CS224n: NLP with Deep Learning

Lecture 6: Language Models and Recurrent Neural Networks

Language Modelling

Definition

- Language Modelling = Predict what word comes next

Given a sequence of words $x^{(1)}, x^{(2)}, \ldots, x^{(t)}$
compute probability distribution of $x^{(t+1)}$:

$$P(x^{(t+1)}|x^{(t)}, \ldots, x^{(1)})$$

- $x^{(t+1)}$ can be any word in a predefined vocabulary of words

n-gram Language Model

- Collect statistics of how often different n-gams occur:
  We just count them in a large corpus of text

$$P(w|students\,opened\,their) = \frac{count(students\ opened\ their\ w)}{count(students\ opened\ their)}$$

Problems

Sparsity problem 1

- "students opened their w" has never occured before
  If a specific n-gram equals 0, it will never be predicted

Solution
→ add a small smoothing term δ to the count of every word, so that they all at least have a small probability

Sparsity problem 2

- "students opened their" has never occured before

Solution: backoff!

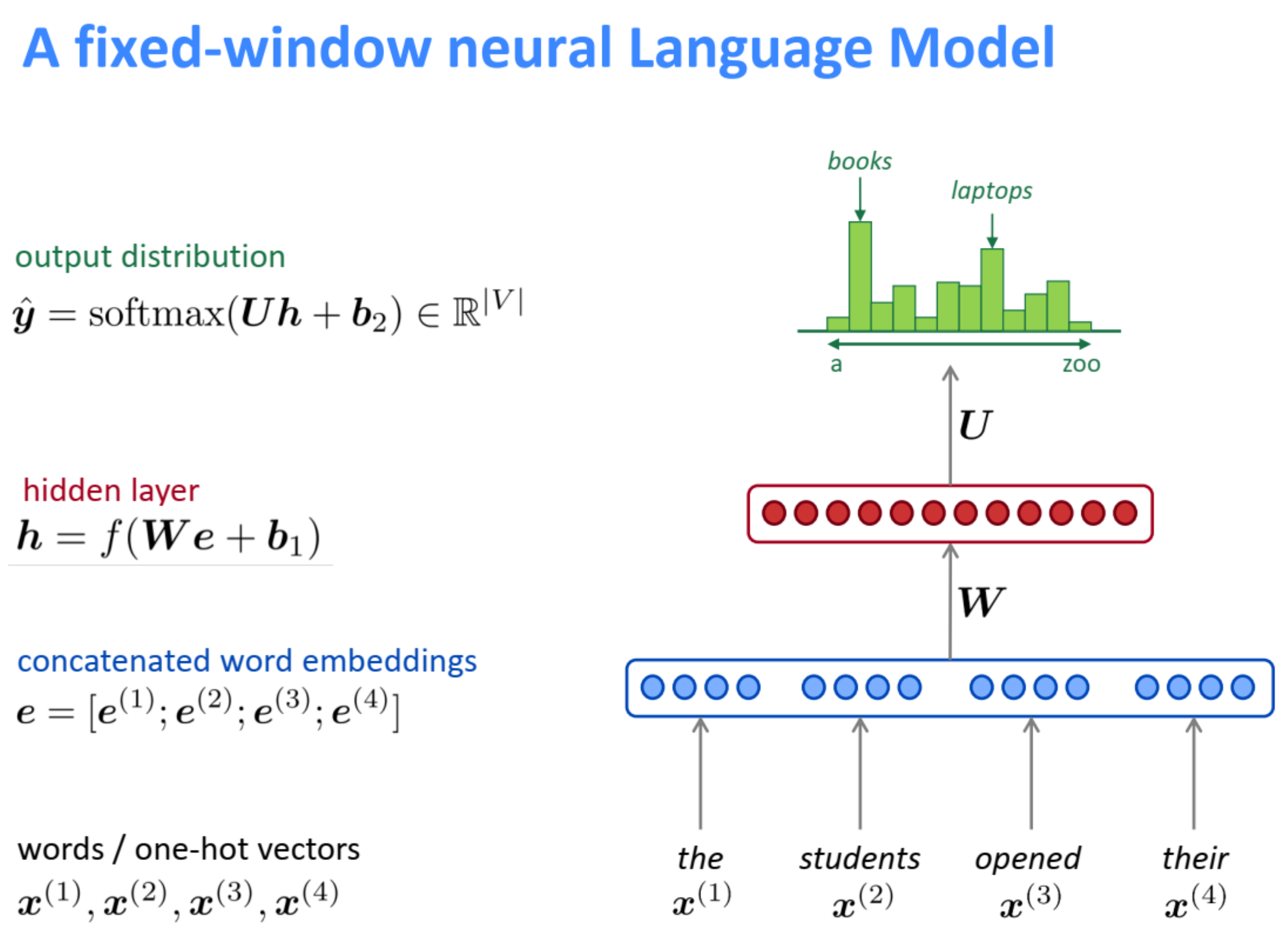
→ Go back to "opened their" to predict the next word

