

Recurrent Neural Networks

CMSC 473/673 - NATURAL LANGUAGE PROCESSING

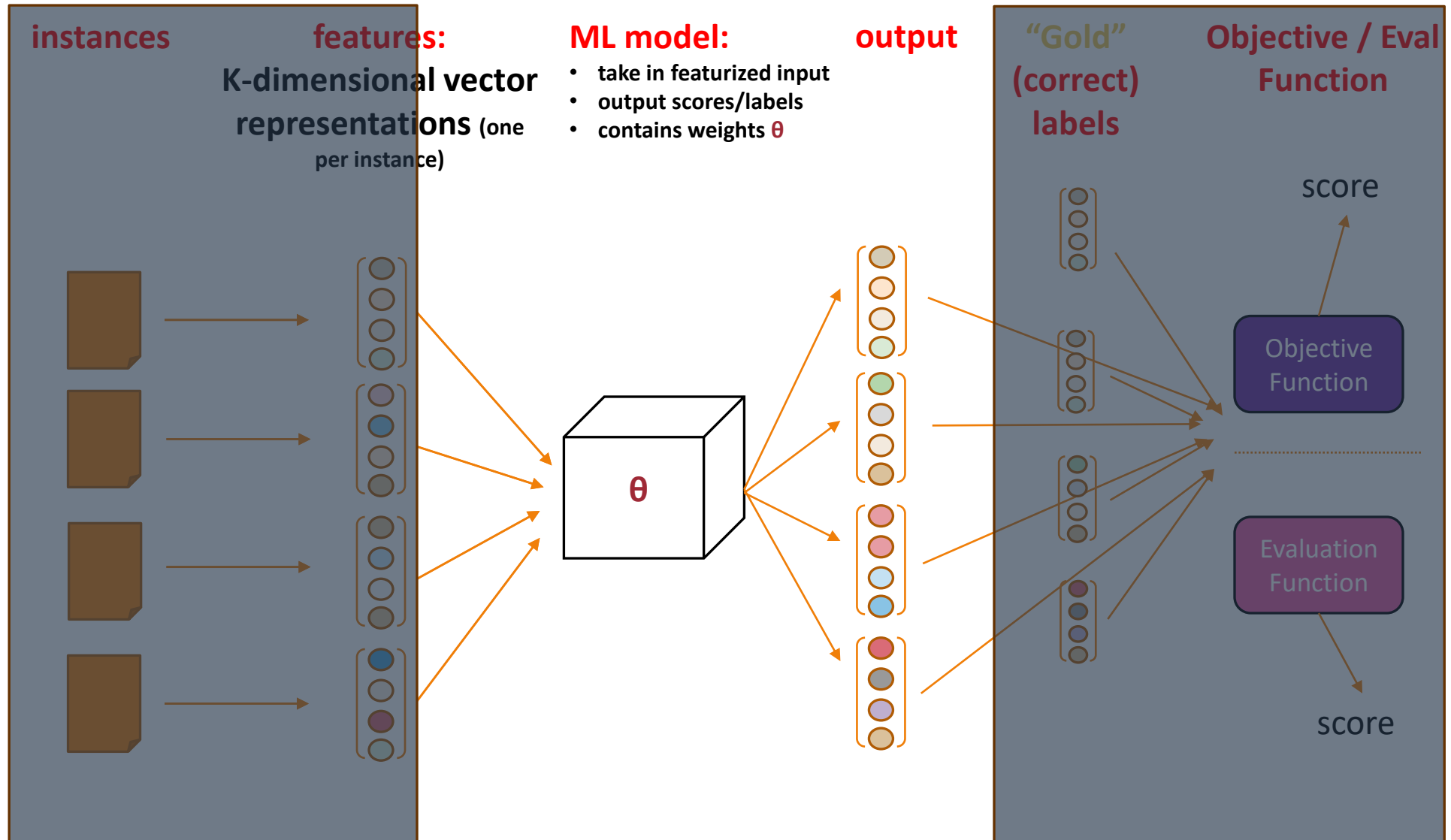
Slides modified from Dr. Frank Ferraro

Learning Objectives

Define the basic cell architecture of an RNN

Backpropagate loss through an example RNN

Create a simple RNN with PyTorch



Review: Maxent Language Models

given some context...



compute beliefs about what is likely...

$$p(w_i | w_{i-3}, w_{i-2}, w_{i-1}) = \text{softmax}(\theta_{w_i} \cdot f(w_{i-3}, w_{i-2}, w_{i-1}))$$

predict the next word

can we learn word-specific weights (by type)?



Review: Neural Language Models

given some context...



can we *learn* the feature function(s) for *just* the context?

compute beliefs about what is likely...



$$p(w_i | w_{i-3}, w_{i-2}, w_{i-1}) = \text{softmax}(\theta_{w_i} \cdot f(w_{i-3}, w_{i-2}, w_{i-1}))$$

predict the next word

can we learn word-specific weights (by type)?



Review: Neural Language Models

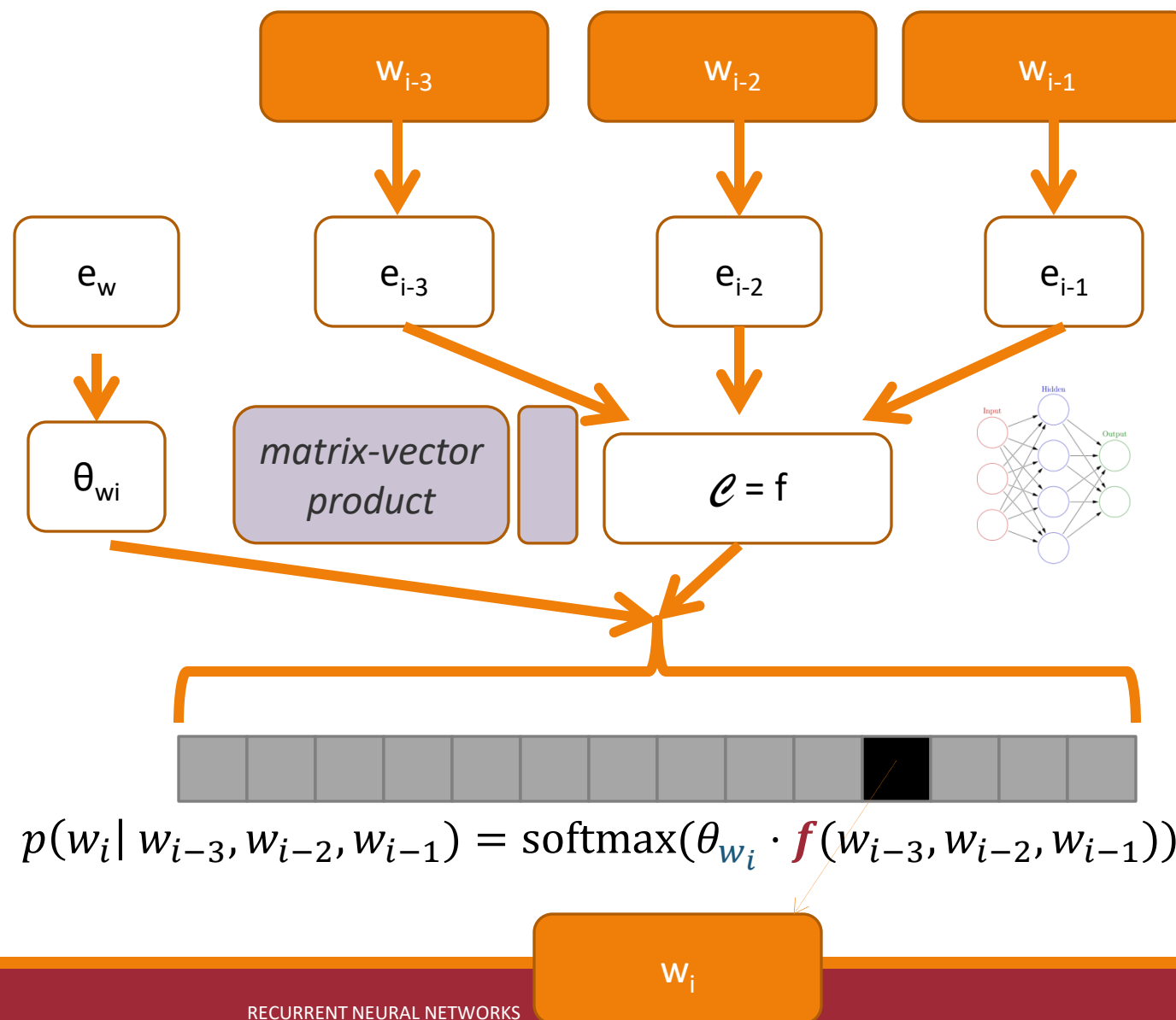
given some context...

create/use
“distributed
representations”...

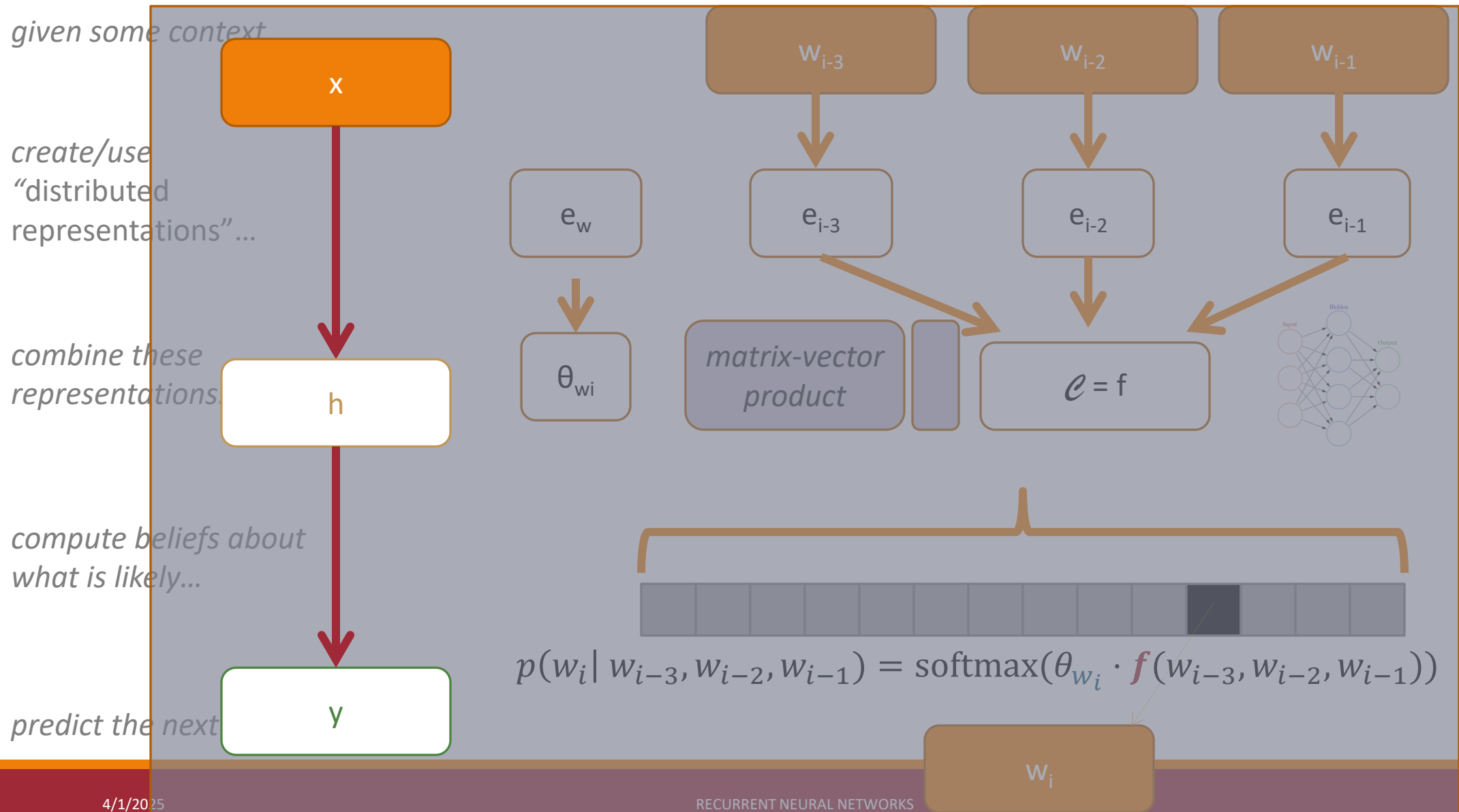
combine these
representations...

compute beliefs about
what is likely...

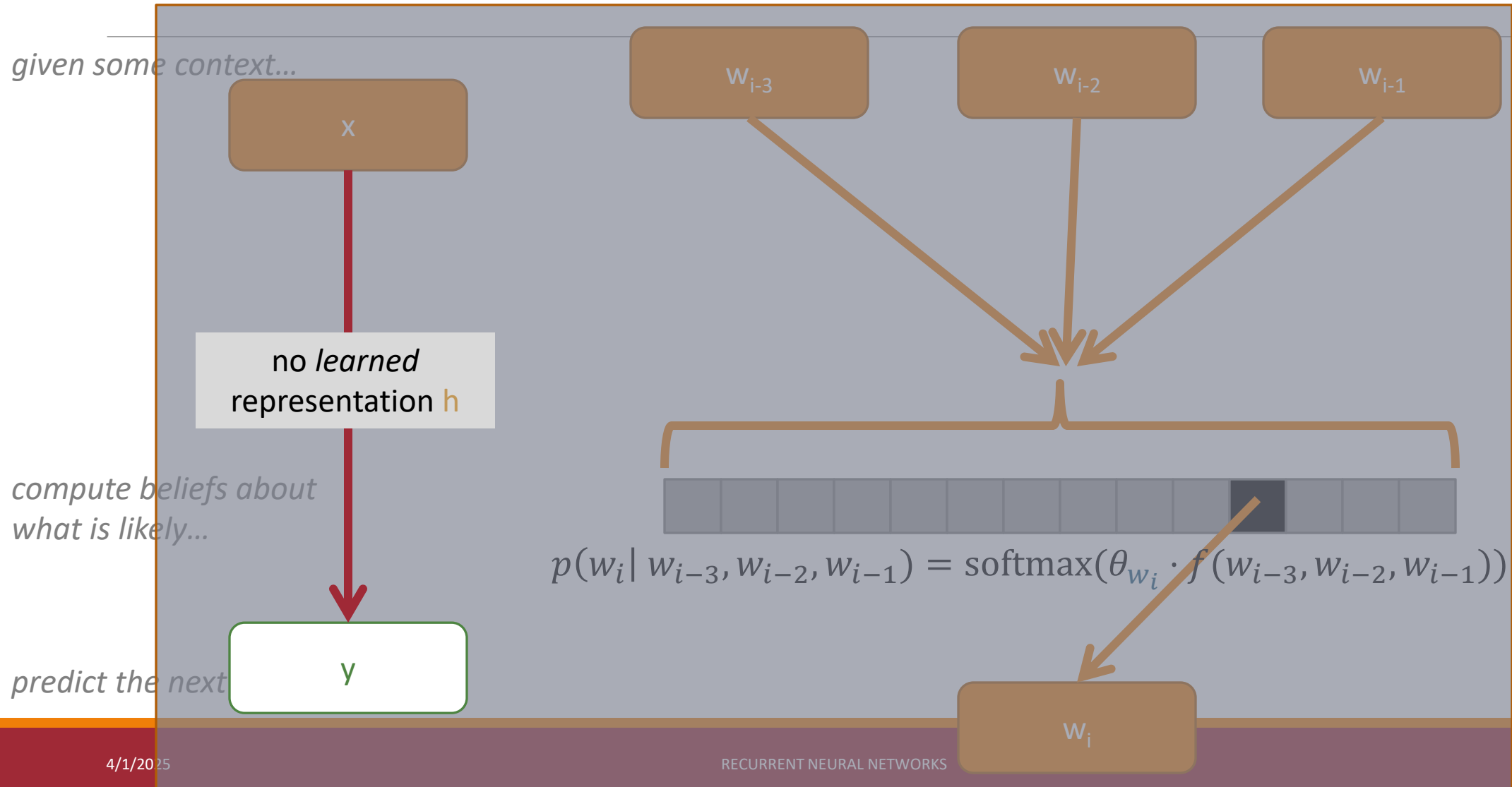
predict the next word



Review: Neural Language Models



Review: Maxent Language Models



Review: LM Comparison

COUNT-BASED

Class-specific

MAXENT

Class-based

Uses features

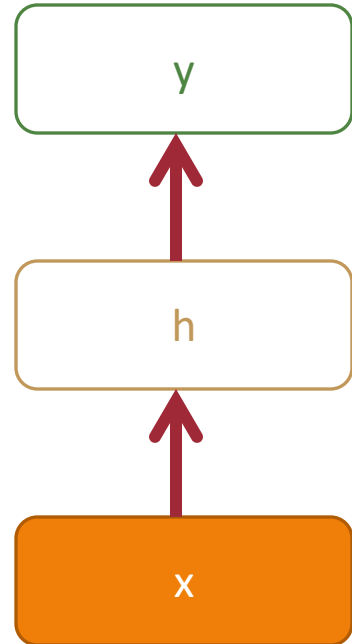
NEURAL

Class-based

Uses *embedded* features

Review:

Network Types: Flat **Input**, Flat **Output**



1. Feed forward

Linearizable feature input
Bag-of-items classification/regression
Basic non-linear model

