Adaptive Supertagging [Clark & Curran, 2007]

Start with an initial prob. cutoff β

He	reads	the	book
NP	$(S[pss]\backslash NP)/NP$	NP/N	N

Adaptive Supertagging [Clark & Curran, 2007]

Prune a category, if its probability is below β times the prob. of the best category

He	reads	the	book
NP	$(S[pss]\backslash NP)/NP$	NP/N	N

Adaptive Supertagging [Clark & Curran, 2007]

Decrease β if no spanning analysis

He	reads	the	book
NP	$(S[pss]\backslash NP)/NP$	NP/N	N
N	$(S\backslash NP)/NP$	NP/NP	$(S\backslash NP)/NP$
N/N	$S\backslash NP$		

Adaptive Supertagging [Clark & Curran, 2007]

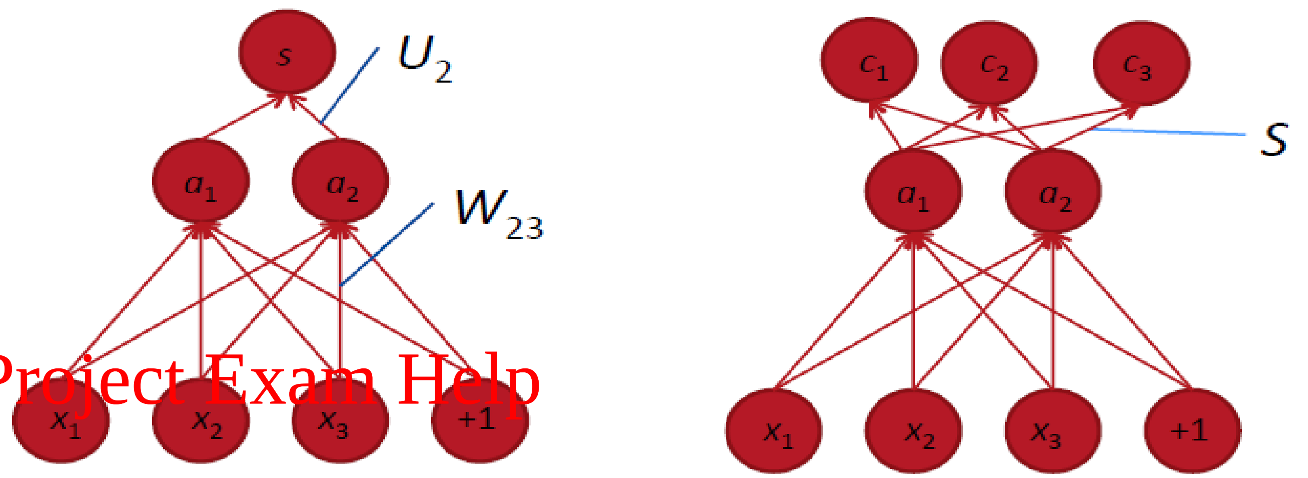
Decrease β if no spanning analysis

He	reads	the	book
NP	$(S[pss]\backslash NP)/NP$	NP/N	N
N	$(S\backslash NP)/NP$	NP/NP	$(S\backslash NP)/NP$
N/N	$S\backslash NP$		
NP/NP	$(S[pt]\backslash NP)/NP$		
	$(S[dcl]\backslash NP)/NP$		

Neural Networks

(Fig: courtesy R Socher)

Neural Networks can be built for different input, output types.



- Outputs can be:
  - Linear, single output (Linear)
  - Linear, multiple outputs (Linear)
  - Single output binary (Logistic)
  - Multi output binary (Logistic)
  - 1 of k Multinomial output (Softmax)

- Inputs can be:
  - A scalar number
  - Vector of Real numbers
  - Vector of Binary

Goal of training: Given the training data (inputs, targets) and the architecture, determine the model parameters.

Model Parameters for a 3 layer network:

- Weight matrix from input layer to the hidden (W_{jk})
- Weight matrix from hidden layer to the output (W_{kj})
- Bias terms for hidden layer
- Bias terms for output layer

Our strategy will be:

- Compute the error at the output
- Determine the contribution of each parameter to the error by taking the differential of error wrt the parameter
- Update the parameter commensurate with the error it contributed.

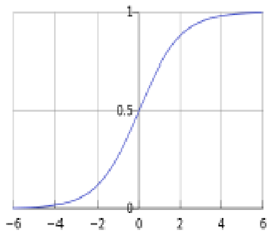
Design Choices

- When building a neural network, the designer would choose the following hyper parameters and non linearities based on the application characteristics:
  - Number of hidden layers
  - Number of hidden units in each layer
  - Learning rate
  - Regularization coefft
  - Number of outputs
  - Type of output (linear, logistic, softmax)
  - Choice of Non linearity at the output layer and hidden layer (See next slide)
  - Input representation and dimensionality

Commonly used non linearities (fig: courtesy Socher)

logistic ("sigmoid")

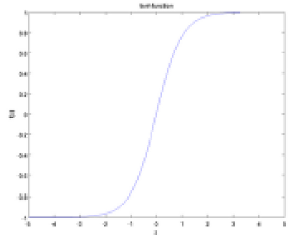
$$f(z) = \frac{1}{1+\exp(-z)}.$$



$$f'(z) = f(z)(1 - f(z))$$

tanh

$$f(z) = \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}},$$

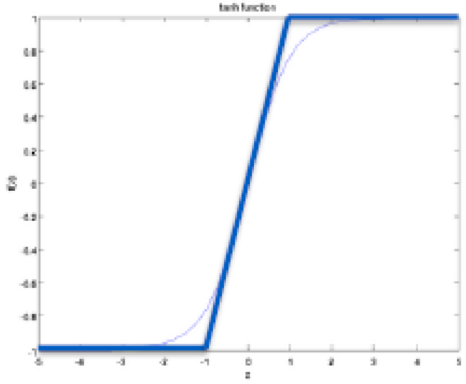


$$f'(z) = 1 - f(z)^2$$

$$\tanh(z) = 2\text{logistic}(2z) - 1$$

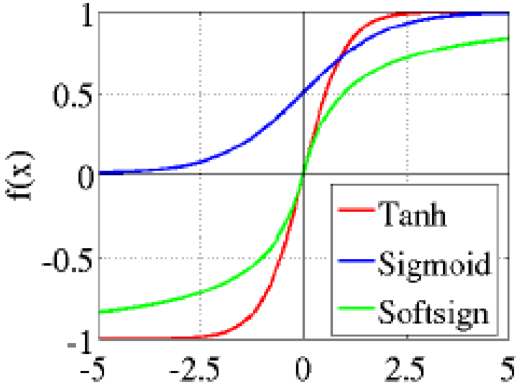
hard tanh

$$\text{HardTanh}(x) = \begin{cases} -1 & \text{if } x < -1 \\ x & \text{if } -1 <= x <= 1 \\ 1 & \text{if } x > 1 \end{cases}$$



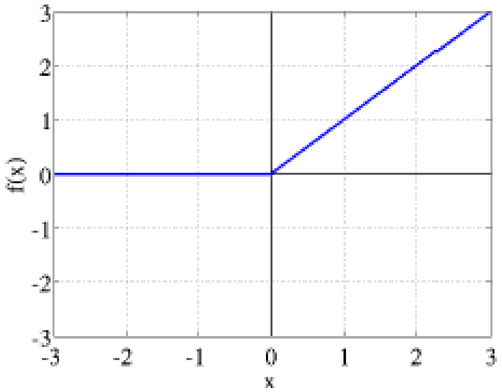
soft sign

$$\text{softsign}(z) = \frac{a}{1+|a|}$$



rectified linear (ReLu)

$$\text{rect}(z) = \max(z, 0)$$



Objective Functions and gradients

- Linear – Mean squared error
  - $E(w) = \frac{1}{2N}\sum_{1}^{N}(t_n - y_n)^2$

- Logistic with binary classifications: Cross Entropy Error

- Logistic with k outputs: k > 2: Cross Entropy Error

- Softmax: 1 of K multinomial classification: Cross Entropy Error, minimize NLL

- In all the above cases we can show that the gradient is: (y_k - t_k) where y_k is the predicted output for the output unit k and t_k is the corresponding target

High Level Backpropagation Algorithm

- Apply the input vector to the network and forward propagate. This will yield the activations for hidden layer(s) and the output layer
  - $net_j = \sum_i w_{ji} z_i,$
  - $z_j = h(net_j)$ where h is your choice of non linearity. Usually it is sigmoid or tanh. Rectified Linear Unit (RelU) is also used.

