Machine Translation

10: Advanced Neural Machine Translation Architectures

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Today's Lecture

so far

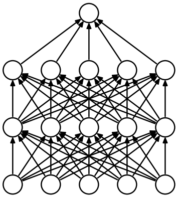
- we discussed RNNs as encoder and decoder
- we discussed some architecture variants:
  - RNN vs. GRU vs. LSTM
  - attention mechanisms

today

- some important components of neural MT architectures:
  - dropout
  - layer normalization
  - deep networks
- non-recurrent architectures:
  - convolutional networks
  - self-attentional networks

1. General Architecture Variants
2. NMT with Convolutional Neural Networks
3. NMT with Self-Attention

Dropout

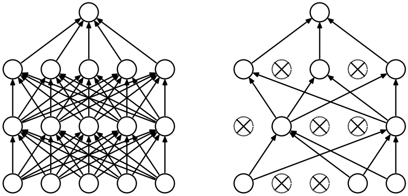


(a) Standard Neural Net (b) After applying dropout.

- wacky idea: randomly set hidden states to 0 during training
- motivation: prevent "co-adaptation" of hidden units
  $\rightarrow$ better generalization, less overfitting

[Srivastava et al., 2014]

Dropout



(a) Standard Neural Net (b) After applying dropout.

- implementation:
  - for training, multiply layer with "dropout mask"
  - randomly sample new mask for each layer and training example
  - hyperparameter p: probability that state is retained
    (some tools use p as probability that state is dropped)
  - at test time, don't apply dropout,
    but re-scale layer with p to ensure expected output is the same
  - (you can also re-scale by $\frac{1}{p}$ at training time instead)

[Srivastava et al., 2014]

Dropout and RNNs

for recurrent connections, applying dropout at every time step blocks information flow

solution 1: only apply dropoput to feedforward connections

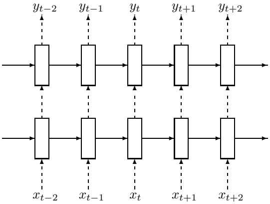


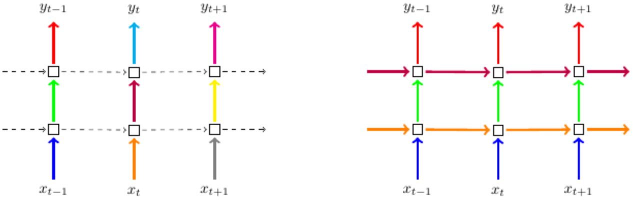
Figure 2: Regularized multilayer RNN. The dashed arrows indicate connections where dropout is applied, and the solid lines indicate connections where dropout is not applied.

[Zaremba et al., 2014]

Dropout and RNNs

for recurrent connections, applying dropout at every time step blocks information flow

solution 2: variational dropout: use same dropout mask at each time step



[Gal, 2015]

Layer Normalization

- if input distribution to NN layer changes, parameters need to adapt to this **covariate shift**
- especially bad: RNN state grows/shrinks as we go through sequence
- normalization of layers reduces shift, and improves training stability
- re-center and re-scale each layer $\mathbf{a}$ (with H units)
- two bias parameters, $\mathbf{g}$ and $\mathbf{b}$, restore original representation power

$$\mu = \frac{1}{H}\sum_{i=1}^{H} a_i$$

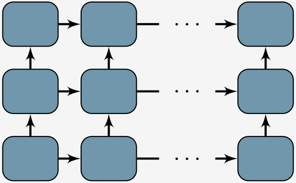
$$\sigma = \sqrt{\frac{1}{H}\sum_{i=1}^{H}(a_i-\mu)^2}$$

$$\mathbf{h} = \left[\frac{\mathbf{g}}{\sigma} \odot (\mathbf{a}-\mu) + \mathbf{b}\right]$$

Deep Networks

- increasing model depth often increases model performance
- example: stack RNN:

$$h_{i,1} = g(U_1 h_{i-1,1} + W_1 x_i)$$
$$h_{i,2} = g(U_2 h_{i-1,2} + W_2 h_{i,1})$$
$$h_{i,3} = g(U_3 h_{i-1,3} + W_3 h_{i,2})$$



Deep Networks

- often necessary to combat vanishing gradient: residual connections between layers:

$$
\begin{aligned}
h_{i,1} &= g(U_1 h_{i-1,1} + W_1 x_i) \\
h_{i,2} &= g(U_2 h_{i-1,2} + W_2 h_{i,1}) + \mathbf{h_{i,1}} \\
h_{i,3} &= g(U_3 h_{i-1,3} + W_3 h_{i,2}) + \mathbf{h_{i,2}}
\end{aligned}
$$

