# Recurrent Neural Networks

Lesson 9 – Section 4

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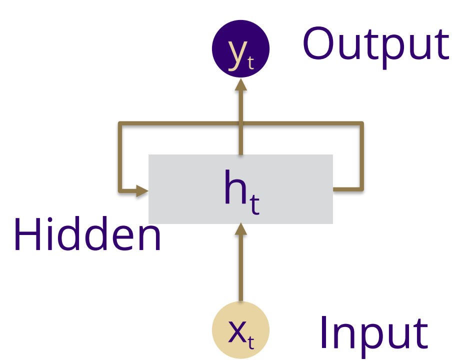
## What are RNNs

- ANN for sequential or times series data
- Perform the same task for every element of a sequence

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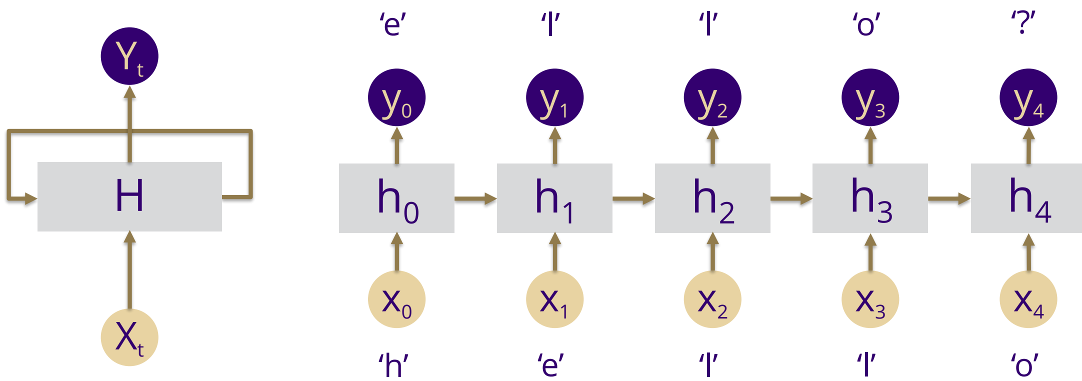
# Unfolding the RNN

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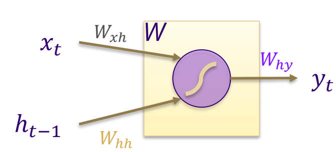
# RNN Cell

- Model Parameters:

>$h_t = \tanh(W_{hh} h_{t-1} + W_{xh} x_t)$

>$y_t = W_{hy} h_t$

Weight: hidden to hidden | Weight: hidden to hidden | Weight: input to hidden




$$P(y_t | x_1, \dots, x_t)$$

```
class RNN:
 def step(self, x):
    self.h = np.tanh(np.dot(self.W_hh, self.h) +
                 np.dot(self.W_xh, x))
    y = np.dot(self.W_hy, self.h)
    return y
```

Karpathy

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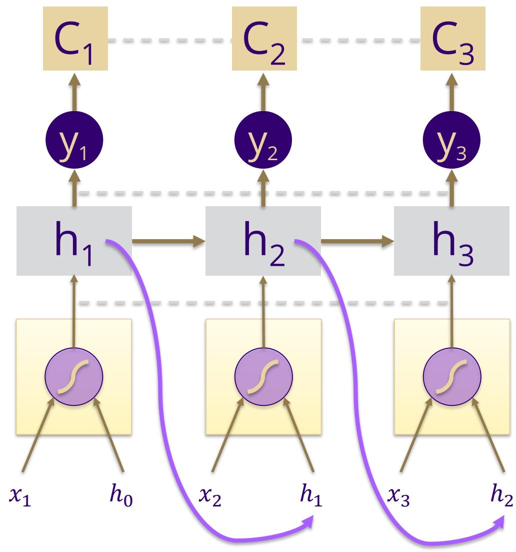
## RNN Forward