- Evaluate the error δ_k for all the output units

  $\delta_k = o_k - t_k$ where o_k is the output produced by the model and t_k is the target provided in the training dataset

- Backpropagate the δ's to obtain δ_j for each hidden unit j

$$\delta_j = h'(z_j) \sum_k w_{kj} \delta_k$$

- Evaluate the required derivatives

$$\frac{\partial E}{\partial W_{ji}} = \delta_j z_i$$

Recurrent neural networks (RNN)

Recurrent neural networks

- Use the same computational function and parameters across different time steps of the sequence
- Each time step: takes the input entry and the previous hidden state to compute the output entry
- Loss: typically computed every time step

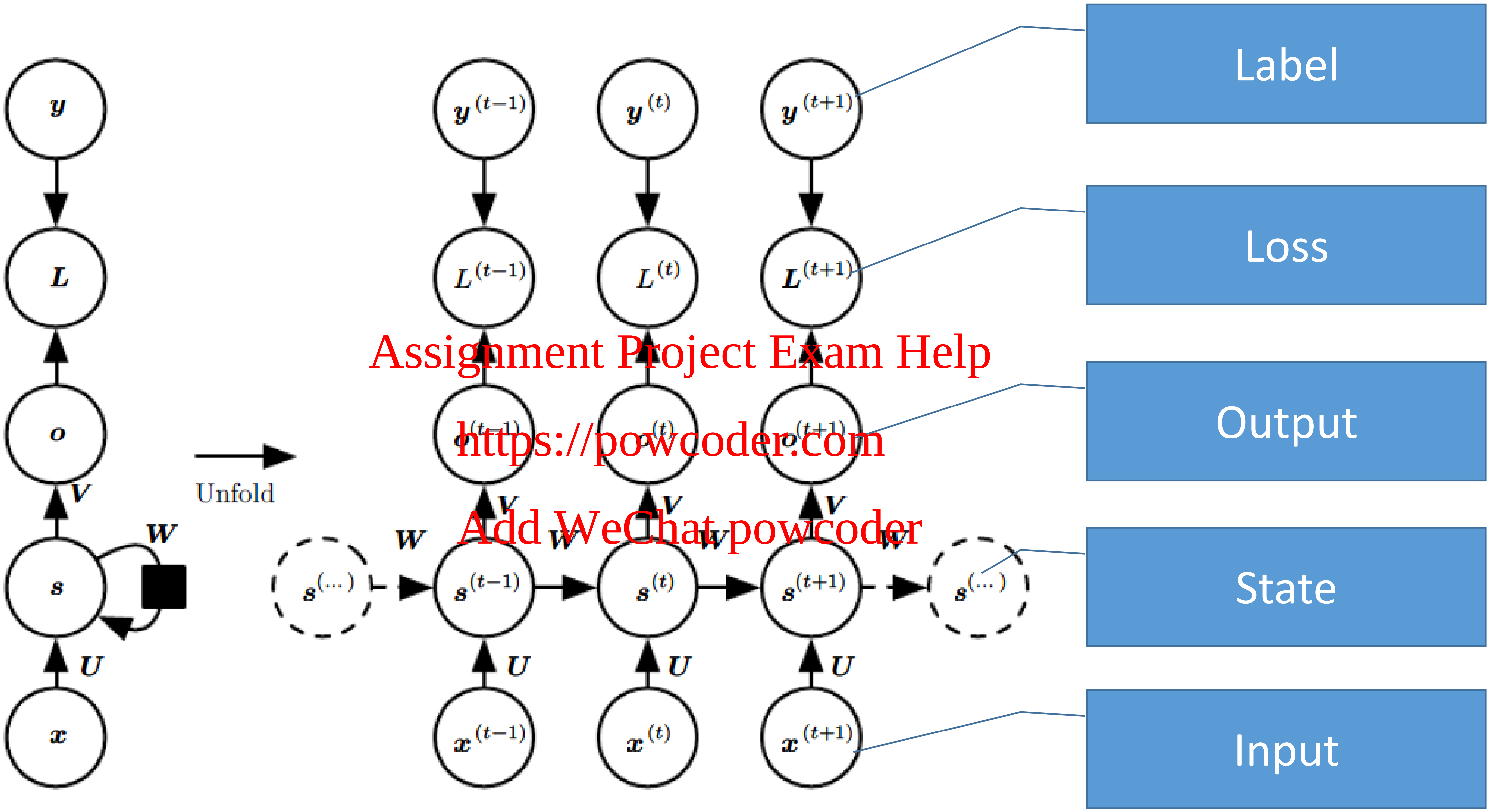
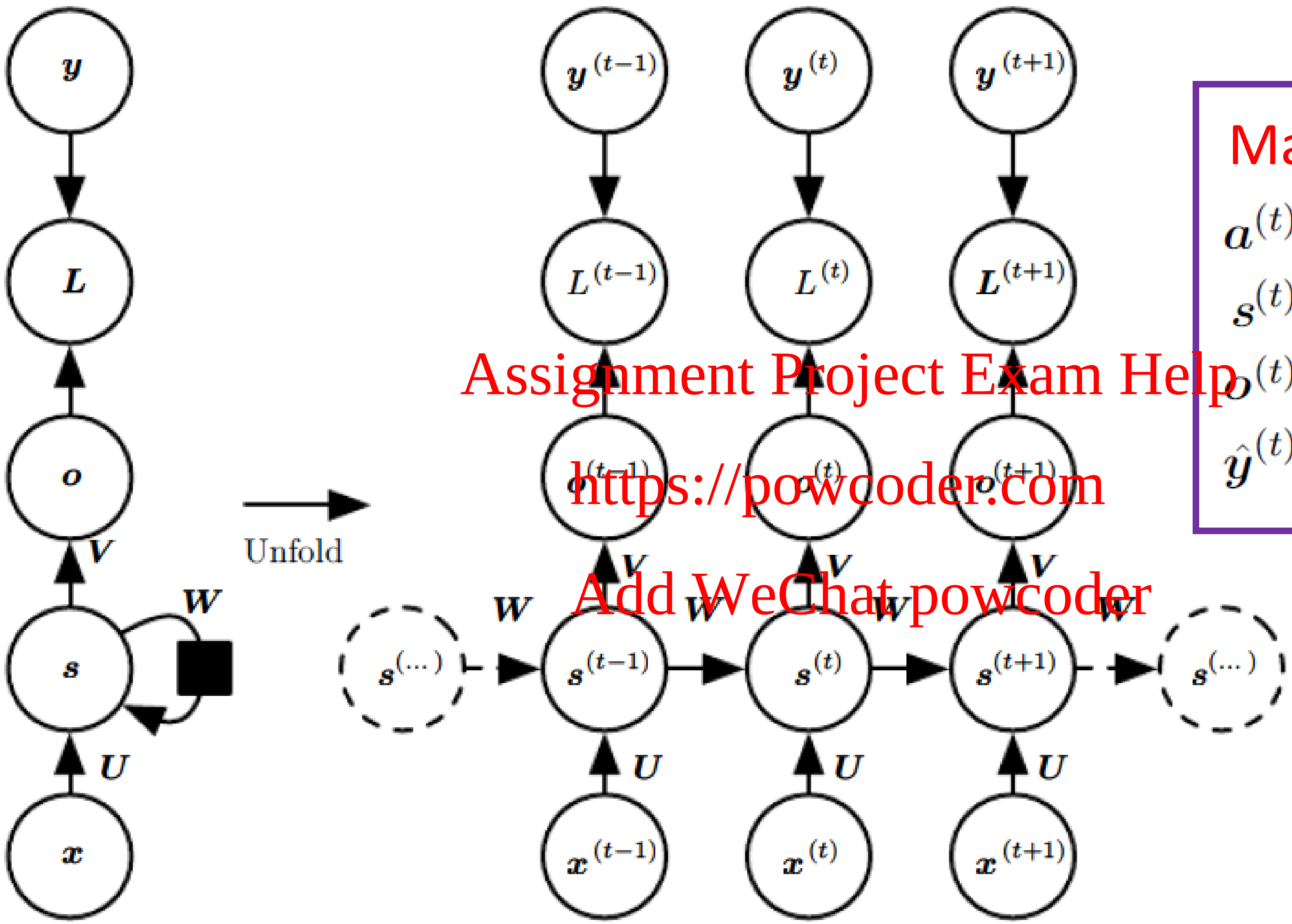


