CS7015 (Deep Learning) : Lecture 13
Visualizing Convolutional Neural Networks, Guided Backpropagation, Deep Dream, Deep Art, Fooling Convolutional Neural Networks

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Acknowledgements

- Andrej Karpathy Video Lecture on Visualization and Deep Dream*

*Visualization, Deep Dream, Neural Style, Adversarial Examples
Module 13.1: Visualizing patches which maximally activate a neuron
Consider some neurons in a given layer of a CNN.
- Consider some neurons in a given layer of a CNN
- We can feed in images to this CNN and identify the images which cause these neurons to fire
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- We can then trace back to the patch in the image which causes these neurons to fire
- Let us look at the result of one of such experiment conducted by Grishick et al., 2014
• They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire
• One neuron fires for people faces
They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire.

Another neuron fires for dog faces.
• They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire
• Another neuron fires for flowers
• They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire
• Another neuron fires for numbers
• They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire
• Another neuron fires for houses
• They consider 6 neurons in the pool5 layer and find the image patches which cause these neurons to fire
• Another neuron fires for shiny surfaces
Module 13.2: Visualizing filters of a CNN
Recall that we had done something similar while discussing autoencoders.

\[
\max_x \{w^T x\} \\
\text{s.t. } ||x||^2 = x^T x = 1
\]

Solution: 
\[
x = \frac{w_1}{\sqrt{w_1^T w_1}}
\]
Recall that we had done something similar while discussing autoencoders.

We are interested in finding an input which maximally excites a neuron.

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\max_x \{ w^T x \} \\
\text{s.t.} \quad ||x||^2 = x^T x = 1 \\
\text{Solution:} \quad x = \frac{w_1}{\sqrt{w_1^T w_1}}
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Recall that we had done something similar while discussing autoencoders.

We are interested in finding an input which maximally excites a neuron.

Turns out that the input which will maximally activate a neuron is \( \frac{W}{\|W\|} \).

\[
\begin{align*}
\max_x \{ w^T x \} \\
\text{s.t. } \|x\|^2 = x^T x = 1 \\
\text{Solution: } x &= \frac{w_1}{\sqrt{w_1^T w_1}}
\end{align*}
\]
Now recall that we can think of a CNN also as a feed-forward network with sparse connections and weight sharing.
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Once again, we are interested in knowing what kind of inputs will cause a given neuron to fire.

\[ h_{11}, h_{12} \]

\[ \begin{array}{cccc}
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & 2 \\
\cdot & \cdot & \cdot & \cdot \\
\end{array} \]

\[ * \]

\[ \begin{array}{cccc}
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\end{array} \]

\[ = h_{14} \]
Now recall that we can think of a CNN also as a feed-forward network with sparse connections and weight sharing.

Once again, we are interested in knowing what kind of inputs will cause a given neuron to fire.

The solution would be the same ($W \parallel W \parallel$) where $W$ is the filter ($2 \times 2$, in this case).
Now recall that we can think of a CNN also as a feed-forward network with sparse connections and weight sharing.

Once again, we are interested in knowing what kind of inputs will cause a given neuron to fire.

The solution would be the same \((\frac{W}{\|W\|})\) where \(W\) is the filter \((2 \times 2\), in this case\).

We can thus think of these filters as pattern detectors.
We can simply plot the $K \times K$ weights (filters) as images & visualize them as patterns.

\[
\max_x \ \{w^T x\} \\
\text{s.t.} \quad ||x||^2 = x^T x = 1 \\
\text{Solution:} \quad x = \frac{w_1}{\sqrt{w_1^T w_1}}
\]
\[
\max_x \{ w^T x \}
\]
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s.t. \quad ||x||^2 = x^T x = 1
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Solution: \[ x = \frac{w_1}{\sqrt{w_1^T w_1}} \]

- We can simply plot the \( K \times K \) weights (filters) as images & visualize them as patterns
- The filters essentially detect these patterns (by causing the neurons to maximally fire)
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- The filters essentially detect these patterns (by causing the neurons to maximally fire).
- This is only interpretable for the filters in the first convolution layer.
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\max_x \{w^T x\}
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s.t. \quad ||x||^2 = x^T x = 1
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Solution: \[x = \frac{w_1}{\sqrt{w_1^T w_1}}\]

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This is only interpretable for the filters in the first convolution layer (Why?)
Module 13.3: Occlusion experiments
Typically we are interested in understanding which portions of the image are responsible for maximizing the probability of a certain class.
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- We could occlude (gray out) different patches in the image and see the effect on the predicted probability of the correct class.
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For example, this heat map shows that occluding the face of the dog causes a maximum drop in the prediction probability.
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We could occlude (gray out) different patches in the image and see the effect on the predicted probability of the correct class.

