Deep Learning

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CompSci 370

With thanks to Kris Hauser for some content

Late 1990's: Neural Networks Hit the Wall

- Recall that a 3 layer network can approximate any function arbitrarily closely (caveat: might require many, many hidden nodes)

- Q: Why not use big networks for hard problems?
- A: It didn't work in practice!
  - Vanishing gradients
  - Not enough training data (local optima, variance)
  - Not enough training time (computers too slow to handle huge data sets, even if they were available)

Why Deep?

- Deep learning is a *family of techniques* for building and training ***large*** neural networks
- Why deep and not wide?
  - Deep sounds better than wide ☺
  - While wide is always possible, deep may require fewer nodes to achieve the same result
  - May be easier to structure with human intuition: think about layers of computation vs. one flat, wide computation

Examples of Deep Learning Today

- Object/face recognition in your phone, your browser, autonomous vehicles, etc.
- Natural language processing (speech to text, parsing, information extraction, machine translation)
- Product recommendations (Netflix, Amazon)
- Fraud detection
- Medical imaging
- Image enhancement or restoration (e.g, Adobe Super resolution) https://blog.adobe.com/en/publish/2021/03/10/from-the-acr-team-super-resolution.html
- Quick Draw: https://quickdraw.withgoogle.com

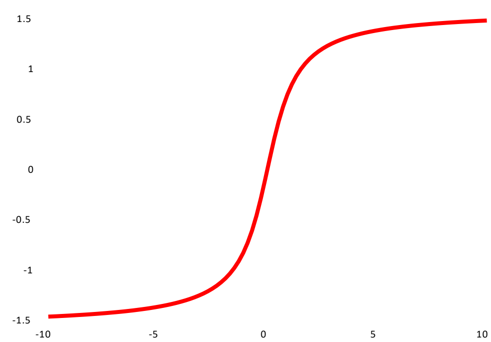
Vanishing Gradients

- Recall backprop derivation:

$$\delta_j = \sum_k \frac{\partial E}{\partial a_k} \frac{\partial a_k}{\partial a_j} = h'(a_j) \sum_k w_{kj} \delta_k$$

- Activation functions often between -1 and +1
- The further you get from the output layer, the smaller the gradient gets
- Hard to learn when gradients are noisy and small

Related Problem: Saturation



- Sigmoid gradient goes to 0 at tails
- Extreme values (saturation) anywhere along backprop path causes gradient to vanish

Summary of the Challenges

- Not enough training data in the 90's to justify the complexity of big networks (recall bias, variance trade off)
- Slow to train big networks
- Vanishing gradients, saturation

Summary of Changes

- Massive data available
- Massive computation available

- Faster training methods
- Different training methods
- Different network structures
- Different activation functions

Estimating the Gradient Efficiently

- Recall: Backpropagation is gradient descent
- Computing exact gradient of the loss function requires summing over all training samples
- Thought experiment: What if you randomly sample one (or more) data point(s) and compute the gradient?
  - Called online or stochastic gradient
  - Expected value of sampled gradient = true value of gradient
  - Sampled gradient = true gradient + noise
  - As sample size increases, noise decreases, sampled gradient -> true
  - Practical idea: For massive data sets, estimate gradient using sampled training points to trade off computation vs. accuracy in gradient calculation
  - Possible pitfalls:
    - What is the right sampling strategy?
    - Does the noise prevent convergence or lead to slower convergence?

Batch/Minibatch Methods

- Find a sweet spot by estimating the gradient using a subset of the samples
- Randomly sample subsets of the training data and sum gradient computations over all samples in the subset
- Take advantage of parallel architectures (multicore/GPU)
- Still requires careful selection of step size and step size adjustment schedule – art vs. science

Other Tricks for Speeding Things Up

- Second order methods, e.g., Newton's method – may be computationally intensive in high dimensions
- Conjugate gradient is more computationally efficient, though not yet widely used
- Momentum: Use a combination of previous gradients to smooth out oscillations
- Line search: (Binary) search in gradient direction to find biggest worthwhile step size
- Some methods try to get benefits of second order methods without cost (without computing full Hessian), e.g., ADMM