Figure from *Deep Learning*, by Goodfellow, Bengio and Courville



Math formula:

$$\begin{aligned} \boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{s}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\ \boldsymbol{s}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\ \boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{s}^{(t)} \\ \hat{\boldsymbol{y}}^{(t)} &= \operatorname{softmax}(\boldsymbol{o}^{(t)}) \end{aligned}$$

Figure from *Deep Learning*, Goodfellow, Bengio and Courville

Advantage

- Hidden state: a lossy summary of the past
- Shared functions and parameters: greatly reduce the capacity and good for generalization in learning
- Explicitly use the prior knowledge that the sequential data can be processed by in the same way at different time step (e.g., NLP)

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- Yet still powerful (actually universal): any function computable by a Turing machine can be computed by such a recurrent network of a finite size (see, e.g., Siegelmann and Sontag (1995))

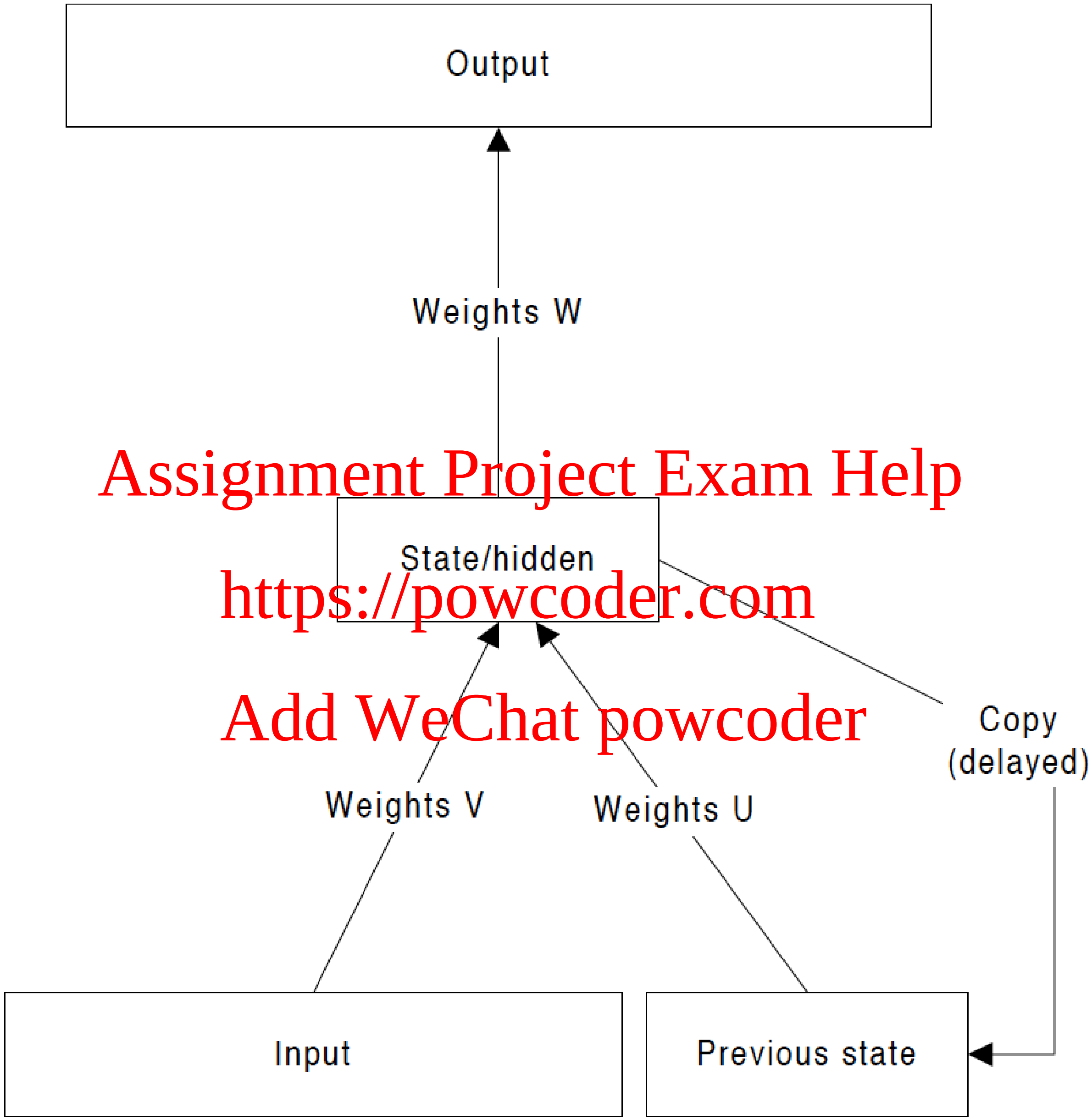

Figure 4: A simple recurrent network.

Recurrent Network Variations

- This network can theoretically learn contexts arbitrarily far back
- Many structural variations
  - Elman/Simple Net
  - Jordan Net
  - Mixed
  - Context sub-blocks, etc.
  - Multiple hidden/context layers, etc.
  - Generalized row representation
- How do we learn the weights?

Simple Recurrent Training – Elman Training

- Can think of net as just being a normal MLP structure where part of the input happens to be a copy of the last set of state/hidden node activations. The MLP itself does not even need to be aware that the context inputs are coming from the hidden layer
- Then can train with standard BP training
- While network can theoretically look back arbitrarily far in time, Elman learning gradient goes back only 1 step in time, thus limited in the context it can learn
  - Would if current output depended on input 2 time steps back
- Can still be useful for applications with short term dependencies

BPTT – Backprop Through Time

- BPTT allows us to look back further as we train
- However we have to pre-specify a value *k*, which is the maximum that learning will look back
- During training we *unfold* the network in time as if it were a standard feedfoward network with *k* layers

  - But where the weights of each unfolded layer are the same (shared)
- We then train the unfolded *k* layer feedforward net with standard BP

- Execution still happens with the actual recurrent version
- Is not knowing *k* apriori that bad? How do you choose it?
  - Cross Validation, just like finding best number of hidden nodes, etc., thus we can find a good *k* fairly reasonably for a given task
  - But problematic if the amount of state needed varies a lot

