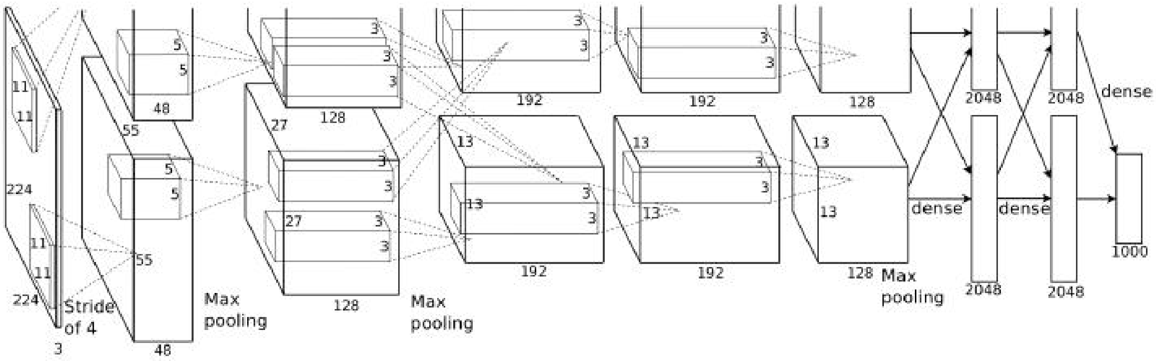
5 - Deep Learning I

Common architectures

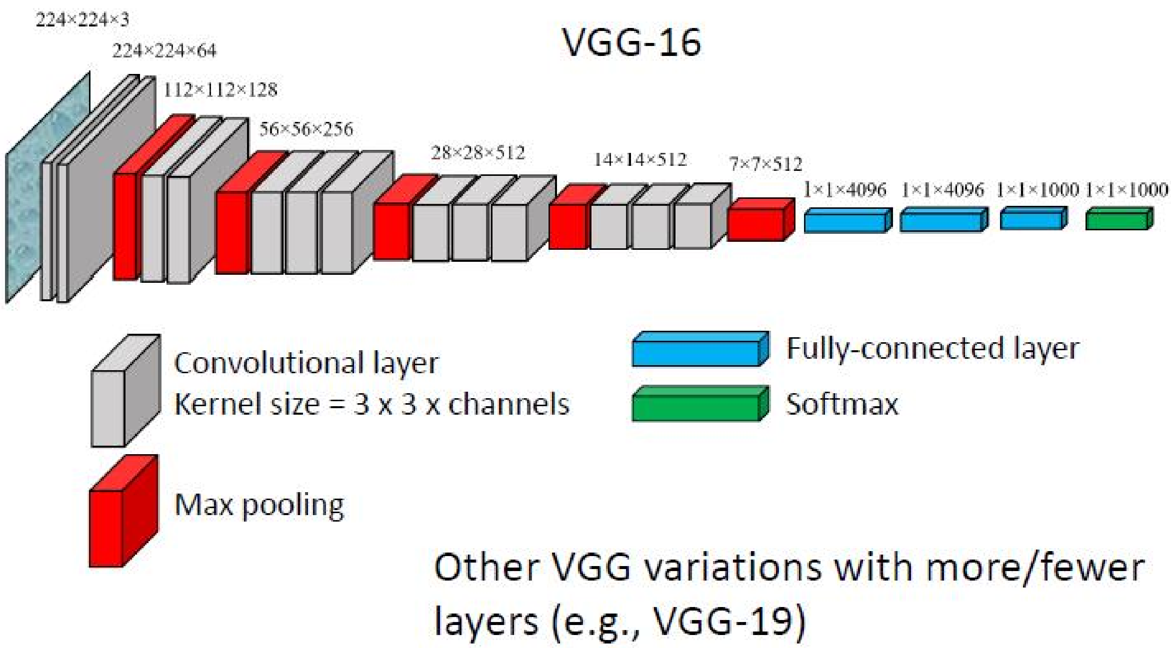
AlexNet



Innovations

- ReLU (Rectified Linear Unit) activation function - faster training
- Training on GPU - parallelisation allows faster training (actually required 2 GPUs at the time!)
- Overlapping max pooling regions, response normalisation after ReLU - small accuracy increase
- Data augmentation reduces overfitting
- Dropout reduces overfitting

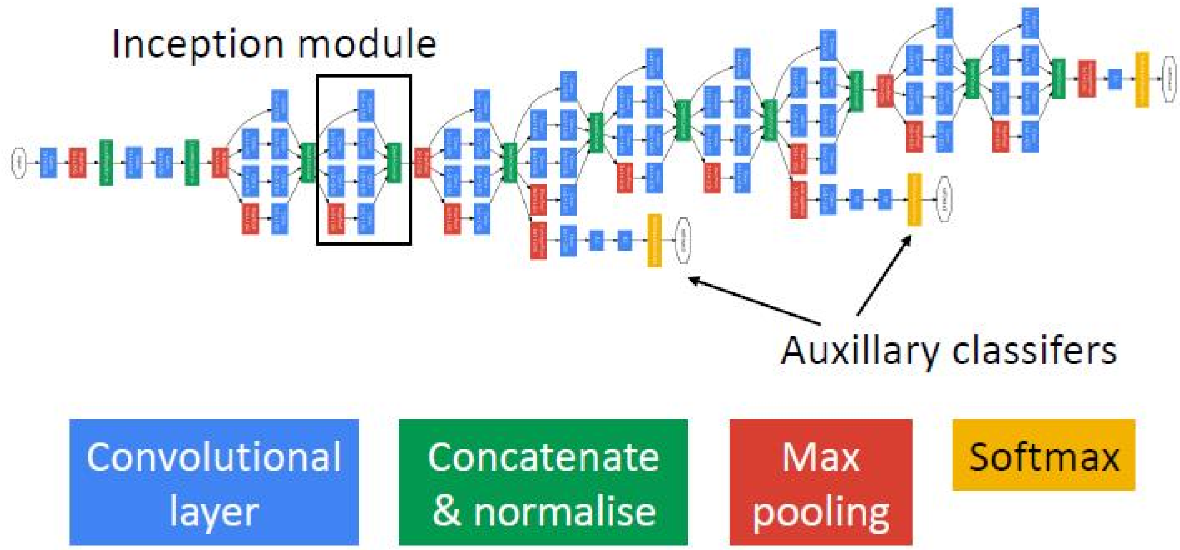
VGG



Innovations

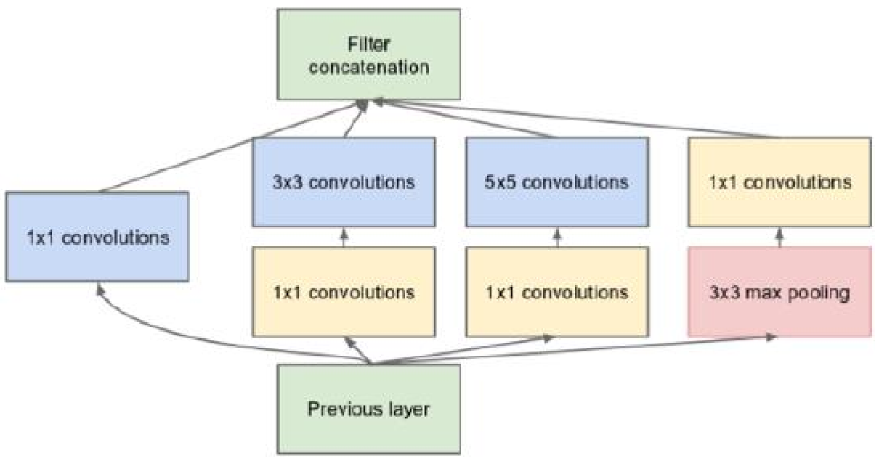
- Stacked 3x3 convolutional layers
  - VGG stacks multiple 3 x 3 convolutional kernels to effectively make larger kernels:
    - Two 3 x 3 conv. layers = effective receptive field of 5 x 5
    - Three 3 x 3 conv. layers = effective receptive field of 7 x 7
  - Learn more complex features thanks to additional non-linearities
  - Fewer parameters than 1 layer with the equivalent receptive field
- Doesn't use AlexNet's response normalisation allows faster training with only very small accuracy drop

GoogleNet (Inception)



Innovations

- Inception module
  - Choosing the right kernel size in CNNs is difficult because objects/features can appear at any scale
  - Solution: use multiple kernel sizes and concatenate
  - Learns features at a variety of kernel sizes/scales
  - 1x1 convolutional layers reduce the number of channels (dimensionality reduction)

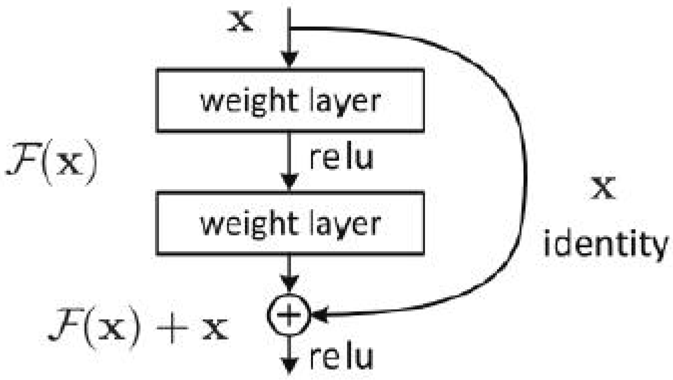


- Auxillary classifiers

- Used during training only - classify images based on early layer representations and update parameters
- Helps with vanishing gradient problem

ResNet

- Will deeper neural networks will always give better performance?
  - No, performance saturates and then decreases
  - Not due to overfitting - performance is worse on the training set
- It should be possible to learn parameters in the deep network that would allow it to act like the small network
  - For example, some conv. layers learn identity kernels, while others learn the shallow network's kernels
- However, deep CNNs cannot learn this solution (at least, not within a reasonable training time)
- Solution: Add "shortcut connections" that skip some layers
- Residual learning - Reformulate the learning problem:
  - Traditional network: input x, output $\mathscr{H}(x)$, which is the feature representation of x
  - Residual network: input x, learn $\mathscr{H}(x) - x$, which is then added to x to get $\mathscr{H}(x)$
  - Makes it easier to learn identity mapping
- Residual block
  - Simplifies the learning problem by making it easier for networks to learn identity mapping
  - Allows deeper networks to improve accuracy



MobileNet

- Lightweight architecture for mobile apps
- Separable filters
  - Recall that filtering with a 2D filter is equivalent to filtering with two orthogonal 1D filters
  - Similarly, filtering with a 3D filter is equivalent to filtering with a 2D filter and an orthogonal 1D filter
- Depthwise separable convolution
  - MobileNets uses depthwise-separable filters - 2D filters in x,y and 1D filters over channels
  - Fewer parameters and less computation
  - Limits what kernels the model can learn not - all kernels are separable
- Smaller and faster than other architectures

    - Lower accuracy than VGG, ResNet, etc.
    - But better suited for real time applications, phones

Choice of architecture depends on your application

- Runtime, memory, processing power

Classification results L5.1 P26-28 L5.2 P6

- Objects that are larger in the world are easier to recognize
    - Possibly because the background is consistent for large objects
- Natural objects are more easily recognized than man-made
- More highly textured objects are more easily recognized

ImageNet classification

- 1000 object classes
- Model output = a probability distribution (from softmax) over 1000 class labels
- Top-1 accuracy
    - For each test image, model is correct if the most likely class == ground truth class
- Top-5 accuracy
    - For each test image, model is correct if any of the 5 most likely classes == ground truth class

Generalisation

- Features from neural networks are good representations for a range of tasks

Summary

- 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

Transfer learning

Pixels are a poor space for classification

- High dimensional space: 256 x 256 x 3 image = 196,608 attributes
- Irrelevant transformations (translation, lighting change, scale change, rotation, etc.) cause large changes in pixel values

A good feature space for image recognition

- Is lower dimensional e.g., 1000s of values per image
- Projects images from the same class into a similar part of the space (images with the same class label have similar features)

Using pretrained networks

- CNNs convert images from pixels to high level features that are good for classification (feature embedding)
- These high level features give good performance on a range of computer vision tasks
- Transfer learning - use features from a CNN trained on a large scale task (e.g., ImageNet classification) as input for another task, with minimal retraining

Transfer learning

- Embedding of an input = the network's response to the input at some layer
- Extract the representation from a late layer of a CNN trained on ImageNet
  - E.g. For each image take the activations from the 4096 neurons that feed into the 1000 way ImageNet classification
- Use the neurons' activations as the attributes for a classifier of your choice (e.g., SVM, K-NN etc.)
- More efficient: Remove the output layer of a CNN trained on ImageNet
- Replace with an appropriate output layer for your task
- Intialise your new layer and train only this layer; freeze all other network parameters
- Or, optionally, train some of the later layers but freeze earlier layers

Retraining layers

- Finetuning = retraining layers of a pretrained CNN
- How many layers to fine tune depends on dataset size and how similar it is to ImageNet
  - More dissimilar datasets may need more retraining of lower layers
  - If dataset size is limited, training lower layers may just lead to overfitting

Summary

- ImageNet trained CNNs produce state-of-the-art performance on image recognition tasks
- It's common to use CNNs pretrained on ImageNet for a variety of computer vision tasks, either as is ("off the shelf" feature embedding) or with some finetuning

Model visualisation

Visualising feature space

- How are images organised in this feature space?
- It's a high dimensional space, so we can't just plot all images in this space
  - Can use dimensionality reduction
    - PCA (principal component analysis)
      - Show the dimensions with the most variance
      - Simple but often hard to interpret since only a few dimensions can be visualised simultaneously
    - t-SNE (t-distributed stochastic neighbor embedding)

        - Flatten high dimensional data into 2D or 3D so that near neighbours stay nearby
    - Or look at local regions (what images are near neighbours in this space?)
- Look at individual neurons

Visualising convolutional kernels

- Visualising the first convolutional layer kernels is easy because the input channels are RGB
- Visualising layer conv kernels is harder because the channels are high dimensional and represent complex features

Maximally activating patches

- Choose a layer and channel
- Run many images through the network and find patches that give the highest response in this channel

Guided backprop

- Compute gradient of neuron value with respect to image pixels
- Which pixels matter most for correct classification?
- ReLU activation function means neurons with response < 0 are set to 0
- Traditional backprop does not pass back gradient when neuron response is 0
- Guided backprop also does not pass back negative gradient

Visualising image regions

- What parts of an image are most important for determining the class label?
    - Can help show what features the model uses to determine class
    - Can help debug problems (e.g. using background to classify object, label confusion when there are multiple objects)
- Occlusion method: mask image and see how much class probability changes   L5.2 P19

CAM (Class Activation Mapping) L5.2 P20

- Add a Global Average Pooling (GAP) layer before classification layer, use weights of this layer to determine where the class relevant features are.
- Disadvantage
    - Most models don't use GAP, so the GAP layer must be added to a pretrained network and then finetuned
    - Only allows visualisation of the last layer
- More flexible alternative: Grad-CAM (Gradient-Weighted Class Activation Mapping)

Grad-CAM L5.2 P23

- Take response from some layer A$\in\mathbb{R}^{HxWxK}$
- Compute gradient of class score with respect to layer response
- Global Average Pool (average over image x,y) the gradients to get a vector of weights α_k (1 weight per channel)
- Compute activation map $ReLU$(sum($\alpha_k A_{h,w,k}$))

Visualising classes

- Usually based on gradient ascent - synthesize image that maximises class label response
    - Initialise an image with zeros or small random noise
    - Run image through network, compute gradient
    - Update image pixels in a direction that minimises loss
- Problem: there are many possible arrays of pixels that can generate very high model response; not all of these will look like realistic images

Summary

- Various ways to visualise what a model is doing
    - Feature space visualisations
    - Visualising image regions that support a class decision
    - Class visualisations
- Each method provides different information, so it's usually best to try multiple approaches

Invariance & generalisation

Invariance / tolerance

- Lighting, Translation, Image plane rotation, Scale, 3D rotation / pose
- BagNet shows most informative patches L5.2 P33
- CNNs are tolerant to variation included in the training data
- But often not tolerant to variation that didn't appear in the training data
- Classification tends to rely on recognizing a few key features / local texture elements

Shape and texture

- VGG-16, trained on ImageNet
- The performance drops from 90% to 79% on texturised images.

Adversarial images L5.2 P39

- Adding small amounts of noise to an image can completely change the model's perception

Generalisation

- Models are very sensitive to some types of noise L5.2 P36
- ImageNet vs. ImageNetV2 L5.2 P40
    - Drop of about 10% suggests some overfitting to quirks of ImageNet

Summary

- ImageNet-trained features are used for a variety of visual tasks
- But ImageNet-trained CNNs have some issues:
    - Very sensitive to noise
    - Recognize local texture features but not global shape
    - Generalisation errors on very similar datasets
    - Biases due to dataset construction

- Geographic bias L5.2 P41