$>y_t = F(h_t)$

$>C_t = Loss(y_t GT_t)$

Shared Weights

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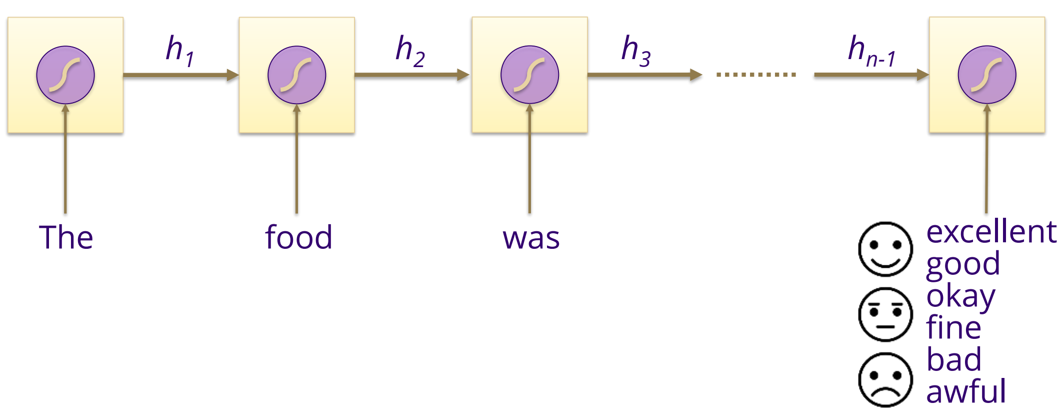
## Word-based Example: Sentiment Classification

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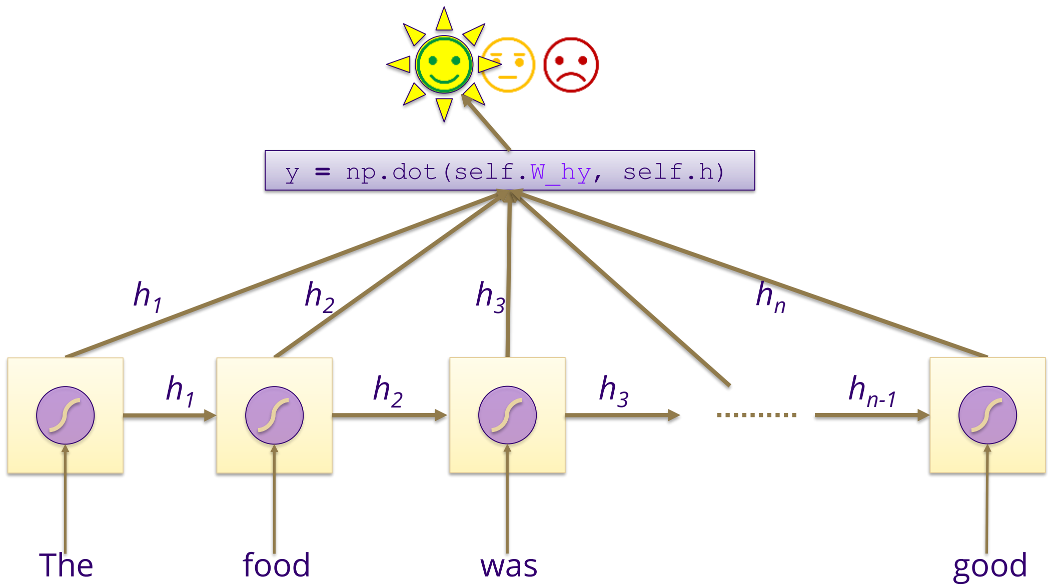
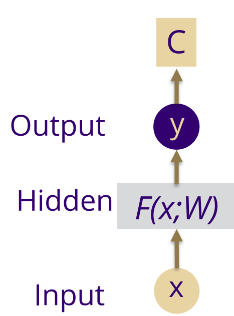



# Standard Backpropagation and SDG

Finding the Derivatives of cost with respect to any variable




- $y = f(x; W)$
- $C = loss(y, y_{GT})$

SGD

- $W \leftarrow W - \eta \frac{\partial C}{\partial W}$
- $\frac{\partial C}{\partial W} = \left(\frac{\partial C}{\partial y}\right)\left(\frac{\partial y}{\partial W}\right)$

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# Backpropagation Through Time (BPTT)

