Self-Supervised Learning w/ Recurrent Neural Nets

CSCI 601 471/671
NLP: Self-Supervised Models
https://self-supervised.cs.jhu.edu/sp2023/

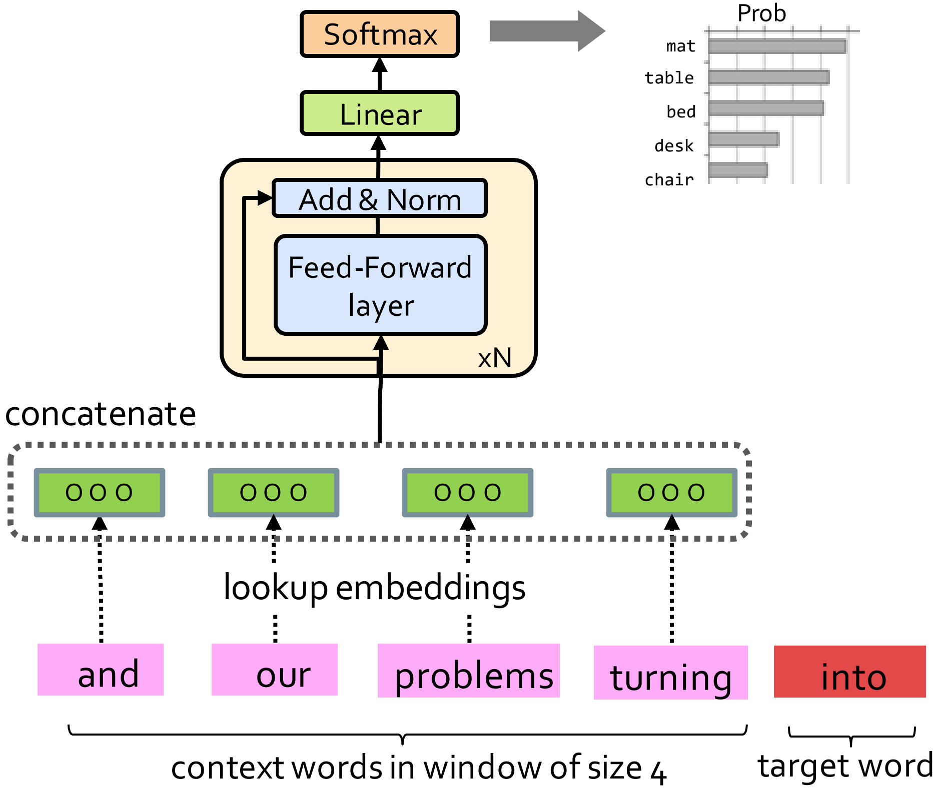
JOHNS HOPKINS UNIVERSITY

[Slide credit: Chris Tanner, Mohit Iyyer, Chris Manning and many others]

Recap

- Neural Language Models: neural networks trained with LM objective.

- Fixed-window Neural LM: first of many neural LMs we will see in this class.



What Changed from N-Gram LMs to Neural LMs?

- What is the source of Neural LM's strength?
- Why sparsity is less of an issue for Neural LMs?

- **Answer:** In n-grams, we treat all prefixes independently of each other! (even those that are semantically similar)

```
students opened their ___
pupils opened their ___
scholars opened their ___
undergraduates opened their ___
students turned the pages of their ___
students attentively perused their ___
...
```

Neural LMs are able to share information across these semantically-similar prefixes and overcome the sparsity issue.

Aside:

Sampling From LMs

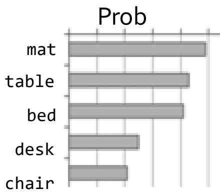
How do we generate language from LMs?

Given:

$$\mathbf{P}(\overbrace{X_t}^{\text{next word}} \,|\, \overbrace{X_1, \ldots, X_{t-1}}^{\text{context}})$$

`“The cat sat on the [MASK]”`

Some model

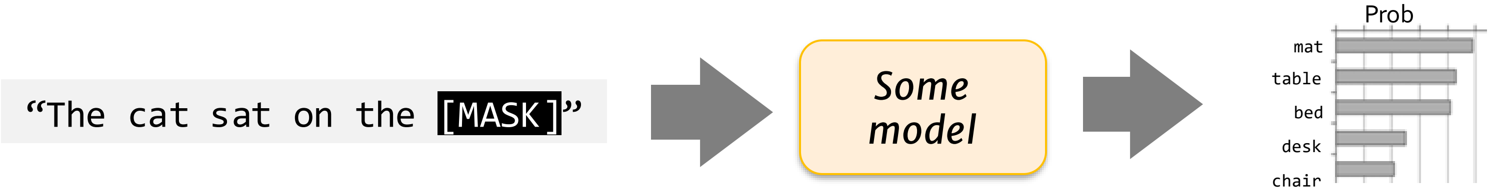


Approach 1: Greedy (Argmax)

- Challenge:
    - Generates boring results — not creative.
    - May repeat itself .

“I went to the place that the place that the place that the place ...”

$$x_t = \text{argmax}\ \mathbf{P}(\overbrace{X_t}^{\text{next word}} | \overbrace{X_1, \ldots, X_{t-1}}^{\text{context}})$$

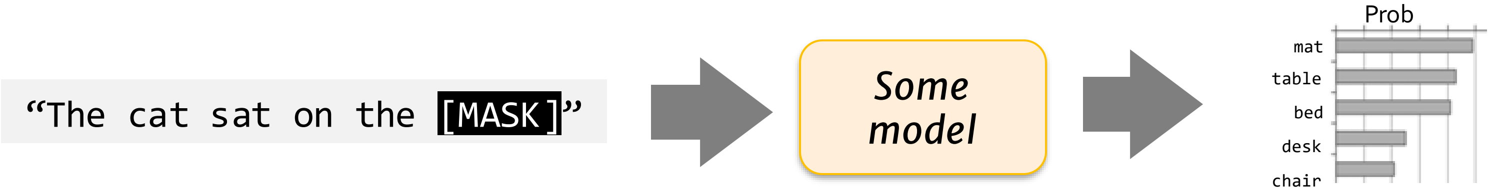


[The Curious Case of Neural Text Degeneration, Holtzman et al., 2020]

Approach 2: Sampling from the whole distribution

- Challenge: Likely to result in lots of nonsensical generations.
- Reason: LMs distribution is more meaningful about high-prob items, but as we get further away from high-prob items, the probs are less meaningful.

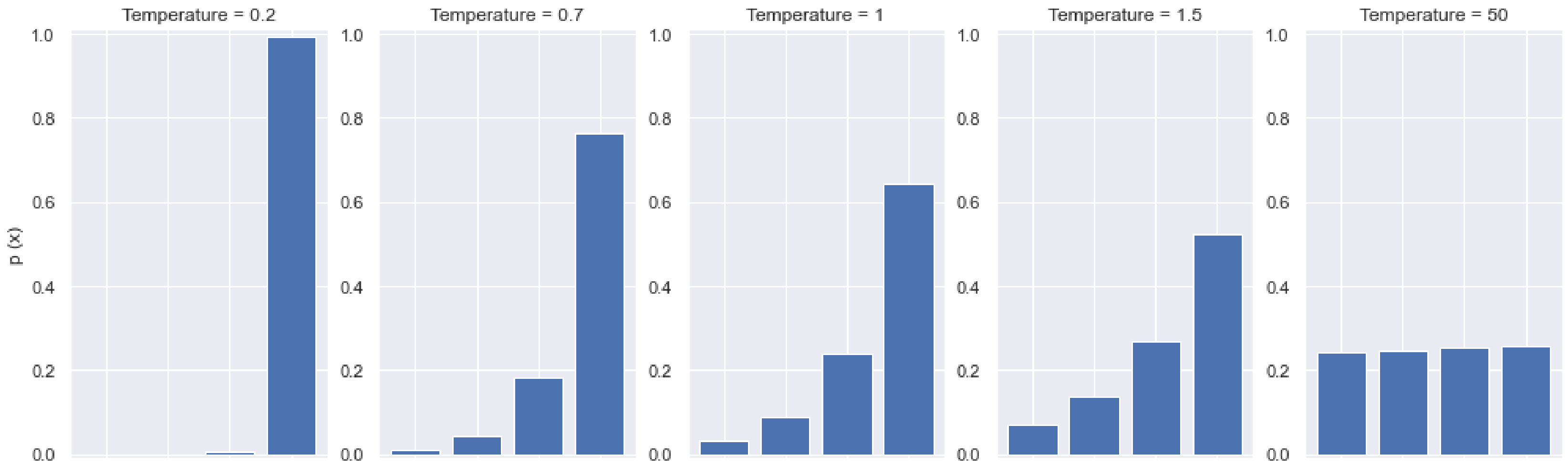
$$x_t \sim \mathbf{P}(\underbrace{X_t}_{\text{next word}} \mid \underbrace{X_1, \ldots, X_{t-1}}_{\text{context}})$$



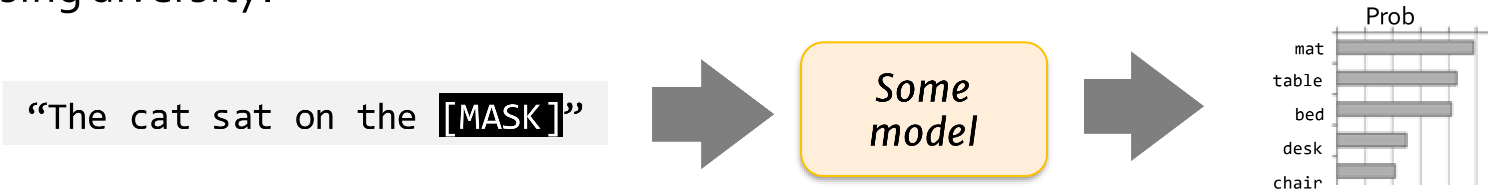
[The Curious Case of Neural Text Degeneration, Holtzman et al., 2020]

Approach 3: Sampling + Temperature

$$\frac{exp(z_i/T)}{\sum_j exp(z_j/T)}$$



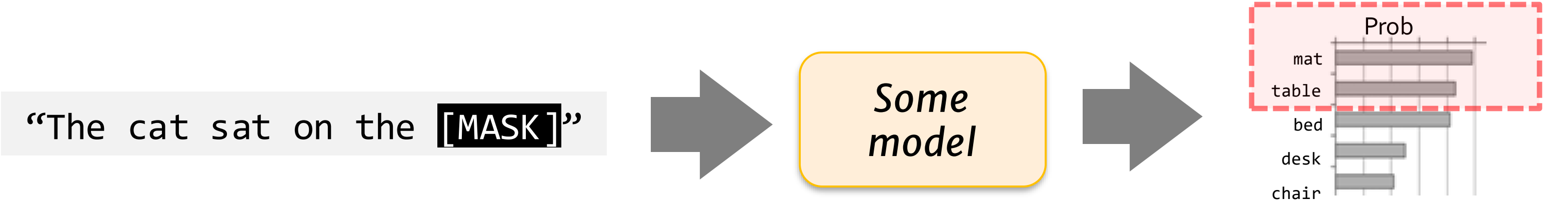
Small-ish T would assign more prob to the top of the distribution, while not losing diversity.



[The Curious Case of Neural Text Degeneration, Holtzman et al., 2020]

Approach 4: Top-p Sampling (Nucleus sampling)

- On each step, randomly sample from the distribution, but restricted to just the top-p most probable words
  - Like pure sampling, but truncate the distribution to high-prob content
- p=1 is basically sampling from the whole distribution



[The Curious Case of Neural Text Degeneration, Holtzman et al., 2020]

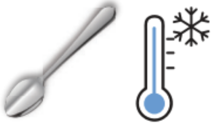
WebText

An unprecedented number of mostly young whales have become stranded on the West Australian coast since 2008.

Local Incoherence

Pure Sampling

The Australian Food Safety Authority has warned Australia's beaches may be revitalised this year because healthy seabirds and seals have been on the move. More than 50,000 seabirds, sea mammals and seahorses have been swept into the sea by the Holden CS118 and Adelaide Airport CS300 from 2013. A major white-bat and umidauda migration across Australia is under way in Australia for the first time, with numbers reaching an estimated 50,000.