- These sparsity problems get worse and worse with *n* increasing: thus, we have to keep $n < 5$

Storage problems

- We have to store counts for a lot of different n-grams

A Neural Language Model



Problem:

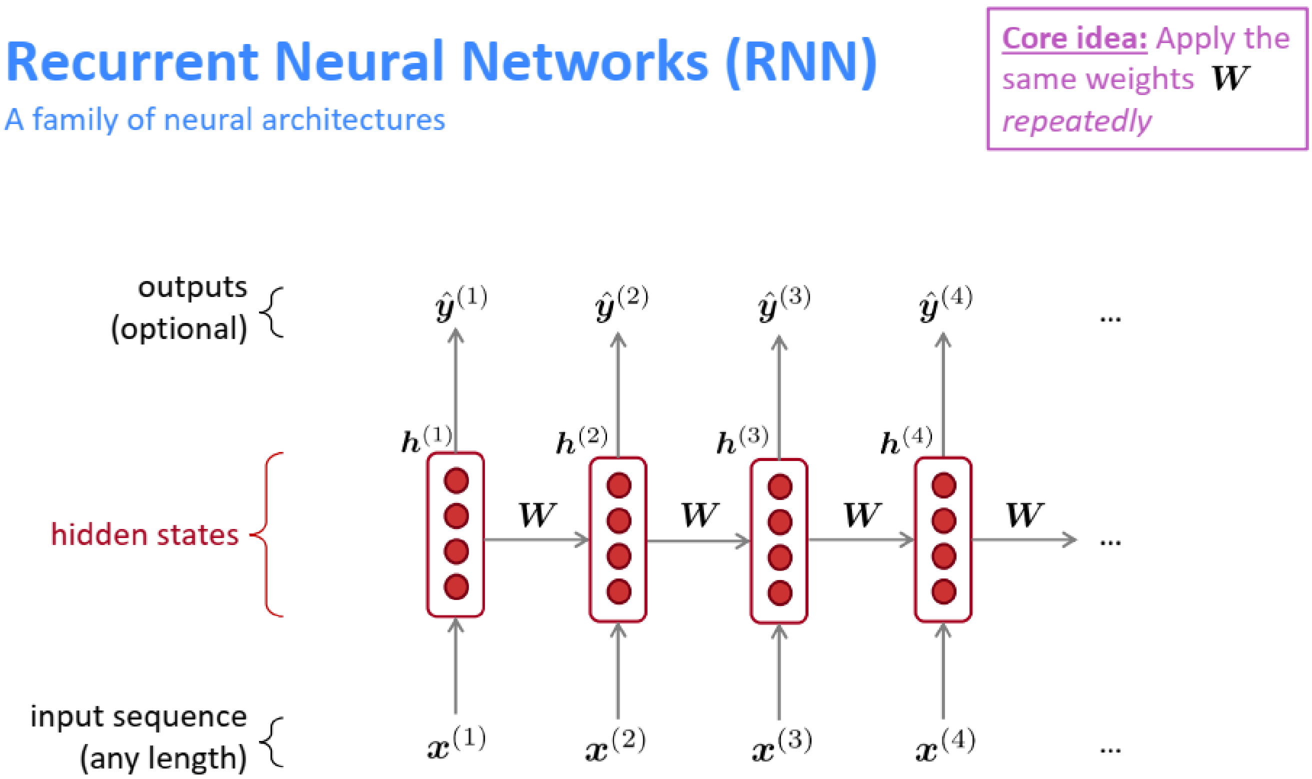
- The weights of all the input words are all completely separated from each other: we learn the same things 4 times, instead of having each word reinforcing our learning

- There should be a lot of commonality in how we treat our way embeddings: processing 1st position shouldn't be too different from 3rd position

→ We NEED an architecture that can process **any length input**

Recurrent Neural Networks (RNN)

Architecture



- Each hidden state is computed using both:
  - the previous hidden state
  - the input at that step

- Timestamp = hidden state (synonym)

