Lecture 10: Recurrent Neural Networks

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COMP-550

Primer by Yoav Goldberg:

https://arxiv.org/abs/1510.00726

Eisenstein, Section 7.6

J&M Chapter 9 (3rd ed)

Reminders

- RA1 deadline is on Friday, due Oct 11
- Week of Oct 14: Thanksgiving & Fall reading break
- Tutorials on RNNs!
  - Check Ed for schedule

Outline

Review of LC-CRF

Review of neural networks and deep learning

Recurrent neural networks

Long short-term memory networks

LSTM-CRFs

Discriminative Sequence Model

The parallel to an HMM in the discriminative case: **linear-chain conditional random fields (linear-chain CRFs)** (Lafferty et al., 2001)

$$P(Y|X) = \frac{1}{Z(X)} \exp \sum_{t} \sum_{k} \theta_k f_k(y_t, y_{t-1}, x_t)$$

sum over all features

sum over all time-steps

Z(X) is a normalization constant:

$$Z(X) = \sum_{\boldsymbol{y}} \exp \sum_{t} \sum_{k} \theta_k f_k(y_t, y_{t-1}, x_t)$$

sum over all possible sequences of hidden states

Features in CRFs

Standard HMM probabilities as CRF features:

- Transition from state DT to state NN

  $f_{DT\rightarrow NN}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_{t-1} = DT)\,\mathbf{1}(y_t = NN)$
- Emit *the* from state DT

  $f_{DT\rightarrow the}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_t = DT)\,\mathbf{1}(x_t = the)$
- Initial state is DT

  $f_{DT}(y_1, x_1) = \mathbf{1}(y_1 = DT)$

Indicator function:

Let $\mathbf{1}(condition) = \begin{cases} 1 & \text{if } condition \text{ is true} \\ 0 & \text{otherwise} \end{cases}$

Features in CRFs

Additional features that may be useful

- Word is capitalized

  $f_{cap}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_t = ?)\mathbf{1}(x_t \text{ is capitalized})$

- Word ends in *–ed*

  $f_{-ed}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_t = ?)\mathbf{1}(x_t \text{ ends with } ed)$

- Let's brainstorm and propose more features
  - $f_{len<5}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_t = ?)\mathbf{1}(len(x_t) < 5)$
  - $f_{1st}(y_t, y_{t-1}, x_t) = \mathbf{1}(y_t = ?)\mathbf{1}(t = 1)$

Inference with LC-CRFs

Dynamic programming still works – modify the forward and the Viterbi algorithms to work with the weight-feature products.

	HMM	LC-CRF
Forward algorithm	$P(X \mid \theta)$	$Z(X)$
Viterbi algorithm	$\underset{Y}{\operatorname{argmax}}\, P(X, Y \mid \theta)$	$\underset{Y}{\operatorname{argmax}}\, P(Y \mid X, \theta)$

Gradient of Log-Likelihood

Find the gradient of the log likelihood of the training corpus:

$$l(\theta) = \log \prod_i P(Y^{(i)} | X^{(i)})$$

Here it is:

$$\sum_i \sum_t f_k\left(y_t^{(i)}, y_{t-1}^{(i)}, x_t^{(i)}\right) - \sum_i \sum_t \sum_{y,y'} f_k\left(y, y', x_t^{(i)}\right) P(y, y' | X^{(i)})$$

Derivation on the next slide.

(Artificial) Neural Networks

A kind of learning model which automatically learns non-linear functions from input to output

Biologically inspired metaphor:

- Network of computational units called neurons
- Each neuron takes scalar inputs, and produces a scalar output, very much like a logistic regression model

$$\text{Neuron}(\vec{x}) = g(a_1 x_1 + a_2 x_2 + \ldots + a_n x_n + b)$$

As a whole, the network can theoretically compute any computable function, given enough neurons. (These notions can be formalized.)

Feedforward Neural Networks

All connections flow forward (no loops); each layer of hidden units is fully connected to the next.