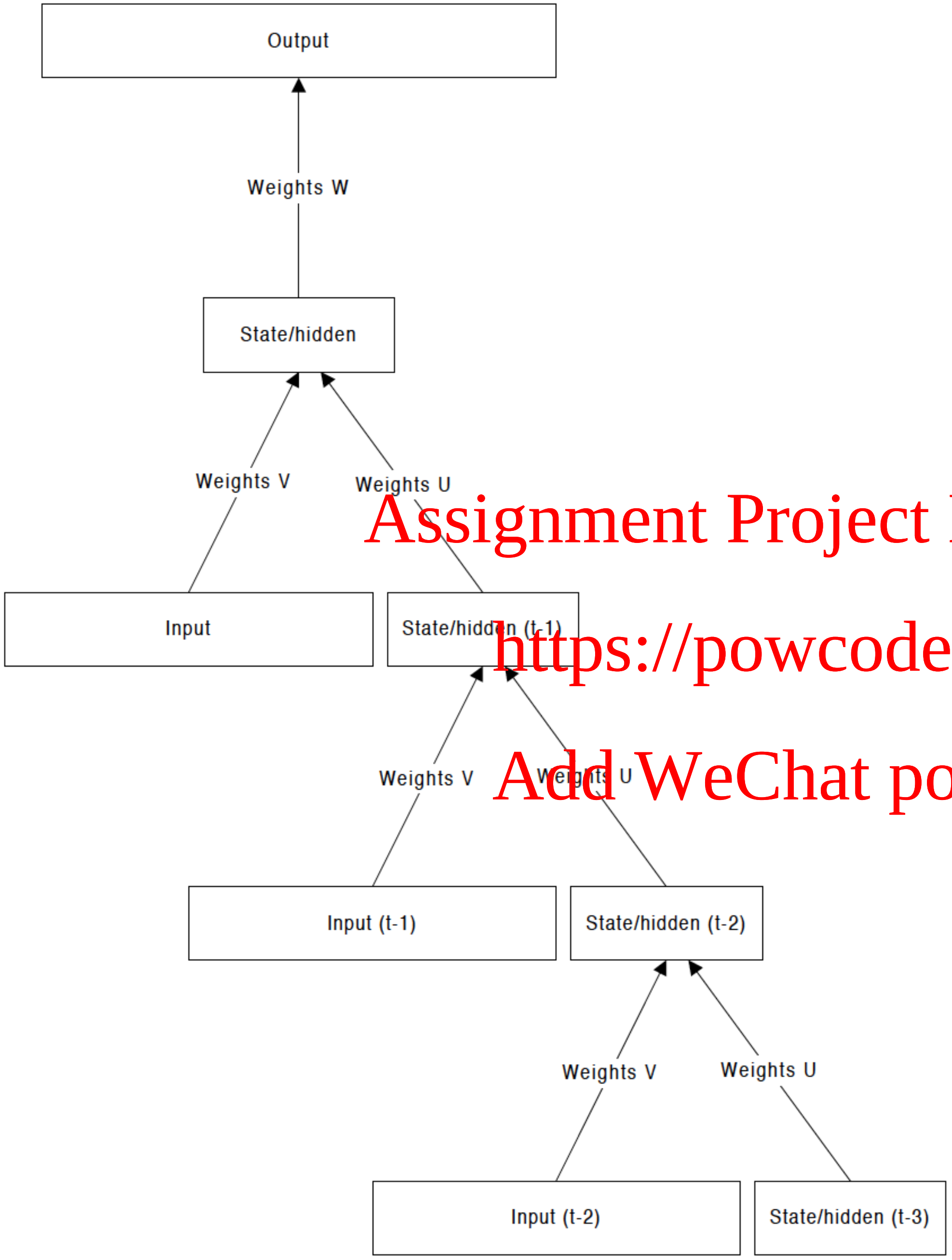

Figure 5: The effect of unfolding a network for BPTT ($\tau = 3$).

- *k* is the number of feedback/context blocks in the unfolded net.
- Note *k*=1 is just standard MLP with no feedback
- 1st block *h*(0) activations are just initialized to a constant or 0 so *k*=1 is still same as standard MLP, so just leave it out for feedforward MLP
- Last context block is *h*(*k*-1)
- *k*=2 is Elman training

Training RNN

- Principle: unfold the computational graph, and use backpropagation
- Called back-propagation through time (BPTT) algorithm
- Can then apply any general-purpose gradient-based techniques

