Deep Learning for Machine Vision

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BACKGROUND
A convolutional network (ConvNet/CNN), is composed of multiple layers of convolutions, pooling and non-linearities.
Convention and terminology

- 2d grids that represent image space are called feature maps. Each value in a feature map represent information about a specific location in the input image.
- The parameters learned for each convolution layer are also ordered as a 2d map - usually called “kernels” or “filters”
- Convolutions can have strides - moving the filters with a fixed step and padded - adding zero values to avoid spatial size decrease
- Bias values are added per-map (number of bias elements is the number of output feature maps)
The first work that popularized Convolutional Networks in Computer Vision was the “AlexNet”, developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton.

- AlexNet was submitted to the ImageNet ILSVRC challenge in 2012 and significantly outperformed the second runner-up (top 5 error of 16% vs 26% error).
- The Network was deeper, bigger, than previous networks - 60M parameters, 8 trainable layers.
The ILSVRC 2014 winner was a Convolutional Network from Szegedy et al. from Google called *GoogLeNet*. It featured some new ideas:

- Inception Module - concatenation of several convolution sizes
- $1 \times 1$ convolutions + Average Pooling instead of Fully Connected layers (both introduced by Lin in “Network-in-network” paper from 2013).
- This dramatically reduced the number of parameters in the network (5M, compared to AlexNet with 60M).
- Google later improved this network by introducing batch-normalization + different inception configuration (Inception v2-v4).
The runner-up in ILSVRC 2014 was the network from Karen Simonyan and Andrew Zisserman that became known as the VGGNet. Its main contribution was in showing that the depth of the network is a critical component for good performance.

- Their best network contains 16 trainable layers
- Features an extremely homogeneous architecture that only performs 3x3 convolutions and 2x2 pooling from the beginning to the end.
- Despite its slightly weaker classification performance, the VGG ConvNet features outperform those of GoogLeNet in multiple transfer learning tasks.
- Expensive to evaluate and uses a lot more memory and parameters (140M).
Residual networks

- Residual Network developed by Kaiming He et al. was the winner of ILSVRC 2015. It features a very deep architecture (152 layers) with special skip connections and heavy use of batch normalization. The architecture is also missing fully connected layers at the end of the network.
Trends in designing CNNs

Some noticeable trends in recent CNN architectures:

- Smaller convolution kernels - $3 \times 3$ is very dominant.

- Deeper - using smaller kernels is rectified by stacking more layers - effectively increasing the receptive field of the network.

- Less pooling - going deeper means we do not want to reduce spatial size too quickly. Modern network have small number (if any) of pooling layers.
Visualizing CNNs
What do convolutional networks learn?

Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]
What do convolutional networks learn?
What do convolutional networks learn?

(a) Input Image
(b) Layer 5, strongest feature map
(c) Layer 5, strongest feature map projections
(d) Classifier, probability of correct class
(e) Classifier, most probable class

True Label: Pomeranian
True Label: Car Wheel
True Label: Afghan Hound
Adapting CNNs to scale
In order to classify images bigger than the size we trained on, we can view fully-connected layers as convolutional kernels:

- Replace the first fully-connected layer that looks at spatial region (e.g. 7 \times 7) with a convolutional layer with kernel of the same size.
- Replace each subsequent layer with a convolutional layer with kernel of 1 \times 1.
- Instead of a single classification, we will receive a class-map, where each spatial location is related to a different region in input image.
Spatial classification

input 1st stage output classifier
convolution pooling conv conv conv

input 1st stage output classifier
convolution pooling conv conv conv

input 1st stage output classifier
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input 1st stage output classifier
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input 1st stage output classifier
convolution pooling conv conv conv
Localization, Detection & Segmentation
As we’ve seen, we can adapt a trained network for new sizes and scales. A natural additional tasks in computer-vision is to try to localize and detect objects in an image.

We need both to classify our object and to localize it

- For detection - we also need to handle multiple objects and reject a lot of false-positives (not-an-object)
Some methods for detection using CNNs when we possess ground-truth bounding boxes

- Most naive approach is to add a regression objective - estimating the bounding boxes of each object (OverFeat - Sermanent 13').

- A more popular and effective method is to use region-proposals (often using “selective-search”), suggested in RCNN (Girshick 14')

R-CNN: Regions with CNN features

1. Input image
2. Extract region proposals (~2k)
3. Compute CNN features
4. Classify regions
The RCNN approach, although accurate, had a bottleneck - generating and evaluating on ~ 2000 proposals. To remedy this, future works suggested:

- Evaluating most of the network on entire image, and pooling the proposals from feature space instead of image space (SPP, Fast-RCNN)
- Moved the region-proposal to be an inherent part of the network (Faster-RCNN)
Another important computer-vision task is to segment whole images. This can be viewed as a classification at the pixel level.

- We might wish to incorporate both global, abstract features, as well as localized low-level features.
- This means using multiple layers for final segmentation (Long 14’).
- As with detection, trend is to build whole end-to-end models by creating object-candidates (Pinheiro 15’).
Another usage is transferring visual knowledge into language domain - such as generating captions or question answering. This is done by augmenting a convolutional network with a recurrent one.

A group of people shopping at an outdoor market. There are many vegetables at the fruit stand.
This can be coupled with attention mechanisms - learn a state-dependent weighting over the input space in order to maximize an objective.
Caption generation
Generative Models
AutoEncoders

Probably the most popular application for unsupervised learning using neural networks, and ConvNets in particular. Autoencoder is composed of:

- An encoder $G(x; w_1)$ that maps an input to a hidden latent representation.
- A decoder $F(y; w_2)$, that maps the representation back into the input space.

The reconstructed output is therefore

$$\hat{x} = F(G(x; w_1); w_2)$$

The criterion used for training is usually the mean squared error (MSE) between the input and reconstruction.

$$\min ||x - \hat{x}||^2$$
One new and and exciting framework for unsupervised, generative models is the *Adversarial network* (Goodfellow 14’). It consists of two networks trained simultaneously:

- A *generative* model $G$ that tries to capture the data distribution and generate new samples.
- A *discriminative* model $D$ that estimates the probability that a sample came from the training data rather than $G$.

The training procedure for $G$ is to maximize the probability of $D$ making a mistake - it is “cheating” by using the gradients with respect to $D$. 
Generative adversarial networks

Generative adversarial networks
We can quantify an image “style” representation with the correlations between the different feature maps. These feature correlations are given by the Gram matrix $G^l \in \mathbb{R}^{N_l \times N_l}$, where for a given layer $l$:

$$S^l_{ij} = \sum_k F^l_{ik} F^l_{jk}.$$ 

Thus we can change the target image $x$ until it generates the same response in a certain layer of the CNN as the original image $y$.

$$L_{style} = \sum_{l=0}^{L} \frac{1}{N^2_l M^2_l} \sum_{i,j} \left(S(x)^l_{ij} - S(y)^l_{ij}\right)^2$$

“A Neural Algorithm of Artistic Style” (Gatys et al)
Style transfer
Style transfer
Another interesting usage is to try and maximize the $L_2$ norm of intermediate layer activations, by optimizing an input image. This can help visualize the role each layer plays in the model.