Layer Normalization and Deep Models: Results from UEDIN@WMT17

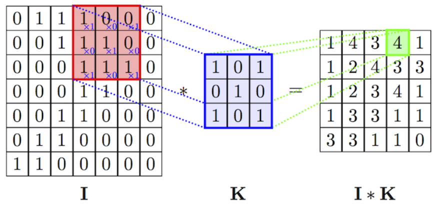
system	CS→EN 2017	DE→EN 2017	LV→EN 2017	RU→EN 2017	TR→EN 2017	ZH→EN 2017
baseline	27.5	32.0	16.4	31.3	19.7	21.7
+layer normalization	28.2	32.1	17.0	32.3	18.8	22.5
+deep model	28.9	33.5	16.6	32.7	20.6	22.9

- layer normalization and deep models generally improve quality
- layer normalization also speeds up convergence when training (fewer updates needed)
- dropout used for low-resource system (TR→EN)

Convolutional Networks

core idea: rather than using fully connected matrix between two layers, repeatedly compute dot product with small *filter* (or *kernel*)

2d convolution with 3x3 kernel

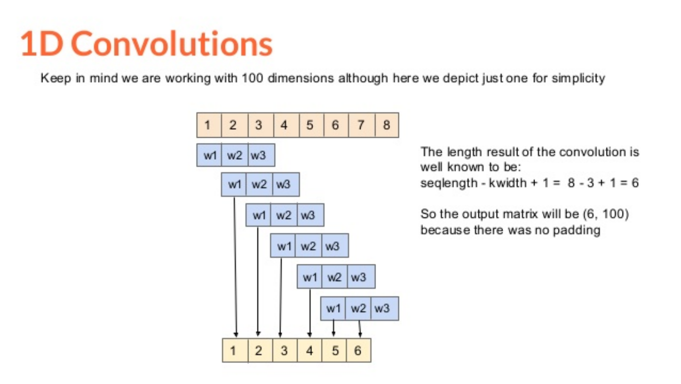


https://cambridgespark.com/content/tutorials/convolutional-neural-networks-with-keras/index.html

Convolutional Networks

when working with sequences, we often use 1d convolutions

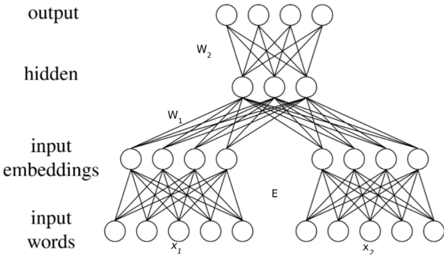
1d convolution with width-3 kernel



https://www.slideshare.net/xavigiro/recurrent-neural-networks-2-d2l3-deep-learning-for-speech-and-language-upc-2017

Convolutional Networks

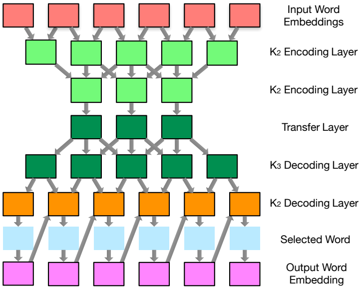
(this is similar to how we obtained hidden state for n-gram LM)



[Vaswani et al., 2013]

Convolutional Neural Machine Translation

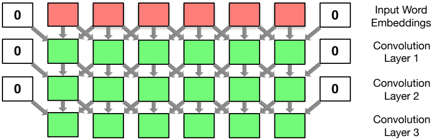
convolutional encoder actually predates RNN encoder



architecture of [Kalchbrenner and Blunsom, 2013], as illustrated in P. Koehn, Neural Machine Translation

Convolutional Neural Machine Translation with Attention

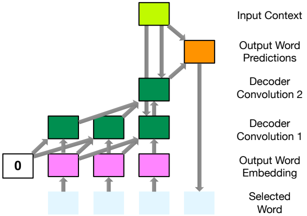
- to keep representation size constant, use padding
  $\rightarrow$ similar variable-size representation as RNN encoder
- kernel can be applied to all windows in parallel



architecture of [Gehring et al., 2017], as illustrated in P. Koehn, Neural Machine Translation

