# Lecture 8: Visualizing and Understanding

# Administrative

- Assignment 2 due tonight
- Assignment 1 grades will be released this week
- Assignment 3 will be released this week
- Quiz 2 this friday

# Choosing Hyperparameters

# Choosing Hyperparameters: Grid Search

Choose several values for each hyperparameter
(Often space choices log-linearly)

**Example**:
Weight decay: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]
Learning rate: [$1x10^{-4}$, $1x10^{-3}$, $1x10^{-2}$, $1x10^{-1}$]

Evaluate all possible choices on this hyperparameter grid

# Choosing Hyperparameters: Random search

Choose several values for each hyperparameter
(Often space choices log-linearly)

**Example:**
Weight decay: **log-uniform** on [$1x10^{-4}$, $1x10^{-1}$]
Learning rate: **log-uniform** on [$1x10^{-4}$, $1x10^{-1}$]

Run many different trials

# Random Search vs. Grid Search

*Random Search for Hyper-Parameter Optimization*
Bergstra and Bengio, 2012

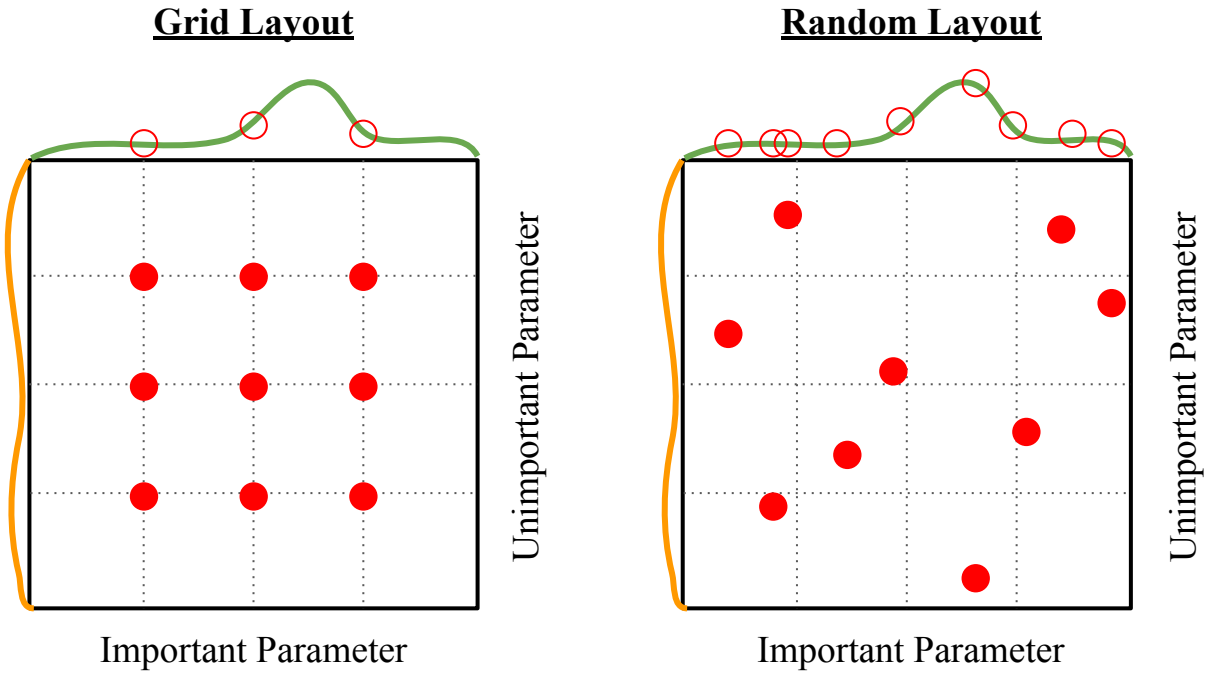



Illustration of Bergstra et al., 2012 by Shayne Longpre, copyright CS231n 2017

# Choosing Hyperparameters

(without tons of GPUs)

# Choosing Hyperparameters

**Step 1**: Check initial loss

Turn off weight decay, sanity check loss at initialization
e.g. log(C) for softmax with C classes

# Choosing Hyperparameters

**Step 1**: Check initial loss
**Step 2**: Overfit a small sample

Try to train to 100% training accuracy on a small sample of training data (~5-10 minibatches); fiddle with architecture, learning rate, weight initialization

Loss not going down? LR too low, bad initialization
Loss explodes to Inf or NaN? LR too high, bad initialization

# Choosing Hyperparameters

**Step 1**: Check initial loss
**Step 2**: Overfit a small sample
**Step 3**: Find LR that makes loss go down

Use the architecture from the previous step, use all training data, turn on small weight decay, find a learning rate that makes the loss drop significantly within ~100 iterations

Good learning rates to try: 1e-1, 1e-2, 1e-3, 1e-4

# Choosing Hyperparameters

**Step 1**: Check initial loss
**Step 2**: Overfit a small sample
**Step 3**: Find LR that makes loss go down
**Step 4**: Coarse grid, train for ~1-5 epochs

Choose a few values of learning rate and weight decay around what worked from Step 3, train a few models for ~1-5 epochs.

Good weight decay to try: 1e-4, 1e-5, 0

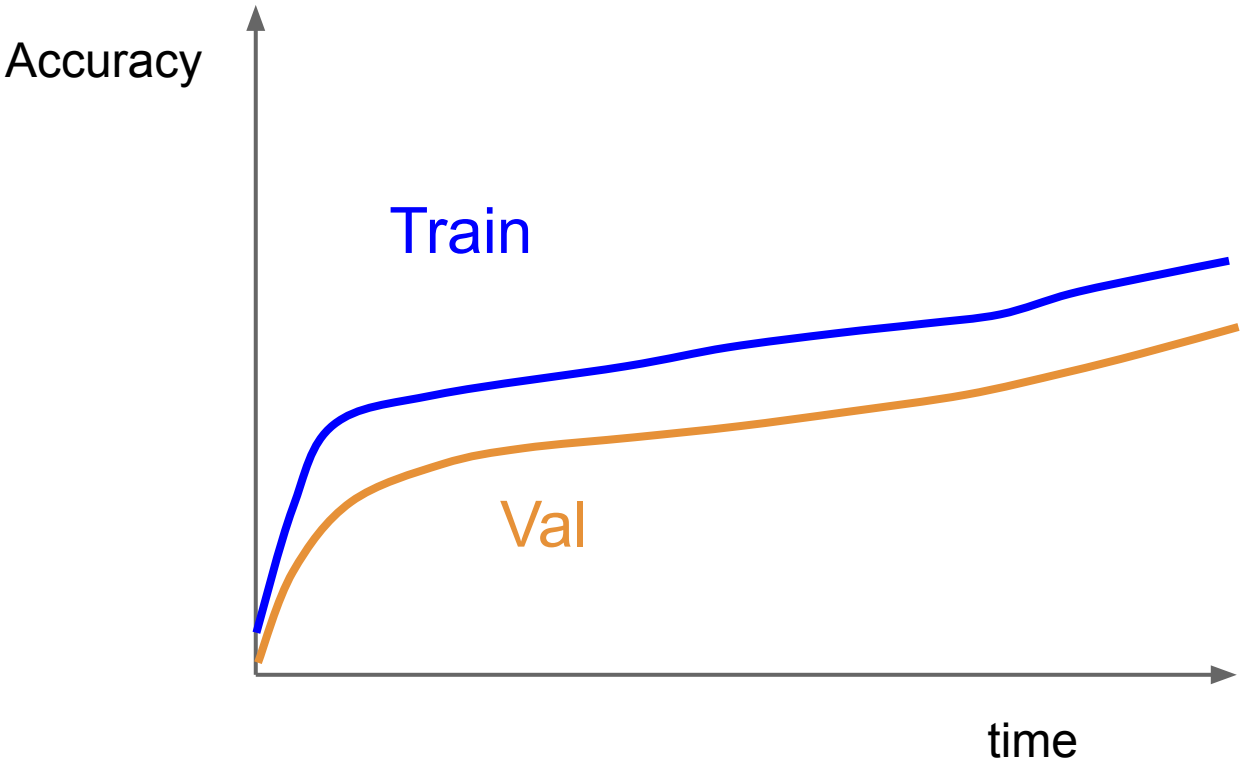
# Choosing Hyperparameters

**Step 1**: Check initial loss
**Step 2**: Overfit a small sample
**Step 3**: Find LR that makes loss go down
**Step 4**: Coarse grid, train for ~1-5 epochs
**Step 5**: Refine grid, train longer

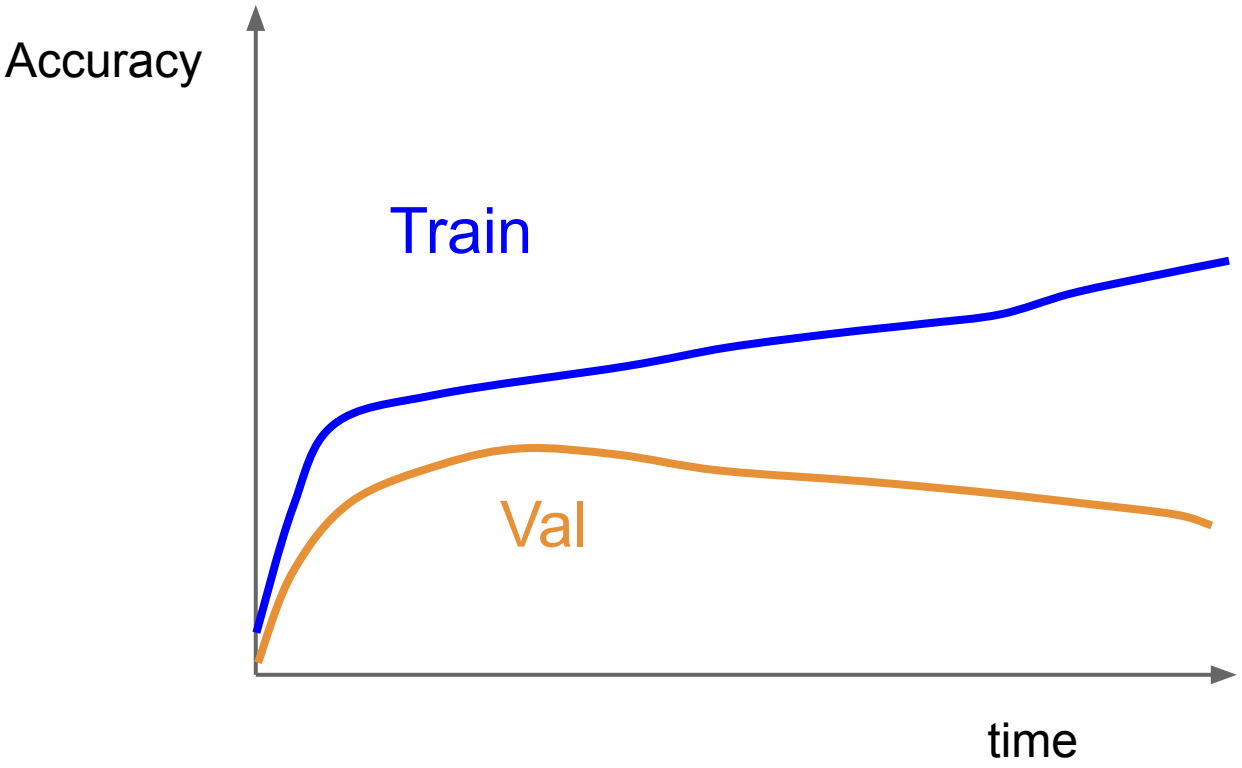
Pick best models from Step 4, train them for longer (~10-20 epochs) without learning rate decay

# Choosing Hyperparameters

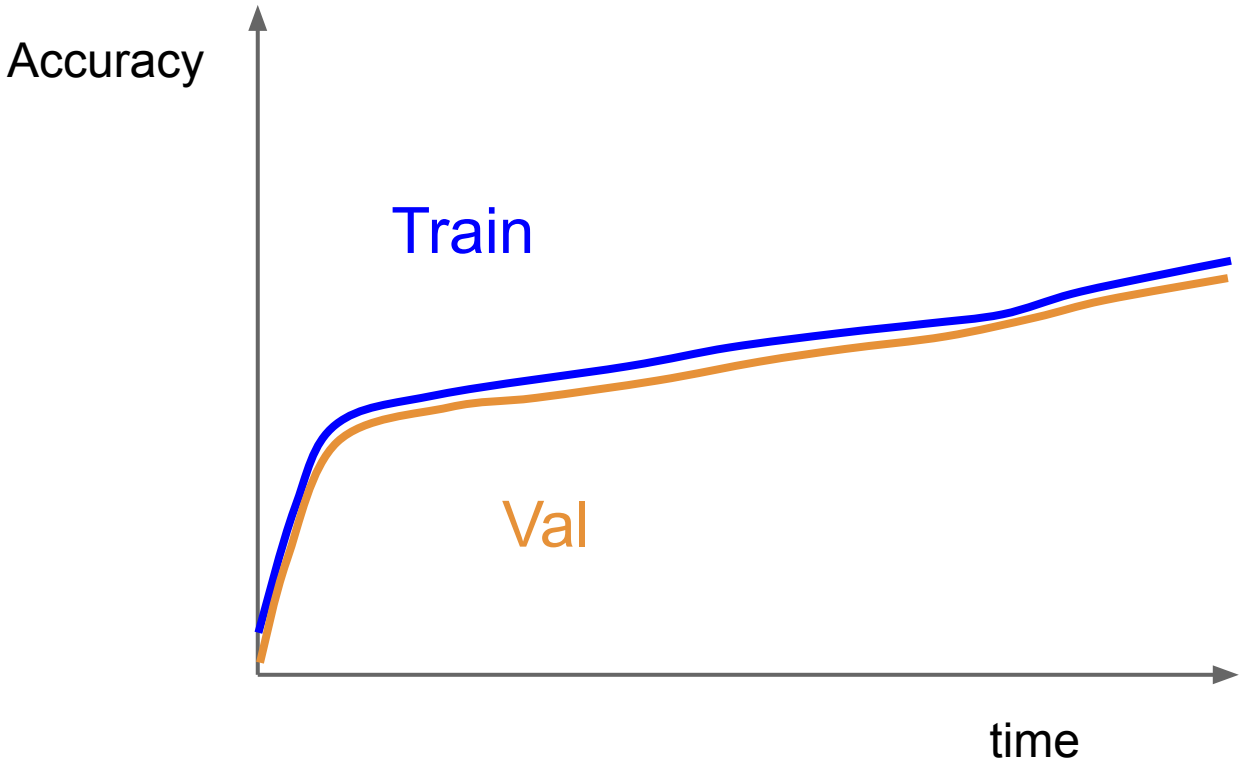
**Step 1**: Check initial loss
**Step 2**: Overfit a small sample
**Step 3**: Find LR that makes loss go down
**Step 4**: Coarse grid, train for ~1-5 epochs
**Step 5**: Refine grid, train longer
**Step 6**: Look at loss and accuracy curves




Q1. You see this. What should you do?



