

# **Generative Adversarial Networks (GANs), Nnet Visualization**

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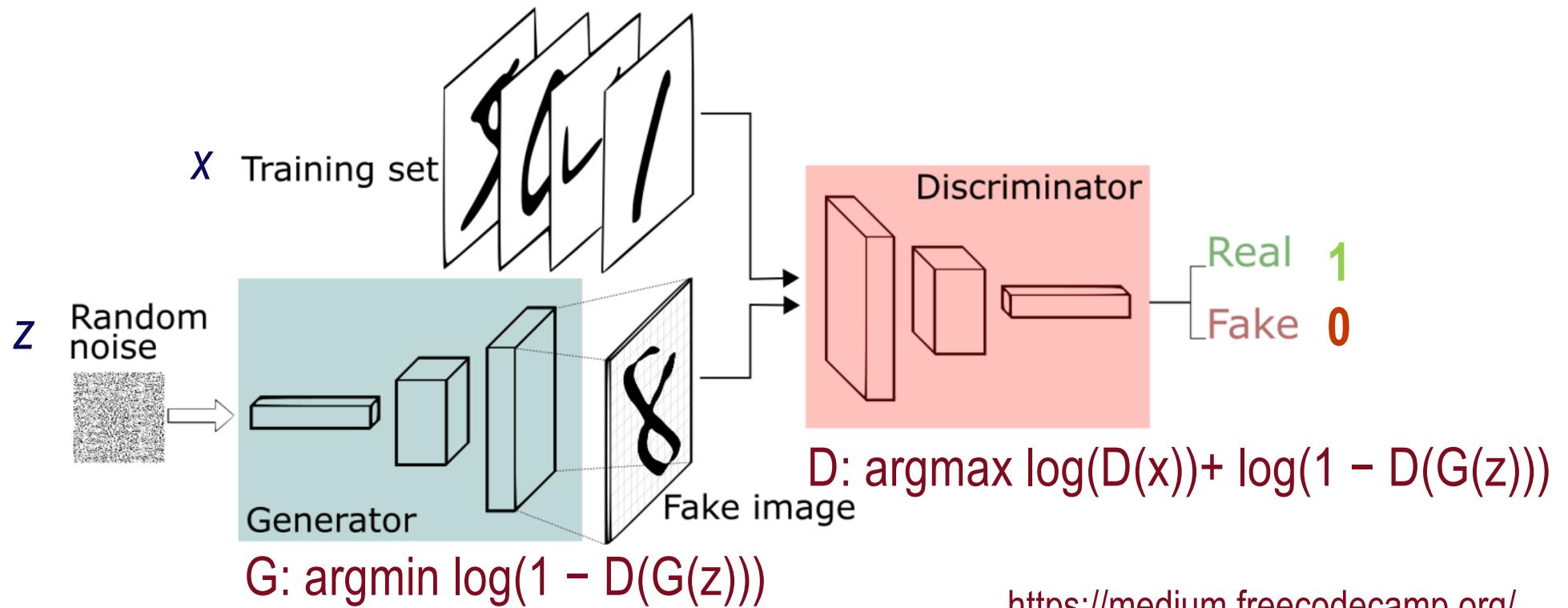
GANS  
Conditional GANS  
Visualization for NNets

# These are ...



<https://sites.google.com/view/cvpr2018tutorialongans/>

# Generative Adversarial Networks: GANs



[https://medium.freecodecamp.org/  
an-intuitive-introduction-to-  
gan-1a2f3a2e3](https://medium.freecodecamp.org/an-intuitive-introduction-to-generative-adversarial-networks-101-1a2f3a2e3)

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

# GANs

- ◆ Make generative model,  $G$ , close to data PDF

$$\theta^* = \arg \min_{\theta} D_{\text{KL}}(p_{\text{data}}(\mathbf{x}) \| p_{\text{model}}(\mathbf{x}; \theta)) = E(\sum p_{\text{data}} \log(p_{\text{model}}/p_{\text{data}}))$$