Sampling, *t*=0.9

Last week's intense storms and a series of powerful cyclones have been officially blamed for the deaths of at least nine large fin whales near Whitsundays - the largest loss of any species globally. The fin whales: packed in the belly of one killer whale thrashing madly in fear as another tries to bring it to safety. When the colossal animal breached the waters of Whitsundays, he'd been seen tagged for a decade.

Nucleus, *p*=0.95

There has been an unprecedented number of calves caught in the nets of whaling stations that operate in WA. Pilot whales continue to migrate to feeding grounds to feed their calves. They are now vulnerable due to the decline of wild populations; they are restricted to one breeding site each year. Image copyright Yoon Bo Kim But, with sharp decline in wild populations the size of the Petrels are shrinking and dwindling population means there will only be room for a few new fowl.

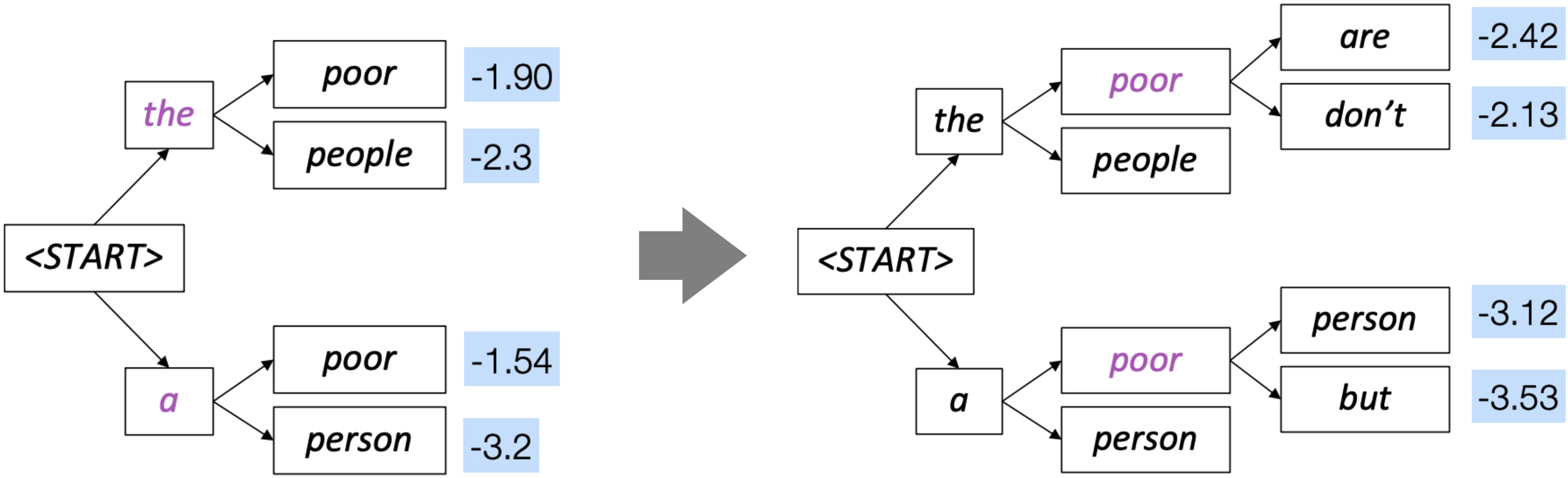
WebText

Poor nutrition has led to a rise in the number of stranded humpback whales on the West Australian coast, veterinary researchers have said. Carly Holyoake, from Murdoch University, at the Australian Veterinary Association's annual conference in Perth on Wednesday, said an unprecedented number of mostly young whales had become stranded on the coast since 2008.

[The Curious Case of Neural Text Degeneration, Holtzman et al., 2020]

Fancier Approaches: Beam Search

- A heuristic search that allows maximizing words probabilities for a window of words
- Out of scope for us. Feel free to check it in your own time.



Summary on Sampling Algorithms

- Greedy decoding: a simple method; gives low quality output

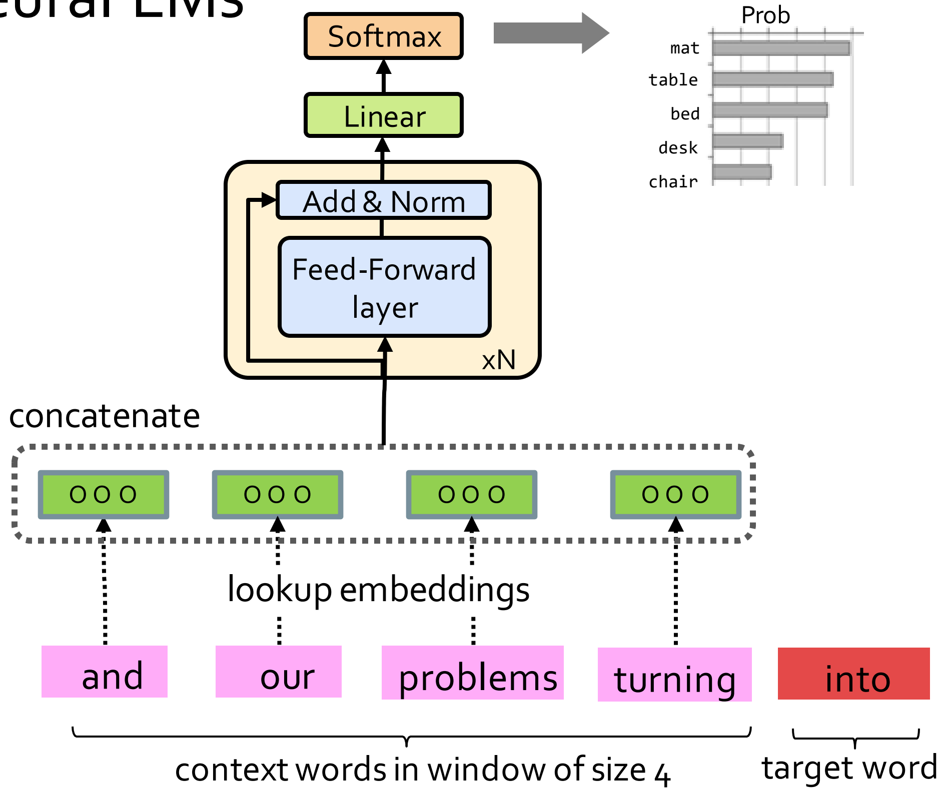
- Sampling methods are a way to get more diversity and randomness
  - Good for open-ended / creative generation (poetry, stories)
  - Top-p sampling allows you to control diversity

- Others: Beam search searches for high-probability output

Aside END!

Moving Beyond Feedforward Neural LMs

- Are competitive at language modeling task
- However, they
  - have difficulty in remembering long range dependencies
  - have a fixed window size
- Key question: how to better capture long-range dependencies?
- Alternative here: a new family of neural networks: recurrent nets



Recurrent LMs: Chapter Plan

1. A new faculty of neural networks: recurrent neural networks
2. A new family of language models: recurrent neural language models
3. Doing things with recurrent LMs
4. Issues with RNNs and fancier variants

Infinite Use of Finite Model

- Main question: how can a **finite** model a **long** (infinite) context?

- Solution: recursion! (recursive use of a model)

- RNNs are a family of neural networks introduced to **learn sequential data** via **recursive** dynamics.
- Inspired by the temporality of human thoughts

[Jeff Elman, "Finding structure in time," 1990]

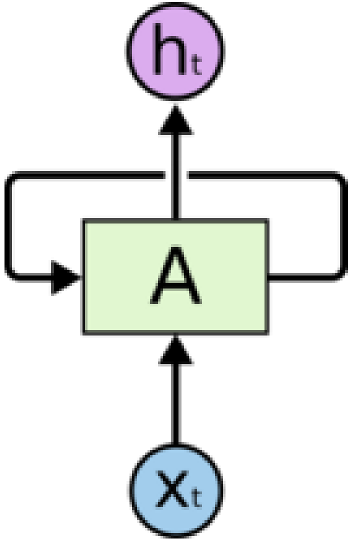
Recurrent Neural Networks (RNNs)

new state

old state

Input vector at t

$$h_t = f(h_{t-1}, x_t)$$

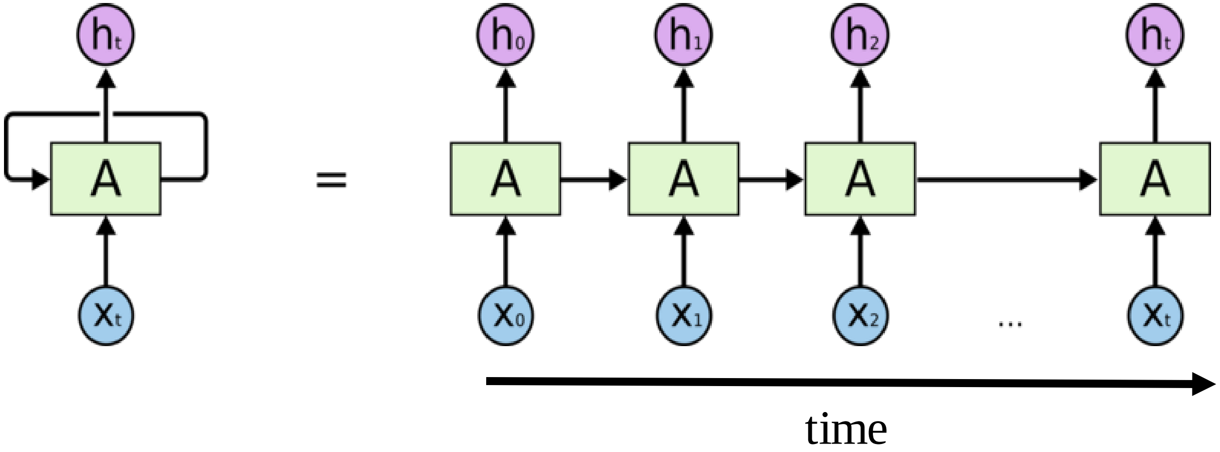


- In the diagram, $f(.)$ looks at some **input** x_t and its **previous hidden state** h_{t-1} and outputs **a revised state** h_t.
- A loop allows information to be passed from one step of the network to the next.

[Jeff Elman, "Finding structure in time," 1990]

Unrolling RNN

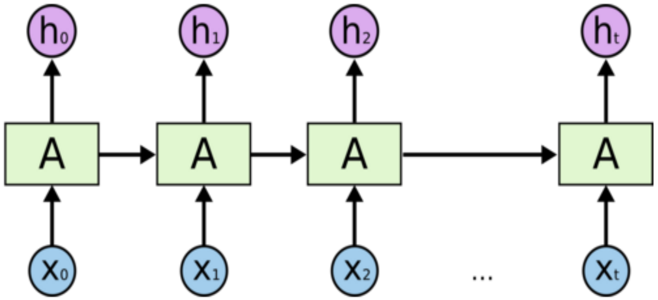
- The diagram above shows what happens if we **unroll the loop**.



- A recurrent neural network can be thought of as multiple copies of the same network, each passing a message to a successor.

[Jeff Elman, "Finding structure in time," 1990]

LMs w/ Recurrent Neural Nets

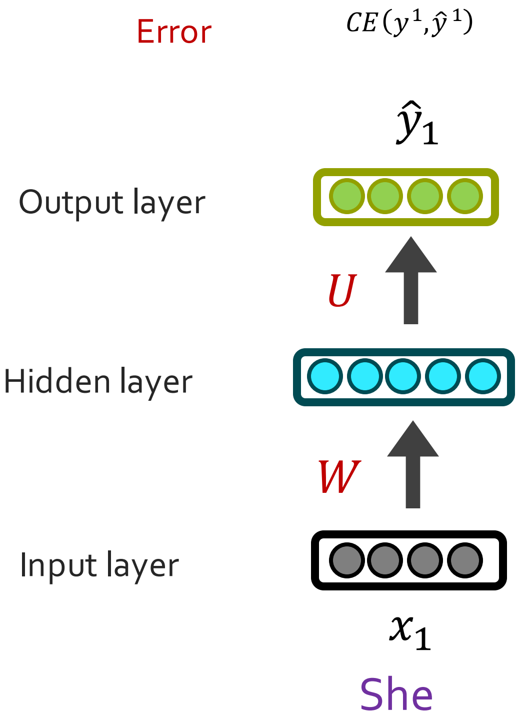


$$\mathbf{P}(\underbrace{X_t}_{\text{next word}} | \underbrace{X_1, \ldots, X_{t-1}}_{\text{context}})$$

- We feed the words one at a time to the RNN.
- A predictive head uses the latest embedding vector to produce a probability over the vocabulary.

