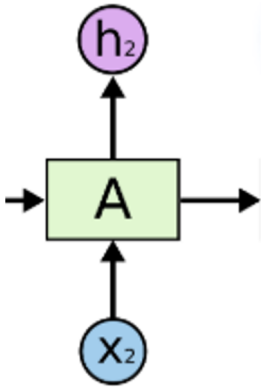
Seq2seq Translation model

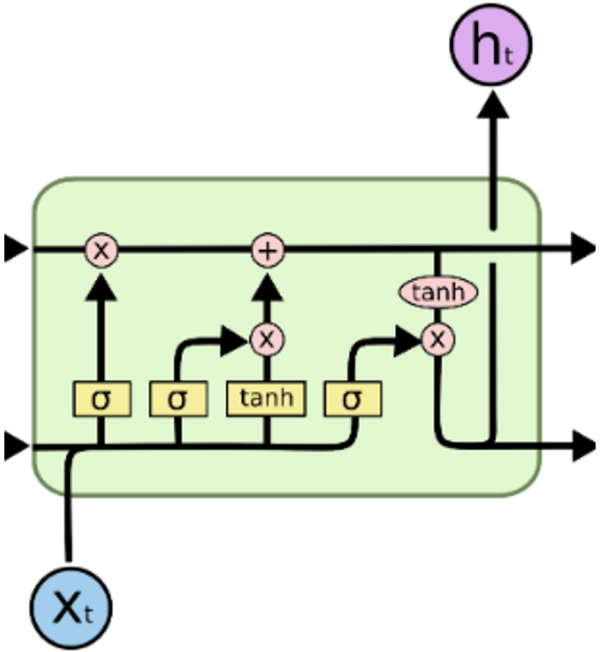
CSC401 / 2511 tutorial
Feb 26, 2020
Zining Zhu

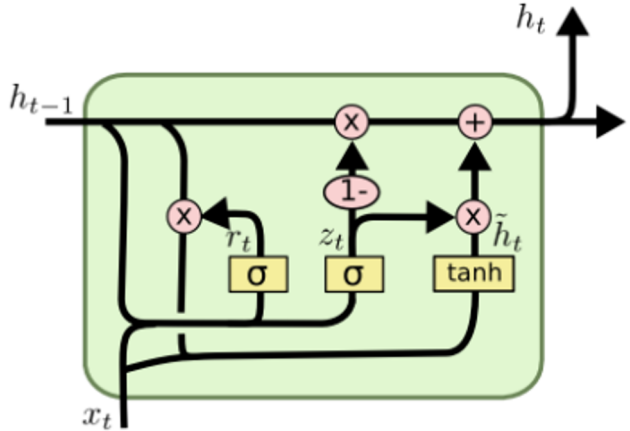
Agenda

- Recap: Recurrent models: RNN, LSTM, GRU
- Seq2seq model
  - Setup
  - Train
  - Run
- Beam Search example
- Misc. reminders for A2
- Questions

RNN vs. LSTM vs. GRU







https://colah.github.io/posts/2015-08-Understanding-LSTMs/

RNN models in PyTorch

- For A2, consider RNN, LSTM, and GRU
- The forward() method:
  - Input: hidden_state, x
  - For the first step, hidden_state contains all 0 by default
  - hidden_state for LSTM vs. RNN / GRU
  - x is a tensor of shape (seq_len, batch_size, dim), unless you want batch_first=True
  - Training and eval difference. module.train(), module.eval()
- Check out pytorch docs for details.
  - https://pytorch.org/docs/stable/nn.html