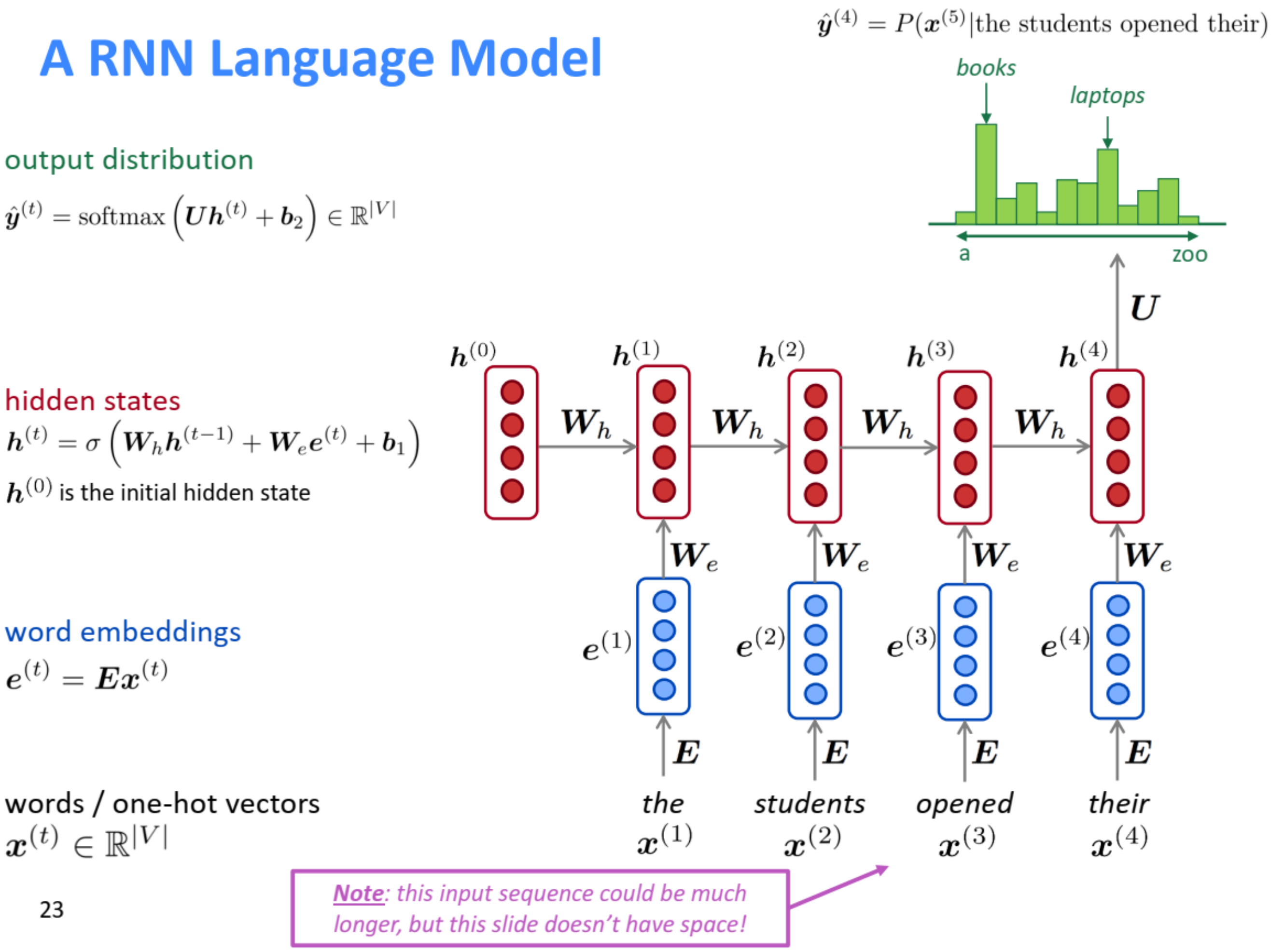
Core idea

- We apply the **same** weights matrix W at every step

- Our outputs $\hat{y}$ can be optionnally computed, for each step, or for a few steps only (depending on our goal)

- The embeddings could be dowloaded, and then fixed, or also fine-tuned, or also learned from scratch

- We learn both W_e and W_h



Advantages

- RNN can process any length of inputs
- When computing step t, we are using information from many steps ago
- Model size is fixed (doesn't depend on the size of input)
- The inputs are processed symmetrically, as the same weights are applied at each step

Disadvantages

- Computation is **slow**, as it is sequential
- In practice, information from many steps back is hard to access

Training a RNN Language Model

- For every step, compute the output distribution
- Compute the loss function on step t:
  Cross-entropy loss between this predicted probability distribution, and the true next word
- Compute the **overall loss** by averaging all these losses, on every word of the training set

Problem

Computing loss and gradients on whole corpus is too expensive !

