Deep Learning
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Lecture-99
Create images from embeddings

The next thing that we will see is how do you Create images from Embedding. So, let me see what; that means.

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So, remember that each of these things can be thought of as an embedding of the image right because, you had this original image which was 227 cross 227 dimensional and now you have a 4096 representation for that or a 256 cross 7 cross 7 representation for that, so you could just flatten it as an out as a vector and you could treat that as a embedding for the original image right.

Now, for any kind of embedding or hidden representation, what do we always want from that representation? Think auto encoders, it should capture all the important characteristics of the original image and in particular I should be able to dash the original image from it.

Student: (Refer Time: 01:03).

We construct the original image from it right. So, that is what I would want from a good embedding. So, let us see if we can do this right, so find an image, this is the optimization problem that I am interested in. Find an image such that, it is embedding a similar to a given embedding. What do I mean by that is suppose, I take a monkey image and pass it through all these layers and compute all these embeddings right.

Now, again I start with a blank image and my optimization problem is such that, for this blank image I want to modify it, so again this blank image is my parameter matrix and I want to modify it such that, the embedding that it produces should be similar to the embeddings that the monkey image produced. So, how can you set this as a optimization problem, what would your loss function be. So, let us call the original monkey images I 1 and let us call this as embedding of I 1.
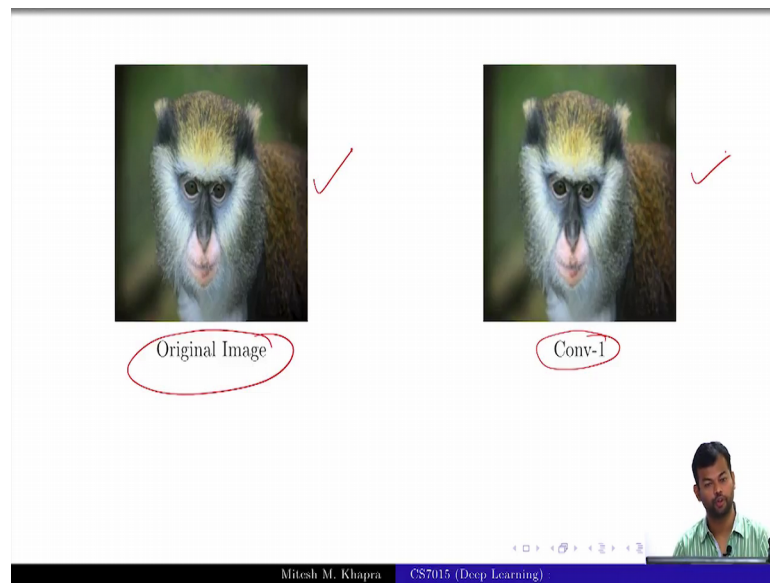
Now, can you tell me what the objective function would be, for the new image that you are trying to create, this entry the first entry in its output that let me call that e I 2 ok. So, e I 2 1 and ei 1 1; that means, the first dimension of the embedding they should both be

Student: very

Very close. So, in such cases what is the error function that we will choose?

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So, let phi 0 be the embedding of the image of interest, let X be a random image and we will report the repeat this. Forward pass using X and compute phi of x right; that means, were computing the embedding of this random image that we have started with. Then we compute this loss function and add appropriate regularization for that and that propagate and update what what will you update?

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Image right, you will update your x matrix right and you will keep doing this till convergence.
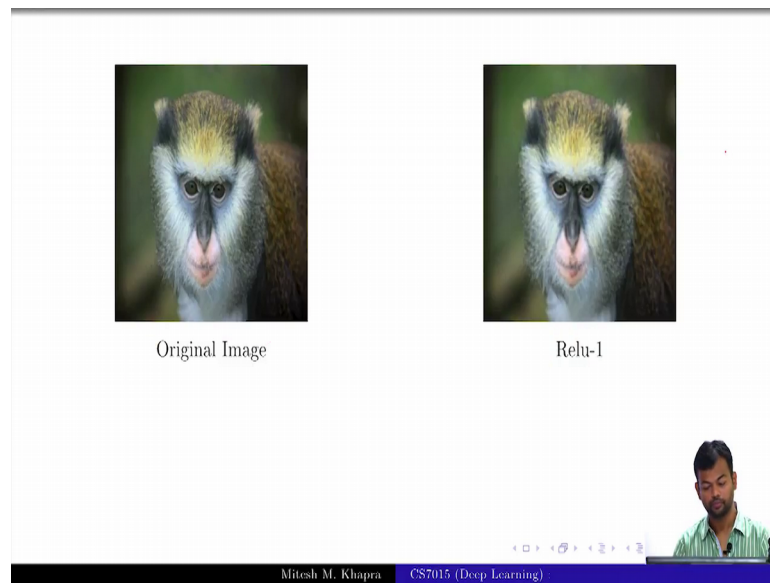
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And let us see what happens, so it is suppose so now, what I am trying to do is, this is my original image and I have the convolution one embedding of it. So, in this I am using convolution one as the embedding and then, I am trying to solve this optimization problem to recreate x such that, it is very close to the original image.