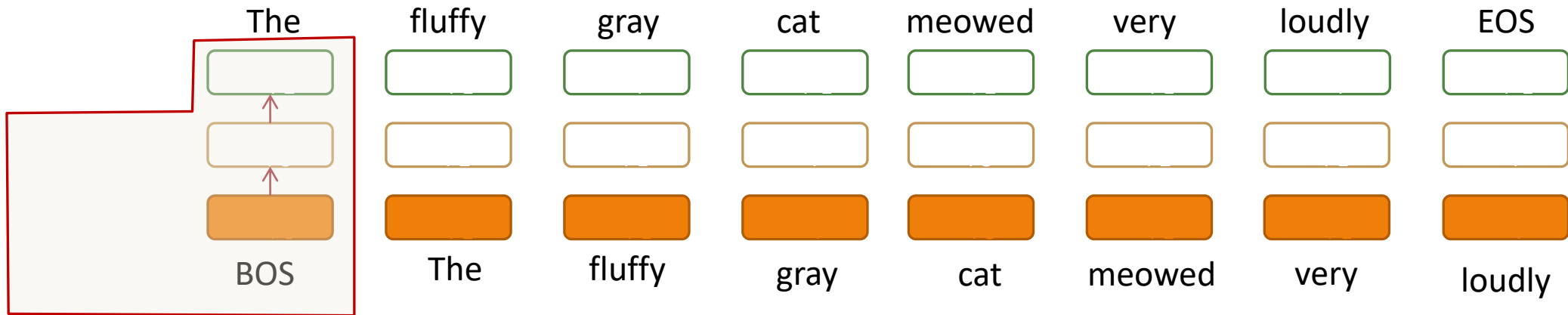
Review: A Neural N-Gram Model

The fluffy gray cat meowed very loudly



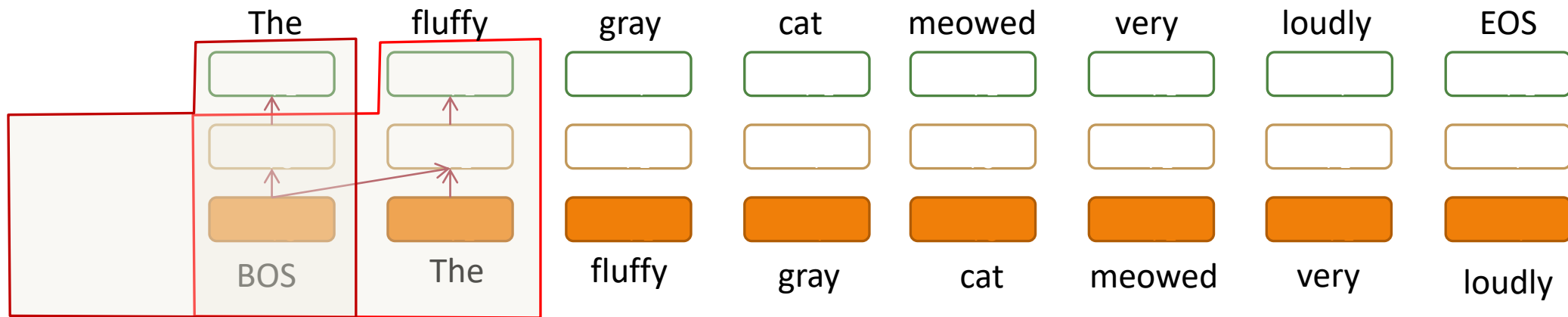
Review: A Neural N-Gram Model (N=3)

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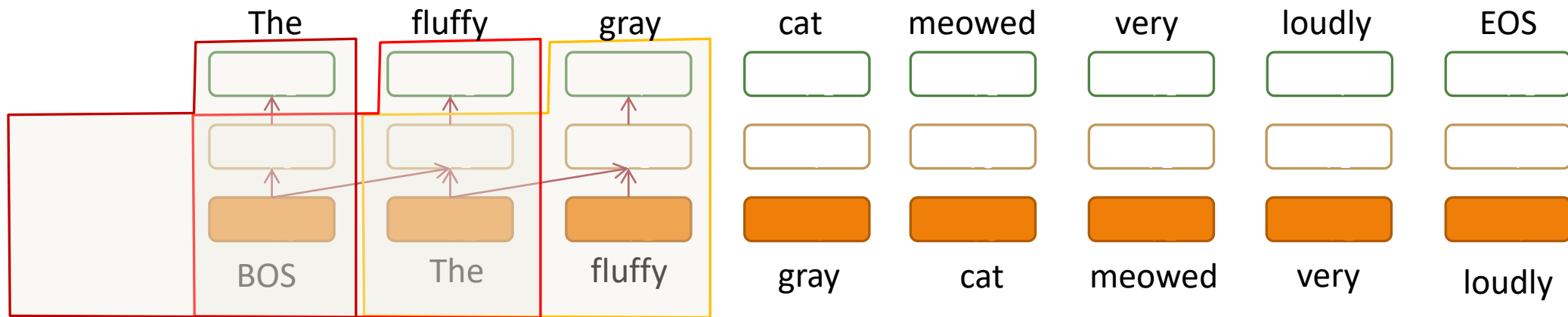
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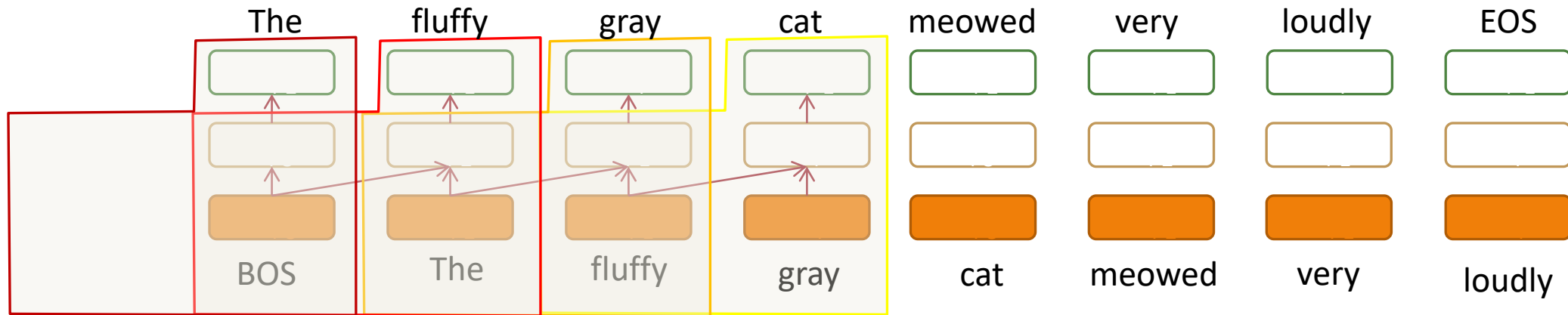
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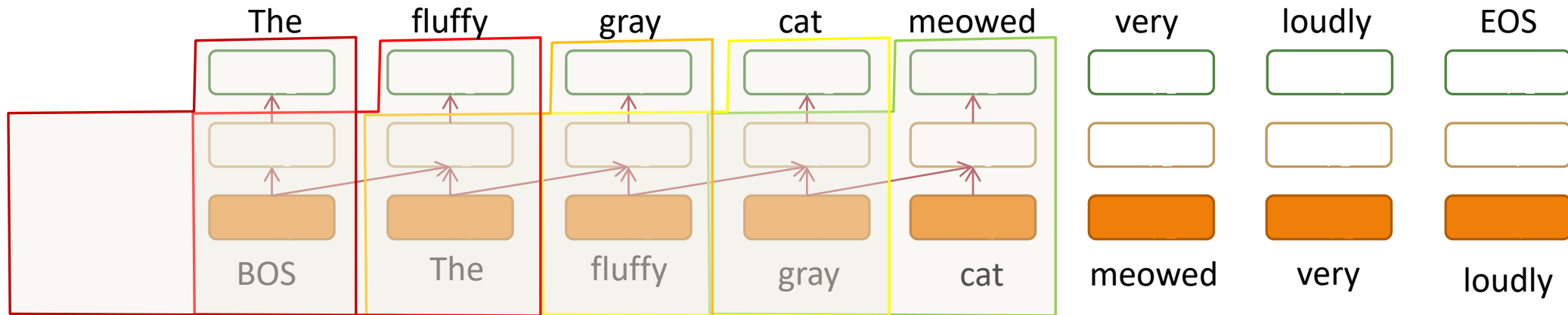
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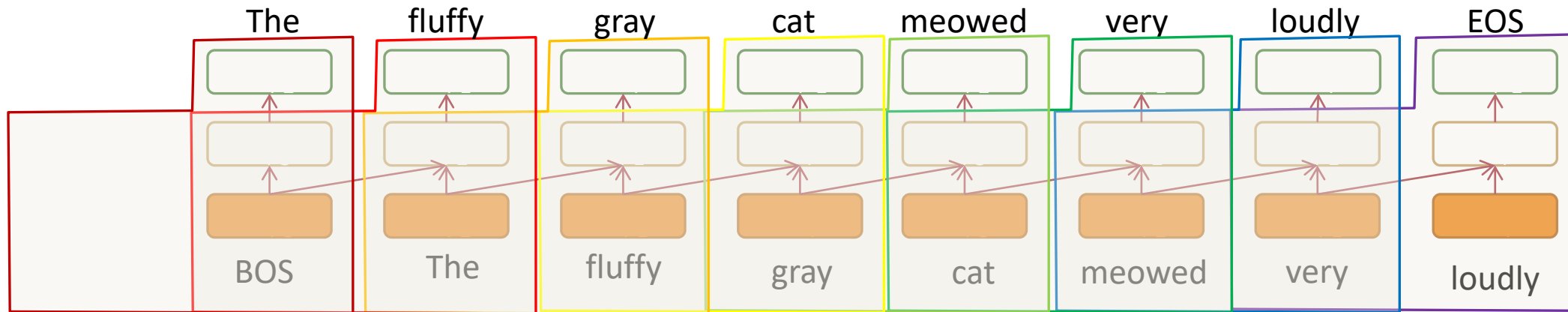
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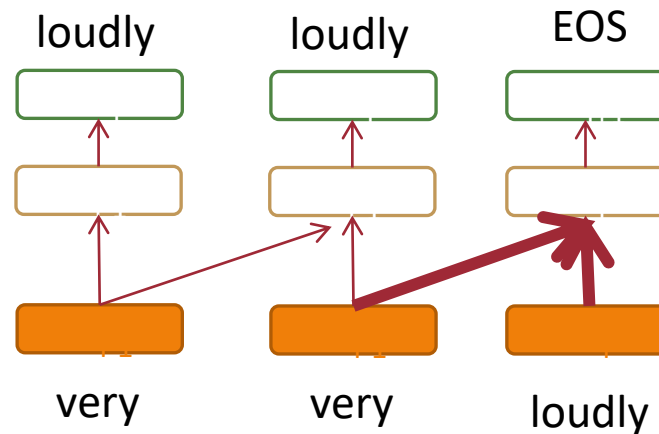
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A Neural N-Gram Model (N=3)

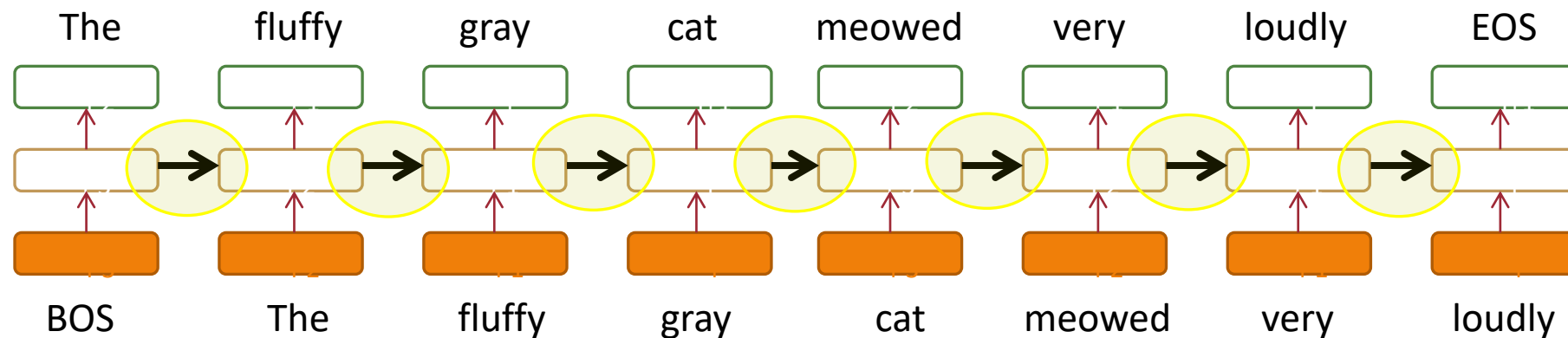
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Critical issue: the amount
of information flow is
fundamentally restricted!!!

A Recurrent Neural Language Model

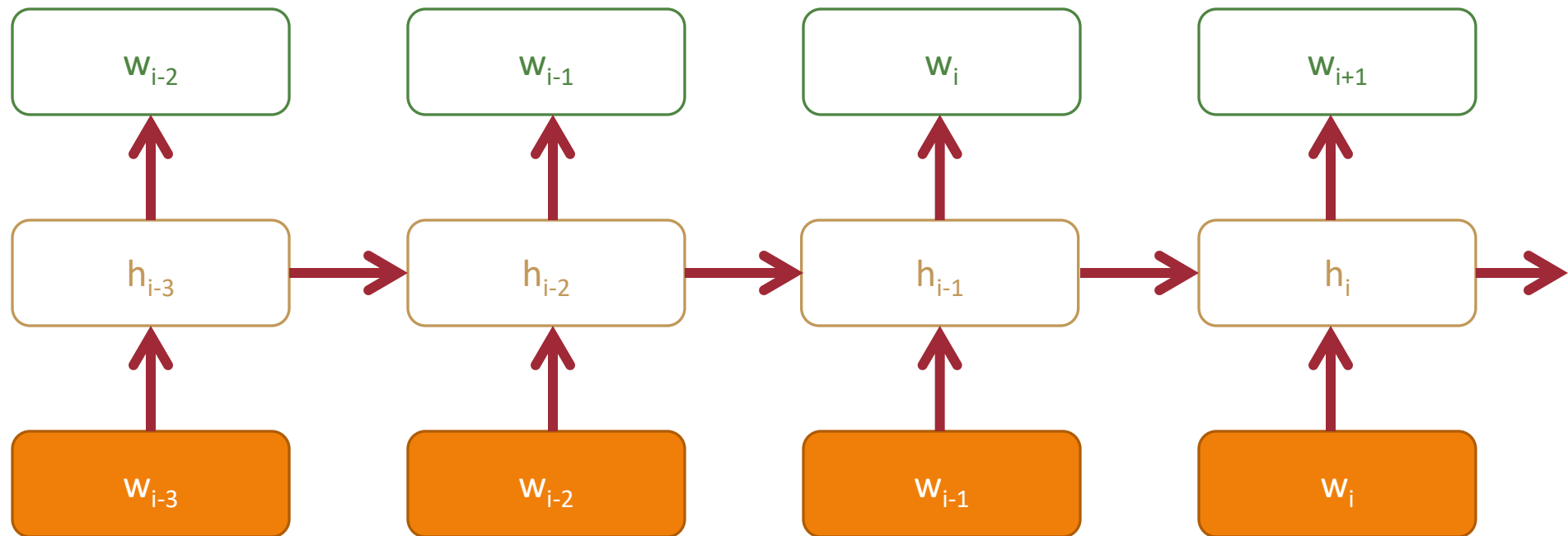
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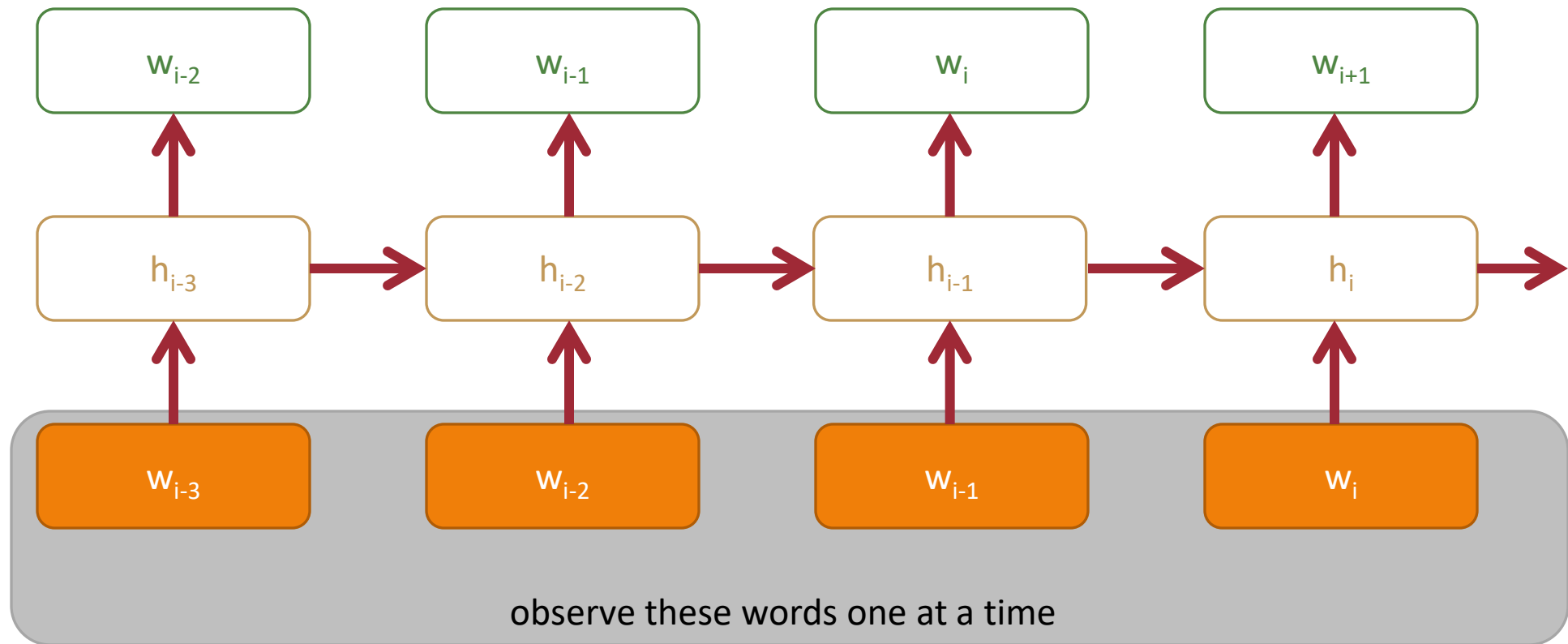
Critical issue: the amount of information flow is fundamentally restricted!!!