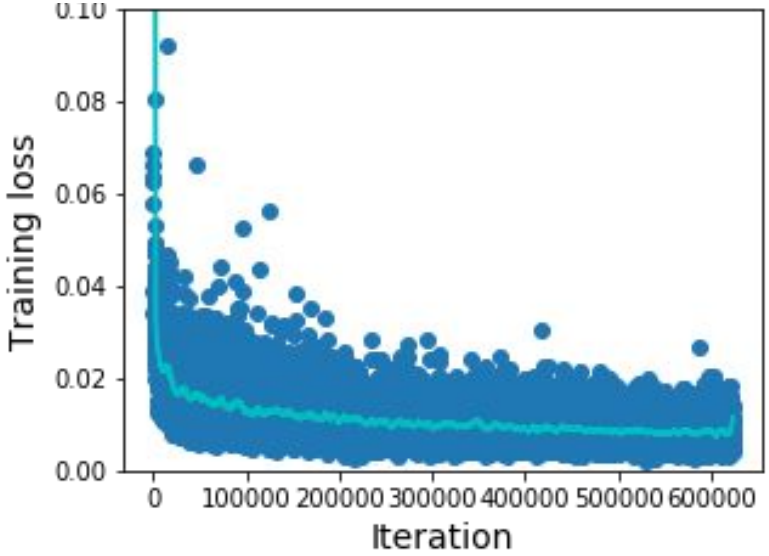

Q2. You see this. What should you do?



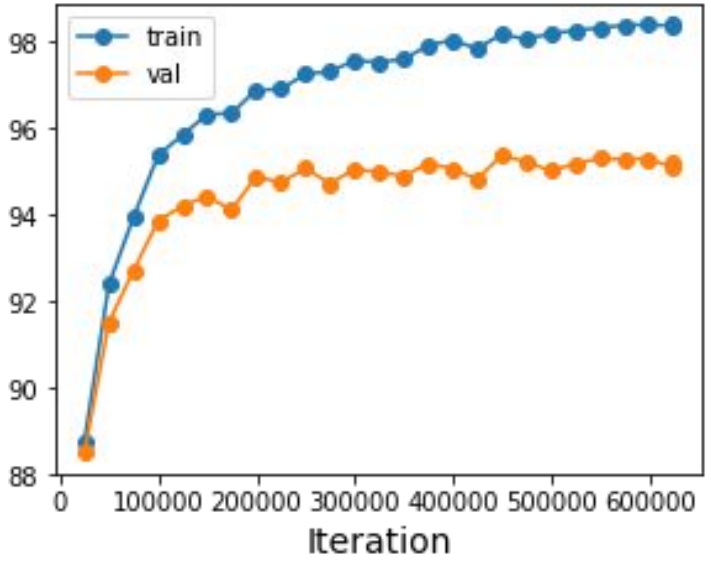

Q3. You see this. What should you do?

# Look at learning curves!

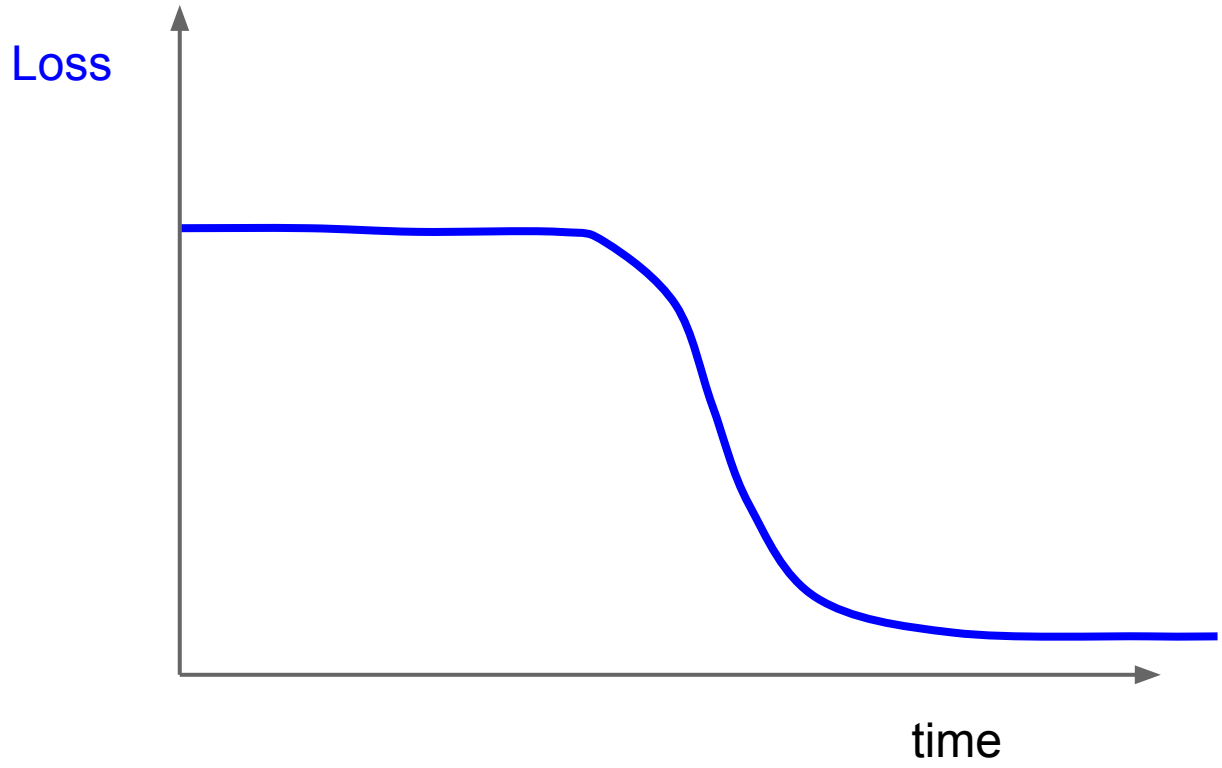
Training Loss



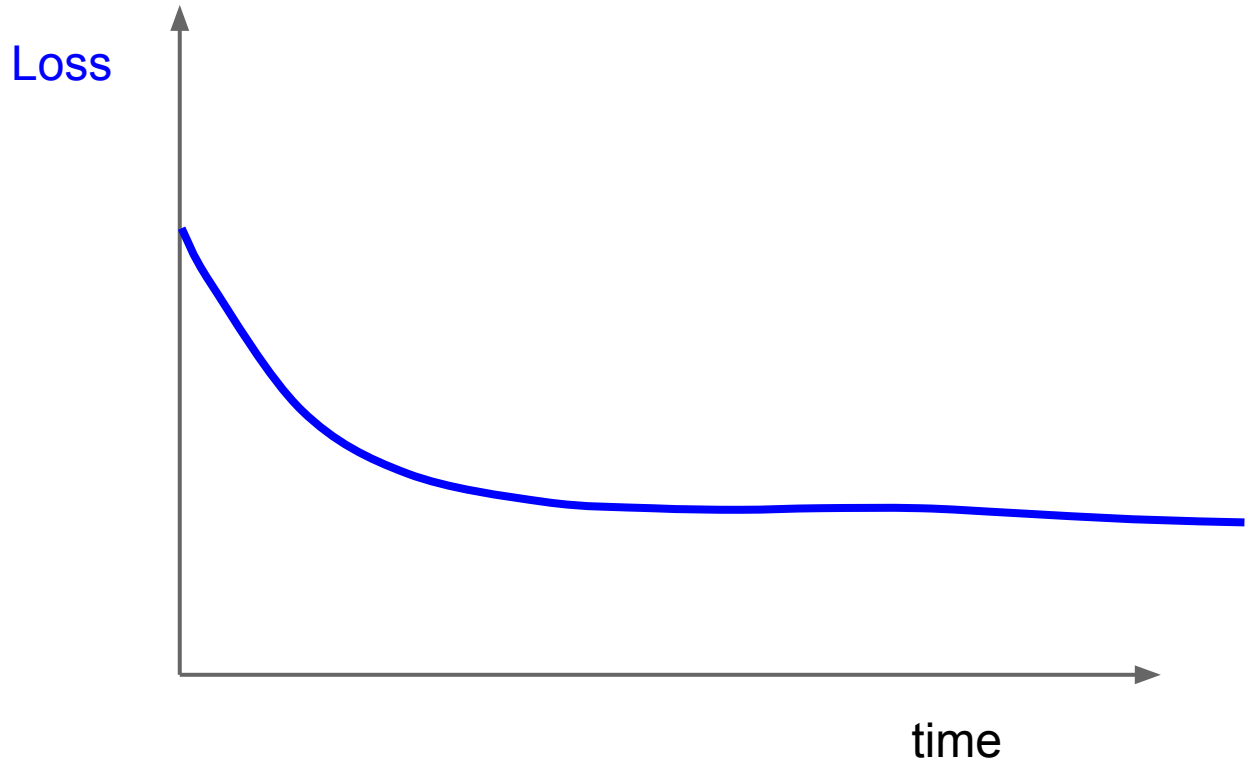

Train / Val Accuracy



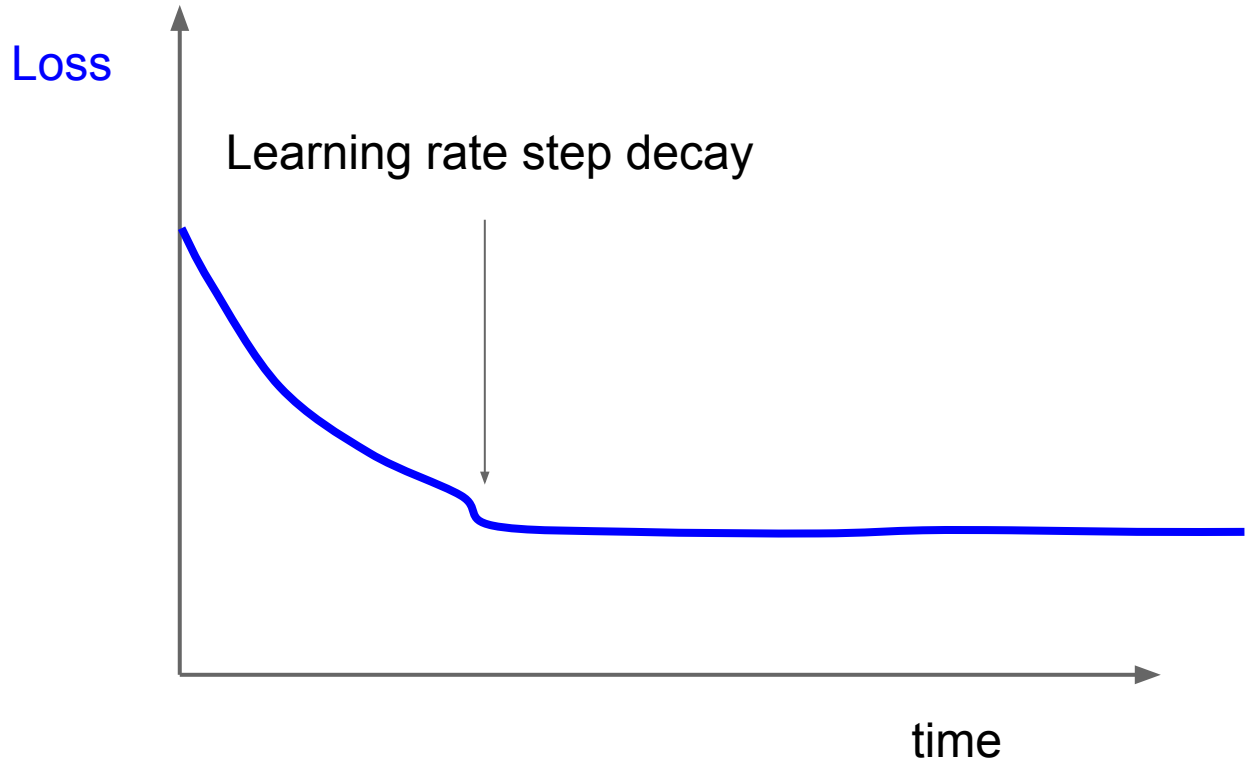

Losses may be noisy, use a scatter plot and also plot moving average to see trends better




Q4. You see this. What should you do?




Q5. You see this. What should you do?