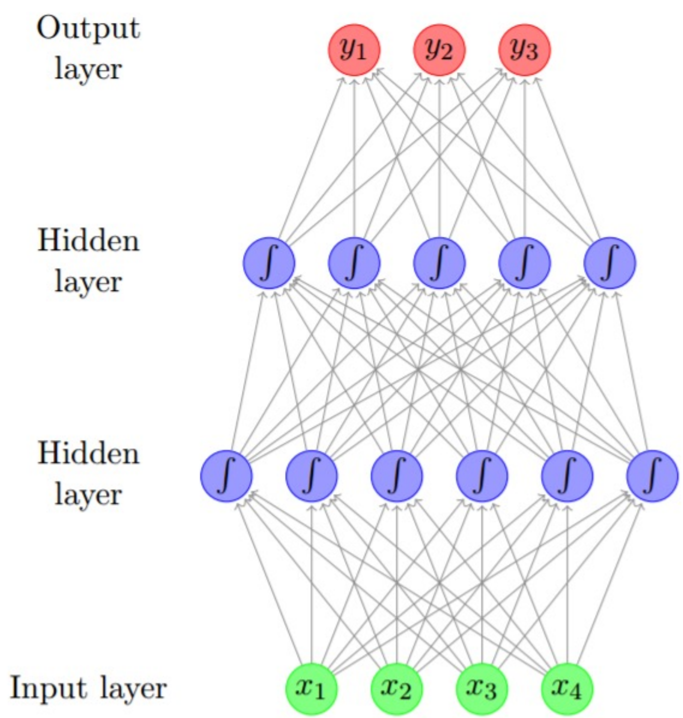


Figure 2: Feed-forward neural network with two hidden layers.

Figure from Goldberg (2015)

Inference in a FF Neural Network

Perform computations forwads through the graph:

$$\mathbf{h}^1 = g^1(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1)$$
$$\mathbf{h}^2 = g^2(\mathbf{h}^1\mathbf{W}^2 + \mathbf{b}^2)$$
$$\mathbf{y} = \mathbf{h}^2\mathbf{W}^3$$

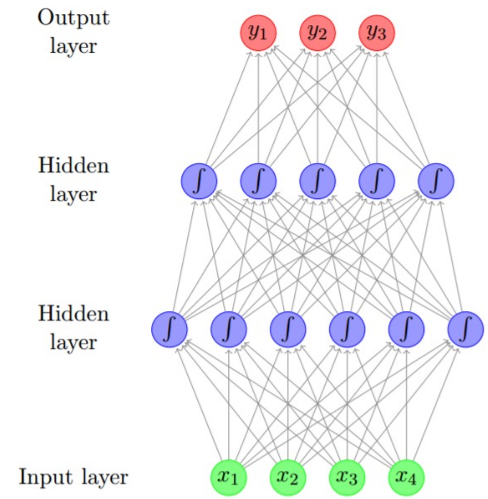


Figure 2: Feed-forward neural network with two hidden layers.

Note that we are now representing each layer as a vector; combining all of the weights in a layer across the units into a weight matrix

Training Neural Networks

Typically done by **stochastic gradient descent**

- For one training example, find gradient of loss function wrt parameters of the network (i.e., the weights of each layer); “travel along in that direction”.

Network has very many parameters!

Efficient algorithm to compute the gradient with respect to all parameters: **backpropagation** (Rumelhart et al., 1986)

- Boils down to an efficient way to use the chain rule of derivatives to propagate the error signal from the loss function backwards through the network back to the inputs

SGD Overview

Inputs:

- Function computed by neural network, $f(\mathbf{x}; \theta)$
- Training samples $\{\mathbf{x}^{\mathbf{k}}, \mathbf{y}^{\mathbf{k}}\}$
- Loss function L

Repeat for a while:

Sample a training case, $\mathbf{x}^{\mathbf{k}}, \mathbf{y}^{\mathbf{k}}$

Compute loss $L(f(\mathbf{x}^{\mathbf{k}}; \theta), \mathbf{y}^{\mathbf{k}})$

Forward pass

Compute gradient $\nabla L(\mathbf{x}^{\mathbf{k}})$ wrt the parameters θ

Update $\theta \leftarrow \theta - \eta \nabla L(\mathbf{x}^{\mathbf{k}})$

In neural networks, by backpropagation

Return θ

Example: Forward Pass

$$\mathbf{h^1} = g^1(\mathbf{x}\mathbf{W^1} + \mathbf{b^1})$$
$$\mathbf{h^2} = g^2(\mathbf{h^1}\mathbf{W^2} + \mathbf{b^2})$$
$$f(\mathbf{x}) = \mathbf{y} = g^3(\mathbf{h^2}) = \mathbf{h^2}\mathbf{W^3}$$