So, let us see what are the different outputs that I get. So, this is the original image and on the right hand side you have the reconstructed image such that, the Conv 1 embedding of both the images is the same. So, you can see that when I am trying to do a reconstruction from the Conv 1 layer, I get almost the same image back. Now, if I keep doing it from different layers what do you expect it to be, if i do it from Conv 2, Conv 3 Conv 4 and so on.
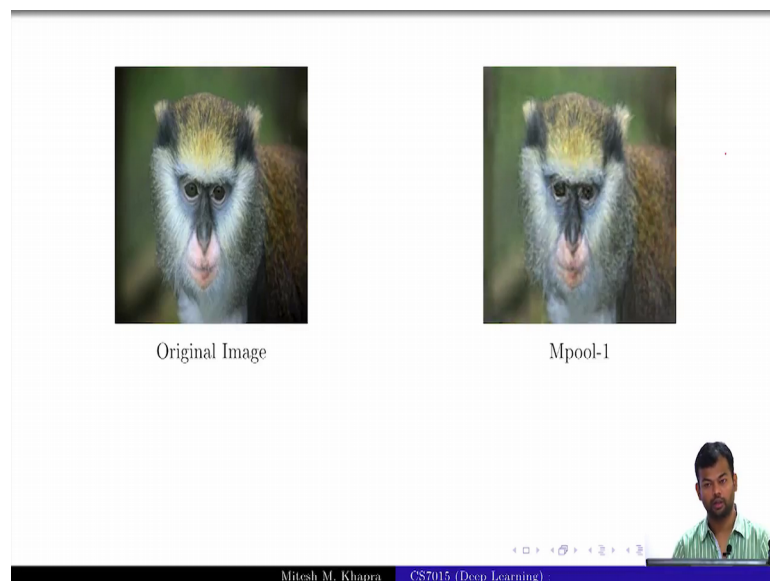
Student: (Refer Time: 03:59).

It would not be so accurate right. So, let us see what happens if, I try to reconstruct it from Conv 2
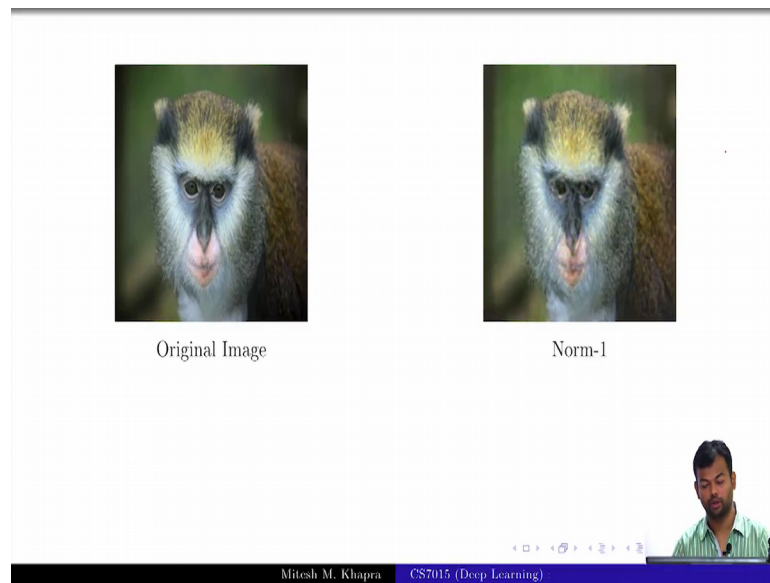
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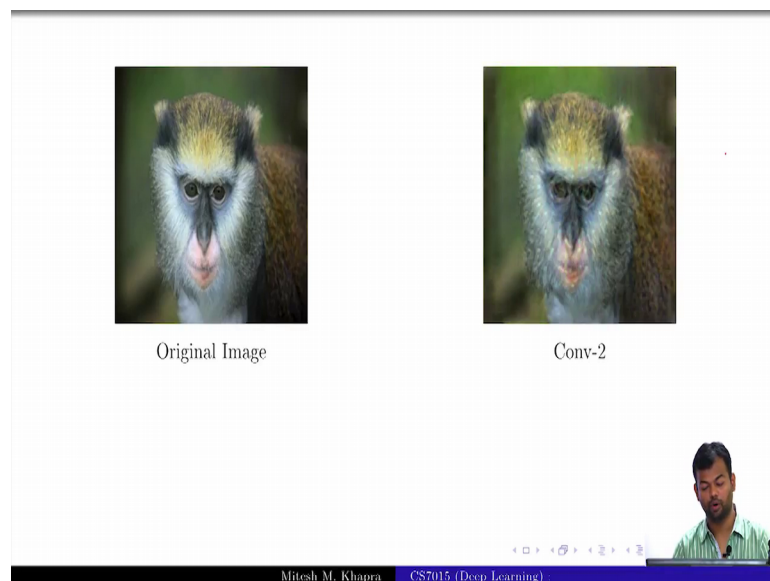