For example, this heat map shows that occluding the face of the dog causes a maximum drop in the prediction probability.

Similar observations are made for other images.
Module 13.4: Finding influence of input pixels using backpropagation
We can think of an image as a $m \times n$ inputs $x_0, x_1, \ldots, x_{m\times n}$.
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We are interested in finding the influence of each of these inputs ($x_i$) on a given neuron ($h_j$).
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If a small change in $x_i$ causes a large change in $h_j$ then we can say that $x_i$ has a lot of influence of $h_j$
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If a small change in $x_i$ causes a large change in $h_j$ then we can say that $x_i$ has a lot of influence of $h_j$

In other words the gradient $\frac{\partial h_j}{\partial x_i}$ could tell us about the influence
We could just compute these partial derivatives w.r.t all the inputs and then visualize this gradient matrix as an image itself.

\[
\frac{\partial h_j}{\partial x_i} = 0 \quad \rightarrow \quad \text{no influence}
\]

\[
\frac{\partial h_j}{\partial x_i} = \text{large} \quad \rightarrow \quad \text{high influence}
\]

\[
\frac{\partial h_j}{\partial x_i} = \text{small} \quad \rightarrow \quad \text{low influence}
\]
We could just compute these partial derivatives w.r.t all the inputs. And then visualize this gradient matrix as an image itself.

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- We could just compute these partial derivatives w.r.t all the inputs
- And then visualize this gradient matrix as an image itself
But how do we compute these gradients?

Recall that we can represent CNNs by feedforward neural networks. Then we already know how to compute influences (gradient) using backpropagation. For example, we know how to backprop the gradients till the first hidden layer:

$$\frac{\partial h_3}{\partial x_2} = 3 \sum_{i=1}^{\partial h_3}{\partial h_1}{\partial h_1}_{i}\frac{\partial h_1}{\partial x_2}$$

$$h_1_{i} = \sum_{j=1}^{w_{ji}} w_{ji} x_j \frac{\partial h_1}{\partial x_2}$$

$$w_{12}$$
But how do we compute these gradients?

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Then we already know how to compute influences (gradient) using backpropagation

For example, we know how to back-prop the gradients till the first hidden layer

\[
\frac{\partial h_{32}}{\partial x_2} = \sum_{i=1}^{3} \frac{\partial h_{32}}{\partial h_{1i}} \frac{\partial h_{1i}}{\partial x_2}
\]

\[
h_{1i} = \sum_{j=1}^{4} w_{ji} x_j
\]

\[
\frac{\partial h_{1i}}{\partial x_2} = w_{12}
\]
This is what we get if we compute the gradients and plot it as an image.
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- The above procedure does not show very sharp influences.

Springenberg et al. proposed "guided back propagation" which gives a better idea about the influences.
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Springenberg et al. proposed “guided back propagation” which gives a better idea about the influences.
Module 13.5: Guided Backpropagation
We feed an input to the CNN and do a forward pass.
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We consider one neuron in some feature map at some layer
- We feed an input to the CNN and do a forward pass.
- We consider one neuron in some feature map at some layer.
- We are interested in finding the influence of the input on this neuron.
We feed an input to the CNN and do a forward pass

- We consider one neuron in some feature map at some layer
- We are interested in finding the influence of the input on this neuron
- We retain this neuron and set all other neurons in the layer to zero
We now backpropagate all the way to the inputs
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Recall that during forward pass relu activation allows only positive values to pass & clamps $-ve$ values to zero.
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- Similarly during backward pass no gradient passes through the dead relu neurons.
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Similarly during backward pass no gradient passes through the dead relu neurons

In guided back propagation any $-ve$ gradients flowing from the upper layer are also set to 0
Intuition: Neglect all the negative influences (gradients) and focus only on the positive influences (gradients)
Intuition: Neglect all the negative influences (gradients) and focus only on the positive influences (gradients).

