CSC321 Lecture 17: ResNets and Attention

Roger Grosse

Overview

Two topics for today:

- Topic 1: Deep Residual Networks (ResNets)
  - This is the state-of-the art approach to object recognition.
  - It applies the insights of avoiding exploding/vanishing gradients to train really deep conv nets.
- Topic 2: Attention
  - Machine translation: it's hard to summarize long sentences in a single vector, so let's let the decoder peek at the input.
  - Vision: have a network glance at one part of an image at a time, so that we can understand what information it's using
  - We can use attention to build differentiable computers (e.g. Neural Turing Machines)

Deep Residual Networks

- I promised you I'd explain the best ImageNet object recognizer from 2015, but that it required another idea.

Year	**Model**	**Top-5 error**
2010	Hand-designed descriptors + SVM	28.2%
2011	Compressed Fisher Vectors + SVM	25.8%
2012	AlexNet	16.4%
2013	a variant of AlexNet	11.7%
2014	GoogLeNet	6.6%
2015	deep residual nets	4.5%

- That idea is exploding and vanishing gradients, and dealing with them by making it easy to pass information directly through a network.

Deep Residual Networks

- Recall: the Jacobian $\partial \mathbf{h}^{(T)} / \partial \mathbf{h}^{(1)}$ is the product of the individual Jacobians:

$$\frac{\partial \mathbf{h}^{(T)}}{\partial \mathbf{h}^{(1)}} = \frac{\partial \mathbf{h}^{(T)}}{\partial \mathbf{h}^{(T-1)}} \cdots \frac{\partial \mathbf{h}^{(2)}}{\partial \mathbf{h}^{(1)}}$$

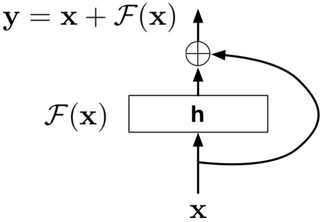
- But this applies to multilayer perceptrons and conv nets as well! (Let t index the layers rather than time.)
- Then how come we didn't have to worry about exploding/vanishing gradients until we talked about RNNs?
  - MLPs and conv nets were at most 10s of layers deep.
  - RNNs would be run over hundreds of time steps.
  - This means if we want to train a really deep conv net, we need to worry about exploding/vanishing gradients!

Deep Residual Networks

- Remember Homework 3? You derived backprop for this architecture:

$$\begin{aligned}\mathbf{z} &= \mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)} \\ \mathbf{h} &= \phi(\mathbf{z}) \\ \mathbf{y} &= \mathbf{x} + \mathbf{W}^{(2)}\mathbf{h}\end{aligned}$$

- This is called a residual block, and it's actually pretty useful.
- Each layer adds something (i.e. a residual) to the previous value, rather than producing an entirely new value.
- Note: the network for $\mathcal{F}$ can have multiple layers, be convolutional, etc.

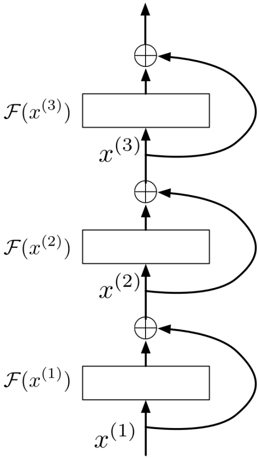


Deep Residual Networks

- We can string together a bunch of residual blocks.
- What happens if we set the parameters such that $\mathcal{F}(\mathbf{x}^{(\ell)}) = 0$ in every layer?
  - Then it passes $\mathbf{x}^{(1)}$ straight through unmodified!
  - This means it's easy for the network to represent the identity function.
- Backprop:

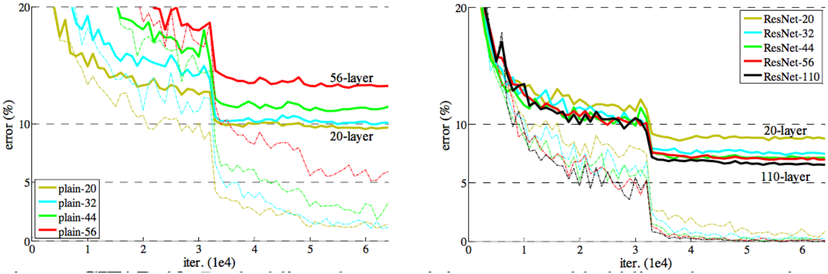
$$\overline{\mathbf{x}^{(\ell)}} = \overline{\mathbf{x}^{(\ell+1)}} + \overline{\mathbf{x}^{(\ell+1)}} \frac{\partial \mathcal{F}}{\partial \mathbf{x}}$$
$$= \overline{\mathbf{x}^{(\ell+1)}} \left(\mathbf{I} + \frac{\partial \mathcal{F}}{\partial \mathbf{x}} \right)$$

- As long as the Jacobian $\partial \mathcal{F} / \partial \mathbf{x}$ is small, the derivatives are stable.



Deep Residual Networks

- Deep Residual Networks (ResNets) consist of many layers of residual blocks.
- For vision tasks, the $\mathcal{F}$ functions are usually 2- or 3-layer conv nets.
- Performance on CIFAR-10, a small object recognition dataset:



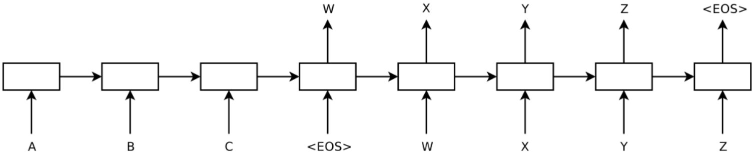
- For a regular convnet (left), performance declines with depth, but for a ResNet (right), it keeps improving.

Deep Residual Networks

- A 152-layer ResNet achieved 4.49% top-5 error on Image Net. An ensemble of them achieved 3.57%.
- Previous state-of-the-art: 6.6% (GoogLeNet)
- Humans: 5.1%
- They were able to train ResNets with more than 1000 layers, but classification performance leveled off by 150.
- What are all these layers doing? We don't have a clear answer, but the idea that they're computing increasingly abstract features is starting to sound fishy...

Attention-Based Machine Translation

- Next topic: attention-based models.
- Remember the encoder/decoder architecture for machine translation:



- The network reads a sentence and stores all the information in its hidden units.
- Some sentences can be really long. Can we really store all the information in a vector of hidden units?
  - Let's make things easier by letting the decoder refer to the input sentence.

Attention-Based Machine Translation

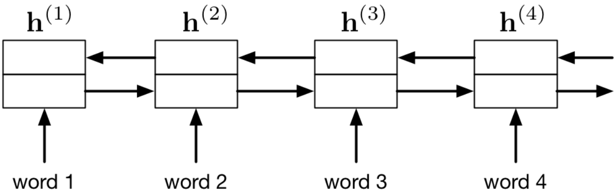
- We'll look at the translation model from the classic paper:

  Bahdanau et al., Neural machine translation by jointly learning to align and translate. ICLR, 2015.

- Basic idea: each output word comes from one word, or a handful of words, from the input. Maybe we can learn to attend to only the relevant ones as we produce the output.

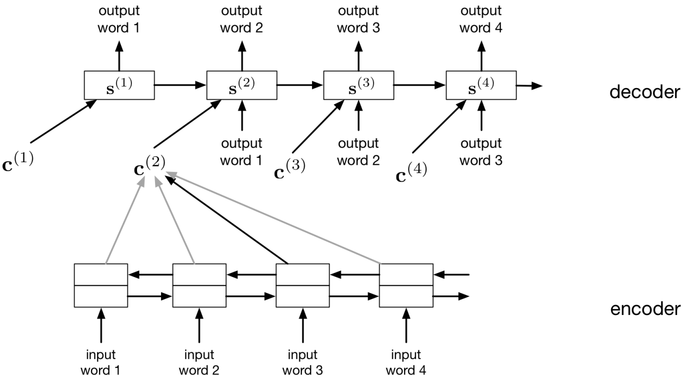
Attention-Based Machine Translation

- The model has both an encoder and a decoder. The encoder computes an annotation of each word in the input.
- It takes the form of a bidirectional RNN. This just means we have an RNN that runs forwards and an RNN that runs backwards, and we concantenate their hidden vectors.
  - The idea: information earlier or later in the sentence can help disambiguate a word, so we need both directions.
  - The RNN uses an LSTM-like architecture called gated recurrent units.