- One of the methods used to train RNNs
- Accepts as an input the entire time series from the (unfolded) generated on the feed-forward pass
- Weights updates are computed for each RNN cell in the unfolded network, which are summed (or averaged) and then applied to the RNN weights

http://www.scielo.org.mx/pdf/cys/v17n1/v17n1a3.pdf

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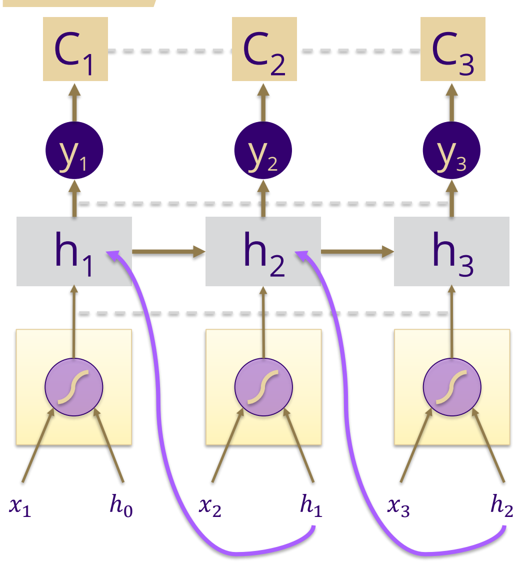
# RNN Backwards




- Treat the unfolded network as a big FF ANN
- Take the entire sequence as input
- Compute the gradients through BP/SDG
- Update the shared weights

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## Challenges of RNNs

Vanishing or exploding gradient problems

>Can use thresholds or normalized clipping

ReLu for RNNs: https://arxiv.org/abs/1504.00941

Long Short-Term Memory (LSTM)



## Long Short Term Memory Networks (LSTM)

- Preserve error backpropagated through time and layers
- Enable the network to continue to learn over longer time steps
- Creates the ability to links causes and effects that are more remote from one another
- Works well when reinforcing signals are sparse or delayed

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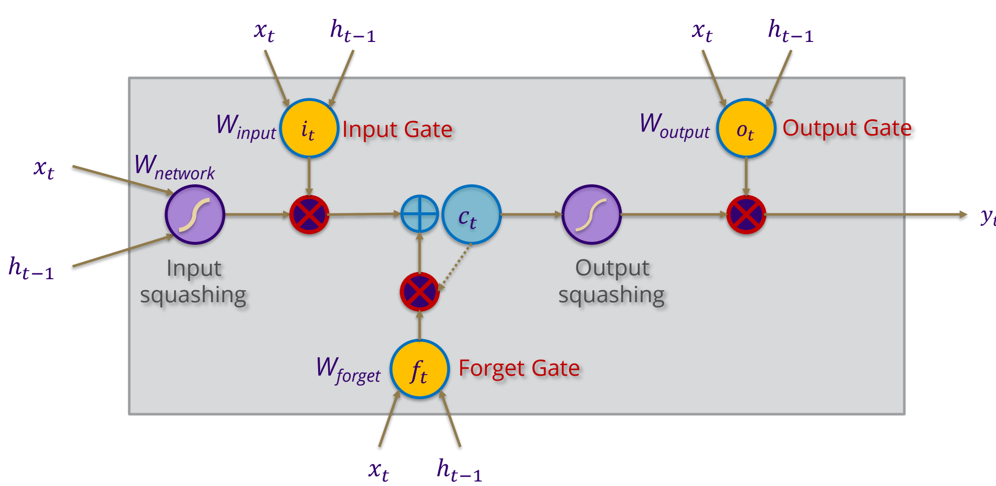
# Components of LSTM

- Gate: Optionally let information through
- Cell state: long term memory
- Forget gate: determine what old information to forget
- Input gate: determine what new information to store
- Output gate: decide what to output



## LSTM Cell



# RNN Hyperparameter Tuning

1. Learning rate is the single most important hyperparameter
2. Normalize the data
3. Try different initialization of the weight
4. Evaluate test set performance at each epoch to know when to stop
5. Try several activation functions, softsign (not softmax) is an alternative to tanh
6. Momentum applies and you can also add other types of updaters (RMSProp and AdaGrad)

Watch out for overfitting

- >You can use regularization to help with overfitting: such as L1 and L2 normalization and dropout among others
- >The larger the network, the more powerful, but it's also easier to overfit→Feature optimization is important
- >More data is almost always better, because it helps fight overfitting
- >Tune the number of epochs (complete passes through the dataset)

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# A Great Resource:

Andrej Karpathy's Blog:

[http://karpathy.github.io/2015/05/21/rnn-effectiveness/](http://karpathy.github.io/2015/05/21/rnn-effectiveness/)

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# Deep Learning

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