- ◆ For actual data this is the MLE:

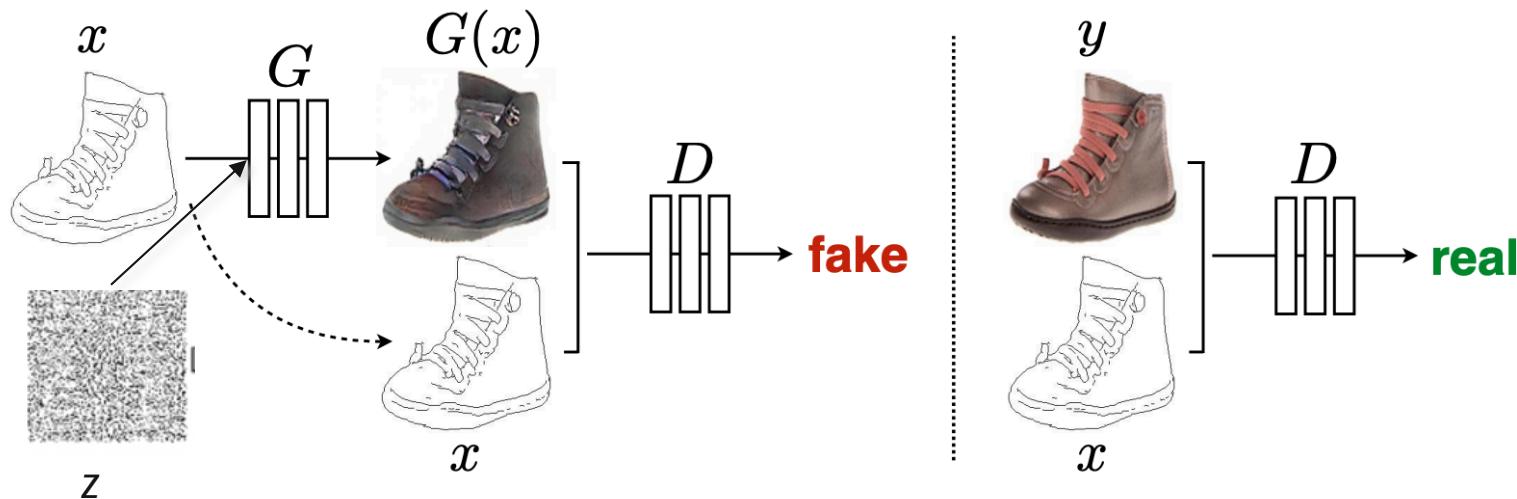
$$\begin{aligned}\theta^* &= \arg \max_{\theta} \prod_{i=1}^m p_{\text{model}}(\mathbf{x}^{(i)}; \theta) \\ &= \arg \max_{\theta} \log \prod_{i=1}^m p_{\text{model}}(\mathbf{x}^{(i)}; \theta) \\ &= \arg \max_{\theta} \sum_{i=1}^m \log p_{\text{model}}(\mathbf{x}^{(i)}; \theta) . \quad E(\sum p_{\text{data}} \log(p_{\text{model}}/p_{\text{data}}))\end{aligned}$$