Loss function: $L(\mathbf{y}, \mathbf{y}^{gold})$

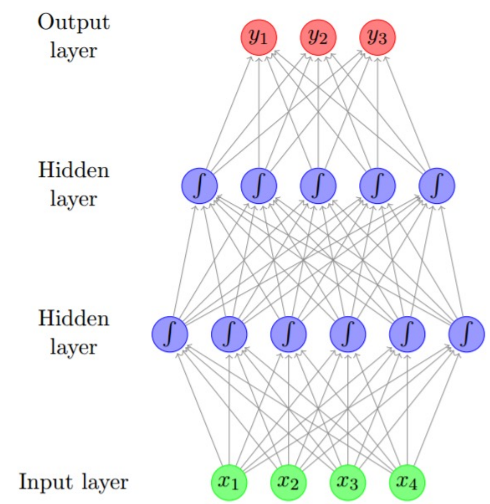


Figure 2: Feed-forward neural network with two hidden layers.

Save the values for $\mathbf{h^1}$, $\mathbf{h^2}$, $\mathbf{y}$ too!

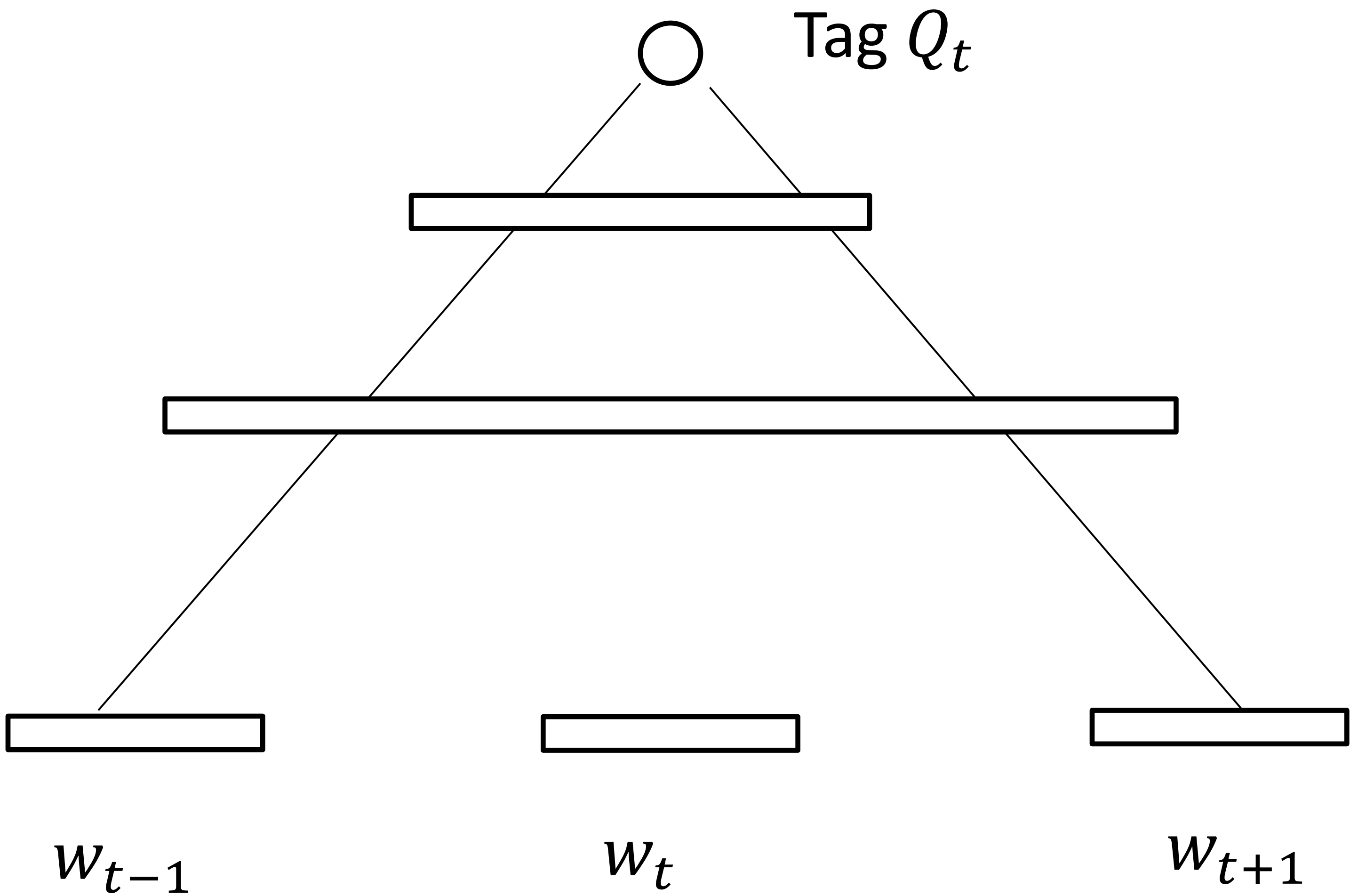
Example: Time Delay Neural Network

Let's draw a neural network architecture for POS tagging using a feedforward neural network.

We'll construct a context window around each word, and predict the POS tag of that word as the output.

Limitations of this approach?

TDNN POS Tagger



Recurrent Neural Networks

A neural network **sequence model**:

$$RNN(\mathbf{s_0}, \mathbf{x_{1:n}}) = \mathbf{s_{1:n}}, \mathbf{y_{1:n}}$$