Attention-Based Machine Translation

- The decoder network is also an RNN. Like the encoder/decoder translation model, it makes predictions one word at a time, and its predictions are fed back in as inputs.
- The difference is that it also receives a context vector $\mathbf{c}^{(t)}$ at each time step, which is computed by attending to the inputs.



Attention-Based Machine Translation

- The context vector is computed as a weighted average of the encoder's annotations.

$$\mathbf{c}^{(i)} = \sum_j \alpha_{ij} h^{(j)}$$

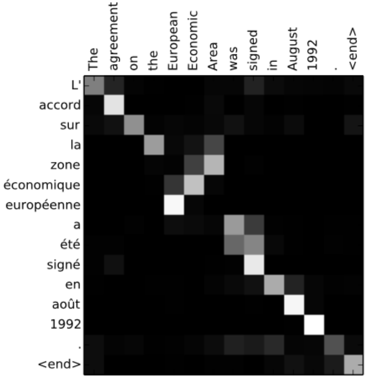
- The attention weights are computed as a softmax, where the inputs depend on the annotation and the decoder's state:

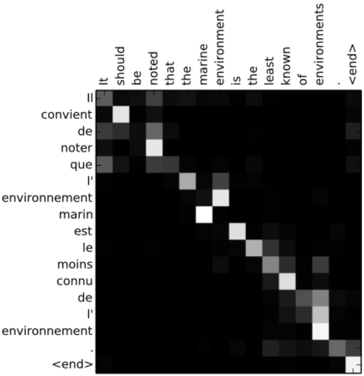
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{j'} \exp(e_{ij'})}$$
$$e_{ij} = a(\mathbf{s}^{(i-1)}, \mathbf{h}^{(j)})$$

- Note that the attention function depends on the annotation vector, rather than the position in the sentence. This means it's a form of content-based addressing.
  - My language model tells me the next word should be an adjective. Find me an adjective in the input.

Attention-Based Machine Translation

- Here's a visualization of the attention maps at each time step.

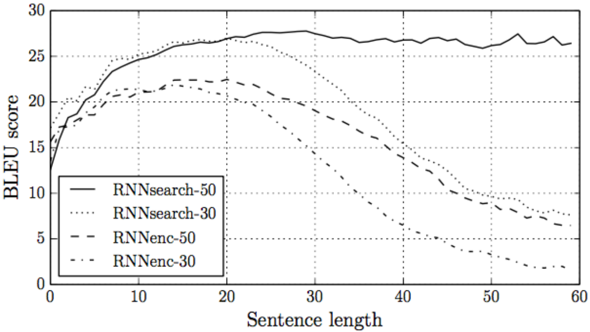




- Nothing forces the model to go linearly through the input sentence, but somehow it learns to do it.
  - It's not perfectly linear — e.g., French adjectives can come after the nouns.

Attention-Based Machine Translation

- The attention-based translation model does much better than the encoder/decoder model on long sentences.



Attention-Based Caption Generation

- Attention can also be used to understand images.
- We humans can't process a whole visual scene at once.
  - The fovea of the eye gives us high-acuity vision in only a tiny region of our field of view.
  - Instead, we must integrate information from a series of glimpses.
- The next few slides are based on this paper from the UofT machine learning group:

  Xu et al. Show, Attend, and Tell: Neural Image Caption Generation with Visual Attention. ICML, 2015.

Attention-Based Caption Generation

- The caption generation task: take an image as input, and produce a sentence describing the image.
- **Encoder:** a classification conv net (VGGNet, similar to AlexNet). This computes a bunch of feature maps over the image.
- **Decoder:** an attention-based RNN, analogous to the decoder in the translation model
  - In each time step, the decoder computes an attention map over the entire image, effectively deciding which regions to focus on.
  - It receives a context vector, which is the weighted average of the conv net features.

Attention-Based Caption Generation

- This lets us understand where the network is looking as it generates a sentence.

A bird flying over a body of water .

A woman is throwing a frisbee in a park.

A dog is standing on a hardwood floor.

A stop sign is on a road with a mountain in the background.

A little girl sitting on a bed with a teddy bear.

A group of people sitting on a boat in the water.

A giraffe standing in a forest with trees in the background.

