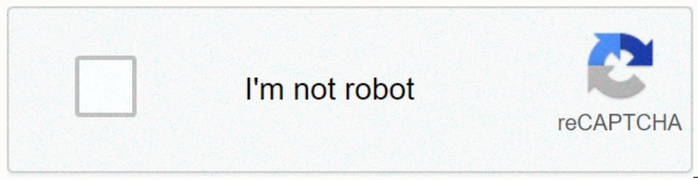

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Make your own neural network pdf

Previous article:DL01: Neural Networks TheoryDL02: Writing a Neural Network From Scratch (Code)DL03: Gradient DescentDL04: BackpropagationNow that we understand backpropagation, let's dive into Convolutional Neural Networks (CNNs)! (There are a lot of pictures in this, so be patient while they load) Code for visualization can be found here (Intuition* Applying feedforward networks to images is extremely difficult. The number of parameters associated with such a network is enormous. A better network of improvements is needed specifically for images.* Hubel and Wiesel perform experiments that have given some intuition on how images are biologically processed by the brain. They found that the brain reacts in specific ways when it sees edges, patterns, etc. The visusal cortex is reportedly divided into layers, in which the layers at the front recognize simple features such as edges, but the layers on the back recognize more complex features. The Basic ConceptUal Concept behind CNNs is filter/kernel. You can think of them as smaller sized images that are then slid through the input image. By sliding through, I mean the same filter is added to the different areas in the image (meaning complex on the photo). Images are represented by a variety of shapes (height, width, depth/channel), including 3 channels (RGB) for color images and 1 channel for grayscale images. For a filter to be complex on the image, it must have the same number of channels as the input. The output is the total of the elementally achieved cause of filter and image elements (which can be considered dotted products). So we can use any number of filters. The output depth size will be equal to the number of filters we use. Source: the animation above, two filters are being used. Note that the depth (or channel) size of each filter is the same as the input depth (in this case 3). The convolution activity is also clearly described in the animations. The output depth size is equal to the number of filters (in this case 2). The input is the summation of the wise element of filters and images across all channels (plus some optional bias terms). Therefore, it can be considered as dot product on 3x3x3 volume (filter_height * filter_width * input_depth). To get better intuition of filters, let's take a look at an example of a filter that detects vertical edges. Source: filter can be considered to detect some parts of the image lighter on the left and darker on the right. Sliding filters also give an additional advantage of translation inerability, because the same features can be detected any i i.m. where they are in Image. In addition, in practice it was found that the original layers tended to learn simpler features such as edges, angles, etc. while deeper layers tended to explore complex features such as eyes, lips, faces, etc. Intuitively, it can be thought that we are combining lower-level features (e.g. edges), and these combinations lead to a combination of such features, thus leading to higher-level features. A simplified example would be, somehow combining two edge detection filters to detect angles:This is only for intuition (made with awwapp.com)So a complete convnet often looks like this:Source: is randomly initialized and then learned through backpropagation. There are mainly 4 types of layers in CNNs: Conv layers: These classes perform convolution activities, as described above. The number of parameters that can be learned in these classes is equal to the number of parameters in each filter by the number of filters i.e. filter_height * filter_width * linear number_of_filtersNon: Conv classes are usually followed by a non-linear layer. Usually ReLU is used. There are no parameters that can be learned in this layer. Pooling layer: This layer is used to downsample images. It leads to smaller parameters in the next layers, and therefore convnet can be done a little deeper. Source: theory, the average synthesizer looks like the best option i.e. taking parts of the image, and averages out that part to give a view value to that part of the image. But in practice, it is found that the maximum angth works better, i.e. taking the maximum from that area in the photo. The synthetic layer maintains depth, i.e. the synthesizer is carried out independently across all input channels. No parameters can be learned in this class.4. Fully connected: They are usually at the end of the convnet. They are simple feedforward classes, and there are many parameters that can be learned as a normal feedforward network would have. One could argue that according to the complex operation described above, the edges and angles of the image are becoming less important than the part in the middle of the image. To fix this, input is usually buffered to no, i.e. a number layer is not added to all edges of the image. In addition, zero-padding allows us to change the size of the input image as required. The size of the jump while sliding the filter on the image is called stride. The more stride, the smaller the image of the input. The formula for calculating the size of the next layer after a conv layer is ((W−F+2P)/S)+1, where W is the size of the image (width for horizontal size and height for vertical size), F is the size of the filter, P is cushioned and S is stride. A cool thought to note as we move deeper into the network, the network, the reception field of the buttons increases, i.e. the node can be considered to look at a larger part of the image than the previous layer. BackpropagationBackprop is performed normally as a feedforward neural network. The derived of all weights (or parameters) that are calculated takes w.r.t. and is updated by the root gradient (or some variant of the gradient root, which will be discussed in a following post). While applying string rules to find w.r.t. loss gradients, the gradient of a weight will come from all nodes in the next layer where the weight has contributed in the front pass (It will be the total of all gradients, according to the multi-variable string rule of difference). VisualizationNow that we understand how a convnet works, let's try to visualize some stuff happening inside the convnet. A great explanation of some famous network architecture can be found here. Imagine the weight of VGG neworks is not used much, as the filters are only 3x3 in size. However, alexnet has a filter size of 11x11. The following image shows some of the filters learned by alexnet. Source: Http://cs231n.github.io/convolutional-networks/From this point, all visualizations are done on VGG16 in Pytorch. The code can be found here. So let's take a look at what the output of each layer looks like:Input image:Output at various layers:Since the number of channels at every layer are different (not 1 or 3), I've averaged over all channels to finally give a grayscale image (the color scheme is because of the default cmap scheme used by matplotlib). Notice that maxpooling is simply downsampling the picture. If we don't take the average across all channels, we can see the input of each channel (i.e. the input of each filter) in a specific layer. Let's take a look: The input from the first conv layer filters (all 64 channels from this layer)The input from the last conv layer filters (the first 484 channels are displayed in a total of 512 channels in this class)We have seen the results of the input from the filters, Now let's see what the filters really look like: 3x3 filters from the first conv layer (64 filters)3x3 filters from the last conv layer (first 484 out of 512 filters in this class)OcclusionNow let's try to see really what part of the image is responsible for classifying an image. First, I use a technique called congestion. In it, we simply delete an area from an image, and then find the probability that the classification of the image is the actual layer. We do this for a lot of areas from the image (basically, we remove the area by sliding across the entire image). If the probability score is high, then we know that the blacked-out area is not important for classification; images are classified correctly without that area. If the probability is low, that means that the blacked-out area is somehow important for exactly Image. The blue section shows the probability of a low point of the outing and the yellow area showing a high probability of the layer of the input. So the blue section describes the important parts to classify. Occlusion HeatmapPretty is impressive, isn't it? But the result is not very good, and the algorithm takes a lot of time to run (because it runs forward passing to classify too many times). So we try a different approach. Outstanding Maps The concept behind the featured map is simple. We find the extract of the input image w.r.t. the point of origin for a pair (image, layer). By definition, the extract shows us the rate at which the w.r.t. classification point is changed. That is, how much the score of the input layer will change if we change a specific photo in the input image. Here are some examples: This runs extremely quickly and the results are pretty good. But as you can see, there is still a huge room to improve. SmoothGrad We can improve outstanding maps (also known as sensitivity maps) using the SmoothGrad technique. I would like to cite the authors of this article here: The obvious noise that one sees in the sensitive map may be due to local variations that are fundamentally meaningless in the part extracts. After all, with typical training techniques, there is no reason to expect smoothly changing leads. The authors added some noise to the image and drew the outputs of the three channels (RGB) w.r.t. output layer scores:Source: (Original SmoothGrad Paper)Here, t