$\mathbf{s_i} = R(\mathbf{s_{i-1}}, \mathbf{x_i})$ # $\mathbf{s_i}$: state vector

$\mathbf{y_i} = O(\mathbf{s_i})$ # $\mathbf{y_i}$: output vector

R and O are parts of the neural network that compute the next state vector and the output vector

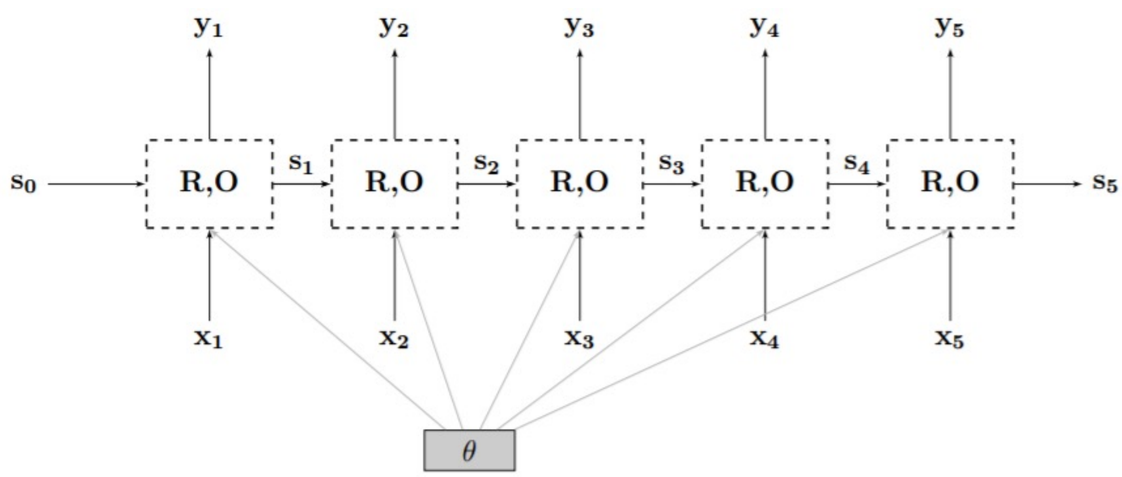


Figure 6: Graphical representation of an RNN (unrolled).

Long-Term Dependencies in Language

There can be dependencies between words that are *arbitrarily* far apart.

- *I will <u>look</u> the word that you have described that doesn't make sense to her <u>up</u>.*
- Can you think of some other examples in English of long-range dependencies?

