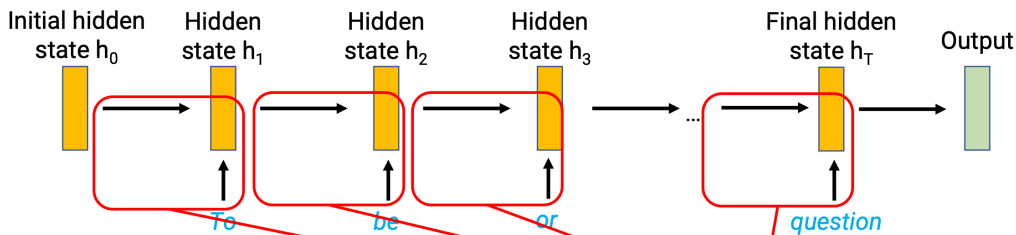


Recurrent NN for sequential data

Handling textual data

- images: inputs are fixed dimensional
 - Can crop/rescale as needed
- text: inputs are variable-sized
- How can we use the same set of model parameters to handle inputs of any size?

Recurrent Neural Networks (RNNs)



• Idea: Recurrence!

- “Read” the input one word at a time
- At each step, update the hidden state of the network
- **Model parameters to do this update are same for each step**

Each step is an application of the **same** neural network

Word embedding

- learn a vector that represents each word
 - Each word w in vocabulary V has vector Vw of size d
 - $|V| \cdot d$ parameters needed
- Similar words get similar vectors

Recurrence vs Depth

- Deep networks (i.e., adding more layers)
 - Computation graph becomes longer
 - Number of parameters also grows; each step uses new parameters
- Recurrent neural networks
 - Computation graph becomes longer
 - Number of parameters fixed; each step uses same parameters

Language Modeling

- At each step, predict the next word given current hidden state
 - Essentially a softmax regression “head”—takes in hidden state, outputs distribution over Vocabulary + [END]
- Start with special [BEGIN] token (so the first word model generates is first real word)
- One step’s output becomes next step’s input (“autoregressive”)
- To mark end of sequence, model should predict the [END] token
- Called a “Decoder” because it looks at the hidden state and “decodes” the next word

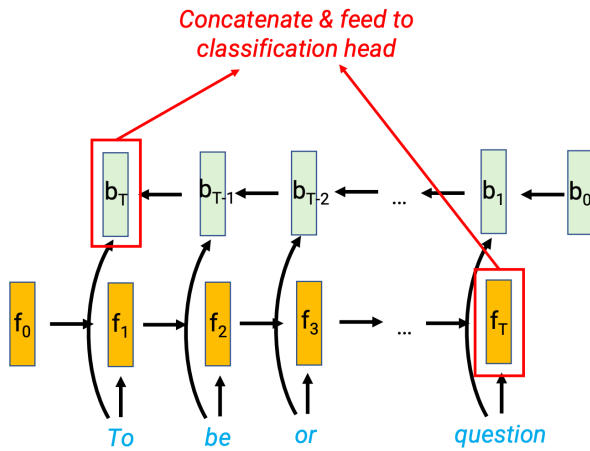
Long-Range Dependencies

- Every step, you update the hidden state with the current word
- Over time, information from many words ago can easily get lost!
- This means RNNs can struggle to model long-range dependencies

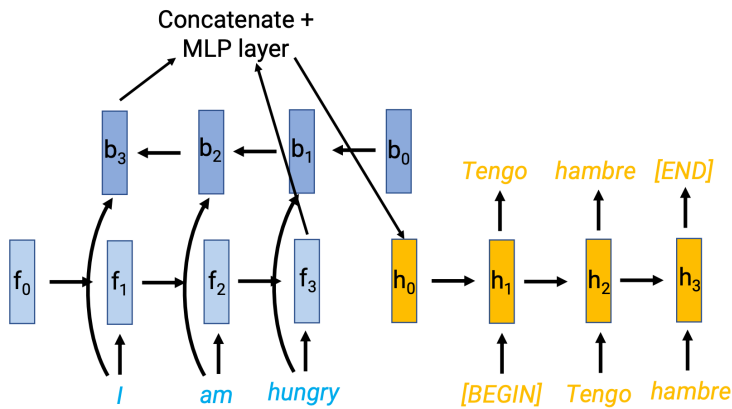
Advanced RNNs

- “Gated” RNNs (GRUs, LSTMs)
- Better at holding on to long-range state
- These are usually preferable to the RNN variant I showed today
- They work the same way, but the recurrence relationship between previous hidden state and next hidden state is more complicated...

Bi-directional encoders



Sequence-to-Sequence



Attention