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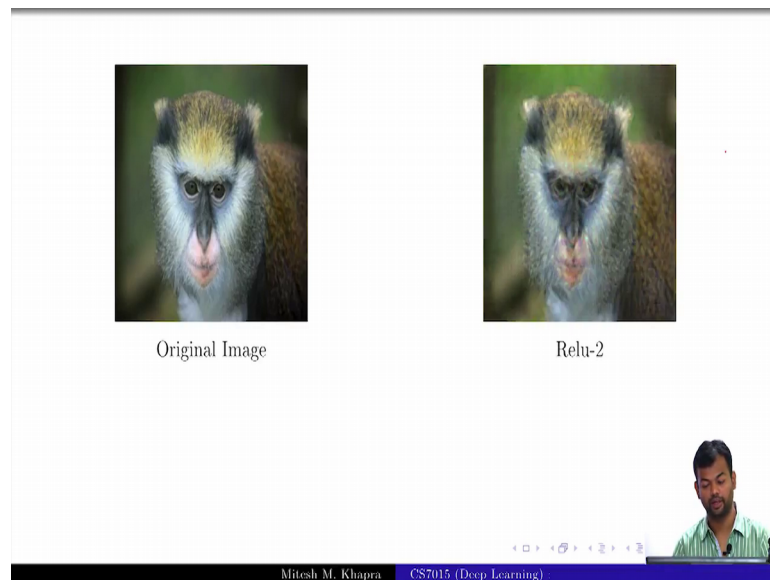

Max pooling

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Norm 1.

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Conv 2.

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Original Image   Relu-2

Relu 2, I am keep I am going deeper and deeper into the network. So, what I am trying to do here is remember that, I have different choices for these embeddings. So, the first thing which I showed you was, when I was trying to the first thing was when I was trying to set my objective function such that, I am trying to map this embedding. The second image that I showed you was, when I was trying to map this embedding and the last image that, I will show is when I was trying to map these to embedding. So, my objective function was to create an image such that this embedding of the created image is the same as this embedding of the original monkey image right. So, that is what I am progressively trying to do.
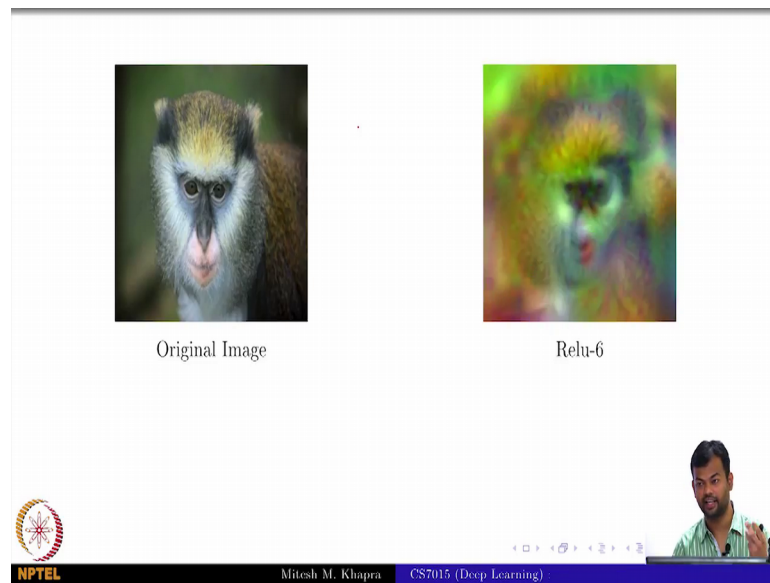
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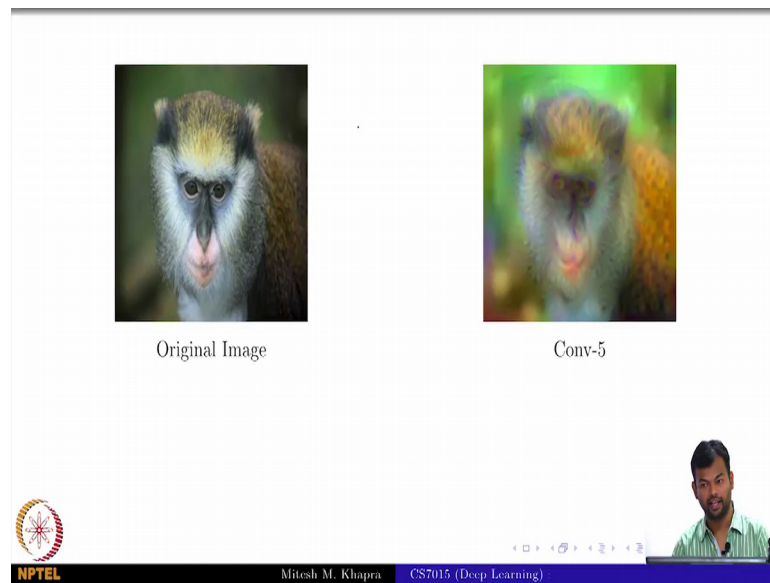
As you can see as I keep going ahead, I get more and more abstracter reconstructions and I do not really get the monkey back.