# GANs Training

## ◆ Training can be slow and unstable

- Better convergence if you alternately train discriminator and generator

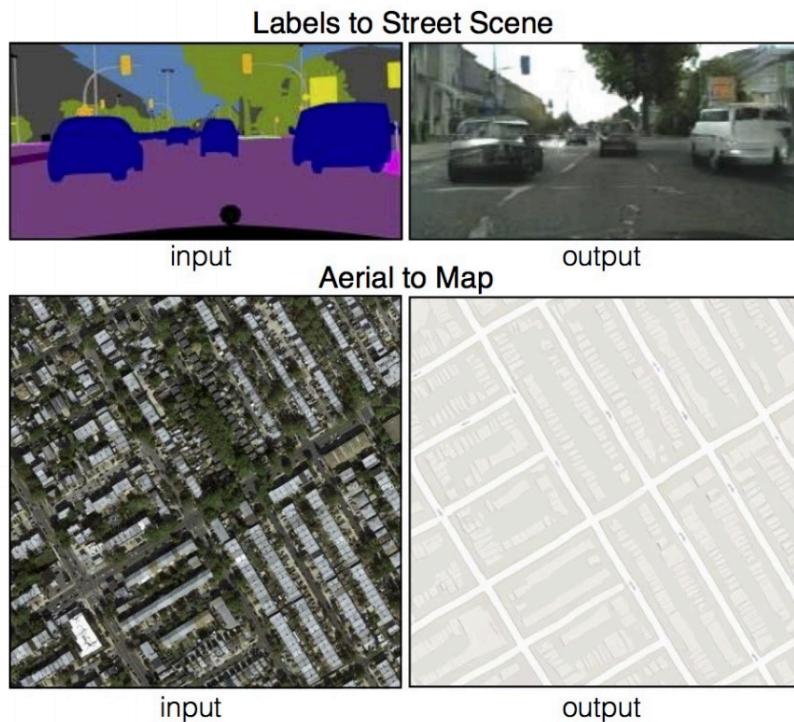
# Conditional GANs for Image Translation (outline to photo)



$$\min_G \max_D V(D, G) = \mathbb{E}_{x,y}[\log D(x, y)] + \\ \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z)))]$$

<https://arxiv.org/pdf/1611.07004.pdf>

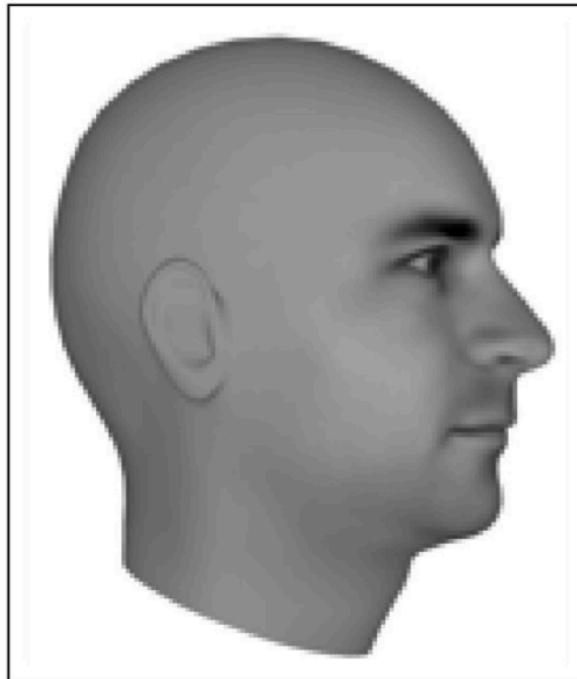
# GANs: Image translation



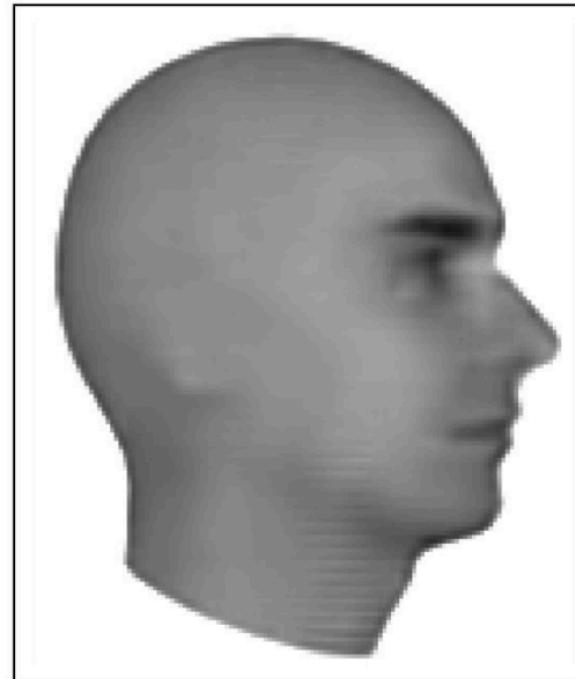
<https://arxiv.org/pdf/1701.00160.pdf>  
Isola et al. (2016)