Allowing signal to flow from one **hidden state** to another could help solve this!

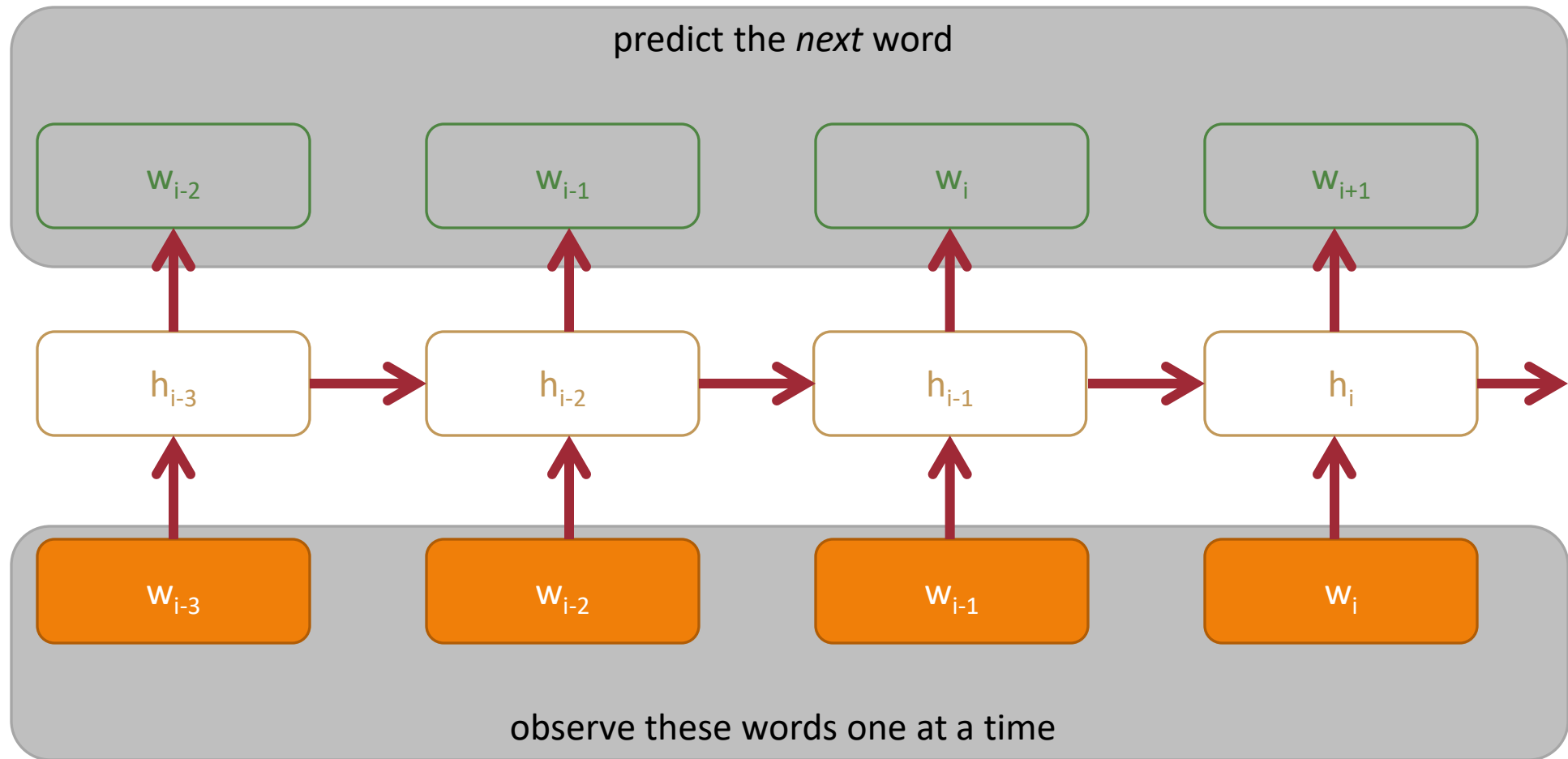
A Classic View of Recurrent Neural Language Modeling



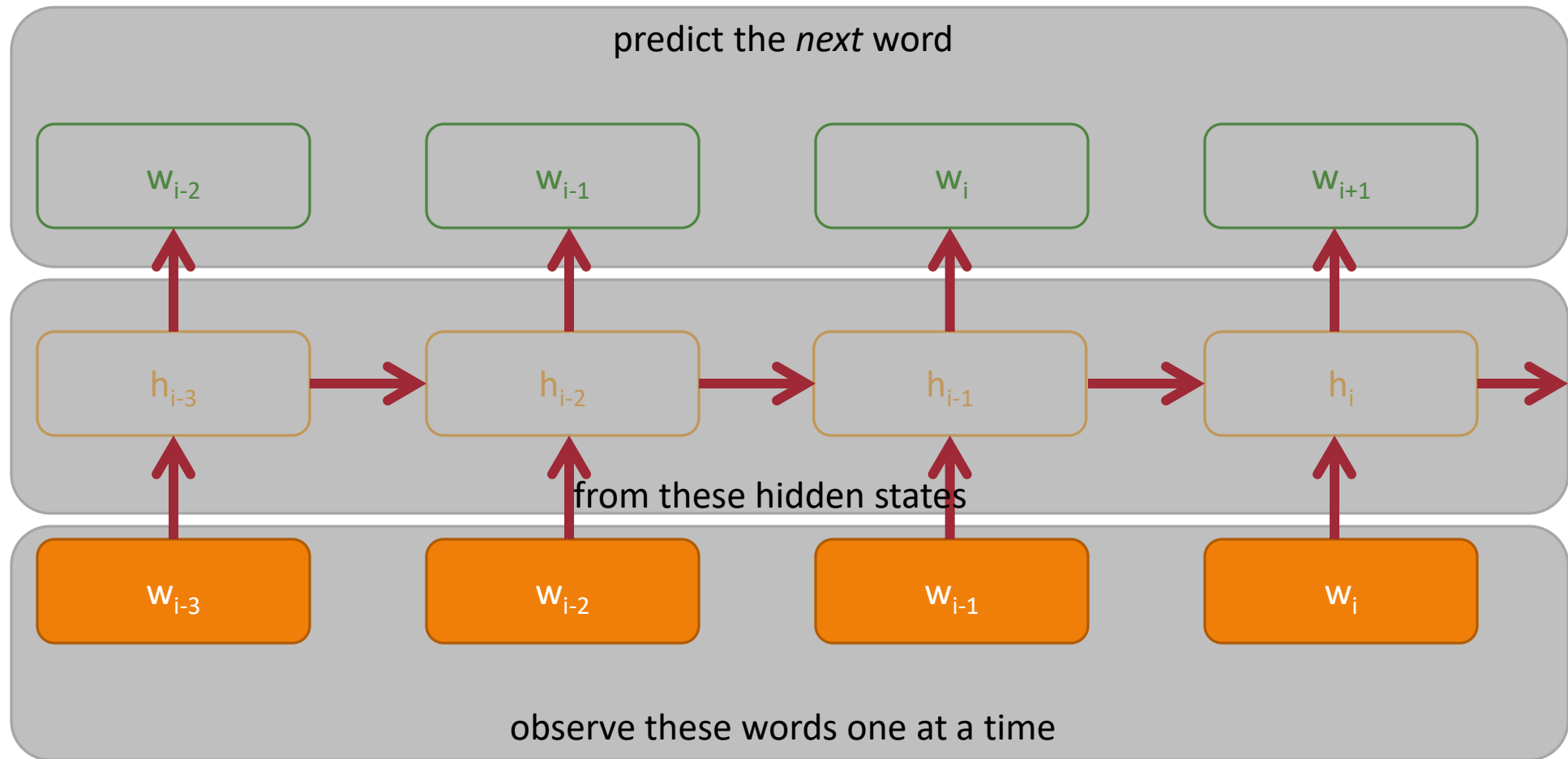
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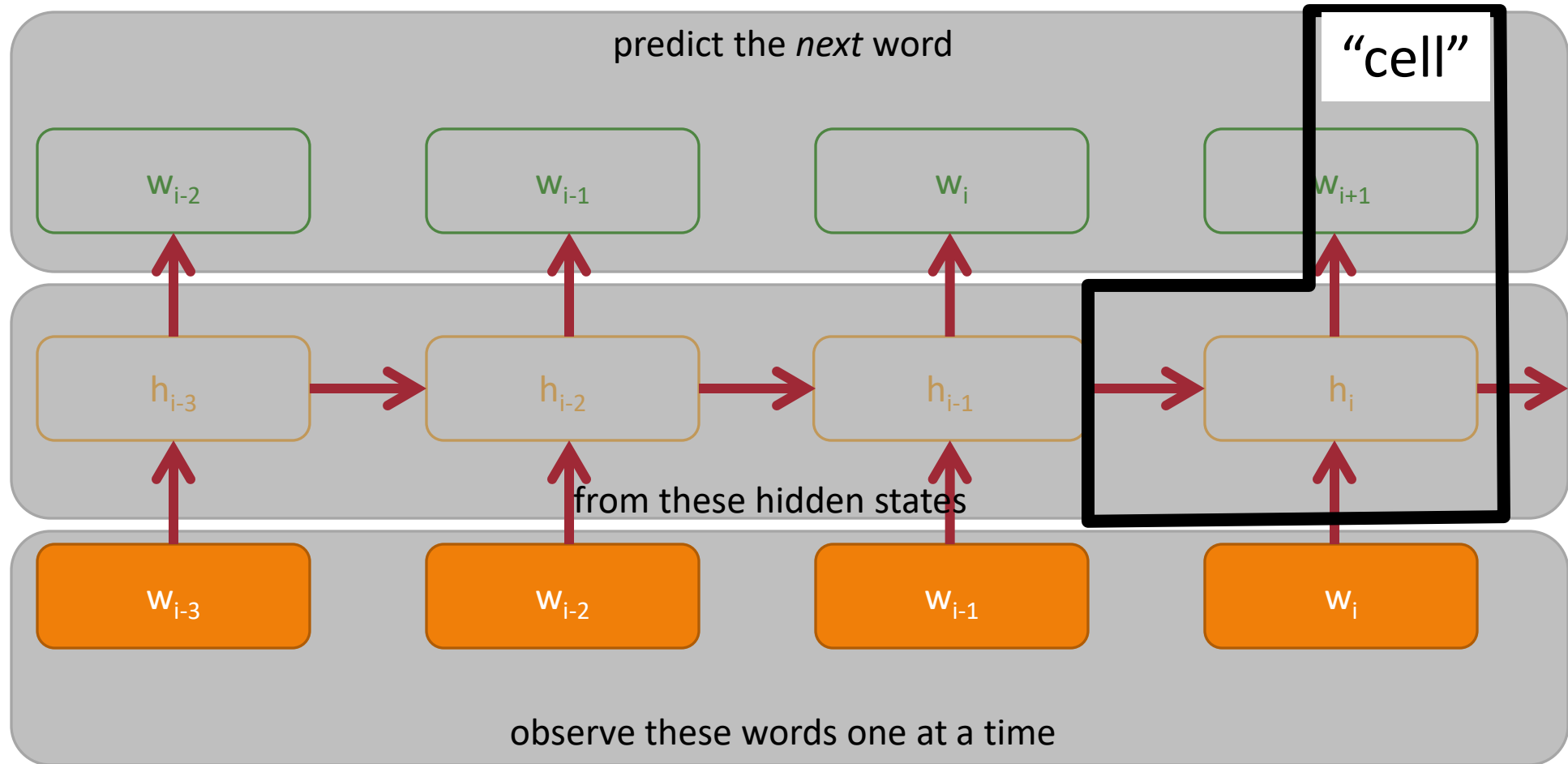
A Classic View of Recurrent Neural Language Modeling



A Classic View of Recurrent Neural Language Modeling



A Classic View of Recurrent Neural Language Modeling



Review: Forward Propagation Example

Calculate outputs to the hidden layer (units h1 and h2):

How do we do this?

Use our activation function!

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

What will be our x ?

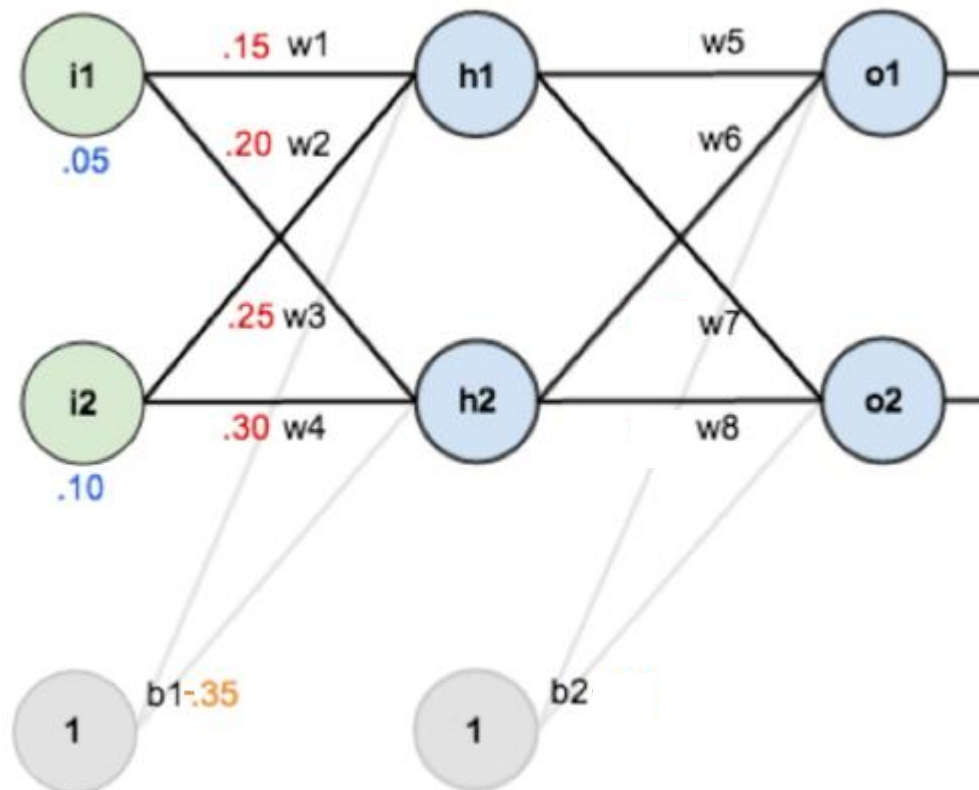
$$\text{in}_{h1} = -.3225$$

$$\text{in}_{h2} = -.3075$$

For each layer:

1. Calculate the weighted sum of inputs to each neuron unit
2. Evaluate the activation function to determine the output of each neuron unit
3. Use outputs as inputs for the next layer