Solution

→ Use a shorter sequence: a sentence, or a document for example

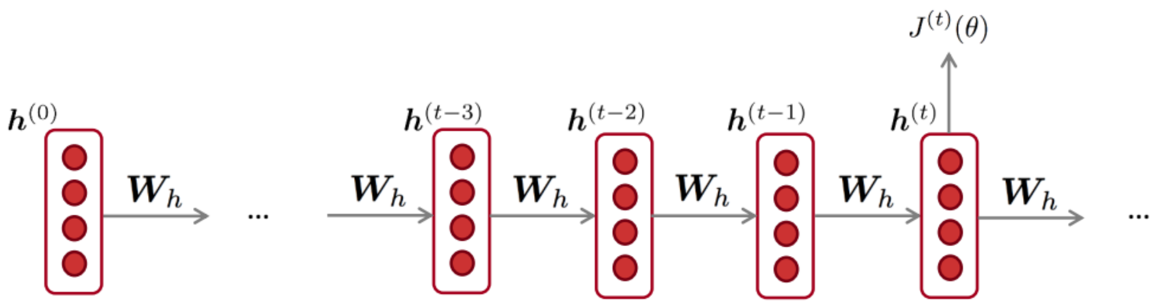
- Use **Stochastic Gradient Descent**:

only compute loss for a few sentences, and then update

Backprop

- The gradient with respect to a repeated weight is the sum of the gradient, for each time step it appears

Backpropagation for RNNs



Question: What's the derivative of $J^{(t)}(\theta)$ w.r.t. the repeated weight matrix $\boldsymbol{W}_h$?

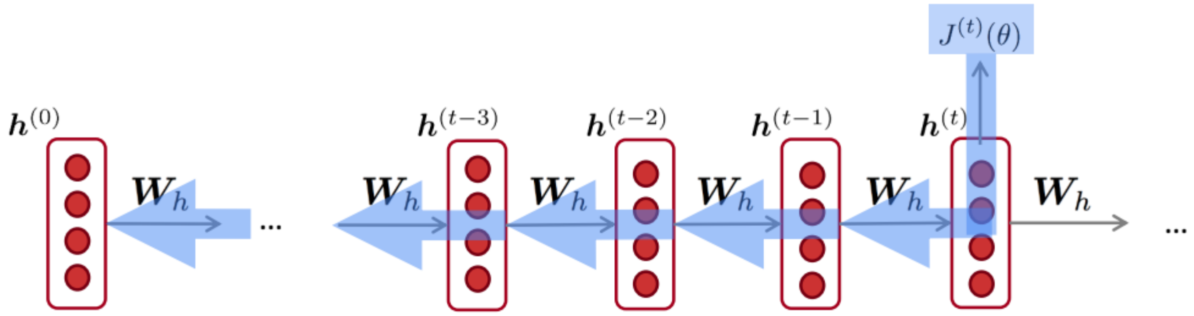
Answer: $$\frac{\partial J^{(t)}}{\partial \boldsymbol{W}_h} = \sum_{i=1}^{t} \left. \frac{\partial J^{(t)}}{\partial \boldsymbol{W}_h} \right|_{(i)}$$

"The gradient w.r.t. a repeated weight is the sum of the gradient w.r.t. each time it appears"

Why?

- These gradients should be calculated cumulatively, by using the previous one

Backpropagation for RNNs



$$\frac{\partial J^{(t)}}{\partial \boldsymbol{W_h}} = \boxed{\sum_{i=1}^{t} \left. \frac{\partial J^{(t)}}{\partial \boldsymbol{W_h}} \right|_{(i)}}$$

Question: How do we calculate this?

