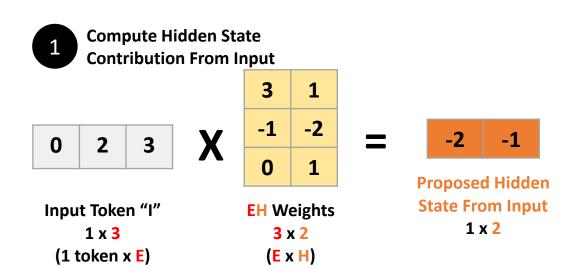
Problem statement: Use an RNN to predict the sentiment of the following document

I love cats \rightarrow 1 (positive)

- (E) Embedding Size = 3
- (H) Hidden State Dimensions = 2
- (Y) Output Dimension = 1



Sequence Step 1/4

Hidden

State

1 x 2

HH Weights

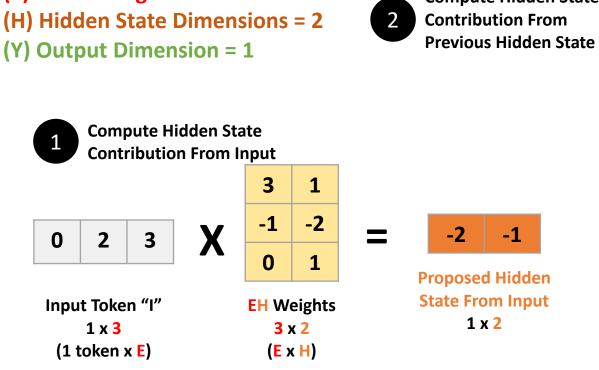
2 x 2

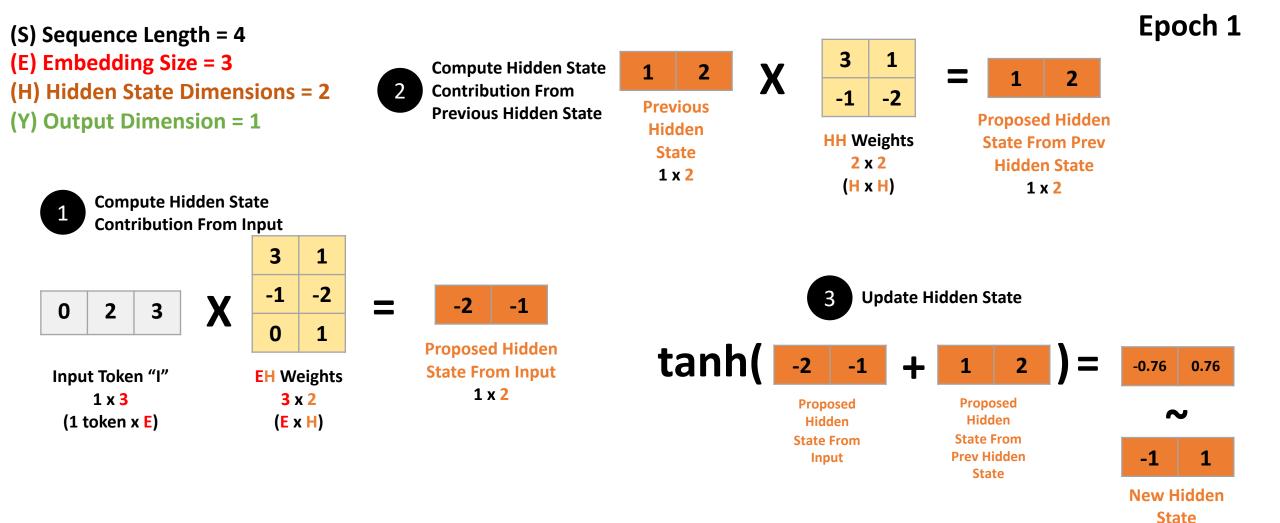
 $(H \times H)$

State From Prev