This gives a better picture of the true influence of the input.
Module 13.6: Optimization over images
Suppose we want to create an image which looks like a dumbell (or an ostrich, or a car, or just anything)
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In other words we want to create an image such that if we pass it through a trained ConvNet it should maximize the probability of the class dumbell
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In other words we want to create an image such that if we pass it through a trained ConvNet it should maximize the probability of the class dumbell

We could pose this as an optimization problem w.r.t $I(i_0, i_1, \ldots, i_{mn})$
Suppose we want to create an image which looks like a dumbell (or an ostrich, or a car, or just anything)

In other words we want to create an image such that if we pass it through a trained ConvNet it should maximize the probability of the class dumbell

We could pose this as an optimization problem w.r.t $I$ ($i_0, i_1, \ldots, i_{mn}$)

$$\arg\max_I (S_c(I) - \lambda \Omega(I))$$

$S_c(I) = \text{Score for class C before softmax}$

$\Omega(I) = \text{Some regularizer to ensure that I looks like an image}$
We can essentially think of the image as a collection of parameters.

Keep the weights of trained convolutional neural network fixed.

Now adjust these parameters (image pixels) so that the score of a class is maximized.
- We can essentially think of the image as a collection of parameters
- Keep the weights of trained convolutional neural network fixed
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- Keep the weights of trained convolutional neural network fixed.
- Now adjust these parameters (image pixels) so that the score of a class is maximized.
- Let us see how...
1. Start with a zero image
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2. Set the score vector to be $[0, 0, \ldots 1, 0, 0]$
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3. Compute the gradient $\frac{\partial S_c(I)}{\partial n_k}$
1. **Start with a zero image**
2. **Set the score vector to be** \([0, 0, \ldots 1, 0, 0]\)
3. **Compute the gradient** \(\frac{\partial S_c(I)}{\partial i_k}\)
4. **Now update the pixel** \(i_k = i_k - \eta \frac{\partial S_c(I)}{\partial i_k}\)
1. Start with a zero image
2. Set the score vector to be $[0, 0, \ldots 1, 0, 0]$
3. Compute the gradient $\frac{\partial S_c(I)}{\partial i_k}$
4. Now update the pixel $i_k = i_k - \eta \frac{\partial S_c(I)}{\partial i_k}$
5. Now again do a forward pass through the network
1. Start with a zero image
2. Set the score vector to be \([0, 0, \ldots 1, 0, 0]\)
3. Compute the gradient \(\frac{\partial S_c(I)}{\partial i_k}\)
4. Now update the pixel \(i_k = i_k - \eta \frac{\partial S_c(I)}{\partial i_k}\)
5. Now again do a forward pass through the network
6. Go to step 2
- Let's look at the images obtained for maximizing some class scores
• Lets look at the images obtained for maximizing some class scores
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• Lets look at the images obtained for maximizing some class scores
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Repeat:
- Feed an image through the network

We can actually do this for any arbitrary neuron in the convnet.
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Repeat:

- Feed an image through the network
- Set activation in layer of interest to all zero, except for a neuron of interest
We can actually do this for any arbitrary neuron in the convnet

Repeat:
- Feed an image through the network
- Set activation in layer of interest to all zero, except for a neuron of interest
- Backprop to image
Repeat:

- Feed an image through the network
- Set activation in layer of interest to all zero, except for a neuron of interest
- Backprop to image

\[ i_k = i_k - \eta \frac{\partial A(I)}{\partial i_k}, \]

\( A(I) \) is the activation of the \( i^{th} \) neuron in some layer.

We can actually do this for any arbitrary neuron in the convnet.
Let us look at some “updated” images which excite certain neurons in some layer.

Layer-8
Let us look at some “updated” images which excite certain neurons in some layer.

Starting with different initializations instead of using a zero image we can get different insights.

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Each of these 4 images are obtained by focusing on one neuron in layer 8 and starting with different initializations.
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We can do a similar analysis with other layers.
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Each of these 4 images are obtained by focusing on one neuron in layer 8 and starting with different initializations.

We can do a similar analysis with other layers.
Module 13.7: Creating images from embeddings
We could think of the fc7 layer as some kind of an embedding for the image.
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**Question:** Given this embedding can we reconstruct the image?
• We could think of the fc7 layer as some kind of an embedding for the image

• **Question:** Given this embedding can we reconstruct the image?