Answer: Backpropagate over timesteps *i=t*,…,0, summing gradients as you go.
This algorithm is called **“backpropagation through time”**

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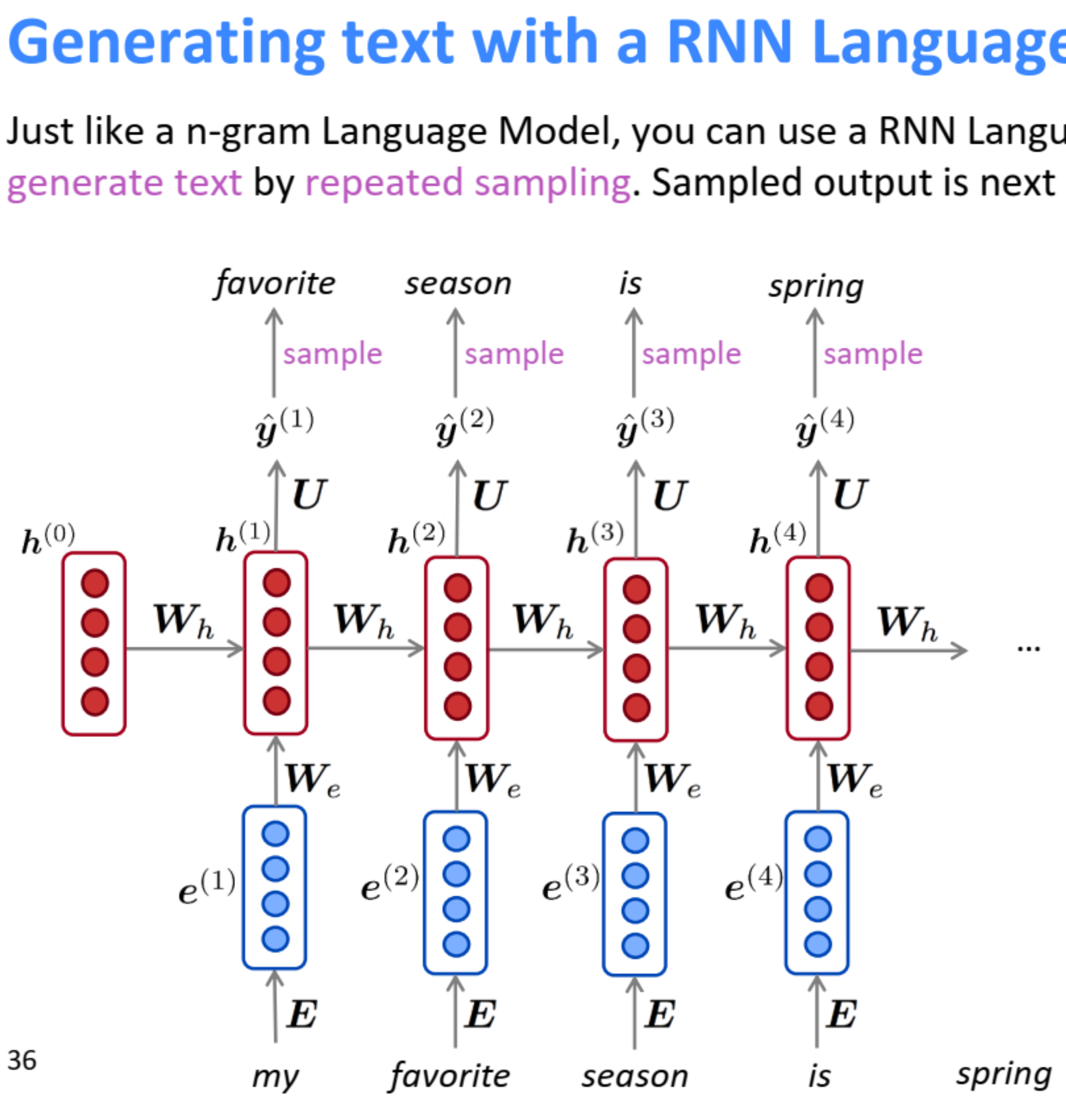
Generating text with a RNN



A few funny examples

- Obama:
  Solemn tone, but incoherent text

- Harry Potter:
  The tone is well done again, but not too much sense either

- Recipe:
  Inability to remember what's happening overall

/!\ Warning:
Need to stay skeptical, as these clickbaity articles have probably been hand-picked by humans for being the funniest ones (or even modified by humans to be funny!)

Evaluating Language Models

Perplexity

- Inverse probability of corpus, according to our Language Model
- We have to normalize it by the number of words, as otherwise the Perplexity would grow larger and larger with the corpus size

Evaluating Language Models

- The standard evaluation metric for Language Models is perplexity.

$$\text{perplexity} = \underbrace{\prod_{t=1}^{T} \left(\frac{1}{P_{\text{LM}}(\boldsymbol{x}^{(t+1)} | \, \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})} \right)}_{\text{Inverse probability of corpus, according to Language Model}}^{1/T}$$

Normalized by number of words

- This is equal to the exponential of the cross-entropy loss $J(\theta)$:

$$= \prod_{t=1}^{T} \left(\frac{1}{\hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}}} \right)^{1/T} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}} \right) = \exp(J(\theta))$$

Lower perplexity is better!

$$Perplexity = \frac{1}{P(corpus)}$$

Importance of Language Modelling

- Language Modelling is a benchmark task, which is used to measure our automatic understanding of language

- Language Modelling is a subcomponent of many NLP tasks:
  - Generating text
  - Estimating probability of text

Why should we care about Language Modeling?