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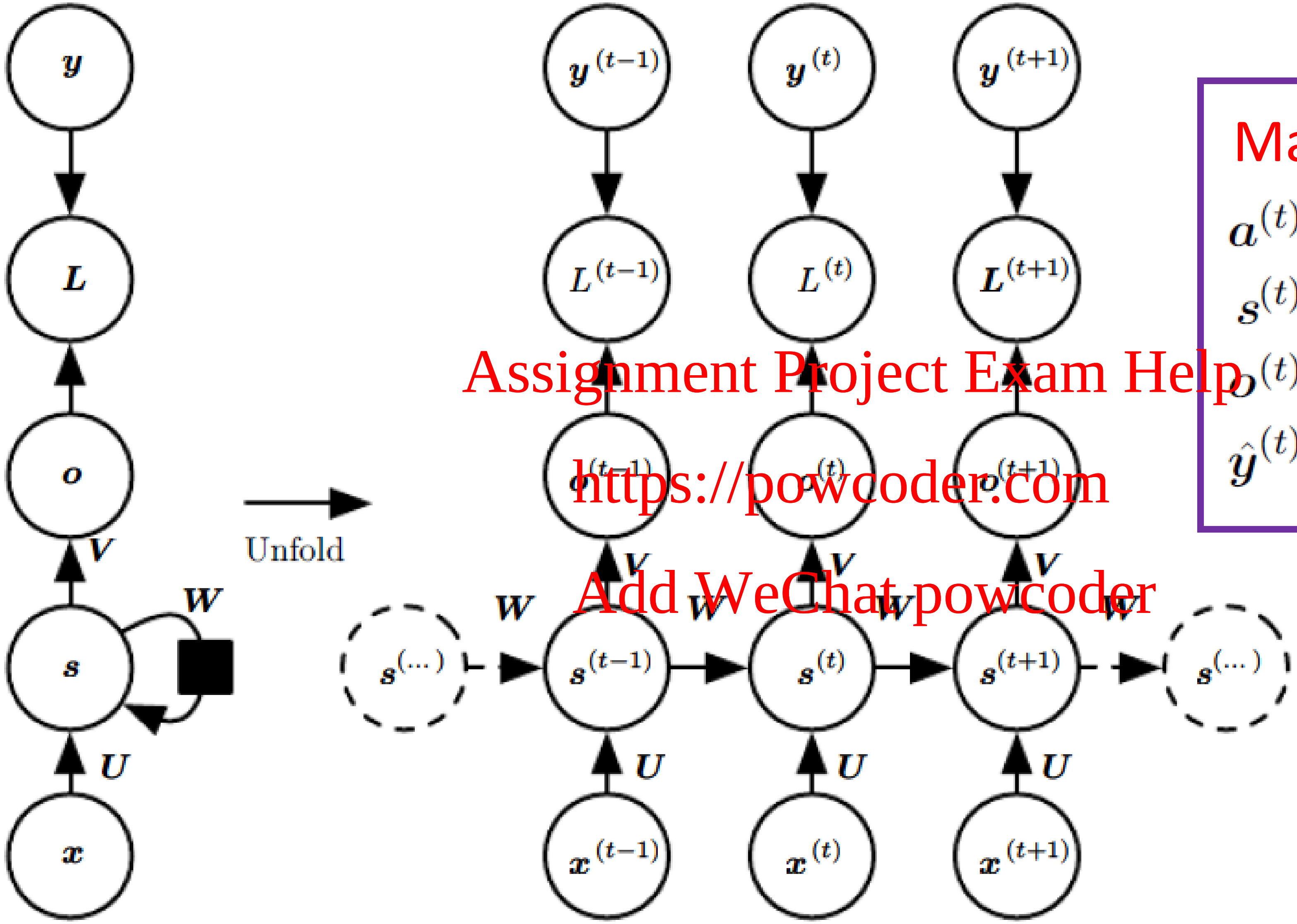
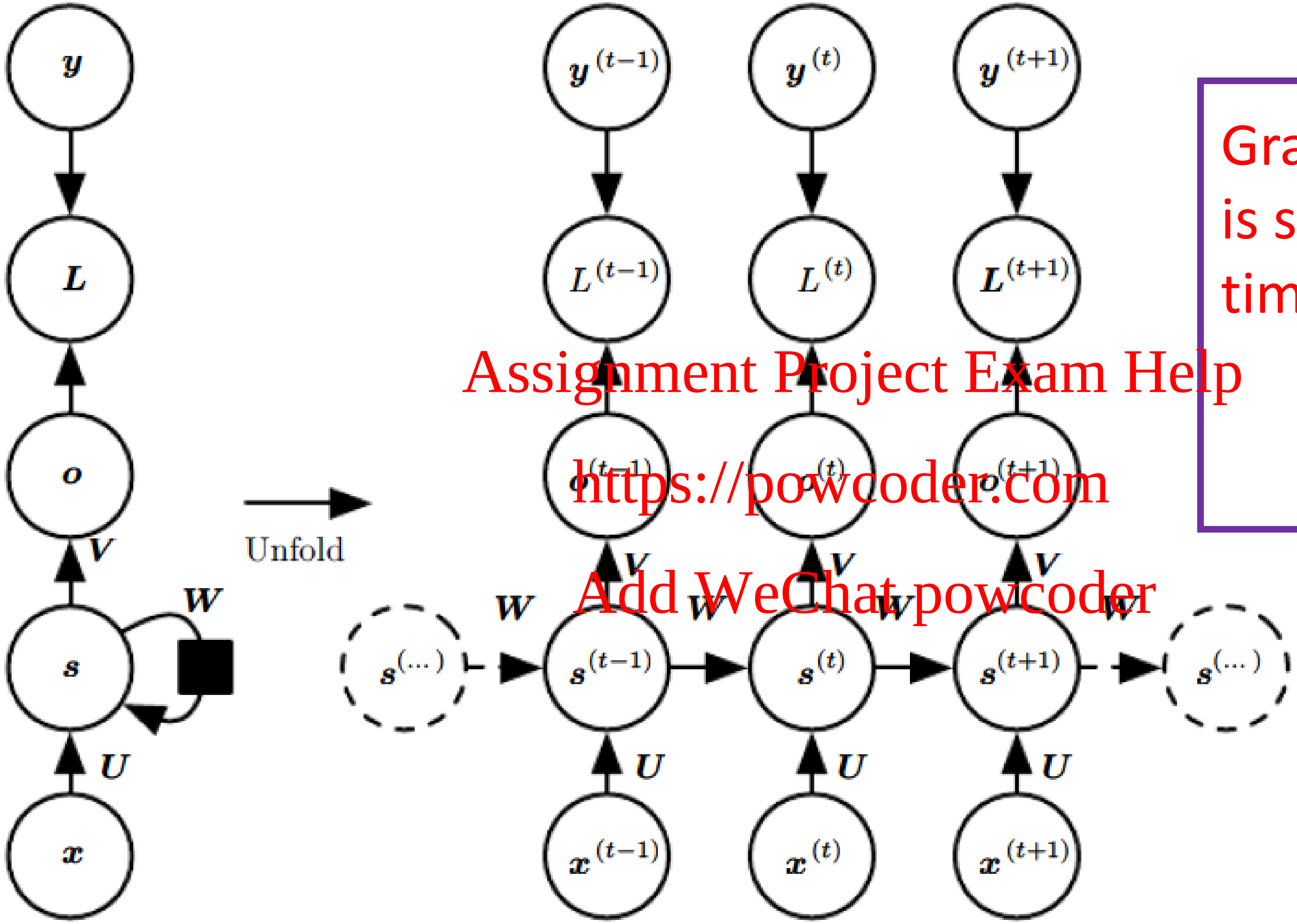
- Conceptually: first compute the gradients of the internal nodes, then compute the gradients of the parameters



Math formula:

$$
\begin{aligned}
\boldsymbol{a}^{(t)} &= \boldsymbol{b} + \boldsymbol{W}\boldsymbol{s}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)} \\
\boldsymbol{s}^{(t)} &= \tanh(\boldsymbol{a}^{(t)}) \\
\boldsymbol{o}^{(t)} &= \boldsymbol{c} + \boldsymbol{V}\boldsymbol{s}^{(t)} \\
\hat{\boldsymbol{y}}^{(t)} &= \mathrm{softmax}(\boldsymbol{o}^{(t)})
\end{aligned}
$$

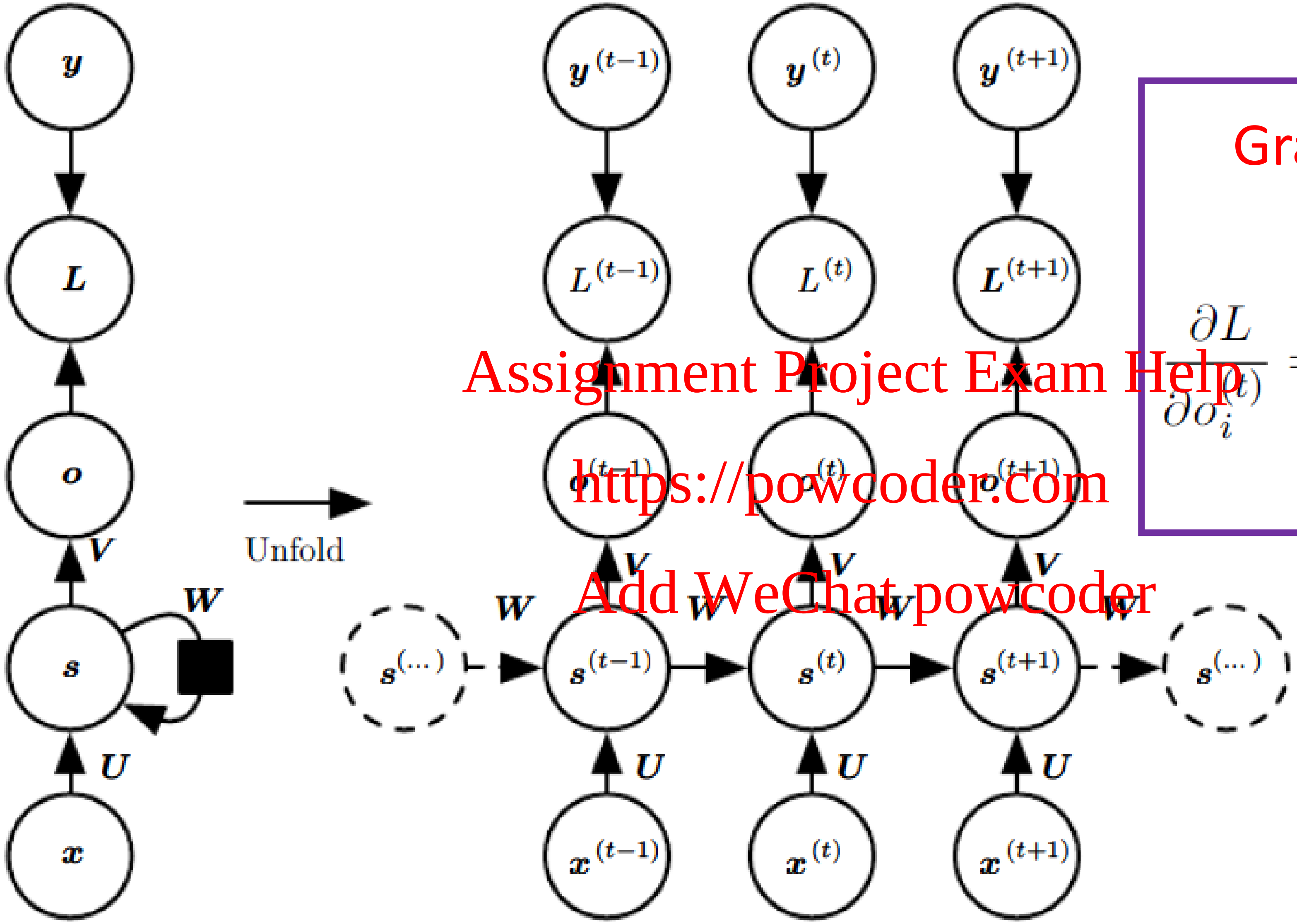
Figure from *Deep Learning*, Goodfellow, Bengio and Courville



