4 - Convolutional Neural Networks

Recognition

- In this section, we'll define image recognition as category level recognition of the whole image
- Category level = group level
  - Groups may be more or less specific ("bird," "duck," "Australian wood duck")
  - Different from instance-level recognition, recognising a specific individual
- Whole image = one label per image
  - Different from detection = locate object in image
  - Different from segmentation = label individual pixels
- Difficulties
  - Inter-category similarity 不同类别相似
  - Intra-category variability 同类别内多样
    - Instances
    - Illumination
    - Scale
    - Viewpoint/pose
    - Background/occlusion
- Goal: Build a representation of the image that
  - distinguishes different categories
  - but is invariant (or tolerant) to variation within a category
- Supervised learning problem map image to class label
- Pre-2010: small number of classes (order of 10-100), hand crafted features
- 2010-now: "large scale" image recognition (order of 1000 10,000 classes), millions of images, deep learned features

ImageNet

- Based on WordNet, a database of English words organised by concepts
- Class images collected online, manually cleaned by human annotators (2.5 years of annotation work)
- Over 5,000 classes, but commonly used dataset includes just 1000 of the classes with most exemplars

Neural network review L4.1 P19

Neural networks

- Multiple layers of neurons working in parallel on the same input
- MLP = multilayer perceptron
- Each neuron on layer L receives input from all neurons on layer L-1 (fully connected layer) and produces one output
- Neuron’s output is a weighted sum of the input, followed by a non linear activation function

$$y = f\left(\left[\sum_j w_j x_j\right] + b\right) = f(\mathbf{w} \cdot \mathbf{x} + b)$$

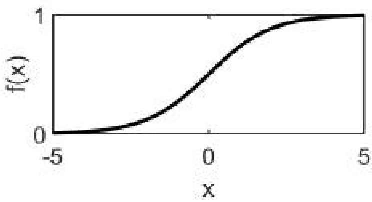
Weights and bias learned from data

- Train through backpropagation (a form of gradient descent)
- Compute gradient of the loss function with respect to network parameters, starting with output layer and propagating to earlier layers, and adjust weights to reduce loss
- Learning rate is a free parameter
- Loss function usually based on difference between ground truth and prediction (supervised learning)
- Advantages:
    - Universal approximator - able to approximate any continuous function on R^n
    - Feature embedding - learns complex features
    - Parallelisable - within each layer, neurons are independent
- Disadvantages:
    - Very large number of parameters - high memory/time/data requirements, prone to overfitting

Non-linear activation function

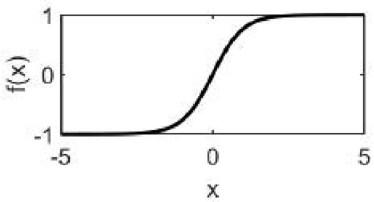
- (logistic) sigmoid (σ):

$$f(x) = \frac{1}{1 + e^{-x}}$$



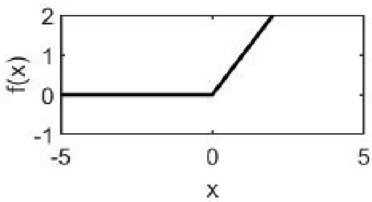
- hyperbolic tan (tanh):

$$f(x) = \frac{e^{2x} - 1}{e^{2x} + 1}$$

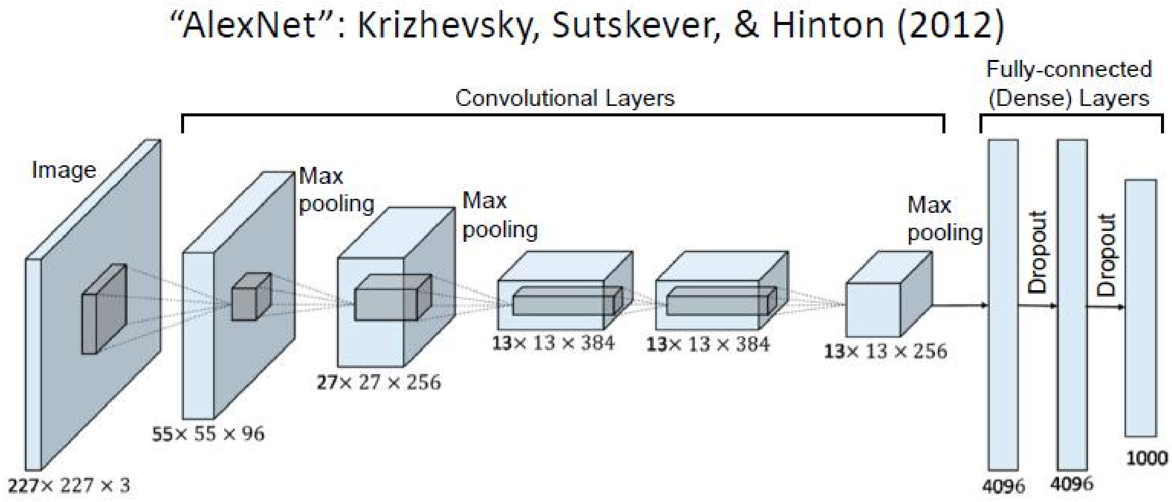


- rectified linear unit (ReLU):

$$f(x) = \max(0, x)$$



Convolutional layers



Regular neural networks can be used for image recognition, but convolutional neural networks are more common for large images.