RNN: Forward Propagation

$$CE(y^i, \hat{y}^i) = -\sum_{w \in V} y_w^i \log(\hat{y}_w^i)$$



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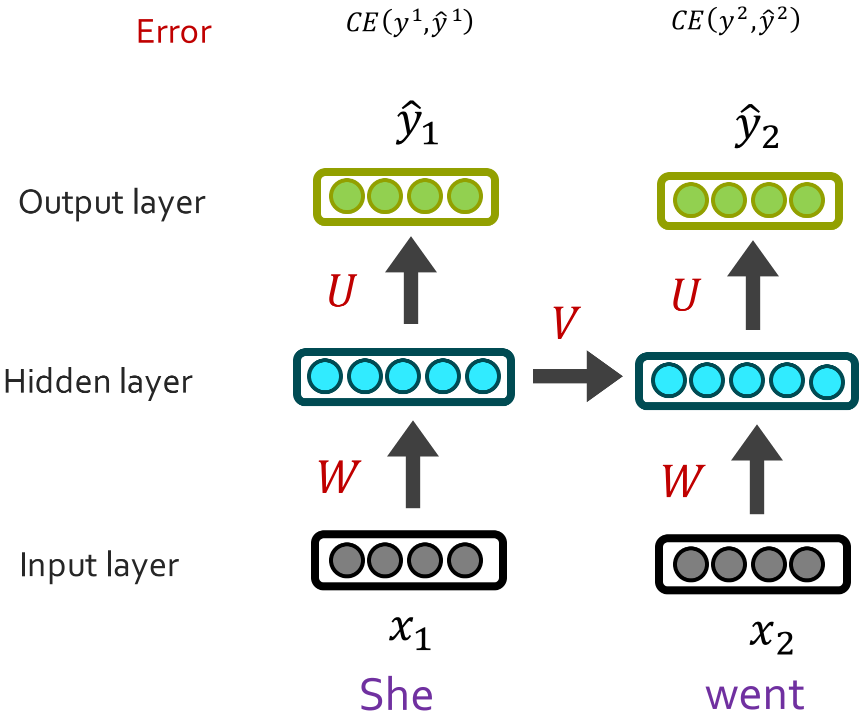

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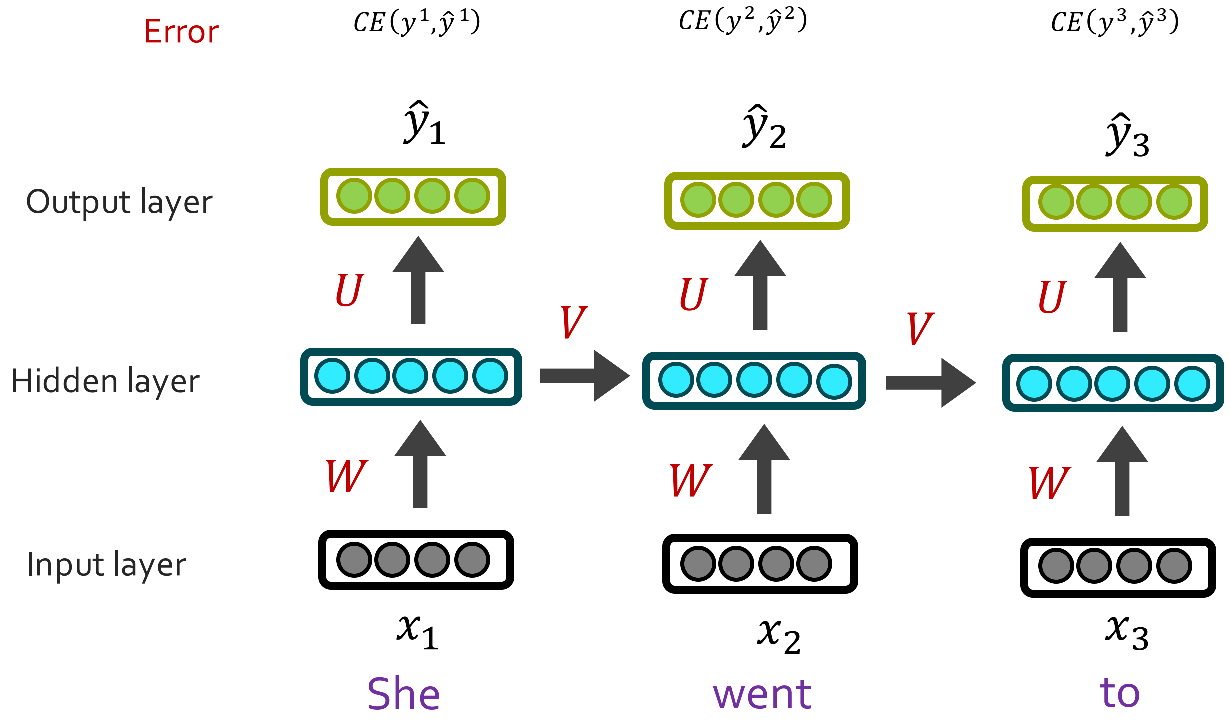

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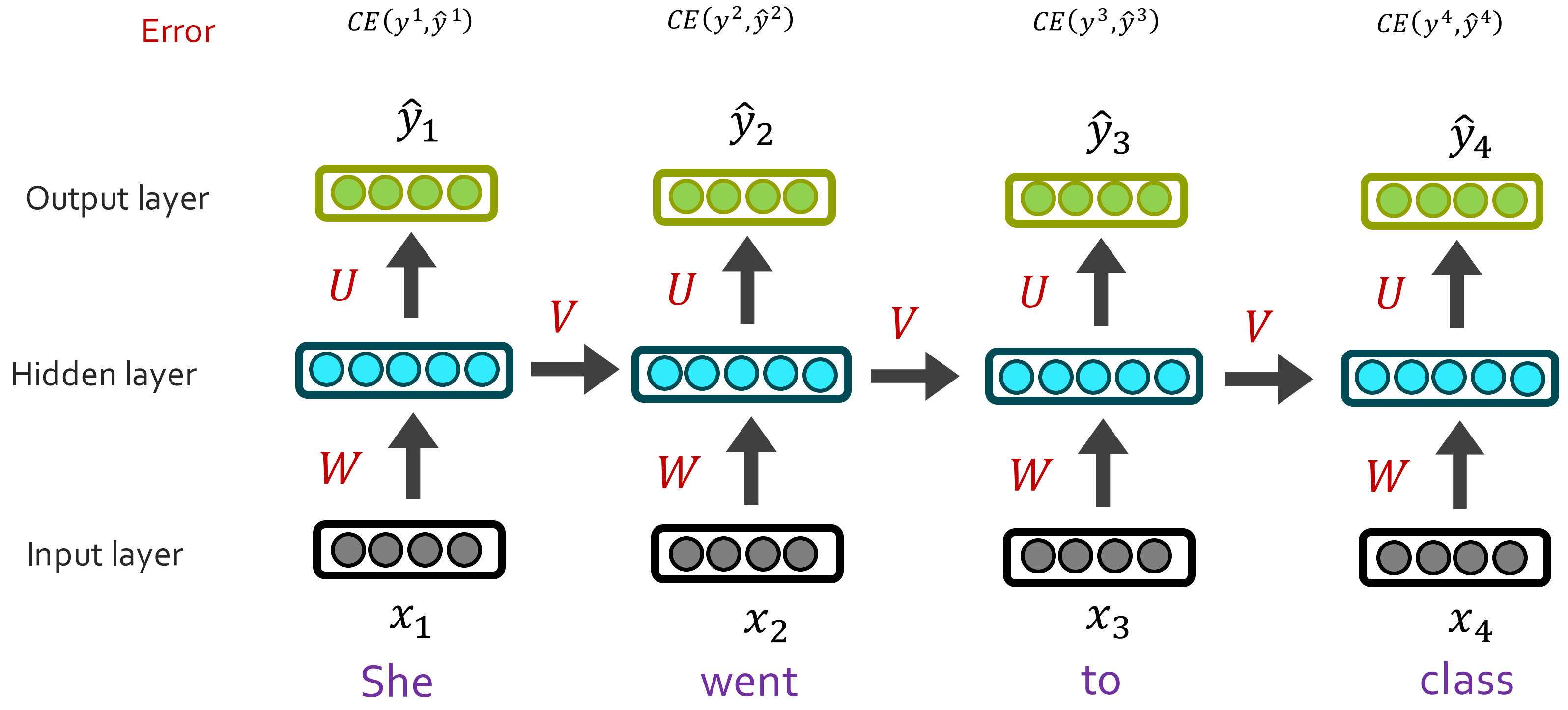


RNN: Forward Propagation

$$CE(y^i, \hat{y}^i) = -\sum_{w \in V} y_w^i \log(\hat{y}_w^i)$$

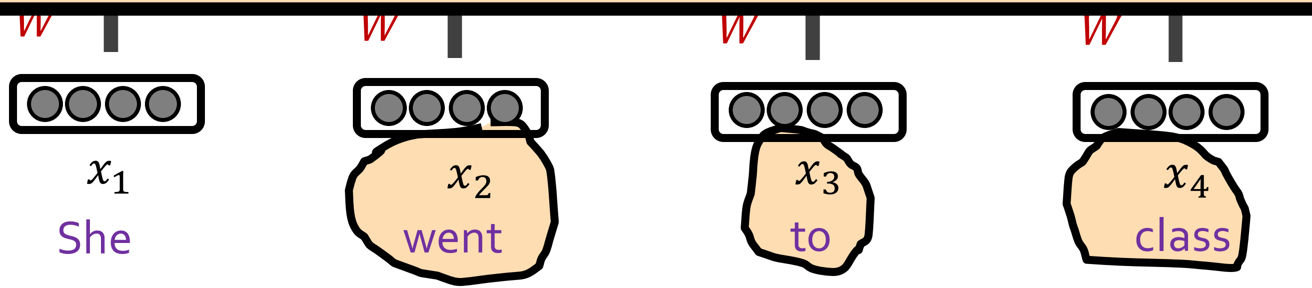
Error

Output layer

During **training**, regardless of our output predictions, we feed in the **correct inputs**

Hidden layer

Input layer



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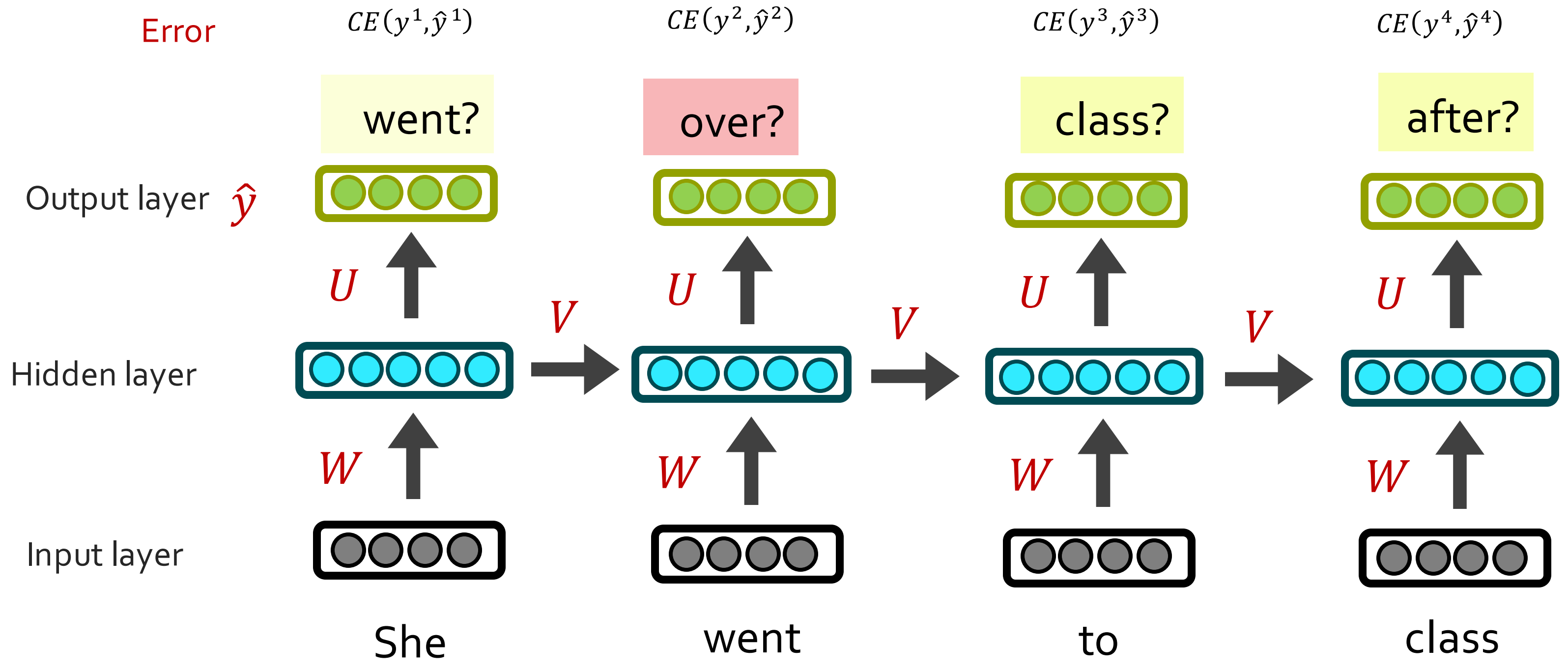