Cannot easily model with HMMs or even LC-CRFs, but can with RNNs

Comparing LC-CRFs and RNNs

	LC-CRFs	RNNs
At each timestep	Linear model (linear between feature values and weights) similar to logistic regression	A neural network (more expressive model, may need more data to train)
Feature engineering		
Inference properties		

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Feature engineering	Necessary for performance	Less critical; neural network can learn useful features given enough labelled data
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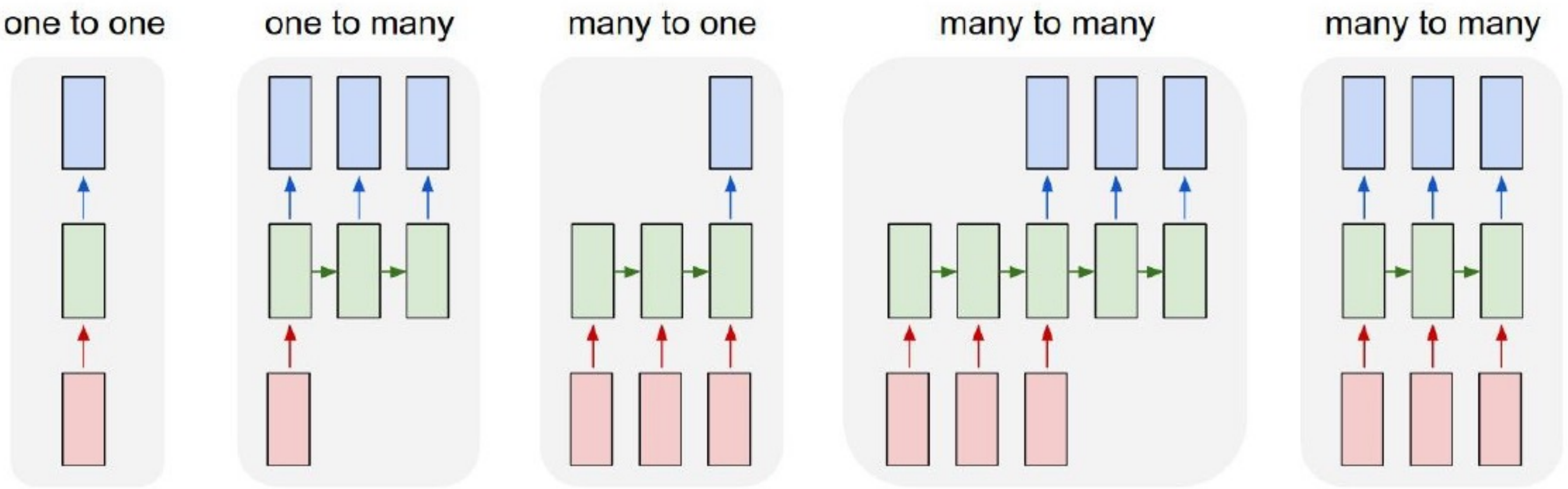
Feature engineering	Necessary for performance	Less critical; neural network can learn useful features given enough labelled data
Inference properties	Exact polynomial-time inference due to strong local independence assumptions	Approximate inference only (greedy or beam search)

Different RNN Architectures

Different architectures for different use cases



Which architecture would you use for:

- document classification?
- language modelling?
- POS tagging?

Long Short-Term Memory Networks

Popular RNN architecture for NLP

(Hochreiter and Schmidhuber, 1997)

Model includes a “memory” cell

- A vector of weights in a hidden layer
- Learned operations to:
    - Forget old information
    - Extract new information
    - Integrate relevant information into memory
    - Predict output at current timestep

Basic Operations / Components

Masking

- Multiply a vector by numbers between 0 and 1 to model forgetting vs. retaining information
- **Ingredients:** Sigmoid function, component-wise multiplication

Integrating information

- Done via component-wise addition and concatenation

Non-linearities:

- Sigmoid function (output between 0 and 1)
- Tanh function (output between -1 and 1)

Visual step-by-step explanation

http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Vanishing and Exploding Gradients

If R and O are simple fully connected layers, we have a problem. In the unrolled network, the gradient signal can get lost on its way back to the words far in the past:

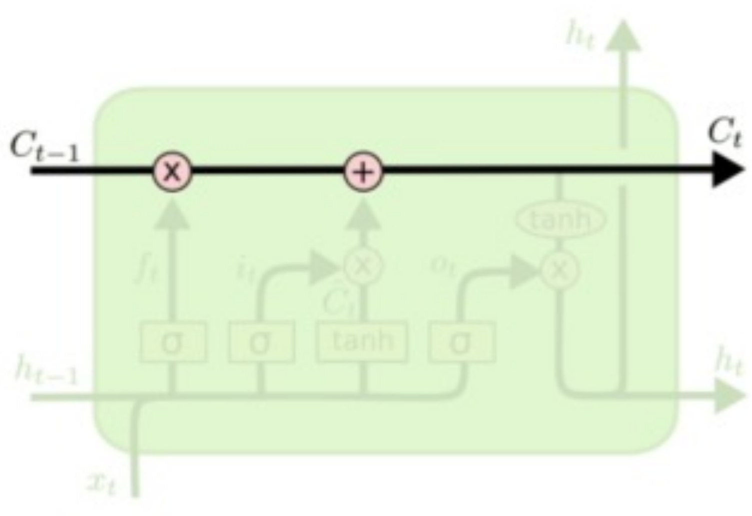
- Suppose it is $\mathbf{W}^1$ that we want to modify, and there are N layers between that and the loss function.

$$\frac{\partial L}{\partial \mathbf{W}^1} = \frac{\partial L}{\partial g^N} \frac{\partial g^N}{\partial g^{N-1}} \cdots \frac{\partial g^2}{\partial g^1} \frac{\partial g^1}{\partial \mathbf{W}^1}$$

- If the gradient norms are small (<1), the gradient will vanish to near-zero (or explode to near-infinity if >1)
- This happens especially because we have repeated applications of the same weight matrices in the recurrence

Fix for Vanishing Gradients

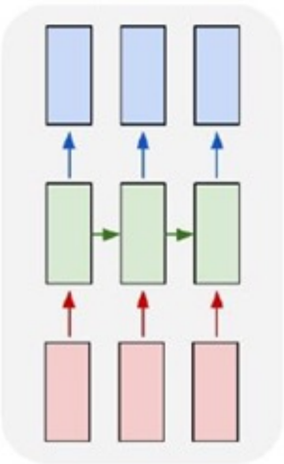
In LSTMs, we can propagate a cell state directly, fixing the vanishing gradient problem:



There is no repeated weight application between the internal states across time!