# GANs: Predict next video frame

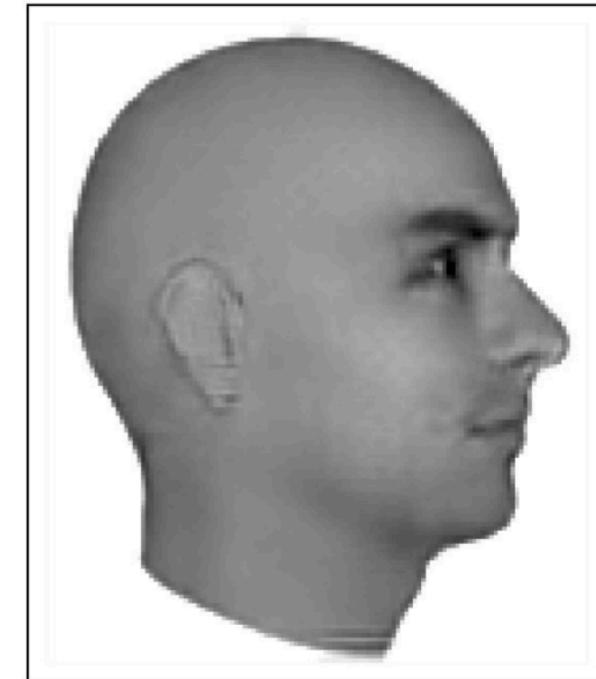
Ground Truth



MSE



Adversarial



<https://arxiv.org/pdf/1701.00160.pdf>  
Lotter et al. 2015

# GANs: Image translation

- ◆ Summer to winter
- ◆ Sketch to photo
- ◆ Low resolution to high resolution photo
- ◆ Young to old
- ◆ Photo to impressionist painting



[https://www.youtube.com/watch?time\\_continue=3704&v=AJJRWfVfNPg](https://www.youtube.com/watch?time_continue=3704&v=AJJRWfVfNPg)



# Questions?

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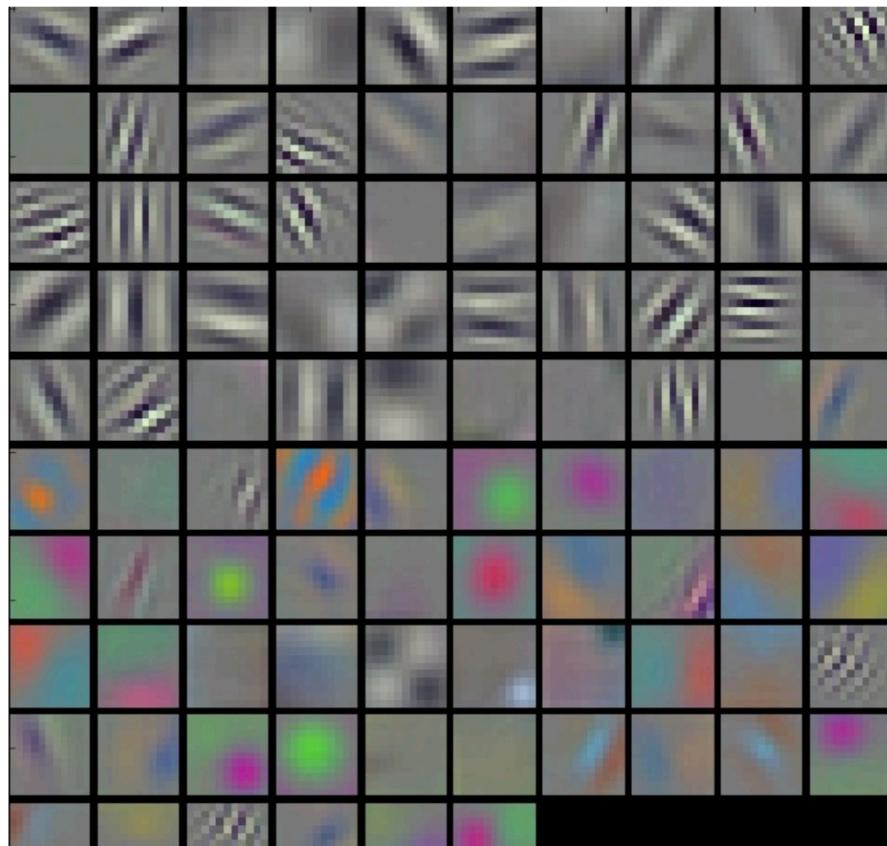
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# Visualizing networks