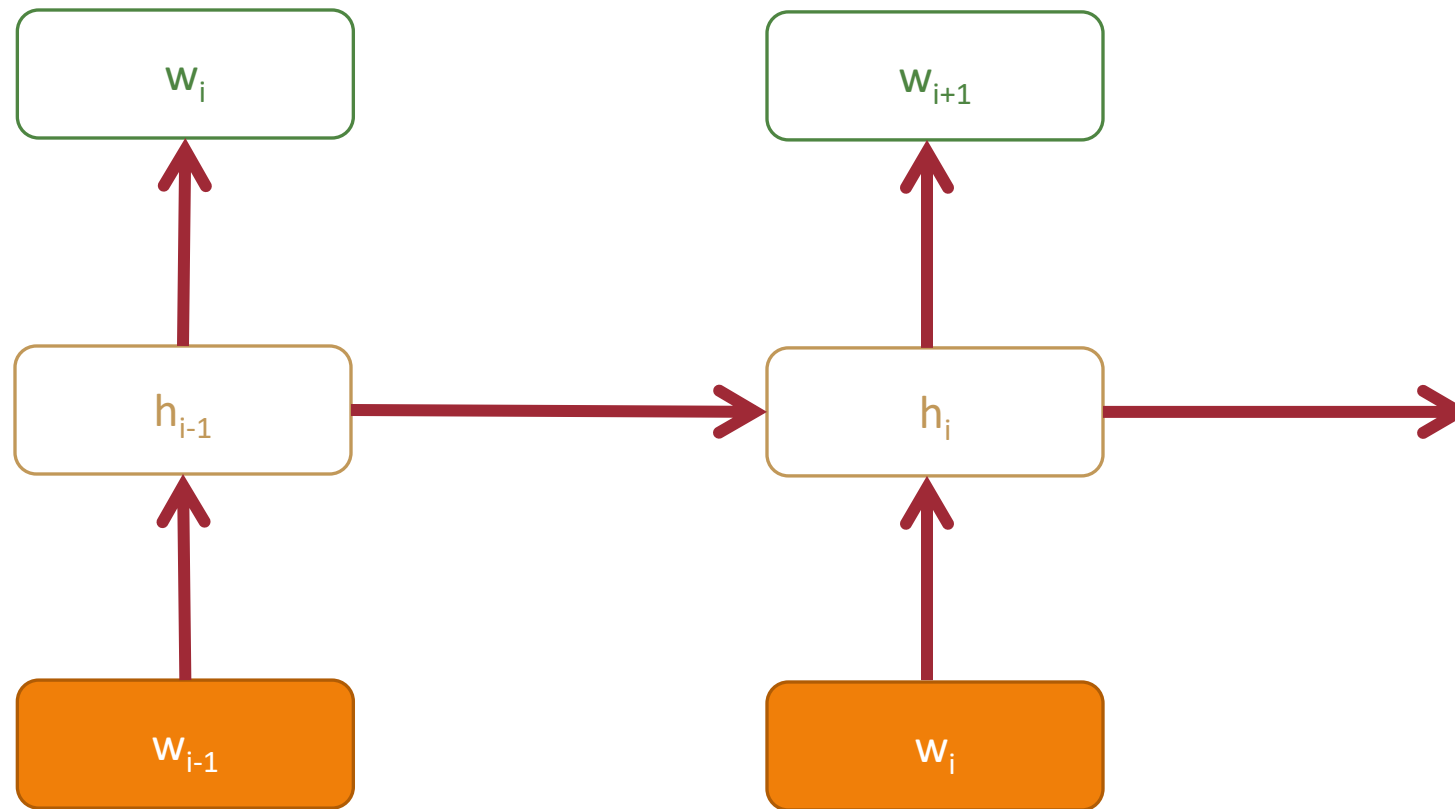
4/1/2025



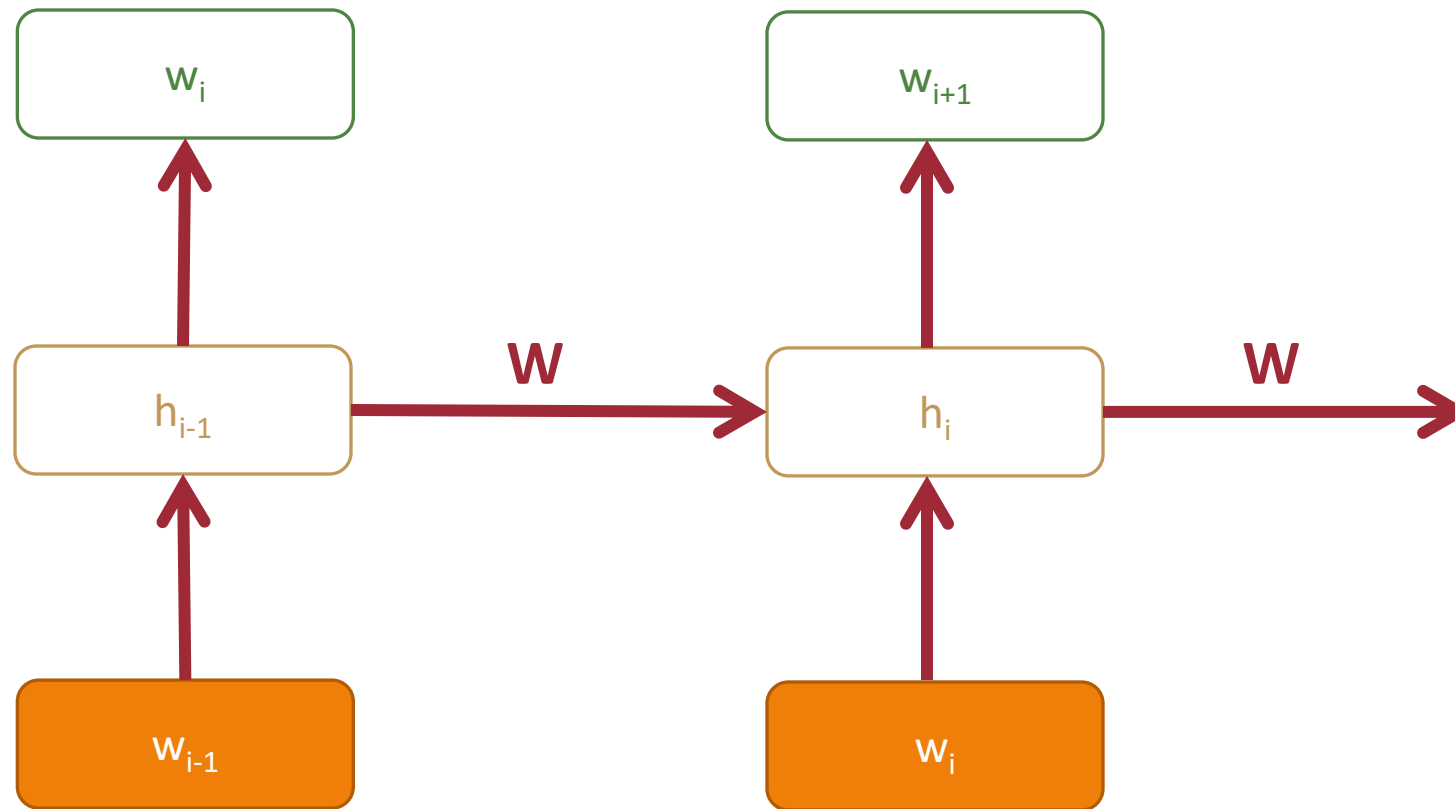
$$\begin{aligned}\text{out}_{h1} &= g(\text{in}_{h1}) \\ &= \frac{1}{1 + e^{-\text{in}_{h1}}} \\ &= \frac{1}{1 + e^{-(-.3225)}} \\ &= .4188\end{aligned}$$

$$\begin{aligned}\text{out}_{h2} &= g(\text{in}_{h2}) \\ &= \frac{1}{1 + e^{-\text{in}_{h2}}} \\ &= \frac{1}{1 + e^{-(-.3075)}} \\ &= .4237\end{aligned}$$

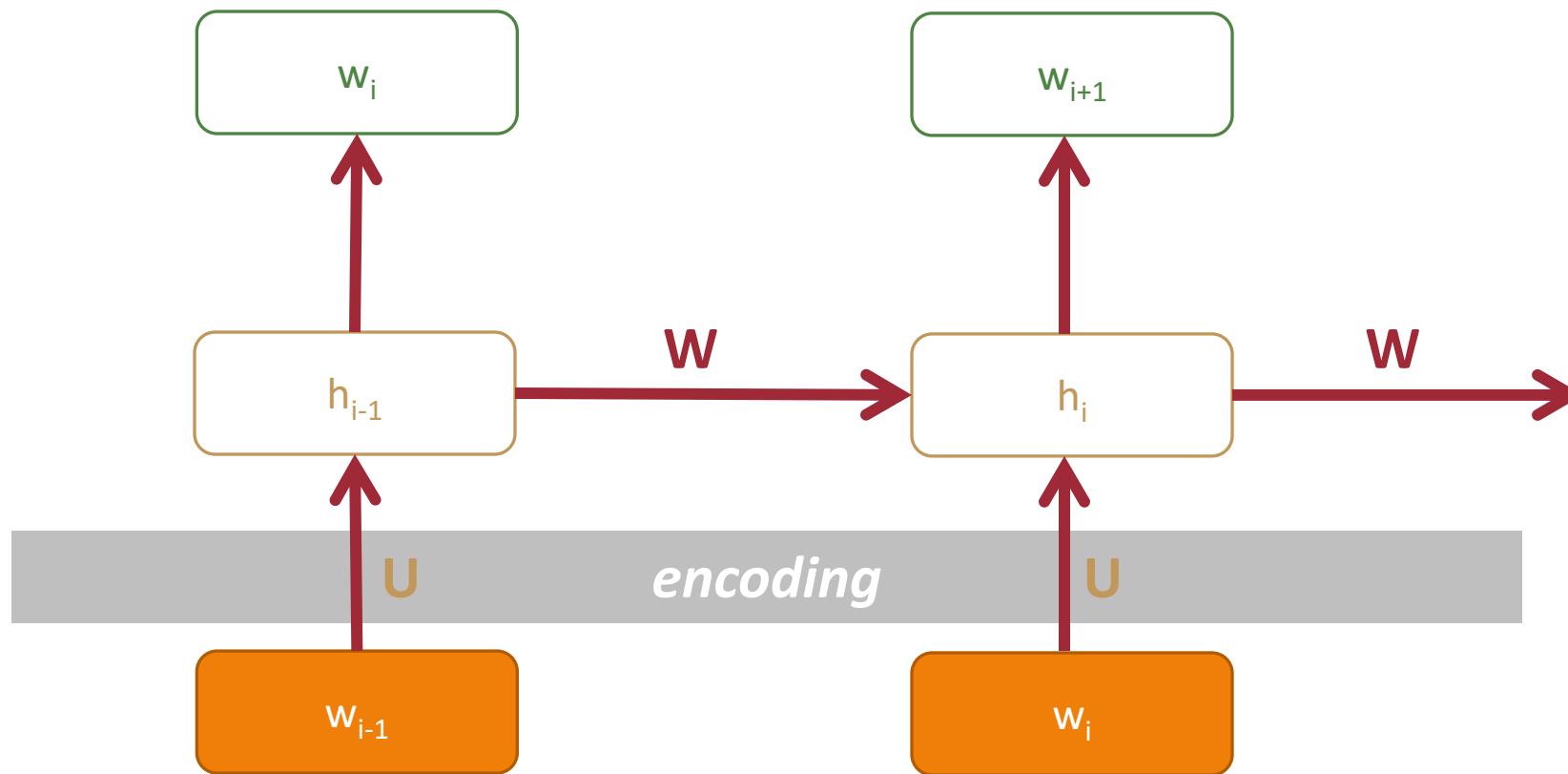
A Recurrent Neural Network Cell



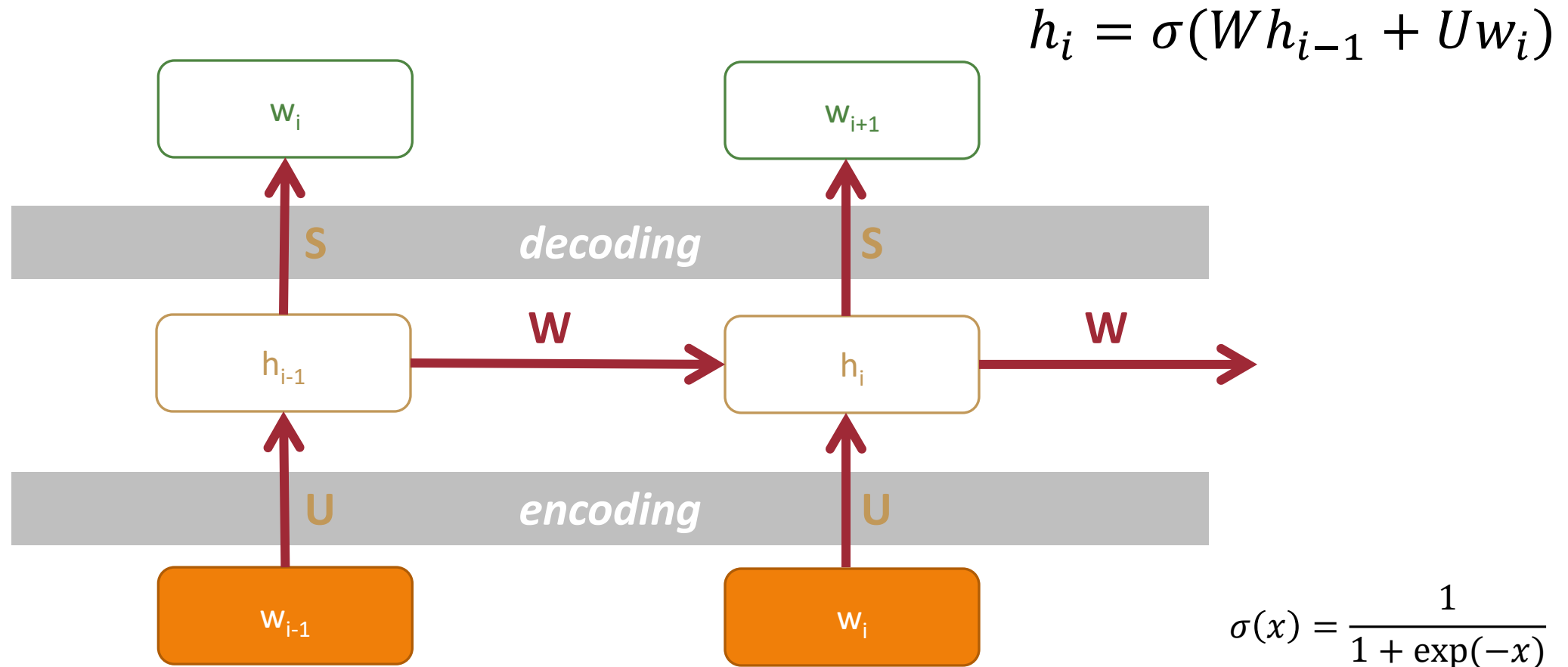
A Recurrent Neural Network Cell



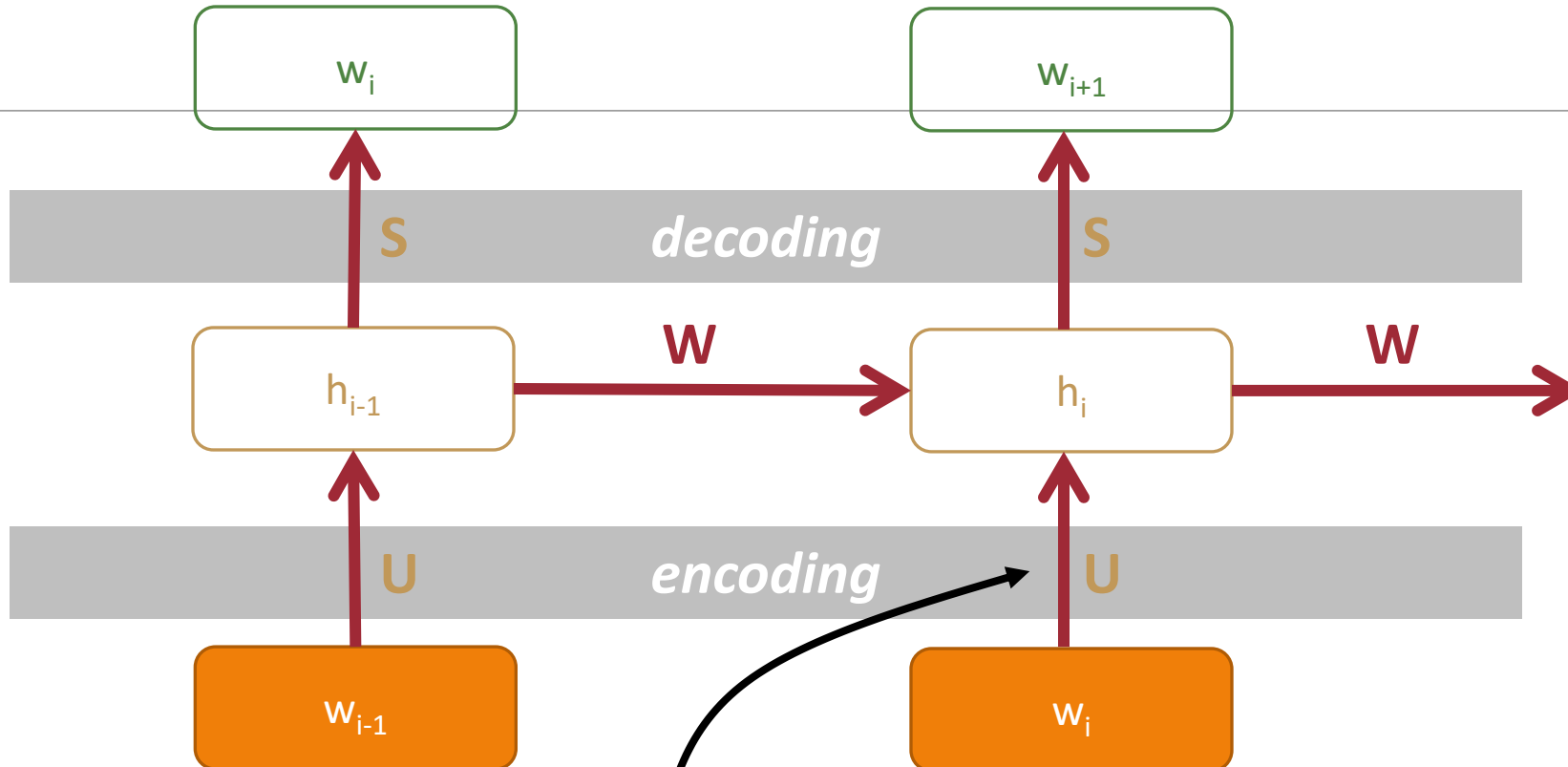
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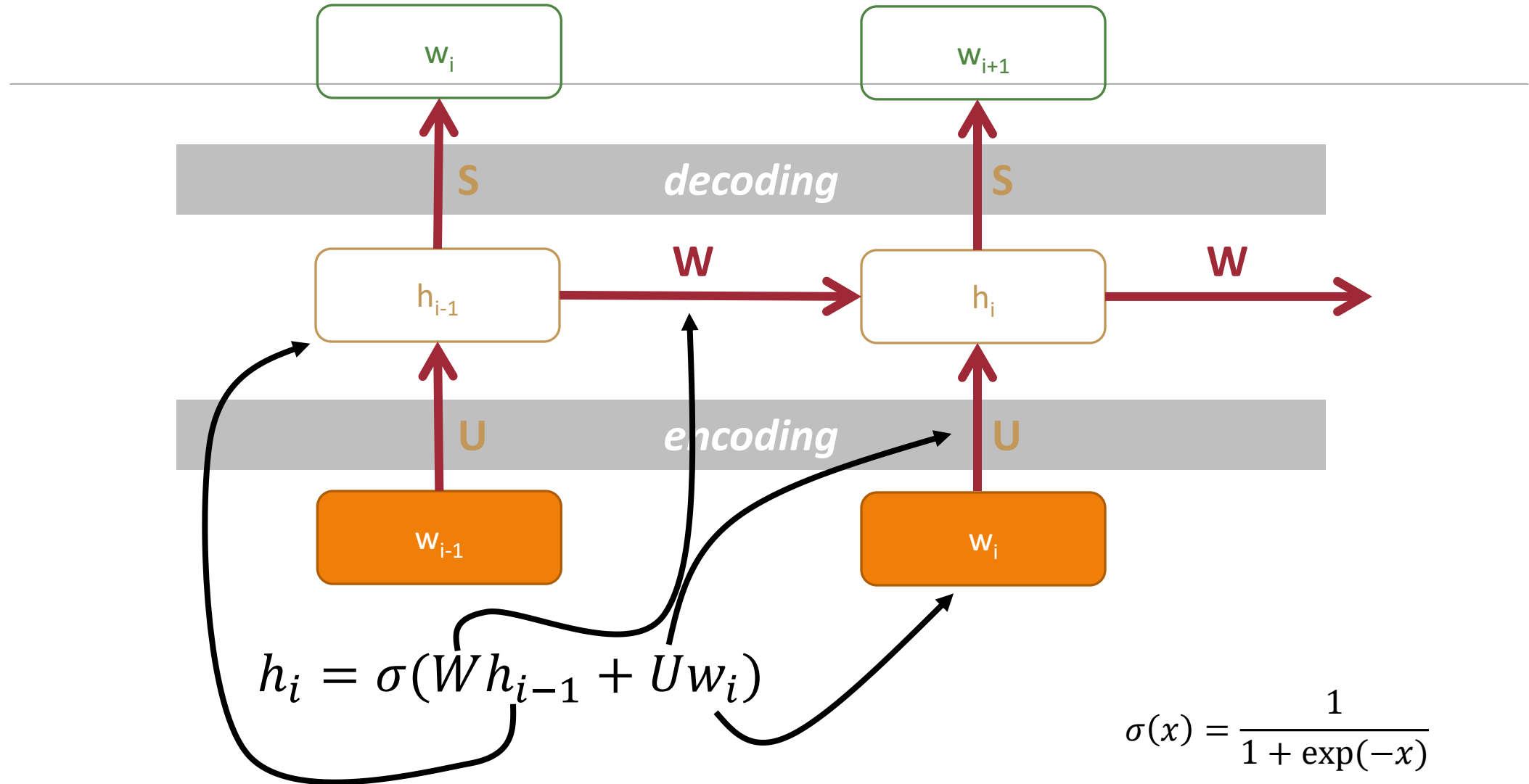
A Simple Recurrent Neural Network Cell