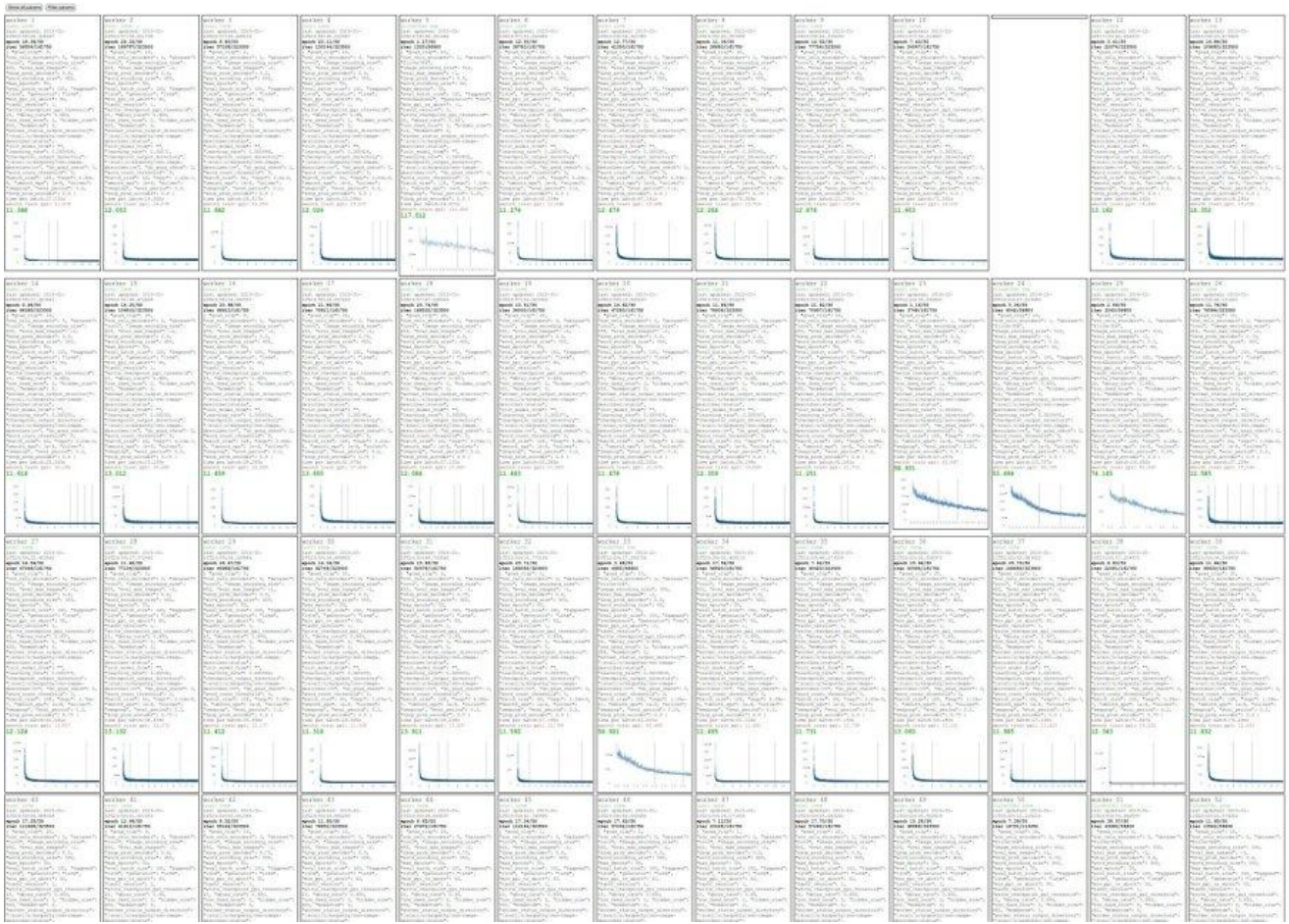



Q5. You see this. What should you do?

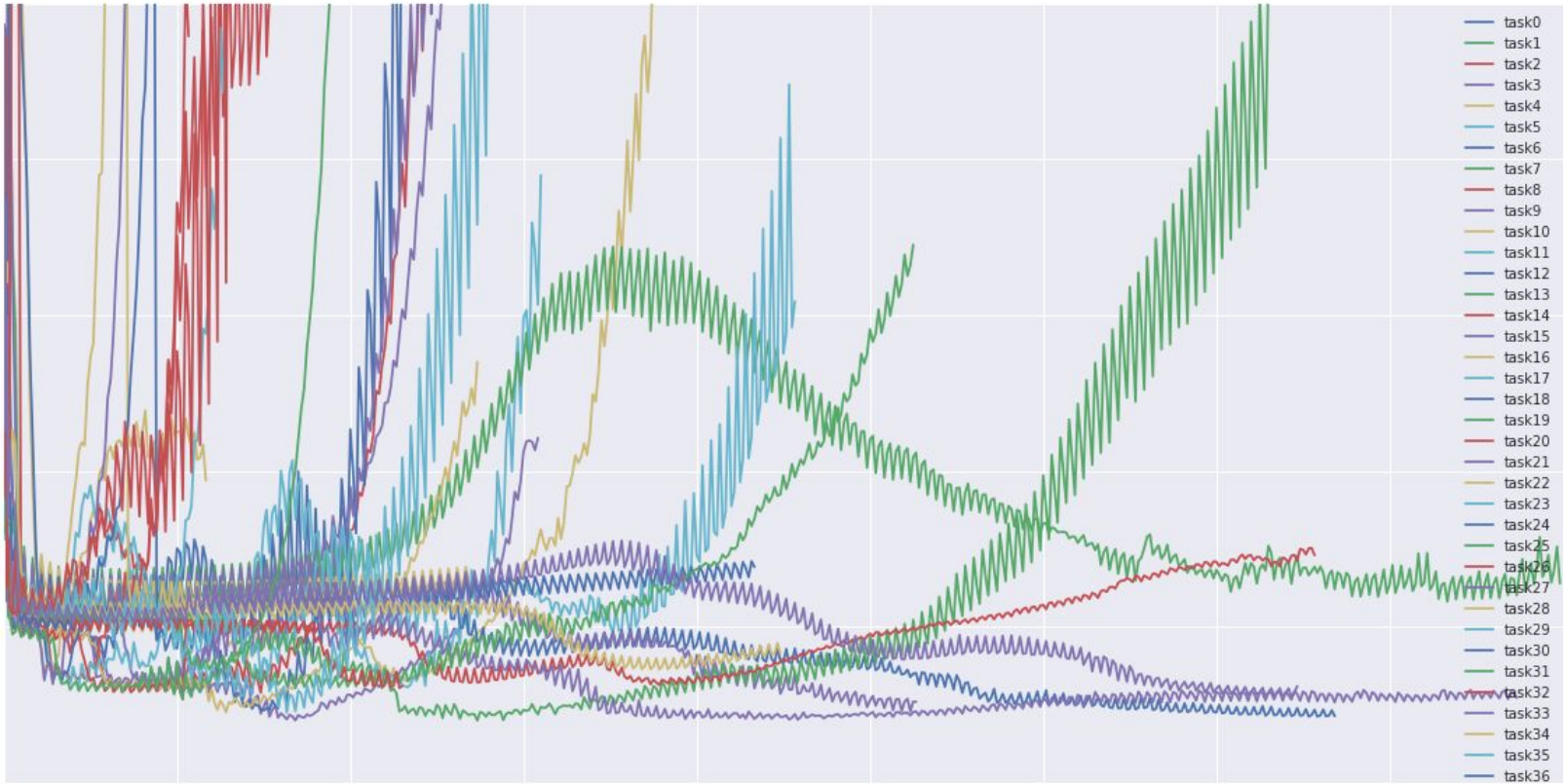
Cross-validation

We develop "command centers" to visualize all our models training with different hyperparameters

check out [weights and biases]



You can plot all your loss curves for different hyperparameters on a single plot



# Choosing Hyperparameters

**Step 1**: Check initial loss
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**Step 4**: Coarse grid, train for ~1-5 epochs
**Step 5**: Refine grid, train longer
**Step 6**: Look at loss and accuracy curves
**Step 7**: GOTO step 5

# Hyperparameters to play with:

- learning rate,
- Its decay schedule, update type
- regularization (L2/Dropout strength)

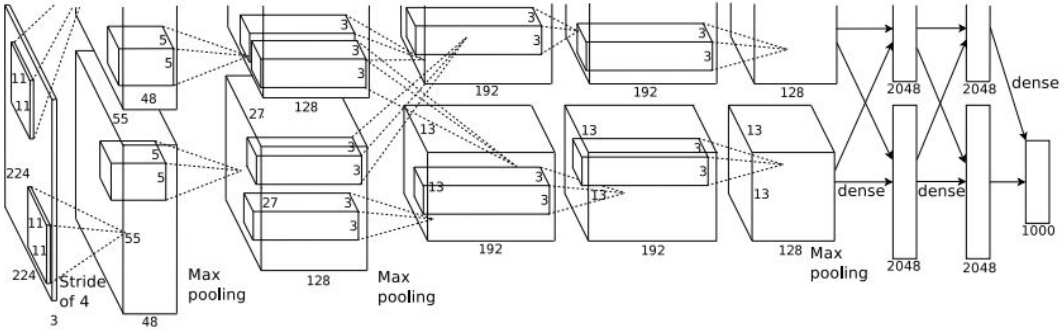
# Summary

- Improve your training error:
  - Optimizers
  - Learning rate schedules
- Improve your test error:
  - Regularization
  - Choosing Hyperparameters

# Visualizing and Understanding

# Today: What's going on inside ConvNets?






Class Scores:
1000 numbers

Input Image:
3 x 224 x 224

What are the intermediate features looking for?

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figure reproduced with permission.

# Today's agenda

**Visualizing what models have learned:**

- Visualizing filters
- Visualizing final layer features
- Visualizing activations

**Understanding input pixels**

- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

**Adversarial perturbations**

# Today's agenda

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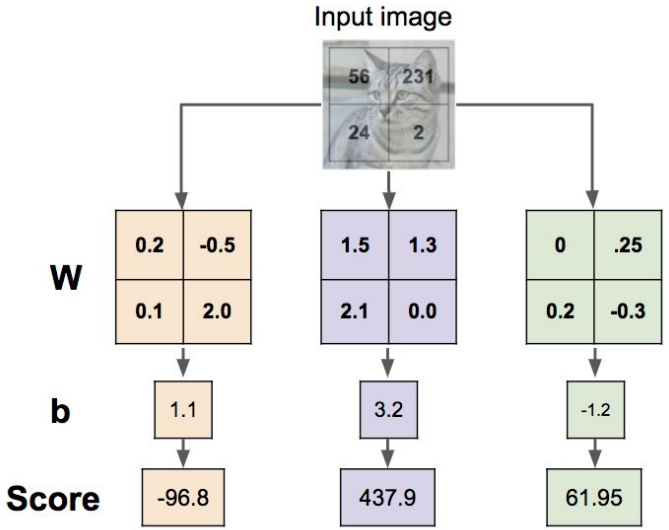
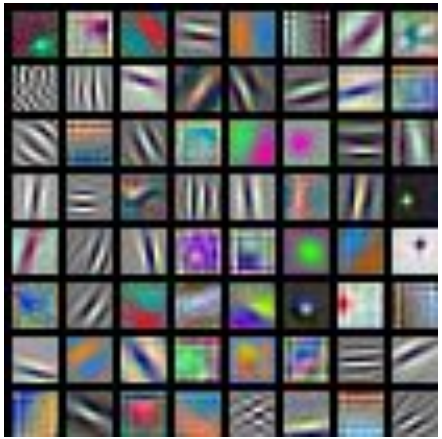
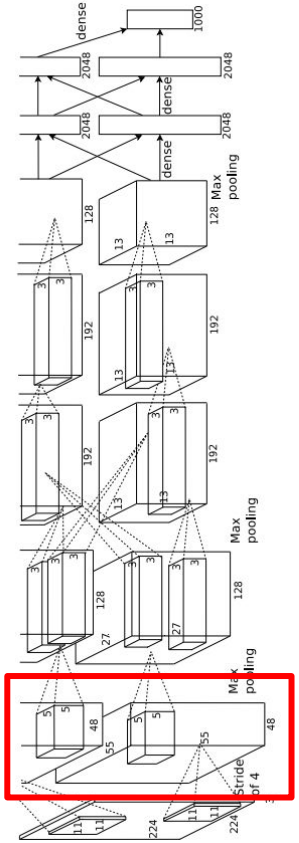
# Interpreting a Linear Classifier: Visual Viewpoint


# First Layer: Visualize Filters

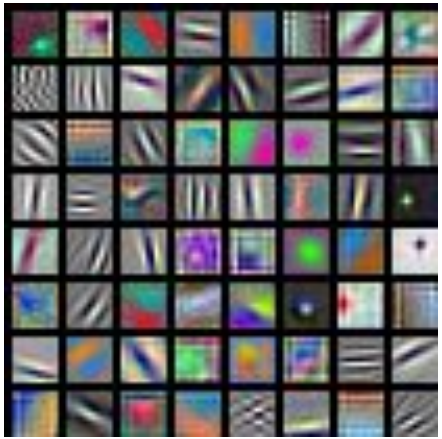


AlexNet:
64 x 3 x 11 x 11




Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
He et al, “Deep Residual Learning for Image Recognition”, CVPR 2016
Huang et al, “Densely Connected Convolutional Networks”, CVPR 2017

# First Layer: Visualize Filters

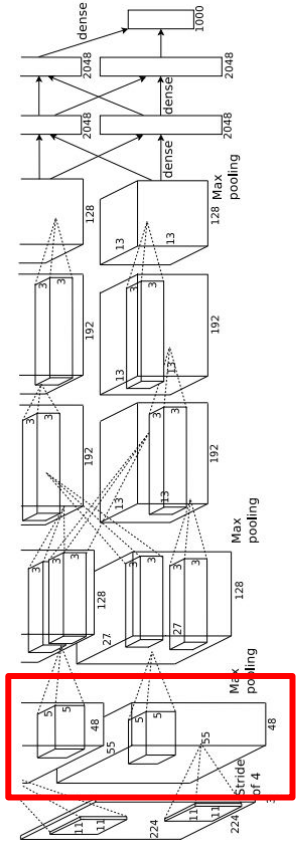


AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7




Krizhevsky, “One weird trick for parallelizing convolutional neural networks”, arXiv 2014
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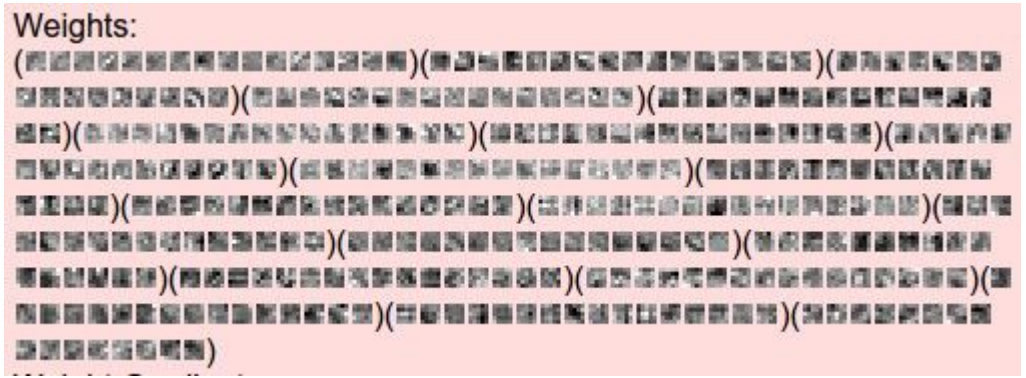
# Visualize the filters/kernels (raw weights)