- ◆ **Display pattern of hidden unit activations**
  - Just shows they are sparse
- ◆ **Show input that maximizes a node's output**
  - Over all inputs in the training set
  - Over the entire range of possible inputs
  - Early layers do feature detection
  - Later layers do object detection
- ◆ **Show how occluding parts of an image affect classification accuracy**

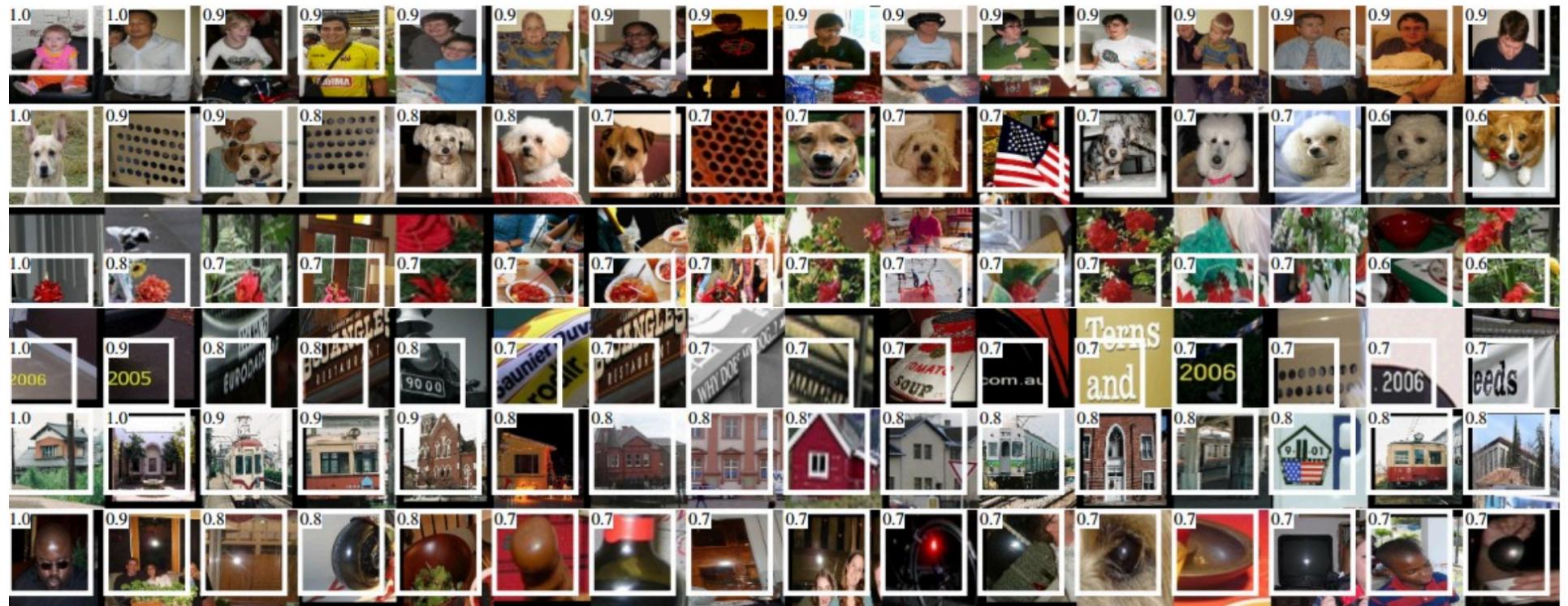
<http://cs231n.github.io/understanding-cnn/>