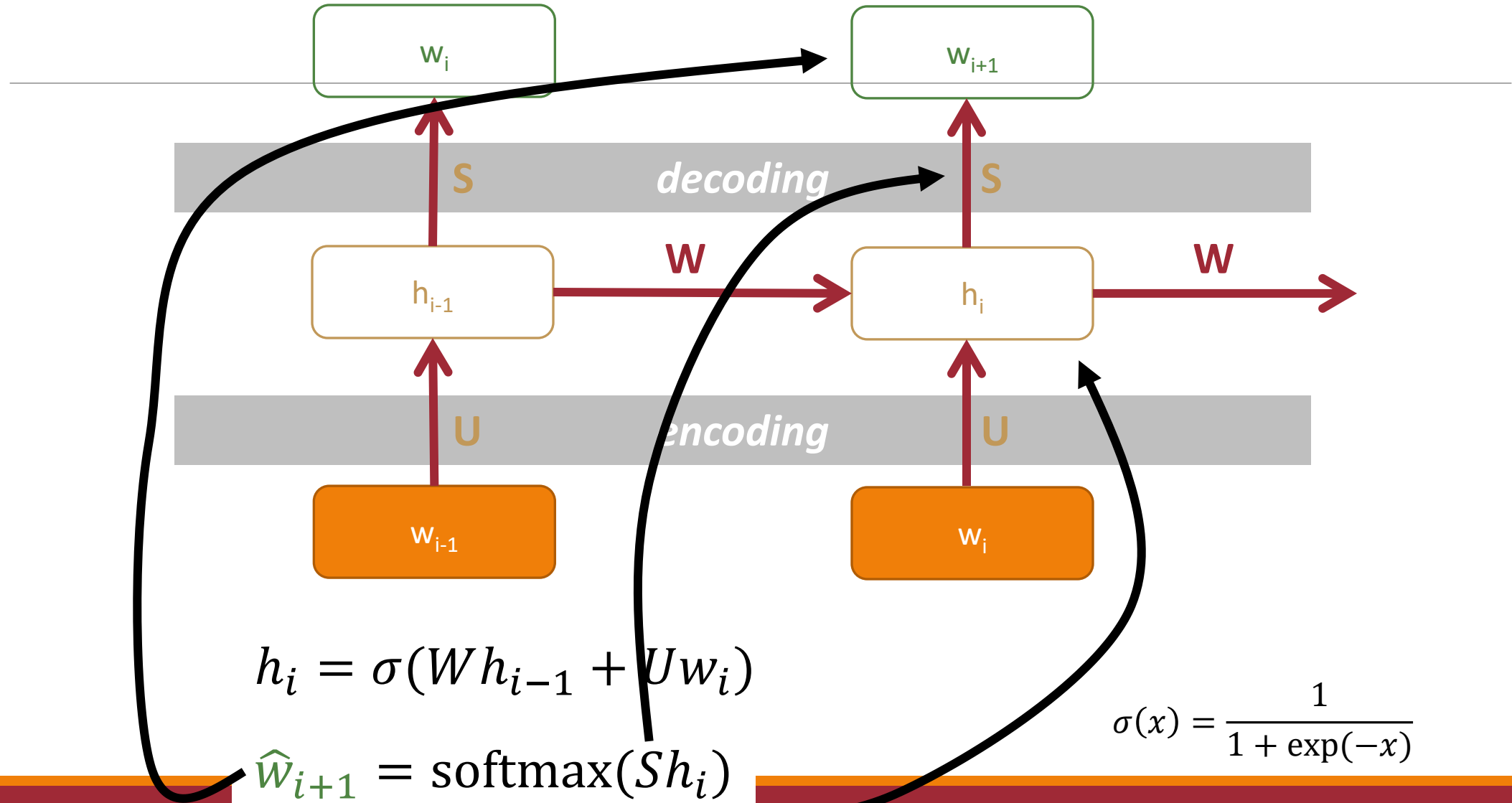
$$h_i = \sigma(W h_{i-1} + U w_i)$$

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

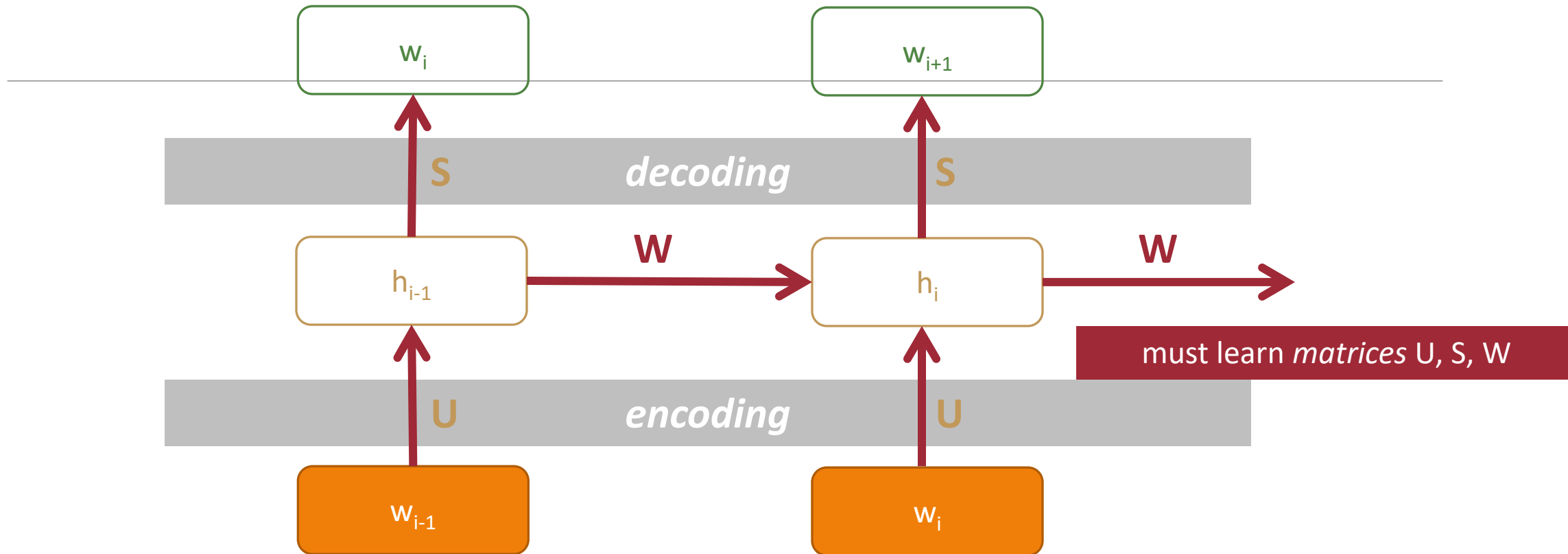
A Simple Recurrent Neural Network Cell



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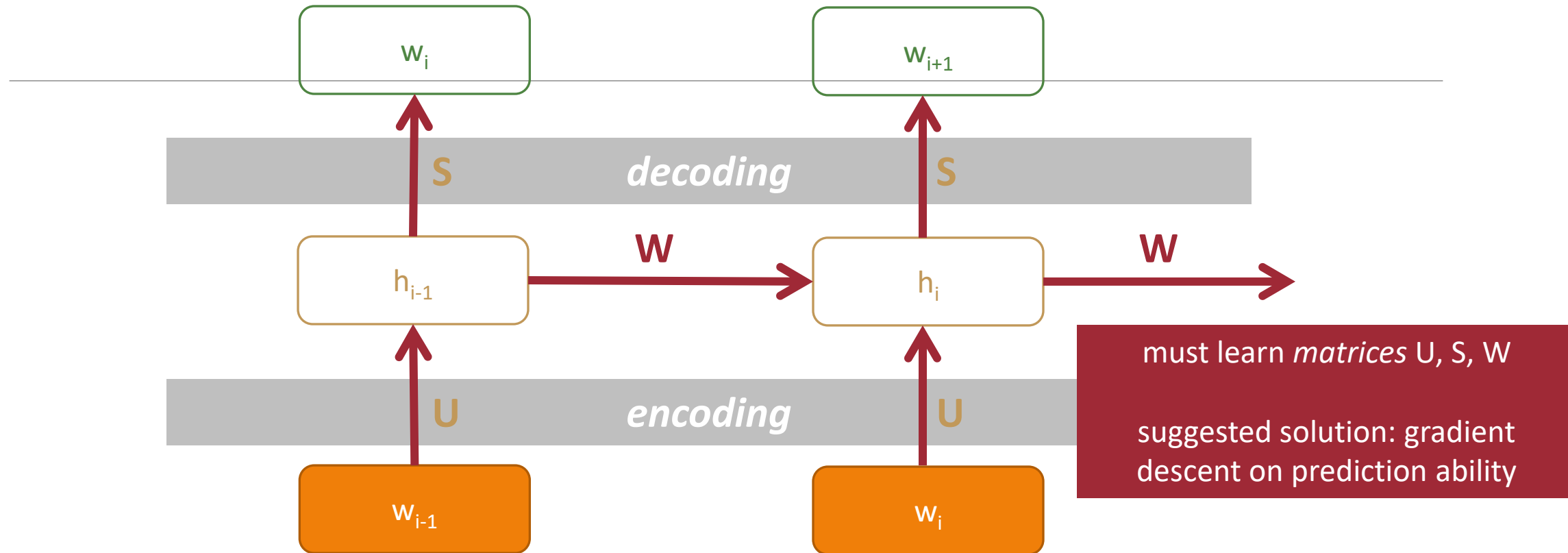
A Simple Recurrent Neural Network Cell



$$h_i = \sigma(W h_{i-1} + U w_i)$$

$$\hat{w}_{i+1} = \text{softmax}(S h_i)$$

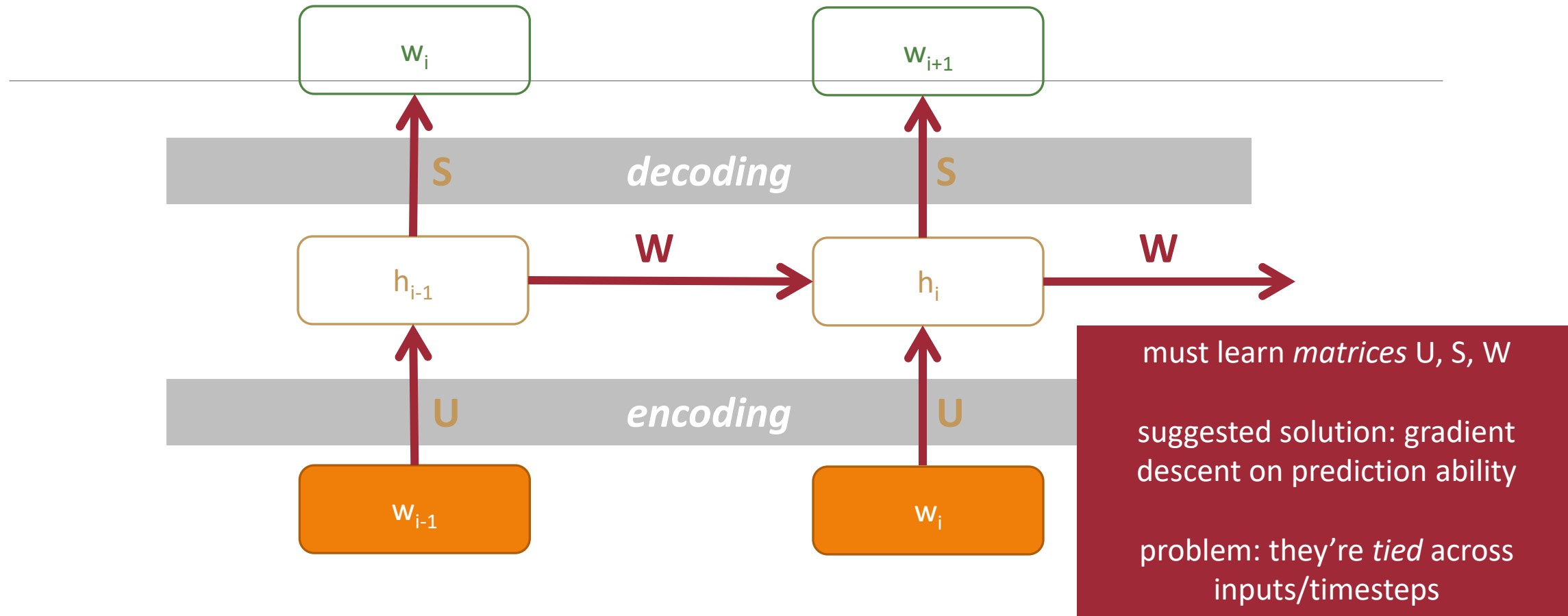
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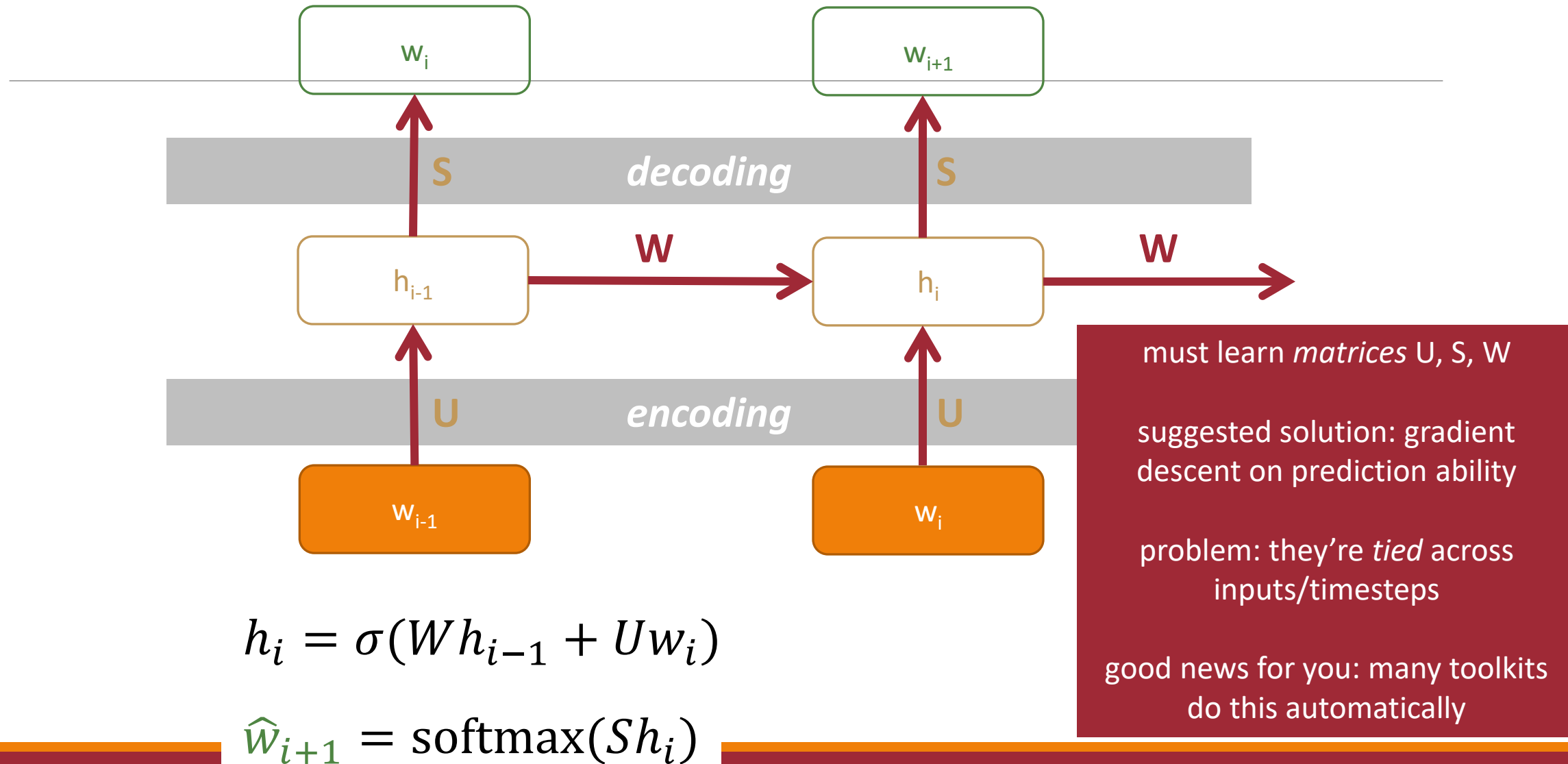
A Simple Recurrent Neural Network Cell