We can visualize filters at higher layers, but not that interesting

(these are taken from ConvNetJS CIFAR-10 demo)


layer 1 weights

16 x 3 x 7 x 7




layer 2 weights

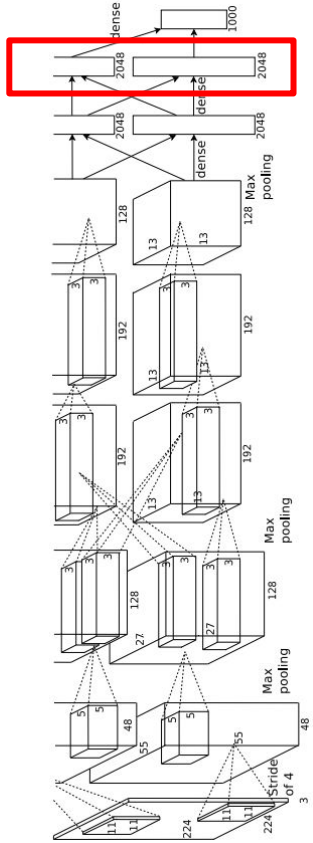
20 x 16 x 7 x 7


layer 3 weights

20 x 20 x 7 x 7

# Last Layer

FC7 layer

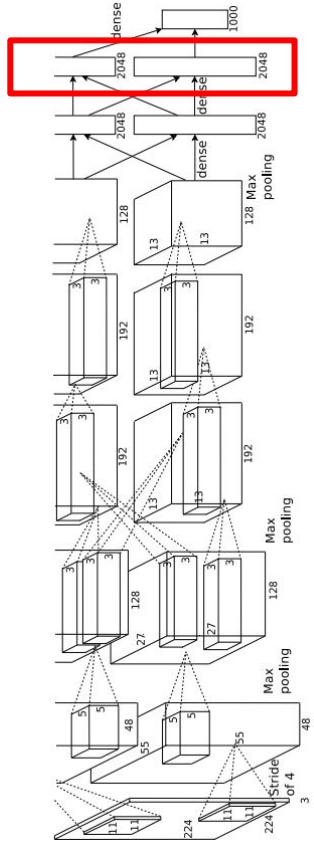



4096-dimensional feature vector for an image (layer immediately before the classifier)

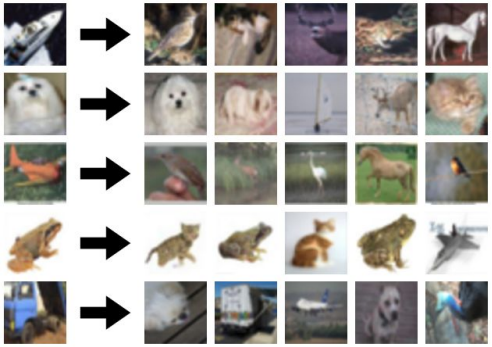
Run the network on many images, collect the feature vectors

# Last Layer: Nearest Neighbors

4096-dim vector




**Recall**: Nearest neighbors in pixel space

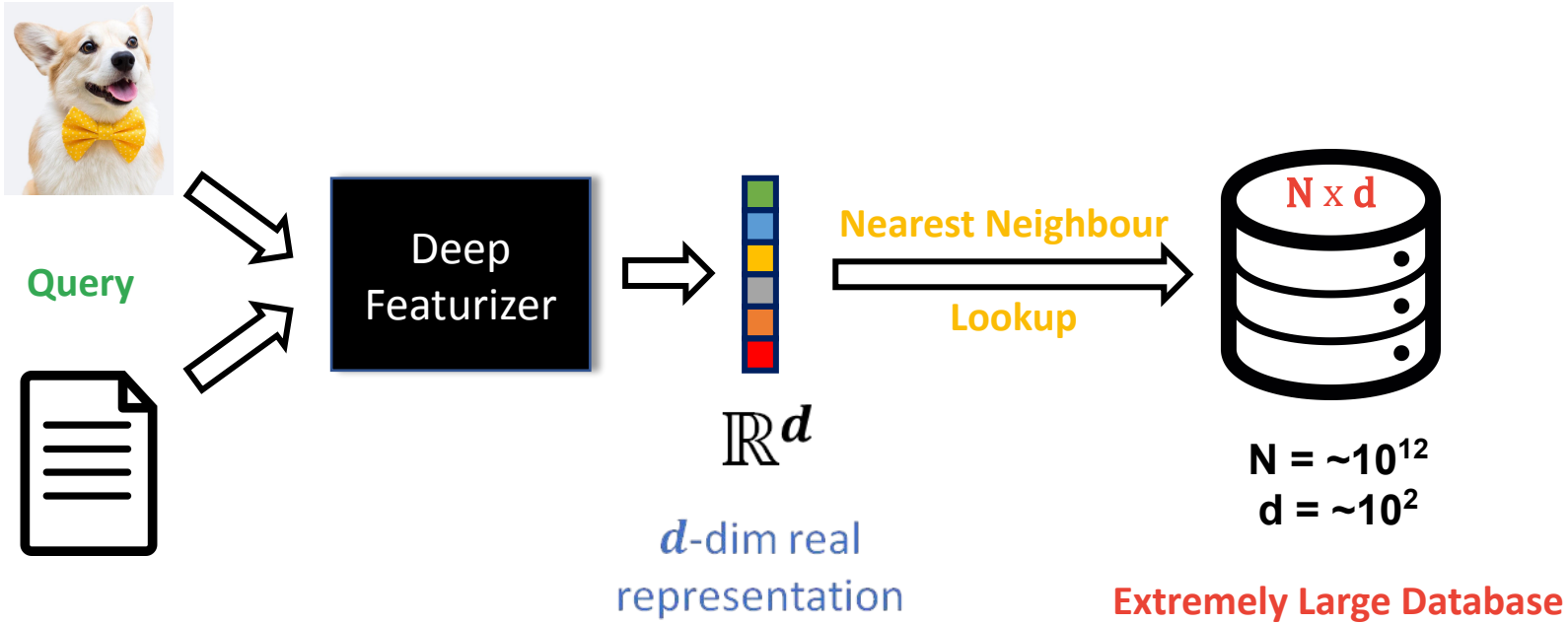


Test image

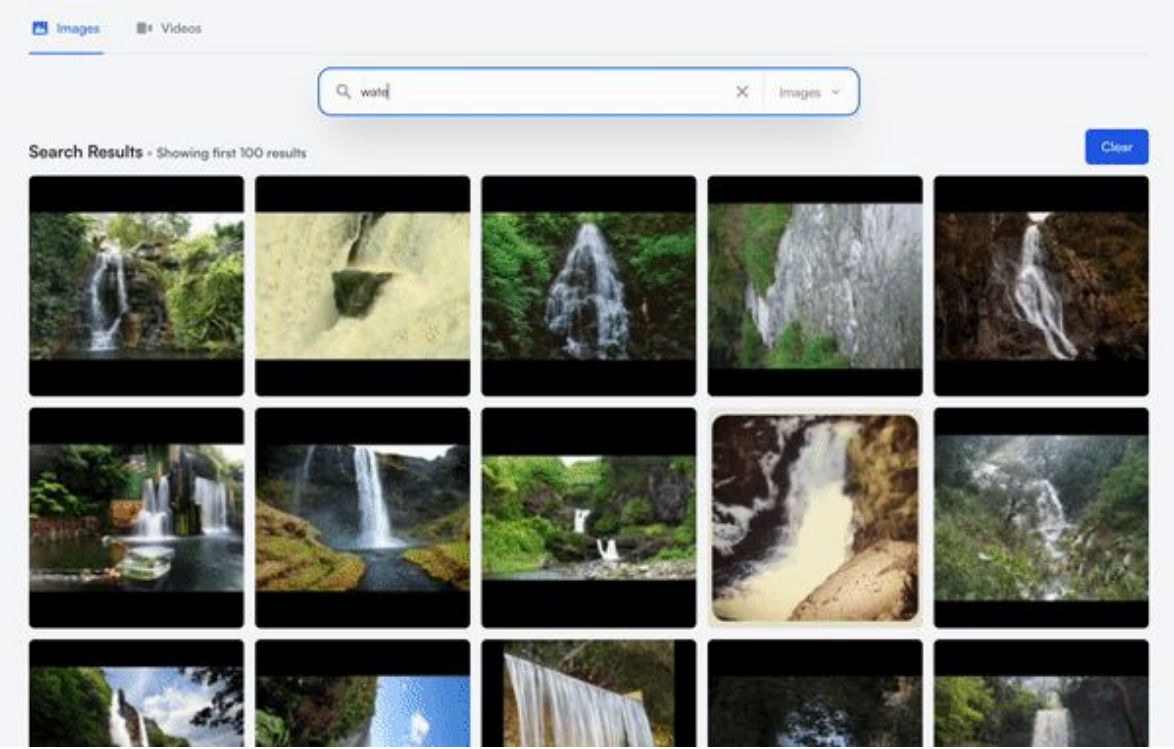
L2 Nearest neighbors in feature space

Krizhevsky et al, "ImageNet Classification with Deep Convolutional Neural Networks", NIPS 2012.
Figures reproduced with permission.

# Last Layer: Learned Metric for “Semantic” Search



# Last Layer: Modern Day Search



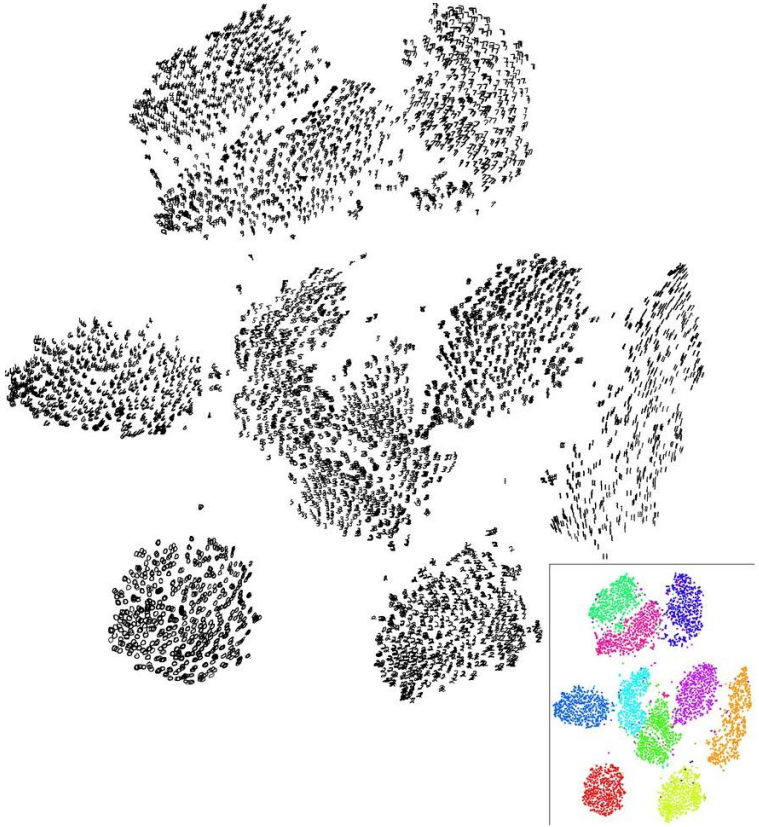

coactive.ai

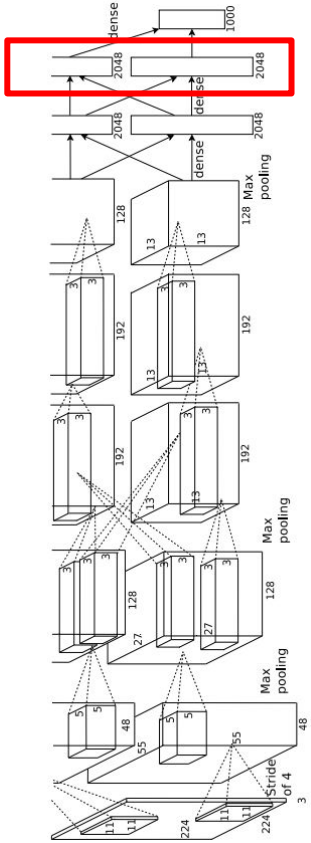
# Last Layer: Dimensionality Reduction

Visualize the “space” of FC7 feature vectors by reducing dimensionality of vectors from 4096 to 2 dimensions

Simple algorithm: Principal Component Analysis (PCA)