determine the amount of noise added to the image. After adding a little noise, the image does not seem to change at all with the naked eye, it seems that it is the same image, this is obvious. However, the extracts of the input image fluctuate greatly. So the authors suggest that we perform multiple iterations, and for each repetition, add a little random noise to the original image. We'll calculate the derivates of the input image (with additional noise) for each time, and then finally take the average of these extracts before drawing it. On average, only those pixels will have a high value of corresponding high-value leads at each time. Therefore, the meaningless local variations in the extracts will be removed. As you can see, the results are much better than simple saliency maps. These techniques are extremely useful and can be used to segment synation using the GrabCut algorithm (which I haven't done myself yet). Source: We can also visualize class models, i.e. what CNN thinks is the best representation for a particular class. This is done by an algorithm called gradient ase ase. We initially create an input image with a non-number (although initially creating it as an average imagenet training examples give slightly better results). Then we make a forward pass, and and grade point for that image. The back pass is where things get interesting. We don't update weights (as we usually do during training). The weight is kept frozen. Instead, we calculate the gradient of the input image w.r.t. point class, and update all the input points in a way that maximizes the output layer score. Side note: We want to maximize grade scores and not softmax probabilities because the probability of softmax can be increased by reducing scores for other classes too, but just want to increase the score of the target class. Various orthodox techniques can also be used here (such as L2, cutting, etc.). In the animation below, we start with a blank image, and notice how the parts resembling the actual objects begin to appear! So let's see this in action! FlamingoMosqueZebraDumbbellIt's all for this one, folks! If you have any questions, leave them in the comments. If you enjoyed this, give me a ⭐ on Github and 📝 on this post :)Join Hacker Noon Create your free account to unlock your custom reading experience. Experience.

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