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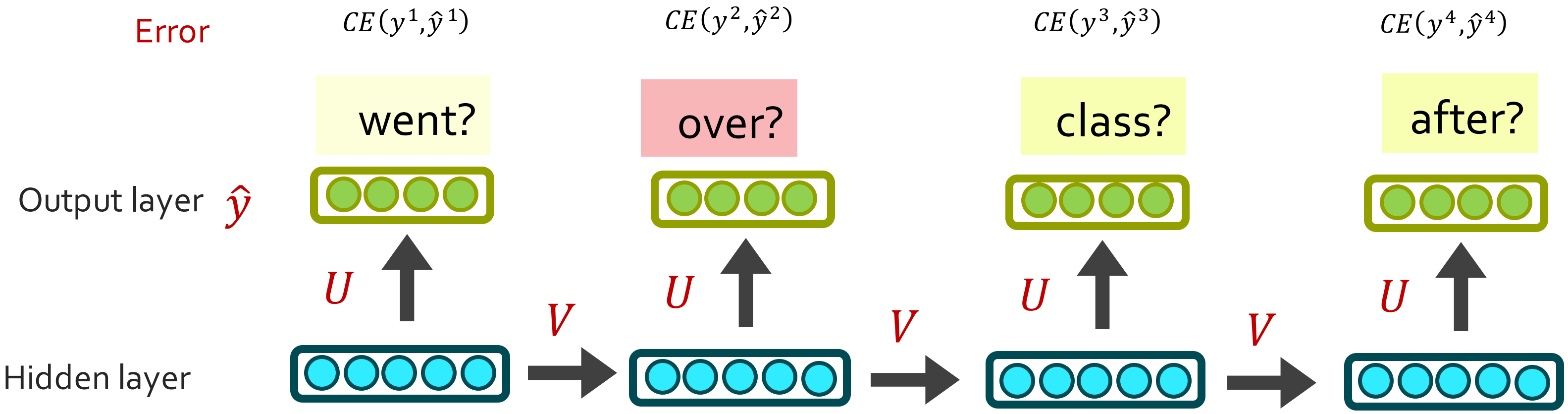


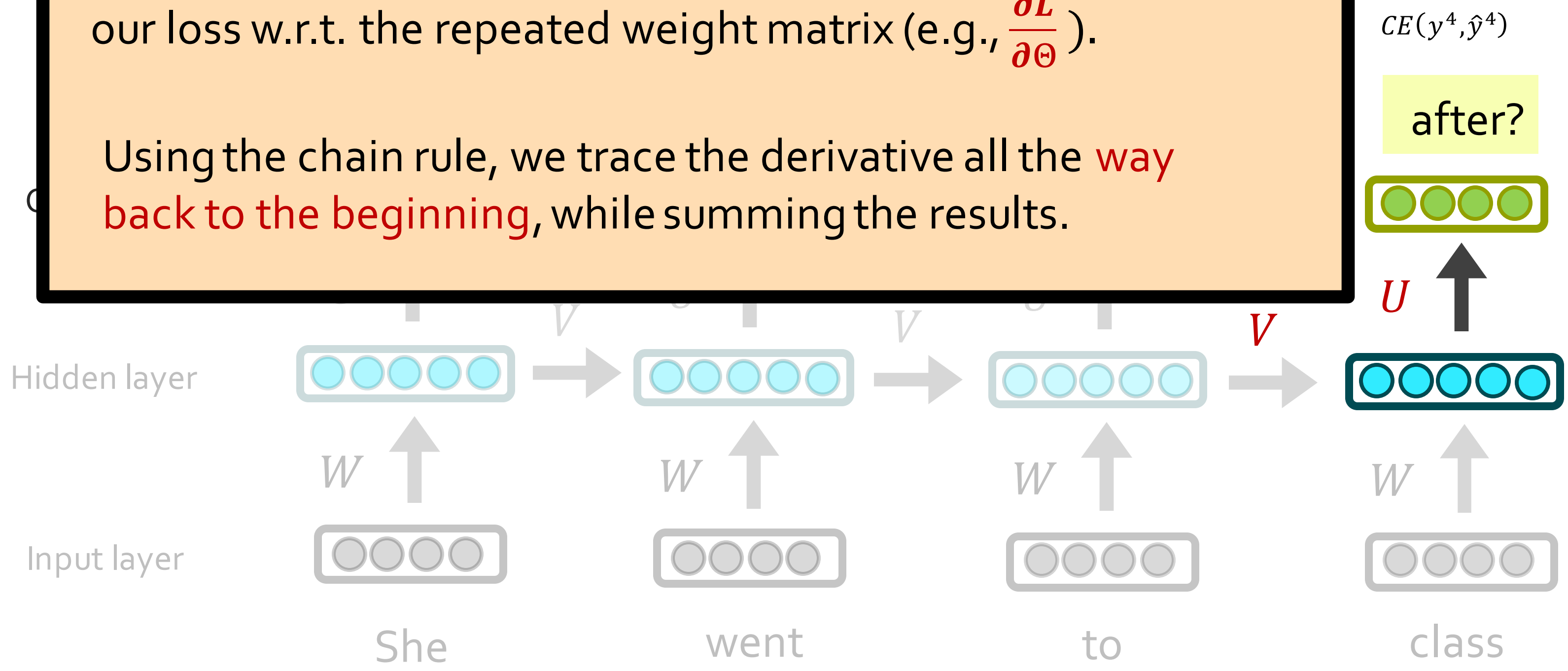
Input layer

Our total loss is simply the average loss across all T time steps

Backward Step

To update our weights (e.g.Θ), we calculate the gradient of our loss w.r.t. the repeated weight matrix (e.g., $\frac{\partial L}{\partial \Theta}$).

Using the chain rule, we trace the derivative all the way back to the beginning, while summing the results.



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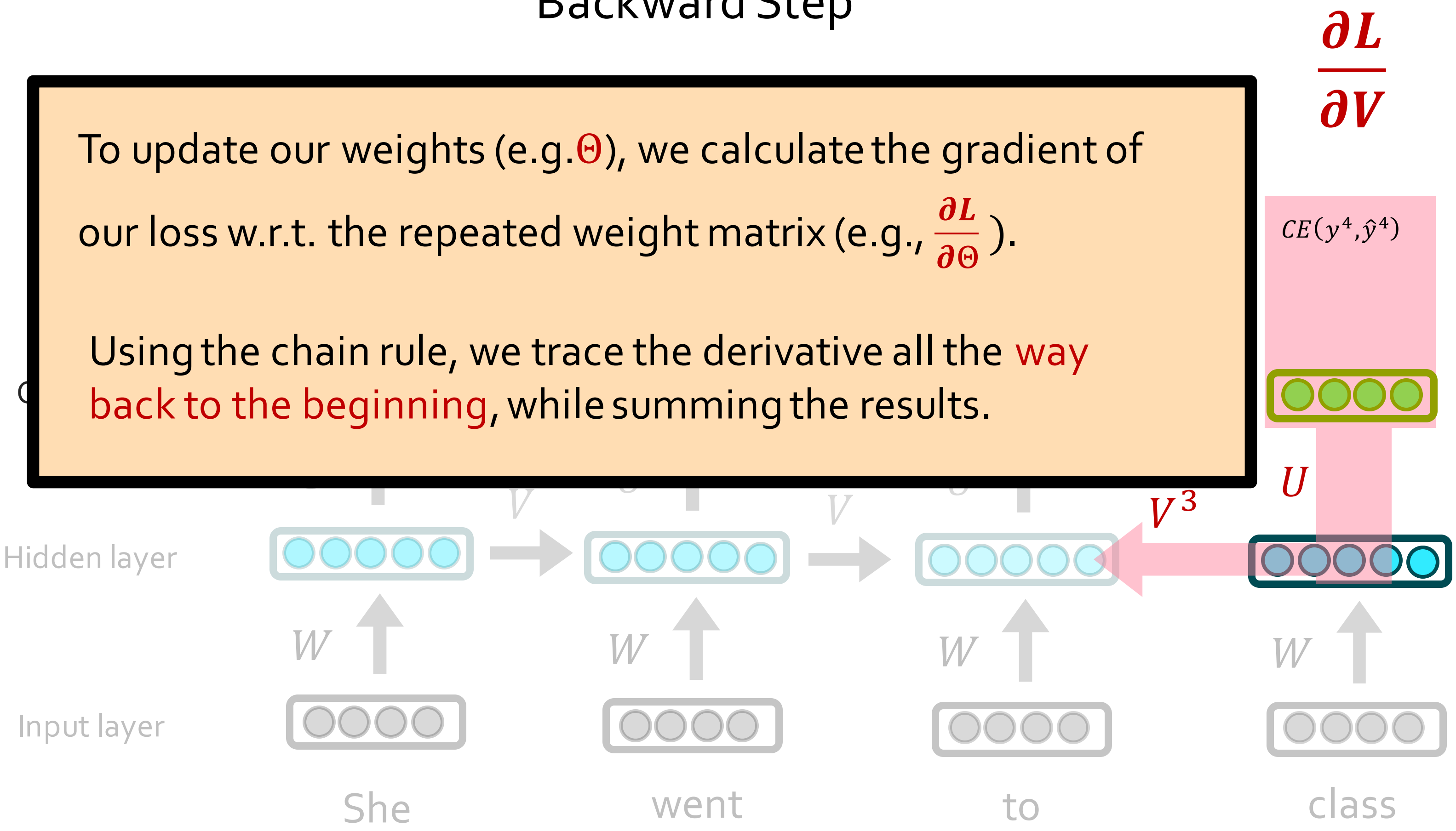