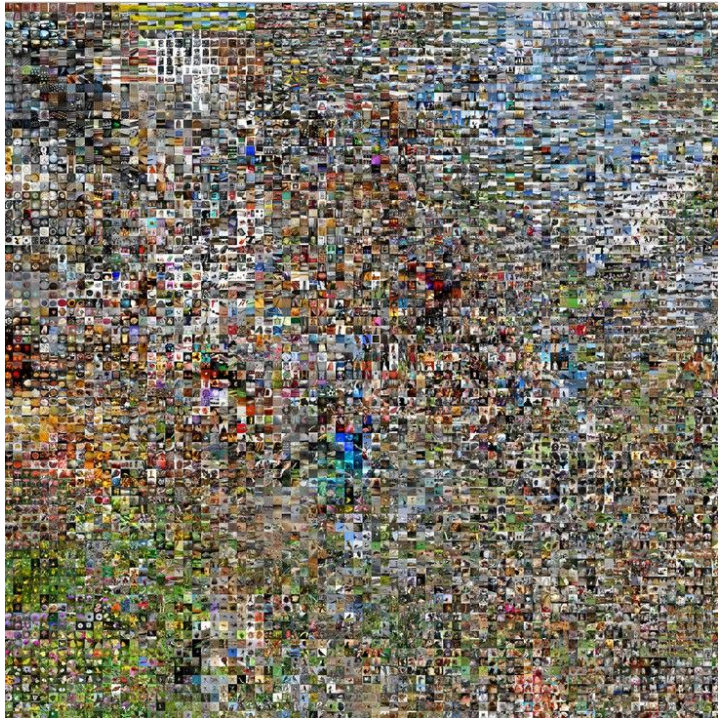
More complex: **t-SNE**

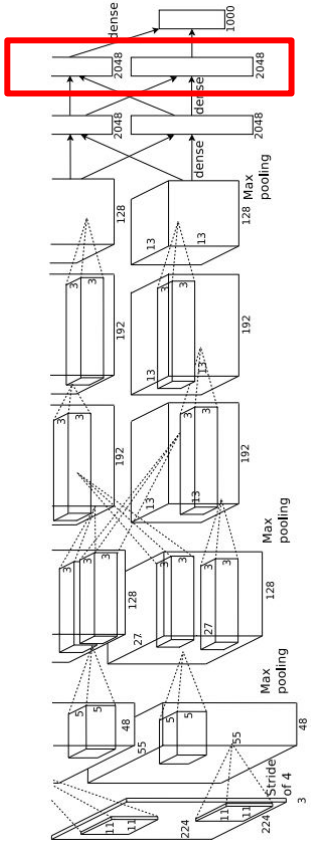





Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008

# Last Layer: Dimensionality Reduction





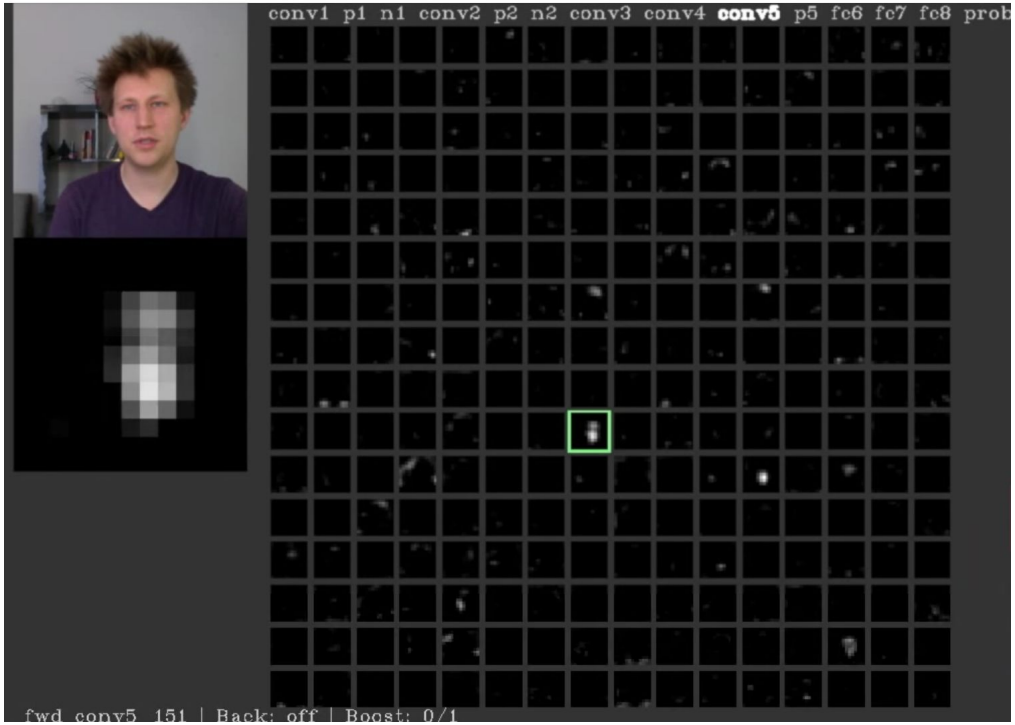

Van der Maaten and Hinton, “Visualizing Data using t-SNE”, JMLR 2008
Krizhevsky et al, “ImageNet Classification with Deep Convolutional Neural Networks”, NIPS 2012.
Figure reproduced with permission.

See high-resolution versions at
http://cs.stanford.edu/people/karpathy/cnnembed/

# Visualizing Activations

https://www.youtube.com/watch?v=AgkfIQ4IGaM

conv5 feature map is 128x13x13; visualize as 128 13x13 grayscale images




Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
Figure copyright Jason Yosinski, 2014. Reproduced with permission.

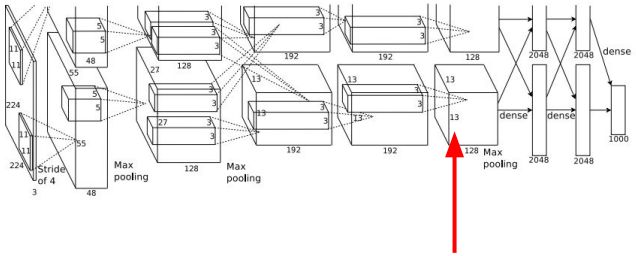
# Today's agenda

**Visualizing what models have learned:**
- Visualizing filters
- Visualizing final layer features
- Visualizing activations

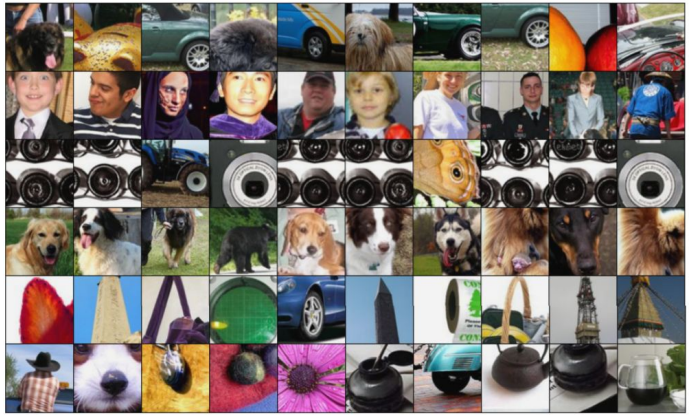
**Understanding input pixels**
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

**Adversarial perturbations**

# Maximally Activating Patches







Pick a layer and a channel; e.g. conv5 is 128 x 13 x 13, pick channel 17/128

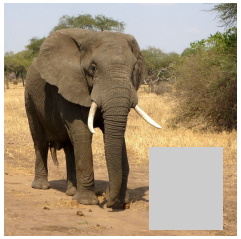
Run many images through the network, record values of chosen channel

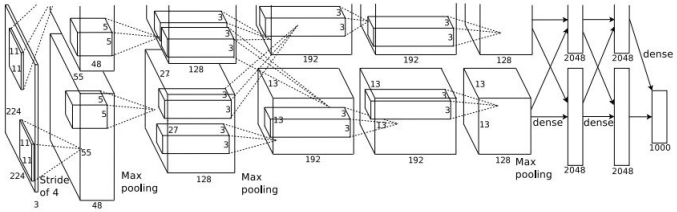
Visualize image patches that correspond to maximal activations

Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

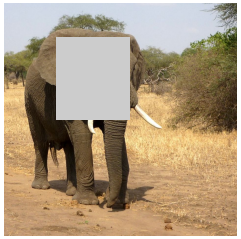
# Which pixels matter: Saliency via Occlusion

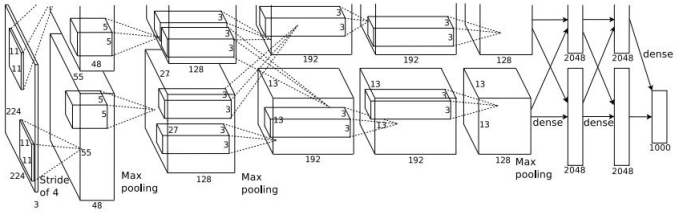
Mask part of the image before feeding to CNN, check how much predicted probabilities change






P(elephant) = 0.95



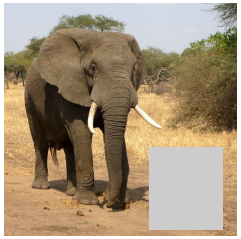


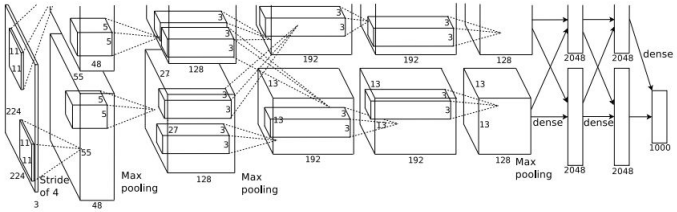

P(elephant) = 0.75

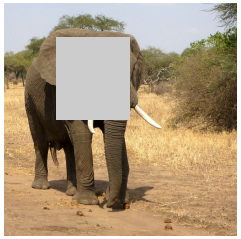
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014

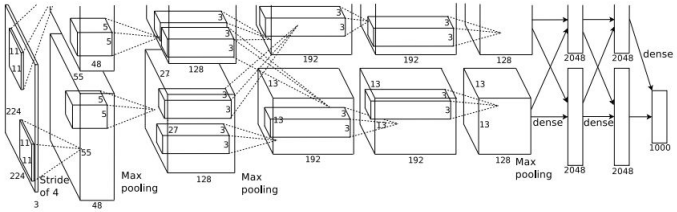
# Which pixels matter: Saliency via Occlusion

Mask part of the image before feeding to CNN, check how much predicted probabilities change



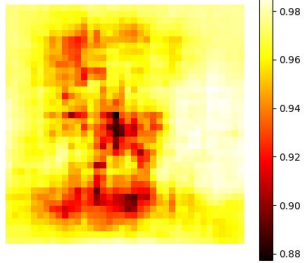


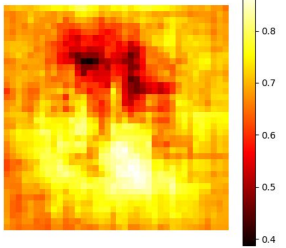



Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014

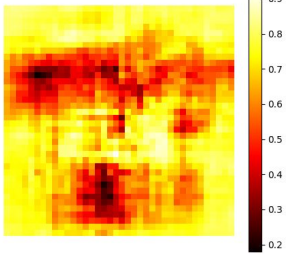
schooner




African elephant, Loxodonta africana



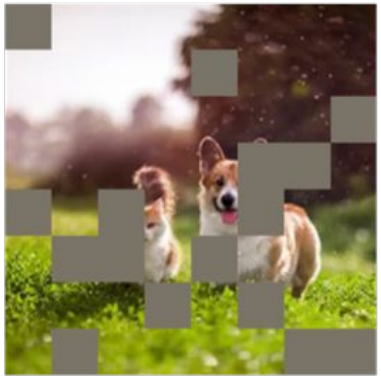

go-kart



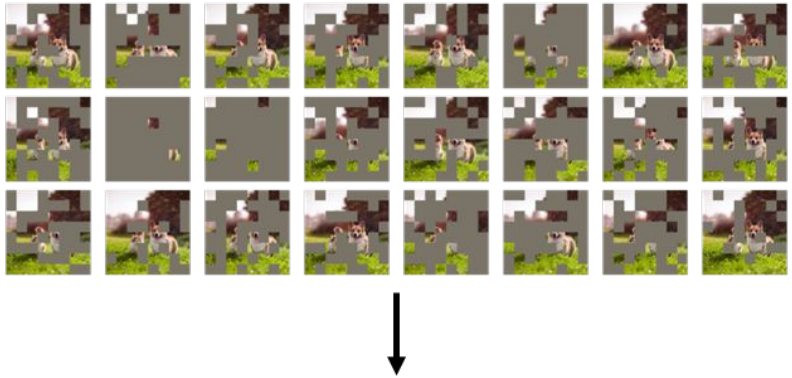

Boat image is CC0 public domain
Elephant image is CC0 public domain
Go-Karts image is CC0 public domain

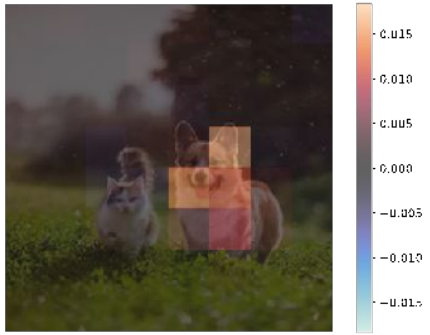
# Saliency via Occlusion: Shapley Values

P(corgi) = 0.99



P(corgi) = 0.8

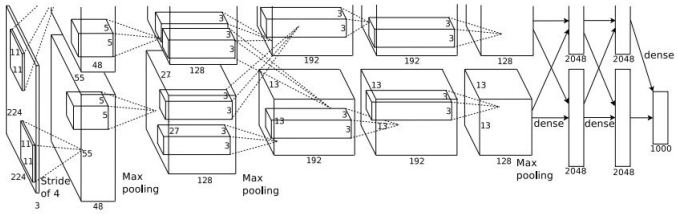




Credit: Ian Covert; Lundberg & Lee 2017

# Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities

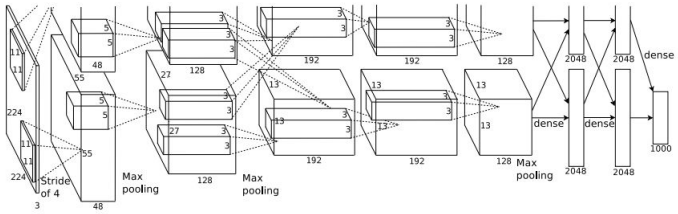



Dog

Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

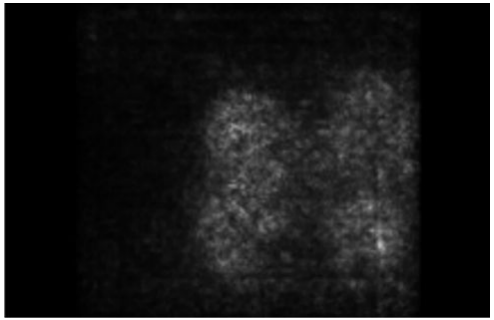
# Which pixels matter: Saliency via Backprop

Forward pass: Compute probabilities



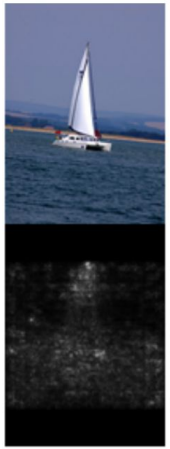
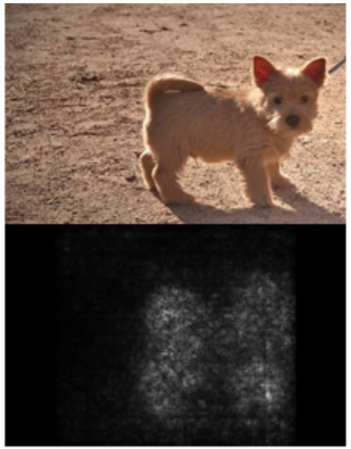
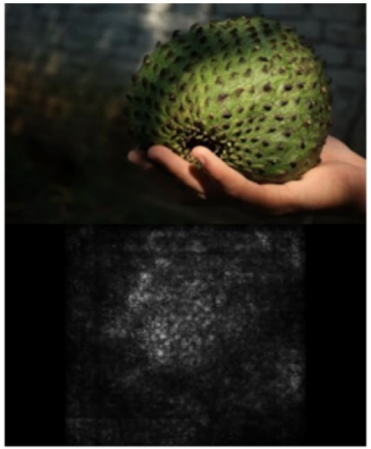

Dog

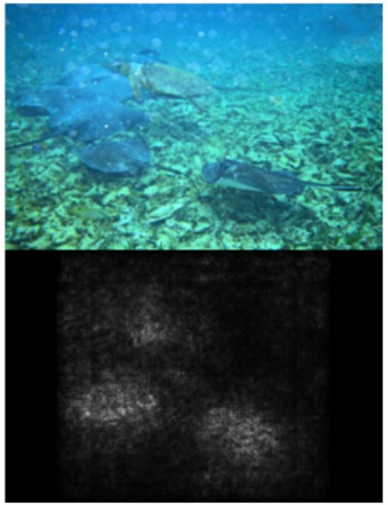
Compute gradient of (unnormalized) class score with respect to image pixels, take absolute value and max over RGB channels



Simonyan, Vedaldi, and Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.