Gradient at $L^{(t)}$: (total loss is sum of those at different time steps)

$$\frac{\partial L}{\partial L^{(t)}} = 1.$$

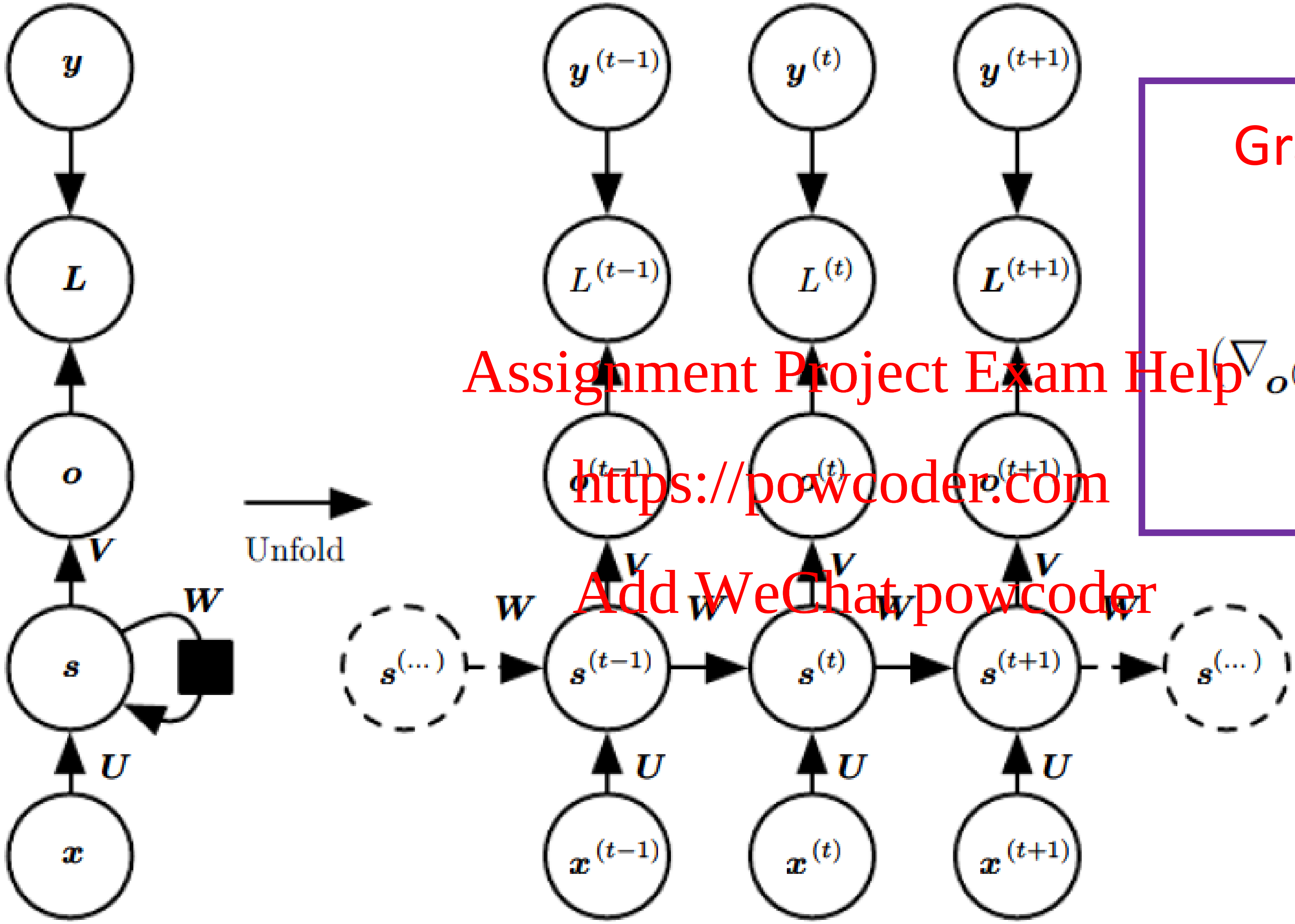
Figure from *Deep Learning*, Goodfellow, Bengio and Courville



Gradient at $o^{(t)}$:

$$\frac{\partial L}{\partial o_i^{(t)}} = \frac{\partial L}{\partial L^{(t)}} \frac{\partial L^{(t)}}{\partial o_i^{(t)}} = \hat{y}_i^{(t)} - \mathbf{1}_{i,y^{(t)}}$$

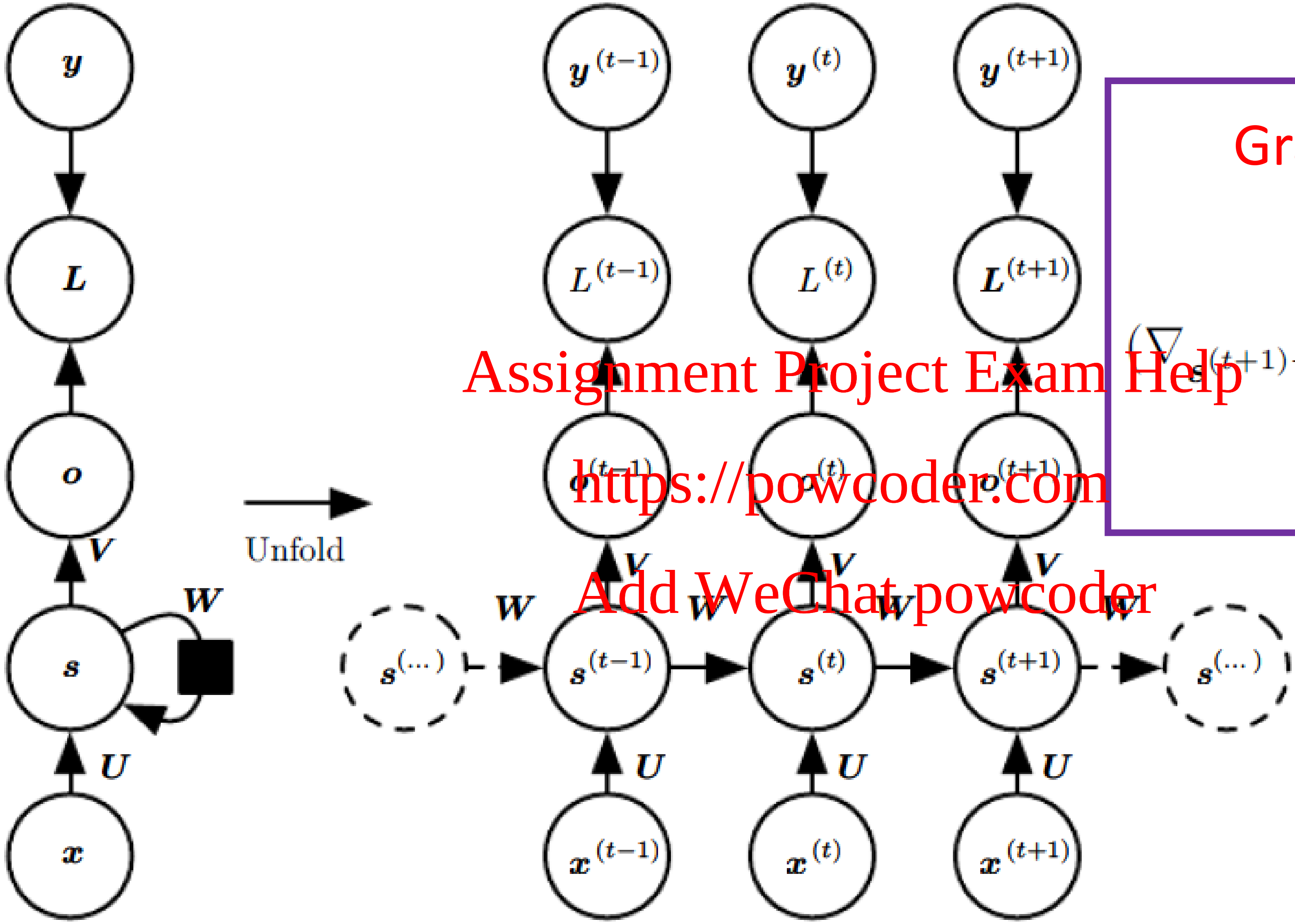
Figure from *Deep Learning*,
Goodfellow, Bengio and Courville