# Maximally activating inputs for the first CONV layer of an AlexNet

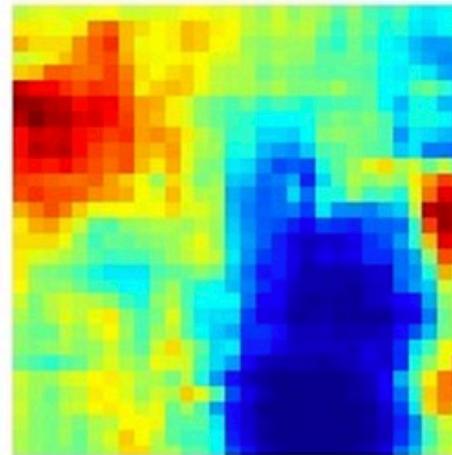
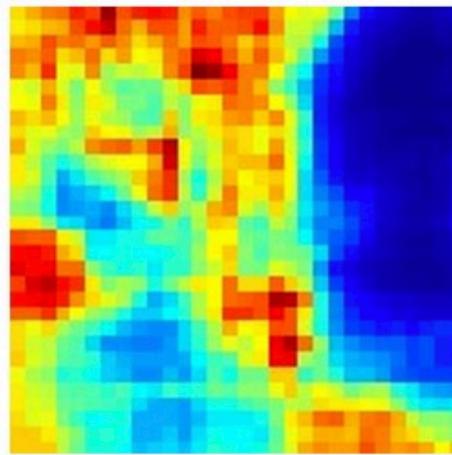
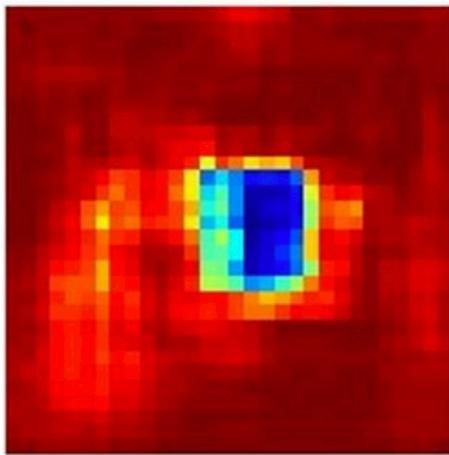
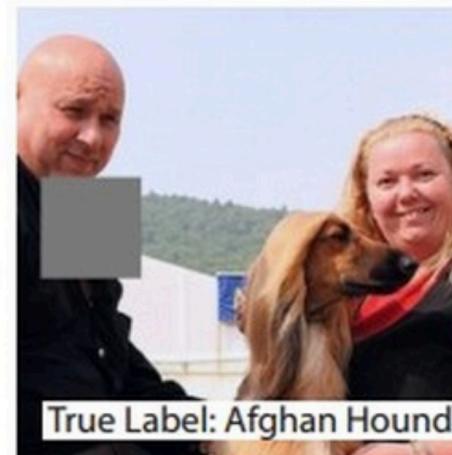


<http://cs231n.github.io/understanding-cnn/>

# Maximally activating images for some 5th maxpool layer neurons of an AlexNet.



# P(correct label) after occlusion



Matthew Zeiler's  
Visualizing and  
Understanding  
Convolutional  
Networks:

# You should know

## ◆ GANS and conditional GANS

- What goes in, what comes out, loss function
- Generative, not discriminative

## ◆ Visualization of Nnets

- Which input (over real images or over all possible inputs) maximizes the output of ('excites') a neuron.
- Sensitivity of prediction to occlusion



# Questions?

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