- Language Modeling is a benchmark task that helps us measure our progress on understanding language

- Language Modeling is a subcomponent of many NLP tasks, especially those involving generating text or estimating the probability of text:
  - Predictive typing
  - Speech recognition
  - Handwriting recognition
  - Spelling/grammar correction
  - Authorship identification
  - Machine translation
  - Summarization
  - Dialogue
  - etc.

Recap

Recap

- **Language Model**: A system that predicts the next word
- **Recurrent Neural Network**: A family of neural networks that:
  - Take sequential input of any length
  - Apply the same weights on each step
  - Can optionally produce output on each step
- Recurrent Neural Network ≠ Language Model
- We've shown that RNNs are a great way to build a LM.
- But RNNs are useful for much more!

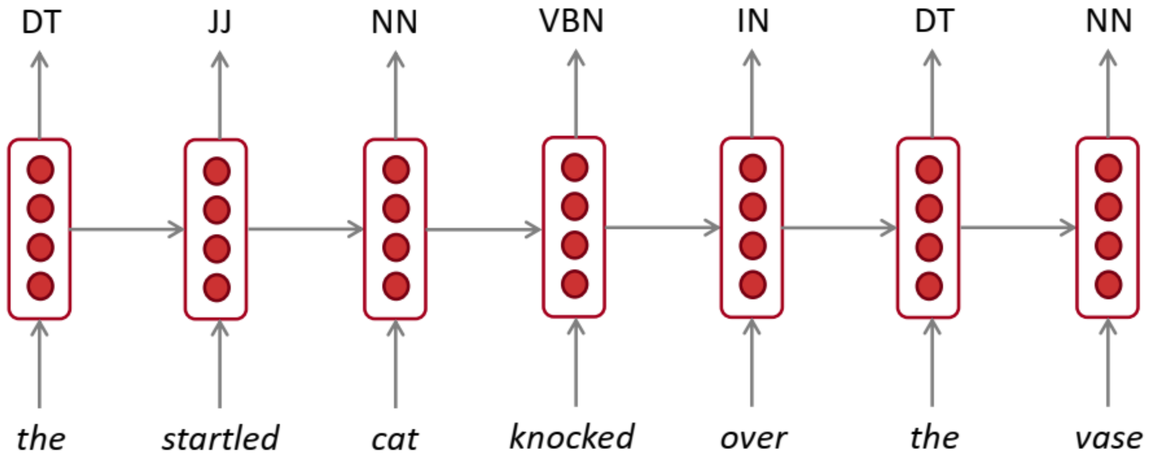
RNN Uses

Tagging

- Part-of-speech Tagging (POS)
- Named Entity Recognition (NER)