Gradient at $s^{(\tau)}$:

$$(\nabla_{\boldsymbol{o}^{(\tau)}} L) \frac{\partial \boldsymbol{o}^{(\tau)}}{\partial \boldsymbol{s}^{(\tau)}} = (\nabla_{\boldsymbol{o}^{(\tau)}} L)\, \boldsymbol{V}$$

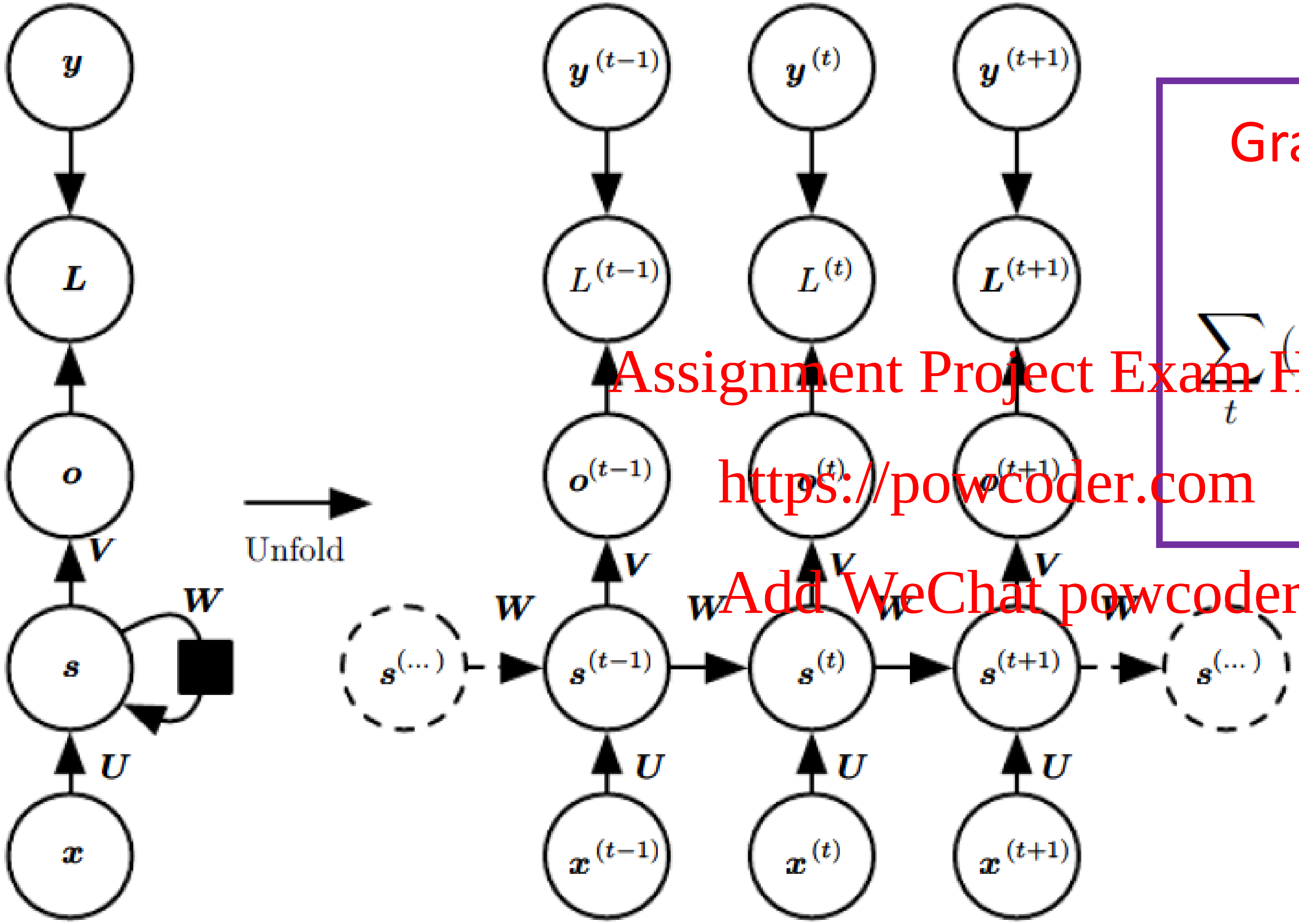
Figure from *Deep Learning*, Goodfellow, Bengio and Courville



Gradient at $s^{(t)}$:

$$(\nabla_{s^{(t+1)}} L)\frac{\partial s^{(t+1)}}{\partial s^{(t)}} + (\nabla_{o^{(t)}} L)\frac{\partial o^{(t)}}{\partial s^{(t)}}$$

Figure from *Deep Learning*, Goodfellow, Bengio and Courville



Gradient at parameter V:

$$\sum_t \left(\nabla_{\boldsymbol{o}^{(t)}} L\right) \frac{\partial \boldsymbol{o}^{(t)}}{\partial \boldsymbol{V}} = \sum_t \left(\nabla_{\boldsymbol{o}^{(t)}} L\right) \boldsymbol{s}^{(t)\top}$$

Figure from *Deep Learning*,
Goodfellow, Bengio and Courville

Dealing with the vanishing/exploding gradient in RNNs

- Gradient clipping – for large gradients – type of adaptive LR
- Linear self connection near one for gradient – Leaky unit
- Skip connections
  - Make sure can be influenced by units *d* skips back, still limited by amount of skipping, etc.
- Time delays and different time scales
- LSTM – Long short term memory - Current state of the art
  - Gated recurrent network
  - Keeps self loop to maintain state and gradient constant as long as needed – self loop is gated by another learning node - forget gate
  - Learns when to use and forget the state

Other Recurrent Approaches

- *LSTM*
- *RTRL* – Real Time Recurrent Learning
  - Do not have to specify a *k*, will look arbitrarily far back
  - But note, that with an expectation of looking arbitrarily far back, you create a very difficult problem expectation
  - Looking back more requires increase in data, else overfit – Lots of irrelevant options which could lead to minor accuracy improvements
  - Have reasonable expectations
  - n^4 and n^3 versions – too expensive in practice
- Recursive Network – Dynamic tree structures
- Reservoir computing: Echo State Networks and Liquid State machines
- Hessian Free Learning
- Tuned initial states and momentum
- Neural Turing Machine – RNN which can learn to read/write memory
- Relaxation networks – Hopfield, Boltzmann, Multcons, etc.