- More efficient learning of local, repeated patterns
- However, limits what the network can learn

Definition of Convolutions

- A **kernel**, which is a matrix overlaid on the image and computes an element wise product with the image pixels.
- A **stride** which defines how many positions in the image to advance the kernel on each iteration.
  - Stride = 1 means the kernel will operate on every pixel of the image.

Demo of convolutional layer L4.1 P33-42

Fully-connected vs. Convolutional

Fully-connected layer

- Each neuron is connected to every neuron in the input
- The neuron learns some combination of the input
- The output to the next layer is the neuron's response

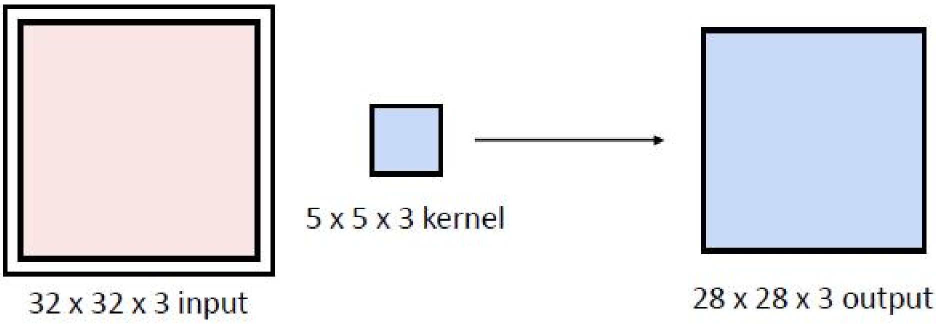
Convolutional layer

- Each neuron is connected to a small patch of the input
- The neuron learns a convolutional kernel on the input
- The output to the next layer is the input convolved with the neuron's kernel

- Number of learned parameters
  - Fully-connected: Size of input + 1 bias
  - Convolutional: Size of kernel + 1 bias

Convolution output size

- Valid convolution (with kernel larger than 1x1) results in output smaller than input
- If same size output is needed, pad the input (zero padding is most common)



Kernels L4.1 P48-51

- In layer 1, kernels mostly learn edges.
- Things learned in higher layers are very abstract.

Summary

- Advantages
    - Efficient: Learns to recognize the same features anywhere in the image, with fewer parameters compared to fully connected layer
    - Preserves spatial relations - output is an image with values indicating where features are present
- Disadvantages
    - Limited kernel size means model is limited to learning local features
- Convolutional neural networks - variation on standard (fully connected) neural networks
- Each convolutional layer learns a set of kernels and outputs activation maps (= input convolved with learned kernel)

Downsampling

- It's common to downsample convolution layer output
- Reduces output size and number of computations needed in later layers
- Can also improve tolerance to translation - small changes in input won't change downsampled output
- Downsampling is common in CNNs to make computation more efficient in later layers and increase translation invariance.
- Methods include strided convolution, max pooling, and average pooling.

Strided convolution

- Convolutional stride = distance between successive convolution windows
- In CNNs, stride can be > 1
- Assuming no padding:
    - **output_size = ceil((input_size - kernel_size + 1) / stride)**
- With padding:

    - **output_size = ceil(input_size / stride)**
- Advantage: Efficient - higher stride means fewer convolution operations
- Disadvantage: Kernel window skips over parts of the image, so important image features could be missed

Pooling

- After convolution, each activation map is separately downsampled
- Pool stride determines the amount of downsampling (output_size = input_size / stride)
- Max pooling:
    - Within a given window in the activation map, take the highest value and discard the rest
- Average pooling:
    - Within a given window in the activation map, average the values
- Advantage
    - Max pooling is most likely to preserve the most important features, compared to strided convolution or average pooling
- Disadvantage
    - Average pooling "blurs" over features; important features may be lost
    - Pooling is slower than strided convolution

Regularisation in CNNs

- Due to the very high number of parameters, CNNs are prone to overfitting, even on large datasets
- Regularisation is usually needed to reduce overfitting
- Common options:
    - L1 or L2 regularisation
        - Free parameters when adding regularisation:
            - How much weight to give regularisation term vs. other terms in the loss function
            - Which layers to include in regularisation all layers or just later layers?
            - Which parameters to include - sometimes only weights are included, not biases
        - Adding regularisation tends to slow down training
        - Too much regularisation can result in underfitting
    - Dropout
        - Randomly discard some neurons (set output = 0)
        - Forces neurons to find useful features independently of each other
        - Effectively, trains multiple architectures in parallel
        - What percentage of neurons to drop is a free parameter (e.g., drop 50% or drop 20%)
        - Can be applied to all layers, or just later layers

        - Different dropout percentages can be applied to different layers typically later layers would have more dropout
      - Adding dropout tends to slow down training
      - Dropout is only used in training when evaluating the network on new data (validation/test), all neurons are active
    - Early stopping
      - Stop training the network when it shows signs of overfitting
      - Monitor performance on a validation set
        - Subset of data not seen in training and not included in test set
        - During training, periodically check model's performance on the validation - set a decrease suggests overfitting
      - Encourages smaller values for network parameters by keeping them close to their initial values (which are typically near 0)
- Frequently unclear which method (or combination) will work best for a given optimisation problem, so it's common to experiment and combine them

Training an Image Recognition CNN

Overview

- Typical architecture for image recognition:
  - Some number of convolutional layers, with downsampling
  - One or more fully connected layers
  - Softmax output with cross entropy loss
- Basic idea:
  - Do feature embedding in convolutional layers
    - Transform images from pixels to useful high level features
  - Fully connected layers are effectively a linear classifier (or MLP) to predict class from high level features

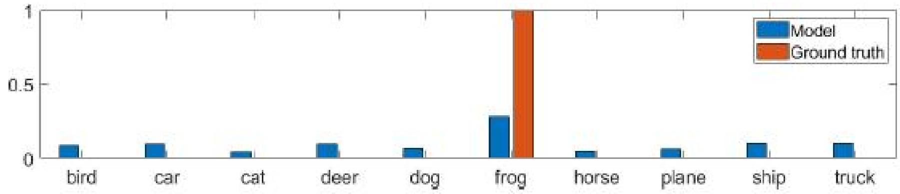
Loss function

Softmax: $\sigma(y_i) = \frac{e^{y_i}}{\sum_{j=1}^{N} e^{y_j}}$

- Apply softmax function to last layer's output
- Produces a vector that has the properties of a probability distribution:
  - All values in range 0 1
  - Values sum to 1

Cross-entropy loss

- Measure of the difference between the model and ground truth probability distributions



- Cross-entropy loss between predicted class and ground-truth class:

Model probability from softmax

$$E = -\frac{1}{N}\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

N classes

Ground truth probability (1 or 0)

Training process

- Split data into train/validation/test sets
- Split training data into batches
- Initialise network weights and bias
  - Typically, weights initialised to small values from a Gaussian distribution around zero
  - Bias initialised to zero or small positive values
- **Set training parameters**
  - Batch size
  - Optimiser
  - Learning rate + decay
- For N = 1 - ?
  - Preprocess a batch of image data
  - Classify batch, compute loss
  - Update model parameters with back propagation
- Monitor training and validation loss
  - Periodically check trained model's performance on the validation set (for early stopping)
  - Stop training when validation loss no longer decreases
- Generally, train until model's performance on a validation set stops improving

Data preprocessing

- Image whitening scale each image to 0-255 range, then normalise so each pixel has mean=0 and (optionally) std=1
- A per-channel mean also works (one value per RGB)

Data augmentation

- Manipulate training data to generate more samples
- Without data augmentation, even smaller networks (e.g., AlexNet) overfit to ImageNet
- Common options:
  - Random crops (e.g., 224 x 224 from 256 x 256 images)
  - Horizontal reflection
  - Small colour/contrast adjustments (to simulate different camera settings or times of day)

- Less common:
  - Random rotation (e.g., +/ 15 degrees) -> slow
  - Random scale -> slow
  - Random occluders (限光器)
- Variations such as vertical reflection and large colour changes are not suitable since they are likely to change the original features.

Batch size

- Batch size (or mini batch size) = portion of the training data used to compute gradient for parameter update
- It's not computationally feasible to use the whole dataset to compute each update
- Dataset is randomly split into N batches of size b
- N updates = 1 epoch (every image has been seen once)
- Smaller batch size
  - More updates (but these are faster to compute)
  - Noisier updates (high variance in gradient)
- Larger batch size
  - Fewer updates (but each update takes longer to compute)
  - More stable updates
- In practice, batch size tends to be limited by memory constraints

Optimiser

- Stochastic Gradient Descent (SGD)
- Root Mean Square Propagation (Rmsprop)
- Adaptive moment estimation (Adam)
  - Keep a moving average of the squared gradient / gradient to divide the learning rate
  - Different from SGD that maintains a single learning rate for different gradients with different magnitudes

Learning rate + decay

- Learning rate = how much to change network parameters on each update
  - Too high - rate unstable training
  - Too low - rate very slow learning

Summary

- Training CNNs can be difficult - parameter space is extremely large
- Data augmentation is usually required to avoid overfitting
- Hyperparameters (batch size, optimizer, learning rate) can affect how well the network learns

CNN results L4.2 P43

- CNNs are the state of the art for image classification, exceeding human performance on ImageNet
- CNN classification errors are often understandable (odd views, small objects), which suggests they learn reasonable features for this task

- But they do show some odd failures, like poor generalisation to ImageNetV2