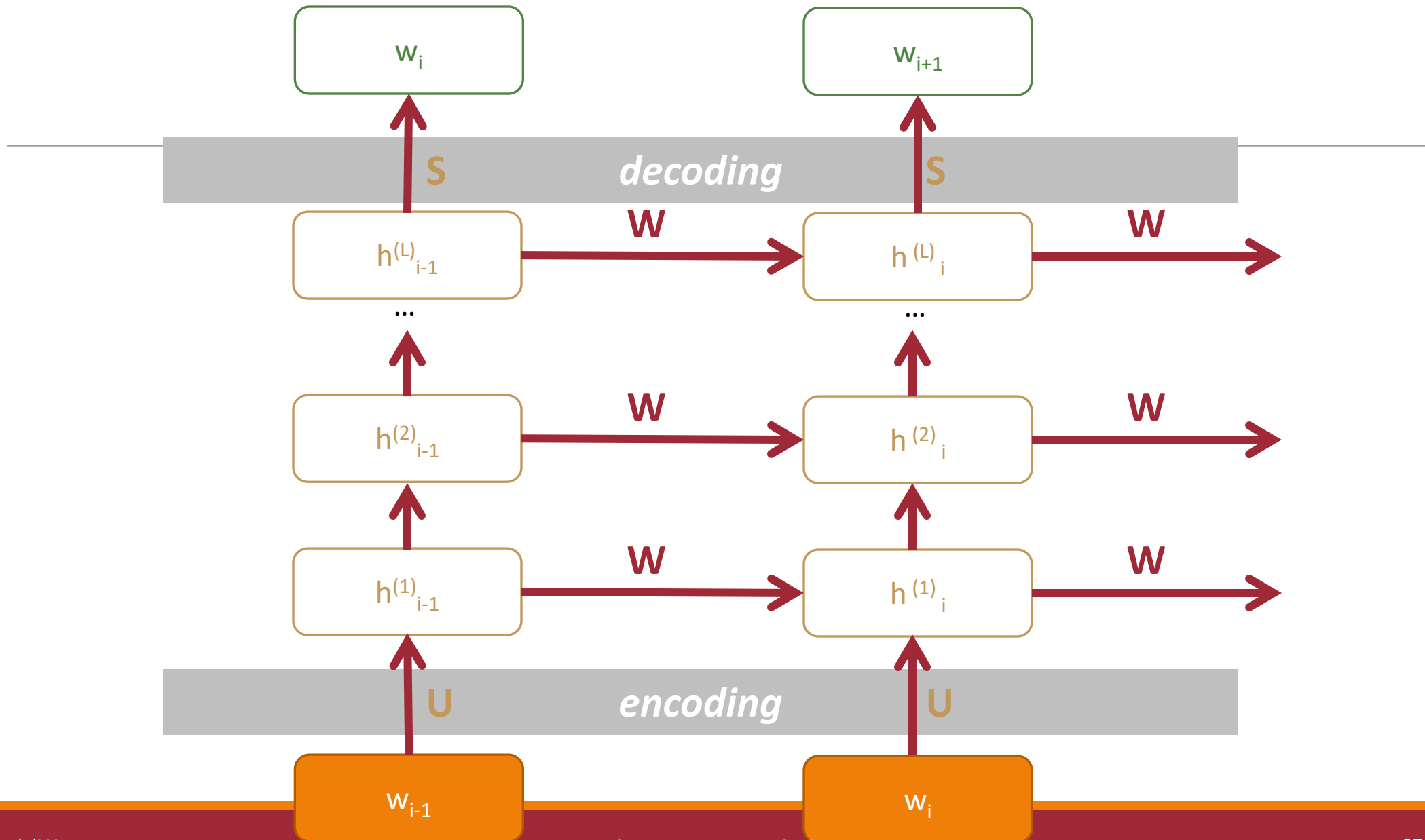
$$h_i = \sigma(W h_{i-1} + U w_i)$$

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A Simple Recurrent Neural Network Cell



A Multi-Layer Simple Recurrent Neural Network Cell



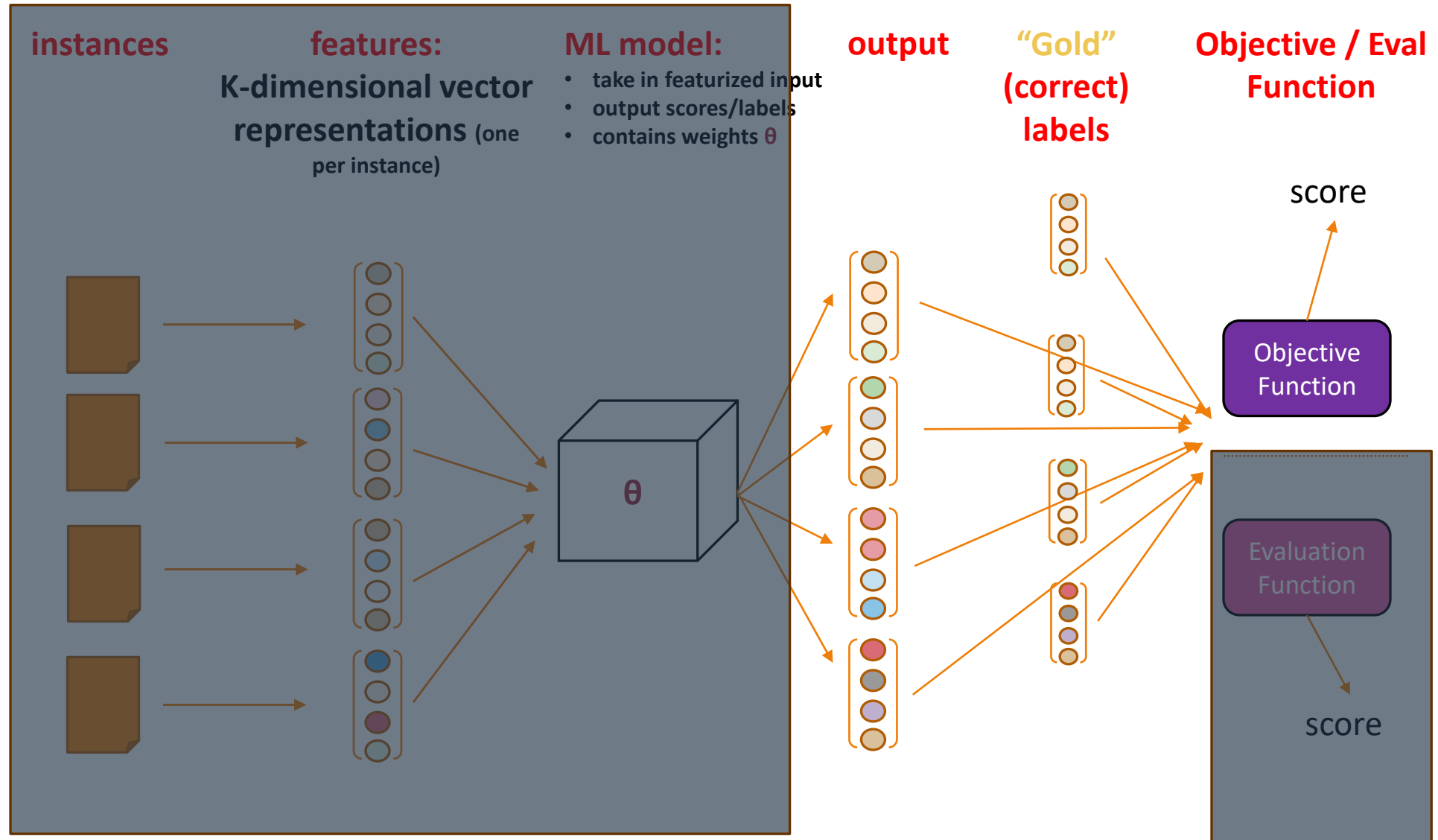
How do you learn an RNN?

As with other approaches: Compute the loss and perform gradient descent

Loss: Cross-entropy, computed per output word

- Just as with prior LM approaches!

Defining the Objective



Review:

Minimize Cross Entropy Loss

Classifier output

True probability (i.e., correct output)

$$L^{\text{xent}}(\hat{y}, y) = - \sum_{\text{label } k} \hat{y}[k] \log p(y = k|x)$$

index of "1" indicates correct value

one-hot vector

The diagram illustrates the cross entropy loss formula. It shows the predicted output \hat{y} and the true output y . The true output y is a one-hot vector, represented as a column vector with 0s and a 1. The index of the "1" indicates the correct value. The formula for the cross entropy loss is $L^{\text{xent}}(\hat{y}, y) = - \sum_{\text{label } k} \hat{y}[k] \log p(y = k|x)$. Arrows indicate the relationship between the labels and the vectors in the formula.

Cross entropy:
How much \hat{y} differs from the true y

objective is convex
(when $f(x)$ is not learned)

Gradient Descent: Backpropagate the Error

Initialize model

Set $t = 0$

Pick a starting value θ_t

Until converged:

for example(s) sentence i:

1. Compute loss l on x_i
 $l = \text{model}(x_i)$
2. Get gradient $g_t = l'(x_i)$
3. Get scaling factor ρ_t
4. Set $\theta_{t+1} = \theta_t - \rho_t * g_t$
5. Set $t += 1$

Core idea: Train the model to predict what the next word is via maximum likelihood (equivalently, minimizing cross-entropy loss).

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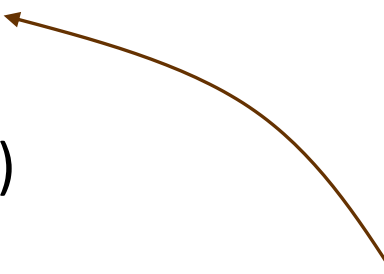
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This **loss** is the sum of the per-token cross-entropy loss

Recurrent NN Loss

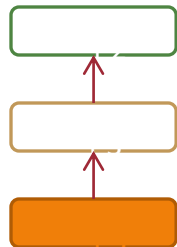
$\log .2$

word	prob.
The	.2
gray	.01
blue	.001
fluffy	.0005
wet	.0005
...	...

Remember: These probabilities are *computed* as a function of the model parameters!

The

The

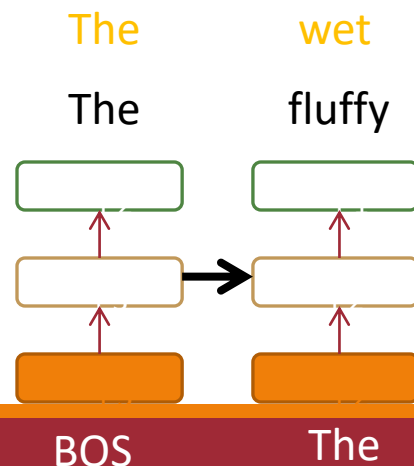


BOS

Recurrent NN Loss

$$\log .2 + \log .12$$

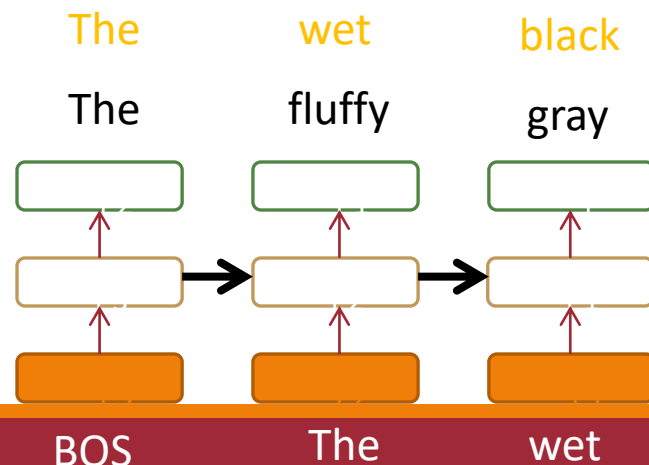
word	prob.	word	prob.
The	.2	black	.2
gray	.01	wet	.12
blue	.001	blue	.001
fluffy	.0005	fluffy	.0005
wet	.0005	gray	.0005
...



Recurrent NN Loss

$$\log.2 + \log.12 + \log.2$$

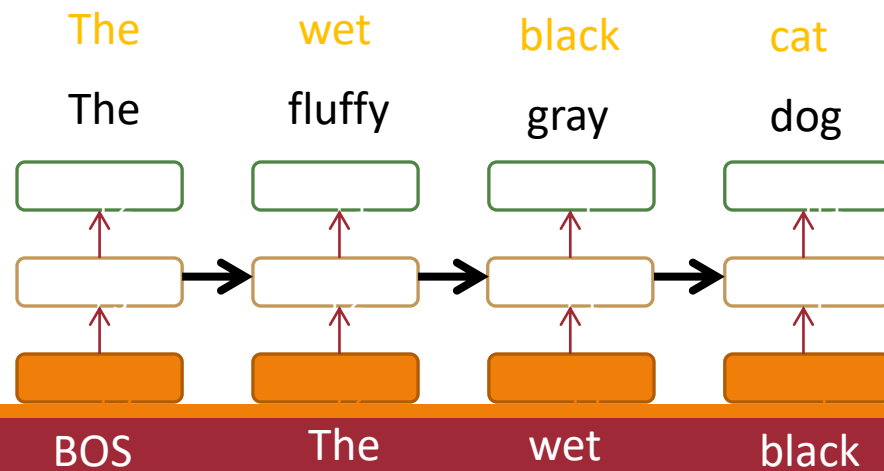
word	prob.	word	prob.	word	prob.
The	.2	black	.2	black	.2
gray	.01	wet	.12	gray	.01
blue	.001	blue	.001	blue	.001
fluffy	.0005	fluffy	.0005	bald	.0005
wet	.0005	gray	.0005	wet	.0005
...



Recurrent NN Loss

$$\log.2 + \log.12 + \log.2 + \log.19$$

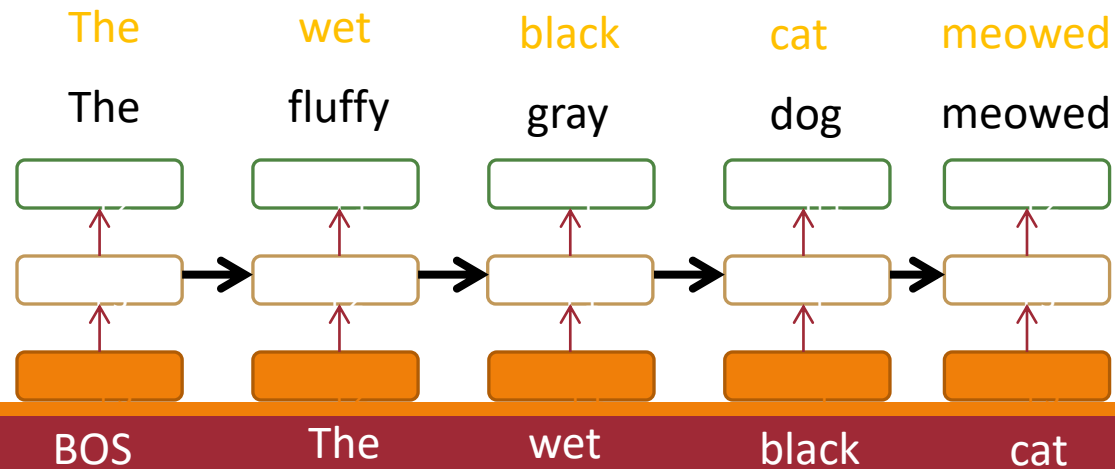
word	prob.	word	prob.	word	prob.	word	prob.
The	.2	black	.2	black	.2	dog	.2
gray	.01	wet	.12	gray	.01	cat	.19
blue	.001	blue	.001	blue	.001	blue	.001
fluffy	.0005	fluffy	.0005	bald	.0005	fluffy	.0005
wet	.0005	gray	.0005	wet	.0005	wet	.0005
...