# Saliency Maps

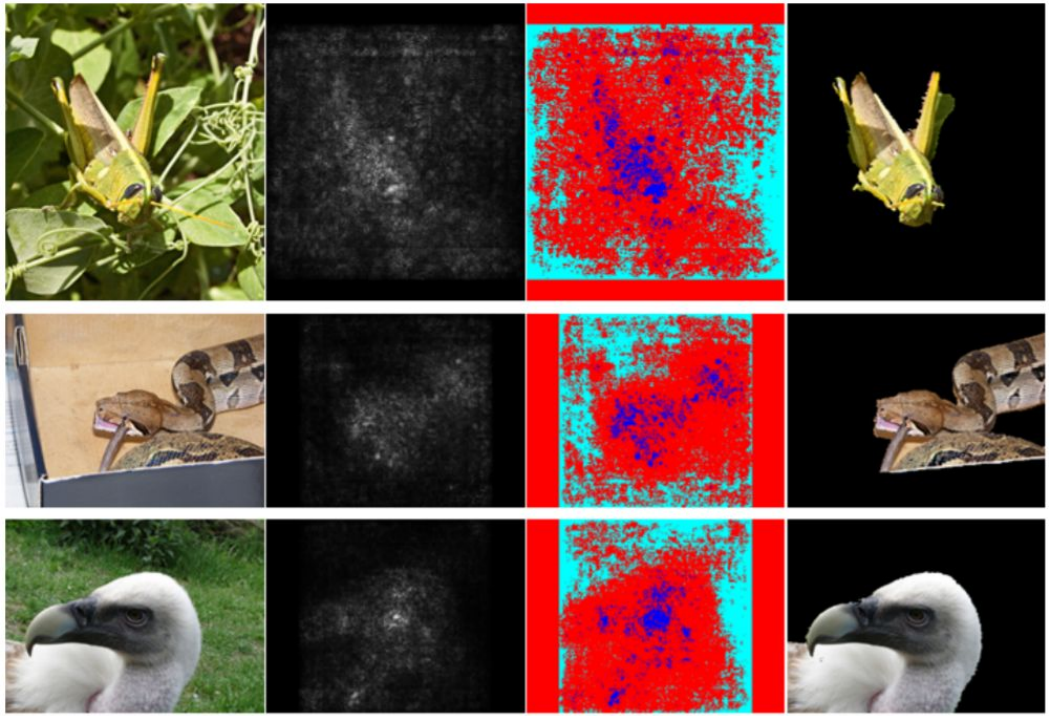






Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

# Saliency Maps: Segmentation without supervision

Use GrabCut on saliency map

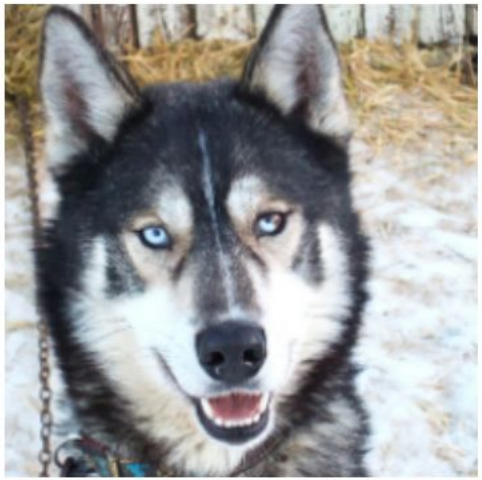


Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.
Figures copyright Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman, 2014; reproduced with permission.
Rother et al, “Grabcut: Interactive foreground extraction using iterated graph cuts”, ACM TOG 2004

# Saliency maps: Uncovers biases

Such methods also find biases

wolf vs dog classifier looks is actually a snow vs no-snow classifier

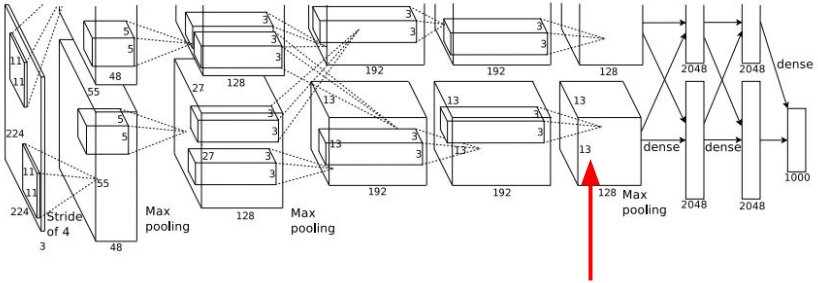


(a) Husky classified as wolf

(b) Explanation

Figures copyright Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin, 2016; reproduced with permission.
Ribeiro et al, ""Why Should I Trust You?" Explaining the Predictions of Any Classifier", ACM KDD 2016

# Intermediate Features via (guided) backprop

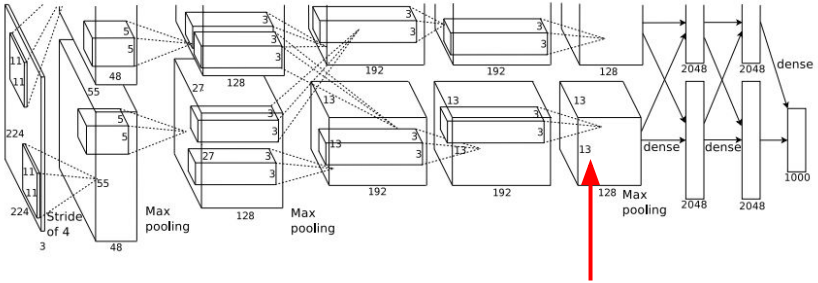



Pick a single intermediate channel, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of activation value with respect to image pixels

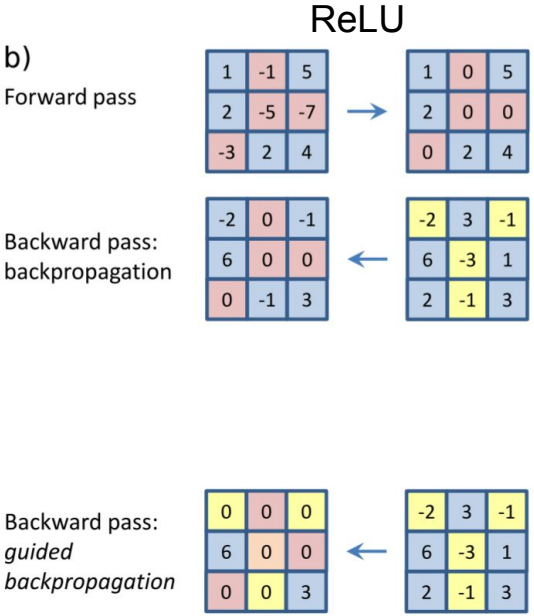
Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

# Intermediate Features via (guided) backprop




Pick a single intermediate neuron, e.g. one value in 128 x 13 x 13 conv5 feature map

Compute gradient of neuron value with respect to image pixels




Images come out nicer if you only backprop positive gradients through each ReLU (guided backprop)

Zeiler and Fergus, "Visualizing and Understanding Convolutional Networks", ECCV 2014
Springenberg et al, "Striving for Simplicity: The All Convolutional Net", ICLR Workshop 2015

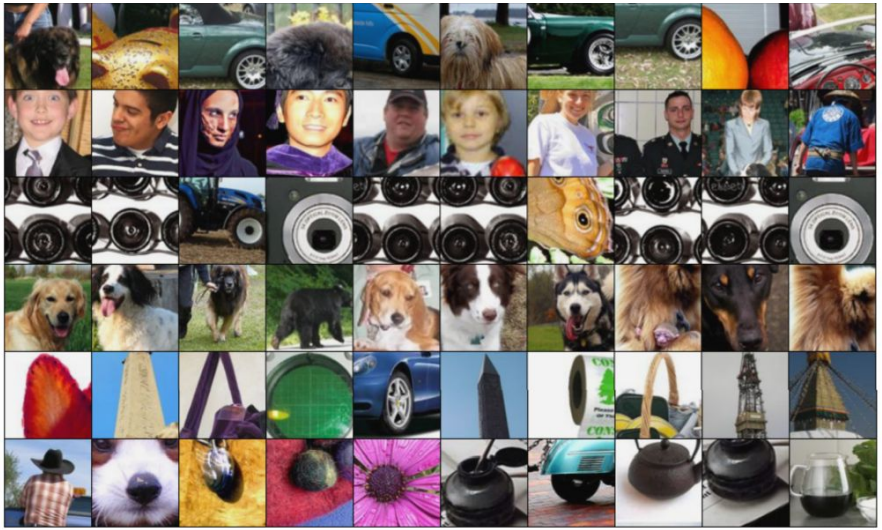
# Intermediate features via (guided) backprop

Maximally activating patches
(Each row is a different neuron)

Guided Backprop

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

# Intermediate features via (guided) backprop



Maximally activating patches
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Guided Backprop

Zeiler and Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014
Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

# Visualizing CNN features: Gradient Ascent

**(Guided) backprop**:
Find the part of an image that a neuron responds to

**Gradient ascent**:
Generate a synthetic image that maximally activates a neuron

$$I^* = \arg\max_I f(I) + R(I)$$

Neuron value

Natural image regularizer

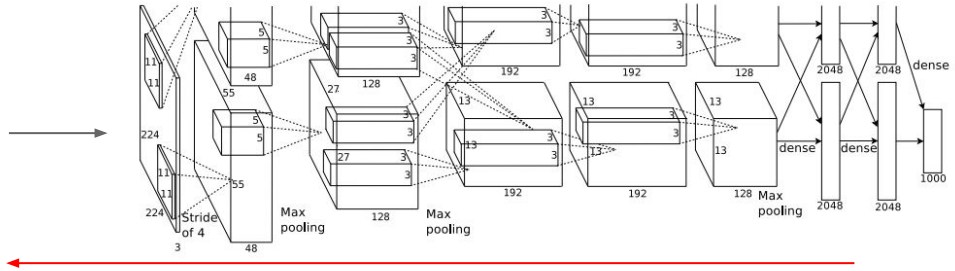
# Visualizing CNN features: Gradient Ascent

$$\arg\max_I \boxed{S_c(I)} - \lambda \|I\|_2^2$$

score for class c (before Softmax)

1. Initialize image to zeros

zero image




Repeat:

2. Forward image to compute current scores
3. Backprop to get gradient of neuron value with respect to image pixels
4. Make a small update to the image

# Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda \|I\|_2^2$$

Simple regularizer: Penalize L2 norm of generated image

Simonyan, Vedaldi, and Zisserman, “Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps”, ICLR Workshop 2014.

# Visualizing CNN features: Gradient Ascent

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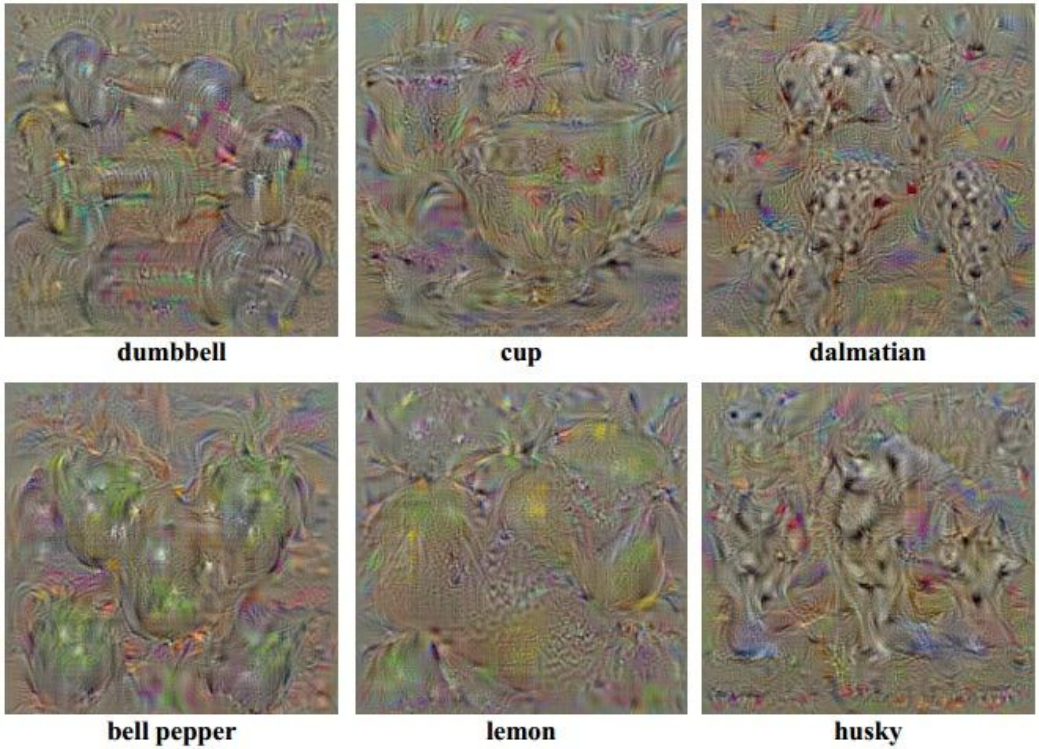