Bidirectional LSTMs – Motivation

Standard LSTMs go forward in time

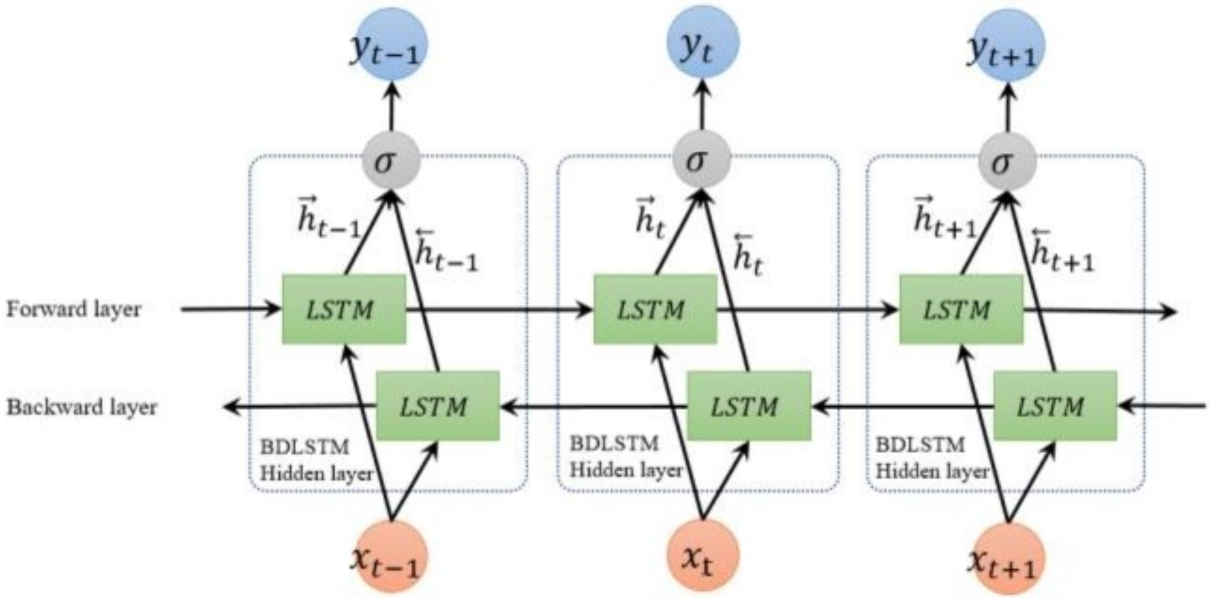


For some applications, this is necessary

For others, we would like to use both *past* context and *future* context

BiLSTMs

Have two LSTM layers, forward and backward in time



Concatenate their outputs to make final prediction

Combining LSTMs and CRFs

LSTMs allow learning of complex relationships between input and output

(LC-)CRFs allow learning of relationships between output labels in a sequence

Can we combine advantages of both?

LSTM-CRFs

Add a linear-chain CRF layer on top of a (Bi)LSTM (Huang et al., 2015; Lample et al., 2016)!

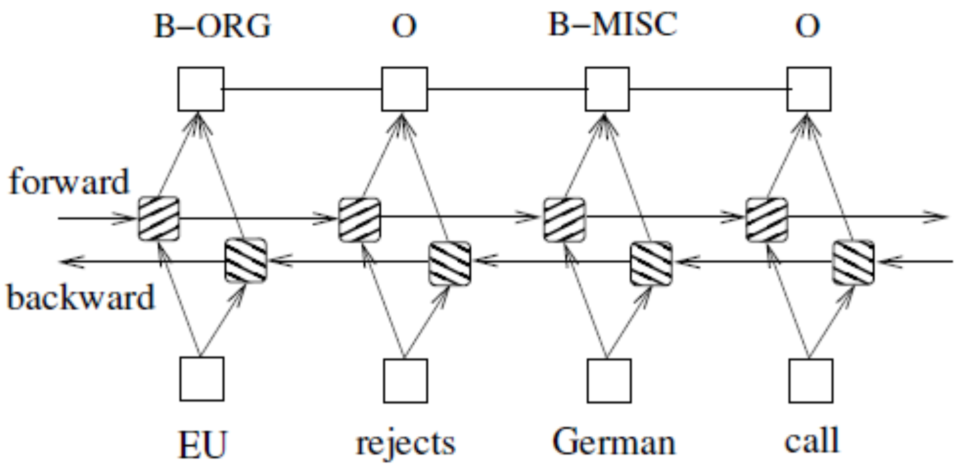


Figure 7: A BI-LSTM-CRF model.

LSTM-CRF

Features of the CRF:

- The output scores of the LSTM
- Transition probabilities between tags (need to be learned)

Score of a sequence in LSTM-CRF:

$$s(\mathbf{X}, \mathbf{y}) = \sum_{i=0}^{n} A_{y_i, y_{i+1}} + \sum_{i=1}^{n} P_{i, y_i}$$

Transition probabilities
size (k x k)

Scores from LSTM
size (n x k)

sequence of length *n*, with *k* possible tags

LSTM-CRF: Inference and Training

The LSTM-CRF is trained to minimize negative log likelihood on the training corpus (same as regular CRF):

Algorithm 1 Bidirectional LSTM CRF model training procedure

```
for each epoch do
    for each batch do
        1) bidirectional LSTM-CRF model forward pass:
            forward pass for forward state LSTM
            forward pass for backward state LSTM
        2) CRF layer forward and backward pass
        3) bidirectional LSTM-CRF model backward pass:

            backward pass for forward state LSTM
            backward pass for backward state LSTM
        4) update parameters
    end for
end for
```

Summary

LSTMs are the backbone of many modern NLP models!

LSTM-CRFs are very high performing on many basic sequence labelling tasks:

- Named entity recognition
- POS tagging
- Chunking
- Competitive with Transformers without language modelling pre-training.

Next, we will start looking at models of hierarchical structure in language.