

Encoder-decoder paradigm for RNNs: with applications in neural machine translation, speech recognition, and image captioning

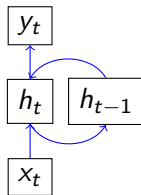
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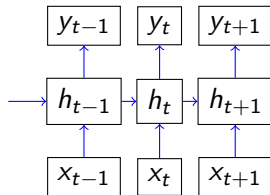
Overview

- ▶ RNNs and RNN language models
- ▶ Alignment problem in translation
- ▶ Encoder-decoder paradigm (also called sequence to sequence)
- ▶ Applications
- ▶ My work

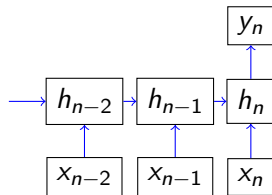
RNNs



a) RNN at t



b) unrolled RNN in time



c) single output RNN

RNNs

- ▶ Allow for arbitrary context length
- ▶ Neural language models are a classifier over $|V|$ classes (generally between 20,000 - 600,000).
- ▶ Recurrently read in words, predict word at the end
 - ▶ (the, cat, sat, on, the) \rightarrow (mat)
 - ▶ $\operatorname{argmax}_{w_n} P(w_n | w_1, \dots, w_{n-1})$
- ▶ RNNs can also make a prediction after every input
 - ▶ (frame 1, frame 2, frame 3, frame 4) \rightarrow (k,k,a,a)
- ▶ If n sized input, an RNN can have m outputs where $m \leq n$

Alignment problem

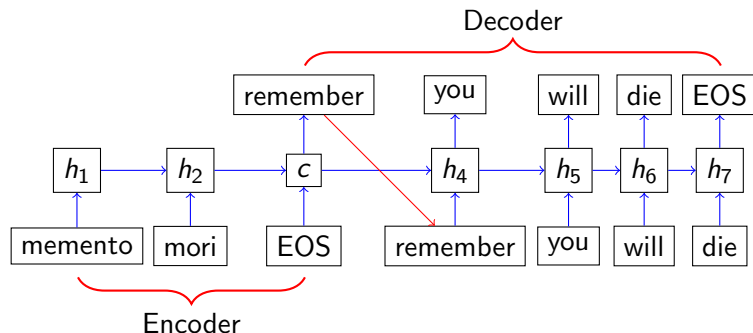
- ▶ What if we want $m > n$?
- ▶ If m is dynamically between 1 and n , how do we determine when to output?
- ▶ Machine translation requires an arbitrary alignment
- ▶ Need a generalized function $(x_1, \dots, x_n) \rightarrow (y_1, \dots, y_m)$ for arbitrary n and m

Solution: Encoder-decoder paradigm

- ▶ Encoder reads in input into a fixed length representation, c
- ▶ Decoder generates arbitrary length output conditioned on c
- ▶ Each decoder output at t serves as input to the decoder at $t + 1$
- ▶ Loops until $\langle \text{EOS} \rangle$ symbol is generated
- ▶ $P(y_1, \dots, y_m | x_1, \dots, x_n) = \prod_{t=1}^m P(y_t | c, y_1, \dots, y_{t-1})$
- ▶ Encoder and decoder are trained in an end to end fashion
- ▶ Not limited to RNNs (CNN encoders are common)

- ▶ *Sequence to sequence learning with neural networks*, Sutskever et al., NIPS, 2014
- ▶ *Learning phrase representations using RNN encoder-decoder for statistical machine translation*, Cho et al., EMNLP, 2014
- ▶ *Two recurrent continuous translation models*, Kalchbrenner and Blunsom, ACL, 2013

Neural machine translation encoder-decoder



Neural machine translation (NMT)

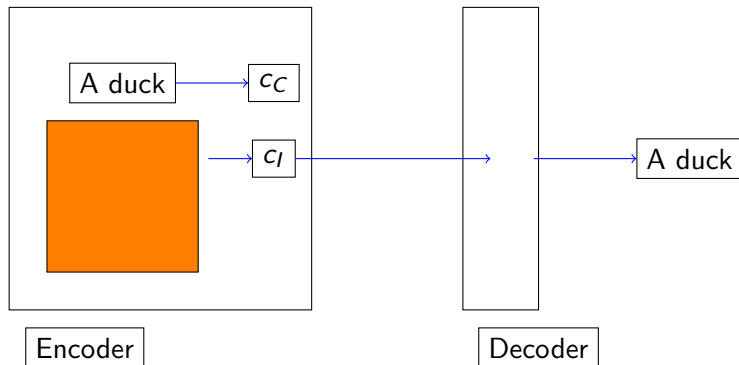
- ▶ Encoder creates a sentence embedding, c , in one language and the decoder is a language model in another language which is conditioned on c
- ▶ $P(f|e) = \prod_{t=1}^m P(f_t|f_1, \dots, f_{t-1}, c)$, a direct modelling of english to french instead of $P(e|f)P(f)$
- ▶ NMT getting state-of-the-art results in only 2 years (using one major extension called attention mechanisms)
- ▶ Generally use stacked bi-directional RNNs, 8 layers deep (4 + 4), and projection layers, LSTM or GRU units
- ▶ Small vocabulary 20,000 – 30,000 words for both the input and output languages
- ▶ *Montreal Neural Machine Translation Systems for WMT15*, Jean *et al.*, Proceedings of the Tenth Workshop on Statistical Machine Translation, 2015

Other applications

- ▶ Sentence summarization
 - ▶ Compress paragraph or article into a fixed length representation, then decoder generates a sentence that summarizes it
 - ▶ Does *abstractive* summarization instead of *extractive*
 - ▶ *A neural Attention Model for Abstractive Sentence Summarization*, Rush et al., preprint, 2015
- ▶ End-to-end RNN speech recognition
 - ▶ Compress a speech utterance into a fixed length representation, then decoder generates a sequence of phones or letters
 - ▶ Very hard to compress a whole utterance: main challenge is designing a good encoder

Other applications - Image captioning

- ▶ Compress a caption to c_C and try to regenerate the caption
- ▶ Compress image to c_I , such that $c_C \approx c_I$



- ▶ *Show, Attend and Tell: Neural Image Caption Generation with Visual Attention*, Xu et al. (Montreal and UofT people), ICML, 2015

My research - morphological language models

- ▶ Closed vocabularies: a set of acceptable input words and a set of output words (classes)
- ▶ Causes out of vocabulary errors, requires OOV token
- ▶ Compositional models: don't assume words as a base unit
- ▶ Helps solve open input vocabulary problem
- ▶ Helps data sparsity: *re-input*, *re-input-ed*, *input-ed*
- ▶ Does it help the open output vocabulary problem?
- ▶ (I, have, been, work, -ing, on) → (re, -input-, ing)
- ▶ Reduces the number of classes: *cat*, *cat-s*
- ▶ Why: Open output vocabularies not really done so far
- ▶ Why: Morphological language models have not been used for speech recognition