Tricks For Breaking Down Problems

- Build up deep networks by training shallow networks, then feeding their output into new layers (may help with vanishing gradient and other problems) – a form of "pretraining"
- Train the network to solve "easier" problems first, then train on harder problems – curriculum learning, a form of "shaping"

Convolutional Neural Networks (CNNs)

- Championed by LeCun (1998)
- Originally used for handwriting recognition
- Now used in state of the art systems in many computer vision applications
- Well-suited to data with a grid-like structure

Convolutions

- What is a convolution?
- Way to combine two functions, e.g., x and w:

$$s(t) = \int x(a)w(t-a)da$$

Entire Domain

- Discrete version

$$s(t) = \sum x(a)w(t-a)$$

Example: Suppose s(t) is a decaying average of values of x around t, with w decreasing as a gets further from t

Convolution on Grid Example

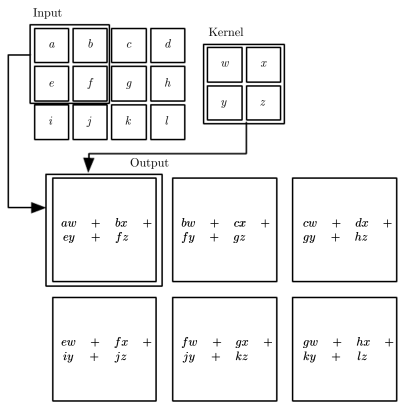


Figure 9.1 from **Deep Learning**, Ian Goodfellow and Yoshua Bengio and Aaron Courville

Convolutions on Grids

- For image I
- Convolution "kernel" K:

$$S(i,j) = \sum_m \sum_n I(m,n)K(i-m,j-n) = \sum_m \sum_n I(i-m,j-n)K(m,n)$$

Examples:

A convolution can blur/smooth/noise-filter an image by averaging neighboring pixels.

A convolution can also serve as an edge detector

https://en.wikipedia.org/wiki/Kernel_(image_processing)

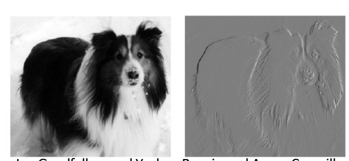


Figure 9.6 from **Deep Learning**, Ian Goodfellow and Yoshua Bengio and Aaron Courville

Application to Images & Nets

- Images have huge input space: 1000x1000=1M
- Fully connected layers = huge number of weights, slow training

- Convolutional layers reduce connectivity by connecting only an mxn window around each pixel
- Can use ***weight sharing*** to learn a common set of weights so that same convolution is applied everywhere (or in multiple places)

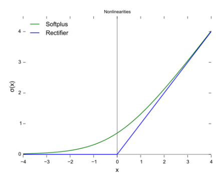
Advantages of Convolutions with Weight Sharing

- Reduces # of weights that must be learned
  – Speeds up learning
  – Fewer local optima
  – Less risk of overfitting

- Enforces uniformity in what is learned
- Enforces translation invariance – learns the same thing for all positions in the image

Additional Stages & Different Activation Functions

- Convolutional stages (may) feed to intermediate stages
- Detectors stages are nonlinear, e.g., ReLU

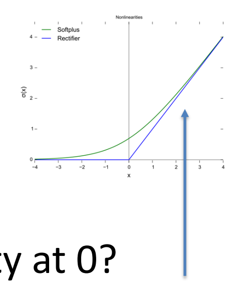


Source: wikipedia

- Pooling stages summarizing upstream nodes, e.g., average (shrinking image), max (thresholding)

ReLU vs. Sigmoid

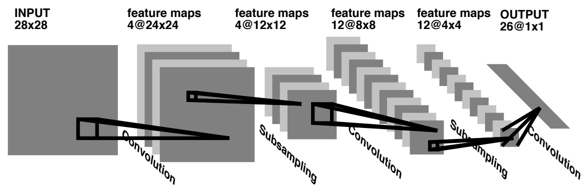
- ReLU is faster to compute
- Derivative is trivial
- Only saturates on one side



- Worry about non-differentiability at 0?
- Can use sub-gradient

Relu in blue

Example Convolutional Network



From, **Convolutional Networks for Images**, Speech, and Time-Series, LeCun & Bengio

N.B.: Subsampling = averaging

Weight sharing results in 2600 weights shared over 100,000 connections.