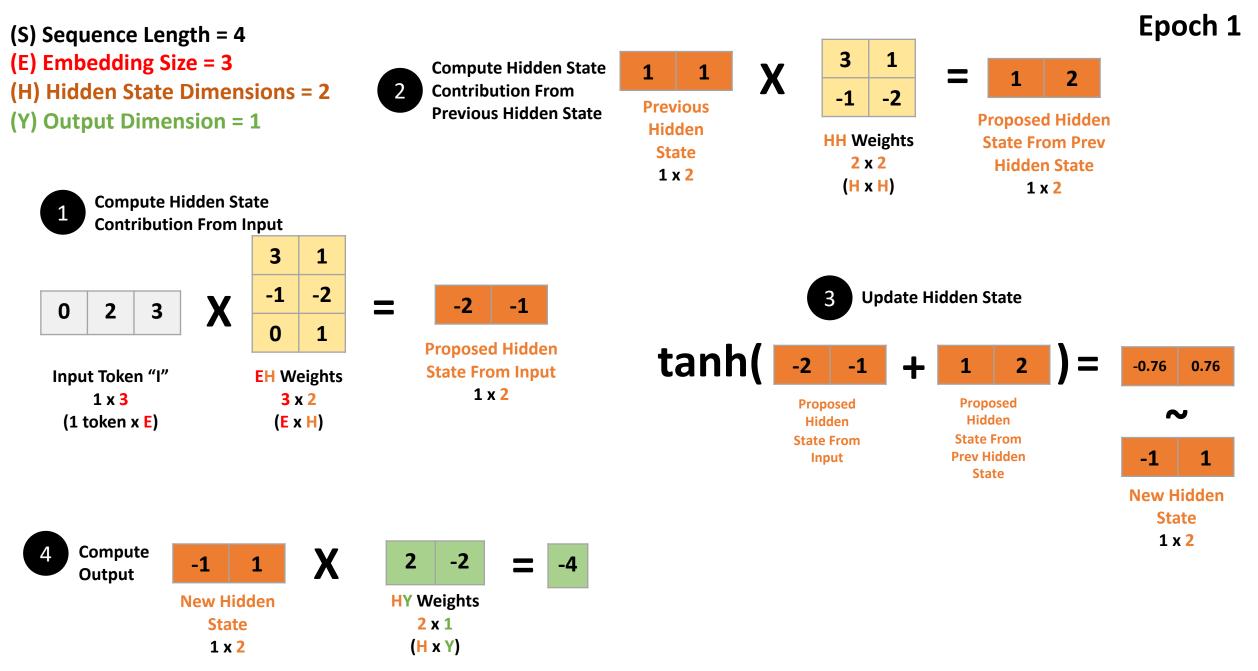
Hidden State

1 x 2

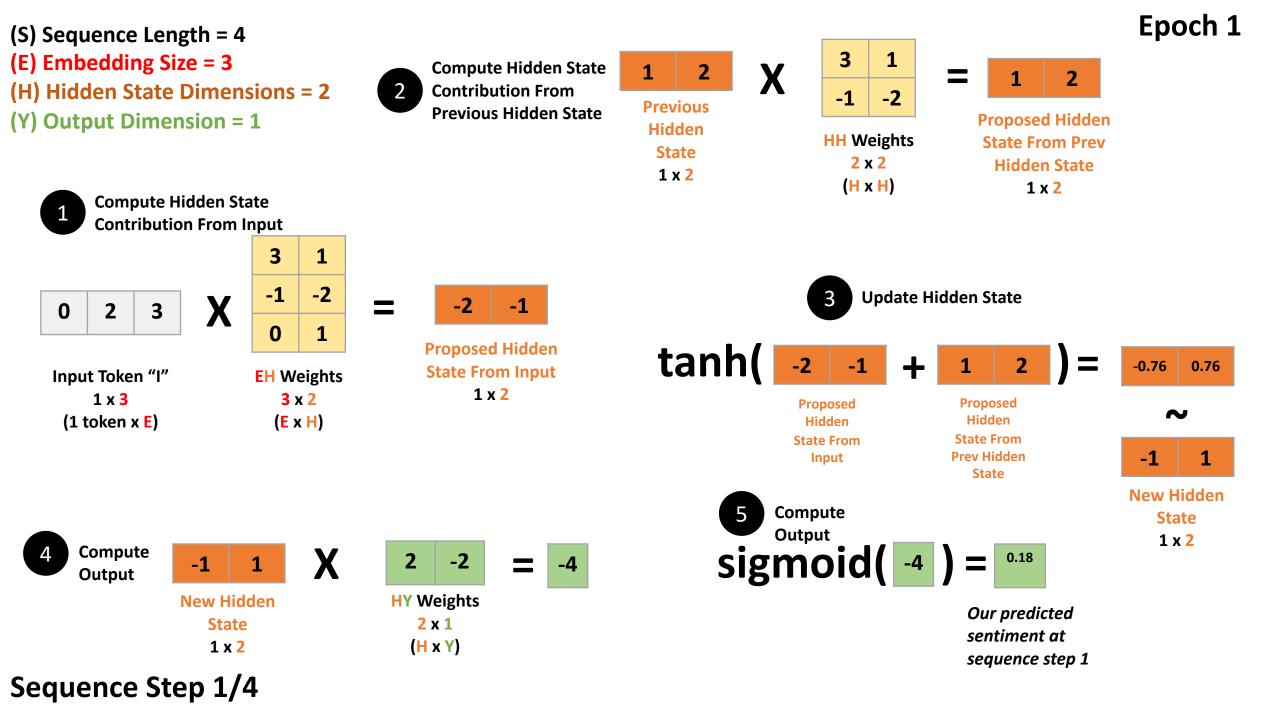




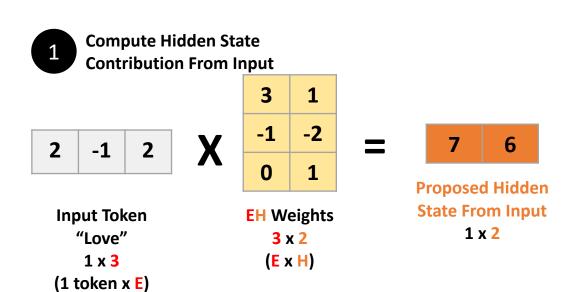
1 x 2



Sequence Step 1/4



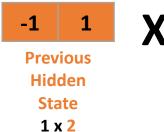
- (E) Embedding Size = 3
- (H) Hidden State Dimensions = 2
- (Y) Output Dimension = 1

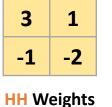


Sequence Step 2/4

- (H) Hidden State Dimensions = 2 **Contribution From**
- (Y) Output Dimension = 1