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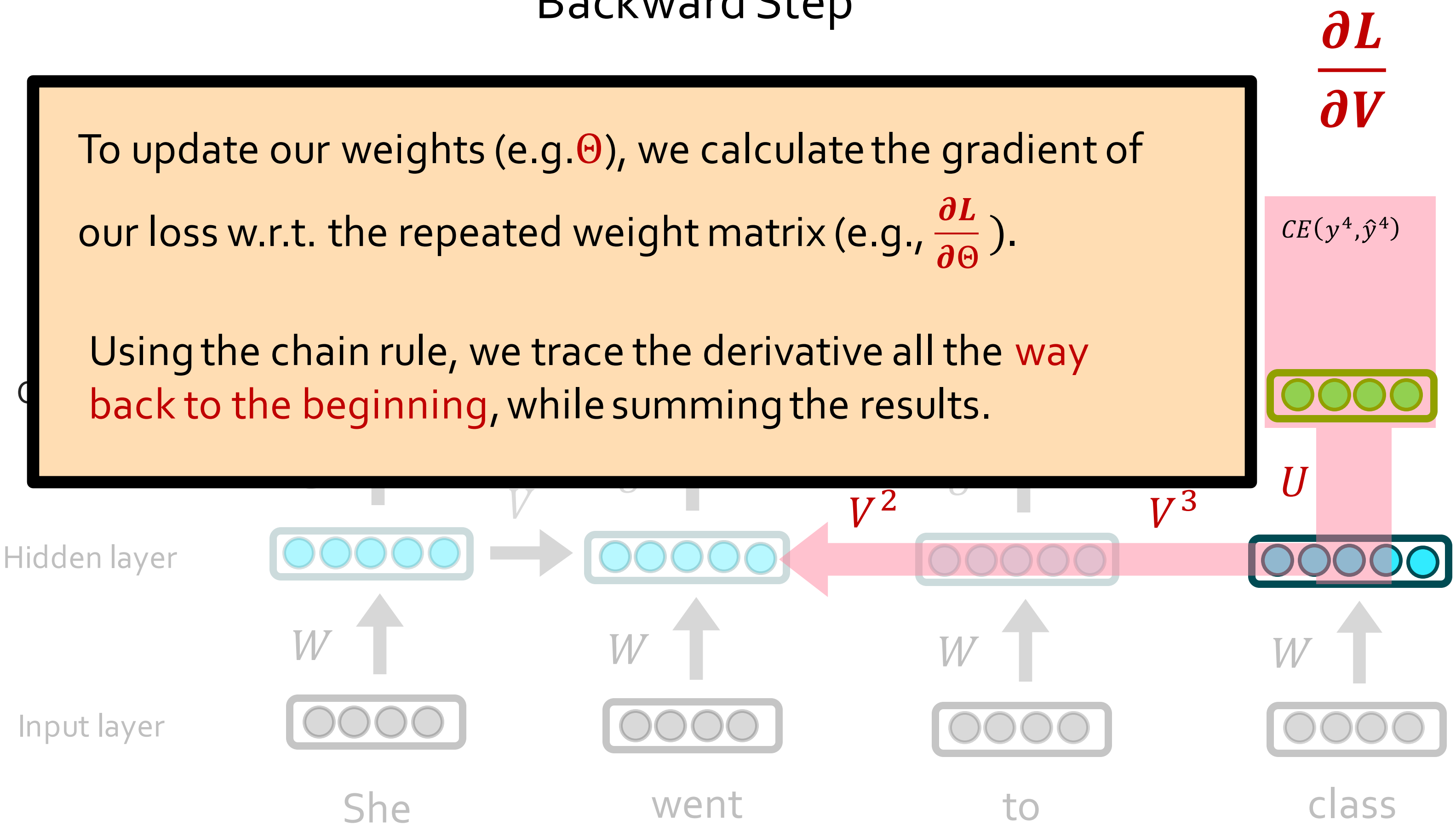

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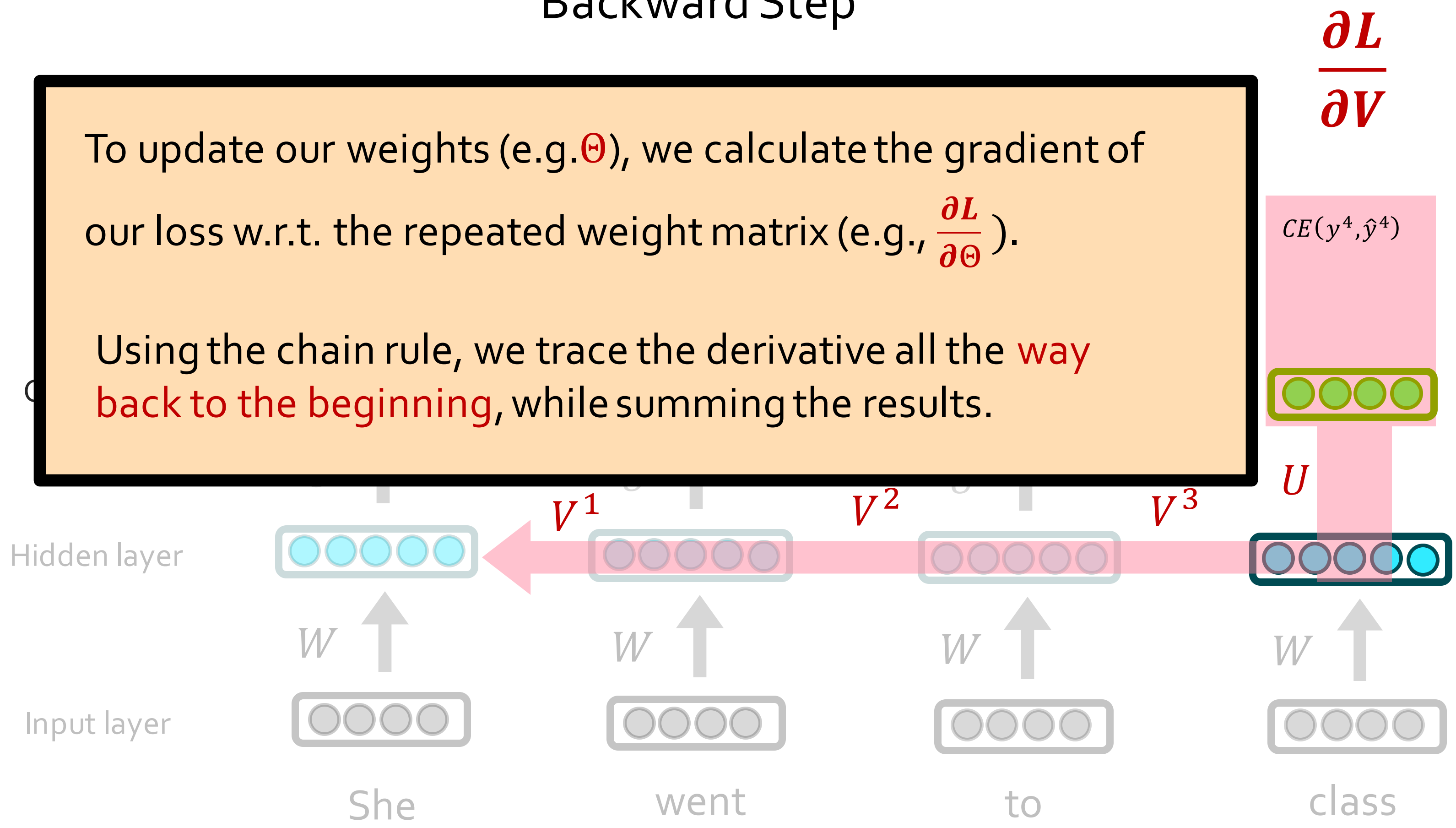
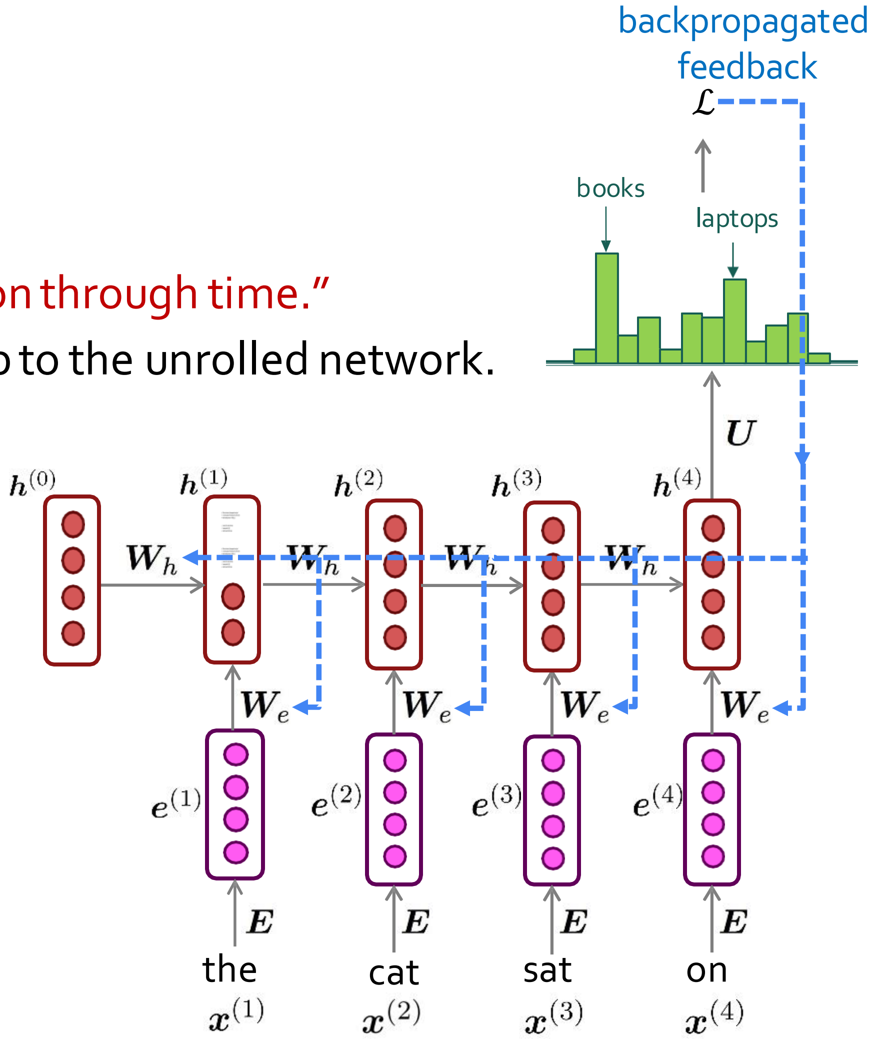


Training RNNs: Summary

- RNNs can be trained using "backpropagation through time."
- Can be viewed as applying normal backprop to the unrolled network.

- Model's learnable parameters Θ

1. Compute $\mathcal{L}(\Theta)$ for a batch of sentences
2. Compute gradients $\nabla_\Theta \mathcal{L}(\Theta)$
3. Update the weights and then repeat



RNN: Generation

We can generate the most likely next event (e.g., word) by sampling from $\hat{\boldsymbol{y}}$
Continue until we generate <EOS> symbol.

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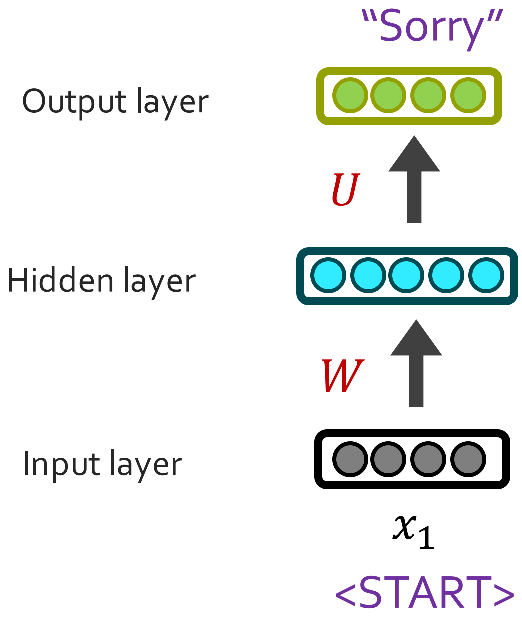

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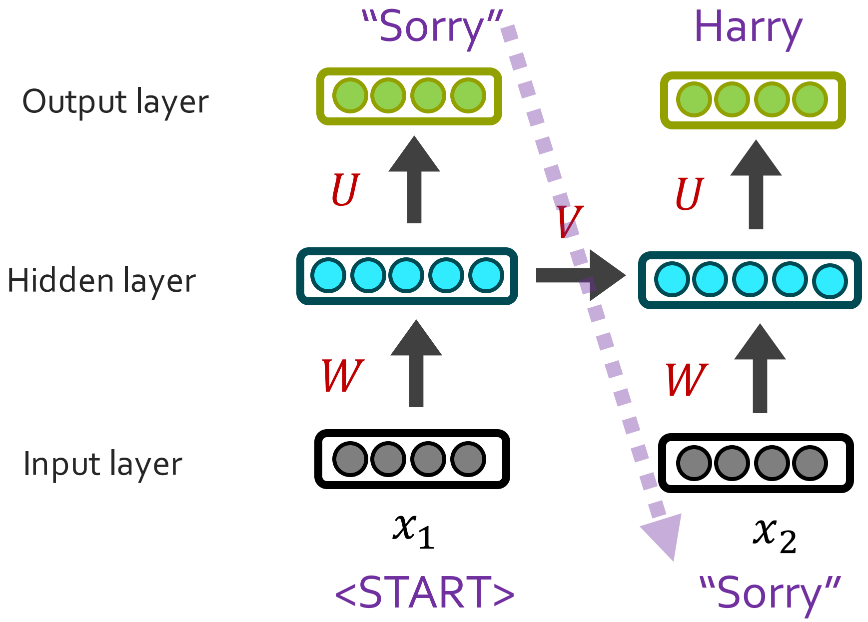