Why This Works

- ConvNets can use weight sharing to reduce the number of parameters learned – mitigates problems with big networks
- Combination of convolutions with shared weights and subsampling can be interpreted as learning position and scale invariant features
- Final layers combine feature to learn the target function
- Can be viewed as doing
  simultaneous feature discovery and classification

ConvNets in Practice

- Work surprisingly well in many examples, even those that aren't images
- Number of convolutional layers, form of pooling and detecting units may be application specific – art & science here

Other Tricks

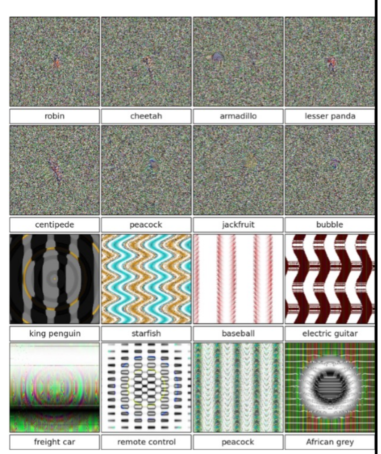
- Convnets and ReLUs tend can can help w/vanishing gradient problem, but don't eliminate it
- **Residual nets** introduce connections across layers, which tends to mitigate the vanishing gradient problem
- Techniques such as image perturbation and drop out reduce overfitting and produce more robust solutions

Putting It all Together

- Why is deep learning succeeding now when neural nets lost momentum in the 90's?
- New architectures (e.g. ConvNets) are better suited to (some) learning tasks, reduce # of weights
- Smarter algorithms make better use of data, handle noisy gradients better
- Massive amounts of data make overfitting less of a concern (but still always a concern)
- Massive amounts of computation make handling massive amounts of data possible
- Large and growing bag of tricks to mitigating overfitting, vanishing gradient issues

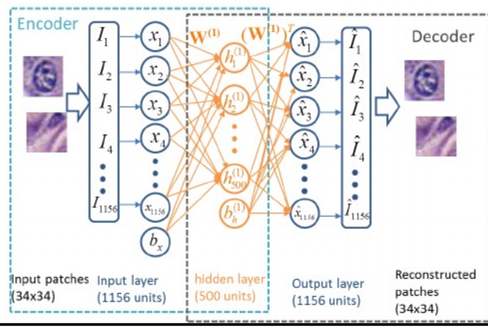
Superficial(?) Limitations

- Deep learning results are not easily human-interpretable
- Computationally intensive
- Combination of art, science, rules of thumb
- Can be tricked:
  - "Intriguing properties of neural networks", Szegedy et al. [2013]



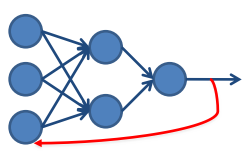
Beyond Classification

- Deep networks (and other techniques) can be used for unsupervised learning
- Example: Autoencoder tries to compress inputs to a lower dimensional representation



Recurrent Networks

- Recurrent networks feed (part of) the output of the network back to the input



- Why?
  – Can learn (hidden) state, e.g., in a hidden Markov model
  – Useful for parsing language
  – Can learn a program
- LSTM: Variation on RNN that handles long term memories better

Deeper Limitations

- We get impressive results but we don’t always understand why or whether we really need all of the data and computation used
- Hard to explain results and hard to guard against adversarial special cases (“Intriguing properties of neural networks”, and “Universal adversarial perturbations”)
- Not clear how logic, high level reasoning could be incorporated
- Not clear how to incorporate prior knowledge in a principled way