Previous Hidden State

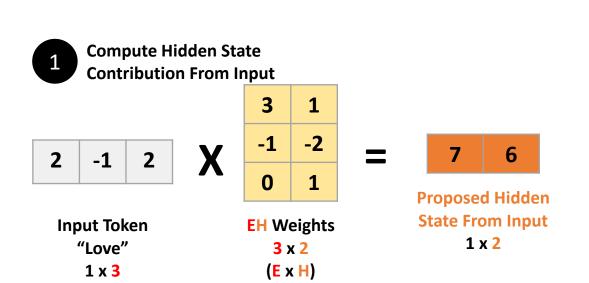




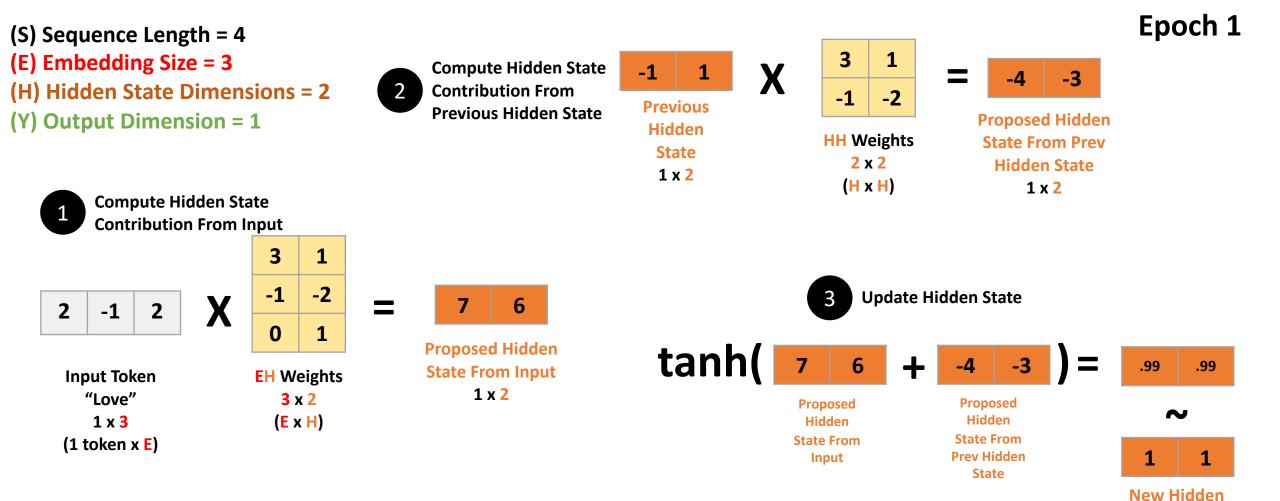
2 x 2

 $(H \times H)$

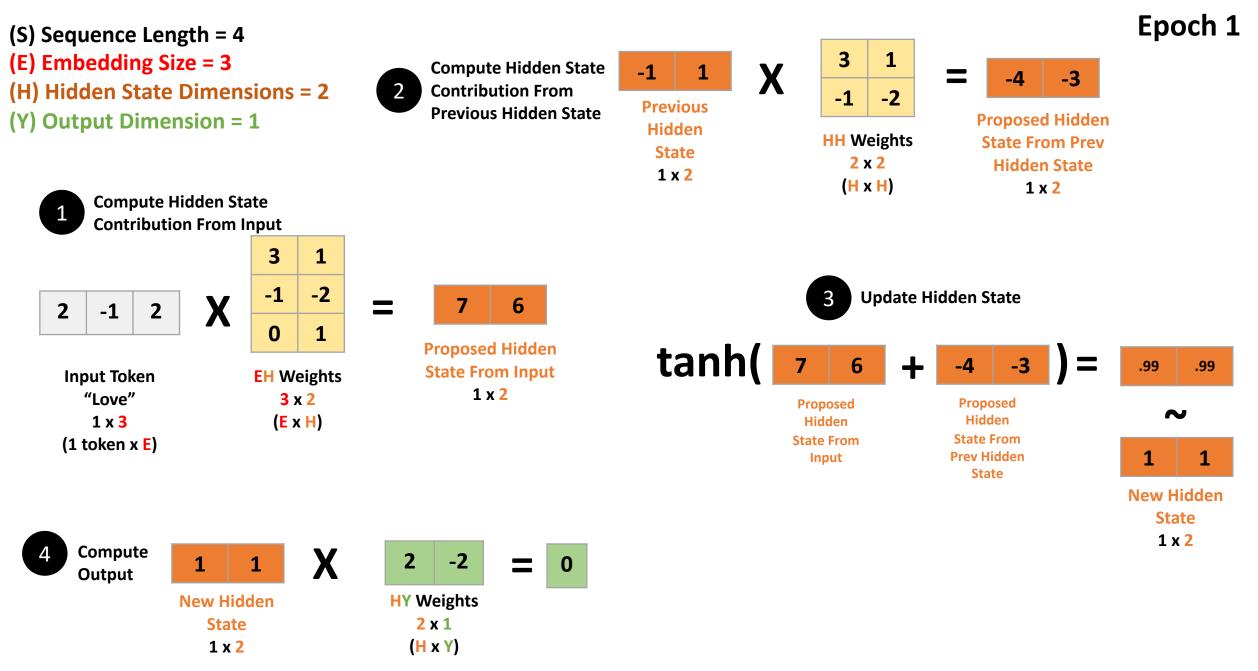




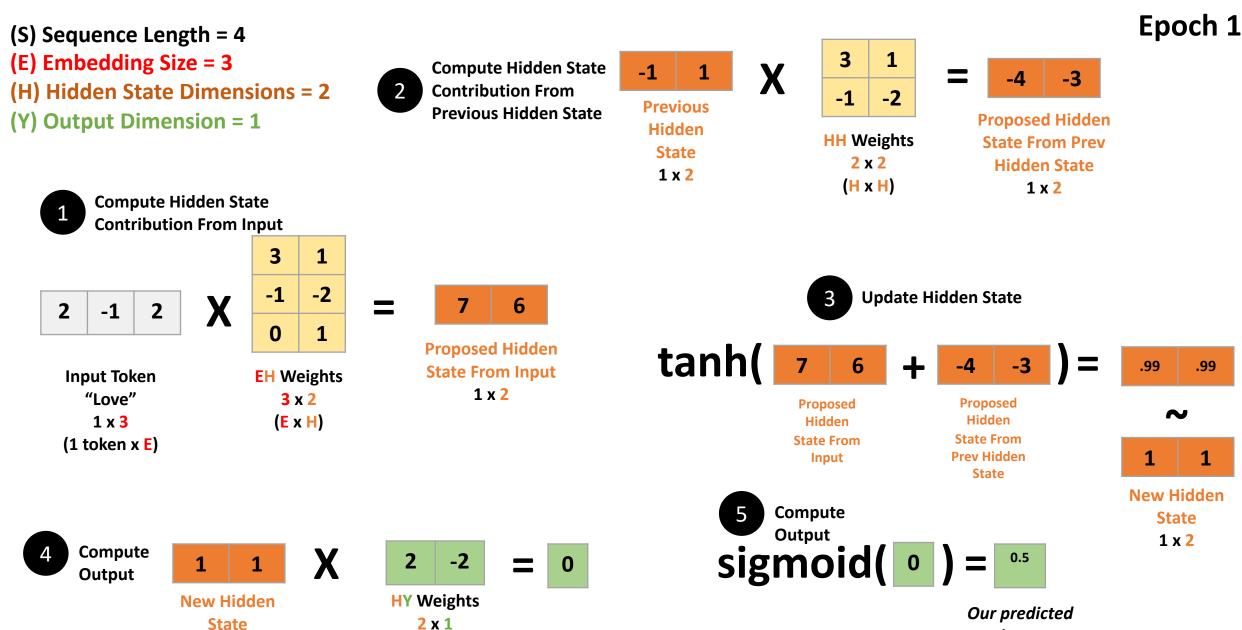
(1 token x E)



State 1 x 2



Sequence Step 2/4



.99

~

State

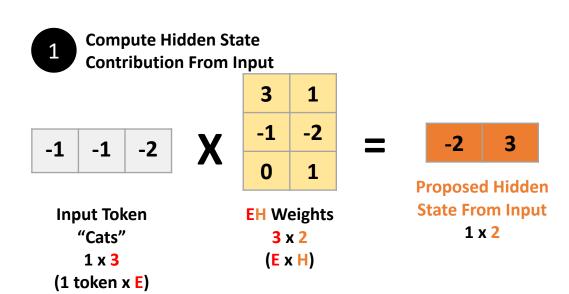
1 x 2

.99

sentiment at 1 x 2 $(H \times Y)$ sequence step 2

Sequence Step 2/4

- (E) Embedding Size = 3
- (H) Hidden State Dimensions = 2
- (Y) Output Dimension = 1



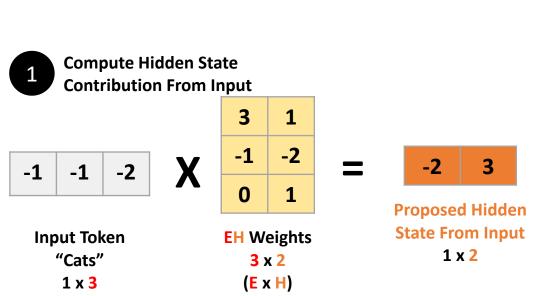
1 x 2

Hidden State

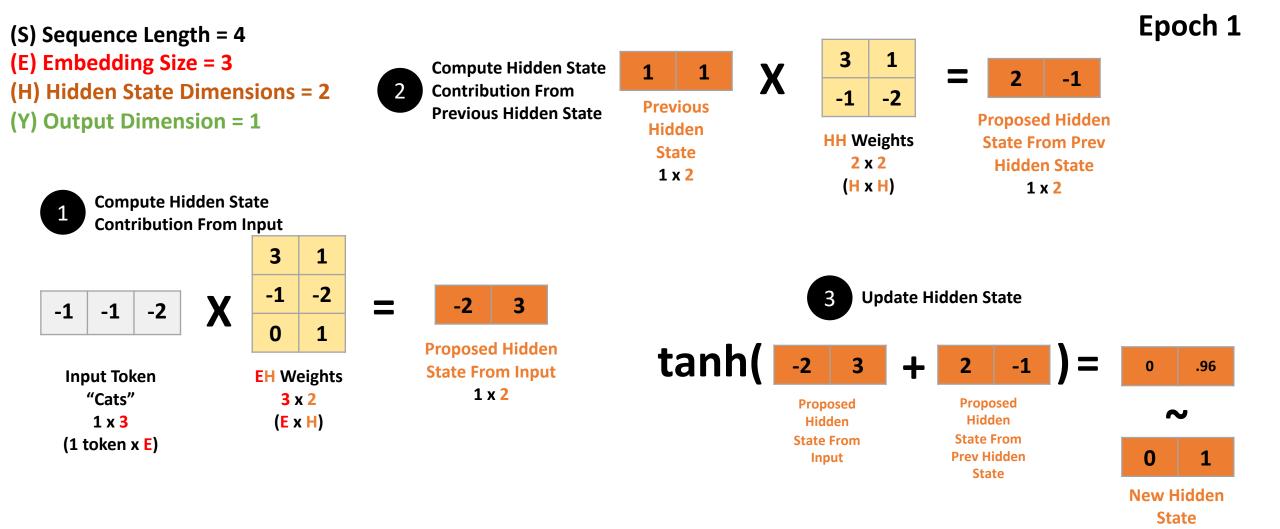
1 x 2

 $(H \times H)$

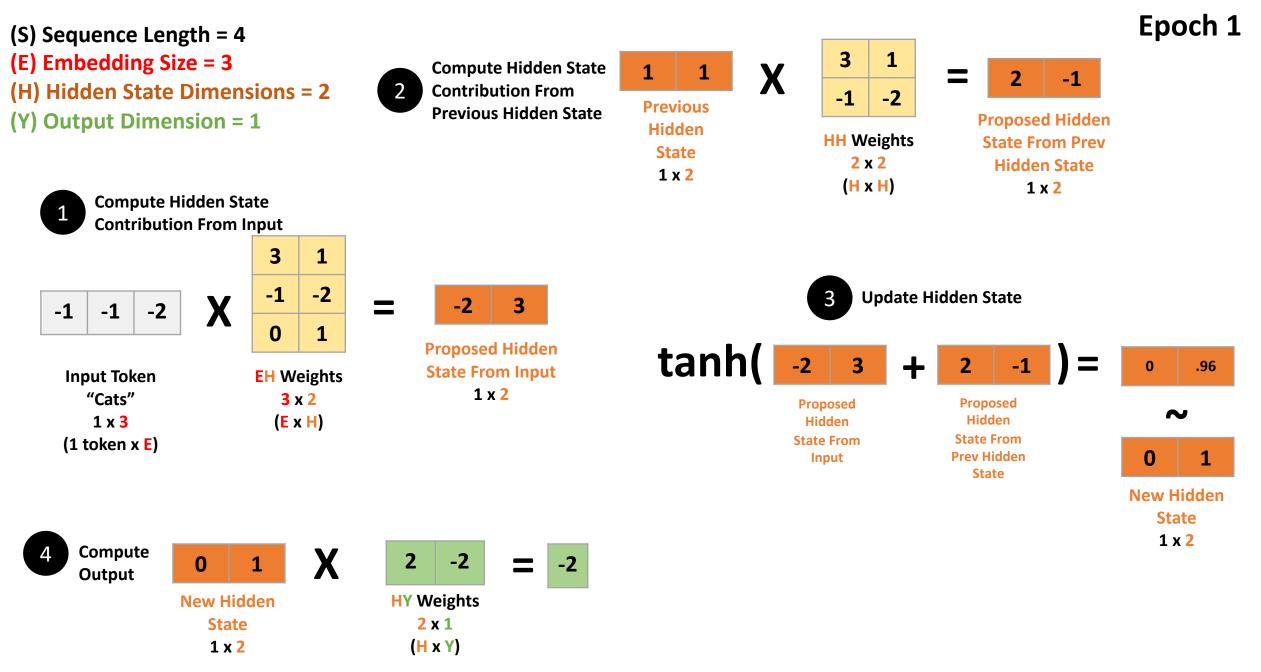




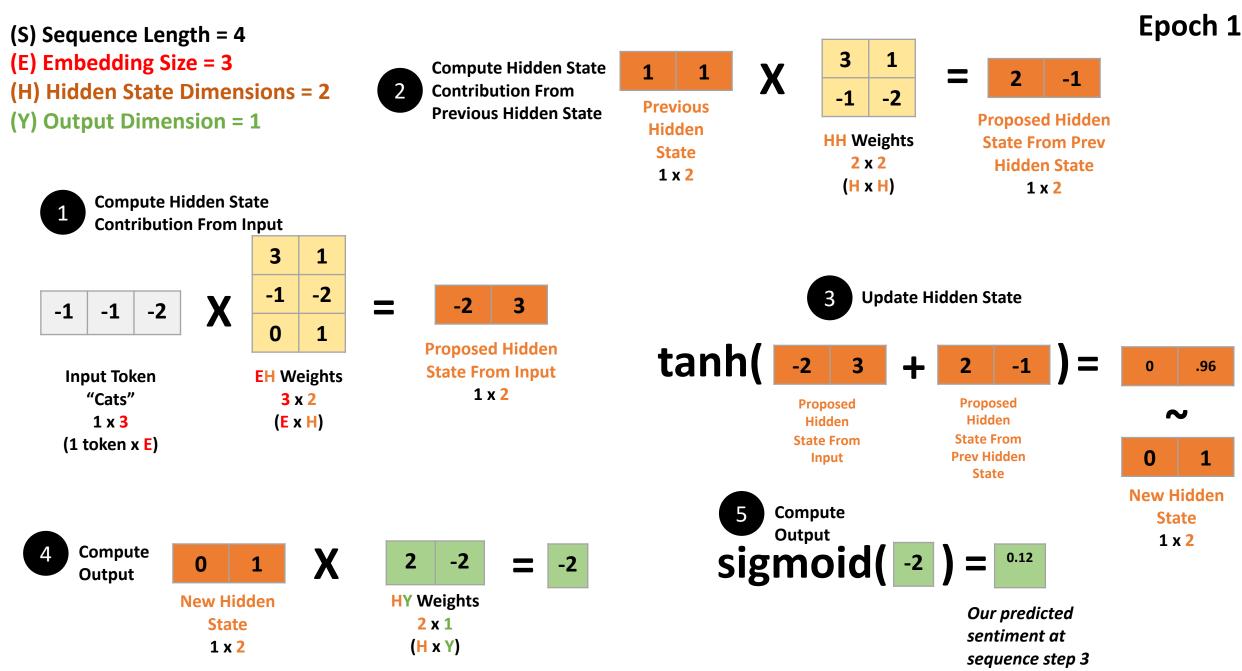
(1 token x E)



1 x 2



Sequence Step 3/4



.96

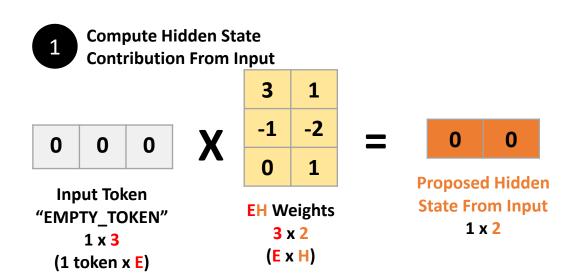
~

State

1 x 2

Sequence Step 3/4

- (E) Embedding Size = 3
- (H) Hidden State Dimensions = 2
- (Y) Output Dimension = 1



Sequence Step 4/4

-2

Proposed Hidden

State From Prev

Hidden State

1 x 2

3

-1

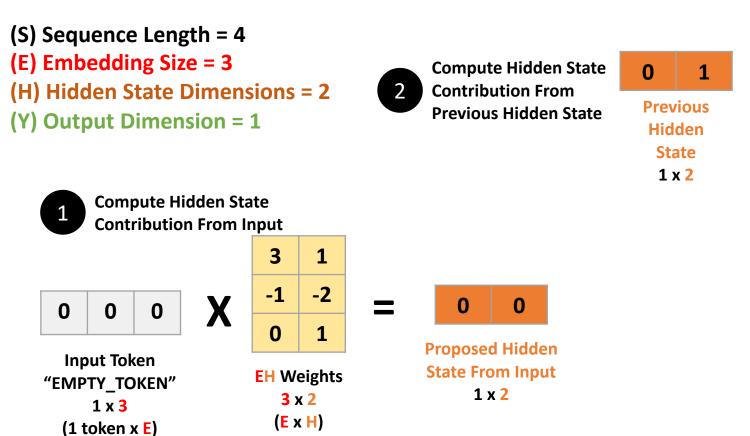
1

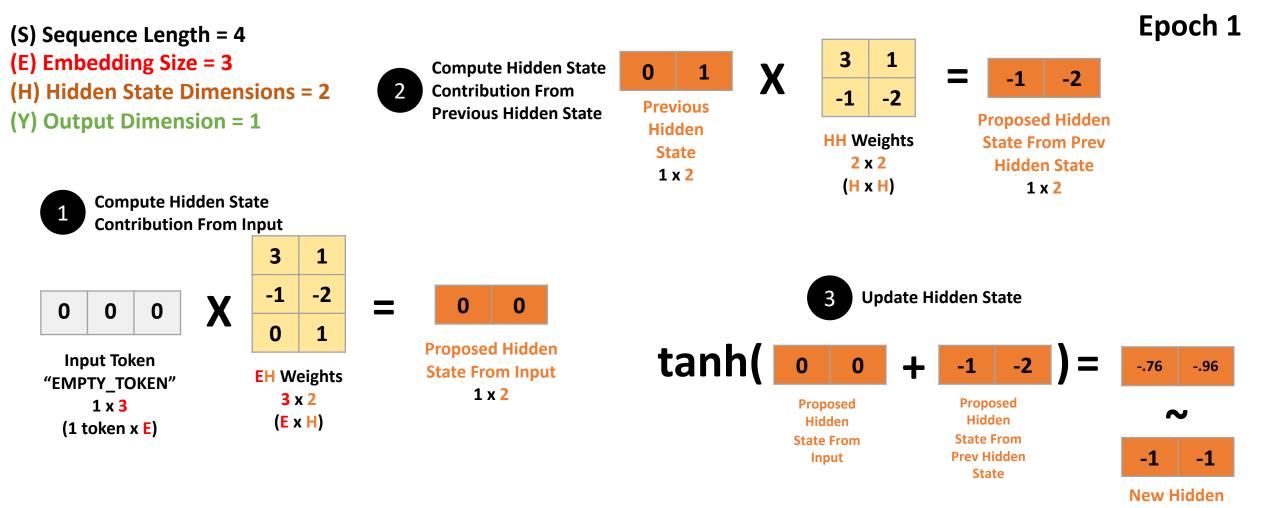
-2

HH Weights

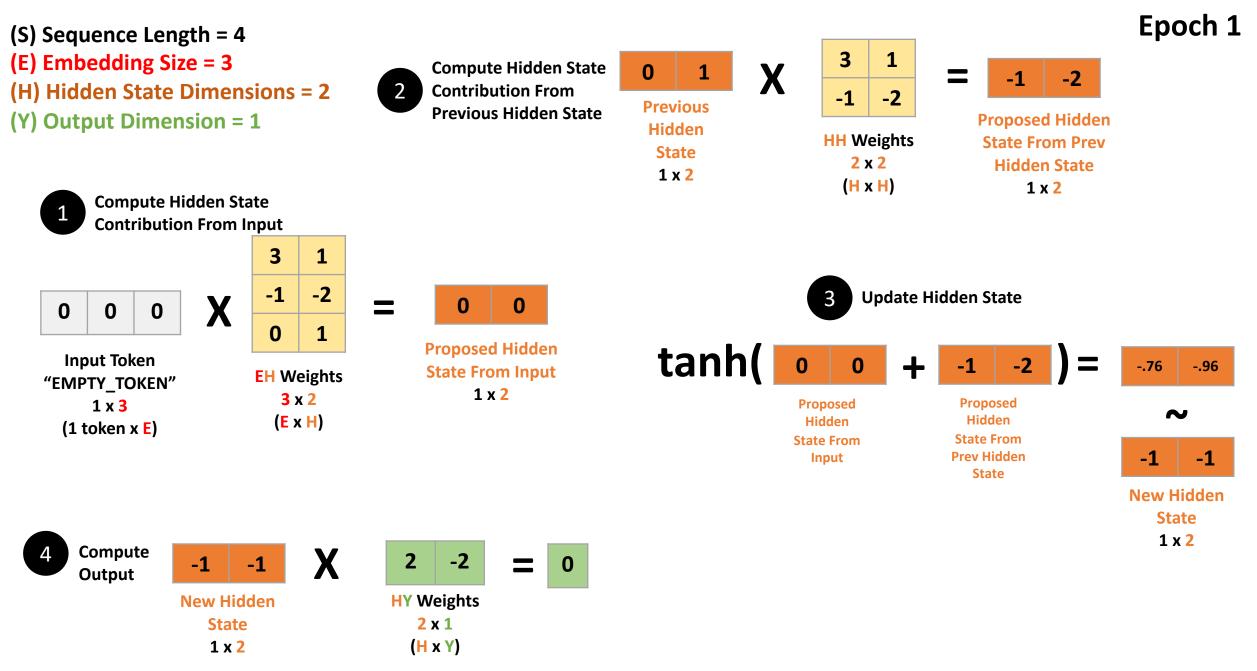
2 x 2

 $(H \times H)$

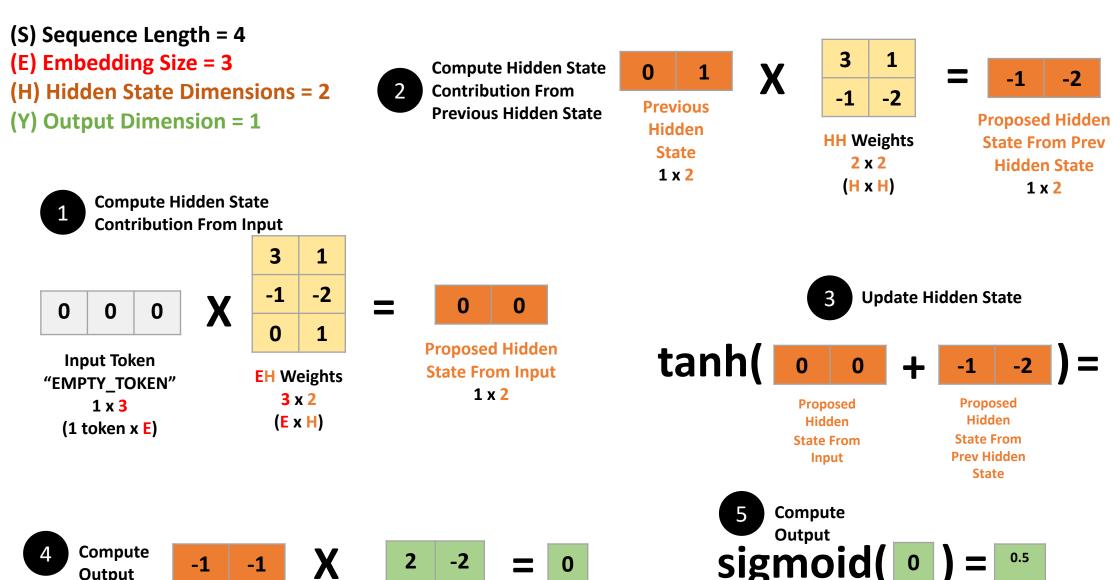




State 1 x 2



Sequence Step 4/4



HY Weights

2 x 1

 $(H \times Y)$

Epoch 1

-.76

~

New Hidden

State

1 x 2

Our predicted

sentiment at

sequence step 4

-.96

-1

Sequence Step 4/4

New Hidden

State

1 x 2

Output

predicted y = 0.5 true y = 1

Binary Cross-Entropy (Log Loss) Function

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

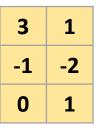
Loss is $-\log(0.5) \rightarrow 0.3$

Binary Cross-Entropy (Log Loss) Function

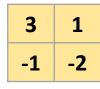
$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Loss is $-\log(0.5) \rightarrow 0.3$

If this was the only sample in our training dataset, we would be done with 1 epoch. We then use our log loss function to calculate the partial derivatives needed to update our weights



EH Weights 3 x 2 (E x H)



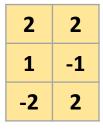
HH Weights
2 x 2
(H x H)

Binary Cross-Entropy (Log Loss) Function

$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Loss is $-\log(0.78) \rightarrow 0.108$

Pretend we update our weights via backpropagation, and make a new prediction for "I love cats" of 0.78.



EH Weights 3 x 2 (E x H)



HH Weights
2 x 2
(H x H)

1 -3

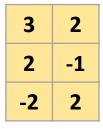
HY Weights
2 x 1
(H x Y)

Binary Cross-Entropy (Log Loss) Function

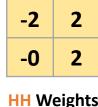
$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$

Loss is $-\log(0.98) \rightarrow 0.008$

Pretend we update our weights via backpropagation, and make a new prediction for "I love cats" of 0.98.



EH Weights 3 x 2 (E x H)



HH Weights
2 x 2
(H x H)

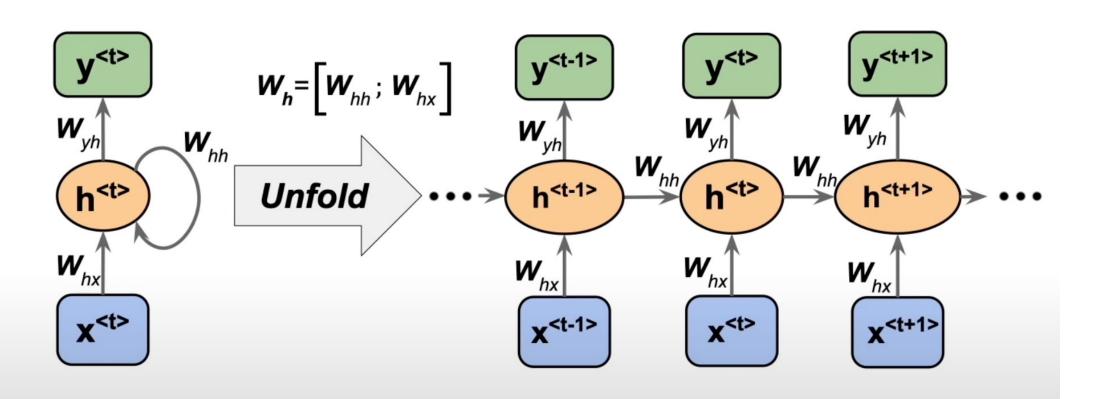
1 -4

HY Weights
2 x 1
(H x Y)

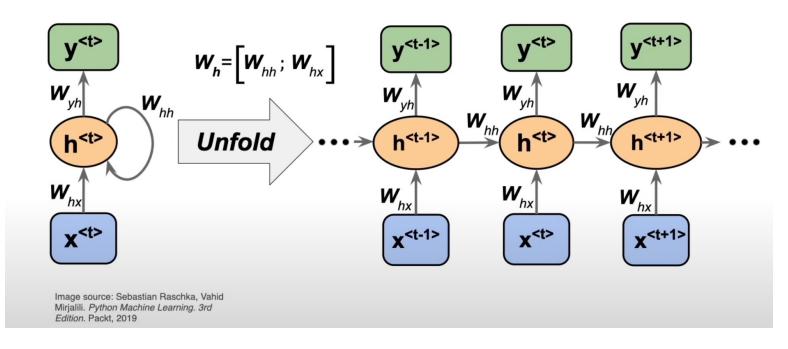
Backpropagation Through Time

Image source: Sebastian Raschka, Vahid Mirjalili. *Python Machine Learning. 3rd*

Edition. Packt, 2019



Backpropagation Through Time



$$L = \sum_{t=1}^T L^{(t)} \quad \frac{\partial L^{(t)}}{\partial \mathbf{W}_{hh}} = \frac{\partial L^{(t)}}{\partial y^{(t)}} \cdot \frac{\partial y^{(t)}}{\partial \mathbf{h}^{(t)}} \cdot \left(\sum_{k=1}^t \overline{egin{matrix} \partial \mathbf{h}^{(t)} \\ \partial \mathbf{h}^{(k)} \end{matrix}} \cdot \frac{\partial \mathbf{h}^{(k)}}{\partial \mathbf{W}_{hh}}
ight)$$

computed as a multiplication of adjacent time steps:

This is very problematic: Vanishing/Exploding gradient problem!

$$\frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{h}^{(k)}} = \prod_{i=k+1}^{t} \frac{\partial \mathbf{h}^{(i)}}{\partial \mathbf{h}^{(i-1)}}$$



$$h_t = \sigma(wh_{t-1}).$$

Hidden state at sequence step t

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

Definition of the sigmoid activation function

$$\sigma'(x) = \frac{d}{dx}\sigma(x) = \sigma(x)(1 - \sigma(x))$$
 Derivative of the sigmoid activation function

$$\frac{\partial h_{t'}}{\partial h_t} = \prod_{k=1}^{t'-t} w \sigma'(w h_{t'-k})$$

Derivative of the hidden state

$$=\underbrace{w^{t'-t}}_{!!!}\prod_{k=1}^{t'-t}\sigma'(wh_{t'-k})$$