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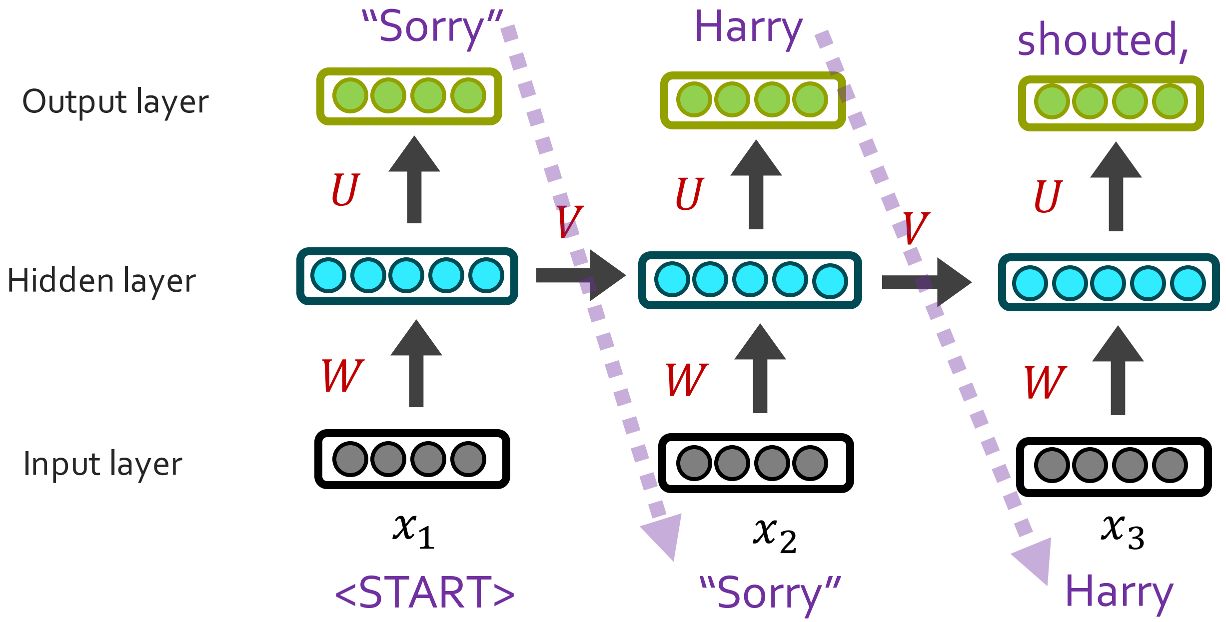

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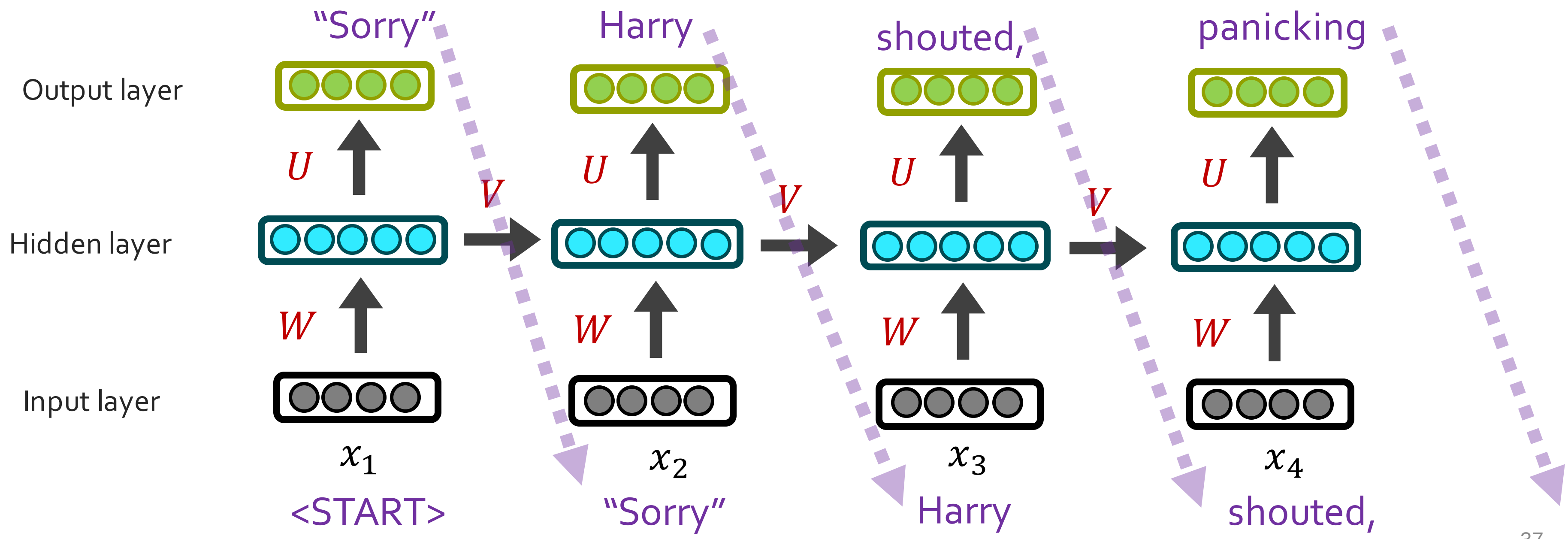
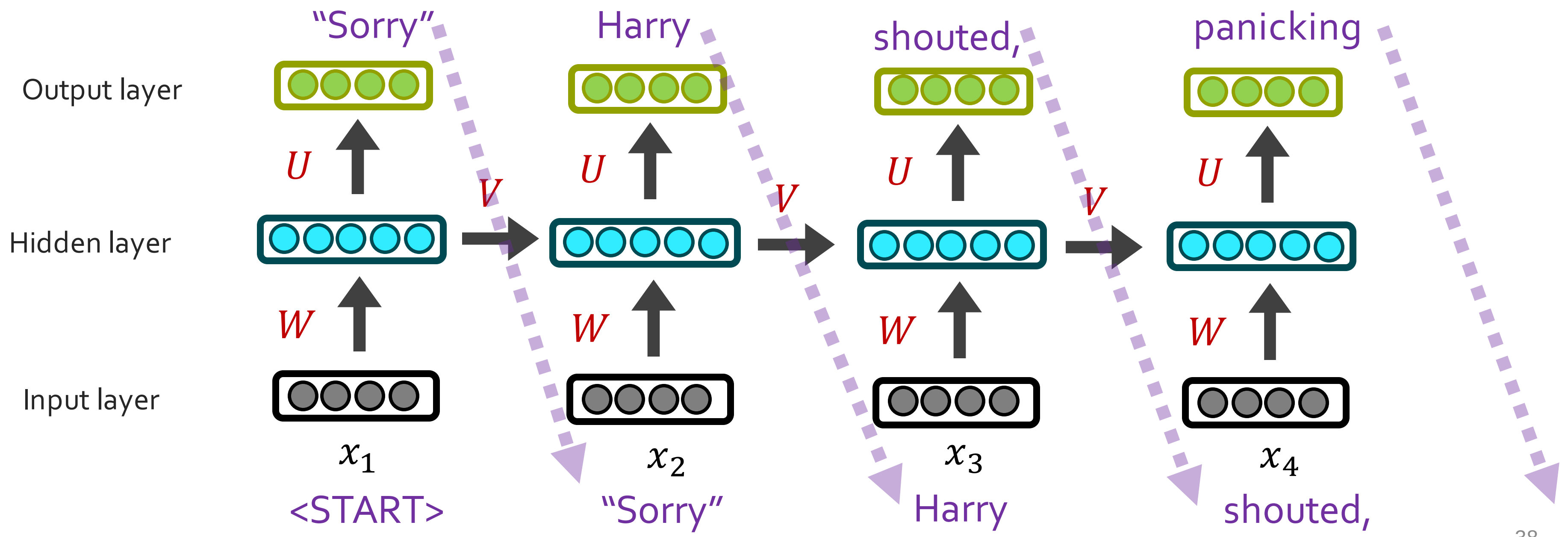


RNN: Generation

- NOTE: we are transmitting contextual information over time.



RNN: Generation

- When trained on Harry Potter text, it generates:

> “Sorry,” Harry shouted, panicking—“I’ll leave those brooms in London, are they?”
>
> “No idea,” said Nearly Headless Nick, casting low close by Cedric, carrying the last bit of treacle Charms, from Harry’s shoulder, and to answer him the common room perched upon it, four arms held a shining knob from when the spider hadn’t felt it seemed. He reached the teams too.

Source: https://medium.com/deep-writing/harry-potter-written-by-artificial-intelligence-8a9431803da6

RNNs: Generation

- RNN-LM trained on Obama speeches:

```
The United States will step up to the cost of a new
challenges of the American people that will share the fact
that we created the problem. They were attacked and so that
they have to say that all the task of the final days of war
that I will not be able to get this done.
```

https://medium.com/@samim/obama-rnn-machine-generated-political-speeches-c8abd18a2ea0

RNNs in Practice

- RNN-LM trained on food recipes:

```
Title: CHOCOLATE RANCH BARBECUE
Categories: Game, Casseroles, Cookies, Cookies
      Yield: 6 Servings

      2 tb Parmesan cheese -- chopped
      1 c  Coconut milk
      3    Eggs, beaten

Place each pasta over layers of lumps. Shape mixture into the moderate oven and
simmer until firm. Serve hot in bodied fresh, mustard, orange and cheese. Combine the
cheese and salt together the dough in a large skillet; add the ingredients and stir
in the chocolate and pepper.
```

https://gist.github.com/nylki/1efbaa36635956d35bcc

Evaluation LMs with Perplexity (2016)

n-gram model →

Increasingly complex RNNs

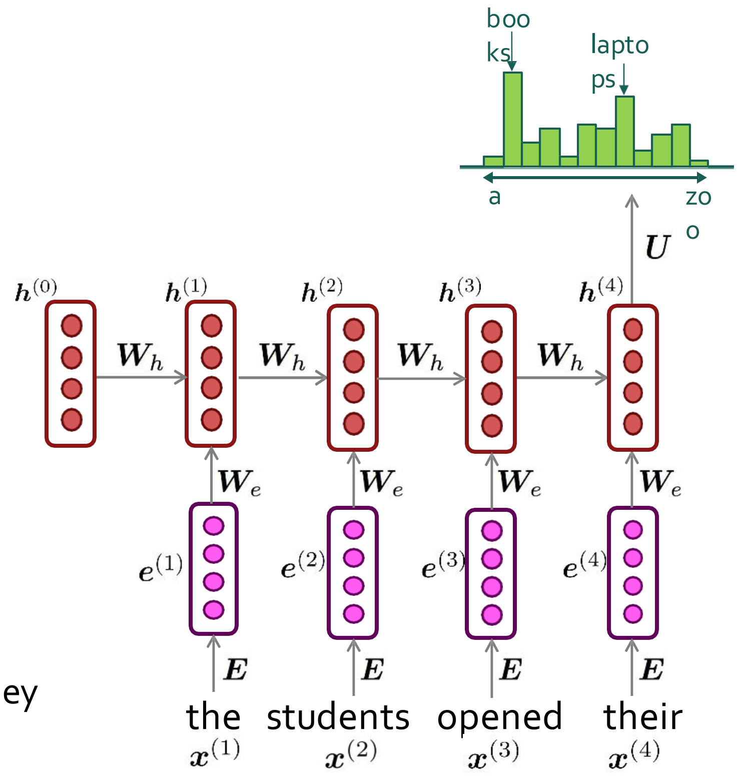
Model	Perplexity
Interpolated Kneser-Ney 5-gram (Chelba et al., 2013)	67.6
RNN-1024 + MaxEnt 9-gram (Chelba et al., 2013)	51.3
RNN-2048 + BlackOut sampling (Ji et al., 2015)	68.3
Sparse Non-negative Matrix factorization (Shazeer et al., 2015)	52.9
LSTM-2048 (Jozefowicz et al., 2016)	43.7
2-layer LSTM-8192 (Jozefowicz et al., 2016)	30
Ours small (LSTM-2048)	43.9
Ours large (2-layer LSTM-2048)	39.8

Source: https://engineering.fb.com/2016/10/25/ml-applications/building-an-efficient-neural-language-model-over-a-billion-words/

RNNs: Pros and Cons

- Advantages:
    - Model size doesn't increase for longer inputs — reusing a compact set of model parameters.
    - Computation for step t can (in theory) use information from many steps back

- Disadvantages:
    - Recurrent computation is slow and difficult to parallelize.
        - Next week: self-attention mechanism, better at representing long sequences and also parallelizable.
    - While RNNs in theory can represent long sequences, they quickly forget portions of the input.
    - Vanishing/exploding gradients.