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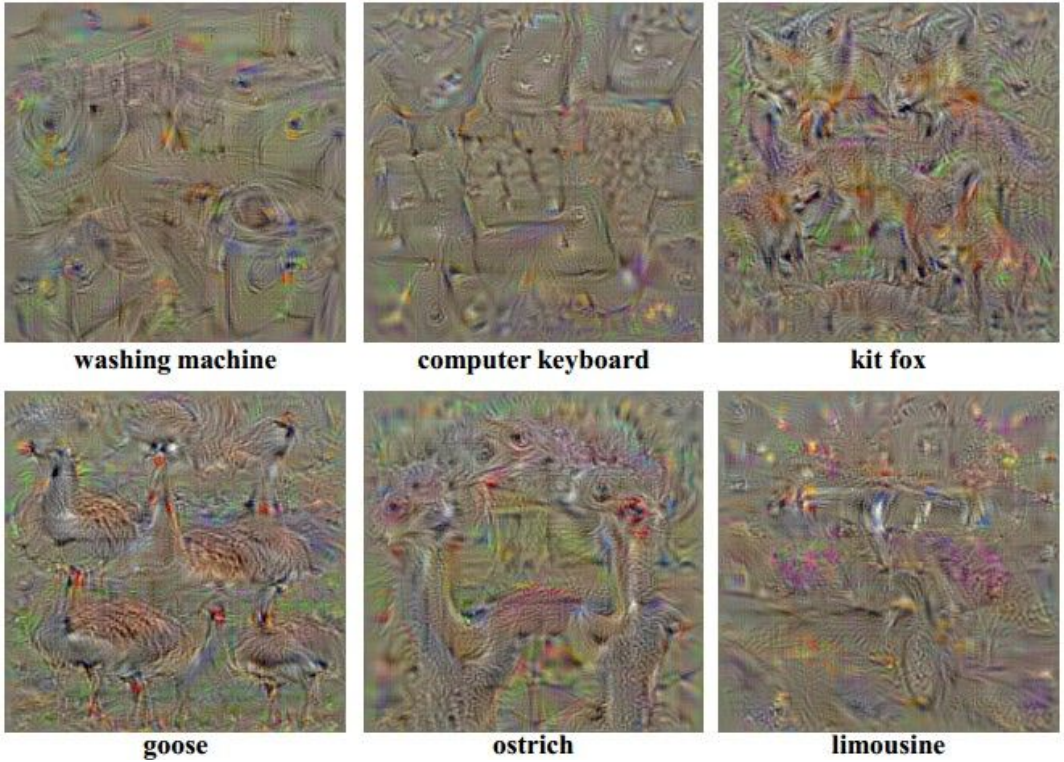



Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014. Figure copyright Jason Yosinski, Jeff Clune, Anh Nguyen, Thomas Fuchs, and Hod Lipson, 2014. Reproduced with permission.

# Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda \|I\|_2^2$$

Better regularizer: Penalize L2 norm of image; also during optimization periodically

(1) Gaussian blur image
(2) Clip pixels with small values to 0
(3) Clip pixels with small gradients to 0

Yosinski et al, “Understanding Neural Networks Through Deep Visualization”, ICML DL Workshop 2014.

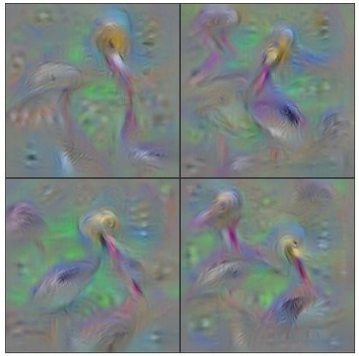
# Visualizing CNN features: Gradient Ascent

$$\arg\max_I S_c(I) - \lambda \|I\|_2^2$$

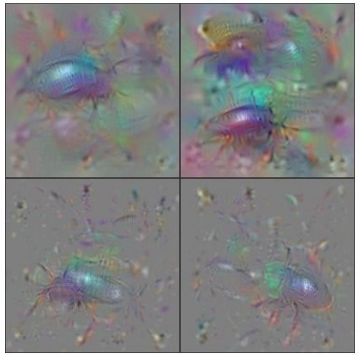
Better regularizer: Penalize L2 norm of image; also during optimization periodically

(1) Gaussian blur image
(2) Clip pixels with small values to 0
(3) Clip pixels with small gradients to 0

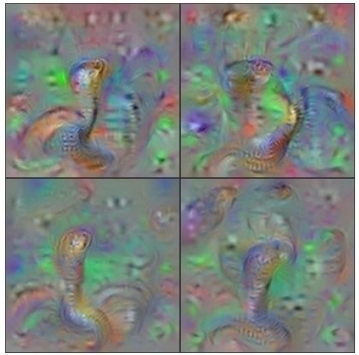
Flamingo



Pelican



Ground Beetle



Indian Cobra

Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

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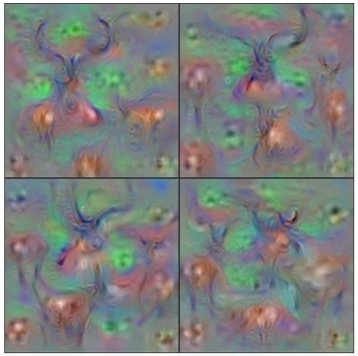
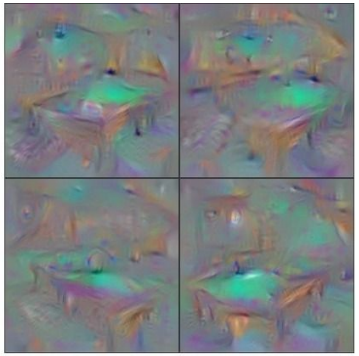
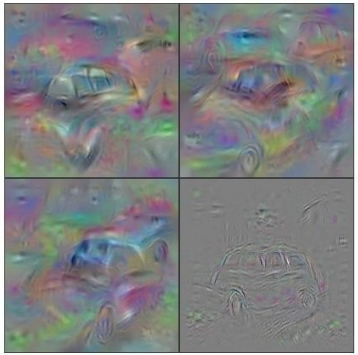


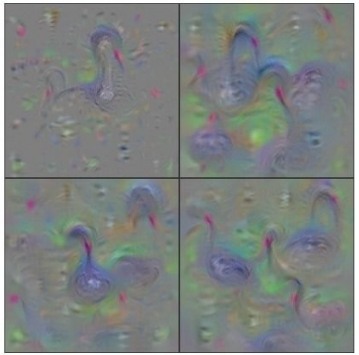
Hartebeest



Billiard Table



Station Wagon

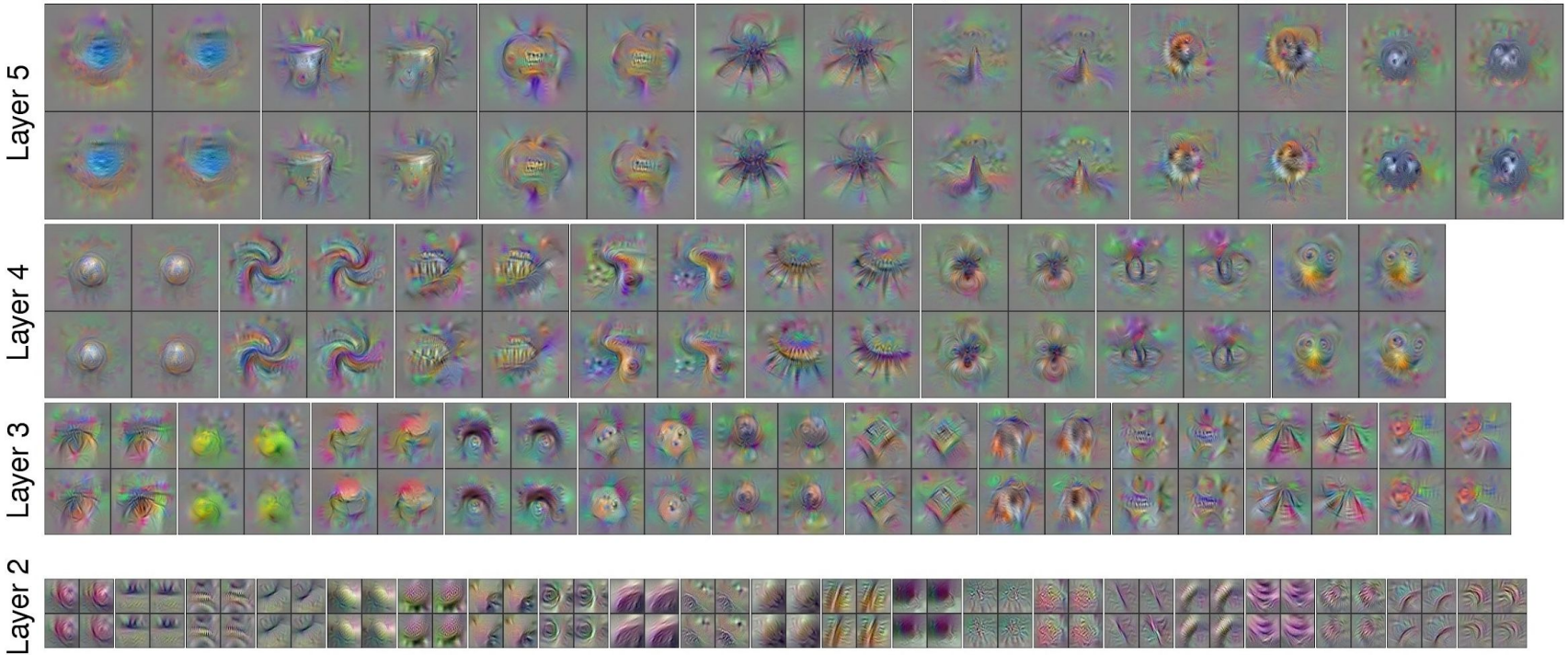


Black Swan

Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.

# Visualizing CNN features: Gradient Ascent

Use the same approach to visualize intermediate features




Yosinski et al, "Understanding Neural Networks Through Deep Visualization", ICML DL Workshop 2014.
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# Visualizing CNN features: Gradient Ascent

Adding “multi-faceted” visualization gives even nicer results:
(Plus more careful regularization, center-bias)

Reconstructions of multiple feature types (facets) recognized by the same “grocery store” neuron

Corresponding example training set images recognized by the same neuron as in the "grocery store" class

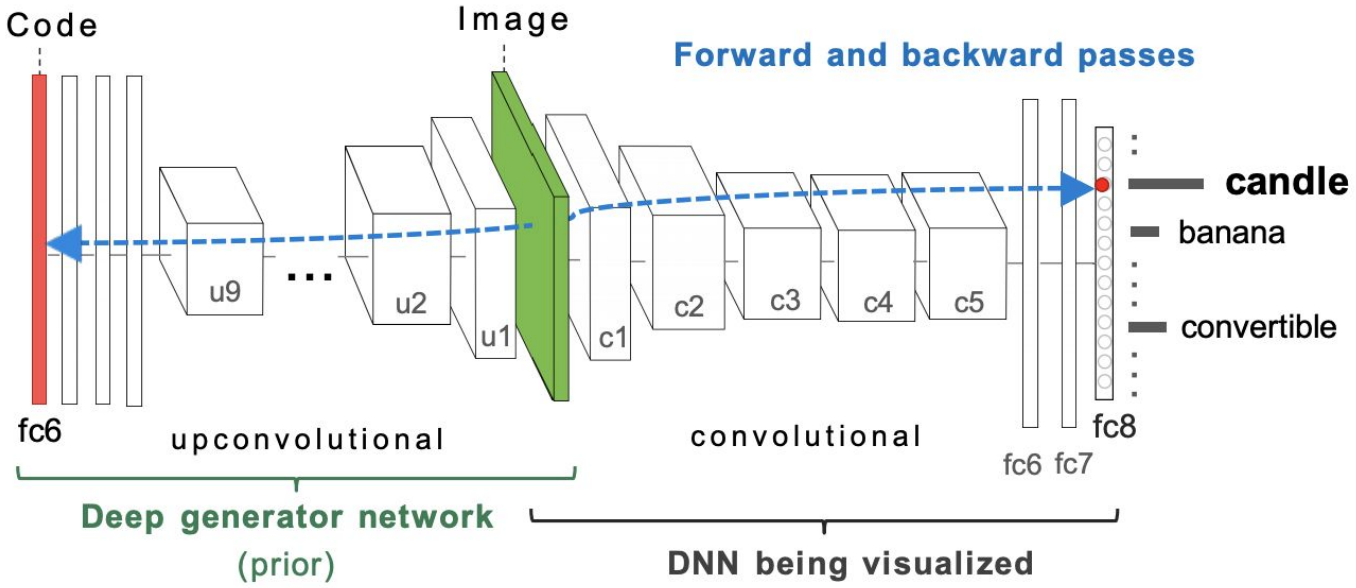

Nguyen et al, “Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks”, ICML Visualization for Deep Learning Workshop 2016.

# Visualizing CNN features: Gradient Ascent


Nguyen et al, "Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks", ICML Visualization for Deep Learning Workshop 2016.
Figures copyright Anh Nguyen, Jason Yosinski, and Jeff Clune, 2016; reproduced with permission.