Recurrent NN Loss

$$\log.2 + \log.12 + \log.2 + \log.19 + \log.3$$

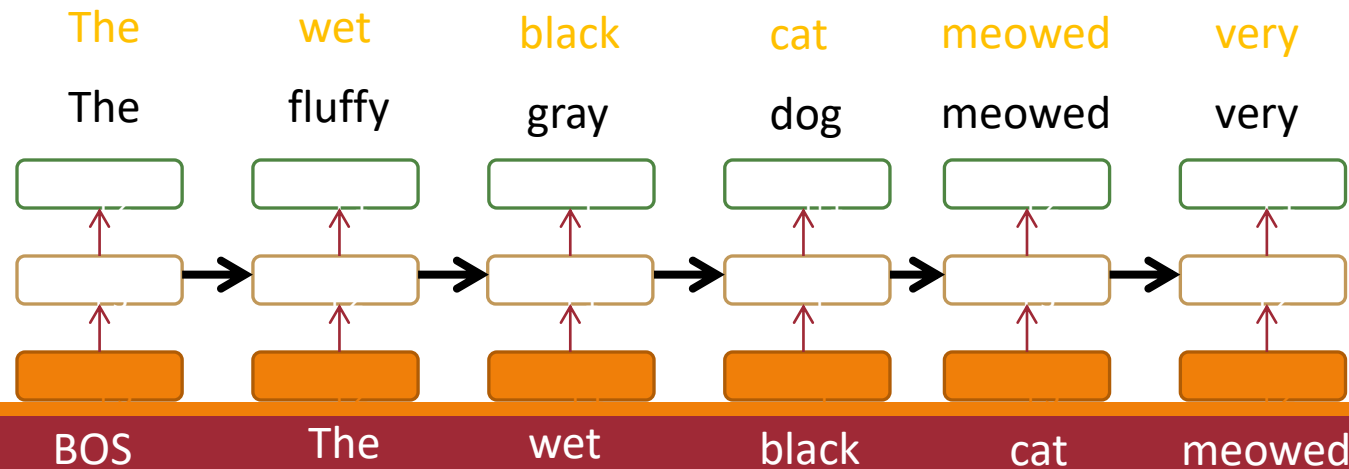
word	prob.	word	prob.	word	prob.	word	prob.	word	prob.
The	.2	black	.2	black	.2	dog	.2	meowed	.3
gray	.01	wet	.12	gray	.01	cat	.19	purred	.2
blue	.001	blue	.001	blue	.001	blue	.001	hissed	.1
fluffy	.0005	fluffy	.0005	bald	.0005	fluffy	.0005	fluffy	.001
wet	.0005	gray	.0005	wet	.0005	wet	.0005	wet	.001
...



Recurrent NN Loss

$$\log.2 + \log.12 + \log.2 + \log.19 + \log.3 + \log.2$$

word	prob.	word	prob.	word	prob.	word	prob.	word	prob.	word	prob.
The	.2	black	.2	black	.2	dog	.2	meowed	.3	very	.2
gray	.01	wet	.12	gray	.01	cat	.19	purred	.2	lots	.1
blue	.001	blue	.001	blue	.001	blue	.001	hissed	.1	softly	.1
fluffy	.0005	fluffy	.0005	bald	.0005	fluffy	.0005	fluffy	.001	fluffy	.0005
wet	.0005	gray	.0005	wet	.0005	wet	.0005	wet	.001	wet	.0005
...

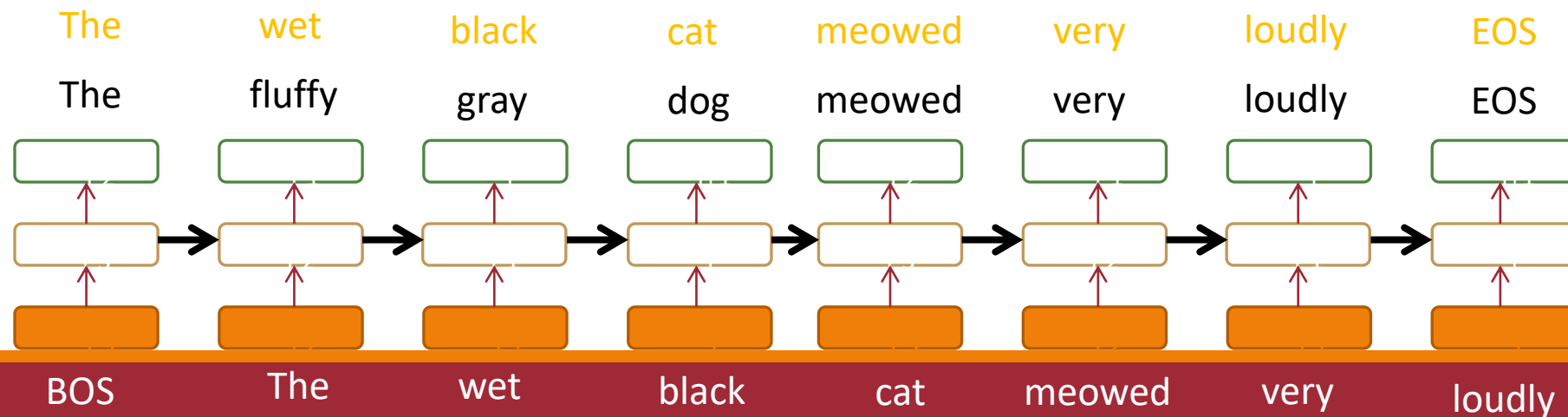


Recurrent NN Loss

(then negate, average)

$\log.2 + \log.12 + \log.2 + \log.19 + \log.3 + \log.2 + \log.2 + \log.2$

word	prob.	word	prob.	word	prob.	word	prob.	word	prob.	word	prob.	word	prob.	word	prob.
The	.2	black	.2	black	.2	dog	.2	meowed	.3	very	.2	loudly	.2	EOS	.3
gray	.01	wet	.12	gray	.01	cat	.19	purred	.2	lots	.1	softly	.01	and	.1
blue	.001	blue	.001	blue	.001	blue	.001	hissed	.1	softly	.1	quiet	.001	blue	.001
fluffy	.0005	fluffy	.0005	bald	.0005	fluffy	.0005	fluffy	.001	fluffy	.0005	fluffy	.001	fluffy	.0005
wet	.0005	gray	.0005	wet	.0005	wet	.0005	wet	.001	wet	.0005	wet	.001	wet	.0005
...



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(then negate, average)

log.2		+	log.12		+	log.2		+	log.19		+	log.3		+	log.2		+	log.2		+	log.2	
word	prob.		word	prob.		word	prob.		word	prob.		word	prob.		word	prob.		word	prob.		word	prob.
The	.2		black	.2		black	.2		dog	.2		meowed	.3		very	.2		loudly	.2		EOS	.3
gray	.01		wet	.12		gray	.01		cat	.19		purred	.2		lots	.1		softly	.01		and	.1
blue	.001		blue	.001		blue	.001		blue	.001		hissed	.1		softly	.1		quiet	.001		blue	.001
fluffy	.0005		fluffy	.0005		bald	.0005		fluffy	.0005		fluffy	.001		fluffy	.0005		fluffy	.001		fluffy	.0005
wet	.0005		gray	.0005		wet	.0005		wet	.0005		wet	.001		wet	.0005		wet	.001		wet	.0005
...

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(mini)batch

epoch

Think-pair-share: When would you want to use batches?

epoch: a single run over all training data

(mini-)batch: a run over a subset of the data

Flavors of Gradient Descent

“Online”

```
Set t = 0
Pick a starting value  $\theta_t$ 
Until converged:

  for example i in full data:
    1. Compute loss l on  $x_i$ 
    2. Get gradient
        $g_t = l'(x_i)$ 
    3. Get scaling factor  $\rho_t$ 
    4. Set  $\theta_{t+1} = \theta_t - \rho_t * g_t$ 
    5. Set t += 1
done
```

“Minibatch”

```
Set t = 0
Pick a starting value  $\theta_t$ 
Until converged:
  get batch  $B \subset$  full data
  set  $g_t = 0$ 
  for example(s) i in B:
    1. Compute loss l on  $x_i$ 
    2. Accumulate gradient
        $g_t += l'(x_i)$ 
  done
  Get scaling factor  $\rho_t$ 
  Set  $\theta_{t+1} = \theta_t - \rho_t * g_t$ 
  Set t += 1
```

“Batch”

```
Set t = 0
Pick a starting value  $\theta_t$ 
Until converged:

  set  $g_t = 0$ 
  for example(s) i in full data:
    1. Compute loss l on  $x_i$ 
    2. Accumulate gradient
        $g_t += l'(x_i)$ 
  done
  Get scaling factor  $\rho_t$ 
  Set  $\theta_{t+1} = \theta_t - \rho_t * g_t$ 
  Set t += 1
```

Why Is Training RNNs Hard?

Conceptually, it can get strange

But really getting the gradient just requires many applications of the chain rule for derivatives

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Vanishing gradients

Multiply the *same* matrices at *each* timestep → multiply *many* matrices in the gradients

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Conceptually, it can get strange

But really getting the gradient just requires many applications of the chain rule for derivatives

Vanishing gradients

Multiply the *same* matrices at *each* timestep → multiply *many* matrices in the gradients

One solution: clip the gradients to a max value

PyTorch RNN LMs

Pick Your Toolkit

PyTorch
Deeplearning4j
TensorFlow
Caffe
Keras

MXNet
Torch
...

Comparisons:

https://en.wikipedia.org/wiki/Comparison_of_deep_learning_software

Defining A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

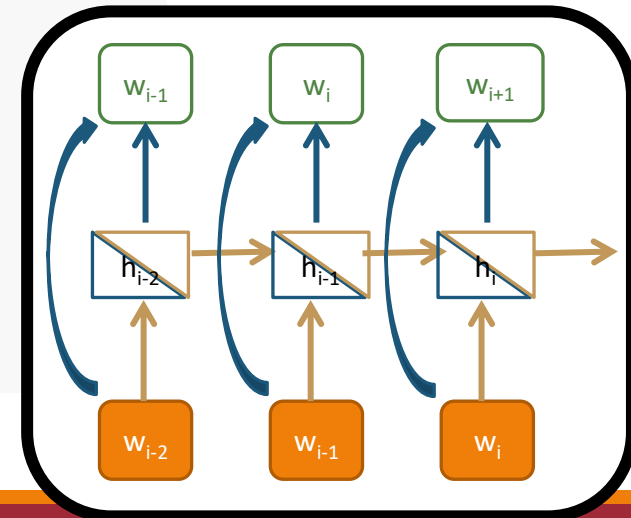
```
import torch.nn as nn
import torch.nn.functional as F

class CharRNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(CharRNN, self).__init__()

        self.rnn = nn.RNN(input_size, hidden_size)
        self.h2o = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, line_tensor):
        rnn_out, hidden = self.rnn(line_tensor)
        output = self.h2o(hidden[0])
        output = self.softmax(output)

        return output
```



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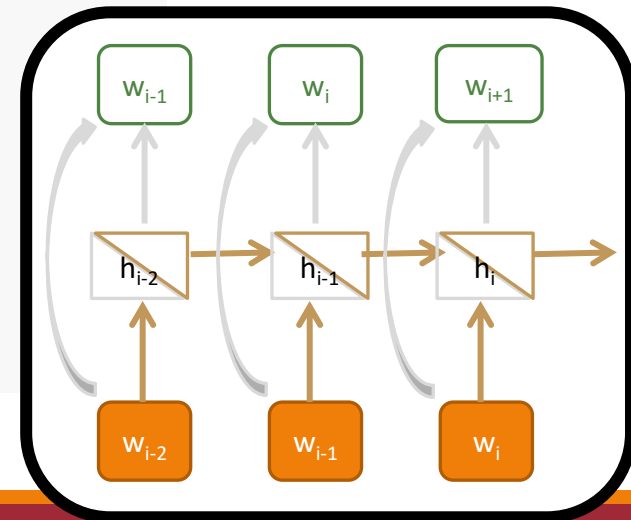
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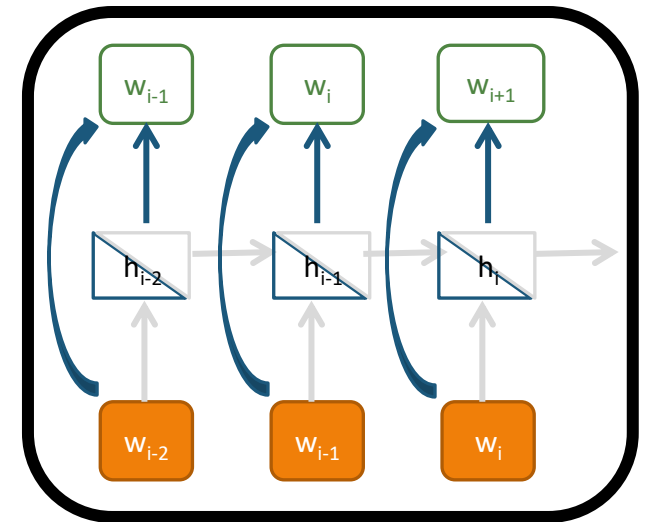
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        self.h2o = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)
```

```
def forward(self,
            rnn_out, hidden)
    output = self.h2o(rnn_out)
    output = self.softmax(output)

    return output
```

SOFTMAX

CLASS torch.nn.Softmax(*dim=None*) [SOURCE]

Applies the Softmax function to an n-dimensional input Tensor rescaling them so that the elements of the n-dimensional output Tensor lie in the range [0,1] and sum to 1.

Softmax is defined as:

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}$$

When the input Tensor is a sparse tensor then the unspecified values are treated as `-inf`.

Defining A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

```
import torch.nn as nn
import torch.nn.functional as F

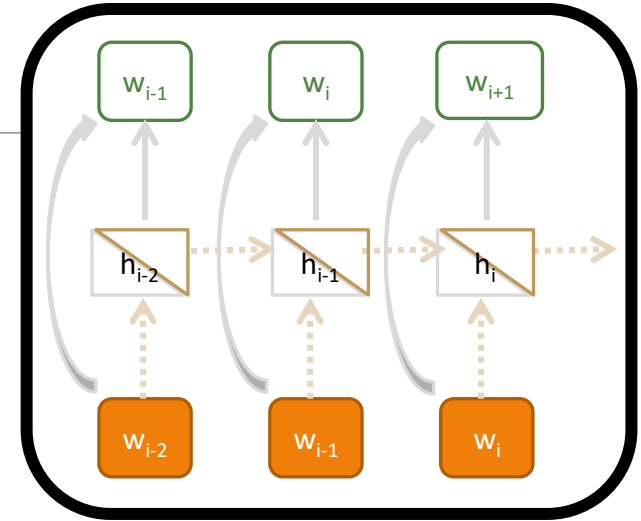
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        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, line_tensor):
        rnn_out, hidden = self.rnn(line_tensor)
        output = self.h2o(hidden[0])
        output = self.softmax(output)

        return output
```

encode



Defining A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

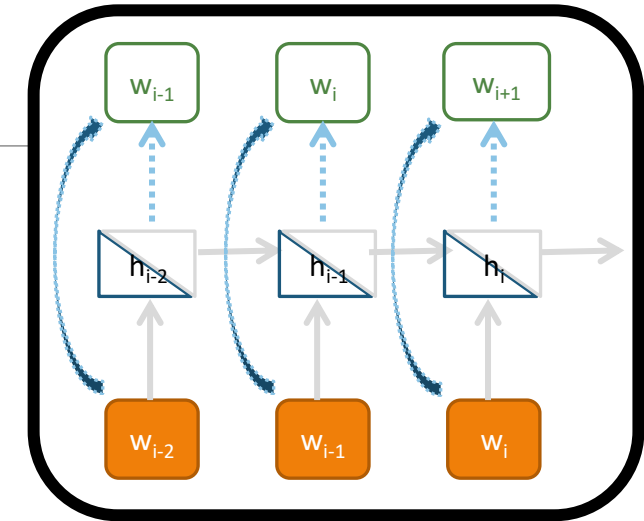
```
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import torch.nn.functional as F

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    def forward(self, line_tensor):
        rnn_out, hidden = self.rnn(line_tensor)
        output = self.h2o(hidden[0])
        output = self.softmax(output)

        return output
```



decode

Training A Simple RNN in Python

Negative log-likelihood

(we'll talk about this)

```
def train(rnn, training_data, n_epoch = 10, n_batch_size = 64, report_every = 50, learning_rate = 0.2, criterion = nn.NLLLoss()):  
  
    Learn on a batch of training_data for a specified number of iterations and reporting thresholds  
    """  
  
    # Keep track of losses for plotting  
    current_loss = 0  
    all_losses = []  
    rnn.train()  
    optimizer = torch.optim.SGD(rnn.parameters(), lr=learning_rate)  
  
    start = time.time()  
    print(f"training on data set with n = {len(training_data)}")
```

Set learning rate
and type of
optimizer

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

Training A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

```
for iter in range(1, n_epoch + 1):
    rnn.zero_grad() # clear the gradients

    # create some minibatches
    # we cannot use dataloaders because each of our names is a different length
    batches = list(range(len(training_data)))
    random.shuffle(batches)
    batches = np.array_split(batches, len(batches) // n_batch_size )

    for idx, batch in enumerate(batches):
        batch_loss = 0
        for i in batch: #for each example in this batch
            (label_tensor, text_tensor, label, text) = training_data[i]
            output = rnn.forward(text_tensor)
            loss = criterion(output, label_tensor)
            batch_loss += loss

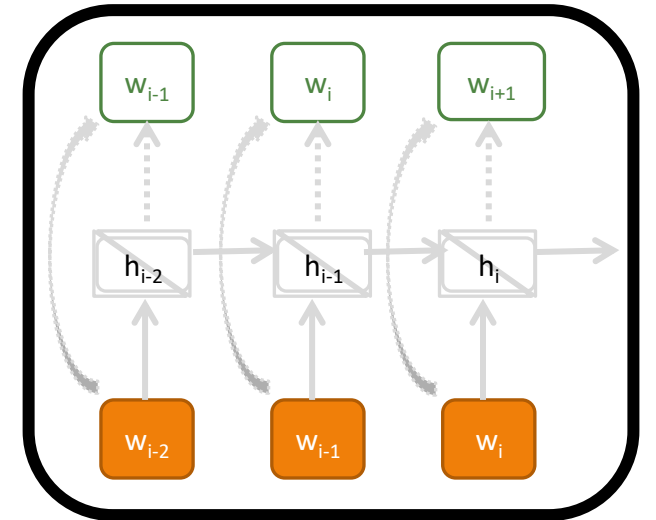
        # optimize parameters
        batch_loss.backward()
        nn.utils.clip_grad_norm_(rnn.parameters(), 3)
        optimizer.step()
        optimizer.zero_grad()

        current_loss += batch_loss.item() / len(batch)

    all_losses.append(current_loss / len(batches) )
    if iter % report_every == 0:
        print(f"{iter} ({iter / n_epoch:.0%}): \t average batch loss = {all_losses[-1]}")
    current_loss = 0

return all_losses
```

get predictions



Training A Simple RNN in Python

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for iter in range(1, n_epoch + 1):
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        batch_loss = 0
        for i in batch: #for each example in this batch
            (label_tensor, text_tensor, label, text) = training_data[i]
            output = rnn.forward(text_tensor)
            loss = criterion(output, label_tensor)
            batch_loss += loss

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            batch_loss.backward()
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        current_loss += batch_loss.item() / len(batch)

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```

get predictions

eval predictions

$$L^{\text{xent}}(\hat{y}, y) = - \sum_{\text{label } k} \hat{y}[k] \log p(y = k|x)$$

Set $t = 0$

Pick a starting value θ_t

Until converged:

for example(s) sentence i :

1. Compute loss l on x_i
2. Get gradient $g_t = l'(x_i)$
3. Get scaling factor ρ_t
4. Set $\theta_{t+1} = \theta_t - \rho_t * g_t$
5. Set $t += 1$

Training A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

