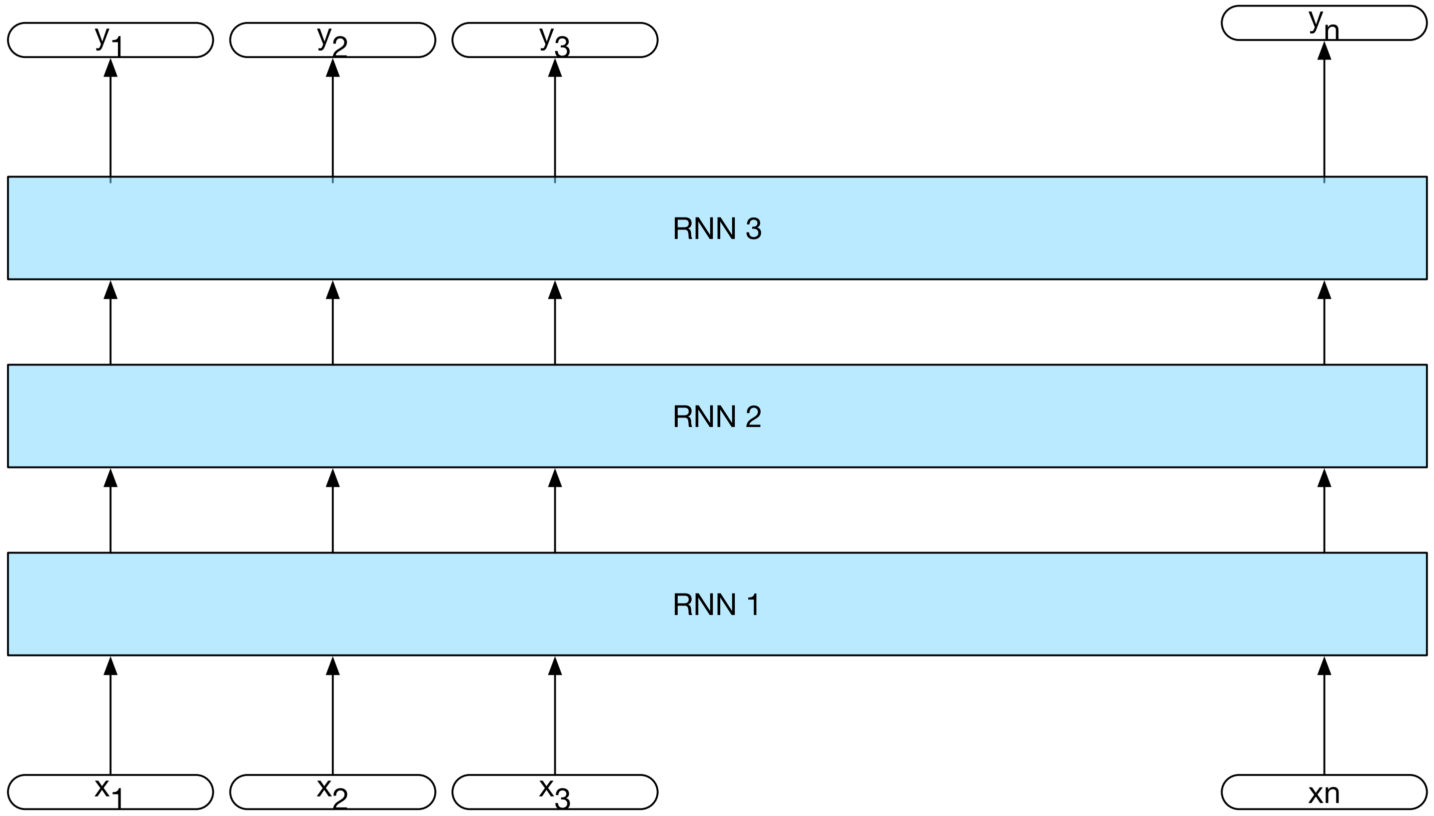
Tag Sequences



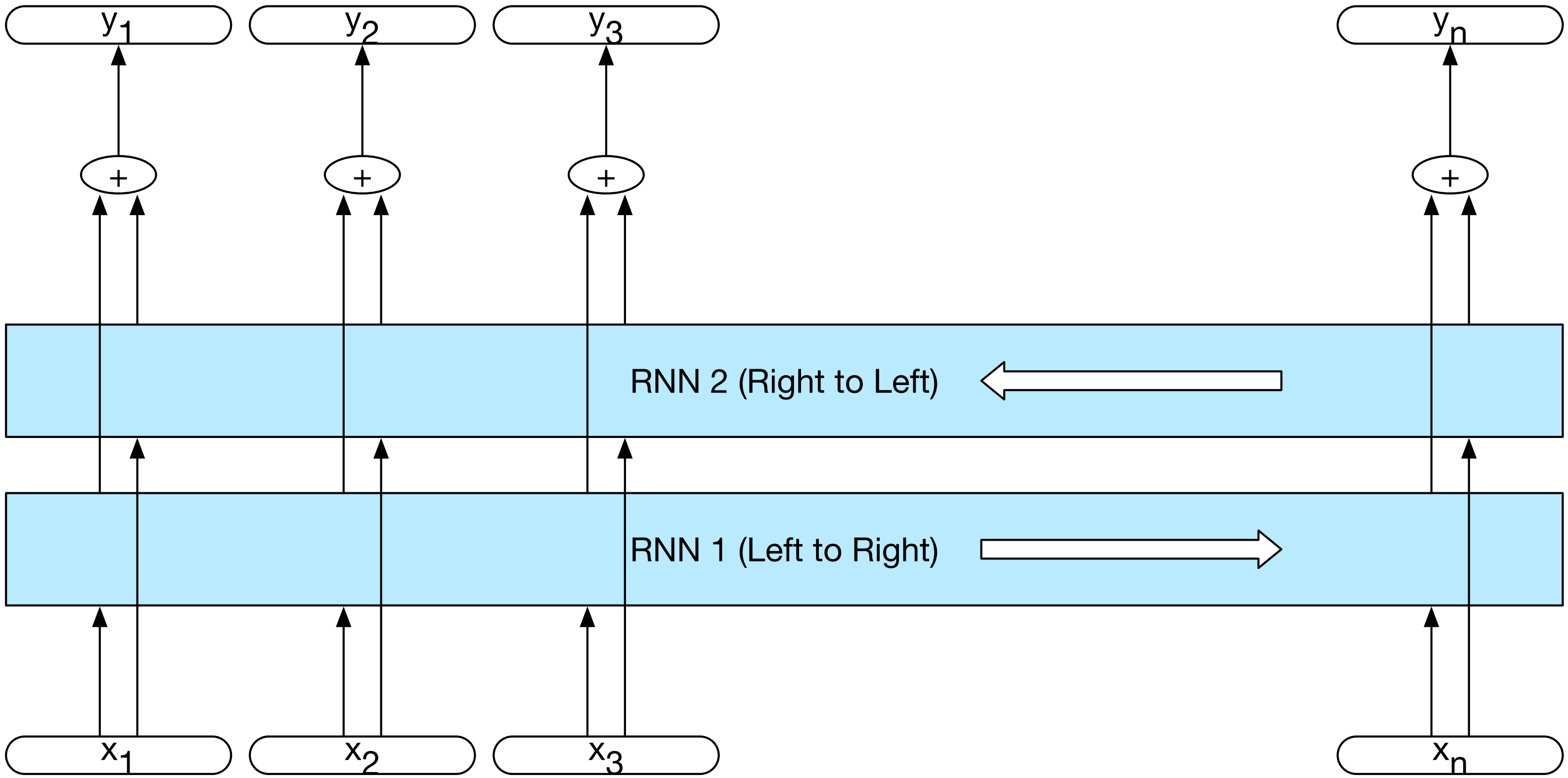
Sequence Classifiers



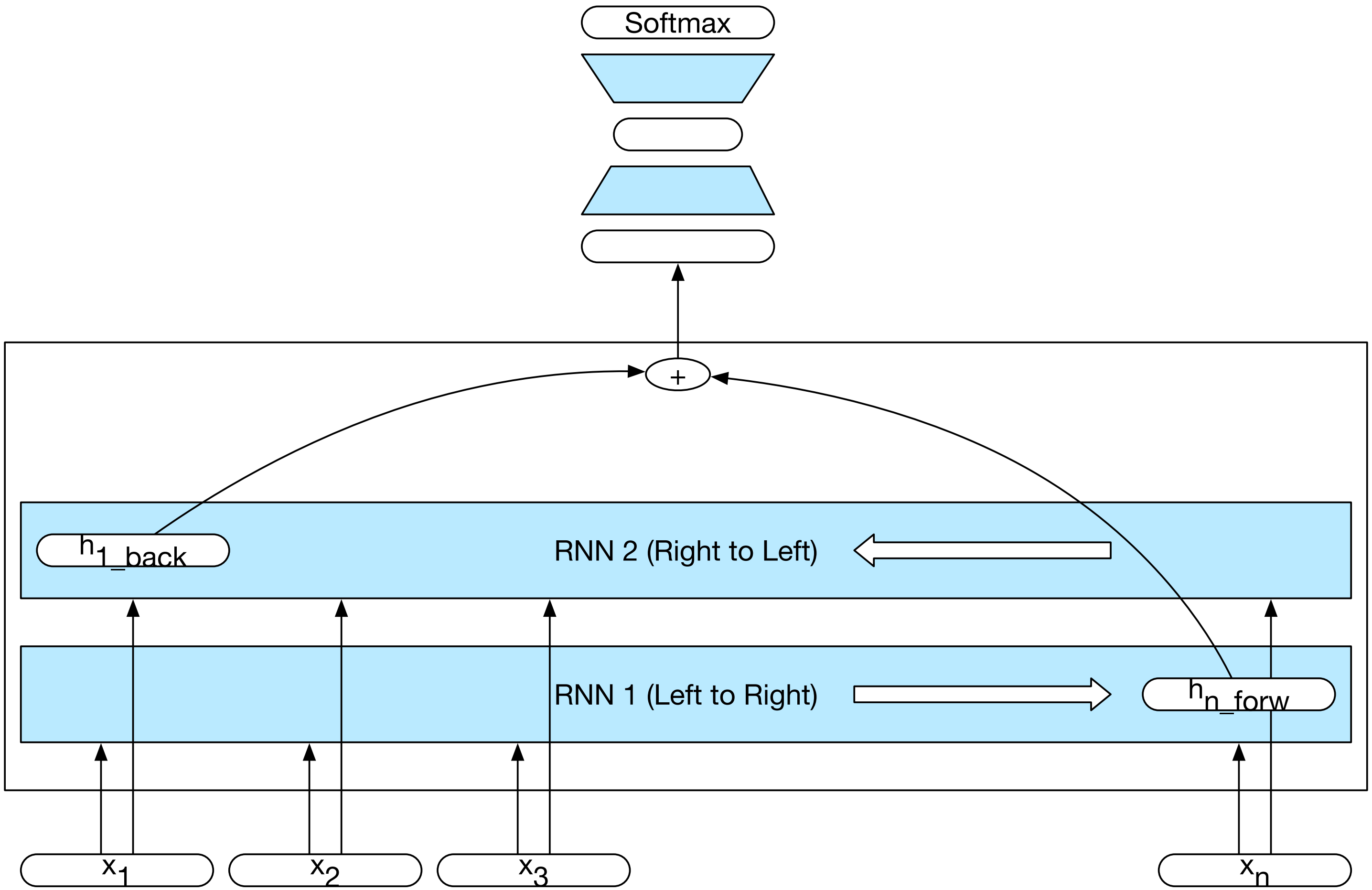
Stacked RNNs



Bidirectional RNNs



Bidirectional RNNs for sequence classification



Current state of the art neural LMs

[ELMo]

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Summary

RNNs allow us to process sequences one element at a time.

RNNs can have one output per input. The output at a point in time is based on the current input and the hidden layer from the previous step.

RNNs can be trained similarly to feed forward NNs are using backpropagation through time.

Applications: LMs, generation, sequence labeling like POS tagging, sequence classification.

Next time: POS tagging!