Seq2seq model: Setup

- Encoder + Decoder
- Both nn.Modules

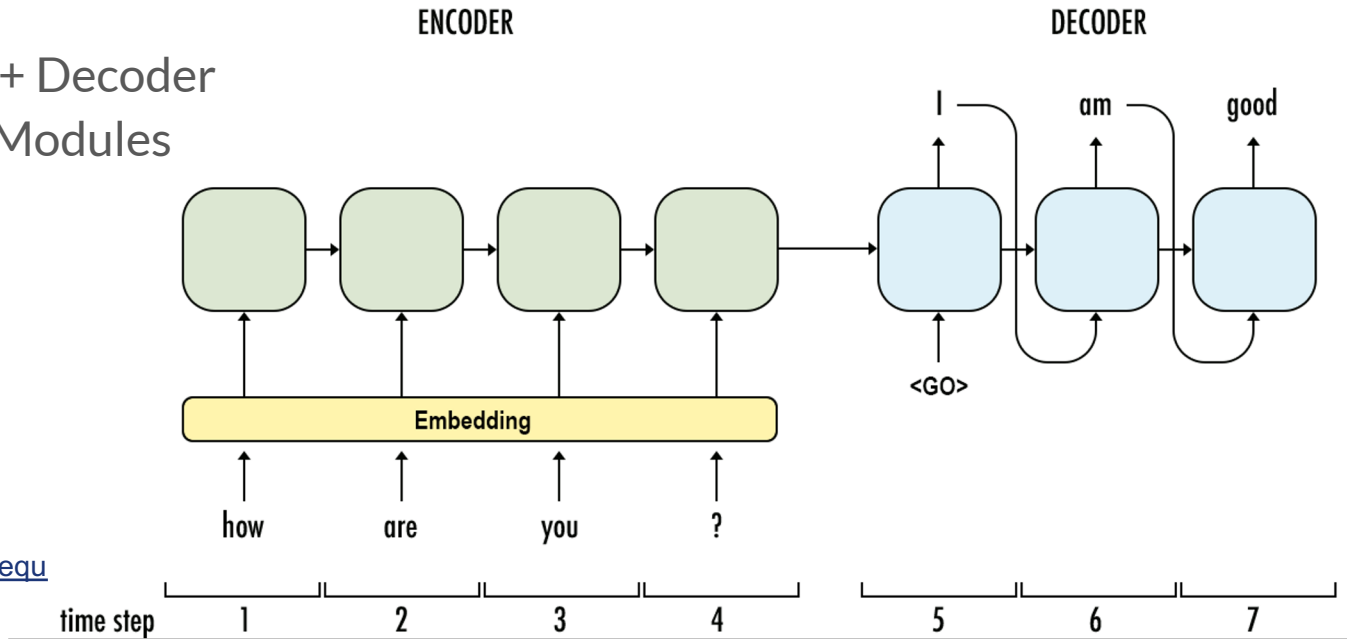


Image source: https://towardsdatascience.com/sequence-to-sequence-model-introduction-and-concepts-

Seq2seq model: Encoder

- Encoder
  - Consists of an nn.Embedding and a bidirectional RNN (one of LSTM, GRU, and RNN)
  - Input: F (sequence len S, batch size N)
  - The nn.Embedding maps input F onto the rnn input, x (S, N, RNN dimension I)
  - Encoder outputs all hidden states: h (S, N, hidden size H*2)
  - Same for both training and running.

Seq2seq model: Setup

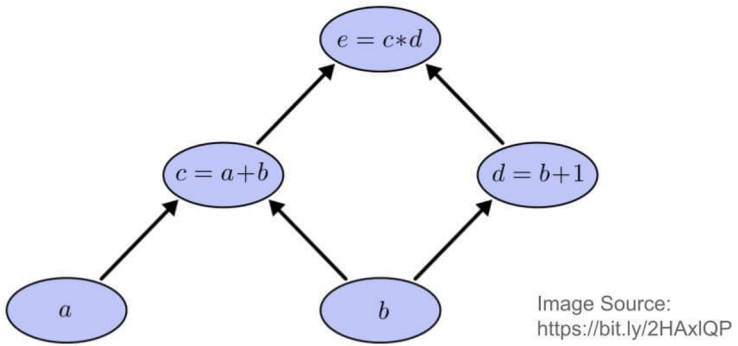
- Decoder
  - Consists of an RNN / LSTM / GRU and a feed-forward Linear layer.
  - Input / output dependent on training and running status.
- Two versions: without and with attention.
  - DecoderWithoutAttention: Encoder -> h -> first_hidden_state
  - DecoderWithAttention: Attend to the h (encoder outputs).
  - Nevertheless, each decoder step computes log prob of current step.

Seq2seq model: Train

- “Teacher forcing”
- For each step: given the input and a first hidden state, should learn the correct output (i.e., next token).
  - The input comes from the current token.
  - See forward() in a2_abcs.py for details.
- Maximum likelihood training
- Train the EncoderDecoder nn.Module end-to-end!
  - Gradient passed through both decoder and encoder
  - Remember to optim.zero_grad() after loss.backward()
  - If computing total loss, use loss.item() not loss (which preserves the massive graph)

Sidenote: computation graph in PyTorch

- At each operation, a graph node is created
  - Each tensor contains reference to the graph
- Gradients are computed in .backward()
- Some intermediate nodes are discarded
  - BackProp 2nd time error
  - optim.zero_grad()
  - See this notebook for examples.
- The graphs could use up your memory.
  - Graph is gc'ed with tensors.
  - tensor.detach() or tensor.item()



Seq2seq model: Run

- “Beam Search Decoding”
- Maintain a “beam” of K partially decoded sentences
- At each step:
  - Compute the likelihood of candidates.
  - Preserve the K candidates with highest likelihood, discard the rest.
- When to stop decoding?
  - When your top candidate comes to an <eos>
- Go over example in slides P55-60

Misc.

- Make sure the shape / types of tensors are correct.
  - Especially in broadcasting / slicing.
  - CPU / GPU tensor types mismatch.
- Debug on small datasets
  - E.g., setting --max-vocab 100 in building vocabulary. See Appendix A.4 on handout.
- Use a GPU to train the large model.
  - BA GPU labs / AWS EC2 / Google Cloud / etc.,
  - Make sure the code will run on teach.cs -- otherwise will receive 0 marks.
- Ask and answer others' questions on piazza
  - But don't post your solution codes.
- Start early! Due March 9 @ 7pm.

Labs with GPU

- See teaching lab availabilities at https://www.teach.cs.toronto.edu/faq.html#ABOUT4
- Sometimes labs are occupied for classes: (dot means “booked”)

time	BA2200	BA3175	BA3185	BA3195
Monday				
10-11am	•	•	•	•
12-2pm				•
2-3pm	•	•	•	•
8-9pm	•	•	•	•
Tuesday				
1-3pm	•	•	•	•
6-8pm	•			
8-9pm		•	•	
Wednesday				
12-2pm		•		
2-4pm	•	•		
4-5pm	•			
6-8pm	•	•	•	•
Thursday				
9-9pm	•	•	•	•
Friday				
10-12pm	•	•	•	•
1-4pm	•	•	•	•
4-6pm	•			