• We can pose this as an optimization problem
Find an image such that
- Find an image such that
- Its embedding is similar to a given embedding
- Find an image such that
- Its embedding is similar to a given embedding
- It looks natural (some prior regularization)
\[ \phi_0 \text{: Embedding of an image of interest} \]
- $\phi_0$: Embedding of an image of interest
- $X$: Random image (say zero image)
• $\phi_0$ : Embedding of an image of interest
• $X$ : Random image (say zero image)
• Repeat
\( \phi_0 \) : Embedding of an image of interest

\( X \) : Random image (say zero image)

Repeat

- Forward pass using \( X \) and compute \( \phi(x) \).
\( \phi_0 \): Embedding of an image of interest

\( X \): Random image (say zero image)

Repeat

- Forward pass using \( X \) and compute \( \phi(x) \).
- Compute

\[
\mathcal{L}(i) = ||\phi(x) - \phi_0||^2 + \lambda ||\phi(x)||_6^6
\]
• \( \phi_0 \): Embedding of an image of interest
• \( X \): Random image (say zero image)
• Repeat
  • Forward pass using \( X \) and compute \( \phi(x) \).
  • Compute
  \[
  \mathcal{L}(i) = ||\phi(x) - \phi_0||^2 + \lambda ||\phi(x)||^6
  \]
  • \( i_k = i_k - \eta \frac{\mathcal{L}(i)}{\partial i_k} \)
Original Image

Conv-1
Original Image

Relu-1
Original Image

Conv-2
Original Image

Conv-3
Original Image

Conv-4
Original Image

Relu-4
Original Image

Conv-5
Original Image

Relu-5
Original Image

FC-6
Original Image

Relu-6
Original Image

FC-7
Original Image

Relu-7
Module 13.8: Deep Dream
Suppose instead of starting with a blank (zero) image we start with an actual image.
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- Suppose instead of starting with a blank (zero) image we start with an actual image.
- We focus on some layer and check the activations of the neurons.
- Suppose instead of starting with a blank (zero) image we start with an actual image.
- We focus on some layer and check the activations of the neurons.
- We want to change the image so that these neurons fire even more.
How would we achieve this?

Suppose we want to boost the activation $h_{ij}$ (some neuron in some layer). We can formulate this as the following optimization problem:

$$\max \mathcal{L}(I)$$

Consider a pixel $i_{mn}$ in the image:

$$\frac{\partial \mathcal{L}(I)}{\partial i_{mn}} = \frac{\partial \mathcal{L}(I)}{\partial h_{ij}} \frac{\partial h_{ij}}{\partial i_{mn}}$$
How would we achieve this?

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Suppose we want to boost the activation $h_{ij}$ (some neuron in some layer)

We can formulate this as the following optimization problem:

$$\max_I \mathcal{L}(I)$$

$$\mathcal{L}(I) = h_{ij}^2$$
How would we achieve this?

Suppose we want to boost the activation $h_{ij}$ (some neuron in some layer)

We can formulate this as the following optimization problem

$$\max_I \mathcal{L}(I)$$

$$\mathcal{L}(I) = h_{ij}^2$$

Consider a pixel $i_{mn}$ in the image

$$\frac{\partial \mathcal{L}(I)}{\partial i_{mn}} = \frac{\partial \mathcal{L}(I)}{\partial h_{ij}} \frac{\partial h_{ij}}{\partial i_{mn}}$$
• Once the image is updated \(i_{mn} = i_{mn} + \frac{\partial L(I)}{\partial i_{mn}}\) we feed it back to the network.
Once the image is updated \( (i_{mn} = i_{mn} + \frac{\partial L(I)}{\partial i_{mn}}) \) we feed it back to the network.

This time the target neurons should fire even more (because we have precisely modified the image to achieve this).
Once the image is updated \( (i_{mn} = i_{mn} + \frac{\partial L(I)}{\partial i_{mn}}) \) we feed it back to the network.

This time the target neurons should fire even more (because we have precisely modified the image to achieve this).

Doing this iteratively would make the image more and more like the patterns that cause the neuron to fire.
Once the image is updated \( i_{mn} = i_{mn} + \frac{\partial L(I)}{\partial i_{mn}} \) we feed it back to the network.

This time the target neurons should fire even more (because we have precisely modified the image to achieve this).