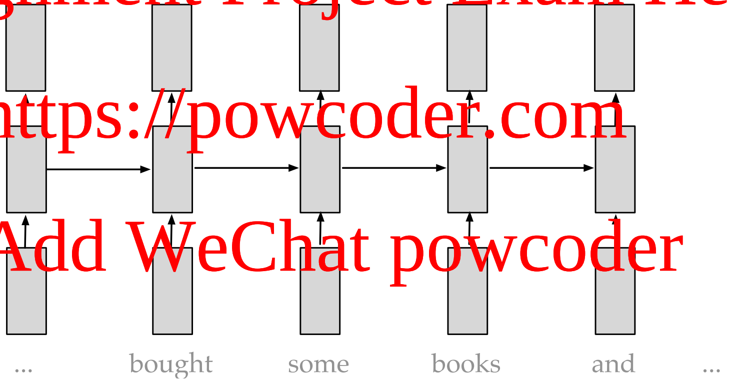
Supertagging with a RNN

- Using only dense features

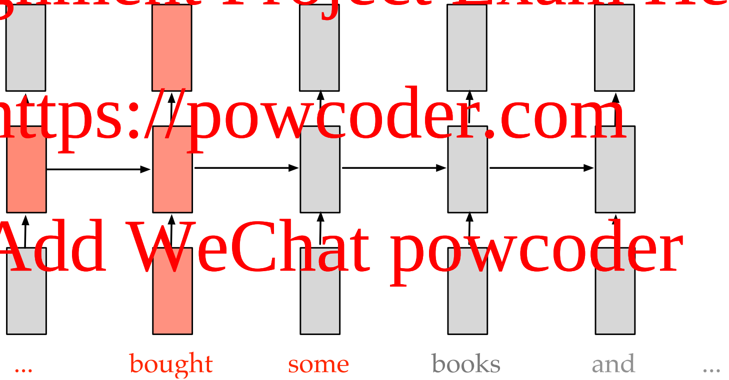
  - word embedding
  - suffix embedding
  - capitalization

- The input layer is a concatenation of all embeddings of all words in a context window

Supertagging with a RNN



Supertagging with a RNN



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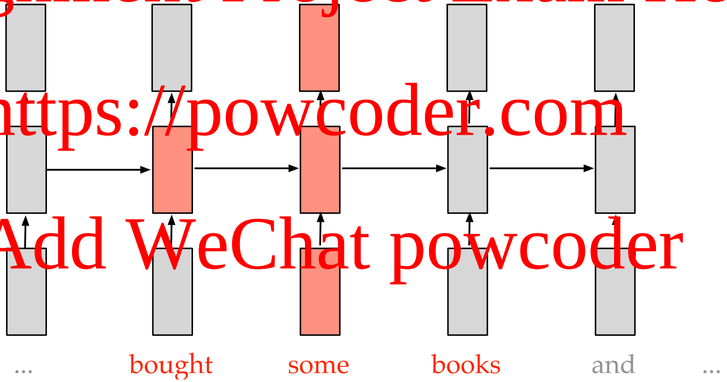

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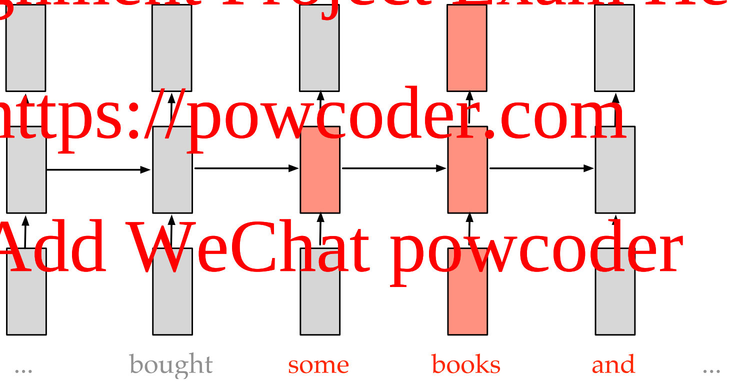
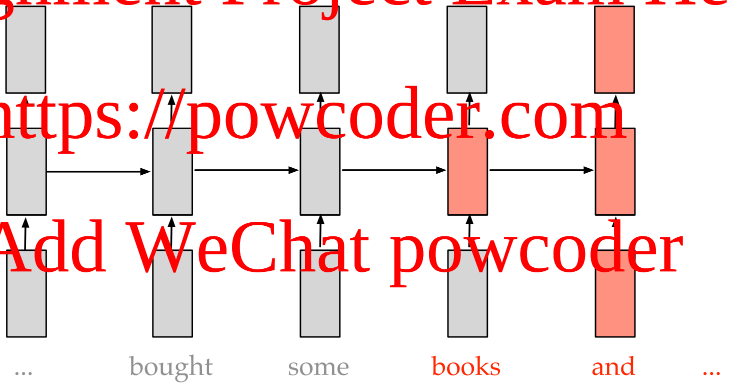


Supertagging with a RNN



1-best Supertagging Results: dev

Model	Accuracy	Time
C&C (gold POS)	92.60	-
C&C (auto POS)	91.50	0.57
NN	91.10	21.00
RNN	92.63	-
RNN+dropout	93.07	2.02

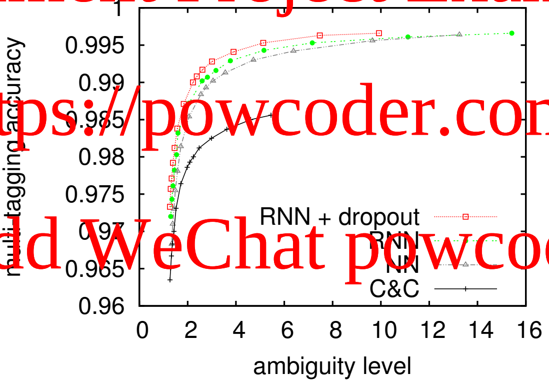
Table 1: 1-best tagging accuracy and speed comparison on CCGBank Section 00 with a single CPU core (1,913 sentences), tagging time in secs.

1-best Supertagging Results: test

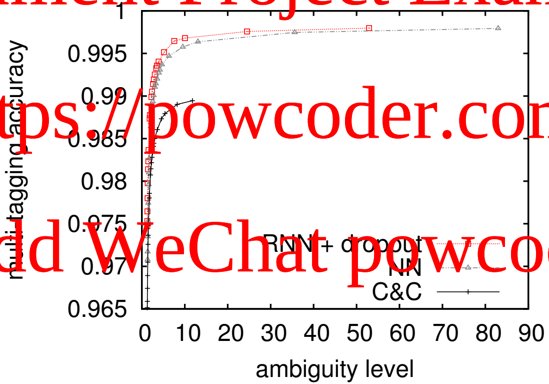
Model	Section 23	Wiki	Bio
C&C (gold POS)	93.32	88.80	91.85
C&C (auto POS)	92.02	88.80	89.08
NN	91.57	89.00	88.16
RNN	93.00	90.00	88.27

Table 2: 1-best tagging accuracy comparison on CCGBank Section 23 (2,407 sentences), Wikipedia (200 sentences) and Bio-GENIA (1,000 sentences).

Multi-tagging Results: dev



Multi-tagging Results: test



Final Parsing Results

	CCGBank Section 23				Wikipedia			
	LP	LR	LF	cov.	LP	LR	LF	
C&C	86.24	84.85	85.54	99.42	81.58	80.08	80.83	99.50
(NN)	86.71	85.56	86.13	99.92	82.65	81.36	82.00	**100**
(RNN)	**87.68**	**86.47**	**87.07**	**99.96**	**83.22**	**81.78**	**82.49**	**100**
C&C	86.24	84.17	85.19	100	81.58	79.48	80.52	100
(NN)	86.71	85.40	86.05	100	-	-	-	-
(RNN)	**87.68**	**86.41**	**87.04**	100	-	-	-	-

Table 3 : Parsing test results (auto POS). We evaluate on all sentences (100% coverage) as well as on only those sentences that returned spanning analyses (% cov.). RNN and NN both have 100% coverage on the Wikipedia data.