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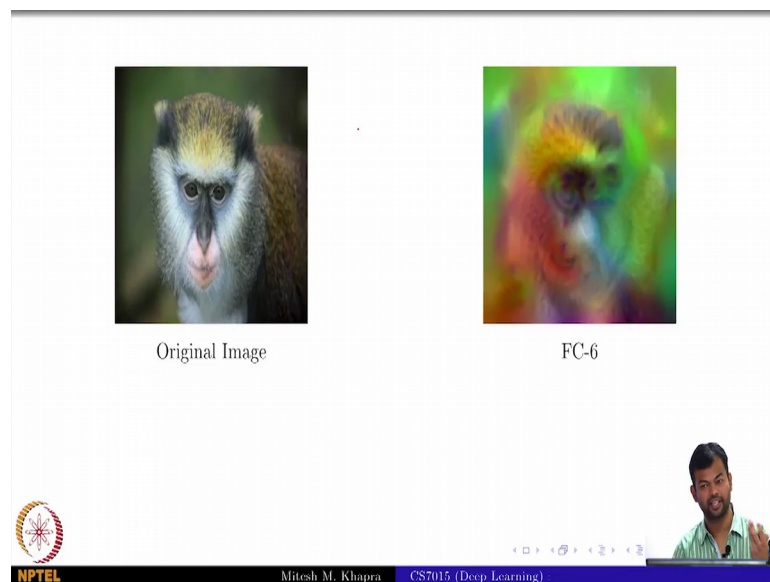
And once I go to the last FC 6 or F 7 layers, I get very weird looking reconstructions.

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Original Image   Relu-6

And that is expected right, because by that layer they have completely abstracted it out right, you have just probably captured there is something like a nose, something like eyes or some for here and there, but you have loss the entire shape and other characteristics of the original image right, from the deeper layer the construction would not be that good and that is kind of expected right.

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Original Image   Relu-7
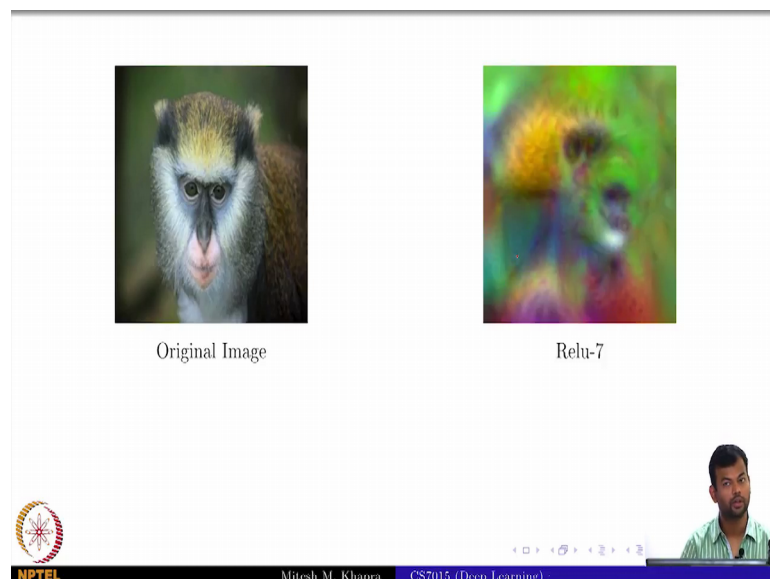
In spite of having the maximum no you could right. A maximal operation is just another embedding, which is that the compression there is much more because, you have ignored

the 4 entries and just taken the max value. So, it becomes harder and harder to do that, but mean you I would not call this as a reconstruction right, what you see here is not except for the Conv 1 and Conv 2 layers, the rest of the things were not really such accurate reconstruction. So, just says that you are losing a lot of information in that abstraction or maybe not, I will do it next time.