# Visualizing CNN features: Gradient Ascent

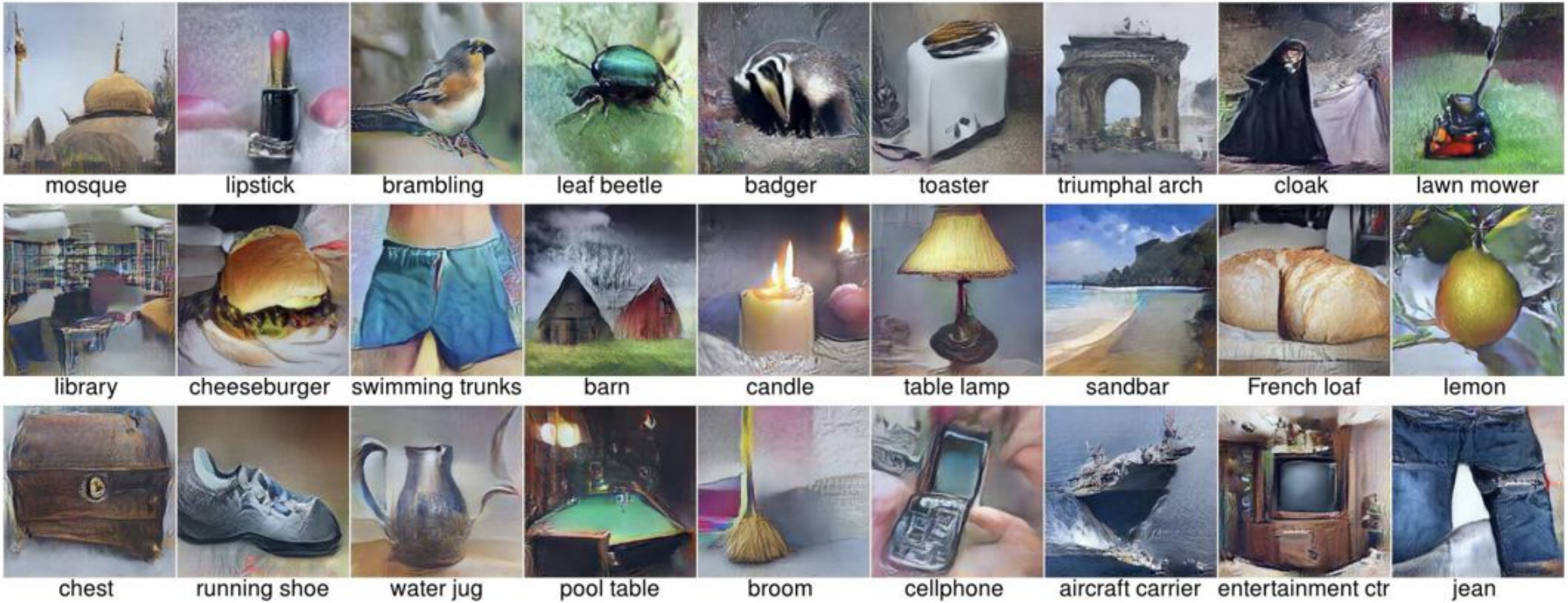
Optimize in FC6 latent space instead of pixel space:




Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016
Figure copyright Nguyen et al, 2016; reproduced with permission.

# Visualizing CNN features: Gradient Ascent

Optimize in FC6 latent space instead of pixel space:




Nguyen et al, "Synthesizing the preferred inputs for neurons in neural networks via deep generator networks," NIPS 2016
Figure copyright Nguyen et al, 2016; reproduced with permission.

# Today's agenda

**Visualizing what models have learned:**
- Visualizing filters
- Visualizing final layer features
- Visualizing activations

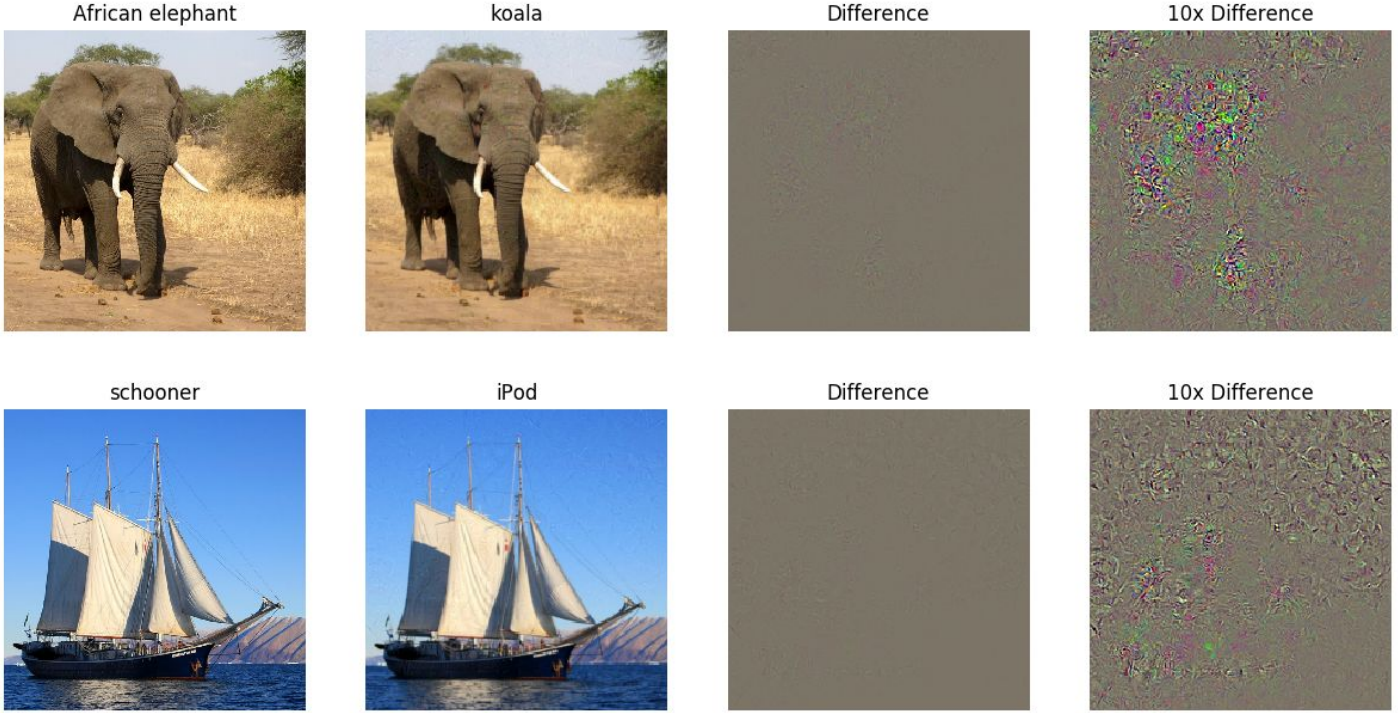
**Understanding input pixels**
- Identifying important pixels
- Saliency via backprop
- Guided backprop to generate images
- Gradient ascent to visualize features

**Adversarial perturbations**

# Fooling Images / Adversarial Examples

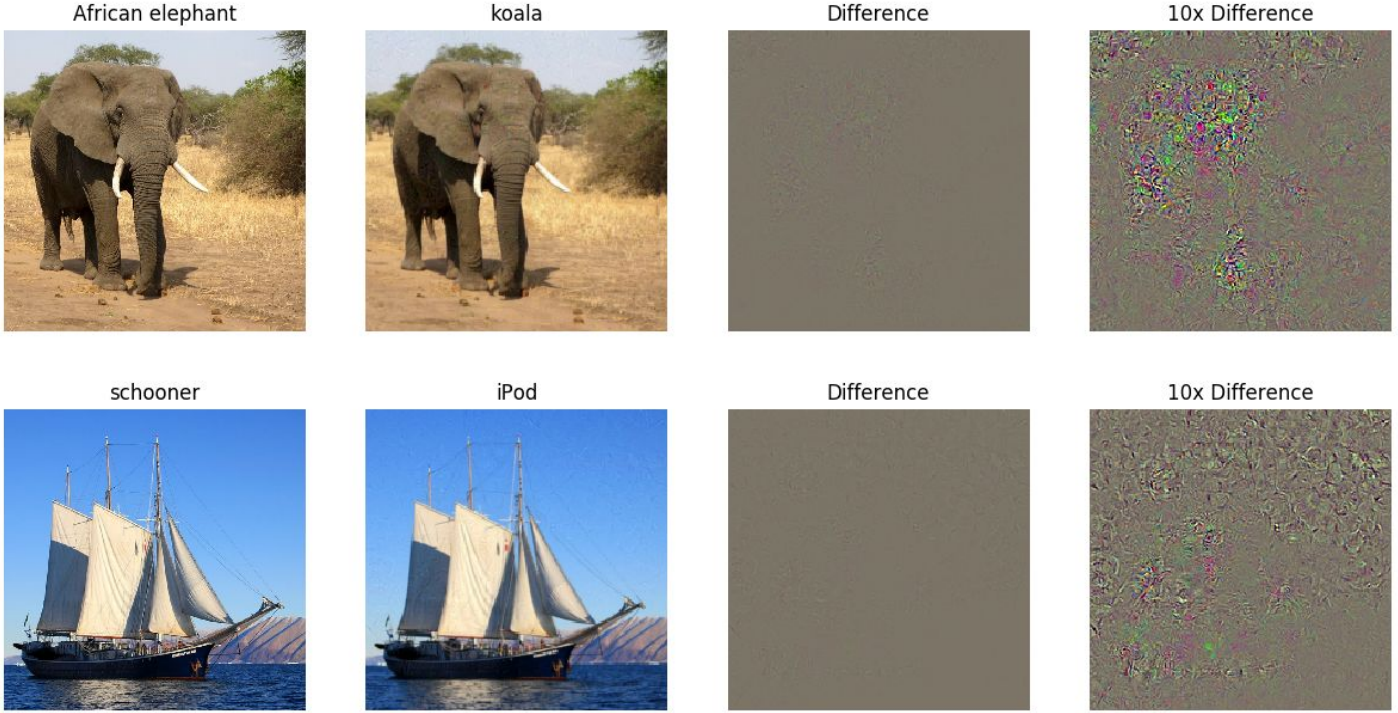
(1) Start from an arbitrary image
(2) Pick an arbitrary class
(3) Modify the image to maximize the class
(4) Repeat until network is fooled

# Fooling Images / Adversarial Examples



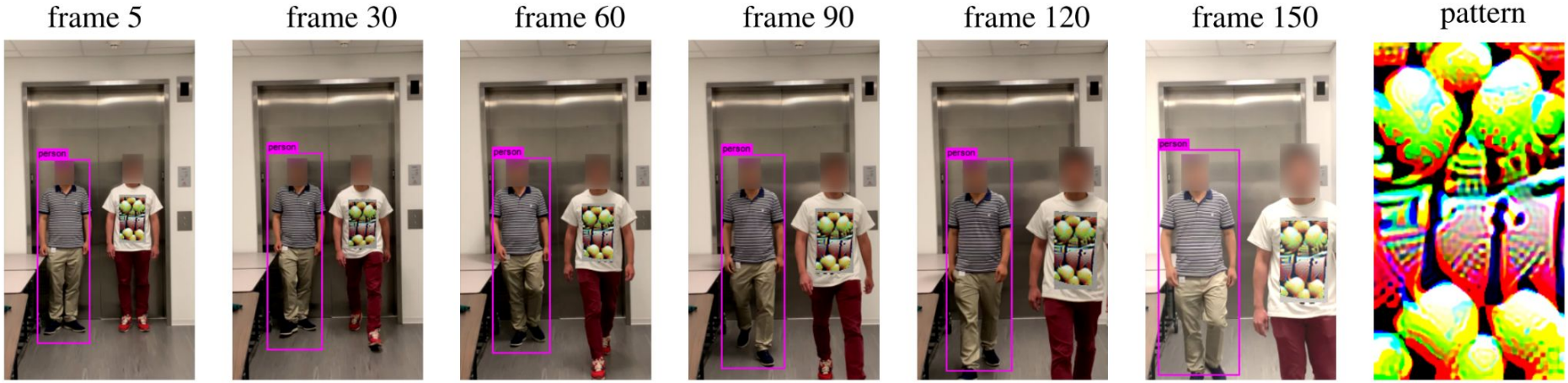

Boat image is CC0 public domain
Elephant image is CC0 public domain

# Fooling Images / Adversarial Examples




Check out Ian Goodfellow's lecture from 2017

# Fooling Person Detectors and Self-driving Cars

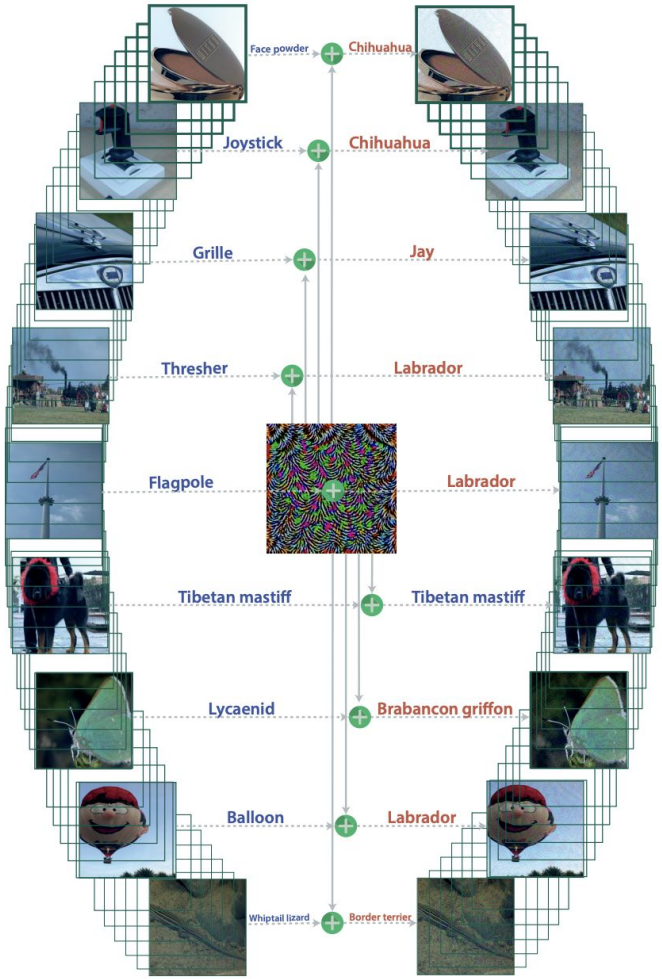




Xu et al., 2019; Eykholt et al., 2018

# Fooling Images / Adversarial Exa

Universal perturbations




Moosavi-Dezfooli, Seyed-Mohsen, et al. "Universal adversarial perturbations." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
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# Summary

Many methods for understanding CNN representations

**Activations**: Nearest neighbors, Dimensionality reduction, maximal patches, occlusion
**Gradients**: Saliency maps, class visualization, fooling images, feature inversion

**Adversarial Examples:** To confuse the models

Next time: **Introduction to language**