RNNs can be used for tagging

e.g. part-of-speech tagging, named entity recognition

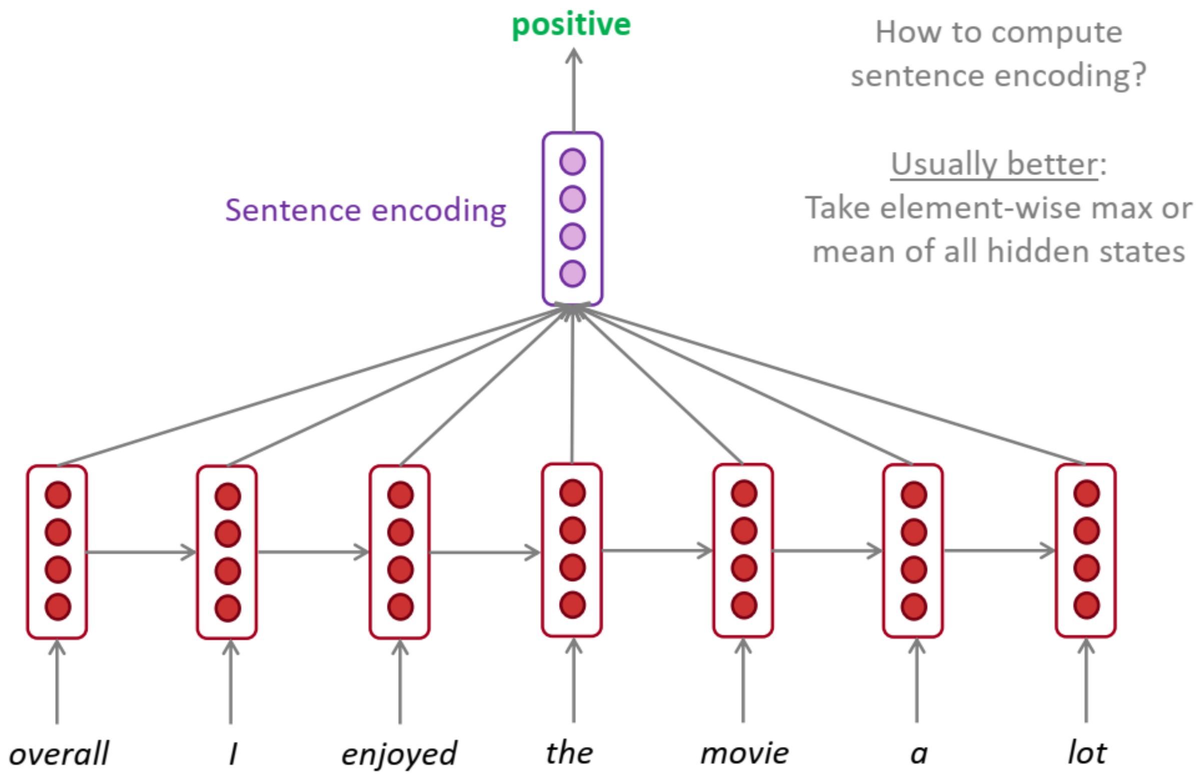


Sentence Classification

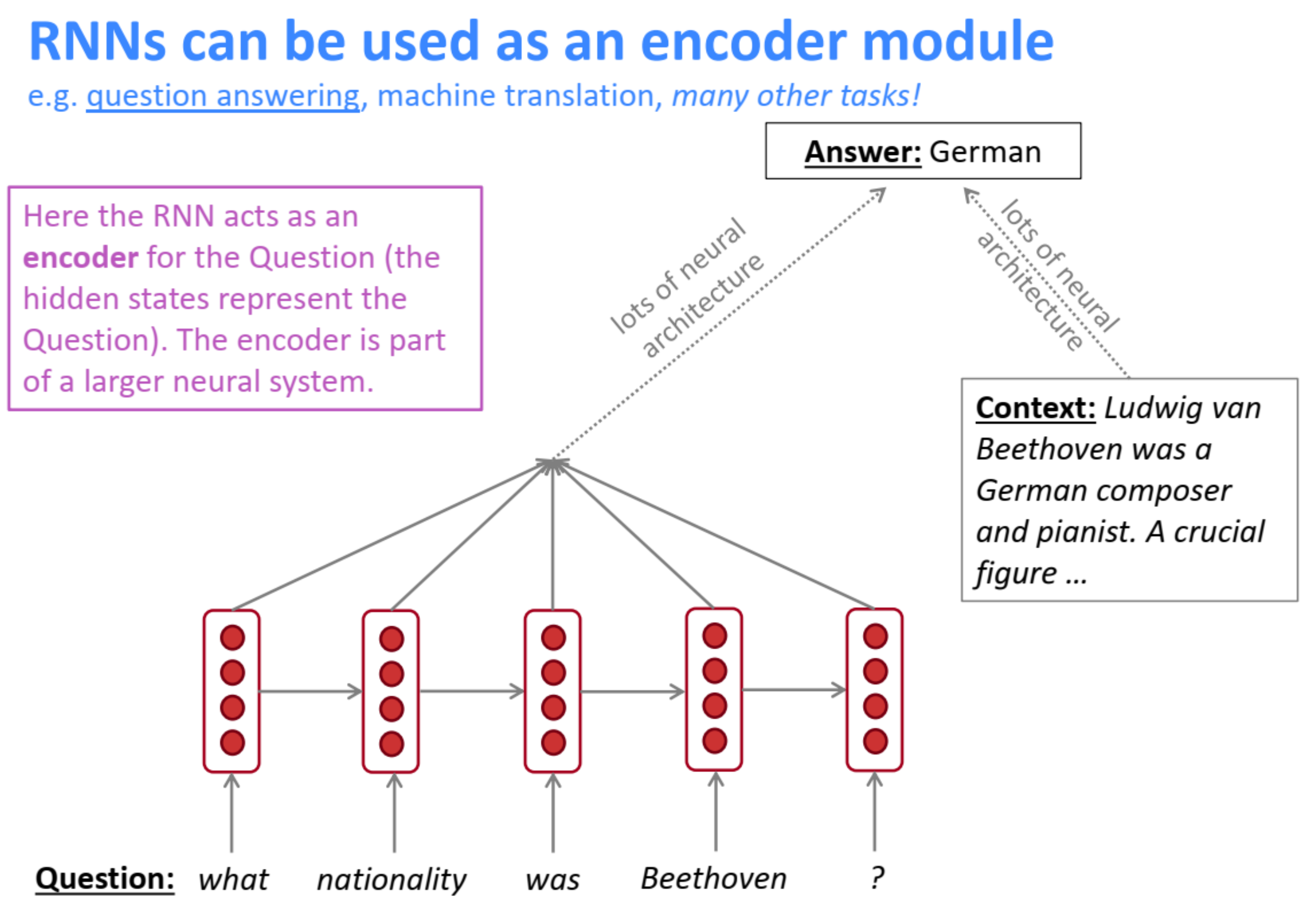
- Sentiment classification

RNNs can be used for sentence classification

e.g. sentiment classification



Encoder Module

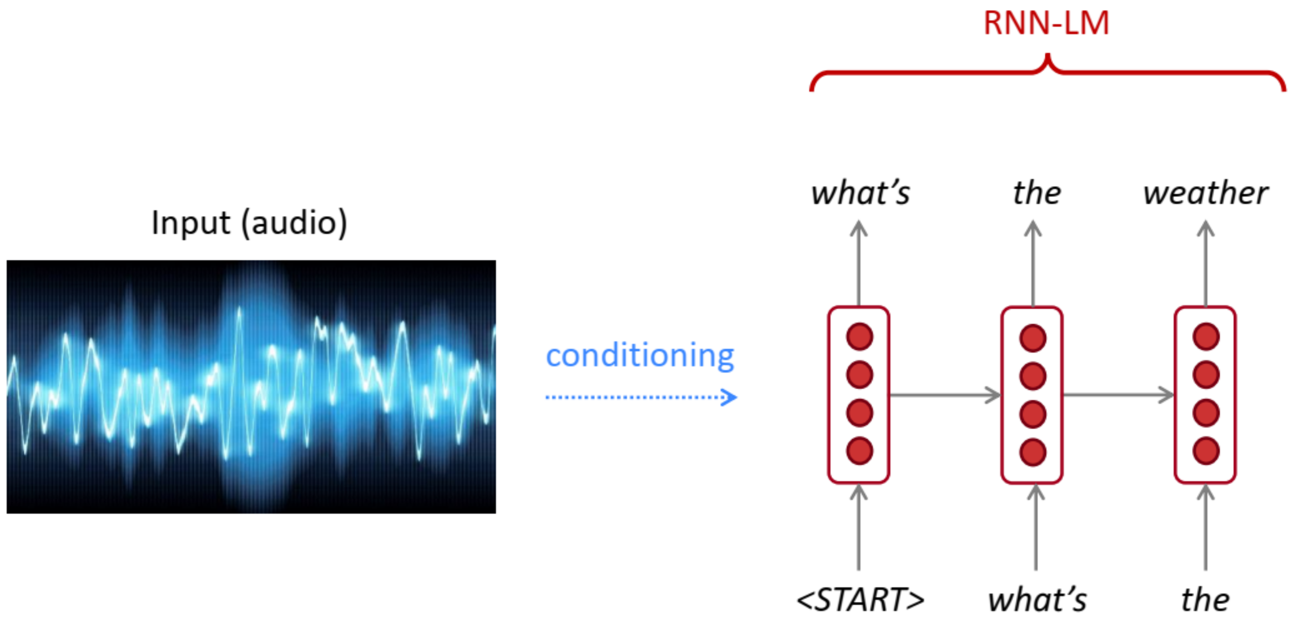


- Represent the question:
  The hidden states that we get using the RNN on the question represent the question

Generating Text

RNN-LMs can be used to generate text

e.g. speech recognition, machine translation, summarization



This is an example of a *conditional language model*.
We'll see Machine Translation in much more detail later.

- We have a Language Model, which is *conditioned* on some kind of input

→ It is a **conditional** language model

Other specific RNNs

More specific RNN architectures:

- GRU
- LSTM
- Multi-layer RNN