```
for iter in range(1, n_epoch + 1):
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    batches = np.array_split(batches, len(batches) // n_batch_size )

    for idx, batch in enumerate(batches):
        batch_loss = 0
        for i in batch: #for each example in this batch
            (label_tensor, text_tensor, label, text) = training_data[i]
            output = rnn.forward(text_tensor)
            loss = criterion(output, label_tensor)
            batch_loss += loss

        # optimize parameters
        batch_loss.backward()
        nn.utils.clip_grad_norm_(rnn.parameters(), 3)
        optimizer.step()
        optimizer.zero_grad()

        current_loss += batch_loss.item() / len(batch)

    all_losses.append(current_loss / len(batches) )
    if iter % report_every == 0:
        print(f"{iter} ({iter / n_epoch:.0%}): \t average batch loss = {all_losses[-1]}")
    current_loss = 0

return all_losses
```

get predictions

eval predictions

compute gradient

Set $t = 0$
Pick a starting value θ_t
Until converged:
for example(s) sentence i :

1. Compute loss l on x_i
2. Get gradient $g_t = l'(x_i)$
3. Get scaling factor ρ_t
4. Set $\theta_{t+1} = \theta_t - \rho_t * g_t$
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Training A Simple RNN in Python

http://pytorch.org/tutorials/intermediate/char_rnn_classification_tutorial.html

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for iter in range(1, n_epoch + 1):
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    # we cannot use dataloaders because each of our names is a different length
    batches = list(range(len(training_data)))
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    batches = np.array_split(batches, len(batches) // n_batch_size )

    for idx, batch in enumerate(batches):
        batch_loss = 0
        for i in batch: #for each example in this batch
            (label_tensor, text_tensor, label, text) = training_data[i]
            output = rnn.forward(text_tensor)
            loss = criterion(output, label_tensor)
            batch_loss += loss

        # optimize parameters
        batch_loss.backward()
        nn.utils.clip_grad_norm_(rnn.parameters(), 3)
        optimizer.step()
        optimizer.zero_grad()

        current_loss += batch_loss.item() / len(batch)

    all_losses.append(current_loss / len(batches) )
    if iter % report_every == 0:
        print(f"{iter} ({iter / n_epoch:.0%}): \t average batch loss = {all_losses[-1]}")
    current_loss = 0

return all_losses
```

get predictions

eval predictions

compute gradient

perform SGD

Set $t = 0$
Pick a starting value θ_t
Until converged:
for example(s) sentence i :

1. Compute loss l on x_i
2. Get gradient $g_t = l'(x_i)$
3. Get scaling factor ρ_t
4. Set $\theta_{t+1} = \theta_t - \rho_t * g_t$
5. Set $t += 1$

Suggested Implementation Changes

```
import torch.nn as nn
import torch.nn.functional as F
```

```
class CharRNN(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(CharRNN, self).__init__()

        self.rnn = nn.RNN(input_size, hidden_size)
        self.h2o = nn.Linear(hidden_size, output_size)
        self.softmax = nn.LogSoftmax(dim=1)

    def forward(self, line_tensor):
        rnn_out, hidden = self.rnn(line_tensor)
        output = self.h2o(hidden[0])
        output = self.softmax(output)

        return output
```

current Pytorch refers
to this a “cell”

PyTorch's
CrossEntropyLoss
does a softmax
and then takes
the log

```
def train(rnn, training_data, = 50, learning_rate =
0.2, criterion = nn.NLLLoss() nn.CrossEntropyLoss())
    """
    Learn on a batch of training_data for a specified number of iterations and reporting thresholds
    """
    # Keep track of losses for plotting
    current_loss = 0
    all_losses = []
    rnn.train()
    optimizer = torch.optim.SGD(rnn.parameters(), lr=learning_rate)

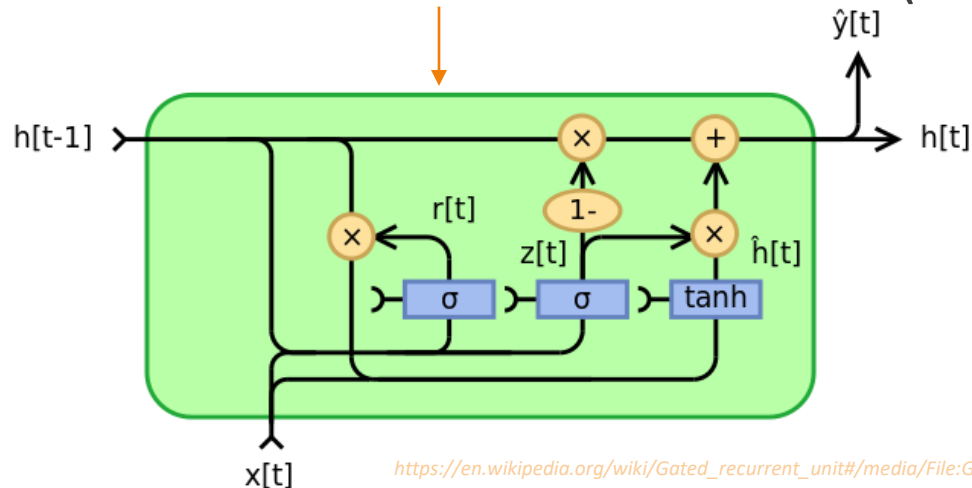
    start = time.time()
    print(f"training on data set with n = {len(training_data)}")
```

Another Solution: LSTMs/GRUs

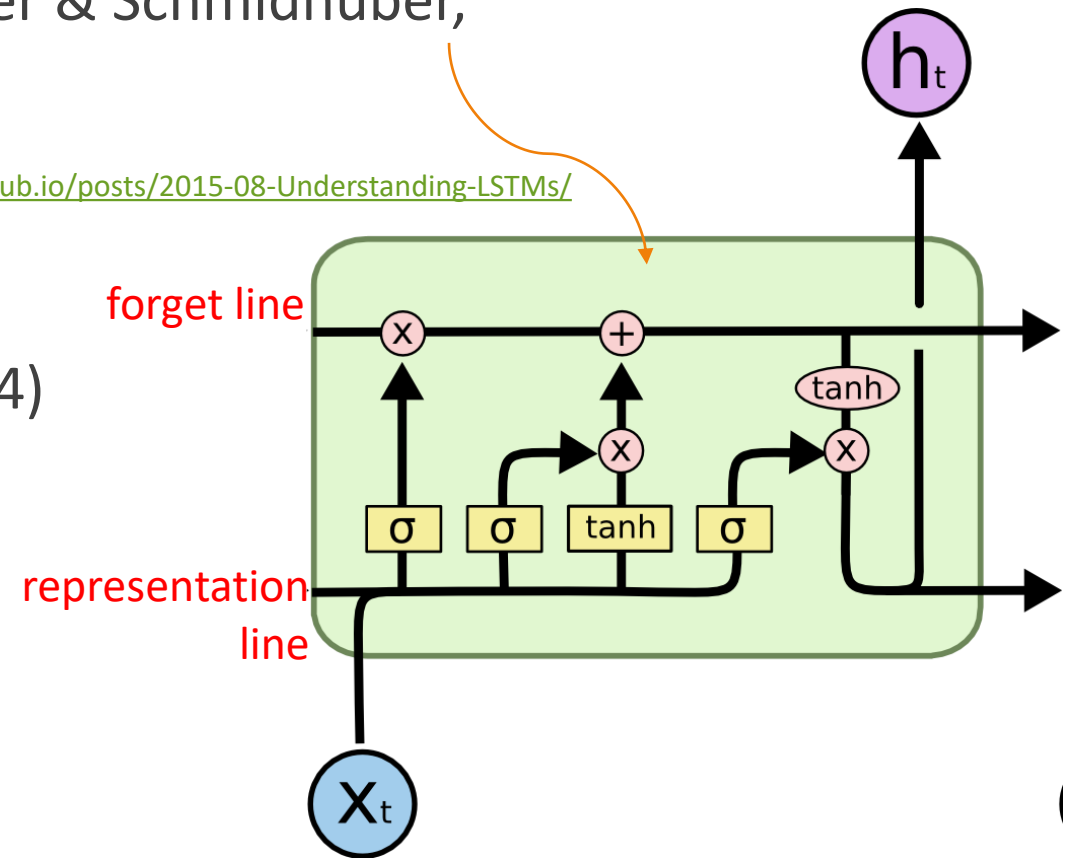
LSTM: Long Short-Term Memory (Hochreiter & Schmidhuber, 1997)

Basic Ideas: *learn to forget* <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>

GRU: Gated Recurrent Unit (Cho et al., 2014)

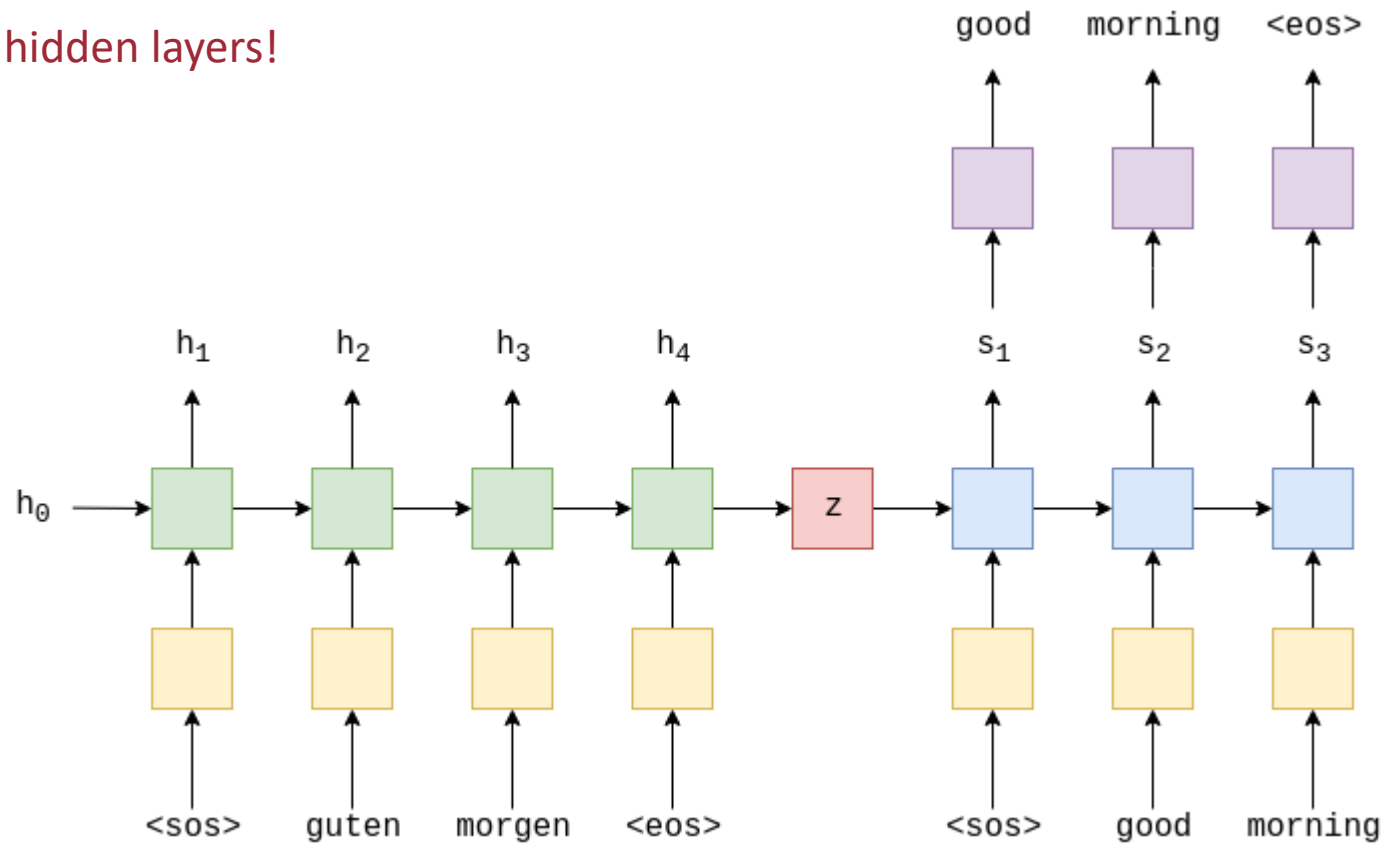


https://en.wikipedia.org/wiki/Gated_recurrent_unit#/media/File:Gated_Recurrent_Unit_base_type.svg



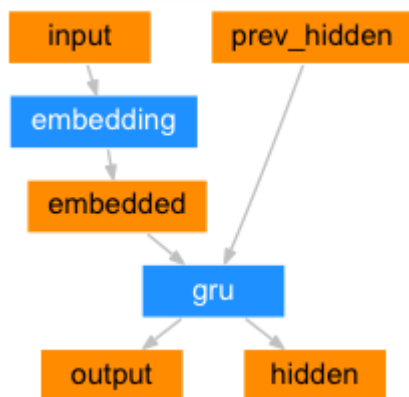
Sequence-to-Sequence

Note that this still has hidden layers!



<https://colab.research.google.com/github/bentrevett/pytorch-seq2seq/blob/main/1%20-%20Sequence%20to%20Sequence%20Learning%20with%20Neural%20Networks.ipynb#scrollTo=k6sRrL4wKsmi>

Encoder



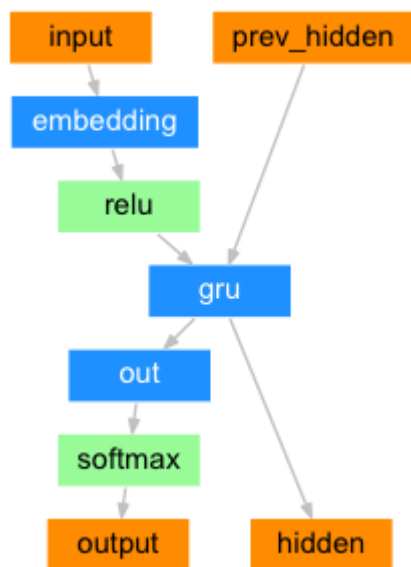
```
class EncoderRNN(nn.Module):
    def __init__(self, input_size, hidden_size, dropout_p=0.1):
        super(EncoderRNN, self).__init__()
        self.hidden_size = hidden_size

        self.embedding = nn.Embedding(input_size, hidden_size)
        self.gru = nn.GRU(hidden_size, hidden_size, batch_first=True)
        self.dropout = nn.Dropout(dropout_p)

    def forward(self, input):
        embedded = self.dropout(self.embedding(input))
        output, hidden = self.gru(embedded)
        return output, hidden
```

https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

Decoder



```
class DecoderRNN(nn.Module):
    def __init__(self, hidden_size, output_size):
        super(DecoderRNN, self).__init__()
        self.embedding = nn.Embedding(output_size, hidden_size)
        self.gru = nn.GRU(hidden_size, hidden_size, batch_first=True)
        self.out = nn.Linear(hidden_size, output_size)

    def forward(self, encoder_outputs, encoder_hidden, target_tensor=None):
        batch_size = encoder_outputs.size(0)
        decoder_input = torch.empty(batch_size, 1, dtype=torch.long,
device=device).fill_(SOS_token)
        decoder_hidden = encoder_hidden
        decoder_outputs = []

        for i in range(MAX_LENGTH):
            decoder_output, decoder_hidden = self.forward_step(decoder_input, decoder_hidden)
            decoder_outputs.append(decoder_output)

            if target_tensor is not None:
                # Teacher forcing: Feed the target as the next input
                decoder_input = target_tensor[:, i].unsqueeze(1) # Teacher forcing
            else:
                # Without teacher forcing: use its own predictions as the next input
                _, topi = decoder_output.topk(1)
                decoder_input = topi.squeeze(-1).detach() # detach from history as input

        decoder_outputs = torch.cat(decoder_outputs, dim=1)
        decoder_outputs = F.log_softmax(decoder_outputs, dim=-1)
        return decoder_outputs, decoder_hidden, None # We return 'None' for consistency in the
training loop

    def forward_step(self, input, hidden):
        output = self.embedding(input)
        output = F.relu(output)
        output, hidden = self.gru(output, hidden)
        output = self.out(output)
        return output, hidden
```

https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

Seq2Seq Tutorial

You will need to download the data. You can run
`!wget https://download.pytorch.org/tutorial/data.zip`
`!unzip data.zip`

https://pytorch.org/tutorials/intermediate/seq2seq_translation_tutorial.html

 Run in Google Colab  Download Notebook  View on GitHub



NLP From Scratch: Translation with a Sequence to Sequence Network and Attention

Created On: Mar 24, 2017 | Last Updated: Oct 21, 2024 | Last Verified: Nov 05, 2024

Author: Sean Robertson

This tutorial is part of a three-part series:

- NLP From Scratch: Classifying Names with a Character-Level RNN
- NLP From Scratch: Generating Names with a Character-Level RNN
- NLP From Scratch: Translation with a Sequence to Sequence Network and Attention

This is the third and final tutorial on doing **NLP From Scratch**, where we write our own classes and functions to preprocess the data to do our NLP modeling tasks.