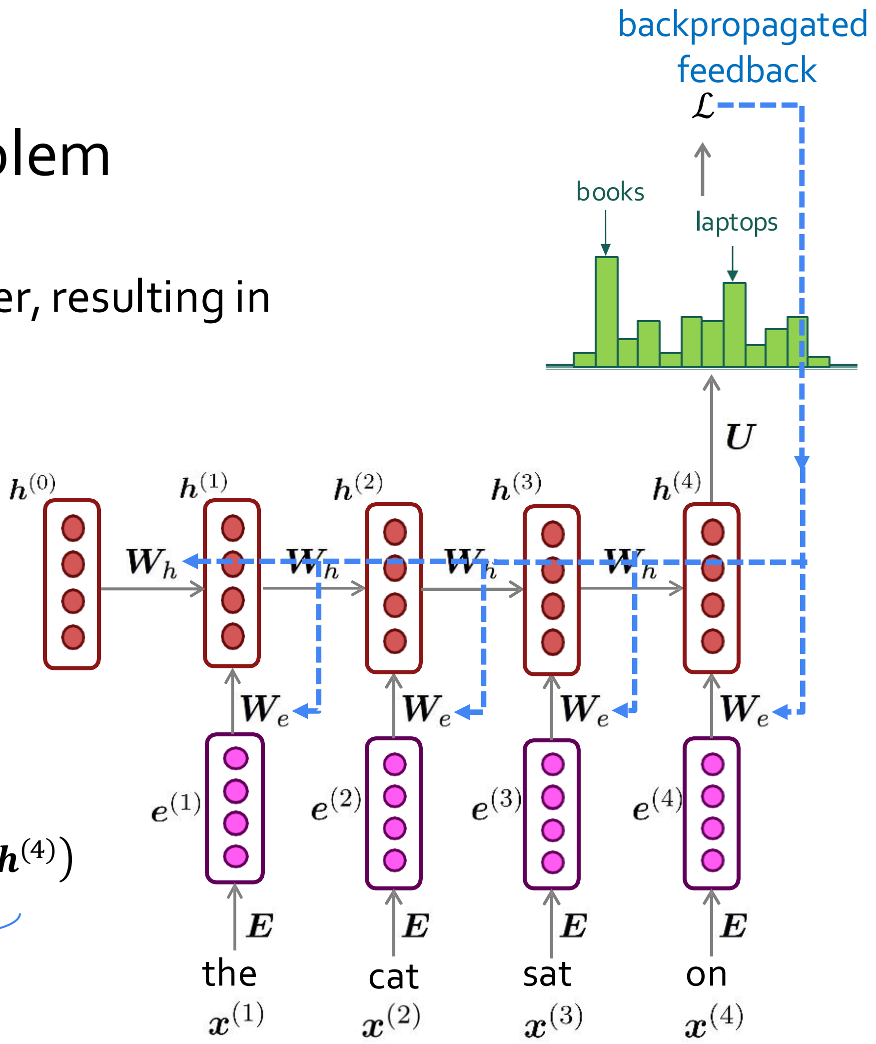


Vanishing/Exploding Gradient Problem

- Backpropagated errors multiply at each layer, resulting in exponential decay (if derivative is small) or growth (if derivative is large).
- Makes it very difficult train deep networks, or simple recurrent networks over many time steps.

$$\nabla_{\mathcal{L}}(\mathbf{W}_h) = \left(\mathbf{J}_{\mathcal{L}}(\mathbf{W}_{L-1})\right)^{\mathrm{T}} = \sum_{t=0} \left(\mathbf{J}_{\mathcal{L}}(\boldsymbol{h}^{(t)})\, \mathbf{J}_{\boldsymbol{h}^{(t)}}(\mathbf{W}_h)\right)^{\mathrm{T}}$$

$$\mathbf{J}_{\mathcal{L}}(\boldsymbol{h}^{(0)}) = \underbrace{\mathbf{J}_{\boldsymbol{h}^{(1)}}(\boldsymbol{h}^{(0)})\mathbf{J}_{\boldsymbol{h}^{(2)}}(\boldsymbol{h}^{(1)}) \times \ldots \times \mathbf{J}_{\boldsymbol{h}^{(4)}}(\boldsymbol{h}^{(3)})\, \mathbf{J}_{\mathcal{L}}(\boldsymbol{h}^{(4)})}_{\text{chain rule}}$$

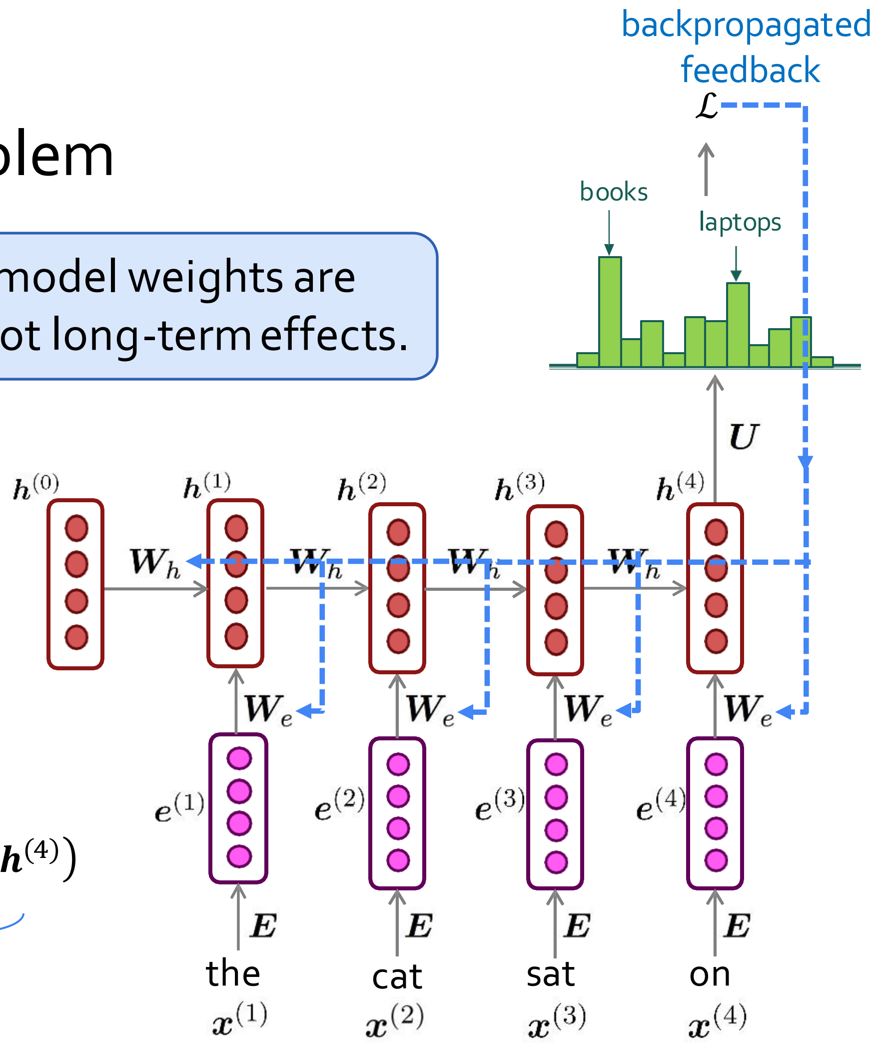


Vanishing/Exploding Gradient Problem

Gradient signal from far away is lost. So, model weights are updated only with respect to near effects, not long-term effects.

- **Note:** instability of matrix powers can be determined from their eigenvalues.

$$\mathbf{J}_{\mathcal{L}}\left(\boldsymbol{h}^{(0)}\right) = \underbrace{\mathbf{J}_{\boldsymbol{h}^{(1)}}\left(\boldsymbol{h}^{(0)}\right)\mathbf{J}_{\boldsymbol{h}^{(2)}}\left(\boldsymbol{h}^{(1)}\right) \times \ldots \times \mathbf{J}_{\boldsymbol{h}^{(4)}}\left(\boldsymbol{h}^{(3)}\right)\, \mathbf{J}_{\mathcal{L}}\left(\boldsymbol{h}^{(4)}\right)}_{\text{chain rule}}$$



RNNs: Difficulty in Learning Long-Range Dependencies

- While RNNs in theory can represent long sequences, in practice teaching them about long-range dependencies is non-trivial.
- **Gradient clipping:**
  - If the norm of the gradient is greater than some threshold, scale it down before applying SGD update.
  - **Intuition:** take a step in the same direction, but a smaller step

Algorithm 1 Pseudo-code for norm clipping

$\hat{\mathbf{g}} \leftarrow \frac{\partial \mathcal{E}}{\partial \theta}$
if $\|\hat{\mathbf{g}}\| \geq threshold$ **then**
$\quad \hat{\mathbf{g}} \leftarrow \frac{threshold}{\|\hat{\mathbf{g}}\|} \hat{\mathbf{g}}$
end if

[“On the difficulty of training recurrent neural networks”, Pascanu et al, 2013]

RNNs: Difficulty in Learning Long-Range Dependencies (2)

- While RNNs in theory can represent long sequences, in practice teaching them about long-range dependencies is non-trivial.
- **Using residual layers:**
  - lots of new deep architectures (RNN or otherwise) add direct connections, thus allowing the gradient to flow)

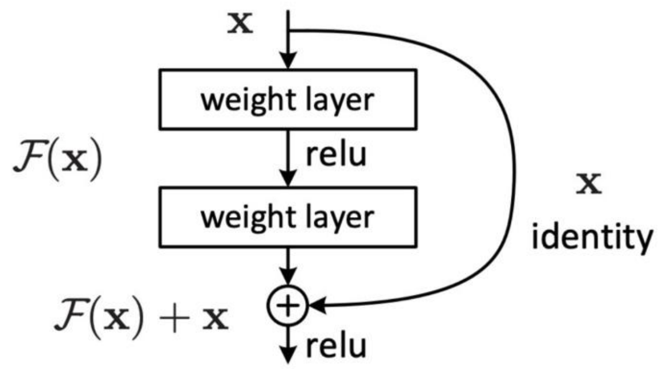
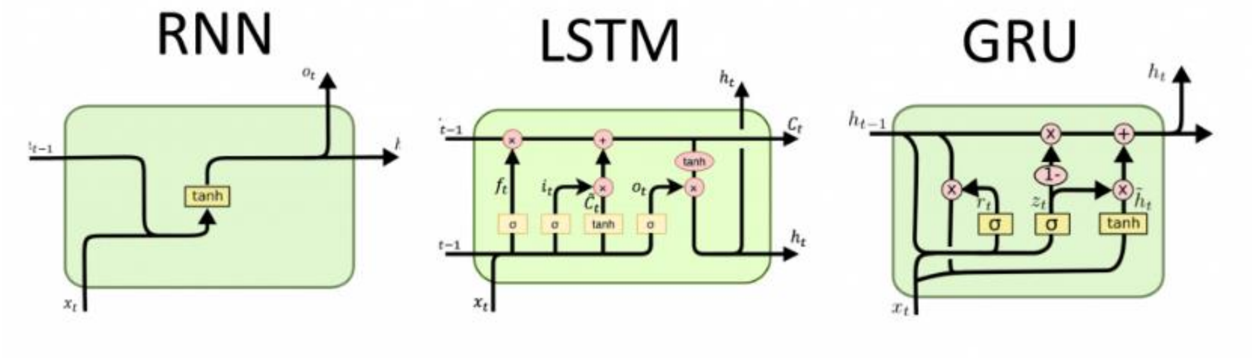


Figure 2. Residual learning: a building block.