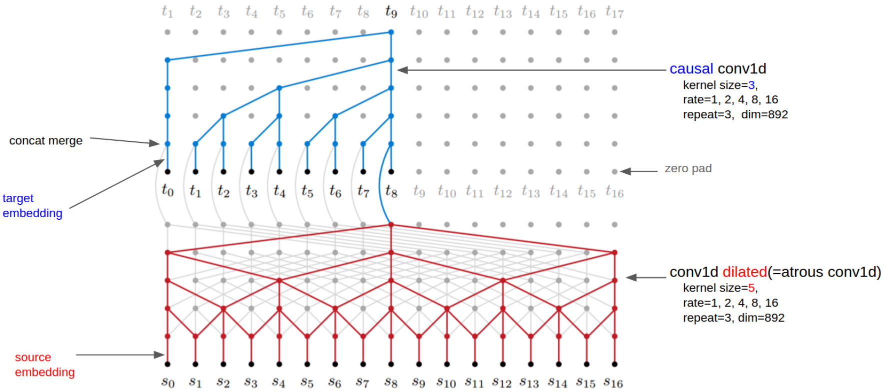
Convolutional Neural Machine Translation with Attention

- use your favourite attention mechanism to obtain input context
- in decoder, information from future tokens is masked during training
- effective context window depends on network depth and kernel size



architecture of [Gehring et al., 2017], as illustrated in P. Koehn, Neural Machine Translation

Convolutional Neural Machine Translation (ByteNet)



architecture of [Kalchbrenner et al., 2016]

Attention Is All You Need [Vaswani et al., 2017]

- same criticisms of recurrent architecture:
  recurrent computations cannot be parallelized
- core idea: instead of fixed-width convolutional filter, use attention
- there are different flavours of self-attention
  here: attend over previous layer of deep network

https://nlp.stanford.edu/seminar/details/lkaiser.pdf

Attention Is All You Need [Vaswani et al., 2017]

Transformer architecture

- stack of N self-attention layers
- self-attention in decoder is *masked*
- decoder also attends to encoder states
- *Add & Norm*: residual connection and layer normalization

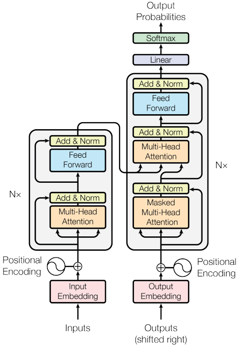


Figure 1: The Transformer - model architecture.

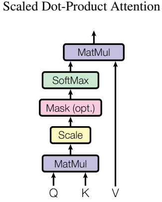
[Vaswani et al., 2017]

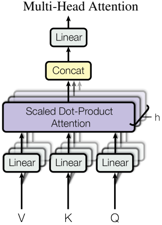
Multi-Head Attention

- basic attention mechanism in AIAYN: Scaled Dot-Product Attention

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

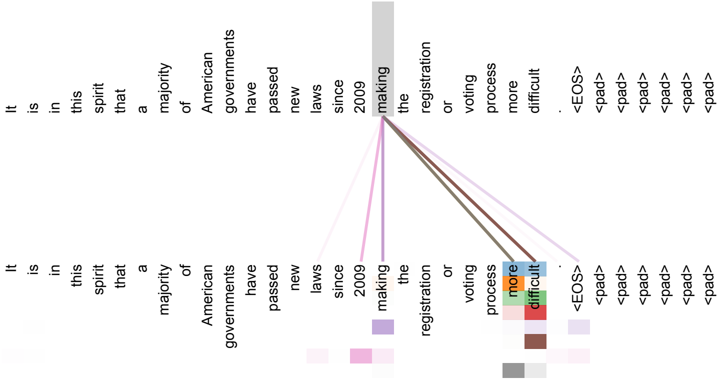
- query Q is decoder/encoder state (for attention/self-attention)
- key K and value V are encoder hidden states
- multi-head attention: use h parallel attention mechanisms with low-dimensional, learned projections of Q, K, and V





Multi-Head Attention

motivation for multi-head attention:
different heads can attend to different states



Comparison

empirical comparison difficult

- some components could be mix-and-matched
  - choice of attention mechanism
  - choice of positional encoding
  - hyperparameters and training tricks
- different test sets and/or evaluation scripts

Comparison

Sockeye [Hieber et al., 2017] (EN-DE; newstest2017)

system	Bleu
deep LSTM	25.6
Convolutional	24.6
Transformer	**27.5**

Marian (EN-DE; newstest2016)

system	Bleu
deep LSTM	32.6
Transformer	**33.4**

https://github.com/marian-nmt/marian-dev/issues/116#issuecomment-340212787

Empiricism vs. Theory

- our theoretical understanding of neural networks lags behind empirical progress
- there are some theoretical arguments why architectures work well... (e.g. self-attention reduces distance in network between words)
- ...but these are very speculative

Further Reading

- required reading: Koehn, 13.7
- consider original literature cited on relevant slides

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