Doing this iteratively would make the image more and more like the patterns that cause the neuron to fire.

Let us run this algorithm.
So what exactly is happening here?

* research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html
So what exactly is happening here?
The network has been trained to detect certain patterns (dogs, cat, birds etc.) which appear frequently in the ImageNet data.
- So what exactly is happening here?
- The network has been trained to detect certain patterns (dogs, cat, birds etc.) which appear frequently in the ImageNet data.
- It starts seeing these patterns even when they hardly exist.

*research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html
So what exactly is happening here?

The network has been trained to detect certain patterns (dogs, cat, birds etc.) which appear frequently in the ImageNet data.

It starts seeing these patterns even when they hardly exist.

If a cloud looks a little bit like a bird, the network will make it look more like a bird. This in turn will make the network recognize the bird even more strongly on the next pass and so forth, until a highly detailed bird appears seemingly out of nowhere. - Google*

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*research.googleblog.com/2015/06/inceptionism-going-deeper-into-neural.html
Module 13.9: Deep Art
To design a network which can do this, we first define two quantities

- **Content Targets**: The activations of all layers for the given content image

Ideally, we would want the new image to be such that its activations are also close to those of the original content image. Let \( \vec{p}, \vec{x} \) be the activations of the content image and the new image (to be generated) respectively.

\[
L_{content}(\vec{p}, \vec{x}) = \sum_{ijk} (\vec{p}_{ijk} - \vec{x}_{ijk})^2
\]
To design a network which can do this, we first define two quantities

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Ideally, we would want the new image to be such that

\[
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Ideally, we would want the new image to be such that its activations are also close to those of the original content image

Let \( \vec{p}, \vec{x} \) be the activations of the content image and the new image (to be generated) respectively

\[
\mathcal{L}_{\text{content}}(\vec{p}, \vec{x}) = \sum_{ijk}(\vec{p}_{ijk} - \vec{x}_{ijk})^2
\]
Next we would want the style of the generated image to be the same as the style image.
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How do we capture the style of the image?
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Turns out that if $V \in \mathbb{R}^{64 \times (256 \times 256)}$ is the activation at a layer then $V^T V \in \mathbb{R}^{64 \times 64}$ captures the style of the image.
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The deeper layers capture more of this style information.
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The deeper layers capture more of this style information.
To ensure that the style of the new image captured by layer $\ell$ matches the style of the style image, we can use the following objective function:

$$E^\ell = \sum_{ij} (G^\ell_{ij} - A^\ell_{ij})^2$$

where $G^\ell$ and $A^\ell$ are the style gram matrices computed at layer $\ell$ for the style image and new image respectively.
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\[
L_{style}(\vec{a}, \vec{x}) = \sum_{\ell=0}^{L} w_\ell E_\ell
\]
The total loss is given by:

\[ L_{\text{total}}(\vec{p}, \vec{a}, \vec{x}) = \alpha L_{\text{content}}(\vec{p}, \vec{x}) + \beta L_{\text{style}}(\vec{a}, \vec{x}) \]
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Module 13.10: Fooling Deep Convolution Neural Networks
Turns out that using this idea of optimizing over the input, we can also “fool” ConvNets.
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• Let us see how
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Turns out that with minimal changes to the image (using backprop) we can soon convince the Convnet that this is an ostrich.
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Turns out that with minimal changes to the image (using backprop) we can soon convince the Convnet that this is an ostrich.

Let us see some examples
Notice that the changes are so minimal that the two images are indistinguishable to humans.
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But the ConvNet thinks that the third image obtained by adding the first image to the second image is an ostrich.

*Intriguing properties of neural networks, Szegedy et al., 2013*
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Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images
Nguyen, Yosinski, Clune, 2014

- We can also do this starting with random images and then optimizing them to predict some class.
Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images Nguyen, Yosinski, Clune, 2014

- We can also do this starting with random images and then optimizing them to predict some class.
- In all these cases the classifier is 99.6% confident of the class.

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Let us see an intuitive explanation of why this happens.

*Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images Nguyen, Yosinski, Clune, 2014*
Images are extremely high dimensional objects ($\mathcal{R}^{227 \times 227}$)
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- There are many many many points in this high dimensional space
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While doing so we also end up taking decisions about the many many unseen points in this high dimensional space (Notice the large green and red regions which do not contain any training points)
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