"Deep Residual Learning for Image Recognition", He et al, 2015. https://arxiv.org/pdf/1512.03385.pdf

RNNs: Difficulty in Learning Long-Range Dependencies (3)

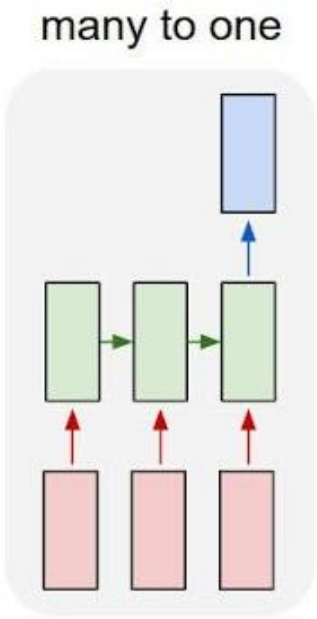
- While RNNs in theory can represent long sequences, in practice teaching them about long-range dependencies is non-trivial.
- Changes to the architecture makes it easier for the RNN to preserve information over many timesteps
  - Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber 1997, Gers+ 2000]
  - Gated Recurrent Units (GRU) [Cho+ 2014]



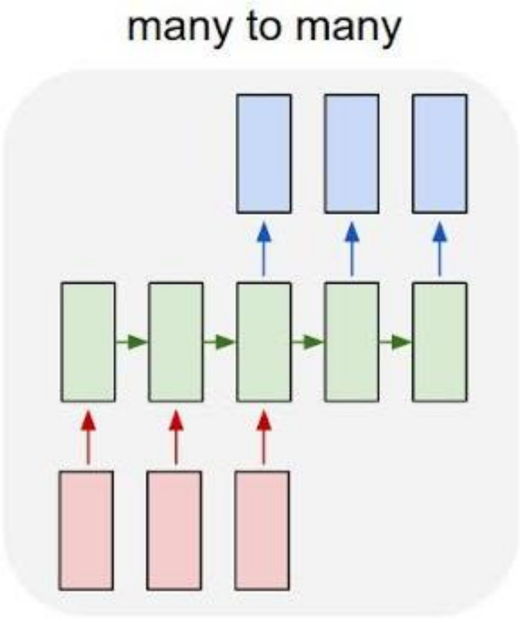
RNNs: Difficulty in Learning Long-Range Dependencies (3)

- While RNNs in theory can represent long sequences, in practice teaching them about long-range dependencies is non-trivial.
- Changes to the architecture makes it easier for the RNN to preserve information over many timesteps
  - Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber 1997, Gers+ 2000]
  - Gated Recurrent Units (GRU) [Cho+ 2014]
- Many of these variants were the dominant architecture of In 2013–2015.
- We will not cover these alternative architecture in favor or spending more time on more modern developments.

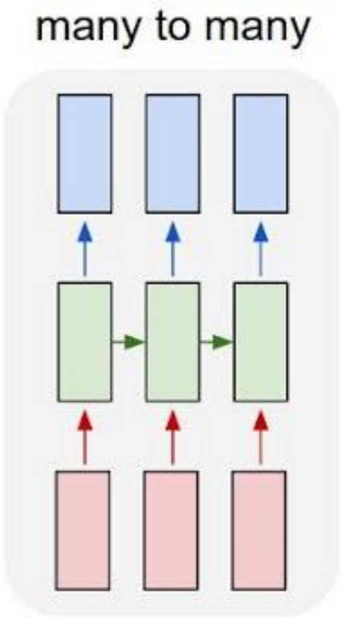
Adapting RNNs to Application



Text Classification



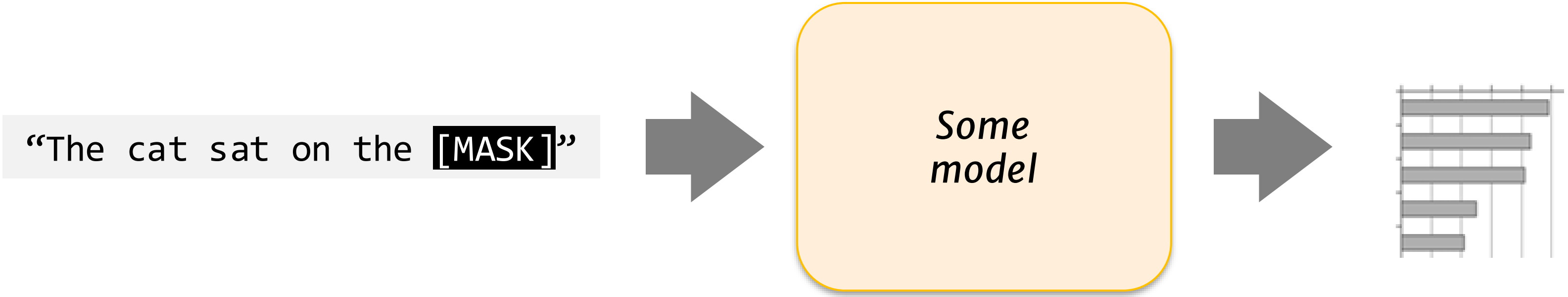
Language Modeling



POS Tags

Encoder-Decoder Architectures

- It is useful to think of generative models as two sub-models.

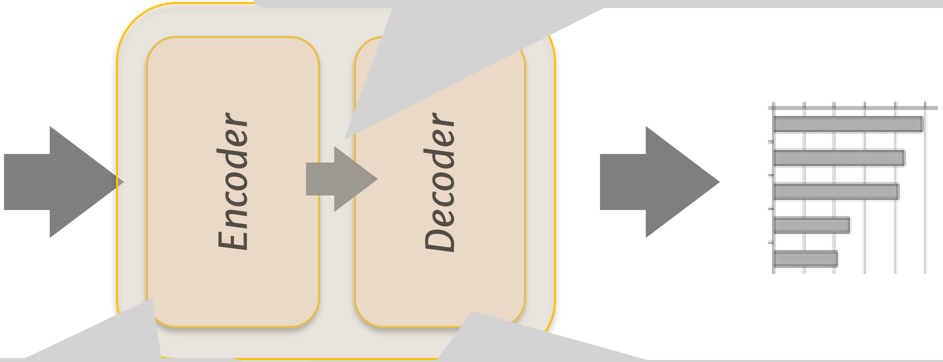


Encoder-Decoder Architectures

- It is useful to think of generative models as two sub-models.

Representation (compression) of the context

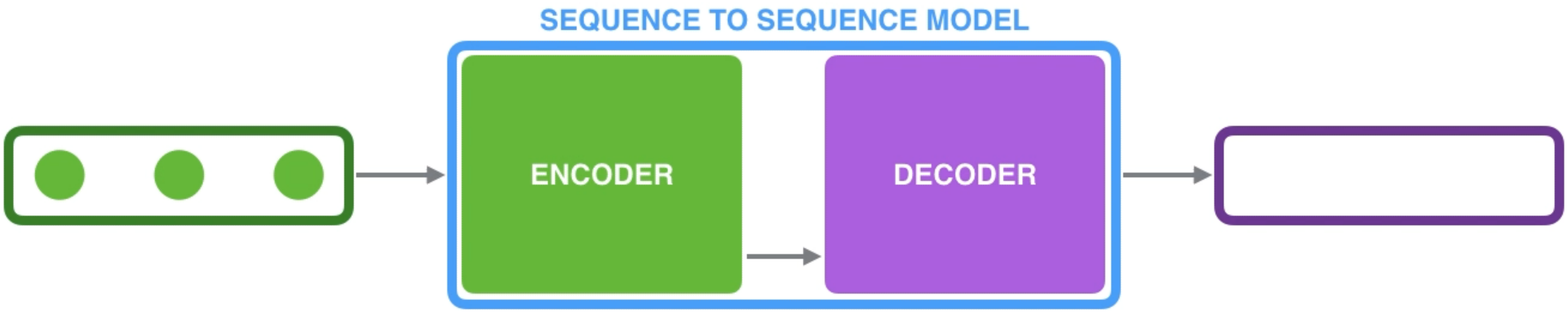
“The cat sat on the [MASK]”



Processes the context and compiles it into a vector.

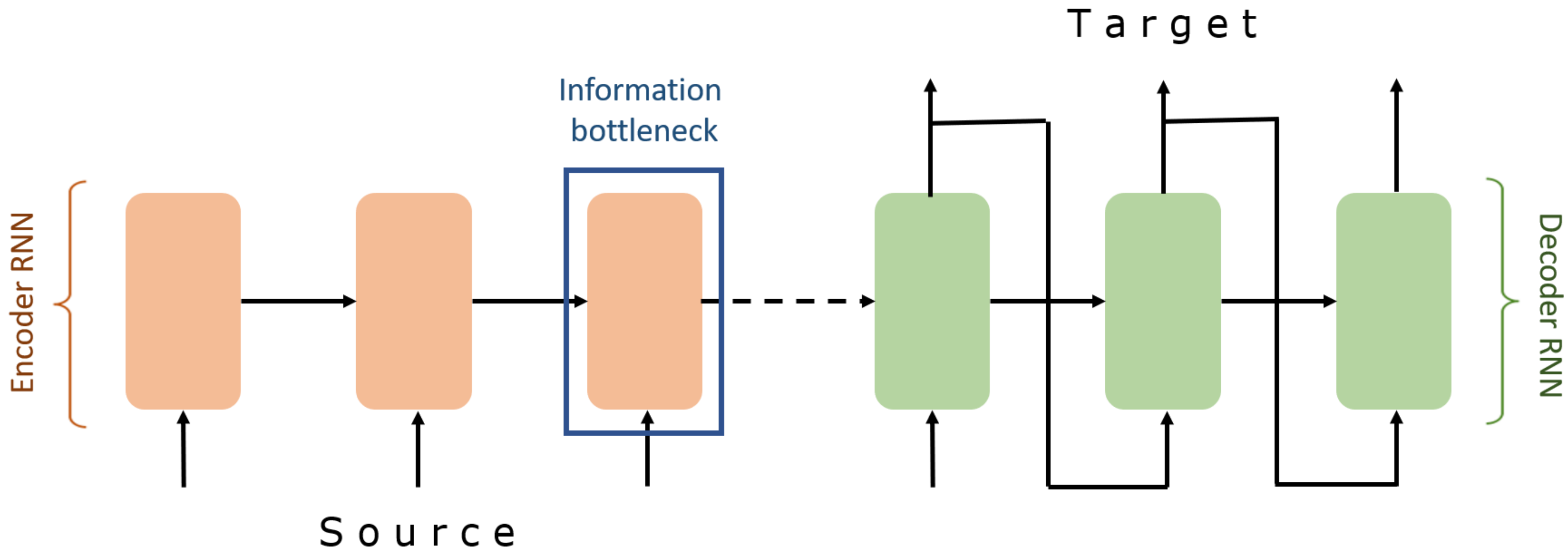
Produces the output sequence item by item using the representation of the context.

Encoder-Decoder Architectures



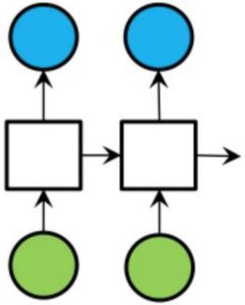
https://jalammar.github.io/visualizing-neural-machine-translation-mechanics-of-seq2seq-models-with-attention/

Encoder-Decoder Architectures

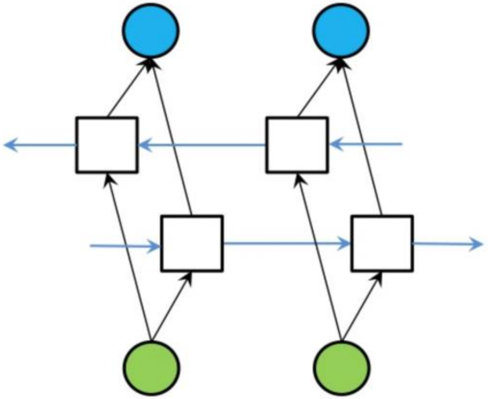


Extending RNNs to Both Directions

- An RNN limitation: Hidden variables capture only one side of the context.
- Solution: Bi-Directional RNNs



RNN



Bi-directional RNN