Attention-Based Caption Generation

- This can also help us understand the network's mistakes.

A large white bird standing in a forest.

A woman holding a clock in her hand.

A man wearing a hat and a hat on a skateboard.

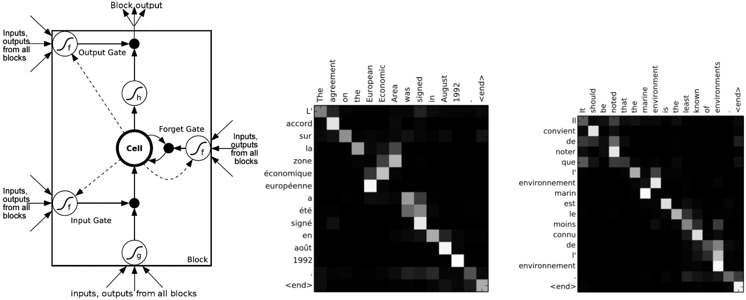
A person is standing on a beach with a surfboard.

A woman is sitting at a table with a large pizza.

A man is talking on his cell phone while another man watches.

Neural Turing Machines (optional)

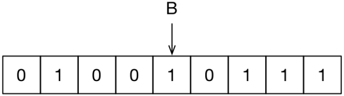
- We said earlier that multilayer perceptrons are like differentiable circuits.
- Using an attention model, we can build differentiable computers.
- We've seen hints that sparsity of memory accesses can be useful:



- Computers have a huge memory, but they only access a handful of locations at a time. Can we make neural nets more computer-like?

Neural Turing Machines (optional)

- Recall Turing machines:

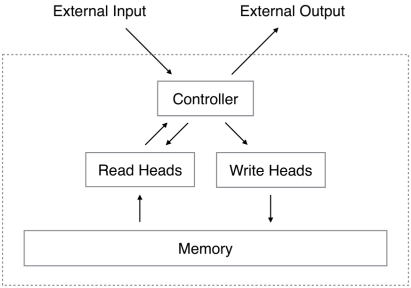


$$\langle A, 0, 0, B, \rightarrow \rangle$$
$$\langle A, 1, 0, A, \leftarrow \rangle$$
$$\dots$$

- You have an infinite tape, and a head, which transitions between various states, and reads and writes to the tape.
- "If in state A and the current symbol is 0, write a 0, transition to state B, and move right."
- These simple machines are universal — they're capable of doing any computation that ordinary computers can.

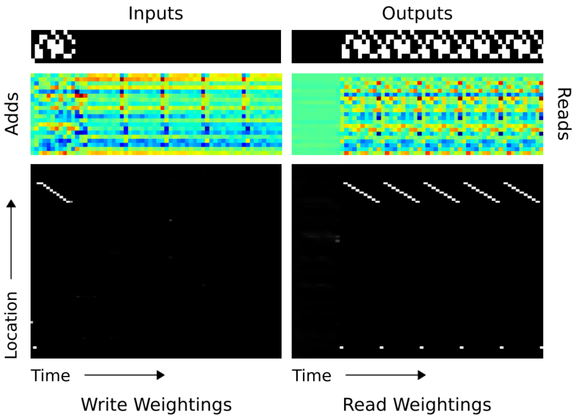
Neural Turing Machines (optional)

- Neural Turing Machines are an analogue of Turing machines where all of the computations are differentiable.
    - This means we can train the parameters by doing backprop through the entire computation.
- Each memory location stores a vector.
- The read and write heads interact with a weighted average of memory locations, just as in the attention models.
- The controller is an RNN (in particular, an LSTM) which can issue commands to the read/write heads.



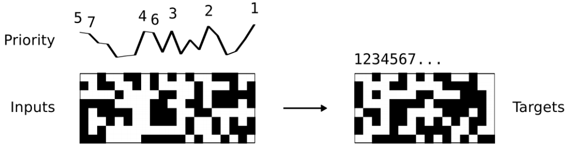
Neural Turing Machines (optional)

- Repeat copy task: receives a sequence of binary vectors, and has to output several repetitions of the sequence.
- Pattern of memory accesses for the read and write heads:



Neural Turing Machines (optional)

- Priority sort: receives a sequence of (key, value) pairs, and has to output the values in sorted order by key.



- Sequence of memory accesses: