Discussion 5

This discussion covers vision applications and introduction to visualizing networks (style transfer, Dream Machine)

1 Review of Vision Problems

For most of the class thus far, when we discuss applying neural networks in practice to vision applications, we have largely assumed an image classification task. That is, given an image, we let the network output the probabilities of the true label belonging to a variety of classes.

However, there are more types of standard computer vision problems. At the high level, we can roughly categorize the computer vision problems into three main categories (the 3R's of vision): **recognition**, **reconstruction** and **re-organization**. Recognition is about attaching semantic category labels to objects and scenes as well as to events and activities. Reorganization is about the partitioning of the image based on semantic information. Reconstruction is about obtaining the 3D information of of the scene that generated the images. Under these broad categories, we can further classify the problems into specific tasks.

Image Classification Given an image, we would like the network output the probabilities of the true label belonging to a variety of classes. This type of problem was the main focus of the course so far.

Object Localization Determine a *bounding box* for the object in the image that determines the class. In this type of problem, only one object is involved, and indeed, we know ahead of time that there is only one object class of interest in the image. Often, the bounding box objective may be simultaneously trained with the classification objective, resulting in a loss objective that is the sum of the two loss terms, the L_2 and the cross-entropy loss, respectively.

Object Detection Determine multiple objects in an image and their bounding boxes, with performance measured by *mean average precision* (mAP). There may be many objects, and several instances of the same object class (for e.g., several dogs) in the same picture. This means that, in contrast to image classification where the network only has to identify one object, the network has to predict a varying number of bounding boxes. In literature, object detection can be solved using R-CNNs (R-CNN, fast R-CNN, faster R-CNN, mask R-CNN).

Semantic Segmentation Label every pixel in the image. Here, we can naively run a CNN classifier for each pixel. However, better solutions, like `UNet`, exists in literature. *Semantic* segmentation means we do not worry about distinguishing between different instances of a class, in contrast to the aptly-named *instance* segmentation problem.

2 Object Detection: R-CNN

Faster R-CNN is a popular technique for object detection problems, and stands for Faster *Region*-CNN. Faster R-CNN uses these regions as areas in the image that are likely to contain objects. More precisely, a *Region Proposal Network* predicts proposals from CNN features. The CNN features were obtained from passing the original input image through several convolutional layers.

The network is trained jointly using four losses, which normally means adding up the objectives (possibly with different weights).

3 Segmentation: Transposed Convolution & U-Net

We briefly comment on an operator called the *transpose convolution*, because it's often used for *upsampling* a convolutional neural network during segmentation tasks. This operator increases the resolution of the intermediate tensors, which we often want if we want the output of our network to be an image (e.g., of the same size as the input images). Note that early convolutional and pooling layers tend to *downsample* or reduce the size of tensors. Please note that it is sometimes referred to as a *deconvolution* operator, but it is not the preferred wording because it is an overloaded term with other definitions commonly used.

The transpose convolution can be thought of as flipping the forward and backward passes of the convolution step. In addition, the naming comes from how it can be implemented in a similar manner as in convolution but with the weight matrix transposed (along with different padding).

Convolutional layers typically downsample images spatially but sometimes we want to upsample. For example in semantic segmentation or in DCGAN where we generate images from random noise of a lower dimension.

Problem 2: 2D Transpose Convolution Mechanics

Let our input be

$$\begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix}$$

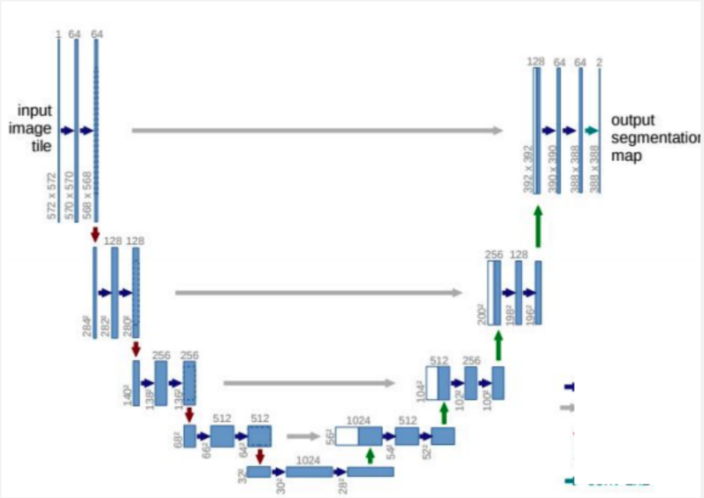
and kernel be

$$\begin{bmatrix} 0 & 1 \\ 2 & 3 \end{bmatrix}$$

Assume input, output channels of 1, padding of 0 and stride of 1, what is the output of transposed convolution layer?

Problem 3: U-Net Potpourri

The figure below shows a U-Net architecture.



Answer the following questions,

(a) What operations are represented by upward arrows in the figure?

(b) What is the role of rightward arrows?

(c) Which of the transformations in the network have learned parameters?

4 Computer Vision for Visualization and Art

Computer vision algorithms can also be used to create art and cool visualizations!

4.1 DeepDream

The main idea behind DeepDream is to exaggerate details in an image that look like recognizable objects. Simply put, the procedure for DeepDream is as follows,

1. Pick a layer
2. Forward propagate to the layer
3. Set the gradient at that layer to the activation at that layer
4. Backpropagate to update the image

4.2 Style Transfer

Style transfer is a class of algorithms to manipulate digital images, or videos, in order to adopt the appearance or visual style of another image. In order to accomplish this task, we need to find representations that extract the content and style of a given image separately. While it is hard to exactly define the notion of content and style of a simple, researchers have discovered that some simple heuristics work decently.

We know that a trained CNN can predict the objects in a given image very well. Therefore it is natural to assume that the activations in the last few layers of a pre-trained CNN summarize the content of a given image. Let us denote the image as p and the activations as $C(p)$. On the other hand, the style of an image is often reflected by the statistics of low level textures and geometric shapes. From the visualization of CNN filters, we know that the first few layers of a pre-trained CNN captures exactly these low level textures. Hence, we can simply use the statistics on top of early layer activations to capture the style. A simple statistics to use is correlation and can be computed by the Gram matrix. Let us denote the Gram matrix of early layer activations as $S(p)$.

Now, given a source image p and a style image a, the goal of style transfer is simply to find another image x such that $C(x)$ approximates $C(p)$, and $S(x)$ approximates $S(a)$. We can formulate this into the following optimization problem and solve it using gradient descent.

$$\arg\min_x \|C(x) - C(p)\|_2 + k\|S(x) - S(a)\|_2$$